



Modeling for Adaptive Management

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Modeling for Adaptive Management: Outline

- I. Definitions
- II. Role of models in adaptive management
- III. Uncertainty, models and learning
- IV. How to build a model
- V. Some examples
 - a. Dynamic models for state variables
 - b. Functional relationship models for vital rates
- VI. Measuring confidence in models (how to learn)

Models: Operational Definitions

- Model
 - Abstraction/simplification of a real-world system
- Hypothesis
 - General: A story about how the world works
 - ARM: A story about how the managed system responds to management actions

Mathematical Models

- Primary purpose:
 - General: to project the consequences of hypotheses about how systems work (science)
 - ARM: to project the consequences of hypotheses about
 - how populations respond to management actions
 - what utilities result from the management actions

Uncertainty, Models & Learning

Sources of Uncertainty

- Ecological (Structural) Uncertainty
 - Nature of system response to management actions is not completely known (i.e., competing hypotheses)
- Environmental variation
- Partial controllability
 - management decision applied to system indirectly
- Partial observability
 - the state of nature is rarely seen perfectly

Ecological (Structural) Uncertainty

- Often, there is uncertainty about the consequences of management actions
- Consider use of multiple models representing competing hypotheses about system response to management actions
- Optimal decisions depend on these models and our relative degrees of faith in them

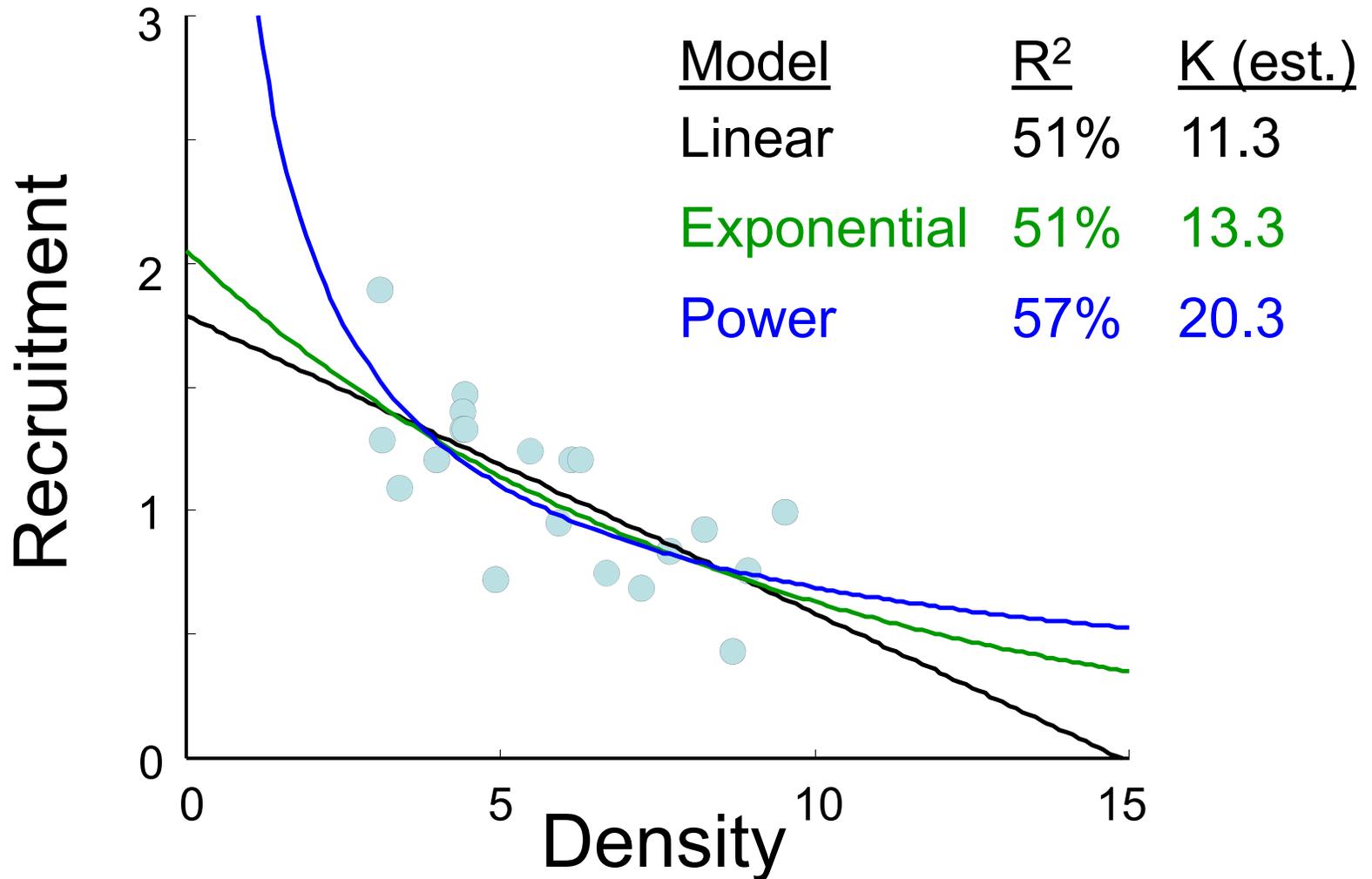
Adaptive Management, Ecological Uncertainty & Learning

- Learning:
 - Developing faith in the predictive abilities of one (or more) model(s)
 - Discrimination among competing models occurs by comparing model-based predictions against estimated system state at each time step
 - Leads to better management
 - Hallmark of adaptive management

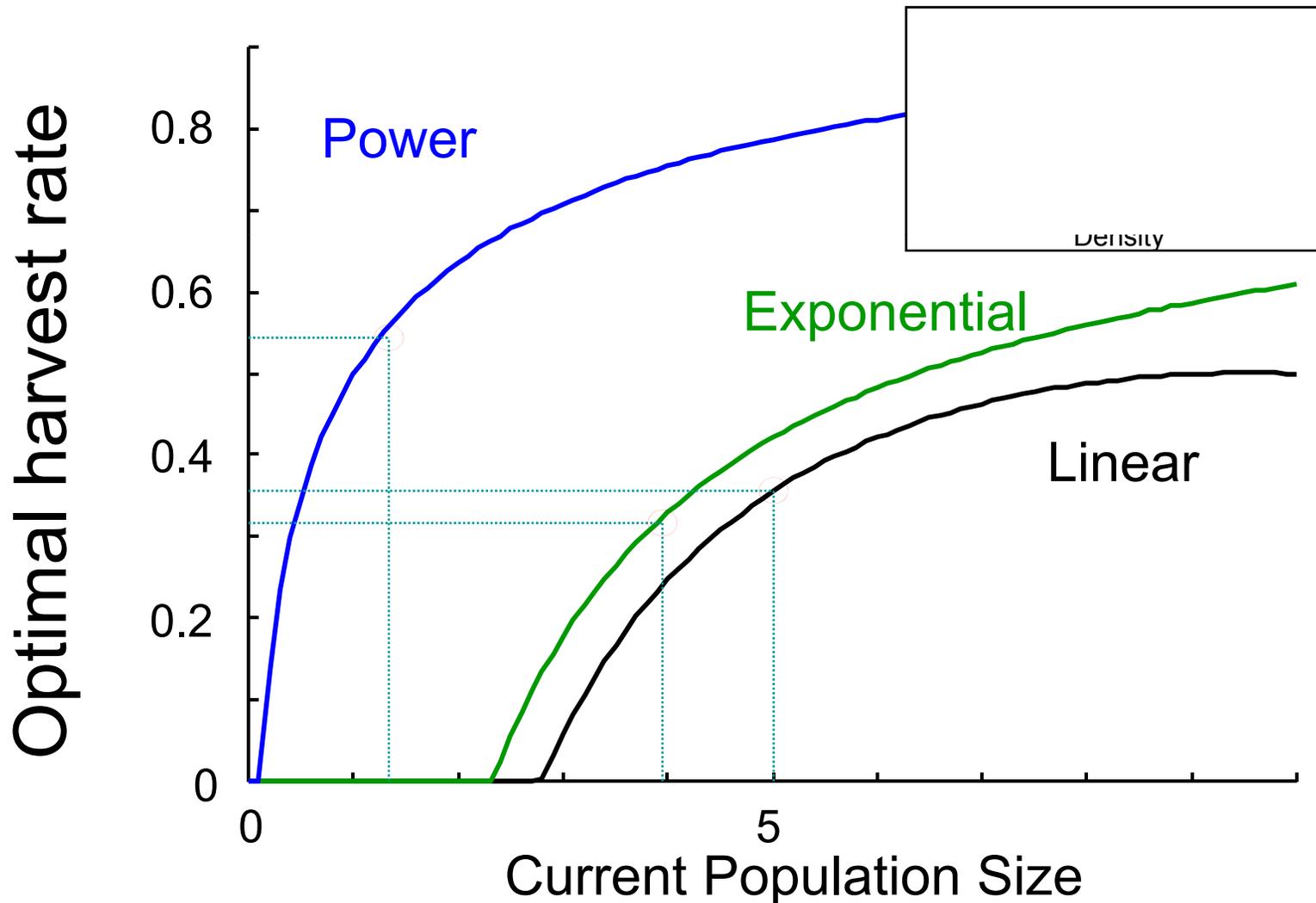
Is Model Discrimination Always Important?

