Assessment of mesh size selectivity

under

commercial fishing conditions

by

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Abstract

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The present study is entirely focus on the analysis of selectivity data from alternate-haul experiments performed on fishing grounds off the coasts of Washington, Oregon and northern California, and in the Bering Sea, under commercial fishing conditions. Participating fishing vessels towed especially designed codends that differed in mesh size and shape, and layers of netting, in predetermined sequence. All other decisions concerning the fishing and hauling operations were left to the skippers of the participant vessels.

After a brief introduction describing the main concepts, experimental designs and estimation procedures related to fish size selection and its controlling factors, pooled selectivity data for ten commercially important flat and rockfish species were analyzed for the first time. The logistic, probit, Gompertz, negative extreme value and Richards curves were fitted to data to obtain the best selection curves for four diamond- and two square-mesh codends with different mesh sizes. The negative exponential curve produced best fits in 28 out of , mostly with rockfish data. Length of 50% retention was found to increase

with increasing mesh sizes. Square-mesh codends appeared to be less selective than diamond-mesh codends of similar mesh size.

Next, a new maximum likelihood estimation procedure based on a multinomial distribution was developed for the analysis of alternate-haul data. The method proved to be better than traditional selection-curve fitting procedures, and a good alternative to the binomial based SELECT method. Alternative non-parametric approaches for the analysis of selection curves are also discussed. Two different approaches, one based on a multinomial likelihood and the other on isotonic regression were used in fitting selection curves for two sets of "uncooperative" data. The parametric maximum likelihood estimation procedure was also used to explore the possibility of a simultaneous estimation of selection curves for experimental and control codends.

Finally, the issues of between-haul variability and uncertainty in alternate-haul assumptions were dealt with in a multiple hauls selectivity analysis of walleyed pollock data for four experimental codends (two diamond- and two square-mesh). A model to assess the effects of codend type, catch size and towing speed that incorporates the uncertainty in alternate-haul assumptions was developed.

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1. Assessing size selection, an introduction

Introduction

Selectivity is the measure of a process in which a subgroup of a target population of fish is distinguished from the whole. The characteristics that create this process range from almost anything intrinsic to the fish (e.g., size, shape, sex, and behavior) to the fishing gear and methods used, and the area fished that will determine what species and size of fish will be selected from the overall population. As such, selectivity has been important to man since the dawn of mankind, or at least since Man became Fisher Man and was able to try and learn different fishing techniques.

Selectivity is important to fisheries and fishery science for two general reasons. Firstly, scientists can rarely study fish populations directly. Generally, they have to rely on the analysis of catches made by the commercial fishery, or by research vessels. Average changes in these catches are often thought to reflect changes in the actual fish population. Since species, size and age composition of catches vary with fishing site, time, and gears used and determine different selection processes, knowledge of these processes may contribute to better assessments of fish populations. Secondly, manipulation of selectivity is an important management tool. Manipulation of size and age-specific fishing mortality provide opportunities for influencing fishery yields. Conceptually, by reducing the fishing mortality of small fish with the potential capacity to grow to a much better size, appreciable long-term benefits to the fishery can be achieved at the cost of some short-term loss of small fish. A good knowledge of the selectivity of the fishery is then necessary to determine what measure (e.g., closures, prohibition of particular gears, mesh size limit, etc) would be adequate to achieve the desired long-term goal.

In this chapter I review the concept of mesh size selectivity for trawl gears (the main focus of this dissertation). I introduce the different models used to describe mesh size selection processes, the type of experiments that were traditionally used to gather the data and the models used for the estimation of selectivity. I will also indicate some of the problems related to the assessment of selectivity such as the effect of catch sizes or towing times. Finally and more important, I introduce the topics of the present thesis.

Size selection, the concept

In the broadest possible sense, the selection of fish by a fishing gear is the process by which the catch of the gear has a different composition from that of the fish population in the geographical area where the gear is used. Selectivity, the measure of this process, can be described as the relative likelihoods that different sizes, shapes, sexes, ages and species of fish would have of being caught by the gear if there were equal numbers of each in the population (Pope et al., 1975; Smolowitz, 1983; Wileman et al., 1995). In this dissertation I will be dealing only with size selection for given species.

The size selection process can normally be described as composed of three phases (Wileman et al., 1995). These are:

1) *Accessibility of the fish*: differences in the probabilities of fish of different sizes being present in the locations where and at times when the gear can be used, given that they are present in the overall geographical area,

2) *Availability of the fish*: differences in the probabilities of fish of different sizes encountering the gear given that they are present at the location when and where the gear is used,

3) *Vulnerability of the fish*: differences in the probabilities of fish of different sizes being retained by the gear once they have encountered it.

The first phase involves the interaction between the geographical and temporal distribution of the fish species and the operational constraints of the fishing gear. For example, different sizes (or age-classes) of fish may concentrate in particular areas, in particular months, at particular heights in the water column and at different times of the day. Many gears are very restricted in height and moreover some cannot be operated over some types of seabed or under given sea conditions. Thus *accessibility* may differ among gears by location and time. The second phase, *availability*, involves the interaction between fish behavior (e.g., fish movement and gear avoidance) and the fishing operation (e.g., towing speed, net vertical and horizontal opening). It is known that different fish species and fish sizes react differently to a coming trawl due to their reactions to visual and sound stimuli as well as their swimming endurance (e.g., Wardle, 1983, 1986, 1990). Thus, there can be large differences in the probabilities that the fish of a given species present at a specific location will encounter the gear simply because the larger fish may swim faster than the towing speed and keep these speeds for a longer time, or they may be more wary or more active and thus be more likely to move out of the path of a trawl before the trawl catches up with them. Moreover some species such as cod (*Gadus morhua*), long rough dab (*Hippoglosoides platessoides*) and herring (*Clupea harengus*) are known to escape under the fishing line of trawls (Engås and Godø, 1989; Godø and Walsh, 1992; Suuronen et al., 1995) what also affects their availability.

This dissertation is restricted to the study of size selection in the narrow sense expressed by the third phase, that is "the differential retention of certain sizes of fish after they come into contact with the gear" (Gulland, 1983). It is further restricted to examining towed gears and will concentrate on the parts of the gear made of netting. That is, I will examine the probability that fish will be retained by the net and hauled to the surface as opposed to escaping out through the meshes during some part of the towing or hauling process. Hereinafter, I will refer to these probabilities as *mesh size selection*, using the notation $r(l)$, meaning retention at given sizes l, generally lengths. Basically, these retention probabilities are a function of the girth of the fish, the lumen of the mesh and the plasticity of the fish to squeeze its body through the mesh. Although this restricted definition of *size selection* does not include the concepts of *accessibility* and *availability*, I recognize the importance of both processes in planning successful selectivity experiments, and I will refer to the difficulties that both processes create when estimating *mesh size selection* with data from some selectivity experiments (e.g., alternate-haul, trouser trawls).

In principle it should be possible to measure the mesh selection of fish through any part of a trawled gear. However, most experiments carried out to measure mesh selectivity have only measured the selection in the codend. Early studies using beam trawls (Todd, 1911) have initially suggested that although fish do escape through other parts of the trawl, most mesh selection occurs in the codend. During the 1950s and 1960s, studies using covers of very small meshes placed on different portions of the trawl have corroborated the importance of the codend in the mesh selection of the trawl. For example, Gulland (1956) reported that only 2 to 5% of the European hake (*Merluccius merluccius*) and 4 to 9% of whiting (*Merlangius merlangus*) escaped through the meshes of the upper belly of the trawl. Clark (1963) determined that for haddock (*Melanogrammus aeglefinus*) and hake most of the mesh selection occurs in the codend, with haddock escaping mostly through the upper part of the after portion of the codend, and hake escaping through the lower side of the codend. Of the small numbers of haddock escaping through forward parts of the net (3 to 9% of the numbers escaping through codend meshes), 10% escaped through the top belly, 30% through the lower belly and 60% through the lower wings. Recent observations made by divers and towed underwater vehicles corroborated that in fact large amounts of fish do escape in the codend and that for most species this is where the main mesh selection occurs (e.g., Suuronen et al., 1995). However, substantial mesh selection of certain active swimming fish species such as herring, sprat (*Clupea sprattus*) and horse mackerel (*Trachurus* spp.) and crustaceans such as *Nephrops* spp. (e.g., Ellis, 1963; Margetts, 1963; Hillis and Early, 1982) may still occur in the main body of the trawl, in particular in its forward parts.

It has been hypothesized that not all the meshes of the codend take part in the mesh selection process. When the trawl is in motion, the actual shape of diagonal meshes will depend on the resultant of two groups of factors, 1) the flow of water thought the meshes, tending to keep them open, and 2) the drag effect of the codend material and fish, tending to close them (Jones, 1963). In a full codend the bulk of fish would stretch the codend and codend meshes. The region just in front of the fish would remain fairly open and rigid due to the drag of the solid fish mass, thus allowing for the escape of fish. Subsequent studies using divided small mesh covers on the various sections of the codends

(Cieglewicz and Strzyzewwski, 1958; Beverton, 1963) suggested that indeed fish escaped mostly from the front and rear parts, and not from the central section of the codends where diamond meshes are normally stretched and closed. Recent remote-controlled underwater observations (e.g., Robertson and Stewart, 1988) have confirmed the results of those early studies. When towed, codends made of diamond meshes fill with fish, the end meshes are obstructed, the water flow is diverted, and the end becomes bulbous. In the central part of the codend the meshes are stretched and closed, preventing the escape of all but the smallest fish. In the forward part of the codend the diameter broadens to join the net and the meshes are more open. Most escapes take place from the few open meshes at the front of the bulb. Robertson and Stewart (1988) also observed that, when the codend is made of square meshes, the codend did not become bulbous and all its meshes remained fully open increasing the area available for escape.

Selection curves and other related concepts

As defined earlier, mesh selectivity whether for the codend or the whole net is the probability that a fish is retained given that it entered the gear. Like all probabilities selectivity may take values between 0 and 1, its values depending on the girth of the fish, the lumen of the mesh and the plasticity of the fish to squeeze its body through the mesh.

With the first studies on the selectivity properties of codends (e.g., Davis, 1929, 1934; Buchanan-Wollaston, 1929), it became common to plot the proportion of fish that entered the net and were retained in the codend or net by size category. Although it is mainly the girth of the fish that determines whether or not a fish is able to pass through a mesh opening, size categories were represented by length categories because length is far easier and faster to measure. Although drawn by eye, those early plots showed some kind of "S" shaped curves with a range of small lengths for which the percent retention was zero or very close to zero, a range of larger lengths for which retention continually increased, and some even larger lengths with 100% retention. These representations of the retention probability by length class ($r(l)$) are termed *selection curves*.

There are two kinds of selection curves, 1) *parametric selection curves*, in which it is assumed that $r(l)$ is a non-decreasing function with range between 0 and 1 that can be modeled by cumulative distribution functions of random variables, and 2) *non-parametric selection curves*, where $r(l)$ is not modeled by cumulative distribution functions but are typically specified via general conditions such as smoothness, symmetry or non-decreasing conditions.

Normally, parametric selection curves have been preferred by researchers over non-parametric ones because their characteristics (i.e., shape) are summarized by two or three constants, *parameters*. Estimates of these parameters for different selectivity studies can later be contrasted by simple comparison or through statistical techniques, and causes for their variation assessed.

Five models have been proposed to describe parametric selection curves (Pope et al., 1975; Wileman et al., 1995). These are:

1) *Logistic (logit)*, which is the cumulative distribution function of a logistic random variable:

$$r(l) = \frac{\exp(\alpha + \beta l)}{1 + \exp(\alpha + \beta l)} \tag{1.1}$$

where α and β are the parameters to be estimated. This curve is also known as the logit curve because $\alpha + \beta l = \log_e\left(\frac{r(l)}{1 - r(l)}\right) = logit(r(l))$.

2) *Normal probability ogive (probit)*, which is the cumulative distribution function of a normal random variable:

$$r(l) = \Phi(\alpha + \beta l) \tag{1.2}$$

where Φ is the cumulative distribution function of a standard normal random variable. This curve is termed probit because it can be rewritten $\alpha + \beta l = \Phi^{-1}(r(l)) = probit(r(l))$.

3) *Gompertz (log-log)*, which is the cumulative distribution function of an extreme value random variable:

$$r(l) = \exp\left(-\exp\left(-(\alpha + \beta l)\right)\right) \tag{1.3}$$

The name log-log derives from the expression: $\alpha + \beta l = -\log_e\left(-\log_e(r(l))\right)$.

4) *Negative extreme value (complimentary log-log)*, which is the compliment of the Gompertz curve:

$$r(l) = 1 - \exp\left(-\exp(\alpha + \beta l)\right) \tag{1.4}$$

which can also be rewritten as: $\alpha + \beta l = \log_e\left(-\log_e(1 - r(l))\right)$.

5) *Richards curve*, which is a generalization of the logistic curve that includes an asymmetry parameter, δ, in the form:

$$r(l) = \left(\frac{\exp(\alpha + \beta l)}{1 + \exp(\alpha + \beta l)}\right)^{1/\delta} \tag{1.5}$$

When δ = 1, the curve becomes a logistic. Therefore the null hypothesis of a symmetric logistic curve can be statistically tested against the asymmetric Richards alternative.

Expression (**1.5**) can be rewritten as: $\alpha + \beta l = \log_e\left(\frac{r(l)^\delta}{1 - r(l)^\delta}\right) = logit\left(r(l)^\delta\right)$.

The logistic (**1.1**) and normal (**1.2**) selection curves are symmetric about the length of 50% retention, with the logistic having slightly heavier tails (Fig. 1.1 *a*). The Gompertz (**1.3**) and negative extreme value (**1.4**) curves are asymmetric about the length of 50% retention. The Gompertz curve has a longer tail to the right of the length of 50% retention, so that some large fish may not be retained. The negative extreme value, on the other hand, has a longer tail to the left, implying that some small fish may be retained (Fig. 1.1 *a*). In Richards curves (**1.5**) the value of the extra parameter δ determines the type of asymmetry. When δ > 1, the curve has a longer tail to the left of the length of 50% retention, behaving more or less as a negative extreme value curve (Fig. 1.1 *b*). Conversely, when δ < 1, the curve behaves as a Gompertz curve.

All previous equations are expressed in terms of at least two parameters α and β, whose meanings are not only difficult to grasp but also differ among curves. In selectivity studies two parameters have been widely used to characterized mesh size selection because of their clear meanings. The first one is the *50% retention length* (L_{50}) which is the length of fish that has a probability of being retained equal to 0.5 (i.e., $r(L_{50}) = 0.5$). The second parameter is the *selection range* (SR) which is the difference in length between the fish that has a 0.75 probability of retention and that with a 0.25 probability of retention (i.e., $SR = L_{75} - L_{25}$). This is a measure of the sharpness of the mesh size selection. A net with a large SR will start retaining fish of a smaller length and will retain less fish of larger lengths than a net with the same L_{50} but shorter SR. Equations (**1.1**) to (**1.5**) can be easily reparameterized in terms of L_{50} and SR by applying the equalities displayed in Table 1.1.

Selectivity experiments

Experiments designed to measure mesh selectivity can be classified into two broad categories. The first is known as *covered codend method* where a direct measurement of the fish escaping through the codend meshes is obtained by placing a small mesh cover around the test codend to collect the fish not retained by the codend (Fig. 1.2). The second category of experiments can be termed *paired-gear methods*, which includes the alternate haul, parallel haul, twin trawl and trouser trawl methods (Fig. 1.3). In each of these methods, two gears of similar overall dimensions are towed alternatively (e.g., alternate haul) or alongside each other (e.g., parallel haul, twin trawl and trouser trawl methods). All paired-gear methods are unable to provide direct measurements of selectivity; instead, they give relative measurements. Basically, they compare the retention of a test codend or gear with that of a standard, usually less selective codend or gear, allowing for the probability that unequal numbers of fish may have entered the two gears.

Being the only way of obtaining direct measurements of fish escaping through the codend, covered-codend experiments have been favored by fisheries researcher since early this century (e.g., Todd, 1911). In theory, provided that the cover is made of meshes small enough to retain all fish within the selection range of the codend meshes, the length composition of the catches in cover and codend will give an approximate measure of the length distribution of the fish population on the path of the net (Fig. 1.4). Only those fish that manage to escape the trawl or that are too small to be retained by the cover will not be represented in the catch of codend and cover. Thus a measurement of the proportion of fish retained by the codend by length class is obtained as $r(l) = \frac{n_{codend}(l)}{n_{codend}(l) + n_{cover}(l)}$, where *n(l)* are the numbers retained by length class. However, the covered-codend method has been suspected of providing biased estimates of mesh selection. Sometimes fish which would normally escape from the codend if it were uncovered are prevented from doing so by the presence of the cover. This effect known as "masking", that have been reported for many experiments (e.g., Davis, 1929, 1934; Guland, 1956; Beverton and Holt, 1958; Templeman, 1963; Fonteyne, 1991), can consist of the cover physically blocking the codend meshes, fish swimming back into the codend from the cover, fish perceiving the presence of the cover, and effects on water flow through the codend (Smolowitz, 1983). Davis (1934) suggested the use of cane hoops (Fig. 1.2) to reduce the risk of physical masking. In recent years this idea has been updated using modern materials (Fig. 1.2). The cover is held away from the codend by attaching two or more hoops around its circumference on the outside of the cover. The hoops aim to prevent any contact between cover and codend especially at the point where the catch expands to form a bulge. The hooped cover method has been used with success on demersal fish and *Nephrops* single trawls, fish and *Nephrops* twin trawls, pair trawls, pair seines and Danish anchor seines (Wileman et al., 1996). The use of hooped covers may be less appropriate for beam trawls (e.g., Fonteyne, 1991) or for certain pelagic fisheries such as walleye pollock, mackerel and herring where large catches may make the hauling procedure and the handling of both codend and cover very difficult. Moreover shooting and hauling may present severe difficulties in poor weather conditions. There is also a limit to the size of the hoops that can be used. Hooped covers may not be feasible with codends with circumferences larger than 10 m (Wileman et al., 1996).

The *parallel haul method* involves two vessels fishing on the same grounds at the same time. The only difference between their gears is the gear design feature whose effect on selectivity is to be measured. When measuring codend mesh selectivity, for example, the experimental gear whose selectivity needs to be measured is towed by one vessel and a gear of identical design but with a small mesh codend is towed by the other in order to obtain an estimate of the population of the target species entering the experimental codend (Fig. 1.5). The two ships fish in the same area and tow at the same speed so that the fishing operation is duplicated closely on the two vessels. The main aim of this method is to avoid the bias caused by a cover. In spite of the advantage that the experimental codend is fished under normal commercial conditions, the parallel haul method presents some drawbacks. Firstly, the need for two vessels will probably double the cost of the experiment. Secondly, the two nets will not normally encounter the same populations despite their proximity (Fig. 1.5). Although this bias can be somewhat handled in the analysis (e.g., Millar, 1992), the estimated variance of the selectivity parameter estimates is likely to exceed that of parameter estimates from covered-codend and trouser trawl experiments due to vessel/gear differences. Moreover, the variance in the parallel haul method is increased compared to the alternate haul methods because of more vessel/gear differences but may be decreased because of the reduction in time and environmental differences.

In *twin trawl methods*, one vessel tows two similar trawls simultaneously side by side (Fig. 1.3 *a*). The experimental codend is attached to one of the twin trawls, and a smaller mesh codend is attached to the other trawl to obtain an estimate of the total fish population entering the experimental codend. A pair of beam trawls (Fig. 1.3 *b*) may be considered as a special case of twin trawls. As with the parallel haul method, the twin trawl method is free from any bias caused by the use of a cover, but it is also subject to the bias produced by not encountering exactly the same fish population (Fig. 1.5). In spite of this disadvantage, the method is particularly adequate for fisheries that traditionally use twin or beam trawls. However, the behavior of the fish ahead of the trawl, and hence their susceptibility to capture, may be affected by the wire rigging between the trawl and the vessel. Thus, twin trawl selectivity experiments cannot be recommended for conventional single trawl fisheries.

The *trouser trawl method* is a variation of the twin trawl method whereby a standard trawl is divided down the middle by a vertical panel (Fig. 1.3 *c*). The experimental and control (small mesh) codends are attached to the aft end, one on each side of the panel. The design is based upon the premise that an equal number of fish with similar length composition will enter each side of the trawl. While the trouser trawl does not have any special rigging which may affect the behavior of fish in the path of the trawl and is free from the bias caused by a cover, sometimes the experimental codend collects more of the larger fish than the small mesh codend (Fig. 1.5). Also, strong currents, inaccurate wire lengths or other effects can cause bias towards one side of the net. Although these differences in catching efficiency between both sides of the trouser trawl can often be dealt with during the statistical analysis (Millar, 1992), the variance of the selectivity estimates are likely to be larger than those from covered codend experiments, but probably smaller than those from parallel haul, twin trawl and alternate haul experiments. It is arguable whether selectivity estimates from trouser trawl experiments are representative of the mesh selection occurring in commercial fishing (Wileman et al., 1996, p. 12). Moreover, it would be very difficult or impossible to design efficient trouser trawls for the large pelagic trawls used in most high-volume pelagic fisheries (e.g., Bering sea walleye pollock).

The *alternate haul method* consists of a vessel alternately towing two (or more) uncovered codends on the same grounds. As with other paired-gear methods one of the codends is made of small meshes, and is used to collect information about the length composition of the fish entering the experimental codend. This method attempts to mimic commercial fishing conditions while avoiding any bias caused by the presence of a cover, by the reaction of fish to a particular rigging or to a split trawl (e.g., twin and trouser trawls, respectively), or by differences due to trawl/gear interactions, that might occur in parallel trawls. Like other methods the alternate haul is not free of disadvantages. Firstly, the population estimate may not represent accurately the population met by the experimental codend which is fished at a different time, under possibly different conditions (e.g., light level, weather, sea currents) and, to certain extent, over a different area of seabed (Fig. 1.6). These difference may be minimized but can never be eliminated. They can cause greater variance in the selectivity estimates, resulting in the need for a longer series of hauls. Secondly, alternate haul experiments require larger number of hauls since two hauls are required in order to calculate a single selection curve for one codend. This increases the cost of the experiment, and places the method at a disadvantage compared to covered codend and trouser trawl methods.

Selectivity estimation

Methods to estimate mesh selection (i.e., fitting a selection curve, either a parametric or a non-parametric) differ between the two main classes of selectivity experiments. If data comes from covered-codend experiments, the estimation procedure needs to fit a selection curve to the observed proportions of fish retained by the codend, $\frac{n_{codend}(l)}{n_{codend}(l)+n_{cover}(l)}$. For paired-gear experiments, on the other hand, the estimation procedure is not trivial since the data are not a direct measurement of selectivity. Estimation is based on the comparison of the numbers retained by the experimental or test codend and those retained in the small mesh or standard codend. Thus it has to deal with two problems, 1) the two codends do not actually fish on the same population, and 2) the codends may fish with different efficiency.

Covered-codend data can be fitted using a number of estimation procedures. In the 1950s and 60s it was customarily to fit straight lines to the 0.25 to 0.75 observed proportions by weighted or unweighted least squares. Nowadays, the whole range of observed proportions can be fitted to any of the parametric selection curves mention earlier using non-linear least squares (Ratkowsky, 1983). Maximum likelihood estimation

(MLE) can also be used. Assuming that the number of length l fish retained in the codend $n_{codend}(l)$ are binomially distributed, the log-likelihood to be maximized becomes $\sum_{l}\left(n_{codend}(l)\log_e r(l)+n_{cover}(l)\log_e(1-r(l))\right)$, where $r(l)$ is any of the parametric selection curves expressed by equations **(1.1)** to **(1.5)**, and $n_{cover}(l)$ is the number of length l fish retained in the cover. MLEs can be obtained using any of the available software packages that use iterative non-linear optimizers (e.g., EXCEL©, SYSTAT©, SAS©,). Pope et al. (1975) gave approximate MLEs based on a crude version of iterative least squares in which the least squares line was fitted by eye, which apparently give estimates very close to the exact MLEs (Wileman et al., 1996, p. 77). Generalized linear models (McCullagh and Nelder, 1989) can also be used when $r(l)$ is represented by the logistic, normal, Gompertz and negative extreme value curves. Some alternative estimation procedures are also available to fit non-parametric $r(l)$s. For example, Millar (1993) used isotonic regression and the PAV (pool adjacent violators) algorithm (Barlow et al., 1972, p. 13) to fit non-parametric, non-decreasing selection curves. Holst and Tschernij (1996) also fitted non-parametric curves, but their curves were not constrained to be non-decreasing (i.e., the proportions of length l fish retained in the codend were allowed to fluctuate between 0 and 1). The technique used in this case is known as Gausian kernel smoother (Hastie and Tibshirani, 1990).

Until the end of the 1980s paired-gear data were fitted to logistic and probit selection curves using what can be termed "ratio methods" (e.g., Pope et al., 1975; Kimura, 1980; Simpson, 1989). These methods attempt to fit the proportions $\frac{n_t(l)}{n_s(l)}$, where $n_t(l)$ are the numbers-at-length retained in the experimental codend, and $n_s(l)$ are the numbers retained in the codend of small meshes (standard). Such approaches are based upon the belief that the length composition of catch by the standard codend represents the fish population that encounters the experimental codend. Since this assumption is rarely true and moreover the fishing efficiency of both codends may differ $\frac{n_t(l)}{n_s(l)}$ is likely to produce biased estimates of mesh selection. Many researchers were well aware of this hindrance of paired-gear data (e.g., Davis, 1934; Beverton and Holt, 1958; Templeman, 1963; Pope et al., 1975), in particular because the ratios $\frac{n_t(l)}{n_s(l)}$ when plotted against length produced very rugged curves with values greater than 1 for most of the largest length classes. Remedy to these problems was found in smoothing the original data and discarding part of it prior to curve fitting. For example, Pope et al. (1975) generalized a correction procedure, initially suggested by Beverton and Holt (1958), by which the original ratios $\frac{n_t(l)}{n_s(l)}$ are multiplied by the factor $\sum_l n_s(l) \Big/ \sum_l n_t(l)$, where the summation is applied to all lengths l for which $\frac{n_t(l)}{n_s(l)}$ is greater than 1. Simpson (1989) smoothed the original ratios by means of a three-point moving average, and discarded all but the first smoothed ratio that exceeded 1. In both approaches the modified ratios were later fitted to logistic curves using least squares.

In recent years better techniques that try to avoid ad hoc corrections, smoothing and the discarding of original data have been developed. An appropriate statistical model for analysis of paired-gear data that accommodates the possibility of different fishing or sampling efficiencies between codends was developed in 1990 (Millar and Walsh 1990, 1992; Millar, 1992). The methodology is now widely used (Wileman et al., 1996) and commonly known as the SELECT (Share Each Lengths Catch Total) method. SELECT makes use of the binomial assumption as a natural generalization of the analysis of covered-codend data. Whereas in covered codend experiments the fate of a length l fish is determined by the probability of being retained by the codend $r(l)$, in paired-gear experiments its fate is determined by the probability of being taken in the experimental codend or in the small mesh codend. The probability of being caught in the experimental codend, $\phi(l)$, is modeled as:

$$\phi(l) = \frac{pr(l)}{pr(l)+(1-p)},$$ where $r(l)$ is the retention probability expressed as any of the parametric functions in equations (1.1) to (1.5), and p is the probability that a fish entered the experimental codend, given that it entered either the experimental or the standard codends. The parameter p has been termed "split parameter" (Millar and Walsh, 1992), "relative fishing intensity" (Millar, 1992) and "relative fishing power" (Wileman et al., 1996, p.70). It is supposed to take account of differences in fishing power, fishing effort, and targeted fish concentrations between experimental and control gears, as well as to quantify differences in sampling fractions when the codend catches are not fully measured (Wileman et al., 1996, p.70). Estimates for p and the selectivity parameters describing $r(l)$ are obtained by maximizing the log-likelihood $\sum_{l}\left(n_t(l)\log_e \phi(l) + n_s(l)\log_e\left(1-\phi(l)\right)\right)$. The maximization of this likelihood requires the use of an iterative non-linear optimizer.

Factors affecting size selection of fish

There are many factors which have been shown, or are suspected, to affect fish size selection. Knowledge of these factors is needed in order to plan successful selectivity experiments. The list of factors affecting size selection is quite extensive. It includes factors related to else the gear and the vessel (e.g., mesh size and shape, codend diameter, codend length, twine characteristics, rope hanging ratio, attachments to codend, cover type, design of gear ahead of codend, hauling procedure, towing speed and towing time), the fish (e.g., fish size and shape, fish population availability, rate of accumulation in net and catch size) or the physical environment (e.g., water temperature, time of the day, sea state, seabed type and water depth). Some of these factors interact in such intricate or unpredictable ways that it is not always possible to control them when planning experiments.

The literature (e.g., Pope et al., 1975) suggests that size and shape of the mesh and their relationships to fish shape and dimensions are probably the most significant factors in all of mesh selection processes. Since the concept of L_{50} began to be used to describe mesh selection (Todd, 1911; Buchanan-Wallaston, 1929) and the simple straight line relationship between L_{50} and the inner length of the mesh was developed (Jensen, 1949), many studies have shown that L_{50} increases as mesh size increases (see reviews in Clay, 1979, and Perez Comas and Pikitch, 1994). These relationships are species-specific because it is the relationship between the cross-sectional shape of the fish (often called girth) and the mesh circumference or shape what ultimately determines the chances that a fish has of escaping the net (e.g., Margetts, 1954, 1957; Gulland, 1956; Jones, 1963; Hodder and May, 1965). Thus, flatfish (e.g., plaice, sole, dab) and roundfish species (e.g., hake, cod, haddock) are expected to have different selection curves for similar codends, simply because they have very different cross-sectional shapes. However, the behavioral response of particular species to a net is also a key factor of mesh selection. For example, Clark (1963) has demonstrated that silver hake has a lower escape response than other demersal species.

The orientation and hanging of the netting (i.e., how it is rigged onto the sevedge ropes) determines how open the meshes will be. Thus these factors operate together with the cross-sectional shape of the fish to influence selectivity. For example, when compare to diamond mesh of similar size, the use of square mesh netting has been shown to increase the L_{50} of roundfish species (Robertson, 1983; Cooper and Hickey, 1987, 1989; Robertson and Stewart, 1988; Dahm, 1991), and to decrease that of flatfish species (Walsh et al., 1992).

Twine material and its characteristics and their influence on mesh selection have received considerable attention (e.g., Boerema, 1956; Cieglewicz and Strzyzewski, 1957; Pope et al., 1958; Roessingh, 1959; von Brandt, 1960; Bohl, 1961, 1967, 1968, 1971;

Shevtsov, 1979; Lowry and Robertson, 1996). However, how this factor operates is still a mystery. Twines may differ in more than a dozen ways, such as fiber type, method of construction, runnage, treatment, elongation properties, strength, flexibility and physical size. All these characteristics may interact with other factors and have an effect on a gear's selectivity (e.g., ICES, 1964, p. 148; Pope et al., 1975, p. 35; Ferro and O'Neill, 1994).

Besides twine material, and yet other gear design characteristics, may also affect selectivity. For example, shortening codend length appeared to increase L_{50} (Dahm, 1991). Moreover, for diamond meshes, any reduction of codend circumference (Galbraith et al., 1994) or reduction of both codend circumference and codend extension (Reeves et al., 1992) seem to make trawls and seines more selective.

Few attempts have been made to determine whether towing speed has an effect on gear selectivity but no consistent result has been found. For example, mesh selection experiments for dab (Boerema, 1956) suggested that variations in towing speed, so long as they were not extreme, had little effect on mesh selection (L_{50}). On the other hand, Saetersdal (1958, 1960) found weak negative correlations between L_{50} and towing speeds within the range 2-4 kn for cod but not for haddock. Experiments to effectively test for the effect of towing speed on selectivity are certainly difficult to design because, among other things, it is difficult to accurately measure the speed of the trawl over the bottom maintaining other parameters constant (Smolovitz, 1983).

For all towed fishing gears using flexible netting it is likely that selection varies considerably during a haul as the catch increases. The number of open meshes available for escape is continuously reduced as the catch bulge increases, and more meshes are blocked by fish (Jones, 1963, p. 120-121; Robertson and Stewart, 1988, p. 148). This process can be accelerated if a codend of a given size, towed at a particular speed, encounters a high density of fish. Moreover, individual fish in densely packed schools entering the net have less probability of approaching an open mesh. In these cases, the resulting fish retention will then be increased. In fact many selectivity experiments have shown a negative correlation between total catch size and selectivity parameters, such as L_{50} (Table 1.2).

Tow duration also appears to influence mesh selection, but as with towing speed experimental results have been somewhat inconsistent. In theory a longer tow provides a fish with more opportunity to attempt escape from the codend, thus longer tows are expected to produce selection curves with larger L_{50}'s. Such tendency has been suggested by selectivity experiments on demersal species (e.g., haddock, hake and whiting) with tow duration ranging from 0.5 to 3 hours (Gulland, 1956; Hillis, 1962; Pope and Hall, 1966). Strong positive correlations between tow duration and L_{50} have been documented in controlled haddock and cod selectivity experiments with tow duration ranging from 0.3 to 0.7 hr (Beverton, 1959, 1964; Clark, 1957,1963). However, other experiments failed to show the influence of tow duration (Parrish and Pope, 1957). Tow duration is closely linked with the size and composition of the catch. Thus, it is expected that when changes in the duration of tow are accompanied by changes in the size of the catch, both factors will interact. The effect of tow duration may be masked, and thus become more difficult to detect.

Scope of this study

The present study is focused on the analysis of selectivity data from alternate-haul experiments. The majority of the examples used in following chapters came from experiments carried out on fishing grounds off the coasts of Washington, Oregon and northern California, and in the Bering Sea. In all the experiments, the only controlled variables were related to the codend. Especially designed codends were distributed among commercial fishing vessels that towed them on their usual fishing grounds. Except for the order in which each vessel towed the various experimental codends and the small-mesh codend, which were determined by the investigators, all other decisions concerning the fishing operation were made by the skippers of the participant vessels. As such, the fishing vessels operated in a way very close to commercial fishing.

In the next chapter I analyze pooled selectivity data for a series of commercially important flatfish and rockfish species. I estimate overall mesh selection curves for a series of codends with meshes of different sizes and shapes. The five parametric curves presented earlier (eqs. 1.1 to 1.5) are used in the analysis to assess the symmetry of the mesh selection curves. The effects of mesh size and shape, and their relation with the fish cross-section are discussed.

In Chapter 3, a new model for the analysis of alternate-haul data is developed and compared with other models traditionally used to fit parametric selection curves. In Chapter 4, I present alternative non-parametric approaches for the analysis of selection curves. The model developed in Chapter 3 is modified in Chapter 5 to explore the possibility of a simultaneous estimation of selection curves for experimental and control codends.

Finally, in Chapter 6, I address the issues of between-haul variability and uncertainty in alternate-haul assumptions. I perform a multiple hauls selectivity analysis of data from experiments for walleyed pollock, and develop an approach to assess the effects of codend type, catch size and towing speed that incorporates the uncertainty in alternate-haul assumptions.

Table 1.1: Equations for reparameterization of models (1.1) to (1.5) in terms of 50% retention length (L_{50}) and selection range (SR).

Selection curve	L_{50}	SR
Logistic **(1.1)**	$-\dfrac{\alpha}{\beta}$	$\dfrac{2\log_e(3)}{\beta}$
Probit **(1.2)**	$-\dfrac{\alpha}{\beta}$	$\dfrac{2\Phi^{-1}(0.75)}{\beta}$
Gompertz **(1.3)**	$\dfrac{-\log_e(-\log_e(0.5))-\alpha}{\beta}$	$\dfrac{\log_e\left(\dfrac{\log_e(0.25)}{\log_e(0.75)}\right)}{\beta}$
N. E. V.[1] **(1.4)**	$\dfrac{\log_e(-\log_e(0.5))-\alpha}{\beta}$	$\dfrac{\log_e\left(\dfrac{\log_e(0.25)}{\log_e(0.75)}\right)}{\beta}$
Richards **(1.5)**	$\dfrac{\log_e\left(\dfrac{0.5^\delta}{1-0.5^\delta}\right)-\alpha}{\beta}$	$\dfrac{\log_e\left(\dfrac{0.75^\delta}{1-0.75^\delta}\right)-\log_e\left(\dfrac{0.25^\delta}{1-0.25^\delta}\right)}{\beta}$

[1] Negative extreme value

Table 1.2: References that illustrate a catch-volume effect on codend selection.

Species	Trawl-type	Codend mesh	Experimental method	Catch volume	Reference
Cod	Demersal	Diamond	Cover	5-110[a]	Beverton (1959)
Redfish	Pelagic	Diamond	Cover	100-2,500[b]	von Brandt (1960)
Redfish	Pelagic	Diamond	Cover	300-1,300[b]	Bohl (1961)
Haddock	Demersal	Diamond	Cover	350-3,100[b]	Clark (1963)
Redfish	Pelagic	Diamond	Cover	250-2,400[b]	Clark (1963)
Haddock	Demersal	Diamond	Cover	200-3,000[b]	McCracken (1963)
Cod	Demersal	Diamond	Cover	200-3,000[b]	McCracken (1963)
Cod	Demersal	Diamond	Cover	5-110[a]	Beverton (1964)
Haddock	Demersal	Diamond	Alternate	3-396[a]	Hodder and May (1964)
Cod	Demersal	Diamond	Cover	48-661[c]	Hodder and May (1964)
Cod	Demersal	Diamond	Cover and Trouser	0.1-2[d]	Isaksen et al. (1990)
Haddock	Demersal	Diamond	Cover and Trouser	0.1-2[d]	Isaksen et al. (1990)
Herring	Pelagic	Diamond and Hexagonal	Trouser	0.2-2.6[d]	Suuronen et al. (1991)
Herring	Pelagic	Diamond and Square	Cover	50-1,800[c]	Dahm (1991)
Mackerel	Pelagic	Square	Alternate	3-60[d]	Casey et al. (1992)
Herring	Pelagic	Diamond and Square	Trouser	0.1-2[d]	Suuronen and Millar (1992)
Whiting	Demersal	Square	Cover	0.2-0.7[d]	Madsen and Moth-Poulsen (1994)
Pollock	Pelagic	Diamond and Square	Alternate	3-60[d]	Erickson et al. (1996)

[a] baskets (1 basket ≈ 43 kg)
[b] individual fish
[c] kg
[d] mt
[c] kg

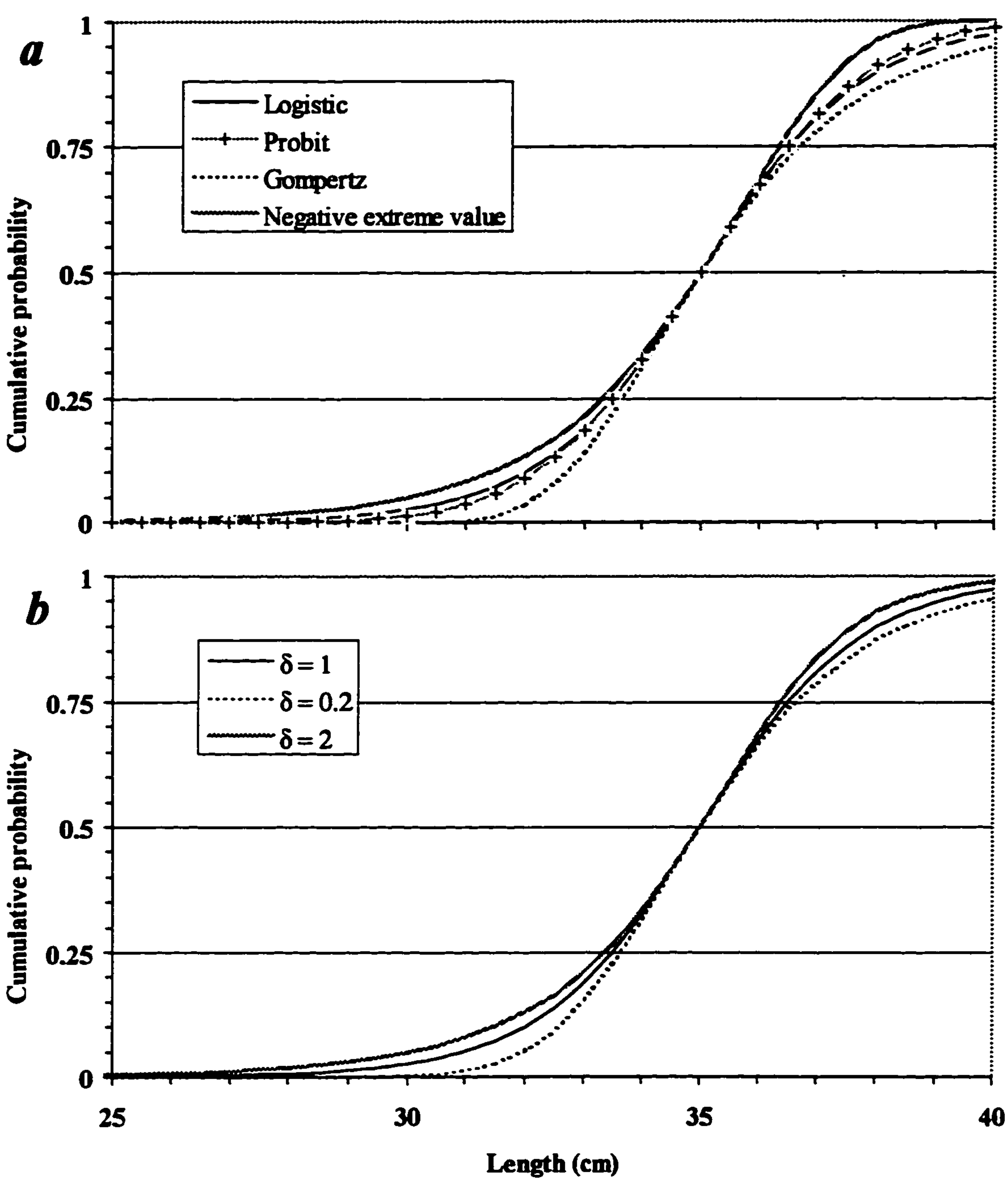

Figure 1.1: Cumulative density functions for 2-parameter (***a***), and 3-parameter (***b***) selectivity curves with L_{50} = 35 cm and SR = 3 cm.

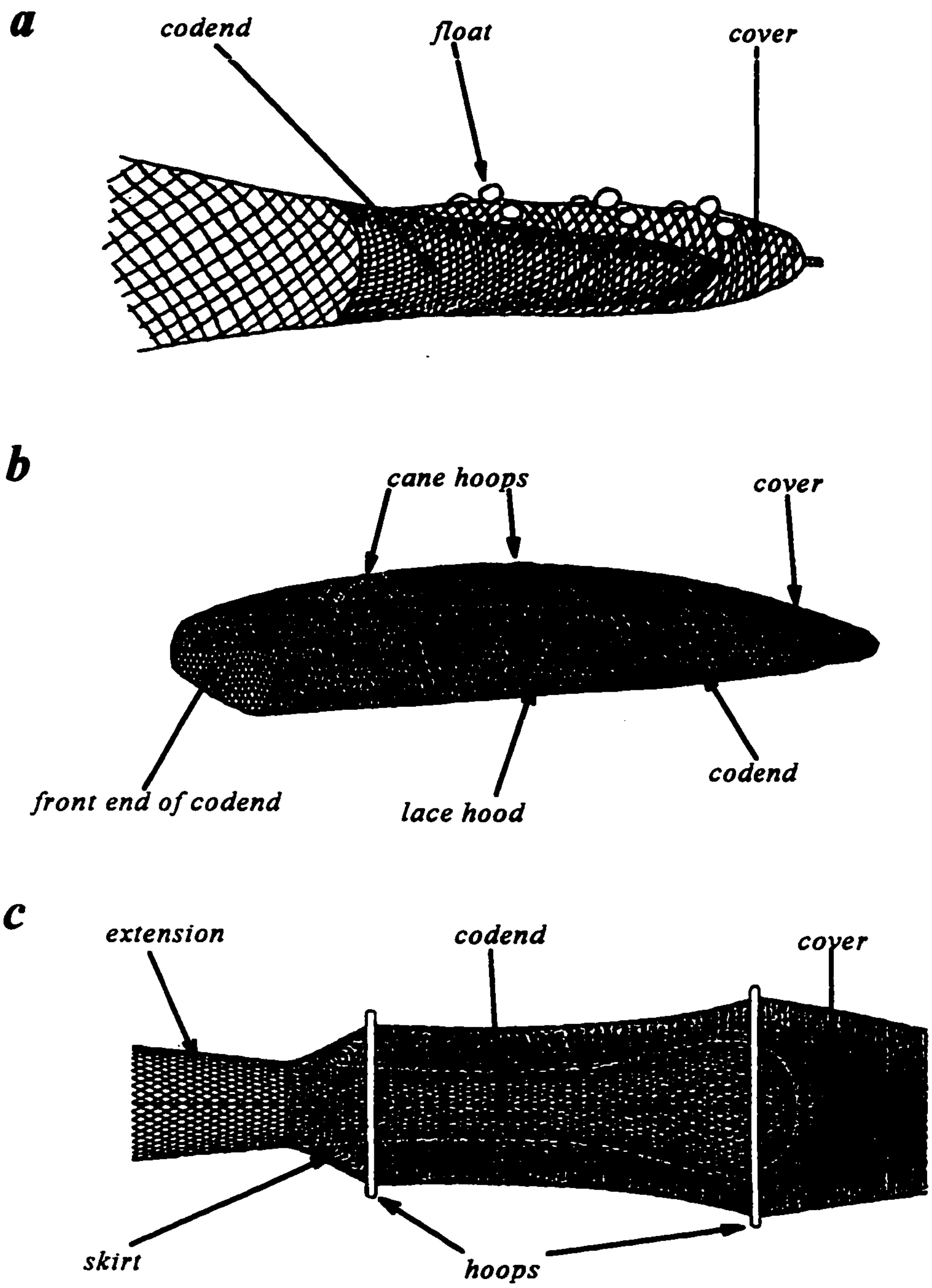

Figure 1.2: Different types of covered codends. ***a***) cover rigged with floats (redrawn from Rijnsdorp et al., 1981), ***b***) cover with inside cane hoops (redrawn from Davies, 1934), ***c***) modern hooped cover (redrawn from Wileman et al., 1996).

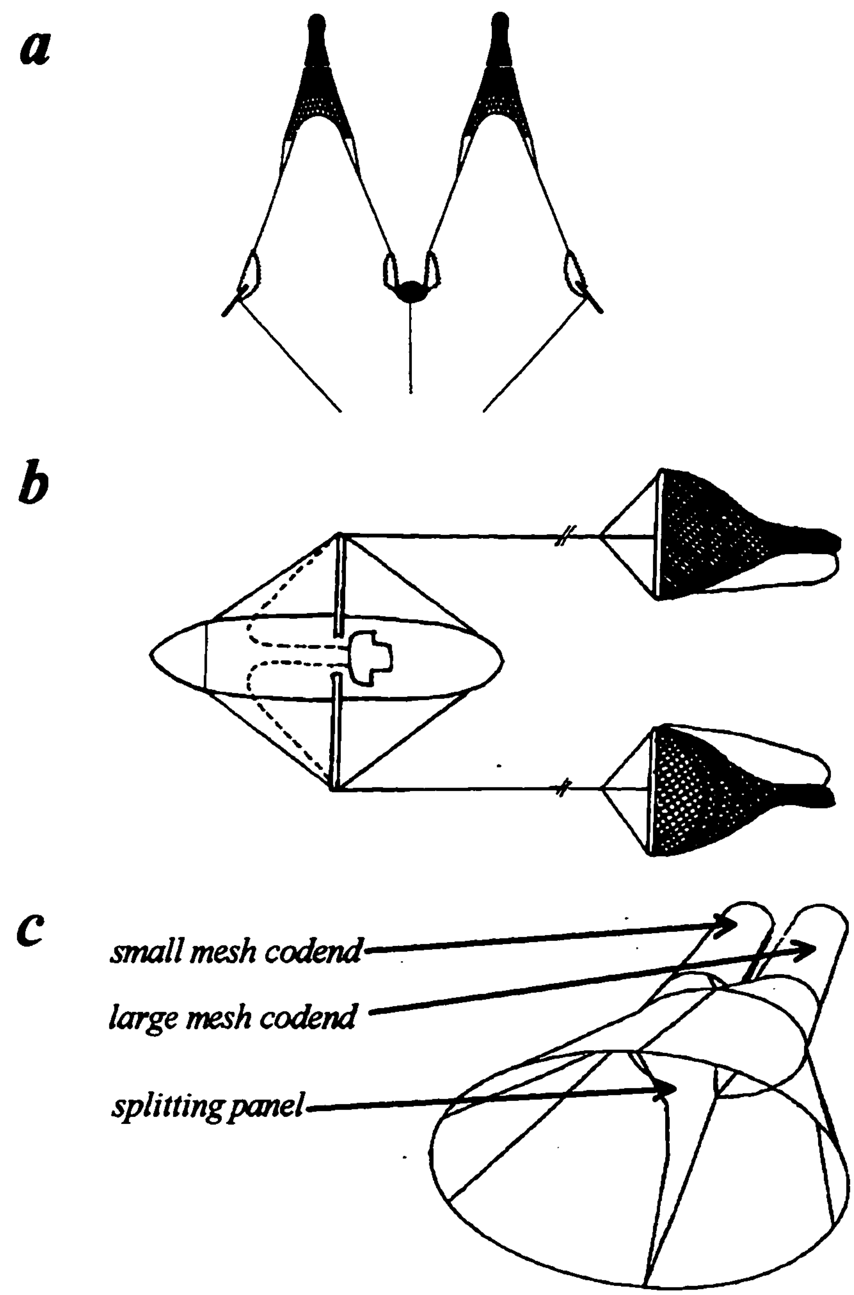

Figure 1.3: Some paired-gear methods. ***a***) twin trawl (redrawn from Wileman et al., 1996), ***b***) pair of beam trawls (redrawn from Fonteyne and M'Rabet, 1992), and ***c***) trouser trawl (redrawn from Wileman et al., 1996).

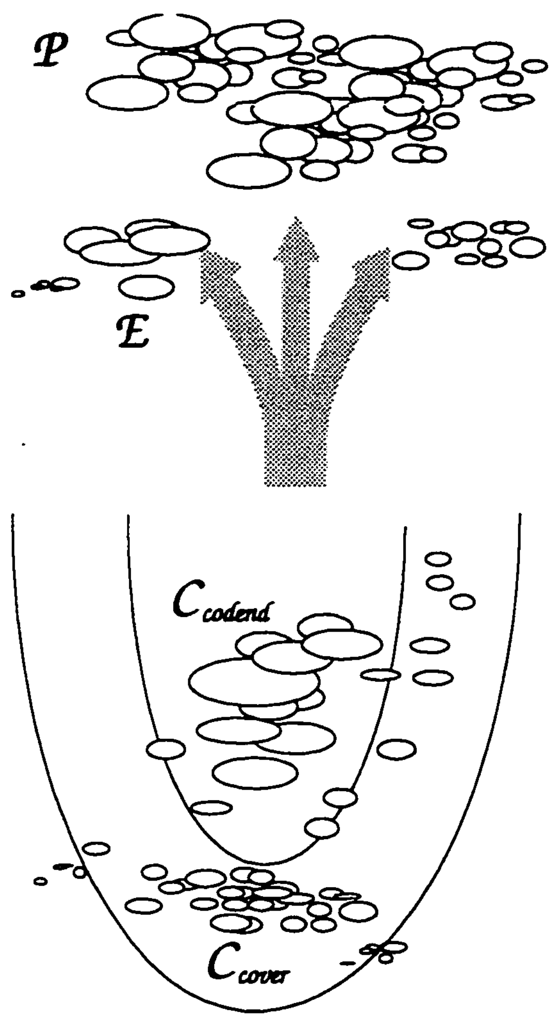

Figure 1.4: Diagram of a covered-codend experiment. For a given fish population ($\mathcal{P}$) on the path of the net, some fish are not caught ($\mathcal{E}$). Of the fish caught, those small enough to pass through the meshes of the codend but not through those of the cover are retained in the cover (C_{cover}). The fish that are too large to pass through the meshes of the codend are retained as catch (C_{codend}).

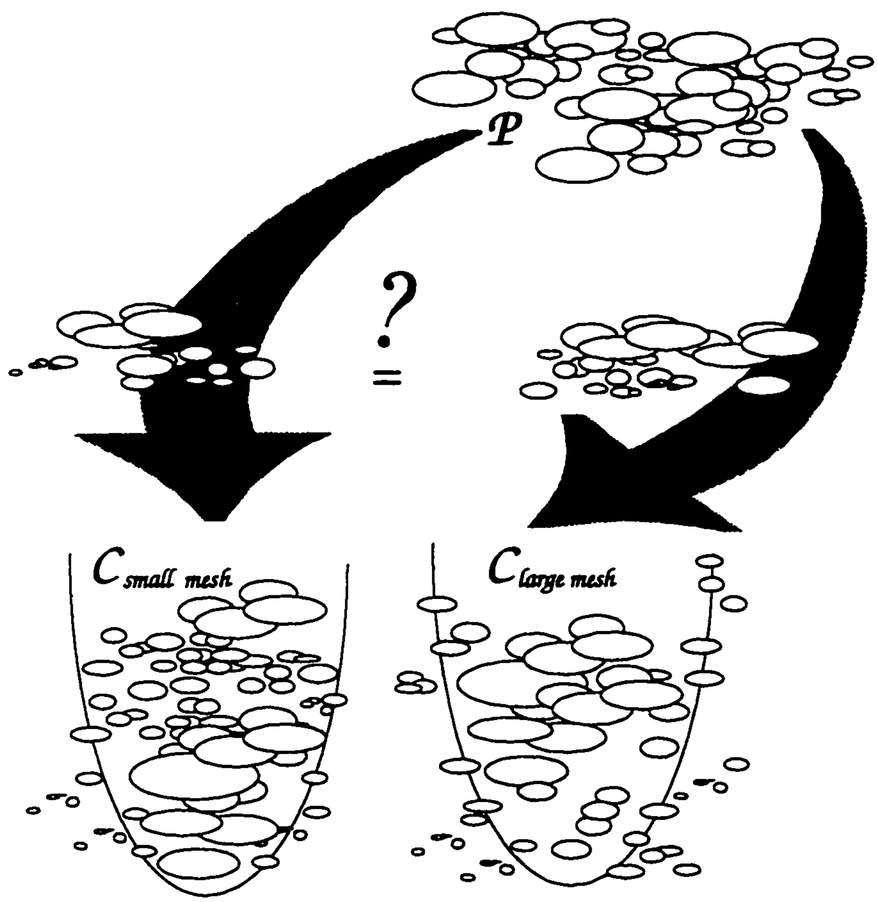

Figure 1.5: Diagram for parallel-haul, twin-trawl, paired beam-trawl or trouser-trawl experiments. For a given fish population ($\mathcal{P}$) on the path of the net, some fish enter the large mesh codend with those too large to pass through the meshes being retained ($C_{large\ mesh}$) and most of the small fish escaping the codend. Other portion of the fish population enters the small mesh codend where more small fish are retained as catch ($C_{small\ mesh}$). The fish entering each codend may not have the same size composition.

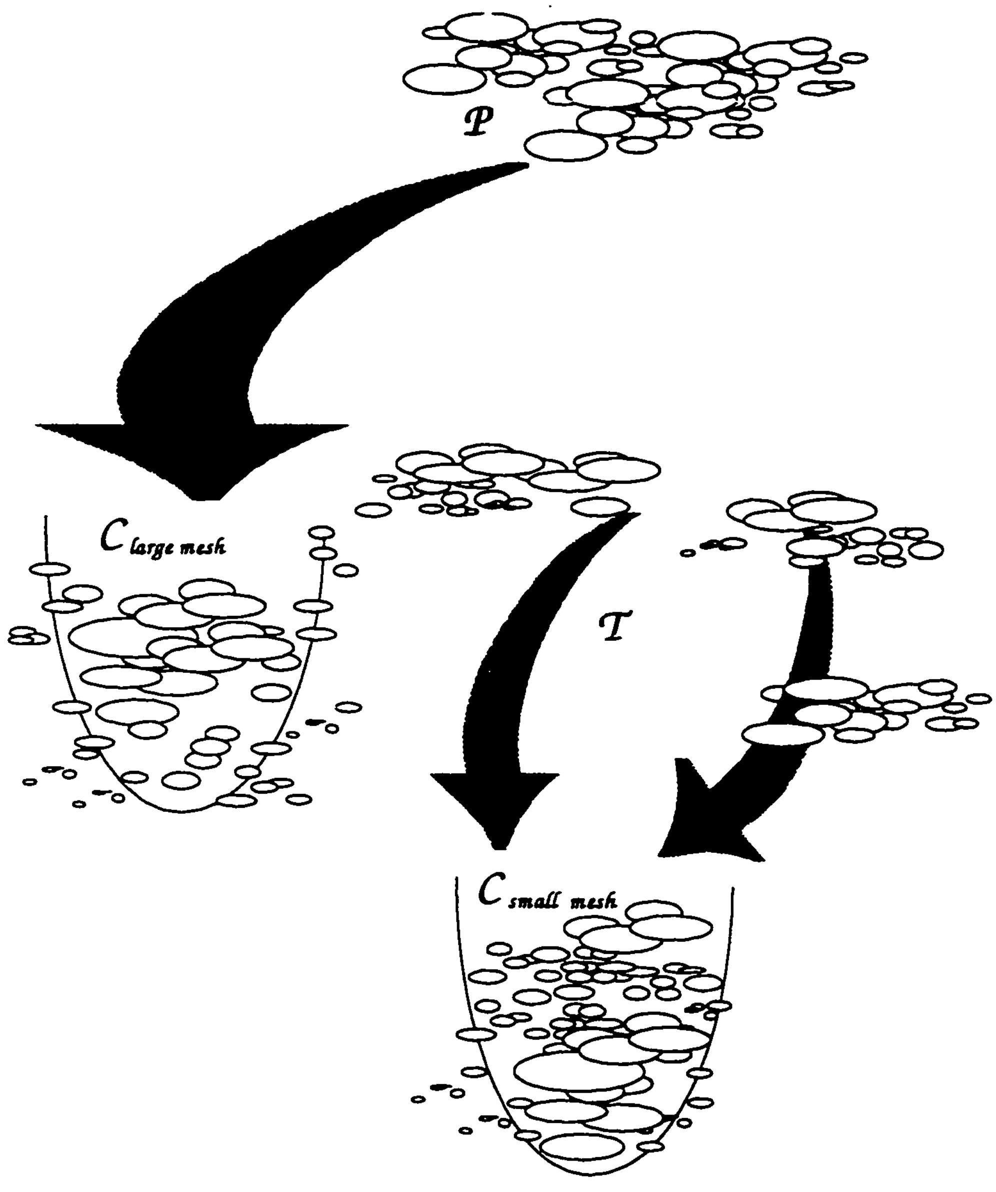

Figure 1.6: Diagram of an alternate-haul experiment. For a fish population ($\mathcal{P}$) on the path of the nets, some fish enter the large mesh codend with those too large to pass through the meshes being retained ($C_{large\ mesh}$) and most small fish escaping the codend. Other fish enter the small mesh codend where more small fish are retained as catch ($C_{small\ mesh}$). As time ($\mathcal{T}$) passes the size composition of the population entering the small mesh codend is likely to change.

2. Determining the shape of the selection curve for West Coast rockfish and flatfish

Introduction

Since early this century researchers studying the size selectivity properties of codends started representing selection as an S-shaped curve of percent retained or percent released by fish length (e.g., Davis, 1929, 1934; Buchanan-Wollaston, 1929). Although drawn by eye, those first attempts clearly show rather smooth curves with a range of small lengths for which the percent retention was zero or very close to zero, a range of larger lengths for which retention increased continually but at different rates, and some even larger lengths with 100% retention. With the coming of probabilistic and mathematical explanations (e.g., Jones, 1963) and the spread of statistical fitting techniques, made known through technical manuals published by international fisheries commissions (e.g., Pope et al., 1975), size selection began to be represented by fitted symmetric curves such as the normal cumulative ogive or the logistic, the latter being more widely used. Almost no attempt was made to fit other non-symmetrical S-shaped curves.

In recent years, the availability of more general estimation procedures and models (e.g., Millar, 1992) and the wide distribution of powerful statistical software allow the representation of size selection by other, not necessarily symmetric, S-shaped curves. Moreover, the choice of best fitted curves to selectivity data have been recently encouraged as a desirable procedure (Wileman et al., 1996).

In this chapter I analyzed the length samples collected by the West Coast Groundfish Mesh Size study off the coasts of Washington, Oregon and California to obtain the selection curves of five flatfish and five rockfish species for a series of diamond and square mesh codends. In doing so, I fitted the data to two symmetric curves (cumulative normal ogive or probit, and logistic) and to three asymmetric curves, the two-parameter Gompertz and negative extreme value curves, and the three-parameter Richards curve, that have been recently proposed as an acceptable alternative to symmetric curves (Millar, 1991). My analysis attempts not only to obtain the best fits to the data which will enable better descriptions of size selection patterns, but also to assess the frequency with which asymmetric curves are better options than the commonly used symmetric logistic curve.

Material and methods

Data collection

The main data used in the present selectivity analysis were collected through the West Coast Groundfish Mesh Size (W.C.G.M.S.) study (Pikitch et al., 1990; 1991a, 1991b), a multiphase, interdisciplinary research effort whose field activities spanned from 1988 to 1990 on an area extending from 48°30'N to 34°40'N and east of 126°W. The research team recognized that there was 1) a need for assessing the potential of mesh size regulations to improve the current management regime for the west coast groundfish fishery, and 2) a need for a careful evaluation of the short-term non-equilibrium effects of a change in mesh size or type. Thus, field experiments were carried out to measure those short-term effects and collect all the information required to develop predictions of long-term responses to mesh size changes. Average size selectivity curves for all the most important target species were part of this desired information. To increase cost-effectiveness and assure credibility of results by management and industry sectors, the experiments were performed on commercial trawl vessels operating under production conditions with an alternate-haul design.

Six types of detachable codends, that differed in mesh size and shape (diamond, D; square S) were designed and used during the 1988-90 field experiments (Table 2.1*a*). These codends had diamond meshes with between-knots openings of 76.2, 114.3, 127 and 139.7 mm (hereinafter referred to in inches as 3"D, 4.5"D, 5"D and 5.5"D), and square meshes with 114.3 and 127-mm openings (referred to as 4.5"S and 5"S). Table 2.1*b* gives their effective mesh sizes (see Pikitch et al., 1990, p. 20 for description of measuring procedure). The 3"D codend was chosen primarily because it corresponded to existing mesh regulations. For analytical purposes this small-mesh codend was taken as the standard (i.e., the one whose length samples represent the length composition of the fish entering the other experimental codends), and thus, it was tried during the three field seasons. The remaining codends were alternated among field seasons to form configurations of two or three codends that were towed, together with the standard, following a randomized block design (Bergh et al., 1990; Pikitch et al., 1990). The participating vessels, carrying the codends of a given configuration, performed sets of three or four consecutive tows directed at a particular assemblage of fish. Within each set, called a block, each of the codends was fished once, according to a predetermined randomized design.

In each field season, considerable amount of data were collected, including information related to both the fishing trip in general (e.g., vessel and gear specifications, target species, revenues and expenses, etc) and the tows performed (e.g., tow duration and position, catch composition and weight, depth at which the tow was performed, etc). For a detailed account on data recording see Pikitch et al. (1990: 17-20).

Length data for some 20 species, identified as commercially important, were collected following a fixed-number sampling design. In the field, the objective was to measure (to the nearest centimeter) the total lengths of 100 fish for each of the 20 commercially important species present in the catch or wedged in the meshes of the codend. Frequently, the objective of 100 length measurements was not met, either because the entire catch was too small or because of time constrains. When the total catch consisted of less than 100 fish for any of the 20 species, all the catch was measured. When time was a limiting factor, sample sizes were reduced to 50 fish for each of the important species abundantly represented in the catch, and those species poorly represented in the catch (less than 10 fish) were not sampled. In all cases the weight of the length sample was recorded.

Although information on some 20 commercially important species was collected during the whole W.C.G.M.S. study, the present selectivity analysis dealt with only 10 of these species: five rockfish and five flatfish (Tables 2.2 and 2.3).

A second and smaller data base, collected during the 1989 triennial West Coast Goundfish survey of the National Marine Fisheries Service (NMFS), was used to check the plausibility of the selectivity estimates. The survey was carried out by two chartered vessels that swept the west coast waters between 48°30'N and 34°35'N. During the survey, samples for the five rockfish and five flatfish were collected at different locations. For each individual three measures were recorded: *a*) total length, *b*) width (i.e., maximum horizontal measurement) and *c*) depth (i.e., maximum vertical measurement). Both width and depth refer to the natural orientation of the fish in the water. All measurements were taken to the nearest millimeter.

Processing of length frequency distributions

Given that the number of fish sampled turned out to be too low to furnish complete and smooth length-frequency distributions on a haul-to-haul basis, and that the objective of the W.C.G.M.S. study was to assess the overall selectivity characteristics of the experimental codends, the length samples from the different hauls were pooled. Before pooling haul samples length data were scaled by the estimated catches of the hauls. An unavoidable effect of this procedure is that the resulting pooled distributions will be dominated by the samples taken in hauls with larger catches.

