Seeking patterns of population variability from fish catch and stock biomass time series

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Abstract

Many exploited fish stocks experience unexpected and large fluctuations as a consequence of climatic variability. It seems therefore inappropriate to manage these stocks by applying principles based on equilibrium assumptions. This study aims to establish a classification or typology of fish stocks to enable suitable management approaches to be matched to fisheries characterised by similar patterns of fluctuations. The approach used builds on previous attempts to classify fish stocks according to the patterns of variability in time series of catch or biomass. Fifty-one catch and biomass time series were decomposed into linear trend, short and long-term fluctuations. Parameters representing total variability and relative amount of short and long-term variations were used to classify stocks into categories, using cluster analysis. Six categories of stock were distinguished. A discriminant analysis was then used to ascertain if there was any link between the ecological features of fish stocks (e.g. growth, mortality, maximum size) and classifications according to patterns of variability. It can be concluded that few fish stock biomass or fishery catch time-series correspond to steady-state ideals. However, there is no strong statistical evidence for a general correspondence between different types of fish (e.g.. small pelagic species, large demersal stocks) and differing patterns and extent of variation in biomass or catch time series.

Introduction

Many fisheries resources fluctuate dramatically from year to year due to climatic variability (Glantz 1992; Bakun 1998). There has long been widespread recognition that constant catch or constant effort approaches to management, based on the paradigm of an achievable optimum sustainable yield, are inappropriate for these fisheries (Beddington and May 1977; Larkin 1977). It is not clear what form of fish stock management, if any, is appropriate for stocks where biomass, and therefore catches, appear to fluctuate independently of fishing effort in previous years.

Caddy and Gulland (1983) proposed, on the basis of a selection of ‘archetypal’ stocks, that fisheries could be classified as either steady-state, cyclical, irregular or occasional. For irregular and occasional stocks, it has proved difficult to demonstrate that overfishing is the cause of either the high variability or the apparent collapse of stocks. Despite the fact that different fisheries are known to have very different patterns of catch series, and that the implications of these different patterns have profound consequences for management, there have been few attempts to test Caddy and Gulland’s proposal to classify fisheries according to extent and patterns of variability.

The most notable attempts are the work of Kawasaki (1983), who attempted to relate Caddy and Gulland's classification to to life history traits of the species. More recently, Caddy and Gulland's typology, which was based on a visual inspection of four representative fish stocks, has been tested empirically by a statistical analysis of pattern in the time series of 32 stocks (Spencer and Collie 1997).

The implications for stock management of Caddy and Gulland's (1983) typology have never been properly considered even by these later, more quantitative analyses. Despite the clear indication that different fisheries have different production dynamics, all continue to be managed, explicitly or implicitly, by application of principles derived from the same class of models, based on equilibrium assumptions. Interpreting Caddy and Gulland's four categories of fisheries in terms of the factors that could drive different patterns of variability (DeAngelis and Waterhouse 1987) suggests that steady and cyclical fisheries are likely to be driven primarily by biotic interactions. Irregular and occasional stocks could be either chaotic systems driven by strong biotic interactions, or systems where biotic interactions are relatively unimportant, and abiotic factors the main influence on stock dynamics. If the latter explanation for the dynamic behaviour of fluctuating stocks is accepted, management based on regulation of biotic interactions is irrelevant.

This study aims to critically examine past attempts to develop a system of classifying fisheries, and propose a strategy for examining the dynamics of stocks for which there are long data series, and to look at some simple associations between the ecological features and stock to develop a set of attributes identifiable with each major category of fishery. This study presents a statistical analysis, using time series of different patterns of variability. We then explore the linkages between different patterns of catches and biomass with main ecological characteristics of stocks, using discriminant analysis. The analysis aims to explore associations between different long-term patterns in catches and biomass and particular fishery characteristics.

Data Sources

Catch and biomass time series were obtained from Ransom Myers' database (Myers et al. 2000). A sub-set of 33 catch and biomass series was selected for the analysis. Selection was on the basis of time series length (at least 30 years); the inclusion of all the tropical and sub-tropical fish stocks in the database (due to the focus of our research on developing-country fisheries) and the exclusion of shellfish (so that we could use maximum body length as a comparable measure of size when exploring correlation between patterns of variability and life-history features). We included some stocks from higher latitudes, selected to provide maximum contrast in life-history features and to include those used by Caddy and Gulland (1983) and Spencer and Collie (1997) for comparative purposes. Because of the geographical focus of our research project, we included additional data on fisheries of Malawian waters, including Lake Malawi and Lake Malombe, and on fisheries of Indonesian coastal waters. These were obtained from official government statistics (GOM, 1999; GOI, 2000). The summary features of the chosen datasets are given in Table A1.

Data on ecological features of stocks were obtained from FISHBASE (Froese and Pauly, 2000). Data include the maximum length, parameters of the von Bertalanffy growth model (L_∞, K), natural mortality (M), length at maturity (L_{mat}), approximate life span and whether the species occupies a predominantly pelagic or demersal habitat. These data are summarised in Table A2.

Methods

In classifying fish catch and biomass time series by patterns of variability, we followed the methods used by Spencer and Collie (1997). However, unlike in Spencer and Collie's study, biomass data and catch data were analysed separately, since we considered that it was inappropriate to conduct the analyses on a combination of the two datasets. Furthermore, both biomass and catch time series were available for 20 of the 51 fish stocks included in our study, which allowed us to compare the results obtained. The 71 time series of marine and freshwater fish stock biomass and catch (Table A1), including 32 biomass time series and 39 catch time series, were each analysed to provide parameters indicative of the extent and pattern of variability in the series. These parameters were then used in a cluster analysis that aimed to distinguish groups of stocks with similar patterns of variability. Our analysis then goes beyond that of Spencer and Collie (1997) by attempting to establish a link between clusters corresponding to different patterns of variability and indicators of life-history patterns, using a discriminant analysis. All statistical analyses were done using the SPSS software.

Analysis of patterns of variability in time series

A regression of abundance (catch or biomass) against year was used to determine if there was a significant overall linear trend, with the sign of the correlation coefficient indicates whether the biomass or catch has increased or decreased. The total variability of each stock was assessed with the coefficient of variation (CV). To assess the relative contributions to variability at long-term and short-term time scales, R^2_{lo} was calculated from a Lowess smoother (Cleverland 1979) applied to each data set, with a smoothing window of 0.3 times the data set length. R^2_{lo} is defined as R^2_{lo} = 1 - [Variance(residuals) / Variance(original data)] where the residuals can be defined as the short-term high-frequency variations and are determined from both the original data and smoothed data (residuals = original data – smoothed data). The value of R^2_{lo} calculated from smoothed data indicates the proportion of variance taking place at low-frequency time scales, with high value of R^2_{lo} indicating predominance of low-frequency variations.

In order to identify significant longer-term periodicity in the time series for the different stocks, an autocorrelation analysis was applied to the logged detrended data. The log-transformation was necessary to remove any relationship between mean catch or biomass and variance as heteroscedasticity violates assumptions of autocorrelation analysis. The log-transformed data was then detrended, as linear trend (i.e. long period in autocorrelation analysis) could mask periods of principal interest (Spencer and Collie 1997). The autocorrelation coefficient R_k, defined here as the highest coefficient in absolute value, which corresponds to the highest secondary peak, and associated lags were determined, as well as apparent period. The apparent period was estimated as the lag related to the second highest value of R_k for positive values of R_k, and as twice the lag for associated negative values of R_k. The significance of the coefficient R_k was used to identify the existence of cyclicity in stocks.

Thus, CV (the relative magnitude of variation), R^2_{lo} (the proportion of variance occurring at relatively low-frequency time scales) and R_k (cyclicity) describe three different aspects of stock variability (Spencer & Collie, 1997). Linear models showed that the three parameters (CV, R^2_{lo} and R_k) were not correlated with the length of time series.

Cluster analysis

Hierarchical agglomerative cluster analysis was used to classify the different fish stocks with respect to the following variables: CV, R^2_{lo} and R_k. The analysis included the computation of the Euclidean distance for each pair of stocks, and the production of a dendogram of stock groups, using average linkage clustering. Average linkage clustering has been preferred to single or complete linkage clustering, as it is the most commonly used method, and other methods did not give significantly different results.

Discriminant analysis

In order to explore the linkages between different patterns of catches or biomass with main ecological characteristics of stocks, a stepwise discriminant analysis was applied. The stepwise discriminant analysis is the most generally applicable method, as it does not give some predictors higher priority than others (Kinnear and Gray 1997). The application of this method aimed at classifying the different fish stocks with respect to the following variables: maximum length, L_∞ and K growth parameters, natural mortality, length at maturity, approximate life span and habitat (demersal or pelagic). Before conducting the discriminant analysis, outliers were identified using boxplots and stem-and-leaf diagrams, then removed from the datasets as suggested in Kinnear and Gray (2000).

