Unravelling the Impact of Insecticide-treated Bed Nets on Childhood Malaria in Malawi

Julie-Anne A Tangena (✉ julie-anne.tangena@lstm.ac.uk)

Liverpool School of Tropical Medicine

Donnie Mategula

Malawi-Liverpool-Wellcome Trust Clinical Research Programme

Luigi Sedda

Lancaster University

Peter M. Atkinson

Lancaster University

Research Article

Keywords: Malaria indicator survey, Malawi, insecticide-treated bed net, bed net use

Posted Date: February 21st, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1366220/v1>

License: This work is licensed under a Creative Commons Attribution 4.0 International License. [Read Full License](#)

Abstract

Background: To achieve malaria elimination it is essential to understand the impact of insecticide-treated net (ITNs) programmes. Here, the impact of ITN access and use on malaria prevalence in children in Malawi was investigated using Malaria Indicator Survey (MIS) data.

Methods: MIS data from 2012, 2014 and 2017 were used to investigate the relationship between malaria prevalence in children (6 to 59 months) and ITN use. Generalised linear modelling (GLM), geostatistical mixed regression modelling and non-stationary GLM were undertaken to evaluate trends, spatial patterns and local dynamics, respectively.

Results: Malaria prevalence in Malawi was 27.1 % (95% CI 23.1 -31.2) in 2012 and similar in both 2014 (32.1 %, 95%CI 25.5-38.7) and 2017 (23.9 %, 95%CI 20.3-27.4). ITN coverage and use increased during the same time period, with population access growing from 33.1 % (95%CI 29.8-36.4) of the population potentially sleeping under an ITN the previous night to 58.4 % (95%CI 56.2-60.6) and ITN use from 41.1 % (95% CI 37.3-44.9) of the population sleeping under an ITN the previous night to 57.4 % (95% CI 55.0-59.9). The behavioural gap disappeared while the ownership gap persisted. Both the geostatistical and non-stationary GLM regression models showed child malaria prevalence had a negative association with ITN population access and a positive association with ITN use. The non-stationary GLM highlighted the large variation in the relationship between childhood malaria and ITN use across the country.

Conclusion: ITNs are effective in controlling childhood malaria in Malawi, although the impact was heterogeneous across the country. This study presents an important modelling approach that allows malaria control programs to spatially disentangle the impact of interventions on malaria cases.

Introduction

Malaria is one of the most important causes of morbidity and mortality in Malawi. Since 2007, mass distribution of insecticide-treated nets (ITNs) to the demographically most vulnerable population groups has been a major part of Malawi's vector control efforts [1]. This, in combination with improved diagnosis and treatment of cases, has resulted in a 36% reduction in malaria cases, from an estimated 5.6 million cases in 2010 to 3.6 million in 2016. Despite this progress, continued investment in malaria control has not led to a further decrease in cases [1], with an estimated 3.9 million cases still occurring in 2019 [2].

The Malawi National Malaria Control Programme (NMCP) aimed to reduce malaria incidence by at least 50% from a 2016 baseline of 386 per 1000 population to 193 per 1000, and reduce malaria deaths by at least 50% from 23 per 100,000 population to 12 per 100,000 population by 2022 [3]. For these targets, it is necessary to understand the impact of current control activities and tailor future vector control to local epidemiological and entomological dynamics [4]. To control the malaria vectors, in 2007, the government started distributing long-lasting insecticide-treated nets (LLINs). It is generally accepted that ITN coverage has helped decrease malaria prevalence in Malawi [5–8]. However, retrospective studies have also found that a 13% increase in bed net access from 2012 to 2014 was not associated with a reduction in malaria burden in children [9]. This was corroborated by a similar study investigating overall trends within the 2012 and 2014 malaria indicator survey (MIS) data [10]. Comparison of data from 2004 and 2016 also showed that community malaria prevalence was not related to ITN use [11]. No personal, and limited community, protection from ITNs was found in a field study from 2012 [12]. These inconsistent conclusions suggest that ITN access and use may have a heterogeneous impact on malaria prevalence.

One of the main challenges for malaria elimination is the heterogeneity of the current malaria landscape [1, 13, 14]. It is not well understood why this heterogeneity has emerged, although the possible varied efficacy of ITNs could be partly responsible. ITNs can impact areas differently due to different vector population compositions and behaviours, climate variation and the presence of resistance [15–17]. Furthermore, gaps may exist between policy and implementation [18], with human behaviour one of the most complex variables involved in malaria transmission. The local population might accept, but not use and maintain nets, use nets for other purposes or migrate to areas with higher malaria risk [19–21]. Further reasons include social factors such as autonomy in health care decisions [22], bed net integrity and insecticide degradation [23].

The best method for measuring the efficacy of ITNs directly is randomized controlled trials, ideally conducted across different parts of a country. Unfortunately, no such randomized control trials have been conducted in Malawi. However, an important alternative source of information exists in the MIS. A search on the National Library of Medicine identifies more than 2,000 papers that have used MIS data in some capacity (search date 16-02-2022). These routine, large-scale household surveys are designed to produce snapshots of the malaria situation at national, regional and urban/rural levels. In Malawi, full MIS were conducted in 2010, 2012, 2014 and 2017 [24–26]. These MIS, together, capture the malaria situation and dynamics throughout the country and represent an essential source of information for policy development [1]. For example, MIS studies helped recognise the possible ineffectiveness of ITNs [9, 10], which led to the recent addition of pyrethroid-Piperonyl butoxide (PBO) nets to the vector control program. The latest MIS survey was conducted in Malawi in April 2021. Data are currently being analysed and have not been released to the public.

Even with the recent addition of PBO nets to the vector control programme, traditional permethrin nets will remain an important part of control efforts in Malawi due to the questionable durability of PBO nets [27] and their additional costs. In this paper, the efficacy of ITN access and use in decreasing malaria prevalence in children was investigated using MIS data from 2012, 2014 and 2017.

