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Estimates of Shark Species Composition and Numbers Associated with the Shark Fin Trade Based on Hong Kong Auction Data

(Elasmobranch Fisheries – Oral)

Shelley Clarke, Murdoch McAllister and Catherine Michielsens

Renewable Resources Assessment Group, Department of Environmental Science and Technology,
Imperial College, London SW7 2BP, United Kingdom

Abstract

In order to quantitatively estimate the species composition and number of sharks utilized by the shark fin trade, a partial set of daily auction records was obtained from the world's largest shark fin trading center in Hong Kong for October 1999 to March 2001. Over 10 000 lot descriptions of shark type, fin position, fin size and fin weight were translated and statistically modeled using Bayesian Markov Chain Monte Carlo methods (WinBUGS). These methods allowed a robust estimation of missing information in individual auction records, as well as entire auctions for which no data are available, through a hierarchical model with uninformative priors. The model provides estimates of the complete data set for the sampled period, including the total auctioned weights of fins by shark type and fin position. Separate studies, conducted in Hong Kong to genetically map trade names to species names, are being used to align the estimates with particular taxa. This paper demonstrates how the traded quantity estimates can be converted to the weight and number of sharks represented based on preliminary conversion factors from the literature and from this research. A potentially more robust Bayesian conversion algorithm, involving fin size classes and stochastic relationships between lengths and weights, is outlined for future implementation.

Introduction

Much of the current concern regarding the sustainable utilization of shark resources centers on the practice of finning and the role of the shark fin trade in driving shark mortality. Short of conducting a detailed case study analysis of the many variables determining whether sharks are targeted and finned in particular fisheries (e.g. McCoy and Ishihara, 1999), market data can used be to assess the numbers of sharks represented by traded quantities of shark fin, and to identify the species composition in trade. Given the absence of extensive and reliable species-specific shark catch statistics, estimates of shark landed weights or numbers generated from fin trade-based studies can also provide useful reference points against which to evaluate reported shark catch rates. In these ways, shark fin market data can contribute to a better understanding of shark utilization rates and provide useful insights into the current pressures facing world shark populations. Similar methods, once proven, can also be applied to other marine or wildlife species of concern.

Hong Kong, which serves as an entrepôt for Mainland China, has been the center of the world trade in shark fins for many decades (Kreuzer and Ahmed, 1978; Parry-Jones, 1996; Vannuccini, 1999; Fong and Anderson, 2002). Estimates of Hong Kong's share of the trade have varied between 50% (Tanaka, 1995, based on data through 1990) and 85% (Vannuccini, 1999, based on 1992 data). In recent years, unprocessed shark fins have been exported to Hong Kong by at least 85 countries on six continents (Clarke and Mosqueira, 2002). Even when a recent trend toward importing more shark fins in frozen form is accounted for, the weight of imports into Hong Kong has increased year-on-year at a rate of 5% (Clarke, 2002). Rather than relying on customs statistics, this study is based on records from daily shark fin auctions held in Hong Kong by approximately 16 different trading houses. A proportion of fins imported to Hong Kong in unprocessed form are auctioned by importers to processors, who generally re-export the fins to Mainland China for low-cost processing. Data collection at this point in the supply chain allows fins to be characterized by shark type, fin type and fin size. Since this market draws large quantities of shark fins from all over the world, detailed characterization of this market can be extrapolated, with appropriate caveats, to depict the global trade.

This paper describes a probabilistic (Bayesian) approach to modeling shark fin auction data and demonstrates how these can be used to derive estimates of total traded fin weights and shark numbers. Although Bayesian statistics are computationally more demanding than frequentist analogs, their use in fishery stock assessment is steadily gaining momentum (Punt and Hilborn, 1997; McAllister and Kirkwood, 1998; McAllister *et al*, 2001). Bayesian methods allow parameters to be treated as random variables rather than as fixed values and thus explicitly account for uncertainty in the statistical modeling, as well as provide a more intuitively obvious interpretation of resulting probabilities. This application of probabilistic statistics involves prediction and filling of missing trade data, resulting in more reliable estimates and probability intervals.

Materials and Methods

Shark fins auctioned in Hong Kong are organized into lots which are described on sheets distributed to all participating bidders. Each sheet lists the name of the trading house, the date, the type of fin (by trade name (some of which are loosely species-specific), size and position), and the number of bags in each lot. These records are usually annotated after the auction by official record keepers to show the weight and official selling price of each lot. Since the records do not provide information about the source location of the fins, it is not possible to draw any conclusions about the country or ocean of origin from these records. Sheets from 148 auctions were obtained spanning the period October 1999 to February 2001, representing a subset of all auctions held. Lot descriptions, weights and prices were translated and transcribed into an Excel database for all 10 669 lots. In addition, a calendar showing the name of the trading houses holding auctions between October 1999 and March 2001 was compiled in order to identify missing auction records. During this period a total of 513 auctions were held, approximately 29% of which were observed.

