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[Article]

An Evaluation of Data Entry Error and Proofing Methods for Fisheries Data

CHRISTOPHER L. JOHNSON,* GABRIEL M. TEMPLE, TODD N. PEARSONS,[1] AND TIMOTHY D. WEBSTER

Washington Department of Fish and Wildlife,
600 Capitol Way North, Olympia, Washington 98501-1091, USA

Abstract.—Reducing data entry error has the potential to improve estimates produced by fisheries practitioners. However, the frequencies of data entry error and evaluations of the recommended protocols for dealing with data entry error have rarely been presented in fisheries-related literature. The objectives of our study were to determine the magnitude of data entry error in a typical fisheries data set, what kind of errors occurred most often, and how those errors might affect commonly generated estimates of abundance, size structure, and species richness. We evaluated four methods of data entry and proofing: (1) a single entry, (2) read-aloud proofing, (3) double-entry proofing, and (4) field use of a personal digital assistant (PDA). We determined the quality of the data after the use of each method and compared common fisheries estimates derived from each with estimates generated from standardized data. Total error discovered in the data set averaged 0.79 ± 0.22% (mean ± SD) and consisted of 44.1% field-related errors and 55.9% data entry errors. We found that numbers of known errors remaining in the data were significantly lower when proofing methods were used. Abundance estimates derived from a single data entry were significantly different from those derived from data that had undergone proofing. However, the magnitude of the difference (2.22%) was less than our limit of acceptable error and far less than the mean confidence interval of the estimates themselves (60.91%). Further, no differences were detected in mark–recapture abundance estimates, estimates of size, or estimates of species richness. This suggests that for most common fisheries estimates, a single entry of data or single entry using a PDA is sufficient. We subsequently found that the use of automated error checking helped to ensure an acceptable level of data quality without the time and expense of more traditional error-checking methods.

Fisheries practitioners strive to provide estimates of fish population characteristics (e.g., abundance, size structure, assemblage structure) of the highest possible quality and for the lowest possible cost. This involves limiting the level of potential sampling error to maximize the precision of subsequent analyses. Sampling error can occur at a variety of stages, such as during the planning of the sampling design, during field sampling, and in the process of data entry. There are resources available to fisheries practitioners to improve sampling designs (Schreck and Moyle 1990; Murphy and Willis 1996) and field-sampling protocols (Johnson et al. 2007). However, the subject of data entry error and how it may affect these estimates has been largely overlooked.

Protocols to reduce data entry error typically involve the implementation of error-checking methods, such as range-checking procedures or more time-consuming and presumably more effective measures that involve comparing each data entry with either the raw data or a second entry of those data (Brown and Austen 1996). Of these, one established technique is the read-aloud method (Kawado et al. 2003) in which a single computer entry is printed and then read aloud to a second individual who simultaneously compares those spoken values directly with those on the original data sheet. Another method is double data entry (Cummings and Masten 1994; Brown and Austen 1996) in which two separate entries of the same field data are entered into a computer and then directly compared using a spreadsheet function. Despite the presence of these protocols within current literature, there is little evidence to suggest the broad use of standardized proofing methods in the fisheries community. The need for such measures, their benefits in improving data quality, and the degree to which those improvements increase the quality of subsequent estimates of population dynamics are largely unknown or unreported.

In contrast, scientists in medical fields have acknowledged the potential implications of data entry error and have published several articles reporting rates of entry error, evaluating methods of error checking, and assessing the potential effect of undiscovered errors. Kawado et al. (2003) found that double data entry was superior to read-aloud checks in the

* Corresponding author: johnsclj@dfw.wa.gov
[1] Present address: Grant County Public Utility District, Post Office Box 878, Ephrata, Washington 98823, USA.

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discovery of data entry error and reported mean single-entry error rates of 0.34% of the data set. Büchele et al. (2005) reported error rates of 0.54% and 0.72% using double data entry. Gibson et al. (1994) and Day et al. (1998) acknowledged that double data entry could be effective in discovering entry error but found that error rates were low enough in some clinical trials that double data entry was deemed unnecessary.

If rates of data entry error from fisheries data are found to be similar to those reported in other fields, then extensive proofing methods may not be necessary. However, depending upon the sensitivity of analysis, greater precaution against error may be required in some situations (e.g., acceptable impact to a listed species). Additionally, the results of such studies may not be directly applicable to the field of fisheries, where data are often collected under conditions that are far less controlled. Factors such as inclement weather, inhospitable sampling locations, and crew fatigue may result in higher rates of data entry error.

Many trade-offs occur when designing and implementing studies to produce the best available estimates of population parameters (Temple and Pearsons 2007). Most, if not all, fisheries practitioners are limited by the amount of time and money that is available to collect data. Excessive effort eliminating data entry errors directly affects productivity and reduces effort that may be better spent in other areas (e.g., increasing sample size). Conversely, failing to reduce data entry error when warranted may limit the researcher's ability to draw valid conclusions from the data and could conceivably lead to misguided management decisions.

