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Full Length Research Paper

Modeling the prevalence of malaria in Niger State: An application of Poisson regression and negative binomial regression models

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In statistics, Generalized Linear Models (GLM) are an extension of the linear modeling process that allow model to be fit to data that follow probability distributions other than the normal distribution. Poisson regression model is a special case of a generalized linear model (GLM) with a log link - this is why the Poisson regression may also be called Log-Linear Model. The Poisson distribution is often used to model rare events while the Poisson regression model is very suitable for modeling count data. One of the problems of Poisson regression is that it is affected by overspreading. In that case, it is advisable to employ the Negative binomial regression. In this work, we study the trend of malaria prevalence in Minna, Niger State using monthly malaria outpatient data collected from the General Hospital, Minna. The Poisson regression and the Negative binomial regression models were used in the analysis. The results from the Poisson regression and the Negative binomial regression models revealed an increase of 0.053 and 0.054 per month respectively. In addition, the incidence rate ratios (IRR) revealed that the prevalence of Malaria in Minna, Niger State increased by approximately 6% every month. Our work therefore recommended that more effective measures by the Nigeria government and NGOs should be geared towards reducing the prevalence and danger posed by malaria in Nigeria.

Key words: Poisson, modeling, malaria, prevalence, negative binomial, regression, models.

INTRODUCTION

Count data are data that are obtained by counting the number of occurrences of a particular event rather than by taking measurement on some scale (Everitt, 2002). We realize count data in almost every fields of endeavour. For example, we realize count data from the following, number of effected persons with HIV/AIDs; number of death from fatal accident, number of admitted student in our higher institution, number of deaths due to child bearer, and so on. The goal of the statisticians and mathematician is to model data resulting either from counting or from measurement. The Poisson and Negative binomial regression models are designed for count data (Piza, 2012).

In statistics, Generalized Linear Model (GLM) are an extension of the linear modeling process that allow model to be fit to data that follow probability distributions other than the normal distribution (Mbata et al., 2009). Poisson regression model is a special case of a generalized linear model (GLM) with a log link - this is why the Poisson regression may also be called Log-Linear Model. Consequently, it is often presented as an example in the broader context of GLM theory (Taylor, 2009). Poisson regression is a form of a GLM where the response variable is modelled as having a Poisson distribution. The Poisson distribution is often used to model rare events (Larget, 2007). On the other hand, the negative binomial regression model is employed in a situation when the Poisson regression is been affected by the problem of overdispersion. Overdispersion is the phenomenon that arises when empirical variance in the data exceeds the nominal variance under some assumed model (Dean, 1992; Everitt, 2002).

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In the econometrics, statistics and modeling of biological data literatures, a lot of work has been carried out. For instance, Dean and Lawless (1989) developed test for detecting extra-poisson variation common to many situations of life. In Gurmu (1991), he formulated some tests for detecting overdispersion in the positive poisson regression model. His work concluded that the proposed tests are special cases of the well known tests in the econometrics and statistical literatures. Barron (1992) investigated the familiar maximum likelihood methods - poisson and negative binomial regression together with the quasi-likelihood approach in the presence of overdispersion and autocorrelated by means of simulations. Barron finally used the methods to model labour unions in the United States. Brannas (1992) considered aspects of statistical inference in poisson regression models with dependent variable subject to truncation and/or censoring using Monte Carlo experiment and labour market data. Dean (1992) proposed a method of testing for overdispersion in poisson and binomial regression model, and reported that the poisson and binomial models remain valid in many situations because of their simplicity and appeal, and that it is of real interest to ascertain when they are applied. Dean concluded that the Pearson statistic is to be a score test for overdispersion in many situations.

In empirical research, the poisson and negative regression models have been used to modeled biological data both in Nigeria and beyond. In the work of Michener and Tighe (1992), they used the poisson regression modeling technique to model highway fatalities resulting from accidents in the United States. Adenomon and Adenomon (2011) in their empirical work modeled reported deaths from HIV/AIDs in Nigeria. They found that the cases of death resulting from HIV/AIDs in Nigeria is on the increase. Piza (2012) used the poisson and negative binomial regression models to measure the influence of risk on crime incident counts of the United States. While in the study of Sarpong and Brobbey (2013), they used poisson regression modeling technique to model the incidence of maternal deaths in Ghana.

