

## Tuna schools/aggregations in surface longline data 1993–98

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**Abstract** Exploratory data analysis of a high-resolution (hook-by-hook), 6-year time series (1993–98) of observed longline catch data for tunas was used to investigate fine-scale spatial patterns along individual sets that may be indicative of social behaviour (i.e., schooling) and/or the response of individual fish to favourable extrinsic conditions (i.e., aggregation). Methods of spatial data analysis (i.e., nearest neighbour analysis) that have previously been applied in various other sciences (e.g., forestry and astronomy) were used. Results indicate strong clustering of individual tunas at characteristic scales within the set. Mean Nearest Neighbour Distances (NNDs) were between 100 and 200 m, compared with NNDs of 200–700 m predicted by a heterogeneous Poisson process on the same spatial domain. The results suggest that these adult tunas were either schooling or aggregating at the time of capture; this may therefore be related either to social behaviour or to sub-mesoscale oceanographic features. An aggregation index was derived from the NNDs,

giving a classification method that may be used for similar data and the development of empirical models attempting to relate patterns in fish catch distributions to environmental variables. The success of such models will ultimately depend on elucidating the ecological processes reflected in oceanographic features at biologically meaningful spatial scales.

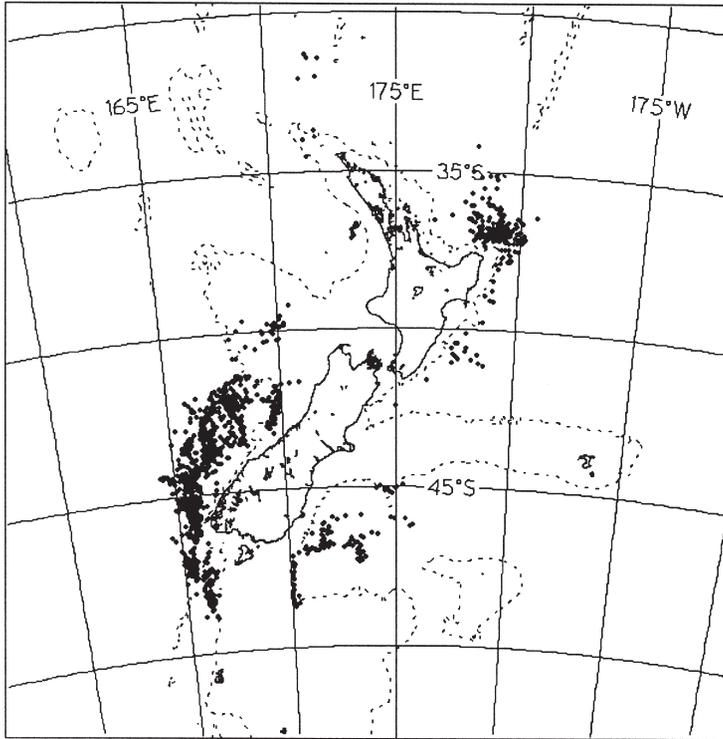
**Keywords** tunas; schooling; aggregation; longline; nearest neighbour distance

### INTRODUCTION

Tunas are not randomly distributed throughout New Zealand waters all year round. The largest scale at which this is apparent can be inferred from the areas where fishers have come to target their effort (Fig. 1). Sharp (1978) estimated that if yellowfin tuna (*Thunnus albacares*) in the eastern tropical Pacific were truly uniformly distributed there would only be one 10 kg fish per 2.8 km<sup>2</sup> of ocean: “they would be so rarely encountered as to be virtually non-existent”. Some species of tuna are normally found in association with many other conspecifics e.g., skipjack *Katsuwonus pelamis* (Bayliff 1988; Hilborn 1991), yellowfin (Klimley & Holloway 1999), and young albacore *Thunnus alalunga* (Laurs et al. 1984), whereas others are thought to be solitary, at least when not forming spawning aggregations (Winkler et al. 1983) e.g., older albacore, bigeye (*Thunnus obesus*), and adult northern and southern bluefin (*Thunnus thynnus* and *Thunnus maccoyii* respectively). The degree of association between conspecifics is of great relevance to fisheries, as it will clearly determine gear type as well as the timing and location of effort. In New Zealand tuna fisheries, schools of skipjack and young albacore are targeted with seine nets and trolling gear respectively, whereas adult southern bluefin, bigeye and yellowfin are targeted by surface longlines.

