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Performance of Deming and Passing-Bablok Regression Analysis in Detecting Proportionality in the Stock-recruitment Relationship

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Abstract

Simulation studies were conducted to investigate whether a simple, Deming, or Passing-Bablok regression analysis can detect proportionality in the stock-recruitment relationship (SRR) when the data contain process and/or observation errors. The results indicated that the Deming and Passing-Bablok regressions were much more able to detect proportionality between recruitment (R) and spawning stock biomass (SSB) than was simple regression analysis. With simple regression analysis, when the number of samples was large and the observation errors in the SSB were large, the detection of proportionality decreased greatly. When the true slope of the regression line of ln(R) against ln(SSB) was less than unity, and the coefficient of variation in the observation error in R was large and that in SSB was small, the probability that Deming and Passing-Bablok regressions erroneously detected proportionality was extremely high. However, simple regression analysis seldom erroneously detected proportionality because it tended to underestimate the slope in response to process and/or observation errors. When the Deming and Passing-Bablok regressions were applied to data for the Japanese sardine *Sardinops melanostictus* (Temminck & Schlegel 1846), Pacific sardine *Sardinops sagax* (Jenyns 1842) , and chub mackerel *Scomber japonicas* Houttuyn 1782, the slopes were not statistically different from unity and no density-dependent effect could be detected.

Introduction

In the field of fisheries management, determining the mechanism that controls population fluctuations is a very important issue. In a fluctuation mechanism, the most important concept is the density-dependent effect.

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Most researchers in this field have assumed that a density-dependent effect exists in the fluctuation mechanisms, because many stock–recruitment relationships (SRRs) show evidence that a density-dependent effect exists. When recruitment (R) is plotted against spawning stock biomass (SSB), the relationship usually shows a domed curve (Ricker 1954) or an asymptotic curve (Beverton and Holt 1957). When reproductive success (RPS=R/SSB) is plotted against SSB, the regression line shows a statistically significant decreasing trend. Therefore, it is widely believed that a density-dependent effect is certain. The density-dependent effect forms the basis of the concept of the maximum sustainable yield (MSY), which is the most important concept in fisheries resource management. Therefore, the existence of a density-dependent effect in SRR is a key concept underlying the management schemes based on the MSY.

However, Sakuramoto (2012) pointed out that the slope of the regression line calculated in natural logarithm of RPS against the natural legalism of SSB showed false decreasing trend in response to observation errors, and he concluded that the RPS should not be used when we try to detect the density-dependent effect. In order to avoid the effect of observation errors that usually exist in the independent variable, Sakuramoto (2012) recommended the use of Deming regression analysis (Deming 1943) when a regression analysis of the natural logarithm of recruitment (R) against the natural logarithm of SSB is performed. The validity of the density-dependent effect in SRR can be discussed in terms of whether the slope of the regression line is statistically equal to unity or less. However, studies in which the Deming (1943) or Passing-Bablok regression (Passing and Bablok 1983) is applied to SRR data are limited in number.

The aim of this study is to determine the performance of these two methods and compare their results with a traditional simple regression analysis using simulation studies. Further, we applied these methods to actual SRR data for the Japanese sardine *Sardinops melanostictus* (Temminck & Schlegel 1846), Pacific sardine *Sardinops sagax* (Jenyns 1842) , and chub mackerel *Scomber japonicas* Houttuyn 1782. We then compared the results and discussed the optimal SRR models.

Materials and Methods

First, we conducted simulation studies in order to compare the ability of simple, Deming and Passing-Bablok regression to detect proportionality for the slopes of three regression lines estimated when ln(R) was plotted against ln(SSB). The programmes used to estimate the parameters by Deming or Passing-Bablok regression were coded by Aoki (2009a; 2009b). The artificial data used in these simulations were produced according to Sakuramoto and Suzuki (2012); i.e., both process and observation errors were added to both R and SSB, respectively. Here process errors were defined as follows: The recruited fish generate the SSB through the survival process, but the survival process differs from year to year because natural mortality and fishing mortality change considerably from year to year.

Therefore, the actual SSB values will differ from the SSB values calculated by the model used to describe the survival process, assuming that constant natural and fishing mortality coefficients are used. Furthermore, SSB produces R through the SRR. In this process, the actual R fluctuates, largely because of environmental conditions. We call these differences between the actual values and those calculated from the models "process errors". Process errors occur in both directions, "from SSB to R" and "from R to SSB". In this situation, the data for SSB and R are linked through the SRR model and the survival process. That is, SSB_i produces R_{i+1}, and R_{i+1} is used to construct SSB_{i+1}, and so on. This process causes the well-known "time-series bias" (Walters and Martell 2004). We produced artificial data using the different values of coefficients of variation (CVs) of process and observation errors assuming that the true SRR model is a proportional model.

Second, we applied these three regression methods to three actual pieces of data, i.e., the SRR data for the Japanese sardine (Wada and Jacobson 1998), those for the Pacific sardine (Jacobson and MacCall 1995), and those for the chub mackerel (Yatsu et al. 2005).

