Estimation of a non-linear parameter when relating CPUE to abundance in an orange roughy fishery

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1 Introduction

Catch per unit effort (CPUE) is commonly used as an index of abundance in stock assessments, usually by assuming direct proportionality between the two. CPUE can simply be the catch divided by a common measurement of effort, or more rigorous statistical techniques may be used (Vignaux, 1994). The proportionality constant, typically noted as q, is also called the catchability coefficient. Let U be CPUE and N be abundance, thus in mathematical notation,

$$U = qN \tag{1}$$

Proprotionality between CPUE and abundance is a simple assumption and Hilborn and Walters (1992) warn "those who use it are running severe risks". They describe three relationships between CPUE and abundance: proportionality, hyperstability, and hyperdepletion. Proportionality was described above and is shown in equation 1. Hyperstability occurs when the CPUE declines at a slower rate than abundance, thus making it difficult to detect depletion when using only CPUE. Hyperdepletion is where CPUE declines more rapidly than the abundance, which can result in an unduly pessimistic view of the stock. Figure 1 shows the three relationships described by Hilborn and Walters (1992).

Little work has been to done to determine if proportionality is a valid assumption for the relationship between CPUE and abundance. Dunn *et al.* (2000) reviewed studies that have addressed this question and have found that there is little support for the proportionality assumption. Harley *et al.* (2001) compiled CPUE and independent abundance data from the International Council for the Exploration of the Sea (ICES) and performed a meta-analysis to test the hypothesis that CPUE is proportional to abundance. They found evidence supporting hyperstability, but hyperdepletion could not be ruled out and was most evident in hake.

Recently, Hicks (2004a) presented results to the New Zealand deepwater working group indicating hyperdepletion was present in CPUE time series calculated from orange roughy stocks in Australia and New Zealand. These results were based on comparisons between CPUE and fishery independent biomass indices such as trawl surveys, acoustic surveys, or stock assessment outputs that did not use fishery dependent indices as input. Hicks (2004a) used a simple monotonic relationship to test for hyperdepletion,

$$U = \alpha N^{\beta}, \tag{2}$$

where U and N are CPUE and abundance, respectively, while α and β are estimated parameters. When the value of β is less than 1, hyperstability is present; when β is greater than 1, hyperdepletion is present; and when β equals 1, equation 2 reduces to equation 1, indicating a proportional relationship. The catchability coefficient, q, is not used in equation 2 because catchability is now a function of the parameters α and β, as well as abundance.

Hyperdepletion may be present in orange roughy populations for a number of reasons. For example, fishing activity may disrupt the schooling behaviour of orange roughy, making them more difficult to catch. Acoustic surveys in Namibia have recorded a steep decline in abundance while fishing was present only to show a quick rebound after a few years of no fishing (Doug Butterworth, pers. comm.). Fishermen may fish known localized aggregations until a threshold catch rate is reached, and then start exploring for other localized aggregations.

Hicks (2004b) developed a prior distribution for the hyperdepletion parameter β for use in orange roughy stock assessments from the meta-analysis results reported by Hicks (2004a). The prior is shown in Figure 2 in log space as estimated in Coleraine and normal space as estimated in CASAL (although CASAL estimates the parameter $1/\beta$ (see Sections 2.1 and 4.1)).

Estimating a hyperdepletion parameter is a new idea for orange roughy assessments, thus stocks with runs having β estimated, also have a run with proportionality assumed between CPUE and abundance (Annala *et al.*, 2004). There is also the question that estimating β in the stock assessment may not be possible resulting in spurious results. Therefore, simulations are presented here that study the ability of the current orange roughy stock assessment models to estimate a hyperdepletion parameter for CPUE and the biases associated with not incorporating non-linear CPUE trends in populations that do show hyperdepletion. Simulations were done using Coleraine, where Coleraine was both the operating and estimation model. Some simulations were done with CASAL as the operating and estimation model to determine if there are any differences in the way CASAL estimates β. A separate operating model is being developed that will be used to simulate data for estimation with both Coleraine and CASAL, but it has not been implemented.

2 Stock assessment models and software

Two software packages are currently being used in New Zealand to estimate the parameters of orange roughy stocks. These are CASAL (Bull et al. 2004) and and a modified version of Coleraine (Hilborn et al 2000). They both have the ability to estimate a hyperdepletion parameter, but do so in different ways. Each software package is described next.

2.1 CASAL

CASAL is an all purpose stock assessment package that can be easily modified to suit most stock assessment needs. Bull *et al.* (2004) describe the model and software in detail. The estimation of curvature in the CPUE series is with a parameter called b, which is the inverse of β.

$$U = aN^{1/b}, \tag{3}$$

Therefore, the lognormal prior described above and shown in Figure 2 was recalculated to correspond to b. The parameter a is not calculated analytically in CASAL when a curvature parameter is estimated, thus is a freely estimated parameter.

2.2 Coleraine

Coleraine (Hilborn *et al.*, 2003) is also a stock assessment software package based on the auto-differentiation minimizer AD Model Builder (Otter Research). The freely distributed version of Coleraine was modified so that curvature in the CPUE series could be estimated. The log of β is estimated, thus a normal prior is used (top of Figure 2). The α parameter is calculated analytically from the likelihood within the model when finding MPD estimates.

3 Operating Models

Coleraine was used as the operating model when estimating β with Coleraine, and CASAL was used as an operating model when estimating β with CASAL. The "true" or simulated population was parameterised as similar as possible for the two operating models, but slight differences in the model implementations between the two software packages resulted in slightly different "true" populations.

The simulated population is a rough representation of the Mid-East Coast (MEC) orange roughy stock as was estimated in 2004 (Annala *et al.*, 2004). It uses deterministic recruitment and the parameters for the "true" population are given in Table 1. The data sources assumed to exist for this simulated population are similar to the MEC assessment and consist of a CPUE series with 19 observations, absolute abundance acoustic surveys in 2001 and 2003, and trawl surveys in 1992, 1993, and 1994. The egg surveys and the trawl survey length at age data were not used.

The maturity and selectivity ogives different in the operating model of Coleraine and maturity was set equal to the selectivity curve in the estimation model. CASAL set the maturity curve equal to the selectivity curve in both the operating and estimation models. The different ogives in the Coleraine runs were done because the effects of setting maturity equal to selectivity were to be investigated. However, that analysis is not complete and the biases introduced in the Coleraine runs are unknown.

The catches and the simulated biomasses are shown in Table 2. Biomass index observations were simulated using the true biomass, selectivity, catchability, and the CV's in Table 2. Different values of β were used and α was 1.5×10^{-8} in Coleraine runs and 1.0 in CASAL runs (Table 1).

3.1 Simulation Design

Coleraine was used for most simulations and a subset of those simulations were done in CASAL as a comparison. Table 3 shows the runs that were done with which data sources. Different values of β were used to see the effect of the estimates to departures from the prior belief of hyperdepletion.

There are basically three sets of simulations. The first set consists of runs with CPUE only and looks at how the prior affects the estimate of β when using no additional data. Additional simulations were done to determine how the cv on CPUE affects the estimate of β. The second set incorporates CPUE and a relative time series of abundance. The last set studies the effect that adding two years of absolute estimates has on the estimate of β. Two assumptions are studied for the relative time series: one mimics the MEC data with three values from 1992–1994, and the second spreads out the values by three year gaps to occur in 1990, 1993, and 1996. All of these sets use three values of β: 0.625, 1.0, and 1.6.

4 Simulations and Results

The results are divided into sections for each model and subdivided into the three sets of simulations according to the data used, as discussed above. Summary statistics for $\hat{\beta}$ and $\%\hat{B}_0$ are shown in Table 4. MSE is also reported and is split into its compnents of Bias and Variance.

4.1 Coleraine estimates

One thousand simulations with Coleraine were performed where data was simulated and then parameters estimated. Simulations with a maximum gradient greater than 1×10^{-6} were excluded because of possible non-convergence.