Results

Patterns of variability in biomass time series

Patterns of variability were analysed for biomass time-series for 32 stocks. These results are summarised in Table A3. The CV measured the relative magnitude of variation in the 32 stocks. The lowest value obtained for the CV was 0.12 for the bigeye tuna (East Pacific) and the highest value 1.10 for the sardine (California) with a median of 0.54. The estimated biomass of 27 of the 32 stocks were significantly correlated with year at the 0.05 level, with 19 of the 27 stocks being negatively correlated and therefore showing decreases over time. However, 6 stocks revealed positive increases over time. Twenty-five of the 32 stocks had significant R^2 values at 0.05 level and 16 stocks had an R^2 above 0.5, which indicates a relatively high relationship between the independent variable 'year' and the abundance. This likely indicates that the overall trend in catches is large compared to stock fluctuations. Three stocks, the Bombay duck (Northwest Coast of India), Herring (Norway) and pacific halibut (North Pacific), had very low R^2 value of respectively 0.26, 0.28 and 0.21.

R^2_{lo} defined as an indicator of high-frequency variations, showed high values for the majority of stocks with 22 R^2_{lo} values > 0.75. This indicates that most of the stocks experienced high-frequency variations in abundance over time. Among these 22 stocks, 6 stocks showed very small high-frequency variation with R^2_{lo} values over 0.95; these included the Atlantic bluefin tuna (West Atlantic), Pacific Ocean perch (Aleutian Islands), red snapper (U. S. Gulf of Mexico), Southern bluefin tuna (Southern Pacific), Southern bluefin tuna 2 (Southern Pacific) and Swordfish (North Atlantic). Two stocks, the Northern anchovy

(California) and Yellowtail flounder (Southern New England), were found to have very high-frequency variations in abundance over time with an R^2_{lo} of 0.16. The remaining 8 stocks, had R^2_{lo} values between 0.41 and 0.75, indicating that high and low frequency variation occurred almost equally for these stocks.

The analysis of the autocorrelation coefficients (R_k) showed apparent periodicities, significant at the 0.01 level for all the stocks except the grey mullet (Taiwan) (Table A3). The apparent period extended from 6 years for the red snapper (U.S. Gulf of Mexico) to 40 years for the pacific halibut (North Pacific).

Patterns of variability in catch time series

Patterns of variability were analysed for catch time-series for 39 fisheries including the fisheries of Malawian waters and fisheries of Indonesian waters for which data on estimated biomass were not available. The lowest and highest values obtained for the CV were respectively 0.22 for the mackerel (western ICES) and 2.42 for the sardine (California) with median of 0.60. Catches of 33 of the 39 fisheries were significantly correlated with year at $p<0.05$, with 12 of the 33 stocks being negatively correlated and 21 stocks revealing positive increases over time. 31 of the 39 stocks had significant R^2 values at 0.05 level, 18 had an R^2 over 0.5 and one fishery, the kambusi (Lake Malombe) had a very low R^2 value of 0.24 (Table A3).

Eighteen stocks had R^2_{lo} values above 0.75 and among these 18 stocks, 7 stocks, all Indonesian fisheries, had R^2_{lo} values over 0.95 including the anchovy (Indonesia), Eastern little tuna (Indonesia), fringescale sardinella (Indonesia), giant seaperch/barramundi (Indonesia), Indian mackerel (Indonesia), skipjack tuna (Indonesia) and trevally (Indonesia). The herring (gulf of Maine) was found to have the highest frequency variations in abundance over time of the dataset with an R^2_{lo} of 0.10. The Bombe (Lake Malawi), Pacific Ocean perch

(Aleutian Islands) and Utaka (Lake Malawi) also had small R^2_{lo} values of respectively 0.39, 0.31 and 0.24. The remaining 17 stocks had R^2_{lo} values between 0.42 and 0.74.

The R_k values showed apparent periods extending from 10 years (usipa - Lake Malawi) to 40 years (king mackerel - West Gulf of Mexico).

Cluster analysis using biomass time-series

Six different groups of stocks were identified by applying a hierarchical agglomerative cluster analysis to the three variables representing different aspects of variability: CV, R^2_{lo} and R_k (Figure 1). An example of pattern of variation for each group is given in Fig. A1. These groups are defined as follows:

- Group 1: low-frequency, cyclic stocks (albacore tuna, Atlantic bluefin tuna, bigeye tuna - West Atlantic, Bombay duck, Brazilian sardine, greater lizardfish, herring - Gulf of Maine, king mackerel, mackerel - NAFO 2 to 6, mackerel - Western ICES, pacific halibut, pacific ocean perch, red snapper, silk snapper, South African anchovy, swordfish and yellowfin tuna - eastern pacific ocean and Indian ocean. All the stocks have high R^2_{lo} values and Rk values greater than 0.43, which indicates a cyclic behaviour for each stock occurring with low frequency. Stocks have CV values between 0.14 and 0.70.
- Group 2: irregular stocks (bigeye tuna - east pacific, grey mullet, southern bluefin tuna 1 and 2). The CV values for these stocks range from 0.12 to 0.54 that indicates moderate levels of variation. Rk values are low (between 0.29 and 0.34), which suggests an irregularity in any possible cyclicity. The R^2_{lo} is between 0.77 and 0.98.
- Group 3: spasmodic stocks (chub mackerel - Pacific coast of Japan 1 and 2, chub mackerel - southern California, gold-spotted grenadier anchovy, herring - north sea, mackerel - black sea and sardine). These stocks have a very high level of variation (CV between 0.81 and 1.07) with strong low-frequency variations (R^2_{lo} between 0.60 and 0.92). Most species in

this group seem to be unpredictable due to the lack of apparent periodicity in their variation. However, one stock in this group, the gold-spotted grenadier anchovy, has smaller CV and R^2_{lo} values (respectively 0.69 and 0.41) than the other fisheries of the group, as well as a highest Rk value (0.61).

- Group 4: high variation, low frequency stock (herring - Norway). This stock has a high CV value of 1.03 and a high R^2_{lo} value of 0.95. The large Rk value of this stock suggests a cyclic pattern that occurs with very low frequency.
- Group 5 and 6: high variation, high frequency stocks (respectively northern anchovy and yellowtail flounder). The values of CV are high for each group (0.82 and 0.79) with very weak R^2_{lo} values of 0.16 for both stocks. The main difference between these stocks is the Rk value, which is weak for the northern anchovy (0.19) and relatively high for the yellowtail flounder (0.45). The latter suggests the existence of a cyclic behaviour at high frequency, which does not appear in group 5 stock.

The six different groups show a range of variation between the low-variability stocks (group 2) and highly variable stocks (groups 3 and 4). Scatterplots of CV against R^2_{lo} and Rk respectively Figure 2 and 3, illustrate the characteristics of each group. Groups 1 and 2 have similar CV and R^2_{lo} values, but very different Rk values, which are high for group 1 and therefore suggest a cyclic behaviour. Group 5 and 6 also present the same characteristics with similar CV and R^2_{lo} values, but with different Rk values. Group 4 has higher low-frequency components (high R^2_{lo} values) and variations (high CV values) than group 3 but similar Rk values.

Figure 1. Dendrogram of stock groups obtained from cluster analysis (using biomass time series). Numbers indicate the stock identification number assigned in Table A1.

