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Improving estimates of body mass in American black bears using morphometrics and non-linear models

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Abstract: Measuring the body mass of American black bears (*Ursus americanus*) can be challenging because of their large size, and if equipment to weigh individuals is undersupplied. Our purpose was to estimate body mass of Florida black bears (*U. a. floridanus*) by developing models (linear and non-linear) that use morphometrics that can be reasonably easy to obtain (e.g., chest girth and body length). We compared our models with a previously published model for Florida black bears to determine whether prediction of body mass could be improved. Our models were built with current data (2012–2018; $n = 532$) collected across Florida, USA, by the Florida Fish and Wildlife Conservation Commission. We partitioned the data into training and test subsets using 10-fold cross-validation with 100 iterations. Model fit was assessed by comparing root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) of observed and predicted values. Based on RMSE, MAE, and R^2, our optimal regression model for predicting mass (M) of both female and male bears used both chest girth (G) and total body length (L) as predictors in the non-linear form $M = aG^b \times L^c$. Our optimal model was a better fit than the previously published model when both were applied to the full data sets from the current and previous study and to an independent data set. We applied our optimal non-linear regression models built from live bear data to morphological data collected from bear carcasses ($n = 544$), mainly road mortalities. We found that the live-bear models acceptably estimated mass of dead bears for both sexes. Estimating the mass of live and dead bears can expedite handling time of individuals, fill in data gaps, and provide valuable information on the Florida black bear; our approach may be applicable to American black bears range-wide.

Key words: American black bear, body size, Florida, linear regression, mass estimation, morphometrics, non-linear regression, *Ursus americanus floridanus*

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In relation to other factors, such as age of individual and population density, body size or body mass can influence the ecology, survival, and reproductive success of a species (Peters 1983, Brown 2004, Hamel et al. 2010). For American black bears (*Ursus americanus*), body mass can indicate spatiotemporal variation in food habits (Mahoney et al. 2001, McLellan 2011), determine litter size of females (Elowe and Dodge 1989, Stringham 1990, Samson and Huot 1995), and influence reproductive success of males (Kovach and Powell 2003, Costello et al. 2009). Therefore, it is important for wildlife managers to measure the body mass and other morphological parameters of bears.

To monitor the physical state of the Florida black bear (*U. a. floridanus*), the Florida Fish and Wildlife Conservation Commission (FWC) has collected morphometric data since 1976 on most live or dead bears handled in the field (e.g., for research, conflict captures, injuries, vehicle collisions). Although body mass is an important metric to monitor, it can be difficult to obtain on a large animal species, especially when the tools needed to weigh individuals are unavailable or are hindered by working in remote locations with dense vegetation. The FWC handles, on average, 200 (live and dead) bears across the state every year, but has a limited amount of equipment to weigh bears to distribute among staff. Alternatively, handling time of bears can be expedited by not weighing every individual. This can be accomplished by using other morphometrics in regression models to predict body mass, a technique previously established for bears (Payne 1976, Glenn 1980, Swenson et al. 1987, Ramsay and Stirling 1988, Hellgren and Vaughan 1994, Durner and Amstrup 1996, Cattet et al. 1997, Cattet and Obbard

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2005, Baldwin and Bender 2009, Bartareau 2017), and for other mammalian species (e.g., Iqbal et al. 2014, Labocha et al. 2014, Martinson et al. 2014, Langner and Casady 2018). Body-mass estimation models typically involve live animals; however, animal carcass mass has been estimated from morphometrics as well (e.g., Zembayashi 1999, Ogah 2011, Assan 2013).

Around 2013, the FWC developed age-specific and non-age-specific regression models for estimating Florida black bear mass from linear combinations of chest girth, total body length, and age (Bartareau 2017). Bartareau (2017) concluded that his models did not require age as a predictor to effectively estimate mass; however, the models were determined to be sex-specific because of significant differences in model intercepts and variable coefficients between sexes. Sex-specific equations of mass prediction have also been developed for bears elsewhere (Glenn 1980, Swenson et al. 1987, Kolenosky et al. 1989, Cattet 1990, Hellgren and Vaughan 1994). Even different populations of bears might need their own mass estimation equations if they exhibit significant morphological variation (Swenson et al. 1987, Cattet et al. 1997). Moreover, the form of predictive models can be important in that non-linear models have been found to outperform linear models when estimating body mass of black bears (Payne 1976, Swenson et al. 1987, Cattet 1990), polar bears (*Ursus maritimus;* Durner and Amstrup 1996), and several other mammalian species (Benyi 1997, Sherfy et al. 2006, Langner and Casady 2018, Rigney and Flint 2018).

