\chapter{

Closed Population Models

}

\markboth{Chapter 3}{}

\label{chapt.closed}

\vspace{.3in}

Having covered the basics of hierarchical models and their implementation in BUGS software,

in this chapter we will consider ordinary capture-recapture (CR)

models for estimating population size in closed populations. We will

see that such models are closely related to binomial (or logistic)

regression-type models. In fact, when $N$ is known, they are precisely

logistic regression models. We consider some important extensions of ordinary closed

population models that accommodate various types of ``individual

effects'' --- either in the form of explicit, observed and measuredcovariates (sex, age,

body mass) or unstructured ``heterogeneity'' in the form of an

individual random effect, which represent effects of unobserved or unmeasured covariates. In general, these models are variations of

generalized linear or generalized linear mixed models (GLMs and GLMMs, respectively).

Because of the paramount importance of this concept, we focus mainly

on fairly simple models in which the observations are individual

encounter frequencies, $y\_{i}$ = the number of encounters of

individual $i$ out of $K$ replicate samples of the population which,

for the models we consider here, is the outcome of a binomial random

variable. Along the way, we consider the spatial context of

capture-recapture data and models and demonstrate that density cannot

be formally estimated when spatial information is ignored. We also

review some of the informal methods of estimating density using CR

methods, and consider some of their limitations. We will be exposed

to our first primitive spatial capture-recapture models which arise as

relatively minor variations of so-called ``individual covariate

models'' (of the \citet{huggins:1989} and \citet{alho:1990}

variety). In a sense, the point of this chapter is to establish that

linkage between non-spatial and spatial capture-recapture models

in a direct and concise manner beginning with the basic

``model $M\_0$'' xxxxx $ought to explain such a thing at first place where it occurs or give a reference$ xxxxx and extensions of that model to include individual

heterogeneity and individual covariates. A special type of

individual covariate models is distance sampling, which could be

thought of as the most primitive spatial capture-recapture model. Xxxx $they will love you in St-Andrews for this$ xxxx In

later chapters we further develop and extend ideas introduced in this

chapter.

We emphasize Bayesian analysis of capture-recapture models and we

accomplish this using a method related to classical ``data

augmentation'' from the statistics literature

\citep[e.g.,][]{tanner\_wong:1987}. This is a general concept in

statistics but, in the context of capture-recapture models where $N$

is unknown, it has a consistent implementation across classes of

capture-recapture models and one that is really convenient from the

standpoint of doing MCMC \citep{royle\_etal:2007,royle\_dorazio:2011}. We use data

augmentation throughout this book and thus emphasize its conceptual

and technical origins and demonstrate applications to closed

population models. We refer the reader to

\citet[][ch. 6]{kery\_schaub:2011} for an accessible and complementary

development of Bayesian analysis of ordinary, i.e., nonspatial closed population models.

\section{The Simplest Closed Population Model: Model $M\_0$}

To start looking at the simplest capture-recapture model, let's suppose

there exists a population of $N$ individuals which we

subject to repeated sampling, say over $K$ ``occasions’’, such as trap nights, where individuals

are captured, marked, and subsequently recaptured. We suppose that

individual encounter histories are obtained, and these are of the form

of a sequence of 0's and 1's indicating capture $(y=1)$ or not $(y=0)$

during any sampling occasion (``sample''). As an example, suppose

$K=5$ sampling occasions, then an individual captured during sample 2

and 3 but not otherwise would have an encounter history of the form

${\bf y}=(0,1,1,0,0)$. Thus, the observation ${\bf y}\_{i}$ for each

individual $(i)$ is a vector having elements denoted by $y\_{ik}$ for

$k=1,2,..,K$. Usually this is organized as a row of a matrix with

elements $y\_{ik}$, see Table \ref{closed.tab.3.1}. Except where noted

explicitly, we suppose that observations are independent within

individuals and among individuals. Formally, this allows us to say

that $y\_{ik}$ are $iid$ Bernoulli random variables and we may write $y\_{ik}

\sim \mbox{Bern}(p)$. Consequently, for this very simple model in

which $p$ is constant, we can declare that the individual

encounter frequencies (total number of captures), $y\_{i} = \sum\_{k} y\_{ik}$,

have a binomial distribution based on a sample of size $K$. That is

\[

y\_{i} = \sum\_{k} y\_{ik} \sim \mbox{Bin}(p,K)

\]

xxxxx

$around here perhaps say that whenever no temporal structure in p is modelled, the original binary detection observations can be aggregated into detection frequencies, and the observation model changes from Bernoulli to Binomial$

for every individual in the population. This is a remarkably simple

model for the observation process and the one which forms the cornerstone of almost all of classical

capture-recapture models, including most spatial capture-recapture

models discussed in this book.

Evidently, the basic

capture-recapture model structure is precisely a simplistic version of

a logistic-regression model with only an intercept term

($\mbox{logit}(p) = \mbox{constant}$). To say that all

capture-recapture models are just logistic regressions is only

slightly inaccurate. In fact, we are proceeding here ``conditional on

$N$'', i.e., as if we knew $N$. In practice we don't, of course, and

that is kind of the point of capture-recapture models as estimating

$N$ is the central objective. Xxxx $last sentence too complicated$ But, by proceeding conditional on $N$ xxxxx $have to define a thing at first place$,

we can specify a simple model and then deal with the fact that $N$ is

unknown using standard methods that you are already familiar with

(i.e., GLMs - see Chapt. \ref{chapt.glms}).

\begin{table}

\centering

\caption{A toy capture-recapture data set with $n=6$ observed individuals and $K=5$ samples. The original detection history data can be summarized in the detection frequency (the total number of detections, $y\_i$), which is shown in the right-most column.

}

xxxxx $generally, I would make legends MUCH more informative, at the expense of some redundancy$

\begin{tabular}{r|ccccc|c}

& \multicolumn{5}{c}{Sample occasion} & \\ \hline

indiv $i$ & 1 & 2 & 3 & 4 & 5 & $y\_{i}$ \\ \hline

1 & 1 & 0 & 0 & 1 & 0 & 2 \\

2 & 0 & 1 & 0 & 0 & 1 & 2 \\

3 & 1 & 0 & 0 & 1 & 0 & 2 \\

4 & 1 & 0 & 1 & 0 & 1 & 3 \\

5 & 0 & 1 & 0 & 0 & 0 & 1 \\

$n=6$ & 1 & 0 & 0 & 0 & 0 & 1 \\ \hline

\end{tabular}

\label{closed.tab.3.1}

\end{table}

Assuming individuals in the population are observed independently, the

joint probability distribution of the observations is the product of

$N$ binomials

\begin{eqnarray\*}

\Pr(y\_1, \ldots, y\_N | p) &=& \prod\_{i=1}^N \mathrm{Bin}(y\_i | K, p) \\

&=& \prod\_{k=0}^K \pi(k)^{n\_k}

\end{eqnarray\*}

where $\pi(k) = \mathrm{Bin}(k | K,p)$ and where $n\_k = \sum\_{i=1}^N

I(y\_i = k)$ denotes the number of individuals captured $k$ times in

$K$ surveys. We emphasize that this expression is conditional on $N$, in which

case we get to observe the $y=0$ observations and the resulting data

are just $iid$ binomial counts. Because this is a binomial regression

model of the variety described in Chapt. \ref{glms}, fitting this model using

a {\bf BUGS} engine poses no difficulty.

The essential problem in capture-recapture, however, is that $N$ is

{\it not} known because the number of uncaptured/missing individuals (i.e.,

those in the zero cell that occur with probability $\pi(0)$) is

unknown. Consequently, the observed capture frequencies $n\_k$ are no

longer independent. Instead, their joint distribution is multinomial

(e.g., see \citet[][p. xyz]{illian\_etal:2008}) xxxxx$ nicer citation is Illian et al., 2008, p. XX. Also, there must surely be better references to the multinomial distribution, perhaps in an appendix to Williams et al. or in the R&D book$:

\begin{equation}

n\_1, n\_2, \ldots, n\_K \sim \mathrm{Multin}(N, \pi(1), \pi(2), \ldots, \pi(K))

\label{closed.eq.multinomial4m0}

\end{equation}

Xxxxxx $Beware of the MN distribution: peopl never understand it, so have to go very slowly here. Also say that pi are called the cell probs$

We denote the

number of uncaptured/missing individuals by

$n\_0$, and the total number of distinct individuals encountered in the $K$ samples

by $n = \sum\_{k=1}^K n\_k$.

Note that $n\_{0}$ appears

in the likelihood as a component of $N = n + n\_{0}$.

To fit the model in which $N$ is {\it unknown}, we can regard $n\_{0}$ as a

parameter and maximize the multinomial likelihood directly.

Direct likelihood analysis of the multinomial model is

straightforward, but that does not prove to be too useful in practice

because we seldom are concerned with models for the aggregated

encounter history frequencies, which entail that capture probabilities are the

same for all individuals. In many instances, including for

spatial capture-recapture (SCR) models, we require a formulation of

the model that can accommodate individual-level xxxxxx $not sure about this hyphen, but I believe this is OK$ covariates to account for

differences in detection among individuals which we

address subsequently in this chapter. Xxxxx $Also: time and behavious ? Refer to some place$

xxxxxx $Perhaps explain how the very basic observation model in all of capture-recapture is Bernoulli: a guy is either seen or not. However, often we analyse a summary of this, for instance in the form of the sum of N Bernoulli trials, leading to a Binomial, or in the form of a Multinomial, which really also is a form of an incomplete summary or something$ xxxxxx

\begin{comment}

\subsection{The Spatial Context of Capture-Recapture}

XXX I WOULD CHANGE THE SECTION HEADING TO SOMETHING LIKE 'POPULATION CLOSURE AND THE SPATIAL

CONTEXT OF CAPTURE-RECAPTURE XXX

A common assumption made is that of population ``closure'' which is

really just a colloquial way of saying (in part) the Bernoulli

assumptions stated explicitly above. In the biological context,

closure means, strictly, no additions or subtractions from the

population during study. This is manifest by the statement that the

encounters are independent and identically distributed (iid) Bernoulli

trials. In practice, closure is usually interpreted by the manner in

which potential violations of that assumption arise. In particular,

two important elements of the closure assumption are ``demographic''

and ``geographic'' closure. If an individual dies then subsequent

values of $y\_{ik}$ are clearly no longer Bernoulli trials with the

same parameter $p$; since the probability of capturing that individual becomes 0. If there is no mortality or recruitment in the

population, then we say that demographic closure is

satisfied. Similarly, animals may emigrate or immigrate. If they do

not, then geographic closure is satisfied. Sometimes a distinction is

made between temporary and permanent emigration or immigration. That

is a relevant distinction in spatial capture-recapture models, because

SCR models explicitly accommodate ``temporary emigration'' of a

certain type, due to individuals moving about their home range.

In contrast, ordinary capture-recapture models cannot explicitly deal

with the fact that, unless we're sampling a fenced enclosure or an

island, individuals are bound to move ``off the trapping grid''

(whatever that means). The

demographic closure assumption can also be relaxed using SCR models,

but we will save that discussion for Chapt. \ref{chapt.scr0}.

XXXX I FEEL LIKE THIS SECTION STILL NEEDS A SENTENCE THAT MAKES THE POINT - SPATIAL CONTEXT; POP CLOSURE AND SCR;

BUT I AM HAVING TROUBLE PUTTING THAT INTO A FEW WORDS RIGHT NOW XXXX

\end{comment}

\subsection{Model Assumptions}

Xxxx andy: this should be about c-r only not scr. Move some of this shit to ch. 4

Xxxxx

Independence, etc.. and why they’re no good. What is the role of model assumptions?

Independence within individuals conditional on s,

Independence of indivdiauls,

Uniformity

The model of detection itself is a phenomenological model…..

Statistical inference: we assume the model is truth – not an approximation to truth but actual truth.

Conversely we also know that no model is correct. We don’t just think they are not good aprpoximations but manifestly wrong……. Cite Gelman paper here…..

How could this model possibly be any good? I mean geez we can use a normal capture-recapture model that doesn’t require these assumptions… can’t we? Well,l not really. They still assume independence of some sort, or tod they? Well actually they throw out almost all the data to use a simpler model ….. and how fucking dumb is that? Fuck you all.

\subsection{Conditional likelihood}

$ xxxxx Drop that section title and simply go on explaining things. Replace title with a topical sentence: for instance, “a typical analysis of this model is based on conditional likelihood (plus some references)”$

We saw that a basic closed population model is a simple logistic

regression model if $N$ is known and, when $N$ is unknown, the model

is multinomial with index or sample size parameter $N$. This

multinomial model, being conditional on $N$, is sometimes referred to

as the ``joint likelihood'' the ``full likelihood'' or the

``unconditional likelihood'' (or ``model’’ in place of ``likelihood’’) $here need a few references -- maybe Sanathanan – maybe Williams et al? Maybe Borchers et al.? $. This

formulation differs from the so-called ``conditional likelihood''

approach in which the likelihood of the observed encounter histories

is devised conditional on the event that an individual is captured at

least once. To construct this likelihood, we have to recognize that

individuals appear or not in the sample based on the value of the

random variable $y\_{i}$, that is, we capture them if and only if

$y\_{i}>0$. The observation model is therefore based on $\Pr(y|y>0)$.

