Chapter 1

ECOLOGICAL DATA FOR FIELD STUDIES

Page

Ecologists collect data, and like other biologists the data they collect are to be used for testing hypotheses or describing nature. Modern science proceeds by conjecture and refutation, by hypothesis and test, by ideas and data, and it also proceeds by obtaining good descriptions of ecological events. Ecology is an empirical science, and it cannot be done solely on the blackboard or in the computer but requires data from the field and the laboratory. This book is about ecological data and how to wrestle it from the real world.

But data or ecological measurements are not all there is to ecology. At best data may be said to be half of the science. Ecological hypotheses or ideas are the other half, and some ecologists feel that hypotheses are more important than data while others argue the contrary. The central tenet of modern empirical science is that both are necessary. Hypotheses without data are not very useful, and data without hypotheses are wasted.

One problem that all the sciences face is what to measure, and the history of science is littered with examples of measurements that turned out not to be useful. Philosophers of science argue that we should measure only those things that theory dictates to be important. In abstract principle this is fine, but every field ecologist sees things he or she could measure about which current theory says nothing. Theory develops in a complex feedback loop with data, and an ecologist measuring the acidity of precipitation or the amount of CO_2 in the air in 1950 would have been declared unfit for serious science. More typically, the mad ecologist is often seen as a person who tries to measure everything. Do not try this, or you will waste much time and money collecting useless data. Data may be useless for several reasons. It may be unreliable or unrepeatable. This is probably the most common fault in ecology. It may be perfectly reliable and accurate but irrelevant to the problem at hand. It may be reliable, accurate, and terribly relevant but not collected at the right season of the year. Or the experimental design may be so hopeless that a statistical analysis is not possible. So start by recognizing:

Rule # 1 Not everything that can be measured should be.

Collect useful data and you have crested the first hurdle of ecological research. But how do you know what data are useful? It is a terrible mistake to think that statistical analysis by itself will give you any crisp insight into what data you should be collecting. Do not get the proverbial statistical cart in front of your ecological horse. Ecological theory and your ecological insight will give you the distinction between useful things to measure and useless ones, and you will not find this absolutely fundamental information in this book. So before you do anything else:

Rule # 2 Find a problem and state your objectives clearly.

Often your objective will be to answer a question, to test an ecological hypothesis. Do not labor under the false impression that a statistician can help you find a problem that is ecologically important or to define appropriate objectives for your research. There are many excellent ecology books that can help you at this step - start with Begon *et al.* *(*2006), Krebs (2009)and move to Sinclair et al. (2006) or Scheiner and Willig (2011) for more advanced discussions of ecological theory. The key here is to find an important problem, a problem that once solved will have many ramifications in ecological theory or in the management and conservation of our resources.

But now, when all the intellectually hard work is over, the statistician can be of great assistance. This book will try to lay out the ways in which some statistical knowledge can help answer ecological questions. We will now proceed to describe in detail the statistical cart, and forget about the ecological horse. But remember the two must operate together.

Rule # 3 **Collect data that will achieve your objectives and make a statistician happy**.

Usually these two goals are the same, but if you ever find a dichotomy of purpose, achieve your objectives, answer your question, and ignore the statistician. In nearly all the cases ecologists have to deal with, a statistician's information can be vital to answering a question in a definitive way. This is a serious practical problem because all too often data are collected which are not sufficient for reaching a firm conclusion. In some cases it is impossible to collect a sufficient amount of data, given normal budgetary constraints.

Some ecologists pick exceedingly interesting but completely impossible problems to study. So please beware of the next possible pitfall of the enthusiastic ecologist:

Rule # 4 **Some ecological questions are impossible to answer at the present time**.

You do not need to get depressed if you agree with this statement, and to realize that adequate data cannot be obtained on some questions would save tax moneys, ulcers, and some marriages. Constraints may be technical, or simply the inability to collect a large enough sample size. It might be interesting, for example, to map the movements of all the killer whales on the Pacific Coast in real time in order to analyze their social groupings, but it is not possible financially or technically to achieve this goal at this time.

Given these generalized warnings about the interface between statistics and ecology, we will review a few basic ideas about designing field studies and taking measurements. We will then consider a few problems with the application of statistical inference to ecological data.

1.1 DESIGNING GOOD FIELD STUDIES

Are the events you wish to study controlled by you, or must you study uncontrolled events? This is the first and most important distinction you must make in designing your field studies. If you are studying the effects of natural forest fires on herb production, you are at the mercy of the recent fire season. If you are studying the effects of logging on herb production, you can hopefully control where logging occurs and when. In this second case you can apply all the principles you learned in introductory statistics about replicated experimental plots and replicated control plots, and the analyses you must make are similar to those used in agricultural field research, the mother lode of modern statistics. If, on the other hand, you are studying uncontrolled events, you must use a different strategy based on sampling theory (Eberhardt and Thomas 1991). Figure 1.1 illustrates these two approaches to ecological field studies. Sampling studies are part of descriptive statistics, and they are appropriate for all ecological studies which attempt to answer the question ***What happened?*** Hypothesis testing may or may not be an important part of sampling studies, and the key question you should ask is ***what is your objective in doing these studies***?