Statistical models were developed to address two key deficiencies in the data set: filling of missing lot weights for a small number of trading houses which refuse to disclose this information, and filling of auctioned quantities for dates on which no records were available. Models were formulated using WinBUGS (Bayesian inference Using Gibbs Sampling) software (http://www.mrc-bsu.cam.ac.uk/bugs) employing a hierarchical modeling approach (Gelman *et al*., 1995).

Although fin lots were described on the sheets using more than 50 different market categories for shark type, this analysis focused on eleven common categories plus one additional category for all other fins. The eleven categories were chosen to complement a parallel study mapping these categories to particular species or genera using DNA polymerase chain reaction techniques (Shivji *et al*., 2002; Clarke *et al*., in prep). Trade category-taxonomic matches currently undergoing testing are shown in Table 1. Traders often record the fin position for each lot, particularly when the market value of the fins depends not only on the type of shark but also on the body position of the fin. The three most commonly recorded fin positions are dorsal, pectoral, and lower caudal, but other fin positions such as anal, upper caudal, and second dorsal, are also observed. In this analysis, only the three most common fin positions were modeled separately. All other fin positions, including large numbers of lots of unspecified fins, were grouped into an “other” category.

The aim of Model A was to use the relationship between the number of bags in the lot and the lot weight for those records where both data were disclosed, to predict the lot weight for records that only revealed the number of bags in the lot (Fig. 1). The relationship was estimated for each shark type and fin type on a per auction basis, using average number of bags and average lot weight in a given auction as the estimation parameters, to reduce the effects of outlier lots. All observations where average number of bags and average lot weight were zero were removed to avoid biasing the relationship. Plots of average lot weight versus average number of bags per lot indicated a linear equation of the form, $y = mx + b$, where y is the average lot weight and x is the average number of bags in the lot, would be appropriate. To avoid negative y values, all weight data were ln transformed for model input and backtransformed for model output. The slope and intercept for each shark type/fin type combination were estimated using normally distributed, uninformative (diffuse) priors and additive effects for shark type and fin type which were also based on normally distributed, uninformative priors. The shark type and fin type effects, were constrained to sum to zero. A normally distributed error term for the regression equation was also included, ie $y = mx + b + e$.

The model estimates a base slope and intercept for all observed shark type/fin type combinations in aggregate as well as separate additive effects (or offsets) for each shark type/fin type individually. The shark type- and fin type- specific slope and intercept are used to predict the average lot weight for that combination. In the final step, the average lot weight is multiplied by the observed number of lots of that combination in each auction to provide a total auction weight for the combination. Although the prior probability distributions (priors) are uninformative (diffuse), the data consist of 1 980 pairs (average number of bags, average lot weight per auction) of points and these exert a strong influence on the estimated slope and intercept parameters (posterior probability distributions or posteriors). Using an in-built capacity of the WinBUGS software for data filling, total auction weights are predicted for 313 auctions with missing lot weights. This result provides a complete set of traded weights for each shark type/fin type combination for every auction (i.e. observed and unobserved) to be calculated.

Model B was designed as a mixed binomial-negative binomial model using the traded weight for each shark type/fin type combination in each auction as the basis for predicting analogous traded weights in unobserved auctions. The mixed model conceptualization was motivated by plots of total auction weight by shark type/fin type combination which showed a large spike of values at zero, ie. no fins of a particular combination auctioned, and a flattened distribution with a long tail for the non-zero values. These data points were found to fit the negative binomial distribution (as given in Hilborn and Mangel, 1997) through chi square testing ($p<0.01$). These plots also suggested that traded weights vary by trading house, thus it was decided to use the model to predict for all combinations of shark type (12), fin type (4) and trading house (16), i.e. 768 combinations in total.

