Supplement file: R code

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Analysis 1

The impact of any indoor residual spraying (IRS) product will be time-dependent because the active ingredient wanes after application. A systematic review of experimental hut trial data (1) has previously assessed the entomological impacts of Actellic 300CS and SumiShield, the two IRS products used here.

Results from the systematic review (1) for either Actellic 300®CS or SumiShield data are modified given the cone bioassay data reported in our study, weighted for the proportion of houses that are constructed with either mud or cement, to estimate the probable outcomes in Matutuine and Boane districts of southern Mozambique (Actellic 300®CS (main manuscript Fig. 5C & 5D), and SumiShield® (main manuscript Fig. 5E & 5F))

A bayesian logistic growth model is fitted to the mortality, successful feeding and deterrence data observed in a systematic review. We provide the RStan model code below (full_model.stan). We then fit the same function to the cone bioassay mortality data measured in our study (log_model.stan) when sampling either mud or cement surfaces.

```
## This is the model from the systematic review fitting to
## mortality
## successful feeding
## deterrence

## full_model.stan
// bernoulli_logistic transformed data function
data {

  int<lower=1> N;                  // rows of data

  int<lower=0> n_t[N];             // Total number of mosquitoes entering IRS huts
  int<lower=0> d_t[N];             // Number mosquites dead sprayed hut
  int<lower=0> fed_t[N];           // Number of mosquitoes feeding in IRS HUTS assuming
                                   // equal feeding for dead and alive ones
  int<lower=0> deterrence_IRS[N];  // Number of mosquitoes in sprayed huts
  int<lower=0> deterrence_total[N]; //Total number of mosquitoes in both sprayed and
                                    //control huts

  vector<lower=0>[N] time;       // predictor

}

parameters {
  //Consider death. This is the proportion of mosquitoes dying (d_t) in treated huts
```

```
  //(n_t)
  real alpha1;
  real alpha2;

  //Consider feeding. This is the proportion of mosquitoes that successfully fed
  //in treatment (f_t)
  real beta1;
  real beta2;

  //Consider feeding. This is the proportion of mosquitoes that successfully fed
  //in treatment (f_t)
  real omega1;
  real omega2;

  //  vector[N_study] study_a;
  //  real<lower=0,upper=10> sigma;
}

model {
  real sp[N];
  real fp[N];
  real det[N];

  alpha1 ~ normal(0,100);
  alpha2 ~ normal(0,100);

  beta1 ~ normal(0,100);
  beta2 ~ normal(0,100);

  omega1 ~ normal(0,100);
  omega2 ~ normal(0,100);

  //  study_a ~ normal(0,sigma);

  for (n in 1:N) {
    sp[n] = alpha1  + alpha2 * time[n];
    fp[n] = beta1  + beta2 * time[n];
    det[n] = omega1  + omega2 * time[n];
  }

  d_t ~ binomial_logit(n_t, sp);
  fed_t ~ binomial_logit(n_t, fp);
  deterrence_IRS ~ binomial_logit(deterrence_total, det);
}


## This is the model adjusted here to fit to
## cone bioassay mortality in data from Southern Mozambique
## log_model.stan
// bernoulli_logistic transformed data function
data {

  int<lower=1> N;                   // rows of data
```

```
  int<lower=0> n_t[N];             // Total number of mosquitoes counted
  int<lower=0> d_t[N];             // Number mosquites killed during the test

  vector<lower=0>[N] time;         // time predictor e.g. months

  int<lower=1> N_eff;              // a random effect eg wall type / location /
                                   // mosquito species etc
  int<lower=1, upper = N_eff> eff[N];

}

parameters {
  //Consider death. This is the proportion of mosquitoes dying (d_t) of
  //all tested (n_t)
  real alpha1[N_eff];
  real alpha2[N_eff];

}

model {
  real sp[N];

  alpha1 ~ normal(0,10);
  alpha2 ~ normal(0,10);

  for (n in 1:N) {
    sp[n] = alpha1[eff[n]] + alpha2[eff[n]] * time[n];
  }

  d_t ~ binomial_logit(n_t, sp);
}

generated quantities{
  real sp_ppc[N_eff, 365];// this is to predict for 365 time points so
                          // adjust time accordingly

    for(v in 1:N_eff){
      for(t in 1:365){
        sp_ppc[v, t] = binomial_rng(365, inv_logit(alpha1[v] + alpha2[v] * t)) / 365.0;
      }
    }
}
```

We then estimate the weighted-average mortality impact on mosquitoes given the ratio of mud vs cement walls in Matutuine or Boane.

These outcomes are then combined with the systematic review to give us a method to track the waning entomological impact (on mosquito mortality, successful blood-feeding and deterrence) of the spray products over time since a household was treated.

The results are shown in Figure 5 main manuscript.

```r
####################################################################
##
## 1 Cone bioassay data from the field
##
#####################################################################

  ## Add in a line to demonstrate the residual efficacy estimated by Mercy in MOZAMBIQUE
  data_list_mud = list(N = N_data, ## number
                   d_t = Con_bio_d_t_mud,
                   n_t = Con_bio_n_t_mud,
                   time = time_sequence,
                   N_eff = 1, ## eg '2' for 2 wall types
                   eff = rep(1,N_data))##[the number of reps for each group in your data]

  data_list_cem = list(N = N_data, ## number
                       d_t = Con_bio_d_t_cem,
                       n_t = Con_bio_n_t_cem,
                       time = time_sequence,
                       N_eff = 1, ## eg '2' for 2 wall types
                       eff = rep(1,N_data))##[the number of reps for each group in your data]


  stan_model_mud <- stan(file="models/log_mod.stan",
                     data=data_list_mud,
                     warmup=500,
                     control = list(adapt_delta = 0.9,
                                    max_treedepth = 20),
                     iter=1000, chains=4)

  stan_model_cem <- stan(file="models/log_mod.stan",
                         data=data_list_cem,
                         warmup=500,
                         control = list(adapt_delta = 0.9,
                                        max_treedepth = 20),
                         iter=1000, chains=4)

  base_moz1 <- extract(stan_model_mud) ## can use this to extract the model parameter estimates
  base_moz2 <- extract(stan_model_cem) ## can use this to extract the model parameter estimates

  ## plot it against your data!
  d_t1 = Con_bio_d_t_mud
  n_t1 = Con_bio_n_t_mud
  DEAD1 = d_t1/n_t1

  d_t2 = Con_bio_d_t_cem
  n_t2 = Con_bio_n_t_cem
  DEAD2 = d_t2/n_t2

  time = seq(1,365,by=1)

  mean_prediction_mud = 1 / (1 + exp(-mean(base_moz1$alpha1[,1]) -
                                  mean(base_moz1$alpha2[,1])*time))
  max_prediction_mud = 1 / (1 + exp(-quantile(base_moz1$alpha1[,1],0.9) -
```

```
                                    quantile(base_moz1$alpha2[,1],0.9)*time))
  min_prediction_mud = 1 / (1 + exp(-quantile(base_moz1$alpha1[,1],0.1) -
                                    quantile(base_moz1$alpha2[,1],0.1)*time))

  mean_prediction_cem = 1 / (1 + exp(-mean(base_moz2$alpha1[,1]) -
                                     mean(base_moz2$alpha2[,1])*time))
  max_prediction_cem = 1 / (1 + exp(-quantile(base_moz2$alpha1[,1],0.9) -
                                    quantile(base_moz2$alpha2[,1],0.9)*time))
  min_prediction_cem = 1 / (1 + exp(-quantile(base_moz2$alpha1[,1],0.1) -
                                    quantile(base_moz2$alpha2[,1],0.1)*time))

  ## The mean prediction is weighted by the proportion of households
  ## with mud or cement walls in each village

  ## percent_mud: 40% for Matutuine, 97% for Boane
  ## percent_cem: 60% for Matutuine,  3% for Boane
  mean_prediction = (mean_prediction_mud*percent_mud) + (mean_prediction_cem*percent_cem)

  feed2 = (1 - mean_prediction) * mean_valsfp_checker4 * (1 - mean_valsdet_checker4)
  death2 = mean_prediction  * (1 - mean_valsdet_checker4)
  rep2 = (1 - (death1 + feed1)) * (1 - mean_valsdet_checker4)
  deter2 = mean_valsdet_checker4

  TOTS2 = feed2 + rep2 + death2 + deter2
```

Analysis 2

The time-dependent efficacy from LLINs is estimated similarly following (2). The successful biting (s_ITN), repeating (r_ITN), and killing (d_ITN) in the presence of LLINs also wanes with time as determined from systematic review of experimental hut data testing unwashed and washed pyrethroid treated mosquito nets (ITNs). We assume the performance of ITNs will be equivalent to nets aged 1.5 years as the mass campaign took place in 2016 - 2017 in Southern Mozambique.