Materials And Methods

Country profile

Malawi is a southern African country with an estimated population of 18.6 million in 2019 [28]. The country consists of the Northern, Central and Southern regions, further divided into 28 districts. Malawi has three seasons, a rainy season from November to April, a cool-dry season from May to August and a hot-dry season from August to November. This sub-tropical climate is favourable for transmission of malaria. The main malaria vector, *Anopheles funestus*, is present throughout the country and throughout the year. The population along Lake Malawi and in the southern lowland are especially at high risk [14], as their environment is also ideal for the secondary malaria vectors *An. gambiae* s.s. and *An. arabiensis* [14, 29]. Even though *An. funestus* and *An. gambiae* s.l. were susceptible to all insecticides in 2007, by 2010 pyrethroid resistance was found in both species [15, 30]. At present it is suspected that pyrethroid and carbamate resistance is widespread across the country [31]. In 2007, the Malawian government started the distribution of LLINs. In 2012, 41% of the population owned at least one ITN with 29% sleeping under it the preceding night [24]. In the same year, the aim of universal bed net coverage (one LLIN per 1.8 people) was expressed. To achieve this, in 2014, 7 million nets were distributed throughout the country, further complemented by an additional 8 million in 2016 [1]. The latest large-scale LLIN campaign was in 2018, when PBO nets were distributed for the first time. During all distribution campaigns hyperendemic and endemic areas were prioritized. To supplement the ITNs, sporadic indoor residual spray (IRS) campaigns were conducted [24, 32].

MIS data

The MIS are designed to provide nationally, regionally and urban/rural representative data on 14 core malaria indicators during peak malaria transmission, including malaria prevalence and malaria control [33]. A different combination of households is surveyed each survey year using a two-stage stratified cluster design [34]. Field teams ask a person aged 15 or over living in each household an array of questions, conduct malaria testing and geo-reference the location [35]. Household anonymity is maintained by displacing the coordinates randomly between 0 and 10 km within the second administrative boundary. The locations of the household clusters and their urban/rural classification are visualised in [supplementary information 1].

For this study, household-level MIS data from 2012, 2014 and 2017 were analysed with 'household' as the unit of analysis. A household is defined as one person or a group of people living together in a housing unit who acknowledge one adult as the head of the household [34]. The 2010 MIS was excluded, as it was not geo-referenced and did not include Rapid Diagnostic Test (RDTs) results.

Child malaria prevalence

In the MIS survey, after verbal consent, children aged 6-to-59 months were tested for malaria using rapid diagnostic tests (RDTs) and microscopy of blood smears [35]. The RDT has a sensitivity of 99.5% and specificity of 98% for *P. falciparum* [36]. A small drop of blood from the finger or heel of a child was tested for *Plasmodium falciparum* and other *Plasmodium* species using the SD Bioline Malaria Ag Pf/Pan rapid diagnostic test (Standard Diagnostic Inc., Korea). The children who tested positive were offered malaria pharmacological treatment according to the current standard procedures for malaria treatment in Malawi [35]. A second blood sample was taken from the children for a thick and thin blood smear to confirm infection. The slides were checked in the laboratory for the presence of *Plasmodium* parasites by two independent microscopists. Both the RDT and blood smear results are shared in the MIS report. The NMCP in Malawi uses only the blood smear results for malaria prevalence calculations, while the RDT results are used for treatment of cases in the field. Correspondingly, the focus in this paper was on blood smear prevalence results.

Insecticide-treated nets

The number of nets in the household was counted and inspected during the questionnaire. From the ITN data, household ownership (indicator 1: proportion of households with at least 1 ITN), household access (indicator 2: proportion of households with at least 1 ITN for every 2 people sleeping in the house the night before), population access (indicator 3: proportion of the population that could potentially sleep under an ITN the previous night) and ITN use (indicator 4: proportion of the population that slept under an ITN the previous night) were calculated as proxies for ITN access and use [33]. A detailed description of the calculations is available in [supplementary information 2]. These indicators were used to identify ownership and behavioural gaps [33]. The ownership gap is the gap between household ownership and population access. This gap highlights that nets are reaching the population, but the number of ITNs is insufficient. The behavioural gap is the gap between population access and ITN use. This gap identifies that net access is sufficient, but ITNs are not being used.

Statistical analysis

The data were analysed in the R software [37–39]. National averages and 95% confidence intervals were calculated for each variable in each survey separately using a weighting system that adjusts for selection probability differences [34]. Paired *t*-tests were undertaken to compare differences in malaria prevalence between RDTs and

blood smear results. Four different model types were used to investigate the relationship between childhood malaria and ITN use in Malawi (Fig. 1). Two assumptions were made: (i) population access is a good representation of the accessibility of good quality ITNs for the population in the area; and (ii) ITN use the previous night is a good representation of the overall use of ITNs by the population throughout the malaria transmission seasons due to the large sample size of the MIS.

An initial investigation was undertaken using the multivariate linear regression model (model 1). As the residuals were not normally distributed, the multivariate linear regression model was extended to a generalised linear model (model 2). Variable selection was based on the Akaike information criterion (AIC) from the binomial generalised linear model (BGLM) family. The selected predictor covariates consisted of the year of survey, urban/rural areas, population access, ITN use and the interaction between population access and urban/rural, with malaria prevalence from blood smear used as the outcome variable. Residuals were mapped and tested for autocorrelation to check if values were independent.

Geostatistical mixed regression modelling

As the BGLM model (model 2) showed autocorrelation in the residuals, data were formally tested for spatial dependence in the variance. Spatial dependence was shown to be significant [see supplementary information 3] and therefore spatial analysis was undertaken by fitting a Binomial generalised geostatistical linear model (BGGLM) [40] to the aggregated malaria prevalence data (model 3) :

$$\log \left(\frac{p(x_i)}{1 - p(x_i)} \right) = \alpha + \beta_1 a_1(x_i) + \beta_2 a_2(x_i) + \beta_3 a_3(x_i) + \beta_4 a_4(x_i) + S(x_i) + Z_i$$

Where α is the intercept; β_1 the linear regression parameter for the survey year, β_2 the parameter for the rural/urban variable at location i ; β_3 the parameter for ITN population access; β_4 the parameter for ITN use; $S(x_i)$ a spatial Gaussian process; x_i the i th spatial location and Z_i the residual extra-binomial variation within a sampling location.

During the MIS, ITN population access and ITN use data were collected independently of each other. However, there is a logical relation between the two variables. Further investigation of these variables indicated weak collinearity (variance inflation factor < 5), for which no adjustment was needed. Monte Carlo maximum likelihood (MCML) estimation was used to fit the binomial model. The MCML estimation was repeated using the parameter values from the initial MCML to improve the MCML estimates [40].

As is common practice, we adopted a mixed model with a geostatistical spatial random effects term. This type of mixed model is justified where the residuals from the linear fixed effects term of the regression model are autocorrelated. The difference between urban and rural areas was accounted for by adding it as a covariate. To account for differences in data collection teams, malaria cycle periods and climate between the different survey years, the year was also included as a covariate.

