

Further sole dynamic Schaefer production model results

DS Butterworth and JP Glazer

Summary

The sole resource is modelled by a dynamic Schaefer production model which allows for a drop in the value of the intrinsic growth rate parameter from 2000 onwards. The model is fit to the available CPUE and survey abundance indices. These data are not sufficiently informative to be able to distinguish amongst fairly wide ranges of pre- and post-2000 intrinsic growth rate parameters. Nevertheless, all suggest that the sole resource has never been substantially depleted (being well above its MSY level), and furthermore that the current replacement yield and MSY are reasonably robustly estimated in the ranges of 300-400 and 500-650 mt respectively.

Introduction

Previously there were two hypotheses to explain low CPUEs for the sole resource over the 2012-2016 period: a decrease in abundance and a decrease in catchability. The increase in CPUE over the last two years (so that CPUE is now back to a similar levels to those before 2012 – see Figure 4) renders the first of these hypotheses now scarcely viable – abundance could not have near doubled in such a short period of only some two years.

This document therefore examines fits of simple dynamic production models to the available data under the assumption of a catchability reduction over the 2012-2016 period, in part to ascertain whether these might be able to provide a basis for updated TAC recommendations.

Methodology

The observation error assessment model applied is as follows

The dynamic Schaefer model is of the form:

$$B_{y+1} = B_y + rB_y\left[1 - \frac{B_y}{K}\right] - C_y \quad (1)$$

where

B_y is the biomass estimated in year y ,

r is the intrinsic rate of population growth (note that as explained further below, the value of r is allowed to change after a specified year),

K is pristine biomass (which is assumed to reflect the biomass at the start of the catch time series in 1920), and

C_y is the annual catch over the period 1920-2018.

The likelihood is calculated assuming that the abundance indices are log-normally distributed about their expected values:

$$I_y^i = q_i B_y e^{\varepsilon_y^i} \quad (2)$$

where I_y^i is the value for abundance index i for year y , $q_i B_y$ is the corresponding model estimate (q_i being the estimated catchability coefficient for each index of abundance), and ε_y^i is the observation error for each index, $\sim N(0, \sigma_i^2)$, for year y .

The contribution of each abundance index to the negative log-likelihood function (after the removal of constants) is given by:

$$-\ell n L_i = n_i \ell n(\hat{\sigma}_i) + \frac{n_i}{2} \quad (3)$$

where n_i is the number of annual data values for index i , and the standard deviation for each index is given by:

$$\hat{\sigma}_i = \sqrt{\frac{1}{n_i} (\sum_y \ell n I_y - \ell n(\hat{q}_i) - \ell n \hat{B}_y)^2} \quad (4)$$

where

$$\ln \hat{q}_i = \frac{1}{n_i} \sum_y \ln \left(\frac{I_y}{\hat{B}_y} \right)$$

The following data have been included in the analyses:

- sole catches (1920-2016),
- nominal CPUE index (1986-2016)
- autumn survey index (utilizing “old” gear),
- autumn survey index (utilizing “new” gear),
- spring survey index (utilizing “old” gear), and
- spring survey index (utilizing “new” gear).

Note that the nominal rather than the standardised CPUE index was used because the former is available for a much longer period, and also because over the period for which both are available, they do not differ greatly.

Results

A number of analyses were undertaken related to r (intrinsic growth rate) and μ (the parameter that quantifies the extent of catchability reduction over the period 2012-2016, which is assumed to better explain the lower CPUE values over that period). Furthermore, r was considered to be period-specific where r_1 (ranging from 0.2-0.5) refers to intrinsic growth for the period 1920-1999 and r_2 (ranging from 0.05-0.2) refers to intrinsic growth for the period 2000-2018. μ is either estimated or fixed.

Table 1 reports the parameter values obtained from each of the model fits for the r_1/r_2 combinations for which μ is estimated. Table 2 shows comparisons of the values of selected parameters, with the results for the three models that fit the data best being highlighted.

Table 3 compares results for $r_1=0.5$ and $r_2=0.15$ (which yields the best fit amongst the different r_1/r_2 combinations considered) for scenarios where μ is either estimated or fixed (at 0.1).

Figures 1-7 show the past catch and biomass trajectories, as well as the fits to the respective indices of abundance.

