

# Spatial Capture-Recapture I: Basics of spatially explicit models



# OUTLINE

## Part 1: Basic SCR

- Basic SCR model. Distance is a covariate. Latent variables. Encounter probability models
- Trap level covariates
- Making density maps
- Behavioral response: local and global.
- Non-spatial covariates (sex specific parameters)
- Model selection
  - Indicator variables

## Part 2: Key assumptions

- Model assumptions
- Robustness and extension

## Part 3: Alternative observation models

- Poisson
  - count detector
- Multinomial (independent)
  - Mist nets
- Single-catch traps

## Part 4: Modeling density

- Discrete state-space
- Density covariates
- Likelihood estimation

# The basic SCR model: model SCR0

SCR models have “distance covariate” built into them formally. **Think of them as a formalization of Model Mx.**

- Step 1: Ordinary Model Mx with DTC
- Step 2: put a prior on  $sbar$ , allowing us to deal with missing values of  $sbar$ , so we can do a “full likelihood” analysis by DA.
- Step 3: Parameterize trap-level encounter process
- Step 4: Regard  $sbar$  as latent (which it really is!)

The result is a full-blown SCR model. It is fully spatially explicit in the sense that (1) model is a trap-level model and (2) the model contains a characterization of where individuals live.

# A model for spatial encounter histories

- With our glorified Model Mx we worked with the full encounter history data
- Y[space AND time]
- We no longer summarize the data over SPACE.

# Space-time encounter histories

- A key point is that for each trap  $J$  we have an ordinary closed population model. i.e., we observe the  $n \times K$  encounter history matrix for each trap.
- So this is just  $J$  version of an ordinary CR model

	Trap=1			Trap = 2			.....	Trap = J		
	k=1	k=2	k=3	k=1	k=2	k=3		k=1	k=2	k=3
Ind 1	1	0	1	0	0	0	.....	1	0	0
Ind 2	0	0	1	1	1	1	.....	0	0	0
Ind 3	1	1	1							
	etc..			.....			.....	.....		

- But the ROWS of this 2-d matrices are NOT INDEPENDENT because they are “repeated measures” on the same set of individuals. But, if we condition on “s” then they are independent.

# MODEL SCR0

- So the SCR model SCR0 looks like a product of binomial likelihoods for each individual in the population:

$$\text{Likelihood}(\text{individual } i) = \prod_{j=1}^J \prod_{k=1}^K \text{Bern}(y_{ijk} | p(x_j, s_i))$$

- **p depends on x and s:**
  - $\text{logit}(p(x,s)) = a_0 + a_1 * \text{dist}(x,s)$
- We don't know  $s_i$ , it is a **latent variable**, a random effect
- So we put a prior distribution on it and analyze by MCMC

# ALTERNATIVE ENCOUNTER PROBABILITY MODELS

A key element of the SCR model is the encounter probability model that links trap locations to individual activity centers

- Typical logit model is widely used in “individual covariate models” including those with “distance to edge” which account for heterogeneity due to space:

$$\text{logit}(p[i]) = a_0 + a_1 * \text{dist}(x,s)$$

- **This model is NEVER used in SCR!**
- Instead SCR models commonly use models inherited from distance sampling

