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The mismatch between current statistical practice and doctoral training in ecology

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Abstract. Ecologists are studying increasingly complex and important issues such as climate change and ecosystem services. These topics often involve large data sets and the application of complicated quantitative models. We evaluated changes in statistics used by ecologists by searching nearly 20,000 published articles in ecology from 1990 to 2013. We found that there has been a rise in sophisticated and computationally intensive statistical techniques such as mixed effects models and Bayesian statistics and a decline in reliance on approaches such as ANOVA or *t* tests. Similarly, ecologists have shifted away from software such as SAS and SPSS to the open source program R. We also searched the published curricula and syllabi of 154 doctoral programs in the United States and found that despite obvious changes in the statistical practices of ecologists, more than one-third of doctoral programs showed no record of required or optional statistics classes. Approximately one-quarter of programs did require a statistics course, but most of those did not cover contemporary statistical philosophy or advanced techniques. Only one-third of doctoral programs surveyed even listed an optional course that teaches some aspect of contemporary statistics. We call for graduate programs to lead the charge in improving training of future ecologists with skills needed to address and understand the ecological challenges facing humanity.

Key words: ANOVA; Bayesian; generalized linear model; JMP; linear regression; mixed effects model; nonparametric; R; SAS; SPSS; statistics; *t* test.

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Introduction

Ecological questions and data are becoming increasingly complex and as a result we are seeing the development and proliferation of sophisticated statistical approaches in the ecological literature. While well-designed experiments amenable to classic statistical tests aimed at rejecting simple null hypotheses still play a powerful role in biological research, many contemporary problems in ecology require the integration of empirical (often observational) data, mathematical theory, and sophisticated statistical tools (Stephens et al. 2007, Hobbs and Ogle 2011). Just as null hypothesis significance testing (NHST) rose to prominence throughout the 20th century (sensu Fisher 1925, Neyman and Pearson 1933, Popper 1959, Platt 1964, Lehmann 1993) and null models in ecology in the 1980s further advanced the body of ecological knowledge (Strong 1980, Simberloff 1983), the current sea change in quantitative rigor and statistical sophistication promises to provide the next major wave of insights and concomitant leaps in conceptual understanding. It is no longer sufficient to only ask "whether" or "which" experimental manipulations significantly deviate from null expectations. Instead, we are moving toward parameter estimation and asking "how much" and in "what direction" ecological processes are affected by different mechanisms (Burnham and Anderson 2002, McCarthy 2007, Bolker et al. 2009, Symonds and Moussalli 2011, Denny and Benedetti-Cecchi 2012).

This discussion is not new (e.g., Quinn and Dunham 1983), and several authors have pleaded for more intensive training in mathematics and statistics in ecology (e.g., Johnson 1999, Ellison and Dennis 2009, Robeva and Laubenbacher 2009, Hobbs and Ogle 2011), including students frustrated by their lack of training (Butcher et al. 2007). Indeed, Barraquand et al. (2014) conducted a survey of early-career ecologists and found that 75% (of 937 respondents) were not satisfied with their understanding of mathematics and statistics and more than 95% wish they had more statistics classes. Moreover, the survey revealed that these early-career scientists thought that nearly one-third of classes in graduate ecology curricula should focus on quantitative techniques. While there is a clear self-perceived lack of statistics training in ecology, no studies have quantitatively assessed the level of quantitative training received by students.

Many of the greatest challenges facing humanity over the next several decades are ecological in nature—climate change, loss of biodiversity and ecosystem services, emerging pathogens, and sustainable management of fisheries, forest, and agriculture. Solving these crises will demand that we are able to tackle increasingly complex problems with big data. These challenges do not fit neatly into the confines of null hypothesis significance testing and are often not amenable to simple experimental designs and manipulations.

Embracing new methods can bolster paradigm shifts and foster new scientific discoveries. In his classic essay, Thomas Kuhn (1962) reasoned that continuity in "normal" science is interrupted by episodes of revolutionary change often spurred by development of new tools or technology or conceptual approaches that inspire practitioners in search of better solutions to old problems. Indeed, being able to ask new questions of old data is often a launchpad for paradigm shifts. The rise of computer programming, computational power, and modern statistical approaches may provide that launchpad by allowing scientists to ask new questions and to extract more information from data than ever before. In addition to ecology, practitioners in psychology, social science, geology, and other fields are now able to gain more insights about phenomena occurring in nature from data even when the mechanisms that underlie them are poorly understood (Germano 2000).

