HW 10

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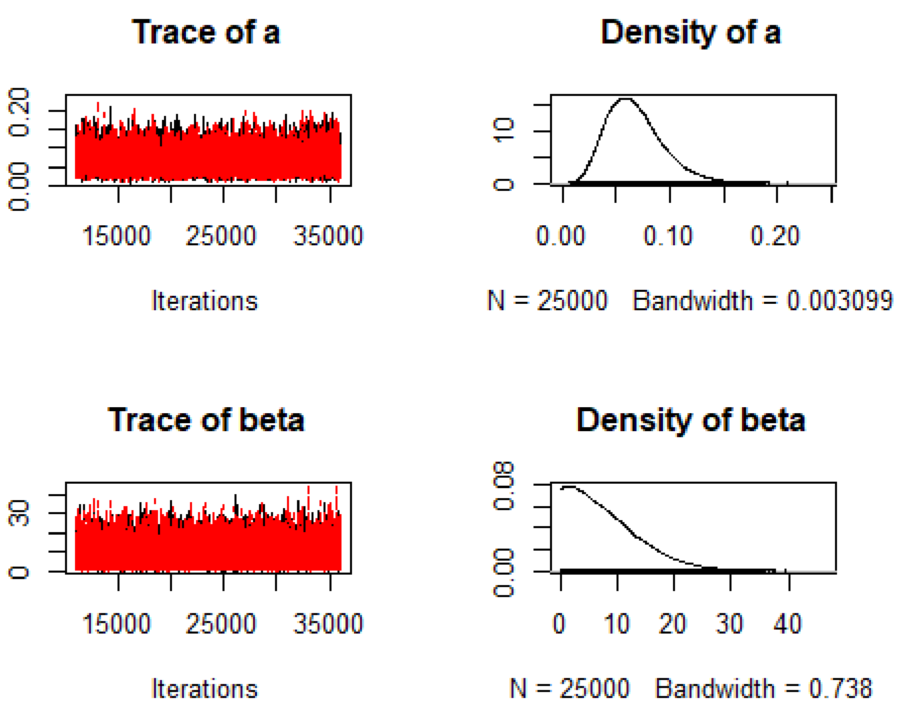
```
library(rjags)
library(geoR)
data("gambia")
```

Question 5

```
# raw data from question 5
y<- c(2, 15, 14, 16, 18, 22, 28)
x<- c(29.9,1761, 1807, 2984, 3230, 5040, 5654)
n<- length(y)

#list to be passed to jag
data   <- list(Y=y,X=x,n=n)


model_string <- textConnection("model{
   for(i in 1:n){
    Y[i]~ dgamma((a*mu[i]*mu[i]),(a*mu[i]))
    logit(mu[i]) <- inprod(X[i],beta)

   }
   beta ~ dnorm(0,0.01)
   a ~ dgamma(0.1, 0.1)
}")


model <- jags.model(model_string,data = data, n.chains=2 ,quiet=TRUE)

update(model, 10000, progress.bar="none")


params  <- c("a", "beta")
samples <- coda.samples(model, variable.names=params, n.iter=25000,
progress.bar="none")

#summary
summary(samples)

##
## Iterations = 11001:36000
```

```
## Thinning interval = 1
## Number of chains = 2
## Sample size per chain = 25000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##          Mean      SD  Naive SE Time-series SE
## a    0.06734 0.02612 0.0001168      0.0001674
## beta 8.00916 6.06109 0.0271060      0.0456313
##
## 2. Quantiles for each variable:
##
##          2.5%     25%   50%      75%   97.5%
## a    0.02646 0.04834 0.064  0.08245  0.1281
## beta 0.34746 3.15948 6.752 11.55616 22.5876
```

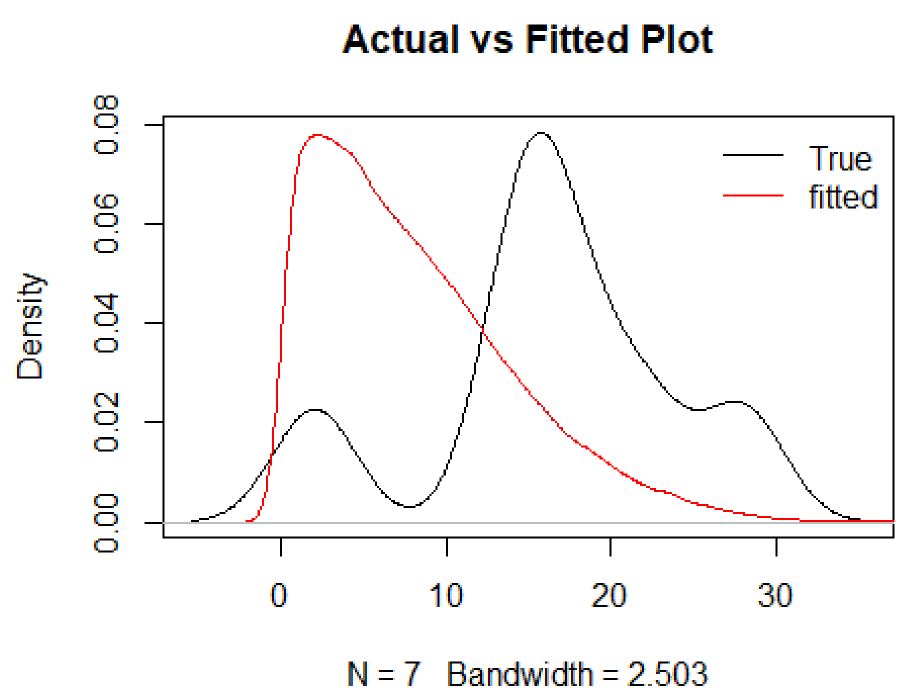
```r
#plots
plot(samples)
```




```r
# Low ESS indicates poor convergence, size sample apperas to be large
effectiveSize(samples)
```

```
##        a     beta
## 24349.67 17657.58
```

```r
# R greater than 1.1 indicates poor convergence
gelman.diag(samples)

