

Lecture 1 - Philosophical Principles

Announcements:

Today - Finish up class period with some philosophy of what it means to “model” something
Next class: Density-independent geometric deterministic single-species growth

Write-up on board during break

“All models are wrong, but some are useful.” – Box
“No model can be general, precise, and realistic.” – Puccia & Levins
“Make your theory as simple as possible, but no simpler.” – Einstein

Categories by Type

What is a model?

Lots of categories; too many to list.

Many different motivations and approaches e.g., Jackson reading

⇒ Context for what we want to cover in course

Conceptual Models vs. Mathematical Models

Ideas

Hypotheses

e.g., diagrams with boxes and arrows

Z (2° consumer)

γ

Y (1° consumer)

α

W

β

X

$$Z = \gamma Y$$

$$Y = \alpha W + \beta X$$

Parameters: α and β

State variables: Y, W, X, Z

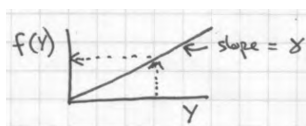
Qualitative vs. Quantitative

$$\Delta Z > 0 \text{ if } \begin{cases} \Delta Y > 0 \text{ and } \gamma > 0 \\ \Delta Y < 0 \text{ and } \gamma < 0 \end{cases}$$

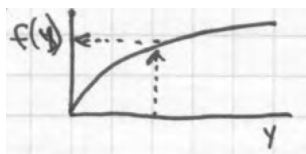
Static Models vs. Dynamical Models

Feeding rate of Z on Y depends on Y 's abundance

$$\Rightarrow f(Y) = \gamma Y$$



Could be non-linear



Iterative in time or space

$$Y_{t+1} = Y_t + (\alpha W_t + \beta X_t - \gamma Z_t) Y_t$$

Value of Y depends on the value before it.

Many other types and categories:

Individual (agent) based
spatially implicit versus spatially explicit
etc.

But categories can quickly break down:

ex1. Dynamical models contain static models
ex2. Typically interested in *qualitative* predictions from *quantitative* models

Categories by Purpose

Quantitative models are tools for *evaluating* hypotheses/conceptual models

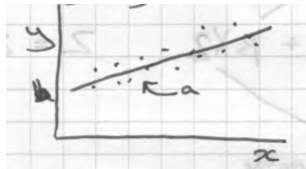
Traditionally:

Statistical Models vs. Process Models

Hypothesis testing & Parameter estimation

⇒ Inference within bounds of data

e.g., linear regression, ANOVA, t-tests



$$y_i = ax_i + b + \epsilon_i$$

a - slope

b - intercept

ϵ - residual errors

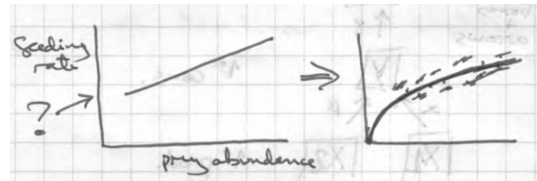
⇒ Pattern

First-principals

Analytical inference

Simulation & Numerical analysis

e.g., intercept = 0 makes no sense for functional response



⇒ Mechanism

The best modern-day quantitative modeling *combines* traditional Statistical and Process modeling

Deterministic (mechanistic) “core” + Stochastic (error) shell

$$\text{Feeding rate} = \underbrace{f(\text{Prey})}_{\text{core}} + \underbrace{\epsilon}_{\text{shell}}$$

$$\epsilon \sim \mathcal{N}(0, \sigma^2)$$

⇒ New world of process-model fitting & information-theoretic model comparisons

Models are *not* the same as hypotheses or theories

Multiple models can encapsulate the same hypotheses

Purpose is often to *refine* hypotheses; a form of quantitative reasoning.

e.g., “Feeding rate increases with prey abundance.” = hypothesis

Model Complexity

In Ecology: wide range of model complexities

Discrete-time Logistic: $x_{t+1} = rx_t(1 - x_t)$
1 parameter & 1 state variable, yet chaotic dynamics possible!
EcoPath, Atlantis (end-to-end models)
100-1000's of parameters
10-100's of state variables

We will be dealing with the former range in this class

Common criticisms of theoretical ecology:

“Where is reality?”
“Too simple” “Irrelevant”
“Real world is way more complex than just a handful of parameters and state variables.”
“Theory applies in general everywhere, but nowhere in particular. Thus useless”

Much work has shown low-dimensional model can explain most of the observed variation.

Low-dimensional models allow:

identify & focus on most critical parameters, variables, processes
rigorous exploration/understanding of uncertainty
decision-making tools
general understanding is the goal

“No model can be general, precise, and realistic.” – Puccia & Levins

R demonstration: Polynomial regression - statistical model

Have population sizes of rabbits at time $t - N(t)$

Model it using polynomial regression:

$$N(t) = \sum_{n=0}^{\infty} \beta_n t^n = \beta_0 \cancel{t^0}^1 + \beta_1 t^1 + \beta_2 t^2 + \dots + \beta_n t^n$$

Group exercise Repeat with random numbers

What have we learned from our polynomial model? Nothing!

Yet this statistical model is a perfect fit to the data!

\Rightarrow Goal of theoretical ecology is understanding (few parameters)

Lotka-Volterra predator-prey model with 4 parameters:

$$\frac{dN}{dt} = N(\alpha - \beta L) \quad \frac{dL}{dt} = L(e\beta N - d)$$

[Turns out LV model is wrong for Lynx-Hare, but took a long time to realize that and provided important insights into pred-prey ecology in general.]

Linear vs. Nonlinear Models

$$f(x) = \alpha + \beta x$$

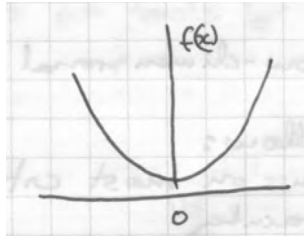
Variable: x

Parameters: α and β



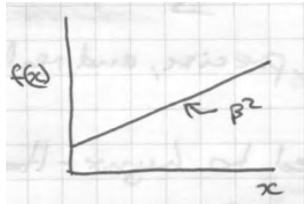
⇒ Linear model

$$f(x) = \alpha + \beta x^2$$



⇒ “Nonlinear” for ecologists & mathematicians
(nonlinear in state variable)
⇒ “Linear” for statisticians
(in parameters)

$$f(x) = \alpha + \beta^2 x$$



⇒ “Linear” for ecologists & mathematicians
⇒ “Nonlinear” for statisticians
(nonlinear in parameters)

My road to Theoretical Ecology

- For some, this class will be easy & intuitive. For others, less so.
- I am not a mathematician (or statistician)! As undergrad, took usual Calculus (even remedial Calculus for biologists). But skipping equations in papers. Took authors on their word (esp. discussion section).
- Went to grad school after 3 yrs. as field ecologists to learn “theoretical ecology”. (But almost failed out of first year stats class; too much calculus; over my head.)

⇒ Your ability and what you learn will come down to your motivation. Keep at it. Persevere.

- My motivation: Conceptual understanding of species interaction strengths & IGP theory.
 - In 3rd year while reading a paper, realized I’d read and actually understood the equations!
 - So much untested and interesting theory exists that is just waiting for empiricists to test & develop & correct
 - Don’t have to be a mathematician, but for Ecology to make progress we need to understand theory (“the math”)
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