

₁ An analysis of the North Sea International Bottom Trawl Survey

₂ Data

₃

₄ **Abstract**

₅ In this research we present nonparametric estimation procedures for calculating abundance at age
₆ indices, and investigate the sensitivity of these estimates with respect to the number of otoliths collected
₇ at sea. The procedures presented are applied to the North Sea International Bottom Trawls Survey data
₈ for cod (*Gadus morhua*) and saithe (*Pollachius virens*). We demonstrate how much information would
₉ be lost if the survey design was defined such that fewer otoliths were collected. Age length keys (ALKs)
₁₀ are used to map lengths to age, and we use ALKs with and without the assumption of constant age length
₁₁ structures over relatively large areas. All abundance at age indices are presented with variance estimates.

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₁₃ **1 Introduction**

₁₄ Fish stock assessments are used by fishery managers for making management decisions regarding catch
₁₅ quotas. The assessments provide fundamental information about the status of the stock, for instance,
₁₆ whether the stock is increasing and support for increased levels of harvest should be given, or whether the
₁₇ stock is decreasing and stricter control on harvest should be implemented. Associated with the parameters
₁₈ used in fish stock assessment is their uncertainty, which should not be ignored when formulating management
₁₉ policies (Walters and Ludwig, 1981; Ludwig and Walters, 1981; Berg et al., 2014). This uncertainty can arise
₂₀ from many sources including natural variability, estimation procedures and lack of knowledge regarding the
₂₁ parameter (Ehrhardt and Legault, 1997). The North Sea International Bottom Trawl Survey (IBTS) data,

22 coordinated by the International Council for the Exploration of the Sea (ICES), provides information on
23 seasonal distribution of stocks and estimates of abundance indices and catch in numbers of fish per age-class
24 without an assessment of the accuracy of these estimates. As stated by Ludwig and Walters (1981) it is
25 relevant for managers to take into the uncertainty related to stock size when making management policies. The
26 indices of abundance at age from IBTS are based on data obtained from a stratified semi-random sampling
27 approach of trawl stations, and it is essential to account for the sampling approach so as to produce reliable
28 variance estimates (Lehtonen and Pahkinen, 2004). If the sampling approach is ignored, the effect on the
29 variance of the parameters could be substantial. In particular, the variance could be greatly inflated due
30 to the clustering effect, which involves intra-cluster correlation of the variables (Aanes and Vølstad, 2015;
31 Lehtonen and Pahkinen, 2004).

32 There are two separate stages for generating abundance indices per age from the North Sea International
33 Bottom Trawl Survey (IBTS) data. The first consist of calculating indices per *length* class, which are
34 obtained by trawling in a stratified manner and counting the number of fish caught. Then that knowledge is
35 transformed to indices with respect to age. The latter part is achieved with an age-length key (ALK), which
36 is constructed by sampling otoliths in a stratified procedure from each haul and/or sub-area. To our best
37 knowledge, there has been no research on how much the uncertainty of the abundance indices is related to
38 these two distinct parts. The main contribution of this research is to shed light on how the indices estimates
39 and their associated uncertainty estimates change if less effort was spent on collection of otoliths. We achieve
40 the reduction of otoliths by mimicking a defined sampling procedure with less effort. We also focus on the
41 spatial distribution of the ALK, and such spatial structures in the ALK has also been investigated in Berg
42 and Kristensen (2012) and Hirst et al. (2012).

43 Currently, abundance indices from IBTS are reported in DATRAS (ICES, 2018c) using an age-length
44 key (ALK) (Fridriksson, 1934) which is assumed to be constant over relatively large areas. In this research
45 we propose two ALKs which accounts for spatial variation: i) a nonparametric haul based ALK, and ii) a
46 spatial model based ALK. These ALKs are described in Section 2. A spatial model based ALK (Berg and
47 Kristensen, 2012; Berg et al., 2014) known as the NS-IBTS Delta-GAM index (ICES, 2016b) is currently
48 being used to calculate standardized age-based survey indices used in assessment for the North Sea stock.

49 And, as far as we are aware the variance estimates of parameters estimated from NS-IBTS Delta-GAM index
50 are *only* utilized for assessment of Herring (*Clupea harengus*) in the North Sea.

51 The spatial ALK model introduced in Berg and Kristensen (2012) is similar to the model used in this
52 paper; the main difference is that we include the spatial structure through a spatial random field (Lindgren
53 et al., 2011) and not through two dimensional splines (Wood, 2017).

54 An overview of the North Sea International Bottom Trawl Survey is given in Section 1.1. The current
55 estimators for ALK and catch per unit effort (CPUE) used by ICES in their database for trawl surveys
56 (DATRAS) and our proposed ALK estimators are given in Section 2. We apply these ALK methods to two
57 case studies in Section 3, and a discussion is given in Section 4.

58 **1.1 Overview of the North Sea International Bottom Trawl Survey**

59 The North Sea International Bottom Trawl Survey was formed in 1991, which is a combination of the
60 International Young Herring Survey (IYHS) and eight national surveys in the North Sea, Skagerrak and
61 Kattegat areas. These surveys began in the 1960's, and the 1970's and 1980's, respectively. The IYHS was
62 developed with the aim of obtaining annual recruitment indices for the combined North Sea herring *Clupea*
63 *harengus* stock (ICES, 2012), but yielded valuable information on other fish species such as cod *Gadus*
64 *morhua* and haddock *Melanogrammus aeglefinus*.

65 The North Sea IBTS began with quarterly surveys providing information on seasonal distribution of
66 stocks sampled, hydrography and the environment, which allows changes in fish stock to be monitored and
67 abundance of all fish species to be determined. These quarterly surveys, however became difficult to sustain
68 as countries experienced budget cuts making it impossible to maintain high levels of research vessel effort.

69 As such, in 1997 countries carried out a survey only twice a year; a first quarter survey (January-February)
70 and a third quarter survey (July-September). The target species of IBTS fished from 1991-2018 includes
71 standard pelagic species: Herring (*Clupea harengus*), Sprat (*Sprattus sprattus*) and Mackerel (*Scomber*
72 *scombrus*); and standard roundfish species: Cod (*Gadus morhua*), Haddock (*Melanogrammus aeglefinus*),
73 Saithe (*Pollachius virens*), Norway Pout (*Trisopterus esmarkii*) and Whiting (*Merlangius merlangus*). There
74 are also several by-catch species (see for example, ICES, 2006)

75 Research vessels from seven nations in the first quarter (Q1) and six nations in the third quarter (Q3)
76 are used for conducting surveys on all finfish species in the North Sea during January–February and July–
77 August, respectively, between 1997–2018 (Table S1.1 in Supplementary Materials S1 gives details of the
78 research vessels). The sampling frame is defined by the ICES index or roundfish areas (RFA) as shown
79 in Figure 1 numbered 1 to 10. These roundfish areas were substratified into small strata defined by non–
80 overlapping statistical rectangles of roughly 30×30 nautical miles (1° Longitude \times 0.5° Latitude), and
81 were convenient to use for IBTS as they were already being used for fisheries management purposes. Most
82 statistical rectangles contain a number of possible tows that are deemed free of obstructions, and vessels
83 are free to choose any position in the rectangles as long as the hauls are separated by at least 10 nautical
84 miles within and between rectangles. However, all countries select tows based on a semi-random approach
85 from databases of national safe tows or DATRAS or commercial fishing data, except Sweden who uses fixed
86 stations and in some cases depth-stratified semi-random sampling design (ICES, 2018b); and England who
87 also uses fixed stations and only conduct surveys during the third quarter. In some rectangles, sampling
88 may be further stratified due to significant changes in seabed depth which may, in turn, cause variations in
89 the fish population. In particular, the North Sea IBTS herring, saithe and sprat data are weighted by depth
90 strata in the statistical rectangle (see Table S3.1 in appendix S3). It is also a requirement that countries
91 avoid clustering their stations between adjacent rectangles in order to reduce positive serial correlation, and
92 thereby maximize survey precision. The latest major reallocation of rectangles occurred in 1991, but since
93 then the survey has tried to keep at least one vessel in every subarea in which it had fished in the most recent
94 years. Minor reallocation of rectangles between Norway, Scotland and Germany was done in 2013. Each
95 rectangle was typically sampled twice by two different countries before 1997, but after that target coverage
96 of two trawl hauls per rectangle per survey was introduced because of national financial constraints (ICES,
97 2015). But in some rectangles in the Eastern English Channel, Southern North Sea and Central North Sea
98 intensified sampling is carried out.

99 The recommended standard trawling gear of the North Sea IBTS is the mulitpurpose chalut à Grande
100 Ouverture Verticale (GOV) trawl (ICES, 2012), which has been used on all participating vessels since 1992,
101 while different pelagic and bottom trawls suitable for fishing finfish species were used before 1992. Standard–

102 ized trawling protocols were adopted with a towing speed of 4 knots but depending on vessel performance,
 103 tide and weather conditions the average towing speed can be at minimum 3.5 and maximum 4.5 knots. From
 104 2000-2018 trawling is done during the daylight hours, which are considered 15 minutes before sunrise to 15
 105 minutes after sunset (ICES, 2012). After each trawl the total catch of the different species is weighed on
 106 board and biological parameters such as length for all fish species caught (to 0.1 cm below for shellfish, to
 107 0.5 cm below for herring and sprat and to 1 cm below for all other species) are collected. Where the numbers
 108 of individuals are too large for all of them to be measured to obtain the length distribution, a representative
 109 subsample of 100 fish is selected. Otoliths are collected on board from a small fraction of all the target
 110 species from all RFAs (Figure 1) to retrieve age reading. Table S2.1 in Supplementary Materials S2 gives
 111 the minimum sampling levels of otoliths for the target species.

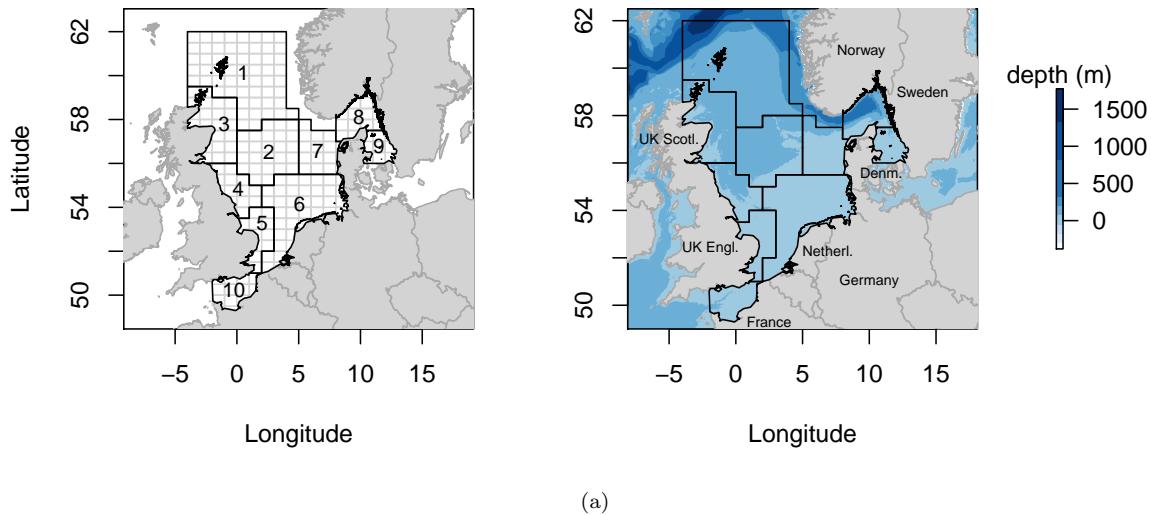


Figure 1: Standard roundfish areas (RFAs) used for roundfish since 1980 and for all standard species since 1991 (left panel). RFA 10 was added in 2009. The number 1, for example, indicates ICES RFA 1. The small grey rectangles in the left panel indicates the statistical rectangles of 30×30 nautical miles (1° Longitude \times 0.5° Latitude). The map in the right panel shows the Norwegian trench and shelf edge (depths 1000-1500).

