

# <sup>1</sup> Chapter 1

## <sup>2</sup> Introduction



## <sup>3</sup> Chapter 2

# <sup>4</sup> GLMS and WinBUGS



## <sup>5</sup> Chapter 3

## <sup>6</sup> Closed population models



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<sup>10</sup> **Chapter 5**

<sup>11</sup> **Other observation models**



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## Chapter 9

# State-space Covariates

Underlying all spatial capture recapture models is a point process model describing the distribution of individual activity centers ( $\mathbf{s}_i$ ) within the state space ( $\mathcal{S}$ ). So far we have focused our discussion on the homogeneous binomial point process,  $\mathbf{s}_i \sim \text{Uniform}(\mathcal{S})$ ,  $i = 1, 2, \dots, N$ , where  $N$  is the size of the population. This is a model of “spatial-randomness”<sup>1</sup> because the intensity of the activity centers is constant across the study area and the activity centers are distributed independently of each other.

The spatial-randomness assumption is often viewed as restrictive because ecological processes such as territoriality and habitat selection can result in non-random distributions of organisms. We have argued, however, that this assumption is less restrictive than may be recognized because the homogeneous point process actually allows for infinite possible configurations of activity centers. Furthermore, given enough data, the uniform prior will have very little influence on the estimated locations of activity centers. Nonetheless, the homogeneous point process model does not allow one to model population density using covariates—a central objective of much ecological research. For example, a homogeneous point process model may result in a density surface map indicating that individuals were more abundant in one habitat than another, but it does not do so explicitly. A more direct approach would be to model density using covariates as is done in generalized linear models (GLMs).

In this chapter we will present a method for fitting inhomogeneous binomial point process models using covariates in much the same way as is done with GLMs. The covariates we consider differ from those covered in previous chapters, which were typically attributes of the animal (*e.g.* sex, age) and were used to model movement or encounter rate. In contrast, here we wish to model covariates that are defined for all points in  $\mathcal{S}$ , which we will refer to as state-space, or density, covariates. These may include continuous covariates such as elevation, or discrete covariates such as habitat type.

---

<sup>1</sup>The phrase “complete spatial-randomness” is reserved for the homogeneous Poisson point process

Borchers and Efford (2008) were the first to propose an inhomogeneous point process model for SCR models, and our approach is similar to theirs with the exception that we will use a binomial rather than a Poisson model because the binomial model is easily integrated into our data augmentation scheme and is consistent with the objective of determining how a *fixed* number of activity centers are distributed with respect to covariates.

The method we use to accommodate inhomogeneous binomial point process models within our MCMC algorithm is simple—we replace the uniform prior with a prior describing the distribution of the  $N$  activity centers conditional on the covariates. Development of this prior, which does not have a standard form, is a central component of this chapter. First we will begin with a review of homogeneous point process models.

## 9.1 Homogeneous point process revisited

The homogeneous Poisson point process is *the* model of “complete spatial randomness” and is often used in ecology as a null model to test for departures from randomness. Given its central role in the analysis of point processes, it is helpful to compare it with the binomial model that we use in our SCR models. The primary descriptor of the homogeneous point process model is the “intensity” parameter,  $\mu$  which describes the expected number of points in an infinitesimally small area. The intensity parameter can also be used to determine the expected number of points in any region of the state-space  $\mathcal{S}$ . To denote this, we say that the expected number of points in region  $B \in \mathcal{S}$  is  $n(B) = A(B)\mu$  where  $A(B)$  is the area of region  $B$ . In words, the expected number of points in  $B$  is simply the area of  $B$  multiplied by the intensity parameter. One property of the Poisson model is that if we divide the entire state-space into  $k = 1, \dots, K$  disjunct regions, the counts  $\mathbf{n}(\mathbf{B})$  are independent and identically distributed, (*i.i.d.*). This is one of the distinctions between the Poisson model and the binomial model, for which the counts  $n(B_k)$  are not *i.i.d.* as we will explain shortly. This difference is also related to another distinction between the two models, namely that the binomial model conditions on the number of points to be simulated  $N$ ; whereas under the Poisson model  $N$  is random. Here is some simple **R** code to illustrate this point.

```
mu <- 4                                # intensity
Np <- rpois(1, mu)                     # Np is random
PPP <- cbind(runif(Np), runif(Np))     # Poisson point process

Nb <- 4                                # Nb is fixed
BPP <- cbind(runif(Nb), runif(Nb))     # Binomial point process
```

