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EXECUTIVE SUMMARY

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This document reports on the two main tasks of Objective 2 of the project ENV2000/02. It examines the representativeness of observer coverage of the squid (*Nototodarus* spp.) trawl fishery in SQU 6T in the 1992–2002 seasons. It also provides estimates of the observer coverage proportion necessary to achieve coefficients of variation (c.v.) of 10%, 20%, and 30% for a future estimate of the total New Zealand sea lion (*Phocarctos hookeri*) captures in a season.

The representativeness of the observer coverage is assessed using tables of observer coverage proportions in relation to numbers of tows, vessels, and nationality and from kernel density plots of the commercial fishing effort plotted beside the observed effort in relation to spatial and temporal variables. On these criteria the observer coverage is a good representation of the commercial fishery especially from 1998 to 2002.

A new method was developed for obtaining the observed proportion of tows required to attain a specified c.v. To estimate all the variation that can occur between tows within a season, the method uses an over-dispersed Poisson generalised linear model with vessel random effects. An over-dispersed component allows for variation in the capture rates due to spatial, temporal, and other external causes, while the vessel random effects introduce correlation between captures by the same vessel. An expression is derived for the c.v. of the predicted total number of captures in the fishery in terms of the parameters of the model, including the variances of the random effects components. Data from 1998 to 2002, which excluded any tows where a Sea Lion Exclusion Device was present with its cover net open, were used to fit the model by Bayesian methods. Once the year effects are accounted for there is virtually no over-dispersion and a Poisson generalised linear model with vessel effects was finally fitted.

The capture rate and total fishing effort for a season appear in the expression for the c.v. as their product. Thus, for a future season, the proportion of observed tows required can be related to the predicted total captures for that season. A figure is presented containing the proportions of observed tows required to attain c.v.s of 10%, 20%, and 30%, plotted against the predicted total numbers of captures. A table of the coverage for various values of the predicted total number of captures is also included. For example, when the predicted total number of sea lion captures is 70, to attain a c.v. of 30% the proportion of tows that need to be observed is about 21%, and to attain c.v.s of 20% and 10%, the proportions of tows that need to be observed are about 42% and 72% respectively.

1. INTRODUCTION

The Ministry of Fisheries has statutory obligations to provide advice on the adverse effects of fishing on associated or dependent species in order to avoid, remedy, or mitigate these effects. The capture of New Zealand sea lions (*Phocarctos hookeri*) during squid (*Nototodarus* spp.) trawl fishing effort, particularly off the Auckland Islands Shelf (in area SQU 6T), has resulted from the overlap of the fishing grounds with the sea lion foraging areas. This species is classified as "range restricted" and therefore "threatened" under the DoC Threat Classification (Hitchmough 2002).

Ministry of Fisheries observers have monitored the SQU 6T squid trawl fishery since 1988, and annual estimates of total captures are obtained by scaling the observed strike rate to the total effort of the fleet (Baird 2001). Since 1993, vessels have complied with an in-season monitoring system that allows estimation of the number of captures during the season (February-June) (Doonan 2001). If this in-season estimate reaches or exceeds the maximum allowable limit of fishing mortality (MALFiRM), the fishery is closed. Early closure of the fishery occurred in all years since 1996, except for 1999 (Baird & Doonan 2002, Annala et al. 2004).

Annual changes in the rates of sea lion capture have been documented in the SQU 6T fishery, with an increasing trend since 1993 (Doonan 2001). These strike rates may be variable within a fishing season. Appropriate levels of observer coverage are required to ensure that statistically robust estimates of total sea lion captures can be provided to the managers of the southern squid fishery. The observer coverage, expressed as the proportion of all tows that are observed, must be representative of the total effort, both spatially and temporally, and of the vessels. The changing nature of the fishery, particularly the testing and use of Sea Lion Exclusion Devices (SLEDs), demands that the amount of observer coverage is reviewed continually.

This report is concerned with Objective 2 of the project ENV2000/02: *For New Zealand sea lions taken in the southern squid fishery, provide estimates of the level of observer coverage required to achieve the point estimates of sea lion capture with target c.v.s of 10%, 20%, and 30%.*

2. METHODS

There are five parts to this methods section. The first subsection outlines the data sources used. In the second subsection, we consider the methods for determining how representative the observer coverage has been in the years 1992–2002. In the third subsection, we examine the approach to calculation of the coefficient of variation (c.v.) of the estimate of total captures that has been used in the past, and present a new approach for consideration. In the fourth subsection, we present a new model for New Zealand sea lion captures that enables the coefficient of variation to be calculated when there is over-dispersion, and a simple structure for the correlation of captures within groups of tows. Finally, we add distributional assumptions to the model so that it can be fitted by Bayesian methods to obtain the parameter estimates used to derive the coverage proportion required to attain a specified coefficient of variation.

2.1 Data sources and treatment

Two primary data sources were used:

- the MFish observer data based on observer logbooks and obtained from MFish databases *obs* and *obs_lfs*.
- the commercial fishing data reported to the Ministry of Fisheries on Trawl Catch Effort Processing Return (TCEPR) forms obtained from MFish catch and effort system *warehou*.

Observer data were extracted for the observed squid trips in SQU 6T for 1992–2002. These trips were generally in the main part of the fishing season (February-June). The following observer data were extracted for each fishing operation: vessel identifier, trip, tow, gear type, latitude and longitude, date, time, number of New Zealand sea lions, as recorded by MFish scientific observers.

The following total fishing effort data for each fishing operation were extracted: vessel identifier and characteristics (including nationality), trip, fishing operation identifier, target species, gear type, starting latitude and longitude, and starting time and date.

Information from the autopsy programme contracted to the Department of Conservation (DoC) under a Conservation Services Programme (CSP) project in which all dead sea lions are returned from the squid fishery for autopsy (for examples, see Duignan et al. (2003)) was used to verify the records in the observer database, including the sex of the animals.

Data on the use of SLEDs were obtained from observer logbooks in 2000 and from the industry data collected for the in season work in other years of SLED use (2001 and 2002). When the device was present it was used with the cover net either tied down or left open. The latter situation allows the potential escape of the sea lion from the net. In 2000, all observed tows with the device present had the cover net tied down. Thus, there are three categories of tow in relation to SLED use: device absent, device present with cover net open, and device present with cover net tied down. For the observer data, 21 of the observed tows, all in 2002, did not have the SLED category available; these involved 6 trips by 4 vessels. The category for these tows was inferred on the basis of the SLED status and gear of the tows adjacent in time to the tow with the missing category.

From a total of 4493 observed tows, 3 were omitted from the final dataset after grooming. One tow in 1994 was omitted as it had no start or finish latitude and longitude coordinates and no start or end times. Two other observed tows, in the 1992 and 2002 seasons, were omitted from the observer data because they had zero duration times. None of these tows appeared in the commercial data.

2.2 Representativeness of observer coverage

Because capture rates (mean number of captures per tow) are likely to vary spatially and temporally over the fishing season, it is important that the extent of the commercial fishery be covered by a representative observer programme. To measure whether the observer coverage is representative, we look at important characteristics that are available in the commercial and observer data, and from other sources, which may relate to possible capture rates. This involves examining, for each season, coverage by tows, by vessels, and by nationality. Following the method used by Doonan (2001), kernel density plots of the commercial and observed tows for the variables latitude, longitude, and day of the year are used to compare the distributions of commercial and observer tows in relation to each variable. The plots include all the observer tows, whether the SLED was present or not.

2.3 Observer coverage to meet a specified coefficient of variation

Determination of the sample size required for a study is a common application of statistical methodology and Lenth (2001) discussed many of the practical issues. An aim of this study is to determine the observer coverage required to meet the criterion of estimating the total New Zealand sea lions captured in a season to the accuracy of a specified coefficient of variation.

In undertaking this work, we have identified a number of problems associated with estimating the coefficient of variation for the total captures of New Zealand sea lions in a season and we discuss these in the next section. We introduce a new approach to the calculation of the coefficient of variation that overcomes many of these difficulties. We also develop a model for sea lion captures that allows for variation in the strike rate between tows, and which also allows for the correlation of captures between tows within some groups of tows. Difficulties can arise in the fitting of the model because of the nature of the sea lion capture data where a very large proportion (over 90%) of tows have no captures and very few tows capture more than one sea lion.

2.3.1 Approaches to the calculation of the coefficient of variation

Adopting the survey sampling notation that upper case letters refer to finite population quantities and lower case letters refer to sample quantities, the ratio estimate of the total number of sea lions captured in a season T, is given by

$$\hat{T} = N\frac{t}{n} \qquad (1)$$

where t is the number of captures observed in the season, N is the total number of commercial tows in the season, and n is the number of observed tows. t/n is the estimated "strike rate" for the season and this is scaled up by the total effort to estimate the total number of captures in the fishery. The primary objective of this study is to estimate the observer coverage proportion

$$f = \frac{n}{N}$$

necessary to estimate the total number of captures accurate to a specified coefficient of variation.

2.3.1.1 A simple random sample approach

Bradford (2001) and Doonan (2001) have used the finite population formula from survey sampling theory to calculate the variance of $\hat{T}$, which assumes that the observed tows are a simple random sample from the population of all commercial tows. This approach follows Cochran (1977), and gives

$$\mathrm{Var}(\hat{T}) = \left(\frac{1}{f} - 1\right) NS^2$$

where

$$S^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(y_i - \frac{T}{N}\right)^2$$

is the finite population variance of the number of captures per tow,

$$T = \sum_{i=1}^{N} y_i$$

is the population total captures and $y_1, y_2, \ldots, y_N$ are the individual captures for the commercial tows. Cochran (1977) presented these formulae applied to sample and population means and it is a simple exercise to rearrange these for the sample total t and the population total T. The coefficient of variation of $\hat{T}$ is

$$\mathrm{cv}(\hat{T}) = \frac{\sqrt{\mathrm{Var}(\hat{T})}}{\mathrm{E}(\hat{T})} = \frac{1}{\mathrm{E}(\hat{T})}\sqrt{\left(\frac{1}{f} - 1\right) NS^2}$$

where $\mathrm{E}\left(\hat{T}\right)$ denotes the mean of the estimated total number of sea lion captures.

Estimation is based on the subset of captures for the observed tows, which we denote by $y_1, y_2, \ldots, y_n$. This subset is "representative" of all the captures because it is assumed to be a simple random sample from the finite population. It follows that the ratio estimate, $\hat{T}$, is an unbiased estimate of T, meaning that $\mathrm{E}(\hat{T}) = T$. Furthermore the sample variance

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(y_i - \frac{t}{n}\right)^2 \quad (2)$$

is an unbiased estimate of the finite population variance S^2 (Cochran 1977). The estimated c.v. is then given by

$$\widehat{\mathrm{cv}(\hat{T})} = \frac{s}{\hat{T}}\sqrt{\left(\frac{1}{f}-1\right)N} \quad (3)$$

The use of the estimate s^2, given by Equation (2), is problematic because the data are count data and s^2 is an inefficient estimator in such situations. Furthermore, in the presence of "outliers", the rare multiple capture tows that can occur, s^2 can be an unstable estimate of the finite population variance S^2.

Another approach is to assume that the finite population, $y_1, y_2, \ldots, y_N$, is an independent sample from a super population. This incorporates the idea of the representativeness of the observer sample because it is a subsample from the same super population. The advantage is that the variance can be related to the estimate of T via the variance function of the distribution of the superpopulation, which enables the calculation of the c.v. for different estimates of the total captures. For example Doonan (2001) assumed the binomial distribution (ignoring multiple captures) for the super population, which leads to a hypergeometric distribution for the finite population given T and gives an estimate of the c.v. of

$$\widehat{\mathrm{cv}(\hat{T})} = \sqrt{\left(\frac{1}{f}-1\right)\frac{1}{\hat{T}}\left(1-\frac{\hat{T}}{N}\right)}$$

that is expressed in terms of the total capture estimate $\hat{T}$.

Doonan (2001) also raised the issue of the simple random sample from a finite population assumption for the observed tows. This assumption is clearly violated, because observers are assigned to vessels not individual tows. Furthermore, the mechanism for placing observers on vessels does not appear to involve randomisation, so it would be wrong to assume that the set of observed vessels is a simple random sample. A vessel is selected to be observed and observers are placed on the vessel when it is in port. We assume that every tow made by the vessel is observed until the vessel reaches port again and the observers disembark. This defines the term *observed trip* and a single vessel may have more than one observed trip in a season. A vessel may visit a port without the observers disembarking and a vessel may also be observed for part of the season and not observed for the other part. In the commercial data there is no record corresponding to trip as defined by port visits, so even if it were appropriate to consider the observed trips a simple random sample there is no sampling frame of trips available.

2.3.1.2 A predictive approach

We adopt a different approach to the calculation of the variance of $\hat{T}$ that does not involve any assumptions that either the observed tows or the observed vessels are a simple random sample.

The total number of captures for the season, T, is estimated from the observed sample by $\hat{T}$ given in Equation (1). In the predictive approach T is predicted, not estimated, because it is not a fixed finite population parameter, but an unknown random quantity. The finite population of a fishery season is not well defined because there is a complex stopping rule that determines the end of the season, which could, in some seasons, involve closing the fishery based on the estimated number of captures. Fishing success also contributes to the variation in the number of tows in the season. This, and the fact that we are trying to predict the total number of captures (which is an unknown random quantity), rather than estimate a parameter make the predictive approach attractive. Using the notation above where the first n values $y_1, y_2, \ldots, y_n$, of the commercial captures $y_1, y_2, \ldots, y_N$, represent the captures on the n observed tows and the last $N - n$ represent the captures on the unobserved tows we see that

$$T = \sum_{i=1}^{n} y_i + \sum_{i=n+1}^{N} y_i = t + \sum_{i=n+1}^{N} y_i \tag{4}$$

The prediction of T requires the prediction of the total of the unknown unobserved captures (for the $N - n$ unobserved tows) and, to do this, it is assumed that the observed sample is representative of the unobserved sample. The advantage of the predictive approach is that it is no longer necessary to make the unreasonable assumption that the observed sample is a simple random sample from some finite population. Prediction of unobserved values based on values of covariates is a common procedure for linear models; see, for example, Neter & Wasserman (1974).