Creating artificial data with intrinsic process and observation errors

Artificial data were created using the following process. First, the initial value of SSB_i was randomly chosen from the range [0, 400]. Using SSB_i to which a process error was added, R_{i+1} was calculated for the proportional model, and the process and observation errors were added according to equation (1):

$$R_{i+1}^{pro+obs} = [a\{SSB_i \exp(\varepsilon_{SSB,i}^{pro})\}] \exp(\varepsilon_{R,i+1}^{pro}) \exp(\varepsilon_{R,i+1}^{obs}) \quad (1)$$

SSB_{i+1} containing the process and observation errors in the next generation was determined as follows:

$$SSB_{i+1}^{pro+obs} = [a\{SSB_i \exp(\varepsilon_{SSB,i}^{pro})\} \exp(\varepsilon_{R,i+1}^{pro})] \exp(-M-F)\, w\,] \exp(\varepsilon_{SSB,i+1}^{obs}) \quad (2),$$

where $\varepsilon_{SSB,i}^{pro}$, $\varepsilon_{R,i}^{pro}$, $\varepsilon_{SSB,i}^{obs}$ and $\varepsilon_{R,i}^{obs}$ are the process and observation errors for SSB and R, respectively, with normal distributions, means of 0, and standard deviations of σ_{SSB}^{pro}, σ_{R}^{pro}, σ_{SSB}^{obs}, and σ_{R}^{obs}, respectively.

The levels of variation were given by coefficients of variation (CVs), and the CVs were set at 0.1, 0.2, ..., 0.6, respectively. Each σ^2 was then calculated as $\sigma^2 = \ln(1 + CV^2)$. M, F, and w denote the natural mortality coefficient, the fishing mortality coefficient, and the mean fish weight, respectively. According to Sakuramoto and Suzuki (2012), we set $\exp(-M - F) = 0.6$ and $w = 1$. We generated 10, 20, 40 or 60 pairs of artificial data sets for $SSB_i^{pro+obs}$ and $R_i^{pro+obs}$.

The parameter estimation was conducted assuming that the SRR model follows the power model,

$\ln R = \ln a + b \ln SSB$

(3)

Then, we evaluated whether or not the estimated parameter *b* was statistically recognised as unity, i.e., whether the 95% confidence interval of *b* was greater than 0 and less than 2. If the slope was recognised as unity, we presumed that the regression method can detect the true proportionality between R and SSB that we assumed in the simulation. In each case, we conducted 1,000 Monte Carlo simulations and counted the number of trials in which the slope of *b* was recognised as unity. Sensitivity tests were conducted to evaluate the opposite effects. That is, we conducted trials in which the Deming and Passing-Bablok regressions erroneously determined that the slope was unity, although in the true SRR model parameter *b* was 0.4, 0.6 or 0.8, respectively.

Results

Results of simulations

Table 1 shows the results of the simulations. The second to fourth columns indicate the CVs of the observation and process errors. We only show the results when CV= 0.2, 0.4 or 0.6. The value of *b* denotes the true slope assumed in equation (3). The figures shown in columns 6 to 17 indicate the number of trials that according to parameter *b* were statistically recognised as unity. For instance, in simulation number 1, which is the case in which the observation and process errors in R and SSB were all 0.2, the results show that in the column for *b*= 1, the figures 583, 942, and 967 indicate the numbers of trials that according to parameter *b* were statistically recognised as unity in each method, respectively.

The results shown in the column for *b*= 1 (shown in column 15 to 17) indicate the following: (1) The power of the Deming and Passing-Bablok regressions to detect proportionality was extremely high compared to the simple regression analysis except in simulation numbers 19 - 24. (2) When the observation error in SSB was large (CV=0.6), the number of trials in which the slope of *b* was correctly recognised as unity by simple regression analysis was significantly lower than in other simulations (simulation numbers 55 - 81). (3) In contrast, even when the process error in SSB was large (CV=0.6), the slope estimated by simple regression analysis was not greatly affected compared to the cases in which the observation error in SSB was large (simulation numbers 3, 6, 9, 12, 15, 18, 21 24, and 27). (4) When the true slope was less than unity, the probability that the Deming and Passing-Bablok regressions erroneously determined that the slope was unity was extremely high when the observation error in R was large (CV=0.4 or 0.6) and that in SSB was small (CV = 0.2) (simulation numbers 10 - 27) except in simulation numbers 12 and 15. When the true value of *b* was less than unity, simple regression analysis seldom erroneously judged that the slope was unity, because simple regression analysis has a tendency to underestimate the slope affected by observation and/or process errors (Sakuramoto and Suzuki 2012).

Table 1 Results of simulation using simple, Deming and Passing-Bablok Regression. The second to fourth columns indicate the CVs of observation and process errors. The value of *b* denotes the true slope assumed in equation (3). The figures shown in column 6 to 17 indicate the number of trials that showed the estimated parameter *b* was statistically recognised as unity. Number of data are all 40.

