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# TUNA SCHOOLS/AGGREGATIONS IN SURFACE LONGLINE DATA 1993-1998

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34 **ABSTRACT**

35           Exploratory data analysis of a high resolution (hook-by-hook), 6 yr time series (1993-  
36 1998) of observed longline catch data for tunas was used to investigate fine-scale spatial  
37 patterns along individual sets that may be indicative of social behaviour (i.e. schooling) and/or  
38 the response of individual fish to favourable extrinsic conditions (i.e. aggregation). Methods  
39 of spatial data analysis (i.e. nearest neighbour analysis) that have previously been applied in  
40 various other sciences (e.g. forestry & astronomy) were used. Results indicate strong  
41 clustering of individual tunas at characteristic scales within the set. Mean Nearest Neighbour  
42 Distances (NNDs) were between 100 to 200 m, compared with 200 to 700 m predicted by a  
43 heterogeneous Poisson process on the same spatial domain. The results suggest that these  
44 adult tunas were either schooling or aggregating at the time of capture; this may therefore be  
45 related either to social behaviour or to sub-mesoscale oceanographic features. An Aggregation  
46 Index was derived from the NNDs, giving a classification method that may be used for similar  
47 data and the development of empirical models attempting to relate patterns in fish catch  
48 distributions to environmental variables. The success of such models will ultimately depend  
49 on elucidating the ecological processes reflected in oceanographic patterns at biologically  
50 meaningful spatial scales.

51

51 **INTRODUCTION**

52 Tunas are not randomly distributed throughout New Zealand waters all year round.  
53 The largest scale at which this is apparent can be inferred from the areas where fishers have  
54 come to target their effort (Fig. 1). Sharp (1978) estimated that if yellowfin tuna *Thunnus*  
55 *albacares* in the eastern tropical Pacific were truly uniformly distributed there would only be  
56 one 10 kg fish per 2.8 km<sup>2</sup> of ocean: ‘they would be so rarely encountered as to be virtually  
57 non-existent.’ Some species of tuna are normally found in association with many other con-  
58 specific e.g. skipjack *Katsuwonus pelamis* (Bayliff 1988, Hilborn 1991), yellowfin (Klimley  
59 & Holloway 1999), and young albacore *Thunnus alalunga* (Laurs et al. 1984), while others  
60 are thought to be solitary, at least when not forming spawning aggregations (Winkler et al.  
61 1983) e.g. older albacore, bigeye *Thunnus obesus* and adult northern and southern bluefin  
62 (*Thunnus thynnus* and *Thunnus macoyii* respectively). The degree of association between con-  
63 specific is of great relevance to fisheries, as it will clearly determine gear type and/or the  
64 timing and location of effort. In New Zealand tuna fisheries, schools of skipjack and young  
65 albacore are targeted with seine nets and trolling gear respectively, while adult southern  
66 bluefin, bigeye and yellowfin are targeted by surface longlines.

67 Various terms are used in the behavioural ecology and fisheries literature to describe  
68 non-uniform or apparently non-random spatial patterns: schooling, shoaling, clustering,  
69 aggregating and congregating are all terms that have been deployed, often inter-changeably.  
70 These words may describe similar patterns but it is useful to let them have different meanings,  
71 in order to distinguish the different causes that can have the same effect. The spatial patterns  
72 observed in fish distributions and the degree of association among con-specifics are  
73 determined by a number of factors. Fish may come together in order to minimise predation  
74 risk or to maximise encounter rates with prey or potential mates (Pitcher & Parrish 1993).  
75 This bio-social attraction is best considered as schooling or shoaling. Individuals may also  
76 come together as a direct response to extrinsic environmental conditions. Such behaviour is

77 more generally termed aggregation. Individuals are considered to be acting independently of  
78 each other but responding in a similar way to some external factor or combination of factors,  
79 e.g. temperature, visibility, prey density etc. The ways in which marine predators respond to  
80 their environment are likely to be scale-dependent, and if variability in population density has  
81 a characteristic spatial scale, subsequent research to determine the conditions favouring  
82 aggregation can focus on this scale (Schneider 1994). The purpose of the analysis described in  
83 this paper was to investigate spatial patterns in longline catch data down to the finest scale  
84 possible. These patterns are likely to result from schooling and/or aggregation.

85         Where point events of interest occur completely at random within a sample space, this  
86 can be formally described as a Poisson process: the presence or absence of an event at a  
87 particular location is not influenced by any other event, and if the process is homogeneous, no  
88 part of the sample domain is any more likely to contain point events than another. A  
89 heterogeneous Poisson process allows for such variation, but the events themselves are still  
90 independent. Such processes provide a base against which to compare other processes where  
91 either clustering or inhibition of events are thought to occur (Cox et al. 2000). The approach  
92 taken to identify the characteristic scales of spatial patterns in these data was to measure the  
93 distances between individual fish in the observed catch data, and to compare the frequency  
94 distributions of these distances with the distributions that result from a heterogeneous Poisson  
95 process. If the fish are randomly distributed along the set, then the set scale (up to 150 km) is  
96 the finest scale at which they can be considered aggregated, and the targeting of research and  
97 fishing effort must focus on this or larger scales. But if they are aggregated *within* the scale of  
98 the set we must consider individual behaviour and the environmental heterogeneity that may  
99 exist at these scales and focus more detailed ecological and oceanographic investigations  
100 accordingly. It may then become possible to use such knowledge for monitoring and  
101 prediction in the fishery.