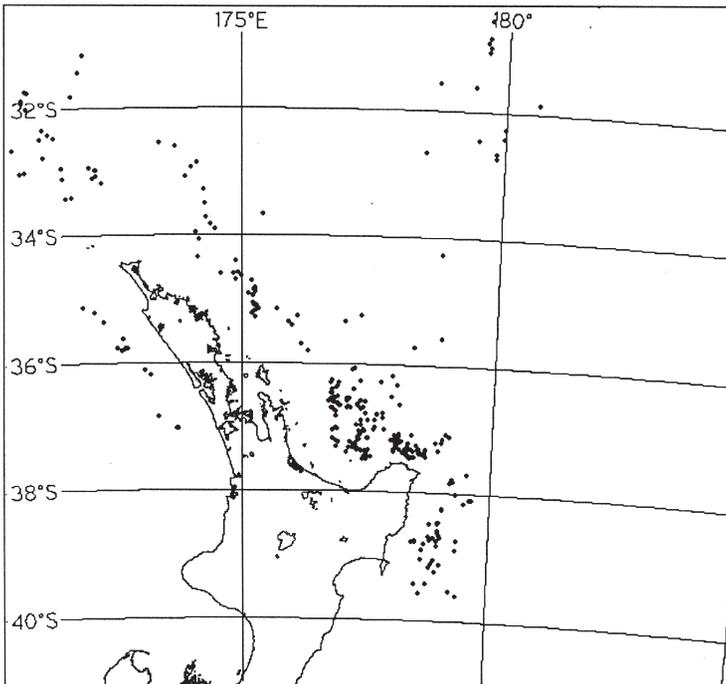
Various terms are used in the behavioural ecology and fisheries literature to describe non-uniform or apparently non-random spatial patterns: schooling,

A



**Fig. 1** Locations of observed surface longline sets in New Zealand waters 1993–98, targeting **A**, southern bluefin *Thunnus maccoyii* (STN) and **B**, bigeye *Thunnus obesus* (BIG).

B



shoaling, clustering, aggregating, and congregating are all terms that have been deployed, often interchangeably. These words may describe similar patterns but it is useful to let them have different meanings, to distinguish the different causes that can have the same effect. The spatial patterns observed in fish distributions and the degree of association among conspecifics are determined by a number of factors. Fish may come together in order to minimise predation risk or to maximise encounter rates with prey or potential mates (Pitcher & Parrish 1993). This bio-social attraction is best considered as schooling or shoaling. Individuals may also come together as a direct response to extrinsic environmental conditions. Such behaviour is more generally termed aggregation. Individuals are considered to be acting independently of each other but responding in a similar way to some external factor or combination of factors, e.g., temperature, visibility, prey density etc. The ways in which marine predators respond to their environment are likely to be scale-dependent, and if variability in population density has a characteristic spatial scale, subsequent research to determine the conditions favouring aggregation can focus on this scale (Schneider 1994). The purpose of the analysis described in this paper was to investigate spatial patterns in longline catch data down to the finest scale possible. These patterns are likely to result from schooling and/or aggregation.

Where point events of interest occur completely at random within a sample space, this can be formally described as a Poisson process: the presence or absence of an event at a particular location is not influenced by any other event, and if the process is homogeneous, no part of the sample domain is any more likely to contain point events than another. A heterogeneous Poisson process allows for such variation, but the events themselves are still independent. Such processes provide a base against which to compare other processes where either clustering or inhibition of events are thought to occur (Cox et al. 2000). The approach taken to identify the characteristic scales of spatial patterns in these data was to measure the distances between individual fish in the observed catch data, and to compare the frequency distributions of these distances with the distributions that result from a heterogeneous Poisson process. If the fish are randomly distributed along the set, then the set scale (up to 150 km) is the finest scale at which they can be considered aggregated, and the targeting of research and fishing effort must focus on this or larger scales. But if they are aggregated **within** the scale of the set we must

consider individual behaviour and the environmental heterogeneity that may exist at these scales and focus more detailed ecological and oceanographic investigations accordingly. It may then become possible to use such knowledge for monitoring and prediction in the fishery.

## DATA ANALYSIS

### Observed longline catch data

Under the New Zealand Ministry of Fisheries (MFish) Observer Programme, an observer is placed on board all visiting foreign licensed surface longline vessels and also a percentage of domestic licensed vessels. Vessels formally target large adult tunas of two species: southern bluefin (STN) and bigeye (BIG). Albacore (ALB) and yellowfin (YFN) are not formally targeted but are a significant and saleable bycatch. Surface longline fishing vessels follow a general pattern of operation over a 24 h period. Larger vessels set the fishing gear in the early hours of the morning to soak the baits during the hours preceding dawn. This operation usually requires 4–8 h and may be followed by 4–5 h of waiting before the gear is retrieved, although longer lines may be retrieved following a shorter waiting time. The catch is processed during the next 12 h. The whole operation is quicker for the smaller vessels of the domestic fleet. A large vessel will set up to 150 km of longline; smaller vessels set 40–80 km of line. From the longline, 2500–3500 snood lines are suspended, each with a single baited hook. For scientific observers, emphasis is placed on getting good information on catch, rather than on the setting operation. The main aspects of the setting operation are nevertheless recorded, including start and finish times and positions, the number of hooks, length of line set, vessel speed, line feeder speed, distance between marker buoys, number of baskets, and basic weather information. At the start and finish of the haul, and at hourly intervals throughout, time and position and basic weather information are recorded. As each specimen is landed on deck, the time is recorded and the specimen identified, weighed, measured and sexed.

All the data gathered by the observers is entered into the MFish database held at National Institute of Water and Atmospheric Research (NIWA) Wellington. For this study, fields of interest were extracted from the database and the positions of individual fish were calculated as described below. ASCII files were generated detailing this

information, and the spatial data analysis was then carried out. (1) An array representing all hooks is constructed with blank position and time details. (2) The first hook is assigned the start-of-haul position and time, and the last hook is assigned the end-of-haul position. (3) Times are calculated for all other hooks, assuming a constant speed while hauling. (4) Hooks closest in time to the hourly haul records are flagged. (5) Between each hook flagged with an hourly haul position, the position of each intervening hook is interpolated by great circle path navigation, using the time assigned. (6) Each recorded specimen is placed on the hook closest to its recorded landing time; if that hook is already occupied, the specimen is placed on the nearest unoccupied hook.