# ALTERNATIVE ENCOUNTER PROBABILITY MODELS

- **bivariate normal encounter probability**

$$p(x,s) = p_0 * \exp(-(1/(2*\sigma^2))*\text{dist}(x,s)^2)$$

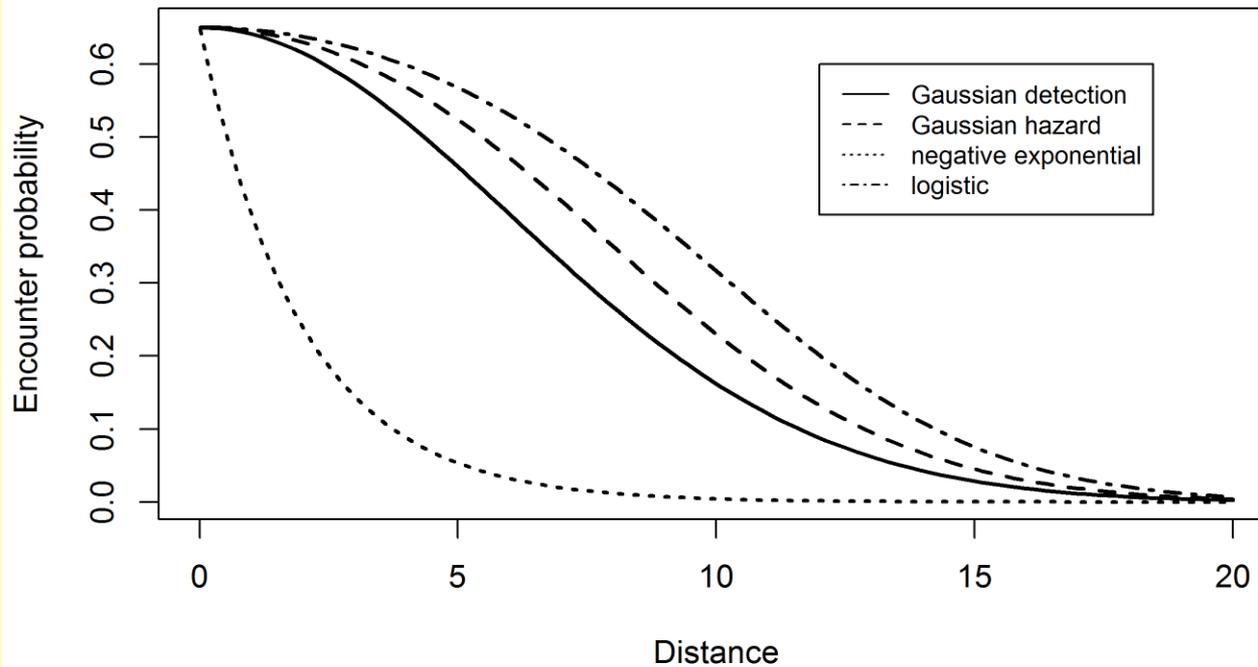
(“half-normal”)

- **Bivariate normal hazard model:**

$$p(x,s) = 1 - \exp(-\lambda_0 * \exp(-(1/(2*\sigma^2))*\text{dist}(s,x)^2))$$

- $\lambda_0$  is the baseline encounter **rate**. Space usage is a Poisson point process with intensity  $\lambda_0 * \exp(-(1/(2*\sigma^2))*\text{dist}(s,x)^2)$
- $\text{cloglog}(p(x,s)) = \log(\text{lambda}0) + \text{alpha}1 * \text{dist}(x,s)^2$
- Bivariate normal encounter probability and bvn hazard models are indistinguishable if baseline encounter rate is low

# ENCOUNTER PROBABILITY MODELS



# THE IMPLIED HOME RANGE MODEL

- Choice of encounter probability model corresponds to a model of space usage: Space use in the vicinity of  $s$  is a point process with intensity function  $p(x,s)$ .
- Thus we can convert encounter probability models to space usage (home range size) by integrating under  $p(x,s)$  until, say, 95% of the density is accumulated.
- Analytic result: For the bivariate normal model corresponds to a bivariate normal home range model for space usage. Thus we can convert an estimate of  $\sigma^2$  a 95% home range area:  $r_{1-\alpha} = \sqrt{q_\alpha} \sigma$  where  $q_\alpha$  is the percentile of a chi-square distribution on 1 d.f.
- Choice of specific models is devoid of biological considerations.
- Should we choose among them?
  - Distance samplers “yes”
  - Andy: “no”

# SPATIAL EXPLICITNESS OF SCR0

- Spatial location of individuals is an explicit part of the model
- Spatial locations of traps (or search effort) is part of the model

# INDIVIDUALS ARE SPATIALLY EXPLICIT IN SCR MODELS

# The latent variables $s_i$

- Conceptually, the points  $s_i$  represent “where animal  $i$  lives”  
– home range center or activity center
- Formally  $s_1, \dots, s_N$  is a realization of a **spatial point process**.
- SCR models are hierarchical models that combine:
  - (1) ordinary capture-recapture models with
  - (2) point process models
- Point process: requires “**state-space**”, where the points can live. Prior distribution for  $s$ .

# THE POINT PROCESS MODEL

- $s[i]$  has a prior, **the state-space, must be prescribed**
- Not sensitive to state-space as long as it is chosen large enough to get essentially all individuals that are captureable
- The model so far has assumed  $s[i] \sim$  uniformly distributed over the state-space. i.e., a priori -- in the absence of specific information. We can extend this model to allow non-uniformity.
- The model assumes each  $s[i]$  is independent of each other  $s[i]$  IN THE PRIOR. Extensions of this model are possible too.

# TRAPS ARE SPATIALLY EXPLICIT IN SCR MODELS

# BENEFIT OF TRAP LEVEL MODEL

- Uses all encounter information (in ordinary CR models, discarded).

