Chapter 9
Education in Study Design and Statistics for Students and Professionals

9.1 Introduction

There is a fear of statistics among the public, state and federal officials, and even among numerous scientists. The general feeling appears to be based on the convoluted manner in which "statistics" is presented in the media and by the cursory introduction to statistics that most people receive in college. Among the media, we often hear that "statistics can be used to support anything you want"; thus, statistics (and perhaps statisticians by implication) become untrustworthy. Of course, nothing could be further from the truth. It is not statistics per se that is the culprit. Rather, it is usually the way in which the data were selected for analysis that results in skepticism among the public.

Additionally, and as we have emphasized throughout this book, "statistics" and "study design" are interrelated yet separate topics. No statistical analysis can repair data gathered from a fundamentally flawed design, yet improperly conducted statistical analyses can easily be corrected if the design was appropriate. In this chapter we outline the knowledge base we think all natural resource professionals should possess, categorized by the primary role one plays in the professional field. Students, scientists, managers, and yes, even administrators, must possess a fundamental understanding of study design and statistics if they are to make informed decisions. We hope that the guidance provided below will help steer many of you toward an enhanced understanding and appreciation of study design and statistics.

9.2 Basic Design and Statistical Knowledge

As undergraduates, we usually receive a rapid overview of frequency distributions, dispersion and variability, and basic statistical tests (e.g., *t* tests). It is our opinion, built on years of teaching and discussing statistics with students, that few receive a solid foundation of basic statistical or mathematical concepts let alone study design. Even if the foundation was thorough, however, it is not reinforced through continual use after the single undergraduate course. In addition, this undergraduate

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exposure comes before the student is sufficiently versed in scientific methodology to see how study design and statistical analysis fit together. This makes it less likely that they will be motivated to retain what they learn. Typically, advanced statistical training and courses in study design do not come until graduate school. Thus, only those continuing on to advanced degrees and associated research projected are given the opportunity to put statistical learning into practice. Even here, such experiences typically are usually limited. At the MS level, there seldom is adequate time to take more than the basic statistical courses that covers analysis of variance (ANOVA) and linear regression and to learn the necessities for evaluating data collected for the MS thesis. At the PhD level, some students take additional courses in more advanced procedures such as multivariate statistics, nonparametric analyses, and perhaps experimental (ANOVA-based) design. However, even for PhD students, most statistical knowledge is focused what is needed to complete the dissertation analysis. Relatively few schools offer study design and statistics courses oriented specifically toward natural resources.

People who do not continue on to graduate school seldom receive any additional training in study design or statistics. Also, there is a serious misconception that those entering management, administrative, or regulatory positions have no need for statistics in their work. We counter, however, that nothing could be further from reality. In fact, a case can easily be made that managers, administrators, and regulators must fully understand the general principles of study design and statistics, including advanced design and analysis methods. Regulators and administrators are called upon to make decisions regarding permit applications that often directly or indirectly impact sensitive species and their habitats. These decisions are based, in part, on the best scientific data available regarding the proposed impact. Because proposed projects usually have proponents and opponents, the regulator–administrator is confronted with opposing opinions on the meaning of the data; remember, "statistics can be used to support anything you want." As such, the regulator–administrator that is naive regarding design and statistics has little hope of making a rational, informed decision. Likewise, managers must sift through myriad published papers, unpublished reports, and personal opinions to make decisions regarding a multitude of land-use practices. It boils down to this: Ecological systems we manage are only partially observable, through sampling. Appropriate study designs and statistical analyses are necessary to extract the signal (i.e., potential causal factors) from the noise (inherent variability) so that the information derived from the scientific method can be maximized and informed management decisions made.

All professionals have a responsibility for making informed decisions; the "buck" does stop somewhere. By analogy, if your accountant reports to you that the budget is in order, but later discovers an accounting error, you will be ultimately responsible for the budget debacle (which could result in disciplinary or even legal actions). A manager must have at least a fundamental understanding of the budget – income and expenditures, basic accounting practices – to make sure that the budget is not grossly out of balance; he will be held accountable. Likewise, if an wildlife administrator cannot adequately evaluate the rigor of an endangered species survey, for example, and cannot determine if appropriate statistics were used, then he or she would look rather foolish blaming a failure to protect the species on his or her staff. That is, how can you manage people if you do not know – at least fundamentally – what they are doing? As noted by Sokal and Rohlf (1995), there appears to be a very high correlation between success in biometry and success in the chosen field of biological specialization.