Note that in both models, the  $N$  points are independent of one another and distributed uniformly throughout  $\mathcal{S}$ . Thus, the intensity at any point  $x \in \mathcal{S}$  is  $\mu = 1/A(\mathcal{S})$  where  $A(\mathcal{S})$  denotes the area of the state-space. In the **R** code above, the area of the state-space is 1 unit, and thus the intensity is  $\mu = 1/1$ .

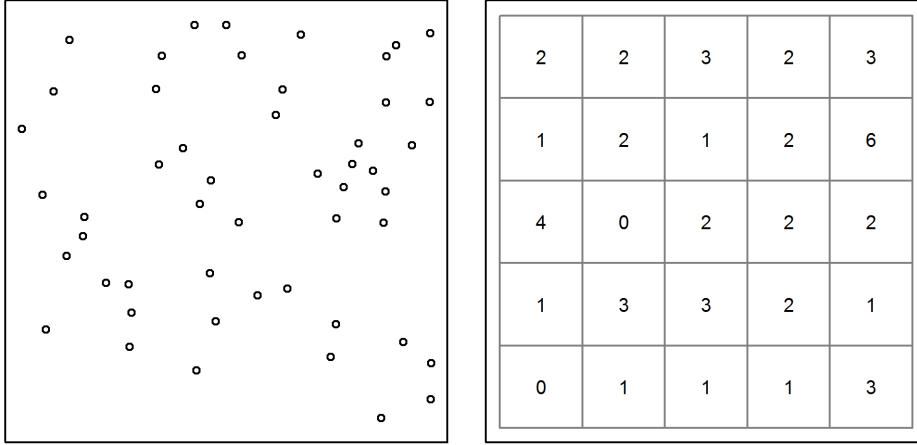


Figure 9.1: Homogeneous binomial point process with  $N=50$  points represented in continuous and discrete space.

Although the Poisson model is typically described in terms of  $\mu$ , the binomial model is not; rather, it is more common to consider a discrete state space, such as a grid with  $K$  pixels. Under the binomial model, the number of points in each region is  $n(B_k) \sim \text{Bin}(N, p_k)$  where  $p_k = A(B)/A(S)$ , ie  $p_k$  is simply the fraction of the state-space area in  $B_k$ . This discrete space representation of the binomial point process is shown in Fig. 9.1. The state-space in this case is the unit square, and thus the probability of a point falling in each of the 25 disjunct regions is  $p_k = 1/25$  and thus the expected counts are simply  $\mathbb{E}(n(B_k)) = Np_k$ . In the figure  $N = 50$  and thus we would expect 2 points per pixel, which happens to be the empirical mean of the data in Fig. 9.1. Note also that these counts are not independent realizations from a binomial distribution since  $\sum_k n(B_k) = N$ . Instead, the model for the entire vector is  $\mathbf{n}(\mathbf{B}) \sim \text{Multinomial}(N, \pi = (p_1, p_2, \dots, p_K))$  (Illian, 2008). The dependence among counts has virtually no practical consequence when the number of pixels is large. For example, if we have 100 pixels, the number of counts in one pixels tells you very little about the expected count in another pixel. However, if there are only 2 pixels, then clearly the number of points in one pixel tells you exactly how many will occur in the remaining pixel. To gain familiarity with the multinomial distribution and the discrete representation of space, use the `rmultinom` function in **R** to simulate counts similar to those shown in Fig. 9.1, for example using a command such as:

```

111 n.B_k <- rmultinom(1, size=50, prob=rep(1/25, 25))
112 matrix(n.B_k, 5, 5)

```

The discrete space representation of the binomial point process is of practical importance when fitting SCR models because spatial covariates are almost always represented in a discrete format, often called “rasters” in GIS-speak. In such cases, we often need to change our definition of the prior for an activity center from  $s_i \sim \text{Uniform}(\mathcal{S})$  to  $s_i \sim \text{Multinomial}(1, \pi)$ . In the latter case, the activity center is simply defined as an integer representing pixel “id”. Note also that the multinomial distribution with an index of 1 (*i.e.* `size=1` in `rmultinom`) is referred to as the categorical distribution, which we will frequently use in the BUGS language.

