Supplementary Information

Simplifying mosquito sampling to estimate community biting exposure and indoor malaria vector control impact

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1 Resumo (Abstract in Portuguese)

Mosquiteiros impregnados com inseticidas de longa duração (MILD) são mais eficazes contra a malária quando os mosquitos tentam picar indivíduos enquanto estão deitados na cama. No entanto, a complexidade do rastreamento da atividade de picada dos mosquitos dificulta a quantificação de uma métrica essencial — a proporção de picadas ocorridas enquanto o indivíduo está deitado na cama. Neste trabalho, testou-se a confiabilidade de um método simplificado de amostragem de picada de mosquitos em comparação com os valores obtidos de uma revisão sistemática publicada. Utilizando esta metodologia no arquipélago dos Bijagós, uma área remota e endêmica para malária da Guiné Bissau, estimou-se que esta proporção é de 0,95 (Intervalo de credibilidade de 95%, CrI: 0,84, 1,00). Assumindo um cenário semelhante ao dos Bijagós, o modelo de transição aplicado sugere que as redes impregnadas apenas com pesticidas piretroides podem evitar 86% dos casos clínicos de *Plasmodium falciparum* em crianças com menos de 5 anos (95% CrI: 77, 89%), em comparação com a ausência de MILDs. Devido às atividades agrícolas típicas da região, alguns residentes do arquipélago dormem sem MILDs em abrigos temporários ao ar livre, o que poderia reduzir o impacto projetado a nível populacional em 35%. A metodologia proposta aumenta a viabilidade do monitoramento do impacto de intervenções de controle de malária no interior de residências em contextos com recursos limitados.

2 Comparing hourly and segmented data collection methods

The studies from a systematic review of mosquito biting behaviour and human activity in Africa [1] that were used to estimate ϕ_{Bed} according to different sampling methods, are shown in Supplementary Table 1.

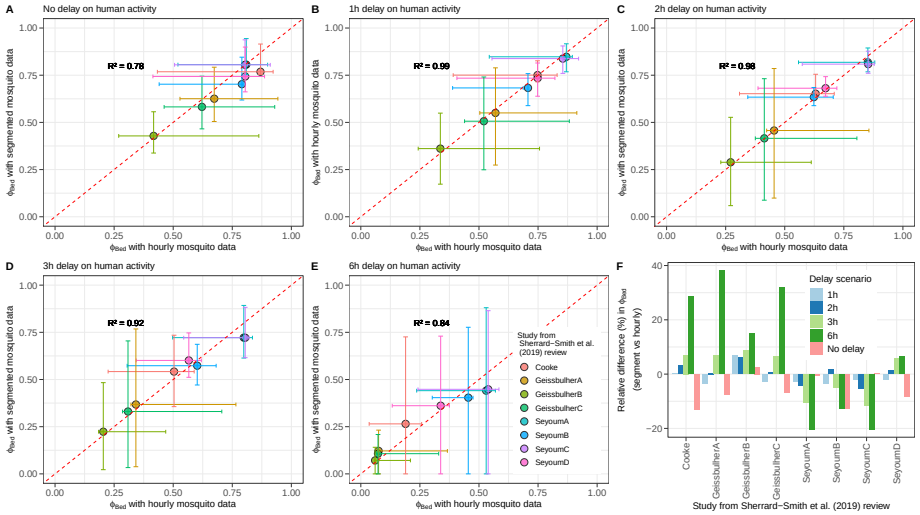
A sensitivity analysis was conducted to identify scenarios in which the segmented method may lead to inaccurate estimates of ϕ_{Bed}. The segmented method assumes that the mean proportion of people indoors and in bed in each time segment adequately represents the underlying human activity in that segment, and this drives differences in ϕ_{Bed} estimates derived by the methods.

For each of the eight studies in the systematic review [1] with paired mosquito and human activity data, four scenarios were explored in which the time when people enter the house for the night, go to bed, get out of bed and leave the house in the morning was delayed by 1 hour, 2 hours, 3 hours and 6 hours, whilst holding the mosquito data constant. The hourly and segmented values of ϕ_{Bed} were re-estimated for each of these scenarios.

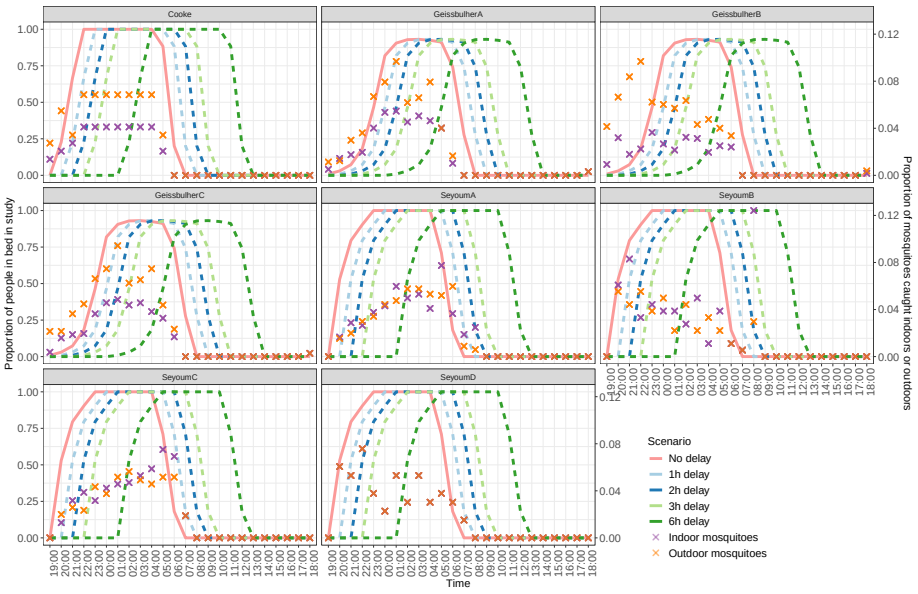
Supplementary Table 1: **References for studies mosquito biting behaviour and human sleeping pattern data, as found in a previously conducted systematic review [1].** The sleeping pattern datasets used to generate uncertainty in the proportion of bites taken when people are in bed (ϕ_{Bed}) are identified.