112

2 METHODS

113 This section gives the estimators of abundance indices. The estimators are haul time-based and utilizes an
 114 ALK approach. We consider the ALK approach used in DATRAS and we propose two ALK estimators.

115 The ALK used in DATRAS for computing abundance indices does not account explicitly for the spatial
 116 distribution in the age-length composition, which may be different and would result in a biased ALK (Kimura,
 117 1977). This difference may be caused either by variation in length-at-age distributions or by variations in
 118 the relative abundance of age classes, that is age-at-length distributions (Gerritsen et al., 2006). To account
 119 for the spatial distribution we propose a design-based ALK estimator that is haul dependent (Section 2.2.2)
 120 and a model based ALK estimator (2.2.3).

121 ***2.1 Catch per unit effort***

122 In this research, the catch per unit effort (CPUE) is defined as the number of fish of a certain species and
 123 age or length which are caught per hour trawl. In this section we define the CPUE mathematically, which
 124 explains how the index is calculated. For a given species of interest, let $n_{h,l}$ be the number of fish with
 125 length l caught by trawl haul h . The CPUE for a given length l by trawl haul h is defined as

$$\text{CPUE}_{h,l} = \frac{n_{h,l}}{d_h}, \quad (2.1)$$

126 where d_h is the duration of the trawl in hours. The CPUE per age class is further defined as

$$\text{CPUE}_{h,a} = \sum_{l \in \mathbf{L}} \text{CPUE}_{h,l} \times \text{ALK}_{a,l,h}, \quad (2.2)$$

127 where \mathbf{L} is the set of all length classes and $\text{ALK}_{a,l,h}$ is the age length key, which represents the estimated
 128 proportion of fish with age a in l th length class in haul h . For a given number of trawl hauls in a statistical
 129 rectangle, the mean CPUE defined as mCPUE in a statistical rectangle can be expressed as the average
 130 CPUE of the trawl hauls in the statistical rectangle:

$$\text{mCPUE}_{s,a} = \sum_{h \in H_s} \frac{\text{CPUE}_{h,a}}{|H_s|}. \quad (2.3)$$

131 Here H_s represents the set of trawl hauls taken in statistical rectangle s , and $|H_s|$ is the number of hauls
 132 taken in the rectangle. The mCPUE in p th RFA is further defined as

$$\text{mCPUE}_{p,a} = \sum_{s \in S_p} \frac{\text{mCPUE}_{s,a}}{|S_p|} \omega_s, \quad (2.4)$$

133 where S_p is the set of all statistical rectangles in RFA p , $|S_p|$ is the number of statistical rectangles in RFA
 134 p , and ω_s is a weight variable for each statistical rectangle. The weight variable ω_s varies between species.

135 For some species ω equals 1 (e.g. *Gadus morhua*) for all s , and for other species it is the proportion of the
 136 statistical rectangle which has depth between 10 to 200 meters, for example *Pollachius virens* (see Table S3.1
 137 in Supplementary Materials S3). The mean catch per unit at age in the whole study area, λ_a , is defined by

$$\lambda_a = \frac{\sum_{p \in \mathbf{P}} A_p m \text{CPUE}_{p,a}}{A_{\text{total}}}. \quad (2.5)$$

138 This is known as the index of abundance at age, where \mathbf{P} is the set of RFAs, A_p is the area of RFA p , and
 139 $A_{\text{total}} = \sum_{p \in \mathbf{P}} A_p$.

140 ***2.2 ALK estimators***

141 The definition of the CPUE of age includes an ALK, see (2.2), which we described in this section. Three
 142 ALK estimators are included in this research, which are named as follows: *i*) DATRAS ALK, *ii*) haul based
 143 ALK and *iii*) model based ALK.

144 ***2.2.1 DATRAS ALK***

145 Let ALK^D denote the DATRAS ALK. The ALK^D is defined as constant within each RFA, and is calculated
 146 for each RFA by aggregating the age observation from each RFA. $\text{ALK}_{a,l,h}^D$ used in equation (2.2) is defined
 147 as the proportion of observed fish with age a in length class l in the RFA h . If there are no observed
 148 fish in length class l in the RFA, ages from length classes close to l is used. The details of the procedure
 149 for borrowing strength from neighbouring length classes are given in Supplementary Materials S4.1. The
 150 underlying assumption of this ALK is that age-length compositions are homogeneous within the RFAs.
 151 This is a rather strong assumption, and any violation would have an unknown impact on the estimates of
 152 abundance indices. Aanes and Vølstad (2015) illustrated that violation of the assumption of constant ALK
 153 leads to biased estimates of CPUEs.

154 ***2.2.2 Haul based ALK***

155 We define a haul dependent ALK by ALK^H . The $\text{ALK}_{a,l,h}^H$ used in equation (2.2) is defined as the average
 156 proportion of observed fish with age a in length class l in haul h . If there are no observed ages of fish in a

157 length class l in the haul, ages from the same length class in the haul close by is used (see Supplementary
158 Materials S4.2 for the procedure).

159 *2.2.3 Model based ALK*

160 In this section we introduce a spatial model based ALK, which we define as ALK^M . Using such a model
161 enables us to obtain smooth structures in the distribution of age given length. It further enables us to utilize
162 spatial latent effects. Spatial model based approach of age-lengths are widely used (Berg and Kristensen,
163 2012; Hirst et al., 2012; Rindorf and Lewy, 2001), and are used for stock assessment in the North Sea (Berg
164 et al., 2014).

165 Let the response variable of the age group of a fish be $a = M, \dots, A$ where M is the youngest age, and A
166 is the oldest age which is typically defined as a "plus group". Suppose $y(l, \mathbf{s})$ is the age of a fish with length
167 l caught at location \mathbf{s} . As in Berg and Kristensen (2012) we use a continuous ratio model for the spatial age
168 given length model. However, in our application we assume for each species we know a length l^* such that
169 all fish above length l^* are above age M , and all fish with length below l^* are of age below A . By including
170 such a variable we reduce the number of parameters in the model by removing one linear predictor. Define
171 the continuous ratio we are modelling as

$$\pi_a[y(l, \mathbf{s})] = \frac{p_a(l, \mathbf{s})}{p_a(l, \mathbf{s}) + \dots + p_A(l, \mathbf{s}) + p_M(l, \mathbf{s})} \quad \text{for } a = M + 1, \dots, A - 1, \quad (2.6)$$

172 where $p_a(l, \mathbf{s})$ is the probability of a fish with length l at location \mathbf{s} to be of age a . Note that either $p_A(l, \mathbf{s})$
173 or $p_M(l, \mathbf{s})$ is known to be equal to zero, and the other is selected such that $\sum_a p_a = 1$. We further assume
174 the logit link

$$\log \left[\frac{\pi_a[y(l, \mathbf{s})]}{1 - \pi_a[y(l, \mathbf{s})]} \right] = f_a(l) + \gamma_a(\mathbf{s}). \quad (2.7)$$

175 Here $f_a(l)$ is a continuous function of length and γ is a mean zero Gaussian spatial random field with Matérn
176 covariance function. The spatial random field is intended to capture any spatial variation in the ALK.

177 The continuous function $f_a(l)$ in (2.7) is modelled with usage of P-splines (Wood, 2017), and these
178 spline regression coefficients are included as a Gaussian random effect. The precision matrix for the spline
179 regression coefficients is constructed such that the variability (or wryggliness) in the spline is penalized, see
180 Wood (2017, page 239) for details. The R package mgcv (Wood, 2015) is used for extracting the precision

181 matrix needed for the spline regression coefficients. We assume that the spatially Gaussian random field in
182 (2.7), γ , follows a stationary Matérn covariance structure:

$$\text{Cov}(\gamma(\mathbf{s}_1), \gamma(\mathbf{s}_2)) = \frac{\sigma_\gamma^2}{2^{\nu-1}\Gamma(\nu)} (\kappa_\gamma \|\mathbf{s}_1 - \mathbf{s}_2\|)^\nu K_\nu(\kappa_\gamma \|\mathbf{s}_1 - \mathbf{s}_2\|), \quad (2.8)$$

183 where σ_γ^2 is the marginal variance, $\|\cdot\|$ is the Euclidean distance measure in kilometres, ν is a smoothing
184 parameter, κ_γ is a spatial scale parameter and $K_\nu(\cdot)$ is the modified Bessel function of the second kind with
185 $\nu = 1$. The spatial field is estimated with the stochastic partial differential equation (SPDE) procedure
186 described in Lindgren et al. (2011). The main concept behind the SPDE procedure is that the precision
187 matrix of a spatial field with Matérn covariance function can be approximated by a sparse matrix on a grid
188 covering the area of interest. Such a grid and sparse precision matrix are constructed with use of the R-INLA
189 package (Rue et al., 2009).

190 The species specific constant l^* is selected as the mid point between the shortest fish of age A and the
191 longest fish of age M in the corresponding year and quarter. A sensitivity analysis of this constant were
192 performed by adjusting it up and down 5 cm for cod in year 2018 in Q1. The point estimate of the mCPUEs
193 then changed in the forth decimal, which is negligible.

194 The model based ALK estimate is obtained by maximizing the likelihood. We maximize the likelihood
195 with use of an R-Package called Template Model Building TMB (Kristensen et al., 2015), combined with the
196 optimizing function `nlminb` in R. In this application TMB is advantageous as it uses Laplace approximation
197 for the latent fields gaining computational efficiency, it also utilizes sparse structures in the latent fields, and
198 uses automatic derivation.

199 **2.3 Uncertainty estimation**

200 In this section we describe how the uncertainty of the CPUE estimates are calculated. We use nonparametric
201 bootstrapping to quantify the uncertainty of the CPUEs. In nonparametric bootstrapping independent sam-
202 ples of lengths and age are drawn with replacement from the original data and approximate 95% confidence
203 intervals are obtained using bias-corrected percentile method (Carpenter and Bithell, 2000). Nonparamet-
204 ric resampling allows us to estimate the sampling distribution of the CPUE empirically without making
205 assumptions concerning the data. The bias-Corrected method adjusts for the bias and skew of the sam-

206 pling distribution of the data (Puth et al., 2015; Karlsson, 2009). The bootstrap procedure is given in
207 Supplementary Materials S5.

208 A bootstrap procedure for estimating the uncertainty of CPUEs in the North Sea is suggested in ICES
209 (2013a). This procedure is given in Supplementary Materials S5. In the rest of this research, we refer
210 to this procedure as DATRAS bootstrap procedure. The DATRAS procedure is divided into two parts;
211 one part which samples CPUE per length (2.1), and another part which samples the ALK used in (2.2).
212 The DATRAS bootstrap procedure is based on the assumption of homogeneous CPUE within RFAs. This
213 assumption is likely to be wrong, and would typically cause an overestimation of the uncertainty. Therefore,
214 we have included a bootstrap procedure, defined as the stratified bootstrap procedure, which instead assumes
215 constant CPUE within each statistical rectangle.

