

Demographic models

SSA 200

Applications to SSAs

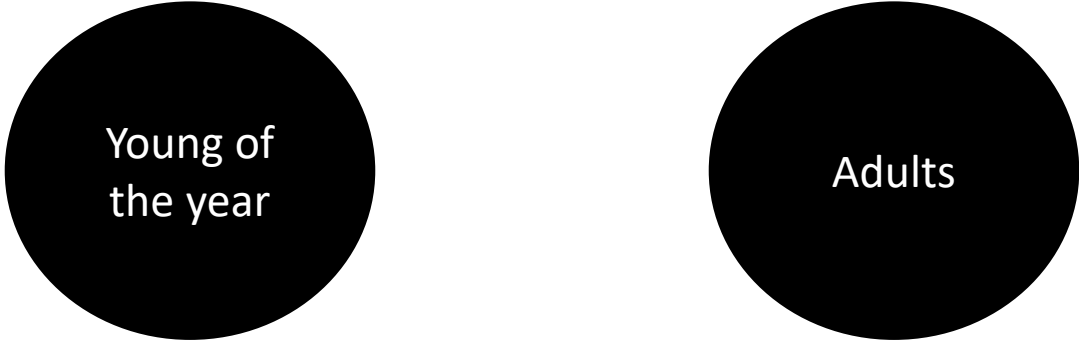
- Models are designed to output useful metrics on future resiliency and redundancy.
 - Metrics like future abundance, future extinction probability, future population growth rate
 - Output metrics are determined by available input data and what metrics will be most useful to decision makers
- Models allow us to predict future condition of the populations and characterize uncertainties in future condition.
 - We will focus on environmental variation and observation/parametric uncertainties

Lecture outline

- We will look at simple model construction
 - From conceptual to quantitative
- We will look at incorporating environmental covariates and density dependence
- We will look at parametric uncertainty

