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EXECUTIVE SUMMARY

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The relationship between the year class strength (YCS) of southern blue whiting and potential environmental predictors was examined using three different analytical approaches. Predictors included the same variables considered by Hanchet & Renwick (1999), plus wind and atmospheric pressure observations from the Campbell Island meteorological station. The analysis consisted of 1) multiple regression, using cross-validation to reduce overfitting and spurious correlation; 2) Tree-based regression, using 'out of the bag' sampling; and 3) discriminant analysis with cross-validation.

Estimates of YCS for the fishing years 1977–2002 were obtained from the 2006 stock assessment and the suite of 26 predictors applied from three seasons: winter, spring, and summer. Regression analyses indicated that sea surface temperature (SST) did not explain any significant variability in YCS, although this analysis may have lacked power, based as it was on a truncated time series (dictated by the availability of SST data). Linear regression identified two variables as potential predictors: winter PC1 (a large high pressure system centred over the Campbell Plateau) and spring HNW (high to northwest, resulting in strong SW winds over the subantarctic region). Both variables were negatively correlated with YCS, suggesting that better recruitment arises from rough winters with a high degree of mixing, followed by relatively calm spring conditions.

Both multiple linear regression and random forest regression provided predictions of YCS that provided a good fit to observed data in average years, but underestimated very strong year classes and overestimated very weak year classes. Discriminant analysis done on YCS classes (weak, medium, and strong) provided a group of eight predictors, the strongest of which were the same two variables identified by regression.

Overall, the models provided good correlation of climate variables and YCS, but had poor predictive power outside the medium range of YCS. This is likely to be because processes affecting recruitment operate at spatial scales smaller than those of our predictor variables. As the southern blue whiting stock depends on occasional very strong year classes to support continuance of the fishery, it may be more important (from a precautionary management perspective) to detect consecutive years of weak recruitment. To achieve this, a longer time series of data is required, which ideally should be coupled with information on predator and prey dynamics during the larval and juvenile stages.

Reference:

Hanchet, S.M.; Renwick, J.A. (1999). Prediction of year class strength in southern blue whiting (*Micromesistius australis*) in New Zealand waters. New Zealand Fisheries Assessment Research Document 99/51. 24 p. (Unpublished report held in NIWA library, Wellington.)

1. INTRODUCTION

This report addresses objective 3 of Ministry of Fisheries project SBW2004-01: *To investigate the prediction of year class strength from environmental variables.* It aims to extend and update earlier work by Hanchet & Renwick (1999), which identified potentially useful predictors of relative year class strength (YCS) based on large-scale climatic conditions. Although many initially encouraging climate-recruitment relationships have been subsequently invalidated by extended time-series of data (Mertz & Myers 1995, Francis et al. 2006), the search for valid predictors is a useful one because of the advance warning of weak year classes that allows management action to be taken. This is especially true for stocks whose fishery is based on only one or a few strong year classes, as is the case with southern blue whiting (Hanchet et al. 2006), since a failure to react to several successive years of weak recruitment may result in stock collapse. Extending time-series of data and applying appropriate analyses may still provide useful predictions of recruitment (Tyler 1992).

Three previous studies have sought predictors of year class strength in southern blue whiting. Shpak & Kuchina (1983) examined the effect of microcirculation and temperature on the number of spawners and the resulting egg densities on the Bounty Platform between 1973 and 1976. They postulated that average temperatures and anticyclonic (stable) water circulation patterns were the most favourable for reproduction. Hanchet (1993) found that YCS in the Campbell Island stock between 1982 and 1992 was positively correlated with the September sea surface temperatures (SST) in the year they were spawned. Hanchet & Renwick (1999) found that three of a large number of environmental variables explained 86% of the variation in YCS on the Campbell Island Rise. The results suggested there was a strong negative correlation between YCS and anticyclonic atmospheric conditions (i.e., that windier, rougher conditions gave rise to stronger YCS).

This study extends the time series of data used by Hanchet & Renwick (1999) using the same predictors, based on updated estimates of YCS from Hanchet et al. (2006). The analysis is extended by inclusion of SST by season as a further group of predictors. A secondary analysis included direct measurements of local climatic data (wind speed, maximum wind gust, and air pressure) from Campbell Island weather station as a group, used as a proxy estimator for the likelihood of rough local sea conditions.

2. ENVIRONMENTAL DATA

The full environmental dataset consisted of 31 explanatory variables which are listed in Table 1. These were presented and outlined in some detail by Hanchet & Renwick (1999) and so they are not further discussed here. Following Hanchet & Renwick (1999), we chose to examine environmental factors over the nine month period July to March, covering the period immediately before spawning until the end of the first summer. This period was divided into three seasons; winter (July–September), spring (October–December), and summer (January–March).

The SST data contain the average monthly sea surface temperature recorded by PF (Pathfinder) and NSA. The PF series extend from January 1985 to December 1999 and the NSA series from January 1993 to March 2006, with an 84 months overlapping period between January 1993 and December 1999 (Figure 1). The NSA data contain a large amount of missing values mainly in the first few years and therefore it was decided to use the PF series up to the end of 1999 and the NSA series from the beginning of 2000. PF data are believed to have often been contaminated by cloud and as a result they appear to be systematically colder than the NSA. Adjustment based on the ratios of the average temperatures of NSA series to those of PF series for each of the four seasons between January 1993 and December 1999 were applied to the PF series to mitigate the bias caused by the cloud algorithm (Figure 2). The final series included the calibrated PF series from 1985 to 1999 and the NSA series from 2000 to 2002, with derived seasonal variables for winter, spring and summer.

3. METHODS

3.1 Summary of analyses

The relationship between year class strength of southern blue whiting and the environmental (seasonal) variables was explored using several statistical tools. Firstly the Pearson correlation coefficient between each individual variable and year class strength was briefly examined. Secondly a multiple linear regression was performed with the estimates of year class strength being treated as a continuous variable. The predictive performance of the model was assessed through the full cross-validation procedure (Francis 2006). The third approach was to use the multiple discriminant analysis, for which the estimates of year class strength were treated qualitatively and the cross-validation was also carried out. The two analyses mainly updated those from the last study (Hanchet et al. 1999) with updated estimates of the year class strengths and the addition of SST variables as potential predictors. Finally analyses using random forest (Breiman 2001) were carried out, firstly based on tree regression (Breiman et al. 1984) and then based on tree classification. The quality of model prediction was scored by mean square error (MSE) for regression and generalisation error for classification, generated internally through a cross-validation like mechanism.

The multiple linear regression analysis was firstly carried out for the entire recruitment data (1977–2002), then the shorter time series (1985–2002) for which the SST variables were included as candidate predictors, and also for the series (1977–1992) analysed in the last study. The random forest regression and classification were both carried out for the entire recruitment data series. A final multiple regression analysis was added that omitted SST (so that the entire 1977–2002 time series of YCS estimates could be used), but included Campbell Island meteorological station measurements of local wind speed, maximum gust, and atmospheric pressure. This last analysis treated some of the predictors as functional groups (e.g., synoptic patterns resulting in westerly winds over the Campbell Plateau), such that they entered or left the stepwise regression model together.

3.2 Multiple linear regression

The model assumed that year class strengths follow a lognormal distribution (Francis 1993) and therefore used log-transformed estimates of year class strength. Due to the high dimensionality and the possible collinearity (a condition where the model's predictors are highly inter-correlated) of the candidate predictors a stepwise regression procedure was carried out to identify variables that explained most of the variation in year class strength and to remove redundant variables that essentially carry the same information. The stopping rule employed in the stepwise regression used a partial F test (Heiberger et al. 2004) at a significance level of 0.01. Note that there appears to be no consensus as to the choice of stopping rules and different methods could sometimes lead to different sets of predictors (Francis et al. 2005). The R^2 based on the selected predictors was calculated. Because of the large number of predictors, a spurious relationship between the predictands and predictors could be established by chance resulting in large values of R^2. The full cross-validation, as explained by Francis (2006), involves predicting each of the year class strengths using a regression equation determined by the rest of data. (For each case, the predictors were reselected using stepwise regression.) The cross-validation calculates the Percent of Variance Explained (PVE, Francis (2006)) statistics as below:

$$1-\frac{\sum_i (y_i-\hat{y}_i)^2}{\sum_i (y_i-\bar{y}_i)^2}$$

where y_i is the ith year class strength, $\hat{y}_i$ and $\bar{y}_i$ are the predicted value and the mean of the year class strengths respectively after the ith case was removed. Francis (2006) observed large PVEs (up to 80%) through cross-validation from models fitted to simulated recruitment data sets where recruitment-environmental relationship exists and small PVEs (up to -200%) from data sets where year class strengths were just random numbers. However, the study also showed that low PVEs were associated with large variability, especially for data which contain a relatively small amount of recruitment data and a large number of explanatory variables.

