Welcome to NRES 746

Advanced Analysis Methods in Natural Resources and Environmental Science

Fall 2023

https://kevintshoemaker.github.io/NRES-746/

Instructor

Kevin Shoemaker
Office: FA 220E
Phone: (775)682-7449
Email: kevinshoemaker@unr.edu
Office hours: Wednesdays at 1pm in FA 220e

Meeting Times

Lecture & Discussion: M, W at noon in FA 109 (50 mins)
Lab: Tuesday at 3pm in KRC 105 (2 hours 45 mins)

Course Objectives

Modern computers have reduced many of the barriers to advanced data analysis, and powerful (and free!) computational tools are now available that enable “ordinary” researchers like you and me to answer questions that would have been considered intractable in previous generations! Armed with basic concepts of probability and statistics, a little programming chops - and a deep understanding of the natural world-ecologists and natural resource professionals can get more out of their data than ever before. **In this course, we embrace computer algorithms (and largely avoid closed-form mathematical solutions)!** This can be time-consuming, but it allows us to focus on the ecological system first and foremost, instead of being constrained by the statistical tools available to us.

By the end of this course, students should have the ability to (1) simulate data under biologically realistic scenarios, (2) make inferences from data using maximum likelihood estimation (MLE) and Bayesian techniques, (3) assess model adequacy, goodness-of-fit and predictive performance, and (4) understand where and when to use a wide variety of additional advanced data analysis methods. The goal is for students to emerge from this course as creative data analysts with the tools and intuition needed to draw inferences from a wide variety of data types.

The course motto: *Be Dangerous*! It is *safer* to use standard analytical tools (e.g., using ‘canned’ stats functions in R) because these methods have been rigorously tested over the years. When we build our own algorithms, we can be entering uncharted territory. And exploring these territories can be dangerous… and your inner voices (and other people’s voices) might tell you not to go there, just play it safe. Don’t listen to those voices! In this class, you are allowed - and encouraged - to live dangerously!

Our general focus will be on *model-based inference*, including regression-based approaches, hierarchical/mixed models, and multi-model inference. Additional student-led modules will cover other advanced analysis topics (we’ll discuss this more in class). In all cases, we focus on the concepts and implementation – we leave the nitty-gritty stats questions to statisticians.

Each student will be responsible for leading discussions, demonstrations and a hands-on 1 hour "mini-lab" on an advanced topic that builds on the main concepts in the course (working in groups). The laboratory portion of the class will provide students the opportunity to try out some of the data analysis methods we discuss in lecture. The first 4 labs will be led by the instructor, and the remainder (second half of the semester) will be student-led.

Student Learning Objectives

Students will be able to:

- Identify and contrast the major classes of statistical models used by ecologists (e.g., Bayesian vs frequentist, likelihood-based, machine learning) and explain how and why ecologists use these models.
- Apply analysis tools such as logistic regression, non-linear regression, and hierarchical (mixed-effects) models on diverse data sets representative of those commonly considered in ecology.
- Learn to explore data sets quantitatively and graphically and to prepare data appropriately for analysis.
- Perform basic programming operations, statistical analysis, data visualization, and simulation modeling with the statistical computing language 'R'.
- Critically evaluate the strength of inferences drawn from statistical models by testing major assumptions and assessing performance.
- Communicate statistical and computational concepts by leading lectures and discussion on advanced topics in data analysis.

Prerequisites

Curious scientific mind, broad research interests, and willingness to engage with equations and computer code. Students are expected to already have a basic foundation in statistical concepts and methods, obtained through other coursework. If this is not the case, they should be prepared to work harder to develop the necessary prerequisite knowledge.

Textbooks and Readings

- We will use the book, *Ecological Models and Data in R*, by Ben Bolker, as a general class reference.
- Additional readings may be assigned -please check the course schedule (which is ever- evolving!).
- Other related books you may find useful include "Statistical Rethinking" by Richard McElreath, and the textbooks on hierarchical models by Kery and Royle.