Many types of commonly collected ecological data do not conform to the assumptions of traditional ecological approaches, and the nature of many large-scale manipulative studies results in small sample sizes and nested designs or data consisting of many zeros that cannot be effectively analyzed using classic tools (Tewksbury et al. 2002, McCoy and Bolker 2008). Furthermore, observational ecological data are often messy and may contain excessive numbers of explanatory variables (many of which may be correlated with one another; e.g., Hughey et al. 2015). In the past, these difficulties have driven ecologists to either simplify their analyses, transform their data (O'Hara and Kotze 2010, Warton and Hui 2010), or resort to descriptive or non-parametric methods (Johnson 1995). The types of data available to the modern ecologist often necessitate the use of sophisticated computer software, potentially including programming, for data analysis. Thus, much as the techniques used in ecology appear to have changed in recent years, so too has the software that ecologists use to analyze their data. Given the complexity and massive volumes of data that modern ecologists have available, and the need to diagnose new large-scale environmental problems and forecast impacts from imperfect data, it is imperative that future ecologists (i.e., doctoral students in ecology-related programs) receive proper training on modern techniques and statistical programs.

In this essay, we report a quantitative examination of recent changes in the use of statistical approaches in ecological research and cogitate on the academic training of ecologists. The trend toward applications of increasingly sophisticated statistics may seem obvious in the literature, but to our knowledge, it has not been objectively quantified and documented. Our goals here are threefold: (1) to document how the use of different statistical techniques have changed since 1990, (2) to assess the change in the use of several commonly cited statistical software programs over that same time period, and (3) to assess whether the current curricula of doctoral programs in ecology in the United States mirrors these trends. We hope that our analysis will inspire ecology programs to re-evaluate their curriculums and improve quantitative training of tomorrow's ecologists.

Materials and Methods

Evaluating ecological literature and doctoral programs

We conducted a full-text literature search of seven leading journals in ecology (*The American Naturalist, Ecology, Ecology Letters, Journal of Animal Ecology, Journal of Ecology, Oecologia,* and *Oikos*) for the years 1990–2013. To ensure complete coverage of the time period, we searched the websites JSTOR.org, esajournals.org, onlinelibrary.wiley.com, and springerlink.com (websites accessed 7–14 April 2014). To quantify the statistical techniques used, we searched for 10 terms associated with classic, NHST statistical techniques and nonparametric approaches, or "contemporary" statistical techniques (Table 1). While many of the techniques we label as contemporary are based on long-standing theory (e.g., Bayesian techniques), this classification represents the rise in the use of these techniques in recent time. Our search was designed to be as unambiguous as possible. Search terms were not case sensitive but were constrained to whole search values (e.g., searching for "mixed effects" would only return articles where the two words were used in succession but not when the words were used independently). To help control for the fact that patterns we might detect could result simply from changes in terminology instead of changing statistical practices, we searched for one term that was program specific, "PROC MIXED," which should return most cited uses of linear mixed effects models implemented in the program SAS since its release in 1992 (SAS Institute 1992). Our choice of search terms was not meant to be an exhaustive list, but instead to be representative of common approaches utilized within each class of approaches. Similarly, we searched for four of the most commonly used statistical programs (Table 1), which collectively account for more than half of the statistical programs cited in the literature.

Table 1. Search terms used in web searches of articles published in seven ecology journals 1990–2013, indicating the number of total articles found and whether each term was classified into a traditional (e.g., NHST) or a "contemporary" statistical framework.

Search term	Total articles	Framework
Statistical techniques		
"ANOVA"	11,031	Traditional
"*t* test"	4054	Traditional
"Mann–Whitney"	1914	Traditional
"Linear regression"	4879	Traditional
"Maximum likelihood"	2728	Contemporary
"Mixed effects" or "random effects"†	2588	Contemporary
"GLM"	2490	Contemporary
"AIC"	1942	Contemporary
"Bayesian"	1133	Contemporary
"PROC MIXED"	593	Contemporary
Statistical programs		
"SAS Institute"	4359	
"R Development Core Team" or "R Core Development Team"‡	2169	
"SPSS"	2003	
"JMP"	1097	

† The two terms were searched for separately but were combined to represent "mixed effects models" as a whole.
‡ Occasionally R is cited incorrectly, with the order of terms reversed.