102



103 **DATA ANALYSIS**

104 **Observed longline catch data**

105 Under the New Zealand Ministry of Fisheries (MFish) Scientific Observer  
106 Programme, an observer is placed on board all visiting foreign licensed surface longline  
107 vessels and also a percentage of domestic licensed vessels. Vessels formally target large adult  
108 tunas of 2 species: Southern Bluefin (STN) and Bigeye (BIG). Albacore (ALB) and Yellowfin  
109 (YFN) are not formally targeted but are a significant and saleable bycatch. Surface longline  
110 fishing vessels follow a general pattern of operation over a 24 h period. Larger vessels set the  
111 fishing gear in the early hours of the morning to soak the baits during the hours preceding  
112 dawn. This operation usually requires 4 to 8 h and may be followed by 4 to 5 h of waiting  
113 before the gear is retrieved, although longer lines may be retrieved following a shorter waiting  
114 time. The catch is processed during the next 12 h. The whole operation is quicker for the  
115 smaller vessels of the domestic fleet. A large vessel will set up to 150 km of longline; smaller  
116 vessels set 40 to 80 km of line. From the longline, 2500 to 3500 snood lines are suspended,  
117 each with a single baited hook. For scientific observers, emphasis is placed on getting good  
118 information on catch, rather than on the setting operation. The main aspects of the setting  
119 operation are nevertheless recorded, including start and finish times and positions, the number  
120 of hooks, length of line set, vessel speed, line feeder speed, distance between marker buoys,  
121 number of baskets, and basic weather information. At the start and finish of the haul, and at  
122 hourly intervals throughout, time and position and basic weather information are recorded. As  
123 each specimen is landed on deck, the time is recorded and the specimen identified, weighed,  
124 measured and sexed.

125 All the data gathered by the observers is entered into the MFish database held at  
126 NIWA Wellington. For this study, fields of interest were extracted from the database and the

127 positions of individual fish were calculated as described below. ASCII files were generated  
128 detailing this information, and the spatial data analysis was then carried out.

- 129 1. An array representing all hooks is constructed with blank position and time details.
- 130 2. The first hook is assigned the start-of-haul position and time, and the last hook is  
131 assigned the end-of-haul position.
- 132 3. Times are calculated for every other hook, assuming a constant speed while hauling.
- 133 4. Hooks closest in time to the hourly haul records are flagged.
- 134 5. Between each hook flagged with an hourly haul position, the position of each  
135 intervening hook is interpolated by great circle path navigation, using the time  
136 assigned.
- 137 6. Each recorded specimen is placed on the hook closest to its recorded landing time; if  
138 that hook is already occupied, the specimen is placed on the nearest unoccupied hook.

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

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

150 There are many factors that can determine the likelihood of a particular hook catching  
151 a fish, including depth of the hook, bait type, and of course the timing and location of effort.



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

### 160 **Set-scale probabilities**

161 Fishing is as much a non-random method of sampling as the skipper can make it. For  
162 target species, the probability of catching at least 1 fish represents the extent of fishers' prior  
163 knowledge, i.e. how well they are targeting large (set scale) areas preferred by the fish. For all  
164 species, the probability of catching more than 1 subject, and the conditional probability of  
165 catching an additional subject having already caught a first, are preliminary measures of fish  
166 aggregation on the scale of the set. We implicitly assume that the skill of the skippers is equal.

### 167 **Generation of simulated data**

168 In order to compare the spatial patterns apparent in the real catch data with what might  
169 be expected from a heterogeneous Poisson process, simulated data were generated by Monte  
170 Carlo simulation. The CPUE for the subject species on that set was used to determine the  
171 probability of each hook catching a fish; this probability was then compared with a random  
172 number to determine whether or not that hook catches a fish. Nearest neighbour distances  
173 were then measured as for the real data (see next section). This was repeated 1000 times for  
174 each set. In the generation of simulated data the geometry of the set was preserved so that the  
175 permitted values of gap distances were the same as for the real data (Fig. 3). Also, the CPUE  
176 for each individual set was used in preference to the pooled mean for the fishery, bearing in

177 mind that ‘...what is considered to be a clustered pattern with the assumption of homogeneity  
178 in force [i.e. using the pooled mean] could also be the result of heterogeneity’ (Ripley 1981).  
179 This reduces our chances of believing that there is clustering at spatial scales smaller than the  
180 set length, when the effect is in fact caused by spatial variation in CPUE at spatial scales  
181 equal to or larger than the set lengths.

## 182 **Aggregation index**

183 For each longline set that caught more than 1 subject, the distances between each  
184 subject and all the other subjects were calculated by spherical trigonometry, i.e. calculating  
185 the Great Circle Path between the two locations. The Nearest Neighbour Distance (NND) is  
186 the distance from 1 subject to the nearest other and for each set there are as many NNDs as  
187 there are subjects caught. In order to permit identification and classification of sets possibly  
188 containing tuna schools and/or aggregations an ‘Aggregation Index’ (AI) was defined,  
189 following Clark & Evans (1954):  $AI = 1 - (\text{mean NND}/\text{mean RanNND})$ , where RanNND is  
190 the mean NND for the simulated data. AI values fall between -1 and 1, with positive values  
191 indicating schooling/aggregation, zero indicating a random distribution, and negative values  
192 indicating repulsion.

## 193 **RESULTS**

194 Frequency histograms of nominal CPUE for the data used in this analysis are  
195 presented in Fig. 2. For the BIG fishery, which takes place in the warm waters off the north-  
196 eastern region (Fig. 1), nominal CPUE was most frequently zero, with occasional catches up  
197 to 10 fish per 1000 hooks. For the STN fishery in northern waters, nominal CPUE was also  
198 most frequently low (<2), but in 10% of cases nominal CPUE was at least 10, and in a few  
199 cases was higher than 20. In southern waters, nominal CPUE for STN was rarely greater than  
200 10, but there were less cases of nominal CPUE being zero, and more cases where nominal  
201 CPUE was greater than 2. In southern waters, nominal CPUE for ALB was most frequently

202 zero and always low. In northern waters however, nominal CPUE for ALB was rarely zero  
203 and could be extremely high (>50) in both the STN and the BIG fisheries. Nominal CPUE for  
204 YFN was most frequently zero, but was often greater than 0 and less than 20.