4.1.1 CPUE data only

The first set of simulations uses CPUE data only and addresses the effect of the prior on the estimate of β. Three simulations were done using a prior and with β equal to 1.6, 1, and 0.625. The prior has a large effect on the estimates of β and as β decreases, the median of the estimated β's comes closer to the median of the prior distribution (Figure 3). When the prior is removed, the estimates are variable, but are centered closer tho their respective true values (Figure 5). A second mode at large values of β can be seen with smaller true betas. These results did show proper convergence, but their behaviour was not studied further.

Further simulations were done to determine if the data could overcome the influence prior by lowering the cv associated with CPUE. Three cv's, constant for all CPUE data points, were tested: 0.3, 0.2, and 0.1. The influence of the prior and the variability in the estimate of β is reduced with smaller cv's, as expected (Figures **??** and Table 5). When a prior on β is not used, the variability in the estimate of β is reduced considerably with smaller cv's.

The MSE for these simulations is larger when not using a prior and when the cv is larger (Table 5). The Bias and Variance show the same pattern. However, the MSE increases with smaller values of β, regardless of whether or not a prior is used. This increase is a result of Bias becuase the Variance decreases with smaller values of β (Table 5).

It is common in current orange roughy stock assessments to perform a run where β is fixed at 1. A simulation was done with β fixed at 1 when the true value of β was 1.6. Figure 6 shows that the estimated beginning of the year spawning biomasses are biased low leading to the conclusion that the stock is more a depleted stock than in actuality. The mean $\%\hat{B}_0$ was nearly one-half the true $\%B_0$.

The MSE for the derived biomass parameters virgin spawning biomass (B_0), the final spawning biomass (B_{2004}), and percentage of final spawning biomass when compared to virgin spawning biomass ($\%B_0$) is shown in Table 6 for the runs C.B16, C.B16noP, and C.B16.Beta1. MSE is smallest for the derived parameter $\%B_0$. Also, MSE is similar for the runs where β is assumed equal to 1 and a prior is used to estimate β. However, the prior median is similar to the ture β, thus the estimate is not far off. These results will be different with different true values of β. Nevertheless, the variability in the derived parameters is quite a bit larger when estimating β, due to the additional estimation error. The bias can be interpreted in two ways: 1) the difference between the mean of the estimates and the true value, or 2) the difference between the median of the estimates and the true value. When looking at the median, the bias is much less when estimating β and assuming β equals 1 in a hyperdepletion scenario results in a pessimistic view of the stock.

4.1.2 CPUE and relative abundance data

Relative abundances are common in orange roughy fisheries in the form of trawl surveys, especially during the 1980's and early 1990's. The MEC stock has had three trawl surveys between 1992 and 1994, which were simulated here. To also test if spacing abundance estimates further apart has an effect on the estimates of β, the years for the three surveys were changed to 1990, 1993, and 1996. More than three years of surveys was not tested.

Figure 7 shows the estimates of β with a prior. The pattern is very similar to the CPUE only with a prior, suggesting that the relative surveys did not help to pin down the estimates when the true value was very different than the prior. Spreading the trawl surveys out to have three year gaps had a small effect of pulling the estimate closer to the true value, but a large bias was still present (Figure 8 and Table 7). When removing the prior on β, the estimates had a median value near the true value, but were highly variable (Figure 9. Some brief simulations, not reported in detail here, showed that smaller cv's helped reduce the bias and variability in the estimate of β. More surveys with similar high cv's did not improve the performance remarkably.

4.1.3 CPUE and absolute abundance data

Adding absolute abundances to the model in 2001 and 2003 greatly improved the ability to accurately estimate β (Figure 11 and Table 7). The two absolute biomasses, even with relatively large cv's pulled the estimated β's from the prior closer to their true values. The farther the true β was from the median of the prior, the more biased the estimate was (although much less biased than without the absolute data), which is expected in a Bayesian analysis.

4.2 CASAL estimates

Five-hundred simulations of the runs with only CPUE were performed using CASAL. No simulations were checked for proper convergence, although often there were convergence difficulties. The estimation of β is different in CASAL, thus the parameter a in equation 3 was given a true value of 1×10^{-3}. Also, in roughy assessments done with CASAL, this parameter is estimated with a log-uniform prior. Therefore, the parameter b was also given a log-uniform prior in the "no prior" runs.

4.2.1 CPUE data only

The simulations performed by CASAL produced different results from the Coleraine simulations reported above (Table 8) in the following ways.

First, when true β was equal to 1, CASAL rarely moved away from the starting value of 1 while still reporting decent convergence. No simulations were done with different starting values for $\hat{\beta}$ and the runs with $\beta = 1$ should be interpreted with caution.

For the run using a prior and where the true β was 1.6 and the cv was equal to 10% (C.B16.cv10), the estimates of β were more variable and more biased (Figure ?? and Table 8).

The "no prior" runs were slightly different than the "no prior" Coleraine runs because a log-uniform prior was used, as is typically used when estimating the parameter q. The runs with $\beta = 0.625$ showed a larger bias than the Coleraine runs at all cv values. Also, the variability and bias in runs with $beta = 1.6$ were much larger when using CASAL (Figure **??** and Table 8).

5 Discussion

These simulations give some insight into the ability to estimate a non-linear parameter for relating CPUE to abundance. One of the key findings is that without data to accurately estimate the biomass, the prior tends to have a lot of pull on the estimated β. Priors do influence the estimated parameters, but the amount of influence they have is a concern when the data going into the model is overpowered by the prior. This seems to be the case when CPUE and/or relative surveys are fit to in the model under these simulation assumptions. Simulations without the prior were less biased, but the variability in the estimates of β were larger.

The cv of the CPUE series is related to the ability of the data to pull the estimate of β away from the prior. However, cv's much lower than expected from orange roughy catch and effort data are needed to obtain reasonable estimates of β without additional abundance data.

The addition of an absolute abundance estimate reduced the bias in the estimated β significantly. Absolute abundance estimates for orange roughy are costly and controversial because of a large number of assumptions. However, even the large cv's in these simulations were able to estimate β with quite good precision. It isn't necessarily the fact that the abundance estimate is absolute, but instead it is that the catchability is not estimated. Test simulations (also not reported here) where the catchability for the relative abundance time series was fixed at its true value also significantly improved the estimates of β.

One simulation was done that explored the effect of assuming a linear relationship between CPUE and abundance when hyperdepletion is actually present. The biomass estimates were biased considerably low and the stock status was nearly half of the true value. However, the MSE was greater when estimating β because of the additional estimation error. MSE incorporates the bias calculated from the mean, and with skewed distributions, as were the estimated biomasses, the median may be a better measure of central tendency. The bias calculated as the difference between the median value and the true value was much less for runs where β was estimated.

There is a trade-off between variance and bias when deciding whether or not to estimate β. One has to decide if it is more important to sacrifice precision to gain a more accurate view of the stock, or if a precise, although inaccurate and possibly conservative view (at least in the case of hyperdepletion) is desired. Misinterpreting the CPUE in orange roughy fisheries has huge effects on the management of the fisheries and on the world view of how New Zealand manages their fisheries. The biological, social, and economic risks associated with the trade-off between bias and variability should be contemplated when deciding on the usefulness of including a parameter to account for non-linearity in the relationship between CPUE and abundance.

References

Annala JH, Sullivan KJ, Smith NWM, Griffiths MH, Todd PR, Mace PM, Connell AM, (Comps). 2004. Report from the Fishery Assessment Plenary, April 2004: stock assessments and yield estimates. 690 pp. (Unpublished report held in NIWA library, Wellington.).

Bull B, Francis RICC, Dunn A, McKenzie A, Gilbert D, Smith MH. 2004. CASAL (C++ slgorithmic stock assessment laboratory): CASAL User Manual v2.06-2004/09/26. NIWA Technical Report 126. 261 pp.

Dunn A, Harley SJ, Doonan IJ, Bull B. 2000. Calculation and interpretation of catch-per-unit effort (CPUE) indices. New Zealand Fisheries Assessment Report 2000/01. 44 pp.

Harley SJ, Myers RA, Dunn A. 2001. Is catch-per-unit-effort proportional to abundance. Can J Fish Aquat Sci 58:1760–1772.

Hicks AC. 2004a. A meta-analysis of CPUE in orange roughy fisheries. WG Deepwater 04/10. (Unpublished report held by Ministry of Fisheries, Wellington).