The binomial portion of Model B estimates the probability of zero traded weight, using, as in Model A, a base parameter with additive effects for shark type, fin type, trader type, and a shark type/fin type interaction term (Fig. 2). The latter is necessary in the binomial portion of the model only, and is due to the fact that some sharks' fins vary considerably in value by fin position and thus are always sorted by fin position and never left unspecified. In contrast, when an particular shark's fins are nearly equal in value regardless of fin position, the fins are frequently left unspecified during trading, resulting in a very low probability of observing a zero weight in the unspecified category. The negative binomial portion of Model B predicts the traded weight of fins when the traded weight is not zero. This portion of the model also uses base parameters and offsets for shark, fin and trader effects. In each Monte Carlo iteration of the model, the product of the binomial parameter, either 0 or 1, and the negative binomial parameter, a positive integer representing traded weight per auction, is generated for each of the 768 combinations, and a probability distribution for each of the combinations is generated.

The final step in Model B involves sampling from the distributions of the 768 combinations to fill in an array representing the auction calendar for the period October 1999 to March 2001. The array consists of the 48 shark type/fin type combinations in one dimension and a vector of the sequence in which trading houses held auctions in the other dimension. Each cell in the array can thus be either filled by an observed traded weight or mapped to one of the 768 distributions and iteratively sampled. Column totals produced through iteration provide total traded weights by shark type and fin type over the 18-month period of interest.

Results

The first step in using Model A was to appropriately simplify the 12 effects terms for shark type and 4 effects terms for fin type. This step both improved the convergence efficiency of the model and increased the estimation power for those shark types with limited observations. To accomplish this, Model A was run using only shark type effects, probability intervals for each shark type effect were observed, and shark types were grouped based on similarities in the intervals. Similar model runs were undertaken to group fin type effects. Results from these initial runs indicated that for the slope parameter the number of effects for shark type could be reduced from 12 to 3, and the number of effects for fin type could be reduced from 4 to 3. For the intercept parameter, the number of shark type effects could be reduced from 12 to 4, but all 4 fin type effects needed to be retained. The full model was then run for the reduced number of effects, ie 14 rather than 32. Convergence was evaluated for all effect parameters, slopes and intercepts using several tests provided within the WinBUGS Convergence Diagnostics and Output Analysis software (CODA).

A final test of Model A involved using the model to simulate data and then evaluating how well the distribution of predicted data approximates the observed data. This was implemented through posterior predictive p-values (Gelman *et al*., 1995), a measure of where in the posterior predictive distribution the observed value lies. P-values of less than 0.05 indicate a significant underprediction by the model. Of the 1 980 p-values examined only 2.4% were <0.05 and thus it was concluded that the model was sufficiently robust. Due to the log-space estimation in Model A, medians rather than means from each of the 313 predicted distributions (Fig. 3) were used as input to Model B. The use of these medians as point estimates for 313 of the 7 104 data points input to Model B tends to narrow the probability distributions resulting from Model B. The use of a unique probability distribution function for each median from Model A would be preferable and will be incorporated in future enhancements.

As with Model A, initial runs of Model B were devoted to examining the overlap in the probability intervals for effect terms to discern whether the number of effects to be estimated could be reduced. Model B requires effects to be assigned for two parameters in the negative binomial portion of the model and one parameter in the binomial portion. Initial results indicated that for trader type, the original 16 effects were reduced to 3 or 4 groups in both portions of the model; for fin type, the original 4 effects could be reduced to 2 groups for two of the parameters but not reduced for the other parameter; and for shark type, the original 12 effects were reduced to either 2, 3 or 4 groups. The interaction term applied only in the binomial portion of the model and was calculated for each unique combination of shark type/fin type from the reduced number of shark type and fin type groups. Convergence for all effects parameters was evaluated using CODA and adjustments were made as required to achieve convergence and improve convergence efficiency.

Evaluation of posterior predictive p-values showed that approximately 4% of the simulated data points significantly underpredicted the actual values. In order to avoid a downward bias in the final results, the predicted values for all observed data points were summed and compared to the sum of all observed data points. The predicted value sum was 91.338% of the observed sum and thus a correction factor of 1 095 was applied in the model to every predicted data point prior to the final array summation.

The results of Model B are the mean and its 95% probability interval for each shark type/fin type combination modeled (Table 2). Each value represents the summation of all observed data, and a number of samples from the predicted data distribution for each combination based on the known number of auctions held and the identity of the trader holding the auction. Nodes were included in the model to iteratively sum the traded fin weights for each shark type (i.e. all fin types combined within each shark type), and overall, to provide a mean and probability interval for each sum (Table 3). The proportion that each shark type forms of the overall traded shark fin weight was also estimated stochastically (Table 3).