Simulation	Observation error		Process error		*b*=0.4			*b*=0.6			*b*=0.8			*b*=1		
No.	SSB	R	SSB	R	Simple	Deming	P-B	Simple	Deming	P-B	Simple	Deming	P-B	Simple	Deming	P-B
1	0.2	0.2	0.2	0.2	0	242	553	0	129	478	0	88	386	583	942	967
2	0.2	0.2	0.4	0.2	0	16	93	0	17	110	0	55	210	784	936	952
3	0.2	0.2	0.6	0.2	0	1	5	0	2	22	0	25	98	866	930	956
4	0.2	0.2	0.2	0.4	0	619	839	0	448	775	6	433	736	631	962	973
5	0.2	0.2	0.4	0.4	0	214	441	0	186	431	4	315	531	743	944	967
6	0.2	0.2	0.6	0.4	0	37	140	0	54	171	2	199	357	821	935	953
7	0.2	0.2	0.2	0.6	0	840	962	0	761	931	36	771	916	666	967	977
8	0.2	0.2	0.4	0.6	0	526	747	0	480	720	28	631	797	730	957	973
9	0.2	0.2	0.6	0.6	0	221	423	0	254	470	25	491	650	771	947	966
10	0.2	0.4	0.2	0.2	0	964	988	0	867	980	50	690	908	754	758	799
11	0.2	0.4	0.4	0.2	0	625	805	0	508	771	40	511	739	871	852	886
12	0.2	0.4	0.6	0.2	0	160	348	0	170	394	27	343	535	912	886	908
13	0.2	0.4	0.2	0.4	0	964	995	0	893	981	93	817	958	730	894	933
14	0.2	0.4	0.4	0.4	0	753	869	0	667	839	71	692	841	811	903	927
15	0.2	0.4	0.6	0.4	0	359	573	0	354	592	53	554	701	873	912	929
16	0.2	0.4	0.2	0.6	0	975	996	0	937	985	128	921	977	715	950	958
17	0.2	0.4	0.4	0.6	0	847	938	0	807	905	111	840	914	766	945	957
18	0.2	0.4	0.6	0.6	0	560	741	0	559	748	88	718	825	818	934	957
19	0.2	0.6	0.2	0.2	0	995	798	13	996	927	248	953	968	834	487	504
20	0.2	0.6	0.4	0.2	0	975	972	6	934	964	218	860	945	903	682	730
21	0.2	0.6	0.6	0.2	0	779	871	4	718	845	151	761	855	928	789	823
22	0.2	0.6	0.2	0.4	0	997	950	13	992	980	272	971	983	797	724	778
23	0.2	0.6	0.4	0.4	0	970	982	12	936	971	237	905	952	858	793	837
24	0.2	0.6	0.6	0.4	0	818	903	4	777	884	186	819	890	896	841	877
25	0.2	0.6	0.2	0.6	0	996	988	11	991	993	275	985	993	777	873	897
25	0.2	0.6	0.2	0.6	0	996	988	11	991	993	275	985	993	777	873	897
26	0.2	0.6	0.4	0.6	0	974	989	13	952	979	253	946	978	812	883	904
27	0.2	0.6	0.6	0.6	0	865	932	11	841	911	205	878	925	864	891	914
28	0.4	0.2	0.2	0.2	0	13	67	0	13	81	0	85	178	172	762	815
29	0.4	0.2	0.4	0.2	0	2	17	0	6	35	0	53	141	431	871	903
30	0.4	0.2	0.6	0.2	0	0	1	0	1	10	0	36	100	600	893	923
31	0.4	0.2	0.2	0.4	0	189	409	0	167	411	7	315	520	341	903	930
32	0.4	0.2	0.4	0.4	0	69	213	0	82	243	6	245	414	502	919	939
33	0.4	0.2	0.6	0.4	0	20	60	0	31	108	4	177	296	624	919	946
34	0.4	0.2	0.2	0.6	0	499	740	0	458	711	21	609	772	466	955	965
35	0.4	0.2	0.4	0.6	0	284	494	0	301	528	23	520	683	552	947	965
36	0.4	0.2	0.6	0.6	0	122	279	0	164	331	18	415	580	648	942	962

