Statistical Methods for Estimating Abundance in Ecology

EPSCoR Wyoming

WEST

MICROBIAL ECOLOGY COLLABORATIVE

UNIVERSITY OF WYOMING

Abundance in Ecology


John Carnemolla

Three approaches to modeling abundance

- N-mixture models
- Distance sampling
- Capture-mark-recapture

Three approaches to modeling abundance

Variable	Marked	Data	Approach	Package	Model
Abundance/Density	No	Count (repeated)	N-mixture	unmarked	Closed Binomial N-mixture
Abundance/Density	No	Count (by distance interval)	Distance Sampling	unmarked	Multinomial-Poisson mixture
Abundance/Density	Yes	Capture-recapture	Capture-mark-recapture	RMark	Closed Population Estimation

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Is distance from observer a major source of variation in detection probability?

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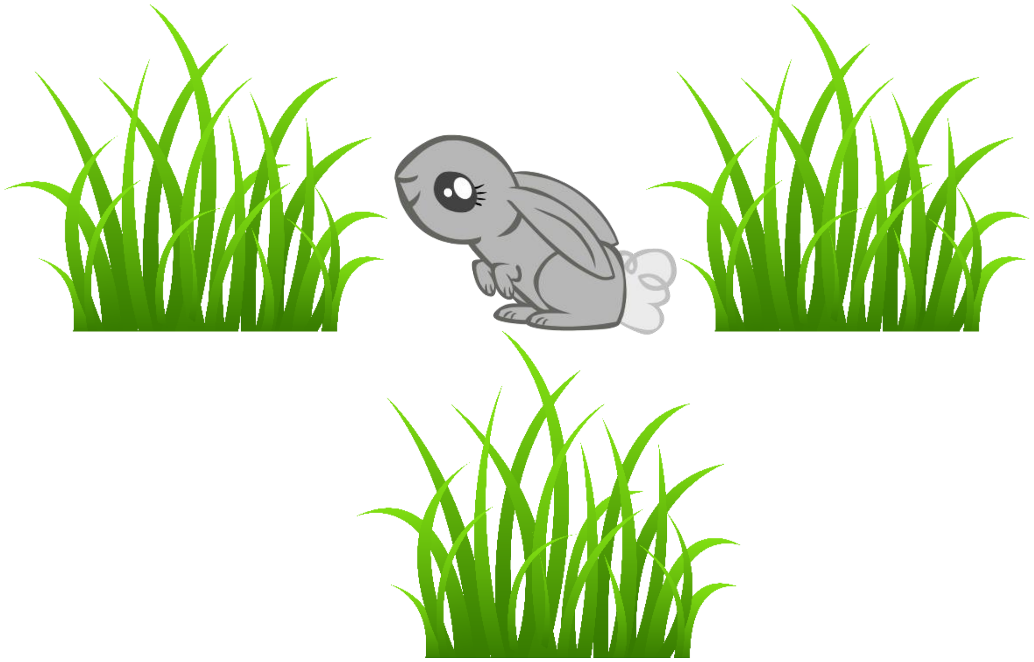
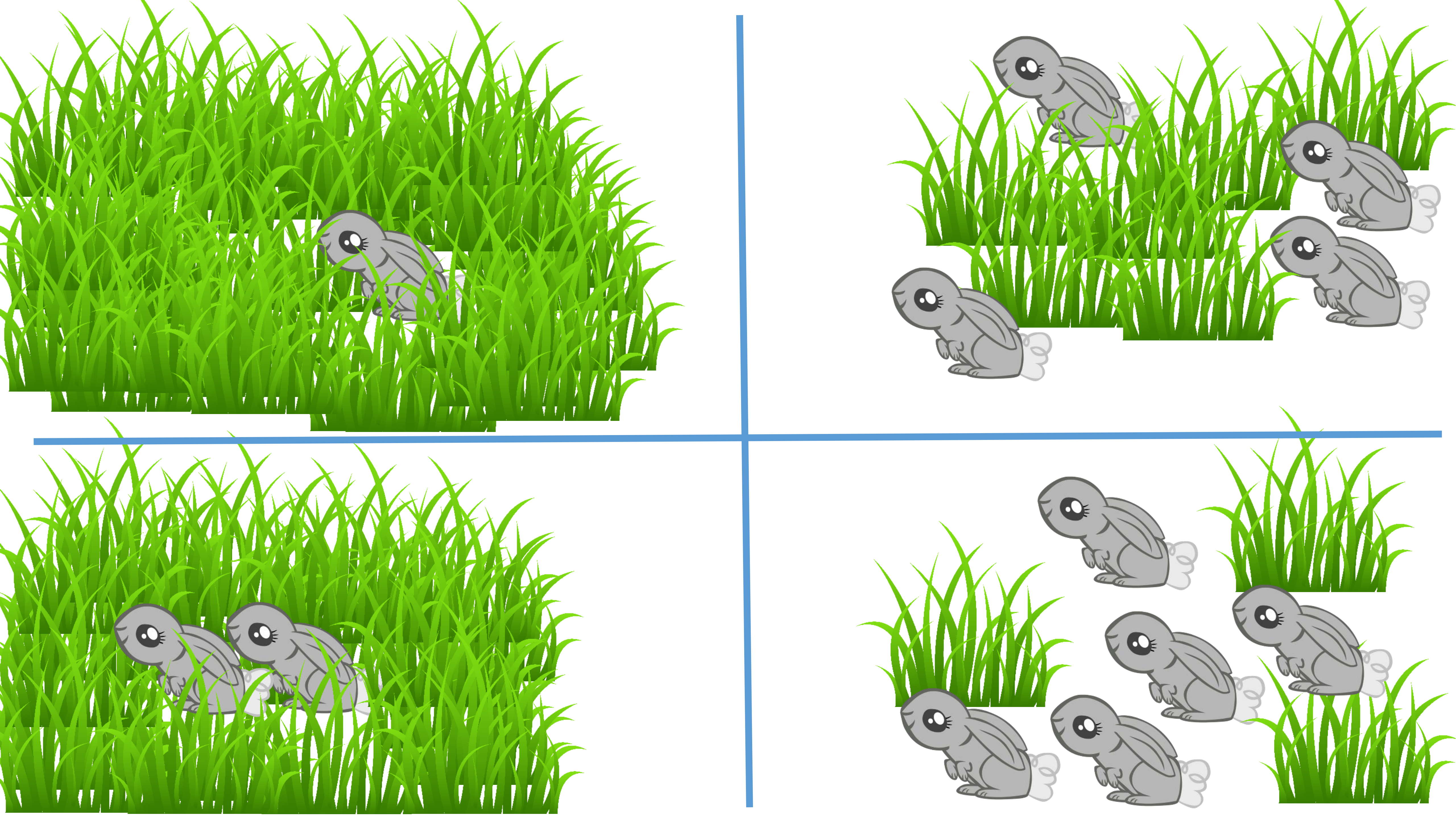
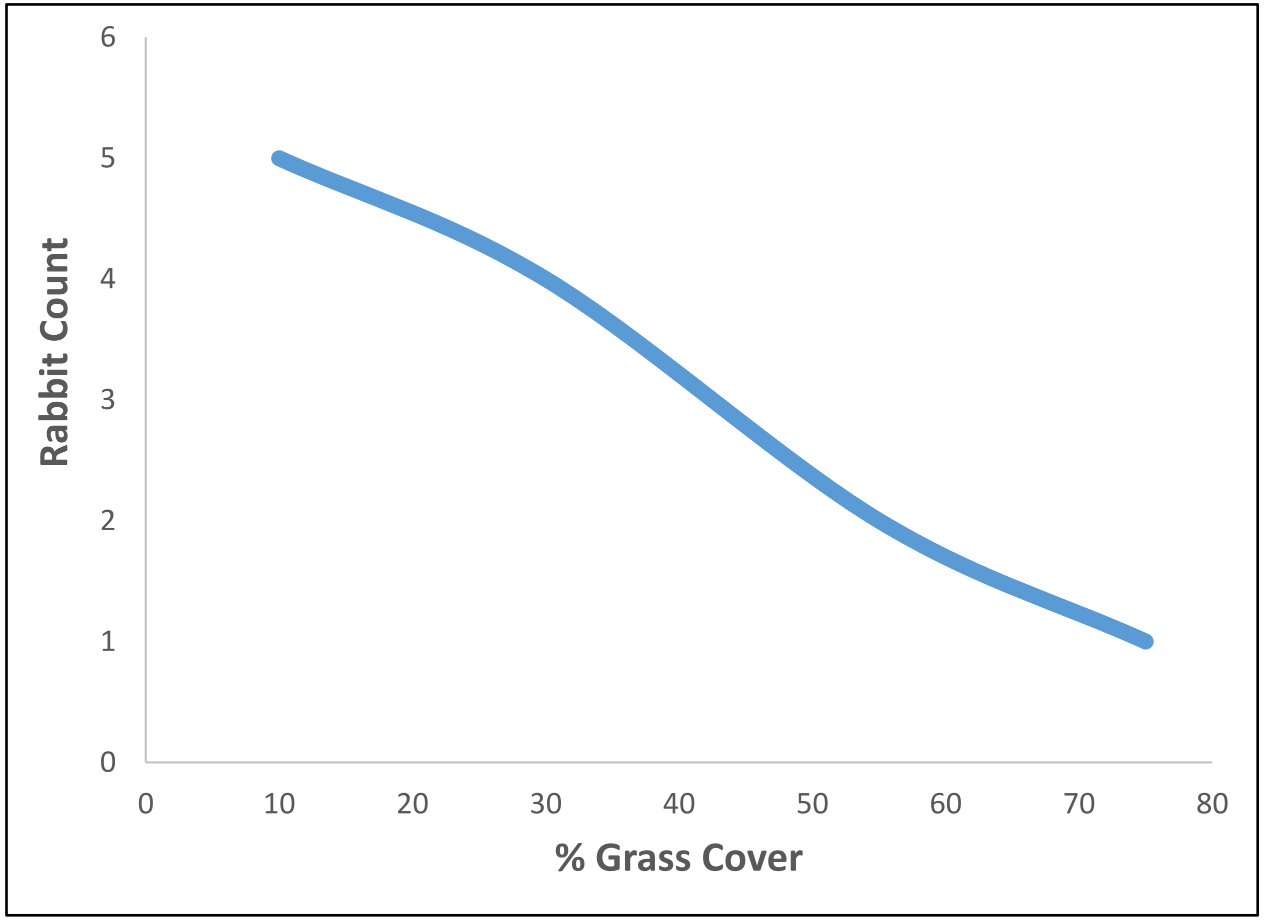
We focus on closed systems (geographically & demographically) and frequentist approaches. However, if you are interested in Bayesian approaches and/or modeling change in abundance over time, we will direct you to some helpful resources.

