523-F

North American Journal of Fisheries Management 30:655–664, 2010
© Copyright by the American Fisheries Society 2010
DOI: 10.1577/M08-097.1

[Article]

Assessing Length-Related Bias and the Need for Data Standardization in the Development of Standard Weight Equations

STEVEN H. RANNEY,*[1] MARK J. FINCEL, MELISSA R. WUELLNER, JUSTIN A. VANDEHEY, AND MICHAEL L. BROWN

Department of Wildlife and Fisheries Sciences, South Dakota State University, Box 2140B, Northern Plains Biostress 138, Brookings, South Dakota 57007-1696, USA

Abstract.—The recently developed empirical percentile (EmP) method, a technique for deriving standard weight (W_s) equations, putatively reduces the length-related biases that often plague such equations. To determine whether the EmP method is superior to the regression line–percentile (RLP) method in reducing length-related biases, we developed new W_s equations by applying both methods to two morphologically distinct species, walleye *Sander vitreus* and black crappie *Pomoxis nigromaculatus*. We also investigated diagnostic approaches to provide quality control for weight–length data. We evaluated the new W_s equations with filtered independent data to determine which equation reduced length bias the most. We suggest a protocol for evaluating length-related bias using an independent data set. Our results showed that for randomly selected walleye populations, the RLP method did not have any length-related biases when relative weight (W_r) was plotted as a function of length. However, the W_r values calculated from the EmP W_s equations were length biased when the latter were applied to those same populations. Both methods generated W_s equations that were length biased when W_r was plotted as a function of length for black crappies. Further, the absolute difference in W_r between the RLP and EmP methods indicates that there is little difference between the methods as far as their relevance to management is concerned.. Based on these results, we believe that revising existing W_s equations using the EmP method is unnecessary and that the RLP technique should remain the standard for developing W_s equations pending the development of an approach that clearly eliminates methodological length bias.

Length and weight data for fishes provide some of the most important information for fisheries management (Anderson and Neumann 1996). Analysis of these length–weight data serve many purposes, frequently providing indices to describe the well-being or condition of fishes (e.g., Le Cren 1951; Wege and Anderson 1978; Murphy et al. 1990; Anderson and Neumann 1996; Bister et al. 2000; Blackwell et al. 2000). Specifically, the deviation between the actual weights of fish within a population and an expected length-specific weight can indicate whether abiotic and biotic conditions are favorable for that population. This information may determine whether management actions (e.g., habitat improvements, prey supplementation, or harvest regulations) should be implemented or whether previous actions have been successful (Cone 1989; Murphy et al. 1990; Blackwell et al. 2000).

The regression line–percentile method (RLP; Murphy et al. 1990) has been the long-standing method for developing standard weight (W_s) equations for both game and nongame fishes (e.g., Bister et al. 2000). However, it is not without flaws. Murphy et al. (1990) suggested that the high degree of linear correlation between $\log_{10}$ weight and $\log_{10}$ length made extrapolation of population regressions relatively safe. Gerow et al. (2004) noted that the linearization and extrapolation of the weight–length relationship for fishes may result in length-related biases. This is particularly problematic if the regression of third-quartile weights by lengths for different populations is nonlinear.

The empirical percentile method (EmP) method was proposed to overcome some of the potential issues of the regression line–percentile (RLP) method (Gerow et al. 2005). The EmP method uses the 75th percentile of the observed weights of fish by 1-cm increments as the statistical population being modeled rather than modeled weights, as used in the RLP technique. Further, the EmP method models a curvilinear relationship between length and weight rather than a linearized $\log_{10}$ relation. Richter (2007) used both the EmP and the RLP method to develop W_s equations for two catostomid species and found that the EmP method reduced length bias compared with the RLP method. Conversely, Rennie and Verdon (2008) developed several new W_s equations for lake whitefish *Coregonus*

* Corresponding author: steven.ranney@montana.edu
[1]Present address: U.S. Geological Survey, Montana Cooperative Fishery Research Unit, Montana State University, Post Office Box 173460, Bozeman, Montana 59717, USA.

Received April 22, 2008; accepted February 21, 2010
Published online May 20, 2010

TABLE 1.—Numbers of walleye and black crappie populations and individuals in the unfiltered and filtered development data sets used to examine standard weight equations. The filtering protocol consisted of removing observations for which the difference in fits, |DFFITS|, was greater than the size-adjusted cutoff value (Belsley et al. 1980).

	Unfiltered		Filtered	
Species	Populations	Individuals	Populations	Individuals
Walleye	102	34,575	102	33,589
Black crappie	84	18,741	84	18,340

clupeaformis and found that the EmP W_s equation was significantly length biased, whereas the RLP W_s equation was not. During model validation Gerow et al. (2005) used only resampled data from a small data set. The use of resampled data is subject to the constraints of the original data set (e.g., sample size, sampling distribution) and assumes that the data set is representative of the true population (Haddon 2001). The original evaluation of the EmP method was done using a small, resampled data set that may or may not have been representative of the population, potentially influencing differences in the determination of length-related bias.

Quality control of weight–length data are important because the quality of any empirical weight–length model hinges on the reliability of that data. In addition, a sound protocol for assessing length-related bias is an important element in the evaluation and recommendation of W_s equations. No current methods for filtering data (i.e., the removal of aberrant data) or for evaluating length-related biases (e.g., the number of populations that should be considered) were found in the literature.