205         The set-scale probabilities of catching the formal target species (i.e. STN or BIG) and  
206 other subject species (e.g. ALB & YFN) are given in Table 1. The proportion of sets that  
207 caught at least 1 [ $p(\text{fish} > 0)$ ] and more than 1 subject [ $p(\text{fish} > 1)$ ] are detailed, followed by  
208 the conditional probability of catching an additional subject having already caught a first  
209 [ $p(\text{fish}_2 | \text{fish}_1)$ ]. It is apparent in these data that fishers were quite effective at targeting STN  
210 [ $p(\text{STN}) \approx 80\text{--}90\%$ ] and that these were not usually found alone [ $p(\text{STN}_2 | \text{STN}_1) \approx 90\%$ ].  
211 When BIG were targeted, the probability of catching at least 1 target was much lower [ $p(\text{BIG})$   
212  $\approx 60\%$ ] and there was only a 50% chance of catching another BIG on the same set. The  
213 probability of catching at least 1 YFN was the same as for the formal target species BIG  
214 [ $p(\text{YFN}) \approx p(\text{BIG}) \approx 60\%$ ], but it was more likely that more than 1 YFN would be caught on  
215 the same set [ $p(\text{YFN}_2 | \text{YFN}_1) \approx 70\%$ ]. ALB were apparently ubiquitous in both the BIG and  
216 STN fisheries off the North Island [ $p(\text{ALB}) \approx 100\%$ ;  $p(\text{ALB}_2 | \text{ALB}_1) \approx 100\%$ ]. This  
217 provides fishers with their basic income, which is then supplemented by less frequent but  
218 more lucrative catches of the target species (T. Murray pers. comm.). ALB were caught less  
219 frequently in the longline fisheries off the South Island [ $p(\text{ALB}) \approx 40\%$ ], where they were  
220 often caught on their own [ $p(\text{ALB}_2 | \text{ALB}_1) = 50\%$ ]. There are separate fisheries for younger  
221 albacore in surface waters that are able to target discrete schools using trolling gear.

222         For each species, NND calculations were carried out for sets that caught more than 1  
223 subject; the mean number of fish per set in this subsample is listed. The NNDs are generally  
224 around 100 m, which is the same order of magnitude but 25–50% shorter than the NNDs  
225 resulting from the Poisson process (RanNND). The frequency distributions for the real and  
226 simulated data are presented in Fig. 4. In all cases the NNDs are skewed to the shorter  
227 distances, mostly less than 200 m. If the subjects were distributed randomly along the set, as

228 they are in the simulated data, the NNDs would be more variable and generally greater. The  
229 AI was calculated for each set and the mean AI for each fishery is listed in Table 1. The  
230 cumulative frequency distributions of AIs for all individual sets are presented in Fig. 5.  
231 Comparing the cumulative frequency distributions for the real AIs with those calculated from  
232 Monte Carlo simulations on the same set we see that while the AIs for the simulated data are  
233 normally distributed about zero in all cases, the AIs for the real data are positively skewed  
234 relative to these, and are normally distributed about peaks at 0.4 to 0.7.

## 235 **DISCUSSION**

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

246 Nearest neighbour distances (NNDs) were calculated for real and simulated data and  
247 the resulting frequency distributions were compared. An Aggregation Index (AI) was defined  
248 that is identical to that of Clark & Evans (1954) (i.e. the ratio of mean NNDs for the real data  
249 to the expected mean NNDs for a random process) except for the scaling (–1 to 1) introduced  
250 here by subtracting the NND ratio from unity. In the real data, NNDs are much shorter than  
251 those predicted by a Poisson process with the same heterogeneity as nominal CPUE. The  
252 NNDs, being on such a small scale (100 to 200 m) are probably determined by individual  
253 behaviour in relation to con-specifics and may therefore be indicative of schooling. However,

254 due to the fairly long soak time of longline sets and the high swimming speeds of tunas it is  
255 not possible to firmly establish that schooling is really the mechanism underlying clustered  
256 NNDs; it is possible that even adjacent hooks were taken several hours apart, which would  
257 only imply aggregation, hence our use of the term ‘Aggregation Index’. More exact  
258 information on the times that fish were hooked would resolve this potential error of  
259 interpretation. This information may be obtained by using a Time Depth Recorder (TDR) on  
260 each snood line. However, while deployment of TDRs is practicable for experimental fishing  
261 it is unlikely to be so for commercial operations. There is an obvious trade-off between data  
262 quality and sample size when comparing data from experimental and commercial fishing; in  
263 this study we have considered >4 million hooks and while the use of TDRs would  
264 undoubtedly have added to the information content of the data, the cost of deployment would  
265 have been prohibitive.

266 We should recall that NND analysis has only been carried out for sets where >1  
267 subject was caught. The results must therefore be interpreted alongside the set-scale  
268 probabilities for catching 1 and >1 fish. With this in mind we might only consider tunas to be  
269 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  
270 catching >1 rather than just 1 fish and the presence of 1 fish implies an increased chance of  
271 catching another. These criteria are only met in the fisheries for STN off both the North and  
272 South Island and ALB and YFN off the North Island. We could conclude that YFN is less  
273 abundant and/or aggregated and that BIG caught off the North Island and the ALB caught off  
274 the South Island are quite solitary.

275 The motivations for aggregations of individuals or schools (i.e. the environmental  
276 properties attractive to tuna) have not been determined in this study. Their interpretation in  
277 relations to the metrics derived here will not be straightforward. The aggregations may be a  
278 direct response to local prey concentrations, which in turn may be the result of local ocean  
279 dynamics and enrichment processes at scales less than 100 km, i.e. sub-mesoscale. But the

280 distribution of tuna prey is itself patchy and is not likely to be phase-locked with production at  
281 lower trophic levels. While tunas are more highly mobile than their prey they have to cross  
282 comparatively empty space in between prey encounters and would be more likely to take a  
283 baited hook during this time (Bertrand et al. 2002b). It is therefore possible that tunas are  
284 conducting non-trophic migrations through New Zealand waters and that proximate  
285 environmental conditions are to be endured whether or not they especially favourable.

