

1

Title

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Authors

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4

1 Abstract

- 5 1. There has been an increasing amount of papers that have been pro-
6 ducing estimated activity centre distributions -the summed posterior
7 distribution of estimated range centres from a Bayesian fit of a homo-
8 geneous Poisson model- and claiming them to be "species distribution
9 models", when this is not the case. In this paper we will demonstrate
10 that these activity centre distributions and predicted density surfaces
11 are not the same.
- 12 2. We illustrate this point through simulation and modelling of real data
13 using the **secr** package (?). We simulate using a grey scale image
14 of the Mona Lisa, using the intensity of greyscale as the density of
15 the "population". Then simulating from three different arrays on this
16 surface, produce estimated activity centre surfaces and compare to the
17 true density image, using models assuming constant density and models
18 with covariates. We also use camera-trap capture-recapture survey
19 data of snow leopards in South Gobi, Mongolia. We create predicted

20 density surfaces as well as estimated activity centre distributions to
21 draw comparisons between the two methods.

- 22 3. There were very apparent differences in the surfaces produced via sim-
23 ulation and using the snow leopard data. The activity centre distribu-
24 tions are not representative of the predicted density surface using **pre-**
25 **d****ictDsurface**. They are very array dependent, even in areas where
26 arrays overlap there are very different surfaces produced. As you move
27 further away from the centre of the array the density also decreases,
28 reflecting the fall in the detection function as you move from the traps.
- 29 4. Overall the results produced by these activity centre distributions do
30 not perform very well, the simulations demonstrate very apparent dif-
31 ferences from the true density. With the snow leopard data, the results
32 are surprising, producing some results that are not probable.

33 2 Introduction

34 Spatial capture-recapture (SCR) models are a set of methods for modelling
35 capture-recapture data obtained from detectors such as camera-traps, hair
36 snag traps and live-capture surveys such that individuals can be identified.
37 Using the location of the detectors (traps) and also the detections of in-
38 dividuals over several occasion (capture histories), a estimate of density of
39 individuals within a population can be obtained as well as an estimate of
40 population size (?). In order to do this, a spatial model of the population
41 and a spatial model of the detection process are fitted to the capture histo-
42 ries of detected individuals. This can be done using inverse prediction and

43 maximum likelihood as well as using data augmentation and Markov chain
44 Monte Carlo methods.

45 SCR combines a state model describing the distribution of activity cen-
46 tres in the landscape and an observation model relating the probability of
47 detecting an individual at a particular detector to the distance from a central
48 point in each animal's home range.

49 Consider a survey in which K traps are placed in a region containing ani-
50 mals having home ranges with fixed centres (also known as activity centres).

51 Once an animal is caught in a trap it remains there until it is released. These
52 traps are checked at regular intervals and marked in such a way that their
53 complete capture history is known and are released. There are S trapping
54 occasions, trap k is located at Cartesian co-ordinates x_k and the location of
55 traps within the survey are at $x = (x_1, \dots, x_k)$. The number of unique animals
56 caught are n . \mathbf{X} is the animal's location and this is its activity centre.

57 Let $\omega_i = 1$ if animal i was captured on any of the s occasions and 0 if
58 otherwise. If animal i was captured on trap k on occasion s ($s = 1, \dots, S$) then
59 $\omega_{is} = 1$ and 0 otherwise. The capture history for animal i is $\omega_i = (\omega_{i1}, \dots, \omega_{iS})$.
60 Let $p_{ks}(\mathbf{X}; \boldsymbol{\theta})$ be the probability that an animal with activity centre at x is
61 caught in trap k on occasion s , where $\boldsymbol{\theta}$ is the capture probability parameter
62 vector.

From (?) the likelihood is the joint distribution of the n animals captured
and their capture histories $\omega_1, \dots, \omega_n$ is

$$L(\boldsymbol{\phi}, \boldsymbol{\theta}|n, \omega_1, \dots, \omega_n) = Pr(n|\boldsymbol{\phi}, \boldsymbol{\theta})Pr(\omega_1, \dots, \omega_n|n, \boldsymbol{\theta}, \boldsymbol{\phi})$$

63 $\boldsymbol{\theta}$ is the vector of capture function parameters and $\boldsymbol{\phi}$ is a vector of parameters
64 of the spatial point process governing animal density and distribution.

When activity centres occur according to a homogeneous Poisson process with rate parameter D , the likelihood is simplified to

$$L(\boldsymbol{\theta}, D) = \frac{Da(\boldsymbol{\theta})^n exp^{-D a(\boldsymbol{\theta})}}{n!} \times \binom{n}{n_1, \dots, n_C} \prod_{i=1}^n \frac{\int Pr(\boldsymbol{\omega}_i | \mathbf{X}; \boldsymbol{\theta}) d\mathbf{X}}{a(\boldsymbol{\theta})}$$

where

$$Pr(\boldsymbol{\omega}_i | \mathbf{X}; \boldsymbol{\theta}) = \prod_s \prod_k p_{ks}(\mathbf{X}; \boldsymbol{\theta})^{\delta_k(\omega_{is})} 1 - p_{.s}(\mathbf{X}; \boldsymbol{\theta})^{1 - \delta_0(\omega_{ks})}$$

and $a(\boldsymbol{\theta}) = \int p_{.s}(\mathbf{X}; \boldsymbol{\theta}) d\mathbf{X}$. An estimate of density can be obtained from the MLE estimate of $\hat{\theta}$ and hence $\hat{a}(\hat{\boldsymbol{\theta}})$ from the conditional likelihood, D is then estimated from $\hat{D} = n/\hat{a}$. If the capture probability and a depend on covariates such as \mathbf{z} then $\hat{D} = \sum_{i=1}^n \hat{a}(\mathbf{z}_i)^{-1}$. D is a fn of covariates, log link it, and also can do splines

By using the estimates of the density model parameters ϕ we can estimate the probability density function of animal home-range centres in area A : $\hat{\pi} = \hat{D}(\hat{\mathbf{X}})/\int_A \hat{D}(\mathbf{X}) d\mathbf{X}$. Given individual i 's and it's capture history $\boldsymbol{\omega}_i$ and an estimate of the capture probability parameter vector $\boldsymbol{\theta}$, the probability density function of \mathbf{X} , the location of this individual's home range centre (activity centre).

$$\hat{f}(\mathbf{X}_i | \boldsymbol{\omega}_i) = \widehat{Pr}(\boldsymbol{\omega}_i | \mathbf{X}_i) \hat{\pi}(\mathbf{X}_i) / \int_A \widehat{Pr}(\boldsymbol{\omega}_i | \mathbf{X}) \hat{\pi}(\mathbf{X}) d\mathbf{X}$$