For the simple case of model $M\_0$, the resulting conditional

distribution is a ``zero truncated'' binomial distribution which

accounts for the fact that we cannot observe the value $y=0$ in the

data set \citep[see][sec. 5.1]{royle\_dorazio:2008}. Both the

conditional and unconditional models are legitimate modes of analysis

in all capture-recapture types of studies, and they provide equally

valid descriptions of the data and for many practical purposes provide

equivalent inferences, at least in large sample sizes

\citep{sanathanan:1972}.

In this book we emphasize Bayesian analysis of capture-recapture

models using xxxxxxparameter-expandes xxxxx data augmentation ( xxxx add references to papers and specific sections xxxx), which

produces yet a third distinct formulation of capture-recapture models

based on the zero-{\it inflated} binomial distribution that we

describe in the next section. Thus, there are 3 distinct formulations

of the model -- or modes of analysis -- for analyzing all

capture-recapture models based on the (1) binomial model for the joint

or unconditional specification; (2) zero-truncated binomial that

arises ``conditional on $n$''; and (3) the zero-inflated binomial that

arises under data augmentation. Each formulation has distinct

model parameters (shown in Table \ref{tab.3.modes} for

model $M\_0$).

\begin{table} %%%%%$nice table$

\centering

\caption{Modes of analysis of capture-recapture models. Closed

population models can be analyzed using the joint or ``full

likelihood'' which contains $N$ as an explicit parameter, the

conditional likeilhood which does not involve $N$, or by data

augmentation which replaces $N$ with $\psi$. Each approach yields a

distinct likelihood.}

\begin{tabular}{ccc}

Mode of analysis & parameters in model & statistical model \\ \hline

Joint likelihood & $p$, $N$ & multinomial with index $N$\\

Conditional likelihood & $p$ & zero-truncated binomial \\

Data augmentation & $p$, $\psi$ & zero-inflated binomial\\

\end{tabular}

\label{tab.3.modes}

\end{table}

\section{ Parameter-expanded data Augmentation }

\label{closed.sec.da}

Xxxxxx $Use the full name of the thing at the start and only later go on to the more abbreviated version$

We consider a method of analyzing closed population models using parameter-expanded data

augmentation (PX-DA; often simply abbreviated to ``data augmentation’’ or DA which is useful for Bayesian analysis and, in

particular, analysis of models using the various {\bf BUGS} engines and

other Bayesian model fitting software. Data augmentation is a general statistical concept

that is widely used in statistics in many different settings. The

classical reference is \citet{tanner\_wong:1987}, xxxx $I am not sure about the comma rules in English, and I recognize that in English one seems to put much fewer than in German. Nevertheless, I suspect that you are a bit thrifty with commas ?$ but see also

\citet{liu\_wu:1999}. Data augmentation can be adapted to provide a

very generic framework for Bayesian analysis of capture-recapture

models with unknown $N$. This idea was introduced for closed

populations by \citet{royle\_etal:2007}, and has subsequently been

applied to a number of different contexts including individual

covariate models \citep{royle:2009}, open population models

\citep{royle\_dorazio:2008,royle\_dorazio:2010, gardner\_etal:2010ecol},

spatial capture-recapture models \citep{royle\_young:2008,

royle\_etal:2010, gardner\_etal:2009}, and many

others. \citet[][Chapt. 6]{kery\_schaub:2011} provides a good introduction to data

augmentation in the context of closed population models.

Conceptually, the technique of data augmentation represents a reparameterization of the

``complete data'' model -- i.e., that conditional on $N$. The

reparameterization is achieved by embedding this data set into a

larger data set having $M> N$ ``rows'' (individuals) and reexpressing

the model conditional on $M$ instead of $N$. The great thing about

data augmentation is that we do not need to know $N$ for this reparameterization.

Although this has a whiff of

arbitrariness or even outright ad hockery to it, in the choice of $M$,

it is always possible, in practice, to choose $M$ pretty easily for

a given problem and context and results will be insensitive to choice

of $M$\footnote{Unless the data set is sufficiently small that parameters are

weakly

identified}.

Then, under data augmentation, analysis

is focused on the ``augmented data set.'' That is, we analyze the bigger

data set - the one having $M$ rows - with an appropriate model that

accounts for the augmentation. This is achieved by a Bernoulli sampling process that determines whether and individual in $M$ is also a member of $N$.

Inference is focused directly on

estimating the proportion $\psi = E[N]/M$, instead of directly on $N$,

where $\psi$ is the ``data augmentation parameter.''

\subsection{DA links occupancy models and closed population models}

%We provide a heuristic description of data augmentation based on the

There is a close correspondence between so-called ``occupancy'' models and closed

population models \citet[see][sec. 5.6]{royle\_dorazio:2008}.

In occupancy models \citep{mackenzie\_etal:2002, tyre\_etal:2003} the

sampling situation is that $M$ sites, or patches, are sampled multiple

times to assess whether a species occurs at the sites. This yields

encounter data such as that illustrated in the left panel of Table

\ref{closed.tab.occ}. The important problem is that a species may occur at

a site, but go undetected, yielding the ``all zero'' xxxxx $consistence in this$ encounter

histories which are observed. However, some of the all-zeros will typically

correspond to sites where the species in fact {\it does}

occur. Thus, while the zeros are observed, there are too many of them

and, in a sense, the inference problem is to partition the zeros into

``structural'' (fixed) and ``sampling'' (or stochastic) zeros, where the former are associated with unoccupied and the latter with occupied sites. More

formally, inference is focused on the parameter $\psi$, the

probability that a site is occupied. In contrast, in classical closed

population studies, we observe a data set as in the middle panel of

Table \ref{closed.tab.occ} where {\it no} zeros are observed. The inference

problem is, essentially, to estimate how many sampling zeros there are

- or should be - in a ``complete'' data set. This objective

(how many sampling zeros?) is precisely the same for both types of

problems if an upper limit $M$ is specified for the closed population

model. The only distinction being that, in occupancy models, $M$ is

set by design (i.e., the number of sites to visit), whereas a natural

choice of $M$ for capture-recapture models may not be

obvious. However, the choice of $M$ induces a uniform prior for $N$ on the integers

$[0,M]$ \citep{royle\_etal:2007}. Then,

one can analyze capture-recapture models by adding $M-n$ all-zero

encounter histories to the data set and regarding the augmented data

set, essentially, as a site-occupancy data set, where the occupancy parameter ($psi$) takes the place of the abundance parameter ($N$).

Thus, the heuristic motivation of data augmentation is to fix the size

of the data set by adding {\it too many} all-zero encounter histories

to create the data set shown in the right panel of Table

\ref{closed.tab.occ} - and then analyze the augmented data set using an

occupancy type model which includes both ``unoccupied sites'' as well

as ``occupied sites'' at which detections did not occur. We call these

$M-n$ all-zero histories ``potential individuals'' because they exist

to be recruited (in a non-biological sense) into the population, for

example during an analysis by MCMC.

To analyze the augmented data set, we recognize that it is a

zero-inflated version of the known-$N$ data set. That is, some of the

augmented all zero rows are sampling zeros (corresponding to actual

individuals that were missed) and some are ``structural'' zeros, which

do not correspond to individuals in the population. For a basic

closed-population model, the resulting likelihood under data

augmentation - that is, for the data set of size $M$ -- is a simple

zero-inflated binomial likelihood. The zero-inflated binomial model

can be described ``hierarchically'', by introducing a set of binary

latent variables, $z\_{1},z\_{2},\ldots, z\_{M}$, to indicate whether

each individual $i$ is ($z\_i=1$) or is not ($z\_i=0$) a member of the

population of $N$ individuals exposed to sampling. We assume that

$z\_{i} \sim \mbox{Bern}(\psi)$ where $\psi$ is the probability that an

individual in the data set of size $M$ is a member of the sampled

population - in the sense that $1-\psi$ is the probability of

realizing a ``structural zero'' in the augmented data set. The

zero-inflated binomial model which arises under data augmentation can

be formally expressed by the following set of assumptions (we include typical priors for a Bayesian analysis):

\begin{eqnarray\*}

y\_{i}|{z\_{i}=1} & \sim &\mbox{Bin}(K, p) \\

y\_{i}|{z\_{i}=0} & \sim & \delta(0) \\

z\_{i} & \stackrel{iid}{\sim} & \mbox{Bern}(\psi) \\

\psi & \sim & \mathrm{Unif}(0,1) \\

p & \sim & \mathrm{Unif}(0,1)

\end{eqnarray\*}

for $i=1, \ldots, M$, where $\delta(0)$ is a point mass at $y=0$.

$ xxxxxWhy did you move away from the old way of describing the model:

z ~ Bern(psi)

y ~ Bern(zp)

?

$xxxxxxxx

Note that, under data augmentation,

$N$ is no longer an explicit parameter of this

model. In its place, we estimate $\psi$ and functions of the latent

variables $z$. In particular, under the assumptions of the zero-inflated

model, $z\_{i} \stackrel{iid}{\sim} \mbox{Bern}(\psi)$; therefore, $N$

is a function of these latent variables:

\[

N = \sum\_{i=1}^{M} z\_{i}.

\]

Further, we note that the latent $z\_i$ parameters {\it can be} removed

from

the model by integration, in which case the joint probability of the

data is

\begin{equation}

\Pr(y\_1, \ldots, y\_M | p, \psi) = \prod\_{i=1}^M \psi \mathrm{Bin}(y\_i | K, p) + I(y\_i=0) (1-\psi)

\end{equation}

Interpreted as a likelihood, we can directly maximize this expression to obtain the MLEs of the structural

parameters $\psi$ and $p$ or those of other more complex models

\citep[e.g., see][]{royle:2006}. We could estimate these parameters

and then use them to obtain an estimator of $N$ using the so-called

``Best unbiased predictor'' \citep[see][]{royle\_dorazio:2011}. Normally, however,

we will analyze the model in its ``conditional-on-$z$'' form using methods of MCMC either

in the {\bf BUGS} engines or using our own MCMC algorithms (see Chapt. \ref{chapt.mcmc}).

\begin{table}

\centering

\caption{Hypothetical occupancy data set (left), capture-recapture data

in standard form (center), and capture-recapture data augmented with

all-zero capture histories (right). }

\begin{tabular}{cccc|cccc|cccc}

\hline

\multicolumn{4}{c}{Occupancy data} &

\multicolumn{4}{c}{Capture-recapture} &

\multicolumn{4}{c}{Augmented C-R} \\ \hline

site & k=1 & k=2 & k=3 & ind & k=1 &k=2 & k=3 & ind & k=1 & k=2 & k=3 \\ \hline

1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\

2 & 1 & 0 & 1 & 2 & 1 & 0 & 1 & 2 & 1 & 0 & 1 \\

3 & 0 & 1 & 0 & . & 0 & 1 & 0 & 3 & 1 & 0 & 1 \\

4 & 1 & 0 & 1 & . & 1 & 0 & 1 & 4 & 1 & 0 & 1 \\

5 & 0 & 1 & 1 & . & 0 & 1 & 1 & 5 & 1 & 0 & 1 \\

. & 0 & 1 & 1 & . & 0 & 1 & 1 & . & 0 & 1 & 1 \\

. & 1 & 1 & 1 & . & 1 & 1 & 1 & . & 0 & 1 & 1 \\

. & 1 & 1 & 1 & . & 1 & 1 & 1 & . & 1 & 1 & 1 \\

& 1 & 1 & 1 & . & 1 & 1 & 1 & . & 1 & 1 & 1 \\

n & 1 & 1 & 1 & n & 1 & 1 & 1 & n & 1 & 1 & 1 \\

. & 0 & 0 & 0 & & & & & . & 0 & 0 & 0 \\

. & 0 & 0 & 0 & & & & & . & 0 & 0 & 0 \\

& 0 & 0 & 0 & & & & & & 0 & 0 & 0 \\

& 0 & 0 & 0 & & & & & & 0 & 0 & 0 \\

& 0 & 0 & 0 & & & & & & 0 & 0 & 0 \\

& 0 & 0 & 0 & & & & & N & 0 & 0 & 0 \\

. & 0 & 0 & 0 & & & & & . & 0 & 0 & 0 \\

. & 0 & 0 & 0 & & & & & & 0 & 0 & 0 \\

M & 0 & 0 & 0 & & & & & . & 0 & 0 & 0 \\

& & & & & & & & . & . & . & . \\

& & & & & & & & . & . & . & . \\

& & & & & & & & . & . & . & . \\

& & & & & & & & M & 0 & 0 & 0 \\

\end{tabular}

\label{closed.tab.occ}

\end{table}

\subsection{Model $M\_0$ in BUGS}

For model $M\_0$, in which we can aggregate the encounter data to

individual-specific encounter frequencies, the augmented data are

given by the vector of frequencies $(y\_{1}, \ldots, y\_{n}, 0, 0,

\ldots, 0)$. The zero-inflated model of the augmented data combines

the model of the latent variables, $z\_{i} \sim \mbox{Bern}(\psi)$ with

the conditional-on-$z$ binomial model:

\begin{eqnarray\*}

y\_{i}|(z\_{i} = 1) &\sim& \mbox{Bin}(K,p) \\

y\_{i} | (z\_{i} = 0) &\sim& \delta(0)

\end{eqnarray\*}

It is convenient to express the conditional-on-$z$ observation model concisely as:

\[

y\_{i}|z\_{i} \sim \mbox{Bin}(K, p z\_{i})

\]

Thus, if $z\_{i}=0$, the success probability of the binomial

distribution is identically 0 whereas, if $z\_{i}=1$, the success

probability is $p$. This is useful in describing the model in the {\bf

BUGS}

language, as shown in Panel \ref{closed.panel.da4m0}.