Non-stationary generalised linear model

The BGGLM (model 3) is a global model in that its parameters are spatially stationary. To investigate the variation of parameters across space, a non-stationary GLM was fitted (model 4). This non-stationary method of regression considers only a portion of the data around the prediction point at a time, and is sometimes referred to as 'local

mapping.' A so-called 'kernel' is moved across the study area and at each location in a pre-defined grid, the regression coefficients are estimated with the GLM (model 2) as its base, using the data weighted by the kernel. The size of kernel can be adaptive, to ensure that sufficient information is included even in areas where data are sparse. In this way, the non-stationary method allows the estimated regression parameters to be mapped throughout the study area [41]. Specifically, it calculates local regression parameters by fitting a regression model for malaria prevalence p such that:

$$p(u_i, v_i) = \alpha_i + \sum_{k=1}^m \beta_k(u_i, v_i) x_{k,i} + Z_i$$

where (u_i, v_i) represents the coordinates at location i ; α_i the intercept at location i ; m the number of independent variables; $\beta_k(u_i, v_i)$ the local regression parameter for the k th independent variable at location i ; $x_{k,i}$ the k th covariate; and Z_i the error at location i . This expression allows the β to vary with the location coordinates (u_i, v_i) , making the model spatially non-stationary; and allows β to be estimated via weighted least squares with the weights matrix obtained from a Gaussian kernel, attributing larger weights to values of predictors from more proximate locations. Analysis was undertaken using the package 'GWmodel' [42]. Standard errors were estimated using the bootstrap function, with coefficients re-estimated 1,000 times at each grid point. The size of the kernel is controlled by the bandwidth, identified using both the cross-validation and AIC corrected (AICc) approach within the package. Collinearity is minimized by the R package.

Results

Exploratory analysis

The MIS data used for this research consisted of 10,538 households in 430 different locations collected during three different years (Table 1). Malaria prevalence calculated using RDT results was higher than when calculated using blood smears for 2012 (paired t -test $P < 0.001$, $df = 139$), 2014 ($P = 0.012$, $df = 139$) and 2017 ($P < 0.001$, $df = 149$). A comparison of malaria prevalence for both RDTs and blood smears on the same children showed more than 80% overlap [see supplementary information 4].

Table 1
Summary of Malawi MIS data from 2012, 2014 and 2017.

		2012	2014	2017
Survey months		March – April	May - June	April – June
Households		3404	3405	3729
Clusters		140	140	150
Average number of household members in household (95% CI)		4.17 (4.07–4.26)	4.12 (3.99–4.25)	4.46 (4.38–4.55)
malaria prevalence (%)	RDT	42.5 (37.0–47.9)	36.2 (29.4–43.0)	36.3 (31.7–40.8)
	Blood smear	27.1 (23.1–31.2)	32.1 (25.5–38.7)	23.9 (20.3–27.4)
ITN data	Total nets	3316	4754	7182
	Total ITNs	2932	4562	6752
	Household ownership (%)	55.0 (51.2–58.9)	70.2 (65.8–74.6)	82.1 (80.0–84.2)
	Household access (%)	19.0 (15.6–22.3)	30.3 (26.8–33.8)	41.7 (39.1–44.4)
	Population access (%)	33.1 (29.8–36.4)	47.1 (43.4–50.8)	58.4 (56.2–60.6)
	ITN use (%)	41.1 (37.3–44.9)	53.1 (49.3–56.9)	57.4 (55.0–59.9)
<i>Averages and proportions are calculated using the Demographic and Health Surveys weighting scheme [34]. ^unsuccessful tests were noted as 'other'. *unsuccessful tests were 'inconsistent data', 'not present', 'refused', 'sample not found' or 'test undetermined'.</i>				

Although malaria prevalence in the different survey years did not differ (Table 1), the number of positive cases decreased in central Malawi (Fig. 2). Malaria prevalence was lower in urban areas compared to rural areas (both RDT and blood smear $P < 0.001$) [see supplementary information 5].

All ITN indicators suggested an increase in ITN access and use through time (Table 1). By 2017, household ownership had increased from 55–82%. Ownership was high throughout the country, with most households owning at least one ITN (Fig. 2) [see Supplementary information 6]. However, this high household ownership did not translate into similarly high household access. In 2017, only 42% of households had sufficient ITNs to cover all sleeping people and ITN access for the population was below 60% for the majority of areas surveyed. Net coverage in central Malawi was slightly lower than for the rest of the country, with also fewer people sleeping under an ITN [see Supplementary information 6]. There is evidence of an ownership gap, with ITN campaigns reaching most

households across the country, but not supplying sufficient numbers for complete coverage (Fig. 3). There is no evidence of a behavioural gap in 2017, with population access increasing sufficiently from 2012 to close this gap.

Bionomial Genearlised Geostatistical linear mixed regression modelling

The BGGLM revealed a negative association between malaria prevalence and ITN population access in all regions in Malawi, with low child malaria prevalence occurring in areas with high population access to nets. In contrast, malaria prevalence was positively associated with sleeping under a net, with high use occurring in areas with high child malaria prevalence (Table 2).

There was a clear relationship between malaria prevalence and the urban/rural variable, with child malaria cases three times higher in rural areas than urban areas. The same model, run independently for each region, indicated that the difference in malaria prevalence between urban and rural areas was demonstrated mainly in central and southern Malawi, where malaria was more than four times higher in rural areas (Table 2). Child malaria prevalence was lower in 2012 than 2014 and lower in 2017 than 2014, but did not differ between 2012 and 2017. The independently run regional models revealed that child malaria prevalence was 65% lower in central Malawi in 2012 compared to 2014.

Table 2

Results of binomial geostatistical mixed regression of blood smear malaria prevalence against selected covariates.

