ESTIMATING SLOTH BEAR ABUNDANCE FROM REPEATED PRESENCE-ABSENCE DATA IN NAGARAHOLE-BANDIPUR NATIONAL PARKS, INDIA

By

ARJUN MALLIPATNA GOPALASWAMY

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To all who wish to save wildlife

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Abstract of Thesis Presented to the Graduate School
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ESTIMATING SLOTH BEAR ABUNDANCE FROM REPEATED PRESENCE-ABSENCE DATA IN NAGARAHOLE-BANDIPUR NATIONAL PARKS, INDIA

By

Arjun Mallipatna Gopalaswamy

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It is notoriously difficult to estimate the abundance of bears in general and most methods that are currently available are too consumptive of time and effort. Sloth bears (*Melursus ursinus*) pose very similar challenges to field biologists trying to estimate their abundances.

I investigated the possibility of estimating abundance of sloth bears using presence-absence data from repeated samples from camera traps. The simulation results generated from the likelihood estimator for small sample sizes showed a positive bias for λ, the mean abundance per site.

To more effectively use data with small sample sizes, a Bayesian approach to the problem was developed so that an informative prior could influence the parameter values to a reasonable range. A Bayesian Markov Chain Monte Carlo simulation procedure using the Gibbs sampler algorithm was developed.

Data were analyzed using two ideas of bear movement that are incorporated into the model. Data were first analyzed with the intention of maintaining the idea of site independence to ensure that a bear will not occur in two sites during the sampling period. This restricted the data set and the uncertainties in the parameter estimates were found to be very high. To

incorporate the missing data, and include more sites into the problem, another assumption was introduced in the model that the immigration and emigration rates to and from a site was a constant. However, the abundance estimates generated by this procedure were also highly variable.

The key issue that emerged from this study was the exceedingly low animal-specific detection probability (between 0.03 and 0.12). This suggested the need for an improved method in photographing bears both in terms of increasing spatial replicates and the actual placement of camera traps for reliable estimates of abundance. With an improved study design, the suggested approach may still seem very plausible to estimate sloth bear abundances.

CHAPTER 1
INTRODUCTION

Background

A variety of methods are available for estimating animal abundances (Lancia, Nichols & Pollock, 1994), but all involve the issue of estimating detection probabilities for specific kinds of count statistics (Buckland, Anderson, Burnham, Laake, Borchers & Thomas, 2001; Seber, 1982; Williams, Nichols and Conroy, 2002). Depending on the species being studied, the techniques available for gathering appropriate data, and incorporating the limitations of time, money and effort, only one or just a few of these methods may be suitable. Capture-recapture methods require repeated efforts to capture or observe animals (Otis, Burnham, White & Anderson, 1978; Pollock, Nichols, Brownie & Hines, 1990) and even observation-based methods such as distance sampling (Buckland *et al.*, 2001) or multiple observers (Cook & Jacobson, 1979; Nichols, Hines, Sauer, Fallon, Fallon & Heglund, 2000) are viewed as being too time and effort consuming (Royle & Nichols, 2003). Despite the logistical constraints, these methods have been widely applied to estimation of large mammal abundance.

Monitoring Sloth Bears

Sloth bears *(Melursus ursinus),* like other bears, are solitary animals (Gittleman, 1989), mostly nocturnal (Joshi, Smith & Garshelis, 1999) and are not easily sighted. Thus, determining their abundance is a major challenge for field biologists. The only rigorous density estimate for any population of this species was made by Garshelis, Joshi and Smith (1999) using mark-recapture models, based on sightings and re-sightings of bears accompanying radio-collared bears in Royal Chitwan National Park, Nepal. They estimated bear density at 27 bears/100 km^2 (excluding dependent young). In the relatively unproductive dry tropical forests of Panna

National Park, India, Yoganand (pers. comm.) used a combination of radio-collared animals and familiarity with unmarked but identifiable animals to derive an estimate of 6–8 bears/100 km^2.

While conducting conventional distance sampling surveys along line transects in India, Karanth (pers. comm.) recorded few sightings of sloth bears, despite considerable effort, and the data collected were inadequate to fit a reliable detection function. Furthermore, photographic mark-recapture sampling (Karanth, Nichols & Kumar, 2004) does not work for sloth bears as individuals cannot be identified. Mark-recapture sampling using noninvasive DNA extracted from hair or scat samples may be used as an alternative to live trapping, but it is very expensive. Additionally, all these methods have technical problems that make them less reliable as well (Mills, Citta, Lair, Schwartz & Tallmon, 2000).

A potential approach to estimating abundance of sloth bears involves changing the focus from numbers of animals to numbers of sample units occupied by animals (Royle & Nichols, 2003). Methods employing this general approach are based on presence-absence data from the sampling units. Royle & Nichols (2003) have developed a model based on this focus to estimate abundance from repeated presence-absence data or point counts. In chapter 2 of this thesis, I investigate the performance of this model with the likelihood-based estimator derived by the authors and also derive a Bayesian alternative to parameter estimation to deal with applying the model with prior distributions. In chapter 3, I use the Bayesian approach on the Royle and Nichols (2003) model to analyze sloth bear data obtained from camera traps in Bandipur-Nagarahole National Parks.

Sloth bear diets vary seasonally and geographically across their range from Nepal southward through India and Sri Lanka, depending largely on the availability of food and hardness of termite mounds (Baskaran, 1990; Baskaran, Sivaganesan & Krishnamoorthy, 1997;

Gokula, Sivaganesan & Varadarajan, 1995; Gopal, 1991; Joshi, Garshelis & Smith, 1997; Karanth *et al.*, 2004; Laurie & Seidensticker, 1977). I make assumptions based on the resource distribution and abundance consequently investigate applicability of the Royle and Nichols (2003) model under varying home range possibilities.

With the absence of a rigorous estimate of sloth bear density in Nagarahole and Bandipur National Parks, the results of this study will be a useful first step in developing a monitoring program for these animals. Further, this will be the first attempt at using the sampling unit based approach towards determining densities or habitat usage rates for bears in general.

CHAPTER 2
PARAMETER ESTIMATION OF THE ROYLE AND NICHOLS (2003) MODEL USING BAYESIAN MARKOV CHAIN MONTE CARLO SIMULATION APPROACH WITH THE GIBBS SAMPLER ALGORITHM

Introduction

Estimating the number of animals of a particular species in forested areas largely revolves around addressing two fundamental issues: extrapolation of inferences from a study area and detection probability (Lancia *et al.*, 1994; Skalski, 1994; Thompson, 1992; Thompson, White & Gowan, 1998; Yoccoz, Nichols & Boulinier, 2001). First, investigators often have to select representative areas within a much larger area of interest. However, this fractional area often has to be estimated and inferences must be extrapolated to the entire area of interest. This is a standard problem in spatial sampling and statistical texts (Cochran, 1977; Thompson, 1992) appropriately deal with this issue by permitting such inferences. In field surveys, it is very rare that investigators detect all animals or signs present even in the fractional area considered. Instead, data collected reflect some sort of a count statistic that only represents a portion of all the available detections present. This issue of 'detectability' is the second fundamental issue an investigator has to deal with in estimating animal abundance. A variety of methods presented in texts (Buckland *et al.*, 2001; Seber, 1982; Williams *et al.*, 2002) and reviews (Lancia *et al.*, 1994) provide different methods of estimation of detection probabilities for specific kinds of count statistics.

Depending on the species studied, the techniques available for gathering appropriate data, and incorporating the limitations of time, money and effort, often only one or just a few of these methods are likely to be suitable. For example, capture-recapture methods require repeated efforts to capture or observe animals (Otis *et al.*, 1978; Pollock *et al.*, 1990). Even observation based methods such as distance sampling (Buckland *et al.*, 2001) and multiple observers (Cook

& Jacobson, 1979; Nichols *et al.*, 2000) are viewed by some as highly time and effort consuming.

In many situations, presence-absence (more properly, detection-nondetection) data on sampling units may more easily be obtained. Methods using such data have been developed independently several times (Azuma, Baldwin & Noon, 1990; Bailey, 1952; Bayley & Peterson, 2001; Geissler & Fuller, 1987; MacKenzie, Nichols, Lachman, Droege, Royle & Langtimm, 2002; Nichols & Karanth, 2002) and appear to be useful for a variety of monitoring programs (e.g. patch occupancy by spotted owls in western North America, area occupancy of tigers in India, wetland occupancy by anurans throughout North America).

Royle and Nichols (2003) have constructed a model by linking the probability of detecting presence and the abundance at a sampling unit. By using repeated detection-nondetection data gathered from occupancy surveys, they suggest a maximum likelihood approach at estimating the parameters (that includes abundance). They also emphasize that likelihood-based inference is not a small-sample procedure, and this should be considered in any study. In spite of the relative ease with which presence-absence data may be gathered, achieving large samples for analysis as suggested by Royle and Nichols (2003) for even practical estimates of the parameters might be difficult.