One method of reducing data entry error may be to eliminate the need for postsampling data entry by implementing the use of a personal digital assistant (PDA). Personal digital assistants have been advocated for a variety of scientific applications (Green 2001; Fletcher et al. 2003; Ice 2004) and have been successfully applied to the collection of some fisheries data (Hollowell 2003; Lang et al. 2006). However, several disadvantages may hinder their practicality. Spain et al. (2001) reported difficulties arising from small screen size, poor system navigation, and inflexibility when entering differing data types. In addition to the screen size limitation, Lang et al. (2006) also experienced an incidence of data loss. A further evaluation of how and the extent to which data obtained from a PDA differ from hand-written data and how those unscreened data may affect fisheries estimates is needed.

The objectives of our study were to determine the magnitude of data entry error in a typical fisheries data set, what kind of errors occurred most often, and how those errors might affect commonly generated estimates of abundance, size structure, and species richness if not prevented through available data-proofing protocols. To accomplish these objectives, we evaluated four methods of data entry and proofing: (1) a single entry of the hard-copy field data, (2) a read-aloud check of those single-entry data, (3) an independent second entry (i.e., double entry) and computer crosscheck of those data, and (4) concurrent recording of those same data while in the field using a PDA. We determined the level of error present in data resulting from each entry and proofing method through direct comparison with data validated using audio recordings of each collection event. We then categorized discovered errors into five distinctive groups and evaluated their frequency of occurrence. We compared estimates of abundance, size, and species richness from data proofed by each method with those from the validated data. Finally, we created a series of logical tests in the form of Microsoft Excel Visual Basic Application (VBA) macros, and evaluated their effectiveness in providing adequate data quality after only a single entry of the data or a single entry onto a PDA. We provide an example of the evaluation of data entry error in a fisheries setting and suggestions for insuring data integrity at a relatively low cost.

Methods

Data were collected from July through September of 2004 and 2005 as part of a long-term hatchery supplementation program. The program provides salmonid population estimates in tributaries of the upper Yakima River in central Washington for purposes of monitoring and evaluation (Pearsons and Temple 2007). Detailed sampling protocols are described in Temple and Pearsons (2007). Briefly, rainbow trout *Oncorhynchus mykiss* and cutthroat trout *O. clarkii* were netted during two to three electrofishing passes conducted in 200-m-long tributary sites. Captured salmonids were anesthetized, examined, measured, marked, and subsequently released. A single fisheries technician made all necessary morphological measurements, conducted observations of fish condition, and then verbally communicated the information to a second technician. The second technician then transcribed those data onto a hard-copy data sheet (Figure 1). Additionally, data were concurrently entered into a PDA by a third technician and recorded with a compact audiocassette recorder for later review. Examples of the types of data recorded and transcribed are specimen species code, length and weight, mark codes used in mark–recapture population estimates, and notes of general condition. A complete list of data collected is presented in Table 1. Hard copies of field

