Estimating Burmese Python Abundance



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Project motivation

A need for demography estimates to study and evaluate control efforts

Traditional mark recapture programs not feasible or desirable

Detection probability extremely low

How can population size be estimated given current data streams?



Currently available data

What data do we have?

Number of snakes removed from SFWMD and FWC removal program

What data do we need for a model?

Survey effort

Survey locations

Methods



Currently available data

Contractor locations and effort

As of February 2021, ESRI's Survey123 app and 'MyTracks' feature used for contractor invoicing

Surveys must be linked to capture success and failure

Results





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Background

Methods

Discussio

An initial model

Starting simple

Starting with a specific site (EFST)* Assuming population closure No birth, death, or migration Short sampling period Beginning with February 2021

Everglades and Francis S. Taylor WMA Study Site

Modeling framework

Methods

Removal model using N-mixture framework

*Brandon Welty

Linking Burmese Python Ecology with Removal Efforts in the Everglades Session 42, 1:50pm

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Results

Analysis workflow

Processing data

4.1	site 🍦	date 🔷	effort_hours	captures	day 🍦
1	C2	2021-02-05	0.9958333	0	1
2	C3	2021-02-05	0.9041667	0	1
3	C4	2021-02-05	0.9602778	0	1
4	E5	2021-02-05	2.2980556	2	1
5	E6	2021-02-05	0.1844444	0	1

February 2021 data

30 sites with associated search effort, searched for 1-17 days

Sites searched 0.5 – 2.5 hrs per site per day

10 python captures

Results

N-mixture removal model

Observation process:

 $C_{i,t} \sim Binomial(N_{i,t}, p_{i,t})$ $logit(p_{i,t}) = \beta_0 + \beta_1 effort_{i,t}$

N_i, 1

$$(C_{i, 1})$$

detection (p_{i,1})
 $N_{i, 2}$
 $(C_{i, 2})$
 $(C_{i, 2})$
 $(C_{i, 2})$
 $(C_{i, 2})$
 $N_{i, 3}$

	site <i>i</i>	time <i>t</i>			
4	site 🍦	date 🔷	effort_hours	captures 🎈	day
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2	C3	2021-02-05	0.9041667	0	
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Underlying state process:

 $N_{i,t} \sim Poisson(\lambda)$ for t = 1

$$N_{i,t} = N_{i,t-1} - C_{i,t} \text{ for } t \ge 2$$

Estimating λ , β_0 , and β_1

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N-mixture removal model

Observation process:

 $C_{i,t} \sim Binomial(N_{i,t}, p_{i,t})$ $logit(p_{i,t}) = \beta_0 + \beta_1 effort_{i,t}$

Underlying state process:
$N_{i,t} \sim Poisson(\lambda)$ for $t = 1$
$N_{i,t} = N_{i,t-1} - C_{i,t} \text{ for } t \ge 2$
Estimating λ , β_0 , and β_1

	site <i>i</i>	time <i>t</i>					
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N-mixture model results

Method	Parameter	Mean	LCI	UCI
Bayesian	λ	1.977	0.723	2.411
Frequentist	λ	2.46	0.806	7.528
Bayesian	β_0	-4.761	-6.259	-4.195
	β_1	0.594	0.319	0.690
	p(1hr)	0.015	0.004	0.064
Frequentist	β_0	-5.005	-6.719	-3.291
	β_1	0.589	0.292	0.887
	p(1hr)	0.012	0.002	0.057

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Discussio

Preliminary Information-Subject to Revision. Not for Citation or Distribution

Incorporating movement

Distance sampling framework

 $p_i = p_0 \exp\left(-\frac{dist_i^2}{2\sigma^2}\right)$

Typically, σ is estimated and distance is known

Potential solution

Using Data Augmentation to estimate number of activity centers

Testing through simulation

Simulated data

100 individuals

5 sampling occasions with removal

Transect divided into 20 potential capture locations

Estimate abundance with and without an informative σ prior

Testing through simulation

Results

Estimated abundance approaches truth when informative σ prior is used

Next steps

Incorporate true space-use ecology of pythons in EFST

 H_{1} H_{2} H_{2

N posterior distribution (uninformed)

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Next steps

Additional covariates

Habitat covariates of density λ

Sex and breeding season covariates of movement $\boldsymbol{\sigma}$

Multiple closed periods

Expand model using 'Robust-Design' framework

Methods

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Discussion

Thank you!

Questions?

Data augmentation and distance

Data augmentation

M = number of potential individuals $z_i \sim Bernoulli(\psi), \qquad N = \sum_{i=1}^M z_i$

Distance

$$p_{i,t} = p_0 \exp\left(-\frac{dist_{i,t}^2}{2\sigma_i^2}\right) * z_i$$
$$c_{i,t} \sim Categorical(p_{i,t})$$

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Discussion

Data augmentation

M = number of potentia	ıl individuals
z _i ~Bernoulli(ψ),	$N = \sum_{i=1}^{M} z_i$

Distance

$$p_{i,t} = p_0 \exp\left(-\frac{dist_{i,t}^2}{2\sigma_i^2}\right) * z_i$$

 $c_{i,t} \sim Categorical(p_{i,t})$