

1 That's not the Mona Lisa!: how to interpret
2 spatial capture-recapture density surface
3 estimates

4 David L. Borchers^{1,*}, Ian Durbach¹, Ben C. Stevenson², Rishika
5 Chopara², Rachel Phillip¹, and Koustubh Sharma³

6 ¹Centre for Research into Ecological and Environmental Modelling,
7 School of Mathematics and Statistics, Univeristy of St Andrews,
8 The Observatory, St Andrews, Fife, KY16 9LZ, Scotland

9 ²Department of Statistics, University of Auckland, Auckland 1010,
10 New Zealand

11 ³Snow Leopard Trust, Seattle, Washington, United States of
12 America

13 *Corresponding author: dlb@st-andrews.ac.uk

14 **1 Summary**

15 1. Non-uniform denisty surfaces obtained from spatial capture-recapture (SCR)
16 analyses are often misinterpreted and this leads to incorrect inferences
17 about the populations under study. Spatial variation in the surface of
18 interest is often counfused with spatial variation in the amount of infor-
19 mation in the sample about the surface of interest. There is also often a
20 lack of clarity about what the surface of interest really is.

2. We focus on three distinct kinds of surface: (1) the estimated activity centre density surface, (2) the estimated activity centre location surface, and (3) the estimated usage surface. The first of these estimates the intensity of the point process generating activity centres, the second estimates the realised activity centre locations, the third estimates the expected space usage. For easy visual interpretation, we use the greyscale image of the Mona Lisa as the true activity centre density surface and illustrate correct and incorrect inferences from simulated SCR surveys with this density. We also illustrate with a real SCR survey of tigers in the Nagarahole game reserve.
3. We show that treating the estimated activity centre location surface as a species distribution map or an estimate of the activity centre density surface results in invalid and misleading ecological inferences. This surface is highly dependent on where the detectors are placed and very different surfaces can be obtained by surveying exactly the same animals with detectors placed at different locations. A correct way to obtain a species distribution map or an estimate of the activity centre density surface is to estimate the intensity of a point process model for activity centres, which may depend on spatially-referenced covariates. Usage surfaces are obtained similarly, but include expected movement about activity centres.
4. To avoid misinterpretation, practitioners should state explicitly the kind of density surface they are estimating and should be careful to draw inferences appropriate to that kind of surface. In particular, estimated activity centre *location* surfaces should not be interpreted as if they were estimated activity centre *density* surfaces.

Keywords: Spatial capture-recapture, density surface

2 Introduction

Spatial capture-recapture (SCR) models (Efford, 2004; Borchers & Efford, 2008; Royle & Young, 2008) are now widely used to estimate animal abundance and distribution from a variety of data types, including that from camera-traps (, for example), hair snares and dung surveys (, for example), live-captures (, for example), acoustic detectors (Dawson & Efford, 2009; Kidney, Rawson, Borchers, Thomas, Marques & Stevenson, 2013; Stevenson, Borchers, Altwegg, Swift, Gillespie & Measey, 2015; Borchers, Stevenson, Kidney, Thomas & Marques, 2015; Loveridge, Kidney, S., S., Eames & Borchers, 2017, for example). These methods use the location of the detectors (traps) and the locations at which animals were detected (their spatial capture histories) to estimate animal density. The methods have two basic components: a spatial model that quantifies animal activity centre density at all points in the survey region, and an encounter model that quantifies the expected detection frequency or detection probability, given the activity centre locations and the detector locations.

SCR density estimates are often presented graphically in the form of estimated density maps, these being easy to absorb and interpret, at least on the face of it. However, there are various kinds of density map that one can produce from SCR analyses and depending on what is presented, it is easy to misinterpret the maps. The most common form of misinterpretation is treating maps that include both spatially varying uncertainty about location and spatially varying activity centre density estimates as if they were maps of activity centre density alone, but there is also a lack of clarity about whether it is activity centre density or space use density that is being presented.

Examples include Dorazio & Karanth (2017) which says that such maps effectively provide “a species distribution model, even in cases where spatial covariates of abundance are unknown or unavailable”, Alexander, Gopalaswamy, Shi & Riordan (2015), which presents a map (Figure 4) that include both spatially varying uncertainty about location and spatially varying activity centre

density and refers to it as the “spatial distribution of snow leopards”, and Elliot & Gopalaswamy (2016), which presents the same kind of map (Figure 2) and refers to it as the “pixel-specific lion density”.

Add more
refs?

The problems with interpretation of such maps arises because (a) there are various kinds of “density”, (b) uncertainty varies spatially and this fact must be (but is often not) taken into account when interpreting estimated density surfaces from SCR surveys, and (c) a failure to distinguish between activity centre density and usage density.

We start by describing different kinds of densities involved in SCR surveys, because in any discussion of density surfaces, we need to be clear about what “density” means.

2.1 Different kinds of density

It is useful to distinguish between four kinds of spatial “density”, two of them dealing with activity centres, and two dealing with space usage. Conceptually, we have some point process that governs how many activity centres there are in the survey region, and where they are. Animals then use (move through and/or send a detectable signal like sound sound through) the space around their activity centres. Activity centres are governed by the point process alone; usage is governed by both the point process and the movement/propagation process about the points. With this in mind, we refer to four kinds of density as follows:

1. **The expected activity centre density** at a point is the intensity of the underlying point process that models where animals’ activity centres are “on average” i.e. over many realizations of the process. It is the expected number of activity centres per unit area within a region, in the limit as the area of the region shrinks to zero. The expected activity centre density surface is the set of these densities at every point. The expected number of activity centres within some region is the volume under this surface over

the region.

2. **The realised activity centre density** is only well defined if continuous space is partitioned into what we will call cells. The realised activity centre density in a cell is the actual (as opposed to expected) number of activity centres per unit area within the cell (i.e., the number divided by the area of the cell) at the time of the survey. The realised activity centres themselves are points in space, not densities.

3. **The expected usage density** in a region is the expected number of visits per unit area of animals to the area, averaged over all possible activity centre locations, over the course of a survey (it is the expected number of visits divided by the area). The expected usage density at a point is the limit of this value as the area shrinks to zero.

4. **The realised usage density** in a region is the expected number of animal visits per unit area to the area over the duration of the survey (the expected number of visits divided by the area), *conditional* on the activity centre locations. The realised usage density at a point is the limit of this value as the area shrinks to zero.

We focus on densities 1, 2, and 4. Figure 1 shows examples of each, except that we show the realised activity centre locations rather than realised activity centre densities in sub-regions of space. Realised activity centre densities can only be plotted when space has been cut into cells; in continuous space the density is zero everywhere except at activity centre locations, where it approaches infinity.

2.2 Estimated density surfaces

If we are interested in explaining why density tends to be high in some places and lower in others, or in characterising the process that governs the distribution of activity centres, then we are primarily interested in estimating a density surface

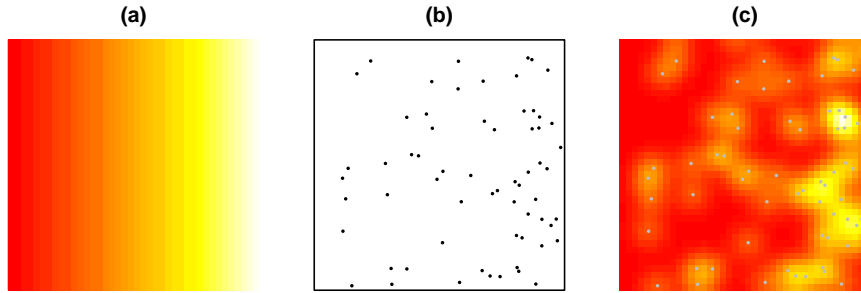


Figure 1: Examples of (a) an expected activity centre density surface, (b) a realisation of activity centres from this density surface, and (c) the associated realised usage density surface (with activity centres shown as grey dots).

like that shown in Figure 1(a). In this example, it is easting that influences this density, but in general it might be any of a wide variety of habitat or environmental covariates, some of which may be unobserved and evidenced only by spatial clustering of activity centres.