All analyses were conducted in R v3.0.2 (R Development Core Team 2013). After compiling our databases of statistical techniques and programs, we compared the proportional change in occurrence of different terms over the 24-yr period. We used generalized linear mixed models (GLMMs) fit using the function glmmadmb (Skaug et al. 2014), assuming a binomial error distribution and logit link function to evaluate change in the usage of techniques and statistical software. We used binomial GLMMs for two reasons: (1) data were proportional—the number of articles in a year for each search term/the total amount of articles published in that year, and (2) it was necessary to include an observation-level random effect to control for overdispersion in the models. Due to obvious nonlinearities in some of the data, we included a second-order polynomial effect of year in all models. We used likelihood ratio tests to evaluate significance of different predictors.

To evaluate the curricula of current ecology doctoral programs in the United States, we searched the websites of 207 schools in the United States listed by the Carnegie Classification of Institutions of Higher Education as "research universities with very high activity" or "research universities with high activity" (Indiana University 2015). Four universities were included twice because they had two distinct but independent ecologically related doctoral programs (e.g., UC Davis doctoral programs in Ecology and Population Biology) resulting in a total of 211 doctoral programs evaluated. All websites were accessed June 2015. We first determined whether the university had an ecologically related doctoral program (e.g., Biology, Botany, Zoology, and Ecology and Evolution, and others), excluding 57 doctoral programs that were clearly not ecological in nature (e.g., The University of Alabama Huntsville's doctoral program in Biotechnology). This resulted in 154 ecological doctoral programs evaluated. We then looked for a published curriculum within a given program's website to determine whether any statistics course was required. Nearly all programs (N = 145) had curricula posted, and we assume these were at least relatively up-to-date. If a curriculum was available, we evaluated any available syllabi or course descriptions for the topics covered. In the event that a curriculum was not available, we searched online course catalogs for graduate-level statistics courses listed within the program. We also evaluated whether optional statistics courses existed as part of the ecology program or were cross-listed from other departments within the university by searching online course catalogs and department homepages. If optional courses were available, we examined any available course descriptions and syllabi to see what training these courses provided. We did not look for courses offered in other programs or departments if they were not cross-listed with the ecology program. Data sets are provided as Supporting Information: Data S1 for (1) statistical techniques and (2) doctoral programs in ecology.

Results

What analyses and computer programs are ecologists using?

Our search of statistical techniques returned 19,526 different papers published between 1990 and 2013, 64.6% of all papers published in the seven journals we searched (searches using no search terms indicated a total of 30,190 papers were published). The number of papers published per year increased substantially, from a 5-yr average of 167 ± 14 papers (mean ± SE) during 1990–1994 to 209 ± 13 papers during 2009–2013. This is partially due to the emergence of a new journal in 1998 (*Ecology Letters*); however, the number of papers published per year increased in the other six journals as well, by as few as 11 papers in *Oecologia* to as many as 88 papers in *Ecology*.

The proportion of ecology papers utilizing classic ANOVA or the nonparametric Mann–Whitney *U* test has decreased in recent years, and the usage of linear regression has appeared to level off (Fig. 1). The fit of models to both ANOVA and linear regression was improved by the polynomial term (Table 2). GLMMs indicated that in general, ANOVA has decreased by 13% since 1990 and 40% since its peak usage in 2001, and Mann–Whitney *U* tests by 71%. There has been no change in usage of *t* test (Fig. 1, Table 2). Ordinary least squares (OLS) regression has steadily increased by approximately 2% per year (Fig. 1).

In contrast to most NHST techniques, usage of contemporary statistical terms—terms associated with sophisticated modeling frameworks and non-Gaussian error distributions (e.g., "GLM," "maximum likelihood," "mixed effects," or "random effects") or with model selection based and information theoretic approaches (e.g., "AIC" or "Bayesian") all increased substantially since 1990 (Fig. 2). Usage of GLM has more than doubled, maximum likelihood has increased nearly six times, Bayesian statistics and mixed effects models have both increased approximately 31 times, and AIC has increased more than 100 times. In 2013, hierarchical or mixed effects models were mentioned nearly as frequently as classic ANOVA (Figs. 1 and 2). The fit of models was improved by the polynomial term in all cases except for Bayesian statistics (Table 2). The polynomial term indicated that usage of GLM may be leveling off (Fig. 2). Similar to our more generic search terms, the usage of the SAS function PROC MIXED for conducting linear mixed effects models has increased since first being published in 1992, but the polynomial term indicates that usage has actually declined in recent years (Fig. 2).