Not all the length samples for the different hauls were pooled since I wanted to eliminate the presence of effects other than size selection. For example, length samples were not included *a*) if for a particular block either the experimental codend or the standard codend caught no, or only a few, fish, *b*) if the block consisted of hauls performed at very different locations, *c*) if the length samples for the experimental codends showed modes at smaller length classes than those observed in the corresponding samples for the standard codend.

Since selectivity is likely to vary between hauls, for example due to variables such as catch size (e.g., Suuronen et al., 1991, 1992; Erickson et al., 1995; Pikitch et al., 1995) and haul duration (e.g., Clark, 1957), the binomial assumption required by the fitting procedure will not remain valid[1], and the estimated standard errors will be too small.

I used a non-parametric estimator known as replication estimate of dispersion (*REP*, McCullagh and Nelder, 1989, p. 127) to evaluate the presence of between-haul variation in the pooled length frequency distributions. For each length distribution the following statistic was calculated:

$$REP = \sum_l \sum_i \frac{\left(n(l)_{t,i} - n(l)_i y(l)\right)^2}{n(l)_i y(l)(1-y(l))}\ , \text{ where } y(l) = \sum_i n(l)_{t,i} \Big/ \sum_i n(l)_i\ ,$$

and $n(l)_{t,i}$ is the number of length l fish caught in the experimental codend in haul i, and $n(l)_i$ is the number of length l fish caught in both the experimental and standard codends in haul i. Only values of $y(l)$ between 0.1 and 0.9 were used in the double summation. *REP* has an approximate chi-squared distribution with *df* degrees of freedom when there is no between haul variation and within-haul variation is binomial. (The degrees of freedoms *df* are equal to the number of terms in the double summation minus the number of length classes.) When between-haul variation is present the approximate chi-square distribution no longer holds because the replicates across different length classess are not independent. Under this situation *REP* provides a correction to both the model deviances and estimated standard errors. Model deviances are corrected by dividing the original value by *REP/df* and standard errors are corrected by multiplying by $\sqrt{REP/df}$.

Models and estimation procedure

The statistical model known as SELECT (Share Each Lengths Catch Total) developed in 1990 (Millar and Walsh, 1990, 1992; Millar, 1992) was used to fit selection curves to the pooled length frequency distributions. The model assumes that the number of fish in the experimental codend (i.e., the 4.5"D, 5"D, 5.5"D, 4.5"S or 5"S codends) is binomially distributed with parameter *n(l)*, the number of fish of length *l* caught in the

[1] The binomial assumption will not hold because the fish encountering the net will not behave independently. This phenomenon is known as overdispersion.

standard codend (i.e., $n(l)_s$) plus those caught in the experimental codend (i.e., $n(l)_t$), and parameter $\phi(l)$, the probability that a fish of length l has of entering and being retained in the experimental codend, given that it was caught during the experiment. This conditional probability is defined as: $\phi(l) = \frac{p \times r(l)}{p \times r(l) + (1-p)}$, where p, called the efficiency parameter, is the probability that a fish has of entering the experimental codend, given that it entered either the experimental or the standard codends. The probability that a fish is retained given it is of length l is $r(l)$, which is defined by the shape of the selection curve used.

Five types of selection curves were used to describe $r(l)$, four of them were 2-parameter curves. These were the logistic or logit curve, the normal probability ogive or probit curve, the negative extreme value (N.E.V.) or complimentary log-log curve, and the extreme value or Gompertz curve. Both the logistic and probit curves are symmetrical about the length of 50% retention (L_{50}), with the logistic having heavier tails. Both the N.E.V. and Gompertz curves are asymmetrical about L_{50}. While the N.E.V. curve has a longer tail to the left of L_{50}, the Gompertz curve has a longer tail to the right of L_{50} (Fig. 2.1*a* and 2.1*b*).

The fifth curve type is the 3-parameter curve known as Richards curve (Millar, 1991). By the presence of a third parameter δ, this curve may describe both symmetric or asymmetric situations. If $\delta = 1$ the curve collapses to a logistic. If $\delta > 1$, it behaves as a N.E.V. curve, and if $\delta < 1$, it behaves as a Gompertz curve (Fig. 2.1*c* and 2.1*d*).

To ease comparison among model fits, the five selection curves were reparameterized to have common parameters L_{50} and SR (selection range, defined as the difference between the lengths of 75 and 25% retention). The formulae are as follows:

Logistic
$$r(l) = \frac{\exp(2\log_e(3)(l - L_{50})/SR)}{1 + \exp(2\log_e(3)(l - L_{50})/SR)},$$

Probit
$$r(l) = \Phi\left(\frac{2\Phi^{-1}(0.75)(l - L_{50})}{SR}\right),$$

N.E.V. $$r(l) = 1 - \exp\left(-\exp\left(\log_e(-\log_e(0.5)) + \log_e\left(\frac{\log_e(0.25)}{\log_e(0.75)}\right)\frac{(l - L_{50})}{SR}\right)\right),$$

Gompertz $$r(l) = \exp\left(-\exp\left(\log_e(-\log_e(0.5)) - \log_e\left(\frac{\log_e(0.25)}{\log_e(0.75)}\right)\frac{(l - L_{50})}{SR}\right)\right),$$

Richards

$$r(l) = \left(\frac{\exp\left(\log_e\left(\frac{0.5^\delta}{1-0.5^\delta}\right) + \left(\log_e\left(\frac{0.75^\delta}{1-0.75^\delta}\right) - \log_e\left(\frac{0.25^\delta}{1-0.25^\delta}\right)\right)(l - L_{50})/SR\right)}{1+\exp\left(\log_e\left(\frac{0.5^\delta}{1-0.5^\delta}\right) + \left(\log_e\left(\frac{0.75^\delta}{1-0.75^\delta}\right) - \log_e\left(\frac{0.25^\delta}{1-0.25^\delta}\right)\right)(l - L_{50})/SR\right)}\right)^{1/\delta}.$$

Parameter estimates for p, and the selectivity parameters L_{50}, SR, and δ were obtained by minimizing the negative log-likelihood function for the data:

$$-\sum_l \left(n(l)_t \log_e \phi(l) + n(l)_s \log_e(1 - \phi(l))\right).$$

Estimation was performed using a nonlinear Quasi-Newton algorithm (SYSTAT©) that also gave the asymptotic standard errors for the parameter estimates.

Model deviances[2], were calculated for the fits to the four 2-parameter selectivity curves and to the 3-parameter Richards curve. The null hypothesis H_o: $\delta = 1$ was always tested first, to decide whether to accept or reject the fit to the 3-parameter curve. The test consists of finding the probability value assigned to the difference between the deviances for the 3-parameter Richards curve and the 2-parameter logistic curve (Δ *dev.*). Under the null hypothesis the deviance difference will distribute as χ^2 with 1 degree of freedom. Decision on best model fit among the four 2-parameter selectivity curves was based on minimum deviance.

[2] Model deviance is defined as:

$$Dev. = 2\left(\sum_l \left(n(l)_t \log_e\left(\frac{n(l)_t}{n(l)_t + n(l)_s}\right) + n(l)_s \log_e\left(\frac{n(l)_s}{n(l)_t + n(l)_s}\right)\right) - \sum_l \left(n(l)_t \log_e \phi(l) + n(l)_s \log_e(1 - \phi(l))\right)\right)$$

(McCullagh and Nelder, 1989; Dobson, 1990).

Empirical relationships

Regression lines between length of percent retention (L_{50} and L_{90}) from best model fits and mesh size were calculated using least squares. In so doing, I expected to detect possible empirical relationships to be used in predicting selectivity characteristics for new flatfish or rockfish species. This procedure has been extensively used in the past (e.g., Jensen, 1949; Clay, 1979), and it has been recently reviewed by Perez-Comas and Pikitch (1994).

I used the data from the 1989 NMFS survey and the least squares technique to obtain proxies for length-girth linear relationships (e.g., Margetts, 1954, 1957; Clay, 1979) for the 10 species dealt with in the present study. These relationships were used to corroborate inferences made when using mesh size- L_{50} empirical relationships. For this analysis, I substituted girth by the maximum horizontal measurement in flatfish, and by the maximum vertical measurement in rockfish (both types of measurement are hereinafter referred as *D*). The reason for such substitution is that either the depth or the width of the fish are probably more relevant than the circumference or girth measurement when laterally compressed fish, such as rockfish and flatfish, try to squeeze though a mesh.

Results

Length frequency distribution and between-haul variation

Haul length samples were scaled to their catch sizes and pooled to obtain the overall length distributions that were used in estimation (Fig. 2.2*a* to 2.2*j*). The number of haul samples pooled was quite variable (*h* in Tables 2.2 and 2.3). Some species-codend length samples were the result of pooling only 2 to 7 haul samples, while others were the result of as many as 89 haul samples (e.g., length distribution of shortspine thornyhead for 4.5"D codends). Thus, the latter are probably better representations of average commercial fishing conditions. The average depth ($\overline{D}$), tow duration ($\overline{T}$) and catch size ($\overline{C}$) of the pooled hauls also varied across codend (Tables 2.2 and 2.3).

Most of pooled length distributions were relatively smooth, and showed appreciable differences between the standard and experimental codends (e.g., Fig. 2.2*a*, Fig. 2.2*h*). Others, on the contrary, displayed little contrast between standard and experimental codends (e.g., Fig. 2.2*b*) or very rugged shapes (e.g., Fig. 2.2*c*, Fig. 2.2*i*). This variability in the appearance of the length distributions is probably due to pooling very different length samples.

I checked for between-haul variability, and found that it was present in the 45 pooled length distributions. The replication estimate of dispersion (*REP*) varied considerably among the 45 studied cases. *REP/df* took values ranging from 6.13 to 662.13 (Table 2.4, Fig. 2.3). In the 45 studied cases *REP* indicated the presence of between-haul variability because the hypothesis that *REP* has a chi-squared distribution with *df* degrees of freedom was always rejected ($\alpha = 0.05$). For example, for the samples of arrowtooth flounders and 5"D codend *REP* was 1079 on 176 degrees of freedom (*REP/df* = 6.13), giving a p-value of 1.2E-129 for the null hypothesis. Consequently, the model deviances and the standard errors of the parameter were corrected to account for the overdispersion that the between-haul variability had originated.

Model deviances and goodness of fit

Model deviances and their corresponding probabilities (i.e., $Prob.(\chi^2_{df} = Dev.)$, where $df = n - p$) suggest that practically all the models fitted the data adequately (*Prob.* > 0.05, Table 2.4). Only the data for arrowtooth flounder caught with 5"D codends showed lack-of-fit for the Logistic, Gompertz and Richards curves, probabilities equal to 0.047, 0.033 and 0.043, respectively (Fig. 2.4).

In none of the 45 studied cases the null hypothesis that $\delta = 1$ was rejected (*Prob.* < 0.05, Table 2.5). Thus the fits to the 3-parameter Richards curves were judged unnecessary for the present data, and were not further analyzed.

The comparison of model deviances for the remaining models showed that differences between the smaller and larger deviance in each of the 45 cases were very small (e.g., 33 cases showed differences smaller than 1, Fig. 2.5). Figure 2.6 illustrates one of these cases for which the deviance difference was 0.65. Data consisted of length frequencies for 24 length classes, and most of the difference among the five model fits focused around the first 4 length classes and the 12 largest lengths, with the N.E.V. and Richards fits favoring the smallest lengths, and the Gompertz fit, the largest (Fig. 2.6*a*). Figure 2.7 is an example of a case with large deviance difference, equal to 5.12. Here data consisted of 57 length classes, and most of the difference among fits occurred on the last 42 length classes (Fig. 2.7*a*). In trying to fit a selection curve with a longer right tail, the Gompertz-based model increased deviance considerably, while the N.E.V.-based model decreased it by doing exactly the opposite (see shortspine thornyhead for 4.5"D in Table 2.4).

Model deviances were ranked from smallest to largest for each of the 45 cases to have a better understanding of overall model performance (Table 2.6*a*). In 28 cases the N.E.V. curve provided the smallest deviance, which in traditional theory implies best fit to the data (see Tables 2.7 and 2.8 for parameter estimates). The Gompertz curve was selected 6 times, and the logistic or probit curves 11 times. Thus, one may infer that, for the present data, size selection was better described by asymmetric curves, in particular those with longer tails to the left of L_{50}. Nevertheless, it is important to remember that this conclusion was based on the comparison of very similar deviances (Fig. 2.5). For example, in 25 cases, out of the 28 where the N.E.V. curve provided the smallest deviance, the change in deviance with respect to the second smallest deviance was less than 1. This second smallest deviance generally corresponded to symmetric curves.

In fact, symmetric curves were not such bad options. Whether they did not always provide the minimum deviance, they had the second smallest deviance in most of the cases (Table 2.6*a*). Moreover, in those cases were the symmetric curves ranked second, differences with the smallest model deviance were very small. For example, the change in deviance with respect to the minimum deviance was smaller than 1 in 18 cases, out of the 21 where the logistic curve ranked second. Similarly, the change in deviance was smaller than 1 in the 15 cases where the probit curve ranked second.

Except for the 6 cases when it provided the minimum deviance, the asymmetric Gompertz curve did not seem an acceptable option for the data. Its fits had the largest deviance in 34 out of the 45 studied cases, and differences with the minimum deviance were greater or equal than 1 in 15 of those cases.

Parameter estimates and coefficients of variation

The four 2-parameter selection curves provided very similar values for the SELECT parameter *p*, but somewhat different estimates for the selectivity parameters L_{50} and *SR*. Differences were in particular more noticeable among selection ranges (Appendix 1). With the probable exception of those for parameter *p*, standard errors were considerably large for all fits. These large standard errors reflect the large between-haul variation present in the data since they were corrected by multiplying the original standard errors by the corresponding *REP/df* value.

Coefficients of variation (*CV* = standard error/estimate) for L_{50} and *SR* were calculated and ranked from smallest to largest for each of the 45 cases to determine their relationship to the four 2-parameter selection curves (Table 2.6*b* and 2.6*c*). The asymmetric N.E.V. curve furnished the smallest *CV* for L_{50} 39 times and the smallest *CV* for *SR* 27 times. Moreover, in 15 cases it provided not only the smallest *CV*'s for both L_{50} and *SR* but also the smallest deviance. Fits to the asymmetric Gompertz curve, on the other hand, resulted in the largest *CV*'s 34 and 28 times for L_{50} and *SR*, respectively. Finally, coefficients of variation and model deviance were found to be negatively correlated, with the Gompertz curve providing the largest *CV*'s and N.E.V the smallest (Fig. 2.8, $r^2 = 0.395$ and $r^2 = 0.405$, for $CV(L_{50})$ and $CV(SR)$, respectively). Moreover, for any given deviance value $CV(SR)$ tended to be slightly larger than $CV(L_{50})$.

Selection curves

Following the minimum model deviance criterion, I chose the best fits to the data. Estimates for the two selectivity parameters (L_{50} and *SR*) and the SELECT parameter *p* together with their corrected standard errors are given in Tables 2.7 and 2.8, for rockfish and flatfish, respectively. The corresponding predicted selection curves are depicted in

Figures 2.9 and 2.10. The negative extreme value curve (N. E. V.) minimized the model deviance in 28 out of the 45 studied cases, and it also produced minimum coefficients of variation for L_{50} and SR in 15 occasions (see asterisks in Tables 2.7 and 2.8).

When compared, selection curves (Fig. 2.9 and 2.10) displayed some clear patterns. First, for diamond mesh codends selectivity increased with mesh size, manifested as increased L_{50}'s accompanied by slight changes in curve steepness. For example, when mesh size increased from 4.5" to 5.0", L_{50} increased on average 4.3 cm, with a minimum of 1.7 cm for petrale sole and a maximum of 8.4 cm for shortspine thornyhead. This change was accompanied by slight increments in the steepness of the selection curves. Only widow rockfish displayed a small decrease in curve steepness. The comparison of the selection curves for 5.0"D and 5.5"D codends showed somewhat similar patterns. L_{50} increased on average 4.1 cm, with a minimum of 1.3 cm for arrowtooth flounder and a maximum of 7.6 cm for shortspine thornyhead. However, the selection curves showed only slight declines of steepness.

Second, the selection curves for square mesh codends also exhibited marked declines in retention with increasing mesh size. As mesh size increased from 4.5" to 5.0", L_{50} increased on average 5.1 cm, with a minimum of 0.9 cm for yellowtail rockfish and a maximum of 9 cm for widow rockfish. Accompanying changes in curve steepness were almost imperceptible for most of the species. Only yellowtail rockfish, canary rockfish, shortspine thornyhead and Dover sole showed changes of some magnitude. While both rockfish showed marked increments of curve steepness associated to minor changes in L_{50} (Fig. 2.9, solid and broken gray lines), Dover sole and shortspine thornyhead showed larger changes in L_{50} associated to moderate changes in curve steepness, an increase for the flatfish and a decrease for the rockfish.

Third, the comparison of selection curves of similar nominal mesh size but different mesh shape (e.g., 4.5"D vs. 4.5"S and 5"D vs. 5"S) also revealed considerable differences. With only two exceptions (yellowtail and canary rockfish), the selection curves for square mesh codends were less selective than those for diamond mesh codends because of changes in both the L_{50} and curve steepness. These changes varied considerably among species. For example, the steepness of the curves for 4.5"S and 4.5"D codends was similar for widow rockfish and rex sole, but the L_{50}'s for the 4.5"S codend were smaller than those for the 4.5"S codend (Fig. 2.9 and 2.10). For Dover sole and shortspine thornyhead, on the other hand, the L_{50}'s for the 4.5"D codend were only slightly larger than those for the 4.5"S codend, but this shift was accompanied by moderate changes in the steepness of the selection curves, an increase for Dover sole, a decrease for shortspine thornyhead. Finally, for the remaining three species the L_{50}'s for the 4.5"D codend were substantially larger (4 to 6 cm) than those for the 4.5"S codend, and accompanied by significant reductions of curve steepness.

Yellowtail and canary rockfish were the only two species for which the square mesh codends were more selective than the diamond mesh codends of similar mesh size (Fig. 2.9). Differences between selection curves were particularly conspicuous for the 4.5" mesh codends. The square codends displayed significantly larger L_{50}'s and a considerable reduction of curve steepness.

Finally, when the selection curves for flatfish are compared to those for rockfish, lengths of percent retention (e.g., L_{50} or L_{90}) tend to be smaller for flatfish than for rockfish (Fig. 2.11 and 2.12).

Empirical relationships

The empirical relationships between L_{50} or L_{90} and mesh size for both diamond and square mesh codends (Fig. 2.11 and 2.12) show that in general flatfish have smaller lengths of retention than rockfish. This suggests that for a given length flatfish have larger girth sizes than rockfish, or, more likely, that the depth of flatfish is larger than the width of rockfish. An empirical relationship between girth size and total length could be used to check for this hypothesis. Unfortunately, no girth measurements were taken during the W.C.G.M.S. study. The data collected during the 1989 NMFS survey allowed me, however, to corroborate the hypothesis.

The species-specific empirical relationships between maximum vertical or horizontal measurement size (*D*) and total length (Fig. 2.13, Table 2.9) show larger slopes for the five flatfish species. Moreover, for any total length within the range common to the 10 species (from 300 to 400 mm) flatfish displayed larger predicted *D*'s than the rockfish species, with the only exception of canary rockfish (Fig. 2.13). Furthermore, the regression line for all the flatfish species combined showed a significant (p-value = 1.37E-26) larger slope than that for all the rockfish combined (Fig. 2.14).

The regression lines between L_{50} and mesh size (Fig. 2.11*a* and 2.12*a*, Table 2.10*a*) showed a common slope for flatfish and rockfish (P-values = 0.299 and 0.816 for diamond and square mesh codends, respectively). They could be used to predict L_{50}'s for unknown new species of flatfish or rockfish (Table 2.10*b*), although the 95% confidence intervals are somewhat large.

Discussion

Albeit based upon small deviance differences, in most cases the present data were best fitted to asymmetric curves (N. E. V. or Gompertz) instead of to symmetric ones (Logistic or Probit) suggesting that, at least for the studied species, and especially for the five rockfish species, very large and very small fish were retained or escaped in larger quantities than those normally expected. The 28 cases best fitted by the negative extreme value curve, 20 of which were rockfish species (Tables 2.7 and 2.8), imply that in those cases more small and very large fish were retained (Figure 2.1*a*). Such a situation may have resulted, for example, from gear saturation by high catch sizes (e.g., Pikitch et al., 1995). Incidentally, it is interesting to note that the average catches and total number of fish for most of the rockfish length frequency distributions were larger than those for flatfish samples (Tables 2.2 and 2.3), and that best fits to asymmetric curves were relatively less common among flatfish (Tables 2.7 and 2.8).

The six cases best fitted by the Gompertz curve (Tables 2.7 and 2.8) imply that more-than expected very small and very large fish escaped from the codend (Figure 2.1*a*).

Such escapement patterns may originate, for example, from longer tows. Hauls of longer duration may increase selectivity by allowing fish more time to escape (e.g., Clark, 1957). This hypothesis, however, does not seem to be corroborated by the average tow duration of my pooled samples (Tables 2.2 and 2.3). Nonetheless, tow duration effect is always difficult to detect (see chapter 1). It may have been present but confounded with that of catch size in some of the haul length-samples. More important, since five out of the six cases best fitted by the Gompertz curve corresponded to square mesh codends (Tables 2.7 and 2.8), mesh shape cannot be discarded as a contributing factor to the suggested escapement pattern. Knotless square meshes will remain undistorted while fishing, and, in the absence of gear saturation, will allow for the escapement of more small fish than knotted diamond meshes of similar size. Thus the resulting selection curve will present a sharper change of slope for the small lengths characteristic of a Gompertz curve.

Best fits to the traditionally favored logistic and probit curves were more common among the flatfish species (9 out of the 11 cases, Tables 2.7 and 2.8). Moreover, in most of the 45 studied cases, fits to symmetric curves displayed the second smallest model deviance (Table 2.6*a*). This suggests that symmetric curves are still potentially acceptable models to describe size selection, but fits to these curves should not be tried alone. Fits to asymmetric curves should also be attempted, as recently recommended by ICES (Wileman et al., 1996). The present results indicate that negative extreme value (complimentary log-log) curves are strong candidates to describe size selection, in particular when dealing with pooled samples coming from hauls with some indication of gear saturation by high catch sizes. Fits to N. E. V. curves are particularly attractive when fits to more flexible models such as the 3-parameter Richards curves are not justified (Table 2.5). Moreover, N. E. V. curves show the advantage of providing smaller coefficients of variation for the selection parameter estimates (Table 2.6*b* and 2.6*c*).

The comparison of the fitted selection curves showed some clear and predictable patterns such as the reduction of retention with mesh size (Fig. 2.9 and 2.10). This pattern, long known and abundantly reported for different species (e.g., Clay, 1979), is probably more clearly expressed by empirical linear relationships between 50% retention lengths and mesh sizes (Fig. 2.11 and 2.12). The scant number of mesh sizes (three for diamond meshes and two for square meshes) tried in the present selectivity experiments precluded the estimation of regression lines between L_{50} and mesh size for each species, though it allowed the estimation of lines for combined rockfish and combined flatfish that were significantly different (Table 2.9). These empirical relationships can certainly be used for descriptive purposes. Their use in predicting 50% retention lengths for unknown new species of flatfish or rockfish, however, should be cautious because the small sample sizes and large variation in the estimates led to large 95% confidence intervals (Perez-Comas and Pikitch, 1994).

The comparison between predicted curves for codends of similar nominal mesh size but different mesh shape (i.e., 4.5"D vs. 4.5"S and 5"D vs. 5"S) revealed that square mesh codends had larger retention probabilities due to smaller L_{50}'s and changes in the selection ranges (e.g., smaller selection ranges for square meshes). This pattern, present in the five flatfish species and in widow rockfish, Pacific Ocean perch and shortspine thornyhead, has been reported for other flatfish species such as winter flounder, *Pseudopleuronectes americanus*, (Simpson, 1989), American plaice, *Hippoglossoides platessoides*, (Walsh et al., 1992) and Belgian sole (Fonteyne and M'Rabet, 1992). The exact opposite pattern, with the square mesh being more selective, has been reported for roundfish such as cupleoids (e.g., Suuronen and Millar, 1992) and gadoids (e.g., Robertson and Stewart, 1988).

Although average mesh sizes did not coincide with nominal sizes (e.g., 4.5"S codends had smaller average mesh sizes while 4.5"D were slightly larger on average, Table 2.1*b*), these differences probably did not contribute significantly to the large differences between the selection curves of square and diamond mesh codends. Jones (1963) suggested that, besides girth size and girth/length variation, the shape (e.g., slope) of the selection curve is determined by the number of escape attempts, the greater vigor of larger fish in squeezing through the netting, and, most importantly, the range in mesh opening in a codend. In a square mesh codend there will be little variation in opening because knotless square meshes are hardly distorted during the tow. All the square meshes remaining fully open, the selection curves of square mesh codends will be steeper (i.e., larger slopes, smaller *SR*) than those of diamond mesh codends, unless high catch sizes saturate the square mesh codend. The smaller L_{50}'s displayed by the square mesh codends are more likely related to the general shape of the fish. Flatfish, for example, have laterally compressed shapes that, unlike roundfish, would favor escapement through the elongated and more easily distorted meshes of the diamond mesh codends but not through rigid knotless square meshes (Clark, 1963; Simpson, 1989). Rockfish are also laterally compressed, more than a typical roundfish such as cod but considerably less than a flatfish. Besides they often possess spiny and relatively large heads, spiny opercula and dorsal fins that, probably, will not facilitate their easy squeezing through square meshes.

Finally, it is important to mention that the present length samples included large between-haul variation. Differences in location, tow duration, gear type, skipper ability and catch sizes may have undoubtedly contributed to the large between-haul variability indicated by the large values of *REP/df*. This variability do not invalidate the results because both model deviances and parameter standard errors were corrected by *REP/df*. The estimates can still be used as the representation of average selection curves, for example, in simulations of long term effects or in more traditional yield-per-recruit analyses. Nevertheless, it would be judicious to study the causes of this inter-haul variability, in particular if it is decided to change the present management regulations. Such a study should be centered in only one, and at maximum two experimental codends and/or target species. It should include as many replicated hauls as possible, and tow location and duration as well as other possible explanatory variables (e.g. length of the codend) should be carefully controlled. Moreover, the number of species sampled for length should be much larger than those in the present study (N = 100 fish per haul and species). Probably, sample sizes ranging from 500 to 1000 fish per haul, or a significant fixed proportion of the catch, will suffice to estimate selection curves for each haul.

Table 2.1: Codend specifications (***a***) and mesh size measurements, in in and mm (***b***). Meshes were streched and measured diagonally (between knots for diamond meshes, and between seams for square meshes) using a mesh measuring gauge. *SE* indicates standard error.

a.

Codend component	Specification	
Web	Diamond mesh:double strand polyethylene, 4-mm diameter Square mesh: Nichimo UC, 4-strand braided knotless, 480 ply	
Rib lines	Polydacron rope, 1-in diameter; seized to every third knot; four rib lines per codend	
Hanging ratio	Three percent with ribline tension at 500 lb in^2	
Codend size	3-in diamond:	112 meshes around x 142 meshes deep
	4.5-in diamond:	80 meshes around x 100 meshes deep
	5-in diamond:	72 meshes around x 90 meshes deep
	5.5-in diamond:	300 meshes around x 100 meshes deep
	4.5-in diamond:	80 meshes around x 200 bars deep
	5-in square:	72 meshes around x 180 bars deep
Restraining straps	Polydacron rope, 1.5-in diameter, 12-ft length, placed 3 ft apart	
Chafing gear	Polypropylene rope, 0.5-in diameter, 12.5-in mesh, three of four panels covered	

b.

Mesh shape	Nominal size	Average (in)	*SE*	Nominal size	Average (mm)	*SE*
D	3	3.4	0.1	76.2	86.4	3.49
D	4.5	4.6	0.12	114.3	117.5	2.13
D	5	5.2	0.1	127	132.3	2.72
D	5.5	5.7	0.11	139.7	143.8	2.83
S	4.5	4.3	0.09	114.3	108.5	2.33
S	5	5.1	0.1	127	129.4	2.89

Table 2.2: Characteristics of the samples used in the selectivity analysis of rockfish: $\overline{D}$, average depth (in fa); $\overline{T}$, average towing duration (in hr); $\overline{C}$, average catch weight (in lb); *h*, of hauls; and *N*, the number of fish in the pooled length distributions.

Scientific name	Common name	Codend *parameters*	4.5"D	5.0"D	5.5"D	4.5"S	5.0"S
Sebastes flavidus	Yellowtail rockfish	$\overline{D}$	79.1	85.2	77.5	78.8	84.0
		$\overline{T}$	1.4	1.6	1.4	1.8	2.4
		$\overline{C}$	608	2149	943	2941	2478
		h	23	21	35	17	13
		N	6840	22146	13161	22647	15281
Sebastes pinniger	Canary rockfish	$\overline{D}$	82.6	77.7	78.9	79.6	83.2
		$\overline{T}$	1.7	1.5	1.5	1.6	1.8
		$\overline{C}$	607	1347	427	773	564
		h	46	12	25	34	7
		N	5216	3103	1966	4717	748
Sebastolobus alascanus	Shortspine thornyhead	$\overline{D}$	302.8	288.4	257.8	286.6	330.0
		$\overline{T}$	5.4	5.3	3.3	4.9	5.0
		$\overline{C}$	434	382	86	356	382
		h	89	37	26	42	35
		N	41657	15877	2259	30678	25641
Sebastes alutus	Pacific Ocean perch	$\overline{D}$	158.2	175.8	170.0	164.9	234.9
		$\overline{T}$	2.6	3.2	1.9	2.4	3.5
		$\overline{C}$	884	644	664	869	186
		h	12	9	5	15	7
		N	5266	2922	1129	6594	543
Sebastes entomelas	Widow rockfish	$\overline{D}$	88.4	93.4	87.5	84.5	115.7
		$\overline{T}$	1.6	1.6	1.1	1.5	1.3
		$\overline{C}$	1609	447	778	829	1394
		h	67	10	21	27	7
		N	58119	1640	6082	9606	3412

Table 2.3: Characteristics of the samples used in the selectivity analysis of flatfish: $\overline{D}$, average depth (in fa); $\overline{T}$, average towing duration (in hr); $\overline{C}$, average catch weight (in lb); h, of hauls; and N, the number of fish in the pooled length distributions.

Scientific name	Common name	Codend *parameters*	4.5"D	5.0"D	5.5"D	4.5"S	5.0"S
Eopsetta jordani	Petrale sole	$\overline{D}$	66.9	96.8			
		$\overline{T}$	2.7	3.0			
		$\overline{C}$	42	170			
		h	5	4			
		N	237	499			
Parophrys vetulus	English sole	$\overline{D}$	76.9	99.5	40.3	70.3	83.0
		$\overline{T}$	3.0	4.9	2.6	2.7	3.2
		$\overline{C}$	135	177	52	127	31
		h	20	4	11	23	2
		N	3414	796	575	4624	63
Microstomus pacificus	Dover sole	$\overline{D}$	240.0	260.5	250.5	200.6	242.2
		$\overline{T}$	4.9	5.0	3.3	3.6	4.2
		$\overline{C}$	931	488	203	663	585
		h	32	39	36	28	49
		N	23264	13610	3579	20124	20097
Atheresthes stomias	Arrowtooth flounder	$\overline{D}$	137.8	144.0	141.0	153.8	109.6
		$\overline{T}$	2.8	3.4	2.6	2.4	2.4
		$\overline{C}$	891	362	1138	775	628
		h	27	17	13	29	7
		N	7605	1824	2963	5855	1469
Glyptocephalus zachirus	Rex sole	$\overline{D}$	173.3			187.9	209.6
		$\overline{T}$	3.8			3.8	4.4
		$\overline{C}$	37			110	33
		h	64			56	27
		N	5127			14816	1681

Table 2.4: Goodness of fit to Millar's model with different selection curves. Correction for between-haul variation (*REP/df*), number of length classes (*n*), model deviance (*Dev.*) and p-values (*Prob.*).

Species	Codend	*REP/df*	*n*		Logistic	Probit	Gompertz	N. E. V.	Richards
Yellowtail rockfish	4.5"D	258.49	25	*Dev.*	1.183	1.172	1.236	1.135	1.105
				Prob.	1	1	1	1	1
	5.0"D	165.15	22	*Dev.*	6.986	6.911	8.057	6.105	5.730
				Prob.	0.994	0.995	0.986	0.998	0.997
	5.5"D	168.95	24	*Dev.*	2.017	2.811	3.733	1.614	1.306
				Prob.	1	1	1	1	1
	4.5"S	97.83	24	*Dev.*	6.898	6.848	7.118	6.472	5.854
				Prob.	0.998	0.998	0.998	0.999	0.999
	5.0"S	80.38	20	*Dev.*	2.958	3.095	4.316	2.900	2.893
				Prob.	1	1	0.999	1	1
Canary rockfish	4.5"D	15.45	34	*Dev.*	12.888	12.858	12.904	12.889	12.888
				Prob.	0.998	0.998	0.998	0.998	0.997
	5.0"D	46.85	24	*Dev.*	5.251	5.242	5.295	5.229	5.239
				Prob.	1	1	1	1	1
	5.5"D	8.74	25	*Dev.*	4.085	4.066	4.098	4.009	3.936
				Prob.	1	1	1	1	1
	4.5"S	14.86	27	*Dev.*	6.117	6.104	6.083	6.105	6.085
				Prob.	1	1	1	1	1
	5.0"S	108.67	22	*Dev.*	0.886	0.887	0.860	0.886	0.860
				Prob.	1	1	1	1	1
Shortspine thornyhead	4.5"D	186.17	64	*Dev.*	10.470	11.603	13.920	8.802	7.645
				Prob.	1	1	1	1	1
	5.0"D	357.86	56	*Dev.*	3.626	4.176	4.676	3.538	3.358
				Prob.	1	1	1	1	1
	5.5"D	129.46	54	*Dev.*	1.743	1.879	2.029	1.750	1.738
				Prob.	1	1	1	1	1
	4.5"S	422.99	60	*Dev.*	3.968	4.668	5.963	3.382	2.944
				Prob.	1	1	1	1	1
	5.0"S	662.13	59	*Dev.*	4.638	4.936	5.282	4.349	3.958
				Prob.	1	1	1	1	1

Table 2.4 (continued)

Species	Codend	*REP/df*	*n*		Logistic	Probit	Gompertz	N. E. V.	Richards
Pacific	4.5"D	100.97	30	*Dev.*	2.147	2.368	2.487	2.097	1.961
Ocean				*Prob.*	1	1	1	1	1
perch	5.0"D	395.51	21	*Dev.*	0.696	0.758	0.775	0.656	0.539
				Prob.	1	1	1	1	1
	5.5"D	172.46	15	*Dev.*	0.634	0.706	0.714	0.610	0.527
				Prob.	1	1	1	1	1
	4.5"S	72.33	20	*Dev.*	1.491	1.482	1.456	1.540	1.456
				Prob.	1	1	1	1	1
	5.0"S	69.78	15	*Dev.*	2.331	2.459	2.702	2.317	2.296
				Prob.	0.999	0.998	0.997	0.999	0.997
Widow	4.5"D	199.43	26	*Dev.*	15.720	15.649	16.173	15.459	15.412
rockfish				*Prob.*	0.867	0.870	0.848	0.877	0.844
	5.0"D	83.96	24	*Dev.*	2.624	2.606	2.655	2.558	2.506
				Prob.	1	1	1	1	1
	5.5"D	106.49	25	*Dev.*	2.229	2.584	2.757	2.107	1.830
				Prob.	1	1	1	1	1
	4.5"S	35.68	29	*Dev.*	7.861	7.826	8.562	7.482	7.404
				Prob.	1	1	1	1	1
	5.0"S	494.95	20	*Dev.*	0.516	0.619	0.814	0.455	0.401
				Prob.	1	1	1	1	1
Petrale	4.5"D	15.72	21	*Dev.*	1.638	1.618	1.638	1.622	1.636
sole				*Prob.*	1	1	1	1	1
	5.0"D	14.35	24	*Dev.*	2.766	2.776	2.769	2.767	2.766
				Prob.	1	1	1	1	1

Table 2.4 (continued)

Species	Codend	*REP/df*	*n*		Logistic	Probit	Gompertz	N. E. V.	Richards
English sole	4.5"D	45.80	27	*Dev.*	2.116	2.027	2.102	2.261	2.059
				Prob.	1	1	1	1	1
	5.0"D	327.22	15	*Dev.*	0.361	0.370	0.395	0.328	0.291
				Prob.	1	1	1	1	1
	5.5"D	118.09	26	*Dev.*	0.430	0.400	0.413	0.448	0.408
				Prob.	1	1	1	1	1
	4.5"S	68.92	27	*Dev.*	2.280	2.590	3.688	1.993	1.979
				Prob.	1	1	1	1	1
	5.0"S	80.78	10	*Dev.*	0.286	0.283	0.279	0.292	0.279
				Prob.	1	1	1	1	1
Dover sole	4.5"D	121.53	31	*Dev.*	2.967	2.978	3.233	3.617	2.871
				Prob.	1	1	1	1	1
	5.0"D	164.71	33	*Dev.*	2.448	3.268	4.294	2.157	2.022
				Prob.	1	1	1	1	1
	5.5"D	61.28	32	*Dev.*	3.092	3.279	3.896	3.562	2.947
				Prob.	1	1	1	1	1
	4.5"S	443.63	30	*Dev.*	1.599	1.582	1.588	1.646	1.587
				Prob.	1	1	1	1	1
	5.0"S	190.02	33	*Dev.*	2.366	2.872	4.565	2.622	2.363
				Prob.	1	1	1	1	1
Arrowtooth flounder	4.5"D	10.29	56	*Dev.*	55.541	54.036	58.409	54.984	55.534
				Prob.	0.379	0.435	0.283	0.399	0.343
	5.0"D	6.13	48	*Dev.*	62.061	61.471	63.881	61.165	61.324
				Prob.	0.047	0.052	0.033	0.055	0.043
	5.5"D	6.91	49	*Dev.*	56.695	56.744	56.536	57.839	56.286
				Prob.	0.134	0.133	0.137	0.113	0.121
	4.5"S	13.02	20	*Dev.*	24.632	24.857	25.991	23.807	23.499
				Prob.	0.103	0.098	0.075	0.125	0.101
	5.0"S	14.28	38	*Dev.*	19.336	19.143	18.438	19.610	18.438
				Prob.	0.985	0.986	0.990	0.983	0.986
Rex sole	4.5"D	12.28	26	*Dev.*	11.435	15.326	16.033	10.155	7.827
				Prob.	0.978	0.883	0.854	0.990	0.998
	4.5"S	44.70	25	*Dev.*	9.826	12.235	14.338	8.524	6.815
				Prob.	0.988	0.952	0.889	0.995	0.998
	5.0"S	42.73	21	*Dev.*	1.812	2.127	2.213	1.721	1.365
				Prob.	1	1	1	1	1

Table 2.5: Results of assymetry test (H_o: $\delta = 1$). Differences between model deviances for the logistic and Richards curves (Δ *dev.*) and p-values (*Prob.*).

Species	Codend	Δ *dev.*	*Prob.*
Yellowtail	4.5"D	0.078	0.78
rockfish	5.0"D	1.255	0.263
	5.5"D	0.711	0.399
	4.5"S	1.044	0.307
	5.0"S	0.065	0.799
Canary	4.5"D	0.0002	0.988
rockfish	5.0"D	0.012	0.913
	5.5"D	0.149	0.7
	4.5"S	0.032	0.857
	5.0"S	0.026	0.872
Shortspine	4.5"D	2.825	0.093
thornyhead	5.0"D	0.268	0.605
	5.5"D	0.005	0.944
	4.5"S	1.025	0.311
	5.0"S	0.680	0.41
Pacific	4.5"D	0.185	0.667
Ocean	5.0"D	0.157	0.692
perch	5.5"D	0.108	0.743
	4.5"S	0.035	0.851
	5.0"S	0.036	0.85
Widow	4.5"D	0.307	0.579
rockfish	5.0"D	0.118	0.731
	5.5"D	0.399	0.528
	4.5"S	0.457	0.499
	5.0"S	0.115	0.735

Species	Codend	Δ *dev.*	*Prob.*
Petrale	4.5"D	0.003	0.96
sole	5.0"D	0.0001	0.994
	5.5"D		
	4.5"S		
	5.0"S		
English	4.5"D	0.057	0.812
sole	5.0"D	0.07	0.791
	5.5"D	0.022	0.882
	4.5"S	0.301	0.583
	5.0"S	0.008	0.929
Dover	4.5"D	0.096	0.756
sole	5.0"D	0.425	0.514
	5.5"D	0.144	0.704
	4.5"S	0.012	0.913
	5.0"S	0.003	0.957
Arrowtooth	4.5"D	0.008	0.93
flounder	5.0"D	0.737	0.391
	5.5"D	0.408	0.523
	4.5"S	1.132	0.287
	5.0"S	0.898	0.343
Rex	4.5"D	3.609	0.057
sole	5.0"D		
	5.5"D		
	4.5"S	3.011	0.083
	5.0"S	0.447	0.504

Table 2.6: Ranks of model deviances (***a***), and coefficients of variation for L_{50} (***b***) and *SR* (***c***) over the 45 analyzed cases. For each of the 45 studied cases the deviances and coefficients of variation for the fits to the logist, probit, Gompertz and N.E.V. curves were ordered from smaller (rank 1) to larger (rank 4). The table shows the frequency of these ranks over the 45 cases.

a.

Ranks	Logistic	Probit	Gompertz	N. E. V.	
1	5	6	6	28	45
2	21	15	3	6	45
3	18	22	2	3	45
4	1	2	34	8	45
	45	45	45	45	

b.

Ranks	Logistic	Probit	Gompertz	N. E. V.	
1	2	1	3	39	45
2	26	14	4	1	45
3	13	27	4	1	45
4	4	3	34	4	45
	45	45	45	45	

c.

Ranks	Logistic	Probit	Gompertz	N. E. V.	
1	0	12	6	27	45
2	18	15	7	5	45
3	20	16	4	5	45
4	7	2	28	8	45
	45	45	45	45	

Table 2.7: Parameter estimates and standard errors (*SE*) for best fits to rockfish data. Asterisks indicate cases with the smallest model deviance and coefficients of variation.

Species	Codend	Model	L_{50}	*SR*	*p*	*SE* (L_{50})	*SE* (*SR*)	*SE* (*p*)	
Yellowtail	4.5"D	N. E. V.	36.04	2.42	0.19	2.61	3.11	0.03	
rockfish	5.0"D	N. E. V.	40.12	2.18	0.36	0.69	0.85	0.03	
	5.5"D	N. E. V.	45.42	3.18	0.34	0.94	1.02	0.04	*
	4.5"S	N. E. V.	39.48	7.65	0.45	1.75	2.99	0.03	*
	5.0"S	N. E. V.	40.42	1.31	0.46	0.50	0.60	0.03	
Canary	4.5"D	Probit	35.51	2.62	0.43	1.96	2.59	0.02	
rockfish	5.0"D	N. E. V.	39.87	2.07	0.44	2.09	2.79	0.04	
	5.5"D	N. E. V.	41.92	2.59	0.44	1.32	2.19	0.02	
	4.5"S	Gompertz	41.71	12.43	0.64	5.45	19.46	0.10	
	5.0"S	Gompertz	43.45	5.46	0.32	12.55	16.03	0.22	
Shortspine	4.5"D	N. E. V.	29.52	8.09	0.54	1.44	1.33	0.04	*
thornyhead	5.0"D	N. E. V.	37.87	8.52	0.58	4.40	2.28	0.10	*
	5.5"D	Logistic	45.42	12.57	0.56	10.33	4.66	0.21	
	4.5"S	N. E. V.	28.72	6.25	0.49	1.91	1.68	0.06	*
	5.0"S	N. E. V.	34.13	11.76	0.51	6.15	4.34	0.12	*
Pacific	4.5"D	N. E. V.	37.26	6.98	0.55	4.40	3.01	0.14	*
Ocean	5.0"D	N. E. V.	40.84	4.94	0.61	7.32	3.37	0.36	*
perch	5.5"D	N. E. V.	45.75	3.66	0.74	7.52	2.45	0.38	
	4.5"S	Gompertz	32.95	1.35	0.66	1.23	1.78	0.04	
	5.0"S	N. E. V.	39.15	1.60	0.48	1.63	1.12	0.16	
Widow	4.5"D	N. E. V.	34.48	1.57	0.42	0.67	1.09	0.02	
rockfish	5.0"D	N. E. V.	39.41	4.25	0.47	2.59	2.56	0.11	*
	5.5"D	N. E. V.	44.97	5.01	0.71	3.04	1.98	0.11	*
	4.5"S	N. E. V.	33.25	1.99	0.46	0.77	1.24	0.02	
	5.0"S	N. E. V.	42.27	1.79	0.73	2.28	1.61	0.17	

Table 2.8: Parameter estimates and standard errors (*SE*) for best fits to flatfish data. Asterisks indicate cases with the smallest model deviance and coefficients of variation.

Species	Codend	Model	L_{50}	*SR*	*p*	*SE* (L_{50})	*SE* (*SR*)	*SE* (*p*)	
Petrale	4.5"D	Probit	28.23	6.67	0.70	7.11	7.28	0.19	
sole	5.0"D	Logistic	29.90	3.67	0.50	2.24	5.30	0.08	
English	4.5"D	Probit	29.54	5.50	0.47	2.44	2.54	0.09	
sole	5.0"D	N. E. V.	32.77	3.85	0.39	5.56	6.85	0.30	*
	5.5"D	Probit	35.37	6.79	0.45	10.78	6.51	0.39	
	4.5"S	N. E. V.	24.78	2.25	0.45	0.86	0.91	0.05	
	5.0"S	Gompertz	31.31	1.37	0.46	5.16	5.39	0.49	
Dover	4.5"D	Logistic	33.77	3.96	0.55	1.01	1.22	0.04	
sole	5.0"D	N. E. V.	38.07	3.07	0.51	0.94	0.68	0.05	*
	5.5"D	Logistic	41.54	3.52	0.58	1.36	0.72	0.08	
	4.5"S	Probit	31.82	6.81	0.44	4.48	5.44	0.15	
	5.0"S	Logistic	36.54	3.28	0.50	0.90	0.70	0.05	
Arrowtooth	4.5"D	Probit	37.09	5.62	0.60	0.64	0.57	0.02	
flounder	5.0"D	N. E. V.	41.24	4.35	0.49	0.72	0.45	0.02	*
	5.5"D	Gompertz	42.55	7.54	0.62	1.49	1.57	0.02	
	4.5"S	N. E. V.	31.02	2.94	0.58	0.75	0.98	0.02	
	5.0"S	Gompertz	36.34	3.25	0.63	2.24	2.70	0.05	
Rex	4.5"D	N. E. V.	34.76	4.16	0.64	1.16	0.31	0.07	
sole	4.5"S	N. E. V.	29.58	3.64	0.56	0.74	0.53	0.04	*
	5.0"S	N. E. V.	35.17	3.77	0.52	2.89	0.94	0.21	*

Table 2.9: Summary statistics for the regressions between depth or width and total length (both in mm) for ***a***) rockfish and ***b***) flatfish. *RSS* stands for residual sum of squares, and *TSS*, for total sum of squares.

a.

	r^2	*n*	*RSS*	*TSS*	*Intercept*	*SE*	*Slope*	*SE*
Yellowtail rockfish	0.766	185	7297.6	31215.8	-4.5308	5.4565	0.2760	0.0113
Canary rockfish	0.893	125	3204.8	29996.4	16.6447	3.9324	0.2496	0.0078
Shortspine thornyhead	0.963	93	528.6	14153.2	-13.9418	1.1985	0.2315	0.0048
Pacific Ocean perch	0.978	345	4747.8	213083.6	-5.8474	0.7409	0.2684	0.0022
Widow rockfish	0.946	103	1391.0	25840.9	-20.8655	2.6939	0.2996	0.0071
All rockfish	0.956	851	48305.2	1107831.5	-23.1560	0.9224	0.3155	0.0023

b.

	r^2	*n*	*RSS*	*TSS*	*Intercept*	*SE*	*Slope*	*SE*
Petrale sole	0.945	165	9390.6	171769.8	-42.3030	3.1666	0.5039	0.0095
English sole	0.896	312	16199.5	156503.8	-14.8677	2.1600	0.3685	0.0071
Dover sole	0.889	360	33932.0	305234.0	-23.6616	2.5594	0.3662	0.0068
Arrowtooth flounder	0.979	177	8957.4	431528.8	-14.7153	1.3603	0.3166	0.0035
Rex sole	0.848	361	14061.5	92299.5	-14.1691	1.8444	0.3089	0.0069
All flatfish	0.840	1375	264709.9	1658282.7	-17.0978	1.3766	0.3542	0.0042

Table 2.10: Empirical relationships between L_{50} and mesh size (both in mm). ***a***) Summary statistics for the regressions. ***b***) Predictions and 95% confidence bounds. *RSS* stands for residual sum of squares, and *TSS*, for total sum of squares.

a.

	Diamond mesh			*Square mesh*		
r^2	0.670			0.539		
Observations	27			18		
RSS	22598.9			2122.9		
TSS	68541.1			4607.6		
	Rockfish intercept	*Flatfish intercept*	*Common slope*	*Rockfish intercept*	*Flatfish intercept*	*Common slope*
Coefficients	-42.7251	-77.6513	3.4566	-104.4562	-159.2849	3.9782
Standard Error	77.3341	73.4351	0.5749	168.8932	168.9979	1.3964
Lower 95%	-226.9416	-194.2877	2.2702	-464.4435	-519.4954	1.0019
Upper 95%	71.6390	108.8376	4.6430	255.5311	200.9256	6.9545

b.

Mesh			*Rockfish*			*Flatfish*		
Size (in)	*(mm)*	*Shape*	*Estimate*	*Lower 95%*	*Upper 95%*	*Estimate*	*Lower 95%*	*Upper 95%*
4.5	114.3	Diamond	352.4	295.9	408.8	317.4	199.5	435.3
5	127		396.3	342.3	450.2	361.3	247.9	474.8
5.5	139.7		440.2	383.7	496.6	405.2	283.1	527.4
4.5	114.3	Square	350.3	213.7	486.8	295.4	213.7	486.8
5	127		400.8	264.2	537.3	345.9	264.2	537.3

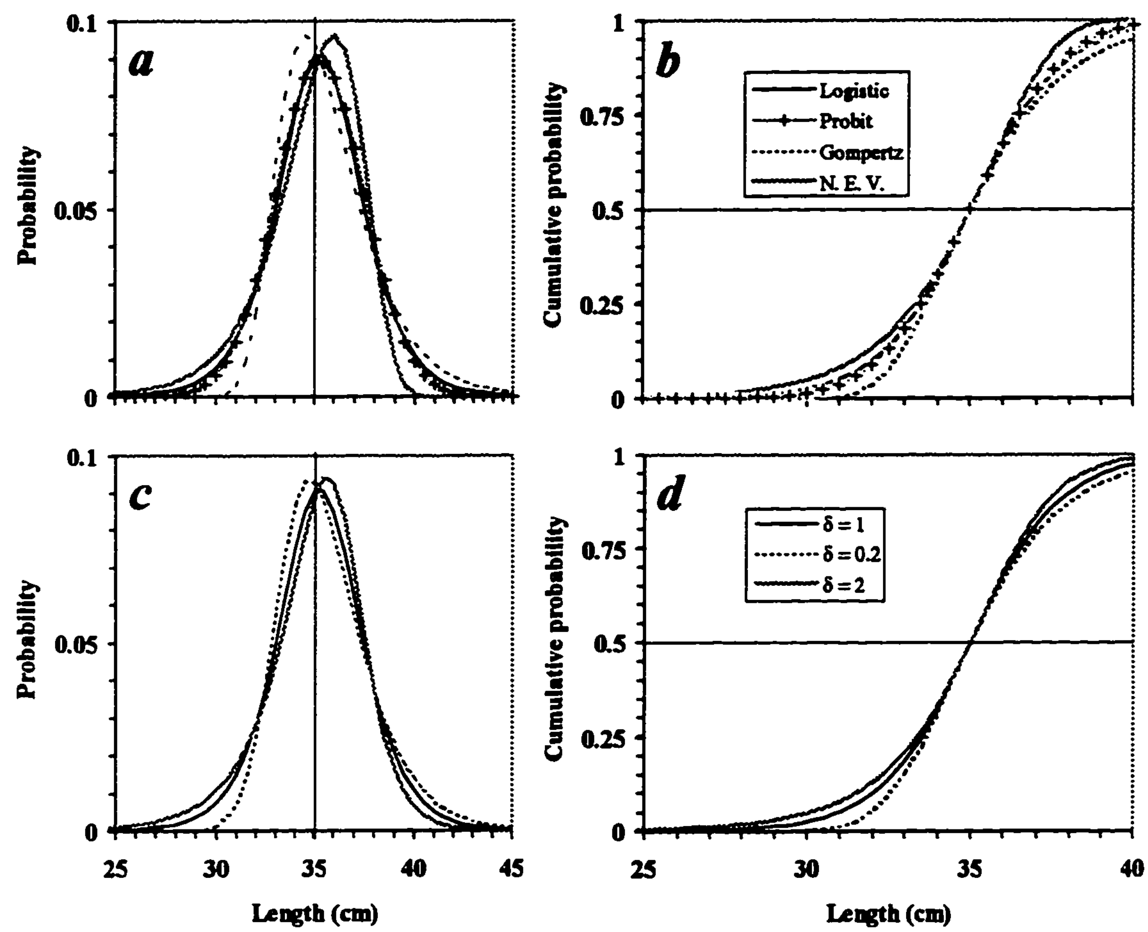

Figure 2.1: Probability density functions and cumulative density functions for 2-parameter (***a*** and ***b***), and 3-parameter (***c*** and ***d***) selectivity curves with L_{50}= 35 cm and SR = 3 cm.

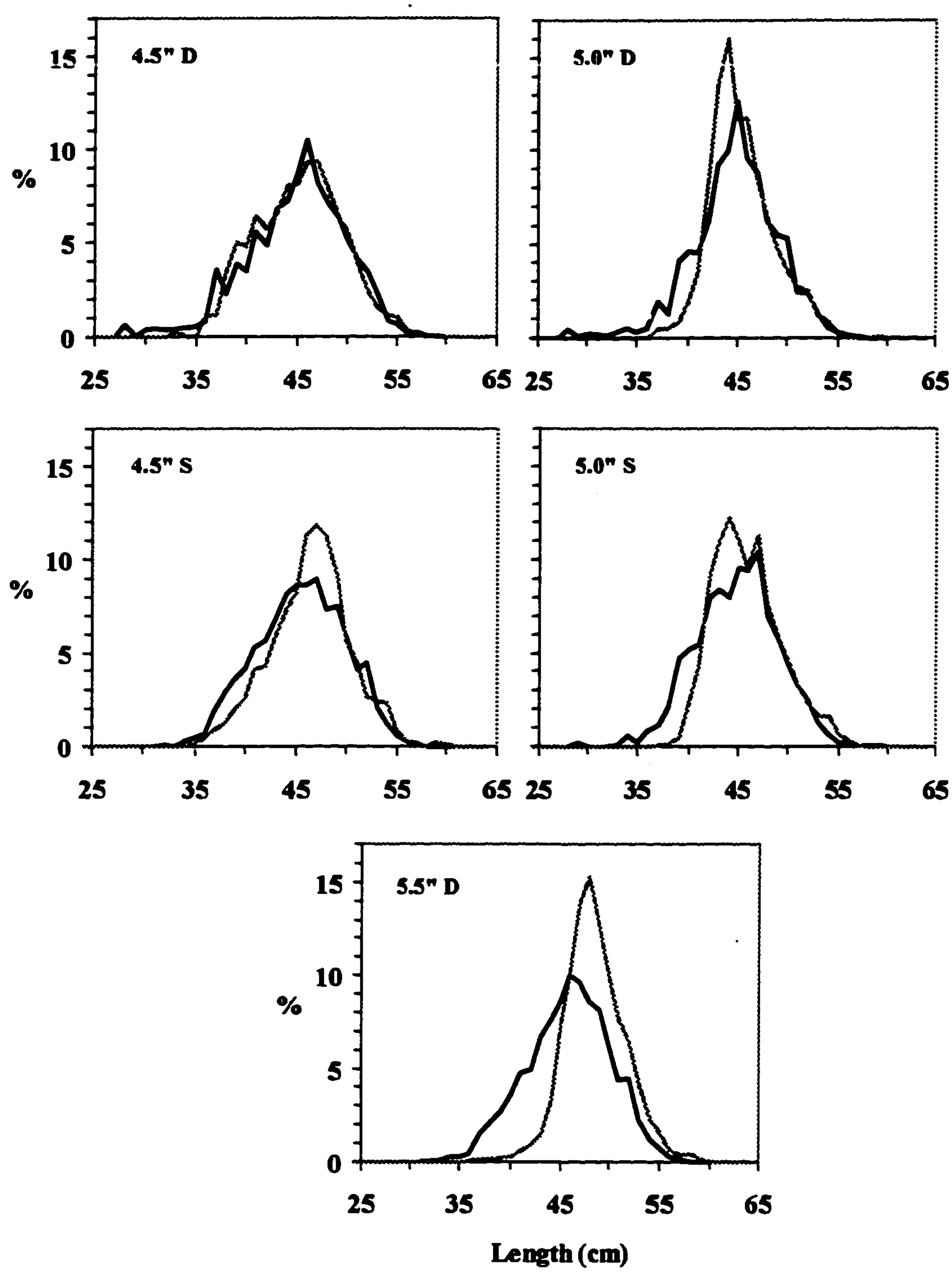

Figure 2.2*a*: Relative length frequency distributions for standard (black line) and experimental (gray lines) codends for yellowtail rockfish (D diamond and S square mesh).

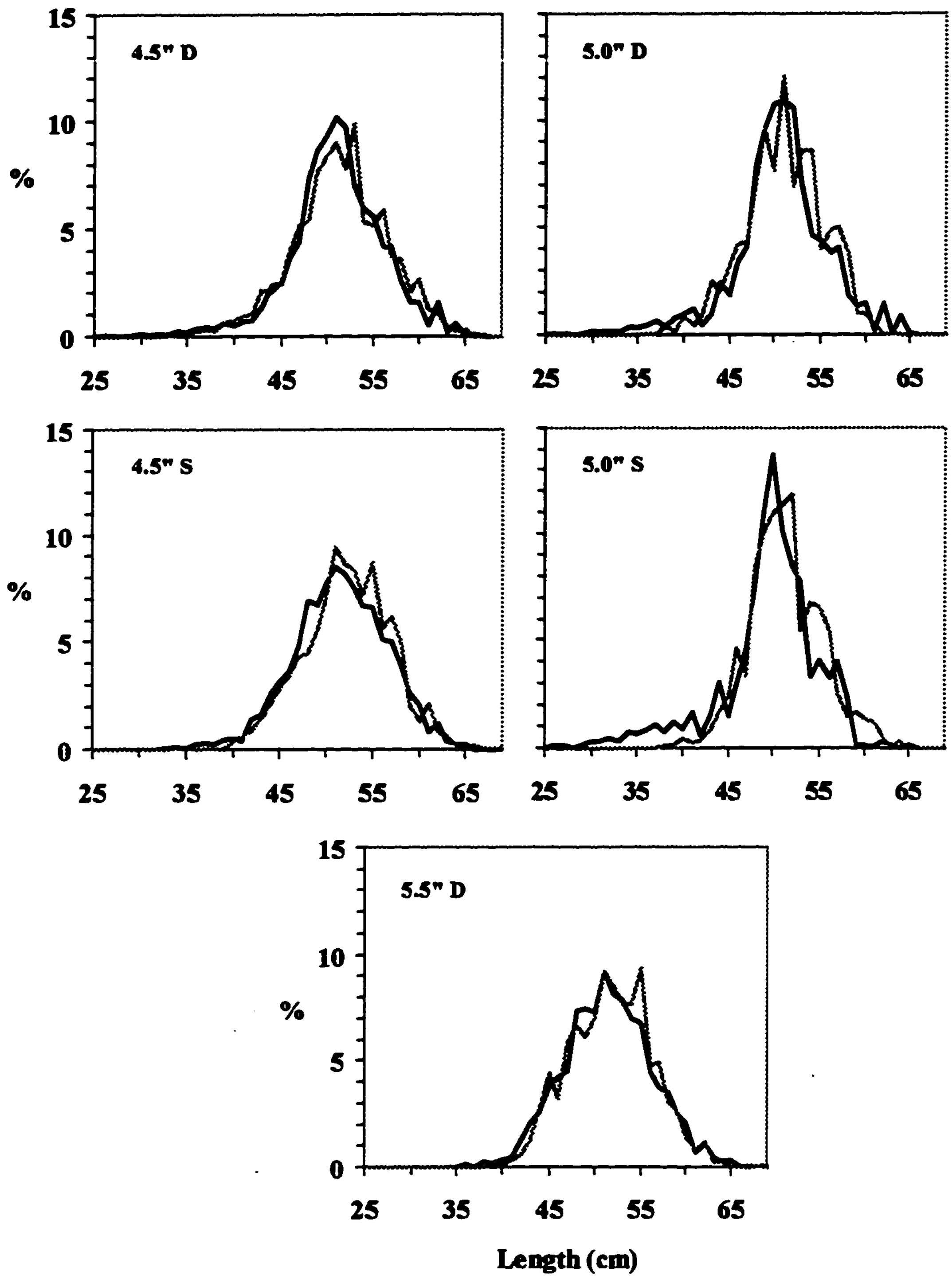

Figure 2.2*b*: Relative length frequency distributions for standard (black line) and experimental (gray lines) codends for canary rockfish (D diamond and S square mesh).

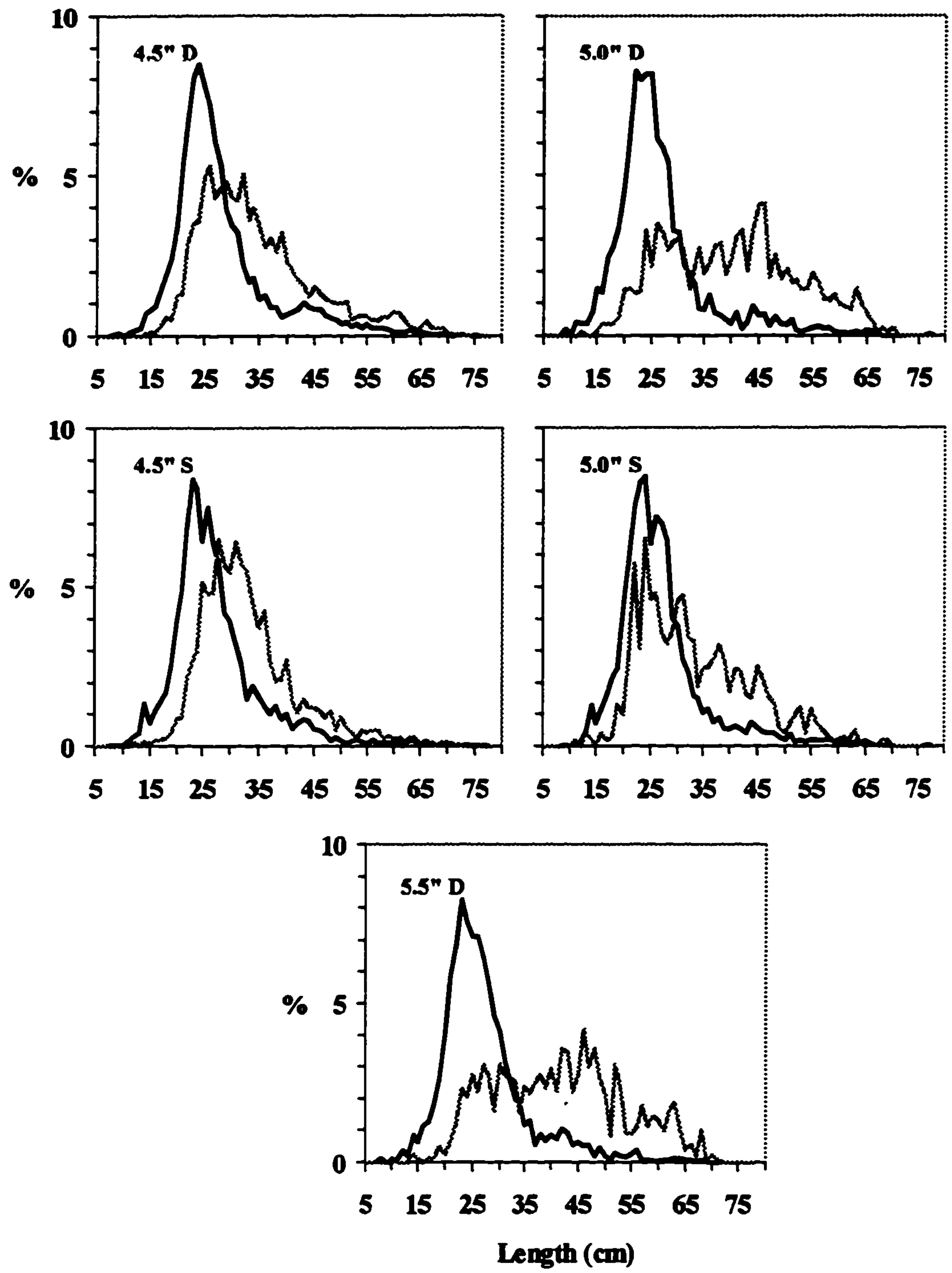

Figure 2.2c: Relative length frequency distributions for standard (black line) and experimental (gray lines) codends for shortspine thornyhead (D diamond and S square mesh).

