Estimating krill density from multi-beam echosounder observations using distance sampling methods

Martin J. Cox, Andrews S. Brierley and David L. Borchers

Abstract

Antarctic krill (Euphausia superba) is a key species in the short Southern Ocean foodweb. The importance of krill as a commercial fishery and food source for many species of Antarctic predators has led to krill being intensively studied and surveyed. As part of Antarctic treaty obligations many nations undertake ‘conventional’ single-beam acoustic surveys to estimate krill biomass. Here we extend recently-developed distance sampling methods and apply them to estimate krill density using observations of krill swarms obtained from a multi-beam echosounder (200 kHz, Simrad SM20). The conventional distance sampling assumption of a uniform distribution of animals is likely violated because krill vertical (depth) distribution is unlikely to be uniform. We relax the uniformity assumption in the vertical dimension and simultaneously estimate density and vertical distribution of krill using a maximum likelihood method. The method accommodates changes in detectability of swarms as a function of radial distance from the echosounder as well as angle (across the multi-beam swath). Model selection was conducted using the Akaike information criterion (AIC) and resulted in selection of a very non-uniform beta probability distribution function for the vertical distribution of krill swarms. Mean krill density was estimated to be 22.6 gm⁻² (95% confidence interval 15.9 to 34.4 gm⁻²) in the study site (area = 14.65 km²) off Livingston Island, Antarctica (62.6° S, 60.3° W). This technique is applicable to both single-target and aggregative organisms sampled using multi-beam echosounders.
Keywords: Acoustic, Antarctic krill, *Euphausia superba*, Multi-beam echosounder, Distance sampling.

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1 Introduction

Antarctic krill (*Euphausia superba*) is a key species in the Southern Ocean foodweb (Mangel & Nicol, 2000). In addition to being a commercial fishery stock, krill is a vitally important food source for many species of air-breathing marine predators. In many regions in the Southern Ocean krill provide a single-step link between primary production and higher trophic levels (e.g. Atkinson, 2001). The importance of krill in many Antarctic ecosystems and the apparently large inter-annual fluctuations in krill density has led to krill being intensely studied and surveyed.

As part their Antarctic treaty obligations many nations undertake ship borne surveys of krill using a combination of net and acoustic samples. Acoustic samples are generally observed using “conventional” hull-mounted vertically-downward looking single- or split-beam scientific echosounders (SBEs) (Demer & Hewitt, 1995; Brierley et al., 1997). SBEs only have a narrow, typically 7° beam width, so sample only a small volume of water under the research vessel. In contrast multi-beam echo sounders (MBEs) have much larger swath widths; typically between 90° and 180°, so sample a much larger volume of water, making them useful for studying organisms, such as Antarctic krill, that exhibit aggregative behaviour (Gerlotto, 1999).

Efforts to estimate pelagic biomass using MBE observations have been hampered by difficulties calibrating the instruments in situ, a paucity of 3D acoustic target strength models (but see Cutter et al. 2009), and the lack of a suitable analysis-framework to incorporate the additional information available from MBEs observations.

Techniques used to estimate krill density from SBE data assume that all krill aggregations within the SBE are detected, which may be a reasonable assumption given the concentration of acoustic
energy in a narrow beam. For many MBEs, however, the acoustic energy density is lower than that of a SBE and may not be uniformly distributed across the swath (there may be lower acoustic energy densities at the swath edges). The MBE swath characteristics may lead to krill swarms being missed at long-ranges and large-detection angles. The potential to miss krill swarms needs to be accounted for to obtain unbiased krill density estimates. In this research we extend and apply distance sampling theory to obtain unbiased krill density estimates and associated measures of uncertainty.

