Model-based data integration: a primer and practical guide

Nick Golding & Saras Windecker ISEC 2022

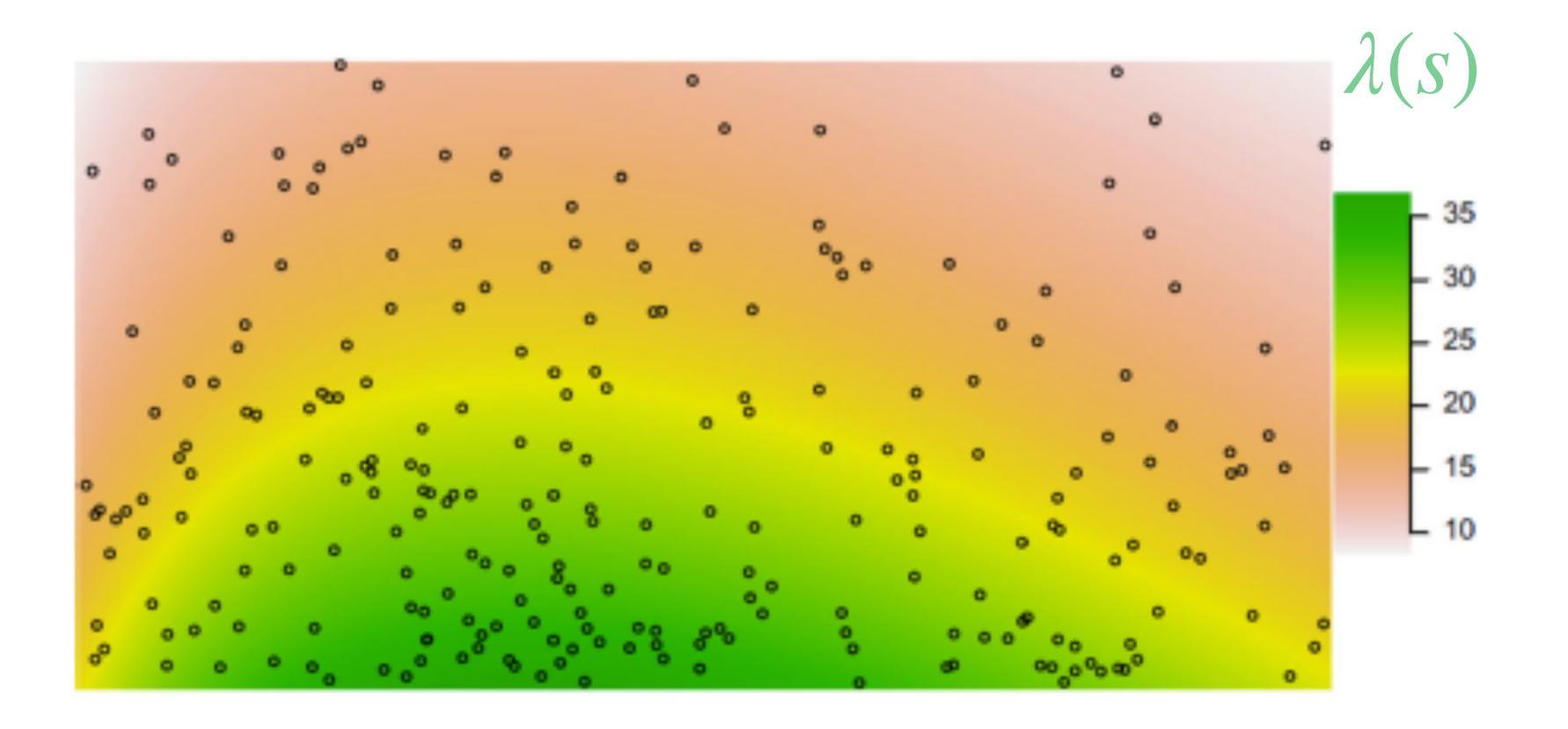
How did we come to this?



Data integration combines datasets by explicitly modelling their data collection processes, incorporating their biases, and propagating as much information as possible about the process of interest. What is the aim of the work?

What is the aim of the work?

Distribution of individuals of a species (relative abundance) across space.



Fithian W, Elith J, Hastie T, Keith DA. Bias correction in species distribution models: pooling survey and collection data for multiple species. Methods Ecol Evol. 2015;6(4):424-438. doi:10.1111/2041-210X.12242

What is the motivation for data integration?

What is the motivation for data integration? Capitalise on many different data types, none of which are perfect.

opportunistic observation

site occupancy

count data

Vary in extent.

