Modeling malaria prevalence rate in Lagos state using multivariate environmental variations

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Abstract. Malaria is the most significant health problem in Nigeria accounting for about 60 % of outpatient consultations and 30 % of hospital admissions (Federal Ministry of Health 2003). The government has identified the burden that malaria places on the health status of the population and has classified malaria as a public health problem. Malaria, though completely preventable and curable, pregnant women and children under five years, are the most vulnerable groups, thus sustainable and evidence based efforts are required to control the malaria disease burden. This research study considered the environmental factors that aid the breeding of malaria carrying vectors. The environmental factors considered in this study are that of rainfall, temperature and relative humidity. The significance of this study centers on how to scale-up malaria related interventions, strengthen of systems, and making a major effort to Roll Back Malaria in Nigeria, (WHO, 2005). The aim of this research is to establish the significant effect of environmental factors on malaria prevalence rate within the Local Government Areas of Lagos State. The methodology used was to carry out a statistical analysis of these various environmental factors with the malaria prevalence cases that was recorded in Lagos State from 2009-2013. GIS was used to show the various local government areas with high severe and low malaria cases. The result obtained from this analysis shows a significant relationship between the malaria prevalence cases and environmental factors of rainfall, temperature and relative humidity, thus leading to development of a predictive model. The outcome of the study can help the government, Lagos state ministry of health and donor agencies at both local and international, identify the local government areas within the state that are most vulnerable to malaria epidemic, and thus providing clear insight in policy formation, planning and strategy implementation.

Keywords: malaria, prevalence rate; Lagos; GIS; multivariate variations.

1. Introduction

Statistics shows that malaria accounts for nearly 110 million clinically diagnosed cases per year, an estimated 300,000 children die of malaria each year (Federal Ministry of Health 2003). The direct health impact of malaria has led to a severe social and economic burden on our communities and country as a whole, with about N132 billion lost to malaria annually in form of treatment costs, prevention, loss of man hours etc. (Federal Ministry of Health 2003). Malaria control will need to be addressed, not as a separate, vertical, disease-specific intervention, but as part of a health systems strengthening effort, to provide holistic services in all facets of care, and as part of a larger community-development effort (Anyamba, A. *et al.*, (2001); Ghulam, M., *et al.*, (2004); and Guinovart, C., *et al.*, (2006)).

Nigeria, being the most populous country in the continent, accounts for about a quarter of its population. Malaria is the country's most significant public health problem. It accounts

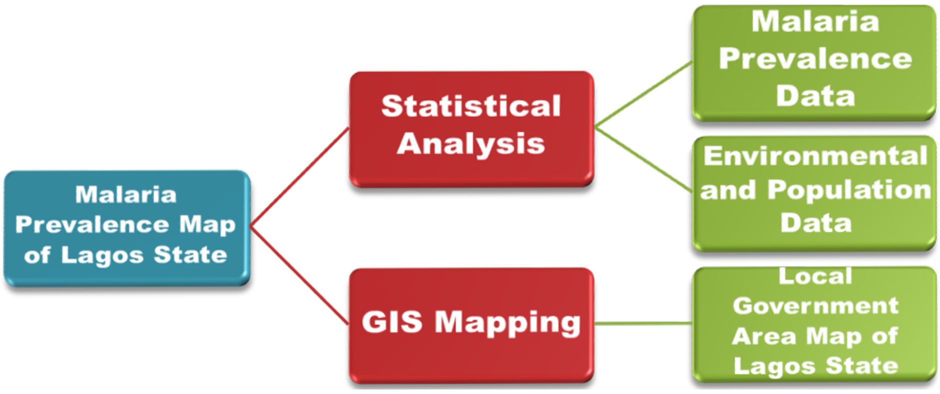

Figure 1: Flow Diagram illustrating the research methodology

for 25 % of under-5 mortality, 30 % childhood mortality and 11 % maternal mortality. At least 50 % of the population will have at least one episode of malaria annually while children aged below 5 years (about 24 million) will have 2 to 4 attacks of malaria annually. While Malaria remains a major public health and development challenge in Nigeria (NMCP (2006); Jason W., (2007); Masound, S. *et al.*, (2008)), we now have a unique opportunity to make a major effort to Roll Back Malaria in Nigeria, (WHO, 2005) . The malaria control plan was built on the National Malaria Strategic Plan (NMSP) for Malaria Control and was developed by the National Malaria Control Programme in partnership with the RBM Partners, States' Ministries of Health and other Stakeholders (Beck, L., *et al.*, (2000); CDCP, (2007 & 2009); & Beier JC, *et al.*, (2000)). The global health and malaria community has developed ambitious and overlapping targets with respect to malaria control in Africa.

On April 25, 2000, at the Abuja Summit in Nigeria, the Roll Back Malaria (RBM) Partnership and African health ministers set targets of exceeding 60 percent coverage for these interventions by 2005. Recent surveys indicate that current national coverage levels in Africa for each of the Abuja targets range from 5 to 40 percent. In understanding the fluctuation of malaria incidence rates in the Lagos State and indeed Nigeria at large, it is necessary to examine the requisite environmental conditions needed to support mosquito vector development and proliferation (Bi, P., *et al.*, (2003); Deichman U (1996) & Brooker, S., *et al.*, (2002 & 2004)). Analyzing satellite-based remotely sensed environmental data (rainfall, temperature, relative humidity) in a Geographic Information System (GIS) is one approach that can be utilized to identify large geographic areas of suitable mosquito habitat. Exploratory analysis of these habitats can also be employed within GIS to create an effective means for showcasing the areas of malaria transmission to surrounding human populations. It is this approach that can improve understanding about the variations in malaria transmission rates when compared to risk, especially in the Nigeria, where access to conduct epidemiological field studies is limited or restricted.

In the field of epidemiology, which involves the scientific study of factors affecting the health and illness of populations, remote sensing technology plays an integral role in the surveillance of many disease-carrying vectors (e.g., the mosquito and tick). The development of remote sensing technology and GIS has opened new avenues in the study of vector-borne diseases, making it now possible to map the densities of a vector species, model potential disease occurrences, and -continuously monitor the critical environmental habitat needed to support

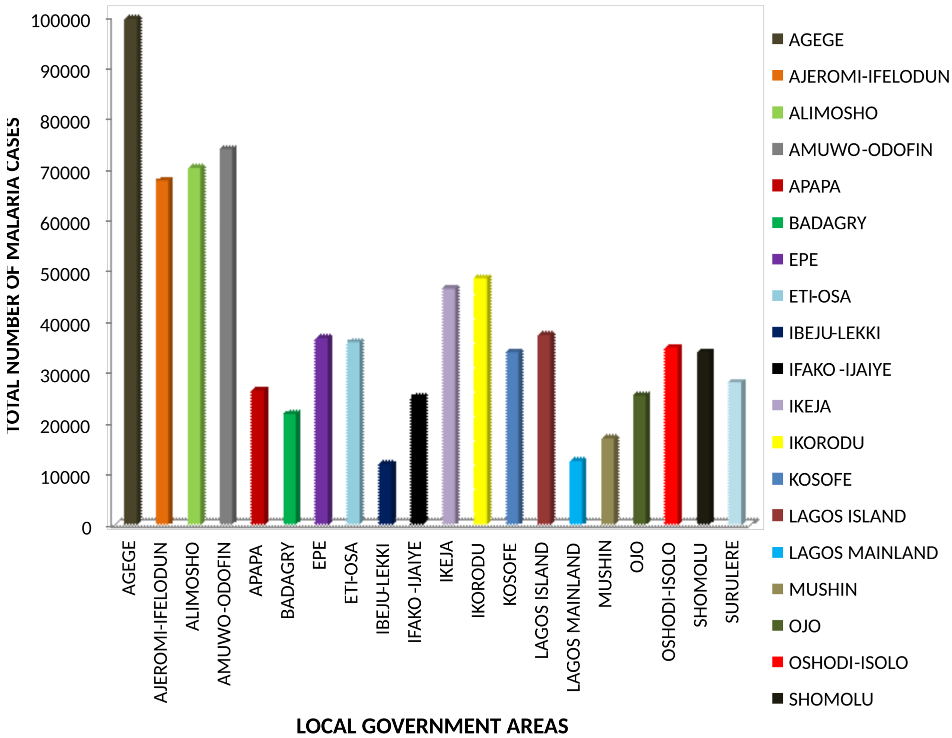

Figure 2: Malaria cases for various LGAs in Lagos State 2009

many infectious diseases (Dhiman 2000). The relevance of developing these technologies appears to be especially important to epidemiologists who have traditionally relied on maps and spatial analysis to link environment to disease (Bruce-Chwatt LJ, *et al.*, (1980); Dossou-Yovo J, *et al.*, (1998) &Carrat F *et al.*, (1992)).

Early applications of remote sensing technology and GIS to the field of epidemiology came largely from government research. The USA in 1996 for instance, the Department of Defense (DoD), Centers for Disease Control (CDC), and other governmental agencies developed the DoD-Global Emerging Infections Surveillance and Response System (DoD-GEIS) to strengthen existing global epidemiological capabilities for military personnel through the centralized coordination of health organizations and the use of information technology (Culpepper and Kelly 2002). One of DoD-GEIS first implementations was the mapping and surveillance of Rift Valley Fever (RVF) epidemics in Eastern Africa using climatic and terrestrial satellite data. The results -from the project assisted military epidemiologists to streamline medical readiness plans for areas susceptible to RVF outbreaks.