Bayesian approaches at parameter estimation have found themselves to be useful in a variety of ecological applications (Dennis, 1996; Dixon & Ellison, 1996; Ellison, 1996; Hilborn & Mangel, 1997) and have many strengths and limitations (Dennis, 1996; Ellison, 1996)**.** Field biologists often encounter logistic difficulties that curtail them to work with very low sample sizes and yet have the need to use such information. Bayesian inferential procedures under certain circumstances better makes use of such prior beliefs in parameter estimation.

In the context of the Royle and Nichols (2003) model, a trade-off between the number of sites and the number of sampling occasions have to be made. However, biologists may also enhance the quality of data collection by better field methods and can induce changes on a parameter such as the animal-specific detection probability. With existing difficulties in animal abundance estimation, Bayesian inferential procedures are likely to be more useful from a management standpoint, especially with low sample sizes. In this chapter,

- I construct a Bayesian Markov Chain Monte Carlo simulation approach using the Gibbs sampler (Gelman, Carlin, Stern & Rubin, 1995) to estimate the parameters in the Royle and Nichols (2003) model.
- I investigate the problems associated with the likelihood-based inference procedure in this model for low sample sizes and suggest the use of a Bayesian approach with an informed prior to more appropriately deal with this problem.

Methods

Royle and Nichols (2003) Model

Royle and Nichols (2003) use the occupancy based approach and assume that the detection probability of a given species at a particular site is directly dependent on the abundance of that species in that site for a given animal-specific detection probability and nothing else. Consequently, the heterogeneity in detection probabilities across a system of sites is caused by the heterogeneity in abundance across those sites. And, by modeling the variation in abundances according to some probability distribution model (e.g., Poisson), they build a model based on maximum likelihood to arrive at estimates of abundance in these sites.

The Royle and Nichols (2003) model is as follows:

$$p_i = 1-(1-r)^{N_i} \tag{2-1}$$

Here p_i is the probability of detecting at least one animal within the site i.
r is the probability of an animal being detected in site i.
N_i is the actual animal abundance at site i.

Parameter Estimation Using the Likelihood-Based Approach

For the construction of the final likelihood equation, Royle and Nichols (2003) recommend imposing a probability model to characterize the underlying distribution of abundances. For animals that are distributed at random, a natural candidate for modeling the abundance may be the Poisson model (Royle, Nichols and Kery, 2005).

The final likelihood equation by using the Poisson model for the abundance is as follows:

$$L(w \mid r, \lambda) = \prod_{1}^{R} \sum_{k=0}^{\infty} {}_{T}C_{w_{i.}} [1 - (1 - r)^{k}]^{w_{i.}} [(1 - r)^{k}]^{T - w_{i.}} \frac{\lambda^{k} e^{-\lambda}}{k!} \tag{2-2}$$

R is the number of sites,
T is the number of repeated samples,
w is the detection vector of the total number of detections from each site i, i.e. a vector of all the individual site-specific detections, $w_{i.}$.
λ is the expected abundance at each site, also the Poisson mean.

For the convenience of numerically maximizing the Equation 2-2, the upper limit of the variable *k* is set to a very large number *K.* So for practical estimation of the parameters, Equation 2-3 is used.

$$L(w \mid r, \lambda) = \prod_{1}^{R} \sum_{k=0}^{K} {}_{T}C_{w_{i.}} [1 - (1 - r)^{k}]^{w_{i.}} [(1 - r)^{k}]^{T - w_{i.}} \frac{\lambda^{k} e^{-\lambda}}{k!} \tag{2-3}$$

Parameter Estimation Using the Bayesian Approach

The Royle and Nichols (2003) model that uses the Poisson distribution to characterize the abundance can be viewed as a hierarchical model of random variables as follows:

$$[w_{i.} \mid T, r, N_i] \sim binomial[T, 1 - (1 - r)^{N_i}] \tag{2-4}$$

$$[N_i \mid \lambda] \sim poisson[\lambda] \tag{2-5}$$

$$r \sim uniform[0,1] \tag{2-6}$$

$$\lambda \sim gamma[a, b] \tag{2-7}$$

Here *a* and *b* are the shape and scale parameters associated with the gamma distribution. Relationships 2-4 and 2-5 jointly represent the likelihood function, while Relationships 2-6 and

2-7 are the prior distributions set for r and λ respectively. Since the gamma prior distribution is the conjugate prior for the Poisson distribution (Gelman *et al.*, 1995), it is a very convenient distribution that can be used, especially in a Bayesian Markov Chain Monte Carlo simulation.

I used the Bayesian Markov Chain Monte Carlo simulation approach using the Gibbs sampler (Gelman *et al.*, 1995) to determine the posterior distribution of the parameters r, λ and N_i. The Gibbs sampler is a particular Markov chain algorithm useful in such multidimensional problems based on alternate conditional sampling. To use the Gibbs sampler, the conditional distributions of each parameter have to be derived by treating the other parameters as known (full conditionals). The unnormalized joint posterior density function is

$$P(\lambda, r, \{N_i\} \mid w) \propto [\prod_i f(w_{i.} \mid T_i, r, N_i) g(N_i \mid \lambda)] P(r) P(\lambda)$$

The objective is to sample from the joint posterior density function repeatedly and the Markov chain that develops represents the joint posterior distribution. However, since this is a hierarchical model and all the probabilities are not independent, an alternative is to sequentially sample from each full conditional derived for each parameter. This is the whole purpose of the Gibbs sampler.

The full conditionals are derived as follows:

Full conditional for λ:

$$[\lambda \mid \bullet] \sim gamma\left[a + \sum_{i=1}^{R} N_i, \left(\frac{1}{b} + R \right)^{-1} \right] \tag{2-8}$$

Full conditional for r:

$P(r) = 1,\ 0<r<1$

In a Monte-Carlo simulation, it is desirable to move in a parameter space that is unrestricted. So to develop a full conditional on r, it would be more useful to use a logit transformation on r

instead of being bounded by the values between 0 and 1. So the full conditional is developed for the parameter η, the variable under the transformation, instead of r, for computational advantages:

$$\eta = \ln\left(\frac{r}{1-r}\right) \Rightarrow r = \frac{e^{\eta}}{1+e^{\eta}}$$

$$P(\eta) = P_r\left(\frac{e^{\eta}}{1+e^{\eta}}\right).\left|\frac{dr}{d\eta}\right|$$

$$P(\eta) = 1.\left[\frac{\left(1+e^{\eta}\right)e^{\eta} - e^{\eta}\left(e^{\eta}\right)}{\left(1+e^{\eta}\right)^{2}}\right]$$

$$\therefore P(\eta) = \frac{e^{\eta}}{\left(1+e^{\eta}\right)^{2}}$$

$$P(\eta \mid \bullet) \propto P(\eta)\prod_{i=1}^{R} f\left(w_{i.} \mid T, \eta, N_i\right)$$

$$P(\eta \mid \bullet) \propto \frac{e^{\eta}}{\left(1+e^{\eta}\right)^{2}}\prod_{i=1}^{R} {}_{T}C_{w_{i.}}\left[1-\left(\frac{1}{1+e^{\eta}}\right)^{N_i}\right]^{w_{i.}}\left[\left(\frac{1}{1+e^{\eta}}\right)^{N_i}\right]^{T-w_{i.}}$$

$$P(\eta \mid \bullet) \propto \frac{e^{\eta}}{\left(1+e^{\eta}\right)^{2}}\prod_{i=1}^{R}\left[1-\left(1+e^{\eta}\right)^{-N_i}\right]^{w_{i.}}\left(1+e^{\eta}\right)^{-N_i\left(T-w_{i.}\right)} \qquad \text{(2-9)}$$

Full conditional for N_i :

$$P\left(N_i \mid \bullet\right) \propto f\left(w_{i.} \mid T, r, N_i\right)g\left(N_i \mid \lambda\right)$$

$$P\left(N_i \mid \bullet\right) \propto {}_{T}C_{w_{i.}}\left[1-(1-r)^{N_i}\right]^{w_{i.}}\left[(1-r)^{N_i}\right]^{T-w_{i.}}\frac{e^{-\lambda}\lambda^{N_i}}{N_i!}$$

Let

$$h\left(w_{i.} \mid r, \lambda\right) = \sum_{k=0}^{\infty} f\left(w_{i.} \mid T, r, k\right)g\left(N_i \mid \lambda\right)$$

$$P\left(N_i \mid \bullet\right) = \frac{f\left(w_{i.} \mid T, r, N_i\right)g\left(N_i \mid \lambda\right)}{h\left(w_{i.} \mid r, \lambda\right)} \qquad \text{(2-10)}$$

Where $N_i = 0, 1, 2, \ldots.$ to K, when $w_{i.} = 0$ and $N_i = 1, 2, \ldots$ to K, when $w_{i.} \geq 1$.