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                 0         5        10        15        20        25
  Stock   Serial +---------+---------+---------+---------+---------+
            No
  Atlbluef    3   ⇩×⇩⇩⇩⬂
  Pacperch   36   ⇩⬃   ▭⇩⬂
  YelltuIO   50   ⇩⇩⇩⇩⇩⬃ ▭⇩⬂
  Greatliz   17   ⇩⇩⇩⇩⇩×⇩⬃ ▭⇩⇩⇩⇩⇩⇩⇩⬂
  HerrGM     20   ⇩⇩⇩⇩⇩⬃   ⇔       ⇔
  MackNAFO   30   ⇩⇩⇩⇩⇩⇩⇩⇩⇩⬃       ⇔
  BigeyeWA    5   ⇩⇩⇩×⇩⇩⇩⇩⇩⬂       ⇔
  Swordfis   45   ⇩⇩⇩⬃     ⇔       ▭⇩⇩⇩⇩⇩⇩⇩⬂
  Albatuna    1   ⇩×⇩⇩⇩⬂   ▭⇩⬂     ⇔       ⇔
  Pachalib   35   ⇩⬃   ▭⇩⬂ ⇔ ⇔     ⇔       ⇔
  MackICES   31   ⇩⇩⇩⇩⇩⬃ ▭⇩⬃ ▭⇩⇩⇩⬂ ⇔       ⇔
  Redsnapp   37   ⇩⇩⇩⇩⇩⇩⇩⬃   ⇔   ⇔ ⇔       ⇔
  Silksnap   40   ⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⬃   ▭⇩⬃       ⇔
  Brazsard    8   ⇩⇩⇩×⇩⇩⇩⇩⇩⇩⇩⇩⇩⬂ ⇔         ▭⇩⇩⇩⇩⇩⬂
  YelltuEP   49   ⇩⇩⇩⬃         ▭⇩⬃         ⇔     ⇔
  Bombduck    6   ⇩⇩⇩⇩⇩×⇩⬂     ⇔           ⇔     ⇔
  Kingmack   28   ⇩⇩⇩⇩⇩⬃ ▭⇩⇩⇩⇩⇩⬃           ⇔     ⇔
  SAancho    42   ⇩⇩⇩⇩⇩⇩⇩⬃                ⇔     ⇔
  Sbluetun   43   ⇩⇩⇩×⇩⇩⇩⬂                ⇔     ⇔
  Sbluetu2   44   ⇩⇩⇩⬃   ▭⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⬂     ⇔     ⇔
  Greymull   18   ⇩⇩⇩⇩⇩⇩⇩⬃           ▭⇩⇩⇩⇩⇩⬃
▭⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⬂
  BigeyeEP    4   ⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⬃           ⇔
⇔
  ChubmaSC   12   ⇩⇩⇩⇩⇩⇩⇩⇩⇩×⇩⇩⇩⬂                ⇔                ⇔
  Sardine    38   ⇩⇩⇩⇩⇩⇩⇩⇩⇩⬃   ▭⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⬂     ⇔
⇔
  HerrNS     21   ⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⬃           ⇔     ⇔                ⇔
  ChubmacJ   10   ⇩⇩⇩⇩⇩⇩⇩×⇩⇩⇩⬂             ⇔     ⇔                ⇔
  ChubmaJ2   11   ⇩⇩⇩⇩⇩⇩⇩⬃   ▭⇩⇩⇩⇩⇩⇩⇩⬂     ⇔     ⇔
⇔
  MackBS     29   ⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⬃       ▭⇩⇩⇩⇩⇩✓⇩⇩⇩⇩⇩⬃
⇔
  Goldanch   16   ⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⬃     ⇔
⇔
  HerrNorw   22   ⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⬃
⇔
  Northanc   33
⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩×⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⬃
  Yellflou   51   ⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⇩⬃
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Figure 2. Scatterplot of CV against R^2_{lo} for the 32 stocks. Numbers represent stock groups.

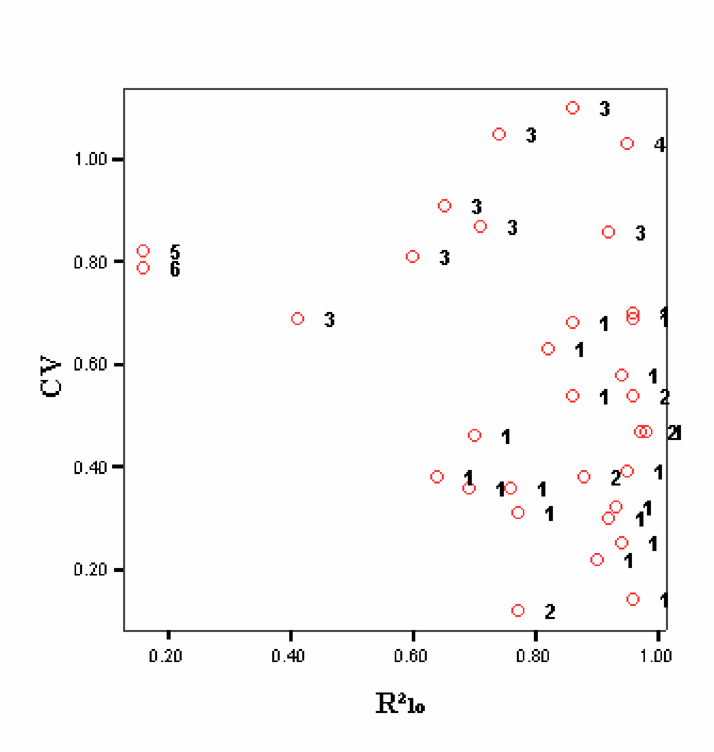
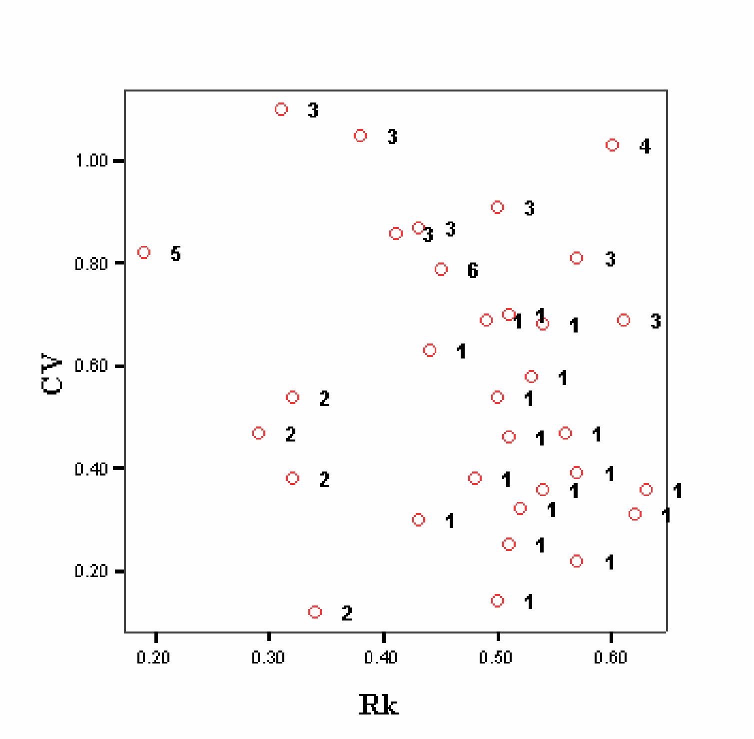


Figure 3. Scatterplot of CV against Rk. Numbers represent stock groups.



Cluster analysis using catch time-series

Six groups were identified (Figure 4).

- Group 1: irregular stocks (albacore tuna, grey mullet, herring - North Sea, Indian oil sardinella, usipa and yellowtail flounder).
- Group 2: low variation, low frequency stocks (anchovy, bigeye tuna - west Atlantic, eastern little tuna, fringescale sardinella, giant seaperch, grouper, Indian mackerel, mackerel - western ICES, narrow barred king mackerel, scad, skipjack tuna and trevally).
- Group 3: high variation, high frequency stocks (Atlantic bluefin tuna, bigeye tuna - east pacific, Brazilian sardine, chambo, gold-spotted grenadier anchovy, herring - Norway, kambusi - Lake Malawi and Malombe, king mackerel, mackerel - black sea and NAFO 2 to 6, northern anchovy and pacific ocean perch).
- Group 4: low frequency, cyclic stocks (Bombay duck, pacific cod, and pacific halibut).
- Group 5: steady state stocks (bombe, herring - Gulf of Maine, kampango and utaka).
- Group 6: spasmodic stocks (sardine).

These groups are similar to the groups identified in Spencer and Collie's study. However, out of seven stocks common to both the studies, only four were found belonging to the same groups in each study, they include the herring - north sea and yellowtail flounder (irregular stocks), pacific halibut (low frequency, cyclic stocks), and sardine (spasmodic stocks). It is also important to note that most of the Indonesian species belong to group 2 (low variation, low frequency stocks). The scatterplots of CV against R^2_{lo} and Rk illustrate the characteristics of each group (Figure 5 and 6).

Figure 4. Dendrogram of stock groups obtained from cluster analysis (using catch time series). Numbers indicate the stock identification number assigned in Table A1.

