STANDARDIZED CATCH RATES FOR YELLOWFIN (*THUNNUS ALBACARES)* FROM THE SPANISH PURSE SEINE FLEET (1984-1995)

by

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SUMMARY

The Spanish purse seine fleet operates in a wide area of the Indian Ocean since 1984. A logbooks system provides detailed information of catches (set by set) and effort. Together with this information, an intensive work of interview during 4 years (1994-1997) has provided technical equipment data. These data have been used to estimate standardized catch per unit effort (CPUE) indices of abundance for yellowfin from the Indian Ocean. Standardized catch rates have been estimated using the Generalized Linear Model (GLM) approach. The model proposed includes factors related with the stock abundance together with factors related with catchability changes.

INTRODUCTION

Traditionally the models used to estimate standardised catch rate from commercial data include only factors related with abundance, assuming a constant catchability. In the tropical tuna purse seine fishery is a fact that the boats have continuously increased their fishing power due to, in one hand the introduction of new technology that increase the efficiency for searching and catching fishes and in other one the bettering of the skipper skill. Until now few attempts have been done to consider these kind of factors in the analysis. In this paper we documents the analitycal methods applied to the spanish purse seine fleet data to estimate standardized catch per unit effort (CPUE) indices of abundance for yellowfin from the Indian Ocean. Standardized catch rates have been estimated using the Generalized Linear Model (GLM) approach, considering factors related with the stock abundance together with factors related with catchability changes.

MATERIAL AND METHODS

Data

The analysis has been done with data from the Spanish tropical purse seine fleet in the Indian Ocean from 1984 until 1995. Two sources of data have been used. Fishing data comes from logbooks that the fleet fills regularly with an approximate coverage of 95%. This data, subsequently corrected with landing information, contains detailed set by set information of catches by species and association type (logs and schools), and effort. Technical equipment data has been obtained from inquiries to skippers and ship-owners, interviews to equipment suppliers, etc. Because the reserved character of this kind of information, the elaboration of this data base, possibly the first that integrates this information in the purse seine fleet, has been a heavy task developed during the period 1994-1997.

Technical equipment

A first selection of the ships that had a better information during a long period was made for the elaboration of the fleet file. After a detailed evaluation of all the technical elements used during the fishing process (detection of schools and catch) and their evolution in the study period, the factors that could affect the increase of the fishing power were defined. They were: net size, sonar, radar, boat speed and skipper. Categories for all of them by equipment characteristics were established. The corresponding categories were assigned to the ships by the quarter when the device was installed, such that an device of X category installed in the first quarter was assigned the X + 0.25 code.

The codification of the different devices were as follows:

Net: By its surface (S), expressed in Km^2, four levels were defined:

1 - < 0.3 Km^2 ; 2 – from 0.3 Km^2 to 0.4 Km^2; 3 – from 0.4 Km^2 to 0.5 Km^2 ; 4 - > 0.5 Km^2

Radar: a four levels classification was preliminary established:

1 = without radar; 2 = with 15 Kilowatts (Kw) radar; 3 = with 30 Kw radar; 4 = with 60 Kw radar.

Although, the analysis suggested to group the two first categories in one because there were no significant

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differences in the yields from this two groups. The sequence of introduction of different models of radar follows the same order, i.e., first, 15 Kw radar appears, after 30 Kw radar, and next 60 Kw radar. There are few years of overlap in the last two categories; 30 Kw radar appears in 1987 and continues until 1990 when it almost disappears. And the 60 Kw radar appears in 1989 until the end of the period, replacing the 30 Kw for detection purposes.

Sonar: three levels were established:

1 = without sonar

2 = with 45 kilocicles (Kc) sonar or 60 Kc sonar, i.e., only one sonar.

3 = with 45 Kc sonar and 60 Kc sonar, i.e., with two sonar.

This classification was made considering that 45 Kc sonar and 60 Kc sonar characteristics are complementary; some ships first install 60 Kc sonar and other ships the 45 Kc sonar, but later, add the other kind of sonar to work with the two models.

Boat speed: There were not established categories. During the period it varies between 10 to 15 knots. It was the less significant variable in the model. This was because there were some differences in the speed between ships, but most of the boats does not change its speed during the study period. Therefore, it is difficult to observe the influence of speed over fishing power.

Skipper: At the beginning, we had information for 52 skippers. We first tried to introduce this variable as a factor in the model, but having so many levels and obtaining an unbalanced analysis, it was necessary to classify the skippers in small groups to simplify the model. This is a difficult classification to make without introducing bias in the analysis. Making this classification is easy to separate a priori the skippers with better performance from those with poorer yields. On the other hand, the presence of a skipper in the fishery is quite diverse, from some that fish only during one year to those present during the whole period. The presence of a skipper in the fishery is already an indication of his efficiency, but is difficult to compare the performance of skippers that have been in the fishery different years and a different number of years. Because the efficiency of a skipper is linked to the experience in the control of the boat's equipment, we decided to limit the study for the skippers that were more than six years in the fishery, to be able to establish differences among those that have worked with the different technological levels that were introduced in the boats along the study period.Codes were established for their identification to preserve their identity. This information is very important because it allow us to analyse skipper ability and his knowledge of the equipment.