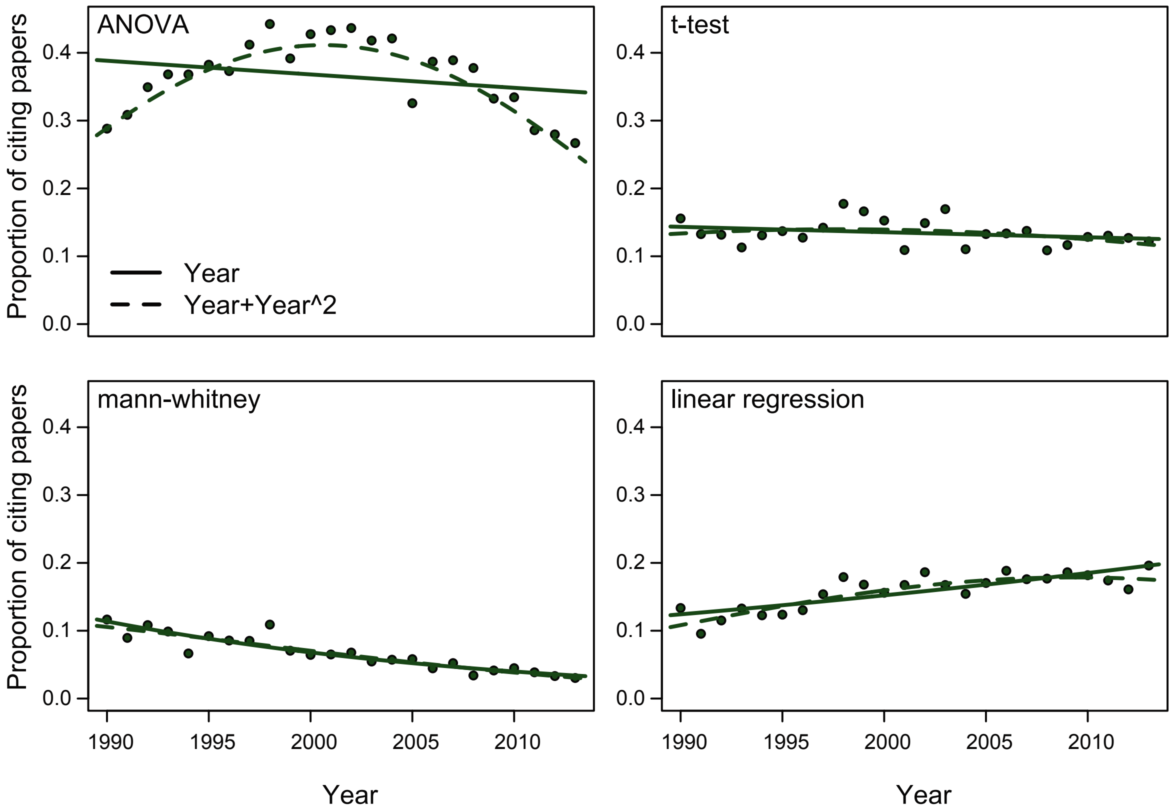

Fig. 1. Changes in the occurrence of search terms indicating four different statistical techniques generally associated with traditional null hypothesis significance testing (NHST) from 1990 to 2013. Changes in usage are shown for ANOVA, *t* test, Mann–Whitney *U* test, and linear regression. Data are the proportion of total papers in seven top ecology journals utilizing each technique. The colored lines in each panel are the predicted best fits from binomial generalized linear mixed models including either only year as a predictor (solid line) or year + year^2 (dashed line).

Along with the rise of contemporary statistical techniques, we also found a major shift in the programs that ecologists are using to analyze their data. From 1990 through 2008, SAS was the dominant program cited by ecologists (Fig. 3). However, while recent usage of SAS, JMP, and SPSS has been flat or decreasing, citations of the open source program R have increased dramatically. Despite only being first cited in 2003, by 2013 R was cited more than three times more often than any other program and in one-third of all ecology articles we surveyed (Fig. 3).

Statistical training in ecology?

Of the initial 211 doctoral programs we evaluated, 154 had programs related to ecology. In stark contrast to the rise of contemporary statistical techniques being published in ecology journals (Fig. 2), only 25% (38) of the 154 doctoral programs that we evaluated required students to take a biostatistics course (Fig. 4) and only 10 of those programs went beyond classic approaches (e.g., ANOVA, OLS regression). More than one-third of programs had no statistics course listed anywhere in their curriculum or course catalog. Approximately half of programs had optional biostatistics courses available to students, and of those two-thirds covered some aspect of contemporary statistical approaches being used in the literature in some form (Fig. 4).