3.3 Random forest

Random forests are an ensemble of unpruned trees (Breiman 2001), with each tree grown by the node-splitting classification (for categorical variable) and regression (for continuous variable) trees method (Breiman et al. 1984). The data used to generate each tree are a random sample (without replacement) of all the cases. Further randomisation is introduced at each node of the tree by using a random subset of predictors for obtaining the split at the node. For a regression analysis, the predicted value is obtained by averaging the outputs of passing the set of predictors down every tree. For a classification analysis, the predicted category is the most frequently occurring of the classes as determined by the individual trees (majority votes).

The estimates of year class strength were converted into weak (under 0.4), medium (0.4–1) and strong (over 1) year classes. The model performance was assessed by generalisation error for classification and MSE for regression (Breiman 2001). The data cases left out for each tree (out of bag samples) are run through the tree and the error rate (or mean square error for regression) of the prediction is computed. The error rates for the trees in the forest are then averaged to give the overall generalisation error rate.

The candidate predictors are ranked by their importance. For each tree the variables for out of bag samples are randomly permuted and the prediction accuracy is recomputed. The average lowering of prediction accuracy across all cases gives the importance of a variable. In this analysis, initial runs were carried out to rank the importance of the variables and only relatively important variables were used for further classification or regression.

3.4 Discriminant analyses

Stepwise discriminant analysis was used as an alternative method to select the variables that contribute most to differentiating weak, medium, and strong year class strengths. These were defined in the same way as for Random Forest classification. The dataset consisted of 26 years (1977–2002) and 72 explanatory variables: all those listed in Table 1 except for SST, but including the 3 meteorological observations (daily averages of mean wind speed, maximum wind gust, and atmospheric pressure) from Campbell Island. Since there were so many predictor variables relative to the number of observations, the probability of entry of predictors was initially set at 0.01, and the analysis then repeated with entry probability set at 0.10. In both cases the probability of a variable exiting from the model at each step was set at 0.15.

Variables identified by the stepwise analysis were subjected to linear discriminant analysis with cross–validation to determine the predictive power of the model, and to a canonical discriminant analysis to determine which of the variables were most strongly correlated with weak, medium or strong year classes.

4. RESULTS

4.1 Correlation

The correlations between the estimates of year class strength and the environmental variables are presented in Table 2. Variables from winter and spring show that most of the significant correlations, and no variables, were significant with the same sign over more than one season. For the entire recruitment data the two highest correlations were with winter PC 1 (-0.551), which is an anticyclonic air pressure system situated over the Campbell Plateau, and spring HNW (-54.2), which refers to the "high to northwest" weather type resulting in a strong westerly flow over the Campbell Island area. For the shorter times series (1985–2002), the two highest correlations were with winter T (64.7), which refers to the "broad trough over New Zealand" weather type, and winter PC 1 (-61.9). None of the SST variables were significantly correlated with the estimates of year class strength.

4.2 Multiple linear regression

The results of the analyses are summarised in Tables 3–5, and the fits are shown in Figures 3–8. Variable winter PC 1 and spring HNW were selected into the model fitted to the recruitment data from 1977 to 2002 and from 1977 to 1992. Only variable winter T entered the model for the 1985–2002 time series and none of the SST variables were significant. Both Winter PC 1 and spring HNW had a negative effect on year class strength. Winter T had a positive relationship with year class strength from 1985 to 2002. The observed vs. fitted values for each of the models described above explained 56%, 85%, and 42% of variations in year class strength respectively. However, the percent variation explained by the cross-validation models was substantially lower. The predicted values of the model fitted to the entire recruitment data tracked the trend of the early (before 1982) and later (after 1996) year class strength and those from 1986 to 1990, with a PVE of -14%. The model fitted to the data from 1977 to 1992 has a PVE of 47% and predicted well for most cases. The model fitted to the 1985–2002 time series predicted poorly with a PVE of -50%.

4.3 Random Forest

4.3.1 Regression

Based on the variable importance given by the initial run of the Random Forest regression (Figure 9), spring HNW, summer TSW, spring PC 2, winter PC 1, winter CI tav, winter R, and summer TNW (each of them lead to a change of MSE by more than 1% through permutation) were used as potential predictors for a second run, which produced fitted values fairly close to the observed estimates of year class strength (Figure 10). A more reliable measure of the model's predictive power is to examine the predicted values based on the out of bag samples using only trees for which the samples were excluded from their construction process. The result showed that the model captured the trend of year class strength from 1977 to 1990 and from to 1996 to 2002 (Figure 11). The predicted values fluctuated more moderately in early years compared to the observed values. The variance explained derived from the MSE based on the out of bag samples was 33%, suggesting improvement of predictive power over the null model which simply predicts year class strength using the mean of the series.

4.3.2 Classification

The Random Forest classified each of the data cases using spring HNW, winter T, winter R, summer CI tav, winter PC 1, spring PC 2, and spring NE as potential predictors according to the ranking of variable importance from an initial run (Figure 12). Overall generalisation error rate based on out of bag samples was estimated to be 38%. The rate broken down by class showed 8 out 10 strong, 6 out of 8 median year classes were correctly classified, but 6 out of 8 weak year classes were misclassified (Table 6). Multidimensional scaling (Cox & Cox 1994) was then performed to extract the scaling coordinates of each case based on their proximity as measured by Random Forest (the proximity of cases i and j increased by 1 if they land on the same terminal node of a tree as the forest grows). The scaling coordinates (Figure 13) showed that the model was able to discriminate between strong and median year classes but not the weak, as the coordinates of the strong and median year classes were clearly apart but were mixed with those of the weak year classes.

4.4 Grouped multiple linear regression

A second form of stepwise multiple regression was performed using the entire dataset, but grouping the variables so that they entered or were removed from the model together. The suite of 12 synoptic flow-patterns (Kidson 1984) was reduced to three groups reflecting predominantly westerly, northerly, or easterly flows. Campbell Island wind and pressure data were added as a group, and SST was omitted. Only two variables were retained in the model (Table 7): winter PC1, and the direct observations from Campbell Island in spring. These two variables provide a model (Figure 14) with similar fit to that achieved by the earlier regression models. As in previous analyses, PC1 was negatively correlated with YCS (Figure 15). Spring wind speed was also negatively correlated with YCS, and spring barometric pressure was positively correlated with YCS (Figure 15).

4.5 Discriminant analyses

With entry probability set at 0.01 for the stepwise discriminant analysis, no variables met the criteria for entry into the model. Setting a less stringent entry criterion of 0.10, 8 of the 72 possible predictors were selected (Table 8). Using these variables, a linear discriminant analysis with cross-validation successfully placed 7 of 8 weak year classes, 5 of 8 medium classes, and 8 of 9 strong year classes into their correct groups (Table 9). Overall misclassification error was thus less than 20%.

A canonical discriminant analysis seeks to find the vector (canonical axis) in multivariate space that best separates *a priori* defined groups. Using the same eight variables, the first canonical axis clearly separated strong year classes from the weaker years, with the exception of 2002, which was placed with the weak years (Figure 16). This is the same "strong" year that was misclassified as weak by the linear discriminant analysis (Table 9). The second canonical axis separated weak from medium year classes (Figure 16). Calculating correlations of the original variables with the axes (Table 10) allows inference of the variables responsible for the separation of groups. This identified spring HNW and winter PC1 as being strongly correlated with weak and medium YCS (i.e., negatively correlated with Can 1), thus agreeing with the results of the regression analyses. No variable was robustly positively correlated with "strong" years. The second canonical axis clearly separated weak from medium year classes. The only variable strongly (over

0.3) correlated with this axis was winter HSE (high southeast of Cook Strait). Its positive correlation indicated that it is associated with weak YCS.

5. DISCUSSION

The results of these analyses reinforce the main result of Hanchet & Renwick (1999), that stronger YCS in southern blue whiting is associated with predominantly rough and unstable winter conditions across the Campbell Plateau. The variable spring HNW and winter PC 1 were picked out by most models as being most likely to explain the variation in year class strength. PC1 characterises a large anticyclone across the area, and was negatively correlated with YCS. This may indicate that mixing of the water column during the early spawning period has important effects on spawning success. Spring HNW is a synoptic pattern that places an anticyclone off the northwest coast of the North Island, resulting in a strong west to southwest flow over the Campbell region (Kidson 1994). HNW was also negatively correlated with YCS, implying that recruitment is more successful if rough winter conditions are followed by relatively calm and stable spring conditions. This is backed up by the second regression analysis that retained PC1 as an important predictor, but replaced Spring HNW with the spring wind speed, gust, and barometric pressure observations from Campbell Island. YCS was negatively correlated with spring wind speed and weakly positively correlated with barometric pressure. Winter T was the only variable entering the model fitted to the data from 1985–2002, but failed to predict most of year class strength. SST did not explain any significant variation in YCS.