The Gibbs sampler algorithm involves sampling random values sequentially from these full conditionals. Each sample is drawn from the full conditional of a parameter using the updated values of each of the other parameters. When this process is repeated arbitrarily a large number of times, a posterior distribution of the parameter of interest will emerge based on the time spent on each point in the parameter space.

The Gibbs Sampler Algorithm for the Royle and Nichols (2003) Model

Step 1: Selecting the initial values for r, λ and N_i.

Iteration 1

$r^{(1)}$: random number chosen from a Uniform (0,1) distribution
So, $\eta^{(1)} = \text{logit}[r^{(1)}]$
$\lambda^{(1)}$: random number chosen from a Gamma (a,b), where a and b are the shape and scale parameters initially selected.
$N_i^{(1)}$: random number chosen from a Poisson$[\lambda^{(1)}]$, where $i = 1, 2, \ldots\ldots R$ sites.

Step 2: Updating the values of r, λ and N_i.

Iteration j [ranging from 2 to a large number]

$[N_i^{(j)} \mid w_{i.}, \lambda^{(j-1)}, r^{(j-1)}]$: random number drawn according to Equation 2-10 where $i = 1, 2, \ldots\ldots R$ sites
$[\lambda^{(j)} \mid \{N_i^{(j)}\}]$: random number drawn according to equation (8). The '{}' indicates the entire vector of site abundances.
$[\eta^{(j)} \mid \{w\}, \{N_i^{(j)}\}]$: random number drawn according to the proportionality relationship of Equation 2-9. Consequently $r^{(j)} = \dfrac{e^{\eta^{(j)}}}{1+e^{\eta^{(j)}}}$

Step 2 is repeated a large number of times. Using the Equations 2-8 and 2-10 the updates for $N_i^{(j)}$ and $\lambda^{(j)}$ can be made quite directly in the Gibbs sampler. However, making the updates for $\eta^{(j)}$ requires the use of the Metropolis algorithm (Gelman *et al.*, 1995) with a Gaussian proposal distribution since Equation 2-9 is only a proportionality relationship.

Simulation Design

Royle and Nichols (2003) have already shown the performance of the model in varying large sample situations and have established that the likelihood-based inference works reasonably well for inferences about estimates of λ for even low values of r and T when R is 200 or greater. However, in their simulation design, they have chosen values for the true value of λ

ranging from 1 to 5 for which the means and medians of estimates of λ were within reasonable limits. In my simulations, I fixed a value of 0.3 for r and 10 for λ as constants and varied the number of sites (100, 50, 25, 10) and the number of sampling occasions (3, 5, 10) to evaluate the performance of the estimates.

I wrote the program in R, a free statistical programming environment (Vienna University of Economics and Business Administration, 2006). Using "direct search" to numerically calculate the values of r and λ to maximize the likelihood Equation 2-7 is very time consuming. Instead, I used the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm and also used the Nelder-Mead algorithm (Press, Teukolsky, Vetterling & Flannery, 1994). I used the logit transformation on r to bind the values of r between 0 and 1 during optimization.

From the likelihood-based estimates, I identified data sets that resulted in estimates quite distant from the true value used in the simulation. I used these data sets to obtain posterior distributions of the parameters r and λ by running the Gibbs sampler algorithm with two informed prior distributions. This algorithm was also programmed in R.

Results

The summary statistics for the estimated parameters r and λ by the likelihood-based inference is shown in Table 2-1. The results for all combinations of number of sites and number of sampling occasions show a positive bias for the estimates of λ. For sample sizes 100, 50 and 25 sites, the median value of λ provided a better estimate of the true value of λ as compared to the mean. The Nelder-Mead algorithm and BFGS algorithms provided different estimates for the mean and standard errors of λ. For example, in the simulation with 50 sites and 5 sampling occasions, the Nelder-Mead estimate of λ(mean) was 26.181 ± 24.476 while the BFGS estimate was 16.813 ± 10.747.

The summary statistics of the posterior distributions of r and λ are shown in Tables 2-2 and 2-3. Further, the likelihood estimates using the BFGS algorithm were not consistent (i.e. they failed to converge to the same estimates every time). The standard deviation of the estimates of r and λ increased with the increased variance in the prior gamma distribution set for λ. Figure 2-1 shows the influence of the prior distributions on the posterior distributions with low sample sizes.

Conclusions and Discussion

Small sample sizes (when R is less than 100 and T is less than 10) produce flat likelihoods. This makes likelihood-based estimation difficult. Computer algorithms like BFGS or Nelder-Mead rely on smooth likelihood surfaces (Press *et al.*, 1994) and also rely on computers capable of high precision for parameter estimation with flat likelihoods. The large standard errors produced when using the Nelder-Mead algorithm is indicative of the flat likelihood surface. The inconsistency in the results from the BFGS algorithm in parameter estimation is also indicative of such a surface.

From the results in Tables 2-2 and 2-3, it may be inferred that Bayesian priors on λ do play an important role in the posterior distribution of the parameters when using the Gibbs sampler algorithm. Hence from a biological standpoint, given low sample sizes, the choice of an appropriate prior is critical to obtain meaningful estimates of animal abundance.

Considering that in this model λ is the important parameter from a wildlife management perspective and very difficult to estimate from field surveys, information obtained even from small sample sizes would be helpful from a long term monitoring perspective. Bayesian approaches do facilitate this process of updating parameter estimates on improved prior beliefs.

Table 2-1. Simulation results for the likelihood-based inference. The true values of r and λ were set at 0.3 and 10 during the simulation. In each case, 1000 data sets were simulated.

R	T	r(mean)	Standard error of r	λ(mean)	Standard error of λ	λ(median)	Optimization method
100	3	0.264	0.1560	16.737	10.4509	13.810	BFGS
100	5	0.268	0.1312	15.666	10.4873	10.264	BFGS
100	10	0.282	0.1013	13.024	7.7381	10.559	BFGS
50	3	0.251	0.1824	21.003	14.0927	17.780	BFGS
50	5	0.265	0.1580	16.813	10.2470	11.663	BFGS
50	10	0.278	0.1381	14.911	9.7201	10.675	BFGS
25	3	0.263	0.2081	17.799	7.5950	16.335	BFGS
25	5	0.260	0.1745	19.517	13.7354	14.972	BFGS
25	10	0.266	0.1690	17.726	11.5440	11.817	BFGS
10	3	0.405	0.3647	20.141	8.0814	17.191	BFGS
10	5	0.301	0.2775	19.039	8.3268	21.894	BFGS
10	10	0.279	0.2406	20.373	12.8811	21.350	BFGS
50	5	0.253	0.1741	26.181	24.4756		Nelder-Mead
50	10	0.276	0.1512	18.832	18.5343		Nelder-Mead
25	10	0.251	0.1826	26.950	24.9698		Nelder-Mead

Table 2-2. The results of the Gibbs sampler algorithm. The likelihood estimates for thesame data set were obtained using the BFGS algorithm for optimization. Prior shape = 10 scale=1. Number of iterations in the Gibbs sampler were 60,000 and the first 20,000 iterations were excluded in calculating the summary statistics.

R	T	Posterior mean of r	Posterior standard deviation of r	Posterior mean of λ	Posterior standard deviation of λ	Likelihood estimate of r	Likelihood estimate of λ
50	3	0.314	0.096	10.035	2.963	0.929	25.511
50	10	0.348	0.087	11.045	2.927	0.564	27.647
25	3	0.264	0.086	9.761	2.997	0.810	14.563
25	10	0.362	0.098	10.583	2.900	0.694	13.897

Table 2-3. The results of the Gibbs sampler algorithm. The likelihood estimates for the same data set were obtained using the BFGS algorithm for optimization. Prior shape = 1 scale=10. Number of iterations in the Gibbs sampler were 60, 000 and the first 20,000 iterations were excluded in calculating the summary statistics.

