INTERACTION BETWEEN LONGLINE AND PURSE SEINE IN THE SOUTH-WEST PACIFIC TUNA FISHERY

by

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Thesis submitted for the degree of Doctor of Philosophy and Diploma of Imperial College in the Faculty of Science of the University of London.

November 1989

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ABSTRACT

While longline effort has remained relatively constant, there has been a marked increase in purse seine effort in the south-west Pacific from 1979 to 1986. Purse seine catches skipjack and young yellowfin, whereas longline takes older yellowfin and a variety of other large tuna and billfish. The aim of this study was to quantify the impact of purse seine on longline.

Standard linear models of purse seine catch per unit effort were found to detect no decline in stock abundance. A theory was then developed to predict the effect of purse seine on the spatial structure of the stock and the dynamics of stock movements.

A detailed model of longline catch rates is presented linking catches to school size and density, and bait loss. The model failed to fully explain observed catches suggesting that the tuna spatial distribution is more complex.

Deterministic models suggest that there will be some interaction. Generalised linear models are used to detect a significant decline in longline catch rates with increasing purse seine activity, after removing other effects recorded in the data set. However there is no direct evidence that it is due to purse seine activities.

If a simple age structure is assumed and purse seine and longline are exploiting the same homogeneous stock, the problem can be approached using optimal control theory. In such a system with fixed gear selectivity and realistic parameter values it is found that the most efficient gear should be allocated sole access to the resource.

The economic implications of the results are discussed from the point of view of both the vessels and the management of the fishery. The interim recommendation is to maintain a mixed gear fishery using the two separate markets. Finally recommendations are made as to the collection and analysis of data.

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Acknowledgements

I would like to thank my supervisor, John Beddington, for his support, which was particularly appreciated during the last phase. I am also grateful to all other members of RRAG with whom I have discussed my project over the years, particularly Dave Gibson, Simon Northridge and Mark Bravington.

I would also like to thank Mr Muller and everyone at the Forum Fisheries Agency, without whom this study could never have been carried out. I hope it proves useful to them.

Thanks are also due to the inhabitants of Eardley, Winston and Fullbrook for moral support, as well as to my parents who haven't seen me much recently. Finally thank you to Gudrun Gaudian, who has been very important in the production of this work and to whom it is dedicated.

Chapter 1

Introduction

1.0 Introduction

This research aimed to discover the degree to which purse seine affects the catch rate of longline. Purse seine tends to select young yellowfin, longline older yellowfin (Cole, 1980), therefore there is a possibility that purse seiners will reduce the size of the stock available to longline.

The thesis falls into four related topics. Chapters two and three look at detailed models of purse seine and longline respectively, seeing how catch rates might relate to fish density. Chapter four assesses the impact of purse seine on longline catch rates up to the beginning of 1986. The fifth chapter builds models describing optimal harvesting of a fishery with a single stock and age structure. The final chapter discusses these results in the context of the south Pacific fishery and suggests some action that might be taken to improve management.

Tuna fishing, like other fisheries, introduces many diverse subjects ranging from biology, fishing techniques, macro and micro economics and politics. Any piece of research cannot cover all these subjects in depth, but if hoping that the results be applied, neither should they be completely ignored. The purpose of this first chapter is to describe the fishery in its entirety, working from what is known about tuna biology through to some political problems in the region. This discussion aims to give a brief overview only, since there are already many detailed reviews. These should be consulted for a more extensive discussion of the areas mentioned below.

1.1 Species and Biology

There are a number of tuna and billfish taken in the region, which are given with their full taxonomic names in table 1.1.

Several detailed synopses on the biology of the main tuna species have been written, such as, Matsumoto et al (1984) for skipjack, Cole (1980) for yellowfin, Bayliff (1980) for eight scombrid species, including yellowfin, bluefin, bigeye and albacore, Shomura and Williams (1975) for the billfish. This section aims to concentrate on tuna, particularly yellowfin, and those aspects that are important to the fisheries. More specific aspects of tuna biology are developed where they needed in other chapters.

Katsuwonus pelamis	(Linnaeus 1758)	Skipjack
Thunnus albacares	(Bonnaterre 1788)	Yellowfin
Thunnus obesus	(Lowe 1839)	Bigeye
Thunnus alalunga	(Bonnaterre 1788)	Albacore
Thunnus maccoyii	(Castelnau 1872)	Southern bluefin
Thunnus thynnus	(Linnaeus 1758)	Northern bluefin
Billfish		
Xiphias gladius	Linnaeus 1758	Swordfish
Makaira nigricans	Lacepede 1802	Blue marlin
Makaira indica	(Cuvier 1831)	Black marlin
Tetrapterus audax	(Philippi 1887)	Striped marlin
Istiophorus platypterus	Shaw and Nodder 1791	Sailfish

Table 1.1 Tuna billfish species taken in the South Pacific region. Bluefin are taken very rarely, and it is uncertain to which species they belong, however both species are included for completeness. Skipjack is mainly taken by purse seine and pole and line, yellowfin by purse seine and longline and all the remaining species are exploited almost exclusively by longline.

1.1.1 Age Structure and Growth

Little work has been done directly on age structure due to difficulties in ageing tuna. However many sample size frequencies have been assembled from different areas, although they do not appear to show any simple patterns (Matsumoto et al, 1984). Complications arise because different gears show different selectivities in relation to size, and size structure varies from area to area.

Yellowfin and skipjack larvae have been found over a wide area of the tropical Pacific. It has also been found that mature yellowfin appear to be more abundant in warmer waters (Lenarz and Zweifel, 1978). The distribution of juveniles extends beyond that of the larvae, corresponding with increased activity and mobility.

A number of growth models with parameter estimates have been presented in the literature, the most recent for yellowfin in the (eastern) Pacific by Wild (1986). Wild chose growth curves from a number of possible models on the basis of best fit between age and a variety of size data. In this work the von Bertanlanffy curve is used exclusively, mainly because of its simplicity in theoretical analysis, its previous wide application and its close approximation to the general growth pattern. For more exact descriptions of growth, other equations suggested by Wild (1986) might be preferable.

1.1.2 Distribution and Migratory Behaviour

The tuna and billfish discussed here are tropical pelagic species. The exception is bluefin tuna which is found predominantly in cooler temperate climes and only occurs rarely in catches of the island states' waters. The horizontal distributions appear to be mostly determined by surface temperature, which tends to be correlated with salinity, currents, and hydrographical features such as upwelling, fronts, convergences and eddies.

The vertical distribution of tuna species appears to be much more mixed than originally thought. Yabe et al (1963) assumed from longline data that tunas are distributed by depth layers in the following order : skipjack (shallowest), bluefin, yellowfin, bigeye and albacore (deepest). Observations by various sources (see Hunter et al, 1986) have shown that all these species have a much more flexible vertical distribution. There appears to be a common diurnal pattern. During the day tuna exhibit dramatic and frequent vertical excursions into deep water (often greater than 400m) from a modal depth of around 200m. The depth of such excursions depends upon the species and vertical temperature structure. During the night they have a much shallower modal depth and fewer vertical excursions. Skipjack seem to have a shallow modal depth, and dive into deep water, while bigeye has a much deeper modal depth (about 250m; Holland et al, 1985), but ascends for short periods up to 50m. The reason for these dives or ascents are unknown, but it has been suggested that it might be a form of hunting behaviour or alternatively for thermoregulation. Observations suggest that fish swim in deeper water when travelling between locations and are able to accurately orientate themselves to specific features such as fish aggregation devices (FAD), banks or seamounts.

Although it is clear that all species are capable of moving quickly over great distances, it is not clear whether this is part of a migration pattern or simply random for most species (SPC, 1980a). There have been no tests of the obvious null hypothesis that such movements are due to non-directional diffusion, subject to the current system.

1.1.3 Schooling

There appears to be some confusion over what constitutes a school. Schools have been described in the literature as any group of tuna, even of mixed species. Literature dealing specifically with schooling behaviour (eg Partridge, 1982) has a much more rigorous definition, based on orientation of fish with respect to each other. To avoid this confusion a cohesive group of fish is referred to henceforth as a school. A group of schools which may assemble under a floating object is defined as an aggregation. This difference is important when modelling tuna movements, since it can be assumed that movements between aggregations occur in the form of schools.

Schooling in tuna may serve a number of purposes. Partridge et al (1983) described possible benefits, including increased hydrodynamic efficiency, reducing the chance of being discovered by predators and reducing risk after detection through anti-predator tactics. The last two will be most useful to juvenile tuna which are vulnerable to a greater number of predators, including larger tuna. Tuna is also a predator, and the advantages of schooling to a predator have been less well researched. However predators may increase their search area and capture rate by co-operative hunting.

Partridge et al (1983) discusses a series of slides of schooling bluefin. The most surprising result is the degree of co-ordination that these fish seem to be capable of. Hydrodynamic gains, increases in collective search area and co-operative hunting are all possible reasons for schooling. So why schools might form is clear, but why they aggregate is not.

There are two types of aggregation defined in the log sheet. Those associated with a large object and those free swimming.

Table 1.2 gives the different types of aggregation that might be found.

Feeding schools will obviously attract others, but it is unknown why floating objects attract schools, although there are many theories, including a food source, for navigational reasons, to find mates and to reform schools and optimise their size. Any one or all these might be true.

Types of free swimming aggregations with and without birds :		
Black spot	:	moving around below the surface
Rippler	:	moving at the surface
Splasher	:	breaking the surface
Aggregations associated with :		
Drifting object	:	single log or accumulated flotsam
Sharks		
Whales		
FAD	:	fixed raft (Fish Aggregation Device)

Table 1.2 Types of school located by purse seine and pole and line vessels.

1.2 Politics and Economics Fishery

There are a number of detailed reviews of the fishery, in particular Doulman (1987) contains papers by a variety of authors on the politics and socio-economics of the fishery. Political aspects appear to be playing a dominant role at present, and have tended to overshadow other factors, such as depletion of the stock, the main subject of this study. It is important to put some of the results from this study into context, to allow a realistic discussion of their use.

1.2.1 History of the Fishery

Before the second world war most fishing by nations was limited to their own inshore and offshore waters. In the case of the Pacific islands this was entirely local artisanal fishing. In the 1940's the second world war caused a decline in the Japanese fishing fleet, which had up to that point been expanding. After the war food shortages in Japan forced the adoption of a policy of fisheries expansion beyond its own waters. In 1952 fishing vessels were released from restrictions imposed as a result of the war, and by 1966, led by a strong market demand for tuna, vessels were fishing in all the major grounds of the world.

The only domestic industry operating in the 1940's was that in Hawaii by United States (US) companies. The gears used were pole and line, fishing for skipjack and juvenile yellowfin, and longline catching albacore. All these fish were canned for the US market. In the 1950s Japanese longliners were based in American Samoa, Fiji and Vanuatu to fish for albacore, which was in high demand in the United States as the best quality canned fish. Operations continued to expand in the 1960's with other fleets based in French Polynesia, Papua New Guinea and the Solomons by US canning companies, predominantly using pole and line vessels. At that time the demand for the high quality raw fish (sashimi) in Japan could not be met by distant water vessels due to the inadequate freezing technology.

In the late 1960's conditions changed. Costs were increasing with declining catch rates and the demand for canned tuna was weakening in the US. At the same time freezers improved to the point where they were able to maintain fish to a high enough quality to supply the sashimi market. This caused a switch in operations of longliners, which needed no longer to be based in foreign ports since they had to supply the market in Japan.

Further economic changes in the 1970's resulted in a different composition of the Japanese fleet. Rising costs of fuel, labour, vessel and gear construction coupled with declining catch rates as exploitation reduced stock sizes and other countries extended their jurisdiction, required rationalisation of the tuna fleet. Meanwhile demand for tuna in Japan began to stabilise at about 17% of the diet as other foods became more available. Therefore the number of distant water vessels were reduced by 20% and purse seiners were encouraged. Table 1.3 shows this change over the period 1970-1984. However the market still suffers as supply to the tuna market of all but a few specialist sashimi species continues to increase, depressing the price.

Number of Vessels		Year	
Unrestricted distant water	1970	1980	1984
pole and line	222	228	138
longline	997	943	762
Restricted offshore			
pole and line	497	343	276
longline	1092	757	633
Purse seine Pacific region			
single	3	13	32
group	0	4	7

Table 1.3 This shows the decline in the number of Japanese tuna vessels. The decline is more marked in the pole and line fleet, as operators switch to more efficient purse seiners. Longline and pole and line vessels less than 120 GRT are restricted in their fishing areas (from Fujinami, 1987).

Meanwhile purse seining developed rapidly during the 1970's in the US, supplying the continual high demand for canned tuna. Initially during the 1960's seiners were supplied from converted pole and line vessels, but were replaced subsequently by larger vessels of the super-seiner class. This increase in efficiency could not wholly be supported by the east Pacific fishery, for which the closing date was moved back further each year to protect the yellowfin stock. The earliest alternative fishing areas were found in the Atlantic.

Serious exploration of the western Pacific did not begin until 1971-2 when the US National Marine Fisheries Service (NMFS) financed a trip by a purse seiner to the Marquesas Islands. The proportion of successful sets was very small, resulting in the conclusion that the net being used needed modification in line with Japanese nets presently being used in the area to cope with the deeper thermocline and clearer water. Fishing for skipjack began in New Zealand waters, and several exploratory trips were made to Papua New Guinea during the 1970's. However expansion did not begin into the area until 1980 when a two year regional agreement was signed between the American Tunaboat Association (ATA) and the maritime authorities for Palau, Micronesia and the Marshall Islands allowing access to these areas. The number of purse seiners operating in the western Pacific from both Japan and the US has increased sharply up to 1986. This expansion of purse seine operations into the south-west Pacific has caused many political problems which are described in the next section.

1.2.2 Regional Economics

The region as a whole is strongly dependent on tuna production, alternative sources of income being scarce. Primary industries are limited due to the small size of many of the islands. Minerals, coconut oil, palm oil, sugar and timber are the other major exports where countries are able to develop these industries, as in Papua New Guinea and Fiji. Common to all the countries are exploitable oceanic resources, the most valuable of these being tuna, which commands a high price on the export market. Economic rent is generated either from licence fee payments (in Kiribati these account for 25% of the government's annual expenditure) or exported processed tuna. Processed tuna accounted for 90% of the value of American Samoa exports, 30-40% of Solomon Islands' exports and about 30% of Vanuatu's exports in 1986 (Doulman, 1987).

Processed tuna takes two forms. Katsuobushi (smoke dried skipjack) is popular in Japan as a stock base for soups. It can be produced where there is enough timber for smoking, and at present two plants are operating, in the Solomon Islands and in the Marshall Islands (Doulman and Kearney, 1986). Although total capacity of these plants is limited to about 9 tonnes of wet fish, the method is labour intensive, employing 100 persons in both plants. The capital investment is comparatively small ($200000 for the Marshall Islands plant in 1984) and the product stores well, making it particularly attractive for processing on many islands. Long term financial viability of these 'stand alone' plants is doubtful (Doulman and Kearney, 1986), probably requiring production on a larger scale with a sustained supply of both skipjack and wood to increase efficiency.

The alternative method is canning which processes fish on a much larger scale and for a much wider market. There are 5 canning factories in operation in the Pacific islands. In 1986, American Samoa had an annual capacity of 155000 tonnes of fish (74% of the total capacity of all factories), Fiji 15000 tonnes (7%), Hawaii 35000 tonnes (17%) and Solomon Islands 5000 tonnes (2%). Doulman and Kearney (1986) give a detailed account of these canneries and their history. The canneries are supplied by pole and liners, purse seiners (for yellowfin and skipjack) and longliners (for albacore), either under contract to the canning companies or owned by them.

The main market for canned tuna is the US, consuming 52% of the world supply. Therefore the price prevailing in the US dominates the world market. Although the market is likely to remain good, canning on the US mainland has been drastically curtailed due to efficient competition from Asian canneries (Waugh, 1987a). This has allowed the market to be penetrated by overseas canneries, particularly from South-East Asia. However the risks involved in processing are great as was demonstrated by the market slump in the early 1980's.

Both the Japanese and European markets for canned tuna are more exotic, including cans of cooked meat with various additives such as soy sauce and vegetables. Japan is increasing in both its consumption and production of canned tuna, and is a net exporter of tuna to outside canneries. Consumption in Europe is on the increase, supply being satisfied mostly from Thailand. The United Kingdom is the only country importing from the South Pacific.

Fresh tuna in the form of sashimi is almost wholly exported to Japan. Since the product is raw, no processing is required, but the market is highly quality conscious (Kitson and L'Hostis, 1983). This limits the fishing method to longline which allows the fishermen to handle the fish with great care. Although the prices are higher in this market, the catch rate for longline is much lower, so that the costs of fishing per unit of resource are also relatively high.

With the exception of bluefin tuna, prices of all tuna have dropped; 18.5% for bigeye and 34% for yellowfin (Waugh, 1987c). In general, lower quality fish has an inelastic demand, making the product more vulnerable to over-supply.

1.2.3 Future Economic Policy

The future economic policy for the region is the subject of some debate. Because there is a high opportunity cost for capital, which is in short supply, there is a strong discouragement for investment in fisheries. The alternative to building up domestic fleets is to collect fees paid by distant water fishing vessels. As it has turned out, both sources of income are fraught with problems (see Waugh, 1988).

There is a strong sense of nationality in the region, supporting development of a national fishing industry. The supposed economic gains from this development, such as increasing employment, foreign exchange and the value added of the product, are undermined by importing the capital necessary for the industry. Coupled with high risks of the industry, the potential gains can be quite small while the potential losses may be large.

Selling fishing rights to foreign nations would appear to be a safer option, but the reality has proved this to be more difficult than expected. The US governments refusal to recognise jurisdiction together with a general unwillingness to pay what the Forum Fisheries Agency considers to be reasonable fees, has slowed the fisheries development. The island states lack the resources to enforce their claims.

1.2.4 The South Pacific Commission and Forum Fisheries Agency

There are two important international organisations covering the region. The South Pacific Commission (SPC) provides technical advice and training in various social and economic fields, health, agriculture, education and resource management (SPC, 1984). There are 27 members of the South Pacific Conference, including colonial states, which govern the commission, and 22 island states, shown in figure 1.1, in which the Commission's programmes are carried out.

An important part of the Commission's work is to assess the stock of tuna and billfish within the island states' waters. This gave rise to the Tuna and Billfish Programme which has carried out a number of tasks, in particular estimating the

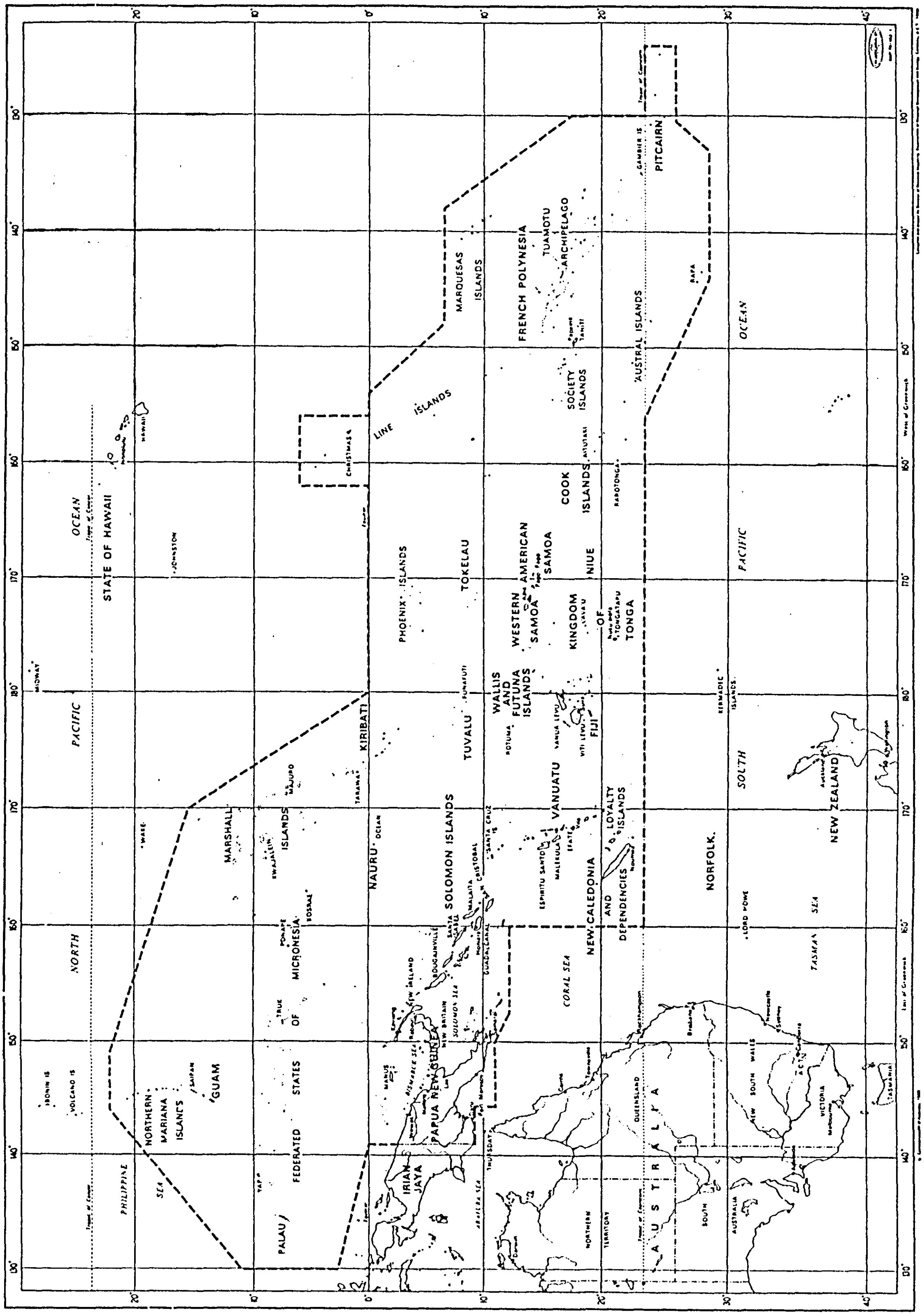


Figure 1.1 Area served by South Pacific Commission delineated by broken line.

resources of baitfish (for pole and line), skipjack and yellowfin. The largest of the projects was a tagging study of skipjack caught by pole and line vessels (SPC, 1981b).

The SPC does not provide a platform for the discussion and resolution of political problems mainly due to the involvement of the colonial powers such as the United States and France, which are a source of many of these problems. Therefore the South Pacific Forum was set up by the independent states to deal with issues outside the jurisdiction of the Commission. The Forum has proved particularly important in the development of islands' tuna resources. In 1979 a convention established the Forum Fisheries Agency (FFA), which has had a key role in fisheries management (Gubon, 1987). Whereas the SPC has concentrated on assessment and the biological problems of fisheries management, the FFA has been involved in the more immediate problems of guaranteeing some economic gain from the resource through advising on fee negotiations with distant water fishing fleets, joint ventures and the expected return on investments in the fishing industry. Therefore the two organisations successfully complement each other.

1.2.5 Law of the Sea

The Law of the Sea as it relates to tuna fishing in the South Pacific region is described by Slayter (1987). The United Nations Convention Law of the Sea (UNCLOS) contains the international law governing the behaviour of nations in the oceans. It has been endorsed by the South Pacific Forum, so that fisheries management policies, if implemented in accordance with UNCLOS and incorporated in national laws, cannot be undermined by the fishing activities of foreign fleets.

The law as it relates to tuna falls into four parts. Firstly those sections of UNCLOS relating to fish resources within territorial seas, internal waters and archipelagic waters of countries, giving exploitation rights which are universally accepted. Secondly sections of UNCLOS related to the 200 mile exclusive economic zone (EEZ) around each nation. This falls within the scope of the FFA convention and the Nauru Agreement, which are agreements between nations on co-operation in exploiting their oceanic resources. Thirdly sections describing the duties of fishing nations exploiting the high seas. Finally, since tuna are capable of moving great distances, and appear to do so frequently (Hunter et al, 1986), UNCLOS defines duties for international co-operation of management.

Of these only the EEZ principle has been seriously disputed. The dispute has arisen ostensibly through the US government's interpretation of parts of UNCLOS as it relates to highly migratory species, which include tuna. The US tuna policy is described by Dyke and Nicol (1987) and this particular dispute by Tsamenyi (1986) and more recently Waugh (1988). The US legal argument rested upon the interpretation of the law related to international co-operation of highly migratory species taking precedence over that related to exclusive economic zones. Therefore the US government would not recognise any management regime to which they had not been made a party. This has led to conflict between the South Pacific island states and the US government through the infringement of the islands' sovereign rights for the purpose of exploiting the tuna resources within their 200 mile EEZ's.

The legal arguments and access negotiations fall well beyond the subject of this present work. However it is worth noting that the management of the fisheries in this region is highly political. This stems largely from the poverty of the island states and subsequently their inability to physically support their claims to sole rights over the resource, coupled with the presence of highly developed nations showing an interest in the region, both for exploitation and to further political aims. This is demonstrated by the reaction of the US to Kiribati offering a licence agreement to the USSR in 1985. The US government was anxious to prevent Soviet influence in the region, so this agreement greatly encouraged the US to negotiate successfully a multilateral treaty with the Forum Fisheries countries (Dyke and Nicol, 1987). These problems have yet to be resolved, mainly due to a lack of co-ordination between the US policy in deriving an agreement between itself and the South Pacific Forum and the fishing activities of the US tuna vessels (Waugh, 1988).

Such political considerations are particularly important since they may override any recommendations from research on stock management. The resource may not only have a simple value based upon its exploitation, but may also be influenced by other factors, such as strategic importance. Hence tied aid, technical support and development projects as well as fees may be offered as part payment for fishing rights.

1.3 The Data Set

The main data set used in these analyses was kindly supplied by the Forum Fisheries Agency. The data consist of log sheet records filled in by fishing vessels operating in the region as part of their agreement of access. These sheets are held by the fisheries offices of the island states, which pass them to the SPC. As part of the arrangement for distributing information these are supplied to the FFA on computer tape. The data consist of two types of record, a header record giving static information on attributes of the vessel (such as its call sign and size) and set records describing single sets of either a purse seine net or longline hooks. There is one header record for a number of associated set records. Table 1.4 gives a list of fields in each type of record for both gears.

The other major gear type present in the region, pole and line, does not appear in this analysis. This is largely due to a lack of time. However many of the results for purse seine can be adapted and extended to pole and line.

The data analysed represents a subset (approximately 2/3) of the total data held by the SPC. Due to difficulties in communication between the SPC and FFA, it was not possible to receive the whole data set. More data were rejected because they were replicates or a critical piece of information (eg date) was missing or unreasonable. The remaining data consisted of 37767 set records for purse seine and 209478 set records for longline. Further records were rejected in each analysis if the required fields were not present or consistent. For instance, in the case of surface water temperature no records were complete for purse seine and only a small minority for longline. It is assumed there is no bias in any of these rejections.

Vessel name
Vessel nationality
Name of captain
Permit number
Vessel registration number
Call sign
Gross registered tonnage
Port of departure
Date of departure
Port of return
Date of return
Number of crew
Bait code (longline only) (up to 2 recorded)

Table 1.4 a Header record for both longline and purse seine

Date	year, month day
Latitude Longitude	degrees and minutes

Number of baskets
Number of hooks
Distance between floats
Length of float line
Length of branch line
Species caught : number of fish and their average weight

Albacore	Black Marlin
Bigeye	Broadbill Swordfish
Yellowfin	Sailfish
Bluefin*	Sharks
Striped Marlin	Other species*
Blue Marlin	

Tuna discards*
Other discards*
Comment
Water temperature

Table 1.4 b Longline set record

Date	year, month day
Latitude Longitude	degrees and minutes
Aggregate type	indicates log etc (see table 1.2)
Time of day	hours and minutes
Skipjack catch Yellowfin catch Other species*	{ total weight in tonnes { average weight of single fish in kilos
Comment	indicates whether day is spent searching or in some other activity
Tuna discards*	
Other discards*	
FAD identification number*	
Surface water temperature*	

Table 1.4 c Purse seine set record

Table 1.4 a-c The fields for the different types of record are shown. A different header record is given for each log sheet, and a separate set record for each set of purse seine net or longline hooks. Fields marked with an asterisk (*) were either not filled in, or so rarely filled in on the log sheets that they were not use in any analysis.

1.4 Previous Work on Fisheries with Two Gears

There are few studies dealing with two gears harvesting the same stock at different ages. Lenarz and Zweifel (1978) look at the problem which is the subject of this work, the interaction between longline and surface fisheries. They found yield per recruit higher for longline and the sex ratio potentially important in estimating the impact of one gear on another. Data on the sex of fish were not available for this work. Finally they pointed out that the spatial distribution of recruits could be used to control gear selectivity.

A more practical approach was carried out by the SPC (1985) to measure the impact of the newly developed purse seine fishery. None was found and it was concluded that purse seiners have little effect on the longline catch rates. However only three years data was available at that time, and no theory was worked out to see how this effect might be expected to appear in the data.

Beddington and Clark (1983) assess the bioeconomic interactions between herring and sprat (young herring) fisheries in the North Sea by estimating the opportunity cost for the sprat fishery. The implication of their analysis was to limit fishing of low-value young herring by any possible means. The analysis was based on simple continuous age structure models.

There have also been a number of theoretical treatments of harvesting age structured populations (see Williams, 1989), although they have tended to concentrate on aspects of recruitment and uncertainty in fisheries and forestry management. The most relevant, Charles and Reed (1985), looks at the problem of optimising harvest allocation between inshore and offshore fisheries, where the offshore fishery takes only adults, the inshore both new recruits and spawners. The analysis is somewhat complicated by recruitment, and only deals with two homogeneous stocks with no explicit age structure. The optimal harvesting policy rests on controlling escapement from each fishery. No fully dynamic model criteria is obtained, but instead the authors find solutions to the open access situation, identifying parameter space where the inshore or offshore fishery coexist or one gear excludes the other.

In order to see how the south-west Pacific tuna fishery should be managed, it is necessary to look in detail at the relation between the longline and purse seine catch rates and the stock size. This will allow management to base decisions on changes in catch rates with greater confidence and allow a more refined estimate of any impact on longliner catch rates caused by the activities of purse seiners. There is also a need to develop a bioeconomic theory based on stock age structure and gear selectivity which can be used to assess and compare the economic efficiencies of different combinations of gears all fishing the same stock.

Chapter 2

Purse Seine Catch per Unit Effort

Introduction - continued

By way of comparison, a linear model of purse seine catch rate developed by Allen and Punsly (1984) is fitted to the data set. Improvements to this model are made by breaking the catch rate down into its component parts of search time, proportion of successful sets and catch per set. This allows a better understanding of the basic assumptions inherent in using the catch rate to monitor changes in abundance of fish.

Splitting up the catch rate also allows models with a sounder theoretical base to be formed. In the case of the search rate this is a Poisson model, and for the proportion of successful sets, a binomial model. These models bring out patterns in the data more clearly, although they do not necessarily help with their interpretation.

A more complex model is required to describe catch per set and how it might change under exploitation. This is only partially developed in this chapter due to the lack of knowledge about tuna behaviour. The catch in a purse seine set depends upon the number and size of schools caught. Models are developed separately for number of schools in an aggregation and school size, looking at how they might change under exploitation both in the long and short term. The importance of short term effects is examined by considering how catch rates change in small areas heavily exploited over a few months. This analysis is used to suggest the factors which might be most important in governing the catch per set.

2.0 Introduction

Before proceeding to look at the interaction between purse seine and longline, it is necessary to consider how the purse seine catch per unit effort (CPUE) relates to the stock size. Longline will provide an alternative estimate of yellowfin abundance, although this will be limited to older fish. For skipjack, detection of changes in abundance will depend entirely upon purse seine data. A study of purse seine fishing effort should also help elucidate the impact this gear is having on the stock.

Purse seine poses a particular problem to the interpretation of its catch data. Fishermen actively look for and capture schools of fish, so their behaviour plays an important part in determining the catch rate. It is possible that management controls of this method may be vulnerable to improvements in technology and skill of the fishermen, which can greatly increase the rate at which fish are located and caught.

This chapter starts by using standard methods, comparable to other works, to tackle these questions. Then more detailed theoretical models of the tuna stock are developed and linked to the data set using generalised linear models.

2.1 Description of Purse Seine Fishing Method

Although purse seining has only recently come into widespread use, it is now one of the most important gears. It is well suited to catching highly aggregated species, notably tuna, anchovies and herring as well as other surface schooling pelagic fish. The method falls naturally into two parts : searching and making a set.

Fishermen searching for tuna will have some idea of the location of fish from previous knowledge. The main fishing grounds for skipjack and yellowfin stretch from 20^{o} north to 20^{o} south of the equator. Within this region the tuna will gather to patches where their prey is of highest density. These prey themselves are ultimately dependent upon plankton, which will be distributed according to the currents in the region.

The trade winds drive the three main surface oceanic currents in the region (see Pickard and Emery, 1982), the North Equatorial (20^{o}-8^{o}N) and the South Equatorial (3^{o}N-10^{o}S) currents flowing west and the North Equatorial Counter (8^{o}-3^{o}N) current flowing east. Together they produce the major permanent divergences (net vertical movement of water is up) and convergences (net vertical movement of water is down). A fourth current, the Equatorial Undercurrent, flows beneath the equator and is of less direct importance for purse seine. Divergences occur between the North Equatorial and North Equatorial Counter currents (8^{o}N) and where the South Equatorial Current and Equatorial Undercurrent straddle the Equator (0^{o}). A convergence occurs between the South Equatorial and North Equatorial Counter currents. Although the currents change in their exact direction, location and force seasonally and under different weather conditions, they are predictable enough to considerably reduce the search area.

Both convergences and divergences may form plankton aggregations. Divergences bring deeper water rich in nutrients to the surface thus increasing phytoplankton productivity. Convergences may physically aggregate plankton resistant to sinking and eddies between currents can trap considerable amounts of plankton (Parsons, Takahashi and Hargrave, 1984). All these areas may be important forage areas for tuna (Murphy and Shomura, 1972; Owen, 1981).

Searching for tuna has become more efficient with the advent of new technology. In particular satellites are able to estimate surface temperatures of the whole ocean as fronts (convergences) and eddies in the open ocean are usually marked by steep temperature gradients (Owen, 1981). Since large areas can be scanned in a very short time, remote sensing allows both temporary and more permanent oceanographic features to be exploited.

Land masses also play an important part in that shallower waters on continental shelves are generally more productive for a variety of reasons. The sea bottom topography forms fronts and eddies which will aggregate fauna (Murphy and Shomura, 1972) and coastal upwelling increases productivity where it occurs at the eastern boundaries of oceans. In the western Pacific there are no major upwellings, but tidal currents and river outflows may still be a source of nutrients and increase vertical mixing.

To illustrate the limited extent of the purse seine fishing grounds figure 2.1 shows the distribution of a sample of sets for 1984. By far the greatest number of sets recorded in the data set were made within 10^{o}N-10^{o}S and 135^{o}E-160^{o}E. However there is a trend expanding the fishing area south east towards the Solomon Islands, although most fishing continues off the coast of Papua New Guinea. There appear to be two groups of sets, one lying on the boundary between the North Equatorial and North Equatorial Counter currents at 5^{o}N which is a convergence, and another larger group spreading east and south along the Papua New Guinea coast. Both groups of sets lie in shallower water where the sea floor topography probably plays a major role in determining water movement. However the oceanic currents may still be important and many of the sets lie close to the equator, the site of the South Equatorial Current and the equatorial convergence.

The effective search area may be greatly increased by co-operation, although this will only be important when a patch is large enough to be exploited by two or more vessels. Formation of vessels into co-operative (code) groups should also decrease interference between vessels and reduce the cost of explorative search. Not surprisingly there is very little known about the amount of information passed within and between these code groups.

There are various signs that fishermen use to detect tuna. Surface schools may be located either by the disturbance of the water surface by tuna or their prey at short range or by direct sight of schools below the surface. A more important sign of a surface school are sea birds that flock to take tuna prey driven to the surface, making it possible to see feeding tuna up to five miles away (MAFF, 1966). It is even possible to obtain information about schools (eg size or whether they are feeding) from the bird behaviour (Nakamura, 1969). In the eastern Pacific porpoises and dolphins are also used as a sign, since they are frequently associated with yellowfin in this area.

Although such feeding schools form a significant proportion of sets in the western Pacific, by far the greatest number of sets are on logs and floating debris under which tuna tend to aggregate. Table 2.1 shows numbers of sets recorded broken down by aggregate type. As can be seen, sets of other types on sharks, whales and fish aggregation devices (FAD) form only a

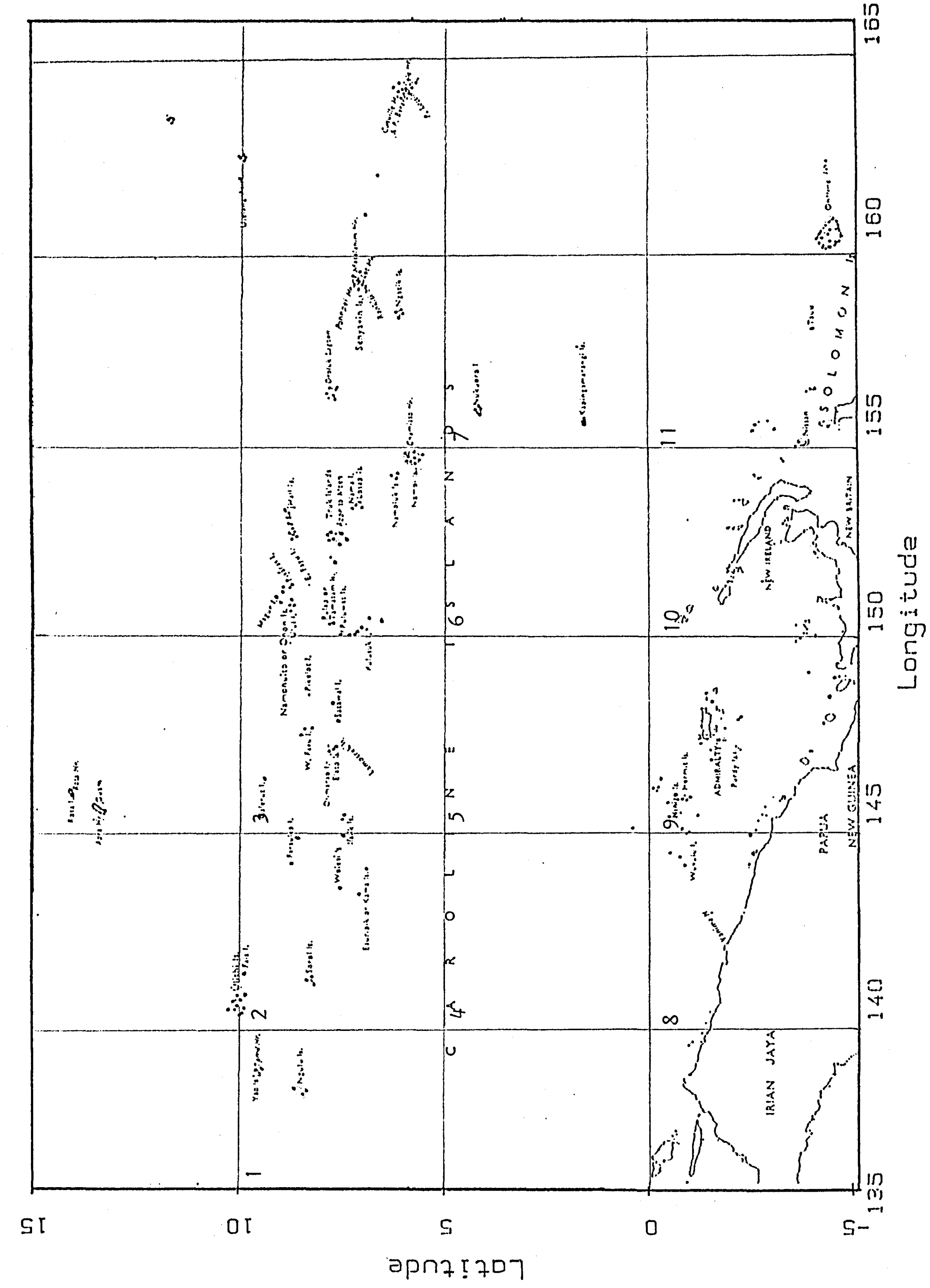


Figure 2 .1 A sample distribution of purse seine sets from 1984. (+ aggregation associated with floating objects, □ other aggregations). Digits in the squares relate to the linear model (see text).

small proportion of the total number of sets. Logs and flotsam are located directly by sight and the numbers of associated fish checked using echo-sounders. This may be the main reason why most of the sets in figure 2.1 are made near land masses, for these will provide logs and other floating objects. It may also explain the group of sets on the convergence between the North Equatorial and the North Equatorial Counter currents, since flotsam will tend to gather at convergences. An area with few sets may not mean there are fewer fish, but may simply indicate the absence of logs and other floating debris.

Aggregate Type	GRT			
	< 400	400 < < 500	500 <	Totals
Log	1108	12131	2456	15695
Flotsam	479	1698	559	2736
Whale	57	528	35	620
Shark	4	103	3	110
Black Spot	153	1331	107	1591
Splasher	300	2443	336	3079
Rippler	21	553	50	624
Payao (FAD)	0	382	13	395
Other	44	81	10	135
Totals	2166	19250	3569	24985

Table 2.1 Total number of sets broken down by set type and size class. The payao (FAD) sets were almost all made by Philippine vessels.

The area searched per unit time can be further enlarged by using a helicopter which moves faster and allows a greater field of vision because of its height above the sea. In all cases sets are only made if the fishing master feels the catch will be of the right size, for sets take time and cost money in terms of wear and tear on gear. Very small catches will obviously be ignored, but very large catches may also be avoided if they create technical problems in hauling and processing. The main problem is small fish getting caught in the mesh, which can take a considerable time to clear. It is possible to estimate the average size of the fish using echo-sounders, allowing aggregations to be rejected before the set is made. Once a suitable log is found the vessel usually waits until the following morning before making a set. Vessels may also mark logs with radio beacons so that they may be found again and deploy logs (FADs) they carry with them (SPC, 1985).

Brandt (1984) and Nomura and Yamazaki (1975) provide descriptions of the gear and making a set. One end of the net is attached to a skiff (usually motorised) and the net is laid to encircle the fish as quickly as possible. Once the vessel meets the skiff again the net is pursed by hauling in a wire that runs through rings hanging along the bottom of the net. While pursing the encircled group of fish may be encouraged not to dive below the net by using "cherry bombs" which explode at depth frightening the fish to the surface. The rings are brought on board and passed through the power block and the net is hauled until the fish are concentrated in the "bunt", a small, strengthened section of the net. The fish may be brought aboard using a brail net or fish pump, frozen in brine freezers to at least -10 C, and then transferred to dry storage freezers. If the set is made on dolphins and porpoises, time may be spent "backing down", a process used in the eastern Pacific allowing porpoise or dolphin schools to escape over the top of the net.

The two big improvements in gear design that greatly enhanced purse seine efficiency were the introduction of nets made with synthetic fibres, notably nylon, and the "power block", a hydraulically driven V-shaped pulley hung from a derrick, which greatly increased the ease with which the net was hauled. The power block decreased the time taken to make a set, thus increasing the catch rate, allowed larger catches to be hauled and reduced the size of the crew, thereby reducing costs. An important characteristic of the net is the rate at which it sinks, since the deeper the bottom of the net reaches the less likely it will be that fish escape. Using synthetic fibres enhanced the net strength while keeping its weight down and increasing its sinking rate. As tuna are fast moving animals, the net required to encircle them is large. Tuna nets are 1000-1400m long and 100-200m deep and weigh about 25 tonnes. Other important factors affecting net design are the net's ability to resist wear, deformation by current and entanglement (Nomura and Yamazaki, 1975).

2.2 Statistical Modelling of Catch per Unit Effort

Most fisheries continue to use catch and effort data to monitor changes, due to the ease and low cost of data collection rather than their value in analysis. To compensate, various theoretical and statistical models have been developed to improve the link between catch and effort data and abundance of fish, the simplest comprehensive approach being the use of statistical models.

Fitting linear models to complicated data sets has proved to be a useful method for estimating different effects on catch per unit effort (CPUE). The method was first developed to adjust for vessels of different fishing power operating in different areas (Beverton and Holt, 1957; Robson, 1966). This linear model approach continues to be widely used because it is simple to interpret and easy to compute. Kimura (1980) fitted an ANOVA model to logarithmic CPUE data comparing different estimates of changes in relative abundance. It was found to be easier to interpret model coefficients statistically when comparing effects rather than adjusted CPUE. All these techniques use least squares fitting which requires additive effects and constant variance. The constant variance and additive criteria are usually fulfilled, at least approximately, by taking logarithms of CPUE data.

Allen and Punsly (1984) and more recently Punsly (1987) fitted and examined a linear model describing yellowfin catch rates of tuna purse seiners in the eastern Pacific. The choice of catch rates as CPUE for purse seine is appropriate since vessels must spend time (effort) searching for fish. The data set they used contains a large number of possible factors and covariates. The final model has over 100 degrees of freedom, but explains only 12.5% of the variance, a common result with fisheries data. Even so, the model still serves its main purpose, that of seeing whether there has been a significant change in relative abundance by looking at the model's year parameter estimates after adjustment for other effects.

Allen and Punsl y state clearly the assumptions necessary to use catch rates as indices of abundance. Although catch rates should fall as fish abundance decreases, the form of this relationship is by no means clear. The relationship may not be linear, but if it remains consistent, there should still be a positive correlation between observed catch rates and stock abundance. However it is possible that small changes in catch rates may be swamped in the random component of the data. There is much theoretical and empirical evidence that the CPUE variation increases as fishing effort increases (Beddington and May, 1977), which is particularly important if the changes in the systematic effect are small.

There are two components to the relationship between CPUE and fish abundance. Usually fisheries managers are most interested in the stock abundance, but they still have to adjust for the other component, catchability. Catchability is a nebulous term that accounts for all factors that affect the relationship between CPUE and stock size other than the stock size itself.

Even if catch and effort are linearly related, the catchability may change over time due to, for instance, a decline in stock range rather than density (Murphy, 1977; Ulltang, 1976) or strong density-dependent recruitment from a larger underlying population to a vulnerable surface stock (Clark and Mangel, 1979). The former illustrates an important problem of the CPUE approach. Fishermen do not sample the fishing area randomly, but will concentrate on areas that provide the greatest catch rate, which is therefore, at best, a measure of the local stock density and not the overall stock size. This is made worse in the case of purse seine using echo-sounders to search logs, where that information is not recorded. If the search is very efficient, many logs may be checked and only a small proportion fished.

Figure 2.2 shows the proportion of sets made at different times of day, with sets being classified into three types : log sets, other flotsam sets and free swimming aggregates. Logs and other flotsam are separate because they have different preferred setting times, possibly because most types of flotsam are difficult to locate at night. For logs, most sets are made in the early morning, implying that the log was located at some time during the previous day. Once a log is found time may be spent

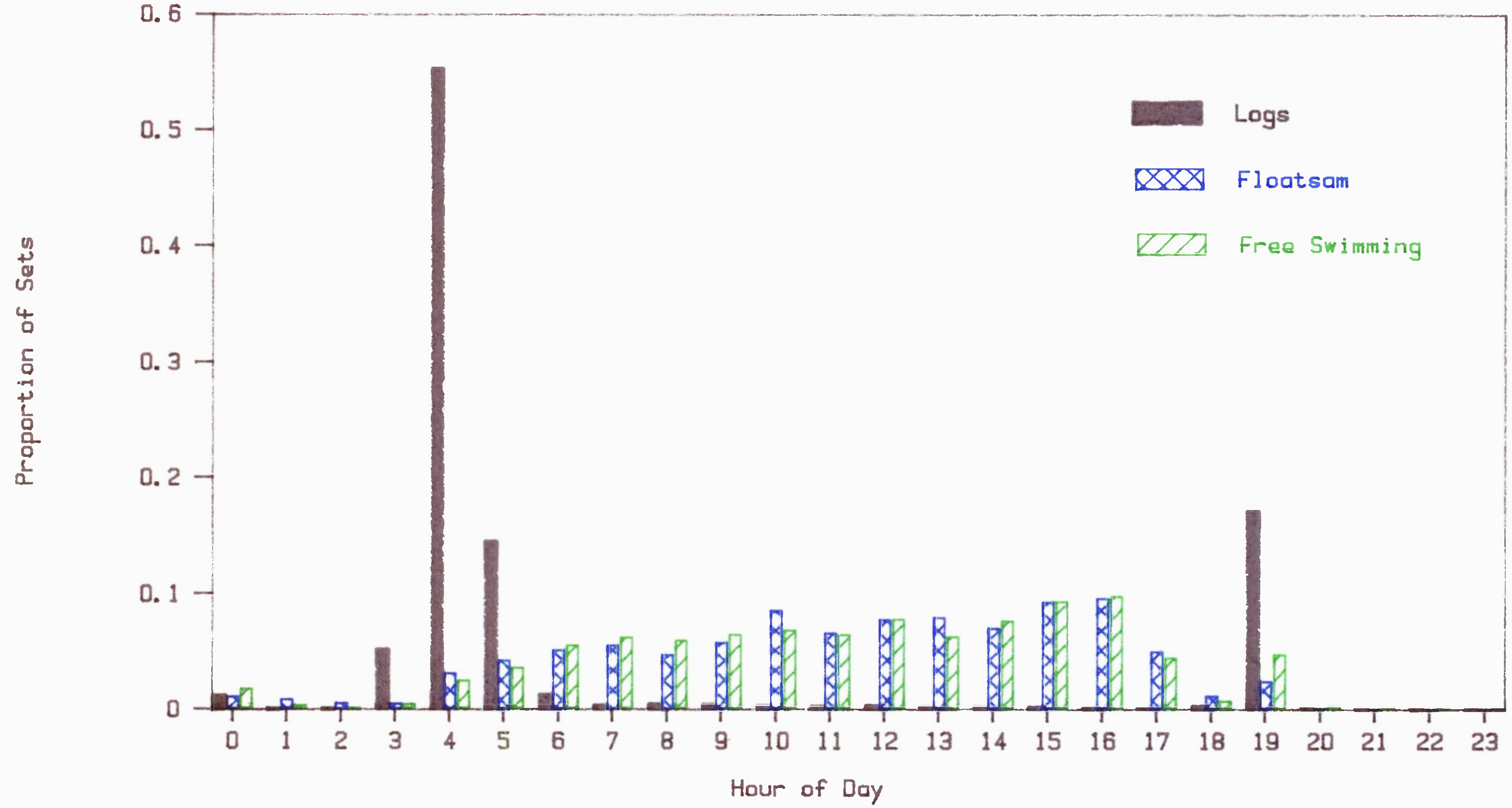


Figure 2.2 Set types by time of day

waiting until the following morning which is a bias on the catch rate, because for many cases the maximum number of log sets per day will be one. Potential search time (daylight) may also be spent on making a set, as well as maintenance and travelling to and from fishing grounds. These effects may cause the number of sets made per day to saturate at some level above which they do not react to changes in the stock abundance.

There are a number of other factors to which the catch rate may be related that are recorded on the log sheet. These include the type and size of vessel, nationality and where the set was made. Of particular interest is whether the fishermen are targeting particular species, which will presumably depend upon the nationality. US fishermen may prefer to take yellowfin since they receive a better price for this fish.

2.2.1 Linear Model of Catch Rate

The model fitted to the data is of the same form as the one fitted by Allen and Punsl·y, except that the time component does not distinguish between search and handling times, and no constant is added to the catch rate before the logarithmic transform to allow a breakdown of the fishing process. Otherwise data used were calculated in the same way. Time searching was calculated from 0600 to 1800 when there was assumed to be enough light. The catch in tonnes of skipjack and yellowfin, the numbers of sets containing each species, the total number of sets and the average fish weight of each species were also recorded. Data were accumulated for each trip as long as the vessel remained in the same stratum defined by the independent variables. Set records were rejected if any value was missing, so that the data set remained homogeneous for all models.

The purse seine catch rate (C/T) can be written :

$$C/T = N/T * C/S * S/N * Exp(E) \qquad 2.1)$$

and after the data has undergone a logarithmic transformation,

$$Ln(C/T) = Ln(N/T) + Ln(C/S) + Ln(S/N) + E \qquad 2.2)$$

where for each stratum :

Ln = logarithm to the base e
C = Total catch of species
T = Total time
N = Total number of sets
S = Number of sets containing species
E = Residual

The models described here go further than Allen and Punsl y in that they explore the different parts of the catch rate. The catch rate (catch per day) can be split into sets per day (N/T), catch per set (C/S) and proportion of successful sets (S/N). As shown above, the relationship is linear if the logarithm is taken of catch rate. This allows effects to be attributed to the searching and/or setting process separately. An important argument for splitting the process in this way is that different parts may not contribute significantly or in different ways to the objective of the analysis. For instance it is possible that the proportion of successful sets will bear no relation to the stock size and that the number of sets per day may more closely estimate the density of logs than fish.

The models were fit by weighted least squares using the statistical package SPSSx (1986). Taking logarithms of the data stabilised the variance over the range of the model. The cases were weighted by the number of observations.

This is appropriate if observations are independent, for the variance of the combined data, if normally distributed, will be reduced by the reciprocal of the number of observations. As might be expected, observations are not entirely independent, but the correlations between sets in the same stratum are not large (see section 2.3). For catch rate and sets per day the weighting is the number of days, for catch per set, the number of successful sets, and for the proportion of successful sets the total number of sets.

Models were fitted separately for each species where appropriate. Although sets per day will be a common factor for the catch rate of either species, catch per set and the proportion of sets containing a particular species needed to be fitted separately.

The data were broken up into four strata : year, season, 5^{o}

square, gross registered tonnage (GRT) and aggregate type. There are 7 years of data starting when the fishery began in 1979 and ending at the beginning of 1986. Seasons have four categories of three months each running from March-May to December-February. Eleven 5^{o} squares within the area $135\text{-}160^{o}W$ and $10^{o}N\text{-}5^{o}S$ (numbered in figure 2.1 1-11), were chosen on the basis that they contained significant effort. Three classes of GRT were used : less than 400 tonnes, between 400 and 500 tonnes and greater than 500. For tax reasons many vessels are made to classify around 499 tonnes, thus the second forms the biggest group. Nationality was not included as a factor, because many vessels grouped by nationality fall into the same size classes as shown in table 2.2. Finally aggregates were put into two types, free swimming and those aggregated to floating objects. Although there are 9 classes of aggregate recorded on the log sheet, many of these contain too few cases to be useful in this analysis.
After fitting vessel size class, both nationality and interaction terms between nationality and vessel size class were found to be insignificant factors.

	GRT			
Nationality	< 400	400 < < 500	500 <	Totals
Japan	1574	18649	96	20319
Taiwan	469	50	488	1007
Korea	0	0	1008	1008
USA	0	18	1265	1283
Philippines	0	432	0	432
Panama	0	11	236	247
Honduras	0	47	0	47
Cayman Islands	12	15	307	333
Mexico	0	0	164	164
Totals	2166	19250	3569	24985

Table 2.2 Number of sets broken down by vessel size class and nationality. US vessels may change nationality if it is to their advantage. The vessels registered as Panamanian, Honduran and Cayman are probably from the United States.

2.2.2 Results

Table 2.3 gives the regression coefficients of each model. The parameters are estimates of the difference of the group mean from the mean of the first classification, and their importance to the overall model is indicated by their size. Although a coefficient may be significantly different from zero ($p < 0.05$, marked by an asterisk *), if it is small it will still not contribute much to the explanatory power of the model. A problem with attaching a probability to a parameter estimate is the assumption that the residuals are normally distributed. Except for the success rate models, the residuals follow a normal distribution fairly closely. For the former, parameter estimates must be interpreted with some care.

Free swimming aggregate give a higher average catch per set and sets per day, but a lower success rate. This could be explained by large numbers of schools being attracted near to the surface to feed, but being very active and able to see the net from further away, increasing their rate of escape. There is no overall effect on skipjack catches, but yellowfin catches are greatly increased. This introduces the possibility of switching where an increase in price of yellowfin more than offsets costs incurred by a lower success rate. However such switching will only be possible if a change in fishing behaviour can increase the encounter rate of free swimming aggregate while decreasing the encounter rate of logs. If sets on free swimming aggregates are the result of chance encounters while searching for logs then such a switch is not possible.

