

# Applied Environmental Statistics

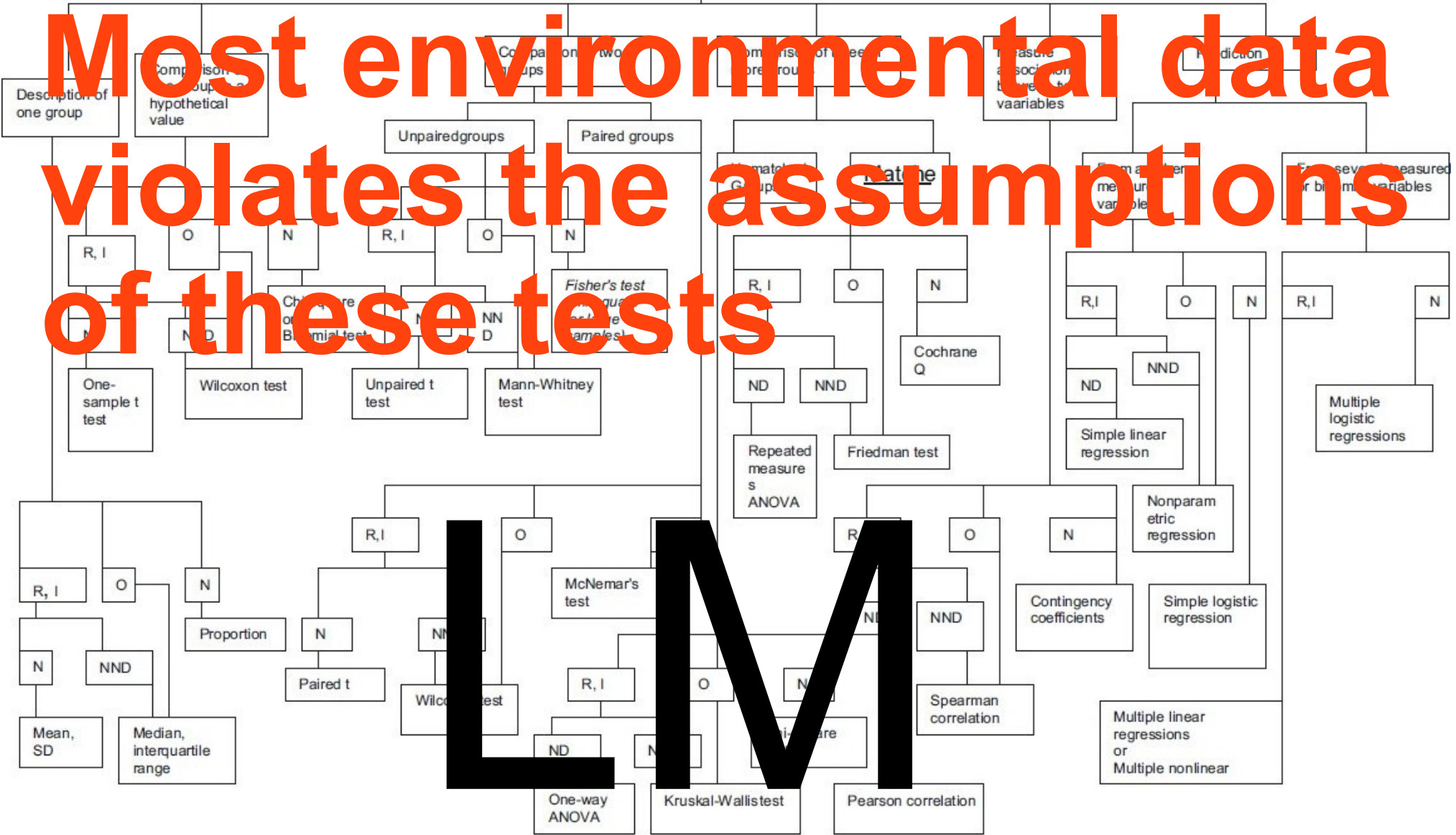
GE 509

Instructor: Prof. Michael Dietze

# Introductions

Goal

Most environmental data violates the assumptions of these tests



LMM

R, I = Ratio and Interval data    O= Ordinal data    N = Nominal data

N = Normal distribution    NND = Non normal distribution

What is statistical modeling?