## Potential scale reduction factors:
##
##      Point est. Upper C.I.
## a             1          1
## beta          1          1
##
## Multivariate psrf
##
## 1

sub<- samples[[1]]

plot(density(y), main = "Actual vs Fitted Plot")
lines(density(sub[,2]), col = "red")
legend("topright", legend = c("True", "fitted"),col=c("black", "red"),
lty=c(1,1), bty = "n")
```



I think we have good convergence based on the Gelman and sample size. Overlaying the actual data to my model density. I don't see a really great fit.

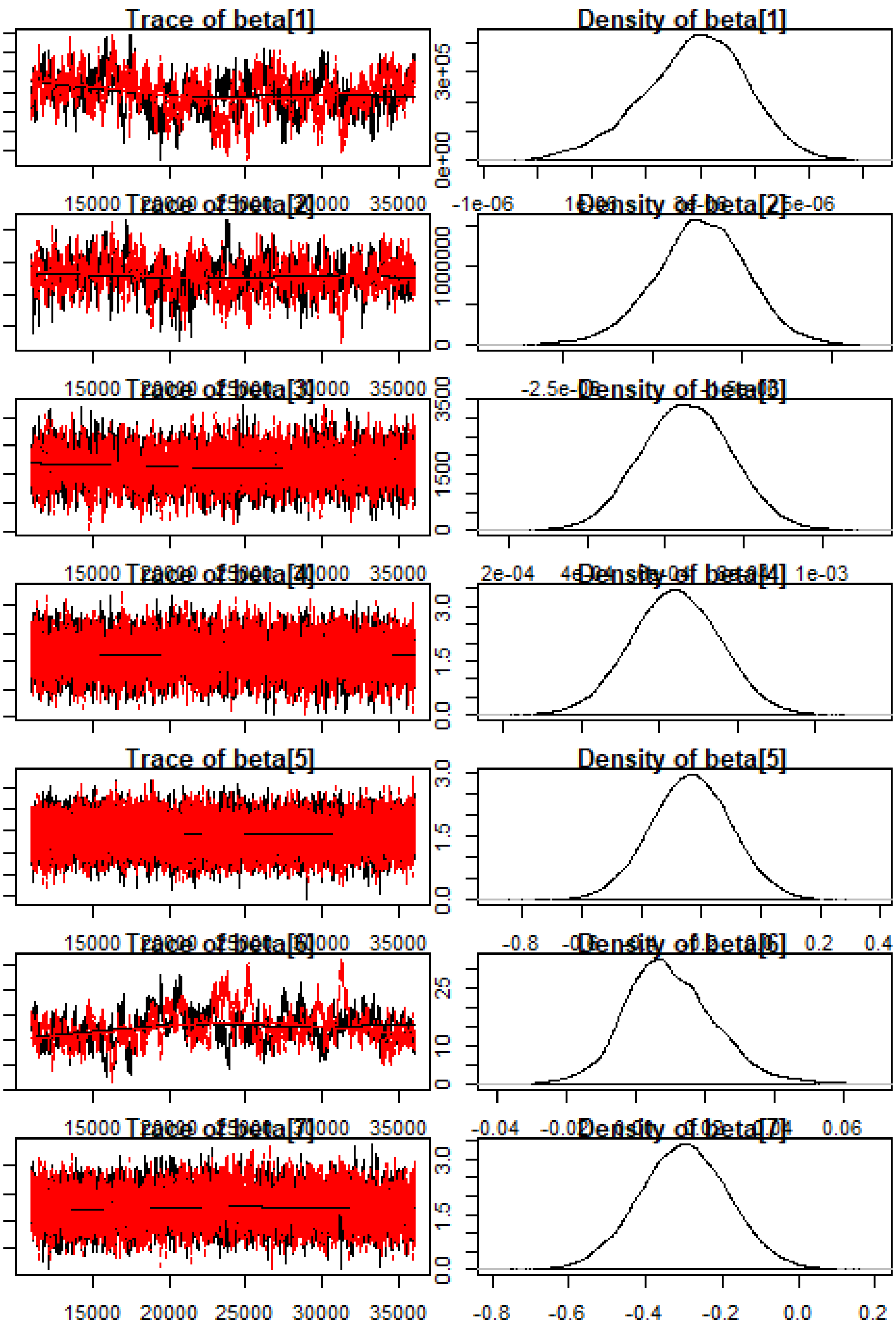
Question 7

(a)

```
par(mar=c(1,1,1,1))

#y variable
y<- gambia$pos

#corvars
x<- as.matrix(gambia[-3])

data <- list(n=nrow(x),p=ncol(x),Y=y,X=x)

model_string <- textConnection("model{

   # Likelihood
   for(i in 1:n){
     Y[i] ~ dbern(pr[i])
     logit(pr[i]) =  inprod(X[i,],beta[])
   }

   # Priors
   for(j in 1:p){beta[j] ~  dnorm(0, 0.01)}
 }")



model <- jags.model(model_string,data = data, n.chains=2 ,quiet=TRUE)



update(model, 10000, progress.bar="none")


params  <- c("beta")
samples <- coda.samples(model, variable.names=params, n.iter=25000,
progress.bar="none")

summary(samples)

##
## Iterations = 11001:36000
## Thinning interval = 1
## Number of chains = 2
## Sample size per chain = 25000
##
## 1. Empirical mean and standard deviation for each variable,
```

```
##    plus standard error of the mean:
##
##                Mean        SD  Naive SE Time-series SE
## beta[1]  2.894e-06 9.626e-07 4.305e-09      7.234e-08
## beta[2] -1.731e-06 2.628e-07 1.175e-09      1.530e-08
## beta[3]  6.537e-04 1.152e-04 5.153e-07      2.376e-06
## beta[4] -5.582e-01 1.152e-01 5.152e-04      1.734e-03
## beta[5] -2.331e-01 1.361e-01 6.088e-04      1.563e-03
