Analysis of presence-type data

SSA 200

Presence only vs. Presence-absence data

Example 1: A National Park office often gets reports from people who have seen wolverines in the park. They keep track of the locations and dates of these sightings.

Presence only

Example 2: A researcher conducts point counts for birds in the same forest plot every month from May – July each year. During point counts they make an effort to detect and record every species within the survey window.

Presence-absence

Example 3: A natural history museum has plant specimens that contain information about the location and date of collection.

Presence only

Example 4: iNaturalist has over 29,000 recorded observations of Monarch butterflies from across their range dating back to 2009.

Presence only

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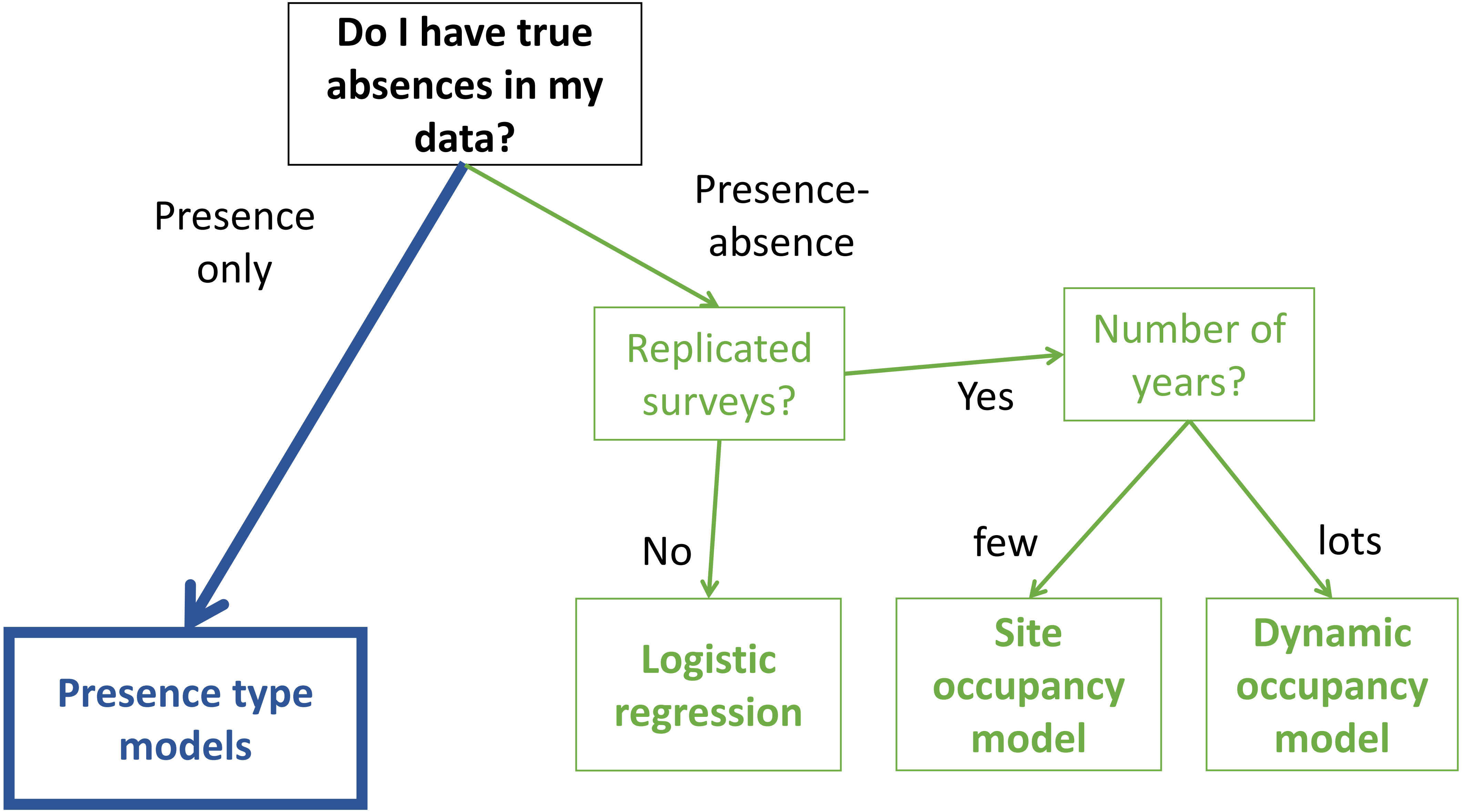


Always check specific model assumptions!

Presence only data

Example data sources

- Information about where/when a species was detected but NOT where/when it was looked for but not found
  - Opportunistic reporting by the public
  - Some eBird checklists (**complete checklists = presence-absence data*)
  - Historical records (e.g. museum specimens, field notes)
  - Others?

Example questions

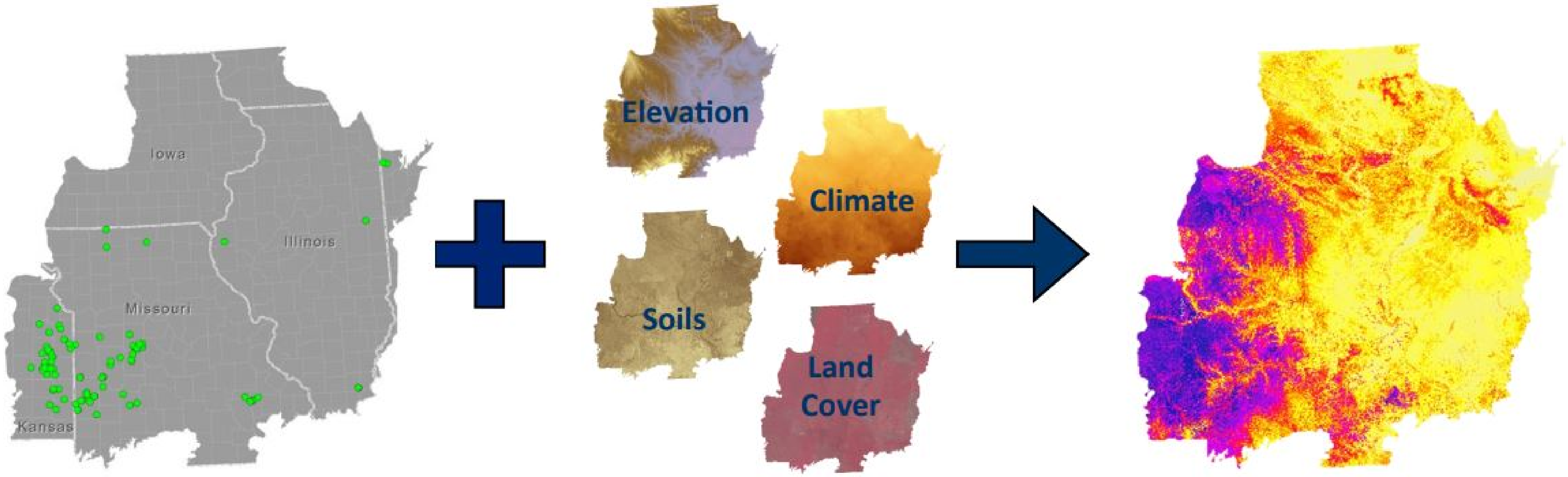
- Where is this species found? *(historic and current condition)*
- What ecological factors best predict its occurrence? *(ecological needs)*

