Guyana Seabob Stock Assessment

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1 Summary

1.1 Stock Status

Currently, the stock is close to a default precautionary target level and can be considered “fully exploited” (Figure 1). The assessment suggests that the stock has recovered somewhat from a state where it might have been considered over-exploited, that is the stock was at greater risk of recruitment overfishing.

Based on the current assessment, fishing mortality has only rarely exceeded fishing mortality at maximum sustainable yield (MSY), so overfishing has rarely taken place (Figure 2). However, F_{MSY} is poorly estimated as it depends on a parameter in the stock-recruitment relationship, which had to be assumed. Therefore, it should represent an upper limit until more information on an appropriate fishing mortality can be obtained. An appropriate MSY based reference point for fishing mortality still needs to be determined.

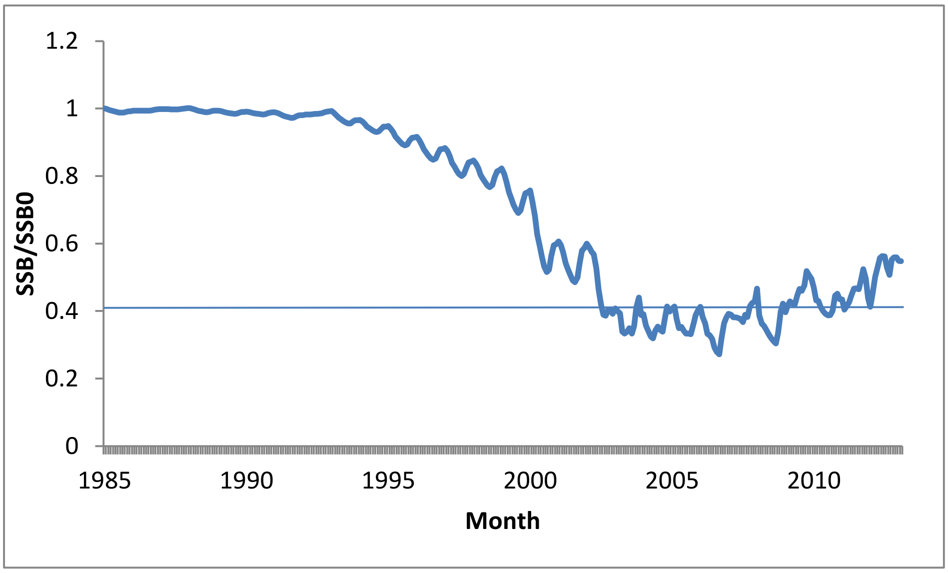


Figure 1 Spawning stock biomass by month estimated from the stock assessment model. The horizontal line is a default provisional target reference point (40% SSB_0). Spawning stock biomass at or above this line would suggest that the stock is not overfished.

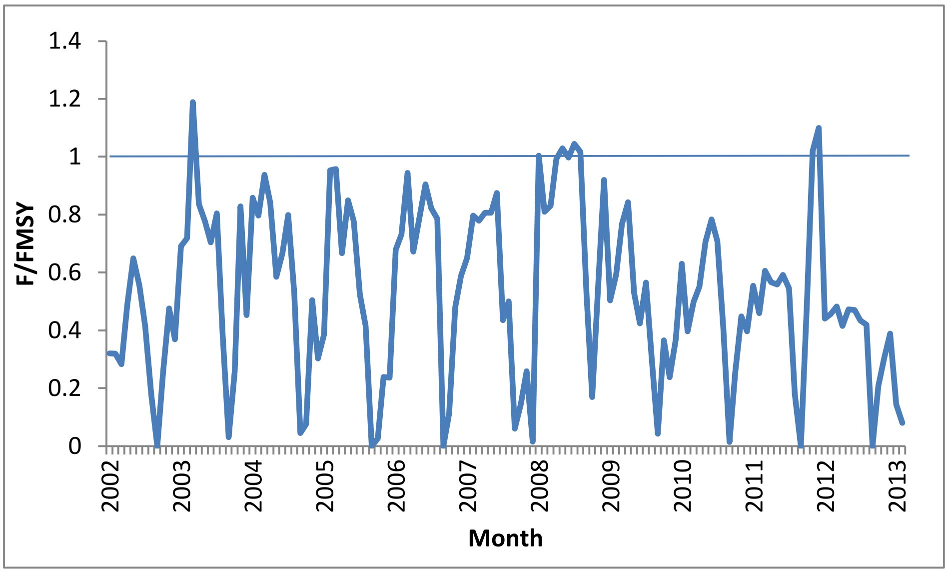


Figure 2 Fishing mortality as a proportion of the estimated fishing mortality at MSY.

2 Data Preparation

2.1 Commercial Size Category

The processing facilities routinely collect average count data from the commercial categories. This should monitor the average size within each category. This information should be useful within the stock assessment model to fit to changes in mean size within the category if such changes are significant. One processing facility provided average counts recorded by the quality control staff.

The change of shrimp size in the population and changes in selectivity will cause not only changes in the landings recorded as change in the amounts of each commercial categories, but may also change size within categories over time. A simple analysis of variance estimating the average count data dependent on the Year term as a factor suggested that Year has a significant effect on within-category size (Table 1). This would indicate that average count data should be included in some form in the stock assessment model.

Table 1 Analysis of variance for average counts in commercial category for a standard log-linear model.

	Residual degrees of freedom	Residual Deviance	Degrees of freedom	Deviance	Pr(>Chi)
AvgCount ~ Category	105404	99057335			
AvgCount ~ Category + Year	105394	97897240	10	1160095	< 2.2e-16
AvgCount ~ Category * Year	105312	90699966	82	7197274	< 2.2e-16

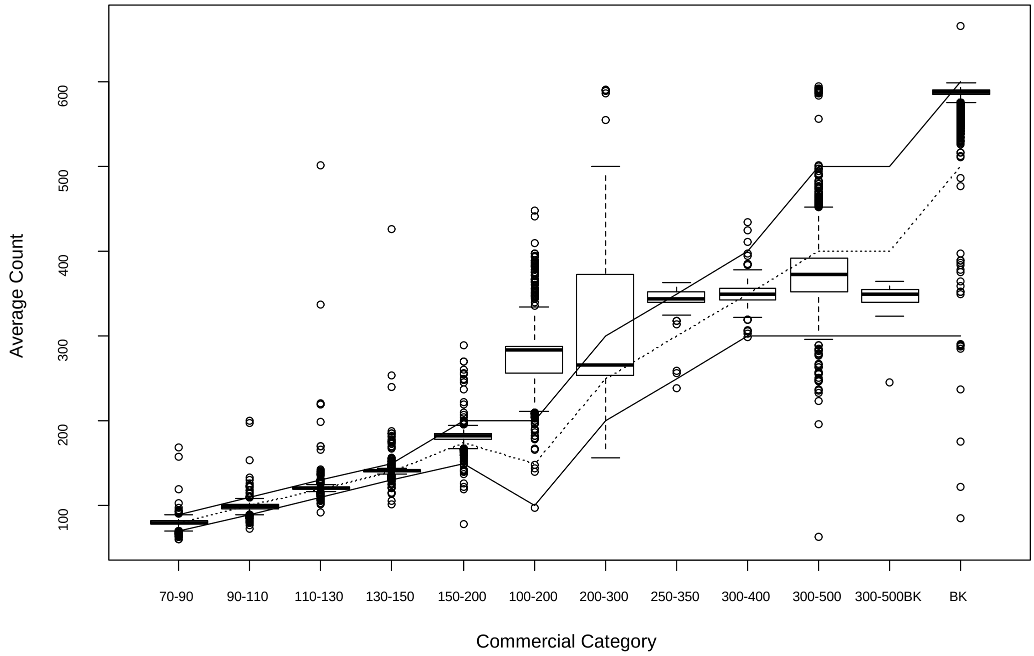


Figure 3 Box and whisker plot for average count data in commercial size categories, showing the median, 25th and 75th percentiles and 1.5 times the interquartile range for the average counts in each category. The solid lines represent the minimum and maximum count for each category (based on the name) and the dotted line is the mid-point.

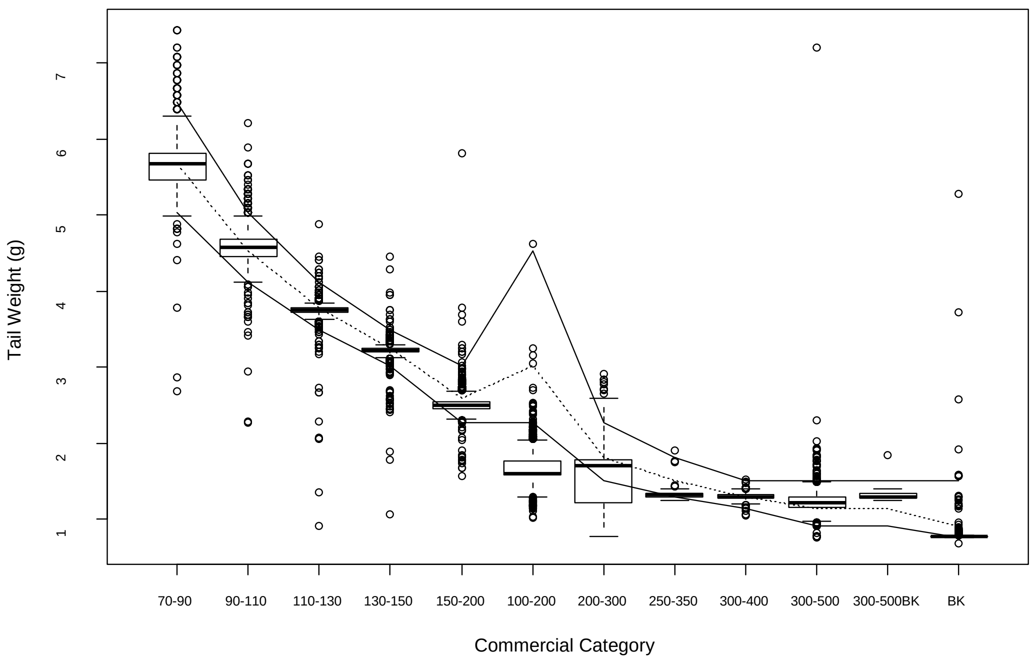


Figure 4 The same data as Figure 3 plotted as peeled tail weight. These data would be used in the stock assessment model.

Average count data can also be used to interpret commercial size category in terms of the size composition. In using commercial size categories, it will be necessary to allocate the estimated catch to each category based on individual tail weight. Ostensibly, each category has an upper and lower count which can be used to define the lower and upper bound on the tail weight to be allocated to that size category. This seems reasonable for all size categories to the 150-200 category (Figure 3, Figure 4). However, it appears that some categories may be combined as they contain very similar sized shrimp. Note that combining categories only loses relative size information, which, if not significantly different, should not be a problem for the model. There is a strong indication that 100-200 and 200-300 categories can be combined, as could all categories 250-350 to 300-500 BK. The broken category “BK” appears smaller, but this might be because they are in pieces, and these could also be combined into a single “small” category.

It is important that the boundaries in allocating the shrimp to their size category are as close to reality as possible. Incorrect boundaries will produce bias in the resulting growth parameters and assessment. Based on the available count and tail weight information (Figure 3, Figure 4, Table 2), each category was allocated a tail weight range (Table 3). All catches within the same size range were combined and these size ranges were then used to reference the estimated catch in each size category in the model. These size allocations may require further adjustment based on model diagnostics (see Section 4).