## beta[6]  1.001e-02 1.340e-02 5.991e-05      1.341e-03
## beta[7] -2.995e-01 1.170e-01 5.231e-04      1.930e-03
##
## 2. Quantiles for each variable:
##
##                2.5%        25%        50%        75%      97.5%
## beta[1]  8.374e-07  2.279e-06  2.953e-06  3.558e-06  4.654e-06
## beta[2] -2.277e-06 -1.895e-06 -1.726e-06 -1.557e-06 -1.227e-06
## beta[3]  4.309e-04  5.754e-04  6.534e-04  7.315e-04  8.790e-04
## beta[4] -7.842e-01 -6.359e-01 -5.586e-01 -4.804e-01 -3.336e-01
## beta[5] -5.011e-01 -3.242e-01 -2.327e-01 -1.415e-01  3.506e-02
## beta[6] -1.439e-02  1.021e-03  8.814e-03  1.807e-02  3.960e-02
## beta[7] -5.293e-01 -3.778e-01 -2.996e-01 -2.205e-01 -6.970e-02
```

```
plot(samples)
```




```r
# Low ESS indicates poor convergence, size sample apperas to be large
effectiveSize(samples)
```

```
##    beta[1]   beta[2]   beta[3]   beta[4]   beta[5]   beta[6]   beta[7]
##   179.9811  295.2678 2351.7204 4486.2973 7595.5101  102.2609 3838.0177

# R greater than 1.1 indicates poor convergence
gelman.diag(samples)

## Potential scale reduction factors:
##
##         Point est. Upper C.I.
## beta[1]       1.01       1.01
## beta[2]       1.00       1.01
## beta[3]       1.00       1.00
## beta[4]       1.00       1.00
## beta[5]       1.00       1.00
## beta[6]       1.03       1.03
## beta[7]       1.00       1.01
##
## Multivariate psrf
##
## 1

sub<- samples[[1]]
```

Overall, I think the sample size is good. I don't think the x and y (beta[1] and beta[2]) are not important. We might have a bit of concern about beta6[6] green with low sample size. However, overall over Gelman test shows good convergence. I think it hard to come to a conclusion, because the intervals of the covariates a so close to zero.

