Socio-Economic and Eco-Environmental Determinants of Malaria in Four Malaria Endemic Provinces of Zambia

By

Nzooma Munkwangu Shimaponda

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ABSTRACT

A large fraction of the global malaria burden occurs in sub-Saharan Africa and its endemicity depends on the interaction of environmental factors, vectors, parasites and the host. In Zambia, the negative effect of the break in interventions experienced in the late 2000s varied by regions. Therefore, it was necessary to determine the malaria determinants through the study of: statistical models that have been employed; knowledge of the community in malaria management and control; prevalence of malaria and presence of social and community-related factors influencing malaria control in selected communities; contribution of other social and environmental determinants of malaria from the household point of view; and also socio-economic and climatic determinants of malaria at provincial level, in Zambia.

This work was achieved through a number of methods beginning with a systematic review of studies that have identified socio-economic and eco-environmental determinants of malaria through the use of statistical models in malaria burden determination and prediction in southern Africa. We also conducted a cross-sectional survey employing a simple random sampling technique to administer questionnaires to 584 household heads from selected communities, on the following components: knowledge, attitude and practices in malaria control; the role of social and community-related structures in malaria burden and control; and water sources and practices as well as housing structures in relation to self-reported malaria infections. Malaria testing was also performed using a rapid diagnostic test (RDT) in 756 individuals sampled from the 584 households. The household-level data was analysed in STATA and WinBUGS whereas the provincial-level malaria cases, government socio-economic and remotely-sensed climatic data were analysed in STATA, WinBUGS and also in R- integrated Nested Laplace (R-INLA)

The focus of the studies conducted in southern Africa reviewed, has mainly been on malaria determinants related to intervention strategies and climatic factors. Additionally, the use of Bayesian statistical modelling was quite low (29.2%) in the studies reviewed. The community knowledge study showed that although knowledge levels in malaria were high they were not interrelated with attitudes and practices. In the malaria testing survey, a higher infection rate was seen in children and the highest RDT malaria prevalence was recorded in communities of Luapula province. Relating malaria burden with the role of community health workers (CHWs) in malaria control, malaria prevalence was inversely related with CHWs presence in Western Province. On the other hand, relating malaria burden with water practices and housing structures, "river" as a water source was the main predictor. The Bayesian hierarchical (or Generalised Linear mixed model) and R-INLA based models showed that region on one hand and region, time and precipitation on the other, were strong predictors of malaria incidence.

More research in the area of statistical modeling as well as in other areas such as behaviour change, strengthening of existing CHW and exploring new avenues with regards to community social structures and ecological and climatic factors by locality is a great need.

PREFACE

The work described in this thesis was carried out in the School of Life Sciences, University of KwaZulu-Natal, Westville campus, from July 2012 to December 2015, under the supervision of the following academic staff:

Professor Samson Mukaratirwa, Dean and Head of School of Life Sciences, University of KwaZulu – Natal, Westville campus, Durban;

Professor Enala Tembo-Mwase, Deputy Vice Chancellor and Lecturer School of Veterinary Medicine, University of Zambia, Great East Road campus, Lusaka;

Dr. Michael T. Gebreslasie, Lecturer School of Environmental Sciences, University of KwaZulu –Natal, Westville campus, Durban.

The studies in this thesis represent original work by the author and have not otherwise been submitted in any form for any degree or diploma to any tertiary institution. Where use has been made of the work of others, it is duly acknowledged in the text.

Signed:______________ Name: Nzooma M. Shimaponda Date: 1st December, 2015

As the candidate's supervisors, we have/have not approved this thesis for submission.

Signed:______________ Name: Professor S. Mukaratirwa Date: 1st December, 2015

Signed:______________ Name: Professor E. Tembo-Mwase Date: 1st December, 2015

Signed:______________ Name: Dr. M. T. Gebreslasie Date: 1st December, 2015

DECLARATION 1 – PLAGIARISM

I, Nzooma Munkwangu Shimaponda declare that:

1. The research reported in this thesis except where otherwise indicated, is my original research.
2. This thesis has not been submitted for any degree or examination at any other university.
3. This thesis does not contain other persons' data, pictures, graphs or other information unless specifically acknowledged as being sourced from other persons.
4. This thesis does not contain other persons' writing unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:
   a. Their words have been re-written, but the general information attributed to them has been referenced
   b. Where their exact words have been used, then their writing has been placed in italics and inside quotation marks, and referenced.
5. This thesis does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source being detailed in the thesis and in the References sections.

Signed:______________ Name: Nzooma M. Shimaponda Date: 1st December, 2015

DECLARATION 2 – PUBLICATIONS

1. **Shimaponda-Mataa NM, Tembo-Mwase E, Gebreslasie M, Mukaratirwa S.** (2015). Socio-economic and eco-environmental determinants of Malaria burden based on Spatial and Temporal Statistical models in Southern Africa: a review. *In press (Infectious Diseases of Poverty)*

2. **Shimaponda-Mataa NM, Tembo-Mwase E, Gebreslasie M, Mukaratirwa S.** (2015). Prevalence of malaria and influence of community health workers in the prevention and control of malaria in four endemic provinces of Zambia: Bayesian multi-level analysis. *In press (Acta Tropica)*

3. **Shimaponda-Mataa NM, Tembo-Mwase E, Gebreslasie M, Mukaratirwa S.** (2015). Influence of water sources and housing location and structure on self-reported malaria: A Bayesian multi-level analysis. *In press (Malaria Journal)*

4. **Shimaponda-Mataa NM, Tembo-Mwase E, Gebreslasie M, Mukaratirwa S.** (2015). Knowledge, attitudes and practices in the control and prevention of malaria in four endemic provinces of Zambia. *In press (South African Journal of Infectious Diseases)*

5. **Shimaponda-Mataa NM, Tembo-Mwase E, Gebreslasie M, Mukaratirwa S.** (2015). Influence of socio-economic factors on the incidence of malaria in four endemic provinces of Zambia: A Bayesian hierarchical analysis. *Not submitted yet*

6. **Shimaponda-Mataa NM, Tembo-Mwase E, Gebreslasie M, Mukaratirwa S. and Achia, T. N. O.** (2015). Modelling the influence of minimum and maximum temperature and rainfall on the incidence of malaria in four endemic provinces of Zambia using a structured additive *Semiparametric Poisson regression* model. *In press(Acta Tropica Journal)*

The first publication is a review paper which focusses on socio-economic and eco-environmental determinants of malaria in southern Africa and was composed by the first author, under the guidance of supervisors, Prof Samson Mukaratirwa, Prof Enala Tembo-Mwase and Dr Michael Gebreslasie. The first author conducted the literature search while Prof Mukaratirwa validated the search outcomes. The first author composed the initial report which the other authors read and edited. All the authors accepted the final version as an accurate representation of their input.

The last five studies were conceptualised by all the authors. The first author proposed the design of the study and collected as well as analysed the data while the supervisors Prof Samson Mukaratirwa, Prof Enala Tembo-Mwase and Dr Michael Gebreslasie guided in the considerations for data collection and analysis. Dr Thomas N. O. Achia guided in the statistical analysis of the last paper. The first author drafted the manuscripts and all authors contributed to the interpretation and presentation of data and read, edited and approved the final manuscript.

Signed: NMMalaa Name: Nzooma M. Shimaponda Date: 1st December, 2015

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LIST OF ABBREVIATIONS

ACT	Artemisinin-based Combination Therapies
AMOVA	Analysis of Moving Variance
ANOVA	One Way Analysis of Variance
ARIMAX	Auto-Regressive Integrated Moving Average
AVHRR	Advanced Very High Resolution Radiometer
BMC	BioMed Central
CAR	Conditional Auto-Regression
CFR	Case fatality rates
CHA	Community Health Assistant
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CHWs	Community Health Workers
CRU	Climatic Research Unit
CSA	Census Supervisory Areas
CSO	Central Statistical Office
DALY	Disability-Adjusted Life-Years
DFA	Dynamic Factor Analysis
DIC	Deviance Information Criterion
GARMA	Generalised Auto-Regressive Moving Average
GIS	Geographical Information System
GLMs	Generalised linear models
GLMMs	Generalised linear mixed models
GMRF	Gaussian Markov Random Field
HMIS	Health Management Information System
ICC	Intra-class correlation coefficient
IPT	Intermittent Preventive Treatment
IRS	Indoor Residual Spraying
ITN	Insecticide Treated Net
KAP	Knowledge Attitude and Practices
LLINs	Long Lasting Insecticide Nets
LP	Luapula
LS	Lusaka
LSM	Larval Source Management

LST	Land Surface Temperature
LP DAAC	Land Processes Distributed Active Archive Centre
MAUP	Modified Areal Unit Problem
MBG	Model-Based Geostatistics
MCMC	Markov Chain Monte Carlo
MDA	Mass Drug Administration
MIS	Malaria Indicator Survey
MODIS	Moderate Resolution Imaging Spectroradiometer
MOH	Ministry of Health
MPAC	Malaria Policy Advisory Committee
MSL	Medical Stores Limited
NDVI	Normalised Difference Vegetation Index
NMCC	National Malaria Control Centre
NW	North-western
PCR	Polymerase Chain Reaction
*Pf*PR	*P. falciparum* Parasite Rate
PHC	Primary health care
PHO	Provincial Health Offices
PMC	PubMed Central
PSU	Primary Sampling Units
RACD	Reactive Case Detection
RDT	Rapid Diagnostic Tests
R – INLA	R version of Integrated Nested Laplace
RR	Relative Risk
RW	Random Walk
SD	Standard Deviation
SEAs	Standard Enumeration Areas
TV	Television
UCSB	University of California, Santa Barbara
UN	United Nations
UNICEF	United Nations Children's Fund
UNZA	University of Zambia
USGS	U. S. Geological Survey

W	Western
WBCs	White Blood Cells
WHO	World Health Organisation
WinBUGS14	Windows version of Bayesian inference Using Gibbs Sampling 14
ZIP	Zero-Inflated Poisson
ZMW	Zambian Kwacha

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LIST OF SYMBOLS

°C	Degrees Celsius
%	Percent
mm	Millimetres
<	Less than
>	Greater than
$f^{(a)}$	Unknown smoothing functions of covariates
β_r	Vector parameters
Z	Critical value
P	Proportion of study group
D	Standard deviation
pD	Effective number of parameters
Pop	Total population
I	Malaria incidence rate
M	New malaria cases

CHAPTER 1

GENERAL INTRODUCTION

1.1 Introduction

Malaria accounts for a global burden estimated at 214 million cases and 438,000 deaths in a given year with 80% of the cases and 90% of the deaths occurring in Africa [1] where it remains the principle reason for ill-health and deaths [1, 2 – 4]. Apart from the well-known key players i.e. the parasite, the host and the vector, in the disease triangle, a number of factors contribute to the burden and these range from biological [5], socio-economic [6] and eco-environmental [7]. Malaria, like many other diseases, is spatially-determined and as such, the determinants vary over space and time [5].

In Zambia, malaria is endemic throughout the country, although the burden of the disease varies by zones [8]. These transmission zones are defined as follows: "Zone I-very low transmission with a parasite prevalence of less than 1%; Zone II-low to moderate stable transmission with a parasite prevalence of 2-14%; Zone III-moderate to high transmission with a parasite prevalence above 15%" [8]. The control of malaria has brought about implementation of various interventions and comprehensive research based on various methods, with the recent being the use of models [9, 10].

The "Primary Health Care" (PHC) programme, a strategy recommended by the World Health Organisation (WHO) [11] to "minimise the critical shortage of human resources in the health sector" [12] is one of the many interventions in Zambia. It utilises Community Health Workers (CHWs) to deliver health care, although the support and performance of this cadre has been varying over the years in different communities [13]. Other interventions have been conducted both at household- and provincial Ministry of Health programme- levels such as, insecticide treated net (ITN) use and or distribution and indoor residual spraying (IRS), rapid diagnostic tests (RDT) and Artemisinin-based Combination Therapies (ACT) coverage, although the net gains fall short of the required resources [1, 14, 15]. Most of these interventions have been recently changed to meet current challenges of drug and treatment resistance at the expense of a moderately performing economy [16].

The economic growth recorded in Zambia over the recent years has not translated into significant poverty reduction [17] as "over half of the population lives below the poverty line" and 42% are considered to be in extreme poverty [17, 18]. In spite of this reality, research reveals a need for more investments to contain the resurgence [8, 19] and reduce the burden of malaria.

The area of water management has not received much attention [20] regardless of the fact that the ecology of the disease in question is closely-linked with water [21] and of varied sources and kinds [21, 22]. The characteristics of water types that support malaria vectors, particularly the *Anopheles gambiae,* the primary vector in Africa [23] have been shown to vary [23, 24], depending on the source i.e. natural or man-made [20, 23 - 28].

Eco-environmental factors such as climate, landscape, housing structure [1] and proximity of households to vector breeding sites contribute to the disease burden either by affecting vector and parasite development [29] or by facilitating exposure of community members to vectors [24]. However, a number of studies conducted with regards to climate have shown variations in factor types influencing malaria [30 – 32].

Another area requiring attention is in malaria knowledge studies where, although Zambia has made significant efforts since the late 90s, appreciation of the contribution of these studies is recent, as in the case of Swaziland [33]. Moreover, malaria knowledge level and its relationship with treatment seeking practices or ITN use have been shown to vary in different communities all over the world [34 – 36].

1.2 Objectives of the study

This study contributes to the body of knowledge with reference to the fluctuating burden of malaria in Zambia. Specifically, and coincidentally similar to the global situation, Zambia reported a drop in malaria cases which was highly associated with the control efforts that had been taking place before the economy-related break in interventions [8]. The break in interventions later reversed the impact of the control efforts and yet the reversal was not uniform across all provinces. This study is in line with the WHO goals to "improve understanding of how climate-related and other ecological factors affect the spread and severity of malaria" [37] and hence contribute to strategies to "reduce malaria deaths to zero by 2015" [38], as it generated Zambia-specific information on the factors contributing to the burden. Until now, socio-economic and eco-environmental studies conducted in Zambia had not been in perspective of the transmission zone stratification nor at the lowest population structure level. The following specific objectives inform the general outline of the study for the specific research areas:

1. To determine the socio-economic factors of malaria at household level in four malaria endemic provinces of Zambia
2. To determine the eco-environmental factors of malaria at household level in four malaria endemic provinces of Zambia
3. To investigate the knowledge, attitudes and practices in malaria control in communities of four malaria endemic provinces of Zambia
4. To determine the influence of socio-economic factors on malaria at province level in four malaria endemic provinces of Zambia
5. To determine the influence of climatic factors on malaria at province level in four malaria endemic provinces of Zambia

1.3 Outline of the thesis

This thesis is presented in eight chapters, as follows: a general introduction (chapter 1), literature review (chapter 2), five research chapters (Chapters 3 -7) and general conclusions (Chapter 8). Six of the eight chapters were prepared in a peer-reviewed publication format and five were submitted to peer-reviewed journals.

CHAPTER 1, 'General Introduction' provides an introduction on the malaria problem in Zambia as well as the justification for the study.

CHAPTER 2, 'Literature Review' explores the potential of studies conducted at various population structure levels and transmission level perspectives, to determine factors responsible for malaria burden and risk and the variation in factors among different localities. The challenges highlighted as encountered with current data in predicting burden or risk in specific communities, were noted. Further, a comprehensive assessment of the information from the reviews on the socio-economic and eco-environmental determinants of malaria identified through spatial and temporal statistical models in burden and risk studies in southern Africa is provided. The review was conducted with a bias in the lowest population structure i.e. the standard enumeration areas (SEAs), and the perspective of different transmission zones. As such, the value of the use of a combination of both the lowest population community structure, the SEAs as well as the provincial levels in perspective of malaria transmission zones and with a balance in both socio-economic and eco-environment to identify factors responsible in malaria risk and burden and through modelling by the versatile Bayesian approach is discussed.

In CHAPTER 3, ‘Socio-Economic Factors of Malaria at Household Level in Four Malaria Endemic Provinces of Zambia’, the prevalence of malaria and influence of community health workers in the prevention and control of malaria in the four provinces is explored using a Bayesian multi-level analysis. An understanding of the factors at the micro-level was necessary as a precursor to the bigger picture in later chapters.

CHAPTER 4, ‘Eco-environmental Factors of Malaria at Household Level in Four Malaria Endemic Provinces of Zambia’ investigates the influence of water sources and housing location and structure on self-reported malaria using a Bayesian multi-level analysis.

CHAPTER 5, ‘Investigating Knowledge, Attitudes and Practices in Malaria Control in Communities of Four Malaria Endemic Provinces of Zambia’ describes the role and knowledge of the community in the malaria triangle, and discusses the potential of communities to contribute to malaria control and prevention in Zambia. The options of enhancing information through available channels such as health facilities, radio and community health workers (CHWs), depending on the local settings and based on tailor-made strategies are explored. We also explored options such as enhanced community-level efforts to assess the needs and cover the different communities with befitting protection. The advantages of addressing socio-cultural issues, along with many factors such as distance to health facilities and environmental issues which remain unique for the various zones are highlighted.

CHAPTER 6, ‘Socio-economic Determinants of Malaria at Province Level in Four Malaria Endemic Provinces of Zambia’ describes and evaluates influence of socio-economic factors on the incidence of malaria in four endemic provinces of Zambia using a Bayesian hierarchical analysis and discusses the challenges of data gaps as well as the potential of data management in the development of models.

CHAPTER 7, ‘Climatic Factors of Malaria at Province Level in Four Malaria Endemic Provinces of Zambia’ describes and evaluates the minimum and maximum temperature and rainfall on the incidence of malaria in four endemic provinces of Zambia using a structured additive *Semiparametric Poisson regression* model.

CHAPTER 8, ‘General conclusions’ provides a concise analysis of the implications of the study findings.

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CHAPTER 2

LITERATURE REVIEW

*This chapter is based on:

Shimaponda-Mataa NM, Tembo-Mwase E, Gebreslasie M, Mukaratirwa S. 2015. Socio-economic and eco-environmental determinants of Malaria burden based on Spatial and Temporal Statistical models in Southern Africa: a review. *In press (Infectious Diseases of Poverty)*

Abstract

Malaria is one of the key public health issues still affecting millions of people around the world, especially in Africa. Temporal and spatial statistical models have been in use globally, to guide malaria control through risk and burden determination and prediction. However, the extent to which these methods have been developed and operationalised in southern Africa and whether they account for the perspective of malaria transmission zones is not clear. It was necessary to review literature focussed on socio-economic and eco-environmental factors of malaria identified using spatial and temporal statistical models.

Literature searches using the terms, “geospatial analysis” OR “temporal analysis” OR “remote sensing” OR “earth observation” OR “geographical information systems” OR “prediction” OR “modelling” OR “statistical” AND “malaria” AND “social economic” OR “socio-economic” AND “ecological environmental” OR “eco-environmental” AND “southern Africa” were conducted on PubMed Central (PMC) and Google Scholar to identify relevant studies published from 2006 to 2015. BioMed Central (BMC) was also searched to reduce bias. English language studies which reported on socio-economic and eco-environmental determinants in southern Africa based on malaria burden statistical models were included.

Out of the 322 potentially relevant studies retrieved, 48 met the inclusion criteria. Generally, 27 (56.3%) out of the 48 relevant studies identified socio-economic factors while the remaining 21 were eco-environmental. Models utilised in the studies included both frequentist and Bayesian approaches, with majority (70.8%) being frequentist. Some of the study results opened new avenues for future research. The following determinants of malaria burden and risk were identified: Indoor Residual Spraying (IRS), Reactive Case Detection (RACD), Insecticide Treated Net (ITN)/Long Lasting Insecticide treated Net (LLIN), serologic diagnostic tools, Intermittent Presumptive Treatment (IPT), fever, age, province, household wealth; country border locations, rainfall, temperature, altitude, parasitaemia prevalence, incidence, elevation and low lying areas, larviciding, travel outside the city, vapour pressure, humidity salinity, vector presence and nocturnal dew point.

The focus in the majority of the studies was on climatic variables and intervention strategies on the eco-environment and socio-economic fronts respectively. No studies were done in perspective of transmission zones and minimal focus was placed on economic factors. Very few malaria burden or risk determination studies utilised the Bayesian analysis approach. We recommend the use of the versatile Bayesian

approach in modelling, with a balance in the use of both socio-economic and eco-environment factors. Further, we propose the implementation of models to be conducted at both the lowest population community structure, the standard enumeration areas (SEAs) as well as the provincial levels and in perspective of malaria transmission zones.

Key words: Malaria, socio-economic, eco-environmental, spatial, temporal, statistical, models, Bayesian, inferential

2.1 Introduction

Globally, large proportions of resources continue to be invested in malaria control, in a bid to alleviate the burden and ultimately eliminate the disease. Numerous efforts in the form of research, goal-setting [1] and actual implementation of treatment, control and elimination programmes [2, 3] have been put forth in the fight against this disease. In 2011, the United Nations (UN) Secretary-General declared a goal to reduce deaths due to malaria to zero by the year 2015 [1] and great progress has been made in this regard as evidenced by the rapid scale-up of control efforts globally [4]. These efforts have so far realised a rapid decrease in morbidity and mortality of malaria [5, 6] although it remains the leading cause [7] in the developing world [4, 8, 9]. The World Health Organisation (WHO) estimates that 198 million cases and 584,000 deaths worldwide per year are attributable to malaria and further reports that 80% of the cases and 90% of the deaths occur in Africa [4].

Determinants of malaria range from biological [10], socio-economic [11] and eco-environmental [12] and they vary over space and time [10]. Disease is a spatially-determined phenomenon considering that space is the stage where factors leading to disease take place [10].

Socio-economic factors for malaria risk and burden at regional level include the availability of financial, insecticide chemical, antimalarial treatment, diagnostic, human and programme-based resources of individual states to the fight against malaria [4]. Apart from the regional level, similar factors also have a bearing at household level. Some of the factors contributing to the malaria burden at household level include: the level of income and education, availability of Insecticide Treated Nets (ITN), Indoor Residual Spraying (IRS) antimalarial treatment and drainage system management as well as the involvement of community members in the uptake of available resources [4]. In the WHO African Region, funding towards malaria control programmes increased “at an annual average rate of 22% and 4% per year between 2005 and 2013 in international and domestic investments” respectively with the region accounting for 72% of total global malaria funding in 2013 alone compared to 50% in 2005. At global level, although the 2013 total malaria funding increased by 3% and exceeded that of any other year in the past, it represented only 52% of the annual estimated requirement of USD 5.1 billion to attain international targets for malaria control and elimination" [4]. With regards to ITN access in sub-Saharan Africa, coverage increased from 5% in 2004 to 67% in 2013, yet in 2013 alone, only 29% of households had enough ITNs for all members [4]. In IRS, the WHO African region accounts for the highest IRS coverage rates among all WHO regions although the proportion of at risk population protected from malaria by IRS had reduced from 11% in 2010 to 7% in 2013 and globally, more than half of the countries using insecticides were not monitoring insecticide resistance in the year 2013. Diagnosis of malaria by testing malaria suspected individuals also ranks highest in the WHO African region compared to other WHO regions with an increase from 47% in 2010 to 62% recorded in 2013. About 90% of countries endemic to *P. falciparum* had adopted the artemisinin-based combination therapy as national policy for first-line treatment in 2013. On the other hand, eco-environmental factors such as climate and topographic factors contribute to malaria transmission by affecting the vector and parasite development regardless of the region while other factors like housing structure [4], proximity of households to vector breeding sites, contribute by facilitating exposure of community members to vectors.

The concept of modelling has been existent from as far back as the 14^{th} to 17^{th} centuries and was mainly applied in the physics field but today it is an integral part of research in many fields, including health [13]. The WHO recognises and recommends modelling to help inform decision-makers in malaria control [14]. The organisation alludes to "the complex biological systems of the disease, the considerable infrastructural and cost requirements of prevention, elimination, and the rapid pace of change in global planning and national programming" as components in the process to eliminate malaria [14]. Generally, models are constructed to assess or interpret causal relationships between response and explanatory variables [15] as well as to "fit past data and predict future trends" [16]. These functions are based on model capability to represent or sufficiently approximate the true generating mechanisms of a phenomenon under study [15]. Specifically, statistical models are defined as a "collection of probabilistic statements that describe and interpret present behaviour or predict future performance and they consist of three components; the response variable, the explanatory variable and a linking mechanism between two sets of variables" [15]. In studying disease such as malaria, this type of modelling involves developing relationships between factors responsible for the infections and the processes involved, in the form of mathematical equations [16]. Until the late 1980s, the classical statistical theory of modelling has been in use much more in comparison to Bayesian statistics which were merely seen as an interesting alternative [15] because of the "intractabilities involved in the calculation of the posterior distribution" [15]. It has been shown that the latter has the capacity to handle more variables [15] and with the rapid evolution of personal computers, allows for analysis of determinants over a wider perspective [15].

Several models have been designed to determine the contributing factors to the malaria burden and variations in findings have been noted [17, 18, 19]: ITNs or long lasting insecticide treated nets (LLINs), IRS and Larva Source Management (LSM) have been shown to be strong predictors in some studies [18, 20, 21] but not in others [17] while yet others recommend the use of the interventions in combination and not as stand-alone [22]. Additionally, among climatic factors, some studies have found only minimum temperature [23], others rainfall only [24] while others a combination of minimum, maximum temperature and rainfall 25]. Further, community factors such as house structures, poverty and level of education [4] also have an impact on malaria burden. It is clear that regardless of the global and regional reduction in the burden, consensus is not yet reached concerning the predictors and the contribution by space and time factors. As such, robust identification of spatial and temporal risk factors remains crucial in prediction, prevention and control of disease [10]. Molecular techniques for species identification, data acquisition, management and analysis systems and tools including modelling, are some initiatives that have dramatically changed the capacity to predict, prevent and control vector-borne diseases [8].

Although studies have been done to determine the factors responsible for malaria burden and risk, the variation in factors among different localities [26] down to the lowest population structure the standard enumeration areas (SEAs), and in perspective of different transmission zones, has not been adequately considered. With current data, it is not easy to predict the burden or risk in specific communities. This review assesses the information from published literature on the socio-economic and eco-environmental determinants of malaria identified through spatial and temporal statistical models in burden and risk studies in southern Africa.

2.2 Review

2.2.1 Materials and methods

2.2.1.1 Sources of information and Literature search

Studies relevant to our purpose were identified through searching online bibliographic databases; PubMed Central (PMC) and Google Scholar databases using the following terms:

“geospatial analysis” OR “temporal analysis” OR “remote sensing” OR “earth observation” OR “geographical information systems” OR “prediction” OR “modelling” OR “statistical” AND “malaria” AND “social economic” OR “socio-economic” AND “ecological environmental” OR “eco-environmental” AND “southern Africa”

The searches were conducted between March and November 2015 to identify relevant studies published from 2006 to 2015 with the last search conducted on 25th November, 2015. The BioMed Central (BMC) database was also searched to widen the search base and reduce bias. All studies that employed statistical methods of spatial and temporal analysis of determinants and predictors of malaria risk and burden in southern Africa were eligible for inclusion. Publication status was not limited to “published-articles” solely for the reason of preventing bias that would result from exclusion of unpublished works. Further, the inclusion criteria were not restricted to specific components of the malaria transmission cycle. The exclusion criteria eliminated studies that provided abstracts only without the full paper, studies that focussed on methods other than statistical studies without original data, studies that involved southern African countries in combination with countries outside southern Africa, studies that were in languages other than English and studies older than 2006 to capture literature within a maximum time frame of ten years.

Examination of the retrieved studies was conducted based on the appropriateness of the title and the abstract to the study focus. Studies whose abstracts met the inclusion criteria were adopted for a full review. The main criterion in the elimination stage was the relevance to our review focus of spatial and temporal statistical models which highlighted socio-economic and eco-environmental determinants and predictors of malaria burden and risk. In some instances, the search words returned studies that did not meet the focus of our review. Such studies were manually eliminated.

2.2.1.2 Selection of relevant studies

A total of 5,186 studies were generated from the PMC and Google Scholar online searches. Three hundred and twenty two studies out of the 5,186 were shortlisted and 41 were selected for consideration in this review. An additional 16 studies were generated from the BMC online search but only seven were added after eliminating repeats, bringing the total number of studies considered in this review to 48. Figure 1

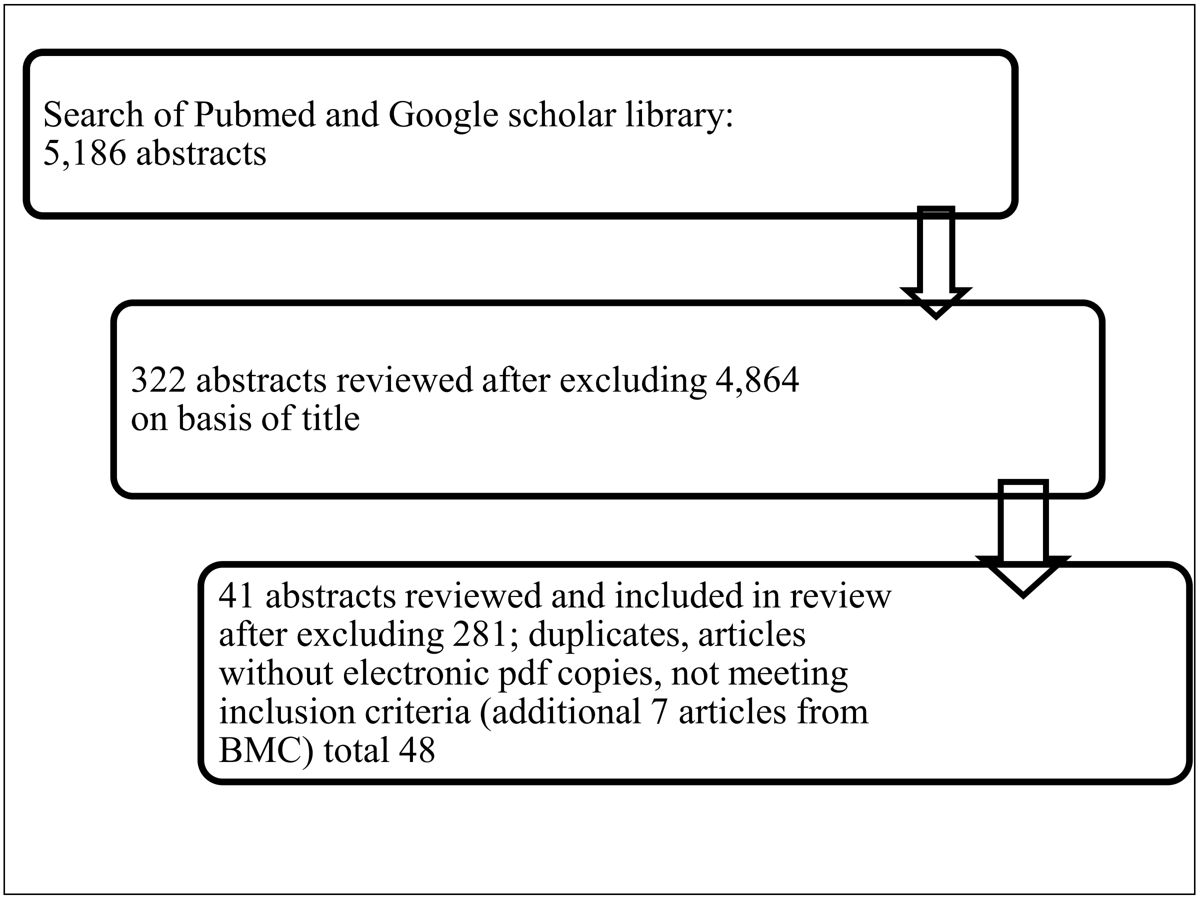

Figure 1: Data retrieval flow chart

2.2.1.3 Data extraction

Data extracted for analysis from the 48 studies was based on the objective of the study and the type of statistical model employed therein. Socio-economic factors in this study were defined as "public and societal and financial resources as well as related coping mechanisms that could help communities reduce their vulnerability to malaria such as control programmes, funding for malaria control and malaria control interventions in terms of ITNs, IRS, treatment" while eco-environmental factors were defined as "organisms, their environment and climatic factors influencing malaria such as mosquito densities, land and / or landscape and climatic variables" both at individual and national (malaria control programme) level. The results of the studies and a summary of their contribution to the body of knowledge were noted.

2.3 Results

2.3.1 Statistical Model types

Overall, our review revealed a variety of statistical models to determine and predict malaria risk and most of the models were hybrid models employed in conjunction with Model-Based Geostatistics (MBG). The logistic regression technique was the frequently applied technique, appearing in 14 studies, with five of them employing it at the multivariate level. Only one study used the Pearson's method and yet another one the proximity analysis in Geographical Information System (GIS). Generalised Linear (GLMs) and Generalised Linear Mixed Models (GLMMs) were used in one and 6 studies respectively while Conditional Auto-Regression (CAR) models were used in three studies with an additional one utilising the CAR structure with Integrated Nested Laplace (INLA). Stepwise regression was applied in three studies, Poisson regression in four and mapping techniques in five. Other techniques encountered in the review although not frequently used, were the Zero-Inflated Poisson (ZIP), Analysis of Moving Variance (AMOVA), Generalised Auto-Regressive Moving Average (GARMA), structured additive, Dynamic Factor Analysis (DFA) time series as well as the Auto-Regressive Integrated Moving Average (ARIMAX) models.

When disaggregated by frequentist versus Bayesian approaches, only 15 studies applied the Bayesian approach in modelling while 33 applied the frequentist approach. The studies demonstrated a combined purpose of both determination and prediction of burden or risk in the statistical models presented.

Tables 1 and 2 present characteristics of the studies that identified socio-economic and eco-environmental determinants, respectively, including details of the statistical models used.

The publications reviewed show that malaria management and control work has mainly been implemented at the two levels of determining the prevailing and predicting the future burden or risk of malaria with regards to the disease itself, the mortality it causes or the vector density. This review assesses the malaria determinants identified through models which are mainly related to control measures [17-20; 27-29], diagnosis and treatment measures [25; 30-43], vector density or potential breeding sites [45-47] and mortality [44].

2.3.2 Socio-economic determinants

The socio-economic factors identified in our review were defined as "public and societal and financial resources as well as related coping mechanisms that could help communities reduce their vulnerability to malaria such as control programmes, funding for malaria control and malaria control interventions in terms of ITNs, IRS, treatment both at individual and national (malaria control programme) level" and were based on how malaria burden or risk relates to factors like intervention strategies including diagnosis, control and treatment [17-19; 27-30; 32, 34, 35, 39-43, 48, 49-53] and individual level characteristics [21, 35-38; 43] and also the relationship between burden or risk in one area to a larger area by means of prediction [32, 42, 54] Table 1.

Table 1: Characteristics of articles retrieved in which models identify socio-economic factors

	Authors	Type of model	Source of data, study design and period	Study location	Outcome of study
1	Skarbinski et al, 2012	Binomial regression; SAS 9.2	Cross-sectional household survey	Targeted endemic areas (SEAs) Malawi	Both direct and indirect IRS associated with parasitaemia and anaemia reduction significantly
2	Chanda et al, 2012	Logistic regression	Retrospective Zambia national Health Management Information System data	Various districts Zambia	Routine surveillance data found valuable for malaria control temporal effects; marked reductions morbidity and mortality with IRS
3	Abilio, 2010	Logistic regression	Data generated in study on vector species abundance, sporozoite rate and insecticide susceptibility; parasite prevalence studies	Mozambique	Assessment of control programme; significant reduction in mosquito abundance and sporozoite rates and malaria prevalence
4	Riedel et al, 2010	Bayesian; Bayesian kriging	MIS data	Nation-wide Zambia	Model to relate parasitaemia risk vs ITN, environmental/climatic predictors of malaria; highest risk in: children of age 5 years and less; in northern province; decreased risk in households with at least one bed net
5	Mace et al, 2015	Poisson regression; SAS 9.3 and procgenmod	Retrospective birth outcomes health facilities based study	Mansa Zambia	Evaluation of SP-IPT; showing each dose and decrease in LBW
6	Hsiang et al, 2011	Poisson regression; SAS 9.2 and STATA 11.0	Study generated data – national cross-sectional study	Swaziland	Model to assess effectiveness of Pooled PCR and ELISA; malaria prevalence was low
7	Kamuliwo et al, 2013	Poisson regression; STATA 11	District surveillance data	Nation-wide Zambia	Model to assess association between IRS, LLIN and malaria burden; reduction observed in some areas with LLIN
8	Roca-Feltrer et al, 2012	Logistic regression; Poisson regression; Stata 10.1	Hospital-based retrospective study Health-facility data	Malawi	Model to assess childhood malaria trends; decline stalled and cerebral malaria admissions not changing significantly even with ITN increase

9	Sutcliffe et al, 2011	Log binomial regression	Satellite image Longitudinal and cross sectional household survey data	Macha Zambia	Model to assess individual-level risk factors; few were correlated with RDT positivity; ITN significant
10	Oliviera et al, 2011	Univariate and multivariate logistic regression; SAS version 9.2	Study generated data – health facility-based survey	Two adjacent districts Mozambique	Model to relate febrility and malaria prevalence; found high prevalence among febrile but both IRS and ITN no relationship with burden
11	Steinhardt et al, 2014	Multivariate logistic regression	National cross-sectional health facility survey	Malawi	models to calculate prevalence ratios and to define determinants of correct malaria case management; ultimately correct malaria treatment – a determinant of burden
12	Hamainza et al, 2014	GLMM	Study generated data	Luangwa and Mumbwa districts, Zambia	Model to assess association of malaria infection with symptoms – significant; and to evaluate association between observed RDT-determined malaria infection status with socio-demo and intervention factors; diagnostic positivity varying at spatial and temporal levels with high consistency across all regions; ITN significant
13	Kobayashi et al, 2012 BMC	Mixed models; linear regression model; Kulldof spatial statistic and a Bernoulli probability model	Serological survey	Zambia	Mixed models - to detect recent malaria infection and identify focal areas of transmission, particularly in a region of declining malaria burden; serological evidence = high malaria risk
14	Sitali et al, 2015	Multivariate logistic regression	Study generated data	Selected districts Zambia	Model to determine malaria burden, species among patients attending public health facilities; age and province determinants of burden
15	Siame et al, 2015	Multivariate logistic regression; Stata 12.2	Cross-sectional study data	Nchelenge, Zambia	Model to assess association between malaria and given age groups; age determinant of burden
16	Chirombo et	Bayesian mapping	MIS data	Malawi	Spatial correlation model for use to estimate malaria

	al, 2014	and structured additive logistic regression			risk factors; i. found that risk factors: increase with approaching age 5; decrease with household wealth; ii. Found nonsignificant association between malaria and rainfall and minimum temperature; iii. but taking into account spatial structure led to more accurate estimates of risk factors iv. Found that biotic and abiotic factors interacting in a complex manner at individual, household and community levels, still relevant as risk factors
17	Namboozi et al, 2014	Multivariate logistic regression	Study generated data	Nchelenge, Zambia	Model to determine malaria burden among patients attending public health facilities; cross-border challenges for intervention coverage and as a result, international collaboration a determinant of burden
18	Gosoniu et al, 2010	Bayesian Logistic regression; Stata 10.0	National Malaria Indicator Survey	Angola	Bayesian Geostatistical models used to assess effect of malaria control interventions along with other factors; parasitaemia and number of children age 5, determinant of country incidence; parasitaemia prevalence and environmental factors
19	Alegana et al, 2013	Bayesian conditional autoregressive; spatial Poisson regression model; Zero-Inflated Poisson (ZIP) model; R version 2.15.2	MOH national service provision assessment survey	Namibia	Bayesian conditional-autoregressive model to model the spatial and temporal variation of incidence; Zero-Inflated Poisson (ZIP) model to handle count data with a lot of structural or excess zeroes; incidence a determinant for risk
20	Noor et al, 2013	Bayesian geo-statistical models; mapping; GLMM	Community-based *Plasmodium falciparum* prevalence data	Namibia	climate risk levels described against rainfall seasons, IRS and mass drug administration (MDA) using community-based survey data from a period of aggressive malaria control Reduction in burden related to interventions varying with periods of time in administering; cross-border challenges

21	Noor et al, 2013	Full Bayesian space-time MBG model	Historical and contemporary *Plasmodium falciparum* prevalence data	Namibia	Maps of *P. falciparum* prevalence; estimate receptive and current levels of malaria risk; highest receptive risks were found along border areas
22	Chirebvu et al, 2014	Pearson's test	Surveys, field observations	Botswana	History of malaria episodes associated with: household income, late outdoor activities, time spent outdoors, travel outside study area, non-possession of ITNs, house structure and homestead location from water bodies
23	Bennett et al, 2013	MBG framework	Cross-sectional community P. F parasite rate data for 2000-2011 from both published and unpublished sources	Malawi	Models to predict mean community *Plasmodium falciparum* rate (*Pf*PR); no evidence of change in 3 consecutive 5 year-periods assessed based on intervention scale-up; need for more investment for change to show ~investment a determinant
24	Sturrock et al, 2013	Forward stepwise Multivariate logistic regression; Stata 12.1	Reactive case detection activities	Swaziland	Model to determine effect of screening radius on probability of detecting RDT positive individuals; showed that the 1km radius is useful but not logistically feasible
25	Searle et al, 2013	Linear regression; logistic regression; MICE or fully conditional specification or sequential regression multivariate imputation ~ for simulation	Cross-sectional household survey data (conducted 5 times per year in two year in each of two study areas	Southern Zambia	Model to predict burden based on extrapolation from known data; reactive case detection within a 500 meter radius from household of an index case would identify more than three quarters of infected individuals
26	Chihanga et al, 2013	Poisson regression; STATA 11	National passive malaria surveillance data	Botswana	Model to assess association between malaria cases and IRS, LLIN coverage; elimination goal in reach; Larviciding a determinant
27	Domarle et al, 2006	Backward stepwise log regression; SPSS 11.5	Serological studies for *P. falciparum*	Madagascar	Model to determine specific seroprevalence; outside city exposure to malaria a determinant

Table 2: Characteristics of articles retrieved in which models identify eco-environmental factors

	Authors	Type of model	Source of study data and study period	Study location	Outcome of the study
1	Kazembe et al, 2006 BMC	Bayesian model-based geo-statistical (MBG)	Point-referenced prevalence data	Malawi	predict malaria risk; maps; elevation and low-lying areas associated with risk
2	Craig et al, 2007 BMC	Spatial-statistical model through staged variable selection procedure; ended with Bayesian geo-statistical	Archived national malaria prevalence survey data	Botswana	Final model of - summer rainfall, mean annual temperature and altitude as predictor variables; predicted malaria prevalence at unobserved locations, produced a smooth risk map
3	Mabaso et al, 2006	Bayesian negative binomial regression; STATA 9.0; WinBUGS	District-level national malaria incidence, climate data	Zimbabwe	Bayesian spatio-temporal model used to describe annual malaria incidence variation ~ climatic risk factors; mean annual temperature, rainfall, vapour pressure and NDVI found to be strong positive predictors of the increased yearly incidence rate
4	Lowe et al 2013	Statistical mixed model; GLMM; hierarchical Bayesian framework	Dataset for malaria cases stratified by age and at spatio-temporal levels	Malawi	The first spatio-temporal model developed for relative risk of malaria; precipitation and temperature related to risk
5	Escaramis et al, 2011 BMC	Proper GLMM at 3 levels; 3 models fitted with GLIMMIX procedure; SAS	Demographic surveillance system (DSS) of mortality study	Mozambique	Model - spatial distribution of mortality similar to spatial distribution of malaria incidence; related to heavy rains
6	Zacharias and Majendler, 2011	Bayesian Poisson regression; CAR and RW	Provincial Health office malaria episodes data and National Institute of Meteorology environmental data;	Mozambique	Bayesian model to determine link of climatic covariates to malaria response; spatio-temporal patterns of malaria incidence driven by humidity and rainfall climatic variables.