If we are interested only in where the activity centres are, and not in explaining why they are there, then Figure 1(b) suffices. But suppose that we observe activity centres with some error. For example, Figure 2 shows the distributions of estimated activity centre locations when the locations are estimated with bivariate normal errors with (a) small standard errors, (b) larger standard errors, and (c) standard errors increasing linearly from the centre of the plot. The estimation uncertainty “spreads” each activity centre according to a bivariate normal distribution, with greater spreading when there is greater uncertainty.

Figure 2(a) gives a reasonable visual representation of where the activity centres are. It is much more difficult to pick out individual activity centres from Figure 2(b), but it gives a reasonable representation of where the high- and low-density regions of activity centres are – much like Figure 1(a), but customised somewhat for this particular realisation of activity centre locations rather than their long-run average locations. Note, however, that these two figures are representations of exactly the same set of activity centres and that if one interprets them as plots of activity centre density, they contradict each other. Figure 2(a) says that almost all the region has low density (red in the

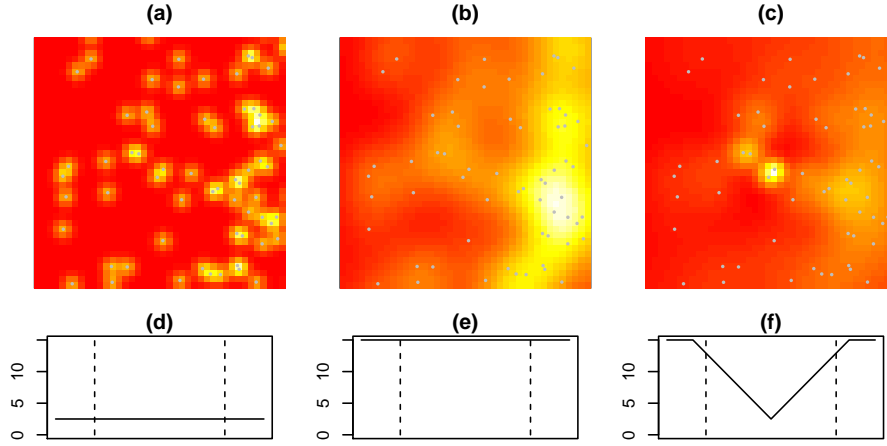


Figure 2: Examples of the density of the activity centres of Figure 1(b), when observed with bivariate normal estimation errors with standard errors (a) $\sigma = 2.5$, (b) $\sigma = 15$, and (c) $\sigma = 2.5$ at the centre of the plot, rising linearly to $\sigma = 2.5$ by the edge of the plot. True activity centres shown as grey dots. The colour scales of panels (a) to (c) are such that the highest and lowest densities in each plot is the same. Panels (d) to (f) plot the standard errors of the observation errors against the x-axis. Vertical dashed lines show the extent of the survey region in panels (a) to (c); a buffer beyond this is included because spreading of points outside it affect the plot within the survey region.

152 plot) and that there are lots of small high-density regions, while Figure 2(b)
 153 says that there is much less variation in density, that there are large swathes of
 154 higher density (the yellow towards the right) and large swathes of low density
 155 towards the left. The reason that Figure 2(b) shows less variation in density
 156 is not that there is less variation in the population (there are exactly the same
 157 activity centres in both (a) and (b)), it is that we are less sure about the location
 158 of the activity centres in (b). To interpret this as less variation in activity centre
 159 density is to invite incorrect ecological inferences.

160 Now what about Figure 2(c)? If this is interpreted as indicating where the
 161 high and low-density regions are, it is misleading. It says that the highest density
 162 region is in the centre of the plot, and that the region with most variation in
 163 density is the central region, which is not true.

164 The fact that there is only small observation error in the centre of the plot
 165 and large observation error at the edges means that the activity centres near

the centre are not spread much and therefore appear as higher peaks in the surface, with low regions where there are no activity centres. Near the edges of the plot, on the other hand, observation error is high and activity centres are spread a lot, which both flattens the peaks at individual activity centre locations and “fills in” the troughs where there are no activity centres. We see the same effect with the usage density maps (Figure 3), but less pronounced because the usage about the activity centres already “spreads” around points before any observation error occurs.

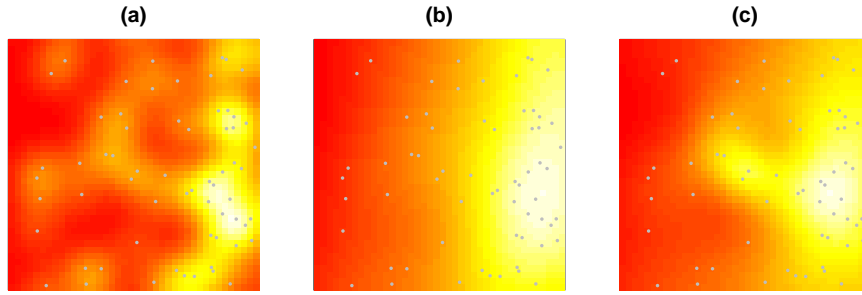


Figure 3: Examples of the usage density of Figure 1(c), when observed with bivariate normal estimation errors with standard errors (a) $\sigma = 2.5$, (b) $\sigma = 15$, and (c) $\sigma = 2.5$ at the centre of the plot, rising linearly to $\sigma = 2.5$ by the edge of the plot. True activity centres shown as grey dots. The colour scales of the three plots are such that the highest and lowest densities in each plot is the same.

It is a feature of SCR surveys that the locations of individuals farther from the detector array tend to be estimated with greater uncertainty than individuals within the array. This is illustrated in Figure 4, which shows the estimated probability density functions for two animals detected on a simulated SCR survey with a 4×4 array placed in the centre of the population shown in Figure 1(b). (The reason contours top right “avoid” the triangle is because the detection function range, estimated from the whole survey, not just the points shown, is large and if the activity centre was near the triangle, other detectors would have high probability of detecting it. The fact that they did not makes them “repel” the activity centre.)

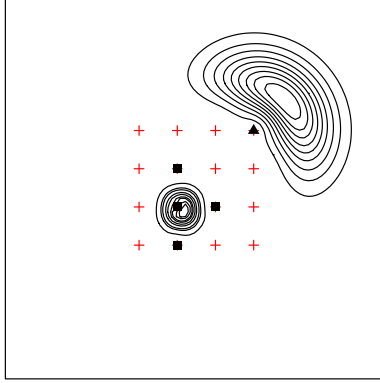


Figure 4: Estimated probability density function contours for two detections of an SCR survey of the population shown in Figure 1(b). Traps are shown as red crosses. The lower left individual was detected at traps indicated by black squares, the upper right individual only by the top right trap indicated by a black triangle.

3 SCR density estimation methods

Maximum likelihood (ML) and Bayesian SCR estimation methods are documented in a good number of papers, starting with Borchers & Efford (2008) and Royle & Young (2008), and we do not repeat the details here. Both ML and Bayesian inference are based on SCR likelihood functions that include a component specifying the activity centre density surface, which may depend on spatially-referenced covariates. (The linear density surface shown in Figure 1(a) is an example.) The density surface is typically of the form $D(\mathbf{s}) = \exp \left\{ \beta_0 + \sum_{k=1}^K \beta_k x_k(\mathbf{s}) \right\}$, where \mathbf{s} is a point in the plane, $x_k(\mathbf{s})$ is the k th of K spatially-referenced covariates, evaluated at \mathbf{s} , β_0 is an intercept parameter, and β_k is the slope parameter for the k th spatially-referenced covariate. ML and Bayesian methods are able to estimate β_0, \dots, β_K , and hence to estimate the density surface. We refer to this as the “estimated density surface”.