The foregoing literature revealed the place of poisson and negative binomial regression models in modeling counts data. In this work therefore, the poisson regression model to study the trend in the prevalence of malaria in Minna, Niger State. Furthermore because of the adverse effect of overdispersion on poisson regression model, the negative binomial regression model would be use to study trend in malaria prevalence in Minna, Niger State.

LITERATURE REVIEW ON MALARIA STUDY

Malaria is one of the most important challenges to public health with about 300 to 500 million cases reported annually. More than 1 million people die from the disease, most of them children under age 5 years. Over 90.0% of the cases and 75% of the deaths occur in sub-Saharan Africa (SSA). These childhood deaths, resulting mainly from cerebral malaria and anaemia, constitute somewhere between 20 and 25% of child mortality in Africa (WHO, 2000; Teklehaimanot and Mejia, 2008).

According to Wenceslaus (2000), the malaria situation in sub-Saharan Africa is grim and the disease now constitutes a leading cause of poverty in the region. This is because sub-Sahara African region has the greatest number of people exposed to malaria transmission, greatest burden of malaria morbidity and mortality in the world (WHO, 1996). The problems associated with malaria treatment in Africa had substantially increased the rates of illness and death (Peter et al., 2000). It is estimated that in Africa, malaria is responsible for over one million deaths of infants and young children each year (Angyo et al., 1996). With regard to morbidity, people in areas of high endemicity usually go through several attacks every year. Such attack episode may last for 5 - 15 days often incapacitating the victim. Furthermore, in these areas, most cases of severe malaria occur among children aged between 1 and 3 years of age.

Due to the severe health and economic cost of malaria epidemics, there is still a growing need for methods that will help to understand the influencing factors, allow forecasting, early warning, so that more effective control measures may be implemented (Gomez-Elipe et al., 2003). Several studies have been done on the subject yielding different results as which factors are most responsible for the increase in malaria. Epidemiology studies on malaria in Africa have identified, in general, an association between climate variables and malaria (Wandiga et al., 2006; Gemperli, 2003). An association between climate variability and the epidemics of malaria has been identified in seven sites of East African highlands in Ethiopia, Kenya and Uganda (Zhou et al., 2003), suggesting that climate variability had an important influence in initiating epidemics in the highlands of East Africa. There was a significant and positive influence of interactions between maximum temperature, minimum temperature and rainfall on malaria transmission. The work of Pemola and Jauhari (2006) investigated the relationship between climate and malaria incidence using Pearson's correlation analysis. The authors found a high positive correlation between monthly parasite incidence and climatic variables (temperature, rainfall and humidity). Gallup and Sachs (2001) have suggested that the location and severity of malaria are mostly determined by climate and ecology. A significant correlation between malaria risk and elevation, annual maximum temperature and rainfall was also described (Kazembe et al., 2006). Another study found that variation in the malaria transmission intensity was strongly associated with basic climatic factors, noting that even small differences in climate variation can significantly affect malaria transmission

intensities (Kleinschmidt, 2006). Rainfall, temperature and altitude were the most plausible predictors of malaria prevalence in Botswana (Craig et al., 2007).

Approximately 50% of the Nigerian population experience at least one episode of malaria per year. However, official estimate suggests as much as four bouts per person per year on the average (WHO, 2002). The trend is rapidly increasing due to the current malaria resistance to first line anti-malarial drugs (WHO, 2000). The magnitude of incidence and death due to it is a multiple of all other tropical diseases put together. It is responsible for over 90% of reported cases of tropical disease in Nigeria. The above suggests that malaria could be the largest contributor to total disease burden and productivity losses resulting from major tropical diseases in the country. Evidence on Nigeria given by the malaria report 2005 shows that malaria incidence throughout the country had been on the increase over the years ranging between 1.12 million at the beginning of 1990 and 2.25 million by the turn of the millennium 2000 and 2.61 million in 2003. The disease carries with it two categories of costs: morbidity and mortality. The disease carries with it two categories of costs: morbidity and mortality costs. Malaria morbidity affects households' welfare (through families' allocation to treatment and prevention of the disease), and decline in productivity, through lost time. In the case of mortality, losses to households include lost of future income and cumulative investment on the dead due to malaria.