Entomological data reference	Entomological context description	Human data reference (for segmented estimate)	Human data reference (for hourly estimate considering full range from all human activity studies)
Cooke	Kenya; *An. arabiensis*; June 2011-May 2012	[2]	Proportion in bed [2–7]. Proportion indoors [2, 4, 6, 8–13].
GeissbulherA	Tanzania; *An. gambiae s.s.*; April-June 2006	[4]	
GeissbulherB	Tanzania; *An. arabiensis*; April-June 2006	[4]	
GeissbulherC	Tanzania; *An. gambiae s.l.*; April-June 2006	[4]	
SeyoumA	Zambia; *An. funestus*; September 2009-March 2010; ITN only site	[6]	
SeyoumB	Zambia; *An. quadriannulatus*; September 2009-March 2010; ITN only site	[6]	
SeyoumC	Zambia; *An. funestus*; September 2009-March 2010; ITN & IRS site	[6]	
SeyoumD	Zambia; *An. quadriannulatus*; September 2009-March 2010; ITN & IRS site	[6]	

ϕ_{Bed} is high if most mosquitoes bite indoors when people are in bed. Delaying these human activity times increases asynchrony between mosquito and human activity, leading to decreases in both the hourly and segmented estimate of ϕ_{Bed} (Supplementary Figures 1A-E). The R^2 of the points from the y = x line is shown. The relative difference (%) in ϕ_{Bed} between the segmented and hourly estimates were compared for each scenario. We show that the greater the delay, the greater the relative difference in the segmented and hourly estimates of ϕ_{Bed}. This is because, with larger delays, the estimate of ϕ_{Bed} is smaller. However, the R^2 is relatively high across all scenarios. This suggests that although the segmented method is less accurate when ϕ_{Bed} is low, this is unlikely to have an impact on epidemiological interpretation. The relative difference in the estimate is smallest if most biting happens when most people are in bed, shown in Figure 2



Supplementary Figure 1: **Sensitivity analysis on segmented sampling method.** The time at which people go indoors for the night, go to bed, get out of bed and leave the house in the morning was delayed by 1 hours, 2 hours, 3 hours and 6 hours to determine the influence of the synchrony between mosquito and human activity on the accuracy of the segmented method for estimating ϕ_{Bed}. A) For each scenario, the R^2 for the y =x line is shown. B) The relative difference (%) in ϕ_{Bed} for each scenario. The greatest relative difference is in the 6h delay scenario, indicating that greater levels of asynchrony between human and mosquito activity introduces more error into the estimates of ϕ_{Bed} from the segmented method.



Supplementary Figure 2: **The proportion of mosquitoes indoors and outdoors and proportion of people in bed for each delay scenario in the studies from the published systematic review [1]**. Delays were applied to the proportion of people indoors and in bed as recorded in the studies, by 1 hour, 2 hours, 3 hours and 6 hours. The proportion of people in bed in these scenarios is shown on the y-axis (left-hand side). The secondary axis (right-hand side) shows the proportion of mosquitoes caught indoors or outdoors, as recorded in the corresponding studies.

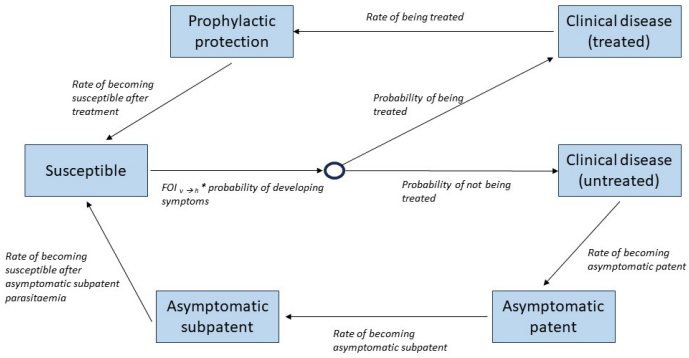
3 Malaria transmission model

3.1 Model structure and vector control interventions

A mechanistic of malaria transmission was used to simulate transmission in a Bijagos-like setting [14, 15]. In this study, the model is used to determine the influence of different values of ϕ_{Bed} on clinical incidence of *P. falciparum* infection in children under 5-years of age per 1,000 persons. The model structure is described in detail in Supplementary Material of the original transmission model paper [14]. Here, we provide a brief overview of the model structure and focus on the implementation of ITNs in this framework.

The human component of this malaria model consists of 6 states of infection/disease. Each state is separated into different biting heterogeneity groups (capturing differences in the risk of exposure to infectious bites), divided into 20 age groups and into intervention groups, depending on the usage of the in-

tervention by the population. Naturally acquired immunity parameters were previously fitted to capture age-specific epidemiological trends in different settings [16]. Once an individual has received an infectious bite, the probability of developing symptoms is dependent on immunity, which in turn is determined by the age and level of exposure in the population. The force of infection from mosquitoes to humans is dependent on, amongst other factors, the number of infectious vectors. The human model is illustrated in Supplementary Figure 3.

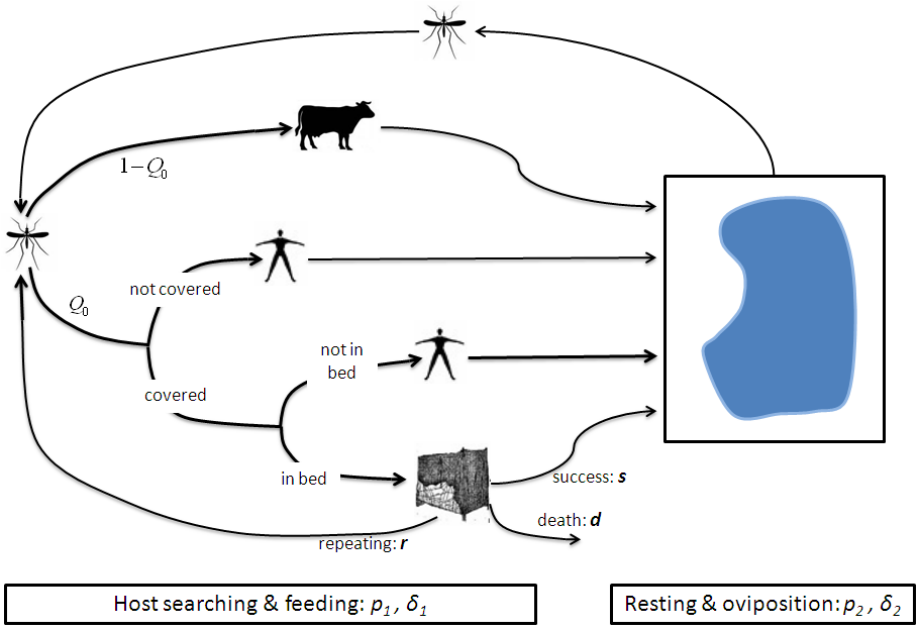


Supplementary Figure 3: **Schematic of the modelling structure of the human malaria model (adapted from Supplementary Material 1.1 [17]**. $FOI_{v \to h}$ denotes the force of infection on humans from mosquitoes.