Under the predictive approach the observed total is known and the $N - n$ unknowns are estimated using the estimated strike rate. Using the representativeness of the observed tows in the sense that, on average, the strike rate of the unobserved tows is the same as the average strike rate for the observed tows, Equation (4) gives

$$t + (N-n)\frac{t}{n} = \frac{N}{n}t = \hat{T}$$

as a predictor of T. To calculate the c.v. of the predictor $\hat{T}$, we need to obtain expressions for its mean and variance. The required expressions for the mean and mean square error of $\hat{T}$ are derived in Appendix A.

The assumption of representativeness of the observer tows says that the marginal distribution of the number of captures for a single tow has a mean μ and a variance σ^2 and that these are the same for every tow, whether observed or unobserved. Correlation structure between some tows can be incorporated by allowing the covariance matrix of the vector of captures $y = (y_1, y_2, \ldots, y_N)$, to have off-diagonal terms, while every entry on the diagonal is σ^2. Under this assumption, the mean of $\hat{T}$ is

$$E(\hat{T}) = \frac{N}{n}E(t) = N\mu = E(T)$$

and consequently $\hat{T}$ is an unbiased estimate of the mean total number of captures. To obtain an expression for the variance and hence the coefficient of variation we allow for the two sources of error in predicting T by $\hat{T}$. These are: the error associated with estimating the mean strike rate μ from the observer sample; and the random error of the true total number of captures in the unobserved tows. Because $\hat{T}$ is an unbiased estimate of the mean of T, the variance of $\hat{T}$ (as a predictor of T) is the mean square error of prediction

$$\mathrm{MSE}(\hat{T}) = E(\hat{T} - T)^2 = E\left(\frac{1}{f}t - T\right)^2 \tag{5}$$

Where no correlation exists between tows it follows from Equation (A1) in the Appendix A with $\kappa = 0$, that the MSE of prediction is

$$\text{MSE}(\hat{T}) = \left(\frac{1}{f} - 1\right) N\sigma^2$$

The c.v. is

$$\text{cv}(\hat{T}) = \frac{\sqrt{\text{MSE}(\hat{T})}}{\text{E}(\hat{T})} = \frac{\sigma}{N\mu}\sqrt{\left(\frac{1}{f} - 1\right)N}$$

which is the same, when the estimates of μ and σ are substituted, as the estimated c.v. for the simple random sample approach given by Equation (3). Calculation of the MSE of $\hat{T}$ is tractable even when there is correlation structure in the tow capture variables and the derivations in Appendix A enable this calculation to made for the model we are proposing.

2.4 Development of a model for sea lion captures

In reply to our initial bid for Objective 2 of ENV2000/02 project, the Ministry of Fisheries requested that we consider correlation structure for the numbers of captures between groups of tows when estimating appropriate levels of observer coverage. When correlation is present, the simple random sample/finite population approach is not practicable, nor is it justified. Even if the simple random sample relates to vessels rather than tows, it becomes impossible to express the coefficient of variation in terms of the sampling fraction of tows. Furthermore, it is a non-trivial task to obtain a suitable model that allows for correlation structure in count data as well as incorporating variation in strike rates between tows.

Before developing a model for New Zealand sea lion captures, we will first discuss sources and the nature of the variability in captures. The mean number of captures for a single tow can depend on a number of factors. These may include the density of sea lions in the area of the tow, the behaviour of sea lions at the time of day and time of year, and the fishing practices and gear used by the vessel crew. The component of the mean capture rate due to the density and behaviour of the sea lions is likely to vary both temporally and spatially over the fishery.

Given the mean capture rate for the particular tow, the number of sea lions captured can be assumed to have a Poisson distribution. Variability in the mean capture rate between tows will ensure that the observed captures have what is known as "extra-Poisson variation" or "over-dispersed Poisson variation". Over-dispersed Poisson models have made extensive appearances in the theoretical and applied literature since the late 1970s and are still an area of active research; see, for example, Cox (1983), Breslow (1984), Morton (1987), Daniels & Gatsonis (1999), and Booth et al (2003).

A common approach to modelling over-dispersion is to use a mixture distribution where the mean of the Poisson distribution is given a probability distribution. It is well known that if y has a Poisson distribution with mean η, and η is distributed according to a Gamma distribution, then the marginal distribution of y is a negative binomial distribution. The negative binomial model is often used to model over-dispersion in a Poisson model (see, for example, Morton (1987)). Unfortunately, other useful mixing distributions used in conjunction with the Poisson model do not give mixture distributions in closed form. However, if we represent the mixture by the Poisson mean scaled by a positive random variable centred on 1, it is possible to calculate the change to the variance of y brought about by the mixing distribution, even when the marginal distribution is not in closed form. We will refer to the scaling random variable as an over-dispersion effect. Any mixing distribution that has a scale invariant form can be represented this way, including the Gamma and other distributions that could be applied in this situation.

Another important contribution to variation is from the possible correlation between tows carried out by the same vessel. There are several forms of correlation that may be present. Serial correlation could result because successive tows are often carried out in close proximity and there may be a spatial variation in the mean catch rate. It could also arise when fishing practices contribute to an increased or reduced capture rate for the vessel. Doonan (2001) raised the issue of correlation between tows and its effect on the c.v. of the estimate and on the confidence intervals. Manly et al. (2002) considered serial correlation in their approach to the coverage required for estimating sea bird captures. The limited numbers of captures in the observer data for New Zealand sea lions per season would appear to preclude fitting anything more than the very simplest of correlation structure.

We use a vessel random effects correlation structure model because vessels are easily identified in both the commercial and the observer data. Because a single random effect is used for each vessel, it will be an average over the tows for the vessel of any serial correlation structure, and it will include any other vessel-related effects, such as vessel fishing practices and where and when during the season it fishes. We model the vessel random effect as the random scaling of the mean capture rate by a random variable with a value that is common to all tows by a vessel, and this results in a correlation between all tows by the same vessel. Where, in the same season, some tows by a particular vessel are observed and some are not, we will assign a single random effect to all observed tows made by the vessel and a second independent random effect to all unobserved tows made.

The partial specification of a model that encapsulates the variation between tows in capture rates and a within-vessel correlation structure is defined below. At this stage, in order to calculate the c.v. of $\hat{T}$, it is unnecessary to make any assumptions about the form of probability distribution models the vessel random effects and the over-dispersion effects have. Additional assumptions about probability models for the random scalings will be made for the process of estimating the parameters of the model. The model, which is defined in the following paragraphs, is the simplest model that satisfies our requirements of a model for estimating variance components to estimate the observer coverage. These requirements are that the model has a fixed strike rate μ for the season, accounts for variation in the strike rate for individual tows by way of a variance component, and accounts for between tow correlation structure in the form of a vessel variance component.

2.4.1 The model

Let y_{jk} denote the number of captures for tow k by vessel j. The model, described below, is a 3 level hierarchical model and is a special case of the model used by Daniels & Gatsonis (1999).

Level 1. Within tow variation. The y_{jk}, conditional on the mean capture rate η_{jk}, have independent Poisson distributions mean η_{jk}.

Level 2. Within vessel variation. The η_{jk} are given by

$$\eta_{jk} = \eta_j u_{jk}$$

where the u_{jk}, conditional on the vessel mean strike rate η_j, are independent random variables with mean 1 and variance ϕ. The u_{jk} are the over-dispersion effects.

Level 3. Between vessel variation. The η_j, are given by

$$\eta_j = \mu v_j$$

where the v_j, conditional on the overall mean strike rate μ, are independent random variables with mean 1 and variance ψ. The v_j are the vessel random effects.

Models of this form have been treated by Morton (1987) and Christiansen & Morris (1997). It follows from the model, that

$$\eta_{jk} = \mu v_j u_{jk}$$

and, taking logarithms, the random effects can be written as

$$\begin{aligned}\log(\eta_{jk}) &= \log(\mu) + \log(v_j) + \log(u_{jk}) \\ &= \beta + b_j + e_{jk}\end{aligned}$$

Consequently the model is a 3-parameter, μ, ϕ, and ψ, random effects model that falls into the class of Poisson hierarchical Generalised Linear Models (GLM) with random effects (having unspecified probability models), with the log link function; (see Lee & Nelder 1996). It differs from a Generalised Linear Mixed Model (GLMM) (see McCulloch & Searle 2001) because we do not assume that the random effects, the b_j and the e_{jk}, are normally distributed, nor do we assume that they have mean 0. The idea of constraining multiplicative random effects by making their means 1, rather than making the mean of their logarithms 0, was introduced by Lee & Nelder (1996) in their work on hierarchical GLMs.

Note that no assumptions have been made at this stage about the form of the distributions of the random scalings u_{jk} and v_j. Nevertheless, an expression can be obtained for the mean square error and consequently for the coefficient of variation of $\hat{T}$.

We need to introduce further notation. n_j is the number of tows by vessel j and M is the number of vessels involved in the season. Numbering the vessels in order so that the first m vessels are the observed vessels, it follows that

$$N = \sum_{j=1}^{M} n_j, \quad n = \sum_{j=1}^{m} n_j, \quad T = \sum_{j=1}^{M} t_j, \quad t = \sum_{j=1}^{m} t_j$$

where

$$t_j = \sum_{k=1}^{n_j} y_{jk}$$

is the total captures for all tows by vessel j. Recall that the same fishing vessel will be counted in both the observed and in the unobserved sets of vessels if, during the season, some but not all of its tows were observed.

Equation (A4) in Appendix A gives the MSE of $\hat{T}$ as

$$\begin{aligned}\mathrm{MSE}(\hat{T}) = &\left(\frac{1}{f}-1\right)N\mu\left(1+\left((1+\phi)(1+\psi)-1\right)\mu\right) \\ &+(1-f)^2\left(\frac{1}{n^2}\sum_{j=1}^{m}\left(n_j^2-n_j\right)+\frac{1}{(N-n)^2}\sum_{j=m+1}^{M}\left(n_j^2-n_j\right)\right)\psi(N\mu)^2 \qquad (6)\end{aligned}$$

The squared coefficient of variation is then

$$\mathrm{cv}^2\left(\hat{T}\right)=\frac{\mathrm{MSE}\left(\hat{T}\right)}{\mathrm{E}\left(\hat{T}\right)^2}$$

$$=\frac{1}{N\mu}\left(\frac{1}{f}-1\right)\left(1+\left((1+\phi)(1+\psi)-1\right)\mu\right)$$

$$+(1-f)^2\left(\frac{1}{n^2}\sum_{j=1}^{m}\left(n_j^{\,2}-n_j\right)+\frac{1}{(N-n)^2}\sum_{j=m+1}^{M}\left(n_j^{\,2}-n_j\right)\right)\psi \qquad (7)$$

since $\mathrm{E}\left(\hat{T}\right)=N\mu$.

At the end of the season the tow numbers per vessel and sampling fraction will be known and all that is needed to estimate the c.v. of $\hat{T}$ is $\hat{T}$ itself and the estimates of μ, ϕ, and ψ. The square c.v. is estimated by

$$\widehat{\mathrm{cv}^2\left(\hat{T}\right)}=\frac{1}{\hat{T}}\left(\frac{1-f}{f}\right)\left[1+\left(\left(1+\hat{\phi}\right)\left(1+\hat{\psi}\right)-1\right)\hat{\mu}\right]$$

$$+(1-f)^2\left(\frac{1}{n^2}\sum_{j=1}^{m}\left(n_j^{\,2}-n_j\right)+\frac{1}{(N-n)^2}\sum_{j=m+1}^{M}\left(n_j^{\,2}-n_j\right)\right)\hat{\psi} \qquad (8)$$

using $\hat{T}$ as the estimate of $N\mu$, $\hat{\mu}$ for the estimated strike rate, and denoting by $\hat{\phi}$ and $\hat{\psi}$ whatever estimates are used for the variance components ϕ and ψ respectively.

It is more difficult to determine the sampling fraction because there are more unknowns. For any future season, the estimate of the mean strike rate, μ, is unavailable, the number of commercial tows, N, is unknown, as are the numbers of tows by individual vessels, observed and unobserved. The estimated strike rate and, more especially, N vary considerably from season to season (Table 1). The standard method of using values from the previous season to calculate coverage required can therefore be quite misleading because the answer will vary considerably with N and μ. The strong dependence of the coefficient of variation on the mean total number of all captures, $N\mu$, apparent from Equation (7), enables us to describe the coverage required in terms of this variable, to a great extent. Rather than producing graphs of the coverage required for a range of N and a range of μ, the coverage required can essentially be plotted against the estimated total number of captures. For example, if you estimate the total number of captures to be 70, then you will need a coverage of about 21% to achieve a coefficient of variation of 30%.

The covariance component in (8) contains the expressions

$$\frac{1}{n^2}\sum_{j=1}^{m}\left(n_j^{\,2}-n_j\right) \text{ and } \frac{1}{(N-n)^2}\sum_{j=m+1}^{M}\left(n_j^{\,2}-n_j\right).$$

Note that the first expression above represents the proportion of possible ordered pairs of tows for the m observed vessels relative to the number of pairs if all n tows had been made by a single vessel. Similarly, the second expression is the proportion of ordered pairs for the $M-m$ unobserved vessels. The number of ordered pairs of tows within each vessel is important in the correlated model because each pair of tows by the same vessel contributes ψ to the total variance. The values of these expressions relate to the numbers of vessels that are likely to fish in the fishery, and if that does not vary much from season to season the values of the expressions will be reasonably static. With the exception of the unusual 2001 season, when almost all tows were observed, there has been little variation in their values from 1998 on (Table 2). The sum of the two proportions varied between 20.9% and 24.7% for the four years when the observer coverage fraction varied between and 23.0% and 38.8% (Table3).