Conceptual model

- Two life stages
 - Adults
 - Young of the year

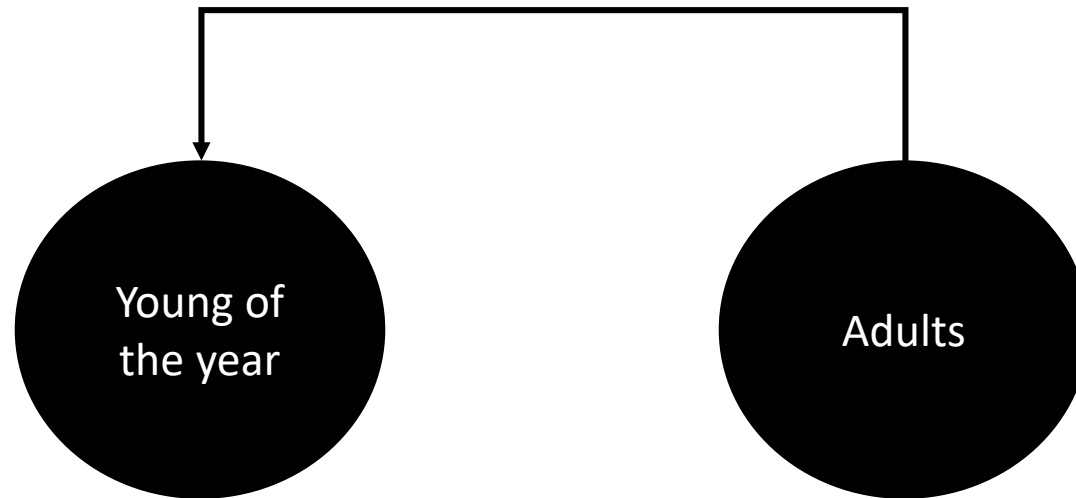


Young of
the year

Adults

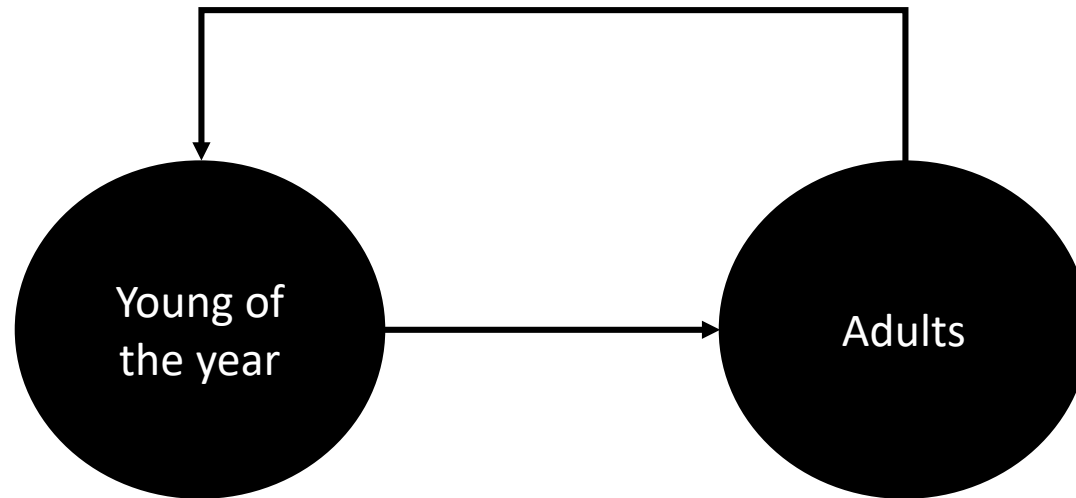
Conceptual model

- Adults reproduce



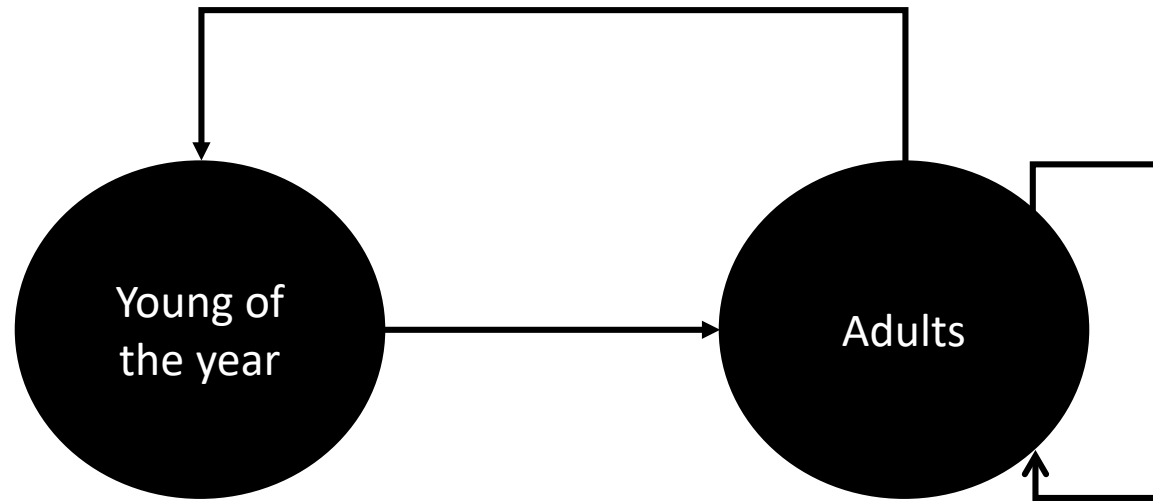
Conceptual model

- Young of the year survive and transition to adults



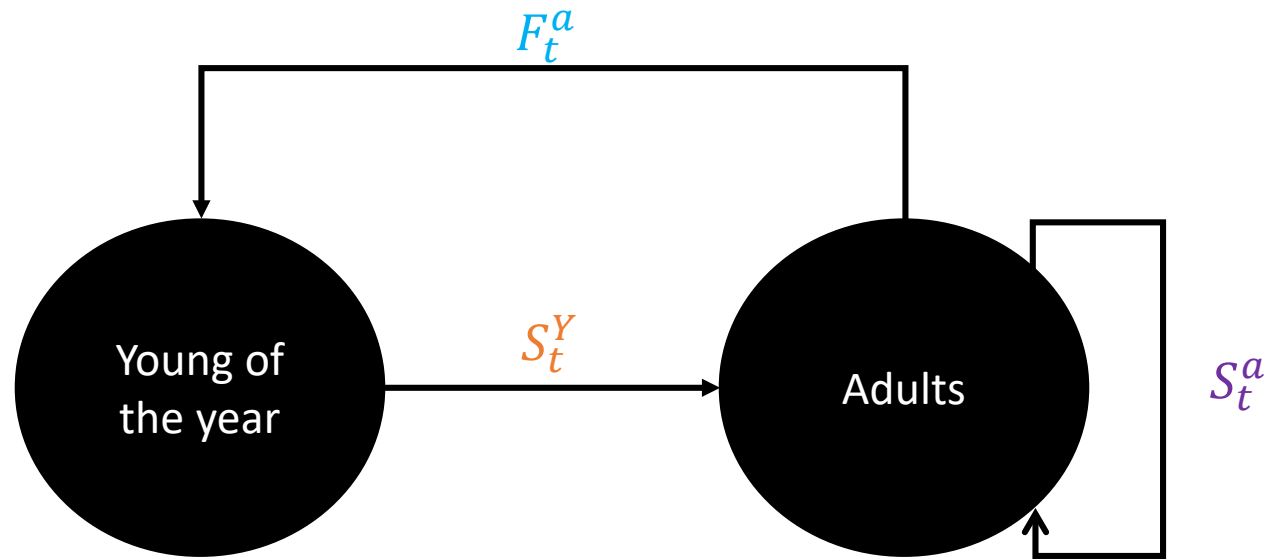
Conceptual model

- Adults survive and remain adults



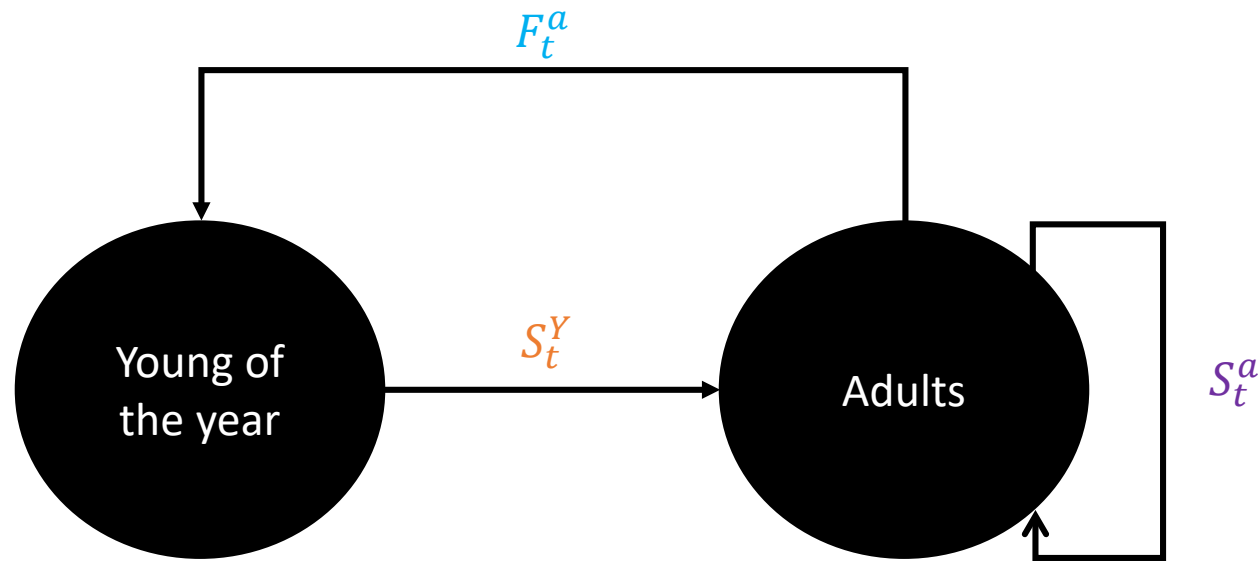
Quantitative model

$$N_{t+1}^a = N_t^a S_t^a + N_t^a F_t^a S_t^Y$$

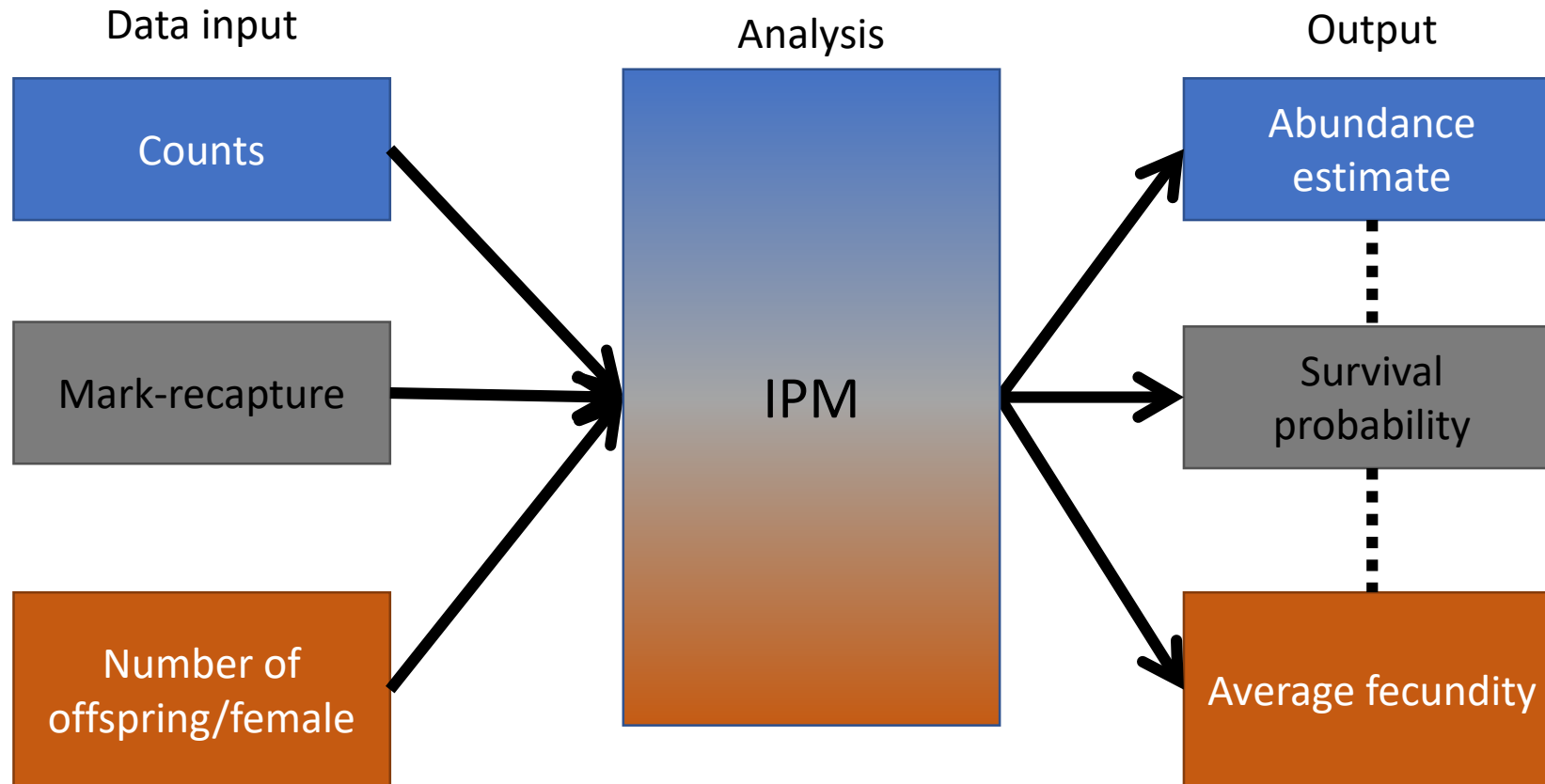


Matrix formulation

$$\begin{bmatrix} N_{t+1}^Y \\ N_{t+1}^a \end{bmatrix} = \begin{bmatrix} 0 & F_t^a \\ S_t^Y & S_t^a \end{bmatrix} \times \begin{bmatrix} N_t^Y \\ N_t^a \end{bmatrix}$$



Integrated population models



- IPM

- Combine demographic data with counts
- Use the model to make projections

Matrix projections

$$\begin{bmatrix} N_{t+1}^Y \\ N_{t+1}^a \end{bmatrix} = \begin{bmatrix} 0 & F_t^a \\ S_t^Y & S_t^a \end{bmatrix} \times \begin{bmatrix} N_t^Y \\ N_t^a \end{bmatrix}$$

$$N_{t+1} = A * N_t \quad \longleftrightarrow \quad N_{t+1} = \lambda * N_t$$

Sensitivity and elasticity

$$\begin{bmatrix} N_{t+1}^Y \\ N_{t+1}^A \end{bmatrix} = \begin{bmatrix} f_{1,1} & f_{1,2} \\ s_{2,1} & s_{2,2} \end{bmatrix} \times \begin{bmatrix} N_t^Y \\ N_t^A \end{bmatrix}$$

$$Sensitivity = \frac{\delta \lambda}{\delta s_{2,2}}$$

Sensitivity is the rate of change in population growth (λ) with respect to a change in any element of the matrix.

$$Elasticity = \frac{s_{2,2}}{\lambda} \frac{\delta \lambda}{\delta s_{2,2}}$$

Elasticity analysis estimates the effect of a **proportional** change in the demographic rates on population growth (λ).

How to estimate sensitivity and elasticity

- Program R – Package ‘PopBio’

Population matrix $\rightarrow \begin{bmatrix} 0 & F_t^A \\ S_t^Y & S_t^A \end{bmatrix} \rightarrow \begin{bmatrix} 0 & 1.2 \\ 0.3 & 0.8 \end{bmatrix}$

Sensitivity matrix $\rightarrow \begin{bmatrix} 0.222 & 0.208 \\ 0.832 & 0.777 \end{bmatrix}$

Elasticity matrix $\rightarrow \begin{bmatrix} 0 & 0.222 \\ 0.222 & 0.554 \end{bmatrix}$

Simple future condition assessments

- Using sensitivity and/or elasticity output
 - Results indicate population growth is most sensitive to **adult survival**
 - Conceptual modeling and literature review suggest that adult survival is negatively affected by drought frequency
 - Climate change predictions suggest that drought frequency will increase over the next 50 years
 - We therefore expect adult survival to decrease and in turn population growth will decrease
 - We conclude that if climate predictions are accurate, future resiliency will decrease

Forms of uncertainty

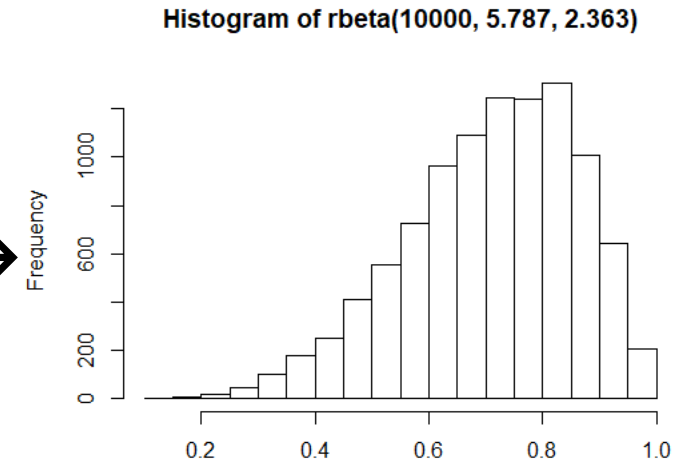
- Partial controllability
- Observational uncertainty
- Environmental variation
- Ecological uncertainty
- Demographic stochasticity

