 

# Modelling of Malaria Risk Factors in the Mpohor District of Ghana using Logistic Regression

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**ABSTRACT**

This study was aimed at assessing and deriving a predictive model for the relationship between malaria prevalence and malaria causing factors (covariates) in the Mpohor District (which is located in the Western Region of Ghana) by logistic regression. Risk factors such as seasonality (wet or dry), altitude, mining community, proximity of water body, vegetation proximity and clinic proximity were assessed using logistic regression.

Collinearity test was performed to avoid information duplicate and multicolinearity by examining the Variance Inflation Factor (VIF) of each covariate. The relationship between malaria and its underlying factors was analysed through stepwise logistic regression where the wald statistics and odds ratio (OR) proved their significance.

The results showed that the risk factors such as altitude, seasonality, water body proximity, vegetation proximity and mining community were significant predictors of malaria morbidity in the District $(p < 0.05)$. However, it was found that proximity of health facility to community was not a good malaria morbidity predictor.

It was recommended among other things, that further research involving more communities in the District and including other known malaria factors be carried out to provide complete and more reliable information that is useful in malaria control.

**Keywords:** Mslaria prevalence, modelling ,odds ratio

## LITERATURE REVIEW

There are over 120 species of the parasite genus of Plasmodium but only four of these infect humans to cause malaria. These four species of Plasmodium parasites are Plasmodium falciparum, Plasmodium vivax, Plasmodium ovale and Plasmodium malariae. Plasmodium falciparum can cause severe malaria and the other three species cannot. P. falciparum are responsible for the most life-threatening form of malaria and cause the majority of the deaths worldwide. Plasmodium falciparum accounts for the majority of infections and is the most lethal (Rashed *et al*., 2000).

Malaria is governed by a large number of environmental factors, which affect its distribution, seasonality and transmission intensity. The peak in morbidity and mortality is generally obtained in the rainy season, the time when malaria transmission is at its peak and the number of deaths during this period has been shown to be over threefold higher than in the rest of the year. High levels of parasiteamia are also found much more frequently in the rainy season than in the dry season, and the mean packed cell volumes are lower in the rainy season than in the dry season (Jaffar *et al*., 1993).

Topography generally has a great influence on mosquito replication and thus affects the rate of malaria cases. Higher topographies results in cooler temperatures, which limits the reproduction rate of the parasite. Entomologic studies in eight villages to investigate the patterns of malaria transmission in different ecologic zones in Eritrea showed a positive relationship between the malaria cases and topography. Mosquito collections conducted for 24 months showed that the biting rates in the higher elevations as a result of the lower temperatures were twice as high as the lowlands. The complexity of topography and landscape in the highlands contributes to the spatial heterogeneity of vector abundance and malaria transmission intensity. It has implications for the survival of the vector for different altitudes (Minakawa *et al*., 2002).

The relationship between malaria vector density and the distance of a settlement from a river is an important indicator of malaria transmission. Decreased risk of malaria was associated with increased distance from the forest fringe and swamps and increased risk was associated with longer distance to the health center in highland areas of west Kenya. Anopheline larval habitat during the dry season was significantly more clustered compared with the rainy season at the distances up to 0.3 and 0.6 km in valley bottoms. Anopheles mosquito proliferation requires the abundance of blood-meals and therefore, a travel distance is required from breeding sites to households where the vector-host contact becomes possible. Reviewed articles about anopheles mosquito flight distance found that the average flight distance for *anopheles sp.* was around 1000 m. However, the flight distance depends on the habits of the species and some species have a stronger dispersal capacity than others (Stoler *et al.*, 2009).