Discriminant analyses also highlighted winter PC1 and spring HNW as important separators of stronger from weaker year classes, but also separated weak and medium YCS using winter HSE – like PC1, a synoptic pattern that should result in relatively low windspeeds and settled weather. A biological explanation for this result is that rough winter conditions reduce the probability of predation on freshly spawned eggs, whereas calm summer conditions facilitate feeding for newly hatched larvae.

Sea surface temperature (SST) had no predictive value in these models, despite being of importance in assessments of other species (e.g., Francis 1993). In the current analysis, however, SST data were available for less than 20 years, and therefore may have been undervalued in the regressions because of low statistical power.

In situations where model over-fitting and spurious correlations are possible due to the few predictants and many potential predictors, the performance of the model should be evaluated by its predictive accuracy on "fresh data" that the model is unfamiliar with. This was achieved through cross-validation in the multiple linear regression and linear discriminate analyses, and as a built-in process in the Random Forest.

Among various models, Random Forest regression seems to have produced better correlation than multiple linear regressions on the entire recruitment data and has captured the trend of year class strength for years. The multiple linear regression models fitted to the three sets of time series (1977–2002, 1985–2002 and 1977–1992) gave distinct PVE (-14%, -50%, and 47%) and this was consistent with the study of Francis (2006) that PVE were variable when the potential predictors far outnumbered the predictants.

Although matches between fitted and observed values of YCS were achieved at intermediate YCSs (between -1 and 1 on the log scale), all the prediction methods were unsuccessful in predicting very strong (1991) or very weak (1982, 1989) year class strengths. This is probably because the predictors available describe patterns over larger spatial scales than that at which the biological processes affecting relative YCS operate. Although it is possible to achieve reasonable model fits to historical data and thus describe general patterns, especially when the number of predictors is large and tend to covary, correlative approaches will always struggle to accurately predict the particular. It is arguable that for management purposes, in a precautionary context, it is more important to detect a succession of weak year classes that increase the risk of stock collapse than to detect strong recruitment episodes that allow an increase in catch. It is likely that the predictors used here do affect southern blue whiting YCS, but operate indirectly or interact on smaller scales in ways that are difficult to measure. Potential solutions are to either continue to increase the time series of data available for analysis, or seek to obtain data at spatial scales likely to reflect biological influences on recruitment and survivorship. Useful (but currently unavailable) information might include detailed data on mixing or stratification of the water column, distributions and relative availability of major prey species through early development, or the ways in which conditions affect the distribution of predators.

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Table 1: List of environmental variables used in the analysis.

CI Tav	Campbell Island average air temperature
CI gSST	Gridded SST from point nearest Campbell Island
CI oSST	Observed SST from Perseverance Harbour (Campbell Island)
TSW	"Trough in southwest flow" weather type (monthly frequency)
T	"Broad trough over New Zealand" weather type (monthly frequency)
SW	"Southwest flow" weather type (monthly frequency)
NE	"Northeast flow" weather type (monthly frequency)
R	"Ridge across South Island" weather type (monthly frequency)
HW	"High west of South Island" weather type (monthly frequency)
HE	"High east of North Island" weather type (monthly frequency)
W	"Westerly flow" weather type (monthly frequency)
HNW	"High to northwest" weather type (monthly frequency)
TNW	"Northwest flow ahead of trough" weather type (monthly frequency)
HSE	"High southeast of Cook Strait" weather type (monthly frequency)
H	"High over New Zealand" weather type (monthly frequency)
PC 1	Campbell-area 1000hPa height principal component 1 ("high")
PC 2	Campbell-area 1000hPa principal component 2 ("westerly")
PC 3	Campbell-area 1000hPa principal component 3 ("northerly")
thick	1000-500hPa mean depth at Campbell
S.vort	Mean surface vorticity at Campbell
T.adv	Mean lower-troposphere temperature advection at Campbell
V.adv5	Mean mid-tropospheric vorticity advection at Campbell
Z1	Auckland - Christchurch pressure difference
Z2	Christchurch - Campbell pressure difference
M1	Hobart - Chathams pressure difference
M2	Hokitika - Chathams pressure difference
SOI	Southern Oscillation index
Campbell speed	Daily average wind speed measured at the Campbell Island met. Station
Campbell gust	Maximum daily wind gust velocity at Campbell Island
Campbell pressure	Daily average atmospheric pressure at Campbell Island
SST	Sea surface temperature

Table 2: Pearson's correlation coefficients of seasonal variables with logYCS for the period 1977 to 2002 (left) and 1985 to 2002 (right, including SST variables); bolded figures are significant.

	1977-2002		
	win	spr	sum
CI.tav	**-0.412**	0.186	0.153
PC.1	**-0.551**	0.099	0.245
PC.2	-0.166	**-0.415**	-0.364
PC.3	-0.068	0.268	-0.162
SOI	0.221	0.194	0.178
TSW	-0.125	0.172	**0.443**
T	**0.431**	0.101	-0.056
SW	0.310	-0.012	-0.008
NE	0.067	0.175	0.289
R	-0.180	0.265	0.186
HW	**-0.389**	0.256	0.069
HE	-0.302	0.031	-0.091
W	0.314	**-0.411**	-0.114
HNW	-0.005	**-0.542**	-0.220
TNW	0.135	0.035	0.009
HSE	-0.370	0.121	-0.153
H	-0.228	-0.199	-0.304
Z1	**0.431**	-0.292	-0.373
Z2	0.129	-0.351	-0.302
M1	0.055	0.000	0.117
M2	0.200	-0.068	-0.100

	1985-2002		
	win	spr	sum
CI.tav	**-0.431**	0.125	0.006
PC.1	**-0.619**	-0.018	0.109
PC.2	-0.234	-0.321	-0.334
PC.3	-0.096	0.210	-0.226
SOI	0.102	-0.122	-0.094
TSW	-0.059	0.267	0.278
T	**0.647**	-0.029	0.180
SW	0.143	0.124	0.170
NE	0.064	0.121	-0.008
R	-0.297	0.175	0.040
HW	**-0.409**	0.122	0.095
HE	**-0.577**	-0.037	-0.069
W	0.338	-0.194	0.161
HNW	-0.082	-0.340	-0.209
TNW	0.223	0.018	-0.045
HSE	-0.290	-0.084	-0.190
H	-0.199	-0.229	-0.230
Z1	0.530	-0.102	-0.141
Z2	0.017	-0.242	-0.196
M1	0.094	0.240	0.286
M2	0.180	0.151	0.210
SST	-0.251	0.010	0.164

Table 3: Results of multiple regression analysis fitted to recruitment data from 1977 to 2002; PVE is the percent of variance explained from cross-validation.

Regression R2	PVE	Independent variable	Regression coefficient	Standard error
0.5575	-0.1399	(Intercept)	0.8049	0.3802
		PC.1.win	-0.0023	0.0006
		HNW.spr	-0.1965	0.0541

Analysis of Variance	DF	Sum Sq	Mean Sq	F value	Pr(>F)
PC.1.win	1	6.9606	6.9606	15.8040	0.0006
HNW.spr	1	5.7998	5.7998	13.1690	0.0014
Residuals	23	10.1298	0.4404		
Total	25	22.8902			

Table 4: Results of multiple regression analysis fitted to recruitment data from 1985 to 2002; PVE is the percent of variance explained from cross-validation.

Regression R2	PVE	Independent variable	Regression coefficient	Standard error
0.419	-0.4983	(Intercept)	-1.08883	0.30797
		T.win	0.07191	0.02117

Analysis of Variance	DF	Sum Sq	Mean Sq	F value	Pr(>F)
T.win	1	4.9994	4.9994	11.5380	0.0037
Residuals	16	6.9328	0.4333		
Total	17	11.9322			

Table 5: Results of multiple regression analysis fitted to recruitment data from 1977 to 1992; PVE is the percent of variance explained from cross-validation.

Regression R^2	PVE	Independent variable	Regression coefficient	Standard error
0.851	0.4741	(Intercept)	1.2426	0.4113
		PC.1.win	-0.0030	0.0006
		HNW.spr	-0.3051	0.0596

Analysis of Variance	DF	Sum Sq	Mean Sq	F value	Pr(>F)
PC.1.win	1	10.3508	10.3508	48.1070	0.0000
HNW.spr	1	5.6306	5.6306	26.1690	0.0002
Residuals	13	2.7971	0.2152		
Total	15	18.7785			

Table 6 : The number of year class strengths classified by Random Forest classification into each year class category based on out of bag samples; values bolded represent the number correctly classified

	To				
From	weak	median	strong	Total	Classification error
weak	**3**	3	2	8	0.625
median	2	**6**	0	8	0.25
strong	2	1	**7**	10	0.3

Table 7: Results of multiple regression analysis fitted to recruitment data from 1977 to 2002 using grouped predictors.