Table 2 Mean and standard deviations for the average counts per pound for the named categories from Heiploeg Suriname and Noble House Seafoods (Guyana) processors.

	Guyana		Suriname	
Name	Count/lb	Std. Dev.	Count/lb	Std. Dev.
70-90	78.14	4.02	79.87	5.75
90-110	97.05	4.57	100.80	3.40
110-130	120.84	4.65	121.66	6.05
130-150	140.92	2.90	141.34	5.40
150-200	182.43	4.75	179.96	6.77
100-200	285.99	7.84	252.51	21.26
200-300	292.59	57.27	309.74	62.83
250-350	342.13	18.73		
300-400	344.11	8.86	356.40	10.77
300-500	382.28	30.21	359.81	30.12
300-500BK			345.36	19.64
BK	585.35	17.92	208.78	158.54

Table 3 Commercial category allocation and size definitions used in the stock assessment model. ID refers to the identification number for the category, so all categories with the same ID are combined. See section 3.6.2 for the interpretation of these categories.

Categories		Limits from Commercial Count Names		Limits assumed from average counts		Peeled Tail Weights (g)	
Name	ID	Min	Max	Min	Max	Min	Max
41/60	1	40	60	0	90	5.04	10.00
70/90	1	70	90	0	90	5.04	10.00
BK41/60	1	40	60	0	90	5.04	10.00
BK51/60	1	50	60	0	90	5.04	10.00
116BK	2	110	1000	0	1000	0.00	10.00
2/3 J	2			0	1000	0.00	10.00
8-3BK	2			0	1000	0.00	10.00
BK	2			0	1000	0.00	10.00
BK1 LB	2			0	1000	0.00	10.00
BK1LB	2			0	1000	0.00	10.00
BK2/3J	2			0	1000	0.00	10.00
L/R	2			0	1000	0.00	10.00
LARGEPCS	2			0	1000	0.00	10.00
LP	2			0	1000	0.00	10.00
MM	2			0	1000	0.00	10.00
Other	2			0	1000	0.00	10.00
PCS	2			0	1000	0.00	10.00
S/W	2			0	1000	0.00	10.00
S/WATG	2			0	1000	0.00	10.00
SM	2			0	1000	0.00	10.00
SOUR	2			0	1000	0.00	10.00
SP	2			0	1000	0.00	10.00
WB	2			0	1000	0.00	10.00
90/100	3	90	100	90	100	4.54	5.04
90/110	3	90	110	90	100	4.54	5.04
100/120	4	100	120	100	130	3.49	4.54
100/130	4	100	130	100	130	3.49	4.54
100/150	5	100	150	100	150	3.02	4.54
110/150	5	110	150	110	150	3.02	4.12
110/130	6	110	130	110	130	3.49	4.12
130/150	7	130	150	130	150	3.02	3.49
130/150–	7	130	150	130	150	3.02	3.49
150/200	8	150	200	150	200	2.27	3.02
120/200	9	120	200	150	300	1.51	3.02
150/OP	9	150	1000	150	300	1.51	3.02
180/200	9	180	200	150	300	1.51	3.02
180/210	9	180	210	150	300	1.51	3.02
OVER 150	9	150	1000	150	300	1.51	3.02
100/200	10	100	200	200	400	1.13	2.27
100/200BK	10	100	200	200	400	1.13	2.27
130/200	10	130	200	200	400	1.13	2.27
200/300	10	200	300	200	400	1.13	2.27
200/300BK	10	200	300	200	400	1.13	2.27
900	11	900	1000	300	1000	0.00	1.51
250/350	11	250	350	300	1000	0.00	1.51
300/350	11	300	350	300	1000	0.00	1.51
300/400	11	300	400	300	1000	0.00	1.51
300/500	11	300	500	300	1000	0.00	1.51
300/900	11	300	900	300	1000	0.00	1.51
400/600	11	400	600	300	1000	0.00	1.51
BK300/900	11	300	900	300	1000	0.00	1.51
OVER 400	11	400	1000	300	1000	0.00	1.51
OVER 500	11	500	1000	300	1000	0.00	1.51
OVER 900	11	900	1000	300	1000	0.00	1.51

2.2 Catch and Effort

Catch and effort data were obtained from spreadsheet forms used by Noble House Seafoods and Heiploeg Suriname to record landings and processing operations. The spreadsheets are used for internal monitoring of their business. Data were extracted from these forms and held in a database for further manipulation. Using the database, it was possible to match trip information (trip dates of departure and return) with processed landings weight, fuel used and commercial size grades produced.

The landed catch is recorded as pounds of processed shrimp, representing about 43% of the live weight. Effort might be measured in two ways: as days-at-sea and as fuel used. Basing effort on fuel use has significant advantages in costs and real effort (trawl time), but may vary from vessel to vessel with engine size and other characteristics, and will not be available for all trips.

Plots of effort against catch reveal an asymptotic relationship with catch for both measures of effort (Figure 5). The variation in catch at higher levels of effort may be related to abundance, but could also be explained by other factors. Although ideally any standardisation to account for these factors would be included in the stock assessment model, this would become too complex at this stage, although it might be considered for later development. Instead, standardisation was considered externally using generalized linear models.

The aim of standardisation is to adjust abundance indices to account for variation in the index that might be attributed fishing power (catchability) rather than changes in abundance, which apart from reducing noise of the index potentially removes bias. In this case, the only covariate data available with the catch and effort is the vessel name. The aim of the standardisation is not to affect any trends in the index which could be related to abundance, since this might introduce bias as well as eliminate it. For example, standardisation based on vessel name should remove noise related to fishing power without affecting abundance trends as long as vessels have landings over significant periods of the time series.

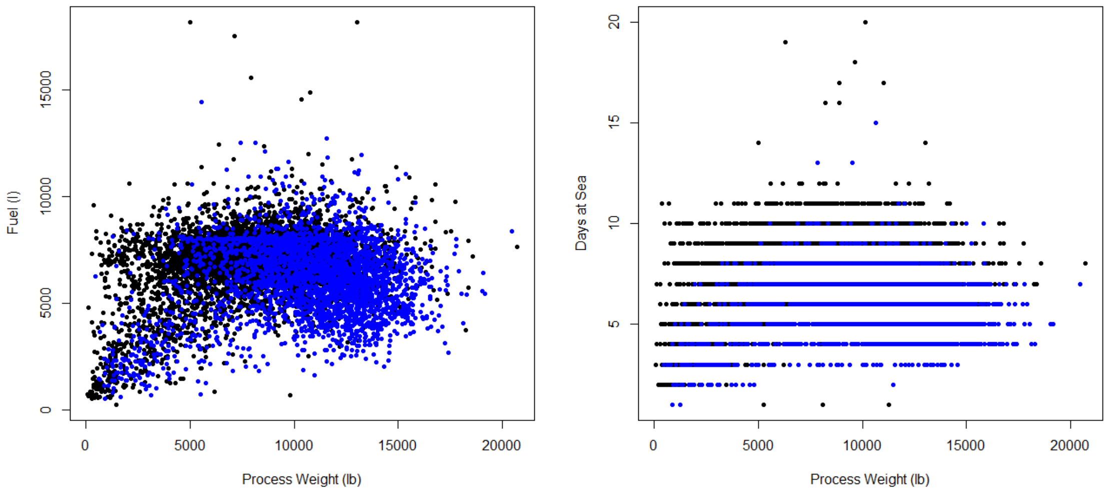


Figure 5 Catch (lb) plotted against the two raw measures of effort: fuel used in litres and days-at-sea for Guyana (black) and Suriname (blue).

A log-linear model was used to estimate the catch on each trip with the available data:

$$C_i = e^{P_i + V_i + M_i + ld_i + lf_i + P_i:M_i} \qquad 1)$$

where C_i is the catch of vessel V_i in year/month M_i using (log) days-at-sea ld_i and (log) fuel lf_i landed at processing facility (country) P_i. Parameters fitted to explain month and month:country interaction should capture any trends in biomass abundance and is therefore required in the base model.

To test which effort variables should be included in the measure of effort and whether the vessel explained significant differences in catch rate, a simple analysis of variance was carried out comparing the three main models (Table 4). All parameters were highly significant and therefore the full model with all main terms should be used for any standardisation. This includes an argument for the inclusion of both measures of effort (days-at-sea and fuel).

To understand seasonal patterns better, a model with separate year and month terms was fitted and alternative models tested (Table 5). There was a clear seasonality which showed a significant difference between countries, but the general pattern of the seasonality was very similar (

Figure 6). It should be noted that whereas the time series covers 2001-2011 for Guyana, data only covered 2001-2007 for Suriname, so any differences may reduce with more data. Annual changes in catch rates show weak annual trends for both countries, with Guyana increasing slightly and Suriname showing a small decrease (Figure 7).

The seasonal peak in catch rate coincides with the period when most large, mature females are caught and it is likely that there is a peak in biomass at this time. The implication is that the standardised catch rates are likely to be tracking biomass.

The results also indicate that the monthly change is also significant (Table 5), which suggests that changes in abundance are unlikely to follow a simple seasonal pattern each year. Because some recruitment is likely to be occurring throughout the year, the seasonal pattern has only a limited capability in explaining abundance changes. This would justify including full interaction terms for year and month in any standardisation model.

There is clear evidence of diminishing returns of trip length when days-at-sea are fitted as a factor rather than covariate (Figure 8). While this might include issues such as increased travel time, weather and so on, it might also include increased time taken to catch seabob due to lower abundance. The data also suggested that longer trips over 12 days resulted in greater variation in catches, partly because there are fewer such trips, but also because the cause for the length of such trips are dominated by factors other than stock size.

Table 4 Analysis of variance for the possible catch-effort standardisation models. P*M indicates full interaction terms for country and month factors, making it the base model.

	Residual degrees of freedom	Residual Deviance	Degrees of freedom	Deviance	Pr(>Chi)
`C ~ P * M`	8937	9235804			
`C ~ P * M + ld`	8936	7860938	1	1374867	< 2.2e-16
`C ~ P * M + ld + lf`	8935	7419680	1	441258	< 2.2e-16
`C ~ P * M + ld + lf + V`	8883	6989686	52	429994	< 2.2e-16

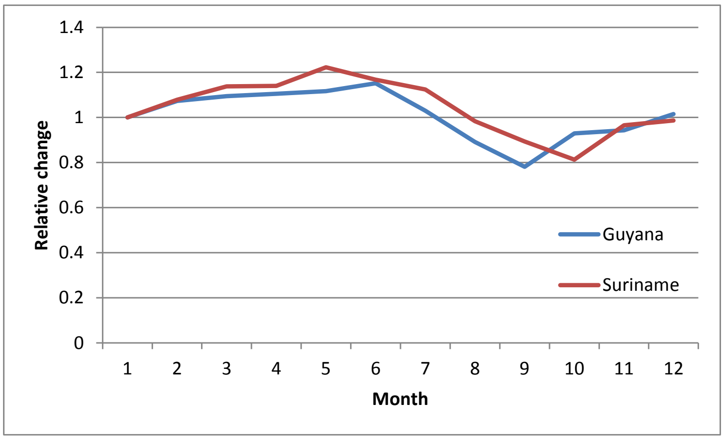


Figure 6 The relative change in seasonal catch rates after accounting for vessel, effort and annual trends. Guyana and Suriname have significantly different catch rate changes but follow very similar patterns.

