

**ZERO-INFLATED COUNT MODELS WITH APPLICATION TO ANNUAL TRENDS
IN THE INCIDENCE OF SELECTED INFECTIOUS DISEASES AMONG UNDER-5
CHILDREN IN OYO STATE, NIGERIA**

BY

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**A DISSERTATION SUBMITTED TO
THE DEPARTMENT OF EPIDEMIOLOGY AND MEDICAL STATISTICS,
FACULTY OF PUBLIC HEALTH, COLLEGE OF MEDICINE,
UNIVERSITY OF IBADAN**

**IN PARTIAL FULFILMENT OF
THE REQUIREMENT FOR THE AWARD OF
MASTERS OF SCIENCE DEGREE IN MEDICAL STATISTICS**

JANUARY, 2016

ABSTRACT

Cases of infectious diseases reported monthly to health facility are usually presented as count data potentially with excess zeros. Poisson and negative binomial regression have been used for modeling count data but do not take into account the presence of excess zeros and the problem of over-dispersion. Hence, this study was designed to model the annual trends in the incidence of infectious diseases among under-5 children using the better of two statistical models - zero inflated negative binomial (ZINB) and zero inflated Poisson regression (ZIP) - to determine the effects of month, year and geographical location on the occurrence of malaria, pneumonia, diarrhoea and measles among under-5 children.

A longitudinal surveillance data of under-5 children was obtained from the Integrated Diseases Surveillance and Response (IDSR) of Oyo State Ministry of Health from 2010 to 2014. The number of cases of malaria, pneumonia, diarrhea and measles per local government area were outcome variables and explanatory variables were month of reporting, year of reporting and the LGAs. Descriptive statistics were conducted to check for the presence of over-dispersion. Model comparisons were performed between ZINB and ZIP and the best model was selected based on the values of Vuong z-statistic, AIC and BIC selection criteria. The ZINB regression model was used to determine the effects of month, year of reporting and LGA on the occurrence of infectious diseases, incidence rate ratios and 95% CI were recorded. The Analyses were conducted using SPSS version 20, Microsoft Excel and R statistical package.

The incidence of malaria cases decreased slightly from 35.81 per 1000 in 2011 to 35.64 per 1000 in 2013. The highest incidence rate of pneumonia was in 2012 (7 per 1000). The incidence rate for diarrhoea was (20.36 per 1000) in 2010. The incidence of measles was static at (1.01 per 1000) from 2011 to 2013. The Vuong z-statistic of the ZINB models were -17.079, 7.952, -12.372 and -3.656, the AIC corrected were -17.079, -7.952, -12.372 and -3.577 and BIC corrected were -17.079, -7.952, -12.372 and -3.355 for malaria, pneumonia, diarrhea and measles respectively. ZINB model showed $V < -1.96$ on the three tests criteria for the four infectious diseases, thus indicating that ZINB had the best fit.

The risk of malaria was highest in 2014 by 258.9% (IRR = 3.589, 95% CI: 3.045, 4.232). The risk of pneumonia was lowest in 2014 by 82.7% (IRR = 0.173, 95% CI: 0.092, 0.324). Risk of diarrhoea was lowest in 2011 by 22.7% (IRR = 0.773, 95% CI: 0.688, 0.867). Risk of measles was lowest in 2012 by 90.4% (IRR = 0.096, 95% CI: 0.043, 0.217).

There was a general decline in the incidence of malaria and diarrhea, a modest increase in measles incidence and an initial rise with subsequent decline in pneumonia incidence. The year of reporting was a predictor of the occurrence of these infectious diseases. The study suggests ZINB as the best model for researchers dealing with count data having excess zeros and over-dispersion.

Key words: Under-5 children. Infectious diseases, Zero-inflated count models, over-dispersion, annual trends

Word count: 499

ACKNOWLEDGEMENTS

My first appreciation goes to the Almighty God, without whose provisions and guidance, my participation in this program of study would have been futile.

I would like to express my heartfelt gratitude to my supervisors Dr. (Mrs.) O.B. Yusuf and Dr. O. M. Akpa, who patiently read and gave their professional guidance during the conduct of this dissertation and to its success.

I thank the Head of Department Prof. (Mrs) O.I. Fawole, my daddy in the department Prof O. Ayeni and other lecturers Dr. Akinyemi, Dr. Adedokun, Dr. Afolabi, Dr. Fagbamigbe, Dr. Adebowale and Dr. Ghadebo in the Department of EMSEH for imparting knowledge in various ways and provided necessary supports throughout the course of my study.

I extend special thanks to Prof. & Prof.(Mrs) B. O. Osinusi for their immense support and encouragement throughout my program.

My thanks goes to my colleagues at the Data Unit, APIN Adults Clinic, College of Medicine, UI, Ibadan for your patience and encouragement throughout my program.

To my friends and course mates who contributed in diverse ways to the success of this program, Ayoola Agbaje, Kayode Fowobaje, Pst. Samson Olorunju, Abimbola Oyedapo, Busayo Aregbesola, Michael Ekholuenetale, Mrs. Grace Odunlami, Mrs. Funmi Adelokun, Mr. Koya Inubile, Miss Olawumi Adewumi, Mariam Jaiyeola, Opeyemi Ojo, Mr. Wegbom Anthony and Miss Linda Ugalahi. I say a big "thank you" to you all.

I thank my mother and late father, Prince and Mrs. P. Akande- Enakpene and my wonderful siblings for their prayers, unending love and support.

Finally, I appreciate my darling and kind hearted husband Dr. O. O. Akinpelu and my darling daughter Glory for their unconditional love and immense support during this study.

DEDICATION

To the Almighty God, in whom are all treasures of wisdom, knowledge and understanding.

To Him be the glory!

To my family for their love and support

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CERTIFICATION

I certify that this work zero inflated count models with application to annual trends in the incidence of selected infectious diseases among under-5 children in Oyo state, Nigeria was carried out by Akinpelu, Kehinde Pamela in the Department of Epidemiology and Medical Statistics, Faculty of Public Health, University of Ibadan under my supervision.



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LIST OF ACRONYMS

ZIP	Zero inflated Poisson
ZINB	Zero inflated negative binomial
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
LGA	Local Government area
WHO	World Health Organisation
CDC	Centre for Diseases Control
MAPS	Malaria Action Programme for States
UNICEF	United Nations Children's Education Fund
NDHS	National Demographic and Health Survey
IDSR	Integrated Disease Surveillance and Response
FMoH	Federal Ministry of Health
ORT	Oral rehydration therapy
HF	Health Facility

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND

Infectious diseases in children still remain a major public health problem in developing countries and globally. A common feature of children all over the world, from the richest to the poorest nations, is that they represent the most vulnerable segment of societies both socially and biologically. There is probably no other aspect of social life in which this is more apparent than in the area of healthcare. The future of a nation is inextricably linked with the wellbeing of its children, which is most readily assessed by the children's health status; thus, improvements in child health are generally a good measure of societal progress. For the avoidance of doubt, the World Health Organisation (WHO) has defined health as "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity". Childhood illness however, still contributes substantially to the global burden of disease (WHO 2008a).

Infectious diseases still constitute the major causes of morbidity among children under-five years of age in Nigeria (Abhulimhen-Iyoha and Okolo, 2012). Infectious disease mortality rates reach between 14 and 17 million people each year and cause significant illness in another 50 million. They cause 63 percent of all childhood deaths and 48 percent of premature deaths worldwide (WHO 2008a). Children under five years of age are particularly vulnerable to infectious diseases with more than 70 percent of all deaths from infectious disease occurring in children under five. These are mostly due to largely preventable diarrheal, measles, pneumonia, and febrile illnesses (WHO 2008 and Layne 2004).

In addition, child morbidity also remains a major problem in developing countries. In Bangladesh for example, morbidity differentials by place, region of residence, level of income, possession of land, level of household education, type of house and access to safe drinking water were investigated by Kabir *et al* (1997). The reports also showed that morbidity in children declined with the increase in the level of education of parents, while children living in houses

built with cement had lower prevalence of morbidity compared to the children who lived in mud houses (Kabir *et al*) in 1997. It has also been demonstrated that the age of a child is a significant factor in the prevalence of Acute Respiratory Infection (ARI), diarrhoea and fever among under-5 children. High morbidity has been reported among children aged 6 - 23 months especially as they were weaned off breast milk and were introduced to complementary food. A significant relationship between morbidity and children's immunization status was also reported (Elizabeth and Raj 2012).

Count data refers to the number of occurrences of an event of interest. Some examples of such data are the number of medical cases of diseases per month, the number of vehicles produced by a firm per year, the number of failures of a machine during a period, number of heart attacks, number of days of alcohol drinking, number of suicide attempts, and number of unprotected sexual encounters during a period of time etc. Such data arise quite often in biomedical and psychosocial research. It is well known that count data may exhibit over/under-dispersion and/or contain too many zeros than expected. These properties therefore necessitate the use of ad-hoc models such as the so called zero-inflated regression models, rather than the usual Poisson regression model which assumes the equality of the mean and the variance of the observations. Once the proportion of excess of zeros is estimated, the estimation can in turn be interpreted as an estimation of the lower bound of the number of occurrences of the event that were not counted. Indeed, an excess of zero count corresponds to an occurrence which, for one reason or another, is not taken into account. Therefore the knowledge of the proportion of excess of zeros in data of the incidence of a given infectious disease can help to improve the analysis of this data.

Zero-inflated models refer to models that are designed to accommodate excess zeros in count data. They are also referred to as added-zero models (Heilbron, 1994). Zero-inflated models have been developed for the Poisson model (Lambert, 1992), the Negative Binomial model (Ridout, Hinde, & Demetrio, 2001) and other models which are used in different fields such as econometrics, demography, medicine, public health, epidemiology, biology etc. One of their main interesting features is that they adjust well to data from a particular mixture of two

populations: one that has only zero counts and another in which the counts are the realizations of a discrete distribution. The main motivation for zero-inflated count models is that real-life data frequently display over-dispersion and excess zeros (Lambert 1992; Greene 1994).

Zero inflated Poisson Model deals with heterogeneity (that is when variation exists) associated with excess zeros and uses Poisson distribution that has been mixed with a point mass at zero to allow for the inclusion of additional structural zeros but does not handle over-dispersion (Dahiya & Gross, 1973; Heilbron, 1994; Lambert, 1992).

Zero inflated Negative Binomial Model (ZINB) model is especially suited to dealing with both over-dispersed and zero-inflated data (Yau *et al*, 2003; Ridout *et al*, 2001).

1.2 PROBLEM STATEMENT

Modelling discrete data in the health sciences continues to pose a challenge even for the most experienced researchers. For discrete outcomes, common methods of data analysis typically involve Poisson and negative binomial modelling techniques. However, these seemingly simple and straightforward approaches to modelling may not be appropriate when observations include large numbers of zeros (Lambert, 1992), such as the number of cases of infectious diseases in under-5 children in the 33 local government areas in Oyo State. The Poisson Regression model has been used to model count regression data which does not take into consideration the problems associated with count data, especially due to excessive number of zeros (Hinde and Demetrio, 1998).

In 1970s, many experts thought that the fight against infectious diseases was over and the threat of infectious diseases was less of a priority for infectious disease surveillance systems. Partly as a result of this, these systems were not maintained in large parts of the developing world, and this has hindered recognition of the magnitude of problems posed by new and re-emerging infectious diseases, and therefore effective action to control them (WHO, 2015)

Surveillance data are interpreted and implemented as a vertical activity in most low- and middle-income countries. Several challenges have been identified with vertical, single disease surveillance strategies. A prominent problem is that most vertical programmes are designed to merely provide data to central levels with little or no co-ordination between those collecting it, analysing it or those using it for decision-making (Revati et al. 2013).

The magnitude of the burden of infectious diseases in under-5 children remains high (Abhulimhen-Iyoha and Okolo, 2012), and this is because children of this age group are more susceptible to infectious diseases (WHO 2008 and Layne 2004). The method of estimation used for analysing infectious diseases may however pose a problem when we fail to account for extra zeros in the count dataset which may subsequently result in biased parameter estimates and wrong inferences while the problem of underestimation of standard error will not occur.

Therefore, this study aims to model annual trends in incidence of the selected infectious diseases among under-5 children in Oyo state surveillance data using zero inflated models. This will help provide accurate and valuable information for needs assessment, provide early warning signals for changes in trend, and help in program planning and evaluation and subsequent eradication of these diseases in under-5 children.

1.3 JUSTIFICATION

For this study, in view of the excess zeros that exist in the number of cases of selected (malaria, pneumonia, diarrhoea and measles) infectious diseases among under-5 children in the surveillance dataset, and to overcome these limitations of not taking into account excess zeros and underestimation of parameters, the Poisson and negative binomial models have been extended to better incorporate the excess zeros, giving rise to Zero Inflated Poisson and Zero Inflated Negative Binomial models. In addition, the use of the surveillance data helps us to know the current pattern of disease occurrence and the potential diseases in the population so that effective investigation, control, and prevention can be planned (Fernando et al. 2007). The choice of the independent variables in this study is that there may be seasonal variation from month to month in the incidence of specific diseases due to the biological nature of the causative

organism(s) or changes in the environmental conditions that influence spread of infectious diseases; the yearly incidences of these infectious diseases may also vary, reflecting absolute increases or decreases in frequency of occurrence, changes in frequency of reporting of new cases or the effects of government interventions. In addition, the local government areas may also exhibit differences in the relative prevalence of particular diseases due to peculiar local environmental and / or social factors. Analyzing the data from all the local government areas using zero inflated models will give a better holistic picture of the effect of these diseases (Fatiregun *et al*; 2014, Fatiregun and Odega, 2013 and Ngatchou-Wandji and Paris, 2011).

Although several studies have investigated cases of various infectious diseases (Ajadi *et al*, 2012; Abdulkarim *et al*, 2013; Siziya *et al*, 2013; Ziad *et al*, 2010; Mengistu *et al*, 2014 and Zhang *et al*, 2012), none of these studies have taken into account the excess zeros found in the data and did not use surveillance data. The magnitude of the effect of the infectious diseases over the years is therefore underestimated and under-reported due to the method of estimation.

This study used the Integrated Diseases Surveillance and Response data of Oyo state Ministry of Health from 2010-2014 to model the annual trends in incidence of the selected infectious diseases (Pneumonia, malaria, diarrhoea and measles) among under-5 children using the two most common zero-inflated models which are ZIP and ZINB models. The study considered the number of zero cases (i.e. the number of non-cases of infectious diseases among under-5 children). These models were also used to determine the effect of effect of seasonal, year of reporting and geographic location on the occurrence of the infectious diseases among under-5 children.

The zero inflated regression has a number of advantages including modelling excess zeros and accounting for over-dispersion. Therefore the knowledge of the proportion of excess zeros in data on the incidence of given infectious disease can help to improve the inference and provide valuable information for policymakers which will enable prompt intervention for the control of diseases.

1.4 OBJECTIVES

1.4.1 Main objective

To model annual trends in incidence of some selected infectious diseases among under-5 children in the 33 local government area of Oyo state, Nigeria.

1.4.2 Specific Objectives

The specific objectives of this study are:

1. To examine the pattern of infectious diseases (Pneumonia, malaria, diarrhoea and measles) among under-5 children over the year 2010 to 2014 in the 33 local government areas in Oyo state
2. To compare ZINB and ZIP models in the analysis of the number of infectious diseases (Pneumonia, malaria, diarrhoea and measles) among under-5 children in the presence of over dispersion.
3. To determine the effect of season, year of reporting and the geographical location on the occurrence of infectious diseases among under-5 children in Oyo state using the better of the ZIP and ZINB models.

CHAPTER TWO

LITERATURE REVIEW

2.1 INFECTIOUS DISEASES AMONG UNDER-5 CHILDREN

Infectious diseases are caused by pathogenic microorganisms, such as bacteria, viruses, parasites or fungi. The diseases can be spread, directly or indirectly, from one person to another. Some are transmitted by bites from insects or animals while others are acquired by ingesting contaminated food or water or exposure to organisms in the environment. Many infectious diseases, such as measles and chickenpox, are vaccine-preventable. Children are often at an increased risk for many of these diseases while their immune systems are still developing simply because of exposure. The hands of young children carry and transmit pathogens by directly contacting infected secretions or surfaces, then touching their own or another child's mucous membranes. Hand hygiene is therefore second only to immunization as an essential component of infection control and prevention (WHO, 2015 and Shope, 2014). The role of the environment cannot be overstated in the epidemiology of infectious disease. Environment not only refers to the natural and built (man-made) components, but also to changing climatic conditions which have far-reaching consequences on the epidemiology of infectious disease (Oluleye *et al.* 2010 and Adekola *et al.* 2014).

Malaria, acute respiratory tract infections and gastroenteritis are recognized by the World Health Organisation as the major causes of under-five morbidity and mortality (either in isolation or in combination with other causes) in developing countries (Bryce *et al.* 2005 and IMCI WHO 1995). The Integrated Management of Childhood Illnesses (IMCI) which targets these diseases (and others) aims to reduce death, illness and disability, and to promote improved growth and development incorporating both preventive and curative elements (*WHO IMCI*). The leading roles of malaria and bacterial infections like pneumonia, gastroenteritis and meningitis as major causes of childhood morbidity and mortality has been documented by other authors from Nigeria (Fagbule *et al.* 1987, Adeyokunnu *et al.* 1980 and Elusiyan *et al.* 2009) and other African

countries such as Ghana, Kenya, Tanzania, Zambia (Petit *et al*, 1995), Sierra Leone (Hodges *et al*, 1998), Ethiopia (Muhe *et al*, 1995) and Mozambique (Sacarlal *et al*, 2009).

Despite the advances in antimicrobial treatment and development of vaccines, it is ironic that infectious diseases still account for over two thirds of childhood mortality in developing countries (Black *et al*, 2003). Nigeria accounts for more than 70 percent of the estimated one million under-five deaths to preventable infectious diseases such as malaria, pneumonia, diarrhea and measles (Layne 2004).

2.2 Brief review and previous research on Malaria among under-5 children

Malaria is a major public health problem and global health challenge especially among children because of their vulnerability (CDC, 2014). Malaria is a parasitic and life threatening disease, transmitted by the bite of the female *Anopheles* mosquito. The symptoms of this disease include fever, nausea, vomiting, body weakness, headaches, constant sweats, dry cough and chills. It usually takes about 10-25 days for the symptoms to manifest. The transmission depends on the parasite, the vector, the human host and the environment. Malaria has been reported to be linked with poverty and the disease may also be a major limitation to economic development in tropical and subtropical regions because rainfall, warm temperatures, and stagnant waters provide habitats ideal for mosquito larvae (Sutherland and Hallett, 2009). Tropical areas like Nigeria have the best combination of adequate rainfall, temperature and humidity allowing for breeding and survival of anopheles mosquitoes. There are four known parasite species that can cause malaria in humans; *Plasmodium falciparum*, *Plasmodium vivax*, *Plasmodium malariae* and *Plasmodium ovale*. The most common of these are the *P. falciparum* and *vivax* but the most deadly of them is the *P. falciparum* (Martens, 1999).

The disease is endemic in over a hundred countries in the world. Approximately half of the world's population is at risk of malaria and nearly one million people die of the disease each year (WHO, 2011 and InterAction Global Health, 2013). Most malaria cases and deaths occur in sub-Saharan Africa. However, Asia, Latin America, the Middle East, and parts of Europe are also affected to a lesser extent. Hence, malaria affects children of all regions both poor and rich (WHO, 2011).

Globally, there were 216 million cases of malaria in 106 endemic countries and territories of the world in 2010; of these 86 percent of the victims were children under five years of age. In 2011, the world malaria report estimated a total of 655,000 malaria deaths in the world, majority of which were under-five children from Africa (WHO, 2011) Thus, the disease remains a leading cause of death in children under five years (Houeto et al, 2007). The World Health Organization and United Nations Children's Education Fund (UNICEF) also indicate in the *African Malaria Report* that an outrageously high number of over 3,000 children die from malaria in Africa daily with one child dying every 30 seconds (WHO 2003).

Malaria is endemic throughout Nigeria with seasonal variation in different geographic zones of the country. The Malaria Action Programme for States (MAPS) has documented that malaria is responsible for the death of more than 300,000 under-5 children annually and currently accounts for nearly 110 million clinically diagnosed cases per year, 60 percent outpatient visits, and 30 percent hospitalizations (NDHS 2008). In addition to the direct impact of malaria, there are also severe social and economic burdens on communities and the country as a whole, with about 132 billion Naira lost to malaria annually in form of treatment costs, prevention, etc. (FMoH and NMCP, 2009). In Nigeria, Malaria has the greatest prevalence, (close to 50%), in children aged 6-59 months in the South West, North Central, and North West regions of the country while the least prevalence, (27.6%), in children aged 6 to 59 months in the South East region. (Nigeria Malaria Fact Sheet). This is important to note because Oyo State, as the focus of this study, is located in the south western Nigeria and has been the recipient of several initiatives to combat the disease in under 5 children. One of the most recent of these intervention policies, the Affordable Medicines Facility-malaria, is a product of the Roll Back Malaria Partnerships and was developed to correct low access to ACTs as well as to prevent the development of resistance to artemisinin based therapies. Distribution of Affordable Medicine Facility-malaria Artemisinin Combination Therapies (AMFm-ACTs) started in Nigeria in 2011, however a recent study by Ajayi *et al* (2013) to assess the level of awareness and utilization of this facility discovered a very low level of awareness with only about 9.1% of respondents aware of its availability. Such lack of awareness greatly hampers the effectiveness of such intervention programmes because

these heavily subsidised drugs usually do not get to the target under-5 population and this is a major factor which may influence the observed pattern of malaria incidence among others.

It is important to take into account the effect of seasonal variations in Malaria transmission in Africa; previous studies have shown that the seasonality of rainfall, minimum temperature and irrigation are important determinants of the seasonality in the entomological inoculation rate (EIR) of Malaria (Musawenkosi *et al*, 2007). Furthermore, environmental factors have been shown to modify malaria transmission with clear differences documented between the patterns of transmission in rural versus urban areas (Donovan *et al*, 2012).