And for a homogeneous Poisson process this simplifies to:

$$\hat{f}(\mathbf{X}_i | \boldsymbol{\omega}_i) = \widehat{Pr}(\boldsymbol{\omega}_i | \mathbf{X}_i) / \int_A \widehat{Pr}(\boldsymbol{\omega}_i | \mathbf{X}) d\mathbf{X}$$

In several papers, there has been some confusion as to the difference between estimated activity centre distributions- the summed posterior distribution of estimated range centres from a Bayesian fit of a homogeneous

73 Poisson model - and density surfaces (????). with the former even being re-
74 ferred to as a "species distribution model" (?) and states that this approach
75 is useful even when the sources of spatial variation in population density
76 are not known. In this paper we will illustrate that the two are not equiva-
77 lent. There are various problems with interpreting these surfaces as "species
78 distribution models" and "density surfaces", attention is only focused on in-
79 dividuals that were caught. The individuals that were not caught but were
80 present are represented by a smoothly varying base level that dominates the
81 outer regions of the plot. The surface also depends on sampling intensity, as
82 more data is added the the surface will change shape systematically and the
83 plots are prone to artefacts (?).

84 3 Materials and methods

85 Estimated density surfaces and activity centre distributions are usually pre-
86 sented as images, these being easier to absorb and interpret. In order to
87 present our argument and results in a way that is easy to interpret we also
88 largely present our results as images.

89 3.1 Simulating a binomial point process

90 We simulate a fixed number of animals distributed across a single dimension
91 according to a linear trend, and then model this data using a binomial point
92 process that incorrectly assumes a uniform distribution of animals across
93 space. Here one can think of, for example, a situation in which true density
94 strongly depends on a covariate that varies in space, but that this covariate

95 is unknown.

96 We place a fixed number of points N at random locations on the interval
97 $0 < x < R$, with $R = 15$. Points are generated according to a probability
98 density that makes them more likely to appear near $x = 0$ than $x = 15$ i.e.
99 $f(x) \propto 1 - x/15$ for $0 < x < 15$ and $f(x) = 0$ otherwise.

100 For simplicity we divide the interval into $R = 15$ equal-sized regions,
101 thinking of these as cells in a one-dimensional grid. Traps are placed in
102 $T = 5$ cells. We make the simplifying assumptions that animals do not move
103 from the cell they are placed in, and that each trap detects animals perfectly
104 within the cell it occupies but cannot detect animals beyond that cell.

105 We simulate with $N = 50000$ animals and with different trap configura-
106 tions.

107 3.2 Simulating a Poisson point process

108 We simulate data from a density surface model based on one of the most
109 recognisable images in Western culture, the Mona Lisa. We created a greyscale
110 version of a region of the original image (Figure ??, “Original”) and down-
111 scaled this to 50x50 pixel resolution (Figure ??, “Low Res”). The greyscale
112 value in each cell of the “Low Res” gives the true density of activity centers
113 in that cell, with lighter areas indicating higher densities.

114 We then used the density surface in the “Low Res” image to generate
115 two realisations of points from the underlying process. In the first of these
116 we generated the number of points from a single draw from a Poisson distri-
117 bution with mean 7500, resulting in 7451 activity centers being generated.
118 These represent the true activity centers in our study region (Figure ??,

119 “Simulated”). This realisation has the advantage of closely reproducing the
120 source image, thereby giving the estimated density surface every opportunity
121 to do the same, but is also much larger than the number of centers that would
122 typically be present in a wildlife survey. We therefore also generated a much
123 smaller second realisation of 84 points (Figure ??, “Simulated small”). This
124 realisation clearly no longer captures the Mona Lisa, but is a more useful aid
125 to understanding some aspects of SCR models.



Figure 1: Input data for the Mona Lisa simulation study. From a grayscale version of the Mona Lisa (“Original”), we created a downscaled 50x50 pixel version (“Low Res”) that represents the true underlying intensity surface and gives the long-run density of activity centers in each cell. We used this surface to generate a single realization of 7451 activity centers (“Simulated”) and 84 activity centers (“Simulated Small”); in wildlife survey terms this image represents the density of the activity centers of all animals present in the study region.

¹²⁶ **3.3 Simulating capture histories**

¹²⁷ We conducted various simulated surveys of the population, using different
¹²⁸ arrays of detectors and also varying the number of detection occasions. Dif-
¹²⁹ ferent arrays and detection functions were used for the large and small realisa-
¹³⁰ tions described above. With a large number of activity centers, we simulated
¹³¹ capture histories using a half-normal detection function with g_0 , the proba-
¹³² bility of detection at a single detector placed in the centre of the home range,
¹³³ set to 0.5, and σ , the spatial scale parameter, set to 2. We used four differ-
¹³⁴ ent 3x4 arrays (Figure ??), with array centers (19, 21), (19, 33), (28, 21), or
¹³⁵ (28, 33). All arrays were spaced such that they have length 8 in the x -plane
¹³⁶ and 12 in the y -plane, and so have an average spacing of $4 = 2\sigma$. We then
¹³⁷ simulated a capture history for either one or 20 occasions on each array.

¹³⁸ When using relatively few activity centers, visual interpretation was made
¹³⁹ easier by increasing the spatial scale parameter, effectively increasing the
¹⁴⁰ distance animals travel from the activity centers, and also by increasing the
¹⁴¹ distance between detectors. For these cases, we increased σ to 4, holding
¹⁴² other detection function parameters at their previous values, and used a 3x4
¹⁴³ array centered on (18, 34) and with an average spacing of 8 between detectors,
¹⁴⁴ double that used previously. We simulated capture histories after one, three,
¹⁴⁵ ten, and 20 occasions.

¹⁴⁶ After simulating these capture histories for these arrays, we then created
¹⁴⁷ an estimated activity centre surface for each of these simulations. In this sce-
¹⁴⁸ nario we assumed a model with constant density and compared the resulting
¹⁴⁹ estimated activity center surface to the true population density surface.

¹⁵⁰ The next step was to introduce covariates into our density model and

see how this affected the estimated surfaces. We generated covariates by manipulating the “Low Res” image to obtain further images using simple image processing operations like blurring and shifting. Covariates are thus all functions of the true densities but the strength of the association between the covariate and true density varies substantially. We generated four covariates: a “strong” covariate that uses a Deriche (blur) filter with a small range, effectively smoothing the image locally; a “moderate” covariate that uses the same blur filter but with a larger range, increasing the amount of smoothing; a “weak” covariate that uses the same degree of blurring as the moderate covariate but in addition shifts the image down and to the right, destroying much of the relationship between covariate and density; and a “locally strong” covariate, which uses the strong covariate values in the top right hand part of the image and the weak covariate values in the remainder of the image. These covariates are shown in the first row of plots in Figure ??.