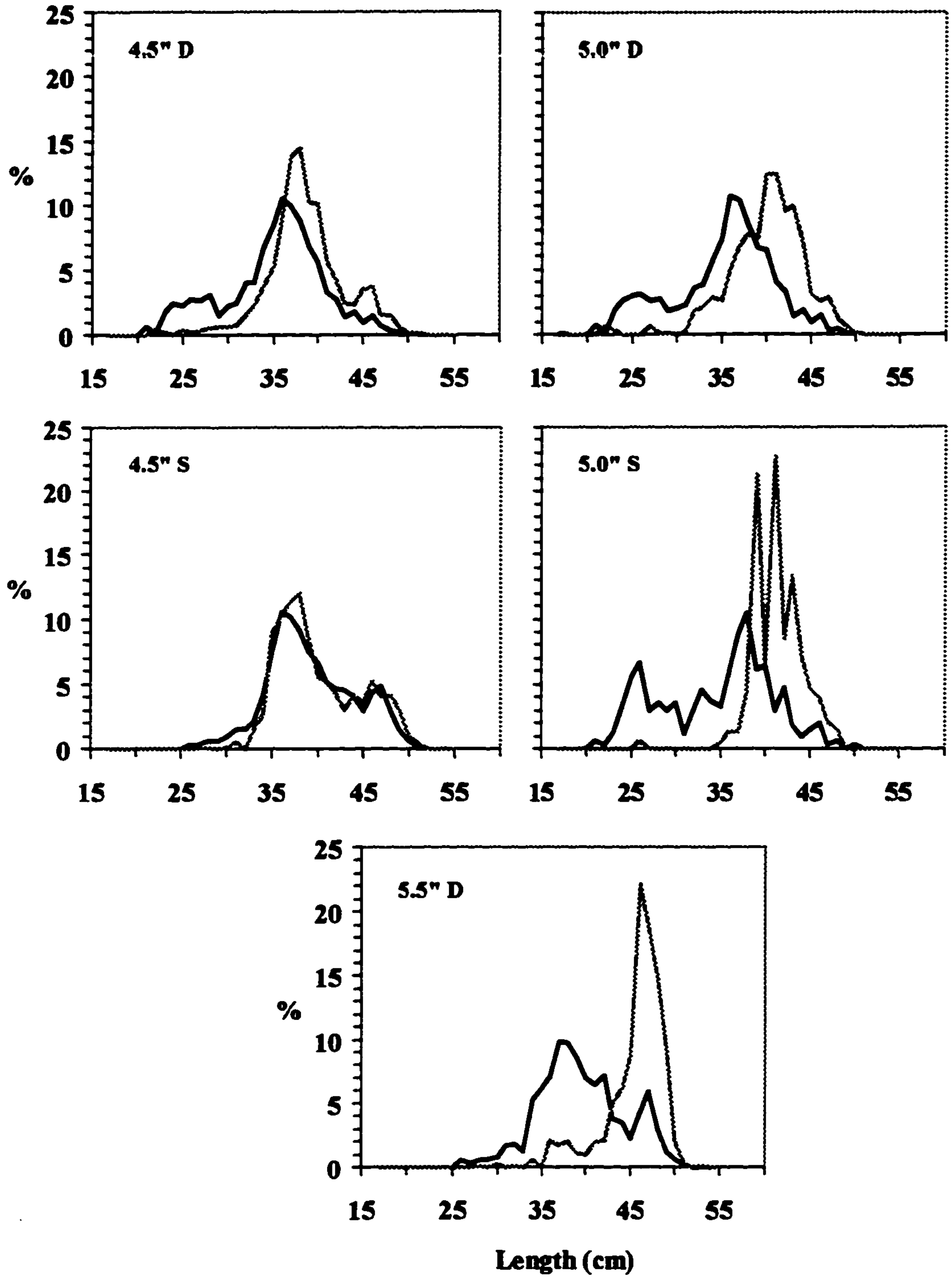

Figure 2.2*d*: Relative length frequency distributions for standard (black line) and experimental (gray lines) codends for Pacific Ocean perch (D diamond and S square mesh).

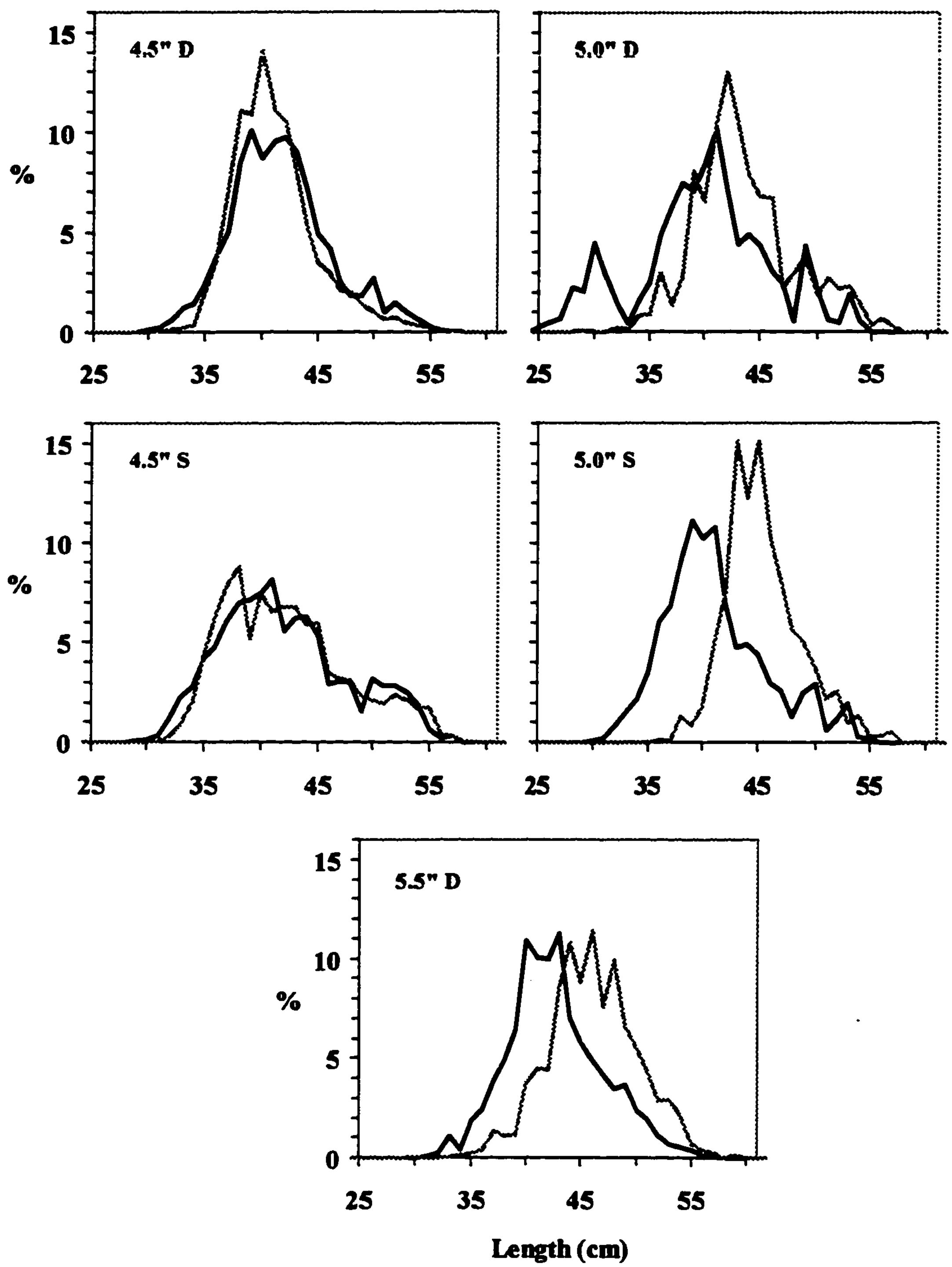

Figure 2.2*e*: Relative length frequency distributions for standard (black line) and experimental (gray lines) codends for widow rockfish (D diamond and S square mesh).

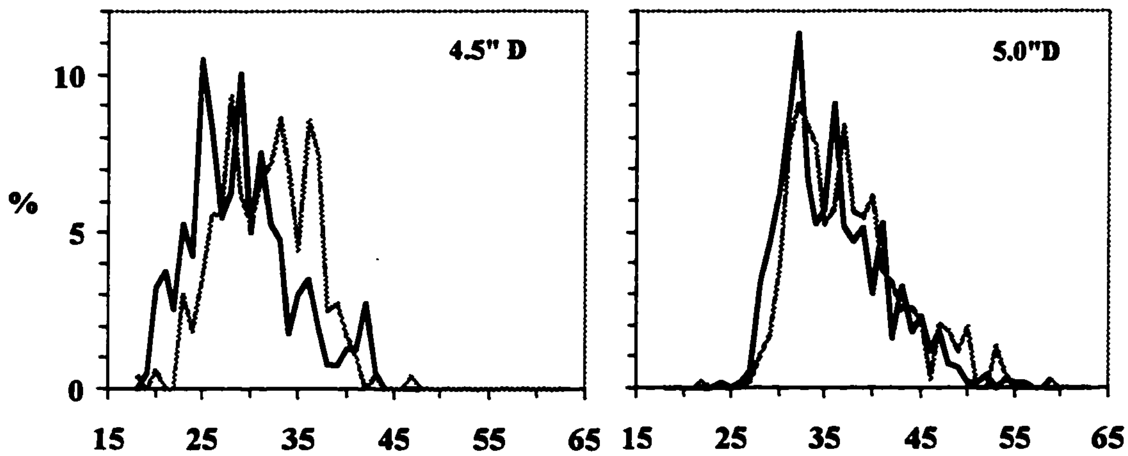

Figure 2.2*f*: Relative length frequency distributions for standard (black line) and experimental (gray lines) codends for petrale sole (D diamond and S square mesh).

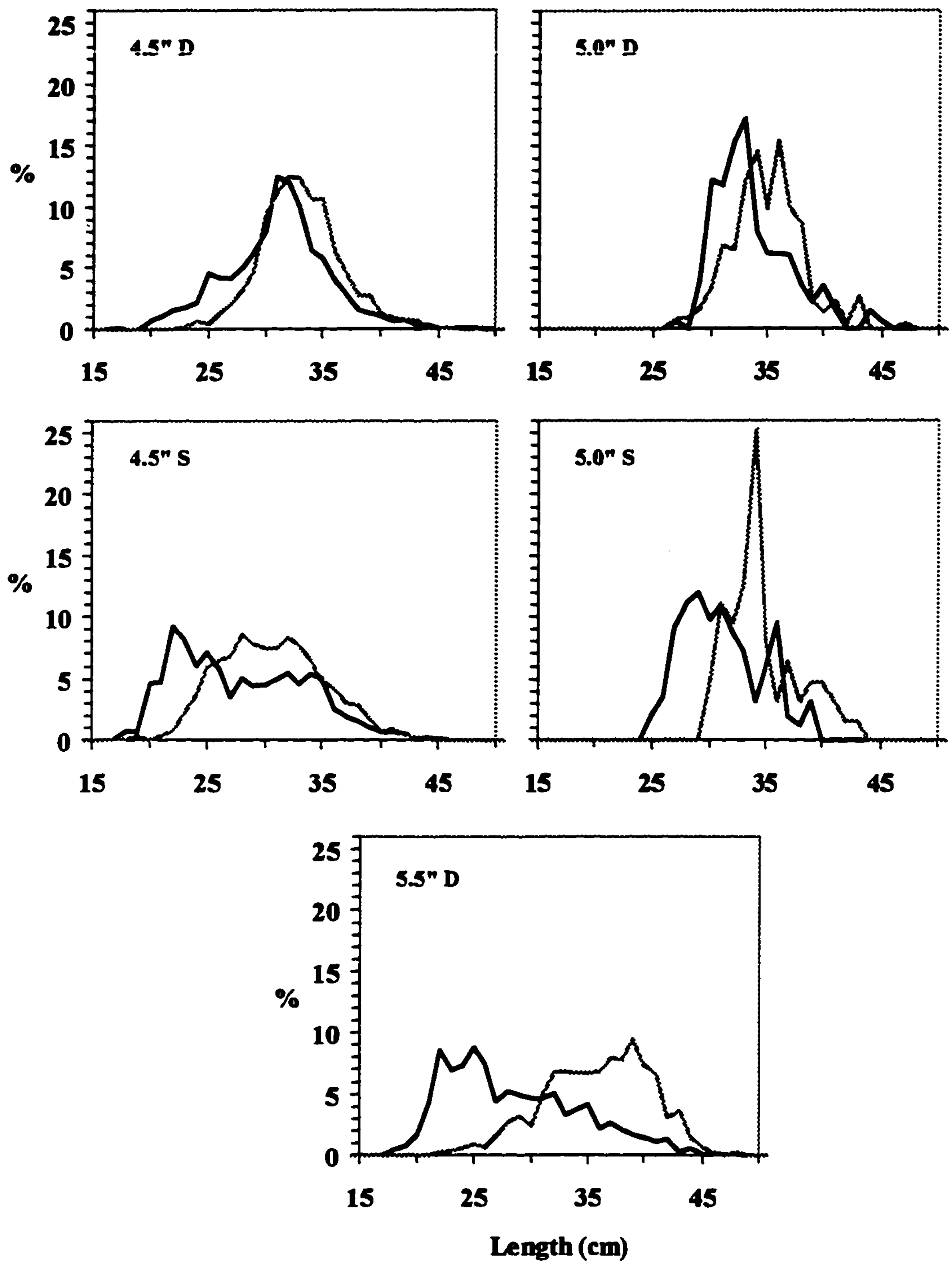

Figure 2.2*g*: Relative length frequency distributions for standard (black line) and experimental (gray lines) codends for English sole (D diamond and S square mesh).

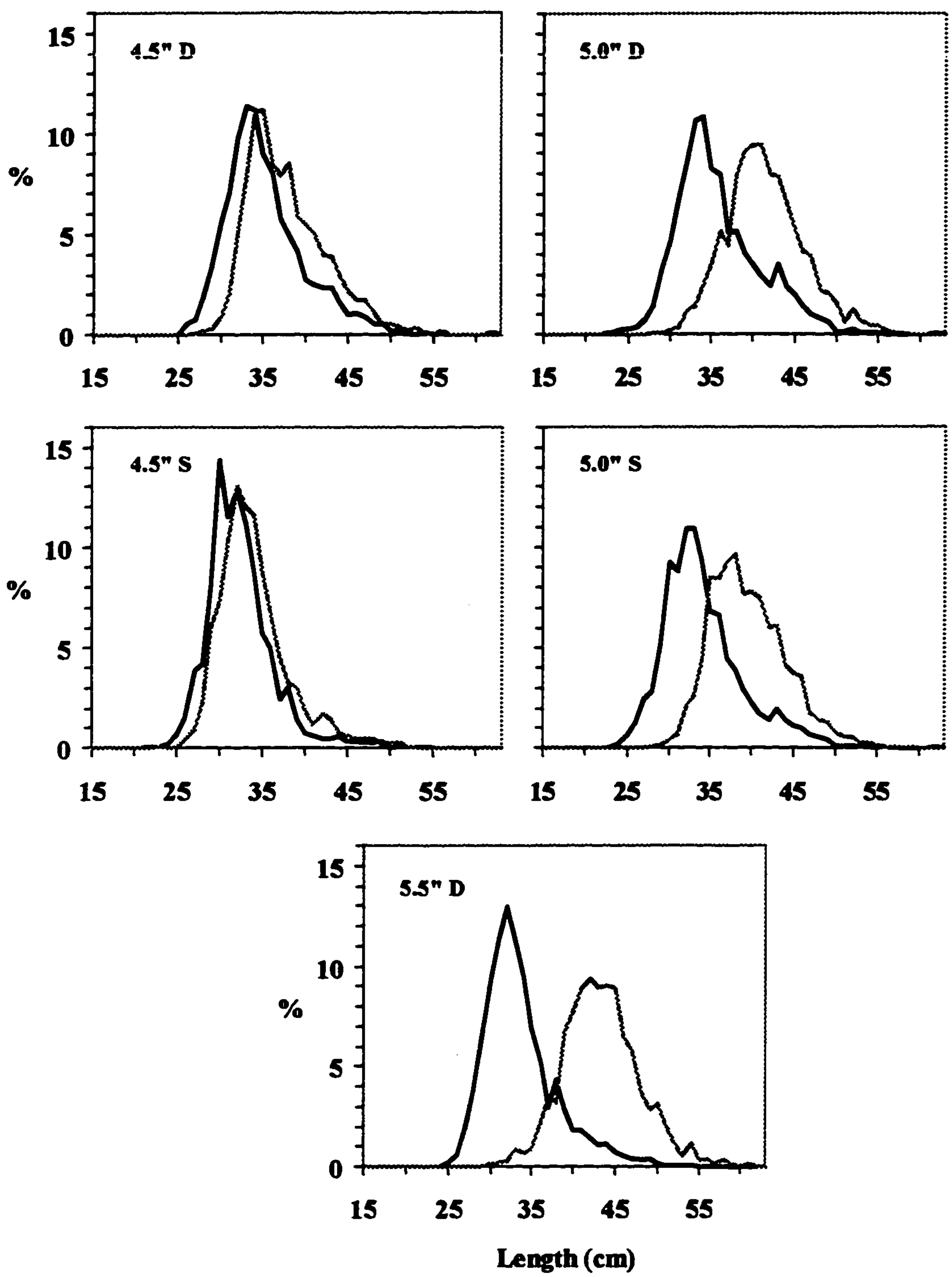

Figure 2.2*h*: Relative length frequency distributions for standard (black line) and experimental (gray lines) codends for Dover sole (D diamond and S square mesh).

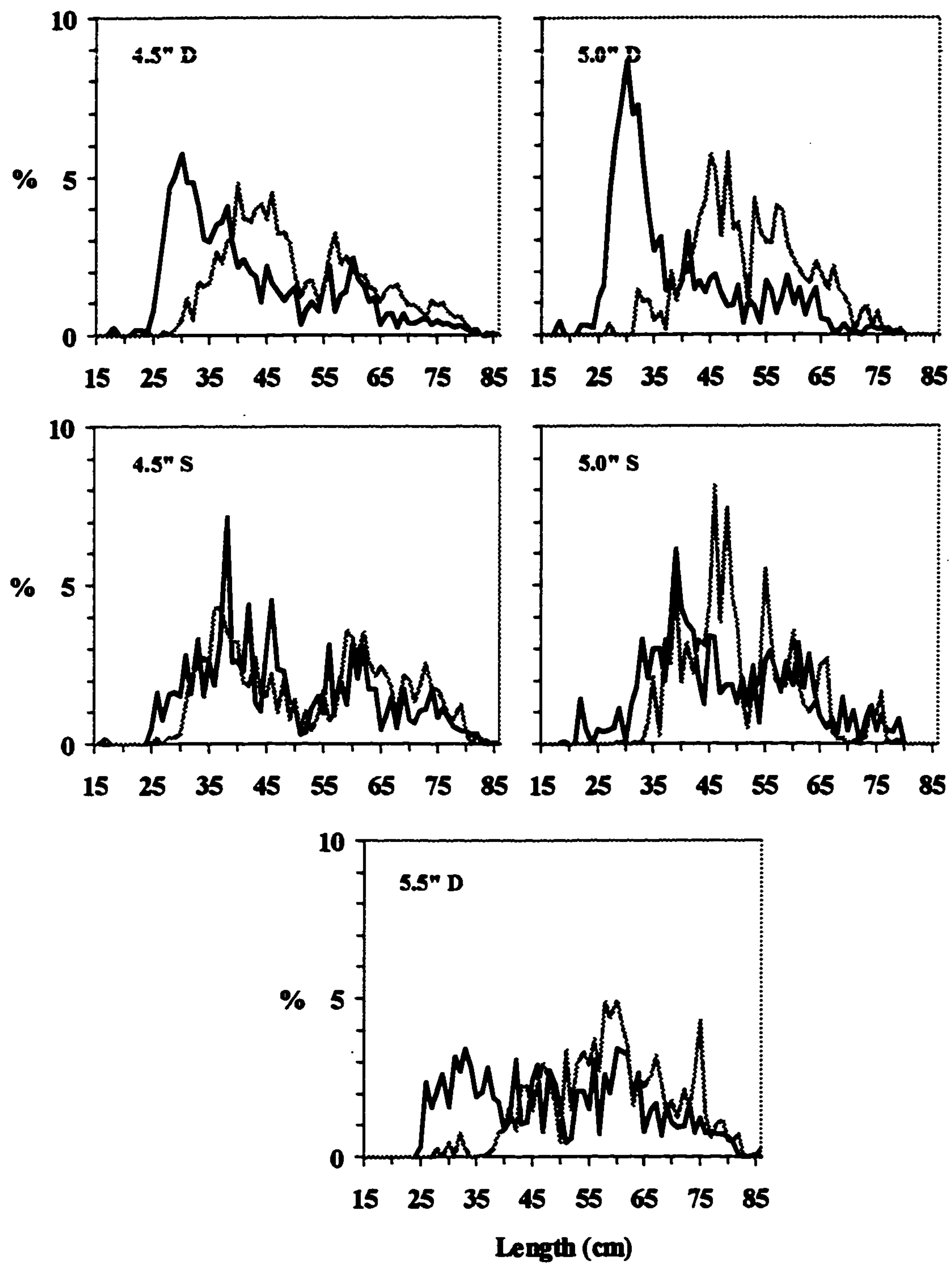

Figure 2.2*i*: Relative length frequency distributions for standard (black line) and experimental (gray lines) codends for arrowtooth flounder (D diamond and S square mesh).

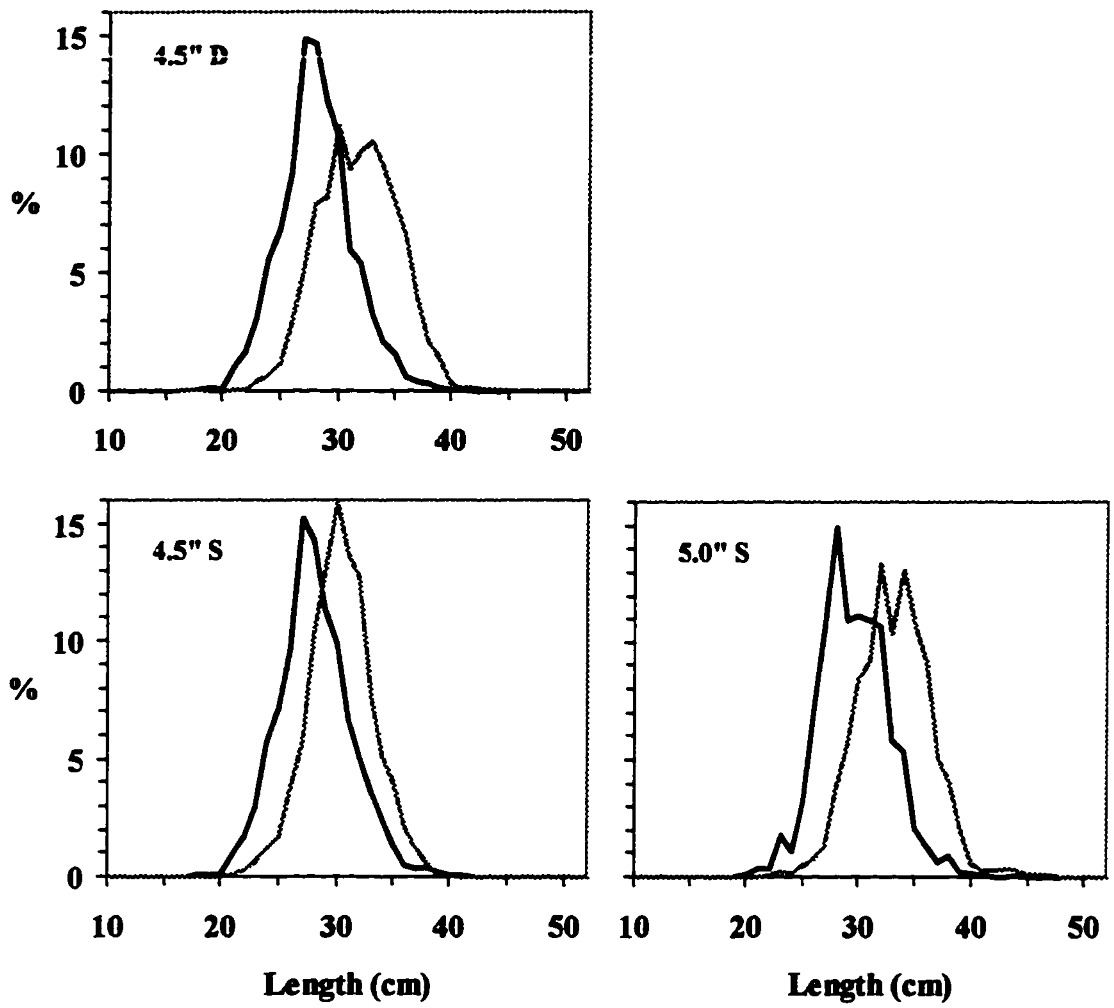

Figure 2.2*j*: Relative length frequency distributions for standard (black line) and experimental (gray lines) codends for rex sole (D diamond and S square mesh).

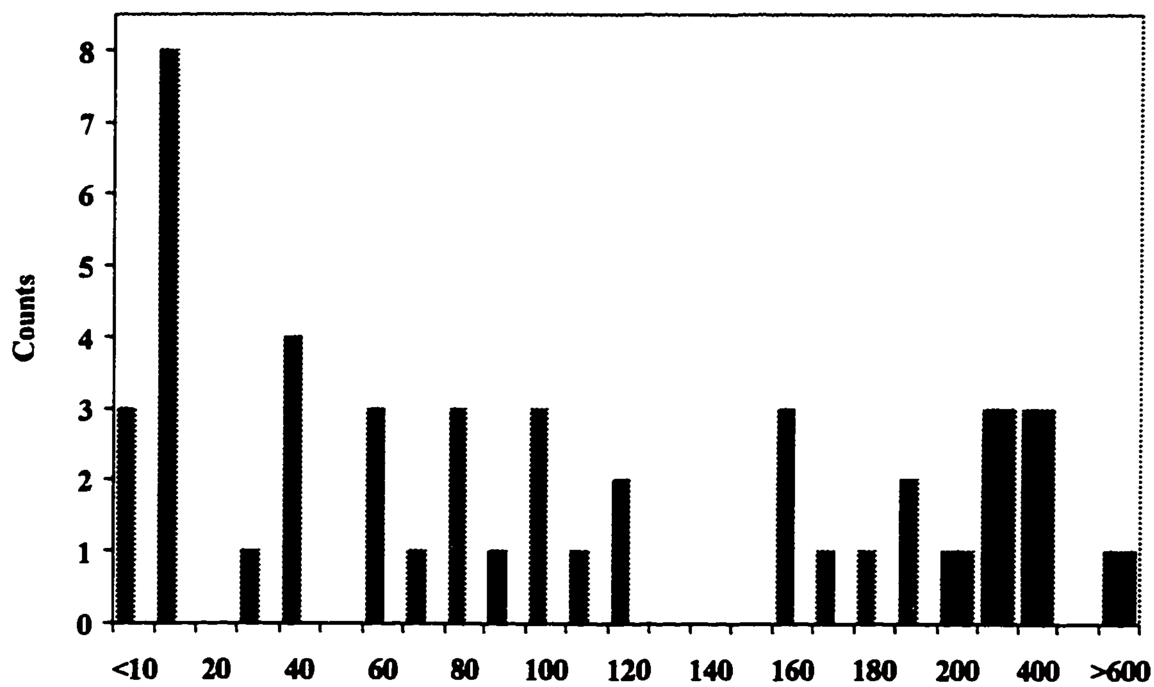

Figure 2.3: Distribution of the correction for between-haul variability (*REP/df*) for the 45 studied cases.

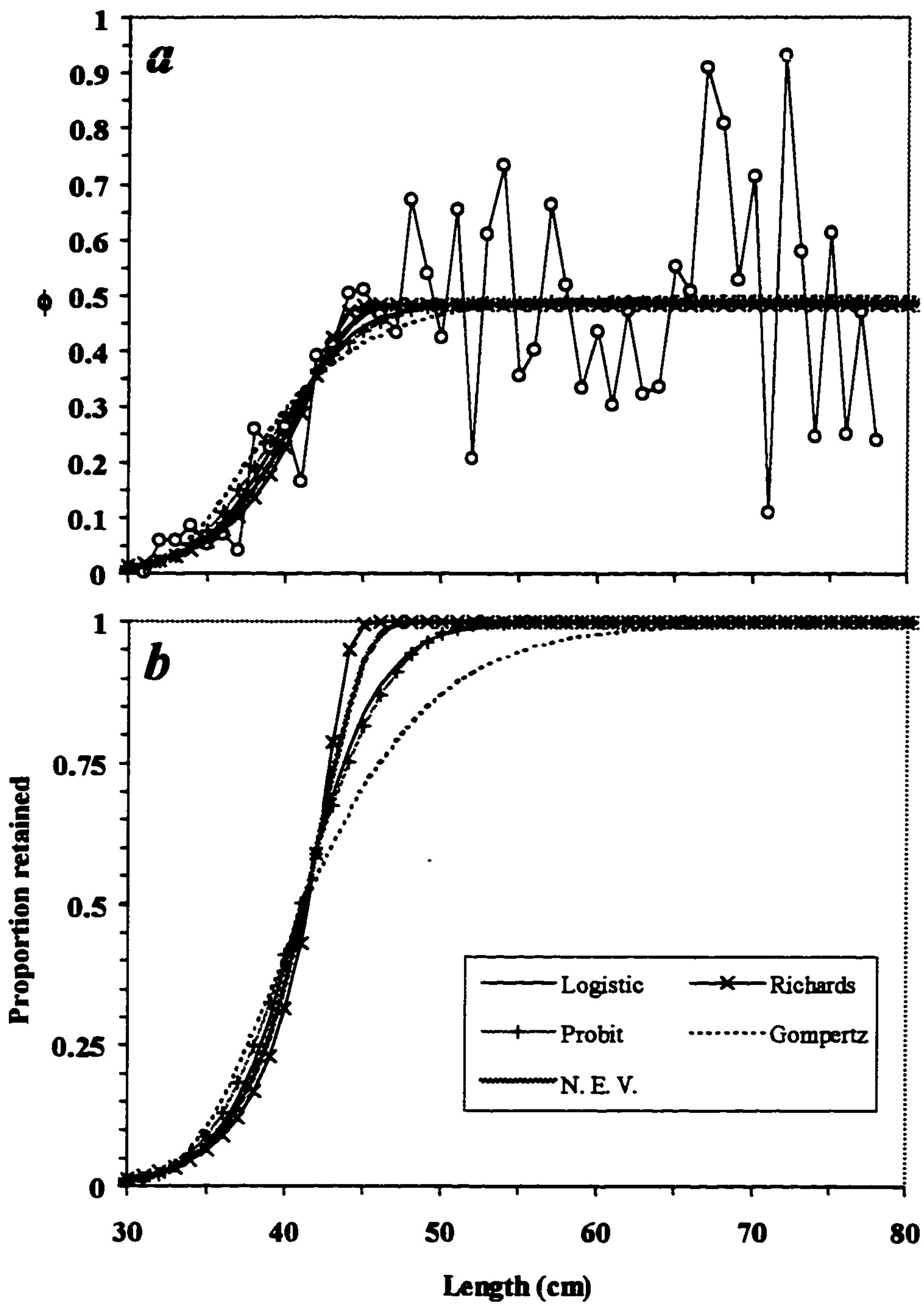

Figure 2.4: Fits of Millar's model to data for arrowtooth flounder and 5.0"D codend. ***a***) Observed (open circles) and fitted conditional retained proportions, ϕ (lines). ***b***) Selection curves.

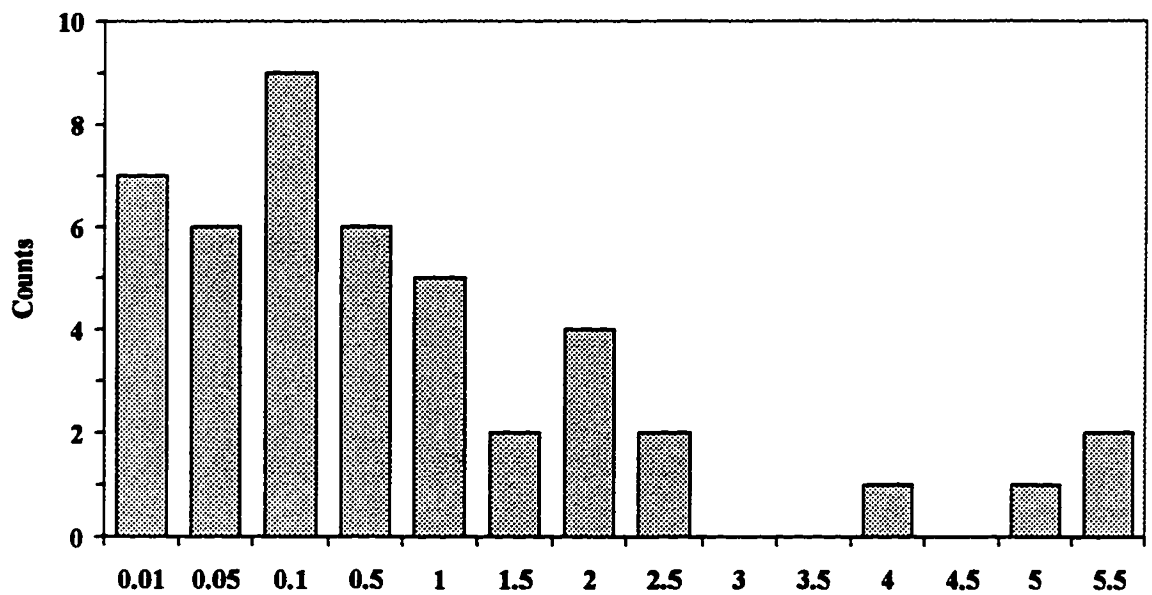

Figure 2.5: Distribution of deviance differences (i.e., maximum model deviance minus minimum model deviance) for the 45 studied cases.

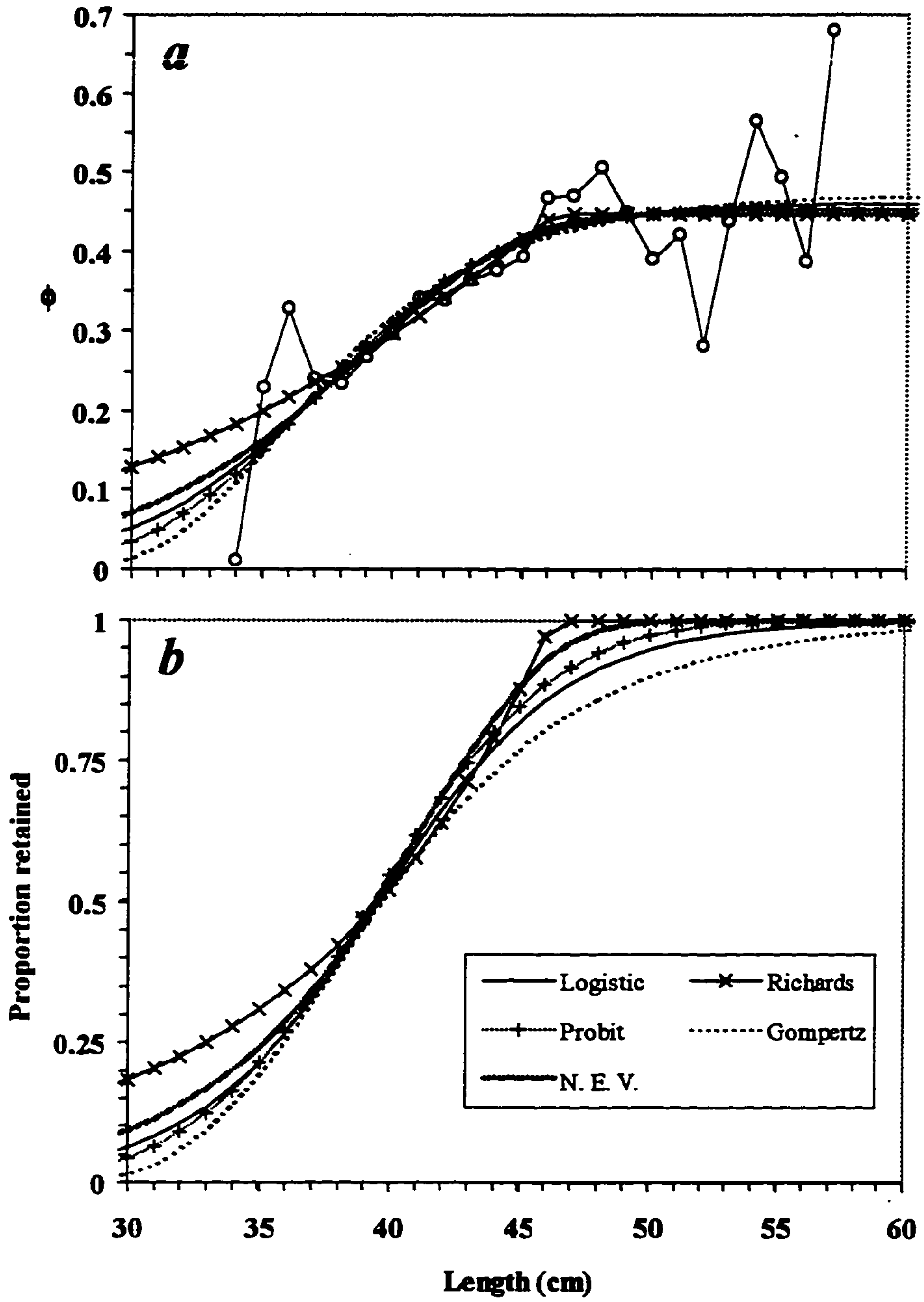

Figure 2.6: Fits of Millar's model to data for yellowtail rockfish and 4.5"S codend. ***a***) Observed (open circles) and fitted conditional retained proportions ϕ (lines). ***b***) Selection curves.

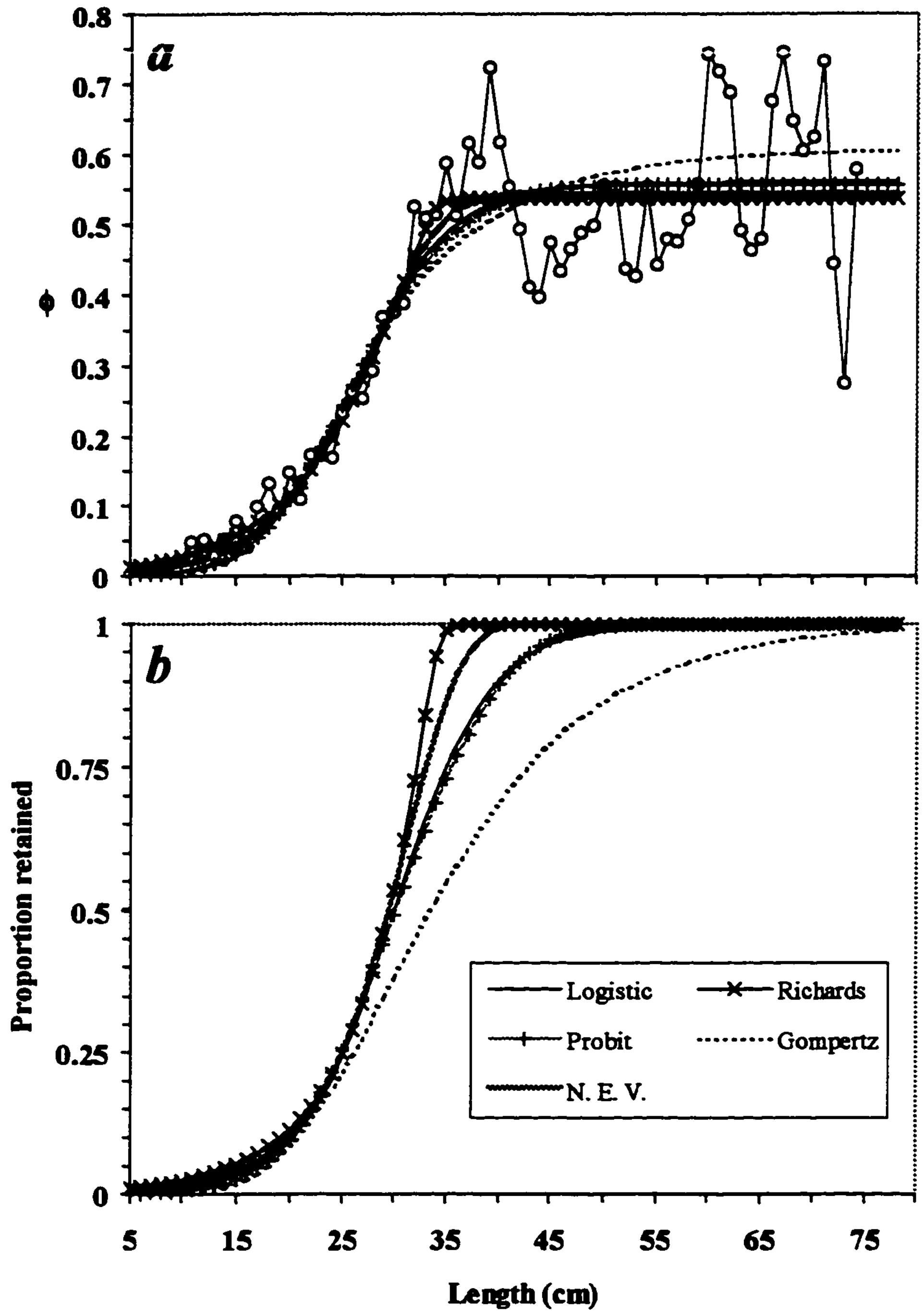

Figure 2.7: Fits of Millar's model to data for shortspine thornyhead and 4.5"D codend. ***a***) Observed (open circles) and fitted conditional retained proportions ϕ (lines). ***b***) Selection curves.

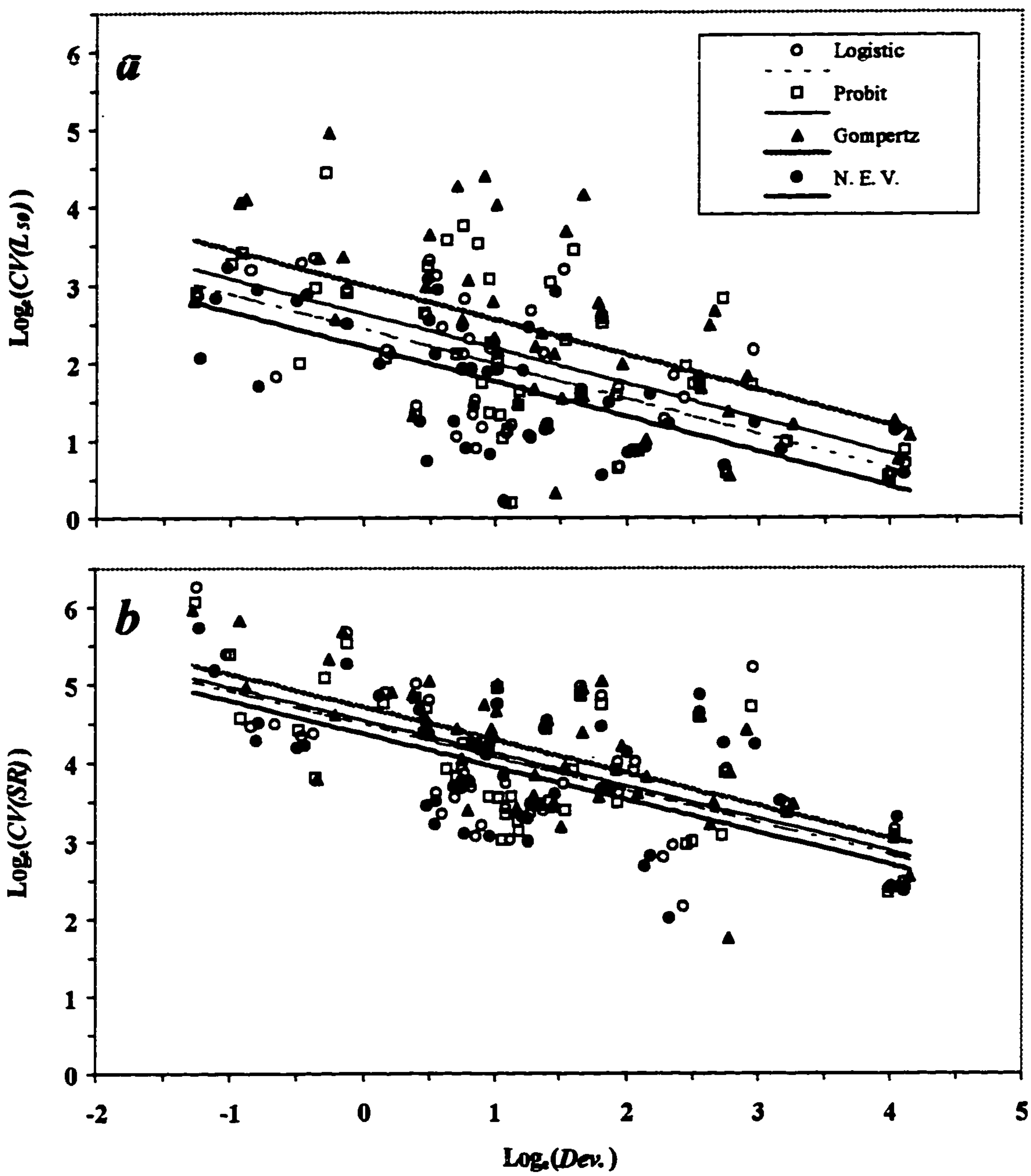

Figure 2.8: Relationships between model deviance and estimated coefficients of variation for ***a***) L_{50} and ***b***) SR. Lines indicate best least-squares fits.

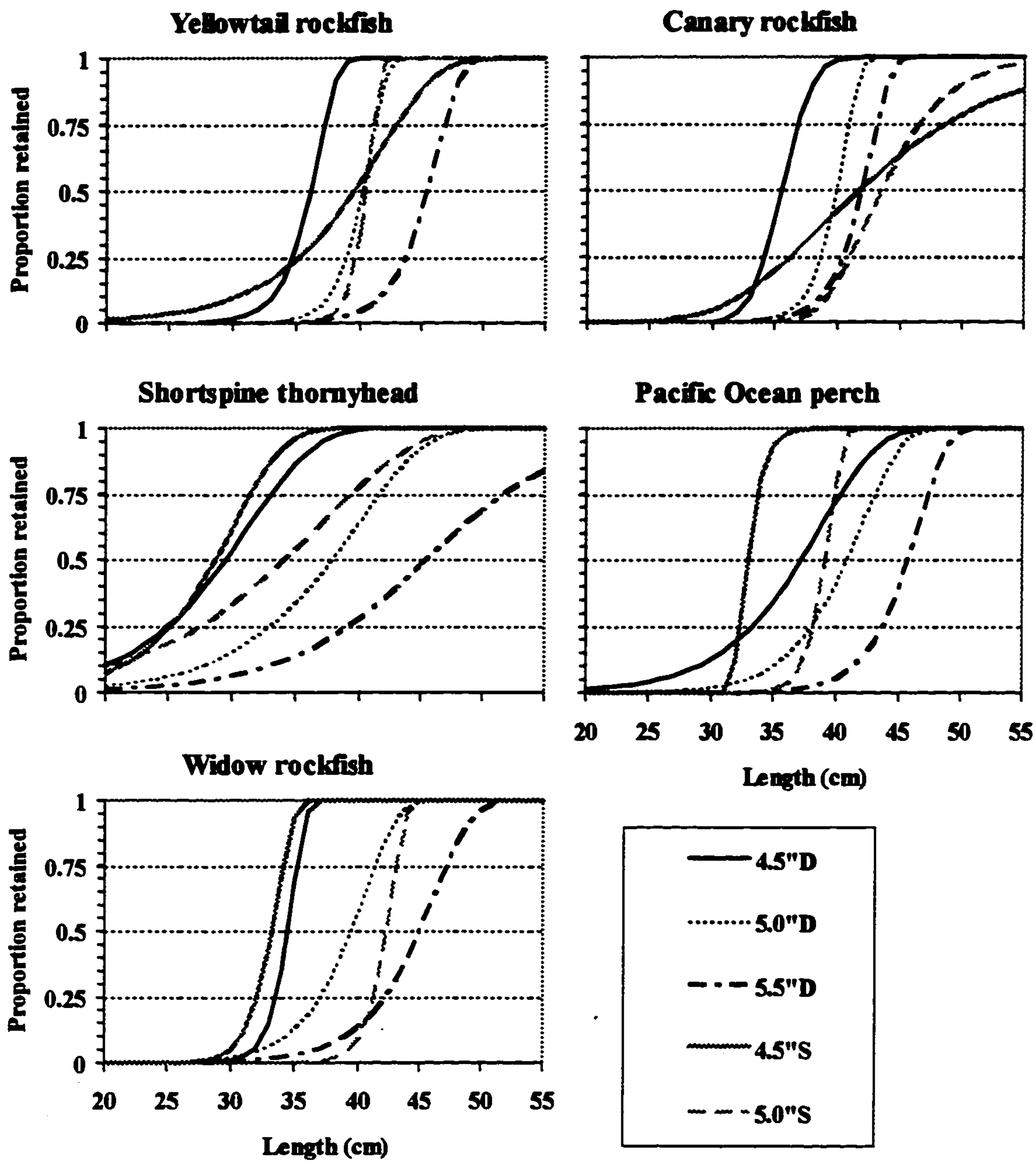

Figure 2.9: Predicted selection curves for rockfish.

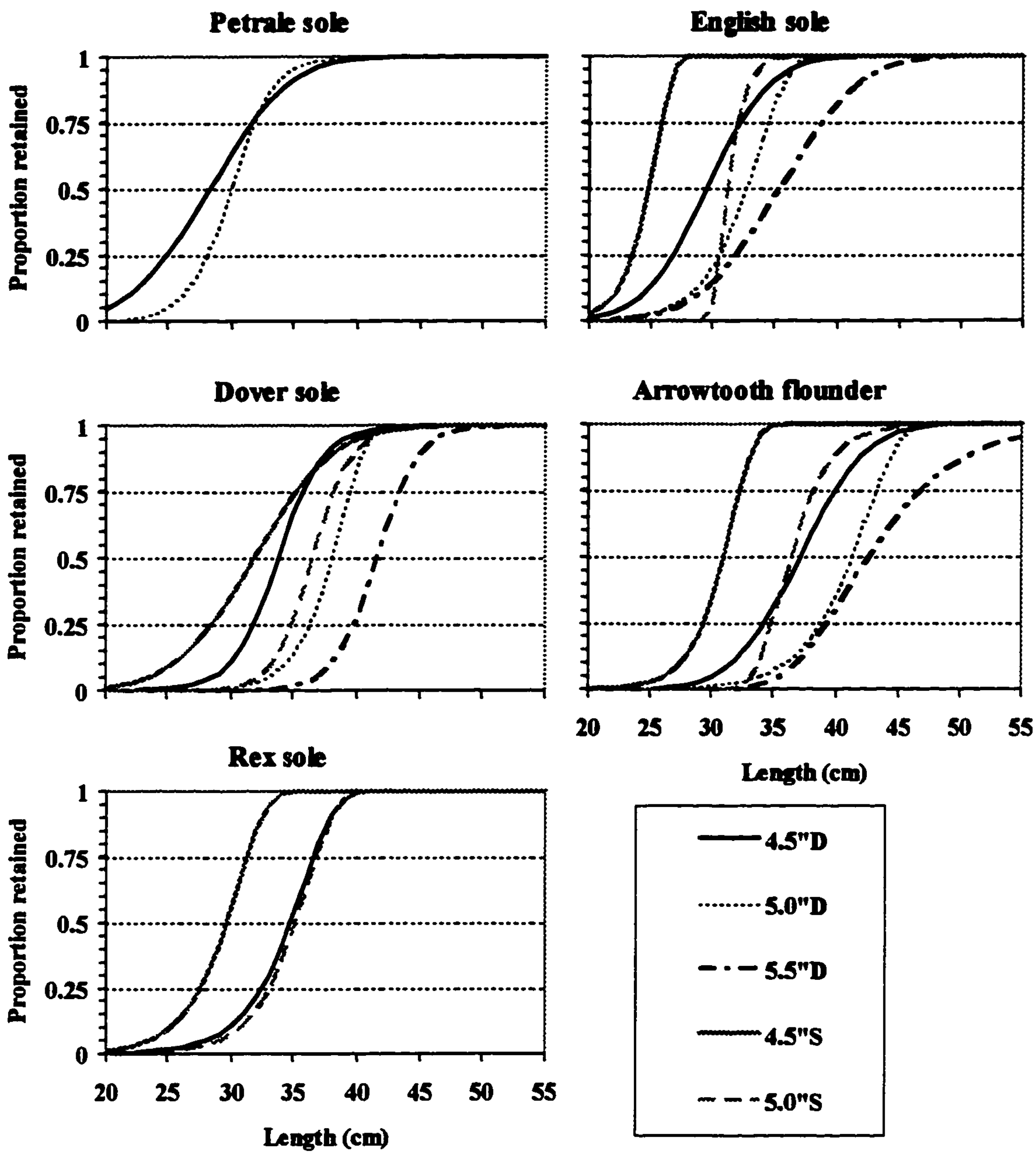

Figure 2.10: Predicted selection curves for flatfish.

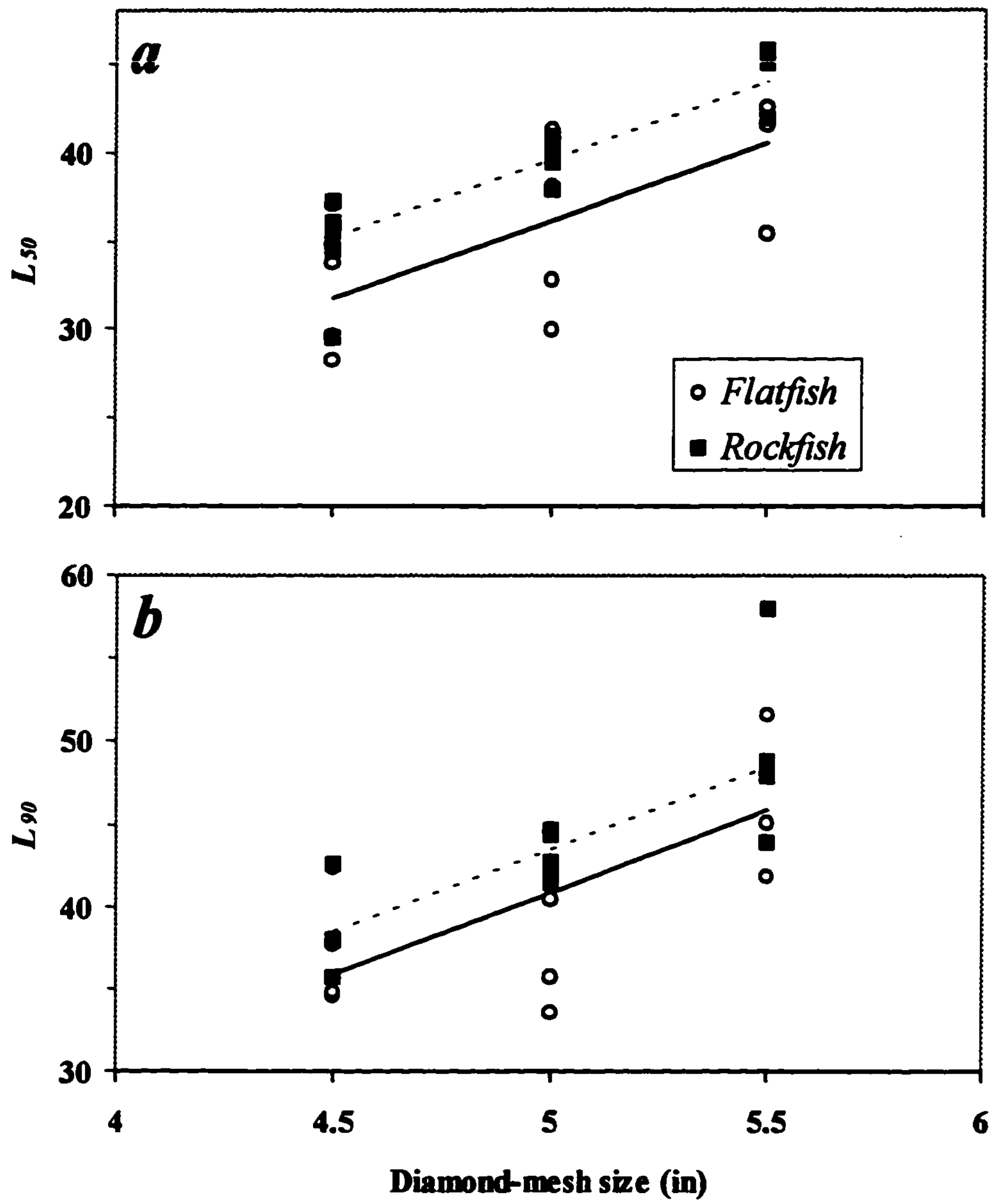

Figure 2.11: Relationships between ***a***) length of 50% retention (L_{50}), ***b***) length of 90% retention (L_{90}) and diamond-mesh nominal sizes. Dotted lines indicate rockfish and solid lines flatfish best fits.

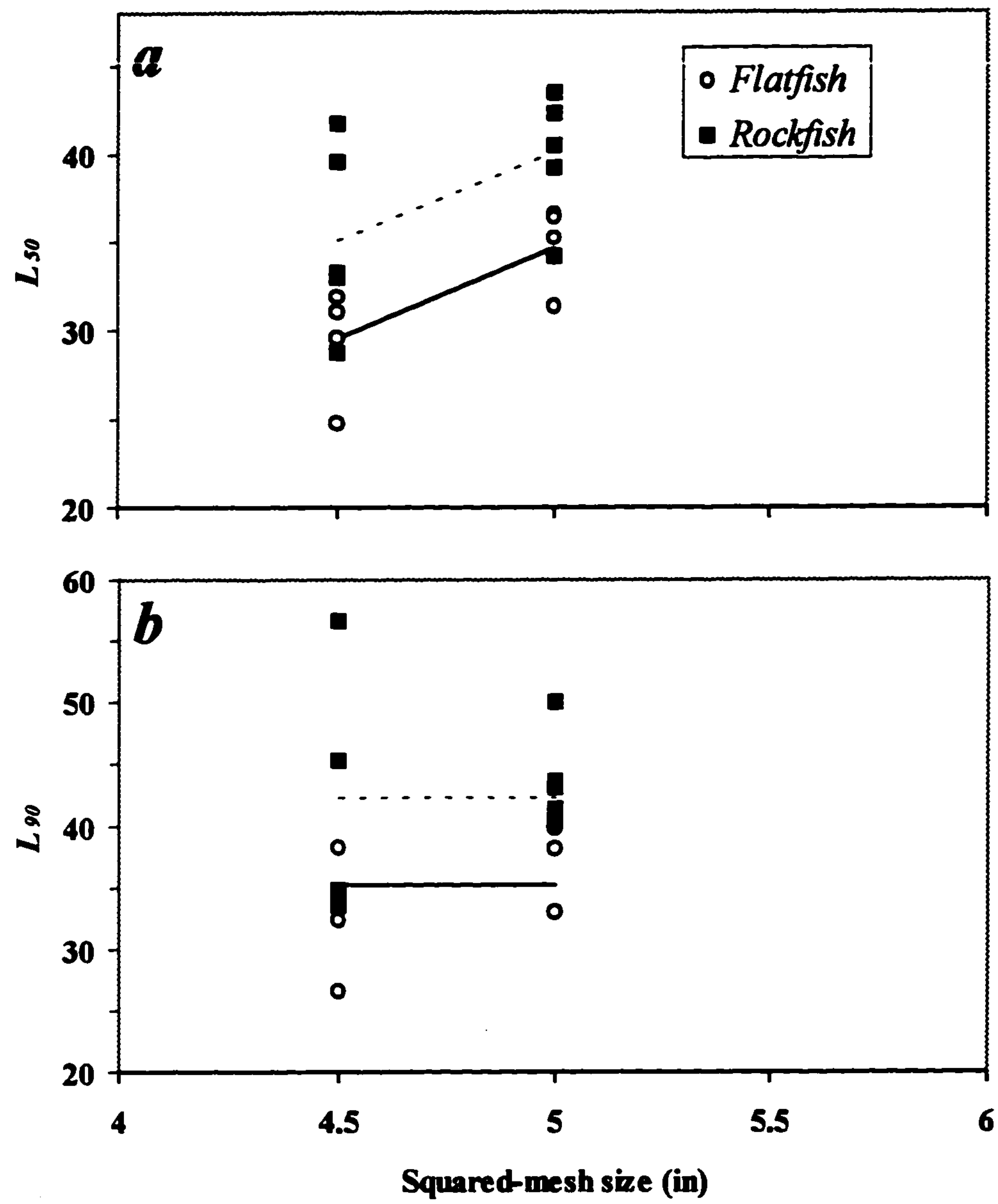

Figure 2.12: Relationships between ***a***) length of 50% retention (L_{50}), ***b***) length of 90% retention (L_{90}) and square-mesh nominal sizes. Dotted lines indicate rockfish and solid lines flatfish best fits.

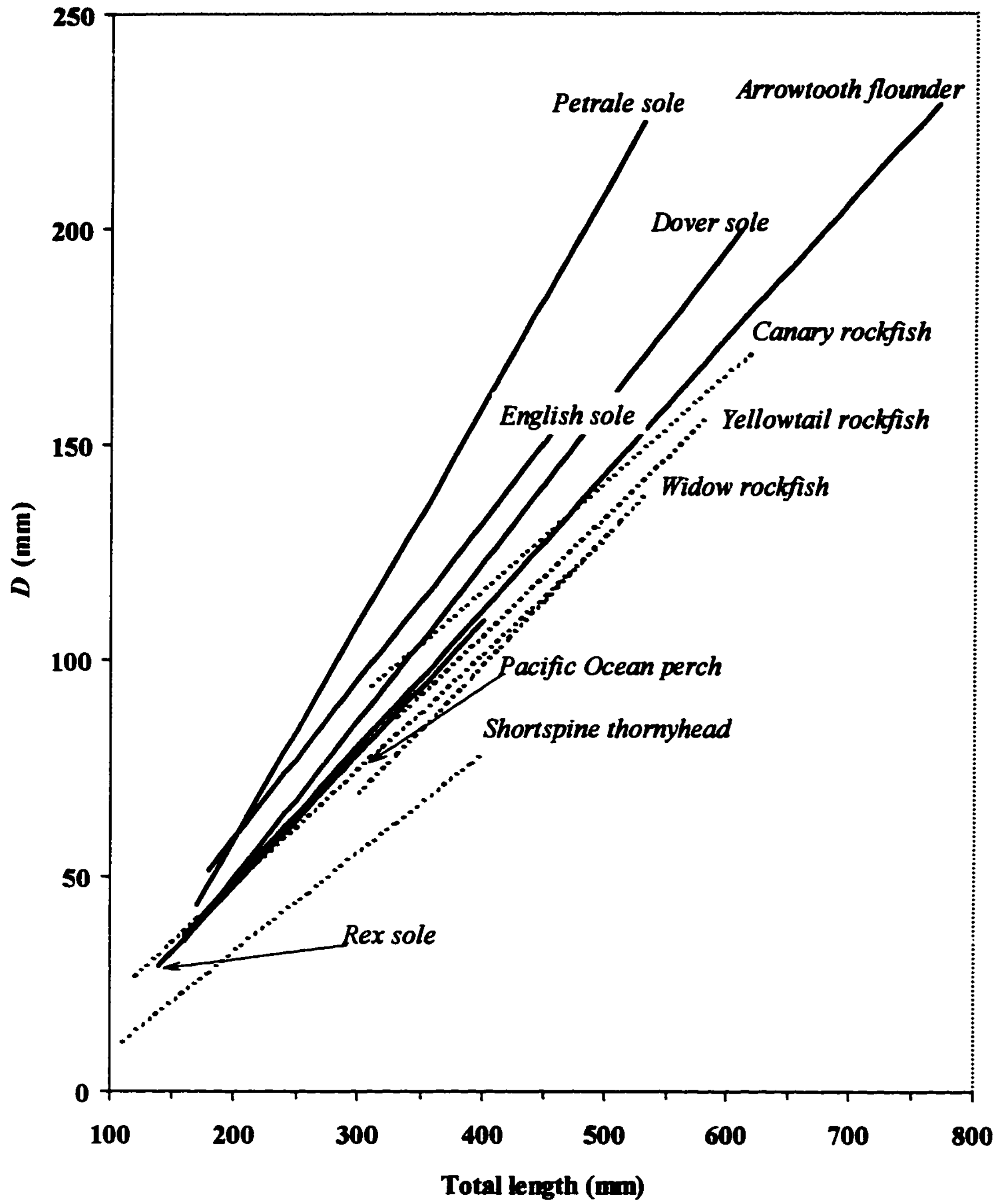

Figure 2.13: Regression lines between depth of rockfish or width of flatfish (*D*, in mm) and total length (mm) for the 10 species of the study. Dotted lines indicate rockfish, and solid lines flatfish.