Estimating Abundance – Imperfect Detection

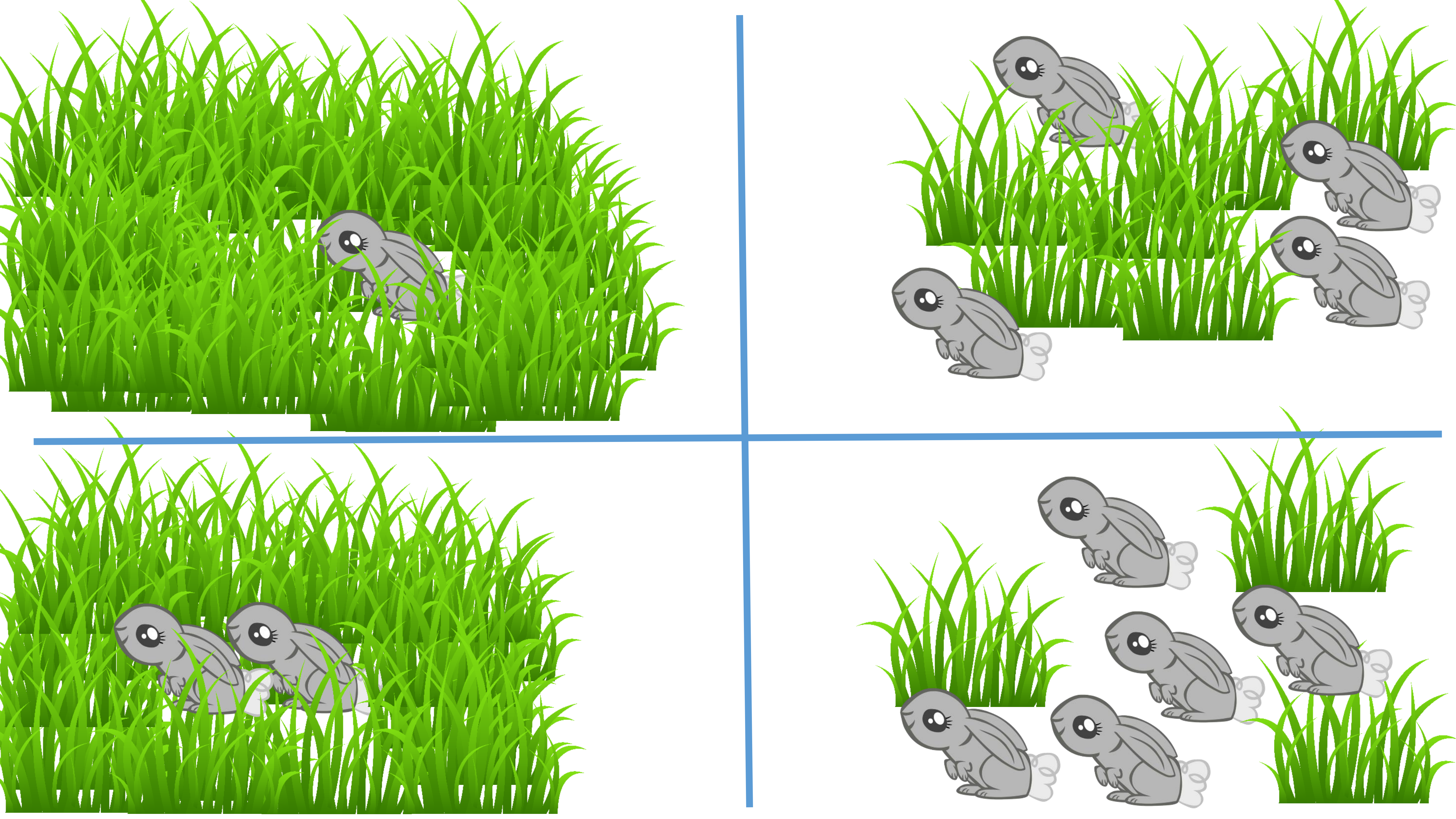
How does grass cover influence
bunny rabbit **abundance**?

