Commentary

Suggestions for Basic Graph Use When Reporting Wildlife Research Results

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ABSTRACT I review concepts of basic graph design and outline general guidance for basic preparation and presentation of data. I comment on the continued use of convenient summary graphics found in our literature where data are often misrepresented and review potential remedies that will improve data description and graphical efficiency for the most frequently used graph types in wildlife data reporting. I suggest that graphics should play a larger role in data description and analysis and less in summarizing study results. (JOURNAL OF WILDLIFE MANAGEMENT 72(5):1272–1278; 2008)

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Since Playfair's (1786, 1801) pioneering work in graphing, groups ranging from academicians and government to businesses and media have relied on graphs to analyze and communicate quantitative information (Cleveland 1984*a*, Larkin and Simon 1987, Tufte 2001). Work by Chambers et al. (1983), Tufte (1983, 2001), Tukey (1977), and Cleveland (1993, 1994) highlighted graphs as a statistical tool for exploring data patterns, discerning quantitative relationships between pattern and process, and confirming or disproving hypotheses (Chambers et al. 1983, Cleveland 1984*a*). Use of graphics should be innate to scientists; organize quantitative information in such a way that patterns and structures within the data can be shown and evaluated (Cleveland and McGill 1984).

Ecological research is descriptive; all that varies is the choice of quantitative methods (e.g., summary statistics, hypothesis tests, estimation procedures, predictive modeling) used to describe data. Over time, ecological studies have undergone various methodological shifts as ecologists have delved deeper into application of statistical methods to ecological data. However, graphical methods for analyzing and communicating data are still underdeveloped and underutilized by many ecologists. Use of graphics is higher in natural sciences than other fields primarily due to natural sciences having a greater quantity of observational data to present (Cleveland 1984*a*, *b*). Thus, ecologists should strive to display data efficiently and accurately using the wide range of graphical options available to researchers (Cleveland 1993, 1994; Maindonald and Braun 2003).

As ecologists, we use graphs to communicate or summarize information or for data analysis (Fienberg 1979). General suggestions for presenting data covering topics such as use of P values, null hypothesis testing, and model selection in ecological studies are well addressed (Cherry 1998, Johnson 1999, Anderson et al. 2001), but little attention has been focused on graphical use, as noted >3 decades ago by Anscombe (1973). There are many potential approaches to presenting data dependent upon the context (presentation, peer-reviewed article) and audience (scientists, agencies, public). However, my comments should be consistent with graphical design for a diverse array of audiences. I will outline a few general principles of graphic design based on my review of the published literature. Next, I will suggest how graphics can be used to better understand the nature of data and provide comparisons and suggestions on those graphical methods and formats which are most appropriate for certain data types. Within this context, I will discuss several common pitfalls and redundancies in basic graph use.

CONCEPTS OF GRAPH CONSTRUCTION

Currently, there are only general standards for graph integrity (Cox 1978, Fienberg 1979, Chambers et al. 1983, Maindonald and Braun 2003, Tufte 2001, Murrell 2006) and no basic theory for how graphs are created for a specific data type (Fienberg 1979; Cleveland and McGill 1984, 1985). As a result, graph creation is largely an unscientific process, based on intuition, rules of thumb, best guesses, colleague suggestions, and hand-me-down approaches from faculty to students (Cleveland and McGill 1984). Many authors have commented on what constitutes good graph design (MacDonald-Ross 1977; Fienberg 1979; Cleveland and McGill 1984, 1985; Tufte 2001) and most indicate that theory for graphic design is limited (Tukey 1977, Cleveland and McGill 1984). Tufte (2001:13) suggested that "excellence in statistical graphics consists of complex ideas communicated with clarity, precision, and efficiency." Good graphs should 1) illustrate the data, 2) induce the viewer to think about the substance rather than methodology, design, or technology of graphic construction, 3) present large datasets coherently and reveal data at several levels, 4) serve a clear purpose (e.g., description, tabulation), and 5) be closely related to the statistical and verbal descriptions of the data (Tufte 2001).

