



Lecture 4: Linking Models to Data

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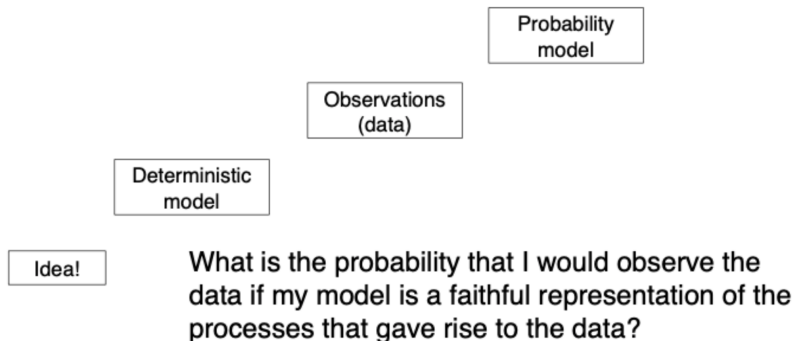
NRES 779

Bayesian Hierarchical Modeling in Natural Resources

Today

- How we link deterministic models to data modeling

Linking Models to Data



Layout of next few lectures

- Today: Linking data to deterministic models
- Friday: Basic laws of probability
- Wednesday: Probability distributions
- Friday: Likelihood and Bayes' Theorem

Learning Objectives

- Introduce first ideas about *support*
- Distinguish between purely empirical models and models symbolizing processes.
- Introduce a set of functional forms useful for composing deterministic models.
- Cross cutting themes
 - A relatively small set of functions can be used to describe a broad array of (ecological) processes.
 - The same process can be represented by different functional forms.
 - The same functional form can be used to represent different processes.

$$f(x_i, \theta)$$

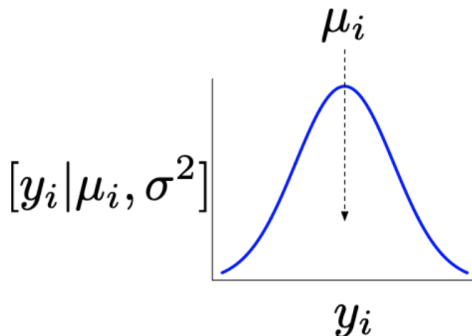
Any type of mathematical function

- linear models
- non-linear models
- systems of differential equations
- systems of difference equations
- integral-projection models
- state-transition models
- matrix models

Any equation or system of equations making a prediction that can be compared with an observation.

Linking Models to Data

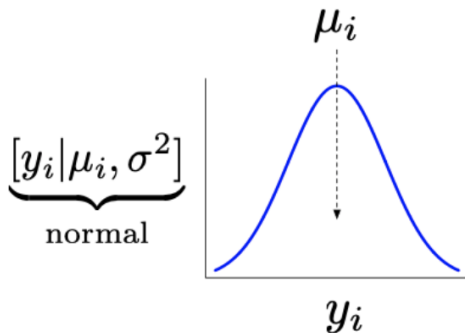
$$\mu_i = f(x_i, \theta)$$



Example

$$\boldsymbol{\theta} = (\beta_0, \beta_1)'$$

$$\mu_i = f(x_i, \boldsymbol{\theta}) = \beta_0 + \beta_1 x_i$$



This model is often a poor choice in biology. Why?

Support

Support refers to the range of values that a variable can realize. A more formal definition will come soon. Describe the support for the following variables:

- Soil organic matter content (gm OM/gm dry matter)
- Observed survival of an individual
- Species richness
- Carbon flux
- Above ground biomass of grassland

Example functional forms for $f(x_i, \theta)$

- Additive effects
- Asymptotic processes
- Power functions

Additive, nonlinear models

- Additive models contain linear functions of coefficients and predictor variables, e.g., $\beta_0 + \beta_1 x_{1,i} + \dots + \beta_d x_{d,i}$
- Often referred to as generalized linear models family because transforming the left hand side results in a linear model.
- Are usually *empirical* - very useful for modeling correlation between predictors and responses.

Generalized linear models

What if response variable is between 0 and 1

- Proportion of plots with invasive species
- Nitrogen content of soil (gN/gOM)
- Proportion of landscape burned
- Survival probability of juveniles
- Prevalence of a disease in a population

Inverse logit function

Let μ = variable that can take on values between 0 and 1.