```
##############################
##
## 2 Estimated impact of ITNs, from Churcher et al. 2016 (2)
##
###############################


## The following parameters are taken from (Churcher et al 2016 (2))
##
itn_half_life = 2.64

d_ITN0 <- 0.51
s_ITN0 <- 0.31
r_ITN0 <- 1-ERG_d_ITN0-ERG_s_ITN0

itn_loss = log(2)/itn_half_life

ITN_interval=3*365
```

```r
## decay in efficacy of net over time
#time=1:(365*3)
ITN_decay = exp(-(time/ITN_interval)*itn_loss)

r_ITN_min=0.24
d_ITN = ERG_d_ITN0 * ITN_decay          ## insecticide mortality rate
r_ITN = r_ITN_min + (ERG_r_ITN0 - r_ITN_min)*ITN_decay
s_ITN = 1 - d_ITN - r_ITN           ## successful protected human biting
```

Analysis 3

To quantify the impact of post-spray wall modification, prolonged spray campaigns, and IRS efficacy on IRS effectiveness, we adapt a mechanistic vector model approach determined in Le Menach 2007 (3) and Griffin et al (2010) (4) and updated in Walker et al 2016 (5). This model outlines how indoor interventions are affecting the number of mosquito bites received per person per time unit which has ramifications for the infectious mosquito bites received per person per year (the entomological inoculation rate, EIR) and malaria transmission. The probability that a blood-seeking mosquito successfully feeds will depend on the species-specific bionomics and behaviors of the mosquito (e.g. the proportion of bites taken on humans, the proportion of bites received indoors or in bed) and the vector interventions that protect the human population. In our case, in the absence of locally available mosquito bionomics data, we use an average estimate for these parameters and keep these consistent between sentinel districts

```r
## These are the Bayesian posterior draws for IRS impact
actellic_details = readRDS("data/actellic_details_v2.Rdata")
sumishield_details = readRDS("data/sumishield_details_v2.Rdata")


## We investigate impacts as per

##  1 the effect if there is no intervention
##  2 with ITNs only
##  3 with IRS only no loss in coverage
##  4 with IRS only loss in coverage
##  5 ITN + IRS no loss
##  6 ITN + IRS loss

actellic_details = readRDS("data/actellic_details_v2.Rdata")
sumishield_details = readRDS("data/sumishield_details_v2.Rdata")

time = 1:365

## see Table 3 main manuscript
## Creating arrays for
w_Acte = w_Sumi = #Probability of successful feeding
yy_Acte = yy_Sumi = #Probability of biting
z_Acte = z_Sumi = #Probability of repellence
    array(dim=c(240,4))
## for district uing Actellic (A, or Acte) or SumiShield (S or Sumi) distinctly


## Assuming mosquito bionomics are constant in each setting
PHI_B_mut = 0.85 ## probability of bites in bed
```

```r
PHI_I_mut = 0.90 ## probability of bites indoors

PHI_B_boa = 0.85 ## probability of bites in bed
PHI_I_boa = 0.9 ## probability of bites indoors

k0 = 0.699 #probability of feeding in the absence of an intervention (Griffin et al. 2010 (4))
ksA = actellic_details[[2]]
lsA = actellic_details[[3]]
jsA = 1 - actellic_details[[2]] - actellic_details[[3]]

s_IRS_Acte = ksA/k0 ##feed2
r_IRS_Acte = (1 - ksA/k0)*(jsA/(lsA+jsA)) ##rep2

ksS = sumishield_details[[2]]
lsS = sumishield_details[[3]]
jsS = 1 - sumishield_details[[2]] - sumishield_details[[3]]

s_IRS_Sumi = ksS/k0 ##feed2
r_IRS_Sumi = (1 - ksS/k0)*(jsS/(lsS+jsS)) ##rep2

## Probability that a mosquito bites and survives in the presence of indoor vector control
w_Acte[,1] = w_Sumi[,1] = rep(1,240)
for(i in 1:240){
  PHI_B = PHI_B_mut
  PHI_I = PHI_I_mut

  ## probability of surviving biting given that there is ITN
  w_Acte[i,2] = 1 - PHI_B + PHI_B*s_ITN[i+547]

  ## probability of surviving biting given that there is IRS
  w_Acte[i,3] = 1 - PHI_I + PHI_I*(1-r_IRS_Acte[i])*s_IRS_Acte[i]

  ## probability of surviving biting given that there is ITN & IRS
  w_Acte[i,4] = 1 - PHI_I + PHI_B*(1-r_IRS_Acte[i])*s_ITN[i+547]*s_IRS_Acte[i] +
    (PHI_I - PHI_B)*(1-r_IRS_Acte[i])*s_IRS_Acte[i]
}

for(i in 1:240){
  PHI_B = PHI_B_boa
  PHI_I = PHI_I_boa

  ## probability of surviving biting given that there is ITN
  w_Sumi[i,2] = 1 - PHI_B + PHI_B*s_ITN[i+547]

  ## probability of surviving biting given that there is IRS
  w_Sumi[i,3] = 1 - PHI_I + PHI_I*(1-r_IRS_Sumi[i])*s_IRS_Sumi[i]

  ## probability of surviving biting given that there is ITN & IRS
  w_Sumi[i,4] = 1 - PHI_I + PHI_B*(1-r_IRS_Sumi[i])*s_ITN[i+547]*s_IRS_Sumi[i] +
    (PHI_I - PHI_B)*(1-r_IRS_Sumi[i])*s_IRS_Sumi[i]

}
```

```r
## Probability of any bite (if there is IRS, a mosquito may bite and then die immediately afterwards)
yy_Acte[,1] = w_Acte[,1]
yy_Acte[,2] = w_Acte[,2]

yy_Sumi[,1] = w_Sumi[,1]
yy_Sumi[,2] = w_Sumi[,2]

for(i in 1:240){
  PHI_B = PHI_B_mut
  PHI_I = PHI_I_mut
  yy_Acte[i,3] = 1 - PHI_I + PHI_I*(1-r_IRS_Acte[i])
  yy_Acte[i,4] = 1 - PHI_I + PHI_B*(1-r_IRS_Acte[i])*s_ITN[i+547] + (PHI_I - PHI_B)*(1-r_IRS_Acte[i])
}
for(i in 1:240){
  PHI_B = PHI_B_boa
  PHI_I = PHI_I_boa
  yy_Sumi[i,3] = 1 - PHI_I + PHI_I*(1-r_IRS_Sumi[i])
  yy_Sumi[i,4] = 1 - PHI_I + PHI_B*(1-r_IRS_Sumi[i])*s_ITN[i+547] + (PHI_I - PHI_B)*(1-r_IRS_Sumi[i])

}

## Probability repelled
z_Acte[,1] = 0
z_Sumi[,1] = 0

for(i in 1:240){
  z_Acte[i,2] = PHI_B*r_ITN[i+547]
  z_Acte[i,3] = PHI_I*r_IRS_Acte[i]
  z_Acte[i,4] = PHI_B*(r_IRS_Acte[i] + (1-r_IRS_Acte[i])*r_ITN[i+547]) + (PHI_I - PHI_B)*r_IRS_Acte[i]