7	Nygren et al, 2014	ARIMAX; kriging, mapping	Weekly NMCC weekly rapid reporting system database; remotely-sensed environmental data; NDVI from MODIS; DWP from MOD07-product; LST from MOD11A; elevation data from ASTER; Rainfall estimation called TAMSAT using satellite data and ground-based observations	Southern Zambia	Models used to implement environmental variables used to model past and forecast future transmission; found nocturnal dew point obtained by remote-sensing significantly associated with malaria transmission especially in areas of general aridity during dry season
8	Ricotta et al, 2014	Logistic regression of ImageJ analysed imagery; R version 3.0.0	Google Earth satellite imagery	Choma and Namwala districts, Zambia	Technique to obtain data (imagery) and model to evaluate local vegetation as risk factor; proper usable images resulted; but no factors identified
9	Moss et al, 2011	Risk maps	Quickbird imagery; Remotely sensed images for sampling frame; cross-surveys of malaria parasitaemia	Southern Zambia	Model to identify environmental risk factors for malaria transmission; residing within 3.75km of third order stream ~ increased risk; households above baseline elevation for the region ~ at decreasing risk
10	Abellana et al, 2008 BMC	Spatial and non-spatial models; Poisson regression analysis, Bayesian methods using Gibbs Sampling	Cohort study data using active case detection methods	Mozambique	To model the incidence of malaria during climate seasons; found climate modifies incidence but does not change spatial pattern
11	Davis et al, 2011	Poisson	Weekly surveillance health facility based data - divided into three transmission zones	Southern Zambia	Early warning system or early detection threshold; thresholds generally conformed to observed seasonal incidence patterns although the system could do better with more years of surveillance data; investment related to burden

12	Zacarias and Andersson 2010 BMC	Bayesian hierarchical Poisson model	District-level malaria incidence data	Mozambique	Two seasonal dependent models used to identify important predictor variables and to produce a malaria distribution map; found that incidence displayed an independent pattern with temperature and rainfall at spatial level
13	Zacarias and Andersson 2011 BMC	Conditional autoregressive (CAR) process	Malaria incidence data	Mozambique	Model found malaria incidence to be influenced by environmental conditions BUT limited use for predicting malaria incidence
14	Campos-Bescos et al, 2013	DFA a multivariate time series (Predict landscape change)	MODIS data remotely sensed of monthly NDVI and a suite of monthly environmental covariates	Southern Africa (i.e. over mostly Angola and Zambia and parts of Botswana, Namibia, Congo;	Model with DFA approach for application to remote sensing products for regional analyses of landscape change shows that temperature and evapo-transpiration crucial
15	Namuchimba, 2007	Stepwise regression then Multiple regression; SPSS 11.0	Thesis generated data in one district	Zimbabwe	Model to determine the correlation between larval density and the ecological variables; abundance of mosquito larvae positively correlated with salinity
16	Clennon et al, 2010	Survey; Univariate logistic regression; GLMM; Stata 8.2	Data obtained through remote sensing as well as landscape indices obtained from terrain methods	Zambia	Model - successful at ruling out potential locations, but limited ability in predicting which anopheline species inhabited aquatic sites but good for area since ground-based methods, challenging; topographic position, slope indices correlated with water and vector presence
17	Kent et al, 2007	Bayesian structural analysis of moving variance AMOVA	Study generated data	Macha and Namwala districts, Zambia	Model to determine spatial and temporal genetic structure of mosquitoes by drought/wet years and to determine genotype frequency difference; little evidence of genetic structuring over the years i.e. drought little impact
18	Sikaala et al, 2014	GLMM; Poisson generalized autoregressive moving average	Study generated data	Luangwa and Nyimba districts, Zambia	Model to estimate how mosquito abundance predicts malaria infection risk among the human population; CB trapping proved practical, effective, cost effective; vector density predictor of risk

		(GARMA)			
19	Norris and Norris, 2013	SaTScan Bernoulli model	Study generated data	Macha Zambia	Model to estimate spatial independence of cases; substantial heterogeneity was seen in malaria risk at household level influenced by ITNs interventions
20	Townes et al, 2013	GLMs	Household level environmental study	Malawi	Model to investigate household level environmental drivers of malaria risk during dry season and found active agriculture as a significant predictor of positive RDT
21	Rakotomanana et al, 2010	GIS	Remotely sensed climatic data	Madagascar	Model using geographical information system to integrate and analyse various data: surface area of rice field, altitude, rainfall, temperature and population density Found no direct relationship between geographical and environmental factors with malaria incidence but they seemed to be supporting suitability of vector development;

A number of studies have used models to determine whether malaria parasitaemia could be estimated based on malaria control methods [18-20; 27], the relationship between interventions such as IRS and ITNs and parasitaemia [18, 20] and to estimate the average effects of particular interventions on prevalence [20]. The association of IRS with low parasitaemia, holding ITN effect and other variables constant [17-18; 28], was demonstrated in studies [18; 28] conducted in targeted endemic areas using the systematic random sampling of the lowest population structure (the SEAs) [18] and in studies conducted based on national district-level malaria case data utilising district-level random effects [17]. This association was shown in circumstances of both direct and indirect IRS exposure [18] where non-IRS areas also experienced reduced parasitaemia based on the community-wide effect of IRS [18]. Other models used to assess spatio-temporal aspects of parasitaemia [19; 30; 34] and Case Fatality Rates (CFR) [19] found IRS but not LLIN related to reduction in mortality. These findings were obtained from district and health facility-based studies respectively conducted to assess interventions [19]. In the health facility-based study the admissions due to malaria did not differ by the period under review although ITN use had increased while IRS coverage remained low [30].

While some studies only showed a relationship between malaria burden and IRS [17-19; 28, 30, 34], other studies demonstrated a relationship between ITNs and malaria burden [29, 34, 43] and yet another [35] found no relationship for both IRS and ITN with malaria status.

Enhanced diagnosis and treatment were also found to be determinants for malaria infection status [43]. The use of serological responses to *Plasmodium falciparum* antigens as a control strategy facilitated to detect recent malaria infection and identify focal areas of transmission using mixed models showing that serological evidence of recent malaria overlapped areas of high malaria risk even when parasite prevalence was low [53]. With regards to treatment as a control measure component, health facility-based studies [27, 41] showed that correct malaria treatment was a determinant of burden [41] and specifically that Intermittent Preventive Treatment (IPT) was related to reduction in malaria parasitaemia [27].

Among the social factors, individual level characteristics have also been identified as determinants of malaria infection [35; 43], prevalence [37; 38] and mixed *Plasmodium* species [37] although over time, the factor composition has been reducing [35]. The reduction is evidenced by the reports of fever only, vomiting, headache, diarrhoea [43], age and province [37] and age only [38], age and ITN ownership [7, 55] and age and household wealth [21, 55], late outdoor activities and the time spent outdoors, travel outside the city, house structure and location from water bodies [55]. A study based on a health facility-level study, attributed the reducing individual level characteristics to lack of uniformity in scaling up malaria control strategies in sub-Saharan Africa [35], qualifying "difficult to reach" locations as determinants for malaria burden. In this regard, another study in a survey forming part of a multicentre study [36], found ITN and IRS coverage to be low in the high malaria transmission setting, and alluded to country border locations as a determinant for coverage of control interventions. Most border areas are difficult to reach due to poor terrain [36] conforming to the suggestion that international collaboration is a factor in reducing malaria burden in such areas [36].

Some models were used to determine risk levels [48, 54], parasitaemia rate in the community over the years [49], number of malaria infected children [32] in relationship to disease burden or risk. The risk levels were described against rainfall seasons, IRS and Mass Drug Administration (MDA) using community-based survey data from a period of aggressive malaria control [48]. In this case, the relationship between factors was demonstrated as a pattern of reduction in burden varying by period of interventions where the earliest period showed lowest incidence reduction, the middle-period significant reduction and a rebound in the last period [48]. To explain this pattern, the authors alluded to, not only intervention coverage but also the lack of it, enhanced by inaccessibility of some places for interventions, cross-border population during war times, chloroquine resistance, climatic anomalies [48] among others. Another study reported highest receptive risks along border areas [54]. Others [49], with the use of compiled community *P. falciparum* parasite rate (*Pf*PR) over a period of malaria control scale-up predicted mean *Pf*PR and showed no evidence of change in prevalence over the scale-up period [49]. These findings confirmed predictions that prevalence reductions in high transmission settings require greater investment over a longer period [49]. Yet other studies predicted and estimated the count of children infected with malaria in that country based on estimating the prevalence of parasitaemia combined with the count of children who had not attained the age of 5 [32] and used the incidence calculated to predict risk [42] respectively.

A Reactive Case Detection (RACD) study to detect cases originally missed by passive surveillance [39] in low malaria transmission settings, found the RACD technique to be an indicator of sufficiency of IRS and ITN coverage suggesting that the apparent protective effect of IRS would be of value in reducing cases around index houses and also that a screening radius of a kilometre or more would be impractical [39]. Other malaria detection studies [50-52] used models to predict malaria burden based on unknown locations [50, 52]. A cross-sectional household survey [50] which employed both passive and active case detection for estimating the proportions of malaria-infected individuals through simulations, extrapolated data from sampled to unsampled households [50] and showed that a radius of 500 meters from an index case was suitable to identify over 70% of Rapid Diagnostic Tests (RDT) positive cases [50].

Other determinants of malaria burden that have been identified in literature are larviciding using *Bacillus thuringensis* a malaria control strategy which contributes to the reduction in the burden through reduction of larval densities [17] and also travel outside the city to endemic areas, a factor that was significantly associated with higher sero-prevalence of malaria [40].

2.3.3 Eco-environmental determinants

Eco-environmental determinants of malaria in this study defined as "organisms, their environment and climatic factors influencing malaria such as mosquito densities, land and / or landscape and climatic variables both at individual and national (malaria control programme) level" have been identified using various models and sources of data (Table 2). In our review the climatic factors identified were elevation [51], temperature [25; 52; 56], rainfall [25; 44; 48; 52; 56; 57], vapour pressure [25], humidity [55] and altitude [21; 52].

A study using empirical data collected from literature, predicted and mapped the risk of malaria in places where data was not observed and showed an association between malaria risk and the variables elevation and low lying areas [51] while another study [52] using a "systematic and practicable variable selection process" in spatial analysis and risk-mapping based on archived malaria prevalence data [52], identified rainfall (that occurred in the summer season), mean annual temperature and altitude as predictor variables for malaria prevalence [52]. They also used the model to predict malaria prevalence at unobserved locations [52].

Similar climatic factors were identified in studies that utilised district level data [25, 56] as well as district level climatic and normalised difference vegetation index (NDVI) data from climatic research unit (CRU) and advanced very high resolution radiometer (AVHRR), employing a year-specific random effect [25]. The studies found that rainfall, average temperature and vapour pressure were strong positive predictors [25, 56] and that while the annual variation in malaria incidence was determined mainly by climate, the spatial risk pattern that resulted could have been influenced by other risk factors [25]. Using Bayesian models to determine the link between climatic covariates and malaria revealed that spatio-temporal patterns of malaria incidence were mainly driven by humidity and rainfall climatic variables [57] while a spatio-temporal analysis of mortality revealed that both mortality and incidence were each related with heavy rains as well as with each other [44]. Some studies [7, 21] based on Malaria Indicator Survey (MIS) data and control interventions estimated malaria risk factors and both models revealed age [7, 21] apart from climatic factors [21] and ITN ownership [7] as other factors.

In "areas of general aridity during dry season" [58], remotely-sensed nocturnal dew point with the use of ARIMAX models was found significantly associated with malaria transmission [58]. Other studies utilised imageries to evaluate land factors [31; 33] as malaria risk factors: one [31] evaluated vegetation cover using a simulation imagery called "ImageJ" based on RDT positivity of cases [31] although they did not identify any specific environmental and climatic factors significantly associated with malaria risk; another [33], using a "pan-sharpened Quickbird" imagery, evaluated a hydrological model in prospective longitudinal and cross-sectional surveys and found that living within a radius of 3.75km of a third order stream was related to increased risk of malaria [33]. They also generated a risk map that allowed for extrapolation of malaria risk [33]. On a similar note but at household level, one study used GLMs to investigate household level environmental determinants of malaria risk during dry season and found active agriculture as a significant predictor of positive RDT [59].

Studies also modelled incidence of malaria using climate season [60, 61] by a hierarchical Bayesian approach in a district-level cohort study [60] and piloting of an early warning system in an area of low malaria transmission [61]. These studies found that the incidence of malaria presented a spatial pattern which was independent of seasonal climatic conditions in that while climate modified the incidence of disease, it did not change the spatial pattern of it [60] and that thresholds generally conformed to observed seasonal incidence patterns although the threshold calculations showed inconsistent reliability and questionable validity [61]. The reliability and validity issues suggested that the system could do better with more years of surveillance data [61]. Further in using seasons to model malaria incidence, a two-season dependent Bayesian hierarchical model was used to identify important predictor variables and to produce a malaria distribution map [62] in a district-level study and found that the incidence of malaria displayed an independent pattern for temperature and rainfall in summer winter respectively at spatial level [62]. Another study, using a CAR model found that malaria incidence was influenced by environmental conditions although their model showed limited use for predicting malaria incidence [63].

In landscape analysis, one study utilised a model with DFA time series approach for application to remote sensing products as a way of identifying the key physical factors responsible for vegetation cover in a particular region [64]. Their study revealed the known predictors precipitation, soil moisture and fire on

NDVI and also the overlooked effects of temperature and evapotranspiration which are critical in higher mean annual rainfall areas [64]. Geographical information systems were used to integrate and analyse various data such as surface area of rice field, altitude, rainfall, temperature and population density in Madagascar. They found no direct relationship between geographical and environmental factors with malaria incidence although these factors seemed to support suitability of vector development while imported malaria cases, the pocket transmission in the city [65].

Malaria vectors as an indication of malaria burden have also been studied along with their determinants. Regression analysis has been employed to identify vector densities and the determinants [45] using stepwise and multiple regressions. The technique has also been used to relate terrain-based landscape indices, along with LandSat imagery, with vector presence [46] using univariate, backwards general linear logistic and generalised linear mixed regression techniques. In a terrain-based study [45] conducted in one district, vector density was positively correlated with salinity but not ecological factors like pH, dissolved oxygen, temperature [45]. Additionally, topographic position and slope indices were correlated with water and vector presence [46]. In another vector study, based on studies that have shown polymorphic chromosomal inversions being influenced by arid climate, Bayesian AMOVA was used to determine the impact of drought on the genetic diversity of vector *An. arabiensis* [47]. The study observed that drought had little overall impact [47]. Other malaria risk studies [66, 67], estimated how mosquito abundance predicts malaria infection risk among the human population [66] and determined malaria risk based on vector density in view of ITN interventions [68]. The former showed how cost-effective tools like solar-recharged light traps can be used to yield vector density which can be used to predict malaria risk infection [66].

2.4 Discussion

Our review revealed opportunities for further research to strengthen the capacities of control programmes in identifying determinants for malaria through modelling and mapping and thereby guide the development of warning systems and targeted control programmes. Malaria modelling has been performed at all levels of the transmission cycle: parasitaemia and incidence at human and parasite level, and vector density and breeding site, all in perspective of socio-economic and eco-environmental factors. Another aspect related to modelling was mapping which cuts across all the levels in the transmission cycle and is used for both determination and prediction of risk or burden. The main focus of this review was to assess the literature on socio-economic and eco-environmental determinants of malaria in southern Africa based on statistical models. Our review revealed the opportunities for further research based on various available models which are not yet employed fully in southern Africa.

We identified in literature, the following variables and their relationship with malaria burden and risk; IRS, RACD, ITN, serologic diagnostic tools, IPT treatment, fever, age, province, household wealth; country border locations, rainfall, temperature, altitude, parasitaemia prevalence, incidence, elevation and low lying areas, larviciding, travel outside the city, vapour pressure, humidity salinity, vector presence and nocturnal dew point.

While some explanations for variations or limitations in findings have been provided, a number of studies highlight the need for further research given the limited predictive abilities [34; 46] and logistical feasibility [39] and regional variation of findings [29]. The evaluation of IRS and ITN effectiveness in reducing the burden of malaria displayed some disparities which were attributed to short study periods [18, 19], small samples [18] and ITN-related factors such as non- or incorrect usage, physical and insecticide treatment condition and effective case management methods [19]. Based on Bayesian modelling, it has been suggested that effective coverage and a longer time scale were required to achieve malaria control gains in high transmission settings [49], which process would utilise larger data sets better handled by Bayesian approaches [49]. On the other hand, the same authors proposed that insecticide resistance and changes in biting behaviour could be an explanation where studies are conducted successfully but ITNs and IRS still seem to have reduced in effectiveness [49].

With regards to individual level factors, the factors identified were varied ranging from fever, headache and vomiting [43], age [34, 35, 38], travel to endemic areas [28, 35, 55], stability and economic development [17], cross border collaborations [17, 21, 28, 29], possibly owing to different research designs and settings.

Among the socio-economic factors, effective diagnosis was identified and serological methods were encountered in the review. Some challenges experienced in the studies reviewed were, difficulty to estimate the relationship between rates of immunoglobulins and malaria transmission intensity [40] and the interchange in malaria symptomatology in RDT positive and negative individuals [34]. The earlier has been explained through the discovery that the level of transmission, the risk of malaria and sero-prevalence may depend on the distance between mosquito breeding sites rather than the total surface area covered [40]. The latter on the other hand was recommended for further research as it poses a challenge to malaria elimination since control depends on identification and treatment [34] which would not be possible if RDT positive individuals being asymptomatic remained untested, creating a reservoir of infection [43]. It has been noted that RDTs have not been very effective [17, 43], have been of low predictive value [28] and misclassified individuals with low parasitaemia [17, 29, 50] and yet for the purposes of monitoring disease burden [43] and preventing data gaps [56], they seem to be more than adequate [43, 50]. As such, caution is given that for purposes of modelling, maintaining sensitivity in diagnostics and continuous reporting are important in real-time modelling [50]. RACD is another strategy identified among the diagnostic tools as malaria determinants and is a necessary highly sensitive technique [39, 43], in the wake of resurgent and persistent hotspots [17, 29] amidst the decline in reported malaria cases. In detecting hotspots of asymptomatic infections, the rationale in the use of RACD is that symptomatic and asymptomatic cases do not overlap spatially [39] although it is noted that RACD especially if targeted to cover all demographic groups helps prevent asymptomatic infections from becoming symptoms and thereby reduces their chances of infecting mosquitoes [39]. The challenge in RACD has been in the variations in proposed minimum distance at which screening is able to identify cases [28, 50] and further research is recommended [28]. It has been suggested that although others have shown low socio-economic levels to be associated with high prevalence of malaria, there is need for studies in the urban context to optimise strategies to fight malaria [40]. Factors that are not directly related to malaria control such as agricultural practices, economic development, housing construction and environmental management of breeding sites for mosquitoes could change and hence contribute to reduction also [17].

In studying the temporal aspects of malaria burden, some constraints such as short study periods [29], inability to survey exact populations or indeed the lack of difference in populations surveyed, omission to include all necessary variables for data collection at the start of a study [34] and utilising data from health facilities which has limitations [30] have been noted. In cases when data from health facilities should be used, it has been suggested that the community-based survey context should be used to interpret such data as such surveys can provide intervention coverage data as well as factors indicative of infection and disease prevalence [30].

With regards to vectors, models have been developed to determine vector density [45], to rule out potential locations of breeding sites [46] and to determine evidence of genetic drift events [47]. Vector density has been based on the presence of swamps, favourable habitats for aquatic plants which cause stagnation suitable for mosquito breeding [45] while on the other hand, ruling out of potential locations of breeding sites has been based on the amount and seasonality rainfall, pool depths, sun illumination and turbidity [46] and evidence of genetic drift on spatial analysis [47]. Through modelling and mapping, and with the use of varied software such as GIS which has excellent mapping capabilities [7], predictive maps have been developed [50] to extrapolate malaria risk based on environmental factors [32, 33] and also on geographical factors such as region and urban versus rural residence locations [21]. Although these models have been developed, their capabilities are not sufficient [46] as expressed through presence of spatial correlation [7, 56] among other challenges.

The sources of limitations that have been identified in modelling range from data types [29, 32, 42, 56, 59, 62], sizes and sources used to presence of confounders [28], cofactors [17] and spatial correlation [7]. Other sources of limitations in data have been the lack of household coordinate records [58]; the use of buffer zones which introduces a spatial error in the data through their average values, affecting results [58]; the availability of malaria data for only a short period, which limits statistical analysis although the information from the spatial component allows for some inference [56]. Data from MIS have exhibited limitations in relevance to the time period they cover only [42] and also in that the surveys are done on small number of locations when they should cover the whole country. Such data, being cross-sectional in nature, may not capture temporal changes [42].

Regardless of the limitations in modelling and mapping such as restricting the usefulness of malaria risk maps to particular times of a given year, prediction challenges in unobserved locations [21], capability to indicate clear limits between hyper-endemic and meso-endemic stable areas [32] and limited predictive ability on the type of vector species inhabiting particular aquatic sites [46], these tools are very useful in providing the burden in morbidity or breeding sites necessary to guide interventions.

Limitations due to time period could be overcome by inclusion of more data and at different time points to draw more stable long term spatio-temporal patterns [42]. To overcome bias introduced through scarcity of data [42] or when over-dispersion or spatial correlation are not considered in a model [56], modelling techniques such as geostatistical modelling [32] give the advantage. It has been suggested that when the inherent spatial correlation in a given data-set is taken into consideration, more accurate estimates of malaria risk factors result. Models that have been fitted without this consideration have not been able to match up to spatial models [21] hence the suitability of geostatistical models which provide estimates of the prediction uncertainty seen in most geographically correlated MIS data [32].

It is additionally advisable to combine geostatistical together with process-based modelling methods a practice which facilitates for predictions of malaria risk at spatio-temporal levels and finer spatial scale areas in unobserved places [7, 56]. The use of high resolution data obtainable via remote sensing has been preferred over coarse resolution data given that the models that result with the latter, have demonstrated inability to capture any variations in malaria at sub-district level, which localised meteorological and social conditions, could be responsible for [56].

Geostatistical models have the capacity to incorporate additional location-specific random effect parameters into models [7, 56] at given survey locations, a feature suited in accounting for spatial correlation. Such models have also been shown to assume that geographical dependence is a function of distance between given locations [7]. Depending on the number of survey locations or how weakly correlated the data being modelled would be, these models can be highly parameterised [7] in the aim of obtaining more accurate parameter estimates [21] or indeed in order to explain the variation in the response variable [57]. Additionally, the inability of the geostatistical approach to account fully for inherent uncertainties is overcome with the use of MBG and the Bayesian approach [69]. Increase in parameters decreases precision of the models and estimation can only be by use of Bayesian inference and Monte Carlo Markov Chain (MCMC) simulation [7]. Modelling using highly parameterised models is possible in the Bayesian approach because Bayesian geostatistical models are capable of estimating very low spatial correlation and although when included, random effects present yet another cause of variability into a model to capture the impact of unknown or unobserved confounding factors [42, 56], they are necessary to increase the accuracy of the model-based risk predictions [7]. Generalised linear models (GLM) and GLMMs have been used to account for extra variation [7, 56] and to evaluate [67] and assess [46] methods and models. It has also been shown that in some cases the correlated spatial structure may be less important; instead, the conjugated spatio-temporal trend would have large influence on the incidence of malaria in a region of interest [57]. As such, the "different environmental correlations relating to different levels of transmission imply that it would be difficult to create models that fit in different settings due to the complex and local interaction between environment and transmission" [57].

More methods such as the Bayesian CAR, Gaussian Markov Random Field (GMRF), regression coefficients and ARIMAX models have been employed to ease the challenges or limitations of modelling which may be inevitable such as over or under reporting in routinely collected data [29], bias through secular changes in reporting [29], bias through grouping of data [57, 61] and change in size and shape of spatial polygons such as through modified areal unit problem (MAUP) [42]. Bayesian CAR addresses several sources of uncertainty generally [42] and other than MCMC and or Laplace, the GMRF offer an alternative simulation approach due to the sparseness of resulting covariance matrixes, allowing for faster computation with desirable Markov properties [42]. Regression coefficients [7], adjusted analysis [28] and multivariate Poisson regression models [27] can also be useful in prediction models to ease the challenges. ARIMAX models have been shown to be invaluable for their capacity to account for the autoregression and to provide the opportunity to use exogenous variables [58].

Apart from remote sensing, ImageJ [31] and pan-sharpened Quickbird [33] imagery are some methods used to source data for use to identify risk factors for malaria. The strength of the pan-sharpened Quickbird imagery lies in the fact that measurements are performed using satellite images [33], avoiding the bias of passive detection at health facility or limited to symptomatic individuals. ImageJ is advantageous for its capacity to eliminate the need for complex calculations to quantify vegetation such as in NDVI because the output from the programme provides raw numbers to be imported directly into statistical software [31]. Statistical modelling is important in identifying malaria determinants as it allows room to settle on a minimal but most suitable model among a number of potential ones which is usually a major obstacle and can easily become a matter subjected to chance [56].

Much modelling work in malaria management has been done in southern Africa although most of this work is based on the frequentist approach. The moderately few studies conducted based on the Bayesian approach give an indication that the majority of researchers in southern Africa may still be in the process of acquainting with the approach. In this regard, some countries in southern Africa have taken deliberate efforts to impart the skill to researchers using the higher institutions of learning, focussing on elementary to mixed-effects models and comparing both frequentist and Bayesian methods (Personal communications – Post Newspaper Zambia 26 May 2015).

2.5 Conclusions

In this review we identified socio-economic and eco-environmental factors in malaria based on models employed for burden or risk determination as well as prediction. The focus in many of the studies was on climatic variables and intervention strategies, eco-environment and socio-economic fronts respectively, as they relate to the disease burden or risk. The studies used data from varied sources such as the readily available remotely-sensed world-wide datasets, local field-generated data, and or terrain-based data, and health management information system data and were conducted at various levels from province, health facility and community. However, none were done in perspective of transmission zones and minimal focus was placed on economic factors. Very few malaria burden or risk determination studies utilised the Bayesian analysis approach relying heavily on the frequentist approach. We propose the use of a combination of both the lowest population community structure, the SEAs as well as the provincial levels in perspective of malaria transmission zones and with a balance in both socio-economic and eco-environment to identify factors responsible in malaria risk and burden. We further recommend modelling by Bayesian approach given the versatility of this approach. We recommend to the Government of the Republic of Zambia to streamline research by initiating calls for research that enhance themes towards conducting research across all community and programme levels and using Bayesian statistics. We further recommend for the Government to introduce Bayesian statistics training for researchers in the learning and research institutions as well as national statistics institution the CSO.

2.6 Abbreviations

PMC: PubMed Central; BMC: BioMed Central; IRS: Indoor Residual Spraying; ITN: Insecticide Treated Net; LLINs: Long Lasting Insecticide Nets; RACD: Reactive Case Detection; IPT: Intermittent Presumptive Treatment; SEAs: Standard Enumeration Areas; LSM: Larval Source Management; UN: United Nations; WHO: World Health Organisation; MBG: Model Based Geostatistics; GIS: Geographical Information System; GLMs: Generalised Linear Models; GLMMs: Generalised Linear Mixed Models; CAR: Conditional Auto-Regression; INLA: Integrated Nested Laplace; ZIP: Zero-Inflated Poisson; AMOVA: Analysis of Moving Variance; GARMA: Generalised Auto-Regressive Moving Average; DFA: Dynamic Factor Analysis; ARIMAX: Auto-Regressive Integrated Moving Average; CFR: Case Fatality Rates; IPT: Intermittent Preventive Treatment; MDA: Mass Drug Administration; *Pf*PR: *P. falciparum* Parasite Rate; NDVI: Normalised Difference Vegetation Index; AVHRR: Advanced Very High Resolution Radiometer; CRU: Climatic Research Unit; MIS: Malaria Indicator Survey; RDT: Rapid Diagnostic Tests; MCMC: Monte Carlo Markov Chain; GMRF: Gaussian Markov Random Field; MAUP: Modified Areal Unit Problem;

2.7 Competing interests

The authors as well as the funders declare that they have no competing interests in the manuscript.

2.8 Authors' contributions

All authors conceptualised the development of the paper; NMS-M conducted the literature search while SM validated the search outcomes; NMS-M drafted the initial copy of the paper which the other authors read and edited. All the authors affirmed the final version and agree to be accountable for any aspects of the work.

2.9 Authors' information

NMS-M (Nzooma M. Shimaponda-Mataa[1,2]) is a Medical Parasitologist and Lecturer at the University of Zambia and holds MSc Parasitology degree; SM (Samson Mukaratirwa[2]) is a Parasitologist and Professor, Dean and Head of School and Lecturer at the University of KwaZulu-Natal in Durban, South Africa and holds PhD in Parasitology; MG (Michael Gebreslasie[4]) is a Geographer (geospatial methods) and Lecturer at the University of KwaZulu-Natal in Durban, South Africa and holds PhD in Geography; ET-M (Enala Tembo-Mwase[3]) is Parasitologist and Professor, Deputy Vice Chancellor and Lecturer at the University of Zambia and holds PhD in Parasitology

[1]University of Zambia School of Medicine, Department of Biomedical Sciences, Ridgeway Campus, Lusaka, Zambia.[2]University of KwaZulu-Natal, School of Life Sciences, Westville Campus, Durban, South Africa.[3]University of Zambia, School of Veterinary Medicine, Great East Road Campus, Lusaka, Zambia.[4]University of KwaZulu-Natal, School of Agriculture, Earth and Environmental Science, Westville Campus, Durban, South Africa

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CHAPTER 3

Prevalence of Malaria and Influence of Community Health Workers in the Prevention and Control of Malaria in Four Endemic Provinces of Zambia

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Abstract

Although Africa has sparse data on the major causes of death, the available data is sufficient to show that the burden of malaria is high. Zambia's current success in malaria control can be enhanced through structures such as community health workers (CHWs). This study was conducted to determine the prevalence of malaria and the influence of social and community-related factors in the control of malaria in selected communities. A simple random sampling technique was employed in a cross-sectional survey conducted in Luapula, Lusaka, North-western and Western provinces, representing the three malaria transmission zones in the country. We administered questionnaires to 584 household heads and tested for malaria 756 individuals in those households by a rapid diagnostic test (RDT) and further confirmed the positive results by molecular methods. Determinants of malaria prevalence and the role of CHWs were examined from the data using descriptive and inferential statistics in Excel 2010 and STATA 11, after which, three sets of two-level random effects logistic models were fitted in WinBUGS14. Out of the 756 persons tested for malaria, 13.5% were RDT-positive and of these, 41.2% were males and 58.8% females with 57.1% and 55% being children; males and females, respectively. Infection rates were higher (75%) in the children and the prevalence was highest (85.7%) in communities of Luapula Province. The prevalence of malaria was inversely related with CHW presence in the Western Province ($p < 0.001$) where the proportion of household heads that reported interaction with CHWs was also highest (Western = 74.2%; $p < 0.001$). Among individuals who identified with the CHWs social structure, only 4.9% tested RDT positive ($p = 0.0006$), while 75.5% reported gaining sustainable malaria control support ($p < 0.0001$) and 86.7% used antimalarial medication as an alternative to going to a health facility ($p < 0.0001$). In multilevel models, utilising the church as a source of malaria information and being unemployed, predicted RDT positivity (OR = 2.2, 95% CI: 1.0,5.0; OR = 2, 95% CI: 1.2,2.0); attaining secondary school education or higher and identifying with the two social structures (church and CHWs), predicted benefiting from sustainable malaria control support (OR = 1.7, 95% CI: 1.1, 2.6; OR = 1.9, 95% CI: 1.1, 3.2; OR = 5.6, 95% CI: 2.7, 12.1); and utilising friends and CHWs as sources of information, predicted antimalarial use (OR = 2.98 95% CI: 1.3, 7.0; OR = 5.1, 95% CI: 2.7, 9.9). The CHWs were found to contribute significantly in the prevention and control of malaria in communities of Western Province. We conclude that the existing CHWs system must be strengthened alongside planning and implementation of long term behaviour change strategies.

Key words: Community social structures, community health workers, malaria, prevalence, Zambia

3.1 Introduction

Malaria is a major contributor to disease burden despite the sparse data where only a third of the whole world produces statistics on death causes [1]. The available data are sufficient to reflect the high malaria burden in sub-Saharan Africa [1] and the world over. In 2008, the disease was ranked as the sixth cause of death worldwide [2] and in 2010, the World Health Organisation estimated 219 million cases of malaria and 660,000 deaths worldwide [3], a burden which, however, reduced to 214 million cases and 438,000 deaths in 2015 [4]. Despite the reduction in the global malaria burden, this disease remains the top cause of morbidity and mortality in sub-Saharan Africa [5; 6]. In Zambia, malaria is endemic throughout the country, although the burden of the disease is higher in rural populations [7]. Recently, there has been a shift in malaria stratification from the urban–rural criterion to characterised transmission zones, which are based on malaria parasite prevalence in children, as established through Malaria Indicator Surveys (MIS) conducted from 2008 to 2010 [7]. These transmission zones are defined as follows: "Zone I-very low transmission with a parasite prevalence of less than 1%; Zone II- low to moderate stable transmission with a parasite prevalence of 2-14%; Zone III- moderate to high transmission with a parasite prevalence above 15%, all in children under 5 years old" [7].

Primary health care (PHC) is among the initiatives that have been employed to ease the burden of malaria [8] and in Zambia, this programme started in 1981 with the stated goal "to make basic health care available to all people", expecting their full participation in the initiative [8]. The PHC programme utilises community health workers (CHWs) to deliver health care, a strategy recommended by the World Health Organisation (WHO) [8] to minimise the critical shortage of human resources in the health sector [9]. By the 90s, the CHWs programme, among other community health care programmes in Zambia, was not effective, due to the then prevailing economic recession that resulted partly from the political changes, including the multi-party democracy system, that was introduced in the country in 1991 [10]. This situation affected several developmental projects negatively, including the project popularly termed "Health Reforms", whose cornerstone was the community-based health care programmes [10].

The CHWs system which operates on four different levels of motivation: individual, family, community and organisational [9], was re-started in Zambia in 2011. The system is intended to reduce the use of formal health care [10] and works to the advantage of communities that do not have such facilities. While the success of this system creates confidence in community members to be served and also bridges the gap between the community and the formal health system [8], it depends crucially on an all-inclusive selection criterion, which requires the CHWs to:

- "be members of the communities where they work",
- "be selected by the communities";
- "be answerable to the communities for their activities";
- "be supported by the health system but not necessarily a part of the organisation; and"
- "have shorter training than professional workers"

[8]

Effective malaria monitoring and evaluation in the goal of elimination demands increased inter-sectoral collaboration and community involvement [11] among other initiatives. The main aim of this study was to determine the prevalence of malaria and the role and effectiveness of CHWs in malaria prevention and control.

3.1.1 Background

In most areas where the malaria burden in Zambia is high [7], the distance to health facilities is long. As such, the magnitude of cases not represented in surveillance data is not clear considering that some communities depend entirely on CHWs for malaria management.

Figure 1 shows the study area.

Luapula Province covers a total land surface area of 50,567 km^2 and it borders with the Democratic Republic of Congo. The province shares administrative boundaries with Central and Muchinga provinces in the south, and Northern Province in the east. It consists of seven (7) districts namely: Chienge, Kawambwa, Mansa, Milenge, Mwense, Nchelenge and Samfya, with Mansa, a semi-urbanised district, being the provincial capital. The population is estimated at 991,927 with 49.3% men and 50.7% women. The rural areas harbour 80.4% of the people, while the remaining 19.6% live in the urban area [12].

Lusaka Province is the highly urbanised capital city of Zambia. It is geographically the smallest among our study sites, covering a total land surface area of only 21,896 km^2, and bordering with Mozambique in the east and Zimbabwe in the south. The province shares provincial boundaries with Central Province in the north, Southern Province in the south and Eastern Province in the east. It consists of five districts namely: Lusaka, Chongwe, Luangwa, Kafue and Chirundu. The latter was formally part of Southern Province but was added to Lusaka Province in 2011. The population of Lusaka Province is estimated at 2,191,225 (49.4% men and 50.6% women) with 15.3% of the population living in the rural and 84.7% in the urban environment [13].

Figure 1: Map of the study sites by district in the three transmission zones in Zambia

North-western Province is one of the largest provinces in the country and covers a total land surface area of 125,826 km^2. It borders with the Democratic Republic of Congo as well as with Central, Western and Copperbelt provinces and consists of eight districts namely: Chavuma, Ikelenge, Kabompo, Kasempa, Mufumbwe, Mwinilunga, Solwezi and Zambezi with Solwezi being the semi-urbanised provincial capital. The population in North-western Province is estimated at 727,044 with 49.3% males and 50.7% females out of which, 77.4% live in the rural areas and 22.6% in the urban areas [14].

Western Province is also vast with a total land surface area of 126, 386 km^2, just slightly bigger than North-western Province. It borders with Angola and Namibia at the country level. At the province level it borders North-western, Southern and Central provinces. Western Province consists of seven districts namely: Kalabo, Kaoma, Lukulu, Mongu, Senanga, Sesheke and Shang'ombo. Mongu is the semi urbanised provincial capital. The population is estimated at 902,974 (48% males and 52% females) with 86.7% of the population living in rural areas and 13.3% in the urban areas [15].

Both public and private health facilities exist in all provinces with CHWs and/health posts, pharmacies or drug stores and traditional outlets as other alternatives.

3.2 Methods

This study was based on malaria testing as well as designing, piloting and administering a structured household questionnaire.