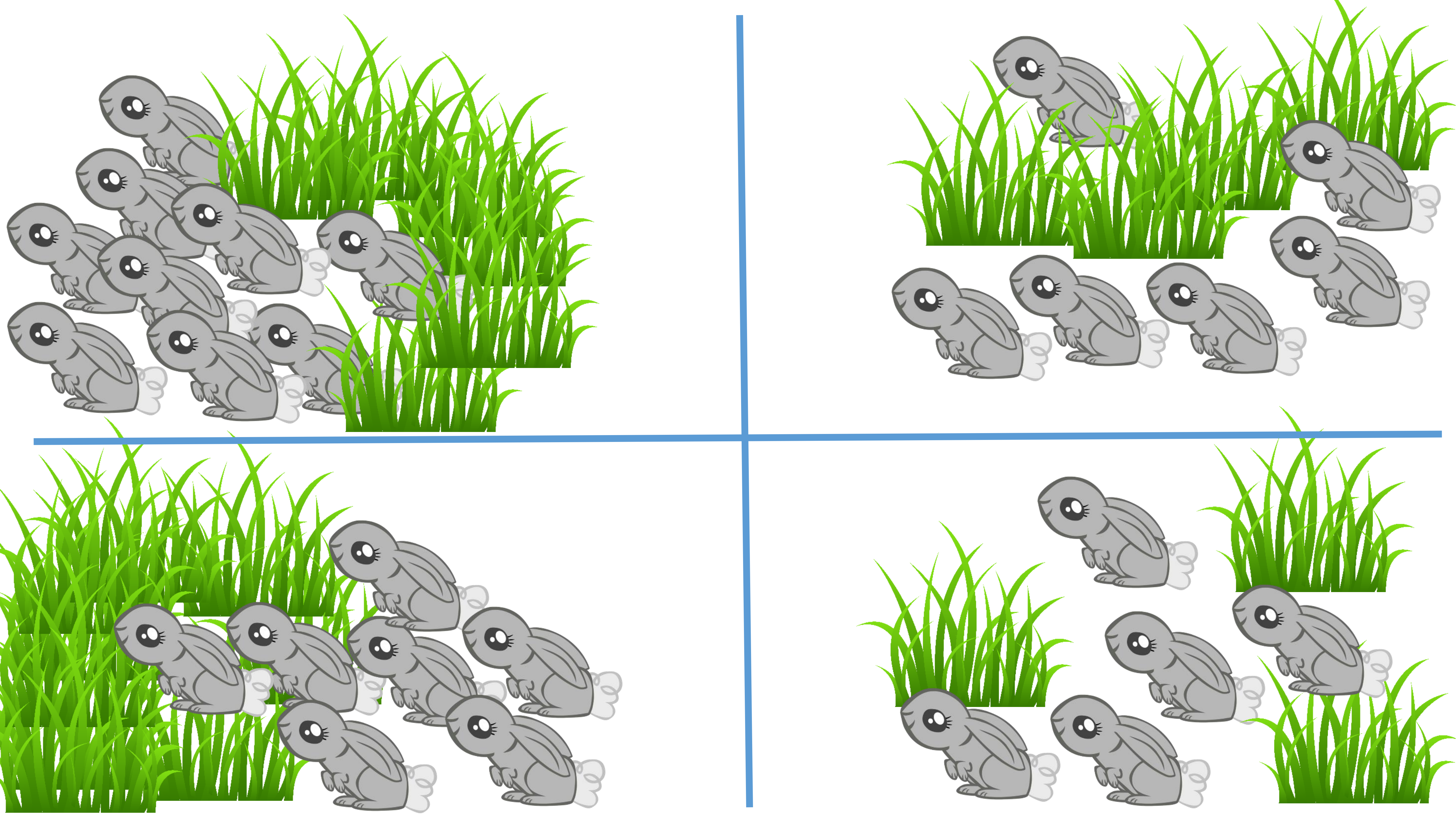






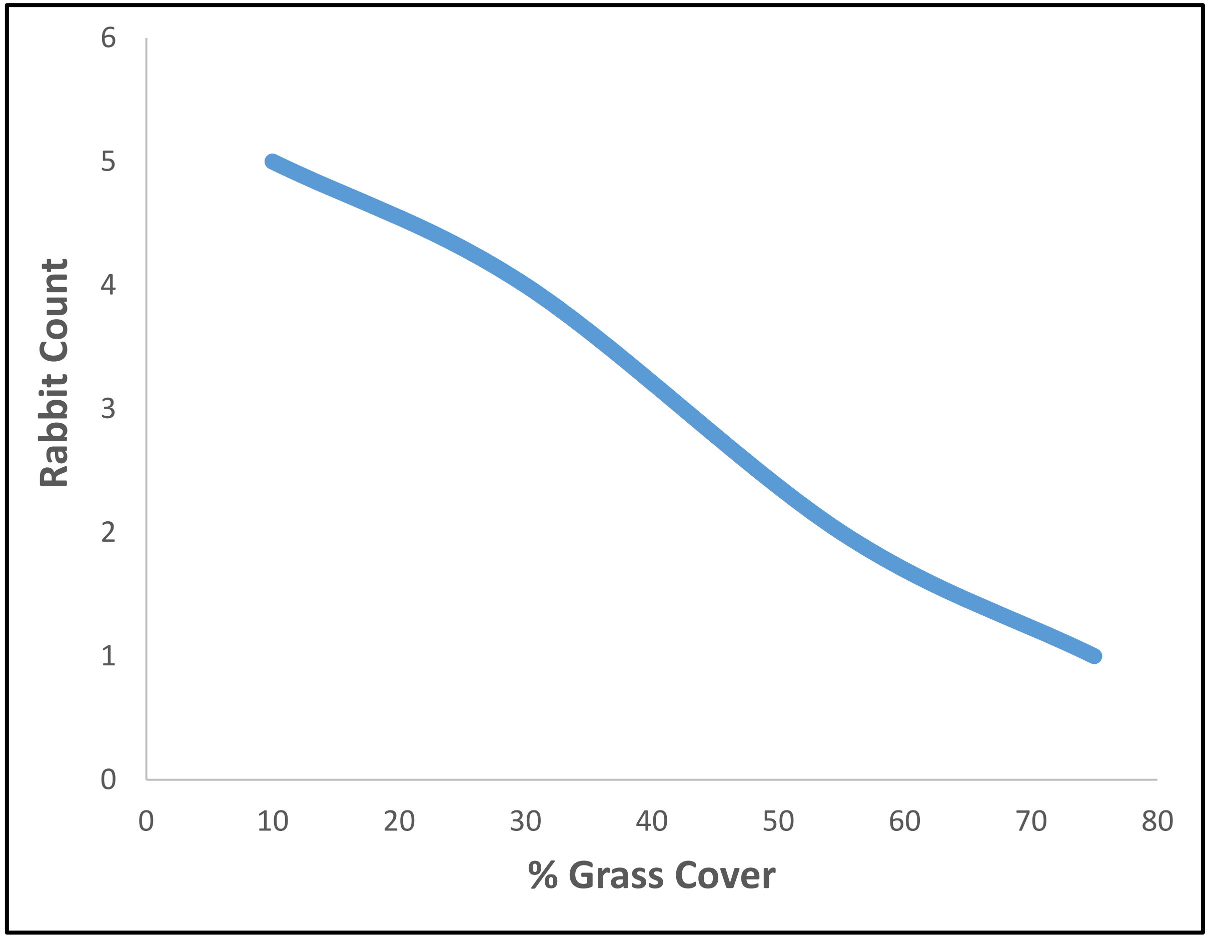
Rabbit Count
6
5
4
3
2
1
0
0
10
20
30
40
50
60
70
80
% Grass Cover



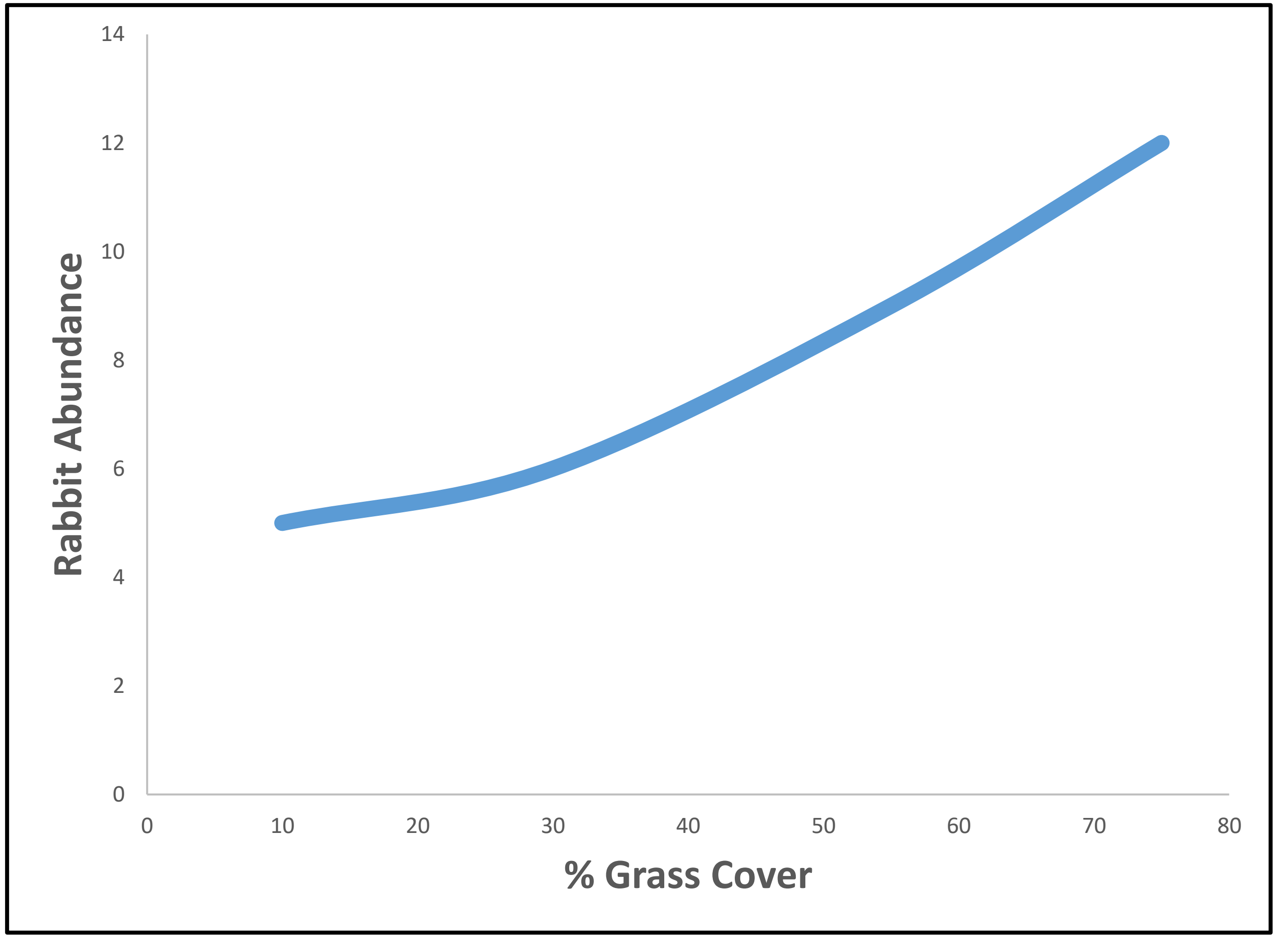


Estimating Abundance – Imperfect Detection

Our Data



Reality



Estimating Abundance – State and Observation Processes

1. **State process** (e.g., population size)
2. **Observation process** (e.g., population count)

For example, the **state process** describes the dynamics of **population size** over time (N_t), whereas the **observation process** describes the **error-prone population counts** (C_t).