Course components

Student-led lectures and mini-labs: Each student will work with a small group (2-3) to lead a 50 minute lecture/demonstration and a 1-hour hands-on 'mini-lab' activity that introduces a relevant data analysis method (for this course, must be likelihood-based, and implemented in R/JAGS/stan). The lecture component will provide an overview of the method along with some published real-world applications of the method. The mini-lab will consist of a worked example (clear, concise, informative tutorial) and additional activities that provide classmates with an opportunity to test their knowledge of the method. Presenters are encouraged to work with the instructor (and other faculty, graduate students!) to develop their lectures and mini-lab activities.

Class Participation: Students are expected to actively participate in the classroom. Don't be afraid to ask questions- fear of embarrassment can be a major impediment to learning. This a safe space for making mistakes- this is part of *being dangerous!*

Laboratory Reports: Students will submit (1) an R script ('.R' file); here, a set of R functions, each of which performs a specific assigned task, and (2) a brief written report (in Word or Google Docs, submitted via WebCampus) succinctly answering any questions, and stating any questions or points of confusion with the lab exercises. While students are encouraged to work on the labs in small groups, all lab submissions must be made individually.

Grading

Course component	*Weight*
Student-led topics	40%
Participation	20%
Laboratory exercises	40%

Course Schedule

NOTE: the course schedule is subject to change, so please check back frequently!
https://kevintshoemaker.github.io/NRES-746/schedule.html

Week	Lecture 1	Lab	Lecture 2	Material Covered	Readings
Aug. 28	Course Introduction	Lab #1: Programming algorithms in R	Algorithms	Review syllabus, algorithmic approach to data analysis, basic programming in R	Clark Ch. 1; Touchon and McCoy 2016
Sept. 4	No class (labor day)	Lab #1: Programming algorithms in R (continued)	Algorithms	Basic probability calculus, working with probability distributions	Bolker ch. 4
Sept. 11	Probability	Lab #2: "Virtual Ecologist"	Probability	Generating data algorithmically, mechanistic models, power analysis, goodness-of-fit	Bolker Ch. 1, Ch 5.; Zuur et al. 2010 (optional)

Week	Lecture 1	Lab	Lecture 2	Material Covered	Readings
				testing	
Sept. 18	The Virtual Ecologist	Lab #2: "Virtual Ecologist" (continued)	Likelihood	Maximum likelihood estimation	Bolker Ch. 6; Hobbs and Hilborn 2006 (optional)
Sept. 25	No class (instructor is away)	No lab (instructor is away)	No class (instructor is away)	(no classes this week)	(no classes this week)
Oct. 2	Likelihood	Lab #3: Maximum likelihood	Likelihood	Optimization algorithms for maximum likelihood inference	Bolker Ch. 7
Oct. 9	Optimization	Lab #3: Maximum likelihood	Optimization	General introduction to Bayesian theory and application	Bolker Ch. 6 and 7 (Bayesian section); Ellison 2004
Oct. 16	Bayesian inference	Lab #4: Bayesian model fitting in JAGS	Markov Chain Monte Carlo (MCMC)	Markov-Chain Monte Carlo	Bolker Ch. 7 and 8
Oct. 23	Markov Chain Monte Carlo (MCMC)	Lab #4: Bayesian model fitting in JAGS (continued)	Model selection and multi-model inference	Model selection	Bolker Ch. 7 and 8
Oct. 30	Model validation and performance evaluation	Lab #5: Model selection and performance evaluation (including cross-validation)	Intro to student-led topics	Bias-variance tradeoff, cross-validation, assessing predictive accuracy	Anderson et al. 2000; Anderson et al. 2001
Nov. 6	student-led lecture/demo	student-led "mini labs"	student-led lecture/demo	Student-led (TBD)	Student-assigned reading (TBD)
Nov. 13	student-led	student-led	student-led	Student-led	Student-