Model specification

Poisson regression

Poisson distribution is the probability distribution of the number of occurrences, X, of some random event, in an interval of time or space. Given by $P\mathrm{r}(\mathrm{X}=\mathrm{x})=\frac{\ell^{-\lambda}\lambda^{x}}{\mathrm{x}!};\ \mathrm{x}=0,1,\ldots$, the mean and the variance of the distribution are both λ. The skewness of the distribution is $1/\sqrt{\lambda}$ and its kurtosis is $3+1/\lambda$. Poisson regression is a method for the analysis of the relationship between an observed count with a poisson distribution and a set of explanatory variables (Everitt, 2002).

Poisson models are widely used in the regression analysis of count data and as a basis for categorical data analysis (Dean and Lawless, 1989). Suppose the observed counts n_i ($n_i \geq 0$) follow a Poisson distribution with parameter λ. Then from Poisson distribution properties, we have $E(n_i)=\lambda$ and $\mathrm{Var}(\mathrm{n}_i)=\lambda$.

We assume here that observed counts occur over a fixed interval, and because these counts are nonnegative, a Poisson regression model is defined in terms of log of expected counts $(\hat{m}_i)$ as: $\ell_i = X'\beta$ where the X represents the explanatory variables (Lawal, 2003).

In this work, we will look at the simple case of a Poisson regression as $\log_e(Y)=\beta_o+\beta_1 X_1$. In other words, the typical Poisson regression model expresses the log outcome rate as a linear function of a set of predictors (www.oxfordjournals.org/tropej/online/ma_chap13.pdf).

Assumptions in Poisson regression: The assumptions include:

1. Logarithm of the disease rate changes linearly with equal increment increases in the exposure variable.
2. Changes in the rate from combined effects of different exposures or risk factors are multiplicative.
3. At each level of the covariates, the number of cases has variance equal to the mean.
4. Observations are independent.

Poisson regression and fitting the Poisson distribution are discussed in Berk (2007), Oyejola and Adebayo (2004), Zar (1999), Anderson (2011), etc.

Negative binomial regression model

Negative binomial distribution is the probability distribution of the number of failures, X, before the kth success in a sequence of Bernoulli trials where the probability of success at each trial is p and the distribution of failure is q=1-p. The distribution is given by:

$$\Pr(X=x)=\binom{k+x\text{-}1}{x\text{-}1}p^{k}q^{x}\quad 0\leq x<\infty$$

The mean, variance, skewness and kurtosis of the distribution are as follows:

$$mean=kq/p;\ \mathrm{var}iance=kq/p^{2};\ skewness=(1+q)(kq)^{-\frac{1}{2}};\ kurtosis=3+\frac{6}{\mathrm{k}}+\frac{p^{2}}{kq}$$

It is often used to model overdispersion in count data (Everitt, 2002).

Many researchers generally employ more general specifications such as the Negative Binomial regression model because it is the standard choice for basic count data model. In literature, we have basically two types negative binomial models, denoted as NB 1 and NB 2. In most work, researchers prefer NB 2 (Greene, 2008).

Negative binomial 2 (NB 2) model

In literature, the PDF of the NB 2 model is given as:

$$f(y_i;\psi,\mu_i)=\binom{y_i+\psi-1}{\psi-1}\left(\frac{\psi}{\mu_i+\psi}\right)^{\psi}\left(\frac{\mu_i}{\mu_i+\psi}\right)^{y_i}$$

The first two moments of the NB 2 are as follows:

$$E[y_i;\mu_i,\psi]=\mu_i \qquad VAR[y_i;\mu_i,\psi]=\mu_i+\frac{\mu_i^2}{\psi}$$

The log-likelihood function of the NB 2 is given by:

$$\ln L(\psi,\beta)=\sum_{i=1}^{n}\left\{y_i\ln\left(\frac{\psi\mu_i}{1+\psi\mu_i}\right)-\psi^{-1}\ln(1+\psi\mu_i)+\ln\Gamma(y_i+\psi^{-1})-\ln\Gamma(y_i+1)-\ln\Gamma(\psi^{-1})\right\}$$
$$\text{where}\ \mu_i=\exp(x_i'\beta)$$