Malaria infection in mosquitoes is modelled in three states; susceptible (S), pre-infectious (E) and infectious (I) mosquitoes. Mosquitoes become infected upon biting an infectious person, according to the force of infection from humans to vectors (ΛM^v, see Supplementary Equation 8). Mosquitoes surviving the extrinsic incubation period (EIP) become infectious and are able to transmit malaria to humans upon biting. The emergence of adult mosquitoes is influenced by a density-dependent process in larval populations. The per capita mortality rate of mosquitoes is modelled by an exponential distribution (mean mortality rate = 0.1).

ITNs protect individuals through three mechanisms: i) direct protection by a barrier effect; ii) indirect protection by killing mosquitoes and iii) a community impact by deterring mosquitoes from entering houses and thus increasing the time between human bloodmeals. Subsequently, ITN can reduce malaria prevalence in the population.

In each mosquito feeding attempt, mosquitoes can be killed or repelled by an ITN, or successfully take a bloodmeal. This is illustrated in Supplementary Figure 4. The probability of each of these outcomes depends on aspects of mosquito bionomics; the human blood index (Q0) and the proportion of bites taken when people are in bed (ϕ_{Bed}). Mosquitoes which are repelled attempt to feed elsewhere and repeat the feeding attempt process. It is assumed that all bites indoors are on people (the model assumes that all livestock are kept outdoors), therefore ϕ_{Bed} is a reflection of the proportion of bites taken on humans, when they are in bed. This process is described in detail elsewhere [18].



Supplementary Figure 4: **Schematic of the mosquito feeding cycle, from Supplementary Figure 2.1 [14].** These authors adapted a diagram from a previous study [18].

As summarised in Supplementary Information 2 [14], if person i is protected by an ITN, then the probability that vector species v bites host i during a single feeding attempt is y_i^v; the probability the mosquito vector bites and survives the feeding attempt is w_i^v and the probability it is repelled without feeding is z_i^v. For an individual without protection, $y_i^v = w_i^v = 1$ and $z_i^v = 0$ as these probabilities do not include natural vector mortality. As not all mosquitoes will successfully feed upon entering a house, these probabilities consider feeding behaviour of mosquitoes prior to the introduction of insecticides. However, it is difficult to characterise this aspect of mosquito bionomics given the widespread

usage of ITN, therefore in this study, the estimate of ϕ_{Bed} used to parameterise the model is derived from mosquito surveillance in a setting with high ITN usage.

During a single feeding attempt (on either humans or animals), species v will successfully feed with probability W^v, where Q_0^v is the human blood index (in the absence of interventions) and π_i is the proportion of bites on humans that person i receives, also in the absence of interventions:

$$W^v = (1 - Q_0^v) + Q_0^v \sum_i \pi_i w_i^v \tag{1}$$

The probability the mosquito is repelled is given by probability Z^v:

$$Z^v = Q_0^v \sum_i \pi_i z_i^v \tag{2}$$

Z and W refer to the average probability of the mosquito repeating and successfully feeding on human during a single feeding attempt, respectively.

Mosquitoes search for bloodmeals for time δ_1^v and rest for time δ_2^v, respectively. Subsequently, the mosquito feeding rate (f_R^v) is $f_R^v = \frac{1}{\delta_1^v + \delta_2^v}$. It is assumed that δ_2^v is unaffected by interventions, whilst the time searching for a bloodmeal increases to $\delta_1^v = \frac{\delta^v 10}{1 - Z^v}$. Here, δ_{10}^v is the duration of foraging in the absence of interventions.

Each mosquito survives the period of feeding and resting with probability p_1^v and p_2^v. In the absence of interventions, the probability of a mosquito feeding is given by $p_{10}^v = exp(-\mu_0 \delta_{10})$ and of resting is given by $p_2^v = exp(-\mu_0^v \delta_2)$. Here, μ_0^v is the natural death rate of mosquitoes. In the presence of interventions, p_2^v is unchanged but $p_1^v = \frac{p_{10}^v w^v}{1 - Z^v p_{10}^v}$.

The probability of surviving a feeding cycle is $p_1^v p_2^v = exp(\frac{-\mu^v}{f_R^v})$. The mosquito death rate μ_v is then given by the following equation:

$$\mu_v = -f_R^v \log(p_1^v p_2^v) \tag{3}$$

The probability that a feeding cycle ends with a successful bite on a person, q_i^v is given by:

$$q_i^v = \frac{p_{10}^v Q_0^v \pi_i w_i^v}{1 - Z^v p_{10}^v} \tag{4}$$

The probability that a feeding cycle ends with a bite on an animal is given by:

$$q_A^v = \frac{p_{10}^v (1 - Q_0^v)}{1 - Z^v p_{10}^v} \tag{5}$$

Subsequently, the proportion of successful bites on humans in the presence of interventions is given by:

$$Q^v = 1 - \frac{(1 - Q_0^v)}{W^v} \tag{6}$$

The biting rate on humans is summarised as $\alpha^v = Q^v f_R^v$. The rate at which a person is bitten by a mosquito is then given by the following equation:

$$\lambda_i^v = \frac{\alpha^v \pi_i w_i^v}{\sum_i \pi_i w_i^v} \tag{7}$$

The force of infection from humans to vectors is given by the following equation, where c_i is the infectivity of the infectious state that a person is in:

$$\Lambda M^v = \sum_i c_i \lambda_i^v \tag{8}$$

The EIR experienced by each person due to the mosquito is $\lambda_i^v * I_M^v$, where I_M^v is the number of infectious vectors. The total experienced by people is the sum of this over all species.

The degree of protection offered by an ITN is dependent on the proportion of bites that mosquitoes take on humans when they are potentially protected by the intervention, i.e. when they are in bed. This is defined in the main text as ϕ_{Bed} (Equation 9).

