Single Patch *Plasmodium falciparum* model

Mathematical model description

Sheetal Silal^{1,2} & Lisa White²

- ¹ Modelling and Simulation Hub, Africa (MASHA), Department of Statistical Sciences, University of Cape Town, University of Cape Town, Rondebosch, Cape Town 7700, South Africa
- $^{\rm 2}$ Centre for Tropical Medicine and Global Health, Nuffield Department of Medicine, University of Oxford, Oxford, UK

This document provides a description of the methodology, equations and parameters underlying the mathematical model for *P. falciparum* malaria transmission.

Plasmodium falciparum sub-model

We use a compartmental model for the transmission of *P. falciparum* malaria. It's structure is similar to previously published models [1-6]. There are four infection classes in this model representing infections that are: severe; clinical; asymptomatic and detectable by microscopy; asymptomatic and undetectable by microscopy. Each infection class has a distribution of parasitaemia associated with it that is used to estimate the sensitivity of various diagnostic tests. Each infection class also has an infectiousness associated with it based on infectivity data. The probability of individuals entering each class of infection is dependent on their immunity status. We assume that untreated individuals will transition from higher to lower severity infection classes as they recover and that they can be boosted to higher severity classes on superinfection. We assume that treated individuals test positive for HRP2 after clearance of asexual parasitaemia for different durations depending on the detection limit of the test used.

The system is depicted in Figure 1 and described by the following set of ordinary differential equations with compartment descriptions in Table 1:

$$\begin{split} \frac{dS}{dt} &= \mu P(t) - \mu S - \Lambda(t)S + \omega R \\ \frac{dI_n}{dt} &= -\mu I_n + p_{sn}(1-p_s)\Lambda(t)S - r_n I_n + r_a I_a - (1-p_{rn})(1-p_r)\Lambda(t)I_n - p_r \Lambda(t)I_n + p_{rn}(1-p_r)\Lambda(t)(R+H) \\ \frac{dI_a}{dt} &= -\mu I_a + (1-p_{sn})(1-p_s)\Lambda(t)S + (1-p_{sev})r_c I_c - r_a I_a + (1-p_{rn})(1-p_r)\Lambda(t)I_n - p_r \Lambda(t)I_a + (1-p_{rn})(1-p_r)\Lambda(t)(R+H) + ptf(1-ptfc)r_t (T_o + T_v + T_h) \\ \frac{dI_c}{dt} &= -\mu I_c + (1-\tau)p_s \Lambda(t)S + (1-\tau_{sev})(1-\theta_1)r_s I_s - (1-p_{sev})r_c I_c - p_{sev}r_c I_c + p_r (1-\tau)\Lambda(t)(I_n + I_a + R + H) + ptf(ptfc)(1-ptftr)r_t (T_o + T_v + T_h) \\ \frac{dI_s}{dt} &= -\mu I_s - (1-\tau_{sev})r_s I_s - \tau_{sev}r_Q I_s + p_{sev}r_c I_c \\ \frac{dT_o}{dt} &= -\mu I_o + \tau_o p_s \Lambda(t)S - (1-ptf)r_t T_o + p_r \tau_o \Lambda(t)(I_n + I_a + R + H) \\ \frac{dT_v}{dt} &= -\mu T_v + \tau_v p_s \Lambda(t)S - (1-ptf)r_t T_v + p_r \tau_v \Lambda(t)(I_n + I_a + R + H) \\ \frac{dT_h}{dt} &= -\mu T_h + \tau_h p_s \Lambda(t)S - (1-ptf)r_t T_h + p_r \tau_h \Lambda(t)(I_n + I_a + R + H) + ptf(ptfc)(ptftr)r_t (T_o + T_v + T_h) \\ \frac{dR}{dt} &= -\mu R + r_n I_n - \Lambda(t)R - \omega R + \chi H \\ \frac{dH}{dt} &= -\mu H + (1-ptf)r_t (T_o + T_v + T_h) + \tau_{sev} (1-\theta_2)r_Q I_s - \Lambda(t)H - \chi H \end{split}$$