Week	Lecture 1	Lab	Lecture 2	Material Covered	Readings
	lecture/demo	“mini labs”	lecture/demo	(TBD)	assigned reading (TBD)
Nov. 20	student-led lecture/demo	student-led “mini labs”	student-led lecture/demo	Student-led (TBD)	Student-assigned reading (TBD)
Nov. 27	student-led lecture/demo	student-led “mini labs”	No class (thanksgiving holiday)	Student-led (TBD)	Student-assigned reading (TBD)
Dec. 4	student-led lecture/demo	student-led “mini labs”	student-led lecture/demo	Student-led (TBD)	Student-assigned reading (TBD)
Dec. 11	Class wrap-up	TBD	No class (prep day)		Student-assigned reading (TBD)
Dec. 18	NA (classes over)				

Make-up policy and late work:

If you miss a class meeting or lab period, it is your responsibility to talk to one of your classmates about what you missed. If you miss a lab meeting, you are still responsible for completing the lab activities and write-up by the stated due date. Please let your instructor know in advance if you need to miss class or lab.

Statement of Disability Services

Any student with a disability needing academic adjustments or accommodations is requested to speak with the instructor or the Disability Resource Center (Pennington Achievement Center Suite 230) as soon as possible to arrange for appropriate accommodations. This course may leverage 3rd party web/multimedia content, if you experience any issues accessing this content, please notify your instructor.

Statement on Audio and Video Recording

Surreptitious or covert video-taping of class or unauthorized audio recording of class is prohibited by law and by Board of Regents policy. This class may be videotaped or audio recorded only with the written permission of the instructor. In order to accommodate students with disabilities, some students may have been given permission to record class lectures and discussions. Therefore, students should understand that their comments during class may be recorded.

This is a safe space

The University of Nevada, Reno is committed to providing a safe learning and work environment for all. If you believe you have experienced discrimination, sexual harassment, sexual assault, domestic/dating violence, or stalking, whether on or off campus, or need information related to immigration concerns, please contact the University's Equal Opportunity & Title IX office at 775-784-1547. Resources and interim measures are available to assist you. For more information, please visit the Equal Opportunity and Title IX page.

Statement on Academic Dishonesty

The University Academic Standards Policy defines academic dishonesty, and mandates specific sanctions for violations. See the University Academic Standards policy: UAM 6,502
COVID-19 policies

Statement on COVID-19 Face Coverings

Pursuant to Nevada law, NSHE employees, students and members of the public are no longer required to wear face coverings while inside NSHE buildings irrespective of vaccination status.

Statement on COVID-19 Social Distancing

In alignment with State of Nevada guidelines, social distancing is no longer required.
Statement on COVID-19 Disinfecting Your Learning Space
Disinfecting supplies are provided for you to disinfect your learning space. You may also use your own disinfecting supplies.

Contact with Someone Testing Positive for COVID-19

Students testing positive for COVID 19 or exhibiting COVID 19 symptoms regardless of vaccination status will not be allowed to attend in-person instructional activities and must leave the venue immediately. Students should contact the Student Health Center or their health care provider to receive care and who can provide the latest direction on quarantine and self-isolation. Contact your instructor immediately to make instructional and learning arrangements.

Accommodations for COVID 19 Quarantined Students:

For students who are required to quarantine or self-isolate due to 1) COVID 19 infection or 2) exposure while not vaccinated, instructors must provide opportunities to make-up missed course work, including assignments, quizzes or exams. In courses with mandatory attendance policies, instructors must not penalize students for missing classes while quarantined.

Statement on Failure to Comply with Policy (including as outlined in this Syllabus) or Directives of a University Employee:

In accordance with section 6,502 of the University Administrative Manual, a student may receive academic and disciplinary sanctions for failure to comply with policy, including this syllabus, for failure to comply with the directions of a University Official, for disruptive behavior in the classroom, or any other prohibited action. “Disruptive behavior” is defined in part as behavior, including but not limited to failure to follow course, laboratory or safety rules, or endangering the health of others. A student may be dropped from class at any time for misconduct or disruptive behavior in the classroom upon recommendation of the instructor and with approval of the college dean. A student may also receive disciplinary sanctions through the Office of Student Conduct for misconduct or disruptive behavior, including endangering the health of others, in the classroom. The student shall not receive a refund for course fees or tuition.