These results indicate that of the individually modeled market categories of shark type, Ya Jian, thought to correspond to blue shark (*Prionace glauca*) comprises the largest distinct proportion of fins at 18.21%. The next largest proportions were Chun Chi (4.66%) composed of at least two, and probably more, species of hammerheads (*Sphyrna* spp.), and Wu Yang (4.44%), thought to correspond to silky shark (*Carcharhinus falciformis*) and other visually similar Carcharhinid fins (see Table 1). Other fins, including other distinct market categories not included in this study as well as fins which may actually belong to one of the eleven modeled categories but were described as unidentified fins on the auction sheets, comprised approximately 54% of the total traded weight of 2 916 000 catties (1 763 568 kg). The probability interval for the traded weight over the 18-month period extends from 2 748 000 to 3 094 000 catties (1 661 963 to 1 871 220 kg) representing between 1 108 and 1 247 mt per year (mean = 1 176 mt).

Discussion

These results can be extrapolated to the entire quantity of shark fins transiting Hong Kong (i.e. including unauctioned fins), and to the global fin trade. Furthermore, these results can be used to estimate the numbers of sharks represented by these traded weights. For interim reference purposes only, we present simplified assumptions which can be applied to achieve rough approximations of quantities of interest. Estimation of these quantities is currently being implemented in a probabilistic framework and this work is discussed further below.

Firstly, comparison of the point estimate of annual traded weight, i.e. 1 176 mt, to the quantity of fins reported to be imported to Hong Kong in 2000 (Anon, 2001), adjusted for water content of frozen fins and double counting of fins re-imported from Mainland China after thawing (Clarke *et al*., 2002), ie. 5 930 mt, suggests that the results presented in Tables 2 and 3 represent approximately 20% of the shark fins traded through Hong Kong. Since Hong Kong is believed to control about half of the world shark fin trade (Clarke, 2002), the modeling conducted for this study was performed on a sample of approximately 10% of the global market.

These figures assume that a sample drawn from auctioned fins is representative of the shark fin market as a whole. However, it is possible that auctioned fins have a potentially higher value than unauctioned fins, and that is the reason they are offered to the highest bidder on the open market. Hong Kong shark fin traders exhibit a preference for fins which contain longer, thicker and denser fin rays (Fong and Anderson, 2000; Clarke, pers obs), therefore larger fins of high value species may occur more frequently in the auction dataset. Nevertheless, many very small, poor quality shark fins have been observed at Hong Kong auctions and it is not possible to conclusively address this issue on the basis of existing information.

Another key area of concern is the number of sharks represented by traded fin weights. In order to illustrate the utility of the modeling results, simplified assumptions based conversion factors from the literature can be applied to the estimates of Ya Jian fins presented in Table 3. Preliminary genetic testing of a small sample of Ya Jian fins from the Hong Kong market (n = 12) has confirmed the species identity as blue shark (*Prionace glauca*) (Shivji *et al*., 2002), thought to be one of the most abundant and prolific of pelagic sharks (Nakano and Stevens, in prep; Smith *et al*., 1998). Two conservative assumptions are adopted from a previous study (Clarke and Mosqueira, 2002):

- Dried fin weight is 2% of total weight of the shark when landed (Rose, 1996; McCoy and Ishihara, 1999; Anderson and Ahmed, 1993); and
- Small sharks have an average weight of 20 kg and larger sharks have an average weight of 40 kg (based on various datasets including Bonfil 1994).

In addition, it is assumed that the sample from Hong Kong represents 10% of the global trade (see above). Applying these assumptions to the quantities of Ya Jian fins in Table 3 (after conversion, 214 096 kg year^{-1}), indicates that between 2.7 and 5.4 million blue sharks are represented in the shark fin trade each year.

As this estimate is based on highly simplified assumptions, the aim of ongoing research is to extend the Bayesian algorithm both within the existing models and in an additional model calculating the number of sharks represented for each shark type/fin type combination. One enhancement will involve using probability distributions, rather than point estimates, when transferring the output from Model A to Model B. In addition, another model will be developed (Model C) to convert shark- and fin-specific weights in Table 2 into the number of sharks represented. In this model, comparisons between dorsal and caudal-based estimates, where one fin per shark is contributed, are expected to show a strong similarity. Ideally, these estimates would, in turn, be nearly equivalent to 50% of the estimates based on pectoral fins, where two fins per shark are contributed.