Incorporating uncertainty

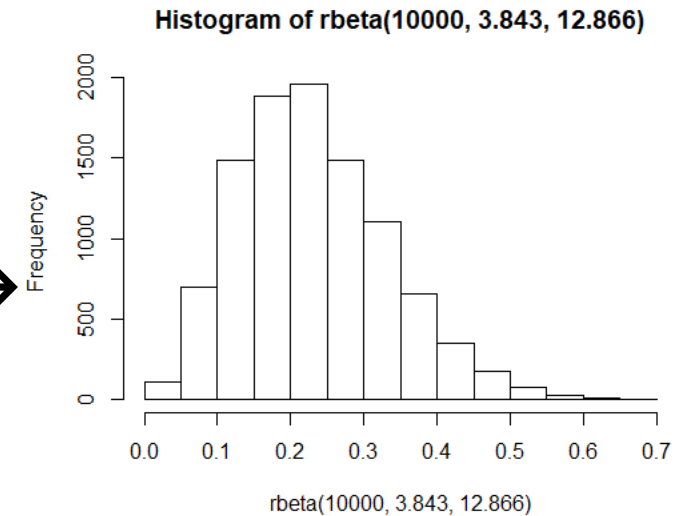
- Environmental stochasticity
 - Survival parameters typically drawn from a beta distribution
 - Convert estimated mean and variance to beta shape parameters
 - Continuous but restricted between 0 and 1
 - Really useful to species with high or low survival
 - Productivity parameters have two typical methods
 - Log-normal, bounded by 0 and infinity
 - Convert estimated mean and variance to log-normal distribution
 - Poisson distribution summed over all the individuals in the population

Survival rates

- $S = 0.71$, S.D. = 0.15 \rightarrow Beta1 = 5.787 Beta2 = 2.363 \rightarrow

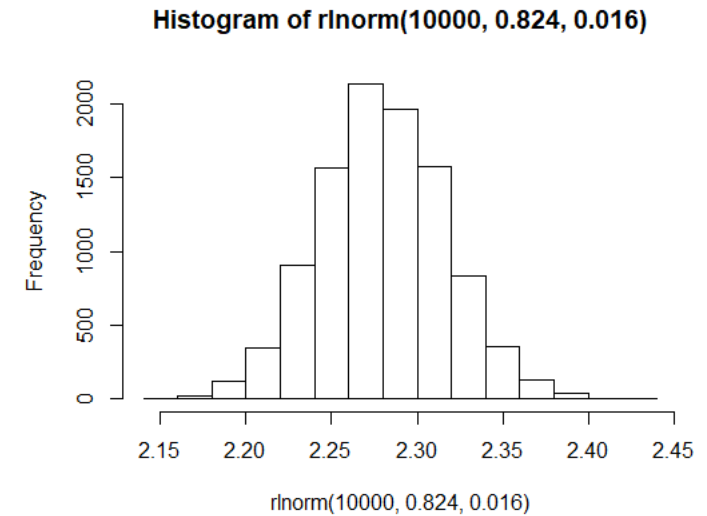


- $S = 0.23$, S.D. = 0.1 \rightarrow Beta1 = 3.843 Beta2 = 12.866 \rightarrow

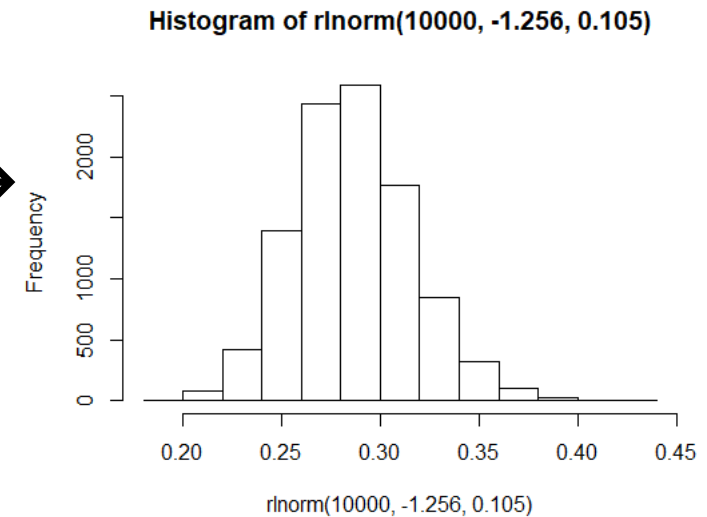


Productivity rates

- $F = 2.3$, S.d. = 0.3 \rightarrow $S1 = 0.824$, $S2 = 0.016 \rightarrow$



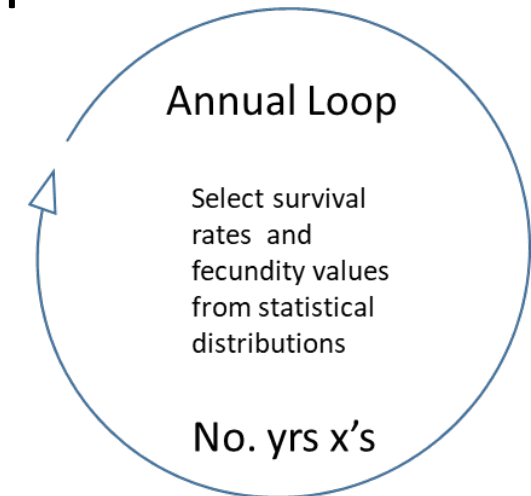
- $F = 0.3$, S.d. = 0.1 \rightarrow $S1 = -1.256$, $S2 = 0.105 \rightarrow$



For loops in simulation models

- Programmers utilize loop functions that tell a program to execute the following set of functions over and over again a specified number of times:

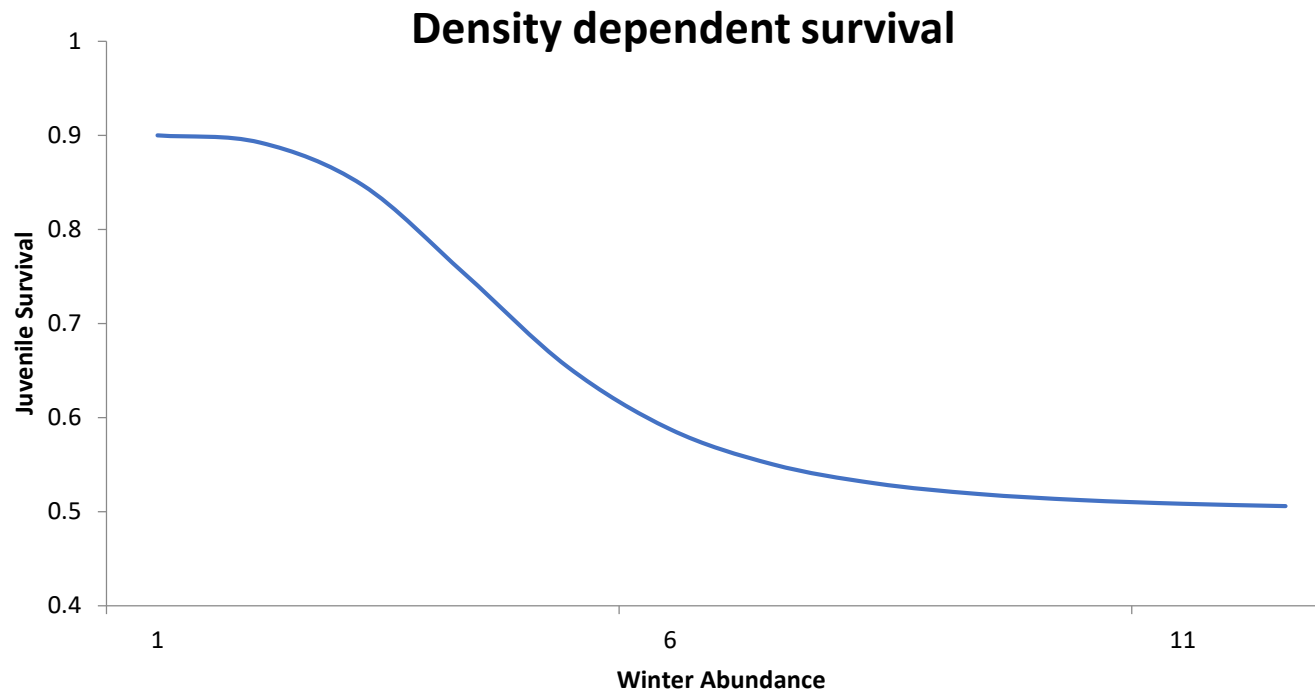
```
for(i in 1:1000){  
  #Tells the computer to repeat a function  
  #1000 times  
}
```



- With in those loops we can choose randomized parameter values and project populations
 - Typically use 2 loops to project time and replicate the simulations