Discussion

Figure 1 shows that catches have been markedly less over the 2004+ period compared to beforehand (this was, at least in part, a consequence of a reduction in the fishing effort applied). However, there is no indication of an associated increase in biomass from the abundance index data available. This results in models with an unchanged value over time of the r intrinsic growth rate parameter being unable to fit the data (without estimating biomass to be at unrealistically high levels).

Consequently, the earlier value of r (r_1) is assumed to drop to a lower value (r_2) from 2000 onwards. Table 1 shows the results of fits for various input combinations of r_1 (from 0.2 to 0.5) and r_2 (from 0.05 to 0.2). Some combinations with r_2 only slightly less than r_1 are omitted; this is because they result in notably worse fits to the data (this is because they suggest recent marked increases in abundance).

The results for the three best fitting models are highlighted in both Table 1 and Table 2. However, there is little to choose between these three and the other combinations for which results are reported. The reasons are clear from the comparisons between abundance data and model predictions in Figures 3 to 7: these data are not really able to discriminate amongst these different r_1/r_2 combinations.

Table 3 (and Figure 3) show the consequences of assuming (by fixing μ at the low value of 0.1) that the low 2012-2016 CPUE values were not entirely a consequence of poor catchability; the resultant fit to the CPUE data is very poor.

A notable feature of the results in Tables 1 and 2, which is also evident from the biomass trajectory plots in Figure 2, is the indication that the resource has never been greatly depleted. The most pessimistic current depletion ($B(2019)/K$) in these Tables is 72%, with the best fits yielding values in the vicinity of 80%.

As regards advice on a TAC, the three best fitting models suggest a current Replacement Yield (RY) in the 320-350 mt range; this estimate seems fairly robust, as estimates for other r_1/r_2 combinations are not that dissimilar (and estimates for the lowest r_2 value shown can probably be discounted as an intrinsic growth rate for sole as low as 0.05 seems implausible). Overall then RY is likely in the range of 300-400 mt.

A case could be made for a TAC that is higher than RY, given that current depletion (about 80%) is estimated to be well above the MSY level of 50%. F_{msy} strategy options, ranging from about 600 to 1200 mt would seem questionably appropriate, including because those values would be expected to decrease over time if such a strategy was implemented. However, some consideration might be given to (a highish proportion of) the MSY estimates, which range from about 400 – 650 mt, or 500 – 650 mt if r_2 values of 0.05 are excluded.

Note that at present, the sole TAC is set at 627 mt, but with an associated TAE of 16767 fishing hours.

Table 1: Parameter estimates and TACs under possible harvest control rules from a suite of dynamic Schaefer production model assessments fitted to the nominal CPUE values over 1986 to 2018, and conducted for various fixed input values of r (r_1 refers to intrinsic growth for the period 1920-1999 and r_2 refers to intrinsic growth for the period 2000-2018). μ is an estimable parameter that quantifies the extent of catchability reduction over the period 2012-2016; such an assumption explains the lower CPUE values over that period than a biomass decline. Biomass and catch units are mt. The three models which best fit the data as indicated by $-\ln L$ are highlighted.

r_1	r_2	μ	$-\ln L$	K	B(2019)	B(2019)/K	MSY $0.25*r_1*K$	Replacement Yield $r_1*B(2019)*(1-B(2019)/K)$	F_{msy} Catch $0.5*r_1*B(2019)$	MSY $0.25*r_2*K$	Replacement Yield $r_2*B(2019)*(1-B(2019)/K)$	F_{msy} Catch $0.5*r_2*B(2019)$
0.2	0.05	0.558	-51.114	31552	23659	0.750	1578	1184	2366	394	296	591
0.3	0.05	0.560	-51.070	33092	26328	0.796	2482	1615	3949	414	269	658
0.4	0.05	0.561	-51.029	34329	28040	0.817	3433	2055	5608	429	257	701
0.5	0.05	0.561	-51.007	35091	29063	0.828	4386	2496	7266	439	250	727
0.2	0.1	0.532	-51.157	20078	14436	0.719	1004	811	1444	502	406	722
0.3	0.1	0.550	-51.446	20558	16109	0.784	1542	1046	2416	514	349	805
0.4	0.1	0.553	-51.383	22204	18203	0.820	2220	1312	3641	555	328	910
0.5	0.1	0.554	-51.344	23355	19564	0.838	2919	1588	4891	584	318	978
0.3	0.15	0.522	-51.239	14799	11640	0.787	1110	745	1746	555	373	873
0.4	0.15	0.537	-51.464	15826	13119	0.829	1583	897	2624	593	337	984
0.5	0.15	0.541	-51.467	17005	14501	0.853	2126	1068	3625	638	320	1088
0.4	0.2	0.509	-51.022	12499	10625	0.850	1250	637	2125	625	319	1063
0.5	0.2	0.522	-51.297	13329	11619	0.872	1666	745	2905	666	298	1162