R	T	Posterior mean of r	Posterior standard deviation of r	Posterior mean of λ	Posterior standard deviation of λ	Likelihood estimate of r	Likelihood estimate of λ
50	3	0.319	0.150	11.347	5.843	0.929	25.511
50	10	0.271	0.118	16.654	8.606	0.564	27.647
25	3	0.285	0.156	11.201	7.150	0.810	14.563
25	10	0.349	0.169	12.959	6.804	0.694	13.897

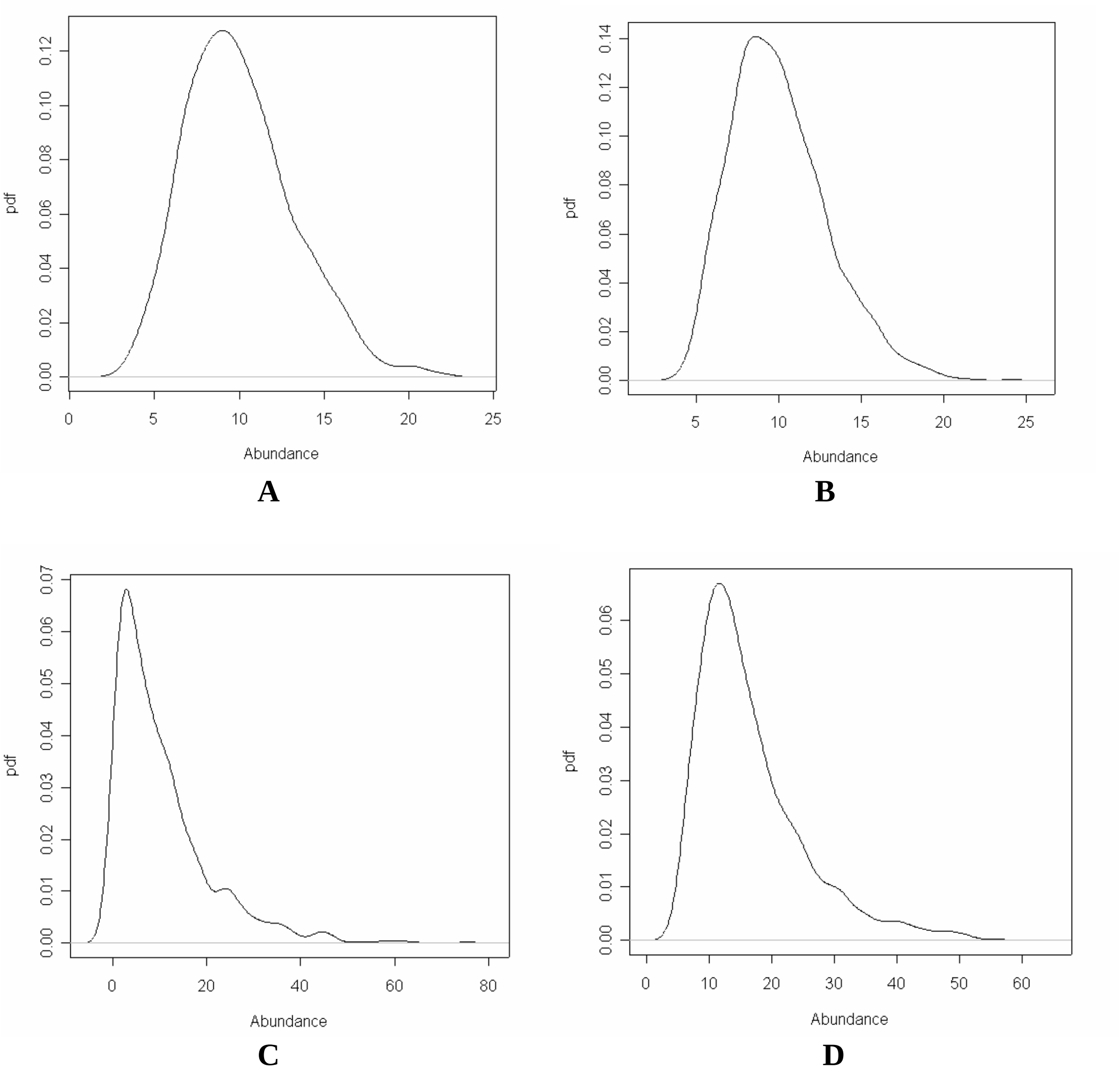

Figure 2-1. Prior and posterior distributions for λ when R=50 and when T=10. A) Prior distribution of λ with shape = 10 and scale = 1. B) Posterior distribution of λ with priors from A. C) Prior distribution of λ with shape = 1 and scale = 10. D) Posterior distribution of λ with priors from C.

CHAPTER 3
ESTIMATION OF SLOTH BEAR ABUNDANCE USING REPEATED PRESENCE-ABSENCE DATA IN NAGARAHOLE-BANDIPUR NATIONAL PARKS, INDIA

Introduction

The estimation of bear abundance involves many difficulties. Many expensive and labor-intensive mark-recapture studies, most aided by telemetry, have been conducted on populations of American black bears (*Ursus americanus*), brown bears (*Ursus arctos*) and polar bears (*Ursus maritimus*) (Garshelis *et al.,* 1999). Such studies are lacking for the other five species of bears due to funding and logistical constraints. Furthermore, the density of these species is perceived to be relatively low, thus making mark-recapture studies highly impractical.

The only rigorous density estimate of sloth bears (*Melursus ursinus*) was derived by Garshelis *et al.* (1999) during their study in Royal Chitwan National Park, Nepal. They used information on bears seen in the company of radio-collared bears as a re-sight sample and estimated bear density using the relatively simple, modified Peterson estimator (Bailey, 1952). During the process of obtaining 3,117 radio-telemetry locations, they sighted 47 bears in the vicinity of radio-collared bears, 42 of which had radio-collars on them. Using the modified Peterson estimator, Garshelis *et al.* (1999) arrived at a density estimate ranging from 27 to 72 bears per 100 km^2 depending on the season and habitat. It took investigators more than a year to obtain a recapture sample of 47 accompanying bears, an effort that may be feasible only when coupled with investigating other questions about sloth bear ecology that requires systematic and repeated visits to the forest.

Sloth bear densities are difficult to obtain by many conventional sampling methods. It is not possible to identify sloth bear individuals from photographs obtained in camera traps, so using a mark-recapture framework to determine densities, as done with tigers (Karanth & Nichols, 1998), is not practical. Further, while conducting distance-sampling surveys along line transects, Karanth (*unpublished data*) recorded few sightings of sloth bears despite considerable effort. A detection function fitted to such limited data is likely to be highly unreliable. Similarly, mark-recapture sampling requires large sample sizes and live trapping of sloth bears is not likely to generate the requisite number of recaptures. Sampling using noninvasive DNA extracted from hair or scat samples may be used as an alternative to live trapping, but it is very expensive. Additionally, all these methods presently have technical problems that make them less reliable as well (Mills *et al.*, 2000).

By sampling a site repeatedly for the presence-absence of a species, Royle & Nichols (2003) constructed a model that may be used to determine the abundance of a species. This is a simple model that makes use of a logical assumption that the detectability of a species is solely dependent on the abundance at that site for a given animal-specific detection probability. In this chapter, I investigate the applicability of this model for repeated presence-absence data of sloth bears obtained using camera traps in Bandipur and Nagarahole National Parks. For reasons discussed in chapter 2 of this thesis, I preferred to use the Bayesian approach in estimating sloth bear abundance.

Study Design

Study Area

The study area comprises two protected areas, Nagarahole and Bandipur, that are geographically separated by the Kabini reservoir (Figure 3-1).

Nagarahole

Nagarahole was originally established in 1955 as a Game Reserve of 288 km^2. In 1974, it was expanded to become the Nagarahole National Park (Area: 644 km^2), now officially renamed "Rajiv Gandhi National Park, Nagarahole" but commonly referred to as Nagarahole. The reserve is located in Kodagu and Mysore districts (76° 00' – 76° 15' E - 11° 15' – 12° 15' N) at altitudes of 700 – 960 m. Nagarahole is contiguous with Bandipur Reserve to the southeast and the Wayanad reserve to the southwest. The reserve receives an average annual rainfall between 1000 – 1500 mm (Karanth & Nichols, 2000). The terrain is gently undulating and drained by several perennial streams and three large rivers: Kabini, Taraka and Lakshmanateertha. An irrigation dam built in 1974 forms the Kabini reservoir that flanks the southern boundary of the reserve.

Two types of tropical, mixed deciduous forests are found in the region. The northwestern areas of the reserve receive higher rainfall and support moist deciduous forests of the *Tectona-Dillenia- Lagerstroemia* series. The dry deciduous forests of the *Terminalia-Anogeissus-Tectona* series occur in the southeastern areas with less than 1000 mm of rainfall. A unique feature of this site is the presence of open grassy swamps in moist areas locally called *hadlus,* where the soil is clayey, perennially moist and supports the luxuriant growth of sedges and grasses year round.

Nagarahole supports an impressive assemblage of herbivorous prey species: elephant (*Elephus maximus*), gaur (*Bos gaurus*), sambar (*Cervus unicolor*), chital (*Axis axis*), muntjac (*Muntiacus muntjac*), chousingha (*Tetraceros quadricornis*), wild pig (*Sus scrofa*), hanuman langur (*Presbytis entellus*) and bonnet macaque (*Macaca radiata*). The tiger (*Panthera tigris*) , leopard (*Panthera pardus*), Asiatic wild dog (*Cuon alpinus*), or dhole, and sloth bear are the large carnivores. Apart from the impressive mammalian fauna, Nagarahole is rich in avifauna, with more than 270 species of birds. The herpetofauna includes a variety of snakes, lizards, turtles and frogs. Among the larger reptiles, the marsh crocodile (*Crocodylus palustris*), monitor lizard (*Varanus bengalensis*) and the rock python (*Python molurus*) occur in Nagarahole.