US vessels receive a higher price for yellowfin than skipjack, and may therefore concentrate on free swimming aggregates. Table 2.2 shows that US vessels almost exclusively fall into the larger size class. However from table 2.1 there is no evidence of targeting aggregate types by size class of vessel, which suggest no such consistent pattern.

Medium sized vessels (mostly Japanese) have the highest catch rates while the largest vessels (mostly United States and Korean) have the lowest. US vessels visit from the eastern Pacific, and they may not be as familiar with western Pacific as the Japanese.

The big effect of the zone fished is the increase in yellowfin presence in catches at lower latitudes. Here targeting for particular species may be detectable if preference is shown for zones where the catch rates of one species are increased at the expense of the other (eg zones 7 or 8).

There appears to be a higher skipjack catch per set during the first season (March to May) and yellowfin catch per set during the first two seasons (March to August). This may be related to the monsoon, but whether it is due to changes in the behaviour of the fish, the type of floating object available or even clarity of the water, which might affect the chance of fish escaping, is not known.

The year effect is usually taken as relating to the stock size once the other effects have been removed. There is a general increase in the catch rates of both species, explained partly by an increase in the number of sets per day and, in the case of skipjack, by an increase in the catch per set. The coefficients could represent improving experience or underlying fluctuations in fish density. In either case there is no evidence from this of a declining stock.

This general result is supported by workers at the South Pacific Commission (SPC, 1985) who have already fitted a simple linear model to the same west Pacific data set searching for declines in relative abundance of yellowfin. Although their model did not explore the different components of the catch rate and used a smaller data set, their results also indicated no decline.

For all the models the percentage of the variance explained (R^2) was very small. The excess variation might be explained by factors not recorded in the data set or it may be intrinsic randomness in the data such as the fish aggregative behaviour. Other factors derived from vessel characteristics may have been included to produce a better fit. However the experience of Allen and Punsl y (1984) demonstrates that not much improvement can be expected from this approach. One method that may capture benefits, while keeping the model parsimonious by avoiding correlations between factors, would be to use principal components rather than the full set of vessel characteristics.

Standardising over time requires that the effects remain constant over time. Interaction terms between year and other factors, although significant, were very small compared to the main effects and therefore do not change the conclusions. Other interaction terms were statistically significant (F statistic, $p < 0.05$), but the gain in R^2 was very small (< 0.01). There is a tendency of large data sets to allow many parameters when using standard criteria (eg minimum gain in F) to decide upon their inclusion. However adding more parameters adds very little to the model when taking into account the data variability.

Factors	Skip-jack catch rate	Yellow-fin catch rate	Sets /day	Skip-jack /set	Yellow fin /set	Skip-jack success rate	Yellow-fin success rate
Unattached Aggregate	0.025	0.469*	0.098*	0.165*	0.719*	-0.466*	-0.571*
GRT <400							
400-499	0.226*	0.286*	0.276*	-0.042	-0.098*	0.069*	0.306*
500<=	-0.135*	-0.075*	-0.090*	-0.085*	-0.010	0.106*	0.197*
Zone 1							
2	-0.088	0.015	-0.011	-0.138*	0.027	0.045*	0.028
3	0.032	0.222*	0.122*	-0.061	0.217*	-0.058*	-0.102*
4	-0.208*	0.169*	-0.092*	-0.070	0.235*	0.008	0.080*
5	-0.014	0.282*	-0.050*	0.047	0.302*	-0.037*	0.053*
6	-0.215*	0.068	-0.125*	-0.073	0.222*	-0.034	0.074*
7	-0.195*	0.115	-0.072*	-0.075	0.363*	-0.128*	-0.135*
8	-0.109*	0.374*	-0.010	-0.021	0.351*	-0.020	0.083*
9	0.078	0.490*	0.024	0.124*	0.446*	-0.067*	0.087*
10	0.018	0.478*	0.018	0.065	0.380*	-0.014	0.197*
11	0.193*	0.545*	0.099*	0.079	0.457*	0.020	0.232*
Season Mar-May							
Jun-Aug	-0.210*	0.072*	0.097*	-0.308*	-0.061*	-0.025*	0.049*
Sep-Nov	-0.198*	-0.086*	0.076*	-0.342*	-0.221*	0.015	0.042*
Dec-Feb	-0.189*	-0.045	0.027*	-0.300*	-0.147*	0.037*	0.073*
Year 79							
80	0.582*	-0.041	0.113*	0.439*	-0.053	0.017	-0.024
81	0.022	0.092	0.065*	0.004	0.047	0.028	0.081*
82	0.420*	0.179*	0.150*	0.274*	0.025	0.048	0.012
83	0.609*	0.103	0.136*	0.491*	0.030	0.018	-0.075*
84	0.416*	0.325*	0.270*	0.341*	0.189*	-0.166*	-0.168*
85	0.508*	0.217*	0.299*	0.278*	0.042	-0.092*	-0.171*
86	0.840*	0.552*	0.312*	0.671*	0.335*	-0.123*	-0.138*
R^2	0.067	0.081	0.097	0.077	0.115	0.163	0.208
Model DF	23	23	23	23	23	23	23

Table 2.3 The table shows the parameter estimates for the different factors fitted to the catch rate and its various components. For the zones see figure 2.1. All factors were highly significant. Asterisks (*) indicate significant parameter estimates ($p < 0.05$).

There is also an estimation problem, when including interaction terms, in the form of empty cells (McCullagh and Nelder, 1983) for which no parameter estimates will exist. This problem is particularly acute in this fishery, where effort is expanding and new fishing grounds are constantly being exploited and new vessels are entering the fishery. In this case fishing did not take place in all years in all zones.

One problem with splitting the catch process into parts is that there may be correlations between different parts, information which will be lost when looking at those parts individually. Correlations between residuals were examined to see how great this effect might be.

Table 2.4 displays the Pearson correlations between the residuals of the different catch rate component models after fitting. There is an interesting large negative correlation between both the success rates and the sets per day. This implies compensation for unsuccessful sets, probably by resetting as soon as a failure is recognised. There are also correlations between the species, both in their presence in the catch (success rate) and in the actual catch per set, implying a degree of association between the species. The other correlations are small, although they may be significant in the cases where the residuals are approximately normally distributed. It would be reasonable to expect a positive correlation between the catch per set and the sets per day components if higher number of schools under a log also means more logs with schools under them. The correlations are positive, but very small.

	Sets /day	Skip-jack /set	Yellow fin /set	Skip-jack success
Skipjack /set	0.049	1.000		
Yellowfin /set	0.060	0.358	1.000	
Skipjack success	-0.285	-0.026	-0.140	1.000
Yellowfin success	-0.262	-0.059	-0.046	0.555

Table 2.4 Pearson correlation coefficients (R) between residuals after weighted least squares fit. All the correlations are significant ($p < 0.05$) if the residuals are normally distributed. This is not the case for the success rates.

Although the model is comprehensive, covering all years and the main fishing zones, it is difficult to interpret the coefficients without more information. In particular the underlying assumptions have not been tested. It is quite easy to imagine the relationship between the stock abundance and catch rates to be so slight as to be undetectable except in the extreme case of there being very few fish. For instance searching may be so efficient that only a few logs out of a large number are chosen to be fished for whatever reason, or the major control on the catch per set may be the number of fish escaping. If this is the case, a decline in the fish stock will be detected too late not to cause damage to the fishery.

2.3 Purse Seine Search Model

To develop an improved model of the catch rate it is necessary to look at the form of effort in more detail. Effort here is generally thought to be represented by the time spent searching, since it is expected that this will increase as the density of fish falls. However without looking at the search process more carefully, it will not be possible to determine the form of this relationship, and hence how sensitive the rate of finding fish is to a decline in abundance.

Mangel (1984) and Mangel and Clark (1986) discuss in detail search theory and its application to natural resource modelling. The most important factor affecting the rate at which objects are found are the qualities pertaining to the objects themselves, such as the distance at which they can be identified, whether they move and their resultant behaviour if they can. If there is little knowledge of these qualities, but they remain constant as might be expected within a species, it should still be possible to monitor relative changes in density. In this case little is known about the behaviour of tuna, however relative abundance may still be estimated. Similarly in a multispecies fishery relative changes can be estimated separately for each species unless there is targeting or switching which will make the interpretation of the catch rate more complex.

The characteristics of the objects of the search will strongly influence the search method chosen. There are two extreme methods of searching, exhaustive and random search, with a whole array of alternatives between. Exhaustive search refers to the method of systematically searching a whole area, so that the rate of discovery will largely reflect the underlying spatial distribution of objects and may be appropriate where the objects are stationary. Random search involves random movement regardless of the rate of encounter, which implies no learning facility. An extension of random search allows the searcher to change the search method dependent upon whether the searcher is looking for an aggregation or is within an aggregation of objects (Hassell, 1978).

The spatial distribution of objects will have different effects on different methods. If objects are randomly distributed, little improvement can be made on random or exhaustive search. In most natural systems there is usually a high degree of aggregation. If searching is random, this will not affect the estimated mean density, but will increase the variance of the rate of encounter. If search is non-random both the mean and variance are higher than in the random spatial distribution case as searching effort is increased in areas of high density.

These factors together will form the relationship between the search time and abundance which can be described by a model. The simplest model assumes a constant probability of encounter, which will lead to a Poisson process (see Cox and Miller, 1965). It can be shown to occur when there is no depletion and objects are distributed randomly or uniformly. In practice the Poisson distribution appears to fit a wide variety of empirical search patterns (Mangel and Beder, 1985). The number of encounters in a unit time will follow a Poisson distribution while time between encounters will be distributed as a negative exponential. Other search models are usually represented as deviations from the Poisson model, hence it is useful as a first step to see how closely empirical frequencies follow these theoretical distributions.

It is possible to calculate the time between sets for this fishery, but this does not simply represent time spent searching before fish are found. The time budget of a vessel is split up in a variety of ways, only a part of which will be spent searching. Firstly searching can only take place during the day since light is needed. Days spent travelling between port and fishing grounds, on maintenance or lost owing to bad weather are recorded on the log sheets, so these create no problem. However time spent actually making sets or simply waiting are not recorded and some adjustment must be made for these factors.

Fishing vessels seem to prefer to make log sets early in the morning, so they will either have to mark the log (eg with a radio beacon) and continue searching to return at evening, or wait nearby. Once a number of logs have been marked or if fishable logs are very easily found a vessel may wait or look for free swimming aggregations. Even for free swimming aggregations there is a marked increase in sets at particular times of the day possibly due to changes in how conspicuous aggregations are or their vulnerability to purse seine (figure 2.2), an effect also found in the eastern Pacific (Whitney, 1969). Time between sets will also include time taken to make the set and to clear the brine freezers, both of which will vary according to the size of catch. However only the daylight lost will reduce search time, and searching might continue while fish are being processed through the brine freezers.

The distribution of the time between sets for logs is shown in figure 2.3. The times have been transformed to whole days to remove both the effects of waiting times and changing probabilities of fish encounters during the day. This method will work as long as the probability of an aggregation being found on each day is the same. After a set, if another was made before day-break following the next search period (0600-1800), it counts as one day, to the second dawn two days and so on. Day-break, when searching can begin, is assumed to occur at 0600.

If search is random with a constant expected encounter rate, this discrete time distribution should follow the geometric distribution. It is significantly different from a geometric with the same mean however (chi-squared, 1090, 5 df) and over-dispersed as might be expected from the obvious aggregation from figure 2.1. Models of non-random search usually assume the objects are aggregated into discrete patches. Over-dispersion of time intervals between sets occur owing to time spent in areas of low fish density. Aggregation of the objects of search therefore leads to over-dispersal of the time periods between captures.

The main problem with using the data in this form is their

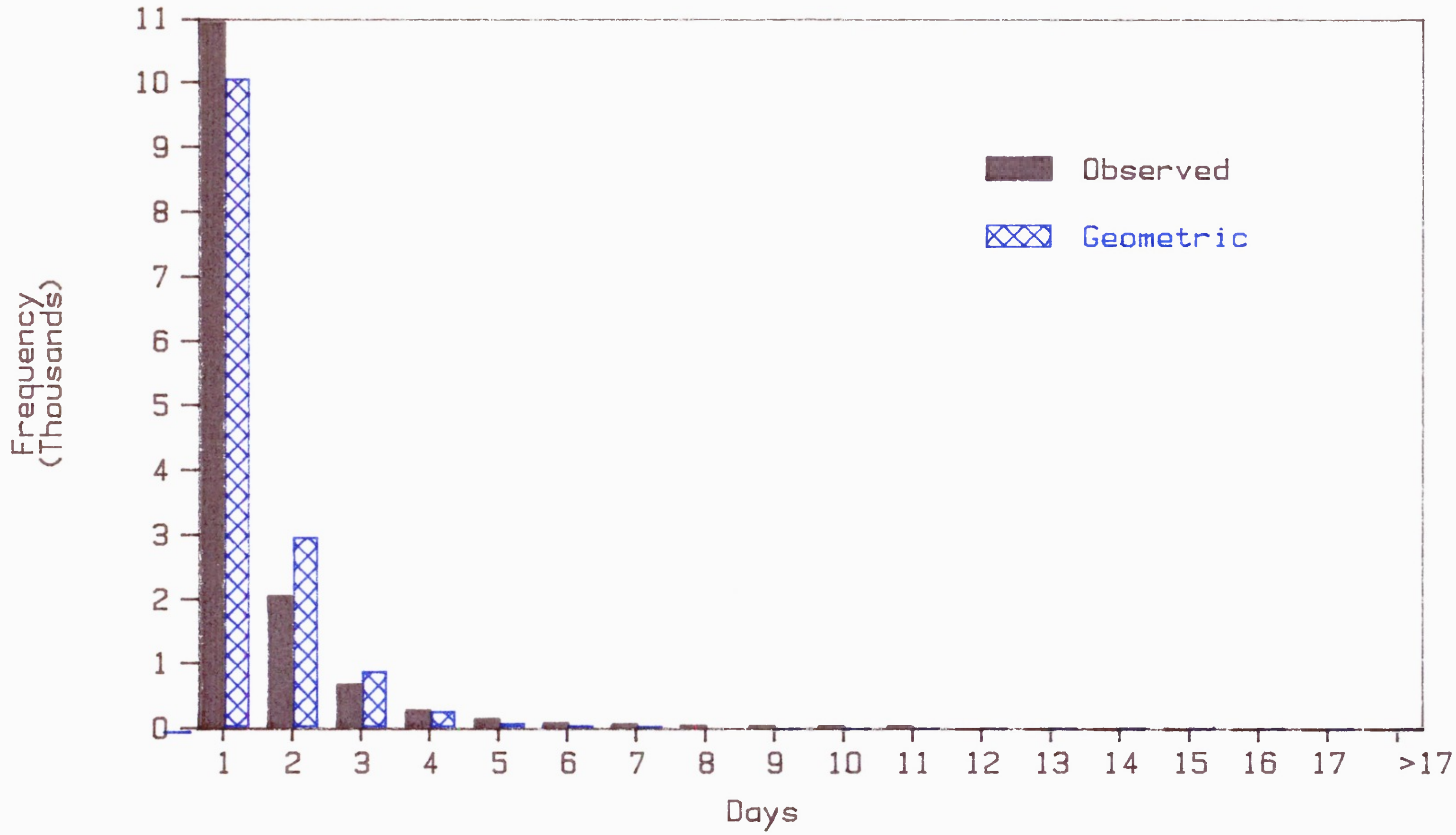


Figure 2.3 Days between log sets

insensitivity to changes in the time distribution. As the number of aggregations fall, the searching time will increase, but mostly only to use up latent waiting times. There should still be more longer waiting times, but this produces a strong dependence on a few observations at the tail end of the distribution. Errors such as failing to record in the log book days lost owing to the weather or breakdown could greatly change the results.

If the over-dispersion of time between sets is largely because of aggregation to patches, there should be strong correlation of time between sets over successive sets on the same trip. However the time between sets is a complex mixed (discrete and continuous) distribution, making autocorrelations inappropriate. Instead this time can be converted to the discrete form as used above and a transformation matrix constructed.

Table 2.5 shows the frequencies of time between sets in whole days between successive sets in the form of a contingency table. If the one time between sets is independent of the next, a simple linear model with two effects should adequately explain the counts (see Everitt, 1977). Although the degree of association is not very great, it is significant (chi-squared, 301, df 81), implying that long periods searching for fish tend to follow one another.

Although it is not possible to completely separate the search method from the underlying spatial distribution, some idea of the degree and form of the contagion can be obtained from the positions and times of sets. The negative binomial and Poisson distributions were fitted to the number of sets in different time and space intervals. A variety of sizes of interval were examined, since the fit will be influenced by the relative size of the quadrat to the sizes of the patches (Elliott, 1977). To define the limits of the sample, the area used consisted of the one month degree squares which contained at least one set in any one year. This is justified in that an area is only relevant if it is possible that a set may be made in it. Obviously the amount of searching carried out within an interval will influence the number of sets, so the model will also reflect this effect as well as the spatial distribution of logs and fish.

		Days Between Previous Pair of Sets							
		1	2	3	4	5	6	7	8
	1	7560 (7377)	1058 (1158)	306 (341)	113 (132)	56 (70)	24 (29)	25 (29)	13 (13)
	2	1170 (1268)	258 (199)	82 (59)	31 (23)	19 (12)	7 (5)	6 (5)	1 (2)
	3	323 (375)	87 (59)	24 (17)	15 (7)	7 (4)	3 (1)	1 (1)	1 (1)
	4	128 (139)	24 (22)	12 (6)	4 (2)	2 (1)	1 (1)	0 (1)	0 (0)
Days Between Pair of Sets	5	68 (76)	16 (12)	3 (4)	3 (1)	2 (1)	0 (0)	2 (0)	1 (0)
	6	36 (36)	7 (6)	2 (2)	1 (1)	0 (0)	0 (0)	1 (0)	0 (0)
	7	34 (36)	6 (6)	2 (2)	0 (1)	2 (0)	1 (0)	0 (0)	0 (0)
	8	8 (14)	7 (2)	0 (1)	0 (0)	0 (0)	0 (0)	0 (0)	1 (0)

Table 2.5 Transition matrix of time between sets (maximum 8 days) demonstrates the tendency for long search periods to follow each other. The expected values (with no decimal places) from a main effects only log-linear model appear in brackets beneath the counts.

The negative binomial distribution was found to provide a better description of the observed frequencies than the Poisson (random) distribution. Table 2.6 gives the results for the maximum likelihood fit of the negative binomial model to the one month by one degree square intervals; other intervals provided an unsatisfactory fit. The negative binomial distribution is not ideal since it was unable to consistently fit all the data sets. However it provides an adequate summary of the data. There are two noticeable results. Firstly the effort (mean number of sets) shows a seasonal change. Secondly the contagion parameters shown in table 2.6 are consistently very small, implying a high concentration into particular one month degree squares. This result suggests an underlying aggregation of logs and fish. Under these conditions the catch rate may be greatly improved by using non-random search.

Simple models of non-random search allow for different search behaviour between and within patches. The definition of a patch relies largely on the change in behaviour of the vessel (Hassell, 1978). In this case this definition is unhelpful since there is no detailed data on the movements of vessels. It might be expected that sets would be aggregated into patches, if they exist. However such patches of logs, as well as being subject to depletion of fish, will move with the prevailing current if there is one, and have a finite life, either sinking as they become water logged or breaking up through water movement.

Logs with no or few fish have not been recorded, hence it is not known whether the spatial distribution is more closely related to the distribution of fish or the distribution of logs. In this particular case the search is for logs and only fish indirectly. The distribution of fish among logs may be dependent on a number of factors. Tuna may have preference for a log or set of logs close to their feeding grounds for instance, so that many logs may have no fish at all. Alternatively there may be a strong density dependent effect on schools in an aggregation, which will tend to spread schools out among sets of logs. Without this knowledge it is impossible to completely separate the search time and the catch per set.

Two Month Periods		Mean	Aggregation Parameter K	Probability
1984	Jan-Feb	0.9626	0.06428	0.12
	Mar-Apr	0.6948	0.05435	0.18
	May-Jun	0.2744	0.09001	0.15
	Jul-Aug	1.6705	0.10461	0.94
	Sep-Oct	2.0813	0.11428	0.70
	Nov-Dec	1.9318	0.09064	0.33
1985	Jan-Feb	1.4513	0.07407	0.97
	Mar-Apr	1.1463	0.07812	0.95
	May-Jun	1.3247	0.16508	0.16
	Jul-Aug	2.0990	0.16995	0.02
	Sep-Oct	2.0860	0.21682	0.04
	Nov-Dec	0.6789	0.18412	0.69

Table 2.6 The table shows the parameter results from the fits of the negative binomial distribution to data made up of one month one degree squares combined over two month intervals. The theoretical and observed distribution were compared using the chi-squared test, and a probability below 0.05 indicates the null hypothesis, that the fitted distribution is equivalent, should be rejected.

2.3.1 Linear Model of Sets per Day with Poisson Errors

A Poisson model may still provide an adequate description of the search process. The data may be a combination of Poisson distributions with different parameters, either due to changing densities (eg between and within patches) or different vessel characteristics. The effects of vessel characteristics and large scale spatial changes may be removed using a linear model. The number of sets is used as the basic dependent variable and the time element is removed as an explanatory variable, so that the Poisson errors are maintained. An advantage of using sets per day is that it is sufficient to accumulate the number of sets and days within each strata if the individual observations are independent. Despite the assumption of independence not being true in this case, combining the data in this way is convenient for picking out these effects, although the model may not accurately predict the individual set data. The time associated with each set is the time between it and the last set. It is assumed that the preceding set has no influence on this time, which would be true if only search time was recorded. In this case there will probably be some influence through the handling time of the previous catch, however this effect may still be insignificant.

A linear model may be fitted to sets per day in a way similar to the model in section 2.2, except Poisson errors are used. The linear model will remove the over-dispersion due to the various constant characteristics represented by the strata. The strata used are the same as in the previous model, except for aggregate type which is replaced by the success rate (proportion of sets containing fish). The success rate is added to the model last, since its parameter estimate is correlated with the other factors (see section 2.4). The effects are related to the number of sets (the dependent variable) through a log link function, so the model is multiplicative. The first effect removed is the total time in each strata. The model is forced to pass through the origin, so that when no time is spent searching automatically no sets are made. This is achieved by transforming the number of days using the natural logarithm. Fitting this parameter changes the dependent variable to sets per day while preserving the Poisson errors.

The results are presented in table 2.7 containing both the explained deviance and the parameter estimates for each factor. The number of days spent fishing is obviously very important in determining the number of sets. The parameter estimate is close to 1.00, implying a linear relationship.

		Estimate	Standard Error	Deviance	Degrees of Freedom
Constant		-0.058	0.077		
Days Searching		0.991	0.008		
GRT 400-499		0.183	0.026	403.9	2
500<		-0.254	0.033		
Zone	2	-0.044	0.044	108.2	10
	3	0.103	0.047		
	4	-0.051	0.036		
	5	-0.053	0.036		
	6	-0.084	0.044		
	7	-0.050	0.066		
	8	-0.023	0.037		
	9	0.005	0.037		
	10	-0.043	0.045		
	11	0.036	0.056		
Season					
Jun-Aug		0.085	0.022	23.2	3
Sep-Nov		0.059	0.023		
Dec-Feb		-0.004	0.022		
Year	80	0.082	0.070	180.7	7
	81	-0.004	0.067		
	82	0.036	0.064		
	83	0.138	0.064		
	84	0.267	0.063		
	85	0.281	0.063		
	86	0.255	0.065		
Success Rate		-0.430	0.037	131.1	1
Error				1007.5	679

Table 2.7 gives the parameter estimates and deviance after fitting different factors to the number of sets made. All the factors are significant ($P < 0.01$), assuming the change in deviance is distributed approximately as chi-squared distribution (see McCullagh and Nelder, 1983).

The change in deviance associated with the size of vessel is high. Larger vessels are significantly worse at locating fish than the smallest vessels, while the medium sized vessels (400-

500 GRT) appear to be the best. Since the larger vessels should be able to travel faster and be better equipped, it is by no means clear why this is the case. Familiarity with the fishing grounds together with better co-operation between vessels may explain this difference.

Both zone and season appear to be less important in determining the number of sets although they are significant. Presumably patches exist on a smaller scale than the 5^{o} square zones. It might be expected that there would be seasonal changes in the availability of floating debris as well as changes in the numbers and distribution of fish and weather conditions for fishing. Although the parameter estimates are consistent with the two seasons (monsoon), the values are not large. An improvement might be made if a factor would be whether a set was made during the monsoon since the time at which the monsoon arrives changes from year to year. However gains made with changes in the weather (such as increased numbers of logs) may be counteracted by other effects (such as poorer visibility or more logs with no associated fish).

There appears to be a single discrete change in the sets per day with year. The parameter estimates for 1980 to 1982 are not significantly different from 1979, but there is a step up to 1983 and again to 1984 from which it remains approximately constant. Although the reason for this is unknown, this increasing set rate is probably related in some way to the expansion of the fishery.

It was found that the deviance associated with aggregate type was entirely explained by the success rate, which was therefore used instead as it was found free swimming aggregates have a much lower success rate than log aggregates. It appears from the parameter estimate in the table that an unsuccessful set can be mitigated by attempting another set soon afterwards. It should be noted the success rate will itself be related in part to the other factors, so the change in deviance associated when it is included as a parameter would be higher if it is included first.

Examination of the residuals indicated no major departure from the assumptions. There were only two outliers, which had very few observations, and unreasonable values (> 6 sets per day) and thus were likely to be caused by data errors. The variance also increased slightly more than was expected. The scale parameter (error deviance / df = 1.48) is close to 1.00, expected if the errors are Poisson, suggesting this model is appropriate. The higher scale parameter implies over-dispersion, probably due to the aggregation.

The model can be improved slightly by employing quasi-likelihood methods, where in this case, the variance is assumed to be proportional rather than equal to the mean (McCullagh and Nelder, 1983). The scale parameter is used to estimate this relationship. Although this does not change parameter estimates, their standard errors are increased slightly.

It was found that the model does not predict well actual number of sets on a trip because of the autocorrelations between sequential search times and the way the times tend to fall into discrete days. However the model adequately picks out the different effects on the average set rate and is more clearly tested and interpreted than the least squares model in section 2.2.

Improved search models have been developed for tuna fisheries, but they can not be applied to data of this form. Pella (1969) and Pella and Psaropulos (1975) modelled searching for tuna as a renewal process, separating the searching and handling times. Mangel and Beder (1985) developed a similar model, but included depletion by fishing. Although these theories are an improvement on the standard catch and effort models, they need further development before being applied to real fisheries. However they do highlight the important factors in a fishery involving search.

There are a number of types of data that would be useful. A detailed time budget could be kept for the fishing vessel, so that, among other things, the actual time spent searching would be known. The two parts making up the catch per set, that is the size of the aggregate and proportion of the aggregate that escapes, could be recorded separately. Separating these two may be important since the size of the aggregate will provide the information on stock size. Finally repeated fishing of the same aggregate should be recorded. This may give a more accurate estimate of the total size of the aggregate. Moreover, even if the size of the aggregate is unrelated to the stock size, the rate at which it is replenished may be.

2.4 Success Rate

The successful set rate is important because a set that catches no fish still costs money in terms of wear and tear on gear and time lost. Also it affects the average time between sets, since a vessel may recover more rapidly from an unsuccessful set and attempt a set again without further search. If the probability of success is independent for successive sets, the numbers of successful sets should follow a binomial distribution, which suggests a logit model. If changes in the probability of a successful set are adequately explained by the factors recorded, the model should provide a good fit.

However building a model of the success rate is more difficult than might first appear. Even if the model fits the data well, information may be lost as to the numbers of schools being set upon. There are two extreme models of escape from the set. The assumption in fitting a separate logit model is complete dependence between the probabilities of fish escaping. This would seem to be reasonable within schools, however may not be true of the aggregation as a whole. The other extreme assumes that an aggregation is made up of schools each having an independent chance of escape, so that the probability of an unsuccessful set will be the last term of the binomial distribution, defined by the number of schools and the chance of a school escaping. If this model is more accurate, the probability of an successful set will be dependent upon the abundance of fish. The proportion of unsuccessful sets therefore may provide information on the number of schools being set upon. The important factor is the cohesiveness of the aggregation, and hence the behaviour of the fish. In reality there is probably some dependence of the probability of escape between schools since schools might well follow each other if startled, although the degree and therefore importance of this dependence is not known.

In the model of section 2.2 species were dealt with separately so that the model could be compared with the catch rate of each species. That model did not, strictly speaking, deal just with probability of fish escaping from the net, since there was no information on whether a particular species was present or not before the set was made. For this model the presence of any species in the catch is used to mark a successful set to avoid this problem.

There are various factors which might be expected to affect the probability a school escapes. Common to all schools will be the depth of the thermocline and general visibility (Nakamura, 1969; Hunter <u>et al.</u>, 1986). An important difference between different schools could be their depth when the set is made. It would seem reasonable to assume the chance a school might escape through the bottom of the net will increase the deeper the school is. The average depth of schools may vary with time of day (Hunter <u>et al.</u>, 1986) and size of fish (Sharp, 1978) and species.

The simplest model is that assuming strong dependence between the probability of schools escaping, so that unsuccessful sets can be dealt with separately, without reference to the number of schools. Although this is probably an over-simplification, it is useful to see how well a binomial model fits the data.

The factors used were the same as those used in the previous models. The model fitted was that usually used for binomial data, namely the logit (log odds) model. Assuming independence between successive sets, it is sufficient to group sets into their appropriate strata.

Table 2.8 gives the results. The most significant factor is obviously the aggregate type. Free swimming aggregates show a much greater ability to escape than aggregates attached to floating objects. This may partly explain the greater preference shown for log sets. The only other factor of some importance is the year which shows a marked decline in the success rate after 1983, at the same time as the rise in sets per day (even after the removal of the compensation for the lower success rate, see previous section). This result is similar to that with the least squares model of section 2.2 except the parameter values show a more marked decline.

The other factors explain much less of the deviance, although they are significant. The larger vessels probably carry larger nets which may decrease the chance of escape. They should also be able to make a set at a greater speed, giving the fish less chance to swim out. The variation between the success rate in different zones is more difficult to explain. One possibility may be varying oceanographic conditions with fresh water runoff, water depth and the thermocline changing near the coast. The seasonal change could be explained in a like manner.

		Estimate	Standard Error	Deviance	Degrees of Freedom
Constant		1.762	0.201		
Unattached Aggregate		-2.068	0.040	2982.0	1
GRT	400-499	0.133	0.063	20.4	2
	500<=	0.148	0.086		
Zone	2	0.435	0.118	85.7	10
	3	0.001	0.116		
	4	0.199	0.092		
	5	0.259	0.091		
	6	0.246	0.118		
	7	-0.018	0.178		
	8	0.343	0.094		
	9	0.335	0.093		
	10	0.392	0.121		
	11	0.523	0.161		
Season	Jun-Aug	0.031	0.057	12.2	3
	Sep-Nov	0.165	0.060		
	Dec-Feb	0.067	0.057		
Year	80	0.212	0.208	251.6	7
	81	0.565	0.204		
	82	0.086	0.184		
	83	-0.139	0.181		
	84	-0.514	0.179		
	85	-0.596	0.179		
	86	-0.479	0.185		
Error				1931.8	680

Table 2.8 The table shows the coefficients and deviance for the fit of the logit model to the success rate. All factors were significant ($p < 0.01$).

Examination of the residuals imply the model could be improved if more information was available on different factors. The errors are over-dispersed (scale parameter 2.84), leaving much variation not explained by the model. What other information might be needed is not clear, but it will probably include oceanographic conditions (eg surface temperature) and aspects of the behaviour and size of the aggregation rather than characteristics of the vessels making the sets. If the probability of success is related to the numbers of schools, the size of the aggregation will be important. The decline in the success rate is not mirrored in the catch per set in table 2.3 which implies that the two effects may be separate. This is further discussed in section 2.6.

2.5 Patch Exploitation

The analyses carried out so far have looked at changes in catch rate on a large spatial and temporal scale. It is impossible to test the underlying assumption of a detectable relationship between catch rate and stock size. Also interpretation of the results is extremely difficult, and although plausible explanations can be provided in each case, there is little improvement in understanding how the fishery and tuna population interact. On a smaller scale, it should be possible to test the assumption that the catch rate declines significantly with abundance of fish, and interpretation of the results should be easier.

Any model must ultimately aim to represent the data set to which it is applied. In this case the data have large rounding errors. This is demonstrated by figure 2.4 which shows the frequency distribution of the skipjack catch per set in tonnes. It is evident that many catches are rounded automatically to the nearest 5 tonnes. Although this will have a negligible effect on larger catches, there will be a significant effect on the sizes of smaller catches when fitting a model. More importantly this makes it very difficult to test some of the models developed beyond very general patterns. For instance if the average school weight is less than 5 tonnes it will be difficult to detect single schools in the data. These problems will detract somewhat from the potential gains made with a more theoretical approach, although such an approach is worth starting if only to show how data collection might be improved in the future.

If exploitation of a small area is intense, it would be expected that there would be a local decline in abundance. This decline in abundance should be detectable through time as a decreasing catch rate. A sub-set of the data was created based on a small time and spatial scale to see if any exploitation

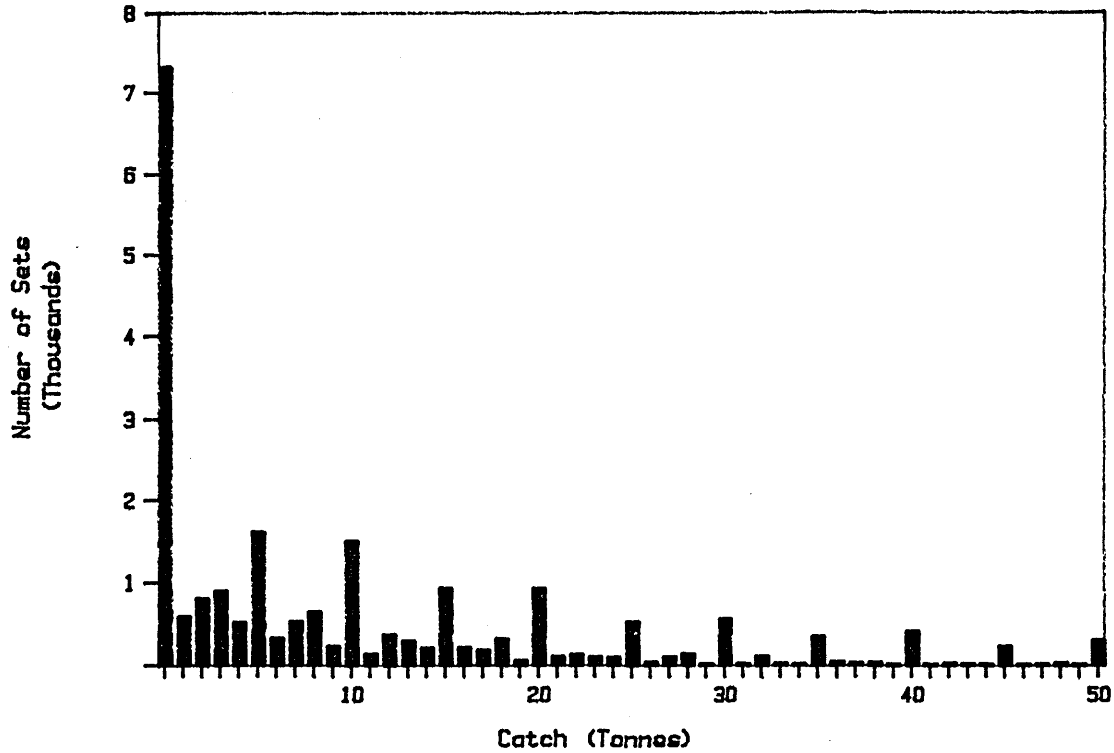


Figure 2.4 Frequency of skipjack catch per set

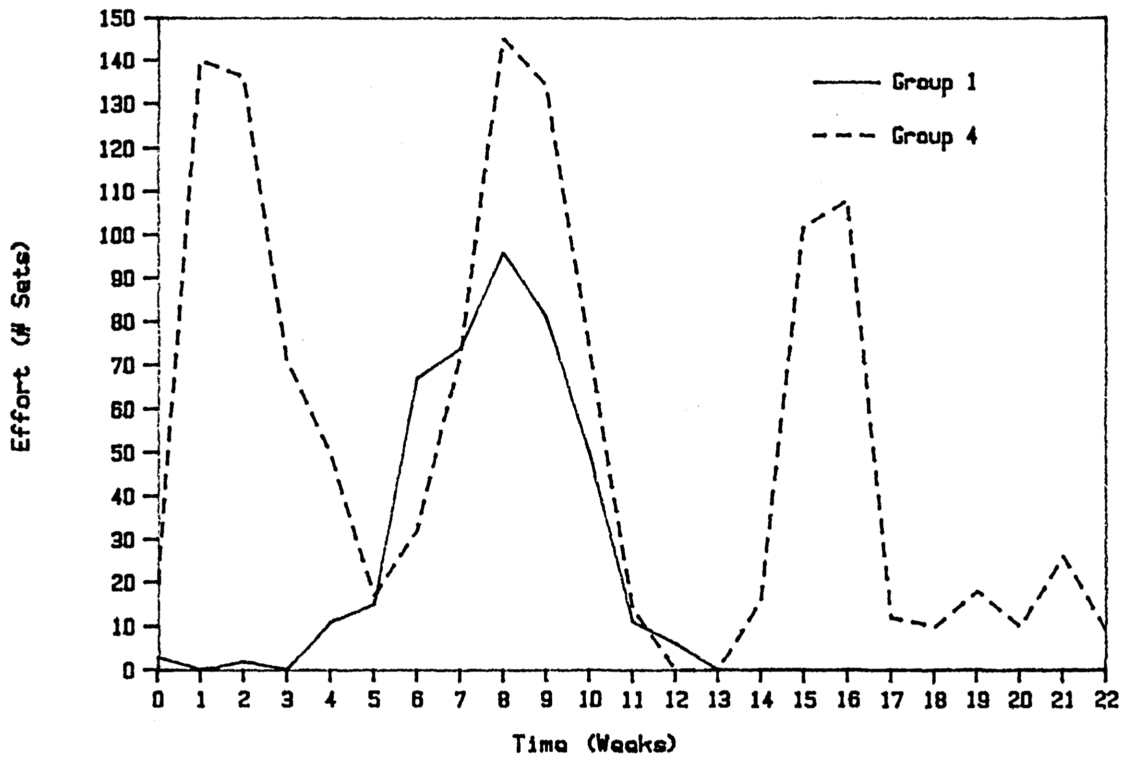


Figure 2.5 Time series of effort per week

patterns emerged and check that such a decline could be detected.

Five separate sub-sets of the data were created, each one being centred upon a degree square having more than 50 sets made in a particular month. Some of these degree squares occurred next to each other, and so these were combined into the same sub-set. Figure 2.5 shows two example time series of the number of sets. The groups of data are referred to in the order in which they occurred. The first group shows the same pattern as that found in all but one of these patches, that is a single high peak in the effort. In the other case (group 4) there are three peaks in the effort, with low numbers of sets recorded between. A similar pattern is seen when plotting catch per set against time, but whether these peaks represent just changes in effort or real changes in the catch per set it is not possible to say without further analysis.

The time series is consistent with patch exploitation. There is an initial increase in effort as vessels are attracted to the site, followed by a decline as the patch is depleted and other areas become more attractive. These particular cases are obviously exceptionally large patches, however this pattern of behaviour may still fit smaller areas where testing the theory may not be possible.

Group 4 with three peaks in effort is worth looking at in a little more detail. Figure 2.6 shows the spatial distribution of sets marked in the three groups identified from the effort time series. Each group is made up from sets separated by the minimum effort between the peaks. There is a spatial overlap between the first patch and the other two. The temporal gap between exploitation of the patches may be due to operational factors (eg weather) or changes in the fish density due to depletion or fish movements.

It is important to recognise the difference between this analysis and one operating on a larger scale. Basically an analysis over many years assumes that the system is at some sort of equilibrium. Over a shorter time period such an assumption may not be applicable. For instance if a small number of logs are rapidly exploited so that fish do not have time to redistribute themselves amongst the logs, no decline in catch per set would be detected, even if a long term decline in the catch per set is occurring as a result of over-exploitation.

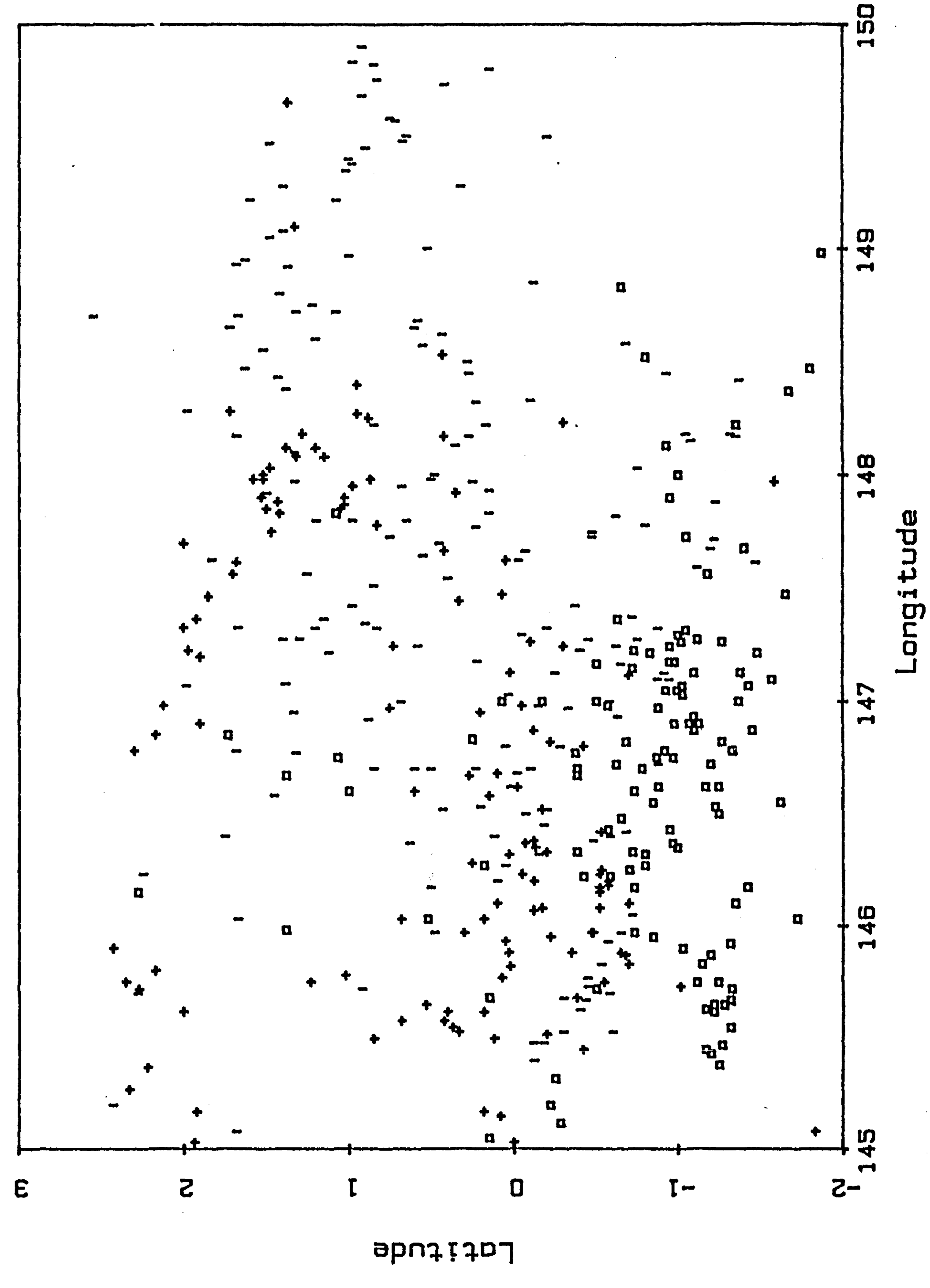


Figure 2.6 Group 4 spatial distribution sets: | subgroup 0, + subgroup 1, □ subgroup 2.

A comprehensive model must include some theory for the probability distribution of the catch per set. This is useful both for the identification and interpretation of suitable models linking the catch rate to abundance. This requires some theoretical discussion of how aggregations are made up and are replenished, as well as the size and structure of tuna schools. Section 2.8 continues the analysis of patch exploitation in the light of the theory developed in the following sections.

2.6 Number of Schools in an Aggregation

Models developed here assume some sort of relationship between the size of an aggregate and the size of the population. The simplest model is one assuming constant arrival and departure of fish, where the ultimate number of fish in an aggregation will form a Poisson distribution. However to include the effects of fishing, this model must be extended.

At any one time there will be many vessels fishing, presumably aggregating to patches of high fish density. Logs will be fished, and the average size of aggregation will fall. There will be a time delay as a log recruits schools either from a separate population or other logs to increase to some equilibrium level. Interference will occur if logs are encountered before reaching their equilibrium.

Interference will appear as an increased number of logs encountered that are not viable to fish and a decrease in the catch per set caused by recent fishing rather than long term population changes. This factor will obviously be important not only because it will affect the catch, but also it may cause an underestimate of the stock size in an assessment.

Co-operation will be an important factor providing information on the location of logs recently fished. Potentially it allows vessels to avoid the worst effects of interference, although interference may still take place, either because co-operation is imperfect or there are groups of non-co-operative vessels.

The importance of interference will depend upon the rate at which a log recovers after fishing as well as the time between sets made on the same log. If fish move around between a set of logs, fishing on one log may affect the catches of others in the region. Such a shared local population could make models of catches much more complicated.

2.6.1 Deterministic School Aggregation

A simple dynamic model is proposed with constant immigration, emigration and mortality. The simple case of a single background population and second population attached to a FAD has already been discussed by Hilborn and Medley (1989). However the purpose of that work was to assess the optimum number of FADs to be deployed under different fish arrival and departure rates. Here the aim is to see how catch rates might be affected through interference in a patch, which can be done by extending that model to many separate populations.

It has been found not all fish under a log are taken in a set (Sharp, 1978) and tuna seem able to locate logs with ease (Hunter et al., 1986). Hence the fish moving in to replace tuna removed by a purse seiner may be those escaping the set, those below the maximum net depth and tuna coming in from other aggregations, as well as new recruits from a background population.

An improved model might include recruitment to a log from different populations, the general form of the model being :

$$\frac{dN_x}{dt} = \alpha_x + \sum_{y=1}^{n} a_{yx}\,\beta_y N_y - (\beta_x + \epsilon_x) N_x \qquad 2.3)$$

where

α_x = rate of arrival of new recruits from a background population

a_{yx} = proportion of fish leaving aggregation y going to aggregation x ($a_{xx} = 0$)

β_x = rate of departure from aggregation x to alternative aggregation within the patch

ϵ_x = mortality and emigration rate of fish associated with aggregation x

This is a set of homogeneous linear differential equations of first order with constant coefficients. This equation can be solved by looking at the associated homogeneous system (see Jones and Sleeman, 1983). The general solution can be shown to be of the form :

$$N_x = C_{0x} + \sum_{y=1}^{n} C_{yx} \, \mathrm{Exp}(\psi_y t) \qquad 2.4)$$

where

ψ = set of eigenvalues of the coefficient matrix

C_{xy} = arbitrary constants dependent upon the initial conditions.

The special case that demonstrates the result of this model is the consideration of two aggregations. This might be thought of in terms of one aggregation being those fish associated with a log and vulnerable to fishing and the other aggregation consisting of fish which are not vulnerable to fishing, but 'know' of the logs existence. Basically it assumes two populations, a local population moving among a set of logs in the vicinity of the log of interest, and a wider background population consisting of migrating fish and new recruits. The whole population associated with the set of logs will behave in the same manner described by a single asymptotic equation (Hilborn and Medley, 1989), the main change being that only a proportion of this population may be fished. The model can be written as two simultaneous differential equations :

$$\frac{dN_1}{dt} = \alpha_1 + \beta_2 N_2 - (\beta_1 + \epsilon_1) N_1$$

$$\frac{dN_2}{dt} = \alpha_2 + \beta_1 N_1 - (\beta_2 + \epsilon_2) N_2 \qquad 2.5)$$

The solution is of the form : 2.6)

$$N_1(t) = \frac{C}{DE} + \frac{AD^2 - BD + C}{D(D-E)} \mathrm{Exp}(-Dt) + \frac{AE^2 - BE + C}{E(D-E)} \mathrm{Exp}(-Et)$$

where

$$A = N_1(0)$$

$$B = (\beta_2 + \epsilon_2) N_1(0) + \beta_2 N_2(0) + \alpha_1$$

$$C = \alpha_1(\beta_2 + \epsilon_2) + \beta_2 \alpha_2$$

$$D,E = \frac{(\beta_1 + \beta_2 + \epsilon_1 + \epsilon_2)}{2} \pm \frac{\sqrt{(\beta_1 + \beta_2 + \epsilon_1 + \epsilon_2)^2 - 4(\beta_1 \epsilon_2 + \beta_2 \epsilon_1 + \epsilon_1 \epsilon_2)}}{2}$$

The model predicts that the system will return to the same equilibrium regardless of the initial values. There are two rates of return, one faster (the larger eigenvalue) than the other. It is assumed here that movements within a patch will be much greater than movements between patches, therefore the local patch population replenishes the aggregation rapidly to some level below that before fishing, which is then topped up from the larger background population. With repeated fishing the whole local population will be depleted.

Figure 2.7 shows the changes in the size of the populations with repeated fishing of a particular log. The rapid rise in the size of the aggregate subsequent to fishing coincides with a rapid fall in the local population. If this process is rapid enough relative to the exploitation rate, there should be a noticeable decline in the catch per set. The model also shows that even if another log is fished in the vicinity, the numbers of fish associated may fall.

The degree of movement of tuna between (α) and within patches (β) is obviously very important. Figure 2.8 demonstrates the most important result from this model. The number of schools associated with a log are shown as they increase after fishing. The different time series represent different departure rates from the aggregation to alternative aggregations within the same patch, relative to the arrival rate from outside the patch. The number of schools associated with the whole patch increases asymptotically to some value completely independent of the within patch departure rates, which decide the distribution of schools among the aggregates within the patch. If the within patch departure rate for this aggregate is relatively low, then the equilibrium number of schools will be high. Clearly the opposite is true if this departure rate is high. However in this case schools build up in alternative aggregations, so that the arrival rate from these other aggregations increases. The net affect of this is to increase the rate at which the equilibrium number of schools associated with the log is reached. This can be seen in figure 2.8 as a more rapid initial rise and rate of deceleration of the curve.

The potential effect on interpreting catch per set could be very great. In the general case, the more rapidly schools arrive and depart within a patch of aggregations relative to the exploitation rate, so the greater the relative change in the average catch per set over this period. If rates of departure

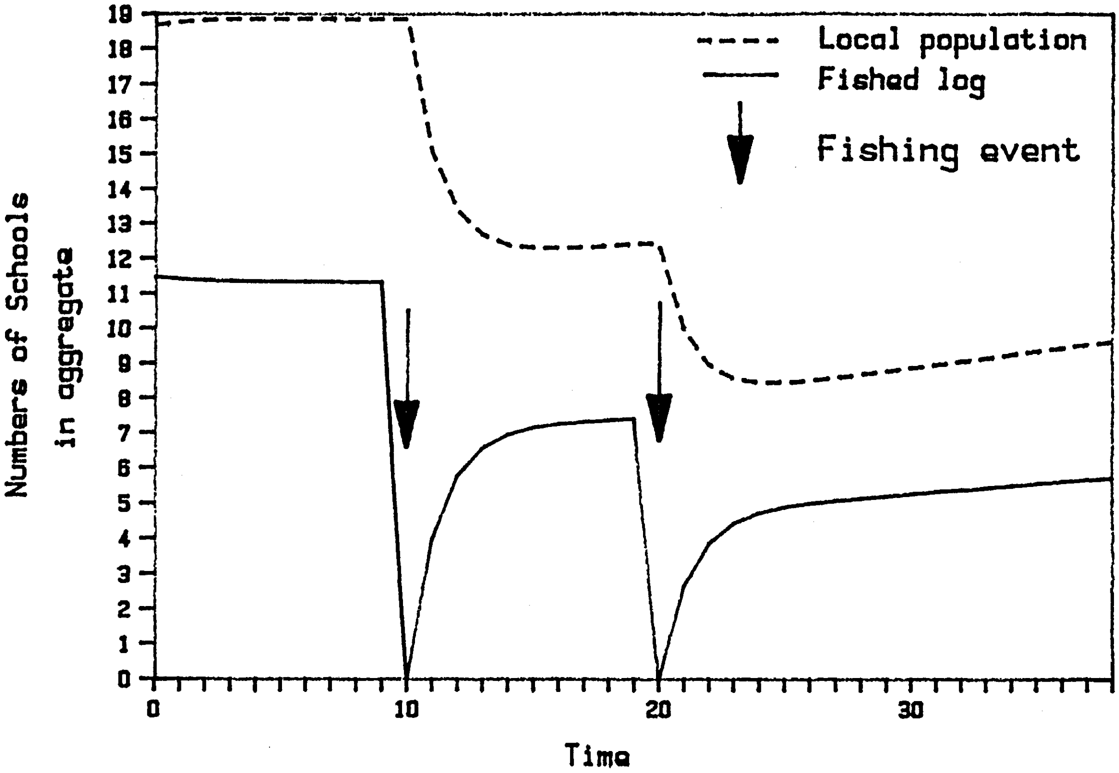


Figure 2.7 Log school model

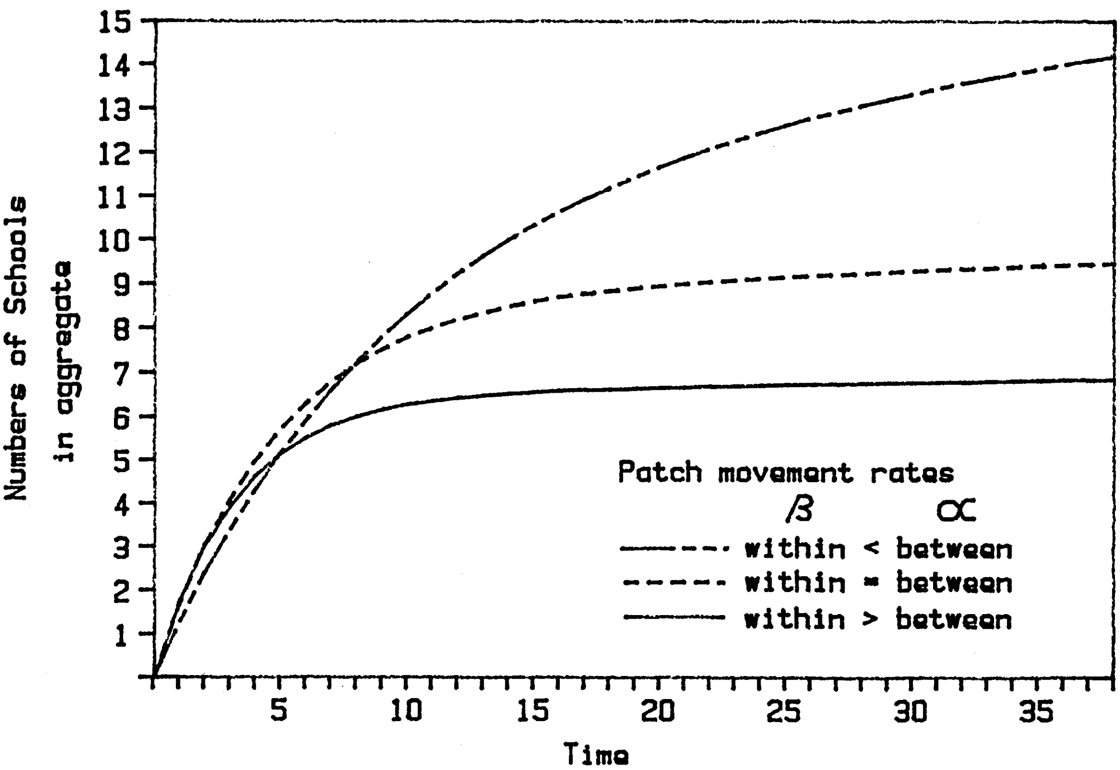


Figure 2.8 Movements between and within patches

and arrival between aggregations within the same patch are relatively small, it is possible that the exploitation rate will be too fast to allow the fish to redistribute themselves, so no decline in the catch per set will be observed.

