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Letters to the Editor

Comment

Re: Kirby, D. S.; Abraham, E. R.; Uddstrom, M. J.; Dean, H. 2003: Tuna schools/aggregations in surface longline data 1993–98. *New Zealand Journal of Marine and Freshwater Research 37*: 633–644.

A recent study by a group including one of the present authors (Kirby et al. 2003) uses a high-resolution (hook by hook) data set on catches of tuna (*Thunnus* sp.) by commercial longliners fishing in New Zealand waters from 1993 to 1998, to estimate mean nearest neighbour distance ($\overline{\mathrm{NND}}$) for several species of interest, and hence to quantify the extent to which tuna form schools or aggregations. For each fishery, their study compares the observed (i.e., true) $\overline{\mathrm{NND}}$s with those derived by Monte Carlo simulation, assuming the target species to be randomly distributed along each longline (RanNND). Any tendency for true $\overline{\mathrm{NND}}$ to be less than $\overline{\mathrm{RanNND}}$ is interpreted as evidence of aggregation, and summarised by an Aggregation Index (AI, defined as 1 – NND/RanNND) where 0 indicates a random distribution, 1 indicates maximum aggregation, and negative values indicate dispersion (see also Clark & Evans 1954). For the seven fisheries summarised in table 1, they report true $\overline{\mathrm{NND}}$s of 71–170 m, and $\overline{\mathrm{RanNND}}$s of 200–560 m. These results lead Kirby et al. (2003) to conclude that tuna are highly aggregated ($0.61 \leq \overline{\mathrm{AI}} \leq 0.71$), at a characteristic spatial scale of 100–200 m.

Even without examining the raw data, it is readily apparent that at least some of these figures are implausible. For example, the North Island fishery for bigeye tuna (*T. obesus*) yields a mean catch per unit effort ($\overline{\mathrm{CPUE}}$) of four bigeye per longline set, with a mean distance between the endpoints of each set of 49 km. If four bigeye were distributed evenly, their mean separation would be approximately one fourth of this distance, or c. 12 km. The reported $\overline{\mathrm{NND}}$ (97 m) is less than 1% of this value, and would, if correct, imply an extraordinarily high degree of aggregation.

We are currently using essentially the same data set analysed by Kirby et al. (2003) to study the relationships between tuna CPUE and sea-surface temperature, and have been unable to reproduce their key results. Our dataset is slightly smaller, because our data screening criteria were more restrictive, but is otherwise identical. On reviewing the analyses used to compute the $\overline{\mathrm{NND}}$ and $\overline{\mathrm{RanNND}}$ estimates given by Kirby et al. (2003), we identified several programming errors which render their results invalid. Our corrected estimates of $\overline{\mathrm{NND}}$ for six of the seven fisheries analysed by Kirby et al. (2003), using the same methodology, range from 1.37 to 14.51 km and are typically 20–90 times larger than their reported values (Table 1). Corrected $\overline{\mathrm{RanNND}}$ estimates for these fisheries are also substantially larger (Table 1), and are much more consistent with the ratio of mean catch to mean set length. Consequently, we obtain different estimates of $\overline{\mathrm{AI}}$ for each fishery, which range from 0.10 to 0.18.

Unfortunately, the errors in the NND calculations reported by Kirby et al. (2003) are large enough to invalidate the subsequent analysis (including their fig. 4 and 5), as well as much of their discussion. The corrected results indicate that bigeye, southern bluefin (*T. maccoyii*), and albacore (*T. alalunga*) tunas in New Zealand waters are aggregated rather weakly, being only slightly closer together (on average) than would be expected if they were distributed randomly. Moreover, as noted by Kirby et al. (2003), the catch distribution on each longline presumably reflects not only any inherent tendency towards aggregation on the part of the tuna, but also the ability of the vessel skipper to target these aggregations. This means that even the modest degree of aggregation evident in the 1993–98 data may overestimate the extent to which tuna were actually clustered.

The revised calculations also lead us to question the validity of $\overline{\mathrm{NND}}$ for each fishery as a measure of the characteristic spatial scale at which tuna can be considered to aggregate. In particular, we note that $\overline{\mathrm{NND}}$ will tend to vary inversely with $\overline{\mathrm{CPUE}}$ irrespective of the extent to which fish are aggregated. For example, if fish are randomly distributed along an idealised straight longline, doubling their mean separation is equivalent to halving the number of fish taken. It follows that $\overline{\mathrm{NND}}$ and $\overline{\mathrm{CPUE}}$ are simply alternative measures of population density, regardless of whether $\overline{\mathrm{AI}}$ is positive, negative, or zero. In this context, $\overline{\mathrm{CPUE}}$ is analogous to the mean number of events per unit area as used in spatial analyses based

Table 1 Mean nearest neighbour distance (NND) and related statistics for six longline fisheries (defined by area: North = North Island, South = South Island; target species, and subject species: BIG = bigeye, STN = southern bluefin, ALB = albacore) as reported in table 1 of Kirby et al. (2003), in parentheses, together with corrected estimates from the present analysis. For each fishery, we show the total number of sets; the number of sets in which more than one of the subject species was caught; mean catch per set; mean NND and RanNND; mean aggregation index (AI); mean set length (distance between the endpoints of each set); and mean line length.