Estimating Abundance – Closed Binomial N-mixture Model

Mark Gocke

Estimating Abundance – Closed Binomial N-mixture Model

$C = 45$
$N = 60$

Count = true abundance * detection probability
$C = N * p$
45 = 60 * p
45/60 = p
Detection probability is 0.75

$C/p = N$
45/0.75 = 60

1. Observation Process $C \sim Binomial(N, p)$

2. State Process $N \sim Poisson(\lambda)$

Estimating Abundance – Closed Binomial N-mixture Model

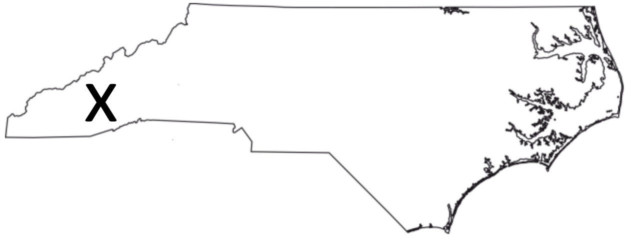
1. Question
2. Field Data
3. Format Data for Analysis
4. Fit Population Model
5. Examine Output and Visualize Results

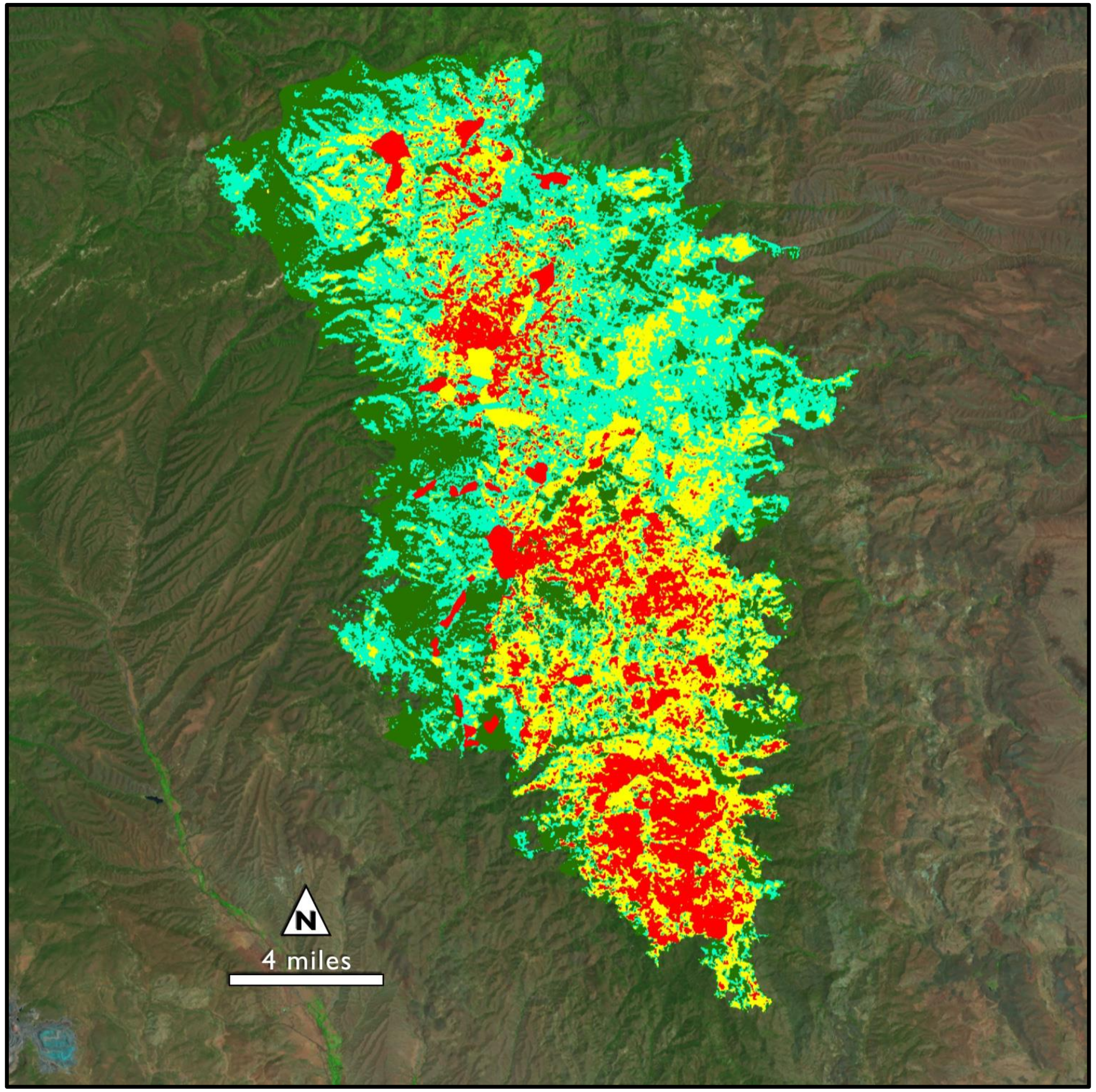
*steps 3-5 in Program R

Estimating Abundance – Closed Binomial N-mixture Model

1. Question

How does wildfire influence salamander abundance?





iNaturalist, USDA Forest Service, Burned Area Emergency Response Team

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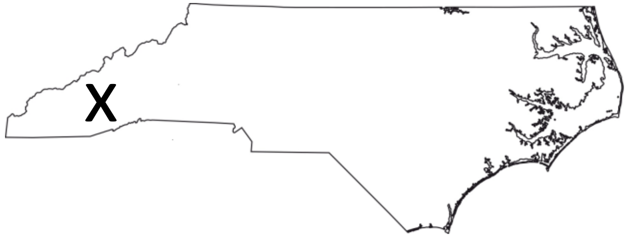