Our first objective was to evaluate techniques for filtering W_s equation-development data sets using both the EmP and RLP methods for two species having distinctly different body morphologies and maximum lengths, walleye *Sander vitreus* and black crappie *Pomoxis nigromaculatus*. Our second objective was to evaluate model fit and determine whether length-related biases exist in either method. Development and evaluation of independently derived W_s equations provided insight on quality assurance of data and the steps necessary for evaluating length-related bias. From that analysis we developed suggestions for filtering data and a protocol to evaluate length-related biases.

Methods

Development and filtering of data for W_s equations.—We used walleye and black crappie data from Gerow et al. (2005) to evaluate length-related biases in

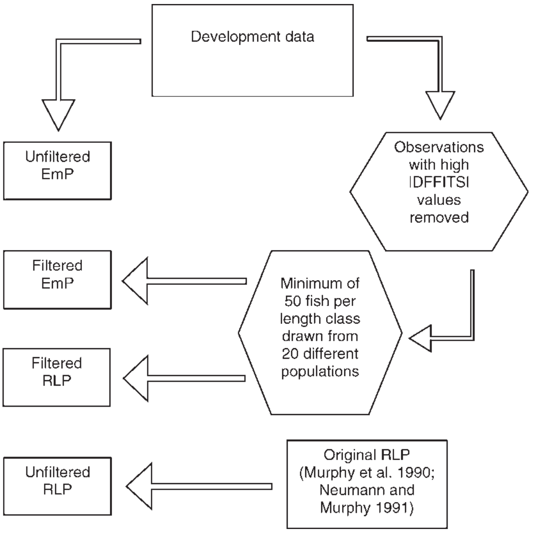

FIGURE 1.—Schematic illustrating the step-by-step process of developing W_s equations for walleyes and black crappies using the empirical percentile (EmP) and regression line–percentile (RLP) methods (see text for additional details).

W_s equations (K. Gerow, University of Wyoming, unpublished data; Table 1). Hereafter, we refer to these data sets as “development data” because they were used to develop new W_s equations. Curvilinear W_s equations were derived from these data using the EmP method, as described by Gerow et al. (2005). Limited quality control was performed on the data before developing these W_s equations; thus, we refer to these equations as the “unfiltered development EmP equations” (Figure 1). Additionally, we used the W_s equations published for walleyes and black crappies as developed via the RLP technique (Murphy et al. 1990; Neumann and Murphy 1991); these equations we termed the “unfiltered development RLP equations” (Figure 1).

Next, a second set of W_s equations were derived by filtering our developmental data set via a diagnostic approach (Belsley et al. 1980) and the recommendations of Gerow et al. (2005; Table 1). Data-filtering standards to assure quality of resulting W_s equations have not received extensive consideration. Additionally, data quality is important in the development of any W_s equation, regardless of the technique used, because aberrant data may influence model fit and bias subsequent prediction (Belsley et al. 1980). The coefficient of determination (R^2) is used to provide a simple interpretation of weight–length model fit (Murphy et al. 1990). However, the interpretation of an acceptable value of R^2 may differ among researchers, and R^2 does not provide any diagnostic utility for detecting suspect individual observations (Kvålseth 1985). Therefore, we used a diagnostic approach to evaluate log-transformed weight–length data by calculating the difference in fits (|DFFITS|) values (Belsley et al. 1980) as an analytical tool for filtering questionable (i.e., large residual effect) observations within populations. To identify potentially influential observations in the model, we used the size-adjusted cutoff

$$\sqrt[2]{\frac{p}{n}},$$

where p is the number of parameters in the model and n is sample size. The size-adjusted cutoff provides a method to objectively remove observations that are influential in relation to others (Belsley et al. 1980). For our filtered development W_s equations, we required a minimum of 50 fish per 1-cm length-class (Gerow et al. 2005) from each of at least 20 different populations. After filtering, the development data sets were truncated to include minimum and maximum lengths of 160–740 mm for walleyes and 130–370 mm for black crappies, as suggested by Gerow et al. (2005). Standard weight equations were developed for both walleyes and black crappies from filtered data sets based on the RLP (Murphy et al. 1990) and the EmP methods (Figure 1; Gerow et al. 2005).

Impacts of data filtering on W_s equations.—We tested homogeneity of slopes and intercepts between filtered and unfiltered species weight–length regressions by using analysis of covariance (ANCOVA) to determine whether filtering significantly altered the regression models. To quantify changes in predictions of weight from the weight–length regression equations from filtering the data, we calculated the percent difference for each length category (Gabelhouse 1984) as

$$\%\text{Difference} = [(\text{predicted} - \text{observed})/\text{observed}] \times 100,$$

where "observed" is the mean observed weight of each length category and "predicted" is the mean predicted weight of each length category calculated from the filtered data set regression. We chose to summarize over length categories because they represent suitable resolution for management applications.

Comparisons of W_s equations for length-related bias with independent data.—Standard weight equations should be free of length-related bias when they are applied to an independent data set (Blackwell et al. 2000). Independent weight–length data from across the geographic range of walleyes and black crappies in the USA were solicited from personnel at state agencies and universities (Table 2). Contributed data sets were screened similar to developmental data sets. Four W_s equations [unfiltered EmP, filtered EmP, unfiltered RLP, and filtered RLP (Murphy et al. 1990; Neumann and Murphy 1991)] were then tested with the independent data to determine which equation had the least amount of length-related bias. We chose to use independent data instead of resampled data to alleviate any potential biases associated with small sample sizes in the original data set and to encompass more natural variability across the geographic range of the two species.

TABLE 2.—Independent black crappie and walleye weight–length data solicited from state agencies and universities from across the species' geographic range. Blank cells indicate that no data were available.