(b)

```
par(mar=c(1,1,1,1))
gam<- gambia

y<- gam$pos

x<- as.matrix(gam[-3])

a<- 0
b<- 0
id<- 0

r<- 65
# to store unique locations
tag<- rep(0, r)
#unique x value
x_<- rep(0, r)
#unique y value
y_<- rep(0, r)
```

```r
#creating id of all the various locations 1-65
for(i in 1:nrow(x)){
  if(x[i,1] != a && x[i,2] != b){
    id= id + 1
    x_[id]= x[i,1]
    y_[id]=x[i,2]
  }
  tag[i]= id
  a= x[i,1]
  b= x[i,2]
}



data <- list(n=nrow(x),p=ncol(x),Y=y,X=x, r= r, tag = tag)


model_string <- textConnection("model{

 # Likelihood
 for(i in 1:n){
  Y[i] ~ dbern(pr[i])
  logit(pr[i]) =  inprod(X[i,],beta[]) + re[tag[i]]
 }

 # Priors
  for(j in 1:p){
    beta[j] ~  dnorm(0, 0.01)
  }
  for(j in 1:r){
    re[j] ~  dnorm(0, tau1)
  }
   tau1 ~ dgamma(0.01,0.01)
 }")



model <- jags.model(model_string,data = data, n.chains=2 ,quiet=TRUE)



update(model, 10000, progress.bar="none")


params  <- c("beta", "re")
samples <- coda.samples(model, variable.names=params, n.iter=25000,
progress.bar="none")
```

```r
summary(samples)
```

```
##
## Iterations = 11001:36000
## Thinning interval = 1
## Number of chains = 2
## Sample size per chain = 25000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##                Mean        SD  Naive SE Time-series SE
## beta[1]  4.614e-06 2.099e-06 9.389e-09      3.043e-07
## beta[2] -1.844e-06 5.455e-07 2.440e-09      6.188e-08
## beta[3]  6.790e-04 1.237e-04 5.533e-07      2.504e-06
## beta[4] -4.339e-01 1.593e-01 7.126e-04      2.924e-03
## beta[5] -3.712e-01 2.167e-01 9.692e-04      3.389e-03
## beta[6] -4.058e-03 2.768e-02 1.238e-04      5.064e-03
## beta[7] -4.465e-01 2.676e-01 1.197e-03      8.317e-03
## re[1]    1.124e+00 4.019e-01 1.797e-03      9.950e-03
## re[2]    4.818e-01 3.475e-01 1.554e-03      1.013e-02
## re[3]    4.262e-01 4.767e-01 2.132e-03      8.049e-03
## re[4]   -1.457e-01 4.513e-01 2.018e-03      9.921e-03
## re[5]    3.211e-01 4.247e-01 1.899e-03      8.335e-03
## re[6]    1.508e-01 4.643e-01 2.076e-03      8.310e-03
## re[7]    1.254e+00 3.794e-01 1.697e-03      9.357e-03
## re[8]   -6.600e-01 4.075e-01 1.822e-03      7.190e-03
## re[9]   -1.350e+00 4.291e-01 1.919e-03      1.061e-02
## re[10]   7.950e-02 4.403e-01 1.969e-03      7.707e-03
## re[11]   1.064e-01 4.738e-01 2.119e-03      1.119e-02
## re[12]   8.910e-01 4.006e-01 1.791e-03      7.148e-03
## re[13]   1.078e+00 4.734e-01 2.117e-03      2.460e-02
## re[14]  -2.697e-01 4.764e-01 2.130e-03      6.980e-03
## re[15]  -7.855e-01 4.562e-01 2.040e-03      1.113e-02
## re[16]  -3.740e-01 4.783e-01 2.139e-03      5.689e-03
## re[17]   5.055e-01 4.345e-01 1.943e-03      7.030e-03
## re[18]   1.358e+00 4.558e-01 2.038e-03      7.287e-03
## re[19]  -1.035e-01 4.456e-01 1.993e-03      5.782e-03
## re[20]   2.972e-01 3.979e-01 1.779e-03      8.097e-03
## re[21]   9.466e-01 3.953e-01 1.768e-03      6.349e-03
## re[22]   9.530e-02 4.211e-01 1.883e-03      9.397e-03
## re[23]   1.216e-01 4.099e-01 1.833e-03      6.553e-03
## re[24]  -1.069e+00 5.823e-01 2.604e-03      7.198e-03
## re[25]   8.244e-01 4.628e-01 2.070e-03      9.255e-03
## re[26]  -4.579e-01 4.352e-01 1.946e-03      4.569e-03
## re[27]   2.875e-01 3.918e-01 1.752e-03      3.980e-03
## re[28]  -1.047e+00 5.093e-01 2.278e-03      4.033e-03
## re[29]  -1.380e+00 6.165e-01 2.757e-03      4.504e-03
## re[30]  -1.376e+00 6.371e-01 2.849e-03      5.708e-03
```