Wildlife professionals must, at a minimum, be able to ask the proper questions needed to interpret any report or paper. Such questions include issues of independence, randomization, and replication; adequacy of sample size and statistical power; pseudoreplication and study design; and proper extrapolation of results (as we developed in Chaps. 1 and 2). You do not, for example, need to know how to invert a matrix to understand multivariate analyses (see Morrison et al. (2006) for some examples). In legal proceedings, one must be clear on the reasons underlying a management or regulatory decision, but does not need to be able to create statistical software.

Thus, it is incumbent on all professionals to not only achieve an adequate understanding of study design and statistics (both basic and advanced), but also keep current on methodological advances. The field of natural resource management is becoming more analytically sophisticated (see Chap. 2). For example, it is now common to use rather complicated population models to assist with evaluation of the status of species of concern – simply plotting trends of visual counts on an *X*–*Y* graph no longer suffices for either peer-review or management planning. Below we outline what we consider adequate training in design and statistics for natural resource professionals, including university training, continuing education, and the resources available to assist with learning.

9.2.1 The Undergraduate

It is an axiom that all education must rest on a solid foundation. Otherwise, any hope of advancement of knowledge and understanding is problematic. Most universities require that undergraduates in the sciences (e.g., biology, chemistry, physics, and geology) have taken courses in mathematics through algebra, trigonometry, and often calculus. Beyond these basic courses, universities vary in their requirements for students specializing in natural resources and their management. Many popular *biostatistics* textbooks are written so as to not require mathematical education beyond elementary algebra (e.g., Hoshmand 2006; Sokal and Rohlf 1995; Zar 1998), or are written in a "nonmathematical" manner (e.g., Motulsky 1995). These are good books that impart a solid foundation of basic statistics – mentioning their requirements imply no criticism. Sokal and Rohlf (1995) noted that, in their experience, people with limited mathematical backgrounds are able to do excellently in *biometry*. They thought there was little correlation between innate mathematical ability and capacity to understand biometric methodologies. However, many more advanced mathematical and statistical methods in natural resources require an understanding of more advanced mathematics, including calculus (e.g., many modeling techniques, population estimators). All students planning on later receiving graduate degrees should take at least an introductory course in calculus as well as an additionally course in probability theory in preparation for advanced methods in natural resources. Otherwise, they will be limited in the types of courses they will be qualified to take in graduate school. In addition, statistical methods are better understood, or at least students are better motivated to understand them, when they have had or concurrently take a course in scientific methodology as applied to natural resources. Such courses should be part of the core curriculum for undergraduates in natural resources.

9.2.1.1 Biometry or Fundamental Statistics?

The heading for this subsection implies a dichotomy between biometric and other approaches to statistics. In reality, textbooks and the way statistics courses are taught vary widely, from very applied, "cookbook" approaches, to highly theoretical instruction into the underlying mathematics of statistical methods. As noted earlier in this chapter, we think that all resource professionals require, at a minimum, a good knowledge of the principles of study design and statistics. Thus, the applied approach, which minimizes formula and mathematics, is adequate in many cases for interpretation of research results. Knowing that ANOVA *somehow* looks for significant differences in two or more groups, that various rules-of-thumb are available to determine necessary sample size, and that pseudoreplication includes the inappropriate calculating of sample sizes will suffice for many biologists, managers, and administrators.