State	Number of populations		Number of individuals	
	Walleye	Black crappie	Walleye	Black crappie
Georgia	11	40	3,378	13,076
Iowa	21	27	948	1,281
Kansas	8		20,816	
Minnesota	71	82	7,423	3,067
Montana	2		3,219	
Nebraska	5	4	435	289
South Dakota	27	19	4,624	2,258
Utah	2		672	
Wisconsin	199	27	26,010	1,346
Total	345	199	67,525	21,317

Using each of the four W_s equations, we separately calculated W_s values for all fish of both species from the independent data set. Residuals were calculated as observed weight minus W_s. We first visually examined plots of third-quartile residuals as a function of total length as a method to assess goodness or lack of fit (Pope and Kruse 2007). We evaluated the management significance of each W_s equation by examining the magnitude of the biases resulting from each equation. Using the third-quartile weight of fish in each length category (Gabelhouse 1984) from our independent data set, we calculated the percent error represented by the third-quartile residuals by length category from each W_s equation.

Assessing equations with independent population data.—In addition to generating the third-quartile residuals, we evaluated each W_s equation at the population level. Using a stratified random design, we selected a minimum of 30 independent data sets from states for both species to test the application of the four W_s equations. For walleyes, we randomly selected five data sets from each state that contributed more than five sets; for the three that did not, we randomly selected one data set from Montana, two from Nebraska, and one from Utah. For black crappies, we randomly selected six data sets from each state that contributed more than six sets; for Nebraska, we randomly selected two of four contributed data sets.

Mean W_r values for each 1-cm length-class were calculated from each W_s equation and plotted as function of total length. We then regressed mean W_r against total length as computed by each of the four W_s equations for both species. To determine which W_s equation best fit the recommendations of a zero slope and intercept of 100 W_r units (Wege and Anderson 1978), we tested the parameters of each population-level W_r regression against total length via simple *t*-tests (H_0: $\beta_0 = 100$ and H_0: $\beta_1 = 0$) using PROC REG in SAS version 9.1 (SAS 2005).

Because we expected some populations to exhibit slopes significantly different from zero (Willis 1989), we examined the total number and directionality of significant slopes and intercepts. For each W_s equation, we summed the number of significant positive and negative slopes and the number of significant intercepts greater than 100 and less than 100. We tested the hypothesis that the number of significant positive and significant negative slopes were equal (H_0: $n_{pos} = n_{neg}$) via a χ^2 goodness-of-fit test. If there were no length-related biases present in W_s equations, we would expect no significant differences in the number of slopes differing from zero in a positive or negative direction. Similarly, we used a χ^2 test to test the hypothesis that the number of intercepts significantly greater than 100 and significantly less than 100 (H_0: $N_{>100} = N_{<100}$) were equal.

Two large ($N > 500$) and two small ($N < 100$) test population data sets for each species (walleye = populations A, B, C, and D; black crappie = populations E, F, G, and H) were used to demonstrate the effect of suspect observations. Large (populations A, B, E, and F) and small (C, D, G, and H) sample sizes were chosen for this evaluation to represent best- and worst-case scenarios regarding the affect of aberrant data on population weight–length models. For these populations, we tested via simple paired *t*-tests whether regression parameters were significantly different for equations derived from development and filtered data and whether predicted weights differed between those equations. For all statistical tests, $\alpha =$ 0.05.

Results

When the EmP technique (Gerow et al. 2004) was applied to the unfiltered development data set it produced the following equations:

$$\log_{10}(W_s) = -9.626 + 6.171 \times \log_{10}(\text{TL}) - 0.714 \times \log_{10}(\text{TL})^2$$

for black crappies and

$$\log_{10}(W_s) = -4.814 + 2.603 \times \log_{10}(\text{TL}) + 0.122 \times \log_{10}(\text{TL})^2$$

for walleyes, where W_s is in grams and total length (TL) is in millimeters.

Following the data filtering protocols, the EmP technique produced the equation

$$\log_{10}(W_s) = -4.934 + 2.734 \times \log_{10}(\text{TL}) + 0.135 \times \log_{10}(\text{TL})^2$$

for black crappies and the equation

$$\log_{10}(W_s) = -4.866 + 2.661 \times \log_{10}(\text{TL}) + 0.111 \times \log_{10}(\text{TL})^2$$

for walleyes; the RLP technique produced the equation

$$\log_{10}(W_s) = -5.523 + 3.304 \times \log_{10}(\text{TL})$$

for black crappies and the equation

$$\log_{10}(W_s) = -5.422 + 3.165 \times \log_{10}(\text{TL})$$

for walleyes. Filtering weight-length data in the development data sets resulted in a 2.9% sample size reduction for individual walleyes and a 2.1% reduction for black crappies (Table 1).

Size-adjusted |DFFITS| cutoff values revealed influential observations in each of the eight test populations (Table 3; Figure 2). Removing questionable observations caused shifts in regression parameter estimates, although shifts were not always significant (Table 3). There were no significant differences in parameter estimates (β_0 and β_1) derived from development and filtered data for walleye populations, but three of the four black crappie populations exhibited a significant shift. Predicted weights from development and filtered data differed significantly in three of the four walleye populations and in three of four black crappie populations (Table 4). We observed a greater number of significantly different predicted weights in large populations compared with smaller populations (Table 4). Due to the obvious differences in unfiltered and filtered data, we proceeded with our analyses using only filtered data.

