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An assessment of the relationship between rainfall and incidence of malaria among pregnant women.

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Abstract

This research work examined the relationship between rainfall and the prevalence of malaria among pregnant women in Abia-South Senatorial District of Abia State, Nigeria. The rainfall data used in this study was extracted from Tropical Rainfall Measuring Mission Satellite while the data on the incidence of malaria among pregnant women from the Headquarters of Primary Health Care Centers in Abia-South Senatorial District, Abia State. Preliminary analysis showed that incidence of malaria cases was on a steady increase while rainfall in the area remained relatively constant across time. The Pearson -Product Moment Correlation was employed to assess the strength of linear relationship between the variables considered. The correlation coefficient ($r = 0.04; p = 0.807$) shows that there is no statistical significant association between amount of rainfall and incidence of malaria among pregnant women in the locality. Further more, the slope of the negative binomial regression model was 0.000114 whose exponent value is 1.000114. The exponent value which is roughly 1 indicates that any change in amount of rainfall will leave cases of malaria among pregnant

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women in the area unchanged since 1 is a multiplicative identity. Therefore, rainfall should not be considered in mitigating the transmission of malaria in the study area. However, further research should be carried out to examine the impact of other climatic variables like temperature and relative humidity on malaria prevalence in the study area as well as other human activities which could be cause of increase in the incidence of malaria among pregnant women in the area.

Keywords: Negative Binomial Regression, Correlation, Rainfall, Malaria, Pregnant Women.

1 Introduction

Malaria remains one of the deadliest diseases in Africa and most of its victims are infants and pregnant women [1]. Malaria is caused by a protozoan from the genus Plasmodium, and it is spread through mosquitoes. A single bite by a malaria carrying mosquito can lead to extreme sickness or death. Malaria presents with an extreme cold, followed by high fever and severe sweating. These can be accompanied by joint pain, abdominal pain, headaches, vomiting, and extreme fatigue. Africa has the largest number of people living in areas with a high risk of malaria, followed by the South-East Asia region [1]. In 2018, there was an estimated 247 million malaria cases worldwide of which 91% (230 million) were caused by *Plasmodium falciparum*. Malaria is by far the most significant insect transmitted disease globally [2]. In 2017, World Health Organization recorded an estimate of 219 million cases of malaria worldwide; with Nigeria, Madagascar and the Democratic Republic of the Congo having the highest estimated increases, all greater than half a million cases. In 2017 there was an estimate of 435 000 deaths from malaria globally, compared with 451 000 estimated deaths in 2016 and 607 000 in 2010. The Africa Region continues to carry a disproportionately high share of the global malaria burden. In 2017, the region was home to 92% of malaria cases and 93% of malaria deaths. In the same 2017, five countries accounted for nearly half of all malaria cases worldwide: Nigeria (25%), the Democratic Republic of Congo (11%), Mozambique (5%), India (4%) and Uganda (4%) [1].

The study location is within a selected part of Abia-South Senatorial District of Abia State in the south east geopolitical zone of Nigeria. The selected parts are specifically Ugwunagbo, Aba North, Aba South, Ukwa East and Ukwa West Local Government Areas and is situated between latitude 7°21' 28.086" E and longitude 4°57' 9.648" N. It has an area of $731km^2$. The region is in the rainforest agro climate zone which is characterized by annual high temperature, high precipitation and extreme weather conditions. The selected part of Abia-South Senatorial District is located within the equatorial belt of Nigeria. The area is dominated by tropical rainforest vegetation. The vegetation zone involves trees. These trees are about 40-45 meters tall and form the first upper tier. Such giant trees with powerful tree-shaped roots, divulging from the base of the trunk, are not afraid of the elemental forces. The trees of the second and third tiers are especially densely strewn with epiphytes, intertwined with lianas that rush towards the sun. The rays of the sun almost do not penetrate through the dense green canopy formed by woody crowns. The annual amount of precipitation exceeds 2,100mm.

Mosquitoes are very sensitive to climatic changes and conditions, which explains why it is most common in tropical climates, where there is sufficient breeding sites and conducive temperatures for mosquitoes [3]. Water is a major contributor to the development of mosquitoes as they breed so well in small pools of water. Increase in rainfall leads to an increase in the breeding grounds for mosquito larvae, which eventually results in more vectors to spread the disease. With little rainfall, there are few places for the mosquitoes to breed [4]. As reported by [5] and [6] changes in the relationship between mosquito population and rainfall in different districts of Kenya were attributed to changes in environmental heterogeneity. Unstable malaria regions are essentially found in warm, semi-arid zones, tropical mountainous regions, and regions where previous levels of control are beginning to fail. It has long been known that in these areas any change in temperature, relative humidity or rainfall can have a major impact on malaria transmission, possibly leading to epidemics [7]. Although, tremendous progress has been made globally in fighting the vector and the parasite [7], the situation is far from being resolved, especially in Africa. Malaria has been identified as one of the indirect causes of maternal and neonatal mortality [8,9].