Table 2: Comparisons of select statistics related to the r_1 and r_2 combinations. The three models which best fit the data as indicated by $-\ln L$ are highlighted.

		-lnL						B(2019)			
		r2						r2			
r1		0.05	0.1	0.15	0.2	r1	0.05	0.1	0.15	0.2	
0.2		-51.114	-51.157			0.2	23659	14436			
0.3		-51.070	-51.446	-51.239		0.3	26328	16109	11640		
0.4		-51.029	-51.383	-51.464	-51.022	0.4	28040	18203	13119	10625	
0.5		-51.007	-51.344	-51.467	-51.297	0.5	29063	19564	14501	11619	

		B(2019)/K						MSY (based on r2)			
		r2						r2			
r1		0.05	0.1	0.15	0.2	r1	0.05	0.1	0.15	0.2	
0.2		0.750	0.719			0.2	394	502			
0.3		0.796	0.784	0.787		0.3	414	514	555		
0.4		0.817	0.820	0.829	0.850	0.4	429	555	593	625	
0.5		0.828	0.838	0.853	0.872	0.5	439	584	638	666	

		RY based on r2						F _{MSY} catch (based on r2)			
		r2						r2			
r1		0.05	0.1	0.15	0.2	r1	0.05	0.1	0.15	0.2	
0.2		296	406			0.2	591	722			
0.3		269	349	373		0.3	658	805	873		
0.4		257	328	337	319	0.4	701	910	984	1063	
0.5		250	318	320	298	0.5	727	978	1088	1162	

Table 3: Comparison of results for $r_1=0.4$ and $r_2=0.15$ where μ is either estimated (0.537) or fixed (at 0.1).

r1	r2	μ	-lnL	K	B(2019)	B(2019)/K	MSY	Replacement Yield	F _{msy} Catch	MSY	Replacement Yield	F _{msy} Catch
							$0.25*r_1*K$	$r_1*B(2019)*(1-B(2019)/K)$	$0.5*r_1*B(2019)$	$0.25*r_2*K$	$r_2*B(2019)*(1-B(2019)/K)$	$0.5*r_2*B(2019)$
0.4	0.15	0.537	-51.464	15826	13119	0.829	1583	897	2624	593	337	984
0.4	0.15	0.1	-8.708	19372	16911	0.873	1937	860	3382	726	322	1268

