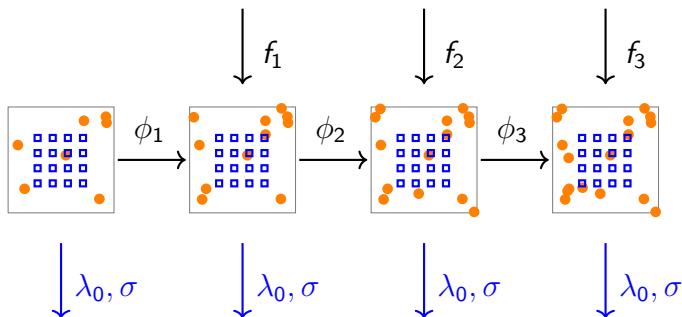


Dispersal kernels for spatiotemporal capture–recapture

Murray Efford and Matt Schofield



Open-population SECR

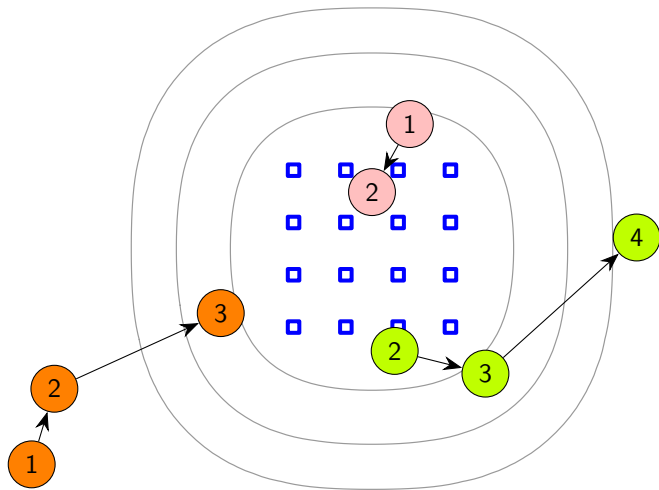


● activity centre

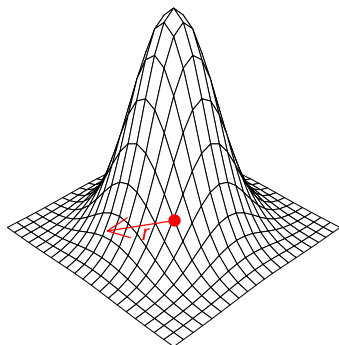
□ detector

- fit open SECR model to estimate $f, \phi, \lambda_0, \sigma$
- e.g., Pradel–Link–Barker formulation (conditioning on n)

What if activity centres shift between primary sessions?



Model as random walk, each step drawn from 2-D movement kernel



Assuming no directional bias
so 2-D pdf is function of distance r

$$g(r)$$

Why model movement?

- Intrinsic interest...

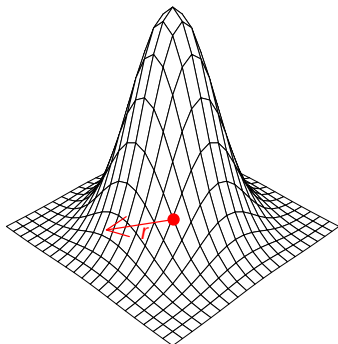
but there are better methods for movement

- Better estimates of vital rates...

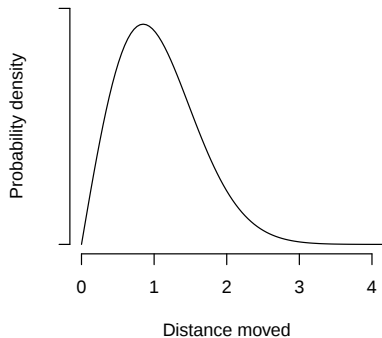
empirically, $\hat{\phi} \uparrow$, $\hat{f} \downarrow$

“separating mortality and emigration”

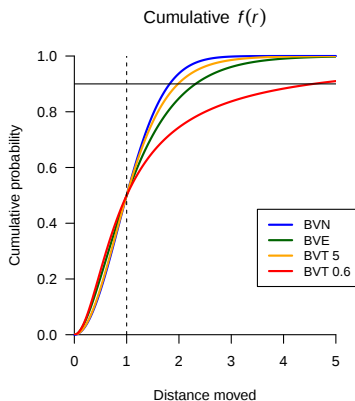
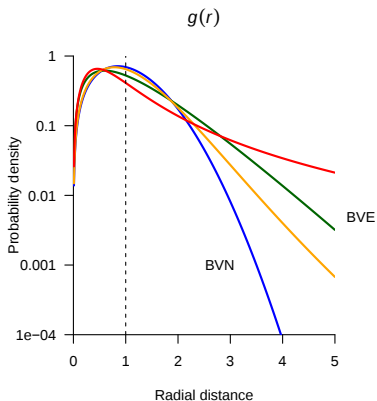
Movement kernel vs distance distribution



$$g(r)$$



$$f(r) = 2\pi r g(r)$$



BVN bivariate normal (Gaussian)