Upon entering a house with an ITN, a mosquito can repeat a feeding attempt (r_N), successfully feed (s_N) or die (d_N). For an unprotected individual, the probability of biting (y_i) and successfully feeding (w_i) are equal to 1, and the probability of being repelled (z_i) is equal to zero. However, in the presence of interventions, these probabilities are modified, as shown in the following equations:

$$w_i = (1 - \phi_{Bed}) + \phi_{Bed} s_N \tag{9}$$

$$y_i = (1 - \phi_{Bed}) + \phi_{Bed} s_N \tag{10}$$

$$z_i = \phi_{Bed} r_N \tag{11}$$

The repellency effect of the insecticide on an ITN decreases over time from a maximum level of r_{N0} to r_{NM}. The repellency effect does not decay to a zero value as ITNs still offer protection (barrier effect) when all insecticide has worn off. The killing effect of the net (d_{N0}) decreases at a constant rate (γ_N). Therefore at time t after nets were distributed, r_N, d_N and s_N are given by the following equations:

$$r_N = (r_{N0} - r_{NM})exp(-t\gamma_N) + r_{NM} \tag{12}$$

$$d_N = d_{N0}exp(-t\gamma_N) \tag{13}$$

$$s_N = 1 - r_N - d_N \tag{14}$$

The values of r_{N0} and d_{N0} vary according to ITN type and the level of insecticide resistance and are estimated from experimental hut trials, using previous work [19]. As ITNs cause mosquitoes to repeat the feeding attempt in either of two ways (due to the insecticide repelling the mosquitoes or the barrier effect of the ITN) and not all mosquitoes will successfully feed on a person without interventions, the probability of repeating, feeding and dying are relative to that without the intervention. The probabilities for r_{N0} and d_{N0} and s_{N0} are derived by:

$$r_{N0} = (1 - \frac{k'_1}{k'_0})(\frac{j'_1}{j'_1 + l'_1}) \tag{15}$$

$$s_{N0} = \frac{k'_1}{k'_0} \tag{16}$$

$$d_{N0} = (1 - \frac{k'_1}{k'_0})(\frac{l'_1}{j'_1 + l'_1}) \tag{17}$$

where N_0 and N_1 are the number of mosquitoes entering a house without (subscript *0*) and with (subscript *1*) an ITN respectively, j_0 and j_1 are the percentage of mosquitoes not feeding, k_0 and k_1 are the percentage of mosquitoes successfully feeding and l_0 and l_1 are the percentage of mosquitoes dying.

3.2 Modelling transmission in a Bijagos-like setting

To simulate transmission in a Bijagos-like setting, the model was parameterised to account for local rainfall patterns and the impact that this has on the density of mosquitoes over time, using a Fourier series [14]. The archipelago has a historic usage of ITNs and a survey on net usage in all 14 villages on Bubaque island revealed usage to be 86% [20]. It is assumed that the same ITN usage applies throughout the archipelago and for simplicity, that ITN usage does not decay over time. In August 2017, it *P. falciparum* prevalence by rapid diagnostic test (RDT) was estimated to be approximately 5.8% and by quantitative polymerase chain reaction (qPCR) to be approximately 16.9%, based on a survey of the population (6 months-79 years-old in Bubaque island) [21]. We assume this translates to a slide prevalence of 5.8% in children under 5-years-old for model calibration purposes [22]. The model was calibrated to these data by

running the model for 5 years in the absence of interventions (so that it reaches equilibrium) and introducing ITNs into the population (86% usage), every 3 years, from year 5.5 to year 14.5 (ITNs are typically distribution in June, every 3 years) and determining the initial EIR value that would give a slide prevalence of approximately 5.8% in children under 5-years-old at the time of the 2017 cross-sectional survey.

Data on the phenotypic resistance of local vectors to deltamethrin (55% mortality in WHO test tube assays) was used to determine the probability of a mosquito dying, being repelled or successfully feeding upon contact with an ITN [23]. These probabilities vary depending on ITN type and were previously estimated [19]. Other aspects of mosquito bionomics were used to parameterise the model and are shown in Supplementary Table 2.

The efficacy of ITNs is estimated as the relative (%) of clinical cases of *P. falciparum* in children under 5-years-old averted by ITNs in a 3-year period since the last ITN campaign (year 11.5 to year 14.5), compared to a counterfactual baseline scenario of no interventions (Equation 1).

4 Generalised linear mixed effect model to estimate the hourly mosquito biting rate

Different model structures were tested and compared to determine the best-fitting generalised linear negative binomial model to estimate the number of mosquitoes caught in a CDC light trap per hour. Four models, using Markov Chain Monte Carlow, MCMC, (each with 4 chains and 1000 iterations per chain), differing in covariate composition, were explored. All models had the sampling location (indoors or outdoors) and time period (evening, night or day) as fixed effects, as estimating ϕ_{Bed} using the simpler sampling method proposed in this study requires information on the number of mosquitoes indoors and outdoors in each time segment. The *log(duration of trapping)* was used as an offset to account for the duration that each trap was run for and that this was different for different time segments. Leave-one-out cross-validation using a Pareto-k threshold of 0.7 was used to select the best-fitting model. The model comparison statistics are shown in Supplementary Table 3. The best-fitting model is model 1, which has location, time period, the interaction between these variables as fixed effects, and the sampling island as a random effect. The model estimates for the number of mosquitoes caught per trap per hour in each time period and sampling location are shown in Supplementary Table 3. The overdispersion parameter was low, justifying the use of a negative binomial distribution: median = 2.73, 95% CrI: 1.89, 4.00.