We simulated capture histories and created an estimated activity centre or “space use” (including movement) surface for each of these simulations and compared them to the true population density surface. All computations were done using the *secr* package in R version 3.4.3.

3.4 Camera-trap survey of tigers in Nagarhole, India

We reanalysed data obtained from a camera trap survey of tigers *Panthera tigris* living in and around the Nagarhole Tiger Reserve of Karnataka, India, as reported in ?. A full description of the survey can be found in the original reference. The original survey used a spatial array of 162 motion-activated

175 camera traps, these being placed at 23 km intervals throughout the area
176 (Figure ??, “All traps”).

177 We reanalyzed this data in a likelihood-based framework, first with a
178 model assuming constant density and with three different trap arrays. The
179 first array was the same one employed in the original study. The second was a
180 subset of traps that excluded a large number traps in the interior of the study
181 region, thus leaving a substantial part of the study area unsurveyed (Figure
182 ??, “Subset #1”). The third used another subset of traps that excluded
183 eight detectors from each of two interior areas of the survey area in which
184 the original survey showed the density of activity centers to be particularly
185 high (Figure ??, “Subset #2”).

186 We then fitted a number of covariate models in which density was assumed
187 to depend on longitude and latitude. We fitted a variety of linear and smooth
188 functions for each of longitude and latitude; the model selected by the AIC
189 was one including a linear effect of latitude only, and we report results from
190 this model only. Finally, we generated space use densities for constant density
191 model with all traps.

192 4 Results

193 4.1 Estimated activity centre surfaces from a 1-D bi- 194 nomal point process

195 Figure ?? shows the expected number of activity centers for $N = 50000$ ani-
196 mals distributed according a binomial point process with density decreasing
197 linearly with x . Under the extremely simplified conditions of this example

198 (no movement of animals, perfect detection within cells), SCR recovers the
199 true number of activity centers in each cell that contained a detector, knows
200 how many animals were *not* detected¹, and distributes the activity centers
201 of these undetected animals evenly across the cells that do not contain a
202 detector².

203 **4.2 Estimated density surfaces when there are many
204 activity centers**

205 **4.2.1 Model with constant density**

206 The same patterns hold in two dimensions under the standard wildlife survey
207 assumptions of Poisson-distributed activity centers (with constant intensity)
208 and detectability inversely related to distance from activity center (Figure
209 ?? and ??). A single sampling occasion was sufficient to capture the broad
210 features of the Mona Lisa, but only close to where detectors were located
211 (Figure ??, first row). Away from the detectors the estimated density quickly
212 reverted to close to the estimated mean intensity of the process. Additional
213 sampling occasions resulted in the density of activity centers close to detec-
214 tors being estimated in much greater detail, but did not affect the surface
215 away from detectors (Figure ??, first row).

¹Here this is because N is known but if N is unknown it can be estimated. A model assuming a constant density and detecting n animals from a perfect survey of T/R of the study area estimates the total number of animals to be $\hat{N} = n/(T/R)$, implying there are $\hat{N} - n$ animals in the area that were not detected by any trap.

² $\hat{N} - n$ activity centers distributed uniformly between $R - T$ trapless cells gives a mean of $(N - n)/(R - T)$ activity centers per cell, close to the mean of the underlying process N/R when $n \ll N$ and $T \ll R$, as would usually be for wildlife surveys.

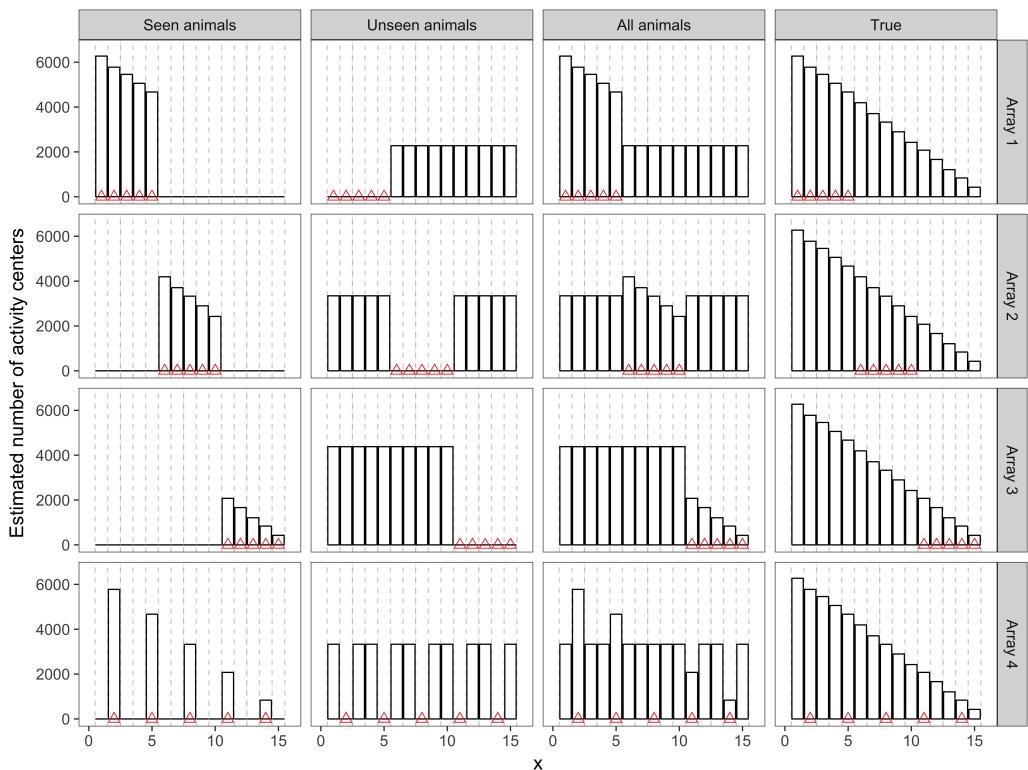


Figure 2: Estimated numbers of activity centers obtained from a binomial point process with $N = 50000$ simulated animals and density decreasing linearly with x , no animal movement, and a step detection function that is perfect within cells and zero otherwise.

Very different relative and absolute densities were obtained depending on where traps are located, even when estimating density *in exactly the same region of the surface and where that region is close to the array* (Figure ?? and ??, second row). With a single occasion, density was always estimated to be highest nearest the corner where the trap is located (Figure ??, second row). This pattern occurred because the inset region happened to occur in an area of above average density. If instead it occurred in a low density region one would see the opposite pattern – low density in the corner containing a trap, increasing away from the trap. This was clearly visible when a single sampling occasion was used, because the estimated surface reverted quickly to the mean intensity. Additional sampling allowed fine detail in the density surface to be estimated close to traps, with slower reversion to mean intensity, but there was still very clear disagreement between the density surfaces returned by the different arrays (Figure ??, second row).

