Modeling for Adaptive Management

Chapter 5

Developed by: James D. Nichols and Michael C. Runge

<u>Session Objectives:</u> **By the end of this session, participants will be able to:**

- Discuss how modeling may be used in adaptive management.

<u>Outline</u>

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

<u>Models: Operational Definitions</u>

- Model
  - o Abstraction/simplification of a real-world system

- Hypothesis
  - o General: A story about how the world works
  - o Adaptive Resource Management (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/imprecisely
- Partial observability
  - the state of nature is rarely seen perfectly

Ecological (Structural) Uncertainty

- Often, there is uncertainty about the consequences of management actions
- Uncertainty can be expressed as
  - Set of discrete models representing different hypotheses
  - Uncertainty about 1 or more key parameters in a general model structure (continuous case)
- Discrete models
  - 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
- Continuous parameter(s)
  - Uncertainty about 1 or more key parameters in a general model structure
  - Optimal decisions depend on the uncertainty associated with this parameter(s)

Adaptive Management, Ecological Uncertainty & Learning

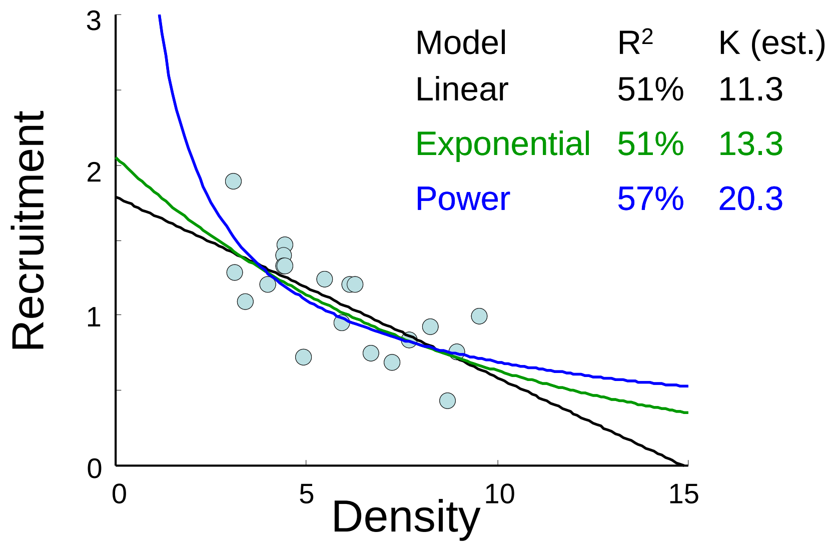
- Learning:
  - o Developing faith in the predictive abilities of one (or more) model(s)
  - o Discrimination among competing models occurs by comparing model-based predictions against estimated system state at each time step
  - o Leads to better management
  - o Hallmark of adaptive management

Is Model Discrimination Always Important?

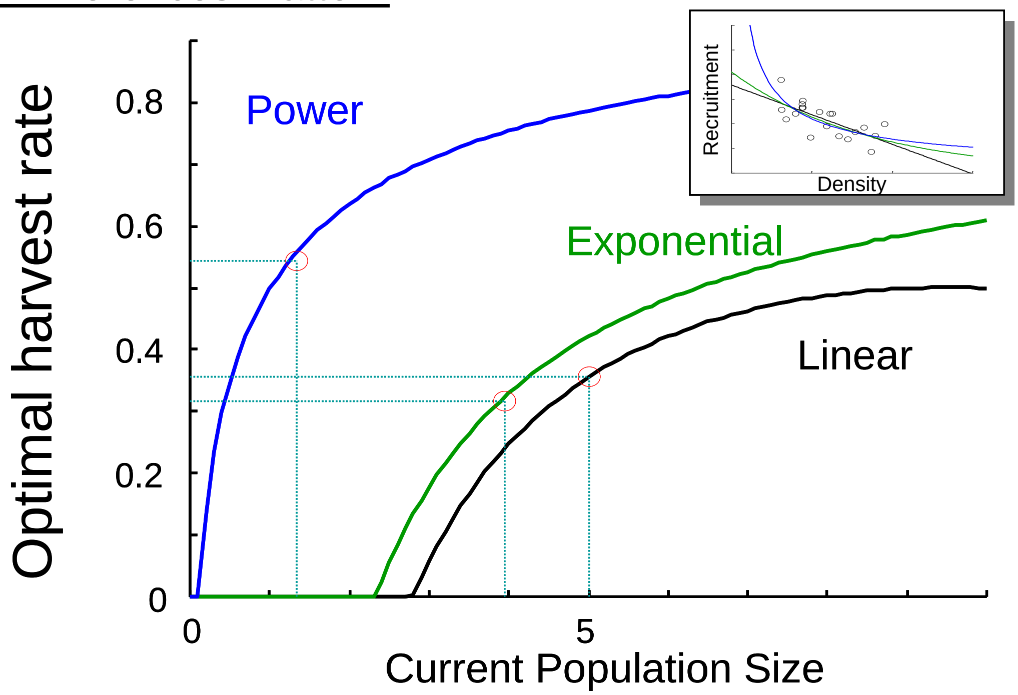
- Do different models, M1 and M2, lead to different management actions?
  "You take M1, I'll take M2,
  There ain't no difference 'tween the two,"
  (paraphrasing Dylan, 1962; adapted from Rev. Gary Davis)