Discussion

The experimental and analytical techniques that are commonly used in ecology are constantly evolving. Analyzing trends in the

Table 2. Analysis of trends in statistical usage as inferred from the occurrence of search terms in seven ecology journals 1990–2013.

Search term	Predictor	AIC	χ^2	*P*-value	Polynomial improves fit?
ANOVA	Year	273.38	1.63	0.20	Y
	Year + Year^2	231.23	44.15	<0.0001	
t test	Year	221.16	2.08	0.15	N
	Year + Year^2	221.62	1.53	0.22	
Linear regression	Year	217.06	26.13	<0.0001	Y
	Year + Year^2	209.73	9.34	0.002	
Mann–Whitney	Year	188.48	49.20	<0.0001	N
	Year + Year^2	188.64	1.84	0.18	
AIC	Year	185.65	72.86	<0.0001	Y
	Year + Year^2	154.00	33.65	<0.0001	
Bayesian	Year	171.58	59.60	<0.0001	N
	Year + Year^2	170.07	3.52	0.06	
GLM	Year	195.46	38.17	<0.0001	Y
	Year + Year^2	188.70	8.75	0.003	
Mixed effects or random effects	Year	177.81	92.73	<0.0001	Y
	Year + Year^2	174.60	5.21	0.02	
Maximum likelihood	Year	192.85	70.21	<0.0001	Y
	Year + Year^2	184.65	10.19	0.001	
PROC MIXED	Year	165.16	40.27	<0.0001	Y
	Year + Year^2	122.75	44.41	<0.0001	

Notes: Occurrence of each term was analyzed using a binomial generalized linear mixed model with (1) year alone or (2) year + year^2 as predictors. AIC scores, chi-square statistics, *P*-values, and whether the addition of the polynomial term improved model fit are shown.

analytical approaches of our field since 1990 clearly demonstrates that the frequency with which sophisticated methods are being used is accelerating. Whereas usage of approaches like ANOVA has declined in recent years, techniques such as mixed effects models and Bayesian inference have increased rapidly over the same time period (Figs. 1 and 2). This trend does not diminish the power and importance of traditionally used methods, but instead reflects the reality that ecological questions and data are increasingly complex and cannot, and often should not, be coerced to fit the assumptions and structure of traditional "normal" or nonparametric approaches (O'Hara and Kotze 2010, Warton and Hui 2010). With pervasive access to tremendous computing power, ecologists are now more able than ever to analyze non-Gaussian error distributions with techniques such as generalized mixed effects models (Pinheiro and Bates 2000, Gelman and Hill 2006, Bolker et al. 2009, O'Hara and Kotze 2010, Warton and Hui 2010). Similarly, modern information theoretic approaches allow ecologists to statistically choose among competing explanatory models based on how well they capture and account for deviation in a data set instead of the classic approach of comparing against a model of no effect (Burnham and Anderson 2002, McCarthy 2007). Further still, ecologists are increasingly able to "roll their own" statistics such that parameters for appropriate ecological models are estimated directly from data rather than extrapolating from canned approaches (Hilborn and Mangel 1997, Bolker 2008).

Along with shifting views about best practices, the trends we document here can be attributed to four factors that have been occurring over the past several decades, most of which stem from advancements in technology. First, the rate at which ecologists collect data has increased by orders of magnitude. It is now commonplace for automated data loggers, GPS trackers, remote sensing, and crowd sourcing to collect thousands or hundreds of thousands of data points about environmental variables (Porter et al. 2005) or animal movements (Kays et al. 2015). Secondly, there has been a rise in powerful desktop and supercomputing available to anyone in