BVE bivariate exponential (Laplacian)

BVT bivariate t -distribution, shape parameter $\beta = \nu/2$

Kernels with same median distance

	$g(r)$	Cumulative $f(r)$
BVN	$\frac{1}{2\pi\alpha^2} \exp\left(\frac{-r^2}{2\alpha^2}\right)$	$1 - \exp\left(\frac{-r^2}{2\alpha^2}\right)$
BVE	$\frac{1}{2\pi\alpha^2} \exp\left(\frac{-r}{\alpha}\right)$	$1 - \left(\frac{r}{\alpha} + 1\right) \exp\left(\frac{-r}{\alpha}\right)$
BVT	$\frac{\beta}{\pi\alpha^2} \left(1 + \frac{r^2}{\alpha^2}\right)^{-(\beta+1)}$	$1 - \left(\frac{\alpha^2}{\alpha^2 + r^2}\right)^\beta$

Scale parameter α , shape parameter β (BVT only)

How to fit?

- State-space Ergon & Gardner 2014; Schaub & Royle 2014 sCJS
- MLE discretized Brownian motion Glennie et al. 2019; BVN only?
- MLE discretized, truncated kernel Efford & Schofield 2020; openCR

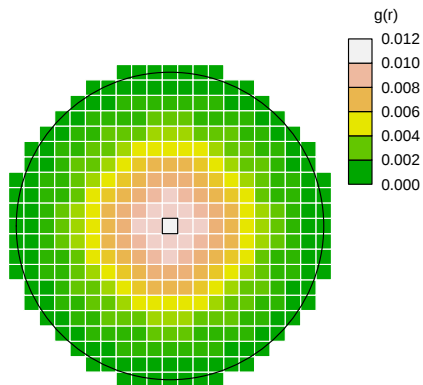
Ergon T, Gardner B (2014) Separating mortality and emigration: modelling space use, dispersal and survival with robust-design spatial capture–recapture data. *Methods in Ecology and Evolution* **5**, 1327–1336.

Schaub M, Royle JA (2014) Estimating true instead of apparent survival using spatial Cormack–Jolly–Seber models. *Methods in Ecology and Evolution* **5**, 1316–1326.

Glennie R, Borchers DL, Murchie M, Harmsen BJ, Foster RJ (2019) Open population maximum likelihood spatial capture–recapture. *Biometrics* **75**, 1345–1355.

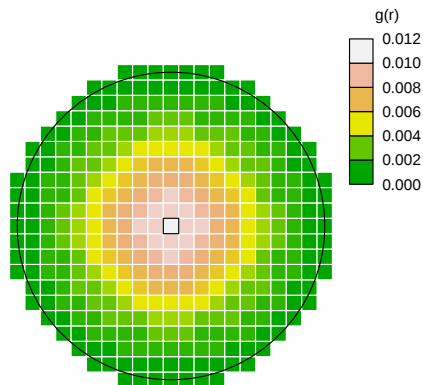
Efford MG, Schofield MR (2020) A spatial open–population capture–recapture model. *Biometrics* **76**, 392–402.

Discretized and truncated kernels (in openCR)

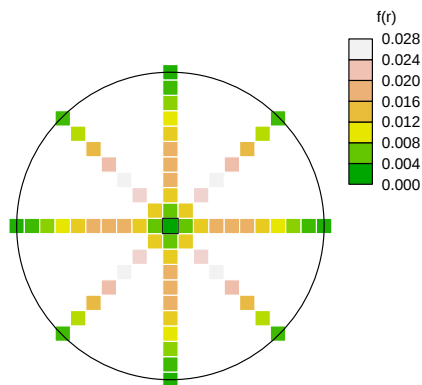


349 cells
scales with radius²
“full”

Discretized and truncated kernels (in openCR)



349 cells
scales with radius²
“full”



69 cells
scales with radius
“sparse”

Ovenbirds in Maryland, USA



Kernel	Radius*	ΔAIC		time s	
		Full	Sparse	Full	Sparse
No movement		31.68		478	
BVN	10	8.85	8.95	1383	974
	20	4.23	4.22	4470	838
	30	3.60	3.71	11455	976
BVE	10	8.84	8.95	1394	988
	20	2.34	2.35	4302	833
	30	0.00	0.35	10097	865