The results will be similar if a larger number of sub-populations are represented, with the different eigenvalues giving the different rates of return. There are two extremes represented by the asymptotic model with one rate of return, and this model with two very different rates of return. The addition of more sub-populations does not much improve the model in terms of representing the system, but does require more parameters.

How well the model represents changes in population sizes of the fish will largely depend upon the fish behaviour, about which little is known. That tuna are capable of leaving an area and moving great distances is not disputed, but it is not known how common this form of movement is.

Evidence suggests tuna move in schools rather than as individuals (Sharp, 1981), and thus it might be better to consider a difference equation model rather than the continuous model considered above, which will be a bad approximation if schools are large. However, in order to see how well such a model with constant arrival and departure rates fits real data, it is better to turn to a stochastic model which will provide both variance and log-likelihood functions.

2.6.2 Stochastic School Aggregation

The type of stochastic model presented here belongs to the wider group known as birth-death stochastic processes (see Cox and Miller, 1965) where the 'birth' or 'death' of a school can be considered a discrete event in continuous time with a fixed probability. The rates represented in the differential equation model above will be similarly represented by the probability of the event of arrival or departure in the stochastic model. Hence a set of equations can be constructed to represent a set of aggregations among which schools move freely. The process for a particular aggregation can be described as follows :

$N_x(i,t+\Delta t)$ = 2.7)

Prob {there are i schools at time t and no birth or death occurs between t and $t+\Delta t$}

+ Prob {there are i-1 schools at time t and one birth occurs between t and $t+\Delta t$}

+ Prob {there are i+1 schools at time t and one death occurs between t and $t+\Delta t$}

+ $O(\Delta t)$

where

$N_x(i,t)$ = probability that the number of schools in aggregation x at time t is i.

$O(\Delta t)$ = sum of the probabilities of all combinations of other (higher order) events. In this case it is the probability of more than one event (birth or death) occurring in Δt, which is assumed to be negligible (ie $O(\Delta t)=0$).

There are two types of birth process in this model :

1) A new school arrives from outside the set of aggregations with probability $\alpha_x \Delta t$. These will be either new recruits or a migrating school.
2) A school moves from another aggregation y where there are j schools to the aggregation represented by the equation with probability $j\beta_y \Delta t$.

Similarly there are two types of death process :

1) A school leaves the set of aggregations either due to mortality or migration where there are i schools with probability $i\beta_x \Delta t$. It would seem unlikely that a whole school would succumb to natural mortality at once, although the term could also represent the combining of schools occurring when they reach some sub-optimum size.
2) A school leaves x for another aggregation when there are i schools with probability $i\epsilon_x \Delta t$.

Although a general model can be developed for a whole set of aggregations, for simplicity only the two sub-population case is solved. For the first aggregation the probability density function is given by :

$N_1(i,t+\Delta t)$ = 2.8)

$$N_1(i,t)(1 - \alpha_1 - \sum\beta_2 N_2(j,t)j - i(\beta_1 + \epsilon_1))\Delta t$$
$$+ N_1(i-1,t)\ (\alpha_1 + \sum\beta_2 N_2(j,t)j\ )\Delta t$$
$$+ N_1(i+1,t)\ (i+1)\ (\beta_1 + \alpha_1)\Delta t$$

The parameters represent the processes described in equation 2.3, except they now represent the probability of an event rather than a rate. The equation can be simplified by multiplying by a new variable, S^i, summing over i and then solving to obtain the probability generating function.

$$\frac{\partial G_1(S,t)}{\partial t} = G_1(S,t)\ (S-1)\ (\ \alpha_1 + \beta_2\ \mu_2(t)\ ) + \frac{\partial G_1(S,t)}{\partial S}\ (S-1)\ (\ \beta_1 + \epsilon_1) \qquad 2.9)$$

where

$G_1(S,t)$ = probability generating function

$\mu_2(t) = \sum_j N_2(j,t)j$ = mean number of schools in the second sub-population

The equation can be solved by using the deterministic model to provide the mean as a trial solution. However a boundary condition is needed. If it is known that all schools were caught in the set, the start position for the size of the aggregation must be zero. Therefore the boundary condition requires that the initial number of schools is fixed. In general, the boundary condition will be :

$$G_1(S,0) = S^{\mu(0)}$$

which gives :

$$G_1(S,t) = \{\ (1 - \mathrm{Exp}(-(\ \beta_1 + \epsilon_1)t) + S\ \mathrm{Exp}(-(\ \beta_1 + \epsilon_1)t) * \mathrm{Exp}(\ (1-S)\ (1-\mathrm{Exp}(-(\ \beta_1 + \epsilon_1)t)\ \}^{\mu(t)} \qquad 2.10)$$

where

$\mu(t)$ = the deterministic mean size of the aggregation given by equation 2.6).

The probability distribution is a compound of the binomial and Poisson distributions. As time progresses the distribution tends to the Poisson and becomes independent of the initial conditions. The mean and variance of the distribution can be found easily from the generating function :

Mean = $\mu(t)$

Variance = $(1 - \mathrm{Exp}(-2(\ \beta_1 + \epsilon_1)t)\ )\ \mu(t)$

It can be seen that the variance never exceeds the mean, but approaches it exponentially.

The model assumes that the initial number of schools is known, hence the initial zero variance. However the number of schools under a log at t = 0 can itself be a random variable representing the number of schools escaping the first set. To include this factor into the model, the boundary condition at t=0 needs to be changed. The complete dependence case, where either all or no schools escape, requires the boundary condition :

$$G(S,0) = 1-p + p\, G(S,T) \qquad 2.11)$$

where

T = time between the previous sets

p = probability all schools were taken

If the case where $T=\infty$ is considered, assuming the distribution is independent of the initial conditions, the simpler generating function is obtained :

$$G(S,0) = 1-p + p\, \mathrm{Exp}(\,(1-S)\,\mu_\infty\,) \qquad 2.12)$$

where

μ_∞ = mean number of schools at $t=\infty$

This leads to :

$$G(S,t) = (1-p)\,\mathrm{Exp}(-(\beta_1+\epsilon_1)t) + (\,1 - \mathrm{Exp}(-(\beta_1+\epsilon_1)t) + p\,\mathrm{Exp}(-(\beta_1+\epsilon_1)t)\,) * \mathrm{Exp}((S-1)\,\mu(t)) \qquad 2.13)$$

with initial condition :

$$\mu(0) = \mu_\infty = N(0) = C/DE \qquad \text{from equation 2.6.}$$

The distribution is Poisson over its non-zero range, with the mean increasing over the time since the last set has been made.

$$\text{Mean} = (\,1 - \mathrm{Exp}(-(\beta_1+\epsilon_1)t) + p\,\mathrm{Exp}(-(\beta_1+\epsilon_1)t)\,)\,\mu(t)$$

$$\text{Variance} = \text{Mean}$$

The alternative hypothesis at the other extreme is that schools escape completely independently. If the number of schools in an aggregation is Poisson before any fishing, and the number escaping follow a binomial, the catch and the escaping schools will also follow a Poisson distribution. This can be shown from considering the number of schools present in an aggregation as a random sum (see Feller, 1960). In this case the initial probability generating function, assuming that the aggregate was at its long-term equilibrium ($T=\infty$), will be :

$$G(S,0) = \mathrm{Exp}(\ (S-1)\ p\,\mu_\infty) \tag{2.14}$$

where

p = probability any one school independently escaped

This boundary condition leads to :

$$G(S,t) = \mathrm{Exp}(\ (S-1)\ (1 - \mathrm{Exp}(-(\beta_1 + \epsilon_1)t) + p\ \mathrm{Exp}(-(\beta_1 + \epsilon_1)t)\ \mu(t)) \tag{2.15}$$

Mean = $(1 - \mathrm{Exp}(-(\beta_1 + \epsilon_1)t) + p\ \mathrm{Exp}(-(\beta_1 + \epsilon_1)t)\ \mu(t)$

Variance = Mean

Interestingly both extreme cases lead to Poisson distributions. Unlike the first model where the initial value was unknown, they remain effectively a Poisson process throughout their range. If the basic model is correct, that is movements between aggregates can be described by a set of constant probabilities, interference will only express itself by affecting the mean catch rather than intrinsically altering the probability distribution. However within a patch the variance to mean ratio of the catch per set may still be expected to rise as catches increasingly include logs previously fished as suggested by the deterministic model. It should be possible to remove this effect with a statistical model using time since last fished as an explanatory variable.

2.7 School Size

Although the number of schools under a log may have a Poisson or related distribution, it is likely the number of fish in a school taken at random will not be. This will obviously be an important factor when looking at catch per set data. Without much more detailed information than is available any model is bound to be flawed, however a simple model of schooling structure can be developed and used as a foundation on which more accurate representations might be built.

Firstly consider all schools containing a fixed number, j, of fish. When a fish dies in school size j+1, the number of schools size j increases by one, but when a fish dies in school size j, the number of schools size j decreases by one. Alternatively a whole school may die at once, which will also reduce the number of schools passing to the next size class. If the probability a fish dies and the probability a whole school dies are constant over all school sizes, a model can be built in the same manner as for the log departure-arrival model in section 2.6.

The full model is of the form :

$$
\begin{aligned}
(N_j(k,t+\Delta t) - N_j(k,t)) S^k \quad = \quad & - \alpha_j S^k N_j(k,t)\Delta t \qquad\qquad 2.16) \\
& - S(mj+f)k\ S^{k-1} N_j(k,t)\Delta t \\
& - \sum_i i\ N_{j+1}(i,t)\ m(j+1)\ S^k N_j(k,t)\Delta t \\
& + S\alpha_j S^{k-1} N_j(k-1,t)\Delta t \\
& + \sum_i i\ N_{j+1}(i,t)\ Sm(j+1)\ S^{k-1} N_j(k-1,t)\Delta t \\
& + (mj+f)(k+1)\ S^k\ N_j(k+1,t)\Delta t
\end{aligned}
$$

where

$N_j(k,t)$ = probability there k schools size j at time t
$m\Delta t$ = probability a fish dies in Δt
$f\Delta t$ = probability a whole school dies in Δt (eg due to fishing)
$\alpha_j\Delta t$ = probability a school is recruited size j
S = variable used to obtain the probability generating function

The inclusion of school mortality as well as individual fish mortality is particularly useful. Although some dependence of fish natural mortality might be expected within a school, it would seem unlikely whole schools would die at once from natural causes. However purse seine, unlike longline, tends to remove whole schools rather than individual fish, so fishing mortality is better represented as school mortality.

The number of schools size j will depend upon the number of schools size j+1. To solve the equations for the non-equilibrium states the initial numbers of all sizes of school will have to be provided. However the simpler approach is to look for the long term equilibrium state. This can be done by setting the right hand term in equation 2.16, $N_j(k,t+\Delta t)-N_j(k,t)$, to zero. Since the system is at equilibrium, time need no longer be included as a variable. Furthermore it is evident that the probability a school is added to size j is dependent only upon the mean number of schools size j+1. Summing over the different numbers, k, of school size j leads to the linear differential equation :

$$(mj+f)\,\frac{dG_j}{dS} = (\alpha_j + m(j+1)\,\mu_{j+1})\,G_j \qquad 2.17)$$

where

G_j = probability generating function for the distribution of the numbers of school size j

$\mu_{j+1} = \sum_i i\,N_{j+1}(i)$ = mean numbers of school size j+1

Which, solved in the standard way, gives :

$$G_j = \mathrm{Exp}\left((S-1)\left(\frac{\alpha_j + m(j+1)\,\mu_{j+1}}{mj+f} \right) \right) \qquad 2.18)$$

By recursively defining each μ_j from some upper school size limit, a general formula for any school size can be formed :

$$\mu_j = \frac{\alpha_j + m(j+1)\,\mu_{j+1}}{mj+f} = \sum_{x=j}^{n} \frac{x}{j!} \frac{x!}{\prod_{i=j,x}(i + f/m)} \qquad 2.19)$$

where

n = largest possible school size (ie recruited school size).

$\mu_0 = 0$

The model can be further simplified by choosing n such that all schools having sizes smaller than or equal to n will receive no schools from the school size larger than itself.

$\alpha_n > 0$

$\alpha_j = 0 \qquad j = 1..n-1$

which gives :

$$\mu_j = \frac{\alpha_n}{j!} \frac{n!}{\prod_{i=j,n}(i + f/m)} \qquad 2.20)$$

This could be justified by assuming recruitment (ie formation) of schools occur over sizes of fish too small to be caught by purse seine and therefore need not be considered. α_n therefore represents arrivals from larger sized schools which are not fished. One of the assumptions of the model is that all recruits would have to pass through school size n.

The probability distribution for the total number of schools will be a convolution of all distributions at each school size. Since the number of each individual size of school is a Poisson variable, the total number of schools will be a Poisson variable as well, with parameter (mean) :

$$\mu = \sum_{j=1}^{n} \mu_j = \frac{\alpha_n \; n!}{\prod_i (i + f/m)} \sum_{j=1}^{n} \frac{\prod_{i=1}^{j} (i + f/m - 1)}{j!} \qquad 2.21)$$

In its present form the model has few useful applications. To apply the model to real data, the probability distribution of the size of a school taken at random is required. If it is known that there is a total number of k schools not size j and x schools size j, then the probability a school taken at random is size j is given by :

$$P(\text{school size } j) = \qquad 2.22)$$

$$\sum_{x=0}^{\infty}\sum_{k=0}^{\infty} P(k \text{ schools not size } j)\; P(x \text{ schools size } j) \; \frac{x}{x+k}$$

$$= \sum_{x=0}^{\infty}\sum_{k=0}^{\infty} \mathrm{Exp}(-\mu_k - \mu_j) \quad \frac{\mu_k^{\,k}}{k!} \frac{\mu_j^{\,x}}{x!} \frac{x}{(x+k)}$$

where for equation 2.20

$$\mu_k = \mu - \mu_j$$

Equation 2.22 is not easily simplified, however a approximation for the sum can be found. The sums in equation 2.22 can be represented as the expectations of $x/(x+k)$. Applying the delta method (Taylor expansion of an expectation function around the mean; Seber, 1982), and dropping all second order and higher terms, it can be shown that for large n the distribution tends to :

$$\frac{\mu_j}{\mu_k + \mu_j} = \frac{\mu_j}{\mu} \qquad 2.23)$$

and by substituting 2.20 into 2.23

$$= \frac{\prod_{i=1}^{j} (i+f/m-1)}{j! \displaystyle\sum_{k=1}^{n} \frac{\prod_{i=1}^{k} (i+f/m-1)}{k!}} \qquad \text{for } f/m > 0 \qquad 2.24)$$

$$= \frac{1}{j \sum_{k=1}^{n} \frac{1}{k}} \qquad \text{for } f/m = 0 \qquad 2.25)$$

The first two moments for this distribution are :

$$E(X) = \frac{N\ f/m}{f/m + 1} + \frac{\prod_{i}^{n}(i + f/m) - n!}{n\ \ n!}$$

$$E(X^2) = \left(1 + (n - 1)\ \frac{(f/m + 1)}{(f/m + 2)}\right) E(X)$$

Where there is no school mortality ($f/m = 0$) and n is large, the mean and variance can be approximated by :

$$\text{Mean} = \frac{n}{\ln(n)}$$

$$\text{Variance} = \frac{n}{\ln(n)} \left(\frac{(n+1)}{2} - \frac{n}{\ln(n)} \right)$$

To understand how this theoretical distribution might relate to data collected from field observations, deviations from the underlying assumptions need to be examined. The assumption of constant parameters will probably not hold. Recruitment will presumably vary yearly and seasonally with the result that the distribution of schools will be subject to peaks and troughs, which will attenuate as the schools get older (smaller). Equation 2.16 is only solved for the equilibrium conditions which does not allow for perturbations. For instance, if recruitment was particularly high in one year, the movement of that set of schools through the different sizes will occur over a long time, with the result that a return to equilibrium will be slow. The model still provides the best long term estimate without any knowledge of the present size distribution of schools, as long as the recruitment is stable in the long term. Perturbations may increase the variation of the numbers of schools of a particular size, but should not effect the long term mean. Apart from varying from year to year and season to season, mortality is probably higher in small fish (larger schools) and declines with age. This will tend to increase the relative numbers of small schools.

A further important deviation from the model will occur if different sized schools mix and combine tending to some optimum size where benefits from living in a group are greatest (see Krebs and Davies, 1981). The schools will still consist of the same size fish, since they must swim at the same speed. Having to find fish of the same size may decrease the degree of mixing.

There are a number of effects that might govern school size, such as predation rates and size of food clumps, their relative importance changing as fish become larger (see Krebs and Davies, 1981). There is also some empirical evidence that schools are not stable through time for more than a few months (Hunter et al, 1986). The model as it stands represents the passive case where there is no recombination or splitting. The inclusion of recombination and splitting produces a complex model which was rejected, since intuitively it is possible to see that the net effect will be to increase the numbers of medium sized schools, which can be included in a simpler way.

The model assumes random sampling of schools. Purse seiners can be selective in both the size of the catch and the size of the individual fish. This might mean that both very large schools with small fish and very small schools might be under sampled relative to their frequency in the population. This will have a similar effect to school recombination, in that it should increase the relative numbers of medium sized schools.

It is likely that the maximum school size will be large. In this case the distribution given by equation 2.24 can be approximated by the negative binomial. A new parameter is introduced to ensure the sum, that simplifies the probability generating function, is not infinite. Although the parameter has to be introduced for mathematical reasons, it produces desirable properties in the distribution, namely the ability of the mode to lie in the centre of the distribution, rather than at either extreme. As has been explained, if schools mix, they will presumably tend to some optimum size. The optimal school size for a particular size of fish is not known, but it should lie above one fish. Therefore small schools at least should combine which may well produce a mode somewhere towards the centre of the distribution.

$$\text{Negative Binomial P.G.F.} = \left(\frac{1-p}{1-Sp}\right)^{f/m} \qquad 2.26)$$

where

p = arbitrary parameter

If there is no school mortality ($f/m = 0$), the distribution will be the log distribution.

The use of negative binomial has been well documented, but rarely has a theoretical meaning been found for the dispersion parameter (Elliott, 1977). Here the dispersion parameter is defined by the ratio of fishing to natural mortality. This captures the effect of fishing on the distribution of school sizes. Without school mortality (fishing) there is a build up of small schools. School mortality will tend to equalise the numbers of schools at different sizes, so that it will tend to increase the mean size of school captured while decreasing the variation in the sizes of school. This, of course, should be accompanied by a drop in the catch rate.

These changing mortalities and behaviours of the fish could produce almost any frequency distribution for school size, of which the simplest is developed above. The simple case gives the distribution towards which a real frequency distribution will tend in the absence of other effects. As knowledge of schooling behaviour is improved, this model might be built upon to provide a more accurate description of the process and sampling. The model may also have wider application in interpreting the fitted negative binomial distribution.

Just fitting this distribution to catches is not a foolproof test. Even if the distribution adequately fits an observed frequency, the theoretical derivation may be incorrect. In these circumstances the parameters cease to have their theoretical meaning and their usefulness is diminished. There is no way to check any of these potential problems from the present data set.

2.7.1 School Weight Distribution

As might be expected, obtaining a theoretical school weight distribution is more difficult. Not only must fish and school mortality be represented, but also growth. The weight of a fish and the numbers of fish are conditional upon the age of the school. The proportion of schools at different ages can be evaluated easily from the previous analysis, if recruitment is constant, as the number of schools containing one fish or more.

The error distribution chosen for the growth is the gamma, since it can be ensured all values are above zero and the distribution is very flexible. Any reasonable non-decreasing decelerating curve might be used for the mean weight. Wild (1986) obtained a good fit using an exponential growth rate model, however it would be too complex for the present model. Hence the von Bertalanffy growth equation was used, because of its simplicity and previous wide use. In practice the choice of distribution and mean weight is not crucial to the results. In order that members of a school can stay together, the fish will have to be the same size. Therefore the school weight distribution at age is found by multiplying the mean by the number of members of the school rather than through a convolution of the distribution, which would be appropriate if the fish sizes were independent.

$$P(\text{school weight } W \mid \text{number fish } x \text{ age } t) = \frac{x\, W^{v-1}\, \mathrm{Exp}(\,-Wv/(xM_t)\,)}{(xM_t/v)^v\, \Gamma(v)} \qquad 2.27)$$

where

M_t = $W_\infty(1 - \mathrm{Exp}(-kt))$ = von Bertalanffy growth curve

v = gamma coefficient of variation parameter

The probability distribution of the number of fish in schools age t, assuming constant mortality, is the binomial with an exponentially declining mean (see Cox and Miller, 1965; p168). Whole school mortality (fishing mortality) can be added without a great increase in complexity. The proportion of schools at each age can be estimated using the zero term of this distribution if the number of schools is very large and recruitment is constant.

$$P(x \text{ fish age } t) = {}^{n}C_{x}\, \mathrm{Exp}(-mxt)\, (1 - \mathrm{Exp}(-mt))^{n-x}\, \mathrm{Exp}(-ft) \qquad 2.28)$$

where

m = fish mortality

f = school mortality

The combined numbers-weight distribution must be integrated over age and summed over numbers of fish to give the school weight frequency.

$$P(\text{school weight } W) = \int_0^{\infty} {}^{n}C_x \ \mathrm{Exp}(\ -(mx+f)t\ )\ (1 - \mathrm{Exp}(-mxt)) * \left(\frac{x\ W^{v-1}\ \mathrm{Exp}(\ -Wv/(xM_t)\ )}{(xM_t/v)^v\ \Gamma(v)\ \sum_{r=0}^{n} {}^{n}C_r(-1)^{r+1}/(rm+f)} \right) dt$$

where

$$\sum_{r=0}^{n} {}^{n}C_r(-1)^{r+1}/(rm+f) \quad = \quad \text{normalising constant}$$

Although this distribution cannot be found directly, the first two moments can be obtained since the order of integration is immaterial.

$$E(W) = \frac{W_\infty k}{\sum_{r=0}^{n} {}^{n}C_r(-1)^{r+1}/(rm+f)} \left(\frac{n}{(m+f)\ (k+m+f)} + \frac{n\ (n-1)}{(2m+f)\ (k+2m+f)} \right)$$

$$\mathrm{Var}(W) = \frac{W_\infty^2 k}{\sum_{r=0}^{n} {}^{n}C_r(-1)^{r+1}/(rm+f)} \left(\frac{n}{(m+f)\ (k+m+f)\ (2k+m+f)} + \frac{3\ n\ (n-1)}{(2m+f)\ (k+2m+f)\ (2k+2m+f)} + \frac{n\ (n-1)\ (n-2)}{(3m+f)\ (k+3m+f)\ (2k+3m+f)} \right)$$

To give some idea of the behaviour of the model, figure 2.9 shows a plot of the mean and standard deviation of school biomass against different school (fishing) and individual (natural) mortalities. These two types of mortality have similar effects, largely because the growth in biomass of the school over time increases initially before declining. Hence fishing mortality serves to increase the relative proportion of young to old schools, which will not increase the mean school biomass, since young schools are made up of more, but smaller individuals. In general increased mortalities of both schools and individuals will decrease the mean and the variance of the school biomass.

The mean and variance of the biomass distribution is more sensitive to natural mortality than school mortality. Natural mortality has the opposite effect on the school biomass distribution to fish growth rate. As natural mortality increases, the school biomass peak will occur at an earlier age,

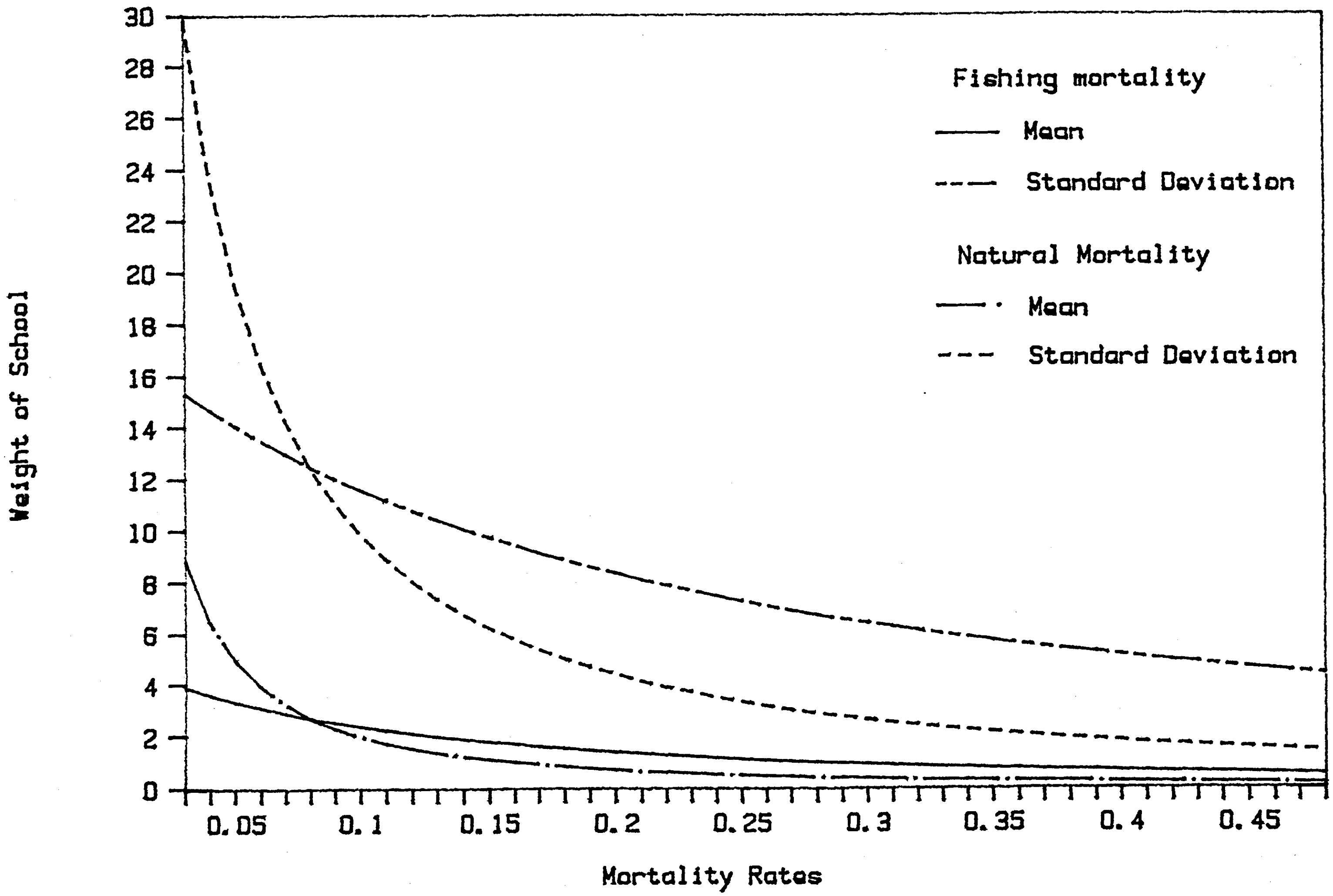


Figure 2.9 Mean and standard deviation of school weight

so that the distribution will be compressed reducing the variation in size. As natural mortality approaches zero, there is an exponential increase in both the mean and variance, levelling off at zero to the mean and variance of the gamma distribution associated with the growth equation.

This model is subject to the same criticisms applied to the model of the numbers of fish since all the assumptions are largely the same, with the additional ones concerning the growth curve. However it is likely that the general results will stand for most reasonable growth functions.

Finally it is possible to see how these results will affect the catch per set. As fishing mortality of schools increase, the total number of schools should decrease, so the average number of schools in an aggregate will also fall. However the average age of the schools will also be lower, so that the numbers of fish in each school will be greater, while the average mass of a school will be little changed. The larger number of individuals in each school will counteract the fall in the number of schools. This suggests catch biomass than fish numbers is a better overall detector of a decline in stock size, as this is a better representative of the number of schools and the age of the fish in each school, both of which are determined by fishing (school) mortality rather than individual (natural) mortality.

2.8 Linear Model of Patch Exploitation

Consideration of the relation between catch and effort can be greatly simplified if a small time and space scale is adopted. Rather than assuming that the stock response to fishing is tracking some equilibrium value, a whole set of catches is taken to be a representative sample of the stock at that time. This hopefully avoids problems of changing stock structure with fishing mortality. The subsets of data chosen are described in section 2.5, corresponding to what appear to be patches which are comparatively rapidly exploited. These groups of data are numbered in the order in which they occurred in time : 1 to 5.

As a patch is exploited, which may take up to a few months, a highly mobile species such as tuna may recolonise logs that have been already fished. This re-distribution could result in a detectable decline in the average numbers of schools per set.

A simple model is needed to relate the mean numbers of schools in a set to the time it was made relative to the start of the patch exploitation. If the number of schools per set is random and independent from set to set (autocorrelations are zero), the time-catch relationship could be described adequately by a linear model with a Poisson error. However the data are not going to follow the Poisson error distribution, since they consist of either numbers or total weight of fish rather than numbers of schools. Even if the exact number or weight distribution of schools is known, the log-likelihood will be complex and difficult to manage. This approach will only be worth while when an estimate of some of the non-linear parameters will provide useful information and where the data set will support such a complex procedure. Although it has been shown that the dispersion parameter may represent the distribution of school sizes and, indirectly, mortality rates, the data set is not refined enough to support this approach. Instead this theory is used to help interpret a more general linear model, where the sensitivity of the results to assumptions can be tested.

Assuming all fish are caught, the catch size distribution will be a random sum of the school sizes (weight or numbers). This gives the new general probability distribution :

$$\text{M.G.F.} = G(S) = \mathrm{Exp}(\lambda F(S) - \lambda) \qquad 2.30)$$

where

= mean number of schools

$F(S)$ = Moment generating function (M.G.F) for the school size ie $S = \mathrm{Exp}(\theta)$

The mean and variance can be found by differentiating with respect to θ :

$$\mu = \lambda F'(1) \qquad 2.31)$$
$$\sigma^2 = \lambda F''(1)$$

Over a small time period the school structure, represented by $F(S)$, should remain constant, so that the variance will be proportional to the mean. This result lends itself to the quasi-likelihood methods (McCullagh and Nelder, 1983) and allows a simple interpretation of results. So although the data will be highly dispersed (scale parameter > 1), there should be no systematic increase in the variance with the mean beyond the first power (ie V $\propto \mu$). The alternative hypothesis is that there is a systematic increase in the variance with higher powers of the mean. This could be due to several effects. The most obvious is that schools may aggregate in some non-random fashion. Alternatively there may be some violation of the assumption of random sampling, for instance selectively fishing schools of a desirable size, or a genuine change in school structure over the period of exploitation. This can be tested to some extent by checking if there is a change in the average size of fish over the interval. In these cases the Poisson distribution would not be appropriate.

Another cause of this over-dispersion may be association between schools when escaping. The two simplest descriptions of this process have already been discussed (section 2.4). Escapement by itself could explain all dispersion of the number of schools above the random case. Although an unsuccessful set might be expected to arise more frequently on logs with few schools and therefore might provide information on the numbers of schools, there are three major problems to be dealt with before including zero catches. The most important is that of a sampling bias discovered in section 2.3, where the most likely explanation of a marked increased setting rate with a decreased success rate was that a repeat set was made on a log if the first set was unsuccessful. This will lead to a sampling bias towards logs with fewer schools.

The degree of association between escaping schools is still not known, so that zero catches may simply add noise to the data making interpretation more difficult. Finally there may be estimation problems with zeros in the data limiting the type of model chosen. Since the inclusion of unsuccessful sets should only support results found without their presence, some idea of whether they should be included may be obtained by comparing models with and without these data.

The degree of school association and escapement has been discussed in section 2.6. At the two extremes either empty sets may be dealt with separately if all or no schools escape, or included if schools escape independently. If schools escape independently, unsuccessful sets will provide useful information in estimating the Poisson parameter. In this the probability generating function is given by :

$$\text{P.G.F. } G(S) = \text{Exp}(\ \lambda(1-p + p\ F(S)\ ) - \lambda\ ) = \text{Exp}(\ p\lambda F(S) - p\lambda\ ) \qquad 2.32)$$

where
 p = probability a school escapes

Hence this simply results in a Poisson distribution with new parameter $p\lambda$. However there is still a difference between all schools escaping (a set is made but the catch is zero) and no fish being present (no set is made), the latter not being recorded. Therefore strictly speaking a model will have to be truncated to allow for this effect. This presents some difficulty since there are no independent estimates of λ, needed for the truncated distribution. These problems can be dealt with by trying different models and comparing results.

There are a wide variety of covariates and factors that can be included in the linear predictor for the catch per set. Firstly those predictors that might be independent of the stock decline, namely the species caught, the school type, size class of vessel, other species present and the degree square of the exploitation. Those covariates related to the non-random exploitation of the patch. These include cumulative catch and effort, the present or some previous level of effort and the sequence number of the set into the trip. In particular the present or previous level of effort should follow the initial increase, if there is one, in catch per set as vessels locate the areas of the highest catches and subsequent decline as the resource is depleted. Finally the time since the exploitation began should show the linear change in the average catch per set.

2.8.1 Results

Models were fitted with both weight and numbers as dependent variables. A large number of models were tested and so the full results of each fit cannot be presented here. Instead the best model is fully described and alternative models compared to it. Firstly unsuccessful sets are excluded because it is unsure how they will relate to underlying numbers of schools, bearing in mind they should only support results obtained from analysis of successful sets. Their exclusion also avoids some problems with estimation.

There are three choices that have be made to build a generalised linear model (McCullagh and Nelder, 1983). Firstly an appropriate deviance function (based on the log-likelihood) must be chosen. Secondly a variance function relating the systematic change of the variance with the mean. Finally a link function must be selected to define the relationship between the linear predictor and the mean.

There is no a priori choice of deviance function, so the simplest have been used. In particular there was found to be insignificant changes in the estimates from using either the Poisson or gamma deviances. However the choice of variance function, as might be expected, was crucial to the results. There is no standard method for choosing a variance function based on a set of data. To simplify the problem two hypotheses were tested. Either the variance was proportional to the mean or alternatively proportional to the mean squared. Choice between the two is based largely on judgement from studying Pearson residuals ((Observed-Expected)/Variance) plotted against fitted values. These plots indicated the variance was increasing at a more rapid rate than the mean, suggesting the variance function should be $V \propto \mu^2$. This can be supported by assuming the variance function is of the form :

$$V = \sigma^2(\mu + k\,\mu^2) \qquad 2.33)$$

The dispersion parameter, k, can be estimated as its value that makes the Pearson Chi-squared statistic equal to its expectation (McCullagh and Nelder, 1983). In effect the μ^2 part of the function is used to explain dispersion not expected in a Poisson process. In this case k was found to be consistently close to 1 for the catch weights and between 0.5 and 0.75 for the catch numbers. The means are large enough so that μ^2 dominates the function supporting the visual judgement.

Another parameter could be added to the variance function to ensure a minimum variance to account for any rounding error. However graphical displays did not support the inclusion of this parameter, and when added it appeared to have little effect on the results. The increased complexity of this extra parameter was therefore not justified.

This systematic change in the variance with mean is an important result. The assumptions leading to equations 2.31 appear not to hold and these smaller data sets seem to resemble in structure the larger data set from which they have been taken. The most likely explanation for this is the spatial distribution of schools among logs which are probably not random even on this scale.

The link function could be chosen on the basis of the minimum deviance. Two link functions were found to work with varying degrees of success for each data group. The reciprocal link is the canonical link for the gamma error and provided the best fit in some cases. However there were problems, since estimated means are not bounded by zero, making this link inappropriate for many models. The log link is the canonical link for the Poisson error. It provided a good fit in all cases and was the best in most, therefore it was used to compare models.

Six variables were found to explain significant variation in one or more of the groups of data. Consistently the most significant variables were the species caught and the aggregate type. The two species were included in the same data file to check if the catches of each were related. Aggregate type was reduced to five due to a lack of data in all categories. The first two are aggregates associated with floating objects. The last three are free swimming aggregates. Time (days) since exploitation began, the previous weeks total effort (number of sets) and catch of the other species (tonnes) proved significant in some models. The sub-patch variable is only relevant to group 4 data, and separates the data in three sub-sets representing the apparent three separate periods of exploitation shown in figures 2.5 and 2.6.

Tables 2.9 and 2.11 give the deviance for the fits of these variables for the catch weight and numbers of fish respectively. In all cases the proportion of deviance explained is still small implying a large degree of residual dispersion. This underlines the problems in detecting a mean decline in catches with high variances. The models presented use the gamma deviance with a log link. It should be noted that although this is the best model out those fitted, the deviances and estimates for the time and effort variables were not sensitive to the changes in the link, variance and deviance functions. The changes in deviance in the table have an approximate chi-squared distribution. The species interaction terms will only be significant if the changes in catch per set due to the factors differ significantly between skipjack and yellowfin. Parameter estimates are only given for significant variables (tables 2.10 and 2.12), since inclusion of non-significant variables will distort their values.

Not surprisingly the species caught and the aggregate type have the greatest effect on both numbers and weight of catch. Yellowfin catches tend to be smaller in weight and numbers. Aggregate type effects are more complex, the estimates not being consistent from data set to data set. In general the catch weight or numbers tends to be higher for all non-log schools. When there was a detectable difference, yellowfin aggregate weight increased while numbers of yellowfin decreased relative to skipjack.

Change in deviance values for the remaining variables is small. The time after exploitation began is of most interest and was fitted next to avoid correlations with subsequent variables. There is a decline in the catch weight per set in groups 1 and 3, in the latter case the decline is limited to yellowfin only. Group 4 shows an increase over time. The pattern is less distinct in the model of numbers per set. These results imply interference may have only a small part to play in the overall variation of the data set. The previous week's effort appears to be negatively related to the catch weight or numbers per set. The catch of the other species in a set tended to be positively correlated with the present species where significant.

The models assume that the factors species and school, and the success rate do not themselves systematically change over time. The sensitivity of the model can be tested easily by adding and removing different factors. The results proved reasonably stable.

Inclusion of unsuccessful sets greatly increased the dispersion, and added nothing to the model. A logit fit of the available explanatory variables to the proportion of successful sets proved aggregate type to be the only significant variable. The species ratio (number of sets containing skipjack :

yellowfin) showed some change. The proportion of skipjack sets is negatively related to the previous week's effort in groups 2 to 4. Finally effort was also found to affect the aggregate types. The numbers of sets of each school type can be treated as polytomous data as described by McCullagh and Nelder (1983). Previous week's effort again was found to have the biggest effect. Species and aggregate type are themselves related, so these may simply be due to the same effects. The parameter estimates however show no clear pattern. Group 1 shows a decrease in the proportion of school types 2 to 5 with the previous week's effort, while groups 3 and 4 show a significant increase.

Least square models were fitted to log transformed data and, as might be expected, the results were very similar to those above. This implies that not much improvement can be made on a model for the data than that described in section 2.2. Furthermore this patch data would seem to have the structure of the data set taken overall. Since no consistent decline in the catch per set was observed during the exploitation of the patch, it would call into question whether the catch per set would decline as the stock declined. It might well be the case that as the stock size is reduced, fewer or smaller patches result rather than fewer schools forming the aggregates.

It is possible that the effect from exploiting the patch is obscured by the immigration and emigration of the fish or a change in their vulnerability. What governs their formation and dispersal is not clear. However it appears that the tuna population and the formation of aggregations is a dynamic process, and may need to be better understood.

The most fruitful area of research at present would probably be in the dynamics of populations moving amongst logs and FADs. If it is understood how aggregates form and disperse under logs, improved models of the catch per unit effort might be formulated and data could be interpreted with greater confidence. Many problems could cleared up simply by monitoring the catch at particular FADs over time and comparing acoustic estimates of aggregate sizes with actual catches. This would allow a direct assessment of factors involved in controlling arrival and departure rates as well as the importance of escapement from the set.

Group	1	2	3	4	5
Species	17.9	57.10	78.4	369.9	137.98
	1	1	1	1	1
Aggregate	65.8	42.18	221.43	187.5	4.6
	4	2	4	4	4
Species.Aggregate	9.7	1.25	6.1	31.9	12.0
	4	2	4	4	4
Time	15.5	1.93	25.5	5.9	0.0
	1	1	1	1	1
Effort	7.9	0.52	1.2	0.1	4.4
	1	1	1	1	1
Species.Time	0.5	0.01	25.9	2.5	0.1
	1	1	1	1	1
Species.Effort	0.2	6.04	0.5	0.2	0.5
	1	1	1	1	1
Other_Catch	8.1	1.46	3.0	17.1	3.8
	1	1	1	1	1
Species.Other_Catch	0.0	1.47	0.1	2.9	0.0
	1	1	1	1	1
Total Deviance	680.77	270.43	1182.8	1893.9	515.92
Degrees of Freedom	559	177	867	1320	377

Table 2.9 The table gives the change in deviance for significant main effects species interaction effects fitted to catch weight per set for each of five patch groups of data. The gamma deviance was used (variance proportional to the square of the mean) with a log link function. Zero catches were not included.

Group	1	2	3	4	5
Constant	3.494	2.306	2.913	3.138	3.363
Species					
Yellowfin	-0.587	-0.571	-0.222	-1.576	-1.540
Aggregate type					
Flotsam	-0.388	1.041	1.112	0.374	-0.374
Black Spot	0.272	0.000	0.662	0.674	-0.284
Splasher	0.532	0.460	1.124	0.572	0.499
Rippler	0.440	0.000	1.044	-0.454	-0.149
Species.Aggregate					
Yf.Flotsam	0.637			0.904	1.367
Yf.Black Spot	0.800			0.740	1.174
Yf.Splasher	0.355			0.840	-0.209
Yf.Rippler	-0.267			1.003	-0.735
Time	-0.004		0.001	0.002	
Yellowfin.Time		-0.010			
Effort	-0.007	0.015			
Yellowfin.Effort		-0.020			
Other Species Catch	0.008			0.006	0.006

Table 2.10 Significant parameter estimates ($p < 0.05$) for catch weight per set linear model.

Group	1	2	3	4	5
Species	290.5 1	192.5 1	800.6 1	1143.8 1	291.8 1
Aggregate	10.2 4	2.22 2	23.0 4	13.2 4	8.0 4
Species.Aggregate	1.4 4	20.14 2	21.2 4	23.6 4	6.2 4
Patch	0	0	0	4.1 2	0
Time	17.8 1	0.22 1	4.7 1	8.7 1	0.6 1
Effort	1.6 1	0.00 1	0.2 1	0.9 1	2.6 1
Species.Patch	0	0	0	8.8 2	0
Species.Time	0.0 1	0.50 1	0.0 1	7.0 1	0.1 1
Species.Effort	0.5 1	7.36 1	0.1 1	0.0 1	0.2 1
Other_Catch	6.3 1	3.25 1	8.0 1	30.6 1	2.6 1
Species.Other_Catch	0.0 1	1.72 1	0.0 1	4.6 1	0.1 1
Total Deviance	820.3	391.10	1772.9	2538.9	670.0
Degrees of Freedom	559	177	867	1320	377

Table 2.11 The table gives the change in deviance for significant main effects species interaction effects fitted to catch number of fish per set for each of five patch groups of data. As with the catch weight the gamma deviance was used with the variance proportional to the square of the mean. Zero catches were not included.

Group	1	2	3	4	5
Constant	3.130	1.557	2.010	2.139	2.617
Species					
Yellowfin	-1.534	-1.313	-1.860	-2.083	-1.983
Aggregate type					
Flotsam	-0.209	0.525	0.673	0.013	-0.387
Black Spot	0.287	0.000	0.030	0.346	-0.607
Splasher	0.193	0.331	0.633	0.240	-0.020
Rippler	0.223	0.000	0.638	-0.940	-0.290
Species.Aggregate					
Yf.Flotsam		-1.044	-0.836	-0.424	
Yf.Black Spot		0.000	-0.474	-0.841	
Yf.Splasher		-1.785	-0.463	-0.049	
Yf.Rippler		0.000	-0.842	1.668	
Time	-0.016		0.002	0.007	
Yellowfin.Time				-0.001	
Effort		0.012			
Yellowfin.Effort		-0.023			
Other Species Catch	0.006		0.006	0.018	
Yellowfin.Other Species Catch				-0.011	
Group 4 patches					
Patch(2)				-0.288	
Patch(3)				-0.529	

Table 2.12 Significant parameter estimates ($p < 0.05$) for catch number per set linear model.

2.9 Summary

A least squares linear model fitted to the purse seine catch rate shows that the catch rate has been increasing since 1979. This is probably because the fishery is expanding and the experience of the fishermen is improving. A more detailed look at the sets per day, success rate and catch per set undermines the assumptions used in the linear model. In particular the method of search and the way fish distribute themselves in a highly aggregated fashion suggest only a weak relationship between catch and effort over the levels of exploitation occurring in the south Pacific at present. Plausible explanations can be provided for all observed patterns without reference to the stock size. There is no obvious immediate improvement that can be made to the basic linear model, although it would be advisable to verify its assumptions. The data set can be greatly improved by recording logs without any associated tuna. ?

For the longer term the analysis suggests that more research is needed for looking at the movements of tuna between logs. By far the largest number of sets are made on logs, so they form the main medium through which purse seiners interact with the stock in the south-west Pacific fishery. Some theoretical models are developed in this study that should help in future work on school movement and catches among FADs and logs.

[illegible] theoretical & applied modelling [illegible]
Species & aggregate type are important [illegible]
[illegible] what is implication [illegible]
tagged [illegible]
No sign of exploitation effect.

Chapter 3

Model of Longline Catch Rates

3.0 Introduction

The aim of this chapter is to look at longline catches in detail, seeing how these might relate to the stock density. The relationship between longline catch per unit effort and the stock density is likely to be simpler than the purse seine relationship due to characteristics of the gear.

Longline is a method for setting a large number of baited hooks, allowing commercial quantities of many species to be caught which would otherwise be uneconomic to exploit. The three main species taken in the south Pacific are bigeye, albacore and older yellowfin. The fishing gear, consisting of a main line to which baited hooks are attached, is particularly well adapted for widely distributed species, because it has the ability to cover a large area, as well as to target specific areas and depths with some degree of accuracy.

Longline is passive in that once the hooks are laid it is up to the fish to find them. The model presented here attempts to describe the fishing process once the line is laid. This removes the problem of modelling the fishermen's behaviour, and therefore removes one layer of complexity from the model of the fishing process. Applying the model to data should also be much easier because the catch tends to be small, so data recording is much more accurate and reliable than for purse seine.

A general description of the gear and method is presented, emphasising the important factors. A stochastic model is subsequently developed. The model relates theoretical catch distributions to the physical behaviour and distribution of fish. These theoretical distributions are related to actual catch distributions and conclusions concerning the adequacy of the model and the data set are determined.

3.1 Description of the Longline Fishing Method

Longline has so far proved to be the best method for exploiting the smaller, deeper tuna schools which are difficult to detect at the surface. Although catch rates of longline are very low, the fish brought aboard are little damaged and of good quality. This allows the low catch rate can be offset by high prices obtained from the *sashimi* market in Japan. All vessels fishing in the south-west Pacific occurring in this 1979-1986 data set were Japanese. Since the value of each fish is high great care is taken finding fishing grounds with the highest density of the target species and in landing the fish caught.

Gibson (1989) and Brandt (1984) provide a detailed description of the method. A more comprehensive discussion of the gear is provided by Nomura and Yamazaki (1975).

Longline vessels used for fishing tuna vary little in size, the average in the south Pacific being about 100 gross registered tonnes (GRT). Apart from the obvious factors such as the trip lengths, expected catches and crew size needed to operate the gear, the main criteria for vessel size are the licence regulations in the country of origin causing vessels to gather at the top of artificial size classes. These vessels are fitted out with large storage capacities for long trips. Particularly important in the tropics are large, efficient storage freezers which will hold the catch below $-45^{o}C$ (for modern vessels below $-55^{o}C$) and powerful blast freezers for cooling fish as quickly as possible.

The nature of the gear requires a well organised stowing system. The mainline is kept at the rear of the vessel either in bins or wound on a drum. A powerful winch is fitted towards the front of the boat to haul the line. The branch lines (in bundles) and buoys are stowed separately, a system of conveyor belts carrying them to their appropriate storage areas.

In general longliners possess very accurate navigational systems, usually including satellite navigational equipment. It is necessary to know the exact position of the line at time of setting as well as at time of hauling. This not only gives information on where the highest densities of fish are, but also on currents over the length of the line. Other equipment includes sonar to search for fish, an echo-sounder to gauge water depth and radar, used to locate buoys should the line be broken, update vessel position between satellite fixes and monitor other vessels in the area. A vessel will also have search lights situated above the bridge to search for buoys at night. Remaining space on the vessel will be taken by the crew which usually numbers between 15 and 20, including a captain and fishing master.

The fishing master is responsible for setting the line and deciding upon the position of the set, the bait and hooks used and the depth of the hooks. In order that a good fishing ground is located as quickly as possible, information is gathered before and during the trip. Previous experience plays an important part, but other sources of information are consulted as well. Groups of vessels will often co-operate by communicating in coded form their catch and location. Before and sometimes during a trip it might be possible to obtain up to date satellite images of the ocean, indicating currents, fronts and water temperatures over a large area. Sets are often made across the current, it being believed that tuna tend to swim parallel to currents. They will also usually be made in comparatively shallow water (1200 - 1750 metres) using submarine topographical features, such as seamounts, where tuna tend to gather.

Catches of longline, like purse seine, are highest in areas of highest tuna density. Therefore longline fishermen use satellite information in the same way as purse seine fishermen. Similarly, the presence of marine mammals and a sharp thermocline between 100 and 200 metres indicates a good site (Nomura and Yamazaki, 1975; Sharp, 1978). Figure 3.1 shows a sample distribution of longline sets from 1984 in the central and south Pacific. There are clearly two groups corresponding to submarine topography and the equatorial currents in the region (see chapter 2). The high number of sets around the Caroline Islands probably correspond to the aggregation and formation of plankton as the oceanic currents run over the island chain.

On closer examination it is also evident that there are some smaller areas which have a particularly high concentration of fishing activity. This suggests that the spatial distribution of fish has an important part to play in the fishing process. Although longline and purse seine share the same general fishing area, they probably concentrate their effort in different places on a smaller scale. Unlike purse seine, longline is vulnerable to entanglement through currents, but does not require floating objects to make a set.

Once a vessel has arrived at a likely fishing ground the set is made. The direction in which the line is laid usually includes practical considerations, such as reducing the chance of tangling of the line, minimising difficulties in setting and

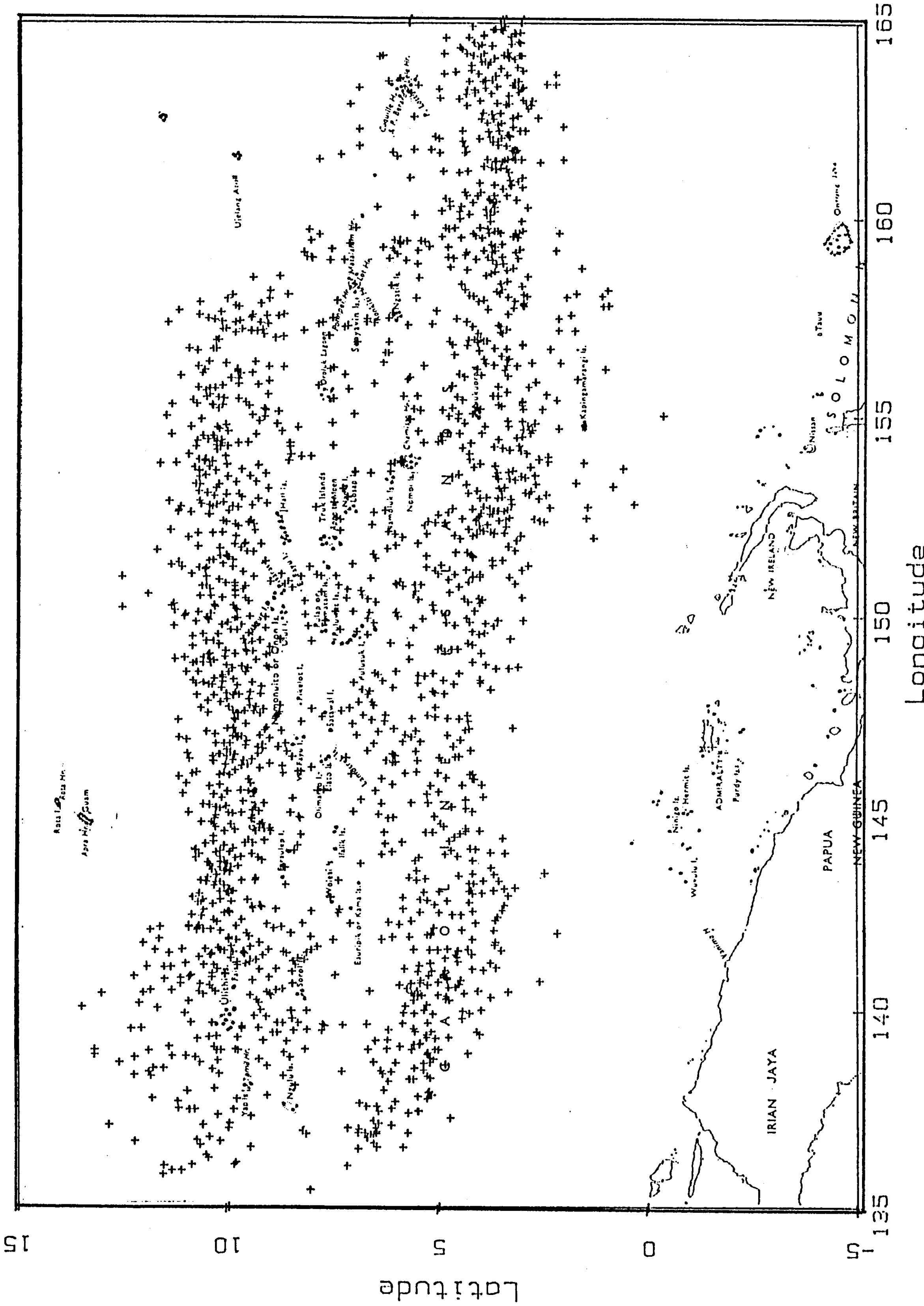


Figure 3.1 A sample distribution of longline sets from 1984.

hauling as well as maximising the catch. Therefore wind and wave direction are included, if either is significant, together with any current system operating. Sets are usually made into waves or wind, few sets being made when the sea is above force 6. Although from the catch point of view it may be desirable to set the line along a current shear, this can result in the line being badly tangled and so is usually avoided. Interference between vessels through tangling with other longline sets may be a further factor to consider.

The time of set is also an important factor in the catch rate. For instance there must be enough light for the tuna to see the bait, but not be put off by the fishing line. The predators may also be more active at particular times of the day, when they have a greater chance of capturing prey (Magnuson, 1969). For a full discussion of factors affecting the longline catch see Olsen and Laevastu (1983a).

A typical set is now described. It is important to note that the gear and distances may vary significantly between vessels and during a trip as the fishing master attempts to increase the catch rate. The set is made by laying out the main line over a line hauler which takes between 7 and 8 hours. The vessel travels at about 10 knots in the desired direction, the line typically being laid at about 6-7 metres/second. Crew members stand at the stern of the vessel playing out the main line and attaching the snoods (branch lines). At intervals of about 6 seconds a note is sounded indicating that a snood with a baited hook is to be attached, the frequency of the signal being set on a constant time interval or on the amount of line that has been laid. A different pitch of note means a buoy should be put out. Both are attached using strong clips which resist sliding along the mainline. They are easily put on and taken off again, the process having to be completed quickly. The vessel may change course during setting, if there is no chance that the line might become entangled. The position of this change in direction is recorded, so that a similar change may be undertaken on hauling to maintain the vessel's course relative to the line.