Bartareau (2017) did not evaluate non-linear models; his linear models performed well with the historical data (collected 2000–2012) on which they were built, but were less accurate in practice in recent years. It is important, therefore, to re-evaluate the previously published models of Bartareau (2017) by applying them to current morphological data and by contrasting them with newly developed non-linear models to estimate body mass of Florida black bears. Furthermore, hundreds of black bears are killed throughout Florida each year, mostly by vehicle strikes (FWC 2019), so there is value in determining whether a model developed from live bear data could be used to reliably estimate body mass of dead bears.

The primary objective of our study was to determine whether newly developed models of mass estimation of Florida black bears improved over previously published non-age-specific models from Bartareau (2017). We developed linear and non-linear regression models based on the relationship between mass, chest girth, and total body length for female and male bears from data collected between 2012 and 2018. The optimal regression model developed from live black bear data was in turn employed to estimate mass of bear carcasses for each sex.

Methods

Data collection

Since 1976, FWC biologists and private contractors have collected morphometric data of live and dead Florida black bears within all 67 Florida counties and within all FWC's 7 Bear Management Units (BMU), which are areas bounded by county or state lines that contain the 7 identified subpopulations of the Florida black bear. Capture and handling protocols for Florida bears, outlined in Bartareau (2017), were concordant with Gannon and Sikes (2007), and were maintained in an FWC handbook adopted in 2010 (FWC 2018), a fluid document periodically updated with improved techniques. For captured live bears, morphological measurements were taken after an appropriate dose of an immobilization drug (e.g., Telazol, Xylazine) had taken effect. Immobilized bears (or bear carcasses) were positioned on their side (right or left) before taking measurements. Chest girth was recorded in centimeters on an exhale; the tape measure was placed immediately behind the shoulder blades and tight beneath the forelimbs. Total body length was measured in centimeters from the tip of the nose to the last vertebra in the tail by resting the tape measure along the contours of the spine while the head was tilted to a slight, natural angle to the body. Body mass was recorded in pounds, converted to kilograms for our study, using hanging scales (heavy-duty digital scales or big game spring scales). To weigh bears, the scales were hung by a chain or rope from a large tree branch in remote locations, from nearby manmade structures (e.g., game check station, fire tower, pole barn), or from a winch arm mounted to the bed of a truck. Bear age was estimated in the field based on tooth wear, or premolars were extracted and sent to an offsite laboratory for analysis of cementum annuli for a more exact estimate (Willey 1974). Estimated age lacked accuracy, exact age data were not available for many records, and age was unessential for predicting Florida black bear mass (Bartareau 2017); therefore, we excluded age as a predictor. All morphological information was stored in the FWC long-term database.

For our study, we only used data records from the FWC database that included complete morphometric fields (body mass, chest girth, and total body length). Before running any analyses, we visually scrutinized the data for obvious outliers by plotting chest girth and total length against mass for females and males separately and filtered the plots by observer to determine whether

Table 1. Morphometric characteristics (mean, standard error [SE], range, and coefficient of variation [CV]) of Florida black bears (*Ursus americanus floridanus*) from data collected between 2012 and 2018 throughout Florida, USA. Morphometrics include body mass, chest girth, total body length, and their ratios (mass:girth and mass:length). Differences between morphometric variables of females (F) and males (M) were assessed with the Mann–Whitney–Wilcoxon (W) test with continuity correction. All $P < 0.05$ were considered significant.

