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ANALYSIS OF VARIABILITY OF KRILL SIZE AND FISH BY-CATCH IN THE JAPANESE KRILL FISHERY BASED ON SCIENTIFIC OBSERVER DATA

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Abstract

To estimate the optimal relative sample size of scientific observer data collected on Antarctic krill commercial fishing vessels, the relationship between statistical precision and sample size was estimated by using variance component analysis. Observer datasets from the Japanese krill fishery from 1995 to 2008 were analysed using a hierarchical Bayesian model. The models were composed of multistage cluster units (i.e. year, subarea, vessel, cruise and haul) based on a state–space model, separating biological process error in the population dynamics from fishery process as observation error. In both krill length and by-catch fish number, the parameters estimated by the Markov chain Monte Carlo (MCMC) method hardly show difference among years, subareas and vessels. The potent interaction effect between year and subarea suggests large spatio–temporal variability in the size structure of the krill population, which is presumably derived from large variability of recruitment causing difficulty in predicting krill population dynamics. Variances of observer datasets were calculated by the multistage sampling formula with the variance terms derived from the Bayesian model. For both krill length and by-catch fish number, vessel sample size shows marked effects on the coefficient of variation (CV), although haul sample size affects CV for only krill length data up to 10% haul coverage. These results suggest that data collection by scientific observers on board commercial vessels provides important information for the management of krill resources and the Antarctic ecosystem, while further discussion is needed about the optimal relative sample size to ensure the statistical precision required for the specific objective of a study that includes consideration of the cost of observer deployment.

Introduction

In the Antarctic, there is much concern about the impact of climate change on biodiversity, species distribution and population dynamics (Turner et al., 2005). If climate change influences the population dynamics and spatial distribution of Antarctic krill (*Euphausia superba*), stock abundance estimates from a single snapshot survey may not provide sufficient information for management. For example, the CCAMLR Scientific Committee noted the importance of investigating the potential impact of climate change on krill recruitment variability, and agreed that a full review of the influence of recruitment variability on the calculation of sustainable yield be undertaken (SC-CAMLR, 2010). In order to allow the continuation of fishing activity while minimising the threats to krill population and their predators, it is necessary to undertake ecosystem monitoring at a broad spatio–temporal scale. Undertaking broad-scale surveys using scientific research vessels in the Antarctic has a range of practical and economic difficulties, for this reason scientific information provided from fishing vessels, including through the CCAMLR Scheme of International Scientific Observation, has garnered attention for its potential to contribute to ecosystem monitoring in this area.

Although broad-scale survey data obtained from fishing vessels through on-board scientific observers is useful to monitor the ecosystem impacts of fishery and other factors (e.g. climate change), the data derived from fishing vessels are liable to have lower statistical precision than the data collected by research vessels. This is primarily because the data collected during fishing operations does not have a systematic design in contrast to scientific research. That is, the data obtained from commercial fishing operation cannot provide an even coverage across spatio–temporal strata of natural ecosystems because fishing operations tend to concentrate at particular spatio–temporal sampling units where target species are expected to be abundant.

The statistical precision of data collected by spatio–temporally biased sampling may be improved by enlarging the number of samples collected. However, since fishery data are not obtained from the spatio–temporal strata where fishing operations are not conducted, enlargement of sample size may simply increase the number of replicates but have little effect in improving data precision. Therefore, it is important to consider the relation between statistical precision and observer coverage and the trade-offs between the precision required for a study and the costs of collection of data by scientific observers. The cost of observation consists not only of financial cost of deploying an observer but also of the time budget for the observer because scientific observers are requested to collect various types of data within a limited time frame. Therefore it would be essential to provide guidance on a cost-effective sampling scheme for scientific observers based on the relationship between the statistical precision required and the sample size necessary to achieve that level of precision.

To estimate optimal relative sample size of scientific observer data collected by commercial krill fishing vessels, the relationship between statistical precision and sample size was examined by using a variance component analysis (VCA). The statistical precision of krill length and number of by-catch fish are the focus of this study, because the former provides important information on recruitment dynamics and biological characteristics of the key species of the Antarctic ecosystem, and the latter is important to assess the impact of the krill fishery on Antarctic fish (particularly larvae fish; Agnew et al., 2010). Krill length data is necessary to determine the relative abundance of juvenile krill, which is important to monitor the recruitment variability of Antarctic krill (e.g. Quetin and Ross, 2003; Kinzey et al., 2011). The total number of by-catch fish may be the simplest indicator of krill fishery impact on Antarctic ichthyofauna. The statistical precision of observer datasets was evaluated using an analysis of the sources of variance, obtained by hierarchical Bayes modelling to estimate the spatio–temporal variation of data caused by biological processes separately from the variation related to the fishery activity and observation.

Materials and methods

Datasets on the Japanese krill fishery in Area 48 from 1995 to 2008 were used for the analysis. In this period, the Japanese krill fishing fleet was composed of one to four conventional trawl vessels. As variables of interest, krill lengths were measured for ca. 100 individuals from a haul, with 9.2% of hauls being sampled. The number of fish by-catch was counted for subsamples (usually 50 kg) of krill catch in a haul, and 7.6% of hauls were sampled. Observed data variation within year, subarea and vessel are shown in Figure 1 (krill length) and Figure 2 (number of by-catch fish). A summary description of the datasets is provided in Okuda et al. (2010).

Hierarchical Bayesian modelling was used to analyse the spatio–temporal variability of krill length and number of by-catch fish. The model was composed of multistage cluster units, which are assumed to corresponded to actual sources of variation in sampling data. As the first cluster, *the biological model* represented the spatio–temporal dynamics of krill length or number of by-catch fish in the natural ecosystem. The second cluster model, *the fishery model*, included the effects of fishing activities on the krill length or the number of by-catch fish. Third, *the observation model* represented the observation error consisting of sampling error and measurement error for individual krill length or by-catch fish in each haul. The data used in this study cannot divide sampling error (variation caused by choice of sample; i.e. individuals for krill length or subsamples for by-catch fish) from measurement error (i.e. mis-measurement/-recording of length or an erroneous count of by-catch fish). This multistage cluster model was constructed based on a state–space model, which can separate process error in the population dynamics from observation error and can accommodate missing data (Clark, 2007).

Models for krill length

Given the life span of Antarctic krill (4–7 years; Ikeda et al., 1985), krill populations consist of multiple cohorts, but it is difficult to estimate age structure by using length composition due to the variability in post-larval growth rates (Ikeda and Dixon, 1982). Japanese krill fishing vessels target adult krill (95% of length data ranging from 31 to 52 mm in this study) in order to produce a homogenous product. That is, although size composition of pooled krill length data in a spatio–temporal stratum may have a multimodal pattern, it is assumed that krill length within a haul would be expected to have a unimodal distribution. To simplify the model and VCA procedure, a multicluster model for krill length data was constructed that approximately followed a normal distribution at each cluster based on a hierarchical Bayesian modelling framework. Given that length data characteristics constrained a positive and non-zero value, the assumption of normality would not be adequate in a rigorous manner. Therefore, normal distributions were approximated and mean and variance alone were used as statistics to describe data distribution.

