



**SCIENTIFIC COMMITTEE
SEVENTH REGULAR SESSION**

**9-17 August 2011
Pohnpei, Federated States of Micronesia**

Developing a spatially adjusted CPUE for the albacore fishery in the South Pacific.

WCPFC-SC7-2011/EB-WP-IP-05

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Executive Summary

1. Standardised CPUE is regularly used as an index of abundance to tune the population dynamics models used to assess the status of tuna stocks in the WCPO. The primary purpose of CPUE standardizations is the removal of the variation in the data not attributable to changes in abundance. In the WCPO these indices have typically been generated to meet the model structures of MULTIFAN-CL and fine scale spatial variation is removed as part of the standardisation. As a result these indices have not been applicable for alternative population dynamics models such as SEAPODYM.
2. An adjusted CPUE index with spatial structure was developed for albacore (*Thunus alalunga*) in the south Pacific, based on operational logsheet data from distant-waters and domestic fleets.
3. To avoid bias due to targeting change, a cluster analysis was carried out for identifying fleets targeting albacore. These data were used in a GLM model to standardize CPUE using year-month, latitude, longitude, vessel, and longitude and latitude aggregated to 5 degrees resolution as factors. The predictor variable explaining most of the logged CPUE variability was the year-month factor (18.9%). The vessel factor explained 10.2% of the variation. The effort correction factor was defined as the exponential of the vessel factor. A total of 1421 vessel coefficients were extracted ($p < 0.05$ for 1142 of these) and used to generate the adjusted CPUE. This index was built using the correction factor for effort, estimated as the exponential of the estimate of the boat parameter from the GLM. This approach assures the equivalency of effort in all ships from the two fleets included in the analysis.
4. The average of the vessel correction factor was 1.39 with a standard deviation of 0.69. Extreme values of the correction factor were defined as those whose value was outside the range of the 95% confidence interval. Rather than remove these data from the analysis we assign them the corresponding values from the limits of the 95% confidence interval. The removal of the influence of these extreme values on the correction factor was required as they increased or decreased the nominal effort to levels that could be considered abnormal.
5. The majority of the effort correction factors were larger than one and their overall effect was to increase the effort and consequently reduce the adjusted CPUE. The results of the temporal annual trend of the nominal and adjusted CPUE show higher values at the beginning of the series. The nominal CPUE for years 1960 and 1961 were 214 and 204 albacore/1000 hooks respectively. The adjusted CPUE values for the same years were 64 albacore/1000 hooks. Both indices presented a decreasing CPUE trend for the period 1960 to 1975. From 1976 to 2009 the CPUE values were stable oscillating between 9 and 22 albacore/1000 hooks for the adjusted CPUE and 12 and 29 albacore for the nominal CPUE. The spatial distribution of the mean adjusted CPUE show higher values in the south of the region.
6. This new index is suitable for use in the SEAPODYM model for albacore and is expected to provide further improvement to the estimates generated by SEAPODYM. This index will, through further statistical analysis, allow the exploration of the relationship between catch rates and environmental variables, including the potential influence of ENSO events on the distribution and abundance of South Pacific albacore.

Introduction

Single-species models have played a central role in fisheries management, establishing target reference points and setting allowable harvest limits. However, fishery managers are increasingly asked to consider different types of interactions in their harvesting decisions and the potential effects on other species and the ecosystem. Unintended consequences of fishing, including habitat destruction, incidental mortality of nontarget species, evolutionary shifts in population demographics, and changes in the function and structure of ecosystems are being increasingly recognized (Pikitch *et al.*, 2004). Therefore, it has been recommended to include ecosystem considerations in fisheries management. The overall objective of the Ecosystem-base fishery management (EBFM) is to sustain healthy marine ecosystems and the fisheries they support (Pikitch *et al.*, 2004). This task requires the development of new complex management tools and the participative inclusion of all stake holders. In particular, in the South Pacific, a spatial ecosystem and population dynamics model (SEAPODYM) has been developed. It is a physical-biological-fisheries model with spatial structure at ocean basin scale with a maximum likelihood estimate approach for parameter estimation (Senina *et al.* 2008), providing a general framework for the integration of diverse areas of knowledge on tuna species. Recent work on SEAPODYM has been focused on the description of new model developments its capacity to capture important features of tuna spatial dynamics species (Lehodey *et al.*, 2008) and the validation of the model through model fitting, parameter and uncertainty estimation. As most of ecosystem and multispecies models, SEAPODYM requires constant improvement; currently SEAPODYM is fitted to spatially-distributed nominal catch-at-age data and size composition data (Senina *et al.*, 2008). Therefore, incorporating a relative index of abundance in the SEAPODYM fitting process is recommendable.

The main objectives of CPUE standardization are removing most of the annual variation in the data not attributable to changes in abundance and detecting trends over time in abundance (Maunder and Punt, 2004). Currently, the Multifan-CL albacore stock assessment uses twelve series of standardized CPUE resulting from combinations of four regions and three distant-water fleets targeting albacore (Bigelow and Hoyle, 2008; Bigelow and Hoyle, 2009). Unfortunately, this procedure eliminates the spatial variability; therefore, this information cannot be used for estimating the albacore spatial distribution and its migration patterns. In the present work, we developed a spatial-temporal structured adjusted CPUE based on fisheries data (information from Pago-Pago and Domestic fleets) targeting albacore in the south Pacific. This approach might improve the SEAPODYM fit and its estimates and therefore its use in fisheries management. In addition, it will provide valuable information to explore through further statistical analyses the relationship between catch rates and environmental variables.

Methods

A potential improvement for SEAPODYM is the inclusion of an adjusted CPUE with spatial-temporal structure to be used in the fitting process. The development of this new index included only catch and effort data from fisheries targeting albacore in the region defined by the coordinates 59.75° latitude south, 9.75° latitude north, 142.25° longitude east, and 111.75° longitude west. This information was taken from operational logsheet data of vessels from distant-water fleets (Korea, Japan and Taiwan) landing at the two major canneries (Pago

Pago, American Samoa and Levuka, Fiji) and data from domestic fleets (American Samoa, Cook Islands, Fiji, French Polynesia, New Caledonia, Tonga and Western Samoa) provided to the Secretariat of the Pacific Community. The first data base included information of 532,262 sets corresponding to 9588 trips and 1398 vessels from 1960 to 2007 (Bigelow and Hoyle, 2009). The domestic fleet data series included information of 408,637 fishing sets; thus the complete initial information included 940,899 sets from 1960 to 2010 containing information such as the flag identification, trip identification, set identification, date, geographical coordinates, number of organisms caught of each tuna species, number of hooks (effort), captain, crew, etc. A total of 2581 fishing boats operated targeting albacore from 1960 to 2007, being the Taiwanese the biggest fleet (Table 1). The information about the number of trips and sets for the domestic fleets is shown in Table 2. The spatial distribution of catch for the domestic, the Japanese, the Korean and the Taiwanese fleets is shown in Figure 1.

Previous studies (Bigelow and Hoyle, 2008, 2009) suggested the possibility that the catchability for albacore could have changed when the Taiwanese fleet switched targeting to bigeye tuna. Also spatial changes in the fishery, the use of deeper longline gear and higher catch rates of bigeye tuna are also believed to have contributed to a change in catchability. Cluster analysis has been used to remove this bias through separating the catch and effort data according to target species (Bigelow and Hoyle, 2009). We applied the same approach in this study. The first step for building the new adjusted CPUE with special-temporal structure was the identification of the South Pacific fleets (distant-waters and domestic) targeting albacore with cluster analysis on species composition for albacore, bigeye and yellowfin tuna. Cluster analysis was implemented in the statistical package R (version 2.10.0 for Linux 64). Longline sets with zero tuna catch were removed because they are uninformative in the cluster analysis (Bigelow and Hoyle, 2009). We assumed that within a trip, targeting did not change; therefore, the cluster analysis was made by trip instead of by set (Appendix A).

In particular, two clustering routines (*hcluster* from the package *amap* and *clara* from the package *cluster*) were used in the analysis. It is important to point out that the *hcluster* routine is a mixture of routines *dist* and *clust* from the package *cluster*. The *hcluster* routine produced dendrograms for determining the appropriate number of clusters (species targeting) represented in the data. For the Pago-Pago data we took advantage of the experience of previous analysis (Bigelow and Hoyle, 2008), where they took in account the change of targeting in the Taiwanese fleet, we also defined two periods of time (1990 – 1998 and 1999-2007) to describe the number of clusters (Bigelow and Hoyle, 2009). For the domestic fleet information, we were more cautious and we decided to carry out the analysis in periods of time of three and four years, depending on the amount of information.