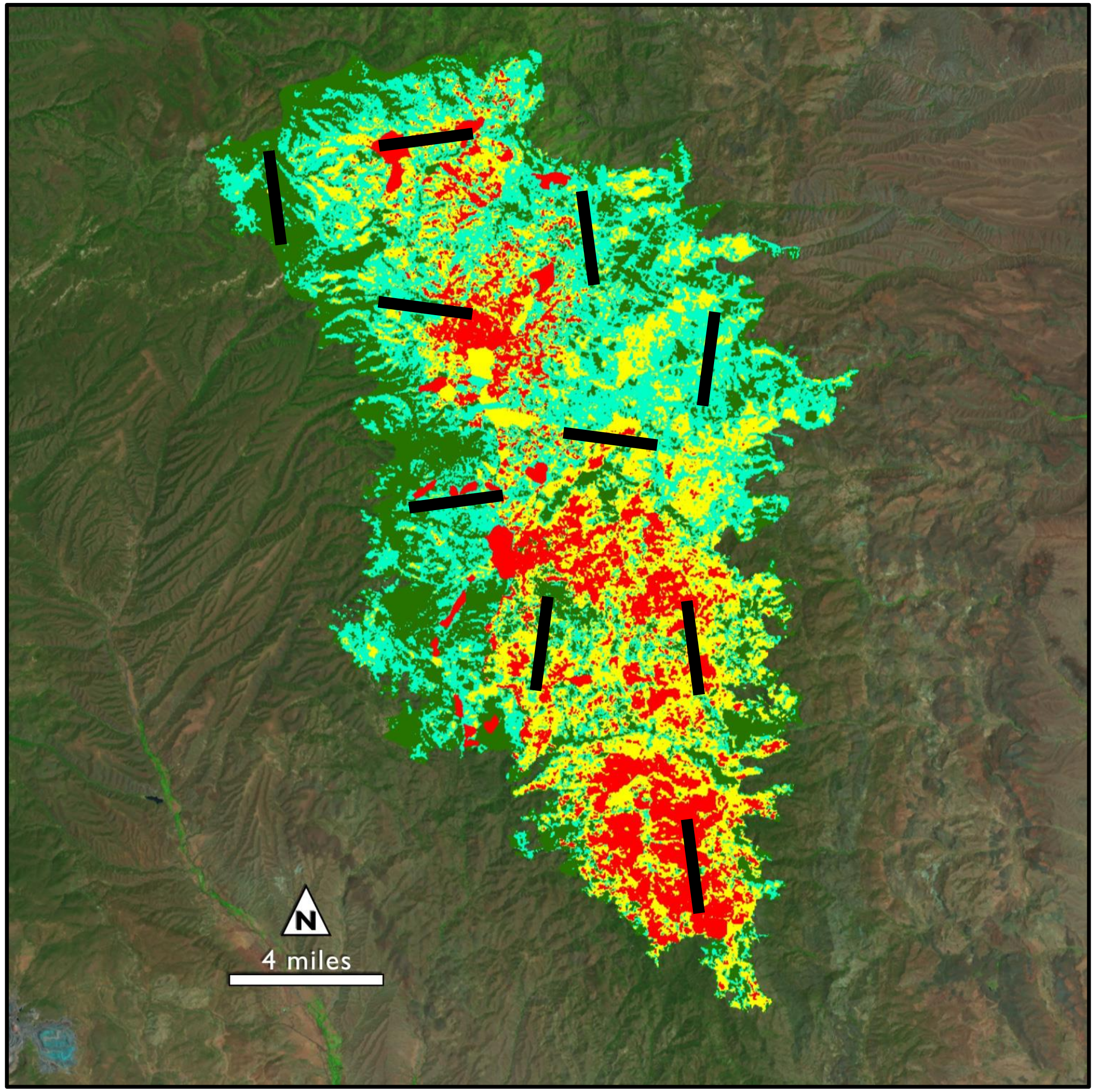

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Estimating Abundance – Closed Binomial N-mixture Model

1. Question
2. Field Data

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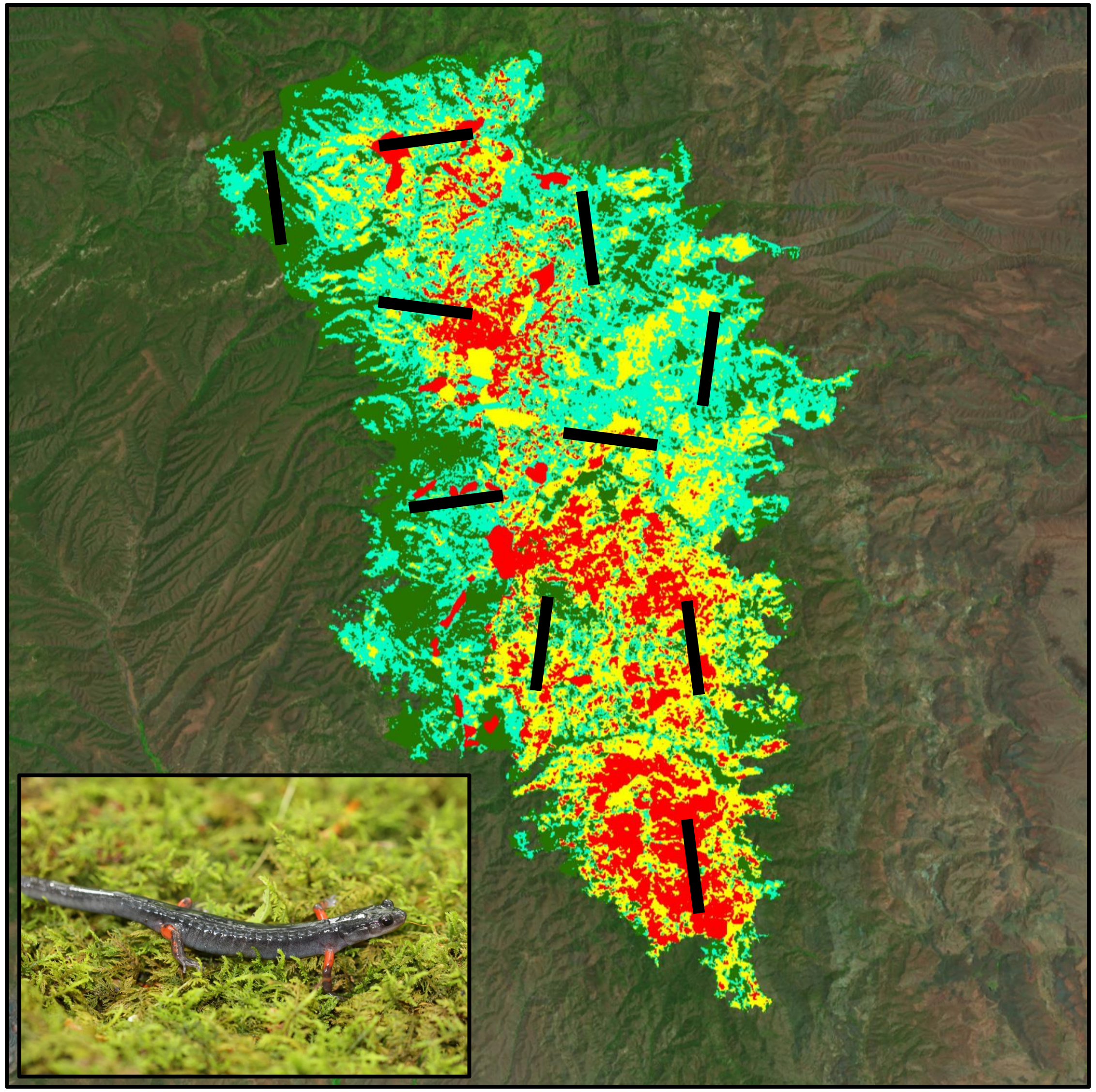
Date	Transect	Survey	Count	% Burned Area	Time of Day



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1. Question
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How does wildfire influence salamander abundance?

Date	Transect	Survey	Count	% Burned Area	Time of Day
6/1/2021	1	1	30	0	7:00
6/2/2021	1	2	28	0	9:00
6/3/2021	1	3	25	0	12:00
6/1/2021	2	1	26	10	8:00
6/2/2021	2	2	24	10	10:00
6/3/2021	2	3	22	10	11:00
6/4/2021	3	1	26	15	7:00
6/5/2021	3	2	25	15	8:00
6/6/2021	3	3	25	15	11:00
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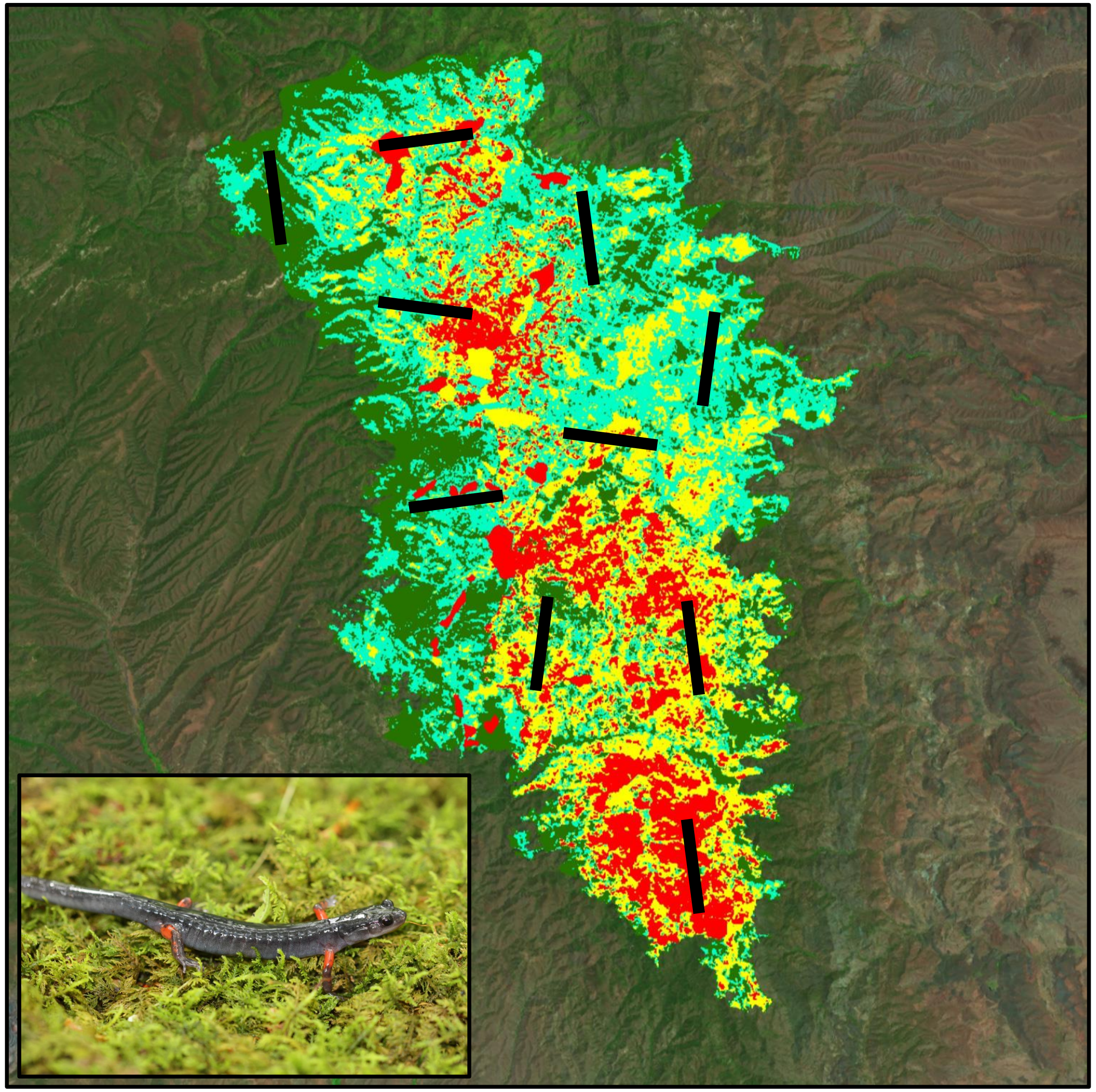