Biological model

The biological model describes year effect, subarea effect and their interaction effect on the variation of krill length as follows:

$$\overline{Y_{ij}} = \mu + \alpha_i + \beta_j + \gamma_{ij} \tag{1}$$

$$\mu \sim \mathrm{N}(0, 10\,000) \tag{2}$$

$$\alpha_i \sim \mathrm{N}\left(0, \sigma_Y^2\right) \tag{3}$$

$$\beta_j \sim \mathrm{N}\left(0, \sigma_A^2\right) \tag{4}$$

$$\gamma_{ij} \sim \mathrm{N}\left(0, \sigma_{YA}^2\right) \tag{5}$$

where $\overline{Y_{ij}}$ is the mean krill length at subarea j in year i; μ is grand mean of krill length in the whole study area during the study period. μ was assumed to follow a normal distribution (N) for the non-informative prior distribution with a mean of zero and a large variance term (10 000 in this model). α_i, β_j and γ_{ij} represent the effect of year i, the effect of subarea j, and their interaction effect respectively. These parameters were assumed to follow a normal distribution for the prior with a mean of zero and the terms σ_Y^2, σ_A^2 and σ_{YA}^2, which were the variance of α_i, β_j and γ_{ij} respectively.

Fishery model

The fishery model was constructed from three components; the vessel effect, the cruise effect and the haul effect on krill length:

$$\overline{Y_{ijkl}} = \overline{Y_{ij}} + \theta_k + \lambda_{ik} + \omega_{ikl} \tag{6}$$

$$\theta_k \sim \mathrm{N}\left(0, \sigma_V^2\right) \tag{7}$$

$$\lambda_{ik} \sim \mathrm{N}\left(0, \sigma_{YV}^2\right) \tag{8}$$

$$\omega_{ikl} \sim \mathrm{N}\left(0, \sigma_H^2\right) \tag{9}$$

where $\overline{Y_{ijkl}}$ is the mean krill length in haul l of vessel k operating at subarea j in year i. The first term θ_k, conforming to a normal distribution, is the effect of vessel k on the krill length. The second term, λ_{ik} represents the cruise effect within each vessel on the krill length surrogated by the interaction among vessel k and year i. In the Japanese scientific observer program for the krill fishery, a scientific observer usually boards a fishing vessel for only one cruise in a fishing season. Therefore, this model cannot directly evaluate the effect of cruise within a vessel. The third term, ω_{ikl} is the effect of haul l of vessel k operating in year i, which assume the three-stage sampling unit; the effect of haul within cruise within vessel. These parameters were assumed to follow a normal distribution for the prior with a mean of zero and the terms σ_V^2, σ_{YV}^2 and σ_H^2, which were the variance of θ_k, λ_{ik} and ω_{ikl} respectively.

Observation model

The observed krill length of individual q in haul l of vessel k operating at subarea j in year i was assumed to follow a normal distribution with the haul mean length $\overline{Y_{ijkl}}$ and the variance σ_O^2 as the observation error.

$$Y_{ijklq} \sim \mathrm{N}\left(\overline{Y_{ijkl}}, \sigma_O^2\right). \tag{10}$$

Models for by-catch fish

Biological model

The biological model describes the year effect, the subarea effect, and their interaction effect on the variation of the number of by-catch fish as follows:

$$\log\left(\overline{Y'_{ij}}\right) = \mu' + \alpha'_i + \beta'_j + \gamma'_{ij} \tag{11}$$

$$\mu' \sim \mathrm{N}(0,1\,000) > \mu' \sim \mathrm{N}(0,10000) \quad (12)$$

$$\alpha'_i \sim \mathrm{N}\left(0,\sigma^2_{Y'}\right) \quad (13)$$

$$\beta'_j \sim \mathrm{N}\left(0,\sigma^2_{A'}\right) \quad (14)$$

$$\gamma'_{ij} \sim \mathrm{N}\left(0,\sigma^2_{YA'}\right) \quad (15)$$

where $\log\left(\overline{Y'_{ij}}\right)$ is the log-transformed mean number of by-catch fish at subarea j in year i; μ' is the grand mean of the log-transformed number of by-catch fish in the whole study area during the study period. Log-transformed μ', i.e. $\log(\mu')$ was assumed to follow a normal distribution for the non-informative prior distribution with a mean of zero and a large variance term (10 000 in this model). α'_i, β'_j and γ'_{ij} represent the effect of year i, the effect of subarea j, and their interaction effect respectively. These parameters were assumed to follow a normal distribution for the prior with a mean of zero and the terms $\sigma^2_{Y'}$, $\sigma^2_{A'}$ and $\sigma^2_{YA'}$, which were the variance of α'_i, β'_j and γ'_{ij} respectively.

Fishery model

The fishery model was constructed from three components; the vessel effect, the cruise effect and the haul effect on the number of by-catch fish. The following model describes the fishery effect on the number of by-catch fish:

$$\log\left(\overline{Y'_{ijkl}}\right) = \log\left(\overline{Y'_{ij}}\right) + \theta'_k + \lambda'_{ik} + \omega'_{ikl} \quad (16)$$

$$\theta'_k \sim \mathrm{N}\left(0,\sigma^2_{V'}\right) \quad (17)$$

$$\lambda'_{ik} \sim \mathrm{N}\left(0,\sigma^2_{YV'}\right) \quad (18)$$

$$\omega'_{ikl} \sim \mathrm{N}\left(0,\sigma^2_{H'}\right) \quad (19)$$

where $\overline{Y'_{ijkl}}$ is the mean number of by-catch fish caught by haul l of vessel k operating at subarea j in year i. The terms θ'_k, λ'_{ik} and ω'_{ikl} were defined as the effect of vessel, cruise and haul respectively on the number of by-catch fish, similar to the krill length model. These parameters were assumed to follow a normal distribution for the prior with a mean of zero and the terms $\sigma^2_{V'}$, $\sigma^2_{YV'}$ and $\sigma^2_{H'}$, which were the variance of θ'_k, λ'_{ik} and ω'_{ikl} respectively.

Observation model

The fish by-catch data contains many zero values and is referred to as 'zero inflated data', therefore the zero-inflated negative binominal (ZINB) mixture model was used as an observation model. The ZINB is the robust statistical approach to treat zero inflated data as negative in the binomial distribution and zero inflated Poisson mixture model (Martin et al., 2005). The observed data Y'_{ijkl}, obtained as subsamples from the haul were modelled by the ZINB with the log-transformed mean number of by-catch fish caught by haul l of vessel k operating at subarea j in year i, $\log\left(\overline{Y'_{ijkl}}\right)$, as follows:

$$Y'_{ijkl} \sim \mathrm{ZINB}\left(\log\left(\overline{Y'_{ijkl}}\right),\phi\right) \quad (20)$$

where ϕ is the overdispersion parameter in situations where large counts have been recorded or alternatively, a large number of zeros have been observed. ϕ was assumed to follow a lognormal distribution for the non-informative prior distribution with a mean of zero and a large variance (10 000 in this model). Details about the treatment of the ZINB on the Bayesian modelling framework is described in Martin et al. (2005) and Ntzoufras (2009).

