



***DETERMINING MALARIA RISK FACTORS IN ABUJA, NIGERIA USING
VARIOUS STATISTICAL APPROACHES***

OGUNTADE EMMANUEL SEGUN

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By

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**Thesis Submitted to the School of Graduate Studies, Universiti Putra
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Doctor of Philosophy**

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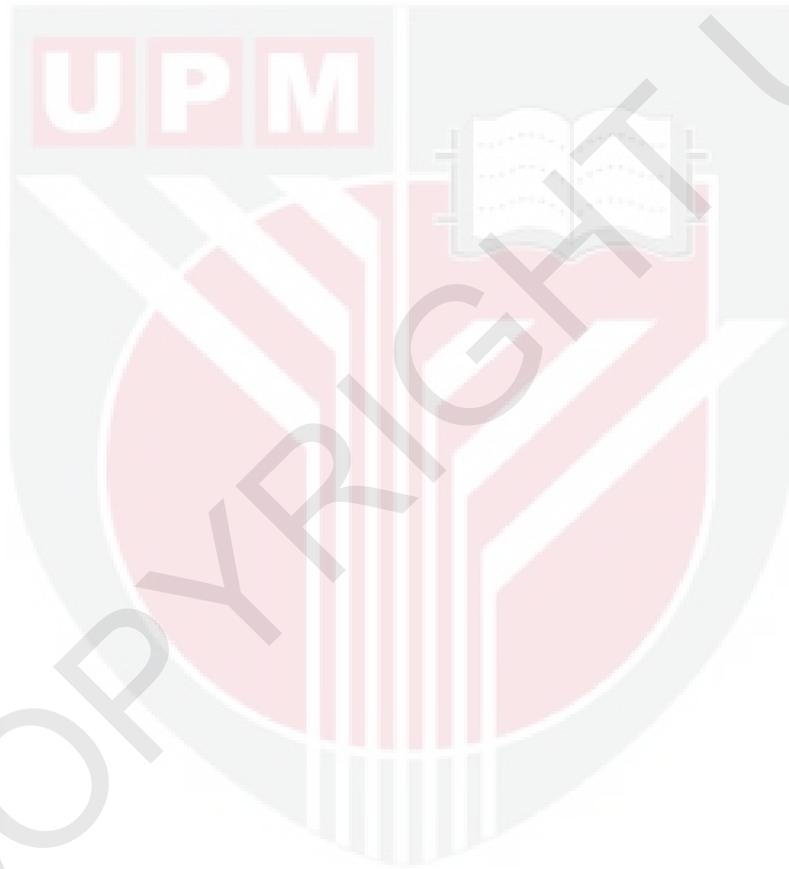
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DEDICATION

This thesis is dedicated to God Almighty, the giver of life and source of inspiration and wisdom.



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Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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By

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December 2018

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Malaria is a widespread infectious disease in the tropics with significant health threat to the inhabitants, especially, the low income earners residing in the remote areas. Studies have identified many driving factors of malaria prevalence; however, there are still missing links as malaria remains endemic in developing nations despite various interventions instituted against it especially in Sub-Saharan Africa (SSA). Previously, several decision support tools have been used to support expert-based opinion in the field of sciences for malaria modelling. However, these conventional techniques have problems of incorporating prior belief, uncertainty representation, missing values, expert judgement and hierarchical relationships among variables. These problems, however, can be overcome using belief networks, which has not been fully explored. Therefore, this current study is aimed at deriving a Bayesian belief network (BBN) for malaria epidemic in Abuja, Nigeria. A total of 384 respondents took part in the present study which is comprised of two phases: pre- and post-intervention. Participants were randomly selected based on stratified sampling according to residential areas. Data on socio-demographic characteristics, knowledge, attitude and practice (KAP) related to malaria and intervention measures were collected using validated questionnaires. The climate data were obtained from the data bank of Agricultural Development Project Gwagwalada, Abuja, Nigeria (1997-2014). Data collected were used for the multilevel analysis, Markov Chain Monte Carlo (MCMC) simulation via WinBUGS algorithm and influence diagrams for BBNs. A non-informative prior was assumed for Bayesian logistic regression and posterior samples generated at different sizes. The spatial heterogeneity in malaria incidence patterns at various sites were estimated with Moran I and semivariogram models. Using BBNs, different learning strategies were explored and compared with k-fold using negative entropy loss. The optimal model based on the parsimony principles was obtained from the hill climbing algorithm with score metrics. The results revealed a high reported cases at the baseline data collection possibly

occasioned by the observed low malaria KAP levels at the pre-intervention study. A Wilcoxon signed rank test showed a significant change in incidence scores of households in the district considered for pre- and post-test interventions. The study revealed that there was an association between level of usage of the intervention measures and malaria cases. The non-usage increases the odds of the disease by 1.79 ([95% CI: 1.06, 3.03]; $p=0.028$) and 1.67([95% CI: 1.06, 2.64]; $p=0.029$) for insecticide-treated nets (ITNs) and window and door nets (WDNs) respectively. The multilevel analysis based on logistic regression identified gender, socio-economic status (SES), household size and intervention measures as predictors while Monte Carlo study of local malaria predictors' results was comparable to logistics especially when n is large (150,000) and with a lower precision level (0.000001). The Moran I index using distance decay method to generate the weight gave a spatial autocorrelation of -0.33. The spatial outliers (a high-low and low-high outliers) of Moran I results reflected an alternation in incidence patterns. To account for spatial random effects in the models, semivariogram autocorrelation models were incorporated and Moran hypothesis tested. The results revealed that the model without autocorrelation structure has the lowest Bayesian information criterion (BIC) value of -6.31, while the highest value of 0.66 was observed with autoregressive error structure of order 1, hence, there was no spatial autocorrelation in the malaria incidence in the study area ($p=0.328$). Therefore, this was not incorporated in BBN models. Based on cross-validation analysis, the score-based algorithm outperformed the constraint-based algorithms in the structural learning. Using hill climbing from search and score algorithms, the Bayesian network analysis revealed that there were associations among the network covariates, while cofounding effects of SES were observed. The BBNs developed revealed that SES, household size and education level have the highest influence on reported cases as variations in response due to global sensitivity of network nodes. Based on the data, an empty graph (a network representing models with the usual independent assumption) was also learned and the results compared with BBNs. However, the loglikelihood and other metrics scores of an empty graph were lower than that of the BBNs. Thus, the BBNs represent the dependencies in the variables better than assuming independence of all the variables. This present study provides a detailed record on the epidemiology of malaria in the study area, Abuja, Nigeria. This in turn could be used to formulate effective control and preventive measures for malaria. The study shows that there is a significant influence of household characteristics on the incidence of malaria. The BBN is expected to contribute to the existing literature on malaria epidemic and in identifying the significant predictors of malaria at household and community levels within the study area.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

**MENENTUKAN FAKTOR RISIKO MALARIA DI ABUJA, NIGERIA
MENGUNAKAN PELBAGAI KAEDAH STATISTIK**

Oleh

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Disember 2018

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Malaria adalah penyakit berjangkit yang menular terutamanya di kawasan tropika dan mengancam kesihatan penduduk khususnya yang berpendapatan rendah dan tinggal di kawasan terpencil. Walaupun banyak kajian telah dijalankan untuk mengenalpasti faktor risiko malaria, ia kekal endemik di negara membangun meskipun pelbagai langkah pencegahan telah diambil terutama di sub-Sahara Afrika (SSA). Sebelum ini, beberapa kaedah sokongan keputusan telah digunakan untuk menyokong pendapat berasaskan pakar dalam bidang sains untuk pemodelan malaria. Walau bagaimanapun, teknik konvensional ini mempunyai kekurangan dari segi menggabungkan amalan sebelumnya, perwakilan ketidakpastian, nilai-nilai yang hilang, penilaian pakar dan hubungan hierarki di kalangan pembolehubah. Ini dapat diatasi menggunakan rangkaian kepercayaan yang masih belum diteroka sepenuhnya terutama berkaitan malaria. Oleh itu kajian ini bertujuan membentuk rangkaian kepercayaan Bayesian (BBN) untuk wabak malaria di Abuja, Nigeria. Seramai 384 responden telah mengambil bahagian dalam kajian ini yang melibatkan dua fasa iaitu pra-intervensi dan pasca-intervensi. Kaedah pensampelan berstrata rawak mengikut kawasan kediaman telah digunakan untuk mendapatkan responden. Data sosio-demografi, pengetahuan, sikap dan amalan (KAP) tentang malaria dan kaedah intervensi telah diperolehi melalui borang soal-selidik yang telah disahkan. Data iklim diperolehi daripada bank data Projek Pembangunan Pertanian Gwagwalada, Abuja, Nigeria (1997-2014). Data yang dikumpulkan ini digunakan untuk analisis pelbagai peringkat dan simulasi Markov Chain Monte Carlo (MCMC) melalui algoritma WinBUGS dan rajah pengaruh untuk BBN. Pengagihan sebelumnya yang tidak bermaklumat telah diandaikan untuk regresi logistik Bayesian dan sampel posterior yang dihasilkan dalam pelbagai saiz. Heterogeniti spatial dalam corak insidens skor malaria di pelbagai kawasan dianggarkan menggunakan model Moran I dan semivariogram. Melalui BBN, strategi pembelajaran yang berbeza telah diterokai dan dibandingkan dengan k-fold dengan

