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Improving Weight-Length Relationships in Fish to Provide More Accurate Bioindicators of Ecosystem Condition

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Abstract

Bioindicators are effective tools for evaluating ecosystem condition. Weight-length models are essential to using fish as bioindicators, providing expected weights for healthy fish of given lengths. The traditional model, $W(L) = aL^b$, is widely used and fits many fish taxa but is error-prone and has undesirably large uncertainties.This study evaluated a proposed improvement, replacing a with scaling parameter L_1: $W(L) = 1000(L/L_1)^b$. The primary hypothesis was that the proposed model would have lower mean parameter uncertainties than the traditional model and smaller uncertainties in most data sets, yielding more accurate bioindicators. The models were compared for 160 data sets including 94 taxa containing 14,102data points. Each set was fit to the traditional model and the proposed improvement with appropriate regression techniques. The improved model yielded lower uncertainties for L_1 but similar uncertainties to the traditional model for b. Lower L_1 uncertainties provide more sensitive bioindicators. The secondary hypothesis was supported: L_1 shows promise as a new bioindicator because its value increases when fish are stressed by suboptimal conditions including the Deepwater Horizon oil spill, oyster reef destruction, and overpopulation of invasive species. L_1 is sensitive, accurate, and valuable in conjunction with condition factor to assess environmental well-being.

Keywords: Bioindicators, Fish, Weight-length, Condition factor, Relative weight, Relative condition factor, Ecosystem condition

1. Introduction

Bioindicators are biological features that can be measured and that tend to change with exposure to negative environmental factors. (Holt & Miller, 2011; Summers *et al*., 1997) Fish inhabit nearly every aquatic habitat and reflect their environment's state of health from molecular to population levels. (Barbour *et al*., 1999; Sedeño-Diaz & López- López, 2012; Summers *et al*., 1997) Fish have been used as bioindicators for testing hazardous metal levels, assessing water quality and ecological risk by the Environmental Protection Agency, (Barbour *et al*., 1999) judging coral reef health, (Grimsditch, 2008) and evaluating damage from oil spills. (Courtney *et al*., 2011) Weight-length models provide expected weight equations, from which prey abundance, interspecies competition, general fish health, and reproductive potential can be assessed. (Blackwell *et al*., 2000) Expected weight equations also provide information for calculating condition factor, a commonly used bioindicator. The condition of fish in a population determines its potential to provide benefits for fisheries in addition to producing data key to preservation of ecosystems with healthy biodiversity. (Froese, 2006)

There is much support for the traditional model for weight-length in fish: $W(L) = aL^b$. The traditional model has been proven to be widely applicable, as weight-length data from most taxa of fish are fit well. (Gabelhouse, 1984) The exponent, b, is independent of system of units chosen and has a straightforward physical meaning. (Froese, 2006) In contrast, the coefficient, a, depends on the units chosen and the value of the exponent, and it lacks an obvious physical meaning. These factors may have led to errors in commonly accepted weight-length parameters in the oft-referenced online database FishBase.org (Cole-Fletcher *et al*., 2011) and numerous errors in the parameters listed in the Carlander Handbook of Freshwater Fishery Biology. (Carlander, 1969; Daviscourt *et al*., 2011) Both the linear least-squares (LLS) and non-linear least-squares (NLLS) fitting methods yield large uncertainties in the best-fit parameter a that results from regression, which results in expected weights with large uncertainties.

The proposed improvement, $W(L) = 1000(\frac{L}{L_1})^b$, has several advantages over the traditional model. Best-fit parameters L_1 and b are determined using the Levenberg-Marquardt non-linear least-squares (NLLS) technique. In contrast to the traditional coefficient a, L_1 as a scaling parameter has a clear physical meaning and retains units that make sense independent of the exponent. L_1 is the typical length of a fish whose weight equals the constant lead coefficient. For length measured in mm and weight in g, L_1 is the typical length of a fish weighing 1000 g. This more meaningful parameter makes errant parameters easier to detect. (Dexter *et al.*, 2011)

1.1 Hypothesis

The primary hypothesis was that the proposed model, $W(L) = 1000(\frac{L}{L_1})^b$, will provide significantly smaller relative uncertainties than the traditional model in L_1 and b for both LLS and NLLS regression and therefore yield more accurate bioindicators. The secondary hypothesis was that L_1 will be a useful new bioindicator of stress in systems known to be stressed.