Figure 1.1 lists 5 types of statistical analysis that are often not familiar to ecologists and will be discussed in subsequent chapters of this book. *Intervention analysis* is a method for analyzing a time series in which, at some point in the series, an event like a forest fire occurs or a power plant is constructed. By comparing some environmental variable before and after the event, you may be able to detect an impact or not (Chapter 8). All of the remaining 4 methods in Figure 1.1 are based on sampling, and they differ in one’s objective in doing the work. Consider a study of the productivity of a complex forest ecosystem which contains many different communities. For an observational study, we may pick two forest communities and compare their production. Descriptive sampling would be applied to all the forest communities in the region to estimate productivity of the entire region, and analytical sampling would use the sampling data to test hypotheses about why one forest community differed in productivity from another. Chapters 6 and 7 discuss these sampling problems. Sampling for pattern implies that one is interested in the pattern of geographical distribution of a species or a pollutant, and we will discuss it in Chapters 3 and 4.

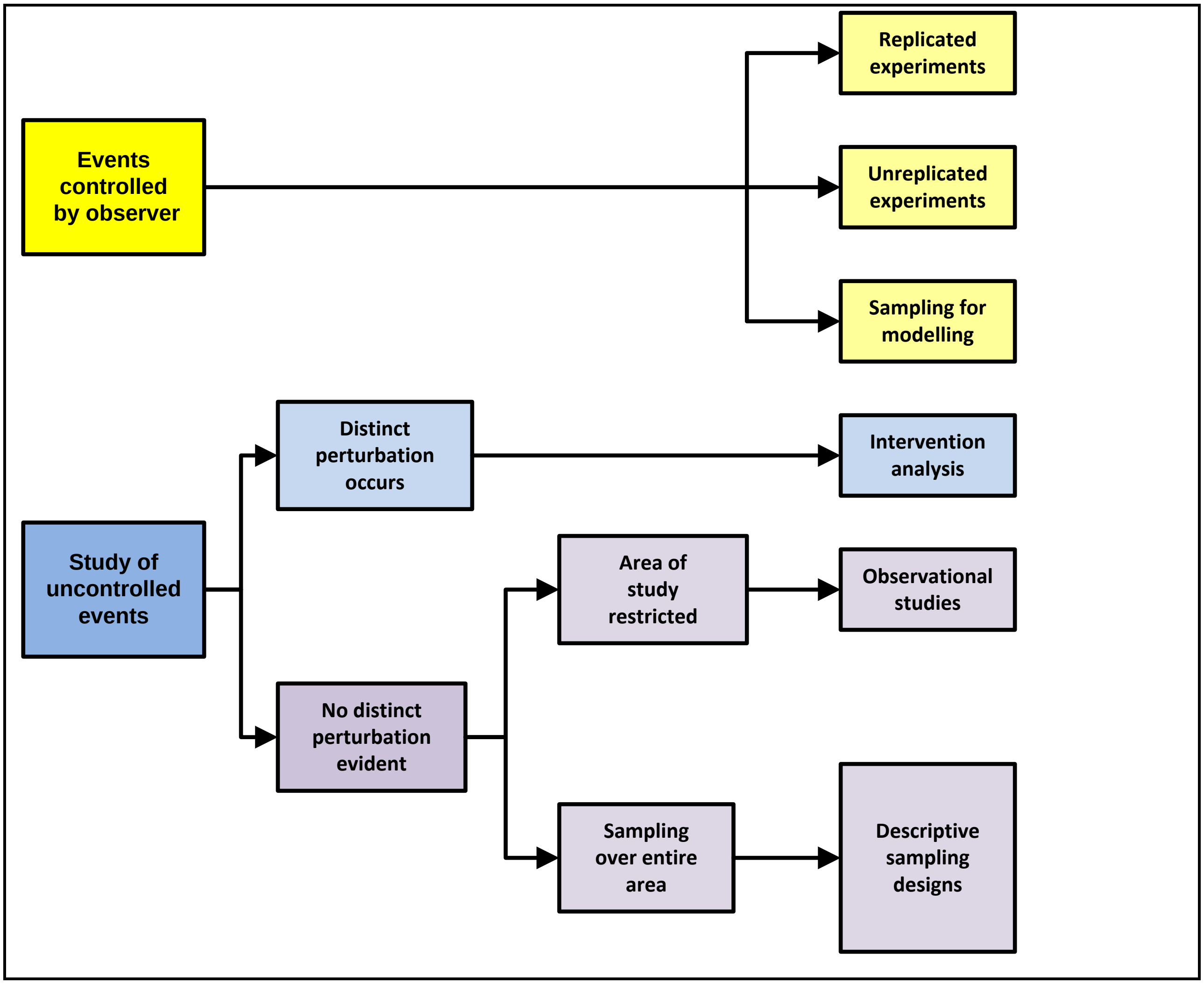

FIGURE 1.1 A classification of the methods used in ecological field studies. The key dichotomy is whether or not you are studying events you can control. If you can control events, you have a manipulative experiment. Studies of uncontrolled events are broadly all described as 'observational studies'. (Modified from Eberhardt and Thomas 1991.)