The mapping and analysis of the environmental landscape through remote sensing technology and GIS allows for a better understanding of temporal and spatial aspects of infectious disease transmission. Yet, turning infectious disease characterizations into preemptive intelligence for a given geographic area can be challenging due to variability of the environmental landscape. Brooker *et al.*, (2002) states that reliable intelligence requires an understanding of whether the predictive models developed for one location can be applied to another because the environmental factors that influence transmission are unlikely to be uniform over large geographic areas. That is why validation of such intelligence is vital if it is to be used for

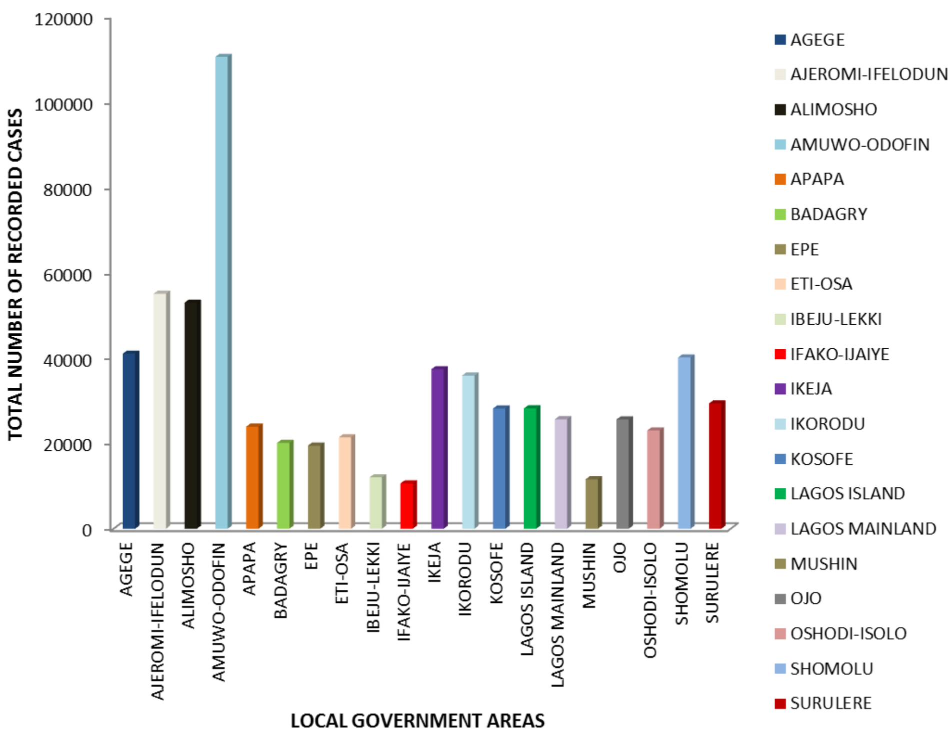

Figure 3: Malaria cases for various LGAs in Lagos State 2010

disease assessment, monitoring, and prevention (Glass, G., (2000); Washino, R., *et al.*, (1994) & Beatty, M. E., *et al.*, (2007)).

GIS can assist in showcasing these challenges by linking field observations and statistical methods to validate outcomes and create usable information. The development of accurate and defensible- preemptive disease intelligence can help supplement more traditional survey methods of disease as well as facilitate informed decision-making. From an operational standpoint, conventional epidemiological assessments of infectious disease have mostly relied on the investigation of specific diseases from a biological perceptive and the use of syndromic surveillance. Syndromic surveillance is the close field observation of an area for the emergence of a group of symptoms that collectively indicate or characterize disease or abnormal conditions within a population (Sharon 2006). The problem with this method is delayed response and control to a disease outbreak due to late reporting of symptoms, inaccurate information, or sparse public health facilities inadequately prepared to support a population. According to the Centers for Disease Control (Sosin and DeThomasis 2004), there is increased skepticism among public health scientists about the effectiveness of syndromic surveillance as a means for early detection of disease. To mitigate this uncertainty, remote sensing technology and GIS can be used together to complement syndromic surveillance by modeling the specific environmental conditions needed to support the vectors that cause disease. Glass (2000) emphasizes a key point: "GIS is able to calculate variables that are, from a practical perspective, nearly impossible to obtain from field studies." Thus, traditional syndromic surveillance techniques are still useful, but are enhanced when the focus is shifted from disease outcomes and population analysis to exposure and risk. The use of remote sensing technology and GIS modeling can facilitate improved accuracy and quality of risk estimates required to plan for

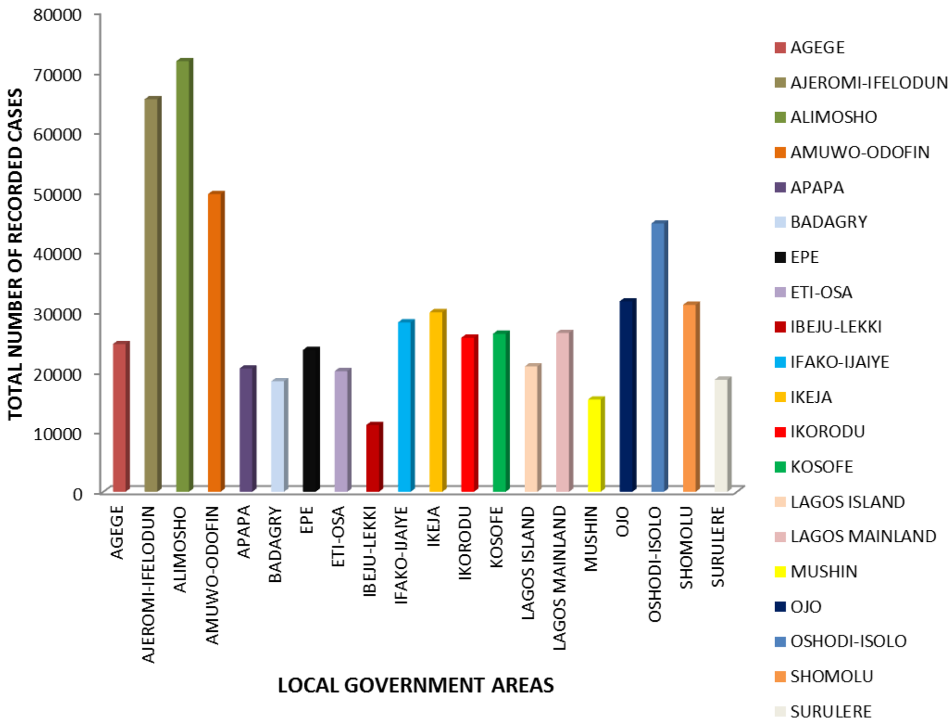

Figure 4: Malaria cases for various LGAs in Lagos State 2011

disease outbreaks before they become widespread human health hazards. Moreover, scientific evidence obtained from utilizing geographic modeling contributes greatly to the theoretical foundation of preemptive disease intelligence, decision support, and response systems, which many countries use to prepare for emerging disease epidemics.

A modeling framework that utilizes remote sensing and GIS technologies has been developed to not only aid in the characterization of disease patterns, but to extend preemptive disease intelligence beyond conventional surveillance. Landscape epidemiology is the process of examining the environmental landscape to observe and ultimately predict disease outbreaks before symptoms appear in a population. This collaborative approach, developed by scientists at NASA's Ames Research Center, involves the identification of geographical areas where disease is transmitted by using holistic approaches involving the interactions and associations between elements of physical and cultural environments (NASA 2006a). Landscape epidemiology theory first conceived by Pavlovsky (1966) follows a fundamental premise; by knowing environmental conditions necessary to support specific pathogens in nature, one can use the landscape to identify spatial and temporal patterns of disease.

One benefit of using the landscape epidemiology framework is that it draws upon a vast resource of archived governmental and commercial remotely sensed environmental data as well as decades of ecological study of disease vectors. Additionally, combining remotely sensed environmental data with GIS and statistical methods can give epidemiologists a practical means to plan and respond to environment attributable, infectious diseases, such as malaria (Culpepper, R., and Kelly, P., (2002); Dhiman, R., (2000) & Diuk-Wasser, M., *et al.*, (2017)).

