Some Comments on Abundance Indices and Probing Surveys

Commentaires sur les indices d'abondance et les campagnes de sondage

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Introduction

It is well known analyses based only on catch and effort statistics do not always produce accurate estimates of stock size. More reliable estimates can be obtained by using ancillary data to "tune" or "calibrate" models used to conduct sequential population analyses (SPA). Ideally, independent and accurate estimates of abundance should be used for this purpose. This can include data from hydro-acoustic censuses, mark-recapture operations, depletion experiments, aerial survey reports, and so forth. Unfortunately, such methods are not routinely applied in a cost-effective fashion to assess the abundance of large pelagic fishes in various regions within short time intervals. As a result, stock-assessment biologists still rely, to a considerable extent, on catch-per-unit-effort (CPUE) indices to calibrate SPA models, usually under the assumption that there is a linear relation between CPUE and abundance. The shape of this relation may be subject to debate, but experts do tend to agree on the need for having reliable and representative statistics for assessment purposes.

Because reliance on fishery catch and effort statistics is so prevailing, fishery agencies typically go through great efforts each year to collect and compile these statistics under the pretext that they are needed for assessments conducted by the working groups of international organizations, commissions or councils. Unfortunately, it is not uncommon to see country representatives show up at the working group meetings with CPUE time series that are most likely un-representative of actual trends, and often incompatible with the model structure and other ancillary data.

This situation described above could be improved by (*i*) identifying a suitable measure of CPUE given the characteristics of the data and the assessment objectives, and by (*ii*) conducting probing surveys (or probing experiments, Walters 1986) to compensate for the lack of information on key aspects of the fishery or stock dynamics. In the following sections, examples will be used to illustrate the problems and the benefits of the recommended approach.

It should be emphasized that the primary objective here is to focus attention on these crucial, but often neglected components of fishery monitoring programs, rather than on providing solutions to fishery-specific problems. It is hoped that this will highlight the need to take appropriate action in the early stage of a fishery monitoring program, to ensure that the resources invested in data collection and assessment activities are not wasted.

Estimation of CPUE

Computing Ratios

Assume the objective is to estimate mean CPUE from a set of catch and effort statistics from the domestic longline fleet of La Reunion (Table 1). Longline CPUE figures are often reported in catch per 1000 hooks, but the 1995-96 records indicate that some sets do not have 1000 hooks, while others exceed this number. Consequently, a method must be used to combine these data and estimate the central tendency in CPUE for a time-area stratum. From a statistical point of view, a CPUE index is a ratio, and several methods can be used to compute

Year	Hooks per set (E)	Catch per set (C)	Catch per 1000 hooks (U)	Year	Hooks per set (E)	Catch per set (C)	Catch per 1000 hooks (U)
1995	600	1	0.0	1996	1300	18	13.8
"	1000	20	20.0	"	1300	6	4.6
"	1000	32	32.0	"	800	0	0.0
"	975	6	6.2	"	800	9	11.3
"	950	6	6.3	"	800	11	13.8
"	900	9	10.0	"	400	5	12.5
"	1050	17	16.2	"	800	0	0.0
"	950	10	10.5	"	800	1	1.3
"	1050	20	19.0	"	450	5	11.1
"	1050	10	9.5	"	800	3	3.8
"	700	1	1.4	"	800	6	7.5
"	500	0	0.0	"	800	5	6.3
"	1000	13	13.0	"	672	7	10.4
"	900	17	18.9	"	938	6	6.4
"	1100	35	31.8	"	1200	21	17.5
"	600	1	1.7	"	1200	15	12.5
"	1000	4	4.0	"	882	6	6.8
"	1000	4	4.0	"	840	4	4.8
"	1000	9	9.0	"	931	8	8.6
"	1100	45	40.9	"	1100	40	36.4
"	920	2	2.2	"	900	1	1.1
"	950	4	4.2	"	600	6	10.0
"	700	21	30.0	"	600	0	0.0
"	1050	20	19.0	"	600	0	0.0
"	1100	17	15.5	"	400	4	10.0
"	1000	10	10.0	"	600	2	3.3
"	500	0	0.0	"	1100	13	11.8
"	800	0	0.0	"	450	0	0.0
"	1100	13	11.8	"	1500	22	14.7
"	950	3	3.2	"	600	2	3.3