$\text{logit}(\mu) = \log\left(\frac{\mu}{1-\mu}\right)$ converts μ to values between $-\infty$ and ∞ .

$$\text{logit}(\mu) = \log\left(\frac{\mu}{1-\mu}\right) = \beta_0 + \beta_1 x_1 + \dots + \beta_d x_d$$

$$\mu = \text{logit}^{-1}(\beta_0 + \beta_1 x_1 + \dots + \beta_d x_d)$$

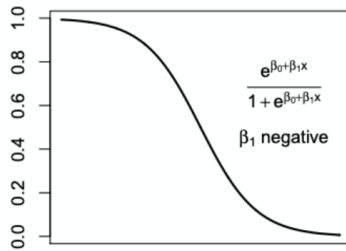
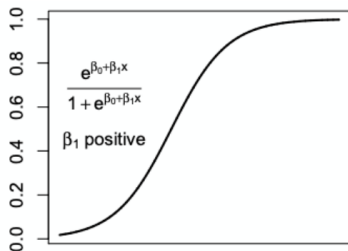
$$\mu = \frac{e^{\beta_0 + \beta_1 x_1 + \dots + \beta_d x_d}}{1 + e^{\beta_0 + \beta_1 x_1 + \dots + \beta_d x_d}}$$

$$\text{You will also see } \mu = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \dots + \beta_d x_d)}}$$

But, be careful about the minus in the exponent!

You can include powers and products of the x s

Inverse logit function



What Not to Do

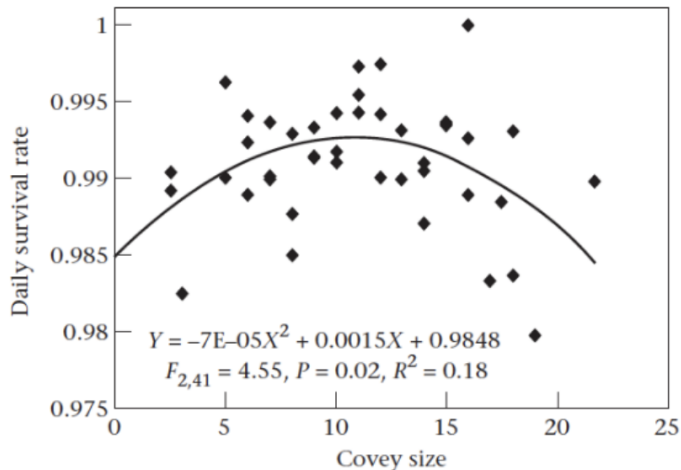


Figure 10. The influence of covey size on individual daily survival between 9 November and 31 January 1997–2000 in east-central Kansas.

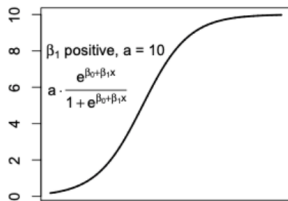
Generalize Linear Models

What if a response is between 0 and a ?

Multiply by a :

$$\frac{a e^{(\beta_0 + \beta_1 x_i + \dots + \beta_n x_n)}}{1 + e^{(\beta_0 + \beta_1 x_i + \dots + \beta_n x_n)}}$$

Always non-negative and does not reach excessively large values



Generalize Linear Models

What if a response must be ≥ 0 ?

For example, we want to model μ_t as an additive function of covariates:

$$N_{t+1} = \mu_t N_t$$
$$\mu_t = f(x_t, \beta)$$

Other example responses that must be non-negative:

- biomass
- energy expenditure
- nitrogen mineralization
- population density
- species richness
- ground water flow

Generalize Linear Models

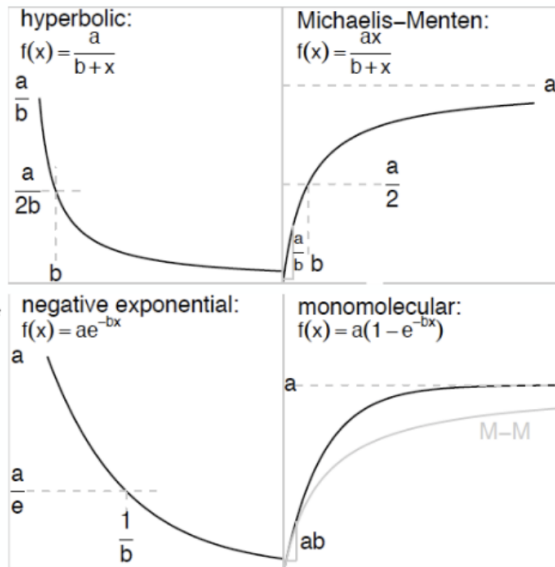
Exponential model

$$\mu_t = \exp(\beta_0 + \beta_1 x_{1,t} + \dots + \beta_d x_{d,t})$$

which is also written as

$$\log(\mu_t) = \beta_0 + \beta_1 x_{1,t} + \dots + \beta_d x_{d,t}$$

Asymptotic Functions



Figures courtesy of
 Bolker, B. 2008.
 Ecological Models and
 Data in R. Princeton
 University Press,
 Princeton, N. J. USA.