Ecologists often attempt to determine the impact of a treatment applied to a population or community. One illustration of why it is important to think about experimental design before you begin is shown in Figure 1.2 Suppose that you are the manager of a nature reserve and you wish to determine if weasel, fox and coyote control on the reserve will increase the nest success of geese. If you do a single measurement before and after the fox removal, you might observe the data shown in Figure 1.2a. These results by themselves would be difficult to interpret. But by collecting data for a longer time period both before and after the experiment (the *time-series* *design*, Kamil 1988), you would be in a stronger position to draw the correct inference. As illustrated in Figure 1.2 (b-e) you might observe no effect, a temporary effect, or a long-term effect of the manipulation. You could further strengthen this study by using a control area, a refuge that is similar to the manipulated one but is not subject to predator control (the *multiple time-series design*, Kamil 1988). The key enemies that confound interpretations are random events and we need to set up our studies to remove the impact of randomness from our conclusions.

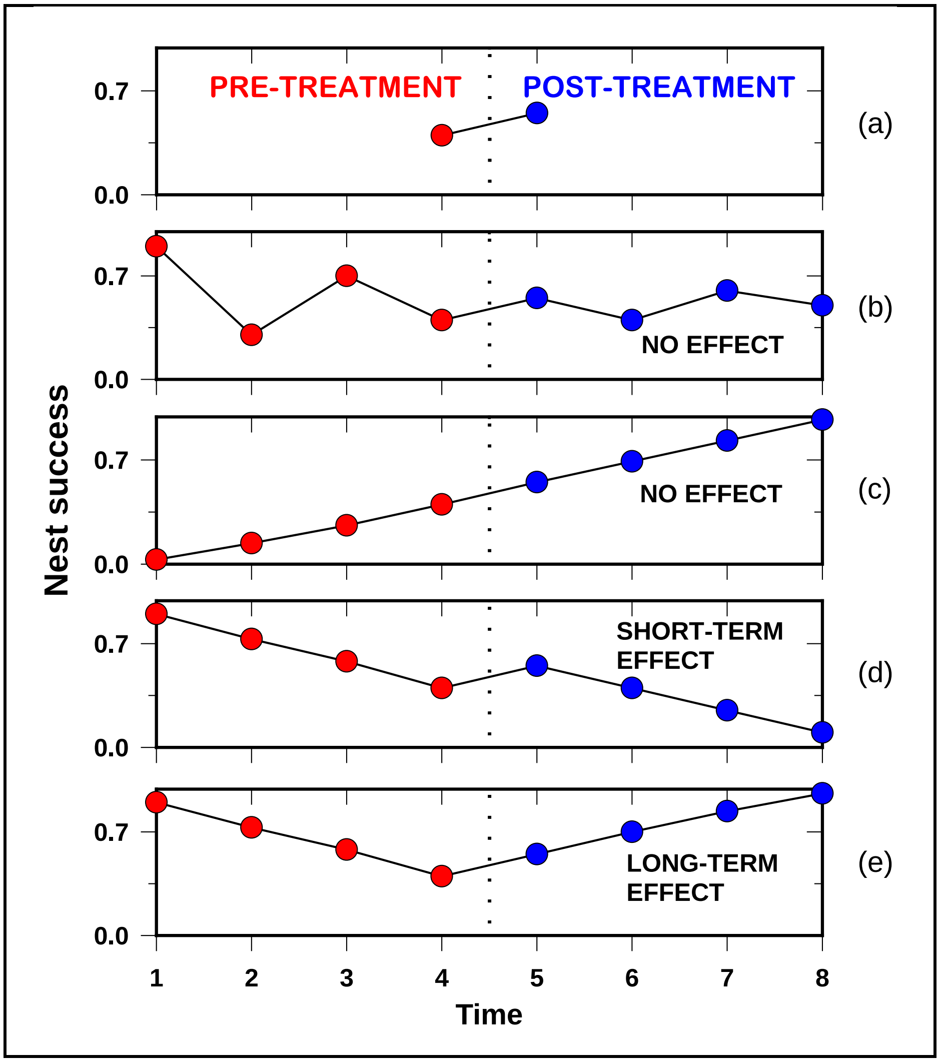

FIGURE 1.2 Advantages of a time-series experimental design. A manipulation is carried out between time 4 and 5 (dashed line). (a) A single pretest (red)–posttest (blue) design with results that are impossible to interpret. (b)–(d) Four possible outcomes if additional pre- and post-manipulation data are available. As shown, these studies are best described as quasi-experimental. By adding an unmanipulated control (not shown here) a much better comparative experiment could be done. (Modified after Kamil 1988.)