Heavy rainfall tends to be related with the adverse effect in breeding sites, while moderate rainfall may favor vector abundance. In addition, it also has a negative effect on flushing small breeding sites and decreasing temperature [10, 11]. The immature stages of An. gambiae require an aquatic environment to develop and are often found in transient, sunlit and generally small pools [12, 13]. The availability of these aquatic habitats depends on rainfall [13, 14]. Rainfall creates new breeding sites and adds water existing ones. The availability, persistence and dimensions of mosquito larval habitats depend to a large extent on the frequency, duration and intensity of precipitation. It has been suggested that rainfall could affect larval population dynamics by flooding habitats and consequently flushing out larvae [3, 14]. [14] observed a high larval mortality in open raindrops on larvae. The possible effect of mortality by the direct hit of a raindrop was studied by [15] who exposed larvae to artificial rain and observed no damaging effect. [14] proposed that the direct damage to anopheline larvae by precipitation may depend on raindrops size. Moreover, an increase in rainfall may have negative consequences for mosquito populations by impacting the immature life stages through excessive flooding or by direct hefts. These effects precipitation have on mosquito populations should be considered in the light of changes in temperature, rainfall would directly affect the development of parasites and the behavior and geographical distribution of the vectors [16]. Therefore, more rainfall not only results in more mosquito breeding sites, which may in turn lead to an increase in malaria vectors, but it will also result in a large increase of the existing immature populations, which leads to a reduction in emerging adults of that generation.

2 Methodology

Medical data on malaria was collected from Headquarters of Primary Health Care Centers in Abia-South Senatorial District, Abia State while the rainfall data was extracted from Tropical Rainfall Measuring Mission Multi-Satellite Precipitation Analysis Rainfall Estimate Product 3B43 Version 7, which merges satellite rainfall estimate(s) with gauge data (G) into gridded estimates on a calendar month temporal resolution and a 0.250 by 0.250 Spatial Resolution Band extending from 500 S to 500 N latitude. The data was a monthly data which spanned a period of 3 years (2016 - 2018) giving a total of 36 observations.

Correlation analysis as well as negative binomial regression were used to study the association between rainfall and the incidence of malaria disease among pregnant women in the study area. The Pearson-Product Moment Correlation Coefficient (ρ) measures strenght of linear relationship between two variables. Here, there is no defined dependent and independent variable. The sample Pearson-Product Moment Corrleation Coefficient (r) is given mathematically as:

$$r = \frac{n\sum_{i=1}^{n} XY - \sum_{i=1}^{n} X \sum_{i=1}^{n} Y}{\sqrt{[n\sum_{i=1}^{n} X^2 - (\sum_{i=1}^{n} X)^2][n\sum_{i=1}^{n} Y^2 - (\sum_{i=1}^{n} Y)^2]}} \tag{1}$$

Here n stands for number of observation and we arbitrarily assign Y to incidence malaria among pregnant women in the area and X to amount of rainfall in the area for the same period of time.

The Negative Binomial Regression is part of the generalized linear model for conducting regression analysis involving count data when there is an overdispersion of the count outcome, that is, when conditional variance exceeds the conditional mean. If the mean and variance were equal or almost equal, Poisson Regression would suffice. According to [17], The negative binomial distribution is another distribution that is concentrated on the nonnegative integers. Unlike the Poisson, it has an additional parameter such that the variance can exceed the mean. The negative binomial distribution has $E(Y) = \mu$ and $Var(Y) = \mu + D\mu^2$. The index D, which is nonnegative, is called a dispersion parameter. AS D tends to zero, the Negative Binomial distribution converges to the Poisson Distribution. Negative binomial GLMs for counts express μ in terms of independent variables. The model is usually represented thus:

$$log\hat{\mu} = \hat{\alpha} + \hat{\beta}x \tag{2}$$

Equation 2 therefore implies that:

$$\mu = exp(\alpha + \beta x) = e^{\alpha}e(^{\beta})^{x} \tag{3}$$

And thus, a unit increase in x has a multiplicative impact of e^{β} on μ. The correlation analysis as well as the fitting of the negative binomial regression model was done using the Statistical Package of Social Scientists (SPSS) version 23 while the figures were created using Gnu Regression Time Series Library (GRETL).

3 Main Results

3.1 Exploratory Data Analysis

In the year 2016, the highest amount of rainfall was recorded in the month of August (427.34mm) followed by June (359.55mm) and then May (322.68mm) while the months of July, August and September had the highest cases of malaria with 160, 156, 164 number of malaria cases respectively for pregnant women. Going forward, in the year 2017, the highest amount of rainfall was recorded in the month of June (378.34mm) followed by March (377.69mm) and then May (287.54mm) while the months of February, May and August had the highest cases of malaria with 368, 228 and 244 number of malaria cases respectively among pregnant women. Lastly, in the year 2018, the highest amount of rainfall was recorded in the month of June (412.46mm), followed by August (429.89mm) and then September (342.40mm) while the months of April, September and October had the highest cases of malaria with 392, 296 and 320 number of malaria cases respectively. It is obvious from the preliminary analysis that the months of highest amount of rainfall in the area and that of incidence of malaria do not coincide and thus suggests zero correlation.