216 *2.3.1 DATRAS and Stratified bootstrap procedure*

217 In this section we describe the bootstrap procedure for catch at length proposed by *DATRAS* (ICES, 2013a)
218 and the stratified procedure, and elaborate how the ALK is simulated. Assume there are N_s trawl hauls
219 in a statistical rectangle. The DATRAS bootstrap procedure consists of sampling with replacement N_s of
220 all trawl hauls in the corresponding RFA, and place them in the statistical rectangle. This procedure is
221 performed independently across all statistical rectangles. It should be remembered that this procedure is
222 based on the assumption that ALK is homogeneous in the whole RFA, and the implication of DATRAS
223 bootstrap procedure on indices of abundance is two-fold. Firstly, DATRAS bootstrap procedure ignores the
224 fine-scale stratification in the sampling process. This would lead to an overestimation of the uncertainty.
225 Secondly, it ignores the sampling procedure of age-length data collected at the haul level. This would lead to
226 an underestimation of the uncertainty. So there are biases in both directions, which are difficult to quantify.
227 The Stratified bootstrap procedure is a modification of the DATRAS bootstrap procedure. Rather than
228 sampling hauls from the whole RFA, we sample the N_s trawl hauls from the list of hauls within the same
229 statistical rectangle. If there is only one trawl haul within a statistical rectangle, we sample either that haul
230 or the closest haul.

231 To estimate DATRAS ALK we sample with replacement age observations within each RFA stratified

232 with respect to length. If there is only one observed age from a given length class, we sample either that age
233 or, at random, an age of the closest length class with observed ages. For both the haul based ALK and the
234 model based ALK, we use the ages in the sampled hauls obtained when simulating the CPUE per length.

235 **2.4 Reducing sampling effort**

236 The current sampling procedure for the North Sea IBTS data is the sampling of one otolith from every
237 observed length group in every trawl (see Table S2.1 in Supplementary Materials S2). We investigate the
238 effect on the estimated index of abundance $\hat{\lambda}_a$ and its variance if the sampling procedure of otoliths changes
239 such that fewer otoliths were collected. To determine this effect we remove otholits in a stratified manner,
240 mimicking a sampling procedure where fewer otoliths are collected. For sampling fewer otoliths, we define
241 wider length groups, for example 1 cm, 2 cm, 3 cm and so on, and simulate the otolith collection such
242 that only one pair of otolith is sampled from every wider length group. Estimated indices of abundance
243 with summary statistics, based on the simulated reduced data sets are then compared with the parameters
244 estimated from using all of data. In principle, we are free to define any length class to reduce the number
245 of observed otoliths. To determine whether there is obvious change in estimated indices of abundance and
246 its uncertainty we propose seven procedures. We sample at random one pair of otoliths from the following
247 length groups: 1 cm, 2 cm, 3 cm, 4 cm , 6 cm or 7 cm.

248 **3 Case studies**

249 In this section we apply the methods described in Section 2 to data from the International Bottom Trawl
250 Survey for the years 2017-2018, which is obtained from the DATRAS database (ICES, 2018c). These years
251 are chosen for two reasons. The first is that in year 2018 new sampling procedures proposed by ICES
252 for the collection of otoliths were introduced in the surveys. For instance, one otolith per length group is
253 sampled for most target species (see Table S2.1 in Supplementary Materials S2 for the sampling procedures
254 for each target species), and this data is appropriate for the application of our proposed sample optimization
255 procedure described in Section 2.4. The second is that IBTS included Age 0 in Q3 surveys, and since data
256 for year 2018 Q3 is not yet available, the data for years 2017 Q3 and 2018 Q1 will be used in our analyses.

257 Also, some species such as saithe that occupies the deeper waters in the northern part of the North Sea
258 and in the Skagerrak and Kattegat, along the shelf edge (ICES, 2018a), the IBTS Q3 data is relevant for
259 analyses compared with data from IBTS Q1 surveys, which do not adequately cover these areas where saithe
260 is distributed (see Figure 1). Note that both IBTS Q1 and Q3 surveys do not adequately cover the whole
261 stock distribution of saithe but the data collected is considered generally representative (ICES, 2016a).

262 In this research, the species of interest are cod and saithe. All samples are caught using the standard
263 GOV gear described in Section 1.1. Cod can be as old as 12 years in the first quarter and 11 years in the
264 third quarter; and saithe as old as 18 years in the first quarter and 17 years in the third quarter. In our
265 analyses we consider the age groups 1 to 6+ in Q1 and 0 to 6+ in Q3 for all ALK methods, where the last
266 group consists of fish of age 6 or older. Saithe are typically older than cod but smaller in length, particularly
267 in Q1. Catch rates are higher in the third quarter, 48% for cod and 164% for saithe, compared with the
268 first quarter. Table S6.1 in Supplementary Materials S6 briefly describes the data for year 2018 in the first
269 quarter and year 2017 in the third quarter.

270 ***3.1 Estimated indices of abundance and variability for cod and saithe***

271 In this section we apply the three ALK methods given in section 2.2 for abundance estimation, and the
272 bias-corrected bootstrap method, given in Section 2.3.1 for estimating variability of estimated indices of
273 abundance. The main assumption of DATRAS ALK is that the age-length compositions of species over large
274 areas are the same. In this section we apply the three ALK methods, given in section 2.2, for estimating
275 abundance at age and the bias-corrected bootstrap method, given in Section 2.3.1, for estimating variability of
276 estimated indices of abundance. The main assumption of DATRAS ALK is that the age-length compositions
277 of species over large areas are the same. Figure 2 illustrates the predicted probability of age of cod given
278 length using the spatial model based ALK (2.7). Figure 2 illustrates that the main assumption of DATRAS
279 ALK of constant age-length compositions over large areas is not valid as a 20 cm long cod is more likely to
280 be two years old in the south and east of Skagerak.

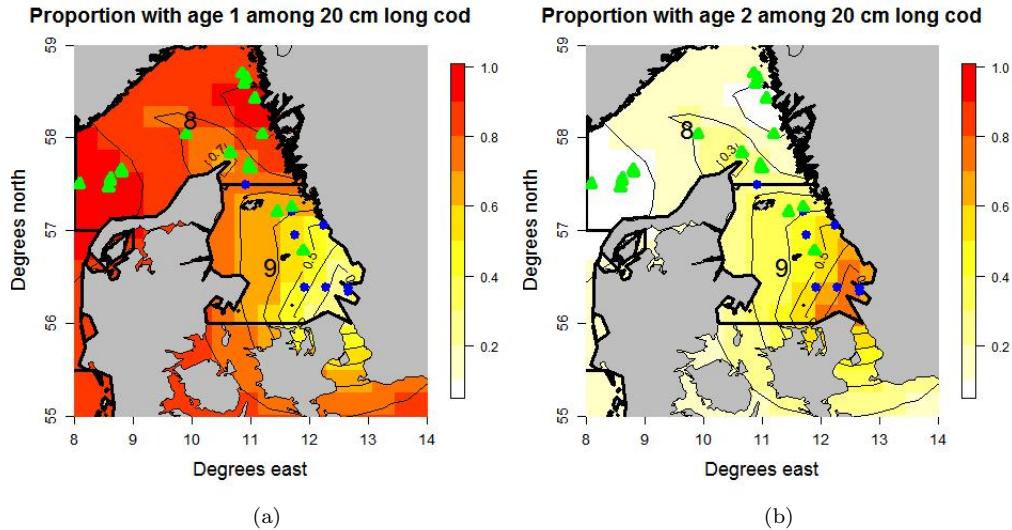
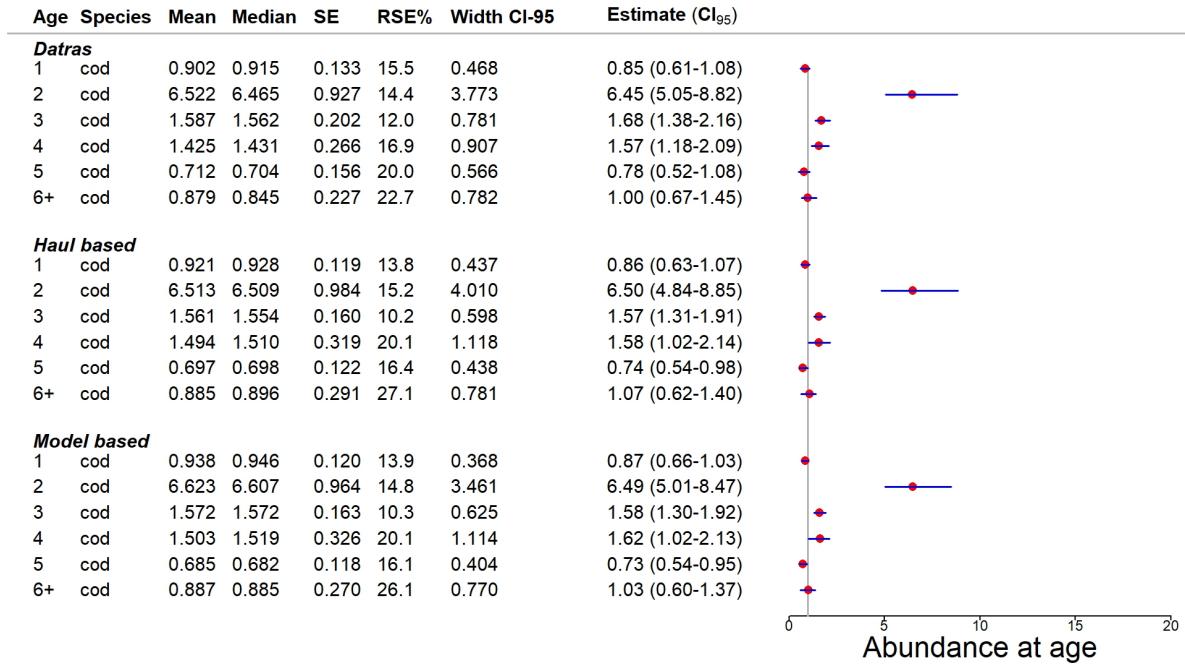
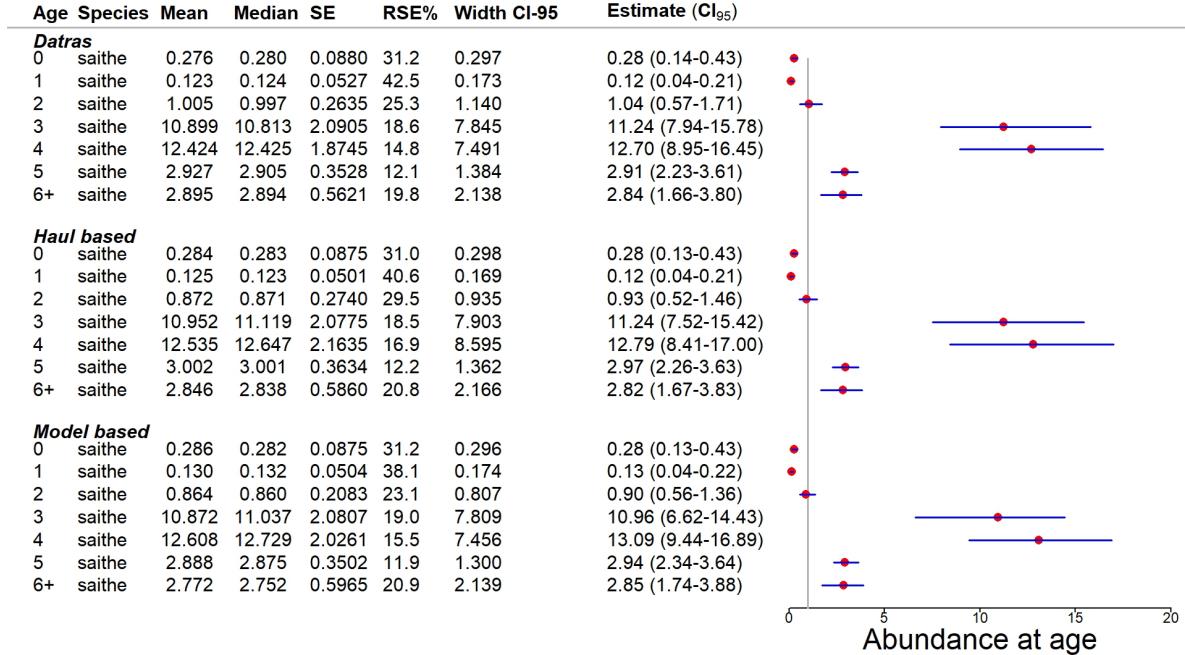