### Nominal catch-per-unit-effort (CPUE)

CPUE for surface longline fisheries is nominally defined as the number of fish caught per thousand hooks. Detailed analysis of individual longline sets shows that even after deliberate targeting by experienced fishers, CPUE is still an over-dispersed quantity, i.e., variance is greater than the mean (Fig. 2). We can therefore view CPUE for tunas as being the result of a heterogeneous Poisson process whereby different areas within the larger fishing area identified by the skippers are more likely to contain more fish, but where the occurrence of each individual is independent of the occurrence of another. Implicitly, the scale of such aggregation is that of the longline set or larger. If no aggregations were apparent at smaller scales, we would conclude that fishers are targeting effort as efficiently as possible, and that the finest scale on which tunas may be considered aggregated is that of the set itself.

There are many factors that can determine the likelihood of a particular hook catching a fish, including depth of the hook, bait type, and of course the timing and location of effort. Fish behaviour is also a factor (see Ferno & Olsen 1994); not all fish that are present will come close enough to detect bait, not all fish that detect bait will bite it, and not all fish that do bite bait will get caught on the hook. Nominal CPUE is therefore only a gross measure of relative abundance that may confound the effects of contributing factors. For the purpose of the analysis presented here, no estimate has been made of the effectiveness of fishing effort. We have not estimated or corrected for these potential errors and therefore implicitly assume that all hooks have the same likelihood of catching a subject should one be present at that point during the fishing period.

### Set-scale probabilities

Fishing is as much a non-random method of sampling as the skipper can make it. For target species, the probability of catching at least one fish represents the extent of fishers' prior knowledge, i.e., how well they are targeting large (set scale) areas preferred by the fish. For all species, the probability of catching more than one subject, and the conditional probability of catching an additional subject having already caught a first, are preliminary measures of fish aggregation on the scale of the set. We implicitly assume that the skill of the skippers is equal.