Common analysis approaches

- Species Distribution Modeling
- Paired points

Species distribution modeling

- Habitat suitability models
- When your data covers a broad spatial scale/most of known range



Species Observation Points for *Asclepias Meadii, a threatened milkweed found in agricultural lands in the Midwest*

Examples of input layers used to characterize the environmental setting

Inputs

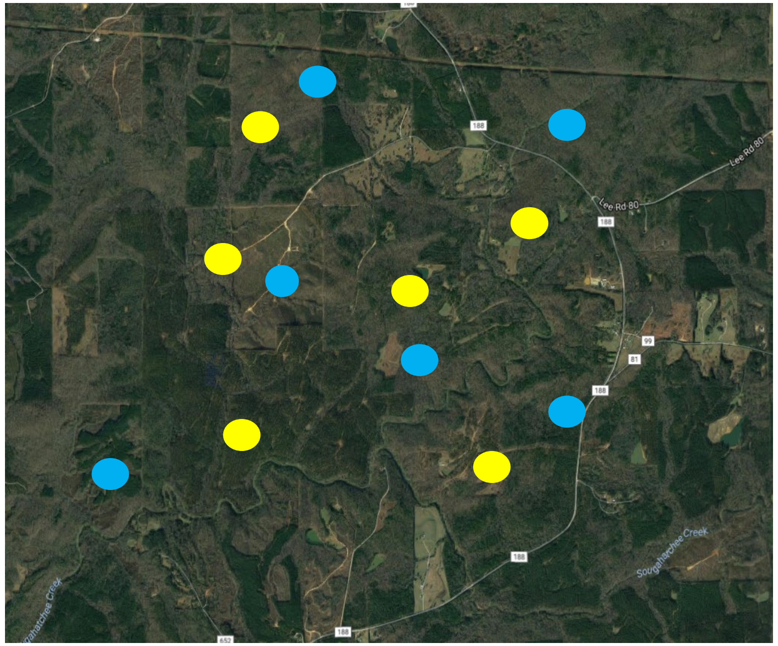
Outputs

Presence data models

Method(s)	Model/software name	Data type
Climatic envelope	BIOCLIM	Presence-only
Gower Metric	DOMAIN	Presence-only
Ecological Niche Factor Analysis (ENFA)	BIOMAPPER	Presence/background
Maximum Entropy	MAXENT	Presence/background
Genetic algorithm	GARP	Presence/pseudo-absence
Regression: Generalized linear model (GLM) and Generalized additive model (GAM)	GRASP	Presence/absence
Artificial Neural Network (ANN)	SPECIES	Presence/absence
Classification and regression trees (CART), GLM, GAM and ANN	BIOMOD	Presence/absence
Boosted decision trees	*(implemented in R)*	Presence/absence
Multivariate adaptive regression splines (MARS)	*(implemented in R)*	Presence/absence

Common analysis approaches

- Species Distribution Modeling
- Paired points – when you have a more limited spatial coverage of observations
    - Randomly select nearby points as “pseudo-absences” – places where the species could have been reported, but wasn’t



Enhance your data!

- Several methods to generate "pseudo-absences"
  - Entire range/study area
  - Within some specified distance of each observation
  - Constrained by environmental variables
- Place random points from the background around your observations
  - Points similar based on the climatic/biological datasets, but where no observation occurred

- Now you have a dataset of 0s and 1s – use logistic regression to estimate effects of environmental covariates

Logistic regression

- A type of **generalized linear model** where the *y* variable is drawn from the Binomial distribution
  - Response variable consists of 1s and 0s (“successes” and “failures”)
- Forms the basis for many more complex models
  - Occupancy analysis
  - Survival analysis
  - Resource selection
- **Assumes perfect detection of the species where it occurs**

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Some caveats about presence-only models*

- Temptation for overfitting
- Potential observation bias
- Be careful with extrapolation (both spatial and temporal)
- Omission & commission errors

**not just presence-only models, these apply to many different modeling cases!*

Some caveats about presence-only models

- Temptation for overfitting
  - The number of terms in the model should not exceed the number of observations
  - Consider ecologically-relevant environmental variables to include