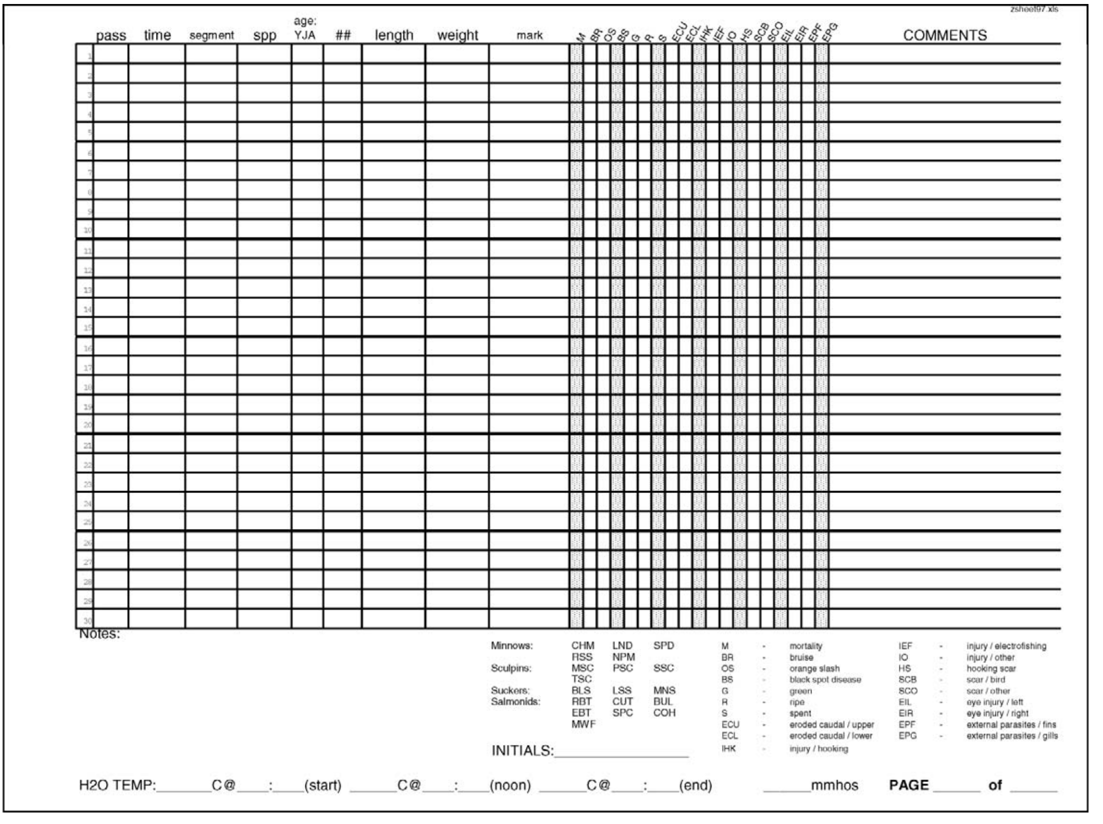

FIGURE 1.—Example of the field data sheets used in the study. Data types are those presented in Table 1.

data were returned to the office daily and stored in binders until they could be entered onto the computer.

Data from each collection site were initially entered into template Microsoft Excel workbooks, which had been formatted to closely resemble field data sheets. To remain consistent with the data entry protocol of previous years, common entry restrictions were left in place. These included cell restrictions to prevent spelling errors when entering a species code, and "check" or "no check" restrictions in cells that indicated presence or absence of various indicators pertaining to fish condition. Technicians also had unrestricted access to standard Excel features, such as those that allowed the "dragging" of values to replicate them down a column or across a row and "auto-completion," which automatically completes a cell entry after the first letter of a recently used text value has been entered. A completed data entry entered by a single technician (hereafter referred to as a single entry) included all data from a single collection event.

A Palm Tungsten E (Palm, Inc., Sunnyvale, California) with the Palm OS 5.2.1 operating system was used as our base PDA. Data entry forms for the PDA were created using Pendragon Forms version 4.0 (Pendragon Software Corporation 2003). This software allowed us to create touch-screen data sheets specific to our data entry needs. An example of the user interface is presented in Figure 2. The PDAs were protected by Otterbox cases that provided water resistance, durability, and flotation while still allowing data to be recorded through a thin, transparent cover. Upon returning to the office, PDA data were uploaded to a Microsoft Access 2000 database, a prerequisite for the Pendragon software, and then exported to Microsoft Excel workbooks so that all data were consistently formatted.

We implemented two data-proofing methods on our single-entry data: the read-aloud method and double data entry. The read-aloud method (Kawado et al. 2003) compares the original hard-copy field data sheet with a printed copy of a single electronic entry. One individual reads the data from the hard copy aloud, while another checks it visually against the electronic printout. Discovered errors were highlighted on the printout and then corrected in an electronic copy of the single-entry data. Read-aloud checks were performed on the single-entry data from each of the collection

TABLE 1.—Definition of data sheet fields (see Figure 1) and their required entry types. Data descriptions are in order of their appearance on the field data sheet.

Data field	Required entry	Definition
pass	Numerical	Electrofishing pass
time	Numerical	Electrofishing sampling time (s)
segment	Categorical	Sample segment
SPP	Categorical	Species
age: YJA	Categorical	Nontarget species age
##	Numerical	Number (if multiple)
length	Numerical	Specimen length
weight	Numerical	Specimen weight
mark	Categorical	Mark code
M	Checkbox	Specimen status mortality
BR	Checkbox	Bruising due to electrofishing
OS	Checkbox	Orange slash, often present in rainbow trout–cutthroat trout hybrids
BS	Checkbox	Presence of black spot disease
G	Checkbox	Spawning status, green
R	Checkbox	Spawning status, ripe
S	Checkbox	Spawning status, spent
ECU	Checkbox	Erosion of the upper caudal fin
ECL	Checkbox	Erosion of the lower caudal fin
IHK	Checkbox	Hooking injury
IEF	Checkbox	Electrofishing injury
IO	Checkbox	Other injury
HS	Checkbox	Hook scar
SCB	Checkbox	Bird scar
SCO	Checkbox	Other scar
EIL	Checkbox	Injury of the left eye
EIR	Checkbox	Injury of the right eye
EPF	Checkbox	Presence of external fin parasites
EPG	Checkbox	Presence of external gill parasites
COMMENTS	Text	Short notes on unique events

events in a closed and quiet room where distractions could be minimized. The double-data-entry method (Cummings and Maston 1994; Brown and Austen 1996) compares directly, with the aid of a spreadsheet function, cell-by-cell differences between two independent spreadsheet entries. Data from each collection event were entered into an Excel spreadsheet a second time and then compared directly with the single entry. To reduce the likelihood of repeated error, single and double data entries were performed by different technicians. Discovered errors were highlighted, corrected, and saved in the same format as the single entry.