2 Materials and methods

2.1 Data description

Krill swarms were observed using a SM20 200 kHz MBE (Simrad-Mesotech, Vancouver, Canada). MBE data were collected in 41 line transects (length = 2.5 and 3.5 km), from the 2nd to the 9th February 2006 in the vicinity of Cape Shirreff, Livingston Island, South Shetland Islands, Antarctica (65.5° S, 60.8° W; Fig. 1). A total of \( n = 1,006 \) krill swarms were located entirely within the MBE swath (see Cox et al., 2009a for further survey description). Krill swarm boundaries were identified from the MBE data using the acoustic processing software Echoview v3.5 (Myriax, Hobart, Australia). MBE mean volume backscattering strength observations (\( S_v \)) were calibrated using the technique described by Cox et al. (2009b) and scaled using the Demer & Conti (2005) krill target strength model. Key data used in analysis are shown in Table 1 and Fig. 2.
Fig. 1. Cape Shirreff study site, South Shetland Islands. Depth contours and MBE line transects within the MBE study area (greys indicate different observation days) are shown (from Cox et. al, 2009b).
Fig. 2: MBE swath geometry and measurements for the $i$th detected krill swarm. One half of the swath is shown. In common with standard distance sampling methods the swath is folded about $\theta = 0$. The maximum swath observation angle is $\theta = \pi/3$ rad. Data beyond $w$ are truncated. $y^*$ is the depth at which swath width is maximum in the $x$ dimension.
<table>
<thead>
<tr>
<th>Observation</th>
<th>Symbol</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Swarm centre horizontal distance</td>
<td>x</td>
<td>m</td>
</tr>
<tr>
<td>Swarm centre depth</td>
<td>y</td>
<td>m</td>
</tr>
<tr>
<td>Swarm centre radial distance</td>
<td>r</td>
<td>m</td>
</tr>
<tr>
<td>Swarm centre angle</td>
<td>θ</td>
<td>rad</td>
</tr>
<tr>
<td>Swarm volume</td>
<td>V</td>
<td>m$^3$</td>
</tr>
<tr>
<td>Swarm mean volume backscattering strength</td>
<td>$S_v$</td>
<td>dB re 1m$^{-1}$</td>
</tr>
</tbody>
</table>

Table 1: Swarm data derived from MBE observations used in this analysis.

2.2 Distance sampling

There are two main types of distance sampling survey, point transect and line transect (see Buckland et al., 2001). During line transect surveys the observer move along a set of lines and survey a two-dimensional (2D) region. During point transect surveys an observer surveys a circle, or a fraction of a circle at each of a set of points. Although the MBE survey here traversed a set of lines (Fig. 1) it is convenient to think of the survey as a point transect survey (angular segment, $\theta = 2\pi/3$ rad) with each krill swarm being observed in the depth and perpendicular-to-transect (across-track distance) dimensions (Fig. 2), with the along transect dimension collapsed.

A key assumption of conventional distance theory is that survey lines or points are randomly placed which allows the distribution of animals in 2D space to be treated as known and uniform (see Buckland et al., 2001, pp 18-19). Unfortunately, krill are known to exhibit a non-uniform depth distribution (Demer and Hewitt, 1995). Without the uniformity assumption the detection probability, $g(r)$, and animal distribution with respect to the observer, $\pi(r)$, are confounded and
not separately estimable. We can, however, make use of the 2D MBE observations (e.g. krill swarm range, \( r \) and angle \( \theta \)) to estimate parameters for a detection function determined by range and angle, \( p(r, \theta) \) and a joint probability density function (pdf) of \( r \) and \( \theta \), which can be written as 
\[
\pi_{r, \theta}(r, \theta) = \pi_r(r) \pi_{\theta|r}(\theta|r).
\]

Since we placed the line transects randomly on the sea surface (Fig. 1), distances in the \( x \) direction (perpendicular distance-to-transect, Fig. 2) we can treat the pdf of distances within \( 0 \leq x \leq w \sin(\pi/3) \) as known (uniform) and equal to \( 1/w \sin(\pi/3) \), where \( w \) is the MBE maximum search range.

In common with standard distance sampling methods we “fold” the MBE swarm observations about the vertical (centre of the swath, \( \theta = 0 \), Fig. 2) giving a maximum swath width of \( \pi/3 \) radians. Given the random placement of line transects we can treat \( x \) as independent of \( y \) so 
\[
\pi_{xy} = \pi_y(y)/w \sin(\pi/3),
\]
where \( \pi_y \) is a smooth pdf with unknown parameter vector \( \phi \).

