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Poisson Regression Models of Malaria Incidence in Jayapura, Indonesia

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ABSTRACT

This study analyzes malaria risk factors using Poisson and Classical Regression Analysis. The distribution of the discrete dependent variable (malaria incidence) was checked to ascertain the necessity for Poisson regression. Goodness-of-fit test indicate that both the normal as well as Poisson distribution do not describe the complete data set well. Cluster Analysis revealed that the data set (132 cases) contains three distinct groups/clusters. Models were constructed per cluster using Poisson and Classical regression. Poisson regression and classical regression are comparable based on the mean absolute percentage error (MAPE). Poisson regression though is advantageous over classical regression in terms of parsimony. In count data, Poisson regression is not troubled by the stochastic assumptions that the data should satisfy. Classical regression however, could encounter problems due to skewness, nonnegative value of the response, and nonconstant variance inherent to discrete random variables. The paper also illustrates a practical consideration in analyzing data from a heterogeneous group.

Keywords: Cluster Analysis, Poisson Regression, Prevalence Rate, Indirect Estimate, Malaria

1. INTRODUCTION

One of the primary concerns of any government is public health. In Indonesia, higher prevalence of malaria triggered the government to intensify activities towards mitigating the effects. The impact could be wide-ranging: morbidity, disability or even mortality. Malaria also does considerable indirect harm to economic development, productivity and quality of life in general. The vulnerability of a population can be attributed to the degree of exposure to detrimental environmental condition, especially among those people living in remote and inaccessible rural areas.

The malaria vector, *anopheles* mosquito is known to live and breed only in the tropics or subtropics. It is reported that each year, there are 300 million to 500 million new malaria cases and 1.5 million to 7.5 million deaths globally from malaria in the world, most of them occur in Sub Saharan Africa.

There is no vaccine yet against malaria. Thus, efforts to reduce morbidity, mortality and disability are limited to preventing contact between the population and the *anopheles* mosquitoes that transmit the infection, to the early detection of the infected people. In this case, educational campaign is a very powerful instrument towards mitigation. Actually, there are some anti-malaria drugs developed for curing disease, however, some may have already developed resistance by a certain *plasmodium* (NIAID, 2000).

Malaria transmission occurs in more than 100 countries, mostly along the equator zone. Regions include Africa, Asia, and Islands of the South, West, and Central Pacific

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Ocean, Latin America, certain Caribbean Islands and Turkey, possess tropical or subtropical zones wherein *anopheles* mosquito habitats exist. Western Pacific Region perhaps the most heterogeneous regions with geography and topography vary from low-laying coral atolls surrounded by endless kilometers of ocean to vast land masses make these areas as "malaria risk" areas. These countries are Cambodia, China, Laos, Indonesia, Malaysia, Papua New Guinea, Philippines, Republic of Korea, Solomon Islands, Vanuatu and Vietnam (WHO, 2000).

In Indonesia, malaria is still endemic until now, especially in some areas outside Java-Bali. In 1997, several provinces outside Java-Bali had a Parasite Rate (PR) higher than the national average of 4.78%. Over all, Irian Jaya (Papua) has the highest incidence rate (21.21%), followed by East Timor (12.28%), Maluku (7.38%), and North Sulawesi (5.45%). The incidence in Java-Bali is declining continuously from 1989 to 1996; however, the incidence outside Java-Bali is not significant declining in the same period (WHO Representative to Indonesia, 1999).

In Irian Jaya, now called Papua, it is reported that there is no malaria-free areas. From a malariometric survey conducted by the Department of Health Jayapura in 1993-1998, all of villages in Papua are malaria endemic areas. In addition, about 84% of the villages belong to a High Prevalence Areas (Parasite rate > 2%), while the rest with only about 16% belong to Low Prevalence Areas. In Jayapura, malaria is still recorded as the number one disease from time to time, followed by lung disease and skin diseases (Department of Health Jayapura, 2000).