4.2.2 Model with density depending on covariates

Introducing covariates into the density models allowed us to recover features of the Mona Lisa across the entire image, not just near where detectors were located, although good estimation of activity center locations depended heavily on the availability of good covariates (Figure ??). With our “strong” covariate we recovered all of the broad features of the Mona Lisa, and many of the fine scale features such as eyes, shading of clouds, *etc.* With the “moderate” covariate we recovered broad scale features but no finer details. With a “weak” covariate, the estimated density surface essentially reverted to the mean intensity of the process across the entire region. With a “locally

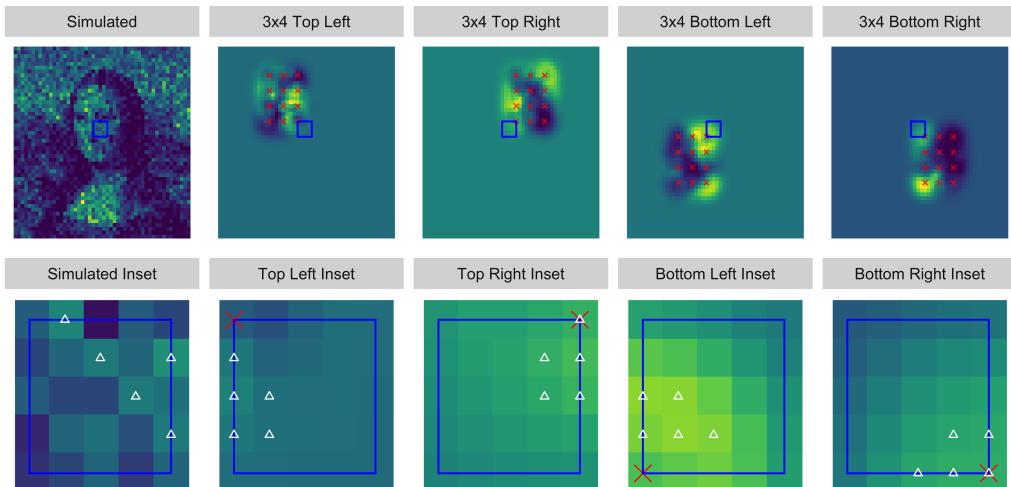


Figure 3: True activity center densities in this realisation (“Simulated”) compared with activity center surfaces estimated using different arrays after a single sampling occasion. High density areas are indicated in yellow, low density areas in blue. Detectors are shown as red crosses. Blue squares show the same 4×4 square centered at $(25, 29)$, whose vertices are corner detectors from each of 3×4 arrays. Each plot in the second row shows an enlargement of the blue square in the plot above it. White triangles denote the five cells with the highest estimated densities in each of the second row plots.

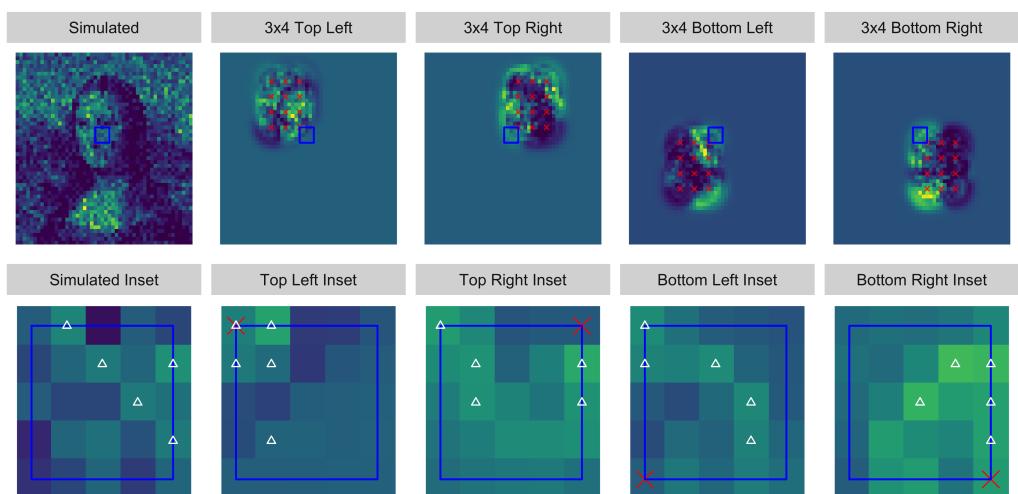


Figure 4: True activity center densities in this realisation (“Simulated”) compared with activity center surfaces estimated using different arrays after 20 sampling occasions. High density areas are indicated in yellow, low density areas in blue. See the caption to Figure ?? for further annotation details.

240 strong” covariate – one that is a good indicator of density in some parts
241 of the study region but poor elsewhere – the dependency on array location
242 was reintroduced. If the array was located where the covariate was strong,
243 the estimated density surface was accurate in that vicinity. If the array
244 was located where the covariate was weak, then the model estimated no
245 relationship between covariate and density and reverted back to the mean
246 intensity everywhere in the region (Figure ??).

247 **4.3 Estimated density surfaces when there are few ac-
248 tivity centers**

249 **4.3.1 Model with constant density**

250 We observed similar patterns under the more “wildlife survey appropriate”
251 condition in which we generated only 85 activity centers across the study
252 region (Figure ??). In this case there is a large difference between the mean
253 intensity surface (the Mona Lisa) and the activity center surface in this re-
254 alization (85 points), and so it is not surprising that the estimated activ-
255 ity center surface looks nothing like the Mona Lisa (Figure ??, first row).
256 Nevertheless, a model assuming constant density gives increasingly accurate
257 estimates of the locations of activity centers in the vicinity of detectors as
258 survey effort increases, but very little information is obtained elsewhere, and
259 this does not change with survey effort (Figure ??, first row). This gives
260 the estimated activity center surfaces a characteristic pattern – the surface
261 becomes increasingly peaked or “spiky” around detectors as survey effort
262 increases, but remains flat away from the array.