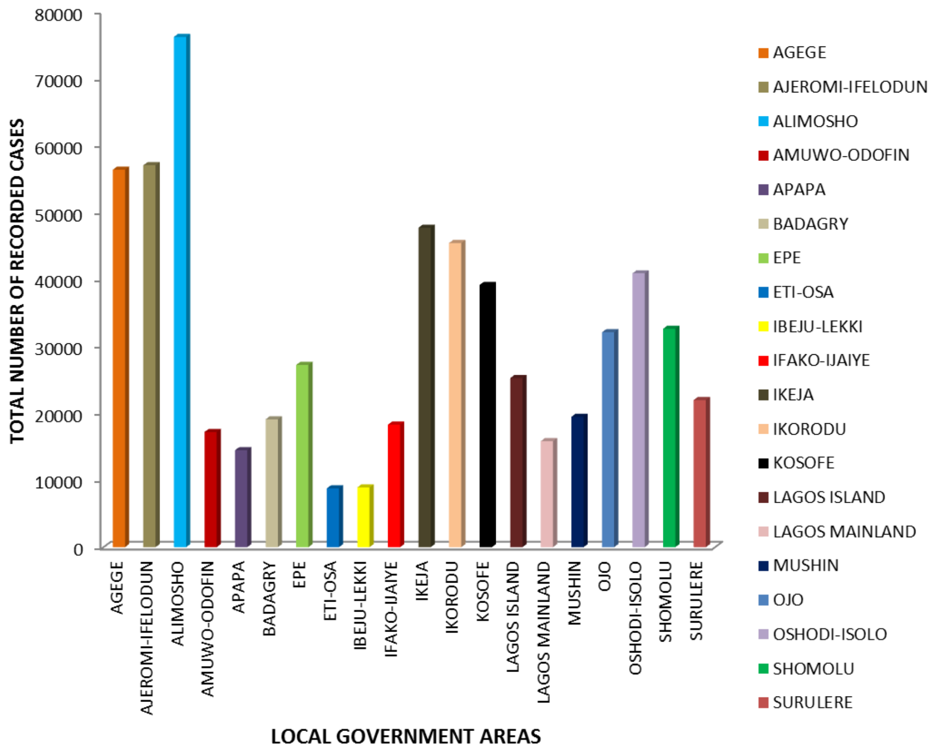

Figure 5: Malaria cases for various LGAs in Lagos State 2012

1.1. Aim of Research

The aim of this research is to establish the significant effect of environmental factors on malaria prevalence rate within the Local Government Areas of Lagos State.

Research Objectives

1. To determine the relationship between environmental variations and prevalence of malaria cases in Lagos state
2. To determine the correlation between the population density of Local government areas in Lagos state and reported cases of malaria by using linear regression model.
3. To determine the significant difference in the prevalence rate of malaria across the seasonal variation in Lagos within a 5years period
4. Produce maps showing the various endemic low and high areas of malaria prevalence in Lagos State

1.2. Significance of Study

The significance of this study centers on how to scale-up malaria related interventions, strengthen of systems, and make a major effort to Roll Back Malaria in Nigeria, (WHO, 2005), knowing fully that malaria remains a major public health and development challenge in Nigeria.

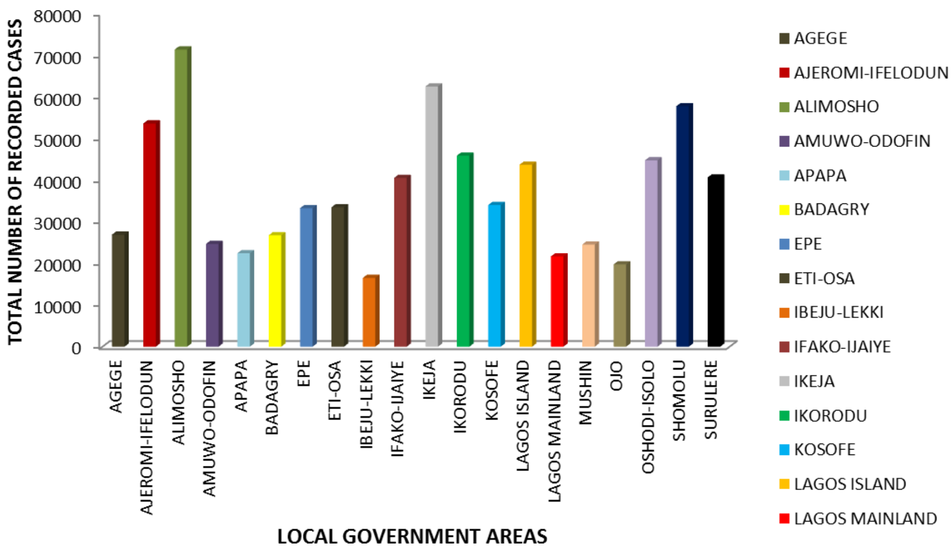

Figure 6: Malaria cases for various LGAs in Lagos State 2013

Definition of Terminology Used

1. Non-Severe Malaria Cases: These are patient suffering from malaria fever but are not admitted in any medical facilities. These patients are giving prescriptions of drugs by physicians or medical personnel from these health facilities.
2. Severe Malaria Cases: these are patients that are under the watchful eye of the medical personnel in order to monitor and manage their current health conditions.
3. Malaria among Pregnant women: These are malaria cases recorded for women that are pregnant. This covers for only the pre-natal cases and excluded the post-natal malaria cases

1.3. Study Area

The study area covers a surface area of approximately 3,345 square kilometers, which is about 0.4 % of the total land area of Nigeria, Lagos is located at 6.5833oN and 3.7500oE. The state is located in the southwest geopolitical zone of Nigeria, bordered in the north and east by Ogun State, in the west by the Republic of Benin and in the south by the Atlantic Ocean. Lagos State has a coastline of approximately 180 km. Underlain by sedimentary rocks; the State is on a coastal plain characterized by predominantly flat terrain, with an average elevation of less than 1.5m above sea level. The land slopes gently from the interior to the sea. Water bodies and wetlands cover over 40 % of the total land area of the state and an additional 12 % is subject to seasonal flooding. The coastal areas consist of lagoons, creeks and swamps, separated from the open sea by a strip of sandy land that varies in width from 2 to 16 kilometers. The entrance into Lagos Lagoon is the only major outlet through which the lagoons and creeks drain into the sea. Wetlands and upland forest (Rain Forest) are the dominant ecozones (FAO (1978); Clarke, K., *et al.*, (1996); Cromley, E, (2003)). In fact, the state falls within the Tropical Rain Forest zone, but the vegetation cover by none built up areas is mostly a mosaic of mangrove swamps, freshwater swamps, secondary forest,

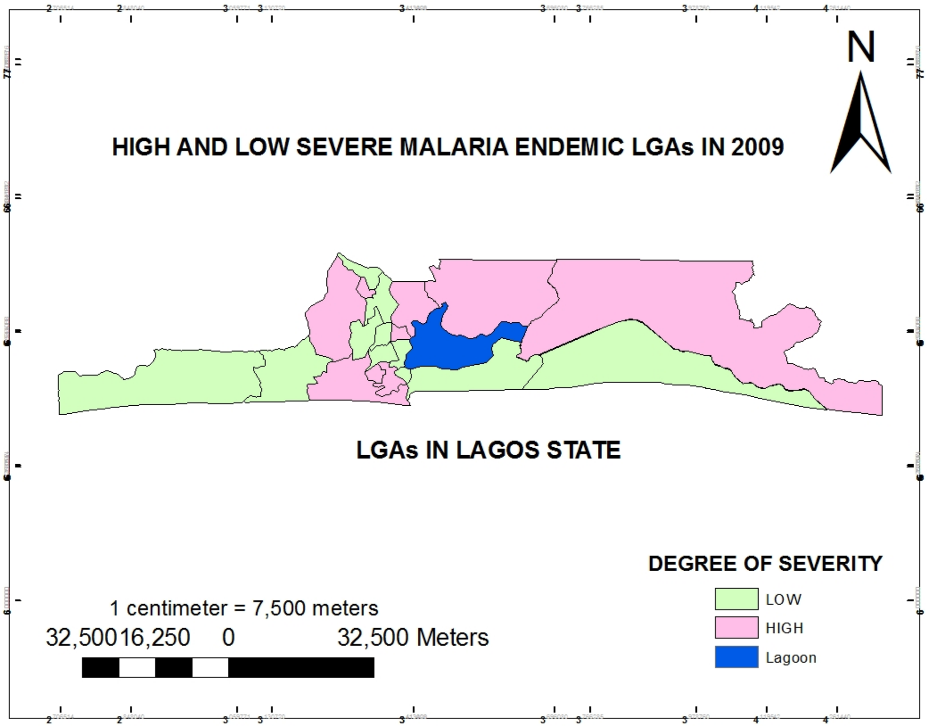

Figure 7: Endemic Local Government Areas in 2009 with both low and high severe malaria cases

farmland and fallow land. The topography is gently sloping throughout and the soils are mostly deep and poorly drained. The state is divided into 5 administrative provinces with 20 Local Government Areas (Local Government Areas) and 37 Local Council Development Areas (LCDAs). It is the commercial center of Nigeria with a population of over 17 million people (LSG 2006 population census).

2. Research methodology

The data used for this research work are secondary data gotten from the monthly collated data by the Lagos State Ministry of Health on malaria prevalence for the 20 Local Government Areas within a 5 years period of 2009-2013. These include:

1. Variables such as the monthly non-severe malaria cases, severe malaria cases and malaria in pregnant women during pregnancy for each Local Government Areas of the State for 5years period (2009-2013).

2. Lagos State Population Projection data 2007-2015 by Lagos Bureau of Statistics using Annual Growth Rate of 3.2 %. This data is more comprehensive than the population data from the National population census commission.