Intermediate scale **Broad scale** site opportunistic observation occupancy count data Fine scale

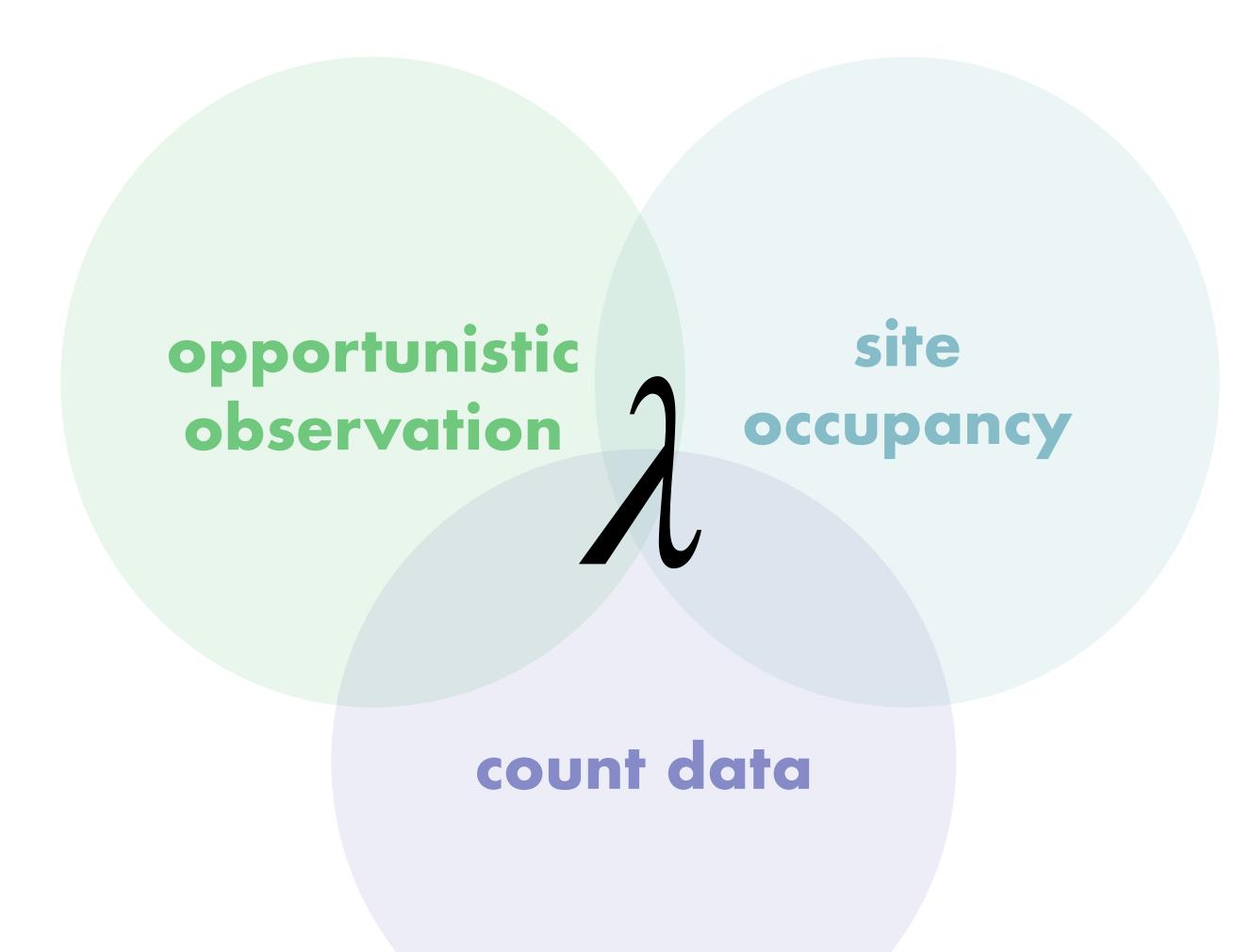
Vary in extent. And unique biases.

Broad scale site opportunistic Biased observation occupancy count data Fine scale

Intermediate scale
Imprecise

Expensive/hard to get

Can use a mechanistic link between data types to establish a common parameter of spatial distribution.



count data

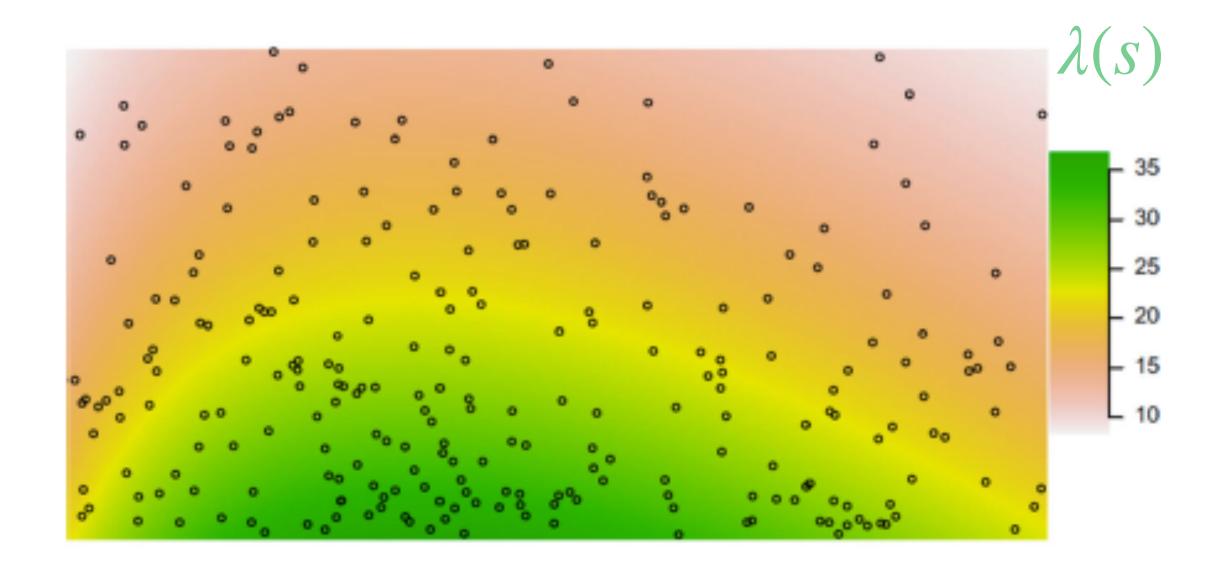
Spotlighting count of possums in 5 min search of 50 m radius.