menggunakan kerugian entropi negatif. Model optimum berdasarkan prinsip parsimoni diperolehi daripada algoritma pendakian bukit dengan skor. Hasil analisis menunjukkan jumlah kes yang dilaporkan tinggi pada pengumpulan data asas yang mungkin disebabkan oleh tahap KAP malaria yang rendah dalam kajian pra-intervensi. Ujian pangkat Wilcoxon menunjukkan perubahan signifikan dalam skor insiden isi rumah di daerah yang dipertimbangkan untuk pra-intervensi dan pasca-intervensi. Dapatan analisis menunjukkan bahawa terdapat kaitan antara tahap penggunaan kaedah intervensi dan bilangan kes malaria. Ketidakpenggunaan meningkatkan kemungkinan mendapat malaria kepada 1.79 ([95% CI: 1.06, 3.03]; $p = 0.028$) dan 1.67 ([95% CI: 1.06, 2.64]; $p = 0.029$) untuk jaring yang dirawat racun serangga (ITN) dan jaring bagi tingkap dan pintu (WDN). Analisis pelbagai peringkat berdasarkan regresi logistik mengenal pasti jantina, status sosio-ekonomi, saiz keluarga dan kaedah intervensi sebagai peramal manakala kajian Monte Carlo mengenai hasil ramalan malaria tempatan adalah setanding dengan logistik terutamanya apabila n adalah besar (150,000) dan dengan tahap ketepatan tinggi (0.000001). Indeks Moran I global menggunakan kaedah peluruhan jarak jauh untuk menghasilkan berat memberikan autokorelasi spasial pada -0.33. Penciran ruang hasil Moran I mencerminkan perubahan dalam pola insidens. Untuk mengambil kira kesan rawak ruang dalam model, model autokorelasi semivariogram dimasukkan dan hipotesis Moran diuji. Hasil kajian menunjukkan bahawa model tanpa struktur autokorelasi mempunyai nilai kriteria maklumat Bayesian terendah (BIC) -6.31, manakala nilai tertinggi 0.66 diperhatikan dengan struktur kesilapan autoregressive order 1, maka tiada autokorelasi spasial dalam kejadian malaria di kawasan kajian ($p = 0.328$). Oleh itu, ini tidak dimasukkan dalam model BBN. Berdasarkan analisis silang-pengesahan, algoritma berasaskan skor mengatasi algoritma berasaskan kekangan dalam pembelajaran struktur. Menggunakan kaedah pendakian bukit daripada algoritma carian dan skor, analisis rangkaian Bayesian menunjukkan perkaitan antara kovariat rangkaian, manakala terdapat kesan bersama SES. BBN yang dibangunkan menunjukkan bahawa status sosioekonomi, saiz isi rumah dan tahap pendidikan mempunyai pengaruh tertinggi terhadap kes malaria yang dilaporkan sebagai variasi kesan tindakbalas terhadap kepekaan global nod rangkaian. Berdasarkan data, graf kosong (rangkaian mewakili model dengan andaian bebas yang biasa) juga dipelajari dan hasilnya dibandingkan dengan BBNs. Walau bagaimanapun, log kemungkinan dan skor metrik graf kosong lebih rendah daripada BBN. Oleh yang demikian, BBN mewakili kebersandaran dalam pembolehubah yang lebih baik daripada mengandaikan kebebasan semua pembolehubah. Kajian ini menyediakan rekod terperinci tentang epidemiologi malaria di Abuja, Nigeria. Hasil dapatan kajian ini boleh digunakan untuk merumuskan kawalan berkesan dan langkah-langkah pencegahan malaria. Selain itu, kajian ini menunjukkan bahawa terdapat pengaruh signifikan ciri-ciri isi rumah terhadap insiden malaria. Model BBN dijangka menyumbang kepada kajian sedia ada mengenai wabak malaria dan mengenal pasti peramal malaria yang signifikan di peringkat isi rumah dan komuniti di kawasan kajian.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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LIST OF ABBREVIATIONS

ACF	Autocorrelation Function
ACT	Artemisinin Combination Therapy
AIC	Akaike Information Criterion
AR	Autoregressive Model
ARMA	Autoregressive Moving Average
BASICS	Basic Support for Institutionalizing Child Survival
BBN	Bayesian Belief Network
BDE	Bayesian Dirichlet
BDS	Bayesian Dirichlet Sparse
BIC	Bayesian Information Criterion
BLR	Bayesian Logistic Regression
BMA	Bayesian Model Averaging
BUGS	Bayesian Inference Using Gibbs Sampling
CI	Confidence Interval
CPT	Conditional Probability Table
CV	Coefficient of Variation
DAG	Directed Acyclic Graph
DDT	Dichloro Diphenyl Trichloroethane
EIR	Entomological Inoculation Rate
FCT	Federal Capital Territory
FLR	Frequentist Logistic Regression
FMOH	Federal Ministry of Health
GAC	Gwagwalada Area Council
IRS	Indoor Residual Spray

ITNs	Insecticide-Treated Nets
KAP	Knowledge, Attitude and Practice
K2	Cooper and Herskovits
K-S	Kolmogorov-Smirnov
LL	Log-Likelihood
LRM	Logistic Regression Model
LSMOH	Lagos State Ministry of Health
MBDE	Bayesian Dirichlet (intervention Data)
MBR	Man Biting Rate
MCMC	Markov Chain Monte Carlo
MLE	Maximum Likelihood Estimation
MPT	Marginal Probability Table
NGO	Non-Governmental Organization
NMCP	National Malaria Control Programme
NMCP	Nigeria Malaria Control and Prevention Program
NPC	National Population Commission
RBM	Roll Back Malaria
SANDH	South Africa National Department of Health
SE	Standard Error
SES	Socio-economic Status
SSA	Sub-Sahara Africa
SW	Shapiro-Wilk
WDNs	Window and Door Nets

CHAPTER 1

INTRODUCTION

1.1 Background

Malaria is a protozoan disease caused by a single cell parasite called *Plasmodium* and transmitted by infected female mosquitoes of the genus *Anopheles* (Afoakwah *et al.*, 2018; Mohammadkhani *et al.*, 2016), as it seeks blood for its egg development (Yahaya, 2012). The malaria infection is the product of interactions between the human intermediate host, mosquito vector which lives symbiotically with the *Plasmodium* agent and the immediate environment where the various interactions take place. The suitability of the various environmental factors predisposes the disease prevalence as the host vector thrives well within certain favourable environmental conditions (Ssempiira *et al.*, 2018; Lingala, 2017; World Health Organization (WHO), 2016; Babajide *et al.*, 2015; Siraj *et al.*, 2014;). Hence, the spatial distribution of the numerous strains of mosquitoes which serve as a vector of *Plasmodium* networking is enhanced. For instance, an average temperature between 18°C-30°C favours the breeding of mosquitoes and malaria parasites (Beck-Johnson *et al.*, 2013). Also, a relative humidity of 60% - 90% enhances their breeding and multiplication while a relative humidity below 60% decreases their population (Akinbobola & Omotosho, 2013).

Malaria is the most prevalent tropical parasitic disease with most of the tropical and subtropical countries endemic in recent times (Osakunor, Sengeh, & Mutapi, 2018). More than one-third of the world's population is at risk with the adverse consequences of the disease affecting children, adults and communities (Bocoum *et al.*, 2014). It is the most deadly communicable disease with a mortality rate of two children per minute in Sub-Saharan Africa (SSA) (Ashikeni, Envuladu, & Zoakah, 2013; De-Castro & Fisher, 2012; WHO, 2003). In 2015, there were 438,000 deaths from estimated 214 million malaria cases worldwide (Haddawy *et al.*, 2018). Only ten percent (43,800) of the global deaths occurred outside Africa while the remaining 90% (390,200) of the global deaths occurred in SSA (Adu-Prah & Tetteh, 2015; WHO, 2015). Asia has the second highest cases and deaths from malaria (Roll Back Malaria (RBM), 2012). Basically, malaria occurs in 106 countries worldwide out of which 35 countries are responsible for the majority of total annual global deaths (Andrew, 2014; ; Nyarko & Cobblah, 2014; Mohon *et al.*, 2012; Kitua *et al.*, , 2011; WHO, 2010). Most of these high-risk countries are in Africa and South-East Asia (RBM, 2009). While the disease has been eliminated in Northern African countries (Snow *et al.*, 2012; Africa Malaria Report (AMR), 2003), the SSA countries remain in the control stage of the WHO malaria elimination continuum (control, pre-elimination, elimination and prevention of reintroduction) (Onyiri, 2015; WHO, 2007). There exists more malaria cases per thousand populations in SSA nations and in particular Nigeria where over 97% of the population are at risk of the disease (Uzochukwu, Ossai, Okeke, Ndu, & Onwujekwe, 2018).

To date, despite interventions and control initiatives globally, the malaria trend persists and there exist uncertainties regarding the disease trend in near future (Usman & Adebayo, 2011; Alaba & Alaba, 2009). Malaria trend, however, hangs on the influence of weather variability with other ecological factors, socio-cultural and human related factors which continue to play a major role in the dynamism of the disease transmission. Such environmental impact is enormous and remains an open subject for consideration.

1.2 Problem Statement

Malaria endemicity leads to economic loss, poverty and lack of longevity for the populace in endemic nations (Afoakwah et al., 2018). Malaria is commonly associated with poverty since the prevalence trends observed in low gross domestic product (GDP) nations were high (Gimba, 2014; WHO, 2006). Therefore, predictions and target interventions are vital elements in effective control of malaria (Eunice et al., 2017; Mohammadkhani et al., 2016; WHO, 2012). There is a need to study the framework and methodology to further understand the disease causes, trends and influencing variables so as to enhance early warning, disease epidemiology, effective measures and interventions (Evans & Adenomon, 2014). There are a number of techniques used and documented in literature on modelling malaria incidence (Eunice et al., 2017; Adigun et al., 2015; Zinszer et al., 2015; Zinszer et al., 2012). However, there exist gap in literature as some of the proposed paradigms were insufficient in selecting best variant of malaria risk factors as preliminary analysis is not capable of capturing the spatial-temporal random effects (Andrew, 2014; Yadav, Dhiman, Rabha, Saikia, & Veer, 2014) and cannot account for uncertainty in the model parameters (Berger, 1980). Also, issues of assuming known dependencies between response and covariates of interest in the classical models instead of actual dependencies among variables serve as another open problem in the conventional approaches (Haddawy et al., 2018; Landuyt, Broekx, & Goethals, 2016; Nguefack-Tsague, 2011).

Due to local movement of the disease vectors and variations in the climate conditions across communities, spatial autocorrelation or heterogeneity in incidence patterns need be incorporated into such models for effective design of interventions towards disease control (Ssempiira et al., 2018). Most notable literature focused on preliminary analysis or used predetermined variables (Andrew, 2014) while others purposely excluded some natural risk factors which are paramount in scaling up interventions possibly due to paucity of reliable data (A Moran, 2013; Noor, Omunbo, Amin, Zurovac, & Snow, 2006). There is a need for a more accurate tool to identify malaria risk factors that compensates the inadequacies of existing models. This study, therefore explored the potential of Bayesian belief networks (BBNs) in malaria modelling.