Onwuemele (2013), commenting on the pattern of malaria infection in Nigeria, noted that “the rate of malaria infection across space depends on dynamic processes involving complex climatic, environmental, physical, and social variables operating differently in space”. This study analysed the spatial variation in the rate of malaria infection using principal component analysis (PCA). Such analysis can help to explain variations and provide a basis for policy intervention.

In a study by Abdullahi *et al*, (2009) working in Sokoto, it was demonstrated that the highest prevalence rate was recorded in the month of August with 59.5% positive cases and the month of March had the least infection rate of 9.18%. Also the age group 0 - 5 years had the highest infection rate of 43.77%. Umaru and Uyaiabasi (2012), found an infection prevalence rate of 11.7% among children less than five years in Kaduna while a study by Edelu *et al* (2014), found malaria to be the leading cause of emergency room mortality (43%) among children between 1 to 5 years of age in a case series review conducted at the Children Emergency Unit of the University of Nigeria Teaching Hospital (UNTH), Enugu.

In a study by Olayemi *et al*, (2009) working among symptomatic patients who sought medical attention in Minna, Nigeria on “Epidemiology of malaria in relation to climatic variables between 2004 and 2007 demonstrated that the mean annual malaria incidence rates were significantly different over the 4-year study period with a drastic decline in malaria cases from 2005 through 2007. The monthly/seasonal climatic results revealed that the malaria incidence

rate were higher in the months of June to August and the highest malaria incidence rate of 170.75 ± 131.86 was recorded in August and this was not significantly different from the relatively lower rates recorded in September and October. There was therefore distinct seasonality in the monthly mean hospital attendance and malaria rates. Higher numbers of cases were recorded in the rainy than dry season. The study concluded that malaria incidence rates have decreased over the 4 years and that malaria transmission in the area is highly seasonal and strongly influenced by rainfall and relative humidity.

In a prevalence study on malaria in the Highlands of Obudu cattle ranch, Nigeria among individuals with malaria cases from 13 years and above, recorded the highest cases of malaria (34.6%) in 2010 with prevalence rate of 82.29/1000 and lowest cases (16.0%) in 2008 with prevalence rate of 39.61/1000. Children ages 5 and 14 years were recorded to be highest and under-5 years contributed 24.69%. Varying incidence rates were observed in the years within the period with 102 cases (31.5%) reported in dry season and 222 cases (68.5%) in the wet season. The study concluded determining the trend of incidence in the highland of Obudu cattle ranch would require further respective study in order to assess the influence of climate change on the transmission pattern. (Ukpong *et al.* 2015).

Finally, a study in Benin city by Enosolease and Awodu, 2003 who worked on seasonal variation of malaria parasitaemia in an urban tropical city from January to December 2001 found that the highest malaria incidence were in the months of July, August and September 56.7% and the lowest was found in the month of June. The study revealed that the peak of malaria incidence coincided with the height of raining season and low incidence in dry season which is between November and April accounted for 43.3%

2.3 Brief review and previous research on diarrhoea among under-5 children

Diarrhoea is as an abnormal increase in daily stool fluidity, frequency, and volume from what is considered normal for an individual. Diarrhoea can be caused by infectious organisms, including viruses, bacteria, protozoa, and helminths, that are transmitted from the stool of one individual to the mouth of another (feco-oral transmission). The disease is produced by a variety of etiological

agents, in which intestinal parasitic infection contributes to some extent. It remains one of the most important causes of morbidity and mortality in developing countries, especially in African countries. Diarrhea kills an estimated 2.5 million people each year and about 60-70% of them are under-5. The disease is responsible for over a quarter of the deaths of children in the world today. Most of these deaths occur in developing countries where an estimated 25% of under-five mortality is directly attributed to diarrhoea disease (Yilgwan and Okolo, 2012).

The main cause of morbidity of under-5 children from acute diarrhea is dehydration, which results from loss of fluid and electrolytes in stool. A simple and effective response to dehydration is a prompt increase in fluid intake. Exposure to diarrhoea causing agents is frequently related to the use of contaminated water and to unhygienic practices in food preparation and disposal of excreta (NDHS, 2008). Diarrhoea death from dehydration is preventable by oral rehydration therapy (ORT) which includes administration of a solution prepared from pre-formulated ORS packets or homemade fluid recommended by the National Diarrhoea Control Program. (i.e. recommend home fluid (RHF) such as sugar saltwater solution). Administration of increased fluids is also considered a type of ORT (Sule, 2003).

Seasonal variations have also been described in the incidence of acute diarrhoea disease in some studies. For example, researchers in Thailand and Mexico have shown from their investigations, clear variations in the incidence of diarrhea diseases in the winter season as compared with the summer / rainy seasons (Pinfold et al, 1991 and Villa et al, 1999).

Nearly one-third of episodes of severe diarrhoea are preventable by vaccination (i.e., against rotavirus and cholera), whereas vaccine-preventable pneumonias (i.e., those caused by *Streptococcus pneumoniae*, *Haemophilus influenzae* type b, and the influenza virus) account for at least a third of severe episodes and two-thirds of deaths.

Repeated analyses of the global burden of diarrhoea diseases have revealed secular trends and shown an impact of public health (Snyder and Merson, 1982, Berner et al, 1992 and Kosek et al, 2003). The estimates of diarrhoea incidence appeared relatively low before 1980 but this has

been attributed to methodological differences in statistical research (Bernet *et al*, 1992). These estimates are therefore, not directly comparable with the persistently high rates of diarrhoea noted in the 1990s especially among children between 6 to 24 months of age, hence the trends are the most relevant index (Gerald *et al*, chapt.9). It is notable that, though the estimated median incidence of diarrhoea disease in children under five in developing countries has not changed much since the early 1990s, incidence rates in Sub-Saharan Africa remain among the highest in the world (Gerald *et al*, chapt.9) and continue to show a peak in infant age 6 to 11 months, dropping steadily thereafter.

According to Davidson *et al*, (1998), the identified causes of diarrhoea in sub-saharan Africa include malnutrition, Vitamin A deficiency, and pathogens (commonly Rotavirus, *C. jejuni*, enterotoxigenic *E. coli*(ETEC), enteropathogenic *E. coli*(EPEC), *Vibrio cholerae*, *Shigella*spp., *Aeromonas* spp., *Salmonella* spp., *Plesiomonas shigelloides*, *Yersinia enterocolitica*, *Cryptosporidium*, *Giardia lamblia*, *Entamoeba histolytica*, *Strongyloides stercoralis* and *Isospora belli*— in decreasing order of frequency). Several workers (Charyeva *et al*, 2015, Aguwa *et al*, 2010 and Ande *et al*, 2004) have carried out studies to highlight not only incidence rates of diarrhoea diseases in Nigeria but also to assess the effects of identified risk factors, healthcare workers' knowledge and government interventions on the incidence of diarrhoea diseases. Most of these studies have only used basic statistical methods however, to analyse their findings.

2.4 Brief review and previous research on pneumonia among under-5 children

Pneumonia is a form of acute respiratory infection that affects the lungs. The leading cause of severe pneumonia in children in developing countries is *Streptococcus pneumoniae* bacteria, or pneumococcus. Pneumonia is spread in a number of ways by viruses and bacteria that are commonly found in a child's nose or throat, and can infect the lungs when inhaled. They may also spread via air-borne droplets from a cough or sneeze. The disease may spread through blood, especially during and shortly after birth (WHO, 2014). Symptoms of pneumonia can include cough, fever, diarrhoea, shortness of breath, chest pain and particularly chest retraction during respiration in under-5 children. Pneumonia is the world's leading killer of children under five, taking the life of one child every 23 second and accounting for 15% of deaths worldwide.

Pneumonia has been found to be associated with measles infection, and thus has been recognised as a major cause of death from measles in sub-Saharan Africa (Wesley *et al*, 1971 and Morton 1986). In the last decade, global health leaders have worked to turn the tide on pneumonia, which brought about a global movement to save children's lives through annual recognition of World Pneumonia Day (Erchick *et al*, 2011).

In 2010, according to recent WHO estimates, 868,000 under-5 children died in Nigeria and pneumonia is the second leading cause of death in this age group, killing more than 140,000 children each year. As a result of a high child mortality rate and a large population, Nigeria is second only to India in the total number of childhood deaths. Considering Nigeria's wealth of human and natural resources, access to health services are generally low by comparison and coverage rates for interventions that protect against, prevent, and treat pneumonia are lower than many other countries in the region. Pneumonia prevention in children is an essential component of a strategy to reduce child mortality. Immunization against Hib, pneumococcus, measles and whooping cough (pertussis) is currently considered the most effective way to prevent pneumonia (Erchick *et al*, 2011).

Notwithstanding the disease burden, Nigeria has made extraordinary progress in improving access to vaccination in recent years. Coverage for all vaccines increased substantially over the 2000-2010 decade. According to WHO/UNICEF estimates, DTP3 coverage more than doubled from 29% to 69% during this time period. In late 2011, Nigeria conducted an important mass campaign to deliver a new meningitis vaccine. In June 2012, Nigeria introduced the pentavalent vaccine, which protects against Hib, pneumonia and meningitis, along with four other childhood diseases (Erchick *et al*, 2011).

It is also important to note that childhood pneumonia is a climate-sensitive disease and must be described in the contexts of climate change and seasonal variations. In temperate settings, respiratory illness is most common in the winter months, while in tropical environments, the greatest incidence is during the rainy season (Paynter *et al*, 2010 and Dowell *et al*, 2003). Studies have also shown a strong association between the incidence of pneumonia (lower respiratory

tract infection) and exposure to environmental factors, most notably air pollution. Evidence especially incriminates indoor air pollution from domestic fires burning biomass fuels, primarily in the less-developed world, while the rising importance of traffic-related air pollution has also been identified (Smith et al 2011 and Laumbach et al, 2012).

Different researchers have identified the roles of poor living conditions and a hazardous environment in the incidence of pneumonia (acute infectious respiratory disease) (Singh and Singh, 2014, Akanbi *et al.* 2009). Akanbi *et al.*, reviewing the burden of respiratory disease in Nigeria, confirmed that acute respiratory infections are a major cause of morbidity and mortality among children, accounting for 20% of all deaths in under-5 children between 2000 to 2003 (Akanbi *et al.* 2009). The study also noted the seasonal variation in acute respiratory infections in Nigerian children with more episodes occurring during the rainy season.

2.5 Brief review and previous research on Measles among under-5 children

Measles is a highly contagious disease caused by the measles virus (a member of the paramyxovirus family) and it is normally passed through direct contact and through the air. The virus infects the mucous membranes, and then spreads throughout the body (WHO, 2015). Measles is usually characterized by fever of $\geq 38^{\circ}\text{C}$; maculopapular rash of about 3 days or more; with one or more of a combination of coryza, cough, conjunctivitis and Koplik's spots in the oral mucosa of measles infected individuals (Takeuchi *et al.* 2002).

The disease remains one of the leading causes of death among young children globally, despite the availability of a safe and effective vaccine. Approximately 145,700 people died from measles in 2013, mostly under -5 children in developing countries in parts of Africa and Asia. Measles infection is still prevalent in many developing countries most especially in parts of Africa where more than 20 million measles cases are reported annually (WHO, 2009).

In Nigeria, measles outbreaks have been increasingly common with 30, 194 and 256 outbreaks reported in 2006, 2007 and 2008 respectively. Most of these outbreaks occurred in the first

quarter of the year affecting mostly under-five children (WHO and AFRO, 2008). The disease exhibits a seasonal pattern with increasing incidence during the dry season in November-May.

It was estimated in Nigeria by the 2008 Demographic Health Survey (DHS) that the national measles coverage for children aged 12–13 months was 46% nationally, 60% in urban areas and 33% in rural areas (Fatiregun *et al*; 2014).

According to World Health Organization African Region (WHO AFRO, 2006), a measles outbreak is defined as “five or more reported suspected cases of measles in a health facility or local government area in one month with a plausible means of transmission” (FMOH and WHO, 2006). This defines the threshold that should elicit appropriate control measures like case finding, line listing of additional cases, improved case management and concentrated immunization activities in that local government area.

Children in Nigeria are given monovalent measles vaccine at 10 months of age. In 2005 and 2006, the Federal Government of Nigeria (FGN) through the National Programme on Immunization (NPI) conducted an integrated catch-up measles campaign in the south and north, respectively (WHO, 2007) and a nationwide follow-up campaign in 2008 (Goitem *et al.*, 2011), in collaboration with local and state governments.

As with the other disease under study, seasonal occurrence of measles has been identified and characterized by both local and international researchers (Omonijo *et al.*, 2011). Notably, Omonijo *et al* working in Ondo State, Nigeria, demonstrated a high disease transmission rate of measles in the months of January to May (dry season). This clearly demonstrates the importance of the thermal environment in the disease transmission (Omonijo *et al.*, 2010).

In a descriptive epidemiological study on the analysis of measles case-based surveillance data, it was found that between January 2007 and December 2012, 10187 suspected cases of measles were investigated through the case-based surveillance system. It was also revealed that the annual incidence of measles in Southwest, Nigeria rose from 1 case per million in 2007 to 23 cases per million in 2011. Cases were confirmed from all six states within the zone and most

(97.4%) were in individuals aged less than 20 years. In addition, the seasonal variation was confirmed with peaks of infection in the first and second quarters of the year. The study concluded that there was an increasing trend in the number of expected cases based on projections and the case-based surveillance provided an insight into understanding the epidemiology of measles infection in Southwest Nigeria (Fatiregun *et al*; 2014).

Furthermore, in a study on secular trend and epidemiology of measles in the Kingdom of Saudi Arabia to determine incidence of measles and progress towards its elimination, it was shown that measles incidence per 1,000,000 populations increased from 3.2 in 2009 to a peak of 12.8 in 2011 and a slight fall to 9.9 in 2012. About 50% of cases were in children under-five years, 12% were infants and 33% were 15 years and above. Of this total, 39% were unvaccinated and 16% had unknown vaccination status. Fifty-five percent of infants were not due for vaccination. Of children <5 years, 42% received vaccination. It was seen that spatial distribution is not countrywide in each of the four years but was seen to concentrate in the central and South West regions with 40% in Jizan and Jeddah. However the findings concluded that there was a general gradual downward trend in the occurrence of cases and peaks were seen in 2010 and onwards, the trend is slow and the peak is more flattened. It was further seen that high incidence of confirmed measles among unvaccinated infants requires strengthening of the immunization services and improvement in measles case surveillance for completeness of vaccination status (Ziad *et al*, 2014).

According to a study conducted by Fatiregun and Odega, (2013) on "Representativeness of suspected measles cases reported between January 2007 to June 2008 in local government area, Delta state", it was revealed that in the LGA records, 10% cases were individuals older than 14 years, compared with 20% in the same age group in the health facility record. Also it was seen based on the geographic location that 53% of measles cases among the hospital records came from a single location, in contrast to only 30% of the cases among the LGA records. It was demonstrated with time analysis that 30% of the cases in the LGA records occurred in August 2007, whereas 20% of hospital cases were reported in February and May 2008 respectively and

the study concluded that the two records types differed considerably in all of the characteristics used for comparison.

Lastly, a study on the impact of declining vaccination coverage on measles control in Abia state revealed that most of the cases of measles infection occurred in the dry season, with peaks in January and February (Umeh and Ahaneku, 2013).

2.6 Integrated Disease Surveillance and Response and Notifiable Diseases in Nigeria

Integrated Disease Surveillance and Response (IDSR) is a strategy and a tool to promote rational use of resources by integrating and streamlining common disease surveillance activities. Before the adoption and implementation of IDSR system in Nigeria, many disease control and intervention programmes still rely on their own disease surveillance system making efforts to improve their ability to obtain reliable and timely data in order to use information for taking action (FMoH, 2009. Isere et al, 2015).

After the adoption by the World Health Organization (WHO), African region of the Integrated Disease Surveillance and Response (IDSR) strategy as a regional strategy for disease control in 1998, Nigeria commenced efforts towards implementation of the IDSR strategy in June 2000 with an orientation workshop held to sensitize national programme managers of vertical programs and partners on IDSR. In January 2001, a steering committee on IDSR was inaugurated to steer the implementation process and all the 36 states in the Federation, including the Federal Capital Territory are currently implementing IDSR (FMoH, 2005).

The Integrated Disease Surveillance system seeks to ensure that an effective and functional IDSR system is available at each level of the health system, from health facilities to Local Government Areas (LGAs), states and at the national level. IDSR focuses on the LGA level where information generated is used for timely action consequently leading to reduction of morbidity, disability and mortality. LGA level is the main focus in the IDSR system in Nigeria because it is the first level in the Nigerian health system with full time staff dedicated to all aspect of the health of the public such as monitoring health events in the community, mobilizing

community action and accessing regional resources to protect the health of communities (FMoH, 2009 and Kasolo *et al*, 2010).

The Federal Ministry of Health (FMoH) has selected 40 communicable and non-communicable diseases and public health related conditions for the IDSR system in Nigeria. These diseases were selected based on the following criteria; top cause of high morbidity and mortality in the country, epidemic potential, surveillance required internationally, availability of effective control and preventive intervention for addressing the public health problem they pose, ease of identification using simple case definition and availability of intervention programmes supported by the WHO for prevention and control, eradication or elimination of the diseases.

Early detection of outbreaks is necessary for effective and rapid control. The primary goal of a functional disease surveillance and notification system, among others, is to detect and monitor diseases and other events with potential threat to the health of the public with respect to source, time, person, population and place in order to provide rationale for public health action. This key goal of disease surveillance and notification has made it an effective tool for disease outbreak prevention and control.

2.6.1 Purposes and Uses of Surveillance

The purpose for conducting surveillance is to learn the ongoing pattern of disease occurrence and the potential for disease in a population so that there can be effective in investigating, controlling, and preventing the disease in that population. Surveillance data can be used as the basis for planning more effective disease control and prevention activities. Surveillance can be justified for two additional purposes: First, through surveillance one can learn more about the natural history, clinical spectrum, and epidemiology of a disease (who is at risk, when and where it occurs, the exposures or risk factors that are critical to its occurrence). This knowledge may lead to the development of prevention and control measures. Second, surveillance will provide us with a baseline of data which can be used to assess prevention and control measures when they are developed and implemented. Surveillance routinely uses data in a variety of ways which are

related to monitoring disease and providing linkage to prevention and control programs(Thacker, 1988).

2.7 BRIEF REVIEW OF ZERO INFLATED MODELS

In health research, outcomes of interest often consist of count variables. For this type of count data, the standard framework for explaining the relationship between the outcome variable and a set of explanatory variables includes the Poisson and negative binomial regression models. However, the basic Poisson regression model forces the conditional variance of the outcome to equal the conditional mean. The negative binomial regression can be written as an extension of Poisson regression and this allows greater flexibility in modelling the relationship between the conditional variance and the conditional mean compared to the Poisson model. In addition, an often encountered characteristic of count data is that the number of zeros in the sample can exceed the number of zeros predicted by either Poisson or negative binomial model (Fang, 2008). Zero-inflated models are interpreted as a mix of structural and sampling zeros from two processes; the process that generates excess zeros from a binary distribution which are the structural zeros, and the process that generates both non-negative and zero counts from Poisson or NB distributions which are the sampling zeros (Zamani and Ismail 2013) . The following four regression models, zero-inflated Poisson (ZIP) regression, zero-inflated negative binomial (ZINB) regression, hurdle regression, and zero-inflated generalized Poisson (ZIGP) regression are frequently used to model zero-inflated count data (Fang, 2008).

2.7.1 Zero Inflated Poisson regression model (ZIP)

Zero inflated Poisson model deals with heterogeneity (that is when variation exists) associated with excess zeros. It uses a Poisson distribution that has been mixed with a point mass at zero to allow for the inclusion of additional structural zeros but does not handle over-dispersion (Dahiya & Gross, 1973; Heilbron, 1994; Lambert, 1992). The ZIP regression model was first introduced by Lambert, 1992 who applied ZIP regression model defects in manufacturing detects (Lambert, 1992). Lambert provides a motivation application of these models and discusses the case of zero-inflated Poisson. In a study by Ridout *et al.* (1998) who worked on various ZIP regression models for an apple shoot propagation data, it was discovered that the ZIP models were

inadequate for the data as there was still evidence of over dispersion. Other contemporary applications for the ZIP regression model can be found in dental epidemiology (Bohning *et al.*, 1999), occupational health (Lee *et al.*, 2001), and children's growth and development (Cheung, 2002). In practice, after accounting for zero-inflation, the non-zero part of the count distribution is often over-dispersed. In this regard, Greene (1994) has described an extended version of the negative binomial model for excess zero count data, the Zero-Inflated Negative Binomial (ZINB). The ZIP parameter estimates can be severely biased if the non-zero counts are over-dispersed in relation to the Poisson distribution.

2.7.2 Zero-Inflated Negative Binomial regression model (ZINB)

Zero inflated negative binomial deals with both over-dispersed and zero-inflated data (Yau *et al.*, 2003; Ridout *et al.*, 2001). It assumes there are two distinct data generating processes. The result of Bernoulli trial is used to determine which of the two processes is used. For observation i , with probability π_i the only possible response of the first process is zero counts, and with probability of $(1-\pi_i)$ the response of the second process is governed by a negative binomial with mean λ_i . The zero counts are derived from the first and second processes, where a probability is estimated for whether zero counts are from the first or the second process. The overall probability of zero counts is the combined probability of zeros from the two processes (Fang, 2008). In a study by Fang, 2008 who applied the ZINB regression model to human microbiota sequence data with random effects discovered that the model is useful for analysis of over-dispersed count data with an excess of zeros and repeated measures. It was revealed that the simulation study used indicated that the method of estimation gave unbiased results for both fixed effects and random effects. The study concluded that the application of the model to the three selected organism from the microbiota data revealed the importance of this method.