- If not, little management value in discriminating between these 2 competing hypotheses?

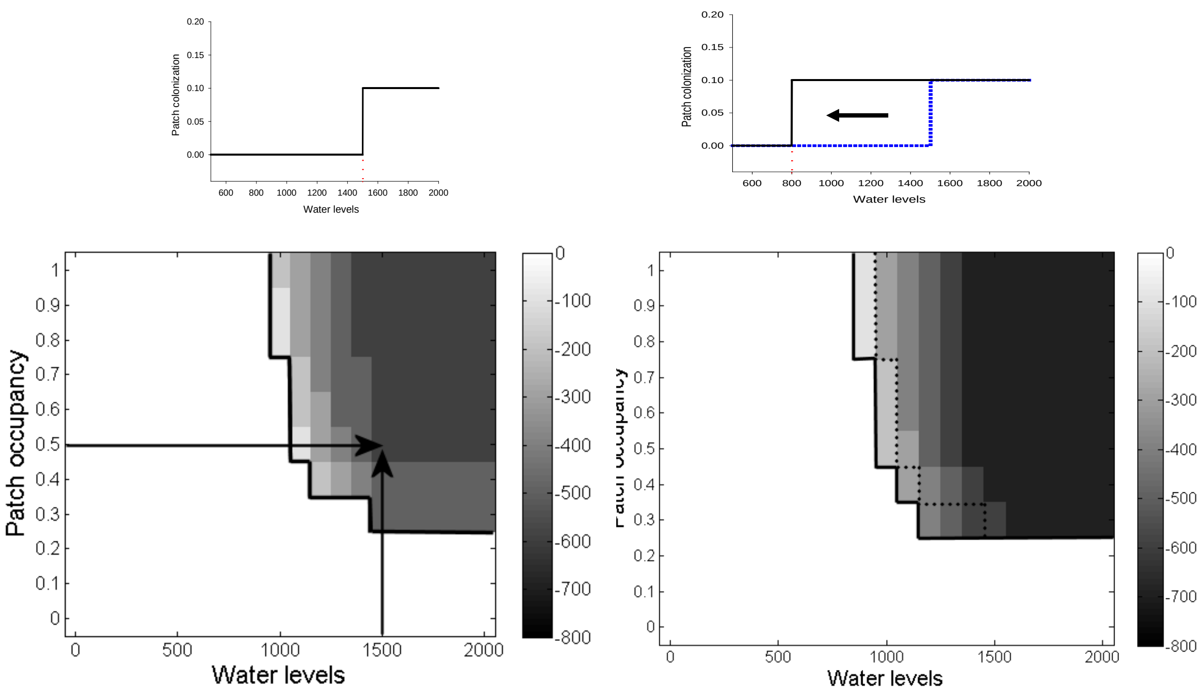
Functional Uncertainty



Do the Differences Matter?