To date, in Nigeria, there is inadequate information regarding the exact number of incidences and deaths due to malaria in rural areas where there are so many unreported cases (Uzochukwu et al., 2018; Eunice *et al.*, 2017). Also, shortage of geostatistical data on basic meteorological variables such as temperature, humidity, precipitation and land covered among others constitute a great problem in malaria epidemiological research. Additionally, weak and fragmental nature of existing health information systems and variation in weather condition leads to sporadic change in malaria incidence (Adu-Prah & Tetteh, 2015; Badaru, Adejoke, Abubakar, & Emigilati, 2014). The malaria trend constitutes a problem which the present study seeks to answer through the following questions:

- (1) What are the risk factors responsible for the prevalence of malaria?
- (2) What are the individual, group or collective effects of the risk factors on the prevalence of malaria?
- (3) Does the existing intervention cause any significant change or reduction in the prevalence of malaria?
- (4) Does altering some of the parameters of the Bayesian network nodes produce a significant effect in mitigating the epidemic of malaria?

1.3 Significance of the Study

The results of this study will delineate the causes, transmission and prevention of malaria coupled with solving problems relating to attitude and cultural beliefs about the epidemics in the study area. The research will also help policy makers to improve decision-making process in public health services related to malaria. A graphical probability network, a BBN template for local malaria risk factors in Nigeria will also be created. Likewise, assist the government, support health groups and organizations both locally and internationally to access level of effectiveness of various measures employed to circumvent malaria epidemics. Add value to the growing body of knowledge and provide community data on key malaria indicators in Nigeria. Finally, it will provide a BBN template that can be used for other vector-borne diseases in Nigeria.

1.4 Objectives

The general objective of this research is to build a hierarchical model depicting complex inter-relationships of malaria risk factors capable of identifying key malaria predictors in the Federal Capital Territory (FCT) Abuja and by extension Nigeria. Such a model, when developed is capable of incorporating uncertainty in the parameter of interest and makes valid inferences which can help policy makers formulate intervention measures to curtail the disease prevalence. Also, a Bayesian probability network is developed to incorporate expert opinions and prior belief regarding the network nodes in the formulated belief network.

Specifically, the study intends to:

- (1) To compare pre- and post-intervention knowledge, attitude and practice (KAP) on malaria awareness at local communities and determine its efficacy
- (2) To identify climate risk factors, demography and socio-economic characteristics as well as control/prevention intervention variables associated with malaria infections in Abuja using two different approaches: logistic regression model and Monte Carlo Markov Chain (MCMC) simulation using Gibbs sampling.
- (3) To assess spatial heterogeneity in incidence patterns across Abuja
- (4) To derive a Bayesian belief network (BBN) for malaria epidemics in Abuja.

1.5 Scope of the Study

This study covers Gwagwalada Area Council (GAC), Abuja, Nigeria. The study respondents are the household heads in the selected sites in GAC. The study sites are: Dobi, Dagiri, Ledi and Tunga Maje. The focus of this study is divided into a malaria survey study, determination of malaria incidence based on self-reporting and determination of the complex interrelationships between target variable (incidence) and human-related malaria risk factors alongside climate variables for Gwagwalada and its environment. Therefore, this study is relevant to be applied on the subjects at household levels in identifying significant predictive factors of malaria using Bayesian graphical probability model and Monte Carlo simulation analysis. Also, it can be applied on subjects when spatial autocorrelations are involved in prevalence scores and such dependency measured with semivariogram models.

1.6 Organization of the Thesis

This dissertation examines and identifies malaria risk factors in Abuja, Nigeria using Bayesian frameworks. There are eight chapters in this thesis. The chapters are grouped into three parts. The first part (Chapters 1 to 3) consists of the general introduction to the study, review of related literature and research materials and methods. Chapters 4 to 7 are results and discussions based on the stated research objectives. Chapter 8 gives the summary and conclusion of the study.

Chapter 1 is the introduction to the current study. It comprises the background to the study and highlights on the problem statement, significance of the study, research objectives along with the scope of study and structure of thesis. Chapter 2 examines and appraises related literature on malaria epidemiology, environmental related risk factors and malaria control interventions. It also outlines and reviews Bayesian approaches and spatial models on disease modelling. Chapter 3 gives the general materials and methods to all the stated objectives in Chapter 1 of this study. It outlines data collection procedures and management, model formation and development.

Chapters 4 till 7 are results and discussion based on individual objectives stated in Chapter 1. Thus, each chapter begins with a brief introduction and review of related study on the subject of interest under consideration for the chapter. The method section contains the specific details of the variables of interest and explicit data analysis procedures used in obtaining the desired research outcomes. The theoretical framework is as detailed in chapter 3 but additional analysis procedures are provided for some chapters when necessary and captioned under data analysis. The summary of the study findings based on the statistical analysis conducted is provided by the results. The last section for each of the result chapters is the discussion section, whereby comparison of the findings of this present study and previous related studies reported in literature are made and detailed explanations based on the present study documented. The last chapter of this study is Chapter 8 which discusses the general conclusion and recommendations based on the research findings.



REFERENCES

- Abegunde, D., Orobato, N., Sadauki, H., Bassi, A., Kabo, I. A., & Abdulkarim, M. (2015). Countdown to 2015: Tracking maternal and child health intervention targets using Lot Quality Assurance Sampling in Bauchi State Nigeria. *PLoS ONE*, *10*(6), 1–13.
- Abiodun, G. J., Maharaj, M., Witbooi, P., & Okosun, K. O. (2016). Modelling the influence of temperature and rainfall on the population dynamics of *Anopheles arabiensis*. *Malaria Journal*, *15*(364), 1–15.
- Adedokun, O., & Adeyemi, G. E. (2013). Mother's socio-economic status and malaria prevention: implications for infant mortality in Nigeria. *Humanities and Social Sciences Review*, *2*(4), 65–82.
- Adedotun, A. A., Morenikeji, O. A., & Odaibo, A. B. (2010). Knowledge, attitudes and practices about malaria in an urban community in South-western Nigeria. *Journal of Vector Borne Disease*, *47*, 155–159.
- Adigun, A. B., Gajere, E. N., Oresanya, O., & Vounatsou, P. (2015). Malaria risk in Nigeria: Bayesian geostatistical modelling of 2010 malaria indicator survey data. *Malaria Journal*, *14*(156), 1–8.
- Adler, N. E., Boyce, T., Chesney, M. A., Cohen, S., Folkman, S., Kahn, R. L., & Syme, S. K. (1994). Socioeconomic status and health: The challenge of the gradient. *American Psychologist*. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/19610638>
- Adu-Prah, S., & Tetteh, K. E. (2015). Spatiotemporal analysis of climate variability impacts on malaria prevalence in Ghana. *Applied Geography*, *60*, 266–273.
- Afoakwah, C., Deng, X., & Onur, I. (2018). Malaria infection among children under-five: The use of large-scale interventions in Ghana. *BMC Public Health*, *18*(536).
- Agbo, H., Envuladu, E., Enokela, E., & Zoakah, I. (2014). Malaria Preventive Practices among Semi-Urban Dwellers as a Score Card towards Achieving Mdg 6. *Journal of Dental and Medical Sciences*, *13*(5), 1–5.
- Ahmad, A., Ahmad, S. P., & Ahmed, A. (2016). Classical and Bayesian approach in estimation of scale parameter of Nakagami distribution. *Journal of Probability and Statistics*, (ID7581918), 1–8.
- Ajadi, K. O., Olaniran, H. D., Alabi, F. M., & Adejumobi, D. O. (2012). Incidence of malaria among various rural socioeconomic households. *Greener Journal of Medical Sciences*, *2*(3), 051–063.

- Akinbobola, A., & Omotosho, J. B. (2013). Predicting malaria occurrence in Southwest and North central Nigeria using meteorological parameters. *International Journal of Biometeorology*, 57, 721–728.
- Alaba, A.O. Alaba, O. (2002). Malaria in children: Implications for the productivity of female caregivers in Nigeria. Nigeria: Annual Conference of the Nigerian Economic Society.
- Alaba, A. O. (2007). Malaria in children: Economic burden and treatment strategies in Nigeria. Nairobi: Malaria and Poverty in Africa.
- Alaba, O. A., & Alaba, O. B. (2009). Malaria in rural Nigeria: Implications for the millennium development goals. *African Development Review*, 21(1), 73–85.
- Ali, T. M., Abd Karim, M. F., & Kamil, A. A. (2015). Mathematical model of dengue fever and its sensitivity analysis. *Pakistan Journal of Statistics*, 31(6), 717–731.
- Amoran, O. E. (2013). Impact of health education intervention on malaria prevention practices among nursing mothers in rural communities in Nigeria. *Nigeria Medical Journal*, 54(2), 115–122.
- Amoran, O. E., Ariba, A. A., & Iyaniwura, C. A. (2012). Determinants of intermittent preventive treatment of malaria during pregnancy (IPTp) utilization in a rural town in Western Nigeria. *Reproductive Health*, 9(1), 12.
- AMR. (2003). The burden of malaria in Africa. The Africa Malaria Report.
- Andraszewicz, S., Scheibehenne, B., Grasman, R., Verhagen, J., & Wagenmakers, E.-J. (2015). An introduction to Bayesian hypothesis testing for management research. *Journal of Management*, 41(2), 521–543.
- Andrew, O. (2014). An assessment of the spatial pattern of malaria infection in Nigeria. *International Journal of Medicine and Medical Sciences*, 6(2), 80–86.
- Ashikeni, M. A., Envuladu, E. A., & Zoakah, A. I. (2013). Malaria and the use of the insecticide-treated net (ITN) among under-five children in Kuje Area Council of the Federal Capital Territory Abuja, Nigeria. *Journal of Mosquito Research*, 3(1), 45–53.
- Babajide, S., Perry, B., Huffer, F. W., Onubogu, O., Dutton, M., Becker, A., & Saleh, R. (2015). Effect of meteorological variables on malaria incidence in Ogun State, Nigeria. *International Journal of Public Health and Epidemiology*, 4(10), 205–215.
- Badaru, Y. U., Adejoke, A. O., Abubakar, A. S., & Emigilati, M. A. (2014). Rainfall Variations as the Determinant of Malaria in the Federal Capital Territory Abuja, Nigeria. *Journal of Environment and Earth Science*, 4(20), 149–159–159.