Wachira (2014) used logistic regression to model malaria prevalence in Kisumu County District in Kenya. The predictive results of the Logistic Regression Model to the disease prevalence gives credence to the fact that the covariates used which were forest and land cover, temperature, rainfall and elevation had different and independent influence on the malaria prevalence. There was a significant varied effect of elevation with the disease prevalence. This varied statistical relationship may have resulted from the small spatial scale of the district with elevation differences less than 50 m. There was a general trend of high disease incidence between 1-3 km from the forest edge and different factors beyond 4 km. The annualized rainfall pattern showed a relationship with the disease prevalence. With the high levels of rains increasing the disease occurrence as it served as effective breeding grounds for the mosquitoes to thrive. The formulated model is as follows:

$$\log\left(\frac{p}{1-p}\right) = -1.04-0.23tem+0.62rai+0.27top+0.42for \qquad (1.0)$$

Where;

- temp =Temperature
- rai= Amount of rainfall
- top= scale of topography of the region
- for = scale of forest cover and land use

Tuyishimire (2013) assessed the relationship between malaria prevalence and malaria causing factors in the Ruhuhar District of Rwanda by logistic regression. The logistic regression proved an increase of malaria infection with increase in household size, household with infected people and proximity to irrigated farmland. It was also proved higher with increased number of houses made of mud compared to unburnt brick walls. It was found that malaria decreases when house walls are made with cement or burnt bricks. In addition to the significant factors considered in his work, proximity of community to health centre was found to be a significant factor contributing to the high level of malaria prevalence in the district of Ruhuhar. Malaria infection was also found to have increased in males than females.

The flaw with Tuyishimire's work was the low predictive power state of the model $(\text{Nagelkerk } R^2 = 13\ \%)$ which rendered the model unfit of any practical use.

This current study proposed new paths in malaria modelling and prevention. Tools of logistic regression analysis were used to obtain a significant predictive power by use of the Receiver Operation Characteristic (ROC) Curve to obtain high predictive rule which qualified the model of practical use in the Mpohor District.

It sought to determine the relationship that the malaria causing factors have with the prevalence. The results from this research would inform the distribution of the malaria control measures such as mosquito treated nets and other artificial malaria control measures such as mosquito repellents to communities with higher prevalence rates.

**INTRODUCTION**

It is on record that, Sub-Saharan Africa accounts for 90 % of the world's 300 – 500 million cases and 1.5 –2.7 million deaths annually. About 90 % of all these deaths in Africa occur in young children. Economists believe that malaria is responsible for a 'growth penalty' up to 1.3 % per year in some African countries of which Ghana is no exception. When compounded over years, this penalty leads to substantial differences in Gross Domestic Product (GDP) between countries with and without malaria and severely restrains the economic growth of the region.

The Mpohor District is among the Districts in the Western Region of Ghana with high Crude Death Rates (CDR). The CDR of 9.1 (per 1,000 populations) for the Mpohor District is higher than the 6.2 for the Western. With malaria being the leading cause of morbidity and mortality in the Mpohor District, it impedes economic growth and long term development of the District. This is because it is the major cause of student and employee absenteeism and the decreased level of productivity that the District continues to experience.

With 64 % of the population of the district engaging in Agriculture where the most predominant cash crops are cocoa and oil palm, the extent of economic loss cannot be underestimated; this loss robs the country of some percentage of its Gross Domestic Product (GDP). The overall labor force is weakened by the disease aside the pain, suffering and uncertainty associated with the disease. Poor families and people in the rural areas are mostly at higher risk due to lack of resources to seek proper treatment of the disease even in complicated and life threatening cases.

Although Insecticide Treated Nets (ITN's) provide a cost effective means of ameliorating the effects of malaria, this measure will be expensive if large human populations must be protected in the District. This study, therefore, seeks to assess and derive a predictive model for the relationship between malaria prevalence and malaria causing factors in the Mpohor District.

**METHODS**

*1.1 Study Area and Source of Data*

The Mpohor District is one of the 22 Districts in the Western Region. The District is located at the south-eastern end of the region and was carved out from the erstwhile Mpohor Wassa East District in 2012 and established with a Legislative Instrument (L.I).

The population of the Mpohor District, according to the 2010 Population and Housing Census, is 42,923 representing 1.8 percent of the region's total population. Mpohor District has four Area Councils namely Mpohor, Adum Banso, Manso and Ayiem. The malaria morbidity cases in the Mpohor, Adum Banso, Manso and Ayiem health centres were used in the study.