Thus, "biometrics" courses tend to sacrifice fundamentals of theory and inference for applications and interpretation. This is appropriate if the course is considered a self-contained survey of common procedures, and not considered a prerequisite to more advanced statistics courses. However, if your expectation is that you will be conducting independent research and writing and evaluating scientific publications, then a better understanding of the mathematical underpinnings of statistics is required. Using our previous examples, advancing from simple one-way ANOVA to tests of interactions and blocking, properly anticipating sample size requirements (e.g., through power analysis), and understanding the statistical basis of pseudoreplication all require that the mathematics of the procedures be understood at least in general terms. The ability to interpret an ANOVA computer printout is much different from being able to explain how the residuals (error) were calculated. The single-semester "biometrics" courses often offered in biology and natural resource programs do not provide these fundamentals.

When graduate school is the goal, it is probably better to sacrifice application (i.e., the single-semester biometrics course) for fundamentals. Many universities offer a two-semester "fundamentals" course within the statistics department; many also offer a version of these courses for nonstatistics majors. Such courses usually require, for example, that each step in an ANOVA can be interpreted – calculation of degrees of freedom, sources of variation, and interaction terms. Such understanding is necessary to properly analyze and interpret complicated data, and is fundamental to more advanced parametric techniques (e.g., multivariate analyses). It is unlikely that the undergraduate will have time to take additional statistics courses.

9.2.2 *The Graduate*

The first task of many new graduate students is to fulfill the courses they missed (or avoided) at the undergraduate level. Many universities offer graduate level statistics courses in the Statistics Department aimed at nonmajors to fill these gaps. Such courses often cover two semesters and offer a detailed coverage of the fundamentals of statistics. However, most frequently these courses focus only on application of statistical approaches, rather than delving into the theory behind those applications. This is where the advantage of solid, fundamental mathematical and statistical training during one's undergraduate training begins to show its advantages. Such courses usually allow graduate students to step directly into more advanced courses such as sampling, nonparametric statistics, categorical data analysis, multivariate statistics, and experimental design.

9.2.2.1 The Importance of Formal Experimental Designs

As outlined throughout this book, fundamental to study design is an understanding of experimental methodologies. Most ecological studies are complex, and are made all the more difficult by a host of confounding factors. Although we hold to the notion that natural history observations qualify as science, natural historians nevertheless need to understand experimental designs and their associated statistical analyses. Even when a hypothesis is not specified and an experiment not initiated, advanced statistical procedures are often needed to try and isolate the factors causing the response variable to behave in the manner observed. For example, it is often difficult to know at what scale a process may be operating, such as the ecological processes influencing abundance at several spatial scales. Thus, it can be confusing to know how to start a sampling procedure. Nested sampling designs are one method to help determine the spatial pattern (Underwood 1997, p. 275). However, implementing such a design – except by luck – requires knowledge of the more advanced area of nested (or hierarchical) ANOVA. Ignorance of such procedures naturally limits even how the natural historian could approach a problem. Thus, we recommend that, following the introductory two-semester statistics courses, students enroll in an ANOVA-based experimental design course. A popular textbook that concentrates on these procedures is Underwood (1997).

9.2.2.2 Parametric vs. Nonparametric Methodologies

There are often several tests available to analyze a data set; choosing the most appropriate test can often be tricky. A fundamental decision that must be made, however, involves choosing between the two families of tests: namely, parametric and nonparametric tests (e.g., see Motulsky (1995) for a good discussion). Many sampling problems in natural resources involve small populations and/or populations that do not exhibit a normal distribution, i.e., they are skewed in some fashion. Large data sets usually present no problem. At large sample size, nonparametric tests are adequately powerful, and parametric tests are often robust to violations of assumptions as expected based on the central limit theorem. It is the small data set that represents the problem. It is difficult to determine the form of the population distribution, and the choice of tests becomes problematic: nonparametric tests are not powerful and parametric tests are not robust (Motulsky 1995, p. 300).

The researcher is presented with two major choices when dealing with samples that do not meet parametric assumptions. The choice initially selected by most researchers is to perform transformations of the original data such that the resulting variates meet the assumptions for parametric tests. Transformations, in essence, “linearize” the data. To some, implementing transformations seems like “data grinding,” or manipulation of data to try and force significance (Sokal and Rohlf 1981, p. 418). Further, most people have a difficult time thinking about the distribution of the logarithm of tree height, or the square root of canopy cover. Although it may take some getting use to, there is no scientific necessity to use common linear or arithmetic scales. For example, the square root of the surface area of an organism is often a more appropriate measure of the fundamental biological variable subjected to physiological and evolutionary forces than is the surface area itself (Sokal and Rohlf 1981, p. 418).