Parameter estimation

The models were fitted to the data by the Markov chain Monte Carlo (MCMC) method in WinBUGS (Spiegelhalter et al., 2003) with statistical software R (R Development Core Team, 2010). In all Bayesian models for both krill length and by-catch fish, the variance terms, σ^2, were derived from independent and non-informative uniform hyper-prior distribution. To confirm independence of the posterior probability on initial values, three independent iterations were conducted. Estimates were obtained from 10 000 iterations after a burn-in of 1 000 iterations, thinning at intervals of 50. Convergence of the posterior distribution was assessed by an autocorrelation function of each parameter and the R statistics (Gelman et al., 2004). For all model parameters, the criterion of convergence was < 1.1.

Variance component analysis

The source of variability in krill fishery observer data was examined with multistage cluster sampling units. Variance of the unbiased estimator of the population total of krill length $Y\left(\hat{Y}\right)$ could be decomposed to sources of variation in each cluster according to sampling theory (Cochran, 1977; Thompson, 2002). An unbiased estimator of the variance of the mean of the lowest cluster sampling unit, $\widehat{\text{var}}\left(\overline{Y}\right)$, was obtained following equations that changed depending on the population of interest and sampling procedure between krill length and by-catch fish as response variables.

The population of interest in the krill length model was assumed to be the theoretically very large number of notional samples, because the population of interest was all krill that were not caught in the fishery. Therefore, a VCA was conducted to evaluate the source of variability in the mean krill length as a simple indicator of the statistical precision of observer dataset using the following revision of equation (10.14) in Cochran (1977) as follows:

$$\widehat{\text{var}}\left(\overline{Y}\right)=\frac{1}{n}s_V^2+\frac{1}{nm}s_C^2+\frac{1}{nmr}s_H^2+\frac{1}{nmru}s_I^2 \tag{21}$$

where n, m, r and u are the observed number of vessel, cruise, haul and individual respectively. In this formula (equation 21), terms of sample coverage applied to equation (10.14) in Cochran (1977) are negligible since the population of interest (e.g. number of notional krill fishing hauls, R) is very large, and then sample coverage (e.g. r/R) becomes close to zero. To simplify the analysis, the mean number of observed samples at each cluster unit was used. The terms of variances (s_V^2: unbiased estimator of variance among vessels, s_C^2: unbiased estimator of variance among cruises within vessel, s_H^2: unbiased estimator of variance among hauls within cruise within vessel and s_I^2: unbiased estimator of variance among individuals within haul within cruise within vessel) were applied to the posterior median from MCMC samples obtained from hierarchical Bayesian models (σ_V^2, σ_{YV}^2, σ_H^2 and σ_I^2).

The by-catch fish model assumed finite population corrections, because the population of interest was the total of all hauls carried out by all vessels in a given year and area as the effect of the krill fishery on the fish by-catch. Therefore, a VCA was conducted to evaluate the source of variability for log-transformed mean number of by-catch fish per 50 kg subsample of each haul using the following revision of equation (10.14) in Cochran (1977):

$$\widehat{\text{var}}\left(\log\left(\overline{Y'}\right)\right)=\frac{1-e'}{N'e'}s'^2_V+\frac{1-f'}{n'M'f'}s'^2_C+\frac{1-h'}{n'm'R'h'}s'^2_H \tag{22}$$

where N' is the number of fishing vessels, M' is the number of fishing cruises within vessel, and R' is the number of hauls conducting fishing within cruise within vessel for fish by-catch observer data. To simplify the analysis, it was supposed that each cluster unit had the same number of lower cluster units. The observer coverage of fish by-catch data was assumed as $e' = n'/N'$, $f' = m'/M'$, $h' = r'/R'$. In these equations, n', m' and r' are the observed number of vessel, cruise and haul respectively. The terms of variances (s'^2_V: unbiased estimator of variance among vessels, s'^2_C: unbiased estimator of variance among cruises within vessel, and s'^2_H: unbiased estimator of variance among hauls within cruise within vessel) were applied the posterior median from MCMC samples obtained from hierarchical Bayesian models ($\sigma^2_{V'}$, $\sigma^2_{YV'}$ and $\sigma^2_{H'}$).

To investigate the variability in the coefficient of variation (CV) arising from the variation in observer coverage derived from fishery activity, the sample size or observer coverage of vessel and haul was modified, and the CVs to krill and fish by-catch calculated under each coverage scenario with fixed variance and the number of population sample (i.e. N, M and R). The relative sample size of year and subarea level was omitted from the VCA, because of the focus on statistical precision depending on sample size obtained by the scientific observer. CV was calculated using the following equation with unbiased estimator of mean krill length $\left(\overline{Y}\right)$ or log-transformed number of by-catch fish $\left(\log\left(\overline{Y'}\right)\right)$:

$$CV=\frac{\sqrt{\widehat{\text{var}}\left(\overline{Y}\right)}}{\overline{Y}}. \tag{23}$$

Results

Models for krill body length

The posterior distribution adequately converged for the krill length model. For all estimated parameters, R statistics were substantially smaller than 1.1. The model assumed normal distribution with nested cluster sampling units showing approximately good fit overall (Figure 3). Temporal fluctuations in mean krill length in the three subareas are shown in Figures 4(a) to 4(c), and the difference of mean krill length among subareas is presented in Figure 4(d). Overall trends show a faint temporal fluctuation of annual mean krill length through the subareas. Among subareas, krill length does not show any obvious difference. Among vessels, there is little difference in krill length and its 95% confidence interval (CI) (Figure 4e). Within each year, krill lengths differed between subareas, but there is no obvious regional bias (Figures 4a to 4c). The divergence of krill length at each subregion in each year from the overall trends reflects the interaction effect between year and subarea. The variance term is largest at the individual krill length level, and the variance terms of haul-effect and the interaction between year and subarea follow (Figure 4f). Compared to the variance terms for the fishery and observation model, the variance term for the biological model has a broad 95% CI, except for overall year trends of adult length (Figure 4f).

Models for by-catch fish

Similar to the krill length model, the posterior distribution sufficiently converged for the by-catch fish model (R statistics < 1.1). The frequency distribution of the observed and estimated fish by-catch indicates the good fit of the model estimates to the data (Figure 5). The variation of number of by-catch fish among year, subarea and vessel are derived from the estimated parameter of their effect (Figures 6a to 6e). The estimated number of by-catch fish is very small. There is no obvious trend in the estimated number of by-catch fish among year, subarea and vessel. 95% CI of the interaction effect between year and subarea tended to have a wide range (Figures 6a to 6c). The degree of variance shows no clear trend among sampling levels (Figure 6f). 95% CI of the estimated variance parameter is largest in among area variation.