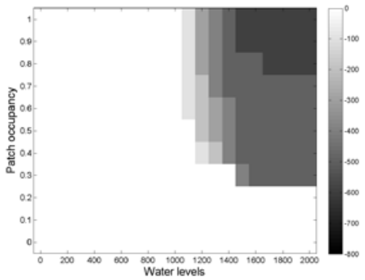


Different Ecological Thresholds

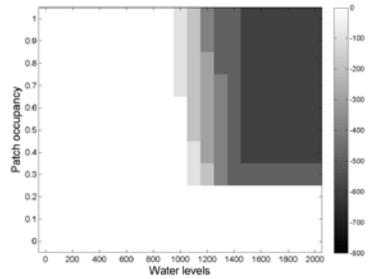


Incorporate Multiple Models in the Optimization

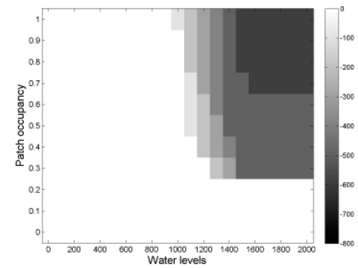
T = 1500



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

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

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

Effect of Hunting on Survival: Different β = Different Models

- Effect of hunting on annual survival

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

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)
κ_t = Pr (die from hunting in year t | alive in fall of year t)
β = coefficient defining effect of hunting

Ways to Express Structural Uncertainty

- Functional Uncertainty
  - o Discrete alternative models (previous discussion)

- Parametric uncertainty
  - o Single functional form with different parameter values

Example

- Effect of hunting on annual survival

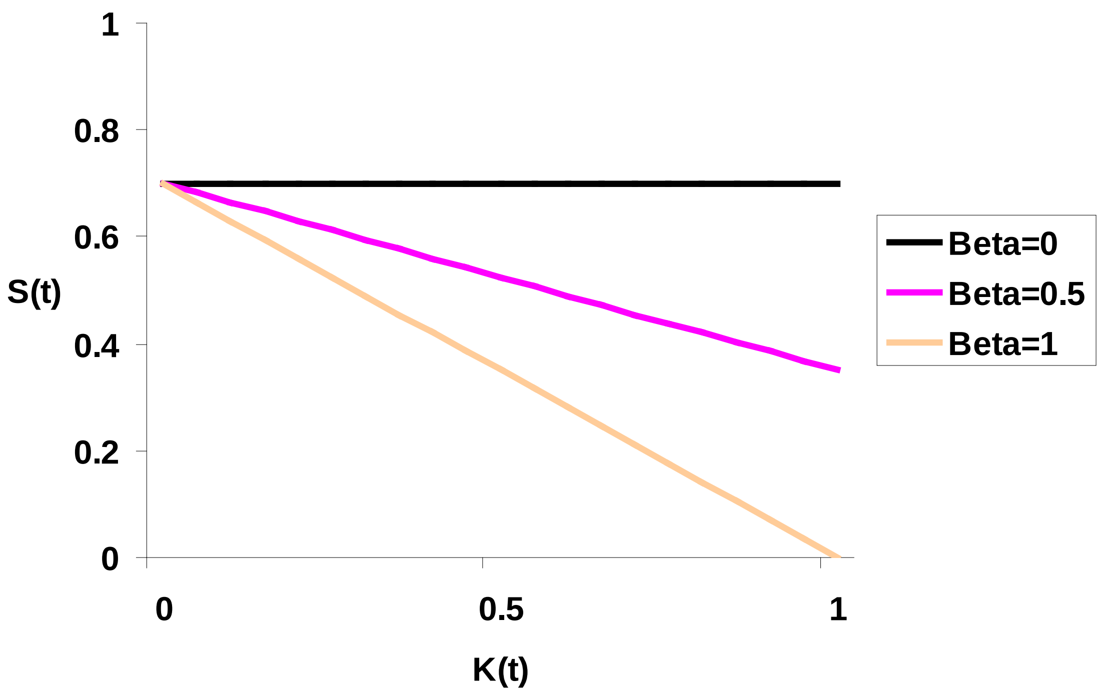
$$S_t = \theta(1 - \beta\kappa_t)$$

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)
κ_t = Pr (die from hunting in year t | alive in fall of year t)
β = coefficient defining effect of hunting