  z_Sumi[i,2] = PHI_B*r_ITN[i+547]
  z_Sumi[i,3] = PHI_I*r_IRS_Sumi[i]
  z_Sumi[i,4] = PHI_B*(r_IRS_Sumi[i] + (1-r_IRS_Sumi[i])*r_ITN[i+547]) + (PHI_I - PHI_B)*r_IRS_Sumi[i]

}


## waning usage of IRS with time
## from Table 1 main manuscript
prop_mod_Acte = 1 -  c(rep(0,10), ## august &  & oct
                       rep(14/129,4), ## nov
                       rep(14/129,4)+rep((12+7)/(117+88),4), ## dec
                       rep(14/129,4)+rep((12+7)/(117+88),4)+rep((20+10+4)/(117+86+27),4), ## jan
                       rep(14/129,4)+rep((12+7)/(117+88),4)+rep((20+10+4)/(117+86+27),4)+
                         rep((20+10+3)/(116+85+25),4), ## feb
                       rep(14/129,4)+rep((12+7)/(117+88),4)+rep((20+10+4)/(117+86+27),4)+
                         rep((20+10+3)/(116+85+25),4)+rep((12+7+1)/(115+85+25),4), ## mar
                       rep(14/129,4)+rep((12+7)/(117+88),4)+rep((20+10+4)/(117+86+27),4)+
                         rep((20+10+3)/(116+85+25),4)+rep((12+7+1)/(115+85+25),4)+
                         rep((16+6+1)/(84+25),4), ## apr
                       rep(14/129,4)+rep((12+7)/(117+88),4)+rep((20+10+4)/(117+86+27),4)+
                         rep((20+10+3)/(116+85+25),4)+rep((12+7+1)/(115+85+25),4)+
                         rep((16+6+1)/(84+25),4)+rep((4+1)/(81+25),4)) ## may
```

```
prop_mod_Acte


true_cover_irs_Acte =  rep(prop_mod_Acte*prop_houses_sprayed_WeeklyM,each=7)

#House coverage: Matutuine district 96 %
irs_cov_no_loss_Acte = rep(0.96,30*8)
irs_cov_Acte = rep(prop_mod_Acte*0.96,each=7)

prop_mod_Sumi = 1 - c(rep(0,10),##aug & sep & oct
                      rep(4/153,4),#nov
                      rep(4/153,4)+rep((4+4)/(144+113),4),#dec
                      rep(4/153,4)+rep((4+4)/(144+113),4)+rep((2+0+3)/(141+89+76),4),#jan
                      rep(4/153,4)+rep((4+4)/(144+113),4)+rep((2+0+3)/(141+89+76),4)+
                        rep((2+1)/(138+88+75),4),#feb
                      rep(4/153,4)+rep((4+4)/(144+113),4)+rep((2+0+3)/(141+89+76),4)+
                        rep((2+1)/(138+88+75),4)+rep((2+1)/(137+86+75),4),#mar
                      rep(4/153,4)+rep((4+4)/(144+113),4)+rep((2+0+3)/(141+89+76),4)+
                        rep((2+1)/(138+88+75),4)+rep((2+1)/(137+86+75),4)+rep(0,8)#apr-may
)


true_cover_irs_Sumi = rep(prop_mod_Sumi*prop_houses_sprayed_WeeklyB,each=7)

#House coverage: Boane district 97 %
irs_cov_Sumi = rep(prop_mod_Sumi*0.97,each=7)

## Figure 3A
plot(irs_cov_no_loss_Acte[61:240] ~ time[61:240],ylab = "Community IRS cover (%)",
     ylim=c(0,1),col="black",pch="",
     main = "",cex.main=1.2,xlim=c(1,240),xaxt="n",
     xlab="Time in months",yaxt="n",cex.lab=1.4,cex.axis=1.4,cex=1.4)
axis(2,las=2,at=seq(0,1,0.2),labels=seq(0,100,20),cex.lab=1.4,cex.axis=1.4)
axis(1,at=seq(0,230,30)+15,
     labels = c("Sep","Oct","Nov","Dec","Jan","Feb","Mar","Apr"),cex.axis = 1.4)

lines(irs_cov_no_loss_Acte[61:240] ~ time[61:240],lty=1,lwd=2,col = "darkblue") ## IRS only no loss
lines(irs_cov_Acte[61:240] ~ time[61:240],lty=3,lwd=2,col = "darkblue") ## IRS with loss

lines(irs_cov_no_loss_Sumi[61:240] ~ c(time[61:240]+1),lty=1,lwd=2,col = "aquamarine3")
lines(irs_cov_Sumi[61:240] ~ time[61:240],lty=3,lwd=2,col = "aquamarine3")

legend("bottomleft",
       legend = c("Matutuine","Boane","IRS cover, no loss", "IRS cover, observed loss"),
       col = c("darkblue","aquamarine3","black","black"),lwd = 2, lty=c(NA,NA,1,3),
       pch=c(15,15,NA,NA),cex=1.2,bty="n")


## Define the net use estimates
cov1A = cov1S = cov2A = cov2S = array(dim=c(240,4))

## Table 1 data
matu_net_cov = c(27.9,  ## nov
```

```r
                 mean(c(32.6,42.1)), ##dec
                 mean(c(43.4,43.2,33.3)),##jan
                 mean(c(55.0,44.3,48.2)),##feb
                 mean(c(61.2,56.8,40.7)),##mar
                 mean(c(51.9,61.4,66.7)),##apr
                 mean(c(48.9,55.6)),##may
                 29.6)##june

itn_cov_Acte_temp = c(rep(mean(c(matu_net_cov)),10),
                      rep(mean(c(32.6,42.1)),4), ##dec
                      rep(mean(c(43.4,43.2,33.3)),4),##jan
                      rep(mean(c(55.0,44.3,48.2)),4),##feb
                      rep(mean(c(61.2,56.8,40.7)),4),##mar
                      rep(mean(c(51.9,61.4,66.7)),4),##apr
                      rep(mean(c(48.9,55.6)),4),##may
                      rep(29.6,4))##june



boan_net_cov = c(57.5,  ## nov
                 mean(c(64.6,74.5)), ##dec
                 mean(c(68.1,71.9,67.1)),##jan
                 mean(c(62.8,71.2,79)),##feb
                 mean(c(70.8,82.4,86.8)),##mar
                 mean(c(65.5,81.8,81.6)),##apr
                 mean(c(78.4,84.2)),##may
                 10.5)##june

itn_cov_Boan_temp = c(rep(mean(c(boan_net_cov)),10),
                      rep(mean(c(64.6,74.5)),4), ##dec
                      rep(mean(c(68.1,71.9,67.1)),4),##jan
                      rep(mean(c(62.8,71.2,79)),4),##feb
                      rep(mean(c(70.8,82.4,86.8)),4),##mar
                      rep(mean(c(65.5,81.8,81.6)),4),##apr
                      rep(mean(c(78.4,84.2)),4),##may
                      rep(10.5,4))

itn_cov_Acte = rep(itn_cov_Acte_temp,each=7)/100
itn_cov_Sumi = rep(itn_cov_Boan_temp,each=7)/100