**For rare species this is critical!**

- Can model trap level effects
  - Type of trap (baited or not, type of bait)
  - Variable trap operation schedule
- Behavioral response:
  - Encounter in any trap changes subsequent encounter probability in all traps (“global response”)
  - Trap-specific behavioral response (“local response”)

# MODELING TRAP LEVEL COVARIATES: 4 TYPES

1. Trap level stuff: baited or not baited
2. Habitat covariates: More used habitat should have a higher  $\text{pr}(\text{encounter})$ .  $X(j)$  = measure of habitat quality around the trap. Resource selection. [will talk about this more tomorrow]
3. Variation in trap operation
4. Trap effort. Traps don't have to be physical devices but can be spatial grid cells or transect segments and "effort" (time searched, or area searched) should be treated as a covariate.

# TRAP COVARIATE

- R work session

# VARIABLE TRAP OPERATION

## Wolverine camera trapping study from SE Alaska

```
library(scrbook)
data(wolverine)
```

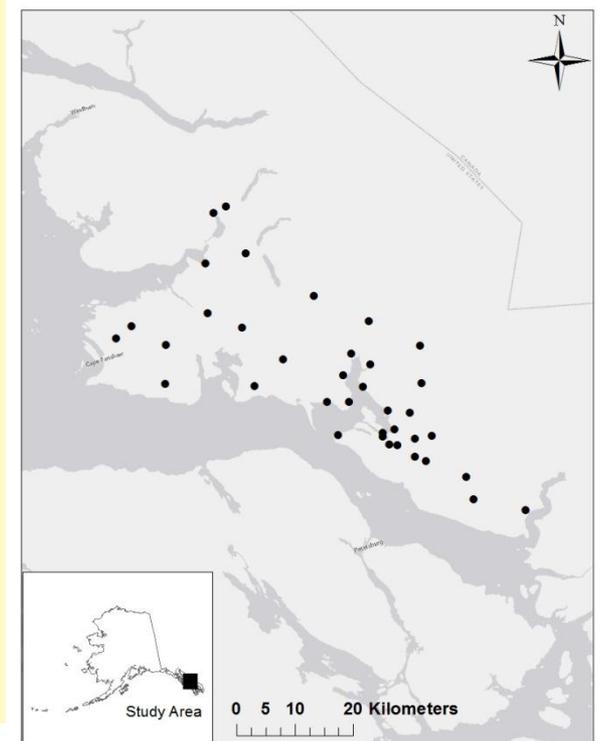
```
> names(wolverine)
[1] "wcaps"    "wtraps"   "grid8"    "grid4"    "grid2"
"wsex"
```

### Reference:

Royle, J. A., Magoun, A. J., Gardner, B., Valkenburg, P., & Lowell, R. E. (2011). Density estimation in a wolverine population using spatial capture-recapture models. *The Journal of Wildlife Management*, 75(3), 604-611.

# VARIABLE TRAP OPERATION

```
library(scrbook)
data(wolverine)
> names(wolverine)
[1] "wcaps" "wtraps" "grid8" "grid4" "grid2"
"wsex"
```



# WOLVERINE DATA

```
> str(wolverine)
List of 6
 $ wcaps : num [1:115, 1:4] 1 1 1 1 1 1 1 1 1 1 1 ...
  ..- attr(*, "dimnames")=List of 2
  .. ..$ : NULL
  .. ..$ : chr [1:4] "year" "individual" "day" "trap"
 $ wtraps:'data.frame': 37 obs. of 168 variables:
  ..$ 1:37 : int [1:37] 1 2 3 4 5 6 7 8 9 10 ...
  ..$ Easting : int [1:37] 632538 634822 638455 634649 637738 625278 631690 632631 631374 634068 ...
  ..$ Northing: int [1:37] 6316012 6316568 6309781 6320016 6313994 6318386 6325157 6316609 6331273
6328575 ...
  ..$ 1 : num [1:37] 0 1 0 0 0 0 0 0 0 0 ...
  ..$ 2 : num [1:37] 0 1 0 0 0 0 0 0 0 0 ...
  ..$ 3 : num [1:37] 0 1 0 0 0 0 0 0 0 0 ...
.....
  ..$ 92 : num [1:37] 1 1 1 0 1 1 1 0 1 1 ...
  ..$ 93 : num [1:37] 1 1 0 0 1 1 1 0 1 1 ...
  ..$ 94 : num [1:37] 1 1 0 0 1 1 1 0 1 1 ...
  ..$ 95 : num [1:37] 1 1 0 0 1 1 1 0 1 1 ...
  ..$ 96 : num [1:37] 1 1 0 0 1 1 1 0 1 1 ...
  .. [list output truncated]
 $ grid8 :'data.frame': 157 obs. of 2 variables:
  ..$ UTMx: num [1:157] 601677 609674 617670 589840 597836 ...
  ..$ UTMy: num [1:157] 6425005 6425162 6425320 6416773 6416930 ...
 $ grid4 :'data.frame': 619 obs. of 2 variables:
  ..$ UTMxX: num [1:619] 607596 611594 615592 601677 605676 ...
  ..$ UTMxY: num [1:619] 6429121 6429200 6429279 6425005 6425084 ...
 $ grid2 :'data.frame': 2466 obs. of 2 variables:
  ..$ Xutm: num [1:2466] 612554 614553 607596 609595 611594 ...
  ..$ Yutm: num [1:2466] 6431219 6431258 6429121 6429161 6429200 ...
 $ wsex : num [1:21] 1 1 0 1 0 1 1 1 0 1 ...
```