- Functional uncertainty (3 discrete models):

β = 0.9; mostly additive mortality hypothesis
β = 0.5; partial compensation hypothesis
β = 0.1; mostly compensatory mortality hypothesis

- Parametric uncertainty (single model):
  - o Task is to estimate *β*, thus specifying the model
  - o Uncertainty is expressed by $S\hat{E}(\hat{\beta})$



Expected Value of Perfect Information (EVPI)

	Harvest Yield ($x10^6$)		
Harvest rate	β=0.1	β=0.9	β^{AV}
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

β^* = (4+1.8)/2 = 2.9

EVPI = (2.9 - 2.4) = 0.5

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

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”
  - o Restrict loss to variables/processes that are least relevant to objectives
  - o Retain variables/processes most relevant to objectives

- Match model complexity with intended model use

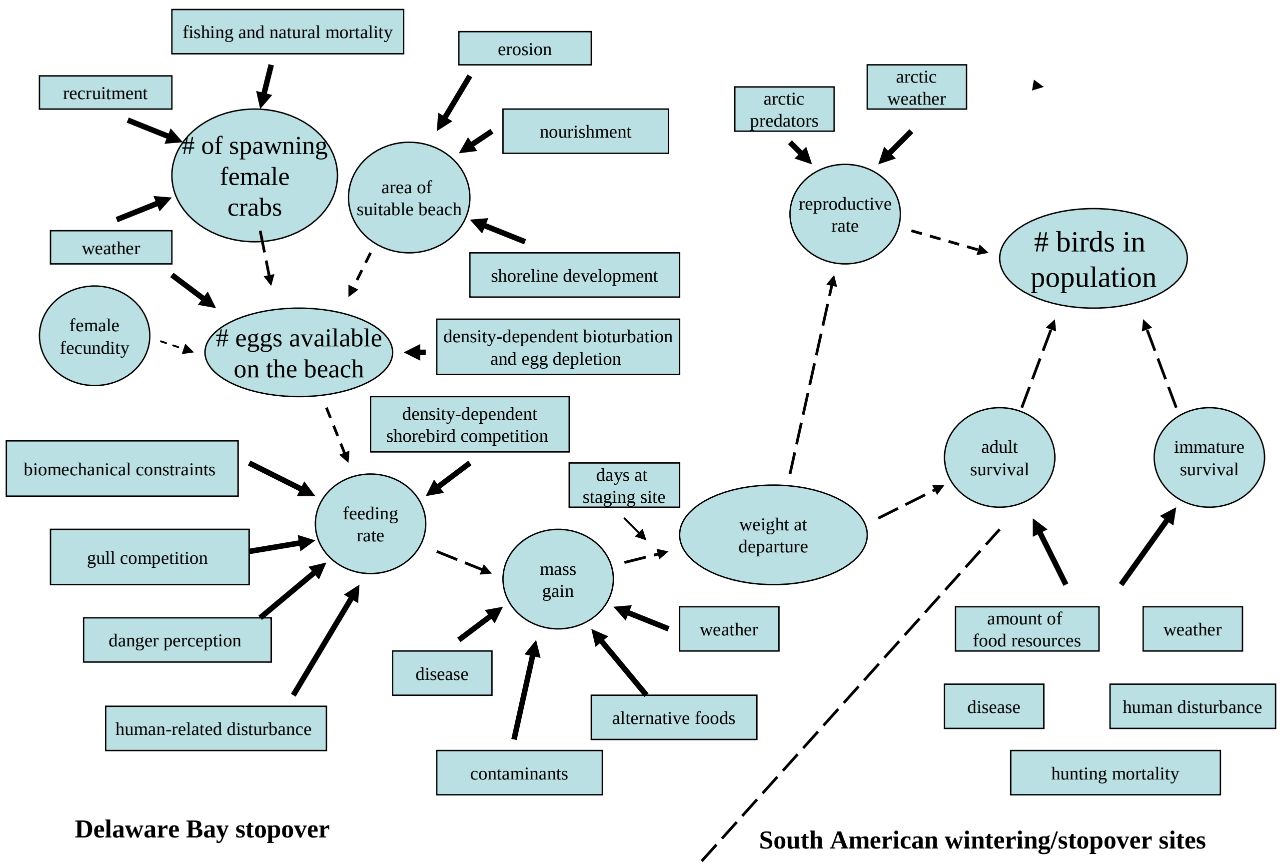
“The best person equipped to do this (the science of geographical ecology) is the naturalist…But not all naturalists want to do science; many take refuge in nature’s complexity as a justification to oppose any search for patterns.” (MacArthur 1971:1)