- Do different models, M1 and M2, lead to different management actions?
 - “You take M1, I’ll take M2,
There ain’t no difference ‘tween the two,”
(paraphrasing Dylan, 1962; adapted from Rev. Gary Davis)
- If not, little management value in discriminating between these 2 competing hypotheses?

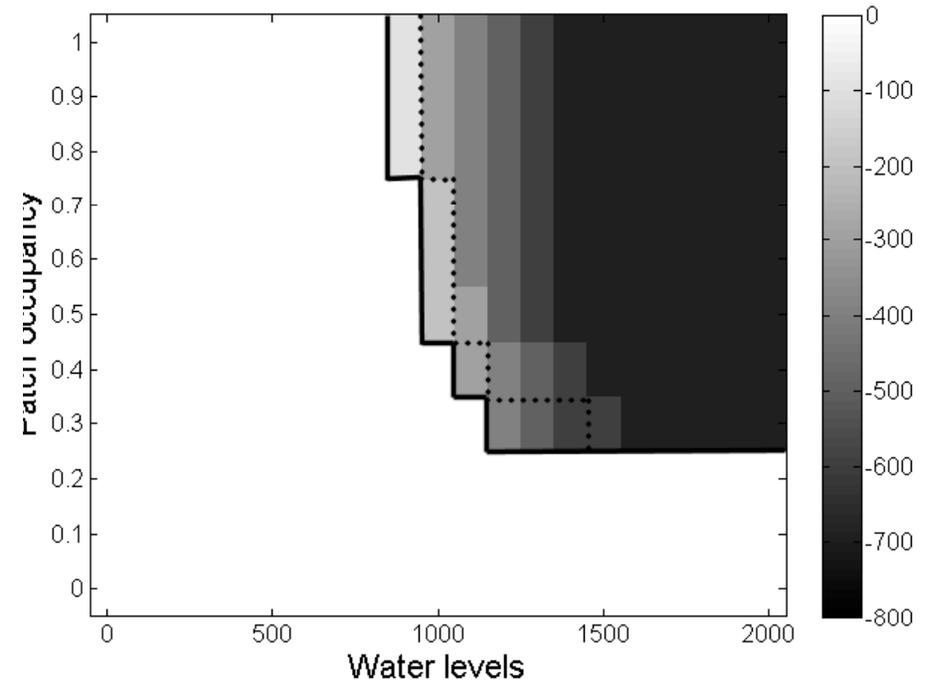
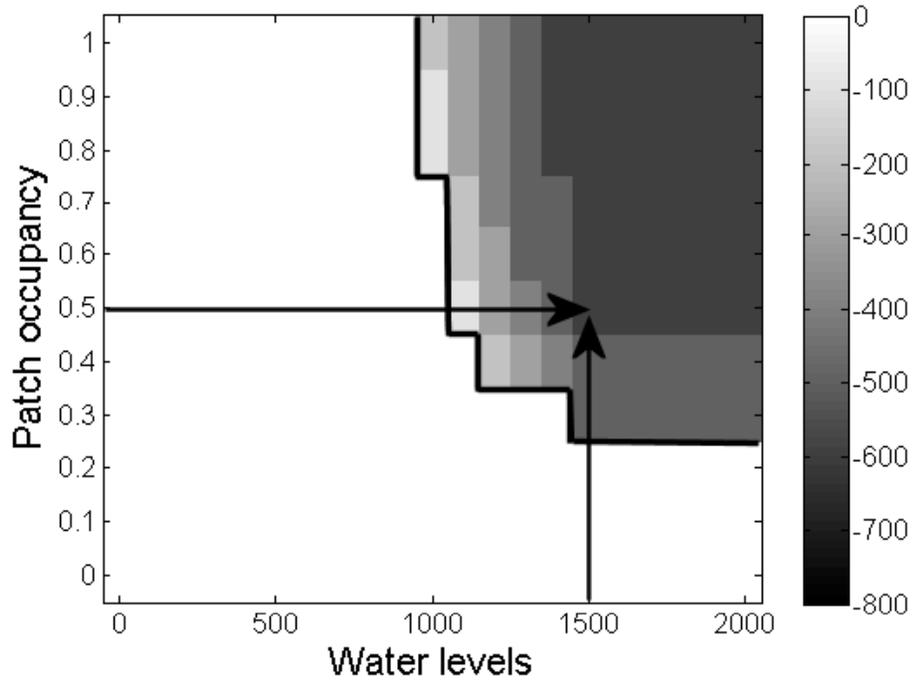
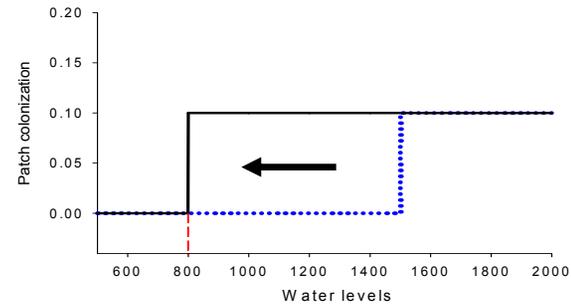
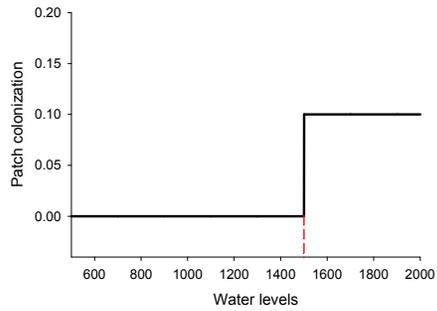
Functional Uncertainty



Do the Differences Matter?