3.2.1 Study area

Zambia is a landlocked country surrounded by eight countries [16]. The country is located in southern Africa between latitudes -8^{o} and -18^{o} South and longitudes 22^{o} and 34^{o} East [16] (Figure 1). The population in Zambia, according to Census of 2010, is estimated at 13,046,508 people [17], all of whom are at risk of malaria [18] as the disease is endemic in Zambia's all ten provinces [19]. Malaria peaks during the rainy season and the burden is generally higher in rural areas compared to urban areas [19]. As recommended by WHO, cases of malaria in Zambia are mainly detected when patients visit a health facility for treatment, although surveillance detection also occurs [20].

3.2.2 Study frame

The sites selected for this survey included standard enumeration areas (SEAs) from the following four provinces of Zambia namely; Lusaka (LS), North-western (NW), Western (W) and Luapula (LP). The selected study areas represent the low (Zone I), low to moderate (Zone II) and moderate to high (Zone III) transmission zones [7], respectively. The list of SEAs constituted the sampling frame for the study and each SEA on the frame had information on the number of households and population of the area. A sampling frame was created for each of the four provinces. To provide implicit stratification, each frame was sorted by district, constituency, ward, region, census supervisory area (CSA) and SEA number.

Once the frame was sorted, SEAs were selected, independently from each province, using the probability proportional to size method [21]. The procedure is described below.

"

i. For the list of SEAs for each province, the cumulated measure of size was calculated by adding the number of households down the list;
ii. A sampling interval I_h was calculated by dividing the total number of households (final cumulated measure of size), N_h, by the number of sample SEAs allocated to the province, n_h;
iii. A random number between 1 and I_h which was be the random start (R_h) for the systematic PPS selection of SEAs, was drawn;
iv. When determining the selected SEAs from the selection numbers, the calculations was as follows: $S_{hi} = R_h + [I_h * (i-1)]$, where $i = 1,2,---,n_h$, rounded up to the next integer. The i^{th} sample SEA in the province is the one with the cumulated measure of size closest to s_{hi} without exceeding it." [21].

Each selected SEA on the frame had information on the province, district, constituency, ward, region, and CSA where it is located.

Systematic randomisation was conducted at the SEA level for the selection of households as follows: the first household was selected randomly as the first point for administering questionnaires and rapid diagnostic test (RDT) testing for malaria. Thereafter, questionnaires were administered and malaria testing conducted at a predetermined interval based on the number of estimated households in a particular SEA. If there were no respondents present, a schedule to visit the household another day, during duration of the survey in a particular area, was made. Provision was made to substitute a household with an adjacent one where the respondents were not present or did not consent to participate in the survey.

3.2.3 Study design and data collection

This study was a cross-sectional survey conducted from November 2013 to January 2014 with the aim to determine the prevalence of malaria in the study population, excluding severe cases. It was assumed that the cases prevailing in the community would be uncomplicated cases of malaria. Therefore, assuming that 6% of clinical malaria cases would result in uncomplicated malaria [22] (6% of the total country population malaria cases of 4,300,000 [23] was 258,000 uncomplicated cases), the study utilised a prevalence of 2.1%. Sample size of the study was calculated by the sample size formula:

$$\text{Sample size } (n) = Z^2 \, [P\,(1-P)]/D^2;$$

where Z= the critical value, p=the proportion of patients with uncomplicated malaria (2.1%) and D=the margin of error [24]. To determine the number of households that were required to be sampled in order to obtain thirty-two cases of malaria in each province, the MIS malaria prevalence for each province (Lusaka 2%, North-western and Western 6% and Luapula 10%) [25], and the average number of persons per household [17], were used. A total of 16 SEAs: three in Luapula; eight in Lusaka; two in North-western and three in Western provinces were randomly selected for the study. The number of households sampled in each province for both malaria testing and questionnaire administration in Lusaka, North-western, Western and Luapula were 311, 106, 105 and 67, respectively.

A random stratified sampling method was used to select the study areas in each province using the Central Statistical Office (CSO) sampling frame developed from the 2010 Census of Population and Housing [17]. This study was conducted in one province of each of the three transmission zones. However, an extra province was selected in the low to moderate transmission zone by design. This addition was in consideration of the greater number of provinces in the low to moderate zone in comparison to the other two zones [7]. As such, the total number of provinces studied was four.
Based on the sampling frame [17], the country is administratively demarcated into nine provinces, which are further divided into 72 districts. The districts are further divided into 150 constituencies, which in turn are divided into wards. In addition to these administrative units, and for the purpose of conducting

household based surveys, the wards are further divided into convenient areas called CSAs. The CSAs are in turn subdivided into the SEAs, which constitute the primary sampling units (PSUs) [17]. The actual sample was drawn through the following sampling steps:

3.2.4 Malaria testing

Individuals of all age groups were eligible for enrolment into the malaria testing survey except those who had severe malaria or any other infection and such persons were referred to a health facility.
Malaria testing was performed by two qualified staff, a biomedical scientist and a nurse from the local provincial hospitals in the various provinces. The SD *Pf* malaria test kit (manufactured by Standard Diagnostics, Inc., Korea) was used to screen for *Plasmodium falciparum* malaria according to the manufacturer's instructions. Whenever the RDT strips were positive for malaria, consent for further blood samples was obtained and samples collected for the preparation of thick and thin blood films for microscopy and dried blood spots. Thereafter, referrals to the nearest health facility for medical attention were made. Microscopy was performed at the University of Zambia Ridgeway Campus Pathology and Microbiology Laboratory in Lusaka Zambia. Briefly, parasitaemia was determined by a count of malaria parasites against a count of either 200 or 500 of white blood cells (WBCs), depending on the degree of parasitaemia, in Giemsa-stained blood slides for microscopy. Molecular confirmation was done as per the test manufacturer's instructions using the F-547 Phusion Blood Direct polymerase chain reaction (PCR) Kit (manufactured by Thermo Fisher Scientific Inc. USA and supplied by Inqaba biotech, South Africa) at the Tropical Diseases Research Centre, Molecular Biology Laboratories, in Ndola, Zambia.

In malaria testing, the study exceeded the minimum required sample size of 584 by 172 individuals tested. The number of persons tested for malaria in each province depended on the actual number of persons found and who consented in a particular household: 389 in Lusaka; 150 in Western, 124 in North-western; 93 in Luapula, bringing the total to 756 persons.

3.2.5 Questionnaire administration

The questionnaire was administered by two trained enumerators from the Zambia Central Statistical Office (CSO) at the various local offices in each province. This process was monitored by the study supervisor on a daily basis for quality control. The questionnaire was administered to a total of 584 randomly selected households; 105 households in Western Province, 106 in North-western Province, 62 in Luapula Province and 311 in Lusaka Province. Verbal consent to interview was obtained before a questionnaire was administered.

Socio-economic factors were determined through the questionnaire and for this study they were defined as "public and societal and financial resources as well as related coping mechanisms that could help communities reduce their vulnerability to malaria such as control programmes and the activities they do e.g. funding for malaria control, implementing malaria control interventions in terms of ITNs, IRS, treatment both at individual and at national (malaria control programme) level"

3.2.6 Data analysis

Data collected from both the household and individual surveys were entered and initially analysed in Microsoft excel 2010 and STATA 11 and later in WinBUGS14. ArcMap 10 (ESRI, Redlands, CA, USA) was used to generate the map.

This study considered three outcome variables: the malaria RDT status of persons tested, the malaria control support community members gained from the CHWs and other community social structures and the alternative treatment options household heads considered. Age of persons tested, education level, employment status and income level of the household head, their source of malaria information and the community social structures in the community were the explanatory variables analysed with the first outcome variable. Age, employment status, income and education levels of the household heads, their source of malaria information and the CHWs and other community social structures in the community were the explanatory variables analysed with the second outcome variable. Age, education level, employment status of household heads, their source of malaria information and the community social structures in the community were the explanatory variables analysed with the last outcome variable. With the exception of age which was continuous and took absolute values, all were represented as dummy variables. The malaria RDT status variable took on the value of 1 for positive status and 0, otherwise. We considered sustainable malaria information and treatment and emergency aid in severe malaria as the two possible benefits community members could gain from CHWs and other community social structures. Each of the two benefits took on the value of 1 where the benefit was present and 0, otherwise. The two alternative treatment options we analysed in this study were the use of antimalarial medication and the use of pain killers. Each of the two options took on the value of 1 where the option was used and 0, otherwise. In the communities studied, we determined two community social structures; church and CHWs. Each of the two structures took on the value of 1 where the structure was reported utilised and 0, otherwise. Education, income and occupation were placed in categories. Each of these took on the value of 1 where the level in question was applicable and 0, otherwise. Gender took on the value of 1 for males and 0, otherwise.

3.2.7 Estimation process

The dependent variables were binary response variables; hence a logistic regression model was used to examine the effects of the explanatory variables.

Frequency tables were generated for relevant variables. Descriptive statistics, such as means, medians and standard deviations were used to summarise continuous variables and percentages of frequencies were used to describe the prevalence of malaria and proportions of household heads or representatives who responded to the questionnaire. The parametric One Way analysis of variance ANOVA test was used to examine whether the proportions of household heads and the relationships observed by descriptive statistics varied by province. Relationships between the outcome variables and each explanatory variable were first explored using the non-parametric chi square test in bivariate analysis before a multivariate logistic regression was performed. The 95% confidence level was used to establish the significance of the differences observed in the relationships examined. We included in the logistic model the explanatory variables associated with the outcome variables after the bivariate analysis. Based on previous modelling studies [26; 27] and methods [28], random effects logistic models were fitted. The models included fixed effects and group-level intercepts as random effects [26]. This accounts for the two-level nested nature of the data; individuals tested or surveyed, nested within regions. This process is important given the three transmission zones in Zambia across which characteristics such as malaria burden vary. Given the two-level data;

"We assume $Yi \sim$ Binomial $(pi,1)$, where

$$\text{Logit}(pi) = b0+b1 + b2 + b3 + b4+ uj(i)$$

We provide non-informative priors for all fixed effects, assuming $bk \sim$ Normal $(0,0.000001)$. The second parameter was the precision giving variance of one million. We further assume that

$$uj(i) \sim N(0, t), \text{ where}$$

precision t has a gamma prior with parameters 0.001 and 0.001, thus the mean is one and the variance is 1000

To specify the model in WinBUGS, we used a declarative language that lists deterministic and stochastic nodes. For each of the N observations we took the outcome to be Bernoulli, and we specified the logit of the probability, which depends on the x's and a random effect u. For each of the M groups, we specified the random effect as normally distributed. We then specified the prior of each coefficient and the hyper prior of the precision.

The models were as follows:

For predictors of RDT positivity:

```
rdt[i]~dbern(p.bound[i])
p.bound[i]<-max(0,min(1,p[i]))
logit(p[i])<-
[26, 27, 28]
 bcons+bage_rdt*age_rdt[i]+bnoeduc*noeduc[i]+bunemp_subs_invalid*unemp_subs_invalid[i]+
blowincome*lowincome[i]+btv*tv[i]+bchurch*church[i]+bchurchsocstr*churchsocstr[i]+
u[group[i]]
```

For predictors of malaria control benefit accessed by community members:

```
benefit[i]~dbern(p.bound[i])
p.bound[i]<-max(0,min(1,p[i]))
logit(p[i])<-bcons+bage_hhh*age_hhh[i]+bsecondary_and_above*secondary_and_above[i]+
bincome12to35*income12to35[i]+bemployed*employed[i]+bhf*hf[i]+bchw*chw[i]+
bchurchsocstr*churchsocstr[i]+bchwsocstr*chwsocstr[i]+u[group[i]]
```

For predictors of alternative malaria treatment community members would take:

```
antim[i]~dbern(p.bound[i])
p.bound[i]<-max(0,min(1,p[i]))
logit(p[i])<-bcons+bage_hhh*age_hhh[i]+bsecondary_and_above*secondary_and_above[i]+
bemployed*employed[i]+bfriend*friend[i]+bhf*hf[i]+bchw*chw[i]+bchurchsocstr*churchsocstr[i]+bchw
socstr*chwsocstr[i]+u[group[i]]
```

where b represented fixed effects and Ui, random effects. Ui is the estimation of the variance across all the regions included in the study. Where the variance was large, the outcome of interest was taken as dependent on the region, otherwise explained solely by the measured characteristics.

The value of random effects represents the mutual dependence that exists in responses from the same regions. This implies that the correlation between individuals from the same regions is fully explained by their occurrence in the same regions. The variance measures the degree of heterogeneity in the probability of the RDT being positive, the benefit from social structures being the desired sustainable and the alternative treatment being the antimalarial medication, that cannot be explained by simply classifying by RDT status, benefit obtained or antimalarial medication used or not.

Initial values for the betas for the fixed effects were estimates from an ordinary logistic regression while for tau we used the arbitrary value 1. For the random effects ui(j), we generated the initial values using WinBUGS [26, 27, 28].

Another important measure employed in this study was the Intra-class correlation coefficient (ICC) which is a measure that describes dependencies in the data by measuring the extent to which individuals within the same group are more similar to each other than they are to individuals in different groups [26]. The ICC (represented by rho ρ) was calculated by the formula:

$\rho = \tau/(\tau + \pi^2/3)$

where τ = estimated variance and π = 3.142” [26, 27, 28]

3.3 Results

3.3.1 Prevalence of malaria

Overall, 13.5% (102/756) of the persons tested for malaria using the RDT were positive and analysing the proportion of RDT-positives by province showed that there was a significant difference ($p < 0.0001$).

Figure 2 shows malaria prevalence in the SEAs tested in each province. The SEA which had the highest proportion of individuals testing positive was in Chipita Ward, Kawambwa District, Luapula Province (85.7%). This was followed by a SEA in Sandang'ombe Ward, Solwezi District, North-western Province (53.8%). The third was a SEA in Mwatishi Ward, Nchelenge District, Luapula Province (45.8%). Other SEAs, which had slightly high proportions of persons testing positive were a SEA in Muchinka Ward, Mansa District, Luapula Province (25%), a SEA in Mwinyilamba Ward, Ikelenge District, North-western Province (19.4%) and a SEA in Kambale Ward, Kafue District, Lusaka Province (16%). The remaining SEAs sampled in Lusaka and in Western Province had lower than 10% proportions of RDT positive persons, with some at zero percent in Lusaka.

Sixty-nine percent (523/756) of the persons who were tested for malaria in all the four provinces were children and 30.8% (233/756) were adults.

Out of the 584 household heads interviewed, 76.3% were males and 23.7% were females. By individual provinces, the proportion of males was still higher (LP = 69.4%; LS = 77.8%; NW = 86.8%; W = 65.7%). The mean age (± SD) of the household heads was 41.9 ± 13.8 years in the range 17 – 85 years. The demographic characteristics of the study population include the level of education, occupation and income level. Generally, illiteracy levels (no education) were very low 13% (76/584) although the proportion of those who had attained primary education combined with those without any education was significantly higher than the other groups ($p<0.0001$). By province, North-western illiteracy levels were as high as 35%. Generally, in Luapula, North-western and Western provinces, most of the household heads had qualifications lower than, or equal to, primary education level (LP = 69.4; NW = 64.1%; W = 59.0%) whereas in Lusaka, most household heads had attained secondary or tertiary education level (LS = 69.8%).

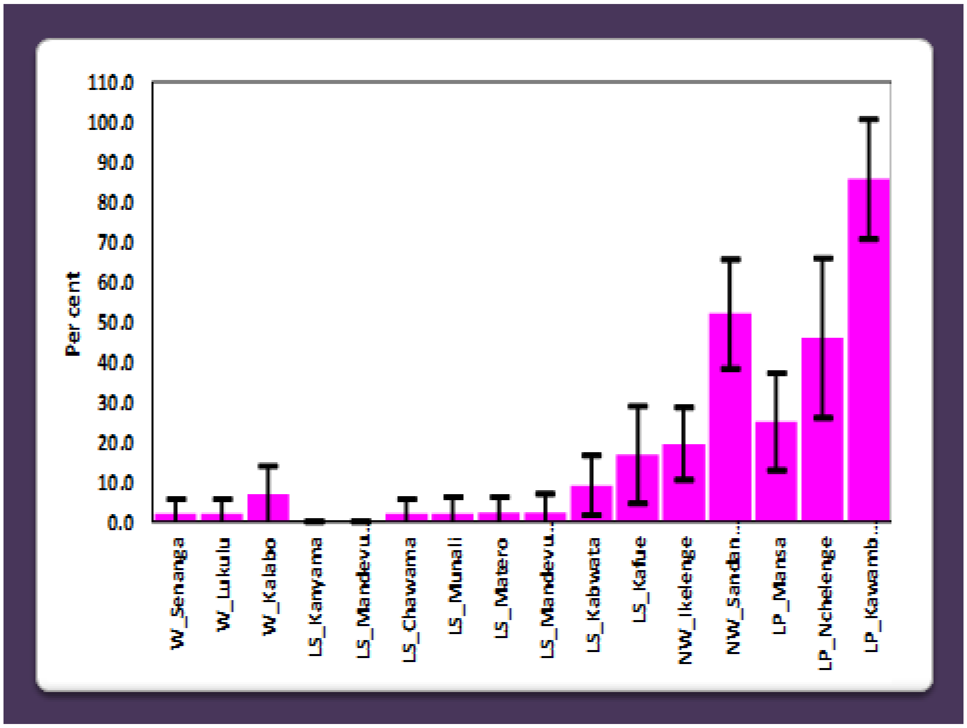

Figure 2 Malaria prevalence in the Standard Enumeration Areas (SEAs) sampled in the wards of the various districts and provinces in the study; W=Western province; LS=Lusaka province; NW=North-western province; LP=Luapula province

Out of the 102 persons, who tested positive for malaria, 96.1% (98/102) had low parasitaemia (asexual forms <100 000 per µl) while only 3.9% (4/102) had high parasitaemia (asexual forms ≥ 100, 000 per µl) observed in 75% of the children and in 25% of the adults. Malaria pigmentation (hemozoin) was seen in 9/98 persons with low parasitaemia and none in persons with high parasitaemia. Considering age categories, 55.9% (57/102) were children and the rest 44.1% (45/102) adults. Figure 2 shows that Chipita Ward, Kawambwa District in Luapula Province had the highest prevalence (85.7%) of malaria in the study population of 16 communities drawn from the four provinces.

Sixty-two of the 102 RDT malaria-positive cases were confirmed as *P. falciparum* both by microscopy and molecular methods (PCR) while in 35 of the RDT-positive cases, the two methods could not detect parasitaemia or *Plasmodium* DNA, respectively. In another five of the RDT-positive cases, microscopy could not detect parasitaemia although PCR confirmed these individuals as positive. Out of the persons that tested RDT-positive, 41.1% were males and 58.9% females. Among the males, 57.1% (24/42) were children and 42.9% (18/42) were adults, while 55% (33/60) were children and 45% (27/60) were adults among the females.

Whereas females and children were higher in proportion, both among the 756 who were tested (females = 60%; children = 69.8%) and those positive for malaria (females = 58.8%; children = 55.9%), there was no significant association between sex and age category. Also, malaria prevalence varied significantly between Western and Lusaka provinces against North-western and Luapula provinces (Figure 3).

3.3.2 Social structures related to malaria control and prevention

The community social structures we identified in the study populations were: church, schools, CHWs, community leadership and voluntary malaria grouping. The functions of the structures were placed in two categories, the first of which received sustainable malaria control support (regular malaria information and treatment) while second only received emergency support (to manage severe malaria). Study participants who did not interact with any social structure regardless of knowledge about them, and those who did not know about the social structures, were also recorded. The majority of the participants in all the four provinces acknowledged interacting with at least one community social structure although the proportion of participants in Lusaka was significantly lower than in the other three provinces; LS = 56.5%; W = 84.8%; NW = 90.6%; LP = 95.2%; ($p < 0.0001$).

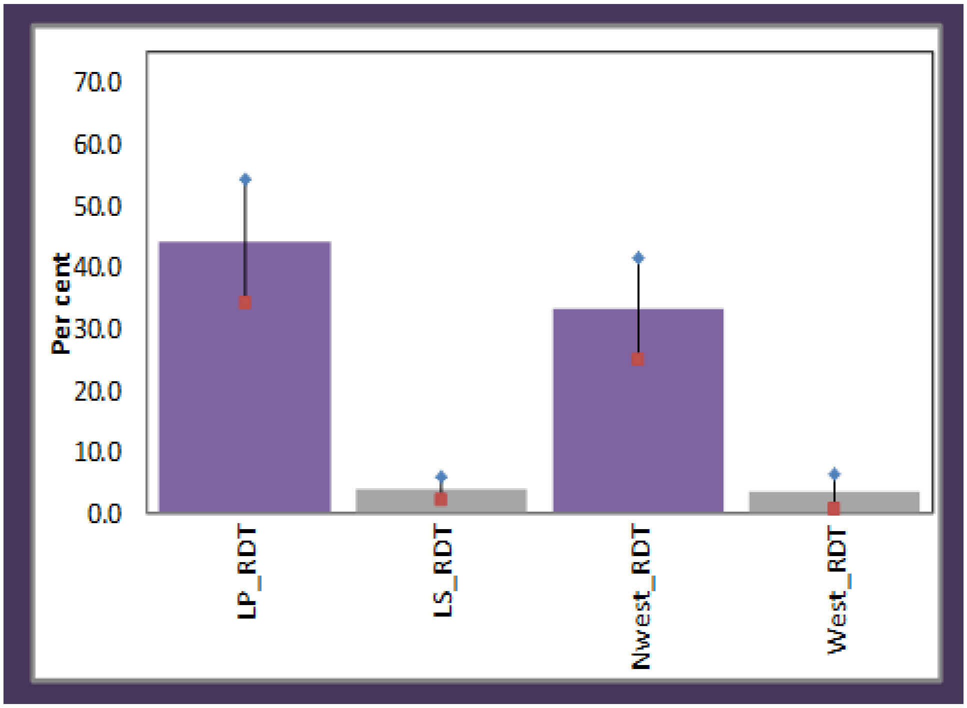

Figure 3 Malaria prevalence by rapid diagnostic test (RDT); West=Western province; LS=Lusaka province; Nwest=North-western province; LP=Luapula province

When the structures were disaggregated by type of community social structure, there was a significant difference between proportions of household heads that reported interacting with the churches compared to other community social structures (church = 78.7%; voluntary malaria groups = 0.23%; community leadership = 0.23%; community health workers = 17.2%; and school = 3.6%) ($p < 0.0001$)

However, in relation to the support type, there was a significant difference in the proportions of the study population interacting with the social structures as follows: sustainable malaria control support = 35.9%; emergency support = 18.2%; no benefit = 45.9%; and those who did not know about the structures = 28.1% ($p < 0.0001$) The proportion of household heads, who interacted with structures that provided sustainable malaria control support, was significantly higher in Western compared to other provinces [LS = 17.2%; LP = 30.5%; NW =38.7% in North-western; W = 74.2%; ($p < 0.0001$).

3.3.3 CHWs and malaria prevalence

The prevalence of malaria was significantly inversely related with CHW presence ($p < 0.001$). Out of the 102 persons who were RDT-positive for malaria in the 756 households, 81 belonged to households where the household heads interacted with various community social structures. Among the households of heads who interacted with CHWs, only 6.2% (5/81) were RDT positive whereas among households of heads who interacted with other social structures, 93.8% (76/81) were RDT positive ($p < 0.0001$); Figure 4.

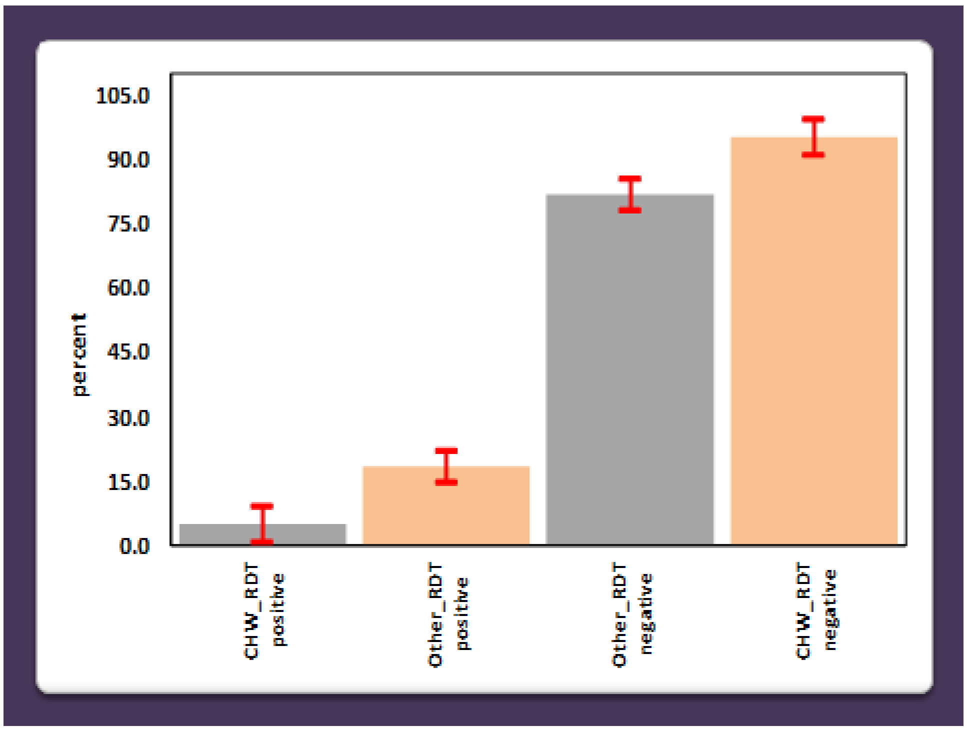

Figure 4: Percent rapid diagnostic test (RDT) positive individuals belonging to household where heads interacted with CHWs vs other community social structures

Household heads who had interacted with CHWs and obtained malaria information and treatment had higher RDT negative testing individuals in their households ($r = 0.999$); the numbers of RDT negative individuals inversely correlated with number of household heads obtaining sustainable malaria control support from CHWs.

The proportions of household heads who would resort to pain killers as alternative treatment when attendance of health facility was not feasible were higher in communities without CHWs ($r = -0.999$. On the other hand, the use of anti-malarial medication as alternative treatment, was positively correlated with CHWs presence ($r = 0.988$).

3.3.4 Bivariate analysis

Tables 1-3 show the associations between the following: RDT positivity and the hypothesised predictors; malaria control support to community members and the hypothesised predictors; alternative malaria treatment sought by community members and the hypothesised predictors. All of the predictors were significantly related to outcome variables in question.

A total of 41 (44.1%) individuals tested RDT positive in Luapula province including 2 asymptomatic cases, 15 (3.9%) in Lusaka including 1 asymptomatic case, 41 (33.1%) in North-western and 5 (3.3%) in Western ($p < 0.0001$). Five (4.9%) individuals tested RDT positive among those who identified with CHW social structure compared with 74(23.2%) who identified with Church social structure ($p = 0.0006$).

Out of the: 147 who earned an income in excess of 12,000 per annum, 9 (6.1%) tested RDT positive while 138 (93.9%) did not ($p = 0.004$); 470 RDT tested individuals from households where the heads were in employment, 42 (8.9%) tested positive compared with 60 (21%) from household heads who were unemployed ($p < 0.0001$); 52 RDT tested individuals whose malaria information source was the Church, 15 (28.9%) tested positive compared with 7 (6%) whose source was TV ($p = 0.0004$); Table 1.

A total of 18 (30.5%) individuals reported gaining sustainable malaria control support in Luapula province, 30 (17.2%) in Lusaka, 36 (37.5%) in North-western and 66 (74.2%) in Western ($p < 0.0001$). Eighty (75.5%) individuals reported gaining sustainable malaria control support among those who identified with CHW social structure compared with 89 (22.6%) who identified with Church social structure ($p < 0.0001$).

Table 1: RDT Status versus various community social structures, information source and socio-economic factors

	Individuals by RDT status			Chi	p-value
	Positive	**Negative**	**Total**		
Province					
Luapula	41(44.1)	52(55.9)	**93(100)**		
Lusaka	15(3.9)	374(96.1)	**389(100)**		
N-western	41(33.1)	83(66.9)	**124(100)**	159.5	<0.0001
Western	5(3.3)	145(96.7)	**150(100)**		
Total	102(13.5)	654(86.5)	**756(100)**		
Social Structure					
CHW	5(4.9)	97(95.1)	102(100.0)		
Church	74(23.2)	319(76.8)	393(100.0)	11.7	0.0006
	79(16.0)	**416(84.0)**	**495(100.0)**		
Income ZMW					
Above 12,000	9(6.1)	138(93.9)	147(100.0)		
Below 12,000	92(15.2)	512(84.8)	604(100.0)	8.4	0.004
	101(13.5)	**650(86.5)**	**751(100.0)**		
Occupation					
Unemployed+ subsistence + invalid	60(21.0)	226(79.0)	286(100.0)		
Employed	42(8.9)	428(91.1)	470(100.0)	22.1	<0.0001
	102(13.5)	**654(86.5)**	**756(100.0)**		
Information source					
TV	7(6.0)	109(94.0)	116(100.0)		
Church	15(28.9)	37(71.1)	52(100.0)	15.5	0.0004
Other	205(14.5)	1212(85.5)	1417(100.0)		
	227(14.3)	**1358(85.7)**	**1585(100.0)**		
Age category					
Child	59(11.3)	464(88.7)	523(100.0)		
Adult	43(18.5)	190(81.5)	233(100.0)	7.1	0.007
	102(13.5)	**654(86.5)**	**756(100.0)**		

* (1 USD ~ 5 ZMW in 2014)

Out of the: 142 whose source of malaria information was the CHW, 81 (57%) reported gaining sustainable malaria control support compared with 267 (26.8%) and 99 (19.1%) whose sources were the health facility and a combination of other sources respectively ($p < 0.0001$); 393 individuals who had attained secondary education or above, 89 (22.7%) reported gaining sustainable malaria control support whereas among those with primary education or below, 104 (29.4%) did ($p = 0.04$); 462 individuals in employment 73 (15.8%) reported gaining sustainable malaria control support compared with 120(42.1) unemployed individuals who also reported gaining sustainable malaria control support ($p <0.0001$); 99 individuals whose annual income ranged from 12,000 to 35,999, 18(18.2%) reported gaining sustainable malaria control support compared with 175(27.9%) in other income brackets ($p = 0.04$) Table 2.

Table 2: Malaria control support versus various community social structures, information source and socio-economic factors

	Malaria control support			Chi	p-value
	Sustainable	Emergency	Total		
Province					
Luapula	18(30.5)	41(69.5)	59(100.0)		
Lusaka	30(17.2)	144(82.8)	174(100.0)	83.8	<0.0001
N-western	36(37.5)	60(62.5)	96(100.0)		
Western	66(74.2)	23(25.8)	89(100.0)		
Total	**150(35.9)**	**268(64.1)**	**418(100)**		
Community Social Structure					
Church	89(22.6)	304(77.4)	393(100.0)	104.0	<0.0001
CHW	80(75.5)	26(24.5)	106(100.0)		
Total	**169(33.9)**	**330(66.1)**	**499(100.0)**		
Source of Malaria information					
HF	99(19.1)	420(80.9)	519(100.0)		
CHW	81(57.0)	61(43.0)	142(100.0)	79.9	<0.0001
Other	267(26.8)	655(73.2)	922(100.0)		
Total	**447(28.2)**	**1136(71.8)**	**1583(100.0)**		
Education Status					
Secondary and above	89(22.7)	304(77.3)	393(100.0)		
Primary and below	104(29.4)	250(70.5)	354(100.0)	4.4	0.04
Total	**193(25.8)**	**554(74.2)**	**747(100.0)**		
Occupation					
Employed	73(15.8)	389(84.2)	462(100.0)	63.7	<0.0001
Unemployed + subsistence + invalid	120(42.1)	165(57.9)	285(100.0)		
Total	**193(25.8)**	**554(74.2)**	**747(100.0)**		
***Income level p.a. (ZMW)**					
12,000 – 35,999	18(18.2)	81(81.8)	99(100.0)	4.1	0.04
Other <12,000 ($1,200)&> 36,000	175(27.9)	453(72.1)	628(100.0)		
Total	**193(26.6)**	**534(73.4)**	**727(100.0)**		

* (1 USD ~ 5 ZMW in 2014)

Table 3 shows that a total of 8(16.7%) individuals used antimalarial medication as an alternative to going to a health facility in Luapula province, 18(7.2%) in Lusaka, 2(3.9%) in North-western and 31(83.8%) in Western ($p < 0.0001$). Twenty-six (86.7%) individuals used antimalarial medication as an alternative to going to a health facility among those who identified with CHW social structure compared with 18(9.1%) who identified with Church social structure ($p < 0.0001$). Of the: 56 individuals whose source of malaria information was the CHW, 30(53.6%) used antimalarial medication as an alternative to going to a health facility compared with 26(27.1%), 32(12.2%) and 63(17.9%) whose sources were friends, the health facility and a combination of other sources respectively ($p < 0.0001$); 188 individuals who had attained secondary education or above, 22(11.7%) used antimalarial medication as an alternative to going to a health facility whereas among those with primary education or below, 36(19.8%) did ($p = 0.03$). Of the 276 individuals in employment, 26 (9.4%) used antimalarial medication as an alternative to going to a health facility compared with 33(30.0) unemployed individuals who also used antimalarial medication as an alternative to going to a health facility (p <0.0001).

Table 3: Antimalarial use versus various community social structures, information source and socio-economic factors

	Alternative Malaria Treatment			Chi	p-value
	Antimalarial **drugs**	Pain killers	Total		
Province					
Luapula	8(16.7)	40(83.3)	48(100.0)		
Lusaka	18(7.2)	232(92.8)	250(100.0)		
N-western	2(3.9)	49(96.1)	51(100.0)	151.9	<0.0001
Western	31(83.8)	6(16.2)	37(100.0)		
Total	59(15.3)	327(84.7)	386(100.0)		
Community Social Structure					
Church	18(9.1)	180(90.9)	198(100.0)		
CHW	26(86.7)	10(13.3)	30(100.0)	79.5	<0.0001
Total	**44(19.3)**	**184(80.7)**	**228(100.0)**		
Source of Malaria information					
Friend	26(27.1)	70(72.9)	96(100.0)		
HF	32(12.2)	230(87.8)	262(100.0)	53.8	<0.0001
CHW	30(53.6)	26(46.4)	56(100.0)		
Other	63(17.9)	288(82.1)	351(100.0)		
Total	**151(19.7)**	**614(80.3)**	**765(100.0)**		
Education Status					
Secondary and above	22(11.7)	166(88.3)	188(100.0)		
Primary and below	36(19.8)	146(80.2)	182(100.0)	4.6	0.03
Total	**58(15.7)**	**312(84.3)**	**370(100.0)**		
Occupation					
Employed	26(9.4)	250(90.6)	276(100.0)	25.7	<0.0001
Unemployed + subsistence + invalid	33(30.0)	77(70.0)	110(100.0)		
Total	**59(15.3)**	**327(84.7)**	**386(100.0)**		

3.3.5 Multivariate analysis

After controlling for all the predictors simultaneously in the three different multi-level models, fewer predictors remained significant (Table 4). From the set of predictors for RDT positivity, only church as a source of malaria information and unemployment predicted the outcome while age of RDT tested individual, TV as a source of malaria information, income level and social structures dropped out as predictors in this set. From the set of predictors for sustainable malaria control support, attaining secondary school education and higher and identifying with the two social structures church and CHW predicted the outcome while age of household head, source of malaria information, occupation and income levels dropped out as predictors in this set. From the set of predictors for use of antimalarial medication as an alternative to going to a health facility only friends and CHW as sources of information predicted the outcome while age of household head, social structures, education and occupation levels dropped out as predictors in this set.

Community members that obtained malaria information from church and those in unemployment were more likely to test RDT positive than those that obtained malaria information from TV and those in employment respectively (OR = 2.2, 95% CI: 1.0,5.0; OR = 2, 95% CI: 1.2,2.0). Those who attained secondary education and above and those who identified with church and CHW as social structures were more likely to obtain sustainable malaria control benefit than those who attained primary level or below and those who identified with other social structures respectively (OR = 1.7, 95% CI: 1.1, 2.2; OR = 1.9, 95% CI: 1.1, 3.2; OR = 5.6, 95% CI: 2.7, 12.1). Those who utilised CHW and friends as sources of information were more likely to use antimalarial medication as an alternative malaria treatment than those who utilised health facility (OR = 2.98, 95% CI: 1.3, 7.0; OR = 5.1, 95% CI: 2.7, 9.9).

The estimated between region variance translated to ICC of 0.01, 0.03 and 0.05 in the three categories respectively.

The model convergence was assessed by Gelman-Rubin statistics and model fit by Deviance Information Criterion (DIC). The models with the smallest DIC were adopted.

We adequately account for the possibility of transmission zone being a confounder based on the similar (less than 1) risk ratios of being RDT positive when interacting with CHWs regardless of zone as such, zone is not a confounding factor.

Table 4: Multilevel Logistic Regression analysis for determinants of RDT positivity, malaria control benefits and alternative malaria treatment seeking

	Odds ratios bivariate analysis	Odds ratios	Credible interval (95%)	MC error(5%mean)
Social structure determinants of RDT positivity				
Age of RDT tested individual	1.8 (1.2 – 2.7)	1.0	0.9 – 1.0	5.09E-05 (0.00)
Source of malaria information				
Church	2.5 (1.4 – 4.7)	2.2	1.0 – 5.0	0.005(0.04)
TV	0.4 (0.2 – 0.8)	1.9	0.7 – 5.2	0.006(0.03)
Education level				
No education	1.3 (0.7 – 2.3)	0.6	0.3 – 1.1	0.004(-0.03)
Occupation				
Unemployment	2.7 (1.8 – 4.1)	2.0	1.2 – 2.0	0.004(0.04)
***Income levels ZMW**				
Income below 12,000 pa	2.8 (1.4 – 5.6)	1.5	0.7 – 3.6	0.01(0.02)
Social structures				
Church social structure	4.5 (1.8 – 11.5)	0.70	0.4 – 1.3	0.006(-0.02)
rho		0.01		
Determinants of malaria control benefits				
Age of household head		1.0	0.9 – 1.0	1.16E-04(0.00)
Source of malaria information				
HF	0.5 (0.4 – 0.6)	0.4	0.3 – 0.7	0.005(-0.04)
CHW	3.9 (2.7 – 5.6)	1.2	0.6 – 2.1	0.004(0.01)
Social structures				
Church social structure	0.1 (0.06 – 0.2)	1.9	1.1 – 3.2	0.004(0.03)
CHW social structure	10.5 (6.4 – 17.4)	5.6	2.7 – 12.1	0.006(0.09)
Education level				
Secondary and above	0.7 (0.5 – 0.1)	1.7	1.1 – 2.6	0.003(0.02)
Occupation				
Employed	0.3 (0.2 – 0.4)	0.5	0.3 – 0.9	0.004(-0.03)
***Income levels ZMW**				
Income 12,000 to 35,999 pa	0.6 (0.3 – 1.0)	1.6	0.8 – 3.1	0.004(0.02)
rho		0.03		
Determinants of alternative malaria treatment				
Age of household head		1.00	0.9 – 1.0	1.81E-04(0.00)
Social structures				
Church social structure	0 (0 – 0.05)	0.63	0.3 – 1.5	0.007(-0.02)
CHW social structure	65 (20.4 – 207.1)	1.96	0.7 – 5.8	0.01(0.03)
Source of malaria information				
CHW	5.6 (3.2 – 9.8)	2.98	1.3 – 7.0	0.009(0.05)
Health facility	0.4 (0.3 – 0.7)	1.9	0.9 – 4.1	0.008(0.03)
Friend	1.6 (1.0 – 2.6)	5.1	2.7 – 9.9	0.006(0.08)
Education level				
Secondary education and above	0.5 (0.3 – 0.96)	0.8	0.3 – 1.4	0.004(-0.01)
Occupation				
All occupation vs unemployed +subsistence farming+invalid	0.2 (0.1 – 0.4)	1.0	0.5 – 2.1	0.006(0.00)
rho		0.05		

* (1 USD ~ 5 ZMW in 2014)

3.4 Discussion

The overall prevalence of malaria of 13.5% in this study was high contrary to a study conducted in Ghana, which reported a prevalence of 8.75% [29]. However, in comparison to a prevalence of 34.2% in Nigeria [30], the prevalence in our study was moderately low. Analysing by provinces revealed that malaria is more prevalent in some communities in Luapula Province and almost non-existent in some communities in Lusaka Province agreeing with the general trend in the Malaria Indicator Surveys (MIS) [31], that malaria is consistently low in Lusaka Province and consistently high in Luapula Province which led to the classification of these provinces in the different transmission zones [7]. However, the actual prevalence rates in our study cannot be compared to those obtained in the MIS or incidence studies [17-20, 31, 32] because the data from our study are based on the lowest community level, the SEA, while the MIS data, on an aggregation of SEAs. Further, our study was not within a similar scope with the MIS as it tested persons of all age groups whereas the MIS tested children only [31]. The high prevalence of malaria in communities of Kafue district, Lusaka, a province in a very low transmission zone, could be explained by the proximity of the SEAs to a dam [33]. Additionally, the malaria cases observed in the other SEAs of Lusaka Province such as in Chilenje, Zanimuone and Ng'ombe were reported in patients resident in Lusaka who had travelled to high transmission zones such as Nchelenge in Luapula Province.
The MIS 2010 statistics for the Western Province show a rising malaria pattern compared to those of previous years [31]. It is possible that the communities in our study may have experienced a reduction in malaria prevalence due to specific CHWs interventions and or that our sampled sites were not the specific sampled sites under the MIS. Malaria prevalence differs within different sections of a particular area, due either to population density or environmental factor differences [29]. In this regard, stratification of malaria transmission by zones is an initiative onto which tailor-made strategies for various communities can be developed [7]. The finding of 13.5% persons serologically testing positive for malaria, more than half of them being children, is in agreement with other studies [34, 35, 36]. In our study, 2.9% participants who tested positive for malaria were asymptomatic as has been demonstrated before [37]. Therefore, it is important to conduct prevalence studies regularly in order to ascertain the burden regardless of malaria symptoms in the community.