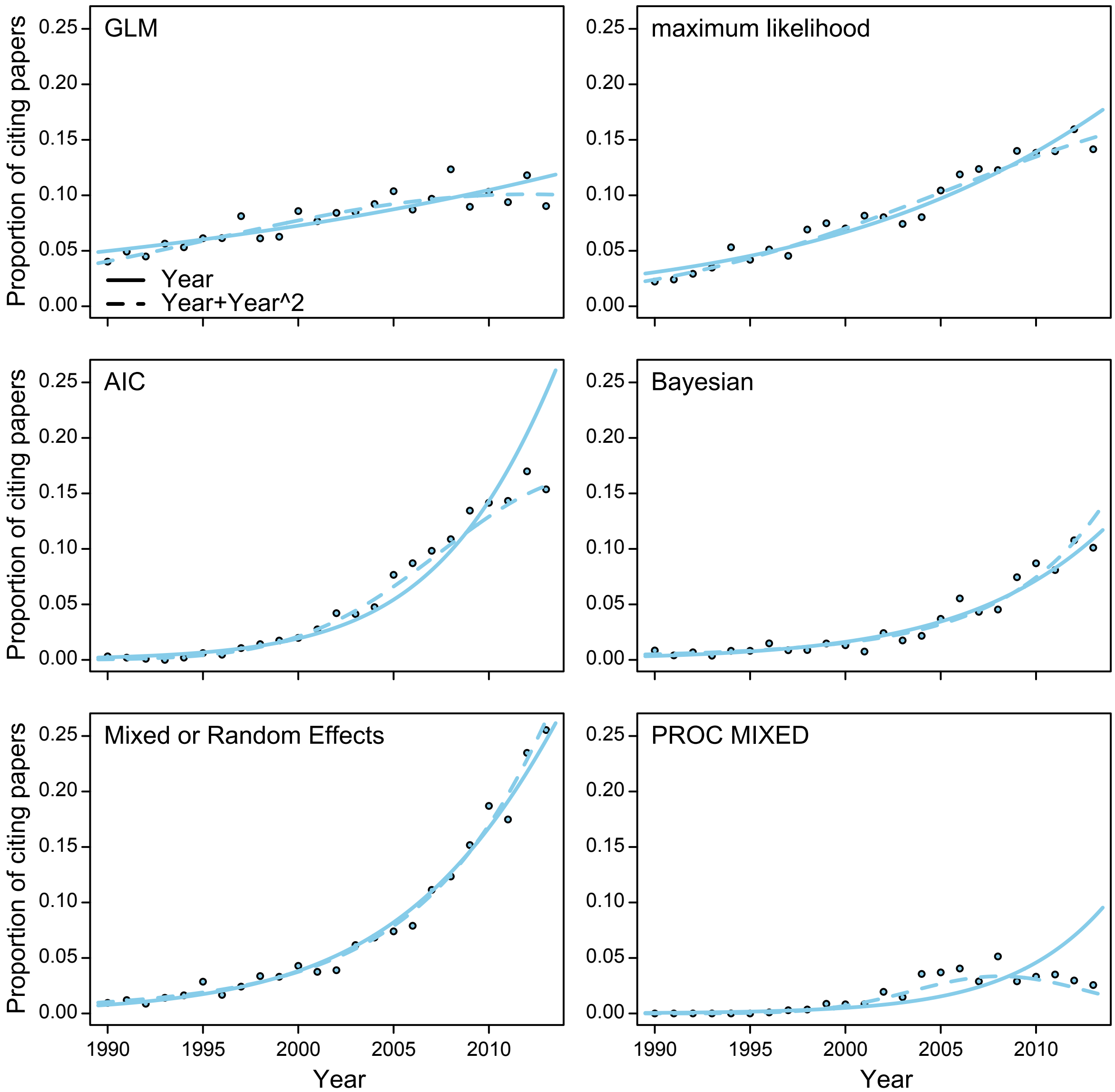

Fig. 2. Changes in the occurrence of search terms indicating six different statistical techniques generally associated with modern modeling and inference based statistical approaches from 1990 to 2013. Changes in usage are shown for GLM, maximum likelihood, AIC, Bayesian methods, mixed effects models and PROC MIXED, the SAS function for conducting mixed effects models. Specific search terms are listed in Table 1. Data are the proportion of total papers in seven top ecology journals utilizing each technique. The colored lines in each panel are the predicted best fits from binomial generalized linear mixed models including either only year as a predictor (solid line) or year + year^2 (dashed line).

a university setting. Third, and partly as a result of the increase in computing power available, there has been an explosion in new analytical techniques (e.g., Pinheiro and Bates 2000, Gelman and Hill 2006, McCarthy 2007, Bolker 2008, Legendre and Legendre 2012). The rise of powerful, freely available, open source analytical software like R (R Development Core Team 2013) and associated wiki's, blogs, and listservs where users consult with specialists and find code written by

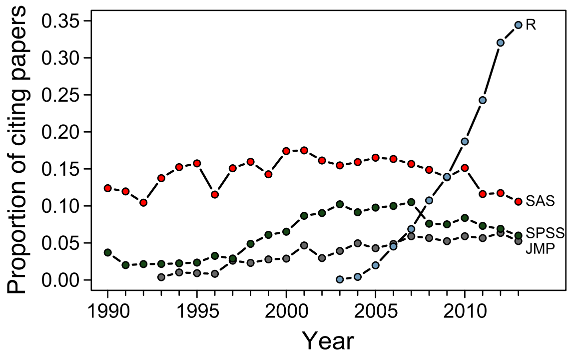

Fig. 3. Changes in the usage of four leading statistical programs from 1990 to 2013. Gray circles indicate the program JMP, blue circles indicate the program R, red circles indicated the program SAS, and green circles indicate the program SPSS. Data are the proportion of total papers in seven top ecology journals utilizing each technique.