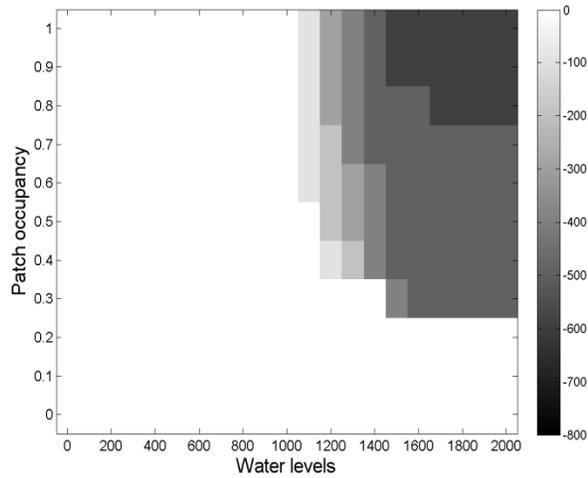


Different Ecological Thresholds

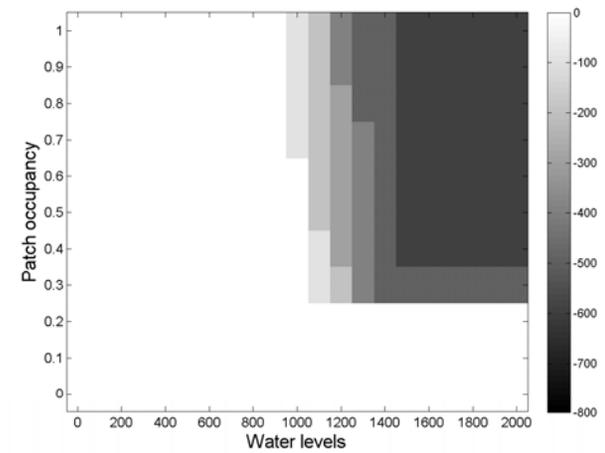


Incorporate Multiple Models in the Optimization

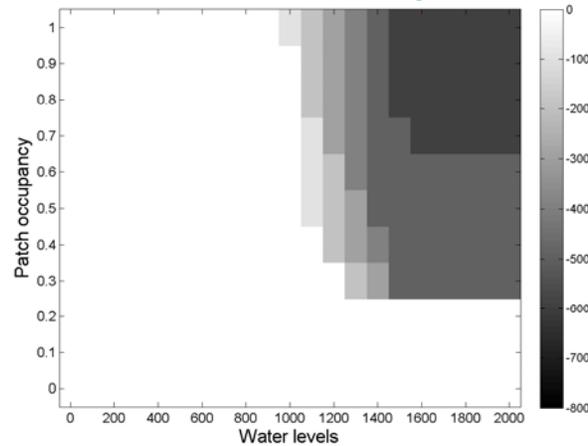
T=1500



T=800



Equal Model Weights



Is Model Discrimination Always Important?

- Expected value of perfect information (EVPI) quantifies the importance of model discrimination
- Basic idea: how much better is it to know which model is “best” than to base decisions on average (across models) model performance

Is Model Discrimination Always Important?

- Expected value of perfect information (EVPI) compares:
 - weighted average of model-specific maximum values, across models
 - maximum of an average of values (based on average model performance; value under best nonadaptive decision)

$$EVPI = \sum_i p_i(t) \left\{ \max_{A_t} V_i(A_t | x_t) \right\} - \max_{A_t} \sum_i p_i(t) V_i(A_t | x_t)$$

Effect of Hunting on Survival: Different β = Different Models

- Effect of hunting on annual survival

$$S_t = \theta(1 - \beta K_t)$$

S_t = Pr (alive in fall, yr $t+1$ | alive in fall, year t)

θ = Pr (alive in fall, yr $t+1$ | alive at
end of hunt season, year t)

K_t = Pr (die from hunting in year t |
alive in fall of year t)

β = coefficient defining effect of hunting; 2 models:
($\beta = 0.1, 0.9$)



Expected Value of Perfect Information

<u>Harvest rate</u>	<u>Harvest Yield (x10⁶)</u>		
	<u>$\beta=0.1$</u>	<u>$\beta=0.9$</u>	<u>β^{AV}</u>
0.05	1.0	0.8	0.9
0.10	2.0	1.4	1.7
0.15	3.0	1.8	2.4
0.20	4.0	0.6	2.3

$$\beta^* = (4 + 1.8) / 2 = 2.9$$

$$EVPI = (2.9 - 2.4) = 0.5$$

Ways to Express Structural Uncertainty

- Functional Uncertainty
 - Discrete alternative models (previous discussion)
- Parametric uncertainty
 - Single functional form with different parameter values

Ways to Express Structural Uncertainty: Example

- Effect of hunting on annual survival

$$S_t = \theta(1 - \beta K_t)$$

$S_t = \Pr$ (alive in fall, yr $t+1$ | alive in fall, year t)

$\theta = \Pr$ (alive in fall, yr $t+1$ | alive at
end of hunt season, year t)

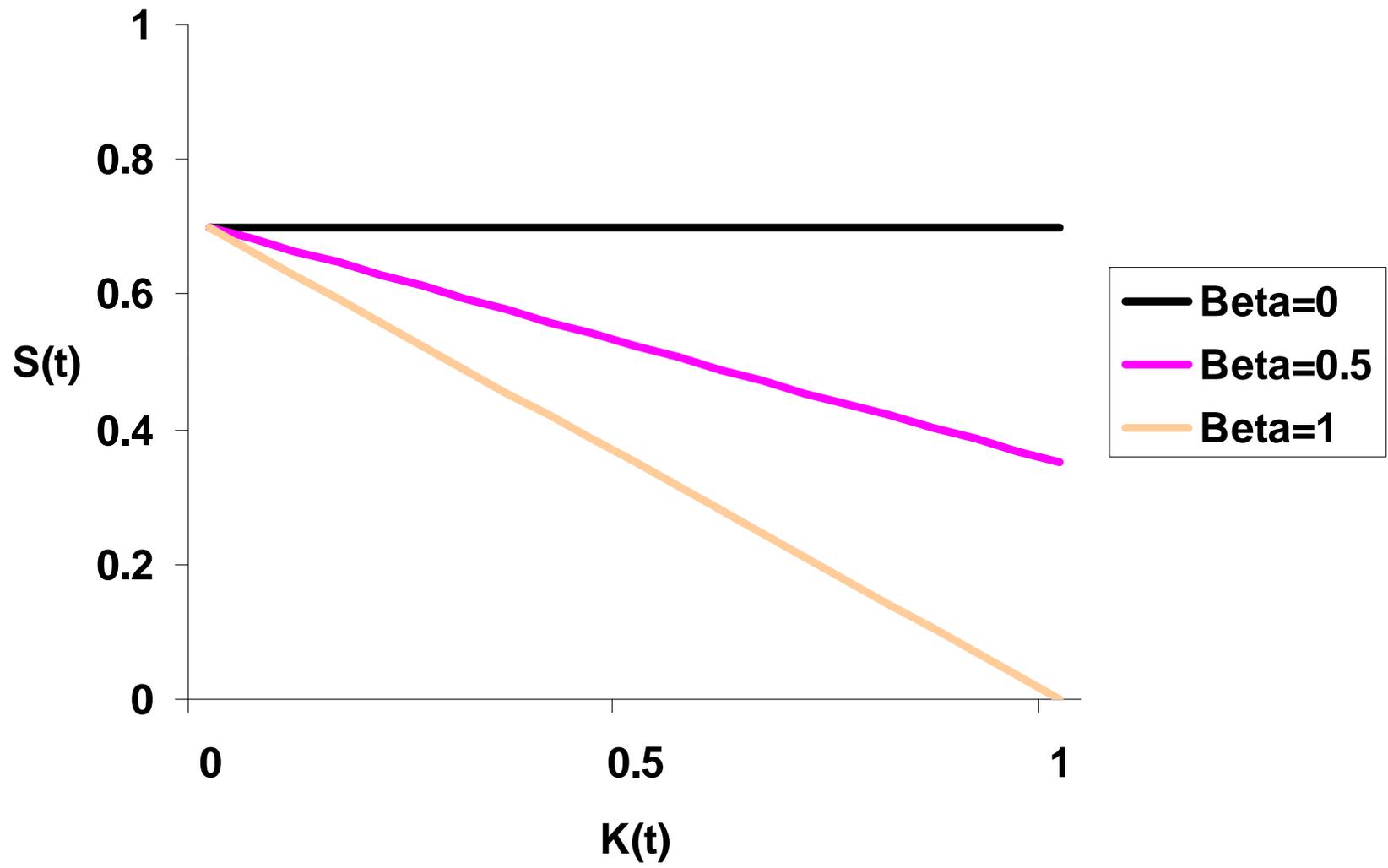
$K_t = \Pr$ (die from hunting in year t |
alive in fall of year t)

$\beta =$ coefficient defining effect of hunting

Ways to Express Ecological Uncertainty: Example

$$S_t = \theta(1 - \beta K_t)$$

- Functional uncertainty (3 discrete models):
 - $\beta=0.9$; mostly additive mortality hypothesis
 - $\beta=0.5$; partial compensation hypothesis
 - $\beta=0.1$; mostly compensatory mortality hypothesis
- Parametric uncertainty (single model):
 - Task is to estimate β , thus specifying the model
 - Uncertainty is expressed by $S\hat{E}(\hat{\beta})$



How to Build a Model

Keys to Successful Model Use: General

- (1) Clearly state the objective of the modeling effort (how is the model to be used in the conduct of science and/or management?)
- (2) Develop the model by extracting those features of the modeled system that are critically relevant to the objective (tailor model to its intended use)

Objective of Modeling Effort: Adaptive Management

- Model roles are well-defined in adaptive management process
 - Project system response to management actions based on competing hypotheses
 - Purposes:
 - Make optimal decisions
 - Learn (discriminate among competing models) for better future management

How to Build Model: Adaptive Management

- Tailor model to intended use
- Adaptive management: focus on hypotheses about how management actions translate into system responses
 - Typically, actions influence vital rates
 - Vital rates then influence state variable(s) and goal-related variable(s)

General Dichotomies Illustrate Ideas About Model Development

- Simple vs. complex?
- Phenomenological vs. mechanistic?
- More vs. less integrated parameters?