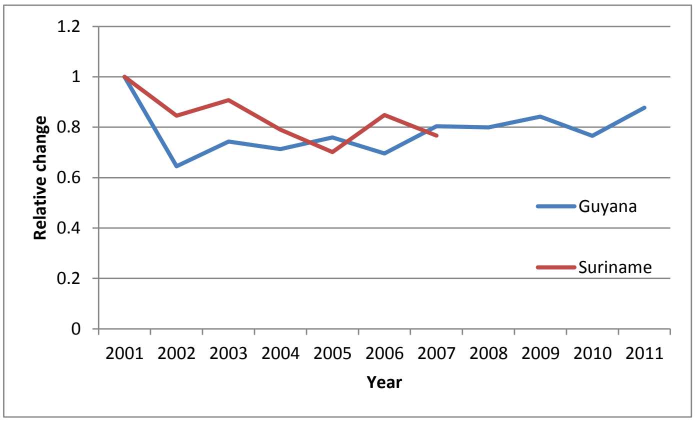


Figure 7 Relative annual change in catch rates.

Table 5 The analysis of variance for time series terms consisting of average season across countries (M), different seasonal trends across countries (P*M) and inconsistent seasonal changes across the whole time series (Y*M).

Model	Residual degrees of freedom	Residual Deviance	Degrees of freedo m	Deviance	Pr(>Chi)
C ~ P*Y + M + lf + ld + V	9055	8532917			
C ~ P*Y + P*M + lf + ld + V	9044	8473048	11	59869	1.11E-10
C ~ P*Y + P*M +Y*M + lf + ld + V	8944	7330849	100	1142199	< 2.2e-16

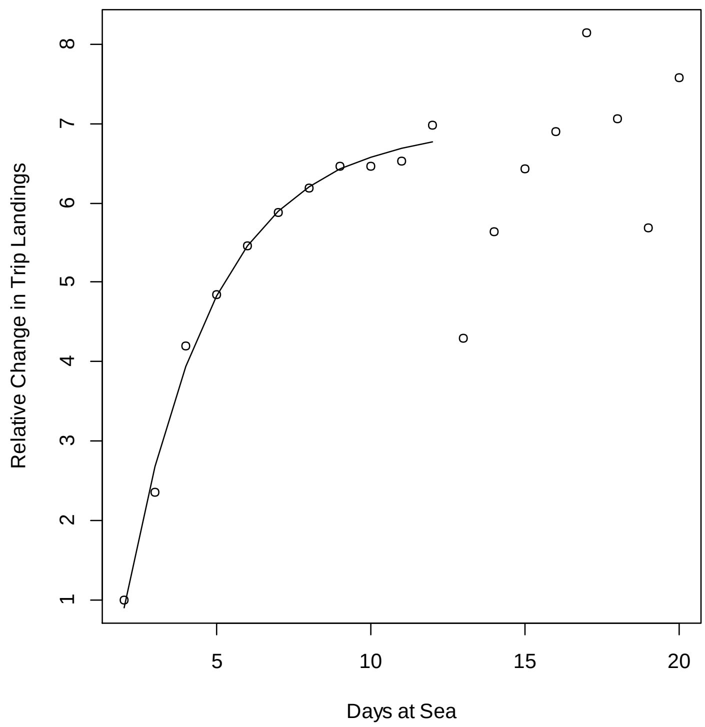


Figure 8 Relative change in catch for days-at-sea fitted as a factor in the standardisation model.

The asymptotic effect of trip length (Figure 8) can described as:

$$S = a\left(1 - e^{-b(f+c)}\right)$$

with parameters:	a	b	c
	6.955081	0.348347	-1.60215

Catch effort data were retained from only two processors (BEV and NHS). PSI and GQS catch and effort data were rejected as CPUE seemed to be on a different scale and inconsistent (Table 6). Processors GQS and PSI report much higher landings per day than NHS and BEV. NHS CPUE is based on processed weight from internal production reports, suggesting BEV is reported in much the same way. GQS and PSI is likely reported as whole weight, so processed landings are multiplied by some constant. Data from these processors needs to be investigated to ensure that they are consistent with other reported landings.

Fishing effort was calculated on a per-trip basis. NHS data was derived from internal production reports. Other processor data was derived from reports submitted to the Fisheries Department.

Categories were not entirely consistent within each month. In particular, the largest category was rarely 70-90, so the next category (90-100, 90-110, 100-150 etc.) would most likely include all larger shrimp. This could be taken into account where no 70-90 category was recorded within a month, but otherwise was not directly addressed, although effort was correctly adjusted for the 70-90 category.

It could be addressed by grouping trips into the set of size categories they report within each month. However, ignoring this difference should only lead to a small decrease in precision.

Table 6 Reported average CPUE in kg per standardised day-at-sea by year and processor.

Year	BEV	GQS	NHS	PSI	Total
2001			43.25		43.25
2002		163.43	32.60		60.79
2003			41.61		41.61
2004			38.56		38.56
2005			52.02		52.02
2006			35.88	159.43	36.24
2007		90.76	41.61	217.55	74.42
2008			41.59	244.09	42.27
2009	48.29	315.05	43.97	248.72	63.55
2010	49.55		38.97	213.47	59.82
2011	58.60		43.09		46.71
2012	61.18				61.18
Total	53.24	162.41	41.80	224.12	52.40

For standardisation, various options from the analyses above were possible. An adjustment can be made on the basis of the average catch rate of each vessel to the effort measure. Furthermore, a nonlinear adjustment to fuel and days-at-sea effort measures was considered in developing a better measure of effort. In applying an adjustment specific to vessel effects, the index would remain unchanged with respect to average monthly change. However, various options would reduce the data available, while contributing little to the precision of the index.

Four possible indices were considered: a full GLM standardised CPUE model (Table 5), nominal catch per day-at-sea, nominal catch per litre of fuel, and catch per day at sea adjusted for trip length using the asymptotic catch model (Figure 8). All indices follow the same trend (Figure 9), but the standardised indices and indices based on fuel generally were more closely related than the ones based on days at sea.

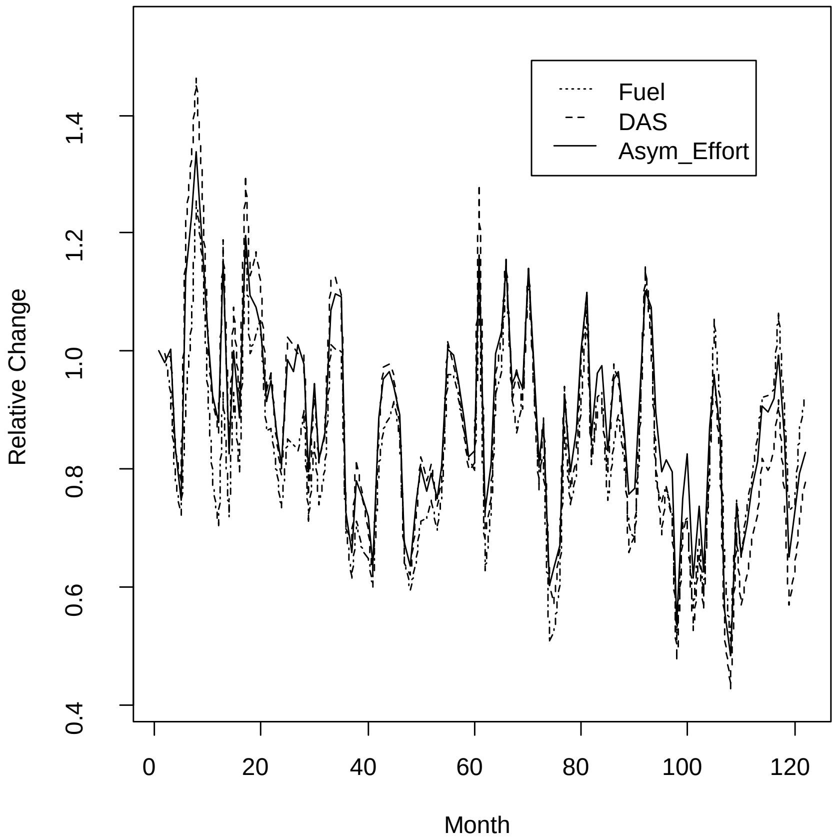


Figure 9 Possible abundance indices calculated using different measures of effort.

Based on these results, the Shrimp and Groundfish Working Group decided at the 2013 intersessional meeting (CRFM 2013) and the 2013 scientific meeting (this report) to simplify and standardise the catch and effort in the following ways:

- Nominal catch and effort was used as this was simple and it was believed that these should not bias the result and provide the most data. Some corrections were applied to the data as below.
- Only BEV and NHS catch effort data were retained as these provided a consistent measure.
- Effort was based on days at sea. Fuel was not used because the number of trips for which this information was available was small.
- Trips exceeding 12 days or less than 2 days were excluded. Remaining trips were validated, and provided catch rates within a reasonable range.
- Trip effort (days at sea) was corrected for the asymptotic trip length (Figure 8).
- Suriname and Guyana catch and effort data were separated.
- Vessels were not used as a standardising factor. The relationship between vessel characteristics and resulting catch needs to be better understood before this standardisation can be done.

It is worth noting that a constraint could be placed on any time-based factors using mixed effects models, so that trends are not removed. However in this case care would be need to ensure that seasonality would not be removed and therefore such a model would require careful development. It is not clear that the additional work required would benefit the final index.

Variations in selectivity among vessels was only cursorily considered. All vessels ostensibly apply the same gear, so consistent variation in shrimp size could only be the result of fishing practice (fishing location, time of fishing, discarding etc.). While there is significant variation in the landed size among vessels (Figure 10), the reason for this is unclear. Many vessels have reported very few trips, so whether this is due to attributes of the vessel rather than variations in fishing time or location is unclear. This would be worth further investigation, but more and better data would be required from individual vessel operations before a full understanding might be obtained.

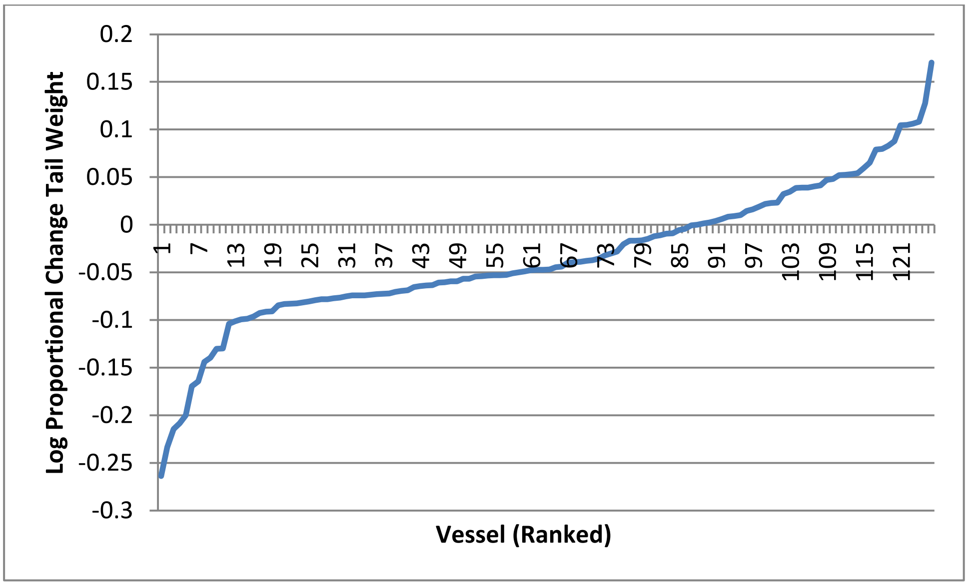


Figure 10 Variation in mean tail weight across all vessels.