The second clustering routine (*clara*) was used to partition the data sets into appropriate number of clusters as determined by the dendrograms. The long line gear set up for targeting albacore also catches yellowfin tuna because these two species are found at the same deep and are attracted by the same bait. Therefore, depending on the season, sometimes boats targeting albacore catch mostly yellowfin tuna (Ashley Williams, personal communication, Secretariat of the Pacific Community). Therefore the criterion used for defining a fishery targeting albacore was the sum of the proportion of these two species, if the sum was less than 80% we defined that fishery as not targeting albacore.

Once we had identified the fisheries targeting albacore. We built a file with the information from the Pago-Pago and the domestic fleets data base, including the entire Japan

and Korean time series and the albacore clusters for Taiwanese fisheries targeting this species (Table 3). The fisheries from domestic fleets excluded from this file are shown below (Table 4). The data included in the file was: flag identification, trip identification, number of albacore caught, number of tuna caught, year and quarter of the set, effort (number of hooks), month of the set, boat identification, latitude registered, longitude registered, superficial temperature, latitude aggregated by five degrees, longitude aggregated by five degrees, weight associated to each fishing trip, and cluster information. To avoid bias, we eliminated from the information those boats operating four or less quarters (Bigelow and Hoyle, 2008, 2009). Therefore the information was reduced to a total of 788,982 records of fishing sets. Contrary to the CPUE standardization for albacore in MFCL, we did not allocate the data into four regions. We used the whole region to take advantage of the SEAPODYM spatial structure that allows predicting the albacore migration patterns and zooming at the exclusive economical zone (EEZ).

Previous work (Bigelow and Hoyle, 2008; Bigelow and Hoyle, 2009) tested several generalized linear models containing different types of predictor variables and selected the following model also used in the present analysis:

$$\ln(C/E) = \text{year_quarter} + \text{month} * \text{lat}^3 + \text{lat5} * \text{long5} + \text{vessel_id} + \varepsilon$$

Where the response variable is the natural logarithm of CPUE, C is the catch, E the effort. The predictor variables were all considered as factors and lat represented the local latitude and $lat5$ and $long5$ represented the latitude and longitude aggregated at 5 degrees resolution. Because the individual sets within a trip are often highly correlated, each set was weighted by the factor $(1/\sqrt{\text{number of sets by trip}})$.

It is important to point out that a standardized CPUE is comprised of the exponentiated year_quarter coefficients. In our case, we did not use this approach, instead, we extracted the exponentiated parameter estimate of the vessel factor and used it as a correction factor for the fishing effort. The correction factors have a great variation with some extreme values; therefore, we decided to use only those values that were in the 95% confidence interval of the correction factor ($\mu \pm 1.96\sigma$). Instead of erasing the information outside this interval, we decided to replace those values with the corresponding upper and lower limits of the 95% confidence interval. The corrected effort was estimated multiplying the registered effort by the correction factor. The adjusted CPUE (number of albacore per 1000 hooks) with spatial structure was calculated aggregating the corrected effort and the albacore catch by flag id, year, month and geographical coordinates (one degree resolution) in a pivot table in Excel 2007. The aggregation of this information reduced the file size to 183,954 records.

For comparison purposes, a nominal and an adjusted CPUE with temporal structure were built aggregating catch and effort by year. The temporal trend of the albacore nominal CPUE was estimated dividing the total catch (number) divided by the total number of hooks aggregated by year using all information from Pago Pago and the domestic fleets. For building the adjusted CPUE with temporal trend, the catch and the corrected effort from the total information file were aggregated by year using a pivot table in Excel 2007.

Results

In the area defined for this analysis, the total annual albacore catch from distant-waters and domestic fleets presented a first period increase from 1960-1967. From 1968 to

1974, catches were stable around 1.0×10^6 albacore. From 1974 to 2000 most of the annual catches were smaller than one million tuna. In the last period (2001-2008) we observed a period of increased catch with an important decrease in the last two years (Figure 2). Concerning the effort, after an initial period of increase (1960-1967) the effort varied between 18.7 and 55.6 millions of hook from 1968 to 2001. In the last period of time an important increase in effort was observed between 100 and 150 millions of hooks (Figure 2).

Regarding the results from the cluster analysis for identifying targeting, as mentioned, the entire Korean and Japanese fleets were assumed targeting albacore during the whole period of time. In agreement with Bigelow and Hoyle (2009), we defined two periods of time for the Taiwanese data defining: 1989-1998 and 1999-2010. For the first period of time, we assumed that the fishery targeted albacore; in the second period, results suggested the existence of two clusters targeting albacore and one targeting big eye tuna (Table 3).

The cluster analysis for the domestic fleet information was more complicated. During different periods of time, for the majority of the national fleets (American Samoa, French Polynesia, New Caledonia, Tonga and Western Samoa), two clusters targeting albacore were found as shown below (Figure 3). In the case of Cook Islands, in some periods of time, clusters targeting albacore were found; however, three clusters did not target albacore. Similarly, for Fiji two clusters were found targeting big eye (Table 4). The information targeting big eye was excluded in the final file used in the generalized linear model used to standardize the CPUE.

GLM results suggested the model explained 50.6% of the variability observed in the logged CPUE. The predictor variable explaining most of the variability was the factor year-month associated to the fishing set (18.9%). The vessel factor also explained an important amount of variation (10.2%) and the cubic latitude explained 8.8% of the observed variability. The remaining predictor variables explained less than 5% of the variability observed (Table 5).

A total of 1866 parameters (coefficients) were estimated; in particular, for the vessel factor, out of 1421 parameter estimates, 1142 estimates were significant (p -value < 0.05). As mentioned, the effort correction factor was defined as the exponential of the vessel factor estimate and their average was 1.39 with a standard deviation of 0.69; therefore, the lower limit of the 95% confidence interval was 0.02807 and the upper limit was 2.743597. It is important to point out that extreme values of the correction factor would increase or decrease the nominal effort to levels that could be considered abnormal. Therefore, we considered that a minimum of 0.25 was reasonable because it would increase the effort by a factor of four. Out of 788574 correction factors, only 2757 were smaller than 0.25 and 18826 were larger than the upper limit; thus, we decided that instead of erasing those values, we would assign them the corresponding values from the limits of the 95% confidence interval. The original correction factor distribution is shown below (Figure 4). As seen, the majority of the correction factors are larger than one. Therefore, the overall effect of the effort correction factor was to increase the effort (Figure 5a) and consequently the adjusted CPUE was reduced (Figure 5b).

These results were confirmed when the temporal annual trend of nominal and adjusted CPUE were compared. Both indices had their higher values at the beginning of the series; the nominal CPUE for years 1960 and 1961 were 214 and 204 albacore/1000 hooks respectively. The adjusted CPUE values for the same years were 64 albacore/1000 hooks. Both indices presented a decreasing CPUE trend for the period 1960 to 1975. From 1976 to

2009 the CPUE values were stable oscillating between 9 and 22 albacore/1000 hooks for the adjusted CPUE and 12 and 29 albacore for the nominal CPUE. In general, the nominal CPUE was larger than the adjusted CPUE, suggesting that the effect of correcting effort by vessel probably reduces the overall catch rate estimate (Figure 6). Finally the spatial distribution of the mean adjusted CPUE is shown below (Figure 7). As shown higher values are found in the south of the region defined.

Discussion

Indices of abundance have played an important role in fisheries management and are commonly used to tune stock assessment models. Fishery independent indices are costly or difficult to collect and in most situations stock assessment fitting is carried out with fishery-dependent data (Maunder and Punt, 2004). In tuna fisheries, an index of relative abundance (catch per unit effort, CPUE) has been used for management or for fitting single-species stock assessment models. This approach is based on different statistical techniques to standardize the index and remove the effects of several factors and possible change of targeting with the aim of detecting trends over time in abundance. Therefore, most of standardized CPUE for tuna species include only temporal trend of abundance (Chang *et al.*, 2011; Hsieh *et al.*, 2008; Hazing *et al.* 2008). To our knowledge, a relative index of abundance with temporal-spatially structure has not been built for any tuna species using standardization methods. Consequently, existing indices are not particularly useful for population models with high resolution spatial structure such as SEAPODYM. In this work we built an index with this characteristic that will help to improve SEAPODYM data fitting and the overall model performance.