- 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



<u>Mechanistic vs. Phenomenological</u>

- 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

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

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)
κ_t = Pr (die from hunting in year t | alive in fall of year t)
β = coefficient defining effect of hunting

Example: More Mechanistic

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

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

<u>How to Build Model: Adaptive Management</u>

- 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

- 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
    - May be especially important for climate change

  (2) Do not explicitly incorporate, but view as component of environmental variation

Modeling Examples

<u>Dynamic Models for State Variables</u>

- 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

- 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

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

N_t = abundance at time t
λ_t = rate of population change
S_t = survival rate, P[survive to t+1| 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 λ

Occupancy Dynamics

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

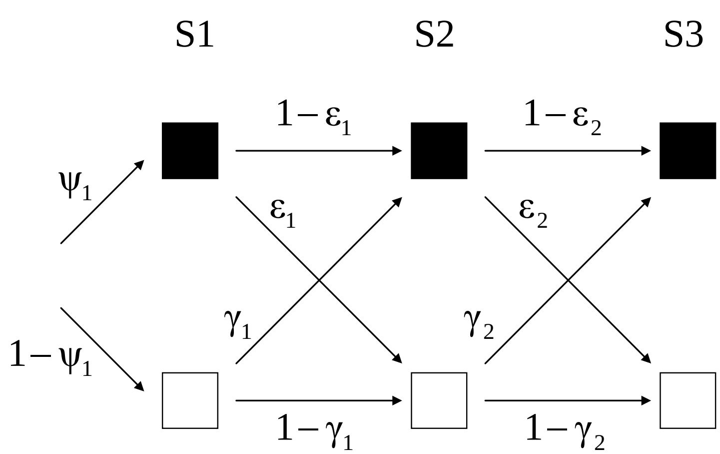
Occupancy Dynamics: Notation

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:

  $\psi_{t+1}^{[s]}$ = proportion of patches or sample units in habitat state *s* at time *t*

  $\varphi_t^{[sr]}$ = Pr (patch in habitat s at time *t* +1 | patch in habitat *r* at time *t*)

- Habitat dynamics, e.g.,

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

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

$$\Psi_t = \begin{bmatrix} \psi_t^{[0]} \\ \psi_t^{[1]} \\ \psi_t^{[2]} \end{bmatrix} \qquad \phi_t = \begin{bmatrix} \varphi_t^{[0,0]} & \varphi_t^{[0,1]} & \varphi_t^{[0,2]} \\ \varphi_t^{[1,0]} & \varphi_t^{[1,1]} & \varphi_t^{[1,2]} \\ \varphi_t^{[2,0]} & \varphi_t^{[2,1]} & \varphi_t^{[2,2]} \end{bmatrix}$$

Modeling Examples

Functional Relationship Models for Vital Rates

Summary: Common elements of examples

- Focus on state variables that are relevant to the decision problem
- Model state dynamics as functions of key vital rates (particular to state variables)
- Management actions typically influence these vital rates

Modeling of vital rates

- Management actions typically influence system dynamics by acting on 1 or more vital rates
- Focus on modeling vital rates as functions of environmental factors, possible intrinsic factors (e.g., density) and management actions