Audio recordings were used to create a benchmark data set, which could be compared directly with data resulting from each of the entry–proofing methods. Reviews were made by listening to the audio from each sampling event while viewing those data that had already undergone the double-data-entry proofing process. Discovered errors were then noted as either transcription errors made while in the field (field error) or errors made while transferring data to electronic copy (data entry error). The data entry portion of the discovered error was further checked against data that had undergone read-aloud checks. This ensured that no

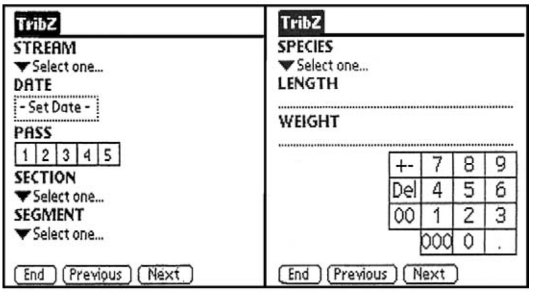

FIGURE 2.—Example personal digital assistant (PDA) screen. Forms for the PDA were created using Pendragon software and were used in the study.

previously discovered errors had been overlooked in the audio-reviewed data. Audio recordings were reviewed by one of two senior technicians. When sections of the audiotape were inaudible, corresponding sections in the electronic copy were removed and not included in the analysis. Corrections were made only when the discovered errors were indisputable. These data are hereafter referred to as audio-reviewed data, and the discovered errors in these data (both field and data entry errors combined) are referred to as the total error. It is possible that error could be introduced while reviewing the audio of field sampling events. This might happen if erroneous data were verified or if data entry errors were to occur while correcting discovered errors. However, verification of erroneous data would require a clear verbal communication of an incorrect datum in the field and a silent correction of that value to only one of the two entry methods. Additionally, data entry error during the audio review would not affect entry method comparisons. We assume that errors introduced during the audio review process are inconsequential to our analysis. Subsequently, both field and data entry errors were further classified as one of five distinct error types. Error types included numerical errors (e.g., incorrect recording of length or weight), categorical errors, (e.g., an incorrect species code), missing data (e.g., a missed mark on a recapture survey), misplaced data (e.g., critical text comment on the wrong entry line), or drag-type errors in which one physical entry was then autofilled in a number of cells. For PDA data sets, entries that resulted in broad errors over multiple entries (e.g., electrofishing pass, collection site) were considered drag-type errors. The scope of our study is limited to the assessment of data entry and transcription errors. Therefore, we do not provide an evaluation of error introduced before recording the data (e.g., measurement or verbal errors).

Before all statistical analyses, general parametric test assumptions of normality and homogeneity of variance were evaluated using the Shapiro–Wilk test and the Brown–Forsythe test, respectively (Zar 1999). If test assumptions were not met or could not be met through data transformation, nonparametric tests were used as an alternative. When appropriate, post hoc pairwise comparisons were made using Tukey's honestly significant difference (HSD) test or nonparametric methods as described by Zar (1999). Confidence intervals (CIs) presented for nonnormally distributed data were calculated using standard bootstrapping methods (Manly 2007). All tests were performed in STATISTICA version 8.0 (StatSoft 2007) with significance at *P*-values of 0.05 or less.

We investigated potential bias in the estimation of error rates attributable to pseudoreplication between years (Hurlbert 1984). Unforeseen events in the two sampling seasons (e.g., dead batteries in the audio recorder, forgotten PDA, too few technicians on a given day) prevented consistency in locations sampled between years (i.e., some locations were sampled in both years, and some locations were sampled in only one year). If variables such as site complexity were to affect the level of entry error in data collected at a particular sampling location, collection events at that location in both years may introduce pseudoreplication. We used Spearman's rank correlation coefficient (r_s) to determine whether the proportion of total error within each replicate collection event was correlated in locations sampled in both years. Calculation of r_s and correcting it for tied ranks (r_{sc}) were performed according to the methods of Zar (1999). We used a Student's *t*-test to detect differences in the level of total error between years in all sites (year effect). Total error was expressed as a proportion of the total number of data entries in each replicate and arcsine transformed to meet test assumptions.

We investigated the sources of entry error within our data set using nonparametric tests. We used a Wilcoxon matched-pairs test to detect differences in the mean level of error made while in the field and while entering the data onto the computer and *G*-tests to compare the frequency of error categorically (e.g., numerical error, drag error). We tested for differences in rates of error by technicians in the field and in the office using a Kruskal–Wallis analysis of variance (ANOVA) with individual technician as the treatment, collection event as replicates, and the number errors per entry as the response variable. We also investigated the possibility that differences in error rate by the individual entering data in the field could bias comparisons of hard-copy and PDA data collection methods. We used a *G*-test to compare the error frequency of each technician using each of the field data entry methods.