To calculate the coverage fraction required, we need to solve the following cubic equation for f

$$c^2 = \left(\frac{1}{f} - 1\right)\frac{1}{N\mu}A + \left(1 - f\right)^2 B \tag{9}$$

where c is the specified coefficient of variation,

$$A = 1 + \left(\left(1+\phi\right)\left(1+\psi\right) - 1\right)\mu$$

and

$$B = \left(\frac{1}{n}\left(\frac{\sum_{j=1}^{m} n_j^2}{n} - 1\right) + \frac{1}{N-n}\left(\frac{\sum_{j=m+1}^{M} n_j^2}{N-n} - 1\right)\right)\psi$$

A is the contribution to the c.v. from the Poisson error variance plus over-dispersion variance plus the vessel random effects variance, and B is the contribution from correlation between tows within each vessel.

Rearranging Equation (9) and substituting the estimates for the parameters gives the cubic equation that is solved to obtain the observer coverage required for different values of $\hat{T}$.

$$\hat{B}f\left(1-f\right)^2 + \left(c^2\hat{T} + \hat{A} - \hat{B}\right)f - \hat{A} = 0 \tag{10}$$

where $\hat{A}$ and $\hat{B}$ are estimates of A and B respectively and $\hat{T}$ is the estimate of $N\mu$.

The next subsection addresses the methods for estimating ϕ and ψ so that suitable estimates of A and B, $\hat{A}$ and $\hat{B}$, can be found and used to calculate sampling fractions as solutions to the cubic equation (10) for different values of $\hat{T}$.

2.5 Estimation of the components of variance

Different methods are proposed in the large literature for fitting mixed Poisson generalised linear models. However, there is no real consensus as to which method is best. Most concentrate on the problem of estimating the fixed effects coefficients. The accuracy of the estimation of any random effects is only secondary and relates only to the construction of approximate confidence intervals or to other approximate inferences. To estimate coverage required, we are primarily concerned with obtaining good estimates of the components of variance associated with the random effects, a much more difficult problem. Methods that provide sound estimates of fixed effects are often not satisfactory for estimating random effects parameters. The difficulties of estimating components of variance in the Generalised Linear Model setting were addressed by Tsutakawa (1988), Pauler et al. (1999), Daniels & Kass (1999), and Lee & Nelder (2001).

We decided to use Bayesian methods for fitting the model for several reasons. Frequentist-based methods, which include generalised estimating equations, penalised likelihood, and empirical Bayes methods are primarily based on approximations to the likelihood, which is unavailable in closed form. Maximum likelihood estimates of variances in Poisson random effects models are well known to be problematic, and Aragon et al. (1992) showed that infinite maximum likelihood estimates of random effects parameters are possible. There appears to be no general agreement as to which methods are appropriate in different situations, though Lee & Nelder (2001) showed via simulations that their method greatly reduces the estimation of variance components bias that exists in the methods of Schall (1991) and Breslaw & Clayton (1993). Different methods can give widely differing estimates of the variance components, even when both methods give estimates of fixed effects that agree to a great extent. Booth et al. (2003) compared two methods that yield very different estimates of the random effects parameter for the same data.

The Bayesian approach allows more flexibility in the models that can be fitted (Daniels & Gatsonis 1999) and the availability of the program WinBUGS (Gilks et al. 1994) for fitting a variety of Bayesian models makes the approach attractive. The approach also works especially well for predictive models, as all sources of uncertainty are accounted for if a full Bayesian analysis is carried out.

To implement a Bayesian approach to estimation of the random effect variance, we need to assign probability distributions to the overdispersion and vessel random effects and prior distributions to the unknown parameters.

For the overdispersion effects (level 2 of the model) we will use the Gamma distribution, so that the u_{jk} are independent Gamma random variables with shape parameter = θ_1 and rate parameter = θ_1. This ensures the mean of all the overdispersion effects are is 1 and the variance is

$$\phi = \frac{1}{\theta_2}$$

Using the Gamma distribution is equivalent to the assumption that the distributions of the y_{jk}, conditional on the vessel means μ_j, are independent negative binomial random variables with means μ_j and common heterogeneity parameter θ_1.

The assignment of a distribution to the vessel random effects, together with the assignment of a prior distribution to any fixed parameters, requires care for two reasons. In practice, it is difficult to check any distributional assumption for the random effects without huge amounts of data. The second problem concerns the prior on the variance of the random effects distribution. In a Bayesian approach without strong prior information, it is common to use a non-informative prior that may be improper in the sense that the integral of its density is infinite. Natarajan & Kass (2000) have shown that for GLMMs an improper prior on the variance of the random effects always gives an improper joint posterior distribution for the parameters. A consequence of this is that estimates of the random effects parameters are unreliable because the Markov Chain Monte Carlo (MCMC) method used for fitting does not converge. Maximum likelihood methods, which can be related to Bayesian methods with uniform improper priors, do not escape the consequences either and can yield an unreliable estimate of the random effects variance. In some situations the maximum likelihood estimate is at infinity (Aragon et al. 1992).

Because flexible correlation structure can be incorporated, it is common in the literature to assume that the logarithms of the vessel effects (as we define them) have a normal distribution with mean 0. This is the assumption that the model is a GLMM and is equivalent to assuming a lognormal distribution for the v_j. However we want to allow a thick tail in the distribution of the v_j which gives larger probabilities of a large value for a vessel effect than the lognormal distribution does. With this in mind we have chosen to use a Gamma distribution for the vessel random effects. Thus we have assumed that the v_j are independent Gamma random variables with shape parameter = θ_2 and rate parameter = θ_2. Again, this ensures that all the vessel random effects have mean 1 and variance

$$\psi = \frac{1}{\theta_2}$$

Since θ_1 and θ_2 are the reciprocals of the variances they can be described as precision parameters.

The priors for the various parameters of the distributions of random effects need to be specified. If an unsuitable prior is chosen, the posterior distribution may be improper (having an infinite integral) or close to being improper. Some non-informative priors have this property, and other standard priors have proved unsatisfactory. Christiansen & Morris (1997) and Daniels & Kass (1999) suggested the use of a "uniform shrinkage prior" for the precision parameter where a Gamma prior is used for the random effects. This type of prior distribution is proper and produce sound estimates of the random effects variance parameters in simulations carried out by Natarajan & Kass (2000) on a logit model. Nevertheless, the prior on the precision parameter is diffuse because it has an infinite mean, as has the corresponding prior induced for variance.

The shrinkage referred to here is the shrinkage of the predicted values of the random effects towards 1. With no shrinking of the predicted random effects towards 1, very small values will be assigned to random effects for those vessels that had no captures and large values will be assigned to those vessels that had well above average capture rates. This type of over-fitting occurs because of the nature of Poisson responses. With over-fitting of the vessel random effects the estimate of the variance of these effects will be too high. Without compensating for over-fitting of the vessel effects, we are ignoring the possibility that, more often than not, a vessel with an observed zero capture rate will have an under-predicted random effect, and a vessel with a well above average observed capture rate will have an over-predicted random effect. Daniels & Kass (1999) gave the argument that leads to the derivation of the density for the prior on a precision parameter θ, which is equivalent to a uniform prior on the amount of shrinkage of the predicted random effects towards 1. This density is

$$f(\theta)=\frac{\nu}{(\nu+\theta)^2}, \theta>0, \tag{11}$$

where ν is a hyper-parameter that is the median of the prior distribution. The smaller ν is, the more diffuse the prior is and the smaller the degree of shrinkage towards 1, that occurs in the predicted random effects. This prior is used for the precision parameters for both the over-dispersion and the vessel random effects.

The data used for fitting the model using the WinBUGS program comprised the observed tows from the 1998 to the 2002 squid seasons in SQU 6T. These years were selected because they represent the current levels of activity in terms of the numbers of tows in the season and the current regime of observer coverage. From the 1999 season onwards, SLEDs were used on some tows. All tows where the SLED was present with the cover open were excluded from the analysis. Thus 1667 tows are in the data set for fitting the model, and for these tows 100 sea lions were captured.

Because the data cover five different years, the model for estimating the random effects variances includes a different mean capture rate for each year. A hierarchical normal prior structure was used for the logarithms of the year capture rates with a diffuse normal hyper-prior on the mean and a diffuse Gamma(0.001, 0.001) hyper-prior for the variance. Any vessel that fished in SQU 6T in more than one year was assigned a different random effect for each year.

Because we require only estimates of the over-dispersion and random effects variances, the year means are nuisance parameters for our purposes.

It is assumed that the variances of the random effects and over-dispersion effects do not vary over the five years of the data used in fitting the model.

3. RESULTS

3.1 Representativeness of coverage

To investigate the representativeness of coverage, data from all 11 seasons from 1992 to 2002 are used. Start positions of the commercial tows and the observer tows are shown in Figure 1. Coordinates of the latitude and longitude in the commercial data are truncated to the next 0.1° and this would result in a grid pattern of commercial tow positions in Figure 1. We added random values between 0.0° and 0.1° to all commercial coordinates to break up the grid pattern in this plot. While it is difficult to judge the density of effort from Figure 1, in most years the observer coverage follows the commercial coverage.

Density plots of observer tows and commercial tows against latitude, longitude, and date are presented in Figures 2–7. These show that the temporal and spatial representativeness of the observer coverage is good, especially in recent years. From the 1998 season a coverage level of at least 20% of commercial tows was targeted in the fishery and the increased emphasis on representativeness of the observer coverage is apparent in Figures 5–7. In 2001, coverage was 98.5%; however small differences between the commercial and observed densities by latitude and longitude are apparent in Figure 6. These are due to the coarse truncation towards 0 to the next 0.1° for the coordinates in all the commercial data. The effects of truncation has been only partially compensated for by adding 0.05° to the latitudes and longitudes when making the density plots.

A breakdown of the numbers of commercial and observed tows and percentage coverage by nation for the 11 seasons is given in Table 3. Coverage is variable by nation over the different seasons. However, coverage of the principal nation group, the Commonwealth of Independent States (CIS) that carried out 66.7% of all commercial tows in the fishery, is very similar to the coverage of all tows for each season. The numbers of tows by year for the commercial fleet including those vessels that had observers present and the corresponding percentage coverage for each fishing season and for all seasons combined are given in Table 4. The table also gives the numbers of vessels involved in the fishery and their coverage percentage.

Overall, the observer coverage represents the commercial effort well in the SQU 6T fishery, for the characteristics investigated here (temporal, spatial, vessel and nationality).

3.2 Coverage required to estimate the total captures with a specified coefficient of variation

Fitting the Bayesian model, using the program WinBUGS, to estimate the components of variance involved three steps and used the data for the seasons 1998 to 2002. These data exclude all tows where a SLED was present with the cover open because the model takes no account of any effect of an open SLED on the mean capture rate. Firstly, attempts were made to fit the full model with over-dispersion and vessel random effects components. This proved unsuccessful because there was little evidence of convergence of the Markov Chain Monte Carlo (MCMC) sequence that BUGS produced. Additional attempts were made to fit the model using a purpose built Gibbs' sampling program (see, for example, Gamerman (1997, chapter 5) in the statistical package R (Ihaka & Gentleman 1996). Convergence was never attained despite trying numerous variations on lengths of the chains, numbers of iterations for the burnin of the chain, prior distributions on the parameters and distributions on the over-dispersion random effects and vessel random effects.

The frequencies of the observed numbers of captures are compared with the expected frequencies (Table 5) if the distribution of the number of captures is Poisson with mean equal to the strike rate for the year (given in Table 1). It is clear that for the seasons 1998–2001 (and for most of the earlier seasons) the Poisson model has an extremely good fit, and this explains why fitting a model with both over-dispersion effects and random effects was not successful. Only 2002, when there was one tow where four sea lions were captured, and 1997 show small signs of over-dispersion. There is simply no evidence in the data of over-dispersion. This may be because the sample sizes for each year are not large enough. While over-dispersion may be occurring because of different capture rates for different tows, the capture rates are so small that there are insufficient data to detect it. Therefore it did not appear to be possible to fit a model that had both over-dispersion effects and random effects.

Consequently we fitted the Poisson model with vessel random effects but no over-dispersion effects. The model has six parameters in all, five mean capture rates (one for each of the years included in the data) and the precision parameter of the vessel random effects. The prior on the vessel random effects precision parameter, θ_2, is the prior given by the density in Equation (11). A value for the hyperparameter ν is required and the assignment of a value is difficult. This parameter determines the degree of shrinkage of the random effects towards 1; the smaller ν, the less the shrinkage. There appears to be insufficient additional information in the data to help assign a value to ν because a run under WinBUGS with a non-informative prior assigned to ν did not converge. The mean, median and the 95% credible interval for the posterior distribution of the variance of the vessel random effects are given in Table 6. It is clear that the variance increases as ν decreases; however the rate of increase reduces as ν gets smaller. It was decided to use $\nu = 0.05$ because this represents a low level of informativeness in the prior on the variance.

A run of WinBUGS using 3 chains, each with different starting values and each with a burn-in of 5000 was carried out. After burn-in, each chain was run for 10 000 iterations retaining every 5th iteration. Convergence was checked by comparing the characteristics of the three chains in Figure 8 and by the Rhat statistic in Table 7. The near coincidence of the medians and intervals of the 3 chains and the values of Rhat close to 1 suggest that the chains have converged. The time series plots of the recorded values of the chains are given in Figure 9 and these appear stationary, which also suggests that convergence has been reached.

As a check on the fit of the model, we plot the residuals against the predicted values of the strike rates. The predicted strike rates include predicted values of the vessel effects. The results are plotted in Figure 10. Panel (a) plots the raw residuals, which are in bands because the number of captures takes only values 0, 1, 2, and in one tow 4. Because interpretation is difficult we have plotted the randomised residuals, using the method of Dunn & Smyth (1996), in panel (b). This method spreads out the residuals over a continuum and makes interpretation of discrete model fits easier. Each vertical band in panel (b) represents the residuals for the tows from a single vessel. There does not appear to be any problem with the fit of the model based on the residual plots.