# What is statistical modeling?

“Confronting models with data”

- Model fitting / parameter estimation
- Model comparison
- Estimation, partitioning, and propagation of uncertainties

# What is statistical modeling?

“Confronting models with data”

**Design the statistical analysis to fit the data rather than the data to fit the test**

# What is a model?

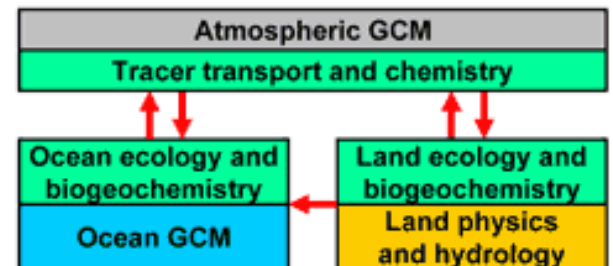
# What is a model?

A conceptual, graphical, or mathematical representation / abstraction of some empirical process(es).

A mathematical function that formalizes our conceptual model / theory

$$f(x) = a$$

$$f(x) =$$





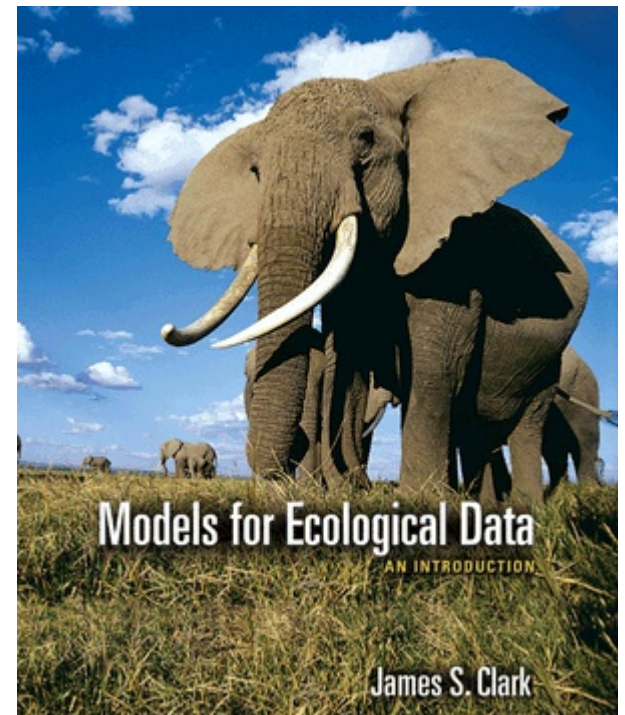
# What is a model?

Models are  
**HYPOTHESES**

# Syllabus

# Course Materials

- Reading assignments, lecture slides, project details, etc. are all posted on the lab website <http://people.bu.edu/dietze/Bayes2018/GE509.htm>
- Primary Text:  
“Models for Ecological Data”  
Clark 2007 Princeton U Press
- Software:
  - R / RStudio
  - OpenBUGS / JAGS
  - Git / GitHub



# Grading

Grading will be based on lab reports, a semester-long project, and four exams.

Lab reports/problem sets (10 points each)		= 150
Semester project ( <b>GRAD</b> )		= 95
project proposal	2/9	(10)
model description	3/2	(15)
preliminary analysis	4/9	(20)
Final report	before exam 4	(50)
Exams (30, 25, 30, 30 points )		= 115
[non-cumulative]		
	Total	= 360

# Labs

- **LAB IS MANDATORY**
- Labs will be posted in git repository  
<https://github.com/mdietze/EE509>
- Due FOLLOWING WEEK by the start of lab
- Must be turned in individually
- Can work together

# Semester Project

- Final product:
  - “Journal article” on a data analysis
    - You choose topic
    - ENCOURAGED to use your own data
    - Analysis must be new, use concepts from class
    - “Methods” heavy
- Four milestones
- One lab is peer critique

# Lecture & Exams

- Four sections
  - Probability theory and Maximum Likelihood
  - Bayesian methods
  - Hierarchical/mixed models
    - Linear regression → nonlinear, non-gaussian
  - Advanced topics
    - Time series
    - Spatial

# Exams

- Multiple Choice
- Matching
- Fill in the blank
- Short Answer / Derivation
- ~15 questions