In concurrence with other studies that cases of low parasitaemia are the majority in endemic areas [38], we found an overwhelming proportion (96.1%) of cases with low parasitaemia. However, low parasitaemia may be accompanied with malaria hemozoin pigment, an indicator for severity of malaria [36]. Based on the occurrence of hemozoin in the 8.8% RDT positive persons, all being in low parasitaemia cases and none in persons with high parasitaemia, parasitaemia alone may not be a good predictor of severity but coupled with pigmentation commonly found in low parasitaemia smears [36]. Whereas a study involving children only showed that the higher prevalence of severe malaria demonstrated by high occurrence of hemozoin was in children [36], the hemozoin observed in our all-age category study, occurred in smears of six adults and only three children. Our study shows that while malaria prevalence may be high in children, severe cases may also be seen in adults, a fact that has been overlooked because studies are generally tilted towards children and women [38].

In this study, 66% of the cases were positive by both RDT and PCR whereas 34% were positive by RDT but negative by microscopy and PCR. This observed disparity could be explained by the possibility of antigenaemia persistence after treatment [39] in persons who could have suffered from malaria earlier, explaining the positive RDT observed many days later. However, it is also possible that such individuals could have had other infections besides malaria considering that blood smears negative for malaria in positive patients are not uncommon in the tropics, indicating that malaria could be present, but at sub-patent levels [39]. The finding of five negative cases by microscopy but positive by the confirmatory test PCR agrees with literature that it is possible to miss very low parasitaemia which are still detected by RDT and PCR [40] since the latter tests utilise products and not actual malaria parasites [40]. Further, the accuracy and reduced limit of detection of microscopy are major confounders when comparing microscopy with PCR [41], which makes it critical to validate test kits against other methods [42].

The bivariate analysis of this study showed that low income (<12,000 ZMW per annum), unemployment and utilising the church for both malaria information and as a community social structure were associated with high RDT positivity. However, multivariate analysis showed that only unemployment and obtaining malaria information from the church were the major predictors. Some studies also found that malaria prevalence was higher among the poor [27] and also unemployed and low income groups [29] suggesting that differences in the standard of living could be an indicator of the differences in capacities to prevent and manage malaria episodes [27; 29].

Further, the CHWs in our study were exemplary and effective social structures which relieved both simple fevers and the malaria infection and also provided information in malaria control in contrast to the other community social structures that were only available in crises of severe malaria. Evidence on the effective contribution by CHWs in providing preventive interventions in diseases including malaria exists although it has not been sufficient to make conclusions [43]. In Zambia a number of studies have shown

the effectiveness of CHWs [44; 45] but our study is the first to compare their contribution at the very lowest level. The CHWs structure in the Western province, although not working exclusively to prevent malaria, is successful mainly at the management and treatment of malaria [9, 10]. A high proportion of household heads (83.8%), who had experienced clinical malaria prior to the study, reported having taken antimalarial medication through the encouragement from CHWs who conduct door to door visits in the community. Based on the bivariate analyses in our study, identifying with CHWs as a social structure as well as a source of malaria information was associated with good outcomes of low RDT positive rates, higher rates of sustainable malaria support reports and higher rates of antimalarial medication use. Proper use of antimalarial medication, in areas where awareness through education on home management and control of malaria has been raised, can facilitate to reduce the malaria infection reservoirs and hence reduce prevalence. However, it has also been shown that the higher rate of self-medication in one study did not reduce the prevalence of malaria, citing a possibility of drug resistance due to rampant use [29].
The MIS conducted in Zambia so far show that knowledge levels in malaria are sufficiently high and similar in all provinces, with Western province ranking lowest [31]. In like manner, both the bi- and multi-variate analyses in our study show that the access to sustainable malaria support and the use of antimalarial medication among the community members did not seem to be informed by community knowledge or awareness. The low malaria prevalence in the communities in Western Province is attributable to the vigilance of CHWs and not the merits or capacity of community members. Association with and peer influence by CHWs and friends as opposed to education or employment status, were determinants for antimalarial medication use. However, while malaria treatment especially when offered by structures like CHWs will be available for all community members regardless of education, income and employment status, our multivariate analysis shows that appreciating and appropriating the sustainable support in form of receiving the information and treatment is associated with attaining higher education.

As a matter of fact, cases of malaria existed also among participants with higher education, indicating that behaviour change is an important aspect in the prevention of infections regardless of education status. However, it is only achievable in the long term as was evidenced by the low recognition and poor attitude of community members to seek out to the CHWs in Western Province and also the low uptake, by community members, of the abundant health facility services and CHWs in Luapula Province. Although studies have shown that the relevance of CHWs is impacted by the presence or absence of health facilities [46], the CHWs in Luapula Province still have a good platform to make an impact as communities have confidence in them. Another study [47] showed the possibility of a working CHWs system even in places with health facilities nearby as long as the CHWs were supported with the necessary facilities to use. They suggest that the CHWs structure can be taken as an initiative to reduce the workload at primary health centres [47].

Although the CHWs system in the Western Province is based on the individual motivation operating level [9], and may not be running satisfactorily, the system has potential in the management and reduction of disease prevalence if run optimally [8, 10, 44, 45] and we recommend for its introduction or revival in places where the distance between communities and health facilities is long. Furthermore, the CHWs structure can bridge the gap in malaria monitoring and evaluation that exists due to sparse surveillance data, by improving case detection and management. Improved case detection would create sufficient surveillance data, which currently lacks in many malaria-endemic countries in Africa, constrained by a small proportion of patients attending public facilities for malaria diagnosis and treatment [3]. Considering the controversy that still exists around whether to institutionalise the CHWs system or not and to remunerate or not [8], the new Community Health Assistant (CHA) system in Zambia, a structure in between the non-remunerated CHWs and the other regular salaried health workers, can be used as a link between the health facilities and the CHWs. Nevertheless, we caution that the improvement of the CHWs system must be regarded as a short term measure which must go hand in hand with long term behavioural change policies. Strategies must be developed and implemented for longer term goals in securing the participation of communities in malaria prevention and control.

3.5 Conclusions

While overall use of CHWs structures was low in our study, very few RDT-positive cases were reported in communities where the CHWs were strong. We recommend to the Government of the Republic of Zambia to develop policies in line with the determinants outlined in this study such as to strengthen CHWs and steer behaviour change in all communities but with emphasis on places where health facilities are far and education levels in the community are low. We also recommend that the Government creates a deliberate policy to work with the church in malaria control. Our study also shows that regional factors may be more influential in the risk of RDT positivity, gain in malaria support and use of antimalarial medication than are the identified factors such as community social structures. We therefore further recommend to the Government of the Republic of Zambia to develop a deliberate policy on criteria for applying interventions which will provide for regional variations. The determinants specific to communities in the transmission zones as well as the mechanism through which CHWs affect the malaria situation may need to be investigated further.

3.6 Ethical approval

The study protocol was approved by the University of Zambia (UNZA) Biomedical Research Ethics Committee (IRB00001131 of IORG0000774).

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CHAPTER 4

Eco-Environmental Factors of Malaria at Household Level in Four Malaria Endemic Provinces of Zambia

*This chapter is based on:

Shimaponda-Mataa NM, Tembo-Mwase E, Gebreslasie M, Mukaratirwa S. (2015). Influence of water sources and housing location and structure on self-reported malaria: A Bayesian multi-level analysis. *In press (Malaria Journal).*

Abstract

Background: Malaria in Zambia is among the chief causes of morbidity and mortality and is also one of the three major vector-borne diseases whose prevalence can be attributed to agricultural water development. Water and structure of houses are some of the environmental factors that influence malaria endemicity. The malaria control programme in Zambia has made great strides to reduce the disease burden although the contribution of household level environmental determinants has not been studied in the different endemic areas. This study sought to determine the relationship between water sources, practices, housing structures and self-reported malaria in four endemic provinces.

Methods: A simple random sampling technique was employed in a cross-sectional survey conducted in endemic provinces representing the three malaria transmission zones in the country. We administered questionnaires to 584 household heads to gather information on water sources and practices, housing structures and self-reported malaria. Determinants of self-reported malaria were also examined from the data using descriptive and inferential statistics STATA 11 and later fitted a two-level random effects logistic model in Windows version of Bayesian inference Using Gibbs Sampling 14 (WinBUGS14).

Results: Out of the 584 household heads interviewed, 30.7% had experienced self-reported malaria and disaggregated by province, self-reported malaria was highest in Luapula Province and lowest in Lusaka Province (Luapula = 56.5%; Western = 44.8%; North-western = 37.7%; Lusaka = 18.3%; $p < 0.0001$). The common water source between Luapula and Lusaka provinces was tap and well (Luapula = 38.7%; Lusaka = 54%; $p < 0.0001$) respectively although river and dam were also prominent in Luapula and Lusaka Provinces respectively. In North-western Province, the main water source was the well (48.1%) while in Western Province, the well (42.9%) and borehole (46.7%) water sources were almost represented equally ($p<0.0001$). The practice of dumping waste from agricultural produce or other nature was observed in all provinces although it was more pronounced in Lusaka and North-western than in the other provinces. Based on the bivariate analysis, the household heads who reported having suffered from malaria were as follows: among the household heads whose source of water was the river, 55.2% ($p<0.001$); among those who lived in stick and mud houses, 42.7% ($p<0.0001$); among those who lived in grass thatched houses, 39.6% ($p<0.0001$); among those who had attained primary education level and below, 40.4% ($p<0.0001$); and among those who utilised community health workers (CHWs) as a source of information, 44.3% ($p<0.0001$). In a multilevel model, utilising river as a source of water (OR = 2.76, 95% CI: 1.56, 4.9), attaining primary education or below (odds ratios (OR) = 2.06, 95% CI: 1.3, 3.3) and utilising the radio as a source of information (OR = 1.94, 95% CI: 1.21, 3.1) predicted the outcome.

Conclusions: Living in the vicinity of rivers was the strongest predictor of self-reported malaria. Water practices that exist in the communities are capable of creating vector breeding sites. Additionally, housing structures and education levels were also found to be great contributors to self-reported malaria prevalence. The need for integrated malaria and vector control and management programmes, encouraging community involvement with emphasis on places where education levels are low, cannot be overemphasised. The contribution of various dump types to self-reported malaria may need to be explored further.

Key words: *Self-reported malaria, water, housing structure*

4.1 Introduction

Malaria occurs mostly in tropical and subtropical regions and weighs more than 90% of its burden on Sub-Saharan Africa [1]. It is among the top five causes of death among under-fives [3] and the death toll in all age groups is estimated about 438,000 annually [1]. This disease is among the “three major vector-borne diseases whose increase or decrease can be attributed to agricultural water development” [3].
The burden of malaria in Zambia is high [4], the disease being the leading cause of morbidity and mortality. In 2007, four million suspected cases and 6,000 deaths were reported [5] while in 2010 malaria accounted for an annual incidence of 330 cases per 1000 [6]. Within the country, all provinces are malaria endemic [5] although the transmission intensities vary mainly depending on environmental factors [7] as they interact with the vectors. Unnatural processes such as disasters [8] and other practices engineered by man through day to day activities, also contribute to malaria transmission.

Malaria research has, until recently after the 1990s, been focussed on many other control interventions but water management [9] notwithstanding the fact that the ecology of the disease is closely associated with water [2]. Water that sustains malaria transmission varies in its source from natural habitat to that which results from water resources development [2] although other sources of water in the environment such as “breakdown in water management, maintenance problems of local irrigation systems” [2] or even leakages in city sewerage systems [10] may exist.

The early life stages of mosquito development, such as the larvae develop in different water body types depending on their water-ecological requirements [2]. The water bodies can be "sun-lit or shaded, with or without aquatic vegetation, stagnant or slowly streaming, fresh or brackish" [2]. In Africa, the primary vector that transmits malaria is *Anopheles gambiae* [11]. This vector breeds in numerous small pools of water that form due to rainfall [11] or by artificial means or even natural disasters, which have been shown to expose people to epidemics of flood-linked water borne diseases such as malaria [12]. Human activities such as brickmaking or construction works contribute to creating potential breeding sites for *Anopheles gambiae* larvae by leaving burrow-pits in the ground [11]. Additionally, the United Nations Children's Fund (UNICEF) allude also to "poor drainage and uncovered water tanks" as other breeding sites for malaria mosquitoes [13] that result from human-related activities. It has also been observed that malaria outbreaks and even intensified malaria transmission are supported by the presence of impounded water, usually an aftermath of the development of new irrigated agriculture areas [2; 9; 14] and or reservoirs [2; 15]. Impounded water can also result unintentionally through damping of non-biodegradable polythene and other wastes which block water systems [16]. Polythene wastes are successful in impounding water since water cannot percolate through them [16]. Regardless of the source, eliminating standing water in the environment would reduce the mosquito population in households and communities [13].

Zambia is considered to be among the leading nations in malaria control [17, 5], with the research and practice of the larval source management (LSM) method [10] being one of the control efforts the country has participated in along with other countries including Brazil, Egypt, Indonesia, Europe, the US and many other parts of the world. These efforts are conducted with recognition of the fact that malaria control is not only about managing water bodies near households but also a consideration of the differences in the risk of infection [18] considering that clinical attacks can occur over varying distances and that the acquisition of protective immunity may be delayed where transmission intensity is lower [18]. The ability for larvae to develop within a few days and soon escape their aquatic environment before it dries out, makes prediction of when and where the breeding sites will form, to be difficult [11]. Acknowledging climate [19] and other factors, it is clear that water is not the only determinant of malaria transmission although even where it plays an essential role in the ecology of diseases, it may be a challenge to single out the relative importance of aquatic components of the local ecosystems [12]. Apart from the challenge to predict breeding sites, the human and material resources may not suffice to conduct the same in low income areas.

Our study sought to determine the influence of water sources and housing location and structure on self-reported malaria.

4.1.1 Background

Research has shown that house location and or structure [20; 21] and water practices like irrigation [20; 21] and unintentional practices like dumping [16; 22] facilitate the development of the breeding sites and the exposure of communities to malaria vectors.

Based on the methodology described elsewhere [23], we selected the following provinces as study sites: Luapula, Lusaka, North-western and Western provinces. Briefly, Luapula Province covers a total land surface area of 50,567 km^2 and it borders with the Democratic Republic of Congo. The province shares administrative boundaries with Central and Muchinga provinces in the south, and Northern Province in the east. It consists of seven (7) districts namely: Chienge, Kawambwa, Mansa, Milenge, Mwense, Nchelenge and Samfya, with Mansa, a semi-urbanised district, being the provincial capital. The population is estimated at 991,927 with 49.3% men and 50.7% women. The rural areas harbour 80.4% of the people, while the remaining 19.6% live in the urban area [24].

Lusaka Province is the highly urbanised capital city of Zambia. It is geographically the smallest among the study sites, covering a total land surface area of only 21,896 km^2, and bordering with Mozambique in the east and Zimbabwe in the south. The province shares provincial boundaries with Central Province in the north, Southern Province in the south and Eastern Province in the east. It consists of five districts namely: Lusaka, Chongwe, Luangwa, Kafue and Chirundu. The latter was formally part of Southern Province but was added to Lusaka Province in 2011. The population of Lusaka Province is estimated at 2,191,225 (49.4% men and 50.6% women) with 15.3% of the population living in the rural and 84.7% in the urban environment [25].

North-western Province is one of the largest provinces in the country and covers a total land surface area of 125,826 km^2. It borders with the Democratic Republic of Congo as well as with Central, Western and Copperbelt provinces and consists of eight districts namely: Chavuma, Ikelenge, Kabompo, Kasempa, Mufumbwe, Mwinilunga, Solwezi and Zambezi with Solwezi being the semi-urbanised provincial capital.

The population in North-western Province is estimated at 727,044 with 49.3% males and 50.7% females out of which, 77.4% live in the rural areas and 22.6% in the urban areas [26].

Western Province is also vast with a total land surface area of 126, 386 km^2, just slightly bigger than North-western Province. It borders with Angola and Namibia at the country level. At the province level it borders North-western, Southern and Central provinces. Western Province consists of seven districts namely: Kalabo, Kaoma, Lukulu, Mongu, Senanga, Sesheke and Shang'ombo. Mongu is the semi urbanised provincial capital. The population is estimated at 902,974 (48% males and 52% females) with 86.7% of the population living in rural areas and 13.3% in the urban areas [27].

Both public and private health facilities exist in all provinces with community health workers (CHWs) and/health posts, pharmacies or drug stores and traditional outlets as other alternatives.

4.2 Methods

The study involved administering a component of a structured household questionnaire whose details and the methods used are described elsewhere [23].

4.2.1 Study area

The study area description is based on the methodology provided elsewhere [23]. Briefly, Zambia is a landlocked country surrounded by eight neighbouring countries [28]. The country is located in southern Africa between latitudes -8^{o} and -18^{o} South and longitudes 22^{o} and 34^{o} East [28]. The population in Zambia, according to census of 2010, is estimated at 13,046,508 people [29], all of whom are at risk of malaria [30] as the disease is endemic in the country's ten provinces [31]. Malaria peaks during the rainy season and the burden is generally higher in rural areas compared to urban areas [31]. As recommended by the World Health Organisation (WHO), cases of malaria are mainly detected when patients visit a health facility for treatment, although surveillance detection also occurs [32].

Sites selected for this survey included standard enumeration areas (SEAs) from the following four provinces of Zambia; Lusaka (LS), North-western (NW), Western (W) and Luapula (LP). The selected study areas represent the low (Zone I), low to moderate (Zone II) and moderate to high (Zone III) transmission zones [33], respectively (Figure 1).

Figure 1: Map of the study sites by district in the three transmission zones in Zambia

4.2.2 Study design and data collection

The study was a cross-sectional survey and the sampling procedure, including sample size determination, the sampling frame used and the sample selection criteria are described in detail elsewhere [23].

Briefly, the study population excluded severe cases on assumption that the cases prevailing in the community would be uncomplicated cases of malaria. Therefore, assuming that 6% of clinical malaria cases would result in uncomplicated malaria [34; 35] the study utilised a prevalence of 2.1% and given that the questionnaires were administered in the same households selected for malaria testing [23], the number of households was determined based on the number of households that were required to be sampled in order to obtain thirty-two cases of malaria in each province. The Malaria Indicator Survey (MIS) malaria prevalence for each province, i.e. Lusaka 2%, North-western and Western 6% and Luapula 10% [36] and the average number of persons per household [29] were used. A total of 16 SEAs: three in Luapula; eight in Lusaka; two in North-western and three in Western provinces were randomly selected for the study. The number of households sampled in each province for both malaria testing and questionnaire administration in Lusaka, North-western, Western and Luapula were 311, 106, 105 and 67, respectively.

A random stratified sampling method was used to select the study provinces. Further, the samples in each province were selected randomly. The samples were drawn using the Central Statistical Office (CSO) sampling frame developed from the 2010 Census of Population and Housing [29]. This is described in detail elsewhere [23] based on the United Nations (UN) for probability proportional to size [37].

Households were located in SEAs and Zambia has 140,000 SEAs with 1,361 households. SEAs constituted the Primary Sampling Units (PSUs) and there was approximately an average of 103 households in each SEA. Being an average approximation, some SEAs had fewer households. Provision to cover a neighbouring SEA in the event that a sample in a SEA was not met, was made in advance of the survey and the team ensured to countercheck the map and record the details for the new SEA.

4.2.3 Questionnaire administration

The questionnaire was administered as described elsewhere [23], to a total of 584 randomly selected households; 105 households in Western Province, 106 in North-western Province, 62 in Luapula Province and 311 in Lusaka Province. Verbal consent to interview was obtained before the questionnaire was administered.

4.2.4 Data analysis

Data collected from the household survey were entered and initially analysed in STATA 11 and later in WinBUGS14. ArcMap 10 (ESRI, Redlands, CA, USA) was used to generate the map.

This study considered self-reported malaria as the outcome variable and age, education level, employment status and income level of the household head, their source of water, source of malaria information, wall and roof type and owning an insecticide treated net (ITN) as the explanatory variables.

With the exception of age which was continuous and took absolute values, all were represented as dummy variables. The self-reported malaria variable took on the value of 1 for a status of having experienced malaria and 0, otherwise.

In the communities studied, the following explanatory variables were determined: four sources of malaria information; i.e. family, radio, television (TV) and CHWs; two water sources; i.e. river and combination of well and tap; four wall types; i.e. mud blocks, stick and mud, burnt bricks, and cement blocks; and two roof types; i.e. grass and a combination of all other roof types; Each of the categories took on the value of 1 where the information source or water source or wall type or roof type was reported or applicable and 0, where not. Education, income, occupation and owning an ITN were placed in categories. Each of these took on the value of 1 where the level in question was applicable and 0, where it did not apply. Gender took on the value of 1 for males and 0, females.

4.2.5 Estimation process

The dependent variables were binary response variables; hence a logistic regression model was used to examine the effects of the explanatory variables.

Frequency tables were generated for relevant variables. Descriptive statistics, such as means, medians and standard deviations were used to summarise continuous variables and percentages of frequencies were used to describe the prevalence of self-reported malaria and proportions of household heads or representatives who responded to the questionnaire. Relationships between the outcome variable and each explanatory variable were first explored using the non-parametric chi square test in bivariate analysis before a multivariate logistic regression was performed. The 95% confidence level was used to establish the significance of the differences observed in the relationships examined. We included in the logistic model the explanatory variables associated with the outcome variable after the bivariate analysis. Based on two studies [38; 39], random effects logistic models were fitted. The models included fixed effects and group-level intercepts as random effects [38]. This accounts for the two-level nested nature of the data; individuals surveyed, nested within regions. This process is important given the three transmission zones in Zambia across which characteristics such as malaria burden vary. Following a method in literature [40] and given the two-level data;

“We assume Yi ~ Binomial (pi,1), where

Logit(pi) = b0+b1 + b2 + b3 + b4+ uj(i)

We provide non-informative priors for all fixed effects, assuming bk ~ Normal (0,0.000001). The second parameter was the precision giving variance of one million. We further assume that

uj(i) ~ N(0, t), where

precision t has a gamma prior with parameters 0.001 and 0.001, thus the mean is one and the variance is 1000.

To specify the model in WinBUGS, we used a declarative language that lists deterministic and stochastic nodes. For each of the N observations we took the outcome to be Bernoulli, and we specified the logit of the probability, which depends on the x’s and a random effect u. For each of the M groups, we specified the random effect as normally distributed. We then specified the prior of each coefficient and the hyper prior of the precision

The model was as follows:
For predictors of self-reported malaria:
had_malaria[i]~dbern(p.bound[i])

```
p.bound[i]<-max(0,min(1,p[i]))
logit(p[i])<
bcons+bage_hhh*age_hhh[i]+briver*river[i]+bwell_tap*well_tap[i]+bmudblks*mudblks[i]+bsticknmud*sticknmud[i]+bburntbrks*burntbrks[i]+bcementblks*cementblks[i]+bgrass*grass[i]+bmix*mix[i]+bitn*itn[i]+bprinbelow*prinbelow[i]+blowincome*lowincome[i]+bunempall*unempall[i]+bfamily*family[i]+bradio*radio[i]+btv*tv[i]+bchw*chw[i]+u[group[i]]
```

where b represented fixed effects and Ui, random effects. Ui is the estimation of the variance across all the regions included in the study. Where the variance was large, the outcome of interest was taken as dependent on the region, otherwise explained solely by the measured characteristics.

The value of random effects represents the mutual dependence that exists in responses from the same regions. This implies that the correlation between individuals from the same regions is fully explained by their occurrence in the same regions. The variance measures the degree of heterogeneity in the probability of the self-reported malaria status being positive, the benefit from information sources being desirable, the water practices and housing structures being desirable that cannot be explained by simply classifying by self-reported malaria status, information benefit obtained or good housing structure and water practices or not.

Initial values for the betas for the fixed effects were estimates from an ordinary logistic regression while for tau we used the arbitrary value 1. For the random effects ui(j), we generated the initial values using WinBUGS.

Another important measure employed in this study was the intra-class correlation coefficient (ICC). ICC is a measure that describes dependencies in the data by measuring the extent to which individuals within the same group are more similar to each other than they are to individuals in different groups [38]. The ICC (represented by rho ρ) was calculated by the formula:

$\rho = \tau/(\tau + \pi^2/3)$

where τ = estimated variance and $\pi = 3.142$”

[38, 39, 40].

4.3 Results

4.3.1 Study Population

Out of the 584 household heads interviewed in this study, 76.4% were males and 23.6% were females. By individual provinces the proportion of males was still higher than that of females (LP = 69.4%; LS = 77.8%; NW = 86.8%; W = 65.7%). The mean age of the household heads was 41.9 ± 13.8 years and range between 17 and 85 years.

4.3.2 Water source and practices

Table 1 shows avenues for exposure of household heads to potential breeding sites and malaria vectors through water sources and practices and housing structures. The water sources in the four provinces varied significantly. The main water sources in Luapula and Lusaka provinces were tap and well (LP = 38.7%; LS = 54%). River, well and borehole water sources had a similarly distributed representation in both Luapula and Lusaka provinces. The main water sources in North-western and Western provinces were the well (NW = 48.1%) and borehole (W = 46.7%) respectively. However, Western Province also had the well as another major water source (W = 42.9%). The water practices and housing structure are described in detail in Section 4.3.3 and 4.3.4 respectively.

4.3.3 Self-reported malaria prevalence and water source and practices

Figure 2 shows that prevalence of self-reported malaria was highest in Luapula Province and lowest in Lusaka Province (Figure 2) and the overall prevalence of self-reported malaria across all four provinces was 30.7%.

Table 1 shows that household heads that had self-reported malaria in Lusaka and Luapula provinces reported both closed and open water sources while in North-western and Western provinces household heads that had self-reported malaria reported mainly open water sources ($p < 0.0001$). Majority (with 57.1% in North-western as the lowest and 78.1% in Western province as the highest proportions) of household heads in all provinces lived within 500 meters away from open water sources or stagnant water.

Table 1: Exposure of household heads to potential breeding sites and vectors through water and housing structure

	Luapula		Lusaka		N-western		Western		
	(n = 62)		(n = 311)		(n = 106)		(n = 105)		
	n	%	N	%	n	%	n	%	p value
Water source									
River	17	27.4	21	6.8	31	29.2	18	17.1	*<0.0001*
Well	14	22.6	76	24.4	51	48.1	45	42.9	
Borehole	8	12.9	67	21.5	26	24.5	49	46.7	
Tap and well	24	38.7	168	54.0	8	7.5	0	0.0	
Water practices creating potential breeding sites									
Dumped wastes	56	90.3	88	28.3	38	35.8	53	50.5	*<0.0001*
Pools	2	3.2	78	25.1	28	26.4	5	4.8	
Trenches	5	8.1	31	10.0	13	12.3	39	37.1	
Construction or irrigation	0	0.0	13	4.2	1	0.9	3	2.9	
Fishpond	0	0.0	20	6.4	13	12.3	0	0.0	
No water practices	0	0.0	55	17.7	10	9.4	5	4.8	
Distance to open / stagnant water									
Within 500 m	44	71	235	76.6	60	57.1	82	78.1	*<0.0001*
501 – 1000 m	16	25.8	40	13.0	42	40	14	13.3	
Over 1000 m	2	3.2	32	10.4	3	2.9	9	8.6	
Roof types - facilitating exposure to vectors									
Grass	54	87.1	0	0.0	44	41.9	79	75.2	*<0.0001*
Tiles	0	0.0	3	1.0	0	0.0	0	0.0	
Asbestos	0	0.0	88	28.6	0	0.0	0	0.0	
Inverted Box Rib (IBR)	0	0.0	2	0.7	2	1.9	0	0.0	
Iron sheets	8	12.9	215	69.8	59	56.2	26	24.76	
Wall types - facilitating exposure to vectors									
Mud or clay	50	80.7	72	23.4	71	67.6	22	21.0	*<0.0001*
Burnt bricks	11	17.7	31	10.1	33	31.4	4	3.8	
Stick and mud	1	1.6	1	0.3	1	1.0	79	75.2	
Cement blocks	0	0.0	204	66.2	0	0.0	0	0.0	

With regards to water practices, Table 1 further shows that all provinces had dumped wastes where water collected regardless of the source of water. The dumped wastes were either of agricultural produce or other nature such as plastics and domestic waste. In Lusaka and North-western provinces pools of reserved water and dumped wastes of plastics and other domestic waste were common. On the other hand, in Luapula and Western provinces, dumped wastes of agricultural produce were common although trenches were also abundant in Western Province.

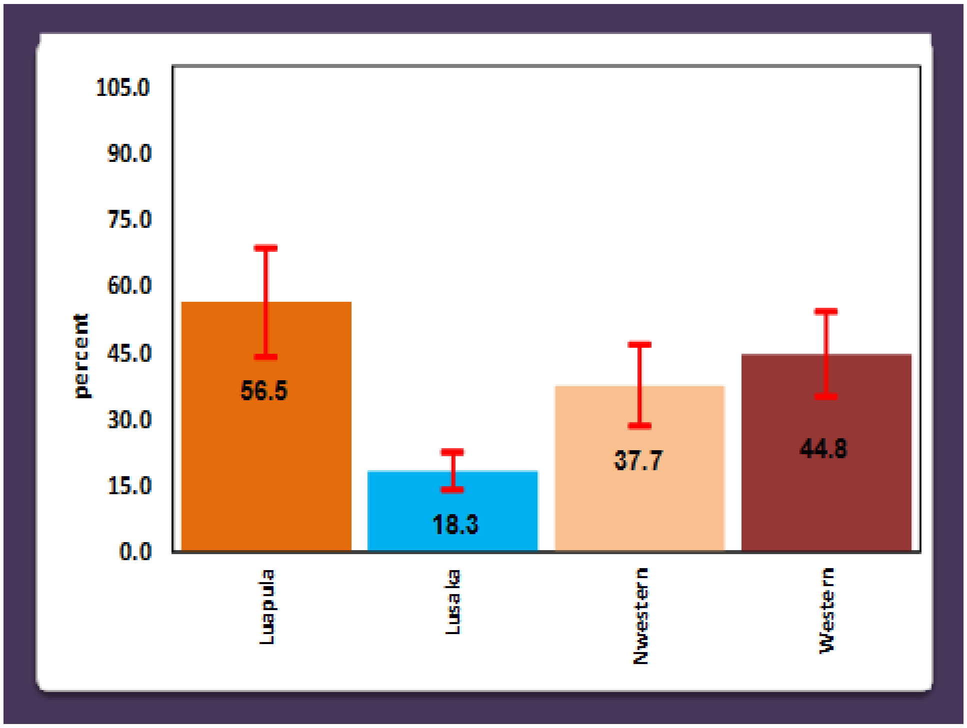

Figure 2: Prevalence of self-reported malaria among household heads selected in the provinces of Zambia.

Although the relationship between water practices and distance to water source was not significant, Table 1 shows that household heads that lived within half a kilometre to water sources practiced dumping more than those who lived beyond that distance. Among the household heads with self-reported malaria in the previous year, majority of them lived within half a kilometre to open water regardless of whether it was a natural water body or as a result of dumping and other activities ($p < 0.0001$).

4.3.4 Type of dwelling (roof and walls)

All the four provinces had house structures of all types considered in this study i.e. mud or clay block, burnt brick, stick and mud and cement block-structures. However, Luapula and North-western provinces were predominated with structures made out of mud or clay (LP = 80.7%; NW = 67.6%; $p < 0.0001$).

These two provinces also had some burnt brick-structures (LP = 17.7%; NW = 31.4%; $p < 0.0001$). Western Province was predominated with stick and mud-structures (W = 75.2%) although it also had mud or clay-structures (W = 21.0%; $p < 0.0001$). Lusaka was predominated with cement block-structures (LS = 66.2%; $p < 0.0001$) but had some mud or clay-structures (LS = 23.4%; $p < 0.0001$) (Table 1).

The roof types in our study sites varied significantly although there were similarities between Luapula and Western and also between Lusaka and North-western provinces. In Luapula and Western provinces grass thatched roofs were dominant (LP = 80.7%; WP = 75.2%) while in Lusaka and North-western provinces iron sheet roofs were (LS = 69.8%; NW = 56.2%) although North-western province also had some grass thatched roofs (NW = 51.9%) ($p < 0.0001$).

4.3.5 ITN and indoor residual spraying (IRS)

In the communities we studied, on average 23.1% (NW = 15.1%; LS = 20.3%; W = 33.3; LP = 33.9%) households had received IRS in the last 12 months prior to the study. In the same communities, on average 67% (NW = 51.5%; LP = 54.8%; LS = 65.3%; W = 98.1%) owned ITNs.

Of the household heads who had ITNs, only 33.2% had self-reported malaria ($p = 0.03$). Further, among household heads whose households received IRS, only 32.8% had self-reported malaria. However, the differences between households that received IRS and those that did not were not statistically significant.

4.3.6 Bivariate analysis

Table 2 shows the associations between self-reported malaria and the hypothesised predictors. All the predictors were significantly related to the outcome variables in question. A total of 35 (56.5%) individuals had self-reported malaria in Luapula Province, 57 (18.3%) in Lusaka, 40 (37.7%) in North-western and 47 (44.8%) in Western ($p < 0.0001$). Out of the 87 persons that reported rivers for water sources, 55.2% had self-reported malaria compared with 40 (20%) that reported well and tap ($p < 0.0001$). Out of the 82 individuals that lived in stick and mud-structures, 42.7% individuals had self-reported malaria compared with 32 (40.5%) who lived in burnt brick-structures and 80 (37.2%) who lived in mud or clay block-structures ($p < 0.0001$). Out of the 177 individuals whose structures were roofed with grass, 70 (39.6%) had self-reported malaria compared with 6 (6.3%) whose structures had roofs of highly priced roof materials i.e. tiles, asbestos and IBR ($p < 0.0001$). Out of the 391 individuals who had ITNs, 130 (33.2%) had self-reported malaria compared with 45 (24.1%) who did not have ITNs ($p < 0.0001$). Out of the 272 persons who had attained only primary education or less, 110 (40.4%) had self-reported malaria compared with 69 (22.1%) who had attained secondary education ($p < 0.0001$). Out of the 462 individuals who earned incomes of Zambian Kwacha rebased (ZMW) 12,000 and below per annum *(1 United States Dollar (USD) ~ 5ZMW in 2014), 157 (34%) had self-reported malaria compared with 22 (18.8%) who earned more ($p < 0.0001$). Out of the 212 household heads who were not in any form of employment, 96 (45.3%) had self-reported malaria compared with 83 (22.3%) who were in employment ($p < 0.0001$) (Table 2).

Although water practices and distance to water source varied significantly by province and it is expected that they would be factors for malaria, they were not significant in bivariate analysis

Table 2: Bivariate analysis of self-reported malaria status versus water, information source, housing structure and social factors

	Self-reported malaria (%)			χ^2	p-value
	Yes	No	Total		
Province					
Luapula	35(56.5)	27(43.5)	**62)**		
Lusaka	57(18.3)	254(81.7)	**311**		
N-western	40(37.7)	66(62.3)	**106)**	54.0	*<0.0001*
Western	47(44.8)	58(55.2)	**105**		
Total	179(30.7)	405(69.3)	**584**		
Water source					
River	48(55.2)	39(44.8)	87		
Well and tap	40(20.0)	160(80.0)	200	34.9	*<0.0001*
Other	110(32.7)	226(67.3)	336		
Total	**198(31.8)**	**425(68.2)**	**623**		
Walls					
Mud/clay blocks	80(37.2)	135(62.8)	**215**		
Burnt bricks	32(40.5)	47(59.5)	**79**		
Stick and mud	35(42.7)	47(57.3)	**82**	38.0	*<0.0001*
Cement blocks	30(14.7)	174(85.3)	**204**		
Total	177(30.5)	403(69.5)	**580**		
Roof					
Grass	70(39.6)	107(61.4)	**177**		
Mix (tiles/asbestos/IBR)	6(6.3)	89(93.7)	**95**	33.8	*<0.0001*
Other	101(32.8)	207(67.2)	**308**		
Total	177(30.5)	403(69.5)	**580**		
ITN					
Yes have ITN	130(33.2)	261(66.8)	391		
No do not have ITN	45(24.1)	142(75.9)	187	34.9	*<0.0001*
Total	**175(30.3)**	**403(69.7)**	**578**		
Education status					
Primary and below	110(40.4)	162(59.6)	272		
Secondary and above	69(22.1)	243(77.9)	312	23.0	*<0.0001*
Total	**179(30.7)**	**405(69.3)**	**584**		
***Income ZMW**					
Above 12,000	22(18.8)	95(81.2)	117		
Below 12,000	157(34.0)	305(66.0)	462	10.1	*0.002*
Total	**179(30.9)**	**400(69.1)**	**579**		
Occupation					
Unemployed+ subsistence + invalid	96(45.3)	116(54.7)	212		
Employed	83(22.3)	289(77.7)	372	33.5	*<0.0001*
Total	**179(30.7)**	**405(69.3)**	**584**		
Information source					
Family	10(15.2)	56(84.8)	66		
Radio	87(34.9)	162(65.1)	249	37.5	*<0.0001*
TV	9(9.8)	83(90.2)	92		
CHW	43(44.3)	54(55.7)	97		
Other	210(29.5)	503(70.5)	713		
Total	**359(29.5)**	**858(70.5)**	**1217**		

*(1 USD ~ 5ZMW in 2014)

4.3.7 Multivariate analysis

After controlling for all the predictors simultaneously in the multi-level model, fewer predictors remained significant (Table 3).

Table 3: Multilevel logistic regression analysis for determinants of self-reported malaria

	Odds ratios	**Credible interval (2.5-97.5%)**	**MC error (5%mean)**
Social, water source and housing structure determinants of self-reported malaria			
Age of household head	1.0	0.9 – 1.01	8.02E-05 (0.00)
Water source			
River	2.76	1.56 – 4.9	0.002(0.05)
Well and tap	0.93	0.5 – 1.7	0.003(0.00)
Wall			
Mud and clay	0.10	0.009 – 0.95	0.07(-0.11)
Stick and mud	0.11	0.008 – 1.2	0.07(-0.11)
Burnt bricks	0.15	0.01 – 1.4	0.07(-0.10)
Cement blocks	0.16	0.01 – 1.55	0.07(-0.09)
Roof			
Grass	0.21	0.1 – 0.4	0.006(-0.08)
Mix (Asbestos/Tiles/IBR)	0.24	0.08 – 0.61	0.004(-0.07)
ITN	2.05	1.2 – 3.5	0.004(0.04)
Education level			
Primary and below	2.06	1.3 – 3.3	0.003(0.04)
Occupation			
Unemployment	1.62	0.99 – 2.66	0.003(0.02)
Income levels			
Income below 12,000 pa	0.99	0.5 – 1.9	0.006(0.04)
Source of malaria information			
Family	0.46	0.19 – 1.04	0.003(-0.04)
Radio	1.94	1.21 – 3.1	0.003(0.03)
TV	0.31	0.12 – 0.73	0.004(-0.06)
CHW	1.21	0.66 – 2.18	0.003(0.01)
Rho	0.03		

Only the river as a source of water, owning ITNs, attaining primary education and below and utilising the radio as a source of malaria information predicted the outcome while the well and tap as water sources, not having ITNs, attaining secondary education and above and all housing structure types, employment and occupation levels dropped out as predictors for self-reported malaria.

Household heads whose water sources were rivers were more likely to have self-reported malaria than those whose water sources were well and tap (OR = 2.76, 95% CI: 1.56, 4.9); those who attained primary education and below were more likely to have self-reported malaria than those who attained secondary education and above (OR = 2.06, 95% CI: 1.3, 3.3); those who had ITNs were more likely to have self-reported malaria than those whose who did not have (OR = 2.05, 95% CI: 1.2 3.5); those who utilised the radio as a source of malaria information were more likely to have self-reported malaria than those who used other sources (OR = 1.94, 95% CI: 1.21, 3.1). The estimated between region variance translated to ICC of 0.03. The model convergence was assessed by Gelman-Rubin statistics and model fit by Deviance Information Criterion (DIC). The models with the smallest DIC were adopted.

