Introduction to Model-Data Fusion in Population and Community Ecology
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At the conclusion of this two-week workshop, students will be able to do three things:

1) Build models representing dynamics of populations and communities
2) Estimate values for parameters in those models using multiple sources of data using likelihood and Bayesian methods.
3) Evaluate the strength of evidence in data for competing models

The course will include two weeks of lecture and laboratory exercises, outlined below. During the two weeks preceding the course, students will be given a detailed tutorial on modeling using the R programming language to be completed before the course starts. Hobbs will be available by email to answer student questions as they learn R.

1) Day 1
    a) Morning Lecture: An introduction to deterministic models in population an community ecology
        i) What are models and why are they useful?
        ii) The mathematical basis for dynamic models
        iii) Forward and inverse modeling
        iv) Exponential population growth
        v) Elementary density dependence
    b) Morning Lab: Cycles and chaos with the discrete logistic
    c) Afternoon Lecture
        i) Systems of differential equations
        ii) Numerical integration
        iii) The relationship between probabilities and rates in discrete and continuous time
    d) Afternoon lab: Numerical integration
        i) Dynamics of disease
        ii) Interactions of plants, herbivores, and predators
2) Day 2
    a) Morning lecture: Making population models more realistic
        i) Adding age and sex: age and stage structured models
        ii) Review of linear algebra
        iii) The Leslie matrix
    b) Morning Lab: programming a one sex, three age model in discrete time
    c) Afternoon Lecture: Analyzing matrix models
        i) The population growth rate: eigenvalue analysis
        ii) Stable age distribution and reproduction value: eigenvector analysis
    d) Afternoon lab: analyzing stage structured models
3) Day 3
    a) Morning lecture: Stochastic models
        i) Review of probability and probability distributions
            (1) Poisson

        (2) binomial
        (3) normal
        (4) lognormal
    ii) Simulating data using probability distributions and deterministic models
    iii) Process variance and observation error
  b) Morning lab: Simulating data using the discrete logistic and stage structured models
  c) Afternoon lecture
    i) More probability distributions
        (1) beta
        (2) multinomial
        (3) negative binomial
        (4) gamma
  d) Afternoon lab: More data modeling
4) Day 4
  a) Morning lecture: risk analysis and population viability
  b) Morning lab: a simple viability model
  c) Afternoon lecture: fusing models with data: Likelihood
  d) Afternoon lab: estimating model parameters using sums of squares and likelihood
5) Day 5
  a) Morning Lecture: Likelihood
    i) likelihood ratios
    ii) profile confidence intervals
  b) Morning laboratory: The Serengeti Wildebeest: fitting a discrete logistic using sums of squares and a normal likelihood under Excel
  c) Afternoon Lecture: Likelihood
    i) Using multiple sources of data to estimate parameters
    ii) Using prior information on model parameters
6) Day 6
  a) Morning Lecture: Information theoretics
    i) Kullback-Leibler information discrepancy
    ii) The Akaike Information Criterion
        (1) AIC_c
        (2) QAIC
    iii) delta-AIC
  b) Morning laboratory: Composing alternative wildebeest models
  c) Afternoon lecture: More AIC
    i) Model likelihood
    ii) Akaike weights
    iii) Model averaging and multi-model inference
    iv) Confidence intervals including model-selection uncertainty
  d) Afternoon laboratory: finding the best wildebeest model
7) Day 7
  a) Morning Lecture: Catch-up and review
  b) Morning Laboratory: Presentations of wildebeest models
  c) Afternoon Lecture: Classical Bayesian analysis

        i) Development of Bayes Law
        ii) The relationship between likelihood and Bayes
        iii) Conjugate priors
    d) Afternoon lab: Introduction to WinBugs
        i) Binomial example
        ii) Non-linear regression example
8) Day 8
    a) Morning Lecture: Hierarchical models
    b) Morning Lab: A simple, dynamic model with process variance
    c) Afternoon Lecture: Monte-Carlo Markov Chain
    d) Afternoon Lab: A state-space model: including process variance and observation error
9) Day 9
    a) Morning lecture: More hierarchical modeling
        i) Including covariates
        ii) Multiple sources of data on state variables
        iii) Random effects
    b) Afternoon lab: Fitting a stage-structured, state-space model
10) Day 10
    a) Morning lecture: Bayesian model selection
    b) Morning laboratory: Fitting a stage-structured, state-space model
    c) Afternoon lecture: Synthesis and next steps in training
    d) Afternoon laboratory: Fitting a stage-structured, state-space model