Figure 1 shows that malaria incidence was on the increase over the time period under study whereas from figure 2, it is evident that amount of rainfall in the area was constant across the period. The rainfall data is also seasonal as suggested by the wave-like pattern of the graph.

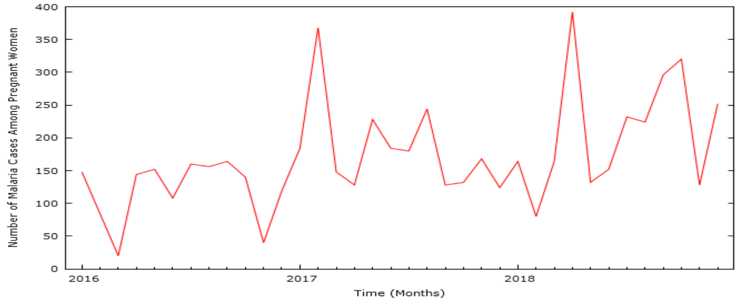

Figure 1: Graph of Actual Incidence of Malaria among Pregnant Women

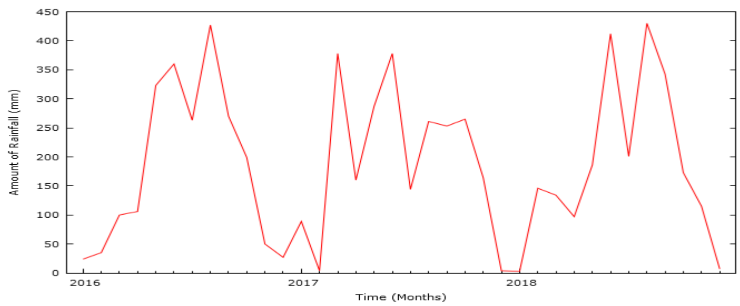

Figure 2: Graph of amount of monthly rainfall in the area of study from 2016 to 2018

3.2 Correlation Analysis

The Pearson-Product Moment Correlation analysis returned a statistic of 0.042 with a p-value of 0.807. The value of the correlation coefficient which close to zero indicates that there is no association between amount of rainfall and incidence of malaria disease among pregnant women in in the study area. A p-value of 0.807 which is greater than 0.05 shows there is no statistical significance in association.

3.3 Negative Binomial Regression Modelling

The mean number ofcases of malaria incidence among pregnant women was 171.86 while the variance was 6422.637. Since the mean and variance are not equal, the use of Negative Binomial Regression is justified. The Negative Binomial Regression Model was fitted using Log link function and Maximum Likelihood Estimation method was used to determine the estimates of the parameters of the model (see Table 1).

Table 1: Maximum Likelihood Estimates of the parameters of the negative binomial regression model.

Parameter	Estimate	Std. Error	95% Wald C.I.	Wald χ^2	Df	Sig.
Intercept	5.119	0.1394	(4.846, 5.392)	1348.680	1	0.000
Rainfall	0.000144	0.0006	(-0.001, 0.001)	0.057	1	0.811
Scale	1					
Negative Binomial	0.225	0.0531	(0.142, 0.357)			

Hence the negative regression model is thus $log\hat{\mu} = 5.119 + 0.000144x$. Going further, an objective goodness of fit test was conducted. A Pearson χ^2 score of 1.018 which is approximately is an indicator of absence of overdispersion and thus we have a good fit. The results for goodness of fit test are summarized in table 2 below.

Table 2: Goodness of Fit.

Criterion	Value	DF	Value/DF
Deviance	37.557	33	1.138
Scaled Deviance	37.557	33	1.138
Pearson χ^2	33.592	33	1.018
Scaled Pearson χ^2	33.592	33	1.018
Log Likelihood	-207.192		

4 Conclusion

Results from analysis showed a very weak correlation between amount of rainfall and incidence of malaria disease among married women living in Abia South Senatorial District. The association was also statistical insignificant. The slope of the negative binomial regression equation is 0.000114 which is so close to zero. The exponent of 0.000114 is 1.000114 which is approximately. This implies that a change in rainfall has no impact on incidence of malaria since 1 is a multiplicative identity. Additionally, with a p-value of 0.811, one can infer that rainfall has no statistical significant impact on incidence of malaria disease among pregnant women living in the study area. It can be concluded on the basis of the research that the residents maybe correctly and consistently using treated mosquito nets, practicing good hygiene such as bush clearing in the surroundings and avoiding indiscriminate refuse dumps as well as other things that encourage mosquito breeding. The association of malaria and other meteorological factors could also be investigated in further studies. It is also evident from figure 1 that number of malaria cases was on the increase for the period studied as mean number of cases were 119.58, 184.67 and 211.33 for 2016, 2017 and 2018 respectively. It will be interesting to find out what other parameter(s) caused this increase. Government and policymakers can forgo rainfall when looking at factors that predisposes pregnant women and perhaps other individuals in the area to malaria disease.

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