Regression R^2		Independent variable	Regression coefficient	Standard error
0.61		(Intercept)	-103.99	51.82
	Group 1	PC.1.win	-0.0028	0.0006
	Group 2	Speed.spr	-0.3188	0.0927
		Pressure.spr	0.1059	0.0507
		Gust.spr	0.0882	0.0461

Analysis of Variance

	DF	Sum Sq	Mean Sq	F value	Pr(>F)
Group 1	1	6.963	6.963	10.49	0.0002
Group 2	3	7.077	7.077	5.6	0.0056
Residuals	21	8.852	0.421		
Total	25	22.892			

Table 8: Variables selected by the stepwise discriminant analysis (with entry probability set at 0.1), their partial correlations, *F* values and associated P values for the test to enter or exit the model.

Variable	Partial R^2	*F*	P
sprHNW	0.319	5.39	0.012
winPC1	0.300	4.72	0.020
winHSE	0.236	3.24	0.059
winM1	0.317	4.63	0.022
sprW	0.265	3.43	0.053
winNE	0.247	2.95	0.078
sumHE	0.322	4.03	0.037
winZ2	0.328	3.91	0.041

Table 9: Cross validation summary from a linear discriminant analysis using the 8 predictor variables selected by stepwise discriminant analysis (sprHNW, winPC1, winHSE, winM1, sprW, winNE, sumHE, winZ2). Bold values represent the number correctly classified.

	To				
From	weak	median	strong	Total	Classification error
weak	**7**	1	0	8	0.125
median	2	**5**	1	8	0.375
strong	1	0	**9**	10	0.100
				Overall error:	0.192

Table 10: Correlations of the individual variables with the canonical axes from the discriminant analysis (Figure 16). Negative correlations with Can 1 indicate variable associated with years of weak or medium YCS, whereas positive correlations indicate strong YCS.

Variable	Can 1	Can 2
sprHNW	-0.629	-0.006
winPC1	-0.525	-0.196
winHSE	-0.235	0.325
sprW	-0.225	0.159
sumHE	-0.138	-0.232
winZ2	0.064	-0.200
winM1	0.072	0.213
winNE	0.093	-0.253

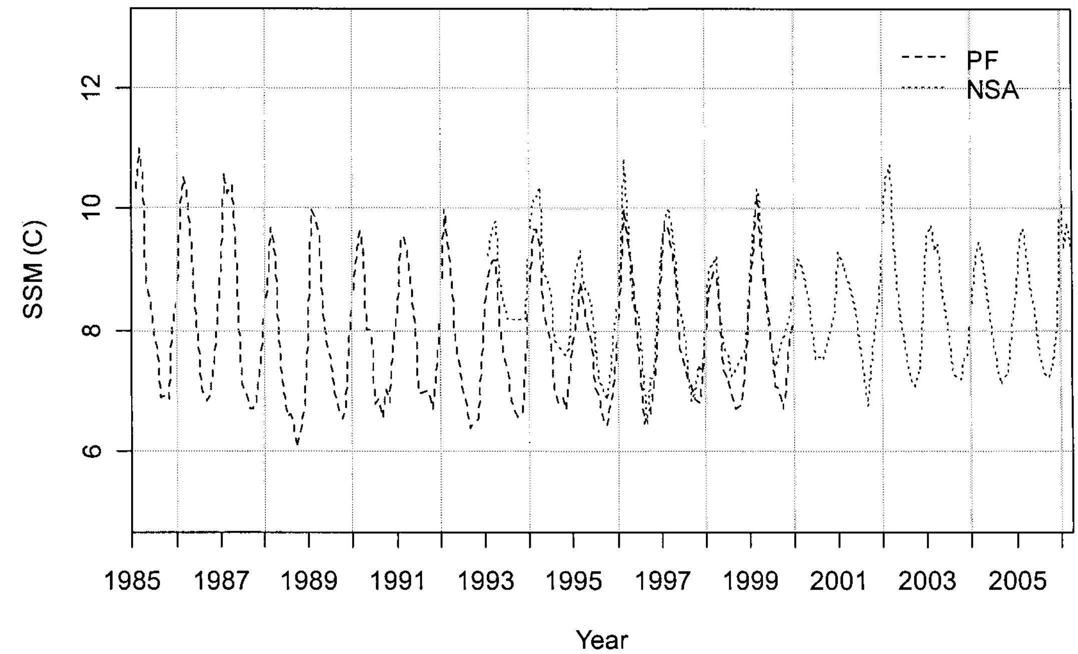

Figure 1: Time series of the average monthly sea surface temperature recorded by PF and NSA. The two series overlap between the beginning of 1993 and the end of 1999.

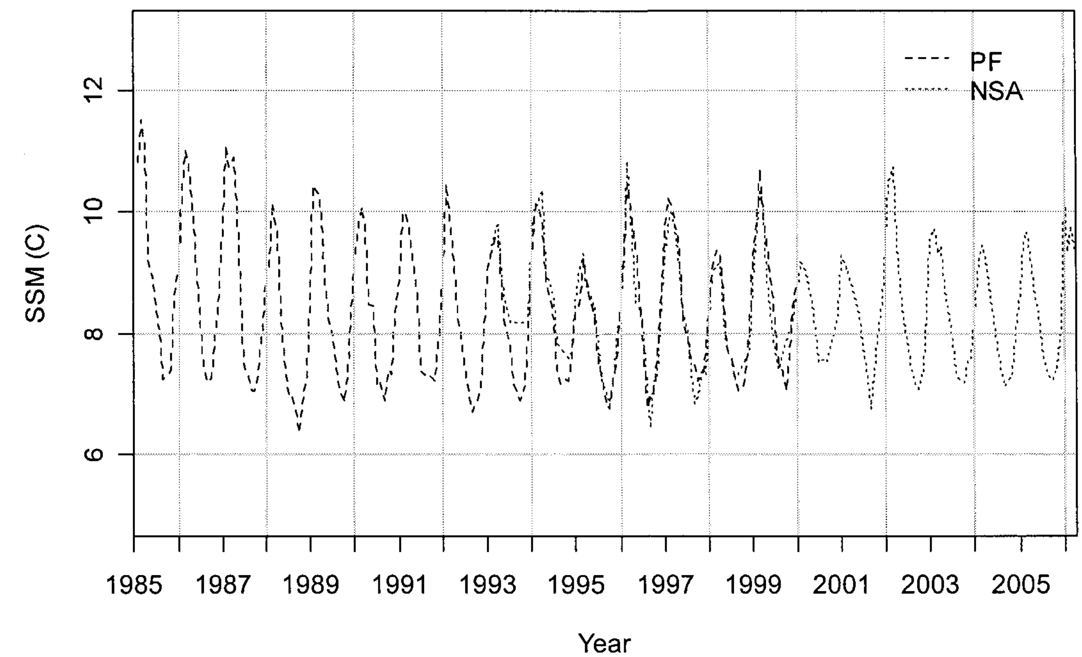

Figure 2: Time series of the average monthly sea surface temperature recorded from PF and NSA. The PF series are adjusted by the ratios of the average temperatures of NSA series for each of the four seasons between January 1993 and December 1999 to those of PF series.

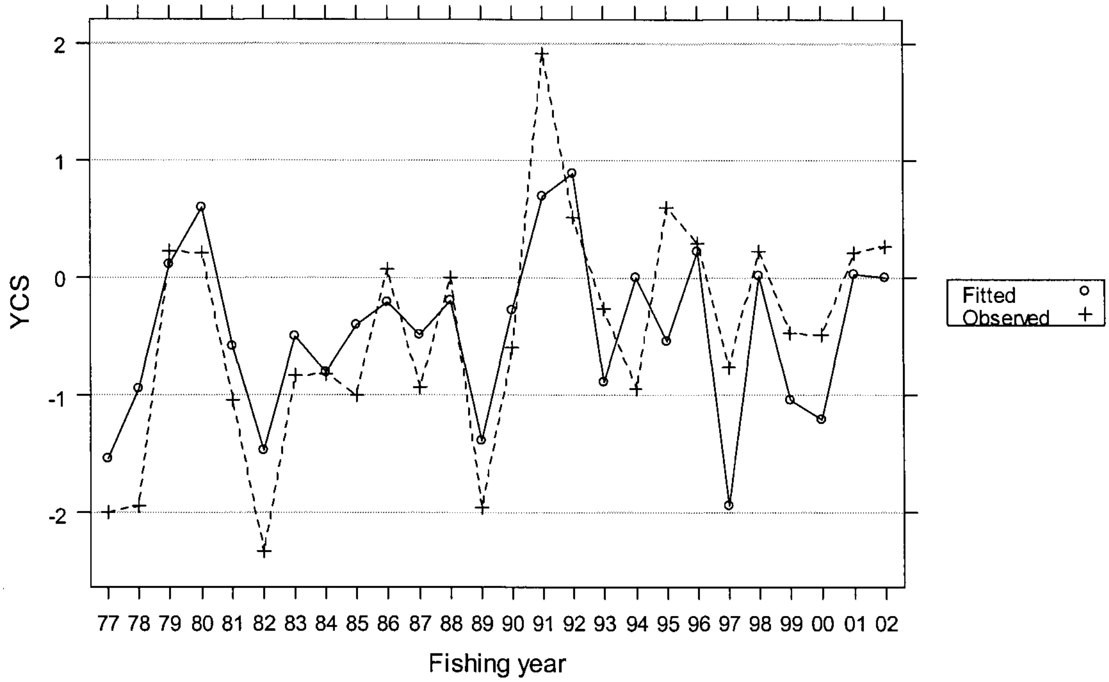

Figure 3 : Observed and fitted year class strength from 1977 to 2002; observed values (log) were based on the results of the population model; fitted values were based on multiple linear regression.