Table 1
Subset of catch, effort and catch-per-1000 hooks (CPUE) records from the domestic longline fishery targeting swordfish in La Reunion during 1995 and 1996. Each record corresponds to a single set.

it. If harvesting (or sampling) does not induce significant stock depletion within the stratum, estimates of mean CPUE can be generated by several methods:

(1) Ratio estimator = $\dfrac{\sum_{n=1}^{N} C_n}{\sum_{n=1}^{N} E_n}$

(2) Arithmetic estimator = $\dfrac{\sum_{n=1}^{N} U_n}{N}$

(3) Regression estimator = $\dfrac{\sum_{n=1}^{N} (C_n - \overline{C})(E_n - \overline{E})}{\sum_{n=1}^{N} (E_n - \overline{E})^2}$

(4) Geometric estimator = $\sqrt[N]{\prod_{n=1}^{N} U_n}$

where:

n = index identifying a given set ($\Sigma n = N$)
C_n = number of fish caught from set n
E_n = fishing effort (1000 hooks, number of hook-hours, or etc.) for set n
U_n = catch-per-unit-effort for set n
$\overline{C}$, $\overline{E}$ = mean catch or effort respectively

Estimates obtained by applying Equations 1-4 to the same data set do not show the same trends in mean CPUE (Table 2), because the suitability of each estimator depends on (*i*) variation in effort between sets in a stratum, (*ii*) the existence of a correlation between the dependent and independent variables, and (*iii*) the weight given to each observation (see Zar 1984, Cochran 1977 for details). Using the wrong estimator may provide an inaccurate picture of actual trends, and may lead us to provide bad advice to industry and management.

An adequate measure of CPUE also depends on the attributes of the stocks and fisheries considered. For longline fisheries, fishing effort is a function of the time hooks remain in the water (soak times), which may vary considerably between sets, and affect the catches obtained

Equation	Estimator	CPUE 1995	CPUE 1996	Δ 1995-96
1	Ratio	12.7	9.1	– 29 %
2	Arithmetic	11.7	8.1	– 31 %
3	Regression	9.9	8.1	– 18 %
4	Geometric	2.4	1.3	– 47 %

Table 2
Estimates of mean CPUE computed from Table 1. Geometric means estimated after substituting null catches by small values (10 E–5). The estimated seasonal change in CPUE (Δ 1995-96) is computed relative to 1995 level.

(Campbell and McIlgorm 1995). Nominal CPUE indices should thus be reported in terms of catch per hook·hours or other equivalent variables. For the longline fishery of La Réunion, the fishing effort associated with a set could be expressed as

$$(5)\quad E = \frac{HT_1}{2} + HT_2 + \frac{HT_3}{2} = 0.5H(T_1 + 2T_2 + T_3)$$

where:

E = Total effort in hook·hours
H = Number of hooks laid out
T_1 = Time used for laying out the main line
T_3 = Time used for retrieving the main line
T_2 = Interval between the end of T_1 and the beginning of T_3

Plots of catch against effort in hooks and hook·hours show similar trends (Figure 1), but the later show less year-to-year change in CPUE (i.e. the slope), and the points are more spread out which helps reveal any non-linearity or homocedasticity in the relation. When catch and effort are correlated, and the variation in catch is uniform over the range in effort, the use of regression estimators is appropriate, and analyses of co-variances can be conducted to assess the influence of various factors on catches.