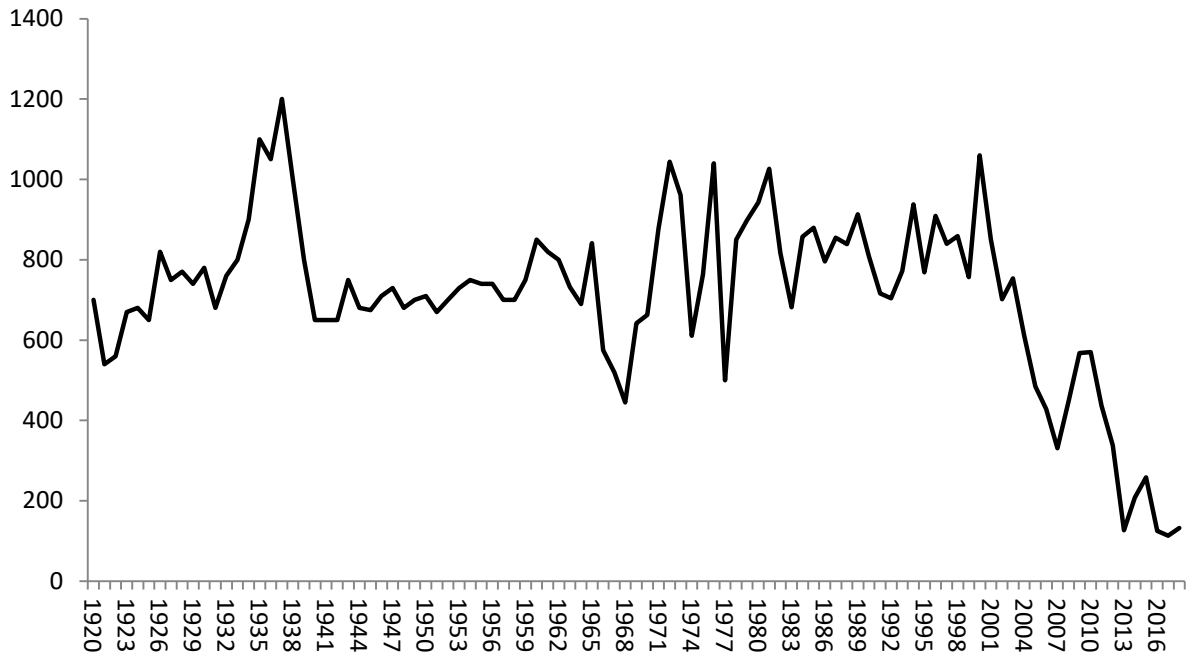


Figure 1: Annual sole catches (units: mt).

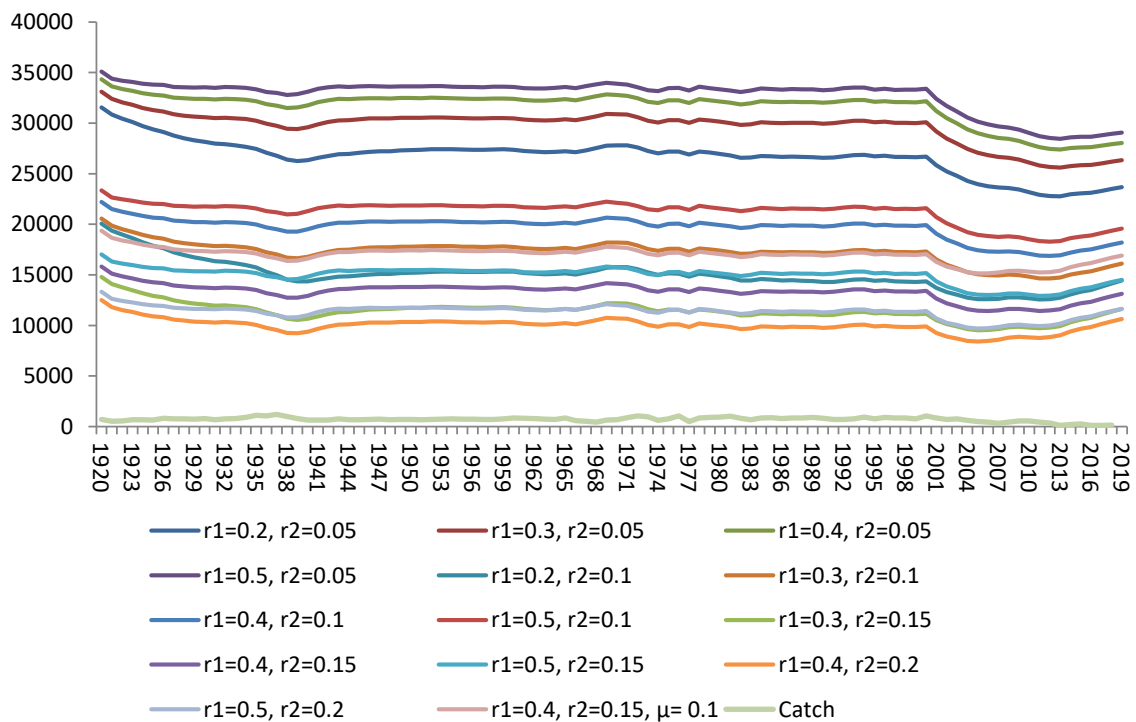


Figure 2: Sole biomass trajectories for r_1/r_2 combinations (units: mt)