We will discuss sampling methods and experimental design in more detail in Chapters 6–9.

1.2 SCALES OF MEASUREMENT

Data may be collected on three basic scales of measurement. While these distinctions may seem trivial to you in this age of computers, you can find in any issue of any ecological journal an example in which the authors do not appreciate these distinctions and their limitations.

(1) Nominal Scale

Nominal data are attributes like sex or species, and represent measurement at its simplest level. We can determine if one object is different from another, and the only formal property of nominal scale data is *equivalence.* Nominal data are very common in ecology, and we often count individuals occurring in different classes. The colors of gastropods on a beach, the sex of squirrels, or the names of different insect species collected in a light trap might be determined to provide nominal scale data.

(2) Ranking Scale

Some biological variables cannot be measured on a numerical scale but individuals can be ranked in relation to another. Items in the diet, for example, might be ranked from more preferred to less preferred on the basis of cafeteria tests. Like the nominal scale, we have a series of classes, but now the classes bear some rank with respect to one another. Two formal properties occur in ranking data: *equivalence and greater than.* We can symbolize our ordered classes by the conventional number or letter order:

1, 2, 3, 4....... or A, B, C, D, E…….

I recommend using the letters rather than numbers because the most common mistake with ranking data is to assume that they are measured on an absolute scale. For example, we might rank 5 deer in a dominance hierarchy from 1 (low) to 5 (high) by means of their relative aggression. One may be tempted to assume erroneously that an animal ranked 4 is really twice as dominant as a bird ranked 2 in the hierarchy, a not uncommon error in ecological papers. Do not confuse ranking numbers with absolute numbers.

Note that any quantitative measurement can also be expressed on a ranking scale. Clearly, if we weigh 14 fish, we can also rank these from lightest to heaviest in weight. In some cases, we may deliberately adopt a ranking scale for ecological measurements because it is faster and cheaper than doing a precise quantitative measurement. An example might be the relative biomass of plants in a series of quadrats of fixed size.

(3) Interval and Ratio Scales

Data of these types have all the characteristics of the ranking scale but, in addition, the distances between the classes are known. We must have a unit of measurement for interval and ratio data – e.g. cm of length, degrees of temperature, kg of biomass, density or abundance of sparrows. If we have a unit of measurement and a true zero point, we have a *ratio scale* of measurement. A true zero point means that the variable being measured vanishes at zero. Thus fish length and biomass are measurements on the ratio scale and a 4 kg fish is twice as heavy as a 2 kg fish. But water temperature is a measurement on the *interval scale* because 0°C is not the lowest possible temperature and 8°C is not twice as hot as 4°C. For statistical purposes these two scales represent a precise, quantitative form of measurement, and much of statistics deals with the analysis of data of this type. Most of the measurements we take in ecological field studies are interval or ratio scale data. Height, weight, age, clutch size, population size, species richness – the list goes on endlessly. Data of this type can be subjected to the normal arithmetic operations of addition, subtraction, multiplication and division because the unit of measurement is a constant – a centimeter is a centimeter is a centimeter.

Ratio scale data may be continuous or discrete. *Discrete data* are usually simple because they take on integer values only: 0, 1, 2, 3 .... Examples abound in ecology: number of plants in a quadrat, number of eggs in a nest, number of fish in a net. No intermediate values are possible with discrete data, and so counts of this type are usually exact (or should be) with no error, at least when the numbers involved are small. A large number of elephants in an aerial photo might not be counted without error since observers may differ in their visual acuity.

Continuous data may be measured to any degree of precision, and so they do not represent such a simple situation. We are compelled first to distinguish *accuracy* and *precision*. *Accuracy* is the closeness of a measured value to its true value and is dependent on having a good measuring device or system. Some ecological data are very inaccurate. For example, estimates of CO_2 changes involved in estimating primary production in forests may show bias as well as low precision (Dragoni et al. 2007). Biodiversity studies of the number of species in an area are often too low (Colwell et al. 2012). Vole population densities estimated from standard live traps may be only one-half the true density (Boonstra and Krebs 1978).