3. The population density data for various local government areas of the State for the period in view.

4. Environmental data drawn from climatic variables of monthly total rainfall amount,

monthly average minimum and maximum temperature and the monthly average relative humidity values in percentage as recorded at 0900z and 1500Z were obtained from the Nigeria Metrological Station (Nimet) Oshodi.

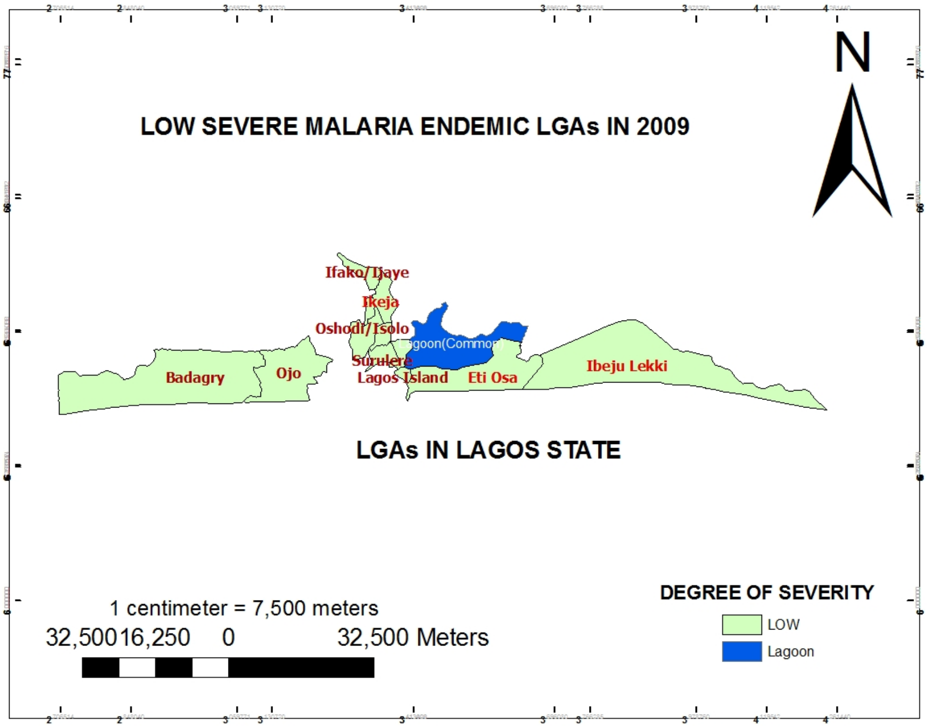

Figure 8: Endemic Local Government Areas in 2009 with low severe malaria cases

Malaria Prevalence Rate in LGAs

The malaria prevalence rates was derived for each year under various local government area by dividing the malaria prevalence values by the projected population of each local government area multiplied by 100 to give a rate called the malaria prevalence rate

$$\mathrm{MPR} = \frac{\textit{Total annual malaria prevelance in each LGAs in 2009}}{\textit{projected population at 2009}} \times 100. \tag{1}$$

It should be noted at this point that this calculation is based on the assumption that the entire population of each local government area was exposed to the risk of malaria during this period, that each person contributed exactly one person per year of exposure. In computing the malaria prevalence rates, the episodes of the subject were considered just as an observed subject for each year.

This MPR was used as the dependent variable in drawing up the regression model for this study. It was also used to correlate with the population density of each local government and the prevalence rate recorded.

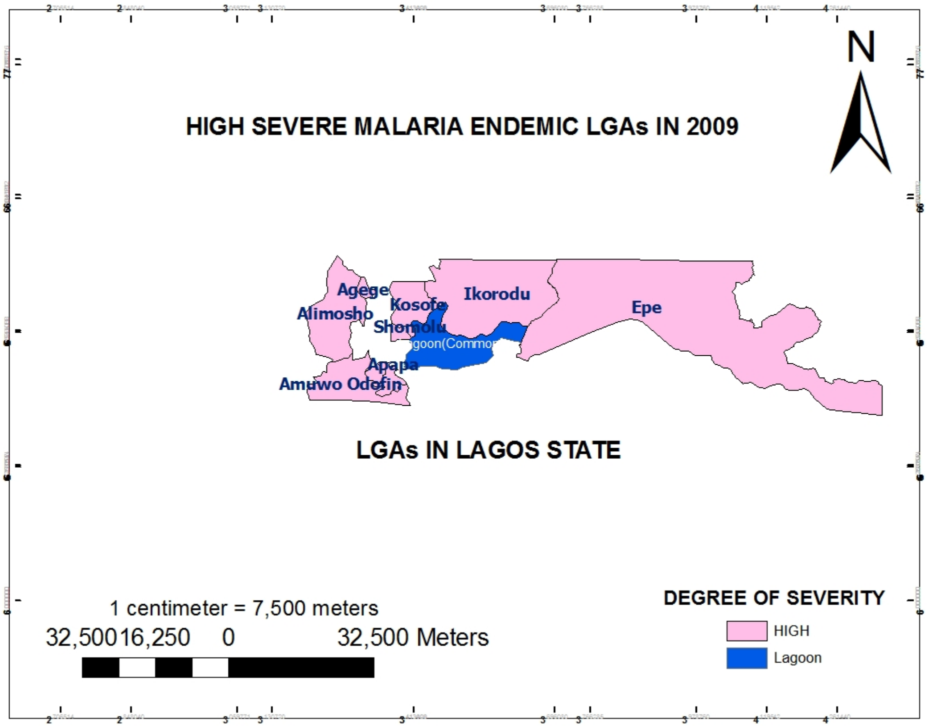

Figure 9: Areas with high severe malaria endemic in 2009

2.1. Climatic and Environmental Data

Distribution of malaria is governed by a large number of factors relating to the parasite, the vector and the host (Molineaux 1988). Predominant among these are climatic and environmental factors, particularly those that affect habitat and breeding sites of the anopheline vectors such as temperature, precipitation, humidity, presence of water, vegetation and man to vector contact (Craig MH, Snow *et al.*,D (1999; Deichman U (1996)). The data used in this study were acquired by the use of GIS and Remotely Sensed data (Rainfall, Temperature and relative humidity) from satellite imagery of same resolution (same scale), for modeling and mapping malaria parasite prevalence, while the environmental predictors are the monthly total rainfall in millimeter, the monthly average minimum and maximum temperature measured in degree Celsius, as well as the monthly average relative humidity values in percentage of 0900Z and 1500Z record. The data falls within the period of 5years (2009-2013).

The wet and dry seasons were defined based on rainfall patterns, the months of April-October were classified as the wet season, while November –March were classified as the dry season. This data was used to observe the seasonal malaria prevalence rate during the wet and dry season. Results from this, show a significant difference on the malaria prevalence rate. It was observed that the malaria prevalence rate was lower during the dry season months as to when compared with the prevalence rate of the wet season months (Carmel, *et al.*, (1993); Cheesebrough, M. (2004) & Epidi, T. T., *et al.*, (2008)).

These environmental figures for malaria prevalence rate were used to derive a regression model analysis using SPSS (version 20). This theory is based on the assumption that all other malaria risk factors remain constant.

The method used in this research work comprises three main stages namely Data collection, Data analysis and GIS maps presentation (Figure 1).

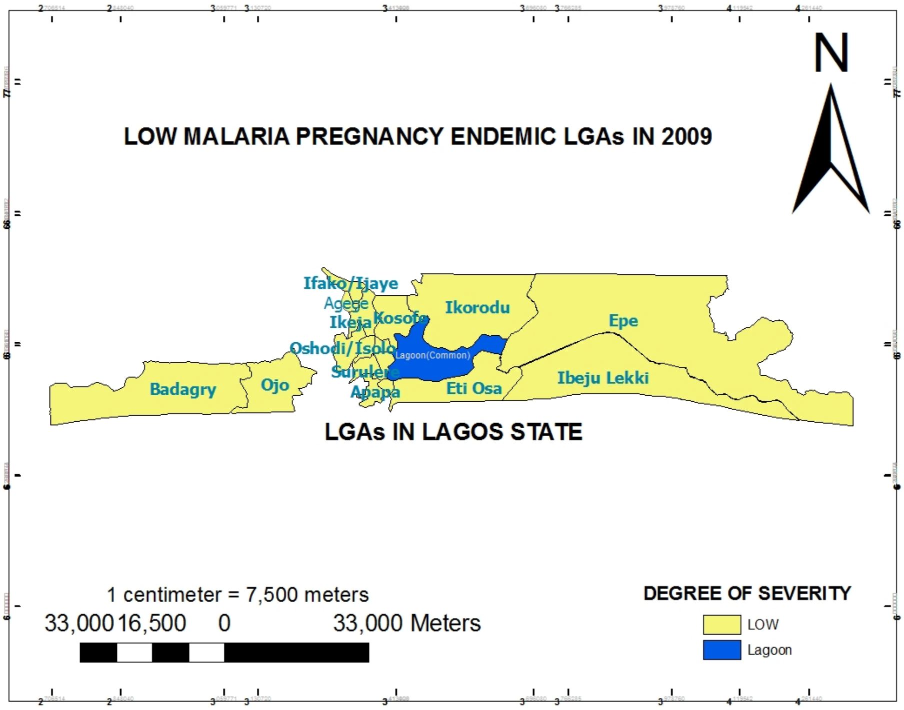

Figure 10: Map representation of Local Government Areas having Low malaria pregnancy endemic in 2009

2.2. Software Used

The GIS computing software used in this study was Environmental Research Systems Institute's (ESRI) ArcGIS - ArcInfo with Spatial Analyst version 9.3. Python interpretive scripting language, version 2.4.1, was leveraged to automate data loading, model iteration, and management of image and tabular outputs. SPSS version 20.0 was use to draw up the statistical analysis of all the variables considered. Microsoft Excel was also utilized to apply the statistical formula and to draw necessary chats, used in comparison of the modeled predictor variables values to the observed malaria prevalence rates.