This study aims to investigate the potential risk factors that may have direct or indirect relationship with the malaria incidence in Jayapura, Indonesia. More specifically, the study aims to determine the relationship between the potential risk factors (demographic composition, geographic location, and delivery of health services) and malaria incidence in Jayapura, Indonesia. In the process, Poisson Regression Analysis and Classical Regression Analysis will be compared in analyzing and predicting a discrete dependent variable. The Mean Absolute Percentage Error (MAPE) will be the primary basis in comparing the classical and poisson regressions analyses. The two procedures uses different model forms as well as different estimation procedures hence, different statistics are generated in the process. The best way to compare the two models then is on how well they can characterize the dependent variable, which is the main objective in modeling. Thus, MAPE will be used prominently in the comparisons of classical regression and poisson regression models.

2. RISK FACTORS OF MALARIA

Like most other researches on malaria, Carter et al. (2000) indicated that the location where the people live is an important risk factor. The malaria transmission was associated with the location of breeding sites.

Gunawardena et al. (1996) found that malaria incidence rates among residents of good and poorly constructed houses are significantly different at 0.51 and 1.23 infections per households, respectively. The risk was about 2.5-fold higher in residents living in the poorly constructed houses. The correlation between the incidence rates of all houses and the distance of the houses from both the forest edge and a source of water was significant. The forest edge is thought to be a good resting place and the source of water to be the potential breeding place of the mosquito vectors.

Giha et al. (2000) investigated the epidemiology of uncomplicated *falciparum* malaria in an area of unstable and seasonal transmission in Eastern Sudan. The study was conducted during 3 consecutive malaria seasons in 1993-1995. They calculated the relative hazard for clinical malaria episodes by age, sex, hemoglobin genotype, blood type and infection in the previous season. They found that malaria incidence was significantly lower in individuals aged 20-88 years than in the 5-19 years age group. The malaria incidence in males lower than in females during 1993 season, during 1994 season the incidences were comparable, whereas the incidence was higher in male than in female during 1995 season.

Mendez et al. (2000) studied the risk factors of malaria in an urban area in a port in the Pacific Cost of Colombia. Prevalence rate decreased with age and with knowledge of disease and preventive measures directed towards elimination of breeding sites. In addition, they found that the incidence was positively correlated with exposure to the forest ($p<0.05$), although 93% of the cases have been acquired in the urban area. They found also that individual having anti-malarial treatment in the previous month had about two times higher chance of being infected again compared to those whoever had malaria treatment. They also suggested that environmental intervention maybe appropriate to decrease the incidence in setting such as that of their study area.

A study conducted by Danis et al. (1999) characterized the risk of Plasmodium vivax in the Lacandon forest in Mexico. Place of birth outside the village of residence (odd ratio, OR=11.67, 95%CI 5.21-26.11), no use medical services (OR=4.69, 95%CI 3.01-7.29), never using bed-nets (OR=3.98, 95%CI 1.23-12.86) and poor knowledge of malaria transmission, prevention and treatment (OR=2.30, 95%CI 1.30-4.07) were significant risk factors of malaria incidence. They suggested that health education will be a more appropriate recommendation for controlling the incidence in the area.

3. RISK FACTORS USED IN THE STUDY

Risk factors pertaining to community characteristics are relevant for purposes of public health management. This study considered the variables that easily fit into policy specifications concerning public health. The variables are described in Table 1.

The risk factors analyzed are community characteristics (demographic composition), geographic characteristics as well as the simple structure of the delivery of health services. Most of the variables are categorical at the individual level (see Table 1), thus community-level characteristics were derived from percentage of individuals possessing the attribute.

For the gender variable, *female* is chosen as the baseline category. Thus, the percentage of *male* population in the village was computed. The females are generally less exposed to the open environment than the males who do most of their chores outside the buildings.

Older people have more stable immune system compare to the younger ones. Thus, for age variable, the older group was considered as the baseline category resulting to the definition of 3 age variables: *Infant* – percent of infant population; *Children* – percent of children; *Adult* – percent of adult members of the community.