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6/5/2021	4	2	17	20	8:00
6/6/2021	4	3	12	20	12:00

Count1	Count2	Count3	Burn	Time1	Time2	Time3
30	28	25	0	7	9	12
26	24	22	10	8	10	11
26	25	25	15	7	8	11
20	17	12	20	7	8	12

Estimating Abundance – Closed Binomial N-mixture Model

1. State Process $N_i \sim Poisson(\lambda)$

2. Observation Process $y_{ij} \mid N_i \sim Binomial(N_i, p)$

Estimating Abundance – Closed Binomial N-mixture Model

R Script: Day1-NMixture_unmarked

Breakout rooms: one person in group will volunteer to share screen

Work through the code: answer each question as a group

Instructors will be available to help you along

Estimating Abundance – Closed Binomial N-mixture Model

Group 1:
What was our site-level covariate?
What was our observational covariate?
Can detection be modeled as a function of the site-level covariate?
Can abundance be modeled as a function of the observational covariate?

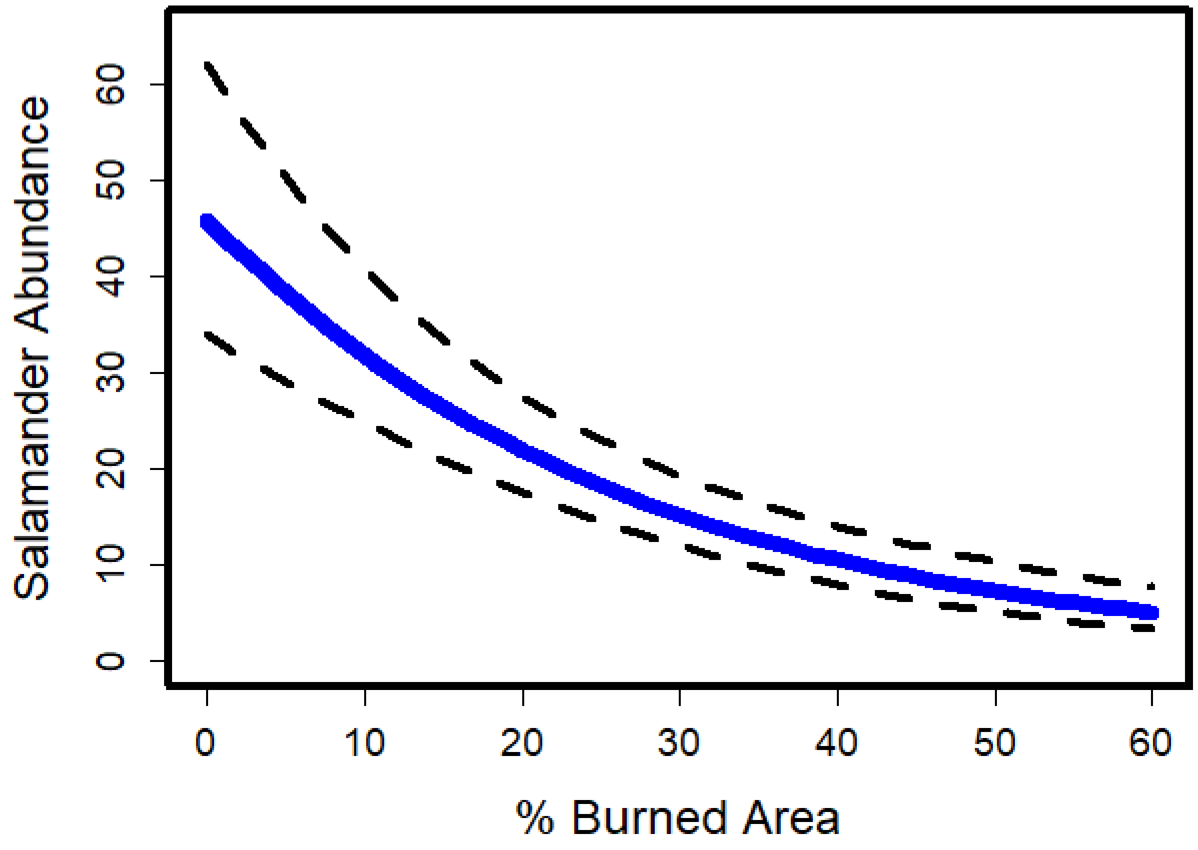
Group 2:
Describe the relationship between % burned area and salamander abundance…
What was the mean predicted abundance when percent burned area was 12%?

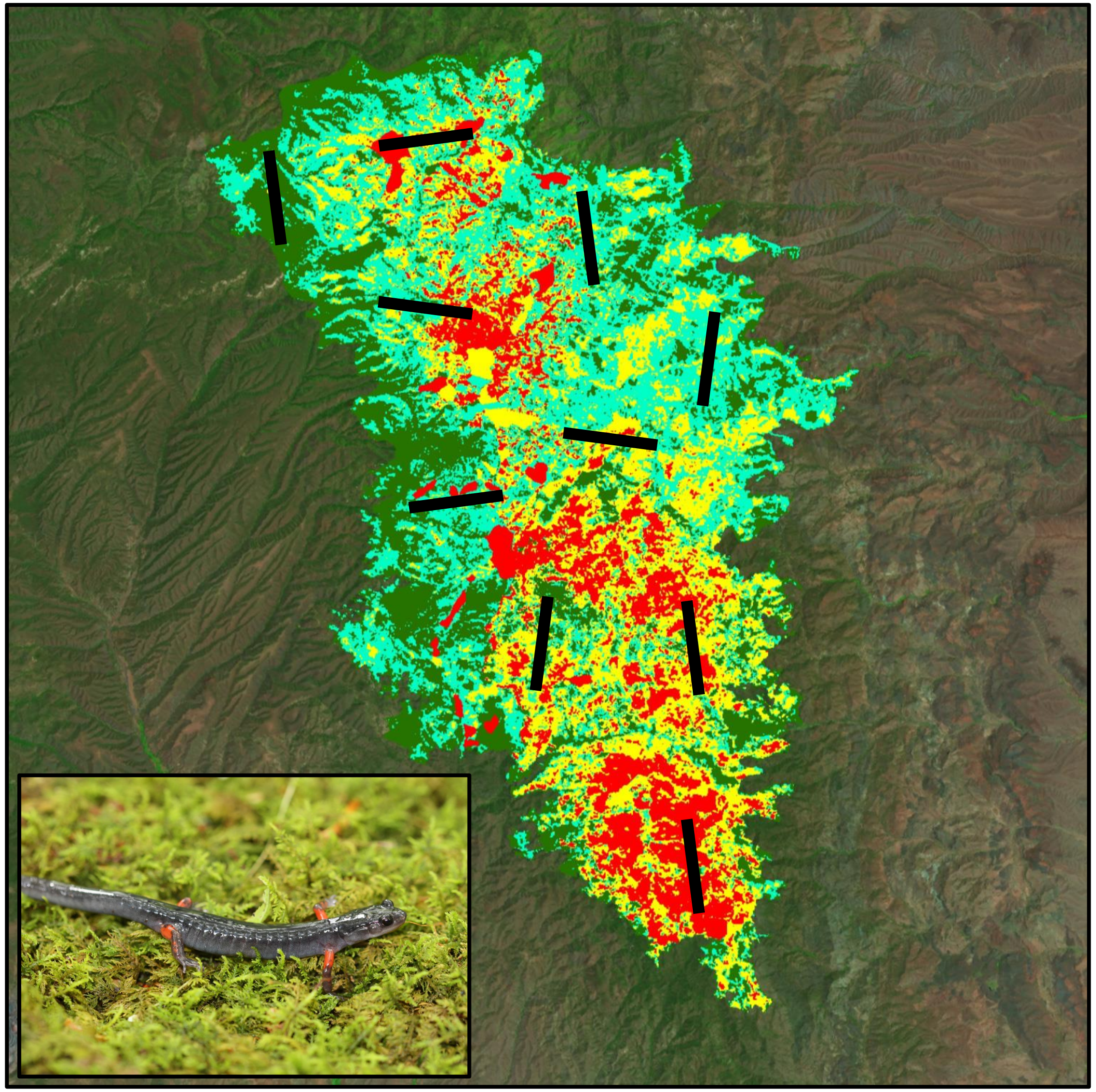
Group 3:
Describe the relationship between time of day and salamander detection…
What is the mean predicted detection probability for surveys conducted at 10am?