Overfitting

Simpler

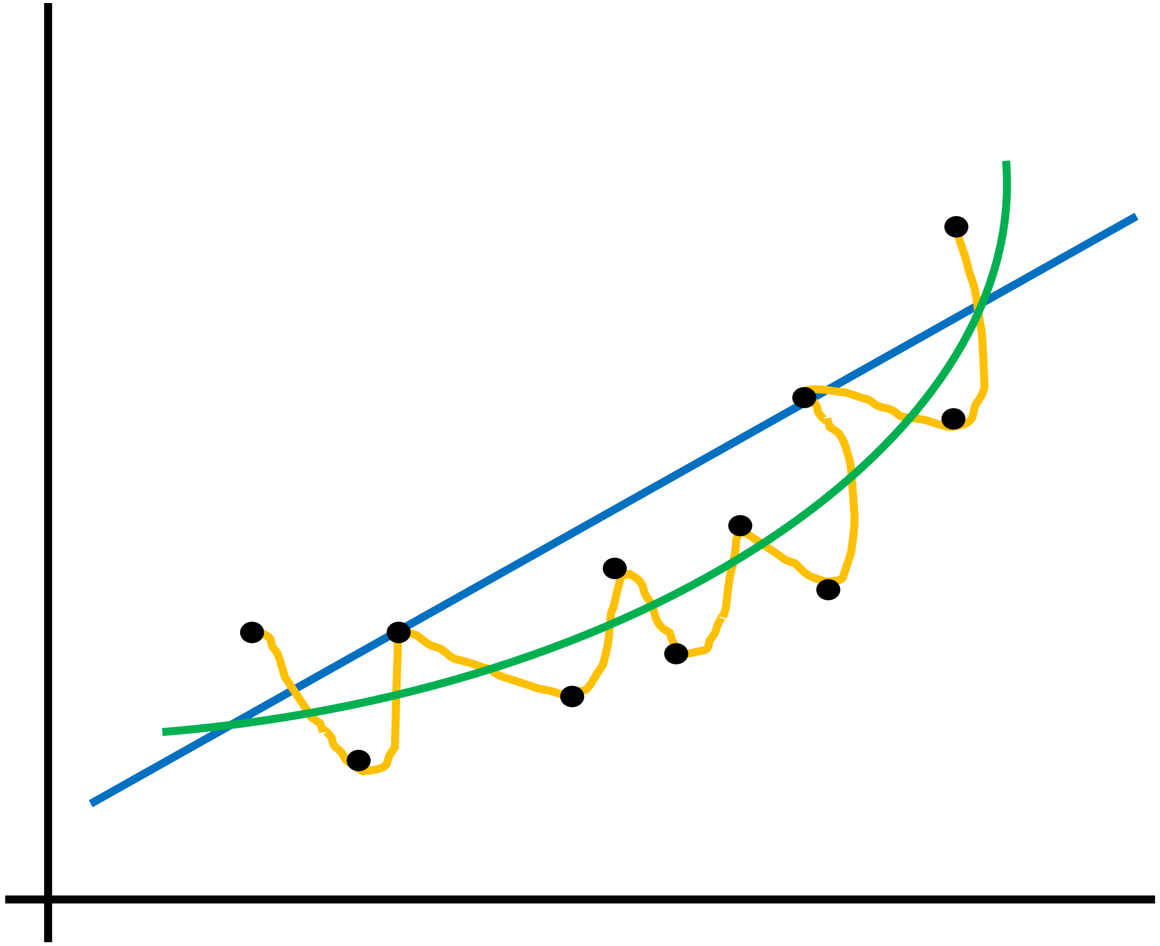
More complex

Worse fit

Best fit

More useful

Less useful



Overfitting

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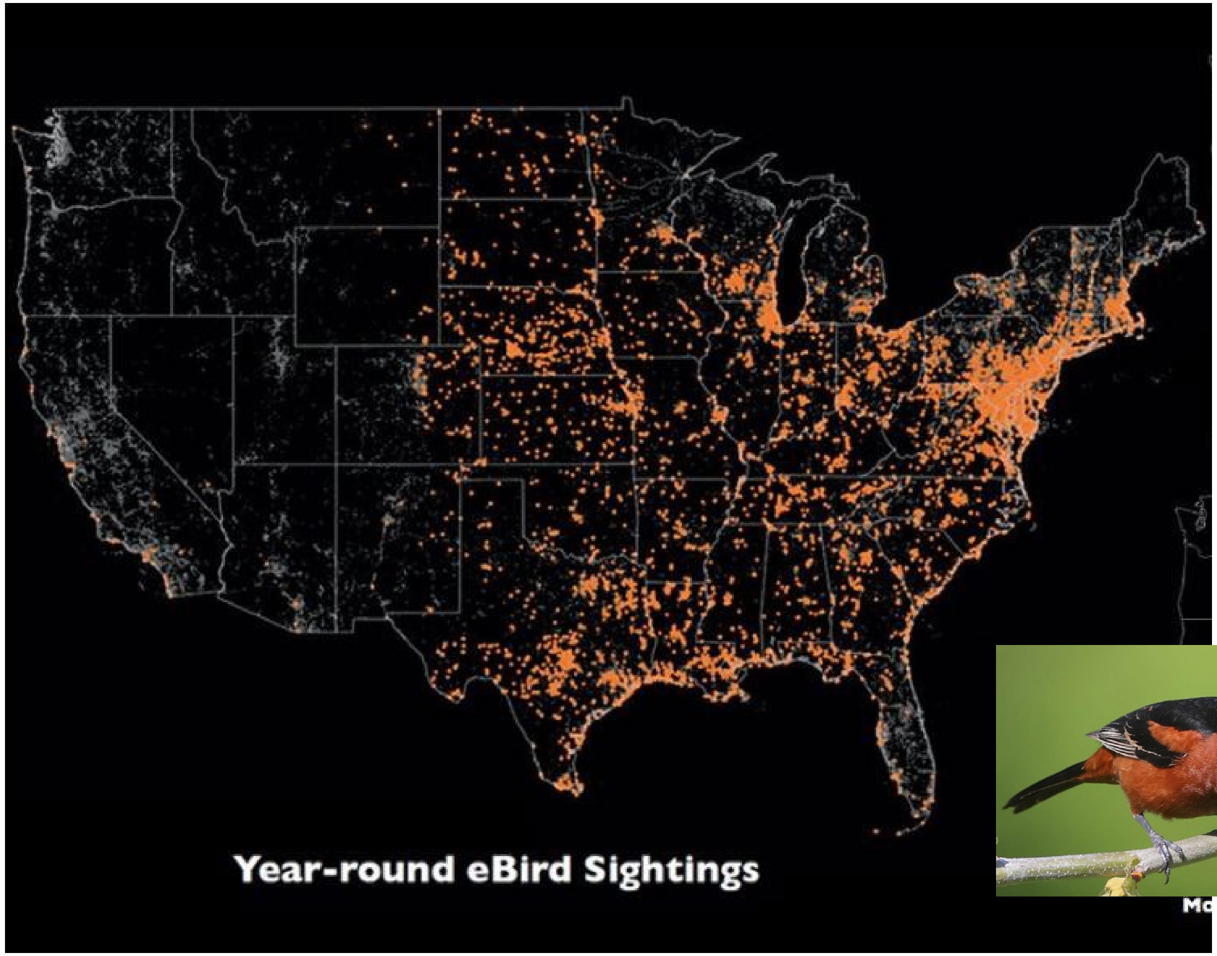
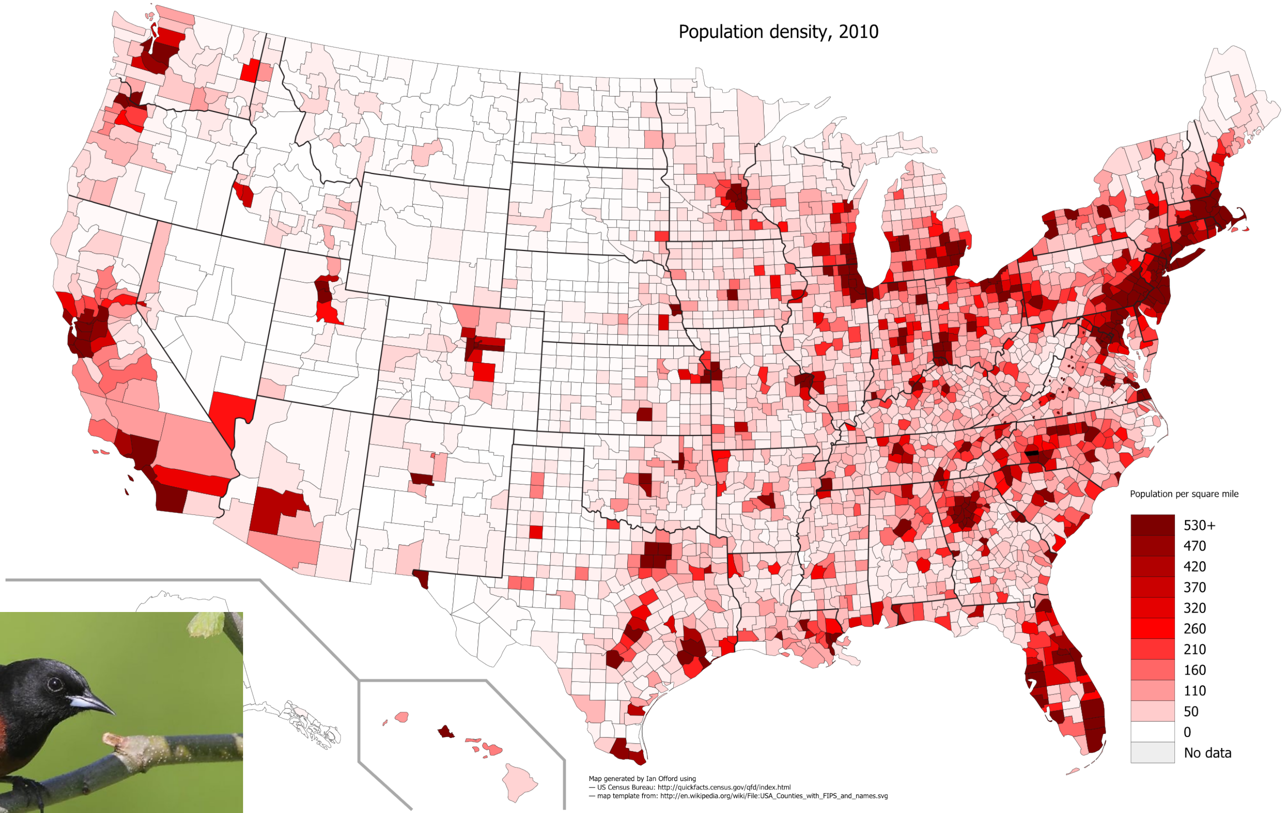
Some caveats about presence-only models