Using CPUE as an index of abundance depends on being able to adjust (i.e. remove) the impact on catch rates of changes over time of factors other than abundance. This objective is generally achieved through regression methods (Maunder and Punt, 2004; Ortiz and Arocha, 2004). In addition, given the requirement to standardize the catch and effort data of a species caught in a multi-species fishery, it seems desirable to use only the effort that was directed at that species (Maunder and Punt, 2004). In our case we have been able to include only catch and effort data of fisheries targeting albacore in the south Pacific through cluster analysis. It is important to point out that due to the amount of data we had to include in the analysis, instead of the typical *clust* subroutine, we used the *hcluster* routine that is a mixture of routines *dist* and *clust* from the package *cluster* with the advantage of not storing the distant matrix; therefore, it uses less memory and carried out the calculations faster (Lucas and Jasson, 2006). This approach reduced significantly the amount of time used in the cluster analysis.

We were able to remove the impact of factors other than abundance through the generalized linear model. Regression diagnostic statistic suggested an acceptable performance of the GLM model and an agreement with the error structure assumed. In contrast to previous approaches where the exponentiated year-month coefficients were used as the relative index of abundance, in our case we used the exponentiated vessel coefficient. This allowed us to be able to adjust the effort data in such a way that 100 hooks of a particular vessel are equivalent to 100 hooks of any vessel from the distant-waters and domestic fleets. The overall effect of the effort correction factor was to increase the effort and reduce the adjusted CPUE. This was also confirmed in the comparison of the temporal annual trend of nominal and adjusted CPUE. A similar tendency was found also for yellowfin tuna in Taiwanese purse seine fishery in the western Pacific from 1988 to 1997 and in yellowfin tuna for the Taiwanese offshore longline fishery in the western Pacific from 1988 to 1997 where

the standardized CPUE was smaller than the nominal CPUE (Sun and Yeh, 1998). The general tendencies found for the mean CPUE agreed with those reported previously. Murray (1993) commented that the Taiwanese longline CPUE is highest and most variable south of 20 °S. Similar results were also found by Hsueh-Jung *et al.* (1998) when they explored the relationship between El Niño/Southern oscillation and the south Pacific albacore.

Even if CPUE is standardized appropriately, the resulting index of relative abundance, in isolation, provides limited information for management advice or about the effect of fishing (Maunder *et al.*, 2006). In general, integrated stock assessment model shows that raw CPUE data from longline vessels for tuna can be misleading if not interpreted in the context of other data, biological information, and population dynamics theory (Hampton *et al.*, 2005). Therefore it is recommendable to use the index in a broader framework. In particular, SEAPODYM offers the opportunity of including this adjusted CPUE data in a framework used to integrate biological and ecological knowledge of tuna species and their responses to fishing pressure. This model is characterized by its spatial structure that allows providing additional information, not available from the current single-species stock assessment used in the south Pacific. Examples of this information include the tuna migration patterns, spatially-distributed biomass estimates at ocean and EEZ level, spawning habitat index and larvae distribution maps etc. Therefore, it is ideal the inclusion of an adjusted CPUE in the model that could potentially improve the overall SEAPODYM performance. It is important to mention that our access to operational level data allowed us building for the first time a relative index of abundance with spatial distribution for albacore in the south Pacific at one degree of resolution. Finally, this index has potential for providing valuable information to explore, through further statistical analyses, the relationship between catch rates and environmental variables, including the potential influence of ENSO events in the spatial distribution of catch, effort, abundance and recruitment.

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Table 1. Fishing vessels by flag operating in the South Pacific from 1960 to 2010.

| Fleet | Number of boats |
|------------------|------------------------|
| Japan | 182 |
| Korea | 503 |
| Taiwan | 713 |
| American Samoa | 111 |
| Cook Islands | 88 |
| Fiji | 228 |
| New Caledonia | 44 |
| French Polynesia | 144 |
| Tonga | 60 |
| Vanuatu | 84 |
| Western Samoa | 424 |
| Total | 2581 |

Table 2. Number of fishing trips and sets from domestic fleets operating in the South Pacific (1979 - 2010).

| Year | A. Sam. | Cook I. | Fiji | FP | Tonga | Vanuatu | W. Samoa |
|-------|----------|----------|------------|----------|----------|----------|-----------|
| 1979 | 0 | 0 | 0 | 0 | 1/96 | 0 | |
| 1980 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 1981 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 1982 | 0 | 0 | 0 | 0 | 5/155 | 0 | |
| 1983 | 0 | 0 | 0 | 0 | 6/147 | 0 | |
| 1984 | 0 | 0 | 0 | 0 | 3/105 | 0 | |
| 1985 | 0 | 0 | 0 | 0 | 3/70 | 0 | |
| 1986 | 0 | 0 | 0 | 0 | 3/122 | 1/51 | |
| 1987 | 0 | 0 | 0 | 0 | 5/196 | 1/52 | |
| 1988 | 0 | 0 | 0 | 0 | 10/173 | 0 | |
| 1989 | 0 | 0 | 9/153 | 0 | 9/198 | 0 | |
| 1990 | 0 | 0 | 14/429 | 0 | 11/164 | 0 | |
| 1991 | 0 | 0 | 29/616 | 0 | 9/153 | 0 | |
| 1992 | 0 | 0 | 213/1453 | 45/569 | 6/195 | 0 | |
| 1993 | 0 | 0 | 111/1263 | 23/157 | 1/57 | 0 | 29/81 |
| 1994 | 0 | 28/144 | 393/2472 | 327/1480 | 21/415 | 0 | 11/29 |
| 1995 | 0 | 72/368 | 389/2528 | 575/2714 | 0 | 8/125 | 0 |
| 1996 | 40/526 | 31/130 | 181/1365 | 624/2675 | 17/70 | 28/420 | 0 |
| 1997 | 119/1534 | 1/2 | 469/3529 | 703/3521 | 60/318 | 8/234 | 0 |
| 1998 | 156/1754 | 0 | 570/4710 | 790/4051 | 41/331 | 2/93 | 4310/4476 |
| 1999 | 155/2105 | 0 | 508/4357 | 738/4784 | 92/508 | 1/41 | 4095/5820 |
| 2000 | 245/2810 | 0 | 774/6836 | 734/5053 | 202/1242 | 13/351 | 656/1107 |
| 2001 | 430/4799 | 6/18 | 1123/9960 | 738/4734 | 290/1844 | 25/781 | 774/1075 |
| 2002 | 514/6901 | 132/865 | 1556/14359 | 659/4799 | 257/2517 | 101/3065 | 855/1756 |
| 2003 | 424/6220 | 450/3114 | 1543/16617 | 889/6847 | 239/2561 | 143/3149 | 498/2179 |
| 2004 | 321/4824 | 453/3834 | 1282/17438 | 886/7705 | 148/1341 | 211/8945 | 466/2003 |
| 2005 | 43/488 | 295/3708 | 1582/21143 | 673/6642 | 169/1428 | 218/8950 | 247/1163 |
| 2006 | 0 | 275/3508 | 1016/14325 | 694/6431 | 201/1590 | 163/9634 | 480/1406 |
| 2007 | 0 | 219/2767 | 630/10296 | 652/5638 | 210/1555 | 157/7928 | 526/1619 |
| 2008 | 5/165 | 166/2406 | 142/2094 | 611/5499 | 172/1164 | 146/7226 | 181/970 |
| 2009 | 7/251 | 141/2087 | 3/87 | 601/5128 | 102/593 | 199/8597 | 414/1768 |
| 2010 | 4/90 | 23/240 | 0 | 0 | 24/118 | 23/458 | 248/1121 |
| Trips | 2463 | 2292 | 12537 | 10962 | 2317 | 1448 | 13790 |
| Sets | 32467 | 23191 | 136030 | 78427 | 19426 | 60100 | 26573 |

Table 3. Taiwanese Fisheries targeting albacore in the South Pacific during the period 1999-2007; bet_perc – average percentage of big eye found in tuna catch, yft_perc - – average percentage of yellowfin tuna, alb_perc - average percentage of albacore found.

| Cluster | bet_perc | yft_perc | alb_perc |
|---------|-------------|-------------|-----------|
| 1 | 0.007355507 | 0.008378652 | 0.9842658 |
| 2 | 0.058588762 | 0.175125337 | 0.7662859 |
| 3 | 0.464638051 | 0.355813285 | 0.1795487 |

Table 4. Cook Island and Fiji Fisheries not targeting albacore (based on cluster analysis results) in the South Pacific; bet_perc – average percentage of big eye found in tuna catch, yft_perc - – average percentage of yellowfin tuna found in tuna catch, alb_perc - average percentage of albacore found in tuna catch.