Variable	Sex	Mean	SE	Range	CV	W	*P*
Mass (kg)	F	58.8	2.3	1.0–132.0	55.8	20,583	<0.001
	M	95.4	3.2	1.1–249.5	60.3		
Chest girth (cm)	F	78.4	1.7	22.0–120.0	30.8	20,800	<0.001
	M	95.0	1.6	23.5–154.5	30.3		
Length (cm)	F	134.8	2.8	37.0–184.0	29.0	20,699	<0.001
	M	155.8	2.2	39.0–222.0	25.6		
Mass:Girth	F	0.67	0.02	0.05–1.24	43.3	20,690	<0.001
	M	0.90	0.02	0.04–1.86	43.3		
Mass:Length	F	0.39	0.01	0.03–0.80	48.7	20,729	<0.001
	M	0.55	0.01	0.03–1.26	49.1		

any errors were potentially caused by the data collector. Prominent deviations of data points appeared to be data entry errors (incorrectly recorded in the field or transcribed in the database), and we discovered that one observer recorded bear mass consistently below the average because of a faulty scale. We removed all outliers from analyses. For bear carcass entries, we excluded any bears with body conditions described as damaged, decayed, or swollen–bloated in the abdomen and chest area because these distortions could affect measurements of chest girth and total body length.

After cleaning the data, we partitioned the live-captured bear data into 3 subsets for our analyses: (1) current records (2012–2018), which we used to develop our regression models; (2) older records (2000–2012) used by Bartareau (2017) to build his regression models; and (3) older records (2000–2012) independent of any modeling efforts. A fourth morphological data set of current records (2012–2018) contained bear carcass data. We labeled these 4 data sets as Full-Current, Full-Prior, Independent, and Carcass, respectively (Table S1, Supplemental material), and used them in the analyses described below.

Morphological comparisons

Using the Full-Current data set, we calculated descriptive statistics (mean, standard error, range, and coefficient of variation) on body mass, chest girth, total body length, and mass:girth and mass:length ratios. Data were not normally distributed, based on Kolmogorov–Smirnov normality tests and examination of Q–Q plots; therefore, we used the Mann–Whitney–Wilcoxon test with continuity correction to test for differences in morphometrics between sexes using Program R programming language (R Core Team 2018).

Body mass estimation models

To assess whether morphometrics could effectively predict body mass of Florida black bears, we developed univariate and multivariate regression models. Preliminary plots of chest girth and body length relationships with mass indicated that data could be pooled across BMUs. However, because morphological variables differed significantly between sexes in our study (Table 1) and the Bartareau (2017) models were sex-specific, we modeled females and males separately. Based on all possible combinations of predictor variables (chest girth and total length), we built 14 models/sex: 9 linear models (2 of which were second-order polynomials) and 5 non-linear models (Table S2, Supplemental material). We constructed models using the lm function for linear models and nls function for non-linear models (R Core Team 2018).

Models were of the general forms:

$$Y = B_0 + B_1X_1 + B_2X_2 ... B_nX_n \text{ (linear)}$$

$$Y = a \times X_1^b \text{ (non} - \text{linear)}$$

where Y was the dependent variable body mass, B_0 was the intercept, X_n was the independent variable, B_n was the coefficient of the independent variable, a was an empirical constant, and b was an empirical exponent.

Model evaluation

We used the createFolds function within the caret package (Kuhn 2019) in Program R to randomly divide the Full-Current data by 10-fold cross-validation into training

(90%) and test (10%) subsets. We repeated this process for 100 iterations and used the set.seed option to ensure reproducibility of data subsets among runs of different models. After training the models, they were deployed through their respective test subsets to determine predictive capability.

For the test-data runs, we evaluated model fit by comparing differences between predicted and observed body mass. Chai and Draxler (2014) suggested that a combination of metrics must often be used to assess model performance. Therefore, using the ModelMetrics package (Hunt 2018) in Program R, we computed 3 error metrics, as defined in Willmott (1982): root-mean-square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2). These 3 metrics have been used concurrently in other studies to determine optimal model fit (Willmott 1982, Schaber and Badeck 2003, Deo et al. 2017). We balanced these 3 metrics using a simple ranking approach, where each metric was ranked across models, we then summed the 3 ranks per model; we ranked the summed values again across models to produce the final order with the highest rank being 1, which we considered the optimal model that contributed the lowest prediction error. To examine variability of error metrics within models, we also calculated 2.5 and 97.5 percentiles for each metric computed over the 100 iterations of model runs.