Given spatial capture histories, ML and Bayesian methods are also able to estimate the locations of activity centres. (Locations like those shown in Figure 1(b), for example.) While activity centres are points, there is always

uncertainty associated with estimating their locations, so that SCR estimates of activity centre locations are probability density functions (PDFs), not points. Estimates of these PDFs are conditional on the spatial capture histories of the individuals concerned – because the capture histories contain information on where each animal's activity centre was (see the capture histories and estimated location densities in Figure 4, for example). Details of how one obtains these estimated activity centre PDFs are contained in Section 4.3 of Borchers & Efford (2008) for ML methods and the section “Estimating derived parameters” on page 3238 of Royle, Karanth, Gopalaswamy & Kumar (2009) for Bayesian methods.

Note that we can obtain activity centre PDFs for undetected animals, because although the animals were unobserved, we know their capture histories – namely no capture at every detector. Note also that all undetected animals will have the same activity centre PDF¹ because they all have the same capture history.

Suppose that we estimate from an SCR survey that there are \hat{N} animals within the survey region. If one adds up the activity centre PDFs for all n detected animals, and the $\hat{N} - n$ activity centre PDFs of the undetected animals, at all points in the survey region, one gets a surface that is in many publications (including those listed in the Introduction) interpreted as a density surface for animal locations. We refer to this as the “estimated activity centre *location* surface”.

What we call an “estimated activity centre *location* surface” has been referred to as the estimated distribution, or density of *animals*. However, animals distribute themselves around their activity centres, so that activity centre density and animal density are not the same thing. Suppose for example, that we are certain that there is exactly one activity centre in a region that has surface area 1 (so that activity centre density in this region is 1). Suppose also that

¹This is not the case if there are individual-level covariates that affect detection probability estimates, but this is a complication that we ignore here in order to present as clear and uncomplicated an exposition of the key points of this paper as we can.

the animal with activity centre in this region ranges wider than this region, and spends exactly half its time in this region. It is not certain that there is an animal in the region at any time, so that animal density will be less than 1. In this example, it would be fair to say that the *animal* density in the region is 0.5. To avoid confusion, we refer to this as the “usage density” rather than “animal density”. Details of how one obtains an estimated usage density surface from an estimated activity centre *location* surface are given in Appendix ??.

Ben/Ian: Can you insert mathematical details? I think we need to do this because there are (to my knowledge) no publications that contain the details. BCS: Sure thing, I'll fill it in here. Basically it's just spreading the point around in the same way you have above for estimation uncertainty. I'm pretty sure this is linked to the idea of what some people call a ‘utilisation distribution’; I'd better do a little reading about these, too.

In summary, there are three kinds of estimated surface of interest here:

- The **estimated activity centre *density* surface**: This is an estimate of the density model component of the SCR model, which governs the location of activity centres.
- The **estimated activity centre *location* surface**: This is the combined estimated activity centre densities of all animals, conditional on each animal's capture history.
- The **estimated usage surface**: This is the combined space usage density of animals, conditional on each animal's capture history.

4 Methods

We illustrate what each of the three kinds of estimated surface gives the practitioner, and what interpretations of the surfaces are valid and useful, by (a) simulating data from a density surface that has easy visual interpretation, and (b) using the Ngarahole SCR tiger survey data kindly provided by the first author of ?.

4.1 Reproducing the Mona Lisa

For easy visual interpretation, we turned one of the most recognisable images in Western culture, the Mona Lisa, into a density surface. We created a greyscale version of a region of the original image (Figure 5, “True Density”) in which greyscale values give the true density of activity centres, and lighter areas correspond to higher densities.

We then used the density surface to generate two realisations of points from the underlying process. In the first of these we generated the number of points from a single draw from a Poisson distribution with mean 7,500, resulting in 7,451 activity centres being generated, which we plot in Figure 5, “Realisation 1” as a density at 50×50 pixel resolution. This realisation has the advantage of closely reproducing the source image, and when we conduct SCR surveys with this population, it gives us an indication of the asymptotic behaviour of SCR density estimators, i.e. as sample size gets very large. We also generated a much smaller second realisation of 84 points (Figure 5, “Realisation 2”). This realisation captures the Mona Lisa only at an extremely gross level (the darkest region corresponding to the hair can be picked out if you squint at the image long enough!), but is a useful aid to understanding some properties of the estimators.

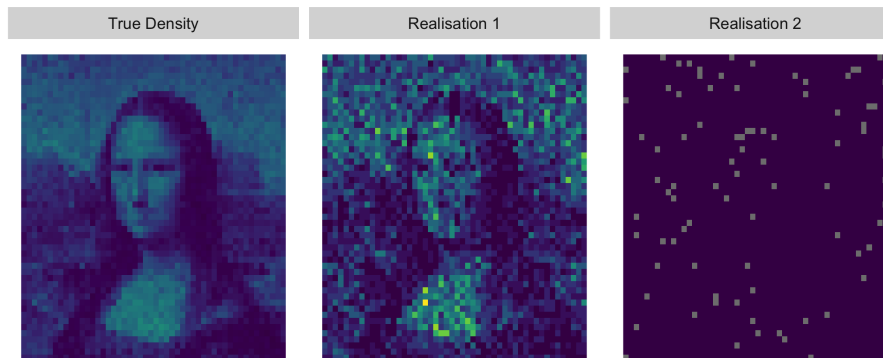


Figure 5: Input data for the Mona Lisa simulation study. A grayscale version of the Mona Lisa (“True Density”) is treated as an activity centre density surface, from which we generated a sample of 7,451 and 84 activity centres and plotted these as densities at 50×50 pixel resolution (“Realisation 1” and “Realisation 2”, respectively).

269 We simulated SCR surveys of the population, using a variety of detector
270 arrays and also varying the number of detection occasions.

I think occasions are a red herring here. If these are count data, then occasion is irrelevant. What we should report is the sample size (total number of detections and number of unique individuals detected).

272 Different arrays and detection functions were used for the large and small
273 populations described above. With the large number of activity centers, we
274 used four different 3x4 arrays (Figure 6), with array centers (19, 21), (19, 33),
275 (28, 21), or (28, 33). All arrays were spaced such that they have length 8 in the
276 x -plane and 12 in the y -plane, and so have an average spacing of $4 = 2\sigma$. We
277 simulated capture histories using a half-normal detection function with g_0 , the
278 probability of detection at a single detector placed at an activity centre, set to
279 0.5, and σ , the spatial scale parameter, set to 2. We then simulated a capture
280 history for either one or 20 occasions on each array.

BCS: I had a look at some R code, and I think I saw that the hazard halfnormal detection function was being used by defining λ_0 and σ . Or maybe this was just a default setting? Anyway I'm just leaving this comment here to remind me to have a look at the code later (or Ian can clarify).

282 When using relatively few activity centers, visual interpretation was made
283 easier by increasing the spatial scale parameter, effectively increasing the distance
284 animals travel from the activity centers, and also by increasing the distance
285 between detectors. For these cases, we increased σ to 4, holding other
286 detection function parameters at their previous values, and used a 3x4 array
287 centered on (18, 34) and with an average spacing of 8 between detectors, double
288 that used previously. We simulated capture histories after one, three, ten, and
289 20 occasions.