Simple vs. Complex

- Abstraction/simplification is needed for understanding, but results in loss of information
- View model development process as a “filter”
 - Restrict loss to variables/processes that are least relevant to objectives
 - Retain variables/processes most relevant to objectives
- Match model complexity with intended model use

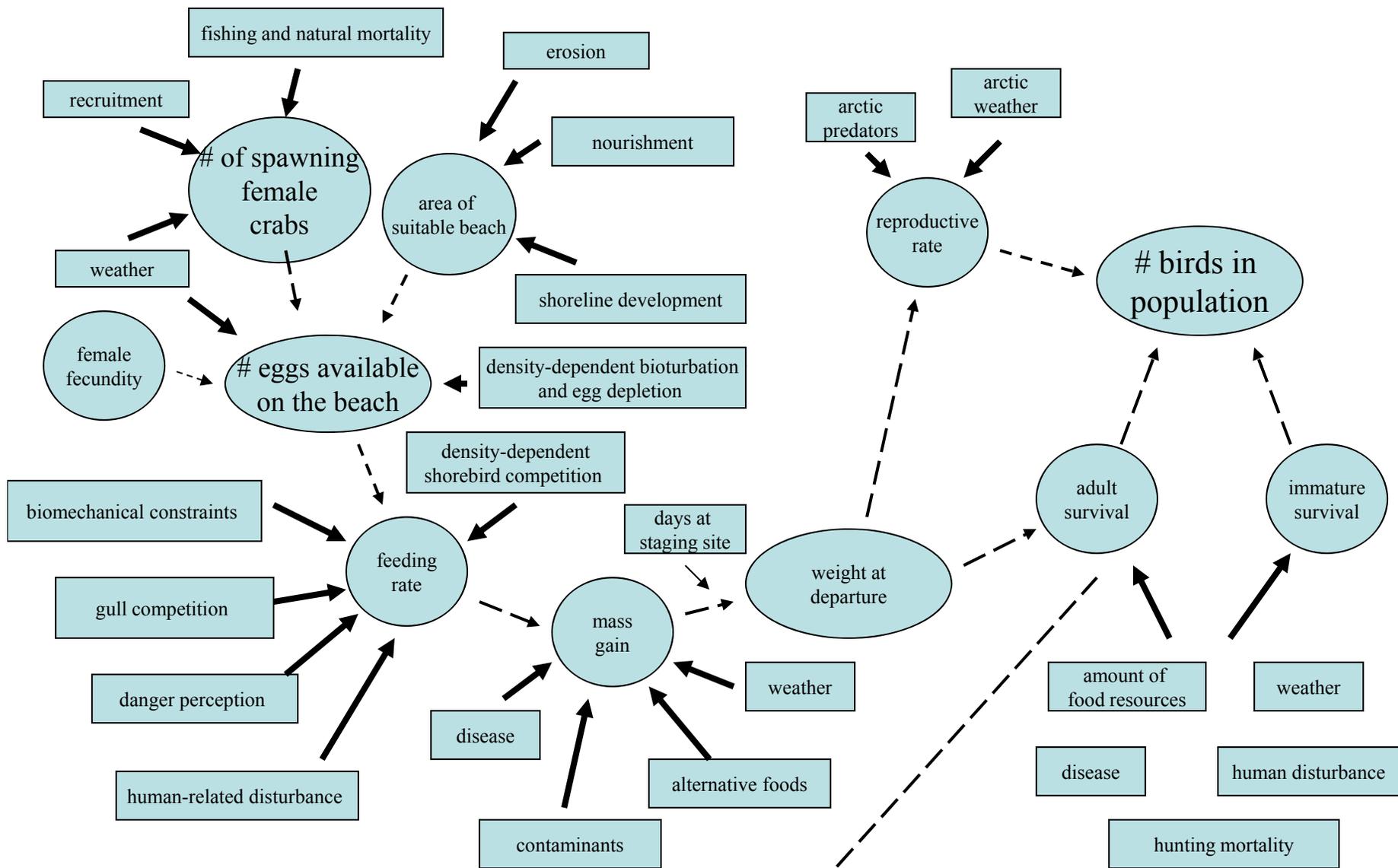
Simple vs. Complex

“The best person equipped to do this (the science of geographical ecology) is the naturalist...But not all naturalists want to do science; many take refuge in nature’s complexity as a justification to oppose any search for patterns.” (MacArthur 1971:1)

Simple vs. Complex

- Example: red knot population dynamics as function of horseshoe crab abundance at Delaware Bay
- First step in model development is to consider the potentially important influences
- Then, return to filter analogy and focus on the effects that are essential to modeling the relevant management actions