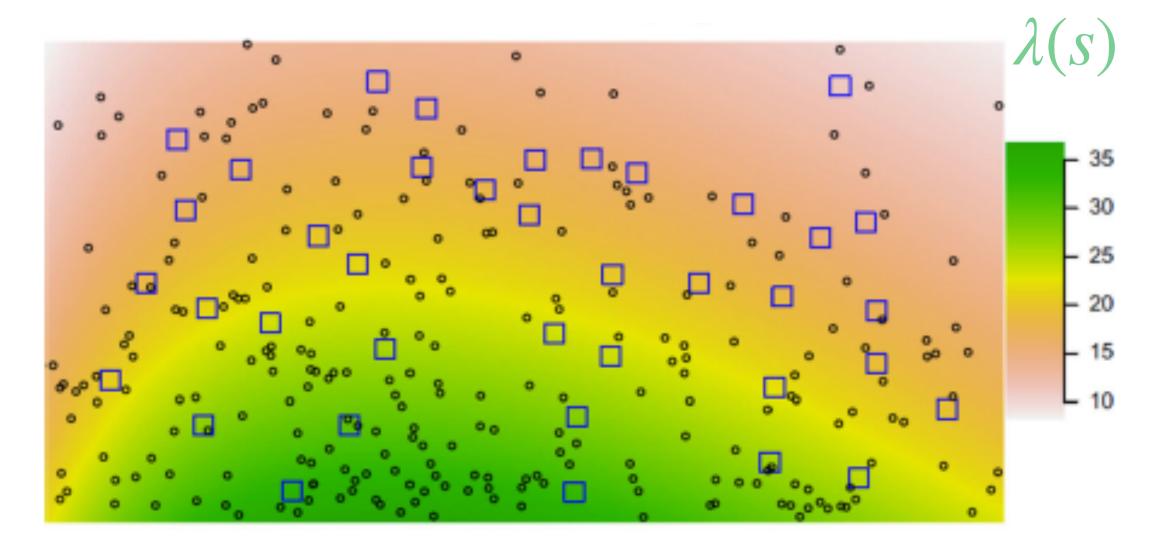
Restricted spatial extent.

"The truth"

What is the data?







Density across space

Structured survey data

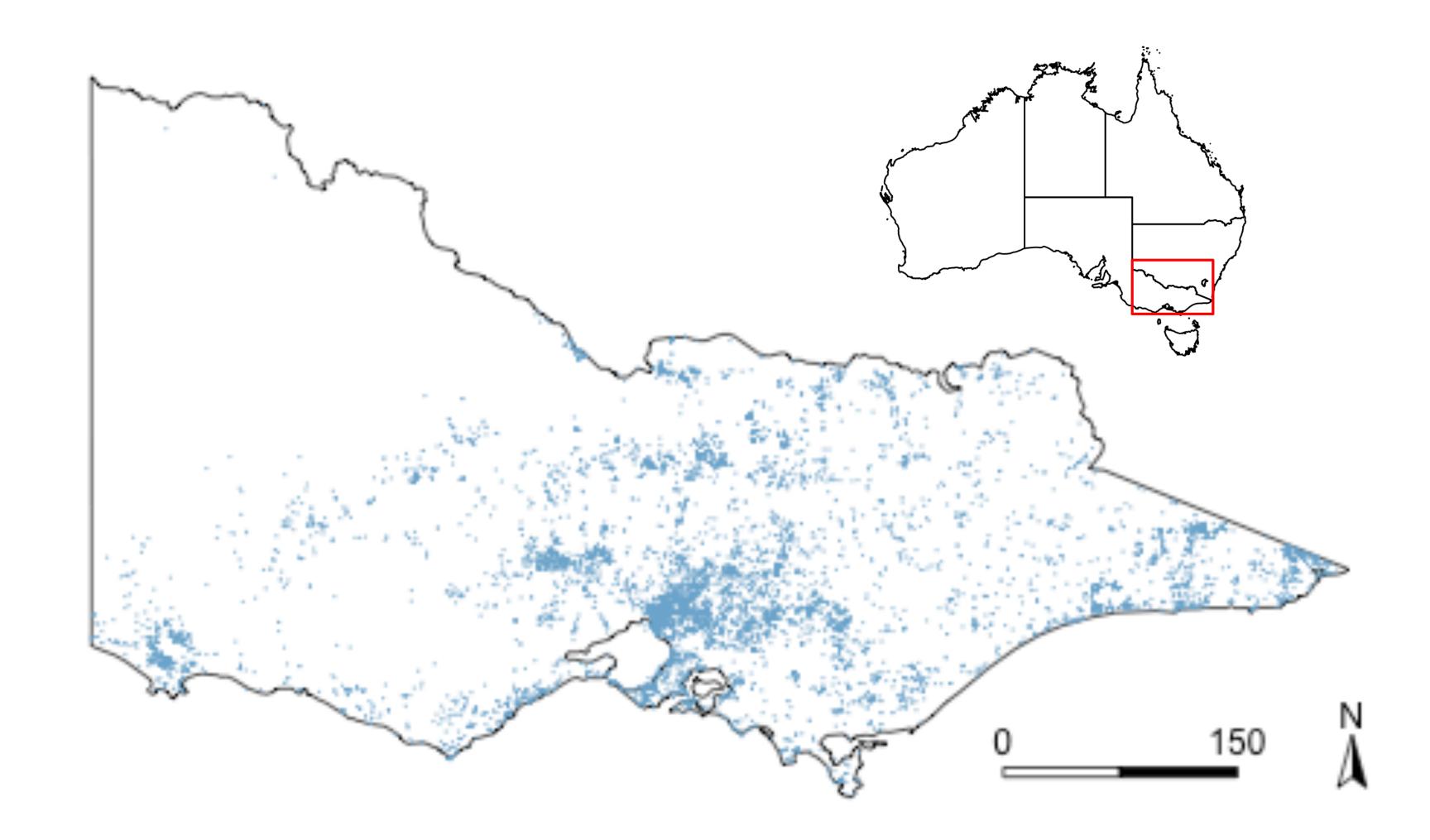
Fithian W, Elith J, Hastie T, Keith DA. Bias correction in species distribution models: pooling survey and collection data for multiple species. Methods Ecol Evol. 2015;6(4):424-438. doi:10.1111/2041-210X.12242