Hicks AC. 2004b. A meta-analysis of CPUE in orange roughy fisheries: creating a prior. WG Deepwater 04/20. (Unpublished report held by Ministry of Fisheries, Wellington).

Hilborn R, Maunder M, Parma A, ERnst B, payne J, Starr P. 2003. Coleraine. A generalized age structure stock assessment model. Unpublished report from university of washington school of aquatic and fishery sciences. 58 pp.

Hilborn R, Walters CJ. 1992. Quantitative fisheries stock assessment: choice, dynamics, and uncertainty. Chapman and Hall, New York, 570 pp.

Vignaux M. 1994. Catch per unit effort (CPUE) analysis of west coast South Island and Cook Strait spawning hoki fisheries, 1987–93. New Zealand Fisheries Assessment Report Document 94/11. 29 pp.

Table 1: Parameters for the simulated population.

Parameter	Value
steepness	0.75
natural mortality	0.045
Commercial a50	40
Commercial aTo95	12
α CPUE	1.5^{-8}
β CPUE	1.6, 1, 0.625
q Trawl surveys	0.03
Trawl Survey a50	12
Trawl Survey aTo95	2
TZ maturity a50	31.31
TZ maturity aTo95	7.07
Intercept L-W	0.0921
Slope L-W	2.71
L_∞	37.19
k	0.065
t_0	-0.5

Table 2: Catches and observations for the simulated population. The spawning biomasses are given for the two operating models. Biomasses are start of the year biomasses. The CPUE and survey observations are used to simulate from.

Year	Catch	Coleraine Spawning Biomass	CASAL Spawning Biomass	CV CPUE	CV Trawl Survey	CV Absolute Survey
1982	700	101 635	101 655			
1983	4 000	101 045	101 063			
1984	9 000	97 686	97 699	0.2772		
1985	10 000	90 212	90 211	0.2900		
1986	10 000	82 133	82 117	0.3048		
1987	10 000	74 329	74 295	0.3048		
1988	12 000	66 813	66 761	0.2966		
1989	11 000	57 993	57 918			
1990	12 000	50 369	50 270	0.2664		
1991	11 000	42 372	42 245	0.2593		
1992	11 000	35 602	35 448	0.2561	0.34	
1993	9 500	29 306	29 126	0.2599	0.25	
1994	7 000	24 544	24 343	0.2631	0.27	
1995	6 000	21 804	21 585	0.2671		
1996	1 900	19 928	19 694	0.2871		
1997	2 200	20 563	20 318	0.2944		
1998	2 300	21 101	20 845	0.2828		
1999	2 300	21 644	21 376	0.2738		
2000	2 600	22 236	21 957	0.2779		
2001	1 800	22 698	22 408	0.2828		0.38
2002	1 500	23 638	23 336	0.3202		
2003	900	24 777	24 465	0.3400		0.76
2004		26 288	25 965			

Table 3: Description of the runs. ‘C’ refers to CPUE, ‘A’ to Absolute survey, and ‘T’ to a relative survey. ‘B’ followed by a number represents the true value of β (1.6, 1, or 0.625). ‘S2M’ means the commercial selectivity was set equal to the maturity curve estimated from the transition zone. ‘noP’ indicates that a prior was not used in the estimation of β. Additional runs were done with a fixed cv for all years and are suffixed by ”.cv” and the value of the cv (i.e., C.B16.cv30).

	C.B16	C.B16noP	C.B1	C.B1noP	C.B625	C.B625noP	C.B16.Beta1
Sel/Mat	Mat2Sel	Mat2Sel	Mat2Sel	Mat2Sel	Mat2Sel	Mat2Sel	Mat2Sel
True Beta	1.6	1.6	1	1	0.625	0.625	1.6
Model Beta	Estimated	Estimated	Estimated	Estimated	Estimated	Estimated	1.0
CPUE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Absolute	No	No	No	No	No	No	No
Relative	No	No	No	No	No	No	No

	CA.B16	CA.B1	CA.B625	CT.B16	CT.B1	CT.B625
Sel/Mat	Mat2Sel	Mat2Sel	Mat2Sel	Mat2Sel	Mat2Sel	Mat2Sel
True Beta	1.6	1	0.625	1.6	1	0.625
Model Beta	Estimated	Estimated	Estimated	Estimated	Estimated	Estimated
CPUE	Yes	Yes	Yes	Yes	Yes	Yes
Absolute	Yes	Yes	Yes	No	No	No
Relative	No	No	No	1992–1994	1992–1994	1992–1994

	CT3.B16	CT3.B1	CT3.B625	CT.B16noPrior	CT.B1noPrior	CT.B625noPrior
Sel/Mat	Mat2Sel	Mat2Sel	Mat2Sel	Mat2Sel	Mat2Sel	Mat2Sel
True Beta	1.6	0.1	0.625	1.6	1	0.625
Model Beta	Estimated	Estimated	Estimated	Estimated	Estimated	Estimated
CPUE	Yes	Yes	Yes	Yes	Yes	Yes
Absolute	No	No	No	No	No	No
Relative	1992–1994	1992–1994	1992–1994	1992–1994	1992–1994	1992–1994

Table 4: Summary of the estimated β and stock status ($\%B_0$) for each run.

Run	True β	mean($\hat{\beta}$)	median($\hat{\beta}$)	sd($\hat{\beta}$)	$\hat{\beta}_{0.025}$	$\hat{\beta}_{0.975}$
C.B16	1.6	1.87	1.79	0.67	0.94	3.35
C.B16noP	1.6	2.61	1.49	3.43	0.88	17.19
C.B1	1.0	1.71	1.67	0.53	0.81	2.80
C.B1noP	1.0	2.67	1.04	3.50	0.50	12.38
C.B625	0.625	1.86	1.90	0.33	1.08	2.45
C.B625noP	0.625	2.42	0.76	2.83	0.29	8.77
C.B16.Beta1	1.6	NA	NA	NA	NA	NA
CA.B16	1.6	1.66	1.62	0.30	1.15	2.36
CA.B1	1.0	1.09	1.08	0.22	0.73	1.58
CA.B625	0.625	0.74	0.72	0.17	0.47	1.13
CT.B16	1.6	1.82	1.71	0.66	0.94	3.33
CT.B1	1.0	1.72	1.69	0.52	0.82	2.78
CT.B625	0.625	1.85	1.87	0.34	1.04	2.46
CT3.B16	1.6	1.78	1.68	0.64	1.70	3.24
CT3.B1	1.0	1.70	1.67	0.57	0.74	2.87
CT3.B625	0.625	1.78	1.82	0.38	0.92	2.47
CT.B16noPrior	1.6	2.47	1.48	3.29	0.85	16.96
CT.B1noPrior	1.0	2.72	1.09	3.52	0.51	12.26
CT.B625noPrior	0.625	2.24	0.72	2.73	0.28	8.40

Run	True $\%B_0$	mean($\%\hat{B}_0$)	median($\%\hat{B}_0$)	sd($\%\hat{B}_0$)	$\%\hat{B}_{0\,0.025}$	$\%\hat{B}_{0\,0.975}$
C.B16	25.87	28.9	28.7	11.2	11.7	50.8
C.B16noP	25.87	28.7	21.2	19.8	11.7	87.2
C.B1	25.87	41.6	42.6	11.35	18.6	60.3
C.B1noP	25.87	35.2	23.9	25.9	11.7	87.2
C.B625	25.87	60.5	62.2	9.3	36.7	73.9
C.B625noP	25.87	40.2	30.5	25.8	11.7	87.2
C.B16.Beta1	25.87	13.4	13.1	1.5	11.7	17.0
CA.B16	25.87	26.8	26.6	5.1	17.1	37.6
CA.B1	25.87	27.9	27.5	5.2	18.9	38.5
CA.B625	25.87	28.7	28.6	5.7	18.4	40.2
CT.B16	25.87	28.2	27.9	11.2	11.7	50.7
CT.B1	25.87	41.9	43.2	11.4	18.3	60.2
CT.B625	25.87	60.1	61.6	9.4	36.2	75.0
CT3.B16	25.87	28.0	27.3	10.9	11.7	49.3
CT3.B1	25.87	41.1	42.4	12.2	16.5	61.1
CT3.B625	25.87	58.5	60.2	10.1	32.8	73.9
CT.B16noPrior	25.87	28.4	21.9	19.5	11.7	87.2
CT.B1noPrior	25.87	36.8	25.7	27.0	11.7	87.2
CT.B625noPrior	25.87	39.8	26.0	30.2	11.7	87.2

Table 5: MSE, Bias, and Variance for the CPUE only runs. "•" in the name of the run refers to the corresponding true β value in the column.