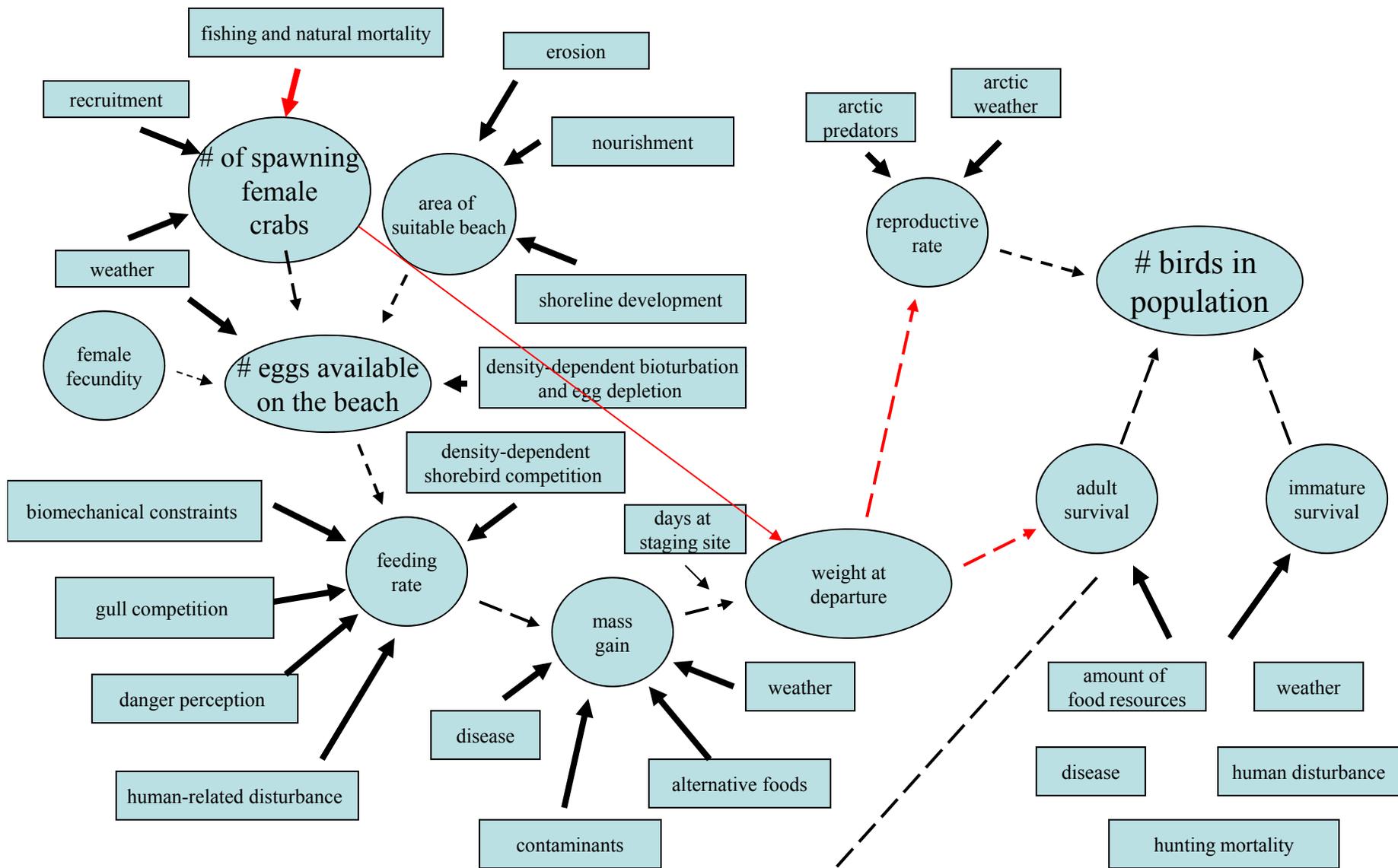
Annual Cycle of *rufa* Red Knots



Delaware Bay stopover

South American wintering/stopover sites

Annual Cycle of *rufa* Red Knots



Delaware Bay stopover

South American wintering/stopover sites

Mechanistic vs. Phenomenological

- Mechanistic models often provide better predictions when state or environmental variables assume values outside observed historical ranges
- Dichotomy closely related to idea of extracting essential features of modeled system

Example: More Phenomenological

- Effect of hunting on annual survival

$$S_t = \theta(1 - \beta K_t)$$

$S_t = \text{Pr}(\text{alive in fall, yr } t+1 \mid \text{alive in fall, year } t)$

$\theta = \text{Pr}(\text{alive in fall, yr } t+1 \mid \text{alive at
end of hunt season, year } t)$

$K_t = \text{Pr}(\text{die from hunting in year } t \mid
alive in fall of year } t)$

$\beta = \text{coefficient defining effect of hunting}$

Example: More Mechanistic

$$S_t = \theta_t(1 - K_t) \quad \theta_t = \frac{e^{a+bN_t(1-K_t)}}{1 + e^{a+bN_t(1-K_t)}}$$

$S_t = \Pr$ (alive in fall, yr $t+1$ | alive in fall, year t)

$\theta = \Pr$ (alive in fall, yr $t+1$ | alive at end of hunt season, year t)

$K_t = \Pr$ (die from hunting in year t | alive in fall of year t)

$N_t =$ abundance in fall of year t

$b =$ parameter related to density-dependence of spring-summer mortality

More vs. Less Integrated Parameters

- More integrated
 - Annual population growth rate
- Less integrated
 - Annual survival and reproductive rates
- Still less integrated
 - Seasonal survival rates, reproductive rate components
- Levins' (1966, 1968) notion of sufficient parameters

How to Build Model: Adaptive Management

- Focus on state (and other) variables that appear in objective function
- Identify key links between management actions and these variables
- Typically, these links involve vital rates that appear in equations for state variable dynamics
- Uncertainty (competing models) will frequently involve different stories about these linkages

How to Build Model: Adaptive Management

- Environmental (not management) variables that affect vital rates can be handled in either of 2 ways:
 - (1) Incorporation in model in order to improve predictive ability
 - Recommended if covariate is easily obtained and very important to prediction
 - (2) Do not explicitly incorporate, but view as component of environmental variation

Modeling Examples

Dynamic Models for State
Variables

Dynamic Models for State Variables

- State variables are used to characterize ecological systems and their well-being
- Most dynamic models for state variables are *Markovian*: state at $t+1$ depends on state at t
- Most dynamic models for state variables also include vital rates, rate parameters responsible for changes in state variables

Dynamic Models for State Variables

- Ecological state variables (lots of possibilities)
 - Population size (single species)
 - Number (or proportion) of patches occupied by a species
 - Species richness
 - Number (or proportion) of patches in a particular habitat category

Change in Animal Abundance: BIDE Model

$$N_{t+1} = N_t + B_t + I_t - D_t - E_t$$

N_t = abundance at time t

B_t = new recruits (births) entering pop between t and $t+1$ and present at t

I_t = immigrants entering pop between t and $t+1$ and present at t

D_t = deaths between t and $t+1$

E_t = emigrants between t and $t+1$

Change in Animal Abundance: Express in Terms of Vital Rates

$$N_{t+1} = N_t (S_t + F_t) \longrightarrow N_{t+1}/N_t = \lambda_t = S_t + F_t$$

N_t = abundance at time t

λ_t = rate of population change

S_t = survival rate, $P[\text{survive to } t+1 \mid \text{alive at } t]$

F_t = fecundity rate, new animals at $t+1$ per animal at t

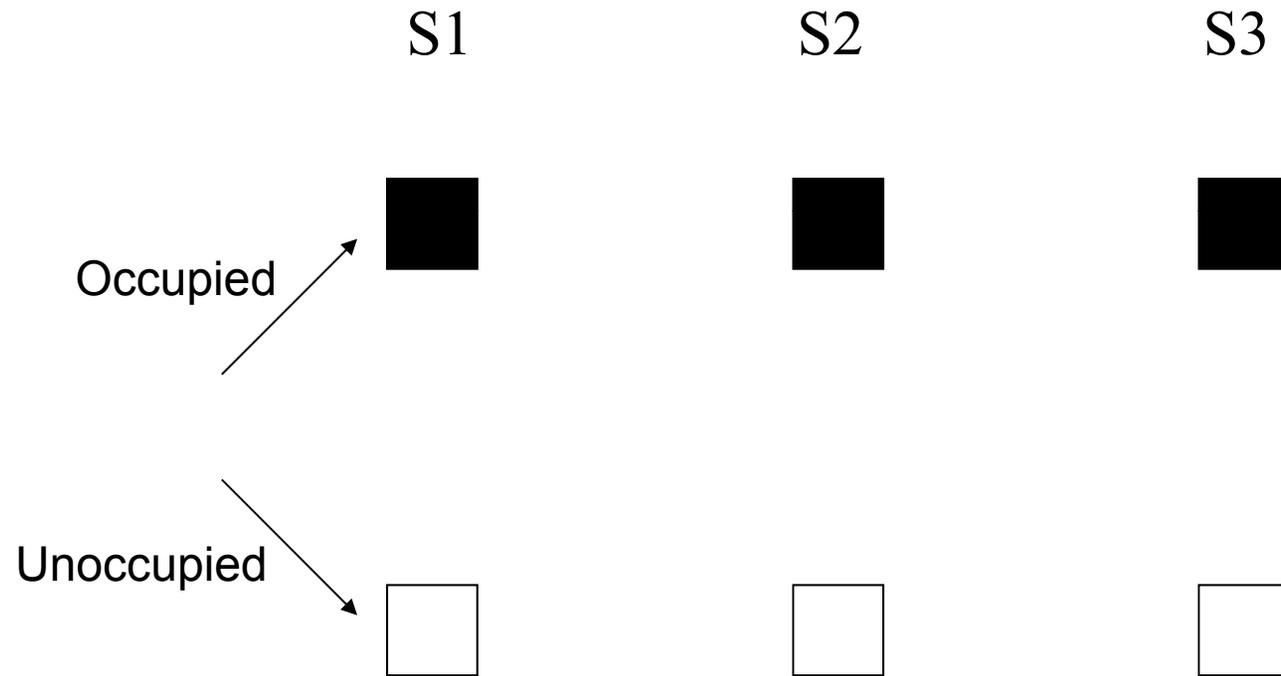
Focus on Vital Rates: Survival, Fecundity, Movement

- Population ecology
 - All changes in abundance come about through the action of these rate parameters
- *Population conservation/management*
 - *Management actions that influence abundance must do so via 1 or more of these parameters*
- Evolutionary ecology
 - Determinants of fitness: survival and fecundity
 - Fitness defined as genotypic \square