Bandipur

The Maharaja of Mysore originally established Bandipur as a hunting reserve in 1931. It was expanded after 1974 to become the Bandipur National Park and Tiger Reserve (Area: 874 km^2). It is one among the first nine tiger reserves created under Project Tiger. Bandipur is located in Mysore and Chamarajanagar Districts (76° 12' –76° 46' E - 11° 37' – 11° 57' N) at an altitude of 680 –1454 m.

Bandipur is the oldest protected area in Karnataka. It is contiguous with Nagarahole on the northwest, Wayanad reserve to the southwest and Mudumalai reserve to the south. The terrain is undulating, and the reserve is bounded by the Moyar River to the south and Kabini Reservoir to the northwest. Bandipur Reserve receives an annual rainfall of 625 – 1250 mm (Karanth & Nichols, 2000). The forests are mostly the mixed dry deciduous series of *Terminalia-Anogeissus-Tectona* type. In the northwestern parts where the rainfall is higher, moist deciduous forests of the *Tectona-Dillenia-Lagerstroemia* series occur. The wildlife of Bandipur is similar to that of Nagarahole; however, three additional large mammal species, blackbuck antelope (*Antelope cervicapra*), striped hyena (*Hyaena hyaena*), and the Indian wolf (*Canis lupus*), occur occasionally on its eastern fringes. The bird life and herpetofauna are similar to Nagarahole.

Methods

Field Methods

I used commercially made TRAILMASTER TR-1550 camera traps (Goodson and Associates, Lenexa, Kansas, USA) equipped with active infra-red tripping devices to obtain photographs of animals. Two cameras, positioned opposite each other, were set along game trails to simultaneously photograph both flanks of an animal that broke the infrared beam. The camera traps were housed in locally manufactured theft-resistant metal trap shells and set about 300-350 cm from the side of a trail with the infrared beam set at a height of 45 cm. To eliminate mutual flash interference, a small delay (approx 0.1 sec) was electronically introduced into the splitting device connecting the two cameras. The sensitivity of the tripping device was set to photograph large-bodied animals. The date and time a photograph is taken is imprinted on the film and recorded on the receiver unit.

The camera traps were placed with the primary intention of maximizing tiger captures and were set along routes where there was tiger sign (scats, scrapes, scent deposits, tracks) and at the intersection of well-used trails. The spacing between camera traps ranged from 1-2 km. All points were marked on maps using a GPS unit. The date, time, and location of all animal captures were noted (Figure 3-2).

Data were collected from the two parks from December until May in 2003-2004 and 2004-2005. Sampling was done at 120 camera-trap locations in Nagarahole and 118 camera-trap locations in Bandipur. Since it was logistically impractical to conduct sampling at all these camera trap locations simultaneously, the trap points were divided into blocks of 40 trap points each. After sampling for 10-15 nights in one block, the camera traps were moved to the next block and sampling would continue 10-15 nights. In total, the study area consisted of 6 blocks. Logistics, weather and budget constraints limited the number of consecutive nights the cameras were deployed at a trap site (Table 3-1).

Application of the Royle and Nichols (2003) Model

Definition of sites

Occupancy surveys that are described in MacKenzie *et al.* (2002) and Royle & Nichols (2003) use sample units as “sites”. Implicitly, it is assumed that each site is independent and no animal will move between sites during the survey period. Unless the movement of animals is very small compared to the selected cell size, setting up a grid system and using these models for adjacent cells will violate the assumption of independence between sites. Thus, using these models for a species that ranges widely, like the sloth bear (Garshelis *et al.*, 1999), will generate results that require an alternative interpretation. To minimize the size of sites based on different possibilities of home range size and to maintain the assumption of independence of abundance between sites, I selected sites from the study areas in Bandipur and Nagarahole National Parks that are geographically separated by more than one expected home-range diameter for the analysis.

A frequently occurring problem associated with using camera traps for converting estimated animal abundances to densities is determining the effectively sampled area. The problem is typically addressed by adding a buffer around the trapping grid; the width of the buffer is addressed by a number of methods (see Wilson & Anderson, 1985). When radio-telemetry information is not available, the mean maximum distance method (MMDM) (Karanth & Nichols, 1998; Wilson & Anderson, 1985) is widely used to add a buffer around the trapping grid instead of assuming geographic closure within the trapping grid to reduce bias. However, Soisalo & Cavalcanti (2006), in their work on jaguars (*Panthera onca*), point out the limitations of using MMDM, and suggest that density estimates based on MMDM are likely to be biased and inflated. With the lack of information on individual bears being trapped in the study, the MMDM method cannot be used in this study. The analysis in this study relies on the assumption of different home range sizes of sloth bears in the absence of real data. Hence, I assume these different assumed home range sizes as the effectively sampled areas for each scenario, without actually defining a buffer around the camera trap grid in each site.

Selection of home range sizes for analysis

Sloth bears have not been radio-collared in either Nagarahole or Bandipur National Parks. So information on home range sizes has to be inferred from other studies in the country. In Chitwan, male sloth bears occupied larger home ranges than females (Joshi, Garshelis & Smith, 1995), which was primarily due to larger wet season ranges. Mean home ranges were 9.4 and 14.4 km^2 for females and males, respectively. Yoganand (unpublished data) observed that sloth bears in Panna had much larger annual home ranges (ranging from 25 – 100 km^2 - 95% kernel estimate) and varying sizes of seasonal ranges.

The diet of the sloth bears consists mostly of social insects and fruits. These are predominantly ground-living ants and termites that are common and found in large colonies, and sugar-rich fruits of commonly occurring plants that produce large fruit crops (Laurie & Seidensticker, 1977; Yoganand, unpublished data). Insects dominated the diet of sloth bears in Chitwan, both during fruiting and non-fruiting seasons (Joshi *et al.*, 1997). In Panna, however, fruits dominated the diet, except during monsoons when they fed on more insects. From the two studies (Garshelis *et al.*, 1999), sloth bears appear to persist in much higher densities in Chitwan than in Panna. The hard soil conditions in Panna may make feeding on termites nearly impossible during the dry season and may explain why insectivory is curtailed during this season. Since sloth bears in Panna show a preference for insects over fruits in the wet season, I presume that the protein-rich insect dominated diet is preferred over a fruit-dominated diet, which probably explains why sloth bears have smaller home ranges in Chitwan than in Panna.

In relation to habitat type and rainfall characteristics, Nagarahole and Bandipur appear to be more similar to Chitwan than to Panna. Accordingly, with the lack of information on sloth bear home range sizes in Nagarahole and Bandipur National Parks, for this study, I considered 4 home range sizes, 10 km^2, 18 km^2, 25 km^2 and 50 km^2 as options for the analysis. The fourth home range size, namely, 50 km^2, was primarily used to study the behavior of the model and is a home range size that may not be realistically expected to occur in Nagarahole or Bandipur National Parks, at least not a home range size expected for a brief period of 15 continuous sampling nights.

Constant *r*

Territoriality has not been observed with sloth bears (Joshi *et al.*, 1999; Laurie & Seidensticker, 1977), hence each camera trap is likely to be within more than one sloth bear's home range. Further, no measurable covariate information to model r were available, hence an assumption of constant r is made in this analysis.

Capture histories for sloth bears

Royle & Nichols (2003) suggest building up capture histories by sites based on captures and recaptures of the species in concern on repeated visits. Since sloth bears move widely (Joshi *et al.*, 1999), it is not likely that a bear captured at a given camera trap location will be caught at that same location with the same probability over subsequent camera trap nights. Instead, I substitute the temporal replicates as suggested in Royle & Nichols (2003) with spatial replicates. By doing this, I assume that all bears have an equal animal-specific detection probability. In this arrangement, a camera-trap location is said to have detected bear presence if a bear appears in that location on any single trap night over all the sampling nights. A capture matrix incorporating such an arrangement is shown in Table 3-2.

The total number of detections at a site i is $w_{i.}$. If a bear appeared once at a camera trap over the period of the entire sampling period, that camera trap is said to have “detected” a bear and marked as ‘1’, as in the matrix (Table 3-2).

Selection of the mass function to model abundance

The selected study areas are protected areas and are fairly homogenous in habitat structure. I also know from sloth bear detections observed in 2004 and 2005 (Figures 3-3 and 3-4), that with the exception of one “hole” in 2005, no other holes or clusters are obvious. With a random spatial occurrence of detections of this nature, based on the recommendation of Royle and Nichols (2003) I assume a Poisson model to describe abundance.

Parameters for the prior distribution of λ

From Equation 2-7 in Chapter 2

$\lambda \sim gamma[a, b]$, where a and b are the shape and scale parameters.