Figure 11 plots the predicted vessel random effects against year. Our model assumes a common variance for all years and there is some evidence that the variance of the random effects differ by year. It would be possible to enhance the model to allow for different variances for different years, possibly by using a hierarchical approach where the variance for each year is chosen from a hyper-distribution. Little is likely to be gained from fitting the more complex model because there are so few captures per year, and also because we are interested in an overall vessel random effects variance to be applied to future seasons.

To obtain the plots of coverage required as a function of the predicted total number of captures $\hat{T}$, we use Equation (10) and obtain estimates of the parameters using the model. We are estimating the variance of the over-dispersion effects, ϕ, to be 0 and therefore we require only the estimate of the variance of the vessel effects, ψ, and the sum of the proportion of ordered pairs of tows by the observed and unobserved vessels to estimate A and B. The posterior median is used as the estimate of ψ for two reasons. Firstly, the posterior distribution of the variance of the vessel random effects is very skewed to the right and the posterior mean might give an inflated estimate. Secondly, the solution of the cubic equation is a non-linear function of the estimate of ψ. When the posterior median is used as the estimate of ψ, the estimated coverage proportions will be median values.

The posterior median of ψ is $\hat{\psi}$ = 0.249 (Table 7). This estimate of the variance of the vessel random effects corresponds to a very small correlation between pairs of tows by the same vessel. If the mean strike rate is 0.05, then the correlation is 0.0124, and if the strike rate is 0.10 the correlation is 0.0244. Nevertheless, the within-vessel correlation makes a significant contribution to the c.v. of the predicted total captures.

In the last five seasons the sum of the proportions of the ordered pairs of tows for each season has been reasonably constant, apart from the 2001 season when almost all tows were observed (Table 2). The large value for this season arises from the fact that only five vessels were unobserved and these made only nine tows in total. As an estimate of this proportion for use in the coverage required calculation, we use the average of the seasons 1998–2000 and 2002. This is 23.5%. The estimate of B is then

$$\hat{B} = 0.235 \times 0.249 = 0.0585$$

The quantity A includes the strike rate, μ, which is unknown. To show that it has little effect on the value of A, we calculate two estimates of A, one with $\mu = 0.05$ and one with $\mu = 0.10$. Because $\hat{\phi} = 0$,

$$\hat{A} = 1 + \hat{\psi}\mu$$

and the estimates of A are:

μ	$\hat{A}$
0.05	1.013
0.10	1.025

The results of solving the cubic equation, Equation (10), for different values of $\hat{T}$ using the two values for $\hat{A}$ are plotted in Figure 12: the two curves are almost the same. Reading from Figure 12, for example, we see that to attain an estimated c.v. of 30% for a predicted total number of captures of 75, we require the coverage to be just over 20%. The curves depend on the estimate of the vessel random effects variance, ψ. The coverage proportions required for c.v.s of 10%, 20%, and 30% for predicted value of T as multiples of 10 in the range 50 to 100, under the two scenarios of the mean capture rate μ equal to 0.05 and 0.10 are given in Table 8.

As a sensitivity check on the effect of the estimate ψ on the coverage required, we carried out a BUGS run with the value of the median of the prior on the vessel random effects of 0.5 (rather than 0.05). For this value there is more shrinkage of the predicted vessel effects towards 1 and it produced an estimate of $\hat{\psi}$ = 0.192 (see Table 6). Figure 13 is a plot of the coverage required curves similar to those in Figure 8 using this estimate. With the reduction in the within-vessel correlation there is a reduction in the coverage required compared with that displayed in Figure 8. Reading from Figure 13, for a predicted total capture of 75 animals the coverage required to attain a c.v. of 30% is now about 18%.

Table 1 includes estimates of the total captures for each year together with estimates of the c.v. The c.v. estimates were obtained from Equation (8) using the estimate $\hat{\psi}$ = 0.249.

4. DISCUSSION

In our approach to estimating coverage required to attain a specified coefficient of variation, we have made a number of changes from what has been done in the past. We have adopted a predictive approach to calculating the variance of the estimator of the total captures through the predictive mean square error. This approach does not assume that the observed tows form a simple random sample from all the commercial tows, and yet still incorporates both the uncertainty about the estimate of the strike rate and the uncertainty about the captures for the unobserved tows.

Past work to obtain coverage proportion required has used bootstrap estimates of the variance of the total number of captures from any one year. The main uncertainties from one year to the next are N, the total number tows in the fishery, and μ, the strike rate for that year. We have shown that the sampling fraction required can be expressed in terms of the estimate of the mean number of total captures in the fishery and therefore almost all the uncertainty about future is subsumed in this quantity.

A vessel grouping of tows comprises the tows made by a single vessel in a single year. There are 54 vessel groups in the 1998–2002 data, with 11 vessels observed every year except 1998. The data involve 29 actual vessels where 12 vessels were observed for only one of the years, 12 vessels were observed for 2 of the years, 2 vessels were observed in 3 of the years and 3 vessels were observed in 4 of the 5 years. It may have been possible to fit a more complex hierarchical model that allowed for differences in the random effects distributions, between the vessels grouped by nation, for example. However, the aim of the analysis was to obtain an estimate of the "typical" random effects variance for use in estimating coverage required, and this combined with the difficulties of fitting a more complex model suggested that the extra complexity was not warranted.

The form of Equation (A4), in Appendix A, for the coefficient of variation highlights the inefficiency of the estimator $\hat{T}$ when there are correlations present. Rearranging Equation (9) the square c.v. of $\hat{T}$ can be written as

$$c^2 = (1-f)\frac{1}{n\mu}A + (1-f)^2 B \qquad (12)$$

where

$$B = \left(\frac{1}{n}\left(\frac{\sum_{j=1}^{m} n_j^2}{n} - 1\right) + \frac{1}{N-n}\left(\frac{\sum_{j=m+1}^{M} n_j^2}{N-n} - 1\right)\right)\psi$$

B is the contribution to the c.v.^{2} from the within vessel correlation and unlike the first part of Equation (12), B does not go to 0 as the observer sample size, n, gets large. A consequence of this is that, no matter how large the observer sample is, a sampling proportion of at least

$$1 - \frac{c}{\sqrt{B}}$$

is required to achieve a specified c.v., c. Using our estimates, this bound is less than 0 for $c = 30\%$ but for $c = 20\%$ and 10% the bounds are 17.3% and 58.7% respectively. The existence of these bounds is suggested by the shape of the curves in Figure 8.

Finally it is important to highlight the paucity of data that are available for estimating important quantities in this fishery. Over the 5 years from 1998 to 2002, 1667 tows have been observed and yet it is very difficult to estimate the vessel random effects variance and we are unable to estimate an over-dispersion variance. One hundred captures were observed over the 5 years and this means that there are typically about 20 captures from which to estimate the year's mean capture rate. If no captures had been made, then very little could be said about capture rate overall, except perhaps that it was below a certain value with 95% confidence, and obviously nothing could be said about any differences between capture rates for the different years. In count data the sample size is relevant only for determining the standard errors of estimates through the expected number of captures in the sample. This is the product of the sample size and the capture rate. Therefore, effectively, the estimated standard errors of the yearly capture rates depend on the total number of captures for the season through the sampling fraction. By this argument the effective sample size for capture data is the number of captures not the number of tows. It is a nice irony that the more effective any mitigation practice is for the reduction of sea lion captures the less certain we are about the degree of their effectiveness.

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Table 1: Numbers of tows in the observed and commercial data sets used in the estimation of coverage analysis together with numbers of captures of New Zealand sea lions and strike for the observed tows. Commercial and observed tows that had open SLEDs (which occurred only in the 2001 and 2002 seasons) are excluded from the data used for this purpose. Also included in the table are the predicted total New Zealand sea lion captures for the commercial fishery (excluding tows with open SLEDs) as well as the estimated c.v. obtained using the random vessel effects model. These estimates are not official estimates.

	Observed			Commercial		Predicted	
Year	Number of tows	Captures	Strike rate (%)	Number of tows	Coverage (%)	total captures	c.v. (%)
1992	218	8	3.7	2 154	10.1	79	40.1
1993	197	5	2.5	707	27.9	18	43.3
1994	433	4	0.9	4 677	9.3	43	52.6
1995	286	8	2.8	4 005	7.1	112	43.0
1996	555	13	2.3	4 460	12.4	104	31.5
1997	731	29	4.0	3 710	19.7	147	21.9
1998	337	15	4.5	1 463	23.0	65	28.8
1999	156	5	3.2	402	38.8	13	38.6
2000	438	25	5.7	1 207	36.3	69	22.0
2001	298	33	11.1	307	97.1	34	3.2
2002	438	22	5.0	1 523	28.8	76	24.9

Table 2: Numbers of observed and unobserved tows and the proportions of all pairs of tows that occur within the same vessel for each year. Also included are the numbers of vessels in the SQU 6T fishery that were observed and the numbers that were unobserved. The data used for this table excludes all tows that had open SLEDs.

	Number of tows		Number of vessels		Proportion of pairs of tows that are within vessel (%)		
Year	Observed	Unobserved	Observed	Unobserved	Observed	Unobserved	Sum
1992	218	1 936	7	44	20.3	3.4	23.7
1993	197	510	9	34	26.0	6.7	32.8
1994	433	4 244	7	41	21.1	2.9	24.0
1995	286	3 719	7	48	29.1	2.5	31.6
1996	555	3 905	9	52	13.9	2.6	16.6
1997	731	2 979	14	40	9.4	3.0	12.5
1998	337	1 126	10	31	15.1	5.8	20.9
1999	156	246	11	32	20.8	6.6	27.4
2000	438	769	11	21	16.6	5.8	22.4
2001	298	9	11	5	19.9	24.7	44.5
2002	438	1 085	11	23	16.5	6.7	23.1

Table 3: Observer coverage by nationality of vessel. The number of commercial tows (Com.) and percentage covered (Cov.) by the observer program is shown for each nationality and for each of the seasons. The total coverage for the combined seasons is also given. CIS denotes the Commonwealth of Independent States, formerly republics within the USSR.

	China		CIS		Japan		Korea		NZ		Poland	
	Com.	Cov(%)	Com.	Cov(%)	Com.	Cov(%)	Com.	Cov(%)	Com.	Cov(%)	Com.	Cov(%)
1992			1 772	9.1	145	36.6	208	1.9	29	0		
1993			617	30.5	34	0	52	17.3	4	0		
1994			3 222	10.2	403	14.1	770	6.0	19	0	263	0
1995	106	98.1	2 579	6.9	299	1.0	676	0.3	80	0	265	0
1996			3 466	12.3	65	0	579	0	3	0	347	36.6
1997	224	27.2	1 772	24.5	57	0	1 209	14.4	71	7.0	377	15.1
1998			1 137	23.4			244	27.9	14	21.4	68	0
1999	2	0	297	42.8	3	0	83	34.9			17	0
2000			622	60.3	2	0	450	14.0			133	0
2001			345	98.0	14	92.9	153	99.3	6	100	67	100
2002			851	43.1	69	71.0%	251	34.3	241	0	236	25.8
Total	332	49.7	16 680	19.1	1091	16.0	4 675	13.5	467	3.0	1 773	17.6

Table 4: Numbers and observer coverage of vessels, trips, and tows for 1992 to 2002 in the SQU 6T fishery. The values in brackets are for the data where all observed tows using an open SLED are excluded. *In 2001 and 2002, 278 and 125 observed tows, respectively, had open SLEDs.* In 2000, the SLED was used on some tows but all had the cover tied down.

Year	Commercial		Observed			Observer coverage	
	vessels	tows	vessels	trips	tows	vessels	tows
1992	49	2 154	7	7	218	14.3	10.2
1993	39	707	9	11	197	23.1	27.9
1994	43	4 677	7	8	433	16.3	9.3
1995	50	4 005	7	7	286	14.0	7.1
1996	52	4 460	9	9	555	17.3	12.4
1997	42	3 710	14	14	731	33.3	19.7
1998	36	1 463	10	11	337	27.8	23.0
1999	35	402	11	11	156	31.4	38.8
2000	26	1 207	11	11	438	42.3	36.3
2001	23	585	(11) 23	(15) 29	(298) 576	100.0	(97.1) 98.5
2002	28	1 648	(11) 12	(13) 15	(438) 563	42.9	(28.8) 34.2
Total	129	25 018	(61) 63	(117) 133	(4 087) 4 490	48.8	(16.6) 18.0

Table 5: Frequencies of tows that caught 0, 1, 2, or 3 or more New Zealand sea lions by year. The columns headed Observed are the actual frequencies observed and the columns headed Expected are the expected frequencies by year assuming that the number of captures followed a Poisson distribution model with mean given by the observed strike rate for that year, obtained from Table 1.

	Observed Captures per tow				Expected Captures per tow			
Year	0	1	2	3+	0	1	2	3+
1992	211	6	1		210.1	7.7	0.14	0.00
1993	192	5			192.1	4.9	0.06	0.00
1994	430	2	1		429.0	4.0	0.02	0.00
1995	278	8			278.1	7.8	0.11	0.00
1996	543	11	1		542.2	12.7	0.15	0.00
1997	706	21	4		702.6	27.9	0.55	0.01
1998	322	15			322.3	14.3	0.32	0.00
1999	151	5			151.1	4.8	0.08	0.00
2000	414	23	1		413.7	23.6	0.67	0.01
2001	268	27	3		266.8	29.5	1.64	0.06
2002	420	16	1	1	416.5	20.9	0.53	0.01

Table 6: Mean, median and 95% credibility interval for the posterior distribution of the variance of the vessel random effects for different values of the hyperparameter ν in the prior on the random effects precision parameter θ_2.