The proposed model was tested against the traditional model for 160 data sets, encompassing 94 taxa containing 14,102 individual data points. For each data set, the length and weight of the fish were fit with the traditional model using LLS and NLLS regression and with the proposed model using NLLS regression. Mean relative uncertainties and P values were then determined and compared for each parameter and method, as well as the number of times each method had the smallest uncertainty for each parameter. The best model was defined to be the one that had the lowest relative uncertainty for each parameter the majority of the time and the most frequently smallest uncertainty in each parameter.

2. Materials and Methods

The models were tested against 41 original data sets encompassing 20 fish taxa and 2,242 samples. Data were gathered using voluntary creel surveys, asking sport anglers (and in one case a commercial fisherman) to weigh and measure fish from their ice chests, usually as they returned to a boat ramp or a fish cleaning station. Weights were measured to the nearest 0.01 kg and lengths were measured to the nearest 3.2 mm (1/8 inch). Original data was supplemented by 61 data sets provided by the Colorado Department of Parks and Wildlife (CDPW) containing 17 taxa and 10,033 samples. The remaining 58 data sets (1,827 data points) were extracted from Carlander's Handbook of Freshwater Fishery Biology. (Carlander, 1969) These sets were selected to expand the number of taxa included, as well as to ensure the model's applicability to atypically shaped taxa like lamprey and eels.

To test the primary hypothesis, weight-length data were plotted for each data set using SciDAVis graphing software. First, the Levenberg-Marquardt non-linear least-squares algorithm was used to determine best fit parameters for both the traditional and the proposed model. Each model's parameters and their respective uncertainties were recorded. Then, log-transformed weight-lengthdata was fit to the traditional model by LLS regression. The accuracy of the SciDAVis fitting routines was validated by comparison with two independent regression programs (Gnuplot v. 4.5 and Lsqrft v. 1.5). Validation on multiple data sets yielded identical parameter values, correlation coefficients, and parameter uncertainties when fitting the same data to the same model.

After the fits were completed and resulting parameters recorded, *a* values from the NLLS and LLS fits for the traditional model were transformed to be equivalent to L_1 for comparison purposes. For the NLLS fit to the traditional model, an L_1 equivalent was determined by $L_{1eq} = (\frac{1000}{a})^{\frac{1}{b}}$. The L_{1eq} parameter was determined for the LLS fit to the traditional model in the same way after converting a_{LLS} to an a equivalent by $a_{eq} = 10^{a_{LLS}}$. The uncertainties of the a_{LLS}, a, and b parameters were then converted to equivalent L_{1eq} uncertainties via standard techniques of error propagation. (Ku, 1966) To convert Δa into ΔL_{1eq} for the LLS traditional fit, $a_{eq} = 10^{aLLS}$ was used again to convert a_{LLS} into the equivalent of *a*. Then $\Delta a_{eq} = \frac{\partial a_{eq}}{\partial a}(\Delta a)$. From there the error was propagated from *a* to L_{1eq} by $\Delta L_{1eq} = \frac{\partial L_{1eq}}{d a_{eq}}(\Delta a_{eq})$. These equivalent L_1 uncertainties were then used for the final comparisons.

3. Results

The primary hypothesis required the proposed model, $W(L) = 1000(\frac{L}{L_1})^b$, to provide significantly smaller relative uncertainties than the traditional model for both LLS and NLLS regression. To determine whether uncertainties were lowered, individual uncertainties were compared across all data sets as shown in Figures 1 and 2. For each data set, it was determined which fit provided the lowest relative uncertainty for each parameter. For the L_1 (or L_{1eq}) parameter, the proposed model had the lowest uncertainty for 139/160 cases (87%).