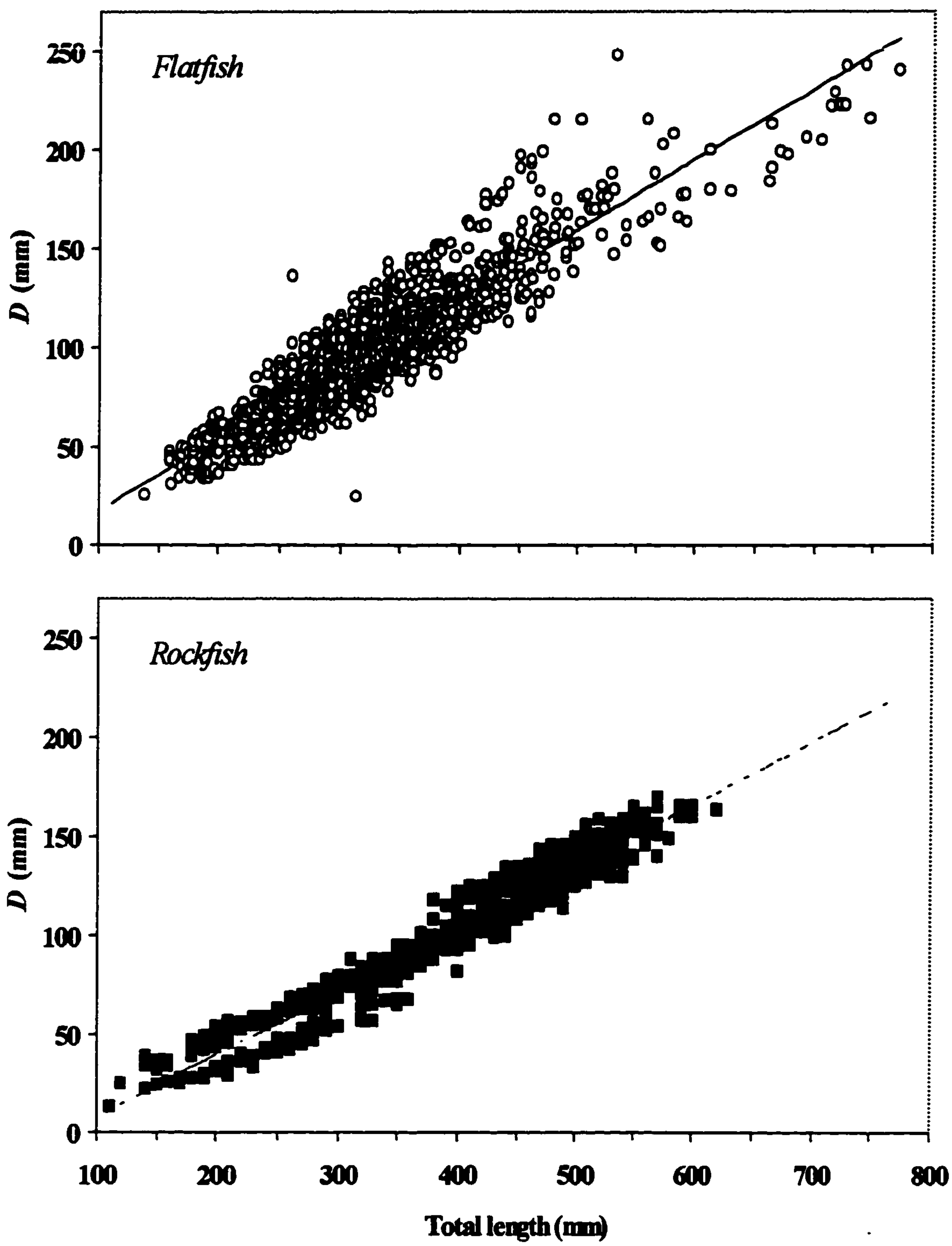

Figure 2.14: Regression lines between depth or width (*D*, in mm) and total length (mm) for flat and rockfish. Dotted lines indicate rockfish, and solid lines flatfish.

3. A multinomial model for size selection in alternate-haul studies

Introduction

In previous chapters I reviewed three methods commonly used in selectivity analyses of alternate-haul data. Two of them, Pope et al. (1975) and Simpson (1989), use ratios between numbers-at-length caught by the experimental and standard mesh codends as dependent variables, and resort to considerable data manipulation and discard to force these ratios to behave as proportions. Contrasting with these methods that do not assume any overlying statistical distribution, the third method (Millar, 1992) assumes a binomial distribution for the numbers-at-length caught and retained in the experimental mesh codend. Since this method is based upon the conditioning on total catch by size category (i.e., numbers caught and retained by both codends by size category), it requires the prior scaling of size frequency data to provide for an equal sampled proportion of the catches (e.g., Suuronen and Millar, 1992) . Despite this inconvenience Millar (1992) method tends to give less biased estimates (Cadigan and Millar, 1992) and utilizes most of the size frequency data.

In this chapter I present an alternative method to fit selectivity data from alternate-haul experiments. Like Millar (1992) method it assumes an overlying statistical distribution for the numbers caught and retained by the codends. In this case the assumed distribution is the multinomial. Multinomial distributions have been used to describe and compare length frequency data from selectivity experiments (Casey et al., 1992) and were the basic feature of the nonparametric maximum likelihood estimation method of Skalski and Perez-Comas (1993). In fact the method hereinafter described is the parametric version of the latter. The statistical model will be described first, followed by three examples illustrating its performance with alternate-haul data. Finally, the results will be contrasted with those from the other three methods.

Examples

Three catch-at-length data sets from alternate-haul experiments will be used to illustrate the estimation procedure. The first example corresponds to selectivity experiments for haddock (Melanogrammus aeglefinus) that were performed in the North Sea, and reported in Pope et al. (1975, pp. 15 and 48). The length frequency distributions for haddock (Fig. 3.1 a) were obtained by summing up the catches of two one-hour hauls performed with a codend of diamond meshes with average 35 mm, used as standard, and by summing up the catches of two one-hour hauls performed with a 87 mm diamond mesh codend. Sample sizes were $N_s = 739$ and $N_t = 787$ fish, for the standard and 87 mm diamond mesh codends, respectively.

The second example corresponds to data collected during comparative fishing experiments for Alaskan pollock (Theragra chalcogramma) performed in the Bering Sea, north of Unimak Island, from 26 September to 17 October 1993. The pollock length frequency distributions (Fig. 3.1 b) were obtained from samples of the catches of a haul performed with a double-layer 86 mm diamond mesh codend, used as standard, and of a haul performed with a 114 mm diamond mesh codend. Sample sizes were $N_s = 526$ and $N_t = 518$ fish, for the standard and 114 mm diamond mesh codends, respectively. Their samples represented 1.15% and 1.04% of the respective catches.

The last example corresponds to data collected during comparative fishing experiments for petrale sole (Eopsetta jordani) performed off the coasts of Washington. The length frequency distributions (Fig. 3.1 c) are from pooled samples of catches taken by one vessel from 5 to 14 July 1988. Sample sizes and codend mesh sizes were $N_s = 266$ and $N_t = 301$ fish, for the standard 76 mm and the experimental 114 mm diamond mesh codends, respectively, and the samples represented 0.60% and 0.44% of the catches.

Multinomial model and maximum likelihood estimation

If the length frequency distributions for the standard and experimental mesh codend have K length classes and sample sizes N_s and N_t, respectively, the following quantities can be defined:

x_{si}, the number of fish in the ith length category in the standard mesh sample,

x_{ti}, the number of fish in the ith length category of the experimental mesh sample,

p_i, the probability that a fish caught by the standard mesh is in the ith length category (i = 1, ..., K), such that $N_s = \sum_{i=1}^{K} x_{si}$ and $\sum_{i=1}^{K} p_i = 1$, and

π_i, the probability that a fish caught by the experimental mesh is in the ith length category, such that $N_t = \sum_{i=1}^{K} x_{ti}$ and $\sum_{i=1}^{K} \pi_i = 1$.

The number of fish by length class of the standard mesh sample are then multinomial random variables with joint likelihood:

$$L(x_s|N_s,p) = \binom{N_s}{x_s}\left(\prod_{i=1}^{K-1} p_i^{x_{si}}\right)\left(1-\sum_{i=1}^{K-1} p_i\right)^{N_s - \sum_{i=1}^{K-1} x_{si}}, \qquad (3.1)$$

subject to the constraints $p_i \geq 0$ and $\sum_{i=1}^{K} p_i = 1$.

Similarly, one can express x_{ti}, the number of fish in the ith length category of the experimental mesh sample as multinomial random variables with probabilities π_i and joint likelihood:

$$L(x_t|N_t,\pi) = \binom{N_t}{x_t}\left(\prod_{i=1}^{K-1} \pi_i^{x_{ti}}\right)\left(1-\sum_{i=1}^{K-1} \pi_i\right)^{N_t - \sum_{i=1}^{K-1} x_{ti}}, \qquad (3.2)$$

subject to the constraints $\pi_i \geq 0$ and $\sum_{i=1}^{K} \pi_i = 1$.

Assuming that both codends have sampled fish from the same size distribution and that size selection has occurred, the capture probabilities p_i and π_i are functions of the length distribution of the fish population and the absolute selectivity coefficients of the standard and experimental mesh codends. Thus

$$p_i = \frac{f_i \times s_i}{\sum_{i=1}^{K} f_i \times s_i}$$

$$\pi_i = \frac{f_i \times t_i}{\sum_{i=1}^{K} f_i \times t_i}$$

where f_i is the probability that a fish is in the ith length category, and s_i and t_i are the probabilities that a fish in the ith length category is retained in the standard or the experimental codend, respectively. If the term $r_i = \frac{t_i}{s_i}$ represents the selectivity of the experimental mesh relative to that of the standard mesh for the ith length class, one can redefine the capture probability for the experimental mesh as:

$$\pi_i = \frac{p_i \times r_i}{\sum_{i=1}^{K} p_i \times r_i} \tag{3.3}$$

Furthermore, r_i can be defined as a sigmoidal function of length with a small number of parameters (α_j for $j = 1, ..., v$ such that $v <<< K$). For example, r_i may be described as a logistic curve, a log-log or Gompertz curve, or a Richards curve, with $v = 2$, 2 and 3, respectively. In the analysis of the examples that follows I adopted a logistic function for the length, parameterized in the following way:

$$r_i = \frac{1}{1 + \exp\left(-(l_i - \mu)/\sigma\right)}$$

where l_i is the length of size category i, and μ and σ are parameters representing the length at 50% retention and the slope of the curve at that point, respectively.

By replacing (3.3) in (3.2), one obtains a reparameterized expression for the likelihood of the x_t:

$$L(x_t|\mathrm{N}_t,p,\alpha)=\binom{\mathrm{N}_t}{x_t}\left(\prod_{i=1}^{\mathrm{K-1}}\left(\frac{p_i\times r_i}{\sum_{i=1}^{\mathrm{K}}p_i\times r_i}\right)^{x_{ti}}\right)\left(1-\sum_{i=1}^{\mathrm{K-1}}\left(\frac{p_i\times r_i}{\sum_{i=1}^{\mathrm{K}}p_i\times r_i}\right)\right)^{\mathrm{N}_t-\sum_{i=1}^{\mathrm{K-1}}x_{ti}} \quad . \tag{3.4}$$

The likelihood model for the joint length frequency distributions of the standard and experimental meshes is the product of equations (3.1) and (3.4):

$$L(x_s,x_t|\mathrm{N}_s,\mathrm{N}_t,p,\alpha)=L(x_s|\mathrm{N}_s,p)\times L(x_t|\mathrm{N}_t,p,\mu,\sigma). \tag{3.5}$$

After taking logarithm and some manipulation of the terms, I obtain a final expression for the log-likelihood function of model (3.5):

$$\ell=\ln(L)=\sum_{i=1}^{\mathrm{K}}n_i\times\ln p_i+\sum_{i=1}^{\mathrm{K}}x_{ti}\times\ln r_i-\sum_{i=1}^{\mathrm{K}}x_{ti}\times\ln\left(\sum_{i=1}^{\mathrm{K}}p_i\times r_i\right). \tag{3.6}$$

where $n_i=x_{si}+x_{ti}$, and constant terms have been eliminated. The K+1 parameters of the model can be estimated by maximizing log-likelihood function (3.6) or minimizing the negative log-likelihood function ($-\ell$). Minimization can be achieved by means of a numerical estimation procedure such as Newton-Raphson or any of the Quasi-Newton algorithms. Standard errors for the parameter estimates $\hat{\mu}$, $\hat{\sigma}$ and $\hat{p}_i$ can be obtained from maximum likelihood theory by taking the square roots of the diagonal elements of the variance-covariance matrix. The $(\mathrm{K}+1)\times(\mathrm{K}+1)$ variance-covariance matrix is the inverse of the Fisher information matrix evaluated at final parameter values (Appendix 2.1). From parameter estimates $\hat{\mu}$ and $\hat{\sigma}$, lengths at which given percent retentions occur ($L_{r\%}$) can be easily derived, and their approximate standard errors can be estimated using Delta method (Appendix 2.2).

The validity of the maximum likelihood estimates and associated standard errors depends upon five assumptions, that are common to the nonparametric method presented elsewhere (Skalski and Perez-Comas, 1993), and to other methods proposed for the analysis of size selectivity from alternate-haul experiments (Pope et al., 1975; Simpson, 1989; Millar, 1992). These key assumptions are as follows:

1) The fate of each fish captured and retained is independent of all other fish.
2) The standard and experimental mesh codends sample the same population of fish with respect to size distributions.
3) The standard and experimental mesh codends sample the fish population independently.
4) The same size classes are used in the likelihoods for both standard and experimental mesh codends.
5) The standard mesh codend representatively samples the size distribution of the fish population. If the standard mesh codend does not representatively sample the size distribution of the fish population (i.e. s_i < 1), then the estimated selectivity coefficients will measure relative selectivity.

Analysis of examples

For the analysis of the examples the following procedure was followed. First, capture probabilities p_i and logistic parameters μ and σ were estimated simultaneously by minimizing the negative log-likelihoods ($-\ell$). The K+1 estimates were obtained using Excel function Solver which uses a Quasi-Newton search algorithm. Second, I calculated the log-likelihood ratio statistic (deviance) for each fit to assess the adequacy of the model. Deviance, defined as $D = 2 \times (\ell_{\text{Full}} - \ell_{\text{Red}})$, where ℓ_{Red} is the log-likelihood function evaluated at final parameter values and ℓ_{Full} is the log-likelihood for the full model[1], will be approximately $\chi^2_{n-\mathrm{p}}$ if the model is good (McCullagh and Nelder, 1989; Dobson, 1990). Third, I calculated lengths at 50%, 65% and 80% retentions ($L_{50\%}$, $L_{65\%}$

[1] The full model is the likelihood corresponding to the same distribution (e.g., multinomial) with number of parameters equal to the total number of observations, n. In our examples, the log-likelihoods for the full model were calculated by replacing the proportions p_i and π_i by their observed values $x_{is}/\mathrm{N_s}$ and $x_{it}/\mathrm{N_t}$.

and $L_{80\%}$) for each fit, and produced approximate standard errors by using equations in Appendices 2.1 and 2.2. Fourth, I applied the methods of Pope et al. (1975), Simpson (1989), and Millar (1992) to obtain alternative parameter estimates. Nonlinear least squares estimation (NLSE) was used for the first two methods, and maximum likelihood estimation (MLE) for the third one. Finally, I contrasted these selectivity estimates with those for the present multinomial model. To evaluate the relative performance of the four estimation methods, I calculated expected length frequency distributions for the experimental codends using the parameter estimates and assumptions of each method. I used chi-squared tests to assess whether the observed length frequency distributions were equal to the expected ones. Significant differences (P < 0.05) among observed and expected distributions were taken as an indication of a bad performance of the estimation method.

Results of multinomial model fits

The resulting fits of the multinomial model to the three examples are displayed in Table 3.1. This table shows the parameter estimates for the logistic curve ($\hat{\mu}$ and $\hat{\sigma}$) and their very tight standard errors (between parentheses). The estimated capture probabilities p_i were very close to the observed values $\frac{x_{si}}{\mathrm{N}_s}$, which are the MLE and moment estimator for likelihood **(3.1)**. All length classes with non-zero frequency in the sample distributions of both standard and experimental codends were used in the analyses, a total of 20, 19 and 24 length classes for haddock, pollock and petrale sole, respectively (Table 3.1).

For the three examples, the multinomial model fitted the data adequately. Deviances were 12.880, 16.871 and 25.876 for haddock, pollock and petrale sole, respectively. These statistics had probabilities equal to 0.845, 0.532 and 0.307 of being χ^2_{40-21}, χ^2_{38-20} and χ^2_{48-25}, respectively.

The approximate standard errors for the lengths at 50%, 65% and 80% ($L_{50\%}$, $L_{65\%}$ and $L_{80\%}$) were relatively tight, and they increased with increasing percent retentions (Table 3.1). $L_{65\%}$ and $L_{80\%}$ for the pollock and petrale example were larger than those for haddock.

Comparison with other methods

The haddock, pollock and petrale examples were also analyzed using the methods of Pope et al. (1975), Simpson (1989) and Millar (1992). Estimates from these fits are displayed in Table 3.2. The resulting selectivity curves are shown in Figure 3.2 together with the curves resulting from the multinomial model fits.

In order to interpret these results it is important to recall that the four methods treat the data differently. While the multinomial model is concerned with the proportions for the k length classes in the length sample from the experimental codend (i.e., $\pi_i \approx \frac{x_{ti}}{\mathrm{N}_t}$), Millar's method uses conditional probabilities, the numbers caught and retained in the experimental codend with respect to the catch by both the experimental and standard codends (i.e., $\phi_i \approx \frac{x_{ti}}{x_{si} + x_{ti}}$). On the other hand, both Simpson (1989) and Pope et al. (1975) approaches use corrected ratios between the catches-at-length of the experimental and standard codends that are less or equal to one (i.e., $\frac{x_{ti}}{x_{si}} \leq 1$). The corrected ratios for Simpson (1989) approach are three-point moving averages of the raw ratios, while those for Pope et al. (1975) are products of the raw ratios times the quotient between the numbers-at-length caught in the experimental codend to those caught in the standard codend for which the raw ratios are greater than one. Finally, while the present multinomial and Millar's estimates are MLEs, those for Pope et al. (1975) and Simpson (1989) are NLSEs.

For the three examples, the estimates of the logistic parameters $\hat{\mu}$ and $\hat{\sigma}$, and lengths-at-retention for the multinomial model were very close to those for Millar's model (Tables 3.1 and 3.2), and both methods incorporated most of the available data in the estimation (see length class range in Tables 3.1 and 3.2). Differences between the selectivity curves predicted by both models were minimal for the haddock and pollock examples (Fig. 3.2 a and 3.2 b). For the petrale example, however the curves differed in their slopes (Fig. 3.2 c).

Estimates for Pope et al. (1975) and Simpson (1989) methods were very different (Table 3.2), and their selectivity curves showed larger retentions for most of the length range (Fig. 3.2). Discrepancies among fits were more acute for the pollock and petrale examples. For the three examples, most of the larger length classes were excluded from the estimation (see length class range used in Table 3.2).

Since selectivity curves obtained from each estimation procedure are considerably different (Fig. 3.2), one may wonder which one, if any, is the best representation of the size selectivity occurring at each case example. This is a question difficult to answer because each method relies upon somewhat different assumptions, uses different estimation procedures (i.e., MLE and NLSE), and, moreover, treats the data differently, in many cases modifying the response variable and discarding information (e.g.,Pope et al., 1975 and Simpson, 1989).

Traditional approaches such as deviance D, used for the multinomial and Millar's appoaches, or coefficients of determination r^2, used for Pope et al.(1975) and Simpson (1989) methods, will not tell us the relative goodness-of-fit of the various $\hat{\mu}$'s and $\hat{\sigma}$'s to represent the actual size selectivity present in each example. For example, judging by the log-likelihood ratio tests, fits to Millar (1992) model were as good as those obtained with the multinomial model. Deviances were 14.301, 17.584 and 32.735 for the haddock, pollock and petrale examples with probabilities of 0.815, 0.550 and 0.110, respectively. The coefficients of determination for the fits of both ratio methods were also large suggesting good fits. For Pope at al.(1975) r^2s were equal to 0.974, 0.98 and 0.894 for haddock, pollock and petrale, respectively. For Simpson (1989) r^2s were equal to 0.967, 0.898 and 0.971, respectively.

In an attempt to evaluate the relative performance of the four estimation methods, and to help us decide among the many possible logistic curves (Fig. 3.2) I estimated expected frequencies distributions (fe_i) for the length distributions of the experimental codends using each method's predicted retentions at length $\hat{r}_i$ and individual model assumptions. Thus, expected frequencies (Tables 3.3, 3.4 and 3.5) were calculated as $\left(\frac{\hat{r}_i \times x_{si}}{\mathrm{N_s}}\right) \times \mathrm{N_t}$ for both ratio methods; as $\hat{\phi}_i \times (x_{si} + x_{ti})$ with $\hat{\phi}_i = \frac{\hat{p} \times \hat{r}_i}{1 - \hat{p} + \hat{p} \times \hat{r}}$ for Millar's method; and as $\left(\frac{\hat{p}_i \times \hat{r}_i}{\sum_{i=1}^{\mathrm{K}} \hat{p}_i \times \hat{r}_i}\right) \times \mathrm{N}_t$ for the present multinomial method. In all cases $\hat{r}_i$ are the predicted logistic retentions at length i depicted in Figure 2.2 that were obtained from estimates $\hat{\mu}$ and $\hat{\sigma}$ in Tables 3.1 and 3.2. The observed (fo_i) and expected (fe_i) frequencies by length class i were used to calculate standardized residuals, $\frac{fo_i - fe_i}{\sqrt{fe_i}}$. These are displayed in Figure 3.3. For the three examples both Pope et al. (1975) and Simpson (1989) methods displayed considerably large residuals ($|r| \geq 2$) not only for the larger length classes that were excluded from the estimation, but also among the length classes actually used in the estimation (Table 3.2). Chi-squared test statistics were calculated to test for equality of expected and observed length frequencies. For the three examples, differences between frequency distributions were significant for both Pope et al. (1975) and Simpson (1989) methods (Tables 3.3, 3.4 and 3.5). Thus test results suggest that the multinomial and Millar's selectivity estimates may be considered in better agreement with the actual selectivities as observed through the length composition of the experimental codend catches.

Discussion

The present method is a parametric version of the nonparametric MLE method of Skalski and Perez-Comas (1993). Like the latter it models changes in length frequency as reapportionments of the size classes in the overall catch of the experimental mesh relative to the standard mesh codend. Unlike the nonparametric model, the present version requires that size-selectivity be described by a select family of sigmoidal curves. Although I use the logistic curve for the analysis of the examples, other curves such as Gompertz or Richards could be easily incorporated.

As pointed out elsewhere (Skalski and Perez-Comas, 1993), the adoption of any sigmoidal curve to describe size selectivity is only a simplification of reality because no mechanistic model for selectivity guarantees such smooth or even monotonic functions, and it may result in systematic bias of the estimation process. However, sigmoidal curves have been traditionally used to describe selectivity and are often preferred when selectivity is incorporated in stock assessment models.

The parametric multinomial model presents certain advantages over classical ratio methods (Pope et al., 1975; Simpson, 1989). It uses real proportions and avoids data manipulation and discard. Data discard and manipulation often introduce biases in the estimates (Cadigan and Millar, 1992, Table 1; Skalski and Perez-Comas, 1993, Fig. 3). For example, the application of Simpson (1989) method to the haddock, pollock and petrale examples required the discard of 14, 12 and 18 length classes whose three point moving average ratios were larger than 1 (Table 3.3). In spite of this data discard and manipulation, systematic biases were probably introduced in Simpson (1989) estimation process. These could explain the significant differences found between the expected and observed length frequency distributions of the experimental codends (Tables 3.3, 3.4 and 3.5). Data discard and manipulation are not substitutes for the lack of an explicit statistical model explaining data not only in terms of probability of retention (i.e., r_i) but also of other important components such as the relative intensity p (Millar, 1992) or the capture probabilities p_i of the present model.

Selectivity estimates for the multinomial (eq. **3.6**) and Millar (1992) fits were very close (Tables 3.1 and 3.2, Fig. 3.2). These similarities are not surprising since *a*) both methods explain data in terms of probabilities, *b*) both methods use MLEs, and *c*) the distribution functions of both methods (multinomial and binomial) are closely related. Differences between both methods do exist, however. While Millar's method uses the proportions of the total catch-at-length caught and retained in the experimental codend (i.e., $\phi_i \approx \frac{x_{ti}}{x_{si} + x_{ti}}$), the multinomial model handles the proportions-at-length for each length frequency sample ($p_i \approx \frac{x_{si}}{\mathrm{N}_s}$ and $\pi_i \approx \frac{x_{ti}}{\mathrm{N}_t}$), separately. Unless all the catch by both standard and experimental codends is sampled, the conditioning upon total catch-at-length of Millar's method (i.e., $n_i = x_{si} + x_{ti}$) requires the scaling of size frequency data to assure that similar proportions of the catches of both codends are used in the analysis. Since the scaling process uses estimates of the total catch and sample weights, it may incorporate extra sources of error in the estimation. Since the multinomial model does not resort to conditional probabilities, it does not require scaling. Thus providing that the length samples are adequate representations of the catch length compositions (i.e., samples should be truly random, and sample sizes large enough), the multinomial model will not introduce extra sources of error.

The multinomial fits were acceptably good for the three examples (deviances were all small). However, the fit for the haddock example (D = 12.88) was slightly better than those for pollock and petrale (probabilities were 0.845, 0.532 and 0.307, respectively). This difference in model performance, that was also shown by the fits to Millar (1992) model (probabilities were 0.815, 0.550 and 0.110) may be attributed to differences in the quality of the length data and probable departures from assumptions 1 and 2. While the haddock example illustrate a typical outcome of a very controlled alternate-haul experiment, with small catches that could be sampled entirely and standardized towing times (e.g., 30 min), the pollock and petrale examples represent outcomes of selectivity experiments carried out under commercial fishing conditions. In such experiments towing speed, towing time, net spread, etc are not standardized in order to mimic a normal fishing operation. Moreover, catches and towing times are usually considerably larger than in traditional controlled experiments (e.g., for pollock the catch was 34 mt and the towing time 3.7 hr). Towing times of 3 to 4 hr may be excessive to assure that both the standard and experimental tows be performed on the same fish population with regard to size distribution (assumption 2), especially for schooling, highly movile species such as pollock. Large commercial catches, on the other hand, not only can not be sampled entirely, but also may violate assumption 1. If fish density is high, after an initial time of effective codend selection the increasing number of fish entangled in the meshes and the bulk of the catch will affect the probability of being retained for other fish entering the net.

Table 3.1: Multinomial model fits. Parameter estimates, estimated lengths at retention ($L_{r\%}$), and standard errors (between parentheses) for three examples.

Parameter	Haddock		Pollock		Petrale	
$\hat{\mu}$	30.1852	(0.316)	45.4051	(0.688)	30.8575	(0.251)
$\hat{\sigma}$	1.108	(0.214)	3.571	(0.221)	3.149	(0.260)
p1	0.019		0.006		0.027	
p2	0.041		0.031		0.030	
p3	0.069		0.085		0.041	
p4	0.075		0.120		0.079	
p5	0.072		0.140		0.091	
p6	0.103		0.144		0.095	
p7	0.138		0.169		0.098	
p8	0.122		0.106		0.088	
p9	0.112		0.092		0.082	
p10	0.085		0.047		0.061	
p11	0.052		0.023		0.042	
p12	0.042		0.010		0.047	
p13	0.017		0.007		0.027	
p14	0.013		0.003		0.033	
p15	0.012		0.003		0.025	
p16	0.012		0.003		0.026	
p17	0.003		0.002		0.015	
p18	0.007		0.002		0.029	
p19	0.002		0.007		0.008	
p20	0.004				0.009	
p21					0.012	
p22					0.008	
p23					0.005	
p24					0.024	
$L_{50\%}$	30.19	(0.316)	45.41	(0.688)	30.86	(0.251)
$L_{65\%}$	30.87	(0.479)	47.62	(0.954)	32.81	(0.753)
$L_{80\%}$	31.72	(0.663)	50.36	(1.226)	35.22	(1.124)
Length classes	27 - 46 cm		37 - 55 cm		28 - 51 cm	

Table 3.2: Parameter estimates, estimated lengths at retention ($L_{r\%}$), and standard errors (between parentheses) from three estimation methods (Millar, 1992; Pope et al., 1975 and Simpson, 1989).

Species	Method Parameter	Millar Estimate		Pope et al. Estimate		Simpson Estimate	
Haddock	$\hat{\mu}$	30.1754	(0.361)	30.0187	(0.023)	29.3905	(0.249)
	$\hat{\sigma}$	1.091	(0.236)	0.887	(0.082)	0.763	(0.221)
	$\hat{p}$	0.573	(0.017)	-			
	$L_{50\%}$	30.18	(0.361)	30.02	(0.023)	29.39	(0.249)
	$L_{65\%}$	30.85	(0.468)	30.57	(0.323)	29.86	(0.155)
	$L_{80\%}$	31.69	(0.623)	31.25	(0.490)	30.45	(0.171)
	Length classes	27 - 46 cm		24 - 39 cm		25 - 32 cm	
Pollock	$\hat{\mu}$	45.4493	(3.216)	41.2840	(0.598)	38.9947	(4.489)
	$\hat{\sigma}$	3.588	(0.998)	2.155	(0.483)	1.769	(1.395)
	$\hat{p}$	0.773	(0.079)	-		-	
	$L_{50\%}$	45.45	(3.216)	41.28	(0.598)	38.99	(4.489)
	$L_{65\%}$	47.67	(3.783)	42.62	(1.359)	40.09	(3.811)
	$L_{80\%}$	50.42	(4.505)	44.27	(1.984)	41.45	(3.102)
	Length classes	37 - 55 cm		37 - 44 cm		38 - 43 cm	
Petrale	$\hat{\mu}$	30.9037	(1.127)	30.5465	(2.729)	28.9080	(0.604)
	$\hat{\sigma}$	2.442	(0.963)	2.018	(0.796)	1.554	(0.122)
	$\hat{p}$	0.670	(0.032)	-		-	
	$L_{50\%}$	30.90	(1.127)	30.55	(2.729)	28.91	(0.604)
	$L_{65\%}$	32.42	(1.518)	31.80	(2.759)	29.87	(0.542)
	$L_{80\%}$	34.29	(2.139)	33.34	(2.914)	31.06	(1.046)
	Length classes	28 - 51 cm		25 - 34 cm		26 - 33 cm	

Table 3.3: Observed and expected length frequency distributions for the haddock catch of the experimental codend, and results of Chi-square tests. Expected length frequencies were obtained from parameter estimates and assumptions of the four methods (see text).

Length (cm)	Observed frequency	Expected frequencies Multinomial	Millar	Pope et al.	Simpson
27	1	1.00	1.07	0.64	0.77
28	5	4.94	4.85	3.66	5.16
29	19	17.38	17.28	15.44	22.70
30	29	33.92	33.95	38.83	51.15
31	51	48.08	48.19	49.15	55.11
32	91	85.24	85.38	82.71	83.78
33	120	126.47	126.55	136.55	132.33
34	118	116.52	116.51	113.85	108.52
35	107	108.90	108.85	109.50	103.76
36	78	83.52	83.46	88.86	84.04
37	52	50.98	50.94	48.39	45.73
38	40	41.84	41.80	43.17	40.79
39	17	16.62	16.61	15.70	14.83
40	17	12.61	12.60	6.54	6.18
41	14	11.47	11.46	7.85	7.42
42	10	11.47	11.46	13.08	12.36
43	4	2.87	2.86	1.31	1.24
44	6	6.88	6.87	7.85	7.42
45	2	2.29	2.29	2.62	2.47
46	6	4.01	4.01	1.31	1.24
	$\chi^2_{(20-1)}$	6.146	6.164	54.274	65.036
	P-value	0.998	0.998	0.000	0.000

Table 3.4: Observed and expected length frequency distributions for the pollock catch of the experimental codend, and results of Chi-square tests. Expected length frequencies were obtained from parameter estimates and assumptions of the four methods (see text).

Length (cm)	Observed frequency	Expected frequencies Multinomial	Millar	Pope et al.	Simpson
37	1	0.84	0.85	0.60	0.89
38	7	5.61	5.66	4.43	6.63
39	22	19.47	19.58	17.83	25.60
40	34	34.90	34.90	37.52	49.74
41	48	51.11	50.99	59.34	70.92
42	65	64.45	64.46	72.06	77.19
43	79	92.08	91.39	115.98	112.49
44	83	69.08	69.81	53.99	48.28
45	68	70.36	70.19	71.41	60.07
46	41	41.19	41.17	37.09	29.87
47	23	22.81	22.81	18.50	14.45
48	13	10.78	10.93	4.74	3.63
49	9	8.30	8.35	4.82	3.64
50	4	3.53	3.56	1.62	1.21
51	4	3.59	3.62	1.63	1.22
52	3	3.63	3.59	3.28	2.43
53	2	2.20	2.19	1.64	1.22
54	2	3.69	3.57	4.94	3.65
55	10	10.39	10.36	6.59	4.87
	$\chi^2_{(19-1)}$	7.201	6.440	63.558	111.669
	P-value	0.988	0.994	0.000	0.000

Table 3.5: Observed and expected length frequency distributions for the petrale catch of the experimental codend, and results of Chi-square tests. Expected length frequencies were obtained from parameter estimates and assumptions of the four methods (see text).

Length (cm)	Observed frequency	Expected frequencies Multinomial	Millar	Pope et al.	Simpson
28	4	3.06	3.49	2.71	3.81
29	4	4.24	3.83	3.58	5.17
30	8	7.17	6.93	6.11	8.40
31	14	16.25	15.64	18.05	22.92
32	19	21.36	21.00	24.69	28.73
33	23	25.21	25.08	29.40	31.64
34	34	28.52	29.77	23.91	24.20
35	36	27.90	29.61	19.08	18.47
36	19	27.53	26.30	39.69	37.29
37	22	21.20	21.48	20.34	18.73
38	12	15.12	14.61	19.28	17.53
39	21	17.63	18.24	12.51	11.29
40	10	10.07	10.04	9.79	8.78
41	13	12.51	12.55	11.23	10.04
42	9	9.57	9.41	9.85	8.79
43	9	10.20	9.91	11.27	10.05
44	5	6.02	5.78	7.05	6.28
45	16	11.45	12.17	4.23	3.77
46	2	3.02	2.80	4.23	3.77
47	2	3.62	3.29	5.64	5.02
48	5	4.83	4.81	4.23	3.77
49	2	3.02	2.80	4.23	3.77
50	2	1.81	1.83	1.41	1.26
51	10	9.67	9.63	8.47	7.53
	$\chi^2_{(24-1)}$	12.152	8.130	83.063	95.922
	P-value	0.968	0.998	0.000	0.000

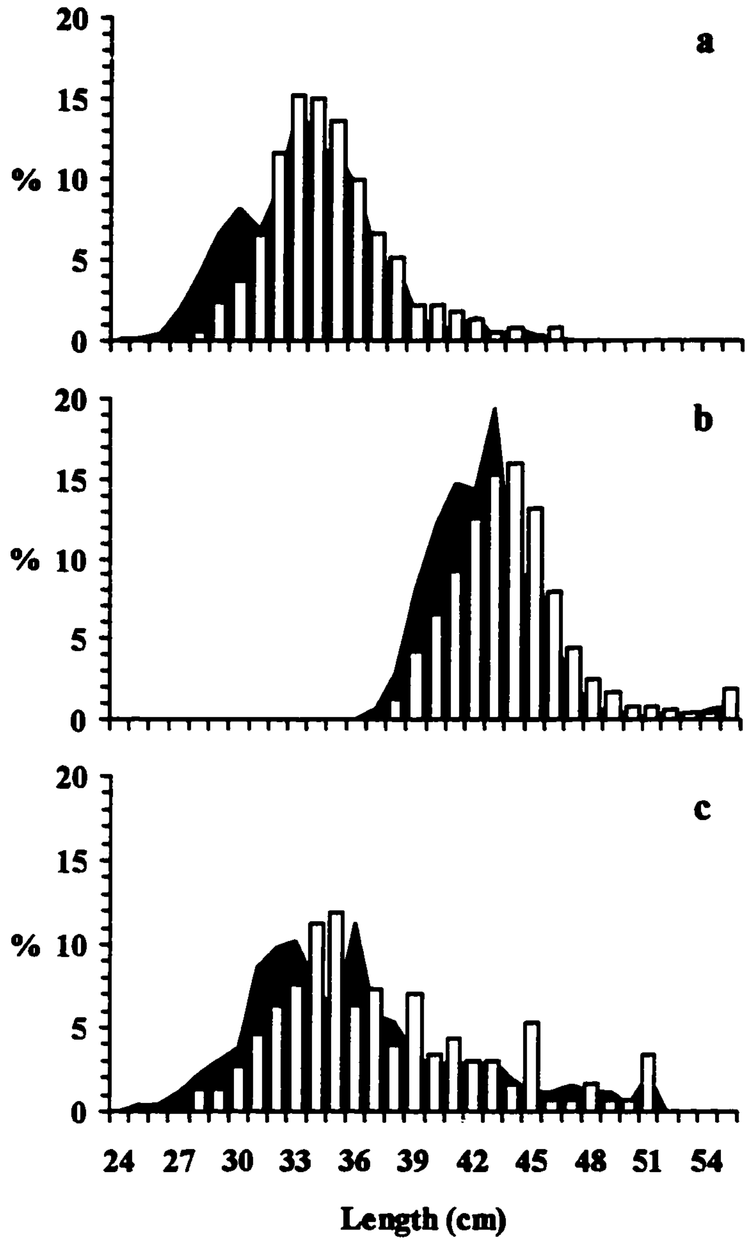

Figure 3.1: Relative length frequency distributions for (a) haddock, (b) pollock and (c) petrale sole. Distributions for the standard codends are indicated by shaded areas, and those for experimental codends by bars.

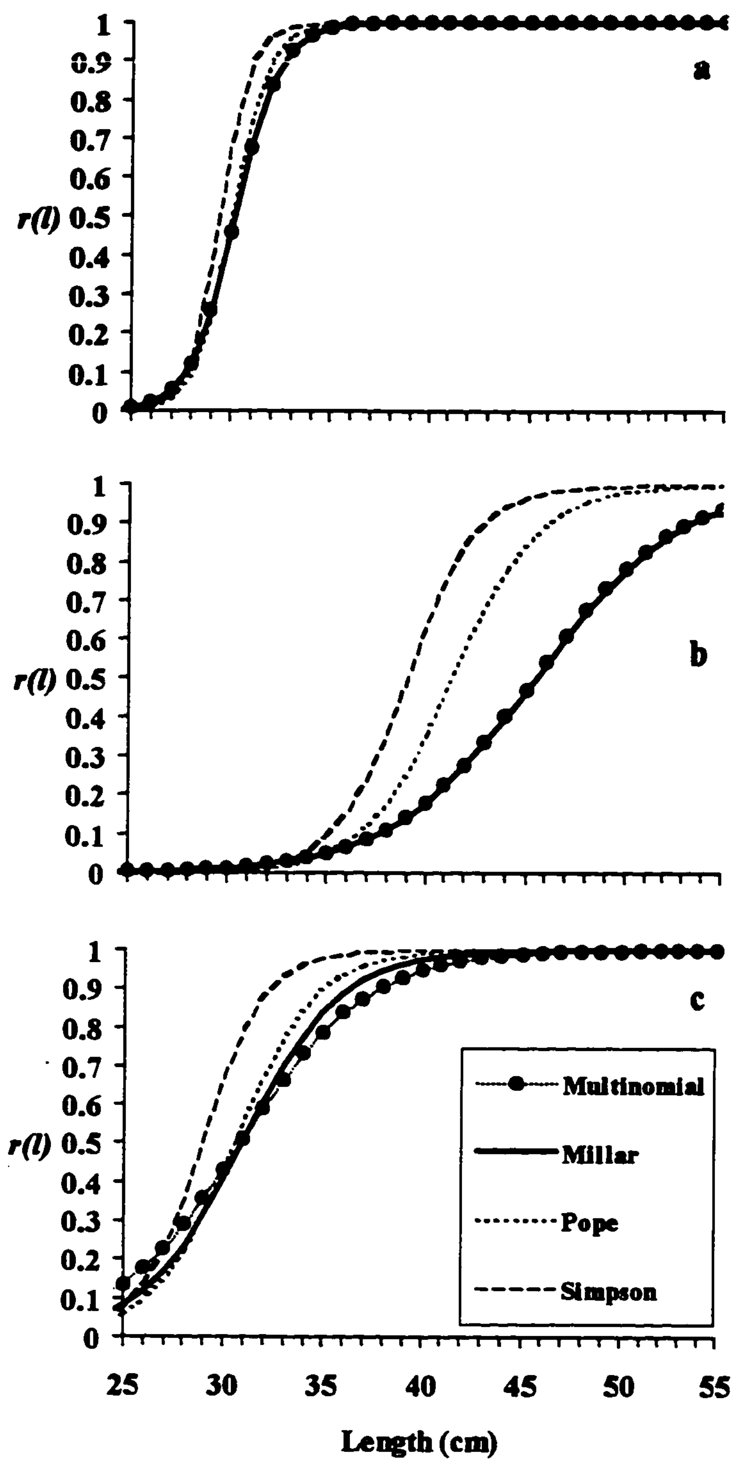

Figure 3.2: Selectivity curves estimated by different methods for (a) haddock, (b) pollock and (c) petrale sole.

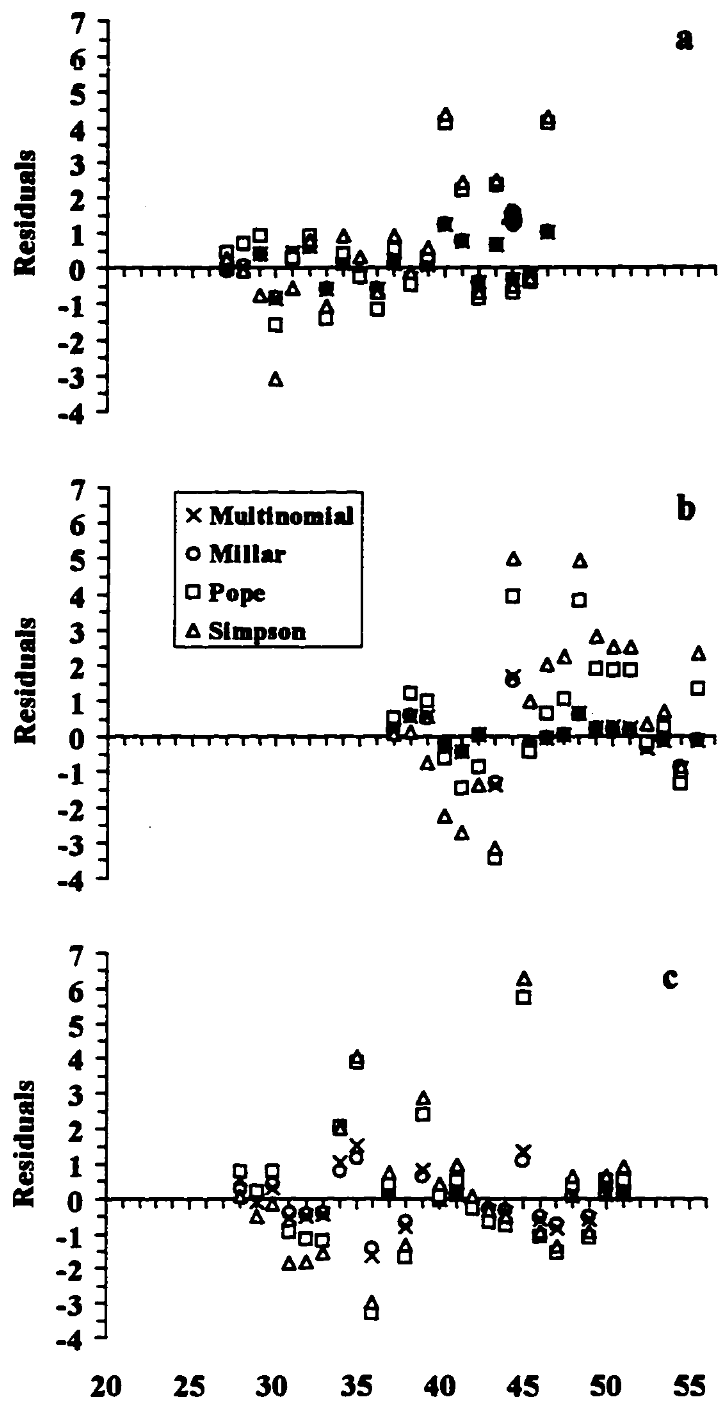

Figure 3.3: Standardized residuals for the expected length frequency distributions of the experimental mesh codends for (a) haddock, (b) pollock and (c) petrale sole (see text for details).

4. Alternative non-parametric approaches for the analysis of mesh size selection in alternate haul studies

Introduction

From time immemorial, scientists have tried to represent complex systems by simple models, often expressed in algebraic form. These models are generally designed to help scientists understand, describe or predict the behavior of the more complex system under study. However, being at best a mere simplification of reality, they cannot always capture all the vagaries in the data collected from the system. Selectivity curves are no exception to this situation.

Probably, the only certified property of size selection is that it will take values of zero for some smallest size categories, and that it will reach a maximum of one at and beyond some large size category. For all remaining size classes size selection will take values larger than zero but smaller than one. Sigmoidal curves, such as the normal cumulative distribution function or probit, the logistic curve, the log-log function or Gompertz curve, and the negative extreme value function, are commonly used to model size selection. They comply with the above mentioned general property of size selection, but they impose a further restriction. Selectivity values have to increase monotonically[1] with size. Often, these parametric curves are good to describe the middle portion of the selection curve, but no mechanistic model for selectivity guarantees that smooth or even monotonic functions are the best or more realistic depiction of the process. Moreover "the tail regions, especially the lower one, of selectivity curves often show very irregular fluctuations" (Pope et al., 1975, p. 28). These "irregular fluctuations" may in part be a consequence of small sample sizes in the tail regions, but may also indicate the inadequacy of the underlying parametric model. For example, high catch sizes may have reduced selectivity in the latter part of the tow by clogging the meshes with fish or distorting them

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[1] A sequence of elements whose successive elements either consistently increase or decrease but do not oscillate in relative value.

by the strain upon the gear. Thus a sample of the length composition for such tow may show large proportions of small fish that would have escape otherwise. Samples of length composition may also come from pools of tows, and these tows may have had catches with different length composition. In both cases, the resulting selection curves may prove too rugged to be fitted by monotonically increasing parametric curves. Finally, in many alternate haul experiments size selection may display "irregular fluctuations" simply because the length-composition samples for the small (standard) and large (trial) mesh codends came from fish schools with different size composition. In all these cases, it would be desirable to express selectivity by less restrictive or non-parametric models.

Recently, Millar (1993) and Skalski and Perez-Comas (1993) have presented two non-parametric models; the former for size selection in covered codend experiments, the latter for size selection in alternate-haul experiments. Millar's (1993) model assumes that the selection curve is a non-decreasing function of length and is based upon the non-parametric estimation procedure known as isotonic regression (Barlow et al., 1972, p. 13). Skalski and Perez-Comas (1993) assumed an even less restrictive selection curve by allowing its values to fluctuate between zero and one, with zero and one for the lowest and largest size classes, respectively.

In this chapter, I will review Skalski and Perez-Comas' (1993) model, and modify the isotonic regression approach of Millar (1993) to fit data from alternate-haul experiments. Two examples will be used to illustrate the calculation procedures. Finally, the selectivity estimates of both non-parametric models will be compared to each other and to those obtained from fitting parametric models.

Examples

Non-parametric and parametric estimation of size selectivity will be illustrated using catch-at-length data sets that represent two situations frequently encountered in alternate-haul experiments. The first example is one of length samples pooled across hauls. The second corresponds to samples that were not pooled, but that were taken from large catches of a schooling and fast moving species. Both situations often present the "irregular fluctuations" (Pope et al., 1975, p. 28) that may be difficult to fit through traditional parametric estimation procedures.

The first example is part of the data collected during the comparative fishing experiments carried out by the West Coast Groundfish Mesh Size Study (W.C.G.M.S.S.) off the coast of Washington, Oregon and California (for details see Chapter 2 and Pikitch et al., 1990; 1991a and 1991b). It consists of length frequency distributions for the catches of arrowtooth flounder (*Atheresthes stomias*) obtained with a small (76 mm) diamond mesh codend and with a large (114 mm) diamond mesh codend (Fig. 4.1 *a*). These length distributions were the result of pooling samples from 10 tows performed with each codend (Table 4.1). The W.C.G.M.S.S. gathered data from commercial vessels, fishing under production conditions. These vessels targeted assemblages of many commercially important species, so that catches were often large and highly mixed. Thus length-sample sizes had to be limited to 100 (often less) fish per species and tow, and these had to be scaled to the estimated catches and pooled across tows to obtain more representative samples for each species. In addition, to the length composition of the catches, lengths of arrowtooth flounder entangled in the 114 mm mesh trawls were recorded separately (Fig. 4.1 *b*) to be used as ancillary information.

The second example corresponds to data collected during comparative fishing experiments for walleyed pollock (*Theragra chalcogramma*) performed in the Bering Sea in 1994. The length frequency distributions (Fig. 4.2) were obtained from samples of the catches of two hauls performed on July 22, one with a double-layer diamond mesh codend and the other with a 85 mm diamond codend (Table 4.1).

In the following analyses the 76 mm diamond mesh codend and the double mesh codend will be treated as the standard codends.

Non-parametric maximum likelihood estimation

The non-parametric maximum likelihood estimation procedure (Skalski and Perez Comas, 1993), hereinafter N.P.M.L.E., is very similar to the parametric method introduced in Chapter 3, but it does not assumed a parametric function to describe size selectivity.

The number of fish by length class ($n_S(l_i)$, $i = 1, \ldots, K$) caught by the standard mesh codend are assumed to be multinomial random variables with joint likelihood:

$$L(n_S(l_i) | N_S, p_i) = \binom{N_S}{n_S(l_i)} \left(\prod_{i=1}^{K-1} p_i^{n_S(l_i)} \right) \left(1 - \sum_{i=1}^{K-1} p_i \right)^{N_S - \sum_{i=1}^{K-1} n_S(l_i)} \qquad (4.1)$$

where $N_S = \sum_{i=1}^{K} n_S(l_i)$ is the total catch and $\sum_{i=1}^{K} p_i = 1$.

Similarly, the catch of the trial or experimental codend, where $n_T(l_i)$ is the number of fish in the ith length category ($i = 1, \ldots, K$), can be represented as a multinomial sample. The probability that a fish caught by the trial codend is in the ith length category is

$$\pi_i = \frac{p_i r(l_i)}{\sum_{i=1}^{K} p_i r(l_i)} \qquad (4.2)$$

where $r(l_i)$ represents the selectivity of the trial codend relative to that of the standard codend and $\sum_{i=1}^{K} \pi_i = 1$. The selectivity coefficients $r(l_i)$ are assumed to be some continuous function of length such that $0 < r(l_i) < 1$ for $i = 1, \ldots, K-1$, and $r(l_K) = 1$. Thus, $r(l_i)$ does not necessarily increase with length but it has a maximum of 1 achievable only at the last and larger length category K.

The multinomial likelihood for the catch of the trial codend can therefore be expressed as

$$L(n_T(l_i)|\mathrm{N}_T, p_i, r(l_i)) = \binom{\mathrm{N}_T}{n_T(l_i)} \left(\prod_{i=1}^{\mathrm{K}-1} \left(\frac{p_i r(l_i)}{1 - \sum_{i=1}^{\mathrm{K}-1} p_i + \sum_{i=1}^{\mathrm{K}-1} p_i r(l_i)} \right)^{n_T(l_i)} \right)$$

$$\cdot \left(1 - \sum_{i=1}^{\mathrm{K}-1} \left(\frac{p_i r(l_i)}{1 - \sum_{i=1}^{\mathrm{K}-1} p_i + \sum_{i=1}^{\mathrm{K}-1} p_i r(l_i)} \right) \right)^{\mathrm{N}_T - \sum_{i=1}^{\mathrm{K}-1} n_T(l_i)} \tag{4.3}$$

The likelihood model for the joint catches of the standard and trial codends is the product of likelihood equations (4.1) and (4.3) where

$$L(n_S(l_i), n_T(l_i)|\mathrm{N}_S, \mathrm{N}_T, p_i, r(l_i)) = L(n_S(l_i)|\mathrm{N}_S, p_i) . L(n_T(l_i)|\mathrm{N}_T, p_i, r(l_i)) \tag{4.4}$$

This model has 2K - 2 parameters and minimum sufficient statistics and provides closed form estimators of the parameters. The estimator for p_i is $\hat{p}_i = \frac{n_S(l_i)}{\mathrm{N}_S}$ with variance $\mathrm{var}(\hat{p}_i) = \frac{p_i(1-p_i)}{\mathrm{N}_S}$ and variance estimator $\hat{\mathrm{var}}(\hat{p}_i) = \frac{\hat{p}_i(1-\hat{p}_i)}{\mathrm{N}_S}$ for i = 1, ..., K. The covariance among any two estimates of p_i (e.g., $\hat{p}_i$ and $\hat{p}_j$) for the standard mesh codend is $\mathrm{Cov}(\hat{p}_i, \hat{p}_j) = \frac{-\hat{p}_i \hat{p}_j}{\mathrm{N}_S}$ for $i \neq j$. The maximum likelihood estimator for the selectivity coefficients is $\hat{r}(l_i) = \frac{n_S(l_\mathrm{K}) n_T(l_i)}{n_T(l_\mathrm{K}) n_S(l_i)}$ for i = 1, ..., K. Since these estimators have the form of odds ratios (Fleiss, 1981, p. 37), their variance can be expressed as $\mathrm{var}(\hat{r}(l_i)) = r(l_i)^2 \left(\frac{1}{\mathrm{N}_S} \left(\frac{1-p_K}{p_K} + \frac{1-p_i}{p_i} + 2 \right) + \frac{1}{\mathrm{N}_T} \left(\frac{1-\pi_K}{\pi_K} + \frac{1-\pi_i}{\pi_i} + 2 \right) \right)$. The estimated variance of a selectivity coefficient is then

$\hat{\mathrm{var}}(\hat{r}(l_i)) = \hat{r}(l_i)^2\left(\frac{1}{\mathrm{N}_S}\left(\frac{1-\hat{p}_K}{\hat{p}_K}+\frac{1-\hat{p}_i}{\hat{p}_i}+2\right)+\frac{1}{\mathrm{N}_T}\left(\frac{1-\hat{\pi}_K}{\hat{\pi}_K}+\frac{1-\hat{\pi}_i}{\hat{\pi}_i}+2\right)\right)$ where $\hat{\pi}_i = \frac{\hat{p}_i\hat{r}(l_i)}{\sum_{i=1}^{\mathrm{K}}\hat{p}_i\hat{r}(l_i)}$. The covariance between estimates of two selectivity coefficients is $\mathrm{Cov}(\hat{r}(l_i),\hat{r}(l_j)) \approx \left(\frac{1}{\mathrm{N}_S}+\frac{1}{\mathrm{N}_T}\right)\left(\frac{p_K^2\pi_i\pi_j}{\pi_K^2 p_i p_j}\right)$ for $i \neq j$. Confidence interval estimates for $r(l_i)$ can be computed using the algorithm $\Phi_{1-\alpha/2} = \frac{\ln\hat{r}(l_i) - \ln r(l_i)}{\left(\hat{\mathrm{Var}}(\hat{r}(l_i))/\hat{r}(l_i)^2\right)^{1/2}}$ where the log transformation is required to normalize $\hat{r}(l_i)$.

Because the joint likelihood model (4.4) produces K-2 parameter estimates for the K-1 length categories in the samples for the standard and trial mesh codends, testing for goodness-of-fit is meaningless.

The validity of the maximum likelihood estimates and associated variances are dependent upon a number of assumptions. These assumptions are:

1) The fate of each fish captured and retained is independent of all other fish.
2) The standard and trial mesh codends sample the same population of fish with regard to size distributions.
3) The standard and trial mesh codends sample the fish population independently.
4) The standard mesh codend either representatively samples the size distribution of the fish population, in which case $\hat{r}(l_i)$ measures the absolute selectivity of the trial mesh codend, or does not representatively sample the size distribution of the fish population, in which case $\hat{r}(l_i)$ refers to the relative selectivity of the trial mesh codend to that of the standard codend. The latter is the most likely case for alternate-haul experiments.
5) The same size classes are used in the likelihoods for both standard and trial mesh codends.

6) The selectivity coefficients $r(l_i)$ are assumed to be some continuous, not necessarily monotonic, function of length such that $0 < r(l_i) < 1$ for $i = 1, ..., K-1$; and $r(l_i) = 1$ for $i \geq K$, where K is a length class known without error for the experimental mesh codend.

Assumptions 1 to 5 are common to most selectivity estimation procedures, both parametric and non-parametric, based upon alternate-haul experiments. Assumption 6 is exclusive to this method. The importance of knowing with exactitude the length class at which $r(l_i)$ becomes one is crucial to the method. Length class K can be found by successively pooling the numbers sampled for the largest length classes and estimating $r(l_i)$ for the remaining length classes (Table 4.2). If any of the estimates is outside the admissible range (0, 1) (e.g., shaded cells in Table 4.2) a new length class is added to the pool and new estimates of $r(l_i)$ obtained. The process stops when all $\hat{r}(l_i)$'s are within the range (0, 1). In some cases (e.g., the arrowtooth example) the distribution of fish entangled in the meshes of the trial codend may help identify length class K. Often the mode of this distribution corresponds to length class K.

Isotonic regression

When it is not possible to specify a parsimonious parametric form for a selection curve, the minimal and reasonable assumption that the curve be non-decreasing can still be kept. In other words, one can still expect that the larger the fish the greater its chances of being retained in the codend. The non-parametric statistical technique of isotonic[2] regressions (Barlow et al., 1972, Chapter 1) fits non-decreasing curves to data. When the data are binomially distributed then the isotonic regression curve is the maximum likelihood fit to the data (Barlow et al., 1972, p. 38). Isotonic regression has been used in the estimation of selection curves to covered-codend data (Millar, 1993). Its application to alternate-haul experiments required only a few modifications.

[2] For X a finite set $\{x_1, ..., x_k\}$ with simple order $x_1 < x_2 < ... < x_k$, a real valued function f on X is isotonic if $x, y \in$ X and $x < y$ imply $f(x) \leq f(y)$.

Following the SELECT approach (Millar, 1992; Millar and Walsh, 1990, 1992), one can assume that the number of fish in the trial codend is binomially distributed with parameters $n_+(l)$ and $\phi(l)$, where $n_+(l) = n_S(l) + n_T(l)$ denotes the total catch of length l fish in the standard and trial mesh codends, and $\phi(l)$ the conditional probability of a length l fish of being caught and retained in the trial codend given that it was caught during the experiment. The conditional probability $\phi(l)$ is defined as:

$$\phi(l) = \frac{pr(l)}{pr(l) + (1-p)} \tag{4.5}$$

where $pr(l)$ is the probability that length l fish entering the gear is retained in the trial codend. The probability that a fish entering the gear is retained in the standard codend is simply the probability of entering that codend, 1 - p. The constant p known as relative fishing power of the experimental codend is the probability that a fish entered the experimental codend, given that it entered either the experimental or the standard codend. The retention probability $r(l)$ is assumed to be a non-decreasing or isotonic function of length, though not described by a parametric function such as the symmetric logistic and probit curves or the asymmetric Gompertz and negative extreme value curves.

Since $r(l)$ is a non-decreasing function and p is a constant then $\phi(l)$ is also a non-decreasing or isotonic function of length. Estimates for $\phi(l)$ can be obtained using the PAV (pool adjacent violators) algorithm (Barlow et al., 1972, p. 13). In this procedure a first estimate of $\phi(l)$ is obtained by calculating $\hat{\phi}(l_i) = \dfrac{n_T(l_i)}{n_S(l_i) + n_T(l_i)}$ for i = 1, ..., K. The resulting estimates are check to detect any violation of the non-decreasing constraint between adjacent length classes (i.e., $\hat{\phi}(l_{i-1}) \le \hat{\phi}(l_i)$ for i = 1, ..., K). Comparisons are performed in a smaller-to-larger length-class direction. If any violation occurs the adjacent length classes are pooled and the estimation of $\phi(l)$ repeated for the remaining K-1 length classes. The process is repeated until no violation occurs among the remaining length classes. Table 4.3 illustrates the application of the PAV algorithm to an hypothetical example.

Once a non-decreasing series of $\phi(l)$ estimates has been obtained, the estimate for the last length class K for which $\phi(l)$ stops increasing is assumed to be an estimate of p (i.e., $\hat{p} = \hat{\phi}(l_K)$). Estimates for $r(l)$ are obtained as

$$\hat{r}(l_i) = \frac{\hat{\phi}(l_i)(1-\hat{p})}{(1-\hat{\phi}(l_i))\hat{p}} \tag{4.6}$$

for i = 1, ..., K. It is evident from the previous equation that the assumption $\hat{p} = \hat{\phi}(l_K)$ implies that $\hat{r}(l_K) = 1$.

Estimates of the standard errors for both $\hat{\phi}(l_i)$ and $\hat{r}(l_i)$ can be obtained by bootstrapping the data (Efron, 1982). For both examples 1000 bootstrapped samples were obtained. In the case of the arrowtooth example the bootstrap resampling scheme included the sampling with replacement from a "population" of 10 length samples of hauls. Finally, bootstrap estimates of 95% confidence intervals for both $\hat{\phi}(l_i)$ and $\hat{r}(l_i)$ were computed by applying the percentile method (Mooney and Duval, 1993, p. 36).

Besides the asumption of a binomial distribution for $\phi(l)$, the estimates obtained by the isotonic regression method (hereinafter I.R.) rely upon the same first five assumptions mentioned for the N.P.M.L.E. method. Three further assumptions are exclusive to the present method:

6) Both $\phi(l)$ and $r(l)$ are non-decreasing functions of length.

7) $\phi(l_l)$ is known without error and assumed to be non-decreasing.

8) $\phi(l_K)$ is assumed to be equal to p.

Parametric methods

Both the arrowtooth and pollock data were also fitted to parametric selection curves. The two estimation procedures used were the SELECT method (Millar, 1992; Millar and Walsh, 1990, 1992) and the multinomial maximum likelihood estimation method (Perez Comas and Skalski, 1996). Both statistical techniques are the parametric equivalent of the non-parametric procedures discussed in previous paragraphs. Since both methods have been introduced, discussed and abundantly illustrated elsewhere (Chapters 2 and 3), it is unnecessary to reexamine them here.

Data were fitted to four types of selection curves, the symmetric logistic and probit curves, and the asymmetric Gompertz and negative extreme value (N.E.V.) curves. To ease comparison of results the four selection curves were reparameterized in terms of the common parameters L_{50} (length of 50% retention) and *SR* (selection range, defined as the difference between the lengths of 75 and 25% retention). The corresponding reparameterized formulae were presented in Chapter 2.

Analysis of examples

Non-parametric maximum likelihood estimation

Tables 4.4 and 4.5 show the $\hat{r}(l_i)$'s, standard errors and 95% confidence intervals resulting from successive analyses using the non-parametric MLE model. The last length class K was allowed to vary among 39 and 41 cm for the arrowtooth example (Table 4.4) and among 34 and 36 cm for the pollock one (Table 4.5). Pooling 41-cm and larger arrowtooth caught in the standard and experimental codends did not provide adequate $\hat{r}(l_i)$'s because $\hat{r}(l_{40})$ was larger than 1. However once the frequencies for 40-cm fish were incorporated to the pool, all $\hat{r}(l_i)$'s were within the (0, 1) interval of allowed values. The assumption that selectivity becomes 1 for 40-cm and larger arrowtooth was further reinforced by the fact that the mode for the sample of entangled arrowtooth laid between the 39 and 40-cm length classes (Fig. 4.3 *a*). The probability of retaining 30-cm arrowtooth was particularly large ($0.1 \leq r(l_{30}) \leq 0.31$), appearing to be largely the result of small sample sizes and an artifact of the pooling process. The percentage of 30-cm and smaller fish was 0.8% in the pooled sample of the trial codend, and these small fish were present only in three of ten sampled hauls as 2.3%, 1.9% and 0.8% of the individual samples. Length of 50% retention (L_{50}) was estimated as 37.5 cm with an estimated 95% confidence interval equal to (35.8, 39.1 cm). The estimates for L_{25} and L_{75} were 35.5 cm and 39.4 cm with respective 95% confidence intervals equal to (35.1, 35.9 cm) and (37.6, 39.7 cm), (Fig. 4.3 *b*).