```
## re[31]  -1.112e+00 4.217e-01 1.886e-03      6.085e-03
## re[32]  -4.767e-01 4.775e-01 2.136e-03      5.470e-03
## re[33]  -1.040e+00 4.334e-01 1.938e-03      8.802e-03
## re[34]  -8.747e-01 4.848e-01 2.168e-03      5.211e-03
## re[35]  -2.600e-01 3.927e-01 1.756e-03      7.806e-03
## re[36]  -7.115e-01 4.994e-01 2.234e-03      5.914e-03
## re[37]  -8.577e-02 4.124e-01 1.844e-03      4.606e-03
## re[38]  -5.196e-01 4.298e-01 1.922e-03      4.684e-03
## re[39]  -6.917e-01 3.906e-01 1.747e-03      9.076e-03
## re[40]  -4.681e-01 4.143e-01 1.853e-03      3.966e-03
## re[41]  -8.269e-01 3.883e-01 1.737e-03      5.847e-03
## re[42]   3.824e-01 4.152e-01 1.857e-03      1.199e-02
## re[43]   2.800e-01 4.005e-01 1.791e-03      7.436e-03
## re[44]  -4.722e-01 4.031e-01 1.803e-03      6.193e-03
## re[45]  -4.989e-01 3.146e-01 1.407e-03      5.364e-03
## re[46]  -6.443e-01 4.164e-01 1.862e-03      5.212e-03
## re[47]   2.592e-02 4.215e-01 1.885e-03      7.630e-03
## re[48]   7.993e-01 5.739e-01 2.566e-03      5.728e-03
## re[49]   1.352e+00 5.720e-01 2.558e-03      6.225e-03
## re[50]   3.067e-01 4.101e-01 1.834e-03      9.660e-03
## re[51]   4.893e-01 4.013e-01 1.795e-03      6.794e-03
## re[52]   9.454e-01 3.961e-01 1.772e-03      5.618e-03
## re[53]   2.035e-02 4.184e-01 1.871e-03      9.842e-03
## re[54]   8.204e-01 4.062e-01 1.817e-03      7.095e-03
## re[55]   3.226e-01 3.794e-01 1.697e-03      2.018e-02
## re[56]   9.139e-01 4.197e-01 1.877e-03      9.345e-03
## re[57]  -2.119e-01 4.123e-01 1.844e-03      7.205e-03
## re[58]   1.338e-01 5.852e-01 2.617e-03      5.018e-03
## re[59]  -1.266e-02 3.940e-01 1.762e-03      8.707e-03
## re[60]   6.700e-01 4.259e-01 1.905e-03      7.119e-03
## re[61]   6.501e-01 4.250e-01 1.901e-03      8.531e-03
## re[62]  -9.832e-01 3.606e-01 1.613e-03      1.129e-02
## re[63]  -4.270e-01 4.023e-01 1.799e-03      9.397e-03
## re[64]   1.114e+00 5.851e-01 2.617e-03      4.925e-03
## re[65]  -1.219e-01 4.053e-01 1.813e-03      1.093e-02
## 
## 2. Quantiles for each variable:
## 
##                2.5%        25%        50%        75%      97.5%
## beta[1]  3.422e-07  3.271e-06  4.591e-06  5.998e-06  8.695e-06
## beta[2] -2.907e-06 -2.216e-06 -1.817e-06 -1.462e-06 -8.409e-07
## beta[3]  4.393e-04  5.960e-04  6.783e-04  7.611e-04  9.227e-04
## beta[4] -7.444e-01 -5.408e-01 -4.341e-01 -3.259e-01 -1.204e-01
## beta[5] -7.954e-01 -5.181e-01 -3.702e-01 -2.244e-01  5.155e-02
## beta[6] -5.728e-02 -2.412e-02 -3.953e-03  1.544e-02  4.951e-02
## beta[7] -9.727e-01 -6.272e-01 -4.472e-01 -2.655e-01  7.253e-02
## re[1]    3.359e-01  8.542e-01  1.123e+00  1.394e+00  1.915e+00
## re[2]   -2.025e-01  2.491e-01  4.833e-01  7.138e-01  1.164e+00
## re[3]   -5.018e-01  1.052e-01  4.241e-01  7.479e-01  1.362e+00
## re[4]   -1.039e+00 -4.467e-01 -1.433e-01  1.606e-01  7.376e-01
```