Table 3.0 : Number of major communities in Mpohor District

| Area Council | Number of Communities |
|---|---|
| Edum Banso | 14 |
| Manso | 9 |
| Mpohor | 8 |
| Ayiem | 6 |
| **TOTAL** | **37** |

The Mpohor district is made up of four (4) Area Councils which has a total of 37 major communities.

*1.2 Location and Size*

The Mpohor District is one of the 22 Districts in the Western Region. The District is located at the south-eastern end of the region and was carved out from the erstwhile Mpohor Wassa East District in 2012 and established with a Legislative Instrument (L.I). It is bounded on the west by Ahanta West District, east by Wassa East District, north-west by Tarkwa-Nsueam Municipal and Shama District (Figure 2.0). The District covers a total land area of 524.533 square kilometers. The District capital Mpohor is located 19 km off the Takoradi-Agona Nkwanta main road (Nyarko *et al*., 2010).


**Figure 2.0 District Map of Mpohor (Source: Ghana Statistical Service, GIS 2014)**

*1.7 Data Collection and Data Management*

Confirmed malaria morbidity data used in this study were obtained as secondary data from four health centres in the Mpohor District, which included Mpohor Health Centre, Manso Community Health Planning Service (CHPS), Edum Banso Community Health Planning Service, and Ayiem Community Health Planning Service. Data collected were considered from January 1, 2008 to December 31, 2013.

The following variables were coded from the data:

Prevalence: (1 = prevalence rate greater than a specified month's average, 0 = prevalence rate less than a specified month's average); Seasonality: (1 = wet season, 0 = dry season); Distance to the hospital: (1 = distance > 1 km, 0 = distance ≤ 1 km); Distance to nearest water body: $\left(1 = \text{distances} < 1000\text{ m}, 0 = \text{distances} > 1000\text{ m}\right)$ ; and Mining community :( 1 = mining community, 0 = not a mining community).

The distance of 1000 m was chosen to reflect mosquito flight distance. Geographic Information Systems (GIS) data of the District was obtained from the Department of Geological Engineering in the University of Mines and Technology, Ghana. The data obtained from the hospital register were analyzed using the Statistical Package for Service Solution (SPSS), ArcGIS and Microsoft Excel.

*1.8 Model Specification, Estimation and Tests*

The response variable in logistic regression is usually dichotomous, that is, the response variable can take the value 1 with a probability of success $\pi$, or the value 0 with probability of failure $1-\pi$. The logistic regression model has the form;

logit(Y) = naturallog(odds)

$$= \ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 x_1 + \ldots\ldots + \beta_n x_n \qquad (1.1)$$

Where $\pi$ is the probability of outcome of interest, $\beta_0$ is the Y intercept, $\beta_1,\ \beta_2, \ldots\ldots\beta_n$ are the regression coefficients.

Taking the antilog of equation (1.1) on both sides, one derives an equation to predict the probability of occurrence of the outcome of interest as follows:

$$\pi = \frac{e^{\beta_0+\beta_1 x_1+\ldots\ldots+\beta_p x_p}}{1+e^{\beta_0+\beta_1 x_1+\ldots\ldots+\beta_p x_p}} \qquad (1.2)$$

The probability that a patient has no malaria is given by $1-\pi(x)$ :

$$\pi = \frac{1+e^{\beta_0+\beta_1 x_1+\ldots+\beta_p x_p} - e^{\beta_0+\beta_1 x_1+\ldots+\beta_p x_p}}{1+e^{\beta_0+\beta_1 x_1+\ldots+\beta_p x_p}}$$

$$\pi = \frac{1}{1+e^{\beta_0+\beta_1 x_1+\ldots\ldots+\beta_p x_p}}$$

The log odds of malaria thus equal,

$$\left(\frac{\pi(x)}{1-\pi(x)}\right) = e^{\beta_0+\beta_1 x_1+\ldots+\beta_p x_p} \qquad (1.3)$$

*1.9 The Wald Test*

The Wald test is a way of testing the significance of particular explanatory variables in a statistical model. In logistic regression we have a binary outcome variable and one or more explanatory variables. For each explanatory variable in the model there will be an associated parameter.