where

$$\begin{split} P &= S + I_n + I_a + I_c + I_s + T_o + T_v + T_h + R + H \\ \Lambda(t) &= (1/\lambda(t) + 1/\gamma_h + 1/\gamma_m)^{-1} \\ \lambda(t) &= seas(t) \frac{b^2 \epsilon_h \epsilon_m \frac{M}{P(t)} I(t)}{(b \epsilon_h \frac{M}{P(t)} + \delta_m)(\frac{\gamma_m}{\gamma_m + \delta_m})} \\ I(t) &= \frac{\zeta_n I_n(t) + \zeta_a I_a(t) + I_c(t) + I_s(t)}{P(t)} \\ seas(t) &= 1 + eln * a * cos(2\pi(t - \phi)) \\ \tau &= \tau_o + \tau_v + \tau_h \end{split}$$

where eln is the Bivariate ENSO (El Niño southern oscillation) index time series standardised between 0 and 1 and smoothed with a running median to estimate effect size. (Accessible at: http://www.esrl.noaa.gov/psd/data/climateindices/).

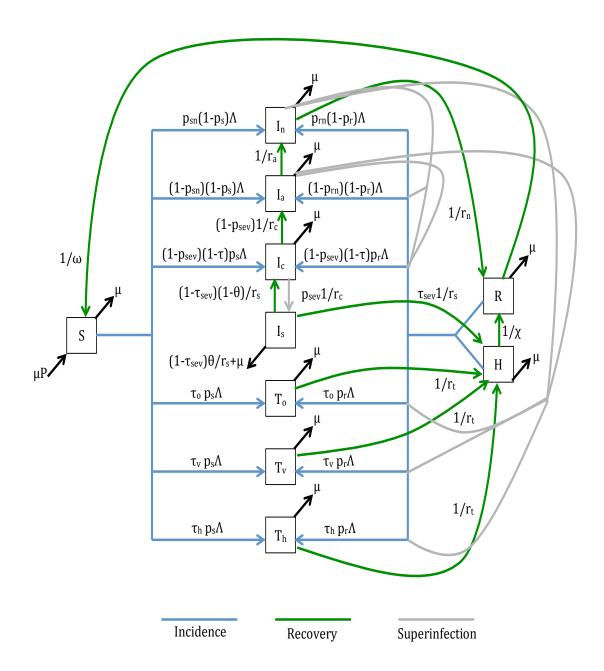


Figure 1 *Plasmodium falciparum* model flow diagram

Table 1 Model Variables

Symbol	Definition				
Falciparum Variables					
S	Uninfected and non-immune population				
Н	Uninfected and immune population who test positive by RDT				
R	Uninfected and immune population				
I _N	Infected and asymptomatic malaria population undetectable by microscopy				
I _A	Infected and asymptomatic malaria population detectable by microscopy				
I _C	Infected and clinical malaria population				
Is	Infected and severe malaria population				
T_0	Population under effective treatment by other means (E.g. Private care)				
T_{V}	Population under effective treatment by Village Malaria Worker				
T _H	Population under effective treatment through Health Information System				

 Table 2 Model Parameters (Ghana-specific parameters italicised)

Symbol	Definition	Value	Units	Sim Range	Source	
Parameters						
	Transmission scale parameter	(58-600)	num		estimated from zonal data	
φ	Month of peak transmission	(7-10)	month		estimated from zonal data	
а	Amplitude of seasonal variation	0.7-1	na	(0,1)	estimated from zonal data	
δ_{m}	Average life expectancy of mosquito	14	days	(10,20)	[7, 8]	
b	Number of mosquito bites per human per day	1/3	day ⁻¹	(0.1,0.5)	[9, 10]	
$\epsilon_{\rm m}$	Probability that a bite from an infectious mosquito will result in infection	50	%	(20,50)	[10-12]	
1/γ _M	Duration of latent period in mosquitoes	10	days	(5, 15)	[7, 13-17]	
eff_{IRS}	Effectiveness of indoor residual spraying	30	%	(25, 35)	[18]	
eff_{ITN}	Effectiveness of bednets	41.7	%	(38, 45)	[18, 51]	
hl_{NET}	Half-life of bednets	1.5	year	(1, 2)	[19]	
eff _{HIS}	Pr(treatment seeking)*Pr(Diagnosis)*Pr(receive treatment)		%		estimated from data	
	Proportion of infections seeking treatment	<i>73.5</i>	%	(70.7, 80.8)	data	
	Proportion of cases receiving diagnosis	91.0	%	(90.5, 91.2)	data	
	Proportion of diagnosed cases receiving treatment	100	%	•	data	
$ au_{ u}$	Treatment seeking with a Community/ Village health worker	n/a				
p_rdt	Proportion of cases detected with RDT	73	%		[52]	