Catch and effort data

A basic catch and effort file was created using the information from the logbook containing catches by set and species, school type, boat, temporal strata and area. The species detailed in the logbooks were yellowfin, skipjack and bigeye.

The following school types were considered: log school, free school and unknown.

Likewise, there were five areas as it shows in Figure 1.

1 = Somalia; 2 = N-W Seychelles; 3 = Mozambique; 4 = S-E Seychelles; 5 = Chagos

Four fishing seasons were considered:

Season 1 = January and February; Season 2 = March, April, May y June

Season 3 = July, August, September y October; Season 4 = November y December.

To evaluate fishing effort different measures were considered: fishing time, searching time, total number of sets and positive and negatives sets. In this preliminary analysis, for practical reasons, we will show the results using fishing time only.

Both files, catch and effort and technical equipment by boat were integrated in a single file.

For this preliminary analysis, only the information related to yellowfin associated in free schools were considered, because that could give us a good indication of the adult yellowfin stock and the possible increments in purse seine fishing power would be better reflected in this type of fishery. The first analysis was very unbalanced. In order to reduce the number of zeros in the data, we group them by fortnight, adding the catch by type of school, boat and skipper.

We used fishing time as the global fishing time because, as we are dealing with multispecies fishery, we do not have the capability yet, to identify the fishing effort directed to every species neither there are information that allow us to differentiate the fishing effort by school type (log / free).

By choosing free school only, the Somalia Area was eliminated because it is an almost exclusive for log fishing. The Chagos Area was also not considered because the expansion of the fishery towards that area was observed only during the last three years of the study period. Table 1 shows catches by species, year and area, all fishing modes combined.

Analysis

Standardized catch per unit effort (CPUE) indices of abundance for yellowfin in the Indian Ocean was estimated by a delta lognormal model. This model treats separately positive cpue observations and the probability of an observation to be positive or null. This two components (probability of cpue to be positive and the distribution of the values different from zero) can be modelled independently to obtain positive cpue probability fitted, and then the expected cpue conditioning to obtain a value of cpue different from zero. The proposed delta model, consists of two generalized linear models using the Bernouilli and lognormal distributions respectively. We obtain the final index as the product of the mean annual effect of the binomial and lognormal components.

The first analysis shows a strong interaction between year and area, so following the recommendation from the ICCAT Working methods group (Anon, 2000), we calculate independent indices for the areas considered.: N-W Seychelles, S-E Seychelles, and Mozambique.

Positive CPUE

For each year and area considered, cpue is:

$$cpue_{yi} = \mu_{yi}\, p_{yi},\ i = 1,2,3. \qquad (1)$$

where μ_{yi} is the annual mean of the standardised cpue of positive catches for each area i. and p_i is the annual mean for the standardised proportion of positives for each area i.

To calculate a relative index in each area, the three indices were weighted by the number of observations in each area, i.e.,

$$cpue_y = N_{y1}cpue_{y1} + N_{y2}cpue_{y2} + N_{y3}cpue_{y3}, \qquad (2)$$

where $cpue_y$ is the mean cpue for year y, N_{yi} is the number of observations in area i for year y, and $cpue_{yi}$ is the annual mean cpue for year y of area i.

As fixed effects year, area, season, skipper, sonar, radar, net, speed and the total log school catch were considered, all of them included in matrix X. The last continuous variable (log catch) was included in the model because it is considered that what is not fish from free schools is caught from log schools, and it is assumed that it would have a negative effect over adult yellowfin cpue. Also, first order interactions between year, season and skipper with boat characteristics were included in matrix Z. The other first order interactions and higher order interactions were not considered to avoid overparametrization of the model.

The model that fits cpue for positive catches is:

$$Ln(cpue) = X\alpha + Z\beta + \varepsilon, \qquad (3)$$

where cpue is the vector of observations, X is the fixed factors matrix , α is the fixed factors parameters vector, Z is the interactions matrix, β is the interactions parameters vector and ε is the vector of errors independently equally distributed that follows a $N(0, \sigma^2)$. Once an estimation of cpue in each area is obtained, we calculate its annual mean, μ_{yi}, and substitute it in (1).

PROPORTION OF POSITIVES

To estimate the proportion of positives, we used all data set. We created a Bernouilli random variable that takes the value 0 if cpue is null and 1 if cpue is positive. Then, we calculate the mean of this variable in each strata defined by the combination of different levels of year, area, season, skipper, sonar, radar, net and speed, and calculate the number of observations in each cell to weight the model.