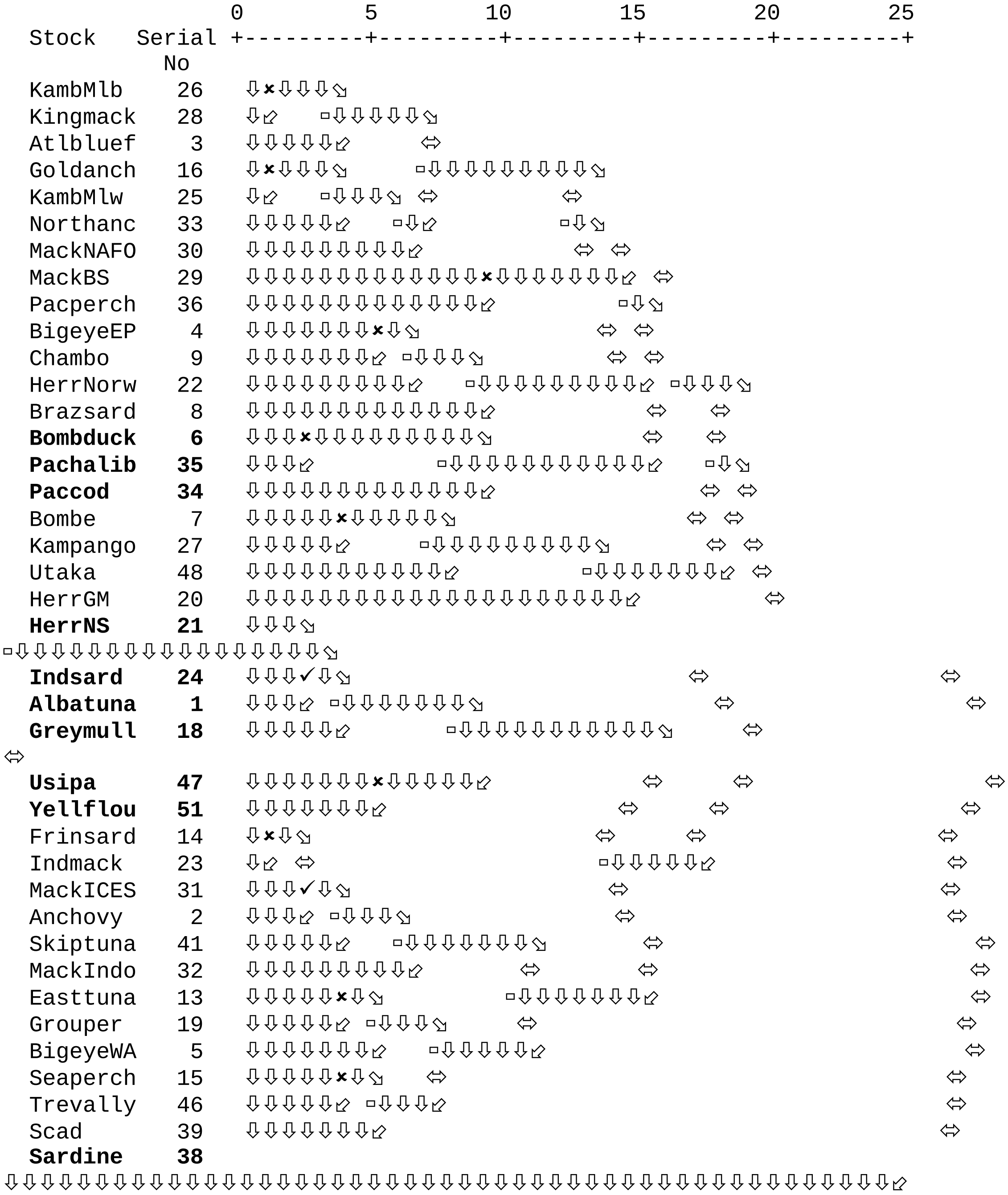


Figure 5. Scatterplot of CV against R^2_{lo} for the 39 stocks. Numbers represent stock groups.

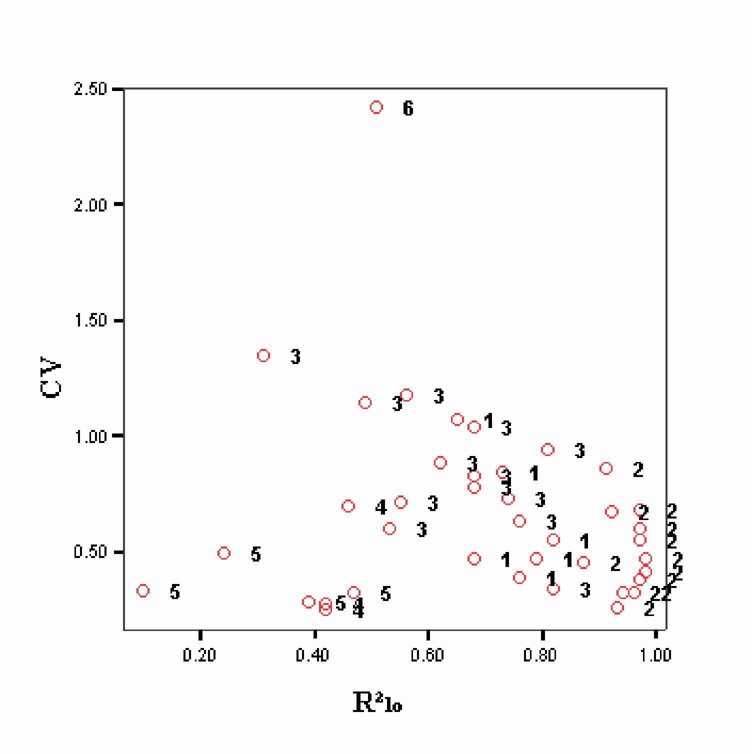
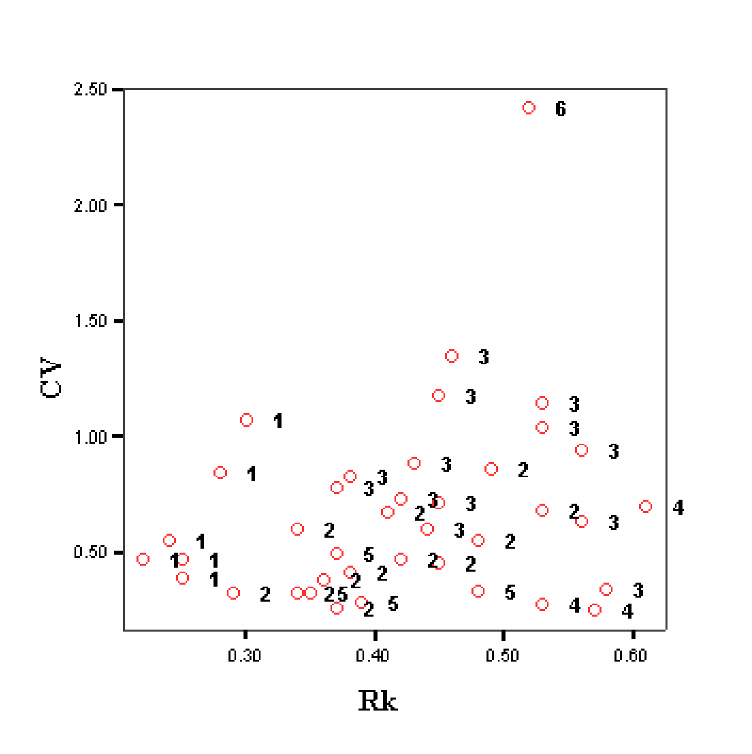


Figure 6. Scatterplot of CV against Rk. Numbers represent stock groups.



Discriminant analysis from biomass time series

A stepwise discriminant analysis was applied to predict category membership from data on several other variables. Seven ecological variables including the maximum length, $L\infty$ and K parameters, natural mortality, length at maturity approximate life span and habitat were used. The discriminant analysis was conducted on the stocks for which all the ecological data were available, due to the lack of data for some stocks. Six fisheries were also removed from the dataset since they were identified as outliers, they include the Atlantic bluefin tuna, mackerel -Black Sea and pacific halibut for their high life span values, Bombay duck, Brazilian sardine and mackerel -Black Sea, which present high natural mortality values, and swordfish with a very high $L\infty$ value.

The result of the stepwise discriminant analysis indicates that the success rate for predictions of membership of the grouping variable's categories using the discriminant functions developed in the analysis is 76%. The analysis demonstrates that groups 2 (irregular stocks), 4 (high variation, low frequency stocks), 5 and 6 (high variation, high frequency stocks) are the most accurately classified with 100% of the cases correct. However it is important to note that groups 4, 5 and 6 only contain one stock, which explains the result obtained for these groups. Group 1 (cyclic stocks) is next with 69.2%, and group 3 (spasmodic stocks) is last with 60%. The results also provide an indication on whether there is a statistically significant difference among the dependent variable means (six different groups) for each independent variable (ecological characteristics). Four of the differences were found to be significant, including maximum length, $L\infty$, life span (significant at the 0.05 level) and length at maturity (significant at the 0.01 level).

We can therefore conclude from the application of the discriminant analysis that four ecological characteristics explain the classification obtained from the cluster analysis.

Discriminant analysis from catch time series

Five outliers, including the albacore tuna, Atlantic bluefin tuna, bigeye tuna, grouper and usipa, were identified and removed from the dataset before conducting the discriminant analysis.