The distribution of entangled pollock was unknown, but the procedure of succesive pools of large length classes showed that acceptable $\hat{r}(l_i)$'s are obtained by pooling 35-cm and larger pollock (representing 54.5% of the sampled length classes and 79.4% of the fish sampled by the trial codend). The pool of 36-cm and larger fish produced an estimated $r(l)$ outside the allowed (0, 1) range (Table 4.5, $\hat{r}(l_{35}) \approx 1.03$). Pollock selectivity estimates showed fluctuations far more dramatic than those encountered in the arrowtooth example (Fig. 4.4). Pollock between 26 and 35 cm had large retention probabilities crossing the lines corresponding to 0.25, 0.5 and 0.75 retention a few times. Consequently, point estimates for L_{25}, L_{50} and L_{75} are hard to assess. Their approximate 95% confidence intervals were extremely wide and overlapping. They were estimated as (25.1, 32.6 cm), (25.4, 34.3 cm) and (25.7, 34.9 cm), for L_{25}, L_{50} and L_{75}, respectively (Fig. 4.4). The large fluctuations of the $\hat{r}(l_i)$'s and their wide 95% confidence bounds cannot be solely attributed to small sample sizes (112 fish of less than 35 cm were sampled for the trial codend). The effect of a reduction of the selective properties of the trial codend due to clogging of the trial codend meshes by an excessive catch, and of a failure to sample the same population in terms of length composition cannot be discarded (Table 4.1, Fig. 4.2).

Isotonic regression

Tables 4.6 and 4.7 show the $\hat{\phi}(l_i)$'s, $\hat{r}(l_i)$'s, estimated standard errors and 95% confidence intervals for the arrowtooth and pollock examples. Small arrowtooth (30 to 34-cm long), arrowtooth of lengths ranging between 38 and 39 cm and between 40 and 73 cm, and large arrowtooth of more than 73 cm were pooled. Thus the curves for $\hat{\phi}(l_i)$ and $\hat{r}(l_i)$ displayed plateaus for these length classes, and steep slopes between the 35 and 40-cm length classes (Table 4.6, Fig. 4.5). Since $\hat{p} = \hat{\phi}(l_{74}) = 0.67$ with a considerably wide 95% confidence interval (0.64, 0.79), the confidence intervals for the $\hat{r}(l_i)$ were also wide, in particular those for length classes greater than 39 cm. $\hat{L}_{25}$, $\hat{L}_{50}$ and $\hat{L}_{75}$ were 35.6, 37.6 and 39.5 cm, respectively. Their 95% confidence intervals were estimated as (34.5, 71.9 cm), (35.8, 80.3 cm) and (37.8, 80.6 cm), respectively. These wide and overlapping confidence intervals reflects considerably large between-haul variability in the 10 original length-composition samples, particularly among large fish. For example, arrowtooth larger than 73 cm constituted 9.3% in the pooled length sample of the trial codend. However, these large fish were absent in three of the original ten samples, they constituted a small amount (1.2 - 2.3%) in three others, and a large percentage (25.5 - 33.7%) in the remaining samples.

In the pollock example, the curves for $\hat{\phi}(l_i)$ and $\hat{r}(l_i)$ were less steep, with five plateaus resulting from pooling fish with lengths between 26 and 29 cm, 30 and 32 cm, 35 and 37 cm, 38 and 42 cm, and 43 and 57 cm (Table 4.7, Fig. 4.6). The estimate of p was $\hat{p} = \hat{\phi}(l_{43}) = 0.61$, with a 95% confidence interval equal to (0.57, 0.78). The estimated 95% confidence intervals for $\hat{r}(l_i)$ are wider as length increases (Fig. 4.6 *b*). $\hat{L}_{25}$, $\hat{L}_{50}$ and $\hat{L}_{75}$ were 29.2, 34 and 34.9 cm, respectively. As with the N.P.M.L.E. method, the 95% confidence intervals for L_{25}, L_{50} and L_{75} were also wide and overlapping, probably reflecting gear saturation by large catches as well as failure to sample schools of similar length composition. The bootstrapped confidence intervals were (25, 37.5 cm), (30.7, 44.2 cm) and (33.3, 44.6 cm), for L_{25}, L_{50} and L_{75}, respectively.

Parametric methods

Three curves, the logistic, the probit and the N.E.V., fitted the arrowtooth data adequately, and none of the four curves fitted the pollock data (*Prob.* ≥ 0.05, Table 4.8). In both cases the N.E.V. curve provided the smallest model deviances suggesting slightly better fits. Fits by both the SELECT and multinomial MLE methods showed somewhat large residuals for arrowtooth lengths between 30 and 35 cm and for lengths larger than 40 cm (Fig. 4.7). The poor fits to the pollock data were marked by even larger residuals spread along the full range of pollock lengths (Fig. 4.8). The estimates of L_{50} and SR

provided by both methods were very similar and their 95% confidence intervals considerably wide (Table 4.9).

Comparison of results

The comparison of the N.E.V. selection curves estimated with the parametric MLE procedure to the selection curves estimated with the analogous non-parametric procedure suggests some systematic biases among the parametric estimates. The parametric procedure appeared to underestimate the selectivity coefficients for small (i.e., 30 cm) and large (i.e., 39 to 41 cm) arrowtooth. On the other hand, the selectivity of arrowtooth with lengths between 33 and 35 cm appeared overestimated (Fig. 4.3 *b*). The selectivity of pollock with lengths between 35 and 40 cm was also underestimated by the parametric procedure (Fig. 4.4), although in this case the comparison may not be totally valid because of the poor parametric fits (*Prob.* ≥ 0.05, Table 4.8). Probably, the parametric procedure could not compensate for the large fluctuations of $r(l)$ by increasing its estimate of *SR*.

The comparison of the N.E.V. selection curves estimated with the SELECT procedure and their analogous I.R. curves did not show any apparent bias. However, the SELECT estimates for arrowtooth of 34 to 39 cm appeared closer to the upper bound of the 95% confidence intervals provided by the isotonic regression procedure (Fig. 4.5 *b*). On the other hand, the SELECT estimates for pollock were more or less centered within the non-parametric 95% confidence intervals, with the exception of those for lengths between 25 and 29 cm (Fig. 4.6 *b*).

Finally, the comparison of the $\hat{r}(l_i)$'s obtained with both non-parametric methods (Fig. 4.9) show that for most lengths i the isotonic regression $\hat{r}(l_i)$'s were smaller than those obtained with the N.P.M.L.E. procedure. Moreover, although both methods produced wide 95% confidence intervals, the width of those obtained with the I.R. method appeared to increase with length, while that of those obtained with the N.P.M.L.E. decreased with length. These differences are related to the I.R. constraint that selectivity must be a non decreasing function of length, and the assumption that $\phi(l_l)$ is known without error. Thus all fluctuations of $r(l)$ are flattened in a general small-to-large direction with the estimates for the larger lengths being more uncertain. The N.P.M.L.E. highly relies upon the assumption that the length class K at which $r(l)$ becomes one is known without error, what determines that the estimates for the smaller lengths would be more uncertain.

Discussion

As many other methods that attempt to fit data from alternate-haul experiments, both the N.P.M.L.E. and I.R. methods rely on common assumptions concerning independence and representativeness of length samples (assumptions 1 to 5). In particular, both methods assume that the standard and trial mesh codends sample the same population in terms of size distribution (assumption 2). Both methods, however, interpret the length frequency data in different ways. While the N.P.M.L.E. treats the number of fish by length class caught by the standard and trial mesh codends as multinomial random variables, the I.R. considers them binomially distributed. Equally or more important both methods use different models to describe selectivity or retention at length $r(l)$.

If we were to classify the models used to describe $r(l)$, a gradient of complexity soon emerges. Size selection can be required to belong to a select family of curves that model $r(l)$ as continuously increasing functions of size such that $0 < r(l) < 1$. These curves are parsimonious ways of describing selectivity. Only two parameters are required to describe their typical "S" shapes. The logistic, probit, Gompertz and N.E.V. curves, here fitted through the SELECT and multinomial MLE methods, belong to this class of models. If the "continuously increasing" constraint is dropped, size selection $r(l)$ can then be described as a non-decreasing function of size such that $0 < r(l) < 1$. The resulting curves are not parsimonious models because they can not be easily expressed by a couple of parameters. The I.R. assumes this type of size selectivity model. Finally, $r(l)$ can be simply described as a function of size such that $0 < r(l) < 1$. This is the model behind the present N.P.M.L.E. method.

Although parsimonious models for size selection *r(l)* have the advantage of providing easily summarized selective curves, the requirement that a selective curve be a member of the sigmoidal family of curves may result in systematic bias of the estimation process (e.g., Fig. 4.3 *b*). Such bias may go undetected if non-parametric estimation procedures are not used. The present I.R. and N.P.M.L.E. methods have variance and confidence interval estimators that are helpful in providing measures of sampling error and characterizing the uncertainty associated with the estimated selectivity coefficients $\hat{r}(l_i)$'s.

Whether both non-parametric methods can be satisfactorily used in evaluating the goodness-of-fit and detecting possible systematic bias of the more conventional parametric estimation procedures, both methods present some limitations. For example, if the length frequency distribution for the trial mesh codend is very similar to that for the standard codend (e.g., because of gear saturation by large catches), the N.P.M.L.E. may require the pool of most of the more abundant length classes to produce only a few $\hat{r}(l_i)$'s for the smaller length classes. The analysis of the pollock data, for example, required the pool of 54.5% of the sampled length classes, approximately 58.8% and 79.4% of the fish sampled with the standard and trial codend, respectively. Similarly, the N.P.M.L.E. required the pool of 79.6% of the arrowtooth length classes, approximately 60.9% and 89.9% of the arrowtooth sampled with the standard and trial codend, respectively.

The isotonic regression method presents an even more serious limitation. In order to obtain the *r(l)* estimates, the I.R. assumes that $\hat{p} = \hat{\phi}(l_K)$, where K is the last length class for which $\hat{\phi}(l_i)$ stops increasing. When $\hat{\phi}(l_i)$ has the same value for most of the larger classes (i.e., the $\hat{\phi}(l_i)$ curve ends in a long plateau), the assumption will probably hold, and the *r(l)* estimates will be unbiased. On the other hand, if the observed conditional probability $\phi(l_i) = \dfrac{n_T(l_i)}{n_S(l_i) + n_T(l_i)}$, for i = 1, 2, ..., K, increases almost constantly without any apparent plateau for the larger length classes, the assumption $\hat{p} = \hat{\phi}(l_K)$ will not be judicious and the *r(l)* estimates will be biased. This situation is more likely to occur when the sampled population does not include fish that are fully retained by the meshes of the trial codend. In some cases, the observed $\phi(l)$ may display some plateau for most of the largest and abundant length classes, but it may take an extremely large value just at the very end of the sampled length range. If this large $\phi(l)$ value is the result of small sample sizes, it may bias $\hat{p}$ and $\hat{r}(l_i)$, because the PAV algorithm will be unable to pool its length class. Thus it is convenient to pool the frequencies of all the largest and poorly sampled length classes, prior to I.R. estimation.

Finally, the two examples chosen to represent frequently encountered cases of "non-cooperative" data from alternate-haul experiments helped to illustrate the utility of non-parametric estimation procedures. For the pooled arrowtooth length distribution, the wide non-parametric confidence intervals for the $\hat{r}(l_i)$, $\hat{L}_{25}$, $\hat{L}_{50}$ and $\hat{L}_{75}$ reflected the between-haul variability present in the original ten length samples. This variability, although large, was mostly centered around the smallest and largest length classes. Consequently, the parametric estimates were not biased for the abundantly sampled middle lengths, and most parametric curves provided statistically good fits (Table 4.8, Fig. 4.3 *b* and 4.5 *b*). The pollock example helped to illustrate an opposite case. Here, all parametric curves failed to fit the data adequately (Table 4.8). The large oscillations of the N.P.M.L.E. $\hat{r}(l_i)$'s (Fig. 4.4), and the wide and overlapping non-parametric confidence intervals for $\hat{r}(l_i)$, $\hat{L}_{25}$, $\hat{L}_{50}$ and $\hat{L}_{75}$ suggest that effects other than those attributed to small sample sizes may be responsible for the lack of fit of the parametric selection curves. A reduction of the selective properties of the trial codend due to clogging of meshes by an excessive catch cannot be discarded (Table 4.1). Moreover, the assumption that both the standard and the trial codend sampled the same population in terms of length composition may be questioned (Fig. 4.2). In any case, the uncertainty associated with the pollock selectivity estimates that is reflected in the non-parametric confidence intervals is so big that the value of the information contained in the data may be contested.

Table 4.1: Haul and sample characteristics of the examples used in the analysis.

Species	Arrowtooth flounder		Walleyed pollock	
Codend type	Standard	Trial	Standard	Trial
Mesh size (mm)	76.2	114.3	82 (88)[1]	85
Mesh shape	Diamond	Diamond	Diamond	Diamond
Hauls	10	10	1	1
Latitude N	44°14'-48°16'	44°14'-48°15'	58°52'-58°53'	58°48'-58°55'
Longitude W	124°14'-125°39'	124°22'-125°30'	174°11'	174°10'
Sample size	88 (37)[2]	105 (26)[2]	551	544
Catch (numbers)	3066	3988	1675027	1115416
Catch (t)	0.44	0.74	44.43	34.47
Tow duration (h)	2.5	2.3	3.6	3.2
Depth (m)	227.5	184.7	129.8	131.7

[1] Codend had two layers of netting. Mesh size of inner layer between parentheses.
[2] Average over ten hauls, and standard error between parentheses.

Table 4.2: Pooling extreme length classes in the nonparametric MLE method; example. Numbers of individuals caught in the standard ($n_S(l)$) and in the trial codend ($n_T(l)$) for each length class (l). The largest length classes are successively pooled, so that the ratio between the number of individuals in these pooled classes caught in the standard ($n_S(K)$) and in the trial codend ($n_T(K)$) can be used to obtain estimates of retention ($r(l)$) for all remaining length classes. Length classes for which the assumption $0 < r(l) < 1$ is violated (shaded cells) indicate the need for further pools.

		Pooled classes	10	10, 9	10, 9, 8	10, 9, 8, 7
		$n_S(K)$	10	30	75	175
		$n_T(K)$	5	35	90	190
		$n_S(K)/n_T(K)$	2.00	0.86	0.83	0.92
l (cm)	$n_S(l)$	$n_T(l)$	$r(l)$	$r(l)$	$r(l)$	$r(l)$
1	19	1	0.11	0.05	0.04	0.05
2	38	2	0.11	0.05	0.04	0.05
3	99	1	0.02	0.01	0.01	0.01
4	95	5	0.11	0.05	0.04	0.05
5	108	12	0.22	0.10	0.09	0.10
6	120	30	0.50	0.21	0.21	0.23
7	100	100	2.00	0.86	0.83	1.00
8	45	55	2.44	1.05	1.00	
9	20	30	3.00	1.00		
10	10	5	1.00			

Table 4.3: Pooling adjacent violators (PAV); example. Length classes (l), and corresponding numbers of individuals caught in the trial codend ($n_T(l)$) and in both the standard and trial codends ($n_+(l)$) that determine the observed conditional probabilities of a fish being retained in the trial codend ($\phi_o(l) = n_T(l)/n_+(l)$). Estimates of conditional probabilities ($\phi_i(l)$, $i = 1, ..., 4$) are obtained from successive pools of the frequencies of length classes for which the assumption $\phi_{i-1}(l_j) \le \phi_{i-1}(l_{j+1})$ is violated. Shadowed cells mark these length classes in the smaller-to-larger direction of comparison adopted by the PAV algorithm.

		Pool order		1	2	3	4
		Pooled length classes		2, 3	1, 2, 3	9, 10	8, 9, 10
		$n_T(l)$		3	4	35	90
		$n_+(l)$		140	160	65	165
l (cm)	$n_T(l)$	$n_+(l)$	$\phi_o(l)$	$\phi_1(l)$	$\phi_2(l)$	$\phi_3(l)$	$\phi_4(l)$
1	1	20	0.05	0.05	0.03	0.03	0.03
2	2	40	0.05	0.02			
3	1	100	0.01				
4	5	100	0.05	0.05	0.05	0.05	0.05
5	12	120	0.10	0.10	0.10	0.10	0.10
6	30	150	0.20	0.20	0.20	0.20	0.20
7	100	200	0.50	0.50	0.50	0.50	0.50
8	55	100	0.55	0.55	0.55	0.55	0.55
9	30	50	0.60	0.60	0.60	0.54	
10	5	15	0.33	0.33	0.33		

Table 4.4: Non-parametric MLE analysis for the arrowtooth example. Length classes, selectivity coefficient estimates ($r_i(l)$), standard errors (*SE*) and 95 % confidence intervals (*CI*) resulting from successive pools of the largest length classes.

Last length class	≥ 39	≥ 40				≥ 41
Length (cm)	$r_i(l)$	$r_i(l)$	*SE*	*CI*		$r_i(l)$
29	0.014	0.014	0.006	0.006	0.032	0.014
30	0.180	0.177	0.050	0.101	0.308	0.178
31	0.054	0.053	0.020	0.025	0.112	0.053
32	0.081	0.079	0.026	0.042	0.150	0.080
33	0.039	0.038	0.016	0.017	0.088	0.039
34	0.025	0.024	0.014	0.008	0.078	0.025
35	0.093	0.091	0.036	0.042	0.197	0.092
36	0.412	0.405	0.078	0.277	0.591	0.408
37	0.414	0.406	0.078	0.279	0.592	0.410
38	0.622	0.611	0.104	0.437	0.853	0.616
39	1.000	0.599	0.098	0.435	0.824	0.604
40		1.000	0.044	0.918	1.000	1.300
41						1.000

Table 4.5: Non-parametric MLE analysis for the pollock example. Length classes, selectivity coefficient estimates ($r_i(l)$), standard errors (*SE*) and 95 % confidence intervals (*CI*) resulting from successive pools of the largest length classes.

Last length class	≥ 34	≥ 35				≥ 36
Length (cm)	$r_i(l)$	$r_i(l)$	*SE*	*CI*		$r_i(l)$
25	0.078	0.074	0.037	0.028	0.196	0.074
26	0.316	0.300	0.282	0.048	1.000	0.301
27	0.791	0.750	1.151	0.037	1.000	0.753
28	0.264	0.250	0.230	0.041	1.000	0.251
29	0.198	0.188	0.168	0.032	1.000	0.188
30	0.508	0.482	0.230	0.189	1.000	0.484
31	0.747	0.708	0.266	0.339	1.000	0.712
32	0.247	0.234	0.097	0.104	0.529	0.235
33	0.593	0.563	0.163	0.319	0.993	0.565
34	1.000	0.587	0.150	0.355	0.969	0.590
35		1.000	0.111	0.804	1.000	1.029
36						1.000

Table 4.6: Isotonic regression for arrowtooth example. Length classes, numbers of individuals caught in the trial codend ($n_T(l)$) and in both standard and trial codends ($n_+(l)$), estimates of conditional probability of a fish being retained in the trial codend ($\phi(l)$) and of selectivity coefficients ($r_t(l)$), standard errors ($SE(\phi(l))$ and $SE(r_t(l))$, respectively) and 95 % confidence intervals (CI).

Length (cm)	$n_T(l)$	$n_+(l)$	$\phi(l)$	$SE(\phi(l))$	$r_t(l)$	$SE(r_t(l))$	*CI*	
≤ 29	9	330	0.026	0.051	0.013	0.083	0.000	0.087
30 - 34	62	549	0.113	0.051	0.063	0.105	0.008	0.150
35	11	71	0.148	0.077	0.086	0.108	0.020	0.264
36	62	142	0.437	0.070	0.383	0.128	0.072	0.563
37	63	143	0.438	0.070	0.385	0.146	0.083	0.643
38 - 39	197	366	0.537	0.061	0.572	0.169	0.123	0.822
40 - 73	3215	4900	0.656	0.026	0.941	0.215	0.217	0.997
≥ 74	370	553	0.670	0.039	1.000	0.214	0.278	1.000

Table 4.7: Isotonic regression for pollock example. Length classes, numbers of individuals caught in the trial codend ($n_T(l)$) and in both standard and trial codends ($n_+(l)$), estimates of conditional probability of a fish being retained in the trial codend ($\phi(l)$) and of selectivity coefficients ($r_t(l)$), standard errors ($SE(\phi(l))$ and $SE(r_t(l))$, respectively) and 95 % confidence intervals (CI).

Length (cm)	$n_T(l)$	$n_+(l)$	$\phi(l)$	$SE(\phi(l))$	$r_t(l)$	$SE(r_t(l))$	*CI*	
25	6	67	0.090	0.084	0.063	0.067	0.000	0.254
26-29	7	27	0.259	0.060	0.223	0.075	0.051	0.334
30-32	36	100	0.360	0.062	0.359	0.110	0.097	0.522
33	27	63	0.429	0.067	0.479	0.150	0.125	0.701
34	36	82	0.439	0.069	0.500	0.179	0.149	0.883
35-37	189	342	0.553	0.058	0.788	0.214	0.221	1.000
38-42	196	337	0.582	0.047	0.887	0.217	0.284	1.000
≥ 43	47	77	0.610	0.053	1.000	0.189	0.331	1.000

Table 4.8: Goodness-of-fit tests for the parametric analyses of the arrowtooth and pollock examples; degrees of freedom (*df*), model deviance (*Dev.*) and p-values (*Prob.*). Asterisks indicate model fits with smallest deviance.

Example	Selection curve	SELECT *df*	*Dev.*	*Prob.*	Multinomial MLE *df*	*Dev.*	*Prob.*	
Arrowtooth flounder	Logistic	51	63.986	0.105	53	63.987	0.143	
	Probit	51	66.247	0.074	53	66.248	0.104	
	N.E.V.	51	60.987	0.160	53	60.988	0.211	*
	Gompertz	51	74.079	0.019	53	74.079	0.029	
Walleyed pollock	Logistic	18	40.433	0.002	20	40.434	0.004	
	Probit	18	40.327	0.002	20	40.327	0.005	
	N.E.V.	18	39.653	0.002	20	39.653	0.006	*
	Gompertz	18	41.230	0.001	20	41.230	0.003	

Table 4.9: Parameter estimates and 95% confidence intervals (*CI*) for the parametric analyses of the arrowtooth and pollock examples.

Example	Selection curve		SELECT Estimate	*CI*		Multinomial MLE Estimate	*CI*	
	Logistic	L_{50}	37.450	36.091	38.808	37.449	36.105	38.856
		SR	4.470	3.210	5.730	4.469	3.365	5.941
		p	0.659	0.625	0.693			
	Probit	L_{50}	37.424	35.981	38.868	37.422	36.009	38.932
Arrowtooth		*SR*	5.148	3.858	6.437	5.144	4.004	6.640
flounder		*p*	0.658	0.624	0.692			
	N.E.V.	L_{50}	37.586	36.326	38.846	37.586	36.479	38.624
		SR	3.773	2.662	4.885	3.772	2.964	4.897
		p	0.657	0.623	0.691			
	Gompertz	L_{50}	37.335	35.509	39.160	37.335	35.604	39.310
		SR	6.975	5.142	8.808	6.976	5.353	9.118
		p	0.662	0.626	0.698			
	Logistic	L_{50}	32.082	29.801	34.362	32.081	29.934	34.966
		SR	6.355	4.008	8.702	6.352	4.415	9.529
		p	0.596	0.537	0.654			
	Probit	L_{50}	31.863	29.549	34.176	31.864	30.216	34.095
Walleyed		*SR*	6.495	4.180	8.809	6.494	3.957	8.173
pollock		*p*	0.591	0.532	0.651			
	N.E.V.	L_{50}	32.017	30.360	33.674	32.017	30.360	33.892
		SR	5.589	3.776	7.401	5.588	4.064	7.911
		p	0.579	0.532	0.626			
	Gompertz	L_{50}	32.498	28.532	36.465	32.503	29.389	39.191
		SR	8.596	4.261	12.931	8.599	5.268	15.670
		p	0.621	0.534	0.708			

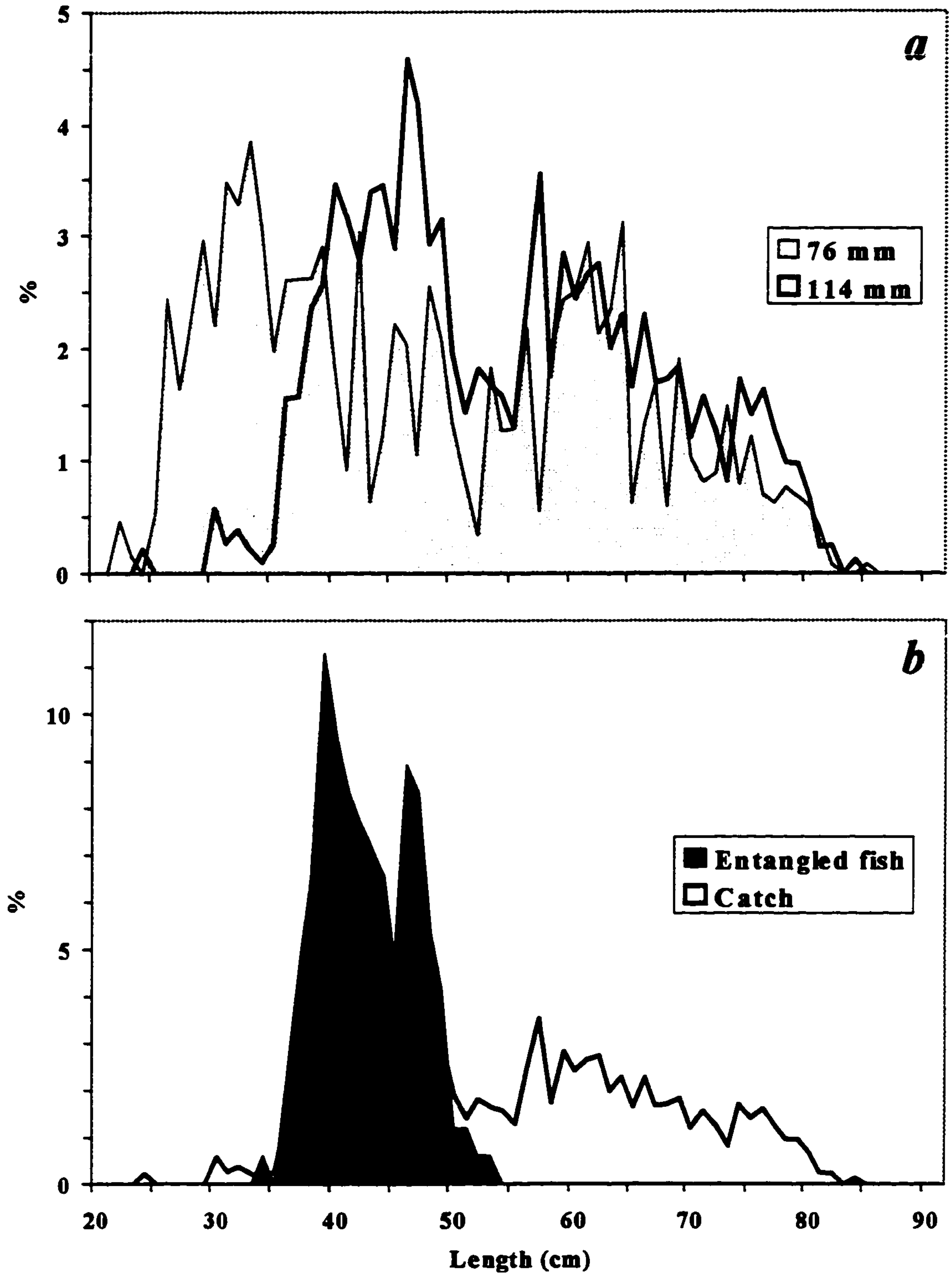

Figure 4.1: Relative composition of arrowtooth flounder by length for: (*a*) 76 mm vs. 114 mm mesh codends, (*b*) fish entangled and caught in 114 mm mesh codends.

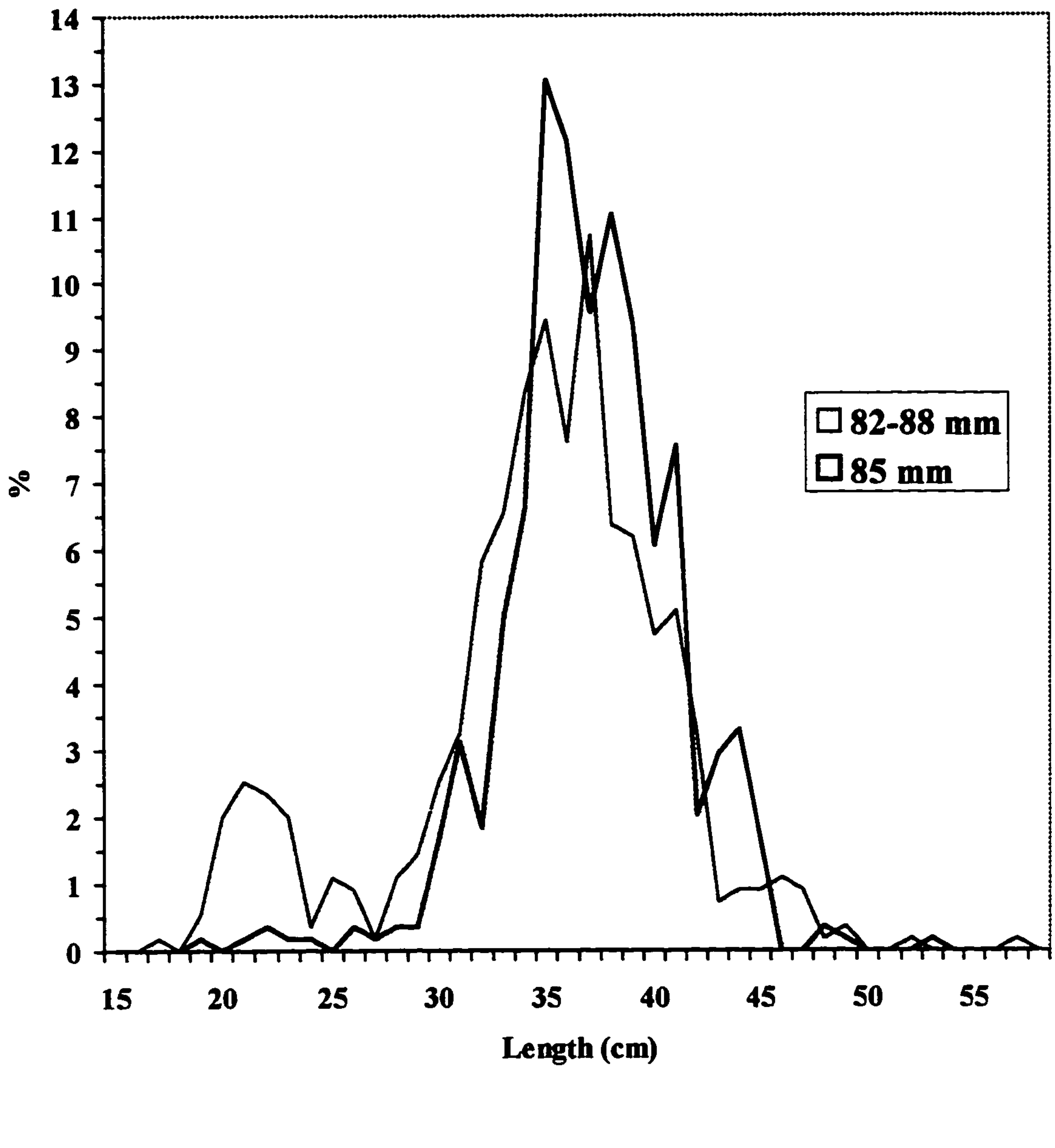

Figure 4.2: Relative composition of walleye pollock by length for double layer 82-88 mm vs. 85 mm mesh codends.

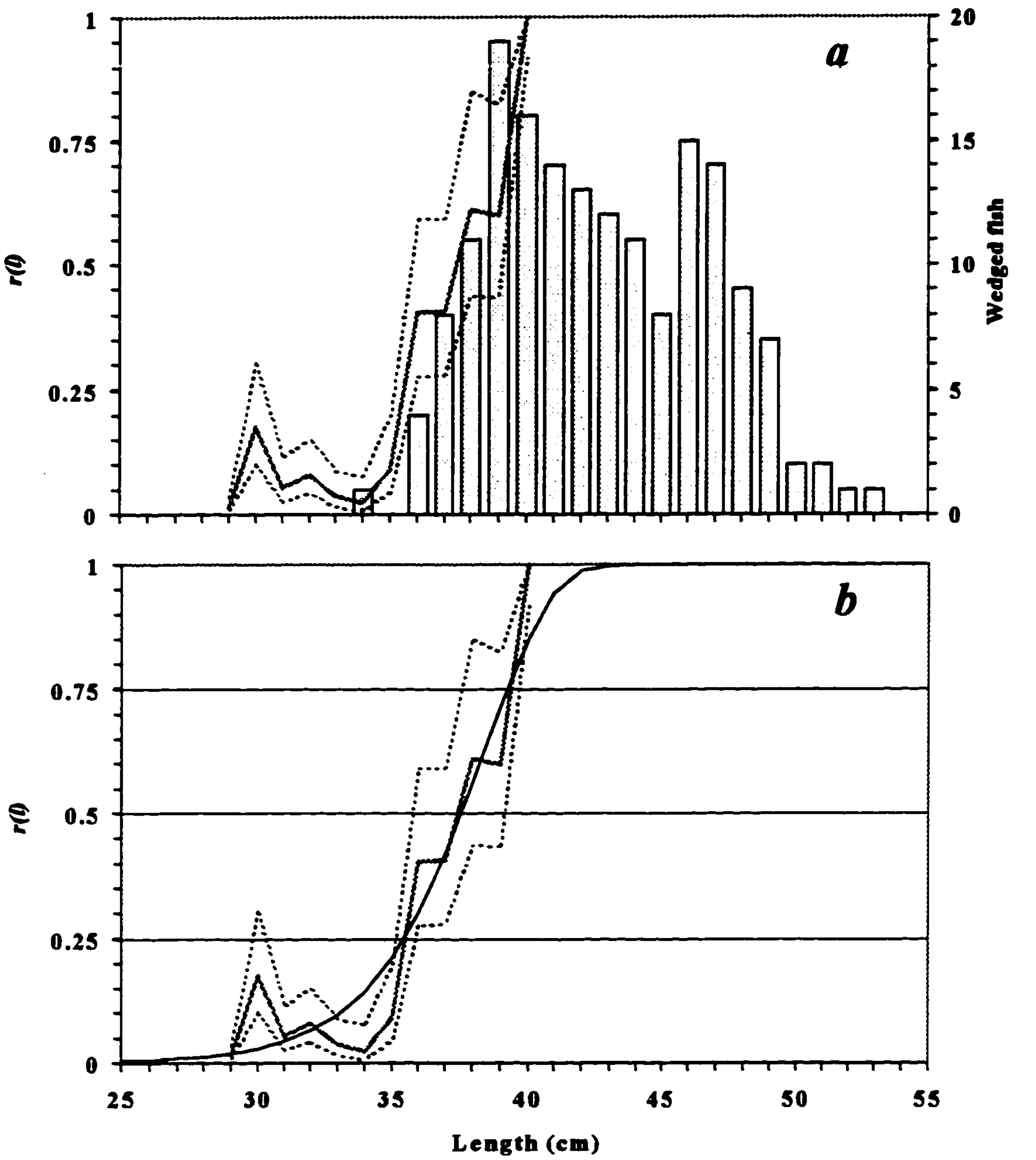

Figure 4.3: Non-parametric MLE fit for the arrowtooth example. ***a***) Comparison of selectivity estimates (*r(l)*) to the distribution of entangled or wedged fish (bars); ***b***) Comparison of parametric (black line) and non-parametric (grey line) MLE selectivity estimates. Dash lines indicate 95% confidence intervals for non-parametric estimates.

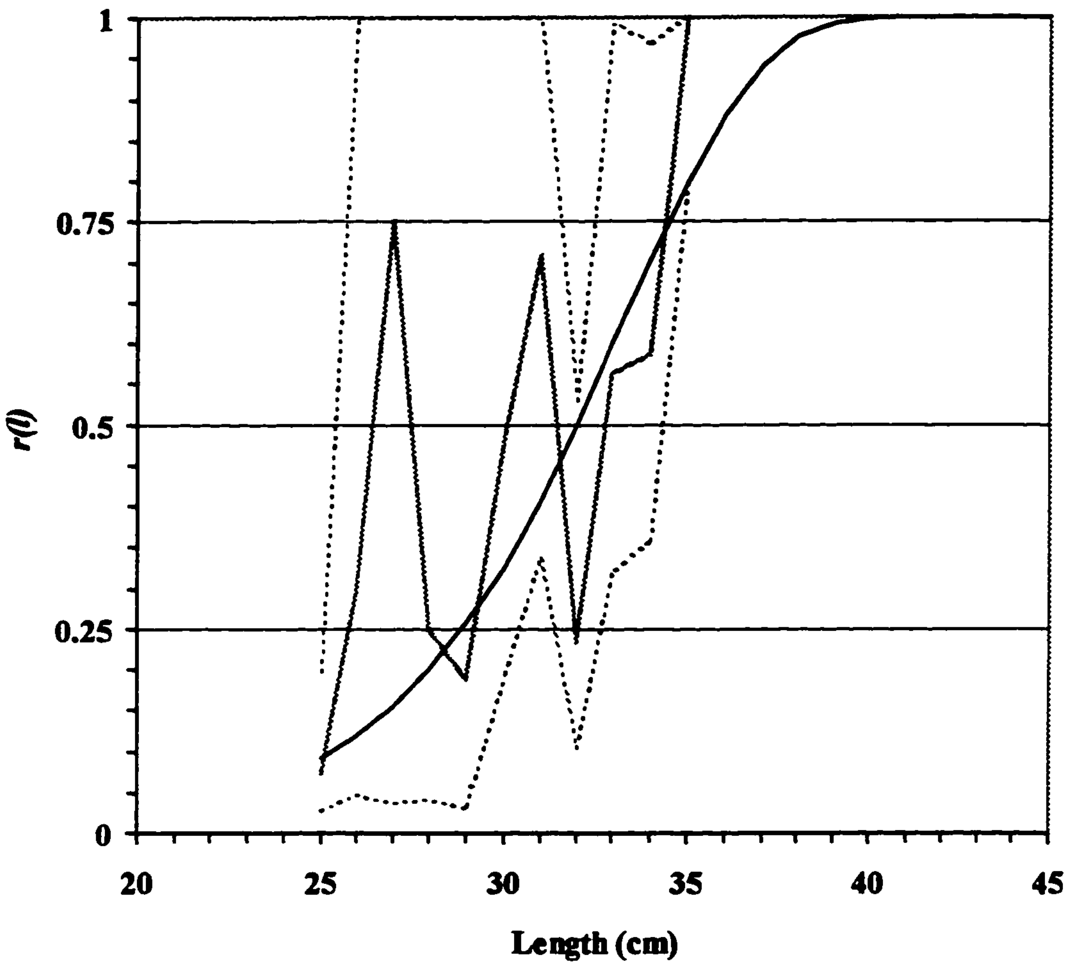

Figure 4.4: Non-parametric MLE fit for the pollock example. Comparison of parametric (black line) and non-parametric (grey line) MLE selectivity estimates ($r(l)$). Dash lines indicate 95% confidence intervals for non-parametric estimates.

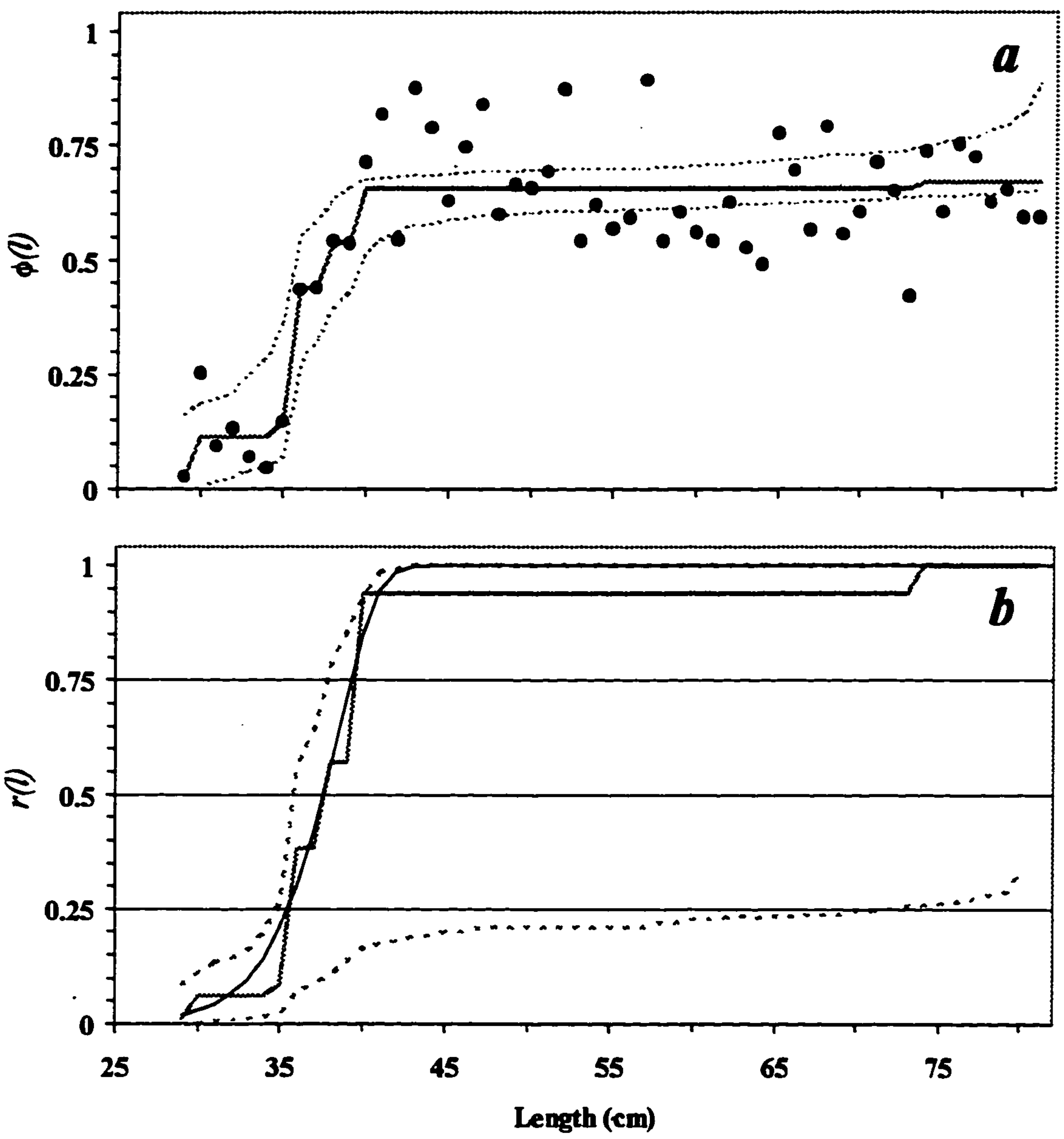

Figure 4.5: Isotonic regression fit for the arrowtooth example. ***a***) Observed conditional probability $\phi(l)$ (black circles), non-parametric estimates (grey solid line) and 95% confidence intervals (grey broken line); ***b***) Parametric (black line) and non-parametric (grey solid line) selectivity estimates ($r(l)$), with 95% confidence intervals (dash line).

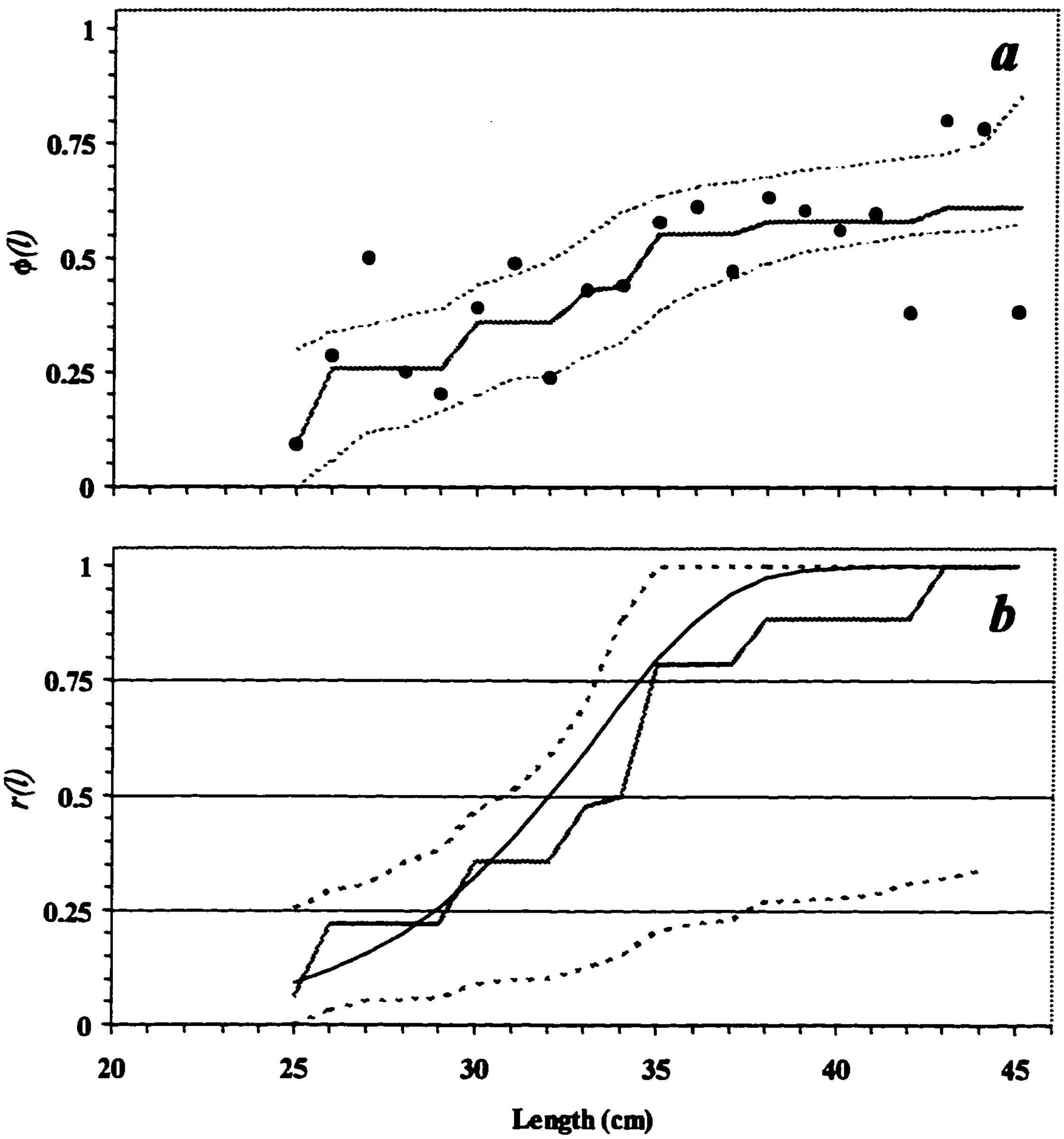

Figure 4.6: Isotonic regression fit for the pollock example. ***a***) Observed conditional probability $\phi(l)$ (black circles), non-parametric estimates (grey solid line) and 95% confidence intervals (grey broken line); ***b***) Parametric (black line) and non-parametric (grey solid line) selectivity estimates ($r(l)$), with 95% confidence intervals (dash line).

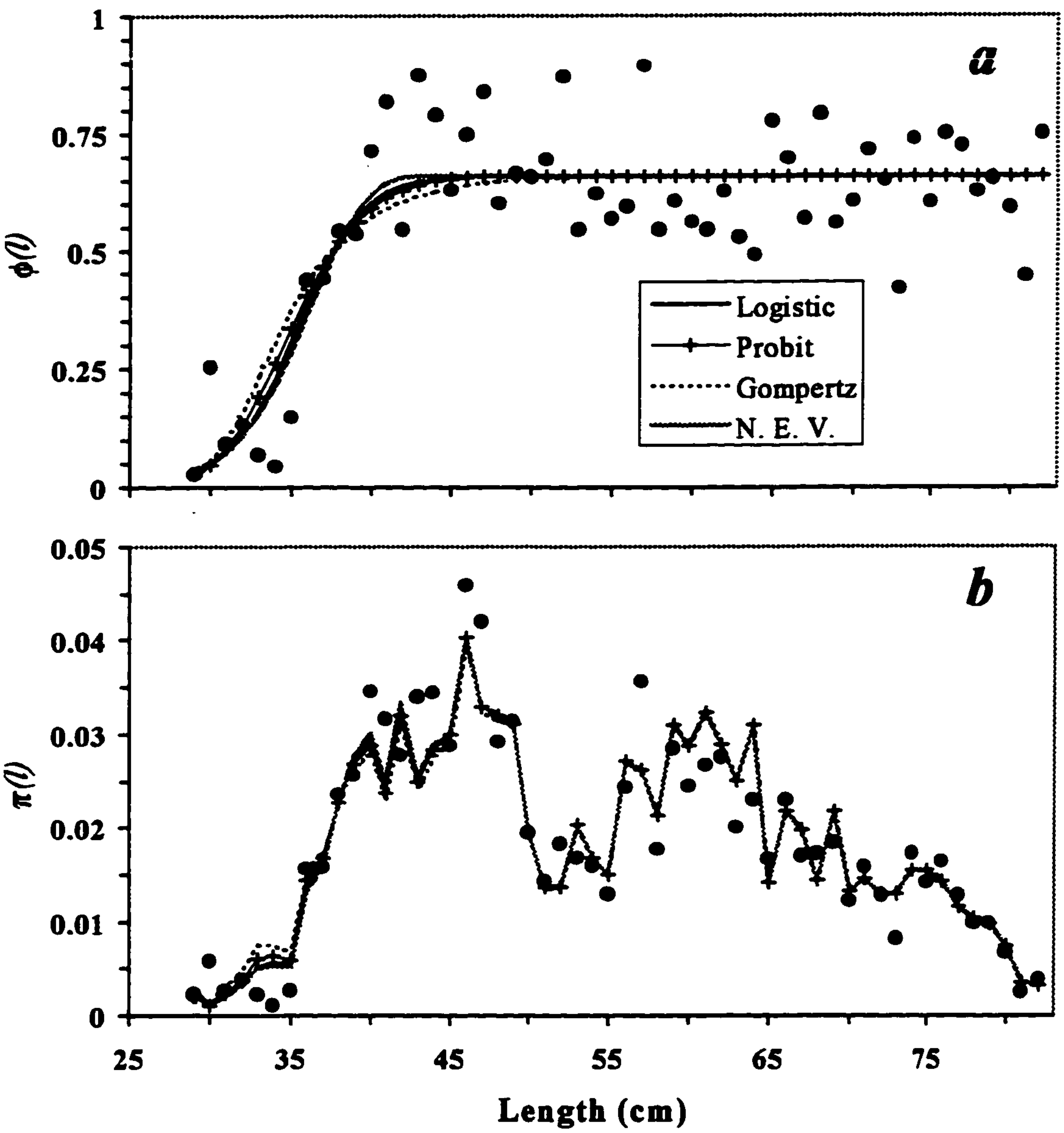

Figure 4.7: Parametric fits for the arrowtooth example; ***a***) Observed conditional probability $\phi(l)$ (black circles), and estimates from SELECT method with four different selection curves (logistic, probit, Gompertz and negative extreme value); ***b***) relative length frequencies for the trial codend $\pi(l)$ (black circles), and estimates from multinomial MLE method for the same selection curves.

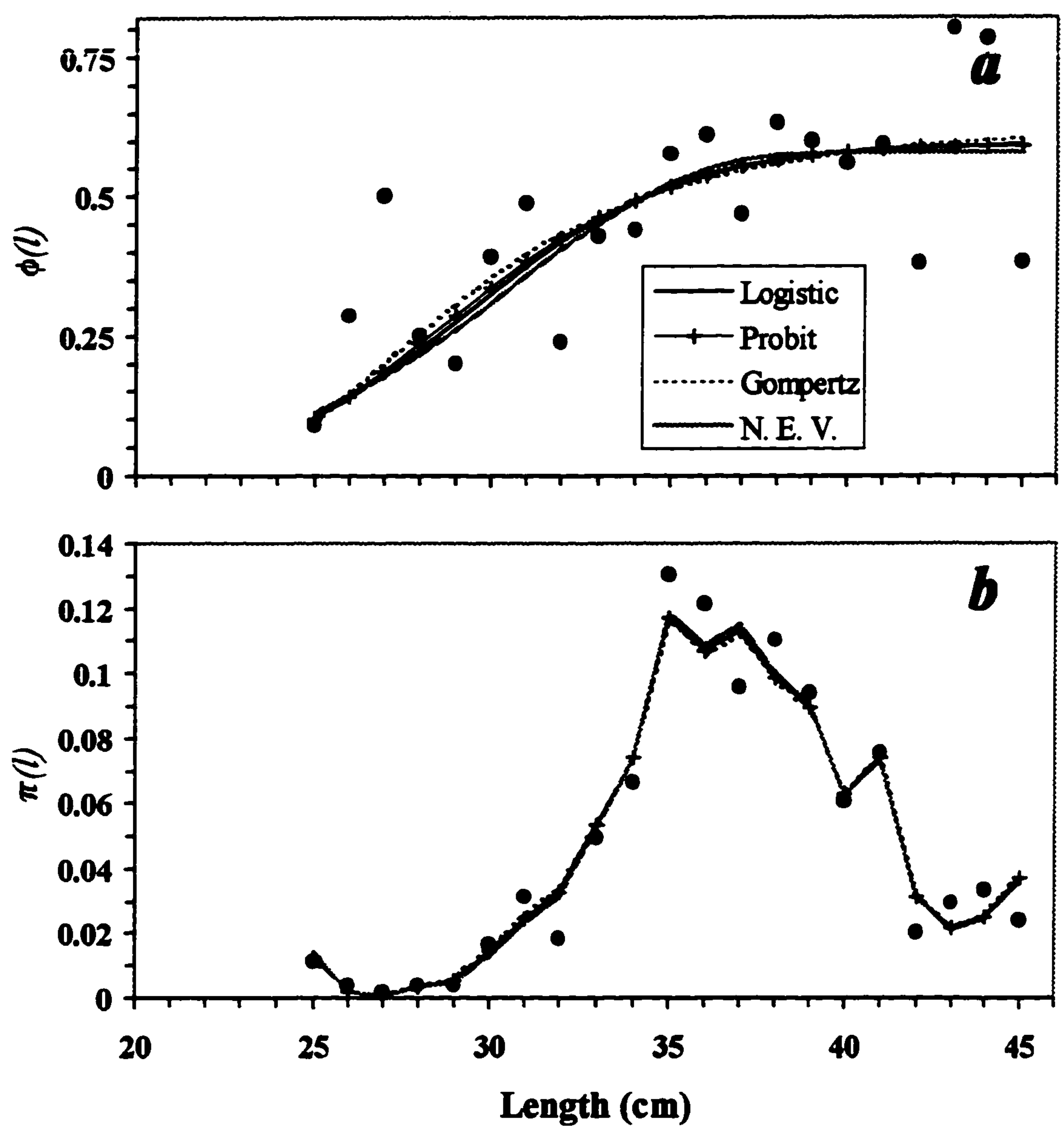

Figure 4.8: Parametric fits for the pollock example; ***a***) Observed conditional probability $\phi(l)$ (black circles), and estimates from SELECT method with four different selection curves (logistic, probit, Gompertz and negative extreme value); ***b***) relative length frequencies for the trial codend $\pi(l)$ (black circles), and estimates from multinomial MLE method for the same selection curves.

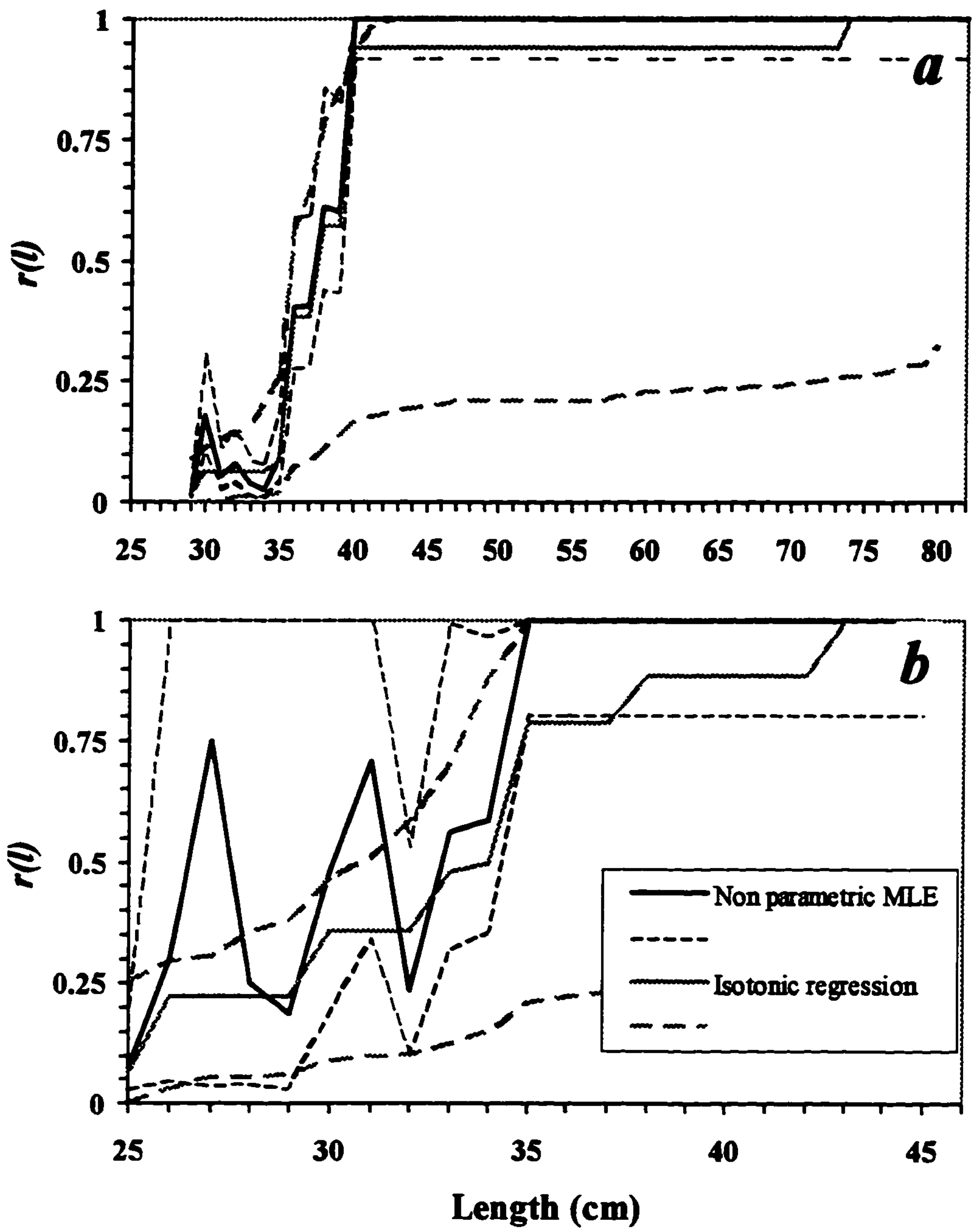

Figure 4.9: Comparison of non-parametric fits for the arrowtooth (*a*) and pollock (*b*) examples. Dash lines indicate 95% confidence intervals for the estimates.

5. The estimation of size selection for standard mesh codends

Introduction

Out of the three experimental methods used in selectivity studies, only the covered-codend method allows the direct measure of fish escapement. Thus it is the only method that provides "absolute", though often biased, estimates of selectivity.

Simple alternate-haul experiments and any of its modified designs, such as the randomized block design (Bergh et al., 1990) used in comparative studies under commercial or production fishing conditions, provide only relative measures of selectivity for all the experimental mesh codends. The selectivity of the small mesh codend used as standard remains unknown, unless an independent measure of the size distribution of the target species at the experimental site is available.

In this chapter I explore the possibility of assuming a simple function to describe the size distribution of the target species at an experimental site where one small mesh and a few large mesh codends were towed. For that purpose I modified the multinomial model of Chapter 3 to attempt the simultaneous estimation of the parameters for the assumed population function and the selection curves of all the codends, standard included, fished at the experimental site. The procedure is illustrated by an example, and the merits and limitations of the estimation approach are discussed.

Example

Data are length frequency distributions (Fig. 5.1) that represent the catch composition of Dover sole (*Microstomus pacificus*) from four hauls performed with four different codends (117 mm diamond, 87 mm diamond, 130 mm square and 133 mm diamond mesh). Hauls were performed by the commercial fishing boat "Star Polaris", a small 375 HP vessel, that carried a modified Aberdeen bottom trawl with 128 meshes of 144 mm in circumference at the intermediate part of the net.

The present four length frequency distributions constituted one of the many blocks of a comparative fishing study performed on the mixed-species ground fisheries off the coast of Washington, Oregon and California during 1988 (Pikitch et al., 1990, 1991a, 1991b; see also Chapter 2). The order in which each codend was towed within the block was randomly chosen. Variables such as towing time, speed, direction and initial location were left to skipper's discretion to assure that each tow mimicked fishing under normal production conditions. Table 5.1 summarizes the characteristics of the hauls. Towing times ($\overline{X} = 5.02$ h, $SD = 0.6$) and Dover catches ($\overline{X} = 379.8$ Kg, $SD = 255.34$) were relatively high and variable within the block, but they were acceptable illustrations of commercial catches and towing times for the Pacific Northwest groundfish fisheries. The 87 mm diamond mesh codend was chosen as the standard.

The modified multinomial model

Assuming that the fish population at the block site can be described by a common length frequency distribution for the four tows of the block, the joint likelihood of $x_{i,j}$ -the number of fish in length category i retained in codend j - becomes:

$$L(x|\mathrm{N}, f, \mu, \sigma) = \prod_{j=1}^{4} \left(\binom{\mathrm{N}_j}{x_j} \prod_{i=1}^{\mathrm{K}} \left(\frac{f_i r_{i,j}}{\sum_{i=1}^{\mathrm{K}} f_i r_{i,j}} \right)^{x_{i,j}} \right) \quad \textbf{(5.1)}$$

where f_i is the probability that a fish is in the ith length category (i = 1, ..., K) and $r_{i,j}$ is the probability that such a fish is retained in codend j. N_j is the sample size for the length sample of codend j. Note that in this analysis the small mesh codend used in traditional analysis to describe the length distribution of the population is treated as another experimental codend. As I did in Chapter 3, I assume that the $r_{i,j}$'s come from logistic functions with parameters μ_j and σ_j, although other curves may be used (see Chapter 2).

Next, if one assumes that for the target population length is a random variable with a simple exponential or gamma distribution with f its probability density, the negative log-likelihood for equation **(5.1)** can minimized by means of a numerical procedure such as the Quasi-Newton algorithm. Thus the log-likelihood functions become:

$$\ell = -\sum_{j=1}^{4} \ln\binom{N_j}{x_j} - \sum_{j=1}^{4}\sum_{i=1}^{K} x_{i,j}\left(\ln\left(\lambda \exp^{-\lambda l_i} r_{i,j}\right) - \ln\left(\sum_{i=1}^{K} \lambda \exp^{-\lambda l_i} r_{i,j}\right)\right) \quad \textbf{(5.2)}$$

for the exponential, and

$$\ell = -\sum_{j=1}^{4} \ln\binom{N_j}{x_j} - \sum_{j=1}^{4}\sum_{i=1}^{K} x_{i,j}\left(\ln\left(\frac{l_i^{\alpha-1} \exp^{-l_i/\beta}}{\beta^{\alpha}\Gamma(\alpha)} r_{i,j}\right) - \ln\left(\sum_{i=1}^{K} \frac{l_i^{\alpha-1} \exp^{-l_i/\beta}}{\beta^{\alpha}\Gamma(\alpha)} r_{i,j}\right)\right) \quad \textbf{(5.3)}$$

for the gamma distribution. In the first case **(5.2)**, one has to estimate one population parameter λ ($\lambda > 0$) besides the four μ and σ parameters from the logistic curves, and in the second case **(5.3)**, two population parameters α and β (α, $\beta > 0$) require estimation.

Definitively, there is not a well-rooted or uncontroversial reason for the choice of a particular statistical function to describe the length frequency distribution of the population. In the present exercise, I chose the exponential distibution because of its simplicity and wide use in ecology. By chosing the exponential, I assume that fish are less probable to be found in the population as they grow older and thus larger because of the cumulative effects of mortality. The Gamma distribution was chosen to mimick a more realistic population where mortality and vulnerability to gear are considered. Fish are more vulnerable to the gear as they grow larger.

Equations **(5.2)** and **(5.3)** were fitted to the Dover data, and the resulting estimates were compared with those coming from the multinomial model version used in Chapter 3 (eq. **3.6**), where besides the selectivity parameters, the probabilities p_i of a fish being in the ith size category are estimated from the length distribution of the catch by the standard or small mesh. Subsequently, I will call this version "relative" because its selectivity estimates are relative to the selectivity of the standard mesh. In the three cases, likelihood profile confidence intervals were used to obtain 95% confidence intervals for the final estimates.

Selectivity analysis

Table 5.2 shows the results for the Exponential, Gamma and Relative versions of the multinomial model. The μ and σ estimates for the three experimental codends (117 mm D, 130 mm S and 133 mm D) were very similar among methods. Estimates of μ differed only in their non-interger parts. Estimates for the relative model (**3.6**) were larger than those for the exponential (**5.2**) and gamma (**5.3**) models. Similarly, σ estimates also differed in their non-interger parts, but the relative model did not always produce the largest estimate (see estimates for 133 mm D codend, Table 5.2).