ν	mean	2.5%	50%	97.5%
0.01	0.315	0.026	0.260	0.888
0.05	0.302	0.026	0.249	0.891
0.10	0.275	0.023	0.219	0.798
0.50	0.246	0.012	0.192	0.787
1.00	0.194	0.010	0.163	0.603
2.00	0.186	0.008	0.151	0.581

Table 7: The mean, standard deviation and percentiles of the posterior distribution of the parameters and the expected deviance obtained from the Markov Chain Monte Carlo sample using the package BUGS. Rhat is the potential scale reduction factor which measures convergence of the chain (at convergence, Rhat = 1) and n.eff is a measure of effective sample size. The mu parameters are the strike rates for the seasons and var.re is the variance of all the vessel random effects.

parameter	mean	sd	2.5%	25%	50%	75%	97.5%	Rhat	n.eff
mu.1998	0.046	0.016	0.022	0.035	0.043	0.054	0.084	1.000	6000
mu.1999	0.032	0.017	0.009	0.020	0.029	0.041	0.073	1.000	6000
mu.2000	0.071	0.024	0.039	0.055	0.067	0.081	0.129	1.001	4000
mu.2001	0.115	0.033	0.065	0.093	0.111	0.132	0.191	1.001	2800
mu.2002	0.052	0.015	0.028	0.041	0.050	0.060	0.087	1.001	6000
var.re	0.302	0.231	0.026	0.132	0.249	0.413	0.891	1.008	730
deviance	751.7	9.156	733.7	745.5	751.8	758.4	768.8	1.002	1100

Table 8: Percentage coverage required to attain c.v.s of 10%, 20%, and 30% when predicted values of the total captures are 50, 60, 70, 80, 90, and 100. Although the differences are only small, sets of values of the coverage required are given where the mean strike rate is 5% and 10%.

Strike rate	Coef. of variation (%)	Predicted total captures					
		50	60	70	80	90	100
0.05	10	75.6	73.8	72.4	71.2	70.2	69.3
	20	46.5	43.9	41.8	40.0	38.6	37.3
	30	25.9	23.3	21.2	19.5	18.1	16.9
0.10	10	75.8	73.9	72.5	71.3	70.3	69.4
	20	46.7	44.1	41.9	40.2	38.7	37.5
	30	26.1	23.5	21.4	19.7	18.3	17.1

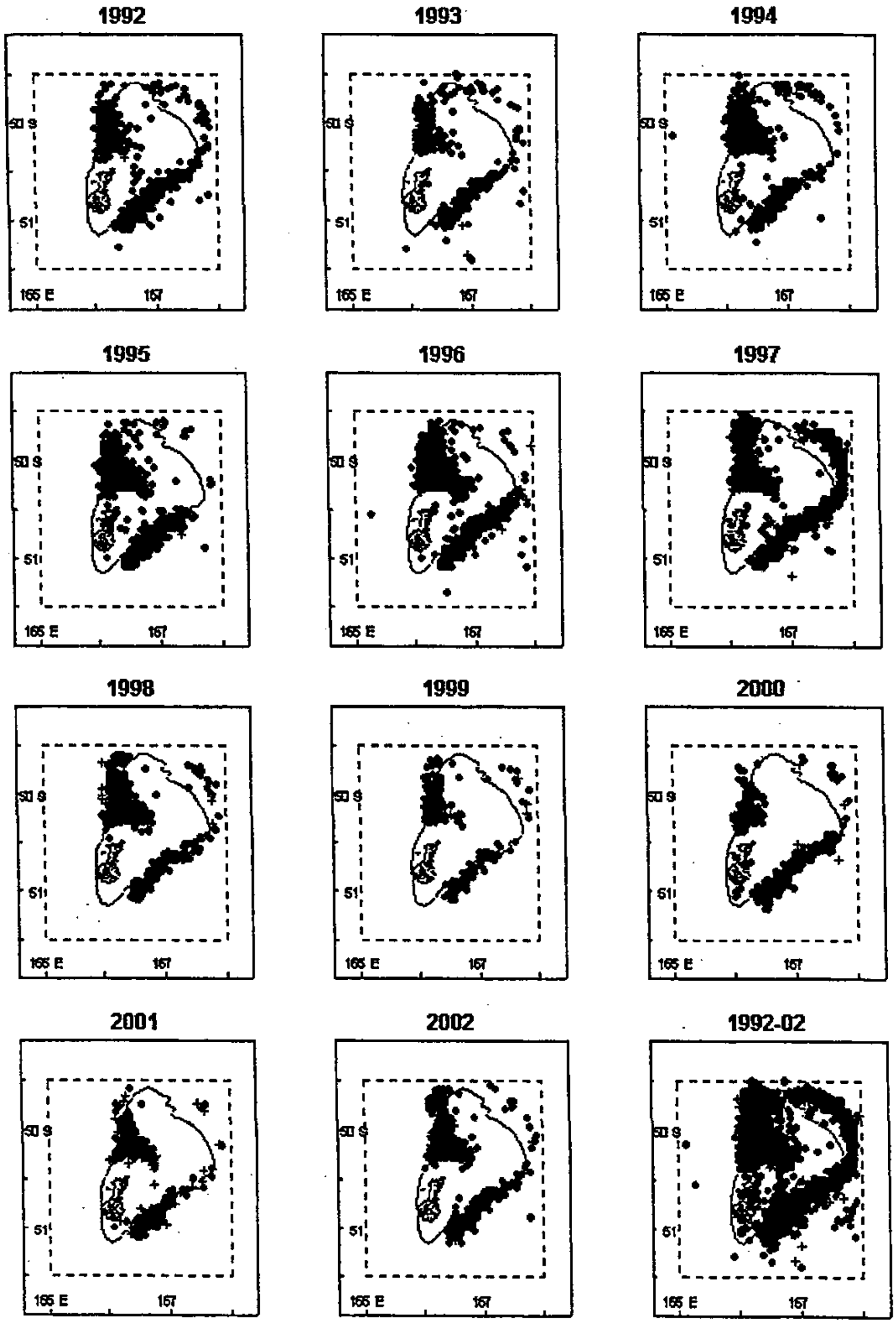

Figure 1: Plots of start positions of observed tows (+) and commercial tows (•) by year. The bottom right panel combines all years. The Auckland Islands, the 200 m depth contour, and the boundary of the SQU 6T area are included. In the original commercial data the coordinates of the tows were truncated to 0.1°. Random positional components have been added to each coordinate to allow for this and to prevent a large number of points coinciding in the plot.

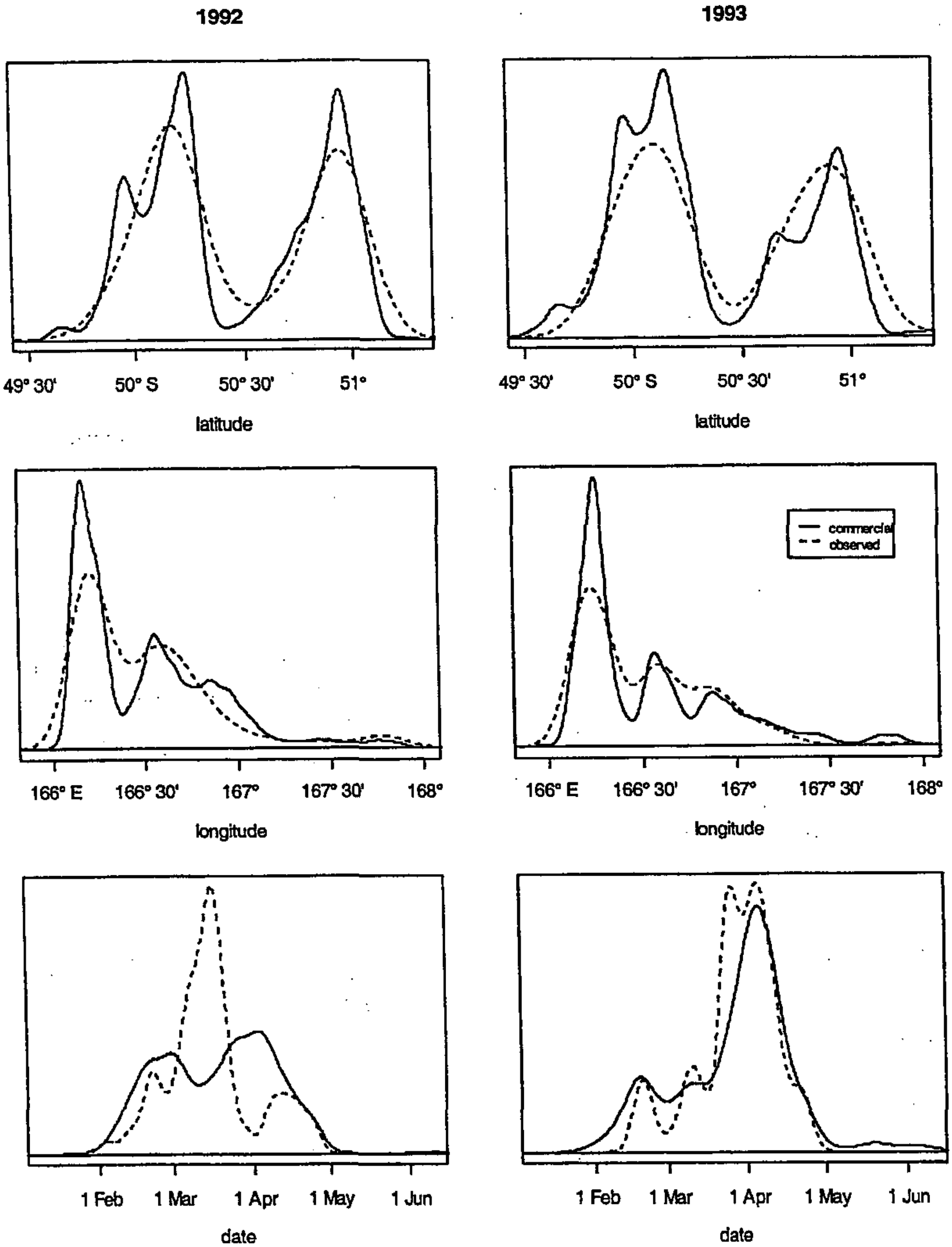

Figure 2: Density plots of observer coverage against latitude, longitude, and day of year for 1992 and 1993 seasons.

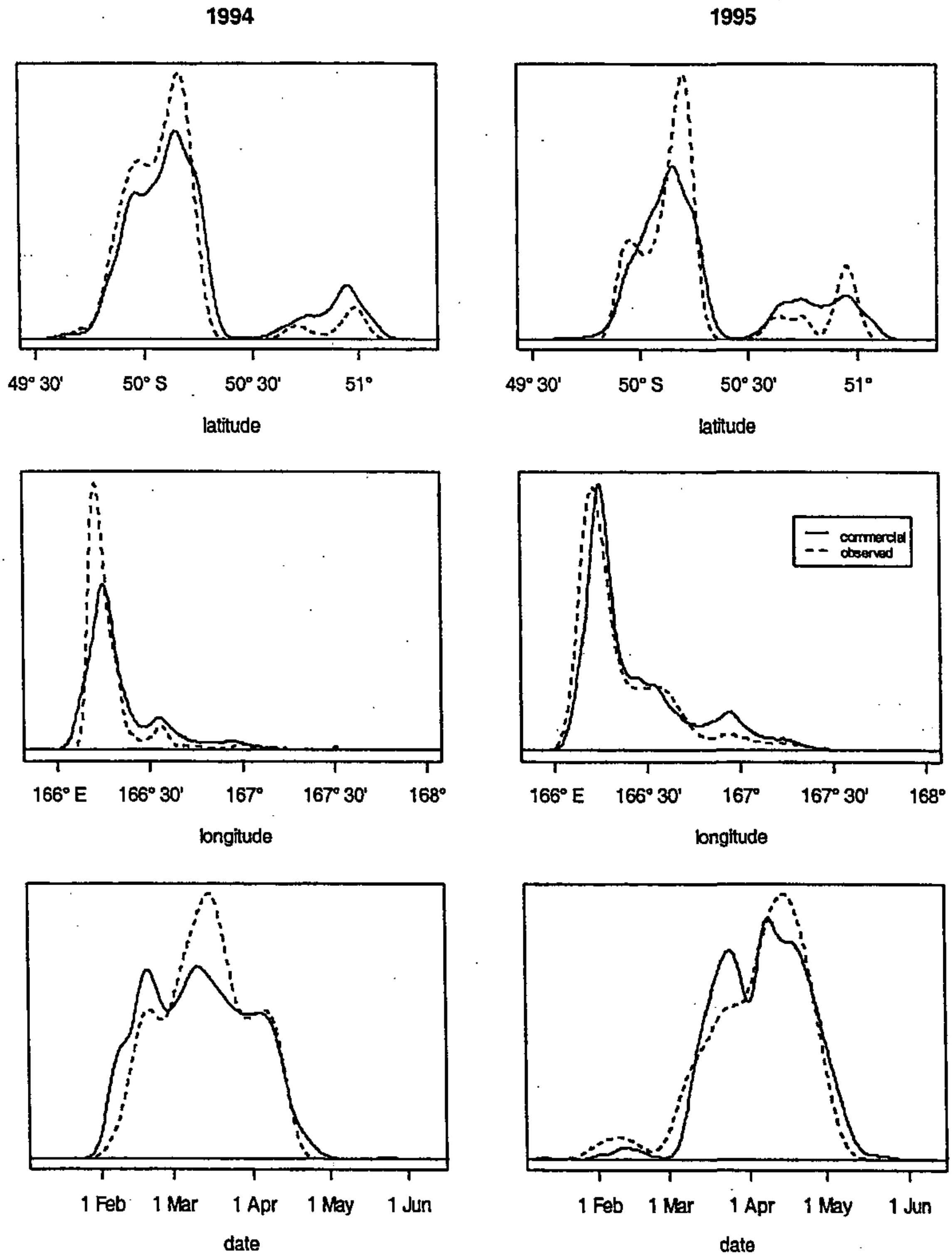

Figure 3: Density plots of observer coverage against latitude, longitude, and day of year for 1994 and 1995 seasons.