2.8 PREVIOUS RESEARCH ON ZERO-INFLATED MODELS

In a study conducted by Ngatchou-Wandji *et al.* (2011) on annual trends in incidences of some occupational allergic diseases (allergic asthma, dermatitis and rhinitis) from 2001 to 2009 in France, data was analysed from the RNV3P of the 32 French centres of occupational diseases, named Centre de Consultation de Pathologies Professionnelles (CCPP). The study followed the

approach of McNamee et al (2009) but used Zero Inflated negative binomial regression model instead of Poisson regression model with random effect. The outcome variable was the number of cases per centre per month and the covariates are the months (Jan-Dec), the years (year 1- 9) and the 32 centres (C01-C32). The data showed an excess of zeros and this led to over-dispersion because the variances were larger than the means. It was found, after adjusting for ZINB regression model that the estimated dispersion parameters were too large. It was demonstrated using plotting residual series and histograms that zero-inflated regression models used were good prediction models for the three sets of data. The study concluded that there is a positive association between the three diseases and the trends in occupational allergic were decreasing for asthma and rhinitis and increasing for dermatitis (Ngatchou-Wandji and Paris, 2011).

Al Mamun in 2014, while studying under-5 deaths in Bangladesh using ZIP, ZINB and Hurdle models, explored how the zero-inflated count data models behaved with different sets of parameters. The investigation revealed that each zero-inflated model has superior performance than the classical count data models (i.e Poisson and negative binomial models). It also showed that from the simulated experiments, the zero-inflated regression models (ZIP, ZINB and Hurdle) were consistent over the changes of the model parameters. It was found that zero inflated count data model performed better than the Poisson and Negative binomial models using the AIC statistic for the model fit of the number of under-5 deaths (Al Mamun, 2014).

In a study by Mouatassim and Ezzahid, 2012 who worked on private health insurance data using Poisson regression and Zero-inflated Poisson regression, the probability integral transform test and Vuong's test were used to compare the two models. It was found that the mean number of claims declared by one insured in 1 year was smaller than the variance, which indicated an over-dispersion of the data and in this regard, the Poisson regression model was not appropriate. Furthermore, it was shown in the histogram that the number of claims highly peaked at zero value because of the preponderance of zeros in the data and large numbers of claims were less frequently observed. It was concluded that the Zero inflated Poisson model gave a better prediction and fits excess zero counts than the Poisson regression (Mouatassim and Ezzahid, 2012).

In addition, Famoye and Singh, 2006 conducted a study on domestic violence data using Zero Inflated Generalized Poisson Regression (ZIGP). It was found that domestic violence data was over-dispersed with 66.4% zeros. However, the ZINB regression model did not converge in fitting the data. The findings indicated that the problem of fitting ZINB regression model to an observed data set was also observed by Lambert 1992 which led to development and to application of ZIGP regression model for modelling over-dispersed data with too many zeros. It was seen that ZIGP regression model is a good competitor of ZINB regression model fitting all the dataset but a clear condition was not stated (Famoye and Singh, 2006).

CHAPTER THREE

METHODOLOGY

3.1 STUDY AREA

The study area comprises the health facilities in all the 33 local government areas of Oyo state. It is the second largest state in the South-West geopolitical zone of Nigeria with a land area of 27,148km² and a population of 6 million. The state was carved out of the former Western State of Nigeria in 1976. Administratively, the state consists of 33 local government areas which are: Akinyele, Afijio, Egbeda, Ibadan North, Ibadan North-East, Ibadan North-West, Ibadan South-West, Ibadan South-East, Ibarapa Central, Ibarapa East, Ido, Irepo, Iseyin, Kajola, Lagelu, Ogbomosho North, Ogbomosho South, Oyo West, Atiba, Atigbo, Saki West, Saki East, Itesiwaju, Iwajowa, Ibarapa North, Olorunsogo, Oluyole, Ogo Oluwa, Surulere, Orelope, Ori Ire, Oyo East and Ona Ara. It is bounded in the south by Ogun State and in the north by Kwara State. In the west, it is partly bounded by Ogun State and partly by the Republic of Benin, while it is bounded in the East by Osun State. The landscape consists of old hard rocks and dome shaped hills, which rise gently from about 500 meters in the southern part, reaching a height of about 1,219 metres above sea level in the northern part. Oyo State has an equatorial climate with dry and wet seasons and relatively high humidity. The dry season lasts from November to March while the wet season starts from April and ends in October. Average daily temperature ranges between 25 °C (77.0 °F) and 35 °C (95.0 °F), almost throughout the year. The vegetation pattern of Oyo State is that of rain forest in the south and guinea savannah in the north. The state operates a three-tier health care service which are primary, secondary and tertiary health centre across urban and rural areas. There are 1,648 health facilities disaggregated into 631 Primary Health Centres (PHCs), 46 Secondary Health Facilities (SHFs), 5 Tertiary Health Centres (THCs) and 968 registered private health facilities (SMoH, 2008).

3.2 STUDY DESIGN

Data for the present analysis was obtained from a longitudinal surveillance data of the Integrated Diseases Surveillance and Response (IDSR) from Oyo State Ministry of Health for the year 2010 to 2014. A secondary data analysis was conducted to answer the study objectives and both ZIP

and ZINB models were fitted to assess the annual trend in incidence of infectious diseases among under-5 children in the 33 local government areas.

3.3 STUDY POPULATION

The population for the 2007 to 2014 Integrated Diseases Surveillance and Response (IDSR), Oyo State Ministry of Health was drawn from outpatient and inpatient aged 0 to 40 years and above from the 764 health facilities in 33 local government areas in Oyo state. For the purpose of the present study, the number of children aged 0-59 months who were infected with malaria, pneumonia, diarrhoea and measles from 2010 to 2014 are the target population.

3.4 DATA COLLECTION

Surveillance data was collected on a monthly routine basis on forty diseases of which 32 were communicable diseases and 8 were non communicable diseases from 764 health facilities in 33 local government areas across the state. The focal persons (head of health facilities) at these sites reported ascertained cases through a review of the outpatient and inpatient registries to the local government disease surveillance and notification officers. The Integrated Disease Surveillance case-based reporting forms were used to collect the reported cases from 2007 to 2014. Data on age of outpatient and inpatient and deaths (0-28 days – 40 years and above) were also collected. The surveillance data was then forwarded to the state epidemiologist at the Ministry of Health. For the purposes of the present study, data on the number of cases for the four infectious diseases (Malaria, pneumonia, diarrhoea and measles) were extracted and returned into excel sheets from 2010-2014 among under-5 children in the 33 LGAs. this process took 3 weeks because data was in bad format.

3.5 SAMPLE SIZE

Overall, a total of 3,719 combined cases of the four selected infectious diseases were extracted for the present analysis. Cases comprised of 1,446 malaria, 609 pneumonia, 1,432 diarrhoea and 232 measles.

3.6 STUDY VARIABLES

3.6.1 Outcome Variable

The study outcome/dependent variable is the number of cases (Pneumonia, malaria, diarrhoea and measles) per local government per month.

3.6.2 Explanatory Variables

The explanatory variables used in this study were:

1. The season of reporting- defined as month of reporting labelled January, February, March, April, May, June, July, August, September, October, November and December.
2. The year of reporting considered as categorical variables labelled as Year1 (2010), Year2(2011), Year3(2012) Year4(2013) and Year5(2014)
3. The geographical locations- defined by the 33 LGs areas in Oyo state and labelled LG1, LG2..., LG32 and LG33.

3.7 DATA MANAGEMENT AND ANALYSIS

Extraction of relevant data into the excel spread sheet from the Integrated Diseases Surveillance and Response was performed for five years (2010-2014). Descriptive statistics for all independent variables were performed such as percentage, sample mean and sample variance. Mean and variance were computed to check for the presence of over-dispersion or under-dispersion. This was done to confirm whether the data followed a normal distribution. The pattern of infectious diseases among under-5 children over the years in the 33 local government areas was examined and their incidence rate ratios were reported. Model comparisons were performed between ZINB and ZIP using Vuong z-statistic, AIC and BIC selection criteria and the better model for the number of cases of malaria among under-5 children was selected based on the values. The zero inflated negative binomial was found to better fit the count data and was used to determine the effect of season defined as month of reporting, year and the geographical location, determined by the 33 local government areas on the occurrence of infectious diseases. Incidence rate ratio (IRR), 95% CI and their p-values were reported. Maximum likelihood technique was used to estimate the parameters of the two models using logit function. The reference month used in the analysis was April, the reference for the year was 2010 and the local government area used

was Afijio (LG1). This is because the R statistical package uses the lowest counts in the dataset and these random choices do not have any incidence on the trend of the data. SPSS version 20 and R statistical package were used for analysis.

3.8 Over dispersion and Under-dispersion

Unlike the normal distribution, the variance of a Poisson random variable rest on the mean, with the mean equal to the variance. Count data often depart from the Poisson distribution due to a large frequency of extreme observations resulting in spread (variance) greater than the mean in the observed distribution. Under dispersion is a situation where there is less variation in the data than predicted and can be determined when the variance is less than the mean (Alexander *et al*, 2005).

3.8.1 Incidence

Incidence is a measure of the number of new cases of a disease or other health outcome that develop in a population of individuals at risk, during a specified time period.

3.8.2 Incidence rate ratio (IRR)

Incidence rate ratio is the ratio of two incidence rates. Incidence rate is the number of events divided by the person time at risk. To calculate IRR, the incidence rate among the exposed portion of the population divided by the incidence rate in the unexposed portion of the population. It gives a relative measure (IRR) of the effect of a given exposure and approximates the relative risk or the odds ratio if the occurrences are rare.

3.9 STATISTICAL MODELS

The statistical models used in this study include the following:

Zero inflated Poisson and Zero inflated negative binomial regression models

3.9.1 ZERO INFLATED REGRESSION MODEL

In a zero-inflated regression model, for every observation there are two possible data generating processes. For observation i , the first data generating process is process 1 which generates only

zero counts and the second data generating process is process 2 generates counts from both Poisson or negative binomial model, where process 1 is selected with probability φ_i and process 2 is selected with probability $1 - \varphi_i$. The two parts of a zero-inflated model are a binary model, usually a logit model to model which of the two processes the zero outcome is related with and a count model, in this case a Poisson model and negative binomial model to model the count process.

In general,

$$Y_i \sim \begin{cases} 0 & \text{with probability } \varphi_i \\ g(y_i) & \text{with probability } 1 - \varphi_i \end{cases}$$

Therefore, the probability of $\{Y_i = y_i\}$ can be described as

$$P(Y_i | x_i) = \varphi_i + (1 - \varphi_i)g(y_i) \text{ for } y_i = 0$$

$$P(Y_i | x_i) = (1 - \varphi_i)g(y_i) \text{ for } y_i \geq 1$$

where $g(y_i)$ follows either the Poisson or the negative binomial distribution.

When the probability φ_i depends on the characteristics of observation, φ_i is written as a function of $z_i' \gamma$, where z_i' is the $1 \times (q + 1)$ vector of zero-inflated covariates to be estimated, associated with the known zero-inflated covariate vector $z_i' = (1, Z_1, \dots, Z_q)$ and γ is the $(q + 1) \times 1$ vector of zero-inflated coefficients to be estimated. (The zero-inflated intercept is γ_0 , the coefficients for the q zero-inflated covariates are $\gamma_1, \dots, \gamma_q$) where p is the number of covariates not including the intercept, and q is the number of the covariates Z 's not including the intercept. The parameter φ_i , which is often referred as the zero-inflation factor, is the probability of zero counts from the binary process. For common choice and simplicity, φ_i is characterized in terms of a logistic regression model by writing as $\text{logit}(\varphi_i) = Z_i' \gamma$.

zero counts and the second data generating process is process 2 generates counts from both Poisson or negative binomial model, where process 1 is selected with probability φ_i and process 2 is selected with probability $1 - \varphi_i$. The two parts of a zero-inflated model are a binary model, usually a logit model to model which of the two processes the zero outcome is related with and a count model, in this case a Poisson model and negative binomial model to model the count process.

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$$P(Y_i | x_i) = (1 - \varphi_i)g(y_i), \quad \text{for } y_i \geq 1$$

where $g(y_i)$ follows either the Poisson or the negative binomial distribution.

When the probability φ_i depends on the characteristics of observation, φ_i is written as a function of $z_i' \gamma$, where z_i' is the $1 \times (q + 1)$ vector of zero-inflated covariates to be estimated, associated with the known zero-inflated covariate vector $z_i' = (1, Z_1, \dots, Z_q)$ and γ is the $(q + 1) \times 1$ vector of zero-inflated coefficients to be estimated. (The zero-inflated intercept is γ_0 , the coefficients for the q zero-inflated covariates are $\gamma_1, \dots, \gamma_q$) where p is the number of covariates not including the intercept, and q is the number of the covariates Z 's not including the intercept. The parameter φ_i , which is often referred as the zero-inflation factor, is the probability of zero counts from the binary process. For common choice and simplicity, φ_i is characterized in terms of a logistic regression model by writing as $\text{logit}(\varphi_i) = Z_i' \gamma$.

The function relating the product $z_i'\gamma$ (which is a scalar) to the probability φ_i is called the zero-inflated link function,

$$\varphi_i = F_i = F(Z_i'\gamma)$$

The zero-inflated link function F can be specified as either the logistic function,

$$F(Z_i'\gamma) = \Lambda(Z_i'\gamma) = \frac{\exp(Z_i'\gamma)}{1 + \exp(Z_i'\gamma)}$$

3.9.2 Zero Inflated Poisson Regression Model

Zero inflated Poisson regression is a statistical method for modelling count dataset that has excess zero counts when the Poisson model is inadequate and violates the equi-dispersion assumption (Lambert, 1992). The excess zeros are generated by a separate process from the count values and the excess zeros can be modelled independently. Also, the ZIP model has two parts, a Poisson count model and the logit model for predicting excess zeros.

The zero inflated Poisson regression second data generating process 2 is

$$g(y_i) = \frac{\exp(-\mu_i)\mu_i^{y_i}}{y_i!} \quad \text{where } \mu_i = e^{x_i'\beta}.$$

Thus the ZIP model is defined as

$$P(y_i|x_i, z_i) = \begin{cases} F_i + (1 - F_i)\exp(-\mu_i) & \text{for } y_i = 0 \\ (1 - F_i)\frac{\exp(-\mu_i)\mu_i^{y_i}}{y_i!} & \text{for } y_i \geq 1 \end{cases}$$

The conditional mean of y_i is given by,

$$E(y_i|x_i, z_i) = \mu_i(1 - F_i)$$

while the conditional variance of y_i is given by

$$V(y_i|x_i, z_i) = E(y_i|x_i, z_i)(1 + \mu_i F_i)$$

The ZIP model exhibits overdispersion since

$$V(y_i|x_i, z_i) > E(y_i|x_i, z_i)$$

The Log-Likelihood function of the ZIP model is given by

$$L = \sum_{i=1}^N \ln[P(y_i|x_i, z_i)]$$

The ZIP model in which the probability φ_i is expressed with a logistic link function, namely

$$\varphi_i = \frac{\exp(Z_i \gamma)}{1 + \exp(Z_i \gamma)}$$

The log-likelihood function is

$$L = \sum_{\{i: y_i=0\}} \ln[\exp(z_i \gamma) + \exp(-\exp(x_i \beta))] + \sum_{\{i: y_i > 0\}} [y_i x_i \beta - \exp(x_i \beta)] - \sum_{k=2}^n \ln(k) - \sum_{i=1}^N \ln[1 + \exp(z_i \gamma)]$$

Y_i = the number of cases of infectious diseases among under 5 children

X_1 = the season defined as month of reporting labelled Jan, Feb, Mar, Apr, May, Jun, July, Aug, Sep, Oct, Nov and Dec

X_2 = the years considered as categorical variables labelled Year1 (2010), Year2 (2011), Year3

(2012) Year4 (2013) and Year5 (2014)

X_3 = the geographical location determined by the 33 LGs areas in Oyo state, labelled LG1, LG2;; LG32 and LG33

3.9.3 Zero Inflated Negative Binomial model

Zero inflated negative binomial regression is used for modelling count variables with excessive zeros and it is usually for over-dispersed count outcome variables. The theory suggests that the excess zeros are generated by a separate process from the count values and that the excess zeros can be modelled independently.

The Zero-Inflated Negative Binomial (ZINB) regression model assumes there are two distinct data generation processes. The result of a Bernoulli trial is used to determine which of the two processes is used. For observation i , with probability π_i the only possible response of the first process is zero counts, and with probability of $1-\pi_i$, the response of the second process is governed by a negative binomial process with mean λ_i . The zero counts are generated from the first and second processes, where a probability is estimated for whether zero counts are from the first or the second process. Zero-inflated Negative Binomial Model (ZINB) model that deals with both over-dispersed and zero-inflated data

This is obtained by specifying a negative binomial distribution for the data generation process 2.

$$g(y_i) = \frac{\Gamma\left(\frac{1 + \alpha\mu_i}{\alpha}\right)}{\Gamma\left(\frac{1}{\alpha}\right)y_i!} \left(\frac{1}{1 + \alpha\mu_i}\right)^{\frac{1}{\alpha}} \left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{y_i}$$

Thus the ZINB model is defined to be

$$p(y_i|x_i, z_i) = \begin{cases} F_i + (1 - F_i) \left(\frac{1}{1 + \alpha \mu_i} \right)^{\frac{1}{\alpha}} & \text{for } y_i = 0 \\ (1 - F_i) \frac{\Gamma\left(\frac{1 + \alpha \mu_i}{\alpha}\right)}{\Gamma\left(\frac{1}{\alpha}\right) y_i!} \left(\frac{1}{1 + \alpha \mu_i} \right)^{\frac{1}{\alpha}} \left(\frac{\alpha \mu_i}{1 + \alpha \mu_i} \right)^{y_i} & \text{for } y_i > 0 \end{cases}$$

Where α is the overdispersion parameter.

In this case, the conditional mean of y_i is,

$$E(y_i|x_i, z_i) = \mu_i(1 - F_i)$$

and the conditional variance of y_i is given by

$$V(y_i|x_i, z_i) = E(y_i|x_i, z_i)[1 + \mu_i(F_i + \alpha)]$$

The logit transformation is defined as log odds and it is represented as;

$$\log\left(\frac{\omega_i}{1 - \omega_i}\right) = -\gamma \log(\mu_{L,i}) \forall i = 1, 2, 3$$

$$\text{where } \omega_i = \frac{\mu_{L,i}^{-\gamma}}{1 + \mu_{L,i}^{-\gamma}}, \text{ and } \mu_{L,i} = \exp(x_i \beta)$$

where x_i represents the explanatory variables (Season defined as month of reporting, year of reporting and geographical location determined by the 33 local government areas).

The ZINB model in which the probability φ_i is expressed with a logistic link function, namely

$$\varphi_i = \frac{\exp(Z_i \gamma)}{1 + \exp(Z_i \gamma)}$$

The log-likelihood function is

$$\begin{aligned} \mathcal{L} = & \sum_{i: y_i = 0} \ln[\exp(z_i' \gamma) + (1 + \alpha \exp(x_i' \beta))^{-\alpha^{-1}}] + \sum_{i: y_i > 0} \sum_{j=0}^{y_i-1} \ln(j + \alpha^{-1}) \\ & + \sum_{i: y_i > 0} \left\{ -\ln(y_i!) - (y_i + \alpha^{-1}) \ln(1 + \alpha \exp(x_i' \beta)) + y_i \ln(\alpha) \right. \\ & \left. + y_i x_i' \beta \right\} \sum_{i=1}^N \ln[1 + \exp(z_i' \gamma)] \end{aligned}$$

Y_i = the number of cases of infectious diseases among under-5 children

X_1 = the season defined as month of reporting labelled Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov and Dec

X_2 = the years considered as categorical variables labelled Year1 (2010), Year2 (2011), Year3 (2012) Year4 (2013) and Year5 (2014)

X_3 = the geographical location determined by the 33 local government areas, labelled LG1, LG2;; LG32 and LG33

3.10 MODEL SELECTION

The following goodness-of-fit tests were used in this study for model selection.

3.10.1 Chi-square -2log likelihood statistic

The maximum likelihood, L , for a given model is the value of the likelihood function when the parameters are substituted with the maximum likelihood estimated and the statistic $-2\log L$, which is used to compare models. It is important for comparing models fitted to the same set of data as the value of both L depends on the number of observations in the data and $-2\log L$ is a measure of agreement between the model and the data. The larger the maximum likelihood the better the agreement between the model and observed data. Consequently, smaller the value of $-2\log L$, the better the model.

3.10.2 Akaike Information Criterion (AIC)

Akaike Information Criterion: This is a method of model selection which is based on a relationship between maximum likelihood estimation and Kullback-Leibler Information developed by Akaike, derived under the assumption that the operating models belong to the approximating family.

$$AIC = -2\log L(\theta) + 2K$$

where $L(\theta)$ is the maximized likelihood function and K is the number of estimated parameters included in the model (the number of variables with the intercept). The log likelihood of the model of the data is the overall fit of the model. The smaller the value of the log likelihood implies a worse fit of the model. Nonetheless, after comparing different models, the model with the minimum AIC value is the best.

In Akaike Information Criterion, the compromise occurs between the maximized log likelihood $-2\log L(\theta)$, which is the lack of fit component and k , the number of free parameters estimated within the model which is a measure of the compensation for the bias in the lack of fit when maximum estimators are used. The term $2K$ is the penalty term and the purpose for the penalty term is to prevent over fitting (Bozdogan, 2000).

Akaike Information Criterion (AIC) was first developed by Akaike (1973) as a way to compare different models on a given outcome. AIC uses the log likelihood which is the probability of obtaining the chosen data under the given model; hence it is better to choose a model that makes the probability as large as possible. The logarithm does not affect the value rather the negative sign affect the value. This reduces the value of the statistics.

3.10.3 Bayesian Information Criterion (BIC)

Bayesian Information Criterion is similar to Akaike Information Criterion; the difference is in the second term which depends on the sample size n .

$$BIC = -2\log (L) + p \log (n)$$

Where L denotes the log likelihood, p is the number of parameters and n is the number of rating of observation used in the model. the smaller the BIC, the better the model. The derivation of

BIC assumes equal priors on each model usually uninformative priors on the parameters, given each model (Zucchini, 2000).