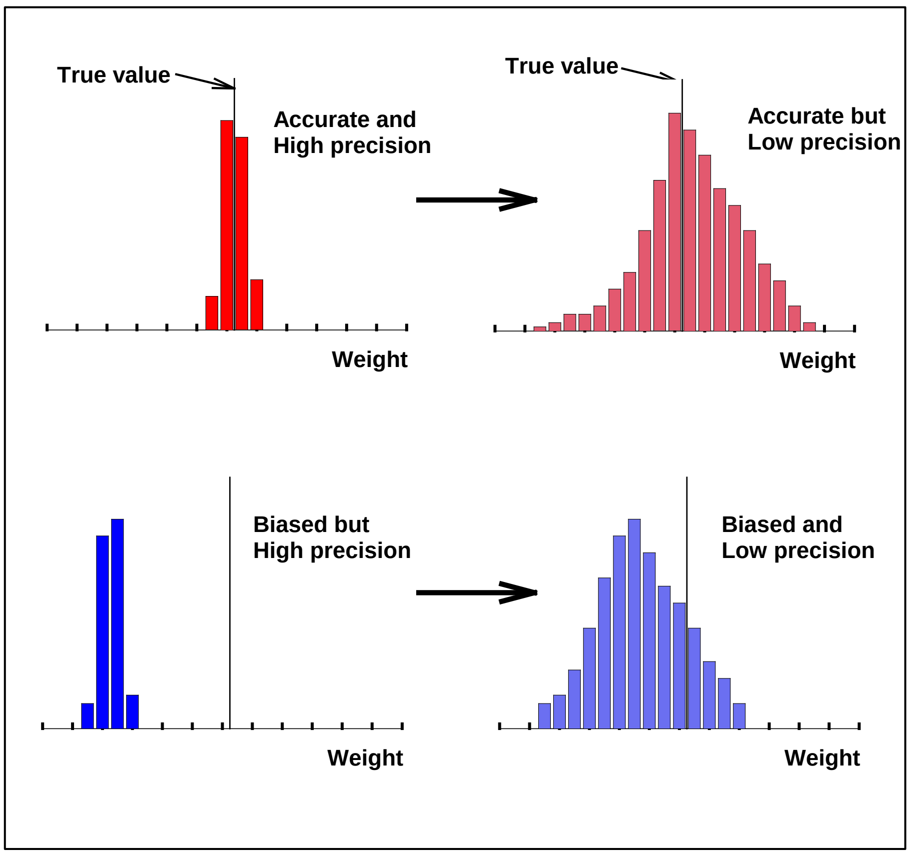

FIGURE 1.3 Illustration of accuracy and precision in ecological measurements. In each case a series of repeated measurements is taken on a single item, e.g. the weight of a single fish specimen

The history of ecological measurement is largely the history of attempts to design better measuring techniques or better sampling devices that permit more accurate measurements (e.g. Biggs et al. 2009).

Precision is the closeness of repeated measurements to each other. A ruler that has been marked off in the wrong places and is too short may give a very precise measurement of a fish's length, because if we are careful every repeated measurement of a fish with this ruler will give nearly the same numerical value. But this precise measurement would be very inaccurate, and the ruler would give a biased measurement. Bias (Figure 1.3) is very important in many ecological measurements and is a recurrent problem with many estimation techniques. We will find that some ecological methods produce biased estimates (Hines and Nichols 2002), and it is important to try to find out the size of the bias. A biased estimate is better than no estimate at all but we must be careful to remember when bias is present in our ecological estimates.

Continuous data are recorded to some fixed level of precision, and every measurement has its implied limits:

Measurement	**Implied limits**
67	66.5 to 67.5
67.2	67.15 to 67.25
67.23	67.225 to 67.235

Large numbers are often presented with less care than they should be, so that the level of precision is not always known. The most common examples of this occur in computer programs like Excel and statistical programs in which, for example, correlation coefficients are given to 4 decimal places for a sample of 5 data points. This deficiency can be overcome by either conventional rounding or the use of exponential notation.

Measurement	**Implied limits**
31,000	not clear - could be any of the following
3.1×10^4	3.05×10^4 to 3.15×10^4
3.10×10^4	3.095×10^4 to 3.105×10^4
3.100×10^4	3.0995×10^4 to 3.1005×10^4

Box 1.1 Methods for determining the number of significant figures to record in your data