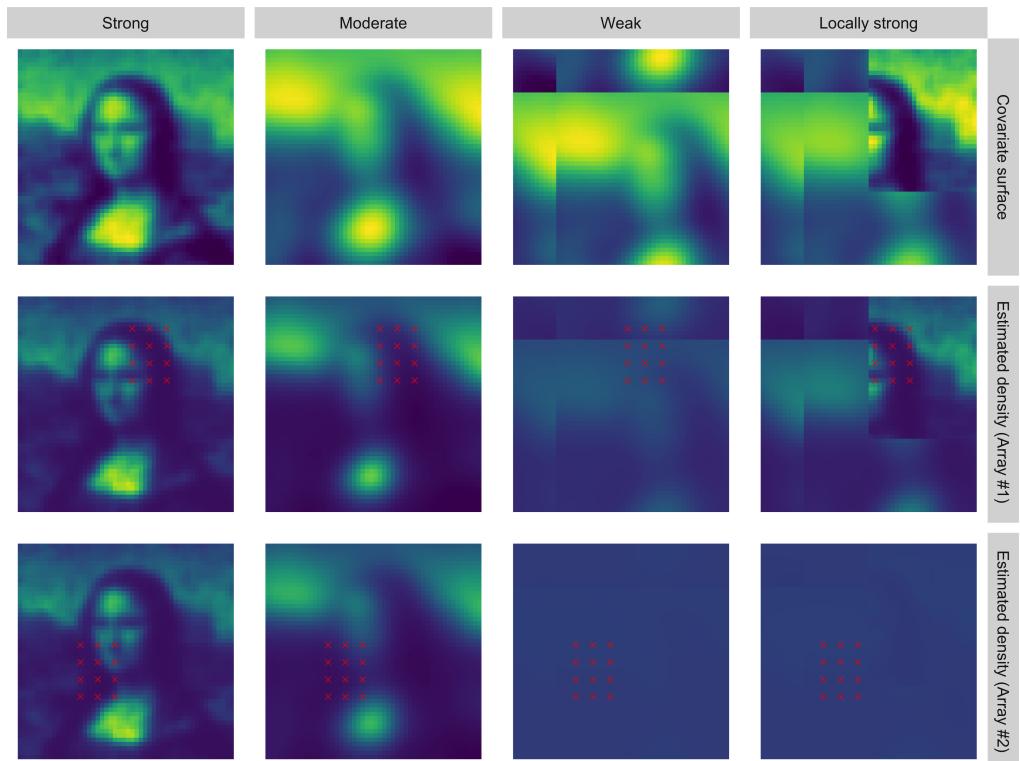


Figure 5: Intensity surfaces estimated using a model with density as a function on one of four simulated spatially-varying covariates. Covariates are shown in the first row of plots, and were generating by manipulating the true intensity surface (Figure ??, “Low Res”) by blurring and shifting operations (see Section ?? for details). High density areas are indicated in yellow, low density areas in blue. Detectors are shown as red crosses.

263 **4.3.2 Model with density depending on covariates**

264 Any covariate model returns a surface that is some multiple of the covariate
265 surface. Whether this is a good approximation of the true mean intensity
266 surface depends on the strength of the covariate and sample size. With a
267 strong covariate and sufficient sampling occasions we recovered the Mona
268 Lisa, but with only a single occasion the direction of the relationship was
269 incorrectly estimated, so that dark areas were predicted as light and light
270 areas as dark (Figure ??, second row). This error was corrected by additional
271 occasions. The same pattern occurred with a moderate covariate, but the
272 effect of the weaker covariate is clear in that we did not recover as good an
273 approximation of the Mona Lisa (Figure ??, third row). Additional sampling
274 would not help with this. Note that in both cases the surface we recovered
275 is an approximation of the mean intensity surface. It does not give a good
276 approximation to the locations of the 85 activity centers in this particular
277 realization.

278 **4.3.3 Space use density surfaces**

279 Space use density surfaces – those that incorporate animal movement – were
280 smoother than the density surface of estimated activity centers and also less
281 sensitive to survey effort (Figure ??). The space use surface adds a movement
282 kernel that is insensitive to surface effort to an activity center surface that
283 becomes more peaked as survey effort increases, so this is to be expected.
284 Space use density surfaces were not “just” smoothed versions of the activity
285 center surfaces, however. In our example unobserved animals were estimated
286 to be spending their time on the outskirts of the study region, far away

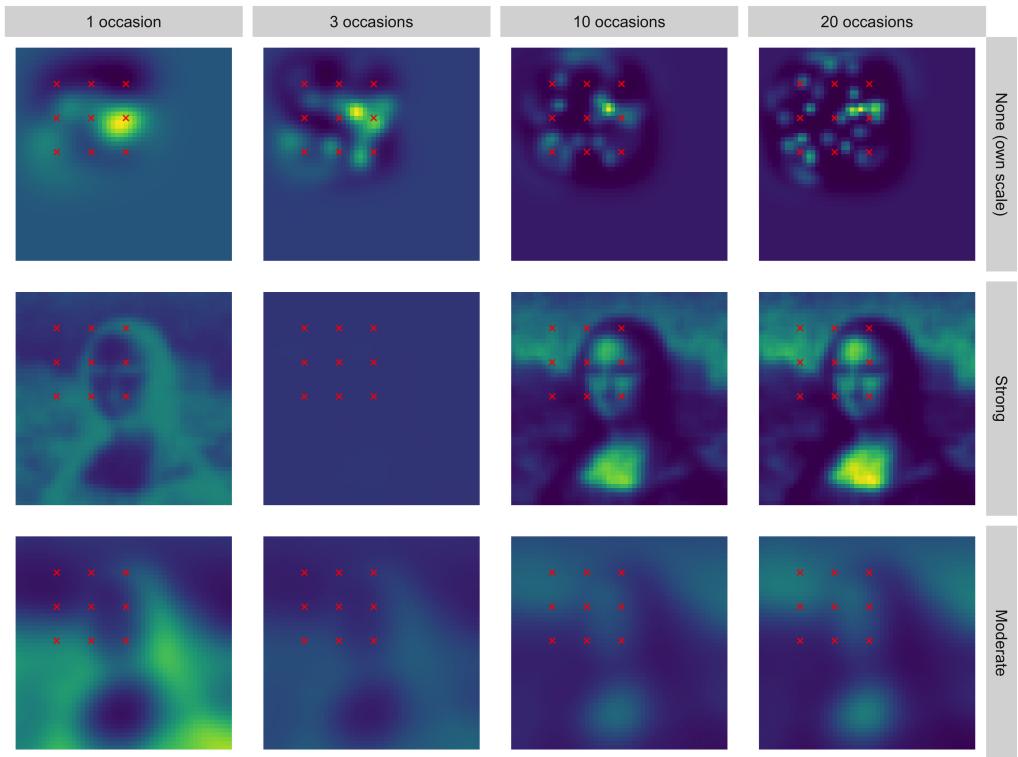


Figure 6: Estimated activity center surfaces from a constant density model (first row) and estimated intensity surfaces from a model with density depending on “strong” or “moderate” covariates (second and third rows respectively, see Section ?? for details of how covariates were simulated). 85 activity centers were generated across the entire image, drawn from a Poisson process with intensity given by the “Low Res” image in Figure ?? . High density areas are indicated in yellow, low density areas in blue. Detectors are shown as red crosses.

287 from any detectors (Figure ??, second row), which is quite different from
 288 the homogenous surface we obtained away from detectors when looking only
 289 at activity centers (Figure ??, first row). In contrast, the space use density
 290 surface for captured animals *was* essentially a smoothed version of the activity
 291 center surface around the detector array, and so very similar in terms of the
 292 broad patterns it showed (Figure ??, third row).