2.3. Approach Employed

For the epidemiological description of the data, three inferential statistical approaches were adopted:

1. The use of a regression model, to determine the relationship between spatial environmental variations and the malaria prevalence in Lagos.
2. A correlation approach was used to observe the linear relationship between population density of each local government areas in Lagos and the rate of occurrences for the

recorded malaria cases.

3. The last approach employed the use of Student Independent sample t- test to determine the mean difference within seasonal variation of Wet and Dry season for malaria prevalence rate in Lagos State.

2.4. Map Representation

ArcGIS software, version 9.3 was also used to develop a map where queries were carried out on the administrative map of the 20 local government areas in Lagos state. The various malaria, Non-severe malaria, Severe and malaria cases among pregnant women was represented using various maps to show areas of high endemic malaria regions and low endemic malaria regions.

These maps focus only on 2009 and 2013 with Severe and malaria in-pregnancy in view only. All maps in this study with regard to the study area were spatially referenced (assigned coordinates). Similarly the data that requires scaling (rainfall, temperature and relative humidity) were acquired from satellite imageries of same resolution hence no need for relative scale.

Query builder was used to develop the various malaria endemic map of high and low in the Local Government Areas.

2.5. Results and Analysis

Table 1 shows the summary of the various malaria prevalence cases that was recorded from all the local government areas of Lagos State from 2009-2013. In general, a total of 3,363,834 cases of malaria were recorded within the 20 Local Government Areas of Lagos State from January 2009 to December 2013. Among these figures, 2,897,006 (86 %) cases were recorded to be cases of malaria that are non-severe, 323,526 (10 %) are severe cases with malaria fever, while 143,302 (4 %) cases are pregnant women having malaria during pre-natal period.

Table 1: Summary of the various Malaria prevalence cases from 2009-2013 in Lagos State

Malaria Prevalence Cases	Cases	Percentage (%)
Non Severe Cases	2,897,006	86
Severe Cases	323,526	10
Malaria Among Pregnant Women	143,302	4
Total	3,363,834	100

Source: Lagos State Ministry of Health, 2014

Table 1 shows the Summary of the various Malaria prevalence cases from 2009-2013 in Lagos State. Table 2 shows the total values of malaria cases as recorded from each Local Government Areas of Lagos State for each year, from 2009-2013. The figures are a combination of both malaria cases of Non-severe, Severe and malaria cases among pregnant women as recorded from each local government area. Furthermore, Figures (2 – 6) shows a comparative chart of the total malaria cases for each year from 2009-2013 in various local government areas of Lagos State. Figure 2 shows malaria cases for various LGAs in Lagos State in 2009, it shows that Agege LGA has the highest number of total recorded cases with 99,786; other LGAs whose figures rose above 60,000 cases were Amuwi-odofin (74,051), Alimosho (70,354) and Ajeromi-ifelodun (67,861). Ibeju-Lekki and Lagos Mainland recorded the lowest number of cases in 2009 with 11,996 and 12,586 cases respectively. Figure 3 shows the malaria cases for various LGAs in Lagos State in 2010, it clearly shows a declined in the malaria cases in the LGAs. This decline (apart from Amuwo-odofin LGA with 110430 cases) falls below 60,000 of recorded malaria cases. Local Government Areas like Ajeromi-Ifelodun, Alimosho and Agege whose figures were above 67,000 cases in 2009, falls down to below 55,000 cases. Ifako-Ijaiye, Mushin and Ibeju-Lekki LGAs all recorded the lowest values of malaria cases in 2010 with 10,613, 11,569 and 12,028 cases respectively.

Table 2: Malaria cases in Lagos State LGAs from 2009-2013

LGAs	2009	2010	2011	2012	2013
Agege	99786	40966	24625	56393	26864
Ajeromi-Ifelodun	67861	54994	65409	57075	53538
Alimosho	70354	52904	71756	76254	71268
Amuwo-Odofin	74051	110430	49597	17209	24656
Apapa	26528	23881	20549	14495	22401
Badagry	21784	20086	18423	19104	26720
Epe	36767	19460	23632	27238	33226
Eti-Osa	36047	21384	20108	8783	33422
Ibeju-Lekki	11996	12028	11130	8923	16494
Ifako-Ijaiye	25241	10613	28222	18304	40476
Ikeja	46533	37326	29922	47739	62420
Ikorodu	48615	35849	25669	45454	45808
Kosofe	33972	28144	26328	39189	33972
Lagos Island	37379	28159	20884	25266	43644
Lagos Mainland	12586	25608	26480	15840	21643
Mushin	16997	11569	15380	19476	24498
Ojo	25491	25571	31735	32108	19726
Oshodi-Isolos	34927	22996	44705	40923	44694
Shomolu	34118	40089	31160	32635	57670
Surulere	28061	29314	18676	21993	40585

Source: Lagos State Ministry of Health, 2014

Figure 3 shows the malaria cases for various LGAs in Lagos State in 2011.Alimosho (71,756) and Ajeromi-Ifelodun (65,409) experienced an increased number of cases different from what was obtained in 2010. It is very important to note that local government like Agege recorded a drastic lower figure in 2011 of 24625. On the other hand, Oshodi-Isolo local government area witnessed its all-time high of 44,705. Ibeju-lekki (11,130) and Mushin (15,380) remains the local government area with the lowest numbers of cases.

Figure 4 gives the malaria cases for various LGAs in Lagos State 2012, it was observed that Local Government Areas such as Alimosho, Ajeromi-Ifelodun; Agege; Ikeja; Ikorodu and Oshodi-Isolo all had number of cases that are above 40,000, with Alimosho having the highest that is over 70,000 cases. Amuwo-odofin recorded its all-time low cases of malaria prevalence of 17,209. Also in this same year, Local Government Areas such as Mushin and Ibeju-Lekki

Table 3: Anova malaria prevalence

Environmental Factors	Sum of Squares	df	Mean Square	F	Sig.
Max. Temperature					
Between Groups	7531395.180	3	2510465.060	5.162	.002
Within Groups	70999784.943	146	486299.897		
Min. Temperature					
Between Groups	2988617.011	3	996205.670	1.925	.128
Within Groups	75542563.112	146	517414.816		
Rainfall					
Between Groups	19819263.104	4	4954815.776	12.237	.000
Within Groups	58711917.019	145	404909.773		
Relative Humidity at 1500Z					
Between Groups	9879977.503	4	2469994.376	5.217	.001
Within Groups	68651202.619	145	473456.570		
Relative Humidity at 0900Z					
Between Groups	10609905.420	2	5304952.710	11.481	.000
Within Groups	67921274.703	147	462049.488		

recorded their all-time lowest of 8,783 and 8,923 respectively.

Figure 5 gives the malaria cases for various LGAs in Lagos State in 2013. It shows that over 9 Local Government Areas recorded cases that were over 40,000 malaria cases with Ikeja shooting to second highest after Alimosho (71,268) with 62,420 malaria cases. Shomolu had the third higher number of recorded malaria cases of 57,670. Other Local Government Areas cases above 40,000 are Ajeromi-Ifelodun Local Government Area (53,538); Ifako-Ijaiye Local Government Area (40,476); Ikorodu Local Government Area (45,808), Lagos Island Local Government Area (43,644); Oshodi-Isolo Local Government Area (44,694) and Surulere Local Government Area (40,585). Although Ibeju-Lekki still maintain the Local Government Area with the least recorded malaria cases, yet the records still shows a 16,494 malaria cases, while local government such as Ojo and Lagos Mainland falls also within the low range with 19,726 and 21,643 malaria cases respectively.

2.6. Results of the Statistical Model

Anova Analysis

Table 3 shows an ANOVA table of malaria prevalence and environmental factors of Temperature, Rainfall and Relative Humidity. The table gave mean square of 2510465.060 and degree of freedom (df) of 3 between groups in maximum Temperature, and f-value of 5.162, with a p-value of 0.002, since this p-value is less than 0.05, this shows a statistical significance effect of maximum temperature to the malaria prevalence in various Local Government Areas of Lagos State within 2009-2013.

Furthermore, the minimum Temperature shows a mean square of 996205.670 with a degree of freedom of 3 between groups, the f-value is 1.925, however, with a p-value of 0.128, which is greater than 0.05, this shows a non- statistical significance level of minimum temperature to the malarial prevalence cases in various Local Government Areas of Lagos State.

On the other hand, with a mean square value of 4954815.776, and a degree of freedom of 4 between groups in rainfall, this have a f-value of 12.237 with a p-value (0.001) which is less than 0.05. Thus this has a significant influence on the malaria prevalence in Local Government Areas of Lagos State.