Table 1: Summary of variables used in the analysis

Variables	Definition
Malaria	Number of malaria cases in each village
Male	Percentage of male residents in each village
Migrant	Percentage of immigrants living in each village
AGE	
Adult	Percentage of adult (> 15 years old) to total population in each village
Children	Percentage of children (6 - 15 years old) to total population in each village
Infant	Percentage of infants (≤ 5 years old) to total population in each village
EDUCATION	
ElemSch	Percentage of residents who completed only/ are still studying Elementary School education in each village
HighSch	Percentage of residents who completed only/ are still studying High School education in each village
PreSch	Percentage of residents who completed only/ are still studying Pre-school education in each village
OCCUPATION	
Agricult	Percentage of residents working in Agriculture sector in each village
Constr	Percentage of residents working in Construction sector in each village
Trading	Percentage of residents working in Trading sector in each village
Service	Percentage of residents working in Service sector in each village
GEOGRAPHIC LOCATION	
NearForest	Percentage of residents living within < 500 meter from the forest edge in each village
NearWater	Percentage of residents living within < 500 meter from the source of stagnant water (like lakes, ponds, swamps) in each village
PoorHouse	Percentage of residents living in a poor construction type of house in each village
UseLand	Percentage of residents cultivating land as a livelihood in each village
HEALTH WORKERS	
Doctor	Number of doctors working in the village
Midwife	Number of midwives working in the village
Nurse	Number of nurses working in the village
IMMUNIZATION	
BCG	Percentage of children receiving BCG vaccine in each village
Hepatitis_B	Percentage of children receiving Hepatitis B vaccine in each village
Smallpox	Percentage of children receiving Smallpox vaccine in each village

For occupation, those in *agriculture* sector, *construction* sector, *trading* sector and the *service* sector are more exposed to the open environment compared to those in the *industry* sector who are usually inside the buildings. Separate variables accounting for percentage in the community with such occupation were defined with *industry* sector as the baseline. Note that the type of occupation may also reflect the quality of living conditions of those people working in these sectors. Thus, indirectly occupation may also account for the quality of life of the residents of the community.

Literacy and education can facilitate the impact of education campaign to mitigate malaria. The higher the educational level of the community is, the lesser is the chance of their becoming vulnerability to the disease. Three variables were defined (*PreSch*, *ElemSch* and *HighSch*) to account for the distribution of the residents by level of education. College graduates were considered as the baseline group.

Stagnant water is an ideal habitat for mosquitoes. Exposure to the vector is thus a function of the distance between the residences of potential victim from a stagnant water source. For this purpose, percentage of residents in a village living within 500 meters distance from stagnant water is computed.

The forest, with its cool, high moisture environment is another ideal habitat for mosquitoes. The percentage of residents in an area within 500 meters distance from a forest is also considered.

Cultivation of land also increases the chance of the person to have contact with the vector. Hence, percentage of residents who actually cultivates land is considered as another possible risk factor.

The structure of the housing unit could also contribute in the exposure of a resident to the vector. Poorly built houses have higher chance of being exposed to the vectors compared to the structures that can protect its resident from the vector. Thus, percentage of residents in the village who are living in poorly built housing structure was also computed.

The immune system of a person can be developed if he is exposed to the threats of the disease. Thus, the percent of migrants to the village is also considered as another risk factor.

The more health workers in a village, the greater is the chance that the community will be informed about preventive measures towards malaria. Thus, doctors, nurses as well as midwives working in the area are counted.

Immunization to specific bacteria could generally develop the immune system of a person. Thus, the final set of indicators includes the percentage of residents having vaccines for Smallpox, Hepatitis B and BCG.

4. THE SAMPLE VILLAGES

The Jayapura regency/municipality consists of 237 villages from 28 districts in Indonesia. It was initially intended to collect community level information in all villages. Inaccessibility as well as insurgency limited the collection of data from 132 villages only. The study may be viewed then as limited only to the 132 villages.

This study used data from the Public Health and District Office. For malaria cases, the data were based on the reference period July to September 2001 (3^{rd} quarter) as reflected on the records of the Public Health office. This means that only those who seek help from the office are accounted for. For other variables, the data were collected either from the Public Health Office, the District Office or interviews from the public health and district officers.

5. POISSON REGRESSION ANALYSIS

A Generalized Linear Model (GLM) assumes that the response data Y_i has a distribution from an exponential family (normal, inverse Gaussian, gamma, Poisson, binomial). The generalized model is written as

$$g(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p \quad (1)$$

where $\mu = E(Y_i)\forall i$, $Y_i \sim$ exponential family and $g(\mu)$ is a non-linear function that links the random component Y_i to the systematic component $(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p)$.