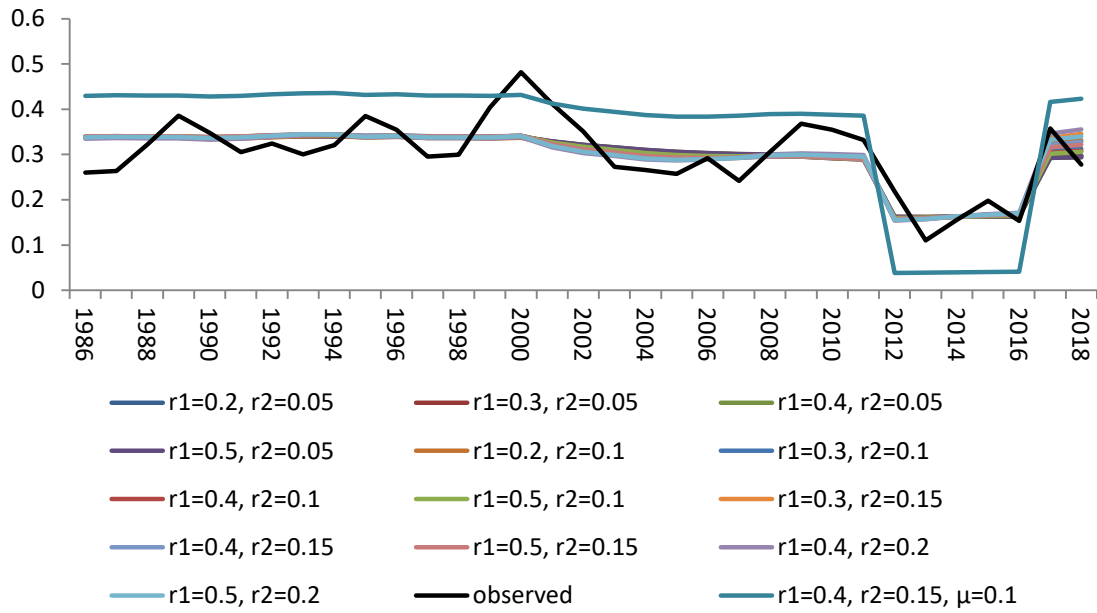


Figure 3: Fits to the commercial CPUE index for r_1/r_2 combinations (units: kg/min)

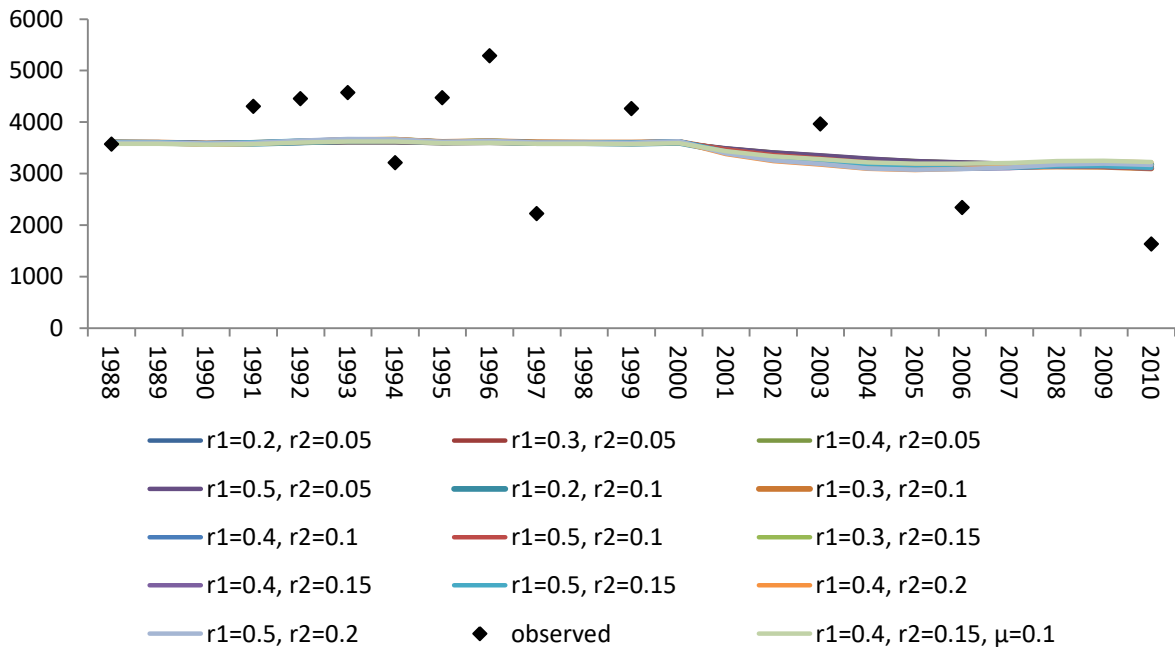


Figure 4: Fits to the autumn index (old gear) for r_1/r_2 combinations (units: mt)