The main line is a continuous length of yarn about 1 centimetre in diameter spliced together up to 130 kilometres long. It is made of tightly wound strands of nylon coated in resin to protect against abrasion. The important properties of the yarn are great strength, elasticity to absorb shocks that occur during hauling and a density greater than that of water, causing it to sink. Typically every 300 metres a buoy is attached. Buoys are made from rigid PVC with a 10 metre line attached below ending in a clip which is connected to the main line. The main line is hung 10 metres below the surface to ensure it is not cut by passing vessels. If the main line should break it is important that the buoys be found. The first and last buoy on the line have a 3 metre pole on top usually carrying means to aid detection such as a flag, reflective tape and a light. The pole may also have a radar deflector or a directional radio beacon. Other buoys vary in what they possess to decrease costs while still allowing the vessel to relocate the line quickly.

The length of line between two floats including one float and all the snoods is called a 'basket', dating back to the time when the longline consisted of separate sections stored in baskets which were tied together at time of setting. Tuna longlines usually have 6 hooks per basket. When the line is set it will lie loose in the water and gradually sink. As the line is supported by the floats it becomes taught and forms a catenary, the hooks in the centre of the basket deeper than those at either edge. Figure 3.2 is a diagrammatic representation of the shape of the line in the water.

Several factors can be controlled to increase the catch rate. The fishing master can control the depth of hook by two means. The first is by varying the speed of the vessel in relation to the rate at which the line is being laid. If the vessel is moving slowly relative to amount of line being laid the buoys will be close together, allowing the line to hang down further. The second way is through adjusting the length of line between buoys, which is determined by the number of hooks per basket. The length of main line between branch lines can be increased, but this is wasteful of line. Although possible, it is much more difficult to increase the length of the branch lines and float lines during a trip. The deepest hook usually lies between 60 and 180 metres below the surface.

The branch line is made up of three parts. The first 10 metres of the branch line has the main line clip at one end and is much the same as the main line except it is less than half the

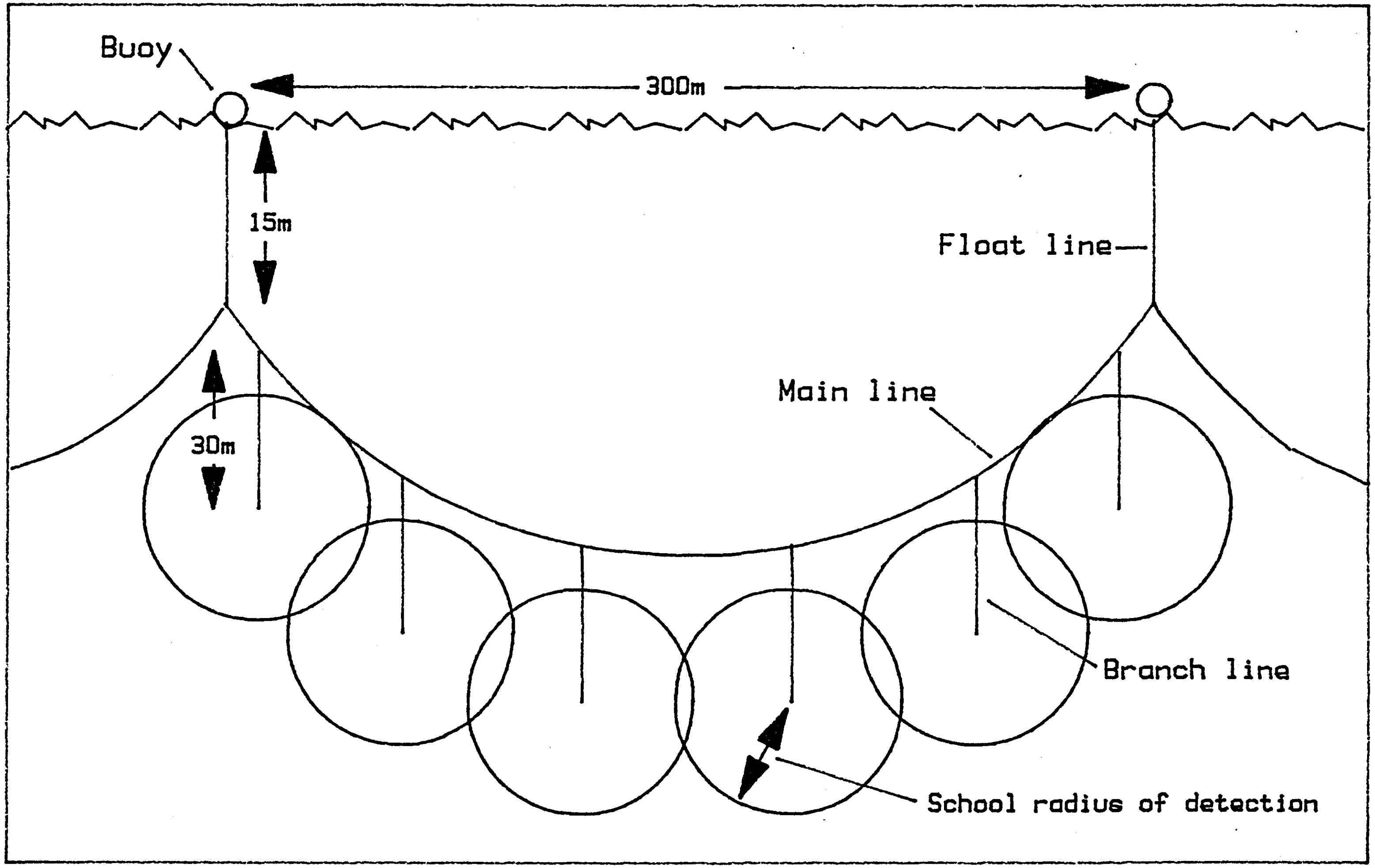


Figure 3.2 Diagram of tuna longline basket

thickness. It is attached by a loop to a 10 metre long monofilament braid (sekiyama), which itself is connected to a 10 metre monofilament line (100 to 200 kilograms breaking strain). Monofilament is preferred because it is more difficult for fish to see. A short length of wire may be used to prevent the fish biting through the line, particularly useful when there are many sharks in the area. A zinc strip may be crimped on this wire shank to reduce corrosion. Tuna hooks are almost circular, made of steel and sometimes have a diamond point. A single hook is connected to the line by a loop covered in an aluminium crimp to reduce the effects of abrasion. The hook is held well away from the main line which otherwise might repel the fish.

The distance between snoods on the main line must be kept at least 1.5 times their length to prevent snagging. It might be thought the distance between lines being attached would have to be twice their length, but in practice lines tend to fall in the same pattern so snoods do not need to be as far apart as that. Towing a weighted line to separate snoods further reduces the chances of one getting caught. Thus snoods are about 32 metres in length and placed about 45 metres apart.

Criteria used to choose the bait include the ability of the bait to stay on the hook, the attractiveness of the bait to the target fish and to other unwanted species and the cost of the bait. It is common practice to supplement a proportion of the bait with lures to reduce costs. Bird scarers are towed behind the vessel to discourage seabirds from taking bait before it sinks. Saury, sardine and mackerel are commonly used for yellowfin and bigeye, sometimes in combination in order to find the most effective bait. Hooks losing bait or taken by unwanted species are important since these hooks then cease to fish. They will affect the choice of area to fish as well as the target species density.

Once the line is laid, it will begin to sink and during this period it will be loose and liable to tangling. As it becomes taught, within about 60 minutes of laying, the mainline will form a catenary with the branch lines hanging below, although the line may not hang vertically. Often lines are laid across currents as Japanese fishermen believe tuna will tend to swim parallel with the current. The direction of flow may not be the same along the length of the line and at different depths, so that the line may not simply move with the local current. Under these circumstances the line will be pushed from the vertical, the angle of hang depending on the relative speed of water flow.

Once the set is complete the last buoy is left adrift. Usually it has a directional radio beacon to allow it to be found again easily. Then the boat heaves to for 4 to 5 hours before relocating the last buoy and grappling it aboard. The fishing master is not needed for hauling which usually lasts from 13 to 16 hours dependent upon the number of hooks and the length of line that has been laid. The line is hauled while the vessel steams parallel to the line at about 5 knots. It is important that the line is hauled aboard at the same speed as the vessel, otherwise if it drags or is pulled too tight it might snap. The line is winched over the side of the ship by a line coiler at a speed controlled by a crew member to ensure the line is pulled in at the correct rate. Other members of the crew queue by the line as it comes on board each one unclipping a snood as it appears, coiling it and striking off the bait if it is still present.

Once coiled the snoods are placed on a conveyor belt to be carried to the stern where they are tied into bundles and stored. The main line is also placed on a conveyor belt and checked for knots and tangles as it passes. If a tangle is large it can be cut out, the tangle undone and the line spliced back together. If a fish is caught, the vessel is stopped and great care is taken bringing the fish aboard, its value being too large to lose it at this stage. The snood is separated from the main line and is partly hauled up. The fish is then played by hand if it is still alive and brought to the surface. Harpoons with wires attached are thrown into the head and, together with a gaff, pull the fish on deck. Damage to the rest of the body apart from the head is avoided as this brings down the value of the fish. The haul can be slowed down by tangled lines and unwanted fish and so both are avoided where possible.

Yellowfin, bigeye, albacore and southern bluefin are the main commercial tuna species. Other desirable species include some sharks (white meat) and billfish, but they generally fetch a lower price. Yellowfin, bigeye and southern bluefin are processed in the same way. The tail is cut off and the fish is put into a seawater tank to bleed if it is still alive. If the fish is dead the blood vessels are washed out with seawater. The fins, guts and gills are then removed and all fish are put in the blast freezer which takes the temperature down to between -55 and -65°C. Albacore are frozen straight with a minimum of processing. The largest fish will have a thermometer placed inside which records the temperature and the freezer is closed until this temperature has dropped below -42°C. The fish are then transferred to the main freezer maintained at a temperature less than -45°C.

It is necessary for an efficient longliner to collect data while fishing to increase its catch rate and to guarantee the quality of the fish to the buyer. Thus an accurate estimate of the hook depth and the position of each hook at time of setting and hauling are recorded. This allows the fishing master to judge the depths and areas with the highest density of fish. All fish will be weighed, since price is very much related to size and the fishing master wishes to increase the value of his daily catch rather than simply the number of fish caught. The next set will use all this information to try and improve the catch.

Although much line may be concentrated in areas thought to hold larger numbers of fish, some line will usually be used to search other areas as circumstances might change. In the sashimi market quality is very important, thus a buyer will often require information to help him agree a price. Tuna caught in the tropics is often of a lower quality than that caught in more temperate waters. The fish tend to be in worse condition mainly because a higher proportion are spawning and have a lower oil content in their flesh (Kitson and L'Hostis, 1983). Fish brought aboard alive also fetch a higher price and this is less likely in warmer waters. So the buyer may wish to know where the tuna was caught. It is also important to check the animal was correctly processed, hence the temperature of each batch is recorded to ensure that the fish were quickly frozen and maintained at a low temperature. Most other information can be judged from the fish itself.

3.2 Single Fishing Hook Model

The mathematical treatment given to transects by Skellam (1958) can equally well be applied to longline hooks. A volume of water around a hook can be defined in which a fish will be able to detect a baited hook. The size and shape of this volume will depend on the perceptions of the tuna.

Tuna use three senses to detect prey at a distance. Sound may be used to find surface schools of prey fish (York, 1972), but will not be useful for locating bait. Smell may have an important role in attracting tuna, particularly if a current flows over the bait (Olsen and Laevastu, 1983b). Presumably a chemical plume would form downstream which a fish could detect and follow. Smell may also decide the efficacy of different types of bait (Ikehara and Bardach, 1981). Tuna also have a well developed sense of sight (Nakamura, 1969b). There is evidence that catches are related to water clarity (Murphy, 1959) and are greatest at midday when light is most intense (Murphy, 1960), which supports the role of sight in the catch rate. Most marine predators that hunt by sight use the silhouette of their prey against a light background, usually the surface. The distance from which the tuna will be able to see the bait will therefore not only depend upon the total amount of light available and the visibility of the water, but also the position of the fish in relation to the hook. A fish passing below the hook will be able to see the bait from a greater distance than a fish passing above it.

It is important to note that this volume of detection is not constant, but will expand and contract, changing its shape with current speed and the amount of light (time of day, amount of cloud and moon phase). A further complication arises because a fish may be discouraged from taking a bait if it sees the fishing line, although longline hooks are often attached to a monofilament line which is not easily seen. Even so, ideal conditions of visibility may not give the highest catches, and there are probably optimum conditions when the difference in probability of a fish finding the bait and being repelled by the line is the greatest. From the fish's point of view there may be an optimum visibility too, when they might be more active. Tuna are larger than their prey and can swim faster over an extended period. However the prey's small size makes them much more manoeuvrable such that the catch rate of tuna may be enhanced by a degree of surprise. Hence tuna may prefer conditions of lower visibility to hunt, for instance at night with a full moon, sunset or sunrise. This may, along with temperature, decide the modal depth.

3.2.1 Mathematical Representation of Hook Encounters

A thin volume of water on the surface of a hook volume can be defined, such that when the fish is in this marginal volume it will detect the bait dt units of time later. The width of the marginal volume will be proportional to the velocity of the fish. Of the population of fish, a proportion $L(\Theta_1, \Theta_2)$ will be moving (in three dimensions) in a particular direction (Θ_1, Θ_2). For all fish moving in this direction at time t there is some probability that they are in the marginal volume and will detect the bait at time t+dt. For any direction (Θ_1, Θ_2) the hook volume will present a surface, whose area, together with velocity of fish moving in that direction, gives the size of the marginal volume. The instantaneous arrival of fish detecting the bait can then be derived by integrating over all directions (Θ_1, Θ_2).

Number of fish detecting hook over time = 3.1)

$$\int_0^T \int_0^{2\pi} \int_0^{2\pi} D \; A(\Theta_1, \Theta_2, t) \; V(\Theta_1, \Theta_2, t) \; L(\Theta_1, \Theta_2, t) \; d\Theta_1 \, d\Theta_2 \, dt$$

where

D	=	density of fish, the parameter which has to be estimated
$A(\Theta_1, \Theta_2, t)$	=	area of cross section perpendicular to (Θ_1, Θ_2) of the hook volume at time t
$V(\Theta_1, \Theta_2, t)$	=	velocity of fish moving in direction (Θ_1, Θ_2) at time t
$L(\Theta_1, \Theta_2, t)$	=	proportion of fish moving in direction (Θ_1, Θ_2) at time t

The equation suggests that detection of the hook by fish might be modelled as a point process.

Fish density might be expected to vary with location, depth and time. These functions may be complex, depending upon visibility, currents and behaviour. Little is known about their form, so that there is no chance of obtaining absolute fish density from longline data at the present time. The density might be thought of as an average over all directions weighted by the proportion of fish moving in a direction coupled with the velocity in that direction and the volume surface presented to that direction. If the velocity and volume surface are uniform over all directions, the density is a simple mean.

Without information on these factors the simplest model is chosen. Both the direction and velocity of fish is presumed to be independent of time. If the volume around the hook is uniform (ie spherical), the proportion of fish swimming in the different directions is unimportant. However its surface area, which is related to its size, is obviously important. The model assumes no change in size over time.

The arrival of a tuna will only be detected if the tuna is caught and remains on a hook. Whether a hook catches a fish is dependent upon the probability distribution of the time intervals between fish detecting the bait. That is, either a fish detects the bait during the time the hook is in the water or does not. Independence between these interval probability distributions is not necessary if the bait is always taken when detected. Adjustments can be made should a proportion of these baits be rejected by the fish. However under these conditions substantial savings in complexity are made if the process of detection is assumed to be a renewal process (ie distribution for the time between detections is identical).

If it is assumed that there is a constant probability independent of time that a hook will be taken, the distribution of time between sets leads naturally to the negative exponential distribution, used to describe a Poisson process (see chapter 2). Equation 3.1 can be used to provide the parameter (p) for this process. If the hook volume is spherical and all functions are independent of time, equation 3.1 can be written as equation 3.2.

Probability fish detects hook = 3.2)

$$\int_0^T \int_0^{2\pi} \int_0^{2\pi} \frac{D\ V\ \Pi\ R^2}{4\ \Pi^2}\, d\theta_1\, d\theta_2\, dt \;=\; \int_0^T D\ V\ \Pi\ R^2\, dt$$

where

D = fish density

V = fish velocity

R = radius of sphere around the hook within which a fish will detect bait

and from equation 3.1

$$A(\theta_1, \theta_2, t) = \Pi R^2$$

$$V(\theta_1, \theta_2, t) = V$$

$$L(\theta_1, \theta_2, t) = \frac{1}{4 \Pi^2}$$

Approximate estimates for these parameters can be suggested from the literature. For yellowfin, 2 m/s (7.2 km/hour) is reasonable for the average speed of a 1 metre long fish (Blaxter, 1969; Nakamura, 1969a). If detection of the bait depends entirely on sight, the radius of the sphere of detection can be estimated. The results of Nakamura (1969b) suggest a yellowfin with ideal visibility (36m depth, bright sun at an angle of 65^o) can detect a bait of 10cm width from a maximum distance of 94 metres. In practice visibility will be lower than this, so that 94 metres is an upper limit.

There is a possibility that when a hook is detected, the fish will still not take the bait. If the underlying process of detection is Poisson and the probability of a bait being taken once detected is constant, the resulting capture rate will still be a Poisson process, but the parameter will be adjusted by the proportion of fish taking the bait. This is a similar problem to that arising from the discussion of school escapement from purse seine sets in section 2.6. Where such rejection is random, the density parameter will be adjusted by the rejection probability. However there is also the possibility of a systematic change in the bait's efficacy. In particular the chance of a bait being taken may change over time. For instance fish may be less hungry at certain times of day or the bait may be less desirable as it begins to rot. However if the probability a fish encounters a hook is small, the chance a fish on a first encounter rejects the bait and another fish on a second encounter takes it is insignificant, so that this effect could be treated in the same way as bait loss.

It is very likely that the hook will be ignored if it holds no bait. This can happen either because the bait has come off through rotting, invertebrate predation or through the hook catching another fish. Bait loss through invertebrate predation will depend upon the density and behaviour of these predators. This is probably best modelled as a separate species in the catch. Other bait loss will occur as bait is softened by the water and bacterial action, so that eventually it will come off of its own accord. The rate of bait loss will depend upon the temperature of the water, the speed and turbulence of the current flowing over the hook, and how well the bait has been fixed to the hook. Both temperature and current will change with latitude and depth, whereas how firmly the bait is attached will vary with the quality of the bait and the skill of the crew. The rate at which bait is lost will probably not be constant, but will increase with time. This may mean that the bait lost through this effect is insignificant, since the line may be hauled before it has much affect. In practice most bait is probably lost while setting and hauling when turbulence is greatest. Bait lost while hauling is obviously unimportant. Bait lost while setting will greatly affect the catch, but will be independent of soak time.

The importance of bait loss is variable. The simulation model of Olsen and Laevastu (1983a) suggests that it ultimately determines the catch. Empirical data tend to show a significant number of baited hooks being brought aboard when the line is hauled (eg Laurs et al, 1981; Hamley and Skud, 1978). At least for tuna, while the catch is not completely decided by bait loss, it should be considered.

Fish loss occurs where a fish has been hooked, but escapes or is eaten or damaged by sharks. Escaping fish cause a problem since they are an unrecorded catch. However it would seem unlikely that once a fish fully takes a well attached bait it will escape, which means that this effect is probably insignificant. Shark damage, assuming at least some of the fish will be left, will only be an economic problem since the catch can still be recorded although its value is low. However, for completeness, fish loss is added to the model.

Whether the bait comes off before a fish encounters the hook can be modelled as a stochastic process. The number of hooks still able to catch a fish at time $t+\Delta t$ will depend upon the number of baited hooks at time t and the probability a hook loses its bait during Δt, either through a fish taking the hook (p) or bait loss (r). This can be written :

$$B(t+\Delta t) = B(t)\ (1 - (p+r)\Delta t)$$

which gives :

$$B(t) = Exp(\ -(p+r)t\ ) \qquad 3.3)$$

where

t = time hook has been immersed (soak time)
$B(t)$ = probability the hook is fishing at time t
$p\Delta t$ = probability that a hook catches a fish in Δt
= $D\ V\ \Pi\ R^2$ from equation 3.2
$r\Delta t$ = probability a hook loses its bait in Δt

Using this result the probability a hook has caught a fish by time t can be derived.

$$C(t+\Delta t) = pB(t)\Delta t + C(t)\ (1 - q\Delta t)$$

which gives :

$$C(t) = \frac{p}{p+q+r}\left(Exp(\ -qt\ ) - Exp(\ -(p+q+r)t\ )\right) \qquad 3.4)$$

where

$C(t)$ = probability that the hook has caught a fish by time t
$q\Delta t$ = probability a fish escapes from a hook in Δt

Figure 3.3 shows how the catch probability of a hook varies over time for three different fish encounter rates (p). If fish loss is greater than 0 the catch probability will peak and decrease asymptotically approaching 0.0, which is the case in figure 3.3. If the rates of both bait and fish loss are 0, the catch probability will asymptotically approach 1.0. If bait loss is greater than 0, but fish loss is 0, the catch probability will asymptotically approach p/(p+q+r), which is less than 1.0.

With hooks placed randomly and independently and soaked for the same length of time, equation 3.4 will lead to a binomial distribution for the total catch. In practice hooks are laid in sequence and hauled in the same manner. Therefore hooks share a dependence in both space and time. This dependence on time will be dealt with first.

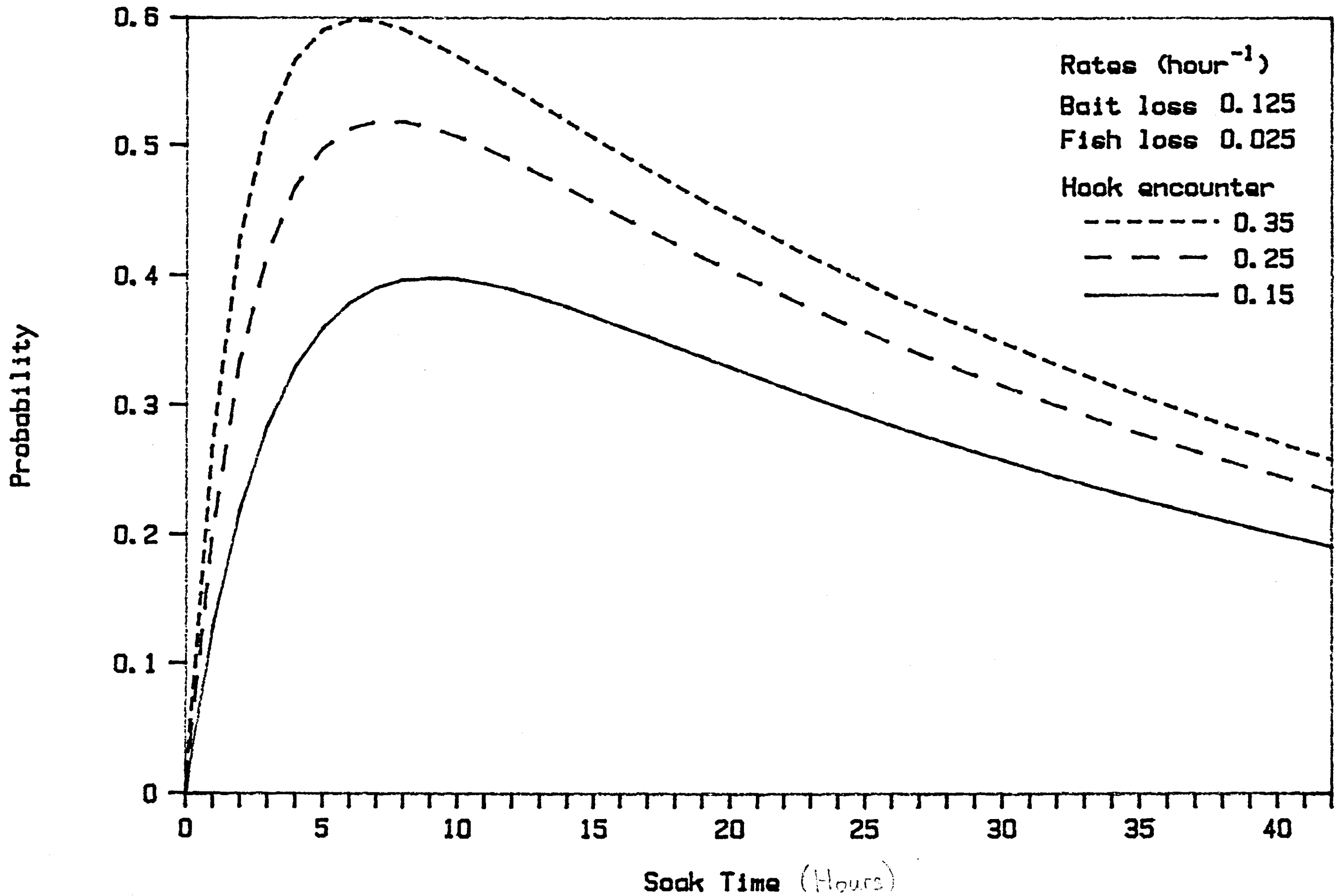


Figure 3.3 Longline Catch Model: single hook catch probability vs soak time with changing hook encounter rates.

3.3 Time Dependence Model

If all hooks are set or hauled at the same constant rate the soak time of a hook can be written as a linear equation of its sequence number on the line.

$$t = an + c \tag{3.5}$$

where

- a = time to set and haul a single hook and associated length of line
- n = hook sequence number between 0 and N-1, N being the number of hooks. Sequence number is in reverse of the setting order.
- c = 'heave to' time between setting and hauling

In practice the rate of hauling will vary with various operational factors such as currents, wind direction, available equipment and tangles in the line. Hauling will also stop each time a hook has a fish, which will significantly increase the time some hooks are immersed if catches are large. However this form of the model is simple and captures the main characteristic of the procedure's effect on the time a hook is in the water.

Equation 3.5 can be substituted into equation 3.4 to give the new catch probability dependent upon the sequence number of the hook. The total catch probability distribution is complicated and is not obtainable in any simple form, since it will consist of combinations of probabilities of a catch on each hook, all of which will vary in a non-linear form. However the mean and variance of the distribution can be obtained fairly easily.

$$\text{Mean} = C(an+c) = \frac{p}{p+q+r}\left(\frac{\text{Exp}(-qc) - \text{Exp}(-q(aN+c))}{1-\text{Exp}(-qa)} - \frac{\text{Exp}(-(p+q+r)c) - \text{Exp}(-(p+q+r)(aN+c))}{1-\text{Exp}(-(p+q+r)a)}\right)$$

which, for large N, simplifies to

$$\text{Mean} = \frac{p}{p+q+r}\left(\frac{\text{Exp}(-qc)}{1-\text{Exp}(-qa)} - \frac{\text{Exp}(-(p+q+r)c)}{1-\text{Exp}(-(p+q+r)a)}\right) \tag{3.6}$$

and the variance simplified for large N :

$$\text{Variance} = \text{Mean} - \frac{p^2}{(p+q+r)^2}\left(\frac{\text{Exp}(-2qc)}{1-\text{Exp}(-2qa)} + \frac{1}{1-\text{Exp}(-2(p+q+r)a)} - \frac{\text{Exp}(-(p+2q+r)c)}{1-\text{Exp}(-(p+2q+r)a)} \right) \tag{3.7}$$

If the probability of catching a fish is small, the variance will be close to, but never exceed, the mean. It is clear from equation 3.4 that both bait loss and fish loss will reduce the final catch. Both effects also interact with time. Bait loss works in the model in the same way as the line being saturated with fish, with saturation (the point in time when the line ceases to fish) occurring more rapidly than when there is no bait loss. Fish loss causes the catch to decline with soak time. Although it is evident that both bait and fish will be lost from a line over time, it is not clear whether these losses will be significant considering the comparatively short time a longline hook is immersed. Hooks are usually immersed for between 6 and 24 hours.

There are several results of interest from the model. The mean catch will vary linearly with the density of fish if the catch is small and saturation is insignificant. Even if the saturation is important, then the final catch may still reflect the fish density if bait loss is significant and time dependent. As the density of fish falls, the probability a fish will find a hook before it has lost its bait decreases. Hence the catch will fall, while the number of hooks without bait will increase. This can be seen from figure 3.3 where the catch (probability) for different stock densities (p) over all soak times are separate, with the lower density giving a lower catch rate even as saturation takes effect. Where bait and fish loss rates are negligible the catch probability will approach 1.0 asymptotically for all stock densities, although at different rates.

It is evident from equations 3.6 and 3.7 that the mean is greater than the variance, and therefore this spread of probabilities, due to the different times hooks are left to soak, does not greatly increase the dispersion of the catch distribution. A variance close to the mean suggests the Poisson distribution as a possible contender to approximate the real more complex distribution. An alternative is the original binomial, where the probability parameter is adjusted to take account of the different hook probabilities. The model distribution can be generated and compared with these two simpler distributions. Since each hook has a different catch probability, the probability for all combinations of catches must be calculated which becomes very time consuming for large numbers of hooks. It is only possible to generate catch distributions for comparatively small numbers of hooks, although these results are adequate for the purpose of finding an approximate distribution.

The model was programmed in Turbo Pascal (1987) based on equation 3.4. The probability for each possible catch combination is calculated and summed to produce a theoretical catch distribution. The parameters chosen are arbitrary and are used to demonstrate the model's behaviour only when expected catches are low. This is then compared to the Poisson and binomial distributions with the same mean.

Table 3.1 shows the results from runs of the program with varying fish densities. The binomial distribution provides the closest approximation over the range of fish densities (encountered rates) considered. However, standard asymptotic theory (see Feller, 1960) shows that as the number of hooks increases and the probability of any single hook catching a fish decreases, the Poisson should also provide a good fit, with the added attraction of only needing one parameter. For longline the catch is low and the number of hooks is large, suggesting the Poisson distribution might be the most appropriate approximation.

In the case shown above, where the catch per hook is low, the relation between the catch and fish density is linear. Obviously as the density increases and saturation (more than one fish encountering the same hook) becomes important, this will no longer be the case. How good an approximation the binomial is to the catch distribution will also be affected.

Figure 3.4 shows how the deviation from the binomial changes as the difference between soak times of the hooks increases. The important consideration is the difference in catch probabilities along the length of the line. If the catch probability of hooks at different points on the line changes by great amounts, the behaviour of the final catch probability distribution will be

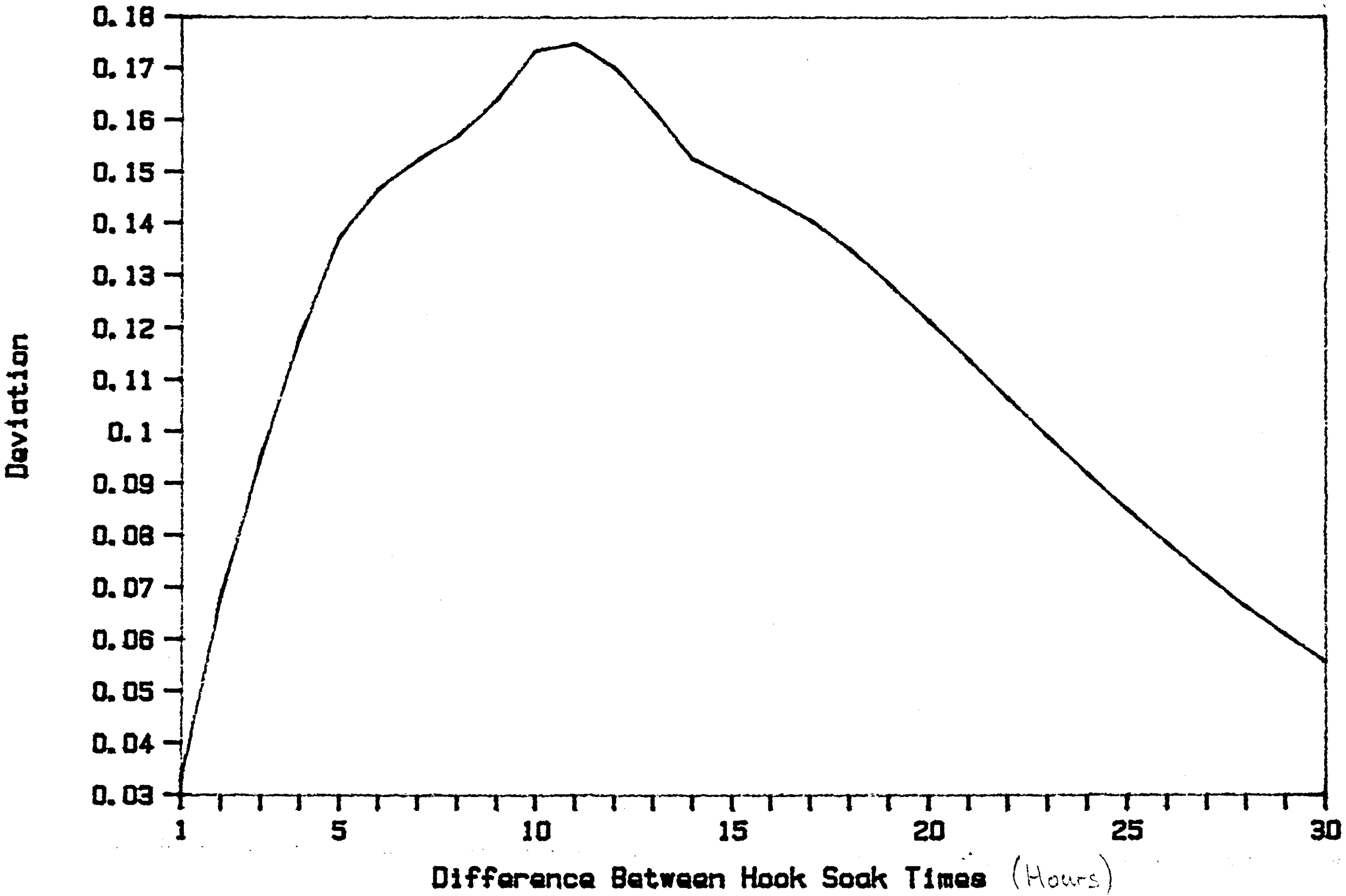


Figure 3.4 Deviation from binomial approximation with varying difference between hook soak times

less close to the binomial. When all the soak times are short, the binomial provides a good approximation as would be expected. When the soaks times are long, the difference between hook soak times is large, but saturation causes the catch probabilities to approach the same asymptote. Hence the greatest deviation from the binomial occurs between these effects. In practice, since the soak times between hooks is constrained to be linear, the binomial approximation is good under most circumstances.

Fish	Catch		Deviances	
Density	Mean	Variance	Poisson	Binomial
0.002	0.3368377	0.3309849	0.0070626	0.000224
0.004	0.6678024	0.6448091	0.0173665	0.000543
0.006	0.9929993	0.9421850	0.0291365	0.000921
0.008	1.3125321	1.2237967	0.0364726	0.001155
0.010	1.6265024	1.4902986	0.0447285	0.001391
0.012	1.9350099	1.7423080	0.0487004	0.001532
0.014	2.2381525	1.9803881	0.0604075	0.001811
0.016	2.5360263	2.2050209	0.0715765	0.002182

Other Parameters			
Number of Hooks	20		
Bait loss	0.001000	Fish loss	0.000050
Soak time (hours)	6.000000	Soak time difference	0.267000

Table 3.1 Difference in longline catches with varying fish density. The deviance is the sum of the absolute difference between the model probability and Poisson or binomial estimate, where 0 is an exact fit, 2 the maximum possible difference.

This model can easily be extended to a multi-species system, where the bait loss parameter includes all catch rates of other species. It can be seen from the mean that catches will be in proportion to the density of each species.

The spatial distribution of hooks and fish presents a much more complex problem to solve than the inclusion of time in the model. However the model developed so far bears little resemblance to longline catch data, which is much more variable than the model would suggest. This implies that the spatial distribution has an important effect on the catch.

3.4 A General Model Including Spatial Heterogeneity

Skellam (1958) suggests that while aggregation of species will affect the variance of the estimates of abundance from a transect, the mean will remain unaffected. This is not the case for longline hooks because they become saturated. This is easily demonstrated by considering fish aggregated into schools. Even if hooks were randomly distributed, at best they would only estimate the density of schools, not the overall density of fish, since a hook will only take at most one fish from any school encountering it. Hence fish aggregation may change the mean as well as the variance of the catch.

Although it is well known that tuna school, it is likely that schools themselves aggregate to areas where their prey density is highest. This theory was invoked to explain the high variation in purse seine catches over short periods of time and small areas. Using the spatial structure of longlines it should ultimately be possible to separate these two effects and see how each contributes to the catch.

Longlines form a series of catenaries hung between buoys as shown in figure 3.2. Each catenary will lie in a particular direction, so that from above in the x y plane the hook distribution will be seen as a series of straight lines between buoys. If a hook catches a fish there will be an increased probability that other hooks around it will also catch fish.

The most natural way to represent aggregation in catches is through conditional probabilities of detection. A model can be built based upon the hauling sequence. The probability of a hook holding a fish can be conditioned upon the previous catch. The most natural way to represent this form of a discrete stochastic model is as a Markov chain, for which a well defined theory already exists (Cox and Miller, 1965). The Markov states can be defined as the different combinations of the catch. Such a model could potentially have a very large number of states and be very complex. The number of states can be limited by considering a decline in dependence between hook catches based upon the distance between hooks. Thus the number of states can be kept to a reasonable level based upon the number of previous hooks' catches affecting the probability of a catch on the next hook. However the problem still remains to link the catch probabilities to the underlying school size and density. For the moment I shall only consider the probability that a fish moves into range so that it is able to detect a baited hook. The relationship between this and catching the fish will be discussed later.

3.4.1 Method

The hook volume described for single fish can be used for a school. It is defined here as the volume around a hook in which, if a predefined point in a school enters, at least one fish in the school will detect the hook. The most convenient shape of school, and one representing a wide range of possible shapes, is the sphere, and the most convenient point in a school will be its centre. Hence the detection volume is the volume around a hook such that when the centre of the school enters it, at least one fish detects the bait. Since it is assumed that the distance from the centre of the school to the edge of its range of detection is constant in all directions, the volume of detection around the hook will also be spherical and of the same size.

Schooling will have a number of effects. Treating a group of fish as one entity will markedly increase the size of the hook volume. Also, in a school of more than one fish, the loss of a fish will only reduce the size of the school, so that a school may run through several hook volumes consecutively. Therefore if one hook is taken, it increases the chance that nearby hooks have also caught a fish.

For simplicity a constant school size is chosen. In reality school size varies with the number of fish it contains as discussed in section 2.7. School size is likely to be related to the the size of its members, which will also control the average fish velocity. Furthermore the shape the school adopts will be important, so that the volume shape will further depend upon fish behaviour.

There is a volume between two hooks such that if the central point of a school moves into it, both hooks will be taken. This volume is the intersection between the two hook volumes. A thin layer on the surface of this volume can be defined such that the centre of a school in this layer will enter the intersection dt units of time later.

The area can be defined for any pair of hooks given a particular angle of approach and the two centres of the detection volumes, which form the reference co-ordinates. The size of the area can be found through integration and depends upon the radius of the circles and the distance between their centres.

$$\text{Area of Intersection} = 2R^2 \text{ArcSin}(b/R) + 2ab \qquad 3.8)$$

where

R = Radius of the circles

a = 1/2 distance between the circle centres

$b = \text{Sqrt}(R^2 - a^2)$

This area must now be integrated over the two angles of approach. It is clear that the surface is uniform over all values of the vertical angle Θ_2, and therefore this variable may be dropped. However the area is not uniform over the horizontal angle of approach, Θ_1, which will change the apparent distance between the hooks. The intersection will be smallest at 90^o to the line, where the circles may not even touch, and will be greatest at 0^o to the line, where the intersection itself will be a complete circle, eclipsing the two single hook volumes. The apparent distance between the hooks can be derived from the cosine of the angle of approach. The integration may be discontinuous if the circles do not intersect over all angles. This problem can be circumvented by integrating over the angle range through which the intersection exists, the remaining area being zero. It is not possible to carry out this integration analytically, and hence it must be done numerically.

$$\text{Intersection surface} = \int_x^{2\pi} \frac{2R^2\text{ArcSin}(b/R) + 2a\,\text{Cos}(\Theta_1)\,b}{2\,\Pi}\,d\Theta_1 \qquad 3.9)$$

where

$b = \text{Sqrt}(R^2 - \{ a\,\text{Cos}(\Theta_1) \}^2)$

$$x = \begin{cases} 0 & R >= a \\ \text{ArcCos}(R/a) & R < a \end{cases}$$

Similarly there may be an intersection volume between three or more hooks. However allowing the hooks to lie on a catenary in the vertical plane greatly increases the complexity in considering more than two hooks intersecting. To allow a more general, simple model, all hooks can be represented as lying on a straight line, which effectively reduces the range of hook positions to lie in one dimension. This has two effects on the model. Firstly, it greatly simplifies the intersections between hooks to linear combinations of all pairs of hooks. Secondly, the vertical angle of direction (Θ_2) is unimportant since the intersection volumes are symmetrical around the horizontal axis.

Figure 3.5a is a diagram of the intersection areas between four hooks from some angle of approach. The intersection between hooks 1 and 4 is entirely enclosed within hooks 2 and 3. The area (A_1+A_2) associated with hooks 2 and 3 only can be calculated from the formula :

Area associated with x and y only =

$$I(x,y) - I(x-1,y) - I(x,y+1) + I(x-1,y+1) \qquad 3.10)$$

Where

x, y = hook sequence numbers (in this case x = 2, y = 3)

I(x,y) = the intersection area between hook x and y

With conditions

$x <= y$

$I(x,y) = 0 \quad x < 0 \text{ and } y > N$

N = maximum number of hooks in a sequence

Since equation 3.10 is additive, it will remain unaffected by integration of the intersection areas over the different angles of approach.

In two dimensions a surface is presented into which a school might swim indicating many hooks being taken. However the original justification for dealing with surface areas (ie small units of time to reduce the equations to a simpler continuous form) is no longer applicable, seeing that a school may have to swim many metres to come into contact with all the hooks associated with a surface. As an example figure 3.5 b shows a horizontal cross section through two hook volumes and an example angle of approach Θ_1. Any school entering a hook volume intersection will pass through the single hook volumes and all other lower order intersections first. Thus a school entering at point Z in figure 3.5 b will have to swim distance D before

Example Hook Volume Surface

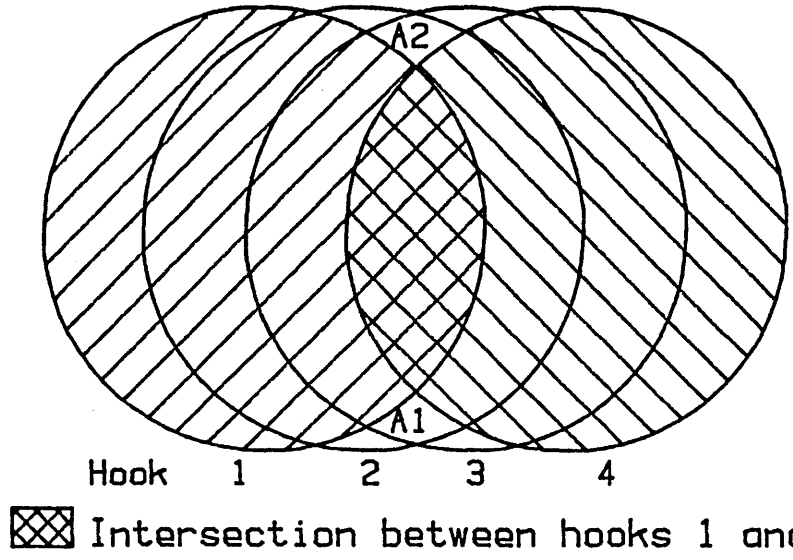


Figure 3.5 a

Horizontal Cross Section
Through Hook Volumes

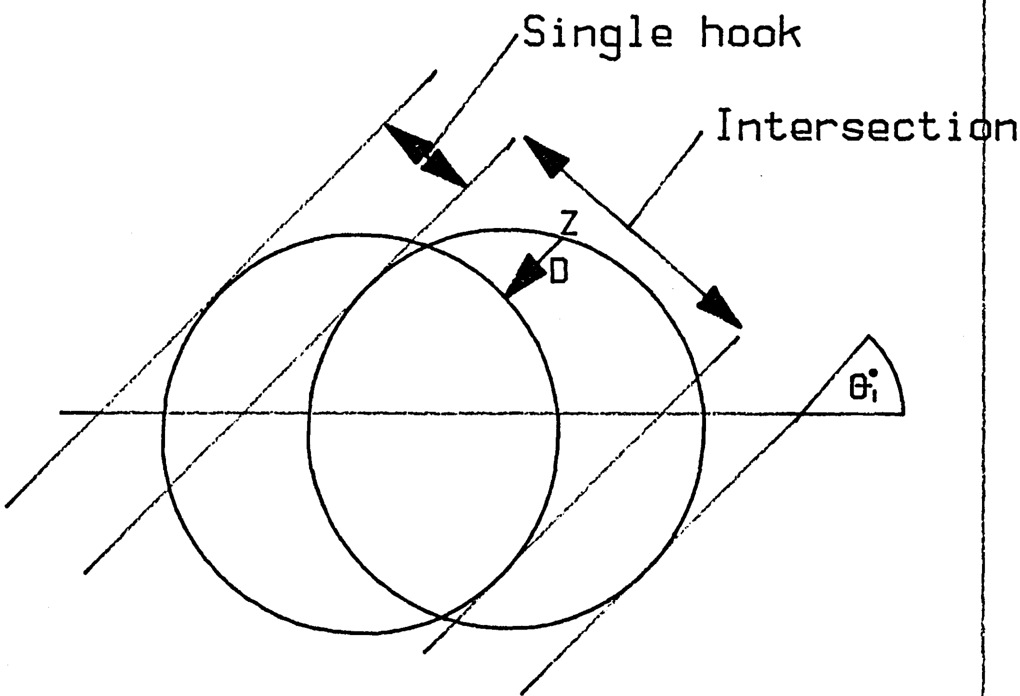


Figure 3.5 b

entering the intersection volume. If the school changes direction while swimming this distance it may miss the intersection volume altogether. The net effect of this distance between hooks will be to decrease the dependence between hooks. This effect can be achieved without attempting to model the distances in detail. If schools turn at a constant rate, then the probability that a school will reach an intersection after entering a hook volume will be related to the fish velocity and the distance between the hooks. This is only approximate because the distance should strictly be measured from the point of entrance of the hook volume to the intersection which will vary on the position of the school.

The net result of introducing a turning rate parameter is to decrease the dependence of the catch between hooks. This can be used to model other important effects. As a school passes through a number of hooks, the school might decrease in size as fish are caught. It is not clear whether this will be important since nothing is known about the adaptive behaviour of a school when one of their number is lost, the density of fish in a school or its size. However the loss of fish will decrease the size of the intersection surface between hooks, and thus the dependence between hooks. This might somewhat crudely be taken into account by the turning rate parameter. While the model has all hooks lying in a straight line, hooks on a longline lie on a catenary. Hence a long catch run may require a school to move up and down with a line. Again this requirement will reduce the dependence between hooks, which can be taken into account in the same way. It is also worth noting that two hooks in every basket will hang at the same depth. Therefore a school moving horizontally may skip a number of hooks before encountering another one. If the catenary shape is included in some way in the model, the three dimension direction of movement of the fish will make a big difference to the form of the catch.

Taking all these effects together the probability of a fish entering a detection volume associated with a sequence of hooks can be given :

$$P(\text{school detect hooks}) = 1 - \mathrm{Exp}(\ -DVS\ \mathrm{Exp}(-t_r\ a/V)\ T\ ) \qquad 3.11)$$

where

D = school density
V = school velocity
T = longest time any hook in the sequence is immersed
S = surface generated by equations 3.9 and 3.10
t_r = turning rate parameter
a = distance between the first and last hook in the sequence

Effectively the mean of the Poisson is adjusted by the probability a school turns away before reaching the intersection. Because of the hierarchical nature of equation 3.10, the probability lost due to the possibility that a school might turn is automatically added to that associated with intersections of hooks which are closer together. The probability that the bait is still present and thus that the last hook in the sequence has caught a fish is given by combining equations 3.4 and 3.11. Fish loss is assumed to be insignificant.

$$P(\text{Hook catches fish}) = \frac{DVS\ Exp(-t_r\ a/V)}{DVS\ Exp(-t_r\ a/V) + B}\ (1 - Exp(\ -DVS\ Exp(-t_r\ a/V)\ T + BT\ ) \qquad 3.12)$$

where

B = bait loss rate

From the model it is clear that if a hook has not been detected by any fish, the catch probabilities for hooks on either side of it will be independent, since they cannot share the same school encounters. This allows the conditional probability to be described in the form of runs (sequences) of hooks. The probability that a hook has been detected by a fish depends upon the length of the previous run.

$$P\ (\text{ next hook detected by fish }) = \frac{P\ (\text{ run is of length } x+1\ )}{P\ (\text{ run is of length } x\ )} \qquad 3.13)$$

Although in theory a run could consist of many hundreds of hooks, for reasons mentioned above the dependence on previous catches should wane rapidly, allowing a comparatively low maximum state. The probability of a particular run can be calculated from the probabilities that fish enter particular combinations of intersection volumes. Generating these combinations is a time consuming process and the main limit on the maximum run size. Similarly, the probability that the first hook in the sequence catches a fish can be calculated.

P (next hook catches a fish) = 3.14)

$$\frac{P(\text{ run is of length } x+1 \text{ \& hook } x+1 \text{ has bait })}{P(\text{ run is of length } x)}$$

If a school finds a hook, many fish are likely to pass through the hook volume. Strictly speaking in order to include bait rejection, the number of fish coming into contact with the hook must be calculated. This extremely complex process is avoided by assuming that the probability of all fish in a school rejecting (randomly and independently) the bait is negligible. Bait loss in the context of the model is better thought of as any random and independent effect that stops a hook fishing, whether it is physical bait loss or another species taking the hook.

One further assumption is necessary to make the process Markovian. In the previous section the effects of differences of hook immersion times were considered. It was found that the resulting catch distribution still closely resembled the binomial and by extension the Poisson distributions. This result is used here to avoid the extremely complex inclusion of time in the matrix. If time is included in the model, the transition matrix would have to be fully recalculated for each hook and most gains made from representing the process in this form will be lost.

A run is now defined as a series of hooks which a fish has approached close enough to detect bait if any was present. From this the probabilities for the three possible events (ie that a hook has bait, no bait or a fish) at time of hauling can be calculated. The state of a hook represents the length of a run. Separate to this is the probability that a hook catches a fish. The general transition matrix can now be given.

$P =$ 3.15)

$$
\begin{bmatrix}
1-B_1-F_1 & 1-B_2-F_2 & 1-B_3-F_3 & \cdots\cdots\cdots & 1-B_{N-1}-F_{N-1} & 1-B_N-F_N \\
B_1-SF_1 & 0 & 0 & \cdots\cdots\cdots & 0 & 0 \\
0 & B_2-SF_2 & 0 & \cdots\cdots\cdots & 0 & 0 \\
0 & 0 & B_3-SF_3 & \cdots\cdots\cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots\vdots\vdots & \vdots & \vdots \\
\vdots & \vdots & \vdots & \vdots\vdots\vdots & \vdots & \vdots \\
0 & 0 & 0 & \cdots\cdots\cdots & B_{N-1}-SF_{N-1} & B_N-SF_N
\end{bmatrix}
$$

where

B_i = Probability the state increases by one, but no fish is caught

F_i = Probability state increases by one, and a fish is caught

S = Probability generating function variable for the catch

N = The maximum run length. Run lengths can be greater than this, however the distribution becomes geometric with no change in the catch probability.

The catch over a number of hooks in sequence can then be described by repeated multiplication of the matrix with an initial state probability vector.

$$V^{(h)} = V^{(o)} P^h \qquad 3.16)$$

where

$V^{(x)}$ = state probability vector of hook x

P^x = transition matrix of hook x, after x multiplications of the initial matrix

o = indicates initial values

h = total number of hooks on the line

The transition matrix can completely describe the behaviour of the system. Bait loss will complicate the analysis only in looking at the final catches. For the analysis of the behaviour of the matrix and changes of state, the bait loss is combined with the catch probability to obtained the probability the hook is detected. It can be ignored when studying the dynamic behaviour of the process. Since all states can be reached from any other state within a finite mean number of transitions and no set of transitions are cyclic (positive-recurrent and aperiodic), the process is ergodic (Cox and Miller, 1965). Therefore the largest eigenvalue associated with this matrix will be equal to 1 and its associated eigenvector will represent the long term occupation probabilities independent of the initial conditions. The second largest eigenvalue will dominate the geometric progression which describes the rate at which the process moves towards this statistical equilibrium. If this eigenvalue is close to 1, the process will be slow to lose its dependency on the initial state.

The catch probability distribution can be found by obtaining the moment generating function from diagonalizing the transition matrix, which includes the generating function variable, S, as shown in equation 3.15. The method is described in Cox and Miller (1965), but even in the simplest 2*2 matrix, the result is complex. However, it can be shown that as the number of hooks increases the catch will become asymptotically normal, with the mean and variance proportional to the number of hooks. The alternative way to obtain an exact catch distribution is to derive it numerically. The general behaviour of this distribution in relation to the parameters can then be obtained.

3.4.2 Implemention of Model

The model was programmed in Turbo Pascal (1987). Numerical routines for integration and eigen systems analysis were provided from Numerical Recipes by Press et al (1988).

The program falls into three parts. The first part calculates the volumes of intersection using numerical integration techniques. The second part calculates the probabilities for runs of different lengths and uses these probabilities to obtain the transition matrix. The final section analyses the transition matrix to obtain eigenvalues and eigenvectors and the final catch probability distribution.

3.4.3 Comparison of the Model with Empirical Catch

In order to calculate probability distributions, catch distributions for the south Pacific data set were obtained and the model parameters adjusted to resemble these empirical values. This aids the comparison between the model results and the data set. Part of the variation in the catch data may be explained from other factors recorded in the data set. It is shown in chapter 4, however, that the variance explained by these other factors is small and so the unadjusted species catch distributions probably closely represent real generalised species catch distributions.

The parameters which are of most interest are the school radius, school density and bait loss effects. Other parameters, such as the interval between hooks, will only duplicate their effects. Table 3.2 shows the parameter estimates used for a 'standard' run. The parameters have been chosen either from other data available where possible (eg velocity; see equation 3.2) or to produce distributions comparable to that observed for yellowfin.

Transition matrix size	:	5	
School radius	:	108.3	metres
Interval between hooks	:	30	metres
Average fish velocity	:	7200	metres hour^{-1}
Bait loss rate	:	0.0	hour^{-1}
School density	:	$2.886*10^{-12}$	metre^{-3}
Soak time	:	10	hours
School turning rate	:	0.0	hour^{-1}
Number of Hooks on Line	:	2000	

Table 3.2 Parameters used for the standard run

The yellowfin catch frequency distribution shown in figure 3.6 is highly dispersed. Figure 3.6 also shows the model catch distribution for the standard parameters which is similar. Although on cursory inspection the model appears to fit well, there are a number of differences which strongly suggest that the model is inadequate in describing the empirical longline catches.