# Expectations

- You have seen basic calculus at some point
  - Primarily need to follow derivations
- Basic familiarity with statistical concepts
  - e.g. experimental design, randomization, mean, median, variance
- Open mind
- You will work hard
- You won't 'get' Bayes the first time they see it (but will need to by the 2<sup>nd</sup> exam)

# Objectives

- Literacy
  - Read and evaluate advanced stats used in papers
- Proficiency
  - underlying statistical concepts
  - Software: R, JAGS
- Exposure to advanced topics
- Paradigm shift

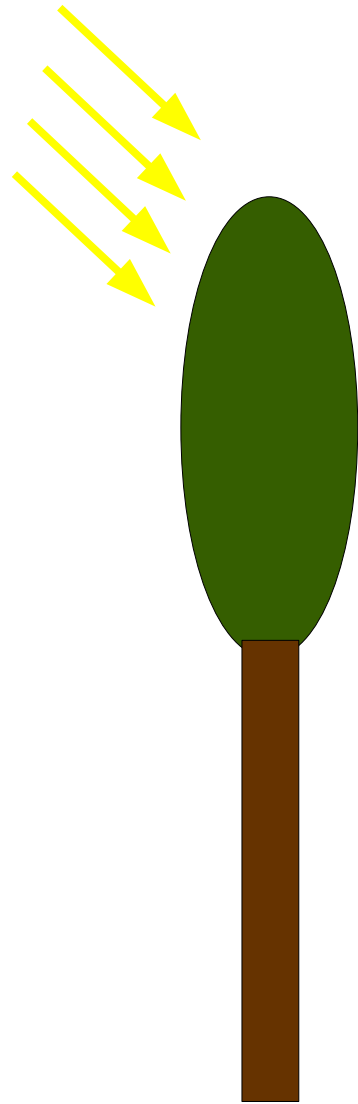
# A bit more on motivation....

Data are usually complex

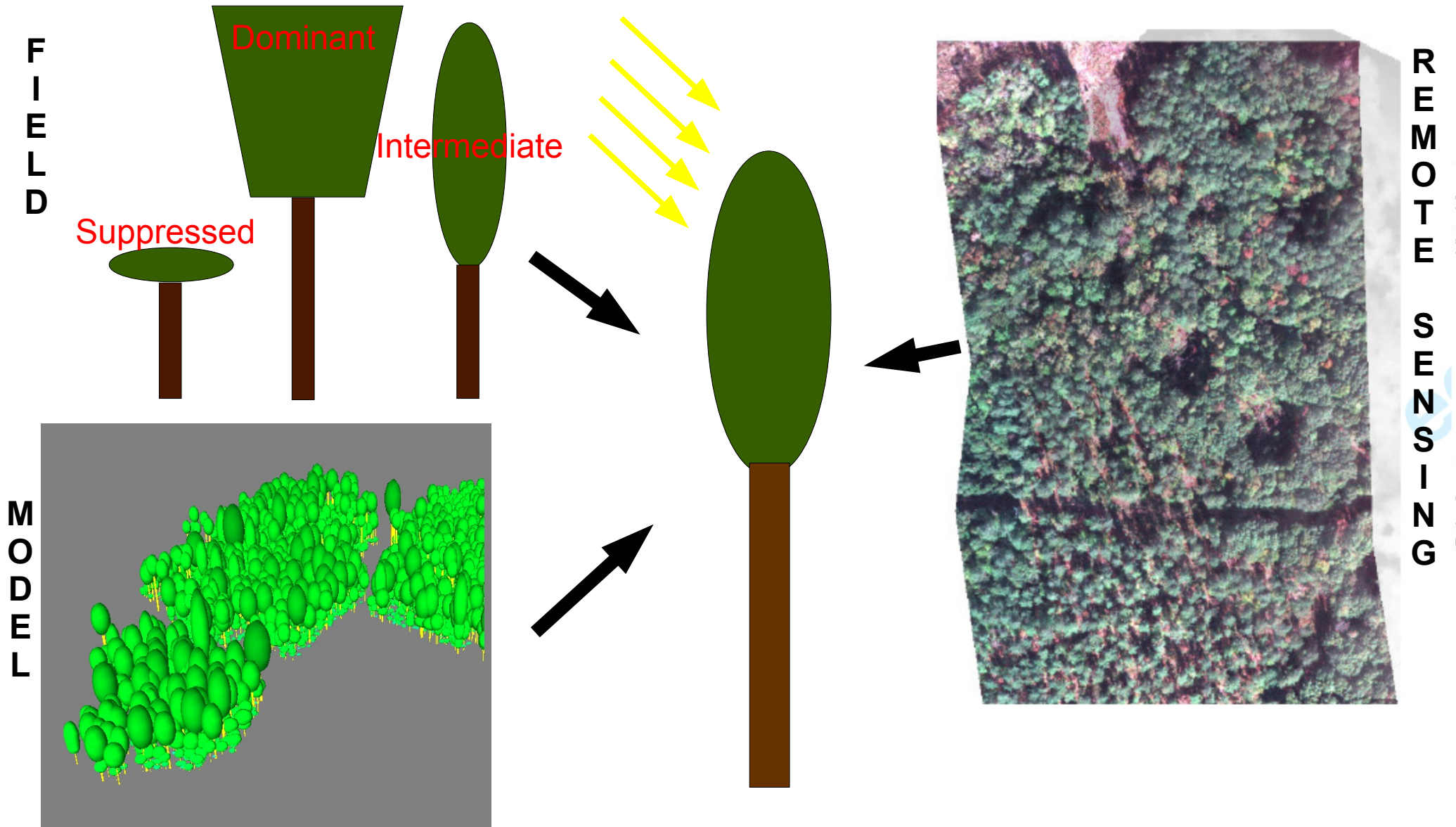
Violate the assumptions of classical tests