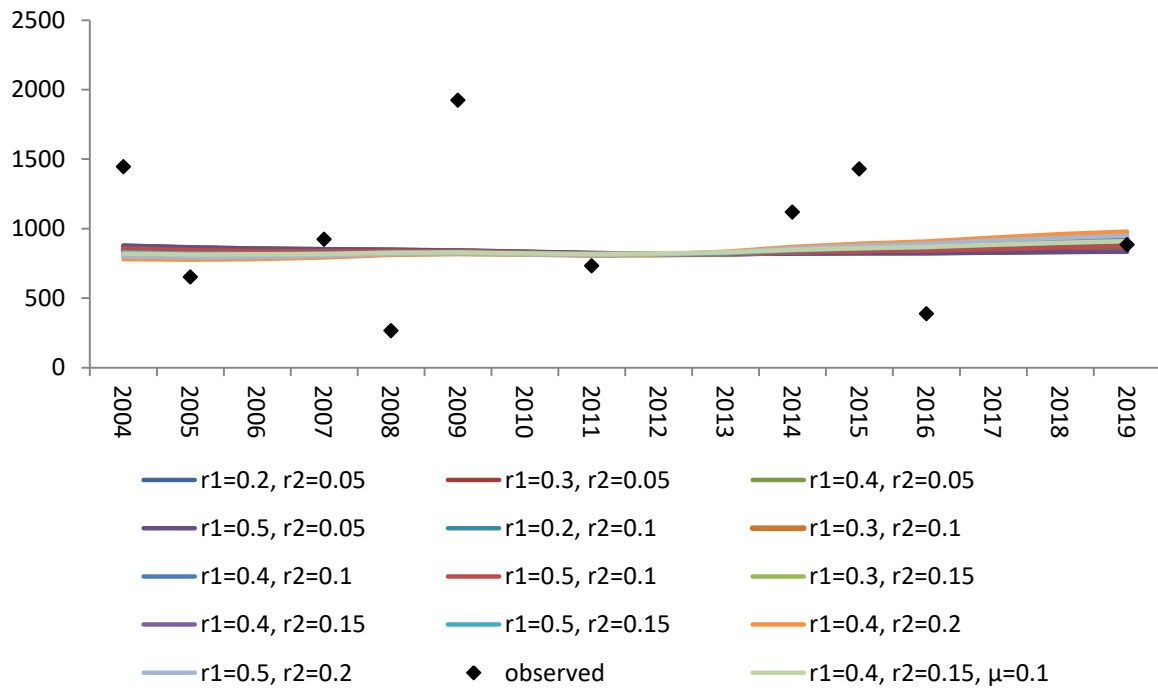


Figure 5: Fits to the autumn index (new gear) for r_1/r_2 combinations (units: mt)