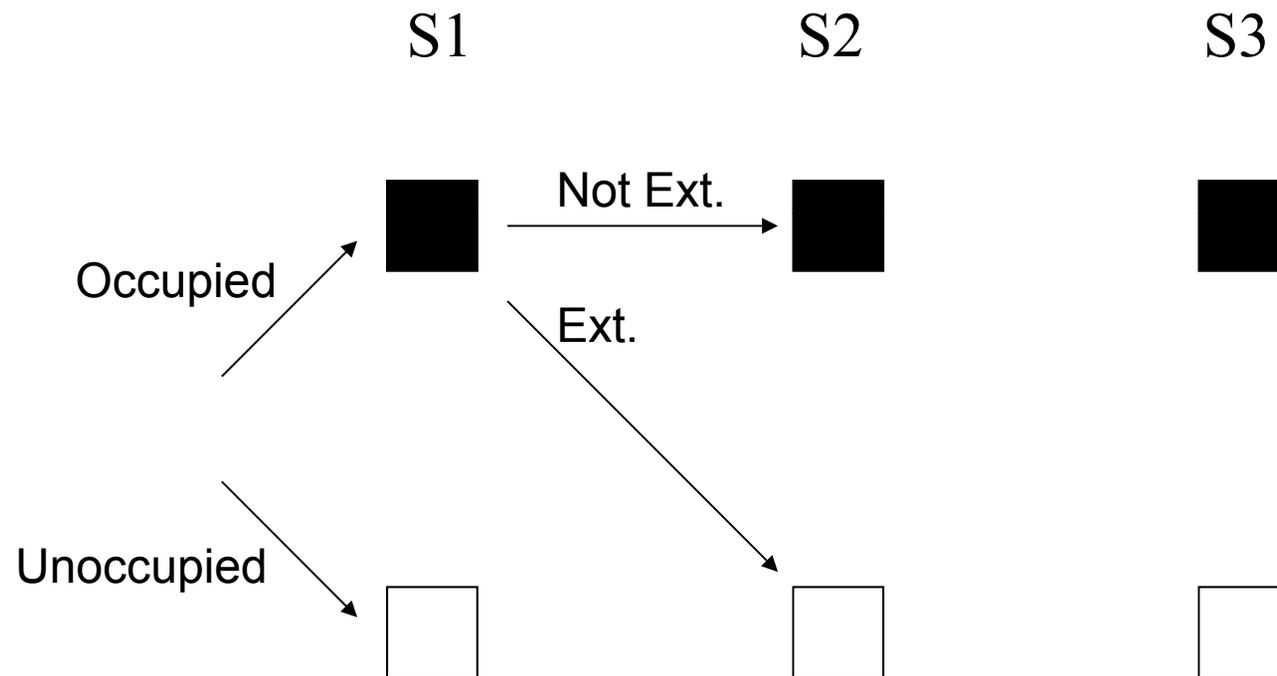
Occupancy Dynamics

- State variable: proportion of patches that is occupied by species of interest
 - Endangered species
 - Invasive species
 - Disease organisms
- Dynamics: focus on changes in occupancy as function of vital rates
 - Probability of local extinction
 - Probability of local colonization