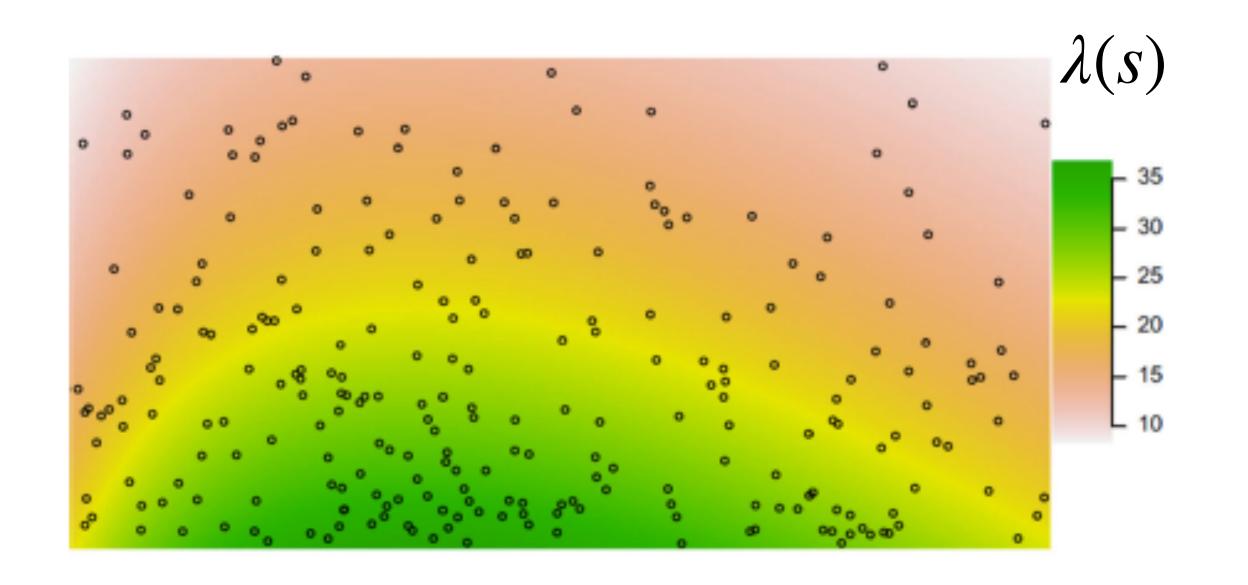
opportunistic observation

Broad scale Atlas of Living Australia presence only possum records.

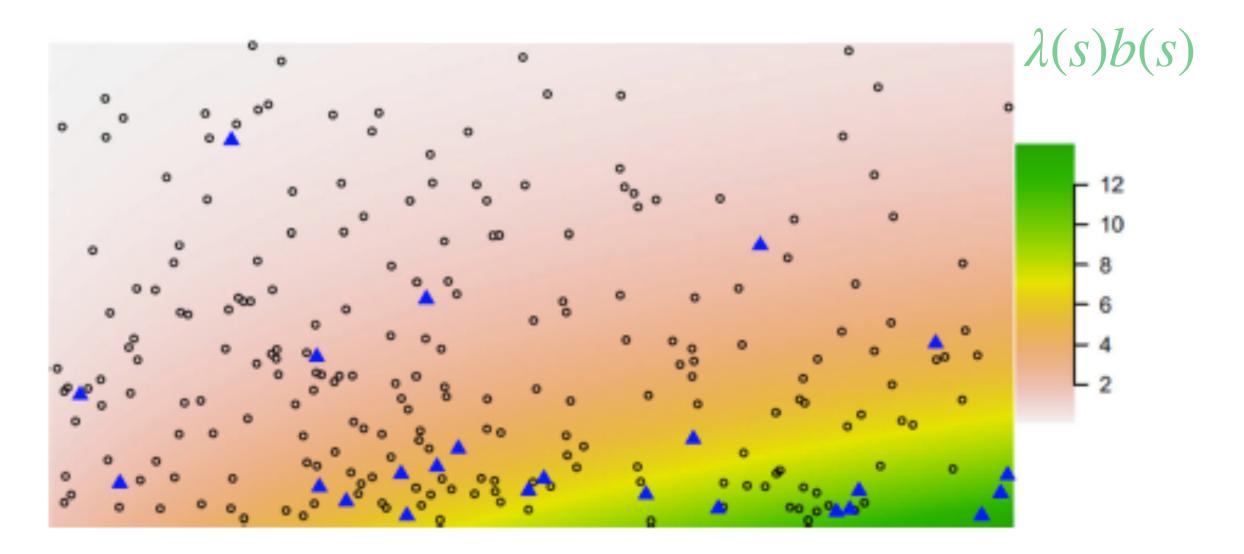
Biased opportunistic/citizen science data.