The success rate obtained for prediction of membership is 69%. Group 4 (cyclic stocks) and 6 (spasmodic stocks) appear to be the most accurately classified with 100% of the cases correct. Group 2 (low variation, low frequency stocks) is second with 90%, and group 5 (steady state stocks) is third with 66.7%. Group 3 (high variation, high frequency stocks) is next with 50%, and group 1 comes last with 25%. None of the differences is significant except 'habitat', which was found significant at the 0.05 level.

The application of the discriminant analysis shows that the ecological characteristics do not explain the classification obtained from the cluster analysis.

Discussion

Time series for 51 fish stocks, including both biomass and catch data sets were used to produce a classification of variability patterns. A comparison of the results of this study with the results of Caddy and Gulland's (1983) and in particular Spencer and Collie's (1997) study shows that most groups have been found to be common to the three studies. These groups are cyclic, irregular, steady state, spasmodic and high variability, high frequency and low variation, low frequency stocks. The analysis of catch time series showed that four out of seven stocks that were common to Spencer and Collie's (1997) and our study, belong to the same groups in both the studies. This in the case for the herring - North Sea and yellowtail flounder (irregular stocks), pacific halibut (low frequency, cyclic stocks), and sardine (spasmodic stocks). The analysis of biomass data also identified similarities between both the studies, with the sardine, which presented the characteristics of spasmodic stocks, herring - Gulf of Maine, Pacific Ocean perch and pacific halibut, which had the characteristics of cyclic stocks. In our study of catch time series, only four stocks having the characteristic of steady-state stocks, hypothesis generally assumed in classical fisheries models, have been identified. These stocks are the bombe (Lake Malawi), herring (Gulf of Maine), kampango (Lake Malawi) and utaka (Lake Malawi). No stocks having these characteristics were identified when conducting the cluster analysis on biomass data only.

A comparison of the groups obtained from the cluster analysis of respectively biomass time series and catch time series was undertaken in order to check the validity of the results obtained. From the observation of the different groups, it appears that only four groups were found to be similar in both the analyses, and include cyclic, irregular, spasmodic and high variation, high frequency stocks. Both biomass and catch time series were available for 20 stocks of the initial data set. Only five stocks out of 20 were found to belong to the same groups within the respective data sets, biomass and catch. One of the five stocks (sardine - California) belonged to the spasmodic stocks for both biomass and catch data. Two of the five stocks, Bombay duck and pacific halibut, belonged to stocks identified as irregular. The grey mullet and northern anchovy presented the characteristics of respectively irregular stocks and high variation, high frequency stocks.

We can conclude from the previous results that the cluster analysis applied to produce stock classification did not give the same results whether biomass or catch estimates were used. It therefore seems inappropriate to conduct a cluster analysis on a mix of data in catch and biomass. This assertion challenges Spencer and Collie's classification, for which estimated biomass, catch and Catch Per Unit Effort were compiled and analysed together.

This study aimed at identifying a system to classify various exploited fish stocks, in order to improve their management, stated by Bakun (1998), as a research priority to understand better how fisheries science can be applied most effectively in support of fisheries management. It has been shown that it is possible to pick up pattern of variations from the analysis, and that the different groups obtained when conducting the analyses on biomass time series, can be partly explained by the ecological features of each stock.

Shortcomings

Although this study made possible the identification of patterns of variation for 51 stocks, several limitations have to be highlighted. As we mentioned before, a cluster analysis carried out on estimated biomass and a cluster analysis conducted on catch data for the same stocks with, in most cases, identical periods of time, gave different classifications. Furthermore similar stocks did not belong to the same groups in both cases. It seems therefore inappropriate to use data indifferently. It is also important to note that statistics on fisheries may not be reliable (Larkin 1996) which would in this case lead to biased results.

Conclusion

In this study, time series of estimated biomass and catches were compiled for 51 stocks. The different aspects of stock variability were explained with the coefficient of variation (CV), R^2 from Lowess (R^2_{lo}), and the coefficient of autocorrelation (Rk), identifying respectively the extent of variation, the relative importance of high and low frequency variations, and occurrence, or not, of significant periodicities. The statistical methods used to characterise various patterns of variation and classify the stocks into groups included respectively linear autocorrelation analysis and cluster analysis. The groups identified, cyclic, irregular, steady-state, spasmodic, high variation, high-frequency and low variation, low frequency stocks, clearly indicate that the majority of fish included in the study do not present the steady-state characteristics assumed in classical fisheries models.

The uncertainties in cluster allocation, weak or ambiguous association between biological features and patterns of variability, and issues with data quality (e.g. the classification of all Indonesian fish stocks, from ocean perch to anchovy, into one group) all suggest that a simple typology would be elusive. However, there is sufficient statistical evidence to reject the notion that all fish stocks tend towards bioeconomic equilibrium.

References

Bakun, A. 1998. Ocean triads and radical interdecadal variation: bane and boon to scientific fisheries management. *In* Reinventing fisheries management. Edited by T. J. Pitcher, P. J. B. Hart and D. Pauly. Kluwer Academic Publishers, London, pp. 331-358.

Beddington, J., and May, R. M. 1977. Harvesting natural populations in a randomly fluctuating environment. Science **197**: 463-465.

Caddy, J. F., and Gulland, J. A. 1983. Historical patterns of fish stocks. Marine Policy **7**(4): 267-278.

Cleveland, W. 1979. Robust locally weighted regression and smoothing scatterplots. Journal of the American Statistical Association **74**(368): 829-836.

Cushing, D. H. 1982. Climate and fisheries. Cambridge University Press, Cambridge, U.K.

DeAngelis, D. L., and Waterhouse, J. C. 1987. Equilibrium and nonequilibrium concepts in ecological models. Ecological Monographs **57**: 1-21.

Froese, R., and Pauly, D. (Editors). 2000. FishBase 2000. World Wide Web electronic publication. http://www.fishbase.org, 20 June 2001.

Glantz, M. H. 1992. Climate variability, climate change and fisheries. Cambridge University Press, Cambridge, U.K.

Government of Indonesia. 2000. National Fisheries Stastistics.

Government of Malawi. Fisheries Department. 1999. Fish stocks and fisheries of Malawian waters. Resources Report. Government of Malawi, Malawi.

Kawasaki, T. 1983. Why do some pelagic fishes have wide fluctuations in their numbers? Biological basis of fluctuation from the viewpoint of evolutionary ecology. FAO Fisheries Report **291**: 1065-1080.

Kinnear, P. R. and Gray, C. D. 1997. SPSS for Windows made simple. Second edition. Psychology Press, Sussex, U.K.

Kinnear, P. R. and Gray, C. D. 2000. SPSS for Windows made simple. Release 10. Psychology Press, Sussex, U.K.

Larkin, P. 1977. An epitaph for the concept of maximum sustainable yield. Transactions of the American Fisheries Society **106**: 1-11.

Larkin, P. A. 1996. Concepts and issues in marine ecosystem management. Reviews in Fish Biology and Fisheries **6**:139-164.

Myers, R. A. 2000. Stock recruitment database. World Wide Web electronic publication. http://www.mscs.dal.ca/~myers/welcome.html, 14 March 2000.

Spencer, P. D., and Collie, J. S. 1997. Patterns of population variability in marine fish stocks. Fisheries Oceanography **6**(3): 188-204.

Appendices

Table A1. Fish stocks used in the study.

Serial No.	**Common name**	***Scientific name***	**Spawning location**	**Method and abundance (unit)**	**Time**
1	Albacore tuna	*Thunnus alalunga*	South Pacific Ocean	Biomass (Index)	1962-1993
1	Albacore tuna	*Thunnus alalunga*	South Pacific Ocean	Catch (Thousand tonnes)	1952-1995
2	**Anchovy**	***Encrasicholina punctifer***	**Indonesia**	**Catch (Tonnes)**	**1971-1998**
3	Atlantic bluefin tuna	*Thunnus thynnus*	West Atlantic	Biomass (Tonnes)	1970-1993
3	Atlantic bluefin tuna	*Thunnus thynnus*	West Atlantic	Catch (Tonnes)	1963-1993
4	**Bigeye tuna**	***Thunnus obesus***	**East Pacific**	**Biomass (Thousand tonnes)**	**1971-1996**
4	**Bigeye tuna**	***Thunnus obesus***	**East Pacific**	**Catch (Number of fish)**	**1971-1996**
5	Bigeye tuna	*Thunnus obesus*	West Atlantic	Biomass (Tonnes)	1961-1995
5	Bigeye tuna	*Thunnus obesus*	West Atlantic	Catch (Tonnes)	1960-1995
6	**Bombay duck**	***Harpodon nehereus***	**Northwest Coast of India**	**Biomass (Millions)**	**1956-1984**
6	**Bombay duck**	***Harpodon nehereus***	**Northwest Coast of India**	**Catch (Tonnes)**	**1956-1984**
7	Bombe	*Bathyclarias spp.*	Lake Malawi	Catch (Metric tons)	1976-1996
8	**Brazilian sardine**	***Sardinella brasiliensis***	**South Eastern Brazil**	**Biomass (Thousand tonnes)**	**1977-1992**
8	**Brazilian sardine**	***Sardinella brasiliensis***	**South Eastern Brazil**	**Catch (Thousand Tons)**	**1977-1992**