In the statistical literature, the Poisson-Gamma model has been defined as $y_i/\lambda_i=Poisson(\lambda_i)\ \ i=1,2,..I$ where the mean of the Poisson is structured as: $\lambda_i=f(X;\beta)\exp(\varepsilon_i)=\mu_i\exp(\varepsilon_i)$ and where f(.) is a function of the covariates, X and β is a vector of coefficients and ε_i is the model error independent of all the covariates with mean equal to 1 and a variance equal to $1/\psi$. The method of estimation of the parameters of the NB 2 is referred to as the maximum likelihood estimation technique. Details are reported in Lord and Park (2014) and Greene (2008).

MATERIALS AND METHODS

The data used in this study are secondary data collected from the General hospital Minna, Niger State. Monthly malaria outpatient data were collected from the General hospital, Minna. The monthly data spanned over a time period of five years (2008-2012). The response variable used is the monthly prevalence of malaria while the predictor is the months coded from 0 to 60 inclusive.

Analysis and interpretation of results

The data collected for this study were analyzed using STATA 8.0 Statistical Software. We begin this section with the Poisson regression model and conclude it with the Negative Binomial regression model.

The coefficients are significant (that is, p-value=0.000 <0.05). This model revealed that an increase unit in time (month) leads to an increase of about 0.053 units in the log prevalence of malaria in Minna. All the value of the coefficients in the model are significant (that is, p-value=0.000 <0.05). The pearson statistic of Goodness-of-fit revealed an overdispersion in the mean. This indicate that the distribution of malaria prevalence significantly differs for a Poisson distribution according to the p-value of 0.0000 (Prob>chi2) (Table 1). Therefore, Negative Binomial regression is more appropriate for modeling the prevalence of malaria in Minna, Niger State.

This model revealed that an increase unit in time (month) leads to an increase of about 0.054 units in the log prevalence of malaria in Minna. All the value of the coefficients in the model are significant (that is, p-value=0.000 <0.05) (Table 2).

The incidence rate ratios (IRR) revealed that the prevalence of malaria in Minna, Niger State increased by approximately 6% with every unit increase in time (that is, the prevalence of malaria in Minna increased by 6% every month) (Table 3).

DISCUSSION OF RESULTS

Poisson regression models are normal used to model count data especially for studying Trends. In this work, the count data on prevalence of malaria in Minna was used as the dependent variable while the independent variable as time coded from 1 to 60. The Negative binomial regression model is normally used to accompany the poisson regression especially when it suffers from the problem of overdispersion. In this work, we study the trend of malaria prevalence in Minna, Niger State using monthly malaria outpatient data collected from the General Hospital, Minna. The Poisson regression and the Negative binomial regression models were used in the analysis. The results from the Poisson regression and the Negative binomial regression models revealed an increase of 0.053 and 0.054 per month respectively (Tables 1 and 2 for the results respectively).

Table 1. Result from Poisson regression model for prevalence of malaria.

Poisson malaria time

Iteration 0: log likelihood = -118675.13
Iteration 1: log likelihood = -118615.6
Iteration 2: log likelihood = -118615.59

Poisson regression — Number of obs = 60
LR chi2(1) = 1667080.16
Prob > chi2 = 0.0000
Log likelihood = -118615.59 — Pseudo R2 = 0.8754

Malaria	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]
Time	0.0531264	0.0000459	1156.89	0.000	0.0530364	0.0532164
Cons	8.609666	0.0021299	4042.35	0.000	8.605492	8.613841

Poisgof
Goodness-of-fit chi2 = 236511.2
Prob > chi2(58) = 0.0000

Poisgof, pearson
Goodness-of-fit chi2 = 244309.3
Prob > chi2(58) = 0.0000

The fitted Poisson model is given as Log_e (Malaria Prev) = 8.60966 + 0.0531264 X.