2.3 Maturity

There is now a considerable data set linking female size (tail weight in grams) to maturity (presence of a “green vein”) in females. This allows the maturity ogive to be estimated, which can be used to estimate spawning stock biomass within the stock assessment model. Because these data are the only data relevant to estimating the maturity ogive, this can be done separately outside the main assessment. In this analysis, a fixed ogive is estimated. Since the status reference points will be based on the ratio of current SSB to unexploited SSB, the final results should be robust to errors associated with these estimates, and therefore errors are not carried forward into the main assessment, but a fixed ogive is used.

Tail length was a much better predictor of maturity than tail weight due to the shape of the curve (Table 7). Therefore tail weight, which is part of the stock assessment model was converted to length within the logistic model.

Maturity may also change over time, by season for example. The available time series was short, and a clear seasonality was not obvious in the data. However, there was a significant change in the proportion of mature females over time (Table 8), which appeared to follow no time-dependent pattern, but varied in the catches from month to month (Figure 11). The time variation in maturity suggested a random effects model was appropriate (Figure 12) to account for these changes. However, random effects had very little influence on the final maturity model (Figure 13). The final model was used to estimate the expected mature proportion by tail weight (Table 9; Figure 14).

Table 7 Analysis of variance comparison between a model explaining maturity based on tail weight and one based on tail length.

	Residual Degrees of freedom	Residual Deviance	Degrees of freedom	Deviance
Intercept	1964	38207		
Tail Weight	1963	8487	1	29720.7
Tail Length	1963	7155	0	1331.7

Table 8 Analysis of variance comparison between time series factors on maturity.

	Residual Degrees of freedom	Residual Deviance	Degrees of freedom	Deviance	Mean Deviance
Tail Length	1963	7155.1			
+Year.Month	1938	3987.9	25	3167.2	126.688
*Year.Month	1913	3629.5	25	358.4	14.336

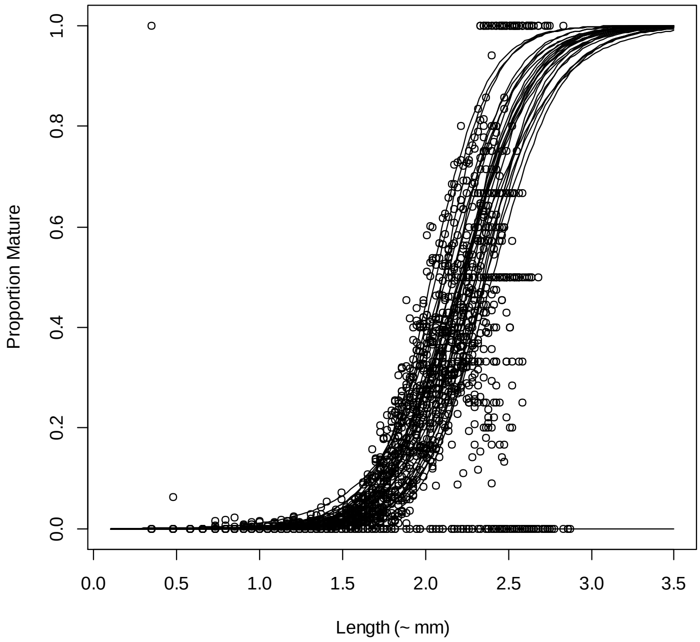


Figure 11 Different maturity ogives (solid lines) for year.month showing some variation in the ogive between months with the observed proportion mature (dots).

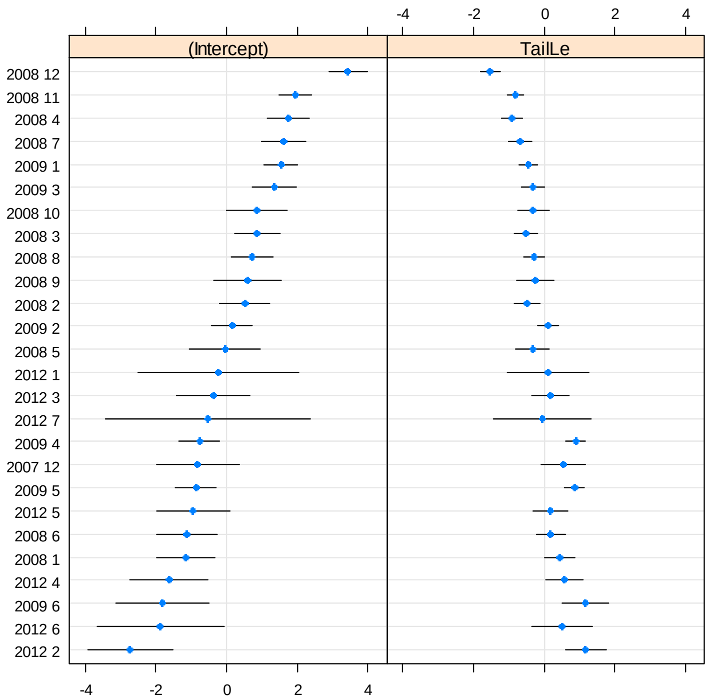


Figure 12 Random effects on the intercept and tail length slope. The blue dots are the conditional modes with error bars for each month.

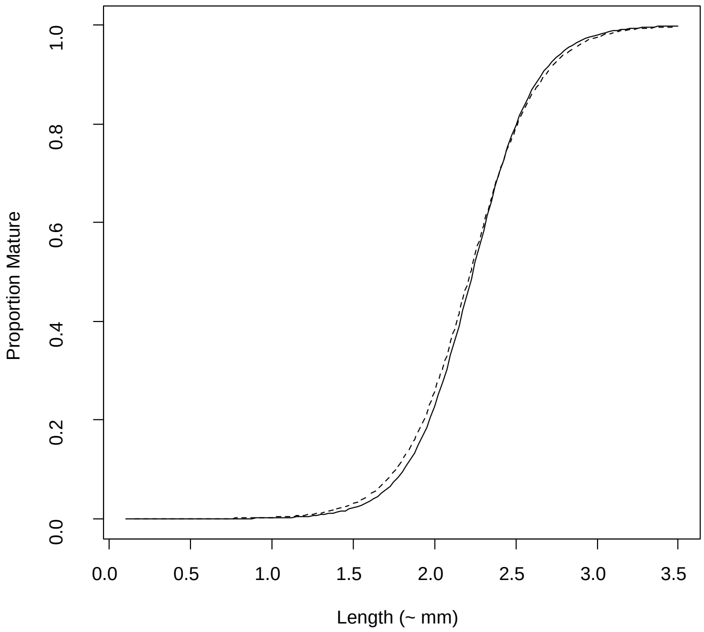


Figure 13 Comparison in the ogive between the mixed effects estimate (solid line) and fixed effect estimate (dotted line).

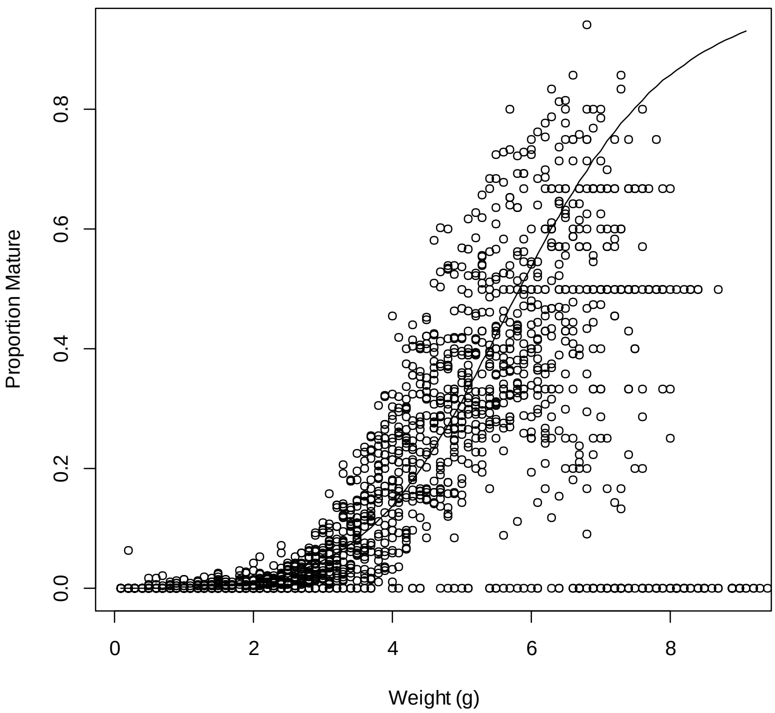


Figure 14 Final ogive estimated from the mixed effects model used in the stock assessment.

Table 9 Logistic model fitted to the proportion mature dependent on tail weight after accounting for random effects.

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-11.5937	0.3224	-35.96	<2e-16
Slope	5.1863	0.1516	34.21	<2e-16

$$\mathrm{M}_p = \frac{1}{1 + exp\left(-Intercept - Slope\left(TailWt^{1/2.19276}\right)\right)}$$

Tail Weight (g)	Proportion Mature	Tail Weight (g)	Proportion Mature
0.1	5.66267E-05	4.7	0.251723231
0.3	0.000184316	4.9	0.291542624
0.5	0.000404286	5.1	0.333857028
0.7	0.000756563	5.3	0.378048224
0.9	0.001291439	5.5	0.423404858
1.1	0.002072341	5.7	0.469167776
1.3	0.003178355	5.9	0.514579832
1.5	0.004706915	6.1	0.558933439
1.7	0.006776598	6.3	0.601609862
1.9	0.009529931	6.5	0.642106256
2.1	0.013135987	6.7	0.680048978
2.3	0.017792455	6.9	0.715194071
2.5	0.023726779	7.1	0.747417507
2.7	0.031195785	7.3	0.776698581
2.9	0.040483112	7.5	0.803099827
3.1	0.051893654	7.7	0.826746288
3.3	0.065744206	7.9	0.847806165
3.5	0.082349609	8.1	0.866474078
3.7	0.102004049	8.3	0.882957442
3.9	0.124957739	8.5	0.897466006
4.1	0.15139014	8.7	0.910204282
4.3	0.181381927	8.9	0.92136641
4.5	0.214889078	9.1	0.931132996

2.4 Tail Weight: Random Samples

The random samples needed to be converted from unpeeled tail weight to processed tail weight to be used in the assessment. The tail weights were multiplied by 0.78 to adjust for peeling based on morphometric data collected in 2007 (CRFM 2009, Table 5 p.115). Unpeeled tails are measured on electronic scales to within 0.01 of a gram. Within the database, these are held as whole numbers (integers) and compiled into 0.2g class frequencies.

2.5 Total Catch

Total landings are reported to governments by each processor. Information reported has not always been consistent, but has improved over the years. There are initiatives to improve data reporting in Guyana so that it is more timely and accurate.

Monthly landings were available from all processors back to January 2002. Before this, monthly data were not consistently available, but annual landings were reported. Landings are reported as total tail weight in pounds by commercial size categories. Annual landings are available as gross weight to the start of the fishery. Discards are assumed to be zero.