The term which governs dispersion is the school radius

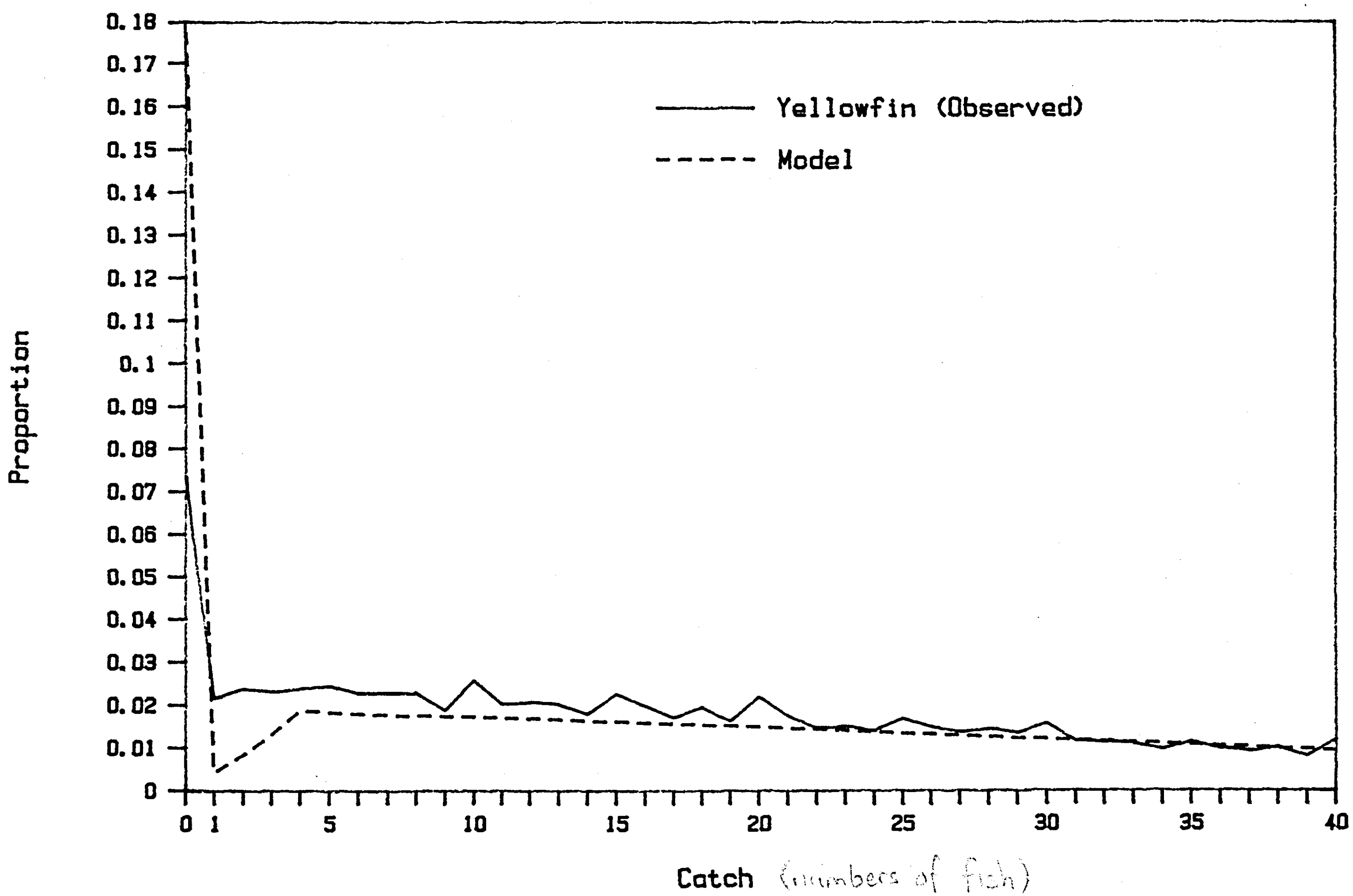


Figure 3.6 Model vs observed catch distribution

parameter, which here has an extremely high value, necessary to explain the empirical dispersion. However this causes a number of differences between the observed and model distributions which cannot be rectified by improved fitting procedures. Firstly the model over-estimates the zero catch frequency. Secondly the model under-estimates the first few catch frequencies. This is because the model predicts such large school sizes, that the chance just one fish is taken from a school is small. Finally as dependence increases, the point at which the transition decays to a geometric is much greater, so that the size of the matrix necessary to represent the process is very large. This last problem is purely practical in calculating results from the model. However it is important to understand its effect, since it cannot be entirely removed from the present analysis.

In the study below the maximum number of previous hooks upon which a hook may be dependent is 5 and the model's general behaviour is obtained from analysis of this smaller matrix. The matrix size can be extended in theory to any number, however the time taken to search out the different catch combinations increases exponentially with the number of hooks and becomes extremely time consuming. Figure 3.7 shows the catch distributions for different sized matrices with the parameters from table 3.2. The smaller matrix models follow approximately their larger counterparts until they decay into a geometric distribution. The modes in the catches occur at multiples of schools encountering the line. As the dispersion increases the inaccuracy of the smaller matrices decreases in representing the process, so that while a 5*5 matrix describes the first mode, it fails to define others as they appear.

Strictly speaking the matrix size should be allowed to vary for any set of parameters until higher states become negligible. However as the size of the matrix is allowed to increase the dispersion of the distribution will decrease, the largest variance for any set of parameters being obtained from a 2*2 matrix. For the standard parameter set, if the matrix was allowed to vary until dependence became insignificant (no significant change in transition probabilities), the estimated size of the school radius would become ridiculously large.

The model does not fit the empirical data well, and therefore the empirical catch distribution represents more than

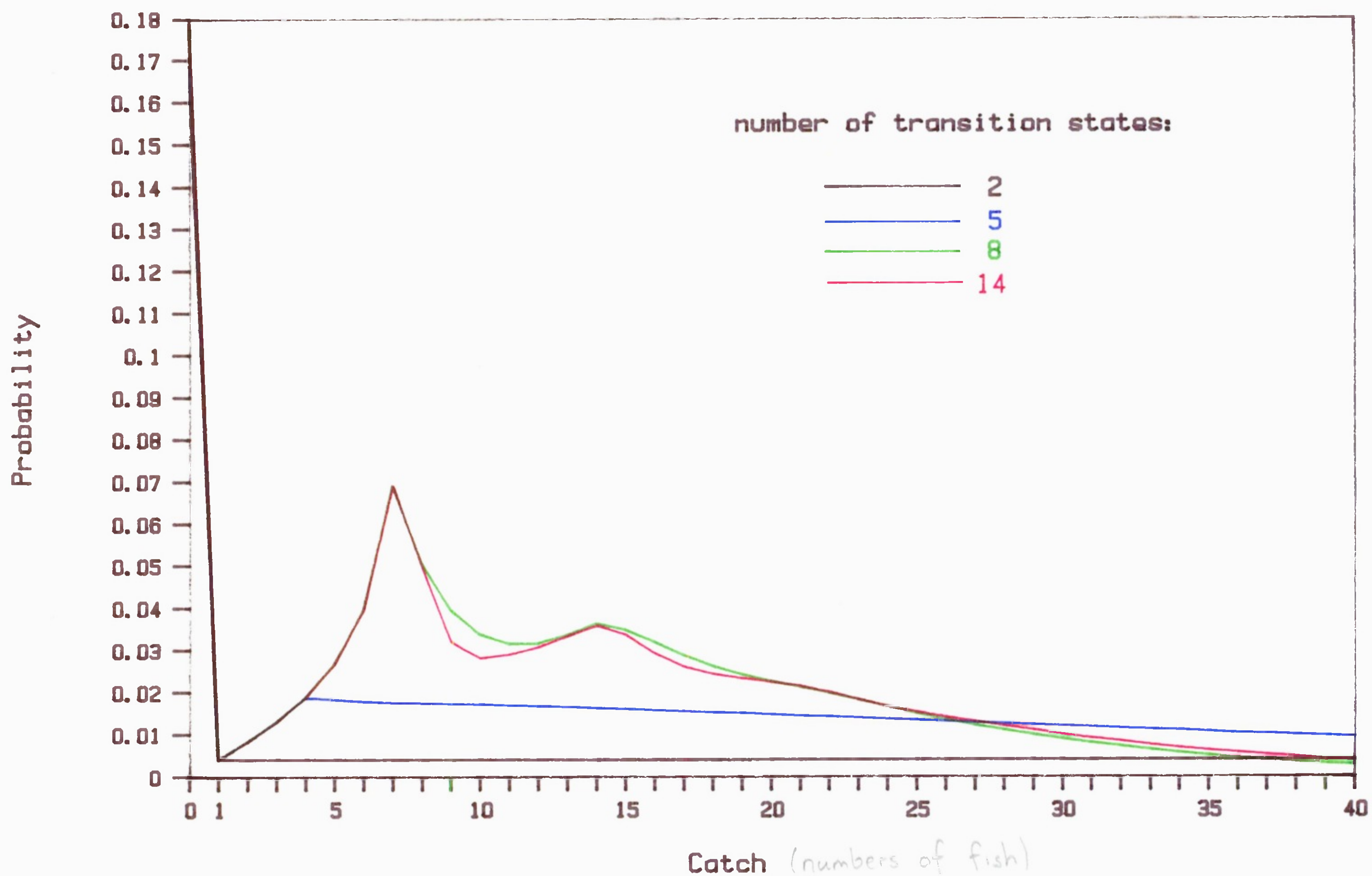


Figure 3.7 Longline model: varying number of transition states

Figure 3.7 The modes in the catch distribution represent combinations of schools encountering the longline. Hence the first mode represents the mean catch from one school, the second from two schools and so on. As the transition matrix is reduced in size, these modes are lost and the distribution decays to a geometric.

just schooling. The other form of aggregation, that of schools to areas of high prey abundance, would seem to be the most important determinant of the catch distribution. Although this can still be modelled in the matrix form, there exists no simple method of describing how the school density will vary along the length of the line. Schooling may still be an important factor, however, so the remainder of the chapter analyses the behaviour of the model in relation to the main parameters.

3.4.4 Analysis of the Behaviour of the School Model

Not using the larger matrices with such strong dependence requires some justification. Apart from the significant increase in computation necessary, the catch distributions produced from the larger matrices bore little relation to the observed catch rates. Therefore a compromise between the model and the observed distribution was adopted. The 5*5 matrix is large enough to produce the first mode in the catch, but suppresses subsequent modes. However it is still possible to ascertain the general behaviour in relation to the parameters. At the same time using this smaller matrix also makes the results comparable to the empirical distribution, which will prove useful for later statistical models fitted to the catch.

No Fish	No Bait	Fish
0.99914262	0.00031537	0.00054201
0.01295100	0.36307173	0.62397727
0.02687055	0.35795276	0.61517669
0.04325477	0.35192777	0.60481746
0.06464093	0.34406350	0.59129558

Table 3.3 Parameters used to generate these probabilities were the same as for the standard run, except bait loss = 0.1

Table 3.3 shows the transition matrix for a standard run using parameters from table 3.2, with the exception that the bait loss parameter was set to a low value to illustrate its presence in the model. On each occasion a hook must increase the state or return to state 0. For the state to increase the hook must either lose its bait before any fish arrive or catch a fish. If no fish detected the hook, whether it lost its bait or not is immaterial to the catch.

For the catch distribution the initial state is important. In all cases the first state was assumed to be at equilibrium, so the initial state vector was the long term equilibrium vector.

The velocity and density of fish form one parameter with respect to the model. This is evident when considering the important factor is the volume of water searched by the fish rather than their number. If, for example, all fish can be divided into two groups, one group swimming twice as fast as the other group, but with half as many members, both groups would cover the same volume of water if fish were searching randomly and independently. However each fish lost from the smaller group results in twice the reduction of volume searched as each fish lost from the larger group. This has important implications when considering the depletion of different species and of different sized animals within each species. There is likely to be a sharper decline in the longline catches of larger individuals than smaller even if the stock size is reduced uniformly.

Figure 3.8 shows how the probability distribution of the catch changes with changing density of schools. The density was varied around the standard run, all other parameters remained constant at their standard values. In all cases the probability of zero catch is high compared to the other probabilities. It does not appear on the graph to improve the clarity of the figure.

It is evident from the distributions that as the school density increases, the mean of the distribution increases with another mode forming around 30 fish. The first mode at a frequency of 4 fish remains. In general the modes remain at the same frequencies, but their relative heights change.

Table 3.4 gives the results from the matrix analysis and the catch distribution for each density parameter value. There is a slight decrease in the size of the eigenvalue, suggesting a slightly decreasing dependence between hooks. As expected the higher states are occupied more frequently as the density increases.

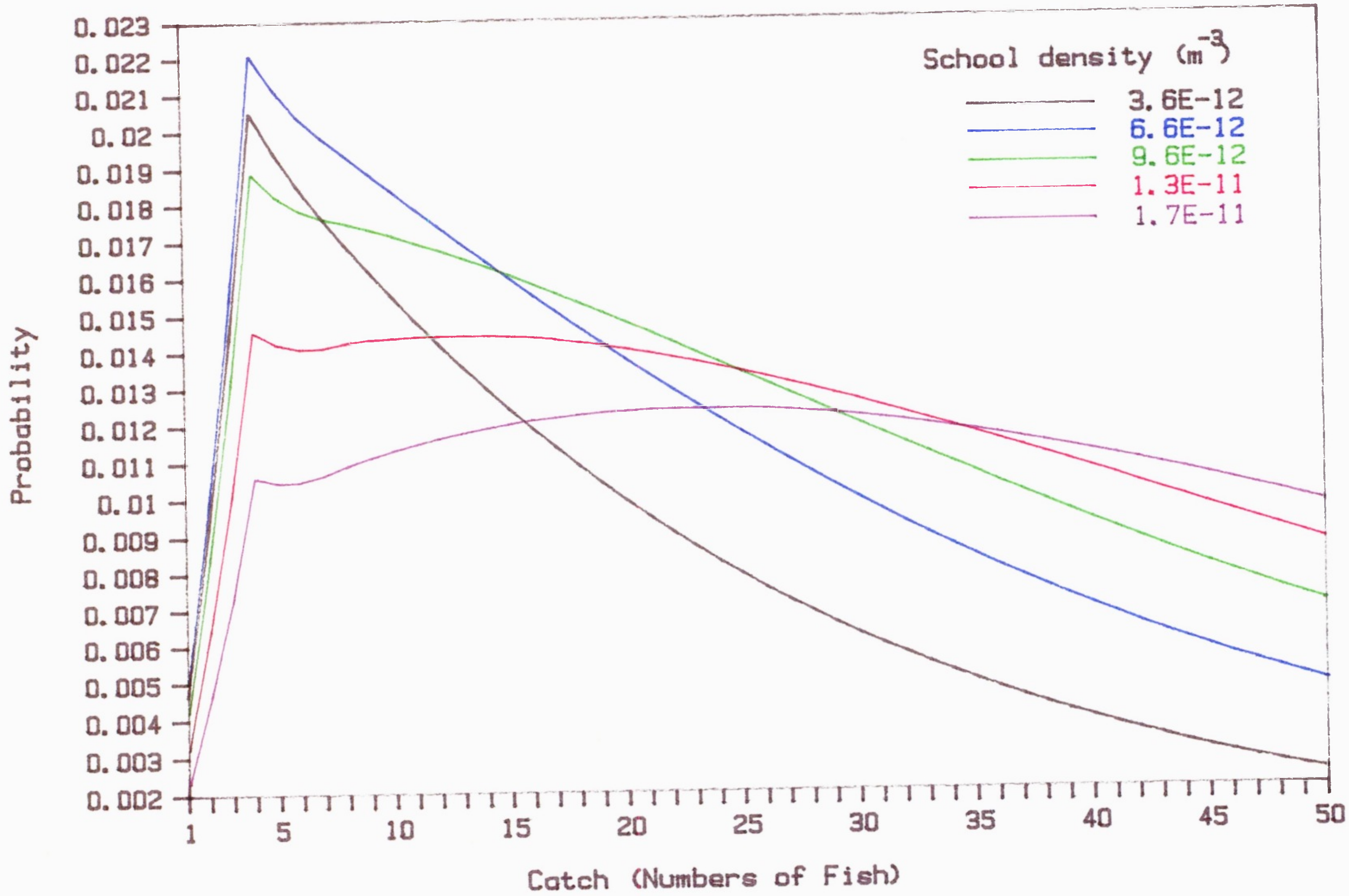


Figure 3.8 Longline model: varying school density

Figure 3.8 As the density of schools increase, the relative sizes of the modes representing higher combinations of schools encountering the line also increase. However their position will not change since the numbers of fish from each encounter will have the same distribution.

Density (metres^{-3})	1.086E-12	1.986E-12	2.886E-12	3.786E-12	4.686E-12
Second Eigenvalue	0.93484	0.93462	0.93440	0.93417	0.93395
Long term occupancy probabilities					
State : 1	0.99450	0.98998	0.98550	0.98104	0.97662
State : 2	0.00032	0.00058	0.00084	0.00110	0.00136
State : 3	0.00032	0.00058	0.00083	0.00109	0.00134
State : 4	0.00031	0.00056	0.00081	0.00106	0.00131
State : 5	0.00455	0.00829	0.01201	0.01570	0.01937
Catch distribution					
Mean	10.99483	20.03317	29.00573	37.91322	46.75632
Variance	325.98161	589.19582	846.27246	1097.34747	1342.55353
Deviation from standard distributions					
Poisson	1.52120	1.42148	1.38934	1.37229	1.36290
Neg Binomial	0.56539	0.49407	0.35887	0.24804	0.17364
Dispersion parameter	0.38378	0.70512	1.02945	1.35677	1.68711

Table 3.4 Model Results : varying school density. The second eigenvalue gives the geometric rate of decay of dependence between hooks. The long term occupancy probabilities give the expected proportion of hooks found in each state. The deviances represent the absolute difference between the model catch distribution and the Poisson distribution with the same mean, and the negative binomial with the same mean and variance.

For the catch distribution, the coefficient of variation remains relatively constant, although the variance is much greater than the mean in all cases. The two distributions fitted are the Poisson and negative binomial. The deviation measure is the sum of the absolute difference between the model probabilities and the Poisson or negative binomial probabilities which have the same mean and, in the case of the negative binomial, the same variance. The maximum deviation is 2. The dispersion parameter has been estimated from the mean and variance of the model distribution. The Poisson distribution provides a very poor fit, the negative binomial a much better approximation. Both improve their fit as the density increases and the distribution becomes slightly less dispersed.

The school radius is the most complex parameter since it increases both the probability of a catch and the dependence between hooks. Figure 3.9 shows how the catch distribution changes with changing school size around the standard parameter set. The most obvious feature is the increasing mean and spread of the distribution as the radius increases. The other important effect is the changing mode position from 4 to 3 fish at a radius of 40 metres. The radius affects the distribution by changing the position of the modes, rather than changing their relative sizes.

Radius (metres)	48.3	78.3	108.3	138.3	168.3
Second Eigenvalue	0.49766	0.82818	0.93440	0.96304	0.97558
Long term occupancy probabilities					
State : 1	0.99868	0.99521	0.98550	0.96864	0.94340
State : 2	0.00038	0.00062	0.00084	0.00106	0.00126
State : 3	0.00035	0.00060	0.00083	0.00105	0.00125
State : 4	0.00029	0.00057	0.00081	0.00104	0.00124
State : 5	0.00030	0.00301	0.01201	0.02821	0.05285
Catch distribution					
Mean	2.64735	9.58300	29.00573	62.71320	113.19521
Variance	11.17402	109.57771	846.27246	3194.34864	8476.37900
Deviation from standard distributions					
Poisson	1.04233	1.12010	1.38934	1.50489	1.57280
Neg Binomial	0.49179	0.43868	0.35887	0.26767	0.19851
Dispersion parameter	0.82195	0.91839	1.02945	1.25588	1.53209

Table 3.5 Model results : varying school radius. See table 3.4 for explanation.

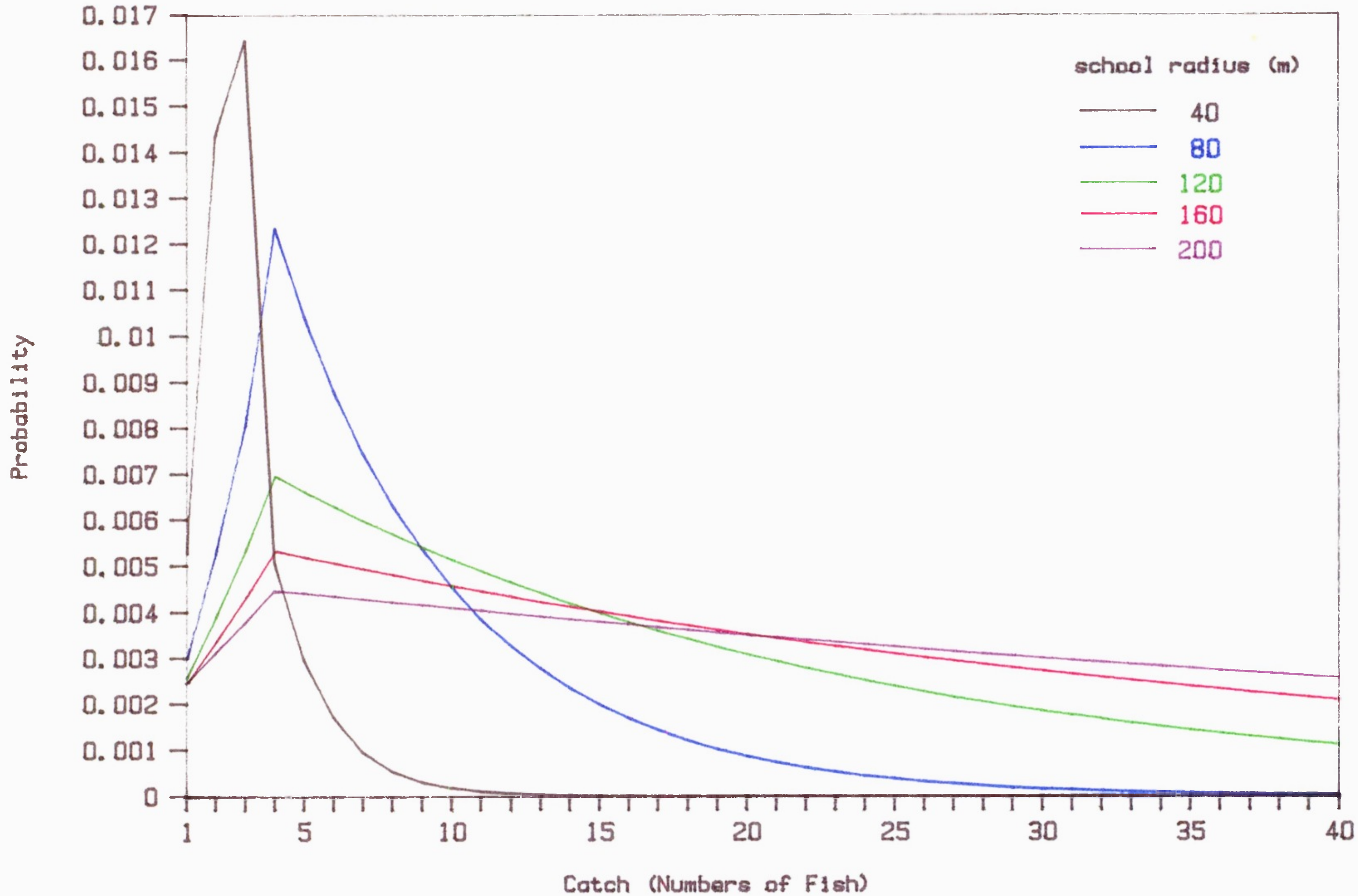


Figure 3.9 Longline model: varying school radius

Figure 3.9 As the school size increases, each mode representing combinations of schools encountering the line will move to higher catches, for the number of fish caught on each encounter also increases. At the same time the modes will flatten out, becoming less distinct.

Table 3.5 presents the results of the matrix and catch distribution analysis. There is a large change in the eigenvalue demonstrating the increasing dependence between hooks on their catches. This effect appears in the long term state frequencies not only as an increase in the frequency of all but state 1, but also as a proportionally larger increase in the frequency of the last state 5. As far as the model is concerned, the behaviour of the matrix transition probabilities after state 5, if calculated, will be important. Both the mean and variance of the catch increase, however the variance increases more rapidly. A Poisson approximation is poor, but the negative binomial fit is better and improves as the mean catch increases.

If fish form approximate spheres when schooling, then a large school radius would require schools with very large numbers of fish. However it is more likely that fish form a shape when searching for food which covers a much greater volume (Pitcher et al., 1982; Partridge et al., 1983). This suggests that the school radius might be more closely proportional to the square of the numbers of fish in a school rather than the cube. Also tuna may be sensitive enough to detect bait over comparatively large distances, so that spacing between fish in a searching school may be large. Even so, the large radius necessary to approximate the empirical catch distribution suggests that large yellowfin form very large schools, which would seem unlikely.

The effect of changes in the bait loss parameter are shown in figure 3.10. While there is a decline in average catch, there is also an increasing central tendency for the distribution. As bait loss increases it comes to dominate the distribution. In this case bait loss is random and independent, and so the distribution will tend to the binomial as it increases.

Table 3.6 shows the results of the distribution analysis. The matrix is left unchanged by the addition of bait loss, since states are a measure of runs of detected hooks, not catches. The catch distribution does change with a decreasing mean and variance as bait loss increases. The rapidly decreasing variance together with the improving fit of the Poisson distribution supports the observed decreasing dispersion. As bait loss, which is completely random, comes to dominate the catch rate, the catch distribution will return to the binomial described in previous sections.

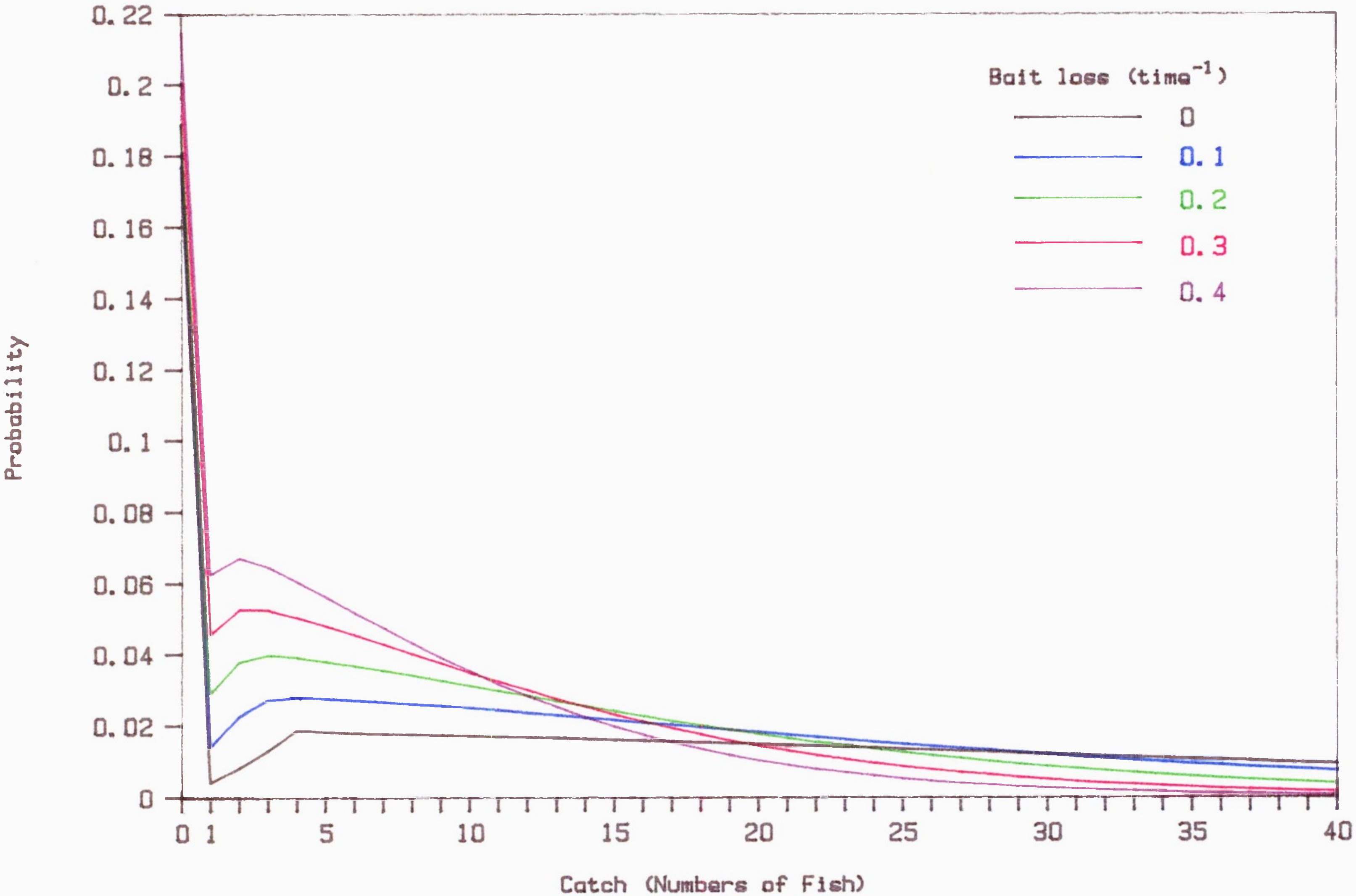


Figure 3.10 Longline model: varying bait loss

Bait loss (hour^{-1})	0.0	0.1	0.2	0.3	0.4
Catch distribution					
Mean	29.00573	18.33626	12.54161	9.18874	7.12007
Variance	846.27246	344.93700	165.33388	91.20614	56.36513
Deviation from standard distributions					
Poisson	1.38934	1.27472	1.16806	1.07833	1.00169
Neg Binomial	0.35887	0.32898	0.29925	0.27180	0.24701
Dispersion parameter	1.02945	1.02945	1.02945	1.02945	1.02945

Table 3.6 Model Results : varying bait loss rate. See table 3.4 for explanation. The results from the eigen analysis do not appear, since the transition matrix is not changed by the baitloss parameter.

Hook spacing will affect the degree of dependence between hooks while keeping the mean catch relatively constant. The turning rate parameter will only decrease this dependence and reduce the dispersion of the catch. Soak time will only change the apparent school density and bait loss, duplicating the effect of changing them both by the same multiple.

3.5 Application of Model to the Longline Data

While the model presented here is more thorough than any formulated previously, it is still far removed from the real fishing process. In particular it models a set of effects, chosen largely on the basis of simplicity rather than empirical evidence. The change in the model's behaviour from changing these effects can be surmised without including them explicitly.

The importance of systematic changes in model parameters over time will depend upon the relative size and form of the change. If these systematic changes are constant between sets, they present no problem in relating model results to catch data. Even if there are changes, but no sample bias, the effect will form part of the error term or can be removed if the data are available. However there is quite likely to be some sample bias in the way that both fishermen and fish behave. Both will wish to maximise the catch of their prey. Fishermen might do this by choosing periods when the fish are more active and the hook volume is at its greatest size. Fish may be more active when the detection volume is at its largest (eg in good visibility) and choose a school formation and move in a direction which maximises the volume surface. These will tend to give an over-estimate of fish density and school size.

With more than one species there may be a significant interaction between them if the catches are high enough. While the effect can be treated as bait loss if the species do not school, interference between schooling species will be complex, essentially increasing the number of parameters in the prior distribution of equations 3.13 and 3.14.

Other sources of variation will include differences in the skill of the fishing master, and the efficiency with which he finds areas of high density. The placing of the line is crucial to the catch. For instance the fishing master may use part of the line to search the area, so that the line may be sampling two separate density distributions.

It is clear from the results that changes in density and school size have different effects on the catch distributions. This implies that the model can be fitted to the catch distribution using maximum likelihood techniques, even if this is a very time consuming process. However the results also suggest that the model does not provide a full explanation of the observed catches, which would mean that the fitted parameters would have little value. Since the model explains dispersion through schooling, a pre-requisite is that non-schooling species have random catches. The billfish do not school and yet their distributions still show heavy contagion. The first two moments of each species distribution appear in table 3.7. The most likely explanation is that these pelagic fish predators are all aggregating to particular areas of the ocean, which gives the distributions another level of spatial organisation above schooling. There is no systematic way of modelling this, therefore a simpler probability model is developed for further analysis in the next chapter.

	Mean	Variance
Albacore	4.2770	214.7642
Bigeye	6.9731	61.6231
Yellowfin	29.2616	945.1387
Blue Marlin	0.9979	2.1885
Black Marlin	0.1148	0.2137
Broadbill Swordfish	0.1623	0.2815
Sailfish	0.1659	1.0125
Shark	0.2087	2.6873

Table 3.7 Mean and variance of longline catch per set for different commercial species.

Although the final catch may not be suitably modelled, catches recording the hook on which each fish was found might still provide a good subject for analysis through a Markov chain. This form of data is not available at present. Chapter 4 goes on to attempt a less theoretical treatment of empirical longline catch rates, estimating the impact of purse seine on longline. Some of the results from this chapter are used to justify the choice of statistical model used. Chapter 6 provides a discussion of both the possible data sets that could be assembled, the method of analyses and the problems that might be solved through this.

3.6 Summary

A model has been developed to provide a sound mathematical base for the estimation of abundance of fish from longline catch per hook data. It has been found that if all hooks have the same chance of catching a fish, the final catch distribution will be the binomial. If hooks have different soak times based on the method of hauling and setting, and the hauling and setting rates are constant, the binomial still provides a good approximation for the catch distribution, as by extension will the Poisson, if the catch is small and the number of hooks is large.

The empirical catch distribution is much more highly dispersed than either of these probability distributions, implying that spatial aggregation is important. A model including schooling fails to reproduce the empirical catch accurately, so that schools must themselves aggregate and this has an important effect on the empirical catch distribution. However the model including schooling may still be useful in analysing data where individual hook records are kept, and will help in the development of future longline models including other forms of aggregation.

Chapter 4

Statistical Detection Of the Effect of Purse Seine Catches On Longline

4.0 Introduction

If purse seine catches do affect longline catch per hook, there should be a decline in longline catch rates since purse seining began in the western Pacific in 1979. This chapter aims to find any detectable change in the longline catch rate coinciding with the increasing purse seine effort in the region.

It is impossible to prove that purse seine catches have caused any decline in longline catch rates, since any observed decline could be due to a number of other changes. Accordingly it would seem sensible to proceed by removing as much of the variation due to other causes as possible before tackling the main issue. The amount of data available running concurrently with the standard catch per unit effort data is limited, hence the analysis reflects this rather than a comprehensive breakdown of factors affecting longline catch.

Different affects are linked empirically using generalised linear models, based upon the theory developed in the previous chapter. Finally the catch rates are linked to the increasing purse seine catch using a time series model to estimate the degree to which longline is being affected.

4.1 Deterministic Model of the Impact of Purse Seine on Longline

The general effect of purse seine on longline can be best understood by looking at a deterministic model of a single cohort subject consecutive fishing from both gears. If they are fishing the same stock at different ages, there must be a fall in the size of the stock available to longline, which it is assumed will decrease the catch rate. If this is not the case then there will be no effect. A simple model assuming constant mortality and recruitment is used to demonstrate this. The model can be written :

$$N_t = N_o \mathrm{Exp}(-(m+F_{p,t}+F_{l,t}) \ t) \qquad 4.1)$$

where

N_0 = number of recruits

N_t = number of fish age t

m = natural mortality

$F_{p,t}$ = fishing mortality due to purse seine at age t

$F_{l,t}$ = fishing mortality due to longline at age t

The mortality exerted by any gear can be any function. For simplicity it is defined here as uniform over different intervals for each gear

$$
\begin{aligned}
F_{p,t} &= 0.15 && T_{p,1} < t < T_{p,2} \\
F_{p,t} &= 0 && \text{elsewhere} \\
\\
F_{l,t} &= 0.1 && T_{l,1} < t < T_{l,2} \\
F_{l,t} &= 0 && \text{elsewhere}
\end{aligned}
\qquad 4.2)
$$

where

l (subscript) refers to longline

p (subscript) refers to purse seine

T_1, T_2 define the selected age ranges for the different gears

There is no reason why the selected ranges should not overlap (ie $T_{p,2} > T_{l,1}$), however the inferences are clearer if the selected ranges do not. Figure 4.1a shows the numbers of fish at each age of a cohort with and without purse seine fishing. There are two periods when the cohort is subjected to fishing mortality. The earlier period causes a sharp decline in numbers, although it lasts a short time. This represents purse seine, which will exert a high fishing mortality over a small age range. Longline exerts a smaller mortality over a longer period. When purse seine is not active, the number of fish arriving to the age at first capture for longline is larger.

Figure 4.1 b shows the expected catch from the different gears at different ages. The numbers of fish caught by longline at all ages has been decreased, and the total number of fish caught reflects this. At equilibrium with constant recruitment figures 4.1 a and b represent the size of the population and catch respectively at each age.

The catch in numbers of fish is greater when both gears are fishing, although the value of each fish is not dealt with in

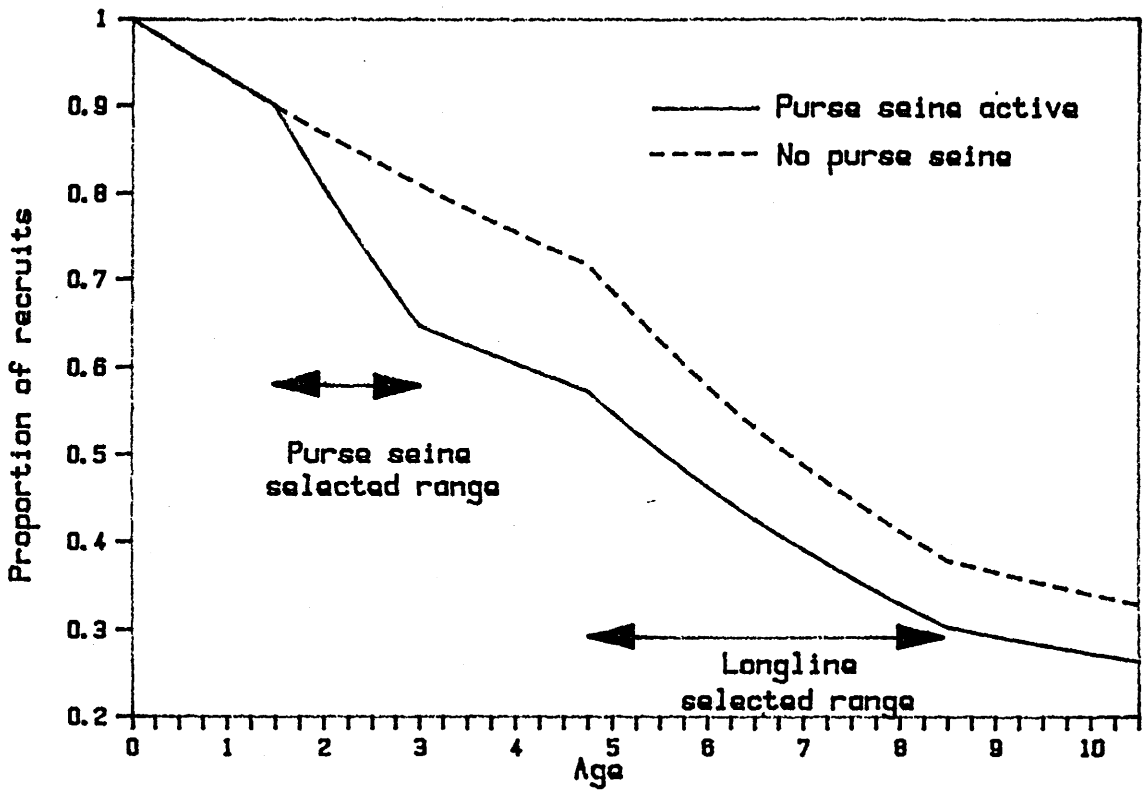


Figure 4.1a Proportion of recruits in a cohort subjected to two separate fishing periods.

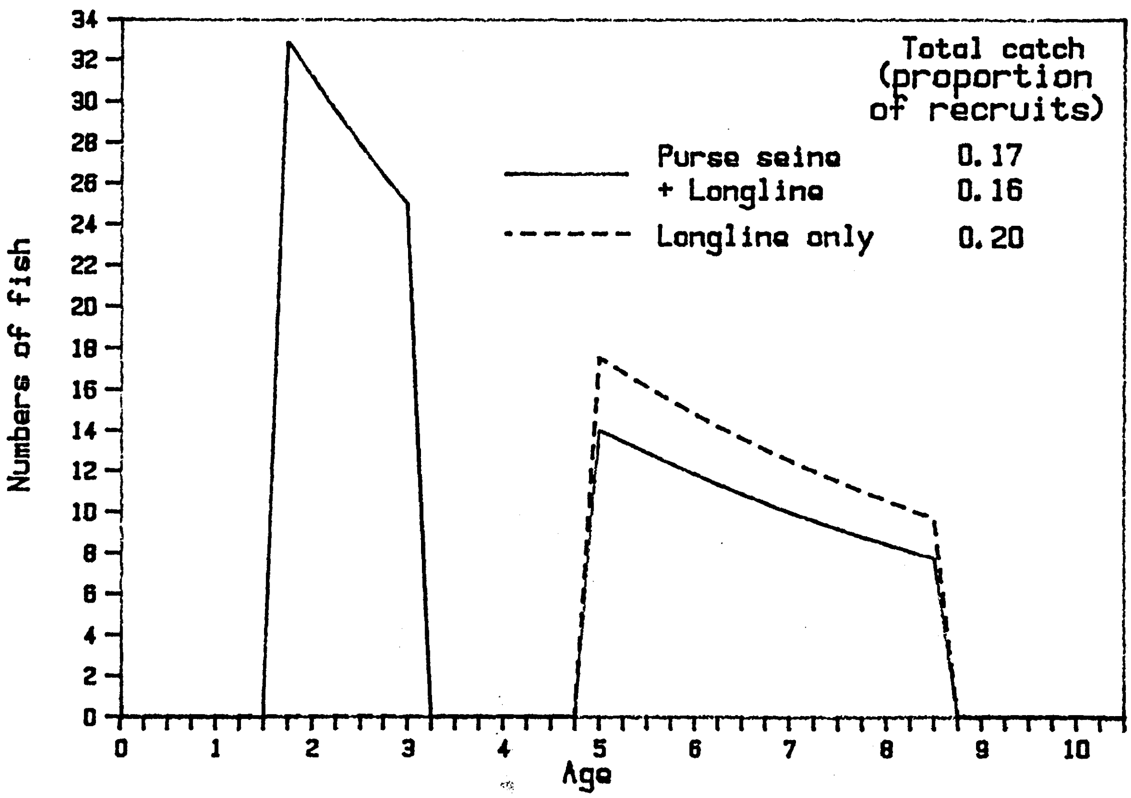


Figure 4.1b Catch in numbers of fish

this analysis, this being the subject of chapter 5. The longline catch falls by about 20% through purse seiners' activities. The fall in catches as a proportion of the longline catch will remain constant for all natural mortalities in this model. However for every 17 fish removed by purse seiners the longliners only lost 4 fish, although this formed a significant proportion of their catch. If the catch in numbers of fish is small and the variation in catches is large, as it is for longline, this fall in the catch rate may be difficult to detect.

Kleiber <u>et al</u> (1983) report an attrition rate (natural mortality and emigration) of between 0.15 and 0.2 months^{-1} for skipjack in the region, however the proportion of this which is due to natural mortality is unknown, so that this estimate is of limited use. In any case natural mortality is likely to be less for yellowfin than skipjack (Cole, 1980) and to decrease with age, so that yellowfin instantaneous natural mortality is likely to be a lot lower than 1.0 year^{-1}. Without a good understanding of tuna movements, such information alone will not be useful.

Although the model is a simple description of the interaction, its general results will apply to almost any system. There are a number of factors which will affect this analysis. Firstly density dependent mortality may decrease the difference between the size of the stock at first capture for longline with and without purse seine. However density dependent mortality may only reduce the effect, but not reverse it. This can be clearly seen when considering that as soon as the density dependent mortality has driven the stock to the same density as that where purse seine was active, they will be subject to the same mortality. Therefore a fished stock can never be driven below an unfished stock through this effect. Secondly the longline catch rate may not react to changes in stock density. From the discussion in the last chapter, this would appear to be very unlikely for longline. Thirdly the two gears may be fishing separate stocks. This can be dealt with in the following analysis by choosing only catch and effort data coming from similar areas.

4.2 Correlations of Catches between Sequential Sets

It is to be expected that longline fishermen will try to lay their lines to maximise the catch of their target species. Like purse seine fishermen they will search for areas of high density, unlike purse seine fishermen they search using their lines, concentrating on those areas where their catch is greatest. Since some of these data, including zero catches, are recorded in the log sheets, the importance of this search process can be explored in relation to the overall catch rates.

Spatial aggregation of fish will appear in the catch data in three ways. The first is as overall trip means, which will be related to a wide number of variables : average density of fish over the whole area visited, characteristics of the vessel and behaviour of the fishermen. These aspects are looked at in other sections. Secondly there may be some sort of trend in catch rates as fishermen react to previous catches and concentrate on those areas yielding the most fish. Finally stationary sequential catches may be autocorrelated. This last effect may be a result of small scale movements of tuna and temporary aggregations that may last only a few days.

The aim of this section is not to build a model of catches within a trip, but to see how important this sequential sampling is to the catches of the different species. Apart from the difficulties in fitting a good model to this sort of data, it is hard to see what value such a model would have without relating changes in catches to relevant outside factors.

Each trip log sheet consists of a header record naming the vessel and providing general information on the trip, followed by a sequence of set records, with the catches for each species recorded. The autocorrelation and partial autocorrelation can be calculated by treating each set sequence as a time series. However in this case each sequence is short, usually consisting of fewer than 20 sets, although it is repeated many times, with over 15976 trips being included in the analysis. No standard method was found for dealing with data in this form.

In order to combine all the trips, the autocorrelation was estimated using the deviations from each trip's mean. The intention was to remove all outside effects that will change the average trip catch, such as the vessel size, crew skill, number of hooks, season and so on. It was found that in order to help stabilise the variance, both the catch in numbers, after adding 1.0, and the average weight had to be transformed using the logarithm. Other power transforms were applied and seemed to perform less well according to the Bartlett's test (see Sokal and Rohlf, 1981). Even so the variance was not completely stabilised and was still increasing slightly over the series for all species. No significant trend was apparent in catches as trips progressed.

Figure 4.2 shows the autocorrelation and partial autocorrelation functions for sequential catches in numbers of fish of the four commonest species. The autocorrelations are increasing slowly with the lag implying the series are not stationary. However these autocorrelations do not get large within these short series, so some interpretation is possible. Since the functions are generated from a large number of concurrent time series, it is not clear how significance levels should be calculated. However since a very large number of trips were included, it is likely even small correlations are significantly different from zero. Even so, their small size suggests how important they might be. The autocorrelations of fish weights were all very low.

Albacore (figure 4.2 a) shows the largest initial autocorrelations. The ACF and PACF suggest catches may follow some sort of autoregressive process. Bigeye and yellowfin (figures 4.2 b and c) show a different pattern. The autocorrelation at lag 1 is small, which suggests that the correlation between sequential sets is of low importance. Blue marlin (figure 4.2 d) shows no correlation at all. Overall it appears that sequential correlations of the catch are small for all species, but albacore.

The results would seem to justify ignoring correlations between sets, with the possible exception of albacore. To develop a model including dependence on previous catches within a trip would require much more work. From these results it might be expected that there is little to be gained from such a model, and therefore this approach is not justified within the context of the present analysis.

Catches of different species may be similar if they are found in similar habitats. Table 4.1 shows the correlation

Figure 4.2 a Albacore

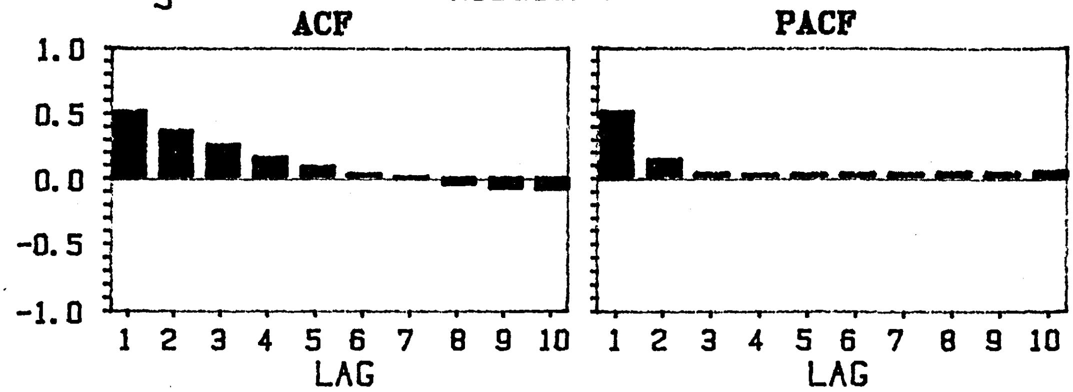


Figure 4.2 b Bigeye

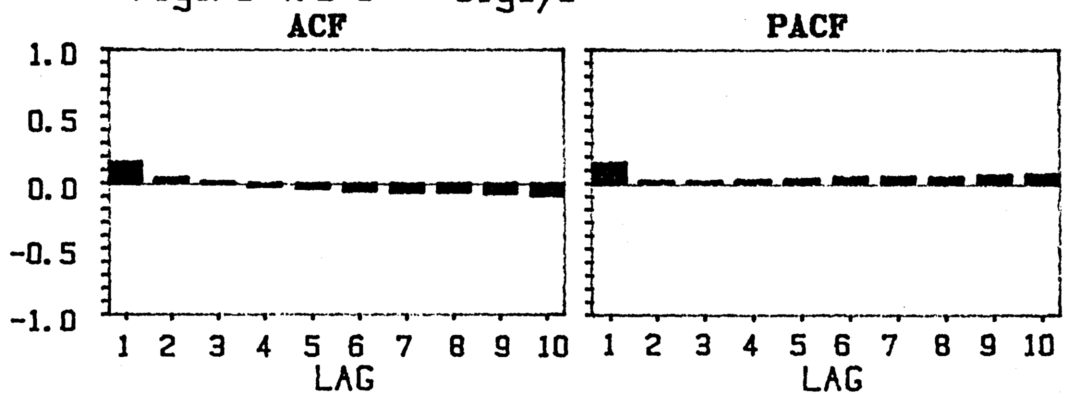


Figure 4.2 c Yellowfin

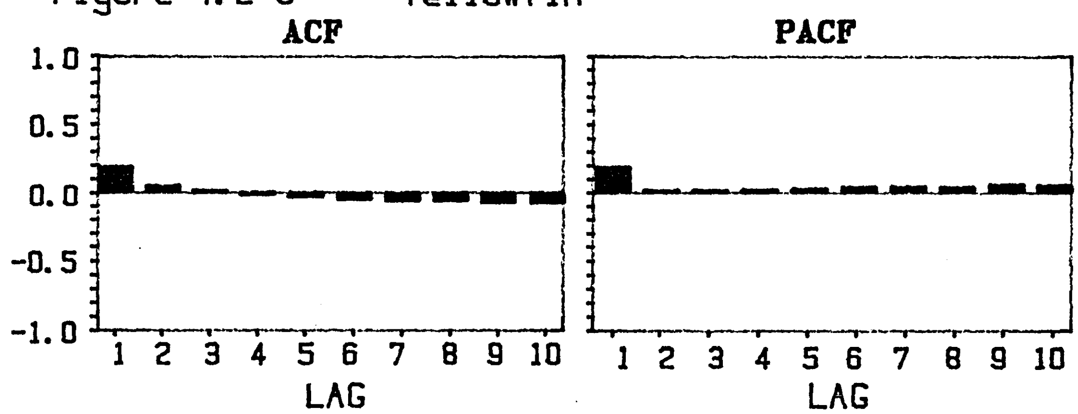
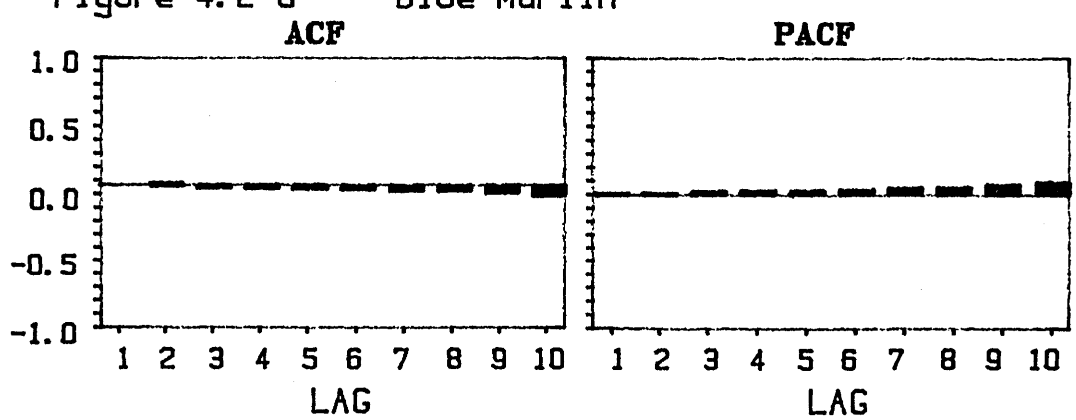


Figure 4.2 d Blue Marlin



matrix for catches between species on the same set. There is a fairly large positive correlation between bigeye and yellowfin, similar species of tuna. Correlation between the weights of different species and between the weights of fish and the number caught were all insignificant.

These results can be born in mind in future analyses. Ignoring autocorrelations introduces bias in estimating the variance of parameter estimates (Gottman, 1981), suggesting a model is better than it actually is. Autocorrelations do not pose a significant problem within trips, with the possible exception of albacore.

Low correlations between species catch indicate little is lost in looking at catches separately, unless a model is specifically needed for changes in catch composition. If correlation between species was high, more parsimonious representations of changes might be made which combined species into a single multivariate analysis.

Species	Albacore	Bigeye	Yellowfin	Blue Marlin
Albacore	1.000	0.052	0.030	0.011
Bigeye		1.000	0.299	0.061
Yellowfin			1.000	0.016
Blue Marlin				1.000

Table 4.1 The table shows the correlation coefficients (Pearson's r) between the catches of different species on the same longline set. The catches have been log transformed to stabilise the variance. Since 209000 set records were used to generate these statistics, all the values will be significant at the 5% level. However only the bigeye-yellowfin correlation is large enough to imply an important association.

4.3 Linear Model Error Distribution

The model presented in chapter 3 could only have a limited application to the longline catch distribution at present because it requires more detail to check that its underlying assumptions are correct. It was suggested that the main anomaly between the theoretical and observed catch distributions will arise because the model does not include other forms of spatial aggregation besides schooling. However the model does suggest a distribution to use as the error for linear models applied to the present catch data. The accumulated catch from a 2*2 transition matrix can be approximated by a mixed Poisson geometric model when the Poisson parameter is small. The Poisson part of the model represents the number of schools finding hooks, the geometric represents the number of fish taken from each school. The model assumes the probability two schools hitting the same set of hooks is small and therefore negligible. It has the following definition.

$$\text{P.G.F.} = \text{Exp}(-\lambda + S\lambda p/(1-qS)) \qquad 4.3)$$

$$\text{Mean} = \lambda(1 + p/q)$$
$$\text{Variance} = \text{Mean} * (1 + 2p/q)$$

where

λ = mean density of aggregations (Poisson parameter)
q = geometric parameter related to the size of aggregation
p = 1-q

The probability distribution in expanded form is somewhat more complex.

$$P(0) = \text{Exp}(-\lambda)$$

$$P(z) = \text{Exp}(-\lambda) \quad \frac{(z-1)! \; (\lambda p)^x \, q^{(z-x)}}{x! \quad (x-1)!} \qquad 4.4)$$

To obtain a useful explicit log-likelihood function a simpler form of the sum in equation 4.4 would have to found.

However this improvement will make little practical difference to the fitting of models to the data. A quasi-likelihood model with the mean proportional to the variance with the scale parameter estimated from the data (McCullagh and Nelder, 1983) would seem appropriate. That this model fits adequately can be tested by analysing the residuals. The deviance function on which the maximisation is based is the Poisson, since this is both efficient and close to the model described above. This will only be a valid approximation where the density of aggregations varies (λ) rather than the size of aggregation (q).

The use and interpretation of this model requires some thought. The assumptions made in it are the same as those in the more detailed model of chapter 3. Changes in mean catches need to be interpreted as a change in the number of aggregations rather than their size. This will obviously not hold over all circumstances, for instance comparing species that will have different sized schools, but should be adequate for this analysis.

It is possible to take advantage of the asymptotic results of the study of Markov chains which support the use of the quasi-likelihood model described above. As the number of hooks increase the mean will remain proportional to the variance and asymptotically tend towards the normal distribution regardless of the transition matrix parameters (Cox and Miller, 1965). Under these conditions the mean should be linearly related to the number of hooks. Care should be taken when looking at classifications where the number of hooks falls to a low value, since these asymptotic results will no longer hold. This suggests a better variance function would have some minimum value to avoid over weighting cells containing less effort. In this particular analysis this did not prove to be a significant problem, so the straight forward Poisson variance was used.