286         Data have only been considered in the horizontal dimension, while longline fishing  
287 gear is targeted at tunas with different depth preferences. Longlines are set deeper for BIG,  
288 therefore they are shorter for the same gear/vessel that might previously have been fishing for  
289 STN. This analysis has been stratified by target species and area for this reason. Considering  
290 some hypothetical sources of error, clustering might be apparent along a fishing line that was  
291 only effectively targeting tuna habitat with e.g. the deepest hooks. The spacing of such  
292 clusters would be comparable to the distance between surface floats. Alternatively, hooks at  
293 intermediate depth might be most effective; in this case there might be 2 clusters in  
294 between floats. The average distance between floats is ca. 500 m. The NNDs are shorter than  
295 this and so neither pattern of effective effort (see Bigelow et al. 2002) is supported by the  
296 NNDs measured in the data. The behaviour of fish that have been caught might modify the  
297 potential for nearby hooks to catch fish; such a tendency would, however, make aggregations  
298 less, rather than more likely. Similarly, a school of fish might swim along the line and so  
299 catches might then appear to be randomly distributed. Such behaviour would indeed result in  
300 spatial patterns analagous to those produced by the Poisson process; AI would therefore be  
301 zero. The presence of caught species other than tuna would interfere with the data in that a  
302 hook that has already been taken by a shark, for example, would no longer be available to a  
303 tuna. However, while it is the case that the majority of the total fish catch on a longline is  
304 bycatch, it is also true that the majority of hooks do not catch anything at all (Francis 1999).  
305 It is therefore unlikely that there is any systematic bias in the data due to bycatch. In fact all

306 the possible errors of interpretation that we have considered would introduce a conservative  
307 bias to the data, i.e. fish would be more randomly distributed along the line rather than more  
308 aggregated.

309         Issues concerning spatial and temporal scale arise frequently in discussions on the  
310 behaviour and spatial dynamics of tunas (Hunter et al. 1986). Tagging studies often report  
311 either long-distance movements or fine-scale behaviour (Kirby 2001), but rarely investigate  
312 behaviour in relation to con-specifics. We struggle with how to use knowledge of physiology  
313 and behaviour in order to understand movement patterns and population dynamics. Modelling  
314 studies have tried to address the conditions under which school formation may occur, based  
315 on food intake requirements (Dagorn et al. 1995), swimming efficiency (Stocker 1999) and  
316 social interaction (Dagorn & Freon 1999) and recent work illustrates how we can study the  
317 conditions favouring aggregation (Bertrand et al. 2002a,b). Further work could assess in more  
318 detail the factors motivating tuna behaviour and spatial dynamics in New Zealand waters.  
319 Specifically, the trophic dynamics of fishing grounds should be investigated (e.g. Roger 1994,  
320 Young et al. 1996a, 1996b, 1997, Bertrand et al. 2002a,b) in relation to observations of  
321 surface oceanography (e.g. Uddstrom & Oien 1999, McClatchie et al. 2001). Experimental  
322 fishing, with simultaneous measurement of in situ physical and ecological variables (e.g.  
323 Bertrand et al. 2002a,b) would start to address cause and effect relationships determining the  
324 spatial distribution of tunas and therefore variability in CPUE. Concurrently, more  
325 comprehensive analysis of historical datasets should be undertaken to estimate fishing depths  
326 and effective effort in comparison with oceanographic data (e.g. Bigelow et al. 2002) and to  
327 explore the spatial patterns and interactions among subject, target and bycatch species. It  
328 would be interesting to establish whether or not the schools/aggregations identified in this  
329 analysis are themselves aggregated at larger scales that are still smaller than the area sampled  
330 by the longline. By identifying the characteristic scales of these patterns it might be possible

331 to distinguish between the two processes. This in turn is likely to enable better forecasting of  
332 fish distributions in relation to oceanographic variability.

### 333 **CONCLUSIONS**

334 CPUE for tunas in surface longline fisheries in New Zealand waters is highly variable  
335 to the point of being statistically overdispersed. It varies greatly among fishing sets even after  
336 targeting of key species by experienced fishers. A partial explanation for this is that tunas are  
337 not randomly distributed throughout the EEZ but are very patchily distributed, forming  
338 schools/aggregations with length scales of  $O(100\text{ m})$  which may themselves be aggregated at  
339 scales that are yet to be determined.

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348



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414 **Figure and Table Legends**

415 Fig. 1 Locations of observed surface longline sets in New Zealand waters 1993 to 1998,  
416 targeting (a) southern bluefin STN and (b) bigeye BIG

417 Fig. 2 Frequency distributions of nominal CPUE (catch per 1000 hooks) for observed surface  
418 longline sets in New Zealand waters 1993–8, by Subject Species, Target Species and Area.