Variance component analysis

Figures 7 and 8 demonstrate the relationship between CV and the observed sample size for krill length and observer coverage for number of by-catch fish, when the sample size of cruise and individual were fixed (one cruise and 100 individuals). For krill length, CV is strongly affected by haul sample size, especially when haul sample size is small. The CV drastically decreases from around 0.09 to 0.03 with increasing hauls from 1 to 50, and then the CV changes very little with haul number larger than 50 hauls. In contrast, the CV keeps decreasing with increasing vessel number. For by-catch fish number, the vessel coverage shows marked effects on the CV, although the haul coverage does not change the CV. The CV decreases from around 2.5 to 0.5 with increasing vessel coverage from 0.05 to 1.0. However, the CV shows little change with haul coverage. These results do not show any difference arising from the sample size of cruise and individual (for krill length) and the observed coverage of cruise (for by-catch fish).

Discussion

A VCA with the variance terms obtained from hierarchical Bayesian modelling indicates that the relationship between sample size and statistical precision shows a sigmoid-type curve, and the relationship would change depending on data type. This suggests that although the lower limit of sample size should be ensured, it is difficult to simply determine the optimal sample size with reference only to data precision. Given the statistical precision for krill length indicated by Figure 7, a concrete recommendation of this study is that the lower limits of haul sample size have to be set for 30–50 hauls within a cruise. Because Japanese krill fishing vessels conduct 10–15 hauls per day during one cruise (usually 70–80 days), 5–10% haul coverage level for the Japanese krill fishery may ensure sufficient statistical precision of krill length. Meanwhile, vessels with fewer hauls per day may need a different level of observer coverage to Japanese vessels in order to sample a minimum of 30–50 hauls to ensure adequate statistical precision.

These results of the hierarchical Bayesian model suggest that the data precision obtained by 9.2% haul coverage of the Japanese observer survey would be practical to examine the spatio–temporal variation of krill length in the Antarctic ecosystem. In Subarea 48.1, the krill body length, especially juvenile size, shows temporal fluctuations which were greatest in 1995 and 2000. These trends are consistent with the result of a research survey that reported the mode of large individuals in these years (Reiss et al., 2008). The krill population at South Georgia is considered not to be self-sustaining locally. The population lies to the north of the maximum extent of winter sea-ice, and the principal source of recruitment into this population is the region near the western Antarctic Peninsula and along the southern Scotia Arc to the South Orkney Islands (Reid et al., 2002). The variation of krill abundance and size structure is affected by the fluctuation of krill recruitment related to oceanic current and sea-ice (Murphy et al., 2007). Therefore, it is likely that the fluctuation of krill length revealed by the Japanese scientific observer data reflects the variation of influx associated with oceanic current and sea-ice. The potential interaction between year and subarea in this analysis suggests large spatio–temporal variability of krill population structure and the difficulty of predicting krill population dynamics. This fact implies that it is possibly insufficient to assess the stock status of Antarctic krill based on a single synoptic survey. For the rational utilisation of the resource without threatening the krill-centred Antarctic ecosystem, it would be important to obtain time series, including for the commercial krill fishery, on krill population dynamics and the environment.

This analysis did not include krill abundance per se to estimate krill population dynamics directly, because krill availability for commercial fishing vessels was not necessarily proportional to local krill density; krill availability is determined not only by local krill density but it is also influenced by the decisions made by fishing masters according to the types of krill aggregations (Kawaguchi et al., 2005) and sea-ice condition encountered (Kawaguchi and Nicol, 2007). Thus, catch in the krill fishery does not necessarily reflect the krill stock abundance directly, and there may be large potential discrepancies between the variation in observation (i.e. catch in fishery) and population dynamics. To deal with this problem, it would be useful to use state–space modelling to consider observation error as in this study, as well as the statistical modelling of datasets such as time series of acoustic data collected by fishing vessels.

For by-catch fish, although the vessel coverage contributes to improve statistical precision, the coverage of haul sampling does not affect statistical precision (Figure 8). This fact and the result of hierarchical Bayesian modelling with the ZINB distribution suggest that the occurrence of fish by-catch is possibly highly aggregated at the haul level. In order to determine the optimal coverage for by-catch fish data precision, it may not be adequate to examine the relationship only between statistical precision and sample size in the current observer scheme; at minimum, further investigation considering variation among subsamples within a haul is required. Despite uncertainty derived from fish concentration among subsamples within each haul, the current Japanese observer scheme for fish by-catch provides appropriate data to examine the variation in the species composition of fish by-catch among years and regions (Iwami et al., 2011). Furthermore, the hierarchical Bayesian modelling also indicates that the observer data for the total number of by-catch fish also show large spatio–temporal fluctuation supported by the interaction effect between year and subarea.

The results of this analysis imply that the current Japanese krill fishery observer scheme would have efficacy at some level for investigating large spatio–temporal fluctuation in both krill length and by-catch fish number. The relationship between the krill population and the surrounding ecosystem and oceanic environment, as suggested by the interaction effect between year and subarea on krill length, may be important information in krill stock management and ecosystem conservation. Incorporating environmental data into the model used in this study would be a first step in this challenging process. Undertaking these investigations would require further environmental data collected by on-board scientific observers and remote-sensing data of the oceanic environment in addition to biological data currently collected. The sample sizes needed for these new survey items may be determined using the procedures described in this study.

To ultimately determine the optimal sample size requires a consideration of the relationship between statistical precision and sampling cost. In the view point of statistical precision, the purpose of a study and the requisite data precision should be determined clearly to set the target sample size. The field of sampling concerns every aspect of how data are selected, from all of the possibilities that might have been observed, whether the selection process has been under the control of investigators or has been determined by nature or circumstance, and how such data are used to make inferences about the larger population of interest (Thompson, 2002). That is, without explicit objective for a study that requests scientific data through on-board observer programs, it may not be possible to evaluate the necessary statistical precision to determine optimal relative sample size.

The schedule (i.e. workable time) of an on-board observer is finite, and so it is difficult to obtain data on all survey items with high precision. Therefore it is necessary to set priorities for survey items and to properly allocate the time budget for each item taking into consideration the working time per day. If scientific observers extend the time they are on the vessel, they will be able to increase the time budget for each item. However, extending the time on board leads to an increased financial cost for scientific observer programs. The results of this study indicate the strong effect of year and vessel in the variation of krill length and number of by-catch fish. Therefore, scientific observer data could be more efficiently collected by allocating sampling effort evenly across vessels and years, rather than concentrating on hauls within a single vessel. To evaluate overall sampling efficiency (in light of the purpose of a study) requires information on both the financial cost per sampling unit and time cost per survey item.

As mentioned above, it is necessary to consider both per-sampling financial cost and handling time cost for obtaining each sample for the rigorous study of sampling efficiency. However, these sampling costs cannot be explicitly incorporated into this study because sample unit costs, especially handling time, largely depend on sampling procedure, and then these sampling costs are difficult to quantify for the scientific observer program. An evaluation of the sampling costs has rarely been considered for scientific observer programs in the Antarctic area; such consideration would increase the complexity of discussion of the optimal relative sample size. Simply assuming a linear relationship between sample size and per-sampling costs would suggest that the optimal relative sample size for the current monitoring scheme of scientific observers with commercial fisheries should: (i) have a lower limit of sample size of 30–50 hauls for sufficient data precision of krill length, (ii) have an on-board scientific observer on all vessels on at least one cruise each year, and (iii) recognise that cruise level and individual haul level sample size may have a small impact on the data precision.