Third-quartile residuals (calculated as observed weight minus W_s) for the independent data set from the two equations produced no consistent pattern with walleye length (Figure 3). For walleyes less than trophy length (760 mm), the biases in both W_s equations represented less than 5% of third-quartile walleye weight (Figure 4). For the filtered RLP and the filtered EmP W_s equations, bias was less than 2% for substock, stock–quality (S–Q), and quality–preferred

TABLE 3.—Regression parameter estimates for two large ($N > 500$) and two small ($N < 100$) test populations (see Figure 2 and Table 4) of walleyes and black crappies used to assess the effects of suspect data. Influential data points were identified and removed using size-adjusted differences in fits, |DFFITS|. Asterisks indicate that the parameter estimates differed significantly (β_0: $P > F$; β_1: $P > |t|$) between regression models based on unfiltered and filtered data sets.

	Unfiltered data				Filtered data					
Population	N	β_0	β_1	R^2	N	β_0	β_1	R^2	|DFFITS| range	Size-adjusted cutoff
Walleye										
A	523	−5.4239	3.1594	0.988	515	−5.4105	3.1531	0.994	0.359–0.666	0.151
B	698	−5.3136	3.0898	0.991	677	−5.3434	3.1021	0.993	0.345–0.340	0.131
C	96	−5.2364	3.0757	0.993	92	−5.2220	3.0706	0.993	0.0002–0.771	0.354
D	90	−5.3196	3.1188	0.940	88	−5.4384	3.1646	0.936	0.0008–0.948	0.365
Black crappie										
E	703	−6.0802	3.5153	0.966	675	−5.9890*	3.4800*	0.979	0.290–0.182	0.131
F	876	−5.9190	3.4570	0.961	849	−5.9260	3.4593	0.965	0.353–0.273	0.117
G	49	−5.3133	3.1977	0.993	47	−5.1072*	3.1118*	0.995	0.002–1.54	0.495
H	74	−5.0067	3.0677	0.974	68	−4.6005*	2.8899*	0.964	0.002–1.44	0.403

(Q–P) length categories. In the preferred–memorable (P–M) and memorable–trophy (M–T) length categories, bias was less than 4.5% for the filtered RLP W_s equation and less than 1.5% for the filtered EmP W_s equation. For black crappie, bias was less than 5% of black crappie weight for both the filtered RLP and the filtered EmP W_s equations in the S–Q, Q–P, P–M, and M–T length categories (Figure 4). In the substock and greater than T length categories, bias was greater than 8% for both the filtered RLP and filtered EmP W_s equations. For length-classes and categories in which individuals are most abundance (S–Q, Q–P, and P–M), the absolute differences in W_r were less than 3.5 for walleyes and 3.0 for black crappies (Figure 5).

Comparisons of regression parameters of mean W_r values (by 1-cm length-class) plotted as a function of total length for randomly selected populations from each state were found to exhibit no geographical pattern for walleyes or black crappies (data available from corresponding author). When W_r was regressed as a function of total length, both equations produced slopes significantly different from zero and intercepts significantly different from 100 W_r units (Table 5; stratified randomly selected data sets by state from both species). The EmP-derived equation for walleyes showed significantly more negative slopes than positive slopes in randomly selected populations. For black crappie, both W_s equations showed significantly more negative than positive slopes when evaluated with independent data. Only one black crappie population from the state of Georgia was significantly positive for both black crappie W_s equations. We also found significant differences in the number of intercepts that were greater than 100 and less than 100 W_r units for both species. For walleyes, the RLP equations had significantly more intercepts greater than 100, but there were no differences between the number of intercepts greater than 100 or less than 100 for the EmP equations. For black crappie, both W_s equations produced significantly more intercepts greater than 100 W_r units.

Discussion

Contrary to Gerow et al. (2005), we found that RLP- and EmP-derived equations performed similarly for walleyes and black crappies. We believe that our findings are different from those of Gerow et al. (2005) because our W_s equations were tested with a large, filtered, independent data set. Gerow et al. (2005) simulated a data set based upon one population from their development data set that probably was of insufficient size and did not encompass the geographic range of the species. The variability inherent in a large, geographically diverse data set would certainly be different from the limited variability found in a data set resampled (even with replacement) and constrained by a limited geographic area and naturally occurring weight at length variability. Though individual fish populations are often considered independent for comparison purposes, modeling fish condition, as is done with W_r, requires a large number of data sets from a large area. Resampling one population that is similar in growth form to those used in model development represents pseudovalidation rather than true model evaluation (Haefner 2005). Although the possibility exists that the differences found between Gerow et al. (2005) and our study were an artifact of the data set we used, we believe that conclusions based upon independent data (rather than resampled data) better reflect the behavior of both the RLP and EmP methods.

We found that W_s equations produced with both the EmP and the RLP methods resulted in length-related biases in larger-sized walleyes and black crappies. We believe a scarcity of data in the upper extreme length