3 Population Model

3.1 Overview

The model used in this assessment was a statistical catch-at-age model (Quinn and Deriso 1999), implemented with the AD Model Builder software (Fournier et al. 2012). In essence, a statistical catch-at-age model simulates population dynamics in time including biological and fishing processes. Quantities to be estimated are systematically varied until characteristics of the simulated populations match available data on the real population. Statistical catch-at-age models share many attributes with ADAPT-style tuned and untuned VPAs.

The model is based on a standard forward-projection design, the same as that used in standard stock assessment software such as stock synthesis. The model used here is at an early stage of development, and in a much simpler form than Stock Synthesis III (NOAA Fisheries Stock Assessment Toolbox website: http://nft.nefsc.noaa.gov/), for example. It was necessary to develop an bespoke model to be able to use the available shrimp weight data. Age data are not available. This implementation also offers the opportunity to develop a model suitable for crustacean fisheries in the Caribbean and the data that has been collected in the region. The model can be adapted and maintained locally, incorporating improvements as they can be identified.

Where possible the observations and model are kept distinct. The model is adjusted to fit a sufficient data set. In some cases, exact fits can be obtained because there are enough parameters to allow the model to closely follow the data. This applies to the total catch. For other data, where observation errors are presumed to be significant, the model may not fit the observations closely, and some error is acceptable.

3.2 Monthly Catches

The basic population model time step is one month, which was considered appropriate for this species. Separate models are run for males and females. When monthly catch and size composition data are available, a simple approach can be used to model the population, clearly separating the model and data. For each sex, the numbers at the beginning of each age are calculated based on mortality parameters and standard negative exponential model:

$$N_{a+1\,t+1} = N_{at} e^{-M_i - F_t S_a}$$

where F_t = fishing mortality in month t and S_a = selectivity at age. Growth is estimated on the von Bertalanffy growth function (Equation 4) for the mean, and another parameter for the variation around the mean. Ages are measured in months, with maximum age of 12 months (0-11), after which there is a plus-group in the default model. An alternative model was also considered where a higher proportion of shrimp die after 12 months, simulating higher mortality after spawning.

Selectivity was modelled as a logistic function based on length. Mid-point values for each weight bin were converted to carapace length for each sex using values obtained from the fitted morphometric model. The resulting selectivity model took the form:

$$S_w = \frac{1}{1+exp\left(-S_{tp}\left((aW)^{1/b}-S_{50\%}\right)\right)} \qquad 2)$$

Where S_w = selectivity for weight bin w, S_{tp} = steepness for the logistic, $S_{50\%}$ = carapace length at 0.50 selectivity, and a and b parameters convert weight to carapace length (Table 10). S_{tp} and $S_{50\%}$ were estimated in the stock assessment.

Table 10 Parameters derived from a morphometric linear model to convert weight to length (see Table 13). This conversion could be done so that each weight bin had a length associated with its mid-point weight.

	Female	Male
a	224.4852	73.14399
b	2.19276	1.798805

3.3 Population Model with Annual Catches

Only annual catches, rather than monthly catches, are available for years 1985-2001. These were divided into months based on the average observed distribution of catches among months for the period 2002-2006. Because only annual data were available, these catches could only be used to help set the initial condition for the full population model and specifically the initial level of depletion. Because the model could not fit an annual fishing mortality to the annual catch data (the Hessian matrix could not be inverted), these catch data were used in an approximation based on Pope (1972).

Observed annual catches were distributed among size categories and months based on a simple linear scheme. The annual catch was distributed among months based on the proportion of catches observed among months were monthly catches are available. The observed catch weight in each month (C_w) is approximately equal to the fishing mortality (F) multiplied by the biomass:

$$C_w \cong F \sum_x \sum_i^A \sum_j^W N_{xi} w_j p_{xij} s_{xj}$$

where the biomass is the population size (N_{xi}) by sex (x) and age (i) multiplied by the proportion of each age in each weight class (p_{xij}), the class weight (w_j) and selectivity (s_{xj}). Therefore, the fishing mortality can be estimated approximately as:

$$F \cong \frac{C_w}{\sum_x \sum_i^A \sum_j^W N_{xi} w_j p_{xij} s_{xj}} \qquad 3)$$

Similarly, the catch in numbers (C_{xna}) at age can be approximately given as:

$$C_{xna} \cong F \sum_j^W N_{xi} p_{xij} s_{xj}$$

and by substituting fishing mortality (F) with equation (3) gives:

$$C_{xna} \cong \frac{C_w N_{xi} \sum_j^W p_{xij} s_{xj}}{\sum_x \sum_i^A N_{xi} \sum_j^W w_j p_{xij} s_{xj}}$$

This estimate can be included as the cohort catch in the population model:

$$N_{x\ i+1} = N_{xi} e^{-M_i} - C_{xna} e^{-M_i/2}$$

In this case, the model is not fitted to the data, but the catch data does provide an estimate of initial conditions (i.e. the level of depletion).

3.4 Growth

Most age related data are available as tail weight. This includes both commercial size category data and scientific sampling (see section 2). The mean growth of seabob is assumed to follow the von Bertalanffy growth curve. However, the stock assessment will require conversion from length to weight in the growth model. The general from of the growth model will be:

$$W_t = W_\infty (1 - e^{-kt})^b \qquad 4)$$

Parameters W_∞, and k will be estimated within the stock assessment for each sex. b can be estimated only from a smaller morphometric data set.

The parameter b depends on the length-weight relationship, and may change dependent on the sex and location (Suriname vs Guyana) of the seabob. To simplify the assessment, this parameter can be estimated outside the main assessment and provided as a fixed number to the assessment model. This will slightly underestimate the uncertainty, but prevent unrealistic parameter estimates and should improve the stability of the fit.

The parameter can be estimated using a log-linear model from the morphometric data collected in 2007/8 (CRFM 2009). The model has the general form:

$$w_i = e^{bc_i + a} \qquad 5)$$

where the independent variable c_i is the log carapace length, the dependent variable w_i is the unpeeled tail weight and the linear predictor contains parameters a and b which can be estimated as part of a generalized linear model.

The first issue is whether it is necessary to estimate separate b parameters for the sexes and countries. A simple analysis of variance chi-squared test was used to check whether these additional factors were necessary (Table 11) and the findings suggested that an interaction term is required for only for sex. This indicates that the shape of a seabob is affected by its sex.

Table 11 The basic model is: tailwt ~ lcl + sex + country + sex:country. These are the full terms for parameter *a* in equation 5. The models add all interaction terms for lcl (log carapace length). Comparison is made between models (Pr(>Chi)) assuming that the change in deviance approximately follows the X^2 distribution, which can be used to guide the minimum model. The only interaction term which would seem to be justified in this case is the lcl:sex parameter. Importantly, there is no significant with country where data were collected.

	Residual degrees of freedom	Residual Deviance	Degrees of freedom	Deviance	Pr(>Chi)
Basic model	862	77.205			
Basic model + lcl:country	861	77.203	1	0.00256	0.8647
Basic model + lcl:sex	860	75.833	1	1.36946	0.000082
Basic model + lcl:sex + lcl:country	859	75.810	1	0.02368	0.6046
Basic model + lcl:sex + lcl:country + lcl:sex:country	858	75.805	1	0.00491	0.8136

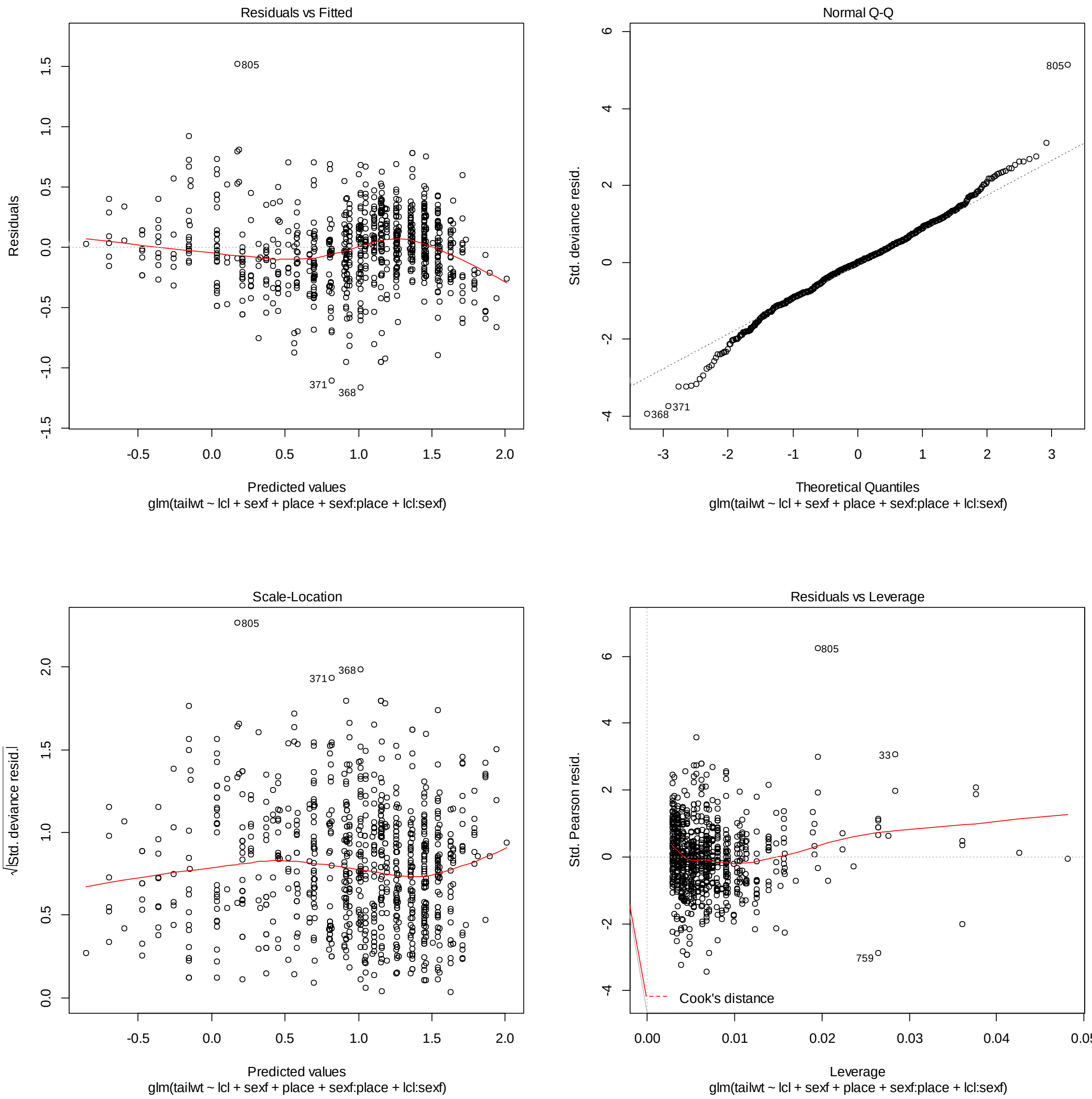


Figure 15 Standard diagnostic plots for the GLM fitted to estimate the exponent parameter *b* in equation 4. The results suggest that the model is stable, no assumptions are violated to an unacceptable degree and parameter estimates should be reasonable.

In Guyana, seabob sex has been recorded as “unknown” as well as “female” and “male”. This unknown category is likely to be a mix of sexes of immature seabob, but is most likely to mainly consist of immature females since male sexual parts are easier to identify. That most are probably female was confirmed from average length-weight relationship (Table 12) and therefore these are allocated to female for the purposes of the model and stock assessment.