Conclusion

The results of this Bayesian model suggest that data collection by scientific observers on board commercial vessels provide important information for the management of krill resources and the Antarctic ecosystem. This study also shows the effectiveness of the VCA with the variance terms obtained from statistical modelling, especially the hierarchical Bayesian approach, to compare sample size and the statistical precision of data. Actually considering the overall sampling scheme for scientific observer programs requires further discussion of the optimal relative sample size to ensure the statistical precision required for the specific objective of a study as well as the financial cost of observer deployment and handling time of each required survey item.

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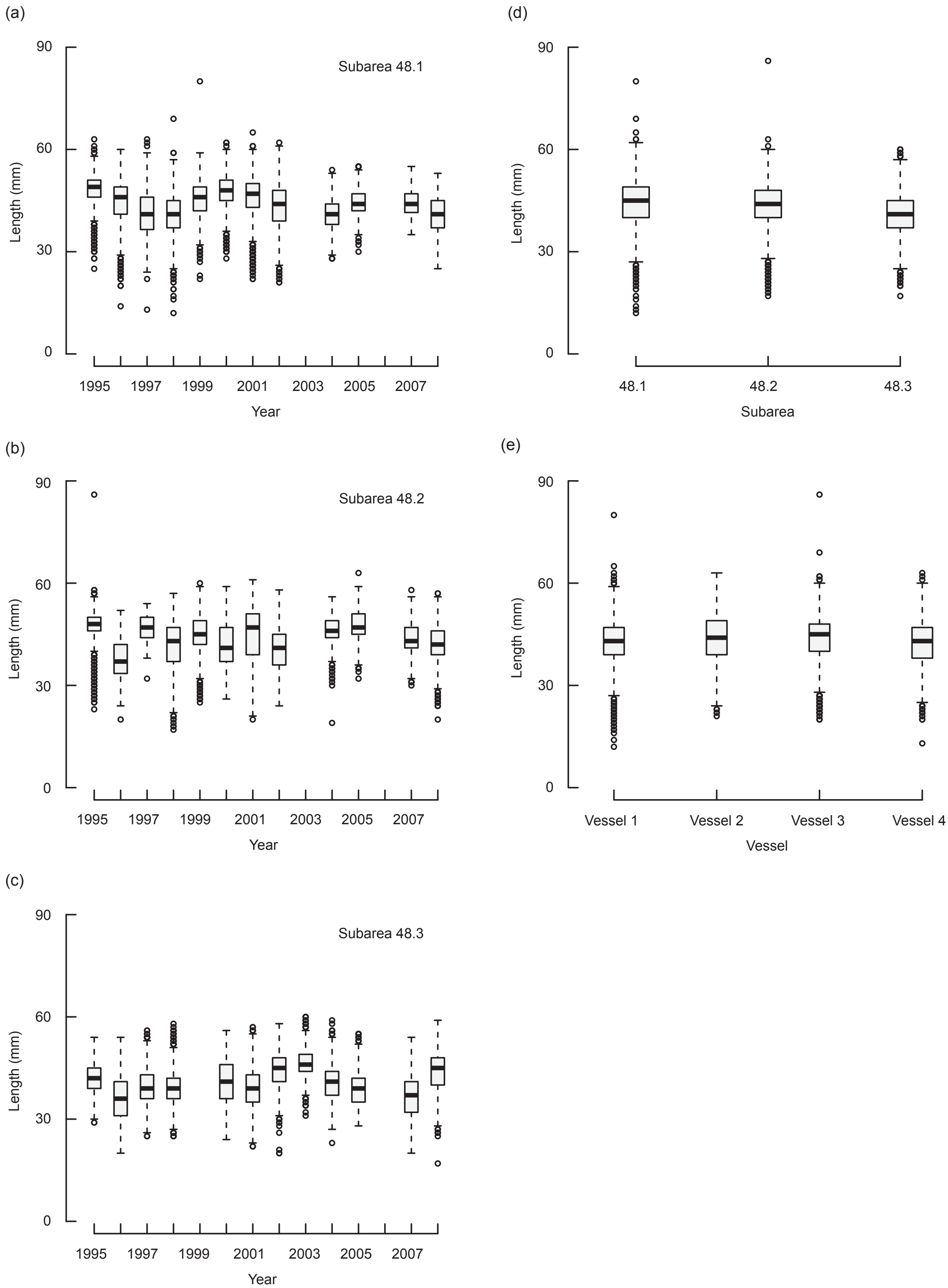

Figure 1: Box plots of krill length showing variations within year (a–c), subarea (d) and vessel (e).