rdt_pos	RDT positivity rate	58	%		[52]
slide_pos	Slide positivity rate	45	%		[52]
$1/\mu$	Average life expectancy of the population	63	year	(68,75)	[20]
p_S	Proportion of non-immune individuals expected to develop clinical malaria after infection	90	%	(80,100)	[15, 21]
p_R	Proportion of immune individuals expected to develop clinical malaria after infection	10	%	(0,77)	[22]
p _{SN}	Proportion of non-immune individuals expected to develop sub-patent infection upon challenge	10	%	(0,20)	assumption
p _{RN}	Proportion of immune individuals expected to develop sub-patent infection upon challenge	50	%	(30,70)	assumption
1/r _S	Duration of symptoms in an untreated severe infection	10	day	(5,15)	[23, 24]
1/r _c	Duration of symptoms in an untreated clinical infection	10	days	(5,15)	[23, 24]
1/r _A	Duration of symptoms in an untreated asymptomatic infection	130	days	(60, 200)	[25-27]
$ au_{ m SEV}$	Proportion of severe malaria that is treated	80	%	(0, 100)	assumption
p_{sev}	Proportion of clinical infections that become severe	3	%	(5,25)	[28, 29]
ζA	Relative infectiousness of asymptomatic infection compared to clinical infection	12.6/27	na	(0,0.50)	[30]
ζn	Relative infectiousness of sub-patent infection compared to clinical infection	3.9/27	na	(0., 0.25)	[31]
$1/\omega$	Duration of immunity in an individual without challenge	5	year	(0.5,10)	[26]
θ_1	Probability that untreated severe malaria progresses to death	70	%	(50,80)	[29]
θ_2	Probability that treated severe malaria progresses to death	2	%	(1,20)	estimated from data
$\epsilon_{ m h}$	Probability that a bite from an infectious human will result in infection	50	%	(7,64)	[14, 32]
1/γн	Incubation period and time to gametocytemia in humans	21	days	(14,24)	[14-17, 33]
1/χ	Period of HRP2 detectability by RDT	28	days	(21,37)	[34-36]
$1/r_T$	Time taken to clear asexual parasites after treatment	3	day	(3,7)	[37]
$1/r_Q$	Recovery time with quinine for severe infections	6	days	(4,8)	[38]
ptf	Baseline probability of treatment failure on ACT	5	%	(1,10)	assumption
ptfc	Probability of being clinical after treatment failure	0.75	%	(0.5, 0.9)	assumption
ptftr	Probability of seeking trt if clinical, after treatment failure	0.27	%	(0.1, 0.4)	assumption

Sub-patent infection and diagnostics

We assume that parasitaemia (parasites per µl) within each infection class (sub-patent, asymptomatic and clinical) is log-normally distributed as described in [39]. We also use a mixture model approach to obtain the distribution for severe infection using the data from [40].

The following table summarises the model parameters and their sources:

Description	Unit	Pf Value	Ref	Pv Value	Ref
Geometric mean parasitaemia for subpatent infections (mn_N)	μl ⁻¹	5	[41]	5	[41, 42]
Geometric mean parasitaemia for asymptomatic infections(mn _A)	μl ⁻¹	5158	[41]	750	
Geometric mean parasitaemia for clinical infections(mn _c)	μl ⁻¹	25000	[40, 43]	5000	[44]
Geometric mean parasitaemia for severe infections(mn _s)	μl ⁻¹	350000	[40]	20000	[45]
Log standard deviation of log-normal parasite distribution for sub-patent infections	-	0.75		0.75	
Log standard deviation of log-normal parasite distribution for asymptomatic infections	-	1.5	[43, 46]	1.5	[40, 43]
Log standard deviation of log-normal parasite distribution for clinical infections	-	1.3	[40, 43]	1.3	[8, 40]
Log standard deviation of log-normal parasite distribution for severe infections	-	0.26	[40]	4	[8]

