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# Spatial and socio-economic effects on malaria morbidity in children under 5 years in Malawi in 2012

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ABSTRACT

*Background:* Malaria is a major health challenge in sub-Saharan Africa with children under 5 being most vulnerable. Identifying regions of greater malarial burden is vital in targeting interventions.

*Methods:* This study analysed malaria morbidity using data from the Malawi 2012 Malaria Indicator Survey that were obtained from Demographic and Health Survey (DHS) program website. These data captured malaria related information on children under 5. Poisson regression was done to determine associations between outcome (number of children under 5 with malaria in household) and explanatory variables. A Bayesian smoothing approach was employed to adjust for spatial random effects on child related variables.

*Results:* There were 1878 households in 140 clusters. The number of children under five was 1900. Spatially structured effects accounted for more than 90% of random effects as these had a mean of 1.32 (95% Credible Interval (CI) = 0.37, 2.50) whilst spatially unstructured had a mean of 0.10 (CI = $9.0 \times 10^{-4}$, 0.38). Spatially adjusted significant variables were; type of place of residence (urban or rural) [posterior odds ratio (POR) = 2.06; CI = 1.27, 3.34], not owning land [POR = 1.77; CI = 1.19, 2.64], not staying in a slum [POR = 0.52; CI = 0.33, 0.83] and enhanced vegetation index [POR = 0.02; CI = 0.00, 1.08]. A trend was observed on usage of insecticide treated mosquito nets [POR = 0.80; CI = 0.63, 1.03].

*Conclusion:* This study showed that malaria is a disease of poverty. Enhanced vegetation index was an important factor in malaria morbidity. The central region was identified as the area with greatest disease burden.



## 1. Introduction

Malaria is a serious problem in developing countries and studies have been carried out in these countries to identify factors that are associated with the disease (Bell et al., 2005; Bowie, 2007; Breman et al., 2004; Brooker et al., 2008; Omumbo et al., 2005; Kazembe et al., 2006; Messina et al., 2011; Snow et al., 2003; Noor et al., 2009; Bennett et al., 2013). Factors that have been identified are both natural as well as human related and these include climatic, geographic and SES variables (Chirombo et al., 2014). Temperature and precipitation are major environmental risk factors (Nobre et al., 2005). Human

*Abbreviations*: CAR, conditional autoregressive model; CI, Credible Interval; DHS, Demographic and Health Survey; DIC, deviance information criterion; DST, Department of Science and Technology; EA, enumeration area; EVI, enhanced vegetation index; GMRF, Gaussian Markov Random Fields; GIS, geographical information system; GLM, generalised linear model; INLA, integrated nested laplace approximation; ITN, insecticide insecticide-treated bed nets; MCMC, Markov chain Monte Carlo; MH, Metropolis–Hastings; MIS, Malaria Indicator Survey; NRF, National Research Foundation; POR, posterior odds ratio; RR, relative risk; SACEMA, South African Centre of Excellence in Epidemiological Modelling and Analysis; SES, socio-economic status; TSI, temperature suitability index; UN, United Nations; WHO, World Health Organization.

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related factors include use of bed nets, access to anti-malarial drugs, poor access to health services, inadequate case management, reduced immunological competence due to malnutrition and socioeconomic factors (Bowie, 2007; Omumbo et al., 2005; Snow et al., 2003; Cox et al., 2007). The human related factors have a strong link to poverty and vulnerability (Snow et al., 2003; Global poverty, 2012). Therefore, the impact of malaria is strongly felt in low income countries.

Malaria is endemic throughout the country of Malawi but areas close to Lake Malawi and the low lying areas which are to the south of Lake Malawi and known as the Shire valley are most affected (Dzinjalamala, 2009) and it is a major public health problem in that country (Wilson et al., 2012). In the year 2010 in Malawi, malaria accounted for the third highest number of deaths (Institute for Health Metrics and Evaluation, 2012). Transmission is highest in areas that experience high temperature and frequent rainfall from October through to April (Bloland et al., 1999). Malaria causes serious health problems in Malawi with the whole population at risk of contracting the disease (Ingstad et al., 2012). In 2011 according to WHO, Malawi experienced 5,338,701 episodes of malaria (World Health Organization, 2012). The presence of water bodies is an important factor in the transmission of malaria. Lake Malawi covers almost the whole length of Malawi and is an important source of income and food for many families through fishing (Ingstad et al., 2012) as well as an important transport route and this puts the people living along the lake under high risk (Bennett et al., 2013; Okiro et al., 2014). Children under five constitute about 50% of the total suspected malaria cases and nearly 60% of all hospital deaths in children under five are as a result of malaria and anemia (Connor et al., 2006).