Note the last line of the model

specification provides the expression for computing $N$ from the

data augmentation variables $z\_{i}$.

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

\begin{panel}[htp]

\centering

\rule[0.15in]{\textwidth}{.03in}

%\begin{minipage}{5in}

{\small

\begin{verbatim}

model{

p ~ dunif(0,1)

psi~dunif(0,1)

# nind = number of individuals captured at least once $better call nind n as in the table and also in the text$

# nz = number of uncaptured individuals added for PX-DA

for(i in 1:(nind+nz)) {

z[i]~dbern(psi)

mu[i]<-z[i]\*p

y[i]~dbin(mu[i],K)

}

N<-sum(z[1:(nind+nz)])

}

\end{verbatim}

}

%\end{minipage}

\rule[-0.15in]{\textwidth}{.03in}

\caption{Model $M\_{0}$ under data augmentation. Here \mbox{\tt y}, \mbox{\tt K}, \mbox{\tt n} and \mbox{\tt nz} are provided as data.}

\label{closed.panel.da4m0}

\end{panel}

Specification of a more general model in terms of the individual

encounter observations $y\_{ik}$ is not much more difficult than for

the individual encounter frequencies. We define the

observation model by a double loop and change the indexing of quantities

accordingly, i.e.,

{\small

\begin{verbatim}

for(i in 1:(nind+nz)) {

z[i]~dbern(psi)

for(k in 1:K){

mu[i,k]<-z[i]\*p

y[i,k]~dbin(mu[i,k],1)

}

}

\end{verbatim}

}

In this manner, it is straightforward to incorporate covariates on $p$

for both individuals and sampling occasions

(see discussion of this below and also Chapt. \ref{chapt.covariates})

as well as to devise other extensions of the model, e.g., what ? xxxxxxxxxxxxxx

\subsection{Formal development of parameter-expanded data augmentation (PX-DA)}

Use of PX-DA, or DA for short, for solving inference problems with unknown $N$ can be

justified as originating from the choice of uniform prior on $N$. The

$\mathrm{Unif}(0,M)$ prior for $N$ is innocuous in the sense that the

posterior associated with this prior is equal to the likelihood for

sufficiently large $M$. One way of inducing the $\mathrm{Unif}(0,M)$

prior on $N$ is by assuming the following hierarchical prior:

\begin{eqnarray}

\label{closed.eq.NgivenM}

N &\sim& \mathrm{Bin}(M, \psi) \\ \nonumber

\psi &\sim& \mathrm{Unif}(0,1)

\end{eqnarray}

which includes a new model parameter $\psi$

(note that we have seen $\psi$ in the previous section as the proportion $E[N]/M$).

This parameter denotes

the probability that an individual in the super-population of size $M$

is a member of the population of $N$ individuals exposed to sampling.

The model assumptions, specifically the multinomial model

(Eq. \ref{closed.eq.multinomial4m0})

and Eq. \ref{closed.eq.NgivenM}, may be combined to yield a

reparameterization of the conventional model that is appropriate for

the augmented data set of known size $M$:

\begin{equation}

\label{closed.eq.multinomial4DA}

(n\_1, n\_2, \ldots, n\_K) \sim \mathrm{Multin}(M, \psi \pi(1), \psi \pi(2), \ldots, \psi \pi(K))

\end{equation}

This expression arises by removing $N$ from Eq. \ref{closed.eq.multinomial4m0} by

integrating

over the binomial prior distribution for $N$. Thus, the models we

analyze under data augmentation arise formally by removing the

parameter $N$ from the ordinary closed-population model - the model conditional on $N$ -

by integrating over a binomial prior distribution for $N$.

Note that the $M-n$ unobserved individuals in the augmented data set

have probability $\psi \pi(0) + (1-\psi)$, indicating that these

unobserved individuals are a mixture of individuals that are sampling

zeros ($\psi \pi\_0$), and belong to the population of size $N$) and

others that are ``structural zeros'' (occurring in the augmented data

set with probability $1 - \psi$). In Eq.~\ref{closed.eq.multinomial4DA} $N$

has been eliminated as a formal parameter of the model by

marginalization (integration) and replaced with the new parameter

$\psi$, the data augmentation parameter.

However, the full likelihood containing both $N$ and $\psi$ can also be

analyzed \citep[see][]{royle\_etal:2007}.

\subsection{Remarks on Data Augmentation}

xxxxxxxxx$Somewhere here could emphasize that DA is trivial to implement in the BUGS language$xxxxxxxxxxxxxxxxxx

Data augmentation may seem like a strange and mysterious black-box,

and likely it is unfamiliar to most people, even to many of those with substantial

experience with capture-recapture models. However, it really is just a

formal reparameterization of capture-recapture models in which $N$ is

removed from the ordinary (conditional-on-$N$) model by integration.

In the case of model $M\_0$, data augmentation produces the zero-inflated

binomial which is distinct from the original model, but

only in the sense that it embodies, explicitly, the $\mbox{Unif}(0,M)$

prior for $N$. Choice of $M$ might be cause for some concern related

to potential sensitivity to choice of $M$. The guiding principle is

that it should be chosen large enough so that the posterior for $N$ is

not truncated, but no larger because large values entail a greater

computational burden. It seems likely that the properties of the

Markov chains should be affected by $M$ and so some optimality might

exist \citep{gopalaswamy\_etal:2012}, xxxxx$don’t understand this$xxxxxx as in occupancy models

\citep{mackenzie\_royle:2005}. Formal analysis of this is needed.

We emphasize the motivation for data augmentation being that it

produces a data set of fixed size, so that the parameter dimension in

any capture-recapture model is also fixed. As a result, MCMC is a

relatively simple proposition using standard Gibbs Sampling. Consider

the simplest context - analyzing model $M\_0$ using the occupancy-type

model. In this case, DA converts model $M\_0$ to a basic occupancy model

and the parameters $p$ and $\psi$ have known full-conditional

distributions (in fact, beta distributions) that can be sampled from

directly. Furthermore, the data augmentation variables - i.e., the collection

of $z$'s - xxxxx $must by a hyphen, or else two commas$ can be sampled from Bernoulli full

conditionals. MCMC is not much more difficult for complicated

models - sometimes the hyperparameters need to be sampled using a

Metropolis-Hastings step (e.g., Chapt. \ref{chapt.mcmc}), but nothing more sophisticated than that is

required.

There are other approaches to analyzing models with unknown $N$, using

reversible jump MCMC (RJMCMC) or other so-called ``trans-dimensional''

(TD) algorithms

\citep{durban\_elston:2005, king\_brooks:2001, king\_etal:2008,

schofield\_barker:2008, wright\_etal:2009}. xxxx$cite chrono, not alpha$ xxxx What distinguishes DA from RJMCMC and

related TD methods is that DA is used to create a distinctly new model

that is unconditional on $N$ and we (usually) analyze the

unconditional model. The various TD/RJMCMC approaches seek to analyze

the conditional-on-$N$ model in which the dimension of the parameter

space is a function of $N$, and will therefore typically vary at each iteration of the MCMC algorithm. TD/RJMCMC approaches might appear

to have the advantage that one can model $N$ explicitly or consider

alternative priors for $N$. However, despite that $N$ is removed as an

explicit parameter in DA, it is possible to develop hierarchical

models that involve structure on $N$ \citep{converse\_royle:2010,

royle\_etal:2011ms} xxxxx$C&R is out ?$xxxxxx which we consider in Chapt. \ref{chapt.hscr}.

\subsection{Example: Black Bear Study on Fort Drum}

To illustrate the analysis of Model $M\_0$ using data augmentation, we use

a data set collected at Fort Drum Military Installation in upstate New

York by the Department of Defense, Cornell University and

colleagues xxxxx$ of what/whom ?$xxxxxx. These data have been analyzed in various forms by

\citet{wegan:2008,gardner\_etal:2009} and \citet{gardner\_etal:2010jwm}.

The specific data used here are encounter histories on 47 individuals

obtained from an array of 38 baited ``hair snares''

(Fig. \ref{fig.3.bears1}) during June and July 2006. Barbed wire

traps were baited and checked for hair samples each week for eight

weeks, thus we distinguished $K=8$ weekly sample intervals. The data are provided

in the {\bf R} package \mbox{\tt scrbook}

and the analysis can be set up and run as

follows. Here, the data were augmented with 128

all-zero encounter histories, resulting in a total sample size of $M=175$.

\begin{figure}

\centering

\includegraphics[height=2.5in,width=1.9in]{Ch3/figs/hairsnares.png}

\caption{Fort Drum Black bear study area and the 38 locations of hair snares.} xxxxxxx$more informative legends$

\label{fig.3.bears1}

\end{figure}

{\small

\begin{verbatim}

library("scrbook")

data("beardata")

trapmat<-beardata$trapmat

nind<-dim(beardata$bearArray)[1]

K<-dim(beardata$bearArray)[3]

ntraps<-dim(beardata$bearArray)[2]

M=175

nz<-M-nind

Yaug <- array(0, dim=c(M,ntraps,K))

Yaug[1:nind,,]<-beardata$bearArray

y<- apply(Yaug,c(1,3),sum) # summarize by ind x rep

y[y>1]<- 1 # toss out multiple encounters

ytot<-apply(y,1,sum) # total encounters out of K

\end{verbatim}

}

The raw data object, \mbox{\tt beardata\$bearArray} is a 3-dimensional

array $\mbox{\tt nind} \times \mbox{\tt ntraps} \times K$ of

individual encounter events (i.e., $y\_{ijk} = 1$ if individual $i$ was

encountered in trap $j$ during occasion $k$, and 0 otherwise). For

fitting model $M\_{0}$ (or $M\_{h}$, see below), it is sufficient to

reduce the data to individual encounter frequencies which we have

labeled \mbox{\tt ytot} above. The {\bf BUGS} model file along with

commands to fit the model are as follows:

{\small

\begin{verbatim}

set.seed(2013) # to obtain the same results each time

library("R2WinBUGS")

data0<-list(y=y,M=M,K=K)

params0<-list('psi','p','N')

zst=c(rep(1,nind),rbinom(M-nind, 1, .5))

inits = function() {list(z=zst, psi=runif(1), p=runif(1)) }

cat("

model {

psi~dunif(0, 1)

p~dunif(0,1)

for (i in 1:M){

z[i]~dbern(psi)

for(k in 1:K){

tmp[i,k]<-p\*z[i]

y[i,k]~dbin(tmp[i,k],1)

}

}

N<-sum(z[1:M])

}

",file="modelM0.txt")

fit0 = bugs(data0, inits, params0, model.file="modelM0.txt",

n.chains=3, n.iter=2000, n.burnin=1000, n.thin=1,

debug=TRUE,working.directory=getwd())

\end{verbatim}

}

This produces the following posterior

summary statistics:

{\small

\begin{verbatim}

> print(fit0,digits=2)

Inference for Bugs model at "modelM0.txt", fit using WinBUGS,

3 chains, each with 2000 iterations (first 1000 discarded)

n.sims = 3000 iterations saved

mean sd 2.5% 25% 50% 75% 97.5% Rhat n.eff

psi 0.29 0.04 0.22 0.26 0.29 0.31 0.36 1 3000

p 0.30 0.03 0.25 0.28 0.30 0.32 0.35 1 3000

N 49.94 1.99 47.00 48.00 50.00 51.00 54.00 1 3000

deviance 489.05 11.28 471.00 480.45 488.80 495.40 513.70 1 3000

[... some output deleted ...]

\end{verbatim}

}

{\bf WinBUGS} did well in choosing an MCMC algorithm for this model --

we have $\hat{R} = 1$ for each parameter, and an effective sample size

of 3000, equal to the total number of posterior samples\footnote{This is even a little

suspicious....}.