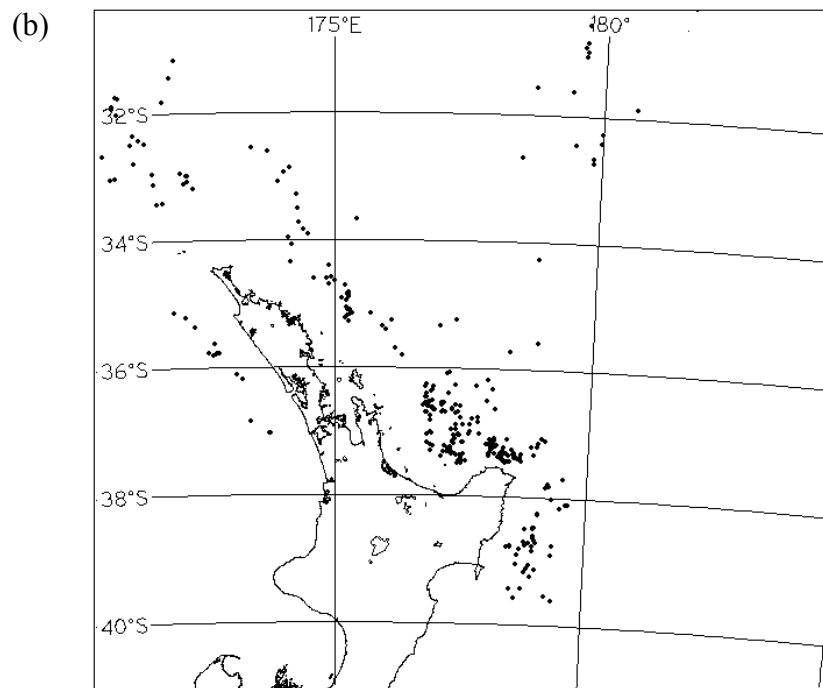
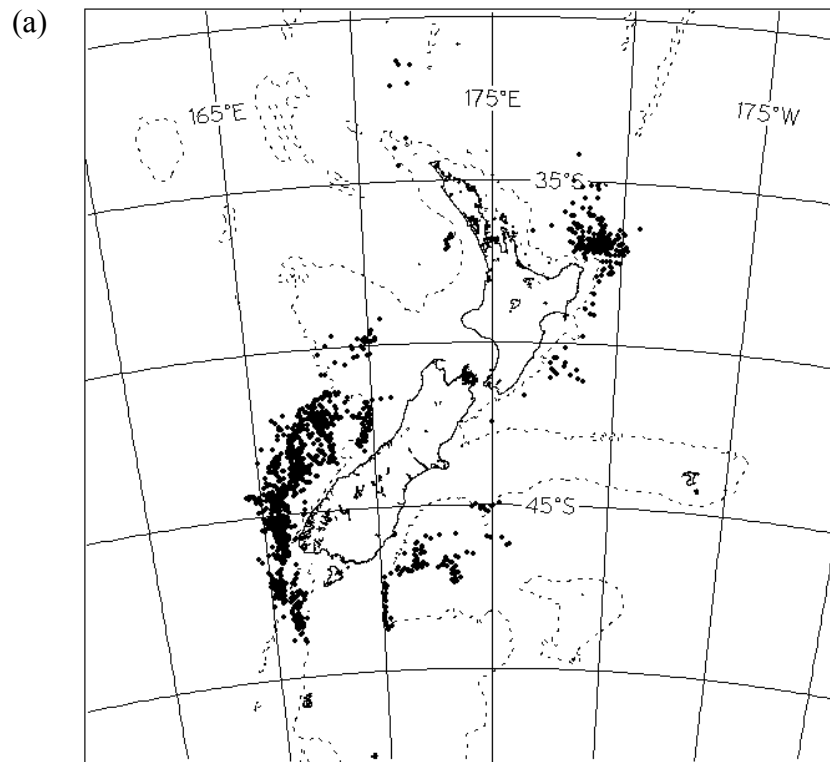
419 Fig. 3 Schematic representation of the calculation of distances between fish. The line  
420 represents the set, stars represent the locations of fish, and small arrows represent the  
421 distances measured between them. On the left, representing an actual set, 4 fish are clustered.  
422 On the right, representing the results of 3 Monte Carlo simulations, the geometry of the set is  
423 preserved and the actual CPUE for that set is used to obtain a similar number of subjects  
424 distributed at random along the line. Nearest Neighbour Distances (NNDs) (small arrows) are  
425 then measured.

426 Fig. 4 Frequency distributions for Nearest Neighbour Distances (NNDs) by Subject species,  
427 Target species and Area.

428 Fig. 5 Cumulative frequency distributions for Aggregation Index (AI) by Subject Species,  
429 Target Species and Area.

430 Table 1. For each fishery (defined by subject species, target species and area) we have listed  
431 the total number of sets analysed, the set-scale probabilities for catching at least 1 subject, the  
432 number of sets that caught at least 1 subject, the set-scale probabilities for catching >1 subject  
433 and the conditional probability of catching a second subject having caught a first, the number  
434 of sets that caught >1 subject (i.e. the subset used for spatial analysis) and the mean number  
435 of subjects caught on this subset. We then present their mean Nearest Neighbour Distances  
436 (NND), the mean NNDs for the heterogeneous Poisson process (RanNND) and the mean  
437 Aggregation Index (AI). ‘Mean set length’ is the mean GCP distance between start and end of  
438 set, a conservative estimate of line length