The probability of positive cpue can be modelled with a GLM with a logit function as link function between the linear component and the response variable, i.e., the presence of positive cpue is a Bernouilli random variable with probability p, given by:

$$Log(p/(1-p)) = X\alpha + Z\beta, \text{ or }, \qquad (4)$$

$$p = 1/(1 + \exp\{ X\alpha + Z\beta \}),$$

where X is the fixed factors matrix that are year, area, season, skipper, sonar, radar, net and speed, α is the vector of the fixed factors parameters, Z is the interactions matrix, and β is the interactions parameters vector. Next, we calculate the annual mean of p in each area, p_{yi}, and substituting its value in (1), we obtain the three $cpue_{yi}$ indices.

Model selection

The statistical package S-PLUS 4.5 was used for data analysis. The function "anova" gives a table with the individual contribution of all the terms. The variables whose F-statistic had a p-value less than 0.05 were considered significant. As the design of the data is not balanced, because it does not exist a temporal overlap between the different levels of every factor, the individual contributions depend on the order of introduction of the factors in the model. To obtain an independent result of this order, in the analysis of variance, we examined the type III error.

The package S-PLUS gives an option to make contrasts, adding a matrix of linear combinations between the levels of each factor. With the "contrast treatment" option, adequate for not balanced designs, each coefficient represent the comparison between each level with the first level (omitting level one). This is equivalent to the constraint $\alpha_1 = 0$ and it facilitates the interpretation of coefficients.

Another approach in variables selection was the use of the function "step", that automates the selection process, and based in the AIC it decides between adding or excluding each variable, making a balance between the variability explained by each factor and the degrees of freedom that is introduced in the model. We have to take in consideration that this function tends to be generous in adding variables and more cautious in excluding them. Occasionally, the GLM fit does not converge after ten iterations, and for this situation, we can fit a robust GLM, in which smaller weights are assigned to observations that can be considered extreme points because their deviations from the mean are too large. Changes in the determination coefficient, R^2, were also used as a measure of goodness of fit.

RESULTS AND DISCUSSION

Figure 2 shows the histograms of total observed cpue, positive cpue and logarithm of positive cpue. We have to stand out the strong asymmetry in the total cpue distribution, with a big proportion of zeros, suggests the existence of two different populations, the positive catches and null catches.

Positive cpue distribution is very asymmetric too, with a heavy right tail, that means that a great number of outliers exists.

Through the logarithmic transformation of positive cpue, we obtain a more symmetric distribution that, in some way, approximates it to a normal distribution and facilitates the gaussian linear model approach for positive data.

Tables 2 to 7 show the results for ANOVA gaussian GLM of the positive data distribution and binomial GLM of positives proportion, for each of the three areas.

Figures 3 to 5 show the graphs of the residuals versus fitted variables, observed variables versus fitted and q-q-plots of gaussian models applied to the three areas studied.

With respect to positive observations, year and season always appear as the most significant variables, because in tropical tuna species, recruitment depends very much on seasonal and annual oceanographic conditions. Also, we have to stand out that log school catch is important and always appears in all the analysis with a negative coefficient, as was expected.

In the N-W Seychelles area, we observe a big difference in cpue for all different levels of sonar, and the yield increases with the improvement of sonar technique. Also we can see significant differences between skippers, specially in Mozambique and it is in this area where the net has a positive effect over the cpue. The only factor that does not seem to be significant in any areas is the radar.

With respect to proportion of positive observations, the analysis does not allow us to observe a great effect of the equipment, and we only find significant factors depending on the abundance, i.e. year and season and their interaction.

Figure 6 and table 8 show the cpue by area and the weighted global index with data related to 1986. By areas, we observe a similar picture in N-W of Seychelles and S-E of Seychelles, without a clear trend during a ten year period. In year 88 there are great yields in both areas and it coincides with the introduction of the level 2 of sonar and radar. Although, the next year is one of the worst for both areas, recovers a increasing trend during the next three years in N-W and in two years in S-E, and finally becomes decreasing in the latter years. In Mozambique, cpue behaves in a different way, because in this area log fishing is more relevant. Also, there are less observations, e.g. no observations in 1988, and only during season 2, from March to June. The overall index trend is close to that presented in the areas around Seychelles.

CONCLUSION

There is a general agreement that to obtain accurate standardized abundance indices from the purse seine data it is necessary to take into account the increase in the fishing power of the boats. This work is a first step in this way.

Although results must be considered preliminar, the analysis made (definition of variables, criteria for coding, definition of models) could be very useful for future analysis. Also the dificulties arose in the analysis can help us to define and plan the collection of new data as well as the design of new analysis.