PERILS OF GRAPHING NON-DATA

Above all, graphs should clearly and concisely show data. Graphs should draw the reader to the substance of data and

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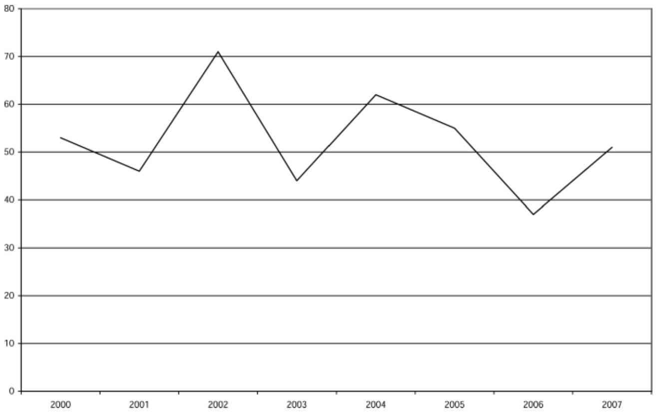

Figure 1. XY plot with gridlines. The data represent observed counts of a hypothetical population over a 7-year period with gridlines incorporated.

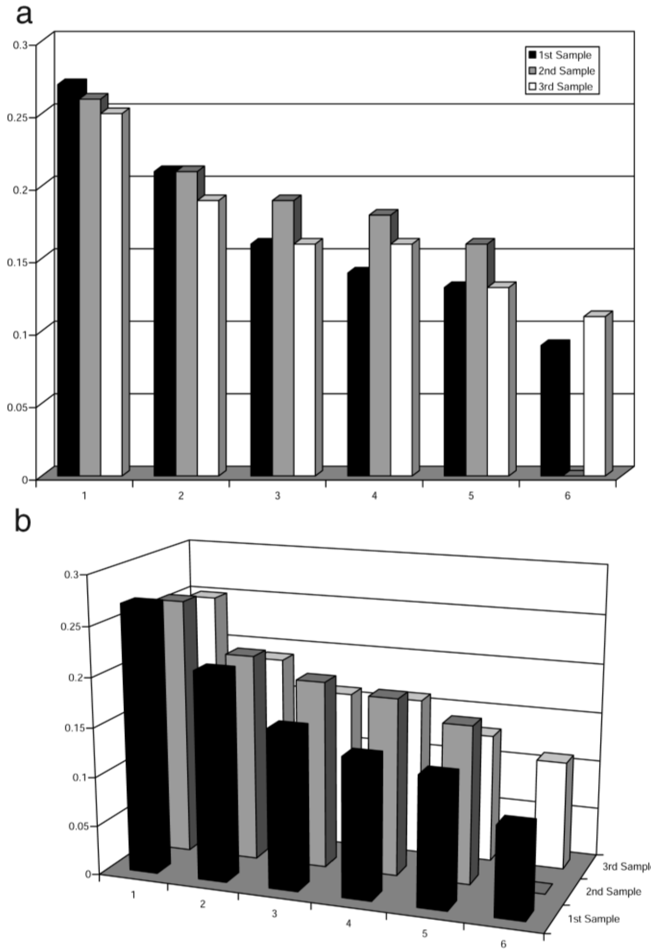

Figure 3. Three-dimensional graphs. The data are the percentage of each sample. (a) Depicts a use of a third dimension in a standard bar plot for comparisons between samples. (b) Depicts use of a third dimension in a stacked depth bar plot for comparisons between samples.

explicitly represent those data. Non-data, or information contained within a graph that does not convey information, has become a serious problem in ecological journals due to the prevalence of graph options provided in computer programs. Availability of easily constructed graphs in such programs has allowed ecologists to replace graph substance with graph convenience.