However, although attempting to transforms your data to meet assumptions of parametric tests might be statistically sound, such actions also likely obscure biological relationships. We go back once again to the fundamental importance of viewing your data graphically before applying any statistical tests. Visual examinations often reveal interesting biological properties of your data, such as nonlinear relationships and distinct thresholds in response variables. Further, applying transformations to data does not usually linearize biological data. Additionally, if data are transformed for analysis, they must be back transformed if biological interpretations to be valid.

The second choice involves the use of nonparametric tests. Most common parametric tests have what we could call nonparametric equivalents, including multivariate analyses (Table 9.1). Nonparametric tests are gaining in popularity as researchers become more familiar with statistics, and concomitantly, as nonparametric tests are increasingly being included on canned statistical packages. Because beginning and intermediate statistics courses spend little time with nonparametric statistics (concentrating primarily on chi-square tests), wildlife scientists are not as familiar with the assumptions or interpreting the results of nonparametric tests as they are with the parametric equivalents. This engenders a resistance among many to use of the nonparametric tests.

So, how do researchers handle the difficulties of small sample size and data that are in violation of assumptions of parametric tests? The procedures are many, although not necessarily always appropriate. In virtually any issue of a major ecology journal you can find studies that:

- Simply conduct parametric tests and say nothing about testing assumptions
- Conduct tests of assumptions but do not say if assumptions were met
- Conduct nonparametric tests without giving the rationale for their use or stating whether these tests met relevant assumptions

- Call parametric tests "robust" to violation of assumptions and conduct no transformations

Fortunately, by the 1990s, most journals insisted that statistical procedures be fully explained and justified; today, few papers lack details on the testing of assumptions. However, in our readings, it is quite common to read that transformations were performed, but no mention is given regarding the success of those transformations in normalizing data. Simply performing transformations does not necessarily justify using parametric tests. Thus, the graduate student would be advised to take a course in nonparametric statistics. There is no doubt that all researchers will have the need to use these tests, especially those listed in Table 9.1.

9.2.2.3 Categorical Data Analyses

Perhaps the most relevant advanced statistical course graduate students in wildlife sciences should consider is one that covers analysis of categorical data. Categorical data analysis, or analyses of data categorized based on a measurement scale consisting of a set of categories (Agresti 1996), has seen a considerable increase in applications to wildlife research. These measurement scales typically are either ordinal (data has a natural ordering such as age classes) or nominal (data has no natural ordering, such as names of different birds species located at a site). Thus, categorical data analysis makes use of both parametric and nonparametric statistical procedures.

For many wildlife studies, we deal with data that are either distributed binomially (0, 1; died or survived) or placed into a categorical framework (counts of individuals within a plot). Thus, fundamental understanding of binomial, multinomial, Poisson, and exponential distributions are necessary for a majority of statistical analyses used in wildlife ecology. For example, estimation of survival is often conducted using logistic regression, a form of a generalized linear model. Logistic regression relies on the logit link function, based on the binomial distribution, so that predictions of survival will be mapped to the range 0–1. Additionally, logit link functions can be used to evaluate proportional odds for ranked data (Agresti 1996) and underpin a host of the current capture–mark–recapture modeling approaches used wild wildlife science (Williams et al. 2002).

Frequently, many data of interest to wildlife ecologists are represented by discrete counts. The primary sampling model for count data is the Poisson regression, which is used to analyze count data as a function of various predictive variables, most frequently as a log-linear model, or a model where the log link function is used (Mood et al. 1974). Categorical data analysis is a field of statistics that has seen considerable research interest, ranging from simple contingency table analyses using chi-square tests to methods for longitudinal data analysis for binary responses. Although perhaps not obvious to many wildlife scientists, a majority of the statistical approaches used in wildlife ecology rely on categorical data analysis theory, thus highlighting its importance to wildlife students.