However, many data sets show increased variation in catches with higher effort levels, and skewed distributions of CPUE scores. In such cases, the scores are often log-transformed to facilitate comparisons

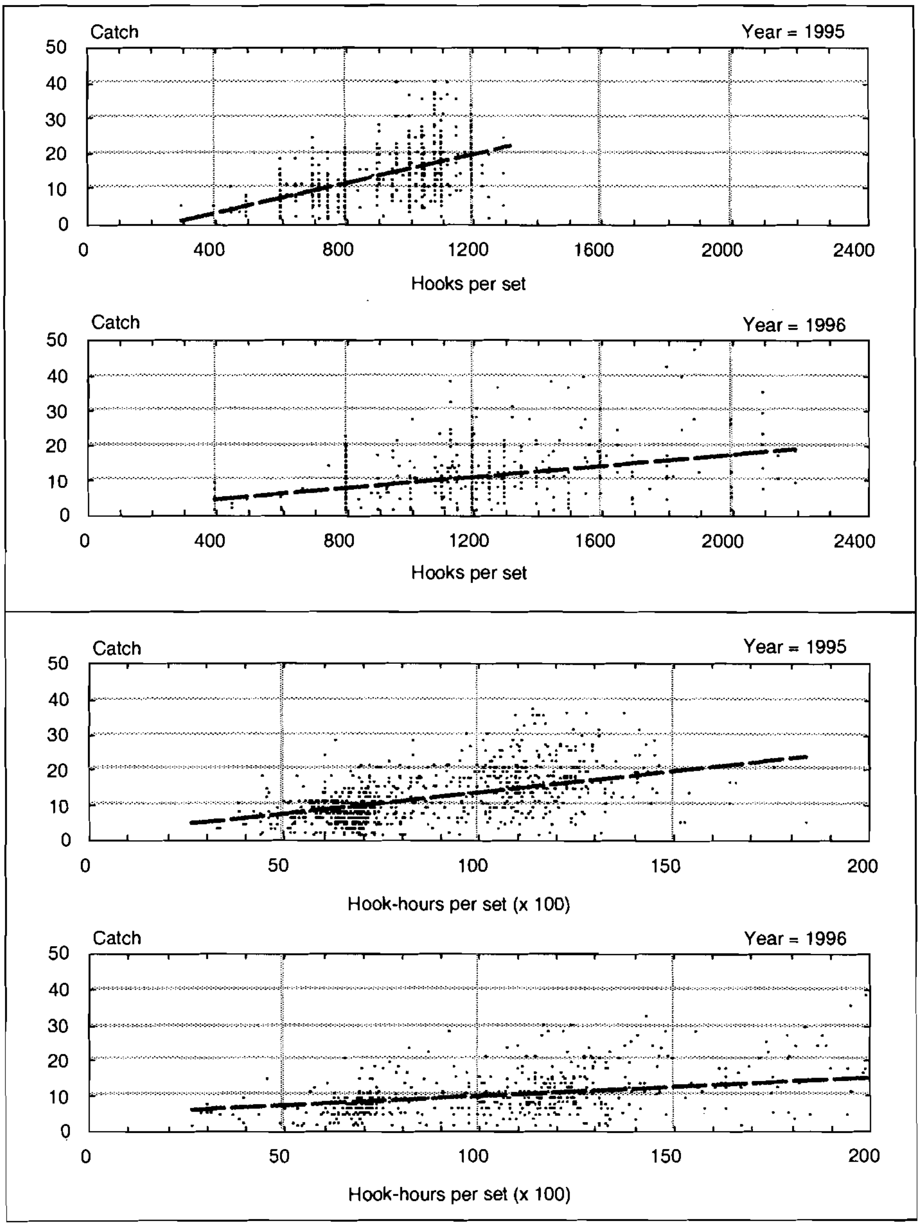

Figure 1
Catch versus effort for the domestic longline fleet during 1995-96.
Effort units are in hooks (top), and hook.hours (below) per set.
Records with no catches omitted.

by parametric methods. However, not all types of ratios and derived variables are normalized by log-transformations (Green 1979), and some CPUE distributions fall in this category. Kolmogorov-Smirnov test results indicate that the 1996 longline CPUE distribution is not log-normal (Figure 2, top). Consequently, the distribution of log-transformed CPUE is not normal (Figure 2, middle). This normalization problem can be just a minor annoyance during the analysis since some statistical tests are robust enough to handle small departures from normality. However, in other cases, the deviations are more pronounced and not easily dealt with.