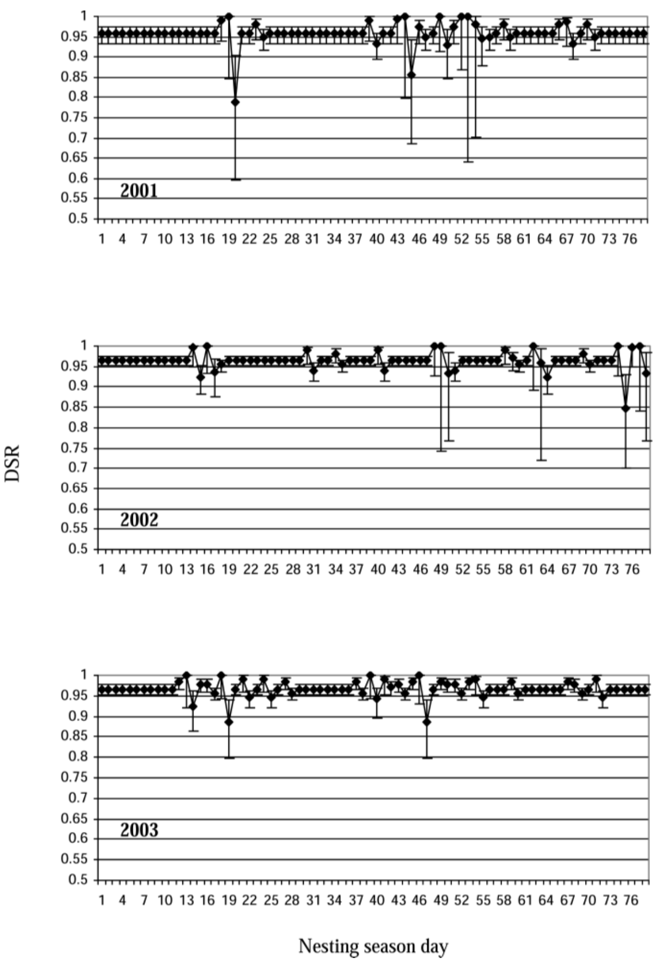

Figure 2. Example XY plot with gridlines that convey no information relevant to the data presented (from Moynahan et al. 2007).

For example, many programs provide graph options distracting from data, hence reducing graph effectiveness. The most common forms of non-data used in ecological graphics are arbitrary gridlines, false dimensions, and unordered moiré effects (superimposing of a repetitive design to produce a pattern). Gridlines (or grids) are common in graphs, because we plot response along the y-axis with our interest being how responses change over the predictor variable on the x-axis. Then, grids are drawn perpendicular to the y-axis to relate the various y-axis values (Fig. 1). Given the level of precision and resolution shown within most time-series plots in ecological studies (e.g., Fig. 2; Moynahan et al. 2007), grids are likely unnecessary.

Another common issue in ecological graphs is use of false dimensions. Whether used as a single (Fig. 3a) or stacked depth figure (Fig. 3b), extra dimensions are inappropriate because they 1) infer an area and volume measurement in the data when there is none, 2) tend to conceal data (Fig. 3b), 3) and increase the amount of data-ink (graph sections that do not contain data; Tufte 2001). In addition, examination of false dimensional graphs will usually show ≥ 2 altitude measurements for the data value of interest; one

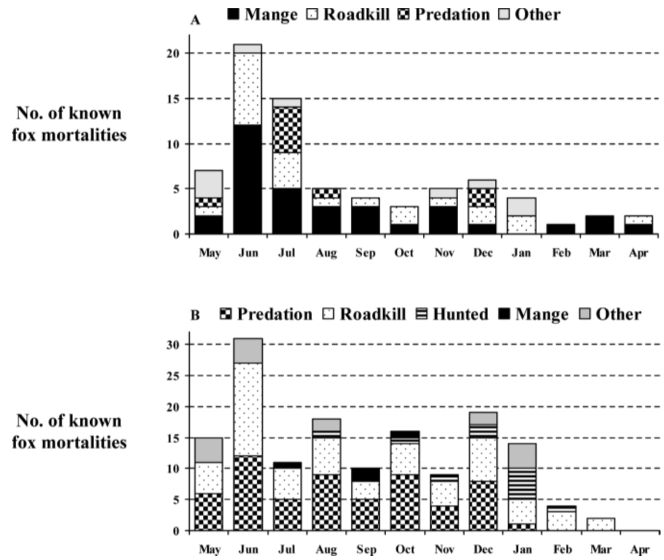

Figure 4. Moiré effects. The data are the percentage of fox mortalities attributed to 4 possible categories (from Gosselink et al. 2007). The moiré effects complicate illustration of data within the graph and can influence perception of the graph. In addition, this graph is a divided bar chart, thus the reader must interpret not only moiré effects but must also make length-area measurements without a common axis.

for the top-front of each bar and one for the top-back of each bar (Fig. 3a). Microsoft Excel (under Office Professional 2003, Microsoft, Redmond, WA, USA) provided ≥15 different types of graphs that incorporate a statistically uninterpretable false dimension, nearly an equal number to the options provided by Excel that do not incorporate false dimensions.