The final model therefore consisted of females (female and unknown) and male, with a single sex interaction term for the carapace length covariate. The parameters can be used to estimate the *b* parameter for both sexes (Table 13).

Table 12 Analysis of variance comparing models where sex "U" (unknown) is allocated to the female (U=F) or male (U=M) category, or kept separate (U=U). The change in deviance represents the loss from combining unknown with females of males respectively. There was a clear significant change if unknown was allocated to males, but the change was not significant for females.

	Residual degrees of freedom	Residual Deviance	Degrees of freedom	Deviance	Pr(>Chi)
U=F	862	76.330			
U=U	860	75.833	2	0.4963	0.05974
U=M	862	77.118			
U=U	860	75.833	2	1.2844	0.00068

Table 13 Parameter estimates for the basic model with sex interaction term and "unknown" allocated to "female". The resulting maximum likelihood estimates for the b parameter for males and females are also given.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-4.292430	0.263996	-16.259	< 2e-16
Lcl	1.798805	0.092706	19.403	< 2e-16
Sex.F	-1.121380	0.285088	-3.933	9.05E-05
Country.Suriname	0.008994	0.026108	0.345	0.730551
Sex.F : Country.Suriname	-0.113920	0.030129	-3.781	0.000167
lcl:Sex.F	0.393955	0.099369	3.965	7.96E-05
b Parameter (Equation 4)				
Male	1.798805			
Female	2.192760			

A conversion from age in months to weight class bin was provided by constructing an age-length matrix from the model, including growth variation. There were 29 weight bins from 0.0g to 6.0g, each of 0.2g width. Weights were rescaled to length, which provided a better model fit. The probability that a seabob was in a particular weight bin given its age is:

$$Pr(w|a) = N\left({u_w}^{1/b}; {W_a}^{1/b}, \sigma\right) - N\left({l_w}^{1/b}; {W_a}^{1/b}, \sigma\right) \qquad 6)$$

Where w=weight bin, a=age in months, $N()$ = cumulative normal, u_w and l_w are the upper and lower bounds for the weight bin, W_a is the expected weight of seabob age a (equation 4), b = length-weight parameter (equation 5 estimated in Table 13) and σ = growth standard deviation. The cumulative normal was set to 1.0 or 0.0 at the weight boundaries (u_w=6.0 and l_w=0.0 respectively). Separate growth was allowed for each sex. The resulting probability matrix (Figure 16) was used to convert age to weight class by multiplying the numbers-at-age vector by this growth matrix.

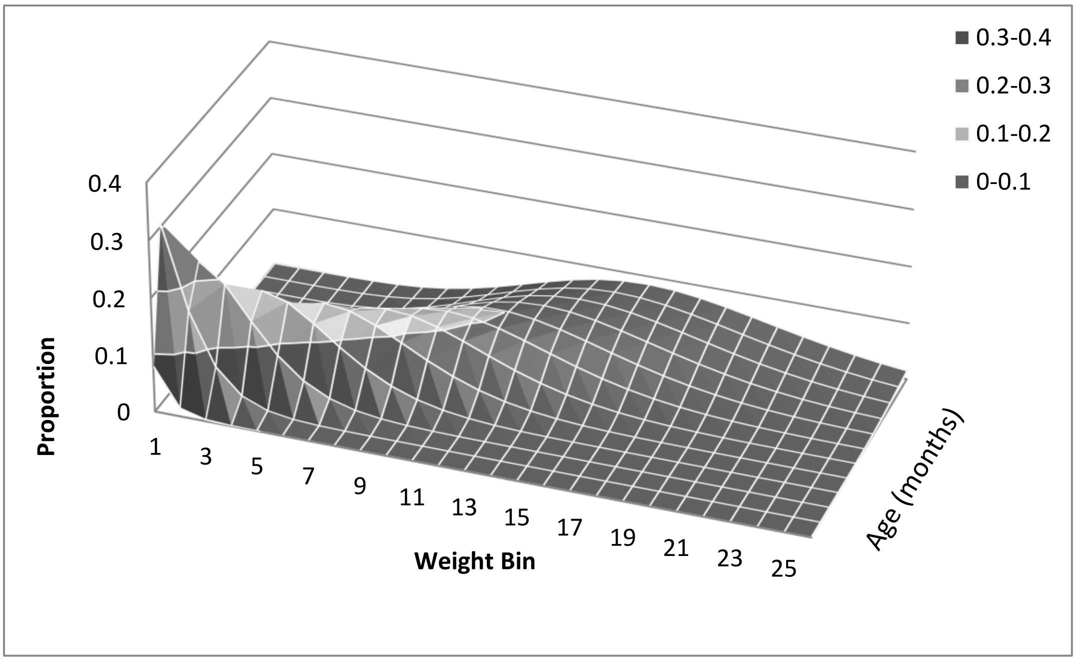


Figure 16 Female age-weight probabilities for bins 1-25 (from 0-28 bins) produced from the growth curve (Equation 4) and a normal distribution on length (Equation 6).

3.5 Recruitment

The stock recruitment model used was the Beverton-Holt, with the "steepness" parameterization:

$$R = \frac{4hR_0S}{R_0S_R(1-h)+S(5h-1)} \qquad 7)$$

Where R=Expected recruitment, S=spawning stock biomass from the previous month or earlier depending on the length of the larval stage, R_0 = expected recruitment when the stock is unexploited, S_0 =spawning biomass per recruit when the stock is unexploited and h =steepness parameter (0.2< h <1.0). The recruitment was modeled as a log normal, with equation 7 the log-normal mean, and individual deviations fitted as parameters from 2002-2013. Before 2002, when only annual catches are available, no deviations from equation 7 are fitted.

3.6 Likelihood

3.6.1 Overview

The log-likelihood was calculated for each data component based on the multinomial or normal log-likelihoods as follows:

- The negative log-likelihood for the size composition by size and sex in the random samples is calculated from the predicted catch proportions in numbers by size and sex and the observed numbers in the sample by size and sex. The scaled multinomial negative log-likelihood for a particular month is given as:

$$LL = \sum_{ij} Ln\left(\left(N\, e_{ij}/C + \varepsilon\right) \Big/ \left(o_{ij} + \varepsilon\right) \right) * o_{ij}$$

Where N = total sample size (number of shrimp measured) within a month, C = predicted total catch in numbers within a month, e_{ij} = predicted catch in numbers of sex i, weight class j, o_{ij} = observed numbers in the samples of sex i, weight class j, and ε = small number constant to avoid zeroes leading to numerical errors during minimization.

- The likelihood for the total catch and catch and effort data were based on the normal. Assuming a Poisson probability function for the catch, the scale parameter was assumed to be the square root of the predicted catch, so the negative log-likelihood would be:

$$LL = \sum_k \frac{(o_k - e_k - \varepsilon)^2}{e_k + \varepsilon} + \mathrm{Ln}(e_k) \qquad 8)$$

Where o_k = observed catch, e_k = predicted catch for a particular month k and ε = small number to avoid numerical errors. The predicted total catch weight is predicted from the model fishing mortality and selectivity, with catches summed over all sizes and sex. The predicted catch weight for a given level of effort is estimated from the population numbers in each weight class:

$$e_k = qf \ \sum_{ij} s_i w_i P_{ij} \qquad 9)$$

Where q = catchability parameter, f = observed effort, s_i = selectivity for weight bin i, w_i = mid-weight point, and P_{ij} = predicted population numbers in weight bin i and sex j.
- The catches and catch and effort within commercial size categories is based on integrating over possible catch allocations among categories. This was necessary because commercial categories overlap and are incomplete. The details are given in section 3.6.2 below.
- The average count per pound was assumed to follow a Poisson and therefore the log-likelihood Equation 8 was used. In this case, the predicted count was the predicted catch number divided by the seabob weight summed over the weight bins in each category ID (see Table 14) converted from grams to pounds. Most categories also had a standard deviation for the observed counts taken in each month which was used as a weight. A minimum standard deviation of 10.28 was applied based on the mean standard deviation where sample sizes exceeded ten observations.
- The negative log-likelihood log-recruitment deviations was the standard sum-of-squares (normal) differences between the parameter and the expected recruitment (Equation 7), with an additional scale parameter (σ_R) which could be fitted or fixed.
- A auto-regressive penalty was added for the recruitment deviations:

$$LL = \sum_t (R_t - R_{t-1})^2$$

This has the effect of penalizing large fluctuations in the recruitment deviations on the basis that good or bad recruitment months will tend to occur next to each other. The importance of this penalty depends upon the weight it is given. For the current model, no additional weight was applied and its contribution to the overall likelihood was small.

3.6.2 Log-Likelihood for Commericial Size Composition

For each size composition, it is possible to estimate the number of seabob within it. This is the sum of seabob over the size category from smallest to largest. For example, the 90-110 count per pound size category would contain sizes varying from 5.04 (1000/(2.20462*90)) down to 4.12 (1000/(2.20462*110)) grams weight. The expected number of seabob in each size category can be obtained from the population model based on the fishing mortality for each size category, population abundance in each category and the fishing selectivity.

All commercial categories can be defined as a subset of a larger category which contains it. In the simplest case, the category contains all the catch, so no larger category is required. Therefore in this case, the "larger" category and the category are the same and the log-likelihood is simply based on the expected landings directly from the model. In this simple case, the likelihood for numbers in a particular size category would be Poisson:

$$L = \frac{\mu_a^{x_a}}{x_a!} e^{-\mu_a} \qquad 10)$$

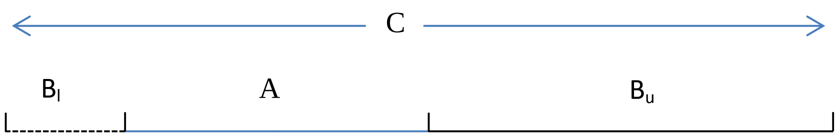
where x_a=numbers observed in the category A and μ_a=expected numbers in category A. The expected numbers can be calculated by simply summing over all sizes from the model within the category. Suitable alternatives to the Poisson can be used to account for over-dispersion and/or to simplify the calculations. Taking advantage of the situation where x_a and μ_a are very large, as in this case, the normal likelihood or log-normal could be used.

Unfortunately, this likelihood cannot be applied in this simple form unless the data are manipulated to allocate all catches to non-overlapping well-defined categories. This should be avoided if possible, since the model would not be fitted to raw data and such manipulations can introduce unknown bias in the result. Instead, it was considered preferable to develop a likelihood which captures what size information there is in the data rather than impose such information by manipulating the data.

In all cases, a significant proportion of the catch will be undifferentiated by size. Any catch allocated to a particular size range can therefore always be defined within the context of a larger size category which is complete. The known catch in the smaller category represents a minimum catch within this range, where other catches within the larger category might also be in the smaller one. The likelihood becomes the sum of likelihoods across possible allocations of catch between the two categories.

To illustrate the basic calculation, we consider categories A and B covering separate size categories (Figure 17) for each of which the statistical model can estimate the expected catch in a particular month. The category B may envelop A (B_l and B_u) or extend it only (B_l or B_u), but it should always be possible to calculate the expected catch for both A and B.

Figure 17



The data however is only available partially for A and B, and otherwise the total catch is made up in C, where C landings have been ungraded among A and B. We need to sum the likelihood over possible allocations of landings in C between A and B, so the likelihood for the joint Poisson likelihood becomes:

$$L = \sum_{x_a=X_a}^{X_c+X_a} \frac{\mu_a^{x_a} \; \mu_b^{(X_c+X_a+X_b-x_a)}}{x_a!\,(X_c+X_a+X_b-x_a)!} e^{-\mu_a-\mu_b} \qquad 11)$$

where X_a, X_b and X_c are the observed landings in A, B and C (unallocated A+B), and μ_a and μ_b are the expected catches in A and B which are estimated from the model.