	ITN population access		ITN use		urban-rural		year 2014		year 2017	
Areas	OR	P-value	OR	P-value	OR	P-value	OR	P-value	OR	P-value
Malawi	0.015 (0.004–0.062)	< 0.001*	15.49 (4.50–53.24)	< 0.001*	3.03 (2.13–4.32)	< 0.001*	1.84 (1.43–2.37)	< 0.001*	1.43 (1.05–1.96)	0.054
north	0.005 (0.0001–0.206)	< 0.01*	34.12 (1.27–918.55)	0.035*	2.29 (0.90–5.88)	0.086	2.12 (0.93–4.82)	0.07	1.04 (0.38–2.88)	0.945
central	0.031 (0.006–0.146)	< 0.001*	9.39 (2.53–34.92)	< 0.001*	4.81 (2.47–9.36)	< 0.001*	1.65 (1.28–2.13)	< 0.001*	1.20 (0.91–1.58)	0.192
south	0.007 (0.0001–0.343)	0.0123*	33.78 (1.89–602.57)	0.016*	4.01 (2.02–7.97)	< 0.001*	1.54 (0.85–2.77)	0.161	1.93 (0.73–5.16)	0.188
<i>Odds ratio (OR) and the 95% confidence intervals (95%CI), calculated from the parameter estimates and the associated standard errors fitted using Monte Carlo maximum likelihood estimation. *Indicates significant difference (P < 0.05)</i>										

When the data were analysed separately for the different MIS years, the MIS in 2017 produced a different relationship between the outcome and predictors compared to other years (Table 3). Child malaria prevalence is negatively associated with ITN access in all years, except 2017. Similarly, child malaria prevalence is positively associated with ITN use, except in 2017. Interestingly, child malaria prevalence is more than eight times higher in rural areas compared to urban areas in 2017, which is an increase from both 2012 and 2014.

Table 3

Results of binomial geostatistical mixed regression of blood smear malaria prevalence against selected covariates in the different survey years.

MIS year	ITN population access		ITN use		urban-rural	
	OR	P-value	OR	P-value	OR	P-value
2012	0.0002 (0.000001–0.028)	< 0.001*	146.94 (3.15–6847.23)	0.025*	2.89 (1.43–5.85)	< 0.001*
2014	0.00034 (0.0000085–0.13)	< 0.01*	311.06 (14.34–6749.34)	< 0.001*	2.48 (1.25–4.93)	< 0.001*
2017	0.78 (0.06–9.76)	0.846	6.11 (0.78–47.85)	0.0828	8.76 (5.16–14.87)	< 0.001*
<i>Odds ratio (OR) and the 95% confidence intervals, calculated from the parameter estimates and the associated standard errors, fitted using Monte Carlo maximum likelihood estimation. * Indicates significant difference (P<0.05)</i>						

Non-stationary spatial generalised linear model

We mapped the non-stationary coefficient estimates for both ITN population access and ITN use for the three different years [see supplementary information 7]. The parameters (i.e., relationship) between child malaria prevalence and the indicators exhibit some geographical variation, although the standard errors are large (Table 4). The north of the country shows parameters consistently significant compared to the south of the country. A temporal difference appears between 2014 and 2017, with the correlation between child malaria prevalence and both indicators reduced in 2017 compared to 2014.

Table 4

Results of the non-stationary generalised linear model of blood smear malaria prevalence against ITN population access and ITN use in the different survey years.

	Survey year	global β estimate (se)	range	global OR (95%CI)	range	P-value
ITN population access	2012	-0.98 (0.32)	-1.29 to -0.35	0.38 (0.20–0.70)	0.28 to 0.70	< 0.01*
	2014	-0.93 (0.24)	-1.29 to -0.55	0.39 (0.25–0.63)	0.28 to 0.58	< 0.001*
	2017	-0.37 (0.13)	-0.47 to -0.11	0.69 (0.53–0.89)	0.63 to 0.90	< 0.01*
ITN use	2012	0.68 (0.28)	0.25 to 0.88	1.97 (1.14–3.42)	1.28 to 2.41	0.0168 *
	2014	0.76 (0.21)	0.56 to 1.22	2.14 (1.42–3.23)	1.75 to 3.39	< 0.001*
	2017	0.37 (0.12)	0.03 to 0.45	1.45 (1.14–1.83)	1.03 to 1.57	< 0.01*
<i>Global parameter estimates and the associated standard errors (se) are shown with its range across the country. Additionally, the odds ratio (OR) and the 95% confidence intervals are presented. * Indicates significant difference (P<0.05)</i>						

Discussion

This study presents an important, key modelling approach that allows malaria control programs to spatially unravel the relationship between child malaria prevalence and ITN distribution. The non-stationary generalised linear model helped visualise variation in the relationship between malaria cases and bed net indicators. The mass distribution of ITNs resulted in a decrease in malaria cases. However, this did not occur homogeneously across the country. The ITN coverage and use increased from 2012 to 2017, while child malaria prevalence decreased only in some areas. The BGGLM regression using MIS survey data showed that child malaria prevalence had a negative association with ITN population access and a positive association with ITN use. Further spatial investigation identified that these correlations reduced from 2014 to 2017, although it is challenging to identify cause and effect without temporally linked data. The MIS data are currently the best information we have to understand the impact of ITNs on malaria prevalence in Malawi.

We found a negative association between malaria prevalence and ITN population access in all regions of Malawi. Areas with high population access to nets had lower malaria prevalence than areas with low access in both 2012 and 2014. This corresponds to earlier work in Malawi, where ITN ownership was found to be protective against malaria parasitemia in children [43, 44]. Surprisingly, we found no negative association in 2017, even though a year prior an additional 8 million LLINs were distributed throughout the country. We assumed reasonably that nets were in good condition and would have had an impact by the time the MIS was conducted in 2017. Yet, the lack of a discernible relationship could indicate that the roll out was slow, some nets were ineffective or that spatial heterogeneity in the efficacy of nets reduced their impact overall. The nets are unlikely to be entirely ineffective, as even with high insecticide resistance the physical barrier of nets and sublethal effect of the insecticides results in a negative relationship between malaria prevalence and ITNs [44–46]. It is likely that other factors affect prevalence, creating artefacts in the relationship between the outcome and predictor. For example, behavioural resistance, with mosquitoes biting when people are not protected by the nets, could play a role [47, 48]. The quality of the nets has also not been considered, while studies have shown that using a mosquito bed net that is more than one year old is a risk factor for malaria in Malawi [49]. Additionally, the ownership gap found in this study, with ITN campaigns reaching a majority of households but not supplying sufficient nets, could have resulted in the absence of an association. Moreover, extreme droughts the year prior could have impacted overall malaria prevalence dynamics [50].