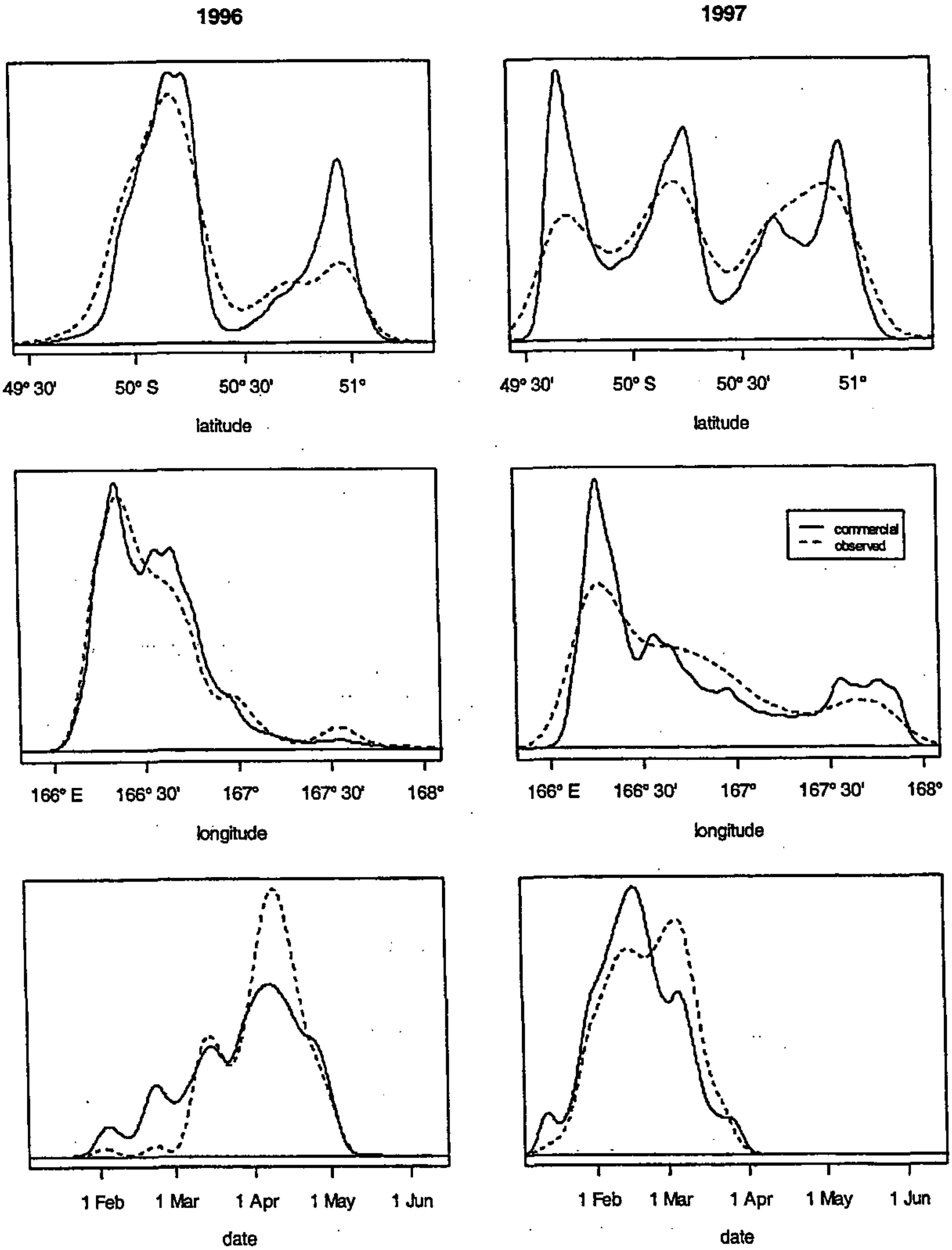

Figure 4: Density plots of observer coverage against latitude, longitude, and day of year for 1996 and 1997 seasons.

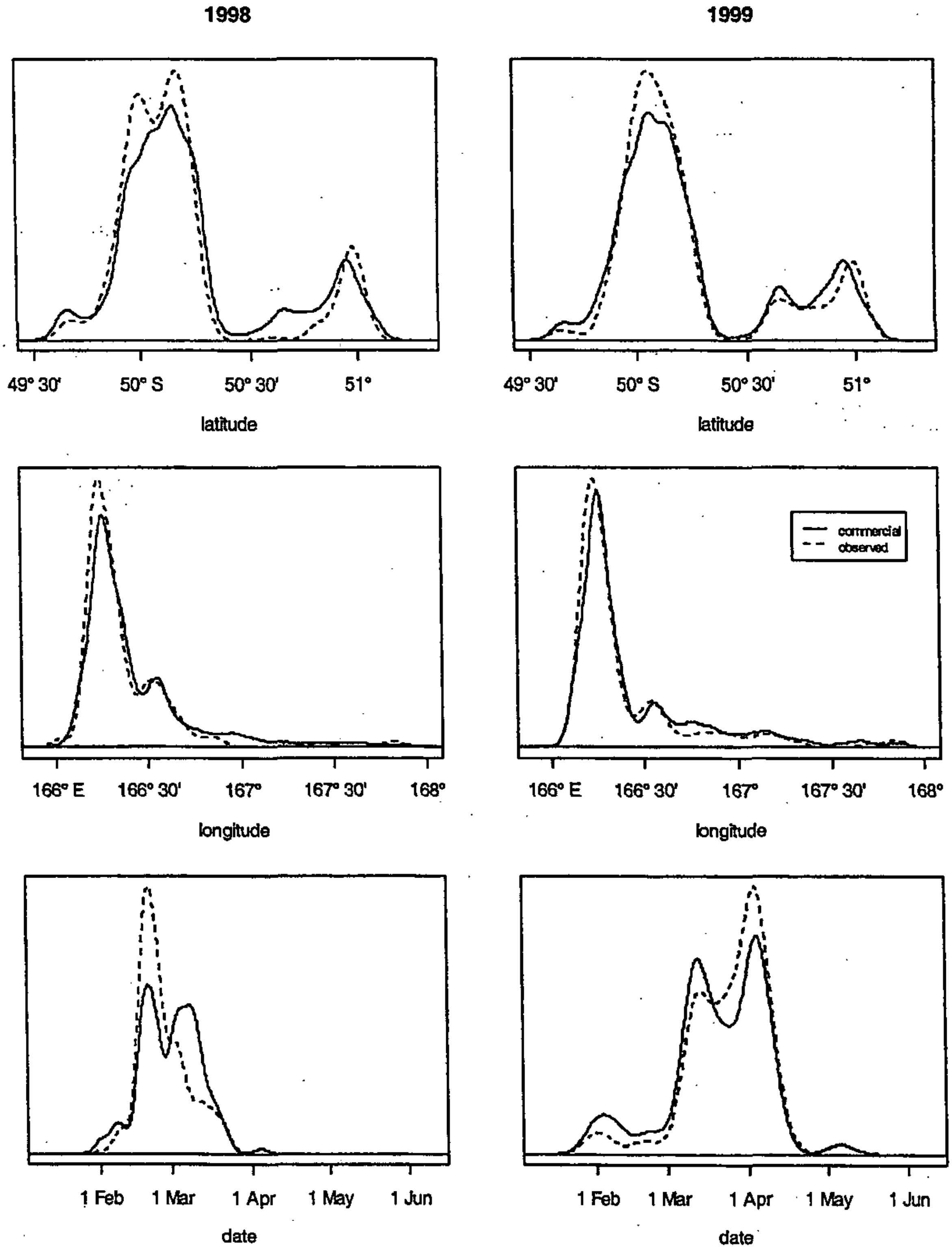

Figure 5: Density plots of observer coverage against latitude, longitude, and day of year for 1998 and 1999 seasons.

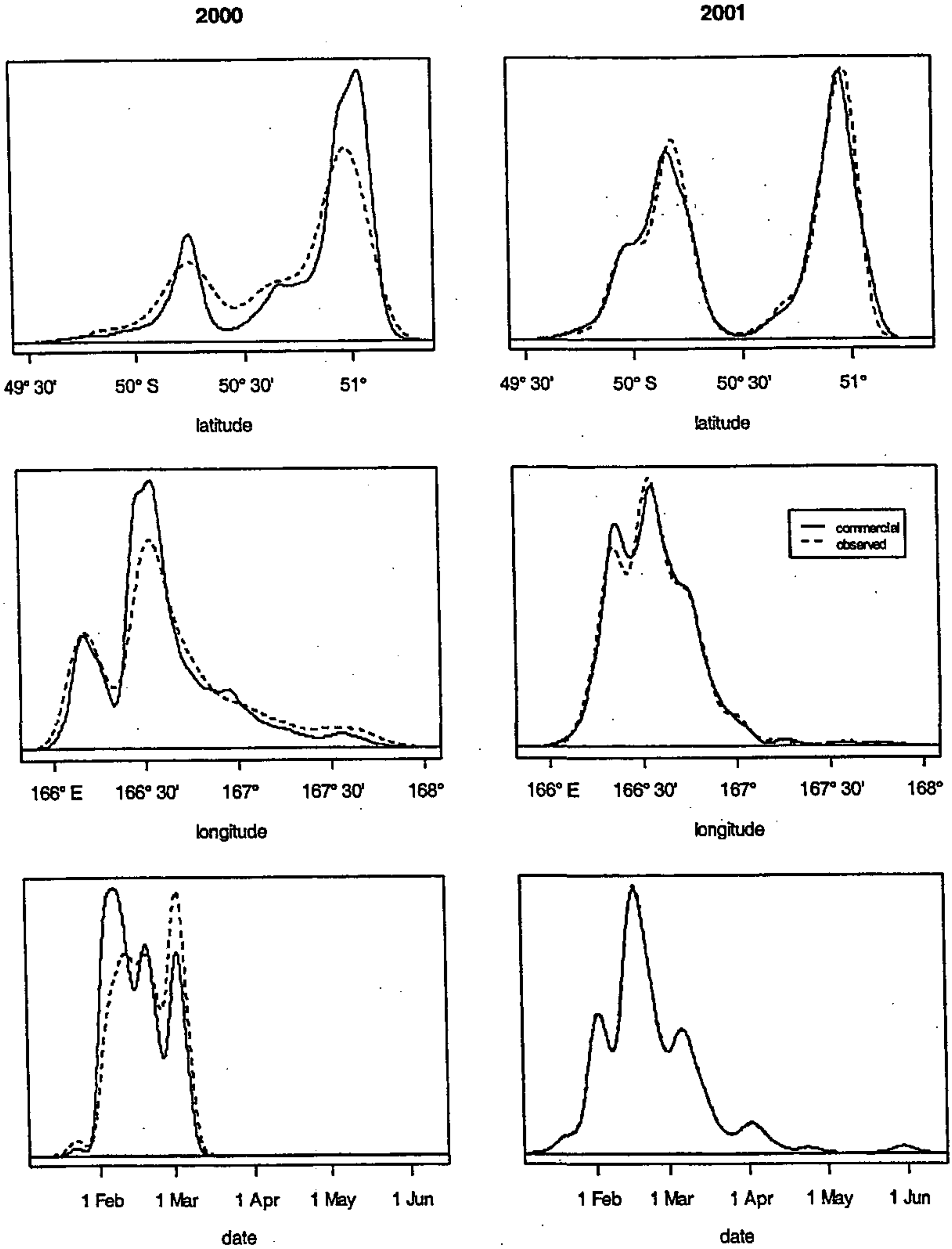

Figure 6: Density plots of observer coverage against latitude, longitude, and day of year for 2000 and 2001 seasons.

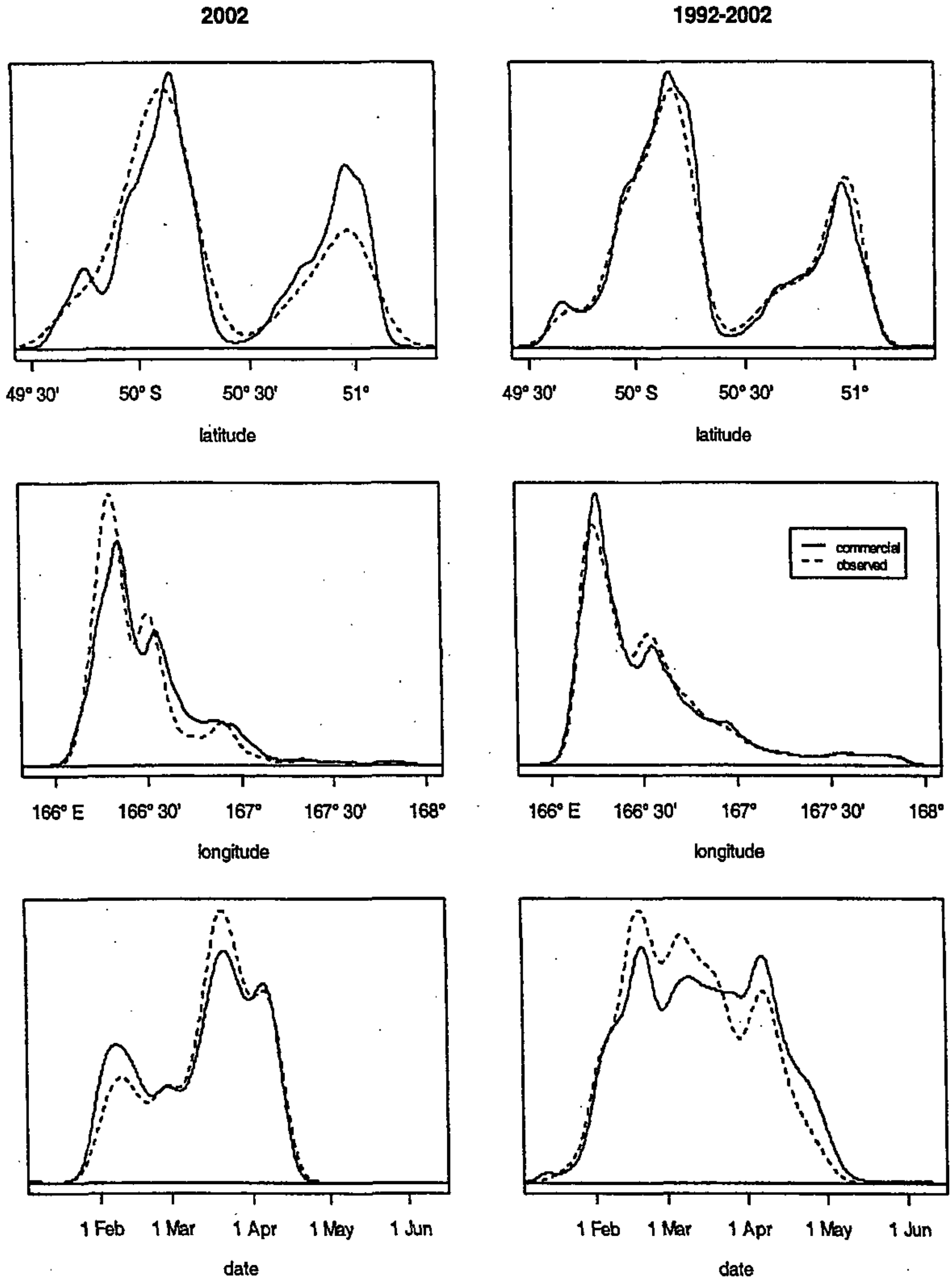

Figure 7: Density plots of observer coverage against latitude, longitude, and day of year for 2002 season and all 11 seasons combined.