What is the data?





Density across space



Biased opportunistic observations

Fithian W, Elith J, Hastie T, Keith DA. Bias correction in species distribution models: pooling survey and collection data for multiple species. Methods Ecol Evol. 2015;6(4):424-438. doi:10.1111/2041-210X.12242

What is the data?

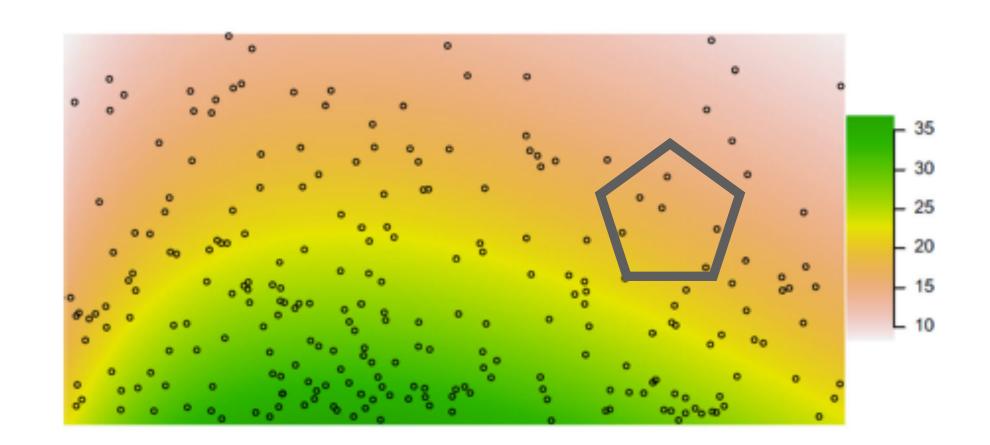
site occupancy

Scats detected/not detected in 10 m radius.

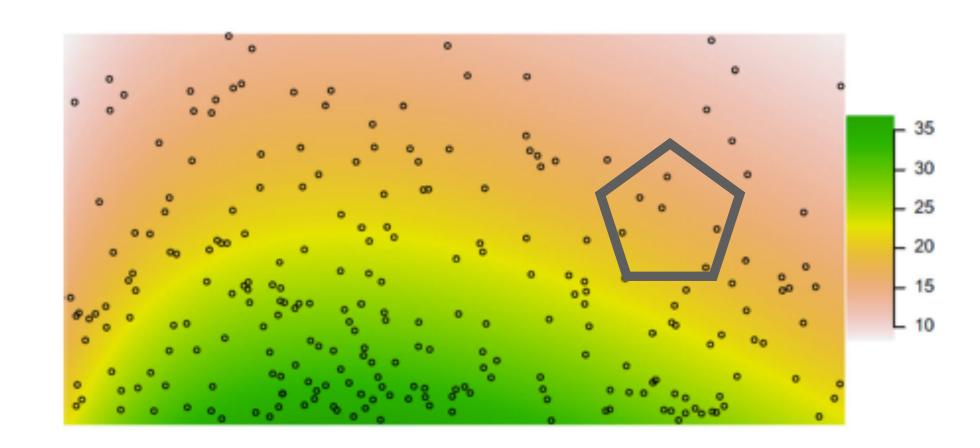
Imprecise proxy for detection of possums.



opportunistic observation site occupancy count data

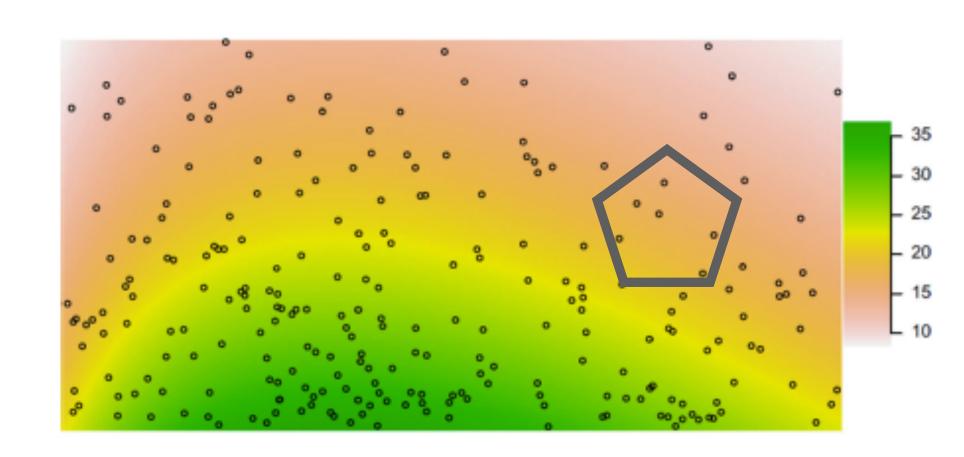


The number of points in any given region is Poisson (regardless of the location, size, or shape of the region)