It is clear (as seen in Figure 1) that the proposed model truly reduced uncertainties in the majority of sets.

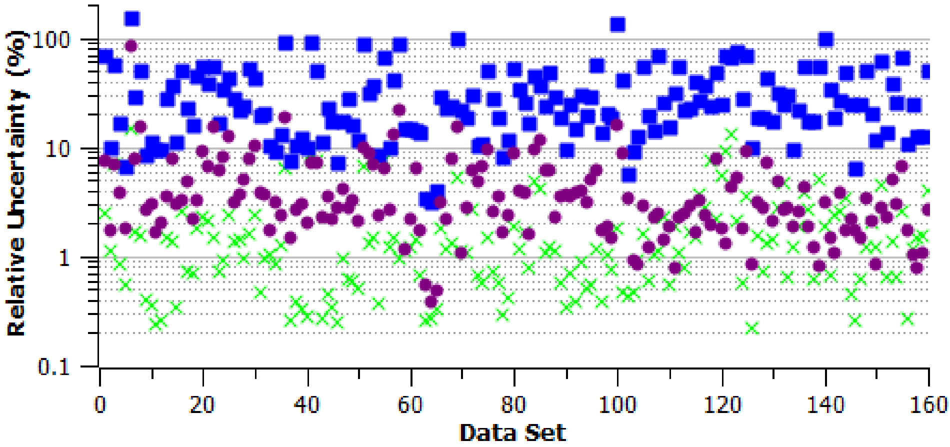

Figure 1. Uncertainty in $L_1$and L_1 equivalent

Notes: Uncertainty comparison graph demonstrates the relative uncertainties for L_1 in the proposed model (green x), traditional LLS (purple circle), and traditional NLLS (blue square) fits. The NLLS fit to the proposed model clearly has the lowest uncertainties overall. The data sets are numbered for convenience of display and are in no particular order.

The improved model's uncertainty for the *b* parameter, though always within 1.6% of the traditional model's uncertainty, was never lowest. The traditional LLS fit had the lowest *b* uncertainty for 121/160 cases (76%), as seen in Figure 2.

This study's secondary hypothesis dealt with the use of scaling parameter L_1 as a new bioindicator. To support the hypothesis, L_1 had to be sensitive to stress in environments previously known to be stressed. Generally, in places where fish are healthier, L_1 is smaller; in places where conditions are poor, L_1 is larger.

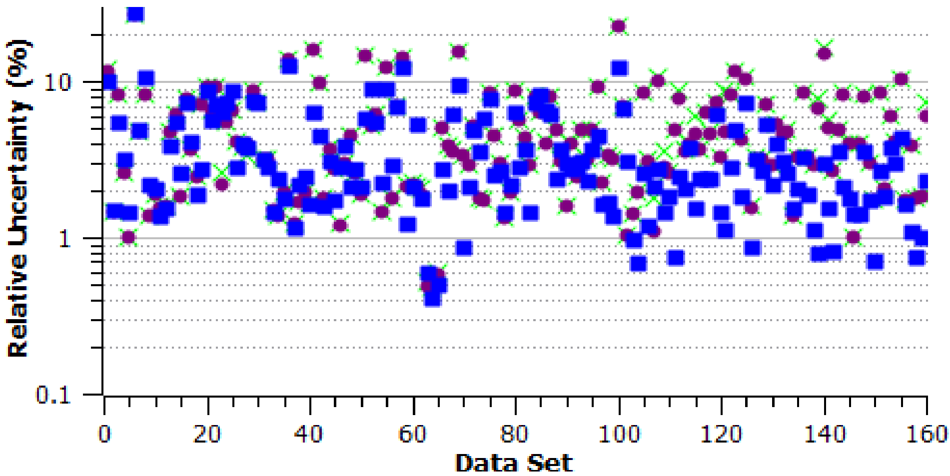

Figure 2. Uncertainty in b.

Notes: The b uncertainty comparison graph demonstrates the relative uncertainties for b in the proposed model (green x), traditional LLS (purple circle), and traditional NLLS (blue square) fits. Relative uncertainties of the three different methods are more comparable with each other for the parameter b than for the parameter L_1 or L_1 equivalent.