To achieve minimization for the Gamma version, the number of parameters had to be reduced by fixing β. The value of β displayed in Table 5.2 was chosen after performing a sensitivity analysis (Fig. 5.2). Increasing values of β affected all parameter estimates. However, for β's larger than 1.5, differences between consecutive estimates of the selectivity parameters were all smaller than 0.1, and the resulting selectivity curves displayed a reasonable pattern. As mesh size increases, smaller proportions of small fish are retained in the diamond codends (Fig. 5.3 A). This expected pattern was not displayed with β's smaller than 0.8 (Fig. 5.3 B). The considerably small retentions predicted for the 117 mm D mesh make the assumption of $\beta < 0.8$ questionable.

The results in Table 5.2 correspond to reduced models with a maximum number of 9 parameters, i.e. one population parameter (λ or α) and four sets of different selectivity parameters μ and σ, one for each codend. However, these 9 parameters may not contribute to deviance reduction in the same way, and a model with fewer parameters may perform as well as the 9 parameter one. I used Analysis of Deviance (ANODEV) to identify this model with fewer parameters in an approach similar to that in Skalski et al. (1993).

ANODEV tables are similar to ANOVA tables. They partition differences between models' log-likelihoods and give F-statistics for treatment effects that are interpreted like F-statistics from ANOVA. Tables 5.3 and 5.4 display the ANODEV tables for the exponential, gamma and relative model versions. For each ANODEV table the analysis starts with the minimization of the log-likelihood for the reduced model with the fewest number of parameters that still allows for selectivity (i.e., μ, σ and λ for the exponential; μ, σ and α for the gamma, and μ and σ for the relative version of the model). The corresponding deviance is defined as twice the difference between its log-likelihood and that for the full multinomial model. Next, new parameters are included in the reduced model, one at a time, determining a set of increasingly more complex models. Their log-likelihoods are minimized and their deviances calculated as twice the difference between the corresponding log-likelihoods and that of the previous and less-complex model. The process continues until the 9 parameters have been included in the model. The residual or error deviance is then calculated as twice the difference in the log-likelihoods of the 9 parameter and full multinomial models. F-statistics for each model are calculated as the ratios between the models' deviances divided by their degrees of freedom and the error deviance also divided by its degrees of freedom. Since the deviances attributed to the new parameters are sequential (i.e., they depend on the order of other parameters already present in the model), I determined the order in which each parameter entered the reduced model by estimating at each step the log-likelihoods for all possible submodels and selecting the one with the smallest negative log-likelihood. For example, to determine which parameter should enter the exponential model after λ and a common μ and σ were entered, I minimized the following 14 negative log-likelihoods and chose the first submodel.

Submodel[1]	Log-	Submodel	Log-

[1] Numbers to the right of greek letters indicate codend towing order. See Table 5.1 for description of corresponding codends.

	likelihood		likelihood
$\mu1 = \mu2 = \mu3, \mu4, \lambda$	1119.195	$\sigma1 = \sigma2 = \sigma3, \sigma4, \lambda$	1134.871
$\sigma1 = \sigma2 = \sigma3 = \sigma4$		$\mu1 = \mu2 = \mu3 = \mu4$	
$\mu1 = \mu2 = \mu4, \mu3, \lambda$	1143.870	$\sigma1 = \sigma2 = \sigma4, \sigma3, \lambda$	1143.527
$\sigma1 = \sigma2 = \sigma3 = \sigma4$		$\mu1 = \mu2 = \mu3 = \mu4$	
$\mu1 = \mu3 = \mu4, \mu2, \lambda$	1142.208	$\sigma2 = \sigma3 = \sigma4, \sigma1, \lambda$	1134.967
$\sigma1 = \sigma2 = \sigma3 = \sigma4$		$\mu1 = \mu2 = \mu3 = \mu4$	
$\mu2 = \mu3 = \mu4, \mu1, \lambda$	1126.294	$\sigma1 = \sigma3 = \sigma4, \sigma2, \lambda$	1141.344
$\sigma1 = \sigma2 = \sigma3 = \sigma4$		$\mu1 = \mu2 = \mu3 = \mu4$	
$\mu2 = \mu1,\ \mu4 = \mu3, \lambda$	1136.148	$\sigma2 = \sigma1,\ \sigma4 = \sigma3, \lambda$	1140.716
$\sigma1 = \sigma2 = \sigma3 = \sigma4$		$\mu1 = \mu2 = \mu3 = \mu4$	
$\mu2 = \mu3,\ \mu4 = \mu1, \lambda$	1143.674	$\sigma2 = \sigma3,\ \sigma1 = \sigma4, \lambda$	1140.322
$\sigma1 = \sigma2 = \sigma3 = \sigma4$		$\mu1 = \mu2 = \mu3 = \mu4$	
$\mu2 = \mu4,\ \mu3 = \mu1, \lambda$	1119.844	$\sigma2 = \sigma4,\ \sigma1 = \sigma3, \lambda$	1134.961
$\sigma1 = \sigma2 = \sigma3 = \sigma4$		$\mu1 = \mu2 = \mu3 = \mu4$	

The ANODEV tables for the three approaches show that for the exponential and gamma versions (Table 5.3) there was no need for further parameters, once the population parameter, the μ's and a common σ have entered the model (P-value = 0.13 and 0.08 for the exponential and gamma, respectively). In similar fashion, for the relative approach a different μ for each codend and a common σ were sufficient to achieve a significant deviance reduction (P-value = 0.045, Table 5.4). Table 5.5 and Figure 5.4 show the parameter estimates for the reduced models selected through ANODEV, and Figure 5.5 displays the corresponding selection curves. The models selected for the three versions require a σ common to all the selection curves. However, the estimates were different.The relative version presented the largest value as well as the widest 95% confidence interval, and the exponential showed the smallest value and tightest confidence interval (Fig. 5.4). Concerning the μ estimates the relative model version produced the largest estimates for both the 117 mm and 133 mm diamond codends. Although the width of the 95%

confidence intervals were quite similar among methods, those for the relative model were not the widest. Confidence intervals were tighter for the exponential and wider for the gamma version (Fig. 5.4).

The comparison of the predicted selection curves (Fig. 5.5) suggests the possibility of bias for the relative model approach. While both the exponential and gamma versions produced rather similar curves for the 117 mm and 133 mm diamond codends, the relative approach predicted considerably smaller retentions for fish larger than 35 cm. On the other hand, for the 130 mm square codend it predicted larger retentions of small (< 35 cm) fish. These diffecences seems to indicate that the relative version may have introduced bias into the estimation procedure by assuming that the length sample for the 87 mm D mesh codend would satisfactorily represent the size distribution of the target population at the experimental site.

Discussion

The present exponential and gamma versions of the multinomial model are attempts to estimate size selectivity for all the meshes involved in comparative fishing experiments. Probably the most important advantage of these approaches over more traditional ones is that they provide estimates for the standard meshes by assuming a functional form to describe the length frequency distribution of the target species at the experimental site. The only other approach that produces estimates for the standard meshes is Kimura's (1980), which presents a series of differences from the present method. Kimura's method is based on quotients between the numbers-at-length caught by a standard and experimental mesh, and it derives from Pope et al.'s (1975) ratio method. Although it does not require any functional description of the population length structure, it does require the assumption of a common slope for the selection ojives of the standard and experimental meshes. Moreover, Kimura's approach provides acceptable estimates only if both tested meshes have overlapping selection ranges.

The assumptions added to the exponential and gamma model versions do not seem to affect any basic inference or conclusion obtained from the fit of the relative version of the multinomial model. The fits to the Dover example were all satisfactory. The selectivity curves predicted by the new model versions presented the same pattern of decreasing retention with mesh size and shape displayed by the curves obtained with the conventional relative approach (Fig. 5.5). The confidence intervals for the functional model versions were not much larger than those for the relative version (Table 5.5, Fig. 5.4). Moreover the final choice of reduced model was similar for the three procedures (Tables 5.3 and 5.4). Finally, selectivity parameter estimates were rather similar for the three model versions, with some differences between the predicted selection curves for the diamond mesh codends suggestive of possible bias introduced by the relative model version.

The exponential and gamma approaches, however, have important limitations that might overshadow the advantage of being able to estimate the selectivity of the standard mesh. First, the choice of statistical function used to describe the length frequency of the population is uncertain. This function has to be simple because there is not enough information in comparative fishing data to attempt the estimation of many population parameters. For certain species whose true length compositions have shapes very different from exponential or bell-shaped curves, the present new approaches will not provide good fits. For example, species such as pollock which has periodic strong year classes which often result in bi or trimodal length frequency distributions that may be hard to describe with functions involving only a few estimable parameters. Moreover, even in the case of simple, two-parameter bell-shaped functions, estimation could become a hard task, as the simultaneous estimation of the gamma parameters for the Dover example showed. This problem could be overcome, however, if some prior information on the possible shape of population function and values of its parameters exist from independent sources (e.g., outcome of current population assessment models, or data from surveys that had sampled the species with nets of considerably smaller mesh size). In such a case, likelihood model

(5.1) could be easily transformed to a Bayesian approach. For example for the gamma model the posterior distribution for α, β, μ's and σ's given the data $X = x$ would be:

$$P(\alpha,\beta,\mu,\sigma|X=x)=\frac{P(\alpha,\beta)P(\mu,\sigma)\prod_{j=1}^{4}\left(\binom{N_j}{x_j}\prod_{i=1}^{K}\left(\frac{f_i r_{i,j}}{\sum_{i=1}^{K} f_i r_{i,j}}\right)^{x_{i,j}}\right)}{\sum\left(P(\alpha,\beta)P(\mu,\sigma)\prod_{j=1}^{4}\left(\binom{N_j}{x_j}\prod_{i=1}^{K}\left(\frac{f_i r_{i,j}}{\sum_{i=1}^{K} f_i r_{i,j}}\right)^{x_{i,j}}\right)\right)}, \text{ where}$$

$f_i = \dfrac{l_i^{\alpha-1}\exp(-l_i/\beta)}{\beta^{\alpha}\Gamma(\alpha)}$, and $P(\alpha,\beta)$ and $P(\mu,\sigma)$ are the prior distributions for the population and selectivity parameters.

A second limitation of the exponential and gamma approaches has to do with intra block variability and the way the block is defined. If the length composition of the population varies among tows within the block, the estimates obtained from the exponential and gamma model versions will be biased, and so will be the estimates from the relative approach. Under these circumstances the Relative version is more likely to give erratic results or fail to converge more often than the other two approaches.

The unwanted effects of intra block variability could be reduced, at least in theory, by a careful definition of the experimental block. The hauls performed with the different codends should be as close as possible, both in time and space. However, determining how close they should be is not a task that can be easily generalized. What constitutes an acceptable block will depend upon the biological and behavioral characteristics of the species under study. Selectivity studies on less gregarious ground fish (e.g., soles and other flatfish) may tolerate blocks with hauls performed 9 nautic miles and 12 hours apart

(Table 5.1) without jeopardizing the estimation procedure or giving doubtful results. However, these blocks will not necessary be suitable for studies on semipelagic, fast moving shoaling species such as pollock. Alternatively, if the possibility of a Bayesian approach exists, the assumption about hauls performed on the same population (i.e., that the block was acceptable) could be tested. For example, changes in the posterior distribution of the population parameters after the length data for all the codends have been analyzed in the right towing order could be compared with the changes in the posterior when the length samples for the various codends are analyzed independently using the same prior.

Table 5.1: Haul and sample characteristics. Asterisk indicates the haul with the standard mesh codend. D and S stand for diamond and square mesh shapes. Distance and time elapsed are estimated with respect to the initial position and trawling time of the haul with the standard mesh codend.

Mesh size (mm)	117	87	130	133
Mesh shape	D	D	S	D
Mesh layers	1	1	1	1
Sample #	1	2*	3	4
Date	10/30/88	10/30/88	10/30/88	10/30/88
Initial trawling time	1:05	7:25	13:55	20:10
Final trawling time	6:55	12:25	18:40	0:40
Initial Position	44°19'N	44°28'N	44°19'N	44°27'N
	124°56'W	124°52'W	124°52'W	124°48'W
Final Position	44°28'N	44°18'N	44°28'N	44°19'N
	124°49'W	124°55'W	124°47'W	124°53'W
Average depth (m)	530	457	307	329
Average speed (nm/h)	2.1	2.1	2.1	2.2
Distance (nm)	9.44	0	9.00	3.03
Time elapsed (h)	6.33	0	6.50	12.75
Total catch (Kg)	1134	2268	1361	454
Dover catch (Kg)	221	481	690	127
Species in catch	11	9	15	13
Dover mean length (cm)	38.5	35.6	36.4	40.9
Variance	19.35	16.00	10.80	16.07
N	100	106	100	105

Table 5.2: Population and selectivity parameters for the Dover sole example obtained with the multinomial model assuming that the probability of each length class in the fish population is described by an exponential or gamma distribution with fixed β, or by the length frequency distribution of the catch by the standard codend (termed "relative").

		Model Version			
		Exponential	Gamma	Relative	
Population Parameters		$\lambda = 0.2087$			
			$\alpha = 19.5676$		
			$\beta = 1.5$	Length	p
				32	0.1509
				33	0.1415
				34	0.1698
				35	0.1038
				36	0.0660
				37	0.0566
				38	0.0943
				39	0.0566
				40	0.0283
				41	0.0189
				42	0.0283
				43	0.0189
				44	0.0094
				45	0.0377
				46	0.0189
Selectivity Parameters					
87 mm D	μ	32.3530	31.6727	NA	
	σ	0.9043	0.9195	NA	
117 mm D	μ	35.3068	35.1361	35.6409	
	σ	1.1231	1.2654	1.4739	
130 mm S	μ	34.0292	33.5212	33.5583	
	σ	1.0129	1.0576	1.2579	
133 mm D	μ	38.1442	38.6821	38.7989	
	σ	1.3452	1.6233	1.5370	
Loglik. Reduced Model		-1105.6719	-1108.6224	-1063.1943	
Loglik. Full Model		-1080.2069	-1080.2069	-1018.2685	
Number of length classes		76	76	76	
Number of parameters		9	9	6 (+ 15)	
Deviance		50.9299	56.8309	89.5162	

Table 5.3: ANODEV tables for the Exponential and Gamma versions of the multinomial model. Parameter numbers indicate sample numbers (see Table 5.1).

Exponential

Source	Parameters	df	Deviance	Deviance/df	F	P-value
Total	μ, σ, λ	73	128.153			
Submodel						
	$\mu1 = \mu2 = \mu3, \mu4, \sigma1 = \sigma2 = \sigma3 = \sigma4, \lambda$	1	50.177	50.177	66.010	1.43E-11
	$\mu1 = \mu3, \mu2, \mu4, \sigma1 = \sigma2 = \sigma3 = \sigma4, \lambda$	1	20.635	20.635	27.146	1.97E-06
	$\mu1, \mu2, \mu3, \mu4, \sigma1 = \sigma2 = \sigma3 = \sigma4, \lambda$	1	4.258	4.258	5.601	0.021
	$\mu1, \mu2, \mu3, \mu4, \sigma1 = \sigma2 = \sigma3, \sigma4, \lambda$	1	1.785	1.785	2.348	0.130
	$\mu1, \mu2, \mu3, \mu4, \sigma1 = \sigma3, \sigma2, \sigma4, \lambda$	1	0.287	0.287	0.378	0.541
	$\mu1, \mu2, \mu3, \mu4, \sigma1, \sigma2, \sigma3, \sigma4, \lambda$	1	0.081	0.081	0.107	0.745
Residual		67	50.930	0.760		

Gamma, $\beta = 1.5$

Source	Parameters	df	Deviance	Deviance/df	F	P-value
Total	μ, σ, α	73	131.052			
Submodel						
	$\mu1 = \mu2 = \mu3, \mu4, \sigma1 = \sigma2 = \sigma3 = \sigma4, \alpha$	1	48.109	48.109	56.717	1.69E-10
	$\mu1 = \mu3, \mu2, \mu4, \sigma1 = \sigma2 = \sigma3 = \sigma4, \alpha$	1	18.483	18.483	21.790	1.51E-05
	$\mu1, \mu2, \mu3, \mu4, \sigma1 = \sigma2 = \sigma3 = \sigma4, \alpha$	1	4.439	4.439	5.234	0.025
	$\mu1, \mu2, \mu3, \mu4, \sigma1 = \sigma2 = \sigma3, \sigma4, \alpha$	1	2.746	2.746	3.237	0.077
	$\mu1, \mu2, \mu3, \mu4, \sigma1 = \sigma3, \sigma2, \sigma4, \alpha$	1	0.283	0.283	0.334	0.565
	$\mu1, \mu2, \mu3, \mu4, \sigma1, \sigma2, \sigma3, \sigma4, \alpha$	1	0.162	0.162	0.191	0.664
Residual		67	56.831	0.848		

Table 5.4: ANODEV table for the Relative version of the multinomial model. Parameter numbers indicate sample numbers (see Table 5.1).

Source	Parameters	df	Deviance	Deviance/df	F	P-value
Total	μ, σ	59	139.561			
Submodel						
	$\mu 1 = \mu 3, \mu 4, \sigma 1 = \sigma 3 = \sigma 4$	1	42.876	42.876	26.344	3.85E-06
	$\mu 1, \mu 3, \mu 4, \sigma 1 = \sigma 3 = \sigma 4$	1	6.832	6.832	4.198	0.045
	$\mu 1, \mu 3, \mu 4, \sigma 1 = \sigma 4, \sigma 3$	1	0.330	0.330	0.203	0.654
	$\mu 1, \mu 3, \mu 4, \sigma 1, \sigma 3, \sigma 4$	1	0.006	0.006	0.003	0.952
Residual		55	89.516	1.628		

Table 5.5: Population and selectivity parameter estimates, and their 95% confidence intervals for reduced models selected through ANODEV. Fixed parameters β and p's take the same values as in Table 5.2.

		Model Version		
		Exponential	Gamma	Relative
Population Parameters	λ	0.2060		
	C.I.	0.1658-0.2520		
	α		19.7521	
	C.I.		17.7081–21.4527	
Selectivity Parameters				
87 mm D	μ	32.5766	31.8383	NA
	C.I.	31.6532-33.5905	30.5594-33.1746	
	σ	1.0889	1.2086	NA
	C.I.	0.8725-1.3587	0.9230-1.5891	
117 mm D	μ	35.2069	34.9718	35.6230
	C.I.	34.1965-36.4394	33.7427-36.5862	34.5081-37.0390
	σ	1.0889	1.2086	1.4634
	C.I.	0.8725-1.3587	0.9230-1.5891	1.1066-1.9664
130 mm S	μ	34.1188	33.6352	33.6216
	C.I.	33.1489-35.1436	32.4215-34.9853	32.1649-34.7588
	σ	1.0889	1.2086	1.4634
	C.I.	0.8725-1.3587	0.9230-1.5891	1.1066-1.9664
133 mm D	μ	37.5697	37.7048	38.6366
	C.I.	36.5168-38.7119	36.4519-39.2181	37.4505-40.1483
	σ	1.0889	1.2086	1.4634
	C.I.	0.8725-1.3587	0.9230-1.5891	1.1066-1.9664
Loglik. Reduced Model		-1106.7484	-1110.2176	-1063.1945
Loglik. Full Model		-1080.2069	-1080.2069	-1018.2685
Number of length classes		76	76	76
Number of parameters		6	6	4 (+ 15)
Deviance		53.0828	60.0214	89.8519

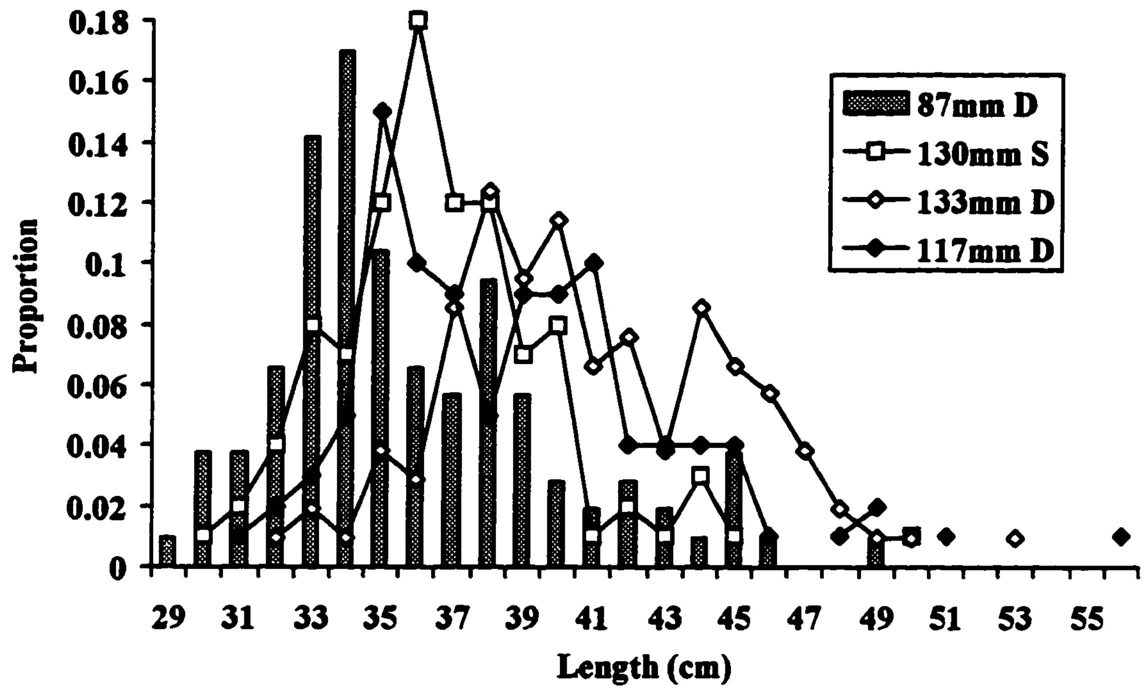

Figure 5.1: Relative length frequency distributions of Dover sole for four hauls. Bars indicate the sample for the standard codend. See Table 5.1 for further references.

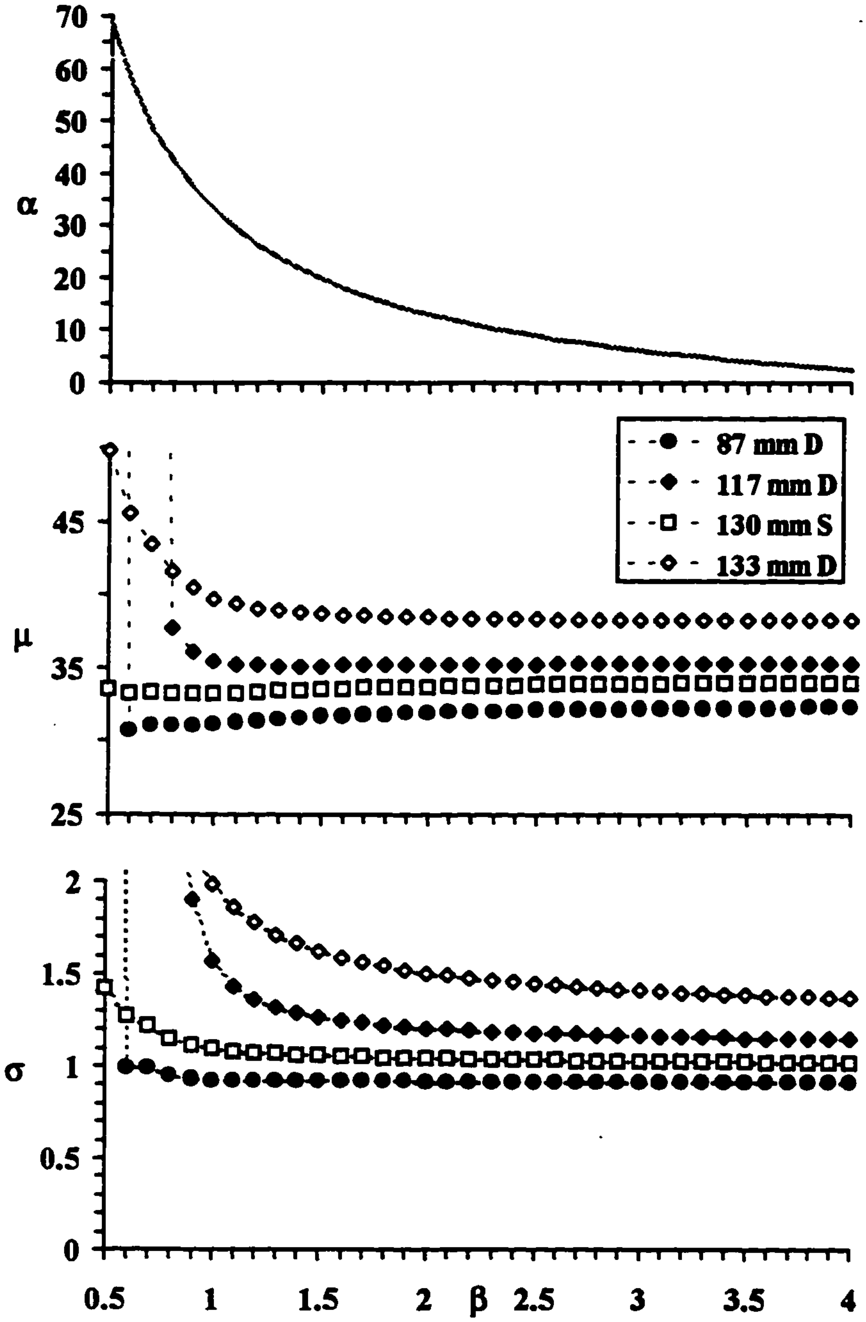

Figure 5.2: Sensitivity analysis for fits of the gamma model (5.3). Estimates of the gamma parameter α and the logistic parameters μ and σ obtained when the gamma parameter β is held constant within the range 0.5 - 4. The gamma distribution was used to describe the length composition of the target fish population, and the logistic to describe size selection.

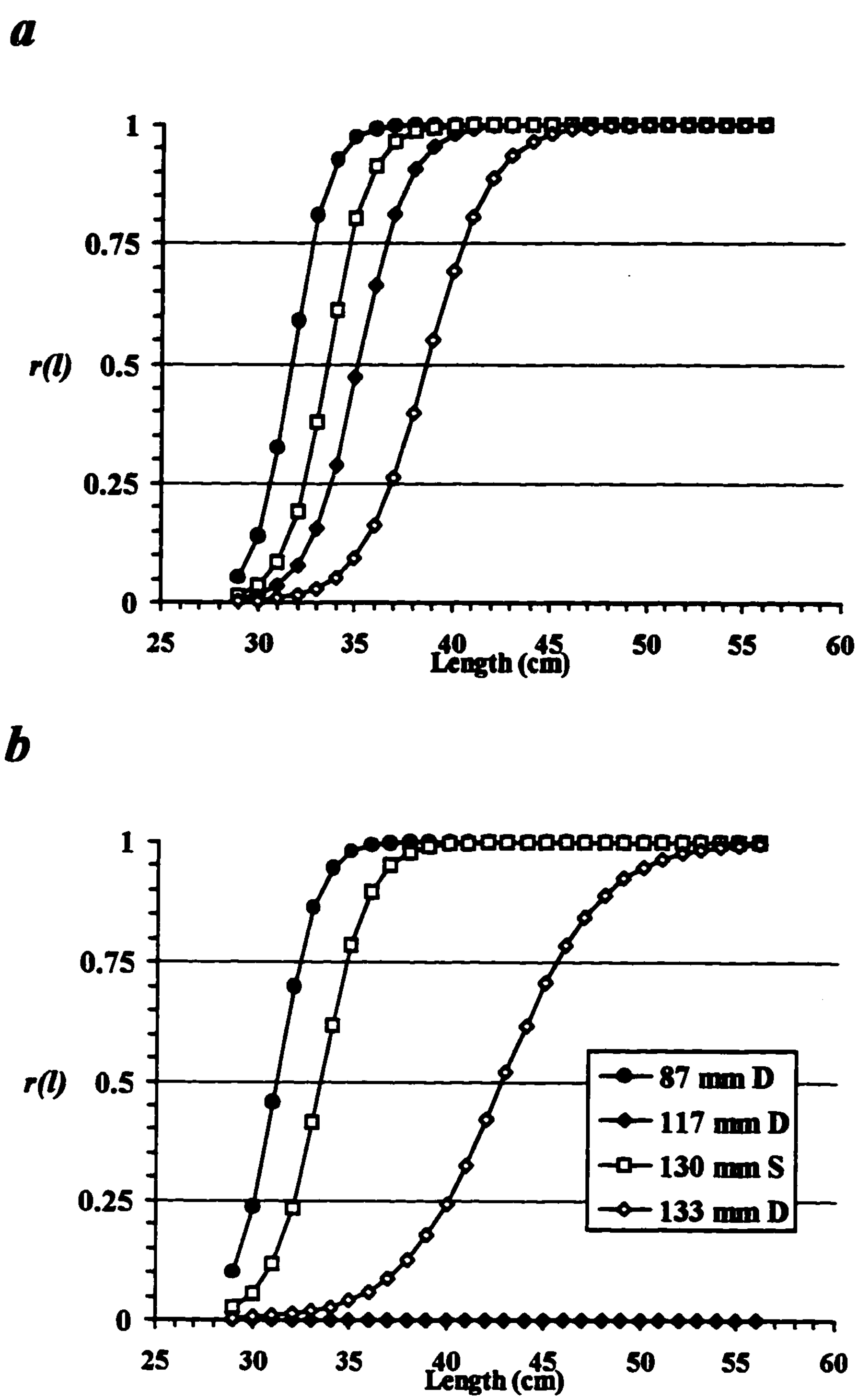

Figure 5.3: Selection curves for the gamma fit with (***a***) $\beta = 1.5$ and (***b***) $\beta = 0.7$.

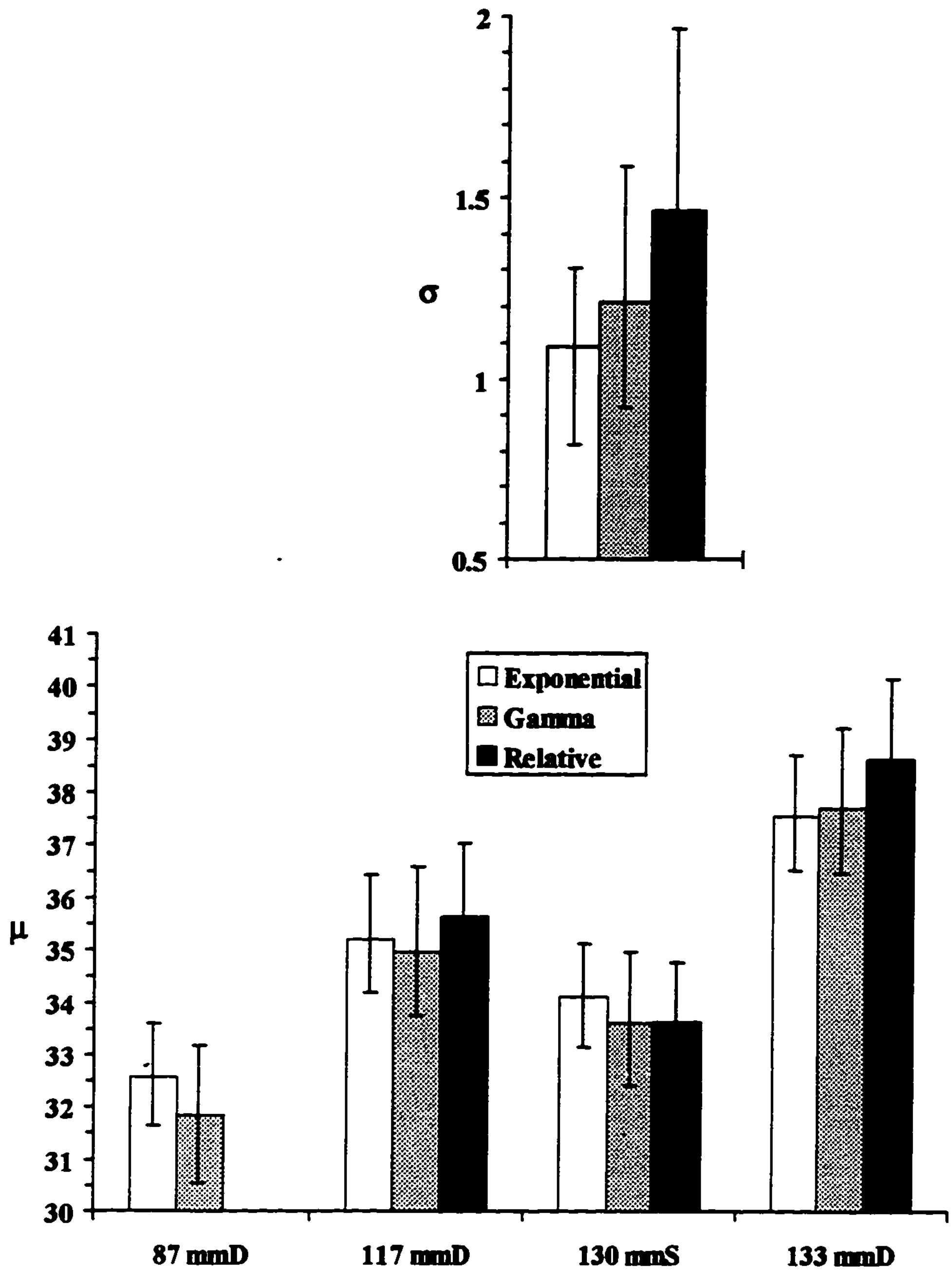

Figure 5.4: Comparison of selectivity-parameter estimates for the reduced models selected through ANODEV.

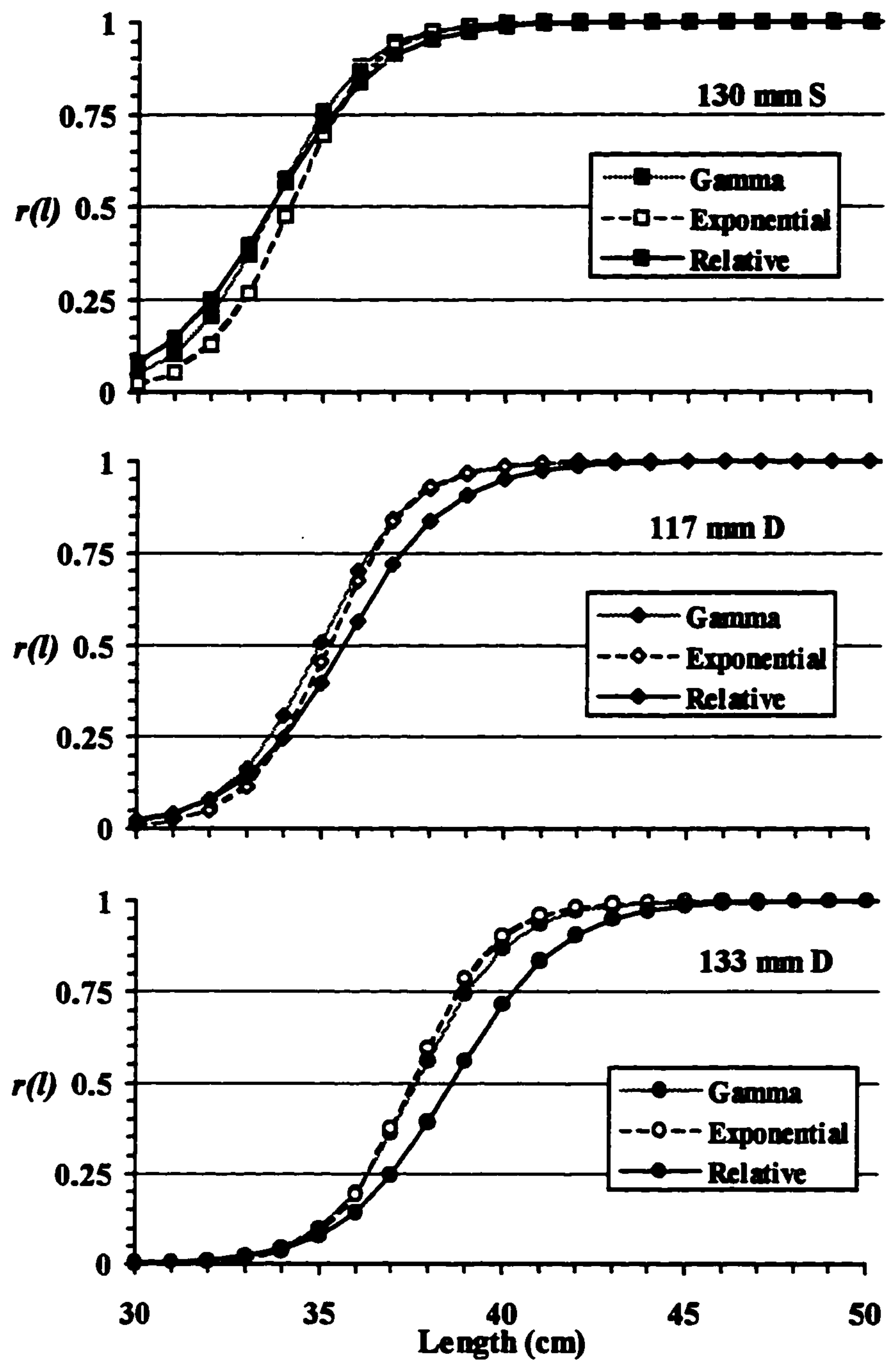

Figure 5.5: Selection curves for the reduced models selected through ANODEV for the square-mesh (S) and the two diamond-mesh (D) experimental codends. Curves were obtained by minimizing the gamma (equation 5.3), exponential (equation 5.2) and relative (equation 3.6) MLE models.

6. Uncertainty and between-haul variation: Multiple hauls selectivity analysis for walleye pollock

Introduction

Generally, the analysis of selectivity experiments involves the study of multiple hauls data. Very often, catch data is combined over all hauls to obtain pooled length frequency distributions that are used in the estimation of what can be viewed as a mean selection curve for the site of the experiment. Although this approach can be used to appraise "controlled" changes in the net, such as a change in codend characteristics or an increase in mesh size, it presents some problems.

First, when catches are sampled it is necessary to combine the estimated total catches from each haul. Hauls with large catches will contribute more to the mean selection curve than those with small catches. Then, if there is an important effect of catch size or volume on the effective selection of the gear, the resulting mean selection curve may be dominated by the large-catch hauls. Moreover, the catch/volume effect may not be easily assessed. Second, the value of the so-called mean selection curves is restricted by the representativeness and number of the hauls that were pooled. Finally, the pooling of length frequency distributions does not accommodate between-haul variation. Thus standard errors for the estimated mean selection curve have to be assessed through bootstrapping or corrected by the replication estimate of dispersion (*REP*, McCullagh and Nelder, 1989, p. 127; see also Chapter 2 of present dissertation).

Although, between-haul variation (i.e., changes in the selectivity of the net from haul to haul in absence of any controlled modification of the net) is often not of direct interest to gear technicians, it must be accounted for in the analysis of selectivity data to avoid making misleading statistical statements about the effects of controlled changes to the nets (Fryer, 1991). Misleading statistical statements could be extremely dangerous, especially if gear regulations are to follow the selectivity experiments.

Analysis of multiple hauls data explicitly accounting for between-haul variation has been developed for and applied to covered-codend experiments (Robertson and Stewart, 1988; Fryer, 1991; Reeves et al., 1992; Galbraith et al., 1994). However, no such analysis has been attempted for alternate-haul experiments. Moreover, most selectivity analyses performed on alternate-haul data failed to recognize a main drawback of alternate-haul experiments: the uncertainty about the overarching assumption that both standard and experimental nets sample the same fish population in terms of length composition.

In this chapter I analyze data from an alternate-haul experiment performed under production fishing conditions. Between-haul variability is here assessed by a regression approach similar to that used by Robertson and Ferro (1988) instead of a modeling approach (e.g., Fryer, 1991). The chapter was organized as follows. First, data were analyzed haul by haul, keeping the blocking design of the experiment, and possible departures from the "same population" assumption were discussed. Second, data were reanalyzed, this time disregarding the blocking design, as a way to incorporate the uncertainty about this assumption and avoid the loss of information. Third, I used the sets of selectivity parameter estimates produced by both analytical approaches to explore possible effects of catch size, towing speed and codend type on the selectivity estimates. Finally, the problems of the uncertainty in alternate-haul assumptions and between-haul variation were summarized in a final discussion.

Selectivity experiment

Research was conducted in the Bering Sea, north of Unimak Island (173°-175° W, 58°20'-59°10' N) from 13 July to 1 August 1994. Four catcher vessels using pelagic gear and detachable codends delivered catches to a factory trawler, where catches were sampled. For a detailed account of the field operations refer to Erickson et al. (1996).

Five codend types were used in the experiments. The standard codend was a double layer polyethylene all-diamond mesh codend with mesh sizes 82 mm and 90 mm, for the inner and outer layer, respectively. Two of the experimental codends had the side and bottom panels made of a double layer polyethylene all-diamond mesh material (similar to that of the standard codend), whereas the top panels of these codends consisted of a single layer of square meshes of sizes 95 mm and 108 mm. Hereinafter, these codends are termed 95 mm S and 108 mm S codends. The other two experimental codends were single layer all-diamond mesh with nominal sizes 88 mm and 113 mm, hereinafter termed 88 mm D and 113 mm D, respectively.

In total the four participant vessels performed 35 tows with standard codends, and 14, 9, 13 and 8 tows with 88 mm D, 113 mm D, 95 mm S and 108 mm S codends, respectively. Each vessel towed sequentially the standard codend and one or two experimental codends at about the same location and in a similar manner (e.g., towing speed, depth, etc). The order in which each codend was towed was randomly determined. These sequences of hauls constituted 27 randomized blocks (Bergh et al., 1990). Every attempt was made to ensure that all tows within blocks were comparable (e.g., made in the same area on the same day and under similar circumstances), and a set of rules was implemented to reduce potential between-haul variation (Erickson et al., 1996).

The basic data gathered during these experiments consist of length frequency distributions obtained from sampling each catch delivered to the mothership. A stratified sampling regime was employed to ensure that all portions of the catch were equally represented. Truncated fork lengths (cm) were recorded on a Polycorder data storage device for each fish in the samples. On average 523 fish were measured for each tow (SD = 61). For the selectivity analysis the resulting length distributions were paired according to the 27 blocks. Thus 44 pairs of experimental and corresponding standard mesh codend length distributions were determined (e.g., Fig. 6.1, 6.2 and 6.3).

The remaining data consist of haul information. For each haul, the skipper always recorded date, haul number, time and position for the start and end of the tow, towing speed, headrope depth, vertical opening and cable out. Total catch weight was also estimated for each haul, using a volumetric technique.

Multiple hauls analysis for "field-assigned" pairs of hauls

The simplest form of the multinomial model (**equation 3.6**, Chapter 3) was used to fit length frequency data for each of the 44 "field-assigned" pairs of hauls performed with standard and experimental mesh codends. The logistic curve parameterized as: $r = \dfrac{1}{1+\exp(-(l-\mu)/\sigma)}$ was chosen to describe size selection.

Prior to estimation the smallest and largest length classes were grouped to assure that the same number of length classes were represented in both the standard and experimental mesh samples (model assumption 4, Chapter 3). As in previous chapters minimization of the negative log-likelihoods was accomplished with Excel function Solver.

Results for the 44 independent fits are reported in Table 6.1. Only estimates for μ and σ are reported here because only these parameters are required to fully describe the selectivity pattern of the experimental mesh codends (The remaining K-1 estimates correspond to the capture probabilities p_i of the standard mesh). For each fit, the degrees of freedom (*df*), deviances and their associated probabilities, $P\left(\chi^2_{df} \le D\right)$ are also reported.

Ten pairs of samples (Table 6.1 trial hauls 16, 26, 27, 28, 30, 35, 41, 50, 58 and 80) showed negative $\hat{\mu}$ and probabilities smaller than 0.05. Negative $\hat{\mu}$'s suggest that even the smallest fish are retained. That is, for these hauls the selective properties of the codends should be considered null. On the other hand, the small probabilities may indicate lack of fit. An inspection of the original length frequency data (Fig. 6.1) hints at possible reasons for these unusual results. For seven pairs of hauls (trial hauls 16, 26, 27, 30, 35, 41 and 58) the mode of the length frequency distribution for the experimental mesh codend lay toward the left of that for the corresponding standard mesh length sample. For the remaining three pairs (trial hauls 28, 50 and 80) the length frequency distributions for both codends approximately matched each other. The patterns of the length distributions in Figure 6.1 are not the ones expected from hauls where size selection has occurred. If size selection had occurred the modes of the length frequency distributions for the experimental mesh codends should have lain toward the right of the modes for the corresponding standard mesh length samples.

While showing positive $\hat{\mu}$, twelve other pairs of samples (Table 6.1 trial hauls 12, 17, 23, 32, 33, 34, 40, 44, 60, 66, 73 and 78) also fitted the multinomial model poorly (P < 0.05). Finally, for the remaining 22 length-sample pairs the multinomial model with logistic selectivity curves fitted the data adequately (Table 6.1). In these cases deviances were small and close to *df*, which assures probabilities greater than 0.05. Parameter estimates for these 22 length-sample pairs were quite variable, but within reasonable ranges (35.51, 32.89 and 41.49 were the median, and 25 and 75 percentiles for $\hat{\mu}$, and 2.47, 1.95 and 3.02 the corresponding statistics for $\hat{\sigma}$). Only four sample pairs produced very extreme $\hat{\mu}$'s (Table 6.1 trial hauls 21, 48, 63 and 77).

Reasons for the lack of fit of the multinomial model and the extreme $\hat{\mu}$'s could have been due to: a) a bad choice of the curve used to describe retention (r), or b) a bad choice of likelihood function. I explored the first possibility by fitting the samples in Figures 6.2 and 6.3 to the multinomial log-likelihood (**equation 3.6** Chapter 3) with r expressed as a Richards curve instead of a logistic (see chapters 1 and 2 for equations). To assess the second possibility, I fitted Millar (1992) model to the samples. As it was mentioned elsewhere (Chapters 1, 2 and 3), Millar (1992) model uses binomial instead of multinomial log-likelihood functions. For these fits I utilized the fully parameterized version of the model that allows for the estimation of the "efficiency coefficient" p and the three parameters that describe a Richards curve (μ, σ and δ).

Replacing the logistic by the Richards curve in the multinomial model did not improve the fits of any of the sixteen pairs of samples. Millar (1992) model produced adequate fits ($P \geq 0.05$) only in three occasions (Table 6.2, trial hauls 21, 48 and 63). These hauls also produced fits with $P \geq 0.05$ for the multinomial model (Table 6.1), although the estimates for Millar (1992) model seem more acceptable. For example, the $\hat{L}_{50}$ ($\hat{\mu} = \hat{L}_{50}$) for fits to Millar (1992) model were 51.5, 53.5 and 27.0 for hauls 21, 48 and 63, respectively, whereas for the multinomial model fits $\hat{L}_{50}$ was 69.0, 63.4 and 6.5 for the same hauls.

The fact that both the multinomial and Millar (1992) encountered difficulties in fitting the pairs of length samples represented in Figures 6.2 and 6.3 suggests that the problem is not simply related to a wrong choice of model. More likely, some basic assumptions of the models are not met by the data. Both models assume that selection occurs, and that it can be detected by comparing the length frequency distributions of the catches by the standard mesh codend to those by the experimental codends. Both the multinomial and Millar (1992) models rely upon the assumption that "the fate of each fish captured and retained is independent of all other fish" (Chapter 3, assumption 1). Moreover both the standard and experimental mesh codends should sample the same population of fish in terms of size distribution (Chapter 3, assumption 2).

If for a given pair of hauls the mode of the length frequency distribution for the experimental mesh codend lies toward the left of that for the corresponding standard mesh length sample (Fig. 6.1 trial hauls 16, 26, 27, 30, 35, 41 and 58, and Fig. 6.2 hauls 12 and 34), one may suspect that both hauls were performed upon fish schools with different size composition. Had the hauls been performed on the same population, the mode for the experimental codend sample should have been shifted toward the right of, or coincided with the mode of the length sample for the standard codend, in presence or absence of mesh size selection. However, a right-shifted mode does not necessarily warrant that both hauls were performed on the same fish population, as attested by the lack of fit of both the multinomial and Millar (1992) models for the length distributions of trial hauls 17, 33, 40, 44, 60 and 66 (Tables 6.1 and 6.2, Fig. 6.2). Thus, for this selectivity experiment it is questionable whether assumption 2 held for many pairs of length samples. Moreover, the validity of the independence assumption (Chapter 3, assumption 1) is also questionable for hauls 28, 50 and 80 (Fig. 6.1), hauls 23, 32, 73 and 78 (Fig. 6.2), and haul 63 (Fig. 6.3). If these hauls and those performed with the standard mesh codend were performed on the same fish schools, their length distributions suggest lack of selection. A similar pattern, however, may result, for example, if a dense school is fished upon for a considerable time. After an initial time of effective codend selection, the increasing number of fish entangled in the meshes and the bulk of the catch will affect the retention probability of other incoming fish. Thus assumption 1 is violated and the final or observable length distribution may suggest lack of selection.

In spite of the extreme care taken during the experiment, the previous discussion suggest that the "field-assigned" pairs of hauls should not be trusted since in many cases they violated model assumptions. This assertion is further reinforced by inspection of the distributions of differences in tow starting time, tow location and footrope depth between "field-assigned" pairs of hauls (Fig. 6.4). It is unlikely, for example, that for a fast moving schooling species, such as pollock, hauls separated by 8 or 16 hours, or by more than 2 miles could have targeted the same fish schools in terms of length composition. The failure to comply with this "same population" assumption of most "field-assigned" haul pairs more likely springs from the field operation setup. Before towing a new codend, each participant catcher vessel had to deliver the catch from the previous tow to a mothership. In such a situation, the likelihood of finding the same school or one with similar length composition is low, even with the help of echosounders or other tracking devices. This uncertainty is thus part of the experimental design and should be explicitly incorporated in the estimation procedure.

Multiple hauls analysis with uncertain haul pairing

As discussed previously for the present selectivity study, the pairs of standard and experimental hauls assigned on the field can not be entirely trusted. Many pairs probably violated model assumptions with the consequent result that only 22 out of the 44 "field-assigned" pairs of length samples produced adequate fits to the multinomial model ($P \geq 0.05$). This considerable loss of information may hamper our ability to infer the effects of various factors on selectivity parameters. For example, if we wished to infer the effect of codend type we would have to use the 22 pairs that provided acceptable fits. These 22 pairs produced 7 selectivity parameter estimates for the 88 and 113 mm D codends, 6 estimates for the 95 mm S codend, and only 2 for the 108 mm S codend. This is a very unbalanced design. Moreover, some pairs produced suspiciously extreme $\hat{\mu}$'s (Table 6.1 trial hauls 21, 48, 63 and 77) that might have an unwelcome leverage in the outcome of subsequent regression analyses.

One possible solution to overcome the above-mentioned problems is to incorporate the uncertainty on the pairing of hauls into the analysis. The multinomial model and its likelihood function (**equation 3.6** Chapter 3) can thus be used to obtain selectivity parameter estimates for all possible combinations of length samples of the catches from hauls performed with the standard and experimental codends. For the present study this approach involved the evaluation of the multinomial model 1,540 times (since there were 35 hauls performed with the standard codend and 44 with the experimental codends).

The 1,540 pairs of samples produced 629 adequate fits ($P \geq 0.05$) that are reported in Appendix 3. A large percentage of sample pairs (59%) did not fit the model because the modal length classes for the standard codend samples were larger than those for the experimental codend samples (Fig. 6.1). The comparison of the frequency distributions for the 22 $\hat{\mu}$'s and $\hat{\sigma}$'s obtained with the previous "field-assigned" approach with those for the 629 newly obtained estimates shows that although the modal classes remain the same, the new distributions are better defined, in particular at their tails (Figure 6.5). The break down of the 629 $\hat{\mu}$'s and $\hat{\sigma}$'s by codend type (Table 6.3) show appreciable shifts for the mean, median, and 25th and 75th percentiles. Moreover, if the 117 new estimates for the 108 mm S codend provide better depictions for the distributions of the parameters μ and σ, the two estimates obtained with the "field-assigned" approach ($\mu = 32.9$, $\sigma = 3.73$ and $\mu = 101.6$, $\sigma = 6.96$) should be considered rather extreme, lying beyond the 25th and 75th percentiles.

Effect of catch size, towing speed and codend type on selectivity estimates

To explain part of the large variability displayed by the $\hat{\mu}$'s and $\hat{\sigma}$'s obtained from both the "field-assigned" and "all-pairs" approaches (Table 6.3), I attempted to model both $\hat{\mu}$ and $\hat{\sigma}$ as linear functions of codend type, catch size (C) and towing speed (Sp). Since the estimates were not normally distributed (Fig. 6.5), and the variances were not constant the response and explanatory variables were log transformed. For both sets of $\hat{\mu}$'s and $\hat{\sigma}$'s the initial model was:

$$\log_e \hat{s}_{i,j} = \sum_{i=1}^{4}\left(\beta_{oi} + \beta_{1i}\log_e C_{i,j} + \beta_{2i}\log_e Sp_{i,j}\right) + \varepsilon_{i,j}\ , \tag{6.1}$$

where $\hat{s}_{i,j}$ is the j^{th} μ or σ estimate for codend type i (i = 1, 2, 3, 4 if codend is 88 mm D, 113 mm D, 95 mm S or 108 mm S, respectively, and j = 1, ..., 22 or j = 1, ..., 629 for the "field-assigned" and "all-pairs" approaches, respectively), and ε is the normally distributed error term with mean 0 and variance 1.

The model was fitted to both sets of estimates using the least squares approach, and the statistical significance of the β estimates were tested using analysis of covariance (ANCOVA). The final regression models were used to predict μ's and σ's for selected catch sizes and towing speeds. Confidence intervals for the predictions were calculated using formulae 7.55 (Neter et al., 1985, p. 246).

1. Field-assigned pairs of hauls

The 22 transformed $\hat{\mu}$'s minimized model **(6.1)** with residual sum of squares (SSE) equal to 1.5541 (r^2 = 0.688). Since the interactions between codend type and $\log_e C$, and between codend type and $\log_e Sp$ were not significant ($\beta_{1i} = c_1$ and $\beta_{2i} = c_2$, Table 6.4 *a*), I selected an alternative reduced model with common coefficients β_1 and β_2, which was minimized at SSE = 2.3177 (r^2 = 0.535). Further testing of this model showed that only $\log_e C$ explained significantly the pattern displayed by the transformed $\hat{\mu}$'s (P-value = 0.005, Table 6.4 *a*). Thus the final regression was $\log_e \hat{\mu} = 4.472 - 0.275\log_e C$ (r^2 = 0.373, SSE = 3.1227, Fig. 6.6).

The 22 transformed $\hat{\sigma}$'s minimized model **(6.1)** at SSE = 1.3779 (r^2 = 0.595). The ANCOVA approach showed that the interactions between codend type and catch, and between codend type and speed were non-significant (P-values = 0.995 and 0.408, Table 6.4 *b*). Moreover, for the alternative model with common coefficients β_1 and β_2 (SSE = 1.8826, r^2 = 0.447) the effects of both catch and speed were not statistically significant either (Table 6.4 *b*). The pattern of the 22 transformed estimates was thus best described by the average of the estimates (Fig. 6.6): $\log_e \sigma_{88D} = \log_e \sigma_{113D} = 0.775$, $\log_e \sigma_{95S} = 0.963$ and $\log_e \sigma_{108S} = 1.628$.

Therefore, the set of selectivity parameter estimates obtained for the field-assigned pairs of hauls only showed a significant relationship between μ (i.e., L_{50}) and catch size, and significant differences among the means of the σ's corresponding to the different codend types. The existence of a negative correlation between L_{50} and catch size for pollock is an important result because of its implications in management (Erickson et al., 1996). Such relationships have been reported in the past for a series of fish species (e.g., Hodder and May, 1964, and Table 1 in Pikitch et al., 1995). However, it is unfortunate that we were unable to show clear differences among the selection curves for the four codend types (Fig. 6.9, bottom panel). Probably the small sample size (only 22 of the field-assigned pairs of hauls provided reliable selectivity estimates, Table 6.1, P-values $\geq$ 0.05) and the unbalanced distribution of the μ and σ estimates among codend types (e.g., only two reliable estimates were found for the 108 mm S codend) contributed to this result.

2. Uncertain pairs of hauls

Model **(6.1)** was initially fitted to the 629 reliable μ and σ estimates coming from the "all-pairs" approach (Appendix 3, Table 6.3) using a simple unweighted least squares procedure. With a larger sample size and less unbalanced distribution of estimates among codend types, the interactions between codend type and catch, and between codend type and speed were significant for both μ and σ estimates (Table 6.5). Thus a unique relationship between the transformed μ and σ estimates and the two covariates could be ascribed to each codend type. The two diamond-mesh codends were represented by

$$\log_e \hat{\mu} = 4.09 - 0.09 \log_e C - 0.19 \log_e Sp,$$

$$\log_e \hat{\sigma} = 1.85 - 0.25 \log_e C - 0.28 \log_e Sp,$$

for the small mesh codend (88 mm), and

$$\log_e \hat{\mu} = 3.81 - 0.18 \log_e C + 0.30 \log_e Sp,$$

$$\log_e \hat{\sigma} = 0.03 - 0.30 \log_e C + 1.15 \log_e Sp,$$

for the 113 mm codend. The equations for the 95 mm S codend were

$$\log_e \hat{\mu} = 4.48 - 0.18 \log_e C - 0.20 \log_e Sp, \text{ and}$$

$$\log_e \hat{\sigma} = 0.85 - 0.24 \log_e C + 0.54 \log_e Sp.$$

Finally , the 108 mm S codend was represented by

$$\log_e \hat{\mu} = 2.36 - 0.20 \log_e C + 1.57 \log_e Sp, \text{ and}$$

$$\log_e \hat{\sigma} = -3.21 - 0.22 \log_e C + 3.59 \log_e Sp.$$

The negative effect of catch size is still present, though varying in degree among codend types. Larger catches produce smaller L_{50}'s and shorter selection ranges (i.e., smaller σ's, or sharper selection ogives). The effect of speed on the selection parameter estimates seems to be more mesh size dependent. For example, for a given catch level an increase in towing speed produces a decrease in L_{50} or μ for the small meshes 88 and 95 mm, and an increase for the large meshes 113 and 108 mm (Fig. 6.7). Table 6.7 and Figure 6.9 illustrate the selectivity parameters and the selection ogives expected for a catch of 38.34 t and towing speed of 3.6 kn., which are the averages for all the hauls performed with experimental codends during the study. For these average values the 108 mm S codend retains considerably less fish than any of the other codends at any given length, and all the codends have clearly distinctive selection ogives with a coherent pattern, very different from that obtained from regressing the 22 estimates of the field-assigned pairs of hauls (Fig. 6.9).

Regressing the 629 reliable μ and σ estimates from the "all-pairs" approach produced encouraging results. Not only catch size but also codend type and towing speed had a significant effect on the selectivity estimates. These results are the probable consequence of increasing the sample size by relaxing the conditions on the pairing of hauls to be used in the minimization of the negative log-likelihood for the multinomial model (**equation 3.6**). It may be argued, however, that a simple unweighted least-squares procedure is not adequate because each haul performed with an experimental codend is represented by more than one $\hat{\mu}$ or $\hat{\sigma}$ (as many as 35 if all the pairs of the particular experimental haul and each of the standard hauls produced reasonable estimates), and because many of these $\hat{\mu}$'s and $\hat{\sigma}$'s may not represent true estimates of selectivity (when the alternate-haul assumption that both standard and experimental hauls were performed on fish populations with the same length composition did not hold). Thus some kind of weight measuring how certain we are that the estimates are true representations of selectivity (i.e. that the "same population" assumption held) should be used. Unfortunately, the expectation of finding such weights are very low. A criterion based upon proximity in time or space between the two paired hauls is not endorsed because this criterion was used, albeit loosely (Fig. 6.4 *a* and *b*), to assign hauls pairs during the experiment, and it resulted in many pairs with clearly different length frequency distributions (Fig. 6.1). Similarly, a criterion based upon the comparison of some simple feature of the length frequency distributions, such as the relative position of the modes, is not fully advocated either because it cannot always discern whether the pair represents the true outcome of selection (Fig. 6.3). Instead, we chose the inverse of the sample variance of the transformed $\hat{\mu}$'s and $\hat{\sigma}$'s as weighting criterion. Since each experimental haul may have an associated distribution of $\hat{\mu}$'s and $\hat{\sigma}$'s according to the number of possible pairs (e.g., up to 35 in the present case), in the regression analysis one may give more weight to the estimates of those hauls with smaller sample variances. If the number of estimates for a given experimental haul is relatively large, a small variance suggests that the haul is less sensitive to pairing, that is less sensitive to departures from the "same population" assumption.

Fitting model (6.1) to the 629 $\hat{\mu}$'s and $\hat{\sigma}$'s with a weighted least square procedure and weights inversely proportional to the sample variances of the transformed $\hat{\mu}$'s and $\hat{\sigma}$'s produced somewhat different results to those from the unweighted procedure (Table 6.6). A main difference was the lack of significant interactions between codend type and towing speed for the $\hat{\sigma}$'s. The two diamond-mesh codends were represented by

$$\log_e \hat{\mu} = 4.31 - 0.11 \log_e C - 0.33 \log_e Sp \text{, and}$$

$$\log_e \hat{\sigma} = 0.77 - 0.38 \log_e C - 0.84 \log_e Sp,$$

for the 88 mm mesh and by

$$\log_e \hat{\mu} = 3.59 - 0.09 \log_e C + 0.22 \log_e Sp \text{, and}$$

$$\log_e \hat{\sigma} = 0.1 - 0.17 \log_e C + 0.84 \log_e Sp,$$

for the 113 mm mesh. The equations for the 95 mm S codend were

$$\log_e \hat{\mu} = 4.48 - 0.01 \log_e C - 0.71 \log_e Sp \text{, and}$$

$$\log_e \hat{\sigma} = 0.16 - 0.12 \log_e C + 0.84 \log_e Sp,$$

while those for the 108 mm S codend were

$$\log_e \hat{\mu} = 2.67 - 0.20 \log_e C + 1.31 \log_e Sp \text{, and}$$

$$\log_e \hat{\sigma} = -0.14 - 0.04 \log_e C + 0.84 \log_e Sp.$$

The differences between the outcomes of the weighted and unweighted procedure are better seen by comparing the selection curves predicted for a catch of 38.34 t and a towing speed of 3.6 kn. (Fig. 6.9, Table 6.7). For the square mesh codends, the weighted procedure predicted selection curves that were closer to each other (Fig. 6.9). The 95% confidence intervals for μ (Table 6.7; also contrast Fig. 6.7 and 6.8) and σ (Table 6.7) were wider for the weighted regressions. The comparison of predicted μ's and 95% confidence intervals for fixed catches and towing speeds (Fig. 6.8) shows that $\hat{\mu}$

decreases with larger catches for all codends. Moreover for small mesh codends and increasing towing speeds $\hat{\mu}$ decreases, but for large mesh codends and increasing towing speeds $\hat{\mu}$ increases. These patterns were similar to those observed with the unweighted procedure (Fig. 6.7). However, the point estimates were somewhat different, and the confidence intervals wider for the weighted procedure.

Uncertainty and between-haul variation

The selectivity of a fishing net may have two sources of variation. One is due to "controlled" changes in the net or the way it is fished (e.g., mesh size and shape, extension length, codend diameter, towing speed and time, etc). However, selectivity may vary from haul to haul without any alteration of the net or the fishing strategy. This between-haul variation could be due to a number of "uncontrolled" factors such as towing direction, wind speed, and the density, size composition and behavior of the fish encountered by the net. Any of these factors may produce changes in the size composition of the catch and affect selectivity estimation. Even in the more desirable case of covered-codend experiments, where fish escaping through the meshes are retained, and thus a "true" estimate of retention-at-length can be obtained (i.e., if one obviates possible bias due to masking effect), between-haul variability could be very large. For example, it is not uncommon for L_{50} to vary between hauls by over 10 cm for a given net (Fryer, 1991). Ignoring this variability (e.g., by pooling data, and presenting a "mean selection curve") could lead to misleading statistical statements and in turn to wrong managerial decisions. Assessing between-haul variability either by a simple regression approach (Robertson and Stewart, 1988) or a more sophisticated modeling approach (Fryer, 1991; Reeves et al., 1992; Galbraith et al., 1994) can certainly avoid these problems.

If there is a substantial between-haul variability in covered-codend experiments, the one present in alternate-haul experiments is even larger. Alternate-haul experiments are based upon comparison of length frequency distributions for hauls performed with a standard (small mesh) codend, and with one or more experimental codends, often of larger mesh size or different mesh shape. Thus all those "uncontrolled" factors affecting the composition of the catch are present twice, increasing the probability of having different selectivity estimates from pair to pair of hauls. Moreover, given that they are based on comparisons of hauls, selectivity estimates for alternate-haul experiments will also vary due to a "pairing effect". For example, the estimate for experimental codend A used at haul 1 may be very different if its length frequency distribution is compared with those for hauls 2, 3 or 4, all performed with standard codend B. Although, one may decide "a priori" which hauls should be paired, for example by pairing those hauls closest in time and space, there is always some uncertainty on the rightness of the decision (i.e., that both the standard and the experimental nets sampled the same fish population in terms of length composition).