The purpose of Bayesian Information Criterion is to find the best model for prediction using highest posterior probability while the purpose of AIC is to identify the model that most plausibly generated the data. Both AIC and BIC can be used whether the models are nested or not.

Information criterion gives information on the strength of evidence for each model; it does not make use of a significance level rather it is used on maximum likelihood. It has a high potential of selecting the best model as it is independent of the order in which the models are computed. In this study all selection models were used; this was to ensure agreement between the two model selection methods in order to select the best model.

3.10.4 Vuong's test

The Vuong test is designed to compare two models fit to the same dataset using maximum likelihood. Specifically, it tests the null hypothesis that the two models fit the dataset equally well. The comparison is based on the predicted probabilities of two models that do not nest which was introduced Vuong (Vuong, 1989) to compare ZIP regression to other non-nested model for counts data.

Let $P_N(y_i/x_i)$ be the predicted probability of an observed count for case i from the model N , m_i is then defined as:

$$m_i = \text{Log} \left(\frac{P_1(y_i/x_i)}{P_2(y_i/x_i)} \right)$$

Therefore, the Vuong's test for the hypothesis $E(m) = 0$ is given by

$$V = \frac{\sqrt{n} \left(\frac{1}{n} \sum_{i=1}^n m_i \right)}{\sqrt{\frac{1}{n} \sum_{i=1}^n (m_i - \bar{m})^2}}$$

under the null hypothesis, the Vuong's statistic is asymptotically normally distributed. At 5% significance level, the first model is preferred if $V > 1.96$. If $V < -1.96$, then the second one is preferred and the two models are equivalent when $|V| < 1.96$. (Vuong, 1989).

A large, positive test statistic provides evidence of the superiority of model 1 over model 2, while a large, negative test statistic is evidence of the superiority of model 2 over model 1. Under the null that the models are indistinguishable, the test statistic is asymptotically distributed standard normal.

Table 3.1: Vuong Model comparison evidence table

Test statistic	Vuong decision
+Test statistic	Model 1 is superior than model 2
-Test statistic	Model 2 is superior than model 1

CHAPTER FOUR

RESULTS

4.1 Descriptive statistics of the selected infectious diseases among under-5 children

Table 1 below shows the descriptive statistics for each of the selected infectious diseases (Malaria, pneumonia, diarrhoea and measles) among under-5 children from 2010 to 2014. The dataset consist of a large number of zeros: 534 for malaria, 1371 for pneumonia, 548 for diarrhoea and 1748 for measles. Also, for malaria, the mean number of cases was 204.15, the variance was 158215.404, the minimum was 0 (no case reported) and the maximum number was 10925. For pneumonia, the mean number of cases was 8.69, the variance was 1865.203, the minimum number was 0 and the maximum number was 544. For diarrhea, the mean number of cases was 48.22, the variance was 6599.938, the minimum number of cases was 0 and the maximum number was 1220. Finally, for measles, the mean number of cases was 0.39, the variance was 4.955 the minimum number of cases was 0 and the maximum value is 49.

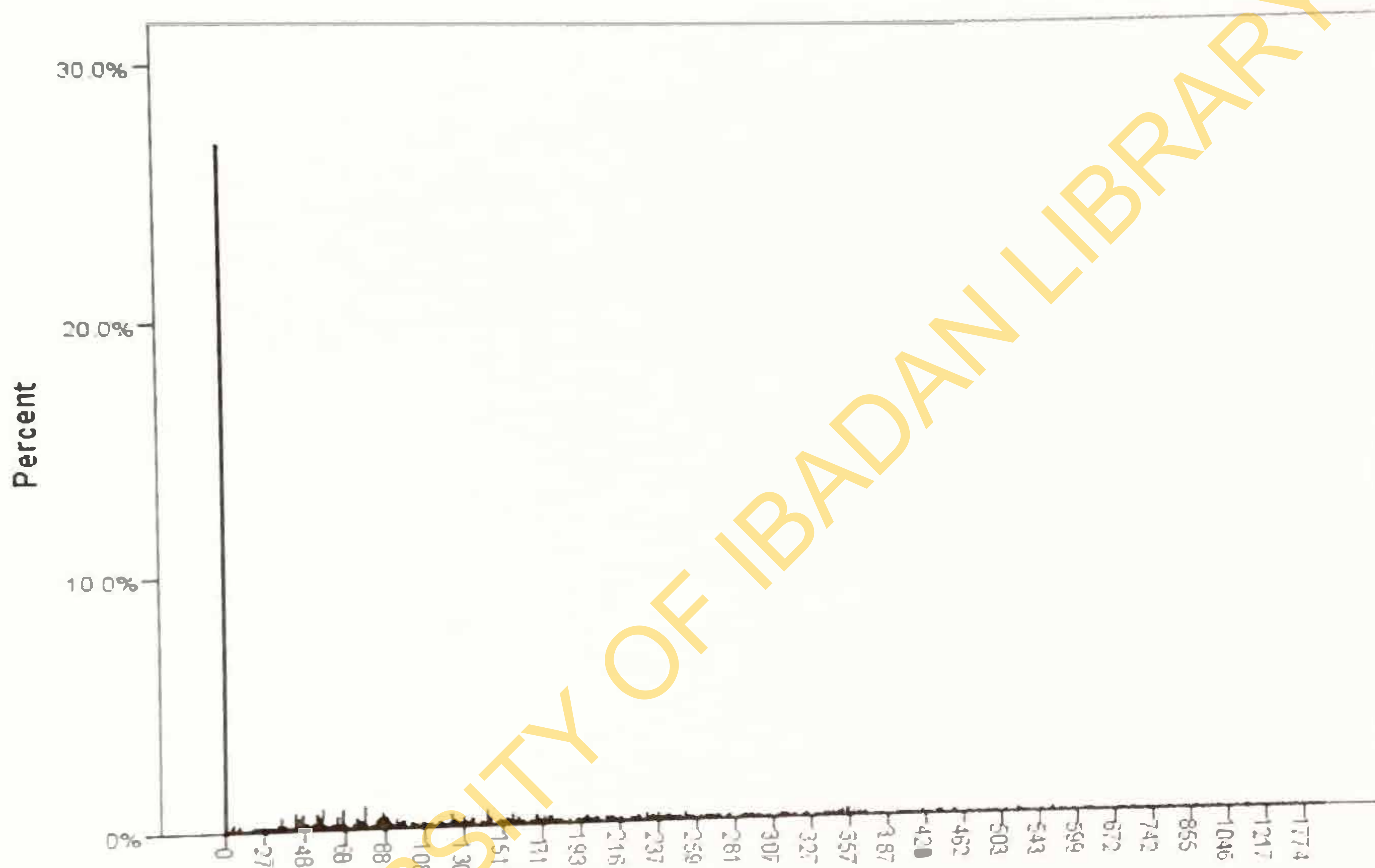
Table 4.1: Descriptive statistics of the selected infectious diseases among under 5 children in 2010 to 2014

	N	Mean	Variance	Min	Max	No of zero cases (%)	No of zero cases
Malaria in under 5 children	1980	204.15	158215.404	0	10925	534(27.0%)	1446(73.0%)
Pneumonia in under 5 children	1980	8.69	1865.203	0	544	1371(69.0%)	609(31.0%)
Diarrhea in under 5 children	1980	48.22	6599.938	0	1220	548(27.7%)	1432(72.3%)
Measles in under 5 children	1980	0.39	4.955	0	49	1748(88.3%)	232(11.7%)

4.1.1 Distribution of the selected infectious diseases among under-5 children

The figures 4.1-4.4 below also show and confirmed the amount of excess zeros present in the dataset. These features of excess zeros in the data suggest the use of zero-inflated negative binomial and zero-inflated Poisson regression for fitting the models.

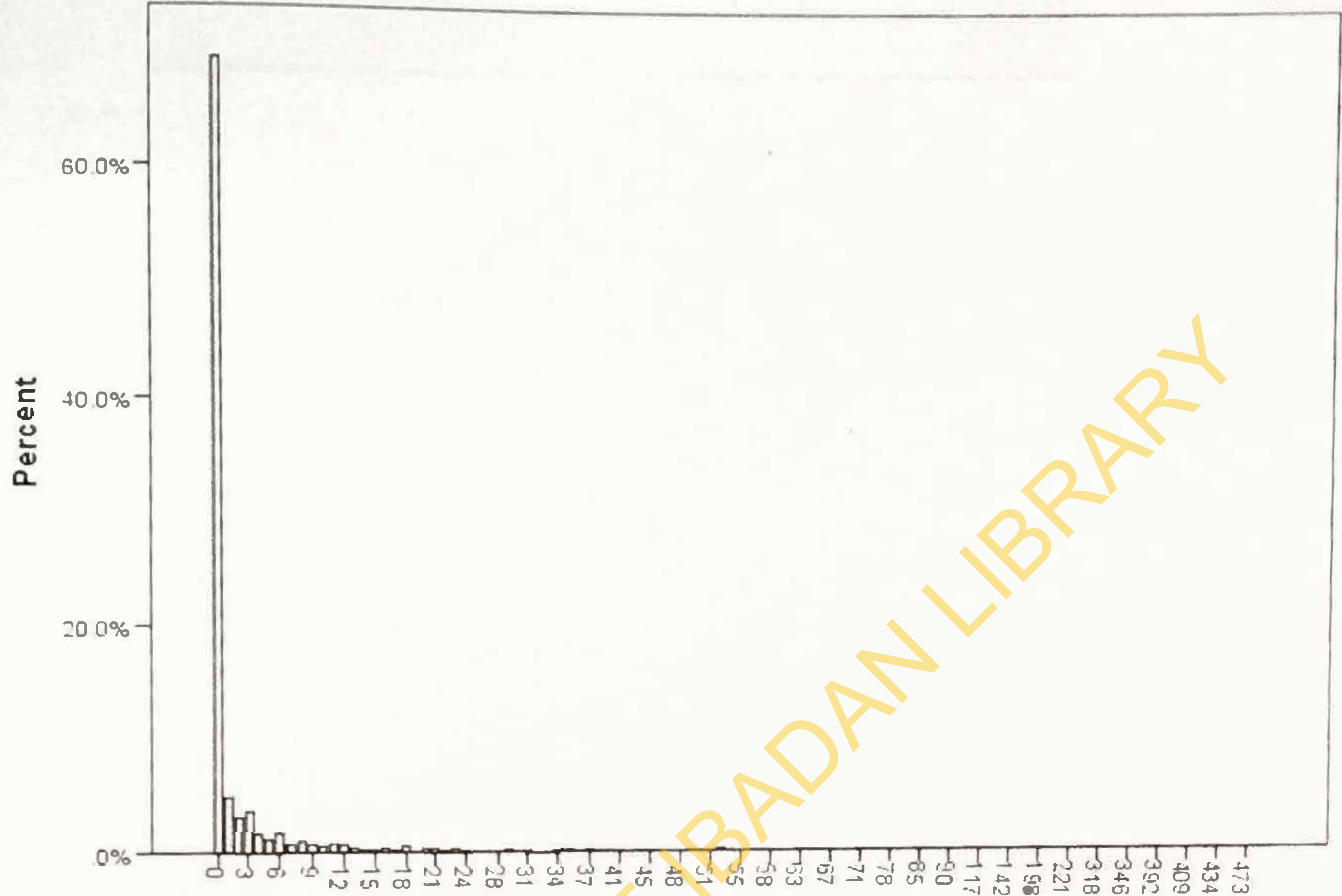
Figure 4.1 below shows the chart which illustrate the number of cases of malaria. The zero cases of malaria among under-5 children is 27%.



Number of cases of Malaria among under-5 children

Figure 4.1: Distribution of Malaria cases among under-5 children in the year 2010 to 2014

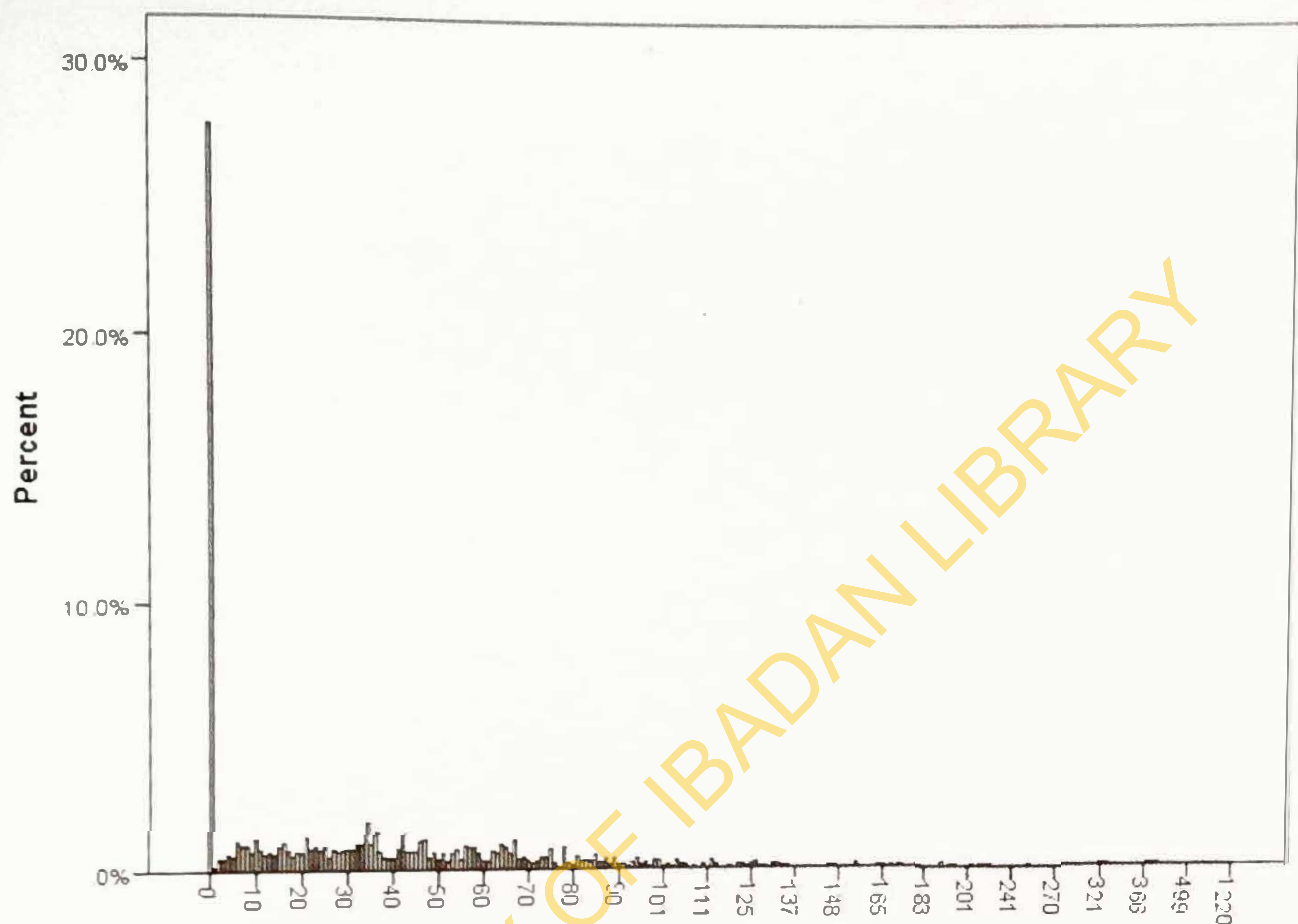
Figure 4.2 below shows the chart which illustrate the number of cases of pneumonia. The zero cases of pneumonia among under-5 children is 69%.



Number of cases of Pneumonia among under-5 children

Figure 4.2: Distribution of Pneumonia cases among under-5 children in 2010 to 2014

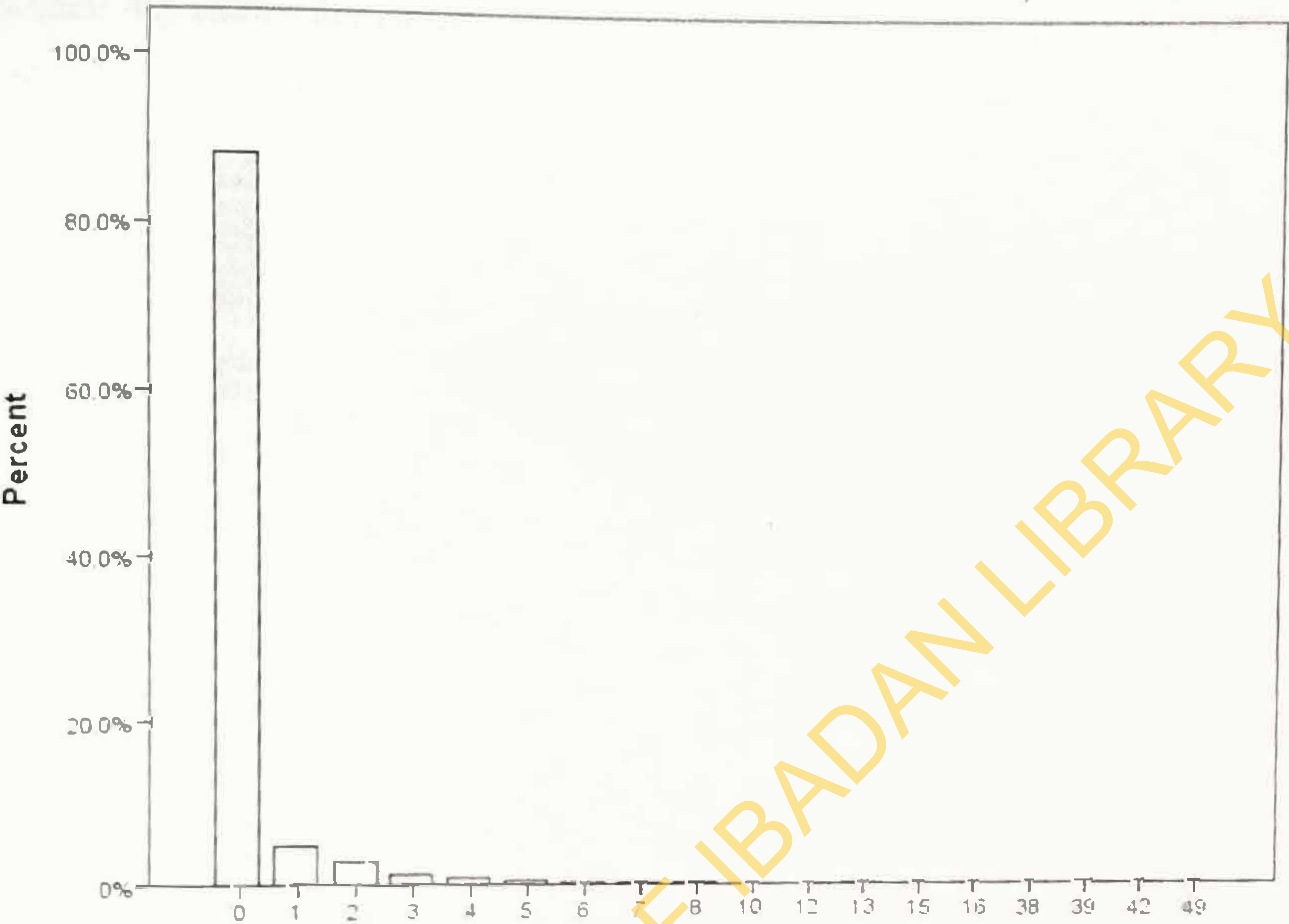
Figure 4.3 below shows the chart which illustrate the number of cases of diarrhoea. The zero cases of diarrhoea among under-5 children is 27.7%.



Number of cases of Diarrhoea among under-5 children

Figure 4 3: Distribution of Diarrhoea cases among under-5 children in the year 2010 to 2014

Figure 4.4 below shows the chart which illustrate the number of cases of measles. The zero cases of measles among under-5 children is 88.3%.



Number of cases of measles among under-5 children

Figure 4.4: Distribution of Measles cases among under-5 children in the year 2010 to 2014

4.1.2 Pattern of infectious diseases among under-5 children over the 5 years in the 33 local government areas

Figure 4.5 shows the pattern of malaria from 2010 to 2014. The incidence of malaria cases among under-5 children decreased from 35.81 per 1000 in 2011 to 35.64 per 1000 in 2013. The incidence of malaria however subsequently increased in 2014 to 35.72 per 1000.