```
## re[5]   -5.262e-01  3.566e-02  3.245e-01  6.069e-01  1.152e+00
## re[6]   -7.767e-01 -1.555e-01  1.555e-01  4.591e-01  1.054e+00
## re[7]    5.246e-01  9.977e-01  1.249e+00  1.507e+00  2.007e+00
## re[8]   -1.490e+00 -9.295e-01 -6.492e-01 -3.815e-01  1.187e-01
## re[9]   -2.222e+00 -1.630e+00 -1.341e+00 -1.056e+00 -5.324e-01
## re[10]  -8.001e-01 -2.137e-01  8.244e-02  3.760e-01  9.407e-01
## re[11]  -8.483e-01 -2.079e-01  1.150e-01  4.295e-01  1.020e+00
## re[12]   1.048e-01  6.217e-01  8.922e-01  1.159e+00  1.677e+00
## re[13]   1.473e-01  7.583e-01  1.076e+00  1.398e+00  2.001e+00
## re[14]  -1.228e+00 -5.822e-01 -2.626e-01  5.175e-02  6.402e-01
## re[15]  -1.715e+00 -1.085e+00 -7.749e-01 -4.737e-01  7.961e-02
## re[16]  -1.351e+00 -6.862e-01 -3.612e-01 -4.555e-02  5.278e-01
## re[17]  -3.646e-01  2.160e-01  5.111e-01  8.025e-01  1.337e+00
## re[18]   4.906e-01  1.047e+00  1.346e+00  1.659e+00  2.286e+00
## re[19]  -1.004e+00 -3.986e-01 -9.527e-02  2.019e-01  7.439e-01
## re[20]  -4.893e-01  3.055e-02  2.972e-01  5.676e-01  1.072e+00
## re[21]   1.731e-01  6.806e-01  9.474e-01  1.212e+00  1.722e+00
## re[22]  -7.385e-01 -1.890e-01  9.598e-02  3.806e-01  9.176e-01
## re[23]  -6.840e-01 -1.524e-01  1.247e-01  3.986e-01  9.232e-01
## re[24]  -2.281e+00 -1.442e+00 -1.041e+00 -6.675e-01 -8.429e-03
## re[25]  -6.908e-02  5.104e-01  8.192e-01  1.132e+00  1.744e+00
## re[26]  -1.335e+00 -7.452e-01 -4.483e-01 -1.585e-01  3.703e-01
## re[27]  -4.889e-01  2.515e-02  2.913e-01  5.522e-01  1.047e+00
## re[28]  -2.111e+00 -1.375e+00 -1.026e+00 -6.976e-01 -1.054e-01
## re[29]  -2.683e+00 -1.771e+00 -1.344e+00 -9.527e-01 -2.711e-01
## re[30]  -2.717e+00 -1.781e+00 -1.345e+00 -9.375e-01 -2.086e-01
## re[31]  -1.967e+00 -1.387e+00 -1.104e+00 -8.218e-01 -3.160e-01
## re[32]  -1.456e+00 -7.894e-01 -4.658e-01 -1.511e-01  4.342e-01
## re[33]  -1.922e+00 -1.323e+00 -1.026e+00 -7.471e-01 -2.195e-01
## re[34]  -1.875e+00 -1.189e+00 -8.575e-01 -5.409e-01  2.732e-02
## re[35]  -1.041e+00 -5.232e-01 -2.539e-01  4.088e-03  4.979e-01
## re[36]  -1.731e+00 -1.036e+00 -6.986e-01 -3.717e-01  2.336e-01
## re[37]  -9.138e-01 -3.585e-01 -7.951e-02  1.943e-01  7.035e-01
## re[38]  -1.394e+00 -8.028e-01 -5.099e-01 -2.275e-01  2.967e-01
## re[39]  -1.474e+00 -9.508e-01 -6.879e-01 -4.253e-01  6.508e-02
## re[40]  -1.301e+00 -7.402e-01 -4.630e-01 -1.883e-01  3.309e-01
## re[41]  -1.600e+00 -1.086e+00 -8.213e-01 -5.618e-01 -8.310e-02
## re[42]  -4.290e-01  1.007e-01  3.779e-01  6.614e-01  1.211e+00
## re[43]  -4.946e-01  8.704e-03  2.737e-01  5.491e-01  1.070e+00
## re[44]  -1.272e+00 -7.389e-01 -4.695e-01 -1.975e-01  3.037e-01
## re[45]  -1.126e+00 -7.076e-01 -4.953e-01 -2.869e-01  1.120e-01
## re[46]  -1.480e+00 -9.215e-01 -6.367e-01 -3.618e-01  1.518e-01
## re[47]  -8.094e-01 -2.580e-01  2.826e-02  3.068e-01  8.479e-01
## re[48]  -2.848e-01  4.053e-01  7.857e-01  1.180e+00  1.969e+00
## re[49]   2.849e-01  9.582e-01  1.336e+00  1.724e+00  2.535e+00
## re[50]  -4.944e-01  2.896e-02  3.088e-01  5.829e-01  1.113e+00
## re[51]  -2.831e-01  2.169e-01  4.859e-01  7.555e-01  1.289e+00
## re[52]   1.768e-01  6.786e-01  9.437e-01  1.208e+00  1.733e+00
## re[53]  -7.975e-01 -2.605e-01  1.789e-02  3.001e-01  8.479e-01
## re[54]   3.687e-02  5.440e-01  8.166e-01  1.092e+00  1.628e+00
```