In the fight against malaria, there is need to ensure that adequate information on the disease and prevalence in specific areas (Snow et al., 1996) is available and this is based on the notion that people living in a household as well as those living close together have exposures that are similar (Musenge et al., 2013; Elliott et al., 1995).

Transmission of malaria varies from place to place, mapping this variation is important in identifying populations at risk as well as the different risk levels, comparing and interpreting malaria interventions in different places, and evaluating options for controlling the disease (Gething et al., 2011; Lowe et al., 2013). Disease maps can be used and these show how the disease is geographically distributed by highlighting the areas with high and low incidence of the disease (Musenge et al., 2013; Sun et al., 2000). This is important in order to target the available limited resources to areas of where they are required the most for the greatest effect in malaria control (Kazembe, 2007).

Bayesian statistical methods are applied in spatial analysis and disease mapping because they enable the integration of spatial correlation and modelling of fixed variables and random effects (Lawson et al., 1999; Wakefield, 2007). Spatial modelling creates spatial random effects thus providing parameter estimates of clusters adjusted for spatial covariates (Clements et al., 2006; Riedel et al., 2010; Gosoniu et al., 2006). MCMC algorithms are used in Bayesian statistics. MCMC algorithms are used in sampling probability distributions beginning with an initial value with conditional probabilities being used in generating new values (Lawson, 2013). MCMC algorithms deliver dependent outcomes, which are correlated (Banerjee et al., 2004). Gibbs sampling and MH are some of the ways used in MCMC (Fruhwirth-Schnatter, 2013; Geman and Geman, 1993; Casella and George, 1992; Chib and Greenberg, 1995). Gibbs sampling is used when the joint distribution is unknown or is difficult to sample directly, but the conditional distribution of each variable is known and is from a normal distribution (Geman and Geman, 1993; Arminger and Muthén, 1998). We also performed the analysis using an integrated nested laplace approximation (INLA) well suited for Gaussian Markov Random Fields (GMRF) as opposed to the commonly used MCMC (Rue et al., 2009). This has the advantage of a reduced computational burden and could do in hours what usually took days. These methods were utilised in this paper.

This study aimed to understand the spatial associations between malaria morbidity and environmental and behavioural determinants of malaria in Malawi in the year 2012. The study also aimed to compare three different approaches used in spatial analysis that is WinBUGS, INLA and BayesX to see which approach produced the best fit with the data available. This was achieved through applying a Bayesian smoothing approach that was able to handle spatial random effects. Three different Bayesian smoothing approaches were implemented which assisted in fully understanding the determinants of malaria as well as the influence of different geographical areas and environmental effects in malaria prevalence.

Understanding fully the determinants of malaria in a low income sub-Saharan country is useful in assisting the development of health programs targeted at helping to reduce the burden of malaria with available resources and interventions in order to reduce the burden of malaria on the population.

## 2. Materials and methods

### *2.1. Study area*

Malawi is a landlocked country located in southern Africa with an area of approximately 120,000 $km^2$ and is divided into three regions (Northern, Southern and Central). The country is bordered by Zambia, Mozambique and Tanzania (Lowe et al., 2013). Malawi has a subtropical climate with a rainy season from November to May and a dry season from May to November (Bennett et al., 2013). The presence of many water bodies especially on the eastern side with Lake Malawi being the most prominent at a length of 580 km makes the nation vulnerable to malaria morbidity and mortality (Bowie, 2007; Bennett et al., 2013; Dzinjalamala, 2009).

### *2.2. Malawi Malaria Indicator Survey data*

The 2012 Malaria Indicator Survey (MIS) data that were used in this study came from a sample of households that were selected throughout the three regions (Northern,