290 After simulating these capture histories for these arrays, we created an estimated activity centre surface for each simulation. In this scenario we assumed
291 a model with constant density and compared the resulting estimated realised
292 activity center surface to the true population density surface (the Mona Lisa).
293

294 The next step was to introduce covariates into our density model. We gener-

DLB: Or encounter functions?

Same comment about occasions applies - and 20 occasions is very rare, so not great example in this way.

Same comment about occasions applies.

ated 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 8. For each covariate we estimated a corresponding expected activity center density.

We simulated capture histories and created an estimated realised animal density surface i.e. including movement, 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.

4.2 Results

4.2.1 Estimated realised activity centre densities with many activity centers

The same patterns hold in two dimensions under the standard wildlife survey assumptions of Poisson-distributed activity centers (with constant intensity) and detectability inversely related to distance from activity center (Figure 6 and 7). A single sampling occasion was sufficient to capture the broad features of the Mona Lisa, but only close to where detectors were located (Figure 6, first row). Away from the detectors the estimated density quickly reverted to close to the estimated mean intensity of the process. Additional sampling occasions

DLB: I
think we
should re-
move the
shifting

323 resulted in the density of activity centers close to detectors being estimated in
 324 much greater detail, but did not affect the surface away from detectors (Figure
 325 7, first row).

326 Very different relative and absolute densities were obtained depending on
 327 where traps are located, even when estimating density *in exactly the same region*
 328 *of the surface and where that region is close to the array* (Figure 6 and 7, second
 329 row). With a single occasion, density was always estimated to be highest nearest
 330 the corner where the trap is located (Figure 6, second row). This pattern occurred
 331 because the inset region happened to occur in a region of above average density.
 332 If instead it occurred in a low density region one would see the opposite pattern
 333 – low density in the corner containing a trap, increasing away from the trap.
 334 This was clearly visible when a single sampling occasion was used, because the
 335 estimated surface reverted quickly to the mean intensity. Additional sampling
 336 allowed fine detail in the density surface to be estimated close to traps, with
 337 slower reversion to mean intensity, but there was still very clear disagreement
 338 between the density surfaces returned by the different arrays (Figure 7, second
 339 row).

The densities in these plots should really be expected densities (i.e. averages over lots of simulations) - particularly for the bottom row of estimates, since you might expect substantial random variation in these from sample to sample. The top images illustrate fairly convincingly how the SCR “torch” does pretty well where it “shines” but can’t see beyond, without the need to use expected values, but because you can’t see pattern in the bottom ones, you are more inclined to say “So what that they are not the same - there is sampling variation.” Also, we need to give sample sizes for these surveys (number detections and number of different individuals).

341 4.2.2 Estimated expected activity center densities with many activ- 342 ity centers

343 Introducing covariates into the density models allowed us to recover features
 344 of the Mona Lisa across the entire image, not just near where detectors were
 345 located, although good estimation of activity center locations depended heavily

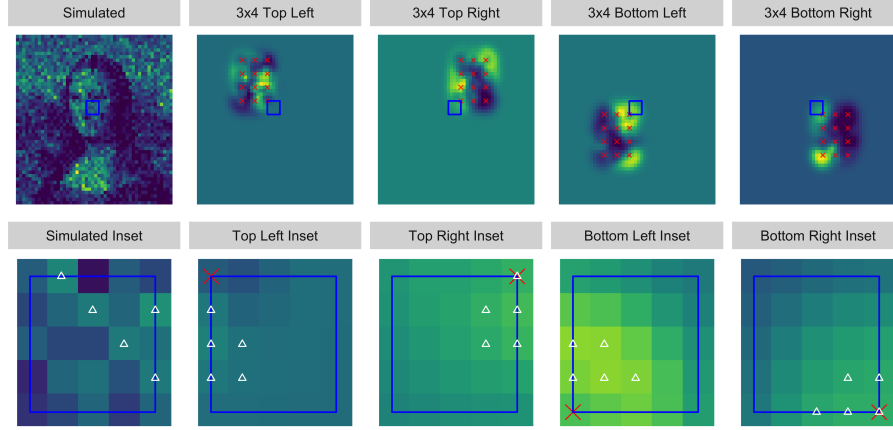


Figure 6: True activity center densities in this realisation (“Simulated”) compared with realised activity center surfaces estimated using different arrays after a single sampling occasion. High density areas are indicated in yellow, low density areas in blue. Detectors are shown as red crosses. Blue squares show the same 4x4 square centered at (25, 29), whose vertices are corner detectors from each of 3x4 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.

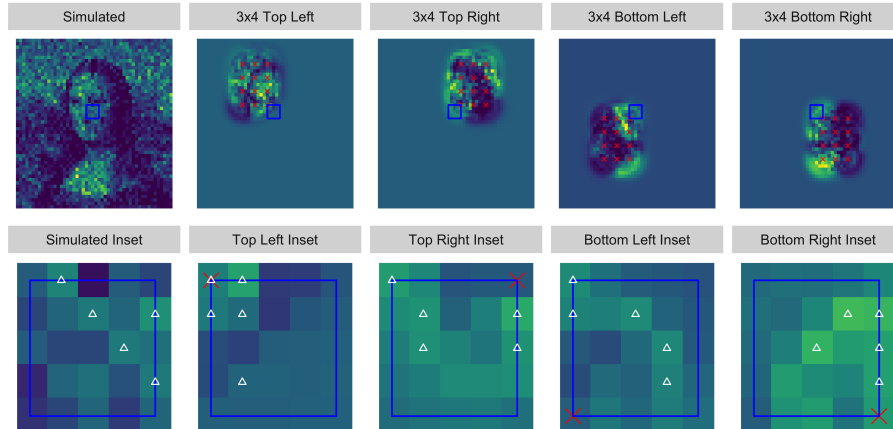


Figure 7: True activity center densities in this realisation (“Simulated”) compared with activity center surfaces estimated using different arrays after 20 sampling occasions. High density areas are indicated in yellow, low density areas in blue. See the caption to Figure 6 for further annotation details.

on the availability of good covariates (Figure 8). 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 strong” covariate – one that is a good indicator of density in some parts of the study region but poor elsewhere – the dependency on array location was reintroduced. If the array was located where the covariate was strong, the estimated density surface was accurate in that vicinity. If the array was located where the covariate was weak, then the model estimated no relationship between covariate and density and reverted back to the mean intensity everywhere in the region (Figure 8).

4.2.3 Estimated realised activity centre densities with few activity centers

We observed similar patterns under the more “wildlife survey appropriate” condition in which we generated only 85 activity centers across the study region (Figure 9). In this case there is a large difference between the mean intensity surface (the Mona Lisa) and the activity center surface in this realization (85 points), and so it is not surprising that the estimated realised activity centre density surface looks nothing like the Mona Lisa (Figure 9, first row). Nevertheless, a model assuming constant density gives increasingly accurate estimates of the locations of activity centers in the vicinity of detectors as survey effort increases, but very little information is obtained elsewhere, and this does not change with survey effort (Figure 9, first row). This gives the estimated activity center surfaces a characteristic pattern – the surface becomes increasingly peaked or “spiky” around detectors as survey effort increases, but remains flat away from the array.