The number of points in any given region is Poisson (regardless of the location, size, or shape of the region)

Expected # points in a region R (parameter of Poisson) =
$$\int_{R} \lambda(S) dS$$



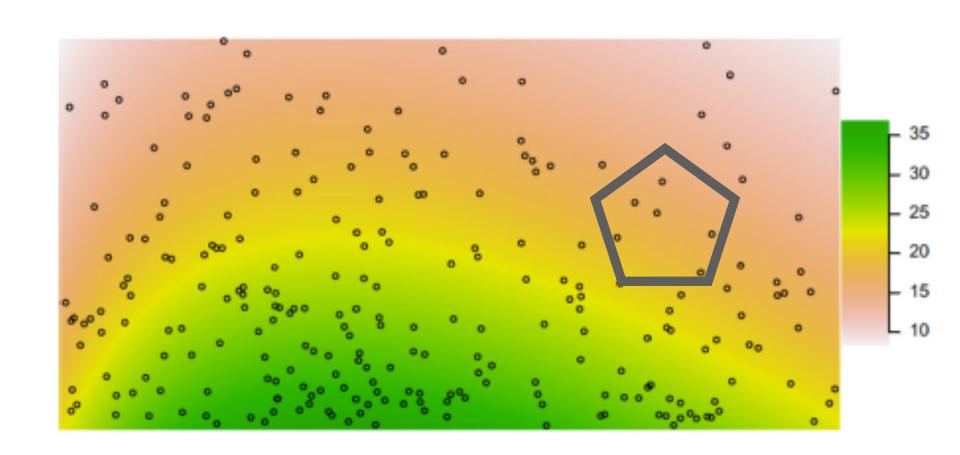
The number of points in any given region is Poisson (regardless of the location, size, or shape of the region)

Expected # points in a region R (parameter of Poisson) =
$$\lambda(S)dS$$

If $\lambda(s)$ is constant over R, with $\lambda(s) = \lambda_R$ and has area A_R then:

Expected number of points in
$$R$$

$$A_R$$

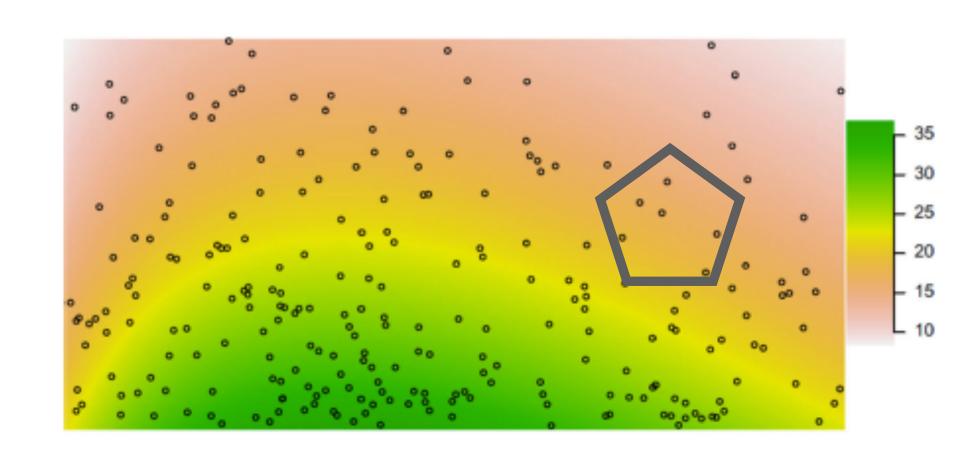


The number of points in any given region is Poisson (regardless of the location, size, or shape of the region)

Expected # points in a region R (parameter of Poisson) =
$$\lambda(S) dS$$

If $\lambda(s)$ is constant over R, with $\lambda(s) = \lambda_R$ and has area A_R then:

Expected number of points in
$$R = \lambda_R = \text{density of points (same units as } A_R)$$



The number of points in any given region is Poisson (regardless of the location, size, or shape of the region)

Expected # points in a region R (parameter of Poisson) =
$$\lambda(S)dS$$

If $\lambda(s)$ is constant over R, with $\lambda(s) = \lambda_R$ and has area A_R then:

Expected # points in $R = \lambda_R A_R$

Expected number of points in
$$R = \lambda_R = \text{density of points (same units as } A_R)$$

The possum density process model linking all data types

Expected # possums in region
$$i$$
 =
$$\int_{i}^{\infty} \lambda(s) ds \approx \lambda_{i} a_{i}$$

The possum density process model linking all data types

Expected # possums in region
$$i$$
 =
$$\int_{i}^{\infty} \lambda(s) ds \approx \lambda_{i} a_{i}$$

Possum density in i: $log(\lambda_i) = \alpha + \beta * TreeCover_i$

The possum density process model linking all data types

Expected # possums in region
$$i$$
 =
$$\int_{i}^{\infty} \lambda(s) ds \approx \lambda_{i} a_{i}$$