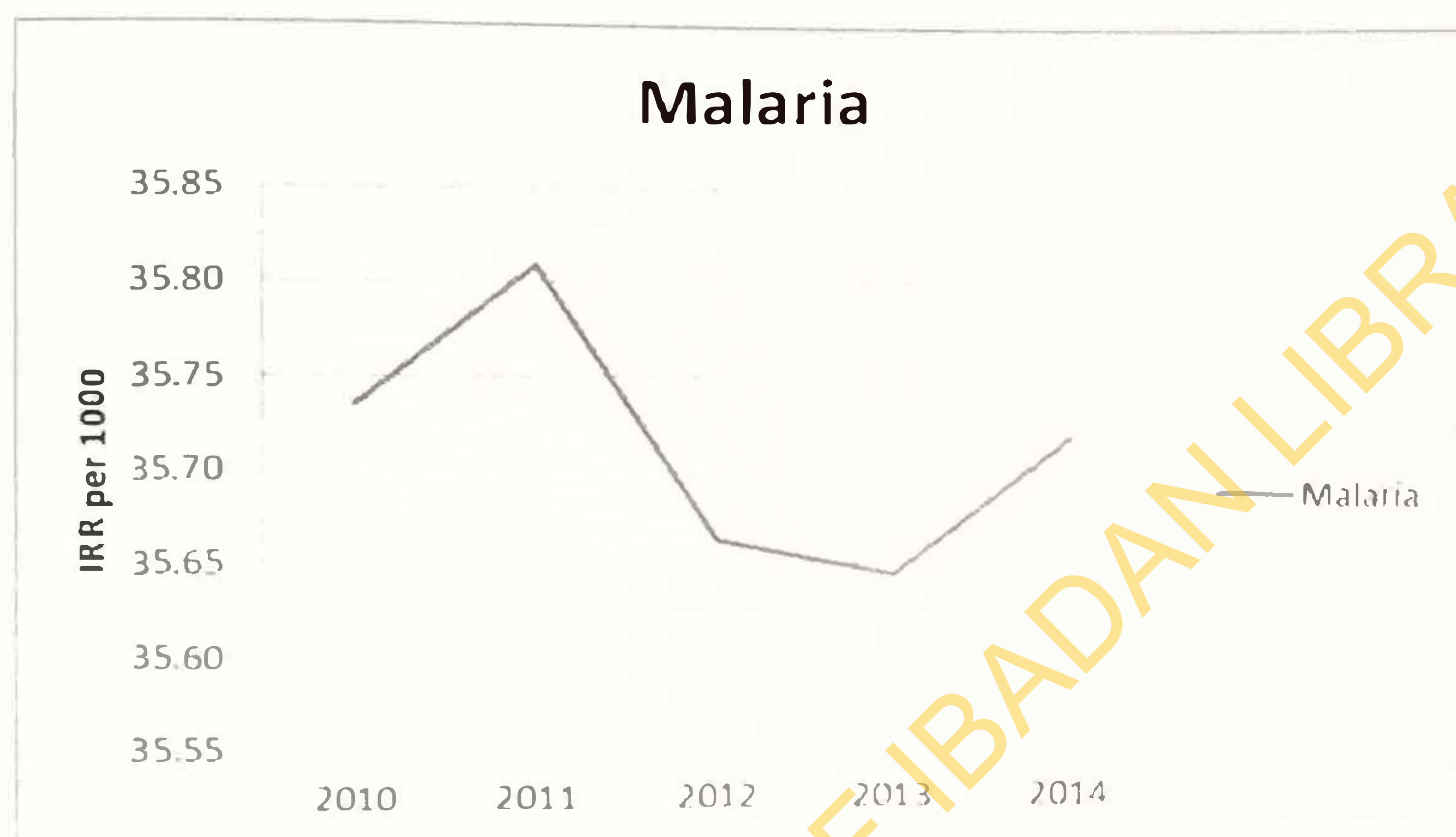


Figure 4.5: Pattern of malaria cases among under-5 children in 2010 to 2014

Figure 4.6 shows the pattern of pneumonia from 2010 to 2014. The highest incidence rate of pneumonia among under-5 children was in 2012 (7 per 1000) and it decreased over the years till 2014 (0.5 per 1000).

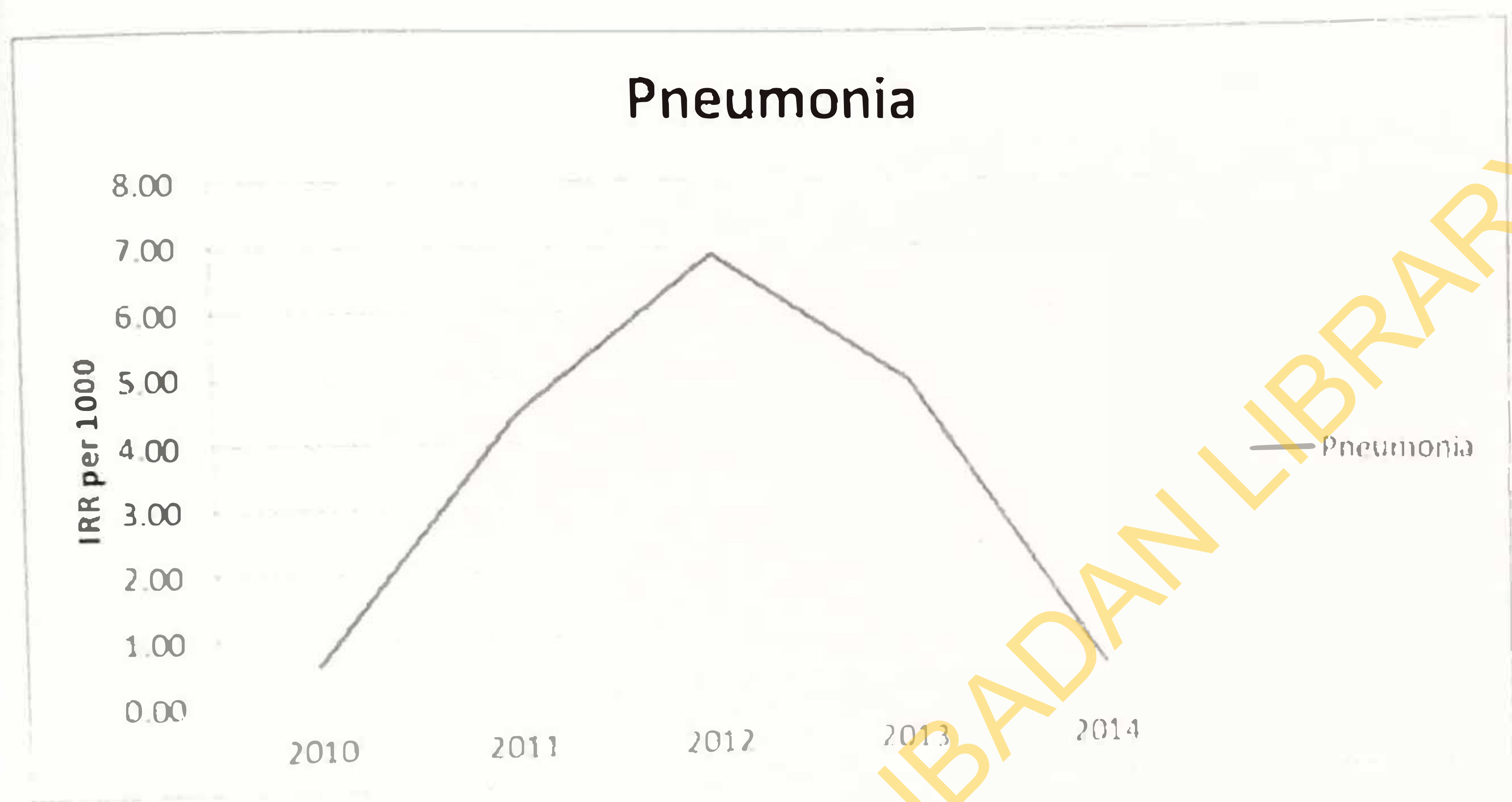


Figure 4.6: Pattern of pneumonia among under -5 children in 2010 to 2014

Figure 4.7 shows the pattern of diarrhoea from 2010 to 2014. The highest incidence rate for diarrhoea (20.36 per 1000) was observed in 2010 and it decreased over the years till 2014 (20.20 per 1000).

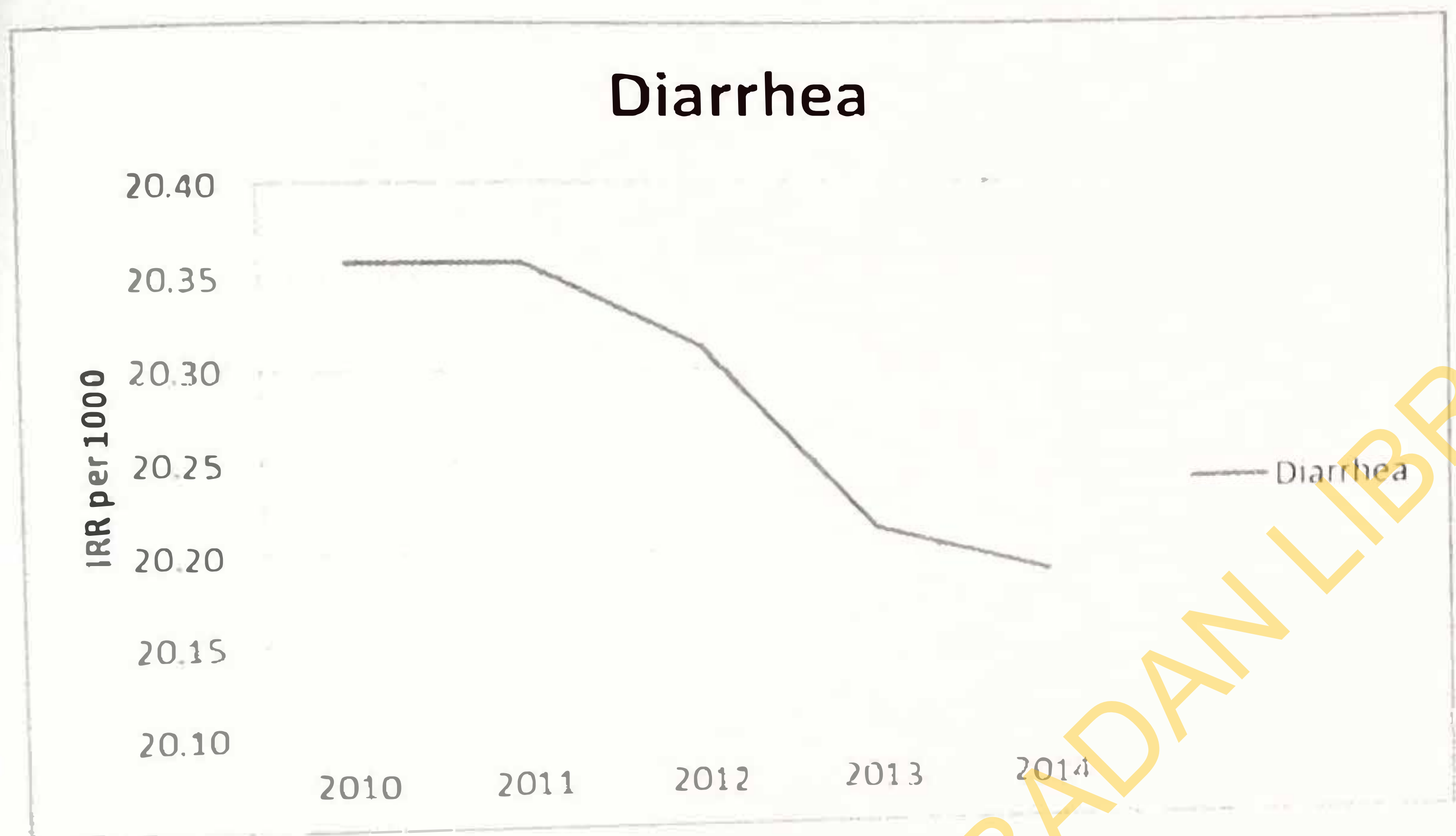


Figure 4.7: Pattern of Diarrhoea among under-5 children in 2010 to 2014

Figure 4.7 shows the pattern of diarrhoea from 2010 to 2014. The highest incidence rate for diarrhoea (20.36 per 1000) was observed in 2010 and it decreased over the years till 2014 (20.20 per 1000).

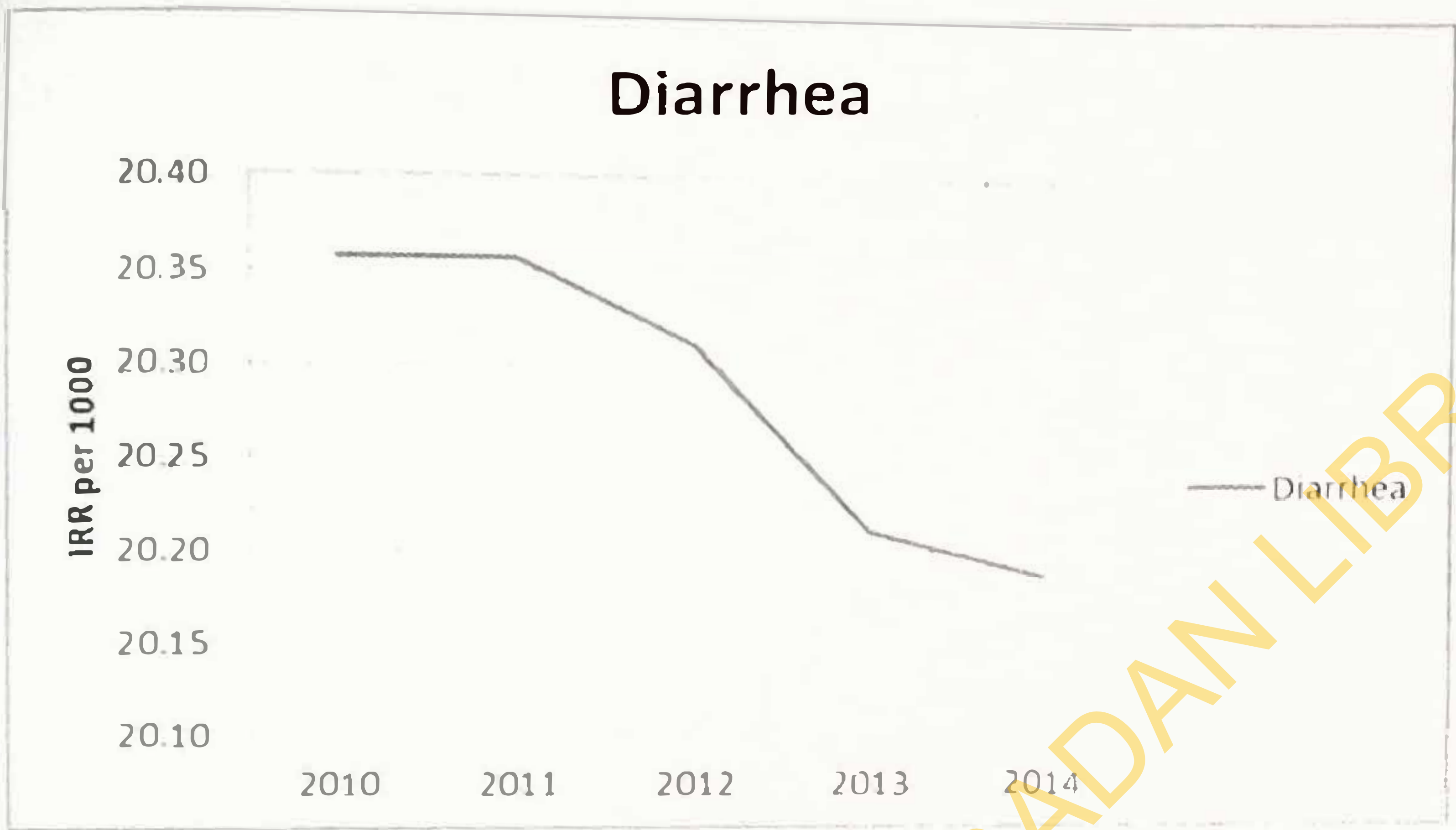


Figure 4.7: Pattern of Diarrhoea among under-5 children in 2010 to 2014

Figure 4.7 shows the pattern of diarrhoea from 2010 to 2014. The highest incidence rate for diarrhoea (20.36 per 1000) was observed in 2010 and it decreased over the years till 2014 (20.20 per 1000).

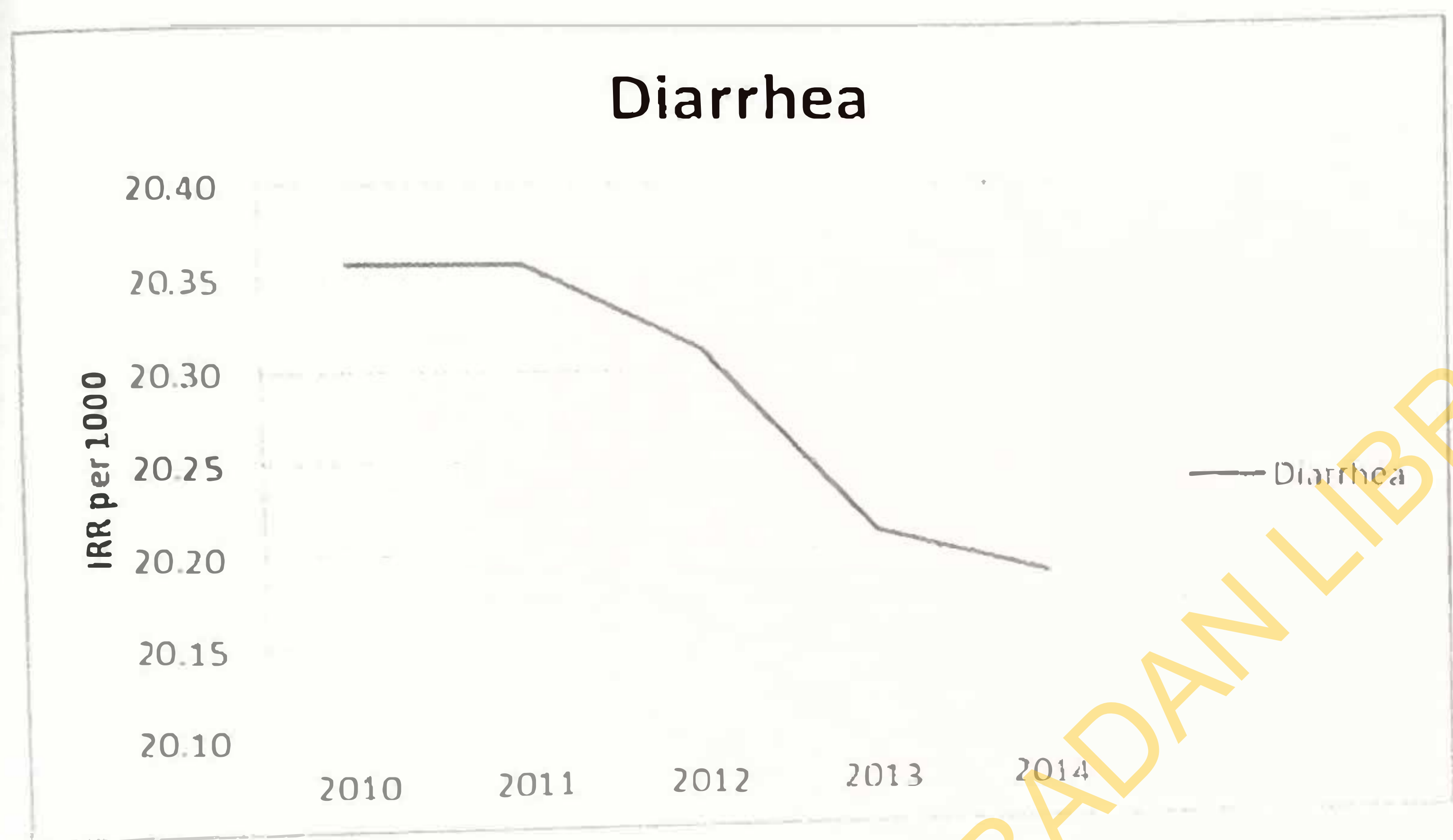


Figure 4.7: Pattern of Diarrhoea among under-5 children in 2010 to 2014

Figure 4.8 shows the trend in the incidence of measles among under-5 children; the incidence rate was static at (1.01 per 1000) from 2011 to 2013 and thereafter it increase in 2014 (1.04 per 1000).

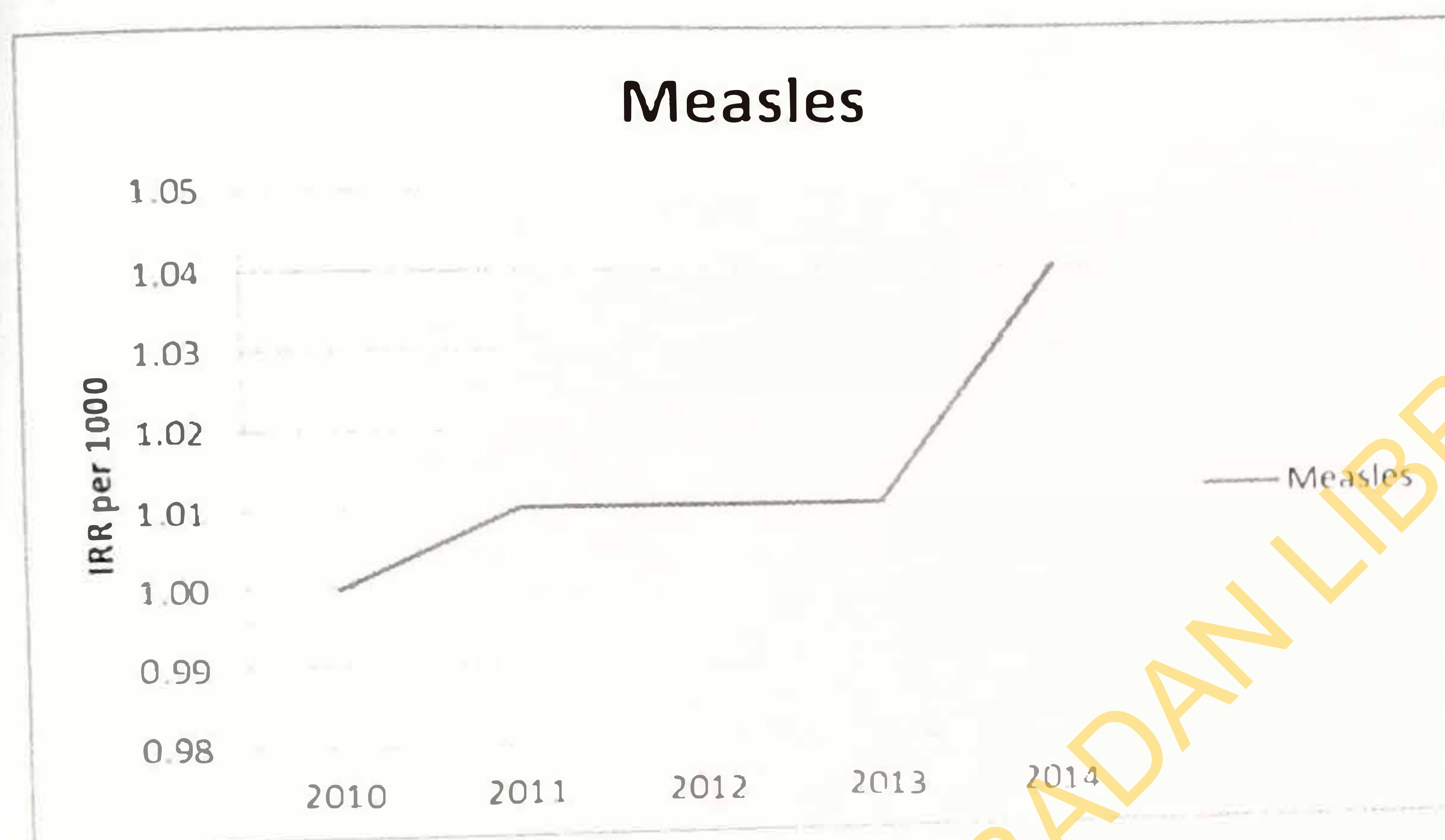


Figure 4.8: Pattern of Measles among under-5 children in 2010 to 2014

Figure 4.8 shows the trend in the incidence of measles among under-5 children; the incidence rate was static at (1.01 per 1000) from 2011 to 2013 and thereafter it increase in 2014 (1.04 per 1000).