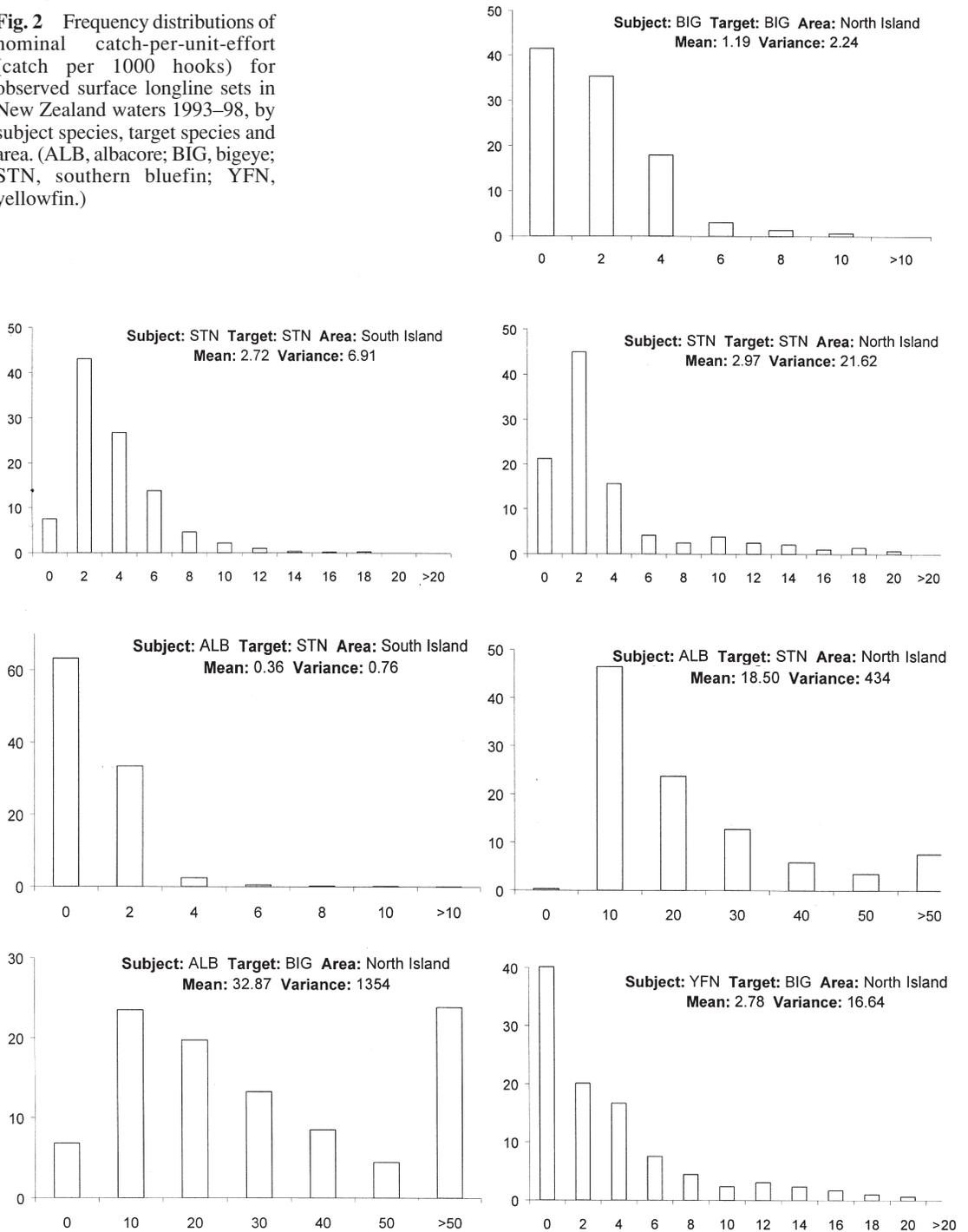
### Generation of simulated data

To compare the spatial patterns apparent in the real catch data with what might be expected from a heterogeneous Poisson process, simulated data were generated by Monte Carlo simulation. The CPUE for the subject species on that set was used to determine the probability of each hook catching a fish; this probability was then compared with a random number to determine whether or not that hook catches a fish. Nearest neighbour distances were then measured as for the real data (see next section). This was repeated 1000 times for each set. In the generation of simulated data the geometry of the set was preserved so that the permitted values of nearest neighbour distances were the same as for the real data (Fig. 3). Also, the CPUE for each individual set was used in preference to the pooled mean for the fishery, bearing in mind that "...what is considered to be a clustered pattern with the assumption of homogeneity in force [i.e., using the pooled mean] could also be the result of heterogeneity" (Ripley 1981). This reduces our chances of believing that there is clustering at spatial scales smaller than the set length, when the effect is in fact caused by variation in CPUE at spatial scales equal to or larger than the set lengths.

### Aggregation index

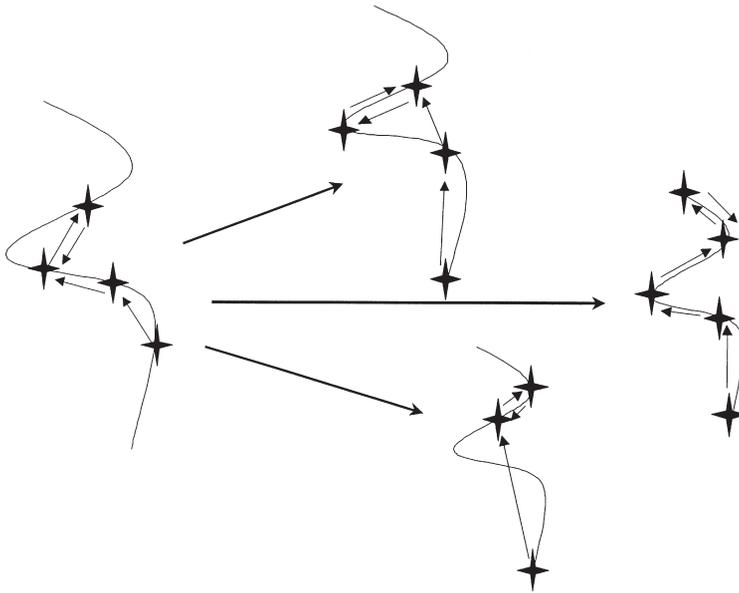
For each longline set that caught more than one subject, the distances between each subject and all the other subjects were calculated by spherical trigonometry, i.e., calculating the Great Circle Path between the two locations. The Nearest Neighbour Distance (NND) is the distance from one subject to the nearest other and for each set there are as many NNDs as there are subjects caught. In order to permit identification and classification of sets possibly containing tuna schools and/or aggregations an Aggregation Index (AI) was defined, following

**Fig. 2** Frequency distributions of nominal catch-per-unit-effort (catch per 1000 hooks) for observed surface longline sets in New Zealand waters 1993–98, by subject species, target species and area. (ALB, albacore; BIG, bigeye; STN, southern bluefin; YFN, yellowfin.)



Clark & Evans (1954):  $AI = 1 - (\text{mean NND}/\text{mean RanNND})$ , where RanNND is the mean NND for the simulated data. AI values fall between -1 and 1, with

positive values indicating schooling/aggregation, zero indicating a random distribution, and negative values indicating repulsion.



**Fig. 3** Schematic representation of the calculation of distances between fish. Curved line represents the set, stars represent the locations of fish, and small arrows represent the distances measured between them. Left, representing an actual set, four fish are clustered. Right, representing the results of three Monte Carlo simulations, the geometry of the set is preserved and the actual catch-per-unit-effort for that set is used to obtain a similar number of subjects distributed at random along the line. Nearest neighbour distances (NNDs; small arrows) are then measured.