## 9.2 Inhomogeneous binomial point process

As with the homogeneous model, the inhomogeneous binomial point process model is developed conditional on  $N$ . The primary distinction is that the uniform distribution is replaced with another distribution allowing for the intensity parameter to vary spatially. To arrive at this new distribution, define  $\mu(x, \beta)$  to be a function of spatially-referenced covariates ( $\beta$ ) available at all points of the state space. To be concise we will subsequently drop the vector of coefficients from our notation, and simply use  $\mu(x)$ . Since an intensity must be strictly positive, it is natural to model  $\mu(x)$  using the log-link.

$$\log(\mu(x)) = \sum_{j=1}^J \beta_j v_j(x), \quad x \in \mathcal{S}$$

where  $\beta_j$  is the regression coefficient for covariate  $v_j(x)$ . To be clear,  $v(x)$  is the value of any covariate, such as habitat type or elevation, at location  $x$ . This equation should look familiar because it is the standard linear model used in log-linear GLMs. Note, however, that we have no need for an intercept because it would be confounded with  $N$ . This should be intuitive since an intercept would represent the expected value of  $N$  when  $\beta = 0$ , but we already have a parameter in the model for expected abundance, namely  $\mathbb{E}[N] = \psi M$ . Thus an intercept would be redundant, and without it we are still able to achieve our goal of describing the distribution of  $N$  activity centers as a function of spatial covariates.

Now that we have a model of the intensity parameter  $\mu(x)$ , we need to develop the associated probability density function to use in place of the uniform prior. Remembering that the integral of a pdf must be unity, we can create a pdf by dividing  $\mu(x)$  by a normalizing constant, which in this case is the integral of  $\mu(x)$  evaluated over the entire state-space. **ANDY, is there a better justification for this?** The probability density function is therefore

$$f(x) = \frac{\mu(x)}{\int_{x \in \mathcal{S}} \mu(x) dx} \quad (9.1)$$

Substituting this distribution for the uniform prior allows us to fit inhomogeneous binomial point process models to spatial capture-recapture data. We can

also use this distribution to obtain the expected number of individuals in any given region. Specifically, the proportion of  $N$  expected to occur in any region  $B$  when heterogeneity in density is present is  $p(B) = \int_B f(x) dx$ . These are also the multinomial cell probabilities if the regions are disjoint and compose the entire state-space.

As a practical matter, note that the integral in the denominator of  $f(x)$  is evaluated over space, and since we almost always regard space as two-dimensional, this is a two-dimensional integral that can be approximated using the methods discussed in refChXXX. These methods include Monte Carlo integration, Gaussian quadrature, etc... Alternatively, if our state-space covariates are in raster format, *i.e.* they are in discrete space, the integral can be replaced with a sum over all pixels, which is much more efficient computationally.

We now have all the tools needed to fit inhomogeneous point process (IPP) models. Before doing so, we note that the IPP for the activity centers results in another IPP for the observation process,  $\lambda(x)$ . As a reminder,  $\lambda(x)$  is the expected number of captures for a trap at point  $x$ . As was true for the homogeneous model, this intensity function is a product of the point process intensity and the encounter rate function,  $\lambda(x) = \mu(x)g(x)$ .

In the next section we walk through a few examples, building up from the simplest case where we actually observe the activity centers as though they were data. In the second example, we fit our new model to simulated data in which density is a function of a single continuous covariate. Example three shows an analysis in discrete space using both **secr** (Efford, 2011) and **JAGS** (Plummer, 2003). In the last example, we model the intensity of activity centers for a real dataset collected on jaguars (*Panthera onca*) in Argentina.