Model comparisons

To determine the overall optimal model for predicting mass of Florida black bears, we compared our top-ranked model from test-data runs with the non-age-specific model of Bartareau (2017) by running each of them through the Full-Current, Full-Prior, and Independent data sets. The Bartareau (2017) linear regression models for estimating live body mass (M) were multivariate (chest girth = G, total body length = L) for females ($M = -25.19 + 8.75 \times 10^{-3}G^2 + 0.20L$) and males ($M = -10.82 + 9.05 \times 10^{-3}G^2 + 0.12L$). We used the error metrics RMSE, MAE, and R^2 to evaluate model fit to each data set. To further assess the performance of the overall optimal model, we plotted confidence intervals of the fitted lines to the morphometrics using the Full-Current data set.

Finally, after determining the overall optimal model from the 3 data set comparisons above, we applied it to the Carcass data to determine whether the live body mass model was an acceptable estimator of dead bear mass. We examined the same model error metrics (RMSE, MAE, R^2) to determine model performance on the Carcass data for females and males and we plotted confidence intervals of the fitted lines to the morphometrics.

Results

Data description

After cleaning the data, our entire data set (2000–2018) consisted of 1,661 records that were predominantly from independently sampled individuals (resamples were <4%). The Full-Current data set contained 532 records ($n = 199$ females and $n = 333$ males); the Full-Prior data set contained 309 records ($n = 124$ females and $n = 185$ males); the Independent data set contained 276 records ($n = 120$ females and $n = 156$ males); and the Carcass data set contained 544 records ($n = 243$ females and $n = 301$ males), of which 70% were road mortalities. Each data set included records within each BMU and within at least 32 (of 67) Florida counties. Within the Full-Current data set, morphological variables differed significantly between sexes (Table 1).

Body mass estimation models

Our optimal models from test data were multivariate non-linear for both females ($M = 0.00032G^{1.57} \times L^{1.05}$) and males ($M = 0.00018G^{1.48} \times L^{1.33}$), according to ranks of error metrics (Table 2). When our sex-specific models were applied to their Full-Current data sets, the ranks of the top 9 models were the same order as found in Table 2. Our optimal non-linear model outperformed the Bartareau (2017) model for both sexes when running them through the Full-Current and Independent data sets, though not entirely for the Full-Prior (Table 3). Furthermore, for both sexes in all 3 data sets, the Bartareau (2017) model predicted negative values for body mass (as low as −14.6 kg) for up to 29 records near the low end of mass range. Our optimal non-linear model for each sex appeared to fit well to its respective Carcass data set based on model-error metrics (Table 3). Overall, the confidence intervals of our optimal non-linear models for live and dead bears were narrow along the fitted lines, though at larger values of chest girth (at all levels of total length) the intervals become relatively wider, and thus models appeared to lose some accuracy at predicting mass of especially large bears (Fig. 1).

Discussion

For captured Florida black bears, we found that sex-specific non-linear models performed best in predicting body mass from chest girth and total body length. Besides determining model form (e.g., linear or non-linear), incorporating more than a single metric to predict body mass can help reduce observer-induced error (Eason 1996) and improve body mass predictions across broad geographic

Table 2. Univariate and multivariate linear and non-linear regression models and their root-mean-squared error (RMSE), mean absolute error (MAE), and squared correlation coefficient (R^2) based on differences between observed and predicted body mass of female and male Florida black bears (*Ursus americanus floridanus*) from data collected between 2012 and 2018 throughout Florida, USA. Chest girth (*G*) and total body length (*L*) were used to predict body mass (*M*) by running the models through 100 iterations of 10-fold cross-validation subsets of test data. Numbers in parentheses represent 2.5 and 97.5 percentiles for each error metric computed over 100 iterations. The optimal models for each sex are indicated with an asterisk under Rank.