This fin weight to shark number conversion model will incorporate market-derived data on the size distributions of each shark type/fin type combination from the auction records. For example, for Ya Jian/blue shark, as many as fifteen fin size categories from the auction sheets have been reclassified into six size ranges with each given a probabilistic distribution based on empirical data and auction observations (Clarke, unpublished data). A value from within one of these fin size ranges is then converted to a fin weight using regression coefficients estimated from the data (in total, n = 408) for each shark type/fin type combination (Clarke, unpublished data). This probabilistically derived weight can then be divided into the appropriate estimated quantity from Table 2 to generate an estimate of the number of fins, and for each fin type, the number of sharks. Other means of converting from traded fin weights to indicators of shark catches such as total captured biomass are also being explored.

Existing market databases embody substantial uncertainties which can be only partially addressed through even the most advanced statistical modeling techniques. Therefore, trade-based assessments of the total take of fishery or wildlife species such as those described in this paper are not a substitute for effective monitoring at the point of capture or landing. Although shark catch reporting and independent monitoring requirements are increasing incrementally with time, even in the best managed fisheries they still fall far short of addressing the question of whether vulnerable shark species are being overexploited. For this reason, further development and refinement of trade-based methods should be pursued as an important complement to ongoing and improved future management systems for shark resources. In the short term, targeting monitoring efforts toward trading centers, particularly when major entrepôts monopolize the flow of the product from numerous locations worldwide, may be the most cost-effective means of gathering a large amount of meaningful data. Obtaining accurate trade data on an ongoing basis will require the cooperation of both governments and business people, which should thus be encouraged and incentivized. Working from both the fishery and market ends of the supply chain can provide new insights for management and facilitate the sustainable utilization of shark resources.

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Table I. Hypothesized matches between trade names used in the Hong Kong shark fin market and scientific taxa. Detailed testing and verification of these matches is the subject of a parallel study (Shivji *et al.*, 2002; Clarke *et al.*, in prep).

Trade Name	**Trade Name in Chinese**	**Taxa**
Ya Jian	? ?	*Prionace glauca*
Qing Lian	? ?	*Isurus oxyrinchus* or *I. paucas*
Wu Yang	? ?	*Carcharhinus falciformis, C.galapagensis, C. amboinensis,* or *C. albimarginatus*
Hai Hu	? ?	*Carcharhinus obscurus*
Bai Qing	? ?	*Carcharhinus plumbeus*
Ruan Sha	? ?	*Galeocerdo cuvier*
Chun Chi	%⊕	*Sphyrna zygaena, S. lewini, S. mokarran* or *Sphyrna* spp.
Gu Pian	? ?	*Sphyrna mokarran* or *Sphyrna* spp.
Wu Gu	? ?	*Alopias* spp. or *Isurus paucus*
Sha Qing	? ?	*Carcharhinus leucas* or *Carcharhinus* spp.
Liu Qiu	? ?	*Carcharhinus longimanus*

Table II. Estimates of total traded shark fin weight by shark type (trader's nomenclature) and fin type for Hong Kong auctions held from October 1999 through March 2001 (figures in the Chinese unit of catties: 1 catty = 0.60479 kg).

Trader's Market Category	**Dorsal Fins mean (95% probability interval)**	**Caudal Fins mean (95% probability interval)**	**Pectoral Fins mean (95% probability interval)**	**Unidentified Fins mean (95% probability interval)**
Ya Jian	100,900 (83,880 to 120,000)	84,640 (67,440 to 104,300)	339,900 (293,500 to 392,700)	5,465 (179 to 16,590)
Qing Lian	18,960 (15,510 to 22,670)	20,540 (17,300 to 24,170)	53,230 (44,120 to 63,460)	1,154 (0 to 3,470)
Wu Yang	24,390 (21,010 to 28,220)	24,020 (20,600 to 27,880)	79,490 (70,460 to 89,590)	1,383 (247 to 3,634)
Hai Hu	9,966 (8,118 to 12,140)	9,451 (7,528 to 11,690)	29,380 (24,590 to 34,810)	857 (259 to 2045)
Bai Qing	14,260 (11,550 to 17,350)	10,990 (8,243 to 14,100)	28,770 (21,530 to 37,070)	42,110 (32,700 to 52,810)
Ruan Sha	933 (557 to 1,455)	776 (409 to 1,308)	2,570 (1,573 to 3,967)	277 (32 to 954)
Chun Chi	16,510 (13,770 to 19,700)	16,060 (13,400 to 19,280)	38,790 (31,440 to 47,400)	64,450 (55,210 to 74,730)
Gu Pian	5,568 (4,180 to 7,211)	5,293 (3,816 to 6,890)	15,090 (11,230 to 19,640)	25,630 (20,580 to 31,620)
Wu Gu	19,660 (16,310 to 23,320)	19,090 (15,690 to 22,940)	51,230 (42,170 to 61,720)	2,273 (1,155 to 4,526)
Sha Qing	12,530 (9,862 to 15,490)	9,951 (7,224 to 12,980)	29,540 (22,130 to 37,890)	49,450 (39,740 to 60,220)
Liu Qiu	11,820 (9,962 to 13,950)	10,370 (8,474 to 12,520)	31,440 (26,240 to 37,070)	605 (0 to 1,823)
Other	252,100 (228,500 to 278,600)	236,300 (212,900 to 262,200)	525,100 (457,100 to 600,700)	562,600 (491,100 to 642,000)