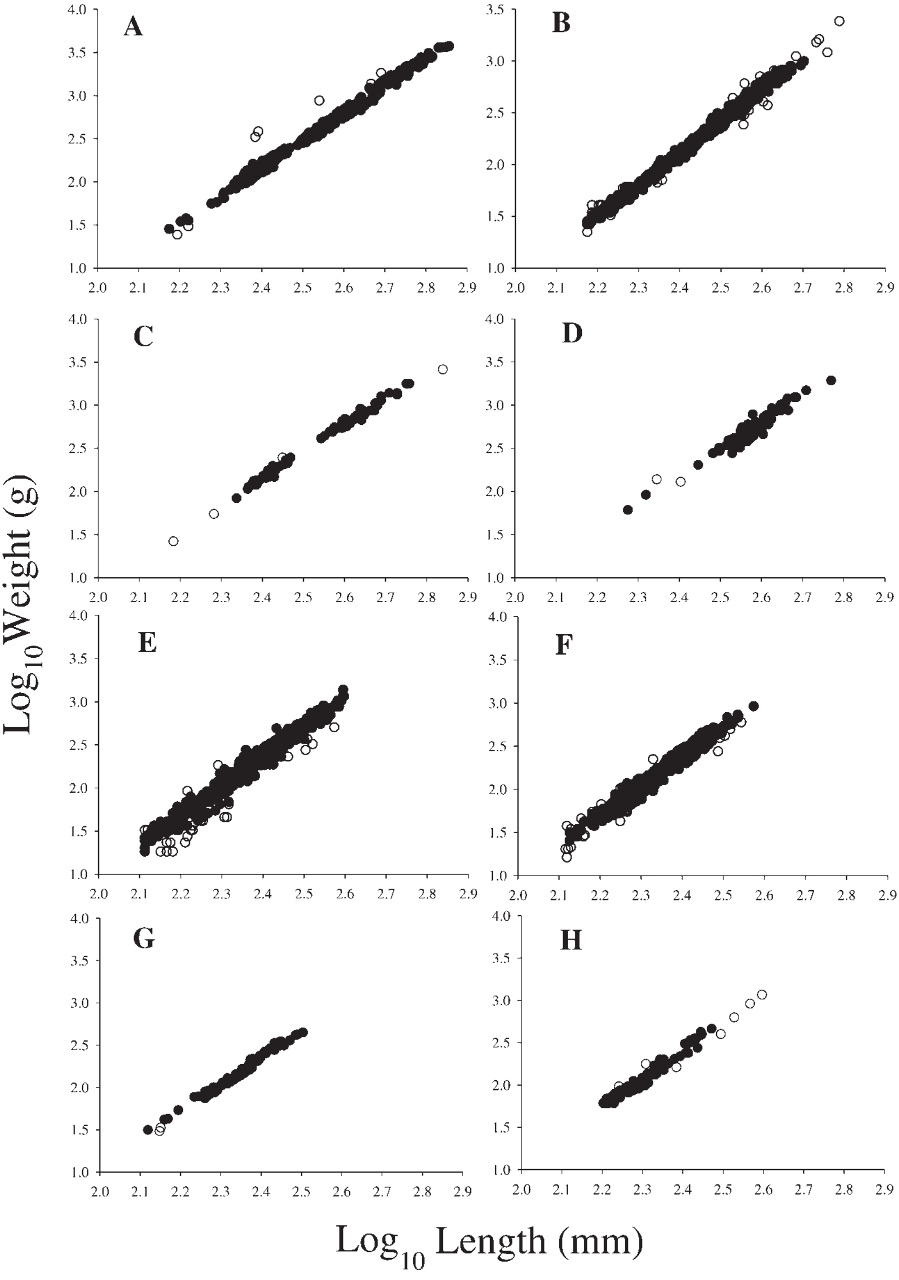

FIGURE 2.—Relationships between $\log_{10}$ transformed weight and length data for **(A)–(D)** four walleye populations and **(E)–(H)** four black crappie populations. The eight populations include four large ones ($N > 500$; panels A, B, E, and F) and four small ones ($N < 100$; panels C, D, G, and H). See Table 3 for additional details.

ranges for both walleyes and black crappies probably contributes to the length-related biases observed in W_s equations derived from either technique. Though the independent data set in our study was large, there were still only 16 walleyes and 80 black crappies greater than trophy length derived from seven different walleye populations from five states and 16 different black crappie populations from four different states. In length categories for which individuals were most abundant, (i.e., S–Q, Q–P, and P–M), predictions of third-quartile weight from filtered RLP and EmP W_s equations differed by no more than 4.12%. For

TABLE 4.—Percent differences in predictions of mean weight calculated from regressions based on unfiltered and filtered $\log_{10}$ transformed weight–length data for four test populations of walleyes and black crappies (see Figure 2 and Table 3). Blank cells indicate that no fish of that length category (see Figure 5 or 6) were in that population. Asterisks indicate populations for which the predicted weights from filtered data were significantly different (paired *t*-test; $P < 0.05$) from those from unfiltered data.

		Length category[a]				
Population	*n*	S–Q	Q–P	P–M	M–T	> T
Walleye						
A*	523	−0.6	−0.6	−0.7	−0.8	
B*	698	0.2	0.5	0.9		
C*	96	0.4	0.2	0.1		
D	90	−0.5	0.3	1.6		
Black crappie						
E*	703	−9.5	−11.2	−12.4	−13.4	−14.4
F*	876	0.3	0.3	0.3	0.3	
G	49	3.5	0.5	−0.6	−1.8	
H*	74	1.3	−2.2	−5.4	−9.8	−11.9

[a] S = stock, Q = quality, P = preferred, M = memorable, and T = trophy.