Table 1*(cont.)*

Simulation	Observation error		Process error		*b*=0.4			*b*=0.6			*b*=0.8			*b*=1		
No.	SSB	R	SSB	R	Simple	Deming	P-B	Simple	Deming	P-B	Simple	Deming	P-B	Simple	Deming	P-B
37	0.4	0.4	0.2	0.2	0	534	789	0	440	730	20	474	720	315	941	967
38	0.4	0.4	0.4	0.2	0	223	443	0	222	458	16	399	583	560	940	961
39	0.4	0.4	0.6	0.2	0	59	169	0	89	206	12	283	436	702	934	956
40	0.4	0.4	0.2	0.4	0	705	874	0	629	836	39	657	830	453	958	973
41	0.4	0.4	0.4	0.4	0	437	660	0	414	661	36	577	740	583	942	967
42	0.4	0.4	0.6	0.4	0	191	355	0	225	415	27	459	608	688	939	960
43	0.4	0.4	0.2	0.6	0	827	933	0	784	909	73	822	914	537	962	968
44	0.4	0.4	0.4	0.6	0	644	798	0	627	796	65	749	837	608	959	977
45	0.4	0.4	0.6	0.6	0	371	593	0	415	640	55	650	761	681	942	966
46	0.4	0.6	0.2	0.2	0	956	984	3	926	986	120	847	960	453	828	845
47	0.4	0.6	0.4	0.2	0	822	924	5	772	893	99	775	887	668	861	892
48	0.4	0.6	0.6	0.2	0	518	724	2	529	717	75	669	793	787	891	911
49	0.4	0.6	0.2	0.4	0	965	987	3	946	981	155	906	968	566	889	924
50	0.4	0.6	0.4	0.4	0	854	941	2	826	924	132	839	913	671	895	925
51	0.4	0.6	0.6	0.4	0	646	787	1	639	782	106	755	832	761	907	931
52	0.4	0.6	0.2	0.6	0	977	992	5	951	983	171	945	984	612	924	953
53	0.4	0.6	0.4	0.6	0	896	960	5	879	948	156	907	948	664	929	952
54	0.4	0.6	0.6	0.6	0	734	846	3	752	852	132	831	895	738	920	954
55	0.6	0.2	0.2	0.2	0	0	5	0	3	13	0	62	93	49	457	532
56	0.6	0.2	0.4	0.2	0	0	2	0	3	10	0	51	94	175	672	748
57	0.6	0.2	0.6	0.2	0	0	0	0	1	4	0	43	85	362	798	845
58	0.6	0.2	0.2	0.4	0	34	131	0	47	163	5	217	325	172	736	787
59	0.6	0.2	0.4	0.4	0	16	67	0	27	107	4	181	298	286	795	837
60	0.6	0.2	0.6	0.4	0	6	19	0	15	57	1	146	240	419	854	883
61	0.6	0.2	0.2	0.6	0	199	403	0	238	446	9	468	596	282	872	904
62	0.6	0.2	0.4	0.6	0	118	288	0	161	323	9	413	541	366	880	909
63	0.6	0.2	0.6	0.6	0	45	153	0	96	223	10	337	460	472	890	923
64	0.6	0.4	0.2	0.2	0	100	292	0	105	298	7	311	437	79	794	861
65	0.6	0.4	0.4	0.2	0	47	155	0	63	178	5	273	395	264	887	915
66	0.6	0.4	0.6	0.2	0	19	60	0	34	109	7	225	325	460	907	936
67	0.6	0.4	0.2	0.4	0	284	528	0	304	528	13	492	651	236	888	923
68	0.6	0.4	0.4	0.4	0	169	339	0	208	396	15	433	582	371	908	930
69	0.6	0.4	0.6	0.4	0	65	177	0	122	252	11	372	487	499	918	943
70	0.6	0.4	0.2	0.6	0	529	721	0	529	713	28	671	788	350	941	959
71	0.6	0.4	0.4	0.6	0	363	570	0	398	596	29	622	742	449	932	956
72	0.6	0.4	0.6	0.6	0	203	382	0	273	452	26	539	651	527	929	961
73	0.6	0.6	0.2	0.2	0	642	871	0	630	835	33	708	834	164	942	960
74	0.6	0.6	0.4	0.2	0	455	703	0	475	692	35	634	767	385	937	961
75	0.6	0.6	0.6	0.2	0	233	446	0	297	489	30	542	675	550	935	958
76	0.6	0.6	0.2	0.4	0	751	908	1	732	883	55	777	881	322	948	963
77	0.6	0.6	0.4	0.4	0	597	786	1	599	774	48	723	825	446	944	961
78	0.6	0.6	0.6	0.4	0	363	583	1	430	624	46	649	751	569	941	957
79	0.6	0.6	0.2	0.6	0	818	930	1	820	925	83	858	929	427	957	974
80	0.6	0.6	0.4	0.6	0	706	846	1	737	851	75	820	891	512	954	975
81	0.6	0.6	0.6	0.6	0	537	717	1	590	730	66	751	827	583	942	967

Table 2. Results of sensitivity tests when the number of data was set at 10, 20, 40 or 60. The second to fourth columns indicate the CVs of observation and process errors, and *n* denote the number of data. The figures shown in columns 6 to 17 indicate the number of the trials in which the estimated parameter *b* was statistically recognized as unity. The results in simulation number 55 to 81 indicate the cases when simple regressions greatly underestimated the slope. True *b* = 1 in all cases.

Simulation	Observation error		Process error		*n*=10			*n*=20			*n*=40			*n*=60		
No.	SSB	R	SSB	R	Simple	Deming	P-B	Simple	Deming	P-B	Simple	Deming	P-B	Simple	Deming	P-B
1	0.2	0.2	0.2	0.2	730	902	954	640	936	968	583	942	967	577	940	956
2	0.2	0.2	0.4	0.2	848	897	942	808	933	965	784	936	952	777	937	946
3	0.2	0.2	0.6	0.2	887	894	939	871	930	967	866	930	956	842	934	944
4	0.2	0.2	0.2	0.4	732	936	970	657	963	977	631	962	973	649	968	974
5	0.2	0.2	0.4	0.4	805	918	955	770	945	977	743	944	967	752	962	963
6	0.2	0.2	0.6	0.4	853	910	947	834	938	966	821	935	953	817	960	960
7	0.2	0.2	0.2	0.6	768	944	979	673	976	986	666	967	977	679	978	987
8	0.2	0.2	0.4	0.6	792	932	970	751	959	976	730	957	973	753	976	979
9	0.2	0.2	0.6	0.6	826	923	962	809	943	971	771	947	966	798	968	972
10	0.2	0.4	0.2	0.2	855	919	893	788	872	865	754	758	799	751	748	783
11	0.2	0.4	0.4	0.2	885	898	910	874	866	916	871	852	886	854	856	875
12	0.2	0.4	0.6	0.2	908	886	930	915	893	940	912	886	908	886	887	902
13	0.2	0.4	0.2	0.4	826	927	937	755	929	938	730	894	933	751	894	915
14	0.2	0.4	0.4	0.4	852	914	937	822	910	940	811	903	927	826	914	926
15	0.2	0.4	0.6	0.4	880	902	930	867	915	947	873	912	929	859	923	939
16	0.2	0.4	0.2	0.6	818	938	974	739	956	964	715	950	958	748	955	966
17	0.2	0.4	0.4	0.6	836	936	964	797	948	971	766	945	957	796	946	957
18	0.2	0.4	0.6	0.6	853	923	943	838	936	964	818	934	957	834	947	953
19	0.2	0.6	0.2	0.2	879	899	803	853	739	661	834	487	504	828	444	474
20	0.2	0.6	0.4	0.2	905	888	858	911	760	803	903	682	730	885	662	700
21	0.2	0.6	0.6	0.2	921	876	901	935	819	864	928	789	823	906	772	801
22	0.2	0.6	0.2	0.4	881	918	882	822	856	841	797	724	778	819	731	756
23	0.2	0.6	0.4	0.4	886	906	902	866	855	874	858	793	837	866	798	826
24	0.2	0.6	0.6	0.4	898	893	913	897	860	907	896	841	877	879	838	870
25	0.2	0.6	0.2	0.6	860	938	931	786	914	907	777	873	897	808	866	876
25	0.2	0.6	0.2	0.6	871	923	927	837	906	932	812	883	904	834	889	897
26	0.2	0.6	0.4	0.6	877	910	934	867	901	929	864	891	914	863	902	913
27	0.2	0.6	0.6	0.6	344	737	876	222	768	857	172	762	815	149	767	796
28	0.4	0.2	0.2	0.2	587	831	914	449	851	903	431	871	903	395	861	887
29	0.4	0.2	0.4	0.2	724	861	930	623	879	928	600	893	923	575	898	917
30	0.4	0.2	0.6	0.2	515	846	946	370	897	943	341	903	930	351	908	927
31	0.4	0.2	0.2	0.4	637	854	941	522	906	947	502	919	939	491	915	939
32	0.4	0.2	0.4	0.4	735	876	945	656	909	955	624	919	946	613	921	939
33	0.4	0.2	0.6	0.4	601	895	967	495	946	970	466	955	965	471	955	967
34	0.4	0.2	0.2	0.6	671	891	960	579	945	967	552	947	965	550	957	960
35	0.4	0.2	0.4	0.6	736	893	952	668	934	963	648	942	962	634	948	959
36	0.4	0.2	0.6	0.6	730	902	954	640	936	968	583	942	967	577	940	956