- Temptation for overfitting
- Potential observation bias

Observation bias





Population density, 2010 US Census

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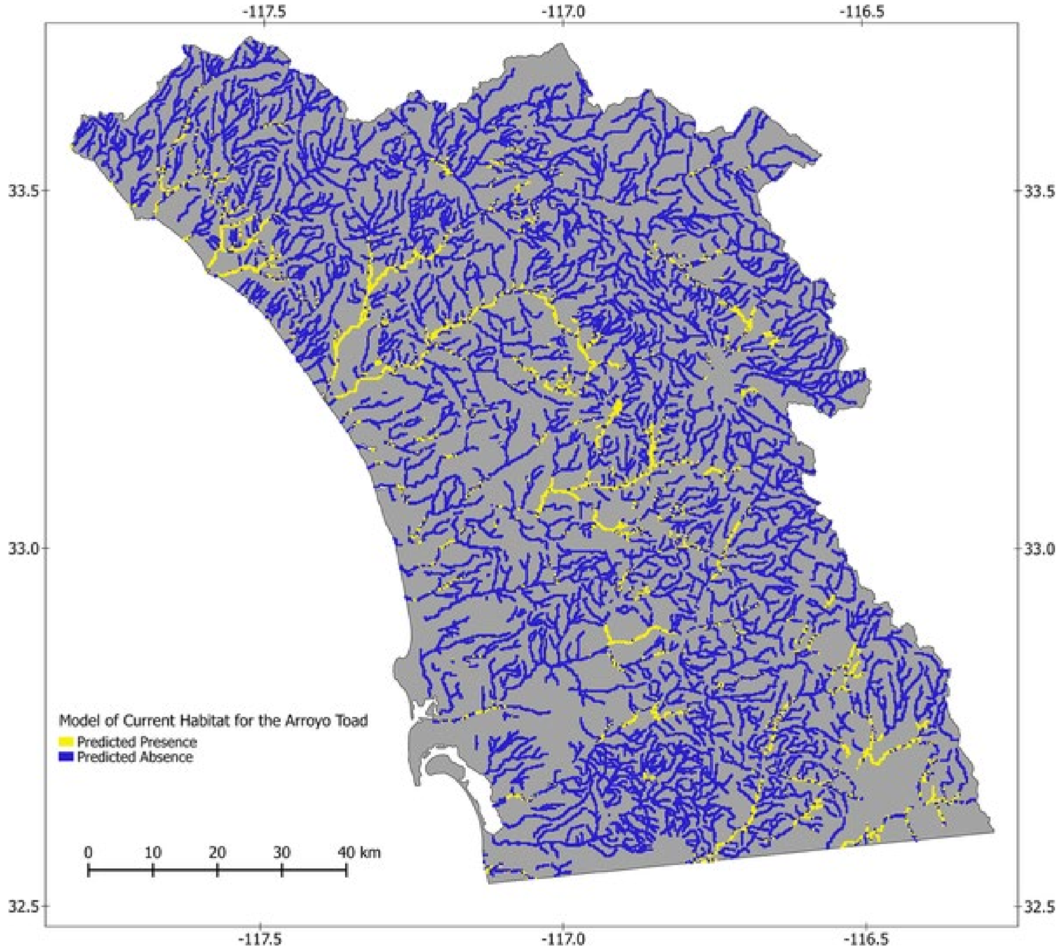
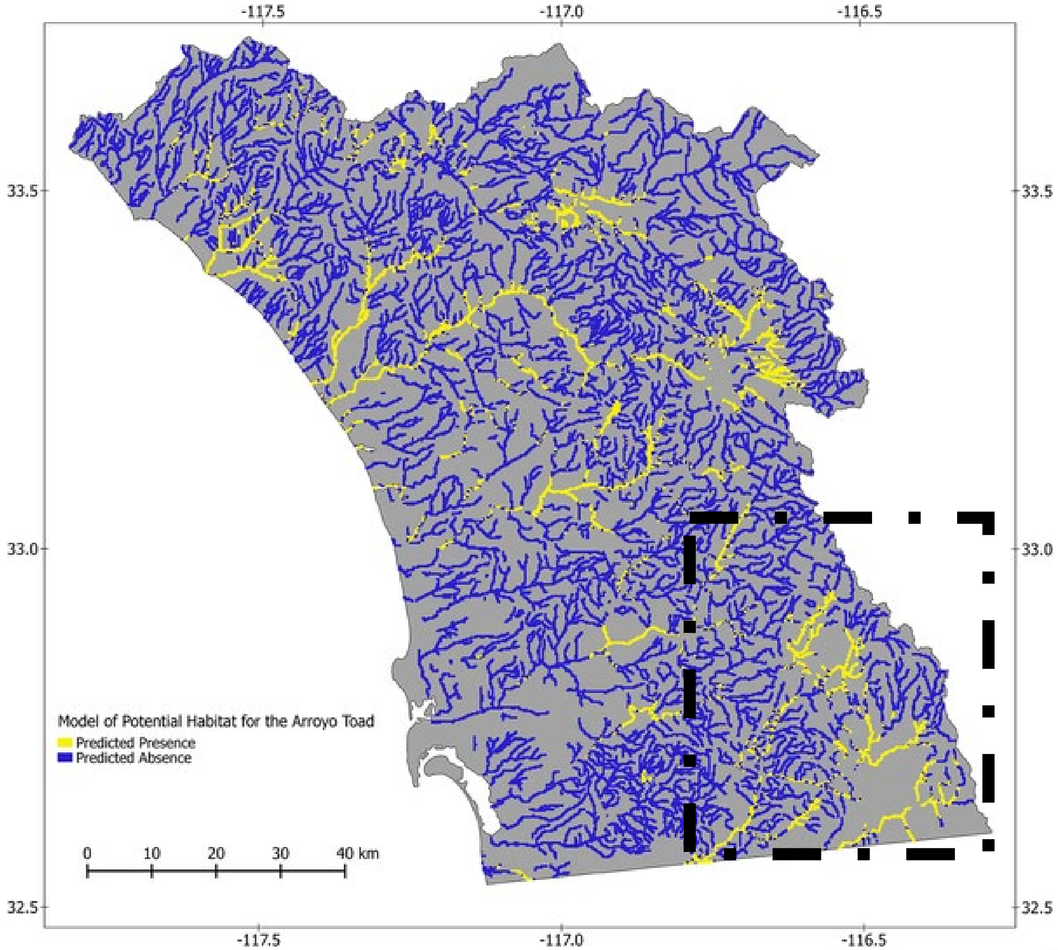
Some caveats about presence-only models