Table 2. Result from Negative Binomial regression model for prevalence of malaria.

nbreg malaria time, dispersion (mean)

Fitting comparison Poisson model:
Iteration 0: log likelihood = -118675.13
Iteration 1: log likelihood = -118615.6
Iteration 2: log likelihood = -118615.59

Fitting constant-only model:
Iteration 0: log likelihood = -697.33791
Iteration 1: log likelihood = -696.59624
Iteration 2: log likelihood = -696.59021
Iteration 3: log likelihood = -696.59021

Fitting full model:
Iteration 0: log likelihood = -671.95478
Iteration 1: log likelihood = -643.72748 (backed up)
Iteration 2: log likelihood = -628.17314
Iteration 3: log likelihood = -627.77331
Iteration 4: log likelihood = -627.76737
Iteration 5: log likelihood = -627.76736

Negative binomial regression — Number of obs = 60
LR chi2(1) = 137.65
Prob > chi2 = 0.0000
Log likelihood = -627.76736 — Pseudo R2 = 0.0988

Table 2. Cont'd.

	Malaria	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]
Time	0.0538781	0.0023296	23.13	0.000	0.0493122	0.058444
Cons.	8.572047	0.0822731	104.19	0.000	8.410795	8.7333
lnalpha	-2.272964	0.1796072			-2.624988	-1.920941
alpha	0.1030064	0.0185007			0.0724406	0.1464691
Likelihood-ratio test of alpha=0: chibar2(01) = 2.4e+05 Prob>=chibar2 = 0.000						

The fitted negative binomial regression model obtained is given as: Log_e (Malaria Prev) = 8.572047 + 0.0538781 X-2.272964(log_ealpha).

Table 3. Result from Negative Binomial regression model with reported incidence rate ratios for prevalence of malaria.

nbreg malaria time, dispersion (mean) irr

Fitting comparison Poisson model:
Iteration 0: log likelihood = -118675.13
Iteration 1: log likelihood = -118615.6
Iteration 2: log likelihood = -118615.59

Fitting constant-only model:
Iteration 0: log likelihood = -697.33791
Iteration 1: log likelihood = -696.59624
Iteration 2: log likelihood = -696.59021
Iteration 3: log likelihood = -696.59021

Fitting full model:
Iteration 0: log likelihood = -671.95478
Iteration 1: log likelihood = -643.72748 (backed up)
Iteration 2: log likelihood = -628.17314
Iteration 3: log likelihood = -627.77331
Iteration 4: log likelihood = -627.76737
Iteration 5: log likelihood = -627.76736

Negative binomial regression — Number of obs = 60
LR chi2(1) = 137.65
Prob > chi2 = 0.0000
Log likelihood = -627.76736 — Pseudo R2 = 0.0988

	Malaria	IRR	Std. Err.	z	P>|z|	[95% Conf. Interval]
Time	1.055356	0.0024585	23.13	0.000	1.050548	1.060186
lnalpha	-2.272964	0.1796072			-2.624988	-1.920941
alpha	0.1030064	0.0185007			0.0724406	0.1464691
Likelihood-ratio test of alpha=0: chibar2(01) = 2.4e+05 Prob>=chibar2 = 0.000						

While the incidence rate ratios (IRR) revealed that within the period under study, the prevalence of Malaria in Minna, Niger State increased by approximately 6% with every unit increase in time (that is, the prevalence of malaria in Minna increased by 6% on monthly basis). Our result is similar to that reported in Wenceslaus (2000).

CONCLUSION AND RECOMMENDATION

The implication of our results is that despite effort on roll back malaria programme in Minna, Niger State, there are evidences that the prevalence of malaria in Minna, Niger State is still on the increase by 6% on monthly basis. We

therefore recommend the following:

1. To reduce the menace of malaria, more efforts by the NGOs and the government in the roll back malaria programme in Minna, Niger State should be reviewed in order to know the way forward on the fight against malaria.
2. To reduce the menace of malaria, more efforts by the NGOs and the government in the roll back malaria programme in Minna, Niger State should be on top gear in the wet seasons especially in months of August and October.
3. Mosquito treated net by NGOs and the government should be distributed to the inhabitants of Minna and its environ during the wet seasons.
4. Regular insecticides and proper sanitation of the environment should be carried out by the inhabitants both in the dry and wet seasons.

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