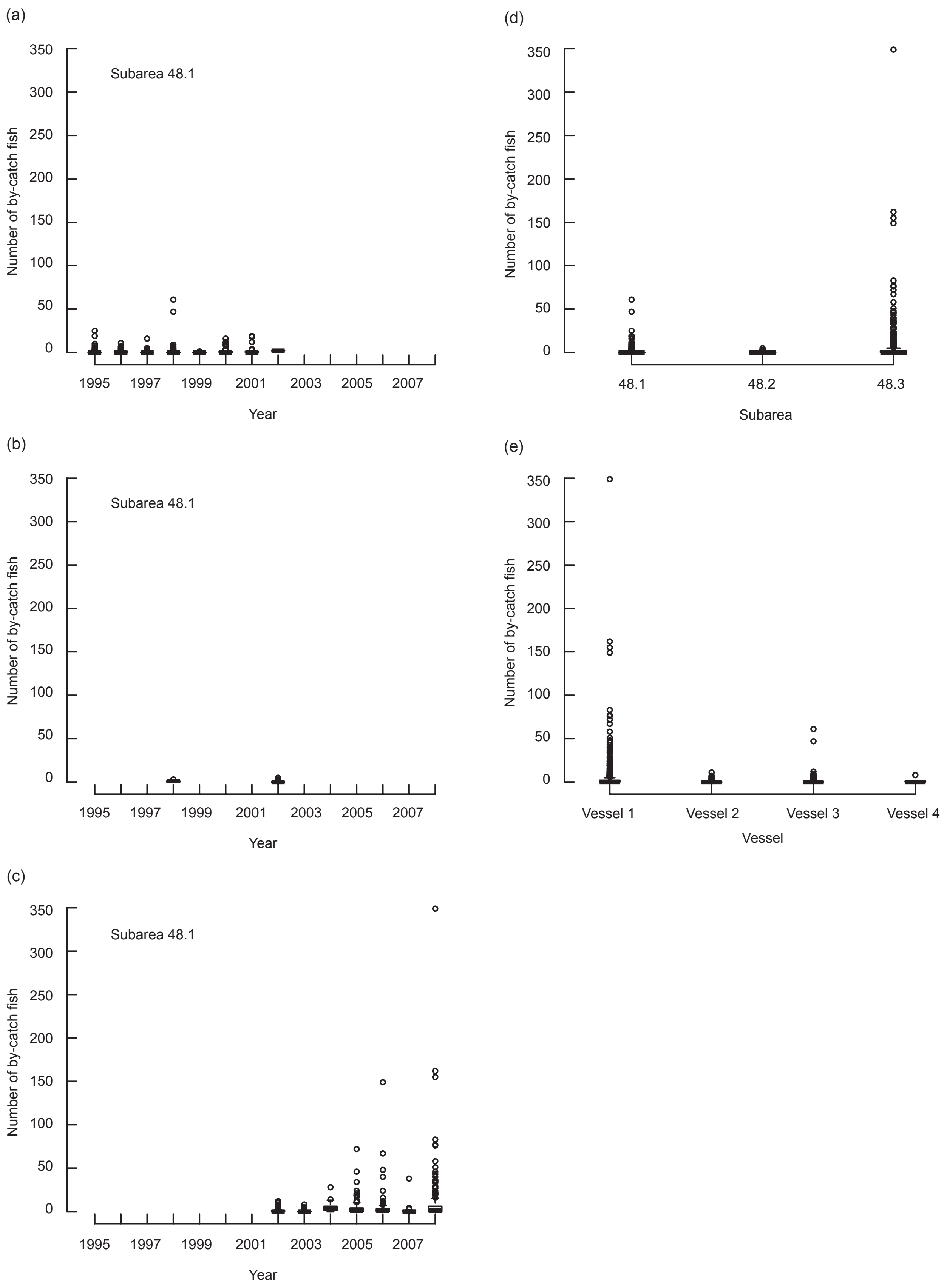

Figure 2: Box plots of number of by-catch fish showing variations within year (a–c), subarea (d) and vessel (e).

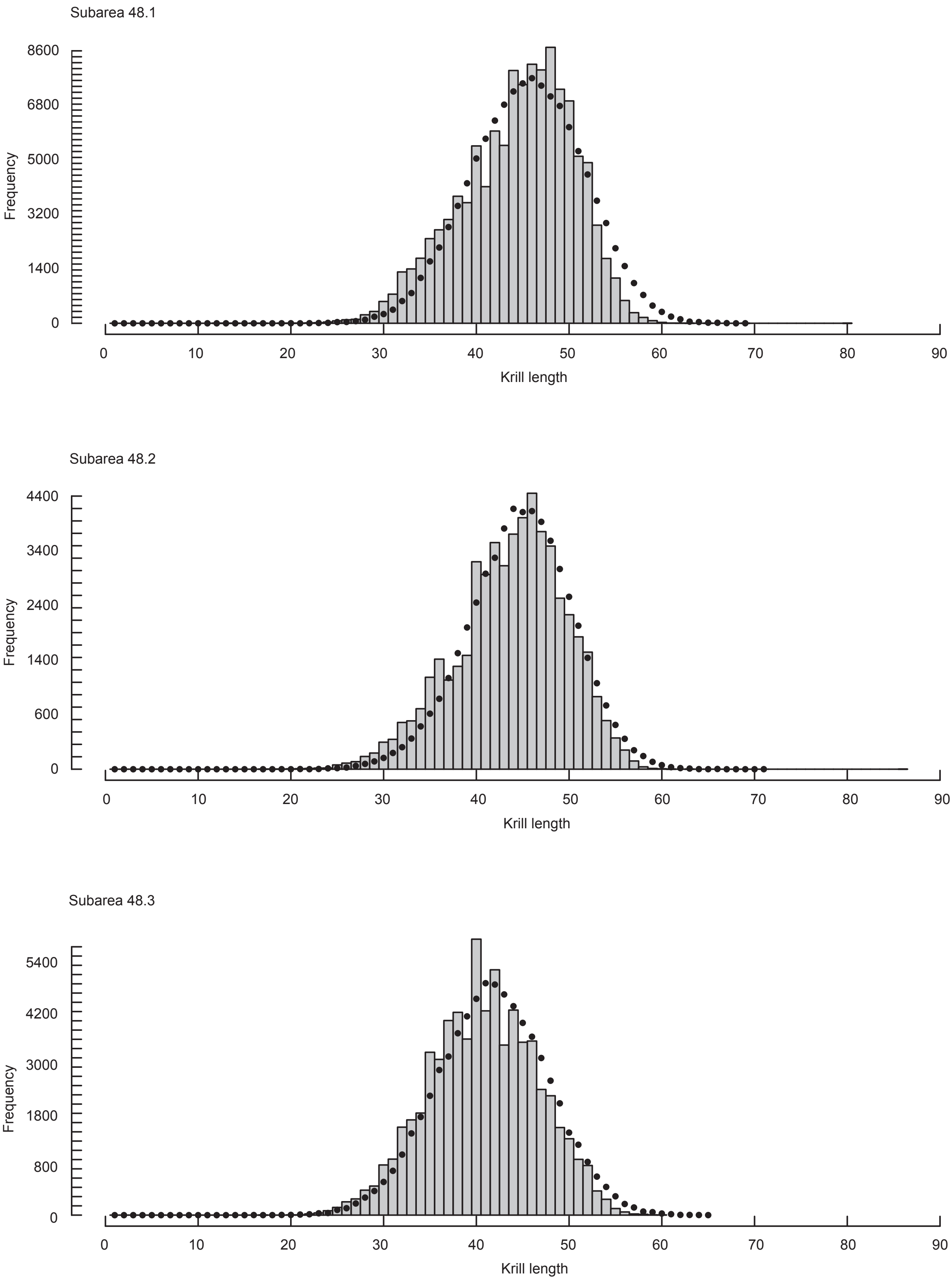

Figure 3: Frequency distribution for observed krill length (bar plot) and expected krill length (black dot). Expected krill length is calculated from parameters estimated by using hierarchical Bayesian modelling with normal distribution.