Rank	Model	RMSE	MAE	R^2
Female				
1*	$M = 0.00032G^{1.57} \times L^{1.05}$	8.23 (8.09, 8.38)	5.71 (5.65, 5.79)	0.928 (0.922, 0.936)
2	$M = 0.00037G^{1.59} \times L$	8.83 (8.66, 8.96)	6.19 (6.14, 6.24)	0.931 (0.926, 0.938)
3	$M = –9.09 + 0.007G^2 + 0.001L^2$	8.33 (8.21, 8.46)	6.23 (6.17, 6.31)	0.927 (0.921, 0.933)
4	$M = 0.00016G \times L^{1.7}$	8.54 (8.39, 8.65)	6.22 (6.17, 6.30)	0.924 (0.918, 0.930)
5	$M = -14.41 + 0.008G^2 + 0.15L$	9.42 (9.27, 9.56)	7.03 (6.98, 7.09)	0.920 (0.915, 0.928)
6	$M = -11.15 + 0.008G^2 + 0.22G$	9.80 (9.65, 9.93)	7.18 (7.13, 7.25)	0.913 (0.907, 0.922)
7	$M = -4.36 + 0.009G^2$	9.83 (9.70, 9.97)	7.18 (7.13, 7.24)	0.913 (0.906, 0.922)
8	$M = 0.0062G^{2.08}$	10.01 (9.87, 10.14)	7.67 (7.62, 7.73)	0.912 (0.904, 0.920)
9	$M = -41.38 + 1.28G$	11.18 (11.09, 11.28)	8.83 (8.79, 8.88)	0.889 (0.883, 0.897)
10	$M = -40.2 + 1.39G - 0.07L$	11.18 (11.07, 11.31)	8.77 (8.71, 8.84)	0.888 (0.882, 0.895)
11	$M = -10.37 + 0.0035L^2$	11.88 (11.74, 11.97)	9.93 (9.86, 10.00)	0.853 (0.845, 0.861)
12	$M = 0.00005L^{2.83}$	11.89 (11.73, 12.03)	9.16 (9.08, 9.24)	0.853 (0.844, 0.863)
13	$M = 14.29 + 0.006L^2 - 0.55L$	13.97 (13.78, 14.13)	10.44 (10.38, 10.51)	0.825 (0.818, 0.834)
14	$M = -39.54 + 0.73L$	16.11 (15.93, 16.25)	13.11 (13.06, 13.17)	0.765 (0.756, 0.778)
Male				
1*	$M = 0.00018G^{1.48} \times L^{1.33}$	13.81 (13.66, 13.96)	10.00 (9.94, 10.07)	0.945 (0.942, 0.948)
2	$M = 0.00029G^{1.64} \times L$	13.96 (13.83, 14.11)	10.10 (10.05, 10.16)	0.944 (0.941, 0.948)
3	$M = 0.00005G \times L^{1.95}$	14.87 (14.71, 14.99)	10.91 (10.86, 10.95)	0.936 (0.934, 0.939)
4	$M = -22.34 + 0.008G^2 + 0.0015L^2$	14.99 (14.83, 15.12)	11.55 (11.49, 11.61)	0.935 (0.933, 0.939)
5	$M = -30.01 + 0.009G^2 + 0.218L$	16.04 (15.87, 16.17)	12.22 (12.15, 12.28)	0.925 (0.922, 0.930)
6	$M = -10.07 + 0.011G^2$	16.67 (16.47, 16.84)	12.07 (12.00, 12.15)	0.919 (0.915, 0.924)
7	$M = -10.33 + 0.006G^2 + 0.011G$	16.71 (16.49, 16.90)	12.10 (12.03, 12.18)	0.919 (0.915, 0.924)
8	$M = 0.0042G^{2.18}$	16.94 (16.74, 17.13)	12.41 (12.34, 12.50)	0.918 (0.914, 0.923)
9	$M = -82.06 + 1.87G$	20.64 (20.46, 20.78)	16.40 (16.35, 16.50)	0.878 (0.873, 0.885)
10	$M = -79.68 + 1.96G - 0.07L$	20.67 (20.47, 20.83)	16.36 (16.29, 16.46)	0.877 (0.872, 0.884)
11	$M = 0.000006L^{3.26}$	22.29 (22.04, 22.49)	16.63 (16.55, 16.72)	0.856 (0.850, 0.862)

Table 2. Continued.

Rank	Model	RMSE	MAE	R^2
12	$M = 40.77 + 0.0096L^2 - 1.24L$	22.41 (22.21, 22.6)	17.09 (17.02, 17.18)	0.854 (0.849, 0.859)
13	$M = -32.87 + 0.005L^2$	24.57 (24.40, 24.73)	19.92 (19.85, 20.01)	0.824 (0.819, 0.830)
14	$M = -95 + 1.22L$	30.44 (30.25, 30.61)	25.01 (24.92, 25.13)	0.735 (0.725, 0.749)

areas (Cattet 1990; but see Baldwin and Bender 2009). Our optimal model provided acceptable estimates of body mass (mean of ± 6.2 kg for females and ± 10.0 kg for males), although predictive error increased for larger bears. We also effectively estimated body mass of recently deceased bears using our optimal model, which can help decrease handling time of bear carcasses and expand spatial coverage of bear morphology data across the state where captured bear data are lacking. For example, most bear captures (approx. 75%) come from 2 BMUs (Central and East Panhandle), so in areas with sparse data (South and South Central), adding carcass data almost doubles the number of records from 69 (capture only) to 131.