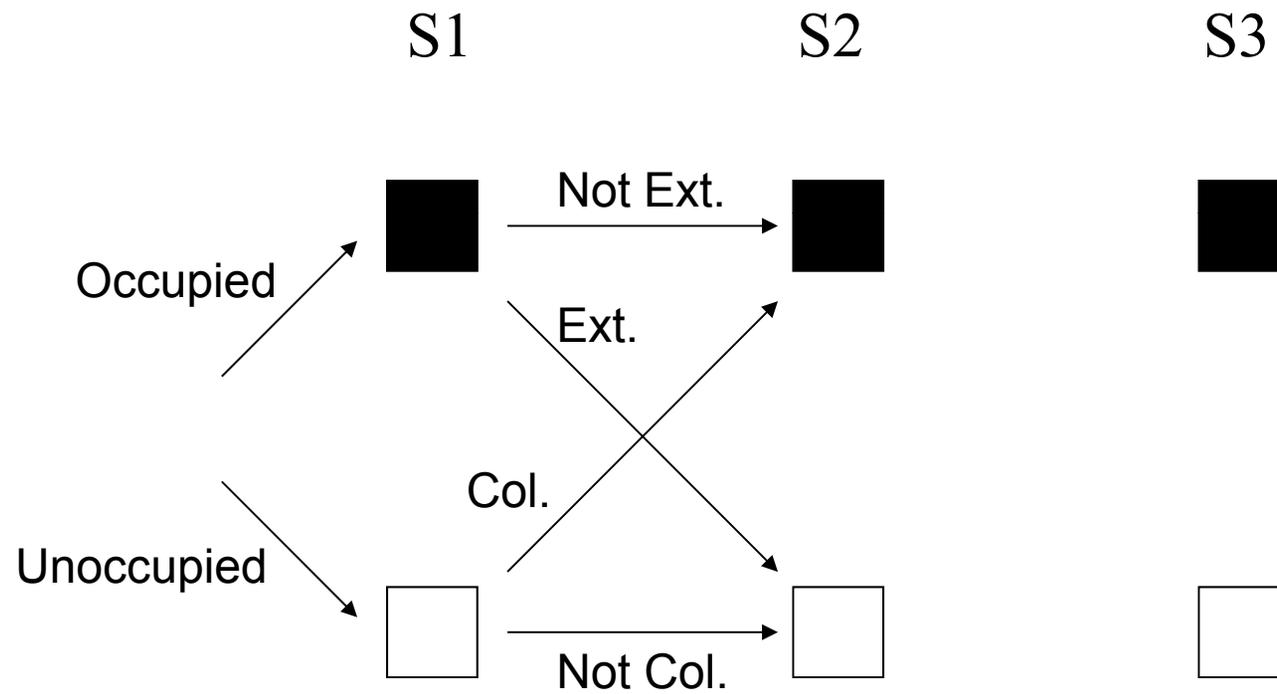
Occupancy Dynamics



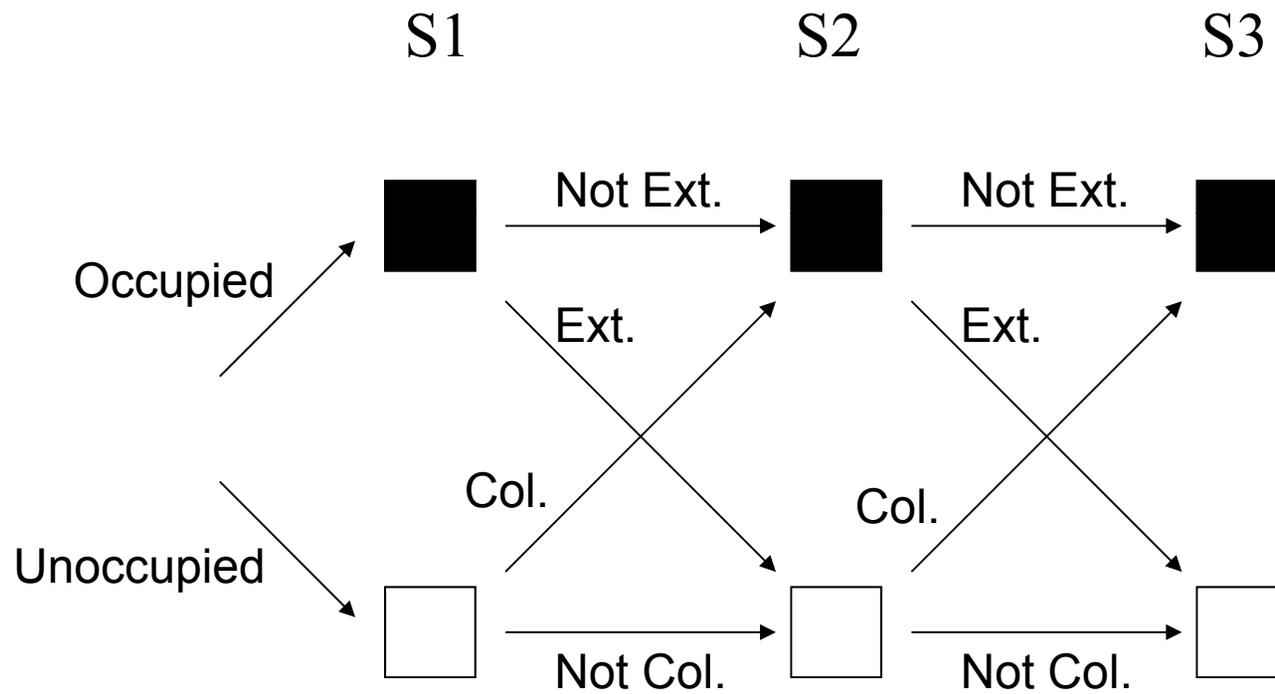
Occupancy Dynamics



Occupancy Dynamics



Occupancy Dynamics



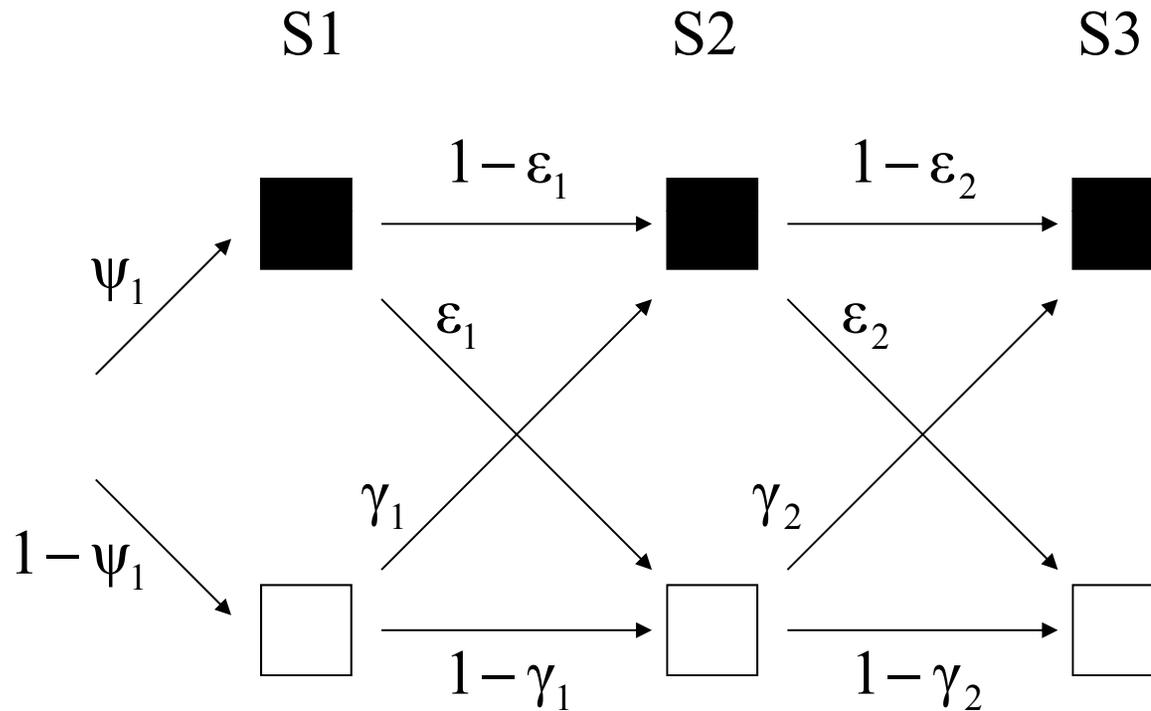
Occupancy Dynamics: Notation

ψ_1 = probability unit occupied in season 1

ε_t = probability a unit becomes unoccupied
between seasons t and $t + 1$

γ_t = probability a unit becomes occupied
between seasons t and $t + 1$

Occupancy Dynamics



Occupancy Dynamics: Fundamental Equation

Dynamics:

$$\Psi_{t+1} = \Psi_t (1 - \varepsilon_t) + (1 - \Psi_t) \gamma_t$$

Equilibrium:

$$\Psi^* = \frac{\gamma}{\gamma + \varepsilon}$$

Community Dynamics

$$N_{t+1} = N_t(1 - \varepsilon_t) + (K - N_t)\gamma_t$$

- N_t = local species richness at time t
- K = total species in regional pool
- ε_t = Pr (species not locally present at $t+1$ | locally present at t)
- γ_t = Pr (species locally present at $t+1$ | not locally present at t)

Habitat Dynamics

- State variable:
 - $\psi_t^{[r]}$ = proportion of patches or sample units in habitat state, h , at time t
 - $\varphi_t^{[rs]}$ = Pr (patch in habitat s at time $t + 1$ | patch in habitat r at time t)
- Habitat dynamics, e.g.

$$\psi_{t+1}^{[s]} = \sum_r \psi_t^{[r]} \varphi_t^{[rs]}$$

Habitat Dynamics

$$\Psi_{t+1} = \Phi_t \Psi_t$$

$$\Psi_t = \begin{bmatrix} \psi_t^{[0]} \\ \psi_t^{[1]} \\ \psi_t^{[2]} \end{bmatrix}$$

$$\Phi_t = \begin{bmatrix} \phi_t^{[0,0]} & \phi_t^{[0,1]} & \phi_t^{[0,2]} \\ \phi_t^{[1,0]} & \phi_t^{[1,1]} & \phi_t^{[1,2]} \\ \phi_t^{[2,0]} & \phi_t^{[2,1]} & \phi_t^{[2,2]} \end{bmatrix}$$

Modeling Examples

Functional Relationship Models
for Vital Rates

The Logit Link

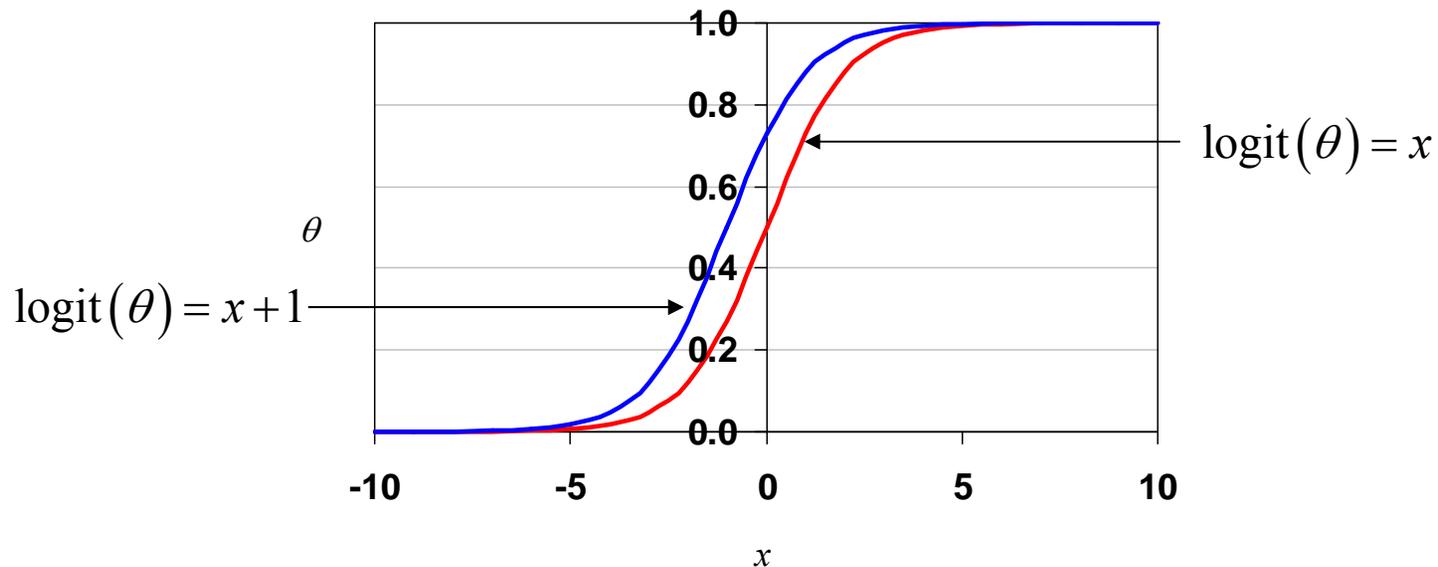
$$\text{logit}(\theta_i) = \ln\left(\frac{\theta_i}{1-\theta_i}\right) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots$$