```
## re[55]  -4.216e-01  6.663e-02  3.218e-01  5.779e-01  1.066e+00
## re[56]   1.078e-01  6.293e-01  9.085e-01  1.195e+00  1.744e+00
## re[57]  -1.028e+00 -4.880e-01 -2.094e-01  6.726e-02  5.834e-01
## re[58]  -9.978e-01 -2.605e-01  1.273e-01  5.248e-01  1.303e+00
## re[59]  -7.829e-01 -2.762e-01 -1.358e-02  2.524e-01  7.608e-01
## re[60]  -1.539e-01  3.821e-01  6.660e-01  9.551e-01  1.521e+00
## re[61]  -1.657e-01  3.641e-01  6.425e-01  9.297e-01  1.506e+00
## re[62]  -1.704e+00 -1.224e+00 -9.772e-01 -7.398e-01 -2.860e-01
## re[63]  -1.225e+00 -6.955e-01 -4.261e-01 -1.575e-01  3.530e-01
## re[64]   2.451e-02  7.117e-01  1.092e+00  1.495e+00  2.319e+00
## re[65]  -9.108e-01 -3.951e-01 -1.232e-01  1.493e-01  6.753e-01
```

```r
su<- summary(samples)

# Low ESS indicates poor convergence, size sample apperas to be large
effectiveSize(samples)
```

```
##     beta[1]     beta[2]     beta[3]     beta[4]     beta[5]     beta[6]
##    47.54952    82.43096  2440.95655  2976.23093  4108.06151    31.29610
##     beta[7]       re[1]       re[2]       re[3]       re[4]       re[5]
##  1033.71457  1622.62513  1171.30998  3509.32895  2074.64614  2596.95923
##       re[6]       re[7]       re[8]       re[9]      re[10]      re[11]
##  3136.79696  1643.39827  3205.47073  1647.99409  3307.77330  1900.79455
##      re[12]      re[13]      re[14]      re[15]      re[16]      re[17]
##  3142.96445   403.19596  4737.79432  1758.78487  7059.71306  3823.73493
##      re[18]      re[19]      re[20]      re[21]      re[22]      re[23]
##  3913.52236  5938.80237  2417.30819  3872.16723  2029.12649  3907.73211
##      re[24]      re[25]      re[26]      re[27]      re[28]      re[29]
##  6626.08083  2667.58622  9070.28019  9748.95622 16185.64469 18728.33029
##      re[30]      re[31]      re[32]      re[33]      re[34]      re[35]
## 12475.39432  4800.95604  8053.93885  2484.65554  8881.72233  2548.10882
##      re[36]      re[37]      re[38]      re[39]      re[40]      re[41]
##  7483.92570  8600.82826  8436.65851  1861.94892 10979.83866  4416.22334
##      re[42]      re[43]      re[44]      re[45]      re[46]      re[47]
##  1294.54164  2961.33651  4383.58075  3488.08972  7042.10139  3077.37275
##      re[48]      re[49]      re[50]      re[51]      re[52]      re[53]
## 10160.22220  8447.30385  1915.96192  3603.39103  5275.71525  1806.02319
##      re[54]      re[55]      re[56]      re[57]      re[58]      re[59]
##  3450.68468   379.91978  2154.35099  3272.16573 13600.09645  2051.88754
##      re[60]      re[61]      re[62]      re[63]      re[64]      re[65]
##  3584.40440  2553.53205  1024.09267  1850.45487 14114.93758  1417.70115
```

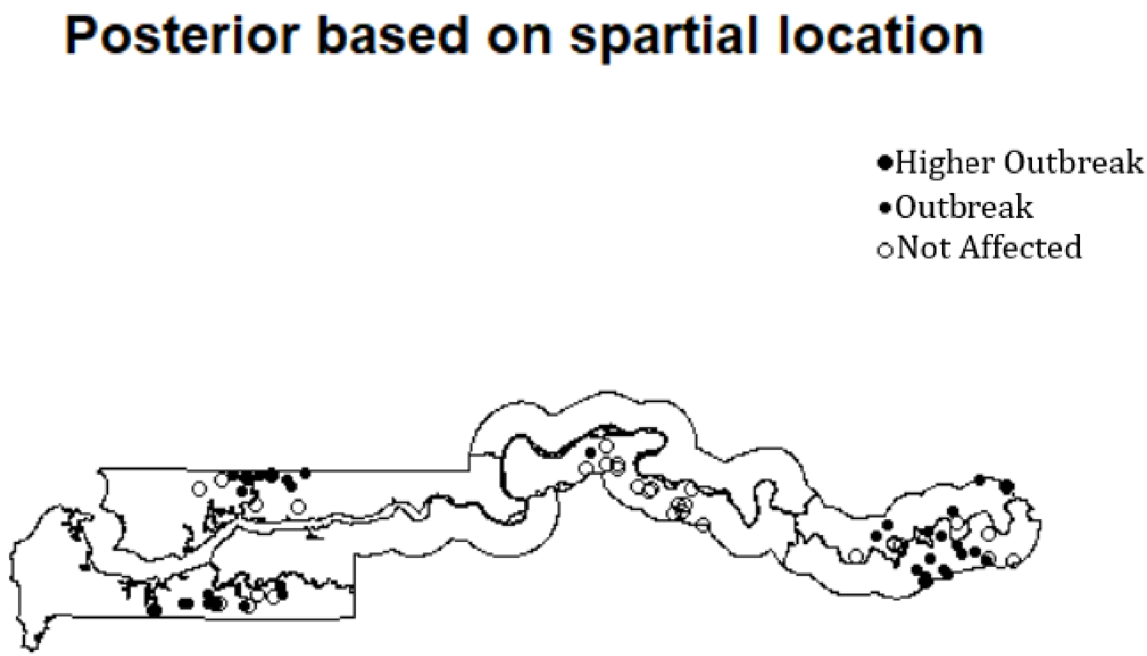
```r
# R greater than 1.1 indicates poor convergence
gelman.diag(samples)
```

