# Mapping patterns of occupancy and richness in a community characterized by strong philopatry

## Appendix S1: Model Code

The model was run indivudally for each species, using data extracted from the main Antarctic Site Inventory database.

Code from one species (Gentoo Penguin) is displayed here.

#### **Data Preparation:**

```
jags.path="/usr/local/bin/jags/"
library('R2jags')
library('coda')
library('gtools')
library('boot')
library('reshape')
library('reshape2') # used for acast function
library('snowfall') # used to run in parallel
library('parallel') # used to run in parallel
library('SpatialEpi') # used to run in parallel
seaice.data <- read.csv("SeaIceNov.csv", header = TRUE)</pre>
visit.data <- read.csv("GEPE.visit.csv", header = TRUE)</pre>
temp.data <- merge(visit.data, seaice.data, by="Site", all.x=TRUE)
# Taking out any sites for which no sea-ice data exist:
temp.data <- subset(temp.data, is.na(Mean.Nov.Ice)==FALSE)</pre>
temp.data <- temp.data[order(temp.data$Site, temp.data$Season),]</pre>
# Creating simpler data columns:
temp.data$seaice <- as.numeric(temp.data$Mean.Nov.Ice)</pre>
temp.data$state <- as.numeric(temp.data$State+1)</pre>
# Labels the number of repeat visits in a year
temp.data$visit <- 1
for (i in 2:dim(temp.data)[1]){
  if (temp.data$Site[i] == temp.data$Site[i-1] &
      temp.data$Season[i] == temp.data$Season[i-1])
    temp.data$visit[i] <- temp.data$visit[i-1]+1</pre>
}
# turning variables into numeric for ease in modeling
temp.data$site <- as.numeric(as.factor(temp.data$Site))</pre>
temp.data$season <- as.numeric(as.factor(temp.data$Season))</pre>
final.data.matrix <- subset(temp.data, select=c(site,season,visit,state))</pre>
# Creating sea-ice object
```

#### The JAGS model:

```
sink("Occupancy.jags")
cat("
    model {
    #### Priors ####
    beta.psi ~ dnorm(0,0.386)
    beta.r ~ dnorm(0,0.386)
    alpha.psi ~ dnorm(0,0.386)
    alpha.r ~ dnorm(0,0.386)
    gamma.psi ~ dnorm(0,0.386)
    gamma.r ~ dnorm(0,0.386)
    p2 ~ dunif(0,1)
    p3[1:3] ~ ddirch(alpha.p3[1:3])
    for (i in 1:3){
      alpha.p3[i] <- 1
    #### Likelihood ####
    ## states-space model ##
    # First year:
    for (i in 1:S){
      logit(mu.psi[i,1]) <- alpha.psi + beta.psi*seaice[i]</pre>
      logit(mu.r[i,1]) <- alpha.r + beta.r*seaice[i]</pre>
      z1[i,1] ~ dbin(mu.psi[i,1], 1)
      z2[i,1] ~ dbin(mu.r[i,1]*z1[i,1], 1)
      z[i,1] \leftarrow c(1-\max(z1[i,1], z2[i,1]),
                   z1[i,1]-z2[i,1],
                   z2[i,1]
                   ) \%*\% c(1,2,3)
```

```
# Subsequent years:
for (i in 1:S){
  for (j in 2:Y){
   logit(mu.psi[i,j]) <- alpha.psi +</pre>
                             beta.psi*seaice[i] +
                             gamma.psi*z1[i,j-1]
   logit(mu.r[i,j]) <- alpha.r +</pre>
                          beta.r*seaice[i] +
                          gamma.r*z2[i,j-1]
    z1[i,j] ~ dbin(mu.psi[i,j], 1)
    z2[i,j] ~ dbin(mu.r[i,j]*z1[i,j], 1)
    z[i,j] \leftarrow c(1-\max(z1[i,j], z2[i,j]),
                 z1[i,j]-z2[i,j],
                 z2[i,j]
                  ) %*% c(1,2,3)
  }
}
## observation model ##
# Define observation matrix
p[1,1] <- 1
p[1,2] <- 0
p[1,3] <- 0
p[2,1] <- 1-p2
p[2,2] \leftarrow p2
p[2,3] \leftarrow 0
p[3,1] \leftarrow p3[1]
p[3,2] \leftarrow p3[2]
p[3,3] \leftarrow p3[3]
for (i in 1:S){
  for (j in 1:Y){
    for (k in 1:V){
      y[i,j,k] \sim dcat(p[z[i,j],])
      y.new[i,j,k] \sim dcat(p[z[i,j],]) # for posterior predictive check
  }
}
#### Derived values ####
## phi = the probability of being in each state
for (i in 1:S) {
  for (j in 1:Y) {
    phi[i,j,1] <- 1 - mu.psi[i,j]
    phi[i,j,2] \leftarrow mu.psi[i,j] * (1 - mu.r[i,j])
    phi[i,j,3] <- mu.psi[i,j] * mu.r[i,j]</pre>
  }
}
```

```
## eval = the probability of recording each state
    for (i in 1:S) {
      for (j in 1:Y) {
        eval[i,j,1] \leftarrow (phi[i,j,1] * 1) +
                         (phi[i,j,2] * (1 - p2)) +
                         (phi[i,j,3] * p3[1])
        eval[i,j,2] \leftarrow (phi[i,j,1] * 0) +
                         (phi[i,j,2] * p2) +
                         (phi[i,j,3] * p3[2])
        eval[i,j,3] \leftarrow (phi[i,j,1] * 0) +
                         (phi[i,j,2] * 0) +
                         (phi[i,j,3] * p3[3])
      }
    }
    }",fill = TRUE)
sink()
```