The following table describes the detection limits also described in [39]:

Description	Units	Pf Value	Ref
Detection limit for conventional RDT	μ l $^{-1}$	200	[47]
Detection limit for microscopy	μ l $^{-1}$	100	[47]
Detection limit for proposed RDT	μl ⁻¹	5	[48, 49]
Detection limit for conventional qPCR	μ l-1	0.2	[50]

Test sensitivity:

The parameters above are used to compute diagnostic sensitivity. For each disease class, i, the sensitivity of a test, x, with detection limit, d_T , is given by the formula: $sens_{i,x} = 1 - \frac{1}{2} \left[1 + erf\left(\frac{d_T - \mu_i}{\sigma_i^2 \sqrt[3]{2}}\right) \right]$

$$sens_{i,x} = 1 - \frac{1}{2} \left[1 + erf\left(\frac{d_T - \mu_i}{\sigma_i \sqrt[2]{2}}\right) \right]$$

Where μ_i and σ_i are the log-mean and the log-standard deviation of the log-normal distribution of parasitaemia for disease class i ε (sub-patent, asymptomatic, clinical, severe).

Test specificity:

It has been shown that treated individuals remain positive by conventional RDT for approximately 28 days after successful clearance of asexual parasites [34-36]. An H compartment (individuals recently recovered who are not infected but test positive by RDT) has therefore been included in the model in order to simulate this. The duration of time spent in the H compartment is dependent on the sensitivity of the RDT to detect HRP2 which is assumed to be linearly correlated with its asexual parasite detection limit.

Duration in each infection class:

For severe, clinical and asymptomatic infection the duration of infection is well documented. For sub-patent infection, we assume that the duration of sub-patent infection, δ_N , can be extrapolated from the duration of infection of asymptomatic infection, δ_A , and an assumption of log-linear decline in parasitaemia using the following formula:

$$\delta_N = \delta_A \frac{\mu_N - d_0}{\mu_A - \mu_N}$$

Where μ_N is the log-mean of the log-normal distribution of parasitaemia for sub-patent infection, μ_A is the log-mean of the log-normal distribution of parasitaemia for asymptomatic infection and d_0 is the detection limit of the most sensitive test (qPCR). Using the parameters above, we would expect sub-patent infection to be detectable by qPCR for 75 days.

Force of infection and Seasonality

The force of infection on humans, λ is derived by assuming that mosquito dynamics of an SEI model are at a steady state resulting in the following:

$$\Lambda(t) = (1/\lambda(t) + 1/\gamma_h + 1/\gamma_m)^{-1}$$

$$\lambda(t) = seas(t) \frac{b^2 \epsilon_h \epsilon_m \frac{M}{P(t)} I(t)}{(b \epsilon_h \frac{M}{P(t)} + \delta_m)(\frac{\gamma_m}{\gamma_m + \delta_m})}$$

$$I(t) = \frac{\zeta_n I_n(t) + \zeta_a I_a(t) + I_c(t) + I_s(t)}{P(t)}$$

$$seas(t) = 1 + eln * a * cos(2\pi(t - \phi))$$

where eln is the Bivariate ENSO (El Niño southern oscillation) index time series standardised between 0 and 1 and smoothed with a running median to estimate effect size. (Accessible at: http://www.esrl.noaa.gov/psd/data/climateindices/).

Model Interventions

The table below summarises the impact that each of the interventions modelled has on model parameters/equations.