Possum density in
$$i$$
: $log(\lambda_i) = \alpha + \beta * TreeCover_i$

count data

What is the model?

$$count_i \sim Poisson(\lambda_i)$$

count data

$$count_i \sim Poisson(\lambda_i)$$

$$log(\lambda_i) = \alpha + \beta * TreeCover_i$$

count data

$$count_i \sim Poisson(\lambda_i)$$

$$log(\lambda_i) = \alpha + \beta * TreeCover_i$$

count data

$$count_i \sim Poisson(\lambda_i A_{search})$$

$$log(\lambda_i) = \alpha + \beta * TreeCover_i$$

50 m search radius = A_search

count data

Equivalent to:

$$count_i \sim Poisson(\lambda_i)$$

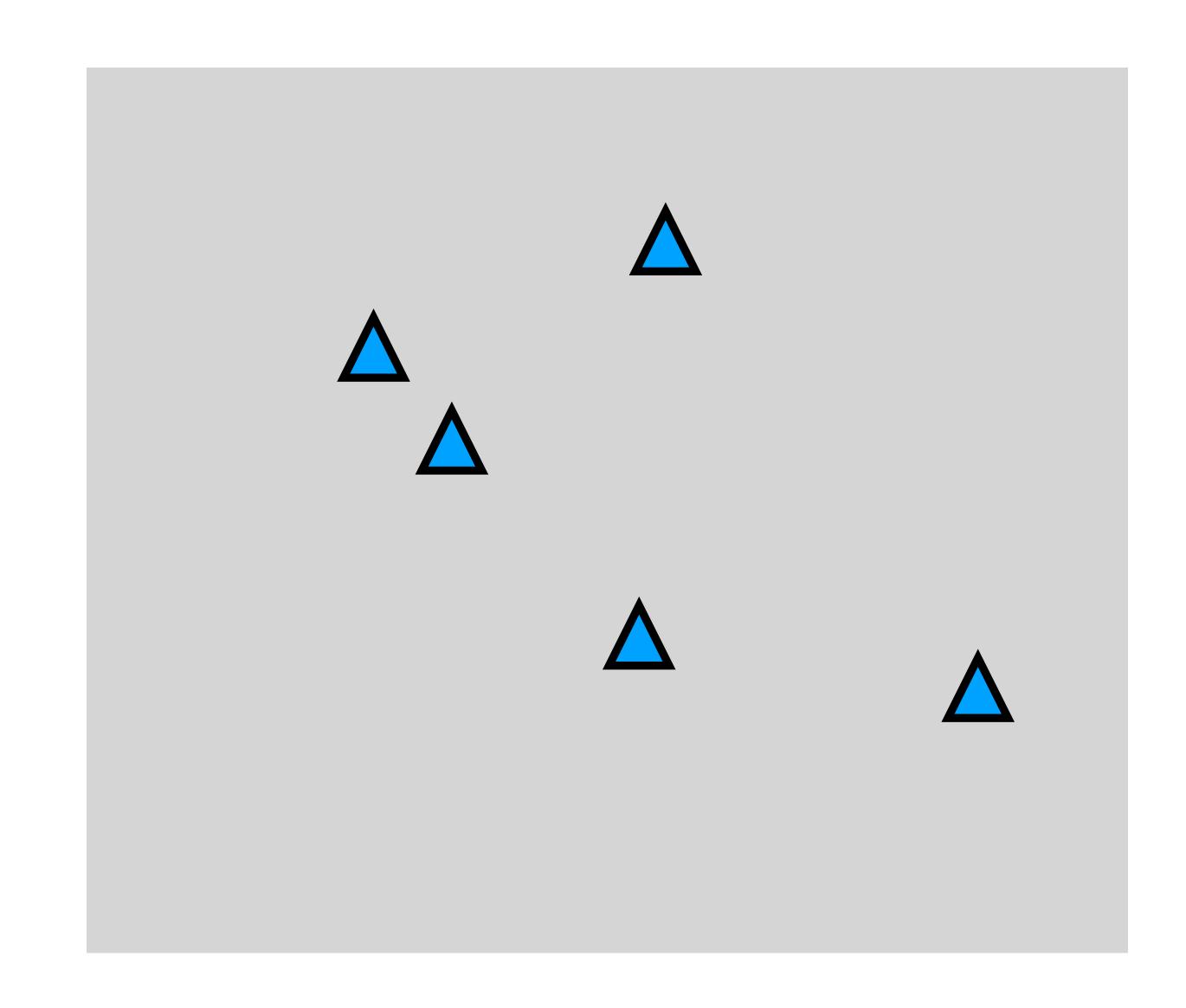
$$log(\lambda_i) = \alpha + \beta * TreeCover_i + log(A_{search})$$

opportunistic observation

What is the model?

$$po \sim IPPP(\lambda(s)b(s))$$

How to fit IPP to point data (cellwise count method)



0	0	1	0	0
0	2	0	0	0
0	0	1	0	1
0	0	0	0	0

0	0	1	0	0
0		0	0	0
0	0	1	0	1
0	0	0	0	0

J = 20

opportunistic observation

What is the model?