The rapid and broad introduction of new technical equipment by the fleet has been one of the main problem detected. This fact reduce the possibility of equipment overlapping making the analysis very unbalanced.

A pending issue, that might affect this type of analysis, is the discrimination of fishing effort by species and/or fishing mode. The logbook system established in the Indian Ocean does not allow us to separate the effort by species and/or fishing mode.

Further analysis with this model should be made using different effort units as searching time and number of sets.

In the frameof the EU funded programme called ESTHER[3], it is planned to extend this type of analysis to a longer period and to the European and associated fleet operating in the Atlantic and Indian Oceans. The extension in the time period and the inclusion of a larger portion of the fleet might help us to clarify some aspects that are not very clear at this stage.

ACKNOWLEDGEMENTS

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[3] **E**fficacité des **S**enneurs **T**honiers et **E**fforts **R**éels (= Tuna purse seine efficiency and real effort)

REFERENCES

AITCHISON, J., 1955: On the distribution of a positive random variable having a discrete probability mass at the origin. Journal of the american statistical association, 50: 901-908.

BISHOP, J., WANG, Y. G. Y DIE. D., 2000: A generalised estimating equations approach for analysis of the impact of the new technology on a trawl fishery. Australia New Zealand Journal of statistics.

COOKE, J. G, K. LANKESTER, 1977: Consideration of statistical models for catch-effort indices for use in tuning VPA's. SCRS/95/77.

COOKE, J. G., 1996: A procedure for using catch-effort indices in bluefin tuna assessments. SCRS/96/63.

DRAPER, N. R., Y SMITH, H., 1981: Applied reggression analysis. Ed. Wiley series in probability and mathematical statistics, second ed.

GAVARIS, S., 1980: Use a multiplicative model to estimate catch rate and effort from commercial data. Can. J. Fish. Aquat. Sci. 37: 2272-2275.

HOEY, J., CONSER, R Y DUFFIE, E., 1988: Catch per unit of effort information from the U.S. swordfish fishery. ICCAT working document. SCRS/88/21.

HSU, C. C. Y LIU, H. C., 1999: The updated catch per unit of effort of bigeye tuna for Taiwanese longline fishery in the Atlantic. SCRS/99/130.

LALOE, F., 1998: Model identification for flexible multifllet-multispecies fisheries. A simulation study. Fish. Res., 37: 193-202.

LARGE, P. A., 1992: Use a multiplicative model to estimate relative abundance from commercial CPU data. ICES J. Mar. Sci., 49: 253-261.

LO, N. C. H., N., L. D. JACOBSON Y L. J. SQUIRE, 1992: Indices of relative abundance from fish spotter data based on Delta-Lognormal models. Can. J. Fish. Aquat. Sci. 49: 2515-2526.

MCCULLAGH, P. AND NELDER, J. A., 1989: Generalized linear models, second ed. Ed. Chapman & Hall.

MEYERS, R. A. Y PEPIN, P., 1990: Biometrics, 46: 1185-1192.

MILLISCHER, L. Y GASCUEL, D., 1998: Individual based modeling of fishing tactics. ICES anual conference.

MIYABE, N., 1988: Estimation of standarized cpue for the atlantic swordfish using the data from the japanese logline fishery. SCRS/88/20.

MIYABE, N., 1991: Trend of cpue for atlantic swordfish caught by the japanese logline fishery in the Atlantic ocean. SCRS/91/34.

NEYMAN, K., 1997: Bayesian averaging of generalized linear models for passive integrated trnsponder tag recoveries from salmonids in the Snake river. N. Am. J. Fish. Manage., 17: 362-377.

O'BRIEN, C.M., KELL, L. T., SANTIAGO, J. Y ORTIZ DE ZÁRATE, V., 1997: The use of generalized linear models for the modelling of catch-effort series. II. Aplicaton to north atlantic albacore surface fishery. ICCAT working document. SCRS/97/49.

O'BRIEN, L. Y RAGO, P., 1996: An application of the generalized additive model to grounfish survey data with atlantic cod off the northeast coast of the United States as an example. NAFO Sci. Coun. Studies, 28: 79-95.

ORTEGA-GARCÍA, S. Y GÓMEZ-MUÑOZ, V., 1992: Standarization of fishing effort using principal component analysis of vessel characteristics: the mexican purse-seiners. Sci. Mar., 56: 17-20.

ORTIZ, M., TURNER, S. C. Y BROWN, C. A., 1998: Standarized catch rates for small bluefin tuna, Tunnus thynnus, from the reel fishery off the northeast United States from 1980-1997. ICCAT working document. SCRS/98/59.

PENNINGTON, M., ON TESTING OF LOGNORMAL-BASED MODELS, 1971: Biometrics, 47: 1623-1624.

PENNINGTON, M., 1996: Estimating the mean and variance from highly skewed marine data. Fishery Bulletin 94:498-505.