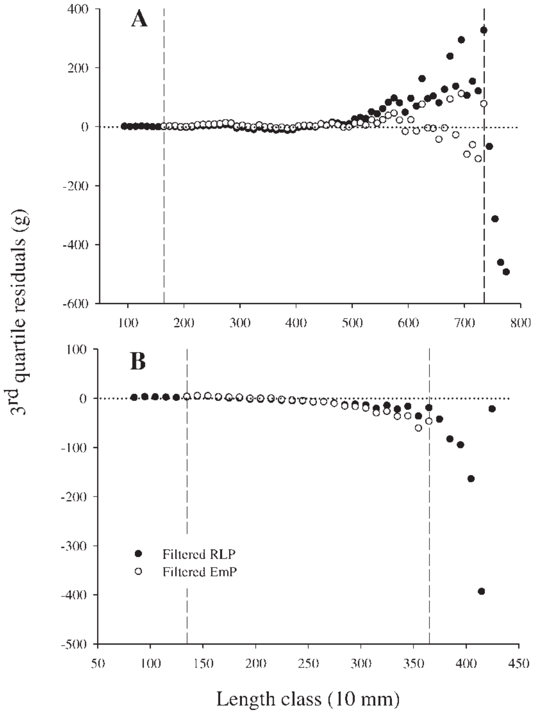

FIGURE 3.—Third-quartile residuals (observed weight less W_s) calculated from W_s equations developed with the regression line–percentile (RLP) and empirical percentile (EmP) methods using filtered data only. The residuals were calculated from an independent data set for **(A)** walleyes ($N = 67{,}142$) and **(B)** black crappies ($N = 21{,}317$) from nine different states across the United States. The dashed vertical lines represent the upper and lower limits of the applicable length range for the EmP method; the dotted horizontal lines indicate residuals of zero.

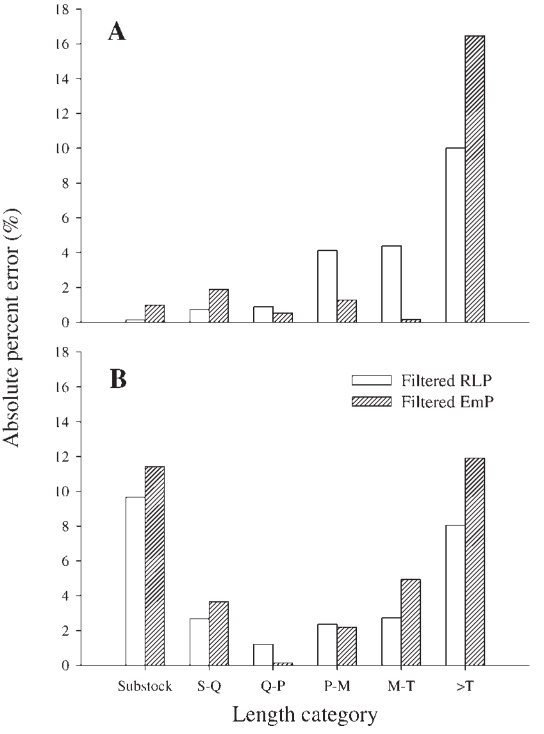

FIGURE 4.—Absolute percent errors associated with the predictions of third-quartile weights from W_s equations derived from filtered data for **(A)** walleyes and **(B)** black crappies. Length category abbreviations are as follows: S = stock, Q = quality, P = preferred, M = memorable, and T = trophy.

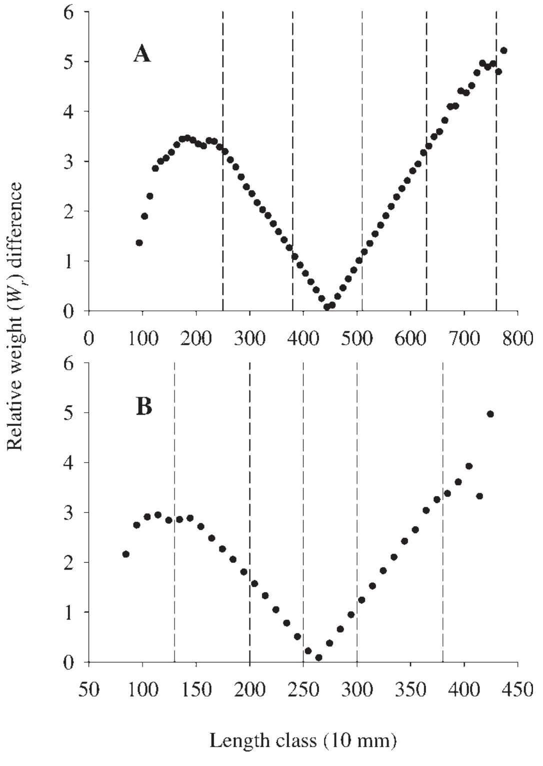

FIGURE 5.—Absolute differences in mean relative weight based on standard weight equations derived from the regression line–percentile and empirical percentile methods with filtered data for **(A)** walleyes and **(B)** black crappies. The absolute differences are highest at the extremes of the length ranges but are still less than 6 for all length categories for both species. The dashed vertical lines mark the length categories noted in Figure 4 (S, Q, . . ., T).

walleyes, the RLP and the EmP methods produced estimates of third-quartile weights that deviated from observed values by up to 16.5% for large (>trophy size) and 11.4% for small (≤substock) fish.

Sampling deviations in the largest and smallest size-classes may have high influence on the generation of W_s equations by both the RLP and EmP methods. Models are only as good as the data used in their construction (Burnham and Anderson 2002), and as data points in the upper length-classes become scarce, the precision of those data decrease. Further, size bias in data for the smaller size-classes may also weaken models. In our study, biased standard weight predictions were observed in the largest size -classes for walleyes and in the smallest and largest size-classes for black crappie. However, very few fisheries are managed for trophy or substock fish. The relatively small deviation we found between observed and predicted weights in the moderate-sized length categories may not be a pragmatic concern for fisheries managers.