This can be simplified to some extent by reformulating to create a Poisson term for the total catch in A+B and a sum of binomial terms for the proportion in category A:

$$L = e^{-\mu_a-\mu_b} \frac{(\mu_a+\mu_b)^{(X_c+X_a+X_b)}}{(X_c+X_a+X_b)!} \sum_{x_a=X_a}^{X_c+X_a} \frac{(X_c+X_a+X_b)!}{x_a!\,(X_c+X_a+X_b-x_a)!} \left(\frac{\mu_a}{(\mu_a+\mu_b)}\right)^{x_a} \left(\frac{\mu_b}{(\mu_a+\mu_b)}\right)^{X_c+X_a+X_b-x_a} \qquad 12)$$

Similarly, the likelihood for several categories within a larger category can be described using a multinomial.

For large catches it is not possible to sum over possible catches and Eq. 12 can only be simplified by closely approximating the binomial with a normal probability. The binomial term then becomes:

$$B\left(p = \frac{\mu_a}{(\mu_a+\mu_b)}, n = (X_c+X_a+X_b)\right) \approx N\left(\frac{(X_c+X_a+X_b)\mu_a}{(\mu_a+\mu_b)}, \sqrt{\frac{(X_c+X_a+X_b)\mu_a\mu_b}{(\mu_a+\mu_b)^2}}\right) \qquad 13)$$

Similarly, the total catch likelihood can be approximated with a normal density:

$$L \approx N\left((X_c+X_a+X_b); (\mu_a + \mu_b), \sqrt{(\mu_a + \mu_b)}\right) \int_{x_a=X_a}^{(X_c+X_a)} N\left(\frac{(X_c+X_a+X_b)\mu_a}{(\mu_a+\mu_b)}, \sqrt{\frac{(X_c+X_a+X_b)\mu_a\mu_b}{(\mu_a+\mu_b)^2}}\right) dx_a \qquad 14)$$

The cumulative normal can be well approximated numerically (West, 2004), so the likelihood can be calculated reasonably easily for each datum.

The binomial part of the likelihood is only informative on landings below those expected in category A. As the expected landings fall below the observed landings in category A, the log-likelihood declines. Clearly, as higher landings have been observed than those estimated, the estimated landings become less likely. Conversely, since any ungraded landings in C could be allocated to A, there is no information on higher estimated landings in A as all are equally possible. Therefore, the log-likelihood asymptotically approaches 1.0 as the expected catch increases. As the expected landings exceed the total landings observed (A+C), then the likelihood begins to decline again (Figure 18). In this case, the estimated landings in A exceed the possible observed landings in A (A+C), and the estimate becomes less likely. The result is a flat-topped likelihood, where the flat top covers the likely range of the landings within the category. Because the likelihood will include a term for the total catch as well, the likelihood should have a mode for the full model, but additional information is likely to be required to be able to estimate parameters defining stock size composition.

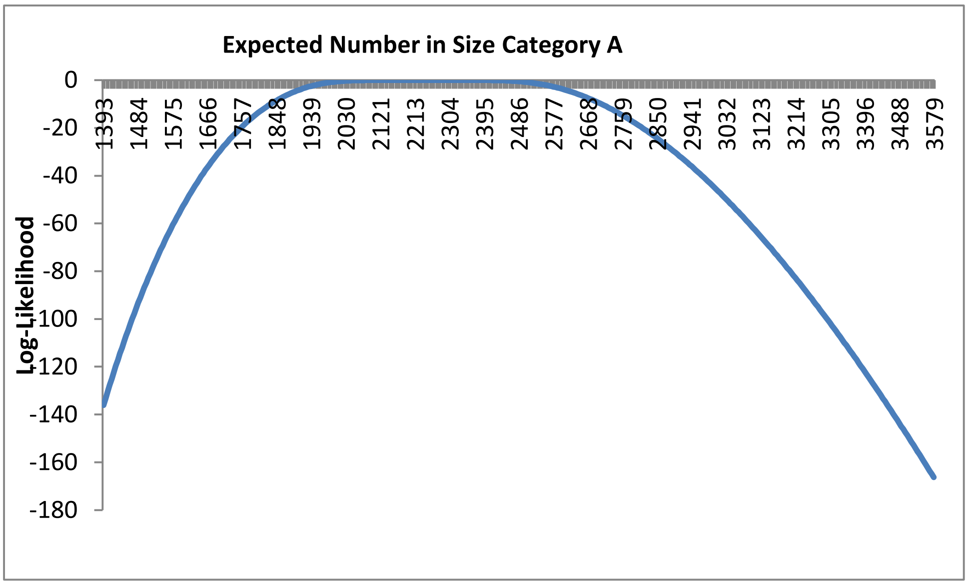


Figure 18 Example conditional log-likelihood of expected number in a category (parameter μ_a) where the observed catch in categories A and C are 2000 and 500, so 500 may or may not belong to category A.

In reality several commercial size categories may overlap (Table 14) and therefore the likelihood (Equation 14), which assumes categories are independent, with the exception of the overlap between categories A and C, is not strictly correct. Calculating the likelihood correctly over several overlapping categories would strictly require summing over all combinations of allocating non-graded catch among overlapping categories, which would become more complicated. However, because the likelihood is flat when the observed landings within a specific category is less than the expected landings, how ungraded landings are distributed is uninformative and the assumption of some independence should provide a good approximation to the likelihood as long as the total landings are also fitted.

To capture the dependency between categories, landings can be combined within categories forming hierarchical relationships. For example, category 7 has landings within categories 5 and 2 added to it, but all other categories would be excluded (Table 14). This leads to a complete set of likelihood calculations based on the category landings in each month (Table 15).

The smallest and largest category in each month would include the smallest and largest shrimp. Not all months contain all categories. So, for example, Category 1 is often not present. In these months Category 3 would be assumed to cover all larger shrimp (i.e. combines with Category 1 sizes). For smaller shrimp, the categories show less discrimination, so a category 11 is present in every month.

Table 14 Commercial size categories based on “counts per pound” to be used in the stock assessment model. Categories are numbered from 1 to 11 for identification purposes only. So, for example category one includes all larger shrimp in the 90 and below count, whereas category 4 includes counts 100-130 per pound. Category 2 would include all catches which have not been allocated to a size category, such discarded ungraded catch. Actual commercial category allocation to category ID is given in Table 3.

<table>
<tr><th>Lower Bound of Count</th><th></th><th></th><th></th><th></th></tr>
<tr><td>0</td><td>1</td><td rowspan="2" colspan="2"></td><td rowspan="9">2</td></tr>
<tr><td>90</td><td>3</td></tr>
<tr><td>100</td><td></td><td rowspan="2">4</td><td rowspan="3">5</td></tr>
<tr><td>110</td><td>6</td></tr>
<tr><td>130</td><td>7</td><td></td></tr>
<tr><td>150</td><td>8</td><td rowspan="2">9</td><td rowspan="4"></td></tr>
<tr><td>200</td><td rowspan="2">10</td></tr>
<tr><td>300</td><td rowspan="2">11</td></tr>
<tr><td>400</td><td></td></tr>
<tr><td>1000</td><td></td><td></td><td></td><td></td></tr>
</table>

Table 15 Likelihood calculations (CID) for category combinations based on allocation to category A, B and C in Equation 14 and Figure 17. Category A consists of all complete categories with well-defined boundaries, C any potentially overlapping categories and B all categories which would be excluded. The number of likelihood calculations is the same as the number of categories (11), preserving the degrees of freedom.

CID	A	B	C	Category A Count Range	Calculated
1	1-11			0-1000	For all months
2	1	3-11	2	0-90	Where 1 exists
3	3	1,4-11	2	90-100	Where 3 exists Including <90 if no larger category
4	4,6	1,7-11	2,5	100-130	Where 4 exists Including <100 if no larger category
5	6	1,3,7-11	2,4,5	110-130	Where 6 exists Including <110 if no larger category
6	4,5,6,7	1,3,8-11	2	110-150	Where 5 exists Including <110 if no larger category
7	7	1,3-4,6,8-11	2,5	130-150	Where 7 exists
8	8	1,3-7,10-11	2,9	150-200	Where 8 exists
9	8,9	1,3-7,11	2,10	150-300	Where 9 exists
10	10	1,3-8	2,9,11	200-400	Where 10 exists
11	11	1,3-9	2,10	300-1000	Where 11 exists

Table 16 Example landings in kilograms tail weight by size category in 2004.

	1	2	3	4	5	6	7	8	9	10	11
1	584	220601	6592	2756	6814	22194	44992	178989	0	544252	131274
2	0	74136	929	3290	8096	0	0	0	0	141195	18424
3	313	296615	5238	3886	9135	20865	32194	122156	0	401671	146774
4	118	293066	12072	8090	16568	43915	62272	199271	0	452643	198056
5	1385	225885	7500	0	0	23477	32994	114893	0	321880	183980
6	576	231786	3438	0	0	34619	46379	159091	0	330705	139831
7	2092	367871	14156	7193	10227	25689	54256	201972	35814	503004	141161
8	1473	186498	4163	1842	6592	7252	13222	115028	22772	252127	179220
9	324	55278	994	129	390	3465	2775	30041	0	58044	36880
10	0	7623	9	270	596	0	0	0	0	8804	6524
11	907	173842	2843	6157	7737	10645	13423	52010	0	247989	133886
12	3641	186048	6086	0	0	16600	21997	77631	0	225774	145369

4 Results

4.1 Model Configuration

The base case was determined from reviewing various configurations for the model (Table 4). This model was used to determine stock status and as the basis for carrying out MCMC simulations to estimate uncertainty.

The resulting base model estimates fishing mortality, recruitment deviations and other parameters on growth and productivity (Table 18). Stock status and fishing mortality are reported in section 1.1. There is little evidence of a strong seasonal pattern in recruitment (Figure 19).

Table 17 Deliberations of the working group to decide upon the base case and lower and upper credible bounds for the model structure.