PEÑA, D., 1998: Etadística, modelos y métodos. Vol. 1 y 2. Ed. Alianza Editorial.

PUNSLY, R. Estimation of the relative annual abundance of yellowfin tuna, Thunnus Albacaresn in the easternPacific ocean durin 1970-1985.

PUNT, A. E., WALKER, T. I., TAYLOR, B. L. Y PRIBAC, F., 1999: Standarization of catch and effort data in a spatially-structured shark fishery. Fish. Res. 45: 129-145.

ROBINS, C. M., WANG, Y. G. Y DIE. D., 1999: The impact of global psitioning systems and plotters on fishing power in the northern prawn fishery, Australia. Canad. J. Fish. Aquat. Sci., 55: 1645-1651.

ROBSON, D. S., 1966: Estimation of the relative abbundance fishing power of individual ships. ICNAF Res. Bul., 3: 5-14.

SMITH, S. J., 1988: Evaluating the efficiency of the delta-distribution mean estimator. Biometrics, 44: 485-493.

SWARTZMAN, 1992: Spatial analysis of Bearing sea groundfish survey data usin generalised additive models. Can. J. Fish. Aquat. Sci, 49: 1366-1378.

SWARTZMAN, G., SILVERMAN, E., WILLIAMSON, N., 1995: Relating trends in walleye pollock (Theragra chalcogramma) abundance in the Bearing sea to environmental factors. Can. J. Fish. Aquat. Sci. J. Can. Sci. Halieut. Aquat., 52: 369-380.

STEFÁNSSON, G., 1996: Analysis of groundfish survey abundance data: combining the GLM and delta approaches. ICES Journal of Marine Science, 53: 577-588.

WADE, P. R., 1999: A comparison of statistical methods for fitting poplation models to data. Marine mammal survey and assessment methods, Garner et al. (eds), 249-270.

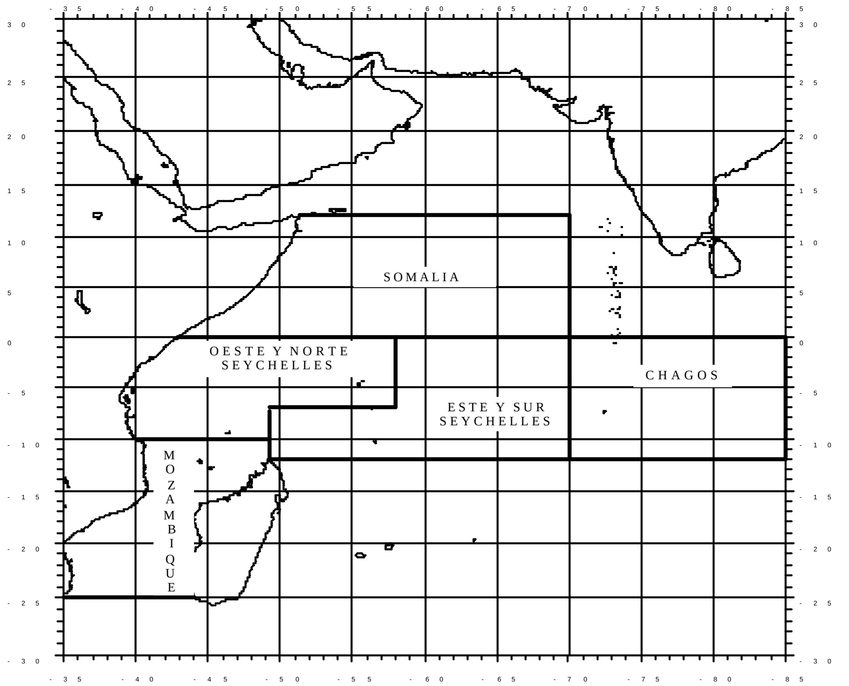

Figure 1.- Areas considered in the analysis.