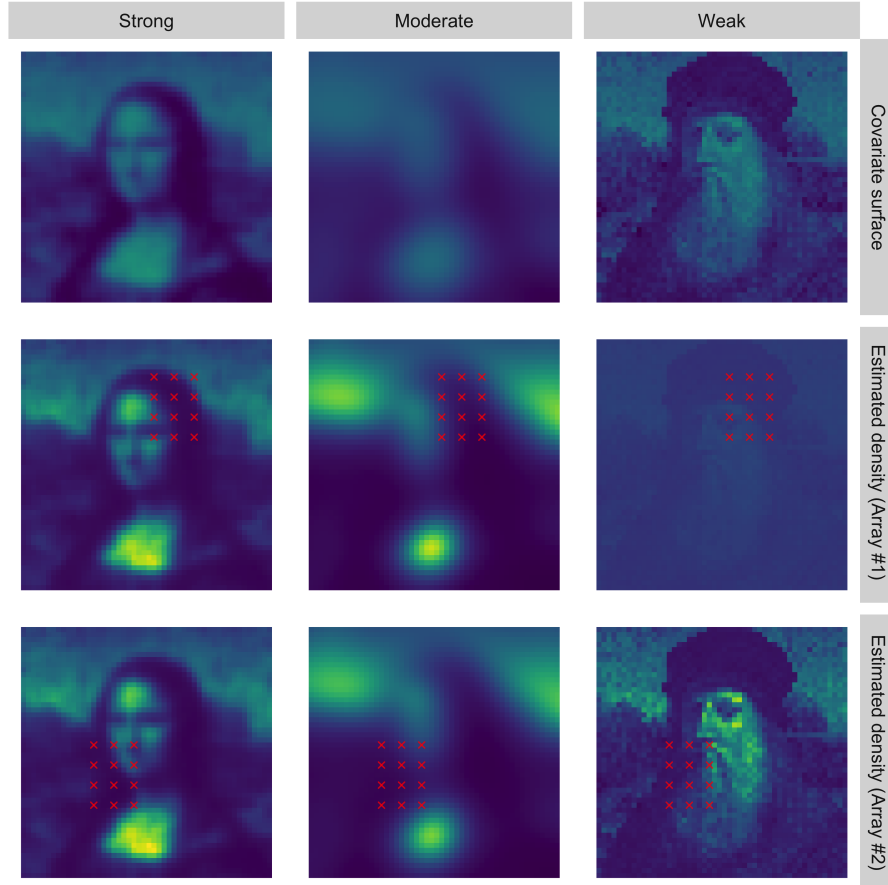


Figure 8: Expected activity center surfaces estimated using a model with density a function on one of four simulated spatially-varying covariates. Covariates are shown in the first row of plots, and were generating by manipulating the true intensity surface (Figure ??, “Low Res”) by blurring and shifting operations (see Section ?? for details). High density areas are indicated in yellow, low density areas in blue. Detectors are shown as red crosses.

373 4.2.4 Estimated expected animal densities with few activity centers

374 Any covariate model returns a surface that is some multiple of the covariate sur-
 375 face. Whether this is a good approximation of the true mean intensity surface
 376 depends on the strength of the covariate and sample size. With a strong covari-
 377 ate and sufficient sampling occasions we recovered the Mona Lisa, but with only
 378 a single occasion the direction of the relationship was incorrectly estimated, so
 379 that dark areas were predicted as light and light areas as dark (Figure 9, second
 380 row). This error was corrected by additional occasions. The same pattern oc-
 381 curred with a moderate covariate, but the effect of the weaker covariate is clear
 382 in that we did not recover as good an approximation of the Mona Lisa (Figure
 383 9, third row). Additional sampling would not help with this. Note that in both
 384 cases the surface we recovered is an approximation of the mean intensity sur-
 385 face. It does not give a good approximation to the locations of the 85 activity
 386 centers in this particular realization.

387 4.2.5 Estimated realised animal densities when there are few activity 388 centers

389 Estimated realised animal density surfaces – those that incorporate animal
 390 movement – were smoother than the density surface of estimated realised ac-
 391 tivity centers and also less sensitive to survey effort (Figure 10). The estimated
 392 realised animal density surface adds a movement kernel that is insensitive to
 393 survey effort to a realised activity center surface that becomes more peaked as
 394 survey effort increases, so this is to be expected. Estimated realised animal
 395 density surfaces were not “just” smoothed versions of the realised activity cen-
 396 ter surfaces, however. In our example unobserved animals were estimated to
 397 be spending their time on the outskirts of the study region, far away from any
 398 detectors (Figure 10, second row), which is quite different from the homogenous
 399 surface we obtained away from detectors when looking only at activity centers
 400 (Figure 10, first row). In contrast, the realised animal density surface for cap-
 401 tured animals *was* essentially a smoothed version of the realised activity center

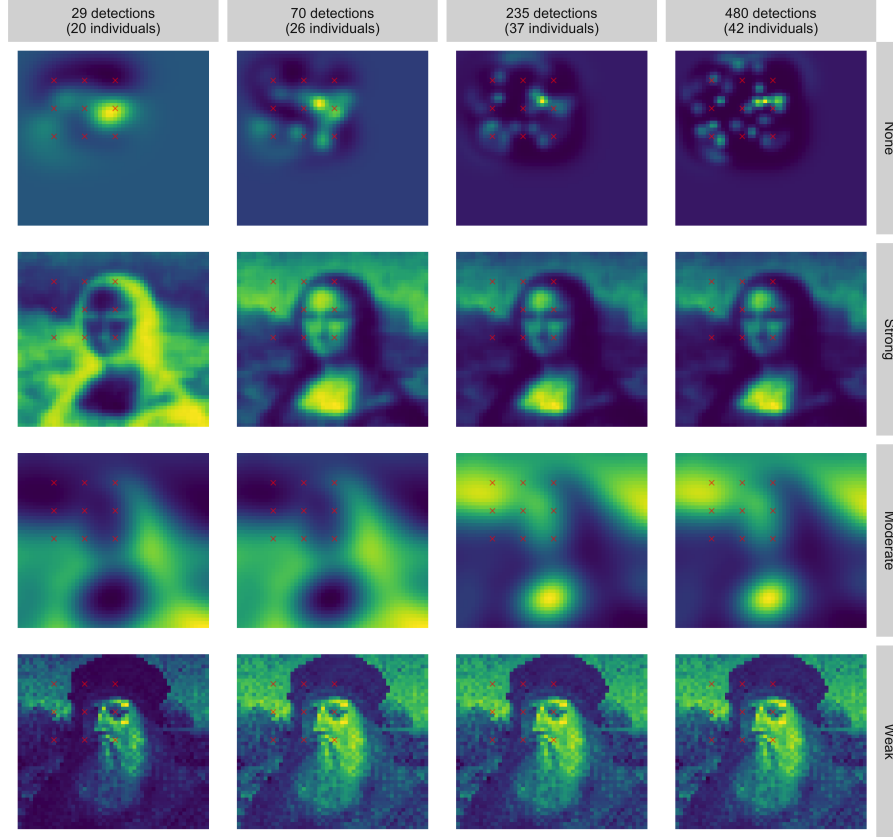


Figure 9: Estimates of realised activity center density surfaces from a constant density model (first row) and expected activity center density surfaces from a model with density depending on “strong” or “moderate” covariates (second and third rows respectively, see Section ?? for details of how covariates 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.

402 surface around the detector array, and so very similar in terms of the broad
 403 patterns it showed (Figure 10, third row).