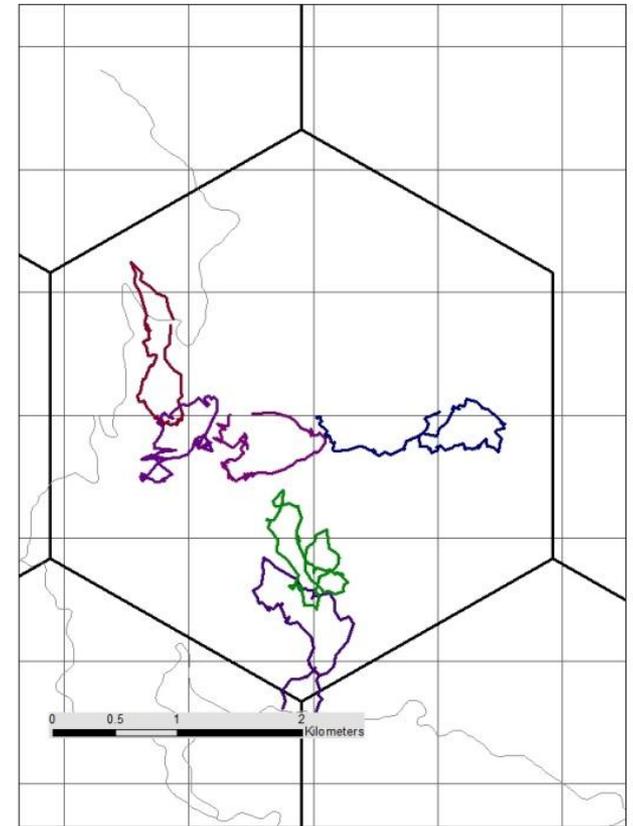
# AREA SEARCH MODELS WITH PSEUDO-TRAPS: EFFORT AS A COVARIATE

- When there are not physical traps but effort expended searching grid cells or other spatial areas, then the effort spent searching can be used as a “trap level” covariate, with trap = grid cell centroid
- Requires grid cells to be small relative to typical animal home range (< .5 home range radius)

# FISHER DATA

## California fisher study

- Thompson, C. M., Royle, J. A., & Garner, J. D. (2012). A framework for inference about carnivore density from unstructured spatial sampling of scat using detector dogs. *The Journal of Wildlife Management*, 76(4), 863-871.



# MAKING DENSITY MAPS

# GLORIOUS DENSITY MAPS

- Because the model has an explicit representation of where individuals live, we can build a density **map**
- Have to save the MCMC output for the activity centers AND the data augmentation variables ( $z$ )
- Subset the activity centers at each iteration to only those for which  $z=1$
- Remember: This is “local density” (i.e., the estimated posterior of where actual individuals live) not “prior density” (which is constant).

# SCRdensity function

The prototype function `SCRdensity` processes the MCMC output for activity centers and DA variables to produce a density map:

```
SCRdensity(obj, nx=30, ny=30,  
           scalein=1, scaleout=100)
```

```
obj = list(Sx=Sx, Sy=Sy, z=z)
```