The Wald test is one of a number of ways of testing whether the parameters associated with a group of explanatory variables are zero. If for a particular explanatory variable, or group of explanatory variables, the Wald test is significant, then we would conclude that the parameters associated with these variables are not zero, so that the variables should be included in the model. If the Wald test is not significance then these explanatory variables can be omitted from the model. When considering a single explanatory variable, a t-test is used to check whether the parameter is significance.

For a single parameter the Wald statistic is just the square of the t-statistic and so will give exactly equivalent results. An alternative and widely used approach to testing the significance of a number of explanatory variables is to use the likelihood ratio test. This is appropriate for a variety of types of statistical models.

The Wald statistics is given by:

$$\text{Wald (z)}=\frac{\beta}{S_{E\beta}} \tag{1.4}$$

Where $\beta$ is the coefficient of the variable, $S_{E\beta}$ is the standard error (Tuyishimire, 2013).

2.0 The Odds Ratio (OR)

It is the indicator of the probability resulting from the change in the predictor.

$$OR = \frac{\pi}{1-\pi} \tag{1.5}$$

$\pi$ is the probability occurrence while $1-\pi$ is the probability that the event will not occur. Odds ratio greater than 1 indicates that the value of the predictor increases, the probability of the event occurrence increases also. If the Odds ratio is less than 1, the value of the predictor decreases, the probability of the event occurrence decreases (Tuyishimire, 2013).

### *2.1 Multicollinearity*

It is a phenomenon in which there exists a perfect/high or exact relationship between predictor variables. This makes it difficult to come up with reliable estimates of their individual coefficients. It can inflate the variance parameter estimates. It can also cause serious problems with the estimation of the slope parameter.

Multicollinearity can be detected by (i) Examining the correlation matrix (ii) Variance inflation factor and (iii) Eigen system Analysis of correlation matrix. Large correlation coefficient in the correlation matrix of predictor variables indicate multicollinearity (Montgomery, 2001).

### *2.2 Variance Inflation Factor (VIF) Analysis*

VIF complements collinearity analysis process. Every variable with a VIF greater than 10 is excluded from the model. VIF quantifies the severity of multicollinearity regression Analysis (Montgomery, 2001). The stepwise logistic model will be used to test the relationship between malaria prevalence and its causing factors.

Actually, the stepwise regression will help detect the model improvement if new predictors are added and it is better for logistic regression with dummy variables (Field, 2009). Odds ratio, Chi-square test ,Wald statistics will be used to test the significance of the predicted coefficients (Lubetzky-Vilnai *et al*., 2013).

The VIF model is given by:

$$VIF_j = \frac{1}{1-R_j^{\,2}} \tag{1.6}$$

## RESULTS

### *3.1 Collinearity Test*

After viewing the collinearity matrix, there were high correlations between season and water body proximities $(r = 0.61)$, between forest and stream proximities $(r = 0.56)$ and clinic and vegetation proximities $(r = 0.61)$. So variance inflation factor (VIF) was used as the next step to test for collinearity. Since all the variables had $\text{VIF} < 10$ as shown in Table 3.1, collinearity was not a problem. The screened variables were inputed in a stepwise logistic regression model. If VIF values exceed 10, there exists multicollinearity (Montgomery, 2001).

**Table 3.1 Independent Variables VIF Calculation**

| **Variable** | $\mathbf{R^2}$ | **VIF** |
|---|---|---|
| Season | 0.32 | 1.103 |
| Altitude | 0.49 | 1.244 |
| Water body | 0.73 | 1.535 |
| Clinic | 0.55 | 1.305 |
| Mininig | 0.61 | 1.376 |
| Vegetation | 0.72 | 1.521 |

*3.2 Logistic Regression*

The relationship between malaria and its underlying factors was analyzed through a stepwise logistic regression where the Wald statistics and the OR proved their significance as shown in Table 3.2. All the variables were good malaria predictors $(p < 0.05)$ and were all therefore included in the final model as shown in Table 3.2.