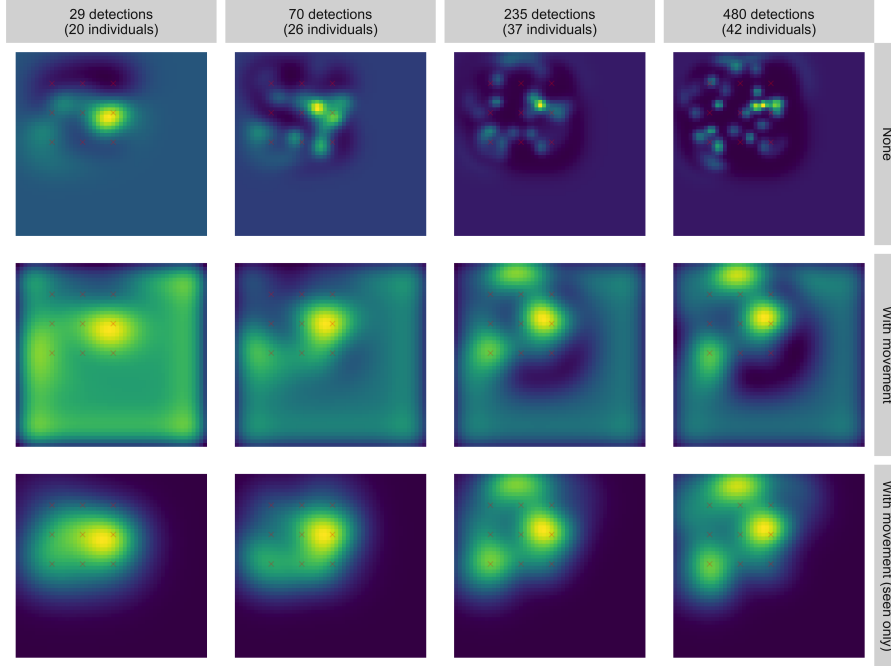


Figure 10: Estimates of realised activity center density surfaces from a constant density model (first row) and realised animal density surfaces incorporating animal movement for both observed and unobserved animals (second row) and for observed animals only (third row). High density areas are indicated in yellow, low density areas in blue. Detectors are shown as red crosses.

404 5 Camera-trap survey of tigers in Nagarahole, 405 India

406 5.1 Materials and methods

407 We reanalysed data obtained from a camera trap survey of tigers *Panthera*
 408 *tigris* living in and around the Nagarahole Tiger Reserve of Karnataka, India,
 409 as reported in ?. A full description of the survey can be found in the original
 410 reference. The original survey used a spatial array of 162 motion-activated
 411 camera traps, these being placed at 2–3 km intervals throughout the area (Figure

412 11, “All traps”).

413 We reanalyzed this data in a likelihood-based framework, first with a model
 414 assuming constant density and with three different trap arrays. The first array
 415 was the same one employed in the original study. The second was a subset
 416 of traps that excluded a large number of traps in the interior of the study region,
 417 thus leaving a substantial part of the study area unsurveyed (Figure 11, “Subset
 418 #1”). The third used another subset of traps that excluded eight detectors from
 419 each of two interior areas of the survey area in which the original survey showed
 420 the density of activity centers to be particularly high (Figure 11, “Subset #2”).

say how
many and
what pro-
portion

421 We then fitted a number of covariate models in which density was assumed
 422 to depend on longitude and latitude. We fitted a variety of linear and smooth
 423 functions for each of longitude and latitude; the model selected by the AIC
 424 was one including a linear effect of latitude only, and we report results from
 425 this model only. Finally, we generated realised animal densities for a constant
 426 density model with all traps.

427 5.2 Results

428 The same broad patterns were visible in our reanalysis of the Nagarhole tiger
 429 survey (Figures 11 to 13).

430 5.2.1 Estimated realised activity center densities

431 The full array of traps used in the original Nagarhole study clearly showed
 432 three areas of high activity center density in the interior of the study region,
 433 along $E \approx 625$ and $N = 1324, 1330, 1336$ respectively (Figure 11, “All traps, no
 434 cov.”).

435 When we reran the survey on a subset of traps that excludes traps in the
 436 interior of the study region, high density areas in the interior of the region were
 437 replaced by a flat surface indicating a homogenous low density, and the three
 438 high density regions described above were not detected (Figure 11, “Subset #1,
 439 no cov.”). We also observed some regions where estimated density *increased*

after the removal of the interior traps (see the easternmost detectors in Figure 11, “Subset #1, no cov.”). This occurs when animals have their activity centers near to, but outside, the area circumscribed by an array – estimated activity centers then tend to be pulled towards the traps that they are closest to.

With the second subset of traps, which exclude eight detectors from each of two high density interior areas, the constant density model still recognized that activity centers are located in these areas, but the estimated locations of these activity centers showed a clear shift from what was found in the original survey (Figure 11, “Subset #2, no cov.”). The estimated location of the northernmost of the two activity centers moved to the south east, while the other activity center moved to the south.

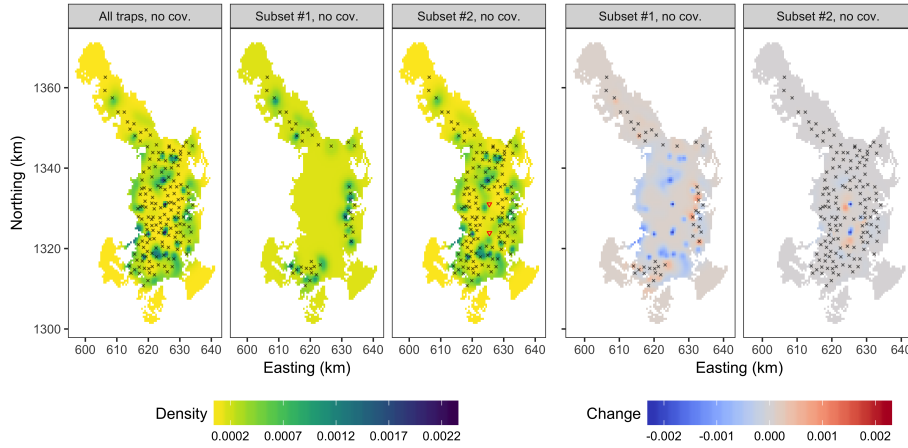


Figure 11: Estimated realised activity center densities of tigers in Nagarahole Tiger Sanctuary, India, obtained using different camera trap arrays. Plots (a), (b), and (c) show estimated densities; plots (d) and (e) show differences between the estimated densities obtained using using trap subset #1 and #2 and those obtained using all traps. Detectors are shown as black crosses.

5.2.2 Estimated expected activity center densities

The model with the lowest AIC was one expressing mean intensity as a linear function of latitude. The estimated density surface obtained from this model showed the estimated mean intensity increasing southwards across the region, with mean intensity in the extreme south roughly four times that in the extreme

456 north (Figure 12, “All traps, northing”). Estimates of expected activity center
 457 density were much less variable than estimates of realised activity center density,
 458 and were also less sensitive to changes in the array of traps, provided that the
 459 array provided sufficient coverage of the covariate space to estimate the covariate
 460 relationship (Figure 12, “Subset #1, northing” and ‘Subset #2, northing”).

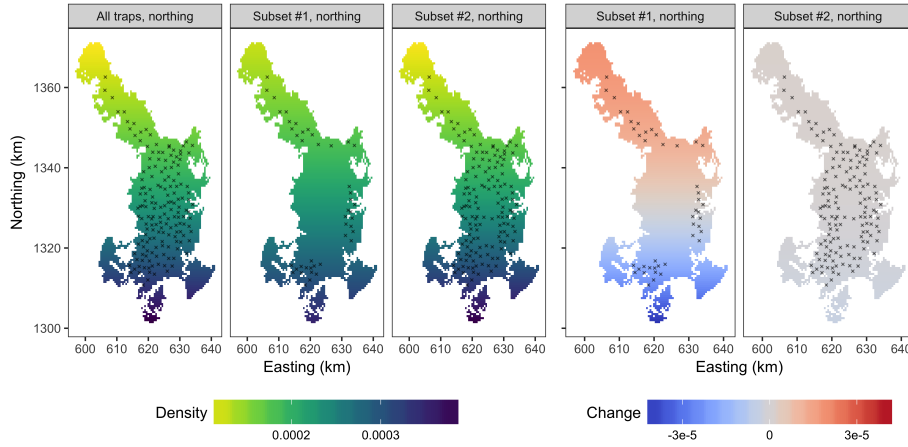


Figure 12: Estimated expected activity center density of tigers in Nagarahole Tiger Sanctuary, India, obtained using different camera trap arrays. Plots (a), (b), and (c) show estimated intensities (expected activity center densities); plots (d) and (e) show differences between the estimated intensities obtained using using trap subset #1 and #2 and those obtained using all traps. Detectors are shown as black crosses.