Poisson Regression Analysis is a technique for modeling the dependent variable Y_i that describes count data. It is a general linear model that assumes that the response data $g(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p$ follow a Poisson distribution (Agresti, 1996).

The canonical link function for Poisson distribution is log link and it links the expected mean of the response variable to the systematic component (linear predictor) that can be written as:

$$\log(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p \quad (2)$$

where $\log(\mu)$ is a logarithmic function.

The parameters are usually estimated using maximum likelihood procedure. Wald test is used for testing $H_0 : \beta = 0$ for a GLM model. The Wald test is based on the behavior of the log-likelihood function at the Maximum Likelihood (ML) estimates $\hat{\beta}$, having chi-squared form $(\hat{\beta}/\text{ASE})^2$, where ASE stands for Asymptotic Standard Error.

A Generalized Linear Model (GLM) will give an accurate description and inference if it fits well the model into the data. Pearson χ^2 goodness-of-fit statistic is used to test whether the model adequately fits the data or not. The Pearson χ^2 statistic has the form:

$$\chi^2 = \sum_{i=1}^{n} \frac{(y_i - \mu_i)^2}{\mu_i} \quad (3)$$

where y_i is the i-th of the response variable and μ_i is a mean of the response.

Poisson distribution reveals three main problems in the application of regression analysis following classical assumption. First, the Poisson distribution is skewed, while traditional regression assumes a symmetric distribution of errors. Second, the Poisson distribution is non-negative, while classical regression might assume a distribution of values that maybe negative. Third, the variance of a Poisson distribution increases as the mean increase, while traditional regression assumes a constant variance. Thus, Poisson regression is considered in case the dependent variable shows unbounded explosion of variance and other distributional problems.

6. OVERALL MODEL

Poisson regression and classical regression were fitted using all observations on the 132 villages. For Poisson regression, 5 of 22 variables were important risk factors. The average number of malaria cases was predicted and the Mean Absolute Percentage Error (MAPE) was 338.62%. Classical regression analysis yields a coefficient of determination of 21.19% and 4 of 22 variables turned out to be important risk factors. The MAPE was computed at 327.92%.

The 132 sample points consist of observations from a heterogeneous mix of villages. Two or more subpopulations may exist and as the next step, the histogram of the number of malaria cases was examined. The data reflects a multi-modal population, affirming the hypothesis regarding the heterogeneity of the sample. Regardless of the hypothesized distribution (Poisson or normal), the assumption of the single distribution governing the residuals will be invalid. This explained the failure of the models constructed using all 132 observations.

A test of goodness of fit was also done to verify whether Poisson or normality assumption is valid. The response variables neither follow the Poisson distribution ($p<0.01$), nor the normal distribution ($p<0.01$).

The test confirmed the initial patterns reflected in the histogram that the data are heterogeneous. It was suspected that possibly, that data contains several Poisson subpopulations. Thus, the villages were subjected to Cluster Analysis to unmask possible grouping (subpopulations).

7. CLUSTERING OF VILLAGES

Cluster Analysis grouped together similar villages based on the 23 variables (including the dependent variable). The data appeared to have three natural groupings.

Cluster 1 composed of 49 villages has an average of 52 malaria cases per village. Villages falling under Cluster 1 are mostly urban centers. This cluster grouped together the villages that have lower incidence of malaria that is explained by its urbanity status. This cluster is called ***Low Malaria Incidence Group***.

Cluster 2 composed of 52 villages has an average of 178 malaria cases per village is dominated mostly by rural areas. These areas are near the stagnant water and near the forest. The geography here explains the higher incidence of malaria compared to cluster 1. This cluster is then called ***Moderate Malaria Incidence Group***.

Cluster 3 with 24 villages has the highest incidence of malaria at 369 cases per village. These are also mostly rural areas and most of them are near stagnant water sources as well as near forest areas. This cluster is then called ***High Malaria Incidence Group***.

Cluster 4 with only 7 villages was left out in modeling for insufficiency of observations.

8. LOW MALARA INCIDENCE GROUP

The mean malaria incidence during the period of July 2001 to September 2001 (3rd quarter) is 51.9318 with standard deviation of 18.3295 malaria cases per village.