4.4 Discussion

The overall prevalence of self-reported malaria of 30.7% found in this survey is comparable with the prevalence of 28.1% obtained in a study conducted in Kenya [41]. Other studies [38; 39] involving children only, obtained lower rates of 13% and 19% respectively. Analysing by province, our study showed that self-reported malaria was more prevalent in Luapula followed by Western and North-western provinces and lowest in Lusaka Province. As did others [401, we demonstrate that self-reported malaria may be an indicator of a significant health problem in the communities studied [41]. An earlier study conducted in the same study population [23] reported malaria prevalence of 3.3% using the rapid diagnostic test (RDT) for the Western Province communities, an apparent disparity with the 44.8% self-reported malaria prevalence in this analysis. Malaria prevalence could be as high as the self-reported statistics with the disparity being accounted for by CHW system in the area [23]. Although the high proportion (44.3%) of individuals whose source of malaria information was CHWs and yet experienced self-reported malaria in our bivariate analysis was not significant, it is clear that the malaria control support provided by the CHWs in the community, contributed to the low prevalence obtained at the time of RDT testing [23]. The study showed that the CHWs were taking a leading role in the curative more than the preventive side of malaria control [23]. A study in Ethiopia also demonstrated that the use of antimalarial drugs in a community could contribute to reduced prevalence rates [7].

Our multilevel analysis revealed that among the sources of information considered, the radio was a predictor of self-reported malaria. It is possible that while the radio is widely used in our study communities, the health messages broadcasted may not be effectively appropriated due to low education levels [23; 42]. In contrast to the findings by others [23; 42] that unemployment and low income levels predicted malaria prevalence, the bi- and multivariate analyses in this study showed that low education (primary and below) was the demographic predictor of self-reported malaria. A study conducted in Ghana [43] showed that the highest proportion of malaria was among children whose mothers had primary school education although with further analysis, this factor did not qualify as a determinant.

IRS was reportedly conducted only in few of the communities we studied. In the same vein, not many households owned ITNs. However, our bivariate analysis showed that there were higher proportions of individuals who had ITNs who had self-reported malaria compared with those who did not have. This could be explained by the possibility that ITNs were selectively distributed and or owned by individuals exposed to higher malaria burden. Coupled with that, the study also observed worn out ITNs in most of the communities considering that some nets were distributed as early as the year 2005 [44]. One study reviewed [38] found no association between possession of bed nets and fever and another [44] also found that the impact of long lasting insecticide treated nets (LLINs) on the reduction of malaria mortality and case fatality rates was not significant [44]. While provision of IRS and ITN services may be low or the available services ineffective, it is also possible that where such control measures are present and functional, they are being challenged by the adapting strategies of mosquitoes [45]. This is illustrated by a study conducted in Ghana which showed that *Anopheles gambiae* may be more exophilic in urban than rural areas posing a challenge to IRS and ITN use [45].

Both the bi- and multi-variate analyses in our study also showed that self-reported malaria was higher in communities that utilised rivers as water sources. In Luapula and Western provinces, rivers were the main sources of water for domestic use and agricultural produce processing, while in Lusaka and North-western provinces, wells were the main sources of water for domestic use. Cassava processing was a common practice in both Luapula and Western provinces, a process which utilises the rivers as water source. With such practices, the creation of mosquito breeding sites is enhanced [46] from the pools and pockets of water inevitably created in the process. Another study also showed that in irrigation processes, the small pockets of water around the main irrigation water pools, support mosquito breeding [47].

In the communities of Kafue, Lusaka Province, the main source of water was the dam which allows for small scale farming. This farming activity creates breeding sites for malaria vectors both from the dam water and the smaller pockets of water along the dam shores [15; 47]. Construction of dams is a noble initiative intended to strengthen economies and contribute to poverty reduction [15; 48] although both environmental and public health impacts on the communities are usually neglected during the planning process [15; 48] which could be a reason for the high prevalence of malaria in the Kafue communities. However, with the recent knowledge that irrigation systems can be developed with a provision for vector control [50], it is possible to make a double contribution of a good investment for water resources while securing the health of the communities. Another study [51] further showed that improvements of already functioning dams, which were made without consideration to public health and the environment, were still possible [51]. These improvements could be explored for the dam in Kafue district.

Although the water practices in the North-western Province and in the rest of the communities in Lusaka Province were not significantly related to self-reported malaria prevalence, the nature of the residential areas promoted the development of breeding sites through dumping of plastics and other non-agricultural wastes [45]. The wastes, being impermeable, cause blockage of drains and water passages [49] an occurrence common in shanty compounds - unplanned expansions of cities which are poor, underdeveloped suburbs [52] - with housing units built as close as one meter apart. This type of residential areas was common in most of the Lusaka communities sampled while in Sandang'ombe, one of two North-western province communities studied, they were the only type. The water bodies with decomposing matter [45] such as water impounded in dump sites and also water from broken pipes and pools formed at construction sites could support the breeding of *Anopheles gambiae* [45]. Open water sources in form of wells [53], observed in both provinces also contribute to the creation of potential mosquito breeding sites [15; 49] although this may not always be the case as shown in one study that depending on the stage or age of the water body, some wells may not harbour *Anopheles gambiae* larvae [45]. Additionally, it has been shown that in exceptional cases: the *Anopheles gambiae* vector may not always be infective [54]; vectorial capacity may be negative at high densities [55]; adult density may be inversely related to anthropophily [55]; *Anopheles gambiae* may be more exophilic in urban than rural areas posing a challenge to IRS and ITN use [45]; vectors that have the capacity to transmit malaria in one area may not in other areas [56]; and water types may, with time and change of conditions, support secondary vector types [56]. It is clear therefore, that regardless of general facts known about characteristics of water that would support mosquito breeding, not all water reserves may be identified correctly as being breeding sites or otherwise [57]. Apart from adapting, vector species can also change in density or in composition in particular places over time, owing to many factors including urbanisation [45; 58; 59]. Therefore, the assumption that urbanisation leads to a decrease in malaria prevalence based on the reduction of *Anopheles gambiae* breeding sites, reduced biting rates, better access to treatment, improved housing [45], may only be changing vector species type. As such, with the rampant indiscriminate dumping of household and market waste in and around towns in developing countries [58], it is important to enhance efforts to reduce such water practices. Although not significant as predictors for self-reported malaria, our study also demonstrated the presence of other water reserves such as trenches and pools upon which, mosquitoes can lay eggs and breed [53] increasing malaria transmission.

Our study revealed that water practices and proximity to water sources were not related to self-reported malaria possibly because, in places where a particular practice was deemed important for sustenance such as cassava processing in Luapula and Western provinces, distance was not a factor. Regardless of our finding, one study demonstrated that people were more at risk for being in close proximity to breeding sites [60] although the material distance can range from 60 meters [61] to 2000 meters [7].

The wall types in Luapula, North-western and Western provinces were mainly made of mud or mud-related materials compared to the cement-walled structures in Lusaka. From the bivariate analysis, household heads who lived in stick and mud houses were more likely to have malaria compared to those who lived in burnt bricks and muddy block houses. Mud walls are known for being positively associated with malaria infection [62] possibly in relation to the capacity of the wall types to sustain IRS chemicals. Regardless of the prominence of mud housing structures in Zambia, the vision for success in controlling malaria must not be marred considering that wall types are not the only factor in determining success of IRS programmes [63]. The type of IRS chemical with regards to the durations of spray cycles [63] and the condition of the housing structures [64] must also be considered. As a matter of fact, mud-walled structures deteriorate rapidly in terms of cracks in blocks and or breaking of old mud blocks [64], facilitating an increase in indoor mosquitoes in mud-walled structures compared to concrete-walled structures [64].

Coupled with the mud-walled structures, grass thatched roofs were also a common feature in Luapula, North-western and Western provinces. Iron–sheet roofs were also prominent in the same provinces although by our bivariate analysis, only the grass roofs were related to high self-reported malaria prevalence. This finding was in agreement with a study conducted in Nigeria [65] that the type of roofing material used in the dwelling is among the important risk factors for co-morbidity. In some studies, it has been shown that iron sheets do not provide an enabling environment for mosquitoes to rest, owing to their structure and the heat they conduct [66]. This proposition is acceptable if other factors including general housing structural conditions [66; 67] such as sealed eaves and protected windows [69] and also environmental factors [7; 70], are accounted for, as it has been shown that the factors on which increase in malaria transmission depends on are those that relate to the local context such as vector management and epidemiological settings, socioeconomic factors and health seeking behaviour [71]. For our study, in Luapula and North-western provinces, all conditions remained right; presence of water and or breeding sites, unscreened windows on houses, unsealed eaves, rendering the negative impact from the iron roofing, ineffective. However, in Lusaka Province, the control measures applied in the immediate past could still be taking effect [58] while for Western Province the sustainable malaria control support [7] received through CHWs [23] is attributable regardless of all conditions being right for vector breeding or house entry [69] and resting. Proper housing structures are an important component in malaria interventions as house design "represents a promising target for future interventions even in highly endemic areas" [72]. Literature [73] recommends "house modifications that are tailored to local conditions such as insect screen ceilings made from locally available materials and small ITNs incorporated in house construction, although these modifications must be used in combination with other control strategies" [73; 74] such as management of larval habitats [68] to create a barrier between humans and malaria vectors. The performance of such control measures at local settings is crucial considering that local housing and resources available differ [68]. This therefore, calls for the involvement of community members, which though a challenge, is crucial given that some low transmission areas like Lusaka Province, have low [7] and delayed [75] immunity which increases chances of increased transmission in case of epidemics.

4.5 Conclusions

While rivers, as sources of water, were the strongest predictor of self-reported malaria, water practices that exist in all the communities are capable of creating breeding sites. Additionally, housing structures and education levels were also found to be great contributors to self-reported malaria prevalence. The need for integrated malaria and vector control and management programmes, encouraging community involvement with emphasis on places where education levels are low, cannot be overemphasised. Our study also shows that regional factors may be more influential in the risk of self-reported malaria than are the identified factors such as water sources. The determinants specific to communities in the transmission zones and the contribution of various dump types to self-reported malaria may need to be explored further. We recommend to the Government of the Republic of Zambia to develop tailor-made guidelines for malaria prevention and control for various regions with regards to water bodies and housing structures and in light of education levels in various regions. We also recommend for development of general guidelines to prevent the development of breeding sites.

4.6 Ethical approval

The study protocol was approved by University of Zambia (UNZA) Biomedical Research Ethics Committee (IRB00001131 of IORG0000774).

4.7 Abbreviations

WinBUGS14: Windows version of Bayesian inference Using Gibbs Sampling 14; CHWs: community health workers; OR: odds ratios; UNICEF: United Nations Children's Fund; LSM: larval source management; WHO: World Health Organisation; SEAs: standard enumeration areas; LS: Lusaka; NW: North-western; W: Western; L: Luapula; MIS: Malaria Indicator Survey; CSO: Central Statistical Office; UN: United Nations; PSU: Primary Sampling Units; ITN: insecticide treated net; TV: television; ICC: intra-class correlation coefficient; IRS: indoor residual spraying; ZMW: Zambian Kwacha rebased; USD: United States Dollar; RDT: rapid diagnostic test; LLIN: long lasting insecticide treated nets; UNZA: University of Zambia.

4.8 Competing interests

The authors declare that they have no competing interests in the manuscript.

4.9 Authors' contributions

All authors conceived the study and contributed to the study design; NMS-M designed the malaria household questionnaire; SM, MG, ET-M edited the questionnaire; NMS-M conducted the survey; NMS-

M and SM analysed the data; NMS-M drafted the manuscript; All authors contributed to the interpretation and presentation of data and read, edited and approved the final manuscript.

4.10 Authors' information

NMS-M (Nzooma M. Shimaponda-Mataa[1,2]) is a Medical Parasitologist and Lecturer at the University of Zambia and holds MSc Parasitology degree; SM (Samson Mukaratirwa[2]) is a Parasitologist and Professor, Dean and Head of School and Lecturer at the University of KwaZulu-Natal in Durban, South Africa and holds PhD in Parasitology; MG (Michael Gebreslasie[4]) is a Geographer (geospatial methods) and Lecturer at the University of KwaZulu-Natal in Durban, South Africa and holds PhD in Geography; ET-M (Enala Tembo-Mwase[3]) is Parasitologist and Professor, Deputy Vice Chancellor and Lecturer at the University of Zambia and holds PhD in Parasitology

[1]University of Zambia School of Medicine, Department of Biomedical Sciences, Ridgeway Campus, Lusaka, Zambia.[2]University of KwaZulu-Natal, School of Life Sciences, Westville Campus, Durban, South Africa.[3]University of Zambia, School of Veterinary Medicine, Great East Road Campus, Lusaka, Zambia.[4]University of KwaZulu-Natal, School of Agriculture, Earth and Environmental Science, Westville Campus, Durban, South Africa

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CHAPTER 5

Investigating Knowledge, Attitudes and Practice in Malaria Control in Communities of Four Malaria Endemic Provinces of Zambia

*This chapter is based on:

Shimaponda-Mataa NM, Tembo-Mwase E, Gebreslasie M, Mukaratirwa S. (2015). Knowledge, attitudes and practices in the control and prevention of malaria in four endemic provinces of Zambia. In press (*South African Journal of Infectious Diseases).*

Knowledge, attitudes and practices in the control and prevention of malaria in four endemic provinces of Zambia

Abstract

This study sought to determine malaria knowledge levels, attitudes and practices of the communities in malaria in four endemic provinces of Zambia. A cross-sectional survey on knowledge, attitude and practices (KAP) on malaria transmission, prevention and control was conducted among 584 household heads of randomly selected communities in Luapula, Lusaka, North-western and Western provinces in Zambia. Data was analysed by both descriptive and inferential statistics. Knowledge levels in malaria with regards to the mosquito being the vector and the capacity of malaria to kill were high in all the provinces and did not vary statistically. The two main sources of malaria information were health facility and radio. From the regression analysis, pain killer use was associated with high incomes, employment, secondary education or higher and the knowledge of fever as a sign for malaria. There is a need to enhance information through available channels such as health facilities, radio and community health workers (CHWs).

Key words: *Malaria, knowledge, attitudes, practices, community, Zambia*

5.1 Introduction

Malaria is a major cause of morbidity and mortality in Zambia. In 2007 four million suspected malaria cases and 6,000 deaths [1] were reported while in 2010 the disease accounted for an annual reported incidence of 330 cases per 1000 [2]. The disease is endemic throughout Zambia [1] although the transmission levels vary depending mainly on environmental factors, including disasters [3], which influence the availability of vectors. The three components in the malaria transmission triangle; the host, the parasite and the vector, all interact within the influence of environmental factors. The contribution of the host has a distinct role in the transmission process, based on its capacity to affect the reservoir base of parasites through treating infections, which would ultimately affect the transmission intensity of malaria [4]. Knowledge in malaria reinforces the capacity of the host or community to affect transmission intensity through informing attitudes and behaviour towards malaria [5]. While communities through cooperating with health facilities and or related structures such as that of the community health workers (CHWs) have recorded strides in malaria prevention and control [5], they have a unique role to play.

Zambia is considered among the leading nations in malaria control [1, 6] and the efforts demonstrated attest to the fact. The fight against malaria in Zambia has been supported through global funding, and local country efforts with tremendous enabling factors in terms of good governance and political will [6]. Zambia has also made significant efforts in knowledge studies from as far back as the late 90s, although as in the case of Swaziland [7], it is only recently that the importance of these studies has been recognised for use in the control efforts. The nation has also made strides in reaching the global World Health Organisation (WHO) targets in control efforts [8] including Long Lasting Insecticide-treated Nets (LLIN) distribution, high Indoor Residual Spraying (IRS) coverage and treatment.

There have been varying reports regarding the knowledge on malaria in different communities around the world, with some studies reporting improvements in the knowledge of the mosquito being the vector although that knowledge did not translate to an improvement in treatment seeking or insecticide treated nets (ITN) use [9, 10]. On the other hand, others have demonstrated the relationship between knowledge in malaria and the practices to prevent and control it in the communities studied [11].

Studies involving community knowledge, attitudes and practices, have shown that many factors [12, 13] including education levels in some [12], are related to behaviour in malaria control [12]. It is clear that behaviour change is an important component in malaria prevention and control, but even crucial is the basis of the behaviour. It is important to determine the levels of malaria knowledge and the attitude and practices of the community in malaria in order to develop tailor-made behavioural change strategies for each area and provide befitting protection.

Our study sought to determine the level of malaria knowledge and the attitude and practices (KAP) to malaria with regards to its transmission and control in the community in four malaria endemic provinces in Zambia.

5.2 Methods

In this study, we administered a component of a structured household questionnaire whose methods are described elsewhere [14] and are adapted for this study.

5.2.1 Study area

Zambia is a landlocked country surrounded by eight neighbouring countries [20]. The country is located in southern Africa between latitudes -8° and -18° South and longitudes 22° and 34° East [14]. The population in Zambia, according to Census of 2010, is estimated at 13,046,508 people [21] all of whom are at risk of malaria [22] as the disease is endemic in the country's all ten provinces [23]. Malaria peaks during the rainy season and the burden is generally higher in rural areas compared to the urban areas [23]. As recommended by the World Health Organisation (WHO), cases of malaria are mainly detected when patients visit a health facility for treatment, although surveillance detection also occurs [24].

As described in elsewhere [14], we sampled from communities in four different provinces as follows: Lusaka (LS), North-western (NW), Western (W) and Luapula (LP) which represent the low (Zone I), low to moderate (Zone II) and moderate to high (Zone III) transmission zones [15], respectively. Briefly, Luapula Province covers a total land surface area of 50,567 km^2 and it borders with the Democratic Republic of Congo. The province shares administrative boundaries with Central and Muchinga provinces in the south, and Northern Province in the east. It consists of seven (7) districts namely: Chienge, Kawambwa, Mansa, Milenge, Mwense, Nchelenge and Samfya, with Mansa, a semi-urbanised district, being the provincial capital. The population is estimated at 991,927 with 49.3% men and 50.7% women. The rural areas harbour 80.4% of the people, while the remaining 19.6% live in the urban area [16].

Lusaka Province is the highly urbanised capital city of Zambia. It is geographically the smallest among the study sites, covering a total land surface area of only 21,896 km^2, and bordering with Mozambique in the east and Zimbabwe in the south. The province shares provincial boundaries with Central Province in the north, Southern Province in the south and Eastern Province in the east. It consists of five districts namely: Lusaka, Chongwe, Luangwa, Kafue and Chirundu. The latter was formally part of Southern Province but was added to Lusaka Province in 2011. The population of Lusaka Province is estimated at 2,191,225 (49.4% men and 50.6% women) with 15.3% of the population living in the rural and 84.7% in the urban environment [17].

North-western Province is one of the largest provinces in the country and covers a total land surface area of 125,826 km^2. It borders with the Democratic Republic of Congo as well as with Central, Western and Copperbelt provinces and consists of eight districts namely: Chavuma, Ikelenge, Kabompo, Kasempa, Mufumbwe, Mwinilunga, Solwezi and Zambezi with Solwezi being the semi-urbanised provincial capital. The population in North-western Province is estimated at 727,044 with 49.3% males and 50.7% females out of which, 77.4% live in the rural areas and 22.6% in the urban areas [18].

Western Province is also vast with a total land surface area of 126, 386 km^2, just slightly bigger than North-western Province. It borders with Angola and Namibia at the country level. At the province level it borders North-western, Southern and Central provinces. Western Province consists of seven districts namely: Kalabo, Kaoma, Lukulu, Mongu, Senanga, Sesheke and Shang'ombo. Mongu is the semi urbanised provincial capital. The population is estimated at 902,974 (48% males and 52% females) with 86.7% of the population living in rural areas and 13.3% in the urban areas [19].

In the four provinces sampled, both public and private health facilities exist and CHWs and/health posts, pharmacies or drug stores and traditional outlets are other alternatives.

The sites selected for this survey included standard enumeration areas (SEAs) from the four provinces as shown in Figure 1.

Figure 1: Map of the study sites in the three transmission zones

5.2.2 Study design and data collection

The study was a cross-sectional survey based on the sampling procedure, sample size determination, sampling frame sample selection criteria and guidelines on identification and consideration of severe cases described in detail elsewhere [14].

Briefly, the study population excluded severe cases on assumption that the cases prevailing in the community would be uncomplicated cases of malaria. Therefore, assuming that 6% of clinical malaria cases would result in uncomplicated malaria [25; 26] the study utilised a prevalence of 2.1% and given that the questionnaires were administered in the same households selected for malaria testing [14], the number of households was determined based on the number of households that were required to be sampled in order to obtain thirty-two cases of malaria in each province. The Malaria Indicator Survey (MIS) malaria prevalence for each province, i.e. Lusaka 2%, North-western and Western 6% and Luapula 10% [27] and the average number of persons per household [21] were used. A total of 16 SEAs: three in Luapula; eight in Lusaka; two in North-western and three in Western provinces were randomly selected for the study. The number of households sampled in each province for both malaria testing and questionnaire administration in Lusaka, North-western, Western and Luapula were 311, 106, 105 and 67, respectively.

A random stratified sampling method was used to select the study provinces. Further, the samples in each province were selected randomly. The samples were drawn using the Central Statistical Office (CSO) sampling frame developed from the 2010 Census of Population and Housing [21]. This is described in detail elsewhere [14] based on the United Nations (UN) method for probability proportional to size [28].

Households are located in standard enumeration areas (SEAs) and Zambia has 140,000 SEAs with 1,361 households. SEAs constitute the Primary Sampling Units (PSUs) and there is approximately an average of 103 households in each SEA. Being an average approximation, some SEAs have fewer households. As such, provision to cover a neighbouring SEA in the event that a sample in a SEA was not met, was made in advance of the survey and the team ensured to countercheck the map and record the details for the new SEA.

5.2.3 Questionnaire administration

The questionnaire was administered to a total of 584 randomly selected households; 105 households in Western Province, 106 in North-western Province, 62 in Luapula Province and 311 in Lusaka Province. Verbal consent to interview was obtained before a questionnaire was administered.

5.2.4 Data analysis

Data collected from the household survey were entered and analysed in STATA 11. ArcMap 10 (ESRI, Redlands, CA, USA) was used to generate the map.

Both descriptive and inferential statistics were employed to address the overall goals of the study. Using descriptive statistics, the general demographic characteristics of individuals admitted to the study were established. Percentages of frequencies as well as confidence intervals were used to describe the proportions of participants who responded to questions in the sections on; malaria knowledge, attitude and practices with regards to prevention and control for the survey.

Chi-square test and cross-tabulations were used to perform association tests between malaria knowledge, attitude and practices against demographic characteristics of household heads in the four provinces and the 95% confidence level was used to establish differences statistically significant in the relations examined.

The parametric test One Way Analysis of variance (ANOVA) was used to examine whether the proportions of household heads and relationships observed in the descriptive statistics section varied by province. This provided a way to determine whether the relationship between malaria knowledge, attitude and practices and demographic characteristics weighed differently by province and transmission zone. Logistic regression was used to predict the odds of independent variables such as province and demographic characteristics and malaria knowledge influencing dependent variables such as malaria attitude and practice.

5.3 Results

5.3.1 Study Population

Out of the 584 household heads interviewed from the four provinces, 76.4% were males and 23.6% were females (LP = 69.4% males versus 30.6% females; LS = 77.8% males versus 22.2% females; NW =

86.8% males versus 13.2% females; W = 65.7% males versus 34.3% females) with a mean age of 41.9 years (range: 17 – 85 years; standard deviation: 13.8). Table 1 shows the demographic characteristics of the study population including the level of education, occupation and income level. Generally illiteracy levels were very low 13% (76/584) although household heads who had attained primary education and below put together were significantly more (46.6%) than the other individual categories ($\chi^2 = 59.8$; $p < 0.0001$). In Luapula, North-western and Western provinces, most of the household heads had qualifications lower than or equal to primary education level (LP = 69.4; NW = 64.2%; W = 59.1%; LS = 31.8%) whereas in Lusaka, most household heads had attained secondary or tertiary education level.

The unemployed category (including the subsistence farmers, the over age and those who had any other incapacitation), were significantly more than the other individual categories (36.1%; $\chi^2 = 141.7$; $p < 0.0001$) and this was influenced mainly by Luapula and Western provinces (LP = 74.2%; W = 70.5%; LS = 17.0%; NW = 35.9%) whereas in Lusaka and North-western provinces the prominent occupations were more than one. The "other" category included household heads who were involved in various income generating activities and for our purposes, farm workers, Military personnel, retired and fishermen were put in this category. Those who earned incomes below ZMW 12,000 (1 USD ~ 5 ZMW in 2014) were the majority (79.8%) and these were mainly in Luapula, North-western and Western provinces (LP = 93.6%; NW = 90.5%; W = 95.2%) while in Lusaka the proportion in this category was slightly lower (68.1%); Table 1.

Table 1: Demographic characteristics of household heads selected in the study

	Luapula (n = 62)		Lusaka (n = 311)		N-western (n = 106)		Western (n = 105)				
Characteristics	n	%	n	%	n	%	n	%	Total	χ^2	*p value*
Mean age range											
In years	22 – 78		17 - 85		19 - 85		20 - 84				
Gender											
Male	43	(69.4)	242	(77.8)	92	(86.8)	69	(65.7)	446(76.4)		
Female	19	(30.6)	69	(22.2)	14	(13.2)	36	(34.3)	138(23.6)	15.0	*0.002*
Education											
Primary& <	43	(69.4)	99	(31.8)	68	(64.2)	62	(59.1)	272(46.6)	59.8	*<0.0001*
Secondary	18	(29.0)	121	(38.9)	30	(28.3)	30	(28.6)	199(34.1)		
Tertiary	0	(0.0)	50	(16.1)	3	(2.8)	11	(10.5)	64(11.0)		
Crafts	0	(0.0)	13	(4.2)	0	(0.0)	0	(0.0)	13(2.2)		
Other	0	(0.0)	3	(1.0)	0	(0.0)	0	(0.0)	3(0.5)		
Not known	1	(1.6)	25	(0.0)	5	(4.7)	2	(1.9)	33(5.7)		
Occupation											
*Unemployed	46	(74.2)	53	(17.0)	38	(35.9)	74	(70.5)	211(36.1)	141.7	*<0.0001*
Trained employee	3	(4.8)	69	(22.2)	2	(1.9)	6	(5.7)	80(13.7)		
Small trader	11	(17.7)	64	(20.6)	14	(13.2)	8	(7.6)	97(16.6)		
Civil servant	1	(1.6)	9	(2.9)	4	(3.8)	5	(4.8)	19(3.3)		
**Other	1	(1.6)	116	(37.3)	48	(45.3)	12	(11.4)	177(30.3)		
*****Income Level ZMW**											
Above 120,000	0	(0.0)	4	(1.3)	0	(0.0)	0	(0.0)	4(0.7)	56.4	*<0.0001*
60,000 – 119,999	0	(0.0)	8	(2.6)	0	(0.0)	0	(0.0)	8(1.4)		
36,000 – 59,999	1	(1.6)	21	(6.8)	4	(3.8)	1	(1.0)	27(4.7)		
12,000 – 35,999	3	(4.8)	65	(21.2)	6	(5.7)	4	(3.8)	78(13.5)		
****4,800 – 11,999& below	58	(93.6)	209	(68.1)	95	(90.5)	100	(95.2)	462 (79.8)		

*Unemployed including subsistence farmers, overage and invalids

**Other (occupation) including farm workers, military, retired and fishing

*** (1 USD ~ 5 ZMW in 2014)

**** Minimum wage and below

5.3.2 Knowledge and attitudes to malaria and source of information

Out of the 584 household heads interviewed in all the four provinces, 97.4% (569/584) had heard about malaria and majority of them heard through the health facility although the proportions varied significantly across the provinces (LP = 91.9%; LS = 69.1%; NW = 76.4%; W = 47.6%; p = 0.002). Other prominent sources of malaria information varying by provinces were: radio -58.1%, CHW – 33.9% and friends – 32.3%, in Luapula; radio - 37.0%, Television (TV) - 27.3% and friends – 23.2% in Lusaka;

radio – 40.6%, community – 20.8% in North-western; and radio - 52.4% and 48.6% - CHW in Western Province, Table 2; Figure 2.

Table 2 Knowledge about malaria among household heads selected in the study

	Luapula		Lusaka		N-western		Western			
	(n = 62)		(n = 311)		(n = 106)		(n = 105)			
	n	%	n	%	n	%	n	%	Total	χ^2; p value
Has respondent heard of malaria										
Yes	62	(100)	306	(98.4)	96	(90.6)	105	(100)	569(97.4)	
No	0	(0.0)	5	(1.6)	10	(9.4)	0	(0.0)	15(2.6)	
Yes, heard from whom?										
Friend	20	(32.3)	72	(23.2)	19	17.9)	13	(12.4)	124(21.2)	
Fam member	3	(4.8)	48	(15.4)	2	(1.9)	13	(12.4)	66(11.3)	
Pamphlet	1	(1.6)	6	(1.9)	0	(0.0)	2	(1.9)	9(1.5)	
Newspaper	0	(0.0)	5	(1.6)	0	(0.0)	2	(1.9)	7(1.2)	
Radio	36	(58.1)	115	(37.0)	43	(40.6)	55	(52.4)	249(42.6)	
TV	0	(0.0)	85	(27.3)	1	(0.9)	6	(5.7)	92(15.8)	
School	1	(1.6)	17	(5.5)	3	(2.8)	4	(3.8)	25(4.3)	
Church	12	(19.4)	25	(8.0)	18	(17.0)	1	(1.0)	56(9.6)	
Community	13	(21.0)	50	(16.1)	22	(20.8)	19	(18.1)	104(17.8)	
Health Facility	57	(91.9)	215	(69.1)	81	(76.4)	50	(47.6)	403(69.0)	14.5; 0.002
CHW	21	(33.9)	14	(4.5)	11	(10.4)	51	(48.6)	97(16.6)	
Malaria group	16	(25.8)	8	(2.6)	1	(0.9)	1	(1.0)	26(4.5)	
What transmits malaria?										
Mosquito	53	(85.5)	270	(86.8)	97	(91.5)	96	(91.4)	516(89.6)	-
Untreated drinking water	2	(3.2)	15	(4.8)	0	(0.0)	1	(1.0)	18(3.1)	
Poor hygiene	0	(0.0)	1	(0.3)	0	(0.0)	0	(0.0)	1(0.2)	
Stagnant water	0	(0.0)	9	(2.9)	1	(0.9)	3	(2.9)	13(2.3)	
Dirty surroundings	0	(0.0)	2	(0.6)	0	(0.0)	1	(1.0)	3(0.5)	
It just comes	0	(0.0)	1	(0.3)	0	(0.0)	0	(0.0)	1(0.2)	
Rain	2	(3.2)	1	(0.3)	0	(0.0)	0	(0.0)	3(0.5)	
Not sure	0	(0.0)	2	(0.6)	0	(0.0)	0	(0.0)	2(0.3)	
Trees	0	(0.0)	1	(0.3)	0	(0.0)	0	(0.0)	1(0.2)	
Dirty food	0	(0.0)	1	(0.3)	0	(0.0)	0	(0.0)	1(0.2)	
Weather	1	(1.6)	1	(0.3)	0	(0.0)	0	(0.0)	2(0.3)	
Do not know	4	(6.5)	4	(1.3)	3	(2.8)	4	(3.8)	15(2.6)	
Can malaria kill?										
Yes	62	(100)	293	(95.1)	102	(99.0)	104	(99.0)	561(97.1)	-
No	0	(0.0)	10	(3.3)	0	(0.0)	0	(0.0)	10(1.7)	
Do not know	0	(0.0)	5	(1.6)	1	(1.0)	1	(1.0)	7(1.2)	
What are the signs of malaria										
Fever	62	(100)	278	(89.4)	95	(89.6)	81	(77.1)	516(88.4)	12; 0.007
Headache	13	(21.0)	211	(67.8)	58	(54.7)	81	(77.1)	363(62.2)	21; <0.0001
Body ache	14	(22.6)	170	(54.7)	55	(51.9)	64	(61.0)	303(51.9)	11; 0.01
Chills	0	(0.0)	59	(19.0)	6	(5.7)	28	(26.7)	93(15.9)	
Vomiting	37	(59.7)	106	(34.1)	43	(40.6)	30	(28.6)	216(37.0)	
General malaise	13	(21.0)	12	(3.9)	9	(8.5)	19	(18.1)	53(9.1)	
Appetite loss	22	(35.5)	36	(11.6)	17	(16.0)	25	(23.8)	100(17.1)	
Dizzy	9	(14.5)	18	(5.8)	8	(7.5)	18	(17.1)	53(9.1)	
Other	0	(0.0)	32	(10.3)	0	(0.0)	3	(2.9)	35(6.0)	
Have enough info?										
Yes	49	(79.0)	275	(88.4)	85	(80.2)	37	(35.2)	446(77.4)	134; <0.0001
No	13	(21.0)	31	(10.0)	15	(14.2)	66	(62.9)	125(21.7)	
Do not know	0	(0.0)	2	(0.6)	1	(0.9)	2	(1.9)	5(0.9)	
	62	(100)	308	(100)	101	(100)	105	(100)	576(100)	

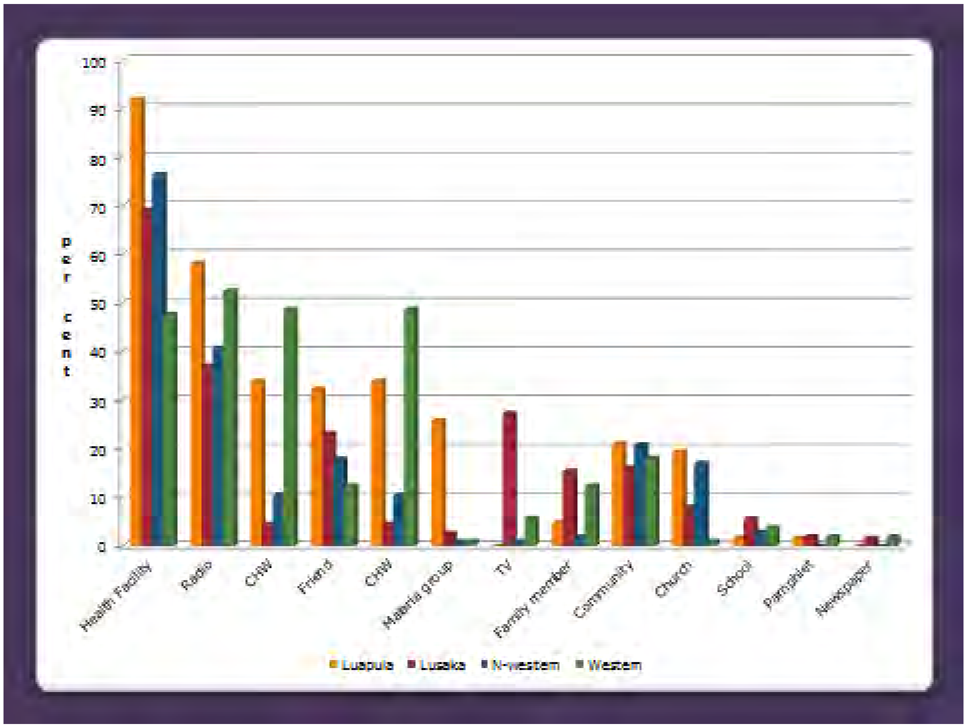

Figure 2: Sources of malaria information among household heads

Overall, majority of the respondents named correctly the mosquito as the vector for malaria transmission (89.6%) with slightly higher but not significant proportions in North-western and Western provinces (LP = 85.5%; LS = 86.8%; NW = 91.5%; W = 91.4%). Very few household heads named unlikely transmission modes such as untreated drinking water, poor hygiene, stagnant water, dirty surroundings, "it just comes", rain, trees, dirty food and weather. Some said that they were not sure while others said that they did not know.

Out of the 578 respondents on the question regarding the capacity of malaria to kill if left untreated, 97.1% demonstrated appropriate knowledge and it did not vary by province.

In all the four provinces, fever, headache and body-aches were the three most frequently mentioned signs of malaria. Overall, 88.4% named fever ($p = 0.007$); 62.2% headache ($p < 0.0001$), and 51.9% body aches ($p = 0.01$). Other signs of malaria the household heads mentioned were chills, appetite loss, dizziness, vomiting and general malaise and not many household heads mentioned them across all the provinces (Figure 3).

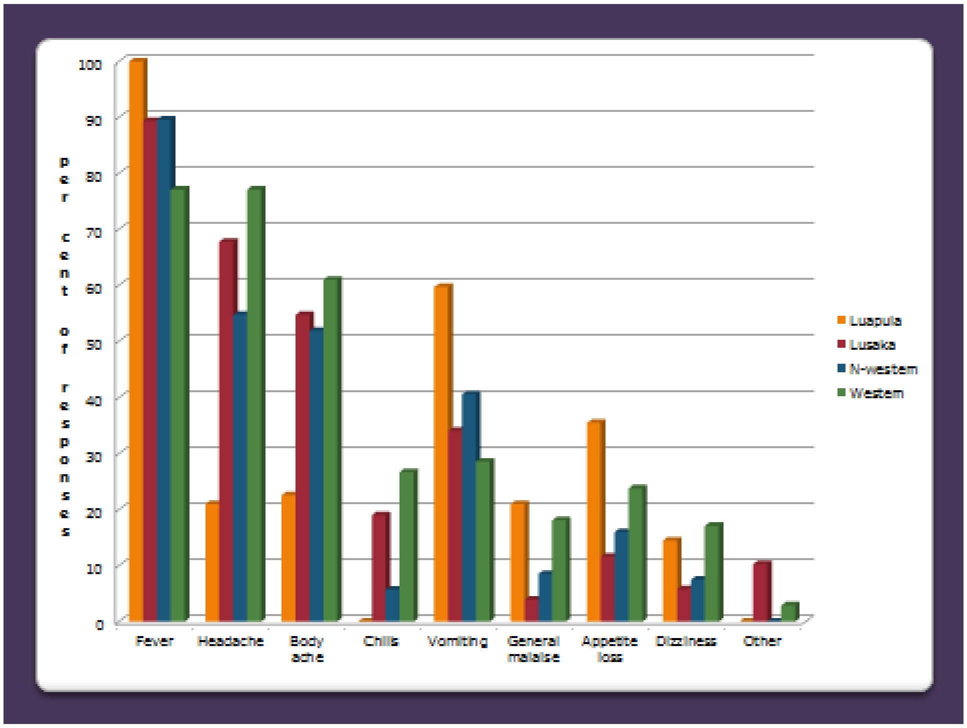

Figure 3: Signs and symptoms of malaria among household heads

Household heads in Luapula, Lusaka and North-western provinces were generally confident that they had enough information on malaria (LP = 79%; LS = 88.4%; NW = 80.2%) compared with those in Western Province, only 35.2% ($p < 0.0001$).

There was a relationship between the source of information and the signs known by the study population. The relationships between Health facility and /or health-facility related sources such as CHW and the signs known were significant ($p = 0.02$). The sources of information on the commonly reported signs of malaria (Fever, headache, body-aches and vomiting) were significantly associated ($p < 0.0001$) with Radio, Health Facility and CHW in all provinces.

On the other hand, the relationships between media related sources of information such as the Radio and television (TV) and signs known were not significant. Similarly, relationships between informal structure sources of information like friends, family and community members and signs known were also not significant.

There was no relationship between the education level and occupation of the participants in all the provinces and the malaria signs they knew. Fever, the most important sign for malaria was well known across all provinces, gender, education, occupation and income levels.