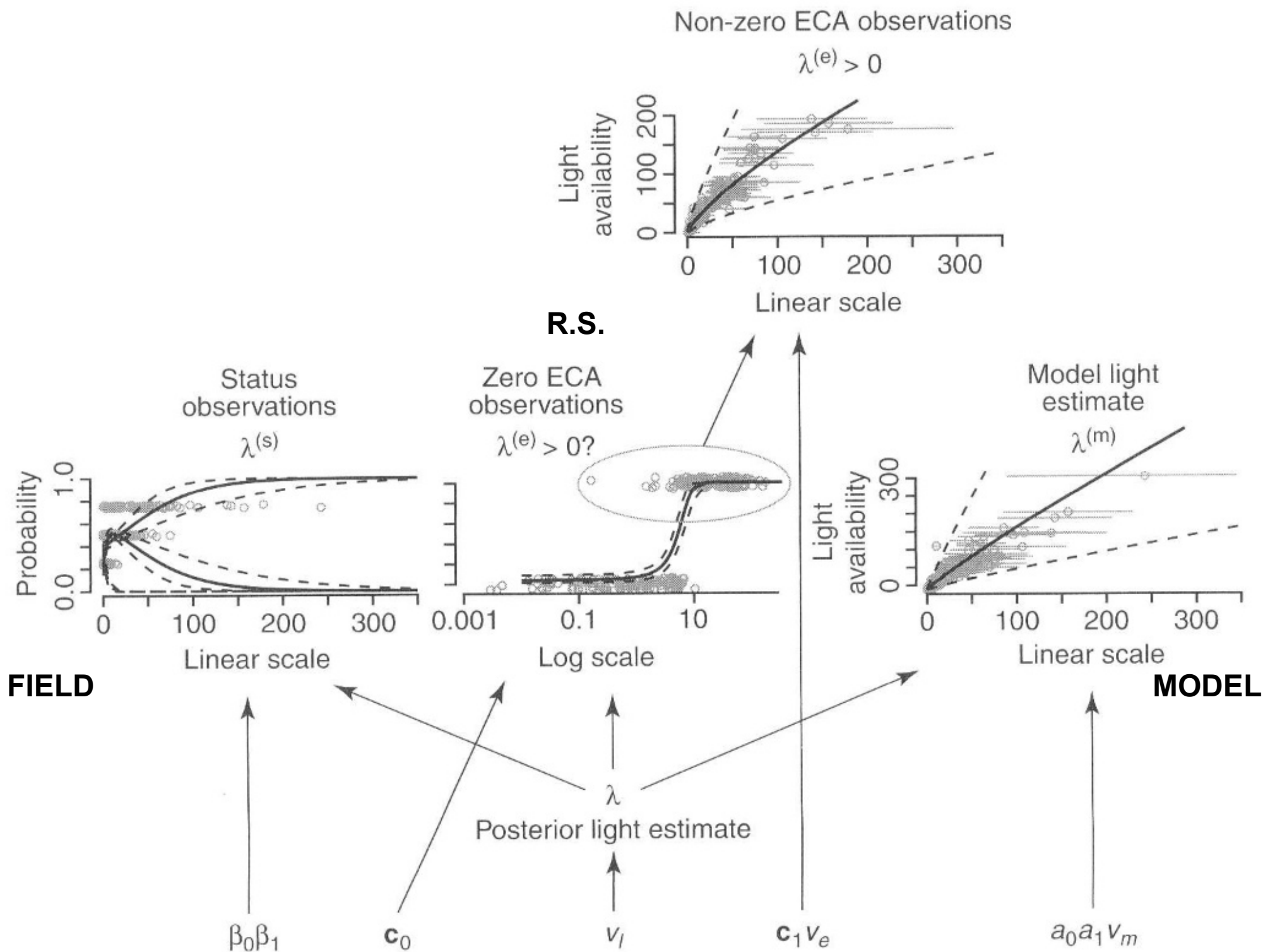
This complexity can be addressed with modern  
techniques