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One test of L_1 as a bioindicator involved taking parameters published by Jenkins (2004) for Calcasieu Estuary, Louisiana, calculating an expected L_1, and comparing it to L_1 values from original data to assess ecosystem health over time. After many other areas were closed to oyster (*Crassostrea virginica*) harvesting after the Deepwater Horizon oil spill, the Calcasieu Estuary in southwest Louisiana was left open and experienced overharvesting. (Louisiana Oyster Stock Assessment Report, 2012) This depleted a direct food source for the black drum (*Pogonias cromis*), and also degraded valuable oyster reef habitat which is important for many crustaceans and benthos on which other species depend for food. Significantly increased L_1 values from the expected values to 2012 values for all three species shown in Table 1 indicate a problem. The expected length of a 1000 g black drum was 411.5 mm, but in 2012 the typical 1000 g fish had a total length of 435.4 mm. Increased L_1 values for all three species in the same estuary indicates a loss of body condition after the oyster reef destruction. Even though L_1 was not used originally as a bioindicator to diagnose the issue, this analysis shows that L_1 is sensitive to these environmental factors and also illustrates the benefits of the reduced uncertainties obtained with the proposed model.

Table 1. L_1 as a bioindicator of oyster reef damage

		L_1 (mm)	Difference (%)	Relative Uncertainty (%)	Normal Distribution P value
Red Drum	*Expected*	458.2			
2011	Calcasieu	460.6	0.51%	0.85%	0.270
2012	Calcasieu	468.0	2.14%	0.95%	0.014
2013	Calcasieu	445.6	-2.77%	1.26%	0.988
Black Drum	*Expected*	411.5			
2011	Calcasieu	416.1	1.11%	0.85%	0.097
2012	Calcasieu	435.4	5.79%	1.10%	< 0.001
2013	Calcasieu	425.6	3.41%	0.55%	< 0.001
Spotted Seatrout	*Expected*	470.1			
2011	Calcasieu	477.5	1.58%	0.33%	< 0.001
2012	Calcasieu	481.6	2.44%	0.26%	< 0.001
2013	Calcasieu	468.4	-0.36%	0.29%	0.895

Notes: Expected (from analysis of published data) statewide Louisiana L_1 values as compared with L_1 values in Calcasieu Estuary, Louisiana from original data. (Jenkins, 2004) A negative difference from expected L_1 is a positive bioindicator, and a positive difference from expected L_1 is a negative bioindicator.

A second test of L_1 as a bioindicator utilized a comparison of expected L_1 values calculated from Jenkins (2004) with measured values in Louisiana's Lafourche Parish one year after the Deepwater Horizon oil spill. As shown in Table 2, L_1 is sensitive to the effects of the oil spill, showing a decrease in body condition for both red drum (*Sciaenops ocellatus)* and spotted seatrout (*Cynoscion nebulosus*). These two species spend time throughout the water column and are more sensitive to issues like the oil spill that impact the entire water column. Black drum is a benthic species, which means it spends time near the bottom and gathers food from the lower depths. Its condition did not worsen. It is likely that the heavier oil sank to the bottom before reaching Lafourche inshore waters, while the lighter oil remained, affecting only the upper water column and species therein.

Table 2. L_1 as a bioindicator of Deepwater Horizon oil spill damage

Lafourche Parish	2011 Expected L_1 (mm)	Original L_1 (mm)	Difference (%)	Relative Uncertainty (%)	Normal Distribution P value
Red Drum	458.2	467.2	1.95%	1.03%	0.031
Black Drum	411.5	401.2	-2.50%	6.79%	0.647
Spotted Seatrout	470.1	477.2	1.51%	0.39%	< 0.001

Notes: Expected L_1 values from published Louisiana data as compared with L_1 values from original data gathered in Lafourche Parish.