Model diagnostics for model 1 were used to assess the chain convergence, by visual inspection of the trace plots (Supplementary Figure 5), the Rhat values

Supplementary Table 2: **Reference for values used to parameterise the malaria transmission model to the local entomological context of the Bijagos islands archipelago.**

Entomological parameter	**Value**	**Reference**
Human blood index (%)	92	[14, 24–28]
Duration of extrinsic incubation period (days)	10	[14, 29]
Mean life expectancy (days)	7.5	[14, 30–36]
Duration between bloodmeals (days)	3	[14, 37, 38]
Time spent foraging (days)	0.68	[39]
Probability of mosquito dying upon encounter with a new pyrethroid-only ITN in an experimental hut, given a level of resistance	0.280	[19, 23]
Probability of a mosquito being repelled upon encounter with a new pyrethroid-only ITN in an experimental hut, given a level of resistance	0.680	[19, 23]
The half-life of insecticide on the pyrethroid-only ITN, given a level of resistance (days)	832	[19, 23]
ITN usage (%)	86	[20]

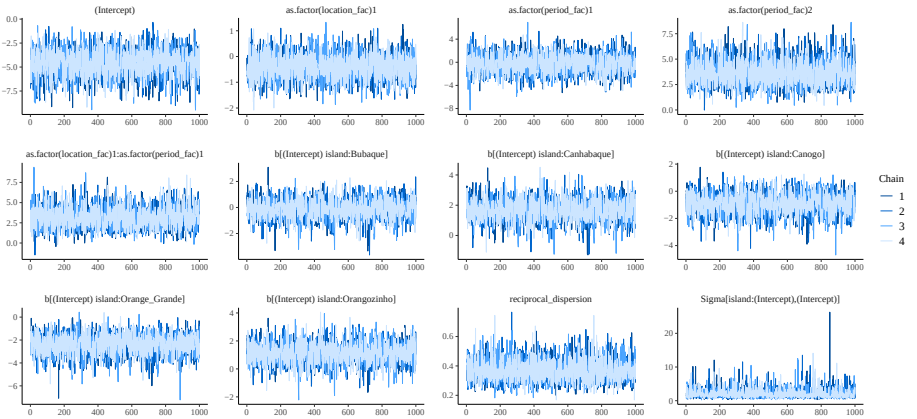
Supplementary Table 3: **Statistics for selecting the best-fitting Bayesian generalised linear model for estimating the number of mosquitoes caught in a CDC light trap per hour**. Statistics are reported in relation to the best-fitting model (model 1). A pareto-k threshold of 0.7 was used for model comparison.

Model	Fixed Effect	Random Effect	ELPD-diff	SE-diff	ELPD-LOO	P-LOO	LOOIC
4	Location + period	NA	-26.1	7.6	-250.9	4.5	501.9
3	Location + period	Island	-2.9	3.2	-227.8	9.9	455.5
2	Location, period + location:period	NA	-22.7	6.8	-247.5	6.4	495.1
1	Location + period +location:period	Island	0.0	0.0	-224.9	10.7	449.7

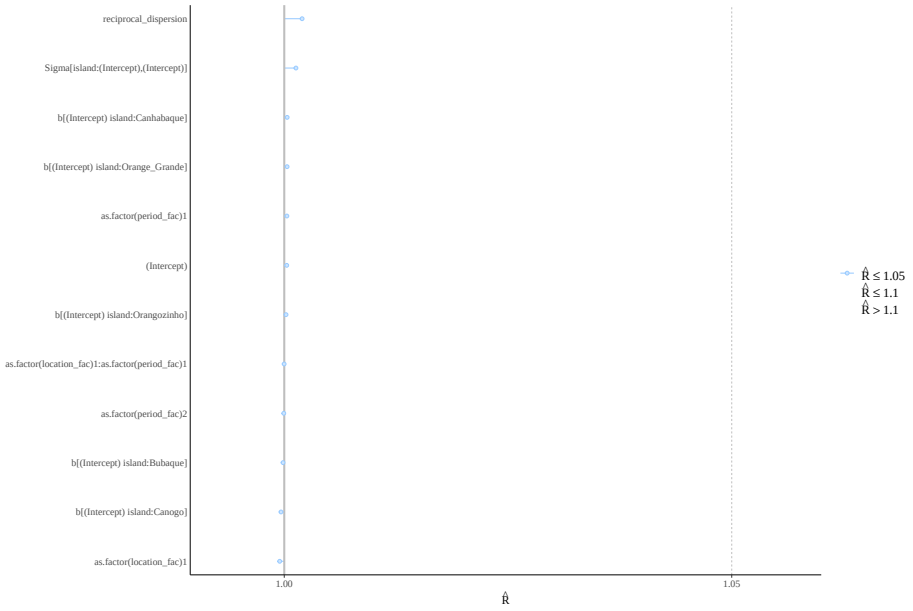
Supplementary Table 4: **Estimates of the number of mosquitoes caught per trap per hour in each time period and sampling location according to the best-fitting generalised linear mixed effect model (negative binomial distribution)**. The fixed effects are time period (day: 7am-7pm, evening: 7pm-10pm and night: 10pm-7am) and sampling location (inside or outside). The random effect is the sampling island.

Time period	Location	Mean number of mosquitoes caught per trap per hour (95% CrI)
Day	Outside	0.02 (0.00, 0.13)
Day	Inside	0.02 (0.00, 0.09)
Evening	Outside	0.02 (0.00, 0.09)
Evening	Inside	0.19 (0.04, 0.60)
Night	Outside	0.56 (0.11, 1.82)
Night	Inside	0.38 (0.08, 1.22)

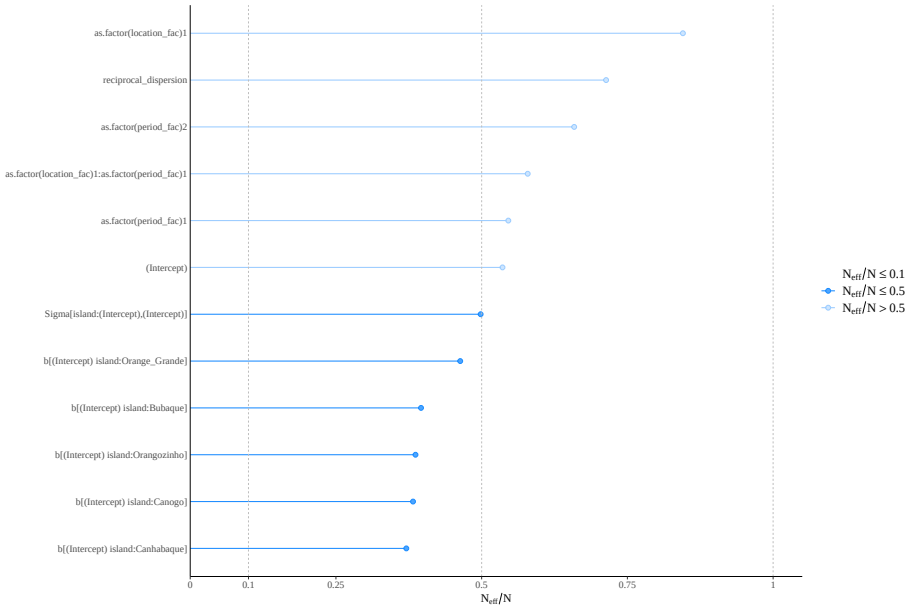
(Supplementary Figure 6) and effective sample size (Supplementary Figure 7).