9	Chambo	*Oreochromis spp.*	Lake Malombe	Catch (Metric tons)	1976-1998
10	**Chub mackerel**	***Scomber japonicus***	**Pacific Coast of Japan**	**Biomass (Thousand tonnes)**	**1971-1988**
11	Chub mackerel 2	*Scomber japonicus*	Pacific Coast of Japan	Biomass (Trillions of eggs)	1951-1970
12	**Chub mackerel**	***Scomber japonicus***	**Southern California**	**Biomass (Million pounds)**	**1929-1968**
13	Eastern little tuna	*Euthynnus affinis*	Indonesia	Catch (Tonnes)	1973-1998
14	**Fringescale sardinella**	***Sardinella fimbriata***	**Indonesia**	**Catch (Tonnes)**	**1972-1998**
15	Giant seaperch/ Barramundi	*Lates calcarifer*	Indonesia	Catch (Tonnes)	1971-1998
16	**Gold-spotted grenadier anchovy**	***Coilia dussumieri***	**Northwest coast of India**	**Biomass (Millions)**	**1960-1985**
16	**Gold-spotted grenadier anchovy**	***Coilia dussumieri***	**Northwest coast of India**	**Catch (Millions)**	**1960-1985**
17	Greater lizardfish	*Saurida tumbil*	East China Sea	Biomass (Index)	1955-1964
18	**Grey mullet**	***Mugil cephalus***	**Taiwan**	**Biomass (Thousands of females)**	**1977-1986**
18	**Grey mullet**	***Mugil cephalus***	**Taiwan**	**Catch (Numbers)**	**1977-1987**
19	Grouper	*Cephalopholis igarashiensis*	Indonesia	Catch (Tonnes)	1973-1998
20	**Herring**	***Clupea harengus***	**Gulf of Maine**	**Biomass (Thousand tonnes)**	**1967-1989**
20	**Herring**	***Clupea harengus***	**Gulf of Maine**	**Catch (Thousand tonnes)**	**1960-1989**
21	Herring	*Clupea harengus*	North Sea	Biomass (Tonnes)	1947-1989
21	Herring	*Clupea harengus*	North Sea	Catch (Tonnes)	1940-1973
22	**Herring**	***Clupea harengus***	**Norway**	**Biomass (Tonnes)**	**1950-1996**
22	**Herring**	***Clupea harengus***	**Norway**	**Catch (Tonnes)**	**1950-1996**

23	Indian mackerel	*Rastrelliger kanagurta*	Indonesia	Catch (Tonnes)	1971-1998
24	**Indian oil sardinella**	***Sardinella longiceps***	**Indonesia**	**Catch (Tonnes)**	**1971-1998**
25	Kambusi	*Lethrinops spp.*	Lake Malawi	Catch (Metric tons)	1976-1995
26	**Kambusi**	***Lethrinops spp.***	**Lake Malombe**	**Catch (Metric tons)**	**1976-1998**
27	Kampango	*Bagrus meridionalis*	Lake Malawi	Catch (Metric tons)	1976-1996
28	**King mackerel**	***Scomberomorus cavalla***	**West gulf of Mexico**	**Biomass (Thousands)**	**1952-1990**
28	**King mackerel**	***Scomberomorus cavalla***	**West gulf of Mexico**	**Catch (Tonnes)**	**1952-1990**
29	Mackerel	*Scomber scombrus*	Black Sea	Biomass (Thousand tonnes)	1952-1968
29	Mackerel	*Scomber scombrus*	Black Sea	Catch (Tonnes)	1942-1992
30	**Mackerel**	***Scomber scombrus***	**NAFO 2to 6**	**Biomass (Thousand tonnes)**	**1962-1990**
30	**Mackerel**	***Scomber scombrus***	**NAFO 2to 6**	**Catch (Tonnes)**	**1960-1990**
31	Mackerel	*Scomber scombrus*	Western ICES	Biomass (Thousand tonnes)	1972-1990
31	Mackerel	*Scomber scombrus*	Western ICES	Catch (Tonnes)	1977-1990
32	**Narrow barred king mackerel**	***Scomberomorus commerson***	**Indonesia**	**Catch (Tonnes)**	**1971-1998**
33	Northern anchovy	*Engraulis mordax*	California	Biomass (Thousand tonnes)	1951-1988
33	Northern anchovy	*Engraulis mordax*	California	Catch (Short tons)	1951-1986
34	**Pacific cod**	***Gadus macrocephalus***	**West Vancouver Island**	**Catch (Thousand tonnes)**	**1954-1989**
35	Pacific halibut	*Hippoglossus stenolepis*	North Pacific	Biomass (Tons)	1935-1981
35	Pacific halibut	*Hippoglossus stenolepis*	North Pacific	Catch (Million pounds)	1929-1989

36	**Pacific ocean perch**	***Sebastes alutus***	**Aleutian Islands**	**Biomass (Tonnes of Females)**	**1960-1989**
36	**Pacific ocean perch**	***Sebastes alutus***	**Aleutian Islands**	**Catch (Tonnes)**	**1962-1995**
37	Red snapper	*Lutjanus campechanus*	U.S. Gulf of Mexico	Biomass (Thousand billion eggs)	1984-1992
38	**Sardine**	***Sardinops sagax***	**California**	**Biomass (Short tons)**	**1932-1965**
38	**Sardine**	***Sardinops sagax***	**California**	**Catch (Thousand Tonnes)**	**1950-1989**
39	Scad	*Decapterus russelli*	Indonesia	Catch (Tonnes)	1971-1998
40	**Silk snapper**	***Lutjanus synagris***	**Zone B – Cuba**	**Biomass (Hundreds tonnes)**	**1962-1978**
41	Skipjack tuna	*Katsuwonus pelamis*	Indonesia	Catch (Tonnes)	1971-1998
42	**South African Anchovy**	***Engraulis capensis***	**South Africa**	**Biomass (Thousand tonnes)**	**1964-1981**
43	Southern bluefin tuna	*Thunnus maccoyii*	Southern Pacific	Biomass (Thousands of tonnes)	1960-1991
44	**Southern bluefin tuna 2**	***Thunnus maccoyii***	**Southern Pacific**	**Biomass (Tonnes)**	**1951-1995**
45	Swordfish	*Xiphias gladius*	North Atlantic	Biomass (Thousand tonnes)	1978-1995
46	**Trevally**	***Carangoide malabaricus***	**Indonesia**	**Catch (Tonnes)**	**1971-1998**
47	Usipa	*Engraulicypris sardella*	Lake Malawi	Catch (Metric tons)	1976-1996
48	**Utaka**	***Copadichromis spp.***	**Lake Malawi**	**Catch (Metric tons)**	**1976-1996**
49	Yellowfin tuna	*Thunnus albacares*	Eastern Pacific Ocean	Biomass (Thousands of tons)	1967-1992
50	**Yellowfin tuna**	***Thunnus albacares***	**Indian Ocean**	**Biomass (Millions of fish)**	**1952-1977**
51	Yellowtail flounder	*Pleuronectes ferrugineus*	Southern New England	Biomass (Thousand tonnes)	1973-1996
51	Yellowtail flounder	*Pleuronectes ferrugineus*	Southern New England	Catch (Thousand tonnes)	1961-1996

Table A2. Ecological features of stocks.

