Bayesian Hierarhical Model

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1 Generalized Linear Mixed Model

1.1 Fixed Effect Intercept and Random Slope (Version 1)

We fit a model to our data, where the occurence of the species ($y_{i,j}$) for site i in projected area j is modeled as,

$$
\begin{aligned}
y_{i,j} &\sim \text{Bernoulli}(p_{i,j}) \\
\text{logit}(p_{i,j}) &= \alpha_0 + \beta_j \times \text{dist.human}_{i,j} \\
\beta_j &\sim \text{Normal}(\mu^{\beta}, \sigma^{\beta})
\end{aligned}
$$

1.1.1 Priors

$$
\begin{aligned}
\alpha_0 &\sim \text{Logistic}(0, 1) \\
\mu^{\beta} &\sim \text{Normal}(0, 3) \\
\sigma^{\beta} &\sim \text{Uniform}(0, 5)
\end{aligned}
$$

1.1.2 JAGS syntax

```
model {

# Priors
  b0 ~ dlogis(0,1)
  mu.b1 ~ dnorm(0, 3)
  sigma.b1 ~ dunif(0,5)
  tau.b1 <- 1/sigma.b1^2

# Likelihood
  for (i in 1:N) {
     y[i] ~ dbern(p[i])
     logit(p[i]) <- b0 + b1[PA[i]]*dist.human[i]
  } #End loop

# Random Slope
  for(j in 1:N.PA){
    b1[j] ~ dnorm(mu.b1,tau.b1)
  } #End loop

} #End Model
```

1.2 Fixed Effect Intercept and Random Slope (Version 2)

$$
\begin{aligned}
y_{i,j} \sim & \text{Bernoulli}(p_{i,j}) \\
\text{logit}(p_{i,j}) = & \alpha_0 + (\beta_1 + \beta_{2,j}) \times \text{dist.human}_{i,j} \\
\beta_{2,j} \sim & \text{ Normal}(0, \sigma^{\beta})
\end{aligned}
$$

1.2.1 Priors

$$
\begin{aligned}
\alpha_0 \sim & \text{Logistic}(0, 1) \\
\beta_1 \sim & \text{Normal}(0, 3) \\
\sigma^{\beta} \sim & \text{Uniform}(0, 5)
\end{aligned}
$$

1.2.2 JAGS syntax

```
model {

# Priors
  b0 ~ dlogis(0,1)
  b1 ~ dlogis(0,1)
  sigma.b1 ~ dunif(0,5)
  tau.b1 <- 1/sigma.b1^2

# Likelihood
  for (i in 1:N) {
     y[i] ~ dbern(p[i])
     logit(p[i]) <- b0 + (b1 + b2[PA[i]])*dist.human[i]
  } #End loop

# Random Slope
  for(j in 1:N.PA){
    b2[j] ~ dnorm(0,tau.b1)
  } #End loop

} #End Model
```