There was a positive relationship between malaria prevalence and ITN use in all Malawian regions in 2012 and 2014, with high net use occurring in areas with high child malaria prevalence. The question ‘did you sleep under a bed net last night?’ was used as a proxy for overall ITN use. The question focuses on ‘last night’ and does not capture the overall ITN use behaviour. The positive association found here between malaria prevalence and net use is likely due to the large numbers of malaria cases activating the population to sleep under nets more regularly in the short term. This positive relationship was not identified in 2017, which could be due to the higher usage overall, even in areas where malaria cases were low. The MIS household surveys are sensitive to recall bias and social desirability factors [51]. Additionally, nightly variables, such as temperature and mosquito density, could also greatly impact the use of nets [52]. For ITN use throughout the malaria season to be related to malaria prevalence, thus identifying its protective ability, temporal studies are necessary where fieldworkers independently confirm bed net use over both space and time throughout the season.

This study revealed some spatial heterogeneity in the relationship between malaria prevalence and the ITN indicators, with child malaria prevalence higher in rural than urban areas. It is widely accepted that malaria

dynamics differ between rural and urban areas due to differences in demographics, socioeconomics, housing, drainage and access to health care [21, 53–56]. Generally, in Malawi malaria is more prevalent in rural areas, although high case numbers have also been reported in urban areas [9, 10, 21, 53, 55, 57]. Malaria control likely has a different impact in the urban and rural habitats, due to environmental differences and population movements. Furthermore, the dichotomization of the factors is inconsistent across the research field, with a more nuanced definition of urban malaria risk and prevention efforts necessary in Malawi [58]. The results from this study further substantiate the complexity of urban/rural malaria dynamics [21, 53] and show the importance of including this factor in the analysis to investigate the impact of vector control for sustainable intervention measures.

Many studies have shown that the scale up of ITNs has protected the Malawi population from Malaria [5–8]. The north of the country shows consistently higher impact of population access and bed net use on child malaria cases compared to the south of the country. Heterogeneity in malaria cases has been identified previously in Malawi [13, 49, 59]. Malaria epidemiology is a complex dynamic between many factors at the individual, household and community levels [59]. The introduction of vector control in this environment can have very different outcomes, with the decline rate in malaria prevalence known to be very different across the country [13]. One possible explanation for spatial heterogeneity in the relationship between malaria prevalence and ITN use is that it captures the heterogeneity in malaria prevalence, with net coverage homogeneously high throughout the country. A small group of households can account for a majority of cases, which results in spatial heterogeneity in even small geographical areas [60]. Another possibility is that insecticide and behavioural resistance of vector species is impacting net efficacy. Little information about the spatial distribution of malaria vectors and their resistance status is available, but reports do indicate heterogeneity in its spread with high resistance reported in the south and around Lake Malawi [3]. Understanding the spatial dynamics will help increase the effectiveness of vector control campaigns, for example, by changing to bed nets that kill resistant mosquitoes more effectively or shifting to different control tools altogether. The fine-scale spatial and temporal heterogeneity and their causes need to be investigated further by implementing field studies designed to answer these specific questions.

In concurrence with the recommendations from the Ministry of Health in Malawi, and in alignment with prior Malawian MIS studies [9, 10], we used blood smear data as the sole proxy for malaria prevalence. Both the RDT and blood smear malaria testing methods have strengths and limitations [61]. As shown here, the RDT generally produces higher positivity rates than blood smears, as it measures antigens that are detectable in the blood up to four weeks after parasite clearance [62]. This is contrary to blood smear tests, which measure the physical presence of malaria parasites. From a modelling perspective, instead of choosing one indicator, joint distribution modelling of RDT and blood smear results could help improve inference. Recently, Amoah et al. (2020) developed a geostatistical framework to combine spatially referenced disease prevalence data from multiple diagnostics [63]. Joint distribution models draw benefit from the combination of different diagnostics, although particular care needs to be taken for diagnostics with large discrepancies in sensitivity and specificity.

It is important to note that malaria prevalence is not the only way to measure malaria burden in a country. Studies have found mortality reduction without a decrease in malaria prevalence, and the other way around [64]. Furthermore, malaria prevalence here is focused on children aged 6-to-59 months, while school-aged children are both at higher risk of infection and asymptomatic infection [65, 66]. Excluding this important risk group from the analysis could have skewed the data and results. Another important limitation is that malaria prevalence is collected at the individual level, whereas ITN indicators are collected at the household level. Additionally, the MIS data are a snapshot and do not include the seasonality of malaria. Although surveys are planned during peak malaria season, as shown by Chirombo et al [14], this peak differs yearly in Malawi. Whether data are collected

during the peak season or two weeks later hugely impacts malaria prevalence estimates. If snapshots of malaria prevalence are compared between the different years without a clear understanding of the seasonal dynamics in these different years, this will greatly influence the analysis and incorrect conclusions can be made. Another limitation is that MIS surveys do not always reach the sample size calculated during the design of the study. A study in Malawi showed that for RDTs a 25% deficit in actual sample size was found for the 2014 MIS survey [67]. It is important to place malaria prevalence from MIS data in the context of the country and investigate how this is linked to mortality and other malaria indicators.

The MIS data are currently the only data available in Malawi to investigate the relationship between malaria prevalence and ITN use. As the MIS has not been designed for this purpose, caution is advised when interpreting the results. Studies designed to investigate the impact of ITNs are indispensable to understand the efficacy of ITNs [64]. Until these studies are available, creative solutions are necessary to analyse MIS data. Two studies have previously used MIS data from 2012 and 2014 to investigate the relationship between child malaria prevalence and ITN use. Contrary to our study, both found that the number of bed nets per household was not significantly associated with malaria morbidity [9, 10]. They also identified a negative association in 2012 and no association in 2014 between the use of bed nets and malaria morbidity [9, 10]. Both studies focused on socio-demographic characteristics, while this study included the spatial coordinates of the data within the analysis. We have shown that the impact of ITNs differs geographically. For vector control programs to make informed decisions about future control activities, it is essential to have access to both country-wide and spatially disaggregated analyses of ITNs impact.

The non-stationary generalised linear model visualised the geographically changing relation between malaria prevalence and the ITN indicators. Although the geostatistical mixed regression model presented the overall relationship between child malaria prevalence and bednet indicators, it did not allow for visualisation of variation across Malawi. The maps produced by the non-stationary model can help vector control programs spatially disentangle the impact of interventions on malaria prevalence for vector control programs. The non-stationary model has some limitations. For example, the bandwidth is optimised based on accurate prediction of the response variable, not on accurate estimation of the coefficients [68]. Especially when the regression model is fitted within a small kernel or with limited data, collinearity can be a problem [69]. Nevertheless, for spatially clustered data such as the MIS data, this method can be appropriate to provide insights into how estimated relations vary across the country. Although relationships are not causal, they could highlight underlying covariates that have been left unmeasured. It is an important tool for eco-epidemiological studies [70–72], especially for a disease such as malaria, that is so closely related to the environment and the sociodemographic dynamics of the population. Yet, spatially non-stationary models have only rarely been used in malaria research.