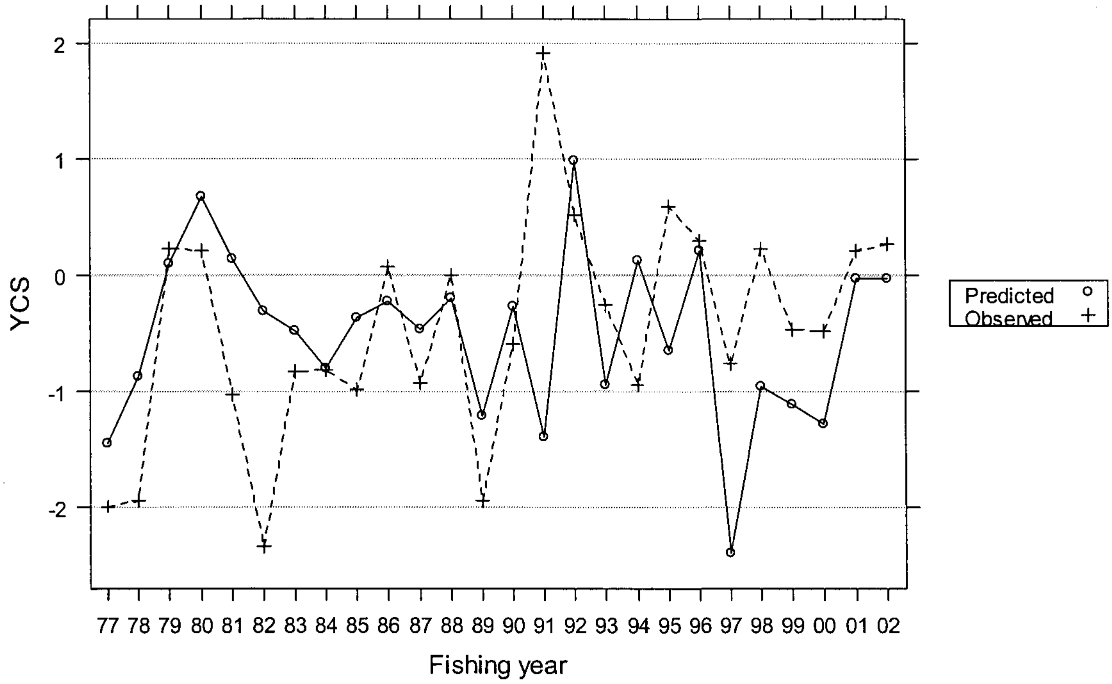

Figure 4: Observed and predicted year class strength from 1977 to 2002; observed values (log) based on the results of the population model; predicted values were based on the full cross-validation of multiple linear regression.

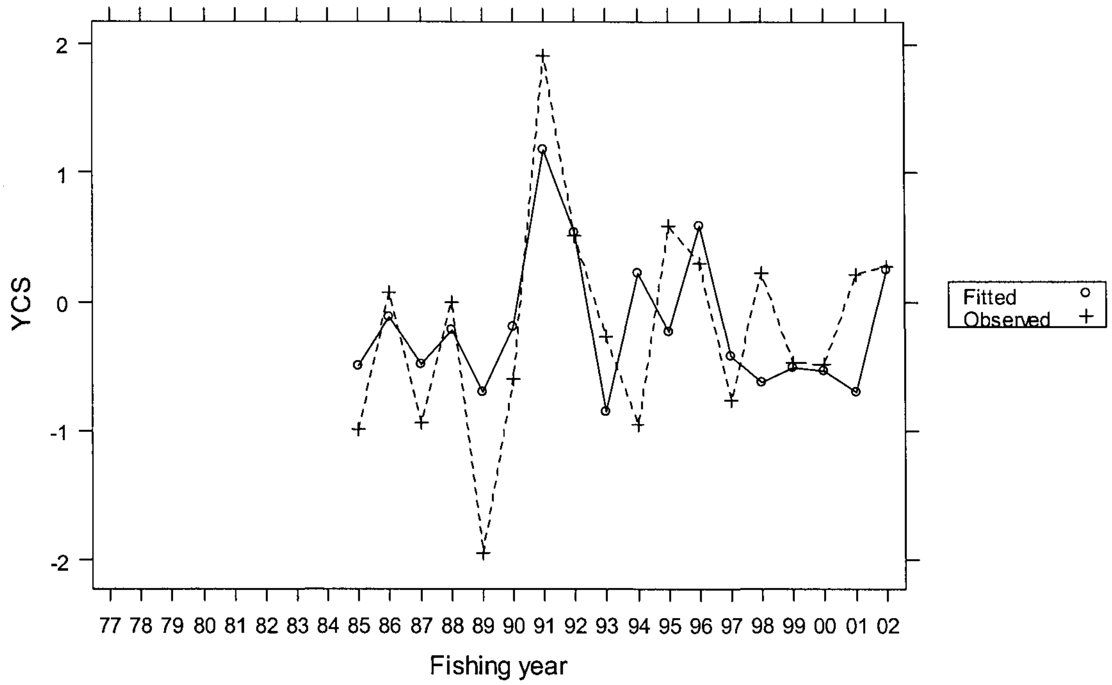

Figure 5: Observed and fitted year class strength from 1985 to 2002; observed values (log) were based on the results of the population model; fitted values were based on multiple linear regression.

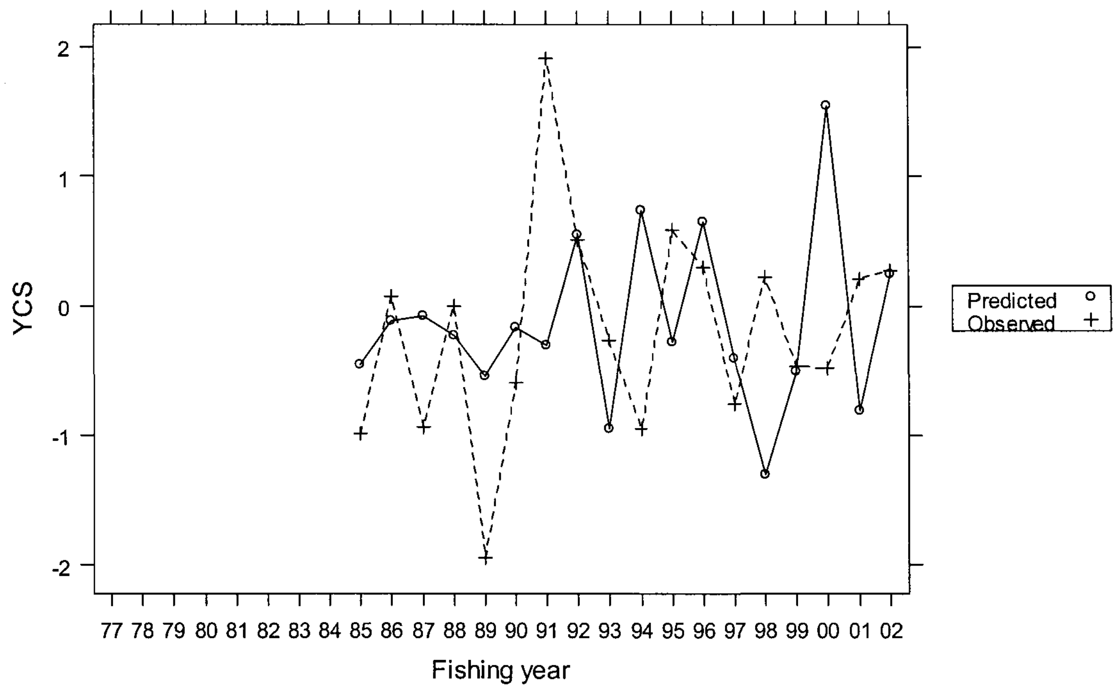

Figure 6: Observed and predicted year class strength from 1985 to 2002; observed values (log) were based on the results of the population model; predicted values were based on the full cross-validation of multiple linear regression.