We see that the posterior mean of $N$ under this

model is $49.94$ and a 95\% posterior interval is $(48,54)$. We

revisit these data later in the context of more complex models.

In order to obtain an estimate of density, $D$, we need an area to

associate with the estimate of $N$, and in Chapt. Xxx $make chap/Chap/Chapt. consistent$ \ref{chapt.intro} we already

went through a number of commonly used procedures to

conjure up such an area, including buffering the trap array by the home

range radius, often estimated by the mean maximum distance moved

(MMDM) \citep{parmenter\_etal:2003},

$1/2$ MMDM \citep{dice:1938} or

directly from telemetry data \citep{wallace\_etal:2003}

\begin{comment}

I HAVE SEEN 2 PAPERS CITING OTIS ET AL 1978 IN THIS CONTEXT

BUT I ONLY FOUND THE SECITON WHERE THEY SUGGEST USING INFORMATION ON ANIMAL HOME RANGE AS

OBTAIN FROM TRAPPING DATA; I GUESS THIS DICE GUY SAID TO USE THE HOME RANGE RADIUS

AND PEOPLE JUST TRY TO GET AT THIS WHICHEVER WAY THEY CAN; BE IT RECAPTURES OR OTHER HOME RANGE INFORMATION XXXXX).

\end{comment}

Typically, the trap

array is defined by the convex hull around the trap locations, and

this is what we applied a buffer to. We computed the buffer by using

an estimate of the mean female home range radius (2.19 km) estimated from

telemetry studies \citep{bales\_etal:2005} instead of using an estimate

based on our relatively more sparse recapture data.

For the Fort Drum study, the convex hull has area

$157.135$ $km^2$, and the buffered convex hull has area $277.011$

$km^2$.

To create this we used functions contained in the {\bf R} package

\mbox{\tt rgeos} and created a utility function \mbox{\tt bcharea}

which is in our {\bf R} package \mbox{\tt scrbook}. The commands are

as follows:

\begin{verbatim}

library("rgeos")

bcharea<-function(buff,traplocs){

p1<-Polygon(rbind(traplocs,traplocs[1,]))

p2<-Polygons(list(p1=p1),ID=1)

p3<-SpatialPolygons(list(p2=p2))

p1ch<-gConvexHull(p3)

bp1<-(gBuffer(p1ch, width=buff))

plot(bp1, col='gray')

plot(p1ch, border='black', lwd=2, add=TRUE)

gArea(bp1)

}

bcharea(2.19,traplocs=trapmat)

\end{verbatim}

The resulting buffered convex hull is shown in Fig. \ref{closed.fig.bch}.

\begin{figure}

\begin{center}

\includegraphics[height=3in,width=3in]{Ch3/figs/bufferedCH}

\end{center}

\caption{Convex hull of the bear hair snare array at Fort Drum, NY buffered by mean female

home range radius (2.19 km).}

\label{closed.fig.bch}

\end{figure}

To conjure up a

density estimate under model $M\_0$, we compute the appropriate

posterior summary of the ratio of $N$ and the prescribed area ($277.011$ $km^2$):

{\small

\begin{verbatim}

> summary(fit0$sims.list$N/277.011)

Min. 1st Qu. Median Mean 3rd Qu. Max.

0.1697 0.1733 0.1805 0.1803 0.1841 0.2130

> quantile(fit0$sims.list$N/277.011,c(0.025,0.975))

2.5% 97.5%

0.1696684 0.1949381

\end{verbatim}

}

which yields a density estimate of about $0.18$ ind/km$^2$, and a $95\%$ Bayesian

confidence interval of $(0.170, 0.195)$.

In summary, we have an estimate of density if we have faith in our

stated value of the ``sample area''. Clearly though this is largely

subjective, and not something we can formally evaluate from the data.

How certain are we of this area? Can

we quantify our uncertainty about this quantity?

More important, what exactly is

the meaning of this area and, in this context, how do we gauge bias

and/or variance of ``estimators'' of it? (i.e., what is it

estimating?).\footnote{Mention the delta approximation from

KARANTH AND NICHOLS (1998)?}

There is no theory to guide us in trying to answer these important questions.

\section{Temporally varying and behavioral effects}

The purpose of this chapter is mainly to emphasize the central

importance of the binomial model in capture-recapture and so we have

considered models for individual encounter frequencies - the number of

times individuals are captured out of $K$ samples. Sometimes we can’t aggregate the encounter data for each individual --

such as when encounter probability varies over time among samples.

Time-varying responses that are relevant in many

capture-recapture studies are ``effort'' such as amount of search time,

number of observers, or trap nights, or when encounter probability

varies over time or as a function of date or season due to species behavior

\citep{kery\_etal:2010}.

A common situation in many animal studies is that in

which there exists a ``behavioral response'' to trapping (even if the

animal is not physically trapped).

%For example, individuals might exhibit

%``trap happiness'' in response to baited traps. Conversely, individuals might learn

%to avoid traps (trap shyness) if the capture experience produces some negative

%stimulus.

Behavioral response is an important concept in animal studies

because individuals might learn to come to baited traps or avoid traps

due to trauma related to being encountered. There are a number of

ways to parameterize a behavioral response to encounter. The

distinction between persistent and ephemeral was made by

\citet{yang\_chao:2005} who considered a general behavioral response

model of the form:

\[

\mbox{logit}(p\_{ik}) = \alpha\_{0} + \alpha\_{1}\*y\_{i,k-1} + \alpha\_{2} x\_{ik}

\]

where $x\_{ik}$ is a covariate indicator variable of previous capture

(i.e., $x\_{ik} = 1$ if captured in any previous period). Therefore,

encounter probability changes depending on whether an individual was

captured in the immediate previous period (ephemeral behavioral

response XXX described by the term $\alpha\_{1}\*y\_{i,k-1}$) or in any previous period (persistent behavioral

response). The former probably models a behavioral response due to

individuals moving around their territory relatively slowly over time

and the latter probably accommodates trap happiness due to baiting or

shyness due to trauma. Spatial capture-recapture models allow us to

include trap-specific covariates, and in such models it makes

sense to consider a local behavioral response that is trap-specific

\citep{royle\_etal:2011jwm} - that is, the encounter probability is

modified for an individual trap depending on previous capture in

that trap.

Models with temporal effects are easy to describe in the {\bf BUGS} language

and analyze and we provide a number of examples in

Chapt. \ref{chapt.covariates} and elsewhere.

\section{ Models with individual heterogeneity}

\label{closed.sec.modelmh}

Here we consider models with individual-specific encounter probability

parameters, say $p\_{i}$, which we model according to some probability

distribution, $g(\theta)$. We denote this basic model assumption as

$p\_{i} \sim g(\theta)$. This type of model is similar in concept to

extending a GLM to a GLMM but in the capture-recapture context $N$ is

unknown. The basic class of models is often referred to as ``model

$M\_h$'', but really this is a broad class of models, each being

distinguished by the specific distribution assumed for $p\_{i}$. There

are many different varieties of model $M\_{h}$ including parametric and

various putatively non-parametric approaches

\citep{burnham\_overton:1978, norris\_pollock:1996, pledger:2000}. One

important practical matter is that estimates of $N$ can be extremely

sensitive to the choice of heterogeneity model

\citep{fienberg\_etal:1999, dorazio\_royle:2003, link:2003}. Indeed,

\citet{link:2003} showed that in some cases it's possible to find

models that yield precisely the same expected data, yet produce wildly

different estimates of $N$. In that sense, $N$ for most practical

purposes is not identifiable across classes of mixture models, and

this should be understood before fitting any such model. One solution

to this problem is to seek to model explicit factors that contribute

to heterogeneity, e.g., using individual covariate models (See

\ref{closed.sec.indcov} below). Indeed, spatial capture-recapture

models seek to do just that, by modeling heterogeneity due to the

spatial organization of individuals in relation to traps or other

encounter mechanism. For additional background and applications of

model $M\_{h}$ see \citet[][Chapt. 6]{royle\_dorazio:2008} and

\citet[][Chapt. 6]{kery\_schaub:2011}.

Model $M\_{h}$ has important historical relevance to spatial

capture-recapture situations \citep{karanth:1995} because

investigators recognized that the juxtaposition of individuals with

the array of trap locations should yield heterogeneity in encounter

probability, and thus it became common to use some version of model $M\_h$

in spatial trapping arrays to estimate $N$. While this doesn't

resolve the problem of not knowing the area relevant to $N$, it does

yield an estimator that accommodates the heterogeneity in $p$ induced

by the spatial aspect of capture-recapture studies.

To see how this juxtaposition induces heterogeneity, we have to

understand the relevance of movement in capture-recapture models.

Imagine a quadrat that can be uniformly searched by a crew of

biologists for some species of reptile (see

\citet{royle\_young:2008}). Figure \ref{closed.fig.quadrat} shows a

sample quadrat searched repeatedly over a period of time. Further,

suppose that species exhibits some sense of spatial fidelity in the

form of a home range or territory, and individuals move about their

home range (home range centroids are given by the blue dots) in some

kind of random fashion.

%It is natural to think about it in terms of a

%movement process and sometimes that movement process can be modeled

%explicitly using hierarchical models \citep{royle\_young:2008,

% royle\_etal:2011mee}.

Heuristically, we imagine that each individual in

the vicinity of the study area is liable to experience variable

exposure to encounter due to the overlap of its home range with the

sampled area - essentially the long-run proportion of times the

individual is within the sample plot boundaries, say $\phi$. We

might model the exposure of an individual to capture by supposing that

$z\_{i} = 1$ if individual $i$ is available to be captured (i.e.,

within the survey plot) during any sample, and $0$ otherwise. Then,

$\Pr(z\_{i}=1) = \phi$. In the context of spatial studies, it is

natural that $\phi$ should depend on {\it where} an individual lives,

i.e., it should be individual-specific $\phi\_{i}$

\citep{chandler\_etal:2011}. This system describes, precisely, that of

``random temporary emigration'' \citep{kendall\_etal:1997} where $\phi\_{i}$

is the individual-specific probability of being ``available'' for

capture.

Conceptually, SCR models aim to deal with

this problem of variable exposure to sampling due to movement in the

proximity of the trapping array explicitly and formally with auxiliary

spatial information. If individuals are detected with probability

$p\_{0}$, {\it conditional} on $z\_{i} = 1$, then the marginal

probability of detecting individual $i$ is

\[

p\_{i} = p\_{0}\phi\_{i}

\]

so we see clearly that individual heterogeneity in encounter

probability is induced as a result of the juxtaposition of individuals

(i.e., their home ranges) with the sample apparatus and the movement

of individuals about their home range.

\begin{figure}

\begin{center}

\includegraphics[height=3in]{Ch3/figs/quadrat}

\end{center}

\caption{A quadrat searched for lizards and the locations of each

lizard over some period of time (simulated data).nice plot ! but, as usual, I would give more info. For instance, I would say something like ‘Successive locations of 10 individual lizards over time are depicted by grey lines; black dots represent the individual activity centers.’}

\label{closed.fig.quadrat}

\end{figure}

We will work with a specific type of model $M\_{h}$ here, that in which

we extend the basic binomial observation model of model $M\_{0}$ so

that

\[

\mbox{logit}(p\_{i}) = \mu + \eta\_{i}

\]

where

\[

\eta\_{i} \sim \mbox{Normal}(0, \sigma\_{p}^2)

\]

We could as well write

\[

\mbox{logit}(p\_{i}) \sim \mbox{Normal}(\mu,\sigma\_{p}^2)

\]

This ``logit-normal mixture'' was analyzed by

\citet{coull\_agresti:1999} and elsewhere. It is a natural extension of

the basic model with constant $p$, as a mixed GLMM, and similar models

occur throughout statistics. It is also natural to consider a beta

prior distribution for $p\_{i}$ \citep{dorazio\_royle:2003} and

so-called ``finite-mixture'' models

are also popular

\citep{norris\_pollock:1996, pledger:2000}. In the latter, individuals are assumed to

belong to a finite number of latent classes, each of which has its own capture probability.

\subsection{Analysis of Model $M\_h$}

If $N$ is known, it is worth taking note of the essential simplicity

of model $M\_h$ as a binomial GLMM. This is a type of model that is

widely applied throughout statistics using

standard methods of inference based either on integrated likelihood

\citep{laird\_ware:1982, berger\_etal:1999}, which we discuss in

Chapt. \ref{chapt.mle}, or standard Bayesian

methods. However, because $N$ is not known, inference is somewhat more

challenging. We address that here using Bayesian analysis based on

data augmentation (DA). Although we use data augmentation in the context of

Bayesian methods here, we note that

heterogeneity models formulated under DA are easily analyzed by

conventional likelihood methods as zero-inflated binomial mixtures

\citep{royle:2006} and more traditional analysis of model $M\_h$ based on

integrated likelihood, without using data augmentation, has been

considered by \citet{coull\_agresti:1999}, \citet{dorazio\_royle:2003},

and others.