- Balogun, O. (2001). *The Federal Capital Territory of Nigeria: A geography of its development*. Ibadan: University of Ibadan Press.
- Bashar, K., & Tuno, N. (2014). Seasonal abundance of Anopheles mosquitoes and their association with meteorological variables. *Parasites & Vectors*, 7(442).
- Baume, C. A., & Franca-koh, A. C. (2011). Predictors of mosquito net use in Ghana. *Malaria Journal*, 10(265), 1–6.
- Baume, C. A., Reithinger, R., & Woldehanna, S. (2009). Factors associated with use and non-use of mosquito nets owned in Oromia and Amhara Regional States, Ethiopia. *Malaria Journal*, 8(1), 264.
- Beck-Johnson, L. M., Nelson, W. A., Paaijmans, K. P., Read, A. F., Thomas, M. B., & Bjørnstad, O. N. (2013). The effect of temperature on Anopheles mosquito population dynamics and the potential for malaria transmission. *PLoS ONE*, 8(11).
- Berger, J. O. (1980). *Statistical decision theory and Bayesian analysis* (2nd ed.). New York: Springer-Verlag.
- Bhutta, Z. A., Sommerfeld, J., Lassi, Z. S., Salam, R. A., & Das, J. K. (2014). Global burden, distribution, and interventions for infectious diseases of poverty. *Infectious Diseases of Poverty*, 3(1), 1–7.
- Bocoum, F. Y., Belemsaga, B., Adjagba, A., Walker, D., Kouanda, S., & Tinto, H. (2014). Malaria prevention measures in Burkina Faso: distribution and households expenditures. *International Journal for Equity in Health*, 13, 108.
- Boelaert, M., Meheus, F., Sanchez, A., Singh, S. P., Vanlerberghe, V., Picado, A., ... Sundar, S. (2009). The poorest of the poor: A poverty appraisal of households affected by visceral leishmaniasis in Bihar, India. *Tropical Medicine and International Health*, 14(6), 639–644.
- Bohling, G. (2005). Introduction to geostatistics and variogram analysis. Retrieved from <http://people.ku.edu/~gbohling/cpe940>
- Böttcher, S. G., & Dethlefsen, C. (2003). Learning Bayesian Networks with R. In *Proceedings of the 3rd International Workshop on Distributed Statistical Computing (DSC 2003) March 20–22, Vienna, Austria*. Australia: Kurt Hornik, Friedrich Leisch & Achim Zeileis (eds.). Retrieved from <http://www.ci.tuwien.ac.at/Conferences/DSC-2003/>
- Buchwalder, T., & Huber-Eicher, B. (2004). Effect of increased floor space on aggressive behaviour in male turkeys (*Meleagris gallopavo*). *Applied Animal Behaviour Science*, 89(3–4), 207–214.

- Cameletti, M., Ignaccolo, R., & Bande, S. (2011). Comparing spatio-temporal models for particulate matter in Piemonte. *Environmetrics*, 22(March), 985–996.
- Cameletti, M., Lindgren, F., Simpson, D., & Rue, H. (2012). Spatio-temporal modeling of particulate matter concentration through the SPDE approach. *Statistical Analysis*, 97(2), 109–131.
- Carrat, F., & Valleron, A.-J. (1992). Epidemiological mapping using the ‘‘Kriging’’ Method: application to an influenza-like illness epidemic in France. *American Journal of Epidemiology*, 135(11), 1293–1300.
- Carter, R., & Mendis, K. N. (2002). Evolutionary and historical aspects of the burden of malaria Evolutionary and historical aspects of the burden of malaria. *Clinical Microbiology Reviews*, 15(4), 564–594.
- Castelo-Branco, C., & Soveral, I. (2014). The immune system and aging: A review. *Gynecological Endocrinology*, 30(1), 16–22.
- CDC. (2012). How can malaria cases and deaths be reduced? CDC. Retrieved from www.cdc.org/malaria/malaria-worldwide/reduction/
- Chap, T. L. (2009). *Applied categorical data analysis and translational research*. Minnesota: Wiley.
- Chen, Y. (2013). New approaches for calculating Moran’s index of spatial autocorrelation. *PLoS ONE*, 8(7).
- Chiaka, S. E., Adam, M. B., Krishnarajah, I., Shohaimi, S., & Guure, C. B. (2015). Bayesian logistic regression model on risk factors of Type 2 Diabetes Mellitus. *Mathematical Theory and Modelling*, 5(1), 113–123.
- Cocchi, D., Greco, F., & Trivisano, C. (2007). Hierarchical space-time modelling of PM10 pollution. *Atmospheric Environment*, 41(3), 532–542.
- Cochran, W. G. (1977). *Sampling techniques* (3rd Editio). New York: John Wiley & Sons.
- Congdon, P. (2001). *Bayesian Statistical Modelling*. New York: Wiley Series in Probability and Statistics.
- Cooper, G. F., & Herskovits, E. (1992). A bayesian method for the induction of probabilistic networks from data. *Machine Learning*, 9(4), 309–347.
- Cowles, M. K. (2013). *Applied Bayesian Statistics With R and OpenBUGS Examples. Springer Texts in Statistics*,. New York: Springer Science+Business Media.

- Dawaki, S., Al-Mekhlafi, H. M., Ithoi, I., Ibrahim, J., Atroosh, W. M., Abdulsalam, A. M., ... Lau, Y. L. (2016). Is Nigeria winning the battle against malaria? Prevalence, risk factors and KAP assessment among Hausa communities in Kano State. *Malaria Journal*, *15*(1), 1–14.
- De Castro, M. C., & Fisher, M. G. (2012). Is malaria illness among young children a cause or a consequence of low socioeconomic status? Evidence from the united Republic of Tanzania. *Malaria Journal*, *11*(i), 1–12.
- DeLeire, T., & Manning, W. (2004). Labour market costs of illness: prevalence matters. *Health Economics*, *13*, 239–50.
- Derbie, A., & Alemu, M. (2017). Five years malaria trend Analysis in Woreta health center, Northwest Ethiopia. *Ethiopian Journal of Health Science*, *27*(5), 465–472.
- Dev, V., Barman, K., & Khound, K. (2016). A cross-sectional study assessing the residual bio-efficacy and durability of field-distributed long-lasting insecticidal nets in malaria endemic ethnic communities of Assam , Northeast India. *Journal of Infection and Public Health*, *9*, 298–307.
- Dhimal, M., Aryal, K. K., Dhimal, M. L., Gautam, I., Singh, S. P., Bhusal, L. C., & Kuch, U. (2014). Knowledge , attitude and practice regarding dengue fever among the healthy population of highland and Lowland communities in central Nepal. *PLoS ONE*, *9*(7), 1–15.
- Diakité, N. R., Guindo-Coulibaly, N., Adja, A. M., Ouattara, M., Coulibaly, J. T., Utzinger, J., & N’Goran, E. K. (2015). Spatial and temporal variation of malaria entomological parameters at the onset of a hydro-agricultural development in central Côte d’Ivoire. *Malaria Journal*, *14*(1), 1–11.
- Diboulo, E., Sié, A., Diadier, D. A., Voules, D. A. K., Yé, Y., & Vounatsou, P. (2015). Bayesian variable selection in modelling geographical heterogeneity in malaria transmission from sparse data : an application to Nouna Health and Demographic Surveillance System (HDSS) data , Burkina Faso. *Parasites and Vectors*, *8*(118), 1–14.
- Digi-geske, I., Olasehinde, I., Fidinad, I., Arogundade, D., & Darby, P. (2018). Epidemiological data of falciparum malaria in Ado/Ota, Southwest Ogun State, Nigeria. *Data in Brief*, *19*(2018), 1398–1402.
- Dlamini, W. M. (2010). A Bayesian belief network analysis of factors influencing wildfire occurrence in Swaziland. *Environmental Modelling and Software*, *25*(2), 199–208.
- Dondeynaz, C., Puga, J. L., & Moreno, C. (2013). Bayesian networks modelling in support to cross-cutting analysis of water supply and sanitation in developing countries. *Hydrology and Earth System Science*, *17*(July), 3397–3419.

- Dormann, F. C., McPherson, M. J., Araújo, M. B., Bivand, R., Bolliger, J., Carl, G., ... Wilson, R. (2007). Methods to account for spatial autocorrelation in the analysis of species distributional data: A review. *Ecography*, 30(5), 609–628.
- Ebenezer, A., Noutcha, A. E. M., & Okiwelu, S. N. (2016). Relationship of annual entomological inoculation rates to malaria transmission indices, Bayelsa State, Nigeria. *Journal of Vector Borne Disease*, 53(March), 46–53.
- Egenti, B. N., Odiba, E. P., Dangana, A., Yalma, R. M., & Nasir, I. A. (2018). Knowledge, attitude and factors affecting voluntary HIV counseling and testing services among women in an Abuja suburb community. *Health Sciences Research*, 5(2), 50–58.
- Eke, S. S., Omalu, I. C., Olayemi, I. K., Egwim, E. C., Hassan, S. C., Otuu, C. A., ... Abdullahi, M. (2018). Malaria Parasitaemia among patients attending General Hospital Minna, North Central Nigeria. *Journal of Bioscience and Biotechnology Discovery*, 3(4), 78–82.
- Erhun, W. O., Agbani, E. O., & Adesanya, S. O. (2005). Malaria prevention: knowledge, attitude and practice in a southwestern Nigerian community. *Journal of Biomedical Research*, 8, 25 – 29.
- Essé, C., Utzinger, J., Tschannen, A. B., Raso, G., Pfeiffer, C., Granado, S., ... Obrist, B. (2008). Social and cultural aspects of “malaria” and its control in central Côte d’Ivoire. *Malaria Journal*, 7, 224.
- Eunice, A., Wanjoya, A., & Luboobi, L. (2017). Statistical modeling of malaria incidences in Apac District, Uganda. *Open Journal of Statistics*, 7, 901–919.
- Evans, P. O., & Adenomon, M. O. (2014). Modeling the prevalence of malaria in Niger State: An application of Poisson regression and negative binomial regression models. *International Journal of Physical Sciences*, 2(April), 61–68.
- Ezeigwe, N. (2013). Summary Proceedings, 4th Annual Malaria Control Program. Lagos: Review Ethiopia and Nigeria Atlanta.
- Fayehun, O. A., & Salami, K. K. (2014). Older persons and malaria treatment in Nigeria. *Etude de La Population Africaine*, 27(2 SUPPL.), 424–433.
- FMOH. (2001). Annual Report of Federal Ministry of Health Nigeria. Abuja: FMOH.
- FMoH/NPC. (2016). Nigeria Malaria Indicator Survey 2015 final report. Abuja, Nigeria: FMoH, NPC/NBS. <https://doi.org/10.1017/CBO9781107415324.004>
- Fortin, M.-J., Dale, M. R. T., & Ver Hoef, J. M. (2002). Spatial analysis in ecology. *Encyclopedia of Environmetrics*, 4, 2051–2058.