Moiré effects are the superimposing of a repetitive design to produce a pattern specific to one category (e.g., age class) causing that category to be distinctive from other categories within the same graph (Fig. 4). Whether moiré effects produce better graphs is unknown, because use is undisciplined, leading to increased chance of illusions of perception due to width or shading (Bertin 1983). Use of moiré effects in ecological literature is likely tied to high use of moiré effects in statistical texts, with 12% to 68% of graphics using moiré effects in those books reviewed by Tufte (2001), and the wealth of potential moiré effects (colors, lines, dots, etc.) provided in basic spreadsheet programs. Thus, while common in ecological literature, moiré effects are usually unnecessary as use of other graph designs negate the need for pattern-based classification.

SIMPLE GRAPH USE AND MISUSE

Early graphical controversies centered on the debate regarding the application of single parameter pie graphs and bar plots to data (Eells 1926, Croxton 1927, Croxton and Stryker 1927, Von Hurn 1927, Kruskal 1982). The current consensus is that pie graphs should not be used to describe data because 1) discerning the exact magnitude of the pie slices is difficult, 2) the assumption that the center angles are proportional to the frequency represented is difficult to justify, 3) comparisons between and within pies

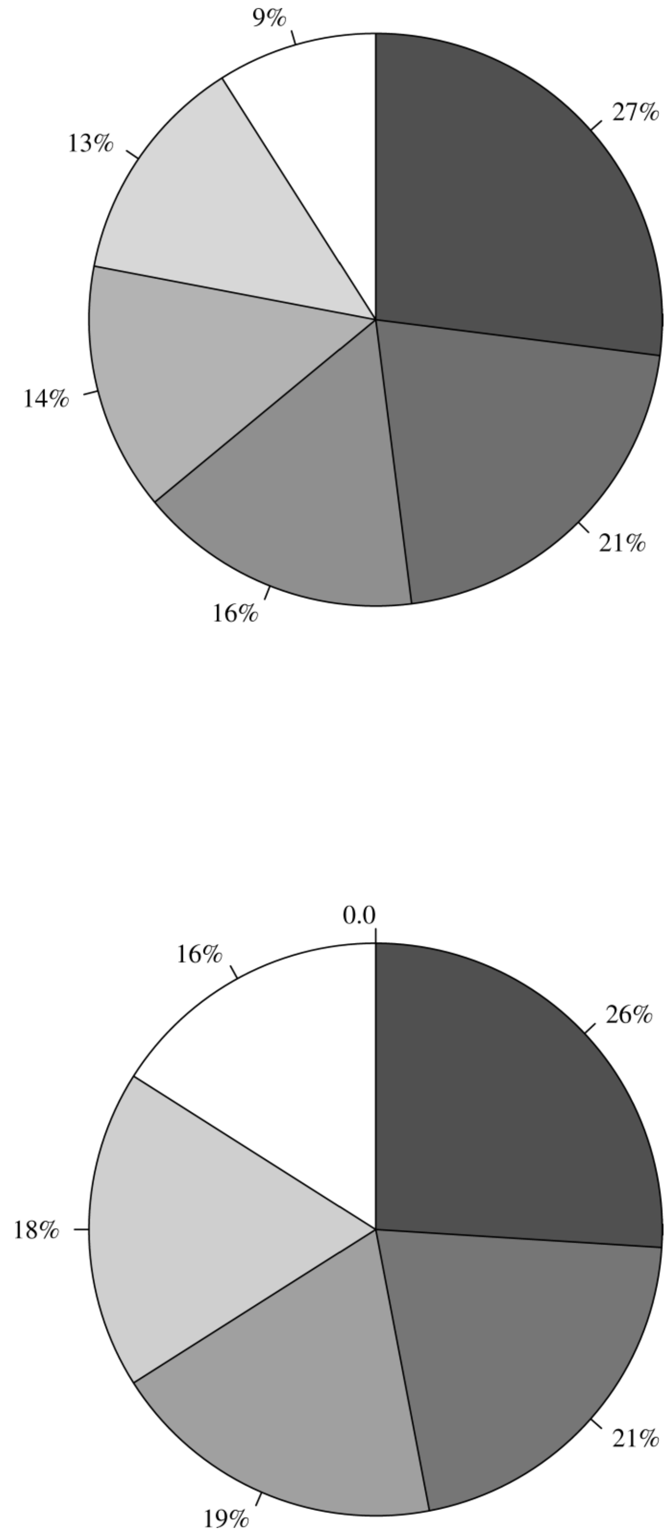

Figure 5. Pie graph. The data are the percentages of each of 2 samples. A pie chart should not be used to represent scientific data because discerning pie slice size is difficult due to angle judgments. If the percentages for each slice are shown in the graph, it negates the need for the pie graph.

are ineffective because it is difficult to judge relative slice size (angle judgments), and 4) area and diameter of the commonly used pie graphs are usually shown as equal, even when sample sizes vary, thus pie size (hence slice size) is not

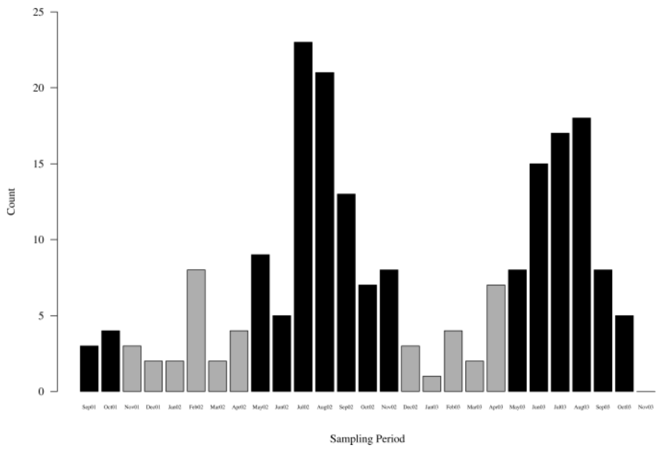

Figure 6. Bar graph. Raw counts of cave salamanders captured over 27 months in Oklahoma, USA (from Fenolio et al. 2006).

proportional to sample size (Fig. 5; although see MacDonald-Ross 1977 for a counter-view). Replacing angle judgments with position judgments would be more conducive to scientific understanding, either a simple bar graph, dot plot (see below), or a table are better presentation options than pie charts (Cleveland and McGill 1983).