Our data allowed for the use of two types of population abundance estimates common in the fisheries literature, multiple removal and Petersen-type mark–recapture, both of which are described by Temple and Pearsons (2007). Multiple-removal population estimates and estimates of mean length of the target species in each replicate were calculated using the Microfish computer program (Van Deventer and Platts 1989). Microsoft VBA macros were used to transfer data to the Microfish program, calculate Petersen-type mark–recapture abundance estimates, and generate species richness estimates for each replicate data set. Because fish were not marked in the first year of our study (2004), mark–recapture estimates were generated from data collected in 2005 only.

We tested for differences attributable to entry method in the number of remaining errors by method and in estimates of abundance, size, and species richness derived from those data. Each comparison was made using a one-way, repeated-measures ANOVA with the four methods of data entry as treatments and collection events as replicates. Either the number of remaining errors within each of the replicates or one of the three estimates derived from those data served as the response variable for each comparison. A Friedman ANOVA was used when parametric assumptions could not be met.

Acceptable limits of bias in estimates resulting from the method of data entry are subjective measures dependent upon objectives specific to each fisheries program. We used the working rule provide by Cochran (1977) in determining whether detectable bias in our estimates should be considered detrimental to the accuracy of the estimate. Cochran (1977) suggested that the effect of bias is significant when it is greater than one-tenth of the standard deviation (SD) of the estimate. When significant differences between estimates were found, we measured bias as the mean difference between estimates generated from the evaluated methods of entry and those generated from audio-reviewed data. We then compared that value to the SD of audio-reviewed replicates. If bias exceeded one-tenth of the SD, then detectable differences were deemed critical to the accuracy of the estimates.

We performed a preliminary post hoc assessment of automated error-checking routines. This assessment is intended as an illustration of the potential for automated routines to provide a basic level of data integrity when using a single data entry as protocol. However, it is not a thorough assessment of their efficacy. We used Microsoft VBA to write an Excel macro, which automated many of the comparisons that would be made while visually reviewing a newly collected data set. The VBA macro consisted of separate modules, each consisting of a target error (e.g., incorrect entry of electrofishing pass) and a logical method of detection (e.g., comparing adjacent data entries such as sampling duration and numerical sequence of the previous pass value). Further examples of target errors include missing data, drag errors, number of sampling units, and outlier values. Modules for each target-error type were combined so that they could be executed in sequence without operator intervention. The finished macro was further refined to run sequentially through multiple data sets placed within a dedicated computer directory. The macro was run on single-entry data sets containing errors that resulted in detectable differences in generated estimates of population metrics and was considered successful if it indicated those errors as suspect.

Results

Our sample consisted of 50 replicate data sets originating from the same number of collection events, 25 in 2004 and 25 in 2005. The number of entries for collection events ranged from 180 to 1,336 (mean = 540.2, SD = 305.5) in 2004 and from 100 to 1,548 (mean = 774.0, SD = 431.4) in 2005. No significant correlation in the proportion of total error was detected in locations that were sampled in both years ($r_{sc} = 0.18$, df = 17, $P > 0.05$). Additionally, no significant difference in mean total error was detected between years (*t*-test: $t = 0.11$, df = 48, $P = 0.91$). Based on these results, we considered replicates independent of collection location and pooled data from both years in subsequent analyses.

Total error averaged 0.79 ± 0.22% (mean ± SD) of the data sets consisting of 0.35 ± 0.16% field-related errors and 0.44 ± 0.15% data entry errors (44.1% and 55.9% of the total error, respectively). We found no significant difference between the mean number of field and data entry errors (Wilcoxon matched-pairs test: $Z = 1.54$, df = 24, $P = 0.12$). Similarly, we found no significant difference in the categorical distribution of field-related errors and data entry errors (*G*-test: $\chi^2 = 0.07$, df = 4, $P = 0.99$) or in the magnitude of error between categories in either field error (*G*-test: $\chi^2 = 0.34$, df = 4, $P = 0.99$) or data entry error (*G*-test: $\chi^2 = 0.46$, df = 4, $P = 0.98$).

We did detect a difference in the mean level of error remaining in each data set attributable to the method of data entry (Freidman ANOVA: $\chi^2 = 68.74$; df = 3, 49; $P < 0.01$). Pairwise comparisons indicated significant differences between PDA entry and all other methods and between single entry and all other methods ($P < 0.05$). Mean percent of total error remaining in the data sets ranged from 0.40 ± 0.16% for data checked using the double-data-entry method to 1.30 ± 0.40% for data entered using a PDA (Figure 3).