Unlike previous analyses, the weights of fish play a much more significant role. Whereas small fish are avoided by purse seine for largely technical reasons, the size of fish is an important factor in the price a longliner gets for its catch. There is no particular model which would provide theoretical insight into the weight error distribution. It was found that the mean was approximately proportional to the square of the variance, which, from quasi-likelihood theory, suggests the gamma error is appropriate (McCullagh and Nelder, 1983). The gamma probability distribution also possesses the advantage of being bounded at zero.

The average fish weight within each classification is weighted by the number of sets that went to make up the value. There are two reasons for using the number of sets as opposed to the number of fish caught on each set. Firstly if the fish school, the weight of each fish will not be independent so that the variance of the estimated weight for a particular set will not decline proportional to the number of fish caught. Secondly it is unwise to give too much credence to estimates of the average fish weight for large catches where the estimate may become less accurate.

One of the major problems of this data set is its physical size. In theory it is better to keep the data in its original form, since this allows the model to be tested within the context of actual catches. The alternative is to collapse catches into sufficient forms that are designed to test particular aspects separately, such as the effect of surface temperature, type of bait used, vessel size and so on. This loses the gains made from the multivariate approach usually adopted, such as testing the significance of interaction terms.

In most cases it had to be assumed that if a factor is going to be significant at all, it will be apparent in the main effects. There is no theoretical justification for this and so where possible some interaction effects have been checked. However it has not been possible for practical reasons to test all interactions between factors.

A similar argument to that used above could support the use of the binomial for the error distribution, where the relationship between the number of hooks and the catch is linear. This last assumption is not necessarily appropriate, particularly for the initial more exploratory analyses. This model was used and compared to the Poisson model for the final time series analysis at the end of the chapter, where the linearity of the hook-catch relationship was supported empirically.

The basic form of the data set adopted for the following analysis is a time series based on the catches for each month. Many of the interesting effects are related to time, so that the explicit inclusion of time was necessary. Where a factor was not dependent on time, the data in this form was still useful for comparison with other analyses. A second reason to breakdown the data set into a form below that absolutely necessary to do an analysis is to check the error variance function and to obtain some idea of the importance of the factor in relation to overall variability. Although the change in the deviance asymptotically follows the chi-squared distribution, it is advisable to have an idea of the underlying error deviance for reference.

The following analyses cover probably the most important factors which can be easily measured. The importance of factors are tested using generalised linear models and time series. In all cases the analyses were carried out in GLIM (1985), which allows different error models to be implemented. For the models of the catch in numbers of fish a Poisson error is assumed with a scale factor estimated from the deviance. The scale factor will not affect the parameter estimates, but will increase the standard errors of those estimates to some more realistic level. The log link is used so the effects are multiplicative. It was found that the logarithm of the number of hooks fitted better than just the number of hooks, implying their effect was, not surprisingly, linear.

For the size distribution the gamma error was used and the link function chosen was the canonical (reciprocal). This choice was largely arbitrary, but both the log and identity links fitted less well.

4.4 Local Water Surface Temperature

The catch log sheets include a field to record the sea surface temperature. Although this was filled in in only 13507 cases out of 175335, this provides a significant subset with which to work. Temperature recorded covers the range from 21-33^{o}C to the nearest degree, most records lying between 27-30^{o}C. There is no a priori form of relationship between temperature and catch, so changes are examined through an analysis of variance.

Temperature might affect catches through a number of ways. The first is a change in the catchability of the fish. In particular the surface temperature indicates the depth of the thermocline which changes the effectiveness of different gears. Secondly temperature may act directly or indirectly on the fish distribution. There may be a number of physiological factors that control fish distribution, one of which is likely to be temperature. Temperature may also indicate oceanographic effects associated with productivity such as upwelling (cooler water).

The data set was broken down by year, month and sea surface temperature to the nearest ^{o}C. This allowed large scale fluctuations (year) and seasonal changes (month) to be removed, so that the temperature effect might represent local temperature effects. Results of only the four commonest species are reproduced here, since these are the only ones which produced significant results. A model was fitted to the numbers of fish and average fish weight in each classification.

Analysis of Deviance Table

Species	Albacore	Bigeye	Yellowfin	Blue Marlin
Total	154633	25262	62446	2217
df	304	304	304	304
Year	43169	15300	24646	508
df	7	7	7	7
Month	49675	1094	3276	329
df	11	11	11	11
Temperature	9100	1481	1932	63
df	11	11	11	11

Table 4.2 The table shows the deviance changes associated with different effects for numbers of fish caught. The total deviance is that remaining after removing the number of hooks set as a factor.

Table 4.2 shows the results of the fit to numbers of the four main species caught. The overall deviance, based upon the Poisson log-likelihood, is high for all catches, implying great variation among catches even combined over months. The change in deviance should be assessed in relation to the overall deviance as well as in absolute size. Yearly fluctuations are large whereas the monthly variation, with the exception of albacore, is small. These time series effects will be dealt with in detail later. The deviance associated with the sea surface temperature in all cases is small compared to the overall deviance. Although temperature may have a significant effect if the change in deviance is closely approximated by a chi-squared distribution, it does not appear to be important.

Table 4.3 shows the deviance associated with different effects on the weight of fish caught. The deviances here are smaller for all species since zero catches are ignored, because they give no information on the weights of fish. The results indicate that the yearly changes are large while seasonal changes small. Temperature here appears to be a more important factor, since it forms a larger proportion of the total deviance.

Species	Albacore	Bigeye	Yellowfin	Blue Marlin
Total	5496	8188	9735	4917
df	256	299	303	272
Year	1785	2233	2926	1596
df	7	7	7	7
Month	528	370	415	254
df	11	11	11	11
Temperature	777	853	1075	401
df	11	11	11	10

Table 4.3 The table shows the deviance changes associated with different effects for the average weight of each fish caught.

Figure 4.3 shows the changes in the mean size of the catch. Outside the range 26-30^{o}C the values have a high standard error since there were very few sets in this range. The most important aspect of the catch sizes is the small peak at the lower temperatures (26^{o}C). This suggests a slightly higher proportion of larger fish in cooler water.

If fish are orienting themselves to ocean fronts, then sets

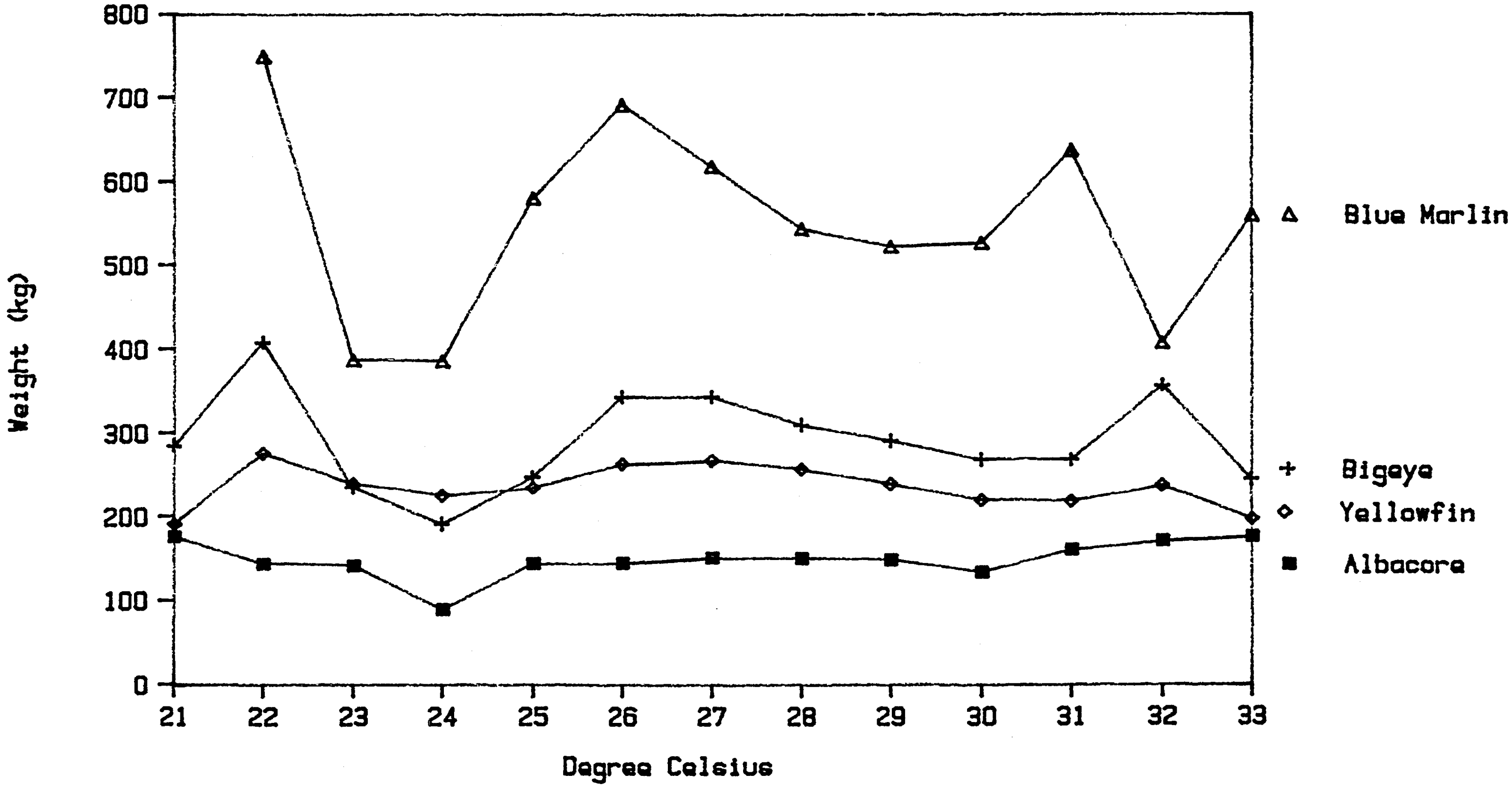


Figure 4.3 Average fish weight vs sea surface temperature

which are made around such a front should have a higher catch. A front could be indicated by sharp changes in a series of sea surface temperatures recorded on a trip. The hypothesis that higher changes in temperature indicate higher catches was tested by summing the absolute change in temperature between sets over a trip and using this as a covariate for modelling the catch. No significant relationship was found, so the hypothesis was rejected.

The analysis overall suggests that temperature in catch data is not very important in explaining the catch variation. This may either be because fishermen use this same data and only make sets (sample) where the temperature, among other things, implies the catches will be high or because the fish do not strongly orient themselves with respect to sea surface temperature. From what is known of the behaviour of fishermen and tuna, the former is the most likely explanation.

4.5 Depth

When the longline settles out, it forms a catenary. The depth of an individual hook will depend upon the length of the float line, branch line and shape of the mainline as it hangs in the water. A catenary in this context can be described by two parameters.

$$y = a \, \mathrm{Sinh} \left(x/a \right) + c \qquad 4.5)$$

where

a = some constant

c = length of branch line and float line combined

The parameter, a, can be found by solving the following equation numerically, which is obtained from the definition of the length of the line between two floats.

$$S = 2a \, \mathrm{Sinh}(L/2a) \qquad 4.6)$$

where

S = length of the line between the floats

L = distance between floats

To obtain the depth of individual hooks may be time consuming and is of no use unless individual hooks are identified as having fish. An alternative is to obtain the average depth of line which will provide a good index of the average depth of hooks in a basket.

$$\text{Mean Depth} = a \operatorname{Cosh}(L/2a) - a \, (a \operatorname{Sinh}(L/a) + L)/2S \qquad 4.7)$$

The total length of line is not provided directly in the data and has to be generated. To obtain reasonable results (ie distance between floats is less than the length of line hung between floats), the number of hooks in a set was multiplied by an arbitrary constant, so equation 4.7 was used to produce an index of depth rather than the actual average depth.

No relationship was found between depth and catch rate or size of fish. However this may be due to the method for calculating the index rather than fish having a equal distribution over depth. The relationship may be non-linear, so that there is a modal depth for each species at each size. From what is known of the behaviour of tuna, they make many rapid vertical movements (Hunter et al, 1986) suggesting that there will be no simple catch at depth relationship. The depth at which fish are caught will depend upon other characteristics such as the temperature profile. All these relationships need to be looked at simultaneously to discover any relationship or decide that there is none.

4.6 Vessel Size

The aim of this analysis was to see how important size of vessel was to the catch per hook. The size is given for each longline vessel operating in the fishery as gross registered tonnage (GRT). Initially the vessels were divided over 150 tonnes into 15 groups, however the analysis revealed that 3 groups explained almost as much of the deviance. The full data set was used since the GRT is given in almost every case. The data was classified by year, month and size class. The catch by species and number of hooks was accumulated into each cell. A model is fitted to each species separately.

The results for the catch estimation are presented in table 4.4. The total deviance represents that remaining after the number of hooks have been fit, since this will obviously be the largest affect on catches if there is great variation in the number of hooks set within any classification. The remaining deviance is related to the spread of the catches. For instance the catches of blue marlin are never large, whereas albacore catches vary a great deal.

The year effect deviance is high for all species implying large year to year fluctuations in the catch rate. The deviance explained by the month is smaller, so the seasonal effect is not strong.

Surprisingly the vessel size is very important to the size of catch, particularly so for albacore where size of vessel explains more than half the deviance. Why this should be so is not immediately obvious. Larger vessels may be better equipped and move faster so that they are able to locate good areas quickly. However the parameter estimates, also presented in table 4.4, show that the largest size class of vessel has a much better chance of catching albacore and lower chance of catching the other three species. It is apparent these larger vessels are targeting for albacore, so that the size class represents a classification of behaviour and equipment.

The other important parameter is that associated with the number of hooks. If the value of the hook parameter is close to 1 the relationship is linear. That is the average number of fish caught is proportional to the number of hooks set, so that the remaining part of the linear model can be interpreted as a probability. The estimates in table 4.3 show the relationship is close to linear. Deviations from the linear relationship might occur for a number of reasons. Fewer fish than expected might be caught as the number of hooks set goes up if depletion occurs over the cell period (1 month). Higher catches might be expected if more hooks are set in areas of high fish density. Finally the number of hooks set may be correlated with other effects being fitted, so that the estimate will change with the model.

Species	Albacore	Bigeye	Yellowfin	Blue Marlin
Total	1660129	126878	500541	40305
df	636	636	636	636
Year	466153	35990	166508	10053
df	7	7	7	7
Month	56225	3062	32533	3336
df	11	11	11	11
GRT Class	1062240	36324	84994	7861
df	2	2	2	2
Parameter Estimates				
Hook	1.348*	0.9222*	0.9942*	0.8703*
GRT Class				
50-99	-1.268*	0.1677*	0.2541*	-0.0907
> 100	4.516*	-0.9519*	-0.8505*	-1.3420*

Table 4.4 Each species is dealt with independently. The total deviance is the Poisson deviance remaining after removing the hook effect. The table shows the changes in the Poisson deviances after fitting the effects. The parameter estimates are selected from the full model, those greater than 2 standard errors from zero are marked *. GRT class is a discrete factor, the parameter estimates representing deviations from the smallest class.

Table 4.5 shows the results from the fit of a gamma model to the average catch size based upon the same classifications as for the number of fish. Since the model no longer deals with numbers of fish caught, the number of hooks is not included. The total deviance represents the gamma deviance around the sample mean. Average yearly and monthly changes seem quite large for all species. Vessel size class seems important only for bigeye and albacore, where the largest vessels tend to catch larger individuals. This may be related to the targeting for albacore referred to earlier.

Species	Albacore	Bigeye	Yellowfin	Blue Marlin
Total	836	723	589	297
df	254	353	355	334
Year	189	40	129	19
df	5	5	5	4
Month	149	93	91	41
df	11	11	11	11
GRT Class	310	250	39	48
df	2	2	2	2

Parameter Estimates

GRT Class				
50-99	0.00008	-0.00002	0.00014	-0.00018
> 100	0.00202*	0.00076*	0.00038	-0.00006

Table 4.5 The total deviance is the gamma deviance after fitting a constant. The table shows the changes in the deviances after fitting the effects. The parameter estimates are selected from the full model, those greater than 2 standard errors from zero are marked *.

Targeting might be achieved through a variety of ways. Vessels may set the depth of the hooks or position of the line. Depth, as shown above, does not appear to be of particular importance, whereas position of set is important. The mean position of sets split up by year, month and vessel size is shown in figure 4.4. Points made up of fewer than 15 sets are not shown. There is a clear division, larger vessels appear to be operating to the south-west of the main area. Removing these sets from the analysis greatly reduces the change in deviance associated with grt. Alternative methods for targeting species include operational factors such as the type of bait used, and this is the subject of the next section.

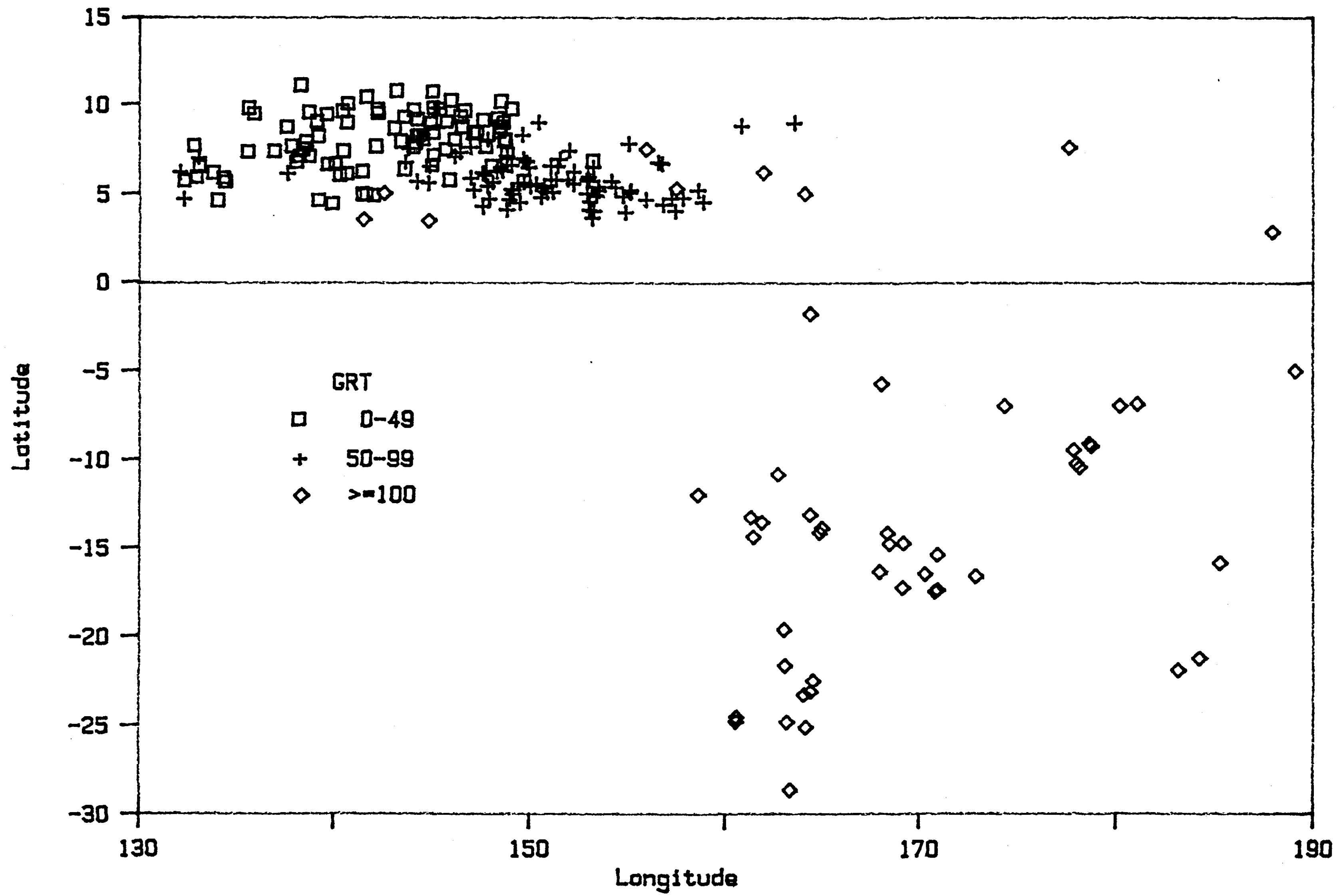


Figure 4.4 Mean longline set position by gross registered tonnage (GRT)

4.7 Bait Types

The header record for each log sheet includes 2 bait fields, allowing the recording of bait combinations. The aim here is to look at the effect of the bait used and whether this is different to the size class effect found in the previous section. The classification used is different to the last analysis.

The year and size classifications remain the same, but the month factor is dropped owing to physical computing limits. This is justified on the basis of previous models which showed that monthly changes are small compared to overall changes. There are 3 other effects which have been added. Firstly the 2 bait fields, which have over 30 different bait codes. However most of these do not have enough values for inclusion in the model. Only 6 of each bait type occurred in significant numbers across the other classifications.

The other factor included was the species caught, so that only one model was fitted instead of the four, one for each species, in previous sections. This approach has the advantage of the multivariate approach, so that changes in species composition can be tested for significance as well as the total catch. The disadvantage is that the variance function may no longer adequately describe the change in the variance among the different species. Strictly speaking different species should probably be weighted based on their degree of aggregation. In practice analysis of the residuals showed no strong deviation from the assumption of the variance being proportional to the mean, so that without any a priori weighting scheme, no more complex analysis was justified.

Table 4.6 shows the deviance associated with the various effects. The total deviance is that remaining after fitting the number of hooks. The species main effect removes the difference between the mean catches of each species. The following terms also have a species interaction effect. The main effect for each one simply measures the change in the overall catch of all species, assuming that the species appear in the catch in the same proportion. If different parameters calculated for each species represent the catch more successfully, this is evidence that the catch composition has changed. It is evident from the species interaction deviances that the species composition of the catch changes considerably with vessel size class. This is simply a repeat of the finding of the previous section, that the vessels are targeting for particular species. The bait effects are small in comparison, unless size class is removed as a factor. Table 4.6 shows the bait deviances fitted without the vessel size class. Clearly the first bait type dominates the type of catch, but is closely related to the species the vessel is targeting. Therefore the position of the set, the type of vessel and the bait used are not separable.

	Main Effect	Species Interaction Effect	Without Size Class
Total	4670475		
df	666		
Species	2792808		
df	3		
Year	52055	562700	
df	7	21	
Size Class	84629	1160754	
df	2	6	
Main Bait	9328	78004	1191852
df	6	18	17
Secondary	830	3634	16415
Bait df	5	15	14
Bait	738		
Combinations	8		
df			
Error	124995		
df	575		

Table 4.6 The results are presented for a combined analysis of catch by species. The main effects and then the species interaction effects were fitted in sequence. Finally the model was fitted again without size class demonstrating the high correlation between bait used and the species being targeted.

The secondary bait and combinations of the primary and secondary baits seem to make little difference to the final catch. This is partly because baits appear to be used in particular combinations. However it would be interesting to know how it is decided which baits to use, bearing in mind that outside factors such as the cost of bait may be the major concern.

Table 4.7 shows the parameter estimates for the primary bait type. The major difference in catches is related to bait type 4, which shows a much higher albacore catch per hook, than for the other species. However since there is probably a tendency to use this bait when targeting for this species (ie in areas where albacore is abundant), this may represent a number of effects.

		Deviation from Main Effect		
Bait Code	Main Effect (Albacore)	Bigeye	Yellowfin	Blue Marlin
2	0.697	-0.869	-0.797	-0.507
3	-0.142	-0.158	-0.146	
4	5.833*	-6.628*	-6.434*	-6.371*
5	1.280*	-1.079	-1.241	-0.703
6	-5.074	4.385	4.702	4.532
10	-0.338	-0.259	-0.277	
Hook	1.125*			

Table 4.7 The parameter values are selected from the model including the year and first bait code effects only. The results show the species interaction terms, the main effect representing albacore, and the other effects deviations from this species. Parameters significantly different from zero are marked *.

Although most of the other parameters are not significantly different from 0, they show a definite pattern. The catch rates for the different species other than for albacore do not appear to differ much. The implication is that the catch composition changes from being dominated by either albacore or the other three species, of which yellowfin forms the largest proportion.

4.8 Yellowfin Catch Time Series

Having looked at a set of possible factors affecting yellowfin catches, it is sensible to proceed to look at longline and purse seine yellowfin catches as a time series, together with time-varying covariates. In the previous analyses the fact that the data was a time series was largely ignored beyond the removal of any trend and seasonal cycling through the year and month effects. This method was adequate to find patterns due to static variables such as vessel size, but does not provide a good parsimonious model to study changes in the catches. Furthermore, if the residuals are autocorrelated, the error variance will be underestimated, so that the model will appear to fit the data better than it actually does (Gottman, 1981).

There are two approaches to dealing with this problem. The first is to weight values according to the residual autocorrelations, which can be estimated iteratively. The second is to fit a multivariate time series model that uses past values to predict the present. In this latter case the residuals should be white noise (uncorrelated). This last approach is adopted here, because it provides a complete representation of the data.

Figure 4.5 shows the time series of the longline catch of yellowfin per hook. There is a noticeable increase in the yellowfin catch per hook in 1983/4, when there was significant El Nino oceanographic event in the Pacific. The other two species, included for comparison, do not show this effect.

Below the catch time series is a monthly time series of sea surface temperature (SST) anomalies for the eastern Pacific taken from Anderson (1989). The sea surface temperature anomaly data is calculated from the difference between the actual average SST in any given month and the grand mean over all months since January 1965 from the Santa Cruz weather station, Galapagos. The temperatures recorded do not directly relate to the western Pacific, but does represent large scale oceanographic effects such as El Nino quantitatively so that this effect can be removed from the catch data.

There is a noticeable lag between the high catch rates in the western Pacific and the sea temperature increase in the east. This is consistent with the hypothesis that the effect starts in the west and moves eastward arriving along the American coast

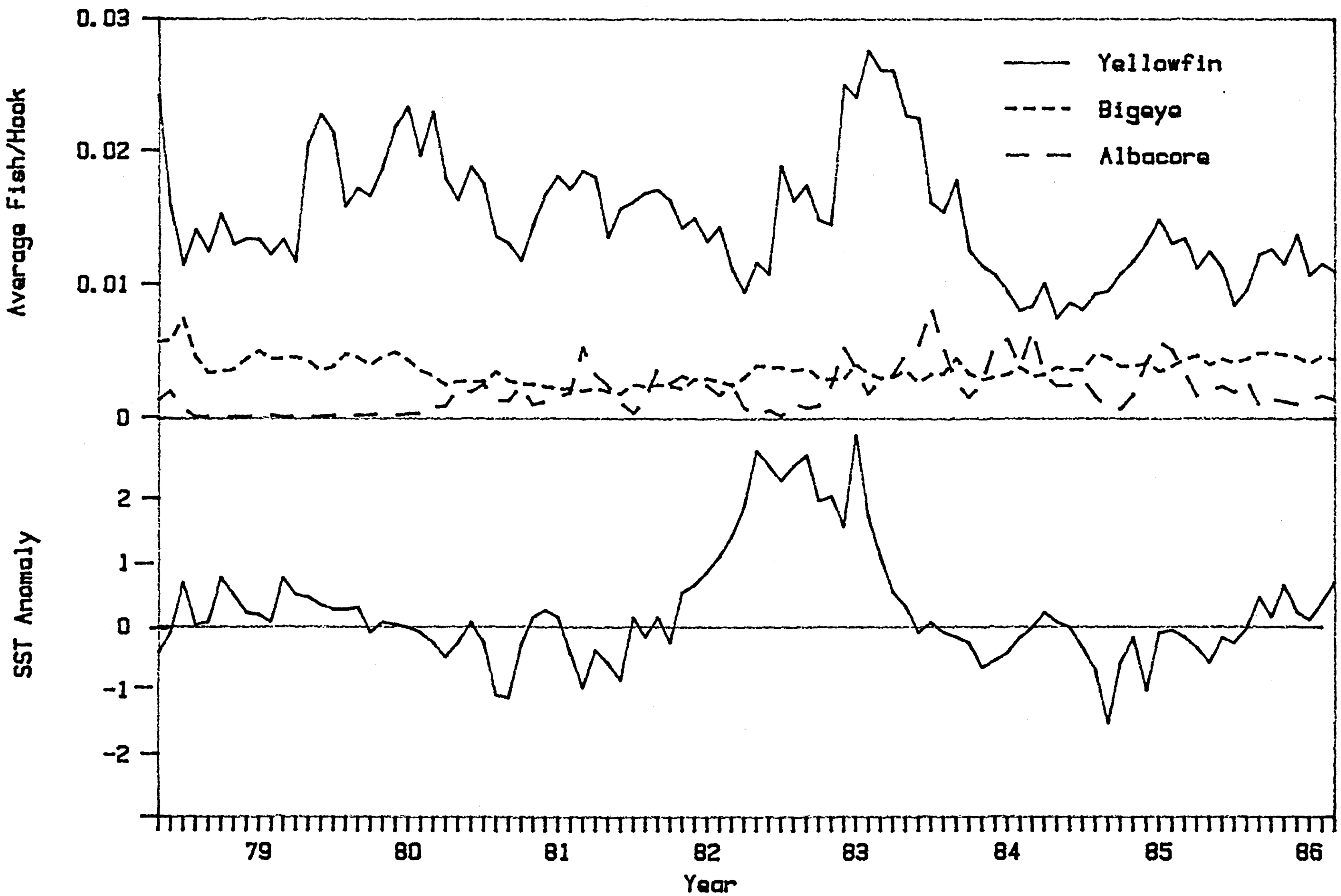


Figure 4.5 Longline Time Series

some months later (Pickard and Emery, 1982).

Figure 4.6 shows the purse seine total yellowfin catch for each month. It is expected that this will reduce the density of yellowfin and, at some point in the future, reduce the longline catch rate. The outlier in 1984 shown in the figure was checked and appears to be genuine. It appears to have been caused by a particularly large influx of US vessels into the fishery.

The actual effect of purse seine on longline will depend upon the delay and the natural mortality as well as the numbers of fish removed. This is discussed in section 4.1, but in general natural mortality will decrease the size of the fall in longline catch rates.

Note that as the purse seine catch is increasing, any decreasing trend in the longline catch rate will cause it to be correlated with this series. There seems to be a slight negative trend in figure 4.5. If significant, this trend is assumed here to be evidence that purse seine is affecting longline catches, hence it is not removed. It is, of course, quite possible that there is no causation between these phenomena.

Figure 4.7 shows the weight distribution of each gear's catch for the whole data set. The age difference between the modes of the two gears can be estimated. From Wild (1986) the lag in age between the purse seine and longline peak selected size frequencies is approximately 1.5 years. Hence the lag between increases in purse seine catches and a decline of longline catch rates should be about the same time.

There are several reasons why such a long lag may not be detected. Firstly random effects may obscure all but the the most well defined relationships between purse seine catches and longline catch rates. Cross-correlations between different time series appear either because of non-stationarity (trends in the mean or variance) or dependence between stationary series. The second of these is usually taken as good evidence of a link between the functions. In this case, after 1.5 years, random natural mortality and growth may well erase such dependence from the series, while a trend may still be present.

Another problem arises because of the selectivity of the gears. For any purse seine set only the average fish size is given. The average size is not a good statistic for estimating the delay of the impact on longline. For any set, smaller fish

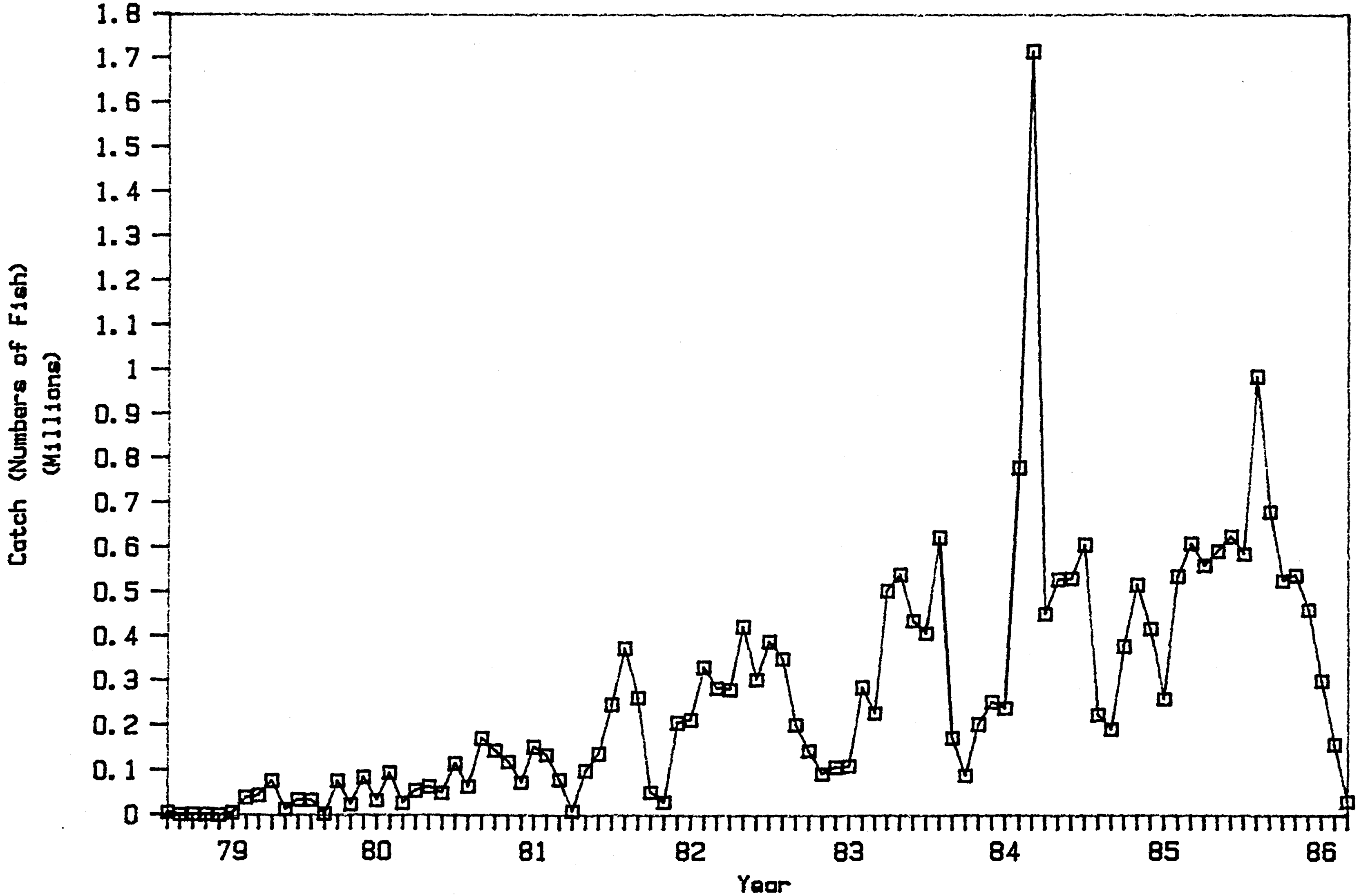


Figure 4.6 Total purse seine yellowfin catch

Figure 4.6 The catch is in numbers of fish calculated from the total catch in tonnes divided by the average weight of individual fish. This is appropriate since the number of individuals killed will affect longline catch rates, rather than the biomass removed.

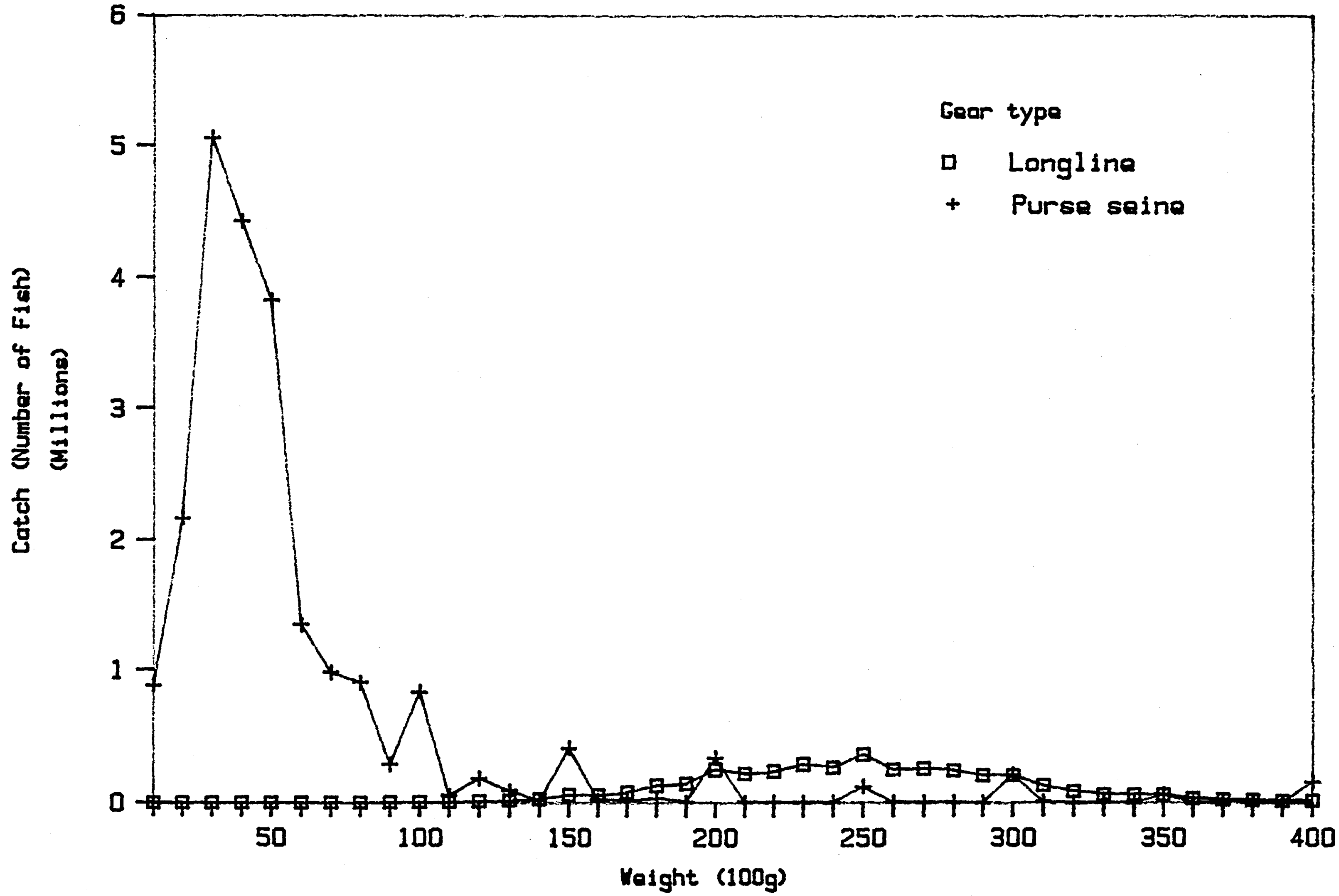


Figure 4.7 Weight frequency by gear type

are likely to make up the largest proportion and will lower the average size. However the impact on longline of each of each age group caught by purse seiners will not be the same. For every large fish removed by purse seiners, there will be a greater, more immediate effect, than for a small fish, since the cumulative natural mortality operating on a large fish will be less before it comes available to longline. A better statistic for the size of fish in the purse seine catch would be one weighted appropriately towards larger individuals.

Figure 4.4 suggests that the position of the set will indicate the species being targeted. This was verified using a model similar to that for the bait type. Including position of the set in some form also accounts for changes in the average density of fish over their range and ensures that the model is only looking at the stock at least potentially shared by both gears. The classification was based upon 10^{O} squares in order to cover the region. Reducing the size of the squares did not significantly improve the fit. The latitude classification was chosen so that the two regions shown in figure 3.1 associated with the currents appeared in separate classes. There are 6 10^{O} classifications for both latitude (37^{O}S - 26^{O}N inclusive) and longitude (125^{O}E - 176^{O}W inclusive).

4.8.1 Method

The models employed here are based upon those presented by Zeger and Qaqish (1988). The method is an extension of the Box-Jenkins approach to allow alternative error distributions, such as the binomial, Poisson and gamma, and quasi-likelihood methods. The basic model was suggested from the autocorrelations and partial autocorrelations for the data set combined over all 10^{O} squares. Figure 4.8 a shows the autocorrelations and figure 4.8 b the partial autocorrelation for the yellowfin catch per hook after a square root transformation. These suggest that an autoregressive process of order 1 (AR(1)) might adequately describe these data.

In addition any weather or oceanographic effect needed to be removed. There is an argument for pre-whitening both the longline catch rate and SST time series. This was not done for

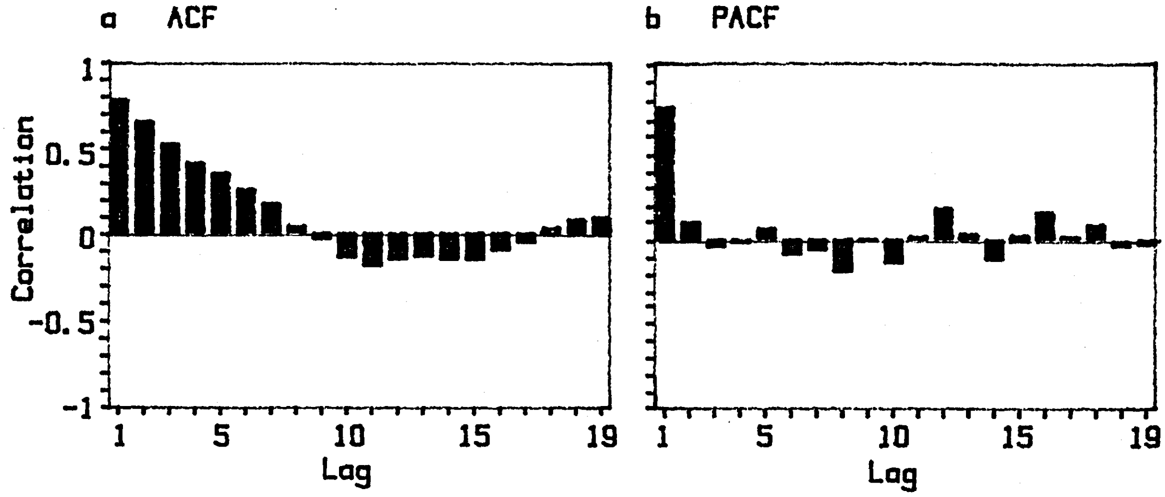


Figure 4.8 Yellowfin ACF and PACF

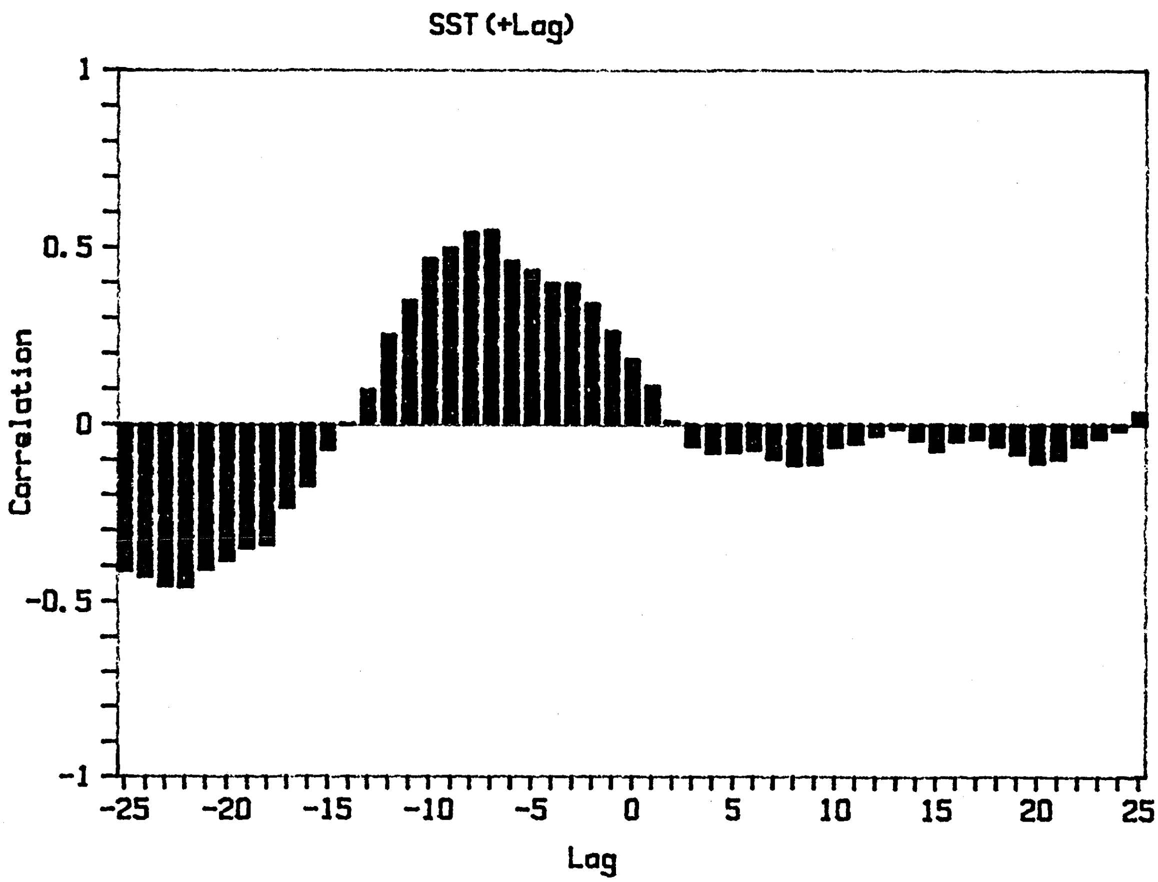


Figure 4.9 CCF : Yellowfin and SST

the final model, since it would have defeated the aim of the analysis. The pre-whitened SST series was found to have no significant correlations with the longline catch rate. The main aim was to remove the weather effect from the catch rate, rather than describe a relationship and argue causation. The null hypothesis adopted is that all variation in catch rates is attributable to effects other than increasing purse seine catches. Hence any variation correlated with changes in oceanographic conditions should be removed to avoid that variation being spuriously related to changes in purse seine catches.

Figure 4.9 shows the cross correlation function between the transformed yellowfin catch per hook and the Galapagos SST anomaly data. There are two possible significant correlations around lags -22 and -7. The relationship between the longline catch and the SST is obviously not bi-directional, since the change in catch rate presumably cannot cause the oceanographic effect, so that the appropriate months' values can be included in a single model predicting the catch through a transfer function.

Ultimately the only way to test the inclusion of a covariate is to see whether it significantly improves a multivariate model. Much of the exploratory analysis was carried out using Minitab (1989). In this case it was necessary to transform the data by taking the square root to stabilise the variance. The transformation was found to be adequate through examination of the autocorrelation and partial autocorrelation functions. The final model was fitted using GLIM (1985), where the variance is assumed to be proportional to the mean. Two models were tested. The first is the Poisson model described in section 4.3 with the addition of an extra term based upon the ratio of the previous observed value to the fitted value estimated from the covariates.

$$= \mathrm{Exp}(X_t'\underline{\beta}) \left[\frac{y^*_{t-1}}{\mathrm{Exp}(X_{t-1}'\underline{\beta})}\right]^{\theta_1} \qquad 4.8)$$

where

y_t = past observation at time t. $y^*_t = \max(y_t,\ c)$

X_t = vector of covariate values at time t

$\underline{\beta}$ = covariate parameter estimates

θ_1 = autoregressive parameter

This model is described by Zeger and Qaqish (1988) in terms of a

Markov process. This form of model seems appropriate for this particular data set. The aim is to use the time series term to account for any dependence the present catch has on the past. Any such change must be relative to other factors, such as the number of hooks set.

This model requires a second level of iteration due to the presence of the fitted value in the autoregressive term. The method described by Zeger and Qaqish does not take discrete factors into account. A more direct method for fitting the model is proposed here:

(i) Calculate $\underline{\beta}$, the parameter estimates for the covariates and discrete factors without the autoregressive term.

(ii) Use the estimated fitted value without the autoregressive term to obtain the new autoregressive covariate ie $y_{t-1}/\mathrm{Exp}(X'_{t-1}\underline{\beta})$.

(iii) Fit the model again with the autoregressive terms to estimate the θ_i's.

(iv) Repeat steps (ii) and (iii) until the deviance (or parameter estimates) converge.

Where discrete factors are used the denominator can be based upon any reasonable combination of fitted values. If the denominator is simply the fitted value for the classification being estimated, the model will be effectively fitted to separate time series which share the same parameters. Interaction terms can be used to vary the θ_i's. For the present model the observed and fitted values were summed across all classifications for each month, so that present catch rates are assumed to be based upon changes in the region as a whole. This provided estimates based upon the previous overall catch rate. This avoided problems with absence of data in some classifications, as well as being parsimonious. By this combination the absorbing state (y_t=0) is avoided, so the extra parameter, c in equation 4.8, need not be estimated.

There is an alternative error distribution besides the Poisson which has some advantages. If the binomial error is used (with a logit link) the relative density of fish according to the Poisson model described in chapter 3 can be estimated directly. This is because the log odds that a hook does not catch a fish can be calculated. If the basic model in chapter 3 is correct, the linear predictor should be directly proportional to the density. The binary model assumes, without testing, that the number of hooks is linearly related to the catch. This suggests a further simplification. Instead of including the ratio of observed to fitted values, the previous observed log-odds ratio can be used instead. This avoids the extra level of iteration. As for the Poisson model, the level of dispersion is higher than that expected for a binomial distribution. Therefore the variance function was adjusted by multiplying by a constant (scale parameter), estimated from the data.

4.8.2 Result

The method described for estimation worked under most conditions. Although it converged under all conditions, it failed to find the minimum deviance when parameters were strongly correlated. Convergence was also slow, particularly if parameters being estimated were correlated.

Because many of the time series parameters are correlated, the order of fit was important. The order presented here is based upon the hypothesis which is being tested, that the purse seine catch is affecting the longline catch rate. Six promising variables were identified and fitted into the models. The autoregressive (AR(1)) parameter was fitted first to remove the autocorrelations, so that any fit had to significantly improve upon this model. The latitude, longitude and SST were fitted in order before the purse seine catch was added. Table 4.8 shows the change in the deviances associated with the different factors and covariates and table 4.9 gives the parameter estimates for the two models. Note that the binomial model is predicting the probability that a hook does not catch a fish, so the parameter estimates have the opposite signs to those of the Poisson model.

The autoregressive term was very significant, showing a strong dependence of the present catch on the past. The autocorrelations of the residuals were very much reduced and no further significant relationship was found. The estimates for the two models are very similar, although the Poisson model performs slightly better in fitting to the data. Allowing the autoregression parameter to vary with latitude or longitude class did not significantly improve the fit.

The addition of latitude greatly improved the fit, longitude less so. Again the binomial model performed slightly less well, although the parameters are similar. The parameter estimates indicate slightly increased catch per hook in the southern fishing area ($17^{O}S-3^{O}N$) relative to the northern area ($3^{O}N-23^{O}N$). However there is the expected marked decline in the area south of $17^{O}S$, where the vessels appear to be targeting for albacore. Models not including latitude and longitude as factors provided a very poor fit in comparison with the present model.

The only SST value that added significantly to the model was the temperature 5 months ahead. There is a positive relationship between the catch rate and the SST, where a high SST represents the El Nino effect. One explanation for this is a change in the SST in the western Pacific reduces the depth range in which the tuna moves. Therefore there is an apparent increase in density of the stock while the effect lasts. This effect could also act through the prey distribution, which could become more aggregated or could be explained by some more direct relationship between recruitment or mortality and sea temperature. In this last case, however, the sharp rise and fall of the catch rates would not be expected to coincide so well with El Nino.

It was found that the purse seine catch was a better explanatory variable after being log transformed. This was at least partly due to the outliers in the purse seine catch series. However the log transform improved the fit even without the largest outlier, so the relationship between the two fisheries may be non-linear. Values from the series at lags of 0 and 3 months were found to explain more deviance than any of the others. A significant negative relationship was found. This was partly due to both series being trended, which explained about half the change in deviance, and partly due to correlations around their trends. Therefore this result does not depend purely on a decline in catch rates. For the binomial model the parameter estimates appear to be within 2 standard errors of the mean, suggesting a high variability in the estimate.

	Poisson Model	Binomial Model
Total	1283692	1309320
df	1208	1209
AR(1)	281032	283866
df	1	1
Latitude	398007	369045
df	5	5
Longitude	42073	68442
df	5	5
SST -5	8252	20829
df	1	1
Purse Seine		
Lag		
-3	1224	5536
df	1	1
0	2260	3053
df	1	1
Chi-Squared	561909	562241

Table 4.8 The table shows the changes in the deviance and degrees of freedom when the parameters are fitted for both the binomial and Poisson models. The chi-square statistics indicate the goodness of fit of the full models and were highly significant ($p < 0.01$).

Overall the model fitted well, explaining about half the deviance. The Poisson chi-squared value, used as a goodness of fit statistic, was very slightly lower than for the binomial model. Whether the binomial model provides a good description of the data depends largely upon the Poisson hook parameter, which, if close to 1, indicates a linear relationship between the number of hooks and the catch as assumed in the binomial model. This is supported by the value very close to 1 shown in table 4.9. It is worth noting that this estimate varied very little with the addition or removal of other effects. This was not the case when other classifications were used and suggests the data in this form fulfils the requirements described in section 4.3. The closeness of the parameter estimates between the models suggests that a direct interpretation of relative density might be put on the linear predictor in the Poisson model.

	Poisson Model		Binomial Model	
	estimate	s.e.	estimate	s.e.
Constant	-8.818	0.788	6.154	0.801
Hook	1.049	0.014		
AR(1)	0.562	0.055	0.500	0.045
Latitude				
$27^oS - 17^oS$	2.082	0.818	-2.070	0.823
$17^oS - 7^oS$	4.104	0.770	-4.105	0.775
$7^oS - 3^oN$	4.196	0.770	-4.212	0.775
$3^oN - 13^oN$	3.670	0.770	-3.723	0.775
$13^oN - 23^oN$	3.704	0.805	-3.597	0.810
Longitude				
$135^oE - 145^oE$	0.051	0.070	-0.095	0.070
$145^oE - 155^oE$	0.153	0.066	-0.232	0.064
$155^oE - 165^oE$	0.067	0.065	-0.145	0.063
$165^oE - 175^oE$	-0.351	0.092	0.328	0.094
$175^oE - 175^oE$	-0.671	0.121	0.667	0.122
SST -5	0.138	0.010	-0.070	0.011
Purse Seine Catch				
Lag				
-3	-0.008	0.003	0.013	0.012
0	-0.007	0.003	0.006	0.003

Table 4.9 The parameter estimates and their associated standard errors for the time series models are shown. The binomial values have the opposite sign to the Poisson estimates because they are estimating the probability a hook does not catch a fish.

The residuals from the final model were analysed to ensure there was no correlation with any effects, and that only white noise remained. The autocorrelation at lag 2 was high and just significant (ACF lag 2 = 0.08, significant if > 0.06). However an AR(2) model did not improve the fit, the second term being insignificant. Although the model appeared to be adequate, this suggests some improvements could be made.

4.8.3 Conclusion

The model is not perfect and some improvements may be possible. Changes just to the model are unlikely to change the final result, although the parameter estimates might be improved. A more fruitful approach would be to make changes to the data set and develop other methods, particularly those based on length, to examine this and other problems in the fishery. These improvements are discussed in chapter six.

The estimated effect of purse seine on longline appears to be small, assuming the observed changes are due to purse seine. The impact on longline catches also appears to occur almost immediately. However removal of younger yellowfin in the more distant past will be difficult to detect as anything other than a trend since accumulated random noise will obliterate the effects of short term changes in purse seine effort. It is, of course, likely that the high purse seine catches in 1984/5 have not yet had their full impact within this data set.

So the results presented here are what might be expected if purse seining was having an effect on longline, and it would be surprising if the decline in longline catch rates was more pronounced at this stage. Therefore, although the result cannot be interpreted with complete certainty, it is the most definitive result that might be expected at this time. The test will come when purse seine levels off or ceases for a time. The prediction is that longline catch rates should react accordingly, steadying or increasing after some delay. Without a longer time series, such a test cannot be carried out.