Variables contributing insignificant information (at 5% level) were dropped one at a time until only the significant variables were left in the Poisson regression model. The malaria risk factors include: occupation and number of health personnel in the area. People working in the *Construction* sector have bigger chance of getting malaria than those working in *other* sectors. Working in the *Service* sector though has a smaller chance of getting malaria than those working in *other* sectors. The more midwives working in the village, the wider is the scope of education campaigns aimed towards mitigating the disease resulting to lower incidence rates.

The summary of the models for the Low Incidence Group is given in Table 2.

Table 2: Model Summaries for Malaria Incidence Rates

Low Malaria Incidence		Number of predictors in the models	MAPE	R^2	Adj R^2	p-value
Poisson Regression	Full Model	All predictors	35.2678	-	-	-
	Reduced Model	3 predictors	48.666	-	-	-
Classical Regression	Full Model	All predictors	32.4025	0.5936	0.1678	0.2251
	Reduced Model	2 predictors	49.0849	0.3103	0.2767	0.0005
Moderate Malaria Incidence						
Poisson Regression	Full Model	All predictors	7.1974	-	-	-
	Reduced Model	7 predictors	8.9989	-	-	-
Multiple Regression	Full Model	All predictors	7.0401	0.6850	0.4461	0.0043
	Reduced Model	6 predictors	9.0897	0.4273	0.3509	0.0002
High Malaria Incidence						
Poisson Regression	Full Model	All predictors	1.1047	-	-	-
	Reduced Model	18 predictors	1.9407	-	-	-
Multiple Regression	Full Model	All predictors	1.1014	0.9939	0.8607	0.2822
	Reduced Model	18 predictors	1.8401	0.9835	0.9240	0.0028

9. MODERATE MALARIA INCIDENCE GROUP

The group consists of 52 observations and the mean malaria incidence during period of July 2001 to September 2001 is 178.40 with standard deviation 26.96 malaria cases per village.

Insignificant variables were dropped one-at-a-time until only significant variables are left in the model at 5% level of significance. The malaria risk factors in this group include: *Adult, PreSch, HighSch, Trading, NearWater, Smallpox* and *Hepatitis_B*. Adult residents, those with High School education only, those working in Trading sector and those living near the source of stagnant water have higher chance of getting malaria than other groups. Those with Pre-School education only are mostly toddlers hence, the category is more reflective of age rather education factor. The Pre-Schoolers have smaller chance of getting malaria than other groups. The more the residents receive immunization vaccine the lesser is their chance of acquiring malaria. (see Table 2)

10. HIGH MALARIA INCIDENCE GROUP

With 24 observations, the mean malaria incidence during the period of July 2001 to September 2001 is 369.125 with standard deviation 63.3756 malaria cases per village. The malaria risk factor includes: *Male, Infant, Children, Adult, PreSch, ElemSch, Agricult, Constr, Trading, Service, NearWater, NearForest, UseLand, PoorHouse, Migrant, Smallpox, Hepatitis_B* and *BCG*. More factors contribute in explaining malaria incidence in high incidence group. The additional variables reflect the socio-geographic composition of the community reflecting the complexity of risk factors associated with the disease. (see Table 2)

11. COMPARISON OF MODELS

The MAPE computed in *Low Malaria Incidence* for both models (Poisson and Classical regression) are very close. This is due to the fact that the both models could very well fit the data within a cluster. Moreover, the MAPE computed in *Moderate Malaria Incidence* are very close as well and smaller than in Low Malaria Incidence. Furthermore, the MAPE in *High Malaria Incidence* are very close and much smaller than the MAPE in the two other clusters with lower malaria incidence rates. This could mean that lower incidence is more difficult to predict than higher incidence rates.

In general, the two models (Poisson regression and Classical regression) exhibited similar set of risk factors for malaria. Classical regression needs more variables in equation to explain as much fit as Poisson regression does. This may be explained by the fact that Poisson regression uses a non-linear link function that accounts for a more complicated effect on the explanatory variables. The classical regression on the other hand accounts for the linear effect of the independent variables only. Thus, classical regression would require more variables than what is needed in Poisson regression. Poisson regression has edge over classical regression in terms of a more parsimonious model. For purposes of implementation, a parsimonious model is desirable since fewer variables need to be monitored.