## 9.3 Examples

### 9.3.1 Simulation and analysis of inhomogeneous point processes

In SCR models, the point process is not directly observed, but in other contexts it is. Examples include the locations of disease outbreaks, the locations of trees in a forest, or the locations of radio-tracked animals. Indeed Eq. 9.1 has been used extensively in the radio-telemetry literature to model so-called “resource selection functions” (Manly, 2002; Lele and Keim, 2006). In such cases where the point locations are directly observed, estimating the parameters  $\beta$  is straightforward as demonstrated in the following example. This example also illustrates the fundamental process that we will later embed in our MCMC algorithm used to fit SCR models.

Suppose we knew the locations of 100 animals’ activity centers. To estimate the intensity surface  $\mu(x)$  underlying these points, we need to derive the likelihood for our data under this model. Given the pdf  $f(x)$  (Eq. 9.1) and assuming that the points are mutually independent of one another, we may write the likelihood as the product of  $R$  such terms, where  $R = 100$  is the sample size in

191 this case, *ie* the observed number of activity centers.

$$\mathcal{L}(\beta|\mathbf{x}_i) = \prod_{i=1}^R f(x_i)$$

192 Having defined the likelihood we could choose a prior and obtain the posterior  
 193 for  $\beta$  using Bayesian methods, or we can find the maximum likelihood estimates  
 194 (MLEs) using standard numerical methods as is demonstrated below.

195 First, let's simulate some data. Simulating data under an inhomogeneous  
 196 point process model is often accomplished using indirect methods such as rejection  
 197 sampling. Rejection sampling proceeds by simulating data from a standard  
 198 distribution and then accepting or rejecting each sample using probabilities defined  
 199 by the distribution of interest. For more information, readers should consult  
 200 an accessible text such as Robert and Casella (2004). In our example, we  
 201 simulate from a uniform distribution and then accept or reject using the (scaled)  
 202 probability density function  $f(x)$ . Note that we first define a spatial covariate  
 203 (elevation) that is a simple function of the spatial coordinates increasing from  
 204 the southwest to the northeast of our state-space.<sup>2</sup>

205 The following **R** commands demonstrate the use of rejection sampling to simulate  
 206 an inhomogeneous point process for the covariate depicted in Fig. 9.3.1.  
 207 The code uses the **cuhre** function in the **R2Cuba** package to integrate the intensity  
 208 function over space (Hahn et al., 2011).

```

209 # spatial covariate (with mean 0)
210 elev.fn <- function(x) x[1]+x[2]-1
211 # intensity function
212 mu <- function(x, beta) exp(beta*elev.fn(x=x))
213
214 # Simulate PP using rejection sampling
215 set.seed(300225)
216 N <- 100
217 count <- 1
218 s <- matrix(NA, N, 2)
219 beta <- 2 # parameter of interest
220 int.mu <- R2Cuba::cuhre(2, 1, mu, beta=beta)$value
221 elev.min <- elev.fn(c(0,0)) #elev.fn(cbind(0,0))
222 elev.max <- elev.fn(c(1,1)) #elev.fn(cbind(1,1))
223 Q <- max(c(exp(beta*elev.min) / int.mu, #2d(beta),
224           exp(beta*elev.max) / int.mu)) #2d(beta))
225 while(count <= 100) {
226   x.c <- runif(1, 0, 1); y.c <- runif(1, 0, 1)
227   s.cand <- c(x.c,y.c)
228   pr <- exp(beta*elev.fn(s.cand)) / int.mu #2d(beta)
229   if(runif(1) < pr/Q) {
230     s[count,] <- s.cand
231     count <- count+1

```

---

<sup>2</sup>Such functional forms of covariates are rarely available, which is why continuous spatial covariates are more often measured on a discrete grid.