One procedure used to overcome such limitations was developed by Richards and Schnute (1992). The authors proposed a model to normalize CPUE distributions, using maximum likelihood methods to estimate the normalizing parameters, the central tendency in CPUE, and the associated likelihood-based confidence regions. This model was used to transform the 1996 longline CPUE distribution into one that does not differ significantly from the normal (Figure 2, bottom).

Problems with Zeros

Another common problem with CPUE transformations is due to the fact that some fishing effort may yield no catch. Delta-lognormal or delta-gamma models are now being used to describe CPUE trends when the data sets include many zero catches (Pennington 1983, Stefánsson 1996). These compound distributions compute the joint probabilities of detecting the fish, and of catching a certain number given that they are found. This approach appears to be promising, but should not be applied blindly to all data sets including zeros. This problem is best illustrated using records from the French purse seine fleet that harvest bluefin tuna (*Thunnus thynnus thynnus*) in the Mediterranean.

Staff from the Affaires Maritimes do not routinely collect logbooks from seine vessels that target bluefin, so information on CPUE trends is derived from sale records provided by fish traders or "mareyeurs" (Labelle *et al.* 1996). Note that when no bluefin are caught during a trip, no record is produced because no bluefin are sold after the trip. This causes some discrepancy between the activity of seiners, and the estimated effort and age-disagregated catch obtained by processing sale records (Table 3). In this fishery, unsuccessful sets can result