Table 3: Attitudes and Practices in malaria control among household heads selected in the study

	Luapula		**Lusaka**		**N-western**		**Western**			
	(n = 62)		(n = 311)		(n = 106)		(n = 105)			
	n	%	n	%	n	%	n	%	Total	χ^2; *p value*
How soon seek treatment										
One day (within 24 h)	55	(88.7)	166	(53.9)	68	(66.0)	74	(70.5)	363(62.8)	*<0.0001*
2 – 3 days	6	(9.7)	133	(43.2)	35	(34.0)	28	(26.7)	202(35.0)	
4 – 6 days	1	(1.6)	3	(1.0)	0	(0.0)	1	(1.0)	5(0.87)	
7 days or more	0	(0.0)	6	(2.0)	0	(0.0)	2	(2.0)	8(1.4)	
Alternative to seeking treatment										
Nothing other than HF	26	(41.9)	73	(23.7)	42	(40.8)	58	(55.2)	199 (35.3)	34.9; *<0.0001*
Antimalarial	5	(8.1)	12	(3.9)	1	(0.97)	24	(22.9)	42(7.3)	47.3; *<0.0001*
Pain killers	26	(41.9)	187	(60.7)	46	(44.7)	4	(3.8)	263(45.5)	112.1;*<0.0001*
Traditional antimalarial	5	(8.1)	20	(6.5)	14	(13.6)	19	(18.1)	58(10.0)	
Prayers	0	(0.0)	2	(0.67)	0	(0.0)	0	(0.0)	2(0.3)	
Malaria preventable										
Yes	55	(88.7)	248	(79.7)	93	(87.7)	99	(94.3)	495(85.6)	
No	6	(9.7)	55	(17.7)	8	(7.5)	4	(3.8)	73(12.6)	15.2; 0.002
Do not know	1	(1.6)	5	(1.6)	2	(1.9)	2	(1.9)	10(1.7)	
Have bed nets?										
Yes	34	(54.8)	201	(65.3	53	(51.5	103	(98.1)	391(67.7)	62.3; 0.000
No	28	(45.2)	107	(34.7	50	(48.5	2	(1.9)	187(32.3)	
Who owns nets?										
Father	21	(33.9)	159	(51.1)	46	(43.4)	65	(61.9)	291(49.8)	Not sig
Mother	32	(51.6)	143	(46.0)	34	(32.1)	75	(71.4)	284(48.6)	
Children > 5 yrs.	14	(22.6)	90	(28.9)	20	(18.9)	43	(41.0)	167(28.6)	
Children < 5 yrs.	21	(33.9)	80	(25.7)	19	(17.9)	51	(48.6)	171(29.3)	
Other	0	(0.0)	1	(0.3)	2	(1.9)	1	(1.0)	4(0.7)	
NA	0	(0.0)	0	(0.0)	2	(1.9)	1	(1.0)	3(0.5)	
Happy with spray service										
Yes	20	(32.3)	56	(18.8)	14	(15.1)	29	(27.6)	119(21.4)	10.1; 0.02
No	1	(1.6)	5	(1.7)	1	(1.1)	6	(5.7)	13 (2.3)	
N/A (not sprayed)	41	(66.1)	236	(79.5)	78	(83.9)	70	(66.7)	426(76.3)	

5.3.3 Attitudes and Practices in malaria control and prevention

Table 3 shows the findings on the attitudes and practices in malaria and concerning promptness to seeking malaria treatment, 62.8% (363/584) of the whole study population stated that they would attend health facilities within 24 hours of noticing malaria signs (LP = 88.7%; LS = 53.9%; NW = 66%; W = 70.5%; χ^2 = 31.4; $p < 0.0001$).

The attitude towards correct treatment seeking behaviour was poor and reflected through the large proportion of household heads 45.5% (263/578) who would resort to painkillers as an alternative to attending a health facility, with a higher proportion in Lusaka (LS = 60.7%; NW = 44.7%; LP = 41.9%; W = 3.8; χ^2 = 112.1; $p < 0.0001$).

With regards to attitude, 85.6% (495/578) of the household heads in all the provinces believed that malaria could be prevented. This proportion of household heads was higher in Western Province (LS = 79.7%; NW = 87.7%; LP = 88.7%; W = 94.3%) ($p = 0.007$).

Overall, 67.7% household heads reported having ITNs with the highest proportion in Western followed by Lusaka provinces (LP = 54.8%; LS = 65.3%; NW = 51.5%; W = 98.1%; χ^2 = 62.3; p < 0.0001). The attitude towards prioritising ITN ownership among household members in all the provinces reflected through the higher proportions of ITN ownership by fathers 53.1%, was not good although the difference with the proportions of other family member categories was not significant. The practice varied in Western and Luapula provinces against Lusaka and North-western provinces where mothers (W = 71.4%; LP = 51.6%) and fathers (LS = 51.1%; NW = 43.4%) were prioritised respectively.

Acceptance of IRS determined by those who indicated they were happy with the spray service showed that 21.4% (119/557) were happy, with the highest proportion seen in Luapula Province (LP = 32.3%; LS = 18.0%; NW = 13.2%; W = 27.6%; χ^2 = 10.1; 0.02). Majority (76.4%) of the homes had not been sprayed.

5.3.4 Association of Practices with knowledge and attitudes

Table 4 shows that among the household heads that believed malaria could kill if left untreated, those who attended health facilities within 24 hours were more 63.3% (355/561) than those who did so in 48 hours or more although the difference was not significant (63%; χ^2=1.9; 0.17). By odds ratios, the odds of attending health facilities within 24 hours among household heads in the category that believed malaria could kill if left untreated, were 1.9 times the odds of household heads who did not believe (*p = 1.9*; 95%CI = 0.7 – 5.1) although insignificant also.

Although the use of pain killers as an alternative to attending health facilities was common in all education levels, it was higher in household heads who had secondary education and higher (62%; χ^2=14.1; 0.0002). In this regard, the odds of using pain killers among household heads who had attained secondary education or higher, were 1.6 times the odds of those who had attained primary education and below (p = 0.005; 95%CI = 1.2 – 2.22). Additionally, the use of pain killers as an alternative to attending health facilities was higher in the following categories: the employed than in the unemployed household heads (76.8%; χ^2 = 36; p < 0.0001) and the odds of using pain killers among those in this category, were 2.8 times the odds of those in the unemployed category (*$p < 0.0001$*; 95%CI = 1.9 – 3.9); those who knew fever as a sign of malaria than those who did not (93.5%; χ^2 = 6.3; p = 0.01) and the odds of using pain killers among those in this category, were 2.2 times the odds of those who did not know (p = 0.005; 95%CI = 1.3 – 3.8); those who earned incomes higher than ZMW 12,000 per annum than those who earned lower incomes (55.2%; χ^2 = 5.6; p = 0.02) with the odds of using pain killers among those in this category, at 1.6 times the odds of those in the lower income category (*$p = 0.02$*; 95%CI = 1.1-2.4). Further, the use of antimalarial medicine as an alternative to attending the health facility was higher 57.1% (24/42) among the households heads who were not in employment (including subsistence farmers), than in those who were employed (23.2%; χ^2 = 20.8; p < 0.0001) and the odds of using antimalarial medication among those in this category, were 2.6 times the odds of those in employment (*$p = 0.002$*; 95%CI = 1.4 – 4.9).

Table 4 Relationship between knowledge and attitude with practices

		Pain killers	Have ITN	Accept IRS	Use antimalarial med	Seek treatment in 24h
High income	OR	1.6				
	P	0.02				
	95% CI	1.1 – 2.4				
		55.2%; χ^2=5.6; 0.02				
Employed	OR	2.8				
	P	<0.0001				
	95% CI	1.9 – 3.9				
		76.8%; χ^2=36; 0.02				
Secondary & above	OR	1.6	1.8			
	P	0.005	0.001			
	95% CI	1.2 -2.2	1.3 – 2.6			
		62%; χ^2=14.1; 0.0002	56.5%; χ^2=4.6; 0.03			
Unemployed	OR			1.6	2.6	
	P			0.02	0.002	
	95% CI			1.1 – 2.5	1.4 – 4.9	
				27%; χ^2=5.8; 0.02	57.1%; χ^2=20.8; <0.0001	
Malaria can kill	OR					1.9
	P					1.9
	95% CI					0.7 – 5.1
						63%; χ^2=1.9; 0.17
Mosquito as vector	OR			1.9		
	P			0.01		
	95% CI			1.1 – 3.2		
				94.4%; χ^2=9.7; 0.002		
Knowing fever	OR	2.2				
	P	0.005				
	95% CI	1.3 – 3.8				
		93.5%; χ^2=6.3; 0.01				

There was a relationship between education levels (secondary education and above) and owning an ITN (56.5%; χ^2 = 4.6; p = 0.03) and in this vein, the odds of having ITNs among household heads who had attained secondary education and above, were 1.8 times the odds of those with primary education and below (*p = 0.001*; 95%CI = 1.3 – 2.6).

With regards IRS, acceptance was higher among the unemployed 27% (54/200) than the employed (18.2%; χ^2 = 5.8; p = 0.02) and the odds of acceptance among the unemployed, were 1.6 times the odds of those in the employed category (p = 0.02; 95%CI = 1.1 – 2.5). IRS acceptance was also higher among those who knew the mosquito as a vector 94.4% (102/108) than those who did not (χ^2 = 9.7; *p = 0.002*) and the odds of IRS acceptance among this category, were 1.9 times the odds of those who did not know (*p = 0.01*; 95%CI = 1.1 – 3.2).

5.4 Discussion

This study was conducted to determine the KAP related to malaria in selected endemic provinces in Zambia; Luapula, Lusaka, North-western and Western among household heads. The household head age ranged from 17 up to 85 years with the youngest age (17 years) obtaining in Lusaka and North-western provinces. It is not very common occurrence, especially in urban as it would be in rural Zambia, to have young adults heading households as evidenced in a study by UNWFP where only one household was headed by a 15 year-old child [29].

While the population in Zambia is dominated by females (51%) over males (49%) [21], or 52.4% females versus 47.6% males [27], household headship rests heavily on males (74.9%) than females (25.1%) [27, 30] demonstrated also in our study, where 66% to 87% were male household heads compared to 13% to 34% female.

In our study, knowledge about malaria was quite high as evidenced by the proportion of household heads (89.6%) who knew the mosquito as a vector of malaria, comparable with 85% obtained in another study [12]. Other studies have shown a variation in the levels of the knowledge of the mosquito as a vector of malaria 99.7%, 32.3%, 72.6%, 27.7% and 58.4% [7; 10; 31; 32; 33] respectively. Taking the provinces in our study individually, Lusaka and Luapula provinces recorded the lowest proportion, a startling finding for Lusaka where malaria control efforts are working well.

While knowledge has been related to correct attitudes and hence behaviour, in certain cases, correct behaviour is hindered by a lack of or limited experience [11; 34]. It has further been suggested that malaria knowledge tends to reduce with the lowering of malaria levels [7], which explains the low knowledge levels in Lusaka Province and further justifying a suggestion [35] that improvement in knowledge, attitudes and practices related to malaria may be attained only after considering its predictors at micro level [35]. The need to expose behaviour determinants in successful behaviour change programmes at local levels cannot be over emphasised.

Education in our study was not related to malaria knowledge levels as was found in one study [12] while in another [32], only the knowledge on preventive methods was inversely related to education levels. In that study [32], a higher proportion of household (34%) heads who knew the preventive methods of malaria had attained primary education level compared to 26.5% who had attained secondary education level [32]. A number of studies have demonstrated no advantage of higher education levels in the knowledge and practices in malaria control. In agreement with one study [33] which found that most household heads who knew the capacity of malaria to kill were from rural areas, attributing the finding to the high endemicity of the disease in those areas [33], our study also, found the knowledge of the capacity for malaria to kill if left untreated lowest in Lusaka Province, the most urban of all provinces in the country. Surprisingly, to the question whether the respondents had enough malaria information, Lusaka scored highest when it was the lowest in the various specific knowledge questions. Another study [12] reported high malaria knowledge regardless of the lack of correlation between education levels and malaria risk, showing that malaria knowledge was only marginally better in areas with higher education levels [12].

A study in Nepal [31] revealed that illiteracy was an important factor [31], proposing that while communities may not get a formal education, health education was necessary to guide behaviour change messages [32; 33; 36; 37] in context. Another study [38] showed high malaria knowledge but low ITN and IRS acceptability due to their effect on bees [9, 38] in a bee-keeping community. This occurrence is a typical illustration of the need to embrace socio-economic and socio-cultural aspects of a community in malaria control.

From results of the studies conducted in Colombia [12] and Tanzania [13] showing high knowledge in malaria regardless of low education, we concur that formal education does not relate significantly with malaria risk and in agreement with such findings, other studies recommend that with high knowledge in ITN and IRS, improving the manner in which information reaches the communities through use of proper channels with special attention to illiterate community members was still necessary [13] and also that while owning and hanging nets were determinants to use, tailor-made messages to encourage hang up which would bridge owning and use [39] were necessary.

Our study, found fever, headache and body aches as the commonly reported signs, with high proportions of participants reporting health facilities as their main source of malaria information, agreeing with a study conducted in Swaziland [7]. The prominence of fever among all signs of malaria in our study is in line with other studies [12; 33; 40; 41] and accurately shows that Zambia considers fever as a key predictor of malaria which households must know [30] and that the message has been well received in communities. However, in children, one study showed that with diarrhoea, fever as a predictor of malaria would fail [42].

Attitude, a compound of affect, cognition and behaviour [43], is an important component in malaria control although it has not been adequately considered in the design of interventions such as health education promotion messages, hindering the achievement of sustainable control [44].

With regards to seeking treatment early, 62% of our research participants, most of whom had attained primary and education and below, attended health facilities within 24 hours of noticing malaria signs, compared to the proportions (88.1% and 28.4%) reported by others [7; 10]. Those with higher education attainments displayed an attitude of complacency towards seeking healthcare especially from the health facility possibly owing to the easy access to alternative means of treatment at their disposal, a finding specifically true for Lusaka Province which scored the lowest in early treatment seeking. Based on our regression analysis, our study showed that seeking early treatment was also related with the knowledge of the capacity for malaria to kill if left untreated. In the same vein, other studies have demonstrated a correlation between increased knowledge and good treatment seeking behaviour although with gaps in translating knowledge to improved practice of prevention [45] and in understanding what aspects of malaria to be preoccupied with, for instance differentiating between mosquitoes being a nuisance as opposed to them being a source of infection [46]. It has also been shown in another study [11] that there is improved case management with higher knowledge although preference for home treatment was also high

[11] possibly based on attitude towards such treatment. One study in Nigeria where the best antimalarial therapy was limited to chloroquine [47] showed that attitude can limit behaviour.

With respect to the alternative treatment seeking practices household heads took when the health facility option was not easily accessible, our regression analysis shows that high income, employment and education (secondary education or higher) were positively related to the use of pain killers while unemployment to the use of antimalarial medication. This shows that household heads advantaged socioeconomically such as those in Lusaka and North-western provinces which had highest proportions of pain killer use, take for granted their exposure by neglecting to practice good treatment seeking measures compared with the uneducated persons who religiously heed guidance from the health care providers. Further, treatment seeking behaviour of those who knew fever as a sign of malaria did not relate to the knowledge they had as evidenced by the majority of the household heads in Luapula, Lusaka and North-western provinces who knew fever as a sign for malaria but still opted for painkillers. It is possible that the attitude of community members is informed by the inaccurate consideration that malaria was equivalent to headache and fever without relating it to the parasite as the basis for the symptoms. Knowledge of signs and belief in pain killers alone is not sufficient for effective malaria control.

While accounting for cultural beliefs in the design of control measures and messages, is critical [48], and in the light of the fruitful efforts in reducing malaria burden there is need to recognise the regional differences in terms of transmission levels and region-specific cultural backgrounds [12]. This was highlighted as a gap in Colombia [12] and has been shown in Zambia also where ITNs have been used for fishing [19]. Additionally, factors such as “presence of malaria in remote areas with limited access to health and education services, political instability and several others”, varying by region, are some constraints to fully achieving Ministry of health goals [12]. Our study highlights such realities in areas such the Western and North-western provinces of Zambia where access to healthcare and education is limited and further recommend for investigation into the basis of behavioural challenges revealed in low community uptake of appropriate services like antimalarial medication in areas like Lusaka Province, even when available.

Further, 85.6% household heads in our study believed malaria was preventable, 61.5% of which believed it was preventable by ITNs. Other studies [7; 31] also reported higher proportions (78% and 90.1% respectively) of study participants who believed malaria was preventable although the proportions of those who believed it was preventable by ITN were low 15.6% [7].

With regards to ITN use, overall, the proportion of fathers using the ITNs was higher than all family members. The mother and children under 5 were next in priority and then the children above 5 years. However, at province level, Luapula and Western provinces had higher proportions of mothers using ITNs, but in both cases, fathers were the next in line of beneficiaries, the exact opposite for Lusaka and North-western provinces. It is possible that the higher proportions of fathers using ITNs could be by default where if married, share beds with the mothers who, being vulnerable mostly use ITNs. Efforts to educate communities, particularly women who are already convinced of their vulnerability, can yield more results in control. A study conducted in Zambia [39] reported marked improvement in translating attitudes to practice over four years where the proportion of women of child-bearing age who believed the chemical on the ITN was dangerous to the foetus reduced by four times after four years [39] resulting in less men and children 5-14 years and more children under 5 using the family net [39]. The vulnerable children under 5 became rightfully as or more likely than a woman of child-bearing age to be sleeping under a net [39]. We concur with the recommendation [11] that delivering educational information on malaria knowledge to women can help increase net ownership and use. As such, if the women were educated on the vulnerability of the children under 5, the default benefit would turn into a deserved benefit. In the study conducted in Swaziland [7], the communities seemed to be well informed and with good attitude in that the proportions of children under 5 and mothers that owned ITNs were highest (46.8% and 43.5% respectively) while only few of the children above 5 and fathers, owned nets (8.9% and 4.8% respectively) [7].

Furthermore, although a good number of ITNs were reported among the unemployed, our study shows a significant relationship between having an ITN and attaining secondary education or higher. The high ITN proportions among the unemployed could be explained by the Ministry of Health (MOH) ITN distribution campaigns in Zambia which have made a significant contribution in the equity in ITN ownership, increasing coverage from 38% in 2006 to 64% in 2010 [8]. The regression analysis findings of our study showed that household heads with secondary and tertiary education levels were more likely to have ITNs compared to those with primary or no education could be explained by the possibility that having been distributed as early as 2005 [49], the MOH distributed ITNs could have worn out and the ITNs reported in our study could have been obtained by individual effort.

A number of participants equated owning an ITN to receiving it as a donation and never considered purchasing as an option. This is in agreement with studies [50] which reported that individuals would not seek out testing or treatment even when services were subsidised mainly because the services was not absolutely free [50] and [31] which showed that majority of the respondents reported that they could not afford ITNs. It is possible that free distribution of ITNs has led the communities to develop a dependency syndrome on handouts. It is important to maintain presence and use of ITNs in endemic areas as a way to maintain protection in case of disaster as the sustainability of the ITN effect has been demonstrated in some disaster areas in Zambia where malaria prevalence did not increase amidst disasters owing to use of ITN and other measures [3].

Attitude to and acceptability of IRS in our study was determined based on the experience community members had with the most recent spray and also the reasons advanced by household heads for their displeasure with the spray service. One study [10] reported that only 5.4% believed malaria was preventable by IRS but this did not hinder the IRS acceptability as 42.7% of the respondents had their houses sprayed [10]. Similarly, in our study, the reasons given against IRS did not seem to affect the decision to permit the spraying activity in their homes, with the main one being that the IRS programme did not take place. Our study also showed that acceptability of prevention interventions such as IRS was higher in areas of low development and education like Luapula and Western provinces. However, sustainability is not guaranteed without behaviour assessment, interventions and change, particularly considering the fact that, owing to low understanding or as necessitated by the short term nature of the muddy structures, households in such areas are often re-plastered [31], negating the IRS effect.

There are varying factors that influence malaria control, not only between but also within transmission zones such as was the case between Lusaka and North-western provinces versus Luapula and Western provinces. This was displayed in the differences in education levels, knowledge, attitudes and practices, with Lusaka Province displaying higher education levels but lower malaria KAP. As such, this study is in agreement with one study [51] that “there is no universal truth with regards utilisation of healthcare” and that “every situation and every district has its own specific characteristics which make the outcome of decision-making process different every time” [51]. Our study revealed the unique factors that influence malaria transmission and control in the various zones which must be addressed with tailor-made measures at the lowest level. This must be done while taking into account the one underlying factor in all intervention efforts, behaviour change.

5.5 Conclusion

Malaria knowledge and the attitudes and practices in malaria with regards to its transmission and control in the three transmission zones though similar in some respects, varied in levels at province level. Community members have the knowledge in malaria although disjointed with their practices in terms of access and use of protection or treatment. As such there is need to enhance information through available channels such as health facilities, radio and CHWs depending on the local settings. This process must be based on area-specific tailor-made strategies given that malaria knowledge which goes with experience through higher endemicity is low in low transmission zones. Considering that IRS coverage was quite low, while that of ITNs higher but moderately effective possibly due to the wearing out of the distributed ones and apathy for personal procuring, we recommend enhanced community-level efforts to assess the needs and cover the different communities with befitting protection. Socio cultural issues along with many factors such as distance to health facilities and environmental issues which remain unique for the various zones must also be considered in malaria control. We recommend to the Government of the Republic of Zambia to utilise the identified effective media for information dissemination for the specific regions as well as to develop prevention and control messages tailored for low transmission zone areas separate from the moderate to high transmission areas. We also recommend for the Government to facilitate tools and or equipment required for particular socio-cultural activities that are key to livelihood in various transmission zones such as subsidised fishing equipment in Luapula and Western provinces to curtail the use of mosquito nets as fishing nets and to investigate the need for facilitating bee management tools in North-western provinces in a bid to prevent apathy in IRS in case of assumptions that it would interfere with bee management.

5.6 Ethical approval

The study protocol was approved by University of Zambia (UNZA) Biomedical Research Ethics Committee (IRB00001131 of IORG0000774).

5.7 Abbreviations

KAP: knowledge, attitude and practices; ITN: insecticide treated net; IRS: indoor residual spraying; CHWs: community health workers; WHO: World Health Organisation; LLIN: long lasting insecticide-treated nets; LS: Lusaka; NW: North-western; W: Western; L: Luapula; SEAs: standard enumeration areas; MIS: Malaria Indicator Survey; CSO: Central Statistical Office; UN: United Nations; PSUs: Primary Sampling Units; ANOVA: Analysis of variance; TV: television; OR: odds ratios; MOH: Ministry of Health; UNZA: University of Zambia;

5.8 Competing interests

The authors declare that they have no competing interests in the manuscript.

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CHAPTER 6

Socio-Economic Determinants of Malaria at Province Level in four malaria endemic provinces of Zambia

*This chapter is based on:

Shimaponda-Mataa NM, Tembo-Mwase E, Gebreslasie M, Mukaratirwa S. (2015). Influence of socio-economic factors on the incidence of malaria in four endemic provinces of Zambia: A Bayesian hierarchical analysis. *Not submitted yet*

Abstract

Background: Malaria is a global problem affecting poor countries through redirecting their meagre resources and reducing their economic growth. Although Zambia has a strong malaria control programme based on the integrated approach and studies have evaluated the effectiveness of malaria control methods and related the burden with control methods, the country has had to make decisions that call for higher expenditure through the incorporation of rapid diagnostic tests (RDTs) and a change of antimalarial drugs amidst high poverty levels. Notwithstanding, research reveals a need for more investments to contain the resurgence and reduce the burden of malaria and yet the specific contributions of socio-economic factors at programme level have not been studied in the different endemic areas. This study characterised the variations in malaria morbidity and explored the contribution of socio-economic factors in four endemic provinces using a Bayesian hierarchical model.

Methods: Malaria cases reported through the Health Management Information System (HMIS) at both Provincial Health Offices (PHO) and Ministry of Health (MOH) headquarters were used in the analysis. Malaria control interventions implemented through both the MOH and Medical Stores Limited (MSL) were the determinants examined from the data. We used descriptive and inferential statistics in STATA 11 and later fitted a hierarchical Bayesian model in Windows version of Bayesian inference Using Gibbs Sampling 14 (WinBUGS14).

Results: Malaria incidence varied in the four provinces over the years 2006 to 2012 but demonstrated a uniform pattern of high burden in 2006, a steep decline in 2009 and thereafter an increasing burden up to 2012. Malaria control funding and indoor residual spraying (IRS) as intervention variables displayed uniform coverage in all the provinces while insecticide treated net (ITN) coverage and insecticide distribution varied generally. The supply of antimalarial drugs and RDTs was also generally uniform. Province (Luapula) (OR = 2.7, 95% CI: 2.7, 2.8) was the strongest predictor although ITN (OR = 1.1, 95% CI: 1.1, 1.2) also showed positive and significant results with weak effect while malaria control funding showed a negative but insignificant relationship (OR = 0.8, 95% CI: 0.79, 0.81).

Conclusions: Province was the strongest predictor of malaria incidence in our analysis although ITN also weakly predicted the outcome. Malaria control funding, IRS, drug, insecticide and RDT distributions were found to be potential predictors if utilised and analysed effectively. The need to explore both

Programme and community contribution for specific communities is necessary to elucidate regional factors.

Key words: Socio-economic, malaria, incidence, Zambia

6.1 Introduction

Malaria is a global health problem causing a burden of an estimated 214 million cases and 438,000 deaths worldwide per year [1]. Over 90% of the burden occurs in sub-Saharan Africa, the poorest region in the world and poverty plays a major role [2, 3]. The disease is responsible for about 1.3 percent reduction in the average annual rate of economic growth for countries with the highest burden [2].

Although malaria control funding, Insecticide Treated Nets (ITN), Indoor Residual Spraying (IRS) and Artemisinin-based Combination Therapies (ACT) coverage in the World Health Organisation (WHO) Africa region increased between the years 2005 and 2013, the annual gains in 2013 alone did not meet the required resources [1]. In Zambia, malaria control was reinforced by "the evidence-based planning informed by operational research, use of WHO-recommended strategies, interventions and increased technical and financial support from partners" in the 2000s. This resulted in substantial funding availed for the expansion of intervention coverage and utilisation of malaria control services such as long lasting insecticide nets (LLINs), IRS, Rapid Diagnostic Tests (RDTs) and ACTs [4]. The country is considered to be among the leading nations in malaria control programme [5, 6] and in the late 2000s, it recorded great successes. Likewise, many countries recorded successes in malaria control aiming towards pre-elimination but with dwindling donor-dependent resources in these high risk areas [7], resurgence has been inevitable [4, 8]. In such circumstances, two solutions are advanced: to either utilise a new control tool which would work best at lowest cost or to make what is already existing work [7]. Either of the two options would demand resources although working with an already existing option is more feasible regardless of the fact that individual effectiveness, coverage and community effectiveness would need to be monitored [7].

Due to drug and insecticide resistance, Zambia had to make decisions that call for higher expenditure [9] through the incorporation of RDTs and a change of antimalarial drugs. In 2003, the Ministry of Health

(MOH) adopted the use of ACT as treatment for uncomplicated malaria [10] and later the use of RDTs along with microscopy or as sole diagnostic tools where microscopy was not possible.

Studies have analysed the economic effects of malaria and it has been shown that most of them hinge more on mathematical significance of malaria [2]. Only a few provide analyses of disease and poverty, a relationship well known [2]. Further, most studies have assessed malaria burden and its relationship with socio-economics shown as a negative correlation [3]. These studies confirm that the disease is a social and economic problem [2] and a disease of poverty [3]. In specific terms, malaria has been shown in some cases to consume about United States dollar (US$) 3.5million in government funding and US$2.3million from other stakeholders in the form of various control attempts in 2013 [2].

Within the last decade, WHO concluded that “the climatic changes that had occurred since the mid-1970s could already be causing annually over 150,000 deaths and five million disability-adjusted life-years (DALY), mainly in developing countries” [11]. This is revealed through economic empowerment efforts by governments which are hindered by loss of productive days due to malaria [2] coupled with high costs to deal with drug and insecticide resistance, choking the economies [1, 2].

Although Zambia has experienced economic growth in the past, the growth has not translated into significant poverty reduction [12]. Sixty percent of the population lives below the poverty line and 42% are considered to be in extreme poverty [12, 13] and yet research reveals a need for more investments to contain the resurgence [4, 8] and reduce the burden of malaria.

A number of studies in Zambia have evaluated the effectiveness of malaria control methods [14] and also related the burden with control efforts [4, 15]. It has been shown that the “presence of *An. arabiensis*, a species that is typically difficult to control by Indoor Residual Spraying (IRS) and Insecticide Treated Nets (ITNs), and the predominance of the *An. gambiae ss*. which is characteristically amenable to control by IRS and ITNs, could have implications for the malaria control programme” [16]. Different studies have demonstrated positive effects on malaria burden of IRS [14] and LLIN [15] with the latter recommending for further reinforcement in vector and insecticide resistance mapping in hotspots, enhanced efforts in larviciding and cross-border collaborations [15]. Other recommendations have been for the re-orientation of strategies and interventions to improve malaria control and pre-elimination based on the current epidemiological strata [4]. Considering that the decline in physical integrity of LLINs was cited for possible contribution to the malaria resurgence in 2009-2010 [4] and that majority of Zambian populations depend on donations for provision of ITNs [17], there is need to study both programme and household level socio-economic factors. It is clear that so much work has been done in both implementation of malaria control programmes from treatment- to prevention-oriented in the 1990s and 2000s respectively [4], and in assessments of the malaria status. The assessments so far reveal varying results of positive impact of IRS and not ITNs [14] and also LLINs and not IRS [15]. There is need to study the matter in perspective of varying transmission settings in order to add a new dimension to understanding the role of larger regional factors in malaria at local levels and to determine the need and direction for further research. This would reveal the malaria status in the country [4, 14, 15] and also its variation by transmission zones.

In this study, the relationships between socio-economic factors and malaria burden in Zambia were explored using a Bayesian hierarchical model.

6.2 Methods

6.2.1 Study area

The description of the selected study area is based on the methodology provided elsewhere [17]. In brief, Zambia is a landlocked country surrounded by eight countries [18]. The country is located in southern Africa between latitudes -8^o and -18^o South and longitudes 22^o and 34^o East [18]. It has a “pleasant tropical, but seldom unpleasantly hot, climate with three seasons: a cool dry season (April-August), a hot dry season (August-November) and a warm wet season, which is even hotter, (November-April)” [19]. “Climate is mainly affected by the movement of the inter-tropical convergence zone” [19].

“The annual rainfall pattern over the whole country is similar between November and March and the amount of rain varies considerably [19]. In the north (Zambia), rainfall is 1,250 mm or more a year decreasing southwards to Lusaka where it is about 750 mm and even further to between 500 and 750 mm south of Lusaka [19]. Average temperatures in Zambia are moderated by the height of the plateaux. Maximum temperatures vary from 15 ^{0}C to 27 ^{0}C in the cool season and from 27 ^{0}C to 35 ^{0}C in the dry season” [19].

The population in Zambia, according to Census of 2010, is estimated at 13,046,508 people [20], all of whom are at risk of malaria [21] as the disease is endemic in Zambia's all ten provinces [22]. Malaria peaks during the rainy season and the burden is generally higher in rural areas compared to urban areas [22]. As recommended by WHO, cases of malaria in Zambia are mainly detected when patients visit a health facility for treatment, although surveillance detection also occurs [23].

6.2.2 Study frame

This study selected four provinces of Zambia namely; Lusaka (LS), North-western (NW), Western (W) and Luapula (LP) which represent the "low (Zone I), low to moderate (Zone II) and moderate to high (Zone III) transmission zones" [4], respectively. The selection of the study areas follows the study frame described elsewhere [17].

Luapula Province covers a total land surface area of 50,567 km^2 and it borders with the Democratic Republic of Congo. The province shares administrative boundaries with Central and Muchinga provinces in the south, and Northern Province in the east. It consists of seven (7) districts namely: Chienge, Kawambwa, Mansa, Milenge, Mwense, Nchelenge and Samfya, with Mansa, a semi-urbanised district, being the provincial capital. The population is estimated at 991,927 with 49.3% men and 50.7% women. The rural areas harbour 80.4% of the people, while the remaining 19.6% live in the urban area [24].

Lusaka Province is the highly urbanised capital city of Zambia. It is geographically the smallest among our study sites, covering a total land surface area of only 21,896 km^2, and bordering with Mozambique in the east and Zimbabwe in the south. The province shares provincial boundaries with Central Province in the north, Southern Province in the south and Eastern Province in the east. It consists of five districts namely: Lusaka, Chongwe, Luangwa, Kafue and Chirundu. The latter was formally part of Southern Province but was added to Lusaka Province in 2011. The population of Lusaka Province is estimated at 2,191,225 (49.4% men and 50.6% women) with 15.3% of the population living in the rural and 84.7% in the urban environment [25].

North-western Province is one of the largest provinces in the country and covers a total land surface area of 125,826 km^2. It borders with the Democratic Republic of Congo as well as with Central, Western and Copperbelt provinces and consists of eight districts namely: Chavuma, Ikelenge, Kabompo, Kasempa, Mufumbwe, Mwinilunga, Solwezi and Zambezi with Solwezi being the semi-urbanised provincial capital. The population in North-western Province is estimated at 727,044 with 49.3% males and 50.7% females out of which, 77.4% live in the rural areas and 22.6% in the urban areas [26].

Western Province is also vast with a total land surface area of 126, 386 km^2, just slightly bigger than North-western Province. It borders with Angola and Namibia at the country level. At the province level it borders North-western, Southern and Central provinces. Western Province consists of seven districts namely: Kalabo, Kaoma, Lukulu, Mongu, Senanga, Sesheke and Shang'ombo. Mongu is the semi urbanised provincial capital. The population is estimated at 902,974 (48% males and 52% females) with 86.7% of the population living in rural areas and 13.3% in the urban areas [27].

6.2.3 Study design and Data description

6.2.3.1 Malaria data

This study aimed at assessing socio-economic factors contributing to malaria incidence as such, data on malaria morbidity in the four provinces were collected from Ministry of Health headquarters and the provincial health offices for the period from 2006 to 2012. The estimated population for the selected provinces for period under study was obtained from the Central Statistical Office (CSO) [20] and the malaria incidence rate (I) was calculated as the number of new cases of malaria (M) divided by the total population (Pop) and multiplied by 100,000 based on the formula:

I=M/PopX100, 000 [28]

6.2.3.2 Socio-economic data

Data for the study period 2006 to 2012, on malaria control funding allocations was obtained from Ministry of Finance and Economic Planning and Development [29-35] and data on the distribution of malaria control and treatment supplies, from National Malaria Control Centre (NMCC) and Medical Stores Limited (MSL).

6.2.4 Data analysis

Data collected from both the household and individual surveys were entered and initially analysed in STATA 11 and later in WinBUGS14.

This study considered malaria incidence as the outcome variable and socio-economic factors including availability of nets, diagnosis and treatment, IRS chemicals and funding as explanatory variables. The explanatory variables were represented as continuous variables.

6.2.4.1 Estimation process

Relationships between the outcome measure and the explanatory variables were studied using both frequentist and Bayesian analysis. Both the 95% confidence and credible intervals were used to establish the significance of the differences observed in the relationships examined.

The hierarchical analysis was used owing to the factor that the study investigated the variable of interest at different levels, district and province level. In the frequentist method of analysis, the incidences were plotted against time variable so as to establish the relationship by looking at trend lines across five year period.

To model the dependence of malaria incidence on socio-economic factors including availability of nets, treatment, IRS chemicals and funding in a given province for the period 2006 to 2012, the model was fitted in WinBUGS 14 and a Bayesian analysis implemented via a Bayesian framework using Markov Chain Monte Carlo (MCMC). We assumed that socio-economic factors have an effect on disease burden based on the contribution to the community or programme capacity to access protection and seek treatment [1] and appropriate them.

We included in the hierarchical model the explanatory variables associated with the outcome variable and based on previous modelling studies and methods [36], the model was fitted. The model included the region (province) and the period (year) to account for the four different provinces and the varied time periods considered in the study.

“We assumed Yi ~ Poisson (mu,1), where [36]

Yi is malaria incidence rate

Logit(mu) = beta1+beta2+beta 3+beta4+...$beta_i$

We provided non-informative priors, assuming beta[j] ~ Normal (0,0.001).

Based on literature, with well-identified parameters and large sample sizes, reasonable choices of prior distributions have minor effects on posterior inferences [37, 38, 39, 40]. For this study, all categorical covariates were dummy coded and the first factor levels were considered as reference categories.

Specifying Priors and Distribution:

The inference in this model was fully Bayesian and based on MCMC simulations. As opposed to the classical way, all model parameters and variances specified in this model were treated as random variables. Prior distributions of the model parameters were all specified as normal as they have been reported to assume a distribution that take both positive and negative values [39, 41]. For all the beta priors zero mean was assigned to all parameters with variance of =0.001 as recommended for the standard choice for a weakly informative prior [39, 41].

Prior: For fixed-effect parameters β independent diffuse prior’s π (β)/constant were assumed. Typically inverse-Gamma IG (aj, bj) priors (3) were assigned to all unknown variances tau (t), where constant parameters aj > 0 and bj > 0, and aj =b j =0.001is a standard choice for a weakly informative prior. Below is how the priors were specified:

Sensitivity Analysis:

Sensitivity analysis to the choice of prior parameters was carried out with different pairs for all parameters used. Common values of the hyper parameters included a= b=0.00001, a=1, b=0.005, and a =b=0.00001 as guided by several other studies, were adopted and used in this study [39, 41].

Initial Values for the Model: In this model the following initial values were assumed

Beta[j] =0,

For all the betas in the equations

Simulations:

For each fitted model, inference was based on Markov Chain Monte Carlo simulation techniques. The results were based on 1000 samples generated with 10000 iterations, 1000 burn-ins by taking every 10th sample. The estimated models were compared based on the Deviance Information Criterion (DIC) values which provide a measure of goodness-of-fit for comparing nested Bayesian models. The smaller the DIC, the better the fit [42-46].

The model was as follows:

```
Incidence[i]~dpois(mu[i])

log(mu[i])<-beta[1]+
beta[2]*equals(Province[i],1)+
beta[3]*equals(Province[i],3)+
beta[4]*equals(Province[i],4)+
beta[5]*MOHfunding[i] +
beta[6]*ITN[i]+
beta[7]*equals(Year[i],2)+
beta[8]*equals(Year[i],3)+
beta[9]*equals(Year[i],4)+
beta[10]*equals(Year[i],5)+
beta[11]*equals(Year[i],6)+
beta[12]*equals(Year[i],7)
```

where beta represented the explanatory variable (effects). Initial values for the betas were based on the betas themselves" [36].

6.3 Results

6.3.1 Incidence data (Annual trends)

Table 1 presents data on malaria incidence and economic factors for the provinces under study. The first section in the Table shows the annual trends of malaria incidence in the four provinces. The data show that during the years 2006 to 2008 malaria incidence was high and generally the burden did not differ significantly among the provinces. In 2009 the incidence declined drastically in all provinces after which and onwards, the burden in all provinces varied significantly in each subsequent year and from each other.

Table 1: Malaria and related data from 2006-2012 for the four provinces

	Province				95 CI p value
	Luapula	Lusaka	Nwestern	Western	
	Malaria incidence				
2006	49,110	29,921	45,740	46,366	*<0.0001*
2007	39,239	23,872	43,263	41,543	
2008	31,423	20,382	28,640	32,001	
2009	14,479	1,927	7,179	2,212	
2010	24,377	2,119	12,500	5,380	
2011	31,685	2,761	20,860	9,757	
2012	42,050	2,637	27,589	21,931	
	National Budget Malaria control funding (Kwacha)				
2006	974,185,068	772,399,458	710,623,605	656,607,338	*<0.0001*
2007	645,306,089	463,680,251	530,336,350	729,798,600	
2008	1,246,365,522	1,239,615,302	636,413,851.5	1,170,279,633	
2009	1,507,735,427	1,170,216,398	1,113,762,058	850,650,585	
2010	2,195,907,478	3,274,290,677	1,314,076,766	2,545,859,192	
2011	3,556,102,614	3,735,727,671	2,054,002,109	3,837,763,795	
2012	3,052,500,068	2,955,111,733	2,098,292,236	2,912,671,392	
	MOH ITN coverage				
2006	150.6	14.1	125.6	206.6	*<0.0001*
2007	211.4	33.3	36.8	26.4	
2008	35.7	34.9	56.4	39.5	
2009	79.6	27.7	89.5	167.3	
2010	32.1	18.0	53.1	47.6	
2011	480.6	15.9	347.3	29.5	
2012	45.2	15.5	32.0	154.0	
	MOH IRS coverage				
2006	0	88.2	69.4	0	*<0.0001*
2007	0	94.3	85.9	0	
2008	0	97.3	83.4	0	
2009	100.4	89.7	89.9	90.5	
2010	90.3	70.7	82.6	88.9	
2011	0	0	0	0	
2012	88.9	58.8	61.8	86.6	
	Medical Stores Limited (MSL) Coartem distribution				
2009	314,580	744,210	241,380	287,880	*<0.0001*
2010	899,910	436,530	191,670	270,450	
2011	1,075,920	992,040	546,780	497,220	
2012	1,362,930	547,170	853,200	797,010	
	Medical Stores Limited (MSL) Insecticide distribution				
2009	116	532,776	113	113	*<0.0001*
2010	46,800	203,440	13,160	22,520	
2011	142,354	278,055	40,720	38,040	
2012	6,680	60,600	0	0	
	Medical Stores Limited (MSL) Rapid diagnostic tests (RDTs) distribution				
2009	182,400	132,100	103,725	69,675	*<0.0001*

2010	394,400	372,950	115,800	132,775
2011	947,225	1,005,450	434,525	403,850
2012	713,575	464,200	370,375	293,100

1 USD ~ 5 ZMW in 2014

Figure 1 shows that in the year 2009 malaria incidence in Western Province had reduced significantly attaining the levels of burden prevailing in Lusaka Province, with no significant difference. In the same period, the burden in Luapula and North-western provinces remained significantly higher than Lusaka and Western but also significantly different from each other.