- FOS. (1992). Nigeria Demographic and Health Survey 1990. Federal Office of Statistics, Lagos. Lagos, Nigeria: Federal Office of Statistics Lagos, Nigeria.IRD/Macro International Inc. Columbia, Maryland USA.
- Freeman, P., Perry, H. B., Gupta, S. K., & Rassekh, B. (2012). Accelerating progress in achieving the millennium development goal for children through community-based approaches. *Global Public Health*, 7(4), 400–419.
- Friedman, N., Geiger, D., & Goldszmit, M. (1997). Bayesian Network Classifiers. *Machine Learning*, 29, 131–163.
- Fu, W. J., Jiang, P. K., Zhou, G. M., & Zhao, K. L. (2014). Using Moran ' s I and GIS to study the spatial pattern of forest litter carbon density in a subtropical region of southeastern China. *Biogeosciences*, 11(8), 2401–2409.
- Ghazi, H. F., Elnajeh, M., Azri, A., Abdalqader, M. A., Faez, M., & Al-abed, A. A. (2017). Knowledge and beliefs on female breast cancer among male students in a private University, Malaysia. *Malaysian Journal of Public Health Medicine*, 17(1), 8–13.
- Gimba, U. N. (2014). Assessment of entomological and parasitological parameters of malaria transmission in Gwagwalada area council Abuja Nigeria. *International Journal of Environmental Science and Toxicology Research*, 2(11), 217–222.
- Githeko, A. K., Ogallo, L., Lemnge, M., Okia, M., & Ototo, E. N. (2014). Development and validation of climate and ecosystem-based early malaria epidemic prediction models in East Africa. *Malarial Journal*, 13(1), 329.
- Gobena, T., Berhane, Y., & Worku, A. (2013). Women's knowledge and perceptions of malaria and use of malaria vector control interventions in Keresha, Ethiopia. *Global Health Action*, 6, 1–8.
- Goesch, J. N., Schwarz, N. G., Decker, M., Oyakhirome, S., Borchert, L. B., Kombila, U. D., ... Grobusch, M. P. (2008). Socio-economic status is inversely related to bed net use in Gabon. *Malaria Journal*, 7, 60.
- Greenwood, B. M., Bojang, K., Whitty, C. J., & Targett, G. A. (2005). "Malaria." *Lancet*, 365, 1487 – 1498.
- Gunda, R., Chimbari, M. J., Shamu, S., Sartorius, B., & Mukaratirwa, S. (2017). Malaria incidence trends and their association with climatic variables in rural Gwanda, Zimbabwe, 2005-2015. *Malaria Journal*, 16(1), 1–13.
- Guttorp, P., & Gneiting, T. (2010). On the Whittle-Matern correlation family. Washington: NRCSE Technical Reports Series, University of Washington.

- Haddawy, P., Hasan, A. H. M. I., Kasantikul, R., Lawpoolsri, S., Sa-angchai, P., Kaewkungwal, J., & Singhasivanon, P. (2018). Spatiotemporal Bayesian networks for malaria prediction. *Artificial Intelligence in Medicine*, *84*, 127–138.
- Hagenlocher, M., & Castro, M. C. (2015). Mapping malaria risk and vulnerability in the United Republic of Tanzania: a spatial explicit model. *Population Health Metrics*, *13*(2).
- Hanninen, M., & Kujala, P. (2012). Influences of variables on ship collision probability in a Bayesian belief network model. *Reliability Engineering and System Safety*, *102*, 27–40.
- Hänninen, M., & Kujala, P. (2014). Bayesian network modeling of Port State Control inspection findings and ship accident involvement. *Expert Systems with Applications*, *41*(4 PART 2), 1632–1646.
- Haque, ., Sunahara, T., Hashizume, M., Shields, T., Yamamoto, T., Haque, R., & Glass, G. E. (2011). Malaria prevalence, risk factors and spatial distribution in a Hilly forest area of Bangladesh. *PLoS ONE*, *6*(4).
- Haque, U., Overgaard, H. J., Clements, A. C. A., Norris, D. E., Islam, N., Karim, J., ... Glass, G. E. (2014). Malaria burden and control in Bangladesh and prospects for elimination: An epidemiological and economic assessment. *The Lancet Global Health*, *2*(2), 98–105.
- Haque, Magalhães, R. J. S., Mitra, D., Kolivras, K. N., Schmidt, W., Haque, R., & Glass, G. E. (2011). The role of age , ethnicity and environmental factors in modulating malaria risk in Rajasthali, Bangladesh. *Malaria Journal*, *10*(367), 1–7.
- Hassan, M. R., Ghazi, H. F., Mohamed, A. S., & Jasmin, S. J. (2017). Knowledge and practice of breast self-examination among female non-medical students in Universiti Kebangsaan Malaysia (UKM) in Bangi. *Malaysian Journal of Public Health Medicine*, *17*(1), 51–58.
- Hay, J. L., & Pettitt, a N. (2001). Bayesian analysis of a time series of counts with covariates: an application to the control of an infectious disease. *Biostatistics*, *2*(4), 433–44.
- Heckerman, D. (1996). A Tutorial on Learning with Bayesian Networks. Retrieved from <http://research.microsoft.com/pubs/69588/tr-95-06.pdf>
- Ho, S. H., Speldewinde, P., & Cook, A. (2017). Predicting arboviral disease emergence using Bayesian networks : a case study of dengue virus in Western Australia. *Epidemiology and Infection*, *145*(May), 54–66.
- Hoff, P. D. (2009). *A first course in Bayesian statistical methods*. Media (Vol. 64). New York: Springer Science+Business Media.

- Homan, T., Maire, N., Hiscox, A., Di Pasquale, A., Kiche, I., Onoka, K., ... Takken, W. (2016). Spatially variable risk factors for malaria in a geographically heterogeneous landscape, western Kenya: An explorative study. *Malaria Journal*, 15(1), 1–15.
- Howe, L. D., Hargreaves, J. R., & Huttly, S. R. (2008). Issues in the construction of wealth indices for the measurement of socio-economic position in low-income countries. *Emerging Themes in Epidemiology*, 5(3).
- Ibrahim, N. K., Alwafi, H. A., Sangoof, S. O., Turkistani, A. K., & Alattas, B. M. (2017). Cross-infection and infection control in dentistry : Knowledge , attitude and practice of patients attended dental clinics in King Abdulaziz University Hospital , Jeddah , Saudi Arabia. *Journal of Infection and Public Health*, 10(4), 438–445.
- Idowu, A., Olowookere, S. A., Fagbemi, A. T., & Ogunlaja, O. A. (2016). Determinants of cervical cancer screening uptake among women in Ilorin, north central Nigeria : A community-based study. *Journal of Cancer Epidemiology*, 2016.
- Ishaya, S., Mashi, S. A., & Ifatimehin, O. O. (2008). Application of remote sensing and GIS techniques in mapping areas favourable for fadama farming in Gwagwalada, Abuja, Nigeria. *American-Eurasian Journal of Sustainable Agriculture*, 2(3), 196–204.
- Iwuafor, A. A., Egwuatu, C. C., Nnachi, A. U., Ita, I. O., Ogban, G. I., Akujobi, C. N., & Egwuatu, T. O. (2016). Malaria Parasitaemia and the use of insecticide-treated nets (INTs) for malaria control amongst under-5year old children in Calabar, Nigeria. *BMC Infectious Diseases*, 16(1), 1–12.
- Jean-Michel, M., & Christian, R. (2007). *Bayesian core: A practical approach to computational Bayesian statistics*. USA: Springer.
- Jimoh, A., Sofola, O., Petu, A., & Okorosobo, T. (2007). Quantifying the economic burden of malaria in Nigeria using the willingness to pay approach. *Cost Effectiveness and Resource Allocation : C/E*, 5, 6.
- Jombo, G. T. A., Mbaawuaga, E. M., Ayegba, A. S., & Araoye, M. A. (2011). Anaemia, malaria burden and its control methods among pregnant women in a semi-urban community of northern Nigeria. *Journal of Public Health and Epidemiology*, 3(7), 317–323.
- Kamara, M. (2016, March 31). As Artemisinin defeats malaria... Chinese traditional medicine set for international market. Retrieved from [hht://awoko.org/2016/03/31/sierra-Leone-news-As-artemisinin-defeats-malaria-Chinese-traditional-medicine-set-for-International-market/](http://awoko.org/2016/03/31/sierra-Leone-news-As-artemisinin-defeats-malaria-Chinese-traditional-medicine-set-for-International-market/)
- Karunamoorthi, K. (2011). Vector control: A cornerstone in the malaria elimination campaign. *Clinical Microbiology and Infection*, 17, 1608–1616.