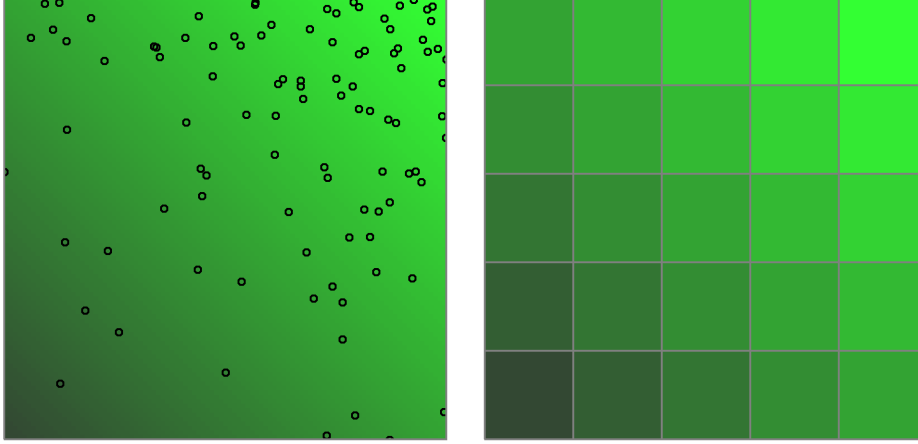


Figure 9.2: An example of a spatial covariate, say elevation, and a realization of a inhomogeneous binomial point process with  $N=100$  and  $\mu(x) = \exp(\beta \text{Elev})$  where  $\beta = 2$ .

```
232     }
233 }
```

234 The simulated data are shown in Fig 9.3.1. High elevations are represented  
 235 by light green and low elevations by dark green. The activity centers of one  
 236 hundred animals are shown as points, and it is clear that these simulated animals  
 237 prefer the high elevations. Perhaps they are mountain goats. The underlying  
 238 model describing this preference is  $\log(\mu(x)) = \exp(\beta \times \text{Elevation}(x))$  where  
 239  $\beta = 2$  is the parameter to be estimated and  $\text{Elevation}(x)$  is a function of the  
 240 coordinates at  $x$ , as displayed on the map.

241 Given these points, we will now estimate  $\beta$  by minimizing the negative-log-  
 242 likelihood using R's `optim` function.

```
243 # Negative log-likelihood
244 nll <- function(beta) {
245     int.mu <- cuhre(2, 1, mu, beta=beta)$value
246     -sum(beta*elev.fn(s) - log(int.mu))
247 }
248 starting.value <- 0
249 fm <- optim(starting.value, nll, method="Brent",
250             lower=-5, upper=5, hessian=TRUE)
251 c(Est=fm$par, SE=sqrt(1/fm$hessian)) # estimates and SEs
```

252 Maximizing the likelihood took a small fraction of a second, and we obtained  
 253 an estimate of  $\hat{\beta} = 1.99$ . We could plug in this estimate to our linear model at  
 254 each point in the state-space to obtain the MLE for the intensity surface.

255 This example demonstrates that if we had the data we wish we had, *i.e.*  
 256 if we knew the coordinates of the activity centers, we could easily estimate  
 257 the parameters governing the underlying point process. Unfortunately, in SCR  
 258 models, the activity centers cannot be directly observed, but spatial re-captures,  
 259 that is captures of individuals at multiple locations in space, provide us with  
 260 the information needed to estimate these latent parameters.

### 261 9.3.2 Fitting inhomogeneous point process SCR models

#### 262 Continuous space

263 One of the nice things about hierarchical models is that they allow us to break  
 264 a problem up into a series of simple conditional relationships. Thus, we can  
 265 simply add the methods described above into our existing MCMC algorithm  
 266 to simulate the posteriors of  $\beta$  conditional on the simulated values of  $\mathbf{s}_i$ . To  
 267 demonstrate, we will continue with the previous example. Specifically, we will  
 268 overlay a grid of traps upon the map shown in Fig. 9.3.1. We will then simulate  
 269 capture histories conditional upon the activity centers shown on the map. Then,  
 270 we will attempt to estimate the activity center locations as though we did not  
 271 know where they were, as is the case in real applications.