As with model $M\_{0}$, we have the Bernoulli model for the

zero-inflation variables: $z\_{i} \sim \mbox{Bern}(\psi)$ and the model

of the observations expressed conditional on these latent variables

$z\_{i}$. For $z\_{i}=1$, we have a binomial model with

individual-specific $p\_{i}$:

\[

y\_{i}|{z\_{i} \! = \! 1} \sim \mbox{Bin}(K,p\_{i})

\]

and otherwise $y\_{i} |{ z\_{i} \! = \! 0} \sim \delta(0)$. Further, we

prescribe a distribution for $p\_{i}$. Here we assume

\[

\mathrm{logit}(p\_{i}) \sim \mbox{Normal}(\mu,\sigma^2)

\]

The basic {\bf BUGS} description for this model, assuming a

$\mbox{Unif}(0,1)$ prior for $p\_{0} = \mbox{logit}^{-1}(\mu)$, is given

as follows:

{\small

\begin{verbatim}

model{

p0 ~ dunif(0,1) # prior distributions

mup<- log(p0/(1-p0))

taup~dgamma(.1,.1)

psi~dunif(0,1)

for(i in 1:(nind+nz)){

z[i]~dbern(psi) # zero inflation variables

lp[i] ~ dnorm(mup,taup) # individual effect

logit(p[i])<-lp[i]

mu[i]<-z[i]\*p[i]

y[i]~dbin(mu[i],K) # observation model

}

N<-sum(z[1:(nind+nz)]) # N is a derived parameter

}

\end{verbatim}

}

\subsection{Analysis of the Fort Drum data}

The logit-normal heterogeneity model was fitted to the bear data from

the Fort Drum study, and we used data augmentation to produce a data

set of $M=500$ individuals. We ran the model using {\bf JAGS} with

the instructions given as follows:

{\small

\begin{verbatim}

[... get data as before ....]

set.seed(2013)

cat("

model{

p0 ~ dunif(0,1) # prior distributions

mup<- log(p0/(1-p0))

sigmap ~ dunif(0,10)

taup<- 1/(sigmap\*sigmap)

psi~dunif(0,1)

xxxxxx It might confuse people if you use the gamma prior on the precision in the immediately preceding example and here a uniform for the SD. make the same or else briefly comment on it.xxxxx

for(i in 1:(nind+nz)){

z[i]~dbern(psi) # zero inflation variables

lp[i] ~ dnorm(mup,taup) # individual effect

logit(p[i])<-lp[i]

mu[i]<-z[i]\*p[i]

y[i]~dbin(mu[i],K) # observation model

}

N<-sum(z[1:(nind+nz)])

}

",file="modelMh.txt")

data1<-list(y=ytot, nz=nz, nind=nind,K=K)

params1= c('p0','sigmap','psi','N')

inits = function() {list(z=as.numeric(ytot>=1), psi=.6, p0=runif(1),

sigmap=runif(1,.7,1.2),lp=rnorm(M,-2)) }

library("rjags")

jm<- jags.model("modelMh.txt", data=data1, inits=inits, n.chains=3,

n.adapt=10000)

jout<- coda.samples(jm, params1, n.iter=500000, thin=1)

\end{verbatim}

}

This produces the posterior distribution for $N$ shown

in Fig. \ref{closed.fig.bearMh}. Posterior summaries of parameters are

given as follows:

{\small

\begin{verbatim}

> summary(jout)

[... output deleted ...]

Iterations = 500001:1e+06

Thinning interval = 1

Number of chains = 3

Sample size per chain = 5e+05

1. Empirical mean and standard deviation for each variable,

plus standard error of the mean:

Mean SD Naive SE Time-series SE

N 119.11050 57.85859 4.724e-02 1.285748

p0 0.07228 0.05545 4.527e-05 0.001064

psi 0.23928 0.11669 9.528e-05 0.002562

sigmap 2.08650 0.53532 4.371e-04 0.010903

xxxxxx$Could you explain this output a little more ? I later saw that you do later on, but I would always explain new stuff where it first appears. For instance, I had no clue what the naive SE meant ? Seems to be the Monte Carlo error ?$xxxxxxxx

[... output deleted ... ]

\end{verbatim}

}

We used $M=500$ for this analysis and we

note that while the posterior mass of $N$ is concentrated away from this

upper bound (Fig. \ref{closed.fig.bearMh}), the posterior has an

extremely long right tail, with some posterior values at the upper

bound $N=500$, suggesting that an even higher value of $M$ may be

called for.

To characterize the posterior distribution of density we produce the

relevant summaries of the posterior distribution of $N/277.11$ where,

recall, the buffered area of the convex hull is 277.11 $km^2$:

{\small

\begin{verbatim}

N<-c(jout[[1]][,"N"],jout[[2]][,"N"],jout[[3]][,"N"])

summary(N/277.11)

Min. 1st Qu. Median Mean 3rd Qu. Max.

0.1696 0.2959 0.3681 0.4298 0.4908 1.8040

> quantile(N/277.11,c(0.025,0.50,0.975))

2.5% 50% 97.5%

0.2237379 0.3680849 1.0284724

\end{verbatim}

}

so the point estimate, characterized by the posterior mean, is around

$0.43$ bears per square km. xxxx$may want to give the 95% CRI, or else delete last R command$xxxxx

The model runs effectively in {\bf WinBUGS} but sometimes with apparently

inefficient mixing for reasons that may be related to bad starting

values. In some cases this was resolved if we supplied starting values

for the $logit(p\_{i})$ parameters and $\tau$. We provide a user-friendly {\bf R}

function \mbox{\tt modelMhBUGS} in the package \mbox{\tt scrbook} which will

fit the model using either {\bf JAGS} or {\bf WinBUGS} as specified by

the user.

In addition, for fun, we construct our own MCMC algorithm using a Metropolized

Gibbs sampler for model $M\_{h}$ in Chapt. \ref{chapt.mcmc}, where we

also develop the MCMC algorithms for spatial capture-recapture models.

\subsection{Comparison with MLE}

Because of the skewed posterior we see that the posterior mean

($N=119$) is considerably higher than the posterior median

($N=102$). Moreover, posterior summaries are estimated with a

relatively high error: The ``Time-series'' or Monte Carlo SE of around

1.2 (see secs. for discussion of this quantity

\ref{glms.sec.convergence} \ref{mcmc.sec.mcmcsummary}) even despite

the high number of iterations we ran here (each of 3 chains based on

500000 iterations). Further, it may be surprising that the posterior

mode does not compare well with the MLE xxxxxx$as yet, we don’t know the MLE$xxxxxxxxx. To compute the posterior mode

we could easily find the posterior value of $N$ with the highest mass

because $N$ is discrete. But we want to smooth out some of the Monte

Carlo error a bit so we used a smoothing spline to the posterior

frequencies of $N$ as follows (here we take only the first 80 values):

\begin{verbatim}

tt<-table(jout[[1]][,"N"])[1:80]

xg<-as.numeric(names(tt))

plot(xg,tt)

sp<- smooth.spline(xg,tt,df=9)

sp$x[sp$y==max(sp$y)]

[1] 81

\end{verbatim}

The \mbox{\tt df} argument controls the degree of smoothing and we

find in this case that the modal value (i.e., 81) is not too sensitive

to the smoothing parameter but this should be checked in any specific

instance\footnote{we need to give examples of using \mbox{\tt

density()} to obtain modes}.

To compare this with the MLE, we used

the {\bf R} code contained in Panel 6.1 on p. XXX of \citet{royle\_dorazio:2008}. The

MLE of $log(n\_{0})$, the logarithm of the number of uncaptured

individuals, is $\widehat{log(n0)} = 3.86$ and therefore $\hat{N} =

exp(3.86)+47 = 94.47$ which is not at all consistent with the

mode in

Fig. \ref{closed.fig.bearMh}.

%\footnote{We note that the result is inconsistent with Gardner et

% al. (2009) who reported an MLE of 104.1 ($density = 0.437

% inds/km^2$) although we do not know the reason for this at the

% present time.}

%To convert this to density we use the buffered area

%as computed above (255.3 $km^2$)\footnote{WRONG \#} and perform the

%required summary analysis on the posterior samples of $N$, which

%results in about $0.37$ individuals/$km^2$. The reader should carry

%out this analysis to confirm the estimates, and also obtain the $95\%$

%confidence interval.

\begin{comment}

We reflect for a moment on the whole idea of using

capture-recapture to estimate density. It seems pointless to argue about ``buffer width'' when

we can't even decide on an estimate of $N$! Maybe this reflects poorly

on the desire to have a point estimate of a quantity more than our

ability to provide

\end{comment}

{\bf Remarks:}

First of all the posterior for this model and data set is

very sensitive to prior distributions. While MLEs are invariant to

transformation of the parameters, the posterior distribution

definitely is {\it not} invariant. In the present case, the use of a

$\mbox{Unif}(0,1)$ prior for $p\_{0} = \mbox{expit}(\mu)$ is somewhat

informative -- in particular, it is not at all ``flat'' on the scale

of $\mu$ -- and this affects the posterior. We generally always

recommend use of a $\mbox{Unif}(0,1)$ prior for $\mbox{expit}(\mu)$ in such

models. That said, we were surprised at this result, and we

experimented with other prior configurations including putting a flat

prior on $\mu$ directly. That specific prior suggests the possibility

that the posterior distribution may be improper for that prior

specification. This kind of small sample instability has been widely

noted in model $M\_h$ \citep{fienberg\_etal:1999, dorazio\_royle:2003},

as has extreme sensitivity to the specific form of model $M\_{h}$ \citep{link:2003}.

In summary, while the mode is well-defined, the data set is relatively

sparse and hence inferences are poor and sensitive to model choice.

\begin{figure}

\centering

\includegraphics[height=4.5in,width=4.5in]{Ch3/figs/bear-modelMh-post}

\caption{Posterior of $N$ for Fort Drum bear study data under the

logit-normal version of model $M\_h$.

}

\label{closed.fig.bearMh}

\end{figure}

\begin{comment}

To begin, we first collect all of our model components

which are as follows: $[y\_{i}| p\_{i},z\_{i}]$,

$[p\_{i}|\mu\_{p},\sigma\_{p}]$, and $[z\_{i}|\psi]$

for {\it each} $i=1,2,\ldots,M$ and then prior distributions

$[\mu\_{p}]$, $[\sigma\_{p}]$ and $[\psi]$.

The joint posterior distribution of all unknown quantities in the model

is proportional to the joint distribution of all elements

$y\_{i},p\_{i},z\_{i}$ and also the prior distributions of the prior parameters:

\[

\left\{ \prod\_{i=1}^{M} [y\_{i}|p\_{i},z\_{i}][p\_{i}|\mu\_{p},\sigma\_{p}]

[z\_{i}|\psi] \right\} [\mu\_{p},\sigma\_{p},\psi]

\]

For prior distributions, we assume that $\mu\_{p},\sigma\_{p}, \psi$ are

mutually independent and for $\mu\_{p}$ and $\sigma\_{p}$ we use

improper uniform priors, and $\psi \sim \mbox{Unif}(0,1)$. Note that

the likelihood contribution for each individual, when conditioned on

$p\_{i}$ and $z\_{i}$, does not depend on $\psi$, $\mu\_{p}$, or

$\sigma\_{p}$. As such, the full-conditionals for the structural

parameters $\psi$ only depends on the collection of data augmentation

variables $z\_{i}$, and that for $\mu\_{p}$ and $\sigma\_{p}$ will only

depends on the collection of latent variables $p\_{i}; i=1,2,\ldots,M$.

The full conditionals for all the unknowns are as follows:

{\bf (1)} For $p\_{i}$:

\begin{eqnarray\*}

[p\_{i}|y\_{i}, \mu\_p, \sigma\_{p},z\_{i}=1] &\propto &

[y\_{i}|p\_{i}][p\_{i}|\mu\_p,\sigma\_{p}^{2}] \mbox{ if $z\_{i}=1$ } \\

& & [p\_{i}|\mu\_p,\sigma\_{p}] \mbox{if $z\_{i}=0$ }

\end{eqnarray\*}

{\bf (2)} for $z\_{i}$:

\[

z\_{i} | \cdot \propto [y\_{i}|z\_{i}\*p\_{i}] \mbox{Bern}(z\_{i}|\psi)

\]

{\bf (3)} For $\mu\_{p}$:

\[

[\mu\_{p} | \cdot ] \sim \prod\_{i} [p\_{i}| \cdot] \*\mbox{const}

\]

{\bf (4)} For $\sigma\_{p}$:

\[

[ \sigma\_{p}|\cdot ] \sim\prod\_{i}[p\_{i}| \cdot ]\*\mbox{const}

\]

{\bf (5)} For $\psi$:

\[

\psi|\cdot\sim \mbox{Beta}(1 + \sum z\_{i}, 1 + M - \sum z\_{i})

\]

We've identified each of the full conditional

distributions in sufficient detail to apply the

Metropolis-Hastings algorithm. With the exception of $\psi$ which has

a convenient analytic solution -- it is a beta distribution which we

can easily sample directly. In truth, we could also sample $\mu\_{p}$

and $\sigma\_{p}^{2}$ directly with certain choices of prior

distributions. For example, if $\mu\_{p} \sim \mbox{Normal}(0, 1000)$

then the full conditional for $\mu\_{p}$ is also normal, etc..