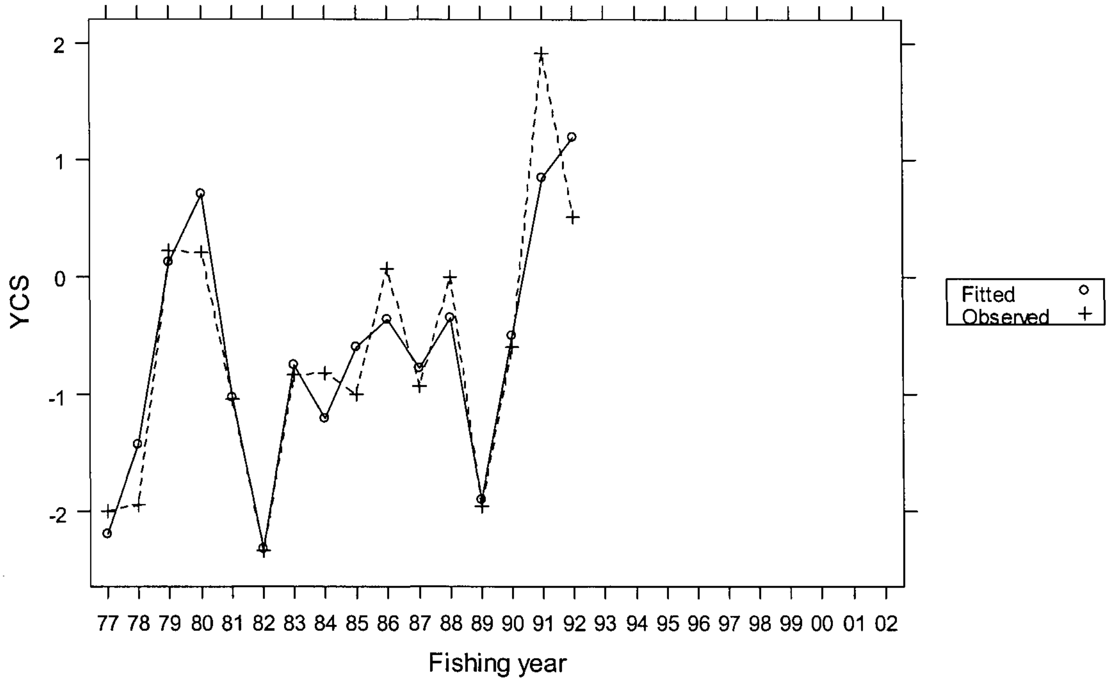

Figure 7: Observed and fitted year class strength from 1977 to 1992; observed values (log) were based on the results of the population model; fitted values were based on multiple linear regression.

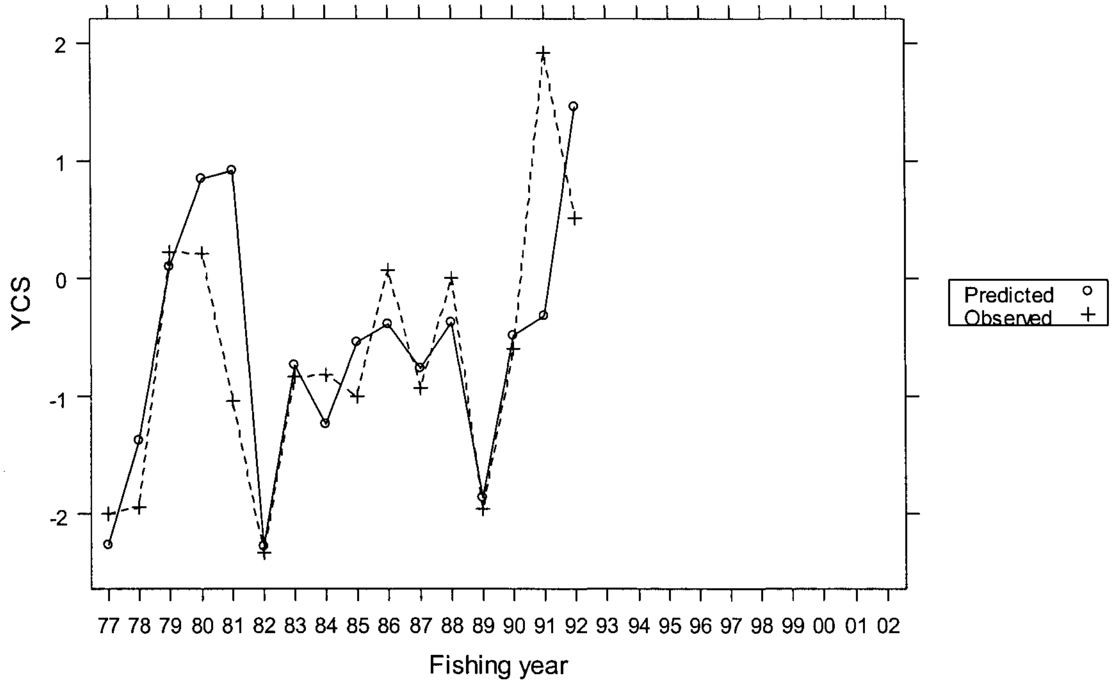

Figure 8: Observed and predicted year class strength from 1977 to 1992; observed values (log) based on the results of the population model; predicted values were based on the full cross-validation of multiple linear regression.

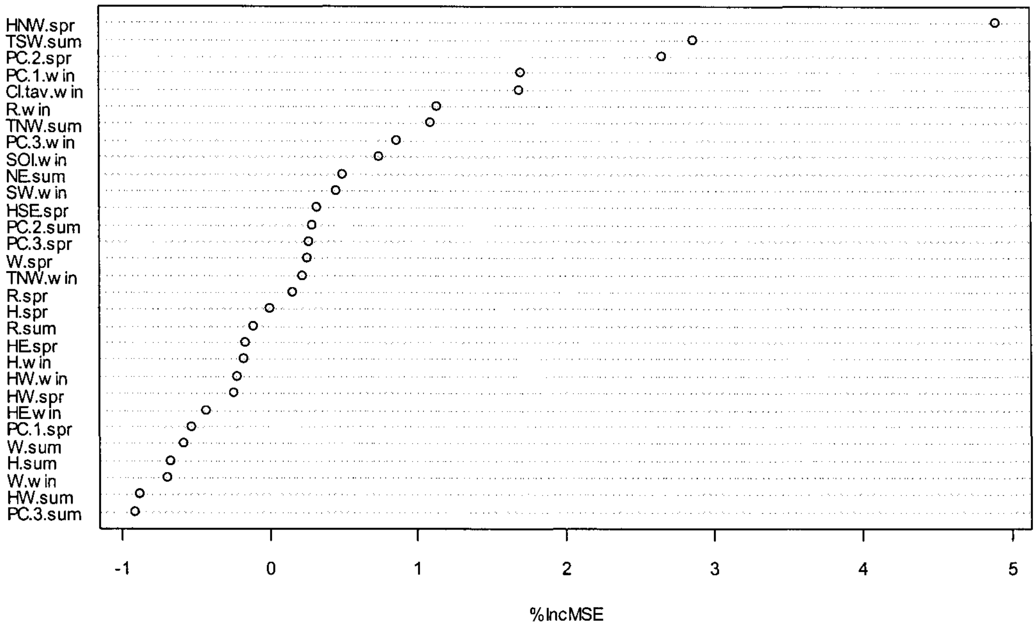

Figure 9 : Variable importance as measured by a Random Forest regression. To measure the importance of a predictor variable, the MSE is computed on the out-of-bag samples for each tree, and then the same computed after permuting a variable; the differences are averaged to give the importance of the variable.