Table 2 (cont.)

Simulation	Observation error		Process error		*n*=10			*n*=20			*n*=40			*n*=60		
No.	SSB	R	SSB	R	Simple	Deming	P-B	Simple	Deming	P-B	Simple	Deming	P-B	Simple	Deming	P-B
37	0.4	0.4	0.2	0.2	556	901	960	393	934	971	315	941	967	271	930	951
38	0.4	0.4	0.4	0.2	734	912	949	614	932	963	560	940	961	522	931	951
39	0.4	0.4	0.6	0.2	810	919	943	744	930	971	702	934	956	696	929	947
40	0.4	0.4	0.2	0.4	641	912	961	496	947	975	453	958	973	443	946	961
41	0.4	0.4	0.4	0.4	730	902	954	640	936	968	583	942	967	577	940	956
42	0.4	0.4	0.6	0.4	795	908	945	736	930	970	688	939	960	693	942	950
43	0.4	0.4	0.2	0.6	669	925	971	587	966	978	537	962	968	541	962	975
44	0.4	0.4	0.4	0.6	730	918	958	652	946	973	608	959	977	622	954	964
45	0.4	0.4	0.6	0.6	776	913	959	729	943	966	681	942	966	704	953	958
46	0.4	0.6	0.2	0.2	710	935	934	544	916	888	453	828	845	432	782	817
47	0.4	0.6	0.4	0.2	815	927	934	727	904	926	668	861	892	647	850	890
48	0.4	0.6	0.6	0.2	858	914	948	811	908	938	787	891	911	768	893	911
49	0.4	0.6	0.2	0.4	725	930	939	620	940	929	566	889	924	559	867	891
50	0.4	0.6	0.4	0.4	793	922	943	705	924	945	671	895	925	672	891	913
51	0.4	0.6	0.6	0.4	845	914	938	775	918	950	761	907	931	762	905	932
52	0.4	0.6	0.2	0.6	744	936	951	656	949	950	612	924	953	613	925	942
53	0.4	0.6	0.4	0.6	791	922	947	716	935	959	664	929	952	685	926	937
54	0.4	0.6	0.6	0.6	818	915	944	764	932	957	738	920	954	750	930	936
55	0.6	0.2	0.2	0.2	137	533	739	69	473	616	49	457	532	39	437	464
56	0.6	0.2	0.4	0.2	343	691	844	220	690	792	175	672	748	172	664	692
57	0.6	0.2	0.6	0.2	518	789	891	389	786	867	362	798	845	322	786	826
58	0.6	0.2	0.2	0.4	312	704	867	200	722	841	172	736	787	142	747	759
59	0.6	0.2	0.4	0.4	437	774	890	315	791	868	286	795	837	270	804	837
60	0.6	0.2	0.6	0.4	566	819	915	449	833	895	419	854	883	401	843	880
61	0.6	0.2	0.2	0.6	432	812	933	305	849	918	282	872	904	282	877	893
62	0.6	0.2	0.4	0.6	522	825	932	391	864	933	366	880	909	376	884	908
63	0.6	0.2	0.6	0.6	609	846	940	499	881	937	472	890	923	465	901	923
64	0.6	0.4	0.2	0.2	299	769	921	129	788	888	79	794	861	62	796	838
65	0.6	0.4	0.4	0.2	484	834	933	326	858	921	264	887	915	241	870	896
66	0.6	0.4	0.6	0.2	626	863	930	510	885	934	460	907	936	409	893	921
67	0.6	0.4	0.2	0.4	434	830	937	261	878	939	236	888	923	212	891	913
68	0.6	0.4	0.4	0.4	554	849	927	413	891	945	371	908	930	334	904	933
69	0.6	0.4	0.6	0.4	658	864	930	534	902	949	499	918	943	478	908	933
70	0.6	0.4	0.2	0.6	517	879	960	383	920	964	350	941	959	331	934	952
71	0.6	0.4	0.4	0.6	594	878	955	466	922	963	449	932	956	425	936	950
72	0.6	0.4	0.6	0.6	672	873	949	572	925	958	527	929	961	516	933	950
73	0.6	0.6	0.2	0.2	474	878	961	247	930	968	164	942	960	119	930	947
74	0.6	0.6	0.4	0.2	621	902	956	445	930	966	385	937	961	330	925	948
75	0.6	0.6	0.6	0.2	732	911	953	601	932	959	550	935	958	506	924	948
76	0.6	0.6	0.2	0.4	556	900	962	375	938	975	322	948	963	283	939	950
77	0.6	0.6	0.4	0.4	644	902	956	511	940	966	446	944	961	422	933	956
78	0.6	0.6	0.6	0.4	725	908	946	631	934	963	569	941	957	546	933	946
79	0.6	0.6	0.2	0.6	609	914	964	474	946	973	427	957	974	402	949	962
80	0.6	0.6	0.4	0.6	667	911	955	549	946	973	512	954	975	493	942	953
81	0.6	0.6	0.6	0.6	730	902	954	640	936	968	583	942	967	577	940	956