Seabed depth varied throughout the survey region (Fig. 1). Observations of seafloor depth were used to model the probability that the sea at a randomly selected location was no less than \( y \) deep. We refer to this as the depth attenuation function, which is modelled as 
\[
a(y) = (1+\exp(-(y-\beta_0)/\beta_1))^{-1}
\]
To determine the density of krill swarms in a rectangle of dimensions $0 \leq x \leq w \sin(\pi/3)$ and $0 \leq y \leq w$ we deal with on detections occurring outside of the folded MBE swath by defining $p(r, \pi)$ to be zero for $r > w$ and $\theta > w \sin(\pi/3)$. The expected probability of detecting a krill swarm in the rectangular area is

$$P^* = \int_0^w \int_0^{w \sin(\pi/3)} p(\sqrt{x^2 + y^2}, \tan^{-1}(x/y)) \pi_y(y) \frac{1}{w \sin(\pi/3)} a(y) \, dx \, dy$$

(1)

Given models for $p(r, \theta)$ with an unknown parameter vector $\phi$ and $\pi_y(y)$ with unknown parameter vector $\varphi$ and that $n$ krill swarms, with centres $(x_1, y_1), \ldots, (x_n, y_n)$ were observed the likelihood for $\phi$ and $\varphi$ is

$$L(\phi, \varphi) = \prod_{i=1}^n \frac{p(\sqrt{x_i^2 + y_i^2}, \tan^{-1}(x_i/y_i)) \pi_y(y_i) \frac{1}{w \sin(\pi/3)} a(y)}{P^*}$$

(2)

The central ideas of this distance sampling framework are taken from Marques (under revision).

### 2.3 Krill density estimators

Krill areal density was estimated using

$$\hat{D}_s = \frac{n}{L \cdot 2w \sin(\pi/3) \hat{P}}$$

(3)

where $L$ is the total line transect length and $\hat{P}$ is $P$ evaluated at the maximum likelihood estimates of $\hat{\phi}$ and $\hat{\varphi}$. Krill swarm abundance in the survey region (with area $A$) is estimated by $\hat{N} = A \hat{D}_s$.

To avoid bias that may arise from size-selectivity conventional distance sampling determines mean group size by regressing log-group size against distance and the value of the regression line at distance zero (see Buckland et al., 2001, pp 73-75). We expect the mean biomass of observed swarms to decrease with detection angle, $\theta$, because detection probability decreases with $\theta$. We
regressed log of observed swarm biomass against $\theta$ and used the transformed, bias corrected, estimated intercept to estimate mean biomass, $\hat{E}[b]$.

Total biomass in the survey region was estimated by $\hat{B} = \hat{E}[b]\hat{N}_s$ and areal krill density by $\hat{\rho} = \hat{B} / A$.

Variance and 95% confidence intervals were estimated using nonparametric bootstrap with 1,000 replicates, using transect as the sampling unit. Confidence intervals were estimated using the percentile method.

2.4 Krill detection function models
The probability of detecting a krill swarm using the MBE is modelled as $p(r; \theta) = g(r)q(\theta)$.

Standard distance sampling function, in this case the half-normal, with a single parameter $\phi_1$, can be used to model $g(r)$:

$$g(r) = \exp\left[-\frac{r^2}{2\phi_1^2}\right]$$

We used the beam-by-beam angular sensitivity of the MBE to provide information on $q(\theta)$ and overcome the confounding between $q(\theta)$ and $\pi_s(y)$. The beam-by-beam sensitivity was estimated using measurements of MBE noise. Noise was assumed to be isotropic and estimated using $S_v$ data collected at the Cape Shirreff study site.
The beam-by-beam $S_v$ observations were transformed to the linear domain ($s_v = 10/(S_v/10)$) and inverted, giving a relative measure of krill swarm detection probability. The following hazard-rate functional form with parameters $\alpha_0$, $\alpha_0$ and $\alpha_1$ was found to the adequate:

$$q(\theta) = \alpha_0 \left[ 1 - \exp\left\{ -\left( \frac{\theta}{\alpha_0} \right)^{-\alpha_1} \right\} \right]$$

(5)

2.5 Krill depth distribution models

Krill swarms are known to generally have a very low density at the surface and are expected to have a low density at the deepest depths covered by the line transects with a peak density occurring at intermediate depths. To model this behaviour we considered the following smooth pdfs for $\pi_y(y)$: normal, log-normal, beta and uniform.

3 Results

3.1 Seabed depth distribution model

The attenuation function, $a(y)$, model provided a very good fit to the survey area seabed depths $\hat{\beta}_0 = -0.115$ (CV = 18%) and $\hat{\beta}_1 = -5.920$ (CV = 0.013%).