Deterministic Functions From Past Classes

Meredith Brehob, Lambert-Beer Law (depth of light penetration)

Negative exponential function:

$$I_z = I_0 e^{-k_d z}$$

$$\mu_i = \beta_0 e^{-\beta_1 x},$$

Deterministic Functions From Past Classes

Mia Goldman, Discrete Logistic Growth

$$N_{t+1} = N_t + rN_t\left(1 - \frac{N_t}{K}\right)$$

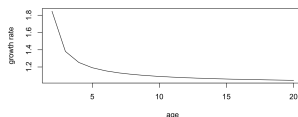
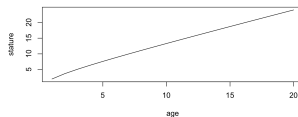
Deterministic Functions From Past Classes

Chris Wolfe, human structural growth

$$\mu_i = \beta_0 + \beta_1 x_i + \beta_2 \log(x_i),$$

where

- μ_i is stature of individual i .
- x_i is the age of individual i



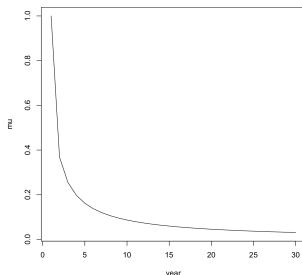
Deterministic Functions From Past Classes

Meghan Keating, Ricker model

$$\mu_t = \beta_0 \mu_{t-1} e^{-\beta_1 \mu_{t-1}},$$

where

- μ_t is population size at time t .



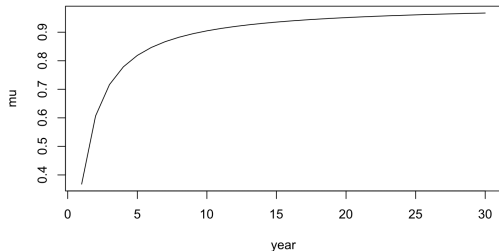
Deterministic Functions From Past Classes

Steve Hromada, Arrhenius equation

$$\mu_t = \beta_0 e^{-\frac{\beta_1}{\sigma^2 t}},$$

where

- μ_t thermal rate constant at temperature t .
- β_0 the “pre-exponential factor” (called a scale parameter in statistics)
- β_1 is the activation energy for the reaction
- σ^2 The universal gas constant.



Deterministic Functions From Past Classes

Elaine Chu, Logistic equation

$$\text{logit}(\mu_i) = \beta_0 + \beta_1 x_{i,1} + \dots + \beta_d x_{i,d},$$

where

- μ_t is the “probability” of being female.
- β s are the “weights” associated with morphological features x_i
- x_i are morphological features typical of males and females from the pelvis and/or cranium.

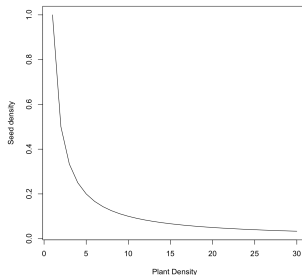
Deterministic Functions From Past Classes

Sage Ellis, Hyperbolic function

$$\mu_i = \frac{\beta_0}{x_{i,1}},$$

where

- μ_t is, for example, seed density.
- β_0 is some constant.
- x_i is plant density.



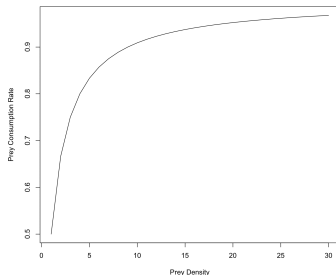
Deterministic Functions From Past Classes

Madeleine Lohman, Holling Type II Functional Response

$$\mu_t = \frac{\beta_0 x_t}{1 + \beta_0 \beta_1 x_t},$$

where

- μ_t is the prey consumption rate.
- β_0 is the attack rate.
- x_i is prey density.
- β_1 is the handling time.



Deterministic Functions From Past Classes

Jason Gundlach, Holling Type III Functional Response

$$\mu_t = \frac{\beta_0 \beta_1 x_t}{1 + \beta_0 \beta_2 x_t},$$

where

- μ_t is the prey consumption rate.
- β_0 is the attack rate.
- β_1 total time spent.
- β_2 is the handling time.
- x_t is prey density.