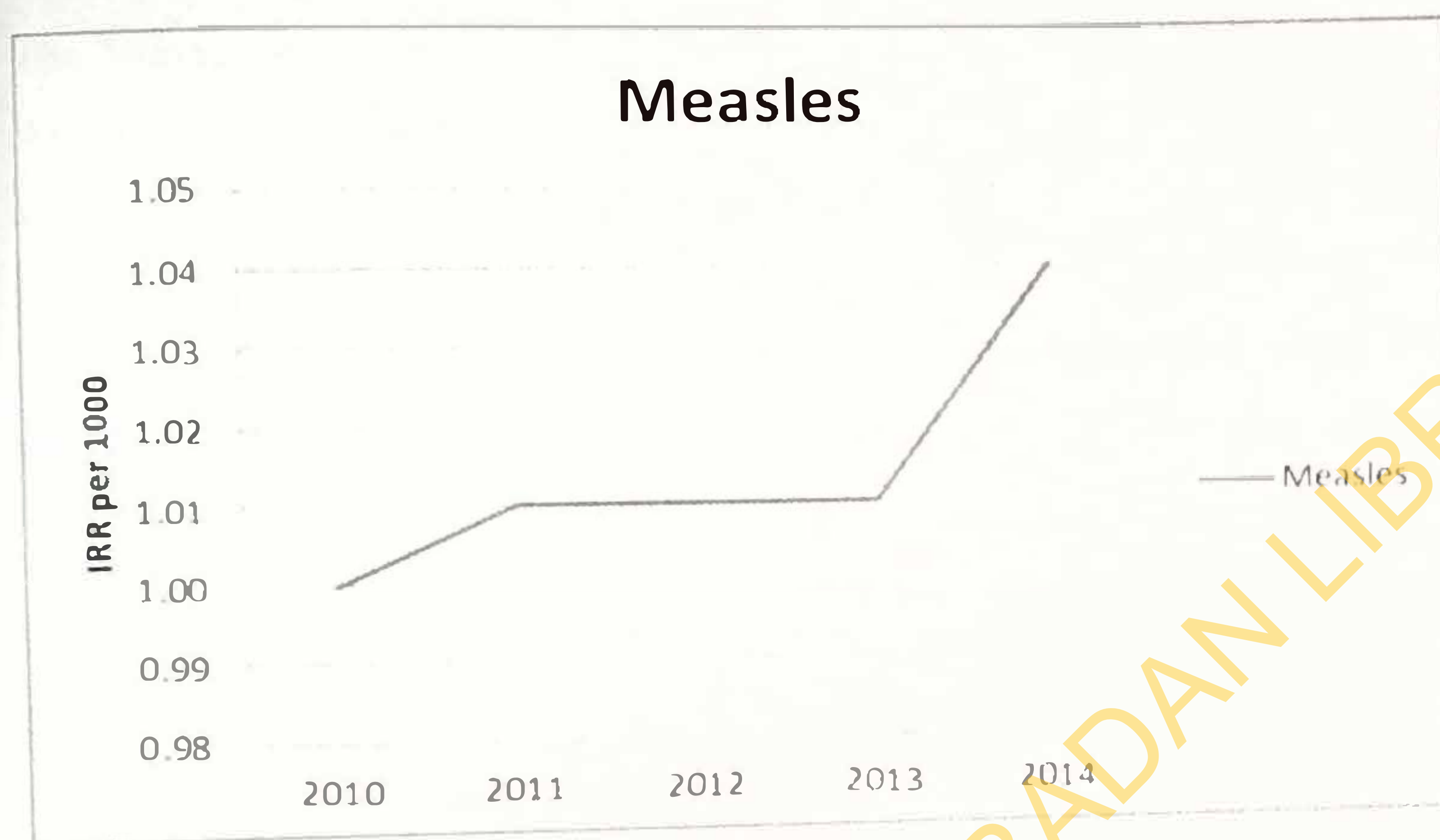


Figure 4.8: Pattern of Measles among under-5 children in 2010 to 2014

4.2 Comparison of ZINB and ZIP regression models using the AIC, BIC and the Vuong's test.

4.2.1 Test for the comparison of the model for Malaria among under-5 children

Table 4.2 shows the model comparison for malaria among under-5 children.

The Vuong z-statistic shows a large negative value lesser than 1.96 ($V < -1.96$) $V = -17.07876$, $AIC = -17.07876$, $BIC = -17.07876$.

H_0 : Model 1 & Model 2 are indistinguishable

H_1 : Model 1 & Model 2 are distinguishable

Table 4.2: Test for the comparison of the model for Malaria among under-5 children

Model comparison for Malaria			
Model 2: Zero-Inflated Negative Binomial			
Model 1: Zero-inflated Poisson	Vuong z-statistic		p-value
	Vuong statistic	-17.07876	<0.001
	AIC corrected	-17.07876	<0.001
	BIC corrected	-17.07876	<0.001

Test-statistic is asymptotically distributed $N(0, 1)$ under the null hypothesis

4.2.2Test for the comparison of the model for Pneumonia among under-5 children

Table 4.3 shows the model comparison for pneumonia among under-5 children.

The Vuong z-statistic shows a large negative value lesser than 1.96 ($V < -1.96$) $V = -7.952249$, $AIC = -7.952249$, $BIC = -7.952249$

Ho: Model 1 & Model 2 are indistinguishable

Hi: Model 1 & Model 2 are distinguishable

Table 4.3:Test for the comparison of the model for Pneumonia among under-5 children

	Model comparison for Pneumonia		
	Model 2: Zero-Inflated Negative Binomial		
Model 1: Zero-inflated Poisson		Vuong z-statistic	p-value
	Vuong statistic	-7.952249	<0.001
	AIC corrected	-7.952249	<0.001
	BIC corrected	-7.952249	<0.001

Test-statistic is asymptotically distributed $N(0, 1)$ under the null hypothesis

4.2.3Test for the comparison of the models for Diarrhoea among under-5 children

Table 4.4 shows the model comparison for Diarrhoea among under-5 children.
The Vuong z-statistic shows a large negative value lesser than 1.96 ($V < -1.96$) $V = -12.37188$,
 $AIC = -12.37188$, $BIC = -12.37188$

Ho: Model 1 & Model 2 are indistinguishable
Hi: Model 1 & Model 2 are distinguishable

Table 4.4:Test for the comparison of the models for Diarrhoea among under-5 children

	Model comparison for Diarrhoea		
	Model 2: Zero-Inflated Negative Binomial		
Model 1: Zero-inflated Poisson		Vuong z-statistic	p-value
	Vuong statistic	-12.37188	<0.001
	AIC corrected	-12.37188	<0.001
	BIC corrected	-12.37188	<0.001

Test-statistic is asymptotically distributed $N(0, 1)$ under the null hypothesis

4.2.3Test for the comparison of the models for Diarrhoea among under-5 children

Table 4.4 shows the model comparison for Diarrhoea among under-5 children.
The Vuong z-statistic shows a large negative value lesser than 1.96 ($V < -1.96$) $V = -12.37188$,
 $AIC = -12.37188$, $BIC = -12.37188$

Ho: Model 1 & Model 2 are indistinguishable

Hi: Model 1 & Model 2 are distinguishable

Table 4.4:Test for the comparison of the models for Diarrhoea among under-5 children

	Model comparison for Diarrhoea		
	Model 2: Zero-Inflated Negative Binomial		
Model 1: Zero-inflated Poisson		Vuong z-statistic	p-value
	Vuong statistic	-12.37188	<0.001
	AIC corrected	-12.37188	<0.001
	BIC corrected	-12.37188	<0.001

Test-statistic is asymptotically distributed $N(0, 1)$ under the null hypothesis

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Table 4.4:Test for the comparison of the models for Diarrhoea among under-5 children

	Model comparison for Diarrhoea		
	Model 2: Zero-Inflated Negative Binomial		
Model 1: Zero-inflated Poisson		Vuong z-statistic	p-value
	Vuong statistic	-12.37188	<0.001
	AIC corrected	-12.37188	<0.001
	BIC corrected	-12.37188	<0.001

Test-statistic is asymptotically distributed $N(0, 1)$ under the null hypothesis

4.2.4Test for the comparison of the model for Measles among under-5 children

Table 4.5 shows the model comparison for Measles among under-5 children.
The Vuong z-statistic shows a large negative value lesser than 1.96 ($V < -1.96$) $V= -3.655775$.
 $AIC = -3.576543$, $BIC=-3.355055$

Ho: Model 1 & Model 2 are indistinguishable
Hi: Model 1 & Model 2 are distinguishable

Table 4.5:Test for the comparison of the model for Measles among under-5 children

Model comparison for Measles			
Model 2: Zero-Inflated Negative Binomial			
Model 1: Zero-inflated Poisson	Vuong z-statistic		p-value
	Vuong statistic	-3.655775	<0.001
	AIC corrected	-3.576543	<0.001
	BIC corrected	-3.355055	<0.001

Test-statistic is asymptotically distributed $N(0, 1)$ under the null hypothesis

4.3 The effect of the month, year and local government area on the occurrence of Malaria disease among under-5 children using ZINB regression model

Table 4.6 shows the regression parameters for zero inflated negative binomial regression model. The risk of malaria among under-5 children was higher by approximately 166.6% in the year 2011 compared to year 2010 (IRR = 2.166, 95% CI: 1.953, 2.403). In 2012, there was an excess risk of approximately 155.5% compared to year 2010 (IRR = 2.555, 95% CI: 2.307, 2.829). In 2013, the risk of malaria among under-5 children was approximately higher by 204% compared to 2010 (IRR=3.040, 95% CI: 2.714, 3.406). And lastly in 2014, there was an increase of 258.9% compared to year 2010 (IRR = 3.589, 95% CI: 3.045, 4.232).

For the months of reporting in the ZINB model, the risk of malaria among under-5 children increased by 28.7% in August (IRR = 1.287, 95% CI: 1.087, 1.523), 32.2% in July (IRR = 1.322, 95% CI: 1.117, 1.564), 25.6% in June (IRR = 1.256, 95% CI: 1.063, 1.484), 28.5% in May (IRR = 1.285, 95% CI: 1.086, 1.521), 46.8% in October (IRR = 1.468, 95% CI: 1.145, 1.883) and 28% in September (IRR = 1.284, 95% CI: 1.070, 1.541) compared to the risk of malaria among under-5 children in the month of April. However, the risk of malaria among under-5 children in reporting months of February and January decreased by 17.6% (IRR= 0.824, 95% CI: 0.701, 0.970) and 19.6% (IRR = 0.804, 95% CI: 0.685, 0.944) respectively compared to the risk of malaria in the month of April.

In the local government areas, the risk of malaria among under-5 children was higher by 49.8% in Akinyele (IRR = 1.498, 95% CI: 1.129, 1.986) , 366.6% in Atiba (IRR = 4.665, 95% CI: 3.518, 6.186), 204.9% in Egbeda (IRR = 3.049, 95% CI: 2.291, 4.060), 304.7% in Ibadan North (IRR = 4.047, 95% CI: 3.022, 5.420), 162.5% in Ibadan North East (IRR = 2.625, $p<0.001$), 79.7% in Ibadan North West (IRR=1.797, $p<0.001$), 171.3% in Ibadan South East (IRR = 2.713, $p<0.001$), 121.7% in Oyo East (IRR = 2.217, 95% CI: 1.665, 2.951) and 376.8% in Saki West (IRR= 4.768, 95% CI: 3.582, 6.348) compared to the risk of malaria among under-5 children in Afijio local government area. However, the risk of malaria were lower by about 44% in Ibarapa North (IRR = 0.558, 95% CI: 0.418, 0.744), 30.9% in Irepo (IRR = 0.691, 95% CI: 0.539, 0.886), 27% in Oghomoso South (IRR = 0.727, 95% CI: 0.546, 0.968) and 37.7% in Orelope

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(IRR = 0.623, 95% CI: 0.458, 0.848) compared to the risk of malaria among under-5 children in Afijio local government area.

For the zero inflated group, in 2011, the odds of a malaria case being in the certain zero group is 6 times higher by 495.4% compared to year 2010. (IRR = 5.954, 95% CI: 2.243, 15.801). In 2013, the odds of a malaria case being in the certain zero group was 3 times higher by 242% (IRR = 3.421, 95% CI: 2.641, 4.431) compared to year 2010. However in year 2012, the odds of a malaria case being in the certain zero group was lowered by 99.5% (IRR = 0.005, 95% CI: 0.000, 0.115) compared to year 2010.

In the months February, January and March, the odds of a malaria case being in the certain zero groups were lowered by 90.1% (IRR = 0.099, 95% CI: 0.024, 0.216), by 90.1% (IRR = 0.099, 95% CI: 0.024, 0.216) and by 97.8% (IRR = 0.022, 95% CI: 0.078, 0.709) respectively compared to the month of April. Conversely, in the month of September, the odds of a malaria case being in the certain zero group was 4 times higher by 297.9% (IRR = 3.979, 95% CI: 1.122, 14.114) compared to the month of April.

Table 4.6: Parameter estimates in the Zero inflated negative binomial for Malaria among under-5 children

Parameters	ZINB				
	Standard	IRR	95% CI for IRR		P value
	Error		Lower Bound	Upper Bound	
Intercept	0.121	67.021	52.87	84.958	< 0.001
2010 (Year 1) *					
2011 (Year 2)	0.053	2.166	1.953	2.403	< 0.001
2012 (Year 3)	0.052	2.555	2.307	2.829	< 0.001
2013 (Year 4)	0.058	3.04	2.714	3.406	< 0.001
2014 (Year 5)	0.084	3.589	3.045	4.232	< 0.001
April *					
August	0.086	1.287	1.087	1.523	0.003
Dec	0.096	1.399	0.944	1.376	0.170
Feb	0.083	0.824	0.701	0.970	0.020
Jan	0.082	0.804	0.685	0.944	0.008
July	0.086	1.322	1.117	1.564	<0.001
June	0.085	1.256	1.063	1.484	0.007
March	0.083	0.976	0.830	1.149	0.775
May	0.086	1.285	1.086	1.521	0.003
Nov	0.094	1.125	0.936	1.353	0.207
Oct	0.127	1.468	1.145	1.883	0.002
Sept	0.093	1.284	1.070	1.541	0.007
Afijio *					
Akinyele	0.144	1.498	1.129	1.986	0.005
Atiba	0.144	4.665	3.518	6.186	<0.001
Atisbo	0.145	1.079	0.812	1.434	0.601
Egbeda	0.146	3.049	2.291	4.060	<0.001
Ibarapa central	0.147	1.455	1.091	1.941	<0.001
Ibadan North	0.149	4.047	3.022	5.420	<0.001
Ibadan North East	0.146	2.625	1.972	3.494	<0.001
Ibadan North West	0.146	1.797	1.350	2.392	<0.001
Ibadan South East	0.148	2.713	2.030	3.626	<0.001
Ibadan South West	0.146	1.674	1.257	2.228	<0.001
Ibarapa East	0.146	1.004	0.754	1.337	0.977
Ibarapa North	0.147	0.558	0.418	0.744	<0.001
Ido	0.146	1.528	1.148	2.034	0.004
Irepo	0.127	0.691	0.539	0.886	0.003
Iseyin	0.144	1.397	1.053	1.852	0.021

Itesiwaju	0.146	0.815	0.613	1.086	0.162
Iwajowa	0.146	0.515	0.387	0.685	<0.001
Kajola	0.145	0.992	0.747	1.318	0.958
Lagelu	0.145	1.489	1.121	1.978	0.006
Ogbomoso South	0.146	0.727	0.546	0.968	0.029
Ogbomoso North	0.147	2.259	1.694	3.014	<0.001
OgoOluwa	0.145	0.899	0.676	1.194	0.461
Olorunsogo	0.147	0.811	0.608	1.082	0.156
Oluyole	0.145	1.455	1.095	1.933	0.010
Onaara	0.148	1.998	1.495	2.670	<0.001
Orelope	0.157	0.623	0.458	0.848	0.003
Orire	0.146	1.081	0.812	1.439	0.594
Oyo East	0.146	2.217	1.665	2.951	<0.001
Oyo West	0.145	1.063	0.800	1.412	0.674
Saki East	0.145	0.826	0.622	1.098	0.189
Saki West	0.146	4.768	3.582	6.348	<0.001
Surulere	0.145	0.803	0.604	1.066	0.131
Inf.Intercept	1.231	0.009	0.000	0.011	<0.001
Inf.2010 (Year 1) *					
Inf.2011 (Year 2)	0.498	5.954	2.243	15.801	<0.001
Inf.2012 (Year 3)	1.601	0.005	0.000	0.115	<0.001
Inf.2013 (Year 4)	0.132	3.421	2.641	4.431	<0.001
Inf.2014 (Year 5)	1.365	0.003	0.000	0.037	1.000
Inf.April *					
Inf.August	0.887	0.306	0.054	1.741	0.182
Inf.Dec	0.687	3.838	0.998	14.754	1.001
Inf.Feb	0.562	0.099	0.024	0.216	<0.001
Inf.Jan	0.562	0.099	0.024	0.216	<0.001
Inf.July	0.788	0.478	0.102	2.240	0.349
Inf.June	0.917	0.298	0.049	1.797	0.186
Inf.March	0.562	0.022	0.078	0.709	<0.001
Inf.May	0.799	0.478	0.100	2.287	0.355
Inf.Nov	0.653	1.939	0.539	6.972	1.001
Inf.Oct	0.937	4.693	0.748	29.445	1.001
Inf.Sept	0.646	3.979	1.122	14.114	<0.001
Inf.Afijio *					
Inf.Akinyele	1.205	0.295	0.028	3.126	0.311
Inf.Atiba	1.216	0.142	0.013	1.535	0.108
Inf.Atisbo	1.197	0.611	0.058	6.380	0.681
Inf.Egbeda	1.156	1.143	0.119	11.021	0.907

Inf.Ibarapa central	1.118	1.958	0.219	17.519	0.548
Inf.Ibadan North	1.090	3.059	0.361	25.904	0.305
Inf.Ibadan North East	1.156	0.143	0.119	11.021	0.907
Inf.Ibadan North West	1.157	1.142	0.118	11.031	0.909
Inf.Ibadan South East	1.090	3.059	0.361	25.904	0.305
Inf.Ibadan South West	1.156	0.143	0.119	11.021	0.907
Inf.Ibarapa East	1.155	1.196	0.124	11.505	0.877
Inf.Ibarapa North	1.125	1.898	0.209	17.219	0.569
Inf.Ido	1.157	1.139	0.118	10.998	0.910
Inf.Irepo	1.020	1.143	0.155	8.442	0.896
Inf.Iseyin	1.205	0.295	0.028	3.126	0.311
Inf.Itesiwaju	1.161	1.124	0.115	10.941	0.920
Inf.Iwajowa	1.191	0.600	0.058	6.199	0.669
Inf.Kajola	1.191	0.601	0.058	6.205	0.669
Inf.Lagelu	1.191	0.601	0.058	6.205	0.669
Inf.Ogbomoso South	1.161	1.124	0.115	10.941	0.920
Inf.Ogbomoso North	1.118	1.954	0.218	17.484	0.549
Inf.OgoOluwa	1.191	0.601	0.058	6.205	0.669
Inf.Olorunsogo	1.154	1.652	0.172	15.861	0.664
Inf.Oluyole	1.191	0.601	0.058	6.205	0.669
Inf.Onaara	1.095	2.951	0.345	25.234	0.323
Inf.Orelope	2.608	2.362	0.014	395.314	0.273
Inf.Orire	1.159	1.133	0.117	10.986	0.914
Inf.Oyo East	1.156	1.143	0.119	11.021	0.907
Inf.Oyo West	1.191	0.601	0.058	6.205	0.669
Inf.Saki East	1.191	0.601	0.058	6.205	0.669
Inf.Saki West	1.156	1.143	0.119	11.021	0.908
Inf.Surulere	1.191	0.601	0.058	6.205	0.669
Dispersion	2.196				

* Reference category

4.4 The effect of the month, year and local government area on the occurrence of Pneumonia disease among under-5 children using ZINB regression model

Table 4.7 shows the estimate parameters of Zero inflated negative binomial regression model. The risk of pneumonia among under-5 children were lower by approximately 76.2% in year 2011 (IRR = 0.238, 95% CI: 0.150, 0.379), 78.2% in year 2012 (IRR = 0.218, 95% CI: 0.136, 0.347), 79% in year 2013 (IRR = 0.209, 95% CI: 0.128, 0.341) and 82.7% in year 2014 (IRR = 0.173, 95% CI: 0.092, 0.324) compared to the risk of pneumonia among under-5 children in year 2010.

The risk of pneumonia among under-5 children were increased by 54.9% in August (IRR = 1.549, 95% CI: 1.043, 2.302) and 75.1% in July (IRR = 1.751, 95% CI: 1.167, 2.627) compared to the risk of pneumonia in the month of April.