## Here we are creating a matrix
## with the coverage or use of nets waning with time
## and the coverage of IRS either staying fixed, or also waning
## when walls are washed
cov1A[,1] = 1
cov1A[,2] = itn_cov_Acte[1:240] ## ITN only
cov1A[,3] = irs_cov_no_loss_Acte ## IRS only
cov1A[,4] = itn_cov_Acte[1:240]*irs_cov_no_loss_Acte ## both interventions

cov2A[,1] = 1
cov2A[,2] = itn_cov_Acte[1:240] ## ITN only
cov2A[,3] = irs_cov_Acte[1:240] ## IRS only
cov2A[,4] = itn_cov_Acte[1:240]*irs_cov_Acte[1:240]## both interventions
```

```r
cov1S[,1] = 1
cov1S[,2] = itn_cov_Sumi[1:240] ## ITN only
cov1S[,3] = irs_cov_no_loss_Sumi ## IRS only
cov1S[,4] = itn_cov_Sumi[1:240]*irs_cov_no_loss_Sumi ## both interventions

cov2S[,1] = 1
cov2S[,2] = itn_cov_Sumi[1:240] ## ITN only
cov2S[,3] = irs_cov_Sumi[1:240] ## IRS only
cov2S[,4] = itn_cov_Sumi[1:240]*irs_cov_Sumi[1:240] ## both interventions


## Table 2
## Entomological model parameters to estimate

Q0 = 0.92  ## this is anthropophagy - we can use human blood index
chi = 0.86 ## this is endophily (pi_i)

fv0 = 0.333 ## biting rate 1 bite every 3 days
tau1 = 0.69 ## duration of host seeking, assumed to be constant between species (delta_10, altered to d
tau2 = 1/fv0-tau1  ## indoor feeding endophagy (delta_2)
av0 = Q0*fv0
mu0 = 0.132 ## background mortality from external sources
p10 = exp(-mu0*tau1) ##
p2 = exp(-mu0*tau2)  ## probability of surviving resting period in absence of intervntion


## These are the adjusted w, z, when coverage is changing
## so these are the intervention coverages
zhi1A = whi1A = zhi2A = whi2A = array(dim=c(240,4))
zhi1S = whi1S = zhi2S = whi2S = array(dim=c(240,4))
zhi1A=cov1A*z_Acte[1:240,]
whi1A=cov1A*w_Acte[1:240,]

zhi1S=cov1S*z_Sumi[1:240,]
whi1S=cov1S*w_Sumi[1:240,]


zhi2A=cov2A*z_Acte[1:240,]
whi2A=cov2A*w_Acte[1:240,]

zhi2S=cov2S*z_Sumi[1:240,]
whi2S=cov2S*w_Sumi[1:240,]


zbar1A = wbar1A = zbar2A = wbar2A = array(dim=c(240,4))
zbar1S = wbar1S = zbar2S = wbar2S = array(dim=c(240,4))
for(i in 1:4){
  zbar1A[,i] = Q0*zhi1A[,i]
  wbar1A[,i] = (1 - Q0) + Q0*whi1A[,i]
  zbar2A[,i] = Q0*zhi2A[,i]
  wbar2A[,i] = (1 - Q0) + Q0*whi2A[,i]

  zbar1S[,i] = Q0*zhi1S[,i]
```

```r
  wbar1S[,i] = (1 - Q0) + Q0*whi1S[,i]
  zbar2S[,i] = Q0*zhi2S[,i]
  wbar2S[,i] = (1 - Q0) + Q0*whi2S[,i]
}

## From Walker et al 2016 (5)
## Mosquito feeding rate (tau1 is delta10, tau2 is delta2 in the methods)
fR1A = 1 / ((tau1/(1 - zbar1A)) + tau2)
mu1A = -fR1A*log((wbar1A*p10/(1 - zbar1A*p10))*p2)
Q1A = 1 - (1-Q0)/wbar1A

fR2A = 1 / ((tau1/(1 - zbar2A)) + tau2)
mu2A = -fR2A*log((wbar2A*p10/(1 - zbar2A*p10))*p2)
Q2A = 1 - (1-Q0)/wbar2A


fR1S = 1 / ((tau1/(1 - zbar1S)) + tau2)
mu1S = -fR1S*log((wbar1S*p10/(1 - zbar1S*p10))*p2)
Q1S = 1 - (1-Q0)/wbar1S

fR2S = 1 / ((tau1/(1 - zbar2S)) + tau2)
mu2S = -fR2S*log((wbar2S*p10/(1 - zbar2S*p10))*p2)
Q2S = 1 - (1-Q0)/wbar2S


## Rate at which a person in the popn is bitten by mosquitoes is
lambda1A = lambda2A = array(dim = c(240,4))
lambda1S = lambda2S = array(dim = c(240,4))
for(i in 1:4){
  lambda1A = (Q1A*fR1A*yy_Acte[,i])/whi1A[,i]
  lambda2A = (Q2A*fR2A*yy_Acte[,i])/whi2A[,i]

  lambda1S = (Q1S*fR1S*yy_Sumi[,i])/whi1S[,i]
  lambda2S = (Q2S*fR2S*yy_Sumi[,i])/whi2S[,i]
}



## Actually we want to look at the comparison so:
## Figure 3B main manuscript
plot(lambda1A[61:240,1] ~ time[61:240],ylim=c(0,2.5),pch="",
     ylab = "Mosquito bites received per person per day",
     col="black",
     main = "",cex.main=1.2,xlim=c(1,240),xaxt="n",
     xlab="Time in months",yaxt="n",cex.lab=1.4,cex.axis=1.4,cex=1.4)
axis(2,las=2,at=seq(0,2.5,0.5),cex.lab=1.4,cex.axis=1.4)
axis(1,at=seq(0,230,30)+15,labels = c("Sep","Oct","Nov","Dec","Jan","Feb","Mar","Apr"),cex.axis = 1.4)

for(i in 4){
  lines(lambda1A[61:235,i] ~ time[61:235],col="darkblue",lty=2,lwd=2) ## Nets and IRS no loss
  lines(lambda2A[61:235,i] ~ time[61:235],col="darkblue",lty=4,lwd=2) ## Nets and IRS with loss

  lines(lambda1S[61:235,i] ~ time[61:235],col="aquamarine3",lty=2,lwd=2)
```

```
  lines(lambda2S[61:235,i] ~ time[61:235],col="aquamarine3",lty=4,lwd=2)

}
for(i in 3){
  lines(lambda1A[61:235,i] ~ time[61:235],col="darkblue",lty=1,lwd=1) ## IRS only no loss
  lines(lambda2A[61:235,i] ~ time[61:235],col="darkblue",lty=3,lwd=1) ## IRS only with loss

  lines(lambda1S[61:235,i] ~ time[61:235],col="aquamarine3",lty=1,lwd=1)
  lines(lambda2S[61:235,i] ~ time[61:235],col="aquamarine3",lty=3,lwd=1)

}


legend("topleft",legend = c("Matutuine (ITN use)",
                            "Boane (ITN use)",
                            "IRS no modification, no ITN",
                            "IRS with household modification, no ITN",
                            "IRS no modification, with ITN use",
                            "IRS with household modification, with ITN use"),
       col = c("darkblue","aquamarine3","black","black","black","black"),
       lwd = 1,pch=c(15,15,NA,NA,NA,NA),
       lty=c(NA,NA,1,3,2,4),cex=1.2,bty="n")

## Additional infectious bites per person per year
Estimated_added_EIR = array(dim=c(240,2))
Estimated_added_EIR[,1] = (lambda2A[,4] - lambda1A[,4])
Estimated_added_EIR[,2] = (lambda2S[,4] - lambda1S[,4])

## Additional infectious bites per person per year
Estimated_propn_increase_EIR = array(dim=c(240,2))