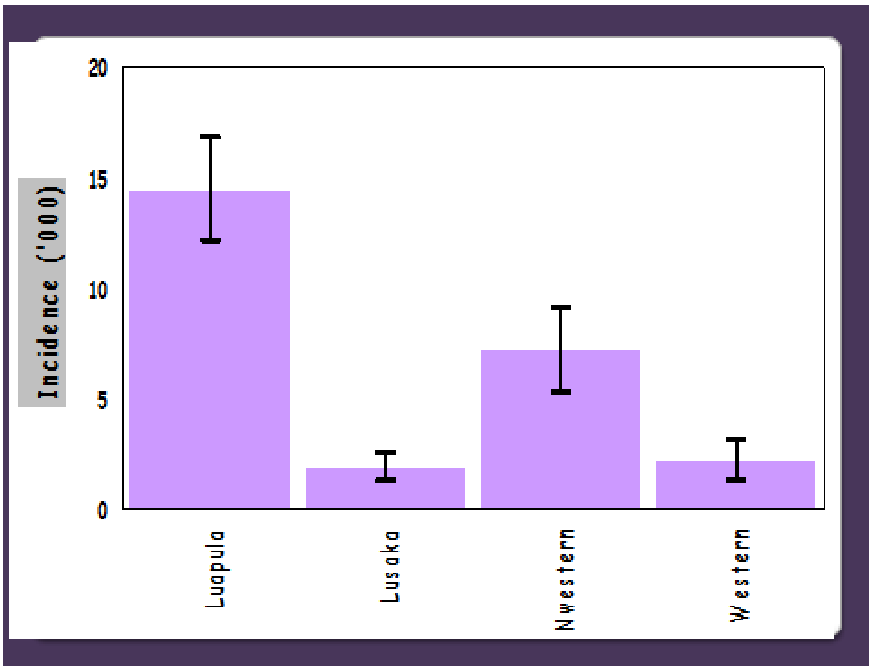

Figure 1: Significantly *(<0.05CI)* reduced and varying malaria incidence for the four provinces in 2009

In 2010 to 2012 the malaria incidence rose and varied significantly among all the four provinces although Lusaka increased by only a small margin in 2010 and 2011 and declined thereafter in 2012.

6.3.2 Malaria funding data (Annual trends)

Section 2 of Table 1 shows that malaria control funding from the National budget during the period under study (2006 – 2012), generally rose steadily year after year except for the years 2007 and 2012 when it declined for the three provinces Luapula, Lusaka and North-western. For Western Province, the funding decline was observed in 2009.

6.3.3 ITN Coverage data (Annual trends)

Assuming a targeted coverage of one insecticide treated net (ITN) to 5.1 persons per household [20], the data in Section 3 of the same Table (1) show that the Ministry of Health ITN coverage in Lusaka compared to the other three provinces was consistently lower than 50% throughout the whole study period. In Luapula and North-western provinces in majority of the study period the ITN coverage exceeded 50% whereas in Western Province a balance of both less and more than 50% coverage was observed.

ITN coverage was substantively raised and it varied significantly in all the four provinces in 2006 and 2011 while in the years 2009, 2010 and 2012, only some provinces (Lusaka and Western in 2009 and 2012 and Lusaka and Luapula in 2010) showed significantly different coverage (reduced in Lusaka and raised in Western in 2009and 2012 and reduced in all including Lusaka and Western in 2010).

In relation to the significantly reduced malaria incidence in Western Province in 2009, Figure 2 shows that ITN coverage was significantly raised for Western Province in the same period.

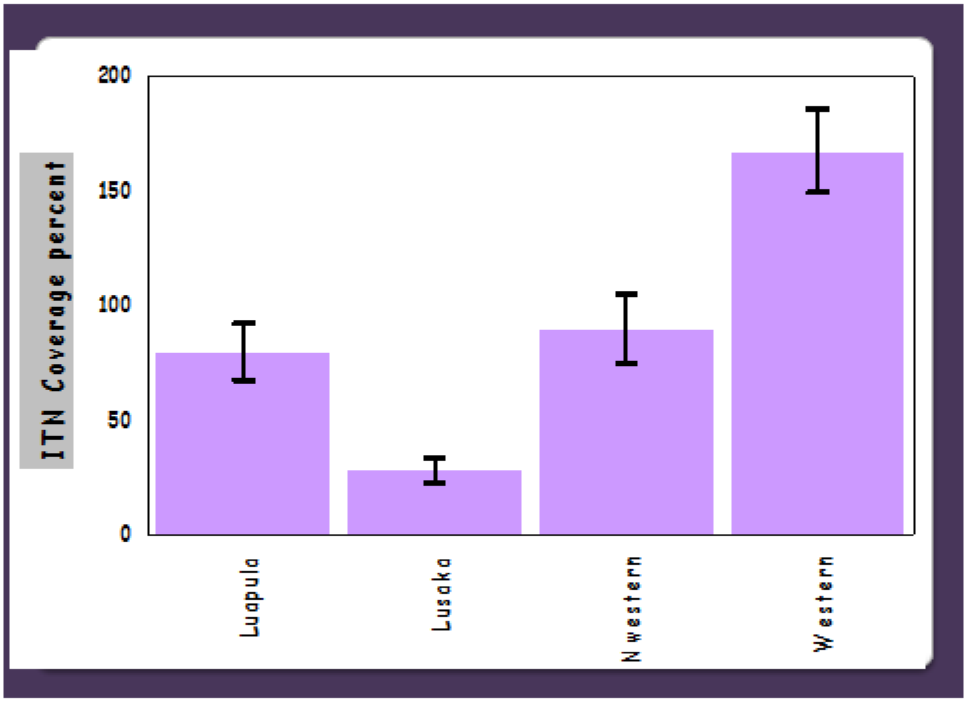

Figure 2: Significantly *(<0.05CI)* increased Insecticide treated net (ITN) coverage for Western Province in 2009

6.3.4 IRS Coverage data (Annual trends)

Ministry of Health IRS coverage data in section 4 of Table 1 show that spraying in Luapula and Western provinces only started in 2009 but where it occurred, coverage was uniform in significance in all the four provinces throughout the study period.

However, as per Figure 3, in 2012 coverage was significantly different and more in Luapula than Lusaka although malaria incidence was highest in Luapula in the same period. IRS did not take place in 2011 for the whole country.

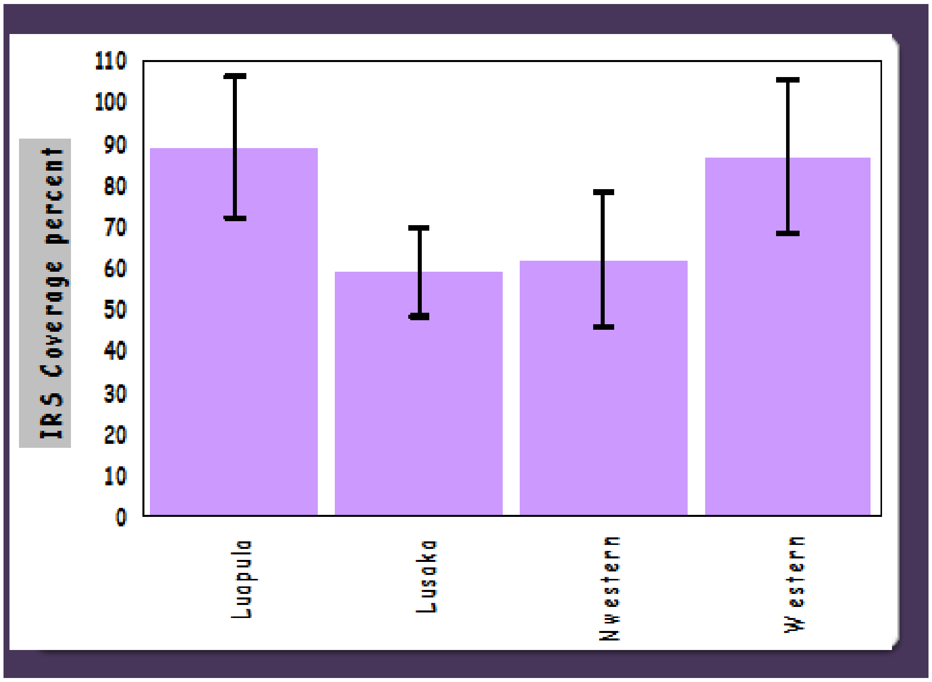

Figure 3: Significantly *(<0.05CI)* higher Indoor residual spraying (IRS) coverage for Luapula Province (than Lusaka) in 2012

6.3.5 Medical Stores Limited (MSL) Coartem, Insecticides and RDTs distribution data (Annual trends)

The Medical Stores Limited (MSL) data show initial distributions of malaria control supplies in 2009 with Lusaka being the sole recipient (out of the four provinces under consideration) initially while thereafter, Lusaka and Luapula generally receiving higher quantities of supplies of Coartem, Insecticides and RDTs.

Apart from Lusaka receiving largest quantities of Coartem in 2009, Luapula Province received largest quantities in the rest of the years Coartem was supplied although malaria incidence was highest in that province. In 2009 and 2010, Coartem supply in North-western Province was lower than in Western while in 2011 and 2012, the opposite was observed.

Insecticides were mainly supplied to Lusaka Province all throughout the study period followed by Luapula Province which was supplied with half or less than the Lusaka quantities.

Luapula province received the largest quantities of RDTs all throughout the study period except for 2011 when the quantities were higher in Lusaka. North-western on the other hand received larger quantities of supplies compared to Western Province apart from the year 2010 when the situation was vice versa.

6.3.6 Incidence data vs Funding, ITN and IRS coverage and Coartem, Insecticide and RDT distribution

Figure 4 shows that in Luapula, ITN and Funding were related to the initial decline in incidence while increased funding and ITN along with introduction of IRS and RDTs were related to the major decline in 2009. In 2010 when malaria incidence started to rise, ITN distribution had not occurred while IRS coverage had declined. In 2011, malaria incidence further increased in the same period IRS did not take place. The other factors (RDT distribution, Funding, Coartem, Insecticide and RDT quantities) remained in high supply during the years the incidence increased from 2010. In 2012 when the increase in incidence was highest, funding, ITN coverage, RDT quantities and insecticide quantities had declined while Coartem quantities and IRS coverage increased.

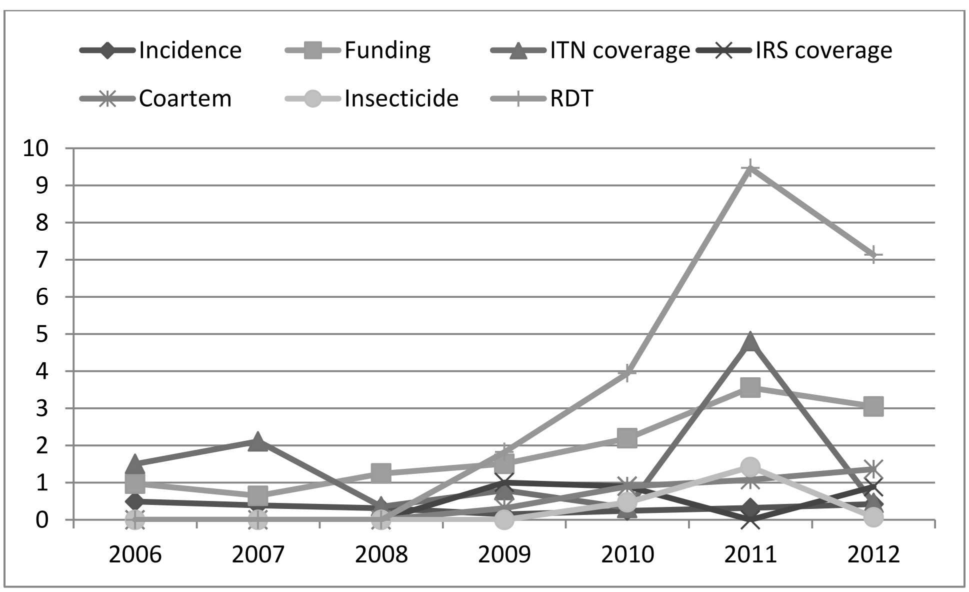

Figure 4: Malaria incidence vs intervention factors in Luapula for the period 2006 - 2012

Figure 5 shows that in Lusaka, the initial significant decline in incidence occurred in 2007 although funding had declined and only ITNs and IRS were available and with increased coverage. The major decline in incidence in 2009 coincided with the additional interventions of Coartem, Insecticide and RDT distribution. These additional interventions were fluctuating while funding kept increasing steadily until 2012 when it declined.

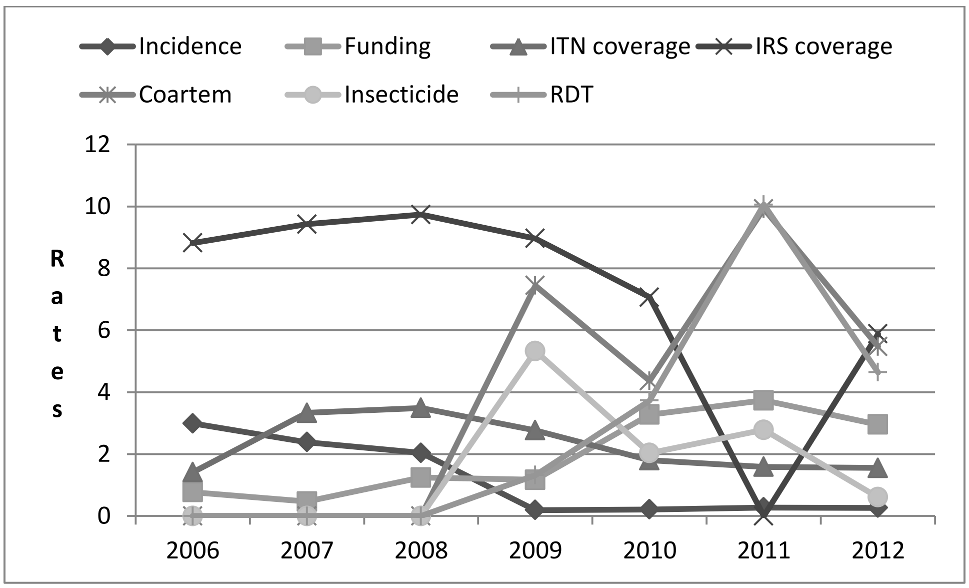

Figure 5: Malaria incidence vs intervention factors in Lusaka for the period 2006 - 2012

Figure 6 shows that in North-western province, the initial significant decline in incidence was in 2008 and coincided with ITN coverage and funding increase as well as consistently high IRS coverage. In 2009 incidence declined even further coinciding with increased funding, ITN coverage, sustained high IRS coverage and the start of other interventions i.e. Coartem, Insecticide and RDT distribution. In 2010 incidence rose by a small but significant margin during the period IRS coverage started to decline and in 2011 the increase in incidence was large and significant when IRS was not available at all. Although IRS coverage rose in 2012, incidence increased further, coinciding with funding, RDT and Insecticide distribution decline.

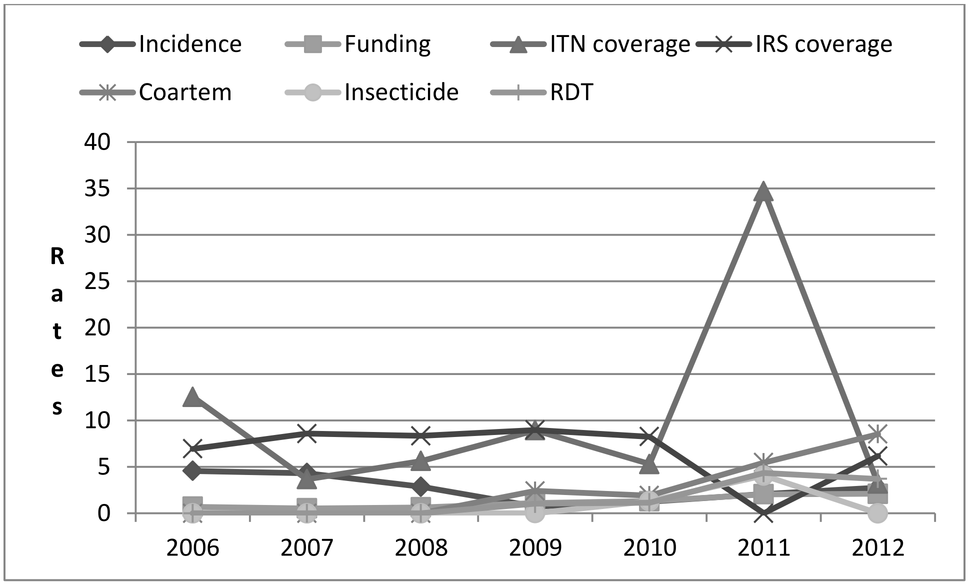

Figure 6: Malaria incidence vs intervention factors in North-western for the period 2006 - 2012

Figure 7 shows that in Western Province, the initial significant decline in incidence was in 2008 when ITN coverage and funding had increased. In 2009, malaria incidence declined by a huge and significant margin when ITN and IRS coverage increased and other interventions i.e. Coartem, Insecticide and RDT distribution started although funding had reduced. Incidence increased steadily in 2010 and 2011 when ITN and IRS coverage declined. In 2012 incidence increased further by a significant margin. In this period, although both IRS and ITN coverage and Coartem distribution increased, funding, RDT and Insecticide distribution had declined.

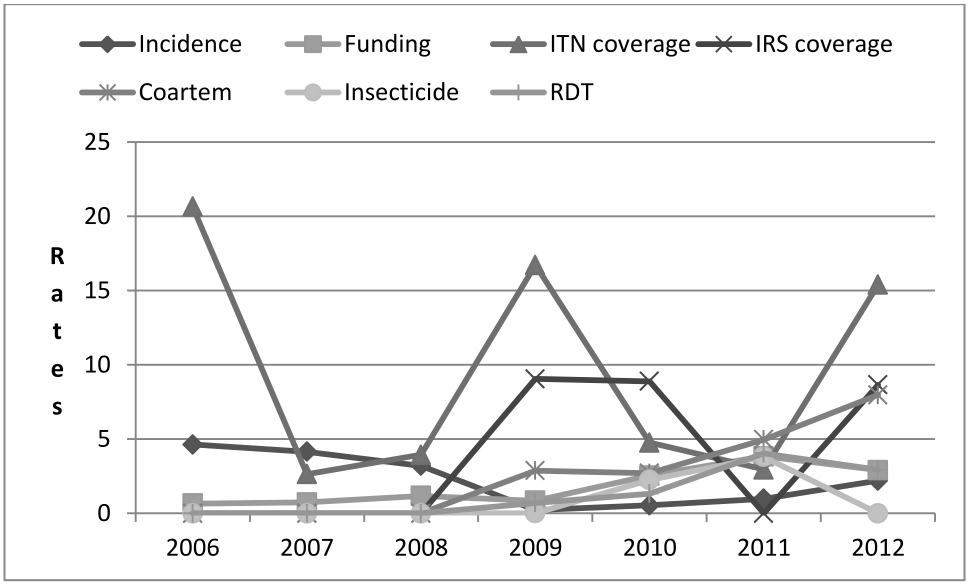

Figure 7: Malaria incidence vs intervention factors in Western for the period 2006 - 2012

6.3.7 Modelling

Table 2 shows regression coefficients from the hierarchical model for the relationship between annual malaria incidences and socio-economic conditions. Province, ITN and Funding showed a relationship with malaria incidence. Province and ITN were positively correlated while funding was, negatively correlated but not statistically significant. We note that ITN was weakly correlated with malaria incidence. Although effective interventions like IRS and funding were almost evenly distributed, incidence in Luapula Province was 2.7 times more likely to be higher than in other provinces.

Table 2: Hierarchical modelling for socio-economic determinants of malaria

Parameter	Mean	Credible Interval (2.5-97.5%)
Luapula	1.007	2.7 – 2.8
Nwestern	0.6725	1.9 – 2.0
Western	0.623	1.85 – 1.88
MOH funding	-0.2257	0.79 – 0.81
ITN	0.1211	1.1 – 1.2
2007	-0.1812	0.83 – 0.84
2008	-0.3413	0.70 – 0.72)
2009	-1.797	0.163 – 0.168
2010	-1.024	0.35 – 0.37
2011	-0.4573	0.62 – 0.65
2012	-0.1443	0.85 – 0.88

6.4 Discussion

Our analysis shows that the pattern of malaria incidence kept varying through the study period. The lack of significant difference among all the provinces in the early years under study and the significant variation in incidence during the middle part of the period under study, do not qualify the four provinces to fit in the current malaria transmission stratification [4]. However, isolating the last part of the period under study, the year 2012, only Luapula and Lusaka provinces which fall in the low (Zone I) and moderate to high (Zone III) transmission zones [4] respectively, showed significantly varying malaria incidences from the other two provinces. Thus the incidence pattern in the year 2012 fitted the stratification accurately although one year or season may not suffice to make conclusions on the malaria status. It is clear that the stratification was based on the period 2000 to 2008 and resulted from reinforced malaria control interventions [4] which most likely have changed in the latter period. An analysis of programme data in another study also showed that the burden of malaria in Zambia was changing with the burden persisting in north-eastern Zambia while reducing in Western and Southern provinces [15].

Although our inferential analysis showed that malaria control funding declined in some years, it generally consistently and steadily increased in all the provinces. However, our model showed a negative but insignificant relationship between funding and malaria incidence. The negative relationship indicated a correct ideal relationship where more resources should translate into lower malaria burden [3] except that national budgets and funding are never met sufficiently [1] for the relationship to be statistically significant. With regards to global resources against malaria, it has been shown that while the resources are not adequate, the spending needs to get smarter, targeting the neediest areas [47]. Amidst the inadequate resources, efforts are being made to ensure effective spending although it is difficult to obtain a complete picture of resource allocations. WHO works in collaboration with committees such as Malaria Policy Advisory Committee (MPAC) concerning advice on the most effective interventions for malaria control and the strategies for allocating the limited funds [48]. However, it has been challenging to monitor and assess disbursements of resources directly availed by donors to countries [49].

From both our inferential and Bayesian analyses, ITN coverage was shown to be a significant determinant of malaria incidence. In some years and provinces when coverage was significantly high, malaria incidence also significantly declined. Other studies have also showed that ITNs are significant contributors to malaria burden [15, 50, 51] although others have shown the opposite [14, 50; 52 – 56].

In our study IRS was quite significantly related to malaria incidence although it was only analysed inferentially given the many gaps in data. Our study shows that with the exception of Lusaka, the other three provinces experienced a significant increase in malaria incidence in the year IRS was not conducted. Our study also shows some periods of incidence decline coinciding with periods when ITN and IRS occurred together. This occurrence is different from some studies that exclusively found only either ITN or IRS but not both as determinants of malaria burden [14, 15, 50 – 55]. Besides these findings, others did not find a relationship for both IRS and ITNs with malaria status [56]. We also found that in Luapula Province, malaria incidence remained high in a year when IRS was highest both within the province in that particular year and in comparison to other years as well as between provinces. Our study further reveals that IRS intervention was one of the interventions conducted with almost uniform coverage across the four provinces except its effect was not uniform. It is possible that other factors are at play and therefore, we recommend more and deliberately planned studies in the area of interventions.

Although many interventions were available for the provinces under study and for Lusaka in particular, the MSL distributions were provided only for Lusaka Province for the year 2009. The contribution of these distributions cannot be ignored. It is possible that even though all the other interventions were enhanced during this period, the MSL distributions availed to Lusaka Province only also made a significant contribution, explaining the consistently low incidence in the after years. We did not include these distributions in our model because of large data gaps both with regards to the later commencement of the distributions and also unavailability in later years after the distributions were in operation. However, from our inferential statistics, it is clear that when these supplies were available, they contributed to the effect on malaria incidence although it seemed necessary that they were administered along with IRS and ITNs. Studies have shown that integrated malaria control which involves a combination of interventions, including timely diagnosis and treatment using reliable diagnostic test and effective drugs; indoor residual spraying with long lasting and safe insecticides; and the use of bed nets treated with long lasting insecticides to protect people from mosquito bites at night [57] have brought about major gains. As with IRS intervention discussed earlier, Luapula Province was second to Lusaka with regards to large quantities of MSL supplies although the malaria burden remained highest.

Our Bayesian hierarchical model showed that Province and ITN were positive predictors of increased annual malaria incidence in Zambia while malaria control funding was an insignificant, negative predictor. The odds of malaria incidence being higher in Luapula compared to the other three provinces were almost 3 times. This shows that although the general burden and transmission zones may keep changing, each locality may have different determining factors at a given time [58] and as such interventions must be provided based on consistent studies.

Diagnosis and treatment of malaria and the capacity of programmes in that regard are other crucial economic factors contributing to malaria burden [1, 57]. RDT and drug supply and use were only studied by inferential statistics in our study due to data gaps. Additionally, it is challenging to measure uptake of these components as they are supplied from varied sources, ranging from international donors to drug stores. According to the 2011 World Malaria Report, a "general decline in the global resource requirements for malaria control was estimated at US$ 5 billion per year between 2010 and 2015 and US$ 4.75 billion between 2020 and 2025 mainly due to a projected reduction in the need for diagnostic testing and treatment" [49]. This projection was based on the successful control programmes in low malaria transmission countries. However, this may change as long as the continuing risk of malaria transmission exists [49]. As such, regardless of the challenges in monitoring and assessing the contribution of diagnostic tools and treatment formulations, efforts must be made to secure this information whether as pledges or actual supplies [49] in order to ensure alert systems in case of changes in transmission.

Analysing socio-economic factors is not complete without a consideration of the social aspects of the programming side of malaria control, which entails assessing the attitudes and capabilities of programme executors and the programmes themselves. Although it is difficult to assess the direct contributions made by executors of the programmes, it is clear from the levels of interventions reported, that the programme in Zambia is working very well. The malaria control programme in Zambia has been shown to be one of the strongest and leading programmes in Africa [5, 6]. However, the need for such assessments remains if good performance may even be sustained and enhanced.

6.5 Conclusions

Province was the strongest predictor of malaria incidence in our analysis although ITN also weakly predicted the outcome. Malaria control funding, IRS, drug, insecticide and RDT distributions were also potential predictors if utilised and analysed effectively. Regional factors may also have a role in malaria risk, stressing the need to explore both Programme and community contribution for specific communities. We recommend to the Government of the Republic of Zambia to develop a transmission zone and needs-based malaria control programme and funding policy at all levels. We recommend also for the Government of the Republic of Zambia to facilitate the introduction of income generating activities in communities to enhance household capability to replenish ITNs.

6.6 Ethical approval

The study protocol was approved by University of Zambia (UNZA) Biomedical Research Ethics Committee (IRB00001131 of IORG0000774).

6.7 Abbreviations

RDTs: rapid diagnostic tests; HMIS: health management information system; PHO: Provincial Health offices; MOH: Ministry of Health; MSL: Medical Stores Limited; WinBUGS14: Windows version of Bayesian inference Using Gibbs Sampling 14; IRS: indoor residual spraying; ITN: insecticide treated net; ACT: artemisinin-based combination therapies; WHO: World Health Organisation; LLINs: long lasting insecticide nets; US$: United States dollar; DALY: disability-adjusted life-years; LS: Lusaka; NW: North-western, W: Western; LP: Luapula; CSO: Central Statistical Office; NMCC: National Malaria Control Centre; MCMC: Markov Chain Monte Carlo; CI: credible interval; CI: confidence interval; MPAC: Malaria Policy Advisory Committee.

6.8 Competing interests

The authors as well as the funders declare that they have no competing interests in the manuscript.

6.9 Authors' contributions

All authors conceived the study and contributed to the study design; NMS-M designed the study, collected and analysed the data. SM, ET-M and MG guided in the considerations for data collection and analysis; NMS-M drafted the manuscript; All authors contributed to the interpretation and presentation of data and read, edited and approved the final manuscript.

6.10 Authors' information

NMS-M (Nzooma M. Shimaponda-Mataa[1,2]) is a Medical Parasitologist and Lecturer at the University of Zambia and holds MSc Parasitology degree; SM (Samson Mukaratirwa[2]) is a Parasitologist and Professor, Dean and Head of School and Lecturer at the University of KwaZulu-Natal in Durban, South Africa and holds PhD in Parasitology; MG (Michael Gebreslasie[4]) is a Geographer (geospatial methods) and Lecturer at the University of KwaZulu-Natal in Durban, South Africa and holds PhD in Geography; ET-M (Enala Tembo-Mwase[3]) is Parasitologist and Professor, Deputy Vice Chancellor and Lecturer at the University of Zambia and holds PhD in Parasitology

[1]University of Zambia School of Medicine, Department of Biomedical Sciences, Ridgeway Campus, Lusaka, Zambia.[2]University of KwaZulu-Natal, School of Life Sciences, Westville Campus, Durban, South Africa.[3]University of Zambia, School of Veterinary Medicine, Great East Road Campus, Lusaka, Zambia.[4]University of KwaZulu-Natal, School of Agriculture, Earth and Environmental Science, Westville Campus, Durban, South Africa

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CHAPTER 7

Climatic Factors of Malaria at Province Level in Four Malaria Endemic Provinces of Zambia

*This chapter is based on:

Shimaponda-Mataa NM, Tembo-Mwase E, Gebreslasie M, Mukaratirwa S. and Achia, T. N. O. (2015). Modelling the influence of minimum and maximum temperature and rainfall on the incidence of malaria in four endemic provinces of Zambia using a structured additive *Semiparametric Poisson regression* model. *In press (Acta Tropica).*

Abstract

Background: Although malaria morbidity and mortality is greatly reduced globally owing to great control efforts, it remains the leading cause of morbidity and mortality. Within the country, all provinces are malaria endemic although the transmission intensities vary mainly depending on environmental factors as they interact with the vectors. Generally in Africa, possibly due to the varying perspectives and methods used there is no consensus on the relative importance of malaria risk determinants despite the many studies done so far. In Zambia, it is equally not clear what the role climatic factors play on malaria case rates, as no current studies have determined the factors over space and time using robust methods in modelling, considering the reversal in malaria reduction after the year 2010 and the variation by transmission zones. **Methods:** Using a geoadditive or structured additive *Semiparametric Poisson regression* model, we determined the influence of climatic factors on malaria incidence in four endemic provinces of Zambia. **Results and Conclusions:** We demonstrate a strong positive association between malaria incidence and precipitation as well as minimum temperature. The risk of malaria was 95% lower in Lusaka (ARR=0.05,95%CI=0.04-0.06) and 68% lower in the Western Province (ARR=0.31, 95% CI=0.25-0.41) compared to Luapula Province. North-western Province did not vary from Luapula Province. The effects of geographical region are clearly demonstrated by the unique behaviour and effects of minimum and maximum temperatures in the four provinces. Environmental factors such as landscape in urbanised places may also be playing a role.

Key words: Eco-environmental, climate, malaria, incidence, Zambia

7.1 Introduction

Although malaria morbidity and mortality is greatly reduced globally [1] owing to great control efforts, it remains the leading cause of morbidity and mortality. The disease is responsible for an estimated 214 million cases and 438,000 deaths worldwide per year and 80% of the cases and 90% of the deaths occur in Africa [2]. The decline in the malaria burden has not been achieved uniformly as some countries experience resurgence [1].

Zambia also reported a drop in malaria cases over the recent years [3] and yet the burden continues to be high [4]. In 2007, four million suspected cases and 6,000 deaths were reported [5] while in 2010 malaria accounted for an annual incidence of 330 cases per 1000 [6]. Within the country, all provinces are malaria endemic [5] although the transmission intensities vary mainly depending on environmental factors [7, 8] as they interact with the vectors. Following the break in interventions due to socio-economic problems in Zambia, the impact of malaria control efforts was reversed [3] although the reversal was not uniform across all provinces.

Malaria is a vector-borne disease and eco-environmental factors such as climate, landscape, housing structure [2] and proximity of households to vector breeding sites contribute to the burden either by affecting the vector and parasite development [8] or by facilitating exposure of community members to vectors [9]. The larval development stage of mosquitoes occurs in various types of water bodies depending on their water-ecological requirements [10]. In Africa, the *Anopheles gambiae* vector [11] breeds in numerous small pools of water that form due to rainfall [11] or by artificial means or even natural disasters, which have been shown to expose people to epidemics of flood-linked water borne diseases such as malaria [9].

With regards to climate, a number of studies have shown variations in climatic factors influencing malaria with some suggesting only minimum temperature [12], others rainfall only [13] while others a combination of minimum, maximum temperature and rainfall [14].

The malaria control programme in Zambia is one of the leading programmes in Africa [5, 15] although research in eco-environmental factors still has room for expansion. Some studies have been conducted in Zambia to describe the epidemiology of malaria in the country [3, 16] and it has been shown that malaria is endemic throughout the country [16] varying in transmission intensity across three distinct transmission zones [3]. Studies in Zambia have indicated a marked change in sibling species composition over time due to change in ecology, corresponding to malaria transmission rates in some places. The malaria vectors in Zambia comprise of *An. gambiae ss*., *An. arabiensis*, and *An. funestus* [4]. Other studies conducted in Zambia have been focussed on land ecology as it relates to vector development [17, 18]. One study developed an imagery to obtain and model data to evaluate local vegetation as a risk factor and they obtained proper usable images in southern Zambia [17]. Another tool developed in Zambia was the landscape model which was successful at ruling out potential locations of vector breeding sites although it was limited in predicting the type of vector species that inhabited the sites [18]. An early warning system which conformed to seasonal incidence patterns was also developed in Zambia although it required longer periods of surveillance data to perform better [19]. Additionally, some climatic variables have also been demonstrated to be significantly related to malaria transmission based on geographic patterns of risk in Zambia, namely: low altitude, high normalised difference vegetation index (NDVI), and high day and night land surface temperatures [20].

The “potential impact of climate change on malaria transmission can be calculated based on future climate scenarios from models considering that estimates of future populations at risk of malaria differ significantly between regions and between climate scenarios” [21].

Generally in Africa, possibly due to the varying perspectives and methods used [22] there is no consensus on the relative importance of malaria risk determinants despite the many studies done so far [23]. In Zambia, it is equally not clear what the role of climatic factors on malaria case rates is, as no current studies have determined the factors over space and time using robust methods in modelling, considering the reversal in malaria reduction after the year 2010 [3] and the variation by transmission zones.

“To improve risk assessment and risk management of the synergistic processes of climate and land-use change, more collaborative efforts in research, training and policy-decision support, across the fields of health, environment, sociology and economics, are required” [24]. Therefore, this study sought to determine the influence of climatic factors on malaria incidence in four endemic provinces of Zambia.

7.2 Methods

7.2.1 Study area

Zambia is a landlocked country surrounded by eight countries [25]. The country is located in southern Africa between latitudes -8^{o} and -18^{o} South and longitudes 22^{o} and 34^{o} East [25] (Figure 1). It has a “pleasant tropical, but seldom unpleasantly hot, climate with three seasons: a cool dry season (April-August), a hot dry season (August-November) and a warm wet season, which is even hotter, (November-April) [26].The climate is mainly affected by the movement of the inter-tropical convergence zone [26].

The annual rainfall pattern over the whole country is similar between November and March and the amount of rain varies considerably [26]. In the north (Zambia), rainfall is 1,250 mm or more a year decreasing southwards to Lusaka where it is about 750 mm and even further to between 500 and 750 mm south of Lusaka [26]. Average temperatures in Zambia are moderated by the height of the plateaux. Maximum temperatures vary from 15 ^{0}C to 27 ^{0}C in the cool season and from 27 ^{0}C to 35 ^{0}C in dry season" [26].

The population in Zambia, according to Census of 2010, is estimated at 13,046,508 people [27], all of whom are at risk of malaria [28] as the disease is endemic in Zambia's all ten provinces [16]. Malaria peaks during the rainy season and the burden is generally higher in rural areas compared to urban areas [16]. As recommended by the World Health Organisation (WHO), cases of malaria in Zambia are mainly detected when patients visit a health facility for treatment, although surveillance detection also occurs [29].

7.2.2 Study frame

Four provinces of Zambia were selected based on the malaria prevalence namely; Lusaka (LS), North-western (NW), Western (W) and Luapula (LP) which represent the low (Zone I), low to moderate (Zone II) and moderate to high (Zone III) transmission zones [3], respectively. The selection of the study areas follows the study frame described elsewhere [30].

Luapula Province covers a total land surface area of 50,567 km^2 and it borders with the Democratic Republic of Congo. The province shares administrative boundaries with Central and Muchinga provinces in the south, and Northern Province in the east. It consists of seven (7) districts namely: Chienge, Kawambwa, Mansa, Milenge, Mwense, Nchelenge and Samfya, with Mansa, a semi-urbanised district, being the provincial capital. The population is estimated at 991,927 with 49.3% men and 50.7% women. The rural areas harbour 80.4% of the people, while the remaining 19.6% live in the urban area [31].

Lusaka Province is the highly urbanised capital city of Zambia. It is geographically the smallest among our study sites, covering a total land surface area of only 21,896 km^2, and bordering with Mozambique in the east and Zimbabwe in the south. The province shares provincial boundaries with Central Province in the north, Southern Province in the south and Eastern Province in the east. It consists of five districts namely: Lusaka, Chongwe, Luangwa, Kafue and Chirundu. The latter was formally part of Southern Province but was added to Lusaka Province in 2011. The population of Lusaka Province is estimated at

2,191,225 (49.4% men and 50.6% women) with 15.3% of the population living in the rural and 84.7% in the urban environment [32].

North-western Province is one of the largest provinces in the country and covers a total land surface area of 125,826 km^2. It borders with the Democratic Republic of Congo as well as with Central, Western and Copperbelt provinces and consists of eight districts namely: Chavuma, Ikelenge, Kabompo, Kasempa, Mufumbwe, Mwinilunga, Solwezi and Zambezi with Solwezi being the semi-urbanised provincial capital. The population in North-western Province is estimated at 727,044 with 49.3% males and 50.7% females out of which, 77.4% live in the rural areas and 22.6% in the urban areas [33].

Western Province is also vast with a total land surface area of 126, 386 km^2, just slightly bigger than North-western Province. It borders with Angola and Namibia at the country level. At the province level it borders North-western, Southern and Central provinces. Western Province consists of seven districts namely: Kalabo, Kaoma, Lukulu, Mongu, Senanga, Sesheke and Shang'ombo. Mongu is the semi urbanised provincial capital. The population is estimated at 902,974 (48% males and 52% females) with 86.7% of the population living in rural areas and 13.3% in the urban areas [34].

7.2.3 Study design and Data description

7.2.3.1 Malaria data

This study was longitudinal in nature and aimed at assessing eco-environmental factors contributing to malaria incidence. Data on malaria morbidity in the four provinces were collected from Ministry of Health headquarters and the provincial health offices for the period from 2006 to 2012 although only data from the year 2009 to 2012 is used in this study given that the monthly format data and with specified confirmed cases was only available in the Zambia Health Management Information System (HMIS) from the year 2009. The estimated population for the selected provinces for period under study was obtained from the Central Statistical Office (CSO) [27] and the malaria incidence rate (I) was calculated as the number of new cases of malaria (M) divided by the total population (Pop) and multiplied by 100,000 based on the formula:

I=M/PopX100,000 [35]

7.2.3.2 Meteorological data

Day and night land surface temperature (LST) data were downloaded from the Moderate Resolution Imaging Spectroradiometer (MODIS) from the U. S. Geological Survey (USGS) Land Processes Distributed Active Archive Centre (LP DAAC) [36]. LST data were extracted as averages over 8-day periods at 1km spatial resolution. Both minimum and maximum temperatures were in form of averages over monthly periods.

Precipitation was downloaded from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) from the University of California, Santa Barbara (UCSB) [37. The precipitation data were extracted as averages over monthly periods.

Only maximum, minimum temperature and precipitation data were downloaded for this study.

7.2.4 Data analysis

Data collected from both the MOH and climate websites were analysed in an R version of integrated nested Laplace (R-INLA).

The study considered malaria incidence as the outcome measure and climatic variables as the explanatory variables.

7.2.5 Estimation process

We modelled the dependence of malaria incidence on covariates including precipitation and minimum and maximum temperature. The variation of temperature and precipitation within one province is assumed not significant given that the vector developmental lasts about or over a month [12]. In that regard, we opted to allow for an assumption that malaria incidence in a month would be associated with climatic conditions of the previous two months and hence we lagged the climatic data by two months against the malaria incidence data.