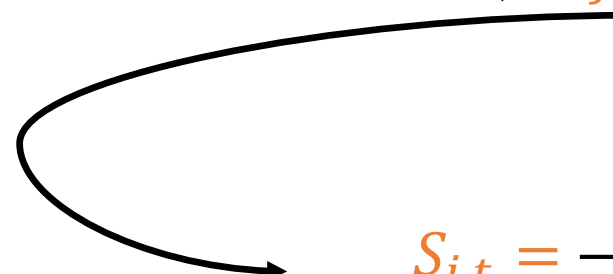
Density dependence

- Model parameters are a function of population density



Applying density dependence

- Incorporated a density dependent function on juvenile survival

$$N_{t+1} = N_t F_{A,t} S_{j,t} + N_t S_{a,t}$$

$$S_{j,t} = \frac{\exp(\alpha - \beta(N_t + N_t F_{A,t}))}{1 + \left(\exp(\alpha - \beta(N_t + N_t F_{A,t}))\right)}$$

Ceiling type density dependence

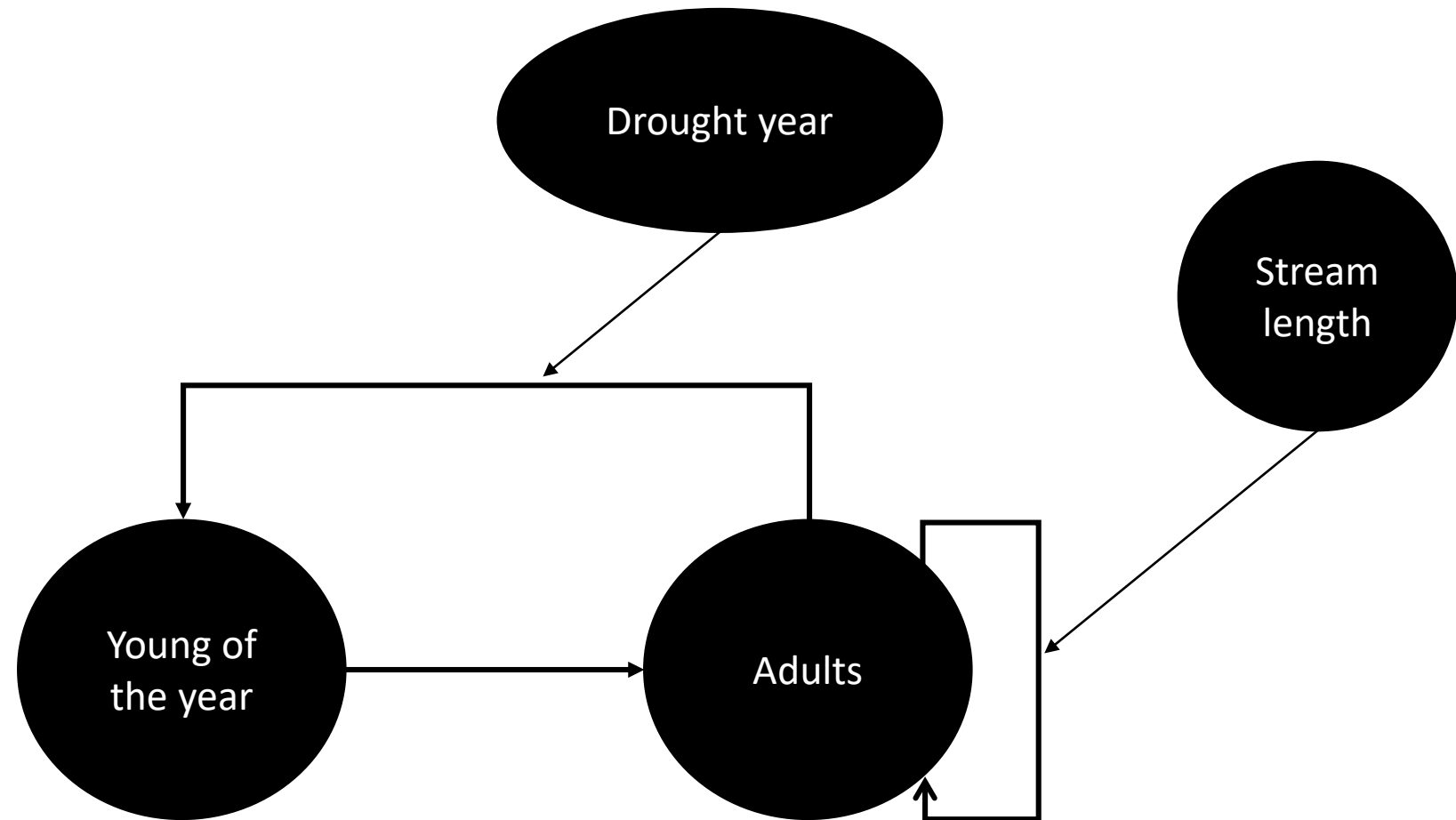
Threshold Density dependence

- “If the population exceeds a ceiling threshold, fecundity is equal to zero”
- if $(n[i,j] > n_{crit}) F[i,j] = 0$

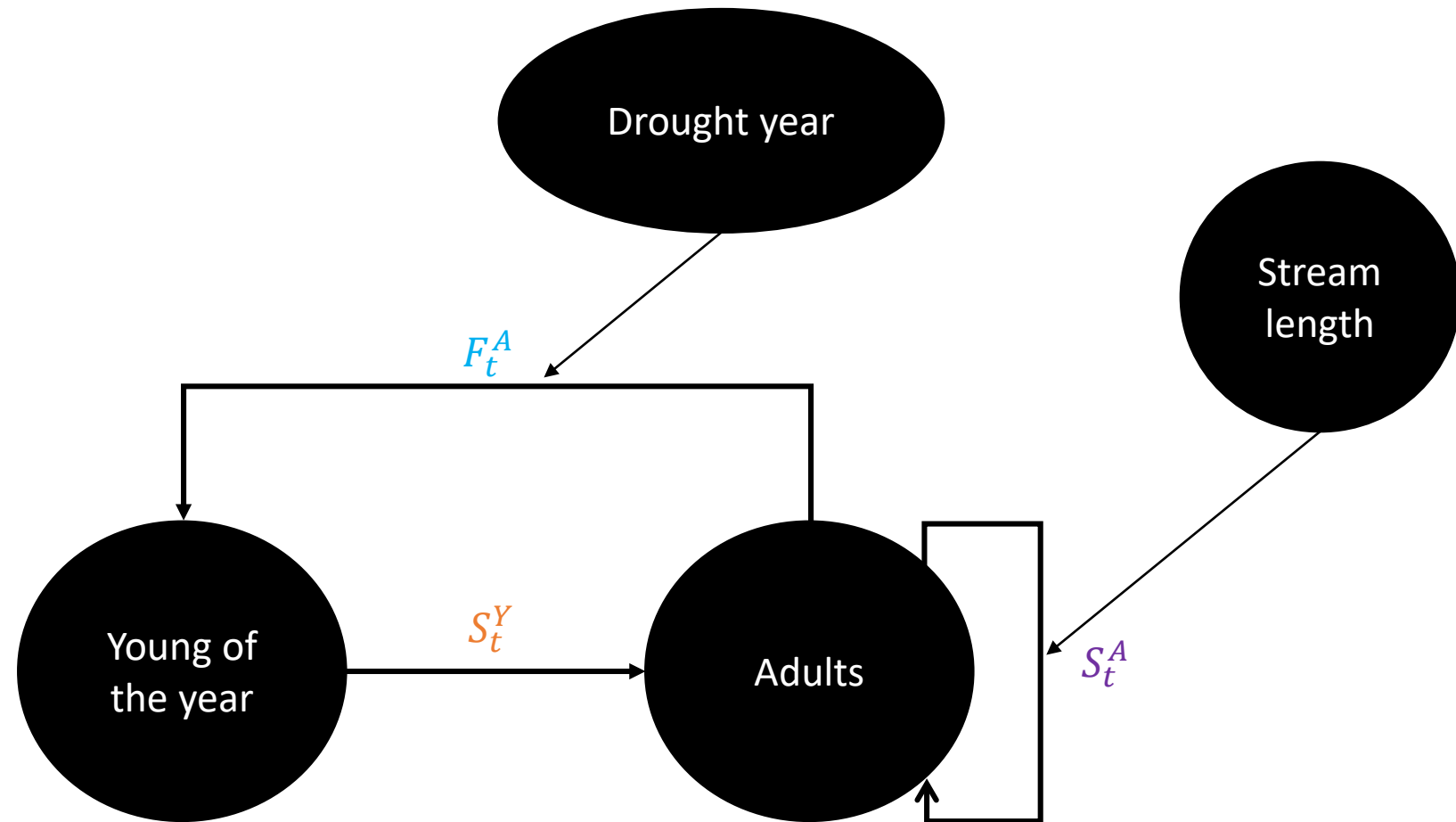
Or

- “As the population approaches some ceiling threshold, fecundity gets smaller and smaller”
- $F[i,j] = F[i,j] * (1 - n[i,j] / n_{crit})$