Conclusion

The mass distribution of ITNs between 2012 and 2017 resulted in a heterogeneous decrease in malaria cases. Child malaria prevalence had a negative association with ITN population access and a positive association with ITN use, with spatial heterogeneity in these relationships. The non-stationary generalised linear model is an important modelling approach that helps vector control programs visualise variation in the relationship between malaria cases and intervention methods.

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The datasets analysed during the current study are available in the DHS program repository, which can be accessed through [<https://dhsprogram.com/>].

Competing interests

The authors declare that they have no competing interests.

Funding

JT is funded by the MRC Skills Development Fellowship. LS is supported by the by the Wellcome Trust Seed Award (212501/Z/18/Z), Wellcome Trust NIHR– Wellcome Partnership for Global Health Research Collaborative Award, CEASE (220870/Z/20/Z), and by the Academy of Medical Sciences GCRF Networking Grant Scheme (GCRFNGR7/1329).

Authors' contributions

JT and PA designed the study. JT conducted the analysis under supervision of PA and LS. During the analysis, valuable feedback was provided by DM. Results were interpreted by all authors and written up by JT. All authors read, edited and approved the final manuscript.

Acknowledgements

Not applicable

References

1. National Malaria Control Programme K-WTRPaLSoHTM, Malawi Liverpool Wellcome Trust Clinical Research Programme. Epidemiology and control profile of malaria in Malawi. 2018.
2. World Health Organization. World Malaria report 2019. Geneva: 2019.
3. Programme NMC. Integrated Vector Control Strategy for Malaria Control Malawi 2020–2024. 2020.
4. Wilson AL, Courtenay O, Kelly-Hope LA, Scott TW, Takken W, Torr SJ, et al. The importance of vector control for the control and elimination of vector-borne diseases. *PLOS Neglected Tropical Diseases*. 2020; 14:e0007831.
5. Escamilla V, Alker A, Dandalo L, Juliano JJ, Miller WC, Kamthuya P, et al. Effects of community-level bed net coverage on malaria morbidity in Lilongwe, Malawi. *Malar J*. 2017; 16:142.
6. Hershey CL, Florey LS, Ali D, Bennett A, Luhanga M, Mathanga DP, et al. Malaria Control Interventions Contributed to Declines in Malaria Parasitemia, Severe Anemia, and All-Cause Mortality in Children Less Than 5 Years of Age in Malawi, 2000-2010. *Am J Trop Med Hyg*. 2017; 97:76-88.
7. Boudová S, Divala T, Mawindo P, Cohee L, Kalilani-Phiri L, Thesing P, et al. The prevalence of malaria at first antenatal visit in Blantyre, Malawi declined following a universal bed net campaign. *Malar J*. 2015; 14:422.

8. Buchwald AG, Coalson JE, Cohee LM, Walldorf JA, Chimbiya N, Bauleni A, et al. Insecticide-treated net effectiveness at preventing *Plasmodium falciparum* infection varies by age and season. *Malar J.* 2017; 16:32.
9. Zamawe CO, Nakamura K, Shibanuma A, Jimba M. The effectiveness of a nationwide universal coverage campaign of insecticide-treated bed nets on childhood malaria in Malawi. *Malar J.* 2016; 15:505.
10. Zgambo M, Mbakaya BC, Kalembo FW. Prevalence and factors associated with malaria parasitaemia in children under the age of five years in Malawi: A comparison study of the 2012 and 2014 Malaria Indicator Surveys (MISs). *PLoS One.* 2017; 12:e0175537.
11. Nkoka O, Chuang TW, Chen YH. Effects of insecticide-treated net access and use on infant mortality in Malawi: A pooled analysis of demographic health surveys. *Prev Med.* 2019; 127:105790.
12. Mathanga DP, Mwandama DA, Bauleni A, Chisaka J, Shah MP, Landman KZ, et al. The effectiveness of long-lasting, insecticide-treated nets in a setting of pyrethroid resistance: a case-control study among febrile children 6 to 59 months of age in Machinga District, Malawi. *Malar J.* 2015; 14:457.
13. Michael GC, Emanuele G, Donnie M, Peter M, Chimwemwe L, Alinane M, et al. Geostatistical analysis of Malawi's changing malaria transmission from 2010 to 2017. *Malar J.* 2019; 18:105790.
14. Chirombo J, Ceccato P, Lowe R, Terlouw DJ, Thomson MC, Gumbo A, et al. Childhood malaria case incidence in Malawi between 2004 and 2017: spatio-temporal modelling of climate and non-climate factors. *Malaria Journal.* 2020; 19:5.
15. Wondji CS, Coleman M, Kleinschmidt I, Mzilahowa T, Irving H, Ndula M, et al. Impact of pyrethroid resistance on operational malaria control in Malawi. *Proc Natl Acad Sci U S A.* 2012; 109:19063-19070.
16. Mzilahowa T, Chiumia M, Mbewe RB, Uzalili VT, Luka-Banda M, Kutengule A, et al. Increasing insecticide resistance in *Anopheles funestus* and *Anopheles arabiensis* in Malawi, 2011–2015. *Malaria Journal.* 2016; 15:563.
17. Riveron JM, Chiumia M, Menze BD, Barnes KG, Irving H, Ibrahim SS, et al. Rise of multiple insecticide resistance in *Anopheles funestus* in Malawi: a major concern for malaria vector control. *Malar J.* 2015; 14:344.
18. Mwendera CA, de Jager C, Longwe H, Kumwenda S, Hongoro C, Phiri K, et al. Challenges to the implementation of malaria policies in Malawi. *BMC Health Services Research.* 2019; 19:194.
19. Mategula D, Ndeketa L, Gichuki J, Zimba B, Ching'ani W, Chipeta MG. Effect of bed net colour and shape preferences on bed net usage: a secondary data analysis of the 2017 Malawi Malaria Indicator Survey. *Malaria Journal.* 2020; 19:428.
20. Berthe S, Harvey SA, Lynch M, Koenker H, Jumbe V, Kaunda-Khangamwa B, et al. Poverty and food security: drivers of insecticide-treated mosquito net misuse in Malawi. *Malaria Journal.* 2019; 18:320.
21. Mathanga DP, Tembo AK, Mzilahowa T, Bauleni A, Mtimaikenena K, Taylor TE, et al. Patterns and determinants of malaria risk in urban and peri-urban areas of Blantyre, Malawi. *Malaria Journal.* 2016; 15:590.
22. Nkoka O, Chuang TW, Chuang KY, Chen YH. Factors associated with insecticide-treated net usage among women of childbearing age in Malawi: a multilevel analysis. *Malar J.* 2018; 17:372.
23. Andronescu LR, Buchwald AG, Coalson JE, Cohee L, Bauleni A, Walldorf JA, et al. Net age, but not integrity, may be associated with decreased protection against *Plasmodium falciparum* infection in southern Malawi. *Malar J.* 2019; 18:329.
24. International. NMCPNMaI. Malawi Malaria Indicator Survey (MIS) 2012. Lilongwe, Malawi, and Calverton, Maryland, USA: NMCP and ICF International., 2012.

