International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

Bayesian Approach to Modelling Malaria Incidence in Pregnant Women in ADO-ODO/OTTA, Ogun State, Nigeria

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Abstract: ***The protection of pregnant women living in malaria-endemic countries has been of particular interest to many National Malaria Control Programmes because, in spite of interventions, there have been much reported cases of mortality of pregnant women including infant mortality due to malaria. This study presents a Bayesian approach to model the incidence of malaria in pregnant women in Ado-Odo /Otta, Ogun State, Nigeria. The study focuses on the impact of gravidity, gestation period, and age on the probability of malaria incidence. The Bayesian inference for logistic regression models was derived using a Markov Chain Monte Carlo MCMC method. The results indicate that gestation and gravidity significantly affect the malaria status of pregnant women, with the incidence of malaria being higher during the first and third trimesters of gestation. The study provides a new perspective on the modelling of malaria incidence in pregnant women using a Bayesian approach.***

Keywords: Malaria Incidence, Gravidity, Gestation period, Pregnant Women, Bayesian Approach, Logistics Regression Models, Markov Chain Monte Carlo

1. Introduction

Malaria control remains a challenge in Africa where 45 countries, including Nigeria, are endemic for malaria, and about 588 million people are at risk (WHO- World Malaria Report, 2008). *Plasmodium falciparum(P.falciparum*) is a unicellular protozoan parasite of humans, and the deadliest species of Plasmodium that cause malaria in humans (Rich*et al.*, 2009). It is transmitted through the bite of a female Anopheles mosquito. It is responsible for roughly 50% of all malaria cases. It causes the malaria's most dangerous form called *falciparum malaria* (Perkin *et al*., 2011). It is therefore regarded as the deadliest parasite in humans, causing a conservative estimate of one million deaths every year (Vaughan *et al*., 2008).

In 2018, an estimated 228 million cases of malaria occurred worldwide (95% confidence interval [CI]: 206–258 million), compared with 251 million cases in 2010 (95% CI: 231–278 million) and 231 million cases in 2017 (95% CI: 211–259 million). (WHO- World Malaria Report, 2019)

As of the latest World Malaria Report of the World Health Organization, there were 216 million cases of malaria worldwide in 2016, up from 211 million cases in 2015. . In Sub-Saharan Africa, over 75% of cases were due to *P.falciparum*, whereas in most other malaria countries, other less virulent plasmodia species predominate (WHO-World Malaria Report, 2008).Children aged under 5 years are the most vulnerable group affected by malaria; in 2019, they accounted for 67% (274 000) of all malaria deaths worldwide(WHO, 2021). Gute *et al*. (2015) studied the risk factors of malaria related in-hospital mortality. They analyzed the data obtained using the classical logistic regression and Bayesian logistic regression approaches. In this effort, the two approaches were compared using standard errors of model parameters. They found that Bayesian simulation analysis found ten of the thirteen predictors statistically significant unlike the classical logistic regression analysis that had eight significant predictors. Model comparison also revealed that, the Bayesian modeling approach has given estimates of the parameters with smaller standard error values with normal prior distribution on the parameter.

Adigun *et al*. (2015) worked on malaria risk in Nigeria by fitting a Bayesian Geostatistical logistic regression model on the observed parasitological prevalence data collected using the standard malaria indicator questionnaires developed by the Roll Back Malaria and the demographic health surveillance programme. Important environmental/climatic risk factors of parasitaemia were identified by applying Bayesian variable selection within Geostatistical model. Various measures of control intervention coverage were derived to estimate the effects of interventions on parasitaemia risk after adjusting for environmental, Socio-economic and demographic factors. Normalized difference vegetation index and rainfall were identified as important environmental/climatic predictors of malaria risk. The population adjusted risk estimates ranges from 6.46% in Lagos state to 43.33% in Borno. They observed that Interventions appear not to have important effect on malaria risk. The odds of parasitaemia appears to be on downward trend with improved socioeconomic status and living in rural areas increases the odds of testing positive to malaria parasites. Older children also have elevated risk of malaria infection.Most works have focused on classical models for malaria in population but using Bayesian approach to model malarial on pregnant women is very rare, hence this study

modelled the incidence of malaria in pregnant women using Bayesian approach.

Afolabi *et.al* (2020) worked on Prevalence of Malaria on Pregnant women in Ado-Odo/Otta, Ogun state, Nigeria. They discovered that pregnant women were infected by malaria. The multigravida group has the highest number of infection. Also, malaria was found to be higher among the age group 20-24, 25-29 and 30-34 is highly affected by malaria. Gestation was significant associated with the malaria status of the pregnant women and the third gestational period is mostly affected by malaria during pregnancy.