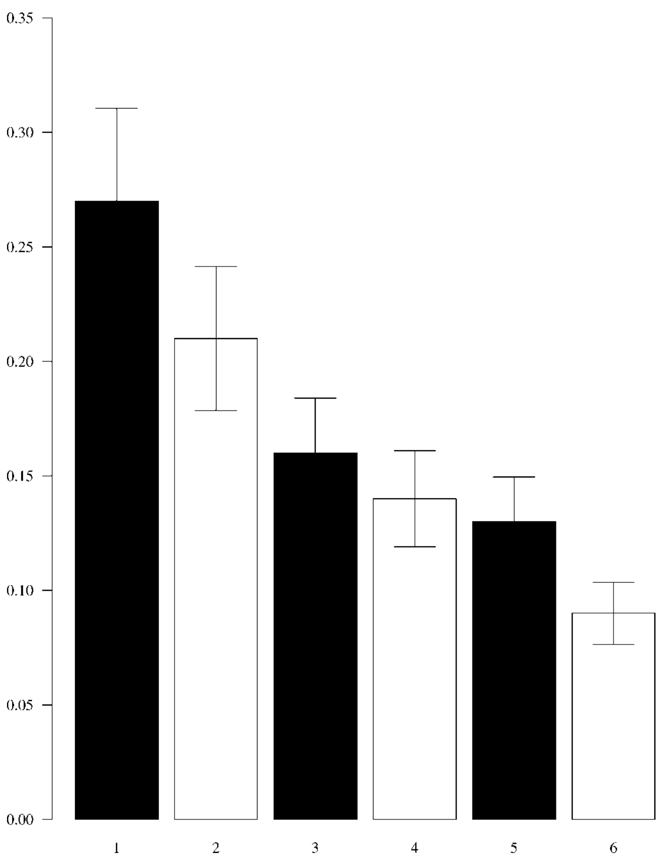

Figure 7. Bar graph. The data are hypothetical means and associated confidence intervals. A bar graph should never be used to represent point estimates because the bar sizes encode meaningless numbers, hide information such as confidence interval lower bounds, and provide redundant measurements of data altitude.

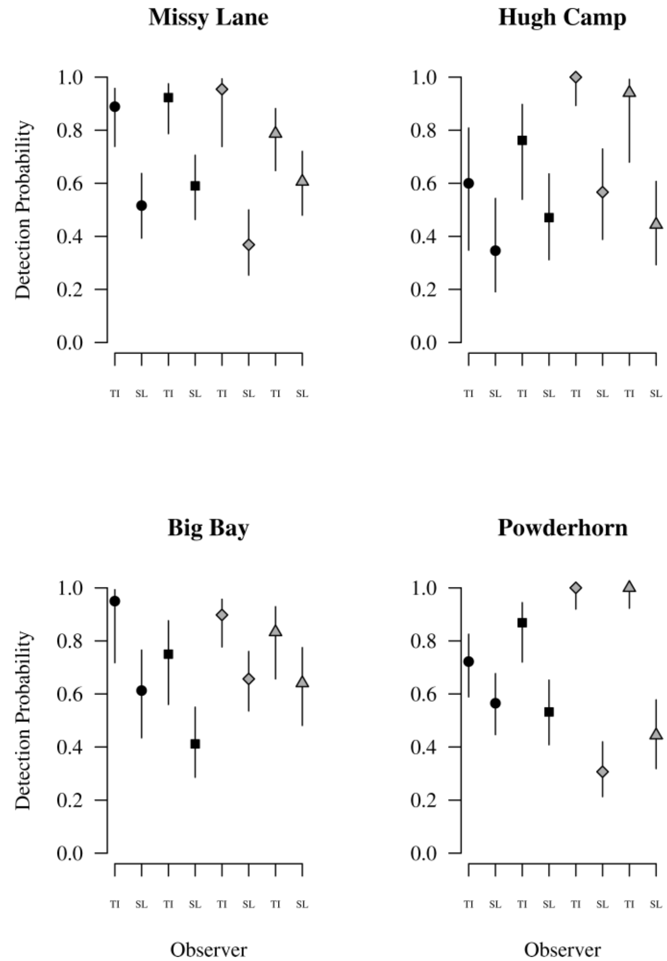

Figure 8. Detection probabilities for thermal imagers (TI) and spotlight (SL) white-tailed deer surveys conducted at Brosnan Forest, South Carolina, USA, during August 2005 (from Collier et al. 2007).

Bar graphs are the most frequently used graph in ecological literature and thus are most prone to poor usage. Bar graphs should be used to provide absolute or relative frequencies (Fig. 6; Fenolio et al. 2006), never point estimates or data means. For example, Figure 7 is intended to represent 6 means and associated confidence interval bounds. However, by using a bar graph, Figure 7 now incorporates use of the bars and shading unrelated to the data (estimated mean), distracting from the information (point estimate) of interest. Also, note that in Figure 7 only certain upper limits of the standard error bars are in view due to shading, a common occurrence that should be discouraged.