272 Here is some **R** code to simulate the encounter histories under a Poisson  
 273 observation model, which would be appropriate if animals could be detected  
 274 multiple times at a trap during a single occasion.

```

275 # Create trap locations
276 xsp <- seq(-0.8, 0.8, by=0.2)
277 len <- length(xsp)
278 X <- cbind(rep(xsp, each=len), rep(xsp, times=len))
279
280 # Simulate capture histories, and augment the data
281 ntraps <- nrow(X)
282 T <- 5
283 y <- array(NA, c(N, ntraps, T))
284
285 nz <- 50 # augmentation
286 M <- nz+nrow(y)
287 yz <- array(0, c(M, ntraps, T))
288
289 sigma <- 0.1 # half-normal scale parameter
290 lam0 <- 0.5 # basal encounter rate
291 lam <- matrix(NA, N, ntraps)
292
293 set.seed(5588)
294 for(i in 1:N) {
295   for(j in 1:ntraps) {
296     distSq <- (s[i,1]-X[j,1])^2 + (s[i,2] - X[j,2])^2
297     lam[i,j] <- exp(-distSq/(2*sigma^2)) * lam0
298     y[i,j,] <- rpois(T, lam[i,j])
299   }

```



```

300 }
301 yz[1:nrow(y),,] <- y # Fill

```

Now that we have a simulated capture-recapture dataset  $y$ , and we have augmented it to create the new data object  $yz$ , we are ready to begin sampling from the posteriors. A commented Gibbs sampler written in **R** is available in the accompanying **R** package **scrbook** (see ?scrIPP). There are two small parts of the **R** code that distinguish it from previous code we have shown to fit homogeneous point processes. First, we need to update the parameter  $\beta$  conditional on all other parameters in the model. The code to do so is:

```

309 D1 <- cuhre(2, 1, mu, lower=c(xlims[1], ylims[1]),
310             upper=c(xlims[2], ylims[2]), beta=beta1)$value
311 beta1.cand <- rnorm(1, beta1, tune[3])
312 D1.cand <- cuhre(2, 1, mu, lower=c(xlims[1], ylims[1]),
313             upper=c(xlims[2], ylims[2]), beta=beta1.cand)$value
314 ll.beta1 <- sum( beta1*elev.fn.v(S) - log(D1) )
315 ll.beta1.cand <- sum( beta1.cand*elev.fn.v(S) - log(D1.cand) )
316 if(runif(1) < exp(ll.beta1.cand - ll.beta1) ) {
317     beta1<-beta1.cand
318 }

```

Next, we need to put the new prior on the activity centers:

```

320 #ln(prior), denominator is constant
321 prior.S <- beta1*cov(S[i,1], S[i,2]) # - log(D1)
322 prior.S.cand <- beta1*(Scand[1] + Scand[2]) # - log(D1)
323 if(runif(1) < exp((ll.S.cand+prior.S.cand) - (ll.S+prior.S))) {
324     S[i,] <- Scand
325     lam <- lam.cand
326     D[i,] <- dtmp
327 }

```

We can apply this modified sampler to our data using the code shown in the help file for **scrIPP**. We obtain posterior distributions summarized in Table 9.2. Mixing is good, and as usual, life is very nice when we are working with simulated data.

Fitting continuous space IPP models is somewhat difficult in **BUGS** because our prior  $f(x)$  is not one of the available distributions that come with the

Table 9.1: Posterior summaries from inhomogeneous point proces model

	Mean	SD	2.5%	50%	97.5%
$\sigma = 0.10$	0.1026	0.0048	0.0935	0.1025	0.1123
$\lambda_0 = 0.50$	0.4419	0.0493	0.3496	0.4400	0.5390
$\psi = 0.66$	0.6826	0.0554	0.5762	0.6820	0.7923
$\beta = 2.00$	2.1601	0.3390	1.5193	2.1583	2.8043
$N = 100$	102.7696	6.2689	92.0000	102.0000	117.0000