Serial No.	Stock	Maximum length (cm)	L ∞ (cm)	K	Natural mortality	Length at maturity (cm)	Life span (year)	Habitat
1	Albacore tuna (south Pacific Ocean)	140	141	0.15	0.22	71.1	19.3	Pelagic
2	**Anchovy (Indonesia)**	**13**	**12.4**	**1.21**	**2.54**	**8**	**2.3**	**Pelagic**
3	Atlantic bluefin tuna (West Atlantic)	420	278	0.17	0.1	169.9	41.6	Pelagic
4	**Bigeye tuna (East Pacific)**	**250**	**187**	**0.38**	**0.6**	**120**	**15.3**	**Pelagic**
5	Bigeye tuna (West Atlantic)	250	222	0.19	0.4	100	15.3	Pelagic
6	**Bombay duck (Northwest coast of India)**	**40**	**39**	**0.53**	**1.01**	**22.4**	**5.4**	**Demersal**
7	Bombe (Lake Malawi)	135	138.2	0.1	0.34	69.8		Demersal
8	**Brazilian sardine (South Eastern Brazil)**	**25**	**27.1**	**0.59**	**1.2**	**16.8**	**4**	**Pelagic**
9	Chambo (Lake Malombe)	36	29	0.72	1.32	17.2	3.9	Demersal
10	**Chub mackerel (Pacific Coast of Japan)**	**64**	**41.6**	**0.33**	**0.56**	**28.9**	**8.6**	**Pelagic**
11	Chub mackerel (Pacific Coast of Japan) 2	64	41.6	0.33	0.56	28.9	8.6	Pelagic
12	**Chub mackerel (Southern California)**	**64**	**41**	**0.22**	**0.5**	**32**	**9**	**Pelagic**
13	Eastern little tuna (Indonesia)	100	90	0.45	0.68	47.5	6.4	Pelagic
14	**Fringescale sardinella (Indonesia)**	**13**	**14**	**1.61**	**3.07**	**8.9**	**1.7**	**Pelagic**
15	Giant seaperch/ Barramundi (Indonesia)	200	143	0.13	0.27	72	22.200	Demersal

16	**Gold-spotted grenadier anchovy (Northwest coast of India)**	**20**	**28.5**	**0.07**	**2.08**	**12.9**		**Pelagic**
17	Greater lizardfish (East China Sea)	60	69.5	0.28	0.46	26.7	4.4	Demersal
18	**Grey mullet (Taiwan)**	**120**	**49.8**	**0.39**	**0.31**	**54.4**	**26.2**	**Pelagic**
19	Grouper (Indonesia)	43	44.8	0.07	0.35	25.4	40.6	Demersal
20	**Herring (gulf of Maine)**	**40**	**35.3**	**0.33**	**0.48**	**20.5**	**8.6**	**Pelagic**
21	Herring (North Sea)	40	30	0.38	0.2	24	8.6	Pelagic
22	**Herring (Norway)**	**40**	**34**	**0.27**	**0.13**	**28**	**8.6**	**Pelagic**
23	Indian mackerel (Indonesia)	35	25.5	1.5	2.44	15.3	1.9	Pelagic
24	**Indian oil sardinella (Indonesia)**	**23**	**27**	**0.55**	**1.2**	**16.1**	**5.2**	**Pelagic**
25	Kambusi (Lake Malawi)	13.1	13.9		1.78	8.9		Demersal
26	**Kambusi (Lake Malombe)**	**13**	**13.8**		**1.77**	**8.8**		**Demersal**
27	Kampango (Lake Malawi)	150	109	0.09	0.21	56.4	32	Demersal
28	**King mackerel (West gulf of Mexico)**	**115**	**115**	**0.16**	**0.16**	**69.3**	**19.3**	**Pelagic**
29	Mackerel (Black Sea)	50	35	0.5	0.82	20.3	16	Pelagic
30	**Mackerel (NAFO 2 to 6)**	**60**	**40.6**	**0.27**	**0.3**	**32**	**20**	**Pelagic**
31	Mackerel (Western ICES)	60	39	0.43	0.15	31.5	20	Pelagic
32	**Narrow barred king mackerel (Indonesia)**	**240**	**184**	**0.26**	**0.4**	**90.3**	**11.1**	**Pelagic**
33	Northern anchovy (California)	24.8	21	0.45	0.6	11.6	6.9	Pelagic

34	**Pacific Cod (West Vancouver Islands)**	**117**	**94**	**0.27**	**0.33**	**49.4**	**10.7**	**Demersal**
35	Pacific halibut (North Pacific)	140	143.2	0.04	0.06	72.1	72.8	Demersal
36	**Pacific Ocean Perch (Aleutian Islands)**	**51**	**47.7**	**0.07**	**0.07**	**33.2**	**21.9**	**Demersal**
37	Red snapper (U.S. Gulf of Mexico)	100	117	0.18	0.15	49.5	16.9	Demersal
38	**Sardine (California)**	**30**	**29**	**0.45**	**0.4**	**21.5**	**8.6**	**Pelagic**
39	Scad (Indonesia)	45	28.4	1.13	2	21.6	2.5	Pelagic
40	**Silk snapper (Zone B – Cuba)**	**80**	**75.7**	**0.1**	**0.19**	**43.3**	**28.7**	**Demersal**
41	Skipjack tuna (Indonesia)	108	79.1	0.64	0.8	42.3	4.5	Pelagic
42	**South African Anchovy (South Africa)**	**20**	**24.6**	**0.32**	**0.59**	**14.8**	**8.8**	**Pelagic**
43	Southern bluefin tuna (Southern Pacific)	245	222	0.14	0.08	119	20.7	Pelagic
44	**Southern bluefin tuna 2 (Southern Pacific)**	**245**	**222**	**0.14**	**0.08**	**119**	**20.7**	**Pelagic**
45	Swordfish (North Atlantic)	480	640	0.15	0.2	112.9	17.1	Pelagic
46	**Trevally (Indonesia)**	**60**	**25**			**15**		**Demersal**
47	Usipa (Lake Malawi)	13	13.8	2.63	4.14	8.8	1.1	Pelagic
48	**Utaka (Lake Malawi)**	**13.2**	**12.1**	**0.78**	**1.85**	**7.8**	**3.6**	**Pelagic**
49	Yellowfin tuna (Eastern Pacific Ocean)	280	190	0.45	0.8	100.4	9.4	Pelagic
50	**Yellowfin tuna (Indian Ocean)**	**280**	**194**	**0.16**	**0.25**	**120**	**9.4**	**Pelagic**
51	Yellowtail flounder (Southern New England)	55	50	0.33	0.15	25.5	13.1	Demersal

Source: Froese and Pauly (2000).

Table A3. Summary of statistical analysis. ***: p<0.0005; **: p<0.01; *: p<0.05; a: p<0.10; n.s.: not significant

Serial No.	**Stock**	**Catch and / or biomass**	**Correlation with year**	**Coefficient of variation CV**	**R²**	**R^2_{lo}**	**Lag**	**Autocorrelation coefficient Rk**	**Apparent period**	**Length of time series**
1	Albacore tuna (south Pacific Ocean)	Biomass	-0.30*	0.25	0.09a	0.94	14	-0.51	28***	44
1	Albacore tuna (south Pacific Ocean)	Catch	0.73***	0.39	0.53***	0.76	19	-0.25	28***	32
2	**Anchovy (Indonesia)**	**Catch**	**0.97*** **	**0.32**	**0.94*** **	**0.96**	**11**	**-0.34**	**22*** **	**27**
3	Atlantic bluefin tuna (West Atlantic)	Biomass	-0.95***	0.69	0.90***	0.96	8	-0.49	16***	31
3	Atlantic bluefin tuna (West Atlantic)	Catch	-0.69***	0.73	0.47***	0.74	8	-0.42	16***	24
4	**Bigeye tuna (East Pacific)**	**Biomass**	**-0.67*** **	**0.12**	**0.45*** **	**0.77**	**10**	**-0.34**	**20*** **	**26**
4	**Bigeye tuna (East Pacific)**	**Catch**	**0.65*** **	**0.63**	**0.42*** **	**0.76**	**9**	**-0.56**	**18*** **	**26**
5	Bigeye tuna (West Atlantic)	Biomass	-0.85***	0.39	0.73***	0.95	13	-0.57	26***	36
5	Bigeye tuna (West Atlantic)	Catch	0.91***	0.45	0.83***	0.87	14	-0.45	28***	35
6	**Bombay duck (Northwest coast of India)**	**Biomass**	**0.51** **	**0.46**	**0.26** **	**0.7**	**13**	**-0.51**	**26*** **	**29**
6	**Bombay duck (Northwest coast of India)**	**Catch**	**0.20 n.s.**	**0.25**	**0.04 n.s.**	**0.42**	**12**	**-0.57**	**24*** **	**29**
7	Bombe (Lake Malawi)	Catch	-0.61**	0.28	0.37**	0.39	11	-0.39	22***	22
8	**Brazilian sardine (South Eastern Brazil)**	**Biomass**	**-0.72** **	**0.36**	**0.50** **	**0.69**	**4**	**-0.63**	**8*** **	**16**
8	**Brazilian sardine (South Eastern Brazil)**	**Catch**	**-0.85*** **	**0.34**	**0.73*** **	**0.82**	**6**	**-0.58**	**12*** **	**16**