We implement an MCMC algorithm for this model in the following block

of {\bf R} code. The basic structure is: initialize the parameters

and create any required output or intermediate data holders, and then

begin the main MCMC loop which, in this case, generates 100000

samples.\footnote{This data grabbing function is not implemented yet}

{\small

\begin{verbatim}

## obtain the bear data by executing the previous data grabbing

## function

temp<-getdata()

M<-temp$M

K<-temp$K

ytot<-temp$ytot

###

### MCMC algorithm for Model Mh

out<-matrix(NA,nrow=100000,ncol=4)

dimnames(out)<-list(NULL,c("mu","sigma","psi","N"))

lp<- rnorm(M,-1,1)

p<-expit(lp)

mu<- -1

p0<-exp(mu)/(1+exp(mu))

sigma<- 1

psi<- .5

z<-rbinom(M,1,psi)

z[ytot>0]<-1

for(i in 1:100000){

### update the logit(p) parameters

lpc<- rnorm(M,lp,1) # 0.5 is a tuning parameter

pc<-expit(lpc)

lik.curr<-log(dbinom(ytot,K,z\*p)\*dnorm(lp,mu,sigma))

lik.cand<-log(dbinom(ytot,K,z\*pc)\*dnorm(lpc,mu,sigma))

kp<- runif(M) < exp(lik.cand-lik.curr)

p[kp]<-pc[kp]

lp[kp]<-lpc[kp]

p0c<- rnorm(1,p0,.05)

if(p0c>0 & p0c<1){

muc<-log(p0c/(1-p0c))

lik.curr<-sum(dnorm(lp,mu,sigma,log=TRUE))

lik.cand<-sum(dnorm(lp,muc,sigma,log=TRUE))

if(runif(1)<exp(lik.cand-lik.curr)) {

mu<-muc

p0<-p0c

}

}

sigmac<-rnorm(1,sigma,.5)

if(sigmac>0){

lik.curr<-sum(dnorm(lp,mu,sigma,log=TRUE))

lik.cand<-sum(dnorm(lp,mu,sigmac,log=TRUE))

if(runif(1)<exp(lik.cand-lik.curr))

sigma<-sigmac

}

### update the z[i] variables

zc<- ifelse(z==1,0,1) # candidate is 0 if current = 1, etc..

lik.curr<- dbinom(ytot,K,z\*p)\*dbinom(z,1,psi)

lik.cand<- dbinom(ytot,K,zc\*p)\*dbinom(zc,1,psi)

kp<- runif(M) < (lik.cand/lik.curr)

z[kp]<- zc[kp]

psi<-rbeta(1, sum(z) + 1, M-sum(z) + 1)

out[i,]<- c(mu,sigma,psi,sum(z))

}

\end{verbatim}

}

{\bf Remarks}: (1) for parameters with bounded support, i.e.,

$\sigma\_{p}$ and $p\_{0}$, we are using a random walk candidate

generator but rejecting draws outside of the parameter space. (2) We

mostly use Metropolis-Hastings except for the data augmentation

parameter $\psi$ which we sample directly from its full-conditional

distribution which is a beta distribution. (3) Even the latent data

augmentation variables $z\_{i}$ are updated using Metropolis-Hastings

although they too can be updated directly from their full-conditional.

\end{comment}

\begin{comment}

\subsection{Exercises related to model $M\_h$}

\begin{itemize}

\item[(1)] Enclose the MCMC algorithm in an R function and provide

arguments for some of the parameters of the function that a user

might wish to modify.

\item[(2)] Execute the function and compare the results to those

generated from WinBUGS in the previous section

\item[(3)] Note that the prior distribution for the ``mean'' parameter

is given on $p\_0=exp(\mu)/(1+exp(\mu))$. Reformulate the algorithm

with a flat prior on $\mu$ and see what happens. Contemplate this.

\item[(4)] Using Bayes rule, figure out the full conditional for

$z\_{i}$ so that you don't have to use MH for that one. It might be

more efficient. Is it?

\item[(5)] Modify the MCMC algorithm so that the prior for $\mu\_{p}$

is an improper flat prior. i.e., $[\mu\_{p}] \propto 1$. Describe the

posterior distribution of $N$.

\end{itemize}

\end{comment}

\section{Individual Covariate Models: Toward Spatial Capture-Recapture}

\label{closed.sec.indcov}

A standard situation in capture-recapture models is when an individual

covariate is measured, and this covariate is thought to influence

encounter probability. As with other closed population models, we

begin with the basic binomial observation model:

\[

y\_{i} \sim \mbox{Bin}(K, p\_{i})

\]

and we assume also a model for encounter probability according to:

\begin{equation}

\mbox{logit}(p\_{i}) = \alpha + \beta x\_{i}

\label{closed.eq.ha}

\end{equation}

Classical examples of covariates influencing detection probability are

type of animal (juvenile/adult or male/female), a continuous covariate

such as body mass \citep[][ch. 6]{royle\_dorazio:2008}, or a

discrete covariate such as group or cluster size. For example, in

models of aerial survey data, it is natural to model the detection

probability of a group as a function of the observation-level individual

covariate, ``group size'' \citep{royle:2008, royle:2009,

langtimm\_etal:2011}.

Such ``individual covariate models'' are similar in structure to model

$M\_{h}$, except that the individual effects are {\it observed} for the

$n$ individuals that appear in the sample. These models are important

here because spatial capture-recapture models can be descrived precisely as a form of

individual covariate model, an idea that we will develop here and

elsewhere. Specifically, they are such models, but where the

individual covariate is a partially observed latent variable for

captured individuals. As such, it is a type of measurement error.

That is, unlike model $M\_h$, we do have some direct information about the

latent variable, which comes from the spatial locations/distribution

of individual recaptures.

Traditionally, estimation of $N$ in individual covariate models is

achieved using methods based on ideas of unequal probability sampling

(i.e., Horwitz-Thompson estimation; see \citet{huggins:1989} and

\citet{alho:1990}). An estimator of $N$ is xxxx$I think it’s Horvitz$xxxx

\[

\hat{N} = \sum\_{i}^{n} \frac{1}{\tilde{p}\_{i}}

\]

where $\tilde{p}\_{i}$ is the probability that individual $i$ appeared

in the sample. That is, $\tilde{p}\_{i} = \Pr(y\_{i}>0)$

where, in closed population capture-recapture models,

\[

\Pr(y\_{i}>0) = (1- (1-p\_{i})^K)

\]

where $p\_{i}$ is a function of parameters $\alpha$ and $\beta$

according to Eq. \ref{closed.eq.ha}. In practice, parameters are

estimated from the conditional-likelihood of the observed encounter

histories which is, for observation $y\_{i}$,

\[

{\cal L}\_{c}(\alpha, \beta | y\_{i}) = \frac{ \mbox{Bin}(y\_{i}|\alpha,\beta) } { \tilde{p}\_{i}}.

\]

Here we take a formal model-based approach to Bayesian analysis of

such models based on the joint likelihood

using data augmentation \citep{royle:2009}. Classical

likelihood analysis of the so-called ``full likelihood'' is covered

by \citet{borchers\_etal:2002}. For Bayesian analysis of

individual covariate models, because the individual covariate is

unobserved for the $N-n$ uncaptured individuals, we require a model to

describe variation among individuals, essentially allowing the sample

to be extrapolated to the population. For our present purposes, we

consider a continuous covariate and we assume that it has a normal

distribution:

\[

x\_{i} \sim \mbox{Normal}(\mu,\sigma^{2})

\]

Data augmentation can be applied directly to this class of models. In

particular, reformulation of the model under DA yields a basic

zero-inflated binomial model of the form:

\begin{eqnarray\*}

z\_{i} &\sim& \mbox{Bern}(\psi) \; \; \; i=1,2,\ldots,M\\

y\_{i}|{z\_{i}\! =\! 1} &\sim& \mbox{Bin}(K,p\_{i}(x\_{i})) \\

y\_{i} |{ z\_{i}\! =\! 0} &\sim& \delta(0) \\

x\_{i} & \sim & \mbox{Normal}(\mu,\sigma^{2})

\end{eqnarray\*}

Fully spatial capture-recapture models use this

formulation with a latent covariate that is directly related to the

individual detection probability (see next section). As with the

previous models, implementation is trivial in the {\bf BUGS} language. The

{\bf BUGS} specification is very similar to that for model $M\_h$, but we

require the distribution of the covariate to be specified, along with

priors for the parameters of that distribution.

\subsection{Example: Location of capture as a covariate.}

If we had a regular grid of traps over some closed geographic system

then we imagine that the average location of capture would be a decent

estimate (heuristically) of an individual's home range center.

Intuitively some measure of typical distance from home range center to

traps for an individual should be a decent covariate to explain

heterogeneity in encounter probability, i.e., individuals with more

exposure to traps should have higher encounter probabilities and vice

versa. A version of this idea was put forth by

\citet{boulanger\_mclellan:2001} (see also \citet{ivan:2012}), but

using the Huggins-Alho estimator and with covariate ``distance to

edge'' of the trapping array. A limitation of this approach is

that it does not provide a solution to the problem that the trap area

is fundamentally ill-defined, nor does it readily accommodate the

inherent and heterogeneous variation in this measured covariate.

Here, we provide an example of this type of heuristically motivated

approach using the fully model-based individual covariate model

described above analyzed by data augmentation. We take a slightly

different approach than that adopted by

\citet{boulanger\_mclellan:2001}. By analyzing the full likelihood and

placing a prior distribution on the individual covariate, we resolve

the problem of having an ill-defined area over which the population

size is distributed. After you read later chapters of this book, it

will be apparent that SCR models represent a formalization of this

heuristic procedure.

For our purposes here, we define $x\_{i} = ||{\bf s}\_{i} - {\bf

x}\_{0}||$ where ${\bf s}\_{i}$ is the average encounter location of

individual $i$ and ${\bf x}\_{0}$ is the centroid of the trap array.

Conceptually, individuals in the middle of the array should have a

higher probability of encounter and, as $x\_{i}$ increases, $p\_{i}$

should therefore decrease. We note that we have defined ${\bf s}\_{i}$

in terms of a sample quantity - the observed mean - which is ad hoc

but consistent with existing applications in the literature. For an

expansive, dense trapping grid we might expect the sample mean

encounter location to be a good estimate of home range center but,

clearly this is biased for individuals that live around the edge (or

off) the trapping array. Regardless, it should be good enough for our

present purposes of demonstrating this heuristically appealing

application of an individual covariate model. A key point is that

${\bf s}\_{i}$ is missing for each individual that is not encountered

and so $x\_{i}$ is also missing. Therefore, it is a latent variable, or random

effect, and we need therefore to specify a probability distribution

for it. As a measurement of distance we know it must be

positive-valued. Thinking about this like a distance sampling xxxx $need to have introduced distance sampling somewhere before in the book, otherwise can’t expect reader to know distance sampling$ xxxxxx problem

lets first try to make $x\_{i}$ uniform from $0$ to some large number,

say $D\_{max}$, beyond which it would be difficult to imagine an

individual being captured. For example, $D\_{max}$ should be at a home

range diameter past the furthest trap from the center. As such, we

use this distribution for the individual covariate ``distance from

center of the trap array''

\[

x\_{i} \sim \mbox{Unif}(0,D\_{max})

\]

where $D\_{max}$ is a specified constant, which we may choose to be

arbitrarily large. In practice, people have

used distance from edge of the trap array but that is less easy to

make sense of.

\subsubsection{Fort Drum Bear Study}

\begin{figure}

\centering

\includegraphics[height=3.5in,width=3.5in]{Ch3/figs/bear\_spiderplot.png}

\caption{Spider plot of the Fort Drum study data.}

Xxxxxxxxx $more info, e.g., “Dots represent the 47 trap locations with thick dots being those where a bear was detected. Lines join traps where the same bear was detected. (is this true ?)” xxxxxxx$

\label{closed.fig.spiderplot}

\end{figure}

We have to do a little bit of data processing to fit this individual

covariate model to the Fort Drum data. We need to compute the

individual covariate ${\bf x}\_{i}$ (distance from the centroid of the

trapping array) using the {\bf R} function \mbox{\tt spiderplot}

provided in \mbox{\tt scrbook}. This function also produces the keen

plot shown in Fig. \ref{closed.fig.spiderplot} which we call a

``spider plot''. The {\bf R} commands for obtaining the individual

covariate ``distance from trap centroid'' and making the spider plot

are as follows:

\begin{verbatim}

library("scrbook")

data("beardata")

toad<- spiderplot(beardata$bearArray,beardata$trapmat)

xcent<-toad$xcent

\end{verbatim}

For the analysis of these data using the individual covariate

"distance from centroid" we used $x\_{i} \sim \mbox{Unif}(0,D\_{max})$

with $D\_{max} = 11.5$ $km^2$, which is about the distance from the

array center to the furthest trap. Once we pick $D\_{max}$ then the

direct implication is that the population size parameter applies to

the area within 11.5 units of the trap centroid and thus we will find

that $N$ does, in fact, scale with our choice of $D\_{max}$ to reflect

the changing area over which the $N$ individuals of the model reside.