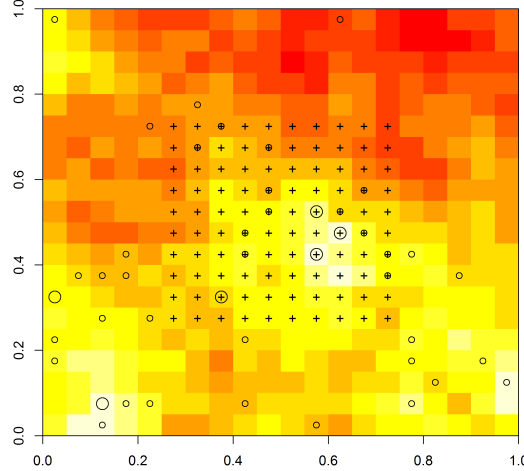


Figure 9.3: Simulated activity centers in discrete space. The spatial covariate, elevation, is highest in the higher areas. Density of activity centers (circles) increases with elevation. Trap locations are shown as crosses.

software<sup>3</sup> **secr** allows users to fit continuous space using polynomials of the x- and y- coordinates, but not for truly continuous covariates. However, these are not really important limitations because discrete space versions are straightforward, and virtually all spatial covariates are defined as such.

### Discrete space

To fit discrete space models, we follow the same steps as outlined in Chapter XXX—we define  $s_i$  as pixel ID, and we use the categorical distribution as a prior. A good example of this is in `+citeKery capricailie`. Here we present an analysis of the simulated data shown in the right panel of Fig. 9.3.1. The spatial covariate, let's call it elevation again, was simulated from a kriging type of model as shown on the help page `ch9simData` in **scrbook**. The points are the number of activity centers in each pixel, generated from a single realization of the IPP  $\mu(x) = 2elev$ .

The **BUGS** code to fit an IPP model to these data is shown in the following panel.

```
model{
  sigma ~ dunif(0, 1)
  lam0 ~ dunif(0, 5)
```

<sup>3</sup>It is possible, if somewhat cumbersome, to add new distributions in **BUGS**.

```

352 beta ~ dnorm(0,0.1)
353 psi ~ dbeta(1,1)
354
355 for(j in 1:nPix) {
356   theta[j] <- exp(beta*elevation[j])
357   probs[j] <- theta[j]/sum(theta[])
358 }
359
360 for(i in 1:M) {
361   w[i] ~ dbern(psi)
362   s[i] ~ dcat(probs[])
363   x0g[i] <- Sgrid[s[i],1]
364   y0g[i] <- Sgrid[s[i],2]
365   for(j in 1:ntraps) {
366     dist[i,j] <- sqrt(pow(x0g[i]-grid[j,1],2) + pow(y0g[i]-grid[j,2],2))
367     lambda[i,j] <- lam0*exp(-dist[i,j]*dist[i,j]/(2*sigma*sigma)) * w[i]
368     y[i,j] ~ dpois(lambda[i,j])
369   }
370 }
371
372 N <- sum(w[])
373 Density <- N/1 # unit square
374 }

```

375 This model can also be fit in **secr**, which refers to the pixel locations as  
376 a “mask”. **R** code to fit the models using **secr** and **JAGS** is available in  
377 **scrbook**, see `help(ch9secrYjags)`. Results of the comparison are shown in  
378 Table ?? and are very similar as expected.

379 Density surface maps can be created for fun, and of course to inform man-  
380 agement decisions. [describe how to do this]

### 381 9.3.3 The jaguar data

382 Estimating density of large felines has been a priority for many conservation  
383 organizations, but no robust methodologies existed before the advent of SCR.

Table 9.2: Comparison of **secr** and **JAGS** results

Software	Par	Est.	SD	lower	upper
secr	$N$	49.2803	5.7535	41.0087	64.3879
	$\beta$	2.1772	0.5628	1.0741	3.2804
	$\lambda_0$	0.9203	0.0764	0.7824	1.0825
	$\sigma$	0.0990	0.0038	0.0918	0.1068
JAGS	$N$	48.2072	5.4053	39.0000	60.0000
	$\beta$	2.1026	0.5323	1.0889	3.1506
	$\lambda_0$	0.9328	0.0766	0.7898	1.0921
	$\sigma$	0.1004	0.0041	0.0929	0.1089