| Country | Period | Cluster | bet_perc | yft_perc | alb_perc |
|--------------|-----------|---------|----------|----------|----------|
| Cook Islands | 1994-1998 | 1 | 0.219 | 0.352 | 0.429 |
| “ | 2003-2006 | 3 | 0.350 | 0.392 | 0.258 |
| “ | 2007-2010 | 3 | 0.246 | 0.426 | 0.328 |
| Fiji | 1989-1991 | 1 | 0.236 | 0.395 | 0.369 |
| “ | 1992-1994 | 2 | 0.220 | 0.400 | 0.382 |

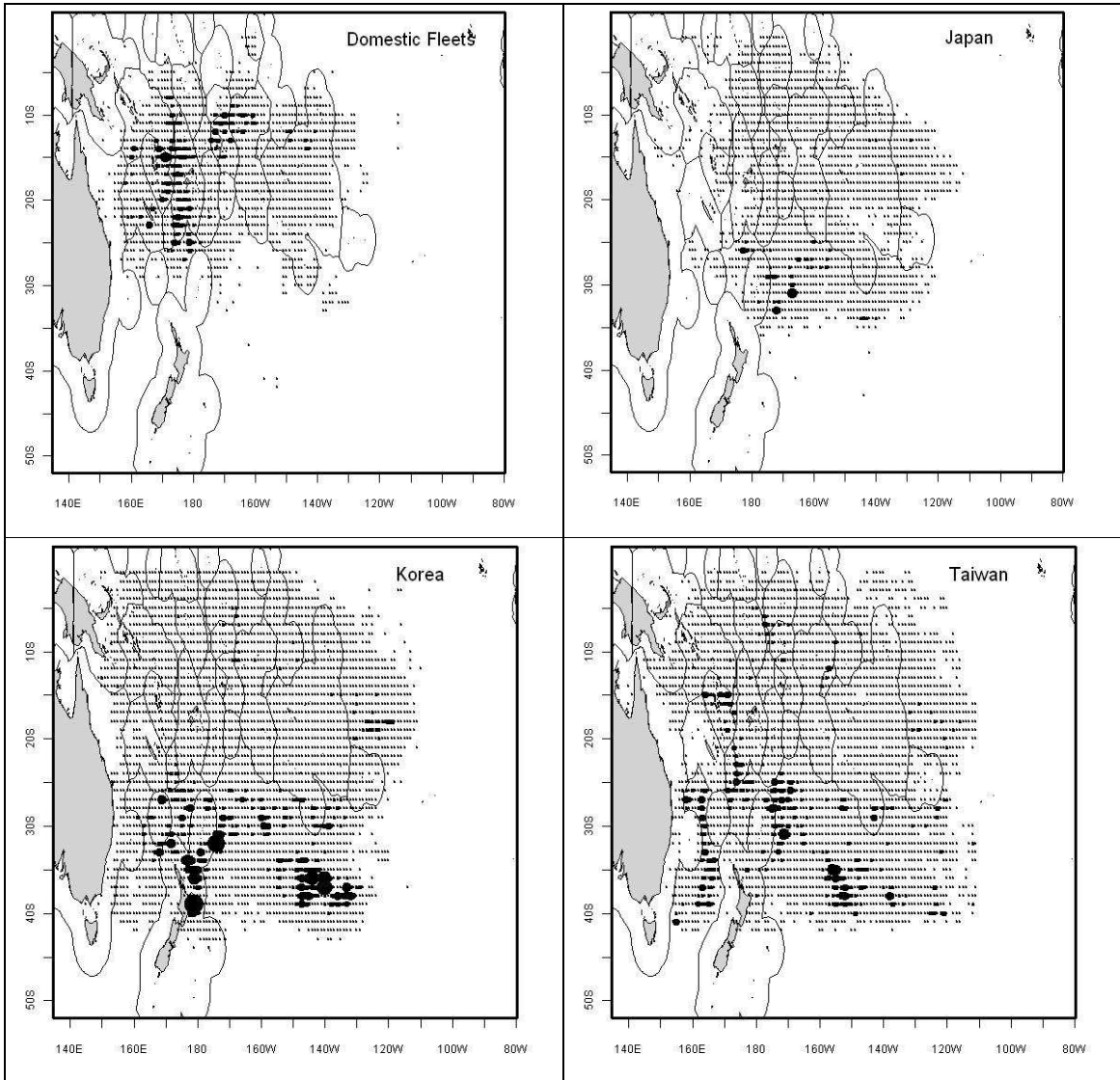


Figure 1. Spatial distribution of albacore catch in the south Pacific, domestic fleets – American Samoa, Cook Islands, Fiji, French Polynesia, New Caledonia, Tonga and Western Samoa.

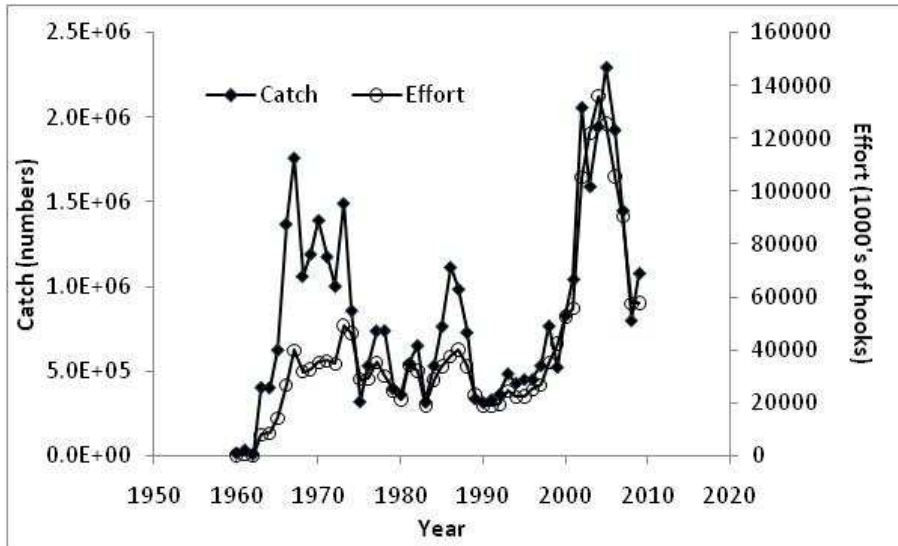


Figure 2. Annual albacore catch and effort in the south Pacific.