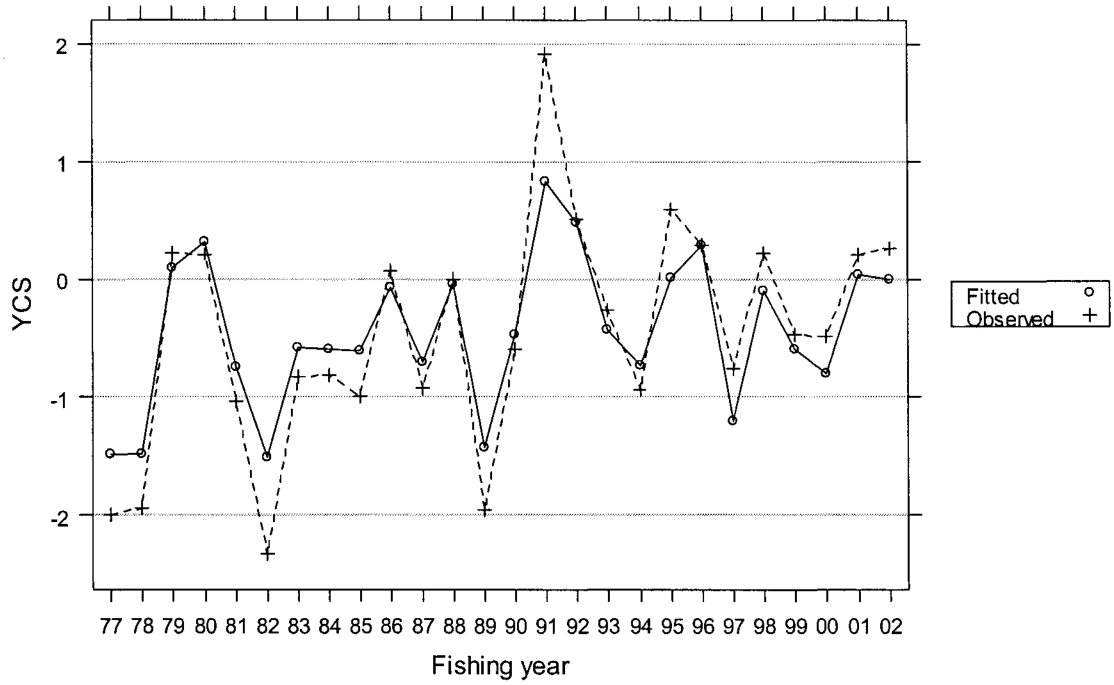

Figure 10: Observed and fitted year class strength from 1977 to 2002; observed values (log) were based on the results of the population model; fitted values were based on Random Forest regression.

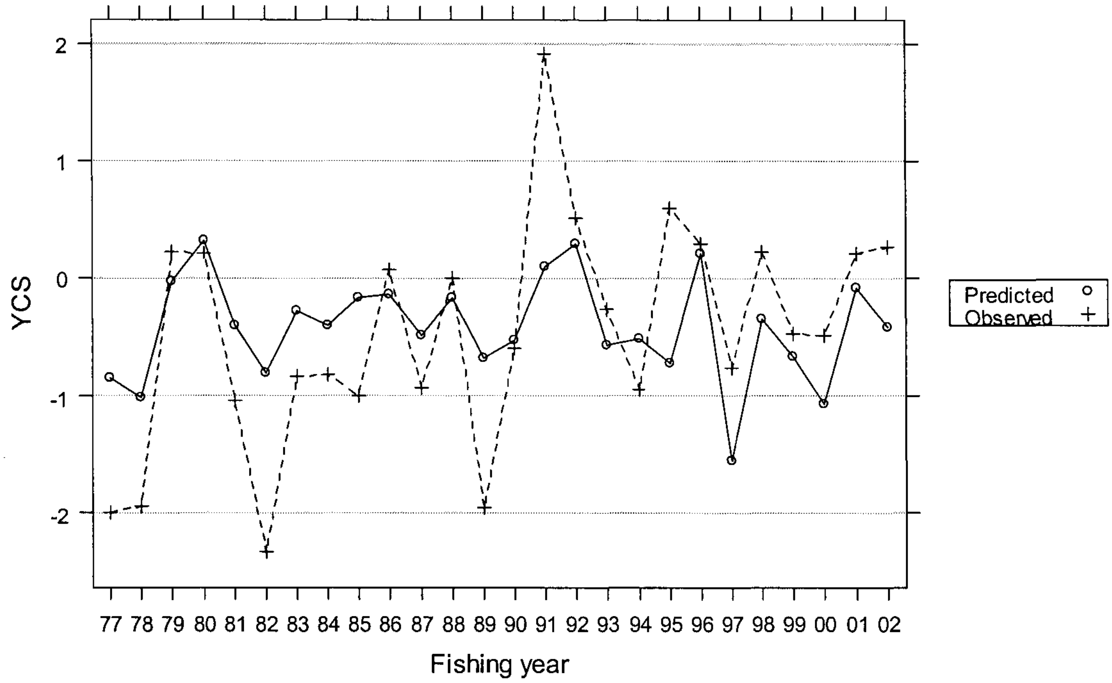

Figure 11: Observed and predicted year class strength from 1977 to 2002; observed values (log) were based on the results of the population model; predicted values were based on out of bag samples from Random Forest regression.

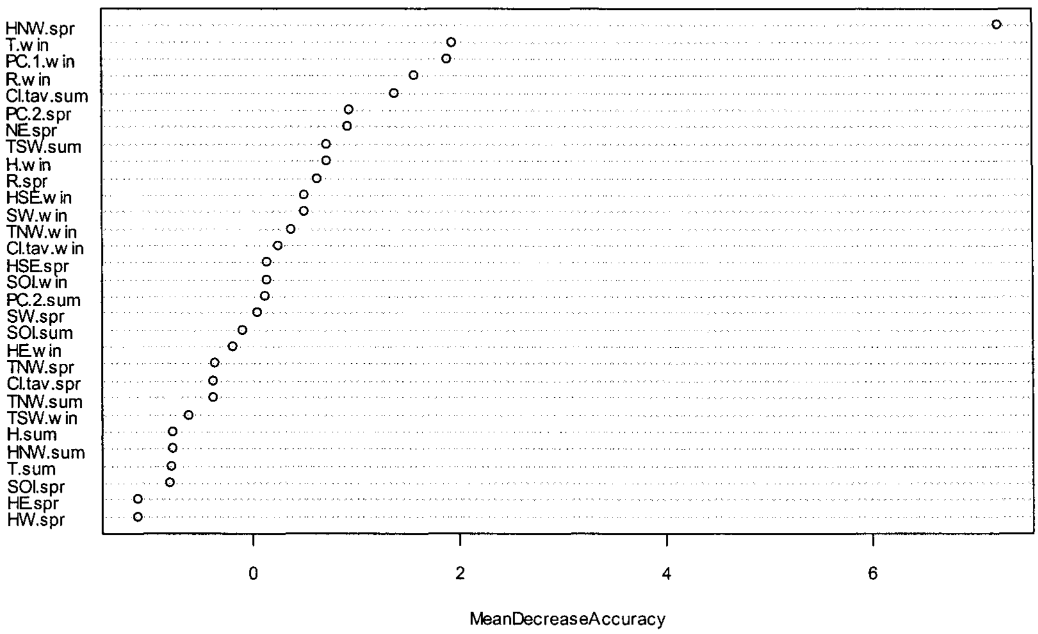

Figure 12: Variable importance as measured by a Random Forest classification. To measure the importance of a predictor variable, the margin of each case (defined as the proportion of votes for its true class minus the maximum of the proportion of votes for each of the other classes) is computed. The average lowering of margin across all cases gives the importance of a variable

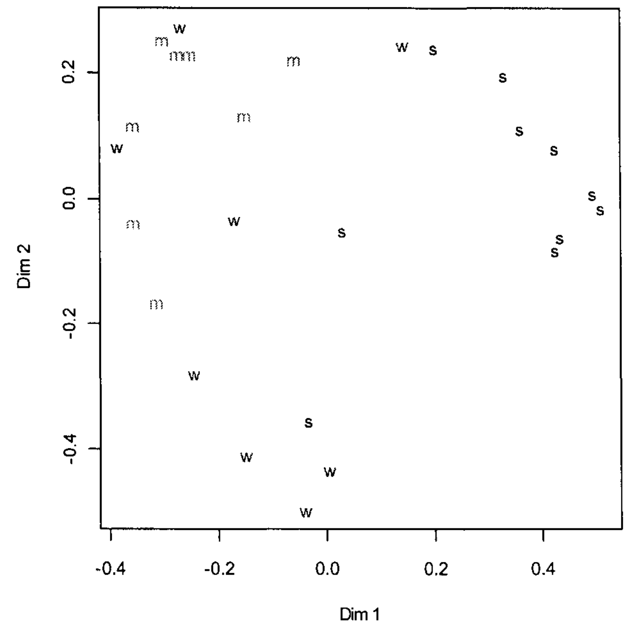

Figure 13: Scaling coordinates based on proximity of year class strengths as measured by Random Forest. The proximity of any two cases is measured by the number of times they land in the same terminal node in the forest. The scaling coordinates were obtained through multidimensional scaling. "w", "m" and "s" represent weak, median and strong year classes respectively.