## RESULTS

Frequency histograms of nominal CPUE for the data used in this analysis are presented in Fig. 2. For the BIG fishery, which takes place in the warm waters off the north-eastern region (Fig. 1), nominal CPUE was most frequently zero, with occasional catches up to 10 fish per 1000 hooks. For the STN fishery in northern waters, nominal CPUE was also most frequently low (<2), but in 10% of instances nominal CPUE was at least 10, and in a few instances was higher than 20. In southern waters, nominal CPUE for STN was rarely greater than 10, but there were fewer instances of nominal CPUE being zero, and more instances where nominal CPUE was greater than 2. In southern waters, nominal CPUE for ALB was most frequently zero and always low. In northern waters however, nominal CPUE for ALB was rarely zero and could be extremely high (>50) in both the STN and the BIG fisheries. Nominal CPUE for YFN was most frequently zero, but was often greater than 0 and less than 20.

The set-scale probabilities of catching the formal target species (i.e., STN or BIG) and other subject species (e.g., ALB and YFN) are given in Table 1. The proportion of sets that caught at least 1 ( $P(\text{fish} > 0)$ ) and more than 1 subject ( $P(\text{fish} > 1)$ ) are detailed, followed by the conditional probability of catching an additional subject having already caught a first ( $P(\text{fish}2 | \text{fish}1)$ ). It is apparent in these data that fishers were quite effective at targeting STN

( $P(\text{STN}) \approx 80\text{--}90\%$ ) and that these were not usually found alone ( $P(\text{STN}2 | \text{STN}1) \approx 90\%$ ). When BIG were targeted, the probability of catching at least 1 target was much lower ( $P(\text{BIG}) \approx 60\%$ ) and there was only a 50% chance of catching another BIG on the same set. The probability of catching at least 1 YFN was the same as for the formal target species BIG ( $P(\text{YFN}) \approx P(\text{BIG}) \approx 60\%$ ), but it was more likely that more than 1 YFN would be caught on the same set ( $P(\text{YFN}2 | \text{YFN}1) \approx 70\%$ ). ALB were apparently ubiquitous in both the BIG and STN fisheries off the North Island ( $P(\text{ALB}) \approx 100\%$ ;  $P(\text{ALB}2 | \text{ALB}1) \approx 100\%$ ). This provides fishers with their basic income, which is then supplemented by less frequent but more lucrative catches of the target species (T. Murray pers. comm.). ALB were caught less frequently in the longline fisheries off the South Island ( $P(\text{ALB}) \approx 40\%$ ), where they were often caught on their own ( $P(\text{ALB}2 | \text{ALB}1) = 50\%$ ). There are separate fisheries for younger albacore in surface waters that are able to target discrete schools using trolling gear.

For each species, NND calculations were carried out for sets that caught more than one subject; the mean number of fish per set in this subsample is listed. The NNDs are generally c. 100 m, which is the same order of magnitude but 25–50% shorter than the NNDs resulting from the Poisson process (RanNND). The frequency distributions for the real and simulated data are presented in Fig. 4. In all

**Table 1.** For each fishery (defined by subject species, target species and area) we have listed the total number of sets analysed, the set-scale probabilities for catching at least one subject, the number of sets that caught at least one subject, the set-scale probabilities for catching >1 subject and the conditional probability of catching a second subject having caught a first, the number of sets that caught >1 subject (i.e., the subset used for spatial analysis) and the mean number of subjects caught on this subset. We then present their mean nearest neighbour distances (NND), the mean NNDs for the heterogeneous Poisson process (RanNND) and the mean aggregation index (AI). (“Mean set length”, mean great circle path distance between start and end of set, a conservative estimate of line length;  $N(\text{sets})$ , total number of sets analysed;  $n(\text{sets})$ , number of sets that caught more than one fish of the subject species. ALB, albacore; BIG, bigeye; STN, southern bluefin; YFN, yellowfin. N, North Island; S, South Island.)

Subject species	Fishery		Total $N(\text{sets})$	$n(\text{sets})$ where		$P(\text{fish} > 1)$	$P(\text{fish} > 0)$	$n(\text{sets})$ where	$n(\text{sets})$ where	Mean $n(\text{fish})$	Mean NND (m)	Mean RanNND (m)	Mean AI	Mean set length (km)
	Target species	Area (Island)		$P(\text{fish} > 1)$	$P(\text{fish} > 0)$									
BIG	BIG	N	294	0.59	173	0.31	0.52	91	4	97	279	0.63	49	
STN	STN	N	291	0.79	230	0.67	0.85	195	12	156	560	0.67	75	
STN	STN	S	1354	0.93	1259	0.84	0.91	1137	10	170	652	0.71	73	
ALB	STN	N	291	1.00	291	0.99	0.99	288	39	155	465	0.63	73	
ALB	BIG	N	294	0.99	291	0.98	0.99	288	37	72	267	0.70	38	
ALB	STN	S	1354	0.37	500	0.18	0.50	243	4	163	557	0.69	72	
YFN	BIG	N	294	0.60	176	0.41	0.69	120	6	71	205	0.61	33	