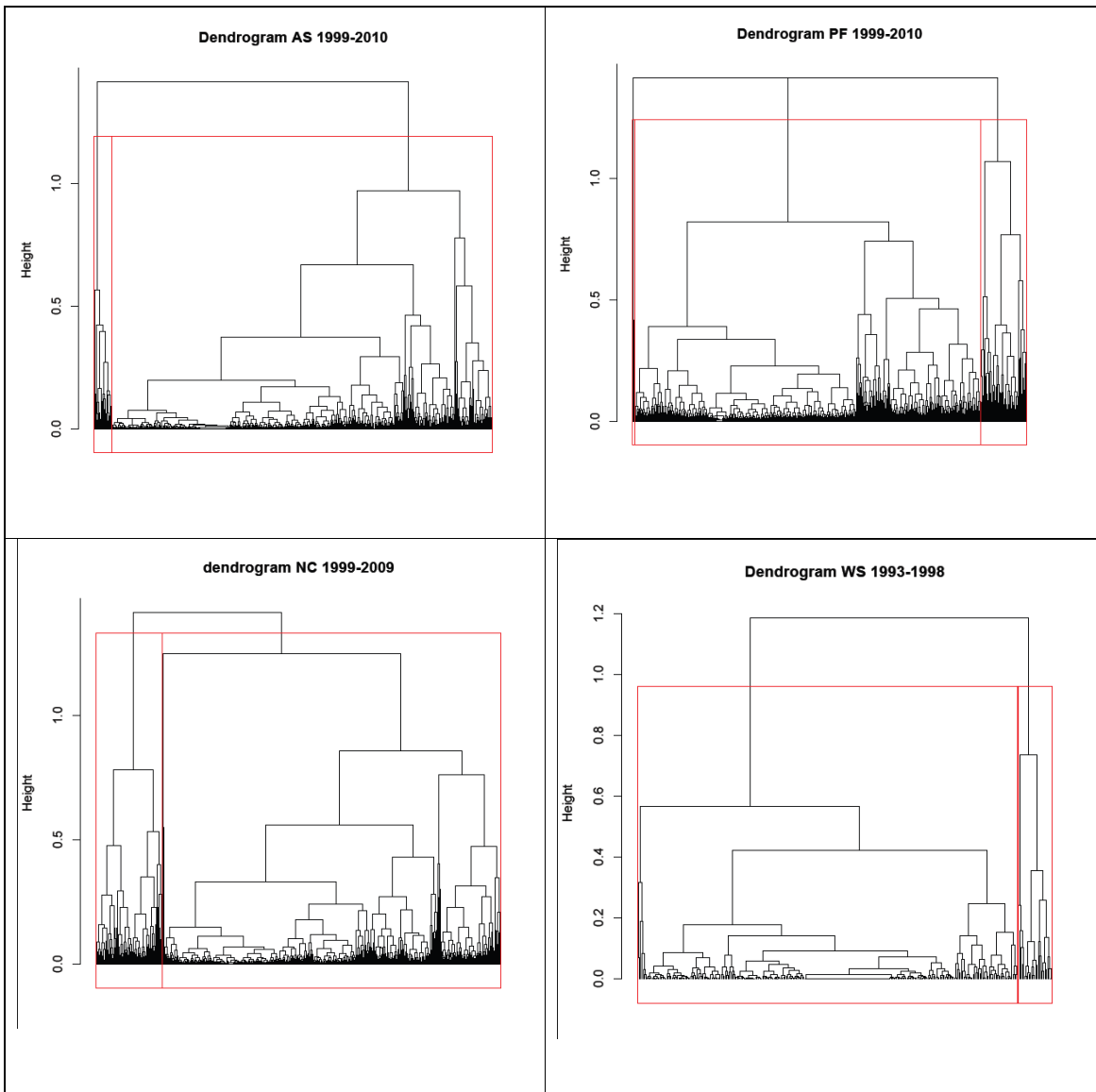


Figure 3. Number of clusters found for: a) American Samoa (199-2010), b) French Polynesia (1999-2010), c) New Caledonia (1999-2010) and d) Western Samoa (1993-1998).

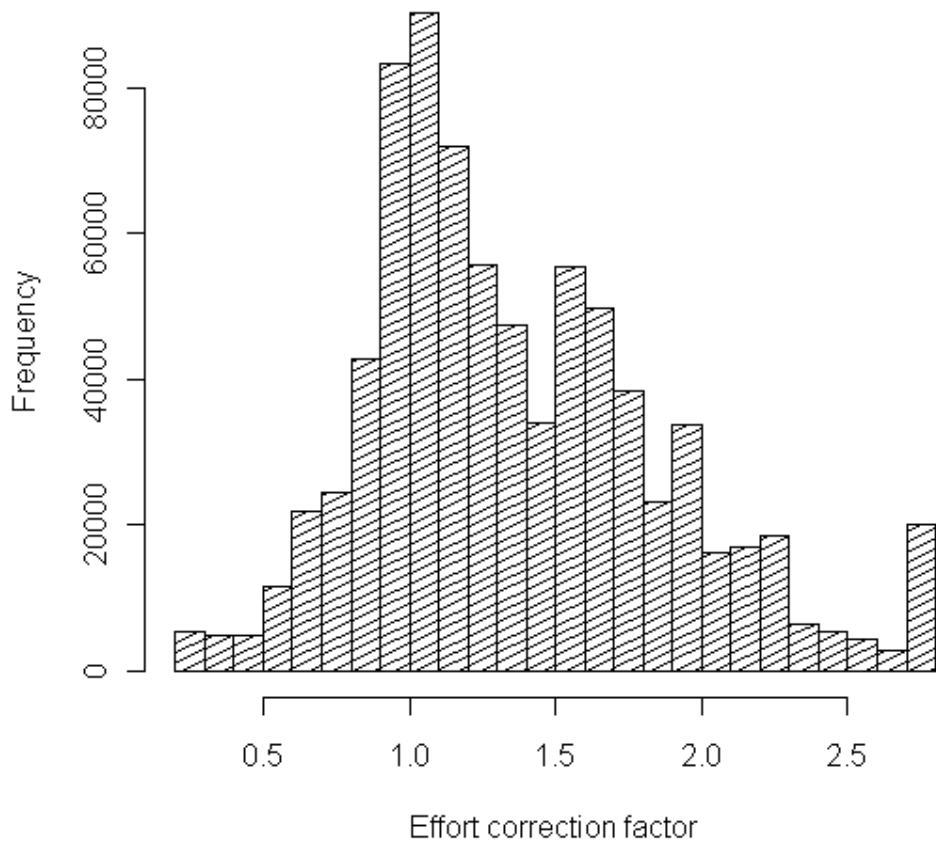


Figure 4. Frequency distribution for the effort correction factors used to estimate the adjusted CPUE with spatial structure in the South Pacific Ocean.

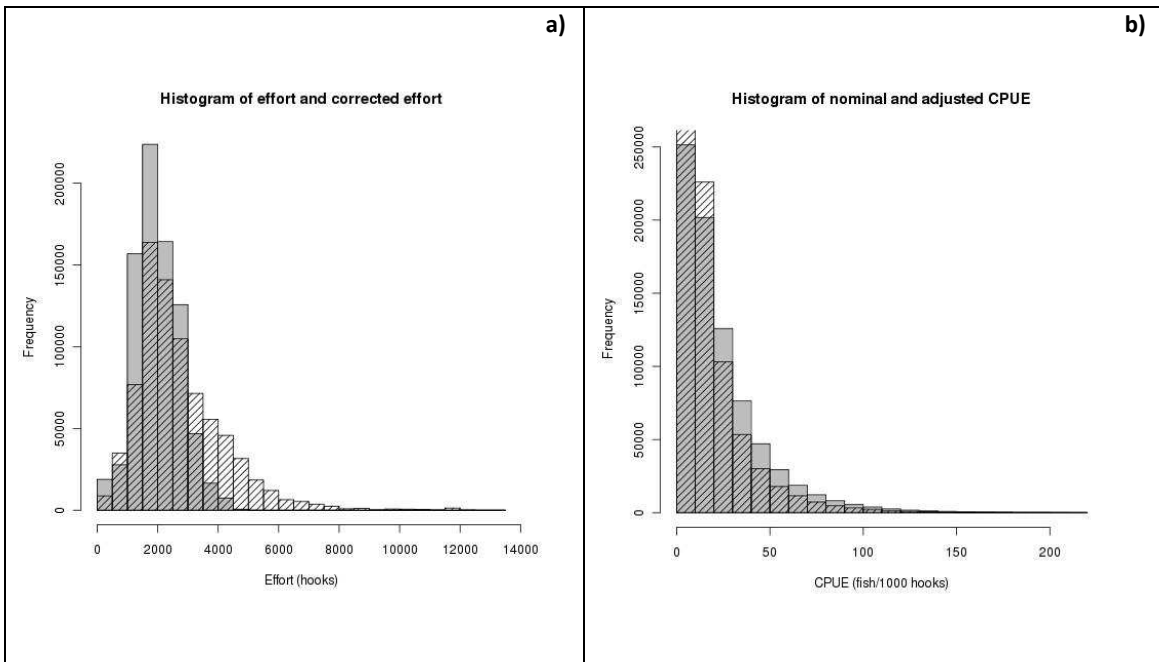


Figure 5. Histograms: a) effort (gray bars) and corrected effort (diagonal stripes), b) nominal CPUE (gray bars), adjusted CPUE (diagonal stripes).

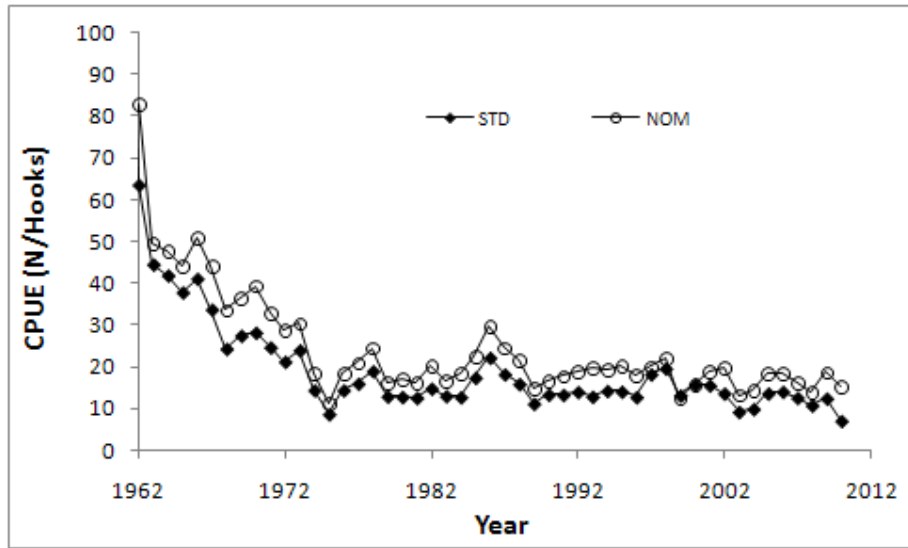


Figure 6. Comparison of the temporal trend of the nominal and the standardized CPUE for the albacore fishery in the South Pacific.