461 5.2.3 Estimated realised animal densities

462 The estimated realised animal density surface differed markedly from the re-
 463 alised activity center density surface, with these differences neatly illustrating
 464 the different purposes of the two surfaces (Figure 13). Activity center densities
 465 were highest in those cells where sufficient information had been gathered to
 466 precisely identify where a single tiger’s activity center was. Adding movement
 467 to the surface had the effect of dispersing each area of high (activity center)
 468 density across a much wider area, the extent of which depended on the esti-
 469 mated range of movement. The estimated spatial scale parameter for the fitted
 470 half-normal detection function we used was $\sigma = 1.85\text{km}$, so that animals can

471 move a substantial distance from their activity centers, relative to the size of
 472 the study area. As a result, animal density was highest in areas in which there
 473 were several activity centers in relatively close proximity to one another, even if
 474 the location of these activity centers was less precisely known than other activ-
 475 ity centers. This occurred in areas near the southern and south-western borders
 476 of the reserve, as well as in a central location near $N = 1340$ (Figure 13). In
 477 contrast, animal density was low in areas that contained only a single activ-
 478 ity center, even if the location of the activity center was precisely known (for
 479 example at $N = 1330$, $E = 624$).

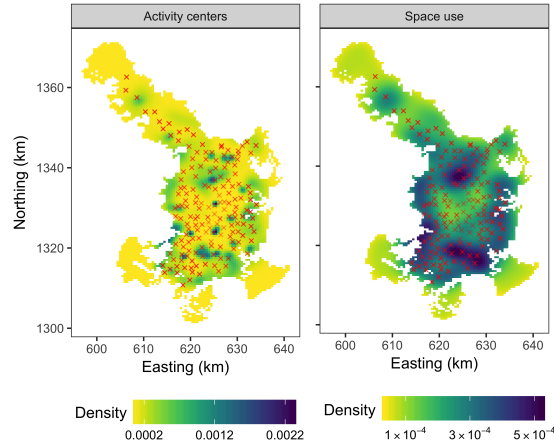


Figure 13: Estimated (a) realised activity center density surfaces from a constant density model and (b) realised animal density surfaces for tigers in Nagarhole Tiger Sanctuary, India. High density areas are indicated in blue, low density areas in yellow. Detectors are shown as red crosses.

480 6 Discussion

481 The realised activity centre density obtained from an SCR model cannot be
 482 interpreted as a species distribution model. Species distribution models pre-
 483 dict where species are likely to occur by correlating environmental covariates
 484 with species occurrence or species density. Their rationale is to find favourable
 485 habitats and predict that animals will be found in similar habitats across the
 486 study region. A species distribution model will tend to place higher densities at

487 locations where environmental covariates are most favourable, and spatial vari-
 488 ation in the density surface will depend mostly on how environmental covariates
 489 change across space.

490 In contrast, the density on a realised activity center surface is often placed
 491 in spikes where the model is most certain that an activity center is located. The
 492 shape and location of these spikes depends on where traps are located and also
 493 on survey effort. Different arrays produce quite different results for the same
 494 populations

DLB: I removed these words “and these results can be improbable, in the
 sense that high density spikes can occur at locations in unfavourable habi-
 tats, if there happen to be activity centers at these locations at the time of
 the survey.” as this seems a weak argument to me.

496 A useful metaphor here is of SCR as a torch shining a light onto the true
 497 activity center density surface – what you see depends on where you shine
 498 the torch (trap locations) and how brightly you shine it (survey effort). If you
 499 interpret the darkness outside of the beam to mean that there is little or nothing
 500 outside the beam, you fundamentally misunderstand the nature of torches and
 501 will draw fundamentally incorrect conclusions.

DLB: Extended the metaphor with this last sentence, which I think works
 well?

503 Realised activity center surfaces tend to be flat away from where traps are
 504 located. It is important to understand that this flatness reflects a lack of knowl-
 505 edge about the density surface away from traps, and not that the density surface
 506 is falt awah from traps. This point is clearly stated in standard SCR texts² but
 507 is misinterpreted whenever researchers explicitly or implicitly treat realised ac-
 508 tivity center densities as maps of the spatial distribution of activity centers
 509 across the study area (unless the study area is very densely surveyed), as is

²“As we move away from ‘where the data live’ (away from the trap array) we see that the density approaches the mean density. This is a property of the estimator as long as the detection function decreases sufficiently rapidly as a function of distance. Relatedly, it is also a property of statistical smoothers such as splines, kernel smoothers, and regression smoothers—predictions tend toward the global mean as the influence of data diminishes” (p165-166 Royle, Chandler, Sollman & Gardner, 2013)

510 done in Alexander *et al.* (2015). Another way to see that flatness away from
 511 traps reflects uncertainty rather than homogenous density is to plot lower and
 512 upper percentiles at each pixel, rather than just the posterior mean – the differ-
 513 ences between these percentiles would be large away from traps and small close
 514 to traps. It seems that this is rarely done, or at least reported in the literature;
 515 a practice that would be worth changing.

DLB: Add
other ex-
amples?

516 More importantly for people actually conducting SCR surveys is that the
 517 realised density estimates obtained close to traps (and even inside the trap
 518 array) *also* depend on where traps are located. The inset plots of Figure 6 and
 519 7 show the same region in space, and this region lies within a 2.5σ range of
 520 all trap arrays, where one would expect to be making inferences about activity
 521 centers. We obtained very different density surfaces in this area depending
 522 on where traps were located. If one was using SCR to identify areas of high
 523 density e.g. for conservation purposes, or to locate animals, different areas would
 524 be identified depending on which array was used.

525 When considering realised activity centres, SCR models answer the question
 526 “where is an animal with *this* spatial capture history likely to have its activity
 527 center?” The answer is always contingent on where traps are located. Changing
 528 the locations of detectors also changes the expected capture history, and thus
 529 the answer to the question of where the activity center is located. This occurs
 530 regardless of whether one works in a Bayesian or frequentist framework. Pre-
 531 cisely the same is true of the estimated realised activity center density surface,
 532 which simply sums estimated activity centers across animals. In this case the
 533 question being addressed is “where are the animals with *these spatial capture*
 534 *histories* likely to have *their* activity centers?” The dependency on trap location
 535 applies to activity centers estimated for detected animals and for those that were
 536 not detected. In the latter case we have limited information and our estimates
 537 thus become just “nowhere near where traps are located”.

538 None of this precludes realised activity center surfaces from being useful
 539 sources of information, but they do need to be interpreted with care. For prac-

540 tical purposes this means always interpreting them with the caveat that they
 541 depend on where traps are located. Realised activity centre densities do not
 542 give proper answers to questions like “where are the high- and low-density re-
 543 gions?” because the highest and lowest points of the surface will always be at
 544 or near traps; not because these are high- or low-density regions of space, but
 545 because this is where the capture histories make us most certain that animals
 546 are, or are not, present. They also cannot answer questions like “are animals
 547 clustered in space?” or “is animal density heterogeneous?” because the realised
 548 density surface will always exhibit variability, even if animal densities are truly
 549 a realisation of a homogeneous Poisson point process.