Results from evaluating W_s equations with independent, randomly selected populations showed a mix of significant and nonsignificant slopes and intercepts when mean W_r was regressed as a function of total length. These results suggest that ensuring a representative sample of the geographic range of the species is essential during W_s development and evaluation. Brown and Murphy (1996), Gerow et al. (2005), and Brenden and Murphy (2006) stated that at least 50 different populations need to be included in W_s equation development for both methods. Murphy et al. (1990) further suggested that the 50-population minimum be collected from the entire range of the species, not just a localized region. For example, if the majority of populations used in W_s development were collected from one state, or small region, then that geographic area would influence how well or poorly the W_s equation may perform across the species range.

When developing W_s equations for species with limited geographic ranges or restricted growth forms, there may be conditions requiring use fewer than 50 populations during W_s equation development (Brown

TABLE 5.—Number of positive (Pos) and negative (Neg) slopes and intercepts (>100 and <100) that were significantly different from zero (slopes) and 100 (intercepts) when relative weights (W_r) derived from empirical percentile (EmP) and regression line–percentile (RLP) W_s equations (using filtered data only) were plotted against 10-mm length-class for stratified-randomly selected populations (N) by state. The P-values are from χ^2 tests of the hypotheses that the number of slopes that were positive would equal the number that were negative and, similarly, that the number of intercepts >100 would equal the number <100.

		RLP				EmP			
		Slopes		Intercepts		Slopes		Intercepts	
Species	N	Pos	Neg	>100	<100	Pos	Neg	>100	<100
Walleye	35	12	8	6	21	3	16	9	16
		$P > 0.10$		$P < 0.025$		$P < 0.005$		$P > 0.25$	
Black crappie	32	1	21	17	3	1	23	18	1
		$P < 0.005$		$P < 0.025$		$P < 0.005$		$P < 0.005$	

and Murphy 1996). Gerow et al. (2005) stated that the best balance between the number of fish populations, the number of fish from each population, and the number of fish per length-class has yet to be determined; however, sample size benchmarks will probably vary because of broad differences in species length ranges and body shapes. Richter (2007) was able to collect the recommended minimum number of populations for bridgelip suckers *Catostomus columbianus* and largescale suckers *C. macrocheilus*, even though both of these species have a small spatial distribution (i.e., Pacific Northwest). Additionally, Didenko et al. (2004) found that the number of populations from which they developed W_s equations for several rare, nongame fishes was acceptable, according to the methods described by Brown and Murphy (1996).

Recommendations

Quality control (i.e., data filtering) should be done before development of a W_s equation. Calculating |DFFITS| values and the size-adjusted cutoff from $\log_{10}$ transformed weight–length regressions will reveal influential observations within each population. From our evaluation, these outliers corresponded well to observations with abnormally high and low relative condition factor (K_n) values relative to the population and extreme condition values ($W_r < 60$ and $W_r > 160$; Brown and Murphy 1991). Removing aberrant data pairs from the data sets used in developing W_s equations will allow for greater confidence in model performance (Belsley et al. 1980; Kutner et al. 2004).

Until specific sample sizes are well described, developers of new W_s equations should use the recommended number of populations and sample sizes (Brown and Murphy 1996; Gerow et al. 2005). Brown and Murphy (1996) suggested a minimum of 50 populations be used during development of the RLP W_s equation. For the EmP method, Gerow et al. (2005) recommended a minimum of 50 fish per length-class or a minimum of 20 fish per length-class if they have been sampled from 50 different populations. In developing new W_s equations, we recommend researchers use a minimum of 50 fish per length-class that have been sampled from at least 20 independent populations. Including at least the accepted minimums will contribute to ensuring a W_s equation that contains a large number of individuals.

We also recommend evaluating any newly developed equations against an equally large, fully independent data set collected from across the geographic range of the species. Without a large, independent data set, evaluating the predictive abilities of W_s equations and determining associated length-related biases would be difficult. We have not investigated the minimum sample size needed for an independent data set. However, the use of an independent data set will avoid the constraints of the original data set (e.g., sample size, sampling distribution) while encompassing more of the natural variability of the entire population, thus providing an unbiased assessment of the equations.

Gerow et al. (2005) made several suggestions with regard to reevaluating existing W_s equations and development methods. One such idea was that the 75th percentile may not be the most optimal target for management purposes. To our knowledge, there have been no comparative investigations into the mathematical properties of the 50th and 75th percentiles across a range of sizes for a given species. However, confidence limits for 50th percentiles are more precise than those of the 75th percentile (Kutner et al. 2004). We conducted a preliminary comparison of the performance of W_s equations generated with the 75th versus the 50th percentiles and found some indication that the 50th percentile could reduce length-related issues currently exacerbating W_s development (unpublished data).

Finally, because our evaluation of *Ws* equations derived from either method showed little difference in length-related biases, we cannot support redeveloping published RLP W_s equations using the EmP method. We believe that the previously published W_s equations should be used for management and research purposes until a new method has been developed from large, quality-controlled data for several different species that has been successfully tested against associated independent and large data sets encompassing the geographic ranges of those species.