Table 3. The optimal non-linear multiple regression model from the current study and a linear multiple regression model from Bartareau (2017) that predicted body mass of Florida black bears (*Ursus americanus floridanus*) from morphological data collected throughout Florida, USA. Models were applied to a Full-Current data set (collection years, 2012–2018), a Full-Prior data set (collection years, 2000–2012) used in Bartareau (2017), and an Independent data set (collection years, 2000–2012). Also, our optimal non-linear regression model was applied to a bear carcass data set (collection years, 2012–2018). Model fit was evaluated with root-mean-squared error (RMSE), mean absolute error (MAE), and squared correlation coefficient (R^2) based on differences between observed body mass and those predicted by the models.

Data	Model	RMSE	MAE	R^2
Female				
Full-Current	Non-linear	8.53	6.20	0.927
	Bartareau	10.75	8.34	0.912
Full-Prior	Non-linear	5.81	4.62	0.962
	Bartareau	5.83	4.65	0.963
Independent	Non-linear	10.24	7.05	0.939
	Bartareau	13.01	10.87	0.930
Carcass	Non-linear	8.54	6.55	0.910
Male				
Full-Current	Non-linear	13.83	9.96	0.948
	Bartareau	16.92	12.77	0.926
Full-Prior	Non-linear	9.06	6.44	0.981
	Bartareau	7.25	5.86	0.982
Independent	Non-linear	10.82	8.25	0.963
	Bartareau	15.87	13.09	0.943
Carcass	Non-linear	13.92	10.21	0.943

Cattet and Obbard (2005) determined that time period of data collection can affect body-mass estimation models. Encouragingly, our optimal non-linear models were acceptably accurate and transferable among subsets (i.e., Full-Current, Full-Prior, and Independent) of a long-term data set sampled across BMUs, indicating our model can help fill in past data gaps where mass values were missing. Furthermore, Cattet and Obbard (2005) recommended that a sample size ≥100 is required for acceptable accuracy of body mass estimation models. Although the Bartareau (2017) model was built on ≥100 samples, it used only a portion (53%) of available data at the time and therefore was likely overfit, not capturing the full variation in the entire data set. It is important, therefore, to periodically reexamine and possibly replace established models, especially if newer models can improve accuracy and precision (e.g., Sherfy et al. 2006).

Future efforts should continually try to improve body mass estimation of black bears. When possible, reducing the number of personnel taking measurements should reduce inter-observer error (Eason 1996). If it is not feasible to substantially limit the number of field responders, then at least isolating the name of the observer taking measurements (if multiple responders are present) could help reveal unusual deviations in the data (e.g., a malfunctioning scale). Moreover, a standardized method of measuring morphological traits can reduce error and variation among estimation models across large regions (Boast et al. 2013), which can be attained by providing comprehensive training and instructional manuals to data collectors.

Although our body mass estimation model will improve efficiency and help fill data gaps, the FWC will continue to intermittently weigh bears with scales. These data can be used to track the performance of mass estimation models and help refine them, as we discovered,