- Karunamoorthi, K. (2014). Malaria vaccine: A future hope to curtail the global malaria burden. *International Journal of Preventive Medicine*, 5(5), 529–538.
- Karunamoorthi, K., Deboch, B., & Tafere, Y. (2010). Knowledge and practice concerning malaria, insecticide-treated net (ITN) utilization and antimalarial treatment among pregnant women attending specialist antenatal clinics. *Journal of Public Health*, 18(6), 559–66.
- Keskin, H., & Grunwald, S. (2018). Regression kriging as a workhorse in the digital soil mapper's toolbox. *Geoderma*, 326(April), 22–41.
- Khanam, S. (2017). Prevalence and epidemiology of malaria in Nigeria : A review. *International Journal of Research in Pharmacy and Biosciences*, 4(8), 10–12.
- Khetarpal, N., & Khanna, I. (2016). Dengue fever: Causes, complications, and vaccine strategies. *Journal of Immunology Research*, 2016(3), 1–14.
- Khodakarami, V., & Abdi, A. (2014). Project cost risk analysis: A Bayesian networks approach for modeling dependencies between cost items. *International Journal of Project Management*, 32(7), 1233–1245.
- Kiang, R. (2009). Malaria modelling surveillance: Benchmark report. Retrieved from https://www.nasa.gov/sites/default/files/files/09Kiang_malaria_benchmark_report.pdf
- Kitua, A. Y., Ogundahunsi, O. A. T., Lines, J., & Mgone, C. S. (2011). Conquering malaria: Enhancing the impact of effective interventions towards elimination in the diverse and changing epidemiology. *Journal of Global Infectious Diseases*, 3(2), 161–165.
- Kleinbaum, D. G., & Klein, M. (2005). *Statistics for biology and health*. New York: Springer Science+Business Media, Inc.
- Kleinschmidt, I., Bagayoko, M., Clarke, G. P. Y., Craig, M., & Sauer, D. Le. (2000). A spatial statistical approach to malaria mapping. *International Journal of Epidemiology*, 29, 355–361.
- Kobayashi, M., Beer, K. D., Bjork, A., Chatham-Stephens, K., Cherry, C. C., Arzoaquoi, Sampson Frank, W., ... Nyenswah, T. G. (2015). Community knowledge, attitudes, and practices regarding Ebola virus disease — Five counties, Liberia, September–October, 2014. *Morbidity and Mortality Weekly Report*, 64(26), 714–8.
- Korb, K. B., & Nicholson, A. E. (2004). *Bayesian artificial intelligence*. USA: Chapman & Hall/CRC.
- Krefis, A. C., Schwarz, N. G., Nkrumah, B., Acquah, S., Loag, W., Sarpong, N., ... May, J. (2010). Principal component analysis of socioeconomic factors and their association with malaria in children from the Ashanti region, Ghana.

Malaria Journal, 9, 201.

- Kumar, V., Mangal, A., Panesar, S., Yadav, G., Talwar, R., Raut, D., & Singh, S. (2014). Forecasting malaria cases using climatic factors in Delhi, India: A time series Analysis. *Malaria Research and Treatment*, 2014.
- Lai, Y., Zhou, X., Utzinger, J., & Vounatsou, P. (2013). Bayesian geostatistical modelling of soil-transmitted helminth survey data in the People's Republic of China. *Parasites and Vectors*, 6, 359.
- Landuyt, D., Broekx, S., D'hondt, R., Engelen, G., Aertsens, J., & Goethals, P. L. M. (2013). A review of Bayesian belief networks in ecosystem service modelling. *Environmental Modelling and Software*, 46, 1–11.
- Landuyt, D., Broekx, S., & Goethals, P. L. M. (2016). Bayesian belief networks to analyse trade-offs among ecosystem services at the regional scale. *Ecological Indicators*, 71, 327–335.
- Lauritzen, S. L., & Sheehan, N. A. (2003). Graphical models for genetic analyses. *Statistical Science*, 18(4), 489–514.
- Lindsay, S. W., & Martens, W. J. (1998). Malaria in the African highlands: past, present and future. *Bull World Health Organ*, 76(1), 33–45.
- Lingala, M. A. L. (2017). Effect of meteorological variables on Plasmodium vivax and Plasmodium falciparum malaria in outbreak prone districts of Rajasthan, India. *Journal of Infection and Public Health*, 10(6), 875–880.
- Liu, J., Chen, F., Yu, H., Zeng, P., & Liu, L. (2014). A two-stage Bayesian method for estimating accuracy and disease prevalence for two dependent dichotomous screening tests when the status of individuals who are negative on both tests is unverified. *BMC Medical Research Methodology*, 14(110), 1–11.
- Loha, E., Lunde, T. M., & Lindjorn, B. (2012). Effect of bednets and indoor residual spraying on spatio-temporal clustering of malaria in a village in South Ethiopia: A longitudinal study. *PLoS ONE*, 7(10).
- LSMOH. (2012). Medium Term Sector Strategy (MTSS) 2013-2015. Health sector zero draft report. Lagos. Retrieved from www.lagosstateministryofhealth.com-file
- Makwe, E., & Ishaya, S. (2014). Assessing the impact of waste dump on Paiko River water quality in Gwagwalada Area Council of Abuja, Nigeria. *American Journal of Science and Technology*, 1(5), 303–309.
- Marchant, B. P., & Lark, R. M. (2007). The Matérn variogram model: Implications for Uncertainty Propagation and Sampling in Geostatistical Surveys. *Geoderma*, 140, 337–345.

- Marcot, B. G., Steventon, J. D., Sutherland, G. D., & McCann, R. K. (2006). Guidelines for developing and updating Bayesian belief networks applied to ecology modelling and conservation. *Canadian Journal of Forestry Research*, 36(12), 3063–3074.
- Mateu, J., & Montes, F. (2002). *Spatial statistics through applications*. United Kingdom: WIT Press.
- McGregor, I. A. (1984). Epidemiology, malaria and pregnancy. *The American Journal of Tropical Medicine and Hygiene*, 33(4), 517–525.
- Menendez, C. (1995). Malaria during pregnancy: A priority area of malaria research and control. *Reviews of Parasitology Today*, 5, 178–183.
- Minasny, T. B., & Mcbratney, A. B. (2005). The Matern function as a general model for soil variograms. *Geoderma*, 128(3–4), 192–207.
- Mohammadkhani, M., Khanjani, N., Bakhtiari, B., & Sheikhzadeh, K. (2016). The relation between climatic factors and malaria incidence in Kerman, South East of Iran. *Parasite Epidemiology and Control*, 1(3), 205–210.
- Mohon, A. S., Elahi, R., Podder, M. P., Mohiuddin, K., Hossain, M. S., Khan, W. A., ... Alam, M. S. (2012). Evaluation of the onsite (Pf/Pan) rapid diagnostic test for diagnosis of clinical malaria. *Malaria Journal*, 11(1), 415.
- Moise, I. K., Roy, S. Sen, Nkengurutse, D., & Ndikubagenzi, J. (2016). Seasonal and geographic variation of pediatric malaria in Burundi: 2011 to 2012. *International Journal of Environmental Research and Public Health*, 13(425), 1–14.
- Mokuolu, O. A., Falade, C. O., Orogade, A. A., Okafor, H. U., Adedoyin, O. T., Oguonu, T. A., ... Callahan, M. V. (2009). Malaria at parturition in Nigeria: Current status and delivery outcome. *Infectious Diseases in Obstetrics and Gynecology*, 2009.
- Moonasar, D., Asomugha, C. L., Baker, L., Blumberg, L., Barnes, K. I., Maharaj, R., & Benson, F. (2011). Preventing disease and saving lives: The malaria season is upon us. *South African Medical Journal*, 101(12).
- Moonasar, D., Nuthulaganti, T., Kruger, P. S., Mabuza, A., Rasiswi, E. S., F.G., B., & Maharaj, R. (2012). Malaria control in South Africa 2000–2010: Beyond MDG6. *Malaria Journal*, 11(294).
- Mwageni, E. (2002). Household wealth ranking and risks of malaria mortality in rural Tanzania Third MIM Pan-Africa Conference on Malaria, Arusha, Tanzania. Arusha: Third MIM Pan-Africa Conference on Malaria, Arusha, Tanzania.

- Nagarajan, R., Scutari, M., & L'ebre, S. (2013). *Bayesian networks in R with application in systems biology*. New York: Springer.
- NARD. (2009, September). Doctors worry over mortality rate. *The NATIONS*, p. 9.
- Nduka, O. K., Egbu, A., Okafor, E. A., & Nwaugo, V. O. (2006). Prevalence of malaria parasites and anaemia in pregnant and non pregnant women in Aba and Okigwe towns Of Southeast Nigeria. *Animal Research International*, 3(3), 508.
- Nguefack-Tsague, G. (2011). Using bayesian networks to model hierarchical relationships in epidemiological studies. *Epidemiology and Health*, 33(e2011006), 1–8.
- NIH. (2007). Understanding malaria: Fighting an ancient scourge. *NIH Publications*. USA: Department of Health and Human Services. Retrieved from www.niaid.nih.gov.
- Nkuo-Akenji, T., Ntonifor, N., Ndukum, M., Kimbi, H., Abongwa, E., Nkwescheu, A., ... Titanji, V. (2006). Environmental factors affecting malaria parasite prevalence in rural Bolifamba, South-West Cameroon. *African Journal of Health Sciences*, 13(1–2), 40–46.
- NMCP/NPC. (2012). Nigeria Malaria Indicator Survey 2010. Abuja: NPC, NMCP and ICF International.
- Noor, A. N., Omunbo, J. A., Amin, A. A., Zurovac, D., & Snow, R. W. (2006). Wealth, mother's education and physical access as determinants of retail sector net use in rural Kenya. *Malaria Journal*, 5(5).
- NPC. (2004). Nigeria Demographic and Health Survey 2003. Abuja: Federal Republic of Nigeria.
- NPC. (2006). National Population Commission's population figures for the Nigeria States for 2006 population and housing census. Abuja: NPC.
- NPC. (2012). National Malaria Control Programme (NMCP) [Nigeria], and ICF International: 2010 Nigeria Malaria Indicator Survey. Abuja, Nigeria: NPC, NMCP, and ICF International. Retrieved from [The 2010 Nigeria Malaria Indicator Survey,.pdf.crdownload](#)
- NPC, & ICF. (2009). Nigeria Demographic and Health Survey 2008. Abuja: National Population Commission and ICF Macro.
- NPC, & ORC. (2004). Nigeria Demographic and Health Survey 2003. Calverton, Maryland: National Population Commission and ORC Macro.
- Nyarko, S. H., & Cobblah, A. (2014). Sociodemographic determinants of Malaria among under-five children in Ghana. *Malaria Research and Treatment*, Vol. 2014(Article ID 304361), 6pages.