Supplementary Figure 5: **Trace plots of each of the four chains used in the Markov Chain Monte Carlo simulation for the best-fitting Bayesian generalised linear mixed effect model for estimating the number of mosquitoes caught in a CDC light trap per hour** Each chain is shown in a different colour. The overlap of the chains shows similar exploration of parameter space by each chain. Model coefficient abbreviations are as follows: *location_fac*0 = outside, *location_fac*1 = inside, *period_fac*0 = day, *period_fac*1 = evening and *period_fac*2 = night.



Supplementary Figure 6: **Rhat statistics for Markov Chain Monte Carlo simulations for the best-fitting Bayesian generalised linear mixed effect model for estimating the number of mosquitoes caught in a CDC light trap per hour**. The Rhat is a statistic used to determine whether the chains of the simulation have converged. If all chains are at equilibirum, the split Rhat values will be the same and Rhat will be equal to 1. If the chains have not converged to a common distribution, Rhat will be greater than 1. Model coefficient abbreviations are as follows: *location_fac*0 = outside, *location_fac*1 = inside, *period_fac*0 = day, *period_fac*1 = evening and *period_fac*2 = night.



Supplementary Figure 7: **The effective same size statistics for the Markov Chain Monte Carlo simulation for the best-fitting Bayesian generalised linear mixed effect model for estimating the number of mosquitoes caught in a CDC light trap per hour**. Samples will often be autocorrelated within an MCMC chain. The effective sample size (Neff) can be used to estimate the number of independent samples these correlated MCMC samples are equivalent to. If there is no autocorrelation, Neff is equal to the actual number of samples (N). If there is strong autocorrelation, Neff is less than the actual number of samples. A large ratio of Neff to N indicates low autocorrelation between samples and reliable posterior estimates. Model coefficient abbreviations are as follows: *location_fac*0 = outside, *location_fac*1 = inside, *period_fac*0 = day, *period_fac*1 = evening and *period_fac*2 = night.

5 Generalised binomial logistic regression model to estimate the proportion of people in bed

Different model structures were tested and compared to determine the best-fitting generalised binomial logistic regression model to estimate the proportion of people in bed in each age group (under 5-years old, 5-14 years-old and over 15-years-old) and time period (day, evening and night). Four models, using MCMC, (each with 4 chains and 1000 iterations per chain), differing in covariate composition, were explored. All models had the age group and time period as fixed effects, as generating an age-weighted estimate of ϕ_{Bed} requires information on the age-specific proportion of people in bed in each time period. Leave-one-

out cross-validation using a Pareto-k threshold of 0.7 was used to select the best-fitting model. The model comparison statistics are shown in Supplementary Table 5. The best-fitting model is model 1 (Supplementary Table 6), which has the age group and time period as fixed effects.

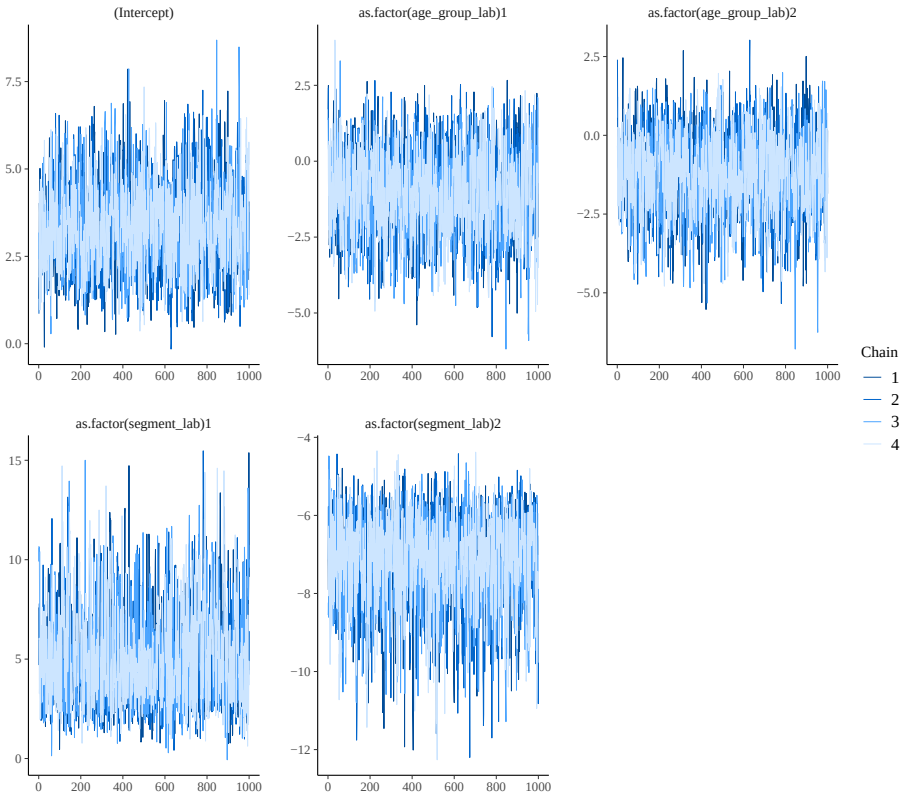
Supplementary Table 5: **Statistics for selecting the best-fitting Bayesian generalised binomial logistic regression model for estimating the age-specific proportion of people in bed in each time period**. Statistics are reported in relation to the best-fitting model (model 1). A pareto-k threshold of 0.7 was used for model comparison.