Area	Target species	Number of sets	Subject species	Number of sets ($n > 1$)	Catch per set	NND (km)	RanNND (km)	AI	Mean set length (km)	Mean line length (km)
North	BIG	283 (294)	BIG	83 (91)	4.4 (4)	7.30 (0.097)	8.44 (0.279)	0.18 (0.63)	35.6 (49)	74
			ALB	256 (288)	38.4 (37)	1.29 (0.072)	1.51 (0.267)	0.11 (0.70)	30.6 (38)	54
	STN	279 (291)	STN	191 (195)	11.8 (12)	9.36 (0.156)	10.43 (0.560)	0.11 (0.67)	57.5 (75)	127
			ALB	269 (288)	38.0 (39)	2.82 (0.155)	3.20 (0.465)	0.10 (0.63)	57.8 (73)	122
South	STN	1331 (1354)	STN	1116 (1137)	9.4 (10)	8.34 (0.170)	9.52 (0.652)	0.12 (0.71)	71.1 (73)	130
			ALB	236 (243)	4.1 (4)	14.56 (0.163)	16.38 (0.557)	0.12 (0.69)	64.2 (72)	126

on Ripley's K function, which measures the expected number of neighbours within a radius *r* of a specified individual (Ripley 1981; Bailey & Gatrell 1995). To fully characterise spatial aggregation for the New Zealand tuna fishery, we should consider not only $\overline{\text{NND}}$ and $\overline{\text{AI}}$ averaged over all longline operations, but also the functional relationships between CPUE, NND, and AI, when examined case by case. We would be justified in identifying a characteristic spatial scale for each fishery only if there were a clearly defined tendency for AI to peak at some specific value of NND. The corrected $\overline{\text{NND}}$s for the six fisheries examined here—7–9 km for bigeye and southern bluefin, and from 1 to 3 km for albacore in North Island waters to c. 15 km for the same species off the South Island—give some insight into the relative abundance of each species, but (on their own) provide no indication of the spatial scale of any underlying aggregations. It is beyond the scope of this note to investigate this topic in more detail, but we hope to undertake a revised analysis, using an updated dataset drawing on catch records up to 2002, as part of our current research programme.

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M. J. UNWIN
National Institute of Water and Atmospheric Research Limited
P.O. Box 8602
Christchurch, New Zealand
email: m.unwin@niwa.co.nz

M. J. UDDSTROM
National Institute of Water and Atmospheric Research Limited
P.O. Box 14 901, Kilbirnie
Wellington, New Zealand

Reply

The work described in the paper by Kirby et al. (2003) was carried out in 1999–2000 while the lead author was a PhD student and Visiting Scientist at NIWA, Wellington. Many of the assumptions implicit in the analysis, most of which were flagged in the original paper, remain untested and are probably untenable. Since doing this work, several colleagues have expressed the opinion that while we were asking the right questions, the data were incapable of answering them. Unwin & Uddstrom have provided a revised analysis confirming that tunas caught on longlines are often aggregated at scales smaller than the set itself. They also highlight the difficulties of interpreting those aggregations in terms of spatial scales that might be characteristic of tuna behaviour and therefore useful in terms of identifying ocean features relevant to fisheries.

Although CPUE itself is an indication of aggregation at the scale of the line length and above, that there is a physical dimension associated with NND (i.e., length) provided the opportunity to analyse CPUE data in a spatially explicit manner at a much finer scale. It was apparent at the time that NND was a function of CPUE. However, the key indicator of aggregation at a scale smaller than the set length is the ratio of NND/RanNND, which is independent of CPUE. With Monte Carlo simulation carried out using CPUE for each set as the rate parameter, the overdispersion of CPUE itself was maintained and therefore prevented from biasing the analysis of fine-scale catch distribution.