Sokal and Rohlf (1995) Method

1. Determine the *range* for your data:

Range = Maximum value - minimum value

2. Divide the range into unit steps numbering between 30 and 300:

$$\frac{\text{Range}}{30} = \text{Minimal desired level of measurement}$$

$$\frac{\text{Range}}{300} = \text{Maximal desired level of measurement}$$

Example: n = 100, $\bar{x} = 173.86$ mm; $s = 12.26$; $s_{\bar{x}} = 1226.$

Maximum value observed = 210.64 mm

Minimum value observed = 143.21 mm

Range = 210.64 - 143.21 = 67.43 mm

Minimal level of measurement = $\dfrac{67.43}{30} = 2.25\,\text{mm}$

Maximal level of measurement = $\dfrac{67.43}{300} = 0.225\,\text{mm}$

If you record your data to the nearest 1 mm, you will have about 67 possible values and if you record your data to the nearest 2 mm you will have about 34 possible values. Both of these would fall within the Sokal and Rohlf rule of 30 to 300 steps, and thus you should record your data to the nearest 1 or 2 mm. If you record to the nearest 0.1 mm you are being overly precise (because you will have over 600 possible values) and if you record to the nearest 5 mm you are being too imprecise.

Barford (1985) Method

1. Determine the relative accuracy of the standard error of your data $(s_{\bar{x}})$:

Relative accuracy of $s_{\bar{x}} \cong \dfrac{1}{\sqrt{n-2}}$

2. Determine the range of probable error of the standard error:

Probable error of standard error = $\pm\left(s_{\bar{x}}\right)\left(\text{relative accuracy of } s_{\bar{x}}\right)$

3. Round the standard error to the precision set by the probable error limits, and measure to the same number of decimal points.

Example: n = 100, $\bar{x} = 173.86$ mm; $s = 12.26$; $s_{\bar{x}} = 1226.$

Relative accuracy of $\left(s_{\bar{x}}\right) \cong \dfrac{1}{\sqrt{100-2}} = 0.1010$

Probable error of $s_{\bar{x}} = \pm(1226)(0.1010) = \pm 0.1238$ mm

Hence the standard error could probably range from 1.226 + 0.1238 = 1.3498 to 1.226 - 0.1238 = 1.1022 and so is precise at most to one decimal point (1.2). Thus the original lengths should be measured at most to one decimal point or 0.1 mm.

In any data set involving 10 or fewer measurements, there is no point in giving the standard error to more than one significant figure. Thus in this example, if n = 10 the probable error of the standard error would be $\pm$0.433 and clearly the standard error could easily range from 0.8 to 1.7, so $s_{\bar{x}}$ = 1 and your lengths should be measured to the nearest 1 mm only.

In determining the number of significant figures to record in your data, Barford's method is slightly more conservative than Sokal and Rohlf's minimal level in recommending more measuring precision.

These calculations can be carried out in Program EXTRAS described in Appendix 1.

Significant figures are defined as the digits in a number which denote the accuracy. In gathering ecological data we must often make some decision about how many significant figures to use. Sokal and Rohlf (1995 p. 14) make a practical rule of thumb, as follows: *the number of unit steps from the smallest to the largest measurement should be between 30 and 300*. For example, if we are measuring fish lengths and the smallest fish is 3.917 cm long and the largest fish is 38.142 cm long, we should record to the nearest centimeter (4 to 38 cm) to give 34 one-cm steps. By contrast if individual weights of zooplankton vary from 0.01 to 0.05, you should measure to three significant digiits to give 40 steps of 0.001 values. There is no point in recording these data to 0.1 or 0.000001 places of significant figures (see Box 1.1). We thus reach the next rule of ecological measurement:

Rule # 5 **With continuous data, save time and money by deciding on the number of significant figures needed in the data BEFORE you start an**

Some ecological measurements are used as part of an equation to estimate a derived variable. For example, the product of the number of locusts per square meter and their rate of food intake per individual per day will give us an estimate of the total food consumption of a locust population. Errors multiply in any calculation of this type, and for this reason one may recommend recording data to one more significant digit than we recommended above. Note, however, that any chain of measurement is only as strong as its weakest link and if we have an estimate with only two significant figures for locust density, there is no point to having an estimate of food intake accurate to five significant figures. Achieving a balanced set of measurements is one of the most difficult of the ecological arts.

1.3 STATISTICAL INFERENCE

Ecological statistics differ in emphasis from most types of statistics because the problems of estimation and the problems of sampling are much more difficult in ecology than they are in other biological disciplines. Descriptive statistics occupy a short part of most statistics books, and random sampling is often discussed only very briefly. This book is very largely concerned with the descriptive statistics of ecology and the types of sampling schemes which ecologists can adopt. For example, the conceptually simple variable *population size* is difficult to measure, and yet is vital for most types of ecological work. Because ecological variables may be difficult to measure, we often tend to forget one of the basic rules of descriptive statistics:

Rule # 6 **Never report an ecological estimate without some measure of its possible error**.

This elementary statistical rule is violated daily, and you can find examples of this in every issue of any ecological journal. We must be humble enough to realize that, even though we may spend two months' hard work obtaining one estimate, that estimate is still subject to error.