Figure 2: Estimated proportion of age 1 and 2 year old cod of length 20 cm long in Skagerak. The green triangles and blue points are observations of one and two year old cod, respectively, which are in the length interval 19 cm to 21 cm.

Figures 3 gives estimates of indices of abundance for cod in years 2018 Q1 and for saithe in year 2017 Q3. Approximate 95% confidence intervals from the bias-corrected bootstrap method for 200 bootstrap replication are estimated from the three ALK methods. The stratified procedure described in 2.3.1 is used in the sampling process to estimate bootstrap confidence intervals. Figures 3 shows that the resulting indices of abundance for cod and saithe turned out to be similar for all ALKs. IBTS is a complex multistage survey design, and since the ALKs are estimated from cluster-correlated data the resulting effective sample for estimating age-composition of fish would be lower than the number of fish measured (ICES, 2013b). Hence, the ALKs are subject to large sampling errors. For example, the estimated percentage relative standard errors from the spatial ALKs for the plus group (6+) for cod are $> 25\%$, suggesting high sampling error in the ALKs. Also, it should be remembered that DATRAS ALK is constant. Aanes and Vølstad (2015) showed that in such cases, and where only the variability of length compositions are allowed for, the estimated age-distributions may appear to be more precise than they truly are since the ALK itself is subject to sampling errors, see for example the estimated relative standard standard errors for ages 2, and the older fish (4, 5 and 6+) for both species.



(a) Cod in year 2018 Q1



(b) Saithe in year 2017 Q3

Figure 3: Estimated confidence intervals (CI₉₅) from bias-corrected bootstrap method for cod in year 2018 Q1 and saithe in year 2017 Q3. Estimated indices of abundance (Estimate), and its standard error (SE), percentage relative standard error (RSE%), bootstrap mean (Mean) and Median estimates and the width of the confidence interval (Width CI-95) are also given.

295 As regards to which spatial ALK method to adopt, it is difficult to identify a method that gives the

best performance over all age groups. While both methods seem to give reasonable estimates, the spatial model based ALK generally gave shorter interval widths for both species (Figure 3). Furthermore, compared with DATRAS ALK and the haul based ALK, the spatial model based ALK allows smooth functions of the spatial effects predicting numbers-at-age. Figure 4 illustrates the estimated age compositions as a function of length for a given haul in RFA 1. The haul selected is the haul with the most number of observed ages of cod in 2018 Q1. Notice that the the model based ALK is smooth, while the DATRAS ALK and the haul based ALK are not. This is an important advantage of the model based ALK, and it is surprising that it did not result in a larger difference in the estimated index of abundance as shown Figure 3. An intuitive reason for this is presumably because there are enough observed ages per length group for the haul based ALK to be representative. But, there are some limitations of the spatial model based ALK. For instance, the uncertainty of relative abundance from the spatial model based ALK is calculated using bootstrapping, as approximation of the joint distribution of the regression coefficient and spatial effect, in some cases, fails to account for the negative correlations between ages. Also, estimating relative abundance at age and its precision from the spatial ALK model can be computationally intensive.

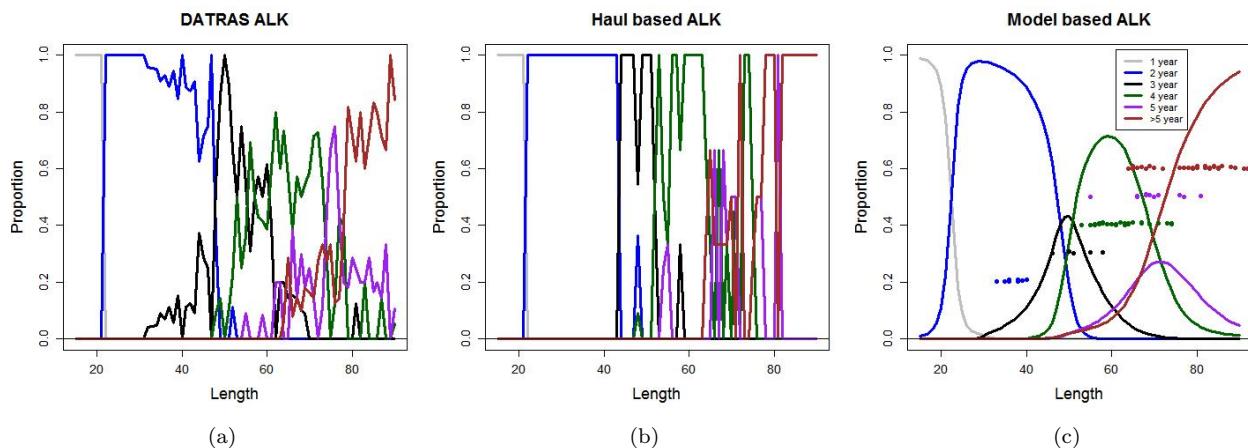


Figure 4: Estimated age compositions of cod as a function of length in a given haul in RFA 1 using a) DATRAS ALK, b) haul based ALK and c) model based ALK. Note that explanation of the colours are only given in c). Each coloured point in c) defines an observed cod with the corresponding length and age in the haul. The haul selected is the haul with most observed ages of cod in 2018 Q1.

We also demonstrate the implications of using DATRAS bootstrap procedure for estimating the uncertainty around indices of abundance (see Figure S1 in Supplementary Materials S7.1). Compared with the

312 stratified bootstrap procedure, DATRAS bootstrap procedure gives an overestimation of the uncertainty for
313 all age groups, suggesting that it is highly relevant to account for the variation in the data over large areas.

314 ***3.2 Alternative sampling procedure for North Sea Cod and Saithe***

315 In this section we investigate the effect of sampling fewer otoliths on the estimated indices of abundance
316 for the North Sea IBTS saithe and cod. **We use the spatial ALK model based approach, although**
317 **the haul based could also be used (see Supplementary Materials.....).** The removal procedure for
318 otolith sampling described in Section 2.4 is applied to data in year 2018 Q1 for cod and year 2017 Q3 for
319 saithe. We sample one pair of otoliths per length group described in Section 2.4: 1 cm, 2 cm, 3 cm, 4 cm,
320 5 cm, 6 cm or 7 cm. Recall that prior to 2018 the standardized IBTS sampling procedure was 8 pairs of
321 otoliths per length group but some nations such as Norway and Netherlands sampled one pair of otoliths
322 per length group from every haul. Although the revised standardized IBTS sampling procedure is one pair
323 of otolith per 1 cm length group for standard round fish as of year 2018 Q1, except for haddock and Norway
324 Pout where 2 otoliths per cm is to be sampled, some nations (Scotland and Sweden) continue to sample
325 more than one pair of otoliths, particularly for older age groups (see Table S2.1 in Supplementary Materials
326 S2).

327 Figure 5 gives the percentage relative standard error of estimated indices of abundance and mean square
328 error for cod and saithe from the seven different sampling procedures described above. Estimates are com-
329 puted from 1000 simulations and 1000 bootstrap replication A total of 1600 pairs of otoliths were sampled
330 for cod in year 2018 Q1, while 2163 pairs of otoliths were sampled for saithe in year 2017 Q3 (see Table
331 S6.1 in Supplementary Materials S6). The proportion of otoliths removed for cod from each of the sam-
332 pling procedures stated above is: 14.4%, 28.6%, 38.4%, 44.5%, 49.3%, 52.6% or 55.6%, respectively, while
333 for saithe the following proportions of otoliths are removed: 27.1%, 48.9%, 59.5%, 65.6%, 69.8%, 73.1% or
334 75.2%, respectively. Notice that 14% of the cod data in year 2018 Q1 is removed for the sampling procedure
335 of a pair of otoliths per 1 cm length group. This should be 0% if all nations followed the revised standardized
336 IBTS sampling procedure of year 2018 Q1.

337

338 **Tables S7.1 and S7.2 in Supplementary Materials S7.2 give results of the estimated indices**
339 **of abundance and approximate 95% bias-corrected bootstrap confidence intervals**
340 **discuss graph**

341

342 • **We discuss and include these in explanations below**

343 • Accuracy of estimates of reduced data compared with estimates from full data

344 • Precision in estimates is measured by standard error (SE) and relative standard error (RSE)

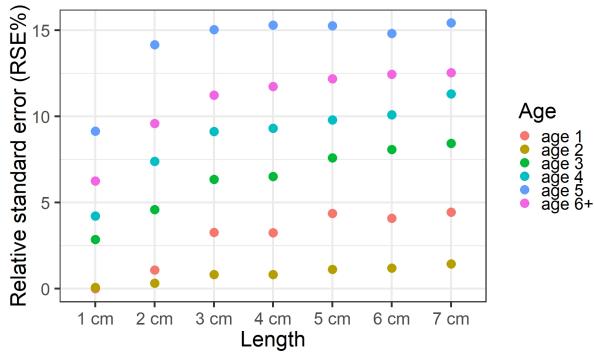
345 • accuracy is measured by root mean square error (RMSE) = $\sqrt{SE^2 + (\text{bias})^2}$. Measures how close, on
346 average, a fitted line is to the data points (measure of goodness of fit). One can compare the RMSE to
347 observed variation in measurements of a typical point (**the two should be similar for a reasonable**
348 **fit**). Can we use this even though we do not have a "true value", which we would never know from
349 large survey data and since we did not simulate synthetic data? Can we consider $\hat{\lambda}_a$ as a "true value"?