MSE

Run	$\beta = 1.6$	$\beta = 1.0$	$\beta = 0.625$
C.B•	0.134	0.339	1.195
C.B•noP	0.532	0.967	1.469
C.B•.cv30	0.129	0.381	1.213
C.B•.cv20	0.117	0.291	1.047
C.B•.cv10	0.058	0.129	0.520
C.B•noP.cv30	0.532	1.217	1.902
C.B•noP.cv20	0.259	0.727	1.317
C.B•noP.cv10	0.071	0.177	0.495

Variance

Run	$\beta = 1.6$	$\beta = 1.0$	$\beta = 0.625$
C.B•	0.126	0.103	0.041
C.B•noP	0.517	0.961	1.386
C.B•.cv30	0.123	0.088	0.034
C.B•.cv20	0.113	0.131	0.079
C.B•.cv10	0.058	0.104	0.177
C.B•noP.cv30	0.523	1.054	1.499
C.B•noP.cv20	0.259	0.660	1.125
C.B•noP.cv10	0.070	0.175	0.466

Bias

Run	$\beta = 1.6$	$\beta = 1.0$	$\beta = 0.625$
C.B•	0.092	0.486	1.074
C.B•noP	0.124	-0.074	-0.289
C.B•.cv30	0.077	0.541	1.086
C.B•.cv20	0.064	0.399	0.984
C.B•.cv10	0.005	0.156	0.586
C.B•noP.cv30	0.095	0.403	0.635
C.B•noP.cv20	0.004	0.259	0.438
C.B•noP.cv10	-0.018	0.042	0.170

Table 6: MSE, Bias, and Variance of the estimates of virgin spawning biomass (B_0), the final spawning biomass (B_{2004}), and percentage of final spawning biomass when compared to virgin spawning biomass ($\%B_0$) for the runs C.B16, C.B16noP, and C.B16.Beta1. "Bias from mean" refers to the bias calculated using the mean of the estimates, and "Bias from median" refers to the bias calculated using the median of the estimates.

MSE

Run	B_0	B_{2004}	$\%B_0$
C.B16.Beta1	354.93	230.72	156.67
C.B16	507.20	440.86	134.71
C.B16.noP	12477.68	12200.73	427.12

Variance

Run	B_0	B_{2004}	$\%B_0$
C.B16.Beta1	5.29	2.62	2.37
C.B16	440.34	372.64	122.44
C.B16.noP	11492.79	11164.59	408.70

Bias from mean

Run	B_0	B_{2004}	$\%B_0$
C.B16.Beta1	-18.70	-15.10	-12.42
C.B16	8.18	8.26	3.50
C.B16.noP	31.38	32.19	4.29

Bias from median

Run	B_0	B_{2004}	$\%B_0$
C.B16.Beta1	-19.14	-15.45	-12.73
C.B16	5.54	5.03	3.36
C.B16.noP	-3.43	-3.04	-2.19

Table 7: MSE, Bias, and Variance for the runs with survey data. "•" in the name of the run refers to the corresponding true β value in the column.

MSE

Run	$\beta = 1.6$	$\beta = 1.0$	$\beta = 0.625$
CT.B•	0.130	0.344	1.173
CT.B•noPrior	0.478	1.145	1.651
CT3.B•	0.122	0.347	1.104
CA.B•	0.032	0.043	0.069

Variance

Run	$\beta = 1.6$	$\beta = 1.0$	$\beta = 0.625$
CT.B•	0.126	0.101	0.043
CT.B•noPrior	0.471	0.972	1.322
CT3.B•	0.120	0.124	0.058
CA.B•	0.031	0.038	0.050

Bias

Run	$\beta = 1.6$	$\beta = 1.0$	$\beta = 0.625$
CT.B•	0.063	0.493	1.063
CT.B•noPrior	0.086	0.416	0.574
CT3.B•	0.047	0.472	1.023
CA.B•	0.021	0.066	0.139

Table 8: MSE, Bias, and Variance for the CASAL runs with only CPUE data. "•" in the name of the run refers to the corresponding true β value in the column.

MSE

Run	$\beta = 1.6$	$\beta = 1.0$	$\beta = 0.625$
C.B•.cv30	0.168	0.191	0.467
C.B•.cv20	0.295	0.382	0.012
C.B•.cv10	1.067	0.979	0.579
C.B•noP.cv30	3.006	2.075	1.094
C.B•noP.cv20	1.399	1.318	0.010
C.B•noP.cv10	1.686	1.288	0.587

Variance

Run	$\beta = 1.6$	$\beta = 1.0$	$\beta = 0.625$
C.B•.cv30	0.070	0.179	0.297
C.B•.cv20	0.198	0.212	0.012
C.B•.cv10	0.265	0.224	0.127
C.B•noP.cv30	1.834	1.921	0.788
C.B•noP.cv20	1.149	1.012	0.010
C.B•noP.cv10	0.752	0.424	0.137

Bias

Run	$\beta = 1.6$	$\beta = 1.0$	$\beta = 0.625$
C.B•.cv30	0.312	0.112	-0.413
C.B•.cv20	0.311	0.413	0.014
C.B•.cv10	0.895	0.869	0.672
C.B•noP.cv30	1.083	0.392	-0.554
C.B•noP.cv20	0.500	0.553	0.002
C.B•noP.cv10	0.966	0.929	0.671

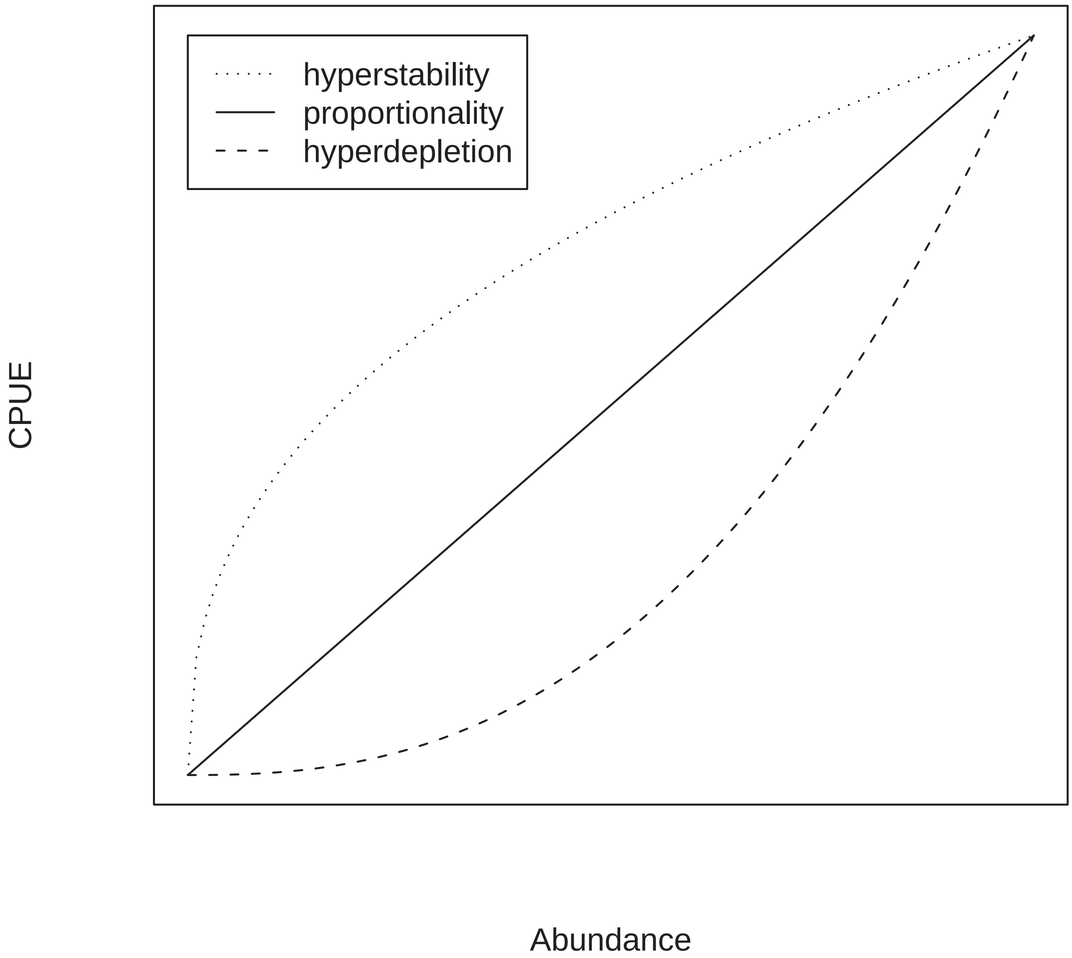
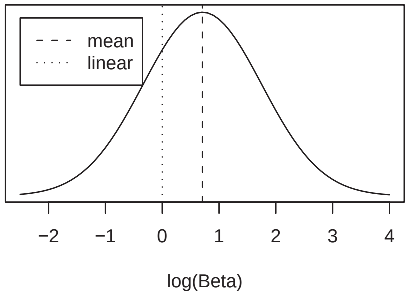