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

DLB: The paragraph above seems both redundant (we have already made
 the point about misinterpretation of activity density surfaces quite well I
 think), and unclear in that I don’t know what “bias” is being referred to in
 it. I suggest we remove the paragraph.

563 There is a way of using SCR so that it can be interpreted as a species
 564 distribution model – by modelling the mean intensity of the underlying process
 565 as a function of enviromental covariates. Covariates allow one to see beyond
 566 the spatial extent of the array (see Figure 8), provided that the relationship

between covariate and response is a good one, and that traps cover a sufficient range of covariate values to estimate that relationship. The resulting surfaces are no longer tied to one particular realisation of the Poisson process. Rather, they show the (estimated) mean intensity of the underlying process assumed to generate activity centers; in other words, the estimated expected density of activity centers across all realisations. Expected densities will be highest where environmental covariates are most favourable (such as further south in Figure 12). They answer the questions “Where are the high- and low-density regions?” and “What spatial variables are good predictors of the high- and low-density regions?” in a way that is consistent with how this question is answered by species distribution models. They predict where we would expect to see activity centers, if we were able to observe multiple independent populations distribute themselves across the study region.

Using covariate models, and associated model-based inference, is not without issues – there is a danger of extrapolating the density surface beyond the range of covariates around the traps, and the relationship with density and covariate is assumed to be the same everywhere as it is around the traps. The extent to which the expected activity center surface predicts where animals have their activity center *in this realization* depends on the strength of the covariate relationship and on the number of activity centers, each of which is an independent draw from the underlying process. In the Nagarahole survey, for example, there is a relatively weak northing covariate and a relatively small number of activity centers, and the estimated expected activity center density surface provides very little information about the location of current activity centers.

The concept of an activity center is central to SCR models, but for many applications of SCR it may be more appropriate to consider a distribution of space use, taking into account all locations where an animal may have been present, rather than a distribution over activity center locations only. The detection function or encounter function estimated as part of an SCR model provides information about how far from its activity center an animal may move.

597 This can be easily integrated with the estimated realised activity center density
 598 to give an estimated realised *animal* density surface. The resulting surface
 599 effectively smooths the realised activity center density surface, with the amount
 600 of smoothing determined by the distances that animals move, as given by the
 601 detection function. As it is based on activity center locations, the animal density
 602 surface also depends on where traps are located and on survey effort. However,
 603 it depends less heavily on these factors than the activity center surface because
 604 the detection function does not depend on them. In particular, the realised
 605 animal density surface quickly stops becoming increasingly “peaked” as more
 606 survey occasions are added.

607 Ultimately, the appropriate density surface to use depends on the aims of the
 608 researcher. We have argued that the estimated realised activity center density
 609 surface should not be used as a species distribution model, because of the strong
 610 dependence on trap location and survey effort. But if the goal is to identify
 611 the activity centers of *some* animals currently in the study region (and it does
 612 not matter which ones) then it may well be an efficient way of locating these,
 613 particularly at the center of the array. If the goal is to actually *find* an animal
 614 in the study region, then it is less important where animals have their activity
 615 centers and more important to know where they spend their time, and the
 616 realised animal density surface is most useful. If the goal is to estimate where
 617 animals (not just the ones in the current realisation) are likely to have activity
 618 centers, then this is a species distribution question and the expected activity
 619 center surface, with intensity a function of covariates, should be used.

BCS:
Should
this say
“realised
usage
density
instead?

620 7 Conclusions

621 This paper demonstrates that the summed posterior distribution of estimated
 622 ranges across animals obtained from SCR – what we call the realised activity
 623 center density surface – cannot be used as a species distribution model. We
 624 illustrated this point in a number of ways, first with a binomial point process,

then by using the Mona Lisa to simulate a Poisson point process, and finally using data from a real-world camera trap survey. All these examples returned the consistent message that realised activity center density surfaces differ depending on trap location. This dependency is most obvious at large spatial scales, where moving a trap array is like “shining a torch” on a particular part of the study area, but is also present within the region in and around the trap array itself. Our main messages are:

1. Realised activity center density surfaces cannot be interpreted as SDMs. This is both because the surface makes inferences about one realisation of a spatial point process, whereas SDMs make inferences about the long run average of the process; and because the surface depends systematically on where traps are located.
2. The realised activity center density surface typically shows highest peaks and deepest troughs close to the center of arrays, defaulting to close to the mean of the underlying process away from the array. A flat density away from traps reflects a lack of knowledge, and not constant density. We should expect some areas away from traps to show substantial deviations from the process mean – it is just that we do not know which areas.
3. An SCR model that models mean activity center density as a function of environmental covariates can be interpreted as a SDM. Here the key difference is that the surface obtained from the covariate model – what we call an expected activity center surface – is a statement about the mean intensity of the underlying process, and is independent of array location provided that the environmental covariate space has been sufficiently sampled.
4. Realised activity center densities can be extended into realised animal densities by the addition of animal movement. This is done by distributing the probability mass associated with each possible location of a particular activity center across the entire region in which, conditional of that loca-

tion being the true one, an animal might be detected. The extent of this region is given by the estimated detection function parameters.

References

- Alexander, J.S., Gopalaswamy, A.M., Shi, K. & Riordan, P. (2015) Face value: towards robust estimates of snow leopard densities. *PlosOne*.
- Borchers, D.L. & Efford, M.G. (2008) Spatially explicit maximum likelihood methods for capture-recapture studies. *Biometrics*, **64**, 377–385.
- Borchers, D.L., Stevenson, B.C., Kidney, D., Thomas, L. & Marques, T.A. (2015) A unifying model for capture–recapture and distance sampling surveys of wildlife populations. *Journal of the American Statistical Association*, **110**, 195–204.
- Dawson, D. & Efford, M.G. (2009) Bird population density estimated from acoustic signals. *Ecology*, **46**, 1201–1209.
- Dorazio, R.M. & Karanth, K.U. (2017) A hierarchical model for estimating the spatial distribution and abundance of animals detected by continuous-time recorders. *PlosOne*, **12**.
- Efford, M.G. (2004) Density estimation in live-trapping studies. *Oikos*, **106**, 598–610.
- Elliot, N.B. & Gopalaswamy, A.M. (2016) Toward accurate and precise estimates of lion density. *Conservation Biology*, **31**, 934–943.
- Kidney, D., Rawson, B., Borchers, D., Thomas, L., Marques, T. & Stevenson, B. (2013) An efficient acoustic density estimation method with human detectors, applied to gibbons in cambodia. *Ecology*, p. submitted.
- Loveridge, R., Kidney, D., S., T., S., E., Eames, J.C. & Borchers, D.L. (2017) First systematic survey of green peafowl pavo muticus in northeastern cambo-

- 679 dia reveals a population stronghold and preference for disappearing riverine
680 habitat. *Cambodian Journal of Natural History*, p. 157–167.
- 681 Royle, J., Chandler, R., Sollman, R. & Gardner, B. (2013) *Spatial capture-*
682 *recapture*. Academic Press, Boston.
- 683 Royle, J., Karanth, K., Gopalaswamy, A. & Kumar, N. (2009) Bayesian in-
684 ference in camera-trapping studies for a class of spatial capture-recapture
685 models. *Ecology*, **90**, 3233–3244.
- 686 Royle, J. & Young, K. (2008) A hierarchical model for spatial capture-recapture
687 data. *Ecology*, **89**, 2281–2289.
- 688 Stevenson, B.C., Borchers, D.L., Altwegg, R., Swift, R.J., Gillespie, D.M. &
689 Measey, G.J. (2015) A general framework for animal density estimation from
690 acoustic detections across a fixed microphone array. *Methods in Ecology and*
691 *Evolution*, **6**, 38–48.