Model	Fixed Effect	Random Effect	ELPD-diff	SE-diff	ELPD-LOO	P-LOO	LOOIC
4	Age group + period + age group:period	NA	-1.7	1.5	-21.1	7.1	42.4
3	Age group + period	Island	-0.8	0.7	-20.4	6.4	40.7
2	Age group + period + age group:period	Island	-1.7	1.2	-21.3	7.9	42.6
1	Age group + period	NA	0.0	0.0	-19.6	4.8	39.1

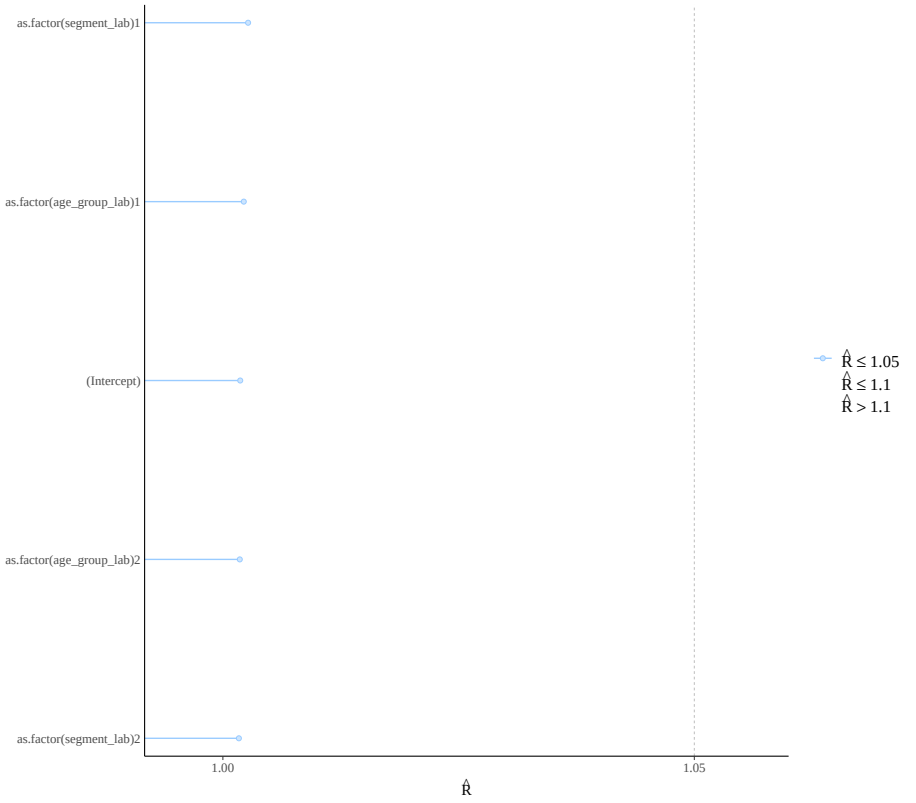
Supplementary Table 6: **Estimates for the proportion of people in bed for each time period and age group according to the best-fitting generalised logistic regression model (binomial distribution)**. The fixed effects are time period (Day: 7am-7pm, Evening: 7pm-10pm and Night: 10pm-7am) and age group (under 5-years-old, 5 to 14-years-old and over 15-years-old).

Time period	Age group	Mean proportion of people in bed (95% CrI)
Day	Under 5-years-old	0.04 (0.00, 0.18)
Day	5 to 14-years-old	0.01 (0.00, 0.06)
Day	Over 15-years-old	0.01 (0.00, 0.04)
Evening	Under 5-years-old	0.94 (0.75, 1.00)
Evening	5 to 14-years-old	0.90 (0.75, 0.98)
Evening	Over 15-years-old	1.00 (0.98, 1.00)
Night	Under 5-years-old	1.00 (0.99, 1.00)
Night	5 to 14-years-old	1.00 (0.98, 1.00)
Night	Over 15-years-old	1.00 (0.98, 1.00)

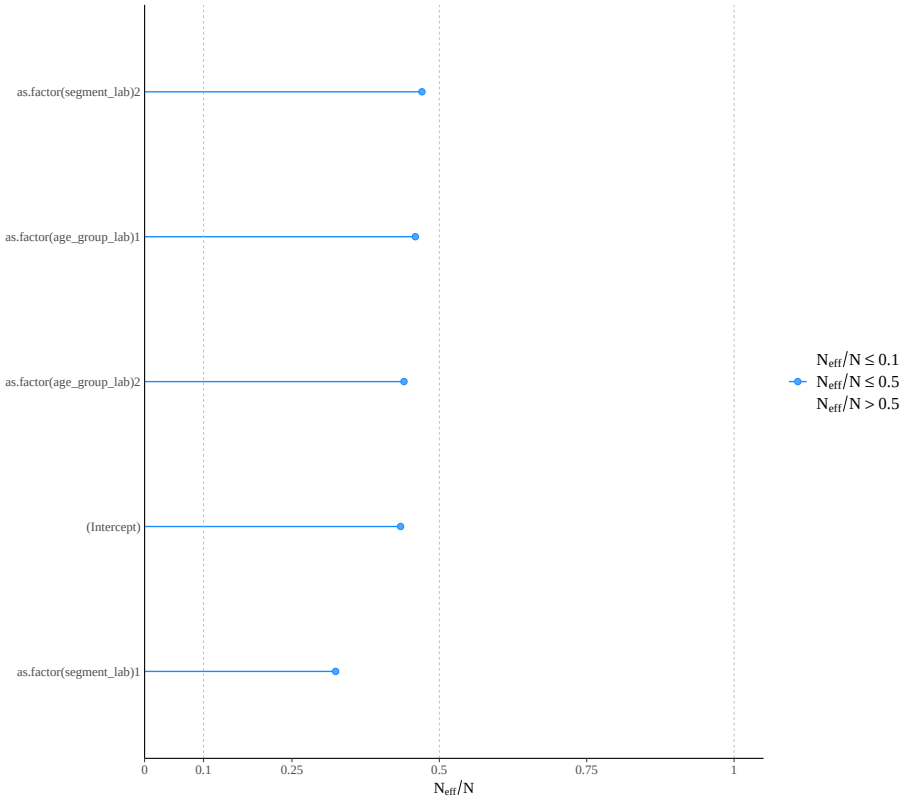
Model diagnostics for model 1 were used to assess the chain convergence, by visual inspection of the trace plots (Supplementary Figure 8), the Rhat values (Supplementary Figure 9) and effective sample size (Supplementary Figure 10).



Supplementary Figure 8: **Trace plots of each of the four chains used in the Markov Chain Monte Carlo simulation for the best-fitting generalised logistic regression model for estimating the proportion of people in bed for each age group and time period.** Each chain is shown in a different colour. The overlap of the chains shows similar exploration of parameter space by each chain. Model coefficient abbreviations are as follows: *age_group_lab*0 = age 0 to 5 years-old, *age_group_lab*1 = age 5 to 14 years-old , *age_group_lab*2 = age 15 years-old and over, *segment_lab*0 = day, *segment_lab*1 = evening and *segment_lab*2 = night.