Lastly, the variable of Relative humidity taken at 1500Z shows a mean square value between groups of 2469994.376 the degree of freedom is 4 and the f-value is 5.217 with a p-value of 0.001, hence the p-value is less than 0.05 and thus, there is a significant effect on malaria prevalence in the state. While the Relative humidity taken at 0900Z shows a mean square value between groups of 5304957.710 with an F-value of 11.48, this also has a significant effect on the malaria prevalent cases in Local Government Areas of Lagos State because the p-value (0.001) is less than 0.05

The Model Summary gives the value of R called coefficient of multiple correlations, R2, or coefficient of determination, and the standard error of the estimate. Table 4 gives the coefficient of determination for the model. The most important statistics are the coefficient of determination, which is represented as R2 = .133, and the Std. Error of the estimate =683.0223. The coefficient of determination, R2 is the proportion of variance in the dependent variable that is explained by the model, and it is 13.3 per cent in this case. I.e. about 13.3 % of the malaria prevalence rate in Lagos State is explained by the three independent variables that were examined. The R2 might not have adequately accounted for the malaria prevalence rate.

Table 4: The coefficient of determination for the model

Model	R	R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
	.364	.133	683.0223	.133	7.445	3	146	.000

Predictors: (Constant), Mean Temperature, Rainfall, Mean Relative humidity

Table 5 shows the ANOVA, summarizes the results of the analysis of variance, showing that the ratio of the variances (mean square) explained by the regression (3473111.919) to the residual or unexplained variance (466519.482), which is an F ratio, is F = 7.445 and the significance of this F ratio is p = 0.001, which is less than p = .05 and is therefore statistically significant by conventional standard. It is reasonable to conclude that the results of the analysis are not merely due to chance.

Table 5: The ANOVA of the model

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	10419335.76	3	3473111.919	7.445	0.000
Residual	68111844.37	146	466519.482		

a. Dependent Variable: Malaria Prevalence Rate

b. Predictors: (Constant), Mean Temperature, Rainfall, Mean Relative humidity

The F-Statistic: Variation Between Sample Means / Variation Within the Samples. The F-statistic is the test statistic for F-tests. In general, an F-statistic is a ratio of two quantities that are expected to be roughly equal under the null hypothesis, which produces an F-statistic of approximately 1. An *F statistic* is a value you get when you run an ANOVA test or a regression analysis to find out if the means between two populations are significantly different.

A small p (probability) - value (typically ≤ 0.05) indicates strong evidence against the null hypothesis, so you reject the null hypothesis. A large p-value (> 0.05) indicates weak evidence against the null hypothesis, so you fail to reject the null hypothesis.

Table 6 shows the Linear Regression model: According to the presented results, one can conclude that with the mean temperature (p = 0.001), rainfall (p = 0.006) and mean relative humidity (p= 0.001), these have a significant effect on Malaria prevalence rate in Lagos. In addition, the sign of the estimates tells us that while rainfall has a direct effect, mean temperature and mean relative humidity have an inverse effect on Malaria prevalence rates.

Table 6: Linear Regression model

Model	Unstandardized Coefficients		Standardized Coefficients					
	B	Std. Error	Beta	*t*	Sig.	Zero-order	Partial	Part
(Constant)	11420.016	1837.426		6.215	.000			
Temp	-187.491	42.367	-.471	-4.425	.000	-.204	-.344	-.341
Rainfall	.265	.595	.040	.446	.006	.043	.037	.034
Relative Humidity	-36.899	9.580	-.422	-3.852	.000	-.083	-.304	-.297

Dependent Variable: Malaria Prevalence

Using the unstandardized coefficient the regression model is:

$$\mathrm{MP} = 11420 - 187.5\mathrm{MT} + 0.3R - 36.9\mathrm{MRH} \tag{2}$$

Where MP = Malaria Prevalence
MT = Mean Temperature in degree centigrade
R = Rainfall in mm
MRH = Mean Relative Humidity

Tables 7, 8 and 9 represent the correlation analyses of the population density of the various Local Government Areas and the various malaria cases from these areas based on annual records. Table 7 shows the relationship between population densities by Non-Severe malaria cases 2009-2013

Among the Population Densities by Non-Severe Malaria, Severe Malaria and Pregnant Women Malaria Cases from 2009-2013 in Tables 7, 8 and 9:

- Using Pearson's correlation to assess the population density from 2009-2013, each of the three cases either showed a weak positive or relationship in all the three cases and the Non-Severe malaria cases in 2009, a weak positive or negative direct or indirect relationships were observed between Pearson's correlation and their corresponding population density values, while the p-values for all (Tables 7, 8 and 9) are greater than 0.05. This implies that the three cases observed are not statistically significant and can be attributed to chance variation.

Table 7: Relationship between population density by Non-Severe malaria cases 2009-2013

Population Density	Non-Severe Malaria Cases	
	Pearson Correlation Coefficient	P-value
2009	0.149	0.529
2010	-0.004	0.986
2011	0.156	0.510
2012	0.254	0.280
2013	0.205	0.386

Table 8: Relationship between population density by Severe malaria cases 2009-2013

Population Density	Severe Malaria Cases	
	Pearson Correlation Coefficient	P-value
2009	0.152	0.521
2010	0.137	0.563
2011	-0.007	0.976
2012	0.109	0.646
2013	0.318	0.172

Student's Independent Sample T- Test

Table 10 gives Student's Independent Sample T-test table. Table 10 shows that when comparing the means of MP within seasonal variation (Wet and Dry seasons), the Wet season recorded a Mean +S.D of 465988.40+ 65657.476 of malaria prevalence, while the Dry seasons recorded a Mean +S.D of 213737.40+ 23514.758 of malaria prevalence. It was observed that the malaria prevalence was higher in Wet season than in the Dry season with a difference of 252251, however, with a p-value (0.004) less than 0.05, this observation is statistically significant, and cannot be attributed to chance thus the malaria prevalence in Wet season is significantly more to the malaria prevalence in Dry season.

Table 9: Relationship between population density by Malaria cases among pregnant women 2009-2013

Population Density	Malaria Cases among Pregnant women	
	Pearson Correlation Coefficient	P-value
2009	0.085	0.723
2010	0.066	0.781
2011	-0.131	0.582
2012	-0.007	0.976
2013	0.033	0.889

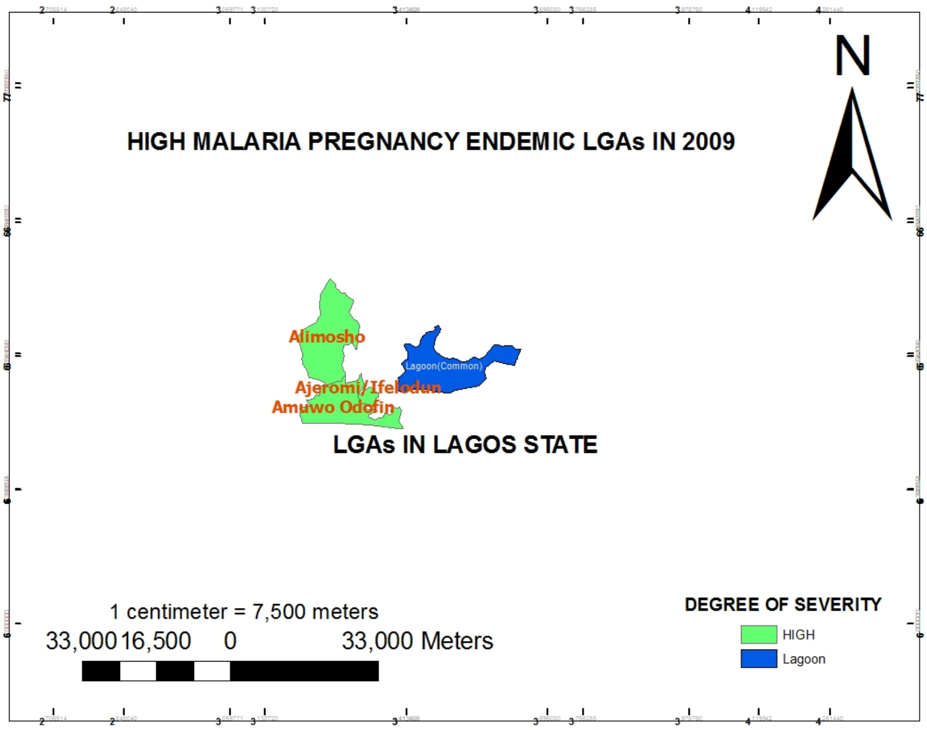

Figure 11: Local Government Areas with high malaria pregnancy endemic in 2009

Table 10: Student's Independent Sample T-test table

	Mean ±S.D.		Mean difference	t-value	p-value
	wet	dry			
Malaria Prevalence Equal Variance assumed	465988.40 ±65657.48	213737.40 ±23514.76	252251	8.088	0.004

Seasonal variations (wet and dry seasons): $t(8) = 8.088$, $p = 0.004$

2.7. Mapping of Malaria Cases in Local Government Areas of Lagos

The geographical mappings of malaria prevalence cases for Lagos State based on the State 20 Local Government Areas are shown in Figures (6,7,8,9,10,11,12,13 & 14). Two main malaria cases where used for this section and that is the records coming from those with severe malaria cases and the malaria cases among pregnant when. Furthermore, only two years that is 2009 and 2013 were considered under this section. The mappings seek to show local government areas with high malaria endemic prevalence and local government with low malaria endemic prevalence within 2009 and 2013.