By the properties of a gamma distribution,

Mean = ab
Variance = ab^2

From the home range information of adjacent sloth bears (Joshi *et al.*, 1999), a maximum density of 6 male bears and 3 female bears were observed using a common area and each bear shared 50% or more of its home range area within the area of other bears. I assume that the degree of overlap is independent of home range size, based on the logic that sloth bear home ranges overlap due to the energetic costs that are involved in sustaining territoriality and the home range size is a function of resource distribution and abundance. Consequently, I assume that bear abundance per home range is invariant of home range size. I use this idea in deciding the shape and scale parameters for the prior gamma distribution.

Using the information from (Joshi *et al.*, 1999), I set the mean as 9 for the gamma distribution. However, there is no prior information on the degree of variation in abundance per home range. While I tried various priors to evaluate the performance of the model, I include results from only two prior distributions, one being more informative than the other.

Analysis of actual data

Sloth bear home range size in the Nagarahole-Bandipur region was expected to lie within the range of 10-25 km^2. To ensure independence between sites and incorporating these home range classes of this order, the analysis had to be performed with relatively low sample sizes (number of sites). By the simulation results from chapter 2 with low sample sizes, I chose to use the Bayesian approach to derive the posterior distributions of λ and r. Four home range classes were selected for the analysis (10 km^2, 18 km^2, 25 km^2 and 50 km^2). Although I tried various combinations of shape and scale parameters for the prior gamma distribution, I present the results from two prior distributions:

- Shape = 2, scale = 4.5 (relatively uninformative)
- Shape = 4.5, scale = 2 (relatively informative)

I conducted the analysis under two model settings:

- By ensuring independence between sites. This resulted in *R* values of 32, 15, 13 and 8 for home range sizes 10 km^2, 18 km^2, 25 km^2 and 50 km^2 respectively. An example of such an arrangement is shown in Figure 3-5 for the 10 km^2 sites.

- By relaxing the assumption of independence between sites. Here, I assumed that the average abundance in each cell remains constant. This resulted in *R* values of 116, 79, 58 and 35 for home range sizes 10 km^2, 18 km^2, 25 km^2 and 50 km^2 respectively. An example of such an arrangement is shown in Figure 3-6 for the 10 km^2 sites.

The Gibbs sampler was run 100,000 times and the first 30,000 iterations were left out in the calculations of the statistics, called the "burn-in period". I checked for auto-correlation and thinned the results from the remaining 70,000 draws to ensure that independent and identically distributed (*iid*) draws are made for the calculations of the statistics. The analysis has been run on one subjective selection of sites based on assumed home range sizes. This selection is based on the criterion that two sites are separated by at least one home-range diameter and does spatially cover the area systematically. Hence, I did not consider it worthy of an effort to derive estimates of the two parameters with other similar selections with the expectation of similar results.

Results

Assuming independence between sites. The posterior summary statistics for the results by ensuring independence between sites are tabulated (Tables 3-3 and 3-4). For the two prior distributions (Figures 3-7 and 3-8) considered, gamma(2, 4.5) has a mean of 9 and a standard deviation of 6.364 while gamma(4.5, 2) has a mean of 9 and a standard deviation of 4.243.

The mean estimates of animal-specific detection probabilities are considerably low (between 0.0377 to 0.1055). The posterior standard deviations for the estimates of either r or λ in an analysis for a given year did not vary by much. There is a reduction in the variability of the estimates in the posterior standard deviation in comparing it with the prior standard deviation. The estimates of posterior means of λ did not differ by much for the different home range assumptions.

Relaxing site independence and instead assuming that the average abundance at each site remains a constant. The posterior summary statistics for the results by ensuring independence between sites are tabulated (Tables 3-5 and 3-6). The mean estimates of animal-specific detection probabilities were still low (between 0.038 to 0.122). The posterior means of λ in 2005 for the home range sizes of 25 km^2 and 50 km^2 were lower than the posterior means of λ in 2004. However, the mean values of λ were influenced by the prior distributions.

Conclusions and Discussion

From these results it is clear that the increase in the number of sites has little effect on the variability of the parameter estimates. By increasing the home range sizes, more spatial replicates were added to each site for analysis and there was a reduction in the number of available sites for analysis. This trade-off is perhaps the largest cause for the less variability in the parameter estimates. After relaxing the assumption that animals detected in one site will not be detected in another site, and instead making the assumption that the abundance at each site at any given point remains a constant irrespective of immigration or emigration to or from the site, the estimate of the animal-specific detection probability is still very low.   Placing more traps per site and placing them in higher probability locations (e.g., near termite mounds or even placing baits to attract bears) may change r to values to provide better estimates of λ. As an alternative, other data gathering tools such as sign encounter surveys in some conditions may serve as better techniques to improve r.

The results from Tables 3-3 to 3-6 may not be indicative enough to derive abundance estimates. However, in the year 2004, with an assumption of an 18 km^2 home range size, the highest animal-specific detection probability (0.122 ± 0.061) was derived and the estimate of λ as 4.16 ± 2.74. The mean value of estimate of λ was quite distant from the prior mean. This result was derived after using the relatively uninformed prior distribution indicating a more data driven posterior distribution for this result.

My data show that on only few cases (<10%) did a camera trap that detected a bear on one sampling night detect a bear subsequently in the remaining nights. So, using temporal replicates, as suggested in Royle and Nichols (2003) for sloth bears, is not likely to change the results by much. Further, in using temporal replicates instead of spatial replicates the number of traps per cell either has to be maintained as a constant (which has not been the case as per this study design) or an additional parameter to model r must be introduced to deal with the problem of having unequal number of traps placed in different cells.

Prior to determining abundances of animals, especially animals that move fairly widely relative to the size of the site defined, basic information regarding the home range size of the animal, daily movement pattern and other behavioral aspects such as feeding behavior and habitat utilization in a particular region of interest will provide invaluable information in designing a study to monitor their abundance. For a widely distributed species such as the sloth bear, it is expected that the above mentioned variables are likely to be quite different in different habitats, as already seen in Panna and Chitwan. Both, from the perspective of identifying high probability sites for sloth bear captures on the field and by having to deal with the model assumptions, information on the above parameters are vital.

The Bayesian approach will be particularly useful from a long term monitoring perspective. If sampling is repeated over multiple years during the same season, the posterior distribution of one year may serve as the prior distribution for the subsequent year making the estimates of abundance more accurate progressively.

Since, sloth bears are not likely to exist in numbers greater than 20 animals per home range area, incorporating Royle and Nichols (2003) model into estimating occupancy rate (MacKenzie *et al.,* 2002) of sloth bears may be necessary. For a reasonable animal-specific detection probability *r*, between 0.2 and 0.8, a great variation in the site-specific detection probability is reflected for a range of abundances between 0 and 30. When the values of abundance are very high (>30), the site-specific detection probability is less sensitive to the changes in abundance. I recommend the use of the Royle and Nichols (2003) model to address any issue with respect to occupancy of sloth bears as compared to the MacKenzie *et al.* (2002) model which implicitly assumes that sites have a constant or nearly constant abundance.

Table 3-1. Sampling effort at each camera trap location.

	Number of sampling occasions per trap site	
Sites	Year 2004	Year 2005
Nagarahole	10	15
Bandipur	13	15

Table 3-2. An example capture matrix for sloth bear detections

	Camera traps in a site						Total number of detections
Sites	1	2	3	4	5	6	$w_{i.}$
Site 1	0	1	0	0	1	0	2
Site 2	1	1	0	0	0	1	3

Table 3-3. Posterior summary statistics by ensuring independence between sites with prior distribution for λ~Gamma(2, 4.5)

	Year 2004				Year 2005			
Home range sizes (in km^2)	Posterior mean of *r*	Posterior standard deviation of *r*	Posterior mean of *λ*	Posterior standard deviation of *λ*	Posterior mean of *r*	Posterior standard deviation of *r*	Posterior mean of *λ*	Posterior standard deviation of *λ*
10	0.1055	0.0681	6.0967	4.2567	0.0748	0.0545	6.1131	4.6529
18	0.0854	0.0582	5.7517	4.4398	0.0487	0.0356	7.2965	5.0511
25	0.0830	0.0557	6.2497	4.4459	0.0771	0.0548	5.8449	4.2864
50	0.0710	0.0461	8.6492	5.2951	0.0476	0.0330	6.8824	4.6002

Table 3-4. Posterior summary statistics by ensuring independence between sites with prior distribution for λ~Gamma(4.5, 2)

	Year 2004				Year 2005			
Home range sizes (in km^2)	Posterior mean of *r*	Posterior standard deviation of *r*	Posterior mean of *λ*	Posterior standard deviation of *λ*	Posterior mean of *r*	Posterior standard deviation of *r*	Posterior mean of *λ*	Posterior standard deviation of *λ*
10	0.0806	0.0463	7.0333	3.5023	0.0538	0.0330	6.9798	3.6714
18	0.0603	0.0382	6.9837	3.7051	0.0408	0.0237	7.3616	3.6405
25	0.0652	0.0381	6.9894	3.7199	0.0537	0.0345	7.1341	3.5928
50	0.0631	0.0340	8.6509	3.7132	0.0377	0.0222	7.5661	3.6745