Figure 1 shows the typical cases in Table 1. That is, only for the cases that the CVs are all 0.4 and the number of samples is 40, the mean and standard deviation for the slopes estimated in 1,000 simulations are shown for each method when true slopes are assumed to be 1.0, 0.8, 0.6 and 0.4, respectively.

Sensitivity tests for the sample size

Table 2 shows the results of sensitivity tests when the number of data was set at 10, 20, 40 or 60. The value of *n* denotes the number of samples used in the simulations. For the simple regression, when the observation error in SSB was small (CV=0.2), the probability of detecting the correct slope was not low regardless of the observation error in R and process error in SSB and R (simulation nos. 1-27). When the observation error in SSB was relatively large (CV=0.4), the observation error in R was relatively large or large (CV=0.4 or 0.6), the probability of detecting the correct slope was not low (simulation nos. 38-54). However, when the observation error in SSB was large (CV=0.4 or 0.6) and the observation error in R was smaller (CV=0.2) than the error in SSB, the probability to detect the correct slope became low (simulation nos. 28-36 and 55-72). In particular, when the number of samples was large ($n \geq 20$), the probability to detect the correct slope was extremely low. In contrast, the Deming and Passing-Bablok regressions were not as sensitive to the number of data as was the simple regression analysis.

Figure 2 shows the typical cases in Table 2. That is, only for the cases that the CVs in observed error in SSB are changed at 0.2, 0.4 and 0.6, the mean and standard deviation for the slopes estimated in 1,000 simulations are shown for each method. The other CVs are all same at 0.4 and the number of samples is 40.

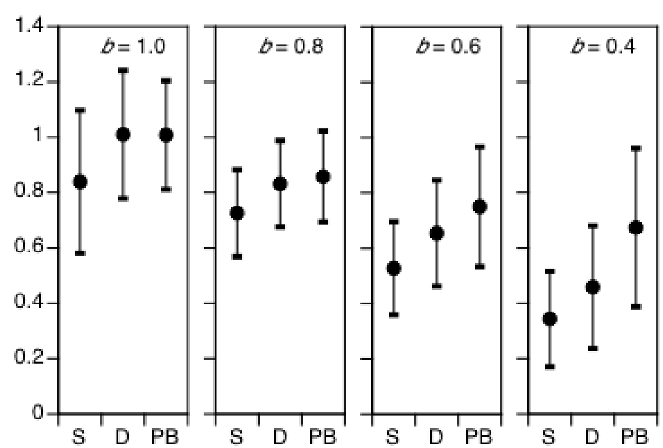

Fig. 1. Mean (*m*) and standard deviation (1.96 *s.d.*) for the slopes estimated in 1,000 simulations are shown for each method when true slopes are assumed to be 1.0, 0.8, 0.6 and 0.4, respectively. The observed and/or process CVs in R and SSB are all 0.4 and the number of samples is 40.

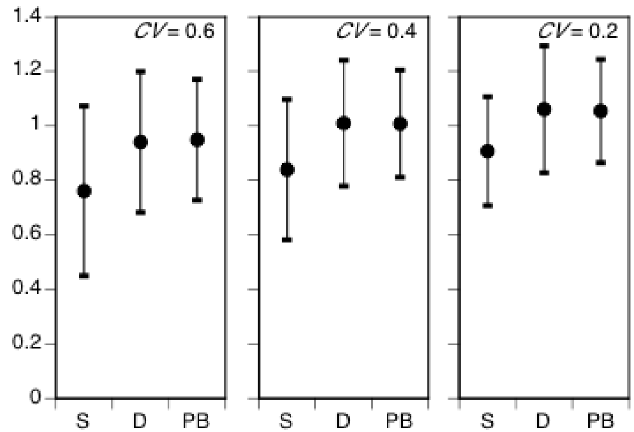

Fig. 2 Mean (*m*) and standard deviation (1.96 *s.d.*) for the slopes estimated in 1,000 simulations are shown for the cases that the CVs in observed error in SSB are changed at 0.2, 0.4 and 0.6, respectively. The other CVs are all same at 0.4 and the number of samples is 40.