Example:  
How much light is a tree getting?



# Example: How much light is a tree getting?





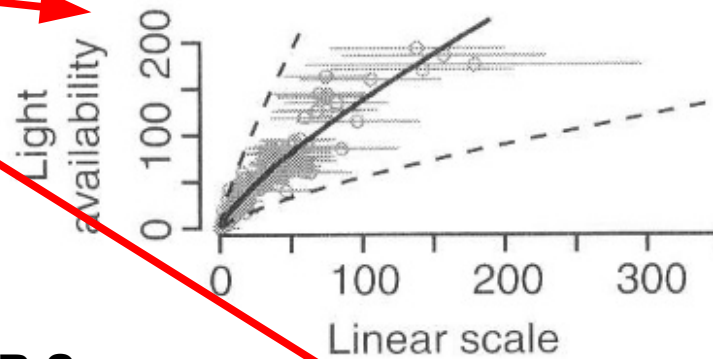
**Linear models**

**Logistic**

**Multinomial**

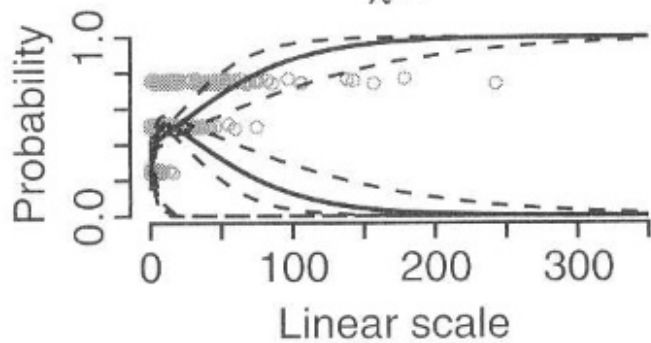
Non-zero ECA observations

$\lambda^{(e)} > 0$

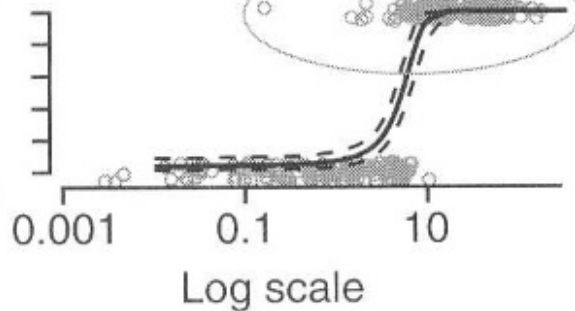


**R.S.**

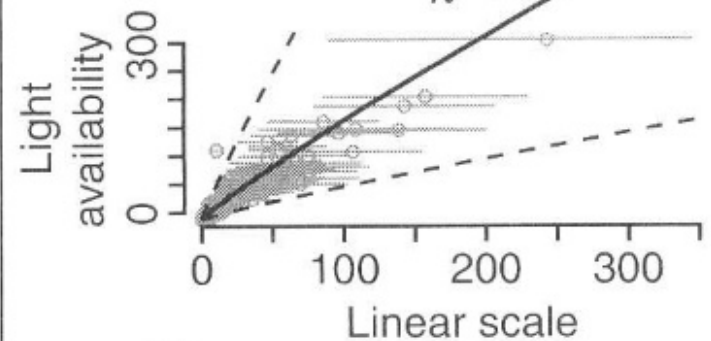
Status observations  
 $\lambda^{(s)}$



Zero ECA observations  
 $\lambda^{(e)} > 0?$



Model light estimate  
 $\lambda^{(m)}$



**FIELD**

**MODEL**

$\lambda$

Posterior light estimate

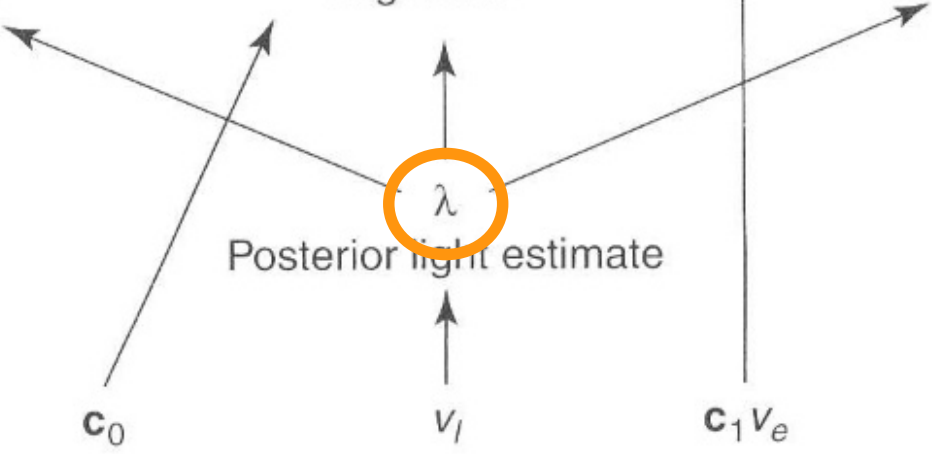
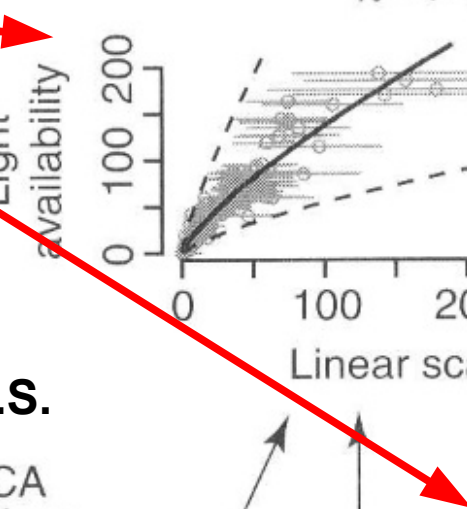
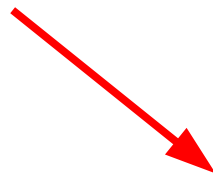
$\beta_0 \beta_1$

$c_0$

$v_l$

$c_1 v_e$

$a_0 a_1 v_m$



# Problem Characteristics

- Multiple data constraints
- Non-linear relationships
- Non-Normal residuals
- Non-constant variance
- Latent variables (response variable not being observed directly)
- Distinction between observation error and process variability
- Missing data



# Statistical Paradigms

- Classical (e.g. sum of squares)
- Maximum Likelihood
- Bayesian

# Statistical Paradigms

	Statistical Estimator	Method of Estimation	Output	Data Complexity	Prior Info
<b>Classical</b>	Cost Function	Analytical Solution	Point Estimate	Simple	No
<b>Maximum Likelihood</b>	Probability Theory	Numerical Optimization	Point Estimate	Intermediate	No
<b>Bayesian</b>	Probability Theory	Sampling	Probability Distribution	Complex	Yes

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The unifying principal for this course is statistical estimation based on **probability**

# Next lecture

- Will cover basics of probability theory
- Read
  - Clark 2007 - Chapter 1
  - **Hilborn and Mangel p39-62** (course website)
- Optional
  - Clark 2007 – Appendix D (Probability)
  - Otto and Day – Appendix 1 (Math) and 2 (Calculus) (course website)