L_1 was also applied to various fishes in Blue Mesa Reservoir, Colorado as shown in Table 3. The values of L_1 for brown trout (*Salmo trutta*), lake trout (*Salvelinus namaycush*), and rainbow trout (*Oncorhynchus mykiss*) were respectively 12.1%, 7.0%, and 6.8% longer than statewide L_1 values (Colorado Department of Parks and Wildlife 2011 data). In contrast, the kokanee salmon (*Oncorhynchus nerka*) in Blue Mesa are plumper than typical in Colorado, with an L_1 4% lower. Colorado scientists have documented the reason for the problem in Blue Mesa: lake trout and brown trout are invasive species that became overpopulated and stressed their food sources. (Johnson and Pate, 2010) This also explains why the kokanee salmon are heavier and therefore healthier. The lake trout have depleted the numbers of kokanee salmon by eating them, so that the salmon are underpopulated; thus they have plenty to eat due to so little competition with other kokanees. L_1 is sensitive to problems that can be documented in other ways, but it is simple and easy to apply, often to data sets that already exist. Because L_1 is a sensitive bioindicator to known problems, it is likely to also be an early indicator of emerging problems. Additionally, because it has lower uncertainties than condition factor, L_1 can yield statistically significant results with fewer samples than condition factor.

Table 3. L_1 as a bioindicator of invasive species effects

	Expected L_1 (mm)	Original L_1 (mm)	Difference (%)	Mean Uncertainty	Location	Normal Distribution P value
Kokanee Salmon	464.8	446.4	-4.12%	1.5%	Blue Mesa	0.997
Brown Trout	454.7	517.5	12.13%	1.6%	Blue Mesa	< 0.001
Lake Trout	456.7	491.2	7.02%	0.7%	Blue Mesa	< 0.001
Rainbow Trout	438	470.0	6.81%	2.4%	Blue Mesa	0.002

Notes: L_1 equivalents calculated from CDPW expected weight equations compared to L_1 as yielded by the original data.

4. Discussion

The primary hypothesis that the proposed model would have significantly lower uncertainties for both L_1 and b was not fully supported. The fit to the proposed model did have the lowest mean uncertainties in L_1 (mean L_1 uncertainty 1.82%) as opposed to the NLLS traditional (mean L_1 uncertainty 31.09%) and the LLS traditional (mean L_1 uncertainty 4.74%) fits. As seen in Table 4, P values less than 0.001 from a two tailed T-test attest to the significance of these results. The LLS fit to the traditional model was most accurate for the b parameter. However, uncertainties in the b parameter only averaged 1.3 times bigger when using the proposed NLLS and the difference between proposed and traditional b uncertainties was never more than 1.6%. This carries several implications when applying the results.

Table 4. Significance testing of primary hypothesis

Two Tailed Two-Sampled	T-Test Unequal Variance				
Model A	Parameter	Mean Uncertainty	Model B	Mean Uncertainty	P value
Proposed	L_1	1.82%	Traditional NLLS	31.09%	<0.001
Proposed	L_1	1.82%	Traditional LLS	4.74%	<0.001
Proposed	b	5.05%	Traditional NLLS	4.95%	0.832
Proposed	b	5.05%	Traditional LLS	3.65%	0.999

Notes: L_1 and b mean uncertainties over 160 data sets for the proposed model vs. the traditional model. P values of < 0.001 for L_1 demonstrate that L_1 is significantly more accurate in the proposed model. P values for b are larger because the proposed model did not reduce uncertainty in b.

The LLS traditional fit is probably the best choice if a research question needs to minimize uncertainty in *b*. If reasonably small errors are needed in both, then the proposed model is the better choice, since equivalent uncertainties in the LLS parameters are three times bigger. If the research question needs to minimize the uncertainty in L_1 or *a*, then the proposed model is the best choice.