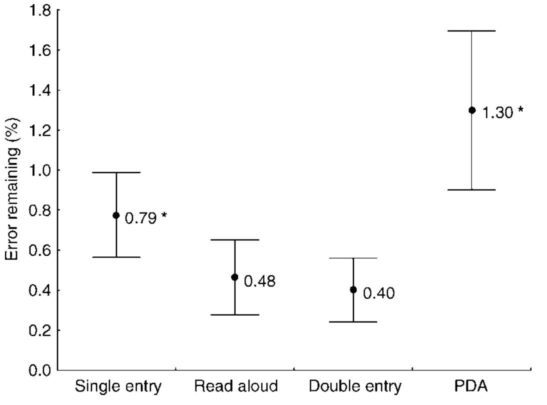

FIGURE 3.—Mean (±95% confidence interval) percent error remaining in the data set after each of four methods of data entry: single entry, read-aloud proofing, double-entry proofing, and field use of a personal digital assistant (PDA). Levels of error remaining after a single entry or PDA entry (both marked with an asterisk) were significantly greater than that of either read-aloud or double-entry proofing.

No difference was detected in mark–recapture estimates attributable to the method of data entry (ANOVA: $F = 0.50$; df = 4, 24; $P = 0.74$), estimates of species richness (Freidman ANOVA: $\chi^2 = 6.00$; df = 4, 49; $P = 0.11$), or estimates of mean size of the target species (Freidman ANOVA: $\chi^2 = 6.79$; df = 4, 49; $P = 0.15$). We did detect a significant difference in the multiple-removal population estimates between the methods of data entry used (ANOVA: $F = 29.96$; df = 4, 49; $P < 0.05$). A Tukey's HSD test revealed that estimates generated from single-entry data differed significantly from those generated from the audio-reviewed data (Tukey's HSD test: $P < 0.05$). Differences between estimates by method of data entry and those generated using the audio-reviewed data ranged from 0.31 ± 0.03% for double-data-entry and read-aloud proofing methods to 2.22 ± 0.98% for the single-entry method (Figure 4). Mean bias of estimates generated from single-entry data (0.19) was 4.5% of the mean SD of audio-reviewed estimates (3.47). Confidence intervals (95%) around the benchmark audio-review population estimates averaged 60.91 ± 48.62%.

No difference was detected in the rate of computer data entry error between individual technicians (Kruskal–Wallis ANOVA: $H = 1.07$; df = 3, 48; $P = 0.78$). However, we did detect differences in the rate of transcription errors made by individuals in the field for both hard-copy entry (Kruskal–Wallis ANOVA: $H = 24.78$; df = 6, 181; $P < 0.01$) and PDA entry (Kruskal–

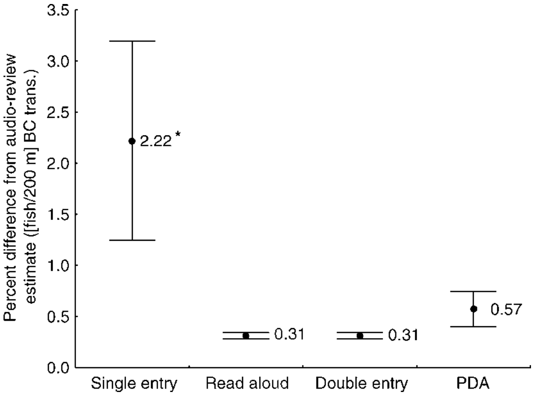

FIGURE 4.—Mean (±95% confidence interval) percent difference between population estimates generated using audio-reviewed data and those generated by four methods of data entry: single entry, read-aloud proofing, double-entry proofing, and field use of a personal digital assistant (PDA). A significant difference in means (marked with an asterisk) was detected between single-entry and audio-reviewed data estimates. Data were Box–Cox transformed (BC) to meet test assumptions.

Wallis ANOVA: $H = 11.99$; df = 5, 182; $P = 0.03$). We did not detect a difference in the frequency of error between the two methods of field data entry attributable to technician (G-test: $\chi^2 = 0.75$, df = 5, $P = 0.98$).

Lastly, automated error-checking routines were successful in detecting all of the errors in single-entry replicates that had resulted in differences from estimates of abundance generated from audio-reviewed data. These errors consisted of two numerical and two drag-type errors present in 4 of the 50 single-entry replicates.

Discussion

The use of intensive error-checking methods such as read aloud or double data entry in lieu of only a single entry or PDA entry appears to be unnecessary if levels of introduced error are similar to those we observed. This is particularly apparent when generating commonly reported estimates of abundance, size, and species richness, where we found no detectable difference between estimates generated from any of the evaluated entry methods. Although we did find significant differences in the quality of data from each of the entry methods, these resulted in detectable differences in only one of the estimates generated from those data. The magnitude of the bias in those estimates, 4.5% of the mean SD, was well below our acceptable level of 10%. The minimal mean difference between single-entry-derived estimates and those from audio-reviewed data (2.2%) is further illustrated by comparison with the CIs around the estimates themselves (mean CI = 60.1%). These intervals are within the range of other studies, which have reported 95% CIs ranging between 24% and 81% of multiple-removal abundance estimates (Heimbuch et al. 1997; Jones et al. 1998; Howell 2006; Pearsons and Temple 2007). Further, using either of the proofing methods presented, a doubling of entry costs would be required to reduce the level of error by an additional 1.91%. We observed similar mean levels of data entry error (0.44%) to those reported in studies within other disciplines (Kawado et al. 2003; Büchele et al. 2005). Our results are also consistent with the results of others outside the fisheries community (Gibson et al. 1994; Day et al. 1998), who concluded that for most practical applications double data entry was unnecessary. Our incurred costs were similar to those of Büchele et al. (2005), who reported the cost of double data entry at 2.5 times that of single entry alone, which may translate into a substantial cost savings for many fisheries programs. It seems evident that with appropriate quality control, a single data entry or PDA entry is sufficient.