Table III. Estimates of total traded shark fin weight by shark type (trader's nomenclature) and overall for Hong Kong auctions held from October 1999 through March 2001 (figures in the Chinese unit of catties: 1 catty = 0.60479 kg). All quantities have been stochastically simulated and thus individual categories may not sum to the total given in the last row.

Trader's Market Category	Mean Traded Weight	95% Probability Interval for Mean	Percentage of Overall Total	95% Probability Interval for Percentage of Overall Total
Ya Jian	531,000	473,200 to 595,300	18.21	16.58 to 19.95
Qing Lian	93,880	83,000 to106,400	3.22	2.84 to 3.65
Wu Yang	129,300	118,400 to 141,600	4.44	4.02 to 4.89
Hai Hu	49,660	43,210 to 57,090	1.70	1.47 to1.96
Bai Qing	96,140	82,600 to 110,700	3.30	2.84 to 3.81
Ruan Sha	4,556	3,028 to 6,627	0.16	0.10 to 0.23
Chun Chi	135,800	121,900 to 151,400	4.66	4.17 to 5.21
Gu Pian	51,580	43,750 to 60,340	1.77	1.50 to 2.07
Wu Gu	92,240	80,990 to 105,000	3.16	2.76 to 3.60
Sha Qing	101,500	87,880 to 116,600	3.48	3.02 to 3.99
Liu Qiu	54,230	47,670 to 61,770	1.86	1.63 to 2.12
Other	1,577,000	1,450,000 to 1,713,000	54.06	51.77 to 56.26
All Categories	2,916,000	2,748,000 to 2,914,000	NA	NA