Estimated_propn_increase_EIR[,1] = (lambda2A[,4] - lambda1A[,4])/lambda2A[,4]
Estimated_propn_increase_EIR[,2] = (lambda2S[,4] - lambda1S[,4])/lambda2S[,4]

mean(Estimated_propn_increase_EIR[15:45,1])##sep
mean(Estimated_propn_increase_EIR[46:75,1])##oct
mean(Estimated_propn_increase_EIR[76:105,1])##nov
mean(Estimated_propn_increase_EIR[106:135,1])##dec
mean(Estimated_propn_increase_EIR[136:165,1])##jan
mean(Estimated_propn_increase_EIR[166:195,1])##feb
mean(Estimated_propn_increase_EIR[196:225,1])##mar
mean(Estimated_propn_increase_EIR[226:240,1])##part april

mean(Estimated_propn_increase_EIR[15:45,2])##sep
mean(Estimated_propn_increase_EIR[46:75,2])##oct
mean(Estimated_propn_increase_EIR[76:105,2])##nov
mean(Estimated_propn_increase_EIR[106:135,2])##dec
mean(Estimated_propn_increase_EIR[136:165,2])##jan
mean(Estimated_propn_increase_EIR[166:195,2])##feb
mean(Estimated_propn_increase_EIR[196:225,2])##mar
mean(Estimated_propn_increase_EIR[226:240,2])##part april

## Figure 3C main manuscript
plot(Estimated_propn_increase_EIR[61:240,1] ~ time[61:240],ylim=c(0,1),pch="",
```

```r
     ylab = "",
     col="black",
     main = "",cex.main=1.2,xlim=c(1,240),xaxt="n",
     xlab="Time in months",yaxt="n",cex.lab=1.4,cex.axis=1.4,cex=1.4)
mtext(side=2, line =4,
      "Relative increase in daily bites ")
mtext(side=2, line =2.7, "due to modifications (%)")
axis(2,las=2,at=seq(0,1,0.2),label=seq(0,100,20),cex.lab=1.4,cex.axis=1.4)

axis(1,at=seq(0,230,30)+15,labels = c("Sep","Oct","Nov","Dec","Jan","Feb","Mar","Apr"),cex.axis = 1.4)

colsd = c("darkblue","aquamarine3")
for(i in 1:2){
  lines(Estimated_propn_increase_EIR[61:240,i] ~ time[61:240],col=colsd[i],lty=2,lwd=2)
}


Estimated_added_EIR = array(dim=c(240,2))
Estimated_added_EIR[,1] = (lambda2A[,3] - lambda1A[,3])
Estimated_added_EIR[,2] = (lambda2S[,3] - lambda1S[,3])

## Additional infectious bites per person per year
Estimated_propn_increase_EIR = array(dim=c(240,2))
Estimated_propn_increase_EIR[,1] = (lambda2A[,3] - lambda1A[,3])/lambda2A[,3]
Estimated_propn_increase_EIR[,2] = (lambda2S[,3] - lambda1S[,3])/lambda2S[,3]

for(i in 1:2){
  lines(Estimated_propn_increase_EIR[61:240,i] ~ time[61:240],col=colsd[i],lty=1,lwd=1)
}


legend("topleft",legend = c("Matutuine (assuming no ITN)","Boane (assuming no ITN)",
                            "Matutuine (ITN use)","Boane (ITN use)"),
       col = c("darkblue","aquamarine3","darkblue","aquamarine3"),lwd = c(2,2,1,1), lty=c(1,1,2,2),cex=



####################################
##
##   Work out the probability
##   whilst considering the prolonged nature of IRS campaigns
##
####################################################

## Campaigns tend to take up to a few months to complete
## We assume the ratio of houses monitored per start month
## reflects the proportion of houses covered by the spray campaign
## in that month

## Again we set up the relevant arrays
w_Acte1 = yy_Acte1 = z_Acte1 = w_Sumi1 = yy_Sumi1 = z_Sumi1 = array(dim=c(365,18,4))

#############################
```

```r
##

## Data from NMCP on the weekly accumulated coverage for IRS campaigns
prop_houses_sprayed_WeeklyB = 0.97*c(0, 0.027219794,    ## August
                                0.077014558,    0.136261919,    0.196901742,    0.250817066, ## Sept
                                0.301047746,    0.347687015,    0.395348206,    0.464541108, ## Oct
                                0.521818166,    0.581372602,    0.643327061,    0.710948828, ## Nov
                                0.777620537,    0.847130239,    0.911498024,    0.930365931, ## Dec
                                0.947042313,    0.96389906, 0.983400068,    0.991357264,     ## Jan
                                0.99238783, 1) ## Feb
prop_houses_sprayed_WeeklyM = 0.96*c(0.065358837,   0.193716785,## August
                                0.334444596,    0.432141444,    0.533708885,    0.614060416,##sep
                                0.667531537,    0.711462198,    0.769981823,    0.880751007,##oct
                                0.919045204,    0.944027976,    0.97443187, 0.990922736,  ##nov
                                0.991873307,    0.99744169,  1,             1,          ##dec
                                1,        1) ## jan

ksA = lsA = jsA = array(dim=c(365,18))
for(w in 1:17){
  ksA[,1] =  actellic_details[[2]][1:365]
  ksA[,w+1] = c(rep(k0,w*7),actellic_details[[2]][1:(365-7*w)])

  lsA[,1] = actellic_details[[3]]
  lsA[,w+1] = c(rep(0,w*7),actellic_details[[3]][1:(365-7*w)])

  jsA[,w] = 1 - ksA[,w] - lsA[,w]

}
jsA[,18] = 1 - ksA[,18] - lsA[,18]


s_IRS_Acte1 = r_IRS_Acte1 = array(dim=c(365,18))
for(w in 1:18){
  s_IRS_Acte1[,w] = ksA[,w]/k0 ##feed2 = when IRS is implemented in month 1 (Nov)
  r_IRS_Acte1[,w] = (1 - ksA[,w]/k0)*(jsA[,w]/(lsA[,w]+jsA[,w])) ##rep2

}


ksS = lsS = jsS = array(dim=c(365,18))
for(w in 1:17){
  ksS[,1] =  sumishield_details[[2]][1:365]
  ksS[,w+1] = c(rep(k0,w*7),sumishield_details[[2]][1:(365-7*w)])

  lsS[,1] = sumishield_details[[3]]
  lsS[,w+1] = c(rep(0,w*7),sumishield_details[[3]][1:(365-7*w)])

  jsS[,w] = 1 - ksS[,w] - lsS[,w]

}
jsS[,18] = 1 - ksS[,18] - lsS[,18]
```

```r
s_IRS_Sumi1 = r_IRS_Sumi1 = array(dim=c(365,18))
for(w in 1:18){
  s_IRS_Sumi1[,w] = ksS[,w]/k0 ##feed2 = when IRS is implemented in month 1 (Nov)