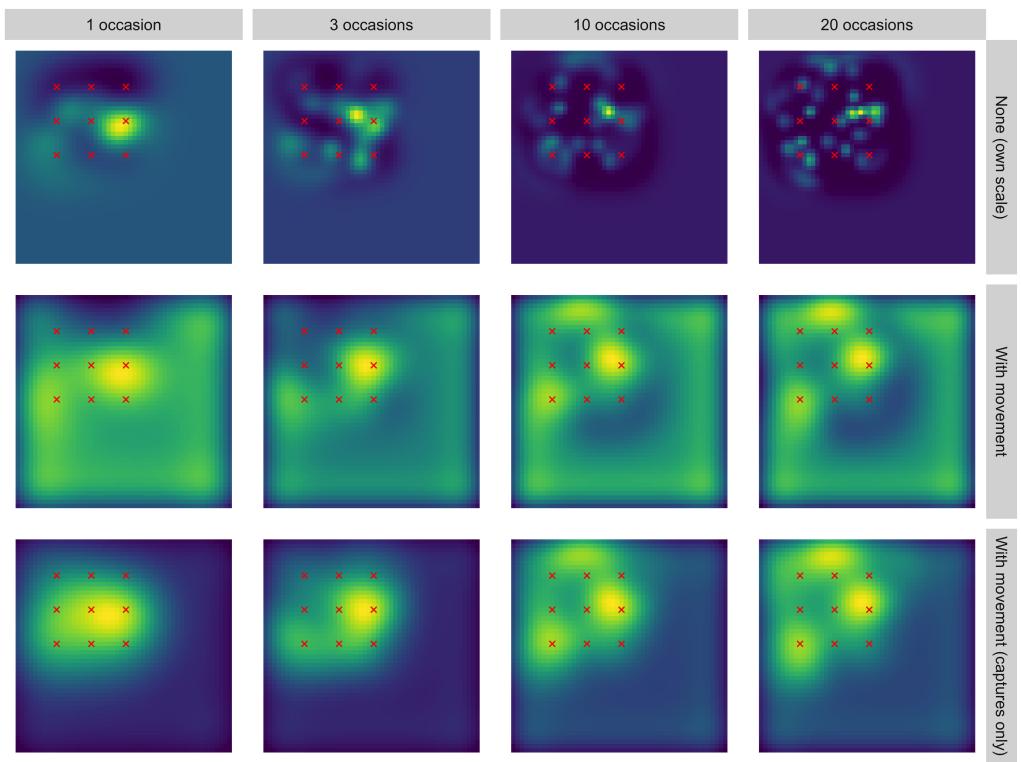


Figure 7: Estimated activity center surfaces from a constant density model (first row) and space use density surfaces incorporating animal movement for both observed and unobserved animals (second row) and for observed animals only (third row). High density areas are indicated in yellow, low density areas in blue. Detectors are shown as red crosses.

293 **4.4 Nagarhole Tiger Sanctuary camera-trap survey**

294 The same broad patterns were visible in our reanalysis of the Nagarhole
295 tiger survey (Figures ?? to ??).

296 **4.4.1 Model with constant density**

297 The full array of traps used in the original Nagarhole study clearly showed
298 three areas of high activity center density in the interior of the study region,
299 along $E \approx 625$ and $N = 1324, 1330, 1336$ respectively (Figure ??, “All traps,
300 no cov.”).

301 When we reran the survey on a subset of traps that excludes traps in the
302 interior of the study region, high density areas in the interior of the region
303 were replaced by a flat surface indicating a homogenous low density, and
304 the three high density regions described above were not detected (Figure
305 ??, “Subset #1, no cov.”). We also observed some regions where estimated
306 density *increased* after the removal of the interior traps (see the easternmost
307 detectors in Figure ??, “Subset #1, no cov.”). This occurs when animals
308 have their activity centers near to, but outside, the area circumscribed by an
309 array – estimated activity centers then tend to be pulled towards the traps
310 that they are closest to.

311 With the second subset of traps, which exclude eight detectors from each
312 of two high density interior areas, the constant density model still recognized
313 that activity centers are located in these areas, but the estimated locations
314 of these activity centers showed a clear shift from what was found in the
315 original survey (Figure ??, “Subset #2, no cov.”). The estimated location of
316 the northernmost of the two activity centers moved to the south east, while

317 the other activity center moved to the south.

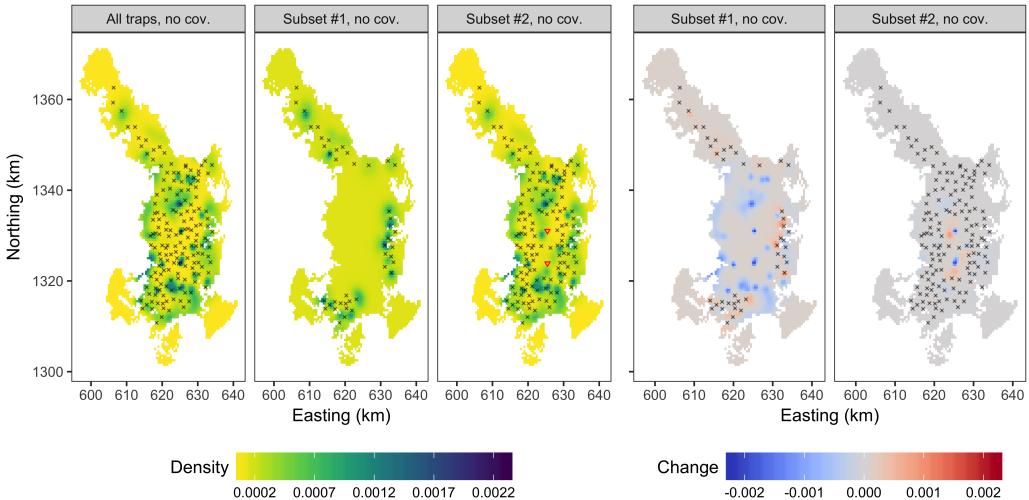


Figure 8: Estimated activity center densities of tigers in Nagarhole Tiger Sanctuary, India, obtained using different camera trap arrays. Plots (a), (b), and (c) show estimated densities; plots (d) and (e) show differences between the estimated densities obtained using trap subset #1 and #2 and those obtained using all traps. Detectors are shown as black crosses.