Structure/ assumption	**Base Case**	**Justification**	**Scenarios**
Sex ratio	The sex ratio will be set at 50:50, and will not be fitted.	There is no known reason why the sex ratio of recruits will be other than 50:50. When fitted, the estimated proportion of females was 0.43. Improvements to the fit were not large, so this parameter was fixed at 0.5.	Estimated proportion female in the recruits
Recruitment Variation	σ_R=0.5	Results were insensitive to reasonable values for the recruitment variation parameter (σ_R). The parameter could not be fitted without a strong penalty function. 0.5 was chosen as a reasonable fixed value, although variation in estimated recruitment deviations suggested a higher figure. Higher values for this parameter (σ_R=>1.0) could not be fitted.	σ_R=0.2, 0.5, 0.8

Structure/ assumption	Base Case	Justification	Scenarios
Recruitment Seasonality	No explicitly seasonality was added to the recruitment model.	Although there may be seasonality in recruitment, it is uncertain what shape function should be used or how many recruitments there are each year. The recruitment deviations should show up any seasonal pattern which can be investigated at a later date.	None
M	M=0.183	Estimates from longevity reported in scientific literature depend on growth estimates. In general, they imply low natural mortality which is not consistent with the catch data (i.e. poor fit if M<0.1 month^{-1}). Estimates in the model are too high to be credible (M>0.6 month^{-1}). Available direct estimates of natural mortality suggest 0.1-0.2 month^{-1}. Estimates from Soomai *et al*. (2012) were used.	M=0.1, 0.2, 0.3, estimated
K, t0	Females: K=0.216; t0=0 Males: K=0.246; t0=0	K cannot be fitted. The estimate from the fit (K>0.6 month^{-1}) is too large to be biologically realistic. Indications suggest males grow faster than females. All published estimates found are less than 0.3 month^{-1}. Higher estimates fitted the data better. Ribeiro De Campos, et al. (2011) were used as the higher estimates available.	K=0.08, 0.15, 0.2, 0.3, 0.22/0.25
SSB survival after 12 months	No extra mortality after 12 months.	It was considered possible that survival after 12 months or after spawning could be low. There is no evidence in the data for this, however, so a standard plus-group for 12 month olds is applied.	None
SSB delay before spawning	Use 2 month delay, as opposed to 1 month	There is a very small improvement in log-likelihood for 2 months as opposed to 1 or 3, so for the current model it makes very little difference. 4-8 week larval stage would seem reasonable for this species.	Delays of 1, 2, 3, 4
Domed selectivity	A logistic curve was used.	The “domed shaped” selectivity will make the perception of the stock much more positive. There is no evidence that a domed-shaped selectivity is appropriate, although it does fit the data better. The logistic should be more precautionary.	Estimated domed parameter
$S_{50\%}$ Sex selectivity	The same selectivity curve was used for both male and female.	There was no significant difference in selectivity between males and females when selectivity was based on length.	Estimated separate $S_{50\%}$ by sex
S_{tp} selectivity steepness	This was fixed to the boundary value (25).	The estimate consistently moved to the boundary, indicating essentially “knife edge” selectivity. Fixing the parameter would avoid additional problems with the MCMC	Estimated

Structure/ assumption	Base Case	Justification	Scenarios
SR Steepness (h)	h=0.8	Estimated steepness very low (h=0.314), but gave the worst case for stock status. There is no evidence of a stock recruit relationship (possible obscured by seasonality). It was concluded that steepness cannot be estimated and the default h=0.8 was considered relatively precautionary for this stock.	h=0.9, 0.8, 0.7, 0.6, Estimated

Table 18 Parameter estimates from base case model for all fitted parameters apart from the monthly fishing mortality and recruitment deviations.

Parameter	Estimate	Standard Deviation	Reference
W_∞ Females	3.87	3.55E-03	Females: Equation 4
W_∞ Males	2.41	1.67E-03	Males: Equation 4
Growth σ	0.24	2.17E-04	Equation 6
Ln(q)	-16.14	3.43E-03	Log Catchability: Equation 9
S50%	12.34	1.37E-03	Equation
Ln(R0)	21.14	3.04E-03	Equation 7

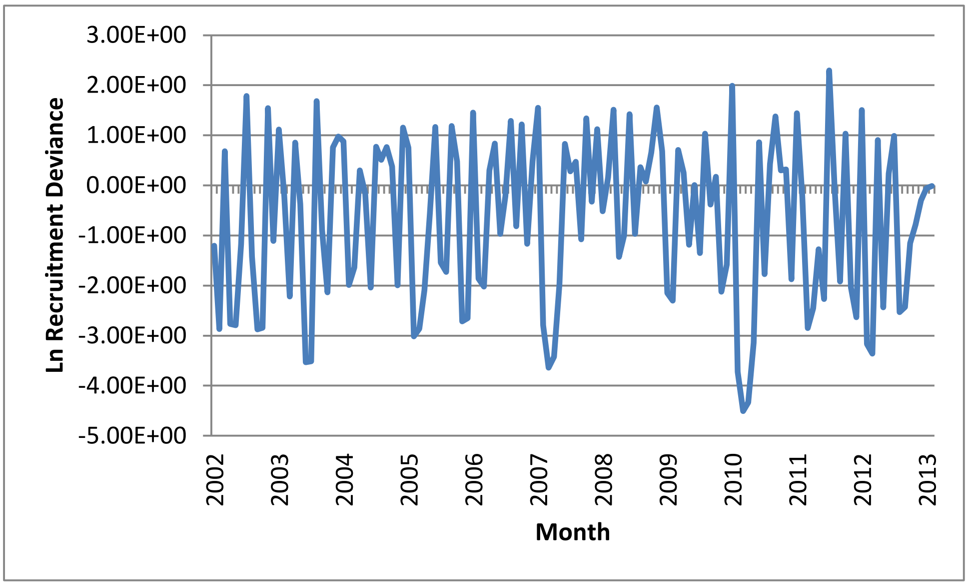


Figure 19 Logarithm of the recruitment deviations from the stock recruitment relationship (Equation 7) fitted in the model base case.

4.2 Diagnostics

Diagnostics were primarily based on plotting standardised residuals. Observed-predicted, predicted-residual, time-residual and, where appropriate, weight bin-residual plots were examined. With some notable exceptions, the model fitted the data well and there were no unacceptable violations of model assumptions. It is not considered likely that there will be any change in the stock status estimate when the problems identified (outlined below) have been addressed.

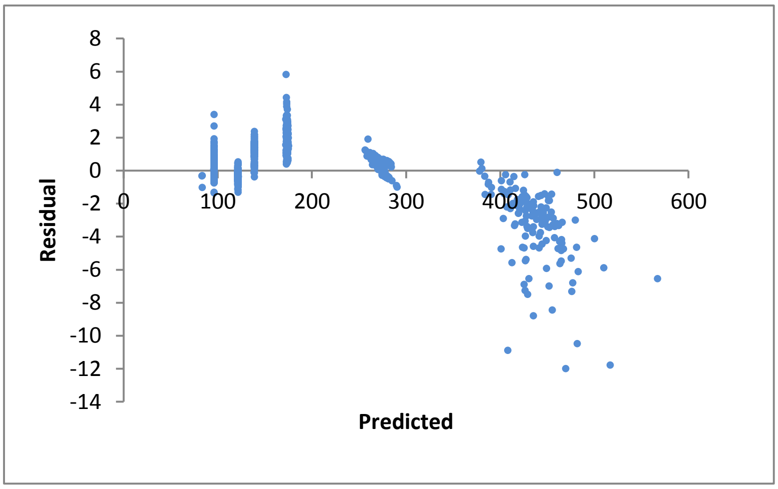
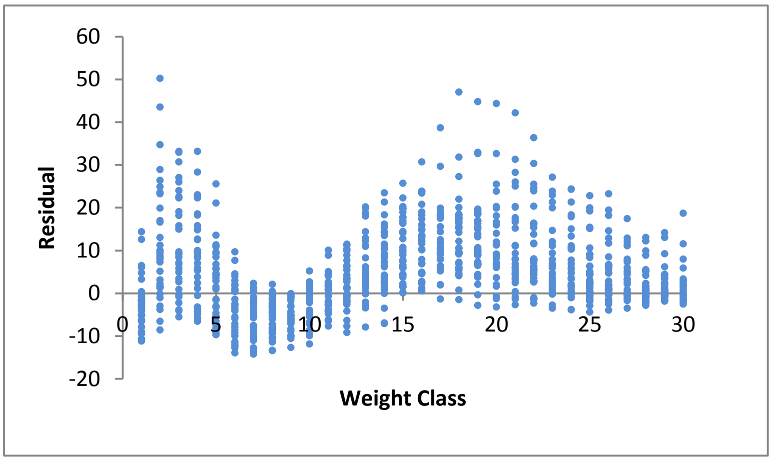


Figure 20 Standardised residuals plotted against predicted values for the average count data.

There were small departures between the observed and expected average counts for the commercial size categories, particularly for the smallest category (Figure 20). In general, the lowest count categories indicated that the predicted count was higher than the observed. Conversely, for the higher count categories the predicted count was lower. This might suggest that the size categories need to be adjusted. However, while this adjustment should be explored, it should also be verified that the higher counts than expected in the smallest size categories are not just due to the increased presence of broken tails. It should also be noted that adjusting the size categories is not a trivial exercise, since it involves altering the data preparation as well. If the smallest commercial size category includes a high proportion of pieces in the count, this category should be removed from this data component.

The other major issue with the model was identified for the random size sampling standard residual plot against weight bin (Figure 21). A clear pattern emerged suggesting that the selectivity model used is flawed. In both males and females, there were fewer shrimp than expected in the catches in the bin range 4-10 (0.8-2.0g peeled tail weight). In addition, males lack a peak of smallest individuals very evident in females and overall the male residual plot appears shifted to the left (Figure 21). One obvious reason for this is that selectivity may also depend on age, which might help explain the difference between males and females since they exhibit different growth. It may also be due to misunderstood life history patterns, since the basic biology of the species is not well understood. It is also possible bias may occur through misallocation between males and females particularly in the youngest categories. Although this last explanation seems unlikely to explain the observed patterns, it does need to be verified. Completion of the Suriname assessment, with its different fishery characteristics, would help understand how these different factors might be affecting size composition.



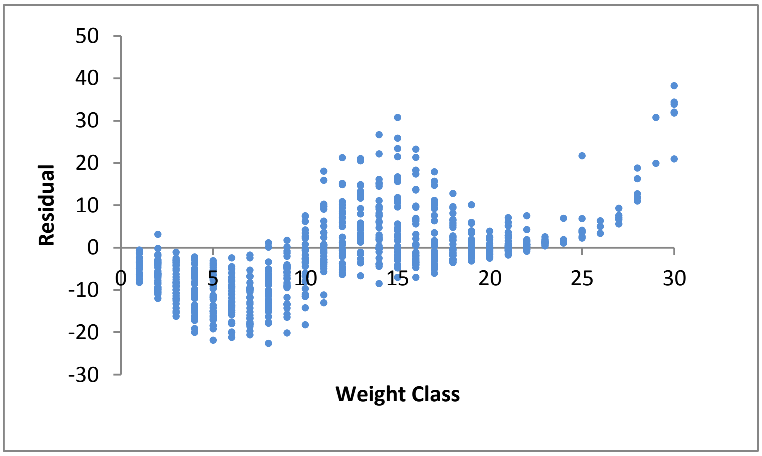


Figure 21 Female (top) and male (bottom) plot of residuals by weight class.

5 Conclusion

The model may be improved, but such improvements are not likely to lead to a dramatic change in the perception of stock status. It appears most likely improvements in the model would come from adjusting the selectivity model and improving the interpretation of the size categories.

Notwithstanding these improvements, the assessment model can be used for scientific advice at this stage of development, conditional on further model development and evaluation. It provides a useful assessment of the history of the fishery, an improved understanding of the impact of the fishery on the population, and a sound basis for developing a harvest control rule.

5.1 Further Work

The following tasks were identified as requiring attention in 2013/14:

- Complete the Suriname stock assessment for comparison.
- Examine average counts of the smallest shrimp to see what proportion are pieces as opposed to whole shrimp.
- Adjust commercial category definitions in the assessment model to improve residual patterns.

- Explore alternative selectivities and life history patterns that might explain the size composition in the landings better.
- Explore increasing the recruitment random walk penalty to examine any recruitment patterns that may emerge.
- The commercial category likelihood is not strictly correct in that it does not take account of allocation of category C landings to categories other than A. So the likelihood only accounts for partial, pair-wise dependency. Further development of the likelihood to account for more category combinations should be considered.

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