Intervention	Description	Model Impact				
Passive treatment	Treatment probabilities ($ au$) for					
	different avenues of treatment (v, h,	See below				
	o) dependent on coverage (cov),					
	treatment-seeking and treatment					
	effectiveness (eff) and diagnostic					
	sensitivity (sens)					
	$\tau_v = cov_v \times eff_v \times sens_v$					
_	$\tau_h = (1 - cov_v eff_v) \times eff_h \times ef$					
ι_o	$= (1 - cov_v eff_v - (1 - cov_v eff_v) eff_h$	$J \times eJ J_0 \times sens_0$				
Long Lasting	Net distribution as a proportion of	See below				
Insecticide-	the population at risk (<i>itn</i>) and the					
treated Nets	half-life of the net (<i>hlnet</i>) are used to					
	compute cumulative coverage					
	(itncov). This, together with usage					
	and ability to prevent transmission					
	(itneff) is used to decrease the					
	transmission function λ					
	$itncov_t = itn_t + 0.5itncov_{t-1}e^{-\frac{1}{2}}$	$\frac{1}{12}/(hlnet)$				
	$\lambda_t^* = (1 - itncov_t \times itneff)$	× λ.				
Indoor residual	Number of people protected by IRS	See below				
spraying	as a proportion of the population at	See Below				
opraying	risk (<i>irs</i>) and the half-life of the					
	insectide (<i>hlspray</i>) are used to					
	compute cumulative coverage					
	(irscov). This, together with ability to					
	prevent transmission (irseff) is used					
	to decrease the transmission					
	function λ					
	$irscov_t = irs_t + 0.5irscov_{t-1}e^{-\frac{1}{12}}$	-/(hlspray)				
$\lambda_t^* = (1 - irscov_t \times irseff) \times \lambda_t$						
(=						
Injectable	Switching from treatment of severe	Parameters decreased:				
artesunate	infections with quinine to injectable	1/r _Q – recovery time				
	artesunate	pmort – probability of death of				
		treated severe infections				
Seasonal Malaria	Active preventative treatment at	Parameters affected				
Chemoprevention	selected coverage levels for a	cov_smc - SMC coverage (data)				
	duration determined by the policy in	dur_smc - Duration of SMC				
	place	(data)				
	tauSMC: rate of deploying SMC					
	tauSMC: rate of deploying SMC nuSMC: rate of recovery from SMC					
	$(-\log(1-\cos SMC))$					
	$tauSMC = \frac{(\log(1 - \cos(MC)))}{1/12}$					
1/12						

nuSMC = 12/durSMC					
Intermittent Preventative Treatment for Pregnant women (IPTp)	Active preventative treatment at selected coverage levels for up to 5 doses determined by the policy in place	Parameters affected: fert rate – fertility rate (data) anc_rate - rate of attendance to Antenatal care (data) iptp_dose_i - coverage of IPTp doses			
$covIPTp = fertrate * ancrate * \sum_{i=1}^{n} iptp_dose_i$ $tauIPTp = \frac{(-\log{(1 - covIPTp)})}{12/12}$					

Model calibration and validation

The model was calibrated to monthly zonal data from the Ghana National Malaria Control Programme. Figure 2 shows the 50% uncertainty range along with the observed reported data. The model was calibrated using data from 2012 to 2017 and validated with data from 2017 for a year (after dashed line). The seasonality is captured fairly well in all three zones with the majority of data points lying within the uncertainty range in the validation set.

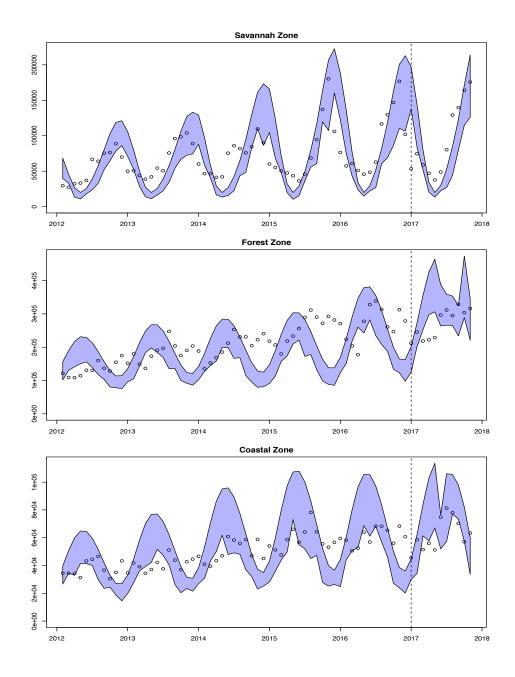


Figure 2 50% projected uncertainty range for reported cases in the three ecological zones in Ghana (blue shaded) with observed reported cases (points). The model was trained with data from 2012 to 2017 and validated with data from 2017 (dashed line).

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