Estimating Abundance – Closed Binomial N-mixture Model

1. Question

How does wildfire influence salamander abundance?





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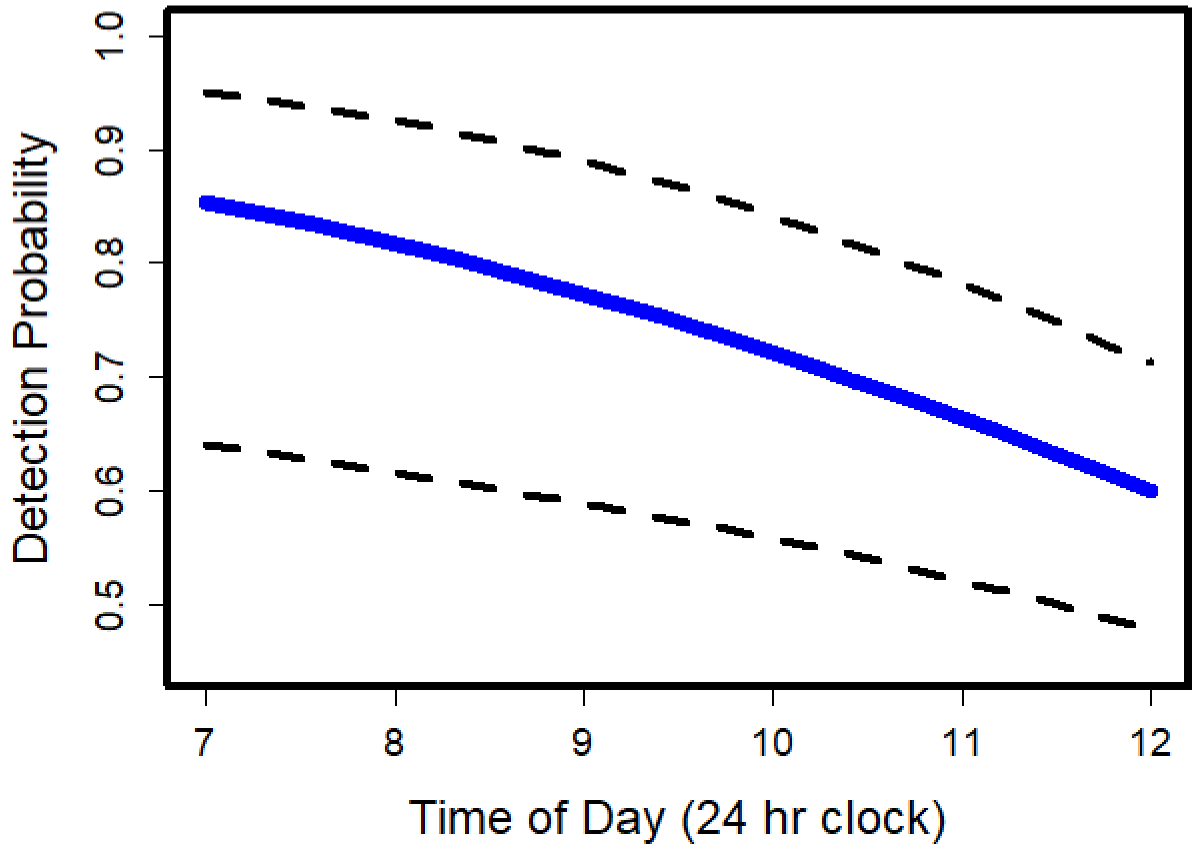