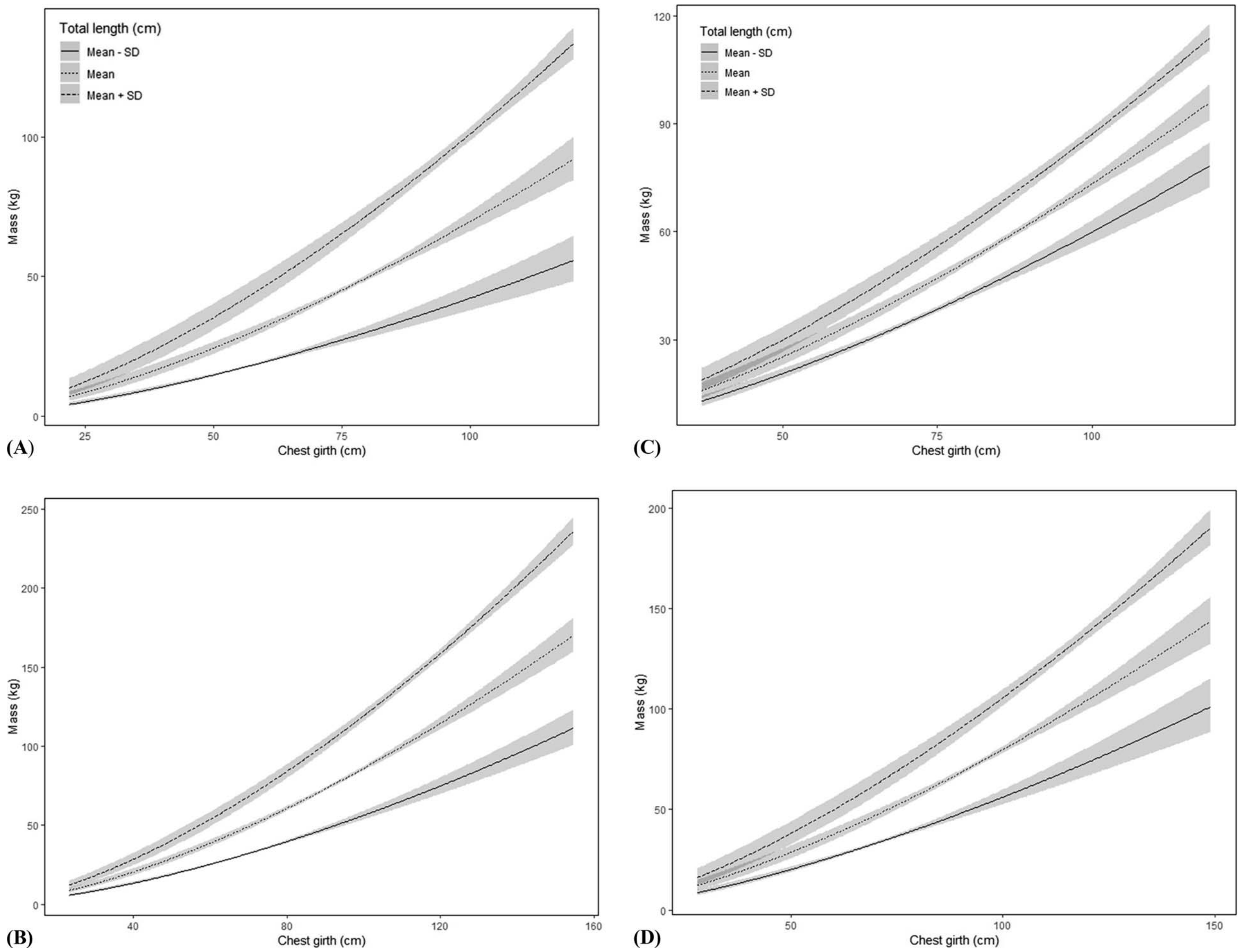

Fig. 1. Confidence intervals were produced around fitted lines from the optimal non-linear regression models that predicted body mass (kg) from chest girth (cm) and total body length (cm) from morphological data of Florida black bears (*Ursus americanus floridanus*) collected between 2012 and 2018 throughout Florida, USA. Plots included data from live-captured bears for females (A) and males (B), and from bear carcasses for females (C) and males (D). For all plots, total length is held constant by its mean and its mean ± standard deviation over the range of chest girth.

and such a protocol is recommended by Cattet and Obbard (2005). Our model is a valid tool in estimating body mass from both capture and carcass bear data, which can help expedite handling time of bears and strengthen the morphological database used to monitor black bears.

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Supplemental material

Table S1. Data used to estimate body mass of Florida black bears (Ursus americanus floridanus) from morphological data collected between 2000 and 2018 throughout Florida, USA. Attributes included data group, sex, data descriptions, collection date, collection location, and morphological variables.

Table S2. Model forms (linear and non-linear) used to estimate body mass of Florida black bears (Ursus americanus floridanus) from morphological data collected between 2012 and 2018 throughout Florida, USA. Rationale for use of the model forms and their associated references were included.