- Temptation for overfitting
- Potential observation bias
- Qualify any extrapolation you make
    - Potential translocation site, historic records from that area, etc.

Extrapolation





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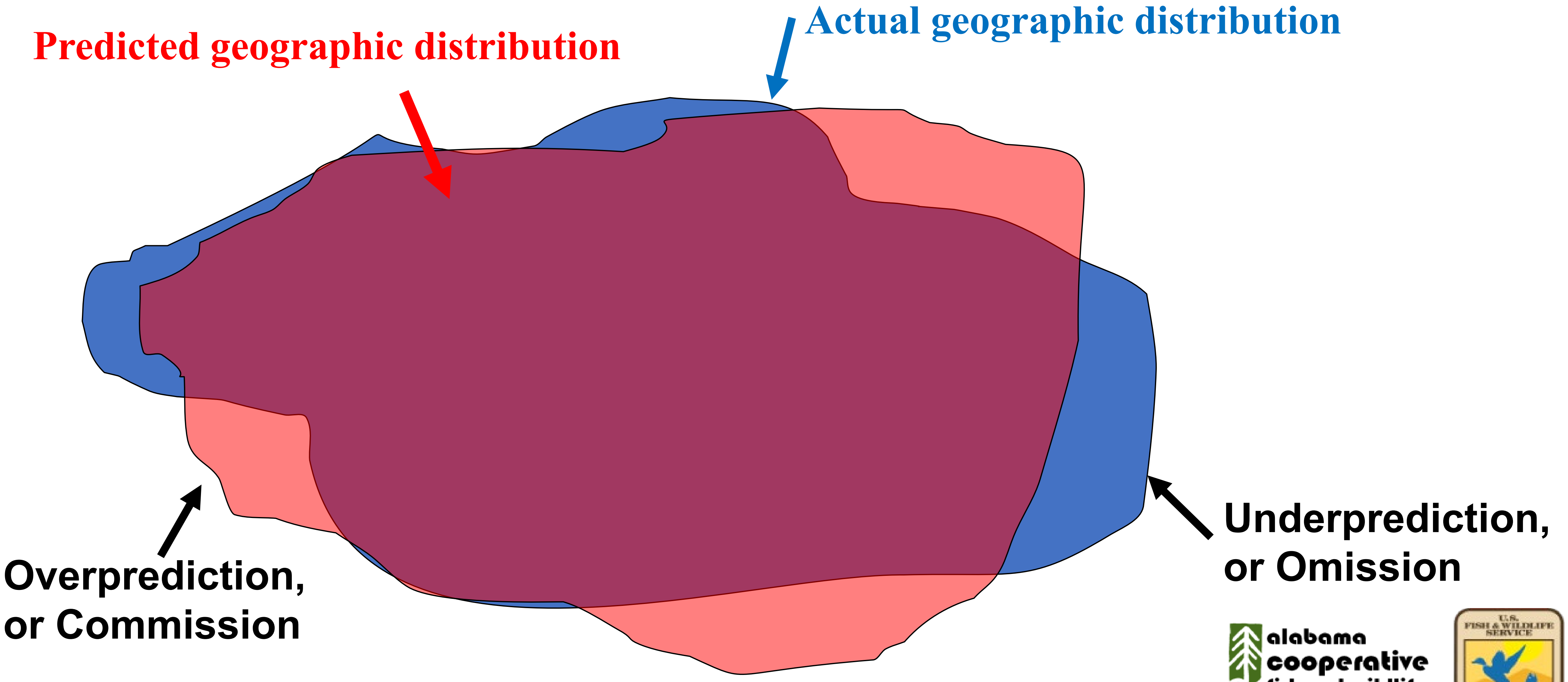
Some caveats about presence-only models

- Temptation for overfitting
- Potential observation bias
- Qualify extrapolation
- Omission & commission errors
    - Area Under the receiving operator Curve (AUC) used to score model omission/commission (AUC > 0.9 considered good)

Omission and commission errors



Presence-absence data

Example data sources

- Information about where/when a species was detected AND where/when it was looked for but not found
  - Transect surveys
  - Point counts
  - Any other systematic survey effort
  - Complete eBird checklists
  - Others?