Resource organizations are increasing their use of large regional databases as a means of communicating data in a standardized way to discover broad-scale trends and patterns (Johnson et al. 2007). One of the concerns about the use of large databases that rely upon different groups to supply data is the unevenness of data-proofing methods. Some data sets may be sound, whereas others might contain high levels of error. It has been our experience that most data sets are subjected to minimal data proofing, which could have serious consequences for the utility of the database if errors are frequent. However, our study suggests that substantial differences in quality between data sets are unlikely due to the chosen method of data entry. In addition, we found no significant difference attributable to the specific individual entering the data either within a given year or between years. This suggests that in most cases, data from programs employing different data entry personnel from year to year should be consistent as long as those personnel are motivated and well trained. This may not be the case in the collection of field data, where we found detectable differences in the rate of transcription errors between individuals. We did not detect differences between the rates of error between sites. However, if database values include those from studies that are unbalanced for potential collection bias, differing levels of field-related error might be of concern.

We found that from a data entry perspective, the PDA was a viable alternative to the other methods of data entry we evaluated. There are, however, some potential disadvantages to using PDAs as a primary data entry protocol. Foremost is the possibility, however remote, of losing data due to a unit malfunction or as the result of a dead battery. Lang et al. (2006) reported data loss due to the malfunction of a refurbished PDA. However, these were minimized through frequent data downloads. Although we did not experience loss of data, we did find that processing speeds decreased as the amount of memory available on the device decreased. At times, this created a situation in which the crew needed to wait while the PDA processed information. If held fish spent a longer period under anesthetic as a result, decreases in survival could occur. We suggest that backup methods of data collection (e.g., a second PDA or hard-copy data sheets) should be part of the collection protocol when PDAs are the primary recording device so that these potential problems can be avoided. From a cost perspective, there is a substantial initial investment for the PDA units themselves and for software to create data collection forms. Our initial costs were approximately US$500 for one unit and the required software. These costs may be prohibitive in some programs. However, when compared with the cost of data entry, particularly with larger data sets and long-term programs, entry directly to electronic format may offset initial setup costs. If these issues can be adequately addressed, there are some potential advantages to PDA use over hand-written data. The primary advantage is the immediate availability of data for analysis and perhaps real-time outlier rejection that could be used in reducing both field- and data-entry-related errors (e.g., measurement error). Overall, we feel that the exclusive use of PDAs for data collection purposes in the field of fisheries shows promise and should be explored further.

Although our results suggest that extensive data-checking methods are unnecessary for data sets similar to ours, the fisheries practitioner is left in need of a cost-effective method that ensures basic levels of data quality are met. Various methods exist to help fisheries practitioners perform basic quality checks on their data (e.g., outlier rejection, verification of known sample size). These methods are based upon logical criteria that must exist for the data to be representative of the population. If data are entered in similar formats, many of these methods can be automated to detect suspect entries using widely available software. Our post hoc use of automated proofing suggests that with a minimal investment in development, automated routines are capable of capturing critical errors and, therefore, providing a basic level of data quality for little operational cost. Once automated proofing routines are developed, they can be employed in minutes, allowing simultaneous, consistent, and economic proofing of large data sets. Further, these routines may be refined over time, thereby increasing their effectiveness in detecting error. If proofing routines are written carefully and monitored sufficiently, this method may provide fisheries professionals an adequate indication of their data quality. We propose that further evaluation be given to automated error-checking routines.

We detected levels of error within our data set attributable to mistakes made in the field that were comparable to the level of error incurred through the data-entry process (44.1% and 55.9%, respectively). This suggests that field-related errors (i.e., transcription errors) are as relevant to data quality as the methods used to enter those data into electronic format. Our detection of field-related error was limited to detection of transcription errors. Therefore, true levels of field-related error, including measurement and verbal errors, are probably greater than those we observed. Evaluation of field-related errors and the performance of newer technologies (e.g., electronic measurement, voice recognition) would be beneficial to the fisheries community.

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References

Brown, M. L., and D. J. Austen. 1996. Data management and statistical techniques. Pages 17–62 *in* B. R. Murphy and D. W. Willis, editors. Fisheries techniques, 2nd edition. American Fisheries Society, Bethesda, Maryland.