Annual mist netting 2005–2009

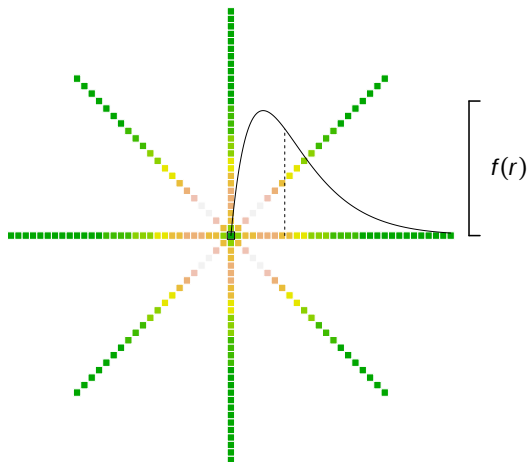
PLB SECR model $\phi \sim 1, f \sim 1, \lambda_0 \sim 1, \sigma \sim 1, \alpha \sim 1$

20-m $\times$ 20-m mask cells

* radius in mask cells



Ovenbird fitted sparse kernel



Median distance moved 147 m

Ovenbird survival

Kernel	Radius	$\hat{\phi}$ (95% CI)	
		Full	Sparse
Nonspatial CJS		0.46 (0.36, 0.57)	
No movement		0.53 (0.41, 0.64)	
BVN	10	0.60 (0.46, 0.73)	0.60 (0.46, 0.73)
	20	0.64 (0.47, 0.77)	0.63 (0.47, 0.77)
	30	0.65 (0.47, 0.80)	0.65 (0.47, 0.79)
BVE	10	0.60 (0.46, 0.73)	0.60 (0.46, 0.73)
	20	0.63 (0.47, 0.77)	0.63 (0.47, 0.77)
	30	0.66 (0.48, 0.81)	0.66 (0.47, 0.80)



Annual mist netting 2005–2009

PLB SECR model $\phi \sim 1, f \sim 1, \lambda_0 \sim 1, \sigma \sim 1, \alpha \sim 1$

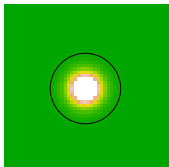
BVT boundary estimate $\hat{\beta} \approx 0$?!

Conclusions

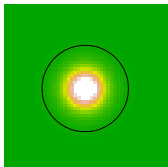
- need large discretized kernel to avoid truncation bias
- sparse kernel makes this possible

Compound movement

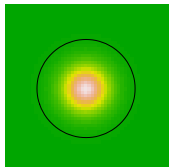
Step 1



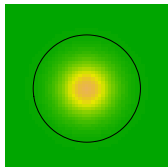
Step 2



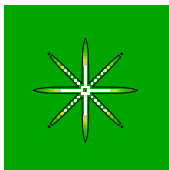
Step 3



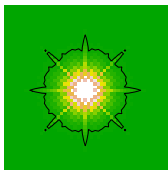
Step 4



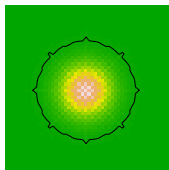
Step 1



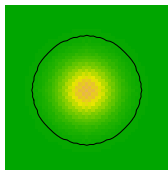
Step 2



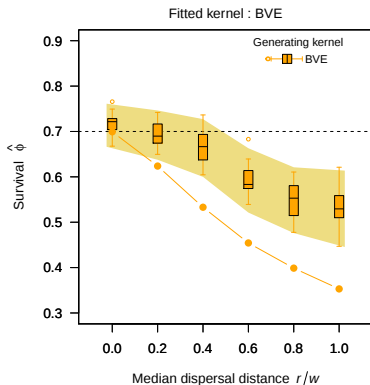
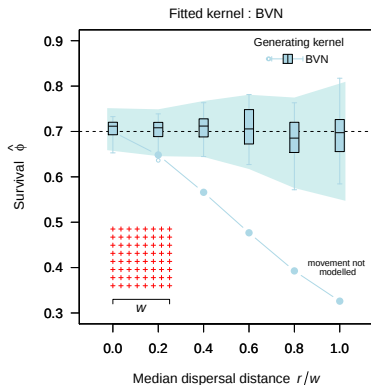
Step 3



Step 4



Some simulations: scale of sampling



- need large discretized kernel to avoid truncation bias
- sparse kernel makes this possible
- extensive movement (r/w large) can still lead to problems
- focus on sampling full range of possible movements
e.g., with clustered detectors