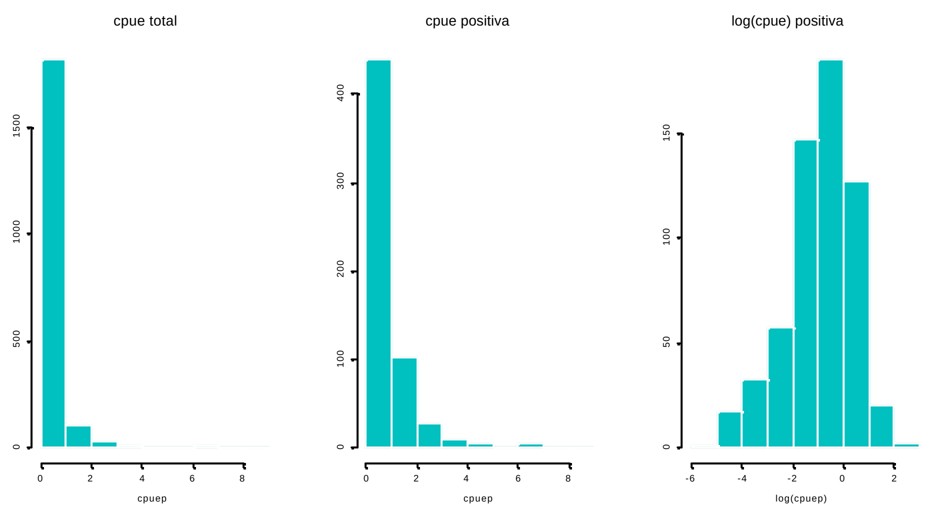

Figure 2.- Distribution of the overall cpue, positive cpue and log transformed positive cpue.

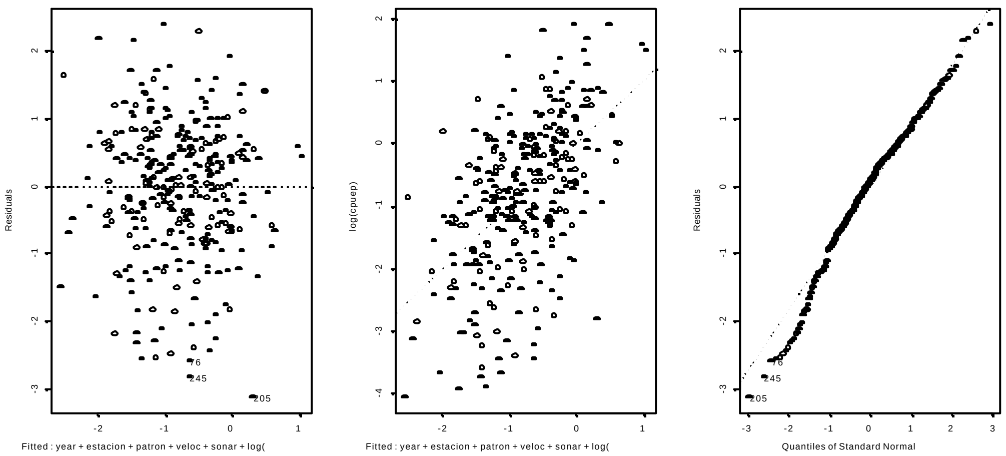

Figure 3: residual plot for the final gaussian model selected for the positive catch rates in area 2 (residual vs. predicted values, dependent variable (log(cpue) vs. predicted and qq-plot).

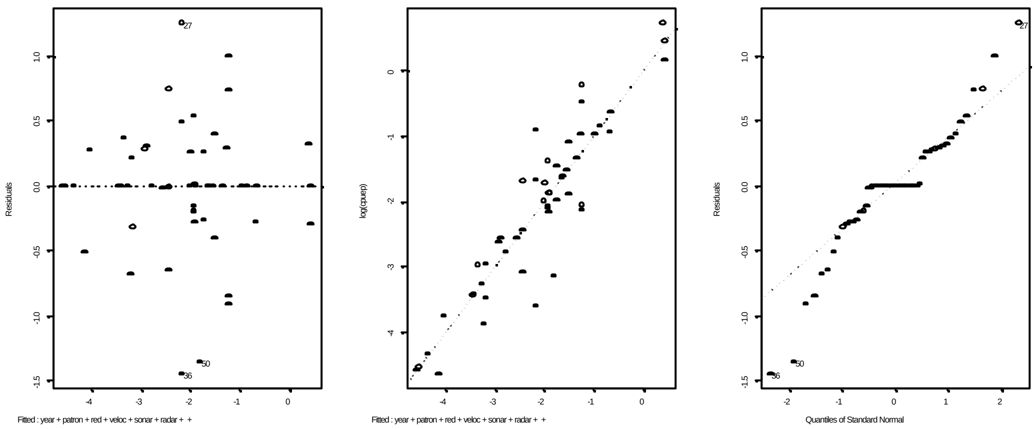

Figure 4: residual plot for the final gaussian model selected for the positive catch rates in area 3 (residual vs. predicted values, dependent variable (log(cpue) vs. predicted and qq-plot).