Figure 1: The three possible relationships between abundance and CPUE as described by Hilborn and Walters (1992).



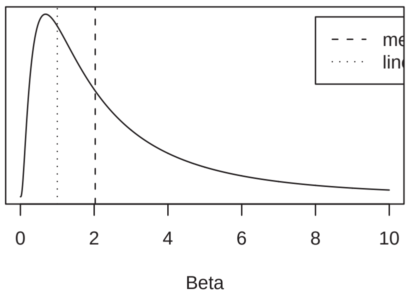


Figure 2: The prior on β in log space (top) and normal space (bottom). The value of beta corresponding to a linear relationship is drawn as a dotted line. The mean in log space and the median in normal space is drawn in a dashed line.

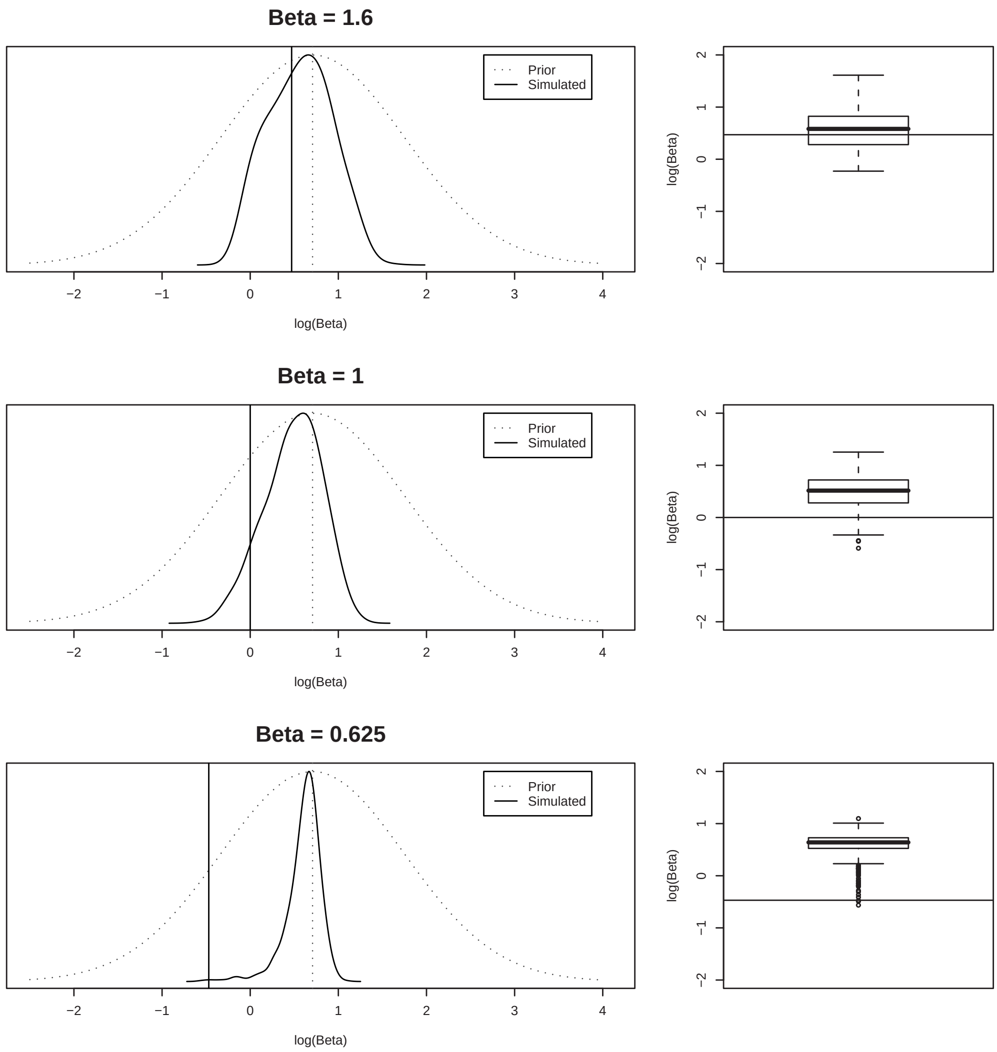


Figure 3: Estimates of β using CPUE only and a prior on β. The value of the true β is shown in the title of each plot.

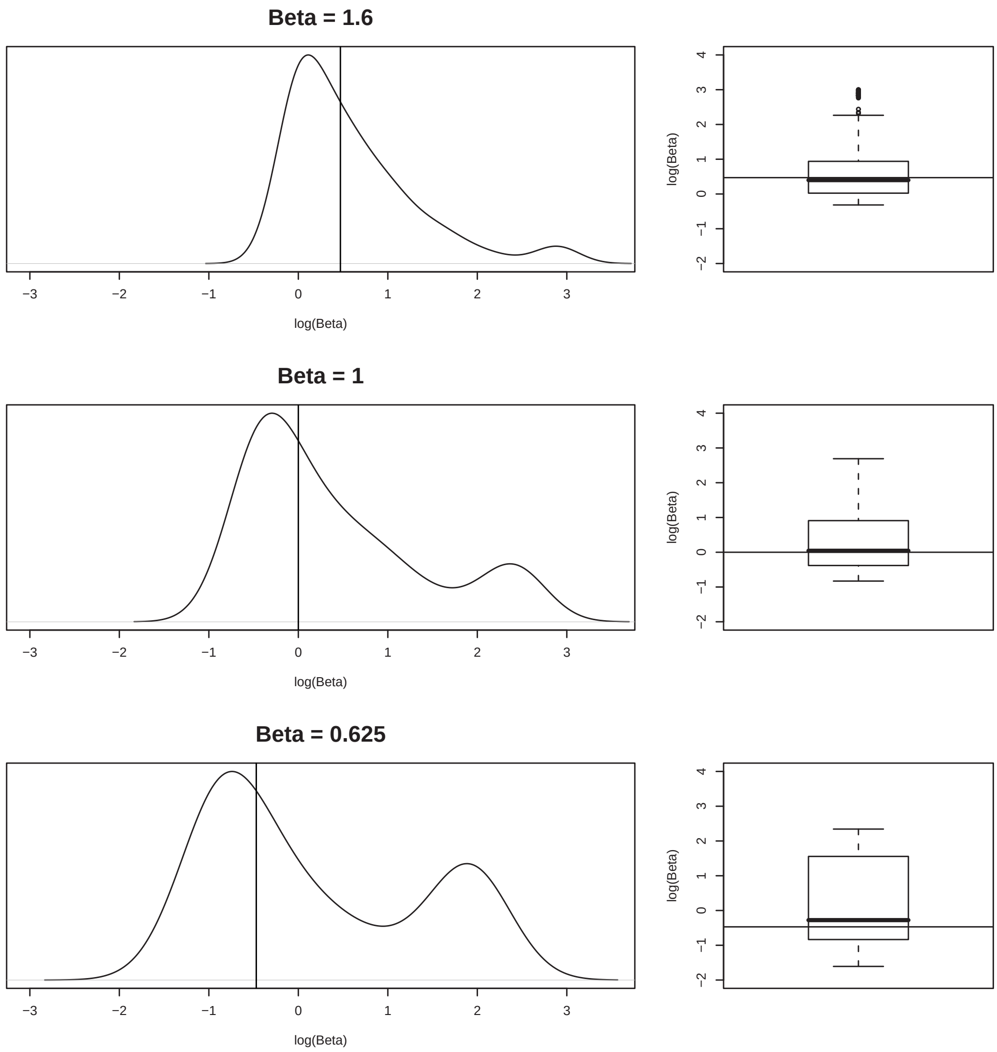


Figure 4: Estimates of β using CPUE only and no prior on β. The value of the true β is shown in the title of each plot.