If purse seine does affect longline, it is necessary to discover what, if any, action should be taken to improve the economic efficiency of the fishery. Chapter 5 presents models of the theoretical bioeconomics of two gears fishing the same stock but at different ages. Once the effect of purse seine on longline has been quantified, this theory should help shed light on the options available to management.

4.9 Summary

The different effects on longline catch rates are explored, with the ultimate aim of seeing how much of the variation in yellowfin longline catch rates is attributable to the activities of purse seine. Correlations with previous catches within a trip are shown to be small for all species except albacore. Bigeye and yellowfin catch per set are strongly correlated, the other correlations between species are small.

Various generalised linear models were fitted, looking for important variables. Sea surface temperature, where it was recorded, showed a weak relationship with the average size of the fish in the catch. An index of hook depth per set failed to explain any significant variation in the longline catch rate. The only important variables that were found, such as vessel size and bait used, indicated the species being targeted. Larger vessels were identified fishing for albacore south-west of the main fishing ground.

A time series model was fitted to longline catches, removing significant effects. Latitude and longitude as factors removed both average regional variations as well as species targeting effects. A separate oceanographic time series data set was used to remove what appeared to be a change in the catch rate owing to El Nino. Finally purse seine catches were shown to still have a significant negative correlation with longline catch rates. However this result is far from definitive and does not prove causation, since much of the correlation was due to trends in the different time series.

Chapter 5

Optimal Harvesting With Age Structure

In previous chapters the analysis has concentrated on looking at the spatial distribution of fish. For this bioeconomic analysis the spatial distribution of fish is not included explicitly, but forms part of the cost function, which relates the cost of catching a fish to the stock size. For demonstration purposes and to allow the results from this study to be compared with other works, a linear cost function is used in most cases. Where possible, the effect of using other cost functions is discussed.

5.0 Introduction

In previous chapters the aim was to assess how catches of purse seine might affect the catch rate of longline and how this might be detected. This chapter adopts a different approach. Given it is known how one gear affects the other, what levels of effort should be allowed to either gear and what other management action is required to obtain as high as possible economic rent from the fishery? This problem is extremely complex since there are so many factors needed to be taken into account. Although no model will be able to describe the full situation, a harvesting theory can be developed which can be used to discuss the best strategy to adopt.

No economic data of sufficient detail was found to allow an analysis which aimed to solve the practical problem. However no other works have dealt with the theoretical aspects, the nearest similar study being Charles and Reed (1985), which looks at the interaction between inshore and offshore fisheries (see chapter one). These authors analyse a fishery with separate homogeneous fish stocks connected through migration. Their model largely avoids the issues of gear selectivity, which forms a critical part of the interaction between purse seine and longline. Therefore a different theory is developed for optimising the harvesting of an age structured population with gears which have fixed age selectivity. This is necessary to ensure that sufficient data is collected and that the subsequent analysis includes those aspects that are the key to managing a fishery with interacting gears.

The economic and biological variables of interest are the discount and mortality rates, and the recruitment, price and cost functions. Together these will define the harvest rate which will maximise whatever criteria management sees as most important. Although gears fish the same stock, the ages available to each gear will depend upon its selectivity. The models are initially developed for the case when gears can perfectly select each age, although the costs for catching a fish of a particular age may vary. This situation might occur in a fish farm. More complex models are then developed describing the situation where selectivity is fixed, which is closer to reality. In this case fishing mortality on particular age groups can only be adjusted by varying effort applied by different gears. This is essentially the situation for longline and purse seine operating on the same yellowfin tuna stock.

There are a number of distinct possibilities for allocating licences. Exclusive access might be given to either purse seine or longline, dependent upon which is more efficient at exploiting the stock. The other alternative is to maintain both in the fishery. If purse seine affects longline, some management decision on rights of access will have to be taken controlling the number of purse seiners in the fishery. Using models, the economic rent from different combinations of effort for each gear can be explored.

Before proceeding to develop models of the fishery, it will be necessary to see how the theoretical models might relate to the real fishery, which will require some information about the economics of purse seine and longline. This is the subject of the next section, which briefly describes the important economic attributes of these gears, highlighting the differences between them.

5.1 Economic Differences Between Gears

The two gears interact through fishing the same yellowfin stock at different ages, but there are many other factors involved in the economics of these gears. These fall into two parts, the costs of operation and the markets to which the the fish are sold. These two aspects are discussed for both purse seine and longline.

Purse seine is relatively capital intensive, with the price of a US 1100 GRT seiner varying from a relatively high US$11 million in 1980 to US$6.5 million in 1987 (Waugh, 1987a). The smaller vessels operated by the Japanese and Taiwanese have a lower price, although they will remain relatively expensive to a longliner. Purse seining is an efficient method for catching schooling fish species. The crew and fuel costs form about a third each of the total operating expense, the approximate total yearly operating cost of a large US purse seiner for 1983 being US$1.8 million (USITC, 1984).

Catch rates are highly variable, although total catches and therefore expected income over the period of a year will be relatively stable. Average catch rates have not so far shown a long term change in the western Pacific, which would be expected as the stock size falls due to exploitation. This may be due to expansion of the fishery to new grounds (see chapter two). Apart form attributes of the vessels themselves, the other major factor large enough to have long-term effects on the catch rate is climate. In the 1982/3 El Nino reduced catch rates in the eastern Pacific, causing vessels to go and fish in the western and central Pacific. Therefore fishermen seem able to offset climatic effects by moving to different regions, so decreasing their economic importance.

The most important controlling factor on this gear has been the market. Over-capitalisation in response to high prices being paid for tuna resulted in increased costs while demand did not rise significantly. Many US canneries and vessels went bankrupt, and there has been a subsequent readjustment in the industry to the present more stable situation. As this adjustment continues, the available economic rent should increase (Waugh, 1987).

The market for canned tuna is generally expanding in many parts of the world, although it is still dominated by the United States (Waugh, 1987c). This market is less quality conscious than the sashimi market, prices varying mostly due to the species (lightmeat - skipjack or yellowfin, or whitemeat - albacore) and the method of packing (flakes, chunks, or solid in brine or oil), solid packed albacore in oil fetching the highest price, skipjack flakes in brine the lowest. On the whole in the US market, most control is centred in a hand full of canneries which own many of the fishing vessels. This allows a much greater control of fishing effort by the market, so that effort may fluctuate with demand.

Longline shows a similar cost structure to purse seine, with fuel and crew costs making up approximately a third each of the total operating cost (Philipson, 1985). Bait forms the next most significant portion of the cost (12%). However the total operating cost for a year is much lower, being approximately US$340000 in 1983, based upon the operation of the Tongan longliner, M.V. Lofa. Kitson and L'Hostis (1983) give the operation cost for a 278 GRT Japanese vessel in 1980 as

US$900000. The purchase cost of a vessel will also be much lower.

More important differences between the two vessel types occur in the catch rates and the markets. Longline catch rates are much lower, but the prices paid for the sashimi quality fish is much greater than that paid for the purse seine catch. By way of example the price paid for 1 kg of good quality sashimi yellowfin in Japan was around 800 Yen (approximately US$3.4) in 1980, as opposed to $1.00/kg for yellowfin from purse seiners (Kitson and L'Hostis, 1983).

Kitson and L'Hostis (1983) give a summary of the main characteristics of the Japanese sashimi tuna market, which is complex and very quality conscious. The main concern is the meat's fat content. In general, the cooler the water in which the fish is caught, the higher the fat content and the higher the price paid. Hence bluefin tuna (Thunnus thynnus) from temperate latitudes fetched a price around 1776 Yen/kg in 1980. Bigeye is the next most highly priced, with yellowfin fetching the lowest price of these larger species. Fish are not priced linearly to their size; larger fish attract higher prices as shown in table 5.1.

	Size Class	Price Yen/kg
Bigeye	> 40 kg	1500
	25-40 kg	1000
	15-25 kg	800
	< 15 kg	600
Yellowfin	> 25 kg	1000
	15-25 kg	700
	< 15 kg	600

Table 5.1 The values represent the differential prices paid for the size of fish for bigeye and yellowfin.

The fishing area and time of year when a fish is caught will also affect its quality. For instance spawning fish will generally be in poor shape and have a low fat content. Solomon Islands tuna is regarded as best from July to October, outside this time becoming too thin and flabby.

The market requires careful handling of the product.

Ultimately this will depend upon a degree of trust between the fishermen and market buyers, which will be lacking for vessels entering the fishery for the first time. Irregularities in handling can be detected on inspection of the fish and vessel, in particular the quality of its freezer. For trusted fishermen, prices may be negotiated at sea. This quality consciousness makes the market vulnerable to over-supply of the less desirable fish, pushing the price down to a level making fishing in more tropical waters unattractive.

As longline and purse seine share a similar cost structure, fluctuations in costs, for instance in oil prices, are likely to affect both gears approximately equally, since these costs form the same proportion of the total costs for each gear type. Changes in the market prices and catch rates of the gears will have a more important role in deciding which vessels should have access to the resource.

Purse seine and longline supply completely unrelated markets, so that a drop in prices in one market may make another gear more attractive. However each gear is unable to affect the prices offered for the catch of the other, so that these markets can be analysed in isolation. The markets are complicated and fall beyond the subject of this work, although an analysis of their behaviour might be necessary to ensure a correct decision as to the allocation of stock.

If purse seine did not affect longline catch rates, licences could be sold completely independently to both gears. However evidence in chapter four indicated that this was not the case, so that some account should be taken of the relationship between them. The aim in the remaining sections is to develop a theory to fully understand how the gears affect each other economically, what factors are important in that relationship and what questions need to be asked about the characteristics of the gears to make decisions about their future involvement in the fishery. The analysis presented here will not lead to a definitive statement as to how each gear should be managed, since this would require economic information which is unavailable. However a theory needs to be developed to make such a statement and, more importantly, to provide for flexibility in management as prices and costs change. Subsequent sections begin building bioeconomic models ultimately looking at the maximum economic rent that might be attained from different combinations of gears and under different conditions.

5.2 Model of Perfect Selectivity

The models presented here are based upon optimal control theory (eg, see Burghes and Graham, 1986). The models describe harvesting regimes (controls) that maximise the net present value of the fishery. Obviously this is not the only criterium a manager might wish to optimise, but it will always be an important consideration, particularly in the present case where the benefits from the fishery consist mostly of fees from foreign vessels.

The general problem is posed in the form of simple models of the stock, fishing mortality, costs and prices. This allows the relationship between the gears to be well defined, so that these different factors can be analysed to see how they might affect management decisions. This aspect of the results is more interesting than the optimal controls themselves, which may not be practical since many constraints on real harvesting are too complex to include in theoretical models.

All the models explore the relationship between the age-price function and the different forms of age selectivity of the gear. Together with the different harvesting costs, these functions capture the major economic difference between purse seine and longline. The aim is to see whether optimal management requires both gears to survive, or in general chooses only the most efficient, denying the other access.

A comparison can be made between the usual situation where there are limits on what might be done to control selectivity and the perfect situation where harvesting can be directed exactly at desired age groups. This will give an indication of the behaviour of the system when constraints on age selectivity apply, as well as suggest how selectivity may be improved. To begin with only one type of fishing gear will be considered.

5.2.1 Single Gear Type

All the models may be written as the following linear equation. The function to be maximised is of the general form:

$$J = \int_0^{\infty}\int_0^{\infty} \mathrm{Exp}(-\, b\ t)\ [P - C]\ H\ da\ dt \tag{5.1}$$

where
t = time
a = age of fish
b = discount rate
P = price function for an individual fish
C = cost function for an individual fish
H = harvest rate function

The function to be optimised is governed by a state equation describing the stock dynamics. The equation without harvesting is described by Nisbet and Gurney (1982). With the addition of a harvesting term it can be shown that :

$$H = -\,N'_t - N'_a - m\,N \tag{5.2}$$

where
F'_x = partial differential of function F with respect to x
$m(t,a)$ = death rate
N = number of fish at each age and time

The solution to this equation can be found by integrating with respect to a new variable, unique for each cohort, a cohort being all fish the same age.

$$N = R(t-a)\ \mathrm{Exp}\ \left(\int_{t-a}^{t} m(x) + h(x)\ dx \right) \tag{5.3}$$

The size of each cohort at any time t will depend upon the history of the death rate over its life span. The renewal criterion, R(t-a), is the number of recruits to the fishery at time t-a. This is subsequently assumed to be constant although it is fairly easy to generalise some results to recruitment varying in time.

There are two extensions to this state equation which will greatly affect the model. If recruitment depends upon the population size, as would seem reasonable, equation 5.3 is inadequate, since there will be delayed repercussions for any harvesting strategy as recruitment will fall. Secondly if mortality is density dependent, the drop in natural mortality due to harvesting would allow an increasing proportion of the stock to be taken. Inclusion of this would require a new solution to equation 5.2. Both these additions greatly increase the complexity of the model, and therefore they are not dealt with directly.

A general method for finding extrema is described by Clark (1976), which can be applied if the control can be replaced by the state equation. Extrema are found by applying the Euler condition, which here had to be adapted to more than one dependent variable (see Craggs, 1973). This derives a singular criterium to be fulfilled by the state equation, which can be achieved since the state equation is subject to the control. The criteria for an extremum, the Euler equation, is given by:

$$\frac{\partial F}{\partial y} - \sum_{K=1}^{2} \frac{d}{dx_k} \left(\frac{\partial F}{(\partial y/\partial x_k)} \right) = 0 \qquad 5.4)$$

where

$x_1 = t$

$x_2 = a$

y = state equation for the stock size = N

Clark (1976) showed that the optimal strategy is to approach this singular path as quickly as possible from the initial state and follow it.

From equation 5.4, to maximise (or minimise) the net present value, the following equation must be satisfied:

$$\begin{aligned} &- m\,(P-C) + C'_N\,(N'_t + N'_a + m\,N) \\ &- b\,(P-C) + P'_t - C'_t + P'_a - C'_a = 0 \end{aligned} \qquad 5.5)$$

If C is a function only of N :

$$C'_t = C'_N\, N'_t \qquad C'_a = C'_N\, N'_a \qquad 5.6)$$

Substituting 5.6 into 5.5 :

$$P'_t + P'_a - (b + m)\,(P - C) + m\,N\,C'_N = 0 \qquad 5.7)$$

This equation is essentially a marginal condition. Fish are harvested to the point at which their marginal price equals their marginal cost. The term, $m\ N\ C'_N$, represents the marginal increase in costs due to the population size decreasing with age. To see how this general solution behaves, further assumptions must be made about the price and cost functions. Reasonable, but tractable price and cost functions have been chosen to demonstrate this criterium. The price curve can be described by a von Bertalanffy growth curve.

$$P = P_\infty (1 - \mathrm{Exp}(-g\ a)) \tag{5.8}$$

The price function is used for illustration purposes only. This captures the main effect of the decelerating price, as the growth of a fish decelerates. However it must be born in mind that prices often go up disproportionately with size, so that the price of a fish may increase more rapidly in later stages.

For the cost curve, in the simplest realistic case,

$H = q\ N\ E$
q = catchability coefficient
E = effort

we find

$C = K / q\ N$

where

K = constant cost rate

and equation 5.7 becomes

$$P'_t + P'_a - (b + m)\ P + b\ C = 0 \tag{5.9}$$

Clark (1976) obtained equation 5.9 in one dimension (age) for harvesting a single cohort, and the results are largely the same for a continuous recruited population at equilibrium. Since all cohorts must be subject to the same fishing mortality through their life, equation 5.9 defines both the optimal age structure of the population at equilibrium and the optimal cohort size over time. The optimal biovalue at each age can be derived by rewriting equation 5.9 in terms of N.

$$P\ N = \frac{K\ P}{q\ (P'_a + P'_t - (b + m)\ P)} \tag{5.10}$$

where

$P\,N$ = biovalue of the resource

Figure 5.1a shows the singular paths defined by equation 5.10 for three different discount rates. The singular path for each discount rate is marked as a different coloured continuous line. For any singular path there are two critical points. Firstly equation 5.10 has an infinite slope, where marginal gain in value of a fish is zero ($P'_a + P'_t - (b+m)P = 0$), marked in the figure as vertical coloured dashed lines. Past this point fishing will begin when the singular path defined by equation 5.10 crosses the unexploited biovalue curve. The second critical point is where the price of a fish equals the cost of fishing it, marked in figure 5.1a by the horizontal blue line. The biovalue (black bold line) is driven along the optimal path until this point. For this model, this will always be when $P'_a + P'_t - m\,P = 0$. Although singular paths defined by equation 5.9 continue outside these bounds, the optimal harvesting strategy will only drive the biovalue along the path within them.

When the discount rate is zero (red), the cost term in 5.9 is lost, so that the stock is harvested as soon as the gain in price equals the loss to natural mortality, resulting in an impulse control at that age. Hence the singular path is defined by the first critical point, so that the harvest age is at the point when the marginal gain in price of the fish equals the loss due to natural mortality. The fishing effort applied will be subject to the second constraint, and therefore when costs are not zero, effort will be finite.

When the discount rate is greater than zero (green), the discounted cost is offset by fishing before the point when the the resource reaches its maximum value. Fishing proceeds to force the stock along the singular path, until the price equals the cost, when fishing ceases and the cohort leaves this singular path.

If the discount rate is infinite, as might be the case in an open access fishery, the only part of equation 5.9 that is significant is $(P-C)=0$, so the optimal solution is to drive the stock along the cost=price line (blue) where the revenue equals the cost of fishing. Therefore the stock is not allowed to gain any value above the cost and the economic rent is dissipated.

Optimal exploitation with age structure
under different discount rates

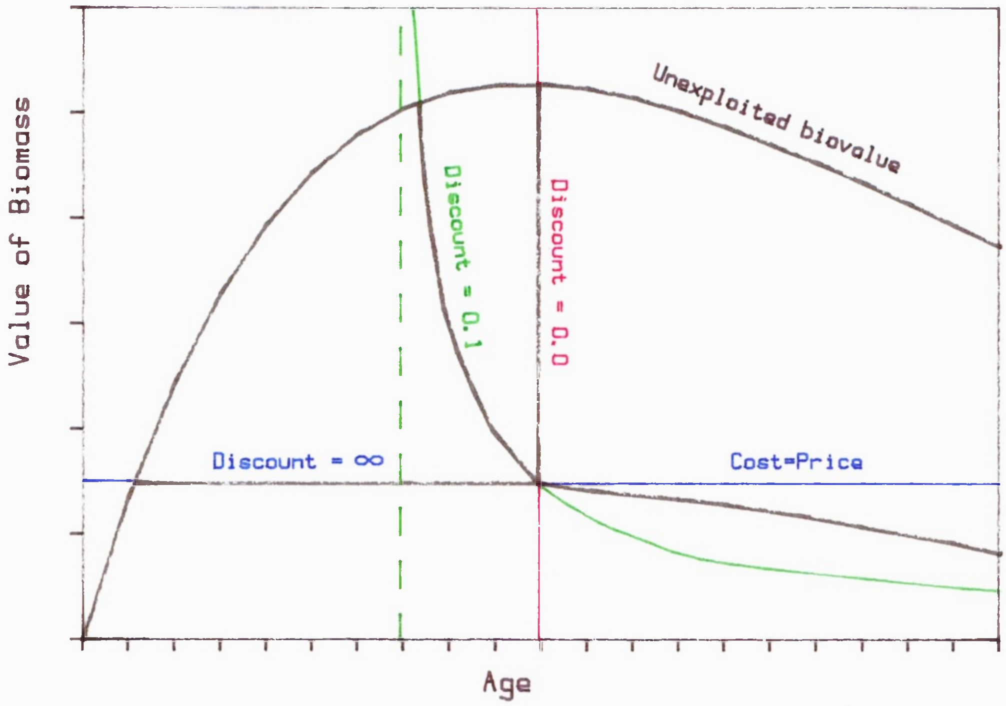


Figure 5.1a Costs proportional to N^{-1}

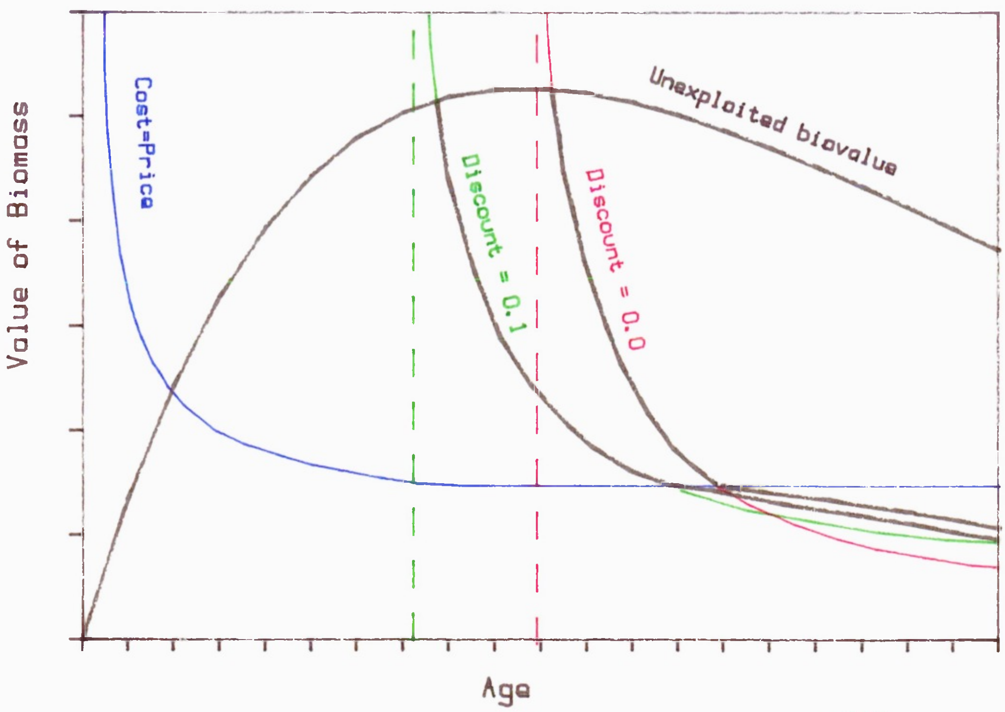


Figure 5.1b Costs proportional to $N^{-1/2}$

The control variable, effort (E), can be derived for each age from equation 5.10. Differentiating equation 5.10 with respect to a and t, the effort applied to the stock to obtain the mortality, $f = q\,E$, at each age should be :

$$E_{opt} = \frac{P''_{aa} + 2\,P''_{at} - (b + m)\,(P'_a + P'_t)}{q\,(\,P'_a + P'_t - (b + m)\,P\,)} - \frac{m}{q} \qquad 5.11)$$

Equations 5.10 and 5.11 can also be obtained from Clark (1976). However the more general result in the form of equation 5.7 developed here can be used to explore other behaviours where the relationship between the catch and effort is non-linear.

Equation 5.9 in fact describes the special case where increasing cost due to a smaller stock size equals the decreasing cost due to a smaller catch, hence the stock death rate has no effect on the marginal cost. To demonstrate the importance of this relationship two alternative cost functions are presented. Firstly costs might fall at a slower rate with respect to the stock size, so that, for instance :

$$C = K \,/\, q\sqrt{N}$$

$$P'_t + P'_a - (b + m)\,P + (b + m/2)\,C = 0 \qquad 5.12)$$

The relationship between the stock density and cost is more elastic, so that costs for catching a fish do not change much with fish density. Because the costs for fishing older fish do not go up so rapidly as their density falls, better advantage may now be taken of their increasing value.

Again equation 5.12 is very simple to solve for N to obtain the singular control necessary for optimal exploitation. Figure 5.1b shows the total stock value under these controls subject to two discount rates. From equation 5.12 it can be seen that the death rate now has almost the same effect as the discount rate on the control. The death rate, with respect to the costs, encourages harvesting to be carried out later since costs are increasing at a less rapid rate than losses in value.

Unlike the previous model, with a zero discount rate (red) there is no impulse fishing of cohorts at a single age. Instead there is a continuous harvest over an age range with harvesting beginning when fish reach their maximum value. As soon as harvesting begins, the stock size is decreased, which results in a small increase in costs, and a much larger increase in value due to growth. A discount rate greater than zero (green) produces a similar singular path, except fishing begins at an earlier age. Both are subject to the same conditions as in the last model. Fishing starts after the first critical point (vertical dashed lines), when the marginal gain in value of a fish is zero, and ceases when the cost equals the revenue for fishing (blue cost=price line).

An infinite discount rate produces the same control as in the previous model, forcing the stock along the line where the cost of fishing equals the price of the catch. However since the costs are no longer linearly related to the stock size, this cost=price line (blue) is also non-linear. Hence fishing does not cease at the same age for all discount rates.

In the extreme case, where costs only depend on the number of fish caught independent of the stock size, equation 5.12 will tend towards :

$$P'_t + P'_a - (b + m)\ (P - K/q) \;=\; 0 \qquad 5.13)$$

Under these conditions natural mortality has an identical effect on the optimal harvest as the discount rate. Since equation 5.13 is independent of N, the singular path will be a vertical control for all discount rates at the age when equation 5.13 is true.

So it can be seen that natural mortality affects the value of harvests in two distinct ways, the first decreasing the value of future harvests in the same way as the discount rate. This is the only effect natural mortality has in equation 5.13. The second effect is through increasing fishing costs as the size of the stock falls. This last will occur where the density of fish falls as the stock size falls, since an increasing area will have to be searched to capture the same number of fish.

The alternative is to have costs increasing at a faster rate as the stock size falls, so that :

$$C = k \,/\, q\, N^2 \quad \text{equivalent to} \quad H = q\, N^2\, E$$

$$P'_t + P'_a - (b + m)\ P + (b - m)\ C \;=\; 0 \qquad 5.14)$$

In this case the cost elasticity in relation to the stock size is very low, so it would be expected that the optimal harvesting strategy will take more account of the change in density of fish with age. This should encourage fishing of younger fish.

Because costs are increasing more rapidly as the stock size falls, the natural mortality has the opposite effect to the discount rate, encouraging earlier fishing of the stock. Figure 5.1c shows three examples of singular controls. Now there is a further critical value. When the discount rate is greater than natural mortality (green), the singular control is similar to those in the previous model. A vertical control occurs when the natural mortality equals the discount rate (violet). At this point the effects on the cost of natural mortality and discounting cancel each other out. When the natural mortality is greater than the discount rate (red), the curve switches around, so that only very young fish are taken. During this period the numbers of fish are high so that the low costs encourage early fishing.

These results also recognise that whereas the discount rate only operates on the profit of the fishery, the natural mortality operates by decreasing the value of the resource while also increasing the costs for fishing it. When the mortality is greater than the discount rate, the increasing costs of fishing as the numbers of fish fall will swamp any other effect.

5.2.2 Conclusion

Clark (1976) explored the relationship between optimal harvesting and the discount rate using the Beverton and Holt (1957) age structured population model, in which the relationship between the catch and stock density is linear. It was found that earlier fishing was carried out to offset discounting costs. However this is shown here to be a special case of a more general model, where the relation between the stock density and the catch can be any of a range of functions.

If there is a large change in costs with changing stock size (inelastic cost function), there will be greater dependence upon natural mortality governing the ages over which fishing occurs. If there is a small change in costs with changing stock size,

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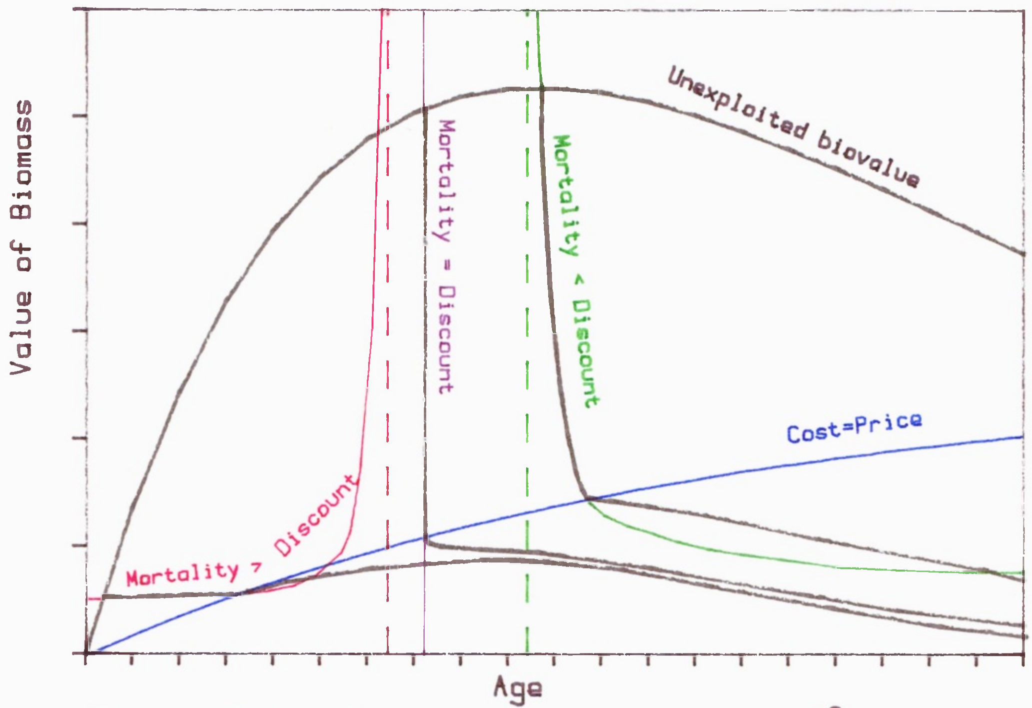

Figure 5.1c Costs proportional to N^{-2}

optimal harvesting will tend towards taking older fish, natural mortality becoming equivalent to the discount rate in the way it affects the behaviour of the system. Hence natural mortality can have two distinct effects on the value of the biomass and on costs of fishing, which suggests it is the most important single parameter.

5.2.3 Two Gear Model with Perfect Selectivity

In the case where two gears are operating with different price and/or cost curves the situation is more complex. However it is possible in principle to derive a rule for the allocation of fishing effort when selectivity is perfect.

What criteria should be used to decide upon which of two gear types should fish a stock? If the aim is to maximise profit, then the stock should simply be allocated to the gear which fishes it for the maximum profit. However for age structured populations the problem may not be so simple, since taking young fish with one gear will incur an opportunity cost in that another gear might otherwise have taken it in its later life.

The model described in the previous section can be extended to two gears, each with different price and cost functions. Again it is assumed here that effort can be directed at individual ages to derive a singular control. The function to be maximised is the net present value of the fishery :

$$J = \int_0^\infty\int_0^\infty \mathrm{Exp}(-b\ t) \quad (P_1 - C_1)\ H_1 + (P_2 - C_2)\ H_2 \quad da\ dt \qquad 5.15)$$

where

the subscripts 1, 2 refer to the gear type

The stock state equation is introduced with an adjoint variable, so the function giving the maximum can be written :

$$F = \mathrm{Exp}(-b\ t) \quad (P_1 - C_1)\ H_1 + (P_2 - C_2)\ H_2 \qquad 5.16)$$
$$+ \quad \lambda(N_t' + N_a' + mN + H_1 + H_2)$$

Applying the criteria for an extremum (equation 5.4) the following equations are obtained.

$$\lambda m \quad - \quad \lambda_t' \; - \; \lambda_a' \; = 0 \qquad 5.17)$$

$$\mathrm{Exp}(-b\ t)\ (P_1 - C_1) + \lambda = 0 \qquad 5.18)$$

$$\mathrm{Exp}(-b\ t)\ (P_2 - C_2) + \lambda = 0 \qquad 5.19)$$

These equations simply describe what could be surmised anyway. Equation 5.17 defines the maximum criteria already given in equation 5.5, which can be generated for either gear by substitution of equation 5.18 or 5.19 into 5.17. The adjoint equations 5.18 and 5.19 describe the point at which this switch is made from one gear to the other. This occurs when the profits from one gear would exceed the other. The switching curve is obtained by subtracting the adjoint equations :

$$\mathrm{Exp}(-b\ t)\ (P_1 - C_1) - (P_2 - C_2) \;= 0 \qquad 5.20)$$

There is no occasion when the optimum is to fish a particular age group with two gears. Either they are equivalent, or one is better suited at fishing a particular age group than the other. However a single cohort may be fished by more than one type of gear during its life and may switch more than once between gears. However with switching 5.17 may no longer provide the global optimal fishing strategy, since it is only looking at immediate price and cost changes. This is also true of a single gear fishery, but multi-modal age-profit curves are more likely to occur when more than one gear is fishing a stock.

To illustrate the solution of this problem, a single cohort with two gears is considered, one better suited to fishing younger fish than the other. This is similar to the purse seine - longline problem, but in principle can be extended to any number of gears. Essentially equations 5.17 - 5.19 provide a partial solution. While a gear is operating it will follow the path dictated by 5.17 and will be the only gear. Ultimately it will cease operating and be replaced by the second gear, possibly after a delay between them. Either gear will obviously not operate if it is uneconomic (ie $P < C$). The important point to note is that the two gears are connected through the population size at the point at which the first gear ceases fishing. The size of population at this point can be controlled by the age at which the first gear stops. Therefore the switching curve needs to be modified to include future losses. For a single cohort, the new equation to be maximised is given by:

$$J = \int_0^s \mathrm{Exp}(-b\ a)\ (P_1 - C_1)\ H_{1opt}\ da + \int_s^\infty \mathrm{Exp}(-b\ a)\ (P_2 - C_2)\ H_{2opt}\ da \qquad 5.21)$$

where

H_{opt} = the optimal harvesting strategy given by equation 5.17.

To find the switching point (s) maximising the net present value of the whole fishery, equation 5.21 can be differentiated with respect to s and set to zero.

$$\mathrm{Exp}(-b\ s) \left\{ (P_1 - C_1)\ H_{1opt} - (P_2 - C_2)\ H_{2opt} \right\} - \int_s^\infty \mathrm{Exp}(-b\ a)\ \left\{ (P_2 - C_2)\ H_{2opt} \right\}'_s\ da = 0 \qquad 5.22)$$

where

s = age at which one gear replaces the other

If $H_{opt} = q\ E_{opt}$

$$\left\{ (P_2 - C_2)\ H_{2opt} \right\}'_s = -(\ m(s) + q_1\ E_{1opt}(s)\ )\ P_2\ H_{2opt}$$

The first, non-integral part of equation 5.22 is equation 5.20 with the optimal harvesting strategy included explicitly. The integral in equation 5.22 is the marginal cost on the second gear with increasing fishing in the first, and is the explicit form of the opportunity cost of the first gear. The effect of this will be simply to force the first gear to stop earlier, if its fishing has any effect on the second gear. There is an exception to the above. If the optimum harvest for the first gear is an impulse at some point in the age range it dominates, the fishing effort applied at this point will have to be lower, rather than than changing the age when fishing occurs.

This general result can also be seen from figures 5.1 a-c. The opportunity cost of fishing will raise the line at which the cost of a fish equals the price. With non-impulse fishing this causes the age at final capture to decrease and with impulse fishing the effort applied will be less.

5.2.4 Conclusion

The problem of allocating an age structured stock to two gears can be broken down into simple parts. Firstly there will be a range over which a particular gear will be more efficient. It should be the only gear allowed to operate over that range, the harvest rate being defined by the price and cost functions in the same way as for section 5.2. If another gear is operating at some point in the future, the opportunity cost on the future gear must be taken into account. Although this will not change the behaviour of the first gear while it is fishing, it will encourage fishing by the first gear to stop at an earlier age to increase escapement.

5.3 Model Of Fixed Selectivity

In the above models it has been assumed that the catchability of the different age groups has been constant for a given gear. This will be untrue for many gears, which will tend to be better adapted to taking fish of particular ages, due to physical characteristics or fish behaviour. This selectivity of the gear might be described as a function of age, defined as

$$\int_0^{\infty} S(a)\, da = q \qquad 5.23)$$

Writing the selectivity into equation 5.1 as part of the cost, the maximum criterium, equation 5.7, becomes :

$$P_t' + P_a' - (m+b)\ (P-C) + C_N' \, m\, N - C_S'\, S_a' = 0 \qquad 5.24)$$

Essentially selectivity here just distorts the cost function. The marginal selectivity function will encourage waiting for the costs to decrease before fishing. Again this function will be inadequate if selectivity has more than one mode, since the criterium will be true for all local maxima. As selectivity only changes the cost structure, its analysis and results will be similar to that of the previous models. A more realistic model is produced if effort is fixed over all age groups, so the control decides upon the number of fish caught, but catches consist of fixed proportions of the population size at each age.

This means that effort cannot be directed at the most profitable age groups.

Finding the dynamic optimum control when selectivity is fixed is difficult, since any fishing will immediately change the age structure. However, from what is known about linear optimal control systems, the control usually takes the form of a pulse or bang-bang control (Williams, 1989). It can therefore be expected to take a similar form here. No general explicit analytical solution has been found to these problems.

Before proceeding some thought must be given to how costs are paid in relation to age. Usually costs are not paid according to the age of the fish, only over time, so that the costs do not go up simply in relation to the width of the selectivity. A cost function is required that when integrated over age, sums to some non-infinite function of time. Hence the control can no longer be the number of fish being harvested at each age, since the cost of harvesting a unit of fish from each age will be infinite for selectivity functions without an upper limit. Therefore the control may be defined as the number of fish harvested, with their age distribution fixed by the selectivity function.

$$J = \int_0^\infty\int_0^\infty \mathrm{Exp}(-b\ t)\ (P - C)\ S(a)\ H(t)\ \ da\ \ dt \qquad 5.25)$$

The solution to 5.25 has essentially already been obtained. It is now necessary to see how the solution to the perfect selection problem relates to the one with fixed selection.

When the harvesting rate applied to all ages is the same, the optimal control will be given by the definite integral of 5.24 over all ages.

$$\int_0^\infty S\ (\ P'_t + P'_a - (m+b)\ (P-C) - C'_t - C'_a\ )\ \ da = 0 \qquad 5.26)$$

Equation 5.26 represents the sum of marginal losses over age, being satisfied when the loss due to the death rate balances the future gain due to price increase. If this is adjustable through the control variable, a maximum will be attained when these two factors cancel. Hence 5.26 gives the marginal change in value of the population. The entire population can be treated in much the same way as an individual cohort, with the population growing in value through time and some optimal harvesting policy forcing it back to a minimum level. The behaviour of 5.26 and whether an analytical or any other solution is possible will depend upon the choice of the selectivity, S.

Equation 5.26 becomes clearer when simplified to the standard catch-effort model, so that the marginal value of effort can be written :

$$\int_0^\infty S \; N \; (\; P_t' + P_a' - (m+b) \; P \;) \; da \;\; + \;\; bK = 0 \qquad 5.27)$$

where

K = costs per unit effort

The costs are not related to selectivity, so effectively they are not included in the integral. The stock is fished through the selectivity function, which distorts the interaction between effort and the stock.

Although this condition may seem simple, it is insoluble without knowledge of the form of control function. The general result can be inferred from the analysis of the system with single cohorts. Figure 5.2 shows diagrammatically the harvesting strategy when the discount rate is zero or costs are independent of the stock size. The value of the stock rises without fishing to some stable age structure. When costs or the discount rate is zero the optimum control is impulse fishing, pushing the stock to the point where the cost equals the value of fishing. Otherwise equation 5.27 suggests a control where the discount cost is offset by some early fishing, similar to the behaviour shown in figure 5.1a. This principle is likely to hold for most situations, where a population has an initial growth phase. For instance, where density dependent mortality operates across age classes (eg cannibalism), the value of the stock may peak and decrease again before stabilising. However harvesting should still take place when the discounted value of the population peaks.

Having obtained at least a qualitative solution to the general problem, some concessions must be made to look at the behaviour of the optimal harvest rate with changing parameters. This can be done by looking at the behaviour of a strategy close to the optimum, and interpreting results in the relation to the general system.

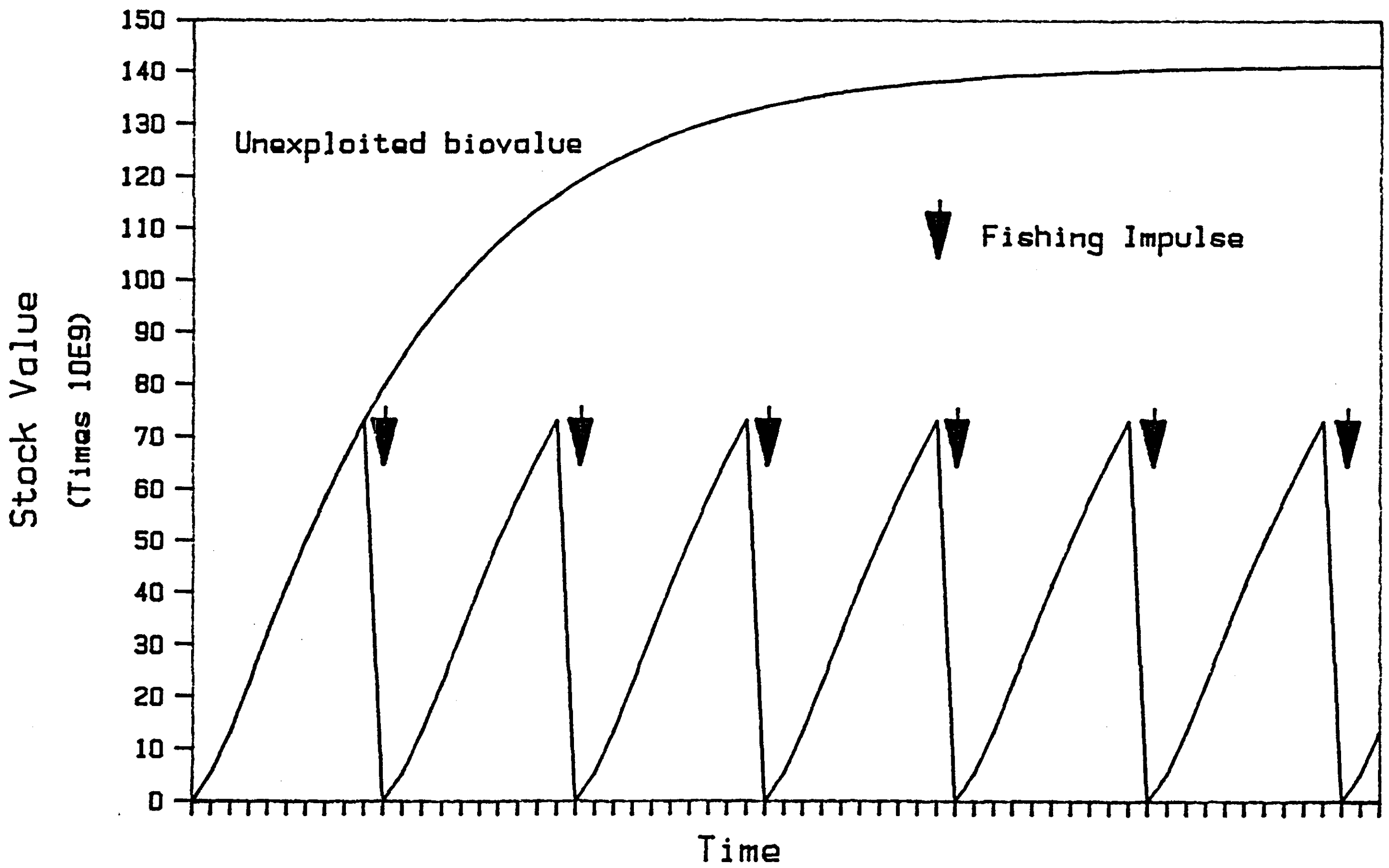

Figure 5.2 Optimal harvesting strategy:
impulse harvest

5.3.1 Fixed Selectivity with a Single Gear and Impulse Controls

To take the analysis further, reasonable representative functions must be provided for equation 5.27. Because of the complexity of the control, simplicity is a major consideration in choosing the selectivity function. At the same time several characteristics common to all systems need to be explored, to see how they might affect the optimal fishing effort. These characteristics can be summarised by two statistics, the central tendency and dispersion of the selectivity distribution. This suggests that the Gaussian or gamma distributions might be a good choices as selectivity functions, however they are complex in that they require numerical integration to obtain the numbers of fish at each age. A alternative is a blocked interval, (uniform distribution) which can change both in width (dispersion) and position (central tendency). Although such functions are a little messy at the (discontinuous) edges, they are simple enough to obtain numerical solutions easily.

Selectivity is chosen such that :

$$S = u \qquad a_1 < a < a_2$$
$$S = 0 \qquad \text{elsewhere}$$

The price function is given by equation 5.8, the population age structure by equation 5.3, where for simplicity, recruitment and natural mortality are constant over age and time. Equation 5.27 can now be written :

$$\int_0^\infty u \; R \; \mathrm{Exp}(m\ a + \int_{t-a}^{t} E \; dx) * P\ (m+b - (m+b+g)\ \mathrm{Exp}(-g\ a)\ )\ da + b\,\mathbf{K} = 0 \qquad 5.28)$$

where

E = fishing mortality applied over the life span of the cohort

There is no simple solution to 5.28 since E is an arbitrary function of time. However for most reasonable parameters, the solution is likely to be close to an impulse control. Constant effort will only be applied with an infinite discount rate, at which point the economic rent will be dissipated. The adequacy of the impulse fishing was checked looking at alternative controls, where effort was applied over a small interval around the impulse control. Unless the discount rate was high, little improvement could be made on the impulse control, suggesting it was close to the optimum.

With pulse fishing all the effort will be applied in a single instant, with the fishery being left to regenerate in between. The regeneration time and amount of effort applied can be obtained by representing fishing as a unit impulse (Dirac delta) function. A fishing pulse will drive the stock to some level beyond which it is too costly to fish, that is :

$$\int_0^{\infty} \mathrm{Exp}(-uE \int_0^{t} D(T-x)\, dx)\ S\ N\ P\ da\ - b\,\mathbf{K} = 0 \qquad 5.29)$$

where

D = unit impulse function
S = selectivity function
N = numbers at age and time
P = price function

Equation 5.29 should be true at time T when the pulse is applied. By definition the Dirac delta function produces a unit pulse at T, elsewhere it is zero, so that the effort needed at time T is found to be :

$$E = \frac{-1}{u}\ \mathrm{Ln}\left(\frac{K}{\int_0^{T} S\ N\ P\ da}\right) \qquad 5.30)$$

The optimum time between pulses can be obtained from the Faustmann formula (Faustmann, 1849) :

$$\frac{V'(T)}{V(T) - C(T)} = \frac{b}{1 - \mathrm{Exp}(-b\ T)} \qquad 5.31)$$

where

$V(T) = \int_0^{T} S\ N\ P\ da\ - K$
$C(T) = K\ E$

The site value, S N P , is calculated in the absence of fishing. Previous pulse fishing will still leave some stock, so that strictly speaking, when costs are greater than zero, the value of fishing (V(T)) should be obtained from summing over all age groups. In practice, it has been found that age groups which have already been fished, being also subject to natural mortality, are reduced to a negligible number. If such stock forms a significant proportion of the catch, earlier fishing will be encouraged.

Equation 5.31 requires a numerical solution since the costs of pulse fishing are variable and discontinuities occur at the boundaries (a_1, a_2). It is therefore just as easy in practice to find the maximum directly. The aim is to maximise the net present value with respect to T.

$$\text{Max} \quad \frac{V(T) - C(T)}{\text{Exp}(b\ T) - 1} \qquad 5.30)$$

This model recognises that there is a site value which will encourage earlier harvesting, therefore allowing for the value of future harvests. This will be an important element of any bang-bang control.

Basic Parameter Set for Optimal Harvest Model

	Purse Seine	Longline	
Days fishing /year	205	205	Waugh, 1987
Catch /day	5.4 tonnes	30 fish	
Cost /year US$ (C)	838100	423300	Waugh, 1987 Japan Yr Bk.,1979
Max price /fish (P_∞)	178	650	Kitson & L'Hostis,1983
Growth rate (k)	0.4	0.1	
Selectivity (a_1-a_2)	0.7-3.0	2.0-7.0	Wild, 1986
Catchability (q)	1.0	0.1	
Recruitment (R)	10^7		
Natural Mortality (m)	0.1		
Discount Rate (b)	0.1		

Table 5.2 Parameter set used as default for looking at the optimal harvesting model. Where possible parameters have been taken from published estimates, adjusted for the single species fishery the model describes. Otherwise parameters have been used which give reasonable results.

The model can be made to represent both longline and purse seine by defining different cost and price structures. It must be emphasised that these models do not aim to accurately represent the different gears. In reality pricing and costs are extremely complicated and attempting to reproduce detailed effects is of little value, particularly in the present context. The model for both gears is the same with parameters varying according to table 5.2.

Figures 5.3 and 5.4 show how the time between impulses and the net present value of the fishery are affected by the discount rate, natural mortality and growth rate in value of the fish. Figure 5.3 describes the behaviour of the model with purse seine parameters, figure 5.4 with longline parameters. The rotation time (time between impulses), shown in figures 5.3a and 5.4a, is of particular interest since it indicates the overall fishing pressure on the population and can be interpreted for a fishery under steady control as related to changes in effort. Parameters are explored over unrealistic ranges to study their effects and how they determine the system.

The discontinuities in the system are due to the selectivity function. For instance, where the optimal rotation time extends beyond the selected age range, the optimum will be constrained to that age range. The other constraint that may come into operation is where costs exceed prices, giving a maximum net present value of zero.

In general the growth and discount rates have an asymptotic effect. As they get larger they tend to force both the rotation time (figures 5.3a and 5.4a) and the net present value (figures 5.3b and 5.4b) to some asymptote. In the case of the discount rate, as it approaches infinity, the rotation time and maximum net present value approach zero. This manifests itself as steady effort at a level stripping the resource of its economic rent. As the growth rate increases the price becomes effectively constant within the selective range. This encourages earlier fishing up to some limit greater than zero, since the rotation period is also being controlled by the discount rate and natural mortality. However, whereas the discount rate decreases the net present value of the fishery, the growth rate increases it as the maximum price for the fish is attained throughout the selective range of the gear.

Natural mortality has two effects. Firstly it behaves in a similar way to the discount rate, reducing the value of the population with respect to age. In this way it produces an

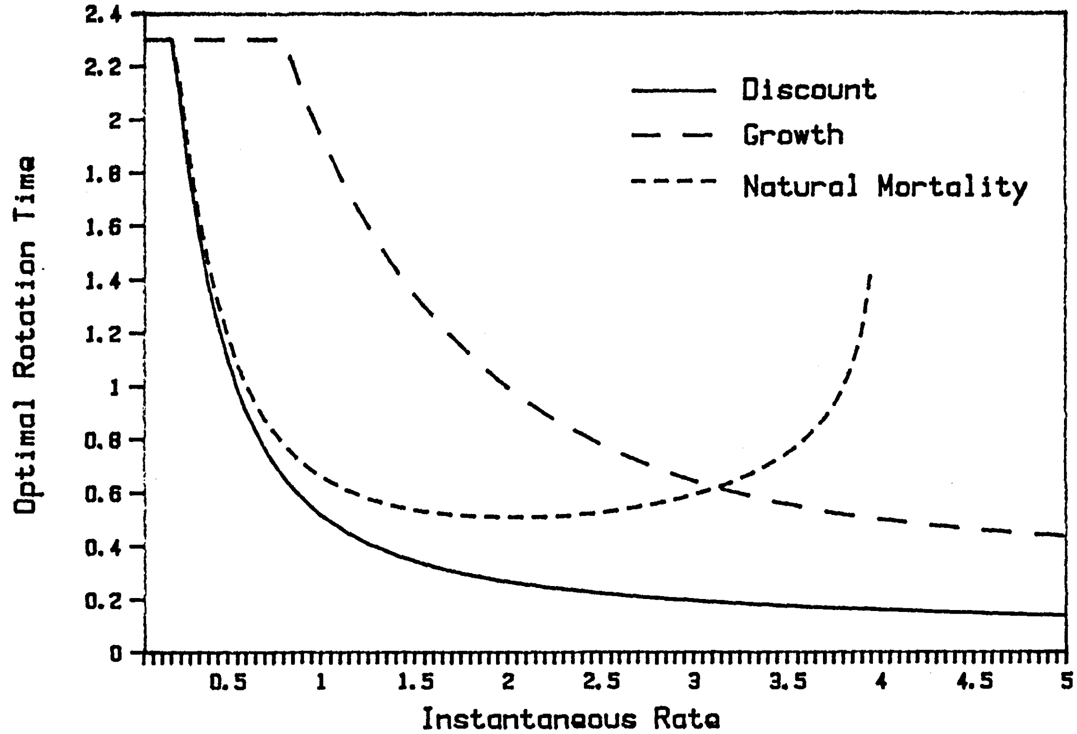

Figure 5.3 a Purse seine changing optimal rotation time with rate parameters.

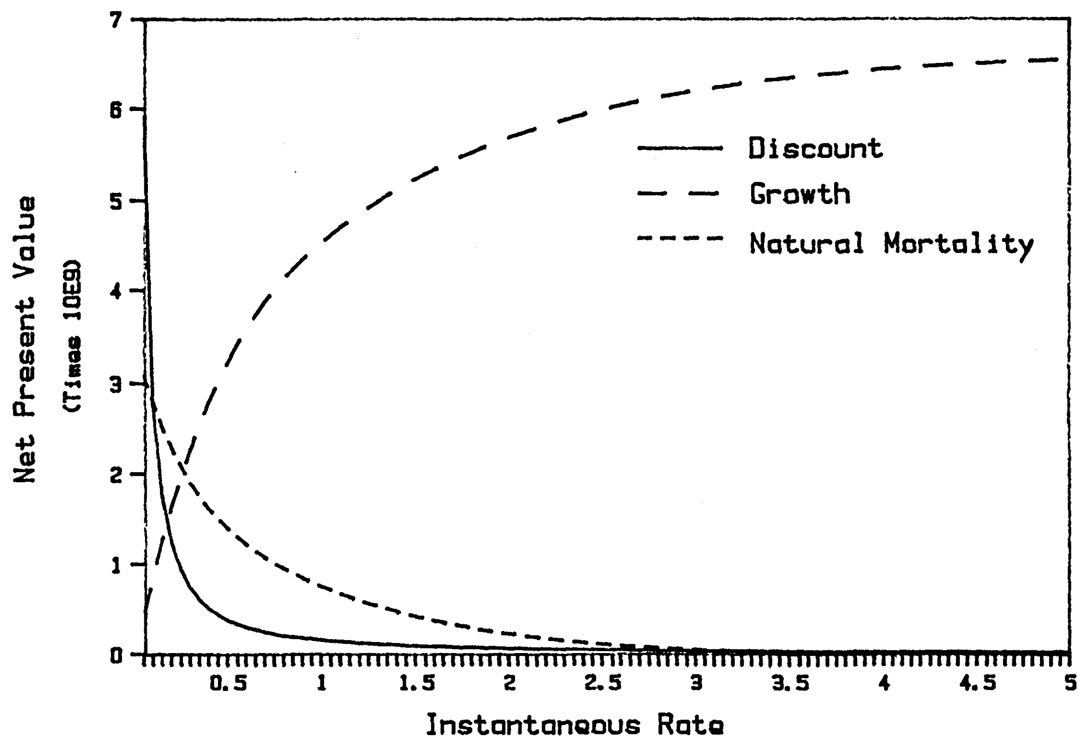

Figure 5.3 b Purse seine changing net present value with rate parameters.