- OECD. (2008). *Handbook on constructing composite indicators*. Paris: The Organisation for Economic Co-operation and Development, JRC European Commission. Retrieved from <http://www.oecd.org/els/soc/handbookonconstructingcompositeindicatorsmethodologyanduserguide.htm>
- Oguntade, E. S. (2010). Time series modelling of malaria pandemic in Nigeria. *Global Journal of Mathematics and Statistics*, 2(1), 61–68.
- Ojua, A. T., & Omono, C. (2012). African sacrificial ceremonies and issues in socio-cultural development. *British Journal of Arts and Social Sciences*, 4(1).
- Ojua, T. A. , Ishor, D. G., & Ndom, P. J. (2013). African cultural practices and health implications for Nigeria rural development. *International Review of Management and Business Research*, 2(1), 176–183.
- Okeke, T. A., Uzochukwu, B. S. C., & Okafor, H. U. (2006). An in-depth study of patent medicine sellers' perspectives on malaria in a rural Nigerian community. *Malaria Journal*, 5(1), 97.
- Okonkwo, I. O., Soleye, F. A., Amusan, T. A., Ogun, A. A., Udeze, A. O., Nkang, A. O., ... Faleye, T. O. O. (2009). Prevalence of malaria plasmodium in Abeokuta , Nigeria. *Malaysian Journal of Microbiology*, 5(2), 113–118.
- Okorie, P. N., McKenzie, F. E., Ademowo, O. G., Bockarie, M., & Kelly-Hope, L. (2011). Nigeria Anopheles vector database: An overview of 100 years' research. *PLoS ONE*, 6(12), 6–7.
- Okorosobo, T., Okorosobo, F., Mwabu, G., Orem, J. N., & Kirigia, J. M. (2011). Economic burden of malaria in six countries of Africa. *European Journal of Business and Management*, 3(6), 42–63.
- Olasunbo, O. I., & Ayo, S. D. (2013). Health seeking behaviour, food habit and nutritional assessment of an elderly group in Ile Ife, Nigeria. *Journal of Community Medicine & Health Education*, 3(5).
- Olayemi, I. K., Omalu, I. C. J., Abolarinwa, S. O., Mustapha, O. M., Ayanwale, V. A., Mohammed, A. Z., ... Chuckwuemeka, V. I. (2012). Knowledge of malaria and implication for control in an endemic urban area of North Nigeria. *Asian Journal of Epidemiology*, 5(2), 42–49.
- Oluwole, A. S., Ekpo, U. F., Karagiannis-Voules, D., Abe, E. M., Olamiju, F. O., Isiyaku, S., ... Vounatsou, P. (2015). Bayesian geostatistical model-based estimates of soil-transmitted helminth infection in Nigeria , including annual deworming requirements. *PLOS Neglected Tropical Diseases*, 4(9), e0003740.

- Omonijo, A. G., Matzarakis, A., Oguntoke, O., & Adeofun, C. O. (2011). Influence of weather and climate on malaria occurrence based on human-biometeorological methods in Ondo State, Nigeria. *Journal of Environmental Science and Engineering*, 5, 1215–1228.
- Onyango, E. A., Sahin, O., Awiti, A., Chu, C., & Mackey, B. (2016). An integrated risk and vulnerability assessment framework for climate change and malaria transmission in East Africa. *Malaria Journal*, 15(551), 1–12.
- Onyebuchi, C. (2012, May 8). Nigeria has the highest malaria cases in the world - Health Minister. *The Nation*.
- Onyiri, N. (2015). Estimating malaria burden in Nigeria: A geostatistical modelling approach. *Geospatial Health*, 10(2), 163–170.
- Osakunor, D. N. M., Sengeh, D. M., & Mutapi, F. (2018). Universal health coverage in Africa: Coinfections and comorbidities. *Trends in Parasitology*, xx, 1–5.
- Otsemobor, O., Ajayi, O. O., Afolabi, B. A., Ajayi, J. A., Turshak, L. G., Fatunbi, B. S., & Sani, S. (2013). Determinants of long lasting insecticidal nets distribution, ownership and use in the Federal Capital Territory, Nigeria-implications for malaria programmes. *Journal of Public Health and Epidemiology*, 5(1), 445–458.
- Pandey, R., & Verma, M. R. (2008). Samples allocation in different strata for impact. *Revista Brasileira Biomedical*, 26(4), 103–112.
- Papakosta, P., & Straub, D. (2016). Probabilistic prediction of daily fire occurrence in the Mediterranean with readily available spatio-temporal data. *iForest*, 10, 32–40.
- Papakosta, P., Xanthopoulos, G., & Straub, D. (2017). Probabilistic prediction of wildfire economic losses to housing in Cyprus using Bayesian network analysis. *International Journal of Wildland Fire*, 26, 10–23.
- Paradis, E. (2011). *Analysis of phylogenetics and evolution with R*. New York: Springer Science+Business Media, LLC.
- Paradis, E. (2017). Moran's autocorrelation coefficient in comparative methods. Retrieved from <https://cran.r-project.org/web/packages/ape/vignettes/MoranI.pdf>
- Pearl, J. (2000). *Causality: Models, Reasoning, and Inference* (2nd ed). UK: Cambridge university press.
- Pullan, R. L., Bukirwa, H., Staedke, S. G., Snow, R. W., & Brooker, S. (2010). Plasmodium infection and its risk factors in eastern Uganda. *Malaria Journal*, 9(2), 1–11.

- Puza, B. (2015). *Bayesian methods for statistical analysis* (2015 ANU e). Australia: Griffin Press.
- Raftery, A. E. (1995). Bayesian model selection in social research. *Sociological Methodology*, 25, 111–163.
- RBM. (2009). Roll Back Malaria (RBM) Partnership update, June 2009. Geneva: RBM. Retrieved from <http://www.rollbackmalaria.org/microsites/wmd2011/rbmeupdate2009-07-03.html>
- RBM. (2012). *Detecting malaria in Asia, the Pacific, Americas, Middle East and Europe. New RBM report highlights malaria burden in Asia Pacific*. Asia Pacific.
- RBM/NMCP. (2004). Malaria control in Nigeria. A strategy for behavioural change communication 2004-2005. Abuja: RBM/NMCP.
- Reed, H. E., & Mberu, B. U. (2014). Capitalizing on Nigeria's demographic dividend: Reaping the benefits and diminishing the burdens. *Etude Population Africa*, 27(2), 319–330.
- Roberts, D., & Matthews, G. (2016). Risk factors of malaria in children under the age of five years old in Uganda. *Malaria Journal*, 15(1), 1–11.
- Roberts, & Walker, W. (2001). Sex-associated hormones and immunity to protozoan parasites, 14(3), 476–488.
- Ruhl, O. and Onuoha, S. (2009, December 4). World Bank commits \$280m to fight malaria in Nigeria. *Daily Trust*, p. 6.
- Sadauki, H. (2013, June). 70% Maternal deaths caused by malaria, eclampsia, postpartum haemorrhage-TSHIP. *Daily Trust*, p. 31.
- Sadiq, B., & Brown, P. (2017). Assessing the impact of climatic variables on malaria cases among pregnant women in South-Western Nigeria. *Universal Journal of Public Health*, 5(7), 392–402.
- Salahi-Moghaddam, A., Khoshdel, A., Dalaei, H., Pakdad, K., Nutifafa, G. G., & Sedaghat, M. M. (2017). Spatial changes in the distribution of malaria vectors during the past 5 decades in Iran. *Acta Tropica*, 166, 45–53.
- Salam, R. A., Das, J. K., Lassi, Z. S., & Bhutta, Z. A. (2014). Impact of community-based interventions for the prevention and control of malaria on intervention coverage and health outcomes for the prevention and control of malaria. *Infectious Diseases of Poverty*, 3(1), 25.

- Salini, S., & Kenett, R. S. (2007). Bayesian network of customer satisfaction survey data. *Pubblicazione Depositata Ai Sensi Della L.* Italy: University of Milan. Retrieved from <http://www.economia.unimi.it>
- Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., & Tarantola, S. (2010). Variance based sensitivity analysis of model output . Design and estimator for the total sensitivity index. *Computer Physics Communications*, *181*, 259–270.
- Samaniego, F. J. (2010). *A comparison of the Bayesian and Frequentist approaches to estimation* (1st ed.). New York: Springer.
- Schantz-Dunn, J., & Nour, N. M. (2009). Malaria and pregnancy: a global health perspective. *Reviews in Obstetrics & Gynecology*, *2*(3), 186–92.
- Scutari, M. (2010). Learning Bayesian networks with the bnlearn R package. *Journal of Statistical Software*, *35*(3), 1–22.
- Scutari, M. (2014). Bayesian network constraint-based structure learning algorithms: Parallel and optimised implementations in the bnlearn R package. *Journal of Statistical Software*, *VV*(Ii).
- Scutari, M. (2018). Dirichlet Bayesian network scores and the maximum mntropy principle. *Behaviormetrika*. <https://doi.org/10.1007/s41237-018-0048-x>
- Scutari, & Denis, J.-B. (2015). *Bayesian networks with examples in R*. New York: A Chapman & Hall Book/CRC.
- Shi, H., He, Q., & Zhang, W. (2018). Spatial factor analysis for Aerosol optical depth in metropolises in China with regard to spatial heterogeneity. *Atmosphere*, *9*(156), 1–14.
- Siden-Kiamos, I., & Louis, C. (2004). Interactions between malaria parasites and their mosquito hosts in the midgut. *Insect Biochemistry and Molecular Biology*, *34*(7), 679–685.
- Siraj, A. S., Santos-Vega, M., Bouma, M. J., Yadeta, D., Ruiz-Carrascal, D., & Pascual, M. (2014). Altitudinal changes in malaria. *Science*, *1154*(March), 1154–1159.
- Smith, T. A. (2008). Estimation of heterogeneity in malaria transmission by stochastic modelling of apparent deviations from mass action kinetics. *Malaria Journal*, *7*(1), 12.
- Smith, & Gelfand, A. E. (1992). Bayesian statistics without tears: A sampling – resampling perspective. *The American Statistician*, *46*(2), 84–88.