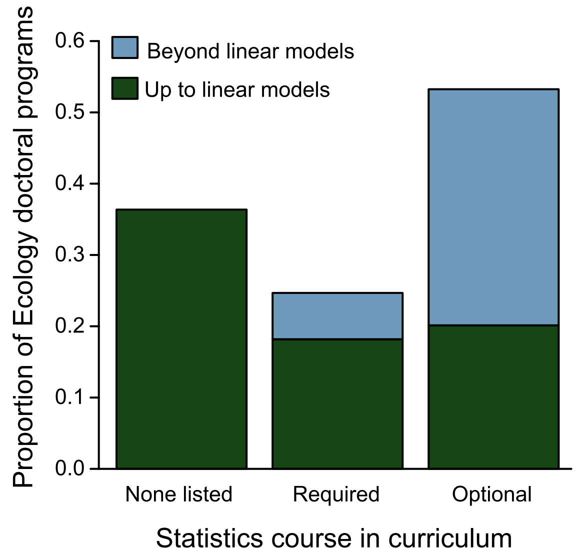

Fig. 4. The proportion of doctoral programs in ecology or related fields in the United States that have required or optional statistics classes as a part of their curriculum, and if those courses include only traditional null hypothesis significance testing (NHST) approaches or if they teach some aspect of advanced contemporary statistics (e.g., Bayesian statistics or generalized linear mixed effects models).

ecologists for ecologists allows the powerful combination of new methods and large data sets to be harnessed by us all. This process has democratized statistical inference, giving the average ecologist the power to conduct analyses previously reserved only for statisticians. Although the analyses that one can conduct in R are often achievable in a program like SAS, the community of ecologist statisticians using R has proliferated rapidly and may be driving change in techniques we document here (although it is admittedly impossible to tease apart cause and effect in this case). This community of users, who share code and advice about analyses, has enabled a great number of ecologists to conduct advanced analyses on their data. Indeed, the flexible nature of statistical programming is what allows those so inclined to "roll their own" statistics. Furthermore, the fact that R and other open source software is free has empowered a global community of users, including those in developing nations that may not have access to commercial costly programs. The fourth and final factor driving the change in statistical practices is that a number of seminal books and papers have fundamentally changed the way many people think about data analyses. To give just one example, Burnham and Anderson's (2002) book on model selection and inference has been cited nearly 30,000 times since its publication in 2002 according to Google Scholar (website accessed 8 December 2015).

With these changes in mind, it is paramount that the next generation of ecologists attain training that reflects the changes observed in the discipline (Butcher et al. 2007), lest those students become professionals without the proper training to critique, interpret, and synthesize current literature. Similar calls have been made at the level of undergraduate education (AAAS 2011). The spread of contemporary statistical techniques we document here means that at least some students are gaining this information, but this does not appear to be the norm. We found that only 6.5% (10 of 154) of ecology programs required a statistics course that covered any aspect of contemporary statistics, and only 36% (56 of 154) of programs offered an optional course in advanced statistics (Fig. 4). We strongly believe that all professional ecologists should be able to understand, interpret, evaluate, and implement the approaches that are clearly becoming the norm in our field and that the current training being required by doctoral programs is insufficient.

Because our search was constrained to only consider courses that were listed directly or cross-listed in ecology curricula, we were unable to quantify courses that may be available as generically listed seminar courses or that are offered in specialized statistics departments at some schools. Similarly, we know anecdotally of several doctoral programs that do offer optional "special topics" courses that provide contemporary statistical training. Thus, we feel our findings accurately represent the current level of required training for graduate students, but probably underestimate the amount of optional training available to students in the top doctoral programs. Regardless, we feel that ecology programs should be leading the charge to ensure that all academic and professional ecologists are quantitatively competent, and that it should not be the obligation of students alone to find and attain such training.