In the present study I have applied this "a priori" pairing approach in what I termed "analysis of field-assigned pairs of hauls" (Table 6.1). Its drawbacks are evident when ones considers that more than 50% of the pairs did not produce acceptable selectivity estimates ($P \geq 0.05$). In fact, many of the discarded pairs of hauls clearly showed that "field-assigned" pairs did not guarantee that the standard and experimental nets sampled the same fish population (Fig. 6.1), even though some were very close in time and space (e.g., trial hauls 16 and 26 were only 0.20 nm and 6 hr, and 0.6 nm and 5 hr apart from their respective standard hauls 20 and 22). A "field-assigned" pairing strategy based on the similarities of the hauls under comparison, like any other "a priori" haul-pairing approach, is somewhat arbitrary, and difficult to execute consistently, especially when the experiment is performed under commercial fishing conditions on fast moving schooling species (Fig. 6.4). Moreover, it may lead to a large reduction in the number of selectivity parameter estimates left for subsequent regression analyses, thus impairing one's ability to show significant codend-type, catch, towing speed or other effects (Table 6.4, Fig. 6.6). Finally, whether the relationships found may significant and consistent with the findings of other researchers (e.g., relationship between catch size and L_{50} in Table 6.4 and Fig. 6.6 consistent with findings by Hodder and May, 1964; Isaksen et al., 1990; Dahm, 1991; Suuronen et al., 1991; Casey et al., 1992; Suuronen and Millar, 1992; Madsen and Moth-Poulsen, 1994), it is arguable that the predicted regression lines could be used for purposes other than purely descriptive ones, because it carries all the uncertainty of the initial haul-pairing process.

We argue that, for alternate-haul experiments, multiple haul selectivity analysis should not be based on "a priori" or "field-assigned" pairs of hauls. Such an approach would be unwise because a great number of hauls may have to be discarded if they fail to produce reasonable selectivity estimates. Thus a large number of new hauls will be required to compensate for those discarded in order to still detect some significant effects of controlled changes to the net or fishing strategy (this is particularly worrisome in times of budget cuts for research). Finally, the uncertainty or arbitrariness of the pairing process used will permeate the outcome of any posterior analysis or inference. As an alternative to "a priori" or "field-assigned" pairing of hauls, we propose the use of all possible combinations of hauls performed with the standard and experimental codends. Although many combinations will not provide acceptable selectivity estimates, the arbitrariness of the pairing process will be reduced, the uncertainty about the "same population" assumption will be incorporated, and data will be more efficiently used. Thus even small numbers of experimental hauls will provide acceptable sample sizes for any posterior analysis on factors affecting selectivity. For example, the 44 experimental hauls of our pollock example rendered 629 acceptable selectivity parameter estimates that in turn allowed the detection of significant effects due to catch size, towing speed and codend type (Tables 6.5 and 6.6). Caution should be taken, however, when incorporating these "all-pairs" estimates into any subsequent analysis because each experimental haul will be represented by a whole distribution of parameter estimates. Some of these estimates may not necessarily correspond to true representations of selectivity because the length frequency distributions from which they were obtained may have come from populations or schools with different size compositions. Thus in subsequent analyses (e.g., regression analysis with catch size, towing speed and codend type) each parameter estimate should carry a weight reflecting this uncertainty. For our pollock example we deemed appropriate to weight each estimate by the inverse of the sample variances for the estimates of each experimental haul. In this way, hauls whose estimates are less variable (i.e., less sensitive to the pairing process and the "same" population assumption) had a larger leverage in the analysis. However, the inverse of the sample variance is not the only weight alternative. With other species and experiments the inverse of the distance between the experimental and standard hauls or of the time elapse between hauls may also prove adequate weights.

The use of all possible combinations of hauls performed with the standard and experimental codends in the estimation of selectivity parameters coupled with a weighted regression analysis of the estimates is not necessarily the only alternative to dealing with between-haul variability and uncertainty of alternate-haul assumptions. However, it is one that may prove adequate for initial studies, when little or no information on size selectivity for the target species is available. For example, a Bayesian analysis of size selectivity, such as the one presented in the discussion of Chapter 5, could be an alternative to the present approach. Yet, Bayesian estimates not only depend upon the information contained in new data but also on that contained in the prior distributions for the parameters. In cases as the present pollock study with no previous information, which would imply the use of flat priors, the few experimental hauls of the study may not be enough to obtain well defined posterior distributions for the parameters.

Table 6.1: Multinomial model fits for 44 field-assigned pairs of length distributions.

Trial Haul	Std. Haul	Codend	$\hat{\mu}$	$\hat{\sigma}$	*df*	Deviance	P-value
10	14	88 mm D	35.891	1.885	16	16.370	0.427
11	15	113 mm D	33.982	2.685	24	26.870	0.311
12	20	95 mm S	4.820	2.413	22	142.772	0.000
16	20	108 mm S	-30.963	3.428	21	82.023	0.000
17	13	108 mm S	75.734	2.091	14	44.729	0.000
18	14	113 mm D	35.409	3.168	19	11.696	0.898
19	15	88 mm D	32.697	1.936	22	21.785	0.473
21	13	95 mm S	68.970	3.021	16	14.328	0.574
23	31	113 mm D	33.619	0.663	21	34.282	0.034
25	29	95 mm S	40.269	1.686	17	15.840	0.535
26	22	113 mm D	-4.303	0.650	22	76.515	0.000
27	31	88 mm D	-251.076	2.798	21	83.584	0.000
28	24	108 mm S	-18.314	5.332	18	48.670	0.000
30	22	88 mm D	-449.895	2.906	21	73.524	0.000
32	24	95 mm S	4.814	2.398	18	46.548	0.000
33	29	108 mm S	90.651	2.199	14	28.104	0.014
34	38	95 mm S	6.578	2.170	24	95.235	0.000
35	43	88 mm D	-76.241	0.886	22	73.028	0.000
39	43	113 mm D	36.675	3.321	23	29.357	0.169
40	36	108 mm S	67.187	2.591	18	35.872	0.007
41	37	88 mm D	-189.066	0.934	19	198.262	0.000
42	38	108 mm S	32.851	3.726	23	19.639	0.664

Table 6.1 (Continued)

Trial Haul	Std. Haul	Codend	$\hat{\mu}$	$\hat{\sigma}$	*df*	Deviance	P-value
44	36	95 mm S	92.804	6.352	20	44.502	0.001
45	37	113 mm D	30.538	1.709	24	32.560	0.144
48	52	95 mm S	63.414	3.906	23	21.750	0.535
50	54	88 mm D	-338.370	0.834	37	55.994	0.023
53	49	95 mm S	45.740	2.540	30	26.183	0.666
55	51	88 mm D	35.610	2.191	27	39.461	0.057
58	62	88 mm D	-135.416	0.712	20	90.109	0.000
60	64	95 mm S	52.851	3.570	20	38.929	0.007
63	59	95 mm S	6.535	2.124	23	18.130	0.750
65	61	88 mm D	32.963	1.870	23	28.272	0.206
66	74	108 mm S	305.756	9.105	26	138.900	0.000
67	71	113 mm D	30.691	0.854	21	19.469	0.555
68	76	88 mm D	30.451	2.406	29	27.549	0.542
70	74	95 mm S	33.915	3.005	22	20.956	0.523
72	76	113 mm D	42.391	2.634	22	29.679	0.126
73	69	95 mm S	18.492	1.028	21	54.730	0.000
75	71	88 mm D	33.232	2.406	22	18.859	0.654
77	69	108 mm S	101.564	6.963	21	31.046	0.073
78	82	88 mm D	32.055	2.878	21	47.454	0.001
80	84	95 mm S	-234.612	4.102	21	111.570	0.000
83	79	88 mm D	41.010	2.732	20	18.529	0.553
86	82	113 mm D	41.650	2.004	19	27.757	0.088

Table 6.2: Fits to Millar (1992) model for 16 pairs of length frequency distributions.

Trial Haul	Std. Haul	Codend	$\hat{p}$	$\hat{\mu}$	$\hat{\sigma}$	$\hat{\delta}$	*df*	Deviance	P-value
12	20	95 mm S	0.485	4.376	1.226	1.046	19	142.770	0.000
17	13	108 mm S	0.999	55.720	1.084	1.928	11	44.732	0.000
21	13	95 mm S	0.988	52.918	1.797	1.681	13	14.439	0.344
23	31	113 mm D	0.501	34.599	0.041	26.790	18	33.775	0.013
32	24	95 mm S	0.527	8.235	2.070	1.056	15	46.548	0.000
33	29	108 mm S	0.999	61.548	2.087	1.049	11	28.142	0.003
34	38	95 mm S	0.505	-3.147	1.735	1.095	21	95.234	0.000
40	36	108 mm S	0.999	61.116	2.086	1.243	15	35.927	0.002
44	36	95 mm S	0.979	64.774	3.833	1.670	19	48.956	0.000
48	52	95 mm S	0.991	54.168	3.394	1.139	20	21.778	0.353
60	64	95 mm S	0.801	47.258	0.065	54.358	17	34.591	0.007
63	59	95 mm S	0.505	26.984	0.199	0.917	20	17.772	0.602
66	74	108 mm S	0.509	7.615	1.445	0.969	23	265.045	0.000
73	69	95 mm S	0.505	10.490	1.088	1.033	18	54.729	0.000
77	69	108 mm S	0.993	73.948	3.246	2.146	18	31.045	0.028
78	82	88 mm D	0.570	35.499	0.078	60.133	18	45.603	0.000

Table 6.3: Summary statistics for the $\hat{\mu}$'s and $\hat{\sigma}$'s obtained with the field-assigned and all-pairs approaches.

Codend		Field-assigned		All-pairs	
		$\hat{\mu}$	$\hat{\sigma}$	$\hat{\mu}$	$\hat{\sigma}$
88 mm D	N	7	7	195	195
	Mean	34.551	2.204	35.281	2.480
	Variance	11.524	0.108	92.308	4.008
	Min	30.451	1.870	4.619	0.074
	25%	32.830	1.910	31.164	1.105
	50%	33.232	2.192	34.290	2.019
	75%	35.751	2.406	37.233	2.972
	Max	41.010	2.732	84.813	10.932
113 mm D	N	7	7	155	155
	Mean	35.905	2.339	37.889	2.225
	Variance	22.600	0.762	150.510	2.658
	Min	30.538	0.854	19.319	0.071
	25%	32.337	1.856	32.604	1.230
	50%	35.409	2.634	35.349	1.883
	75%	39.162	2.927	39.059	2.731
	Max	42.391	3.321	115.778	10.134
95 mm S	N	6	6	162	162
	Mean	43.140	2.714	42.237	2.619
	Variance	503.653	0.607	256.705	1.957
	Min	6.535	1.686	6.535	0.085
	25%	35.503	2.228	33.480	1.691
	50%	43.005	2.773	40.191	2.487
	75%	58.995	3.017	45.806	3.328
	Max	68.970	3.906	112.916	9.263
108 mm S	N	2	2	117	117
	Mean	67.207	5.344	49.842	2.387
	Variance	2360.773	5.239	437.533	1.897
	Min	32.851	3.726	27.110	0.085
	25%	50.029	4.535	33.346	1.541
	50%	67.207	5.344	38.046	2.150
	75%	84.386	6.153	66.719	2.741
	Max	101.564	6.963	105.632	7.497

Table 6.4: ANCOVA results for $\hat{\mu}$'s (*a*) and $\hat{\sigma}$'s (*b*) obtained by means of the "field-assigned" approach.

a.

Hypothesis tests	Δ SSE	Δ df	Δ MSE	F	P-value
$\beta_{1i} = c_1$ and $\beta_{2i} = c_2$	0.7635	6	0.1273	0.819	0.580
$\beta_{1i} = c_1$	0.4364	3	0.1455	0.936	0.459
$\beta_{2i} = c_2$	0.1430	3	0.0477	0.307	0.820
$\beta_{oi} = c_o$, $\beta_{1i} = c_1$ and $\beta_{2i} = c_2$	0.6130	3	0.2043	1.315	0.323
$\beta_{1i} = c_1$ and $\beta_{2i} = 0$	0.3337	1	0.3337	2.147	0.174
$\beta_{1i} = 0$ and $\beta_{2i} = c_2$	1.9484	1	1.9484	12.537	0.005

b.

Hypothesis tests	Δ SSE	Δ df	Δ MSE	F	P-value
$\beta_{1i} = c_1$ and $\beta_{2i} = c_2$	0.5047	6	0.0841	0.611	0.718
$\beta_{1i} = c_1$	0.0098	3	0.0033	0.024	0.995
$\beta_{2i} = c_2$	0.4389	3	0.1463	1.062	0.408
$\beta_{oi} = c_o$, $\beta_{1i} = c_1$ and $\beta_{2i} = c_2$	1.0949	3	0.3650	2.649	0.1062
$\beta_{1i} = c_1$ and $\beta_{2i} = 0$	0.0088	1	0.0088	0.064	0.806
$\beta_{1i} = 0$ and $\beta_{2i} = c_2$	0.2059	1	0.2059	1.494	0.250
$\beta_{1i} = 0$ and $\beta_{2i} = 0$	0.2201	2	0.1100	0.799	0.477

Table 6.5: Unweighted analysis for "all-pairs" selectivity estimates. ***a*** and ***b***) Regression coefficients; ***c*** and ***d***) ANOVA tables; and ***e***, and ***f***) ANCOVA tables, for $\hat{\mu}$ and $\hat{\sigma}$, respectively.

a

	$i =$	**88 mm D**	**113 mm D**	**95 mm S**	**108 mm S**
	β_{0i}	4.086	3.81	4.482	2.357
$\log_e C$	β_{1i}	-0.089	-0.178	-0.182	-0.199
$\log_e Sp$	β_{2i}	-0.194	0.298	-0.199	1.571

b

		88 mm D	**113 mm D**	**95 mm S**	**108 mm S**
	β_{0i}	1.852	0.026	0.854	-3.207
$\log_e C$	β_{1i}	-0.246	-0.295	-0.243	-0.218
$\log_e Sp$	β_{2i}	-0.283	1.146	0.536	3.586

c

Source	SSE	*df*	MSE	F	P-value
Regression	31.681	11	2.88	43.266	<0.001
Error	41.071	617	0.067		
Total	72.752	628			

d

Source	SSE	*df*	MSE	F	P-value
Regression	47.688	11	4.335	9.620	<0.001
Error	278.066	617	0.451		
Total	325.747	628			

e

Test	ΔSSE	Δ*df*	ΔMSE	F	P-value
$\beta_{ji} = c_j$	4.147	9	0.461	6.922	<0.001
$j = 0, 1, 2$					
$\beta_{1i} = c_1$	1.084	3	0.361	5.426	0.001
$\beta_{2i} = c_2$	1.832	3	0.611	9.173	<0.001

f

Test	ΔSSE	Δ*df*	ΔMSE	F	P-value
$\beta_{ji} = c_j$	15.715	9	1.746	3.875	<0.001
$j = 0, 1, 2$					
$\beta_{1i} = c_1$	28.205	3	9.402	20.861	<0.001
$\beta_{2i} = c_2$	10.433	3	3.478	7.717	<0.001

Table 6.6: Weighted analysis for "all-pairs" selectivity estimates. ***a*** and ***b***) Regression coefficients; ***c*** and ***d***) ANOVA tables; and ***e***, and ***f***) ANCOVA tables, for $\hat{\mu}$ and $\hat{\sigma}$, respectively.

a / ***b***

	$i=$	88 mm D	113 mm D	95 mm S	108 mm S	88 mm D	113 mm D	95 mm S	108 mm S
	β_{0i}	4.31	3.589	4.519	2.672	0.774	0.096	0.163	-0.137
$\log_e C$	β_{1i}	-0.114	-0.094	-0.008	-0.201	-0.378	-0.171	-0.114	-0.037
$\log_e Sp$	β_{2i}	-0.334	0.216	-0.707	1.309	0.839	0.839	0.839	0.839

c / ***d***

Source	SSE	*df*	MSE	F	P-value	SSE	*df*	MSE	F	P-value
Regression	2591.52	11	235.59	136.02	<0.001	283.92	11	35.49	19.701	<0.001
Error	1068.65	617	1.732			1116.9	617	1.801		
Total	3660.18	628				1400.82	628			

e / ***f***

Test	ΔSSE	Δ*df*	ΔMSE	F	P-value	ΔSSE	Δ*df*	ΔMSE	F	P-value
$\beta_{ji} = c_j$ $j = 0, 1, 2$	505.59	9	56.176	32.434	<0.001	172.87	9	19.208	10.62	<0.001
$\beta_{1i} = c_1$	209.51	3	69.838	40.322	<0.001	64.042	3	21.347	11.803	<0.001
$\beta_{2i} = c_2$	191.3	3	63.766	36.816	<0.001	0.921	3	0.307	0.17	0.917

Table 6.7: Predicted μ's and σ's and corresponding 95% confidence bounds for a catch of 38.34 t and a towing speed of 3.6 kn.

		μ			σ		
Type of regression		Estimate	Lower	Upper	Estimate	Lower	Upper
All-pairs unweighted	88 mm D	33.53	33.22	33.84	1.81	1.77	1.85
	113 mm D	34.60	34.40	34.80	1.52	1.48	1.55
	95 mm S	35.28	34.95	35.61	1.93	1.89	1.97
	108 mm S	38.31	38.05	38.56	1.81	1.78	1.83
All-pairs weighted	88 mm D	32.07	30.76	33.44	1.60	1.53	1.67
	113 mm D	33.91	32.68	35.18	1.73	1.67	1.79
	95 mm S	36.00	34.40	37.69	2.28	2.18	2.37
	108 mm S	37.20	35.75	38.71	2.23	2.13	2.34
Field-pairs	88 mm D	32.13	31.71	32.56	2.17	2.15	2.19
	113 mm D	32.13	31.71	32.56	2.17	2.15	2.19
	95 mm S	32.13	31.71	32.56	2.62	2.59	2.64
	108 mm S	32.13	31.71	32.56	5.09	5.01	5.18

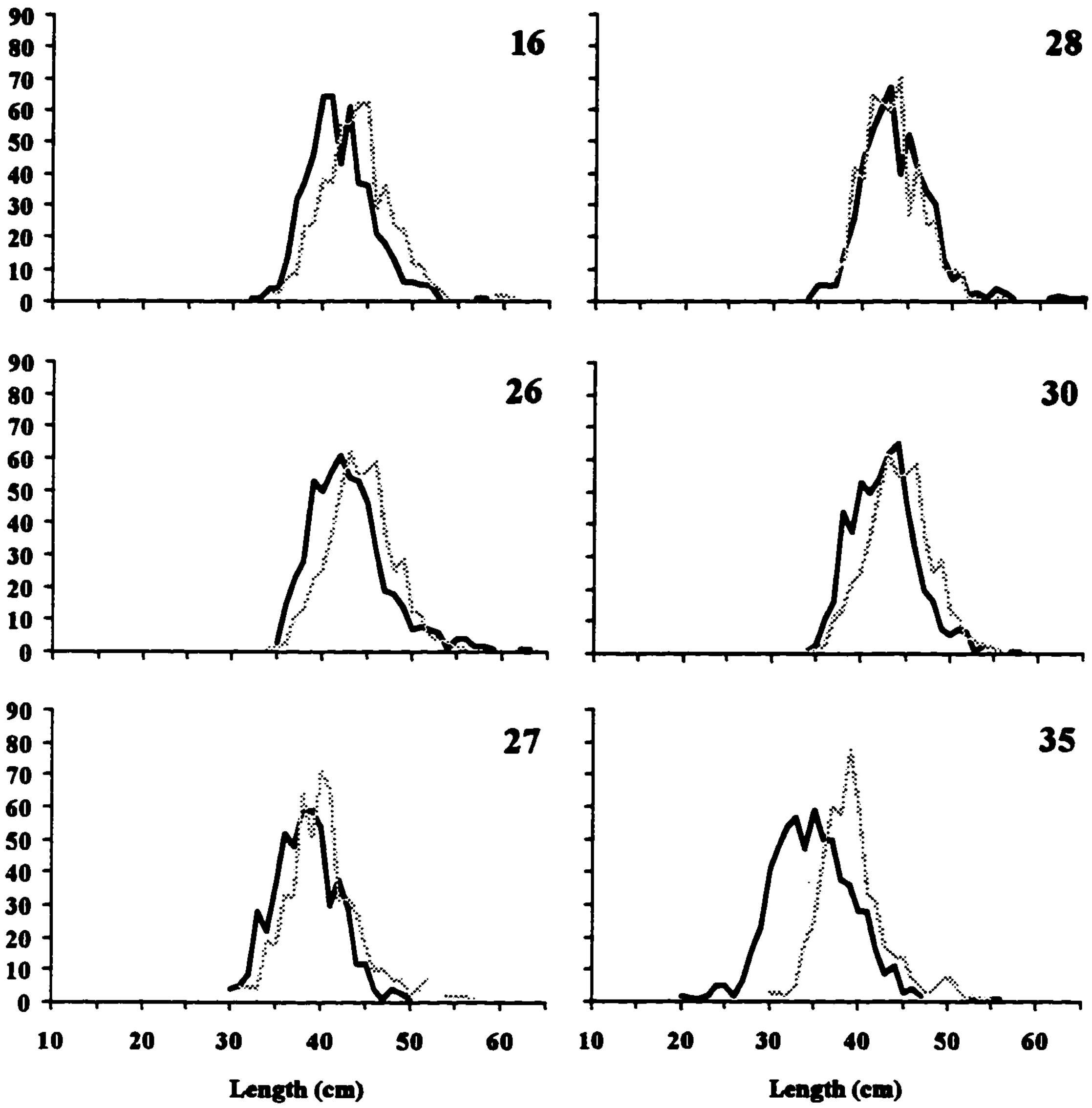

Figure 6.1: Length frequency distributions for pairs of hauls that produced $\hat{\mu} < 0$. Distributions for standard mesh codends are indicated by grey lines, and those for experimental codends by black lines. Numbers at the corner indicate haul numbers.

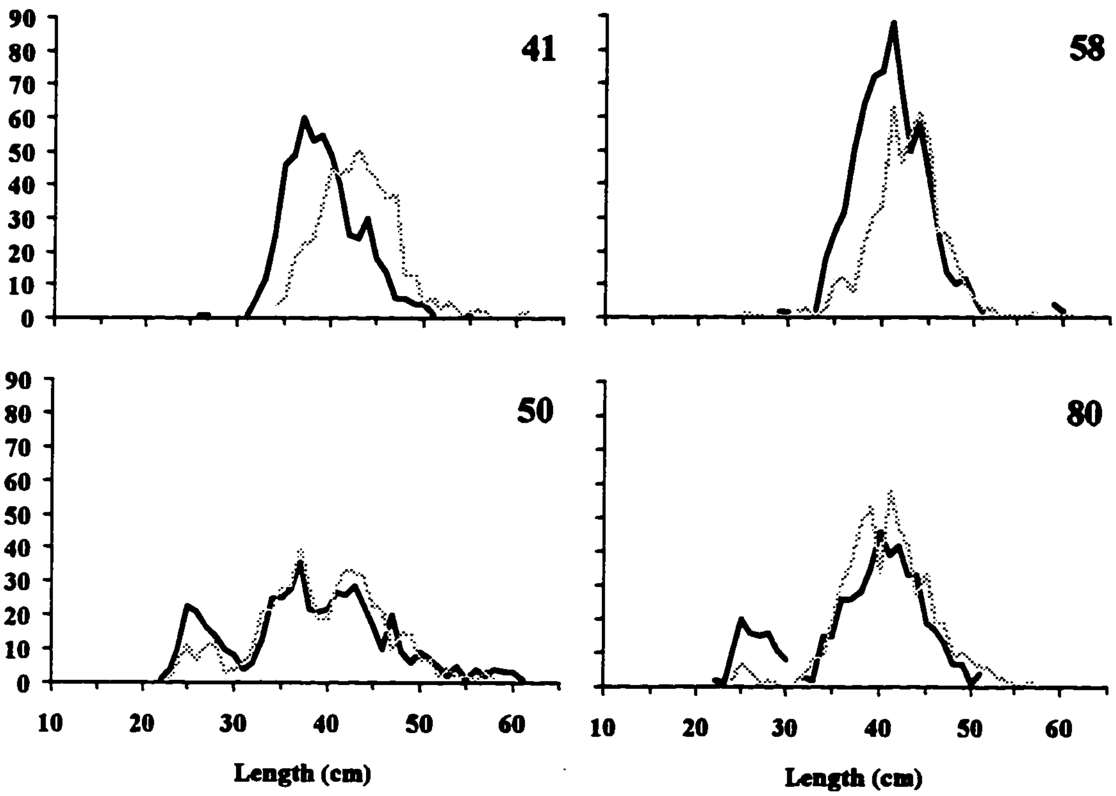

Figure 6.1 (Continued)

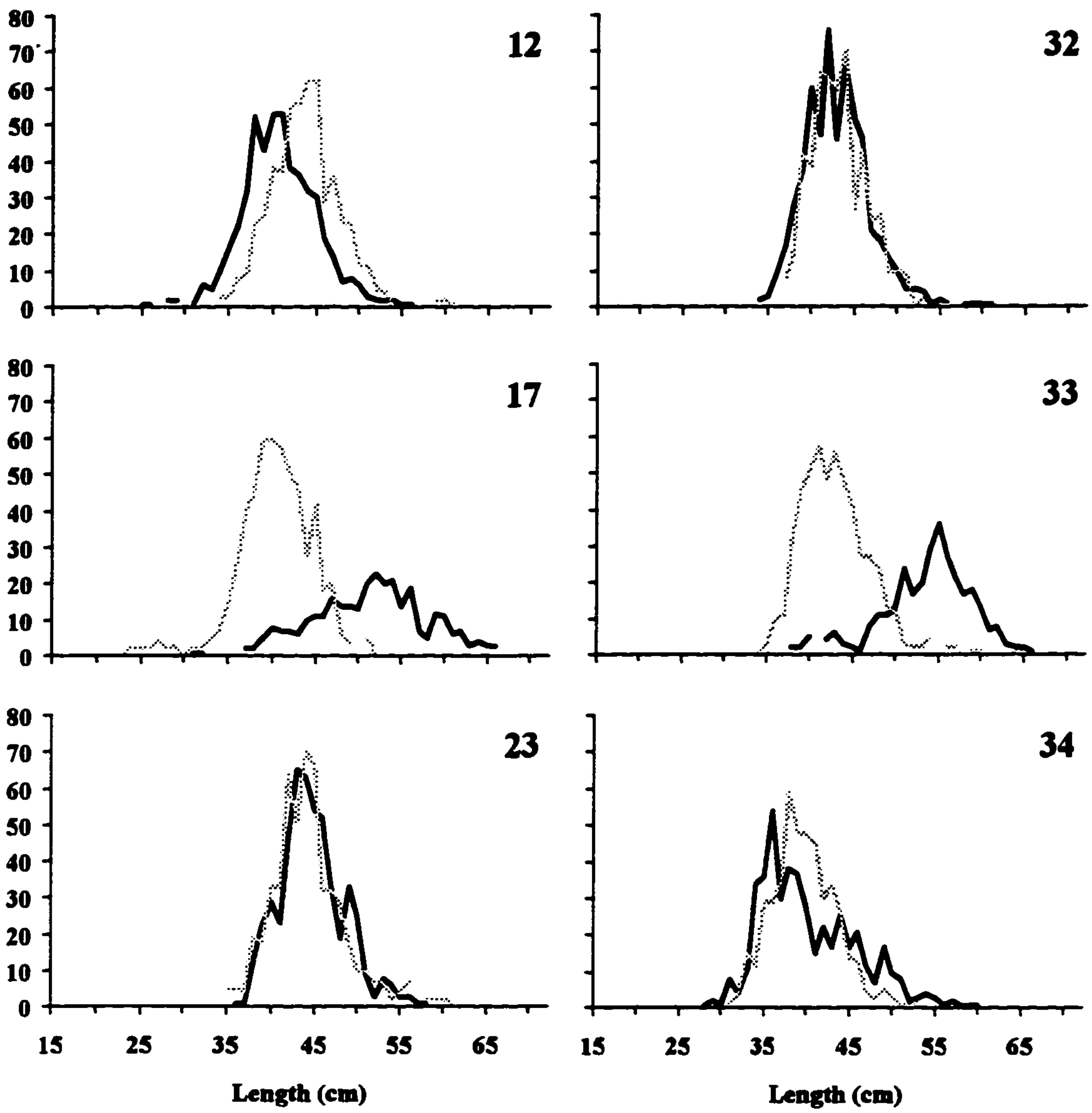

Figure 6.2: Length frequency distributions for pairs of hauls that produced fits with large deviance. Distributions for standard mesh codends are indicated by grey lines, and those for experimental codends by black lines. Numbers at the corner indicate haul numbers.

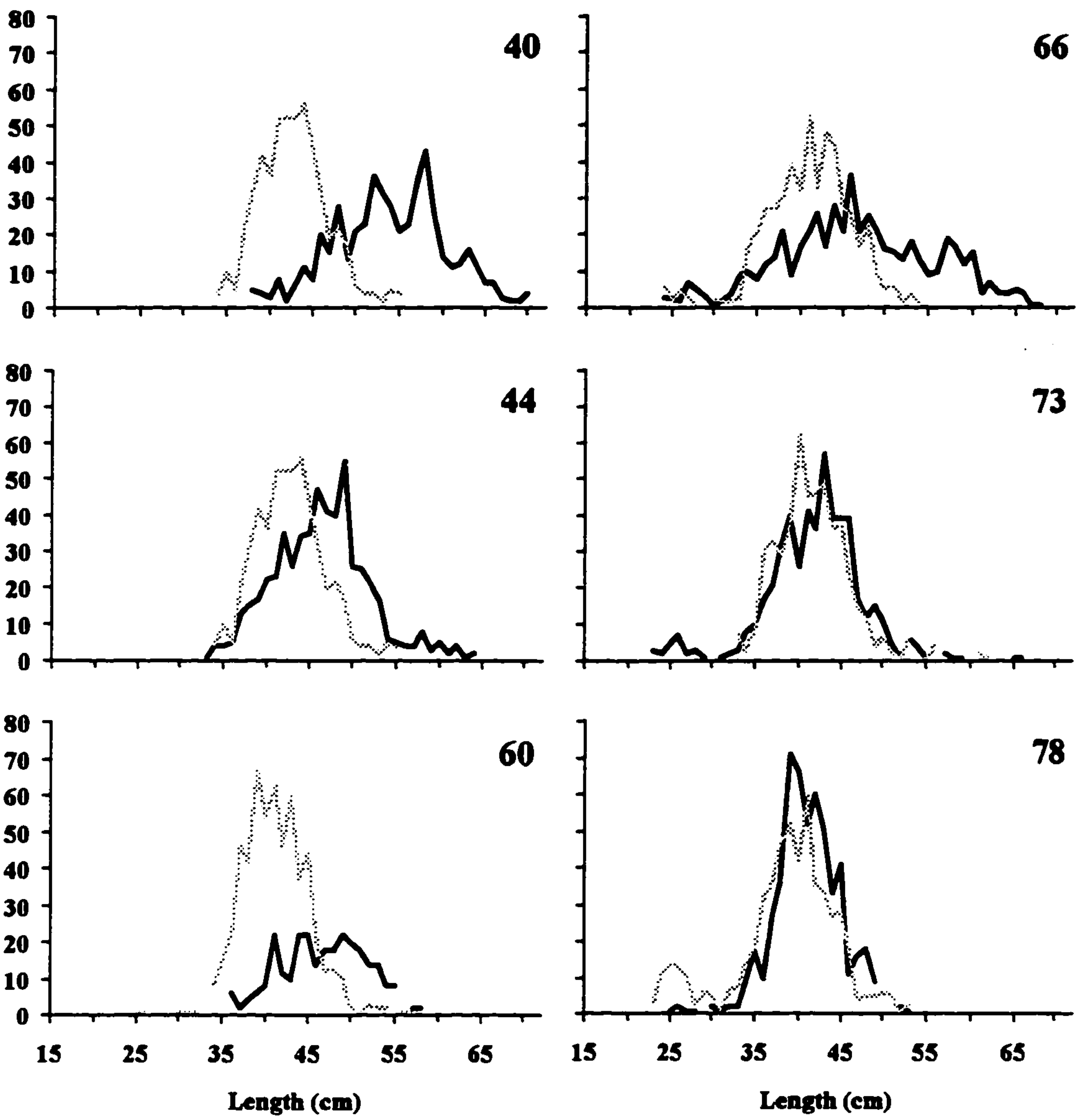

Figure 6.2 (Continued)

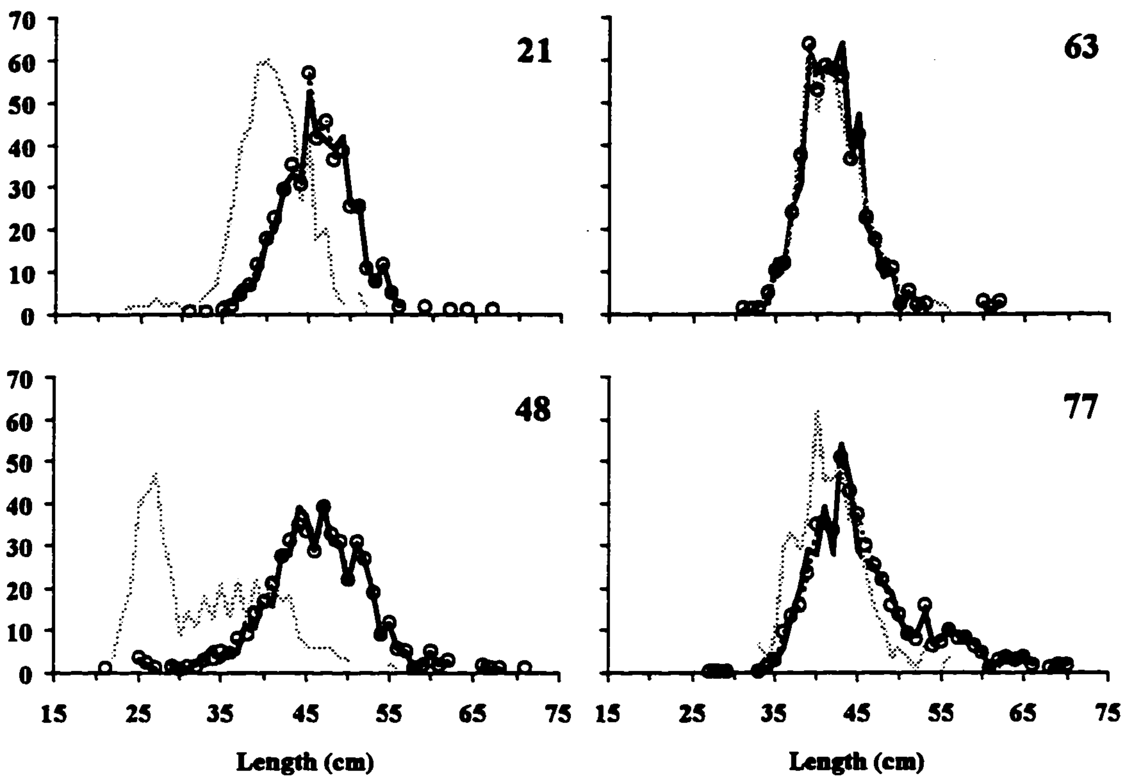

Figure 6.3: Length frequency distributions for pairs of hauls that produced acceptable fits ($P \geq 0.05$) but whose selectivity parameter estimates are questionable. Distributions for standard mesh codends are indicated by grey lines, and those for experimental codends by black lines. Predicted distributions for experimental codends are marked by open circles and dash lines. Numbers at the corner indicate haul numbers.

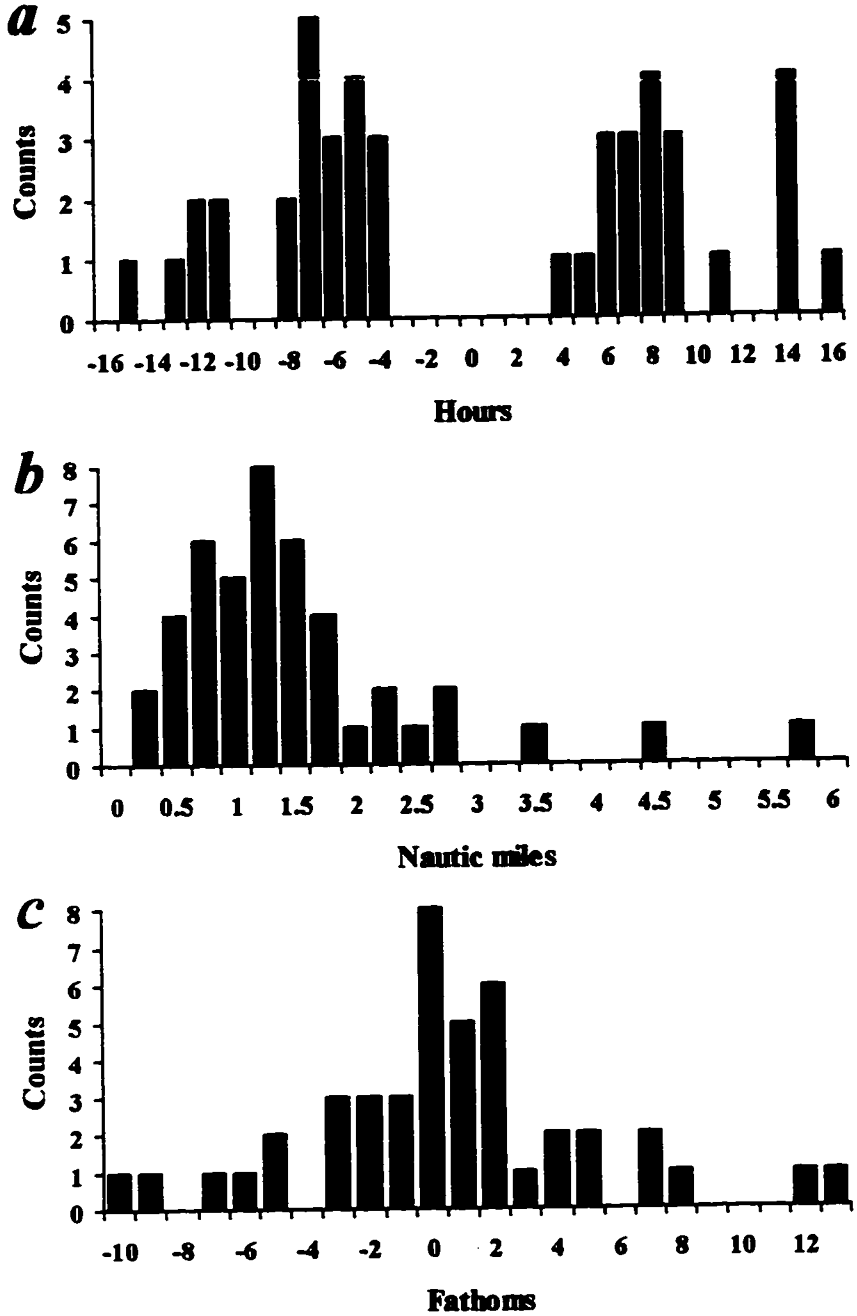

Figure 6.4: Difference between (*a*) tow starting times, (*b*) locations and (*c*) depth of the footrope of "field-assigned" pairs of hauls performed with the standard and experimental mesh codends. Negative values indicate that the standard mesh codend was either towed after the experimental codend or at greater depths.

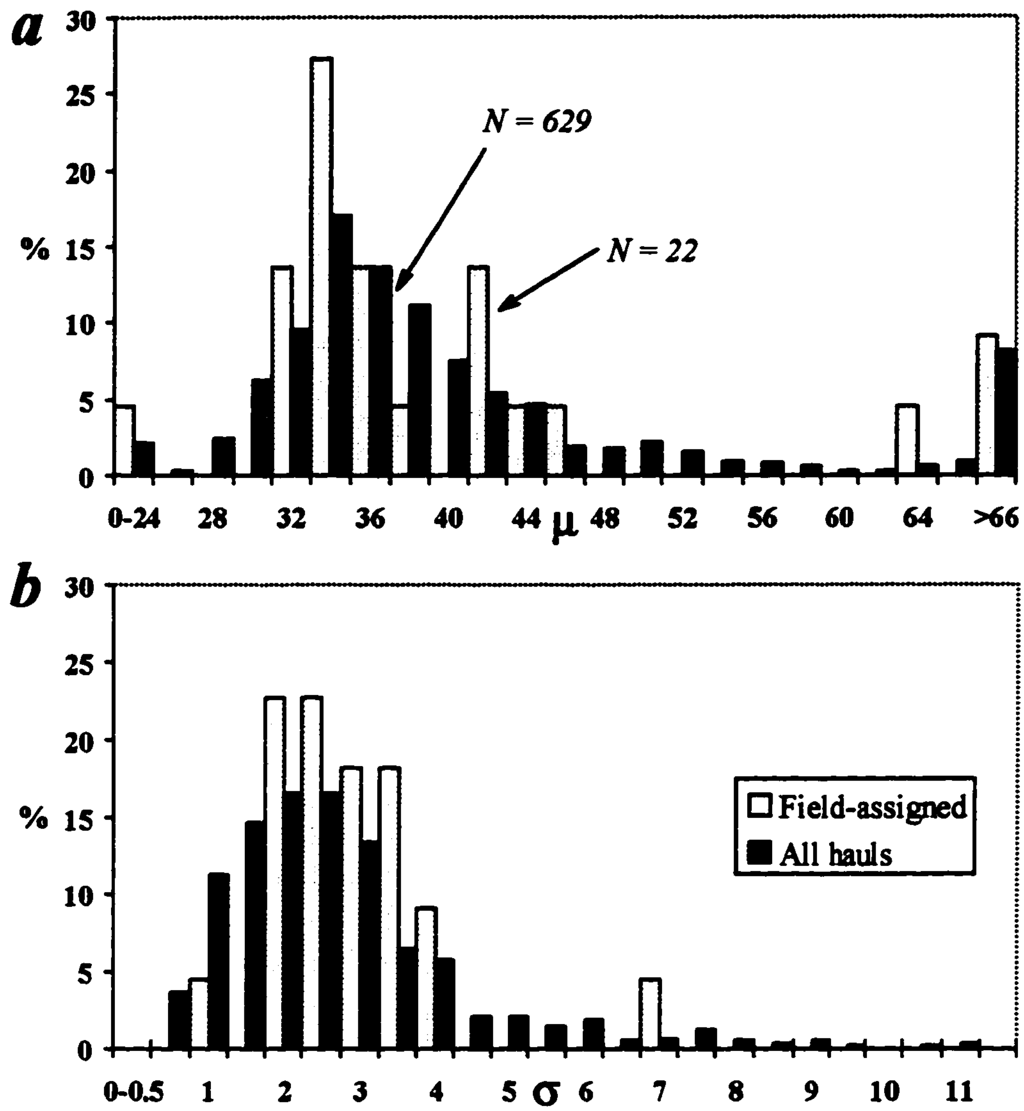

Figure 6.5: Distribution of $\hat{\mu}$'s (*a*) and $\hat{\sigma}$'s (*b*) obtained by fitting the multinomial model to field-assigned and to all possible pairs of length samples from standard and experimental hauls.

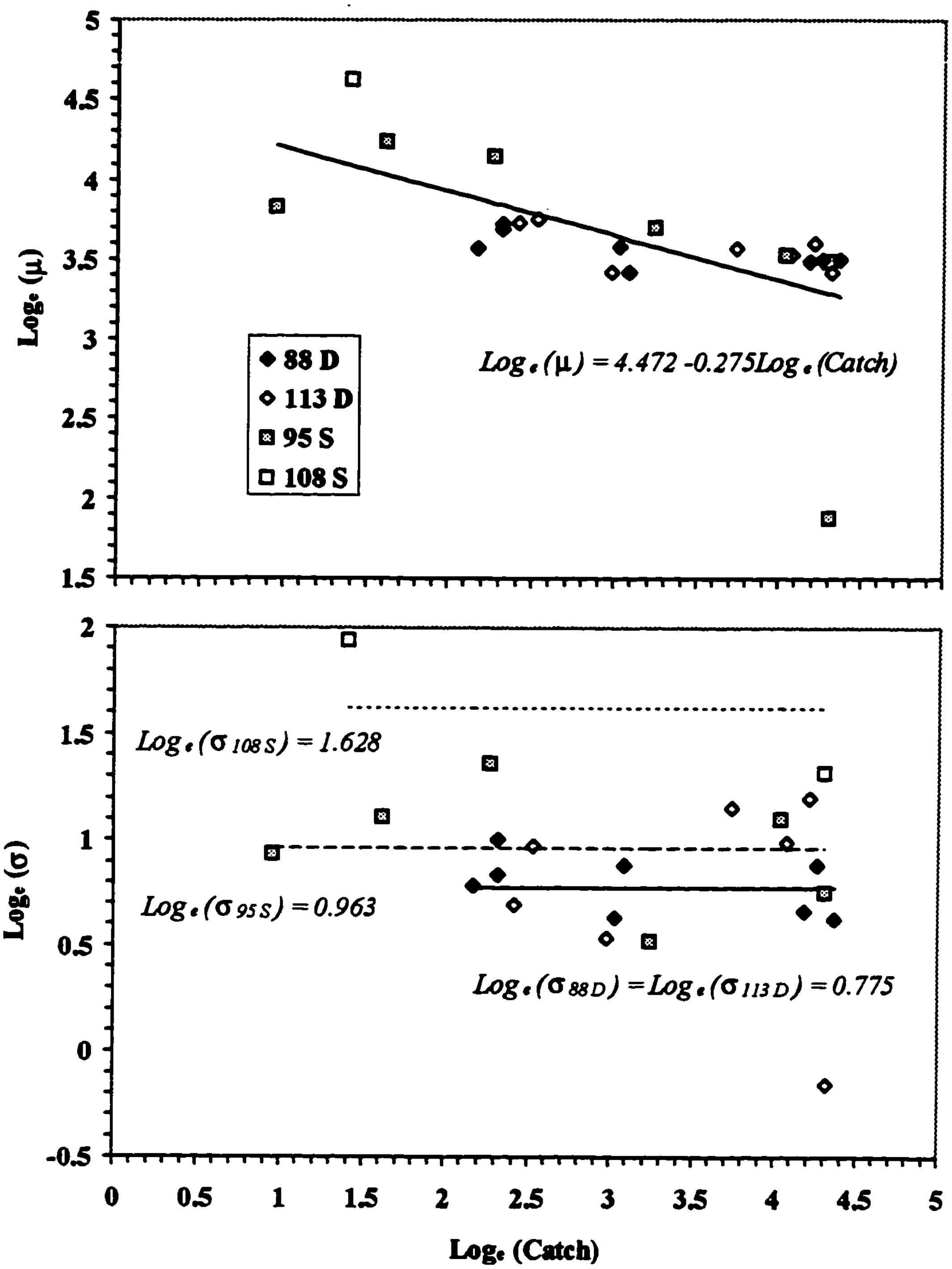

Figure 6.6: Regression lines and scatter plots for the relationships between logarithm of selectivity parameter estimates and logarithm of the catch. Selectivity parameter estimates were obtained with "field-assigned" pairs of hauls (Table 6.1).

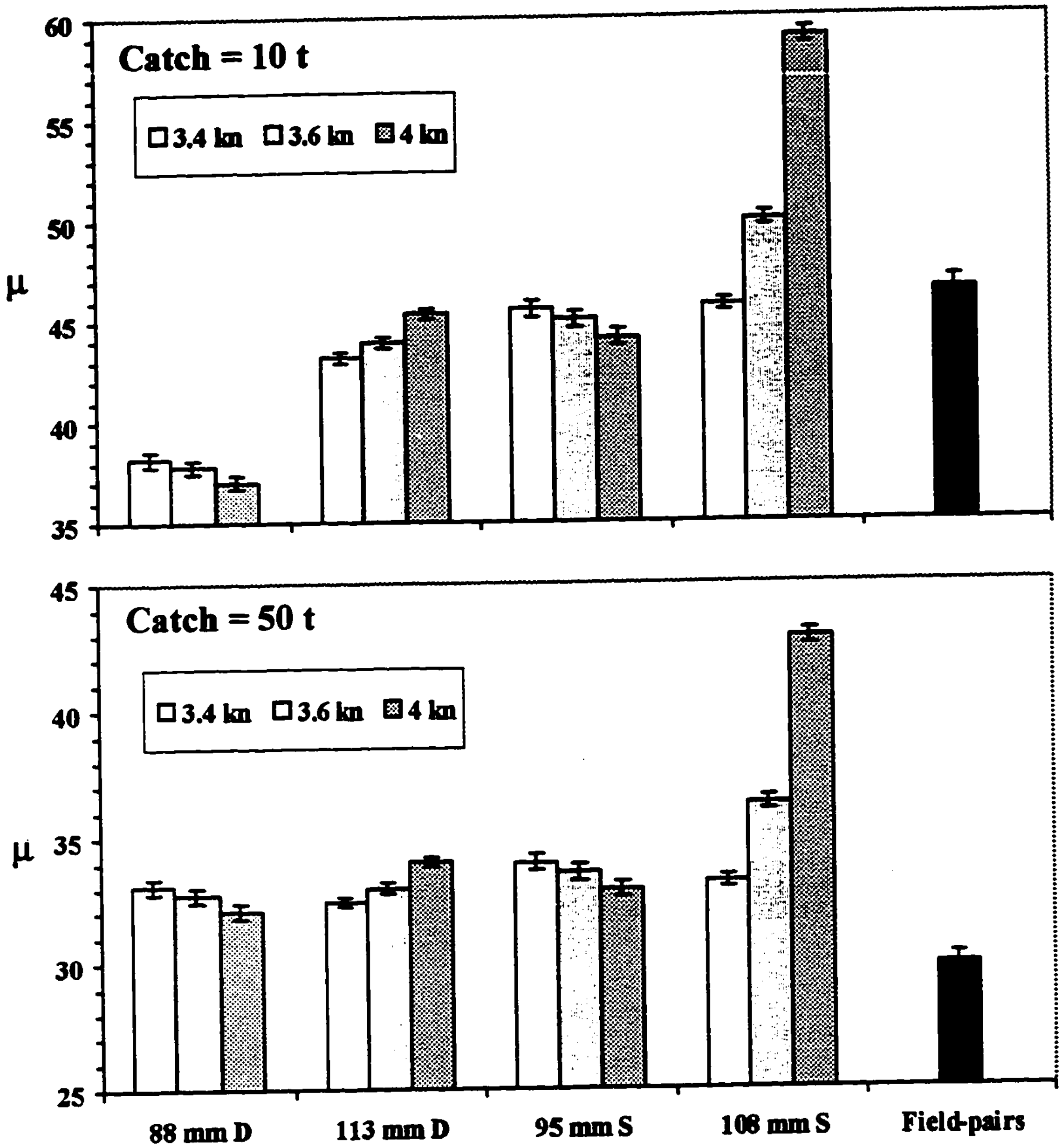

Figure 6.7: Predicted μ's and 95% confidence bounds for catches of 10 and 50 t and towing speeds of 3.4, 3.6 and 4 kn using the unweighted regression on the μ estimates from the "all-haul-pairs" approach, as they compared to those from the regression on μ estimates from "field-assigned" pairs of hauls.

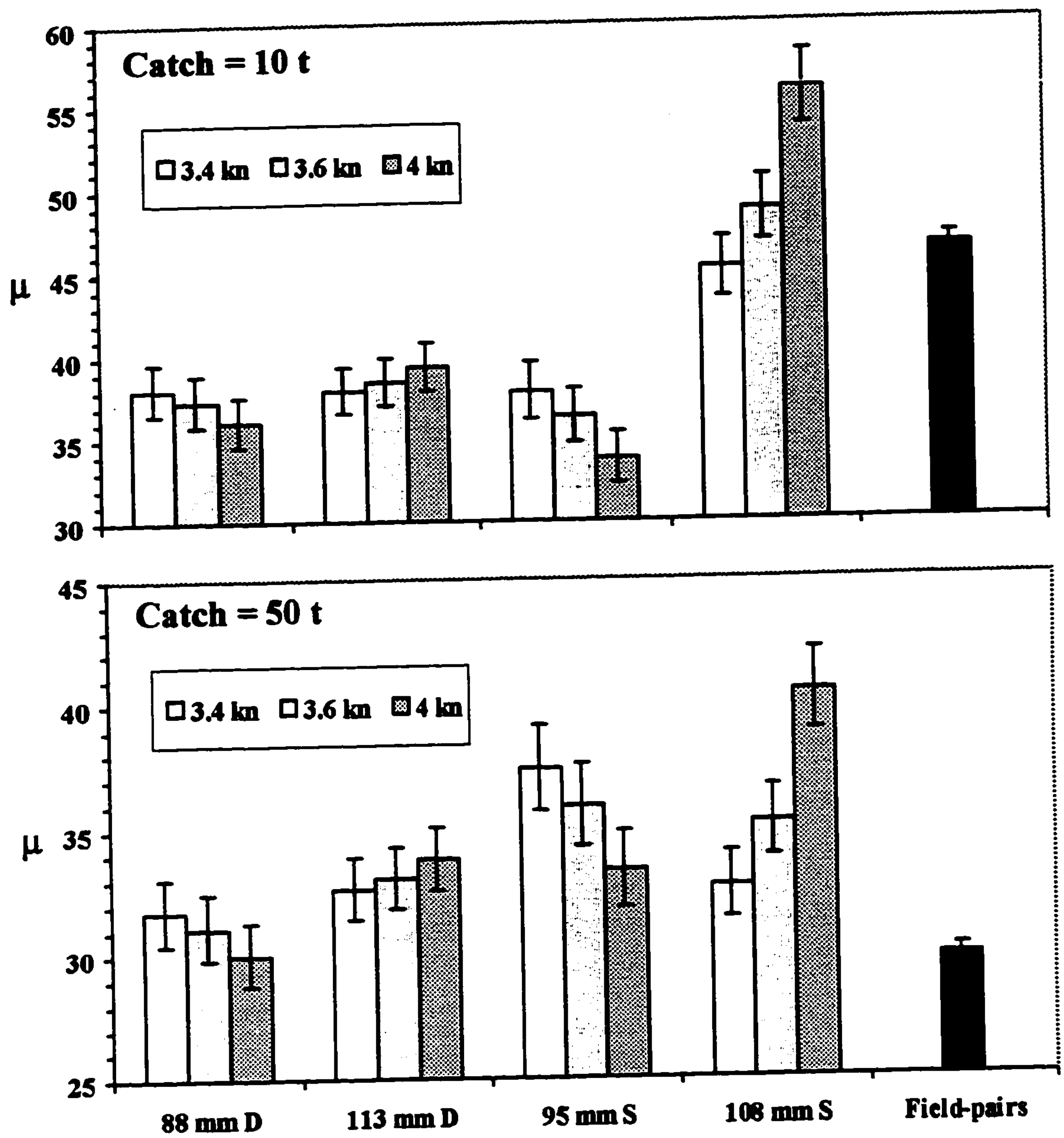

Figure 6.8: Predicted μ's and 95% confidence bounds for catches of 10 and 50 t and towing speeds of 3.4, 3.6 and 4 kn using the weighted regression on the μ estimates from the "all-haul-pairs" approach, as they compared to those from the regression on μ estimates from "field-assigned" pairs of hauls.

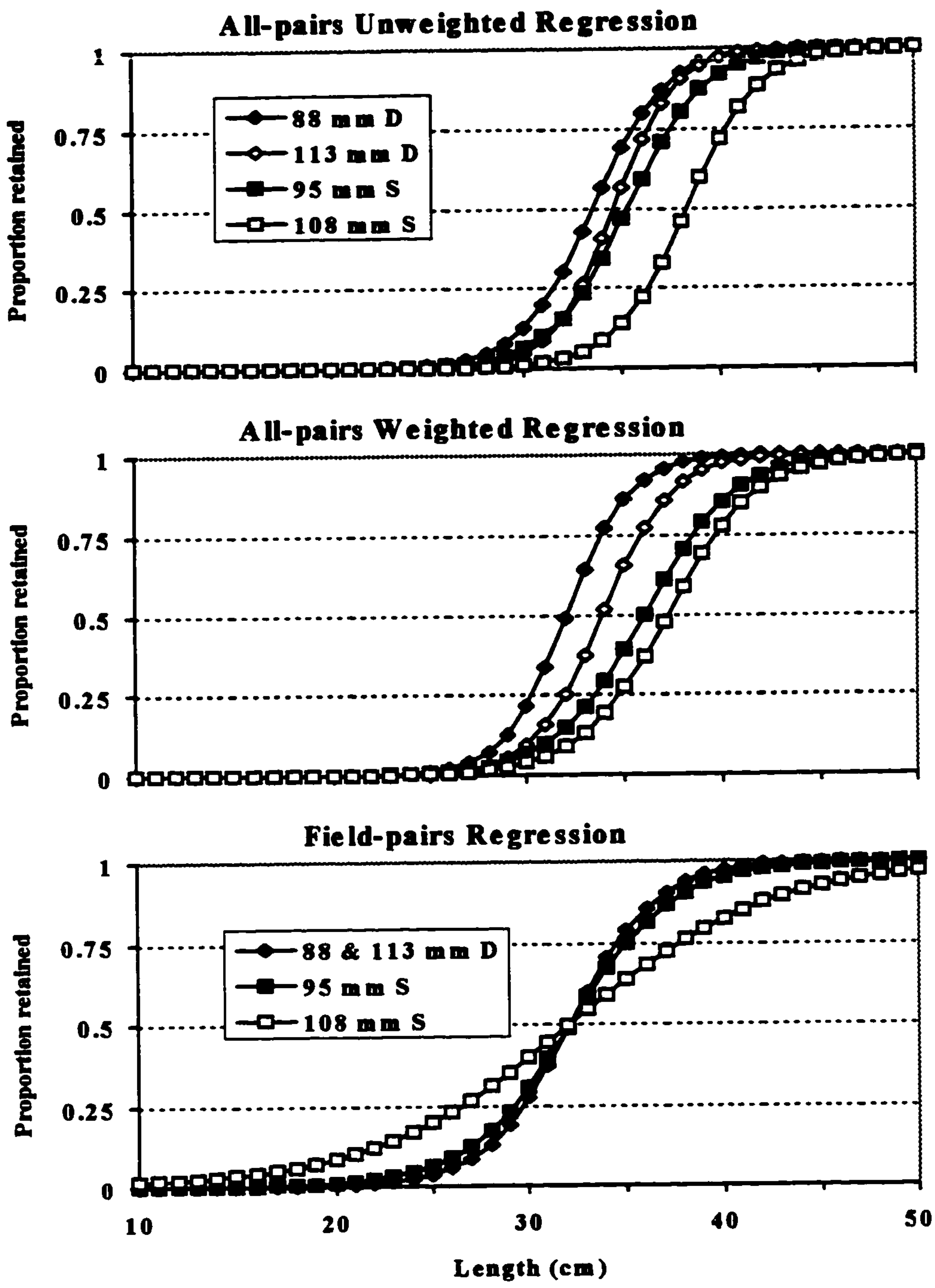

Figure 6.9: Selectivity curves for a catch of 38.34 t and a towing speed of 3.6 kn using the "all-haul-pairs" unweighted and weighted regressions, and the "field-pairs" regressions on μ and σ estimates.

7. Concluding remarks

Along the previous six chapters, I have presented alternative estimation procedures (Chapters 3, 4 and 5), obtained and compared selectivity estimates for rockfish, flatfish and pollock for various types of codends (Chapter 2 and 6), and assessed the shape of the selection curve (Chapter 2) and the effects of catch size and towing speed on mesh size selection (Chapter 6). All the data used in this study were gathered in selectivity experiments carried out under commercial fishing conditions.

Selectivity studies under commercial fishing conditions pose many problems to the design of the experiments, the estimation procedure and the final interpretation of results. In these experiments no direct measure of the length composition of fish escaping the meshes of the codend exist. All estimates are based on the comparison of the catches by the experimental codend to those by a codend with smaller mesh size. This codend is assumed to be non-selective within the selection range of the experimental codend. Thus, its catch length composition is assume to represent the length structure of the fish population targeted by the experimental gear. These basic assumptions imply that all resulting estimates will not be pure measures of size selectivity. Availability will affect the data, and thus be confounded in all resulting selectivity estimates (Chapter 1). Moreover, in some cases the differences in availability between the tows under comparison may be so large that it may preclude any estimation of selectivity (Chapter 6). It has been my main concern in the present study to point out to possible departures from the basic alternate-haul assumptions, to discuss their implication and to propose ways to circumvent them.

A new maximum likelihood estimation method, based upon the product of two multinomial distributions, was developed. The method, that estimates the parameters of selectivity curves for alternate-haul experiments, was presented and contrasted with earlier procedures (Pope et al., 1975; Simpson, 1989) in Chapter 3. Its use was vastly illustrated in the analyses of Chapter 6. Its basic formulae were modified in Chapter 5 to introduce a function describing the length distribution of the fish at the experimental site, and thus allow for the simultaneous estimation of selectivity parameters for both the experimental and the standard (small mesh) nets. The multinomial maximum likelihood estimation method presents many advantages over earlier procedures, many of which are shared with the SELECT method (Millar, 1992). The use of proportions instead of ratios, in a strict statistical formulation, appears prominently among these advantages. Moreover, both the multinomial and the SELECT methods avoid data manipulation and discard, what in turn reduces the possibility of bias in the estimation process. The modification of the multinomial maximum likelihood estimation method presented in Chapter 5, adds up the further advantage of obtaining selectivity estimates for the standard meshes, normally assumed to be non-selective. This advantage, however, is somewhat clouded by the need for a prior knowledge of the functional form of the length distribution of the fish at the experimental site as well as of the range of possible values for the population parameters.

The shape of the selectivity curve was intensively studied in Chapter 2. Traditionally, mesh selection has been described by smooth sigmoidal curves with an asymptote equal to 1. In most selectivity analyses, data are simply fitted to symmetric, generally logistic, curves. The extensive analyses performed in Chapter 2, suggest that other curves, in particular asymmetric ones, such as the negative extreme value, may often describe data better than logistic curves. A best fit to a negative extreme value indicates that more smaller fish are retained in the net. Thus, when the difference between the fits to symmetric and negative extreme value curves is large, stock assessments based on logistic selectivity curves may lead to underestimating the catch of small fish, and overestimating the population allowed to reproduce as well as the long-term yields of the fishery. Therefore, researchers should make the fit to asymmetric selectivity curves a matter of analysis protocol.

Fitting smooth sigmoidal selection curves is not always possible. Sometimes data are consistently uncooperative, and curves that are functions of two or three parameters do not provide good fits. If the researcher considers that the data are the correct representation of reality, that is that no basic assumption was violated during the experiments, he or she may attempt the fit of non-parametric selection curves. In Chapter 4, I developed two estimation procedures that can be used in these situations. One is the non-parametric multinomial maximum likelihood equivalent to the method presented in Chapter 3. The other, is an isotonic regression applied to the SELECT method (Millar, 1992), that was used in Chapter 2. The methods differ in the conditions imposed to the non-parametric selection curve. The first method only imposed the restriction that retention-at-length take values between 0 and 1. The second method is more restrictive, and asks for a non-decreasing selectivity curve.

Selectivity curves for various flatfish and rockfish, and for pollock were estimated for a series of codend types with different mesh sizes, mesh shapes and layers of netting (Chapters 2 and 6). The comparison of these estimates showed some expected patterns. For example, selectivity was shown to increased with mesh size for all species and codend types. Square mesh codends appeared to retain more small fish than diamond mesh codends for the five flatfish species analyzed (Chapter 2). As expected, they also showed to retain less small fish than diamond mesh codends for the one roundfish species investigated, pollock, (Chapter 6). Similarly, catch size was shown to reduce selectivity in the pollock fishery, as it was suspected from earlier studies on other species (Chapter 6, Table 1.2). An unexpected result was the retention of more small rockfish in hauls performed with square meshes (Chapter 2). Rockfish may be considered roundfish in terms of their cross section. Thus it was expected that square mesh codends would retain less small fish than diamond mesh codends. However, the presence of spines, as well as their more rigid and deeper bodies make them different from typical roundfish (haddock, whiting, pollock), and these differences may explain the results.

Generally, the analysis of selectivity experiments involves the study of multiple hauls data. There are two ways of studying these data. First, catch data can be combined over all hauls to obtain pooled length frequency distributions that are used in the estimation of what can be viewed as a mean selection curve for particular fishing grounds. This approach can be used to appraise "controlled" changes in the net, such as a change in codend characteristics or an increase in mesh size. Moreover, it is the only possible approach when sample sizes by haul are poor (Chapter 2).

The second approach, termed multiple-haul analysis, does not pool data. Instead, it attempts the estimation of selectivity parameters for each experimental haul. This approach, that was illustrated in Chapter 6, is particularly desirable when sample sizes are large, and there is an interest in assessing between-haul variability as well as the effects of particular factors such as gear design, catch size, towing duration or towing speed.

In alternate-haul experiments, both approaches may present serious problems to estimation as well as to the interpretation of results, because differences in availabilty among hauls will affect the data. For example, for the pooled approach, different availability between hauls performed with the experimental codends and hauls performed with the standard, or small mesh, codends may produce totally artificial length distributions. Some of these distributions may not even be adequate for selectivity estimation, no matter what estimation method be used. In other cases the differences in availability may be compensated by between-haul differences in catch size, tow duration or other uncontrolled factor, and selectivity estimates may be obtained. However, the standard errors of the estimates are likely to be large, and the interpretation of the resulting curves less than convincing. On the other hand, multiple-haul analysis may not necessarily be better than pooling. Although, it may allow the assessment of between-haul variability and of effects due to gear design, catch size, towing duration or towing speed Differences in availability will also create problems, often precluding estimation for a large portion of the data (Chapter 6).