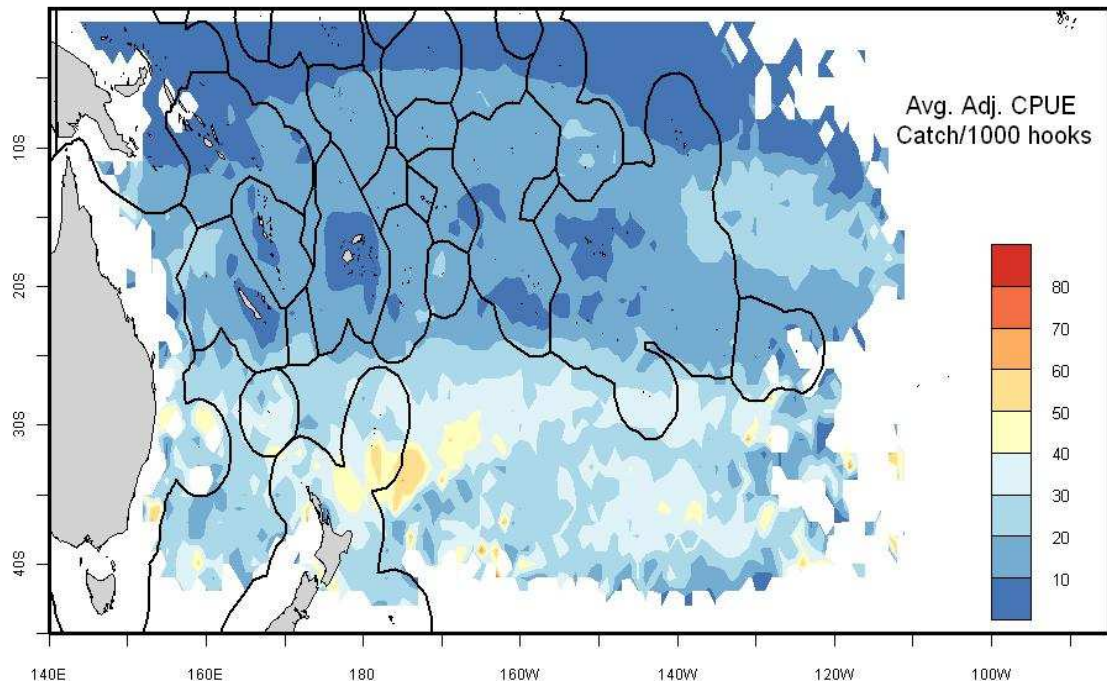


Figure 7. Spatial distribution of the albacore mean adjusted CPUE in the South Pacific.

Appendix A

This appendix shows the code used to build an object that is easier to manage for the cluster analysis by trip. The file `df.RData` contains the information from the domestic fleets

```
load("df.RData")
```

In particular applying the function *tapply* helps to calculate the total number of individuals of each species (albacore, bigeye and yellowfin) and the total number of tuna by trip

```
test4<-  
cbind(tapply(df$bet_n,df$trip_id,sum),tapply(df$yft_n,df$trip_id,sum),tapply(df$alb_n,df$trip_id,sum),tapply(  
df$tuna_n,df$trip_id,sum))
```

The following line helps avoiding the "atomic vector error" when calculating the species composition:

```
test4=as.data.frame(test4)
```

Adding the column names:

```
colnames(test4)<-c("bet_n","yft_n","alb_n","tuna_n")
```

Calculating the species composition

```
test4$bet_perc<-test4$bet_n/test4$tuna_n  
test4$yft_perc<-test4$yft_n/test4$tuna_n  
test4$alb_perc<-test4$alb_n/test4$tuna_n
```

Checking....

```
names(test4)  
test4[1:5,]
```

building an equivalent `trip_id` with the same length as size composition:

```
trip_id<-tapply(df$trip_id,df$trip_id,mean)
```

The following line is magic...it adds the `trip_id` information to the data set `test4`:

```
test4<-cbind(test4,trip_id)
```

Checking:

```
names(test4)  
test4[1:5,]
```

The following lines add the `flag_id` and the `ret_year` information to the data set `test4`. Column 8 in `test4` is `trip_id`, column 1 in `fd` is `trip_id` and column 4 in `df` is `flag_id`

```
test4$flag_id<-df[match(test4[,8],df[,1]),4]  
test4$ret_year<-df[match(test4[,8],df[,1]),107] # check the agreement for columns 107 could be 106 or 108  
test4_backup<-test4
```

Erasing extra info not needed in cluster calculations

```
test4$alb_n<-NULL
test4$bet_n<-NULL
test4$yft_n<-NULL
test4$tuna_n<-NULL
```

Placing the tuna_n in the last column

```
test4$tuna_n<-test4_backup$tuna_n
```

Checking

```
test4[1,]
summary(test4$flag_id)
```

First step for the cluster analysis:

```
install.packages("amap")
library(amap)
df_clust<-test4
```

Methodology applied to New Caledonia. This methodology can be applied to different periods of time depending on the characteristics of the IPCT information.

In this line we select the information from New Caledonia and we only include the data different from zero

```
newjunk3NC<-df_clust[df_clust$flag_id=="NC" & df_clust$tuna_n!=0,]
summary(newjunk3NC$ret_year)
dim(newjunk3NC$ret_year)
#[1] 4375 10
```

Here we select for the first period of time:

```
newjunk5NCprev<-newjunk3NC[newjunk3NC$ret_year>=1990 & newjunk3NC$ret_year<1999,]
dim(newjunk5NCprev)
#[1] 428 10
```

This line carries out the cluster analysis using a subroutine from the amap package:

```
fitNCprev<-hcluster(newjunk5NCprev[4:6],method="euclidean")
```

This line provides the plot of the clusters so we can appreciate the number of different targeting:

```
plot(fitNCprev,labels=FALSE,hang=-1,main="dendrogram NC 1990-1998")
groups<-cutree(fitNCprev,k=2)
rect.hclust(fitNCprev,k=2,border="red")
dev.off()
```

The last code could be adapted for each IPTC taking in account the number of periods of time according to suspected change of targeting. The second step in building the cluster analysis is the use of the *clara* subroutine for partitioning the data sets into the appropriate number of clusters as determined by dendrograms.

```
load("df.RData")
library(cluster)
DF<-test4
```

```
dim(DF)
#[1] 49581 7
junk3FP<-DF[DF$flag_id=="PF" & DF$tuna_n!=0,]
dim(junk3FP)
```

Applying the methodology for French Polynesia:

Includes only data from the first period of time 1990-1999

```
junk5FPprev<-junk3FP[junk3FP$ret_year>=1990 & junk3FP$ret_year<1999,]
dim(junk5FPprev)
```

includes only the data necessary to make the clara analysis avoiding memory waste

```
junk4FPprev <- junk5FPprev[,c("bet_perc", "yft_perc", "alb_perc", "ret_year", "trip_id")]
dim(junk4FPprev)
#[1] 3068 5
```

It uses *clara* with two groups, result from the dendrograms

```
claraFPprev<-clara(junk4FPprev[1:3],2)
junkFPprev<-aggregate(claraFPprev$data, by=list(claraFPprev$clustering),FUN=mean)
junkFPprev
# Group.1 bet_perc yft_perc alb_perc
#1 1 0.07912053 0.0855782 0.8353013
#2 2 0.10105452 0.5295291 0.3694164
junk2FPprev <- table(claraFPprev$clustering)
junk2FPprev
# 1 2
#2473 595
```

Pasting the cluster information

```
junk5FPprev <- cbind(junk4FPprev, claraFPprev$clustering)
dim(junk5FPprev)
names(junk5FPprev)
#[1] "bet_perc" "yft_perc" "alb_perc"
#[4] "ret_year" "trip_id" "claraFPprev$clustering"
```