Example research questions

- What habitat characteristics are associated with species presence and absence? *(ecological needs, stressors)*
- What is the distribution of a species in a given area? *(Representation, Redundancy)*
  - How has that distribution shifted over time? (e.g. due to habitat loss, invasive species, etc.)
- What is the extent of the species range?
- To what extent does this species co-occur with other species?
  - Species interactions, exclusion, etc.
- How many species are found in this area?

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Common analysis approaches

- Logistic regression
  - **Assumes perfect detection**

Common analysis approaches

- Logistic regression
- Site-occupancy models

When is occupancy analysis appropriate?

- Presence/absence data
- Multiple sites (*to estimate effects of ecological covariates*)
- Repeated visits in a **closed** period (*to estimate detection probability*)
    - Assume that true occupancy of a given site does not change between visits
    - Need to be collected within a short enough time-frame for this to be reasonable—depends on species of interest

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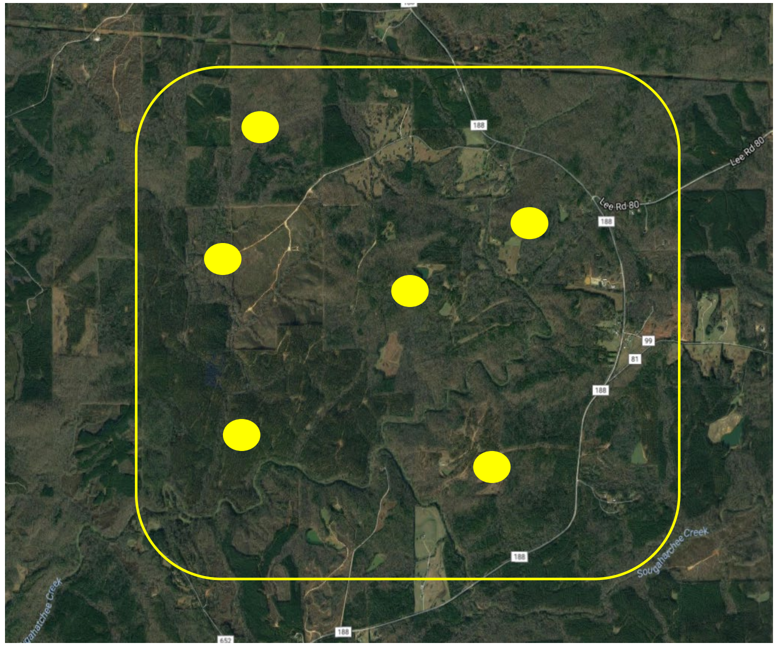
Sampling

- Replication is key
  - **Spatial** – multiple, randomly selected sites or sampling units within the area of interest
  - **Temporal** – repeated visits to each site



Visit 1

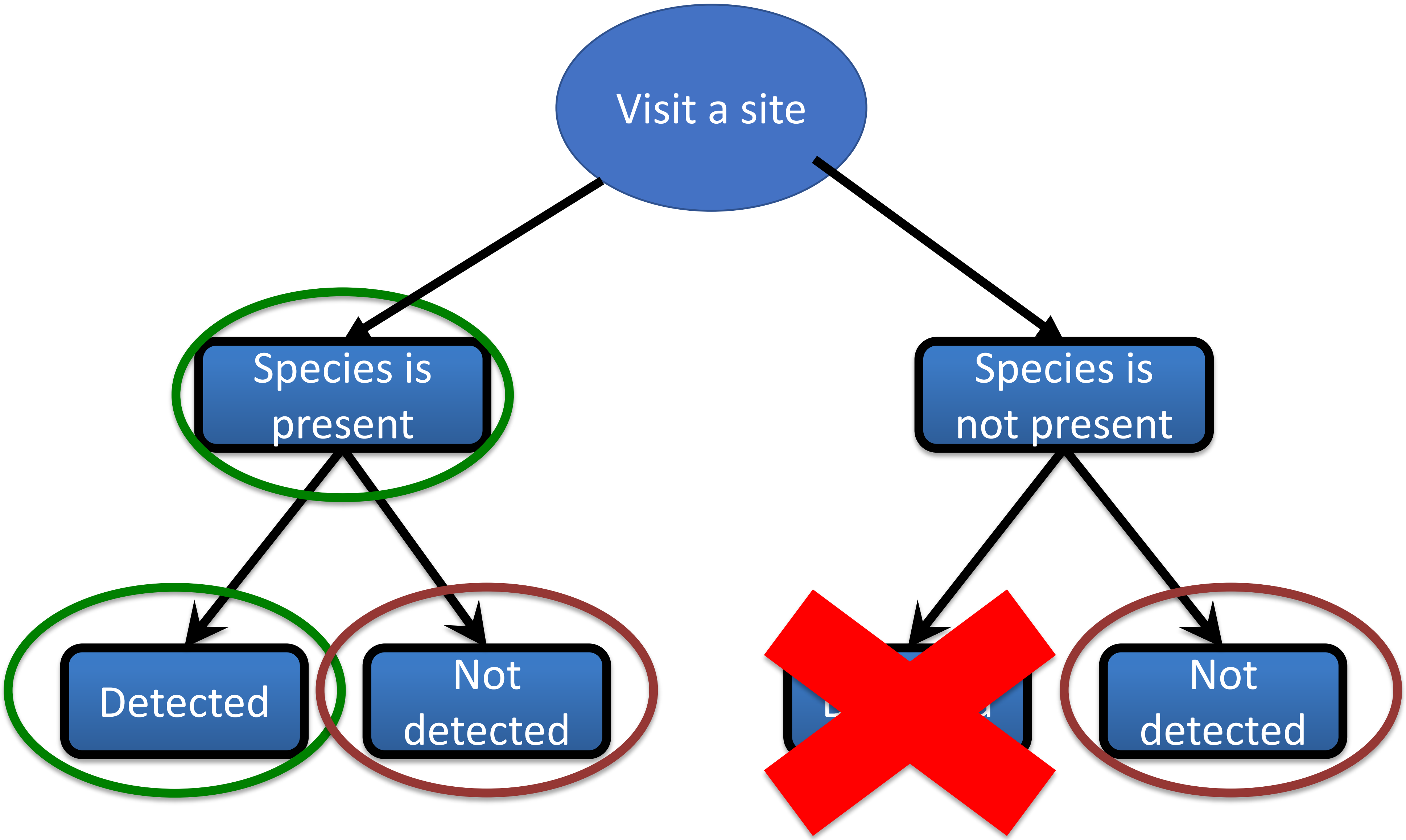
Visit 2

Visit 3

Example occupancy data set

Site	Date	Species detected?
A	6/27/2006	Yes
B	6/28/2006	Yes
C	6/25/2006	No
A	7/3/2006	No
B	7/5/2006	Yes
C	7/2/2006	No
A	7/12/2006	Yes
B	7/11/2006	Yes
C	7/13/2006	Yes