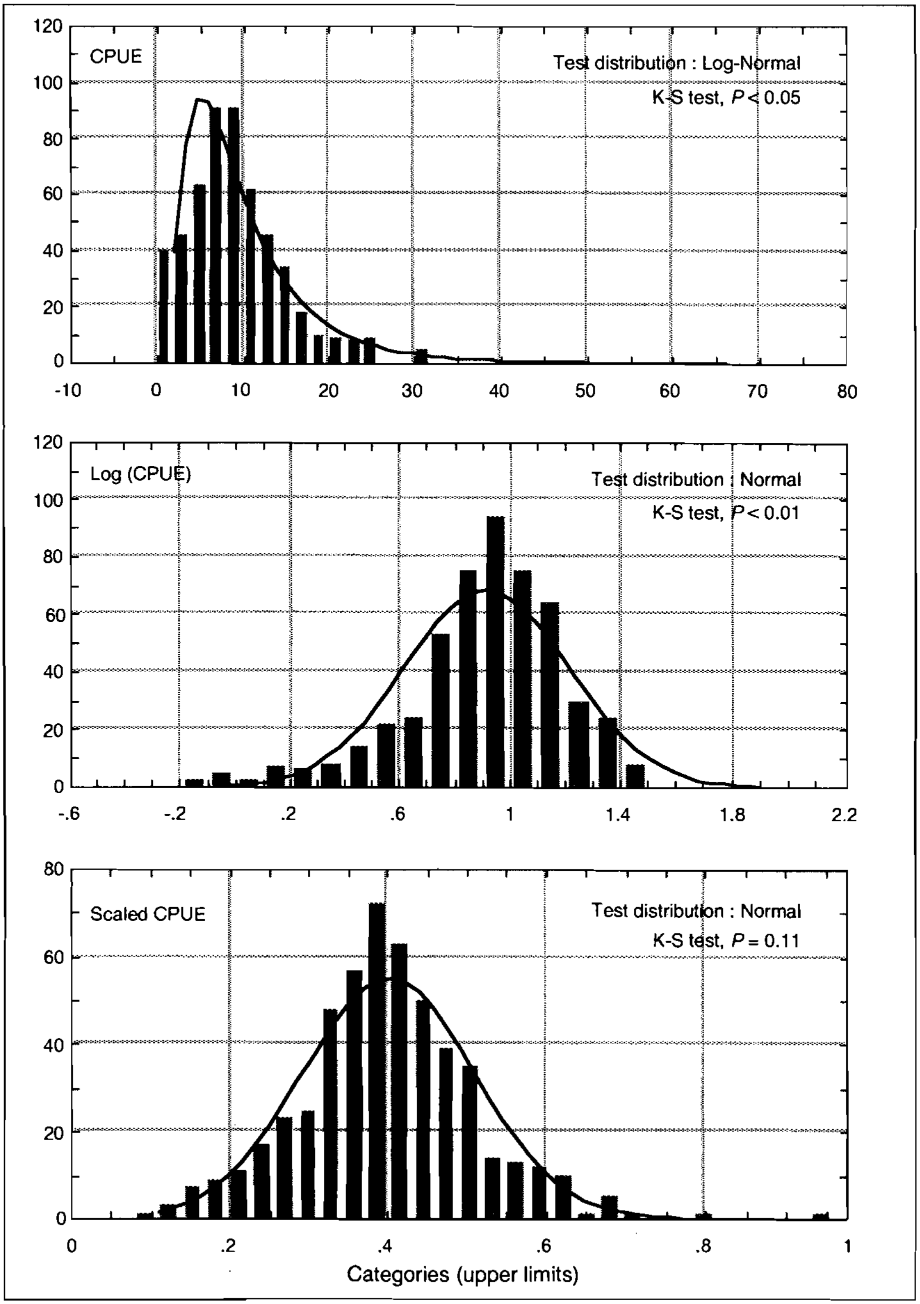

Figure 2
Distribution of catch per 100 hook.hours (CPUE) for individual longline sets in 1996. The records are un-transformed (top), log-transformed (middle), and scaled using the method of Richards and Schnute (1992).
Solid line indicates the test distribution. Records with no catches omitted.

from difficulties during hauling operations, bad weather, damaged nets, the absence of tuna or simply those of a given age. After some careful data processing, what initially appeared to be an apparent log-normal distribution of total catch per set turns out to be an incomplete, atypical and highly skewed distribution of CPUE for a given age class.

Seine sets per day	Bluefin catch	Age 2	Age 3	Comments	Activity detected
1	0	–	–	Catch lost while hauling	No
1	0	–	–	Catch lost while hauling	No
1	0	–	–	Catch lost - net damage	No
2	0	–	–	Empty set	No
1	0	–	–	Empty set	No
1	6	0	0	No age 2 or 3 present	Yes
1	17	0	0	No age 2 or 3 present	Yes
1	3	0	0	No age 2 or 3 present	Yes
1	4	0	0	No age 2 or 3 present	Yes
1	8	0	0	No age 2 or 3 present	Yes
1	2	0	0	No age 2 or 3 present	Yes
1	70	62	8		Yes
1	95	85	10		Yes
1	242	26	26		Yes
1	45	0	0	No age 2 or 3 present	Yes
1	7	0	0	No age 2 or 3 present	Yes
1	4	0	0	No age 2 or 3 present	Yes
1	95	0	95	No age 2 present	Yes
1	7	0	0	No age 2 or 3 present	Yes
..	..	..	..	..	..
..	..	..	..	..	..
..	..	..	..	..	..

Table 2
Example of actual seine fishing activity, and the corresponding reported and estimated catches of age 2 and age 3 bluefin tuna. Activity detected indicates if the fishing activity can be determined from the processing of fish sale records. No data represented by horizontal traits, and other data (omitted) by double dots.

Obviously, the nature of the factor(s) responsible for zero catches must be accounted for when assessing the significance and probability of zero CPUE. How delta models perform when applied to small, age-disagregated data sets should also be investigated before relying too heavily on the resulting abundance indices for calibration purposes. Even sophisticated models can be sensitive to departures of the underlying assumptions, and delta-based estimators fall in this category (Smith 1988, Myers and Pepin 1990, Pennington 1990).