3.2 Angular detection function model

Data collected during the SM20 calibration exercise conducted at Cape Shirreff showed increased noise within the outer beams (beam numbers 0 to 14 and 109 to 127; Fig. 3a). Parameter estimates for the hazard-rate angular detection function model (Fig. 3b) given in Equation 5 were $\alpha_0 = 1.12$ (CV = 1.6%), $\alpha_0 = 0.87$ (CV = 1%) and $\alpha_1 = 10.37$ (CV = 14.1%).
Fig. 3: Variation in angular sensitivity inferred from beam-by-beam noise measurements. Panel (a) shows the beam-by-beam noise, observed as $S_v$ data, which increases on the outer beams. Panel (b) shows the inverse of the $S_v$ data as circles, folded about $\theta = 0$.

3.3 Krill vertical distribution

Parameters for the krill vertical distribution $pdf$, $\pi_r(y)$ and radial distance detection function $g(r)$ were estimated by maximising likelihood (Equation 2). The krill vertical distribution model was selected using Alaike’s Information Crieterion (AIC) and goodness-of-fit was assessed using a $\chi^2$ test, with 10 m depth intervals (Fig. 4). The beta krill vertical distribution model was selected on the basis of AIC.
<table>
<thead>
<tr>
<th>Krill vertical distribution</th>
<th>( \pi_y(y) )</th>
<th>( \hat{\phi}_1 )</th>
<th>( \hat{\phi}_1 )</th>
<th>( g(r) )</th>
<th>AIC</th>
<th>( \Delta\text{AIC} )</th>
<th>( \chi^2 )</th>
<th>( p)-value</th>
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</thead>
<tbody>
<tr>
<td>Beta</td>
<td>2.68</td>
<td>2.38</td>
<td></td>
<td>149.0</td>
<td>7,888.3</td>
<td>0</td>
<td>0.24</td>
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<tr>
<td>Normal</td>
<td>54.4</td>
<td>23.4</td>
<td></td>
<td>128.5</td>
<td>7,899.4</td>
<td>11.1</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>Log-normal</td>
<td>4.26</td>
<td>0.64</td>
<td></td>
<td>99.8</td>
<td>7,949.2</td>
<td>60.9</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Uniform</td>
<td>-</td>
<td>-</td>
<td></td>
<td>122.0</td>
<td>8,042.3</td>
<td>154.0</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Krill vertical distribution, \( \pi_y(y) \), maximum likelihood model parameter estimates and radial distance detection function, \( g(r) \), model parameter estimate. \( \Delta\text{AIC} \) is the difference in AIC from the model with the smallest AIC, the Beta krill vertical distribution model.
Fig 4a: Beta distribution

\( \hat{\phi}_1 = 2.68, \hat{\phi}_2 = 2.38, \hat{\phi}_1 = 149.0 \text{ m} \)

Fig 4b: Normal distribution

\( \hat{\phi}_1 = 54.4 \text{ m}, \hat{\phi}_2 = 23.4 \text{ m}, \hat{\phi}_1 = 128.5 \text{ m} \)

Fig 4c: Log-normal distribution

\( \hat{\phi}_1 = 4.26, \hat{\phi}_2 = 0.64, \hat{\phi}_1 = 99.8 \text{ m} \)

Fig 4d: Uniform distribution

\( \hat{\phi}_1 = 154.0 \text{ m} \)

Fig. 4: Model fits for various krill vertical distribution models (beta, normal, log-normal and uniform) and associated parameters (\( \hat{\phi}_1 \) and \( \hat{\phi}_2 \)) as shown as a dashed line. The radial distance detection function model parameter (\( \hat{\phi}_1 \)) is shown as a dotted line. The expected number of detections for the \( n = 1,006 \) krill swarms detected is shown as a solid line. Both the vertical distribution and the radial distance detection function have been scaled to the solid line. The histogram shows the observed krill swarm frequencies in 10 m depth bins.
3.4 Estimated krill biomass and areal density