350 The nonparametric bias-corrected bootstrap method is adopted for estimating confidence intervals of
351 indices of abundance, and although this method has the advantage of correcting for the bias and skew of
352 the sampling distribution of the data; accounting for some of the variability in the sampling distribution of
353 the CPUE; and does not assume any distribution for the data, there are some limitations of the bootstrap
354 approach. The most important limitation is the assumption that the distribution of the data represented
355 by the sample is a reasonable estimate of the population function from which the data are sampled. If this
356 assumption is violated the random sampling performed in the bootstrap procedure may add another level
357 of sampling error, resulting in invalid statistical estimations (Haukoos and Lewis, 2005). As discussed in
358 Section 1.1 the selection of the trawling locations for IBTS surveys is semi-random where cruise leaders
359 selects "clear" tow locations or "blind" tow locations if no clear tow exists by checking the proposed trawl
360 track for hazardous seabed obstructions with acoustic methods. More recently, selection of tow locations is
361 based on pre-proposed valid tow locations with start and end positions executed in the period 2000-2018.
362 Hence, the lack of a fully randomized sampling process has the potential to result in biased estimates of
363 parameters and their uncertainty. Additionally, prior to 2013, all nations were sampling 8 pairs of otoliths

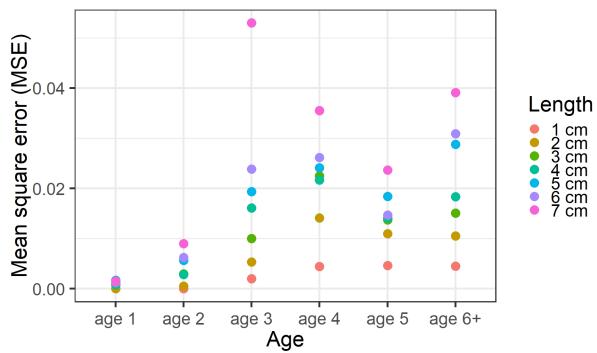
364 per 1 cm length group for our focal species (Table S2.1 in Supplementary Materials S2), and these samples
 365 could be acquired from, for example the first haul (or first few trawl hauls), resulting in an unrepresentative
 366 sample of the population. From 2013, some nations adopted the current sampling procedure outlined by
 367 ICES for IBTS 2018 surveys of 1 pair of otolith per 1 cm length group from each haul, while other nations
 368 continued with sampling 8 pairs of otoliths per 1 cm length group. So, bias was still introduced via the
 369 sampling procedure. Another limitation of the bootstrap is the smaller the original sample the less likely it
 370 is to represent the entire population, thus the more difficult it becomes to compute valid confidence intervals.
 371 Note that the bootstrap relies heavily on the tails of the estimated sampling distribution when computing

372

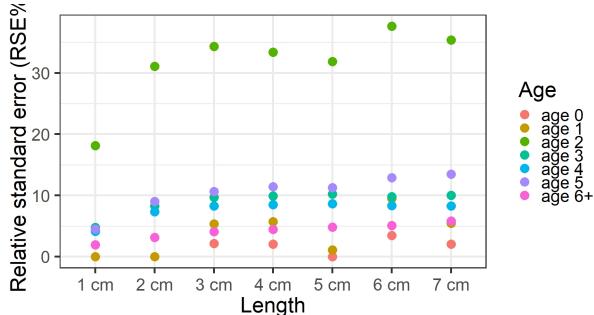
373 these results in the graph are from the haul based ALK procedure. The model based
 374 ALK procedure gave an error, when it's working those will be here and haul based will go in
 375 supplementary materials



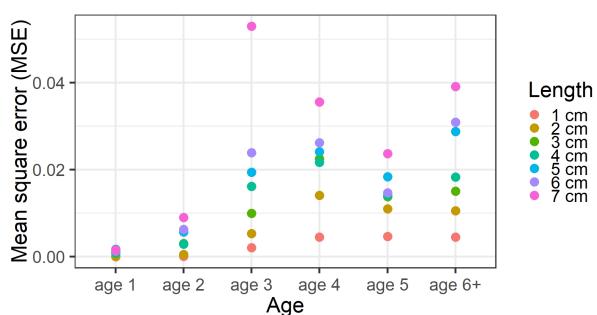
(a) Percentage relative standard error (RSE%) for cod



(b) Mean square error (MSE) for cod



(c) Percentage relative standard error (RSE%) for saithe



(d) Mean square error (MSE) for saithe

Figure 5: Percentage relative standard error (RSE%) and mean square error (MSE) for age given specific length group sampling of otolith for cod in year 2018 Q1 and saithe in year 2017 Q3.

4 DISCUSSION

377 In this research we have determined optimal sampling efforts of otoliths for target species of the North Sea
 378 International Bottom Trawl Survey (IBTS). This was achieved by testing different sampling procedures that
 379 mimic the real data collection procedure but with a reduced number of otoliths. The estimated indices of
 380 abundance and their estimated uncertainty were investigated to determine if there is any real change in the
 381 precision of the estimates. Abundance indices were estimated using age-length keys (ALKs). The database
 382 for trawl surveys (DATRAS) manned by ICES includes an ALK that uses the raw proportions of age given
 383 length assuming constant age-length compositions over relatively large areas. We have developed two spatial
 384 ALK methods to estimate abundance indices and their variance that accounts for spatial variation in the
 385 data: 1) a haul based ALK that produces an ALK for each trawl haul, and which uses the raw proportions
 386 of age given length, and 2) a spatial ALK model that uses logits for modelling the age distribution in catch
 387 data from the length-stratified subsamples. Several studies have used spatial ALK modelling for estimating
 388 abundance indices of the North Sea stocks used in assessments (Berg and Kristensen, 2012; Berg et al., 2014;
 389 Gerritsen et al., 2006). These studies used continuous ratio logits with General Linear Model (GLM) or
 390 General Additive Models (GAMs) to model the spatial effects and found large spatio-temporal variability of
 391 the ALK and relative abundance at age. We proposed to use Gaussian Random Field Theory to model the
 392 spatial effects as a smooth surface to estimate age-at-length and relative abundance for the IBTS data. The
 393 spatial model based ALK and the design based spatial ALK (haul based) gave similar estimates as DATRAS
 394 estimator for relative abundance at age but the spatial ALK estimators gained better precision.

395 The spatial ALK model based estimator appears to be a useful tool to detect significant differences
 396 between ALKs over large areas, although estimation of the uncertainty in the ALK from the joint precision
 397 matrix is problematic. Including the uncertainty of the ALK in the model requires an approximation of the
 398 joint distribution of the regression coefficient and the spatial effect, but this approximation is only as good as
 399 the quality of the data in a given year and quarter. For instance, the approximation of the ALK can predict
 400 juvenile ages given longer lengths, which goes against the natural biology. This occurs presumably because
 401 the approximation fails to account for the negative correlation structures between ages. So the uncertainty
 402 in the relative abundance was, therefore, calculated using bootstrapping as done by Berg and Kristensen

403 (2012); Berg et al. (2014). In future, the model might be expanded to include the probability of recording
404 inaccurate age-at-length data, so that uncertainty in the ALK could be estimated using the joint precision
405 matrix. The model might also be expanded to include covariates such as trawl hauls to capture any haul
406 variation, for example a trawl haul may "hit" a school of fish of a certain age.

407 With regards to how many otoliths to sample per length group, the evidence is clear that

408

409 **discuss DATRAS and Haul based ALK and recommended optimum sampling level of**
410 **otoliths per length group**

411

References

- 412 Aanes, S. and Vølstad, J. H. (2015). Efficient statistical estimators and sampling strategies for estimating
 413 the age composition of fish. *Canadian journal of fisheries and aquatic sciences*, 72(6):938–953.
- 414 Berg, C. W. and Kristensen, K. (2012). Spatial age-length key modelling using continuation ratio logits.
 415 *Fisheries Research*, 129:119–126.
- 416 Berg, C. W., Nielsen, A., and Kristensen, K. (2014). Evaluation of alternative age-based methods for
 417 estimating relative abundance from survey data in relation to assessment models. *Fisheries Research*,
 418 151:91–99.
- 419 Carpenter, J. and Bithell, J. (2000). Bootstrap confidence intervals: when, which, what? a practical guide
 420 for medical statisticians. *Statistics in medicine*, 19(9):1141–1164.
- 421 Ehrhardt, N. M. and Legault, C. M. (1997). The role of uncertainty in fish stock assessment and management:
 422 a case study of the spanish mackerel, scomberomorus maculatus, in the us gulf of mexico. *Fisheries
 423 research*, 29(2):145–158.
- 424 Fridriksson, A. (1934). On the calculation of age-distribution within a stock of cod by means of relatively few
 425 age-determinations as a key to measurements on a large scale. *Rapports Et Proces-Verbaux Des Reunions,
 426 Conseil International Pour l'Exploration De La Mer*, 86:1–5.
- 427 Gerritsen, H. D., McGrath, D., and Lordan, C. (2006). A simple method for comparing age-length keys
 428 reveals significant regional differences within a single stock of haddock (melanogrammus aeglefinus). *ICES
 429 Journal of Marine Science*, 63(6):1096–1100.
- 430 Haukoos, J. S. and Lewis, R. J. (2005). Advanced statistics: bootstrapping confidence intervals for statistics
 431 with difficult distributions. *Academic emergency medicine*, 12(4):360–365.
- 432 Hirst, D., Storvik, G., Rognebakke, H., Aldrin, M., Aanes, S., and Vølstad, J. H. (2012). A bayesian
 433 modelling framework for the estimation of catch-at-age of commercially harvested fish species. *Canadian
 434 journal of fisheries and aquatic sciences*, 69(12):2064–2076.

- 435 ICES (2006). Report of the workshop on implementation in datras of confidence limits estimation of abundance indices from bottom trawl survey data. ices datras report. *International Council for the Exploration*
436 *of the Sea*, DRAFT.
- 437
- 438 ICES (2012). Manual for the international bottom trawl surveys, revision viii. series of ices survey protocols.
439 *International Council for the Exploration of the Sea*, SISP 1-IBTS VIII.
- 440 ICES (2013a). Ns-ibts indices calculation procedure. datras procedure document. *International Council for*
441 *the Exploration of the Sea*, 1.1 NS-IBST indices-2013.
- 442 ICES (2013b). Report of the third workshop on practical implementation of statistical sound catch sampling
443 programmes. *International Council for the Exploration of the Sea*, WKPICS3.
- 444 ICES (2015). Manual for the international bottom trawl surveys, revision ix. series of ices survey protocols.
445 *International Council for the Exploration of the Sea*, SISP 10-IBTS IX.
- 446 ICES (2016a). Ices advice on fishing opportunities, catch, and effort greater north sea and celtic seas
447 ecoregions. *International Council for the Exploration of the Sea*, Book 6.
- 448 ICES (2016b). Report of the benchmark workshop on north sea stocks (wknsea), 14–18 march, 2016.
449 *International Council for the Exploration of the Sea*, ICES CM 2016/ACOM:37.
- 450 ICES (2018a). Ices fishmap: Atlas of the north sea fish, including fact sheets of key species and distribution
451 maps. *International Council for the Exploration of the Sea (ICES FishMap website, 2018*, 1.
- 452 ICES (2018b). Manual for the international bottom trawl surveys, revision x. series of ices survey protocols.
453 *International Council for the Exploration of the Sea*, SISP X-IBTS X.
- 454 ICES, D. (2018c). Datras.
- 455 Karlsson, A. (2009). Bootstrap methods for bias correction and confidence interval estimation for nonlinear
456 quantile regression of longitudinal data. *Journal of Statistical Computation and Simulation*, 79(10):1205–
457 1218.