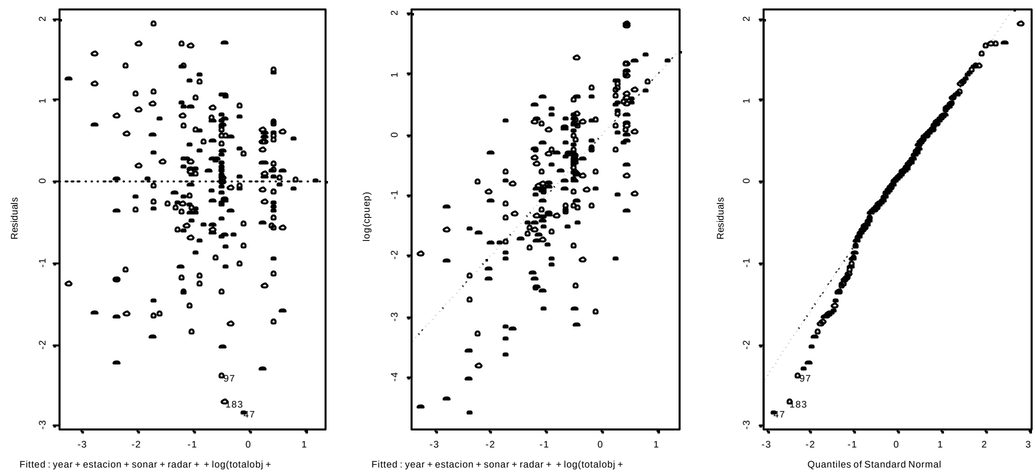

Figure 5: residual plot for the final gaussian model selected for the positive catch rates in area 4 (residual vs. predicted values, dependent variable (log(cpue) vs. predicted and qq-plot).

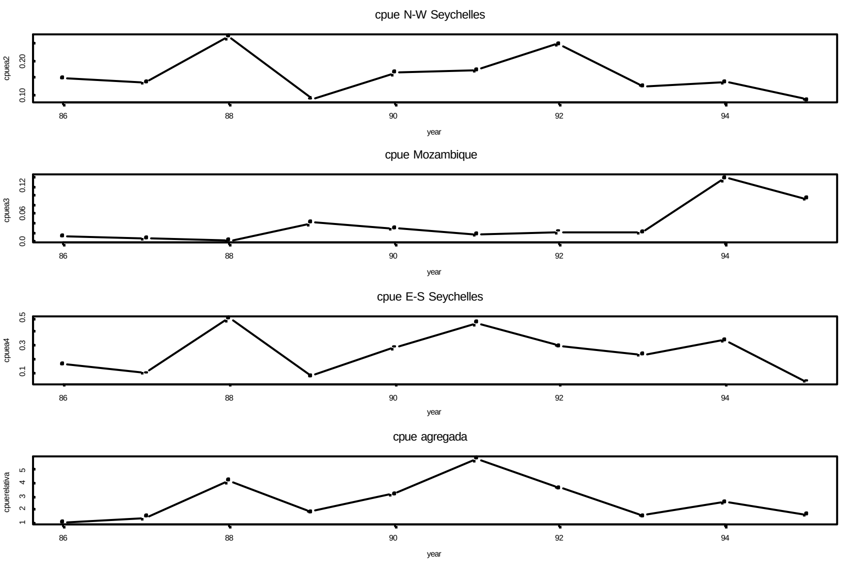

Figure 6.- Standardized yellowfin cpue index by area and overall.

Year	N-Wseychelles	N_2	Mozambique	N_3	S-E Seychelles	N_4	weighed cpue	relative cpue
86	0.15	49	0.01	16	0.15	35	12.61	1.00
87	0.13	93	0.01	32	0.09	52	17.16	1.36
88	0.27	111	0.00	19	0.50	47	52.93	4.20
89	0.09	179	0.04	28	0.06	89	22.29	1.77
90	0.16	142	0.03	31	0.28	53	39.01	3.09
91	0.17	177	0.01	42	0.46	92	73.15	5.80
92	0.25	119	0.02	44	0.29	54	45.64	3.62
93	0.12	88	0.02	16	0.22	33	18.68	1.48
94	0.14	93	0.14	42	0.33	38	31.14	2.47
95	0.09	177	0.09	34	0.03	55	19.65	1.56

Table 7: cpue by area, number of observations in each area, N_i, and whole weighed cpue.

```
log(cpue) ~ year + estacion +   patron + veloc + sonar

                     Df Sum of Sq  Mean Sq F Value      Pr(F)
             year   9   26.1555  2.90617 3.19776 0.00105392
         estacion   3    9.2561  3.08536 3.39493 0.01837287
           patron  19   30.8485  1.62360 1.78651 0.02402464
            veloc   5   10.0482  2.00964 2.21128 0.05334697
            sonar   2   13.0107  6.50533 7.15806 0.00092817
log(totalobj + 0.01)   1   35.6545 35.65452 39.23202 0.00000000
        Residuals 282  256.2849  0.90881
    Null Deviance: 493.9918 on 321 degrees of freedom
Residual Deviance: 310.121 on 282 degrees of freedom
```