Conceptual models environmental effects



Quantitative model



Environmental covariates

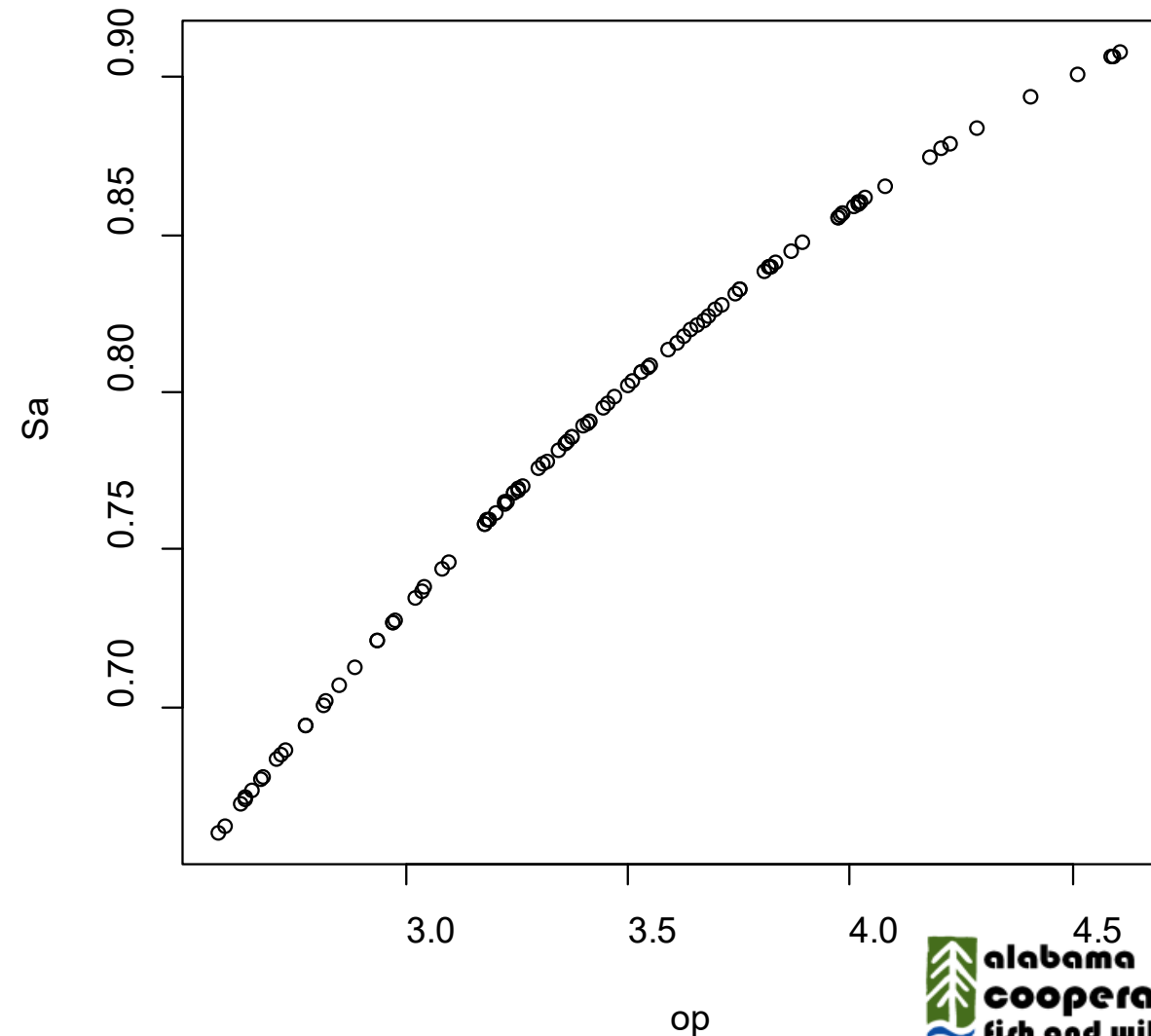
- Conditionally linked events:
 - Use “If→then” statements to link a demographic parameter to some other randomized event
 - E.g., if a Bernoulli trial for drought returns a 1, then mean fecundity is 1.1 offspring per female, but if it returns a 0 then mean fecundity is 2.3 offspring per female

Logit link for population parameters

- Based on logit link functions
- Correlation parameter estimates from survival estimates or occupancy analyses are on the logit scale
 - You can use the logit function to predict the survival rate for any give value of the measured covariates

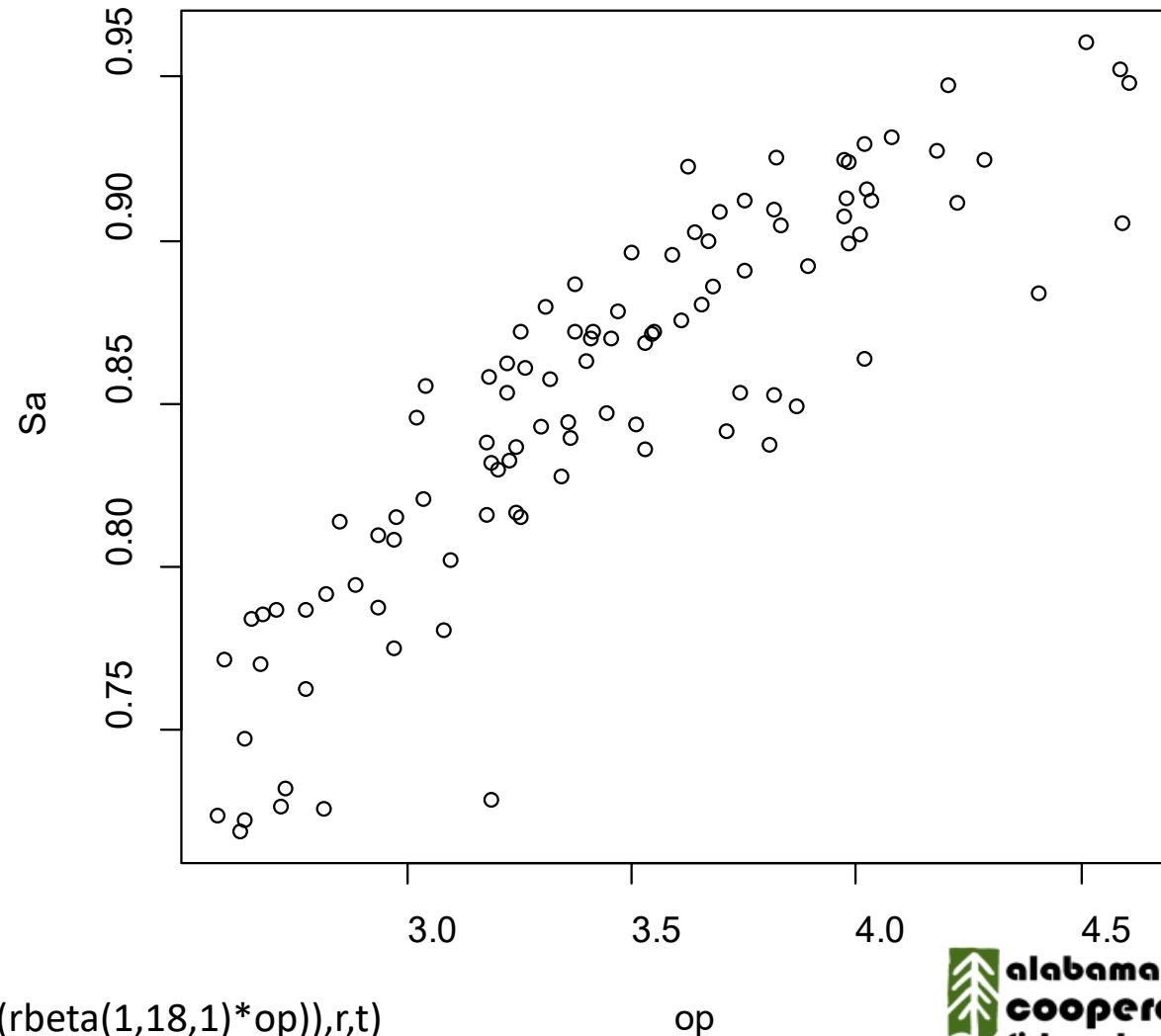
Environmental covariates

- Adult survival (S_a) can be a function of some other environmental parameter/variable
 - (“op” for other parameter, e.g., stream length)



Environmental covariates

- Adult survival (S_a) can be a function of “op” but it has variability



$S_a = \text{matrix}(\text{plogis}(-\text{rnorm}(1, 1.4, .1) + (\text{rbeta}(1, 18, 1) * \text{op})), r, t)$

Parametric uncertainty

- Parameters values are not precisely known
 - Variance or standard deviation estimates for parameters estimated over years conflate environmental variation with sampling variance
 - Sampling variance is the result of only using a specific number of individuals or locations to study a phenomenon
 - Happens with every wildlife study because we can't study every individual in every location