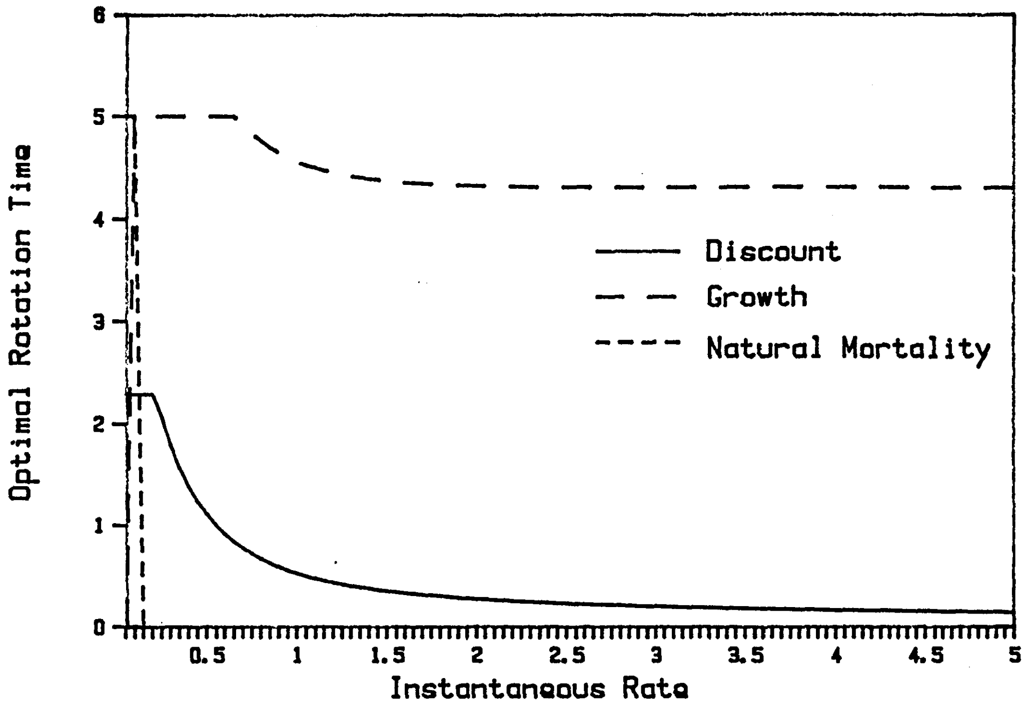

Figure 5. 4 a Longline changing optimal rotation time with parameter rates.

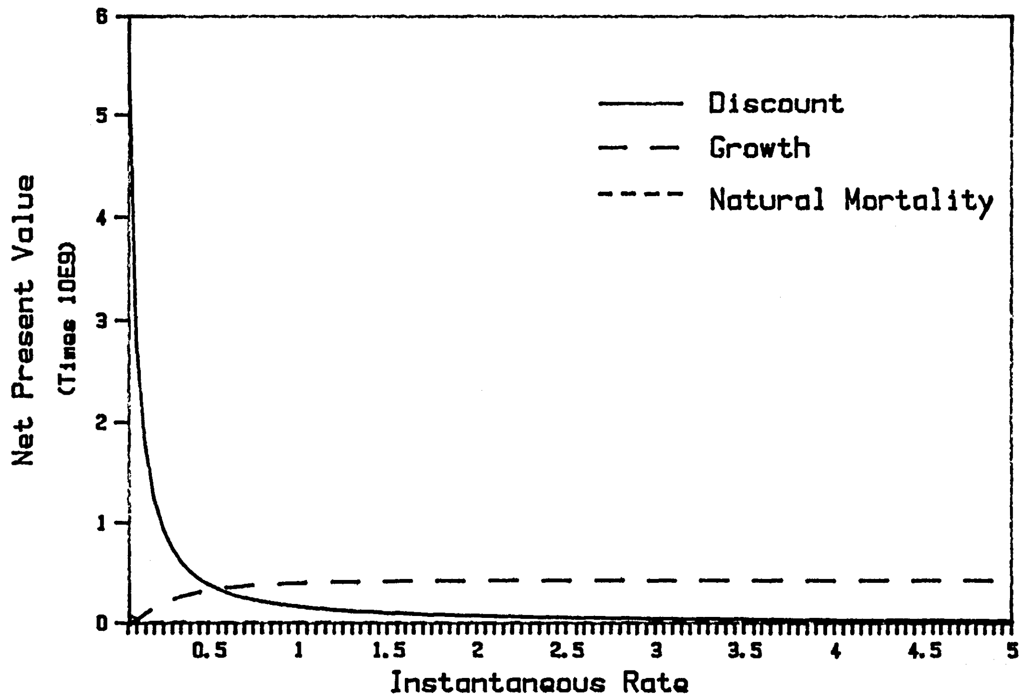

Figure 5. 4 b Longline changing net present value with parameter rates.

optimal age for fishing, as in equation 5.7. However it also acts by reducing the overall size of the population and thereby increases costs. Hence in figure 5.3a the optimal delay between impulses is depressed first of all, so that fish that would otherwise die are caught. As natural mortality continues to increase, the population size drops within the selective region so that the costs of fishing become so great, it is necessary to allow the population to become larger before fishing. Since the catchability is spread over the selective range, it can to some extent be increased by allowing the number of fish in the older age classes to build up. Eventually the population falls to such a low level fishing can no longer be sustained. For the model with longline parameters, a small increase in natural mortality causes the gear to cease operations.

The model with longline parameters is much more sensitive to changes in the rate parameters than the purse seine model as can be seen by comparing figures 5.3 and 5.4. A small increase in natural mortality drives the revenue from fishing below the cost of fishing. Increasing the discount rate causes a sharp decline in the value of the fishery, although it is not driven below zero. This sensitivity is basically due to the selectivity function. The wider age range associated with this method spreads the catchability coefficient, so that the gear is dependent for much of its catch on older fish. Age classes which have required their members to be around over a longer period will be more vulnerable to changes in parameters which operate over time, such as mortality and discount rates. Purse seine takes fish from a narrower age band of younger fish, and is less affected by these changes.

The selectivity, as it appears in the present model, is determined by two characteristics : the position of the central point relative to the optimal age and how large the age range is around this point. These factors can be explored independently using this model with impulse fishing.

In the case where selectivity lies exactly on a particular age, the result can be obtained analytically. As a_1 and a_2 move closer together, the selectivity will tend to a unit impulse function. Inserting this into equation 5.25 and integrating directly over age, it is found that the extremum criterium is :

$$R\, Exp(-m\, a_1 - q\, E)\ (P(a_1) - C(a_1)) = 0 \qquad 5.31)$$

Firstly, the value of the catch is maximised with respect to age when the price attains its maximum value. Secondly, a level of effort must be applied such that the price equals the cost of fishing. Applying the standard catch-effort model, the optimum effort can be found to be :

$$E = \frac{-\ Ln(K\ /\ (q\ R\ P)\ )\ -\ m\ a_1}{q} \qquad 5.32)$$

Since selectivity at this point is infinitely great, the optimal condition can be attained by a finite effort. However if costs are zero, the optimal effort is infinite, so that all fish are removed.

Recruitment to this age is continuous, so the effort must be applied constantly. Effectively the rotation time has reached zero. Where the band of selectivity is narrow, the time between impulses may be so short, that steadily applied effort may provide a control close to the optimum.

Figures 5.5 and 5.6 show the reaction of the model, with purse seine and longline parameters respectively, to changes in the selectivity mean age and age range. Both models show the same pattern. A change in the mean age of the selective function will increase the net present value of the fishery as it approaches the optimum age and will decrease thereafter. At this point the rotation time reaches a minimum and therefore fishing pressure is maximised. Although it is not clear from the figures, the rotation time slowly increases as the mean age increases thereafter. The reaction of the optimum time between harvests is similar for both changing the selective mean age and increasing the natural mortality. As the mean age increases fewer fish are recruited to the gear (reach a_1) which is one of the effects of increasing natural mortality.

There are two ways the age range might be changed. Selected ages might be simply extended without changing the catchability at each age (u constant, a_1 a_2 variable), or the overall catchability (q) is kept constant, so that the catchability at each age (u) is adjusted. In the first case increasing the age

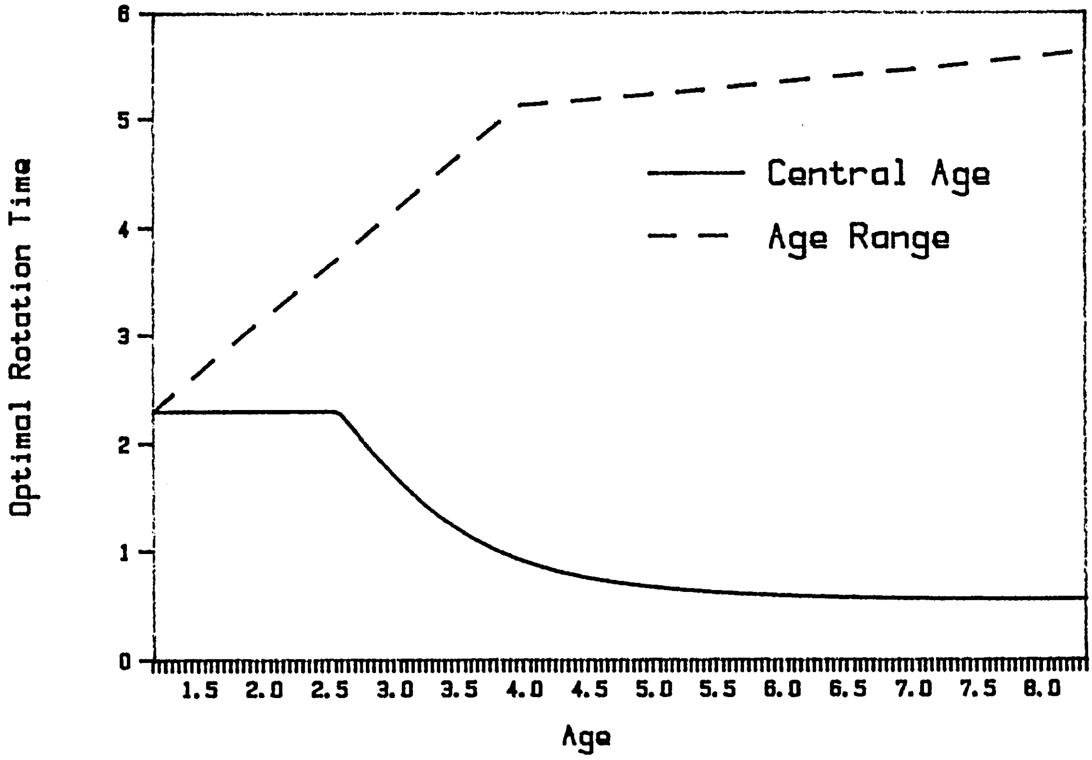

Figure 5.5 a Purse seine changing optimal rotation time with selectivity parameters.

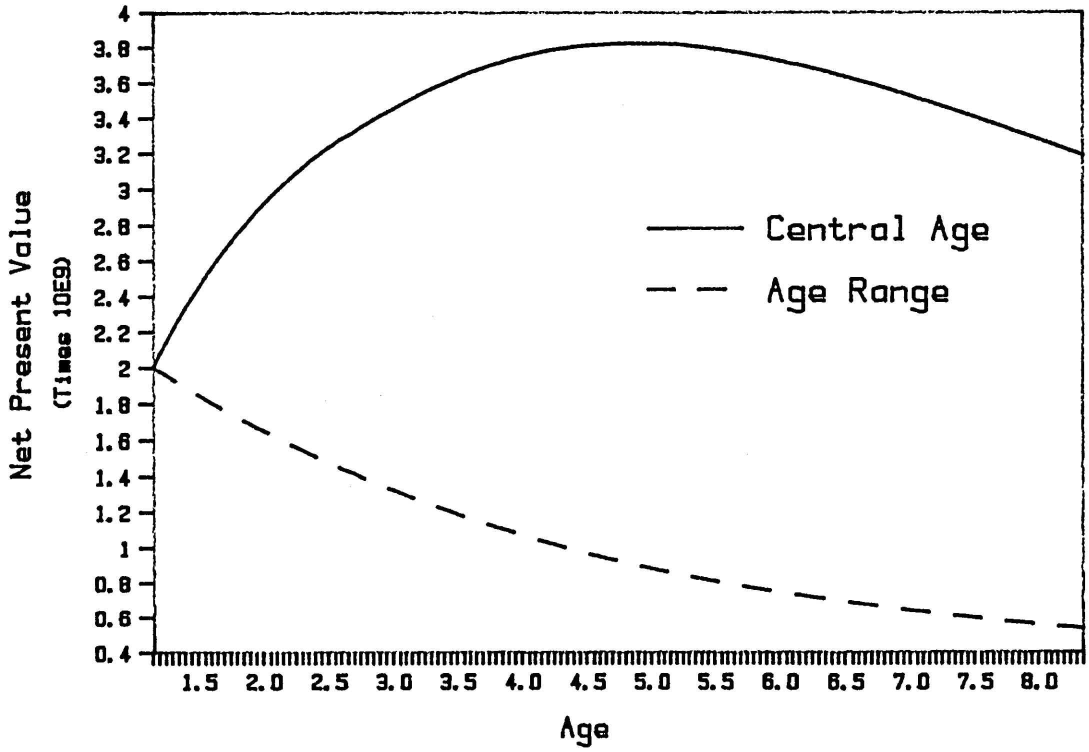

Figure 5.5 b Purse seine changing net present value with selectivity parameters.

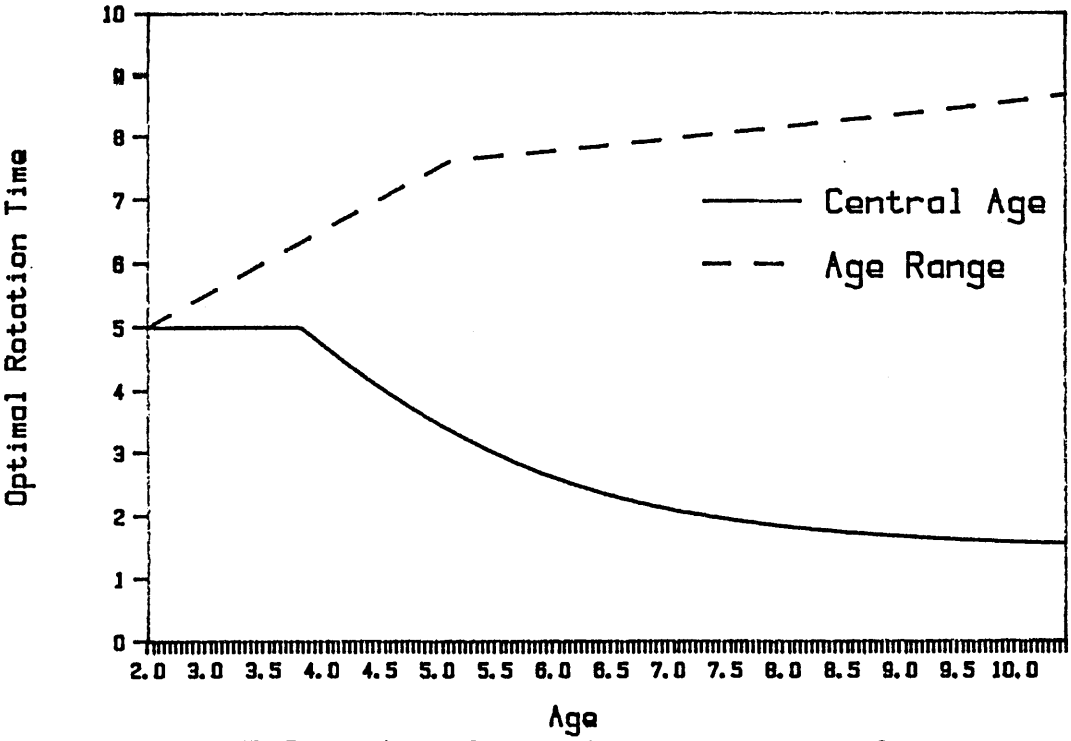

Figure 5.6 a Longline changing optimal rotation time with selectivity parameters.

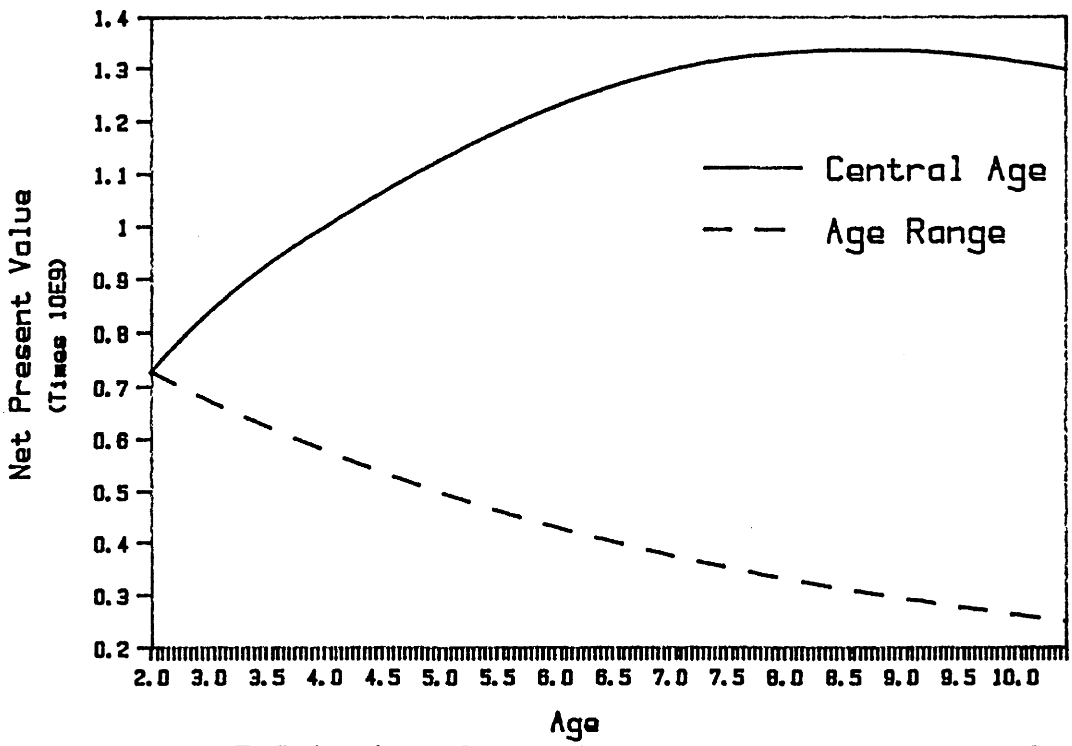

Figure 5.6 b Longline changing net present value with selectivity parameters.

range will clearly increase the overall catch and value of the fishery as the catchability coefficient is effectively increased. The figures 5.5 and 5.6 show the second more interesting case, where the overall catchability is kept constant.

The age range was extended up from zero ($a_1=0$), with the minimum age range of 1 year for purse seine ($a_2=1$) and 2 years for longline ($a_2=2$). For these two gears there is a decrease in the net present value as the age range, governed by a_2, increases. This is because the catchability is spread out over ages with fewer fish, so that the catch falls.

In general the dispersion of the catchability might increase the net present value if the loss in catch was more than offset by the increase in value of fish caught. However benefits from this adjustment are likely to be small in this model and if the optimum age is already within the selected range any increased dispersion will decrease the fisheries net present value.

5.3.2 Conclusion

The economic efficiency of a gear will depend upon how the selectivity function relates to the biovalue defining the value of the stock at each age. For any stock there will be an optimum age to fish, when the gains due to growth, less losses due to mortality and discounting, are maximised. The selectivity function is essentially a two dimensional (catchability and age) representation of the catchability coefficient, and as such it is vulnerable to both discounting and mortality rate changes. Where the selectivity function lies in relation to the optimum age gives an idea of the harvesting efficiency with respect to age.

5.3.3 Fixed Selectivity with Two Gears

Discovering how the stock should be allocated to two gears is difficult. There will clearly be no definitive answer. However some of the principles developed in this chapter can be used to elucidate the problem, identifying the crucial factors involved.

The problem can be described as a dynamic optimising problem of a similar form to the previous models. The equation to be maximised for two gears with fixed selectivity can be written :

$$J = \int_0^\infty\int_0^\infty Exp(-b\ t)\quad (P_1-C_1)\ S_1\ H_1 + (P_2-C_2)\ S_2\ H_2 \quad da\ dt \qquad 5.32)$$

From equations 5.17-5.19, the criteria for extrema is given by :

$$\int_0^\infty N\ S_1(\ m\ (P_1-C_1) - \{P_1-C_1\}'_t - \{P_1-C_1\}'_a\ )\quad da = 0 \qquad 5.33)$$
$$\int_0^\infty N\ S_2(\ m\ (P_2-C_2) - \{P_2-C_2\}'_t - \{P_2-C_2\}'_a\ )\quad da = 0$$

Solving the simultaneous equations in 5.33 is difficult, but the form of the solution can be surmised from the previous analyses. Firstly, they indicate a switch between the different gears, the most efficient being operated in preference to the other. Again the operation of a gear taking younger fish can be thought as incurring an opportunity cost through preventing the second gear from operating.

However this result does not prevent both gears from operating in the same fishery, since competition will not be complete and gears may even complement each other. From previous arguments, the optimum control will be close to some kind of bang-bang or impulse control for relatively small costs and discount rate. It is simple to obtain the net present value of the fishery with different rotation times. This can be extended to the two gear case by considering the age structure to be partitioned either among separate gears or shared by both gears depending on their selectivity functions. Hence a rotation time extended beyond the selectivity of one gear, may enter the second allowing it to fish.

A shared partition is allocated to the most efficient gear first, remaining stock being available to the second gear. If two gears share all the same ages, then the most efficient gear will exclude the less efficient. The rotation time is calculated from the age at first capture for the entire stock, both gears being able to fish. If two gears fish sequential ages, whether it is worth operating can be tested both by finding the rotation time which maximises the net present value, and testing whether the less efficient gear has an optimal effort greater than zero.

The general result from looking at pulse fishing is that under most circumstances one gear should operate. For this not to be the case an argument must be found which justifies a more profitable gear incurring costs to allow a less efficient gear to fish. Such an argument may be tenable where a collection of gears together supply a more efficient distribution of fishing mortality over age than any gear by itself. For instance, it has been seen that the selectivity range limits the rotation time. A second gear may extend this range allowing a extension of the time between pulse fishing, however the gear efficiencies have to be very similar.

Figure 5.7 shows the net present value produced under different discount rates for the purse seine and longline parametered models. In this case using both gears incurs a cost above using just the most efficient gear (purse seine), although the difference between the different regimes is relatively small. In fact the optimal allocation with coexistence represents a local optimum only. If the rotation time was allowed to decrease there would be a decline down to the point where longline ceases to operate, and subsequently an increase in the net present value as the optimum is approached for just purse seiners operating.

To achieve a situation where such an optimum with both gears fishing existed at all, the costs had to be adjusted and the natural mortality and discount rates kept at a very low level. Impulse fishing with both gears is particularly vulnerable to discounting and natural mortality since the selective dispersion is very great, although the catchability increases with additional gears. However for the present model coexistence was not found to be the optimum when given realistic parameter values.

5.3.4 Application of the Results

The above analysis ignores some important characteristics of the fishery. These are pulled into the discussion, and some final conclusions are then drawn.

Firstly the fishery consists of more than one species, so gears are supported by catches other than yellowfin. Any control on their effort directed at yellowfin may also lose catches of these other species, another cost that must be considered.

It has been assumed that recruitment is constant and

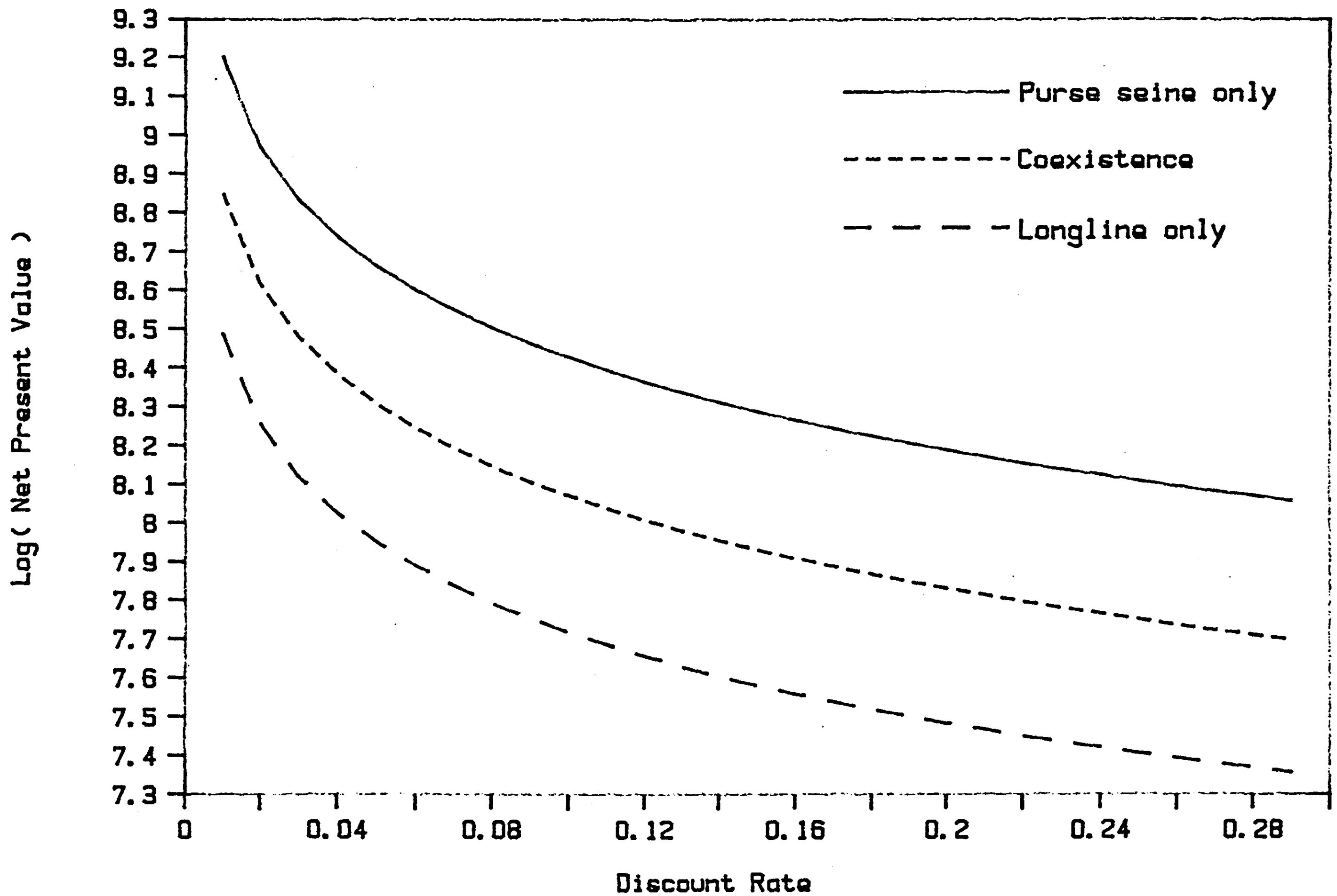

Figure 5.7 Fishery net present value under different regimes

independent of the stock size. A renewal criterion will reduce optimal fishing pressure, balancing present profits against future costs through lower recruitment. Taking fish before reaching maturity will have a greater effect on later stock sizes than taking older fish, giving a distinct advantage to longline.

While it is unlikely that fish available to either gear come from distinct stocks, they may not be completely mixed. In this case the gears will affect each other indirectly through changing immigration and emigration rates, dampening any impact.

Other factors will improve the compatibility between gears. Density dependent mortality, which is likely to be present, will allow heavier fishing of the stock with a smaller effect on the stock size, particularly on the number of older fish. Stochasticity has been ignored due to complexity, but remains an important consideration in management. In this case maintaining both gears mitigates against risk. In particular purse seine and longline exploit different markets, fluctuations in which will affect their profitability. It is less likely that both markets will collapse at the same time, giving greater assurance of at least some income in licence fees.

From the analysis, it can be seen that the fishery interacts with the fish stock through the selectivity function. The selectivity of a gear will be important in deciding its optimal effort and overall efficiency. Although the last section implied coexistence between gears was an unlikely solution, consideration of the points made at the beginning of this section suggest that this may be over simplistic. It may turn out to be better to build up a selection of gears to obtain a better distribution of effort over age. This would appear to need more work to see under what conditions coexistence occurs in more realistic models, particularly with a recruitment-stock.

The key parameters to the problem are the selectivity function, natural mortality and the relationship between costs (catch rates) and stock size. Some idea of the selectivity function for longline and purse seine can be obtained from the frequency distribution of fish sizes shown in figure 4.7. The main differences between the two gears are the different mean age of capture and the much greater dispersion of the longline selectivity function. The analysis above suggests longline will be more vulnerable to increasing natural mortality or discount rates. Also considering that longliners in the region are not fishing the best quality tuna, if only one gear should operate, it may well turn out to be purse seine.

These results, coupled with those from previous chapters, provide enough information to make a general management proposal for the fishery. This proposal is presented and discussed in the following chapter.

5.4 Summary

If it is possible to harvest particular ages with complete accuracy, the fishing mortality with respect to age which maximises the net present value of the fishery is simple to obtain. Where the costs are elastic in relation to stock size, the age range fished will only depend upon the changing value of the cohorts. Where costs are inelastic, the size of the cohort also comes under consideration in relation to the fishing effort needed to harvest it. This can lead to dramatic changes in behaviour.

For more than one gear fishing a stock, any particular age would be allocated to the most efficient gear taking that age. However some account must be taken of other gears catching older fish, and so escapement must be adjusted accordingly by controlling the age at final capture.

The solution to optimal harvesting rate with fixed selectivity is the analogue for optimal harvesting of a cohort, except the single cohort is replaced by the whole population as perceived through the selectivity function. This will be close to pulse fishing for reasonable parameter estimates.

It was found that both the discount rate and natural mortality effects could be offset by increasing fishing pressure. However natural mortality also increased costs of fishing by decreasing the stock density, which could lead to decreasing fishing pressure at high natural mortalities. The efficiency of a gear type strongly depends on its selectivity function. The gear interacts with the stock through this function, which is a two dimensional representation of catchability. The gear efficiency will be the average value of the population weighted by the selectivity. This formulation allows gears to be compared.

Although in theory it might be envisaged that a patch work of gears could direct more fishing effort at optimal ages, in practice this system seems to be very sensitive to differences between gears, and in particular to the natural mortality rate. No region of coexistence was found to be optimal when reasonable parameters representing longline and purse seine were adopted in the model. This particular result needs to be tempered by risk and stock-recruitment relationship. However the general method provides a framework for analysis of a system with two or more gears and indicates the important aspects of their relationship which will need further study.

Chapter 6

Discussion

6.0 Introduction

The South Pacific offers a good opportunity for developing an efficient management regime for tuna. Research for such a regime will be an on-going process as controls are adapted to changing conditions within the fishery. The recommendations presented below are not definitive, but form part of this adaptive process.

Any management regime will be irrelevant until the political situation in the region is settled. In 1988 there were conflicts between the Island states and Japanese vessels refusing to pay fees and US vessels fishing illegally (Waugh, 1988). Clearly, co-operation is required from the distant water fishing nations and until an acceptable stable agreement has been reached, it might not be possible to put improved controls into practice. However it is still desirable to see what options are available to management and what cost and benefits are associated with those options. This should help in the process of negotiating access for distant water fishing nations.

The original question posed was what effect does purse seining have on longline catch rates? There is no simple answer. However, the analysis has shed some light on the future management of the fishery, research needs and data required. This chapter firstly discusses the findings in this work with special reference to the implications for management. It then goes on to discuss possible improvements to the data set and what these improvements might provide.

6.1 Implications for Management

Rather than attempt to model the tuna population, all models have concentrated on the interface between the industry and the stock. This is largely because not enough is known about tuna to apply any more complex model than the Schaefer (1954; 1957) or Beverton and Holt (1957) type models. Much of this more detailed work linking the catch rate to fish density has not been done, so this work will hopefully build towards future research.

The relationship between stock size and catch is an important one. Without making any assumptions about recruitment or natural mortality, a real time estimate of the fish density for each species and age can be obtained. The management can then react by reducing the catch or effort as appropriate, which allows the management to tune the fishery to maximise the economic rent while making as few assumptions as possible about the stock dynamics. Management by monitoring would seem to be the safest way to control the resource side of the fishery at present (Hilborn and Sibert, 1985).

None of the discussion below is relevant to those vessels targeting for albacore in the region. These will need separate management, although the level of effort is so small as to suggest no control is necessary at present.

6.1.2 Interaction between Gears

Analysis of longline catch per hook revealed a decline as purse seine activity increased. It was argued that this decline was due to increased fishing mortality among young yellowfin. If the yellowfin being fished by both gears forms part of the same stock, there is a clear theoretical inference that there must be a fall in longline catch rates.

There are two reasons why this decline might not be detected. First the effect may be small and masked by noise. As data is accumulated the decline should become more apparent, although it may still be negligible. In this case a decline was detected, fitting the expected pattern. The second hypothesis is that the yellowfin available to each gear originate from separate stocks.

Different stocks of yellowfin may have different vertical or horizontal distributions. From what is known of movements of yellowfin separate vertical distributions would seem very unlikely, since they seem able to penetrate a great range of depths (Hunter et al, 1986). Alternatively yellowfin may form separate stocks distributed over the Pacific. Although this seems more plausible, the analysis only dealt with purse seine effort and catches in the immediate area of the longline effort, which means that the analysis was carried out on what was almost certainly a shared stock. Hence it is reasonably certain that some decline should be seen, and the observed fall in longline catch per hook fits this expectation.

The delay between the mean selectivities of purse seine and longline is approximately 1.5 years, although the longline catch rate should fall continuously during the period defined by the longline selectivity age range. Therefore the decline in longline catch rates may continue for some years even if purse seine catches stabilise now. This may be particularly acute if the older fish make up a large part of the catch revenue, since this effect will be felt last.

The hypothesis that the decline described above is due to purse seine can be tested to some extent by examining data received after 1986, the date of the last data records used in this analysis. Essentially, forecasts from the model described in chapter four can be generated and compared with actual catch rates. With a longer time series the model estimates might be updated and ultimately improved.

6.1.2 Allocation of Effort

Given that the effect of one gear on the other can be quantified, what management action should be taken? Chapter 5 has started to develop the theory needed to answer this question. In general the problem revolves around considerations of the opportunity cost of taking a fish and the escapement necessary to offset this cost. Putting this into mathematical form is complex, but some general conclusions can be made.

Given a linear relationship between catch and stock size, the optimal management is likely to deny access to the less efficient gear. The efficiency of the gear will not only depend upon effort costs and price-age function of the fish, but will also depend upon the natural mortality and gear selectivity. If the relationship between catch and stock size is non-linear this may no longer be the case. Particular gears may be more efficient at exploiting the stock at different densities. Purse seine and longline may fit this pattern, with longline better adapted at taking a more widely dispersed population. While the relationship between stock size and catch for longline can be explored fairly easily with the help of models, it will be more difficult for purse seine.

The relative efficiency of each gear will be difficult to ascertain. Purse seine is much more efficient than pole and line (Doulman and Kearney, 1986) and may appear to be more profitable than longline. Longline effort around Papua New Guinea and the Solomon Islands is exploiting low quality yellowfin (Kitson and L'Hostis, 1983), making it vulnerable to over-supply and encouraging the fleet to go elsewhere. Even if this is the case there are advantages in maintaining a longline presence in the region.

First, both types of gears sell to separate markets, insuring against the risk that one market should collapse. Second, longline is unlikely to adversely affect recruitment since it takes fish that have been allowed to reproduce over a longer period before being subject to fishing mortality. If purse seine exploitation has a negative effect on yellowfin recruitment, there may be a more rapid decline in stock size than might be expected, to the detriment of both gears. Such a decline could be modelled as the discounted cost of reduced future recruitment. Finally, for the foreseeable future longline will provide data of a much higher quality and with a sounder theoretical basis than purse seine. This information is valuable, particularly as the fishery is still developing, because it probably produces the best long-term data for monitoring the state of the fishery and, therefore, provides a good basis for management decisions.

Making a decision about which gears are allowed to have access to the fishery may be difficult. If nothing is done, however, purse seine is likely to drive out longline from the immediate area. Heavy purse seine fishing may have even wider effects. Evidence suggests that yellowfin tend to spawn in warmer waters, where purse seiners fish (Cole, 1980). Hence purse seine may decrease the numbers of juveniles supplying more valuable longline fishing grounds as well as taking spawning fish before they are able to return to cooler waters. Although a final decision on what limits should be put on purse seine catch rates may not be taken for some time, it is necessary to clarify what options are available in the management of this fishery.

There are three possibilities that will be dealt with. The first two consider the allocation of the fishery to either purse seine or longline. This would depend upon one gear being shown to be more efficient than the other. The alternative and more interesting strategy is to encourage the coexistence of the gears, limiting the impact of purse seine on longline. This last strategy must be recommended at least until it is clearer which gear, if any, is the most desirable.

6.1.3 Purse Seine Only

This will not require that longliners be denied access, since they will be forced out of the fishery as purse seine effort increases. The problem with purse seine is monitoring changes in the stock size, which may not be evident from purse seine catch rates. This may be due to a contracting distribution rather than reductions in density, which is usually assumed. If declines cannot be detected using CPUE techniques, alternative methods using length frequencies could be applied. As exploitation increases, the proportion of larger fish in the catch should decrease which will give an idea of the state of the fishery and, most importantly, the degree of escapement. However the use of length based methods falls beyond the scope of this work, and the reader is referred to Rosenberg and Beddington (1988) who provide a general discussion of the methods available.

It is particularly important that purse seiners are not allowed to overfish, since the results could be disastrous. Heavy overfishing by purse seine could result in recruitment failure and fishery collapse. Recovery of the fishery could take many years, during which the South Pacific Island states would suffer from a loss of income. To prevent this, careful management and good quality data are required, both of which will be costly to maintain. The extra costs of monitoring and the increased risks must be born in mind when deciding whether to adopt purse seine as the sole gear.

Control of yellowfin and skipjack catches will need to be separate. To achieve this quotas will have to be set for each species, in particular yellowfin, which has been found to be more vulnerable in the eastern Pacific.

Taking the option of only having purse seiners will deny longliners access to other stocks also caught in the region, such as bigeye and billfish. Although these species form a smaller proportion of the longline catch, they are not exploited by any other gear and so represent a loss of revenue to the fishery. This will need to be taken into account.

6.1.4 Longline Only

Longlining presents few problems to management. It tends to take older fish, so it is less likely to cause a recruitment failure through overfishing. If tuna schools are of significant size over the age selected by longline, the stock may be able to support large effort levels with only a small drop in the catch rate. The data is of good quality and quite adequate for CPUE type analyses. It is also easier to switch the dominant fishing method within a fishery from longlining to purse seining than the other way round, since there will be no delay before catch rates increase.

The final model described in chapter four appears to fit the data well. It should detect all major changes in stock size, and has the advantage of simplicity and can be repeated where ever GLIM or a similar linear modelling package is available. Improvements to that analysis and the data set are discussed below.

The biggest problem with longlining in the region is the sashimi market. Yellowfin from tropical waters is of the lowest quality and hence fetches a low price. This will give a very small profit margin and increases the risk if investing solely in this gear. Together with losses of potential catches of skipjack, this looks unlikely to be an successful solution.

6.1.5 Coexistence

For the two gears to coexist successfully some control on purse seining is necessary. Simply limiting the number of purse seine licences may protect longline, but will result in lost revenue from skipjack catches. It would be much better to limit the purse seine catch of yellowfin using catch quotas or preventing vessels making the type of sets which tend to contain higher numbers of yellowfin. This would avoid losses in skipjack catches while protecting yellowfin.

Quotas would be difficult to enforce, since much of the catch is landed outside the region. The alternative policy of changing the fishing behaviour of the purse seiners is more likely to succeed.

There are two ways in which this might be achieved. First, there could be a closed zone in areas where the purse seine yellowfin catch is highest. This has the disadvantage of denying access to the skipjack resource within the zone. Apart from protecting longline, it might improve both yellowfin and skipjack catch rates outside the zone in the long term by ensuring recruitment to fished areas through emigration.

The second method is to control the type of aggregates fished by purse seiners. In chapter two it was shown that non-log aggregate types tended to contain a greater proportion of yellowfin. These yellowfin also tended to be larger than those found under logs. By preventing sets made on free swimming aggregates or floating objects other than logs, two objectives would be met. First, the general fishing mortality of yellowfin due to purse seine would be reduced. Second, a higher proportion of the purse seine catch would be younger yellowfin, which will have a smaller impact on the longline fishery. This is because a larger proportion of the younger fish will die anyway, due to natural causes. It should be possible to enforce this particular regulation where observers are on board the vessel, and through a programme of encouraging FAD fishing through the distribution of fixed FADs in good locations. It should be possible to design experiments to discover how FAD location and form affects the size of the aggregates.

6.2 Other Management Issues

There are a number of other issues which can be touched upon briefly. Many papers have been published on the subjects discussed below, and this section does not aim to provide a detailed account of how they relate to this fishery, but only to mention some important aspects which will need further attention.

6.2.1 The Multispecies Aspect

The multispecies aspect of the fishery has largely been ignored, but the methods for estimating abundance can be adapted to more than one species and more than one size class. There is likely to be predation by older fish on younger, both within the same species and among different species (SPC, 1980b). Competition between different species will depend upon the degree of overlap of their resources. There is some controversy over the importance of competition in better understood systems (Berry, 1989), so until there is evidence to the contrary it is probably better ignored. Large healthy tuna are unlikely to have any real predators, although diseases might be important and could warrant closer attention.

6.2.2 Types of Bioeconomic Control

At present, effort is controlled by limiting the number of licences to fish in the region. Other controls, if it were possible to enforce them, could include closed seasons and areas. Although protecting the stock, they would not control over-capitalisation in the fishery. Other forms of economic control are discussed by Clark (1980). For the South-West Pacific tuna fishery, the simplicity and ease of enforcement of licences will probably make them the preferred method of control for foreign vessels. Taxation on revenue as operated in the Maldives (Christy et al, 1981) could be instituted for the national industry.

An obvious solution avoiding estimating gear efficiency is to auction fishing rights, but this still needs controls on the total number of licences issued. Since purse seine is likely to have a greater impact on the stock, more longline than purse seine licences could be issued. Essentially each licence will have an exchange rate with licences of the alternative gear which would have to be decided upon by the management, even if a free market was set up. Also licence fees should reflect the level of fishing mortality that can be imposed by the licensee; auctioning tends to distort this.

6.3 Data Set Improvements

A number of improvements in the recording of data are recommended. However there is a problem with implementation. While as much detail and accuracy as possible is desirable, the costs of collecting this data will be prohibitive. Where possible a number of different options and their value to analysing catch rates are given.

6.3.1 Oceanographic Data

The fishery is relatively new, particularly for purse seine. This introduces more uncertainty in the interpretation of results, since it is not known whether some effects are due simply to the expansion of the fishery or to some other factor. To make predictions about new fishing grounds, information on the oceanography of the whole region needs to be obtained. Permanent features, for instance ocean bed topography and particularly seamounts, may be closely related to catch rates (Hajime Yamanaka and Anraku, 1969). This extends the concept of different habitats to marine ecosystems rather than assuming the pelagic environment is homogeneous. Oceanographic features may also affect the catchability of the fish as well as their density, for instance with the depth of the thermocline or presence of logs.

Unless an expensive fishing survey is carried out, oceanographic data is the only source of information on areas where there is no fishing. Where fishing occurs more direct and detailed information on stock size is available. It is to be expected that such data will not explain much of the variation in the catch rates, as fishermen probably orient themselves efficiently to the main oceanographic features, removing that effect from the fisheries data. However this data will still be useful for the prediction and understanding of the fish distribution. In particular, it could be used to provide an expected spatial distribution from which deviations could be measured.

6.3.2 Data Inaccuracy

Problems of inaccuracy mainly stem from purse seine data. However, there is evidence that longline data too contains inaccurate estimates of catch and many fields are not filled in. Although most of the recommendations apply to purse seine, some may be important considerations in compiling longline data as well.

There are problems with the present data set both in terms of absence of data and inaccuracies in recording. In general many inaccuracies are overcome by the size of the data set, but fishermen should be encouraged to record accurate and useful data. Where the log sheet does have space, fishermen should record a 'no data' symbol or zero as appropriate to avoid confusion. Space could be made on the logsheet, as suggested below, to record more information useful for analyses.

Purse seine catch size frequencies (shown in figure 2.4) show a tendency for fishermen to round their catches to the nearest 5 or 10 tonnes of fish. This is also observed, to a much smaller degree, in longline catches. For larger scale analyses which combine data looking at overall changes in means, such inaccuracies are not a problem unless biased. Comparisons made in the East Pacific fishery between estimated catches from logsheet data with actual landings suggest that there is no bias (Mullen, pers. comm.). However the problem still exists for more detailed analyses of individual sets.

6.3.3 Additional Purse Seine Data

Purse seine data require very complex analysis if a theoretically more rigorous method is used. The data suggest that searching for fish is a complex mixture of previous and shared knowledge among fishermen rather than pure random search. Furthermore the fish are not distributed randomly, but form aggregates of different sizes which also do not appear to be random. More light might be shed on the processes involved if the catch rate were split into its constituent parts.

Sets per day, catch per set and unsuccessful sets appear to be linked. The success rate increases number of sets per day, as fishermen repeat sets on aggregates of fish which have escaped. Depending on the behaviour of the schools in relation to each other, the success rate of a set may also be related in some way to the size of the aggregate and hence the potential catch per set. The sets per day may be related to the catch per set, depending upon how aggregates are rejected or how aggregates form. An aggregate might be rejected if the weight of the potential catch is considered too small or too large, or the fish size too small. The proportion of aggregates rejected will depend on how schools distribute themselves and how schools themselves are made up. The results of this work suggest an ideal data set designed to solve these problems.

To develop an analysis that takes full advantage of the different parts of the catch rate the following data is required. Each purse seiner should have to account for its time. In particular the times when searching is started and finished. Each time an aggregate or aggregation device (including logs, flotsam, whales, sharks etc) is encountered, it should be recorded with an estimate of the size of the aggregate and the potential catch using acoustic equipment. If no set is made the reason must be given. Otherwise the total catch must be recorded when the set is made and a second estimate might record the size of the aggregate remaining. When a set is repeated on a floating object previously fished, the previous set must be referenced so that a comparison may be made. Fishermen or observers may also be able to estimate the numbers of schools caught in a set by estimating the number of fish length modes in the catch. The assumption is that schools will be made up of similarly sized fish. This would not definitively decide the number of schools, but could be used in conjunction with the size of the catch to formulate an improved model of the way the catch size changes with the population size.

Without more information on tuna behaviour, it will still be difficult to interpret and therefore predict changes in the fishery. The most important question here is how and why do fish schools aggregate. The purse seine fishery depends entirely upon this behaviour of the fish, since without the aggregations, the fishery would no longer be profitable. Much research is being carried out on fish schooling behaviour, and this should be monitored for important results. A more pressing question is why do tuna aggregate to floating objects? If this were known, not only might improvements be made in FAD design, but catches on logs might be better interpreted.

A first step might be to monitor the size of the tuna aggregation over time as fish arrive and leave, and associate this with other factors such as the oceanography and ocean bed topography of the region. This monitoring could be carried out remotely using satellites receiving information from acoustic devices mounted on fixed and free floating FADs. At the same time the size frequencies, sex and maturity of fish and type of prey could be recorded. Together with tagging studies, it could be established the extent to which schools mix, combine and split.

Such a research project is clearly large and would be expensive. Collection of the data describing the search and catches of the purse seine would present various problems of data management that may not be fulfilled. These would include both the physical problems in storing and processing such large amounts of data as well as ensuring such data was recorded accurately. The reality may therefore fall well short of the ideal data set.

Some simple changes may be made to the logsheet which would greatly enhance the results of the analysis. Most obviously all logs and flotsam should be recorded along with a coded explanation as to why it was rejected if no set is made. This allows the distribution of fish under logs to be estimated and monitored directly. The search data will not be redundant however, since the number of fish under a log may depend upon the density of logs. Therefore in addition to other information the time spent searching could be recorded explicitly in the form of start and finish times.

More detailed data might be needed to continue to develop analytical methods, but this does not require all fishing vessels to record detailed data all the time. A more acceptable alternative is to generate a smaller data set to test assumptions and methods. These results can be used to interpret results from the larger data set for all vessels, where detailed information is not available.

6.3.4 Additional Longline Data

The longline data set is more accurate, contains more information and is simpler to interpret. This gives it more potential as a management tool. In particular a rigorous relationship between catch and stock density could be formed.

The model of longline catches presented in chapter 3 could be developed further and fitted to a data set which recorded each fish and the hook on which it was caught. By supplying the distance between floats on setting, the length of line between floats, the length of buoy and hook lines, the depth of each hook could be estimated. By recording the position of each buoy the position of each hook could be estimated. The bait used could be recorded in some form to calculate which hooks had which bait if a mixture of baits were used. Such data would allow a complete longline set to be regenerated.

This type of information would allow accurate fitting of models of a form similar to that described in chapter 3, based upon the Markov chain. However that model only takes into account schooling, not changes in school density along the length of the line. If it is assumed that the line is laid in an area where the density of schools is constant, modelling and fitting the catch is fairly simple. Such a model can be based upon the time series model described in Zeger and Qaqish (1988). This is largely because the catch on a hook is directly dependent on the the catch on adjoining hooks. The degree of dependence can be estimated using linear models, forming a stochastic matrix of the same form as that described in chapter 3. It should be possible to fit and obtain distinct estimates of the number of fish in a school as well as the density of schools, given the other parameters.

The reality is likely to be more complex than this. Not only do fish form schools, but the schools themselves aggregate into particular areas. Fishermen try to find these areas and set lines within them. A longline catch therefore represents a sample line transect across a heterogeneous fish distribution. It should be possible in theory to remove effects such as depth and schooling and estimate the change in school density along the length of the line. This can be done using Kalman filters or similar methods (see Harvey, 1981). These methods allow parameters of a linear model to vary in some pre-defined fashion, so that the observed variable is sampling some underlying process, in this case school density.

A potential problem will be to relate different longline sets to one another. The simplest approach may be to regard all hooks as separate entities distributed in space and time. The probability of a hook catching a fish depends upon which other hooks have caught a fish. The closer the other hooks are to each other, the stronger will be this dependence, suggesting that a discounting method could be used as a first attempt at different catches on different lines. The probability of a hook catching a fish would depend on all hooks exponentially weighted by their distance in space and time. This should be possible since for estimating the catch at any point most hooks could be discarded as their weights would render them of negligible value.

The results from such a model should provide a map of fish densities over the fishing grounds at different times. While this would be of undoubted interest to scientists studying population dynamics of tuna, it is not so clear how important such information would be to fisheries. The cost would be prohibitive, and collecting and managing this information would be an expensive task. Probably it would require automatic recording equipment on board longliners that could monitor the position of the line as well as the length of line between buoys, distance between buoys and so on. Details of the fish could be entered as they are brought aboard. Such information could be directly loaded into a mainframe computer for analysis. The other major cost would be the computer facility that might be necessary to carry out the task. It is evident that the total programme suggested here would need a relatively large investment by international agencies.

The information gained from such a model could be useful for both managers and fishermen, since it could give a real time map of tuna distribution, mainly limited by distribution of vessels. More research would be required to extend these estimates beyond the fishing region, oceanographic data being a contender for this. For management purposes one important result of such an analysis would be identifying a contraction of the distribution of fish as opposed to a reduction of density. This is particularly worth while if fishermen use all or part of their line to sample areas outside the main fishing ground. Such information may be used to look at tuna movements and how patches form and break up, which is invaluable information for solving conflicts between fishing nations over the exploitation of such a highly migratory resource.

A preliminary investigation can be carried out looking at total catch for each set. Such an analysis is unable to remove effects due to schooling or depth, and is spatially accurate only to the average line length (approximately 100 km), although it should indicate whether the approach is worth pursuing, and how important the spatial distribution is to the final catch.

The model suggested that data in the form of 'runs' or sequences of fish taken on a haul would be useful in estimating school size. Sequences in the catch indicate the importance of schooling to the overall catch rate relative to other effects such as bait loss. This does not justify altering the logsheets as they stand, since the alterations may still not capture the most important attributes of the method. It would therefore seem appropriate to carry out a study, collecting the information containing the catch, position and time for each hook as described above for a significant number of longline sets in the region. The data set can be used to formulate and test a detailed model, which can be used to design a logsheet to include only data necessary for management.

The time series model could be improved. The model assumed that each month's catch depended directly upon that of the previous month. In reality the model is sampling an underlying process and again state space models (Kalman filter type models) are probably more appropriate. It would be worth finding out whether these more complex models describe the data any better.

6.3.5 Improved Age and Size Structured Data

So far the methods discussed deal solely with estimating density. The two most important attributes of the stock, the age or size structure and recruitment have not been studied yet. Recruitment presents great practical and theoretical difficulties since it depends not only on the fecundity of the adult population, but also on the early life history of the species.

For the time being recruitment can be dealt with by looking for correlations between estimated stock size and recruits to the fishery after an appropriate delay. Age structure can be used in much more detailed analyses and has a more immediate value.

The age or size structure of the stock provides useful information on the stock status. Under heavy fishing mortality there should be a reduced proportion of older, larger fish, even if the catch size does not diminish. The size structure is particularly important for analysing the relationship between purse seine and longline. These two gears not only have different catchabilities, but also have a tendency to select fish of particular sizes. Heavy exploitation of young fish by purse seine should reduce the number of older animals and hence the size of the longline catch. Dealing with age groups explicitly rather than assuming the stock available to each gear is homogeneous has several advantages.

An adverse effect of purse seine on longline may be detected at an earlier date. There is some overlap of exploited size class between the two gears (see figure 4.6). As these more heavily exploited age groups move into the selective range of longline, the longline catch will fall. The fall will be offset by the normal, higher catches of older fish, so reducing the apparent effect. By monitoring variations in the catch rate for each age, the effects of changing purse seine effort might be detected with a shorter delay and greater confidence.

As estimating the age of tuna is difficult (Wild, 1986), data on age from catches might be collected in the form of size. The problem with this approach is that the estimate of age adds to the uncertainty and complexity of the analysis (Rosenberg and Beddington, 1988). This problem is exacerbated by using weight rather than length as the size data. Methods estimating model parameters are currently being developed, but this approach is comparatively recent. Published results should be monitored to see how well they can be applied to the tuna fishery.

There are a number of potential problems. An important attribute of tuna gears is their selectivity with respect to size of the stock. Unlike trawl nets, where the selectivity usually depends on the physical size of the mesh, and so a knife edge uniform selection can be assumed without too gross an inaccuracy, tuna gears depend upon less well defined fish behaviour. Such behaviour might change naturally over time or as a response to increasing fishing pressure. For instance as purse seine operations deplete younger fish, the older fish, with less competition for space, may come closer to the surface under logs, making them more vulnerable to purse seine and actually increasing the proportion of large fish in the catch.

Another problem is the data itself. Some changes in the recording of data may be necessary to take advantage of length based methods. This particularly applies to purse seine where more than 5 tonnes of yellowfin may be caught, but only the average fish weight may be recorded. The mean fish size is a poor statistic to use for looking at the impact of purse seine catches on longline catch rates. Since there will be fewer larger fish in the population, so the proportion of these fish in the catch can be expected to be small. However their presence is of particular importance if natural mortality is high. A number of young fish taken by purse seiners will have a smaller effect on longline catch rates than an equivalent number of older fish. Since there are fewer older fish overall, smaller catches of these fish may still be significant as a proportion of the total population.

To adopt this approach of using size structure, the data may have to be improved. This might be done either by requiring size surveys to be carried out on board the vessels as they haul their catch or obtaining length data as vessels off load at ports. The first method has many associated logistical problems, since what can be done on board vessels is limited both by physical and economic constraints. The alternative requires data collection outside the control of the island states, but if such data were obtainable, it would be the preferred method.

6.3.6 Summary

There is evidence presented here that longline catch rates are falling and that this may be directly due to purse seine activities in the region. Although this fall is only slight at present, it can be expected to have fallen even lower in the period since 1986. This can be tested with data collected since the last period covered by the data set used in this analysis.

It is subsequently assumed here that purse seine does cause the decline.

If a continued longline presence is thought to be desirable in the region, some managerial action will be necessary to protect catch rates. Longlining has a number of advantages over purse seining and its continued presence in the region should be encouraged, particularly in the developing fishery.

The most appropriate action would be to set up a long term monitoring system to ensure the sustainable use of the tuna resource in the future. Longline catch rates are likely to continue to decline even after purse seine effort has levelled off, hence the full impact on longliners will have to be continually re-estimated with data as it becomes available.

This suggests a cautious increase in purse seine effort in the region while monitoring the effect on recruitment and the longline catch rate. As more information becomes available on the different aspects of the fishery, a decision might be made on the long term allocation of the stock.

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