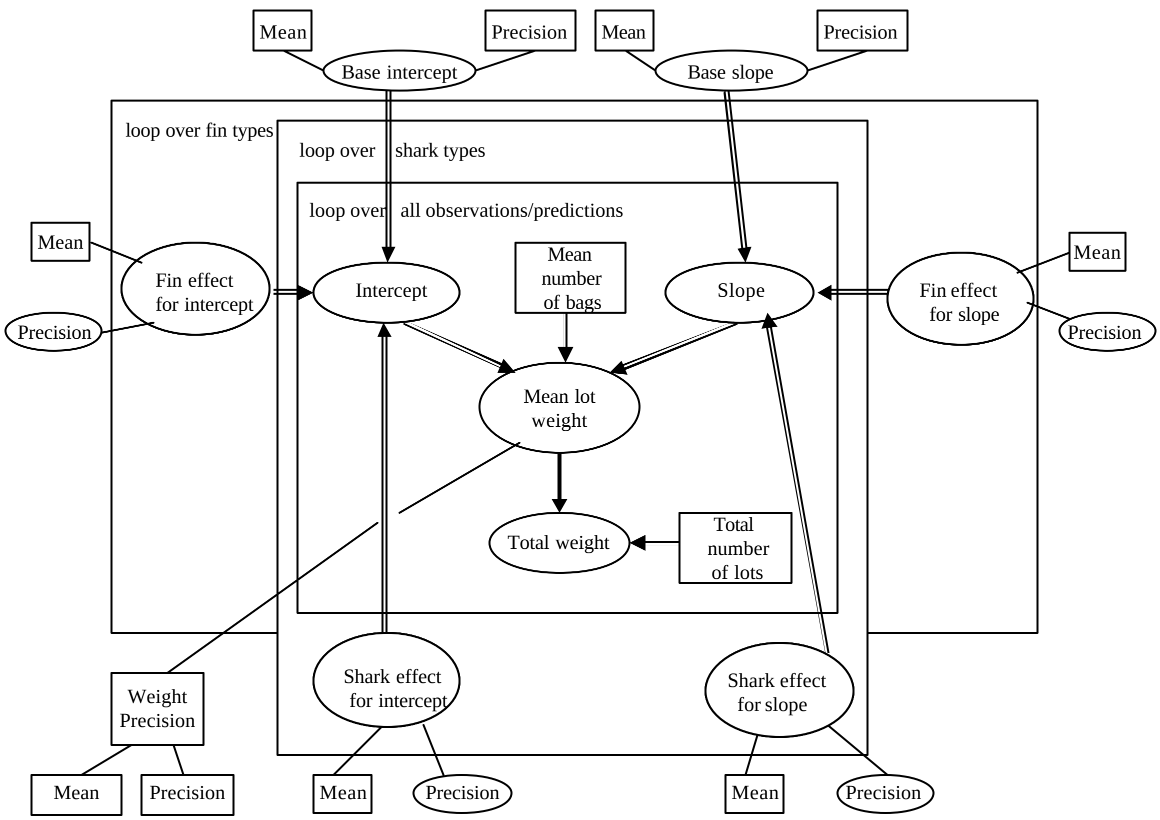

Fig. 1. Directed acyclic graph showing the derivation and relationships between parameters for Model A. Large rectangular boxes represent loops. Ovals represent stochastic nodes, whereas small rectangles represent deterministic nodes, such as fixed priors or data. Single lines indicate that the 'parent' node determines the 'child' node in a stochastic manner. Double lines indicate that the 'child' node is logical and therefore calculated from the 'parent' node.

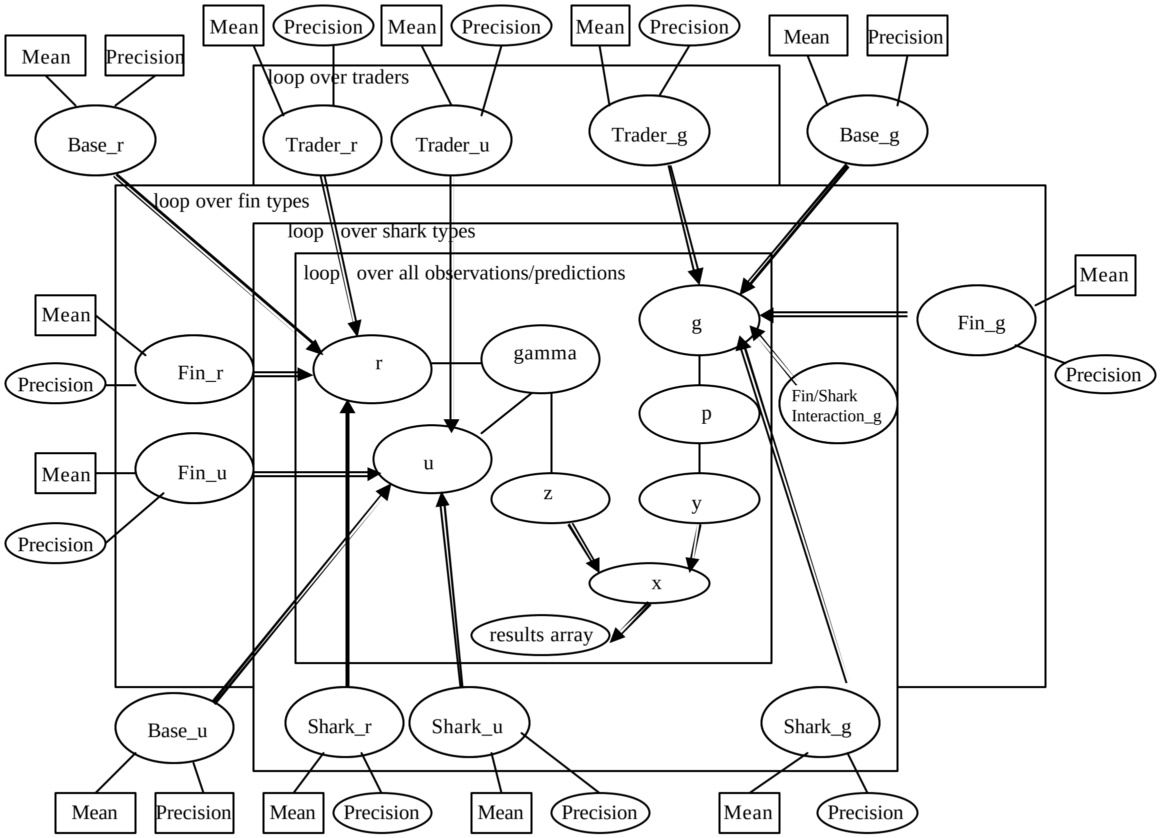

Fig. 2. Directed acyclic graph showing the derivation and relationships between parameters for Model B. Please see the Figure I caption for explanation of icons. Parameters ‘r’ and ‘u’ correspond to the gamma distribution shape and scale parameters which in turn are input as the mean of a normal distribution for ‘z’, the non-zero traded weight. Parameter ‘g’ determines the probability of observing a zero weight and is used to derive ‘y’, a binomial random variable. The product of ‘z’ and ‘y’, ie ‘x’, is the observed/predicted traded weight.