Changing the name for clustering

```
names(junk5FPprev)[6] <- "clustering"
names(junk5FPprev)
#[1] "bet_perc" "yft_perc" "alb_perc" "ret_year" "trip_id"
#[6] "clustering"
```

This procedure is repeated for all IPTC. More information can be found in penguin:

Z/R/R_script_for_clara_run.txt

After all countries have been done, we need to use the equivalent to the following code

```
junk<-
rbind(junk5FPprev,junk5FPpost,junk5NCprev,junk5NCpost,junk5ASprev,junk5ASpost,junk5WSprev,junk5WS
post,junk5FJprev,junk5FJpost,junk5TOprev,junk5TOpost,junk5CKprev,junk5CKpost)
```

However we will do the instructions step by step to exclude those clusters not targeting albacore:

```
junk<-
rbind(junk5FPprev,junk5FPpost,junk5NCprev,junk5NCpost,junk5ASprev,junk5ASpost,junk5WSprev,junk5WSpost)
dim(junk$flag_id)
#[1] 31312 6
junk<-rbind(junk,junk5TOprev,junk5TOprev2,junk5TOprev3)
dim(junk)
#[1] 33746 6
```

For Cook Islands the cluster 1 for the period 1994-1998 will not be included in future analysis; therefore that information has to be excluded:

```
dim(junk5CKprev)
#[1] 129 6
junk5CK<-junk5CKprev[junk5CKprev$clustering=="2",]
dim(junk5CK)
#[1] 60 6
#Same thing for the cluster 3 of the period 2003 - 2006
dim(junk5CKprev3)
#[1] 1399 6
junk5CKb<-junk5CKprev3[junk5CKprev3$clustering!="3",]
dim(junk5CKb)
#[1] 962 6
```

Same thing for the cluster 3 for Cook Island from 2007 – 2010:

```
dim(junk5CKprev4)
#[1] 528 6
junk5CKc<-junk5CKprev4[junk5CKprev4$clustering!="3",]
dim(junk5CKc)
#[1] 423 6
```

We have to add to junk junk5CK, junk5CKb and junk5CKc and junk5CKprev2

```
junk<-rbind(junk,junk5CK, junk5CKprev2, junk5CKb, junk5CKc)
dim(junk)
#[1] 35323 6
```

For Fiji, clusters 1 from the period 1989-1991 and cluster 2 from 1992-1994 will be excluded:

```
dim(junk5FJprev)
#[1] 45 6
junk5FJa<-junk5FJprev[junk5FJprev$clustering=="2",]
dim(junk5FJa)
#[1] 26 6
dim(junk5FJprev2)
#[1] 714 6
junk5FJb<-junk5FJprev2[junk5FJprev2$clustering=="1",]
dim(junk5FJb)
#[1] 371 6
```


Now paste junk5FJa and junk5FJb to junk together with the rest of the FJ cluster results

```
dim(junk)
#[1] 35323 6
junk<-rbind(junk,junk5FJa,junk5FJb,junk5FJprev3,junk5FJprev4,junk5FJprev5,junk5FJprev6,junk5FJprev7)
dim(junk)
#[1] 47126 6
```

The next step is pasting the cluster information to the original file df, matching the trip_id information:

```
names(junk)
#[1] "bet_perc" "yft_perc" "alb_perc" "ret_year" "trip_id"
#[6] "clustering"
```

For back up a csv file a RData were created:

```
write.csv(junk,file="junk.csv")
save(junk,file="junk.RData")
```

Next step is incorporating the cluster information to the file df:

```
names(df)
df$cluster<-junk[match(df[,1],junk[,5]),6]
dim(df)
#[1] 408637 114
#cleaning df
df$dup_t<- NULL
df$dup_r<- NULL
dim(df)
[1] 408637 112
#atot <- df[(df$ret_year<1999 | (df$ret_year>=1999 & df$cluster<3)),]
atot <- df[df$cluster<3,]
dim(atot)
[1] 408568 112
```

Getting rid of the NA's

```
atot1<-atot[atot$cluster==1,]
dim(atot1)
#[1] 292513 112
```

```
summary(atot1$cluster)
# Min. 1st Qu. Median Mean 3rd Qu. Max. NA's
# 1 1 1 1 1 1 66928
```

```
atot1<-atot1[na.omit(atot1$cluster),]
summary(atot1$cluster)
# Min. 1st Qu. Median Mean 3rd Qu. Max.
# 1 1 1 1 1 1
```

```
atot2<-atot[atot$cluster==2,]
dim(atot2)
#[1] 182983 112
summary(atot2$cluster)
# Min. 1st Qu. Median Mean 3rd Qu. Max. NA's
# 2 2 2 2 2 2 66928
```

```
atot2<-atot2[na.omit(atot2$cluster),]
```

```
dim(atot2)
#[1] 116055 112

summary(atot2$cluster)
# Min. 1st Qu. Median Mean 3rd Qu. Max.
# 2 2 2 2 2 2

atot<-rbind(atot1,atot2)
dim(atot)
#[1] 341640 112
```

Saving atot in R format

```
save(atot,file="atot.RData")
```

For carrying out the GLM analysis, it is needed to paste the files from the Pago-Pago (pl) and the domestic fleet (df). After the previous analysis these two files already contain the cluster information.

```
load("pl.RData")
dim(pl)
#[1] 532262 112
```

The dimensions from the two files (df and pl) have to match to paste them. In the file df the column 3 correspond to dup_t, similarly there is another column called dup_r. We need to erase this information:

```
df$dup_t<-NULL
```

Erasing dup_r

```
df$dup_r<-NULL
dim(pl)
#[1] 532262 112
dim(df)
#[1] 408637 112
```

Although the matrices have the same dimension (number of columns), the order in both files is not the same, as shown:

```
names(pl)
#[106] "ret_year"      "ret_month"     "ret_day"
#[109] "cluster"      "tmp"           "sets_per_trip"
#[112] "wt"
names(df)
#[106] "ret_year"      "ret_month"     "ret_day"
#[109] "tmp"           "sets_per_trip" "wt"
#[112] "cluster"
```

To solve this problem we need saving the contents of the column 109 from the file pl, then we need to erase column 109 and paste the information from the back up in the last column.

```

cluster_backup<-pl$cluster
length(cluster_backup)
#[1] 532262
summary(cluster_backup)
#   Min. 1st Qu.  Median    Mean 3rd Qu.   Max.   NA's
#  1.000  1.000   1.000   1.344  2.000   3.000 501256.000
pl$cluster<-NULL
dim(pl)
#[1] 532262 111
pl<-cbind(pl,cluster_backup)
dim(pl)
#[1] 532262 112
names(pl)
#[109] "tmp"          "sets_per_trip"  "wt"
#[112] "cluster_backup"

```

Changing the name of last column:

```

colnames(pl)[112]<-"cluster"
names(pl)
#[109] "tmp"          "sets_per_trip"  "wt"
#[112] "cluster"

```

Paste them in a new file:

```

cpueSP<-rbind(pl,df)
dim(cpueSP)
#[1] 940899 112
write.csv(cpueSP,file="cpueSP.csv")
save(cpueSP,file="cpueSP.RData")

```

Building the input file for the GLM:

Getting rid of the non-targeting from Taiwan:

```
a_tot <- cpueSP[(cpueSP$ret_year<1999 | (cpueSP$ret_year>=1999 & cpueSP$cluster<3)),]
```

Selecting the data for the GLM

```

a_tot <-
a_tot[,c("flag_id", "trip_id", "alb_n", "tuna_n", "set_yrqtr", "hook", "set_mon", "boat_id", "lat.loc", "lon.loc", "temp",
"flag_id", "reg", "lat5", "lon5", "wt", "cluster")]

dim(a_tot)
summary(a_tot$cluster)
save(a_tot, file="a_tot.RData")

```

Filter for active boats:

```

for (vessyrs in c(3)) {
  a <- tapply(a_tot$boat_id, list(a_tot$boat_id, a_tot$set_yr), length)
  a1 <- apply(is.na(a[,,])=="FALSE", 1, sum)
  a1 <- a1[a1>vessyrs]
  activeboats <- c(as.numeric(names(a1)))
  activeboats <- unique(activeboats)
  a <- a_tot[a_tot$boat_id %in% activeboats,]
}