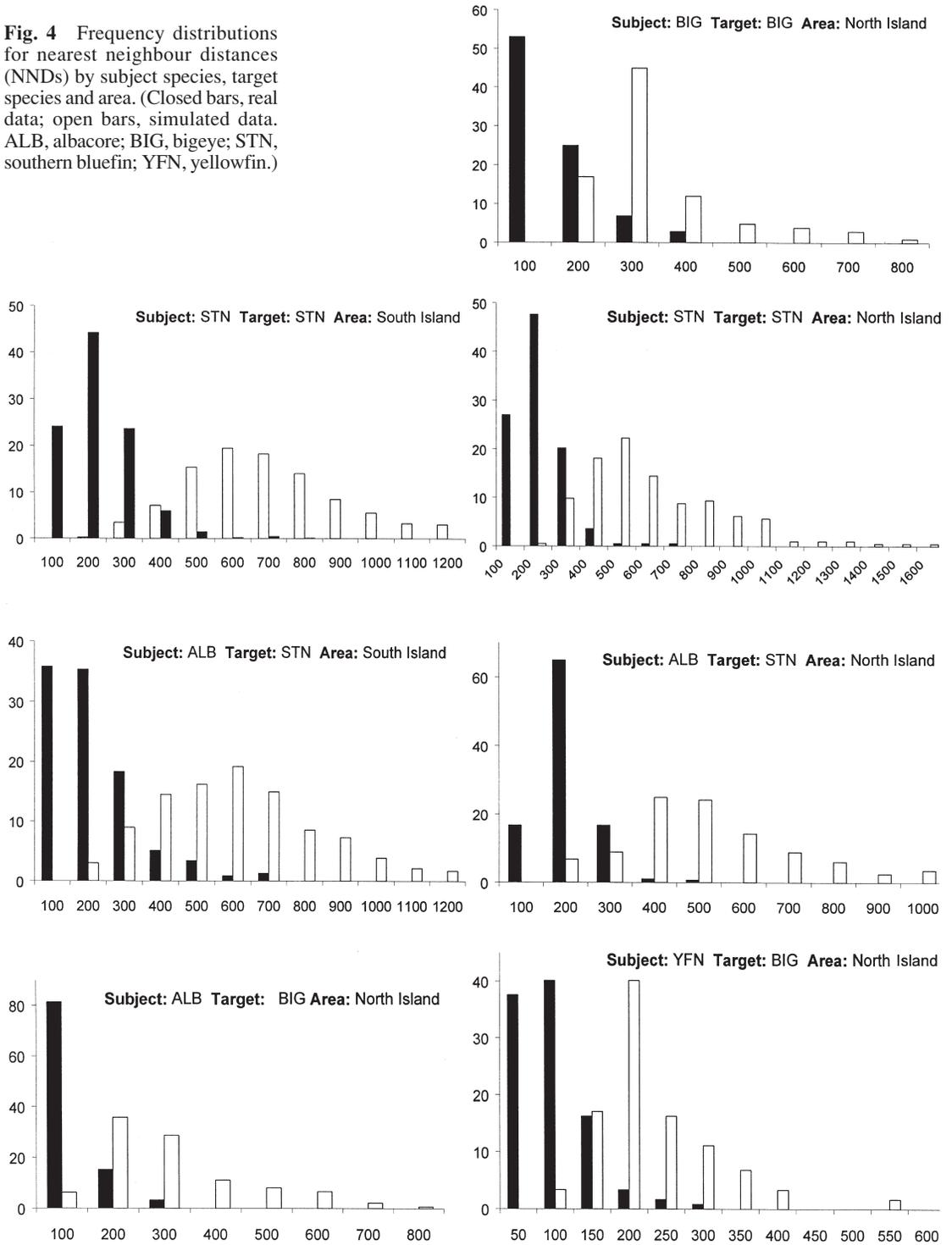
instances the NNDs are skewed to the shorter distances, mostly less than 200 m. If the subjects were distributed randomly along the set, as they are in the simulated data, the NNDs would be more variable and generally greater. The AI was calculated for each set and the mean AI for each fishery is listed in Table 1. The cumulative frequency distributions of AIs for all individual sets are presented in Fig. 5. Comparing the cumulative frequency distributions for the real AIs with those calculated from Monte Carlo simulations on the same set, we see that while the AIs for the simulated data are normally distributed about zero in all instances, the AIs for the real data are positively skewed relative to these, and are normally distributed about peaks at 0.4–0.7.