2. Materials

2.1 Study Area

This study was limited to the data collected on malaria status of 459 pregnant women at different stages of their pregnancies and different gravidities. Data were collected on Gestation, Age, Multigravidity and primigravida of the pregnant women from their medical records. The study modelled the probability of incidence of malaria in pregnant women as a function of generic biological factors of gravidity, gestation period and age, as well as to determine the probability that a pregnant woman will have malaria based on the given factors. The posterior samples, given this prior setting and the likelihood are evaluated by MCMC logistic model

2.2 Methods

2.2.1 Bayesian Logistic Regression

A computationally tractable Bayesian inference for logistic regression models with parametric link is derived utilizing a Markov Chain Monte Carlo algorithm to simulate and facilitate derivation of the joint posterior distribution of the regression and the link parameter. Unlike the classical case of maximum likelihood estimation that considers just a single value for a model parameter, Bayesian approach provides a different route to the problem of unknown model parameters by quantifying the uncertainty about the unknown parameters by using probability distributions so that the unknown parameters are regarded as random variables.

The logistic regression under the Bayesian approach can be expressed in two forms as

$$\mu = sig(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots) \qquad (1)$$
$$y = dbern(\mu)$$

whereμ is a logistic (sigmoid) function of the predictors and the response variable, y follows a Bernoulli distribution.

$$logit(\mu) = \log\left(\frac{p(y=1)}{p(y=0)}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots \qquad (2)$$
$$y = dbern(\mu)$$

The logit function defined as $logit(p) = \log(p/(1-p))$, for $0 < p < 1$,p is the probability
That $y = 1$, and therefore we can have $logit(p(y = 1)) = log(p(y = 1)/ p(y = 0))$.
The ratio, $p(y = 1)/p(y = 0)$, is the odds of outcome 1 to outcome 0.

The Bayesian estimation yields values of the parameters, $\mu$and β_i, given the data and the specified prior.Often we are primarily interested in knowing how big an influence a predictor has on the predicted value, and, specifically, whether that influence is credibly non-zero.

3. Data Analysis

The statistical analysis used was a two-way contingency tables of malaria outcomes and the categorical variables of gestation and gravidity to make sure there are no empty cells.

4. Result

Table 1: Two-way Contingency Table of Malaria Status with Gestation, n = 459

Malaria status	Gestation 1	Gestation 2	Gestation 3
Absence (0)	2	130	101
Incidence (1)	9	33	184

Table 2: Two-way Contingency Table of Malaria Status with Gravidity, n = 459

Malaria status	Multigravidity	Primigravidity
Absence (0)	171	62
Incidence (1)	146	80

Table 3: Summary Statistics on the Continuous Variable, Age

	N	Mean	Sd	Median	Min	Max	range	Skewness	Kurtosis
Age	459	28.71	5.69	28	15	48	33	0.21	-0.38

Table 4: Bayesian Coefficient Estimates

Coefficients	Estimates	Std. Deviation	Naïve SE	Time-series SE
Intercept	1.725682	0.86415	0.0086415	0.040319
Gestation2	-2.971973	0.70713	0.0070713	0.034762
Gestation3	-0.99308	0.70882	0.0070882	0.0342943
Multigravida	-0.542767	0.2412	0.002412	0.0107155
Age	0.008444	0.02036	0.0002063	0.0008507

Table 5: Bayesian Credible Intervals

Coefficients	2.50%	97.50%
Intercept	1.725682	1.725682
Gestation2	-2.971973	-2.971973
Gestation3	-0.99308	-0.99308
Multigravida	-0.542767	-0.542767
Age	0.008444	0.008444

Table 6: Bayesian Posterior Estimates for the factors and their Credible Intervals

Node	Mean	Sd	MC error	2.50%	median	97.50%	Start	Sample
Alpha	0.07996	31.57	0.3003	-61.63	0.1532	62.28	201	11400
beta.age	0.3699	31.32	0.284	-61.57	0.3456	62	201	11400
beta.ges	-0.5135	31.76	0.2692	-63.27	-0.5144	61.83	201	11400
beta.gvd	0.3562	31.59	0.2759	-60.62	0.1988	62.6	201	11400