Site	Visit 1	Visit 2	Visit 3
A	1	0	1
B	1	1	1
C	0	0	1



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Site is **closed** during this time

True presence/absence of the species does not change

Site	Visit 1	Visit 2	Visit 3
A	1	0	1
B	1	1	0
C	0	1	1
D	0	0	0

Confirmed present

Likely absent?

$$\Pr(present|never\ detected) = (1 - 0.67)^3 = 0.04$$

Assumptions

- Sites are closed to changes in occupancy between sampling occasions
    - Appropriate duration between surveys
- Detection process is independent at each site
    - Appropriate distance between sites
- Both detection probability and occupancy probability are constant across all sites **OR** explained by covariates
    - For example, if we think rainfall influences our ability to detect the species, then rainfall should be included in the model

Model parameters

$\boldsymbol{\psi_i}$ = probability that site *i* is occupied

$\boldsymbol{p_{i,t}}$ = probability of detecting the species in site *i* at time *t*, given that the species is present

$\boldsymbol{\beta_k}$ = effect of covariate *k* on occupancy (or detection) probability

- Positive or negative?
- "significant" effect? – does the confidence interval contain 0?
- Importance of covariates often assessed by comparing models using AIC

* *Check text and captions for notation definitions within each paper – not always consistent!*

What influences occupancy probability?

- Potential stressors and threats included as **covariates**
  - Site characteristics (e.g. land cover, vegetation)
  - Weather (rainfall, temperature)
  - Distance to other occupied sites
  - … *etc.* …

- Effect of covariates often expressed as odds or odds ratios
  - Odds = how much more times as likely it is that a site is occupied for a one unit increase in the predictor

Parameter(predictor variables)

Relative support for each model (Relative to the model with the lowest AIC)
If ΔAIC > 2 then top model has the most support

Model weight – another way to assess relative support

Model	AIC	ΔAIC	Np	w_i
S(time) p(.)	684	0	5	0.98
S(.) p(.)	693	9	2	0.01
S(time) p(time)	698	14	10	0.01
S(time + sex) p(time)	710	26	12	0

Usually listed in decreasing order

Number of parameters (sometimes called *k*)

model (Table 2). Consistent with our predictions, this model indicated that per-visit detection probabilities were higher for conspecific surveys ($\hat{p} = 0.66$, SE = 0.03, 95% CI = 0.61–0.71) than for spotted owl surveys ($\hat{p} = 0.48$, SE = 0.04, 95% CI = 0.39–0.56) and that occupancy was positively influenced by the amount of public ownership in the sampling unit ($\beta = 4.67$, SE = 1.69, 95% CI = 1.36–8.00). Using single-visit estimates of detection probability from the best-supported model, the overall probability of

Table 2. Ranking of single-season occupancy models used to examine variation in the probability of detection (p) ar owls in western Oregon, USA, 2009.

Model[a]	No. parameters	AIC_c[b]	ΔAIC_c[b]
$\{\psi(\text{ownership})\ p(\text{survey type})\}$	4	776.28	0.00
$\{\psi(.)\ p(\text{survey type})\}$	3	782.48	6.20
$\{\psi(.)\ p(\text{stage + survey type})\}$	4	783.70	7.42
$\{\psi(\text{ownership})\ p(.)\}$	3	787.86	11.58
$\{\psi(.)\ p(\text{stage} \times \text{survey type})\}$	14	788.86	12.42
$\{\psi(.)\ p(t + \text{survey type})\}$	8	789.03	12.75
$\{\psi(.)\ p(.)\}$	2	793.14	16.86
$\{\psi(.)\ p(t \times \text{survey type})\}$	13	794.03	17.75
$\{\psi(.)\ p(\text{stage})\}$	3	794.86	18.58
$\{\psi(.)\ p(t + \text{stage})\}$	8	797.70	21.42
$\{\psi(.)\ p(t)\}$	7	799.72	23.44

Wiens et al 2011. Barred Owl Occupancy Surveys Within the Range of the Northern Spotted Owl. Journal of Wildlife Management

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Why estimate occupancy?

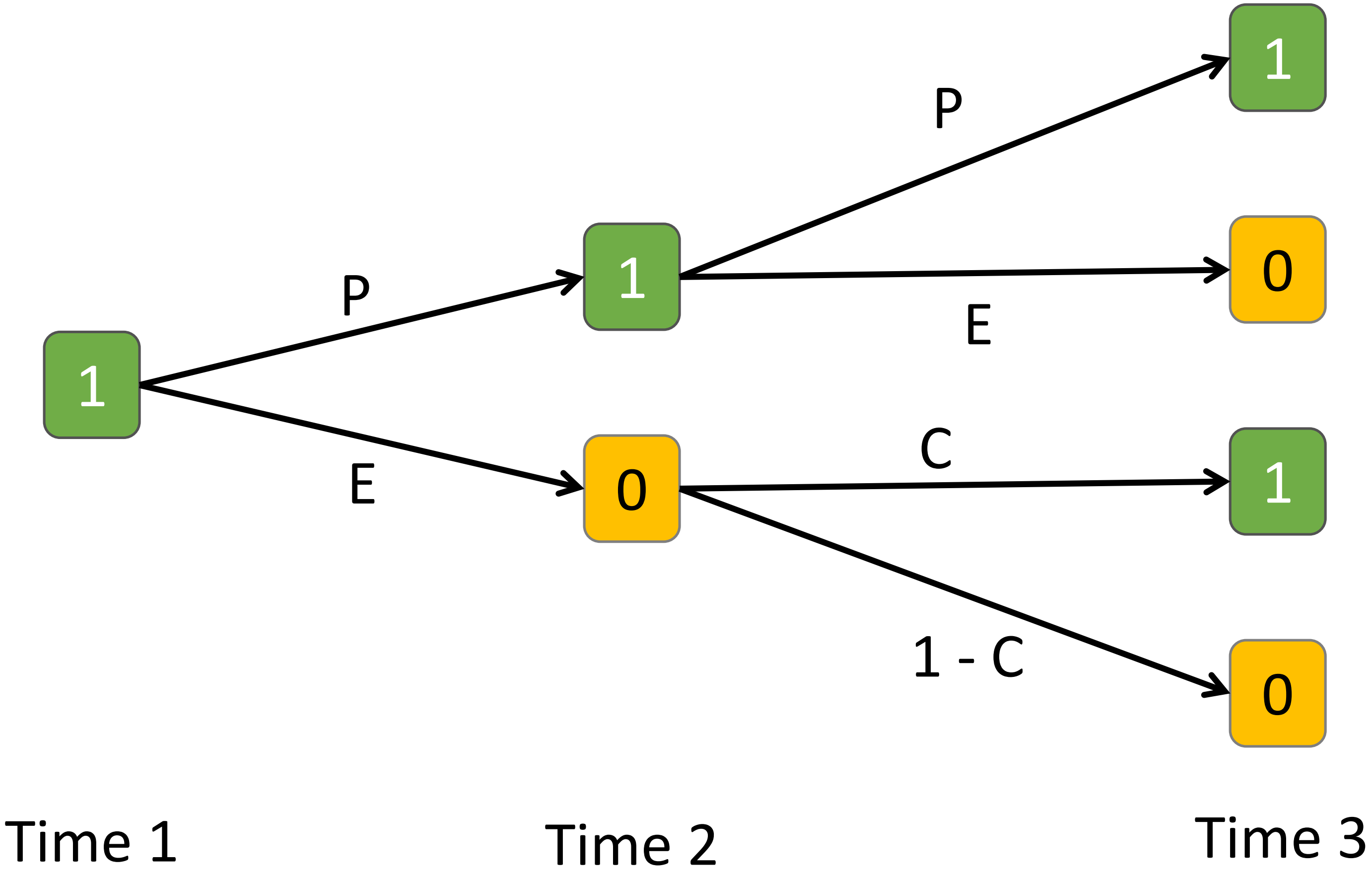
- Abundance can tell you more about species status, site use, and ecology
- More difficult to collect abundance data (time, money) and therefore often limited in spatial and/or temporal scope
- Presence/absence data is typically:
    - Less intensive to collect
    - Cheaper
    - Covers larger area/time scale
    - Can be more practical depending on objectives