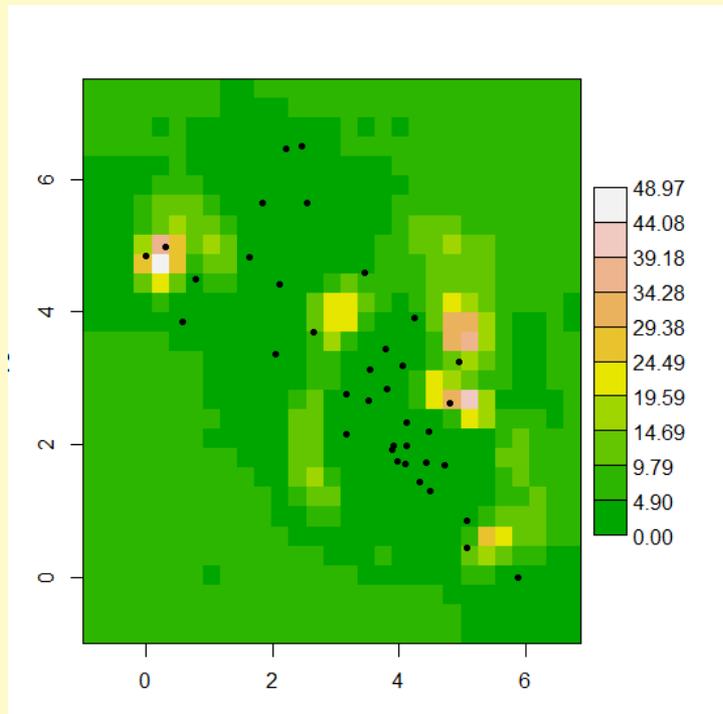
```
nx, ny = number of bins to use
```

```
scalein = 1 means the coordinate scaling has a unit of 1 km2
```

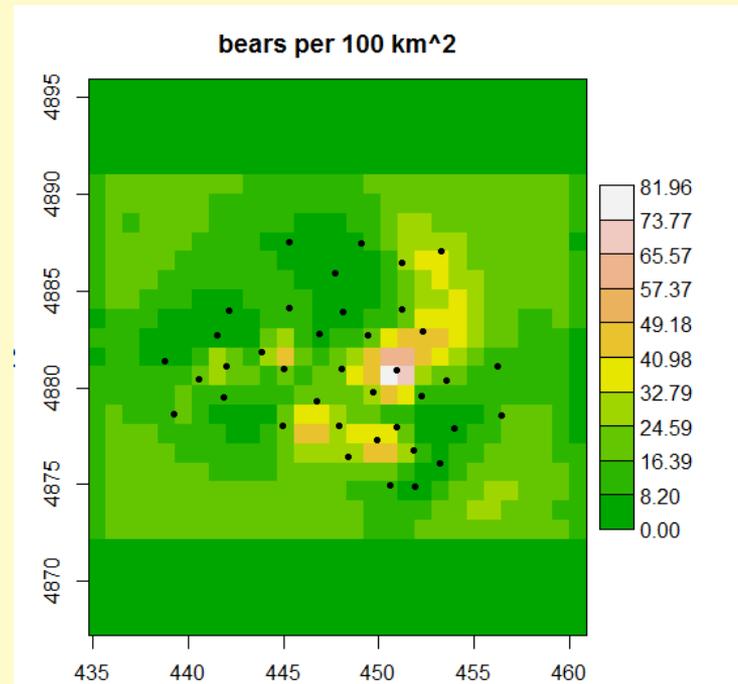
```
scaleout = 100 says express density in units of 100 km2
```

# DENSITY MAPS ARE COOL

■ Wolverines per 1000 km<sup>2</sup>



Fort Drum bears/100km<sup>2</sup>



# BEHAVIORAL RESPONSE IN SCR MODELS

- Trap-specificity of the model allows for more types of behavioral response:
  - Permanent global [**all traps**] response: Capture in any trap changes subsequent capture probability in all traps
  - Ephemeral or transient global [**all traps**] response: Capture in any traps changes subsequent capture probability in all traps for the next sample occasion
  - Permanent local [**trap-specific**] response: Capture in a particular trap changes capture probability only for that trap
  - Ephemeral or transient local [**trap-specific**] response: Capture in a particular trap changes capture probability for that trap, and only for the subsequent time period.

# NON-SPATIAL COVARIATES

- Time covariates or individual covariates (sex specificity) don't depend on trap. So building a model (in the BUGS language) poses no additional complexity

# MODEL SELECTION

- R work session: Behavioral response and sex-specificity of parameters of the black bear model , model selection using the Kuo and Mallick indicator variables

# SUMMARY OF PART 1

- Covariates can be trap specific
  - 4 types of trap level covariates: trap property, effort, variable operation, habitat
- Behavioral response can(should?) be trap specific
- Because individuals are spatially explicit, we can do spatially explicit things. Like make density maps!