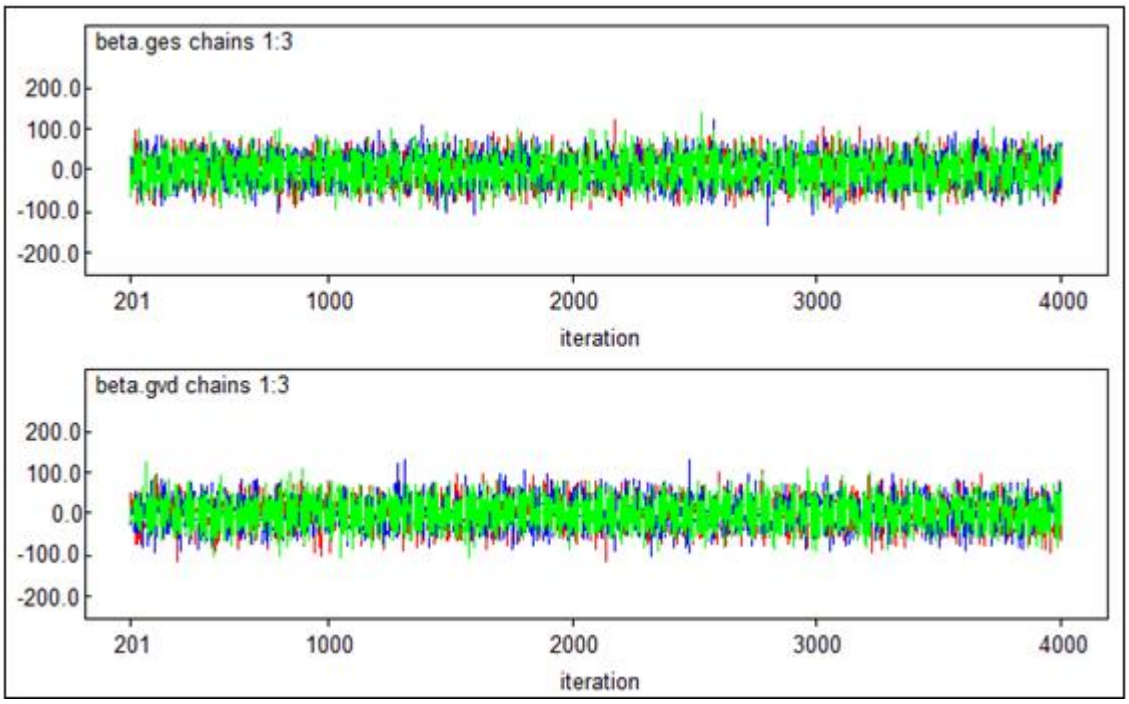

Figure 1: Posterior Diagnostic of Bayesian Logistic Regression

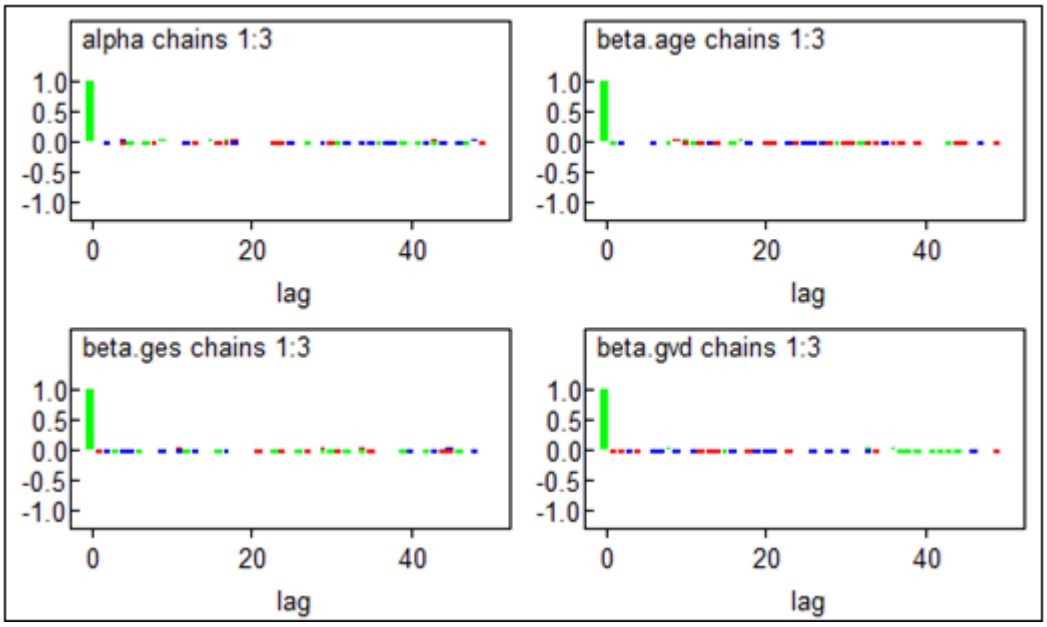

Figure 2: Posterior History Plots for Model Parameters

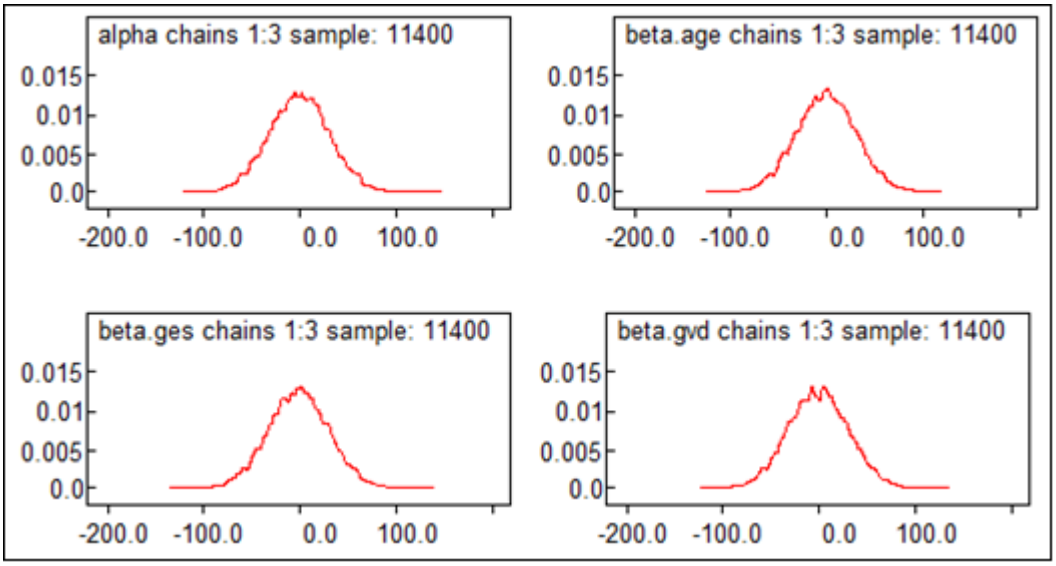

Figure 3: Shows the Posterior Density Plots

5. Discussion

The summary statistics from Table 3 shows that the youngest pregnant woman was a teenager of age 15 years, while the oldest pregnant woman was 48 years of age.

Table 4 shows the Bayesian posterior samples estimates for the logistic regression for the malaria status data, where gestation2 and gestation3 are the levels of gestation period in reference to the first level gestation1. The multigravida is one level of gravidity in reference to the second level primigravida. It was observed that the MCMC error is small for the coefficients.

A woman in 2nd trimester gestation period (gestnGS2), versus being in 1sttrimester gestation (gestnGS1), changes the log odds of incidence of malaria by -2.972.A woman in 3rdtrimester gestation period (gestnGS3), versus being in 1sttrimester gestation period (gestnGS1), changes the log odds of incidence of malaria by -0.993 and we also have the 95% credible intervals given in Table 5

Table 6 shows the results of the posterior means as evaluated in WinBUGS and R. The overall posterior mean estimate for each of the factor parameters of gestation, Gravida and Age with the overall mean (intercept) of the model is shown in Table 6.These estimates fits the Bayesian logistic model defined in equation (2) for the binomial response of incidence or absence of malaria in pregnant women given the factors of gravida, gestation and age.

From figure 1,it can be seen that the history plots for the posterior parameter estimates follow a regular pattern with little deviations from the iterations samples. It was observed from all the history plots that the samples show a random scatter about a stable mean value, which is a sign of convergence and also,the autocorrelation function plot which tells that, for each parameter simulation iterations, there was no autocorrelation and hence there is confidence of convergence of the iterations close enough to the target posterior distributions. This confirms the result from the history plots in figure2.

6. Conclusion

It was seen from the analysis of the malaria status of pregnant women with predictor variables as gestation, gravidity and age, that both gestation and gravidity had significant effect on the malaria status of pregnant women than age does. The second trimester of the gestation period was different from the first and third trimester, which implies that incidence of malaria was more serious at first and third trimester gestation period. The levels of gravidity (primigravida and multigravida) showed no significant difference.

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