Table 9.1 Selecting a statistical test

	Type of data			
Goal	Measurement (from Gaussian population)	Rank, score, or measurement (from non-Gaussian population)	Binomial (two possible outcomes)	Survival time
Describe one group	Mean, SD	Median, interquartile range	Proportion	Kaplan–Meier survival curve
Compare one group to a hypothetical value	One sample *t* test	Wilcoxon test	Chi-square or binomial test	
Compare two unpaired groups	Unpaired test	Mann–Whitney test	Fisher's test (chi-square for large samples)	Log-rank test or Mantel–Haenszel
Compare two paired groups	Paired *t* test	Wilcoxon test	McNemar's test	Conditional proportional hazards regression
Compare three or unmatched groups	One-way ANOVA	Kruskal–Wallis test	Chi-square test	Cox proportional hazards regression
Compare three or matched groups	Repeated-measures ANOVA	Friedman test	Cochrane *Q*	Conditional proportional hazards regression
Quantify association between two variables	Pearson correlation	Spearman correlation	Contingency coefficients	
Predict value from another measured variable	Simple or linear regression or nonlinear regression	Nonparametric regression	Simple logistic regression	Cox proportional hazards regression
Predict value from several measured or binomial variables	Multiple linear regression or multiple nonlinear regression		Multiple logistic regression	Cox proportional hazards regression

Source: From *Intuitive Biostatistics* by Harvey Motulsky. Copyright © 1995 by Oxford University Press. Used by permission of Oxford University Press, Inc

9.2.2.4 Multivariate Analyses?

Beginning in the mid-1970s, multivariate analyses became a regular part of many studies of wildlife–habitat relationships (see Morrison et al. (2006) for review). Multivariate tests are used to analyze multiple measurements made on one or more samples of individuals. Multivariate analyses were applied to natural resource studies because many variables are typically interdependent, and because the many-dimensional concept of the niche and the many-dimensional sample space of multivariate analyses are analogous in many ways (Morrison et al. 2006). Thus, through the 1980s and 1990s, many graduate students chose a course in multivariate statistics as their advanced statistics course. The most commonly used parametric multivariate tests include multiple regression, principal component analysis, multivariate analysis of variance (MANOVA), and discriminant analysis.

Although multivariate analyses – including nonparametric forms – remain useful analytical tools, the emphasis on these methods was probably misplaced. The parametric methods carry assumptions that are similar to their univariate counterparts, but are even more difficult to test for and meet. For example, rather than having to achieve normality for a single variate, a typical multivariate analysis will use 5–10 or more variates, many of which will require different transformations. In addition, multivariate analyses require much large sample sizes than their univariate counterparts (Morrison et al. 2006). And as discussed above, nonparametric procedures are relatively more difficult to interpret given lack of attention they are given in most statistics courses.

9.2.2.5 Empirical vs. Model-Based Analyses

Most ecologists agree that the best decisions are those based on a solid database – the real stuff. However, there are numerous circumstances where the issue of the moment (e.g., management of endangered species) does not allow gathering of the data everyone would desire. For example, where the long-term persistence of a population in the face of development must be evaluated without the benefit of detailed demographic studies. Further, there are numerous situations where a good database exists, but the questions being asked concern the probability of population response to different management scenarios. For example, the influence of different livestock grazing intensities on the fecundity of deer. Model-based analyses are usually required to make such projections. Thus, we recommend that graduate students become familiar with basic modeling and estimation procedures, including analyses of population growth rates, and density estimators. These procedures require an understanding of matrix algebra and calculus.

9.2.2.6 Priorities

Obviously, any person would be well served by taking all of the courses described above. But, given the competing demands of other courses and fieldwork, what should the graduate student prioritize? We would like to see every MS student take a course in basic sampling design as well as the two-semester fundamental statistics courses. PhD students, on the other hand, should not only have Master's level coursework in sampling design, but also have additional courses such as probability theory, and a calculus-based math–stat course covering basic statistical theory and inference. Additional coursework at the PhD level would be simplified as theory and inference are the foundation of all other statistics courses.