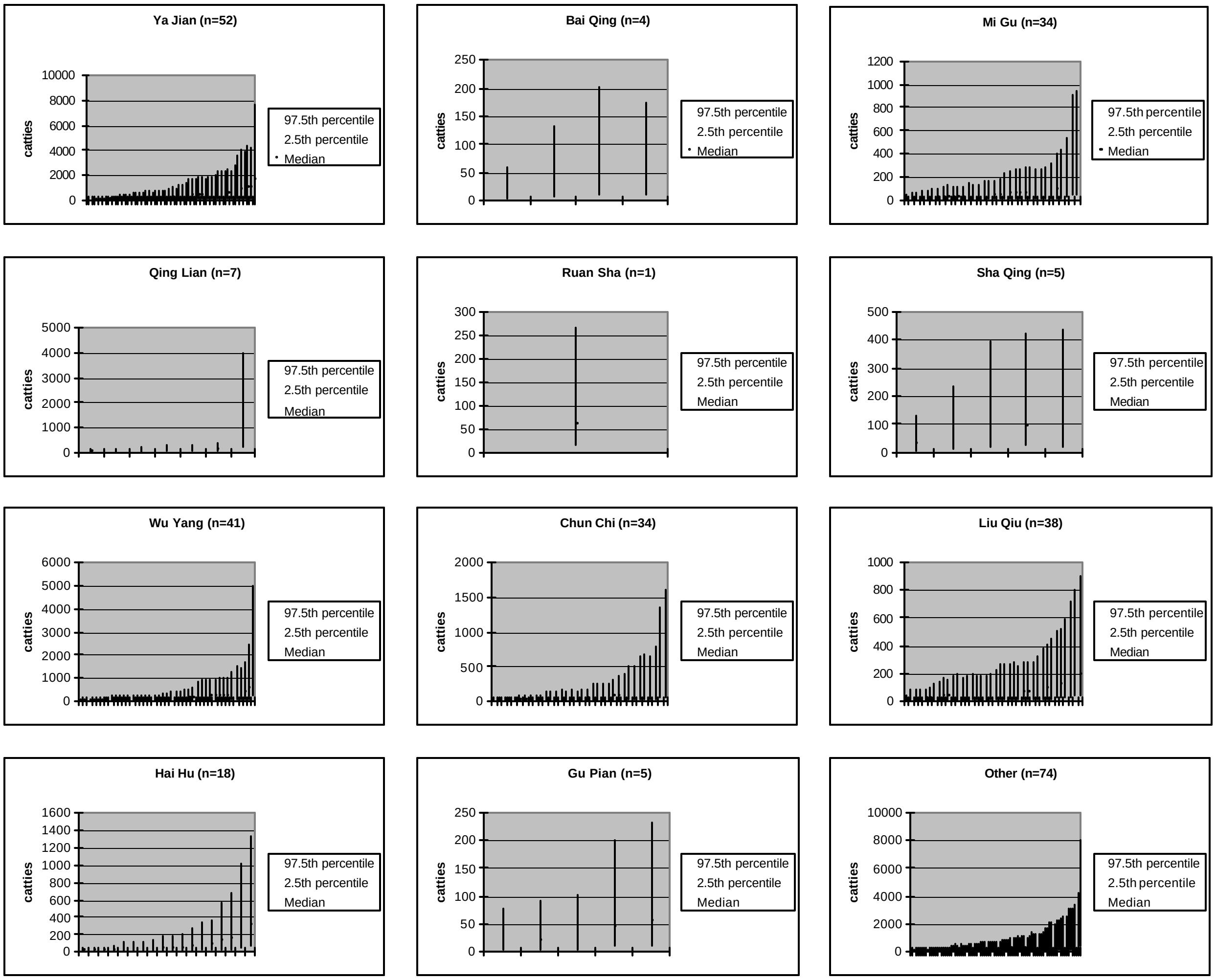

Fig. 3. Results for the 313 missing data points produced by Model A. Separate plots are provided for each of the 12 shark types and missing data points are sorted in ascending order by median in each plot.