Comparability of Poisson and Classical regression may be traced on two things. First, normal approximation to Poisson distribution might be easily attained, i.e., not requiring too "large" samples. Second, the fact that Poisson regression is just an exponential function of the classical regression model could imply interchangeability of the two models. Thus, for fairly "large" samples, even if the dependent variable is discrete (count), classical regression results could still fairly compare to the results of Poisson regression.

12. DIRECT AND INDIRECT ESTIMATES OF MALARIA PREVALENCE RATE

The models may provide an indirect estimate of prevalence rate. For instance, in an area (could be smaller than a village), if the demographic composition, geographic location as well as the presence of health workers are known, the prevalence rate maybe estimated.

In this study, the direct estimate of malaria prevalence rate was computed as a ratio of the average number of malaria cases and the average population in each cluster. In addition, the indirect estimate of malaria prevalence rate was computed by substituting the average value of significant variables for both models in each cluster. For Poisson regression model, the indirect estimate obtained after taking the exponential value of the Log(malaria).

Direct estimates of malaria prevalence rate for ***Low Incidence Group*** is 1.83%. This value is less than the national average of 4.78%. It indicates that villages in this group belong to the Low Prevalence Area, where prevalence rate < 2% (CBS Jayapura, 1999). The direct estimate in ***Moderate Malaria Incidence Group*** is 6.32%. This value is higher than the national average of 4.78%, indicating that the villages are classified as High Prevalence Areas. In the ***High Malaria Incidence Group,*** the direct estimate of malaria prevalence rate is 19.49%. This value is much higher than the national average of 4.78%. The villages included in this group possess all the risk factors associated with malaria.

Indirect estimates of prevalence rate can be computed by substituting the mean of the risk factors in the final model. Table 3 shows the indirect estimate of malaria prevalence rates for Poisson and Classical regression models. The models were able to predict the indirect estimate of malaria prevalence rate very close to the direct estimate. These values are less than 2% showing that the villages in this cluster are belongs to Low Prevalence Area.

Table 3: Estimates of Prevalence Rate

Low Incidence Group		Prevalence Rate (%)
Direct Estimate		1.83
Indirect Estimate	Poisson Regression	1.81
	Classical Regression	1.84
Moderate Incidence Group		
Direct Estimate		6.32
Indirect Estimate	Poisson Regression	6.31
	Classical Regression	6.33
High Incidence Group		
Direct Estimate		19.49
Indirect Estimate	Poisson Regression	19.10
	Classical Regression	19.49
NATIONAL INCIDENCE RATE		4.78

The same table (Table 3) shows the indirect estimates of malaria prevalence rate in Moderate Malaria Incidence Group and for High Prevalence Rate areas. Indirect estimates of prevalence for both groups are also very close to the direct estimates. Given appropriate levels of the risk factors, a carefully formulated regression model (e.g., poisson link function) can be used in estimating prevalence rate of malaria in an area, and perhaps of prevalence rate of other environmental health complications.

13. CONCLUSIONS

Poisson and Classical regression models exhibited similar results in predicting malaria incidence. For purposes of implementation however, Poisson regression is more desirable since it is not troubled by the Poisson distribution conditions (skewness, nonnegative value of the response and nonconstant variance) and fewer variables might be needed in the monitoring system to obtain indirect estimates of prevalence rate. Comparability may be attributed to the ease of attaining asymptotic normality for Poisson distribution. The sample size need not be "too" large for the normal distribution to closely approximate the Poisson distribution.

Even with Poisson Regression, low incidence rates (rare cases) are more difficult to predict compared to high incidence rates. With rare cases, the information contained in the positive cases is easily masked by the information contained in the negative cases, making modeling more complicated.

Demography, urban and regional planning, as well as public health concerns should be taken into consideration in implementing a malaria control program. Residential units should be distanced away from forest edges as well stagnant water sources, otherwise, a regular fumigation routine should be scheduled. Immunization programs can be enhanced (increased coverage) since a vaccine for one disease could generally enhance the defense system of children who are at high risk to malaria. Education campaign with the help of health workers in the local areas can also contribute in the mitigation of the disease. Knowledge on the demographic composition of the community is essential in the formulation of an efficient public health management.

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