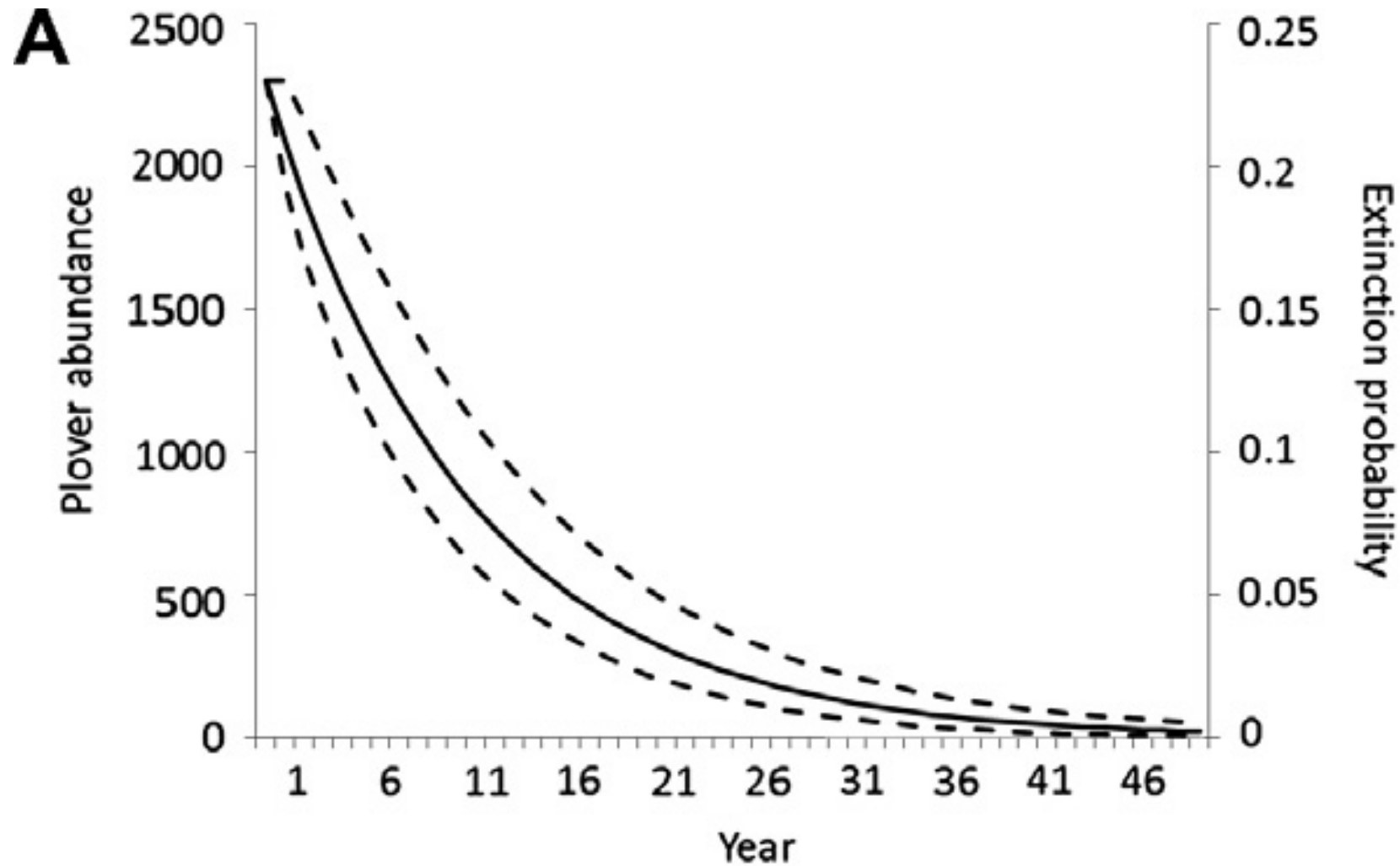
Methods to partition variance

- Link and Nichols, 1994, Oikos
- Gould and Nichols, 1998, Ecology
- $S^2 = \frac{1}{n-1} \sum_{i=1}^n (\hat{A}_i - \hat{\bar{A}})^2$
- $\hat{\tau}^2 = S^2 - \frac{1}{n} \sum_{i=1}^n [Var(\hat{A}_i)]$

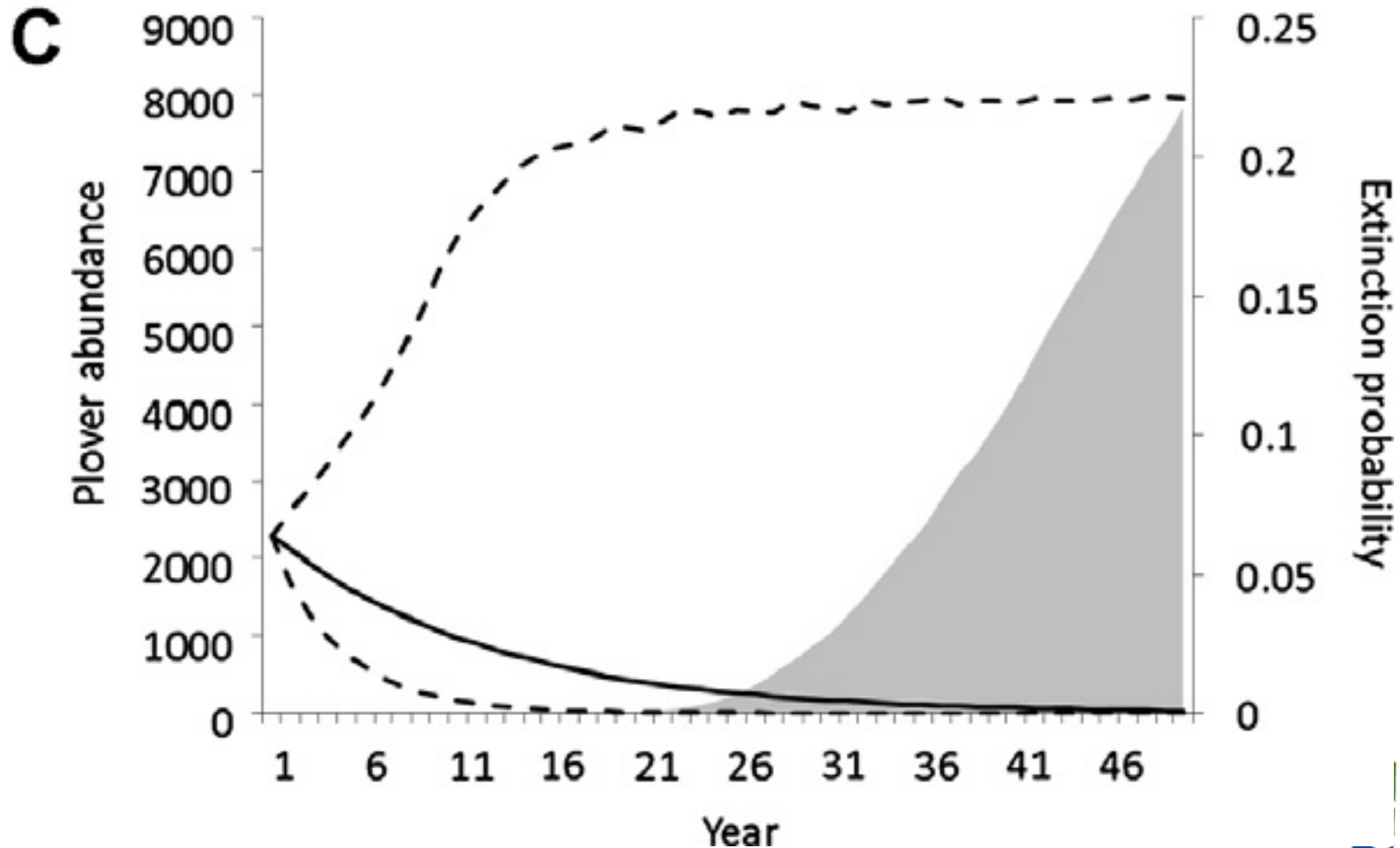
Great, so what do we do about it?

- Most models will discard sampling variance
- Not always a good idea!
 - Pretending that we know system parameters with precision
 - Less variation in the model predictions
 - Could affect assessment of management choices