Point estimates together with associated variance estimates for krill swarm abundance, biomass, determined by linear regression (see Section 2.3) and krill areal density are shown in Table 3.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Point estimate</th>
<th>CV estimate</th>
<th>95% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beta $\hat{\phi}_1$</td>
<td>2.68</td>
<td>0.16</td>
<td>2.20, 4.04</td>
</tr>
<tr>
<td>Beta $\hat{\phi}_2$</td>
<td>2.38</td>
<td>0.12</td>
<td>1.95, 3.09</td>
</tr>
<tr>
<td>Half-normal $\hat{\phi}_1$, m</td>
<td>149.0</td>
<td>0.77</td>
<td>66.3, 500</td>
</tr>
<tr>
<td>Encounter rate, $n/L$ (km$^{-1}$)</td>
<td>9.37</td>
<td>0.14</td>
<td>6.83, 11.48</td>
</tr>
<tr>
<td>$\hat{p}$</td>
<td>0.32</td>
<td>0.13</td>
<td>0.21, 0.35</td>
</tr>
<tr>
<td>$\hat{N}_s$</td>
<td>1615</td>
<td>0.19</td>
<td>1400, 2308</td>
</tr>
<tr>
<td>$\hat{E}[b]$ (kg)</td>
<td>205.1</td>
<td>0.16</td>
<td>143.0, 265.2</td>
</tr>
<tr>
<td>$\hat{B}$ (tonnes)</td>
<td>331.2</td>
<td>0.29</td>
<td>232.6, 504.3</td>
</tr>
<tr>
<td>$\hat{\rho}$ (gm$^{-2}$)</td>
<td>22.6</td>
<td>0.29</td>
<td>15.9, 34.4</td>
</tr>
</tbody>
</table>

Table 3: Krill vertical distribution (beta) and radial distance detection function (half-normal) maximum likelihood point and variance estimates, along with krill biomass point and variance estimates.
4 Discussion

We have successfully adapted the distance sampling theory developed by Marques et al. (under revision) for use with MBE data and in doing so solved part of the problem of estimating biomass using MBE data.

We compared our areal density estimates to those of Reiss et al. (2008) who, as part of the US Antarctic Marine Living Resources Program, used SBEs to survey krill over a much larger area to the west of Cape Shirreff (A = 38,524 km$^2$ cf A = 14.7 km$^2$; see Fig. 1 Reiss et al., 2008). Our mean areal krill density estimate of 22.6 g m$^{-2}$ (95% confidence interval (CI) 15.9 to 34.4 g m$^{-2}$) was substantially lower than the Reiss et al. (2008) SBE derived estimates for 2006 was 80.9 g m$^{-2}$ (95% CI 8.2 to 153.6 g m$^{-2}$). Our MBE krill areal density estimate 95% CI did, however, fall entirely within the 2006 SBE Reiss et al. (2008) krill areal density estimate 95% CIs. The three orders of magnitude difference in survey area prohibit further comparison.

In addition to density and abundance estimates, our distance sampling method also provides predictions for the vertical distribution of krill, which is useful for studying predator-prey interactions. Our optimum model predicts that within the Cape Shirreff study site, the largest numbers of krill swarms were on average found at a depth of 55 m. Given that the mean water depth within the study site was 93 m this result suggests that krill tended to occupy mid-water column depths, rather than attempting to descend as close to the seabed as possible to avoid predation. We therefore suggest that in coastal, shallow water areas, krill behaviour during the day may not be entirely driven by predator avoidance.
The vertical distribution of krill could also be useful for investigating interactions between krill predator species. Using predator diet and satellite data Barlow et al. (2002) suggested that Antarctic fur seals (*Arctocephalus gazella*) were out competing macaroni penguins (*Eudyptes chrysolophus*) for krill at South Georgia. Using our distance sampling technique it is possible to examine the depth distributions of swarms with high or low volumetric densities to explore potential differences in the exploitation of krill by Antarctic fur seals and macaroni penguins. Comparing predator dive data with krill vertical depth distributions may enable assessment of Antarctic fur seal and macaroni penguin foraging niche separation. Antarctic fur seals may be out competing macaroni penguins thereby forcing them to feed on less profitable, lower density, swarms.

We recognise that further work is required before the distance sampling technique presented here. In particular we suggest incorporating a 3D krill target strength model, such as that described by Cutter et. al (2009) would be a sensible next step. We have nevertheless established a framework that can bring together multi-beam observations and 3D target strength models, as they develop, to provide robust biomass estimates.

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