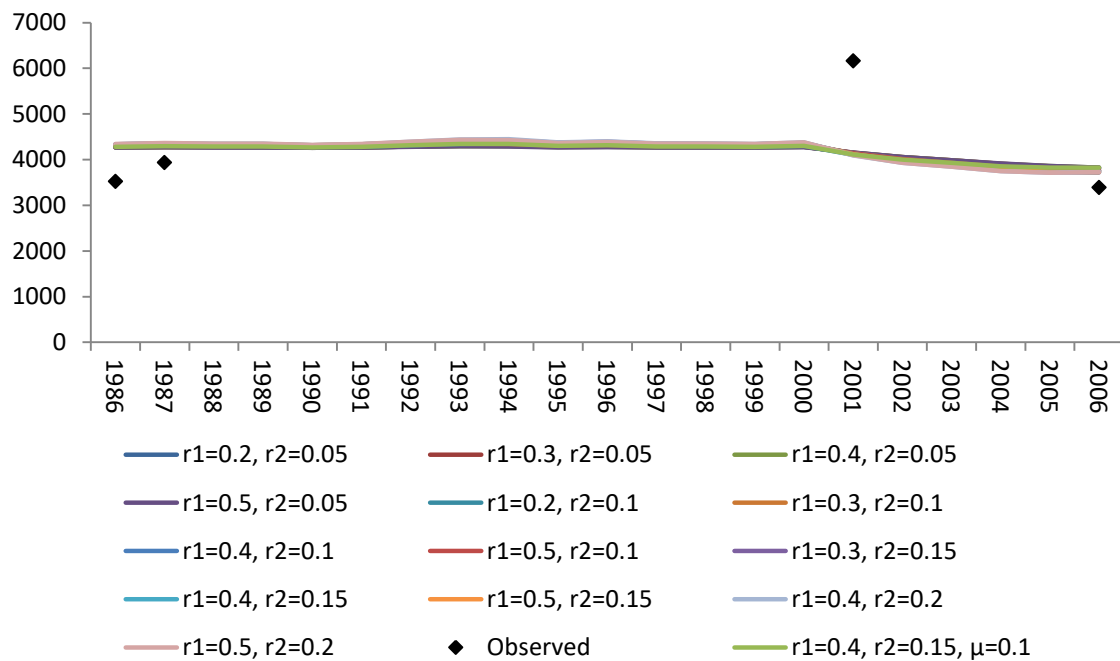


Figure 6: Fits to the spring index (old gear) for r_1/r_2 combinations (units: mt)

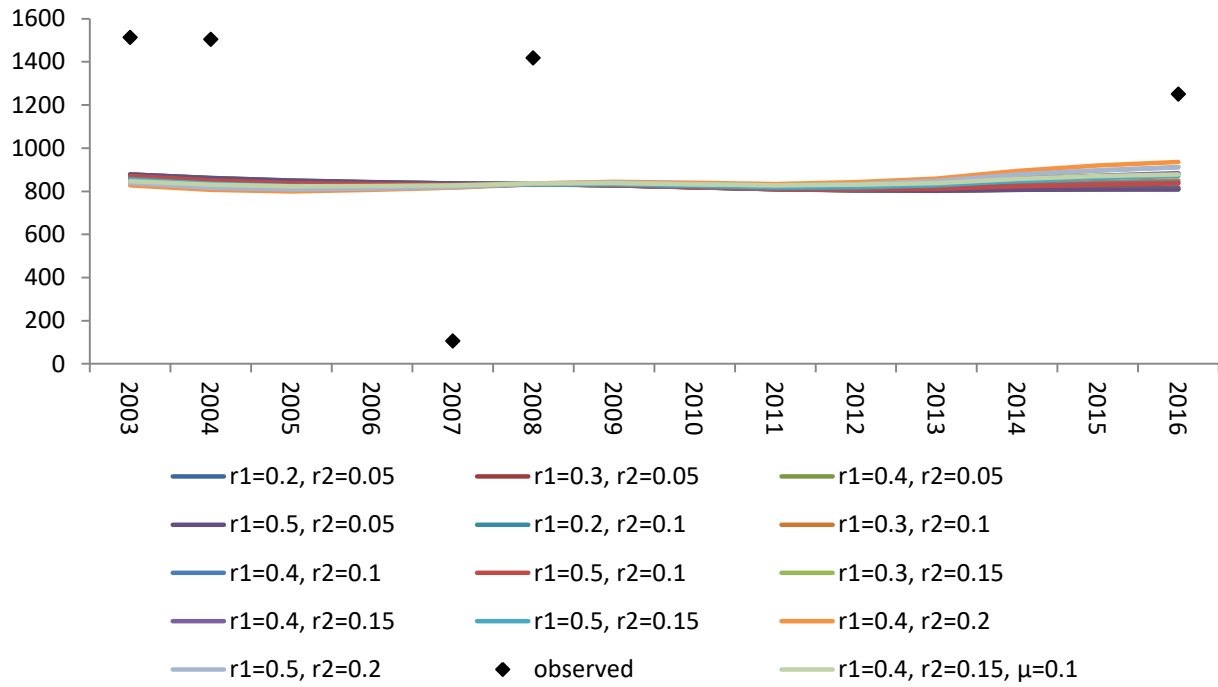


Figure 7: Fits to the spring index (new gear) for $r1/r2$ combinations (units: mt)