Probing surveys

Even in cases where scientifically credible fishery monitoring or port sampling programs are implemented, one might not obtain all the diagnostics needed for stock-assessment purposes. Some of the major problems encountered when assessing the status of pelagic stocks are:

– Fishing effort is distributed throughout the species habitat range. The densities of pelagic species can remain fairly constant in some areas even when the stock size is decreasing (Hilborn and Walters 1992). If fishing is concentrated on the best or traditional areas, one might not obtain the crucial data needed to detect a reduction in overall abundance.

– Multiple gear types are used to harvest the same stock, so various indices may have to be weighted for calibration purposes. The weights are often set to the inverse of the variance. Ideally more weight should be given to the index that is most representative of abundance patterns, but this index may not be clearly identifiable.

– Need to standardize CPUE indices to account for the influence of fish aggregating devices (FAD), changes in gear types or fishing strategies, oceanographic conditions, the incidence of by-catch, the presence of competitors and predators, etc. The effect of each factor cannot always be statistically dissociated because the time series are too short, the data sets lack contrast, or there were no observations made under particular conditions.

Fishery representatives of all states bordering the Indian Ocean can help provide the ancillary data required to improve the reliability of stock assessments. They can do so conducting "probing surveys". These are essentially systematic field investigations conducted to provide knowledge on key attributes of the fishery that cannot be easily obtained through traditional analyses of catch and effort statistics.

To best illustrate the need for probing surveys, consider this realistic scenario. Let's say Generalized Linear Models (McCullagh and Nelder 1989) are to be used to standardize billfish CPUE scores for the effects of various factors, including sea surface temperature (SST). Fishermen might have already been lead to believe that the largest catches occur in areas where SST is 18°, so they get satellite images faxed to them periodically and concentrate their activities in areas with that temperature.

After some period of activity, the records from a set of vessels using similar fishing methods and gear may end up containing no observations outside the 17-20° range (Figure 3, top). Given this type of data set, one cannot determine the shape of the relation between temperature and catch, and it may be difficult to properly standardize the CPUE scores. This problem could be overcome by complementing the logbook collection program with probing surveys. This involves conducting complementary fishing trips at the same time, and with the same gear and method, but in areas with SSTs that differ from where the fleet operates. The resulting data set used for the analysis would be larger, more complete, and might reveal a non-linear relation between SST and catches (Figure 3, bottom). The fishermen may conclude that catches are not sufficiently greater in other areas to justify the extra travel time, cost or effort, but would still benefit from this knowledge, and scientists might be able to standardize CPUE series for SST effects with more certainty.

Probing surveys can be used to test hypotheses concerning the relative catchabilities of different gears, the cost-effectiveness of fishing strategies, the distributions of the target species, or even the suitability of regulations. For instance, a recently introduced regulation in La Réunion prohibited domestic longliners from operating within 20 km from a FAD, to reduce the impact on sport fishermen that operate near it. Unfortunately no evidence was ever provided to show the