Because L_1 has a physical meaning that is easily understood, a study of its distributions is more meaningful than a study of the distributions of the *a* parameter. Fish with a smaller L_1 like the black crappie (*Pomoxis nigromaculatus*, 358.62 mm) have higher (and near constant) ratios of width and girth to length than fish with a higher L_1 such as northern pike (*Esox lucius,* 554 mm) and chain pickerel (*Esox niger*, 534 mm), which tend to be long and torpedo-shaped. At the end of this extreme lie the American eel (*Anguilla rostrata*, 827 mm) and the western brook lamprey (*Lampetra richardsoni*, 784 mm). The clear and easy to interpret physical meaning of L_1 is useful for identifying fish body type and for catching errors when one already knows the body type of a certain species.

When considering the calculation of weight-length parameters, the usefulness of L_1 for catching errors is illustrated by considering erroneous parameters identified in other studies from the commonly used FishBase.org. (Cole-Fletcher *et al.*, 2011) These erroneous parameters resulted from a fit to the traditional model, and errors were not recognized using an error detection method by plotting *log a* vs. *b*. In many species, the maximum and minimum curves produced with the given weight-length parameters predict weights that are clearly absurd. FishBase.org and Froese (2006) advocate using outlier detection to check for parameter errors. Evaluation of L_1 may offer a more straightforward alternative. For example, the given parameters at FishBase.org for the Black Crappie are a = 0.0195 and b = 3.081, yielding an L_{1eq} of 33.78 mm for a 1000 g fish. (Froese & Pauly, 2010) The original data yielded an L_1 of 358.62 mm for Black Crappie. Clearly this is a case where the calculation of L_1 as a check on the parameters would have revealed a sizable error.

Since the proposed model has significantly lower uncertainties for L_1, it will yield more accurate condition indices for use as bioindicators. The accuracy of bioindicators is crucial, as they have been proven useful in evaluating varying environmental issues. The Environmental Protection Agency in the USA has been using fish as bioindicators of water quality in streams and rivers, even going so far as to develop rapid bioassessment protocols in case of emergency. (Barbour *et al.*, 1999) Fish condition as a bioindicator was also key to assessing ecosystem health in the Gulf of Mexico one year after the Deepwater Horizon oil spill and demonstrating a negative impact on the condition of several fish species. (Courtney *et al.*, 2011) In addition, fish bioindicators have been employed to monitor mercury levels, forage abundance, and coral reef health. (Authman, 2008; Grimsditch, 2008; Ighwela *et al.*, 2011) Improving the accuracy of the L_1 and therefore condition indices for use as bioindicators has many applications valuable for preservation and management.

5. Conclusion

The primary hypothesis was that the proposed improved model, $W(L) = 1000(\frac{L}{L_1})^b$, would have smaller parameter uncertainties than the traditional model and smaller uncertainties in most data sets. While uncertainties for L_1 in the improved model were significantly lower than the equivalent uncertainties for the traditional model, uncertainties for b were not improved but comparable. The improved model is more accurate if a study is focusing on the L_1 parameter, which improves evaluations of expected weights, condition indices, and fish population health.

Fish health accurately reflects an aquatic ecosystem's condition. (Barbour *et al.*, 1999; Sedeño-Diaz & López- López, 2012; Summers *et al.*, 1997) Evaluation of the proposed model demonstrated that it will be useful for improving the accuracy of accepted bioindicators like condition index. This is important for increasing certainty about the health of ecosystems. Improved accuracy in assessing weight-length data and condition indices will facilitate improved monitoring and detection of problems in aquatic ecosystems. Higher accuracy also allows for earlier recognition of stress and higher sensitivity to emerging issues.

With regards to the secondary hypothesis, L_1 is an effective bioindicator with several advantages. Multiple test cases demonstrated that L_1 is sensitive to environmental issues previously highlighted by the use of bioindicators such as oyster reef damage, the Deepwater Horizon oil spill, and the damaging effects of invasive species. L_1 can pinpoint a stressor (like the overharvesting of oysters) based on the varying reactions of fish with different feeding habits. Even if these phenomena could be revealed using current bioindicators, the reduced uncertainty of L_1 allows detection of environmental problems with smaller sample sizes than other bioindicators, and use of L_1 is a comparably more sensitive sentinel than existing methods. L_1 is valuable for use in conjunction with condition factor for the improved assessment of ecosystem health.

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