Local government areas having an annual record of 5000 severe cases and below were considered to be malaria endemic areas. On the other hand, local government areas that recorded above 5000 severe malaria cases in a year are ranked considered to be high malaria endemic areas. In the same vein, Local government areas that had recorded malaria among pregnant women of 3000 malaria cases and below falls under the low endemic areas of the State, while annual record with more than 3000 cases among pregnant women are rank as high endemic malaria local government area.

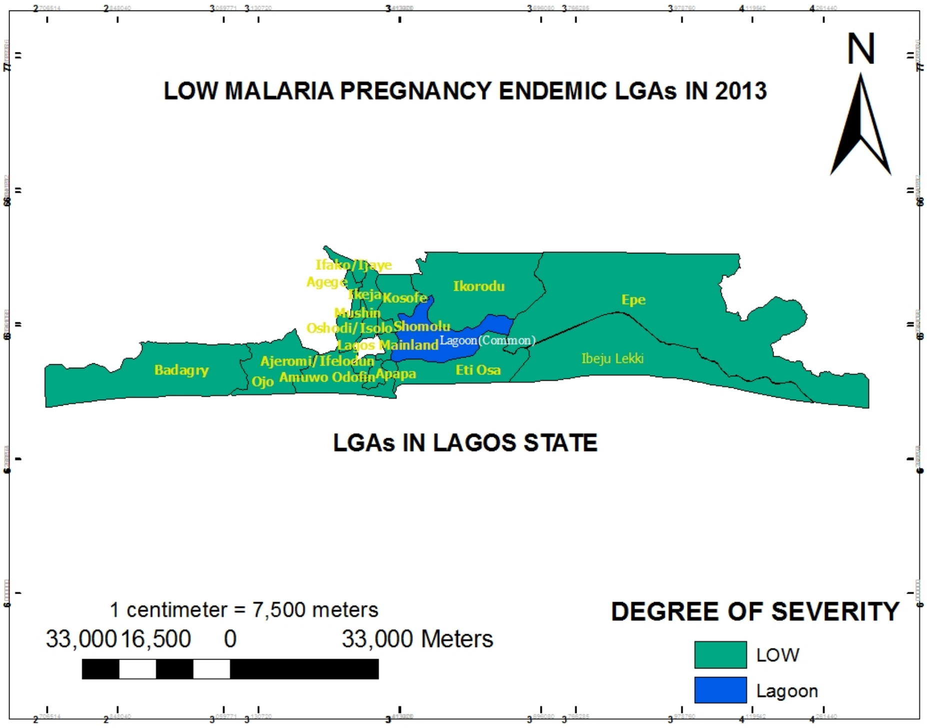

Figure 12: Map representation of Local Government Areas having Low malaria pregnancy endemic in 2013

2.8. Summary of Findings of the Result

1. Recent studies show a decline in prevalence of malaria in various Local Government Areas from 2010 to 2012, but however, 2013 witness an increase of this prevalence figure in Lagos.

2. Alimosho Local Government Area has consistently been on the rise of malaria severe and malaria among pregnant women cases for the past consecutive years (2011-2013).

3. From this study, it is observed that with a coefficient of determination (R2) of 13.3 %, the environmental factors are responsible for only 13.3 % of the malaria prevalence rate. The (R2) might not have adequately accounted for these environmental factors.

4. Environmental variables of relative humidity and temperature have an inverse relationship with the prevalence rate which is very much in line with previous studies done in this area. However, there is a direct relationship with rainfall and malaria prevalence.

5. A regression model was developed which can act as a predictive factors with other things being equal.

6. Independence sample t-test shows that there is a significant relationship between seasonal variation of Wet and Dry season with the malaria prevalence rate. Furthermore,

the mean of malaria prevalence during the Wet season is higher than the malaria prevalence during the dry season.

7. Correlating the population density with the various malaria cases often shows a positive weak linear correlation between these various cases and the population density. Occasions also present itself were the correlation is negatively correlated to the population density.

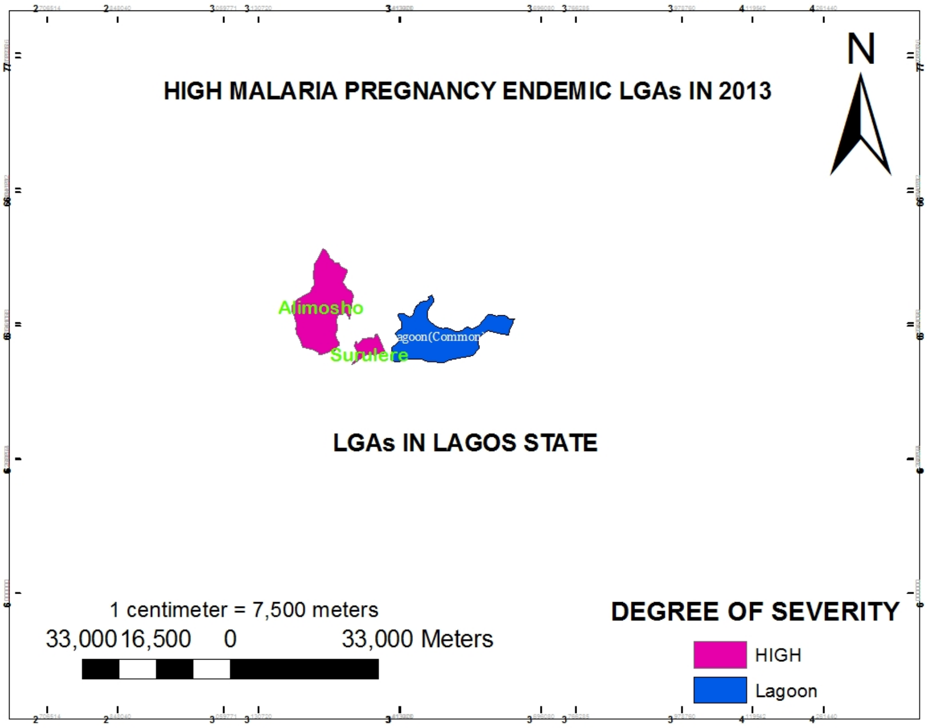

Figure 13: Local Government Areas with high malaria pregnancy endemic in 2013

2.9. Conclusion

The purpose of this study was to see the effects of environmental factors on malaria prevalence and the epidemiological framework to quantify State wide prevalence of malaria transmission to human populations. The findings from this research show that environmental variables only are not strong enough to determine the significant level of the prevalence of malaria within the State. Environmental factors of rainfall, temperature and humidity tends to greatly influence the breeding of vector carrying parasite, but these factors can however aid vector mosquitoes carriers in transmitting malaria parasite to human population. Furthermore, with the combination of other non-climatic factors like demographics, socio-economic activities of the populace, biological factors, National Health Care Status and ecological zonation, etc., and climatic factors, these have great influence on the prevalence rate of malaria in Lagos State.

The following are the summary of findings observed:

A number of researchers have found a strong correlation between the malaria prevalence rate

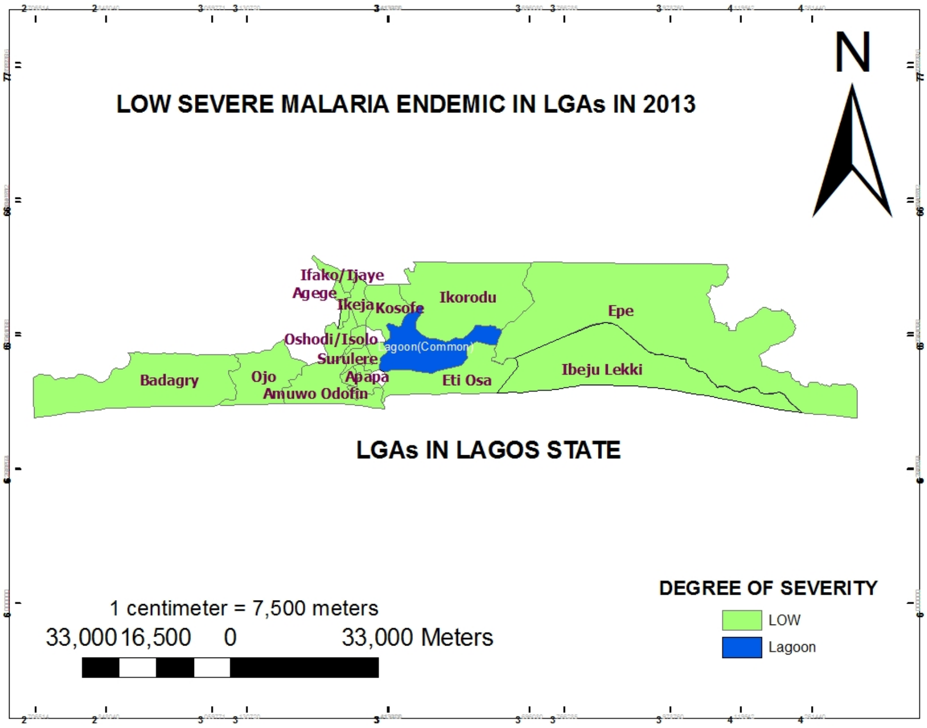

Figure 14: Endemic Local Government Areas in 2013 with low severe malaria cases

and variations in the environmental variable during several preceding months, or with inter annual variation in these variables. In many studies, humidity, temperature and rainfall are considered major risk factors that affect the life cycle and breeding of mosquitoes, and this study confirmed that. More so, the correlation model shows a weak correction between malaria prevalence and rainfall, this confirmed that only reasonable amount of rainfall can create additional breeding sites for mosquitoes, thereby, increasing its population, excess of rainfall wash off the eggs and larvae of mosquito due to erosion, however, stagnated water increases the breeding ground for mosquitos. Considering only environmental factors in statistical models to predict malaria incidence or prevalence rate is complex, and not yet well understood. This has made some researchers to develop models, in which incidence and prevalence rates are standardized with respect to non-climatic variable, so that the influence of climate on fluctuations in the malaria rate can be seen more clearly.