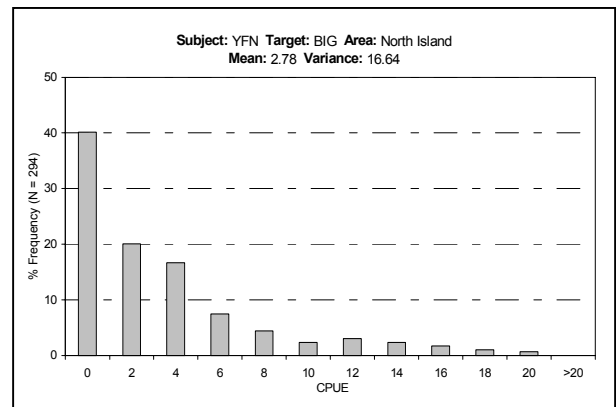
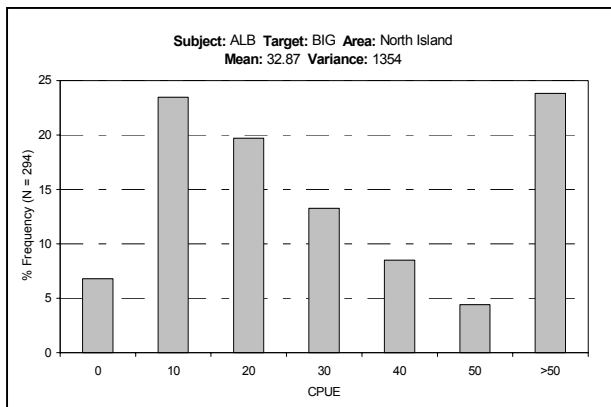
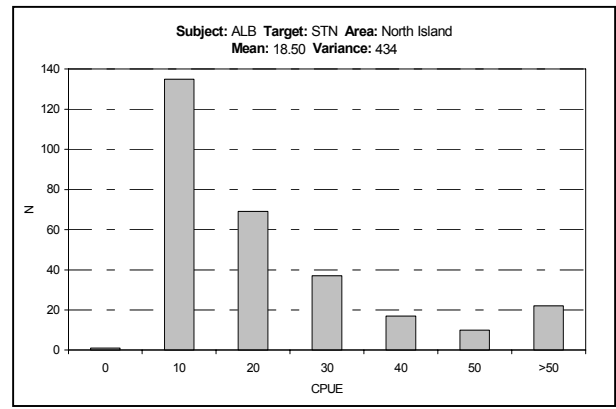
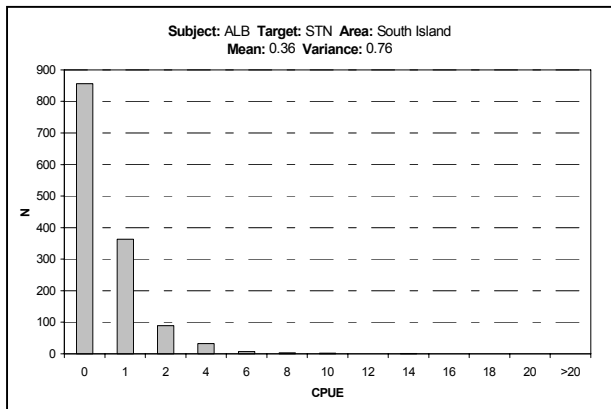
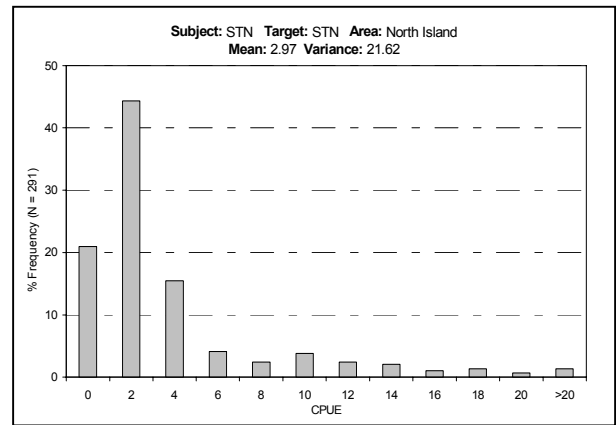
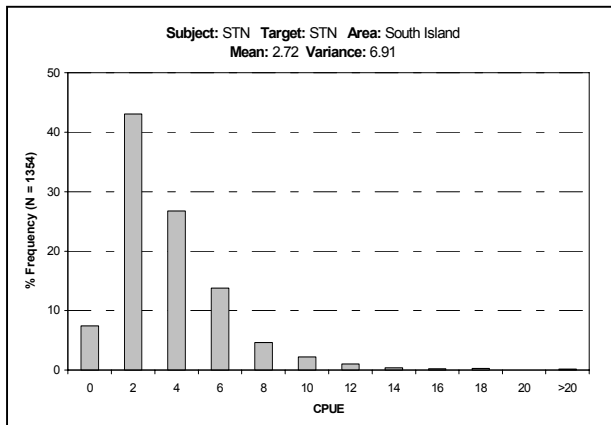
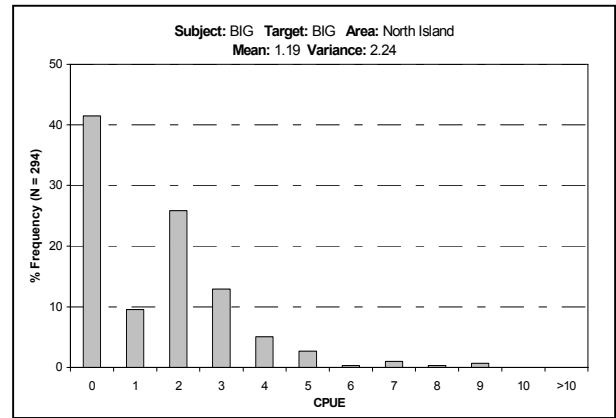
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440 Fig. 2

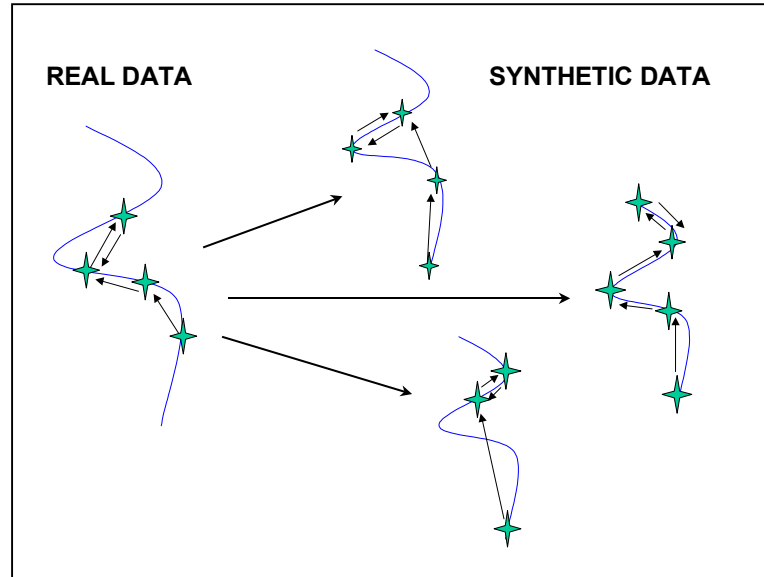
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443 Fig. 3