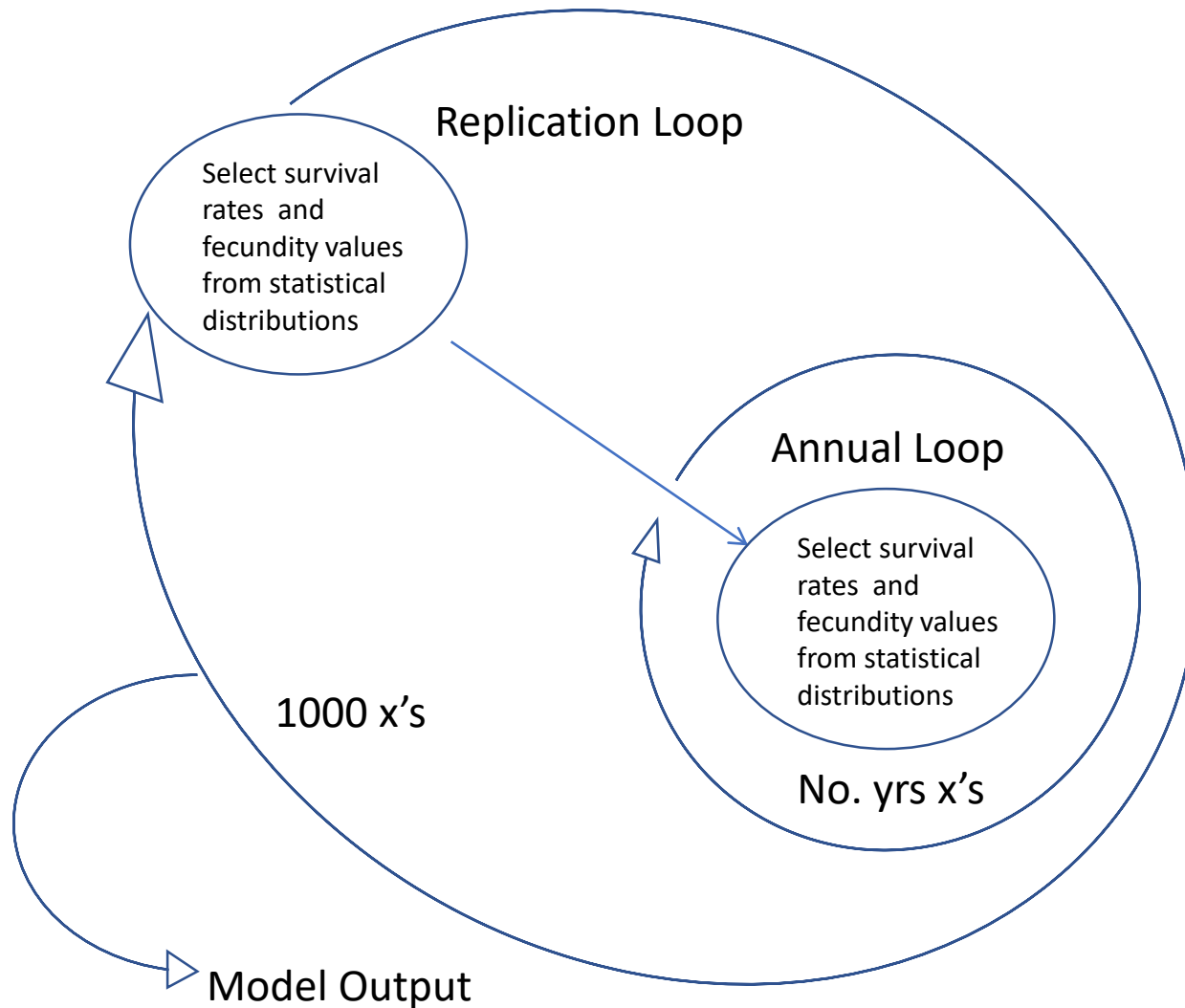
Projection without sampling variance



Projection with sampling variance

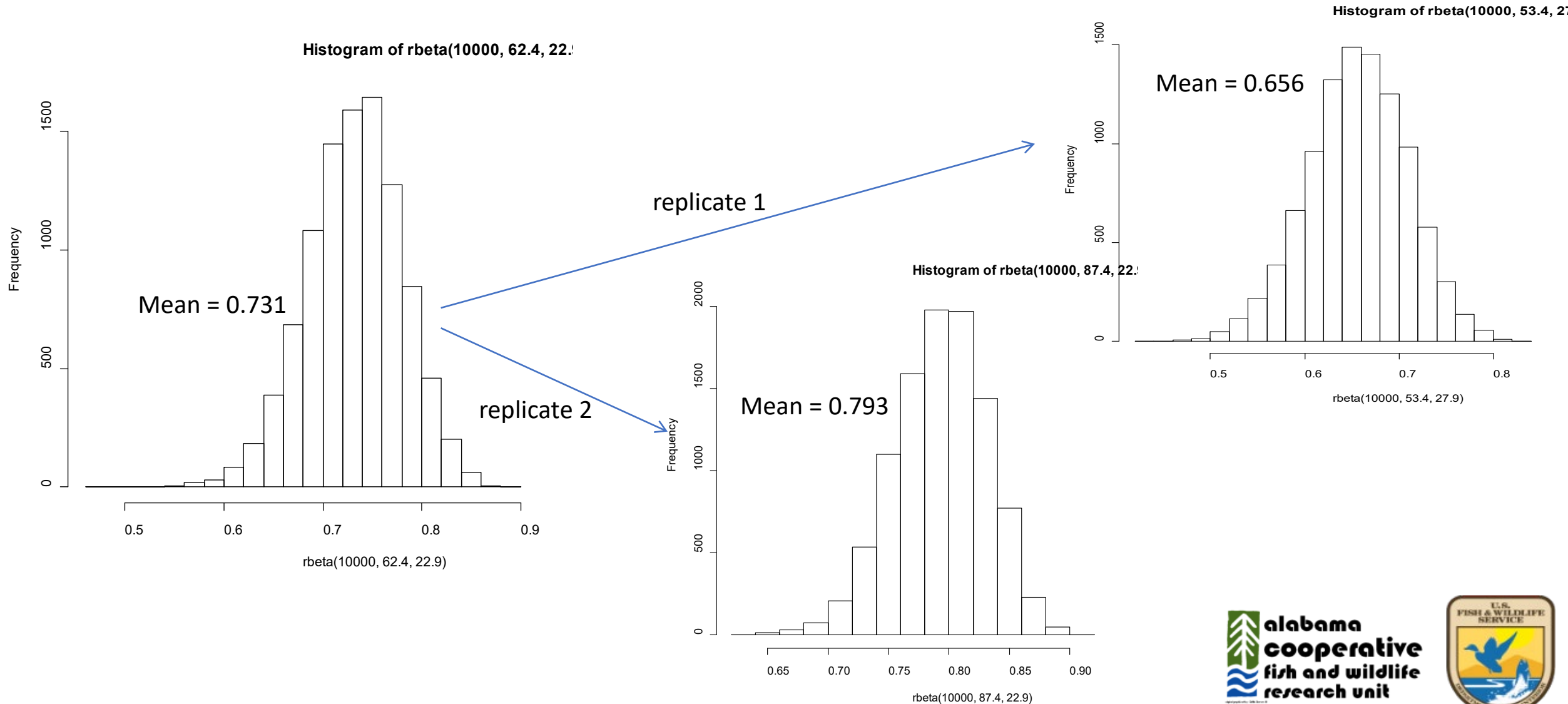


How do we model these uncertainties?



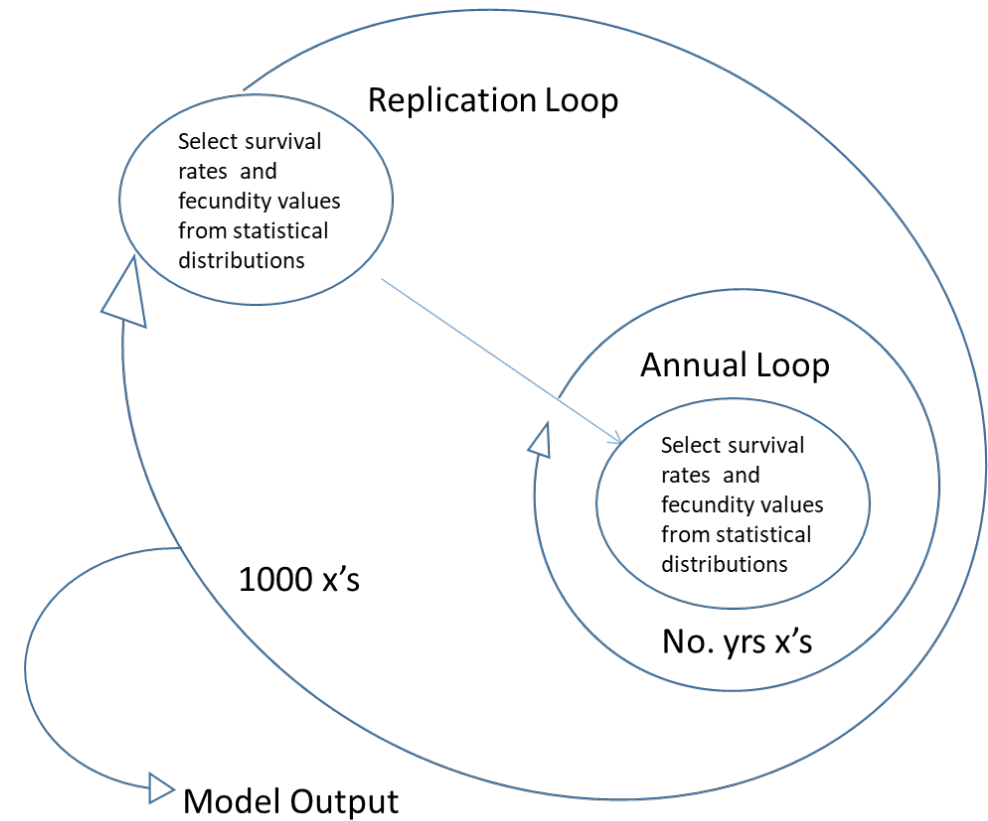
Hierarchical loop structure:
parametric and
environmental uncertainty

Modeling uncertainty in adult survival



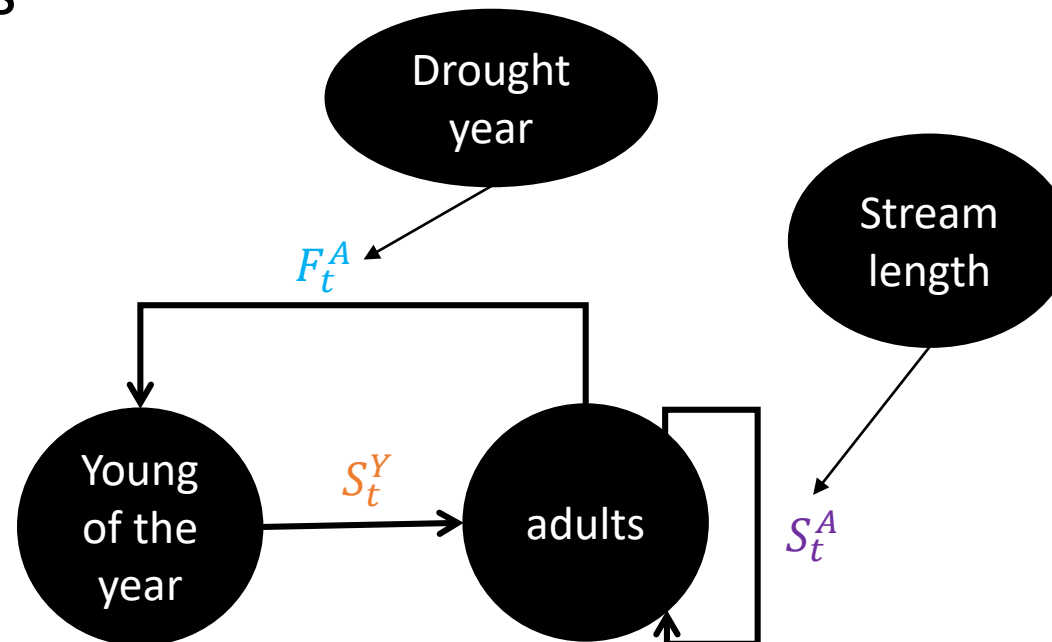
Double for loops

- for(i in 1:1000){
 - #Select mean parameter values a replicate
- for(j in 1:50){
 - #Select values for each year until you reach 50 years then move on to
 - #the next replicate
- }
- #save and summarize output from a replicate until you reach 1000 #replicates
- }