Bar graphs such as Figure 7 often have redundant data-ink (Tufte 2001). Graph 7 locates the point estimate of interest in $\geq$4 unambiguous ways: height of the left and right lines, height of the shading, and position of the horizontal line atop the bar; a fifth way could potentially be the midpoint between the 2 standard error bounds (Tufte 2001). Delete any 4 of these and you are still left with an exact measurement of altitude for these data. In this case, I suggest a different style graph would be more useful if there was requisite data ($\geq$20 data values; Fig. 8; Collier et al. 2007) or in this specific situation conversion to text would

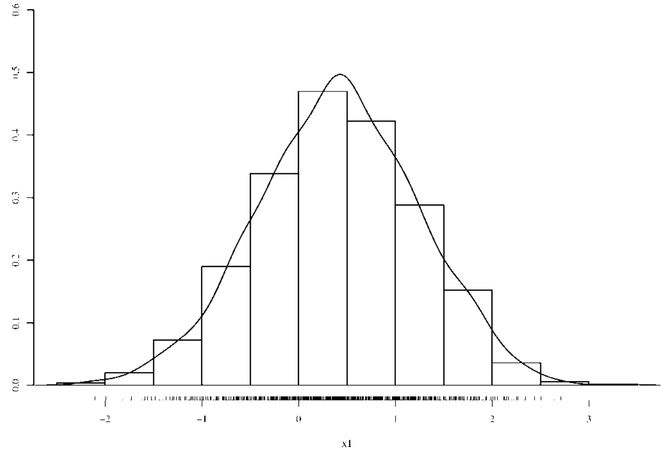

Figure 9. Histogram. The data are a simulated normal distribution ($\mu = 0.4$, $\sigma^2 = 0.8$) with equal bin widths. The data density is represented by the rug under the x-axis.

also be supported as we are providing 6 data points, far too few for a graph.

The legend for graphs such as Figure 6 often identifies this graph as a histogram. Contrary to popular use, mathematical and logical definitions of histograms and bar graphs are different and bar graphs are inappropriately labeled histograms in many computer programs and ecological journals. Histograms provide probability densities which integrate to one; thus bar height is frequency divided by interval width (Fig. 9, Chambers et al. 1983, Venables and Ripley 2002). In bar graphs (Fig. 6), bar heights are not related to interval width (bin width) or data density. Hence, bar width is meaningless for bar graphs. Histogram structure is in part dependent upon not only data density, but in the width chosen for the data bins. A good way to show the actual data density when plotting a histogram is using a rug, or a graph that shows data density directly below the histogram (Fig. 9). Additionally, sometimes plotting a density function rather than a standard histogram is useful (Fig. 9).

Divided bar charts also are commonly used to show relative system measurements (Fig. 4). Divided bar charts require the reader to interpret both position and length (such as pie graphs required judgments of angle; Cleveland 1984*b*, Cleveland and McGill 1985). Divided bar charts can be used to compare total area-length of relative position along one scale (Cleveland 1984). However, fractional areas of divided bar charts can only be compared using area-length judgments because there is no common baseline (e.g., common axis) for comparison of the fractional area being illustrated (Cleveland 1984*b*, Cleveland and McGill 1985). For example, consider Figure 4 (Gosselink et al. 2007). Based on the divided bar chart and moiré effects, it is difficult to determine which categories are variable across the dataset as there is no common baseline on which to judge each provided measure. Errors in judgment of area-length questions were between 40% and 250% larger when a common scale was not available (Cleveland and McGill 1984). Thus, consistently overestimating fractional areas in a divided bar chart can change data perceptions by readers