318 4.4.2 Model with density depending on covariates

319 The model with the lowest AIC was one expressing mean intensity as a
320 linear function of latitude. The estimated density surface obtained from this
321 model showed the estimated mean intensity increasing southwards across the
322 region, with mean intensity in the extreme south roughly four times that in
323 the extreme north (Figure ??, “All traps, northing”). Estimates of mean
324 intensity were much less variable than estimates of activity center densities,
325 and were also less sensitive to changes in the array of traps, provided that
326 the array provided sufficient coverage of the covariate space to estimate the

327 covariate relationship (Figure ??, “Subset #1, northing” and ‘Subset #2,
 328 northing”).

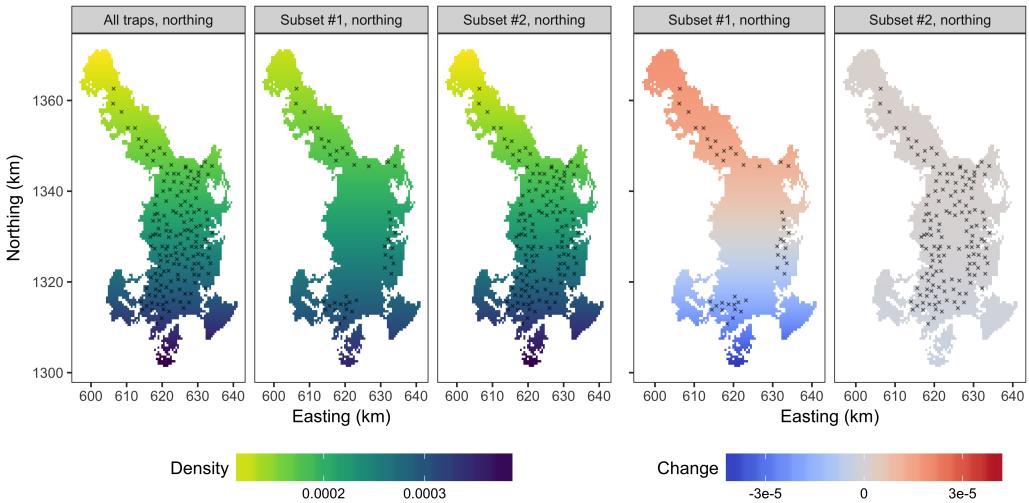


Figure 9: Estimated mean intensity of tigers in Nagarahole Tiger Sanctuary, India, obtained using different camera trap arrays. Plots (a), (b), and (c) show estimated intensities; plots (d) and (e) show differences between the estimated intensities obtained using trap subset #1 and #2 and those obtained using all traps. Detectors are shown as black crosses.

329 4.4.3 Space use density surfaces

330 The estimated space use density surface differed markedly from the activity
 331 center density surface, with these differences neatly illustrating the different
 332 purposes of the two surfaces (Figure ??). Activity center densities were high-
 333 est in those cells where sufficient information had been gathered to precisely
 334 identify where a single tiger’s activity center was. Adding movement to the
 335 surface had the effect of dispersing each area of high (activity center) density
 336 across a much wider area, the extent of which depended on the estimated

337 range of movement. The estimated spatial scale parameter for the fitted
 338 half-normal detection function we used was $\sigma = 1.85\text{km}$, so that animals
 339 can move a substantial distance from their activity centers, relative to the
 340 size of the study area. As a result, space use density was highest in areas
 341 in which there were several activity centers in relatively close proximity to
 342 one another, even if the location of these activity centers was less precisely
 343 known than other activity centers. This occurred in areas near the southern
 344 and south-western borders of the reserve, as well as in a central location near
 345 $N = 1340$ (Figure ??). In contrast, space use density was low in areas that
 346 contained only a single activity center, even if the location of the activity
 347 center was precisely known (for example at $N = 1330$, $E = 624$).

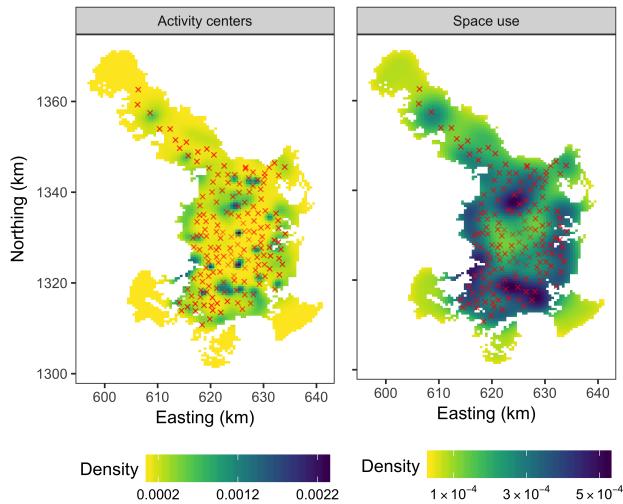


Figure 10: Estimated (a) activity center surfaces from a constant density model and (b) space use density surfaces for tigers in Nagarhole Tiger Sanctuary, India. High density areas are indicated in blue, low density areas in yellow. Detectors are shown as red crosses.

³⁴⁸ 5 Discussion

³⁴⁹ The activity centre density obtained from an SCR model cannot be inter-
³⁵⁰ preted as a species distribution model. Species distribution models predict
³⁵¹ where species are likely to occur by correlating environmental covariates with
³⁵² species occurrence or species density. Their rationale is to find favourable
³⁵³ habitats and predict that animals will be found in similar habitats across the
³⁵⁴ study region. A species distribution model will tend to place higher densities
³⁵⁵ at locations where environmental covariates are most favourable, and spatial
³⁵⁶ variation in the density surface will depend mostly on how environmental
³⁵⁷ covariates change across space.

³⁵⁸ In contrast, the density on an activity center surface is often placed in
³⁵⁹ spikes where the model is most certain that an activity center is located.
³⁶⁰ The shape and location of these spikes depends on where traps are located
³⁶¹ and also on survey effort. Different arrays produce different results and these
³⁶² results can be improbable, in the sense that high density spikes can occur
³⁶³ at locations in unfavourable habitats, if there happen to be activity centers
³⁶⁴ at these locations at the time of the survey. A useful metaphor here is of
³⁶⁵ SCR as a torch shining a light onto the true activity center density surface
³⁶⁶ – what you see depends on where you shine the torch (trap locations) and
³⁶⁷ how brightly you shine it (survey effort).

³⁶⁸ More important for people actually conducting SCR surveys is that the
³⁶⁹ densities obtained close to traps (and even inside the trap array) *also* depend
³⁷⁰ on where traps are located. The inset plots of Figure ?? and ?? show the same
³⁷¹ region in space, and this region lies within a 2.5σ range of all trap arrays,
³⁷² where one would expect to be making inferences about activity centers. We

373 obtained very different density surfaces in this area depending on where traps
374 were located. If one was using SCR to identify areas of high density e.g.
375 for conservation purposes, or to locate animals, different areas would be
376 identified depending on which array was used.