9	Chambo (Lake Malombe)	Catch	-0.76**	0.94	0.58***	0.81	10	-0.56	20***	23
10	**Chub mackerel (Pacific Coast of Japan)**	**Biomass**	**-0.68****	**0.91**	**0.47****	**0.65**	**8**	**-0.50**	**16*****	**18**
11	Chub mackerel (Pacific Coast of Japan) 2	Biomass	0.62**	0.87	0.39**	0.71	9	-0.43	18***	30
12	**Chub mackerel (Southern California)**	**Biomass**	**-0.74*****	**1.05**	**0.56*****	**0.74**	**12**	**-0.38**	**24*****	**40**
13	Eastern little tuna (Indonesia)	Catch	0.98***	0.47	0.96***	0.98	11	-0.42	22***	25
14	**Fringescale sardinella (Indonesia)**	**Catch**	**0.98*****	**0.38**	**0.96*****	**0.97**	**12**	**-0.36**	**24*****	**26**
15	Giant seaperch/ Barramundi (Indonesia)	Catch	0.84***	0.68	0.71***	0.97	12	-0.53	24***	27
16	**Gold-spotted grenadier anchovy (Northwest coast of India)**	**Biomass**	**0.60****	**0.69**	**0.36****	**0.41**	**9**	**-0.61**	**18*****	**26**
16	**Gold-spotted grenadier anchovy (Northwest coast of India)**	**Catch**	**0.73*****	**0.6**	**0.53*****	**0.53**	**9**	**-0.44**	**18*****	**26**
17	Greater lizardfish (East China Sea)	Biomass	-0.94***	0.58	0.88***	0.94	4	-0.53	8**	10
18	**Grey mullet (Taiwan)**	**Biomass**	**-0.86****	**0.38**	**0.74****	**0.88**	**2**	**-0.32**	**4 n.s.**	**11**
18	**Grey mullet (Taiwan)**	**Catch**	**-0.53***	**0.47**	**0.28a**	**0.68**	**7**	**-0.25**	**14 n.s.**	**10**
19	Grouper (Indonesia)	Catch	0.74***	0.67	0.56***	0.92	11	-0.41	22***	25
20	**Herring (gulf of Maine)**	**Biomass**	**-0.07 n.s.**	**0.54**	**0.006 n.s.**	**0.86**	**9**	**0.50**	**18*****	**30**
20	**Herring (gulf of Maine)**	**Catch**	**-0.22 n.s.**	**0.33**	**0.05 n.s.**	**0.1**	**10**	**0.48**	**20*****	**23**
21	Herring (North Sea)	Biomass	-0.79***	0.86	0.62***	0.92	13	0.41	26***	34
21	Herring (North Sea)	Catch	0.58***	0.47	0.34***	0.79	16	0.22	32***	43

22	**Herring (Norway)**	**Biomass**	**-0.53*****	**1.03**	**0.28*****	**0.95**	**18**	**-0.60**	**36*****	**47**
22	**Herring (Norway)**	**Catch**	**-0.64*****	**1.04**	**0.40*****	**0.68**	**16**	**-0.53**	**32*****	**47**
23	Indian mackerel (Indonesia)	Catch	0.97***	0.41	0.95***	0.98	9	-0.38	18***	27
24	**Indian oil sardinella (Indonesia)**	**Catch**	**0.90*****	**0.55**	**0.81*****	**0.82**	**16**	**-0.24**	**32*****	**27**
25	Kambusi (Lake Malawi)	Catch	0.61**	0.71	0.37**	0.55	7	-0.45	14***	20
26	**Kambusi (Lake Malombe)**	**Catch**	**0.49****	**0.78**	**0.24***	**0.68**	**10**	**-0.37**	**20*****	**23**
27	Kampango (Lake Malawi)	Catch	-0.57**	0.32	0.33**	0.47	7	-0.35	14***	21
28	**King mackerel (West gulf of Mexico)**	**Biomass**	**0.18 n.s.**	**0.38**	**0.03 n.s.**	**0.64**	**17**	**-0.48**	**34*****	**39**
28	**King mackerel (West gulf of Mexico)**	**Catch**	**0.81*****	**0.83**	**0.66*****	**0.68**	**20**	**-0.38**	**40*****	**39**
29	Mackerel (Black Sea)	Biomass	0.04 n.s.	0.81	0.002 n.s.	0.6	5	-0.57	10***	51
29	Mackerel (Black Sea)	Catch	-0.65***	1.14	0.43***	0.49	14	-0.53	28***	17
30	**Mackerel (NAFO 2 to 6)**	**Biomass**	**0.75*****	**0.63**	**0.57*****	**0.82**	**10**	**-0.44**	**20*****	**31**
30	**Mackerel (NAFO 2 to 6)**	**Catch**	**-0.02 n.s.**	**1.18**	**0.00 n.s.**	**0.56**	**13**	**-0.45**	**26*****	**29**
31	Mackerel (Western ICES)	Biomass	-0.86***	0.22	0.74***	0.9	8	-0.57	16***	14
31	Mackerel (Western ICES)	Catch	-0.54*	0.26	0.29*	0.93	6	-0.37	12**	19
32	**Narrow barred king mackerel (Indonesia)**	**Catch**	**0.92*****	**0.32**	**0.85*****	**0.94**	**16**	**-0.29**	**32*****	**27**
33	Northern anchovy (California)	Biomass	-0.12 n.s.	0.82	0.01 n.s.	0.16	9	-0.19	18***	36
33	Northern anchovy (California)	Catch	0.26 a	0.88	0.06 n.s.	0.62	12	-0.43	24***	38
34	**Pacific Cod (West Vancouver Islands)**	**Catch**	**0.09 n.s.**	**0.7**	**0.01 n.s.**	**0.46**	**13**	**-0.61**	**26*****	**36**

35	Pacific halibut (North Pacific)	Biomass	-0.46***	0.32	0.21**	0.93	20	-0.52	40***	61
35	Pacific halibut (North Pacific)	Catch	-0.18a	0.27	0.03 n.s.	0.42	18	-0.53	36***	47
36	**Pacific Ocean Perch (Aleutian Islands)**	**Biomass**	**-0.74*****	**0.7**	**0.54*****	**0.96**	**12**	**-0.51**	**24*****	**34**
36	**Pacific Ocean Perch (Aleutian Islands)**	**Catch**	**-0.64*****	**1.35**	**0.41*****	**0.31**	**11**	**-0.46**	**22*****	**30**
37	Red snapper (U.S. Gulf of Mexico)	Biomass	0.94***	0.14	0.89***	0.96	3	-0.50	6**	9
38	**Sardine (California)**	**Biomass**	**-0.87*****	**1.1**	**0.77*****	**0.86**	**16**	**-0.31**	**32*****	**40**
38	**Sardine (California)**	**Catch**	**-0.55*****	**2.42**	**0.30*****	**0.51**	**13**	**-0.52**	**26*****	**34**
39	Scad (Indonesia)	Catch	0.89***	0.86	0.79***	0.91	7	-0.49	14***	27
40	**Silk snapper (Zone B – Cuba)**	**Biomass**	**0.81*****	**0.3**	**0.67*****	**0.92**	**7**	**-0.43**	**14*****	**17**
41	Skipjack tuna (Indonesia)	Catch	0.94***	0.6	0.89***	0.97	7	-0.34	14***	27
42	**South African Anchovy (South Africa)**	**Biomass**	**0.70***	**0.36**	**0.49***	**0.76**	**6**	**-0.54**	**12*****	**18**
43	Southern bluefin tuna (Southern Pacific)	Biomass	-0.97***	0.54	0.95***	0.96	18	-0.32	36***	32
44	**Southern bluefin tuna 2 (Southern Pacific)**	**Biomass**	**-0.97*****	**0.47**	**0.94*****	**0.97**	**15**	**-0.29**	**30*****	**45**
45	Swordfish (North Atlantic)	Biomass	-0.97***	0.47	0.94***	0.98	6	-0.56	12***	18
46	**Trevally (Indonesia)**	**Catch**	**0.96*****	**0.55**	**0.93*****	**0.97**	**10**	**-0.48**	**20*****	**27**
47	Usipa (Lake Malawi)	Catch	0.70***	1.07	0.49**	0.65	5	-0.30	10***	21
48	**Utaka (Lake Malawi)**	**Catch**	**0.39***	**0.49**	**0.15a**	**0.24**	**9**	**-0.37**	**18*****	**21**
49	Yellowfin tuna (Eastern Pacific Ocean)	Biomass	0.38*	0.31	0.14a	0.77	11	-0.62	22***	26
50	**Yellowfin tuna (Indian Ocean)**	**Biomass**	**-0.89*****	**0.68**	**0.8*****	**0.86**	**9**	**-0.54**	**18*****	**26**

51	Yellowtail flounder (Southern New England)	Biomass	-0.30a	0.79	0.09 n.s.	0.16	10	-0.45	20***	36
51	Yellowtail flounder (Southern New England)	Catch	-0.78***	0.84	0.62***	0.73	8	-0.28	16***	24

Fig. A1. Time series of estimated biomass or catches for 6 stocks. Solid line: biomass/catch; doted line: Lowess smoothed trend; dashed line: linear trend.