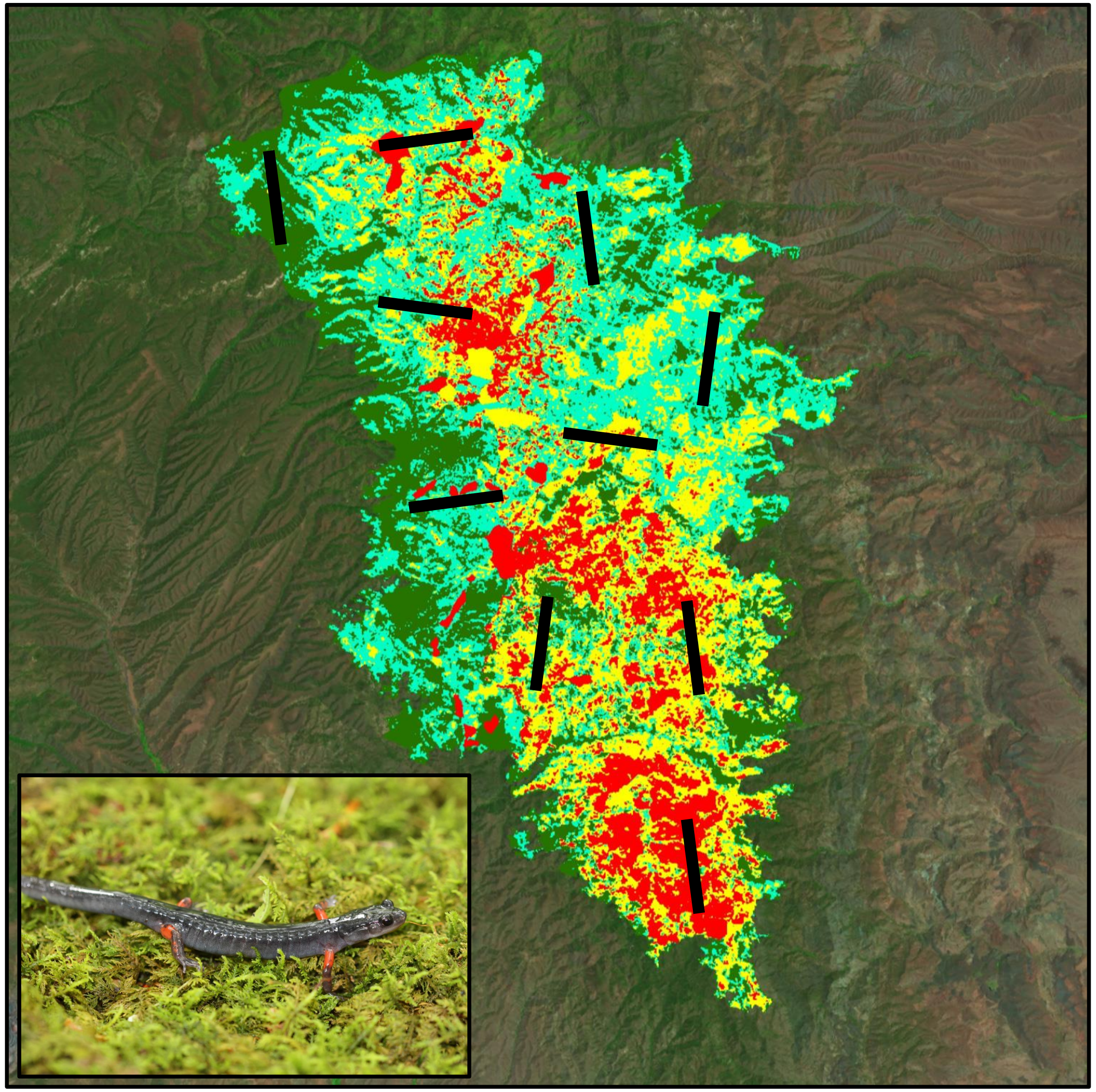

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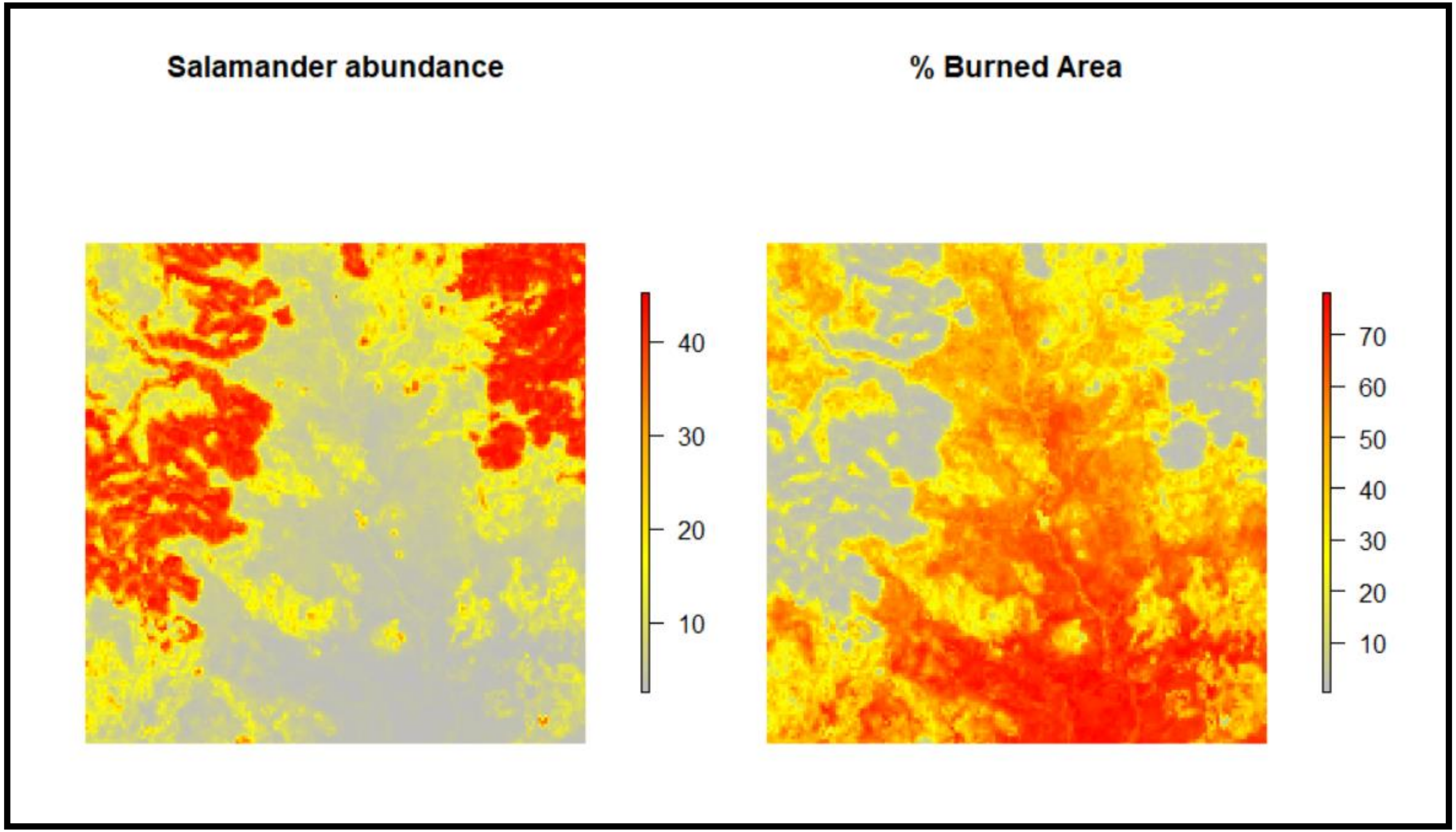

Estimating Abundance – Closed Binomial N-mixture Model

Any questions?

Does anyone want to go over anything again?

Estimating Abundance – Closed Binomial N-mixture Model

BIOMETRICS 60, 108–115
March 2004

N-Mixture Models for Estimating Population Size from Spatially Replicated Counts

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11510 American Holly Drive, Laurel, Maryland 20708, U.S.A.
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SUMMARY. Spatial replication is a common theme in count surveys of animals. Such surveys often generate sparse count data from which it is difficult to estimate population size while formally accounting for detection probability. In this article, I describe a class of models (N-mixture models) which allow for estimation of population size from such data. The key idea is to view site-specific population sizes, N, as independent random variables distributed according to some mixing distribution (e.g., Poisson). Prior parameters are estimated from the marginal likelihood of the data, having integrated over the prior distribution for N. Carroll and Lombard (1985, *Journal of American Statistical Association* **80,** 423–426) proposed a class of estimators based on mixing over a prior distribution for detection probability. Their estimator can be applied in limited settings, but is sensitive to prior parameter values that are fixed a priori. Spatial replication provides additional information regarding the parameters of the prior distribution on N that is exploited by the N-mixture models and which leads to reasonable estimates of abundance from sparse data. A simulation study demonstrates superior operating characteristics (bias, confidence interval coverage) of the N-mixture estimator compared to the Caroll and Lombard estimator. Both estimators are applied to point count data on six species of birds illustrating the sensitivity to choice of prior on p and substantially different estimates of abundance as a consequence.

KEY WORDS: Avian point counts; Binomial population size estimation; North American Breeding Bird Survey.

Ecological Applications, 15(4), 2005, pp. 1450–1461

MODELING AVIAN ABUNDANCE FROM REPLICATED COUNTS USING BINOMIAL MIXTURE MODELS

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[2]*USGS Patuxent Wildlife Research Center, 12100 Beech Forest Rd., Laurel, Maryland 20708 USA*

Abstract. Abundance estimation in ecology is usually accomplished by capture–recapture, removal, or distance sampling methods. These may be hard to implement at large spatial scales. In contrast, binomial mixture models enable abundance estimation without individual identification, based simply on temporally and spatially replicated counts. Here, we evaluate mixture models using data from the national breeding bird monitoring program in Switzerland, where some 250 1-km^2 quadrats are surveyed using the territory mapping method three times during each breeding season. We chose eight species with contrasting distribution (wide–narrow), abundance (high–low), and detectability (easy–difficult). Abundance was modeled as a random effect with a Poisson or negative binomial distribution, with mean affected by forest cover, elevation, and route length. Detectability was a logit-linear function of survey date, survey date-by-elevation, and sampling effort (time per transect unit). Resulting covariate effects and parameter estimates were consistent with expectations. Detectability per territory (for three surveys) ranged from 0.66 to 0.94 (mean 0.84) for easy species, and from 0.16 to 0.83 (mean 0.53) for difficult species, depended on survey effort for two easy and all four difficult species, and changed seasonally for three easy and three difficult species. Abundance was positively related to route length in three high-abundance and one low-abundance (one easy and three difficult) species, and increased with forest cover in five forest species, decreased for two nonforest species, and was unaffected for a generalist species. Abundance estimates under the most parsimonious mixture models were between 1.1 and 8.9 (median 1.8) times greater than estimates based on territory mapping; hence, three surveys were insufficient to detect all territories for each species. We conclude that binomial mixture models are an important new approach for estimating abundance corrected for detectability when only repeated-count data are available. Future developments envisioned include estimation of trend, occupancy, and total regional abundance.

Key words: abundance estimation; binomical mixture model; breeding bird surveys; count data; detectability; index of abundance; monitoring; random effect; replicated counts; Switzerland.

Estimating Abundance – Closed Binomial N-mixture Model

Journal of Statistical Software

August 2011, Volume 43, Issue 10. http://www.jstatsoft.org/

unmarked: An R Package for Fitting Hierarchical Models of Wildlife Occurrence and Abundance

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North Carolina State University

Richard B. Chandler
USGS Patuxent Wildlife Research Center

Abstract

Ecological research uses data collection techniques that are prone to substantial and unique types of measurement error to address scientific questions about species abundance and distribution. These data collection schemes include a number of survey methods in which unmarked individuals are counted, or determined to be present, at spatially-referenced sites. Examples include site occupancy sampling, repeated counts, distance sampling, removal sampling, and double observer sampling. To appropriately analyze these data, hierarchical models have been developed to separately model explanatory variables of both a latent abundance or occurrence process and a conditional detection process. Because these models have a straightforward interpretation paralleling mechanisms under which the data arose, they have recently gained immense popularity. The common hierarchical structure of these models is well-suited for a unified modeling interface. The R package **unmarked** provides such a unified modeling framework, including tools for data exploration, model fitting, model criticism, post-hoc analysis, and model comparison.

Keywords: ecological, wildlife, hierarchical, occupancy, occurrence, distance, point count.