The data are presented in scales and units with malaria incidence being unit-free while precipitation was measured in millimetres (mm) and temperature in degrees Celsius (°C).

Our data were first standardised to avoid the effect of scale. Figure 1 (right) represents the standardised malaria incidences.

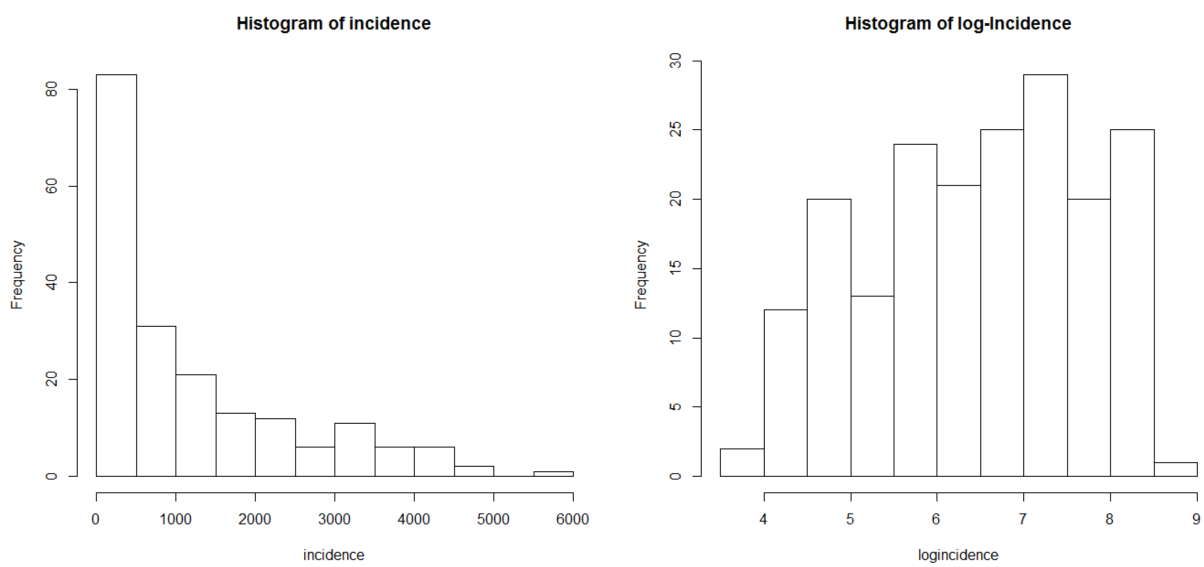

Figure 1 Histogram of malaria incidence (left) and the natural logarithm of malaria incidence (right)

Our study adopted the following notation for the variables: logincidence ~ malaria incidence; precip_{it}~ precipitation, tempmax_{it} ~ maximum temperature, tempmin_{it} ~ minimum temperature.

7.2.6 Modelling

We assumed that the number of malaria cases Y_{it} in region i at time t follows a Poisson distribution with rate $n_{it} \times \lambda_{it}$. Here n_{it} is the number of persons at risk and $\log(\lambda_{it})$ is the linear predictor. The effects of the covariates considered were modelled through a geoadditive or structured additive *Semiparametric Poisson regression* model of the form:

$$\log(\lambda_{ij}) = \beta_0 + \sum_{a=1}^{n_f} f^{(a)}(u_{ij}) + \sum_{r=1}^{n_f} \beta_r x_{ijr}$$

where $f^{(a)}$'s are unknown smoothing functions of the covariates in u, the β_r's represent the vector parameters for the linear effect of covariates x, were fit. The Deviance Information Criterion (DIC) was used to select the best fitting model.

Relationships between the outcome measure (Incidence) and each explanatory variables (minimum, maximum temperature and rainfall) were explored using R-INLA.

To assess whether linear, quadratic or other non-linear terms adequately represented the relationship between the outcome variables and each covariate, the DIC and the corresponding effective number of parameters (pD) was computed. The best fitting model was the one with the lowest DIC.

7.3 Results

Table 1 Correlation matrix

	logincidence	**Precip**	**Tempmax**	**Tempmin**
logincidence	1.00	0.41 (p<0.001)	-0.27 (p<0.001)	0.26 (p<0.001)
Precip		1.00	-0.51 (p<0.001)	0.64 (p<0.001)
Tempmax			1.00	-0.09 (p=0.2389)
Tempmin				1.00

Table 1presents correlations between all the variables considered in this study. The results suggest that malaria incidence most highly correlated with precipitation. There was a strong positive correlation between precipitation and minimum temperature (r=0.64, p<0.001), and a strong negative correlation between precipitation and maximum temperature (r=-0.51, p<0.001). There was no correlation between maximum and minimum temperature.

Table 2DIC and pD for the different univariate (the best among tested models is emphasized)

	Linear		Quadratic		RW1		RW2	
	DIC	pD	DIC	pD	DIC	pD	DIC	pD
Precipitation	289814.3	5.69	281102.8	6.66	**928.09**	186.04	1411.89	180.6
Tempmin	324242.3	5.7	263134	6.68	**784.99**	191.64	882.71	191.68
Tempmax	310403.5	5.71	310403.5	5.71	**1482.61**	190.57	1662.01	189.99
Year	291424.9	5.69	323187.8	4.84	**291056.1**	7.65	291056.1	7.62
month	318561.2	5.71	312402	6.67	**291840.1**	15.45	291840	15.4

Table 2 presents values of DIC and pD computed for univariate models for each covariate assessing the appropriateness linear, quadratic, and random walk terms for each covariate. For each covariate considered, the random walk model of order 1 was found to adequately represent the relationship of malaria risk and the predictor.

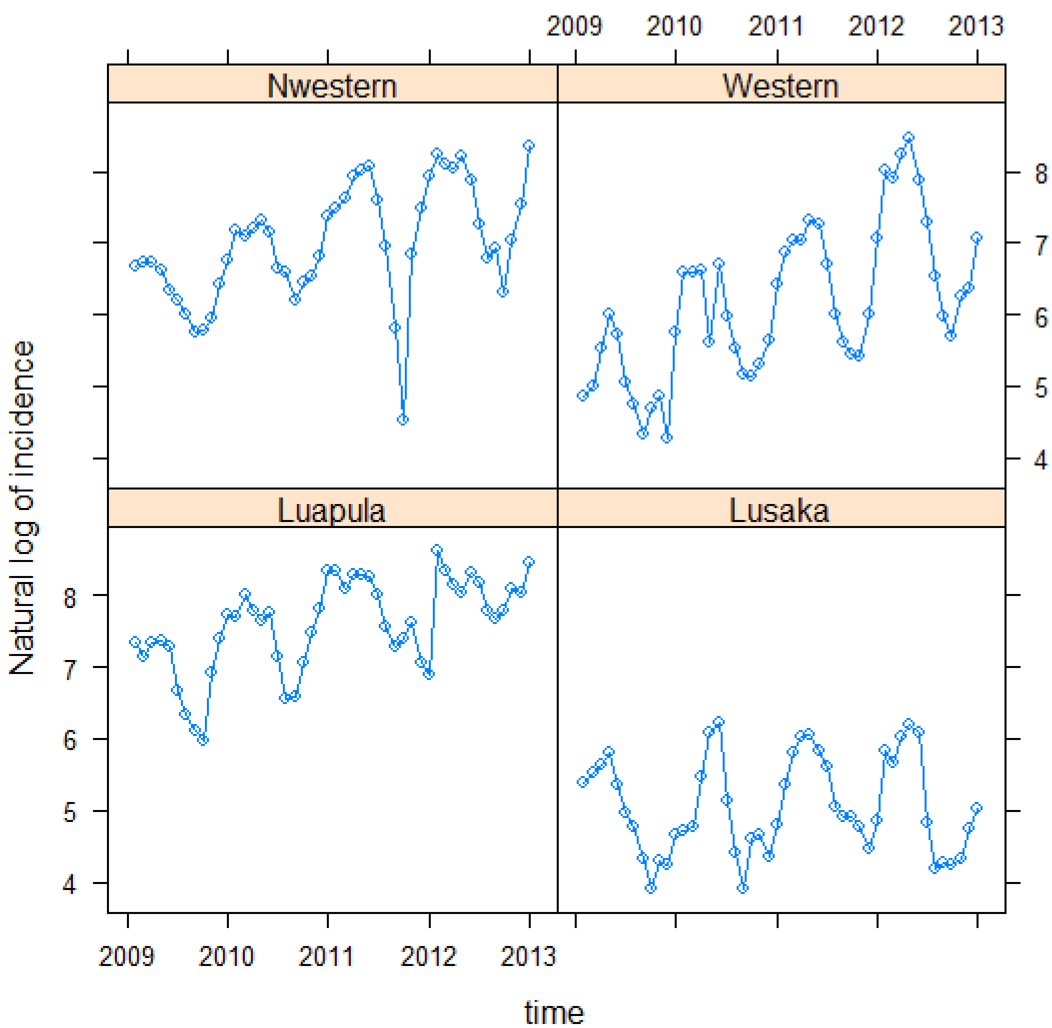

Figure 2: Trellis plot of the natural logarithm of malaria incidence against time

Figure 2 shows the variation of malaria incidence in the four provinces by years, with Lusaka exhibiting consistently low incidence although all provinces initially begin with lower incidences of malaria.

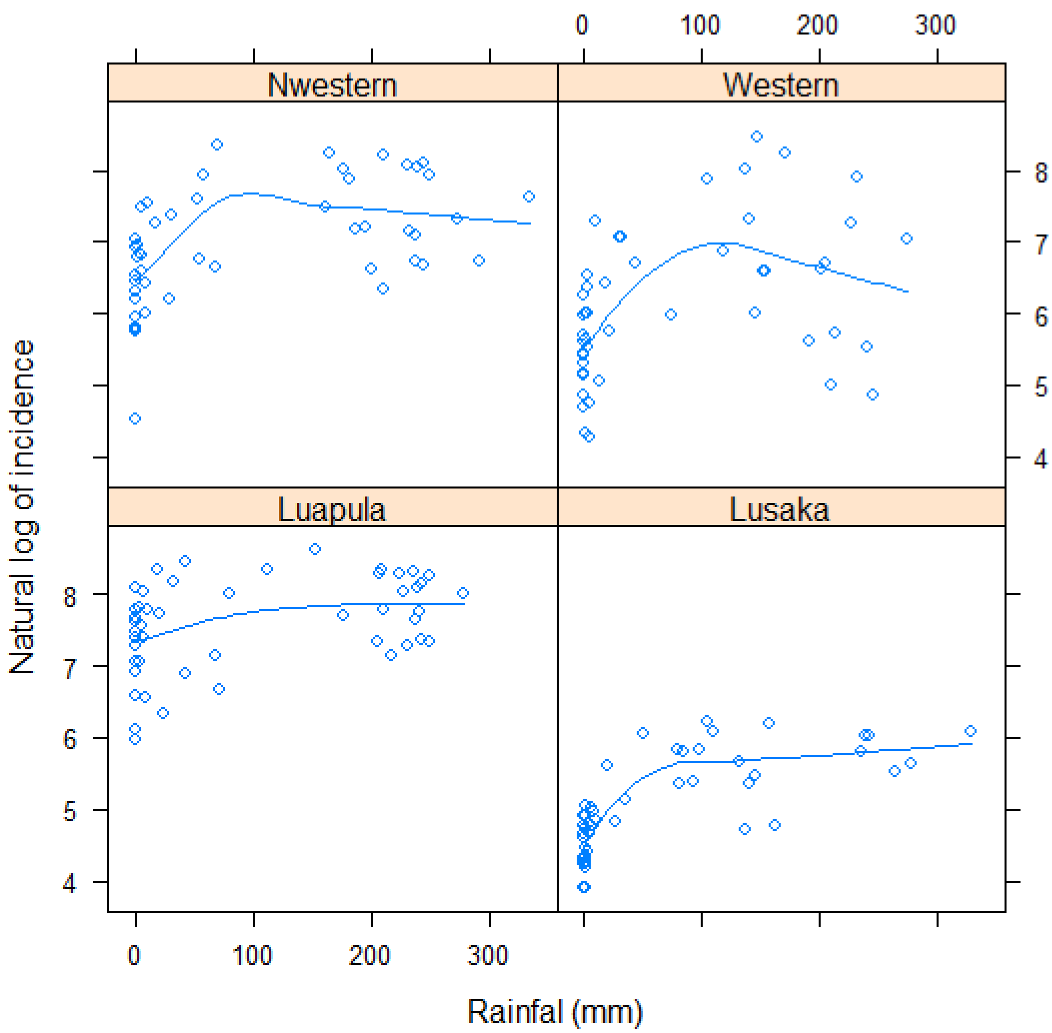

Figure 3: Trellis plot of the natural logarithm of malaria incidence against rainfall

Figure 3 shows a linear relationship between rainfall and malaria incidence and linearity was more pronounced in Luapula Province

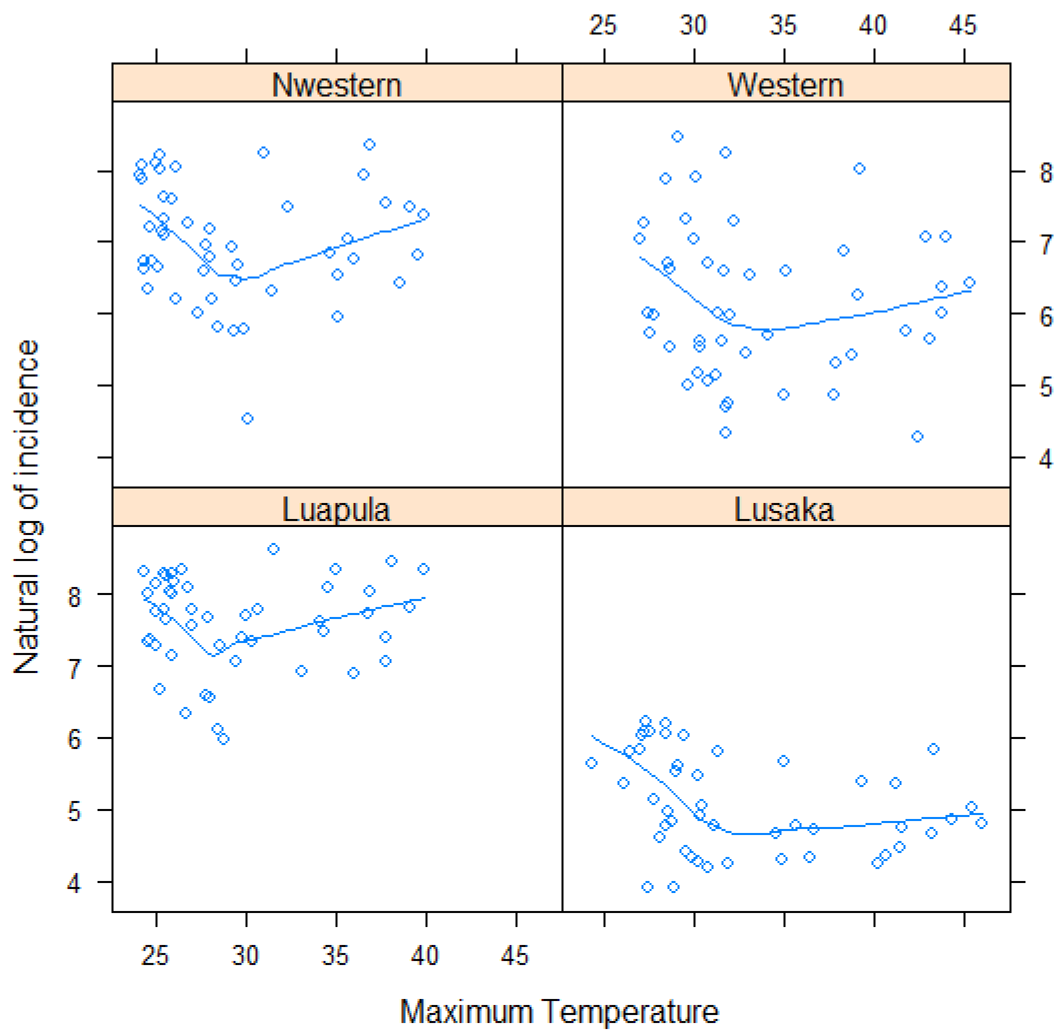

Figure 1 Trellis plot of the natural logarithm of malaria incidence against maximum temperature

Figure 4 shows that the relationship between maximum temperature and malaria incidence is limited to temperatures slightly below 40°C (25-30°C). This effect is pronounced in Luapula and North-western provinces.

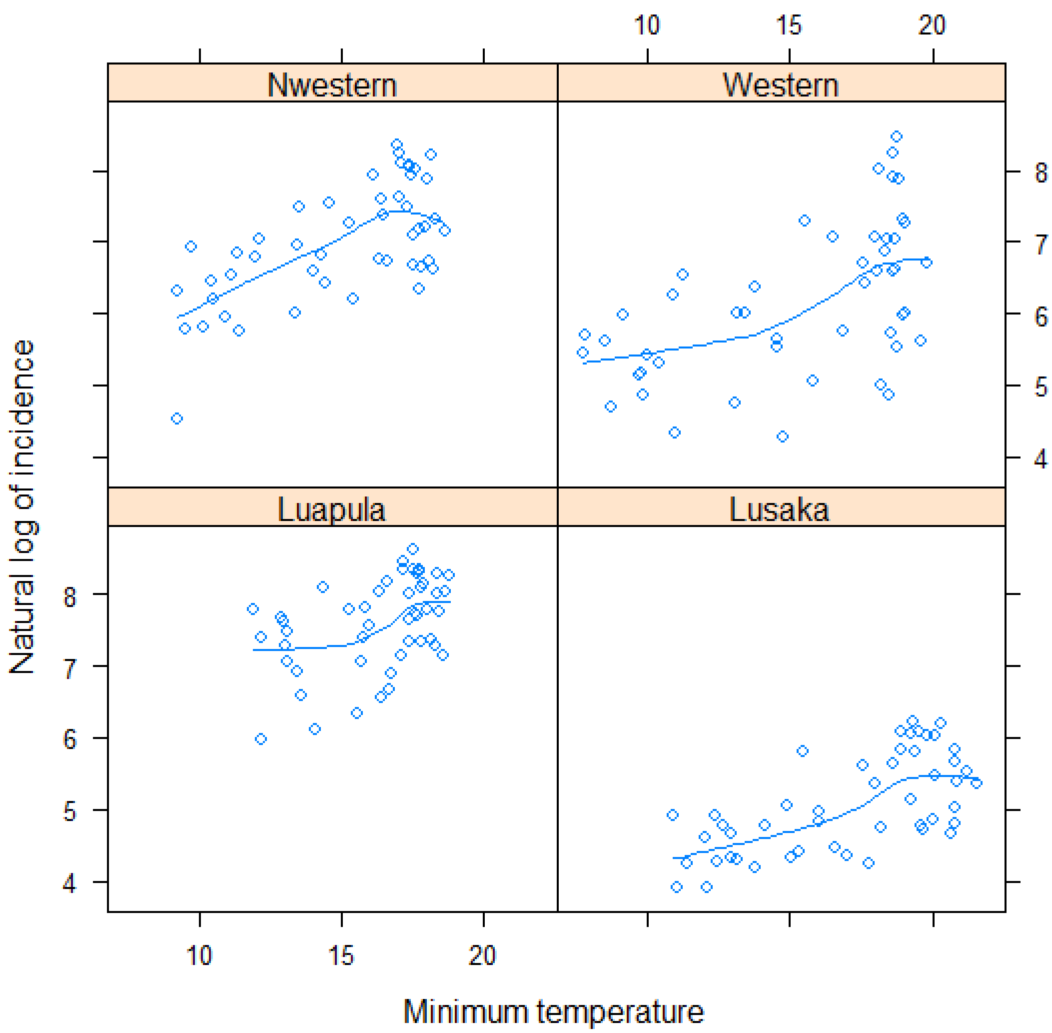

Figure 5: Trellis plot of the natural logarithm of malaria incidence against minimum temperature

Figure 5 shows that with increase in minimum temperature, malaria increases. The effect is observed in all provinces although it is more pronounced in Luapula and North-western where the burden of malaria is also higher at the temperatures 15 – 18^{o}C

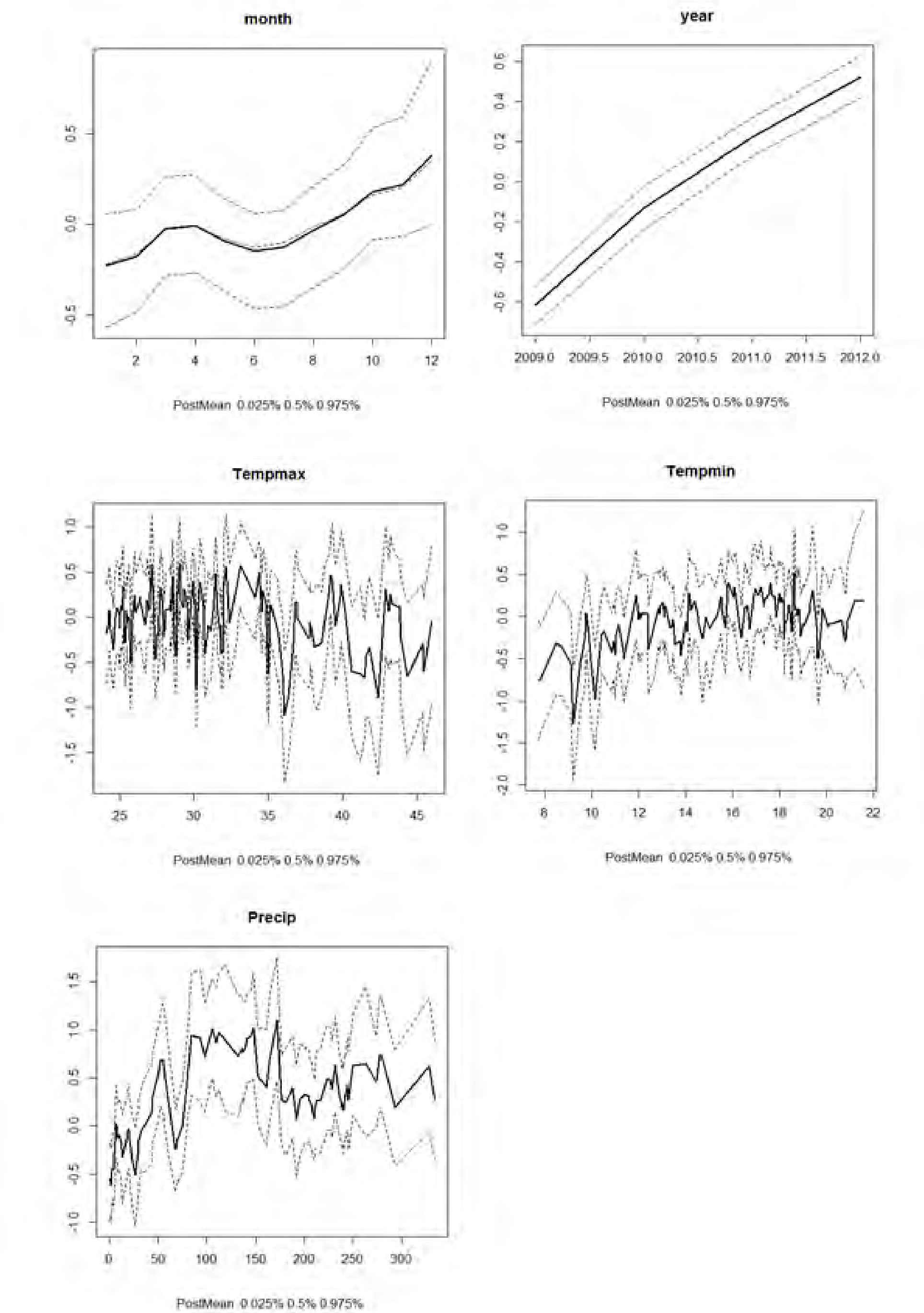

Figure 6 Posterior means (bold), medians (0.5% = 50th percentiles, middle), lower credible limits (0.025% = 2.5th percentiles) and upper credible limits (0.975% = 97.5th percentiles) for month (top-left), year (top-right), maximum temperature (middle-left), minimum temperature (middle-right), and precipitation (bottom)

Figure 6 shows the posterior means plus 95% credible bands, time series plots from the modelling which resembles the observed data shown in Fig. 3 – 5. There was a non-linear relationship between Malaria incidence and minimum temperature. The incidence of malaria increased linearly with minimum temperature, peaking at about 18 degrees and declining gradually thereafter. Malaria incidence increases linearly each year but had a non-linear monthly pattern. Malaria incidence had a dip in the months of June-July, increasing steadily thereafter.

Table 3: Best fitting Poisson geoadditive regression model

	mean	SD	0.025quant	0.5quant	0.975quant	IRR
Fixed effects						
Region (Ref=Luapula)						
Lusaka	-3.10	0.11	-3.31	-3.10	-2.89	0.05(0.04-0.06)
Nwestern	-0.09	0.09	-0.26	-0.09	0.08	0.91(0.77-1.08)
Western	-1.15	0.13	-1.39	-1.16	-0.90	0.31(0.25-0.41)
Random Effects						
Precision for Precip	40.24	22.32	13.70	34.87	97.86	
Precision for Tempmin	1.06	0.56	0.31	0.94	2.46	
Precision for year	10.83	7.19	2.22	9.19	29.13	
Precision for Tempmax	0.67	0.20	0.36	0.64	1.14	
Precision for month	95.48	129.31	11.14	57.09	413.97	

Table 3 presents the results for the best fitting geoadditive Poisson regression model. Adjusting for the effect of precipitation, minimum temperature, maximum temperature, year and month, the risk of malaria was 95% lower in Lusaka (ARR=0.05,95%CI=0.04-0.06) and 68% lower in the Western Province (ARR=0.31, 95% CI=0.25-0.41) compared to Luapula Province. North-western did not vary from Luapula Province

7.4 Discussion

This study modelled the influence of selected climatic variables on the incidence of malaria in the four provinces in Zambia through a geoadditive or structured additive *Semiparametric Poisson regression* model. We utilised standardised data to avoid the effect of scale. Additionally, others suggest scientific evidence with regards to the relationship that exits between vectors and parasites with raw temperature data [38]. It has been suggested that "using raw temp data in spatial statistical models in empirically defined relationships with observed infection prevalence is limited because the mechanisms of temperature dependence on vector and parasite dynamics are highly non-linear and raw temperature values are likely to be only indirectly linked to observed transmission intensity" [38]. However, it may not only be raw temperature data effects but also scarce data on prevalence or incidence that would also contribute in making delineation of areas at risk problematic [38].

In our study, malaria incidence was rising year after year from 2009 to 2012 except for Lusaka which exhibited consistently low incidence. We have demonstrated that the risk of malaria was 95% lower in Lusaka (ARR=0.05,95%CI=0.04-0.06) and 68% lower in the Western Province (ARR=0.31, 95% CI=0.25-0.41) compared to Luapula Province. North-western did not vary from Luapula Province.

We observed that rainfall was linearly related to malaria incidence with a higher effect in Luapula Province. Maximum temperature was higher in Lusaka and Western provinces compared to Luapula and North-western provinces while minimum temperature did not vary by large margins in Luapula and North-western provinces, compared to Lusaka and Western provinces. We also observed a non-linear relationship between malaria incidence and minimum temperature and this was the same with the modelling results. The incidence of malaria increased with minimum temperature, peaking at about 18^{o}C and declining gradually thereafter. Our results show that precipitation was the strongest predictor of malaria incidence followed by minimum temperature. This is proven also in the strong positive correlation between precipitation and minimum temperature shown in our data.

Our observation of a linear relationship between rainfall and malaria incidence is in agreement with some studies [39] where it has been demonstrated that "cumulative amount of rainfall in the 15 preceding days of measurement was significantly positively correlated with the adult *Anopheles* density", an indication of humid air conditions that favour adult mosquito survival. Additionally, our study in our demonstration of a strong relationship between precipitation and minimum temperature also agrees with others who show that the effect of rainfall becomes more immediate in warmer temperatures [23]. Others also found that high annual malaria incidence coincided with high rainfall while "temperature-derived covariates seemed to be important only in the presence of sufficient rainfall" [14].

It has been demonstrated that in cases of too much rainfall which may flush away breeding larvae and reduce vector density [12, 23], malaria may not be associated with rainfall. Other cases when rainfall has not been positively related with malaria incidence have been observed in urban areas due to presence of other water sources for vector breeding [23]. This may be one of the many explanations why Lusaka, a much urbanised city may have low malaria incidence. Other studies have further demonstrated that mosquito abundance is affected by rainfall as well as the presence of surface water [40]. This shows that in urbanised places the landscape changes and so does its capacity for surface water. In other instances, the effect of rainfall in cold districts was shown to be negative at shorter lags [23] equally the effect of minimum temperature in cold districts, positive although delayed and in hot districts, immediate yet insignificant [23]. Our study also demonstrated lower malaria incidences in the colder months of June and July. These findings show that while rainfall and minimum temperature may be positive predictors, these conditions may not be effective if overridden by stronger factors. An example is where certain vectors of malaria, such as *An. funestus*, which are less dependent on rainfall, are abundant, given that their breeding preference of more permanent habitats [40], would not require rainfall as a crucial factor.

It has been shown that in some cases, non-linear relationship between mosquito densities and environmental variables exist with lagged data [41] and our study demonstrated the relationships based on incidence and lagged climatic data. The non-linear relationships have been attributed to the complex nature of interactions between the variables studied which may have specific time lags that would not be captured by the data [41] although in that particular study, rainfall was a significant positive predictor as the mosquito species displayed distinct temporal patterns that have perfect fit with rainfall sequence [41]. While some have shown that one month of rain above 80mm was not sufficient for a transmission season but that three months above 80mm and 7 months above 22^{o}C to allow for seasonal transmission [42, 43], our study demonstrates that a two months lag in our communities was sufficient to sustain transmission.

Plasmodium falciparum malaria parasites develop in the *Anopheles gambiae* vector, the most efficient vectors, only within a certain temperature range [8]. Our study showed higher malaria incidence when minimum temperature was in the range 15 - 17^{o}C. This is in agreement with other studies, where the minimum average monthly temperature for the parasite development to be completed within 1 month was assumed to be 17^{0}C [40]. “The importance of temperature as an environmental determinant of malaria endemicity arises from a series of effects it has on the life cycles of both parasite and vector” [38]. Thus continuous assessment studies are recommended.

Studies have shown that minimum temperature which is observed at night is related to high malaria incidence given that mosquitoes are also more active at night when these conditions prevail [12]. It is also suggested that when night temperatures are high people, when sleeping, do not cover themselves with bedding, increasing the risk of being bitten by mosquitoes [12] although others have demonstrated that while day land surface temperature (LST) was negatively associated with vector density, night was not at all significantly associated with mosquito density [39]. In our study, the two provinces Luapula and North-western that showed higher incidences also showed consistent ranges of minimum temperatures in comparison to Lusaka and Western where the variations were large. It is clear that minimum temperature is positively correlated with malaria incidence especially when not limited by short periods [23]. In our study, the relationship was very clear, attributable to longer seasons which last for a number of months. It is obvious that Zambia's temperatures are very suited for mosquito development and malaria transmission [8] and yet our study illuminates further on the variations by Provinces.

Maximum temperature on the other hand has been shown to have a negative effect on malaria incidence and this has been explained by the interruption of mosquito development that high temperature has [12] and its inhibitory and lethal effect [23]. Specifically, it has been demonstrated that the proportion of parasites surviving decreases rapidly at temperatures over 32–34^{0}C range [40]. Our study is in agreement with these earlier findings, showing that increasing maximum temperatures limited malaria incidence. We demonstrated this in the lower malaria incidences observed at maximum temperatures higher than 25 – 30^{o}C.

As demonstrated in some studies [14] we also found that time had an effect on malaria incidence where incidence increased linearly each year, although like "temperature, intensity and timing of seasonal peak in each year appeared to follow variability in rainfall" [14].

The component of region demonstrated in our model, could be explained by the occurrence of a suitable environment for vector development such as high rainfall and minimum temperatures which were shown to have strong influence in Luapula and North-western provinces compared to Lusaka and Western provinces. However, this does not rule out other climatic and non-climatic factors such as mean or average temperatures, vapour pressure [14] and humidity [38] landscape changes [38] due to human activities, changing the vector composition [4]. Other climatic factors that have been shown to be correlated to malaria incidence but not considered in our study are mean or average temperatures, vapour pressure [14] and humidity [38]. While some have demonstrated that average temperatures were not sufficient since parasites and vectors experience changing temperatures throughout their life span [38], others have shown otherwise that mean temperature along with rainfall and vapour pressure were strong positive predictors of increased annual malaria incidence [14]. Where insufficiency of mean temperatures has been observed, it is explained by the fact that temperature is not the primary climate limitation of transmission [38] as is the case in arid areas where due to lack of humidity amidst temperature, transmission would not occur.

7.5 Conclusions

Our study proposes a geoadditive or structured additive *Semiparametric Poisson regression* model to assess climatic factors associated with malaria incidence based on 2009 to 2012 data in four endemic provinces of Zambia. We demonstrate a strong positive association between malaria incidence and precipitation as well as minimum temperature. The effects of region are clearly demonstrated by the unique behaviour and effects of minimum and maximum temperatures in the four provinces. Environmental factors such as landscape in urbanised places may also be playing a role. We recommend for the Government of the Republic of Zambia to incorporate meteorological parameters, particularly precipitation, minimum temperature and landscape in justification for malaria control programmes in specified regions.

7.6 Ethical approval

The study protocol was approved by University of Zambia (UNZA) Biomedical Research Ethics Committee (IRB00001131 of IORG0000774).

7.7 Abbreviations

R-INLA: R version of integrated Laplace; NDVI: normalised difference vegetation index; WHO: World Health Organisation; LS: Lusaka; LP: Luapula; NW: North-western; W: Western; CSO: Central Statistical Office; HMIS: Health Management Information System; LST: land surface temperature; MODIS: Moderate Resolution Imaging Spectroradiometer; USGS: U. S. Geological Survey; LP DAAC: Land Processes Distributed Active Archive Centre; CHIRPS: Climate Hazards Group InfraRed Precipitation with Station data; UCSB: University of California, Santa Barbara; DIC: Deviance Information Criterion; pD: effective number of parameters; Pop: total population; I: malaria incidence rate; M: new malaria cases; RW: random walk; RR: relative risk;

7.8 Competing interests

The authors as well as the funders declare that they have no competing interests in the manuscript.

7.9 Authors' contributions

All authors conceived the study and contributed to the study design; NMS-M designed the study, collected and analysed the data. SM, ET-M and MG guided in the considerations for data collection and analysis; TNOA led the statistical analysis component; NMS-M drafted the manuscript; All authors contributed to the interpretation and presentation of data and read, edited and approved the final manuscript.

7.10 Authors' information

NMS-M (Nzooma M. Shimaponda-Mataa[1,2]) is a Medical Parasitologist and Lecturer at the University of Zambia and holds MSc Parasitology degree; SM (Samson Mukaratirwa[2]) is a Parasitologist and Professor, Dean and Head of School and Lecturer at the University of KwaZulu-Natal in Durban, South Africa and holds PhD in Parasitology; MG (Michael Gebreslasie[4]) is a Geographer (geospatial methods) and Lecturer at the University of KwaZulu-Natal in Durban, South Africa and holds PhD in Geography; ET-M (Enala Tembo-Mwase[3]) is Parasitologist and Professor, Deputy Vice Chancellor and Lecturer at the University of Zambia and holds PhD in Parasitology; TNOA (Thomas N. O. Achia) is Bayesian statistician and Senior Statistician at Centre for Disease Control and Prevention, Division of Global HIV/AIDS (DGHA), Surveillance and Epidemiology Branch in Kenya and holds a PhD in Mathematical Statistics.

[1]University of Zambia School of Medicine, Department of Biomedical Sciences, Ridgeway Campus, Lusaka, Zambia.[2]University of KwaZulu-Natal, School of Life Sciences, Westville Campus, Durban, South Africa.[3]University of Zambia, School of Veterinary Medicine, Great East Road Campus, Lusaka, Zambia.[4]University of KwaZulu-Natal, School of Agriculture, Earth and Environmental Science, Westville Campus, Durban, South Africa. [5]Centre for Disease Control and Prevention, Division of Global HIV/AIDS (DGHA), Surveillance and Epidemiology Branch, Kenya

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CHAPTER 8

General Conclusions

This thesis has been devoted to the study of socio-economic and eco-environmental determinants of malaria in four endemic provinces in Zambia. Socio-economic factors relate to both social and economic aspects of communities and as such are considered at both household and provincial level. For example, the uptake of prevention and control measures at the household level involves the household's access to the measures. In like manner, uptake of these measures at provincial level can be observed in the capacity of National Malaria Control programmes to access for and channel them to the various provinces. With regards to eco-environmental factors, the same considerations can be applied. For our purposes, access includes both donations from Government or other programmes as well as individually sourced control tools given that donations are usually one-off.

However, as evidenced in this thesis, both levels of the socio-economic and eco-environmental factors have a contribution to the malaria burden experienced both at community and country levels. In this thesis, new perspectives in determining the contributing factors are discussed. Supported by the evidence of the new results obtained from modelling of both household level and provincial level data based on the various transmission zones, we make a number of conclusions.

Firstly, the progress made in malaria control has been studied with regards to the studies conducted to identify socio-economic and eco-environmental determinants of malaria in the region of southern Africa. At household level, the common factors observed related to the capacity of the household members in terms of household income, education and occupation while at provincial level, the interventions in malaria prevention and control were the main focus. Limited attention is given to vulnerability of communities and/or exposure to vectors in southern Africa. Additionally, studies are conducted at a large scale, neglecting community specific factors that would only be identified at small-scale study. There is room to widen the focus on the types of factors studied while narrowing down to the lowest community population structure. This calls for enhancing capacity with regards to modelling capacity using Bayesian approach, given its versatility.

In a Bayesian multilevel model of socio-economic factors of malaria at household level, the potential of CHWs and the crucial role of behaviour change in malaria control are identified. Although the identified factors such as the influence of CHWs are observed at small scale and the study also raises the possibility of provincial factors being influential in the risk of RDT positivity, the results are significant. These results open to further research on the regional factors as well as the mechanism through which CHWs affect the malaria situation in specific communities in the different transmission zones.

In order to improve understanding on the community level contribution to the malaria burden, it was necessary to consider not only the role of CHWs but also the role of the community members with regards to knowledge levels, attitudes and practices in malaria control. The levels of knowledge varied in the communities studied and in some cases, did not synchronise with the attitudes and practices, a possible proxy for behaviour change needs. Additional avenues that could be utilised to enhance information as well as community uptake of preventive and protective materials were identified based on the socio-cultural issues responsible for low and varied information levels.

The other aspect of household level factors investigated using a Bayesian multilevel model was the water related practices and housing structures in their role in exposing community members to malaria vectors. The presence of rivers was the key predictor of malaria identified although other potential predictors were also observed. Community involvement as an enhancement to the integrated malaria and vector control strategy is recommended.

By using malaria incidence data and socio-economic variables at region level in a Bayesian hierarchical model, this study revealed that region was the strongest predictor of malaria although other potential factors that could be investigated further are presented as well. There is need to explore both region and community contribution to the burden of malaria for specific communities.

Further, a model fitted in R-INLA incorporating climatic and malaria incidence data illuminated understanding on the contribution of climate to malaria incidence in the four provinces. While the best fitting model comprised time, region and a non-linear precipitation effect, the role of minimum temperature was also significant but not that of maximum temperature.

This study, through its unique combination of employing statistical modelling methods with the rare use of household level data in different transmission zones, revealed new insights that call for a change in malaria control focus. The climatic conditions prevailing in Western Province only favour malaria vector development to a certain extent and this knowledge must be appropriated in the development of strategies to contain and reduce the burden. As evidenced from this study, enhanced social structures of CHWs contributed to reducing malaria prevalence in the Western Province communities regardless of the poor housing structures and presence of other strong predictors of malaria such as rivers. Lusaka Province has been shown to experience climatic conditions that are even less favourable to malaria vectors compared to Western Province and this coupled with other factors such as urbanisation have worked to an advantage. However, it is clear that the intervention coverages, even during years when Lusaka Province received lesser coverage, consistency contributed to lowering the burden and keeping it in check. In North-western Province the climatic conditions were the main contributors to malaria burden while in Luapula Province it was a combination of climate and presence of rivers. The almost uniform coverage of IRS in all the provinces could have advantaged Lusaka and Western provinces at the expense of North-western and Luapula provinces with more enabling climatic conditions for malaria transmission. Formal education and malaria knowledge were crucial factors although even more crucial was the aspect of attitude and behaviour change which was similar in all the communities. This was evidence of a disconnection between control programmes and the involvement of communities. It is clear that such multi-levelled studies are necessary for each province in the development of tailor-made intervention strategies in liaison with the communities.