Introducing the OccupancyModels package

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The use of occupancy models is quite common, but the expertise to write a Bayesian model to do the analysis is a substantial burden. The package `unmarked` has helped, but it lacks some functionality, particularly for analyses that have an availability component. While the primary focus of the `OccupancyModels` package is to provide a convenient R interface to Bayesian models that include multiple detection devices at a site, we also include this missing functionality.

This vignette is primarily designed to introduce the relevant models with appropriate references, and demonstrate fitting them in the `OccupancyModel` package. If package `unmarked` contains the functionality to fit a particular model, that process will also be demonstrated.

Software issues

The package was designed to use `stan`. To learn more about `stan` and install it and the package `rstan` go to `https://github.com/stan-dev/rstan/wiki/RStan-Getting-Started`.

Introduction stuff

- Ψ = probability that a site is occupied
  - Occupied means species use on at least one day
- $y_{ij} = 1$ denotes a detection at site i on day j
- $Z_i = 1$ denotes if a site is actually occupied
  - Latent variable and not necessarily known (unless a detection is made)
- π is the probability of detection given the the site is occupied
  - $P\left(y_{ij} \mid Z_i = 1\right) = \pi$

Occurrence Models

We will use the terminology of "Occurrence Models" to address a class of models introduced by Mackenzie et al 2002.

- $\Psi_i = \text{logit}^{-1}\left(X_i^T \beta\right)$ where the X_i covariates represent site level information that increase or decrease the occurrence probability and the estimation of the β values is the primary interest of the study.
- $Z_i \sim \text{Bern}\left(\Psi_i\right)$
- $y_{ij} \sim \text{Bern}\left(\, Z_i \cdot \pi \,\right)$
- Assumes the detection probability is constant across days.

- Inappropriate in many cases
- Can aggregate multiple days into multiple sampling periods
  - What is an appropriate number of days to aggregate?

- Can be fit using `unmarked`

Occupancy / Availability models

- Similar to models in Nichols et al, 2008
- Can have a second latent variable that indicates daily availability
  - $\theta_j = 1$ probability an animal is available on day j
  - $W_{ij} = 1$ (latent variable denoting if an animal is available at site i on day j)
- $\Psi_i = \text{logit}^{-1}\left(X_i^T \beta\right)$
- $Z_i \sim \text{Bern}\left(\Psi_i\right)$
- $W_{ij} \sim \text{Bern}\left(\, Z_i \cdot \theta_j \,\right)$
- $y_{ij} \sim \text{Bern}\left(\, W_{ij} \cdot \pi \,\right)$
- Assumptions
  - Availability on day j is the same across sites.
  - Constant value of availability better?

To fit these models, users have had to write their own code in WinBUGS, JAGS, or stan. Fortunately, we have a program to do most of this automatically.

No covariates

We first introduce the produce using a model with no covariates. That is to say that Ψ_i is constant across sites. In our model, this can be coded as $X_i = 1$ for all i and $\Psi_i = \text{logit}^{-1}\left(\beta\right)$.

```r
# tools that allow me to download from GitHub
library(devtools)
install_github('dereksonderegger/OccupancyModels')
library(OccupancyModels)

# Use the make.data function to generate some simulated data
# Check out the help file!
# ?make.data
temp <- make.data(
  Occupancy.p = .4,  # thus beta = logit(.4) = -.405
  Available.p = .5,
  Detection.p = .7,
  n.sites = 40,
  n.days = 5,
  n.cameras = 3)

# What have we made...
head(temp)
```

```
##   site day camera Detections
## 1    1   1      1          0
## 2    1   1      2          0
## 3    1   1      3          0
## 4    1   2      1          0
## 5    1   2      2          0
## 6    1   2      3          0
```

The first step in the analysis is to take our detection data and turn it into a 3-dimensional array, where the dimensions correspond to `site`, `day`, and `camera`.

```r
Y <- acast(temp, site~day~camera, value.var='Detections')
str(Y)
```