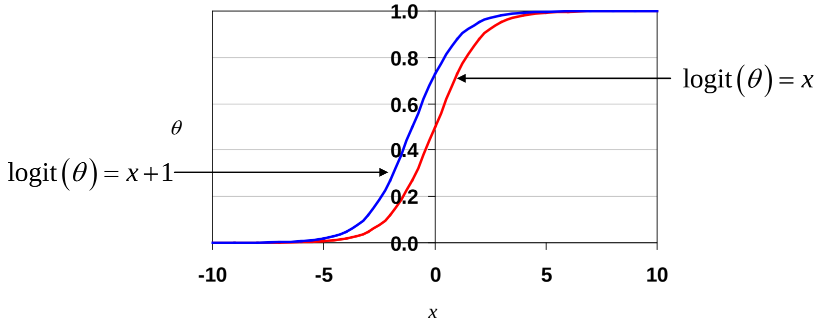
The Logit Link

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

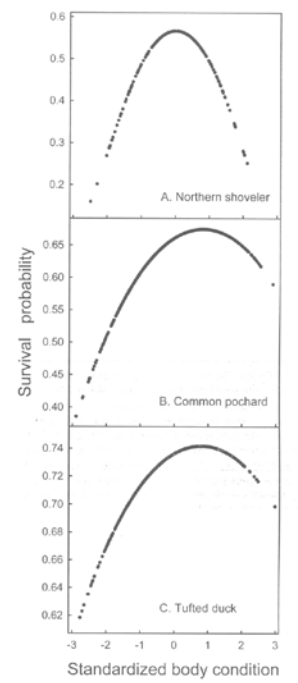
which can be rearranged as

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

- Recall that interpreting the effect of a covariate on the probability *θ* is based on this non-linear relationship.

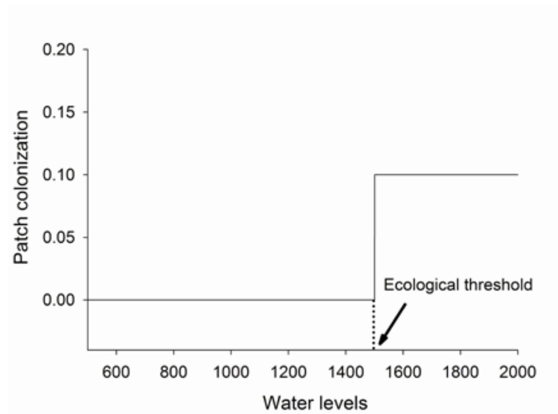


$$S_j = \frac{\exp(\beta_1 + \beta_2 x_j + \beta_3 x_j^2)}{1 + \exp(\beta_1 + \beta_2 x_j + \beta_3 x_j^2)}$$



Thresholds in functional relationships

- Ecological models of vital rates can include "thresholds", where small changes in an environmental variable can bring about a large change in a vital rate
- Patch Occupancy dynamics (MacKenzie et al. 2003)

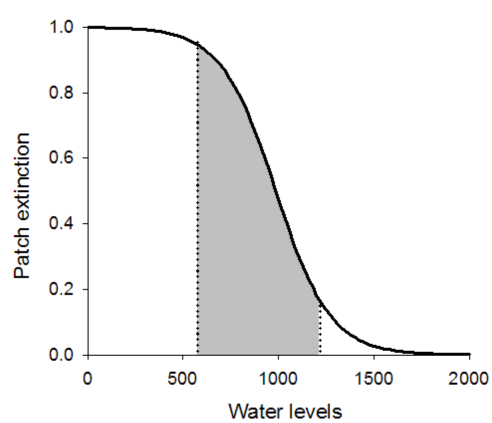


$$\psi_{t+1} = \psi_t \times (1 - \varepsilon_t) + (1 - \psi_t) \times \gamma_t$$

$$\gamma_t = \begin{cases} 0, & \text{if } L_t < T \\ 0.1 & \text{if } L_t \geq T \end{cases}$$

$$\varepsilon_t = \frac{1}{1 + e^{(-\alpha - \beta \times L_t)}}$$

ψ : patch occupancy
γ : patch colonization
ε : patch extinction



Modeling examples: summary

- Examples are simply that; there is no implication that example models should usually/always be used
- Instead, selection of state variables and associated dynamic model structures should be dictated by the decision context
- Select state variables that are relevant to returns and include associated vital rates that are likely to be influenced by management
- Overall model use: to link predicted system state and returns to management actions