25. International NMCPNMal. Malawi Malaria Indicator Survey (MIS) 2014. Lilongwe, Malawi, and Rockville, Maryland, USA: NMCP and ICF International, 2014.
26. ICF NMCPNa. Malawi Malaria Indicator Survey 2017. Lilongwe, Malawi, and Rockville, Maryland, USA NMCP and ICF, 2018.
27. Gleave K, Lissenden N, Richardson M, Ranson H. Piperonyl butoxide (PBO) combined with pyrethroids in long-lasting insecticidal nets (LLINs) to prevent malaria in Africa. *Cochrane Database Syst Rev*. 2017; 2017:CD012776.
28. United Nations Population Division. World Population Prospects Revision. 2019.
29. Bennett A, Kazembe L, Mathanga DP, Kinyoki D, Ali D, Snow RW, et al. Mapping malaria transmission intensity in Malawi, 2000-2010. *Am J Trop Med Hyg*. 2013; 89:840-849.
30. Mathanga DP, Walker ED, Wilson ML, Ali D, Taylor TE, Laufer MK. Malaria control in Malawi: current status and directions for the future. *Acta tropica*. 2012; 121:212-217.
31. President's Malaria Initiative. Malaria Operational Plan FY 2016. USAID, 2016.
32. Chanda E, Mzilahowa T, Chipwanya J, Mulenga S, Ali D, Troell P, et al. Preventing malaria transmission by indoor residual spraying in Malawi: grappling with the challenge of uncertain sustainability. *Malar J*. 2015; 14:254.
33. MEASURE Evaluation, The Demographic and Health Surveys Program, President's Malaria Initiative, Roll Back Malaria Partnership, United Nations Children's Fund, World Health Organization. Household survey indicators for malaria control. 2018.
34. Croft TN, Aileen M. J. Marshall, Courtney K. Allen, et al. Guide to DHS Statistics. Rockville, Maryland, USA: ICF, 2018.
35. ICF. Demographic and Health Surveys Standard Recode Manual for DHS7. T. Rockville, Maryland, U.S.A.: The Demographic and Health Surveys Program, 2018.
36. Tadesse E, Workalemahu B, Shimelis T. Diagnostic performance evaluation of the sd bioline malaria antigen AG PF/PAN TEST (05FK60) in a malaria endemic area of southern Ethiopia. *Rev Inst Med Trop Sao Paulo*. 2016; 58:59-59.
37. R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria. 2019; <https://www.R-project.org/>.
38. R Core Team. foreign: Read Data Stored by 'Minitab', 'S', 'SAS', 'SPSS', 'Stata', 'Systat', 'Weka', 'dBase', R package. version 08-71. 2018.
39. Lumley T. Analysis of complex survey samples. *Journal of Statistical Software*. 2004; 9:1-19.
40. Giorgi EaD, P.J. . PrevMap: An R Package for Prevalence Mapping. . *Journal of Statistical Software*. 2017; 78.
41. Brunsdon C, Fotheringham AS, Charlton ME. Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity *Geographical Analysis*. 1996; 28.
42. Gollini I, Lu B, Charlton M, Brunsdon C, Harris P. GWmodel: An R Package for Exploring Spatial Heterogeneity Using Geographically Weighted Models. *Journal of Statistical Software*. 2015; 63.
43. Hershey CL, Florey LS, Ali D, Bennett A, Luhanga M, Mathanga DP, et al. Malaria Control Interventions Contributed to Declines in Malaria Parasitemia, Severe Anemia, and All-Cause Mortality in Children Less Than 5 Years of Age in Malawi, 2000-2010. *Am J Trop Med Hyg*. 2017; 97:76-88.
44. Lindblade KA, Mwandama D, Mzilahowa T, Steinhardt L, Gimnig J, Shah M, et al. A cohort study of the effectiveness of insecticide-treated bed nets to prevent malaria in an area of moderate pyrethroid resistance,

Malawi. *Malaria journal*. 2015; 14:31-31.