```
## Potential scale reduction factors:
##
##          Point est. Upper C.I.
## beta[1]        1.07       1.28
## beta[2]        1.01       1.02
## beta[3]        1.00       1.00
```

```
## beta[4]       1.00       1.00
## beta[5]       1.00       1.00
## beta[6]       1.07       1.27
## beta[7]       1.00       1.02
## re[1]         1.01       1.05
## re[2]         1.01       1.04
## re[3]         1.00       1.00
## re[4]         1.00       1.01
## re[5]         1.00       1.01
## re[6]         1.00       1.00
## re[7]         1.00       1.01
## re[8]         1.00       1.02
## re[9]         1.00       1.01
## re[10]        1.00       1.01
## re[11]        1.00       1.00
## re[12]        1.00       1.01
## re[13]        1.01       1.05
## re[14]        1.00       1.00
## re[15]        1.00       1.00
## re[16]        1.00       1.01
## re[17]        1.00       1.02
## re[18]        1.00       1.01
## re[19]        1.00       1.01
## re[20]        1.00       1.00
## re[21]        1.00       1.01
## re[22]        1.00       1.00
## re[23]        1.00       1.02
## re[24]        1.00       1.02
## re[25]        1.00       1.00
## re[26]        1.00       1.00
## re[27]        1.00       1.00
## re[28]        1.00       1.00
## re[29]        1.00       1.00
## re[30]        1.00       1.01
## re[31]        1.00       1.01
## re[32]        1.00       1.02
## re[33]        1.00       1.01
## re[34]        1.00       1.00
## re[35]        1.00       1.01
## re[36]        1.00       1.01
## re[37]        1.00       1.00
## re[38]        1.00       1.00
## re[39]        1.00       1.02
## re[40]        1.00       1.01
## re[41]        1.00       1.00
## re[42]        1.01       1.04
## re[43]        1.00       1.01
## re[44]        1.00       1.00
## re[45]        1.00       1.00
## re[46]        1.00       1.00
```

```
## re[47]        1.00       1.00
## re[48]        1.00       1.00
## re[49]        1.00       1.00
## re[50]        1.00       1.02
## re[51]        1.00       1.01
## re[52]        1.00       1.00
## re[53]        1.01       1.03
## re[54]        1.00       1.02
## re[55]        1.03       1.11
## re[56]        1.00       1.01
## re[57]        1.00       1.01
## re[58]        1.00       1.00
## re[59]        1.00       1.02
## re[60]        1.00       1.00
## re[61]        1.00       1.02
## re[62]        1.01       1.03
## re[63]        1.00       1.02
## re[64]        1.00       1.00
## re[65]        1.01       1.03
##
## Multivariate psrf
##
## 1.04
```

```
#mean of random effects
re<- (su$statistics)

re_<- re[8:nrow(re),1]

pch<- rep(NA, 65)

for(i in 1:65){
  if(re_[i] >1 ){
    pch[i]= 19
  }else if(re_[i] <1 && re_[i] > 0){
    pch[i]= 20
  }else{
    pch[i]= 1
  }
}

#plot(x= x_, y =y_, pch = 16, col = "red" )
plot(gambia.borders, type="l", asp=1,axes=F,cex.main=1.5,xlab="",ylab="",main
= "Posterior based on spartial location")
points(x_, y_, pch = pch)
legend("topright", legend = c("Higher Outbreak", "Outbreak", "Not
Affected"),pch= c(19, 20, 1), bty = "n")
```



I think we have good convergence for most of the parameters. There a few parameters with low sample size. However, overall according to our Gelman test we appear to have good convergence and large sample size.

The random effect model is the best because we have covariates grouped according to the location(gam$x and gam$y) or villages. With the previous model in part a we did not account for correlation within the same location. In part b we have posterior mean based on the spatial location which is not the case in part a. Since we have the posterior mean we can identify the areas where malaria is more active based on the map above. Researcher can advocate for more mosquito control with these highly affected areas shown on the map above.