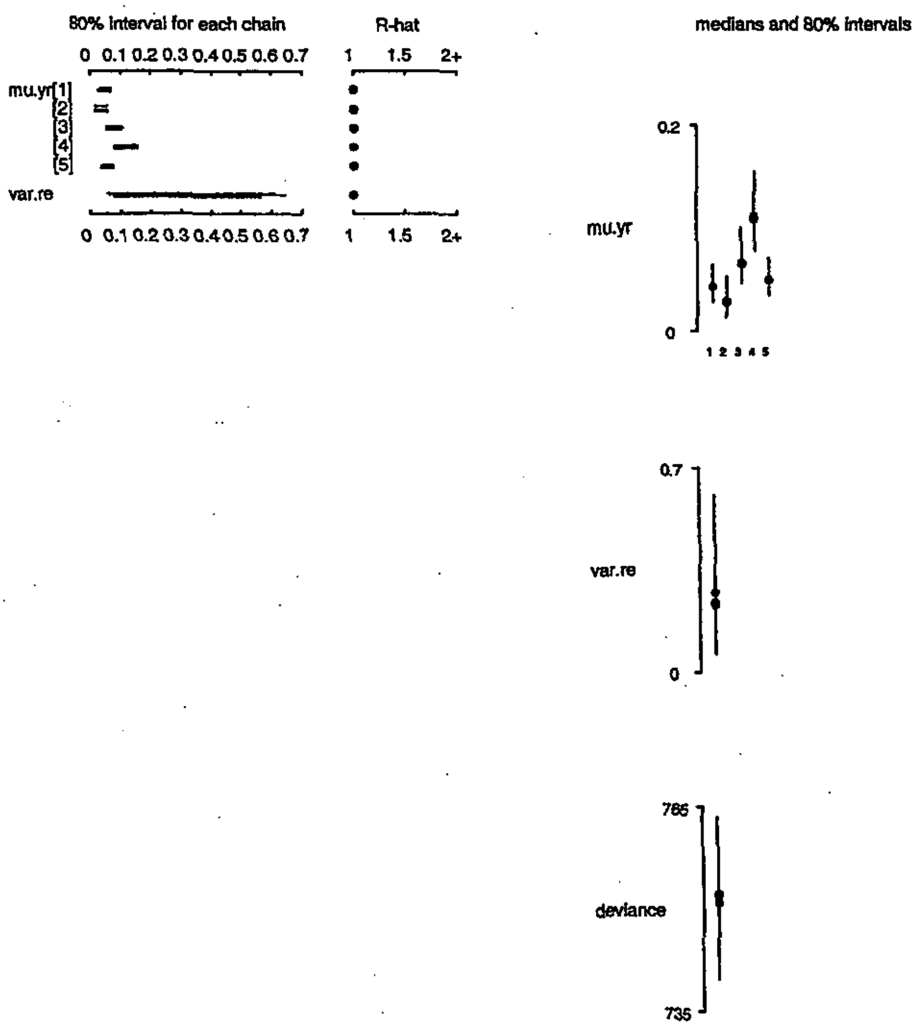

Figure 8: Diagnostic plots for the convergence of the three chains used to estimate the vessel random effects model. mu.yr[1], ..., mu.yr[5] denote the strike rates for the seasons 1998-2002, var.re is the random effect variance and deviance is the deviance at each sample of the parameter values parameter values If convergence of the chains has occurred, the three different chains will give similar medians and intervals. There is little evidence that convergence of the chains has not happened.

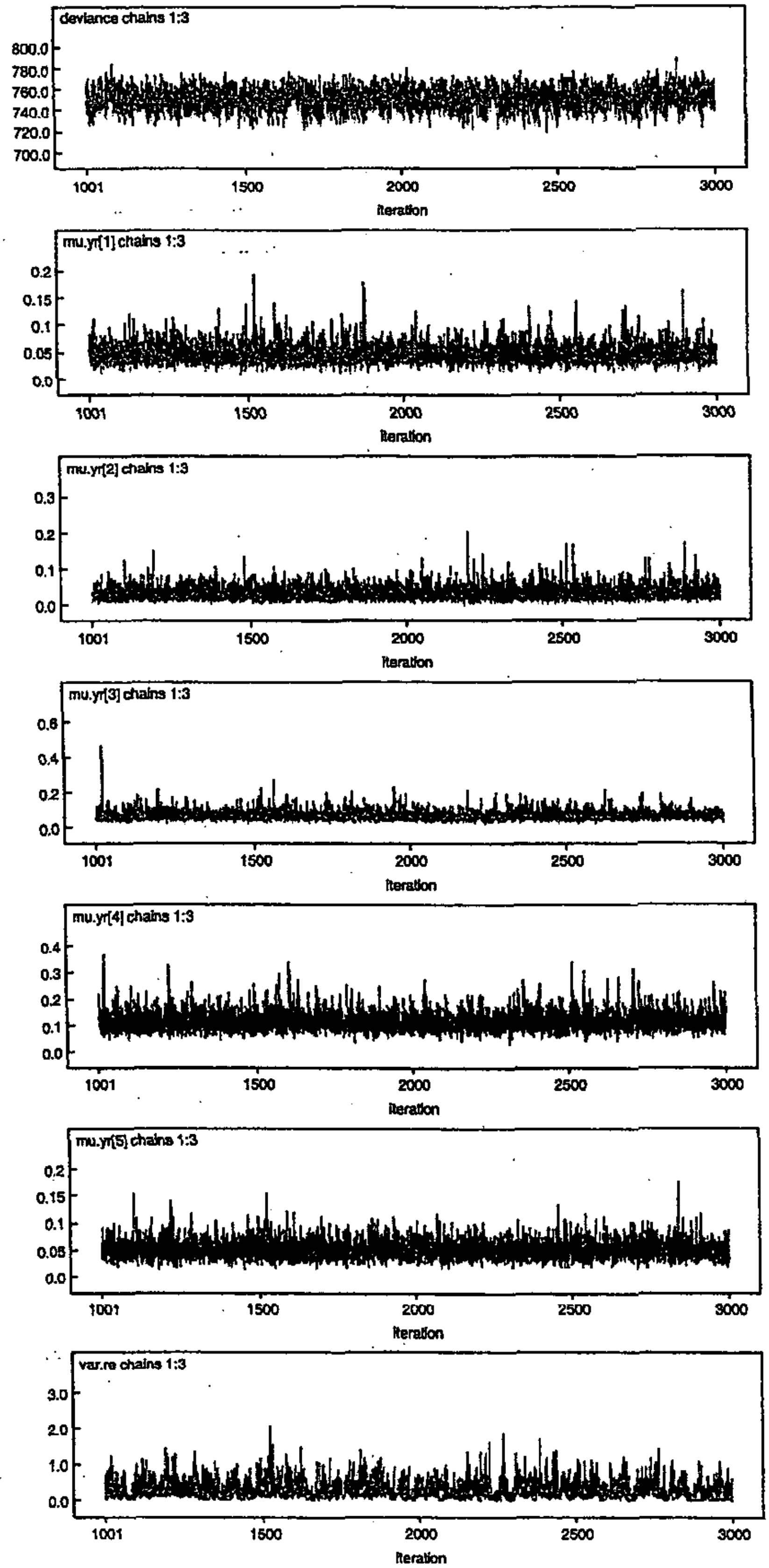

Figure 9: Plots of the 3 chains in the MCMC sample from the posterior distribution of the parameters model used for estimating the variance of the vessel random effects. See the Figure 8 caption for notation.

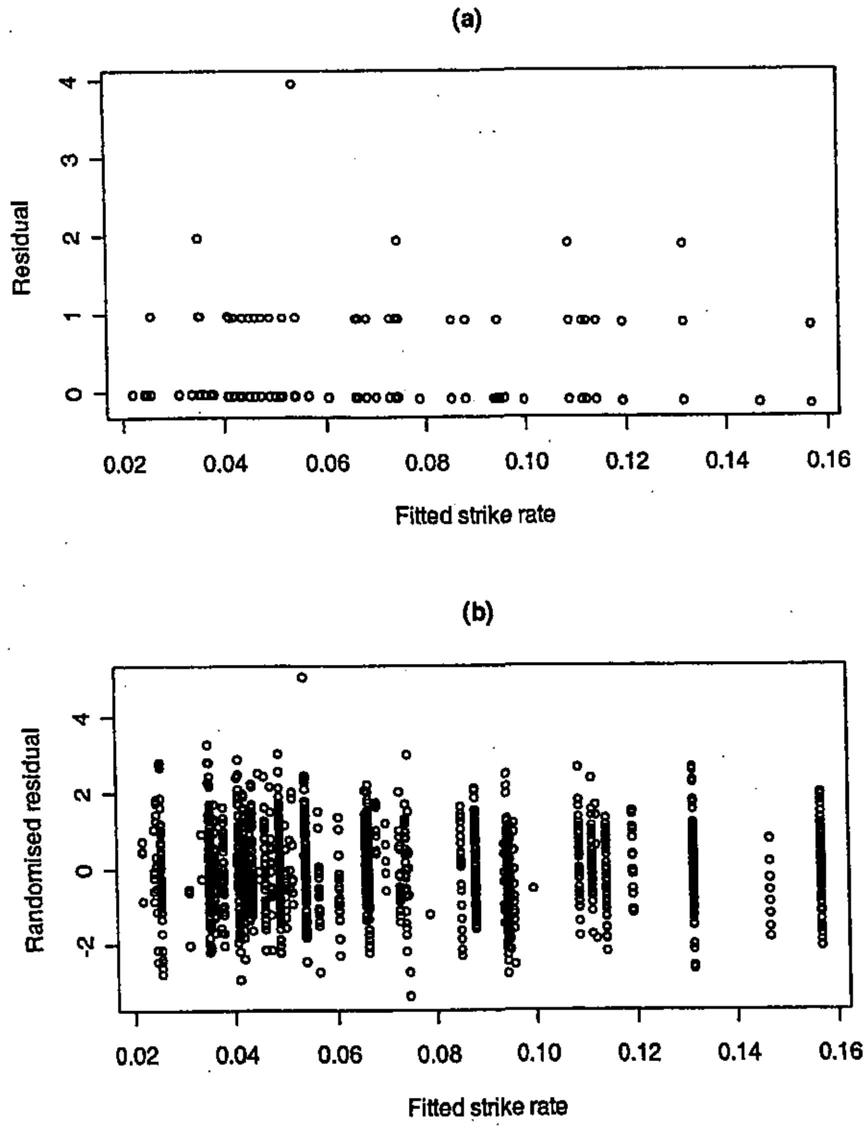

Figure 10: Residual plots of the residuals against the fitted strike rate values. (a) gives the raw residuals and (b) the randomised residuals. Randomisation removes the pattern that is de to the discreteness of the data. Each vertical band contains the tows of a single vessel.

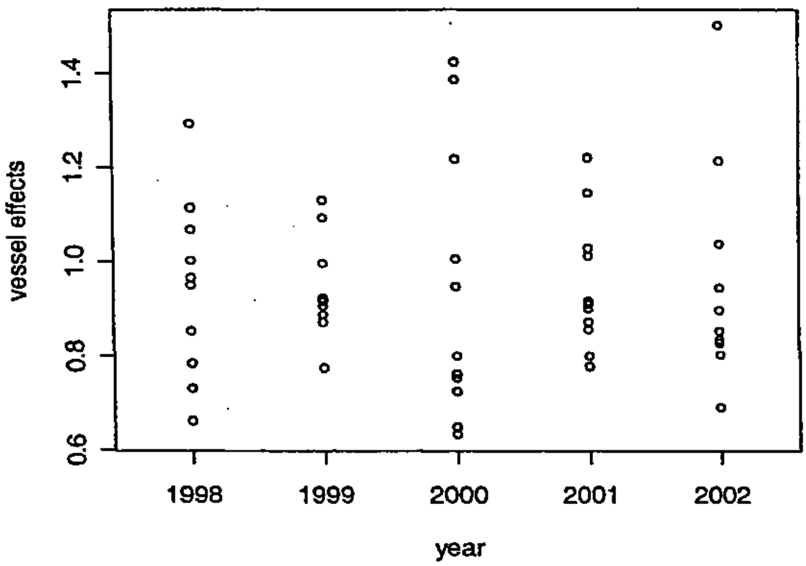

Figure 11: Plot of median predicted vessel random effects against the year of fishing.