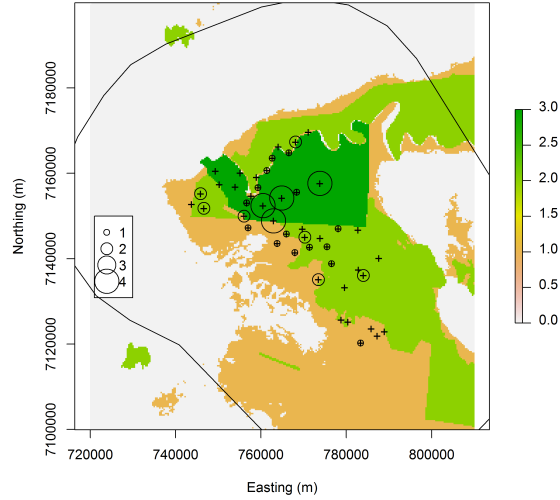


Figure 9.4: Jaguar detections

Distance sampling is not feasible for such rare and cryptic species, and traditional capture-recapture methods yield estimates that are highly sensitive to the subjective choice of the effective survey area. In this example, we demonstrate how readily density can be estimated for a globally imperilled species using SCR. Furthermore, we show how inhomogeneous point process models can be used to test important hypotheses regarding the factors affecting density.

[describe study]

A few aspects of this design are noteworthy. First, the dimensions and configuration of the trap array differed among the regions of the trap array. This fact alone could explain variation in the number of animals exposed to sampling, which would have no biological meaning. Furthermore, the area of inference is an irregular polygon that was not sampled uniformly. Only by estimating density can we hope to extrapolate our estimates from the sampled region to get what we are after. In this case, this is readily accomplished since the entire state-space can be classified as one of the 3 levels of protection from poaching. Of course, it general it is always preferable to sample more uniformly throughout the area of interest in case some unmeasured covariate biases the extrapolation.

To assess the influence of poaching on jaguar density, we considered 2 metrics of poaching pressure, one political and one continuous measure of accessibility (Fig xxx).

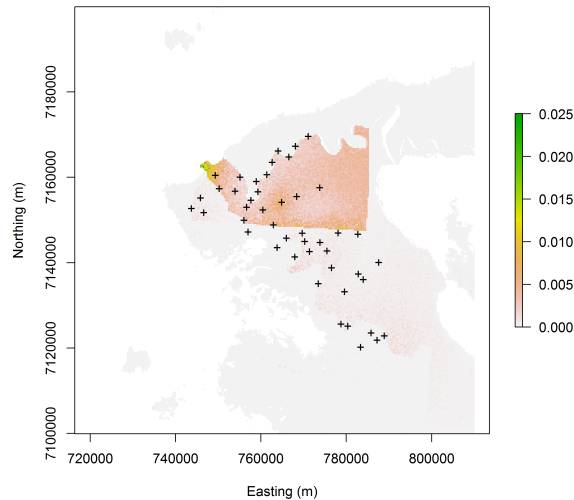


Figure 9.5: Estimated density surface for the jaguar dataset

## 9.4 Summary

When state-space covariates are available, we can model density by replacing the uniform prior on the activity centers with a prior based on a normalized log-linear function of covariates. This yields a model of the inhomogeneous point process describing the location of activity centers, which can be used to test hypotheses about covariates affecting density. In rare cases, these covariates are truly continuous in the sense that they are defined as a function of space. More often, covariates are represented on rasters, which simplifies the analysis. Fitting these models can be accomplished using **BUGS**, **secr**, or the custom **R** code presented in this chapter and found in the package **scrbook**.

All the examples in this section included a single state-space covariate, but this was for simplicity only. Including multiple covariates poses no additional challenges. Likewise, additional model structure such sex-specific encounter rate parameters or behavioral responses can be accommodated.

## 9.5 Other ideas

Should have some discussion on some ideas for building flexible models. Might be cool to use the Ickstadt/Wolpert as a model for the inhomogeneous point process. Don't have to do it, just mention it. Also some kind of a spline model or similar.



## 424 Chapter 10

# 425 Inhomogeneous Point 426 Process





427 **Chapter 11**

428 **Open models**



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