  r_IRS_Sumi1[,w] = (1 - ksS[,w]/k0)*(jsS[,w]/(lsS[,w]+jsS[,w])) ##rep2

}

w_Acte1[,,1] = w_Sumi1[,,1] = rep(1,365)
## Probability that a mosquito bites and survives in the presence of indoor vector control
for(j in 1:18){
  for(i in 1:365){
    PHI_B = 0.85
    PHI_I = 0.9

    ## probability of surviving biting given that there is ITN
    w_Acte1[i,j,2] = 1 - PHI_B + PHI_B*s_ITN[i+547]
    w_Sumi1[i,j,2] = 1 - PHI_B + PHI_B*s_ITN[i+547]

    ##          probability of surviving biting given that there is IRS
    w_Acte1[i,j,3] = 1 - PHI_I + PHI_I*(1-r_IRS_Acte1[i,j])*s_IRS_Acte1[i,j]
    w_Sumi1[i,j,3] = 1 - PHI_I + PHI_I*(1-r_IRS_Sumi1[i,j])*s_IRS_Sumi1[i,j]

    ## probability of surviving biting given that there is ITN & IRS
    w_Acte1[i,j,4] = 1 - PHI_I + PHI_B*(1-r_IRS_Acte1[i,j])*s_ITN[i+547]*s_IRS_Acte1[i,j] +
      (PHI_I - PHI_B)*(1-r_IRS_Acte1[i,j])*s_IRS_Acte1[i,j]

    w_Sumi1[i,j,4] = 1 - PHI_I + PHI_B*(1-r_IRS_Sumi1[i,j])*s_ITN[i+547]*s_IRS_Sumi1[i,j] +
      (PHI_I - PHI_B)*(1-r_IRS_Sumi1[i,j])*s_IRS_Sumi1[i,j]

  }

}

## work out the actual cover each week
prop_this_weekM = c(prop_houses_sprayed_WeeklyM[1],diff(prop_houses_sprayed_WeeklyM)[1:17])
prop_this_weekB = c(prop_houses_sprayed_WeeklyB[1],diff(prop_houses_sprayed_WeeklyB)[1:17])

w_Acte = yy_Acte = z_Acte = w_Sumi = yy_Sumi = z_Sumi = array(dim=c(365,4) )

for(i in 1:365){
  w_Acte[i,1] = sum(w_Acte1[i,,1] * prop_this_weekM)
  w_Acte[i,2] = sum(w_Acte1[i,,2] * prop_this_weekM)
  w_Acte[i,3] = sum(w_Acte1[i,,3] * prop_this_weekM)
  w_Acte[i,4] = sum(w_Acte1[i,,4] * prop_this_weekM)

  w_Sumi[i,1] = sum(w_Sumi1[i,,1] * prop_this_weekB)
  w_Sumi[i,2] = sum(w_Sumi1[i,,2] * prop_this_weekB)
  w_Sumi[i,3] = sum(w_Sumi1[i,,3] * prop_this_weekB)
  w_Sumi[i,4] = sum(w_Sumi1[i,,4] * prop_this_weekB)
}


## Probability of any bite (if there is IRS, a mosquito may bite and
```

```
## then die immediately afterwards)
yy_Acte[,1] = w_Acte[,1]
yy_Acte[,2] = w_Acte[,2]

for(j in 1:18){
  for(i in 1:365){
    PHI_B = 0.85
    PHI_I = 0.9
    yy_Acte1[i,j,3] = 1 - PHI_I + PHI_I*(1-r_IRS_Acte1[i,j])
    yy_Acte1[i,j,4] = 1 - PHI_I + PHI_B*(1-r_IRS_Acte1[i,j])*s_ITN[i+547] +
      (PHI_I - PHI_B)*(1-r_IRS_Acte1[i,j])

    yy_Sumi1[i,j,3] = 1 - PHI_I + PHI_I*(1-r_IRS_Sumi1[i,j])
    yy_Sumi1[i,j,4] = 1 - PHI_I + PHI_B*(1-r_IRS_Sumi1[i,j])*s_ITN[i+547] +
      (PHI_I - PHI_B)*(1-r_IRS_Sumi1[i,j])
  }
}


for(i in 1:365){
  yy_Acte[i,3] = sum(yy_Acte1[i,,3] * prop_this_weekM)
  yy_Acte[i,4] = sum(yy_Acte1[i,,4] * prop_this_weekM)

  yy_Sumi[i,3] = sum(yy_Sumi1[i,,3] * prop_this_weekB)
  yy_Sumi[i,4] = sum(yy_Sumi1[i,,4] * prop_this_weekB)
}

z_Acte[,1] = 0
z_Sumi[,1] = 0

for(j in 1:18){
  for(i in 1:365){
    z_Acte1[i,j,2] = PHI_B*r_ITN[i+547]
    z_Acte1[i,j,3] = PHI_I*r_IRS_Acte1[i,j]
    z_Acte1[i,j,4] = PHI_B*(r_IRS_Acte1[i,j] + (1-r_IRS_Acte1[i,j])*r_ITN[i+547]) +
      (PHI_I - PHI_B)*r_IRS_Acte1[i,j]

    z_Sumi1[i,j,2] = PHI_B*r_ITN[i+547]
    z_Sumi1[i,j,3] = PHI_I*r_IRS_Sumi1[i,j]
    z_Sumi1[i,j,4] = PHI_B*(r_IRS_Sumi1[i,j] + (1-r_IRS_Sumi1[i,j])*r_ITN[i+547]) +
      (PHI_I - PHI_B)*r_IRS_Sumi1[i,j]

  }
}

for(i in 1:365){
  z_Acte[i,2] = sum(z_Acte1[i,,3] * prop_this_weekM)
  z_Acte[i,3] = sum(z_Acte1[i,,3] * prop_this_weekM)
  z_Acte[i,4] = sum(z_Acte1[i,,4] * prop_this_weekM)

  z_Sumi[i,2] = sum(z_Sumi1[i,,3] * prop_this_weekB)
  z_Sumi[i,3] = sum(z_Sumi1[i,,3] * prop_this_weekB)
  z_Sumi[i,4] = sum(z_Sumi1[i,,4] * prop_this_weekB)
```

```
}



## waning usage of IRS with time
## as well as altered cover over time from 3 month time line of campaign
## Data from the NMCP
prop_houses_sprayed_WeeklyB = 0.97*c(0, 0.027219794,    ## August
                               0.077014558,    0.136261919,    0.196901742,    0.250817066, ## Sept
                               0.301047746,    0.347687015,    0.395348206,    0.464541108, ## Oct
                               0.521818166,    0.581372602,    0.643327061,    0.710948828, ## Nov
                               0.777620537,    0.847130239,    0.911498024,    0.930365931, ## Dec
                               0.947042313,    0.96389906, 0.983400068,    0.991357264,     ## Jan
                               0.99238783, 1,1,1,## Feb
                               rep(1,12)## mar-may
                               )
prop_houses_sprayed_WeeklyM = 0.96*c(0.065358837,   0.193716785,## August
                               0.334444596,    0.432141444,    0.533708885,    0.614060416,##sep
                               0.667531537,    0.711462198,    0.769981823,    0.880751007,##oct
                               0.919045204,    0.944027976,    0.97443187, 0.990922736,  ##nov
                               0.991873307,    0.99744169,  1,             1,          ##dec
                               1,        1,1,1,## jan
                               rep(1,16)) ## feb-may



## from Table 1 main manuscript
prop_mod_Acte = 1 -  c(rep(0,10), ## august &  & oct
                 rep(14/129,4), ## nov
                 rep(14/129,4)+rep((12+7)/(117+88),4), ## dec
                 rep(14/129,4)+rep((12+7)/(117+88),4)+rep((20+10+4)/(117+86+27),4), ## jan
                 rep(14/129,4)+rep((12+7)/(117+88),4)+rep((20+10+4)/(117+86+27),4)+
                   rep((20+10+3)/(116+85+25),4), ## feb