The point that the degree of aggregation may be overestimated due to the varying ability of skippers only holds if you are using CPUE and/or absolute NND, not the ratio of NND to RanNND, as your measure of aggregation. With aggregation index (AI) defined as in the original paper, if skippers are highly skilled we would expect low AI, as the whole line would be set in waters equally and highly likely to catch the target species; if the skipper is less skilled we might expect high AI, as only part of the line would be fishing effectively; if the skipper is poorly skilled then the whole line would be set in the wrong place and all hooks would be equally unlikely to catch fish. I was well aware of the importance and potential confounding effect of skipper skill when I was involved in this project, which is why I initiated a new objective to investigate this under the round of FRST proposals at the time. This work was duly funded but I am not aware of what work, if any, was subsequently done on the topic.

In personal communication, Martin Unwin made the point that "trying to draw conclusions about the distribution of fish in any space other than the longline itself opens up some rather ugly cans of worms [which] actually has significant implications for selecting the most appropriate spatial scale for the whole RSF [Remote Sensing for Fisheries] study." This is a fair and important point but the very purpose of the project was to open those cans and to study those worms. The study of aggregation was carried out in order to establish appropriate spatial scales for looking at remotely sensed oceanographic variables. But in retrospect, the project was overambitious at best, if not ill-conceived. Work by Unwin et al. (2003) and others (e.g., Bigelow et al. 1999) suggests that we can only really analyse CPUE versus environment relationships at much larger scales, providing information that may be useful for standardising but not for directing fishing effort.

For a somewhat more statistically rigorous study of another tuna species in another sea, the interested reader is refered to Royer et al. (2004). Their analysis does not suffer from the multiple sampling errors and assumptions associated with commercial longlining, as their tuna distribution data are obtained from aerial surveys. Ripley's K is calculated, as are various other statistical metrics describing the observed fish distributions in relation to environmental variables. The authors note, with reference to Steele (1989) and Flierl et al. (1999), that the interplay between density-independent responses to environmental features and density-dependent social behaviour is likely to produce complex patterns over a variety of scales. The paper by Kirby et al. (2003) was an attempt to identify and understand these patterns at the finest scale possible, using the only data available. That it is flawed, by a combination of sampling and programming error, in no way trivialises the complexity of the questions we have all been seeking to address.

If this work is to continue, simulation experiments should first be carried out to establish whether it is possible to draw meaningful conclusions about the fine-scale distribution of fast-moving fish from observed commercial longline data. Such a study should replicate the behaviour of a fish population with pre-defined spatial properties (i.e., scales of aggregation) and investigate whether data gathered from simulated longlining is capable of capturing those properties. Such a study, grounded in behavioural ecology rather than remote sensing, might have revealed the limitations of the available data some time ago.

For mistakes honestly made (specifically, I am told, an initialisation error that yielded plausible looking but nevertheless incorrect results) I take my share of the responsibility and hereby apologise to the Editor, reviewers, and readership of this journal. I hope that you will grant me the comfort of believing that: "It is better to make a mistake with the full force of your being than to carefully avoid mistakes with a trembling spirit" (Millman 1980).

DAVID S. KIRBY
Oceanic Fisheries Programme
Secretariat of the Pacific Community
BPD5, 98848 Nouméa cedex, New Caledonia

COMBINED REFERENCES

Bailey, T.; Gatrell, A. 1995: Interactive spatial data analysis. Longman Scientific & Technical.

Bigelow, K. A.; Boggs, C. H.; He, X. 1999: Environmental effects on swordfish and blue shark catch rates in the US North Pacific longline fishery. *Fisheries Oceanography 8*: 178–198.

Clark, P. J.; Evans, F. C. 1954: Distance to nearest neighbor as a measure of spatial relationships in populations. *Ecology 35*: 445–453.

Flierl, G.; Grünbaum, D.; Levin, S.; Olson, D. B. 1999: From individuals to aggregations: the interplay between behavior and physics. *Journal of Theoretical Biology 196*: 397–454.

Kirby, D. S.; Abraham, E. R.; Uddstrom, M. J.; Dean, H. 2003: Tuna schools/aggregations in surface longline data 1993–98. *New Zealand Journal of Marine and Freshwater Research 37*: 633–644.

Millman, D. 1980: Way of the Peaceful Warrior. Tiburon, CA, United States, H. J. Kramer. 216 p.

Ripley, B. D. 1981: Spatial statistics. New York, Wiley.

Royer, F.; Fromentin, J. M.; Gaspar, P. 2004: Association between bluefin tuna schools and oceanic features in the western Mediterranean. *Marine Ecology Progress Series 269*: 249–263.

Steele, J. H. 1989: The ocean 'landscape'. *Landscape Ecology 3*: 185–192.

Unwin, M.; Uddstrom, M. J.; Zheng, X. 2003: Hotspots for catching tuna. *Seafood New Zealand 11(8)*: 22–24.