A close observations to this studies shows Local Government Areas where malaria cases recorded high cases are, most often-than-not Local Government Areas having serious sanitation problems such as blocked or very poor drainage system, poor waste disposal system and dirty neighborhood generally. This creates lots of habitat for mosquitoes to breed. Activities like this could greatly increase the malaria risk on the human population which may lead to higher prevalence and incidence of malaria in the society without the influence of climatic factors causing this increase. Other non-climatic factors such as socio-economic and health care status of the communities within the Local Government Areas can greatly influence either positively or negatively the malaria risk on the population. The combination of both the climatic and non-climatic factors is a good indictor to determine the prevalence and incidence rate of malaria in Lagos State.

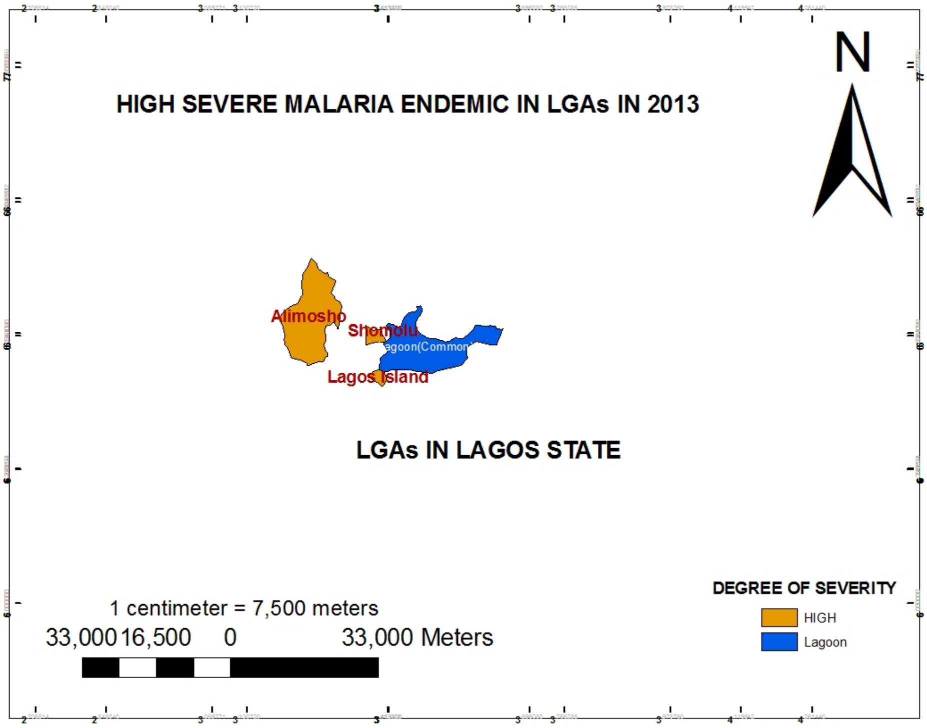

Figure 15: Areas with high severe malaria endemic in 2013

Another finding revealed was the declined of number of malaria cases within the Local Governments Areas most especially from 2010-2012. This decline may not be linked to unfavorable environmental factors of rainfall, temperature and relative humidity that may have occur during this period but rather it can be greatly attributed to the increased of intervention Nigeria received from donor agencies and organizations that help in combating malaria epidemic globally. Nigeria has benefited from increasing support from various partnerships in the fight against malaria. Currently, the largest partners in terms of funding are the Global Fund, including the Affordable Medicines Facility - malaria (AMFm) program, the World Bank, President's Malaria Initiative (PMI) by the US Government, and the United Kingdom Department for International Development (DfID). Other key partners include the Clinton Health Access Initiative, the United Nations Children's Fund (UNICEF), and the World Health Organization (WHO). Nigeria has been a beneficiary country of over \$ 1billions from 2009-2013 (WHO, 2014) from these various donor partners. These interventions is to help the country scale up its malaria prevention and treatment campaign, hence a National Malaria Control Program (NMCP) was developed. The NMCP Strategic Plan 2009-2013 which is based on the National Strategic Health Development Plan 2010-2015 and in line with National Health and Development priorities. The strategy Plan outlines the provision of a comprehensive package of integrated malaria prevention and treatment through the community, primary, secondary, and tertiary levels. The strategy Plan also defines the roles of each health care worker relative to malaria case management and control across all health care services including public, private (including for-profit and not-for-profit), PMVs, and the traditional health providers. Furthermore, the strategy Plan seeks to achieved continuous scale up coverage of the most vulnerable groups — children under five years of age and pregnant women

— with proven preventive and therapeutic interventions, including artemisinin-based combination therapies (ACTs), insecticide-treated nets (ITNs), intermittent preventive treatment of pregnant women (IPTp), and indoor residual spraying (IRS).

Taking antecedent from the above, it can been seen clearly that decreased experience during these period was largely due to the effort made by the various donor partners in combating malaria ensuring that it actually roll back. This has little or nothing to do with the environmental variations. However 2013, experiences an upraised because some of the intervention funds were either reduce or stopped at that period because of the corrupt activities on the part of the implementation officials.

3. Recommendation

The following recommendations are proffer from this research work:

1. Lagos State which is a cosmopolitan state is characterized by urban climate and weather conditions as a result of the cosmopolitan activities that takes place within the state. This can greatly affects the state monthly mean temperature and other climatic variations to such a level that can aid rapid growth and breeding of the vector carrying malaria. Thus it is recommended that eco- friendly activities should be greatly encouraged by all the relevant industrial players in the State. Also, government policy should guide against any form of indiscriminate disposal of industrial and clinical waste that can have an adverse effect on the environment in any form. This is to maintain a clear and healthy environment in the State.

2. Factors related with population vulnerability are also critically important in malaria transmission. The presence of parasite resistance to the usual anti- malaria and to insecticides, population movements and the presence of other underlying infections are responsible for a large part of the variability in the prevalence of malaria. Government should ensure to building of more health facilities and better equip the existing ones in order to effectively serve the exploding population of the State. More so, government should carry out regular indoor residual spraying (IRS) exercise across the Local Government Areas, and continue on the intermittent preventive treatment of pregnant women (IPTp), subsidized the artemisinin-based combine therapies (ACTs) and insecticide-treated nets (ITNs). These consolidated efforts along with other efforts from donor agencies can help roll back malaria and reduces the occurrences to a very significant low level.

3. There should be a better and meaningful understanding of the dynamics of disease transmission, including its associated spatial and temporal patterns, among health workers and those carrying out monitoring and evaluation. This knowledge when shared and apply can better help towards preempting disease outbreaks. Monitoring and Evaluation (M&E) strategy should be establish to harmonized M&E system this can be used by all partners to monitor progress towards agreed-on targets and is used to manage and adjust interventions based on evidence.

4. The need to develop accurate maps of malaria transmission cannot be over emphasized. This can greatly guide interventions strategies, and thus optimize the use of limited and financial resources to areas of utmost need. In addition, early warning systems can be

developed to predict epidemics of malaria from environmental changes.

5. Geographic modeling and analysis add an important technical element to epidemiology that has only recently been subjected to scientific exploration. Opportunities to utilize spatial technologies to provide real-time assessments of disease risk are now available to the public health community. As remote sensing technology and GIS improves and epidemiological methods are refined, disease predictions could soon be as common as those of the weather. Yet, it is important to continue studying diseases we know most about; as the environmental conditions of the world change, so do patterns of disease transmission. For those reasons, further research into the application of remote sensing and GIS technologies with the aim of creating preemptive disease intelligence is not only scientifically beneficial, but a human necessity and moral obligation.

6. The GIS spatial model developed for this study could be improved upon by a more stringent decision rule and inclusion of more variables. A thorough assessment of the input's classification schema and individual analysis of their predictive strength would vastly improve reliability of model outcomes. Furthermore, higher spatial resolution imagery and observed incidence rates recorded at the community level would allow prediction of malaria risk on a local scale to the entire regional or even nationwide scale.

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