### Model selection for the Gambia data

The gambia data in the geoR package includes data for 1332 children in the Gambia. The binary response  $Y_i$  s the indictor that child i tested positive for malaria. Child i lives in village  $v_i \in \{1, \ldots, 65\}$ . We use five covariates in  $X_{ij}$ .

Age: age of the child, in days

Netuse: indicator variable denoting whether (1) or not (0) the child regularly sleeps under a bed-net

Treated: indicator variable denoting whether (1) or not (0) the bed-net is treated (coded 0 if netuse=0)

Green: satellite-derived measure of the greenness of vegetation in the immediate vicinity of the village (arbitrary units)

PCH: indicator variable denoting the presence (1) or absence (0) of a health center in the village

We use the random effects logistic regression model

logit[Prob(
$$Y_i = 1$$
)] =  $\alpha + \sum_{j=1}^{p} X_{ij}\beta_j + \theta_{v_i}$ ,

where  $\theta_v$  is the random effect for village v. We compare three models for the village random effects via DIC and WAIC:

- 1. No random effects:  $\theta_v = 0$ .
- 2. Gaussian random effects:  $\theta_v \sim \text{Normal}(0, \tau^2)$ .
- 3. Double-exponential random effects:  $\theta_v \sim \text{DE}(0, \tau^2)$ .

#### Load the data

```
library(geoR)
## Analysis of Geostatistical Data
## For an Introduction to geoR go to http://www.leg.ufpr.br/geoR
   geoR version 1.9-4 (built on 2024-02-14) is now loaded
## -----
data(gambia)
Y <- gambia[,3]
X <- scale(gambia[,4:8])</pre>
s <- gambia[,1:2]
n <- length(Y)
p \leftarrow ncol(X)
# Compute the village ID
S <- unique(s) # Lat/long of the villages
m \leftarrow nrow(S)
village <- rep(0,n)</pre>
members <- rep(0,m)
for(j in 1:m){
```

# **Village locations**

<25 children</li>
>35 children

## Prep for JAGS

```
library(rjags)

## Loading required package: coda

## Linked to JAGS 4.3.1

## Loaded modules: basemod, bugs

burn <- 1000
  iters <- 5000
  chains <- 2</pre>
```

### Model 1: No random effects

```
mod <- textConnection("model{</pre>
     for(i in 1:n){
       Y[i]
                      ~ dbern(pi[i])
       logit(pi[i]) <- beta[1]</pre>
                                      + X[i,1]*beta[2] + X[i,2]*beta[3] +
                        X[i,3]*beta[4] + X[i,4]*beta[5] + X[i,5]*beta[6]
       like[i]
                    <- dbin(Y[i],pi[i],1) # For WAIC computation</pre>
     for(j in 1:6){beta[j] ~ dnorm(0,0.01)}
   }")
   data
         <- list(Y=Y,X=X,n=n)
   model <- jags.model(mod,data = data, n.chains=chains,quiet=TRUE)</pre>
   update(model, burn, progress.bar="none")
   samps <- coda.samples(model, variable.names=c("like"),</pre>
                           n.iter=iters, n.thin = 5, progress.bar="none")
   # Compute DIC
         <- dic.samples(model,n.iter=iters,n.thin = 5, progress.bar="none")</pre>
   # Compute WAIC
   like <- rbind(samps[[1]],samps[[2]]) # Combine samples from the two chains
   fbar <- colMeans(like)</pre>
        <- sum(base::apply(log(like),2,var))</pre>
   WAIC <- -2*sum(log(fbar))+2*Pw
   DIC
## Mean deviance: 2520
## penalty 6.128
## Penalized deviance: 2526
   WAIC; Pw
## [1] 2525.623
## [1] 6.043563
```

### Model 2: Gaussian random effects

```
mod <- textConnection("model{</pre>
     for(i in 1:n){
       Υſil
                     ~ dbern(pi[i])
       logit(pi[i]) <- beta[1]</pre>
                                       + X[i,1]*beta[2] + X[i,2]*beta[3] +
                        X[i,3]*beta[4] + X[i,4]*beta[5] + X[i,5]*beta[6] +
                        theta[village[i]]
       like[i]
                    <- dbin(Y[i],pi[i],1) # For WAIC computation
     }
     for(j in 1:6){beta[j] ~ dnorm(0,0.01)}
     for(j in 1:65){theta[j] ~ dnorm(0,tau)}
     tau ~ dgamma(0.1,0.1)
   }")
   data <- list(Y=Y,X=X,n=n,village=village)</pre>
   model <- jags.model(mod,data = data, n.chains=chains,quiet=TRUE)</pre>
   update(model, burn, progress.bar="none")
   samps <- coda.samples(model, variable.names=c("like"),</pre>
                           n.iter=iters, n.thin = 5,progress.bar="none")
   # Compute DIC
          <- dic.samples(model,n.iter=iters,n.thin = 5,progress.bar="none")</pre>
   # Compute WAIC
   like <- rbind(samps[[1]],samps[[2]])</pre>
   fbar <- colMeans(like)</pre>
         <- sum(base::apply(log(like),2,var))</pre>
   WAIC <- -2*sum(log(fbar))+2*Pw
  DIC
## Mean deviance: 2278
## penalty 55.36
## Penalized deviance: 2334
  WAIC; Pw
## [1] 2333.263
## [1] 53.43477
```

### Model 3: Double-exponential random effects

```
<- dbin(Y[i],pi[i],1) # For WAIC computation
     }
     for(j in 1:6){beta[j] ~ dnorm(0,0.01)}
     for(j in 1:65){theta[j] ~ ddexp(0,tau)}
     tau
          ~ dgamma(0.1,0.1)
   }")
          <- list(Y=Y,X=X,n=n,village=village)</pre>
   model <- jags.model(mod,data = data, n.chains=chains,quiet=TRUE)</pre>
   update(model, burn, progress.bar="none")
   samps <- coda.samples(model, variable.names=c("like"),</pre>
                           n.iter=iters, n.thin = 5,progress.bar="none")
   # Compute DIC
          <- dic.samples(model,n.iter=iters,n.thin = 5,progress.bar="none")</pre>
   DIC
   # Compute WAIC
         <- rbind(samps[[1]],samps[[2]])</pre>
   like
          <- colMeans(like)</pre>
   Ρw
          <- sum(base::apply(log(like),2,var))</pre>
   WAIC
         <- -2*sum(log(fbar))+2*Pw
   DIC
## Mean deviance: 2276
## penalty 56.79
## Penalized deviance: 2333
   WAIC; Pw
## [1] 2333.039
```

**Summary:** Both WAIC and DIC show strong support for including village random effects but cannot distinguish between Gaussian and double-exponential random effect distributions.

## [1] 54.27449