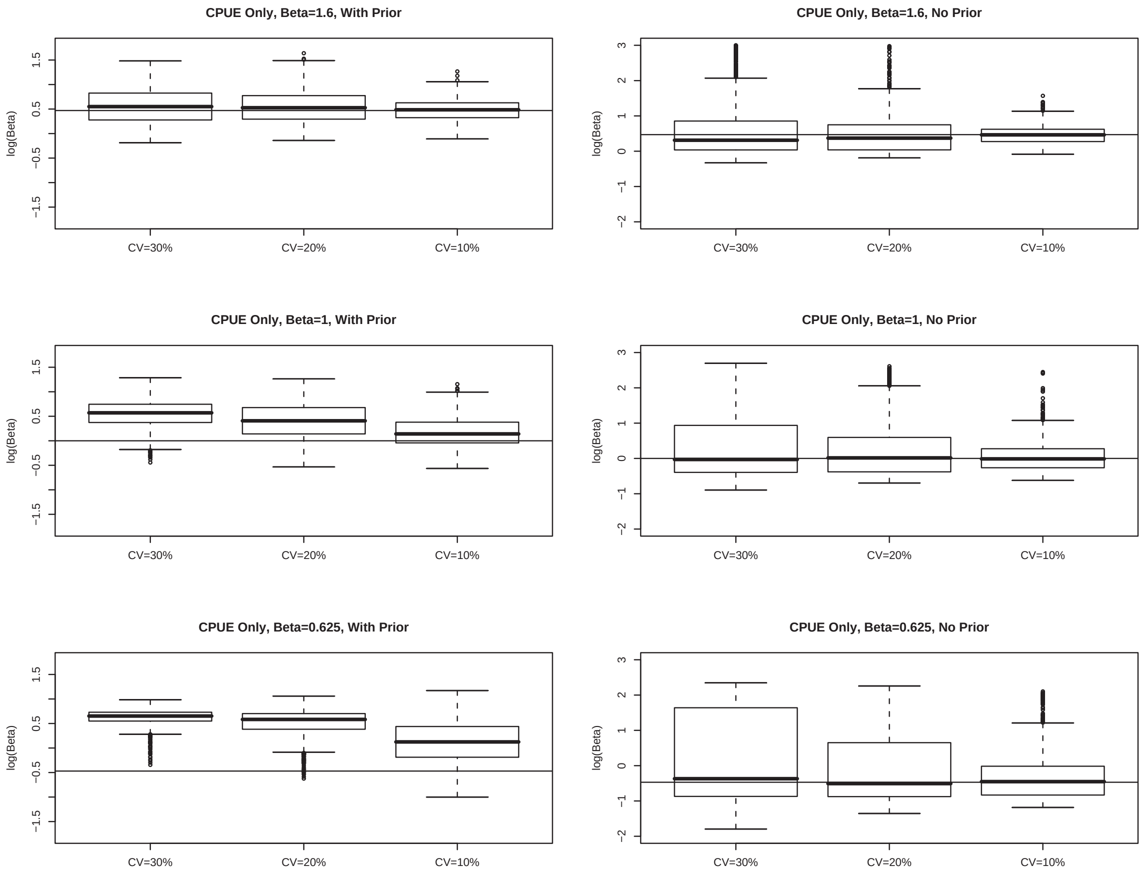


Figure 5: Estimates of β using CPUE only and no prior on β. The value of the true β is shown in the title of each plot.

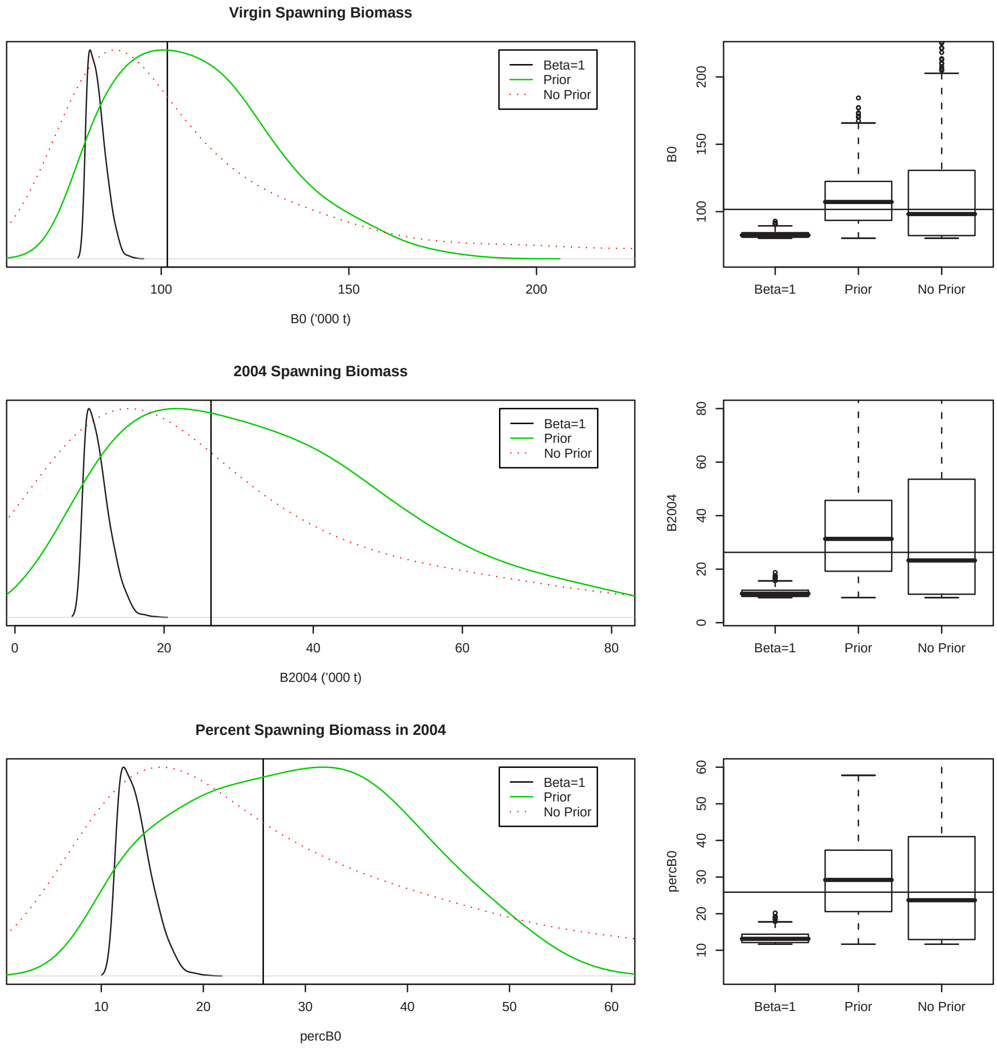


Figure 6: Estimates of beginning of the year spawning biomass using CPUE only when β is fixed at 1 and the true β is 1.6. The vertical lines are the true values.