Common analysis approaches

- Logistic regression
- Site-occupancy models
- Dynamic occupancy models

Dynamic occupancy models

- Estimate change in occupancy over time (colonization and extinction)



Dynamic occupancy models

	closed			*closed*			*closed*		
	Year 1			**Year 2**			**Year 3**		
Site	**Visit 1**	**Visit 2**	**Visit 3**	**Visit 1**	**Visit 2**	**Visit 3**	**Visit 1**	**Visit 2**	**Visit 3**
A	1	0	1	0	0	0	0	1	0
B	1	1	0	0	1	1	1	0	1
C	0	1	1	1	0	1	0	0	0
D	0	0	0	0	1	0	1	1	0

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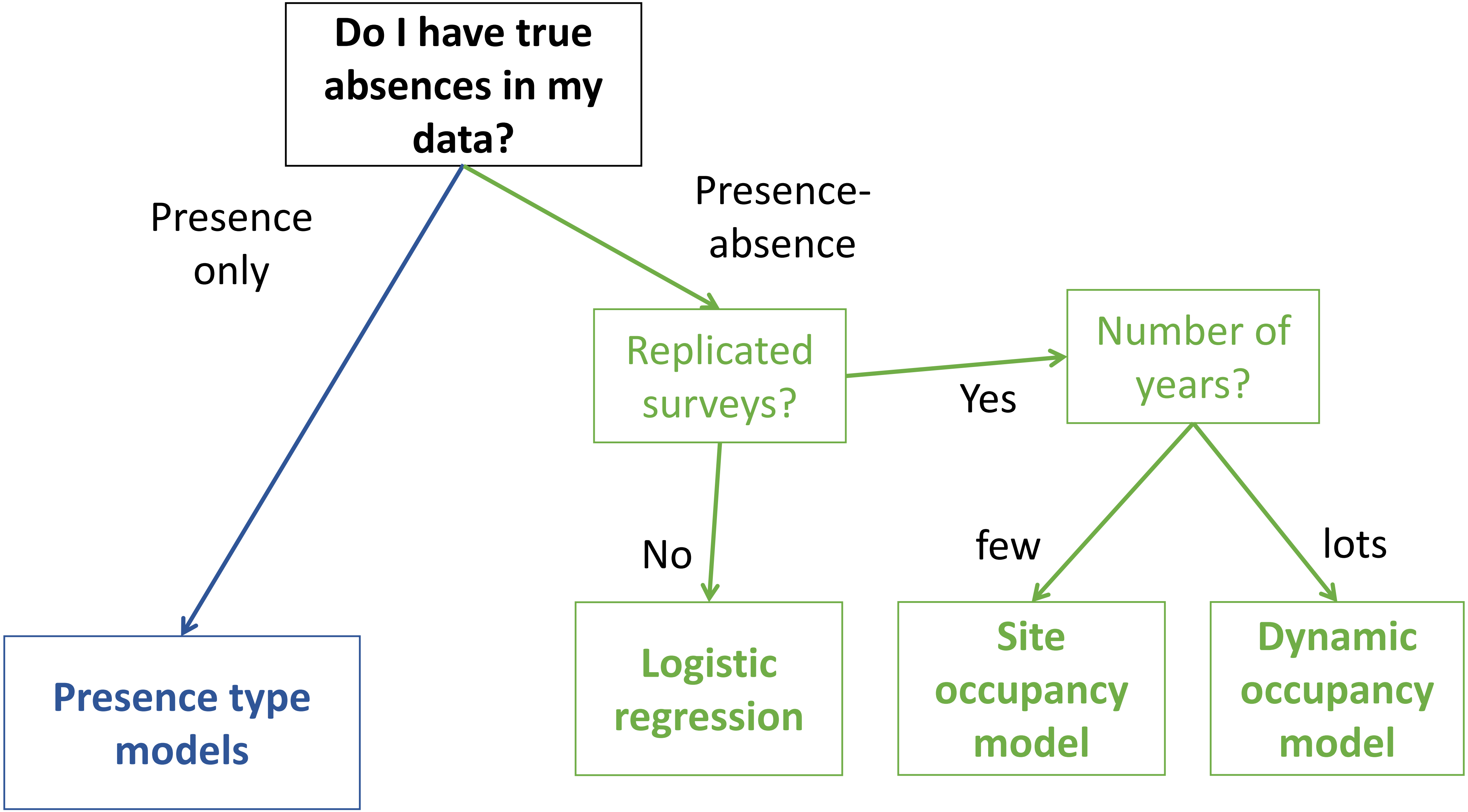
Common analysis approaches

- Logistic regression – *lacking spatial and/or temporal replication*
- Site-occupancy models – *single year, several sites*
- Dynamic occupancy models – *several years, several sites*

Account for imperfect detection

Assume detection is perfect



Always check specific model assumptions!