                 rep(14/129,4)+rep((12+7)/(117+88),4)+rep((20+10+4)/(117+86+27),4)+
                   rep((20+10+3)/(116+85+25),4)+rep((12+7+1)/(115+85+25),4), ## mar
                 rep(14/129,4)+rep((12+7)/(117+88),4)+rep((20+10+4)/(117+86+27),4)+
                   rep((20+10+3)/(116+85+25),4)+rep((12+7+1)/(115+85+25),4)+
                   rep((16+6+1)/(84+25),4), ## apr
                 rep(14/129,4)+rep((12+7)/(117+88),4)+rep((20+10+4)/(117+86+27),4)+
                   rep((20+10+3)/(116+85+25),4)+rep((12+7+1)/(115+85+25),4)+
                   rep((16+6+1)/(84+25),4)+rep((4+1)/(81+25),4)) ## may

prop_mod_Acte


true_cover_irs_Acte =  rep(prop_mod_Acte*prop_houses_sprayed_WeeklyM,each=7)

#House coverage: Matutuine district 96 %
irs_cov_no_loss_Acte = rep(0.96,30*8)
irs_cov_Acte = true_cover_irs_Acte

prop_mod_Sumi = 1 - c(rep(0,10),##aug & sep & oct
                      rep(4/153,4),#nov
```

```
                          rep(4/153,4)+rep((4+4)/(144+113),4),#dec
                          rep(4/153,4)+rep((4+4)/(144+113),4)+rep((2+0+3)/(141+89+76),4),#jan
                          rep(4/153,4)+rep((4+4)/(144+113),4)+rep((2+0+3)/(141+89+76),4)+
                            rep((2+1)/(138+88+75),4),#feb
                          rep(4/153,4)+rep((4+4)/(144+113),4)+rep((2+0+3)/(141+89+76),4)+
                            rep((2+1)/(138+88+75),4)+rep((2+1)/(137+86+75),4),#mar
                          rep(4/153,4)+rep((4+4)/(144+113),4)+rep((2+0+3)/(141+89+76),4)+
                            rep((2+1)/(138+88+75),4)+rep((2+1)/(137+86+75),4)+rep(0,8)#apr-may
)
true_cover_irs_Sumi = rep(prop_mod_Sumi*prop_houses_sprayed_WeeklyB,each=7)

#House coverage: Boane (sumi) district 97 %, Manhica district (Palmeira) 98 %
irs_cov_no_loss_Sumi = rep(0.97,30*8)
irs_cov_Sumi = true_cover_irs_Sumi

## Figure 3D main manuscript
plot(irs_cov_no_loss_Acte[1:240] ~ time[1:240],ylab = "Community IRS cover (%)",
     ylim=c(0,1),col="black",pch="",
     main = "",cex.main=1.2,xlim=c(1,240),xaxt="n",
     xlab="Time in months",yaxt="n",cex.lab=1.4,cex.axis=1.4,cex=1.4)
axis(2,las=2,at=seq(0,1,0.2),labels=seq(0,100,20),cex.lab=1.4,cex.axis=1.4)
axis(1,at=seq(0,230,30)+15,labels = c("Sep","Oct","Nov","Dec","Jan","Feb","Mar","Apr"),cex.axis = 1.4)


lines(irs_cov_no_loss_Acte[1:240] ~ time[1:240],lty=1,lwd=2,col = "darkblue")
lines(irs_cov_Acte[1:240] ~ time[1:240],lty=3,lwd=2,col = "darkblue")

lines(irs_cov_no_loss_Sumi[1:240] ~ c(time[1:240]+1),lty=1,lwd=2,col = "aquamarine3")
lines(irs_cov_Sumi[1:240] ~ time[1:240],lty=3,lwd=2,col = "aquamarine3")

cov1A = cov1S = cov2A = cov2S = array(dim=c(240,4))

## Table 1 data
matu_net_cov = c(27.9,  ## nov
                 mean(c(32.6,42.1)), ##dec
                 mean(c(43.4,43.2,33.3)),##jan
                 mean(c(55.0,44.3,48.2)),##feb
                 mean(c(61.2,56.8,40.7)),##mar
                 mean(c(51.9,61.4,66.7)),##apr
                 mean(c(48.9,55.6)),##may
                 29.6)##june

itn_cov_Acte_temp = c(rep(mean(c(matu_net_cov)),10),
                   rep(mean(c(32.6,42.1)),4), ##dec
                   rep(mean(c(43.4,43.2,33.3)),4),##jan
                   rep(mean(c(55.0,44.3,48.2)),4),##feb
                   rep(mean(c(61.2,56.8,40.7)),4),##mar
                   rep(mean(c(51.9,61.4,66.7)),4),##apr
                   rep(mean(c(48.9,55.6)),4),##may
                   rep(29.6,4))##june
```

```r
boan_net_cov = c(57.5,  ## nov
                 mean(c(64.6,74.5)), ##dec
                 mean(c(68.1,71.9,67.1)),##jan
                 mean(c(62.8,71.2,79)),##feb
                 mean(c(70.8,82.4,86.8)),##mar
                 mean(c(65.5,81.8,81.6)),##apr
                 mean(c(78.4,84.2)),##may
                 10.5)##june

itn_cov_Boan_temp = c(rep(mean(c(boan_net_cov)),10),
                      rep(mean(c(64.6,74.5)),4), ##dec
                      rep(mean(c(68.1,71.9,67.1)),4),##jan
                      rep(mean(c(62.8,71.2,79)),4),##feb
                      rep(mean(c(70.8,82.4,86.8)),4),##mar
                      rep(mean(c(65.5,81.8,81.6)),4),##apr
                      rep(mean(c(78.4,84.2)),4),##may
                      rep(10.5,4))

itn_cov_Acte = rep(itn_cov_Acte_temp,each=7)/100
itn_cov_Sumi = rep(itn_cov_Boan_temp,each=7)/100

## Here we are creating a matrix
## with the coverage or use of nets waning with time
## and the coverage of IRS either staying fixed, or also waning
## when walls are washed
cov1A[,1] = 1
cov1A[,2] = itn_cov_Acte[1:240] ## ITN only
cov1A[,3] = irs_cov_no_loss_Acte ## IRS only
cov1A[,4] = itn_cov_Acte[1:240]*irs_cov_no_loss_Acte ## both interventions

cov2A[,1] = 1
cov2A[,2] = itn_cov_Acte[1:240] ## ITN only
cov2A[,3] = irs_cov_Acte[1:240] ## IRS only
cov2A[,4] = itn_cov_Acte[1:240]*irs_cov_Acte[1:240]## both interventions

cov1S[,1] = 1
cov1S[,2] = itn_cov_Sumi[1:240] ## ITN only
cov1S[,3] = irs_cov_no_loss_Sumi ## IRS only
cov1S[,4] = itn_cov_Sumi[1:240]*irs_cov_no_loss_Sumi ## both interventions

cov2S[,1] = 1
cov2S[,2] = itn_cov_Sumi[1:240] ## ITN only
cov2S[,3] = irs_cov_Sumi[1:240] ## IRS only
cov2S[,4] = itn_cov_Sumi[1:240]*irs_cov_Sumi[1:240] ## both interventions


## These are the adjusted w, z, when coverage is changing
## so these are the intervention coverages
zhi1A = whi1A = zhi2A = whi2A = array(dim=c(240,4))