9.2.3 The Manager

The natural resource manager must balance many competing issues when performing his or her duties. Many or most of the duties involve statistics, e.g., surveys of user preferences for services, designing and implementing restoration plans, managing and evaluating harvest records, monitoring the status of protected species, evaluating research reports, and budgetary matters. The statistical preparation outlined above for the undergraduate also applies here: A minimum of a general biometrics course. It is probably preferable to obtain a solid grasp of applications rather than the more fundamental statistics courses. Obviously, the more the better!

In addition to a basic understanding of statistics, managers need to understand the importance to statistics in making decisions. Personal opinion and experience certainly have a place in management decisions. [Note: we contrast personal opinion with expert opinion. *Personal opinion* implies a decision based on personal biases and experiences. In contrast, *expert opinion* can be formalized into a process that seeks the council of many individuals with expertise in the area of interest.] However, managers must become sufficiently versed in study design and statistics and avoid falling into the "statistics can be used to support anything you want" dogma. Falling back on personal opinion to render decisions because of statistical ignorance is not a wise management action. Using sound analyses avoids the appearance of personal bias in decision making, and provides documentation of the decision-making process; this is quite helpful in a legal proceeding.

Managers should also have an appreciation of statistical modeling and management science (e.g., adaptive resource management). We contend that every manager builds models in that every manager makes predictions (at least mentally) about how the system he or she is managing will respond to any given management action. Knowing the principles of management science will assist the manager in structuring the problem in his or her own thought processes, especially when the problem becomes very complex or other parties (e.g., stakeholders) must be brought into the decision process. These principles help to identify the sources of uncertainty (e.g., environmental variation, competing theories about system dynamics, partial controllability and observability of the system) that must be addressed, and how to manage in the face of them.

Managers require the same formal statistical training as outlined above for graduate students. Many students who were training as researchers – and thus received some statistical training – become managers by way of various job changes and promotions. However, many managers either never proceeded beyond the undergraduate level or completed nonthesis MS options. Unfortunately, most nonthesis options require little in the way of statistics and experimental design.

Thus, as professionals, they are ill-prepared to handle the aspects of their profession on which most management decisions are based (see also Garcia 1989; Schreuder et al. 1993; Morrison and Marcot 1995).

Thus, managers should be sufficiently motivated to obtain advanced training in statistics and design. This training can be gained through a variety of sources, including self-training, college courses, and professional workshops. Further, enlightened administrators could organize internal training workshops by contracting with statistical and design consultants.

9.2.4 The Administrator

The duties of manager and administrator – and sometimes even scientist – are often difficult to separate. Also, as discussed above for the manager, people often become administrators after stints as a manager or researcher. However, others become administrators of various natural resource programs through processes that involve little or no ecological – and especially statistical – training. Such individuals, nevertheless, need to be able to interpret the adequacy of environmental monitoring plans, impact assessments, research papers, personal opinion, and a host of other information. After all, it is the administrator who ultimately gives approval, and is often called upon to justify that approval. It is true that administrators (and managers) can hire or consult with statisticians. However, they must still be able to explain their decision-making process and answer questions that would challenge anyone with only a rudimentary understanding of technical matters.

We recommend that natural resource administrators be at least as knowledgeable as the managers under their supervision. Thus, administrators should possess the knowledge of statistics and design as outlined above for MS students.

9.3 Resources

9.3.1 Books

All natural resource administrators, managers, and researchers should have a personal library of books that are readily available for reference. This costs money, but the alternative is either ignorance or constant trips to a colleague's office or the library. Here, we provide some suggestions for assembling a small personal library that provides references for common study designs and statistical analyses. Fortunately, the basic designs and statistical procedures are relatively stable through time. As such, one does not need to purchase the latest edition of every text. In fact, the basic text used in most reader's undergraduate and graduate courses in statistics and study design certainly form the core of a personal library.