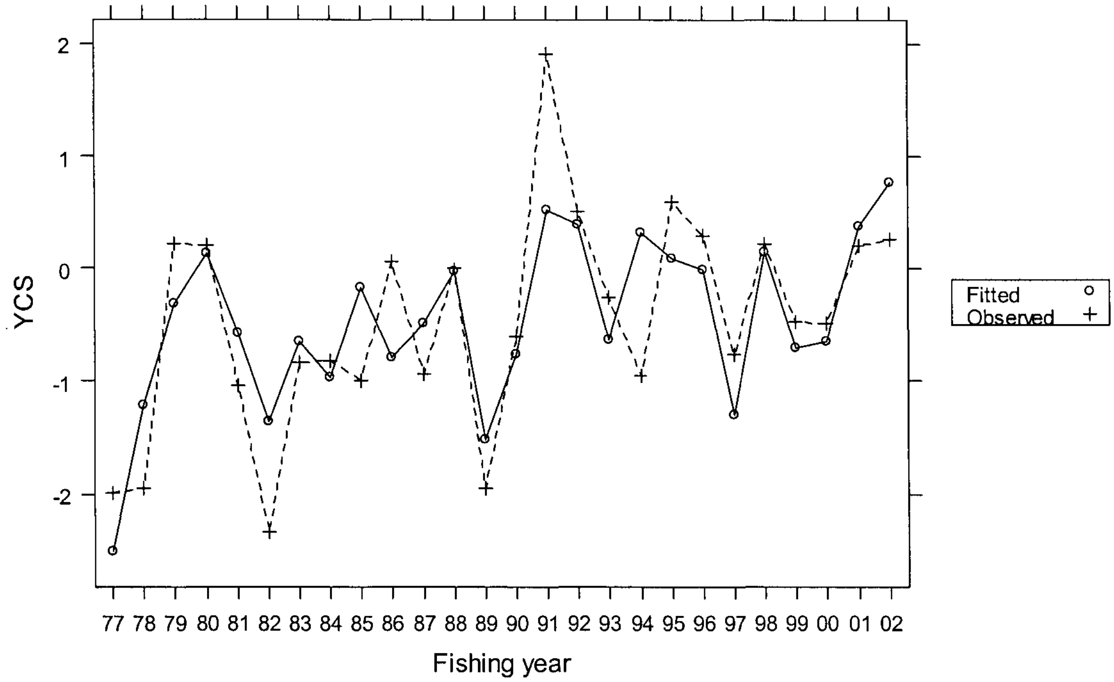

Figure 14: Observed and fitted year class strength from 1977 to 2002; observed values (log) were based on the results of the population model; fitted values were based on a multiple linear regression with two predictors: winter PC1, and Campbell Island meteorological station data (wind speed, maximum wind gust strength, and barometric pressure. The three measurements were grouped and form one term in the regression model).

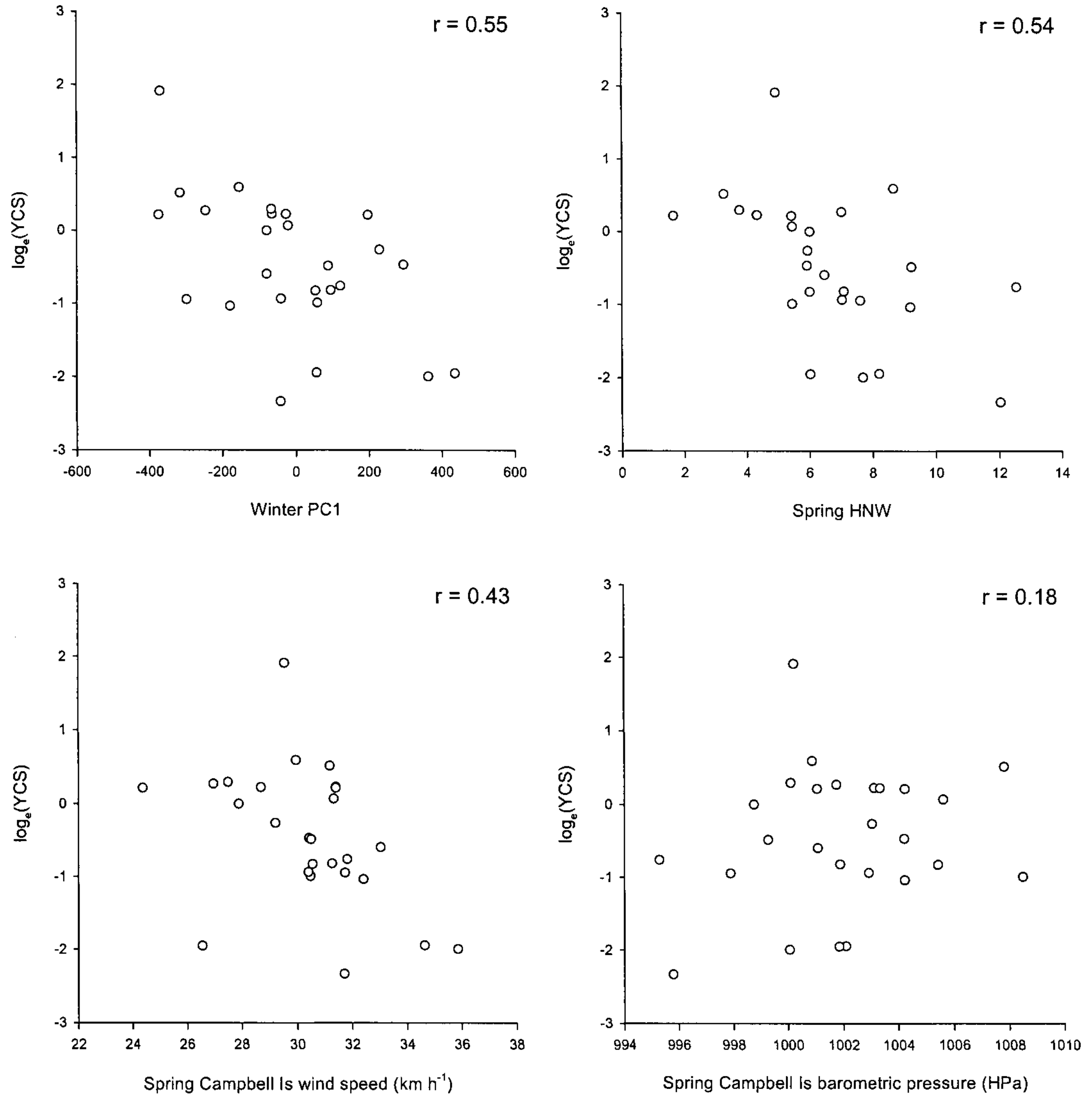

Figure 15: Univariate plots $\log_e$ year class strength versus significant factors identified by stepwise regression.

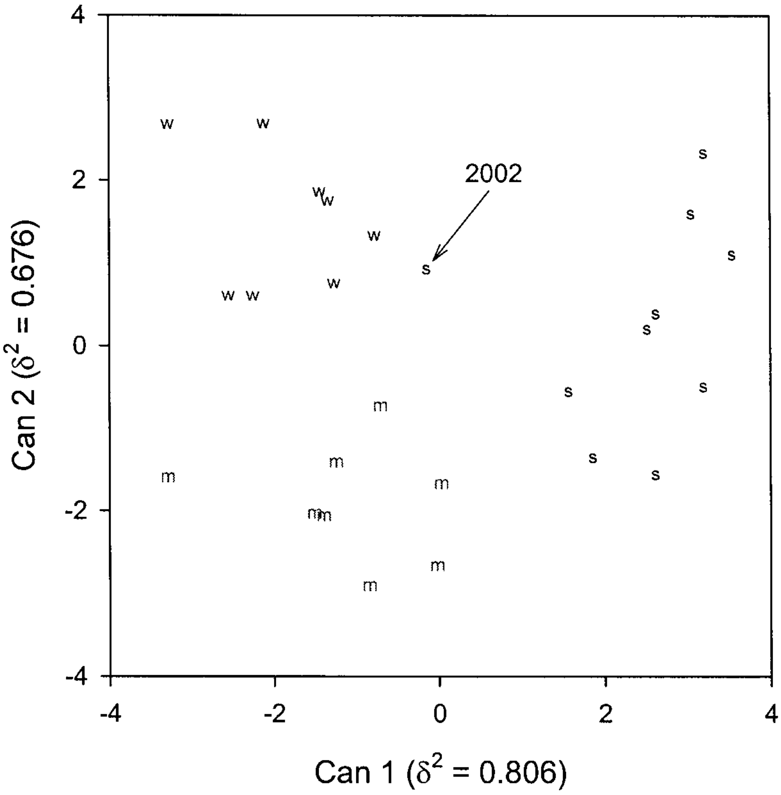

Figure 16: Plot of the first two axes from a canonical discriminant analysis attempting to separate weak (w), medium (m), and strong (s) year classes using 8 environmental variables. δ^2 is the canonical correlation for the axis.