### Running JAGS

```
##### Bundle the data for JAGS #####
Dat \leftarrow list(y = y, S = dim(y)[1], Y = dim(y)[2], V = dim(y)[3], seaice = seaice)
##### Select Initial Values #####
InitStage <- function()</pre>
 list(
    z1 = matrix(1, nrow = dim(y)[1], ncol = dim(y)[2]),
    z2 = matrix(1, nrow = dim(y)[1], ncol = dim(y)[2]),
    beta.psi = runif(1,0.2,0.2),
   beta.r = runif(1,0.2,0.2),
    alpha.psi = runif(1, 0.2, 0.3),
   alpha.r = runif(1, 0.2, 0.3),
   gamma.psi = 0,
    gamma.r = 0,
    p3 = as.vector(rdirichlet(1,c(1,1,1))),
    p2 = runif(1,.1,.9)
}
##### Posteriors to return #####
# Note: it may be necessary to limit this list to limit object size
# (recommend only returning "y.new" OR "z")
```

```
ParsStage <- c("beta.psi","beta.r",</pre>
                "alpha.psi", "alpha.r",
                "gamma.psi", "gamma.r",
                "p2", "p3",
                "mu.psi", "mu.r",
                "eval", "y.new",
                "z")
##### MCMC settings #####
ni <- 100000 # final iterations
nt <- 50 #thinning rate
nb <- 250000 # burn-in
nc <- 3 # number of chains</pre>
n.adapt <- 10000
##### Parallel Execution #####
cl <- makeCluster(3)</pre>
clusterExport(cl, c("Dat", "y", "InitStage", "ParsStage", "n.adapt", "nb", "ni", "nt"))
system.time({
  out1 <- clusterEvalQ(cl, {</pre>
    library(rjags); library(SpatialEpi); library('gtools')
    jm <- jags.model("Occupancy.jags",</pre>
                      data = Dat, InitStage,
                      n.chains=1, n.adapt=n.adapt)
    update(jm, n.iter=nb, thin=nt)
    samples = coda.samples(jm, n.iter=ni, variable.names=ParsStage, thin=nt)
    return(as.mcmc(samples))
 })
})
stopCluster(cl)
zm.GEPE <- mcmc.list(out1)</pre>
save(zm.GEPE,file="GEPE.results.Rdata")
```