Kish (1987, p. vi) and Kish (2004) described the general area of statistical design as "ill-defined and broad," but described three relatively well-defined and specialized approaches (1) *experimental designs* that deal mostly with symmetrical designs for pure experiments, (2) *survey sampling* that deals mostly with descriptive statistics, and (3) *observational studies* including controlled investigations and quasiexperimental designs. There are numerous books that address each of these topics. As one's library grows and specific needs arise, we suspect that these specific topics will be added to the library.

Making recommendations for specific books is difficult because there are a multitude of excellent books available. Below we list some of our favorites, categorized by general analytical family. The fact we do not list a specific title by no means indicates our displeasure with its contents or approach; rather, these are books we have used and know to be useful. Each personal library should contain a book that covers each of the major categories listed below. Topics indented as subcategories provide more detailed coverage of the more common topics listed in the primary categories; these would be useful but not essential (i.e., could be reviewed as needed in a library, or added later as the need becomes evident).

9.3.1.1 Study (Statistical) Design

The books listed first are general overviews of two or more of the subtopics below:

- *Kish* (*1987*). A well-written, although brief, review of the topics of experimental design, survey sampling, and observational studies. A good introduction to these topics. This book has been reprinted as Kish (2004). A related offering is Kish (1995), which is a reprinting of his original 1965 edition.
- *Manly* (*1992*). An advanced coverage, emphasizing experimental designs, and including liner regression and time series methods.

Experimental Design (ANOVA)

- *Underwood* (*1997*). This very readable book emphasizes application of ANOVA designs to ecological experimentation. We highly recommend this book.

Survey Sampling

- Survey sampling can be considered a subclass of the next subtopic, observational studies, but is separated because of its common use.
- *Levy and Lemeshow* (*1999*). A popular book that presents methods in a step-by-step fashion. A nice feature of this book is the emphasis on determining proper sample sizes; also discusses statistical software.

Observational Studies (controlled investigations)

- *Cochran* (*1983*). A short book that begins with some very useful material on planning observational studies and interpreting data.

- *Thompson* (*2002*). A sampling design book for an introductory level graduate student in natural resources or statistics. We highly recommend this book.
- *Rosenbaum* (*2002*). A detailed explanation of designing and analyzing observational studies.

9.3.1.2 Nonmathematical Approaches

These texts assume little or no mathematical knowledge. These texts are not the recommended stepping stone to more advanced statistical procedures:

- *Watt* (*1998*). A beginning text that explains basic statistical methods and includes descriptions of study design as applied to biology.
- *Fowler et al*. (*1998*). Another basic text that is easy to read and provides a good foundation with little use of mathematics for the field biologist.
- *Motulsky* (*1995*). A basic text that uses a minimal amount of mathematics to survey statistics from basics through more advanced ANOVA and regression. This is a good text for those not likely to advance immediately to more sophisticated procedures. It uses examples from the statistical software InStat (GraphPad Software, San Diego, CA), a relatively inexpensive program. The book and software would make a useful teaching tool for basic analyses of biological data.

9.3.1.3 Fundamentals

These texts assume knowledge of college algebra and incorporate fairly detailed descriptions of the formulas and structures of statistical procedures. This type of knowledge is necessary before advancing to more complicated statistical procedures:

- *Sokal and Rohlf* (*1995*). A widely used text that emphasizes biological applications. It covers primarily parametric tests from an elementary introduction up to the advanced methods of ANOVA and multiple regression.
- *Zar* (*1998*). A widely used text that provides introductory yet detailed descriptions of statistical techniques through ANOVA and multiple regression. Zar also provides very useful chapters on analysis of circular distributions.

Nonparametric and Categorical Data Analysis:

- *Agresti* (*2002*). Concentrates on two-way contingency tables, log-linear and logit models for two-way and multiway tables, and applications of analyses. *Le* (*1998*) presents a similar coverage and is readable.
- *Stokes et al*. (*2000*) presents a thorough development of categorical methods using SAS as the analytical system.
- *Hollander and Wolfe* (*1998*). A detailed and comprehensive coverage of nonparametric statistics.

- *Conover* (*1999*). An authoritative, comprehensive, yet readable coverage of nonparametric statistics. This book is loaded with examples and is considered a classic.