zhi1S = whi1S = zhi2S = whi2S = array(dim=c(240,4))
zhi1A=cov1A*z_Acte[1:240,]
whi1A=cov1A*w_Acte[1:240,]
```

```r
zhi1S=cov1S*z_Sumi[1:240,]
whi1S=cov1S*w_Sumi[1:240,]


zhi2A=cov2A*z_Acte[1:240,]
whi2A=cov2A*w_Acte[1:240,]

zhi2S=cov2S*z_Sumi[1:240,]
whi2S=cov2S*w_Sumi[1:240,]

zbar1A = wbar1A = zbar2A = wbar2A = array(dim=c(240,4))
zbar1S = wbar1S = zbar2S = wbar2S = array(dim=c(240,4))
for(i in 1:4){
  zbar1A[,i] = Q0*zhi1A[,i]
  wbar1A[,i] = (1 - Q0) + Q0*whi1A[,i]
  zbar2A[,i] = Q0*zhi2A[,i]
  wbar2A[,i] = (1 - Q0) + Q0*whi2A[,i]

  zbar1S[,i] = Q0*zhi1S[,i]
  wbar1S[,i] = (1 - Q0) + Q0*whi1S[,i]
  zbar2S[,i] = Q0*zhi2S[,i]
  wbar2S[,i] = (1 - Q0) + Q0*whi2S[,i]
}

## From Walker et al 2016
## Mosquito feeding rate (tau1 is delta10, tau2 is delta2 in the methods)
fR1A = 1 / ((tau1/(1 - zbar1A)) + tau2)
mu1A = -fR1A*log((wbar1A*p10/(1 - zbar1A*p10))*p2)
Q1A = 1 - (1-Q0)/wbar1A

fR2A = 1 / ((tau1/(1 - zbar2A)) + tau2)
mu2A = -fR2A*log((wbar2A*p10/(1 - zbar2A*p10))*p2)
Q2A = 1 - (1-Q0)/wbar2A


fR1S = 1 / ((tau1/(1 - zbar1S)) + tau2)
mu1S = -fR1S*log((wbar1S*p10/(1 - zbar1S*p10))*p2)
Q1S = 1 - (1-Q0)/wbar1S

fR2S = 1 / ((tau1/(1 - zbar2S)) + tau2)
mu2S = -fR2S*log((wbar2S*p10/(1 - zbar2S*p10))*p2)
Q2S = 1 - (1-Q0)/wbar2S


## Rate at which a person in the popn is bitten by mosquitoes is
lambda1A = lambda2A = array(dim = c(240,4))
lambda1S = lambda2S = array(dim = c(240,4))
for(i in 1:4){
  lambda1A = (Q1A*fR1A*yy_Acte[1:240,i])/whi1A[1:240,i]
  lambda2A = (Q2A*fR2A*yy_Acte[1:240,i])/whi2A[1:240,i]

  lambda1S = (Q1S*fR1S*yy_Sumi[1:240,i])/whi1S[1:240,i]
  lambda2S = (Q2S*fR2S*yy_Sumi[1:240,i])/whi2S[1:240,i]
```

```r
}



## Figure 3E main manuscript
plot(lambda1A[,1] ~ time[1:240],ylim=c(0,2.5),pch="",
     ylab = "Mosquito bites received per person per day",
     col="black",
     main = "",cex.main=1.2,xlim=c(1,240),xaxt="n",
     xlab="Time in months",yaxt="n",cex.lab=1.4,cex.axis=1.4,cex=1.4)
axis(2,las=2,at=seq(0,2.5,0.5),cex.lab=1.4,cex.axis=1.4)
axis(1,at=seq(0,230,30)+15,labels = c("Sep","Oct","Nov","Dec","Jan","Feb","Mar","Apr"),cex.axis = 1.4)

for(i in 4){
  lines(lambda1A[1:235,i] ~ time[1:235],col="darkblue",lty=2,lwd=2)
  lines(lambda2A[1:235,i] ~ time[1:235],col="darkblue",lty=4,lwd=2)

  lines(lambda1S[1:235,i] ~ time[1:235],col="aquamarine3",lty=2,lwd=2)
  lines(lambda2S[1:235,i] ~ time[1:235],col="aquamarine3",lty=4,lwd=2)

}
for(i in 3){
  lines(lambda1A[1:235,i] ~ time[1:235],col="darkblue",lty=1,lwd=1)
  lines(lambda2A[1:235,i] ~ time[1:235],col="darkblue",lty=3,lwd=1)

  lines(lambda1S[1:235,i] ~ time[1:235],col="aquamarine3",lty=1,lwd=1)
  lines(lambda2S[1:235,i] ~ time[1:235],col="aquamarine3",lty=3,lwd=1)

}

## Additional infectious bites per person per year
Estimated_added_EIR = array(dim=c(240,2))
Estimated_added_EIR[,1] = (lambda2A[,4] - lambda1A[,4])
Estimated_added_EIR[,2] = (lambda2S[,4] - lambda1S[,4])


## Additional infectious bites per person per year
Estimated_propn_increase_EIR = array(dim=c(240,2))
Estimated_propn_increase_EIR[,1] = (lambda2A[,4] - lambda1A[,4])/lambda2A[,4]
Estimated_propn_increase_EIR[,2] = (lambda2S[,4] - lambda1S[,4])/lambda2S[,4]

mean(Estimated_propn_increase_EIR[15:45,1])##sep
mean(Estimated_propn_increase_EIR[46:75,1])##oct
mean(Estimated_propn_increase_EIR[76:105,1])##nov
mean(Estimated_propn_increase_EIR[106:135,1])##dec
mean(Estimated_propn_increase_EIR[136:165,1])##jan
mean(Estimated_propn_increase_EIR[166:195,1])##feb
mean(Estimated_propn_increase_EIR[196:225,1])##mar
mean(Estimated_propn_increase_EIR[226:240,1])##part april


mean(Estimated_propn_increase_EIR[15:45,2])##sep
mean(Estimated_propn_increase_EIR[46:75,2])##oct
```

```r
mean(Estimated_propn_increase_EIR[76:105,2])##nov
mean(Estimated_propn_increase_EIR[106:135,2])##dec
mean(Estimated_propn_increase_EIR[136:165,2])##jan
mean(Estimated_propn_increase_EIR[166:195,2])##feb
mean(Estimated_propn_increase_EIR[196:225,2])##mar
mean(Estimated_propn_increase_EIR[226:240,2])##part april

## Figure 3F main manuscript
plot(Estimated_propn_increase_EIR[,1] ~ time[1:240],ylim=c(0,1),pch="",
     ylab = "",
     col="black",
     main = "",cex.main=1.2,xlim=c(1,240),xaxt="n",
     xlab="Time in months",yaxt="n",cex.lab=1.4,cex.axis=1.4,cex=1.4)
axis(2,las=2,at=seq(0,1,0.2),labels=seq(0,100,20),cex.lab=1.4,cex.axis=1.4)
axis(1,at=seq(0,230,30)+15,labels = c("Sep","Oct","Nov","Dec","Jan","Feb","Mar","Apr"),cex.axis = 1.4)
mtext(side=2, line =4,
      "Relative increase in daily bites")
mtext(side=2, line =2.7, "due to spray campaign & modifications (%)")

colsd = c("darkblue","aquamarine3")
for(i in 1:2){
  lines(Estimated_propn_increase_EIR[,i] ~ time[1:240],col=colsd[i],lty=2,lwd=2)
}


Estimated_added_EIR = array(dim=c(240,2))
Estimated_added_EIR[,1] = (lambda2A[,3] - lambda1A[,3])
Estimated_added_EIR[,2] = (lambda2S[,3] - lambda1S[,3])

## Additional infectious bites per person per year
Estimated_propn_increase_EIR = array(dim=c(240,2))
Estimated_propn_increase_EIR[,1] = (lambda2A[,3] - lambda1A[,3])/lambda2A[,3]
Estimated_propn_increase_EIR[,2] = (lambda2S[,3] - lambda1S[,3])/lambda2S[,3]

for(i in 1:2){
  lines(Estimated_propn_increase_EIR[,i] ~ time[1:240],col=colsd[i],lty=1,lwd=1)
}
```

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