Table 3-5**.** Posterior summary statistics (relaxing site independence) with prior distribution for $\lambda \sim \text{Gamma}(2, 4.5)$

	Year 2004				Year 2005			
Home range sizes (in km^2)	Posterior mean of r	Posterior standard deviation of r	Posterior mean of λ	Posterior standard deviation of λ	Posterior mean of r	Posterior standard deviation of r	Posterior mean of λ	Posterior standard deviation of λ
10	0.10134	0.06130	5.18893	3.65330	0.06243	0.04432	5.92929	4.75334
18	0.12290	0.06185	4.16892	2.74911	0.04822	0.03282	6.74578	4.23767
25	0.06889	0.03957	7.37141	4.57556	0.10504	0.04627	2.77987	1.64058
50	0.05298	0.03016	9.10935	5.33008	0.10094	0.05411	3.27652	2.69101

Table 3-6. Posterior summary statistics (relaxing site independence) with prior distribution for $\lambda \sim \text{Gamma}(4.5, 2)$

	Year 2004				Year 2005			
Home range sizes (in km^2)	Posterior mean of r	Posterior standard deviation of r	Posterior mean of λ	Posterior standard deviation of λ	Posterior mean of r	Posterior standard deviation of r	Posterior mean of λ	Posterior standard deviation of λ
10	0.07188	0.04074	6.48642	3.32368	0.04810	0.03153	6.40936	3.43146
18	0.08380	0.04603	5.92916	3.15890	0.03891	0.02290	7.57562	3.96615
25	0.05990	0.02927	7.54454	3.41925	0.07087	0.03607	4.29506	2.35607
50	0.05120	0.02340	8.42673	3.61803	0.06201	0.03840	5.16315	3.09212

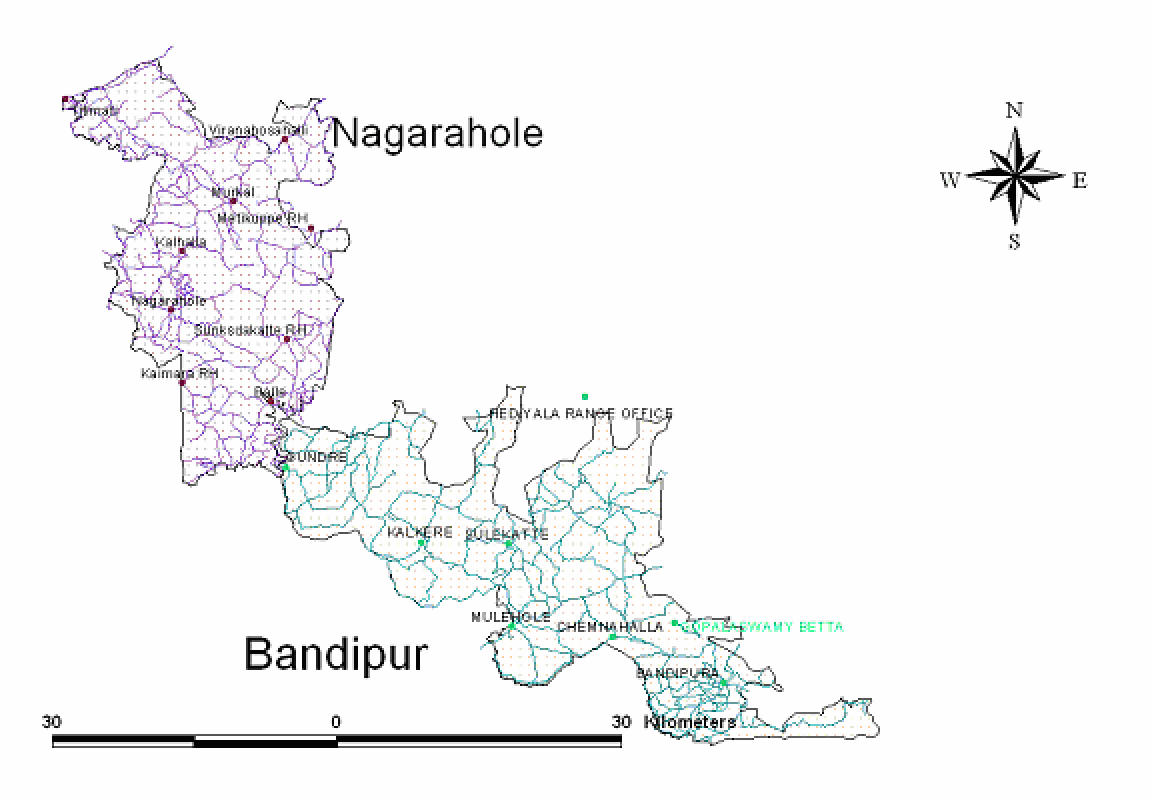

Figure 3-1. Map of the study area comprising of the Bandipur and Nagarahole National Parks.

Figure 3-2. A sloth bear photograph taken from a camera trap.

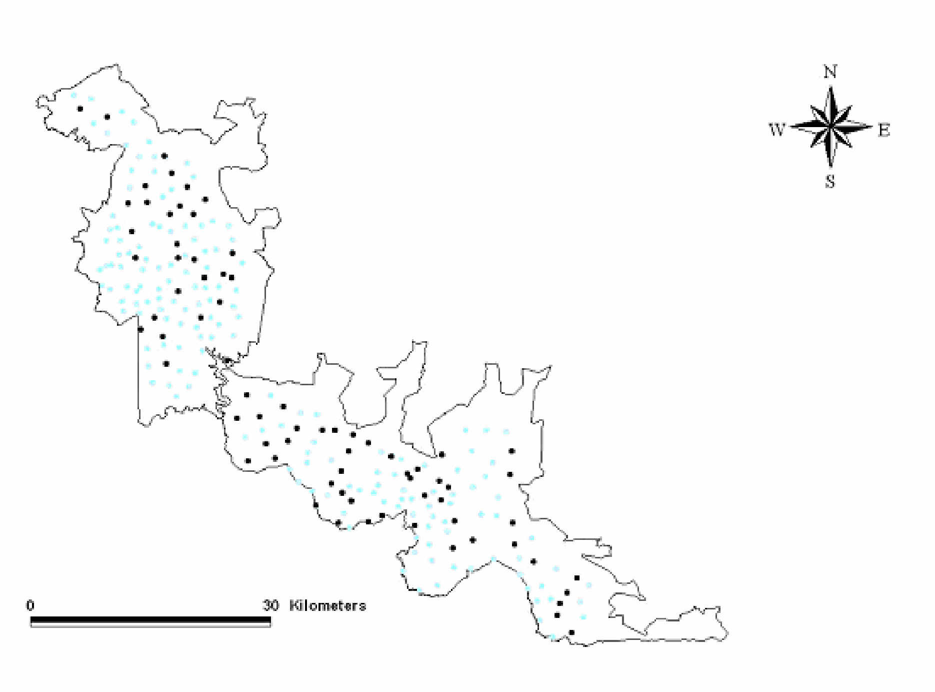

Figure 3-3. Sloth bear detections (year 2004) are shown with black (dark) dots. The other dots represent camera traps that did not detect sloth bears.

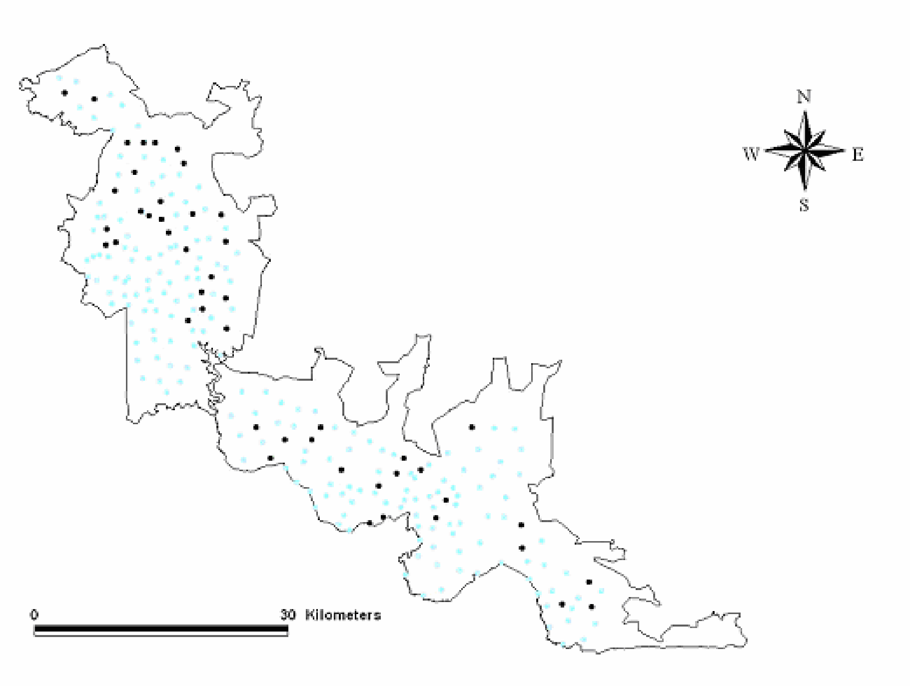

Figure 3-4. Sloth bear detections (year 2005) are shown with black (dark) dots. The other dots represent camera traps that did not detect sloth bears.