- 458 Kimura, D. K. (1977). Statistical assessment of the age-length key. *Journal of the Fisheries Board of Canada*,
459 34(3):317–324.
- 460 Kristensen, K., Nielsen, A., Berg, C. W., Skaug, H., and Bell, B. (2015). Tmb: automatic differentiation
461 and laplace approximation. *arXiv preprint arXiv:1509.00660*.
- 462 Lehtonen, R. and Pahkinen, E. (2004). *Practical methods for design and analysis of complex surveys*. John
463 Wiley & Sons.
- 464 Lindgren, F., Rue, H., and Lindström, J. (2011). An explicit link between Gaussian fields and Gaussian
465 Markov random fields: the stochastic partial differential equation approach. *Journal of the Royal Statistical
466 Society: Series B (Statistical Methodology)*, 73(4):423–498.
- 467 Ludwig, D. and Walters, C. J. (1981). Measurement errors and uncertainty in parameter estimates for stock
468 and recruitment. *Canadian Journal of Fisheries and Aquatic Sciences*, 38(6):711–720.
- 469 Puth, M.-T., Neuhäuser, M., and Ruxton, G. D. (2015). On the variety of methods for calculating confidence
470 intervals by bootstrapping. *Journal of Animal Ecology*, 84(4):892–897.
- 471 Rindorf, A. and Lewy, P. (2001). Analyses of length and age distributions using continuation-ratio logits.
472 *Canadian Journal of Fisheries and Aquatic Sciences*, 58(6):1141–1152.
- 473 Rue, H., Martino, S., and Chopin, N. (2009). Approximate Bayesian inference for latent Gaussian models
474 by using integrated nested Laplace approximations. *Journal of the Royal Statistical Society: Series B
475 (Statistical Methodology)*, 71(2):319–392.
- 476 Walters, C. J. and Ludwig, D. (1981). Effects of measurement errors on the assessment of stock-recruitment
477 relationships. *Canadian Journal of Fisheries and Aquatic Sciences*, 38(6):704–710.
- 478 Wood, S. (2015). Package mgcv. *R package version*, pages 1–7.
- 479 Wood, S. N. (2017). *Generalized additive models: an introduction with R*. CRC press.

480 **Supplemental Materials: Optimizing sampling effort of the North**
481 **Sea International Bottom Trawl Survey.**

482 **S1 Areas fished by different countries in the North Sea IBTS**

483 Typically, two different countries fish each rectangle so that at least two trawl hauls are made per rectangle,
484 but intensified sampling is carried out in the following areas: at least 3 hauls per rectangle are taken in
485 statistical rectangles 31F1, 31F2, 32F1, 33F4, 34F2, 34F3, 34F4, 35F3, 35F4; while six or more hauls per
486 rectangle are taken in statistical rectangles 30F1, 32F2, 32F3, 33F2, 33F3 (ICES 1999). The Skagerrak
487 and Kattegat is fished solely by Sweden, who sample more than once in every rectangle while the west of
488 Shetland (in Q1 and Q3) and inshore areas (Q3) is fished solely by Scotland. The edge of the Norwegian
489 Trench is fished solely by Norway, but inshore areas near Denmark is fished by Denmark. The southern
490 North Sea is fished by Denmark, Germany and England. France, typically, is the only country that surveys
491 the western English Channel. Areas are surveyed by a single country because of the large proportion of
492 untrawalable area (and subsequent gear damage issues experienced by other nations) for efficient logistical
493 purposes. Table S1.1 gives the countries and research vessels participating the North Sea IBTS.

Table S1.1: Survey countries, vessel name, and period research vessels participating in first quarter (Q1) and third quarter (Q3) during 1997-2017.

Country	First Quarter (Q1)		Third Quarter (Q3)	
	Vessel name	Period	Vessel name	Period
Denmark	Dana	January-February	Dana	July-August
France	Thalassa II	January-February	-	-
Germany	Walther Herwig III	January-February	Walther Herwig III	July-August
Netherlands	Tridens 2	January-February	-	-
Norway	G.O. Sars	January-February	Johan Hjort	July
UK England	-	-	Endeavour	August-September
UK Scotland	Scotia III	January-February	Scotia III	July-August
Sweden	Dana	January-February	Dana	August

S2 Otolith sampling per fish species

496 From 1991-2017, most countries conducted quota sampling of otoliths per length group in a RFA. But from
 497 2013 Norway has been sampling one otolith per length class from each trawl haul (to 0.1cm below for shellfish,
 498 to 0.5cm below for herring and sprat and to 1cm below for all other species). From the first quarter in 2018
 499 all countries are required to sample one otolith per length class per trawl haul. Table S2.1 gives the minimum
 500 sampling levels of otoliths for the target species. However, for the smallest size groups, that presumably
 501 contain only one age group, the number of otoliths per length class may be reduced, and more otoliths per
 length are required for the larger length classes.

Table S2.1: Minimum sampling levels of otoliths by species for RFA or per trawl haul.

Period	Species	Minimum sampling levels of otoliths per length class
1991-2017		Number of otoliths per length class in a RFA
	herring	8 otoliths per $\frac{1}{2}$ cm group
	sprat	16 otoliths per $\frac{1}{2}$ cm length class 8.0 – 11.0 cm
		12 otoliths per $\frac{1}{2}$ cm length class \geq 11.0 cm
	mackerel	8 otoliths per $\frac{1}{2}$ cm length class
	cod	8 otoliths per 1 cm length class
	haddock	8 otoliths per 1 cm length class
	whiting	8 otoliths per 1 cm length class
	Norway pout	8 otoliths per 1 cm length class
	saithe	8 otoliths per 1 cm length class
	All target species	From 2013 Norway and Scotland, and Netherlands from 2016 have been sampling 1 otolith per length class from each trawl haul (to 0.1cm below for shellfish, to 0.5cm below for herring and sprat, and to 1cm below for all other species).
2018		Number of otoliths per length class per trawl haul
	herring	1 otolith per $\frac{1}{2}$ cm group
	sprat	1 otolith per $\frac{1}{2}$ cm length class 8.0 – 11.0 cm
		1 otolith per $\frac{1}{2}$ cm length class \geq 11.0 cm
	mackerel	1 otolith per 1 cm length class
	cod	1 otolith per 1 cm length class
	haddock	2 otoliths per 5 cm length class 11 – 15, 16 – 20, 21 – 25, 26 – 30 cm
	Norway pout	2 otoliths per 5 cm length class 5 – 10, 11 – 15 cm
		2 otoliths per 1 cm length class $>$ 15 cm
	saithe	1 otolith per 1 cm length class
	plaice	1 otolith per 1 cm length class

S3 Weightings of Statistical Rectangles

504 The weightings of the some statistical rectangles are allotted to species such as sprat, saithe and herring by
 505 depth strata. Table S3.1 gives these weights, which are used in the analysis of the saithe data.

Table S3.1: Weights used for *Pollachius virens* in equation (2.3).

StatRec	Weight								
31F1	0.6	38F0	1	41F7	1	44F3	1	48E7	1
31F2	0.8	38F1	1	41F8	0.1	44F4	1	48E8	0.9
31F3	0.05	38F2	1	41G0	0.2	44F5	0.9	48E9	1
32F1	0.8	38F3	1	41G1	0.97	44F8	0.25	48F0	1
32F2	1	38F4	1	41G2	0.53	44F9	0.8	48F1	1
32F3	0.8	38F5	1	42E7	0.4	44G0	0.94	48F2	1
32F4	0.01	38F6	1	42E8	1	44G1	0.6	48F3	0.5
33F1	0.3	38F7	1	42E9	1	45E6	0.4	48G0	0.02
33F2	1	38F8	0.3	42F0	1	45E7	1	49E6	0.8
33F3	1	39E8	0.5	42F1	1	45E8	1	49E7	1
33F4	0.4	39E9	1	42F2	1	45E9	1	49E8	0.4
34F1	0.4	39F0	1	42F3	1	45F0	1	49E9	1
34F2	1	39F1	1	42F4	1	45F1	1	49F0	1
34F3	1	39F2	1	42F5	1	45F2	1	49F1	1
34F4	0.6	39F3	1	42F6	1	45F3	1	49F2	1
35F0	0.8	39F4	1	42F7	1	45F4	0.6	49F3	0.5
35F1	1	39F5	1	42F8	0.2	45F8	0.3	50E6	0.1
35F2	1	39F6	1	42G0	0.32	45F9	0.02	50E7	0.6
35F3	1	39F7	1	42G1	0.89	45G0	0.24	50E8	0.7
35F4	0.9	39F8	0.4	42G2	0.64	45G1	0.55	50E9	0.9
35F5	0.1	40E7	0.04	43E7	0.03	46E6	0.4	50F0	1
36F0	0.9	40E8	0.8	43E8	0.9	46E7	0.9	50F1	1
36F1	1	40E9	1	43E9	1	46E8	1	50F2	1
36F2	1	40F0	1	43F0	1	46E9	1	50F3	0.2
36F3	1	40F1	1	43F1	1	46F0	1	51E6	0
36F4	1	40F2	1	43F2	1	46F1	1	51E7	0
36F5	1	40F3	1	43F3	1	46F2	1	51E8	0.5
36F6	0.9	40F4	1	43F4	1	46F3	0.8	51E9	1
36F7	0.4	40F5	1	43F5	1	46F9	0.3	51F0	1
36F8	0.5	40F6	1	43F6	1	46G0	0.52	51F1	1
37E9	0.2	40F7	1	43F7	1	46G1	0.2	51F2	0.5
37F0	1	40F8	0.1	43F8	0.94	47E6	0.8	51F3	0
37F1	1	41E6	0.03	43F9	0.41	47E7	0.6	52E6	0
37F2	1	41E7	0.8	43G0	0.21	47E8	1	52E7	0
37F3	1	41E8	1	43G1	0.7	47E9	1	52E8	0
37F4	1	41E9	1	43G2	0.3	47F0	1	52E9	0.1
37F5	1	41F0	1	44E6	0.5	47F1	1	52F0	0.2
37F6	1	41F1	1	44E7	0.5	47F2	1	52F1	0.5
37F7	1	41F2	1	44E8	0.9	47F3	0.6	52F2	0.1
37F8	0.8	41F3	1	44E9	1	47F9	0.01		
38E8	0.2	41F4	1	44F0	1	47G0	0.3		
38E9	0.9	41F5	1	44F1	1	47G1	0.02		
52F3	0	41F6	1	44F2	1	48E6	1		

507

S4 Imputation for missing age samples

508 Catches of the target species are sampled (or subsampled with a size of 100 if the catches are too large) for
 509 length, and otoliths are typically collected from a subsample of the individuals sampled for length in the
 510 RFA, or per trawl haul as in the case of Norway for determining age of the fish (see Table ??). In the case of
 511 Norway where all trawl hauls are sampled for otoliths, missing age samples would still occur for the following
 512 two reasons: 1) the fish is below minimum length for otolith sampling (unreadable otoliths) or 2) otoliths
 513 are misplaced. Abundance indices by age group are estimated based on three age-length-keys (ALK): 1)
 514 DATRAS ALK estimator, 2) Haul based ALK estimator, and 3) Spatial model based ALK estimator.