## DISCUSSION

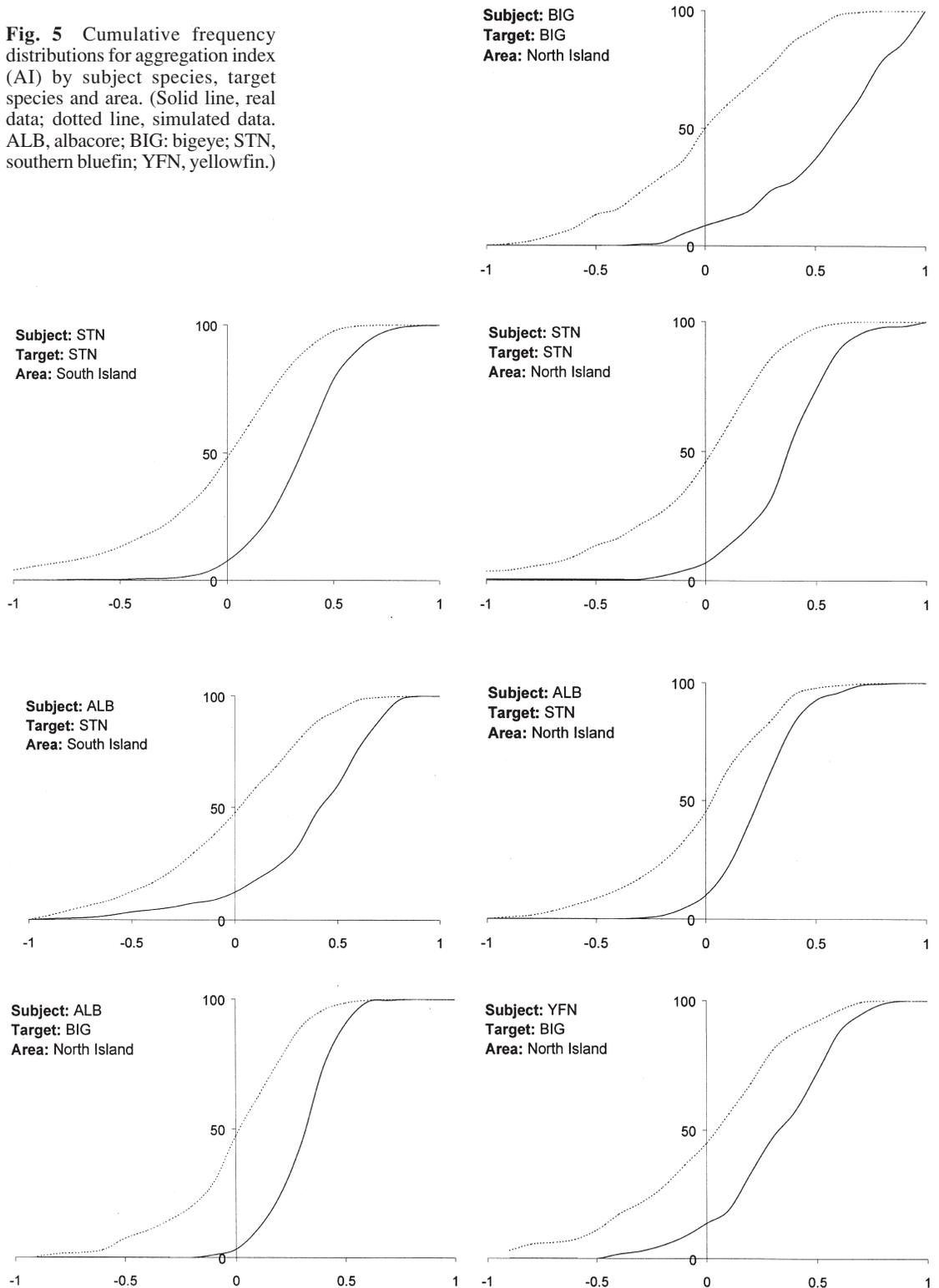
For spatial point processes (as opposed to distributed continuous variables, for which geostatistical methods might be more suitable—see Pelletier & Parma 1994) the Poisson process plays a role corresponding to that of the normal distribution within probability distributions (Cox et al. 2000). Here a heterogeneous Poisson process was used as a base against which to compare the spatial properties of longline catch data for tunas, to establish whether and at what scales clustering of fish along sets was apparent. The Poisson process was chosen because it is the most obvious way to generate stochastic point events within a limited 2-dimensional space, and variable expectations obtained from measured values of CPUE could be used to prevent the variability of CPUE among sets confounding the interpretation of results.

Nearest neighbour distances (NNDs) were calculated for real and simulated data and the resulting frequency distributions were compared. An aggregation index was defined that is identical to that of Clark & Evans (1954) (i.e., the ratio of mean NNDs for the real data to the expected mean NNDs for a random process) except for the scaling (–1 to 1) introduced here by subtracting the NND ratio from unity. In the real data, NNDs are much shorter than those predicted by a Poisson process with the same heterogeneity as nominal CPUE. The NNDs, being on such a small scale (100–200 m) are probably determined by individual behaviour in relation to conspecifics and may therefore be indicative of schooling. However, because of the fairly long soak time of longline sets and the high swimming speeds of tunas it is not possible to firmly establish that schooling is really the mechanism underlying

**Fig. 4** Frequency distributions for nearest neighbour distances (NNDs) by subject species, target species and area. (Closed bars, real data; open bars, simulated data. ALB, albacore; BIG, bigeye; STN, southern bluefin; YFN, yellowfin.)



**Fig. 5** Cumulative frequency distributions for aggregation index (AI) by subject species, target species and area. (Solid line, real data; dotted line, simulated data. ALB, albacore; BIG: bigeye; STN, southern bluefin; YFN, yellowfin.)



clustered NNDs; it is possible that even adjacent hooks were taken several hours apart, which would only imply aggregation, hence our use of the term "aggregation index". More exact information on the times that fish were hooked would resolve this potential error of interpretation. This information may be obtained by using a Time Depth Recorder (TDR) on each snood line. However, although deployment of TDRs is practicable for experimental fishing it is unlikely to be so for commercial operations. There is an obvious trade-off between data quality and sample size when comparing data from experimental and commercial fishing; in this study we have considered >4 million hooks and while the use of TDRs would undoubtedly have added to the information content of the data, the cost of deployment would have been prohibitive.