Suggestions for improving ecological statistics education

Our goal here is not to chastise the current state of ecology or ecological doctoral programs. Instead, we hope to inspire and encourage more prominent recognition of the ecological challenges the world faces and the opportunity to train graduate students to face them. Importantly, most students receiving graduate degrees in ecology will not stay in academia, but will find jobs working in the private sector, with nonprofit organizations or with government agencies. Indeed, it may actually be more important for these professionals to be able to interface with academic ecologists and understand and critically evaluate contemporary literature published in the top journals in order to make competent and informed policy and management decisions. Ideally, all ecologists would receive advanced training in mathematical and statistical theory; however, such change over the short term is unlikely. Nevertheless, we have several recommendations that constitute fairly modest changes to current practices that would initiate positive change.

First, graduate programs should require statistics training for all students. Improving graduate training will have a trickle-down effect on undergraduate education as well (AAAS 2011). Indeed, the need for improved training in statistics and quantitative analysis is reflected in the increased emphasis of "Data-based and Statistical Reasoning" in the recent revision of the MCAT—the Medical College Admission Test (Association of American Medical Colleges 2011). Second, the pedagogical philosophy of many introductory statistics courses could, and probably should, be changed. Most introductory statistics courses and text books for students in the life sciences focus solely on central limit theory, Gaussian error distributions and NHST, rarely introducing alternative error distribution families, or the gamut of more sophisticated, highly useful approaches for analyzing data. It has been our experience that introductory biostatistics courses focused purely on NHST also often fail to introduce students to the explicit interconnectedness of their data and the statistical models they are applying to the biological questions about which they are interested. We believe that considerable progress in statistical training could be achieved with minimal increases in required coursework. We propose introductory statistics courses should focus less on how to detect "if there are effects" and more on the mechanics of model fitting, parameter estimation, and obtaining and interpreting measures of uncertainty and confidence. In fact, courses taught with a more contemporary perspective address many of the topics covered in traditional biostatistics courses (e.g., one-way ANOVA, OLS regression) while simultaneously introducing contemporary techniques (Bolker 2008, Hector 2014). If ecology programs lack faculty suited to teaching the sorts of courses that integrate programming and statistics, then at a minimum the program or department should facilitate student learning by bringing in outside instructors for intensive short courses and workshops. Third, students should be introduced to some form of computer programming (e.g., courses can be taught in R [see Fig. 3], Python, Julia, etc.). Although the need for computer programming may not be obvious to some readers, the use of programming environments (i.e., R, SAS, Python, and others) is prerequisite to the implementation and documentation of many modern approaches. Three features of statistical analysis that are enhanced by programming knowledge include: (1) "literate programming," which is the practice of embedding source computer code inside of detailed documentation that clearly explains in natural language the tasks being performed (Knuth 1984). (2) Learning how to code ones analyses enhances "transparency and repeatability" (Ellison 2010, Hampton et al. 2014). Coding is more repeatable and transparent than point-and-click (or canned) statistical programs because code can be easily passed on to a collaborator or reviewer and mistakes can be traced and corrected. Many journals are now allowing or requiring analytical code to be submitted along with data as a supplement. (3) Although canned statistics packages are increasingly able to perform many contemporary analyses (e.g., generalized linear mixed models), they do not offer the flexibility to develop analyses that are specifically tailored to a particular question or mechanistic model (Hilborn and Mangel 1997, Bolker 2008). Importantly, given that most new statistical techniques are not available in easy-to-use, point-and-click formats, knowledge of statistical programming will also enhance the ability of ecologists to adapt and utilize new techniques as they emerge in the future.

Finally, as an alternative to changing pedagogy outright, ecology doctoral programs could promote avenues for quantitatively gifted students to pursue their dissertations through the development and application of statistical theory using other people's data. This would facilitate training of specialists focused specifically on questions at the interface of statistics, modeling, and the unique problems faced by ecologists. Indeed, this approach would also allow less quantitatively trained or interested students to rely more heavily on the expertise of others, and to form valuable collaborations, rather than analyzing their own data in potentially suboptimal ways. While each of our recommendations is already in practice to varying degrees in many graduate programs around the country, these programs remain the exceptions rather than the norm.

In closing, when Quinn and Dunham (1983) argued against the simplicity of null vs. alternative hypothesis testing more than 30 yr ago, the types of analyses that are now routinely conducted were impossible for the average ecologist. Now, however, we have access to the computational power to make new conceptual advances at the frontier of ecology. We must ensure that we take advantage of these advances so that the next generation of ecologists are not still making these arguments 30 yr from now.

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