The {\bf BUGS} model specification and {\bf R} commands to package the

data and fit the model are as follows:

{\small

\begin{verbatim}

cat("

model{

p0 ~ dunif(0,1) # prior distributions

mup<- log(p0/(1-p0))

psi~dunif(0,1)

beta~dnorm(0,.01)

for(i in 1:(nind+nz)){

xcent[i]~dunif(0,Dmax)

z[i]~dbern(psi) # DA variables

lp[i] <- mup + beta\*xcent[i] # individual effect

logit(p[i])<-lp[i]

mu[i]<-z[i]\*p[i]

y[i]~dbin(mu[i],K) # observation model

}

N<-sum(z[1:(nind+nz)])

}

",file="modelMcov.txt")

data2<-list(y=ytot,nz=nz,nind=nind,K=K,xcent=xcent,Dmax=11.5)

params2<-list('p0','psi','N','beta')

inits = function() {list(z=zst, psi=psi, p0=runif(1),beta=rnorm(1) ) }

fit2 = bugs(data2, inits, params2, model.file="modelMcov.txt",working.directory=getwd(),

debug=T, n.chains=3, n.iter=11000, n.burnin=1000, n.thin=1)

\end{verbatim}

}

This produces the following posterior summary statistics:

{\small

\begin{verbatim}

Inference for Bugs model at "modelMcov.txt", fit using WinBUGS,

3 chains, each with 11000 iterations (first 1000 discarded)

n.sims = 30000 iterations saved

mean sd 2.5% 25% 50% 75% 97.5% Rhat n.eff

p0 0.54 0.07 0.40 0.50 0.54 0.59 0.67 1 1100

psi 0.34 0.05 0.25 0.31 0.34 0.37 0.44 1 3500

N 58.92 5.49 50.00 55.00 58.00 62.00 71.00 1 1900

beta -0.25 0.06 -0.36 -0.29 -0.25 -0.21 -0.12 1 780

deviance 459.51 13.21 435.80 450.20 458.80 467.90 487.40 1 2600

\end{verbatim}

}

It might be

perplexing that the estimated $N$ is much lower than obtained by model

$M\_h$ but there is a good explanation for this, discussed

subsequently. That issue notwithstanding, it is worth pondering how

this model could be an improvement (conceptually or technically) over

some other model/estimator including $M\_0$ and $M\_h$ considered

previously. Well, for one, we have accounted formally for

heterogeneity due to spatial location of individuals relative to

exposure to the trap array, characterized by the centroid of the

array. Moreover, we have done so using a model that is based on an

explicit mechanism, as opposed to a phenomenological one such as Model

$M\_h$. Moreover, importantly, using our new model, {\it the estimated N

applies to an explicit area which is defined by our prescribed value

of $D\_{max}$}. That is, this area is a fixed component of the model and

the parameter $N$ therefore has explicit spatial context, as the number

of individuals with home range centers less than $D\_{max}$ from the

centroid of the trap array. As such, the implied ``effective

area'' of the trap array for a given $D\_{max}$ is a precisely defined

quantity -- it is that of a circle with with radius

$D\_{max}$.

\subsection{Extension of the Model}

This model is actually not a very good model for one important reason:

Imposing a uniform prior distribution on $x$ implies that density is

{\it not constant} over space. In particular, this model implies that

it {\it decreases} as we move away from the centroid of the trap

array. That is, $x\_{i} \sim \mbox{Unif}(0,D\_{max})$ implies constant

$N$ in each distance band from the centroid but obviously the {\it

area} of each distance band is increasing. This is one reason we

have a lower estimate of density than that obtained previously from

model $M\_h$ xxxx M0? Mh?xxxx and also why, if we were to increase $D\_{max}$, we would

see density continue to decrease.

Fortunately, the use of an individual covariate model is {\it not} restricted to

use of this specific distribution for the individual

covariate. Clearly, it is a bad choice and, therefore, we should think

about whether we can choose a better distribution for $D\_{max}$ - one that

doesn't imply a decreasing density as distance from the centroid

increases. Conceptually, what we want to do is impose a prior on

distance from the centroid, $x$, such that density is proportional to

the amount of area in each successive distance band as you move

farther away from the centroid. In fact, theory exists

which tells us what the correct distribution of $x$ is:

$2x/D\_{max}^2$. This can be derived by noting that $F(x) = \Pr(X<x) =

\pi\*x\*x/\pi\*D\_{max}^{2}$ . Then, $f(x) = dF/dx =

2\*x/(D\_{max}^{2})$. This is a sort of triangular distribution in

density

induced because the incremental area in each additional distance band

increases linearly with radius (i.e., distance from centroid). It is

sometimes comforting to verify things empirically:

{\small

\begin{verbatim}

u<-runif(10000,-1,1)

v<-runif(10000,-1,1)

d<- sqrt(u\*u+v\*v)

hist(d[d<1])

hist(d[d<1],100)

hist(d[d<1],100,probability=TRUE)

abline(0,2)

\end{verbatim}

}

It would be useful if we could describe this distribution in {\bf

BUGS} but there is not a built-in way to do this that we are aware

of. One possibility is to use a discrete version of the pdf. We might

also be able to use what is referred to in {\bf WinBUGS} jargon as the

``zeros trick'' (see {\it Advanced BUGS tricks} in the manual)

although we haven't pursued this approach. Instead, we use a discrete

approximation of the density of $x$, and break $D\_{max}$ into $L$

distance classes of width $\delta$, with probabilities proportional to

$2\*x$. In particular, if we denote the cut-points by $xg\_{1}=0,xg\_{2},

\ldots, xg\_{L+1}=D\_{max}$ and the interval midpoints are $xm\_{i} =

xg\_{i+1}-\delta$ then the interval probabilities are $p\_{i} =

2\*xm\_{i}\*\delta/(D\_{max}^{2})$, which we can compute once and then

pass them to {\bf WinBUGS} as data.

The {\bf R} commands for doing all of this (noting that we have

already loaded and processed the Fort Drum bear data) are given as

follows. In the model description the variable $x$ (observed distance

from centroid of the trap array) has been rounded so that the discrete

version of the $f(x)$ can be used as described previously. The new

variable labeled \mbox{\tt xround} is then the integer category label

in units of $\delta$ from 0. Thus, to convert back to distance in the

expression for $lp[i]$, \mbox{\tt xround[i]} has to be multiplied by

$\delta$. Here is the {\bf BUGS} model specification:

{\small

\begin{verbatim}

delta<-.2

xround<-xcent%/%delta + 1

Dgrid<- seq(delta,Dmax,delta)

xprobs<- delta\*(2\*Dgrid/(Dmax\*Dmax))

xprobs<-xprobs/sum(xprobs)

cat("

model{

p0 ~ dunif(0,1) # prior distributions

mup<- log(p0/(1-p0))

psi~dunif(0,1)

beta~dnorm(0,.01)

for(i in 1:(nind+nz)){

xround[i]~dcat(xprobs[])

z[i]~dbern(psi) # zero inflation variables

lp[i] <- mup + beta\*xround[i]\*delta # individual effect

logit(p[i])<-lp[i]

mu[i]<-z[i]\*p[i]

y[i]~dbin(mu[i],K) # observation model

}

N<-sum(z[1:(nind+nz)])

}

",file="modelMcov.txt")

\end{verbatim}

}

To fit the model we do this - keeping in mind that the data objects

required below have been defined in previous analyses of this chapter:

{\small

\begin{verbatim}

data2<-list(y=ytot,nz=nz,nind=nind,K=K,xround=xround,xprobs=xprobs,delta=delta)

params2<-list('p0','psi','N','beta')

inits = function() {list(z=z, psi=psi, p0=runif(1),beta=rnorm(1) ) }

fit = bugs(data2, inits, params2, model.file="modelMcov.txt",

working.directory=getwd(), debug=FALSE, n.chains=3, n.iter=11000,

n.burnin=1000, n.thin=2)

\end{verbatim}

}

This is a useful model because it induces a clear definition of area

in which the population of $N$ individuals reside. Under this model,

that area is defined by specification of $D\_{max}$.

Further, the parameter $N$ of the model is, explicitly, the

population size that applies to the particular value of $D\_{max}$ and,

as such, we will see that $N$ scales with our choice of $D\_{max}$.

This might be disconcerting to some -- we can get whatever value of

$N$ we want by changing $D\_{max}$!

Fortunately, we find empirically, that while $N$ seems

highly sensitive to the prescribed value of $D\_{max}$, density seems to

be invariant to $D\_{max}$ as long as it is chosen to be sufficiently

large. We fit the model for a random of values of $D\_{max}$ from $D\_{max}=12$ (restricting

values of $x$ to be in close proximity to

the trap array) on up to 20. The results are given in Table

\ref{closed.tab.Dmax}.

\begin{table}[htp]

\centering

\caption{Analysis of Fort Drum bear hair snare data using the

individual covariate model, for different values of $D\_{max}$, the upper

limit of the uniform distribution of `distance from centroid of the

trap array'. ``Density'' is the posterior mean of density and SD is

the posterior standard deviation.}

\begin{tabular}{ccc}

\hline \hline

$D\_{max}$ & Density & SD \\ \hline

12& 0.230 & 0.038 \\

15& 0.244 &0.041 \\

17& 0.249 &0.044 \\

18& 0.249 &0.043\\

19& 0.250 &0.043\\

20& 0.250 &0.044

\end{tabular}

\label{closed.tab.Dmax}

\end{table}

We see that the posterior mean and SD of density (individuals per

square km) appear insensitive to choice of $D\_{max}$ once we get away from the maximum observed value of about 11.5. The estimated

density of 0.25 per km$^2$ is actually quite a bit lower than we

reported using model $M\_h$ for which no relevant ``area'' quantity is

explicit in the model. Using MLEs of $N$ in conjunction with buffer

strips (see Table \ref{intro.tab.fdtests}) our estimates were in the

range of $0.32-0.43$ and see sec. \ref{closed.sec.modelmh} above. On

the other hand our estimate of $\hat{D} = 0.25$ here (based on the

posterior mean) is higher than that reported from model $M\_0$ using

the buffered area (0.18). There is no basis really for comparing or

contrasting these various estimates and it would be a useful

philosophical exercise for the reader to discuss this matter. In

particular, application of models $M\_0$ and $M\_h$ are distinctly {\it

not} spatially explicit models -- the area within which the

population resides is not defined under either model. There is

therefore no reason at all to think that the estimates produced under

either either closed population model, based on a buffered ``trap

area'', are justifiable by any theory. In fact, we would get exactly

the same estimate of $N$ no matter what we declare the area to be. On

the other hand, the individual covariate model explicitly describes a

distribution for ``distance from centroid'' that is a reasonable and

standard null model - it posits, in the absence of direct information,

that individual home range centers are randomly distributed in space

and that probability of detection depends on the distance between home

range center and the centroid of the trap array. Under this definition

of the system, we see that density is invariant to the choice of area,

which seems like a desirable feature.

\subsection{Invariance of density to $D\_{max}$}

Under this individual covariate model, and also under models that we

consider in later chapters, a general property of the estimators is

that while $N$ increases with the prescribed trap area (equivalent to

$D\_{max}$ in this case), we expect that density estimators should be

invariant to this area. In the model used above, we note that

$Area(D\_{max}) = \pi\*D\_{max}^{2}$ and $E[N(D\_{max})] =

\lambda\*Area(D\_{max})$ and thus $E[Density(D\_{max})] = \lambda$, i.e.,

constant. This should be interpreted as the {\it prior}

density. Absent data, then realizations under the model will have

density $\lambda$ regardless of what $D\_{max}$ is prescribed to be.

As we verified empirically above, the posterior density is also

invariant to $D\_{max}$ as long as the implied area is large enough so

that the data no longer provide information about density (i.e., ``far

away'').

\subsection{Toward Fully Spatial Capture-recapture Models}

While the individual covariate model resolves two important problems

inherent in almost all capture-recapture studies (induced

heterogeneity and absence of a precise relationship between $N$ and

area), is not ideal for all purposes because it does not make full use

of the spatial information in the data set, i.e., the trap locations

and the locations of each individual encounter, so that we cannot use

this model to model trap-specific effects (e.g., trap effort or type).