$$po \sim IPP(\lambda(s)b(s))$$

$$po_j \sim Poisson(\lambda_j b_j A_j)$$

opportunistic observation

$$po \sim IPP(\lambda(s)b(s))$$

$$po_j \sim Poisson(\lambda_j b_j A_j)$$

 $log(\lambda_j) = \alpha + \beta * TreeCover_j$

opportunistic observation

$$po \sim IPP(\lambda(s)b(s))$$

$$po_j \sim Poisson(\lambda_j b_j A_j)$$

$$log(\lambda_j) = \alpha + \beta * TreeCover_j$$

What is the model?

opportunistic observation

$$po \sim IPP(\lambda(s)b(s))$$

$$po_{j} \sim Poisson(\lambda_{j}b_{j}A_{j})$$

$$log(\lambda_{j}) = \alpha + \beta * TreeCover_{j}$$

$$log(b_{j}) = \alpha_{bias} + \beta_{bias}CityAccess_{j}$$

What is the model?

opportunistic observation

$$po \sim IPP(\lambda(s)b(s))$$

Equivalent to:

$$po_j \sim Poisson(\Lambda_j A_j)$$

$$log(\Lambda_j) = \alpha + \beta * TreeCover_j + \alpha_{bias} + \beta_{bias}CityAccess_j$$

$$occ_k \sim Bernoulli(\psi_k)$$
 $det_k \mid occ_k \sim Bernoulli(occ_k p_k)$

In this case, we are assuming perfect detection $p_k=1$

$$occ_k \sim Bernoulli(\psi_k)$$

$$det_k \mid occ_k \sim Bernoulli(occ_k p_k)$$

so we are modelling ψ_k instead of p_k

$$occ_k \sim Bernoulli(\psi_k)$$
 $det_k | occ_k \sim Bernoulli(occ_k p_k)$
 $\psi_k = 1 - e^{-Abund_k}$

so we are modelling ψ_k instead of p_k

What is the model?

$$occ_k \sim Bernoulli(\psi_k)$$
 $det_k | occ_k \sim Bernoulli(occ_k p_k)$
 $\psi_k = 1 - e^{-Abund_k}$

"cloglog" link

$$occ_k \sim Bernoulli(\psi_k)$$
 $det_k | occ_k \sim Bernoulli(occ_k p_k)$
 $\psi_k = 1 - e^{-Abund_k}$

$$Abund_k = \lambda_k * A_{search}$$

$$occ_k \sim Bernoulli(\psi_k)$$
 $det_k | occ_k \sim Bernoulli(occ_k p_k)$
 $\psi_k = 1 - e^{-Abund_k}$

$$Abund_{k} = \lambda_{k} * A_{search}$$

$$\lambda_{k} = \alpha + \beta * TreeCover_{k}$$

$$occ_k \sim Bernoulli(\psi_k)$$
 $det_k | occ_k \sim Bernoulli(occ_k p_k)$
 $\psi_k = 1 - e^{-Abund_k}$

$$Abund_{k} = \lambda_{k} * A_{search}$$

$$\lambda_{k} = \alpha + \beta * TreeCover_{k}$$

What is the model?

$$Scat_k \sim Bernoulli(\psi_k)$$

 $ScatDet_k \mid Scat_k \sim Bernoulli(Scat_k p_k)$

But we are modelling scats not possums directly

$$\psi_k = 1 - e^{-AbundScat_k}$$

$$AbundPossum_{k} = \lambda_{k} * A_{search}$$
$$\lambda_{k} = \alpha + \beta * TreeCover_{k}$$

What is the model?

$$Scat_k \sim Bernoulli(\psi_k)$$

 $ScatDet_k \mid Scat_k \sim Bernoulli(Scat_k p_k)$

$$\psi_k = 1 - e^{-AbundScat_k}$$

So we need the link between possum abidance of scats

abundance and $AbundScat_k = \alpha_{ScatDet}*AbundPossum_k$

$$AbundPossum_k = \lambda_k * A_{ScatDet}$$

$$\lambda_k = \alpha + \beta * TreeCover_k$$

We do not need to fit these in JAGS, can be fit in glm framework, but we want to make the maths explicit.

Over to the code....

Thank you!

More reading:

Fithian W, Elith J, Hastie T, Keith DA. Bias correction in species distribution models: pooling survey and collection data for multiple species. *Methods Ecol Evol*. 2015;6(4):424-438. doi:10.1111/2041-210X.12242

Guillera-Arroita, G. (2017), Modelling of species distributions, range dynamics and communities under imperfect detection: advances, challenges and opportunities. Ecography, 40: 281-295. https://doi.org/10.1111/ecog.02445

Nick J.B. Isaac, Marta A. Jarzyna, Petr Keil, Lea I. Dambly, Philipp H. Boersch-Supan, Ella Browning, Stephen N. Freeman, Nick Golding, Gurutzeta Guillera-Arroita, Peter A. Henrys, Susan Jarvis, José Lahoz-Monfort, Jörn Pagel, Oliver L. Pescott, Reto Schmucki, Emily G. Simmonds, Robert B. O'Hara. 2020. Data Integration for Large-Scale Models of Species Distributions. Trends in Ecology & Evolution, 35:1, 56-67, https://doi.org/10.1016/j.tree.2019.08.006.

Simmonds, E.G., Jarvis, S.G., Henrys, P.A., Isaac, N.J.B. and O'Hara, R.B. (2020), Is more data always better? A simulation study of benefits and limitations of integrated distribution models. Ecography, 43: 1413-1422. https://doi.org/10.1111/ecog.05146









Australian Government