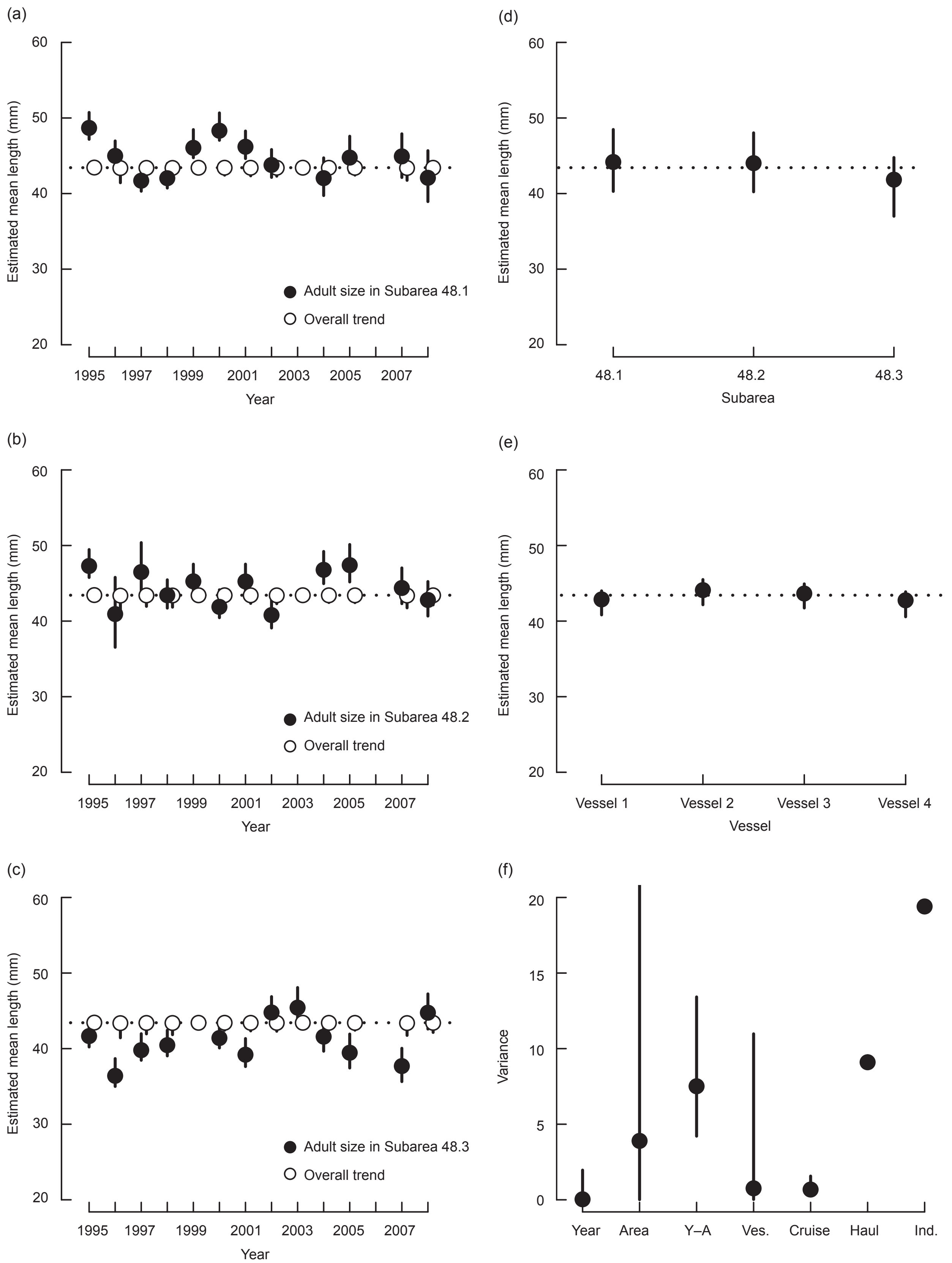

Figure 4: Results of parameter estimation by MCMC for krill length. Temporal fluctuation in estimated mean krill length at (a) Subarea 48.1, (b) Subarea 48.2 and (c) Subarea 48.3. The open circles show overall trends among subareas. (d) The difference of mean krill length among subareas. (e) The difference of mean krill length among vessels. (f) The variance terms of each estimated parameter (Y−A – interaction between year and subarea, Ves. – vessel, Ind. – individual). The horizontal dotted lines indicate grand mean of krill length. The vertical lines are 95% CI of each estimated parameter. Upper limit of CI in variance term of interaction between year and subarea is 95.473.

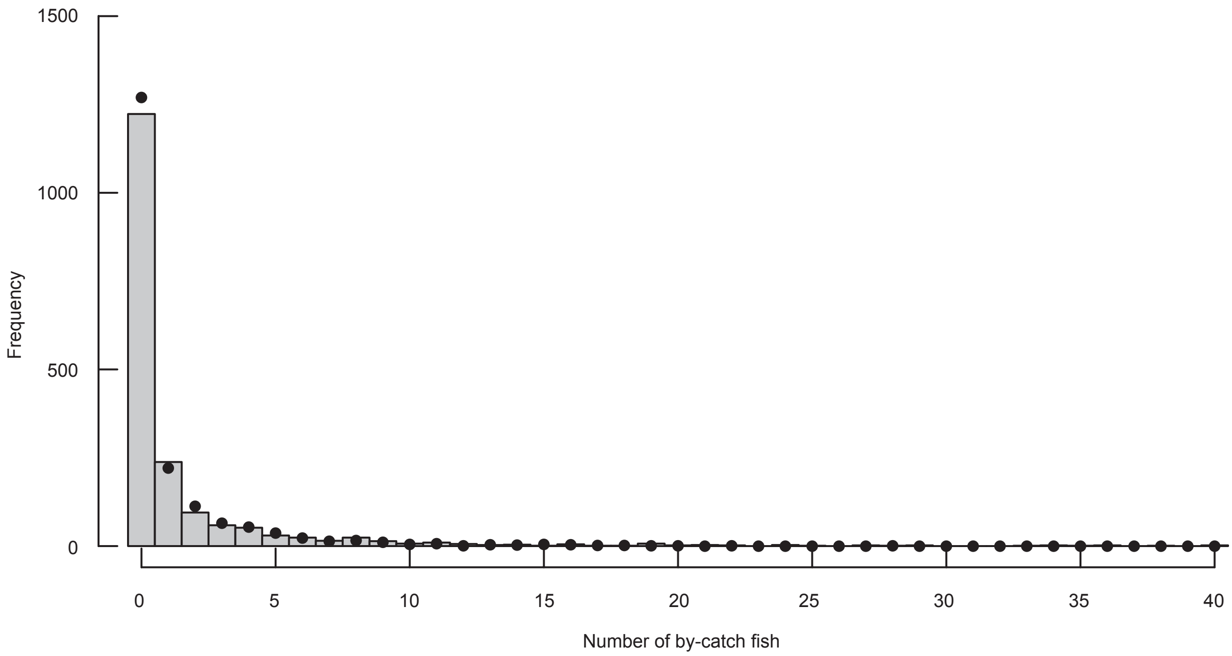

Figure 5: Frequency distribution for observed number of by-catch fish (bar plot) and expected number of by-catch fish (black dot). Expected number is calculated from parameters estimated by using hierarchical Bayesian modelling with ZINB distribution.