```

```
a$latlong<-paste(a$lat5,a$lon5)
save(a, file="a_tot.RData")
```

GLM model:

```
model_test_tot <- glm(log((alb_n+0.5)/hook) ~
as.factor(set_yrqtr)+as.factor(set_mon)*poly(lat.loc,degree=3)+as.factor(lat5)*as.factor(lon5)+as.factor(boat_i
d), data=a_tot, weights=a_tot$wt)
hist(model_test_tot$residuals, density = 12,xlab="Residuals",main=NULL)
savePlot(file="Residuals_tot.jpg",type="jpeg")
hist(model_test_tot$residuals, density = 12,xlab="Residuals",main=NULL,freq=FALSE)
savePlot(file="Residuals_tot_density.jpg",type="jpeg")
plot(model_test_tot$fitted.values,model_test_tot$residuals,xlab="Fitted values",ylab="Residuals",
main=NULL)
savePlot(file="Residuals_fitted_tot.jpg",type="jpeg")
plot(model_test_tot$fitted.values,sqrt(abs(model_test_tot$residuals)), xlab="Fitted
values",ylab="sqrt(abs(residuals))",main=NULL)
savePlot(file="Residuals_sqrt_abs_fitted_tot.jpg",type="jpeg")
plot(model_test_tot$fitted.values,model_test_tot$y,xlab="Fitted values",ylab="ln(CPUE)", main=NULL)
savePlot(file="lnCPUE_fitted_tot.jpg",type="jpeg")
summary_model_test_tot<summary(model_test_tot)
save(summary_model_test_tot, file="summary_model_test_tot.RData")
```

New R session:

```
load("summary_model_test_tot.RData")
coef<-summary_model_test_tot$coefficients
write.csv(coef,file="coeff_tot.cvs")
```

Open the file coeff_tot.cvs in Excel and erase all information not needed.

```
load("a_tot.Rdata")
coeff<-read.csv("coeff_tot.csv, header=TRUE)
a_tot$boat_est<-coeff[match(a_tot[,8],coeff[,1]),2]
write.csv~(a_tot, file="CPUE_SP_raw_tot.csv)
```

Open the file "CPUE_SP_raw_tot.csv" in Excel and get rid of NA's for the coefficients. The total number of records is 788574 after cleaning NA (408). The average correction factor is: 1.385834 and the standard deviation is 0.692736; therefore the inferior limit of the 95% confidence interval is 0.02807 and the superior limit is 2.743597. All values smaller to the inferior limit were set equal to 0.25 and the values greater than the superior bound were set at 2.75. The new corrected effort was effort*correction factor. The aggregation to one degree and five degrees were done in Excel with pivot tables. The corresponding files are: STD_CPUE.csv and STD_CPUE_IRD.csv. The pivot table does not fill the empty spaces. This was done in Visual Basic with the following code:

```
Option Explicit
```

```
Sub rellenar()
```

```
Dim i As Integer, temporal1 As Double, salvar As Double
```

```
For i = 1 To 23614
```

```

temporal1 = Sheets("CPUE").Range("c4").Rows(i)

If (temporal1 <> 0) Then
salvar = temporal1
Else
Sheets("CPUE").Range("c4").Rows(i) = salvar
End If
Next
End Sub

```

Adapt the code, check the number of data so instead of defining i as integer, it is defined as long. The R script for the figure is:

```

##all data

library(maps)
library(mapproj)
library(mapdata)
library(RColorBrewer)

datnew <- read.csv("STD_CPUE_fig.csv",header=T, sep=",")
eez <- read.table("eznew2.txt", sep="", header=F)

##does smmooth/filled contours

filled.contour.adl <- function (x = seq(0, 1, len = nrow(z)), y = seq(0, 1, len = ncol(z)),
  z, xlim = range(x, finite = TRUE), ylim = range(y, finite = TRUE),
  zlim = range(z, finite = TRUE), levels = pretty(zlim, nlevels),
  nlevels = 20, color.palette = cm.colors, col = color.palette(length(levels) -
  1), plot.title, plot.axes, key.title, key.axes, asp = NA,
  xaxs = "i", yaxs = "i", las = 1, axes = FALSE, frame.plot = axes,
  ...)
{
  if (missing(z)) {
    if (!missing(x)) {
      if (is.list(x)) {
        z <- x$z
        y <- x$y
        x <- x$x
      }
      else {
        z <- x
        x <- seq(0, 1, len = nrow(z))
      }
    }
    else stop("no 'z' matrix specified")
  }
  else if (is.list(x)) {
    y <- x$y
    x <- x$x
  }
  if (any(diff(x) <= 0) || any(diff(y) <= 0))
    stop("increasing 'x' and 'y' values expected")
  #mar.orig <- (par.orig <- par(c("mar", "las", "mfrow")))$mar
  #on.exit(par(par.orig))

```

```

#w <- (3 + mar.orig[2]) * par("csi") * 2.54
#layout(matrix(c(2, 1), nc = 2), widths = c(1, lcm(w)))
plot.new()
plot.window(xlim, ylim, "", xaxs = xaxs, yaxs = yaxs, asp = asp)
if (!is.matrix(z) || nrow(z) <= 1 || ncol(z) <= 1)
  stop("no proper 'z' matrix specified")
if (!is.double(z))
  storage.mode(z) <- "double"
.Internal(filledcontour(as.double(x), as.double(y), z, as.double(levels),
  col = col))
if (missing(plot.axes)) {
  if (axes) {
    title(main = "", xlab = "", ylab = "")
    Axis(x, side = 1)
    Axis(y, side = 2)
  }
}
}

#####
## do plotting

par(mfrow=c(1,1), mar=c(0,2,0.5,1), omi=c(0.4,0,0,0))
dat2 <- tapply(datnew$cpue, list(datnew$long, datnew$lat), mean)
catchsum <- round(sum(dat2, na.rm=T),1)
longlabs <- sort(unique(datnew$long))
lat <- sort(unique(datnew$lat))
a <- length(pretty(dat2,9))
cols <- rev(brewer.pal(a-1, "RdYlBu"))

plot(1,1, yaxt="n", xaxt="n", type="n", xlim=c(140,275), ylim=c(-50,0))
lines(eez[,1], eez[,2], col=1)
filled.contour.adl(longlabs, lat, dat2, zlim=range(dat2, na.rm=T), col=cols, yaxt="n", xaxt="n", nlevel=a,
xlim=c(140,275), ylim=c(-45,0))
map('world2Hires', yaxt="n", xaxt="n", add=T, resolution=1)
map('world2Hires', region = c("Korea", "Fiji", "Vanuatu", "Malaysia", "Australia", "Indonesia", "Papua New
Guinea", "China", "Philippines", "Solomon Islands", "Cook Islands", "French Polynesia", "Samoa", "American
Samoa", "New Caledonia", "New Zealand", "Tonga", "Nauru", "Tuvalu", "Line Islands"), fill=T, add=T, yaxt="n",
xaxt="n", col="light grey")
symbols(datnew$long, datnew$lat, datnew$cpue/500, add=T, inches=FALSE, bg=1, fg="black", lwd=2,
yaxt="n", xaxt="n")
lines(eez[,1], eez[,2], col="black", lwd=2.5)
box(lwd=3)
text(260, -7, "Avg. Adj. CPUE", xpd=NA, cex=1.25)
text(260, -9, " Catch/1000 hooks", xpd=NA, cex=1.25)
axis(1, at=c(140, 150,160,170,180,190,200,210,220,230,240,250,260,270,280,290), labels=F)
axis(1, at=c(140,160,180,200,220,240,260,280), labels=c("140E", "160E", "180", "160W", "140W", "120W",
"100W", "80W" ), cex.axis=0.75)
axis(2, at=c(-50,-45,-40,-35,-30,-25,-20,-15, -10,-5), labels=F)
axis(2, at=c(-50,-40,-30,-20,-10), labels=c("50S", "40S", "30S", "20S", "10S"), cex.axis=0.75)

##do legend
y <- lat[2]
yint <- 3
x1 <- 260

```

```
x2 <- x1+5
for (i in 1:length(cols)){
  polygon(c(x2,x2,x1,x1), c(y,y+yint,y+yint,y), xpd=NA, col=cols[i])
  y <- y+yint
}
ymin <- min(pretty(dat2,8))
ymin
ymax <- max(pretty(dat2,8))
ymax
yint2 <- ((length(cols)*yint)/(ymax-ymin))
labs <- pretty(dat2,8)
labs <- labs[labs > ymin & labs < ymax]
loc <- lat[2]+(labs-ymin)*yint2
text(rep(x2+4, length(loc)), loc, labs, xpd=NA, cex=0.85)
text(x1+2, 28, "CPUE index", xpd=NA, cex=1.25, adj=0)

savePlot(file="STD_CPUE_mean.jpg",type="jpeg")
```