It is questionable whether the randomized block design used in the selectivity experiments described in Chapters 2 and 6 is appropriate for alternate-haul experiments performed under commercial fishing conditions, because the difference in availability between the hauls within a block may be too large, and even preclude any estimation of selectivity for many blocks (Chapter 6). Although the total randomization (all hauls) approach proposed in Chapter 6 may be an adequate way to circumvent this problem, better experimental designs may also alleviate the problem. For example, the number of experimental codends and participant vessels should be reduced in order to increase the number of hauls that each vessel can perform with the standard and experimental nets at a given site, in a given field season. In this way, a better assessment of the between-haul and within-block variability could be achieved. Moreover, a reduced list of target species per field season may allow the increase of the length-sample sizes to 400 to 500 fish. This in turn, may result in more precise estimates

The problem of availability confounding the selectivity estimates cannot be avoided in any traditional alternate-haul experimental design. On the other hand, the often more precise covered-codend method has to be excluded as an option for experiments aiming to the measure of selectivity under commercial fishing conditions. However, new non-traditional experiments including both the covered-codend as well as the alternate-haul methods may be designed. For example, for a given fishing ground a chartered or research vessel may performed a series of very standardized covered-codend hauls, while a series of participant commercial vessels may performed a series of uncovered hauls at the same ground and time. All these vessel will use a similar experimental codend but fish with their own gears, their crews fishing in their own ways. The length samples collected in the covered-codend hauls will help to build priors for the distribution of the selectivity parameters and the length composition of the targeted fish population. Then, through a Bayesian approach, such as the one proposed in Chapter 5 (p. 143), the posterior estimates of the selectivity parameters can be obtained from the alternate-haul data.

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Appendix 1: Parameter estimates and standard errors (*SE*) for Millar's model with 2-parameters selection curves.

Species	Codend	Model	L_{50}	SR	p	$SE (L_{50})$	$SE (SR)$	$SE (p)$
Yellowtail rockfish	4.5"D	Logistic	35.58	2.26	0.19	3.05	3.08	0.04
		Probit	35.58	2.44	0.19	2.79	2.86	0.03
		Gompertz	35.03	2.42	0.19	2.96	3.25	0.04
		N. E. V.	36.04	2.42	0.19	2.61	3.11	0.03
	5.0"D	Logistic	39.85	2.24	0.36	0.77	0.84	0.03
		Probit	39.75	2.40	0.36	0.76	0.79	0.03
		Gompertz	39.34	2.74	0.36	0.94	1.00	0.03
		N. E. V.	40.12	2.18	0.36	0.69	0.85	0.03
	5.5"D	Logistic	45.73	3.96	0.37	1.30	1.39	0.06
		Probit	46.01	4.72	0.38	1.72	1.64	0.07
		Gompertz	48.89	8.91	0.48	4.44	4.14	0.14
		N. E. V.	45.42	3.18	0.34	0.94	1.02	0.04
	4.5"S	Logistic	39.60	7.81	0.46	2.10	4.29	0.05
		Probit	39.36	7.39	0.45	1.90	3.68	0.04
		Gompertz	39.74	8.53	0.47	2.86	5.76	0.07
		N. E. V.	39.48	7.65	0.45	1.75	2.99	0.03
	5.0"S	Logistic	40.33	1.41	0.46	0.49	0.59	0.03
		Probit	40.36	1.61	0.46	0.49	0.58	0.03
		Gompertz	40.27	2.07	0.46	0.56	0.65	0.03
		N. E. V.	40.42	1.31	0.46	0.50	0.60	0.03
Canary rockfish	4.5"D	Logistic	35.44	2.42	0.43	2.01	2.54	0.02
		Probit	35.51	2.62	0.43	1.96	2.59	0.02
		Gompertz	35.03	2.41	0.43	1.86	2.40	0.02
		N. E. V.	35.84	2.72	0.43	2.20	3.53	0.02
	5.0"D	Logistic	39.51	1.80	0.44	2.03	2.59	0.04
		Probit	39.56	1.95	0.44	1.94	2.51	0.04
		Gompertz	39.23	1.85	0.44	1.86	2.63	0.04
		N. E. V.	39.87	2.07	0.44	2.09	2.79	0.04
	5.5"D	Logistic	41.72	2.56	0.44	1.39	2.39	0.02
		Probit	41.71	2.53	0.44	1.32	2.13	0.02
		Gompertz	41.52	2.59	0.44	1.36	2.47	0.02
		N. E. V.	41.92	2.59	0.44	1.32	2.19	0.02
	4.5"S	Logistic	41.46	14.41	0.64	5.53	18.72	0.09
		Probit	41.13	13.72	0.63	5.09	15.69	0.08
		Gompertz	41.71	12.43	0.64	5.45	19.46	0.10
		N. E. V.	40.52	16.06	0.63	5.49	13.93	0.06

Appendix 1 (continued)

Species	Codend	Model	L_{50}	*SR*	*p*	*SE* (L_{50})	*SE* (*SR*)	*SE* (*p*)
Canary rockfish	5.0"S	Logistic	42.76	3.35	0.30	7.94	9.60	0.11
		Probit	42.54	3.34	0.30	7.66	8.51	0.11
		Gompertz	43.45	5.46	0.32	12.55	16.03	0.22
		N. E. V.	42.82	2.74	0.30	5.22	5.29	0.10
Shortspine thornyhead	4.5"D	Logistic	30.11	9.81	0.56	1.90	1.85	0.04
		Probit	30.20	10.57	0.56	2.13	2.03	0.05
		Gompertz	33.53	16.68	0.61	4.00	4.17	0.06
		N. E. V.	29.52	8.09	0.54	1.44	1.33	0.04
	5.0"D	Logistic	39.75	11.33	0.62	5.61	3.19	0.11
		Probit	42.94	14.63	0.66	8.79	4.92	0.14
		Gompertz	57.57	30.73	0.79	23.11	16.17	0.19
		N. E. V.	37.87	8.52	0.58	4.40	2.28	0.10
	5.5"D	Logistic	45.42	12.57	0.56	10.33	4.66	0.21
		Probit	49.57	16.50	0.61	17.50	8.32	0.30
		Gompertz	69.73	36.86	0.80	49.17	31.48	0.38
		N. E. V.	43.60	9.58	0.52	8.19	3.18	0.19
	4.5"S	Logistic	29.26	7.69	0.51	2.46	2.28	0.07
		Probit	29.60	8.69	0.51	2.90	2.59	0.08
		Gompertz	32.76	14.32	0.57	5.21	5.11	0.10
		N. E. V.	28.72	6.25	0.49	1.91	1.68	0.06
	5.0"S	Logistic	36.44	15.17	0.55	8.80	6.39	0.15
		Probit	37.43	17.00	0.56	11.78	8.45	0.18
		Gompertz	49.43	31.93	0.67	31.38	25.77	0.29
		N. E. V.	34.13	11.76	0.51	6.15	4.34	0.12
Pacific Ocean perch	4.5"D	Logistic	39.14	9.17	0.61	6.59	4.39	0.18
		Probit	42.14	11.80	0.68	14.38	8.09	0.31
		Gompertz	57.95	27.21	0.85	46.52	31.38	0.37
		N. E. V.	37.26	6.98	0.55	4.40	3.01	0.14
	5.0"D	Logistic	42.94	6.85	0.69	12.20	5.43	0.47
		Probit	47.60	9.89	0.80	40.06	16.06	0.91
		Gompertz	68.84	27.25	0.96	98.17	55.67	0.33
		N. E. V.	40.84	4.94	0.61	7.32	3.37	0.36
	5.5"D	Logistic	47.81	5.17	0.83	12.67	3.97	0.46
		Probit	75.25	13.50	1.00	14.54	6.12	0.00
		Gompertz	118.63	44.83	1.00	33.93	20.13	0.00
		N. E. V.	45.75	3.66	0.74	7.52	2.45	0.38

Appendix 1 (continued)

Species	Codend	Model	L_{50}	*SR*	*p*	*SE* (L_{50})	*SE (SR)*	*SE (p)*
Pacific Ocean perch	4.5"S	Logistic	33.06	1.23	0.66	1.38	1.84	0.04
		Probit	33.10	1.32	0.66	1.24	1.65	0.04
		Gompertz	32.95	1.35	0.66	1.23	1.78	0.04
		N. E. V.	33.29	1.37	0.66	1.15	1.49	0.04
	5.0"S	Logistic	39.19	1.95	0.49	1.79	1.47	0.17
		Probit	39.47	2.55	0.51	2.23	1.67	0.19
		Gompertz	40.52	4.49	0.57	4.12	3.46	0.25
		N. E. V.	39.15	1.60	0.48	1.63	1.12	0.16
Widow rockfish	4.5"D	Logistic	34.28	1.45	0.42	0.63	0.74	0.02
		Probit	34.29	1.57	0.42	0.62	0.76	0.02
		Gompertz	33.99	1.47	0.42	0.59	0.70	0.02
		N. E. V.	34.48	1.57	0.42	0.67	1.09	0.02
	5.0"D	Logistic	39.54	5.06	0.48	3.47	3.46	0.13
		Probit	39.43	5.38	0.48	3.76	3.58	0.14
		Gompertz	40.42	7.87	0.52	6.55	6.72	0.19
		N. E. V.	39.41	4.25	0.47	2.59	2.56	0.11
	5.5"D	Logistic	46.52	6.74	0.76	4.64	2.93	0.13
		Probit	49.10	8.88	0.81	10.53	5.71	0.22
		Gompertz	62.77	21.61	0.93	35.25	23.08	0.18
		N. E. V.	44.97	5.01	0.71	3.04	1.98	0.11
	4.5"S	Logistic	33.06	1.83	0.46	0.77	1.01	0.02
		Probit	33.03	2.00	0.46	0.78	0.99	0.02
		Gompertz	32.70	2.17	0.46	0.89	1.00	0.02
		N. E. V.	33.25	1.99	0.46	0.77	1.24	0.02
	5.0"S	Logistic	42.41	2.27	0.74	2.61	2.02	0.18
		Probit	42.58	2.81	0.74	3.14	2.33	0.19
		Gompertz	43.62	4.83	0.78	5.67	4.89	0.23
		N. E. V.	42.27	1.79	0.73	2.28	1.61	0.17
Petrale sole	4.5"D	Logistic	28.36	6.66	0.70	7.83	8.00	0.20
		Probit	28.23	6.67	0.70	7.11	7.28	0.19
		Gompertz	28.62	8.18	0.71	10.95	12.85	0.25
		N. E. V.	28.74	6.48	0.70	6.20	5.74	0.17
	5.0"D	Logistic	29.90	3.67	0.50	2.24	5.30	0.08
		Probit	29.85	3.58	0.49	2.18	5.05	0.08
		Gompertz	29.88	3.98	0.50	2.58	5.92	0.10
		N. E. V.	29.93	3.52	0.49	2.01	4.04	0.07

Appendix 1 (continued)

Species	Codend	Model	L_{50}	SR	p	$SE\ (L_{50})$	$SE\ (SR)$	$SE\ (p)$
English sole	4.5"D	Logistic	29.50	5.25	0.47	2.45	2.66	0.09
		Probit	29.54	5.50	0.47	2.44	2.54	0.09
		Gompertz	30.24	7.37	0.51	3.81	4.28	0.12
		N. E. V.	29.65	5.02	0.46	2.02	2.12	0.07
	5.0"D	Logistic	33.10	4.67	0.41	8.33	10.18	0.39
		Probit	32.86	4.66	0.40	8.57	10.25	0.39
		Gompertz	34.11	7.07	0.45	19.63	23.93	0.69
		N. E. V.	32.77	3.85	0.39	5.56	6.85	0.30
	5.5"D	Logistic	34.72	5.73	0.43	8.34	4.97	0.32
		Probit	35.37	6.79	0.45	10.78	6.51	0.39
		Gompertz	39.64	12.47	0.56	24.09	18.10	0.64
		N. E. V.	34.52	4.69	0.41	6.40	3.41	0.27
	4.5"S	Logistic	24.68	2.55	0.45	0.93	1.03	0.05
		Probit	24.73	2.89	0.45	0.96	1.02	0.05
		Gompertz	24.93	4.08	0.46	1.30	1.47	0.05
		N. E. V.	24.78	2.25	0.45	0.86	0.91	0.05
	5.0"S	Logistic	31.21	0.92	0.45	5.44	4.77	0.47
		Probit	31.41	1.17	0.46	5.69	5.01	0.49
		Gompertz	31.31	1.37	0.46	5.16	5.39	0.49
		N. E. V.	31.01	0.60	0.43	2.43	1.86	0.40
Dover sole	4.5"D	Logistic	33.77	3.96	0.55	1.01	1.22	0.04
		Probit	33.89	4.29	0.55	1.07	1.23	0.05
		Gompertz	34.49	5.88	0.58	1.51	1.80	0.06
		N. E. V.	33.71	3.53	0.54	0.94	1.15	0.04
	5.0"D	Logistic	38.41	3.92	0.53	1.24	0.96	0.06
		Probit	38.91	4.77	0.55	1.65	1.23	0.07
		Gompertz	41.80	8.83	0.64	3.45	2.90	0.11
		N. E. V.	38.07	3.07	0.51	0.94	0.68	0.05
	5.5"D	Logistic	41.54	3.52	0.58	1.36	0.72	0.08
		Probit	42.93	4.94	0.63	2.17	1.12	0.11
		Gompertz	48.14	10.70	0.78	5.17	3.44	0.13
		N. E. V.	41.13	2.68	0.56	1.19	0.53	0.08
	4.5"S	Logistic	31.84	6.78	0.44	4.38	5.49	0.14
		Probit	31.82	6.81	0.44	4.48	5.44	0.15
		Gompertz	32.49	8.41	0.47	6.38	8.36	0.18
		N. E. V.	31.56	6.29	0.42	4.00	5.01	0.14

Appendix 1 (continued)

Species	Codend	Model	L_{50}	*SR*	*p*	*SE* (L_{50})	*SE (SR)*	*SE (p)*
Dover sole	5.0"S	Logistic	36.54	3.28	0.50	0.90	0.70	0.05
		Probit	36.88	3.93	0.51	1.03	0.79	0.06
		Gompertz	38.43	6.63	0.57	1.81	1.61	0.07
		N. E. V.	36.42	2.68	0.49	0.83	0.57	0.05
Arrowtooth flounder	4.5"D	Logistic	37.07	5.14	0.60	0.64	0.57	0.02
		Probit	37.09	5.62	0.60	0.64	0.57	0.02
		Gompertz	37.11	7.37	0.61	0.79	0.82	0.02
		N. E. V.	37.40	4.53	0.60	0.59	0.49	0.02
	5.0"D	Logistic	41.05	5.25	0.49	0.83	0.58	0.02
		Probit	41.00	5.97	0.49	0.97	0.70	0.02
		Gompertz	41.26	8.38	0.50	1.20	1.07	0.03
		N. E. V.	41.24	4.35	0.49	0.72	0.45	0.02
	5.5"D	Logistic	41.93	4.80	0.61	1.28	1.13	0.02
		Probit	42.31	5.60	0.61	1.35	1.21	0.02
		Gompertz	42.55	7.54	0.62	1.49	1.57	0.02
		N. E. V.	41.53	3.65	0.60	1.30	0.99	0.02
	4.5"S	Logistic	30.83	3.25	0.58	0.82	1.04	0.02
		Probit	30.74	3.43	0.58	0.82	0.99	0.02
		Gompertz	30.62	4.31	0.59	1.03	1.39	0.02
		N. E. V.	31.02	2.94	0.58	0.75	0.98	0.02
	5.0"S	Logistic	35.42	1.58	0.62	3.05	2.93	0.05
		Probit	35.42	1.67	0.62	1.96	1.85	0.04
		Gompertz	36.34	3.25	0.63	2.24	2.70	0.05
		N. E. V.	35.63	1.46	0.62	1.20	1.00	0.04
Rex sole	4.5"D	Logistic	36.63	5.73	0.73	1.71	0.50	0.08
		Probit	46.73	10.23	0.94	7.76	2.21	0.08
		Gompertz	91.77	39.17	1.00	3.59	2.28	0.001
		N. E. V.	34.76	4.16	0.64	1.16	0.31	0.07
	4.5"S	Logistic	30.45	4.76	0.61	1.08	0.77	0.06
		Probit	31.26	5.71	0.64	1.74	1.13	0.08
		Gompertz	37.02	12.00	0.79	5.30	3.94	0.11
		N. E. V.	29.58	3.64	0.56	0.74	0.53	0.04
	5.0"S	Logistic	36.79	5.20	0.61	4.26	1.47	0.26
		Probit	43.06	8.44	0.83	18.21	5.95	0.51
		Gompertz	69.08	27.22	0.99	14.71	8.17	0.02
		N. E. V.	35.17	3.77	0.52	2.89	0.94	0.21

Appendix 2.1: Components of the $(\mathrm{K}+1)\times(\mathrm{K}+1)$ Fisher information matrix

$$\frac{\partial^2 \ell}{\partial p_i^2} = -\frac{n_i}{p_i^2} + r_i^2 \times \frac{\mathrm{N}_t}{\left(\sum_{i=1}^{\mathrm{K}} p_i \times r_i\right)^2} \quad \text{for } i = 1,\ldots,\mathrm{K}\text{-}1$$

$$\frac{\partial^2 \ell}{\partial p_i \partial p_j} = \frac{\partial^2 \ell}{\partial p_j \partial p_i} = r_i \times r_j \times \frac{\mathrm{N}_t}{\left(\sum_{i=1}^{\mathrm{K}} p_i \times r_i\right)^2} \quad \text{for } i \neq j \text{ and } i, j = 1,\ldots,\mathrm{K}\text{-}1$$

$$\frac{\partial^2 \ell}{\partial \mu \partial p_i} = \frac{\partial^2 \ell}{\partial p_i \partial \mu} = -\mathrm{N}_t \times \left(-\frac{r_i \times \left(\sum_{i=1}^{\mathrm{K}} p_i \times r_i^{'}\right)}{\left(\sum_{i=1}^{\mathrm{K}} p_i \times r_i\right)^2} + \frac{r_i^{'}}{\sum_{i=1}^{\mathrm{K}} p_i \times r_i} \right)$$

$$\frac{\partial^2 \ell}{\partial \sigma \partial p_i} = \frac{\partial^2 \ell}{\partial p_i \partial \sigma} = -\mathrm{N}_t \times \left(-\frac{r_i \times \left(\sum_{i=1}^{\mathrm{K}} p_i \times h_i^{'}\right)}{\left(\sum_{i=1}^{\mathrm{K}} p_i \times r_i\right)^2} + \frac{h_i^{'}}{\sum_{i=1}^{\mathrm{K}} p_i \times r_i} \right)$$

$$\frac{\partial^2 \ell}{\partial \mu^2} = -\mathrm{N}_t \times \left(-\frac{\left(\sum_{i=1}^{\mathrm{K}} p_i \times r_i^{'}\right)^2}{\left(\sum_{i=1}^{\mathrm{K}} p_i \times r_i\right)^2} + \frac{\sum_{i=1}^{\mathrm{K}} p_i \times r_i^{''}}{\sum_{i=1}^{\mathrm{K}} p_i \times r_i} \right) + \sum_{i=1}^{\mathrm{K}} \left(-\frac{\left(r_i^{'}\right)^2}{r_i^2} + \frac{r_i^{''}}{r_i} \right) \times x_{ti}$$

$$\frac{\partial^2 \ell}{\partial\mu\partial\sigma} = \frac{\partial^2 \ell}{\partial\sigma\partial\mu} = -\mathrm{N}_t \times \left(-\frac{\left(\sum_{i=1}^{K} p_i \times r_i^{'}\right) \times \left(\sum_{i=1}^{K} p_i \times h_i^{'}\right)}{\left(\sum_{i=1}^{K} p_i \times r_i\right)^2} + \frac{\sum_{i=1}^{K} p_i \times r_i^{'''}}{\sum_{i=1}^{K} p_i \times r_i} \right) + \sum_{i=1}^{K} \left(-\frac{h_i^{'} \times r_i^{'}}{r_i^2} + \frac{r_i^{'''}}{r_i} \right) \times x_{ti}$$

$$\frac{\partial^2 \ell}{\partial\sigma^2} = -\mathrm{N}_t \times \left(-\frac{\left(\sum_{i=1}^{K} p_i \times h_i^{'}\right)^2}{\left(\sum_{i=1}^{K} p_i \times r_i\right)^2} + \frac{\sum_{i=1}^{K} p_i \times h_i^{''}}{\sum_{i=1}^{K} p_i \times r_i} \right) + \sum_{i=1}^{K} \left(-\frac{\left(h_i^{'}\right)^2}{r_i^2} + \frac{h_i^{''}}{r_i} \right) \times x_{ti}$$

Symbols r_i, $r_i^{'}$, $r_i^{''}$, $r_i^{'''}$, $h_i^{'}$ and $h_i^{''}$ used in previous equations represent the logistic function and its derivatives with respect to parameters μ and σ:

$$r_i = \frac{1}{1 + \exp\left(-(l_i - \mu)/\sigma\right)}$$ where l_i is the i^{th} length class

$$r_i^{'} = \frac{\partial r_i}{\partial\mu} = -r_i^2 \times \exp\left(-(l_i - \mu)/\sigma\right) \times \frac{1}{\sigma}$$

$$r_i^{''} = \frac{\partial^2 r_i}{\partial\mu^2} = r_i^{'} \times \left(1 - 2 \times r_i \times \exp\left(-(l_i - \mu)/\sigma\right)\right) \times \frac{1}{\sigma}$$

$$r_i^{'''} = \frac{\partial^2 r_i}{\partial\sigma\partial\mu} = \frac{\partial^2 r_i}{\partial\mu\partial\sigma} = \frac{1}{\sigma} \times \left(h_i^{'} \times \left(1 - 2 \times r_i \times \exp\left(-(l_i - \mu)/\sigma\right)\right) - r_i^{'} \right)$$

$$h_i^{'} = \frac{\partial r_i}{\partial\sigma} = -r_i^2 \times \exp\left(-(l_i - \mu)/\sigma\right) \times \frac{(l_i - \mu)}{\sigma^2}$$

$$h_i'' = \frac{\partial^2 r_i}{\partial \sigma^2} = \left(\left(1 - 2 \times r_i \times \exp\left({-(l_i - \mu)}\big/{\sigma} \right) \right) \times h_i' - 2 \times r_i' \right) \times \frac{(l_i - \mu)}{\sigma^2}$$

Appendix 2.2: Estimation of standard errors for $L_{r\%}$

For an arbitrary $r \times 100\%$ retention with $0 < r < 1$, the estimate of length at retention $l_{r\times 100}$ is given by:

$$l_{r\times 100} = \mu - \ln\left(\frac{1-r}{r}\right) \times \sigma$$

The variance of $l_{r\times 100}$ is then:

$$\mathrm{Var}(l_{r\times 100}) = \mathrm{Var}(\mu) + \left(\ln\left(\frac{1-r}{r}\right)\right)^2 \times \mathrm{Var}(\sigma) - 2 \times \ln\left(\frac{1-r}{r}\right) \times \mathrm{Covar}(\mu, \sigma)$$

where the terms $\mathrm{Var}(\mu)$, $\mathrm{Var}(\sigma)$ and $\mathrm{Covar}(\mu, \sigma)$ are elements in the inverse of the $(\mathrm{K}+1) \times (\mathrm{K}+1)$ Fisher information matrix derived in Appendix 2.1. Standard errors are finally obtained by taking square roots.

Appendix 3: Multinomial model fits for the all-pairs approach

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
10	8	88 mm D	32.807	0.871	20	17.184	0.641
10	9	88 mm D	30.392	0.448	21	32.669	0.050
10	13	88 mm D	37.375	3.010	16	17.323	0.365
10	14	88 mm D	35.891	1.885	16	16.370	0.427
10	15	88 mm D	35.637	1.735	21	23.157	0.336
10	29	88 mm D	16.932	1.972	21	17.685	0.669
10	36	88 mm D	30.720	1.129	21	15.627	0.790
10	37	88 mm D	31.525	1.148	21	18.313	0.629
10	38	88 mm D	37.994	2.366	20	22.103	0.335
10	43	88 mm D	37.662	1.861	21	31.332	0.068
10	46	88 mm D	34.102	0.854	21	25.752	0.216
10	52	88 mm D	33.573	0.672	17	19.290	0.312
10	54	88 mm D	33.508	0.815	21	32.123	0.057
10	57	88 mm D	35.515	2.181	17	20.527	0.248
10	59	88 mm D	33.874	3.144	21	12.560	0.923
10	61	88 mm D	32.840	1.090	21	10.491	0.972
10	62	88 mm D	31.284	0.599	21	24.437	0.272
10	64	88 mm D	35.725	2.933	21	15.619	0.791
10	69	88 mm D	33.737	1.964	20	25.126	0.197
10	71	88 mm D	32.893	0.640	18	25.465	0.113
10	74	88 mm D	33.060	0.967	21	14.991	0.823
10	76	88 mm D	34.097	1.054	21	29.326	0.106
10	79	88 mm D	35.850	2.045	19	24.301	0.185
10	84	88 mm D	34.290	1.513	21	17.601	0.674
11	4	113 mm D	35.604	2.122	24	33.956	0.085
11	13	113 mm D	33.150	4.429	20	15.130	0.769
11	14	113 mm D	33.812	2.858	20	15.433	0.751
11	15	113 mm D	33.982	2.685	24	26.870	0.311
11	38	113 mm D	37.800	3.970	24	21.650	0.600
11	52	113 mm D	33.032	1.274	21	27.343	0.160
11	56	113 mm D	32.274	2.232	24	33.888	0.087
11	57	113 mm D	32.305	3.752	21	24.085	0.289
11	61	113 mm D	29.834	1.374	22	23.630	0.367
11	64	113 mm D	28.500	5.397	21	19.886	0.528
11	69	113 mm D	27.134	2.763	21	23.594	0.313
11	71	113 mm D	31.746	1.261	22	26.064	0.249

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
11	76	113 mm D	32.624	1.723	24	35.641	0.059
11	79	113 mm D	32.338	2.298	23	34.420	0.059
11	82	113 mm D	33.518	2.378	24	26.534	0.327
11	84	113 mm D	31.371	2.483	24	28.665	0.233
12	3	95 mm S	32.227	1.553	22	23.221	0.389
12	4	95 mm S	33.389	2.306	26	26.710	0.425
12	13	95 mm S	26.084	0.391	20	17.517	0.619
12	14	95 mm S	28.929	2.994	20	14.838	0.786
12	15	95 mm S	30.037	3.641	26	25.158	0.510
12	38	95 mm S	19.913	0.588	24	31.454	0.141
12	46	95 mm S	32.326	1.846	25	28.217	0.298
12	52	95 mm S	31.443	1.291	21	21.778	0.412
12	56	95 mm S	26.997	0.540	24	22.553	0.546
12	57	95 mm S	18.475	0.998	21	11.956	0.941
12	61	95 mm S	27.950	0.090	24	28.386	0.244
12	64	95 mm S	6.707	1.799	22	29.946	0.120
12	71	95 mm S	29.532	1.063	22	18.668	0.666
12	76	95 mm S	29.580	1.502	26	26.706	0.425
12	79	95 mm S	27.050	0.589	23	25.110	0.345
12	82	95 mm S	26.183	0.085	24	15.662	0.900
12	84	95 mm S	26.034	0.110	26	16.360	0.927
16	3	108 mm S	34.060	1.269	21	17.853	0.658
16	4	108 mm S	35.190	1.717	23	25.477	0.326
16	13	108 mm S	32.589	2.442	19	15.603	0.684
16	14	108 mm S	33.581	1.995	19	11.168	0.918
16	15	108 mm S	33.649	1.833	23	17.645	0.776
16	38	108 mm S	35.955	2.741	23	19.878	0.649
16	43	108 mm S	36.783	2.395	23	34.044	0.065
16	46	108 mm S	33.428	1.079	23	27.879	0.220
16	52	108 mm S	32.976	0.987	20	14.827	0.786
16	56	108 mm S	32.314	1.467	23	22.066	0.516
16	57	108 mm S	32.578	2.150	20	21.040	0.395
16	59	108 mm S	27.110	1.822	23	20.803	0.593
16	61	108 mm S	30.799	1.133	22	25.065	0.294
16	64	108 mm S	31.089	2.806	21	15.222	0.812
16	69	108 mm S	30.422	1.784	21	19.890	0.528
16	71	108 mm S	31.985	0.953	21	20.367	0.498

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
16	74	108 mm S	31.670	1.262	23	29.184	0.174
16	76	108 mm S	32.803	1.265	23	25.978	0.302
16	79	108 mm S	32.336	1.503	22	26.600	0.227
16	82	108 mm S	33.346	1.701	23	20.206	0.629
16	84	108 mm S	32.185	1.668	23	21.157	0.571
17	3	108 mm S	67.692	2.387	16	21.396	0.164
17	4	108 mm S	48.266	2.247	20	13.217	0.868
17	15	108 mm S	55.000	2.784	22	18.517	0.675
17	37	108 mm S	82.218	3.473	22	26.374	0.236
17	38	108 mm S	70.815	2.445	18	13.102	0.785
17	43	108 mm S	50.276	2.547	20	14.395	0.810
17	46	108 mm S	87.446	3.027	19	24.825	0.166
17	49	108 mm S	47.139	2.537	25	33.491	0.119
17	54	108 mm S	82.528	3.542	23	33.257	0.077
17	56	108 mm S	82.573	2.428	18	20.437	0.309
17	59	108 mm S	69.038	3.143	21	16.218	0.757
17	61	108 mm S	71.042	3.140	21	20.708	0.477
17	64	108 mm S	67.197	2.759	19	21.652	0.302
17	69	108 mm S	66.753	2.970	18	20.884	0.285
17	74	108 mm S	72.641	3.021	19	24.991	0.161
17	76	108 mm S	74.263	2.988	21	27.601	0.152
17	79	108 mm S	68.487	2.482	17	21.399	0.209
17	82	108 mm S	66.719	2.571	18	21.404	0.260
17	84	108 mm S	68.589	3.221	22	13.732	0.911
18	3	113 mm D	34.748	1.551	21	13.571	0.887
18	4	113 mm D	36.268	2.098	25	11.338	0.991
18	8	113 mm D	30.732	1.525	23	32.214	0.096
18	13	113 mm D	49.988	8.421	17	15.421	0.565
18	14	113 mm D	35.409	3.168	19	11.696	0.898
18	15	113 mm D	35.347	2.939	27	18.345	0.893
18	38	113 mm D	39.742	3.979	21	21.062	0.455
18	43	113 mm D	37.841	2.736	23	31.417	0.113
18	46	113 mm D	33.900	1.416	24	28.852	0.226
18	52	113 mm D	33.459	1.258	20	9.613	0.975
18	56	113 mm D	34.530	2.995	23	26.286	0.288
18	57	113 mm D	36.972	5.606	20	22.423	0.318
18	61	113 mm D	30.412	1.693	25	28.264	0.296

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
18	69	113 mm D	19.319	1.135	21	28.656	0.123
18	71	113 mm D	32.307	1.278	21	20.342	0.500
18	76	113 mm D	33.291	1.740	26	23.697	0.593
18	79	113 mm D	34.459	2.973	22	22.902	0.407
18	82	113 mm D	34.928	2.635	23	21.391	0.557
18	84	113 mm D	32.584	2.727	27	19.281	0.860
19	3	88 mm D	33.207	1.212	21	27.591	0.152
19	13	88 mm D	30.222	1.547	19	14.043	0.781
19	14	88 mm D	32.337	1.969	19	12.193	0.877
19	15	88 mm D	32.697	1.936	22	21.785	0.473
19	38	88 mm D	36.147	3.577	22	16.609	0.785
19	46	88 mm D	32.954	1.149	22	29.555	0.130
19	52	88 mm D	32.154	0.897	20	17.647	0.611
19	56	88 mm D	30.892	1.121	22	22.327	0.441
19	57	88 mm D	31.025	2.223	20	12.226	0.908
19	59	88 mm D	27.025	0.249	22	18.745	0.661
19	61	88 mm D	29.328	0.570	21	19.390	0.560
19	64	88 mm D	6.437	2.020	19	15.265	0.706
19	69	88 mm D	28.996	0.074	20	22.800	0.299
19	71	88 mm D	31.014	0.781	21	10.827	0.966
19	74	88 mm D	30.616	1.199	22	25.532	0.272
19	76	88 mm D	31.891	1.203	22	27.624	0.188
19	79	88 mm D	30.867	1.124	22	19.280	0.628
19	82	88 mm D	32.015	1.504	22	25.350	0.281
19	84	88 mm D	30.808	1.532	22	23.296	0.385
21	3	95 mm S	40.365	1.727	18	17.860	0.465
21	4	95 mm S	41.921	1.907	22	21.751	0.475
21	8	95 mm S	44.567	3.648	20	15.859	0.725
21	9	95 mm S	84.930	5.524	18	27.454	0.071
21	13	95 mm S	68.970	3.021	16	14.328	0.574
21	14	95 mm S	55.158	3.022	16	9.189	0.905
21	15	95 mm S	43.797	2.499	23	19.628	0.664
21	20	95 mm S	94.904	7.249	21	20.004	0.521
21	36	95 mm S	48.572	4.519	22	27.077	0.208
21	37	95 mm S	47.276	4.444	23	30.927	0.125
21	38	95 mm S	45.828	2.475	20	17.580	0.615
21	43	95 mm S	41.508	1.864	22	25.196	0.288

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
21	46	95 mm S	40.219	1.988	21	20.270	0.504
21	49	95 mm S	38.433	1.575	23	24.941	0.353
21	52	95 mm S	40.526	1.839	17	23.073	0.147
21	54	95 mm S	40.162	2.410	23	20.628	0.604
21	56	95 mm S	50.821	2.943	20	18.170	0.576
21	57	95 mm S	68.470	3.331	17	12.070	0.796
21	59	95 mm S	45.446	3.310	23	25.667	0.317
21	61	95 mm S	46.351	3.579	23	18.427	0.734
21	64	95 mm S	47.106	3.129	21	26.997	0.171
21	69	95 mm S	45.545	3.281	20	28.075	0.108
21	71	95 mm S	44.562	2.685	18	24.761	0.132
21	74	95 mm S	46.518	3.573	21	20.241	0.506
21	76	95 mm S	42.722	2.514	23	19.450	0.675
21	79	95 mm S	48.133	2.905	19	15.812	0.670
21	82	95 mm S	45.203	2.604	20	20.274	0.441
21	84	95 mm S	43.065	2.809	23	16.250	0.844
23	6	113 mm D	34.173	0.884	22	28.078	0.173
23	14	113 mm D	38.958	1.589	14	19.594	0.143
23	15	113 mm D	39.364	1.670	22	30.707	0.102
23	20	113 mm D	35.524	2.152	19	26.106	0.127
23	22	113 mm D	33.653	0.594	21	19.001	0.585
23	29	113 mm D	38.227	2.453	19	20.060	0.391
23	36	113 mm D	37.983	2.371	20	27.547	0.121
23	37	113 mm D	36.905	1.855	22	30.692	0.103
23	38	113 mm D	40.385	1.734	18	16.643	0.548
23	43	113 mm D	38.749	1.238	20	18.777	0.536
23	49	113 mm D	35.349	0.520	23	25.693	0.316
23	54	113 mm D	34.693	0.460	23	25.817	0.310
23	59	113 mm D	39.059	2.052	21	20.118	0.514
23	61	113 mm D	38.250	1.929	21	26.788	0.178
23	76	113 mm D	37.640	1.312	21	30.632	0.080
25	6	95 mm S	39.648	2.188	20	20.998	0.397
25	9	95 mm S	42.993	2.552	17	20.457	0.252
25	15	95 mm S	40.658	1.285	20	31.189	0.053
25	20	95 mm S	40.610	2.255	16	17.935	0.328
25	22	95 mm S	40.923	2.898	19	15.688	0.678
25	24	95 mm S	43.118	2.454	15	21.518	0.121

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
25	29	95 mm S	40.269	1.686	17	15.840	0.535
25	31	95 mm S	39.814	2.224	19	28.271	0.078
25	36	95 mm S	40.704	1.836	18	20.779	0.291
25	37	95 mm S	40.258	1.770	20	20.997	0.397
25	38	95 mm S	41.262	1.311	16	18.869	0.276
25	43	95 mm S	39.337	0.914	18	20.441	0.309
25	56	95 mm S	42.237	1.561	16	26.263	0.050
25	59	95 mm S	40.504	1.493	19	16.538	0.621
25	61	95 mm S	40.710	1.607	19	27.923	0.085
25	62	95 mm S	42.300	2.180	20	20.002	0.458
25	64	95 mm S	41.642	1.631	17	26.546	0.065
25	79	95 mm S	40.917	1.332	15	17.981	0.264
25	84	95 mm S	39.749	1.264	20	23.511	0.264
26	8	113 mm D	33.082	0.714	19	27.260	0.099
26	15	113 mm D	35.065	1.536	23	31.503	0.111
26	37	113 mm D	31.609	0.442	23	16.035	0.854
26	38	113 mm D	38.392	2.604	19	26.857	0.108
26	43	113 mm D	37.619	1.943	21	23.611	0.312
26	46	113 mm D	33.457	0.582	20	24.723	0.212
26	54	113 mm D	33.137	0.587	24	28.243	0.250
26	59	113 mm D	35.014	5.521	22	19.602	0.608
26	61	113 mm D	31.690	0.236	22	18.255	0.691
26	64	113 mm D	38.641	4.867	20	20.425	0.432
26	69	113 mm D	32.889	1.209	19	17.014	0.589
26	71	113 mm D	32.092	0.224	17	18.878	0.336
26	74	113 mm D	32.246	0.404	20	19.580	0.484
26	84	113 mm D	33.747	1.222	23	23.056	0.457
27	13	88 mm D	37.418	3.555	16	21.309	0.167
27	14	88 mm D	35.805	2.173	16	14.201	0.584
27	15	88 mm D	35.615	2.019	21	32.386	0.053
27	37	88 mm D	30.051	1.223	21	15.624	0.790
27	38	88 mm D	38.164	2.698	20	18.416	0.560
27	46	88 mm D	33.881	0.917	21	28.245	0.133
27	52	88 mm D	33.112	0.635	17	23.593	0.131
27	56	88 mm D	35.574	2.265	20	26.742	0.143
27	57	88 mm D	35.283	2.580	17	19.647	0.293
27	59	88 mm D	32.232	3.891	21	29.267	0.108

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
27	61	88 mm D	32.175	1.111	21	20.233	0.507
27	64	88 mm D	35.301	3.614	21	21.255	0.443
27	69	88 mm D	33.020	2.554	20	22.441	0.317
27	74	88 mm D	32.587	1.039	21	24.693	0.261
27	79	88 mm D	35.624	2.283	19	26.768	0.110
28	3	108 mm S	36.730	1.225	18	25.550	0.111
28	4	108 mm S	37.993	1.572	23	26.922	0.259
28	13	108 mm S	40.915	3.115	17	16.987	0.455
28	14	108 mm S	37.925	2.053	17	16.383	0.497
28	15	108 mm S	37.976	2.042	25	23.316	0.559
28	20	108 mm S	29.330	1.697	21	26.352	0.193
28	29	108 mm S	34.273	4.746	21	20.952	0.462
28	36	108 mm S	34.014	3.082	22	28.487	0.160
28	37	108 mm S	33.797	2.183	24	19.733	0.712
28	38	108 mm S	39.715	2.254	21	18.543	0.614
28	46	108 mm S	35.667	1.204	22	25.584	0.270
28	49	108 mm S	35.491	1.038	25	28.974	0.265
28	52	108 mm S	35.873	1.224	18	21.566	0.252
28	54	108 mm S	34.667	1.116	25	31.097	0.186
28	56	108 mm S	39.682	2.650	21	20.989	0.460
28	57	108 mm S	38.046	2.396	18	14.382	0.704
28	59	108 mm S	37.471	3.077	24	18.140	0.796
28	61	108 mm S	35.436	2.052	24	22.462	0.552
28	62	108 mm S	33.241	2.524	25	22.152	0.627
28	64	108 mm S	38.832	2.964	22	25.795	0.261
28	69	108 mm S	36.936	2.627	21	20.773	0.473
28	71	108 mm S	35.645	1.427	19	21.792	0.295
28	74	108 mm S	35.174	1.672	22	20.531	0.550
28	76	108 mm S	36.127	1.541	24	30.747	0.161
28	79	108 mm S	38.889	2.435	20	22.670	0.305
28	82	108 mm S	38.166	2.068	20	26.663	0.145
28	84	108 mm S	36.405	1.896	25	28.616	0.280
30	13	88 mm D	36.287	2.853	17	24.922	0.096
30	14	88 mm D	35.462	1.911	17	18.175	0.378
30	15	88 mm D	35.181	1.721	22	24.648	0.314
30	29	88 mm D	10.813	0.835	21	21.438	0.432
30	36	88 mm D	10.813	0.835	21	22.248	0.385

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
30	59	88 mm D	32.806	2.969	22	24.510	0.321
30	61	88 mm D	32.390	1.007	22	18.784	0.659
30	62	88 mm D	31.043	0.713	22	24.857	0.304
30	64	88 mm D	34.902	2.855	22	26.127	0.246
30	69	88 mm D	33.083	1.752	21	25.184	0.239
30	71	88 mm D	32.724	0.712	19	15.033	0.720
30	74	88 mm D	32.751	0.914	22	19.443	0.618
30	76	88 mm D	33.718	1.040	22	21.730	0.476
30	82	88 mm D	35.194	1.715	20	26.807	0.141
30	84	88 mm D	33.827	1.464	22	23.245	0.388
32	13	95 mm S	37.877	2.951	16	25.011	0.070
32	14	95 mm S	36.309	1.912	16	18.811	0.279
32	15	95 mm S	36.130	1.809	23	30.780	0.128
32	38	95 mm S	38.292	2.313	20	16.373	0.693
32	43	95 mm S	37.819	1.802	22	25.784	0.261
32	46	95 mm S	34.342	0.897	21	20.595	0.484
32	54	95 mm S	33.675	0.835	23	24.729	0.364
32	56	95 mm S	36.576	2.185	20	26.474	0.151
32	57	95 mm S	36.028	2.219	17	15.053	0.592
32	59	95 mm S	34.704	3.092	23	23.123	0.454
32	61	95 mm S	33.253	1.234	23	22.054	0.517
32	62	95 mm S	31.427	0.623	23	27.856	0.221
32	64	95 mm S	36.318	2.887	21	27.690	0.149
32	69	95 mm S	34.371	2.134	20	16.798	0.666
32	71	95 mm S	33.268	0.732	18	16.359	0.567
32	74	95 mm S	33.375	1.059	21	25.756	0.216
32	76	95 mm S	34.458	1.133	23	32.588	0.089
32	79	95 mm S	36.540	2.160	19	29.978	0.052
32	82	95 mm S	36.243	1.810	20	29.915	0.071
32	84	95 mm S	34.724	1.600	23	27.847	0.222
33	4	108 mm S	48.827	1.646	15	18.220	0.251
33	15	108 mm S	52.387	1.978	17	9.679	0.917
33	38	108 mm S	67.964	1.769	13	17.864	0.163
33	43	108 mm S	52.358	1.992	15	19.904	0.176
33	46	108 mm S	61.445	2.114	14	19.760	0.138
33	49	108 mm S	49.049	1.885	20	21.963	0.343
33	51	108 mm S	50.863	2.025	15	18.960	0.216

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
33	54	108 mm S	53.676	2.284	18	20.687	0.295
33	59	108 mm S	56.079	2.197	16	19.075	0.265
33	61	108 mm S	91.952	2.184	16	16.262	0.435
33	74	108 mm S	64.131	2.054	14	23.357	0.055
33	76	108 mm S	65.806	2.117	16	21.162	0.172
33	84	108 mm S	62.004	2.270	17	17.402	0.427
34	46	95 mm S	28.507	1.438	28	29.953	0.365
34	49	95 mm S	29.857	1.648	34	27.852	0.762
34	51	95 mm S	27.171	0.794	29	42.581	0.050
35	3	88 mm D	28.470	1.428	28	36.142	0.139
35	46	88 mm D	27.677	2.061	28	38.820	0.084
35	52	88 mm D	28.493	1.499	27	26.973	0.465
39	13	113 mm D	29.205	0.372	18	18.593	0.417
39	14	113 mm D	29.891	0.486	18	19.593	0.356
39	15	113 mm D	31.577	1.340	23	25.573	0.321
39	38	113 mm D	36.112	4.109	22	23.293	0.385
39	43	113 mm D	36.675	3.321	23	29.357	0.169
39	46	113 mm D	32.442	0.969	23	21.881	0.527
39	52	113 mm D	31.464	0.632	19	22.924	0.241
39	56	113 mm D	30.074	0.547	22	19.250	0.630
39	57	113 mm D	29.965	0.950	19	18.572	0.485
39	61	113 mm D	29.066	0.329	23	22.249	0.505
39	71	113 mm D	30.358	0.447	20	12.389	0.902
39	74	113 mm D	30.283	0.800	23	31.844	0.103
39	76	113 mm D	31.210	0.827	23	22.187	0.509
39	79	113 mm D	29.956	0.528	21	27.238	0.163
39	82	113 mm D	30.094	0.512	22	26.997	0.211
39	84	113 mm D	29.553	0.472	23	21.963	0.522
40	15	108 mm S	70.593	2.358	20	27.312	0.127
40	38	108 mm S	67.394	1.995	16	16.651	0.408
40	54	108 mm S	54.996	2.737	21	27.938	0.142
40	56	108 mm S	72.731	1.956	16	22.553	0.126
40	59	108 mm S	87.275	2.543	19	24.790	0.168
40	64	108 mm S	65.860	2.225	17	25.923	0.076
40	74	108 mm S	65.368	2.387	17	19.562	0.297
40	82	108 mm S	63.804	2.078	16	25.300	0.065
40	84	108 mm S	65.321	2.614	20	21.669	0.359

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
41	3	88 mm D	29.013	0.426	21	22.750	0.357
41	4	88 mm D	28.392	0.504	22	24.046	0.345
41	52	88 mm D	29.208	0.605	21	28.036	0.139
42	3	108 mm S	31.535	0.888	21	28.161	0.136
42	4	108 mm S	31.761	1.152	25	34.420	0.099
42	13	108 mm S	27.248	0.085	19	24.498	0.178
42	14	108 mm S	29.740	0.905	19	17.316	0.568
42	15	108 mm S	30.553	1.296	25	28.562	0.283
42	38	108 mm S	32.851	3.726	23	19.639	0.664
42	43	108 mm S	35.461	3.875	25	22.771	0.591
42	46	108 mm S	32.142	1.094	24	27.900	0.264
42	52	108 mm S	31.316	0.784	20	26.031	0.165
42	56	108 mm S	29.484	0.749	23	26.946	0.258
42	57	108 mm S	28.738	1.058	20	16.675	0.674
42	71	108 mm S	30.274	0.673	21	23.884	0.299
42	76	108 mm S	30.643	0.964	25	30.922	0.192
42	82	108 mm S	29.877	0.808	23	25.076	0.346
42	84	108 mm S	28.942	0.810	25	32.685	0.139
44	4	95 mm S	43.848	2.456	22	32.812	0.065
44	8	95 mm S	96.601	5.580	21	31.969	0.059
44	14	95 mm S	83.291	3.532	17	25.225	0.090
44	15	95 mm S	48.437	3.424	25	35.019	0.088
44	38	95 mm S	56.847	3.319	21	23.680	0.309
44	43	95 mm S	43.793	2.552	23	28.273	0.206
44	46	95 mm S	41.420	2.544	22	30.503	0.107
44	49	95 mm S	38.595	1.891	28	37.338	0.112
44	54	95 mm S	42.724	3.398	26	35.717	0.097
44	57	95 mm S	92.500	3.832	18	23.657	0.167
44	61	95 mm S	83.365	5.249	24	36.070	0.054
44	74	95 mm S	82.189	5.023	22	28.037	0.174
44	79	95 mm S	112.916	3.713	20	28.974	0.088
44	84	95 mm S	49.759	4.205	25	29.007	0.264
45	3	113 mm D	35.513	1.311	20	28.119	0.107
45	4	113 mm D	36.647	1.638	24	31.996	0.127
45	13	113 mm D	36.244	2.769	18	22.723	0.201
45	14	113 mm D	35.779	2.012	18	12.705	0.809
45	15	113 mm D	35.636	1.885	25	15.099	0.939

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
45	37	113 mm D	30.538	1.709	24	32.560	0.114
45	38	113 mm D	37.538	2.330	22	8.840	0.994
45	43	113 mm D	37.531	1.883	24	35.801	0.057
45	46	113 mm D	34.442	1.107	23	21.093	0.575
45	52	113 mm D	34.226	1.067	19	20.279	0.378
45	56	113 mm D	35.439	2.109	22	30.367	0.110
45	57	113 mm D	35.209	2.211	19	28.282	0.078
45	59	113 mm D	33.026	3.108	25	24.300	0.502
45	61	113 mm D	32.790	1.551	25	16.037	0.914
45	62	113 mm D	30.266	1.144	25	31.478	0.174
45	64	113 mm D	34.959	2.720	22	28.684	0.154
45	69	113 mm D	33.524	2.171	21	19.457	0.556
45	71	113 mm D	33.516	1.129	20	18.206	0.574
45	74	113 mm D	33.219	1.356	23	23.782	0.416
45	76	113 mm D	34.347	1.365	25	22.623	0.600
45	79	113 mm D	35.531	2.139	21	29.223	0.109
45	82	113 mm D	35.682	1.905	22	23.803	0.358
45	84	113 mm D	34.298	1.755	25	30.950	0.191
48	3	95 mm S	51.943	3.648	24	19.523	0.724
48	46	95 mm S	48.853	4.144	27	27.434	0.441
48	49	95 mm S	43.796	3.456	33	34.484	0.397
48	51	95 mm S	43.674	3.800	28	39.648	0.071
48	52	95 mm S	63.414	3.906	23	21.750	0.535
48	54	95 mm S	57.412	5.810	31	39.051	0.152
48	71	95 mm S	97.719	4.645	24	23.771	0.475
53	3	95 mm S	51.393	2.517	21	16.392	0.747
53	46	95 mm S	47.962	2.686	24	29.903	0.188
53	49	95 mm S	45.740	2.540	30	26.183	0.666
53	51	95 mm S	46.955	2.821	25	36.847	0.060
53	52	95 mm S	73.448	2.631	20	17.101	0.646
53	54	95 mm S	50.645	3.206	28	28.106	0.459
55	3	88 mm D	38.803	2.470	23	22.988	0.461
55	4	88 mm D	41.284	2.915	27	32.225	0.224
55	8	88 mm D	35.639	4.601	25	33.885	0.110
55	14	88 mm D	80.773	5.610	21	24.028	0.292
55	15	88 mm D	45.098	4.589	29	36.085	0.171
55	46	88 mm D	37.472	2.536	26	24.080	0.571

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
55	49	88 mm D	36.659	2.086	29	39.241	0.097
55	51	88 mm D	35.610	2.192	27	39.461	0.057
55	52	88 mm D	37.733	2.425	22	23.186	0.391
55	56	88 mm D	84.813	5.466	20	29.054	0.087
55	61	88 mm D	52.483	8.691	25	20.457	0.722
55	71	88 mm D	38.644	3.309	23	19.165	0.692
55	74	88 mm D	49.616	7.749	26	31.933	0.195
55	76	88 mm D	39.864	3.737	28	23.279	0.719
55	79	88 mm D	80.716	5.916	24	29.166	0.214
55	82	88 mm D	48.302	4.780	25	27.393	0.337
55	84	88 mm D	42.650	5.510	28	34.378	0.189
58	13	88 mm D	28.649	0.460	18	24.010	0.155
58	14	88 mm D	29.533	0.656	18	24.362	0.144
58	15	88 mm D	30.759	1.471	20	28.780	0.092
58	38	88 mm D	35.177	5.076	20	17.130	0.644
58	46	88 mm D	32.202	1.119	20	29.940	0.071
58	52	88 mm D	30.925	0.607	19	24.100	0.192
58	56	88 mm D	29.449	0.556	20	23.119	0.283
58	57	88 mm D	28.586	0.819	19	12.617	0.858
58	71	88 mm D	30.057	0.497	20	18.987	0.523
58	76	88 mm D	30.496	0.804	20	24.783	0.210
58	79	88 mm D	29.252	0.482	20	20.227	0.444
58	82	88 mm D	29.600	0.545	20	17.846	0.598
58	84	88 mm D	28.980	0.627	20	24.607	0.217
60	15	95 mm S	46.764	2.931	21	32.609	0.051
60	38	95 mm S	50.010	2.844	19	21.974	0.286
60	43	95 mm S	42.718	2.152	21	27.769	0.147
60	46	95 mm S	41.766	2.320	20	28.288	0.103
60	61	95 mm S	58.211	4.386	21	31.829	0.061
60	74	95 mm S	79.560	4.396	20	23.169	0.281
60	82	95 mm S	50.981	3.096	19	21.385	0.316
60	84	95 mm S	47.618	3.546	21	21.698	0.417
63	4	95 mm S	35.387	1.833	23	28.694	0.191
63	13	95 mm S	32.619	2.813	19	12.466	0.865
63	14	95 mm S	33.683	2.228	19	12.812	0.848
63	15	95 mm S	33.798	2.086	23	20.023	0.641
63	38	95 mm S	36.243	2.975	23	20.121	0.635

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
63	52	95 mm S	32.884	1.043	20	20.007	0.458
63	56	95 mm S	32.294	1.662	23	24.734	0.364
63	57	95 mm S	32.523	2.513	20	18.609	0.547
63	59	95 mm S	6.535	2.124	23	18.130	0.750
63	64	95 mm S	30.684	3.161	20	11.085	0.944
63	71	95 mm S	31.669	0.950	21	24.389	0.275
63	76	95 mm S	32.768	1.403	23	29.646	0.160
63	79	95 mm S	32.327	1.706	22	18.279	0.689
63	82	95 mm S	33.469	1.905	23	28.525	0.197
63	84	95 mm S	31.999	1.882	23	27.026	0.255
65	4	88 mm D	37.202	1.721	22	27.065	0.209
65	14	88 mm D	37.217	2.613	16	24.237	0.084
65	15	88 mm D	37.056	2.480	24	22.710	0.537
65	38	88 mm D	40.594	3.193	20	11.516	0.932
65	43	88 mm D	38.449	2.217	22	28.845	0.149
65	46	88 mm D	34.438	1.098	21	12.799	0.915
65	49	88 mm D	34.596	1.008	26	17.878	0.880
65	54	88 mm D	33.574	1.053	25	33.397	0.121
65	57	88 mm D	38.224	3.714	17	26.937	0.059
65	59	88 mm D	50.211	10.932	21	20.693	0.478
65	61	88 mm D	32.963	1.870	23	28.273	0.206
65	62	88 mm D	30.314	0.892	24	32.178	0.123
65	64	88 mm D	48.043	7.304	21	30.843	0.076
65	69	88 mm D	36.037	4.715	20	22.690	0.304
65	71	88 mm D	33.306	0.920	18	25.427	0.114
65	76	88 mm D	34.566	1.431	23	19.181	0.691
65	82	88 mm D	37.096	2.397	19	19.258	0.440
65	84	88 mm D	34.903	2.261	24	26.539	0.326
67	15	113 mm D	33.738	2.932	24	18.962	0.754
67	38	113 mm D	40.445	5.177	23	23.230	0.447
67	46	113 mm D	33.175	1.419	24	31.638	0.136
67	52	113 mm D	32.145	1.025	20	24.013	0.242
67	57	113 mm D	32.316	5.230	20	27.291	0.127
67	61	113 mm D	28.108	0.071	23	23.127	0.453
67	71	113 mm D	30.691	0.854	21	19.469	0.555
67	74	113 mm D	29.921	1.486	24	27.870	0.266
67	82	113 mm D	32.970	2.315	23	34.233	0.062

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
67	84	113 mm D	30.527	2.274	24	33.485	0.094
68	3	88 mm D	33.843	2.189	24	22.671	0.539
68	4	88 mm D	35.982	3.121	28	28.984	0.413
68	8	88 mm D	26.542	1.461	26	35.533	0.101
68	14	88 mm D	36.361	7.272	22	26.966	0.213
68	15	88 mm D	35.088	6.235	30	18.817	0.944
68	38	88 mm D	83.019	10.830	21	19.094	0.579
68	46	88 mm D	33.281	2.362	27	24.070	0.626
68	52	88 mm D	32.357	1.800	23	16.050	0.853
68	56	88 mm D	29.447	2.875	25	26.310	0.391
68	57	88 mm D	4.619	3.725	22	30.028	0.118
68	71	88 mm D	30.010	1.640	24	17.689	0.818
68	74	88 mm D	25.709	2.035	26	26.198	0.452
68	76	88 mm D	30.451	2.406	29	27.549	0.542
68	79	88 mm D	29.811	3.273	24	23.208	0.508
68	82	88 mm D	32.485	3.974	26	25.640	0.483
68	84	88 mm D	25.875	3.965	28	19.390	0.886
70	14	95 mm S	41.670	4.220	18	26.826	0.082
70	15	95 mm S	39.609	3.641	24	30.605	0.165
70	38	95 mm S	45.120	4.244	22	20.265	0.566
70	46	95 mm S	35.127	1.709	23	16.197	0.847
70	49	95 mm S	34.999	1.464	24	34.339	0.079
70	54	95 mm S	33.510	1.603	24	26.248	0.341
70	56	95 mm S	48.116	5.246	22	31.079	0.095
70	57	95 mm S	52.214	6.830	19	21.462	0.312
70	61	95 mm S	34.329	4.507	24	22.212	0.567
70	64	95 mm S	60.932	9.263	22	31.419	0.088
70	74	95 mm S	33.915	3.005	22	20.956	0.523
70	84	95 mm S	36.396	3.729	23	26.341	0.285
72	3	113 mm D	39.447	1.574	17	18.018	0.388
72	4	113 mm D	41.218	1.867	21	25.654	0.220
72	15	113 mm D	44.168	2.774	23	29.814	0.155
72	38	113 mm D	46.650	2.754	19	29.217	0.063
72	46	113 mm D	39.287	1.856	20	15.800	0.729
72	49	113 mm D	37.696	1.414	26	20.671	0.759
72	52	113 mm D	39.585	1.684	16	21.670	0.154
72	54	113 mm D	39.060	2.275	24	25.396	0.385

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
72	56	113 mm D	65.561	3.399	19	27.486	0.094
72	61	113 mm D	55.606	4.900	22	29.165	0.140
72	71	113 mm D	43.462	2.672	17	26.104	0.073
72	76	113 mm D	42.391	2.634	22	29.679	0.126
72	79	113 mm D	94.809	3.497	18	28.514	0.055
73	3	95 mm S	37.392	2.906	22	30.241	0.113
73	4	95 mm S	41.552	4.033	26	34.267	0.128
73	8	95 mm S	26.360	4.601	24	32.486	0.115
73	46	95 mm S	36.326	3.403	25	29.762	0.233
73	49	95 mm S	35.816	2.739	26	37.439	0.068
73	52	95 mm S	35.368	2.549	21	17.619	0.673
73	54	95 mm S	32.970	3.971	26	35.684	0.098
73	71	95 mm S	34.009	3.193	22	23.494	0.374
73	74	95 mm S	18.346	1.024	23	32.029	0.100
73	76	95 mm S	38.043	5.302	26	18.322	0.864
75	3	88 mm D	36.537	2.428	22	15.892	0.821
75	4	88 mm D	39.220	3.216	26	32.430	0.179
75	8	88 mm D	28.729	2.872	24	29.198	0.213
75	14	88 mm D	52.195	7.428	18	18.021	0.454
75	15	88 mm D	42.017	6.150	27	39.046	0.063
75	46	88 mm D	35.384	2.594	25	30.483	0.207
75	52	88 mm D	34.838	2.130	21	17.800	0.662
75	54	88 mm D	32.973	2.820	27	37.952	0.079
75	56	88 mm D	56.327	7.425	20	10.944	0.948
75	61	88 mm D	28.440	8.870	25	15.921	0.917
75	71	88 mm D	33.232	2.406	22	18.859	0.654
75	74	88 mm D	31.526	7.392	25	23.345	0.557
75	76	88 mm D	35.231	3.553	27	30.877	0.276
75	79	88 mm D	58.890	8.549	23	21.772	0.534
75	82	88 mm D	43.038	5.740	24	26.439	0.331
75	84	88 mm D	36.444	8.195	27	38.233	0.074
77	4	108 mm S	42.279	2.632	24	29.216	0.212
77	14	108 mm S	95.815	4.450	18	22.794	0.199
77	15	108 mm S	55.517	4.764	26	19.107	0.832
77	38	108 mm S	72.473	4.173	21	11.053	0.962
77	46	108 mm S	37.814	2.135	23	35.115	0.051
77	49	108 mm S	36.147	1.510	29	30.609	0.384

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
77	59	108 mm S	102.487	7.497	25	26.533	0.380
77	61	108 mm S	105.632	7.391	25	28.076	0.304
77	64	108 mm S	96.751	5.949	22	25.167	0.289
77	69	108 mm S	101.564	6.963	21	31.046	0.073
77	74	108 mm S	94.206	6.874	23	30.100	0.147
77	82	108 mm S	73.855	4.550	22	29.669	0.127
77	84	108 mm S	96.534	6.599	26	27.339	0.392
78	71	88 mm D	31.002	1.611	21	30.780	0.077
78	79	88 mm D	30.393	2.736	21	24.460	0.271
80	52	95 mm S	31.425	2.704	20	30.752	0.059
80	71	95 mm S	27.217	2.236	21	24.792	0.256
80	76	95 mm S	13.055	2.275	21	31.545	0.065
83	3	88 mm D	37.479	1.400	19	12.866	0.845
83	4	88 mm D	38.715	1.642	23	14.080	0.925
83	8	88 mm D	35.240	1.704	21	21.919	0.404
83	13	88 mm D	48.156	3.808	17	20.429	0.253
83	14	88 mm D	39.523	2.330	17	20.458	0.251
83	15	88 mm D	39.380	2.256	25	16.376	0.903
83	20	88 mm D	11.909	1.078	22	30.957	0.097
83	36	88 mm D	40.216	5.745	22	27.168	0.205
83	37	88 mm D	36.202	3.491	24	21.889	0.586
83	38	88 mm D	41.297	2.414	21	17.742	0.665
83	46	88 mm D	36.375	1.351	22	9.207	0.992
83	49	88 mm D	35.924	1.119	26	17.554	0.891
83	51	88 mm D	35.845	1.228	23	34.161	0.063
83	52	88 mm D	36.830	1.391	18	10.051	0.930
83	54	88 mm D	35.219	1.268	26	18.604	0.853
83	56	88 mm D	43.533	3.157	21	23.308	0.328
83	57	88 mm D	40.902	2.975	18	25.456	0.113
83	59	88 mm D	40.287	3.655	24	17.733	0.816
83	61	88 mm D	37.830	2.868	24	16.465	0.871
83	64	88 mm D	42.333	3.565	22	27.615	0.189
83	69	88 mm D	39.571	3.267	21	23.349	0.326
83	71	88 mm D	36.818	1.687	19	22.858	0.244
83	74	88 mm D	36.582	2.135	22	21.062	0.517
83	76	88 mm D	37.250	1.794	24	24.250	0.447
83	79	88 mm D	41.010	2.732	20	18.529	0.553

Appendix 3 (continued)

Haul	Std haul	Codend	μ	σ	df	Deviance	P-value
83	82	88 mm D	39.757	2.313	21	23.691	0.308
83	84	88 mm D	37.635	2.174	25	16.049	0.913
86	3	113 mm D	38.250	1.123	17	16.697	0.475
86	4	113 mm D	39.588	1.364	21	15.734	0.784
86	6	113 mm D	50.662	7.791	23	30.464	0.137
86	8	113 mm D	38.224	1.875	19	25.610	0.141
86	9	113 mm D	94.765	5.995	20	22.515	0.313
86	13	113 mm D	63.001	2.951	15	21.959	0.109
86	15	113 mm D	41.047	1.921	23	15.049	0.893
86	20	113 mm D	108.364	7.743	20	15.362	0.755
86	22	113 mm D	115.778	10.134	22	24.401	0.327
86	29	113 mm D	44.079	3.822	20	19.102	0.515
86	31	113 mm D	43.044	6.223	22	29.042	0.144
86	36	113 mm D	44.100	3.813	21	21.288	0.441
86	37	113 mm D	43.035	3.664	23	32.073	0.099
86	38	113 mm D	42.391	1.972	19	18.573	0.485
86	43	113 mm D	39.410	1.304	21	12.283	0.932
86	46	113 mm D	37.845	1.247	20	19.582	0.484
86	49	113 mm D	36.434	0.839	26	19.534	0.813
86	51	113 mm D	36.660	0.918	21	26.710	0.181
86	52	113 mm D	38.291	1.218	16	18.518	0.294
86	54	113 mm D	36.672	1.156	24	27.871	0.266
86	59	113 mm D	42.114	2.646	22	12.194	0.953
86	61	113 mm D	42.132	2.794	22	19.026	0.644
86	62	113 mm D	47.245	4.236	23	28.012	0.215
86	64	113 mm D	43.976	2.712	20	17.919	0.593
86	69	113 mm D	42.218	2.644	19	25.558	0.143
86	76	113 mm D	39.679	1.772	22	30.170	0.114
86	79	113 mm D	42.684	2.228	18	17.492	0.490
86	82	113 mm D	41.650	2.004	19	27.757	0.088
86	84	113 mm D	39.825	1.954	23	14.682	0.906

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Degrees

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