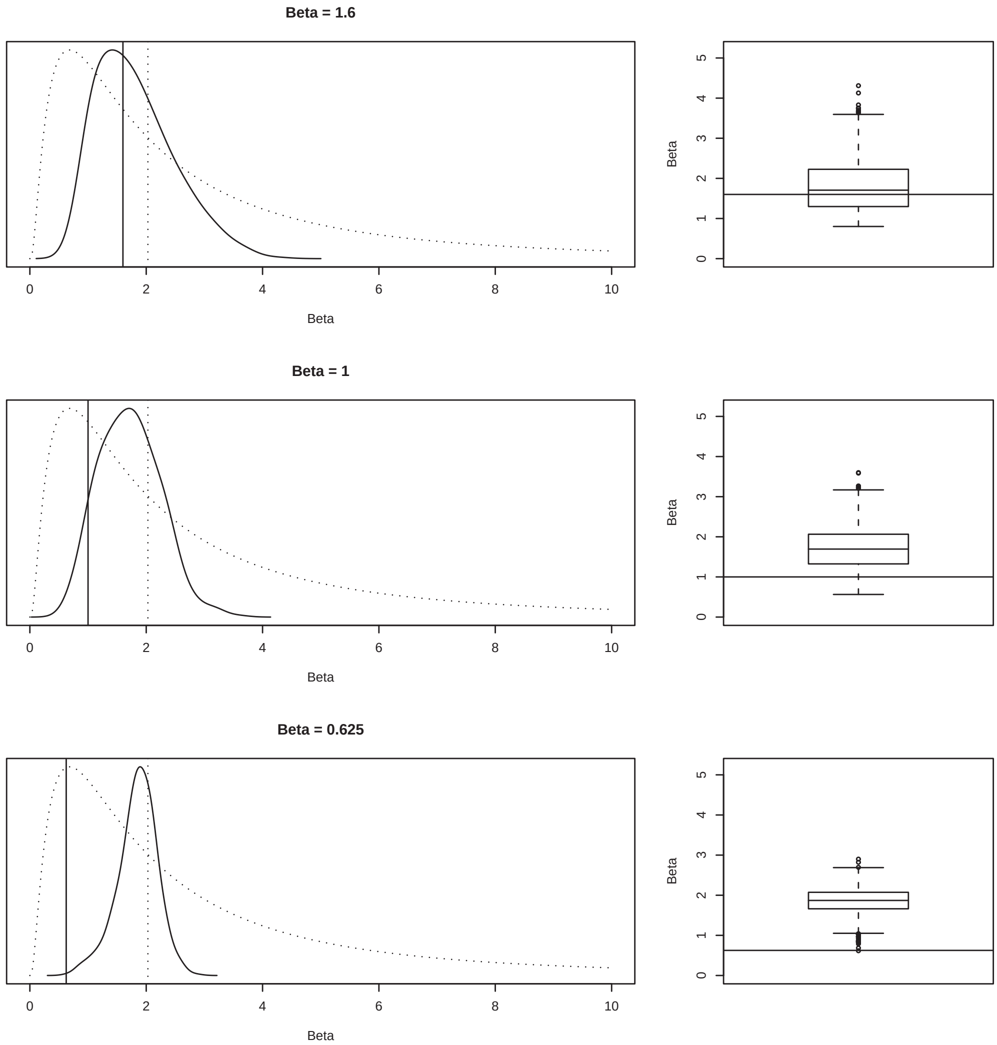


Figure 7: Estimates of β using CPUE and relative abundances from 1992 to 1994 and a prior on β. The value of the true β is shown in the title of the plot.

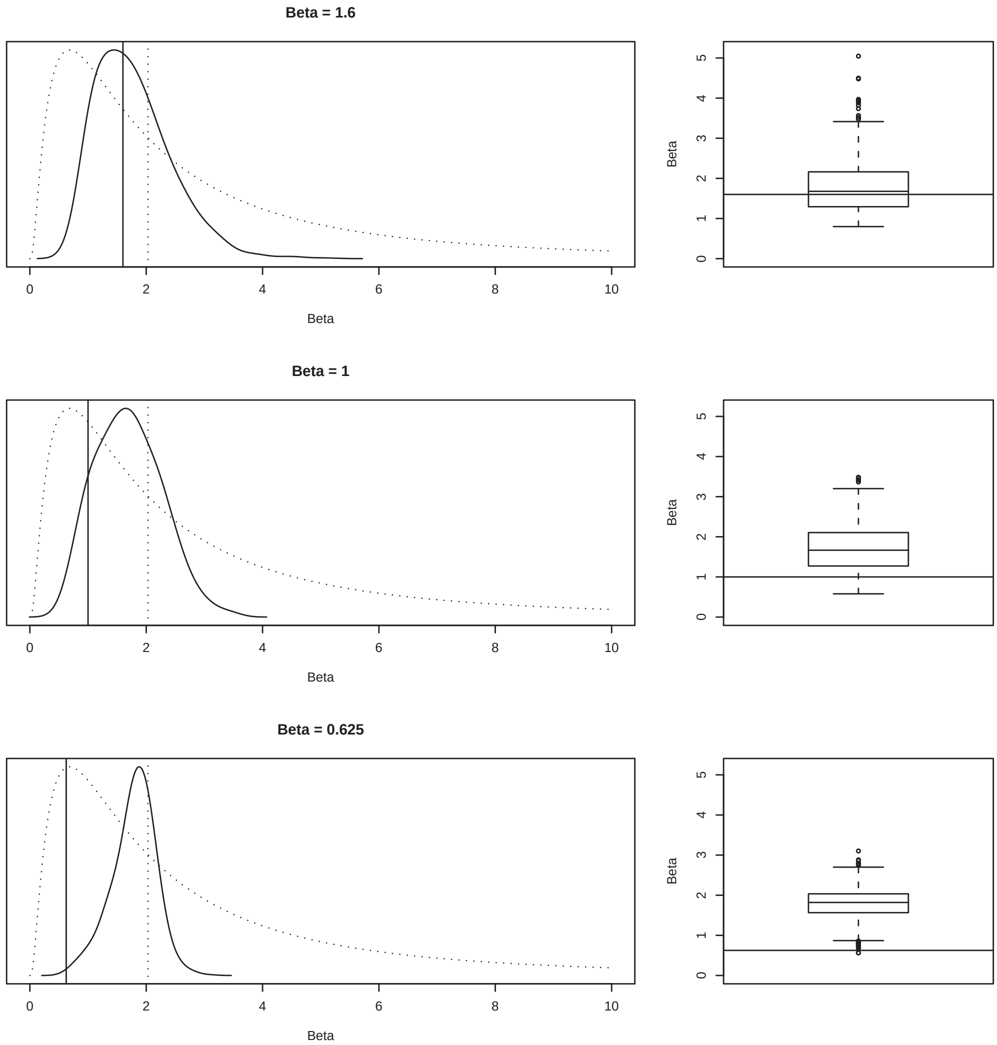


Figure 8: Estimates of β using CPUE and relative abundances from 1990, 1993, and 1996 and a prior on β. The value of the true β is shown in the title of the plot.