515 ***S4.1 DATRAS ALK Borrowing Approach***

516 The ALK proposed in DATRAS (ICES 2013), which is an aggregation of individual samples from a haul
 517 combined over a round fish area (RFA), and missing age samples are imputed as follows:

- 518 1. If there is no ALK for a length in the CPUE dataframe, age information is obtained accordingly
- 519 • If length class (CPUE) < minimum length class (ALK), then age=1 for the first quarter and
 - 520 age=0 for all other quarters
 - 521 • If minimum length class (ALK) < length class (CPUE) < maximum length (ALK) then age is
 - 522 set to the nearest ALK. If the ALK file contains values at equal distance, a mean is taken from
 - 523 both values.

- 524 2. If length class (CPUE) > maximum length (ALK) age is set to the plus group.

525 The underlying assumption of this ALK approach is that age-length compositions are homogeneous within
 526 the RFA.

527 ***S4.2 Haul based ALK Borrowing Approach***

528 The second is an a haul dependent ALK estimator which we propose, and is denoted by ALK^H . Since the age-
 529 length composition of fish may be space-variant, that is, there may be variation in age-length compositions
 530 between trawl stations within a RFA, the spatial dependence of the age-length composition must be accounted

531 for to produce reliable estimates of the CPUE per age estimates. If this spatial dependence is ignored not
 532 only will estimates of abundance be biased but the impact on the variance may be substantial. So for each
 533 trawl haul an ALK^H is produced. To replace missing values for the age distribution in a length class the
 534 method of "borrowing" ages from the same length from neighbouring trawl hauls of maximum radius of two
 535 statistical rectangles within the RFA. If there are no observed ages in the length class from the neighbour
 536 hauls in the RFA, missing values for the age distribution are replaced following the procedure outlined in
 537 the DATRAS ALK procedure (S4.1) in step 1.

538 S5 Nonparametric Bootstrap Sampling procedure

539 Nonparametric bootstrapping is attractive as it makes no distributional assumption, and is suitable for
 540 estimating confidence interval for indices of abundance. Suppose we have a vector \mathbf{x} of m independent obser-
 541 vations, and we are interested in estimating a parameter $\hat{\theta}(\mathbf{x})$ and its variance. The general nonparametric
 542 bootstrap algorithm is as follows:

- 543 1. Sample m observations randomly with replacement from \mathbf{x} to obtain a bootstrap data set, denoted by
 544 \mathbf{x}^* .
- 545 2. Calculate the bootstrap version of the statistic of interest, $\theta^* = \hat{\theta}(\mathbf{x}^*)$.
- 546 3. Repeat steps 1 and 2 a large number of times, say B , to obtain an estimate of the bootstrap distribution
- 547 4. calculate the average of the bootstrapped statistics, $\sum_{b=1}^B \theta^*_{(b)} / B$
- 548 5. compute the variance of the estimator $\hat{\theta}(\mathbf{x})$ through the variance of the set $\theta^*_{(b)}$, $b = 1, 2, \dots, B$, given
 549 by

$$\frac{\sum_{b=1}^B (\theta^*_{(b)} - \theta^*_{(.)})^2}{(B - 1)} \quad (\text{S5.1})$$

550 where $\theta^*_{(.)} = \sum_{b=1}^B \theta^*_{(b)} / B$.

551 The Bias-Corrected method assumes that there is a montonic increasing function and the estimator $\hat{\lambda}_a$ has
 552 a monotonic increasing function $f()$ such that the transformed values $f(\hat{\lambda}_a)$ are normally distributed with
 553 mean $f(\lambda_a) - z_0$ and standard deviation one, where z_0 are the standard normal limits (Puth et al., 2015;

⁵⁵⁴ Karlsson, 2009). Now, let $P^* \left(\hat{\theta}(\mathbf{x}^*) \leq \hat{\theta}(\mathbf{x}) \right)$ denote the proportion of $\hat{\theta}(\mathbf{x}^*)'$ s in the bootstrap sample that
⁵⁵⁵ have a value lower than the value of the parameter estimate $\hat{\theta}(\mathbf{x})$, and let z_0 be defined as

$$z_0 = \Phi^{-1} \left\{ P^* \left(\hat{\theta}(\mathbf{x}^*) \leq \hat{\theta}(\mathbf{x}) \right) \right\}, \quad (\text{S5.2})$$

⁵⁵⁶ where Φ denotes the cumulative distribution function of the standard normal distribution. Also let $\tilde{\alpha}_1$ and
⁵⁵⁷ $\tilde{\alpha}_2$ be defined as

$$\tilde{\alpha}_1 = \Phi(2z_0 + z_\alpha), \quad (\text{S5.3})$$

⁵⁵⁸ and

$$\tilde{\alpha}_2 = \Phi(2z_0 + z_{1-\alpha}), \quad (\text{S5.4})$$

⁵⁵⁹ respectively. A $100(1 - 2\alpha)$ percent confidence interval for $\theta(\mathbf{x})$ is then given by

$$\hat{\theta}_{(\tilde{\alpha}_1(B+1))}(\mathbf{x}^*) \leq \hat{\theta}(\mathbf{x}) \leq \hat{\theta}_{((\tilde{\alpha}_2-1)(B+1))}(\mathbf{x}^*). \quad (\text{S5.5})$$

⁵⁶⁰ S6 IBTS data set for cod and saithe

Table S6.1: Summary of North Sea IBTS cod and saithe (in parentheses) data for third quarter in year 2017 and first quarter in year 2018.

Data	Description
Trawl hauls	Total of 372 trawl hauls in year 2018 Q1; 238 (83) with length and 230 (81) with age information. In 2017 Q3, a total of 345 trawl hauls were taken; 238 (129) with length and 237 (128) with age information.
Age	The age varied between 1 (1) to 12 (18) years in year 2018 Q1 and 0 (0) to 11 (17) in year 2017 Q3.
Length	Length information in cm varied between 11 (13) to 114 (106) cm in year 2018 Q1 and between 6 (10) to 112 (109) cm in year 2017 Q3.
Date	Date of catch in year 2018 Q1 varied between 15.01.2018 to 28.02.2018 and in year 2017 Q3 between 18.07.2017 to 31.08.2018
Duration of haul	Mean duration is 29.37 minutes, with 30 minutes as 83% coverage interval in year 2018 Q1; and in 2017 Q3 with mean duration of 29.26 minutes with 30 minutes as 88% coverage .
Total count for all ages	1600 (822) in year 2018 Q1 and 2330 (2163) 2017 Q3.

Table S6.2: Age and length data for saithe in year 2017 Q3 and cod in year 2018 Q1. Data collected in the first quarter (Q1) has no age 0 group but this is collected in quarter 3 (Q3) surveys.

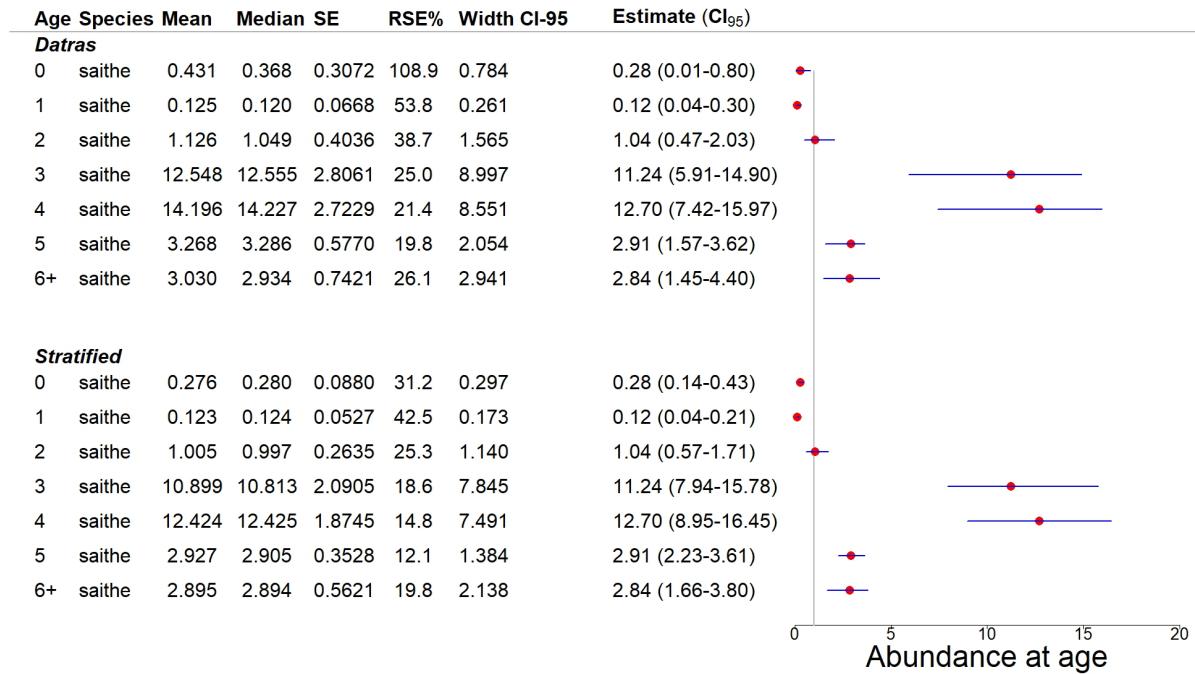
Age	saithe in year 2017 Q3						cod in year 2018 Q1					
	Numbers aged	L _{min}	L _{max}	L _{mean}	Sd(L)	CV(L)	Numbers aged	L _{min}	L _{max}	L _{mean}	Sd(L)	CV(L)
0	21	10	14	12.143	1.195	0.098						
1	26	23	32	27.654	2.297	0.083	149	11	30	18.407	3.693	0.201
2	65	27	47	38.077	3.337	0.088	814	17	53	33.180	6.290	0.190
3	531	34	56	42.041	3.785	0.090	222	30	81	50.654	10.185	0.202
4	767	35	73	48.261	4.521	0.094	189	43	92	64.479	8.399	0.130
5	334	46	78	56.876	6.105	0.107	102	54	96	76.627	9.594	0.125
6	159	50	91	66.025	7.137	0.108	84	54	100	80.871	9.456	0.117
7	127	57	93	73.976	7.163	0.097	28	58	110	84.086	11.308	0.134
8	69	63	94	77.725	7.010	0.090	4	80	94	85.500	6.455	0.075
9	18	64	97	85.333	7.499	0.088	5	66	96	83.400	11.305	0.061
10	22	84	107	92.364	5.803	0.063	1	87	87	-	-	-
11	5	79	102	92.800	9.311	0.100	1	106	106	-	-	-
12	7	91	109	99.429	6.554	0.066						
13	5	94	104	98.800	4.550	0.046						
14	1	108	108	108	-	-						
15	1	105	105	108	-	-						
16	4	93	106	100.250	5.439	0.054						
17	1	109	109	109	-	-						

561

S7 Analysis of real data

562 *S7.1 Estimates from DATRAS and Stratified bootstrap procedures*

563 The bootstrap procedure proposed by DATRAS lacks the potential to account for the spatial variation in
 564 the data. The DATRAS bootstrap procedure ignores the fine-scale stratification in the sampling process,
 565 leading to an overestimation of the uncertainty; and ignores the age-length data collected at the haul level,
 566 resulting in an underestimation of the uncertainty. The results (FigureS1) shows an overestimation of the
 567 uncertainty for all age groups, suggesting that it is relevant to account for the fine-scale stratification when
 568 resampling the data.