Tabla 2: Final model selected and Type III tests for the gaussian glm for positive cpue in area 2.

```
propor ~ year + estacion

           Df Sum of Sq  Mean Sq  F Value   Pr(F)
     year   9   18.5118  2.05686  1.83474   0.06046001
 estacion   3   50.4732 16.82440 15.00751   0.00000000
Residuals 400  448.4262  1.12107

    Null Deviance: 606.1353 on 412 degrees of freedom
Residual Deviance: 515.1864 on 400 degrees of freedom
```

Table 3: Final model selected and Type III tests for the binomial glm for propotion of positive cpue in area 2.

```
log(cpue) ~ year + patron + red + veloc + sonar + radar +log(totalobj+0.01)

                    Df Sum of Sq  Mean Sq   F Value      Pr(F)
                year  8  14.82114  1.85264  4.50698 0.00235552
              patron 15  30.39168  2.02611  4.92898 0.00040288
                 red  2   3.23022  1.61511  3.92913 0.03474889
               veloc  3   7.80946  2.60315  6.33277 0.00292677
log(totalobj + 0.01)  1  12.76466 12.76466  31.05296 0.00001333
           Residuals 22   9.04334  0.41106

Null Deviance: 88.02356 on 51 degrees of freedom
Residual Deviance: 12.35569 on 22 degrees of freedom
```

Table 4: Final model selected and Type III tests for the gaussian glm for positive cpue in area 3.

```
propor ~ year + red

          Df Sum of Sq  Mean Sq  F Value    Pr(F)
     year  9  26.26223 2.918025 3.177186   0.0025151
      red  2   3.97148 1.985742 2.162104   0.1218451
    sonar  2   1.36613 0.683064 0.743729   0.4786362
    radar  2   1.89024 0.945118 1.029057   0.3620833
Residuals 79  72.55602 0.918431

Null Deviance: 134.814 on 94 degrees of freedom
Residual Deviance: 83.8209 on 79 degrees of freedom
```

Table 5: Final model selected and Type III tests for the binomial glm for propotion of positive cpue in area 3.

```
log(cpue) ~ year + estacion + sonar + radar + log(totalobj+0.01) +
year:estacion

                      Df  Sum of Sq   Mean Sq     F Value     Pr(F)
                year   9    67.7813  7.531253     10.16107 0.0000000
            estacion   3    28.2472  9.415750     12.70360 0.0000001
               sonar   2     0.8993  0.449661     0.60668  0.5462642
               radar   2     3.1138  1.556918     2.10057  0.1253599
log(totalobj + 0.01)   1     1.4974  1.497395     2.02027  0.1569327
       year:estacion  15    44.7875  2.985837     4.02845  0.0000027
           Residuals 181   134.1549  0.741187

Null Deviance: 370.6122 on 213 degrees of freedom
Residual Deviance: 168.2984 on 181 degrees of freedom
```

Table 6: Final model selected and Type III tests for the gaussian glm for positive cpue in area 4.

```
propor ~ year + estacion + year:estacion
```

```
               Df Sum of Sq  Mean Sq  F Value   Pr(F)
           year   9   27.0143  3.00159  3.65841     0.00026851
       estacion   3   39.4138 13.13794 16.01284     0.00000000
  year:estacion  27   36.8019  1.36303  1.66130     0.02518658
      Residuals 232  190.3474  0.82046
Null Deviance: 482.8845 on 271 degrees of freedom
Residual Deviance: 219.5806 on 232 degrees of freedom
```

Table 7: Final model selected and Type III tests for the binomial glm for propotion of positive cpue in area 4.

	Area					
year		Somalia	N-W seychelles	Mozambique	S-E Seychelles	Chagos
86	Yft	423	680	125	957	0
	Skj	305	185	996	68	0
	Bet	197	0	0	0	0
87	Yft	2134	1984	13	1275	0
	Skj	1436	478	735	1467	0
	Bet	171	150	0	77	0
88	Yft	159	6328	4	5757	0
	Skj	1260	694	365	1672	0
	Bet	48	482	71	832	0
89	Yft	862	2908	174	2373	0
	Skj	2127	7011	710	2101	0
	Bet	205	264	0	356	0
90	Yft	1942	6687	313	6768	0
	Skj	1127	458	1636	641	0
	Bet	40	362	0	81	0
91	Yft	3008	7752	55	13292	0
	Skj	3703	1322	934	519	0
	Bet	283	130	0	195	0
92	Yft	848	9063	283	3727	0
	Skj	1740	1461	3170	625	0
	Bet	182	104	0	120	0
93	Yft	1095	2789	77	2675	1398
	Skj	708	780	1265	252	0
	Bet	68	139	0	31	10
94	Yft	2769	6267	1188	4695	165
	Skj	1641	2210	4046	706	0
	Bet	170	494	15	84	5
95	Yft	1457	7194	514	515	1393
	Skj	1148	3334	1280	327	122
	Bet	297	559	0	17	10

Table 8: Catches (tons) of yft, skj y bet in the area 1 to 5 during 1986-1987.