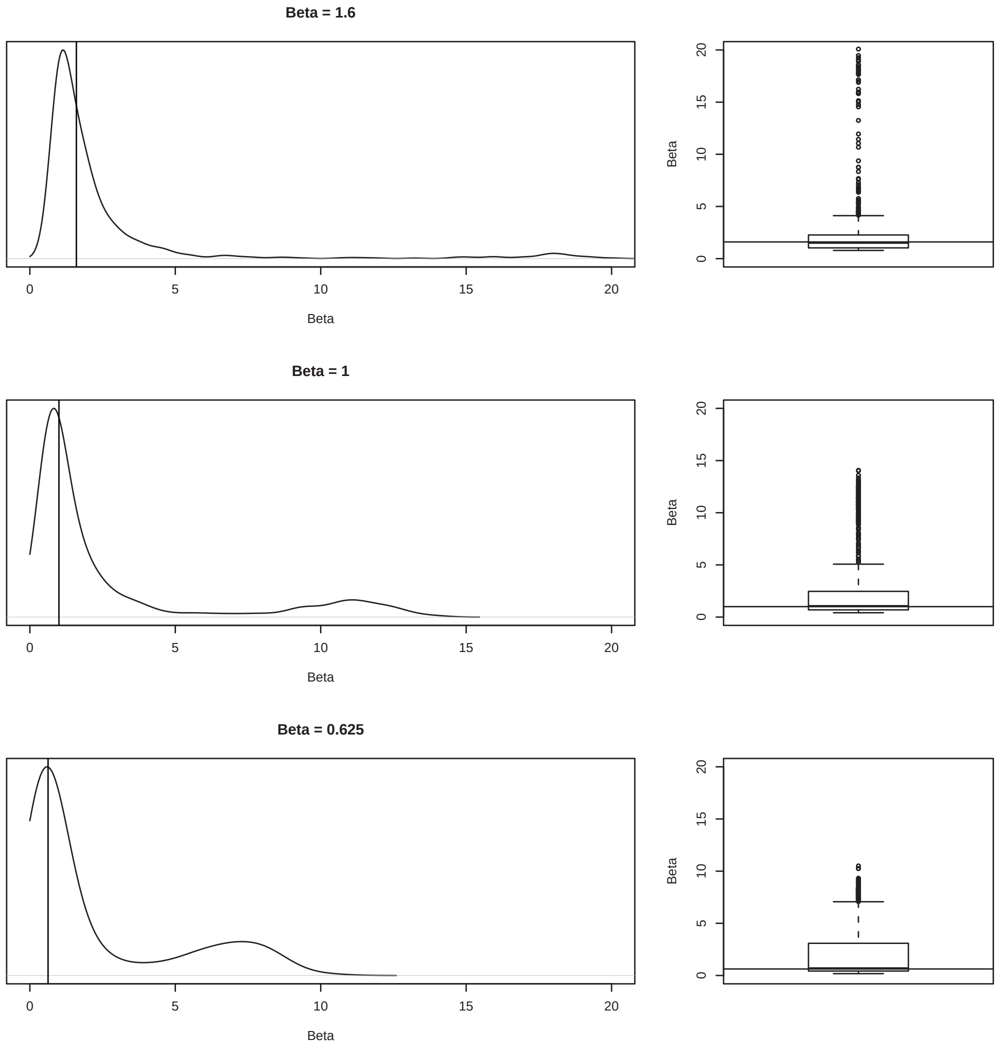


Figure 9: Estimates of β using CPUE and relative abundances from 1992 to 1994 with no prior on β. The value of the true β is shown in the title of the plot.

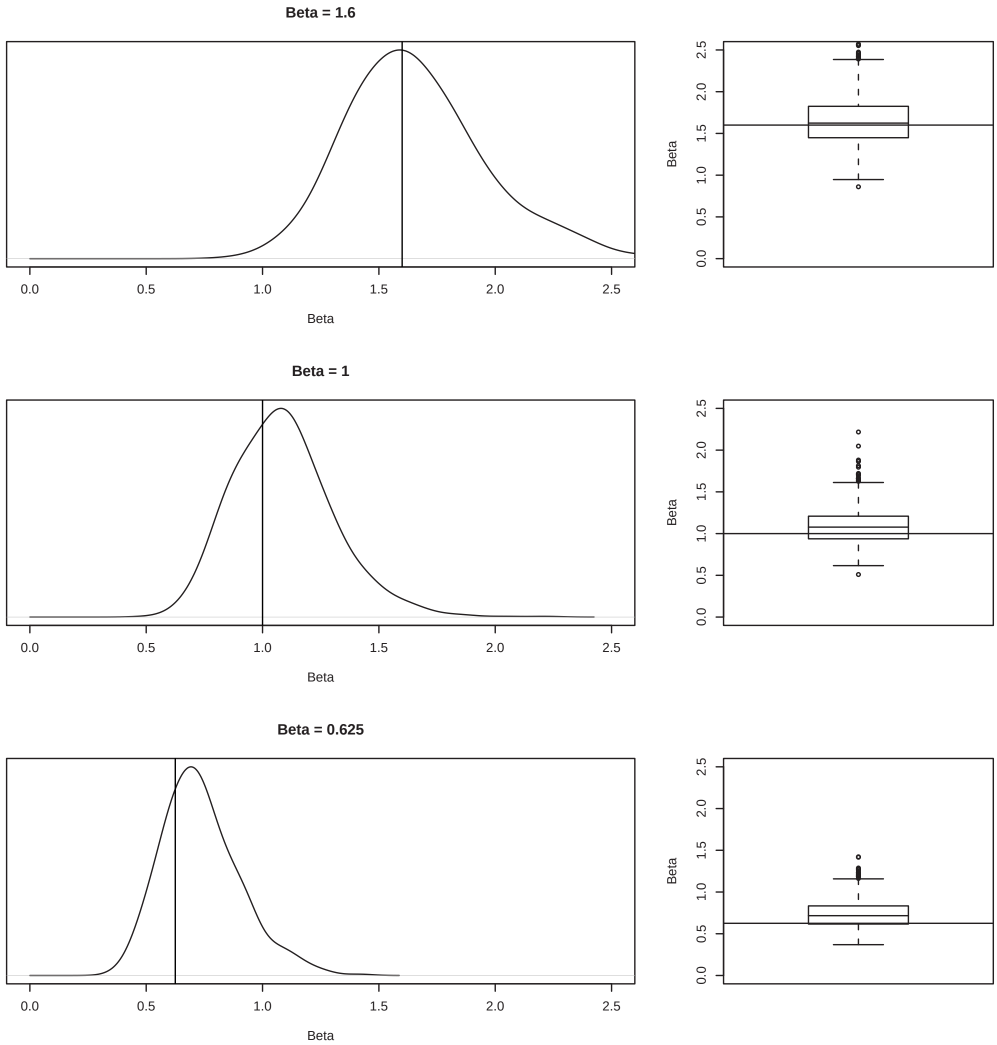


Figure 10: Estimates of β using CPUE and absolute abundances from 2001 and 2003 with a prior on β. The value of the true β is shown in the title of each plot.

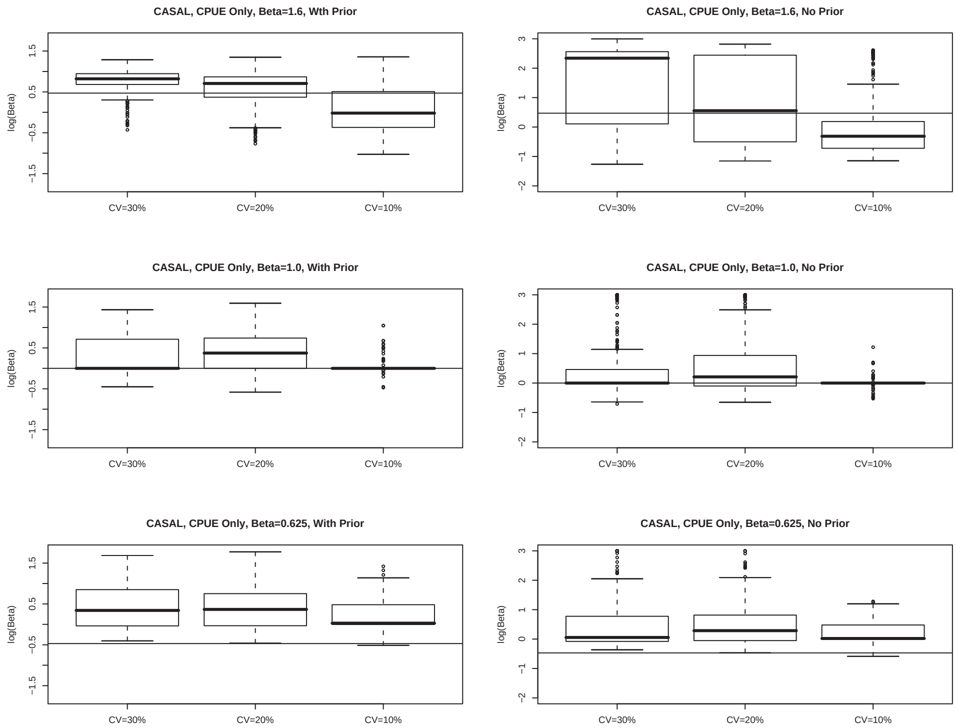


Figure 11: Estimates of β from CASAL using only CPUE with and without a prior on β. The value of the true β is shown in the title of each plot.