Supplementary Figure 9: **Rhat statistics for Markov Chain Monte Carlo simulations for the best-fitting generalised logistic regression model for estimating the proportion of people in bed for each age group and time period.**. The Rhat is a statistic used to determine whether the chains of the simulation have converged. If all chains are at equilibirum, the split Rhat values will be the same and Rhat will be equal to 1. If the chains have not converged to a common distribution, Rhat will be greater than 1. Model coefficient abbreviations are as follows: *age_group_lab*0 = age 0 to 5 years-old, *age_group_lab*1 = age 5 to 14 years-old , *age_group_lab*2 = age 15 years-old and over, *segment_lab*0 = day, *segment_lab*1 = evening and *segment_lab*2 = night.



Supplementary Figure 10: **The effective same size statistics for the Markov Chain Monte Carlo simulation for the best-fitting generalised logistic regression model for estimating the proportion of people in bed for each age group and time period.**. Samples will often be autocorrelated within an MCMC chain. The effective sample size (Neff) can be used to estimate the number of independent samples these correlated MCMC samples are equivalent to. If there is no autocorrelation, Neff is equal to the actual number of samples (N). If there is strong autocorrelation, Neff is less than the actual number of samples. A large ratio of Neff to N indicates low autocorrelation between samples and reliable posterior estimates. Model coefficient abbreviations are as follows: *age_group_lab*0 = age 0 to 5 years-old, *age_group_lab*1 = age 5 to 14 years-old , *age_group_lab*2 = age 15 years-old and over, *segment_lab*0 = day, *segment_lab*1 = evening and *segment_lab*2 = night.

6 Reflexivity statement

6.1 How does this study address local research and policy priorities?

Malaria is endemic in the Bijagos archipelago, Guinea-Bissau, despite the extensive usage of insecticide-treated nets (ITNs). Targeting the transmission that escapes ITNs will be crucial for elimination efforts, and doing so requires a deep understanding of insecticide resistance, ITN usage, mosquito biting behaviours and human activities which render exposure to potentially infectious bites. The former two have been characterised in other studies in the Bijagos [20, 23, 40], through a collaboration between the London School of Hygiene & Tropical Medicine (LSHTM), the Guinea-Bissau Ministry of Health, Bandim Health Project and the country's National Malaria Control Programme (NMCP). However, collecting mosquito biting behaviour data is challenging; it is labour-intensive, costly and time-consuming as standard protocols require hourly mosquito trapping throughout the night. Hence, the simplified sampling methodology that we propose, and methodology for analysing data collected in this way, are useful for improving surveillance and characterising biting risk in this resource-limited island setting. Our transmission modelling shows how this type of surveillance can be used to guide decision-making concerning the local use of indoor vector control interventions.

6.2 How were researchers from Guinea-Bissau involved in the study?

Researchers from the two institutions in Guinea-Bissau - Bandim Health Project and Ministry of Health (FB and ETdS) - and the field assistants (who are from the Bijagos archipelago) provided extremely useful local insights into the type of sampling approach that would be feasible and would be well-received by local communities. They voiced the concern that hourly sampling would not be feasible in the setting, especially due to the disturbance this would cause to households during the night given that it was a harvest period and individuals were working in farmland throughout the day and would be in particular need of rest at night. This was echoed amongst the field assistants as hourly sampling would require working on a rigid sleeping rota throughout the night, which was challenging in a small field team of just 6 people. This then led NC and EP to develop the segmented sampling approach, with supervision from TSC and ESS, and for NC, EP, FB and ETdS to use it to collect data on the archipelago. The field assistants also communicated with local healthcare workers to provide community sensitisation for the study. This was epecially important for minimising observer bias in the sleeping pattern survey. LSHTM have worked closely with the Guinea-Bissau Ministry of Health, NMCP and Bandim Health Project for over a decade on infectious diseases on the Bijagos archipelago, and have several joint research grants and publications. AL, EP, ETdS, FB, JEN, AR, PD and HH are part of this long-standing collaboration, which played a

major role in designing and implementing the study.

6.3 How has funding been used to support the local research team?

Data collection was funded by the Joint Global Health Trials award (National Institute for Health and Care Research, MRC, Wellcome, and the Foreign, Commonwealth and Development Office), funder reference MR/S005013/1 and used to employ the field assistants and local researchers.

6.4 How are research staff who conducted data collection acknowledged?

All colleagues who contributed directly to scientific analysis and data collection in the field are included as co-authors. The team of field assistants who constructed outdoor trapping stations, changed mosquito trap cups and recorded human sleeping activity data are included in the acknowledgements.

6.5 Do all members of the research partnership have access to study data?

Yes, data for this study has been uploaded into a repository, so is accessible for all to access.

6.6 How was data used to develop analytical skills within the partnership?

This was an interdisciplinary project involving field entomology, observational studies on human sleeping patterns and statistical and mathematical modelling. It was not feasible to upskill all authors on quantitative work. Some field assistants received training in morphological identification of *Aedes sp.*, *Culex sp.* and *Anopheles sp.* mosquitoes.

6.7 How will research products be shared to address local needs?

The segmented sampling method and associated analysis frameworks, available in the repository for this study, will be shared so that local researchers have the resources to use this methodology to facilitate local data collection and analysis.

6.8 How is the leadership, contribution and ownership of this work by LMIC researchers recognised within the authorship?

Six of the 15 authors are based in Guinea-Bissau. These authors had a variety of roles including supervision of the field survey, overseeing data collection,

morpholiogical identification of *Anopheles sp.* mosquitoes or were involved in project implementation. The first and senior authors are based in the UK. This was deemed appropriate as the study conception and analysis was led by NC, under supervision from TSC, ESS and AL. Important aspects of the data collection method were based on suggestions from local researchers, who are listed as co-authors in the study.

6.9 How has local and regional research been taken into account in the citations?

Previous research studies, resulting from collaborations between LSHTM, the Bandim Health Project and Ministry of Health, reported estimates of ITN usage [20], malaria prevalence [21] and insecticide resistance [23] and used to parameterise the malaria transmission model.

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