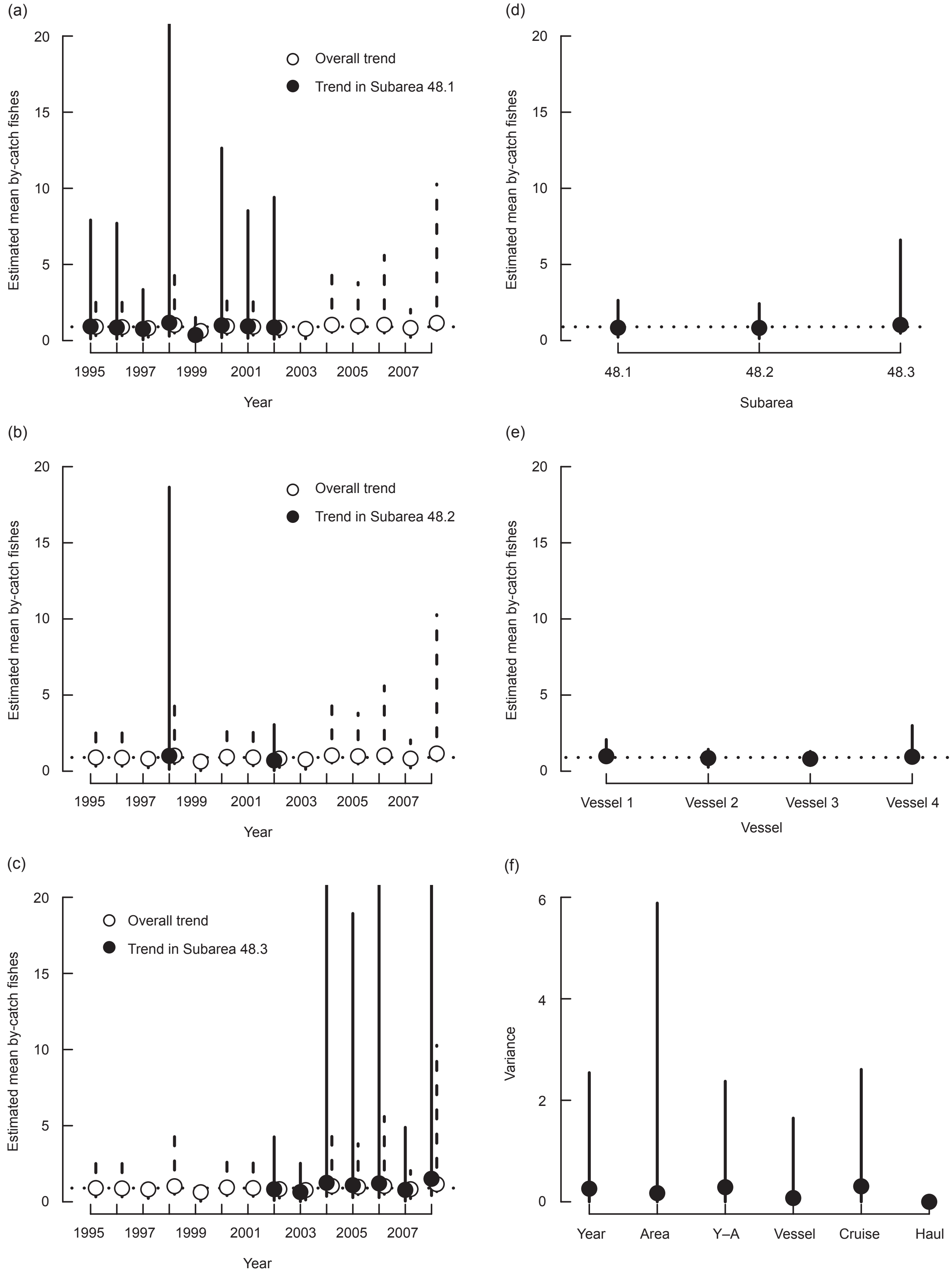

Figure 6: Results of parameter estimation by MCMC for number of by-catch fish. Temporal fluctuation in estimated number of by-catch fish at (a) Subarea 48.1, (b) Subarea 48.2 and (c) Subarea 48.3. (d) The difference of mean number of by-catch fish among subareas. (e) The difference of mean number of by-catch fish among vessels. (f) The variance terms of each estimated parameters (Y−A – interaction between year). The horizontal dotted line indicate grand mean of number of by-catch fish. The vertical lines are 95% CI of each estimated parameter. Four estimated parameters have large upper limits of CI: (a) 1998 – 27.467, (b) 2004 – 28.361, (c) 2006 – 36.688, (d) 2008 – 95.488.

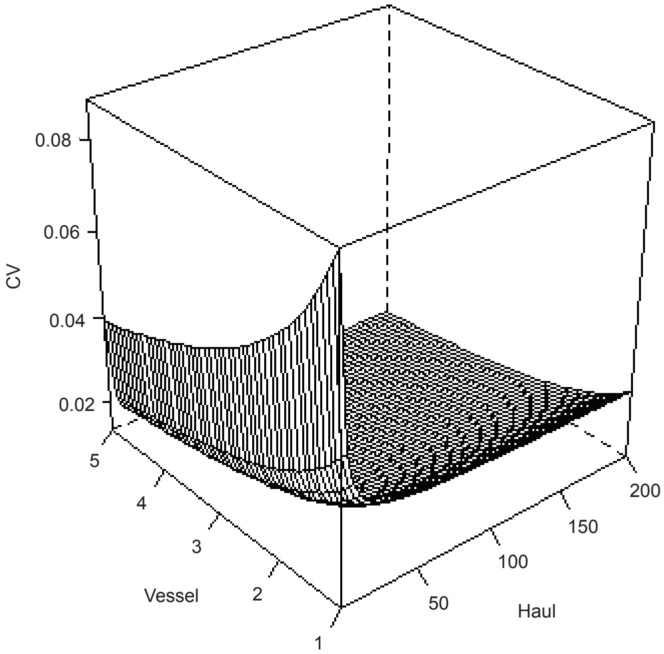

Figure 7: Changes in CV of mean krill length with the shifts in sample sizes of vessel and haul in situations of one cruise and 100 individuals.

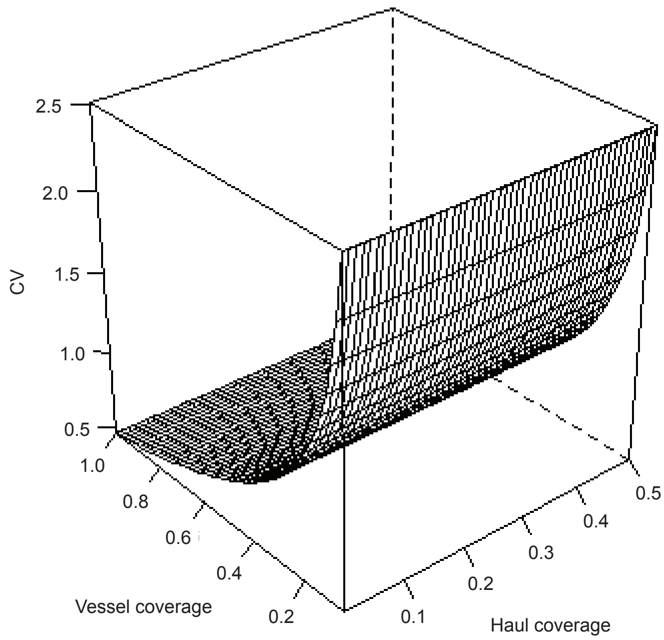

Figure 8: Changes in CV of number of by-catch fish with the shifts in coverage for vessel and haul in situations of cruise coverage 0.5.