Table 3 Results when a simple, the Deming and Passing-Bablok regressions were applied to the actual data of Japanese sardine (Wada and Jacobson 1998), Pacific sardine (Jacobson and MacCall 1995) and chub mackerel (Yatsu et al. 2005).

Data	Method	Data used	No.of sample	estimate of *b*	95% confidence limit of *b*		*P*-value	Judgment of slope *b*
					Lower	Higher		
Japanese sardine	Simple	1951-1995	45	0.769	0.585	0.953	1.16 (10^{-10})	$b < 1$
	Simple	1988-1991were removed	41	0.979	0.801	1.157	4.50 (10^{-13})	$b = 1$
	Deming	1951-1995	45	0.968	0.885	1.133		$b = 1$
	P-B	1951-1995	45	1.086	0.905	1.245		$b = 1$
Pacific sardine	Simple	1935-1990	56	0.781	0.578	0.984	6.09 (10^{-9})	$b < 1$
	Deming	1935-1990	56	0.955	0.791	1.312		$b = 1$
	P-B	1935-1990	56	0.983	0.769	1.268		$b = 1$
Chub mackerel	Simple	1970-2000	31	0.829	0.527	1.131	4.45 (10^{-6})	$b = 1$
	Deming	1970-2000	31	1.211	0.944	1.335		$b = 1$
	P-B	1970-2000	31	1.182	0.971	1.493		

Results applied to the actual SRR and population size data

Figures. 3- 5 and Table 3 show the results for the regression line of ln(R) against ln(egg production) for the Japanese sardine (Wada and Jacobson 1998), the regression line of ln(R) against ln(SSB) for the Pacific sardine (Jacobson and MacCall 1995) and chub mackerel (Yatsu et al. 2005), when the three regression methods were used. If parameter *b* was not statistically different from unity, the acceptable model was a proportional model. That is, a density-dependent effect could not be detected from the SRR data. In contrast, if the parameter *b* was statistically recognised to be less than unity, this implied that a density-dependent effect was detected.

The first case in Table 3 indicates the slope of the regression line estimated using the data of Wada and Jacobson (1998). The slope was significantly less than unity, and a density-dependent effect was detected. However, even when the same simple regression analysis was applied to the data from which 1988-1991 were removed, when extremely low recruitments occurred, the results were dramatically different. That is, the slope was not significantly different from unity, and this implied that a density-dependent effect was not detected. When the Deming and Passing-Bablok regressions were applied to all data, the slopes were not different from unity. The slope estimated by a simple regression analysis of the data with 1988-1991 removed and those estimated by the Deming and Passing-Bablok regressions for all data coincided well (Table 3 and Fig. 3).

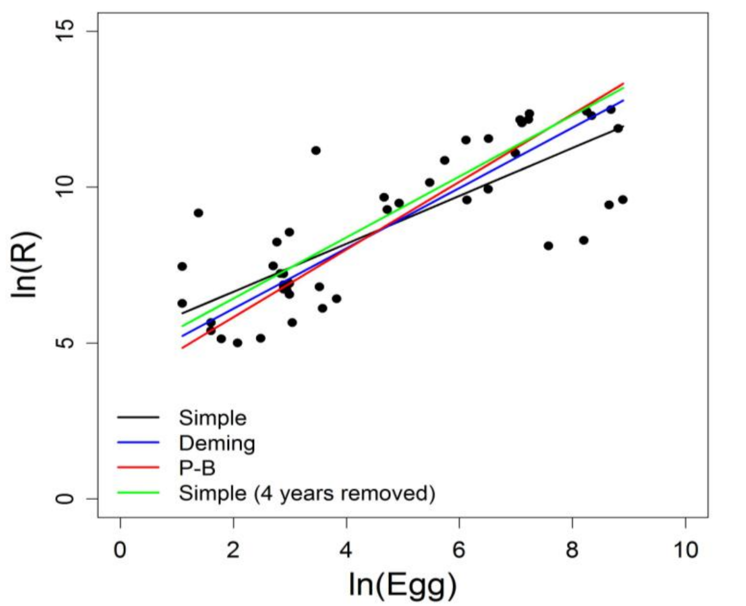

Fig. 3. Results of regression analyses for Japanese sardines. The black line indicates the result when a simple regression analysis was applied. The green line indicates the case when the data for four years from 1988-1991 were removed. The blue and red lines show the results of the Deming and Passing-Bablok regression analyses, respectively

When a simple regression analysis was applied to the data for the Pacific sardine (Jacobson and MacCall 1995), the slope was significantly different from unity, and this implied that a density-dependent effect was detected. When the Deming and Passing-Bablok regressions were applied to the data, a density-dependent effect was not detected (Fig. 4).