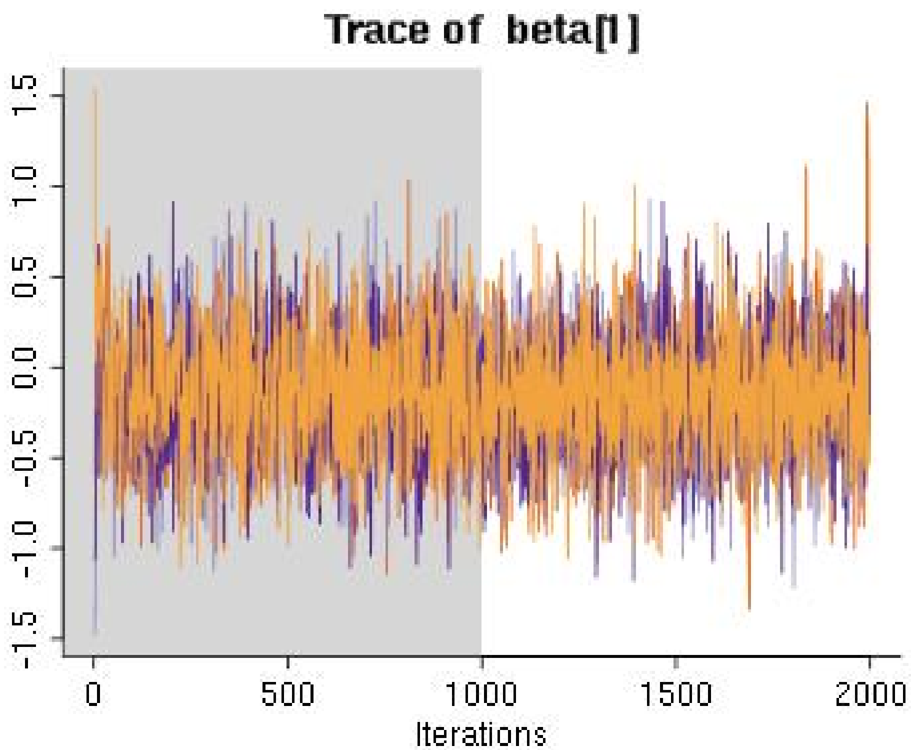
```
##  int [1:40, 1:5, 1:3] 0 0 1 0 0 0 0 0 0 0 ...
##  - attr(*, "dimnames")=List of 3
##   ..$ : chr [1:40] "1" "2" "3" "4" ...
##   ..$ : chr [1:5] "1" "2" "3" "4" ...
##   ..$ : chr [1:3] "1" "2" "3"
```

Next we can call the multiple detection occupancy model `mdOcc`.