Büchele, B., B. Och, G. Bolte, and S. K. Weiland. 2005. Single versus double data entry: letters. Epidemiology 16:130–131.

Cochran, W. G. 1977. Sampling techniques, 3rd edition. Wiley, New York.

Cummings, J., and J. Masten. 1994. Customized dual data entry for computerized analysis. Quality Assurance: Good Practice, Regulation, and Law 3:300–303.

Day, S., P. Fayers, and D. Harvey. 1998. Double data entry:

what value, what price? Controlled Clinical Trials 19:15–24.

Fletcher, L. A., D. J. Erickson, T. L. Toomey, and A. C. Wagenaar. 2003. Handheld computers: a feasible alternative to paper forms for field data collection. Evaluation Review 27:165–178.

Gibson, D., A. J. Harvey, V. Everett, and K. B. Parmer. 1994. Is double data entry necessary? The chart trials. Controlled Clinical Trials 15:482–488.

Green, P. D. 2001. Handheld computers as tools for writing and managing field data: review article. Field Methods 13:181–197.

Heimbuch, D. G., H. T. Wilson, S. B. Weisberg, J. H. Vølstad, and P. F. Kazyak. 1997. Estimating fish abundance in stream surveys by using double-pass removal sampling. Transactions of the American Fisheries Society 126:795–803.

Hollowell, G. 2003. Using an electronic collection system to record field data. Available: www.fishdata.org/newsletters. (May 2007).

Howell, P. H. 2006. Effects of wildfire and subsequent hydrologic events on fish distribution and abundance in tributaries of north fork John Day River. North American Journal of Fisheries Management 26:983–994.

Hurlbert, S. H. 1984. Pseudoreplication and the design of ecological field experiments. Ecological Monographs 54:187–211.

Ice, G. H. 2004. Technological advances in observational data collection: the advantages and limitations of computer-assisted data collection. Field Methods 16:352–375.

Johnson, D. H., B. M. Shrier, J. S. O'Neal, J. A. Knutzen, X. Augerot, T. A. O'Neil, and T. N. Pearsons, editors. 2007. Salmonid field protocols handbook: techniques for assessing status and trends in salmon and trout populations. American Fisheries Society, Bethesda, Maryland.

Jones, K. K., J. M. Dambacher, B. G. Lovatt, A. G. Talabere, and W. Bowers. 1998. Status of Lahontan cutthroat trout in the Coyote Lake basin, southeast Oregon. North American Journal of Fisheries Management 18:308–317.

Kawado, M., S. Hinotsu, Y. Matsuyama, T. Yamaguchi, S. Hashimoto, and Y. Ohashi. 2003. A comparison of error detection rates between the reading aloud method and the double data entry method. Controlled Clinical Trials 24:560–569.

Lang, T., C. Hutt, and W. Neal. 2006. Use of personal digital assistants (PDAs) for collecting angler survey data. University of Arkansas at Pine Bluff. Available: www.fishdata.org. (February 2008).

Manly, B. F. J. 2007. Randomization, bootstrap and Monte Carlo methods in biology, 3rd edition. Chapman and Hall/CRC Press, Boca Raton, Florida.

Murphy, B. R., and D. W. Willis, editors. 1996. Fisheries techniques, 2nd edition. American Fisheries Society, Bethesda, Maryland.

Pearsons, T. N., and G. M. Temple. 2007. Impacts of early stages of salmon supplementation and reintroduction programs on three trout species. North American Journal of Fisheries Management 27:1–20.

Pendragon Software Corporation. 2003. Pendragon forms, version 4.0. Pendragon Software Corporation, Libertyville, Illinois.

Schreck, C. B., and P. B. Moyle, editors. 1990. Methods for fish biology. American Fisheries Society, Bethesda, Maryland.

Spain, K., C. A. Phipps, M. E. Rogers, and B. S. Chaparro. 2001. Data collection in the palm of your hand: a case study. International Journal of Human-Computer Interaction 13:231–243.

StatSoft. 2007. STATISTICA: data analysis software system, version 8.0. StatSoft. Available: www.statsoft.com. (March 2008).

Temple, G. M., and T. N. Pearsons. 2007. Electrofishing: backpack and driftboat. Pages 95–132 *in* D. H. Johnson, B. M. Shrier, J. S. O'Neal, J. A. Knutzen, X. Augerot, T. A. O'Neil, and T. N. Pearsons, editors. Salmonid field protocols handbook: techniques for assessing status and trends in salmon and trout populations. American Fisheries Society, Bethesda, Maryland.

Van Deventer, J. A., and W. S. Platts. 1989. Microcomputer software program for generating population statistics from electrofishing data: user's guide for MicroFish 3.0. U.S. Forest Service General Technical Report INT 254.

Zar, J. H. 1999. Biostatistical analysis, 4th edition. Prentice-Hall, Upper Saddle River, New Jersey.