377 SCR models answer the question “where is an animal with *this* spatial
378 capture history likely to have its activity center?” The answer is always
379 contingent on where traps are located. Changing the locations of detectors
380 also changes the capture history, and thus the answer to the question of
381 where the activity center is located. This occurs regardless of whether one
382 works in a Bayesian or frequentist framework. Precisely the same is true of
383 the estimated activity center density surface, which simply sums estimated
384 activity centers across animals. In this case the question being addressed
385 is “where are the animals with *these spatial capture histories* likely to have
386 *their* activity centers?” The dependency on trap location applies to activity
387 centers estimated for detected animals and for those that were not detected.
388 In the latter case we have limited information and our estimates thus become
389 “nowhere near where traps are located”.

390 None of this precludes activity center surfaces from being useful sources
391 of information, but they do need to be interpreted with care. For practical
392 purposes this means always interpreting them with the caveat that they
393 depend on where traps are located. Activity centre distributions do not
394 give proper answers to questions like “where are the high- and low-density
395 regions?” because the highest and lowest points of the surface will always be
396 at or near traps; not because these are high- or low-density regions of space,
397 but because this is where the capture histories make us most certain that

398 animals are, or are not, present.

399 When estimating the location of a given activity center, the bias caused by
400 trap locations is lowest if the activity center occurs near the center of a dense
401 array of traps, and is highest if traps are all on one side of the activity center
402 or if detections are only made at a single trap. Thus bias can be reduced
403 by using a design that makes it likely that all activity centers in the study
404 region are surrounded by a network of traps. This will be unachievable for
405 most wildlife surveys, as it requires a large number of traps covering an area
406 beyond the study region, and ideally placed at random *[[[note: I say ‘beyond
407 the region’ so that activity centers at the borders are also in the center of some
408 array, but not sure this is correct – ?????]]]*. In summary, it is incorrect to
409 interpret the activity center density surface as if it indicated where animals
410 currently have their activity centers.

411 There is a way of using SCR so that it can be interpreted as a species dis-
412 tribution model – by modelling the mean intensity of the underlying process
413 as a function of environmental covariates. Covariates allow one to see beyond
414 the spatial extent of the array (see Figure ??), provided that the relationship
415 between covariate and response is a good one, and that traps cover a sufficient
416 range of covariate values to estimate that relationship. The resulting surfaces
417 are no longer tied to one particular realisation of the Poisson process, and
418 thus carry less information about where current activity centers are located.
419 Rather, they show the mean intensity of the underlying process assumed to
420 generate activity centers; in other words, the estimated density of activity
421 centers across all realisations. Density will be highest where environmental
422 covariates are most favourable (such as further south in Figure ??). They

423 thus answer the question of “where are the high- and low-density regions?”
424 in a way that is consistent with how this question is answered by species
425 distribution models. They predict where we would expect to see activity
426 centers, if we were able to observe multiple independent populations dis-
427 tribute themselves across the study region. The extent to which this surface
428 predicts where animals have their activity center *in this realization* depends
429 on the strength of the covariate relationship and on the number of activity
430 centers, each of which is an independent draw from the underlying process.
431 In the Nagarahole survey, for example, there is a relatively weak northing
432 covariate and a small number of activity centers, and the estimated mean
433 intensity surface provides very little information about the precise location
434 of current activity centers.

435 The concept of an activity center is central to SCR models, but for many
436 applications of SCR it may be more appropriate to consider a distribution of
437 space use, taking into account all locations where an animal may have been
438 present, rather than a distribution over activity center locations only. The
439 detection function estimated as part of an SCR model provides information
440 about how far from its activity center an animal may move. This can be
441 easily integrated with the estimated activity center density to give an esti-
442 mated space use density surface. The resulting surface effectively smooths
443 the activity surface density, with the amount of smoothing determined by
444 the distances that animals move, as given by the detection function. As it is
445 based on activity center locations, the space use density surface also depends
446 on where traps are located and on survey effort. However, it depends less
447 heavily on these factors than the activity center surface because the detection

448 function does not depend on them. In particular, the space use density sur-
449 face quickly stops becoming increasingly “peaked” as more survey occasions
450 are added.

451 Ultimately, the appropriate density surface to use depends on the aims
452 of the researcher. We have argued that the estimated activity center density
453 surface should not be used as a species distribution model, because of the
454 strong dependence on trap location and survey effort. But if the goal is to
455 identify the activity centers of *some* animals currently in the study region
456 (and it does not matter which ones) then it may well be an efficient way
457 of locating these, particularly at the center of the array. If the goal is to
458 actually *find* an animal in the study region, then it is less important where
459 animals have their activity centers and more important to know where they
460 spend their time, and the space use density surface is most useful. If the goal
461 is to estimate where animals (not just the ones in the current realisation) are
462 likely to have activity centers, then this is a species distribution question and
463 the mean intensity surface, with intensity a function of covariates, should be
464 used.

465 6 Conclusions

466 This paper demonstrates that the activity center density surface obtained
467 from SCR – the summed distribution of estimated ranges across animals –
468 cannot be used as a species distribution model. We illustrated this point
469 in a number of ways, first with a binomial point process, then by using the
470 Mona Lisa to simulate a Poisson point process, and finally using data from
471 a real-world camera trap survey. All these examples returned the consistent

472 message that density surfaces differ depending on trap location. This depen-
473 dency is most obvious at large spatial scales, where moving a trap array is like
474 “shining a torch” on a particular part of the study area, but is also present
475 within the region in and around the trap array itself. Our main messages
476 are:

- 477 1. SCR density surfaces cannot be interpreted not SDMs. This is both
478 because the SCR surface makes inferences about one realisation of a
479 spatial point process, whereas SDMs make inferences about the long
480 run average of the process; and because the SCR surface depends sys-
481 tematically on the survey design.
- 482 2. The SCR density surface typically shows steep peaks and troughs close
483 to the center of arrays, defaulting to close to the mean of the underlying
484 process away from the array. A flat density away from traps reflects a
485 lack of knowledge, and not a homogenous sprawl across which density
486 is constant. We should expect some areas away from traps also to show
487 substantial deviations from the process mean – it is just that we do not
488 know which areas.
- 489 3. An SCR model that models mean activity center density as a function
490 of environmental covariates can be interpreted as a SDM. Here the
491 key difference is that the surface obtained from the covariate model
492 is a statement about the mean intensity of the underlying process,
493 and is independent of array location provided that the environmental
494 covariate space has been sufficiently sampled.
- 495 4. The activity center density can be extended into a space use density

496 by the addition of animal movement. This is done by distributing the
497 probability mass associated with each possible location of a particular
498 activity center across the entire region in which, conditional of that
499 location being the true one, an animal might be detected. The extent
500 of this region is given by the estimated detection function parameters.

501 Some concluding comments...