Advanced

- *Draper and Smith* (*1998*). Provides a detailed description of linear and nonlinear regression techniques. This book is considered a classic, and is well written and easy to interpret. Now includes a diskette containing data files for all the examples and exercises in the text. An understanding of fundamental (elementary) statistics is required.

9.3.1.4 Multivariate Methods

Dillon and Goldstein (*1984*), *Manly* (*2004*), and *Afifi* (*2004*) are all very readable and thorough coverages of standard multivariate methods. We particularly recommend Afifi's text given the emphasis he places on interpretation of results. Included are examples using the more commonly used statistical packages.

Hosmer and Lemeshow (*2000*) details the use of logistic regression, which has become one of the most widely used multivariate procedures in wildlife science.

Kleinbaum (*2005*) is written in an understandable manner for the nonstatistician and is aimed at graduate students.

9.3.2 Web Resources

Here we present some of the many resources available over the internet that focus on design and statistical analyses. We usually provide the IRL for the home page of the organization sponsoring the Web page because the specific within-Web site links often change through time. Only sites offering free access to programs are provided; commercial sites (regardless of the quality of the products offered for purchase) are not listed:

- USGS Patuxent Wildlife Research Center (http://www.mbr-pwrc.usgs.gov/software.html): Contains an extensive list of programs focused on analyses of animal populations, including survival estimation and capture probabilities. Also contains or provides links to documentation of programs and literature sources.
- Illinois Natural History Survey (http://nhsbig.inhs.uiuc.edu): Manages the Clearinghouse for Ecological Software, which provides programs for density estimation, bioacoustics, home range analysis, estimating population parameters, habitat analysis, and more. For habitat analysis, programs such as Fragstats can be located.
- Colorado State University (http://www.warnercnr.colostate.edu): Offers the widely used program MARK (developed and maintained by Dr. Gary White), as well as other widely used programs such as CAPTURE and DISTANCE.

- The Eco-Tools (http://eco-tools.njit.edu/webMathematica/EcoTools/index.html): A Web-accessible means of performing many commonly used calculations; no special software is needed and all algorithms are open source. Programs available include life table calculations, count based PVA, estimating species diversity, and ordination; other programs are available.

9.4 Summary

We have emphasized throughout this book, "statistics" and "study design" are interrelated yet separate topics. No statistical analysis can repair data gathered from a fundamentally flawed design, yet improperly conducted statistical analyses can easily be corrected if the design was appropriate. In this chapter we provided specific guidance regarding the knowledge that we think all resource professionals should possess, including students, scientists, managers, and administrators. All resource professionals must possess a fundamental understanding of study design if they are to make informed decisions. Wildlife professionals must, at a minimum, be able to ask the proper questions needed to interpret any report or paper. Such questions include issues of independence, randomization, and replication; adequacy of sample size and statistical power; pseudoreplication and study design; and proper extrapolation of results.

Because many of the more advanced mathematical and statistical methods in natural resources require an understanding of more advanced mathematics, including calculus, we recommend that students planning on receiving graduate degrees should take at least a beginning course in calculus in preparation for advanced methods in natural resources. Otherwise, you will be limited in the types of courses you will be qualified to take in graduate school. Many "biometrics" courses tend to sacrifice fundamentals for specific applications and interpretation. When graduate school is the goal, it is probably better to sacrifice application (i.e., the single-semester biometrics course) for fundamentals. Graduate students must obtain a good understanding of experimental design, and take the opportunity to receive advanced statistical training in topics such as nonparametric, categorical, and multivariate analyses.

In addition to a basic understanding of statistics, managers and administrators need to understand the importance to study design and statistics in making decisions. Personal opinion and experience certainly have a place in management decisions, but all resource professionals must be able to grasp the strengths and weaknesses of various sampling approaches. Using sound analyses avoids the appearance of personal bias in decision making, and provides documentation of the decision-making process; this would be quite helpful in a legal proceeding.

We also provide guidance on classes to take, books to own and use as reference sources, and other ways in which you can obtain and maintain needed design and analytical skills. We also provide a list of Web sites where you may obtain extremely useful software to aid in ecological analyses.

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