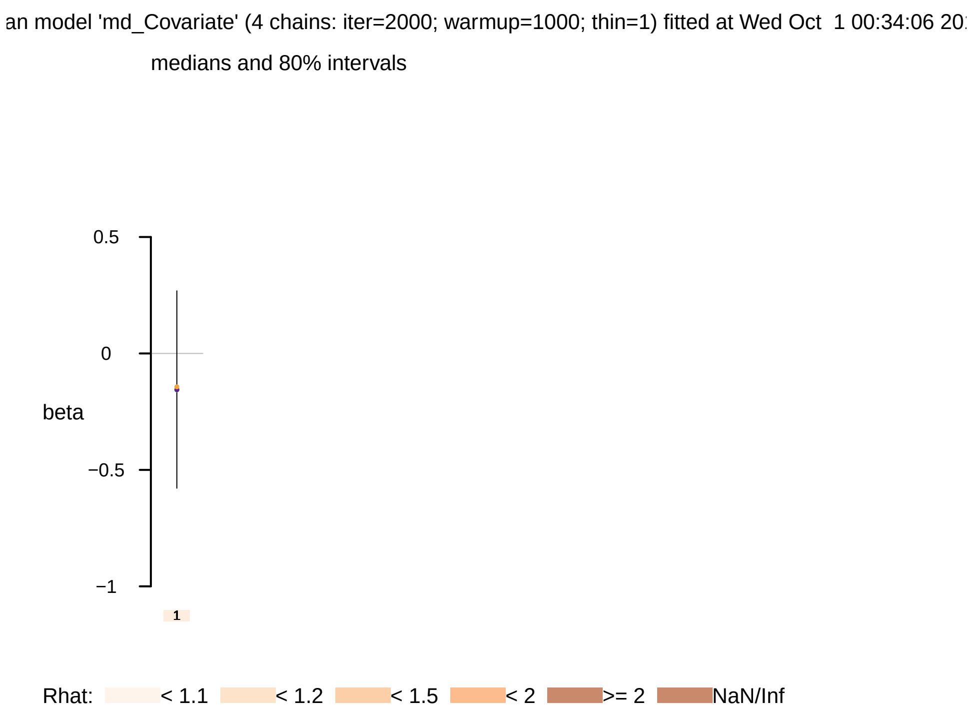
```r
model <- mdOcc(Y) # No covariates
```

We have now run the model through `stan` and can inspect the output. In particular I want to look at the values for β which is the logit transformed occupancy probability.

```r
traceplot(model, pars='beta')
```




```r
plot(model, pars='beta')
```



We can do our own summary statistics by extracting the chains for the β value (which in this simple case is just the inverse logit of the occupancy probability.

```r
beta.posterior <- extract(model, pars='beta')[[1]]
output <- apply( inv.logit( beta.posterior ),
       MARGIN=2,
       quantile, c(.025, .25, .50, .75, .975) )
output

##
##           [,1]
##   2.5%  0.3104
##   25%   0.4073
##   50%   0.4617
##   75%   0.5163
##   97.5% 0.6181
```

This shows us that the posterior distribution of Ψ, the occupancy probability, is between 0.32 and 0.64, and this interval happily includes the true value of $\Psi = 0.4$.

With Covariates

We next allow there to be covariates in the model. In this case, we'll create data with one covariate and set a positive relationship between the covariate and Ψ.

```r
# Number of plots
n <- 50

# make up some site level covariates
site.data <- data.frame(x=rnorm(n, 0, 2))

# relationship between x and Psi
psi <- inv.logit( 0 + (1/2)*site.data$x )

# Make data
sim.data <- make.data(n, n.days=20, n.cameras=3,
                      Occupancy.p=psi, Available.p=.5, Detection.p=.4 )

# reshape the data frame into a 3D array
Y <- acast(sim.data, site~day~camera, value.var='Detections')
```

```r
# Fit the model using the site level covariates
model <- mdOcc(Y, site.data, ~ x)
```

Using the `extract` function as we did before, we obtain the posterior distribution of the β values and also exam the logit^{-1} transformed values as well.

```r
beta.posterior <- extract(model, pars='beta')[[1]]
beta.summary <- apply( beta.posterior, MARGIN=2,
                       quantile, c(.025, .25, .50, .75, .975) )
inv.logit.beta.summary <- apply( inv.logit( beta.posterior ), MARGIN = 2,
                                 quantile, c(.025, .25, .50, .75, .975) )

beta.summary
```

```
##
##              [,1]   [,2]
##   2.5%  -0.50178 0.2876
##   25%   -0.07687 0.4901
##   50%    0.15689 0.6277
##   75%    0.39556 0.7732
##   97.5%  0.87446 1.1005
```

```r
inv.logit.beta.summary
```

```
##
##            [,1]   [,2]
##   2.5%  0.3771 0.5714
##   25%   0.4808 0.6201
##   50%   0.5391 0.6520
##   75%   0.5976 0.6842
##   97.5% 0.7057 0.7504
```