The risk of pneumonia among under-5 children was approximately higher by 225.8% in Akinyele (IRR = 3.258, 95% CI: 1.113, 9.536), 297.9% in Atiba (IRR = 3.979, 95% CI: 1.252, 12.647), 449.6% in Atisbo (IRR = 5.496, 95% CI: 1.918, 15.745), 319.5% in Egbeda (IRR = 4.195, 95% CI: 1.479, 11.902), 347.3% in Ibarapa central (IRR = 4.473, 95% CI: 1.220, 16.403), 345.5% in Ibadan North East (IRR = 4.455, 95% CI: 1.620, 12.248), 260% in Ibadan South East (IRR = 3.600, 95% CI: 1.322, 9.802), 175.7% in Ido (IRR = 2.757, 95% CI: 1.024, 7.417), 423.8% in Iseyin (IRR = 5.238, 95% CI: 1.897, 14.968), 431.7% in Itesiwaju (IRR = 5.317, 95% CI: 1.795, 15.750), 287.7% for Iwajowa (IRR = 3.877, 95% CI: 1.345, 11.172), 359.9% in Ogo Oluwa (IRR = 4.599, 95% CI: 1.375, 15.384), 457.8% in Oluyole (IRR = 5.578, 95% CI: 1.951, 15.952), 469.2% in Orelope (IRR = 5.692, 95% CI: 1.601, 20.229) and 304.7% in Saki East (IRR = 4.047, 95% CI: 1.507, 10.868) compared to the risk of pneumonia in Afijio local government area.

For the zero inflated group. In year 2011, the odds of a pneumonia case being in the certain zero group was lowered by 98.1% (IRR = 0.019, 95% CI: 0.010, 0.037) compared to year 2010. The odds of a pneumonia case being in the certain zero group was lowered by 98.4% in year 2012 (IRR = 0.016, 95% CI: 0.007, 0.037) and in year 2013, the odds of a pneumonia case being in the

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certain zero group was lowered by 93.3% (IRR = 0.067, 95% CI: 0.039, 0.117) compared to year 2010.

In the months December, November and October, the odds of a pneumonia case being in the certain zero group were 5 times, 4 times and 8 times respectively higher by 397.3% (IRR = 4.973, 95% CI: 2.158, 11.461), 302.3% (IRR = 4.023, 95% CI: 1.794, 9.021) and 659.1% (IRR = 7.591, 95% CI: 3.236, 17.807) compared to the month of April. However in the month of March, the odds of a pneumonia case being in the certain zero group was lowered by 60.7% (IRR = 0.393, 95% CI: 0.168, 0.922) compared to the month of April.

In the local government areas, in Ibadan South West, the odds of a pneumonia case being in the certain zero group is 7 times higher by 605.7% (IRR = 7.057, 95% CI: 2.478, 20.098). In Ido, Itesiwaju, Iwajowa, Lagelu, Ogbomoso South, Ogbomoso North, OgoOluwa, Oluyole and Onaara local government area, the odds of a pneumonia case being in the certain zero group were 4 times, 7 times, 4 times, 4 times, 4 times, 3 times, 4 times, 4 times and 3 times respectively higher by 320.3% (IRR = 4.203, 95% CI: 1.844, 14.671), by 574.6% (IRR = 6.746, 95% CI: 2.049, 22.213), by 315.8% (IRR = 4.158, 95% CI: 1.355, 12.758), by 262.2% (IRR = 3.622, 95% CI: 1.262, 10.397), by 262.2% (IRR = 3.622, 95% CI: 1.140, 11.512), by 201% (IRR = 3.010, 95% CI: 1.049, 8.641), by 272.5% (IRR = 3.725, 95% CI: 1.176, 11.793), by 322.5% (IRR = 4.225, 95% CI: 1.475, 12.104) and by 224.8% (IRR = 3.248, 95% CI: 2.980, 3.540) compared to Afijio local government area.

Table 4.7: Parameter estimates in the Zero inflated negative binomial for Pneumonia among under-5 children

Parameters	ZINB				
	Standard	IRR	95% CI for IRR		P value
	Error		Lower Bound	Upper Bound	
Intercept	0.502	0.274	0.102	0.733	<0.001
2010 (Year 1) *					
2011 (Year 2)	0.236	0.238	0.150	0.379	<0.001
2012 (Year 3)	0.238	0.218	0.136	0.347	<0.001
2013 (Year 4)	0.249	0.209	0.128	0.341	<0.001
2014 (Year 5)	0.321	0.173	0.092	0.324	<0.001
April *					
August	0.202	1.549	1.043	2.302	0.030
Dec	0.257	0.872	0.527	1.443	0.595
Feb	0.205	0.769	0.515	1.150	0.200
Jan	0.201	0.874	0.589	1.296	0.501
July	0.207	1.751	1.167	2.627	0.007
June	0.197	1.456	0.990	2.143	0.056
March	0.198	1.009	0.684	1.487	0.963
May	0.207	1.155	0.770	1.733	0.485
Nov	0.237	1.428	0.897	2.272	0.133
Oct	0.275	1.366	0.797	2.342	0.257
Sept	0.225	1.467	0.944	2.280	0.088
Afijio *					
Akinyele	0.548	3.258	1.113	9.536	<0.001
Atiba	0.590	3.979	1.252	12.647	<0.001
Atisbo	0.537	5.496	1.918	15.745	<0.001
Egbeda	0.532	4.195	1.479	11.902	<0.001
Ibarapa central	0.663	4.473	1.22	16.403	<0.001
Ibadan North	0.532	1.430	0.504	4.058	0.101
Ibadan North East	0.516	4.455	1.620	12.248	<0.001
Ibadan North West	0.531	2.557	0.903	7.241	0.201
Ibadan South East	0.511	3.600	1.322	9.802	<0.001
Ibadan South West	0.523	1.554	0.558	4.332	0.201
Ibarapa East	0.547	2.323	0.795	6.788	0.111
Ibarapa North	0.814	3.083	0.625	15.202	0.101
Ido	0.505	2.757	1.024	7.417	<0.001

Irepo	0.500	1.319	0.495	3.515	0.511
Iseyin	0.527	5.238	1.897	14.968	<0.001
Itesiwaju	0.554	5.317	1.795	15.750	<0.001
Iwajowa	0.54	3.877	1.345	11.172	<0.001
Kajola	0.516	1.025	0.373	2.819	0.101
Lagelu	0.522	1.311	0.471	3.648	0.111
Ogbomoso South	0.551	1.812	0.401	3.480	0.201
Ogbomoso North	0.516	2.408	0.876	6.622	0.131
OgoOluwa	0.616	4.599	1.375	15.384	<0.001
Olorunsogo	0.519	1.349	0.488	3.729	0.181
Oluyole	0.536	5.578	1.951	15.952	<0.001
Onaara	1.613	7.308	0.310	172.514	0.217
Orelope	0.647	5.692	1.601	20.229	<0.001
Orire	1.122	6.404	0.710	57.75	0.301
Oyo East	0.537	2.398	0.837	6.872	0.101
Oyo West	0.513	2.392	0.875	6.537	0.331
Saki East	0.504	4.047	1.507	10.868	<0.001
Saki West	0.504	1.379	0.514	3.706	0.271
Surulere	0.550	1.184	0.403	3.480	0.121
Inf.Intercept	2.521	0.129	0.001	18.177	0.418
Inf.2010 (Year 1) *					
Inf.2011 (Year 2)	0.340	0.019	0.010	0.037	<0.001
Inf.2012 (Year 3)	0.408	0.016	0.007	0.037	<0.001
Inf.2013 (Year 4)	0.282	0.067	0.039	0.117	<0.001
Inf.2014 (Year 5)	0.293	0.746	0.420	1.325	0.318
Inf.April *					
Inf.August	0.390	0.779	0.363	1.673	0.521
Inf.Dec	0.426	4.973	2.158	11.461	<0.001
Inf.Feb	0.458	0.419	0.171	1.028	0.058
Inf.Jan	0.430	0.454	0.196	1.055	0.066
Inf.July	0.391	1.062	0.493	2.285	0.879
Inf.June	0.389	0.792	0.370	1.698	0.549
Inf.March	0.435	0.393	0.168	0.922	0.032
Inf.May	0.404	1.154	0.523	2.547	0.722
Inf.Nov	0.412	4.023	1.794	9.021	<0.001
Inf.Oct	0.435	7.591	3.236	17.807	<0.001
Inf.Sept	0.401	1.958	0.892	4.297	0.094
Inf.Afijio *					
Inf.Akinyele	2.561	4.191	0.028	634.324	0.083
Inf.Atiba	2.552	3.789	0.025	563.361	0.113

Inf.Atisbo	2.549	4.983	0.034	736.596	0.071
Inf.Egbeda	2.536	1.446	0.010	208.421	0.334
Inf.Ibarapa central	2.589	6.726	0.042	1075.391	0.223
Inf.Ibadan North	2.54	5.551	0.038	806.255	0.064
Inf.Ibadan North East	2.533	1.817	0.013	260.26	0.070
Inf.Ibadan North West	2.535	1.366	0.009	196.488	0.066
Inf.Ibadan South East	0.532	1.062	0.374	3.012	0.109
Inf.Ibadan South West	0.534	7.057	2.478	20.098	0.051
Inf.Ibarapa East	1.541	4.203	0.205	86.173	0.062
Inf.Ibarapa North	1.631	4.869	0.199	119.076	0.074
Inf.Ido	0.529	5.202	1.844	14.671	0.029
Inf.Irepo	1.524	2.083	0.105	41.307	0.061
Inf.Iseyin	0.541	1.236	0.428	3.569	0.097
Inf.Itesiwaju	0.608	6.746	2.049	22.213	0.034
Inf.Iwajowa	0.572	4.158	1.355	12.758	0.035
Inf.Kajola	2.545	1.063	0.007	155.898	0.111
Inf.Lagelu	0.538	3.622	1.262	10.397	0.021
Inf.Ogbomoso South	0.590	3.622	1.140	11.512	0.018
Inf.Ogbomoso North	0.538	3.010	1.049	8.641	0.006
Inf.OgoOluwa	0.588	3.725	1.176	11.793	0.040
Inf.Olorunsogo	0.569	2.012	0.660	6.136	0.150
Inf.Oluyole	0.537	4.225	1.475	12.104	0.032
Inf.Onaara	0.044	3.248	2.980	3.540	0.007
Inf.Orelope	1.514	2.588	0.133	50.322	0.006
Inf.Orire	1.739	1.175	0.039	35.497	0.301
Inf.Oyo East	1.545	2.221	0.108	45.888	0.059
Inf.Oyo West	1.532	2.604	0.129	52.443	0.118
Inf.Saki East	1.529	1.543	0.077	30.903	0.174
Inf.Saki West	1.528	1.820	0.088	34.949	0.159
Inf.Surulere	1.680	4.166	0.155	112.146	0.365
Dispersion	1.025				

*Reference category

4.5 The effect of the month, year and local government area on the occurrence of Diarrhoea disease among under-5 children using the zero-inflated negative binomial regression model

Table 4.8 shows the regression parameters for zero inflated negative binomial regression model. The risk of diarrhoea among under-5 children was lower by 22.7% in the year 2011 (IRR = 0.773, 95% CI: 0.688, 0.867) and 19.2% in year 2012 (IRR = 0.808, 95% CI: 0.719, 0.907) compared to year 2010.

The risk of diarrhoea among under-5 children was approximately higher by 234% in Atiba (IRR = 3.340, 95% CI: 2.494, 4.473), 84.4% in Atisbo (IRR = 1.848, 95% CI: 1.372, 2.489), 257.2% in Egbeda (IRR = 3.572, 2.657, 4.811), 63.6% in Ibarapa central (IRR = 1.636, 95% CI: 1.209, 2.212), 752.5% in Ibadan North (IRR = 8.525, 95% CI: 6.304, 11.529), 272.5% in Ibadan North East (IRR = 3.725, 95% CI: 2.771, 5.008), 77.9% in Ibadan North West (IRR = 1.779, 95% CI: 1.321, 2.392), 351.3% in Ibadan South East (IRR = 4.513, 95% CI: 3.350, 6.079), 92.9% in Ibadan South West (IRR = 1.929, 95% CI: 1.455, 2.651), 136.1% in Ido (IRR = 2.361, 95% CI: 1.756, 3.174), 102.8% in Iseyin (IRR = 2.028, 95% CI: 1.508, 2.726), and 806.1% in Saki West (9.061, 95% CI: 6.753, 12.158) compared to the risk of diarrhoea in Afijio local government area. However, the risk of diarrhoea among under-5 children was lower by about 37.1% in Ibarapa North (IRR = 0.629, 95% CI: 0.460, 0.859) compared to the risk of diarrhoea under-5 children in Afijio local government area.

For the zero inflated group, in year 2013, the odds of a diarrhoea case being in the certain zero group was 3 times higher by 188.6% (IRR = 2.886, 95% CI: 1.789, 4.656) compared to year 2010. The odds of a diarrhoea case being in the certain zero group in year 2014 was higher by 0.2% (IRR = 1.002, 95% CI: 0.597, 0.681). However in the year 2012, the odds of a diarrhoea case being in the certain zero group was lowered by 52.5% (IRR = 0.475, 95% CI: 0.466, 0.485) compared to year 2010.

In the months December, November, October and September, the odds of a diarrhoea case being in the certain zero were 3 times, 2 times, 13 times and 3 times respectively higher by 188.6% (IRR = 2.886, 95% CI: 1.789, 4.656), by 130.5% (IRR = 2.305, 95% CI: 1.426, 3.725), by

1167.9% (IRR = 12.679, 95% CI: 7.513, 21.398) and 119% (IRR = 2.190, 95% CI: 1.352, 3.547) respectively compared to the month of April. However the odds of a diarrhoea case being in the certain zero group in the months of February, January and March were lowered by 86.2% (IRR = 0.138, 95% CI: 0.056, 0.336), 85.6% (IRR = 0.144, 95% CI: 0.061, 0.341) and 78.8% (IRR = 0.212, 95% CI: 0.101, 0.448) respectively compared to the month of April.

In the Orelope local government area, the odds of a diarrhoea case being in the certain zero group was higher by 5.5% (IRR = 1.055, 95% CI: 0.479, 0.844) compared to Afijio local government area.

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Table 4.8: Parameter estimates in the Zero inflated negative binomial for Diarrhoea among under-5 children

ZINB					
Parameters	Standard	IRR	95% CI for IRR		P value
	Error		Lower Bound	Upper Bound	
Intercept	0.124	27.086	21.242	34.537	< 0.001
2010 (Year 1) *					
2011 (Year 2)	0.059	0.773	0.688	0.867	<0.001
2012 (Year 3)	0.059	0.808	0.719	0.907	<0.001
2013 (Year 4)	0.067	0.911	0.799	1.039	0.165
2014 (Year 5)	0.099	1.057	0.870	1.283	0.577
April *					
August	0.089	1.104	0.927	1.314	0.265
Dec	0.098	1.107	0.914	1.342	0.300
Feb	0.085	0.895	0.758	1.057	0.193
Jan	0.085	0.962	0.814	1.136	0.642
July	0.089	1.147	0.963	1.365	0.122
June	0.089	1.051	0.883	1.252	0.573
March	0.085	0.959	0.812	1.133	0.619
May	0.089	1.169	0.982	1.392	0.080
Nov	0.095	1.043	0.866	1.256	0.659
Oct	0.135	1.138	0.873	1.482	0.340
Sept	0.095	1.075	0.892	1.295	0.447
Afijio *					
Akinyele	0.153	1.116	0.827	1.507	0.472
Atiba	0.149	3.340	2.494	4.473	<0.001
Atisbo	0.152	1.848	1.372	2.489	<0.001
Egbeda	0.151	3.572	2.657	4.811	<0.001
Ibarapa central	0.154	1.636	1.209	2.212	<0.001
Ibadan North	0.154	8.525	6.304	11.529	<0.001
Ibadan North East	0.151	3.725	2.771	5.008	<0.001
Ibadan North West	0.152	1.779	1.321	2.392	<0.001
Ibadan South East	0.152	4.513	3.35	6.079	<0.001
Ibadan South West	0.153	1.929	1.455	2.651	<0.001
Ibarapa East	0.156	1.602	1.179	2.174	0.002
Ibarapa North	0.159	0.629	0.460	0.859	0.003
Ido	0.151	2.361	1.756	3.174	<0.001

Irepo	0.132	1.259	0.973	1.632	0.081
Iseyin	0.151	2.028	1.508	2.726	<0.001
Itesiwaju	0.154	1.013	0.749	2.726	0.935
Iwajowa	0.152	1.034	0.767	1.392	0.830
Kajola	0.152	1.077	0.799	1.451	0.627
Lagelu	0.151	1.719	1.279	2.312	<0.001
Ogbomoso South	0.154	1.246	0.921	1.685	0.154
Ogbomoso North	0.153	3.414	2.529	4.608	<0.001
OgoOluwa	0.154	0.955	0.706	1.292	0.766
Olorunsogo	0.153	1.112	0.824	1.501	0.488
Oluyole	0.151	2.029	1.509	2.729	<0.001
Onaara	0.153	2.201	1.631	2.971	<0.001
Orelope	0.168	1.320	0.950	1.835	0.098
Orire	0.154	2.889	2.136	3.907	<0.001
Oyo East	0.151	2.507	1.865	3.370	<0.001
Oyo West	0.151	1.972	1.467	2.651	<0.001
Saki East	0.151	2.179	1.624	2.924	<0.001
Saki West	0.151	9.061	6.753	12.158	<0.001
Surulere	0.151	1.733	1.289	2.330	<0.001
Inf.Intercept	0.375	0.277	0.133	0.577	<0.001
Inf.2010 (Year 1) *					
Inf.2011 (Year 2)	0.151	1.733	1.289	2.330	0.908
Inf.2012 (Year 3)	0.010	0.475	0.466	0.485	<0.001
Inf.2013 (Year 4)	0.244	2.886	1.789	4.656	<0.001
Inf.2014 (Year 5)	0.264	1.002	0.597	0.681	<0.001
Inf.April *					
Inf.August	0.265	0.967	0.575	1.625	0.898
Inf.Dec	0.244	2.886	1.789	1.538	<0.001
Inf.Feb	0.455	0.138	0.056	0.336	<0.001
Inf.Jan	0.439	0.144	0.061	0.341	<0.001
Inf.July	0.265	0.968	0.576	1.626	0.901
Inf.June	0.266	0.932	0.554	1.570	0.792
Inf.March	0.381	0.212	0.101	0.448	<0.001
Inf.May	0.264	1.002	0.597	1.681	0.994
Inf.Nov	0.245	2.305	1.426	3.725	<0.001
Inf.Oct	0.267	12.679	7.513	21.398	<0.001
Inf.Sept	0.246	2.190	1.352	3.547	<0.001
Inf.Afijio *					
Inf.Akinyele	0.467	1.001	0.401	2.500	0.999
Inf.Atiba	0.482	0.716	0.278	1.842	0.488

Inf. Atisbo	0.462	1.119	0.453	1.019	0.806
Inf. Egbeda	0.466	1.010	0.405	2.518	0.983
Inf. Ibarapa central	0.459	1.236	0.503	3.039	0.644
Inf. Ibadan North	0.453	1.514	0.623	1.303	0.360
Inf. Ibadan North East	0.466	1.010	0.405	2.518	0.983
Inf. Ibadan North West	0.466	1.008	0.404	2.513	0.987
Inf. Ibadan South East	0.458	1.242	0.506	3.049	0.635
Inf. Ibadan South West	0.462	1.119	0.452	2.766	0.808
Inf. Ibarapa East	0.454	1.502	0.617	3.658	0.370
Inf. Ibarapa North	0.460	1.433	0.582	3.531	0.433
Inf. Ido	0.466	1.009	0.405	2.515	0.985
Inf. Irepo	0.403	1.055	0.479	2.325	0.894
Inf. Iseyin	0.471	0.903	0.359	2.273	0.829
Inf. Itesiwaju	0.464	1.103	0.444	2.739	0.833
Inf. Iwajowa	0.472	0.896	0.355	2.259	0.816
Inf. Kajola	0.472	0.897	0.355	2.262	0.817
Inf. Lagelu	0.471	0.902	0.358	2.271	0.827
Inf. Ogbomoso South	0.460	1.226	0.498	3.021	0.658
Inf. Ogbomoso North	0.458	1.244	0.507	3.052	0.635
Inf. Ogo Oluwa	0.464	1.104	0.445	2.741	0.832
Inf. Olorunsogo	0.467	1.002	0.401	2.503	0.996
Inf. Oluyole	0.466	1.008	0.404	2.513	0.986
Inf. Onaara	0.459	1.239	0.504	3.045	0.641
Inf. Orelope	0.403	1.055	0.479	0.844	<0.001
Inf. Orire	0.456	1.370	0.561	3.349	0.489
Inf. Oyo East	0.466	1.009	0.405	2.515	0.984
Inf. Oyo West	0.471	0.903	0.359	2.273	0.829
Inf. Saki East	0.471	0.903	0.359	2.275	0.830
Inf. Saki West	0.466	1.011	0.406	2.520	0.982
Inf. Surulere	0.471	0.902	0.358	2.271	0.827
Dispersion	2.102				

*Reference category

4.6 The effect of the month, year and the local government area on the occurrence of Measles disease among under-5 children using the zero-inflated negative binomial regression model

Table 4.9 shows the regression parameters for zero inflated negative binomial regression model. The risk of measles among under-5 children was lowered by 90.4% in year 2012 (IRR = 0.096, 95% CI: 0.043, 0.217) and lowered by 62.6% in year 2013 (IRR = 0.374, 95% CI: 0.155, 0.906) compared to the risk of measles among under-5 children in year 2010.

In the local government areas, the risk of measles among under-5 children was higher by 462.9% in Ibadan North (IRR = 5.629, 95% CI: 1.479, 21.428), 578% in Ibadan South West (IRR = 6.780, 95% CI: 1.778, 25.860) and 283.1% for Saki West (IRR = 3.831, 95% CI: 1.042, 14.076) compared to the risk of measles among under-5 children in Afijio local government area. However, the risk of measles was lowered by about 87.9% in Surulere (IRR = 0.121, 95% CI: 0.025, 0.576) compared to the risk of measles among under-5 children in Afijio local government area.