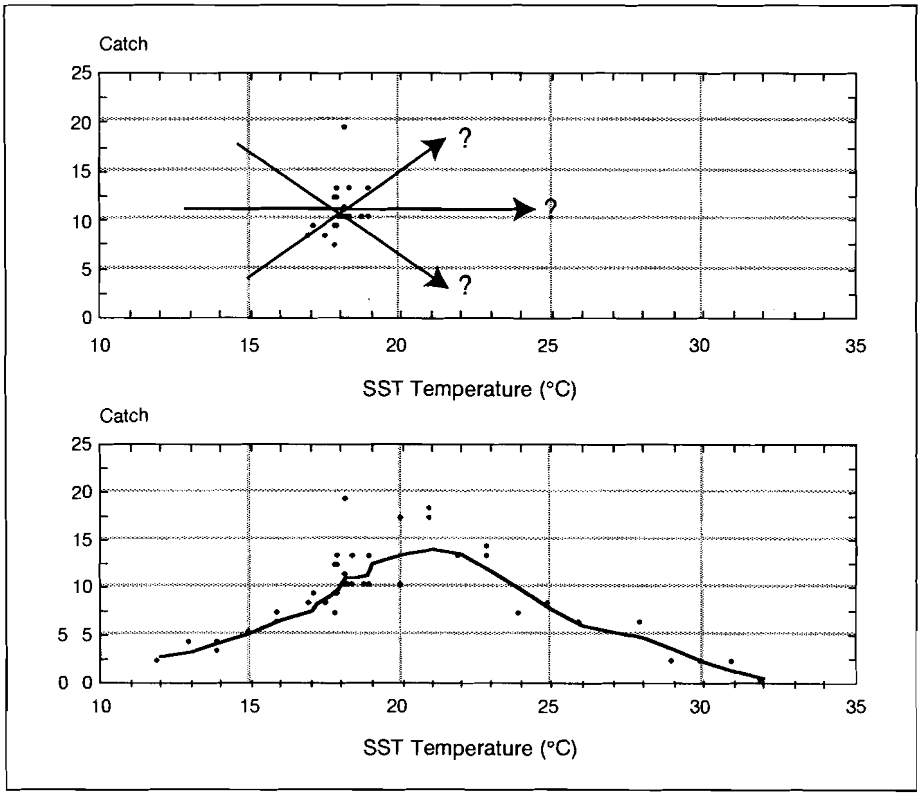

Figure 3
Plots of catch against sea-surface temperature (SST).
Lines drawn through the points show the potential relations between the variables, as hypothesized from logbook records only (top), or from a combination of probing survey and logbook records (bottom).

existence of a negative correlation between sport catch rates and the longliner-FAD distance. Probing surveys could be conducted to test this, by having a few longliners operate at given distances from a FAD. By monitoring the catch rates of FAD fishermen and longliners repeatedly over time, while fishing at fixed distances from each other, one could get the information needed to test the hypothesis that there is an interaction between the two components under certain conditions.

Concluding Remarks

This brief, cursory review of CPUE estimation problems shows that what initially looks like a simple task, may in fact be a complex procedure that is best left to experts. These experts should be consulted *before* the data collection program is implemented, and not *after* just to make the best of a bad situation. In the case of the Mediterranean purse seine fishery for bluefin tuna, experts would have noted that information on why bluefin are not caught on some days is crucial, and should be noted in logbooks and databases designed to assess trends in this fishery. Experts should also help identify a suitable estimator of CPUE, and equally important, design studies to determine the relation between a CPUE measure and the actual density or abundance (see Bannerot and Austin 1983, Richards and Schnute 1986).

The examples also illustrate how probing surveys can complement fishery monitoring programs. The benefits of this approach include the possibility of (*i*) estimating parameters that could not be estimated otherwise, (*ii*) providing answers to important questions faster than by accumulating data for several years, (*iii*) gains in efficiency, since it allows fishermen and processors to optimize their strategies more quickly.

You don't need statistical experts to design probing surveys, or expensive research vessels to conduct them. But you should have good collaboration between the fishermen and the regulatory agencies. It would also be advisable to conduct the surveys with commonly used gear, whenever possible, to ensure that the results are pertinent and readily applicable. The fishermen must be willing to put some effort into these surveys, and comply fully with the experimental survey design established initially.

Fishermen may be reluctant to assist with probing surveys because they anticipate lows catches or benefits if they comply with the plan. Some solutions have been proposed by fishery agencies to overcome this reluctance. The catches of all vessels participating in the program can be pooled and sold together. The money is then distributed among the fishermen according to their operating costs. Alternatively, the fishermen may be guaranteed a minimum salary on survey days. Providing financial incentives costs money to fishery agencies, but the agency may get more and better data for less than it cost to operate an expensive research vessel that can only operate in one location at a time. A third approach used successfully in Australia consists of requiring that fishermen participate to surveys each year as a condition of license (see Hilborn and Walters 1992).

In concluding, I strongly recommend that fishery agencies from states bordering the Indian Ocean collaborate with each other and with industry to conduct probing surveys. Simply sending representatives to stock-assessment meetings with catch and effort figures is not the key to success. Governments that fund data collection and fishery monitoring programs have the every right to demand that these programs be cost-effective, meaningful and scientifically credible.

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