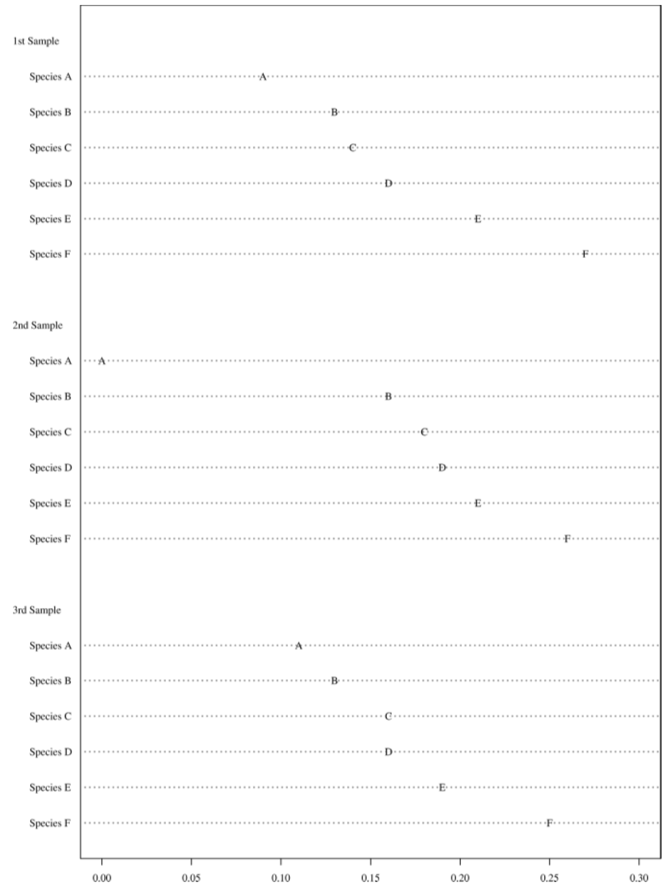

Figure 10. Dot chart. The data are the percentages of the example population for each of 3 samples. In this case, comparisons between and among samples is simplified because the reader has a common axis and does not have to make length-area measurements.

(Cleveland and McGill 1984). Also, because divided bar charts suffer from no implicit natural ordering of categories, moiré effects are a necessity that adds additional complexity and unnecessary information.

One approach that lends itself well as a replacement for pie graphs, bar graphs, and divided bar charts, but that is rarely used, is the dot chart (Cleveland 1984*b*). Cleveland (1984*b*:274) suggests that "A reasonable principle for the design of graphics is to make the graphical elements representing the data as nearly equal as possible; this giving equal visual emphasis to all data values." Both Cleveland (1984*b*) and Chambers et al. (1983) have recommended that use of dot charts replace the current usage of pie graphs, divided bar charts, and in most cases, bar plots. As an example, I took the data used to construct Figures 3a and 3b, and reformatted these data as a dot chart (Fig. 10). Notice how use of a grouped dot chart simplifies interpretation of these data because it 1) provides the data for comparison on a common axis, 2) provides the data in a simple format, 3) reduces the need for area-length judgments, and 4) reduces the need to decipher moiré effects. In Figure 10, although I used letters to represent different point estimates to increase interpretability of both location and comparisons between and among groups for the sake of this manuscript, any unique symbol or shape (e.g., point estimates with confidence intervals) would suffice as long as it was detailed in the graph legend.

SUMMARY

Ecologists have spent considerable time and effort to determine appropriate computational method(s) for analysis of ecological data (Williams et al. 2002) but in the interim have sacrificed substance for convenience when constructing graphs to describe ecological data. Our use of graphs in ecology should focus on organizing quantitative information such that patterns and structures within the data can be deciphered (Chambers et al. 1983; Cleveland 1984*b*; Wainer and Velleman 2001; Tufte 1983, 2001). However, we seem to use graphs to highlight simple results that we suggest merit notice.

Highlighting important results is commendable; however, authors should keep in mind the nature of graphs. Few statistical tools are as powerful as the graph and properly constructed graphics can convey a wealth of information regarding the structure and relationships of data (Chambers et al. 1983, Tufte 2001, Murrell 2006). Graphs should highlight those data that are substantial and reduce information that is not germane. Thus, when constructing basic graphs, I implore scientists to think about presentation of data as rote usage can provide misleading results. In my opinion, the most profound issues of graph creation are tied to the use of spreadsheet or statistical programs that provide "stock" graphical depictions of results that are used as defaults for multiple different data types. These programs may provide a wealth of graphical options; however, few of these meet any of those criteria suggested for good graphs by Tufte (1983, 2001) or Chambers et al. (1983).

I have highlighted and summarized certain aspects of the most frequently used basic graphs in wildlife ecology that I suggest need attention. However, there are many other areas I could have discussed (e.g., legends, graph borders, color, shading) and a host of useful graph types I did not outline (lattice graphs, mosaic graphs, odds ratio plots, 3-dimensional scatter graphs). Thus, my thoughts are obviously not comprehensive with respect to the field of graph construction but rather an initial discussion on basic graph development in the hope that future evaluation and discussion on graph use in ecological sciences will occur.

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