We should recall that NND analysis has only been carried out for sets where >1 subject was caught. The results must therefore be interpreted alongside the set-scale probabilities for catching 1 and >1 fish. With this in mind we might only consider tunas to be aggregated where both  $P(\text{fish} > 1)$  and  $P(\text{fish}_2 | \text{fish}_1) > 0.5$ , i.e. where there is more chance of catching >1 rather than just 1 fish and the presence of 1 fish implies an increased chance of catching another. These criteria are only met in the fisheries for STN off both the North and South Island and ALB and YFN off the North Island. We could conclude that YFN is less abundant and/or aggregated and that BIG caught off the North Island and ALB caught off the South Island are quite solitary.

The motivations for aggregations of individuals or schools (i.e., the environmental properties attractive to tuna) have not been determined in this study. Their interpretation in relation to the metrics derived here will not be straightforward. The aggregations may be a direct response to local prey concentrations, which in turn may be the result of local ocean dynamics and enrichment processes at scales less than 100 km, i.e., sub-mesoscale. But the distribution of tuna prey is itself patchy and is not likely to be phase-locked with production at lower trophic levels. Although tunas are more highly mobile than their prey they have to cross comparatively empty space in between prey encounters and would be more likely to take a baited hook during this time (Bertrand et al. 2002b). It is therefore possible that tunas are conducting non-trophic migrations through New Zealand waters and that proximate environmental conditions are to be endured whether or not they are especially favourable.

Data have only been considered in the horizontal dimension but longline fishing gear is targeted at tunas with different depth preferences. Longlines are set deeper for BIG, therefore they are shorter for the same gear/vessel that might previously have been fishing for STN. This analysis has been stratified by target species and area for this reason. Considering some hypothetical sources of error, clustering might be apparent along a fishing line that was only effectively targeting tuna habitat with e.g., the deepest hooks. The spacing of such clusters would be comparable to the distance between surface floats. Alternatively, hooks at intermediate depth might be most effective; in this instance there might be two clusters in between floats. The average distance between floats is c. 500 m. The NNDs are shorter than this and so neither pattern of effective effort (see Bigelow et al. 2002) is supported by the NNDs measured in the data. The behaviour of fish that have been caught might modify the potential for nearby hooks to catch fish; such a tendency would, however, make aggregations less, rather than more likely. Similarly, a school of fish might swim along the line and so catches might then appear to be randomly distributed. Such behaviour would indeed result in spatial patterns analagous to those produced by the Poisson process; AI would therefore be zero. The presence of caught species other than tuna would interfere with the data in that a hook that has already been taken by a shark, for example, would no longer be available to a tuna. However, although the majority of the total fish catch on a longline is bycatch, it is also true that the majority of hooks do not catch anything at all (Francis 1999). It is therefore unlikely that there is any systematic bias in the data due to bycatch. All possible errors of interpretation that we have considered would introduce a conservative bias to the data, i.e., fish would be more randomly distributed along the line rather than more aggregated.

Issues concerning spatial and temporal scale arise frequently in discussions on the behaviour and spatial dynamics of tunas (Hunter et al. 1986). Tagging studies often report either long-distance movements or fine-scale behaviour (Kirby 2001), but rarely investigate behaviour in relation to conspecifics. We struggle with how to use knowledge of physiology and behaviour to understand movement patterns and population dynamics. Modelling studies have tried to address the conditions under which school formation may occur, based on food intake requirements (Dagorn et al. 1995), swimming efficiency (Stocker 1999) and social interaction (Dagorn & Freon 1999) and

recent work illustrates how we can study the conditions favouring aggregation (Bertrand et al. 2002a,b). Further work could assess in more detail the factors motivating tuna behaviour and spatial dynamics in New Zealand waters. Specifically, the trophic dynamics of fishing grounds should be investigated (e.g., Roger 1994; Young et al. 1996a,b, 1997; Bertrand et al. 2002a,b) in relation to observations of surface oceanography (e.g., Uddstrom & Oien 1999; McClatchie et al. 2001). Experimental fishing, with simultaneous measurement of in situ physical and ecological variables (e.g., Bertrand et al. 2002a,b) would start to address cause and effect relationships determining the spatial distribution of tunas and therefore variability in CPUE. Concurrently, more comprehensive analysis of historical data sets should be undertaken to estimate fishing depths and effective effort in comparison with oceanographic data (e.g., Bigelow et al. 2002) and to explore the spatial patterns and interactions among subject, target, and bycatch species. It would be interesting to establish whether or not the schools/aggregations identified in this analysis are themselves aggregated at larger scales that are still smaller than the area sampled by the longline. By identifying the characteristic scales of these patterns it might be possible to distinguish between the two processes. This in turn is likely to enable better forecasting of fish distributions in relation to oceanographic variability.

## CONCLUSIONS

CPUE for tunas in surface longline fisheries in New Zealand waters is highly variable to the point of being statistically overdispersed. It varies greatly among fishing sets even after targeting of key species by experienced fishers. A partial explanation for this is that tunas are not randomly distributed but are very patchily distributed, forming schools/aggregations with nearest neighbour distances of c. 100 m, which may themselves be aggregated at scales that are yet to be determined.

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