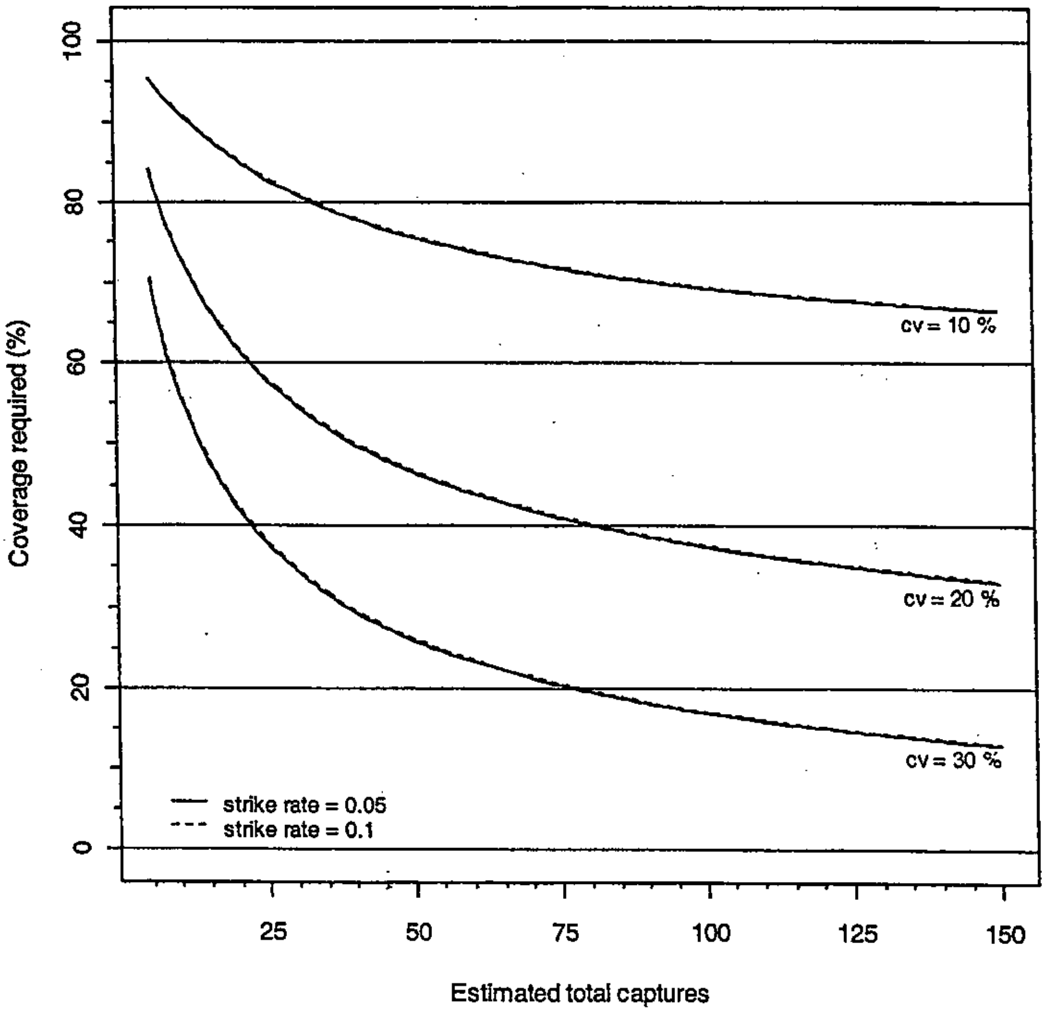

Figure 12: Coverage required to estimate the total number of captures with a coefficient of variation of 10%, 20%, and 30% plotted against the estimated total number of captures in the commercial season. Note that the lines for the alternative strike rates of 0.05 and 0.10 almost coincide. These curves use the estimate of 0.249 for the variance of the vessel random effects.

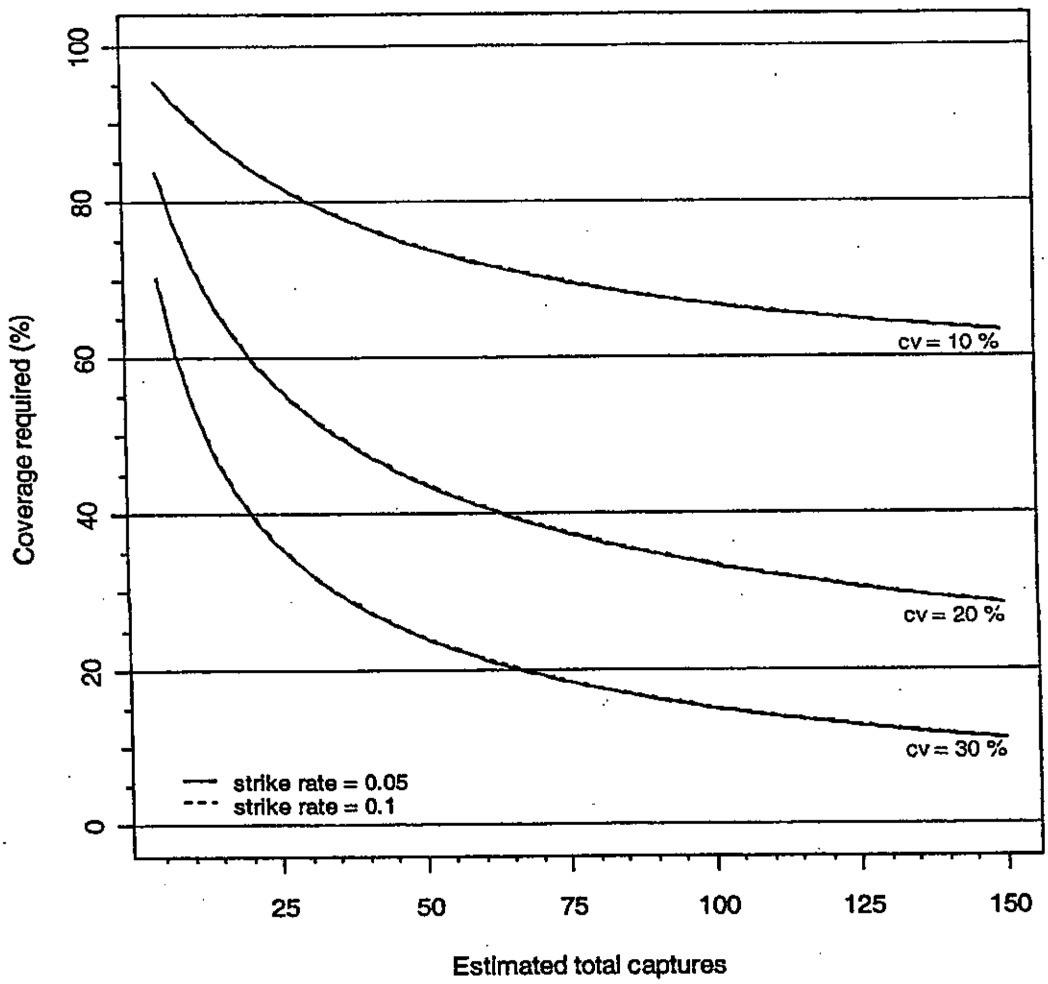

Figure 13: Coverage required to estimate the total number of captures with a coefficient of variation of 10%, 20%, and 30% plotted against the estimated total number of captures in the commercial season. In this plot the variance of the vessel random effects is estimated to be 0.192.

APPENDIX A: CHARACTERISTICS OF THE PREDICTOR OF THE TOTAL NUMBER OF CAPTURES

Using the model described in Section 5.2 we obtain expressions for the mean predictive error and the mean square predictive error using the characteristics of the marginal distribution of the vector of tow by tow captures **y**. **y** comprises the captures for all N tows of the season ordered by observed tows and then the unobserved tows. We will use the notation y_{jk} for number of captures for the k^{th} tow of the j^{th} vessel.

The model implies that mean capture rate for each tow is the same, μ. Thus

$$\mathrm{E}(T)=N\mu$$

$$\mathrm{E}(\hat{T})=\mathrm{E}\left(\frac{N}{n}t\right)=\frac{N}{n}n\mu=N\mu$$

and so the mean predictive error is

$$\mathrm{E}(\hat{T}-T)=0$$

To obtain the mean square predictive error we require the covariance structure of the marginal distribution of all the tows. This is relatively simple under the model assumptions. The model implies that there is no covariance between tows by different vessels and that the covariance between pairs of tows by the same vessel is the same for each pair and does not depend on the vessel. We denote this covariance by κ. The model also assumes the over-dispersion component of variance, ϕ, is the same for each vessel and so the variance of the number of captures, which we denote by σ^2, is the same for each tow. Expressions for σ^2 and κ in terms of μ, ϕ, and ψ are derived at the end of this appendix.

The total captures for vessel j, t_j is given by

$$t_j=\sum_{j=1}^{n_j}y_{jk}$$

where j is ordered so that the first m vessels comprise the observed vessels and the remaining $N-m$ vessels are unobserved.

$$\mathrm{E}(t_j)=n_j\mu$$

$$\mathrm{Var}(t_j)=n_j\sigma^2+\left(n_j^2-n_j\right)\kappa$$

and the covariance between the total captures by different vessels is 0.

The mean square predictive error of $\hat{T}$ is

$$\mathrm{MSE}(\hat{T})=\mathrm{E}(\hat{T}-T)^2=\mathrm{E}\left(\frac{N}{n}t-T\right)^2=\mathrm{E}\left(\left(\frac{1}{f}-1\right)t-(T-t)\right)^2$$

$$=\mathrm{E}\left(\left(\frac{1}{f}-1\right)(t-n\mu)-(T-t-(N-n)\mu)\right)^2$$

$$=\left(\frac{1}{f}-1\right)^2\mathrm{Var}(t)+\mathrm{Var}(T-t)$$

$$=\left(\frac{1}{f}-1\right)^2\sum_{j=1}^{m}\mathrm{Var}(t_j)+\sum_{j=m+1}^{M}\mathrm{Var}(t_j)$$

$$=\left(\frac{1}{f}-1\right)^2\sum_{j=1}^{m}\left(n_j\sigma^2+\left(n_j^{\,2}-n_j\right)\kappa\right)+\sum_{j=m+1}^{M}\left(n_j\sigma^2+\left(n_j^{\,2}-n_j\right)\kappa\right)$$

$$=\left(\left(\frac{1}{f}-1\right)^2 n+(N-n)\right)\sigma^2+\left(\left(\frac{1}{f}-1\right)^2\sum_{j=1}^{m}\left(n_j^{\,2}-n_j\right)+\sum_{j=m+1}^{M}\left(n_j^{\,2}-n_j\right)\right)\kappa$$

$$=\frac{1-f}{f}N\sigma^2+(1-f)^2\left(\frac{1}{n^2}\sum_{j=1}^{m}\left(n_j^{\,2}-n_j\right)+\frac{1}{(N-n)^2}\sum_{j=m+1}^{M}\left(n_j^{\,2}-n_j\right)\right)N^2\kappa \quad \text{(A1)}$$

To obtain expressions for σ^2 and κ in terms of μ, ϕ and ψ we need to confirm that the expected value of y_{jk} is μ and calculate expressions for the variance of y_{jk} and the covariance between the captures for two tows by the same vessel, y_{jk} and $y_{jk'}$.

$$\mathrm{E}\left(y_{jk}\middle|\eta_{jk}\right)=\eta_{jk}=\mu u_{jk}v_j$$

and

$$\mathrm{E}\left(y_{jk}\right)=\mathrm{E}\left(\mathrm{E}\left(y_{jk}\middle|\eta_{jk}\right)\right)=\mu$$

Now

$$\mathrm{E}\left(y_{jk}^{\,2}\middle|\eta_{jk}\right)=\eta_{jk}+\eta_{jk}^{\,2}=\mu u_{jk}v_j+\mu^2u_{jk}^{\,2}v_j^{\,2}$$

Thus

$$\mathrm{E}\left(y_{jk}^{\,2}\right)=\mathrm{E}\left(\mathrm{E}\left(y_{jk}^{\,2}\middle|\eta_{jk}\right)\right)=\mathrm{E}\left(\mu u_{jk}v_j+\mu^2u_{jk}^{\,2}v_j^{\,2}\right)$$
$$=\mu+\mu^2(\phi+1)(\psi+1)$$

and therefore

$$\sigma^2=\mathrm{Var}\left(y_{jk}\right)=\mu+((1+\phi)(1+\psi)-1)\mu^2 \quad \text{(A2)}$$

To obtain the covariance of y_{jk} and $y_{jk'}$ (for different tows by the same vessel) we note that

$$\mathrm{E}\left(y_{jk}y_{jk'}\middle|\eta_{jk},\eta_{jk'}\right)=\eta_{jk}\eta_{jk'}=\mu^2u_{jk}u_{jk'}v_j^{\,2}$$

from which it follows that

$$\mathrm{E}\left(y_{jk}y_{jk'}\right)=\mathrm{E}\left(\mathrm{E}\left(y_{jk}y_{jk'}\middle|\eta_{jk},\eta_{jk'}\right)\right)=\mu^2(1+\psi)$$

Thus

$$\kappa=Cov\left(y_{jk},y_{jk'}\right)=\psi\mu^2 \quad \text{(A3)}$$

Substituting expressions (A2) and (A3) into equation (A1) gives

$$\mathrm{MSE}\left(\hat{T}\right)=\frac{1-f}{f}\left(1+((1+\phi)(1+\psi)-1)\mu\right)N\mu$$
$$+(1-f)^2\left(\frac{1}{n^2}\sum_{j=1}^{m}\left(n_j^{\,2}-n_j\right)+\frac{1}{(N-n)^2}\sum_{j=m+1}^{M}\left(n_j^{\,2}-n_j\right)\right)\psi(N\mu)^2 \quad \text{(A4)}$$