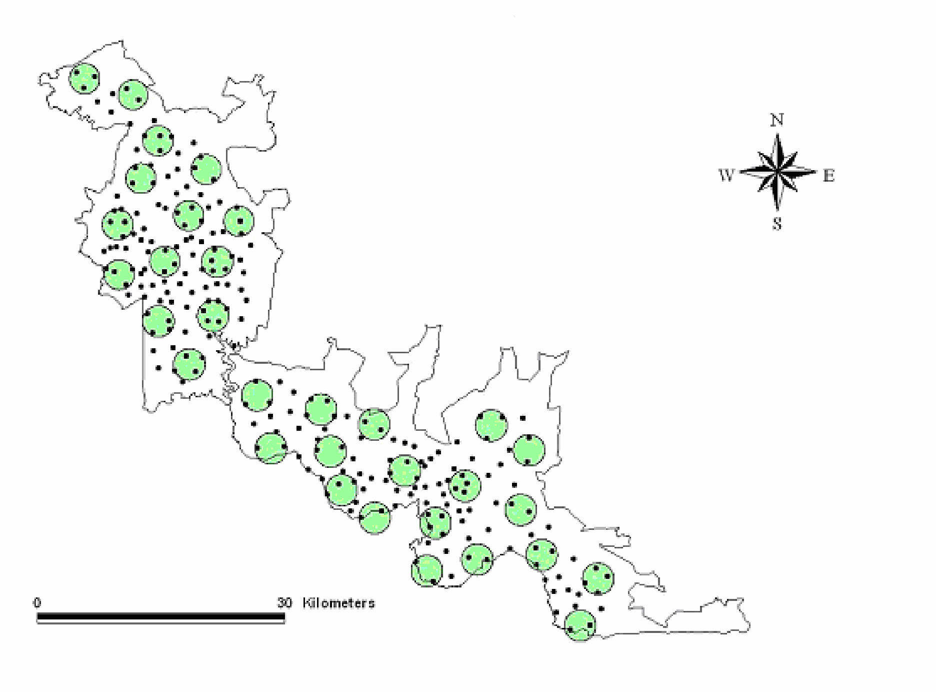

Figure 3-5. A selection of 10 km^2 sites using ArcView 3.2 GIS software. The dots within each site are the camera traps used for analysis. Similar selections were made for 18 km^2, 25 km^2 and 50 km^2 sites.

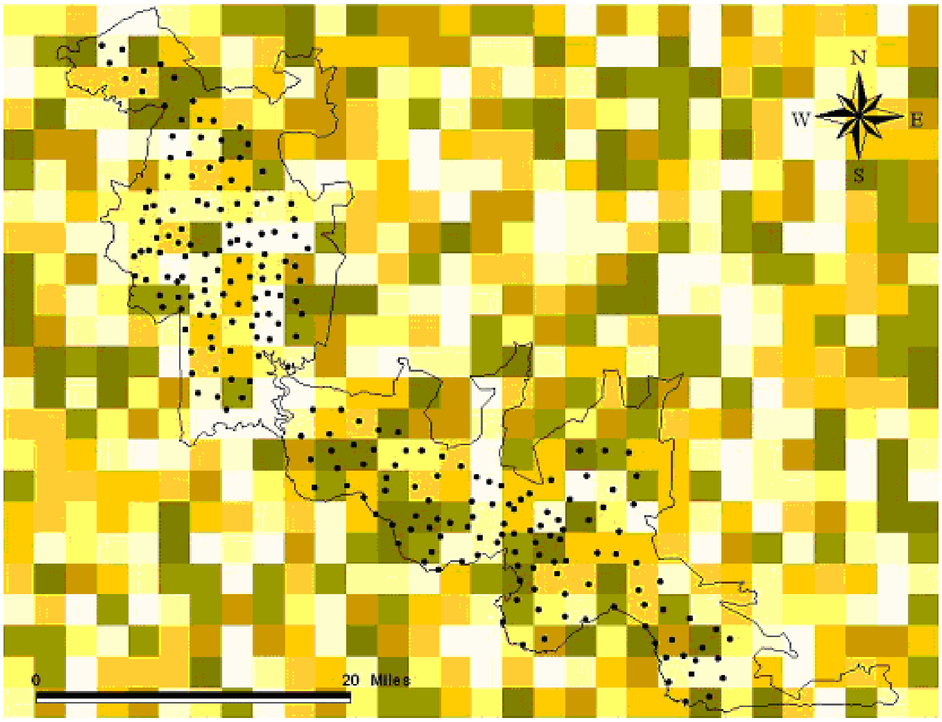

Figure 3-6. An example random grid generated using ArcView 3.2 software with cell size of 10 km^2. Here each cell containing camera traps were used in the analysis. Similar grids for 18 km^2, 25 km^2 and 50 km^2 cell sizes were generated.

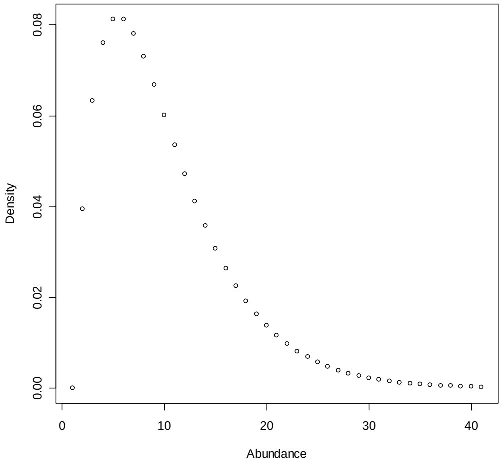

Figure 3-7. Gamma(2, 4.5) prior distribution

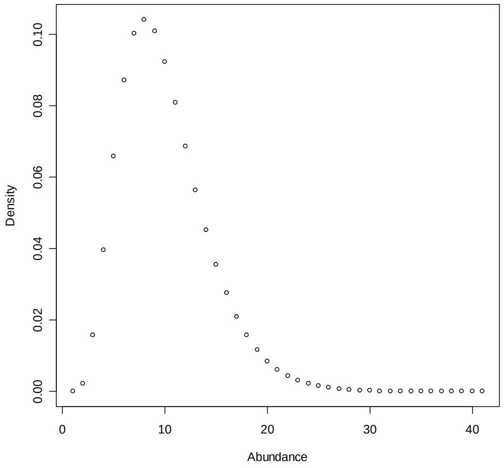

Figure 3-8. Gamma(4.5, 2) prior distribution

CHAPTER 4
CONCLUSIONS AND DISCUSSION

Animal abundance is a very important parameter from a wildlife management perspective. However, most estimation methods require very large sample sizes to obtain reliable estimates of abundance and seldom does such information help for a wildlife manager. The progressively subjective nature of Bayesian approaches at abundance estimation can to some extent be more informative to the wildlife manager (Stow, Carpenter & Cottingham, 1995). Such approaches do facilitate this process of updating parameter estimates on improved prior beliefs and will help wildlife managers use such approaches more effectively in monitoring animal populations (Hilborn and Mangel, 1997).

The simulation results from my study show that the Royle and Nichols (2003) can still be a valuable tool for determining abundance, specially since it is relatively inexpensive to obtain presence-absence data from sites. The data gathered from my study on sloth bears were insufficient for good estimates of animal abundance. However, improving the quality of field data in terms of improving r will go a long way in making this model more useful for determining sloth bear abundance.

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BIOGRAPHICAL SKETCH

Arjun Mallipatna Gopalaswamy was born on 10 June 1976 in Bangalore, India. He grew up in a city with his parents and a sister. While pursuing his undergraduate education, he was actively involved with a mountaineering club in his college which exposed him to myriad landscapes and forests of India. This made him think more seriously about wildlife and nature conservation issues and a future along those lines. He completed his undergraduate education with a bachelor’s degree in industrial engineering in May 1999. He then started his own software business company and was part of it for two years before deciding to dedicate all his time doing ecology related field work. He worked as a field research assistant in a tiger project of the Wildlife Conservation Society – India Program, where he was fortunate to know and benefit from outstanding field biologists and conservationists with whom he worked. In August 2004, he began his graduate study at the University of Florida in the Department of Wildlife Ecology and Conservation. He received his Master of Science in December 2006.