which can be rearranged as,

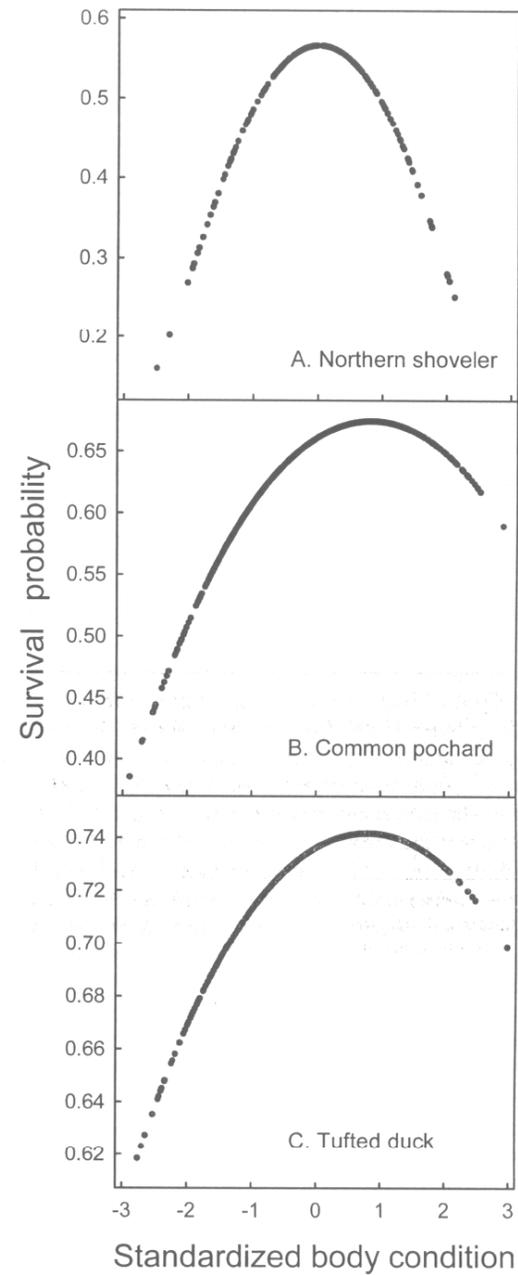
$$\theta_i = \frac{\exp(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots)}{1 + \exp(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots)}$$

The Logit Link

- Interpreting the effect of a covariate on the probability θ can be difficult due to the non-linear relationship.



$$S_j = \frac{\exp(\beta_1 + \beta_2 x_j + \beta_3 x_j^2)}{1 + \exp(\beta_1 + \beta_2 x_j + \beta_3 x_j^2)}$$



Measuring Confidence in Models

How to Learn

Models and Learning

- Basic criterion by which a management model is judged is its ability to predict system response to management actions
- Develop model “weights” reflecting relative degrees of faith in the models of the model set

For a Given Model Set

- Weights assigned to each model add to 1.0 (thus relative credibility)
- Models with higher weight have greater credibility and will have more influence over future management decisions
- If a robust predictive model is in the set its weight should go to 1.0 over time.

Initial Weight Values

- Option 1 – set subjectively
 - Politically
 - Based on expert opinion
- Option 2 – use historical data
 - AIC weights (Burnham and Anderson 1998)
 - Pick previous date, start with equal weights, and update to present time

Weights Updated as Function of:

- The current weight (*prior probability*)
- New information (i.e., the difference between model predictions and what actually occurs, based on monitoring results)
- The new weight is called a *posterior probability*

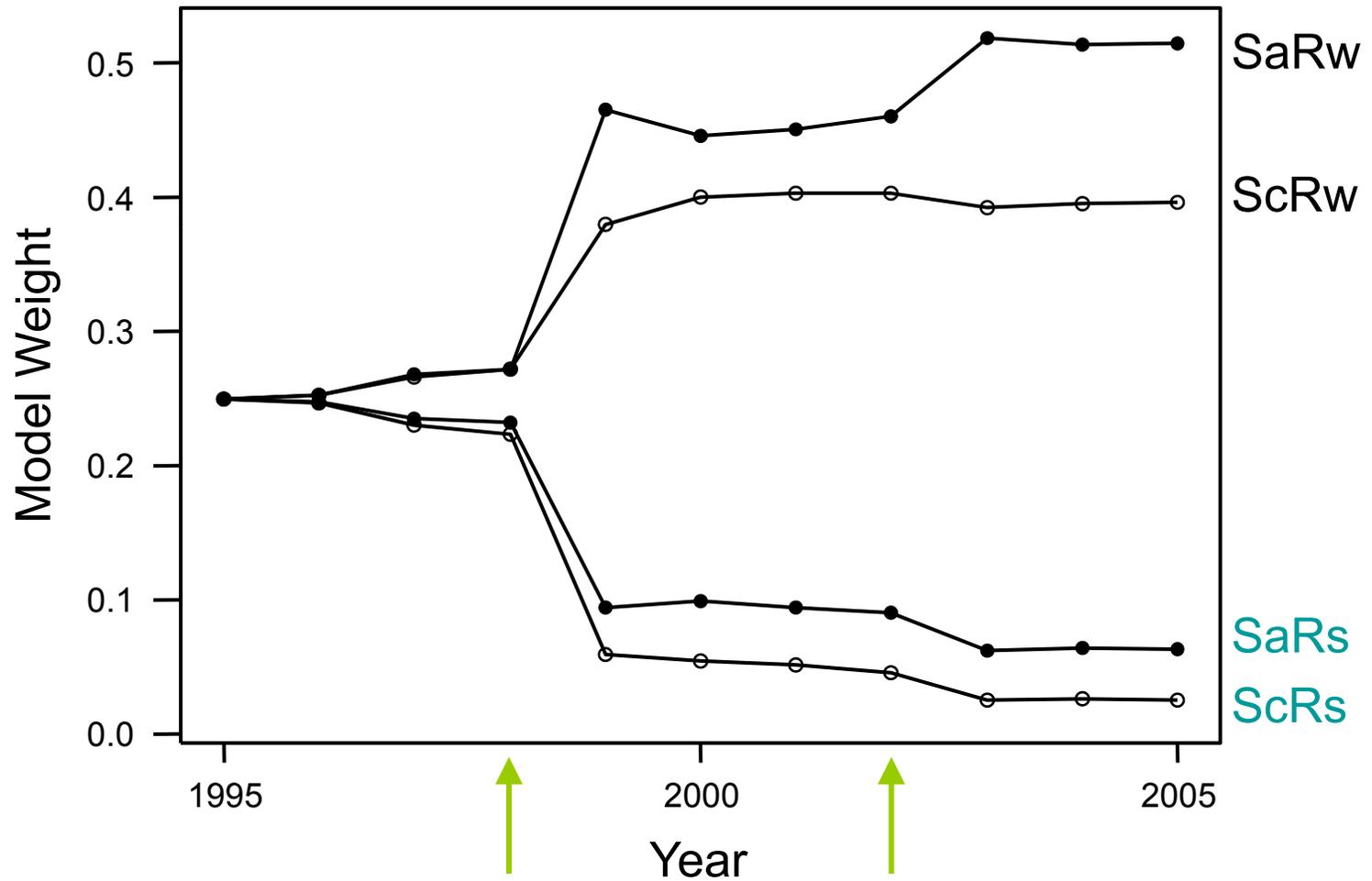
Updating Model Probabilities: Bayes' Theorem

$$p_{t+1}(\text{model } i \mid \text{data}_{t+1}) =$$

$$p_t(\text{model } i) P(\text{data}_{t+1} \mid \text{model } i)$$

$$\sum_j p_t(\text{model } j) P(\text{data}_{t+1} \mid \text{model } j)$$

AHM Learning



Process Furthers Learning When

- A good approximating model is in the model set (i.e., a model that predicts well across the state space)
- Predictions from each model fairly represent the idea that generated them
- An adequate monitoring program is in place for model comparison/discrimination

Model Predictions Should:

- Be unbiased under the ecological hypothesis they represent
 - Bias could change direction of weight changes and lead to throwing out hypothesis erroneously
- Include all relevant uncertainties
 - Model-based stochastic variation
 - Parametric uncertainty – sampling variation due to estimation