**Tabele 3.2 The Initial Step of Logistic Regression Testing the Significance of Predictors**

| | Variables | Score | df | Sig. |
|---|---|---|---|---|
| Step 0 | Season | 19.398 | 1 | 0.000 |
| | Altitude | 24.652 | 1 | 0.000 |
| | Water body | 8.581 | 1 | 0.003 |
| | Clinic | 6.860 | 1 | 0.009 |
| | Mining | 50.035 | 1 | 0.000 |
| | Vegetation | 3.901 | 1 | 0.048 |
| | Overall Statistics | 95.933 | 6 | 0.000 |

| | | | | | | | | 95.0% C.I.for OR | |
|---|---|---|---|---|---|---|---|---|---|
| | | B | S.E. | Wald | df | Sig. | OR | Lower | Upper |
| Step 1[a] | Season | .706 | .305 | 5.354 | 1 | .021 | 2.026 | 1.114 | 3.685 |
| | Altitude | 1.743 | .331 | 27.646 | 1 | .000 | 5.714 | 2.984 | 10.942 |
| | Water body | 2.849 | .518 | 30.266 | 1 | .000 | 17.266 | 6.258 | 47.639 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Mining | -2.433 | .381 | 40.682 | 1 | .000 | .088 | .042 | .185 |
| Vegetation | -1.331 | .478 | 7.755 | 1 | .005 | .264 | .104 | .674 |
| Constant | -1.011 | .296 | 11.689 | 1 | .001 | .364 | | |

**Table 3.3 Relation Between Malaria Infection and its Causing Factors**

**Table 3.4 Area under the ROC Curve**

| Area | Std. Error[a] | Asymptotic Sig.[b] | Asymptotic 95% Confidence Interval | |
|---|---|---|---|---|
| | | | Lower Bound | Upper Bound |
| .859 | .022 | .000 | .816 | .903 |

The higher the area under an ROC curve the better the predictive power of the Logistic Regression Model (Agresti, 2013). In Table 3.4, the predictive power of the Logistic Regression Model is 85.9 %.

This can be interpreted as a randomly selected individual from a positive group has a test value larger than for a randomly chosen individual from the negative group 85.9 % of the time.

The formulated model is given by:

$$\log\left(\frac{\pi}{1-\pi}\right) = -1.011 + 0.706\text{Season} + 1.743\text{Altitude} + 2.849\text{Water body} - 2.433\text{Mining} - 1.331\text{Vegetation} \quad (1.7)$$

Where, Water body = Water body proximity, Mining = Mining community, Vegetation = Vegetation proximity, Season = Seasonality.

Seasonality in the District increase the log odds of malaria prevalence by exp (0.706) = 2.03. For every unit change in Altitude the log odds of malaria increases by exp (1.743) = 5.71. People living within 1 km radius from a water body in the District are exp (2.849) = 17.27 times likely to be infected by malaria than those living above 1 km radius. People living within a mining community are exp (-2.433) = 0.09 times likely to be infected with malaria than people not living in a mining community.

People living within 1 km radius from a vegetation cover are exp (-1.331) = 0.264 times likely to be infected with malaria than people living beyond 1 km radius. Clinic proximity was not significant $(p > 0.05)$ and was not included in the model.

## CONCLUSIONS

A new Logistic Regression Model of high predictive power 85.9 % for malaria prevalence in the Mpohor District has been developed. This model has significant factors such as Seasonality, Altitude, Water body proximity, Vegetation proximity and Mining community.

## RECCOMMENDATIONS

Based on the results of this research, it is recommended that the formulated model is used by government, Health related Non-Governmental Organizations and policy makers to monitor and predict the prevalence of malaria in the Mpohor District in order to provide timely malaria interventions to the communities in the District.

It is recommended that combined processes of classical and spatial statistics are utilized in malaria modeling in the Mpohor District, so that the integrated results could provide complete and more reliable information that is useful for malaria control.

Malaria prevention and control measures such as ITN's (Insecticide Treated Nets), IRS (indoor residual spraying) with insecticides, Mass screening and treatment (MSAT) with effective anti-malarial drugs, use of mosquito coils and repellants should be targeted mostly at rural communities and communities living very close (within a 1 km radius) to water bodies in the Mpohor District.

There is the need to do further research involving more communities in the District and also using more known malaria prevalence factors (such as household proximity, building material, waste disposal etc.) in the determination of the relationship between prevalence and risk factors.

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