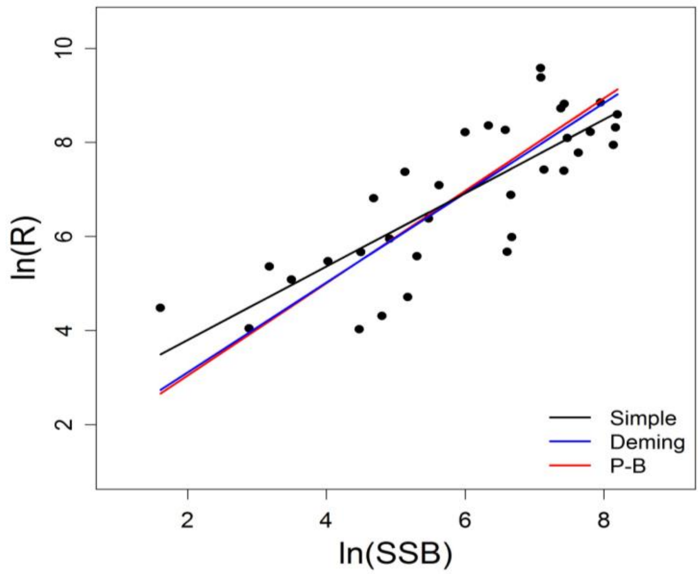

Fig. 4. Results of the regression analyses for Pacific sardines. The black, blue and red lines show the results of simple, Deming, and Passing-Bablok regression analyses, respectively.

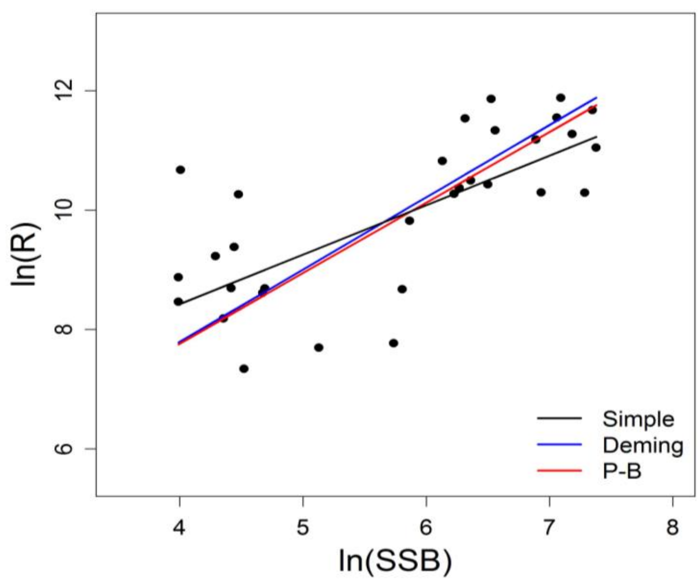

Fig. 5. Results of regression analyses for chub mackerel. Black, blue, and red lines show the results of simple, Deming, and Passing-Bablok regression analyses, respectively.

When a simple regression analysis and the Deming and Passing-Bablok regressions were applied to the data for the chub mackerel (Yatsu et al. 2005), the slope were not significantly different from unity, and this implied that a density-dependent effect was not detected (Table 3 and Fig. 5).

Discussion

The simulation studies indicated that the Deming and Passing-Bablok regressions were much more capable of detecting the proportionality between R and SSB than the simple regression analysis when the observation errors in SSB were large. For the simple regression analysis, the large observation errors in SSB and the large number of samples (in this simulation, n $\geq$20) greatly reduced the probability that proportionality would be detected. However, the effect was reduced when the number of samples was small (in this simulation, n =10).

The probability that the Deming and Passing-Bablok regressions erroneously detected the proportionality in the slope was extremely high when the observation errors in R were high. This is the disadvantage of these methods. However, when the true value of b was less than unity, simple regression analysis seldom erroneously judged the slope to be unity, because the simple regression analysis has a tendency to underestimate the slope in response to the effect of observation and/or process errors (Sakuramoto and Suzuki 2012). Therefore, to avoid the disadvantage of the Deming and Passing-Bablok regressions methods, it is better to compare the results derived from the Deming and Passing-Bablok regressions methods and that derived from single regression analysis. When the former shows a proportionality and the latter does not show the proportionality but the slope is slightly less than unity, the possibility that the relationship really has a proportionality would be extremely high.

When we analysed the actual data, the slopes of the regression lines for chub mackerel were not statistically different from unity in all three regression analyses. As we noted above, when the true SRR had a density-dependent effect, the probability that a simple regression analysis erroneously judged the slope to be unity was extremely low. That is, the result that a density-dependent effect was not detected in the SRR data for chub mackerel strongly indicates that a density-dependent effect does not really exist in the relationship of stock and recruitment.

Similar points have been made by Maelzer (1970), Kuno (1971) and Ito (1972). They noted that in the attempts to detect a density-dependent effect using regression analysis, the error consistently acts as if it were a density-dependent effect. Under the effect of sampling error, the slope b for the regression of log N_{i+1} on log N_i, for example, is expected to become <1 even where there is no density-dependent factor at all; note that N_i denotes the population in year i. Therefore, the result reported in this paper that no density-dependent effect exists in population change or in SRR is plausible. The data of Pacific sardine (Jacobson and MacCall 2005) and mackerel (Yatsu et al. 2005) analysed in this paper are available in the literatures inferred.

Conclusion

The Deming and Passing-Bablok regressions were more reliable to detect proportionality between recruitment (R) and spawning stock biomass (SSB) than was simple regression analysis. With simple regression analysis, when the number of samples was large and the observation errors in the SSB were large, the probability that detects a false density-dependent effect is extremely high.

A density-dependent effect did not play an important role in the population fluctuations and that a proportional model is a reasonable basic model for expressing the SRR in the Japanese sardine, Pacific sardine and chub mackerel.

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