Moreover, we developed this model for the average observed location

and equated it to home range center ${\bf s}\_{i}$. Intuitively, taking

the average encounter location as an estimate of home range center

makes sense but more so when the trapping grid is dense and expansive

relative to typical home range sizes. However, our approach also

ignored the variable precision with which each ${\bf s}\_{i}$ is

estimated and also, as noted previously, estimates of ${\bf s}\_{i}$

around the ``edge'' (however we define that) are biased because the

observations are truncated (we can only observe locations within the

trap array).

However, there is hope to extend this model in order to resolve

remaining deficiencies. In the next chapter we provide a further

extension of this individual covariate model that definitively

resolves the ad hoc nature of the individual covariate approach we

took here. In that chapter we build a model in which ${\bf s}\_{i}$ are

regarded as latent variables and the observation locations (i.e., trap

specific encounters) are linked to those latent variables with an

explicit model. We note that the model fitted previously could be

adapted easily to deal with ${\bf s}\_{i}$ as a latent variable, simply

by adding a prior distribution for ${\bf s}\_{i}$. The reader should

contemplate how to do this in {\bf BUGS}.

\section{DISTANCE SAMPLING: A primitive Spatial Capture-Recapture Model}

Distance sampling is one of the most popular methods for estimating

animal abundance xxxxxxx(cite all the classics)xxxxxxxx. One of the great benefits of distance sampling is

that it provides explicit estimates of {\it density}. The distance

sampling model is a special case of a closed population model with a

covariate. The covariate in this case, $x\_{i}$, is the distance

between an individual's location ``$u$'' and the observation location

or transect. In fact, the model underlying distance sampling is

precisely the same model as that which applies to the

individual-covariate models, except that observations are made at only

$K=1$ sampling occasion. In a sense, distance sampling is a spatial

capture-recapture model, but without the ``recapture.'' This first

and most basic spatial capture-recapture model has been used routinely

for decades and, formally, it is a spatially-explicit model in the

sense that it describes, explicitly, the spatial organization of

individual locations (although this is not always stated explicitly)

and, as a result, somewhat general models of how individuals are

distributed in space can be specified \citep{royle\_etal:2004,

johnson\_etal:2010, sillett\_etal:2011}. xxxxx$with all the excitement that our jay paper caused in the old school, I would definitely cite all the other guys here, i.e., include Hedley and Buckland 2004 and Niemi and Fernandez 2011 or whatever. Add these courtesy cites$xxxxxxx

As before, the distance sampling model, under data augmentation,

includes a set of $M$ zero-inflation variables $z\_{i}$ and the

binomial model expressed conditional on $z$ (binomial for $z=1$, and

fixed zeros for $z=0$). In distance sampling we pay for having only a

single sample (i.e., $K=1$) by requiring constraints on the model of

detection probability. xxxxx$say which constraint: intercept is known$xxxxxx A standard model is

\[

\log(p\_{i}) = \beta x\_{i}^{2}

\]

for $\beta < 0$, where $x\_i$ denotes the distance at which the $i$th

individual is detected relative to some reference location where

perfect detectability ($p=1$) is assumed. This function corresponds to

the ``half-normal'' detection function (i.e., with $\beta =

1/\sigma^{2}$). If $K>1$ then an intercept in this model is

identifiable and such models are usually called ``capture-recapture

distance sampling''\citep{alpizar\_pollock:1996,borchers\_etal:1998}.

As with previous examples, we require a distribution for the

individual covariate $x\_{i}$. The customary choice is

\[

x\_{i} \sim \mbox{Unif}(0,B)

\]

wherein $B>0$ is a known constant, being the upper limit of data

recording by the observer (i.e., the point count radius, or transect

half-width). In practice, this is sometimes asserted to be infinity,

but in such cases the distance data are usually truncated.

Specification of this distance sampling model in the {\bf BUGS} language is

shown in Panel \ref{closed.panel.distance} from \citet{royle\_dorazio:2008}.

\begin{panel}[htp]

\centering

\rule[0.15in]{\textwidth}{.03in}

\begin{minipage}{5in}

\begin{verbatim}

beta~dunif(0,10)

psi~dunif(0,1)

for(i in 1:(nind+nz)){

z[i]~dbern(psi) # DA Variables

x[i]~dunif(0,B) # B=strip width

p[i]<-exp(logp[i]) # DETECTION MODEL

logp[i]<- - beta\*(x[i]\*x[i])

mu[i]<-z[i]\*p[i]

y[i]~dbern(mu[i]) # OBSERVATION MODEL

}

N<-sum(z[1:(nind+nz)])

D<- N/striparea # area of transects

\end{verbatim}

\end{minipage}

\rule[-0.15in]{\textwidth}{.03in}

\caption{Distance sampling model in {\bf BUGS}, using a half-normal

detection function.}

\label{closed.panel.distance}

\end{panel}

As with the individual covariate model in the previous section, the

distance sampling model can be equivalently specified by putting a

prior distribution on individual {\it location} instead of distance

between individual and observation point (or transect). Thus we can

write the general distance sampling model as

\[

p\_{i} = f(\beta,||{\bf u}\_{i} - {\bf x}\_0||)

\]

along with

\[

{\bf u}\_{i} \sim \mbox{Unif}({\cal S})

\]

where ${\bf x}\_{0}$ is a fixed point (or line) and ${\bf u}\_{i}$ is

the individual's location which is observable for $n$ individuals. In

practice it is easier to record distance instead of location. Basic

math can be used to argue that if individuals have a uniform

distribution in space, then the distribution of Euclidean distance is

also uniform. In particular, if a transect of length $L$ is used and $x$

is distance to the transect then $F(x) = \Pr(X\le x) = L\*x/L\*B = x/B$ and

$f(x) = dF/dx = (1/B)$. For measurements of radial distance, see the

previous section.

In the context of our general characterization of SCR models

(Chapt. \ref{modeling.sec.characterization}),

we suggested that every SCR model can be described,

conceptually, by a hierarchical model of the form:

\[

[y|u][u|s][s].

\]

Distance sampling ignores the part of the model pertaining to ${\bf

s}$, and deals only with the model components for the observed

data ${\bf u}$\footnote{Equivalently, we could also say that $[u]$ in

the distance sampling model is $[u] = \int [u|{\bf s}][{\bf s}]

d{\bf s}$}. Thus, we are left with a hierarchical model of the form

\[

[y|{\bf u}][{\bf u}].

\]

In contrast, as we will see in the next chapters, basic SCR models

(Chapt. \ref{chapt.scr0}) ignore ${\bf u}$ and condition on ${\bf s}$,

which is not observed:

\[

[y|{\bf s}][{\bf s}]

\]

Since $[{\bf u}]$ and $[{\bf s}]$ are both assumed to be uniformly

distributed, these are structurally equivalent models! The main

differences have to do with interpretation of model components and

whether or not the latent variables are observable (in distance

sampling they are).

So why bother with SCR models when distance sampling yields density

estimates and accounts for spatial heterogeneity in detection? For

one, imagine trying to collect distance sampling data on tigers!

Clearly, distance sampling requires that one can collect large

quantities of distance data, which is not always possible. For tigers,

it is much easier, efficient, and safer to employ camera traps or

tracking plates and then apply SCR models. Furthermore, as we will see

in Chaptss. \ref{chapt.searchencounter} and \ref{chapt.scrds}, SCR

models can use distance data to estimate all the parameters of our

enchilada, allowing us to study distribution, movement, and

density. Thus, SCR models are much more general and versatile than

distance sampling models (which clearly are a special case), and can

accommodate data from virtually all animal survey designs.

\subsection{Example: Muntjac deer survey from Nagarahole, India }

Here we fit distance sampling models to distance sampling data on the

muntjac deer (Muntiakus muntjak) collected in the year 2004 from

Nagarahole National Park in southern India

(Kumar et al. unpublished data). The muntjac is

a solitary species and distance measurements were made on 57 groups

that were largely singletons with 4 pairs of individuals. Commands

for reading in and organizing the data for {\bf WinBUGS}, followed by

writing the model to a text file, are given below. Note that the total sampled area of

the transects is fed in as ``striparea'' which is $708$ (km of transect walked)

multiplied by the strip width ($B=120 = 0.12$ km) multiplied by 2.

{\small

\begin{verbatim}

library("R2WinBUGS")

data<- read.csv("Muntjac.csv")

hist(data[,3],30)

nind<-nrow(data)

y<-rep(1,nind)

nz<-400

y<-c(y,rep(0,nz))

x<-data[,3]

x<-c(x,rep(NA,nz))

z<-y

cat("

model{

beta~dunif(0,10)

psi~dunif(0,1)

for(i in 1:(nind+nz)){

z[i]~dbern(psi) # DA Variables

x[i]~dunif(0,B) # B=strip width

p[i]<-exp(logp[i]) # DETECTION MODEL

logp[i]<- -beta\*(x[i]\*x[i])

mu[i]<-z[i]\*p[i]

y[i]~dbern(mu[i]) # OBSERVATION MODEL

}

N<-sum(z[1:(nind+nz)])

D<- N/striparea # area of transects

}

",file="dsamp.txt")

\end{verbatim}

}

Next, we provide inits, indicate which parameters to monitor, and then

pass those things to {\bf WinBUGS}:

{\small

\begin{verbatim}

data<-list(y=y,x=x,nz=nz,nind=nind,B=120,striparea=(708\*2\*.120))

params<-list('beta','N','D','psi')

inits = function() {list(z=z, psi=runif(1), beta=runif(1,0,.02) )}

fit = bugs(data, inits, params, model.file="dsamp.txt",working.directory=getwd(),

debug=T, n.chains=3, n.iter=11000, n.burnin=1000, n.thin=2)

\end{verbatim}

}

Posterior summaries are provided in the following table. Estimated

density is pretty low, 1.1 individuals per sq. km.\footnote{ This is much

lower than Samba's estimate produced from WinBUGS accounting for group

size. Reason unknown. }

{\small

\begin{verbatim}

Inference for Bugs model at "dsamp.txt", fit using WinBUGS,

3 chains, each with 11000 iterations (first 1000 discarded), n.thin = 2

n.sims = 15000 iterations saved

mean sd 2.5% 25% 50% 75% 97.5% Rhat n.eff

beta 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1 1100

N 185.73 26.53 138.00 167.00 184.00 203.00 242.00 1 570

D 1.09 0.16 0.81 0.98 1.08 1.20 1.42 1 570

psi 0.41 0.06 0.30 0.36 0.40 0.45 0.54 1 670

deviance 655.74 16.26 626.00 644.50 655.10 666.40 689.80 1 1300

xxxxxxx$Is the first line (beta) reasonable?$xxxxxxxxxx

[.... some output deleted .... ]

\end{verbatim}

}

\section{Summary and Outlook}

Traditional closed population capture-recapture models are closely

related to binomial generalized linear models. Indeed, the only real

distinction is that in capture-recapture models, the population size

parameter $N$ (corresponding also to the size of a hypothetical

``complete'' data set) is unknown. This requires special

consideration in the analysis of capture-recapture models. The

classical approach to inference recognizes that the observations don't

have a standard binomial distribution but, rather, a truncated

binomial (from which which the so-called ``conditional likelihood''

derives) since we only have encounter frequency data on observed

individuals. If instead we analyze the models using data augmentation,

the observations can be modeled using a zero-inflated binomial

distribution. In short, when we deal with the unknown-$N$ problem using

data augmentation then we are left with zero-inflated GLM and GLMMs

instead of ordinary GLM or GLMMs. The analysis of such zero-inflated

models is practically convenient, especially using the various

Bayesian analysis packages that use the {\bf BUGS} language.

Spatial capture-recapture models that we will consider in the rest of

the chapters of this book are closely related to what have been called

individual covariate models. Heuristically, spatial capture-recapture

models arise by defining individual covariates based on observed

locations of individuals -- we can think of using some function of

mean encounter location as an individual covariate. We did this in a

novel way, by using distance to the centroid of the trapping array as

a covariate. We analyzed the ``full likelihood'' using data

augmentation, and placed a prior distribution on the individual

covariate which was derived from an assumption that individual

locations are, a priori, uniformly distributed in space. This

assumption provides for invariance of the density estimator to the

choice of population size area (induced by maximum distance from the

centroid of the trap array). The model addressed some important problems in the

use of closed population models: it allows for heterogeneity in

encounter probability due to the spatial context of the problem and it

also provides a direct estimate of density because area is a feature

of the model (via the prior on the individual covariate). The model is

still not completely general because it does not make use of

the fully spatial encounter histories, which provide direct

information about the locations and density of individuals. A

specific individual covariate model that is in widespread use is

classical ``distance sampling.'' The model underlying distance

sampling is precisely a special kind of SCR model - but one without

replicate samples. Understanding distance sampling and individual

covariate models more broadly provides a solid basis for understanding

and analyzing spatial capture-recapture models.