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445 Fig. 4

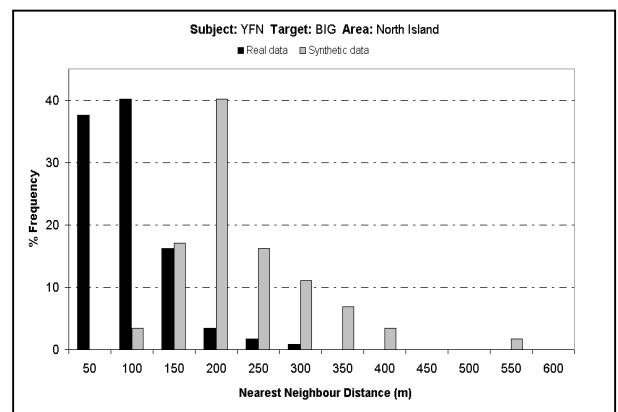
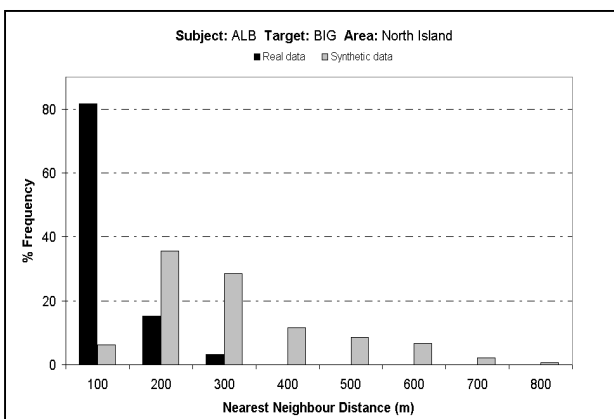
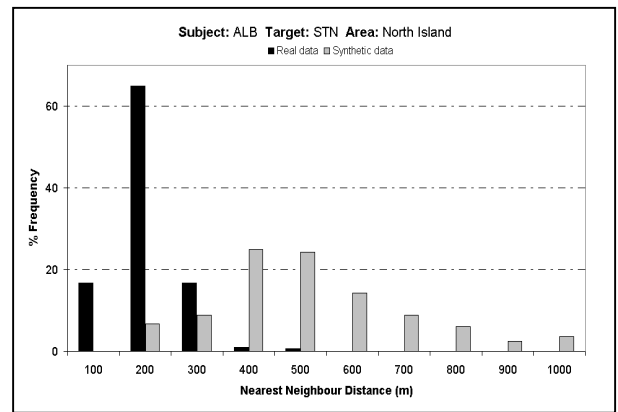
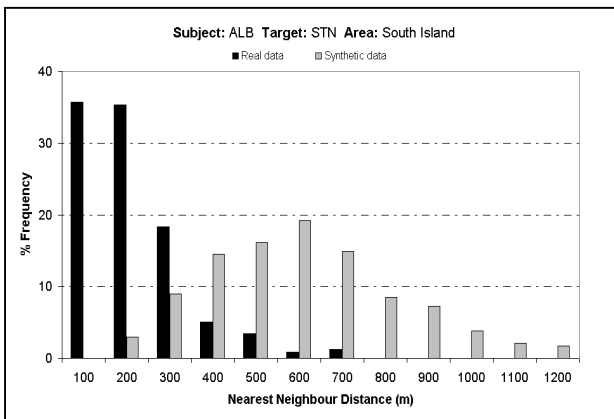
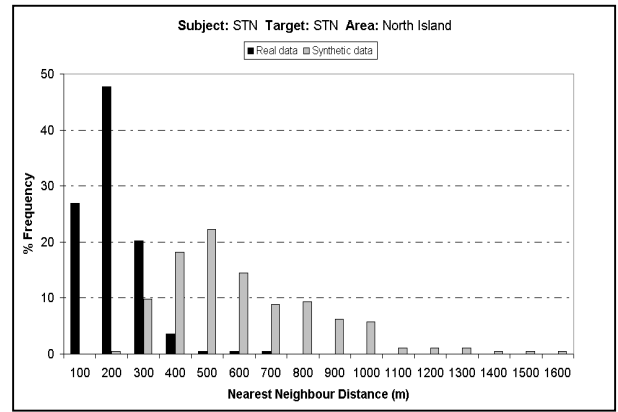
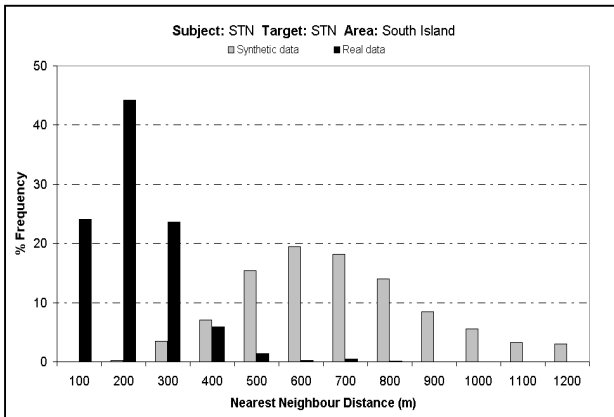
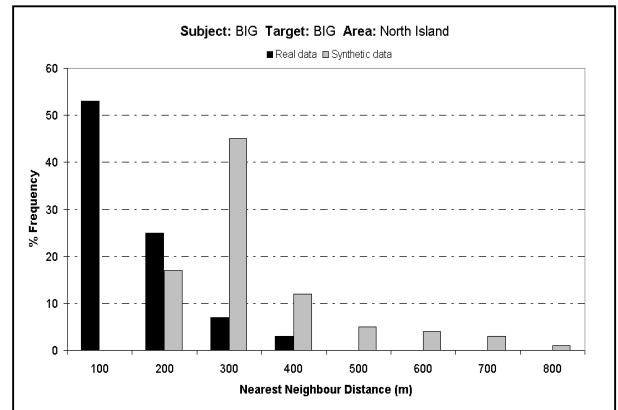
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456 Fig. 5