- Snow, R. W., Amratia, P., Kabaria, C. W., Noor, A. M., & Marsh, K. (2012). The changing limits and incidence of malaria in Africa : 1939 –2009. *Advanced Parasitology*, 78, 169–262.
- Ssempiira, J., Kissa, J., Nambuusi, B., Mukooyo, E., Opigo, J., Makumbi, F., ... Vounatsou, P. (2018). Interactions between climatic changes and intervention effects on malaria spatio-temporal dynamics in Uganda. *Parasite Epidemiology and Control*, 3(3), e00070.
- Stamelos, I., Angelis, L., Dimou, P., & Sakellaris, E. (2003). On the use of Bayesian belief networks for the prediction of software productivity. *Information and Software Technology*, 45, 51–60.
- Stauffer, H. B. (2008). *Contemporary Bayesian and Frequentist statistical research methods for natural resource scientists*. Canada: John Wiley & Sons, Inc.
- Steketee, R. W. (2014). Malaria prevention during pregnancy- Is there a next step forward? *PLoS Medicine*, 11(9), e1001734.
- Steketee, R. W., & Mutabingwa, T. K. (1999). Malaria in pregnant women: research, epidemiology, policy and practice. *Annals of Tropical Medicine & Parasitology*, 93(sup1), S7–S9.
- Steketee, R. W., Nahlen, B. L., Parise, M. E., & Menendez, C. (2001). The burden of malaria in pregnancy in malaria-endemic areas. *American Journal of Tropical Medicine and Hygiene*, 64(1,2), 28–35.
- Stresman, G. H. (2010). Beyond temperature and precipitation: Ecological risk factors that modify malaria transmission. *Acta Tropica*, 116(3), 167–172.
- Suzuki, J. (2016). A Theoretical Analysis of the BDeu Scores in Bayesian Network Structure Learning. *Behaviormetrika*, 44(1), 97–116.
- SYAHD. (2008). Malaria foundation international, embracing humanity worldwide. Lagos: SYAHD Project-Nigeria.
- Sylvester, I. T. (2014). A Post Resettlement Appraisal of the Socio-Economic Condition of Gbagi People in Kubwa , Federal Capital Territory (Fct) Abuja , Nigeria. *Academic Research International*, 5(July), 153–166.
- Szumilas, M. (2010). Explaining odd ratios. *Journal of the Canadian Academy Child and Adolescent Psychiatry*, 19(3).
- Tangpukdee, N., Duangdee, C., Wilairatana, P., & Krudsood, S. (2009). Malaria diagnosis: A brief review. *Korean Journal of Parasitology*, 47(2), 93–102.
- Tekeste, Z., Workineh, M., & Petros, B. (2013). Determining the severity of Plasmodium falciparum malaria in Ethiopia. *Journal of Infection and Public Health*, 6, 10–15.

- Thompson, A. (2004, March 23). Malaria: When politics kills. *This Day Newspaper*. Retrieved from <http://allafrica.com/stories/200403230287.html>
- Thompson, A., & Adegoke, A. (2007). AntiDDT policies are deadly for Africa. Retrieved from <http://allafrica.com/stories/200403230287.html>
- Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, 46, 234–240.
- Tsai, C. (2004). Bayesian inference in Binomial logistic regression: A case study of the 2002 Tapei Moyoral Election. Taipei: Academia Sinica Taipei.
- Tyagi, P., Roy, A., & Malhotra, M. S. (2005). Knowledge, awareness and practices towards malaria in communities of rural, semi-rural and bordering areas of east Delhi (India). *Journal of Vector Borne Diseases*, 42(1), 30–35.
- Ukpe, I. S., Moonasar, D., Raman, J., Barnes, K. I., Baker, L., & Blumberg, L. (2013). Case management of malaria: Treatment and chemoprophylaxis. *South African Medical Journal*, 103(10), 793–798.
- Ukpong, I. G., Opara, K. N., Usip, L. P. E., & Ekpu, F. S. (2007). Community Perceptions about Malaria, Mosquito and Insecticide treated Nets in a rural Community of Niger Delta Nigeria: Implication for control. *Research Journal Parasitology*, 2(1), 13–22.
- United States Embassy in Nigeria. (2011). Nigeria malaria fact sheet 2011. *United State Embassy in Nigeria*. Retrieved from <http://photos.state.gov/libraries/nigeria/231771/Public/December-MalariaFactSheet2.pdf>
- USAID. (2009). Report to congress: Coordinated strategy to accelerate development of vaccines for infectious diseases. Washington D.C.: USAID.
- Usman, A., & Adebayo, M. O. (2011). Socio-economic impact of malaria epidemics on households in Nigeria: Micro evidence from Kwara State. *International Journal of Asian Social Science*, 1(5), 188–196.
- Uzochukwu, B. S. C., Ossai, E. N., Okeke, C. C., Ndu, A. C., & Onwujekwe, O. E. (2018). Malaria knowledge and treatment practices in Enugu State, Nigeria: A qualitative study. *International Journal of Health Policy and Management*, 7(9), 859–866.
- Uzoigwe, J. C., Khaitsa, M. L., & Gibbs, P. S. (2007). Epidemiological evidence for Mycobacterium avium subspecies paratuberculosis as a cause of Crohn's disease. *Epidemiology and Infection*, 135(7), 1057–1068.
- Valle, D., Lima, J. M. T., Millar, J., Amratia, P., & Haque, U. (2015). Bias in logistic regression due to imperfect diagnostic test results and practical correction approaches. *Malaria Journal*, 14(434), 1–9.

- Venkatesan, P., & Srinivasan, R. (2010). Modeling the spatial variogram of tuberculosis for Chennai ward in India. *Indian Journal of Science and Technology*, 3(2), 167–169.
- Victora, C. G., Huttly, S. R., Fuchs, S. C., & Olinto, M. T. (1997). The role of conceptual frameworks in epidemiological analysis: A hierarchical approach. *International Journal of Epidemiology*, 26(1), 224–227.
- Vyas, S., & Kumaranayake, L. (2006). Constructing socio-economic status indices: How to use principal components analysis. *Health Policy and Planning*, 21(6), 459–468.
- WHO. (2005). World Malaria Report, Geneva. Geneva: World Health Organization.
- WHO. (2006). Guidelines for the treatment of malaria. Geneva. Geneva: WHO.
- WHO. (2007). Malaria elimination: A field manual for low and moderate endemic countries. Geneva: WHO.
- WHO. (2010). World Malaria Report 2010. Geneva: WHO. Retrieved from http://www.who.int/malaria/world_malaria_report_2010/en/
- WHO. (2011). World Health Malaria Report 2011. Geneva: WHO. Retrieved from http://www.who.int/malaria/world_malaria_report_2011/en/
- WHO. (2012). World Health Malaria Report 2012. Geneva: WHO. Retrieved from http://www.who.int/malaria/publications/world_malaria_report_2012/en/
- WHO. (2013). World Malaria Report 2013. Retrieved from www.who.int
- WHO. (2015). World Malaria Report 2015. France: WHO. Retrieved from <http://www.who.int/malaria/publications/world-malaria-report-2016/en/>
- WHO. (2016a). climate change and human health, global environmental Change. Retrieved from www.who.int/globalchange/climate/summary/en/index5.html
- WHO. (2016b). *World Malaria Report*. World Health Organization.
- Wikle, C. K., & Berliner, L. M. (1998). Hierarchical Bayesian space-time models. *Environmental and Ecological Statistics*, 5, 117–154.
- Wilde, F., Gammel, B. M., & Pehl, M. (2018). Spatial correlation analysis on physical unclonable functions. *IEEE Transactions on Information Forensics and Security*, 13(6), 1468–1480. <https://doi.org/10.1109/TIFS.2018.2791341>
- Williams, L. L. (1963). Malaria eradication in the United States. *American Journal of Public Health and the Nation's Health*, 53, 17–21.
- Xiao, G., Hu, Y., Li, N., & Yang, D. (2018). Spatial autocorrelation analysis of monitoring data of heavy metals in rice in China. *Food Control*, 89, 32–37.

- Yadav, K., Dhiman, S., Rabha, B., Saikia, P., & Veer, V. (2014). Socio-economic determinants for malaria transmission risk in an endemic primary health centre in Assam, India. *Infectious Diseases of Poverty*, 3(1), 19.
- Yahaya, A. (2012). Environment and socio-economic influence of victim of malaria and typhoid fever in Nigeria. *Journal of Humanities and Social Science*, 2(3), 17–23.
- Yaya, S., Udenigwe, O., Bishwajit, G., Ekholuenetale, M., & Kadio, B. (2017). Knowledge of prevention, cause, symptom and practices of malaria among women in Burkina Faso. *PLoS ONE*, 12(7), e0180508.
- Yusuf, O. B., Adeoye, B. W., Oladepo, O. O., Peters, D. H., & Bishai, D. (2010). Poverty and fever vulnerability in Nigeria: a multilevel analysis. *Malaria Journal*, 9(1), 235.
- Zakkula, G. (1999). *Element of sampling theory and methods*. USA: Prentice Hall Inc.
- Zamora-Vilchis, I., Williams, S. E., & Johnson, C. N. (2012). Environmental temperature affects prevalence of blood parasites of birds on an elevation gradient: Implications for disease in a warming climate. *PLoS ONE*, 7(6).
- Zinszer, K., Verma, A. D., Charland, K., Brewer, T. F., Brownstein, J. S., Sun, Z., & Buckeridge, D. L. (2012). A scoping review of malaria forecasting: Past work and future directions. *BMJ Open*, 2(6), 1–12.
- Zong, F., Xu, H., & Zhang, H. (2013). Prediction for traffic accident severity : Comparing the Bayesian network and Rrgression models. *Mathematical Problems in Engineering*, 2013(ID 475194), p pages.
- Zuur, A. F., Ieno, E. N., Walker, N. J., Saveliev, A. A., & Smith, G. M. (2009). *Mixed effects models and extensions in ecology with R, statistics for biology and health*. UK: Springer Science+Business Media, LLC 2009.