For the zero inflated group, in year 2011, the odds of a measles case being in the certain zero group were lowered by 72.6% (IRR = 0.274, 95% CI: 0.141, 0.530) and lowered by 84.8% in year 2013 (IRR = 1.002, 95% CI: 0.6064, 0.357) compared to year 2010.

In the months August, July, October and September, the odds of a measles case being in the certain zero group were 6 times, 4 times, 17 times and 3 times respectively higher by 455.1% (IRR = 5.551, 95% CI: 1.686, 18.278), 312.1% (IRR = 4.121, 95% CI: 1.148, 14.790), 1627.1% (IRR = 17.271, 95% CI: 2.835, 105.227) and 293.9% (IRR = 3.939, 95% CI: 1.102, 14.083) respectively compared to the month of April.

In Saki West local government area, the odds of a measles case being in the certain zero group was lowered by 96.7% (IRR = 0.033, 95% CI: 0.002, 0.692) compared to Afijio local government area.

Table 4.9: Parameter estimates in the Zero inflated negative binomial for Measles among under-5 children

Parameters	ZINB				
	Standard Error	IRR	95% CI for IRR		P value
			Lower Bound	Upper Bound	
Intercept	0.441	3.189	1.344	7.571	0.009
2010 (Year 1) *					
2011 (Year 2)	0.414	1.244	0.552	2.799	0.598
2012 (Year 3)	0.415	0.096	0.043	0.217	<0.001
2013 (Year 4)	0.451	0.374	0.155	0.906	0.029
2014 (Year 5)	1.506	1.117	0.058	21.387	0.942
April *					
August	0.437	0.686	0.291	1.615	0.388
Dec	0.853	0.230	0.043	1.226	0.085
Feb	0.348	1.011	0.511	2.000	0.975
Jan	0.386	0.572	0.269	1.220	0.149
July	0.49	0.467	0.179	1.221	0.120
June	0.332	0.648	0.338	1.242	0.191
March	0.323	1.122	0.596	2.113	0.722
May	0.336	0.855	0.442	1.651	0.640
Nov	1.086	0.635	0.076	5.336	0.676
Oct	0.604	0.798	0.244	2.606	0.708
Sept	0.507	0.418	0.155	1.129	0.085
Afijio *					
Akinyele	0.731	2.059	0.491	8.626	0.323
Atiba	0.729	0.271	0.065	1.133	0.073
Atisbo	0.710	1.081	0.269	4.347	0.912
Egbeda	0.746	1.349	0.312	5.819	0.689
Ibarapa central	0.720	3.432	0.837	14.072	0.087
Ibadan North	0.682	5.629	1.479	21.428	0.011
Ibadan North East	0.710	3.155	0.785	12.687	0.106
Ibadan North West	0.813	1.578	0.321	7.764	0.575
Ibadan South East	0.858	0.948	0.176	5.097	0.951
Ibadan South West	0.683	6.780	1.778	25.86	0.005
Ibarapa East	0.810	0.408	0.083	1.995	0.268
Ibarapa North	0.700	0.748	0.190	2.951	0.101
Ido	1.045	0.179	0.023	1.391	0.101
Irepo	0.716	3.297	0.810	13.415	0.096
Iseyin	0.911	0.823	0.138	4.906	0.830

Itesiwaju	1.087	0.455			
Iwajowa	0.818	0.739	0.054	3.833	0.469
Kajola	0.862	0.405	0.149	3.670	0.711
Lagelu	0.747	0.748	0.075	2.196	0.295
Ogbomoso South	0.719	1.369	0.173	3.232	0.697
Ogbomoso North	1.027	0.438	0.334	5.603	0.662
OgoOluwa	1.241	0.689	0.059	3.280	0.422
Olorunsogo	0.830	1.498	0.061	7.849	0.765
Oluyole	0.774	3.397	0.294	7.620	0.626
Onaara	0.684	0.634	0.745	15.488	0.114
Orelope	0.897	0.687	0.166	2.422	0.505
Orire	0.747	1.322	0.118	3.987	0.676
Oyo East	0.750	1.379	0.306	5.715	0.709
Oyo West	0.760	2.664	0.317	6.001	0.668
Saki East	0.859	2.092	0.601	11.818	0.197
Saki West	0.664	3.831	0.388	11.264	0.391
Surulere	0.796	0.121	1.042	14.076	0.043
Inf.Intercept	0.432	0.025	0.025	0.576	0.008
Inf.2010 (Year 1) *		2.965	1.272	6.915	0.012
Inf.2011 (Year 2)	0.337	0.274	0.141	0.530	<0.001
Inf.2012 (Year 3)	17.201	0.001	0.001	0.011	0.678
Inf.2013 (Year 4)	0.437	0.152	0.064	0.357	<0.001
Inf.2014 (Year 5)	1.113	4.988	0.563	44.189	<0.101
Inf.April *					
Inf.August	0.608	5.551	1.686	18.278	0.005
Inf.Dec	1.012	5.419	0.746	39.39	0.808
Inf.Feb	0.486	1.652	0.637	4.283	0.302
Inf.Jan	0.526	2.312	0.825	6.482	0.111
Inf.July	0.652	4.121	1.148	14.79	0.030
Inf.June	0.510	0.868	0.320	2.360	0.783
Inf.March	0.487	1.237	0.476	3.214	0.662
Inf.May	0.527	1.223	0.435	3.435	0.703
Inf.Nov	1.144	1.320	0.140	12.432	0.404
Inf.Oct	0.922	17.271	2.835	105.227	0.002
Inf.Sept	0.650	3.939	1.102	14.083	0.035
Inf.Afijio *					
Inf.Akinyele	1.173	0.668	0.067	6.653	0.731
Inf.Atiba	0.010	0.001	0.001	0.011	0.009
Inf.Atisbo	1.591	0.119	0.005	2.690	0.181
Inf.Egheda	1.306	0.520	0.040	6.731	0.617

Inf.Ibarapa central	1.111	0.747			
Inf.Ibadan North	1.091	0.323	0.085	6.590	0.793
Inf.Ibadan North East	1.106	1.225	0.038	2.738	0.300
Inf.Ibadan North West	1.369	1.116	0.140	10.706	0.854
Inf.Ibadan South East	1.358	1.800	0.076	16.334	0.936
Inf.Ibadan South West	1.064	0.931	0.126	25.782	0.665
Inf.Ibarapa East	1.694	0.111	0.116	7.489	0.946
Inf.Ibarapa North	1.010	1.162	0.004	3.069	0.194
Inf.Ido	2.000	0.536	0.160	8.412	0.219
Inf.Irepo	1.201	0.395	0.011	27.004	0.755
Inf.Iseyin	1.352	1.866	0.038	4.162	0.440
Inf.Itesiwaju	1.858	1.412	0.132	26.388	0.645
Inf.Iwajowa	1.312	1.139	0.037	53.876	0.852
Inf.Kajola	1.863	0.214	0.087	14.902	0.921
Inf.Lagelu	1.876	0.079	0.006	8.244	0.408
Inf.Ogbomoso South	1.310	0.314	0.002	3.149	0.178
Inf.Ogbomoso North	1.671	1.631	0.024	4.098	0.377
Inf.OgoOluwa	1.667	3.659	0.062	43.127	0.770
Inf.Olorunsogo	1.333	1.198	1.282	882.995	0.964
Inf.Oluyole	1.141	2.326	0.088	16.341	0.892
Inf.Onaara	1.352	1.865	0.248	21.766	0.460
Inf.Orelope	1.508	2.282	0.132	26.388	0.645
Inf.Orire	1.445	0.296	0.119	43.846	0.584
Inf.Oyo East	1.240	0.701	0.017	5.019	0.399
Inf.Oyo West	1.228	1.511	0.062	7.968	0.775
Inf.Saki East	1.280	2.430	0.136	16.775	0.737
Inf.Saki West	1.553	0.033	0.198	29.868	0.488
Inf.Surulere	1.310	0.314	0.002	0.692	0.028
Dispersion	0.457		0.024	4.098	0.999

*Reference category

CHAPTER FIVE

DISCUSSION

5.1 PATTERN OF MALARIA AMONG UNDER-5 CHILDREN FROM 2010 TO 2014

The incidence of malaria among under-5 children from 2010 - 2014 appears to have a fluctuating pattern. This pattern may be affected by level of reporting of new cases and the health-seeking behaviour of the caregivers of the affected children as well as inconsistencies in the use of malaria preventive strategies. This pattern is similar to findings in a study conducted among symptomatic patients who sought medical attention at the hospital in Minna by Olayemi *et al* (2009) who demonstrated that the mean annual malaria incidence rates were significantly different over the 4 year study period with a drastic decline in malaria cases from 2005 through 2007. In addition, Ukpong *et al* (2015) working among individuals with malaria cases from 13 years and above in Obudu cattle ranch, Nigeria, recorded varying incidence rates of malaria within the years of study. Finally, Onwuemele (2013) commenting on the pattern of malaria infection in Nigeria noted that malaria infection rate across space depends on dynamic processes involving climatic, environmental, physical and social variables operating differently in space.

5.1.1 PATTERN OF PNEUMONIA AMONG UNDER-5 CHILDREN FROM 2010 TO 2014

There was a sharp rise in the incidence of pneumonia among under-5 children which peaked in 2012 followed by a rapid decline to the levels observed in 2014. The relatively sharp rise in the incidence of pneumonia among under-5 children may be due to the general poor living conditions and hazardous environment identified in a study in Nigeria and India by Akanbi *et al* (2009) and Singh (2014). Also Smith *et al* (2011) in Guatemala have associated high incidence of pneumonia with environmental factors such as air pollution, domestic fires burning fuels and traffic-related air pollution. The rapid decrease in the incidence of pneumonia observed in 2014 may be attributed to the progress in improving access to vaccination and mass campaign to deliver new vaccines by the Nigerian government.

5.1.2 PATTERN OF DIARRHOEA AMONG UNDER-5 CHILDREN FROM 2010 TO 2014

The pattern of diarrhoea in under-5 children revealed a downward trend in 2010 up to 2014. The pattern of diarrhoea observed in this study is similar with finding from a study by Bern *et al* (1992) who recorded relatively low estimate of diarrhoea incidence before 1980. Also, a study by Gerald *et al* (Chapt.9), highlighted that the incidence of diarrhoea in under-5 children in developing countries has not changed much since the early 1990s and the incidence rates in Sub-Saharan Africa remain among the highest in the world. The downward trends revealed in the study could be as a result of methodological difference in statistical research stated by Bern *et al* (1992) and improved hygiene practices and government intervention to improved water supply to affected areas.

5.1.3 PATTERN OF MEASLES AMONG UNDER-5 CHILDREN FROM 2010 TO 2014

The pattern of measles among under-5 children showed a gradual upward trend from 2010 to 2014. The pattern observed is similar to a study by Fatiregun *et al* (2014) in southwest Nigeria, who recorded a rise in the annual incidence of measles from 1 case per million in 2007 to 23 cases per million in 2011. Also, the pattern of measles observed in this study is similar to findings of a five-year surveillance study in Saudi Arabia by Ziad *et al* (2014) who recorded a peak of 12.8 in the incidence of measles in 2011, in 2010 and onwards. The upward trend observed in this study could be explained by the 33% immunization coverage of new-borns and infants in the rural areas in Nigeria as estimated by the 2008 Demographic Health Survey.

5.2 MODEL SELECTION: ZERO INFLATED NEGATIVE BINOMIAL AND ZERO INFLATED POISSON REGRESSION MODELS.

This study compared the ZINB regression model and the ZIP regression model in the presence of over-dispersion. The dispersion parameters of the malaria pneumonia, diarrhea and measles among under-5 children models showed values that were greater than zero which means that the zero inflated negative binomial regression model (ZINB) better accommodates over-dispersion in the outcome data than the zero inflated Poisson regression model (ZIP). This finding is in line with a study by Ridout *et al.* (1998) who considered various ZIP regression models for an Apple

shoot propagation data and concluded that the ZIP models were inadequate for the data as there was still evidence of over dispersion and then fitted zero-inflated negative binomial models to the data.

The model selection methods used were the Vuong z-statistic, AIC and BIC. The four infectious diseases models showed a negative value for the three test criteria and were lesser than 1.96. This denotes that model 2 is the better model than model 1. The test criteria established that ZINB regression model is the best model to determine the effects of the season, year of reporting and geographical location on the number of cases of infectious diseases (malaria, pneumonia, diarrhea and measles) among under-5 children. The finding agrees with a study conducted by Muniswamy *et al* (2015) who used Wald, score and likelihood ratio tests to compare ZINB and ZIP models and recorded that ZINB model is a better model than ZIP model.

5.3 EFFECT OF SEASON, YEAR OF REPORTING AND THE GEOGRAPHICAL LOCATION ON THE OCCURRENCE OF MALARIA AMONG UNDER-5 CHILDREN

The incidence of malaria among under-5 children increased in year 2011 to 2014. The years under review had a significant effect on the occurrence of malaria among under-5 children. This finding agrees with a study by Olayemi *et al* (2009) in Minna, Niger state, who demonstrated that the mean annual malaria incidence rate were significantly different over 5 years study period. The cause of change in pattern is unknown but may be due to the influence climatic change on the transmission pattern identified in a study in Cross River by Ukpong *et al* (2015).

The months of May, June, July, August, September and October were found to have an effect on the occurrence of malaria among under-5 children compared to the month of April. The increased incidence of malaria among under-5 children in the observed months correlates with a study in Benin city by Enosolease and Awodu (2003) who found highest malaria incidence in the months of May, July, August, September and October and lowest in the month of June. The study attributed the observed increase in incidence of malaria to the height of the rainy season in Nigeria which lasts from May to October and additionally reported low incidence of disease in the dry season beginning from November to April.

The LGAs were also found to be significant predictors of the occurrence of malaria among under-5 children. The effect of geographical location on occurrence of malaria was well

highlighted in a study conducted by Onwuemele (2013) who commented on the pattern of malaria infection in Nigeria and recorded that the rate of malaria infection across space depends on dynamic processes involving complex climatic, environmental, physical and socio variables.

The certain zero group predicts the odds of a case of malaria among under-5 children, it predicts the likelihood of being in the "always 0" group. The years of reporting and months and the local government areas was found to be predictors for non-cases of malaria. The non-cases of malaria in the month may be due to onset of dry season with reduced mosquito transmission. This finding is in line with a study by Enosolease and Awodu (2003) who documented that in the dry season malaria transmission and infection are relatively low between November to April. The non-cases in the years may be explained by the Oyo state ministry of health intervention programme to combat the disease among under-5 children which was implemented in 2011 to correct low access to ACTs and to prevent the development of resistance to artemisinin based therapies. Also the distribution of ITNs may have influenced the non-cases among under-5 children. (Nigeria Malaria Fact Sheet, 2011)

5.3.1 EFFECT OF SEASON, YEAR OF REPORTING AND THE GEOGRAPHICAL LOCATION ON THE OCCURRENCE OF PNEUMONIA AMONG UNDER-5 CHILDREN

The annual incidence of pneumonia among under-5 children showed a sustained decrease from 2010 onwards with the greatest decrease in year 2014. This reduction in incidence (when the WHO reported a pneumonia mortality of 868,000 under-5 children) appears to coincide with the increased measures to combat pneumonia both locally and globally such as the annual observance of World Pneumonia Day (Erchick *et al.*, 2011), and the introduction of immunization against Hib, pneumococcus, measles and whooping cough (pertussis). It is important to note that in June 2012, Nigeria introduced the pentavalent vaccine, which protects against Hib and pneumococcus, among other childhood infectious diseases.

The analysis of the month of reporting showed that the month had significant effect on the incidence of new cases of pneumonia among under-5 children. This result corresponds with the peak of the rainy season, a finding corroborated by several workers who have made the same observation in their studies that pneumonia illness is most common in the winter months and the greatest incidence during the rainy season (Paynter *et al*, 2010 and Dowell *et al*, 2003). The geographical locations were strong predictors of and had an increasing effect on the occurrence of pneumonia among under-5 children. Singh and Singh, (2014) also have identified a hazardous environment in the incidence of pneumonia and seasonal variation in pneumonia infection was noted by Akanbi *et al*, (2009) to increase episodes in occurring during the rainy season.

The certain zero group predicts the odds of a case of pneumonia among under-5 children, it predicts the likelihood of being in the "always 0" group. The years of reporting, months and the local government areas were found to be predictors for non-cases of pneumonia. The non-cases of pneumonia in the years, months and local government areas may be explained by the extraordinary measures taken in Nigeria to improving access to vaccination in recent years. The coverage for vaccines have increased substantially over the 2000 to 2010 decade. Nigeria introduced in 2012 the pentavalent vaccine which protects against pneumonia among under-5 children.

5.3.2 EFFECT OF SEASON, YEAR OF REPORTING AND THE GEOGRAPHICAL LOCATION ON THE OCCURRENCE OF DIARRHOEA AMONG UNDER-5 CHILDREN

The annual incidence of diarrhoea among under-5 children decreased in years 2011 to 2012. The finding is different from a study by Gerald *et al* (chapt. 9), who noted a high incidence of diarrhoea among under-5 children in developing countries in the 1990s with the highest figures observed in Sub-Saharan African. The decrease observed in this study may be attributed to methodological differences in statistical research identified by Bern *et al*, (1992) in the bulletin of the World Health Organisation. The months of reporting were not statistically significant and had no influence on the occurrence of diarrhoea among under-5 children. Some of the local government areas had significant effects on the occurrence of diarrhoea among under-5 children.

The significant effect observed in some of the geographical locations may be related to the factors identified by the National Demographic Health Survey in 2008, that use of contaminated water and unhygienic practices in food preparation and disposal of excreta can influence the incidence of diarrhoea.

The certain zero group predicts the odds of a case of diarrhoea among under-5 children, it predicts the likelihood of being in the "always 0" group. The year of reporting, month and local government area were found to be predictors for non-cases of diarrhoea. The non-case of diarrhoea may be attributed to the intervention programme by the Nigeria Control of Diarrhoeal Diseases (CDD) in 1988 on prevention and treatment of dehydration, using oral rehydration therapy ORT use have greatly reduced the incidence of diarrhoea. FMoH (1991).

5.3.3 EFFECT OF SEASON, YEAR OF REPORTING AND THE GEOGRAPHICAL LOCATION ON THE OCCURRENCE OF MEASLES AMONG UNDER-5 CHILDREN

The annual incidence of measles among under-5 children showed decreased odds in disease occurrence for the years 2012 to 2013. The two years had a significant effect on the occurrence of measles among under-5 children. The findings is contrary to the results obtained from a five year retrospective surveillance study in Saudi Arabia by Ziad *et al*, (2014) who recorded a peak of 12.6 in 2011 and a slight fall to 9.9 in 2012 and concluded that the high incidence of measles were among unvaccinated infants. WHO and AFRO, (2008) recorded that most outbreaks occur in the first quarter of the year which affected mostly under-5 children. Reduction in incidence may be due to the availability of a safe and effective vaccine throughout the year which drastically reduces the number of cases of measles occurrence reported (WHO, 2007). The reporting months were not statistically significant; hence have no effect on the occurrence of measles among under-5 children. this could be explained by the intervention on the integrated catch-up and follow-up measles campaign of the National Programme on Immunization in south and north in collaboration with local and state governments WHO, (2007). The geographical locations were found to be significant predictors on the occurrence of measles among under-5 children. This finding is in line with a study from Delta state by Fatiregun and Odega (2013) who

recorded 53% increase of measles cases among the hospital records in a single location and found geographical locations to significantly predict the outbreak of measles incidence.

The certain zero group predicts the odds of a case of measles among under-5 children, it predicts the likelihood of being in the “always 0” group. The year of reporting, month of reporting and the local government area were found to be predictors for non-cases of measles. The non-cases in the years, months and local government areas may be attributable to the intervention by the National Programme on Immunization to greatly reduce measles outbreak by routine vaccination.

5.4 LIMITATIONS OF THE STUDY

The study used surveillance data and the reliability of the cases documented by the health workers who were in charge of the records at the health facilities may be limited. Further analysis of the data received could not be performed because sex was not recorded in the dataset and therefore the socio demographic variables could not be assessed.

5.5 CONCLUSION

This study examined the pattern of the four infectious diseases and determined the effects of month of reporting, year of reporting and the geographical location on the occurrence of malaria, pneumonia, diarrhea and measles among under-5 children. The study selected the regression analysis that best models the count data for the number of cases of malaria, pneumonia, diarrhoea and measles in the presence of over-dispersion and found Zero inflated negative binomial to be the best model describing the occurrence of infectious diseases among under-5 children. The incidence of malaria among under-5 children increased over the studied years 2010 to 2014. The effect of month / season of reporting, the year of reporting and the geographical location were strong predictors and had a significant effect on the occurrence of malaria among under-5 children. The non-cases in the always 0 group had decreasing effect on the occurrence of malaria among under-5 children. The incidence of pneumonia among under-5 children had a sustained decrease from 2010 onward and highest in 2014. The year, month of reporting and the geographical location had a significant effect on the occurrence of Pneumonia diseases among under-5 children. The incidence of diarrhoea among under-5 children was decreased 2011 to

2014. The year, month of reporting and the geographical location had a decreasing effect on diarrhoea incidence among under-5 children in Oyo state. The incidence of measles among under-5 children in the state takes a downward trend through the study years and also some local government areas in Oyo state contributed to the disease occurrence. The months of reporting did not contribute to the occurrence of measles among under-5 children.

5.6 RECOMMENDATION

In view of observed increase in the incidence of malaria over the years and locations of study, the government should intensify intervention procedures to combat the disease.

Furthermore, the sustained decrease observed in the disease incidence of pneumonia, diarrhoea and measles in under-5 children should encourage the government to continue with the intervention measures that have brought about this degree of success so far attained.

Lastly, zero inflated negative binomial regression has been proven the best for analyzing count data having excess zeros and over-dispersed and hence should be considered as the statistical method of choice for analyzing such data.

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