Acknowledgments

We thank the contributors of the validation data set and their agencies for allowing us to use their data: Bill Couch, Anthony Rabern, and Dennis Schmitt of the Georgia Department of Natural Resources, Wildlife Resources Division (walleyes and black crappies); Zachary Jackson (Iowa walleyes and black crappies) and Michael Quist (Kansas walleyes) of Iowa State University; Scott Gustafson of the Minnesota Department of Natural Resources (walleyes and black crappies); Heath Hadley and Eric Roberts of the Montana Department of Fish, Wildlife, and Parks (walleyes); Keith Hurley of the Nebraska Game and Fish Commission (walleyes and black crappies); Brian Blackwell (walleyes and black crappies) and David Lucchesi (black crappies) of the South Dakota Department of Game, Fish, and Parks; Chris Penne and Mike Slater of the Utah Department of Natural Resources, Wildlife Division (walleyes); and Nancy

Nate of the Wisconsin Department of Natural Resources (walleyes and black crappies). We also thank the students in the quantitative fisheries science course at South Dakota State University for their helpful discussions on this topic. Finally, we thank David Willis and Kenneth Gerow for comments on an early draft of this manuscript, and we appreciate the comments from three anonymous reviewers. S. Ranney and M. Fincel were supported in part by the U.S. Geological Survey, South Dakota Cooperative Fish and Wildlife Research Unit.

References

Anderson, R. O., and R. M. Neumann. 1996. Length, weight, and associated structural indices. Pages 447–482 *in* B. R. Murphy and D. W. Willis, editors. Fisheries techniques, 2nd edition. American Fisheries Society, Bethesda, Maryland.

Belsley, D. A., E. Kuh, and R. E. Welsch. 1980. Regression diagnostics: identifying influential data and sources of collinearity. Wiley, New York.

Bister, T. J., D. W. Willis, M. L. Brown, S. M. Jordan, R. M. Neumann, M. C. Quist, and C. S. Guy. 2000. Proposed standard weight (W_s) equations and standard length categories for 18 warmwater nongame and riverine fish species. North American Journal of Fisheries Management 20:570–574.

Blackwell, B. G., M. L. Brown, and D. W. Willis. 2000. Relative weight (W_r) status and current use in fisheries assessment and management. Reviews in Fisheries Science 8:1–44.

Brenden, T. O., and B. R. Murphy. 2006. Variance–covariance estimation of standard weight equation coefficients. Journal of Freshwater Ecology 21:1–7.

Brown, M. L., and B. R. Murphy. 1991. Relationship of relative weight (W_r) to proximate composition of juvenile striped bass and hybrid striped bass. Transactions of the American Fisheries Society 120:509–518.

Brown, M. L., and B. R. Murphy. 1996. Selection of a minimum sample size for application of the regression-line-percentile technique. North American Journal of Fisheries Management 16:427–432.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach, 2nd edition. Springer-Verlag, New York.

Cone, R. S. 1989. The need to reconsider the use of condition indices in fishery science. Transactions of the American Fisheries Society 118:510–514.

Didenko, A. V., S. A. Bonar, and W. J. Matter. 2004. Standard weight (W_s) equations for four rare desert fishes. North American Journal of Fisheries Management 24:697–703.

Gabelhouse, D. W. Jr. 1984. A length categorization system to assess fish stocks. North American Journal of Fisheries Management 4:273–285.

Gerow, K. G., W. A. Hubert, and R. C. Anderson-Sprecher. 2004. An alternative approach to detection of length-related biases in standard weight equations. North American Journal of Fisheries Management 24:903–910.

Gerow, K. G., R. C. Anderson-Sprecher, and W. A. Hubert. 2005. A new method to compute standard weight equations that reduces length-related bias. North American Journal of Fisheries Management 25:1288–1300.

Haddon, M. 2001. Modeling and quantitative methods in fisheries. Chapman and Hall, Boca Raton, Florida.

Haefner, J. W. 2005. Modeling biological systems: principles and applications, 2nd edition. Springer, New York.

Kutner, M. H., C. J. Nachtscheim, J. Neter, and W. Li. 2004. Applied linear statistical models. McGraw-Hill, Boston.

Kvålseth, T. O. 1985. Cautionary note about R^2. American Statistician 39:279–285.

Le Cren, E. D. 1951. The length–weight relationship and seasonal cycle in gonad weight and condition in the perch *Perca fluviatilis*. Journal of Animal Ecology 20:201–219.

Murphy, B. R., M. L. Brown, and T. A. Springer. 1990. Evaluation of the relative weight (W_r) index, with new applications to walleye. North American Journal of Fisheries Management 10:85–97.

Neumann, R. M., and B. R. Murphy. 1991. Evaluation of the relative weight (W_r) index for assessment of white crappie and black crappie populations. North American Journal of Fisheries Management 11:543–555.

Pope, K. L., and C. G. Kruse. 2007. Condition. Pages 423–471 *in* C. S. Guy and M. L. Brown, editors. Analysis and interpretation of freshwater fisheries data. American Fisheries Society, Bethesda, Maryland.

Rennie, M. D., and R. Verdon. 2008. Development and evaluation of condition indices for the lake whitefish. North American Journal of Fisheries Management 28:1270–1293.

Richter, T. J. 2007. Development and evaluation of standard weight equations for bridgelip suckers and largescale suckers. North American Journal of Fisheries Management 27:936–939.

SAS. 2005. SAS, version 9.1. SAS Institute, Cary, North Carolina.

Wege, G. J., and R. O. Anderson. 1978. Relative weight (W_r): a new index of condition for largemouth bass. Pages 79–91 *in* G. D. Novinger and J. G. Dillard, editors. New approaches to the management of small impoundments. American Fisheries Society, North Central Division, Special Publication 5, Bethesda, Maryland.

Willis, D. W. 1989. Proposed standard length–weight equation for northern pike. North American Journal of Fisheries Management 9:203–208.