By contrast, hypothesis testing is much the same in ecology as it is in other biological disciplines. Consequently we will not repeat routine statistical procedures in this book but will assume that you can obtain details of statistical tests from other excellent books such as Mead (1988{#16237}), Ramsey and Schafer (2012{ #16238}) or Whitlock and Schluter (2009). Statistical tests which are peculiar to ecological types of data will be given here.

Statistical inference is particularly difficult in ecology. Statistical populations are not biological populations, and the unfortunate dualism of the word "population" is a constant source of confusion. For any valid statistical inference we must specify the statistical population, the "target" population we are studying, and for most ecological studies we cannot do this very rigorously. Biological populations and communities change in space and time in such a complex manner that, if we specify the statistical population very broadly, we cannot sample it in a random manner (Scheiner 1993). This fundamental problem undercuts the very foundation of normal statistical inference in ecology (Morrison and Henkel 1970).

A second major difficulty in ecological statistics is that statistical methods can cope only with random errors. In real situations systematic errors, or bias, may be more important, and no simple statistical test can detect biased data. We try to minimize bias in our measurements, and in this manner to reduce this source of possible error. But the net result of these weak points is to provide a cautionary note:

Rule # 7 Be skeptical about the results of statistical tests of significance.

The conventional approach to a statistical test is too often presented as a black-or-white decision whether to accept or reject the null hypothesis. We would be better off if we viewed this problem of statistical decisions as an area of shades of gray with no pure blacks or pure whites.

The greatest mistake any ecologist can make in the use of routine statistics is to confuse the concept of statistical significance with that of biological significance.

Rule # 8 NEVER confuse statistical significance with biological significance.

Statistical significance is commonly said to be achieved in any statistical test in which the probability of obtaining the given results under the null hypothesis is less than 5%. Biological significance is not a mechanical concept like statistical significance. It refers to the importance of a particular set of measurements in the context of a theoretical hypothesis. Small effects can be important in some ecological processes. For example, a difference in survival rate of 3% per year between males and females of a sea bird population may be very significant biologically but not be statistically significant unless one has large sample sizes. Conversely, by measuring 10,000 whitefish in two lakes one might establish beyond any statistical doubt that whitefish in Lake A are 0.03 grams heavier than whitefish in Lake B. A difference may be biologically trivial but highly significant statistically. In a very real sense the null hypothesis of no difference is irrelevant to ecological statistics because we know as ecologists that every biological population and community will differ from every other one. To demonstrate a difference statistically is trivial and often gets in the way of the real ecological question - *how different are the two populations or communities?* And secondly, are the differences large enough to be ecologically relevant? We come back to the central theme of this chapter, that ecological hypotheses, ecological insights, and ecological theory must be the arbiter of what we measure and how we interpret our results. And we must strive in ecology to build strong feedback loops between theory and data as our science matures.

Alternative approaches to hypothesis testing have been developed which suggest that it is more useful in ecological studies to specify alternative models and to compare the data to the models with information statistics. Anderson (2008) describes an information-theoretic approach to model testing that avoids the standard approach through the null hypothesis. Hilborn and Mangel (1997) present another approach to ecological data that moves us away from standard statistical testing. Some examples of these approaches will be given in later chapters.

1.4 DATA RECORDS

The most mundane aspect of data recording is to decide how to write the data records. Little is said of this technical problem, and one learns by bitter experience how not to record data. Every ecological problem is unique, and so no one can give you a universal recipe for a good data form. Research budgets differ, and access to computers is not uniform. But the trend is very clear, and the gradually improving access to computing equipment dictates the following prescription:

Rule # 9 Code all your ecological data and enter it on a computer in some machine readable format.

To achieve this goal you must set up proper data sheets, decide on significant digits for each type of measurement, and in general organize your data collection procedure. If you do only this and neglect to put data into computer files subsequently, you will have most of the benefit of this exercise. There are many database management programs available for personal computers, or which Microsoft ACCESS is perhaps the most popular, and much larger multi-user systems available from large companies like Oracle. The list will grow every year. What all database managers are consistent about is the recommendation not to use simple programs like Microsoft EXCEL as a data storage system.

You may save yourself an enormous amount of time later by systematic coding in one of these database management programs. The advantages of putting data into computer files may not be large for ecological work which involves only a few observations on a few animals or plants, but I have never seen any ecological data which suffered by coding. With small samples a computer-type data analysis may require the same time and effort as pencil and paper or your pocket calculator. With large samples there is no other way to handle ecological data. Another important advantage of computer analysis is that you know the answers are mathematically correct. Pencils and paper sometimes error. Finally it is important to remember that scientific data should also be stored for later generations, and thus it is important to use standard database methods for describing and storing ecological field data.