(a) Datras and Stratified bootstrap Procedures

Figure S1: Comparison of estimated confidence intervals (CI₉₅) from DATRAS and stratified bootstrap procedures. The bias-corrected bootstrap method is used to give estimates for saithe in year 2017 Q3. Estimated indices of abundance (Estimate), and its standard error (SE), bootstrap mean (Mean), Median estimates, percentage relative standard error (RSE %) and width of confidence intervals are also given.

⁵⁶⁹ S7.2 Estimates from different sampling procedures

Table S7.1: Estimated abundance ($\hat{\lambda}_a$) for cod from the original data in year 2018 Q1 compared with estimated abundance ($\hat{\lambda}_a^*$) from the reduced data for different sampling procedures of length groups (l). The median estimated indices, estimated standard error of $\hat{\lambda}_a^*$ ($SE(\hat{\lambda}_a^*)$), the percentage relative standard error (RSE%) and mean square error (MSE) are also given.

l	$\hat{\lambda}_a$	$\hat{\lambda}_a^*$	(median) $\hat{\lambda}_a^*$	$SE(\hat{\lambda}_a^*)$	RSE%	MSE	CI-95 ($\hat{\lambda}_a^*$)
age 1							
1 cm	0.863	0.863	0.863	0.00910	0.000	0.0000	(0.86, 0.86)
2 cm	0.863	0.865	0.867	0.00939	1.085	0.00009	(0.84, 0.88)
3 cm	0.863	0.856	0.861	0.02803	3.274	0.00083	(0.80, 0.90)
4 cm	0.863	0.857	0.859	0.02791	3.257	0.00082	(0.81, 0.91)
5 cm	0.863	0.845	0.847	0.03694	4.370	0.00044	(0.81, 0.92)
6 cm	0.863	0.860	0.861	0.03514	4.088	0.00125	(0.79, 0.93)
7 cm	0.863	0.854	0.853	0.03803	4.454	0.00153	(0.80, 0.93)
age 2							
1 cm	6.496	6.496	6.491	0.00552	0.085	0.00003	(6.49, 6.50)
2 cm	6.496	6.486	6.486	0.02073	0.320	0.00053	(6.46, 6.53)
3 cm	6.496	6.504	6.506	0.05414	0.832	0.00299	(6.38, 6.60)
4 cm	6.496	6.498	6.500	0.05351	0.823	0.00287	(6.38, 6.60)
5 cm	6.496	6.514	6.517	0.07322	1.124	0.00567	(6.32, 6.65)
6 cm	6.496	6.503	6.507	0.07862	1.209	0.00623	(6.30, 6.65)
7 cm	6.496	6.486	6.491	0.09414	1.452	0.00897	(6.31, 6.64)
age 3							
1 cm	1.571	1.572	1.571	0.04499	2.861	0.00203	(1.49, 1.66)
2 cm	1.571	1.578	1.572	0.07268	4.605	0.00533	(1.45, 1.74)
3 cm	1.571	1.557	1.554	0.09893	6.353	0.00999	(1.41, 1.77)
4 cm	1.571	1.640	1.632	0.10687	6.517	0.00161	(1.38, 1.86)
5 cm	1.571	1.634	1.632	0.12411	7.593	0.01940	(1.31, 1.87)
6 cm	1.571	1.649	1.643	0.13337	8.086	0.02390	(1.31, 1.93)
7 cm	1.571	1.748	1.740	0.14741	8.432	0.05300	(1.28, 2.06)
age 4							
1 cm	1.584	1.581	1.581	0.06670	4.219	0.00446	(1.45, 1.71)
2 cm	1.584	1.597	1.596	0.11810	7.397	0.01410	(1.35, 1.83)
3 cm	1.584	1.613	1.619	0.14715	9.123	0.02250	(1.25, 1.89)
4 cm	1.584	1.563	1.568	0.14581	9.326	0.02170	(1.30, 1.84)
5 cm	1.584	1.586	1.581	0.15534	9.794	0.02410	(1.30, 1.90)
6 cm	1.584	1.596	1.595	0.16125	10.104	0.02620	(1.26, 1.93)
7 cm	1.584	1.502	1.500	0.16988	11.311	0.03550	(1.33, 1.83)
age 5							
1 cm	0.742	0.746	0.751	0.06817	9.1440	0.00466	(0.61, 0.87)
2 cm	0.742	0.738	0.729	0.10457	14.170	0.01100	(0.58, 0.96)
3 cm	0.742	0.765	0.756	0.11506	15.040	0.01380	(0.53, 1.00)
4 cm	0.742	0.764	0.757	0.11686	15.299	0.01410	(0.54, 1.00)
5 cm	0.742	0.801	0.787	0.12230	15.270	0.01840	(0.55, 1.07)
6 cm	0.742	0.779	0.765	0.11546	14.817	0.01470	(0.58, 1.02)
7 cm	0.742	0.828	0.814	0.12779	15.435	0.02360	(0.54, 1.11)
age 6+							
1 cm	1.074	1.073	1.065	0.06707	6.251	0.00450	(0.95, 1.20)
2 cm	1.074	1.067	1.060	0.10236	9.595	0.01050	(0.90, 1.28)
3 cm	1.074	1.036	1.028	0.11648	11.247	0.01510	(0.90, 1.26)
4 cm	1.074	1.009	1.003	0.11837	11.735	0.01830	(0.90, 1.25)
5 cm	1.074	0.950	0.944	0.11578	12.184	0.02880	(0.96, 1.19)
6 cm	1.074	0.944	0.930	0.11745	12.446	0.03090	(0.95, 1.20)
7 cm	1.074	0.913	0.905	0.11462	12.553	0.03910	(1.00, 1.14)

Table S7.2: Estimated abundance ($\hat{\lambda}_a$) for saithe from the original data in year 2017 Q3 compared with estimated abundance ($\hat{\lambda}_a^*$) from the reduced data for different sampling procedures of length groups (l).

l	$\hat{\lambda}_a$	$\hat{\lambda}_a^*$	(median) $\hat{\lambda}_a^*$	SE($\hat{\lambda}_a^*$)	RSE%	RMSE	CI-95 ($\hat{\lambda}_a^*$)
age 0							
1 cm	0.282	0.282	0.282	0.00000	0.00	0.00000	(0.28, 0.28)
2 cm	0.282	0.282	0.282	0.00000	0.00	0.00000	(0.28, 0.28)
3 cm	0.282	0.289	0.295	0.00626	2.17	0.00008	(0.28, 0.29)
4 cm	0.282	0.290	0.295	0.00592	2.04	0.00010	(0.28, 0.29)
5 cm	0.282	0.282	0.282	0.00000	0.00	0.00000	(0.28, 0.28)
6 cm	0.282	0.297	0.295	0.01022	3.44	0.00030	(0.28, 0.31)
7 cm	0.282	0.290	0.295	0.00594	2.05	0.00010	(0.28, 0.29)
age 1							
1 cm	0.123	0.123	0.123	0.00000	0.00	0.00000	(0.12, 0.12)
2 cm	0.123	0.123	0.123	0.00000	0.00	0.00000	(0.12, 0.12)
3 cm	0.123	0.117	0.111	0.00626	5.36	0.00008	(0.11, 0.12)
4 cm	0.123	0.118	0.115	0.00673	5.71	0.00008	(0.11, 0.13)
5 cm	0.123	0.125	0.123	0.00139	1.12	0.000003	(0.12, 0.13)
6 cm	0.123	0.112	0.114	0.01059	9.46	0.00024	(0.11, 0.13)
7 cm	0.123	0.116	0.114	0.00628	5.43	0.00009	(0.11, 0.13)
age 2							
1 cm	0.929	0.930	0.923	0.16851	18.13	0.02840	(0.64, 1.28)
2 cm	0.929	0.916	0.861	0.28468	31.06	0.08120	(0.55, 1.53)
3 cm	0.929	0.966	0.902	0.33158	34.32	0.11000	(0.53, 1.71)
4 cm	0.929	0.955	0.900	0.31885	33.38	0.10200	(0.49, 1.66)
5 cm	0.929	0.992	0.942	0.31609	31.85	0.10400	(0.48, 1.75)
6 cm	0.929	0.966	0.893	0.36374	37.66	0.13400	(0.47, 1.83)
7 cm	0.929	0.989	0.933	0.34996	35.40	0.12600	(0.45, 1.80)
age 3							
1 cm	11.238	11.270	11.249	0.53506	4.75	0.28700	(10.19, 12.30)
2 cm	11.238	11.179	11.187	0.92312	8.26	0.85600	(9.57, 13.11)
3 cm	11.238	11.109	11.082	1.07691	9.69	1.18000	(9.30, 13.27)
4 cm	11.238	11.000	11.009	1.08989	9.91	1.24000	(9.21, 13.15)
5 cm	11.238	10.891	10.871	1.11346	10.22	1.36000	(9.41, 13.03)
6 cm	11.238	10.920	10.905	1.06856	9.79	1.24000	(9.46, 13.04)
7 cm	11.238	10.840	10.839	1.08304	9.99	1.33000	(9.53, 13.05)
age 4							
1 cm	12.789	12.757	12.754	0.52780	4.14	0.28000	(11.79, 13.73)
2 cm	12.789	12.816	12.827	0.93741	7.31	0.87900	(10.76, 14.60)
3 cm	12.789	12.863	12.856	1.06438	8.27	1.14000	(10.68, 14.93)
4 cm	12.789	12.950	12.954	1.09842	8.48	1.23000	(10.56, 15.14)
5 cm	12.789	13.096	13.087	1.12912	8.62	1.37000	(10.51, 15.31)
6 cm	12.789	13.061	13.051	1.08819	8.33	1.26000	(10.42, 15.11)
7 cm	12.789	13.176	13.187	1.09385	8.30	1.35000	(10.33, 15.18)
age 5							
1 cm	2.971	2.971	2.966	0.13399	4.51	0.01800	(2.72, 3.24)
2 cm	2.971	3.048	3.037	0.27486	9.02	0.08150	(2.52, 3.62)
3 cm	2.971	3.000	2.974	0.31856	10.62	0.10200	(2.42, 3.65)
4 cm	2.971	3.038	3.005	0.34723	11.43	0.12500	(2.40, 3.77)
5 cm	2.971	2.971	2.968	0.33433	11.25	0.11200	(2.35, 3.64)
6 cm	2.971	2.980	2.964	0.38418	12.89	0.14800	(2.28, 3.77)
7 cm	2.971	2.940	2.922	0.39677	13.49	0.15800	(2.32, 3.76)
age 6+							
1 cm	2.819	2.818	2.820	0.05409	1.92	0.00293	(2.71, 2.92)
2 cm	2.819	2.787	2.784	0.08700	3.12	0.00860	(2.68, 2.96)
3 cm	2.819	2.808	2.808	0.11451	4.08	0.01320	(2.60, 3.04)
4 cm	2.819	2.800	2.795	0.12424	4.44	0.01580	(2.61, 3.06)
5 cm	2.819	2.793	2.791	0.13520	4.84	0.01890	(2.58, 3.07)
6 cm	2.819	2.814	2.823	0.14353	5.10	0.02060	(2.54, 3.10)
7 cm	2.819	2.800	2.794	0.16239	5.80	0.02670	(2.55, 3.14)