Inputting scenarios

- Use the conceptual model and sensitivity analysis to guide scenarios
 - i.e., what ecological facts affect the most sensitive parameters?
- Design scenarios to explore the expected range of future variation in important covariates



Using this structure to build GLMs

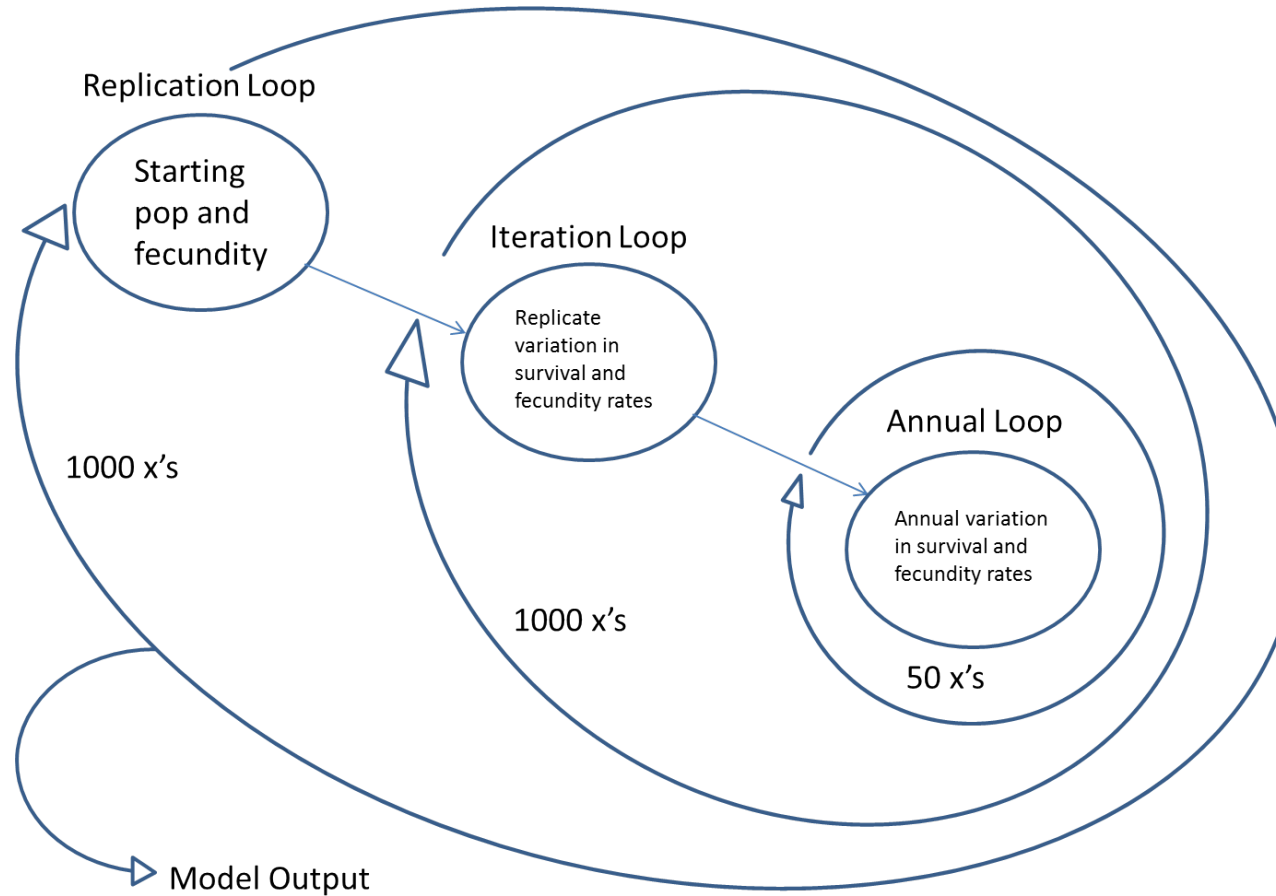
- Generate lots of output values (e.g. abundance, $p(\text{ex})$, etc.) with lots of corresponding input values
- Use a multi-variate GLM to assess the importance of each variable of interest:
 - $p(\text{extinction}) \sim b_1(\text{Initial } N) + b_2(\text{drought freq}) + b_3(\text{fecundity}) \dots$
 - This is a binomial GLM
- What factors most effect the output metric of interest?

Sonora desert tortoise example

- $P(Qe100) = -5.602 + (18.42 \times MDR) - (5.363e - 6 \times NAI) - (1.797e - 6 \times MaxPop)$
- MDR = mean drought rate
- NAI = Initial Number of adults
- MaxPop = habitat based maximum population size
 - You could input different values of MDR, NAI or MaxPop to predict the corresponding $P(Qe100)$, i.e., input alternative future scenarios.

Hierarchical loop structure

Initial population
size, habitat
quantity and
quality, drought

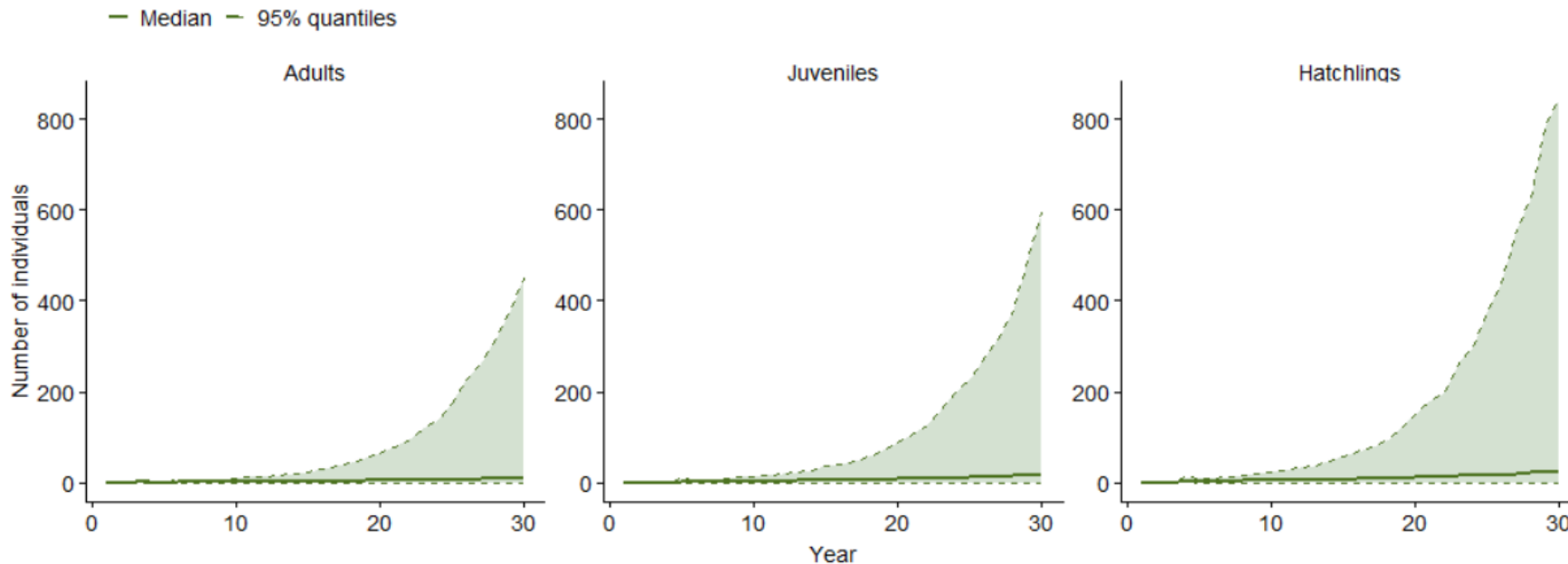


Incorporating posterior observation uncertainty

- What we observe will differ from model predictions
- Could be an issue for recovery planning or delisting decisions
- Use estimates of detectability to adjust abundance outputs
 - Estimates of detection from empirical studies
 - Literature, directed research for the SSA
 - $N_t^{Obs} = N_t^{Act} \times E_t$

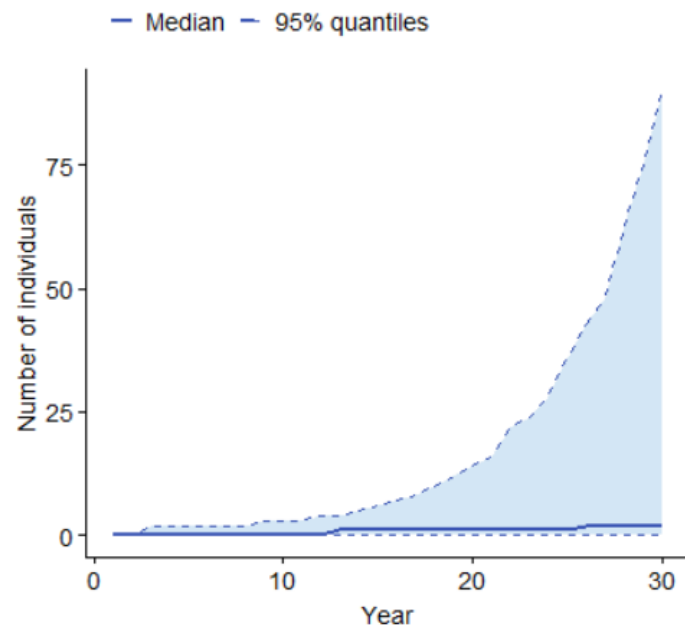
Where E is the counting error

Population projections



Abundance
projections

Observed counts



| True lambda | Observed lambda | Extinction probability |
|----------------|--------------------|---------------------------|
| 1.06 | 0.70 | 0.39 |

Expected counts

Questions?