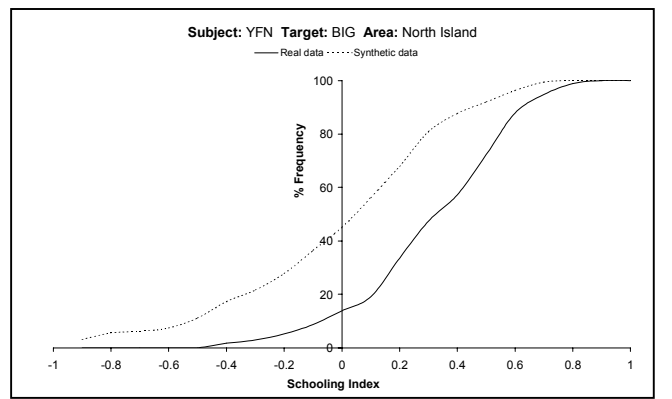
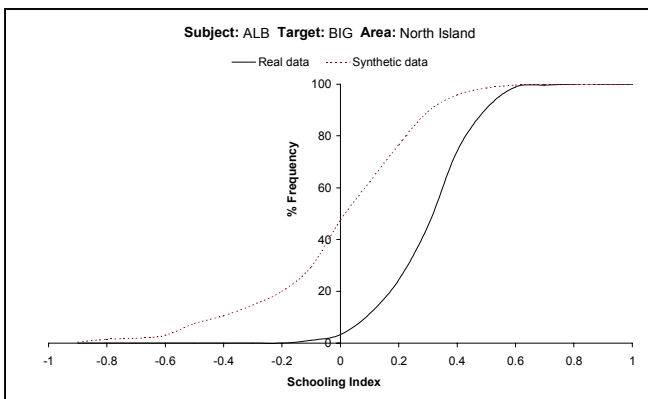
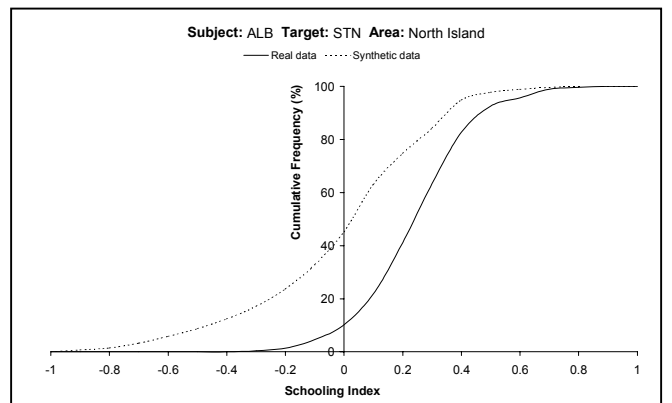
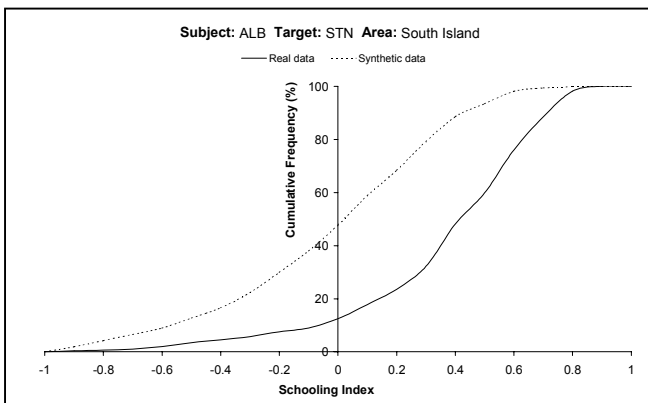
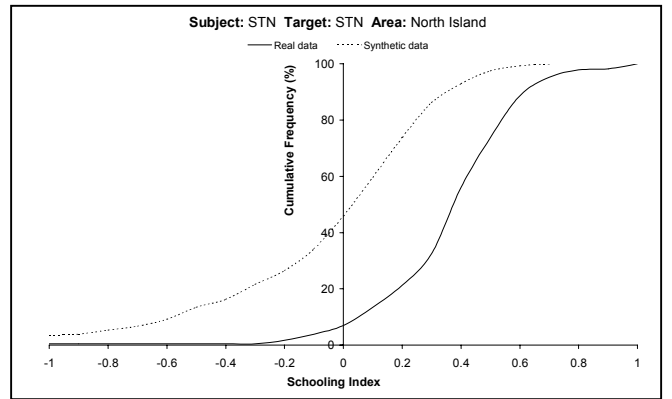
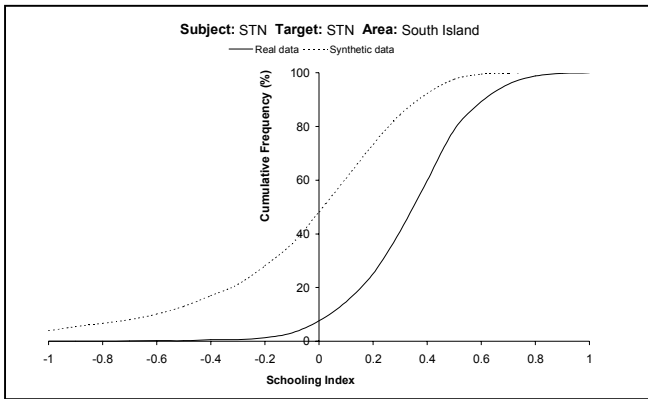
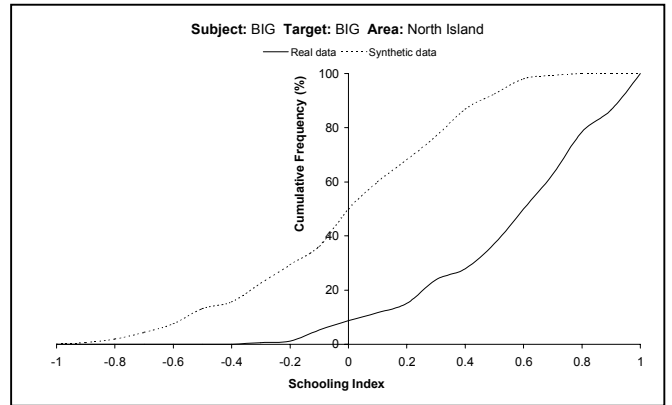
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Table 1

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