Personal computers now have available a large set of statistical programs which can be used directly on data coded in computer files and ecological data are commonly evaluated using standard statistical packages like SAS, SYSTAT, JMP, NCSS, and a variety of packages that improve rapidly from year to year. If you are a novice, it will pay you to search for evaluations of statistical packages in the literature before you decide which to use. Thus, you do not need to be a computer operator or a computer programmer to make use of many standard statistical tests. An additional advantage is that you can recalculate new parameters several years after you collected the data if you suddenly get a bright new idea. If you use computer programs to analyze your data, you should always be aware that some programs may contain “bugs” that produce errors. It pays to check computer programs with data that has the answer already known.

The computer is just another labor-saving device that can be used or abused by ecologists. If we do not take careful measurements, or short-cut proper techniques, we will be no better off with a computer than without it. You can ignore all the assumptions of any statistical test, and the computer will still grind out an answer. The ancient rule applies with particular force to “computerized” ecology and to all ecological statistics:

Rule # 10 Garbage in, garbage out.

Garbage, or poor data, may result from purely technical problems like a balance that is not weighing accurately or from human problems of inattentiveness or a lack of proper instruction in how to take field measurements. A good experimental design can build in data checking procedures by repeated measurements or the injection of known samples. But a good ecologist will always be alert to possible errors in data collection, and will strive to eliminate these. Simple procedures can be highly effective. Persons recording data in the field can reduce errors by repeating data back to those doing the measurements. Ecological data collected carefully may be difficult enough to interpret without adding unnecessary noise.

RECOMMENDED READINGS

Anderson, D.R. 2008. *Model Based Inference in the Life Sciences: A Primer on Evidence.* Springer, New York.

Barford, N.C. 1985. *Experimental Measurements: Precision, Error, and Truth*. John Wiley and Sons, New York.

Berger, J.O. and D.A. Berry. 1988. Statistical analysis and the illusion of objectivity. *American Scientist* **76**: 159-165.

Cleveland, W.S. 1994. *The Elements of Graphing Data*. Hobart Press, Summit, New Jersey.

Eberhardt, L.L. and J.M. Thomas. 1991. Designing environmental field studies. *Ecological Monographs* **61:** 53-73.

Hilborn, R., and Mangel, M. 1997. *The Ecological Detective: Confronting Models with Data.* Princeton University Press, Princeton, New Jersey.

Mead, R. 1988. *The Design of Experiments: Statistical Principles for Practical Application*. Cambridge University Press, Cambridge.

Whitlock, M., and D. Schluter. 2009. *The Analysis of Biological Data.* Roberts and Company, Greenwood Village, Colorado.

Yoccoz, N.G. 1991. Use, overuse, and misuse of significance tests in evolutionary biology and ecology. *Bulletin of the Ecological Society of America* **72**: 106-111.

QUESTIONS AND PROBLEMS

1.1. What is the null hypothesis of basic statistics? Should they be used in ecological data analysis? What are the alternatives to null hypothesis thinking?

1.2. The diameter of 16 pollen grains was obtained as follows:

12.478	12.475	12.504	12.457
12.482	12.473	12.492	12.501
12.470	12.499	12.509	12.477
12.490	12.502	12.482	
12.512			

Use the two methods given in Box 1.1 (page 11) for determining how many significant figures you should record for future data sets. Would these recommendations change if you were to measured n = 100 instead of n = 16? n = 1000?

1.3. What does a statistician mean by a Type I and a Type II error? Suppose you were testing the hypothesis that a particular type of a mine operation was affecting the survival of a fish species in a river. Describe in ecological English the meaning of Type I and II errors for this example. Which type of error do normal statistical procedures minimize?

1.4. You have been given the task of weighing plant samples, and a preliminary analysis like that in Box 1.1 has shown that you should be weighing the samples to the nearest 1.0 g. Unfortunately you have available only a spring scale that weighs to the nearest 5 grams. What do you lose statistically by continuing to weigh your samples to the nearest 5 g ?

1.5. How would you know if you are violating Rule # 1?

1.6. Deming (1975: *American Statistician* **29**: 146) states:

> “We do not perform an experiment to find out if two varieties of wheat or two drugs are equal. We know in advance, without spending a dollar on an experiment, that they are not equal.”

Do you agree with this statement? What cautionary note does it inject into ecological statistics?

1.7 After clear-cut logging in the Pacific Northwest a variety of deciduous trees and shrubs typically begin forest succession. Many experiments have been completed to try to increase the growth of the desired coniferous trees (like Douglas fir) by removing the deciduous trees from early succession. In about half of these studies the conifers grow better on the treated plots, and in the other half of these studies growth is equal on the treated and the untreated plots. Given these facts, what would you conclude if you were responsible for forest management, and what further actions or data collection would you suggest?