45. Glunt KD, Coetzee M, Huijben S, Koffi AA, Lynch PA, N'Guessan R, et al. Empirical and theoretical investigation into the potential impacts of insecticide resistance on the effectiveness of insecticide-treated bed nets. *Evol Appl*. 2017; 11:431-441.
46. Churcher TS, Lissenden N, Griffin JT, Worrall E, Ranson H. The impact of pyrethroid resistance on the efficacy and effectiveness of bednets for malaria control in Africa. *Elife*. 2016; 5:e16090.
47. Kreppel KS, Viana M, Main BJ, Johnson PCD, Govella NJ, Lee Y, et al. Emergence of behavioural avoidance strategies of malaria vectors in areas of high LLIN coverage in Tanzania. *Sci Rep*. 2020; 10:14527-14527.
48. Carrasco D, Lefèvre T, Moiroux N, Penetier C, Chandre F, Cohuet A. Behavioural adaptations of mosquito vectors to insecticide control. *Current opinion in insect science*. 2019; 34:48-54.
49. Hajison PL, Feresu SA, Mwakitunga BW. Malaria in children under-five: A comparison of risk factors in lakeshore and highland areas, Zomba district, Malawi. *PloS one*. 2018; 13:e0207207-e0207207.
50. Drought-Ravaged Malawi Faces Largest Humanitarian Emergency in its History: Center for Strategic and International Studies; 2016 [Accessed: 2022 16-02]. Available from: <https://www.csis.org/analysis/drought-ravaged-malawi-faces-largest-humanitarian-emergency-its-history>.
51. Battle KE, Gumbo A, Hamuza G, Kwizombe C, Banda AT, Chipeta S, et al. Consultative meeting that examined alignment and discrepancies between health facility and household survey data in Malawi. *Malaria Journal*. 2019; 18:411.
52. Koenker H, Taylor C, Burgert-Brucker CR, Thwing J, Fish T, Kilian A. Quantifying Seasonal Variation in Insecticide-Treated Net Use among Those with Access. *Am J Trop Med Hyg*. 2019; 101:371-382.
53. Wilson ML, Krogstad DJ, Arinaitwe E, Arevalo-Herrera M, Chery L, Ferreira MU, et al. Urban Malaria: Understanding its Epidemiology, Ecology, and Transmission Across Seven Diverse ICMR Network Sites. *Am J Trop Med Hyg*. 2015; 93:110-123.
54. Hennessee I, Chinkhumba J, Briggs-Hagen M, Bauleni A, Shah MP, Chalira A, et al. Household costs among patients hospitalized with malaria: evidence from a national survey in Malawi, 2012. *Malaria journal*. 2017; 16:395-395.
55. Mzilahowa T, Luka-Banda M, Uzalili V, Mathanga DP, Campbell CH, Jr., Mukaka M, et al. Risk factors for Anopheles mosquitoes in rural and urban areas of Blantyre District, southern Malawi. *Malawi Med J*. 2016; 28:154-158.
56. Kazembe LN, Mathanga DP. Estimating risk factors of urban malaria in Blantyre, Malawi: A spatial regression analysis. *Asian Pacific Journal of Tropical Biomedicine*. 2016; 6:376-381.
57. Lungu EA, Biesma R, Chirwa M, Darker C. Is the Urban Child Health Advantage Declining in Malawi?: Evidence from Demographic and Health Surveys and Multiple Indicator Cluster Surveys. *J Urban Health*. 2019; 96:131-143.
58. Dear NF, Kadangwe C, Mzilahowa T, Bauleni A, Mathanga DP, Duster C, et al. Household-level and surrounding peri-domestic environmental characteristics associated with malaria vectors *Anopheles arabiensis* and *Anopheles funestus* along an urban-rural continuum in Blantyre, Malawi. *Malaria journal*. 2018; 17:229-229.
59. Chirombo J, Lowe R, Kazembe L. Using structured additive regression models to estimate risk factors of malaria: analysis of 2010 Malawi malaria indicator survey data. *PloS one*. 2014; 9:e101116-e101116.
60. Kabaghe AN, Chipeta MG, Gowelo S, Mburu M, Truwah Z, McCann RS, et al. Fine-scale spatial and temporal variation of clinical malaria incidence and associated factors in children in rural Malawi: a longitudinal study.

Parasit Vectors. 2018; 11:129.

61. Azikiwe CC, Ifezulike CC, Siminialayi IM, Amazu LU, Enye JC, Nwakwunite OE. A comparative laboratory diagnosis of malaria: microscopy versus rapid diagnostic test kits. *Asian Pac J Trop Biomed.* 2012; 2:307-310.
62. Moody A. Rapid Diagnostic Tests for Malaria Parasites. *Clinical Microbiology Reviews.* 2002; 15:66-78.
63. Amoah B, Diggle PJ, Giorgi E. A geostatistical framework for combining spatially referenced disease prevalence data from multiple diagnostics. *Biometrics.* 2020; 76:158-170.
64. Nkumama IN, O'Meara WP, Osier FHA. Changes in Malaria Epidemiology in Africa and New Challenges for Elimination. *Trends Parasitol.* 2017; 33:128-140.
65. Walldorf JA, Cohee LM, Coalson JE, Bauleni A, Nkanaunena K, Kapito-Tembo A, et al. School-Age Children Are a Reservoir of Malaria Infection in Malawi. *PloS one.* 2015; 10:e0134061.
66. Topazian HM, Gumbo A, Puerto-Meredith S, Njiko R, Mwanza A, Kayange M, et al. Asymptomatic Plasmodium falciparum malaria prevalence among adolescents and adults in Malawi, 2015-2016. *Sci Rep.* 2020; 10:18740-18740.
67. Alegana VA, Wright J, Bosco C, Okiro EA, Atkinson PM, Snow RW, et al. Malaria prevalence metrics in low- and middle-income countries: an assessment of precision in nationally-representative surveys. *Malar J.* 2017; 16:475.
68. Gollini I, Lu B, Charlton M, Brunsdon C, Harris P. GWmodel: An R Package for Exploring Spatial Heterogeneity Using Geographically Weighted Models. 2015. 2015; 63:50.
69. Wheeler D, Tiefelsdorf M. Multicollinearity and correlation among local regression coefficients in geographically weighted regression. *Journal of Geographical Systems.* 2005; 7:161-187.
70. Acharya BK, Cao C, Lakes T, Chen W, Naeem S, Pandit S. Modeling the spatially varying risk factors of dengue fever in Jhapa district, Nepal, using the semi-parametric geographically weighted regression model. *Int J Biometeorol.* 2018; 62:1973-1986.
71. Mayfield HJ, Lowry JH, Watson CH, Kama M, Nilles EJ, Lau CL. Use of geographically weighted logistic regression to quantify spatial variation in the environmental and sociodemographic drivers of leptospirosis in Fiji: a modelling study. *The Lancet Planetary Health.* 2018; 2:e223-e232.
72. Lin CH, Wen TH. Using geographically weighted regression (GWR) to explore spatial varying relationships of immature mosquitoes and human densities with the incidence of dengue. *Int J Environ Res Public Health.* 2011; 8:2798-2815.

Figures

Figure 1

The four different model types used to investigate the relationship between ITN use and childhood malaria in Malawi

A **B** **Figure 2**

Malaria prevalence and ITN access in the household clusters surveyed in 2012, 2014 and 2017. A) malaria prevalence in children measured using blood smear test. B) Population ITN access.

Figure 3

Scatterplots visualizing the ownership and behavioural gaps in 2012, 2014 and 2017, with colours indicating the different regions. A) Comparison of household ownership to household access to visualise the ownership gap. B) Comparison of population access to ITN use to visualise the behavioural gap.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [supplementaryinformation.docx](#)