Latent Gaussian models to predict historical bycatch in commercial fishery

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September 29, 2016

Abstract

Knowledge about how many fish that have been killed due to bycatch is an important aspect of ensuring a sustainable ecosystem and fishery. We introduce a Bayesian spatio-temporal prediction method for historical bycatch that incorporates two sources of available data sets, fishery data and survey data. The model used assumes that occurrence of bycatch can be described as a log-linear combination of covariates and random effects modeled as Gaussian fields. Integrated Nested Laplace Approximations (INLA) is used for fast calculations. The method introduced is general, and is applied on bycatch of juvenile cod (*Gadus morhua*) in the Barents Sea shrimp (*Pandalus borealis*) fishery. In this fishery we compare our prediction method with the well known ratio and effort methods, and make a strong case that the Bayesian spatio-temporal method produces more reliable historical bycatch predictions compared to existing methods.

Keywords: Bycatch, Spatio-temporal, Bayesian, INLA, Commercial fishery

1 Introduction

Bycatch in commercial fisheries may potentially threaten a sustainable ecosystem and fishery, and knowledge about historical bycatch is therefore important. If bycatch is not recorded in the fishermen catch logbooks, which is the main source of information within commercial fisheries, historical bycatch needs to be estimated. In this research, we introduce a prediction procedure based on the newly constructed Bayesian hierarchical spatio-temporal bycatch model in Breivik et al. (2016). We further compare our method with the frequently used ratio method (Scheaffer et al., 1996, page 204) and effort method (e.g. Walmsley et al., 2007; Hall, 1996) for a specific fishery.

Typically two sources of data are available for predicting bycatch; the commercial catch logbooks the fishermen are obliged to report, and observations taken for monitoring purposes. The first source, referred to as fishery data, contains only target catch, whiles the latter, referred to as survey data, contains both target catch and bycatch. To predict historical bycatch in the commercial fishery, we combine the fishery data with the survey data.

The ratio method and the effort based method are widely used to predict historical bycatch

(Davies et al., 2009; Vinther, 1999; Ye et al., 2000; Amandè et al., 2010; Ye, 2002; Walmsley et al., 2007). The ratio method scales the commercial target catch with the observed bycatch ratio in the survey data, while the effort based method scales the observed bycatch with the commercial trawl effort.

The model proposed to predict historical bycatch takes a regression approach and utilizes possible important explanatory variables (such as seasonal effects and the size of target catch). It also includes an underlying stochastic structure that partly explains the processes that the explanatory variables fail to capture and simultaneously takes dependence structures into account. By using our bycatch model we can utilize observations taken over several years to describe global structures of bycatch. Our model-based approach is thereby able to provide good realistic bycatch predictions (with uncertainty) even in areas and time periods with few or no inspected trawl hauls.

The prediction method introduced in this research is general and is applied to bycatch of juvenile cod in the Barents Sea shrimp fishery. A sorting grid, which sorts out the larger cod and reduces bycatch, was imposed in this fishery in 1992/1993 (ICES, 1994). Because of the grid, the bycatch is of no commercial value, and is discarded. There is a real time regulation of this fishery with respect to bycatch of juvenile cod, haddock (*Melanogrammus aeglefinus*), redfish (*Sebastes norvegicus* and *Sebastes mentella*), Greenland halibut (*Reinhardtius hippoglossoides*) and undersized shrimp. If the Norwegian Directorate of Fisheries Monitoring and Surveillance Service (MSS) believes that an area has a higher bycatch ratio than allowed, that is e.g. 8 cod per 10 kilogram of shrimps (Fiskeridirektoratet, 2005), the area is temporarily closed. The survey data used in this research have previously been used by MSS to regulate the shrimp fishery (Breivik et al., 2016). See Little et al. (2015) for a summary of management methods with respect to bycatch in several other large fisheries.

Bycatch was also predicted in Breivik et al. (2016) for regulation purposes. Our research differs mainly because we utilize huge amounts of fishery data, resulting in new computational difficulties, and that the data distribution is changed from log-Gaussian to zero-inflated negative binomial. Furthermore, the target catch is in this research a given covariate since it is included in both the fishery data and the survey data, while in Breivik et al. (2016) where future predictions was the focus, the shrimp catch was stochastic. To adapt to the information given in the fishery data, the response variable for bycatch in Breivik et al. (2016) is changed from *bycatch per nautical mile* to *total bycatch*, and with duration trawled included as an offset.

The paper is organized as follows. Section 2 presents the data used for historical bycatch prediction. Section 3 provides a brief overview of historical bycatch prediction methods. Section 4 presents the model and section 5 illustrates the inference and prediction procedure. Section 6 presents the estimated model and predictions of historical bycatch. Section 7 validates the predictions and compares them with the ratio and effort method. Finally, section 8 and 9 present discussion and conclusions.

2 Data

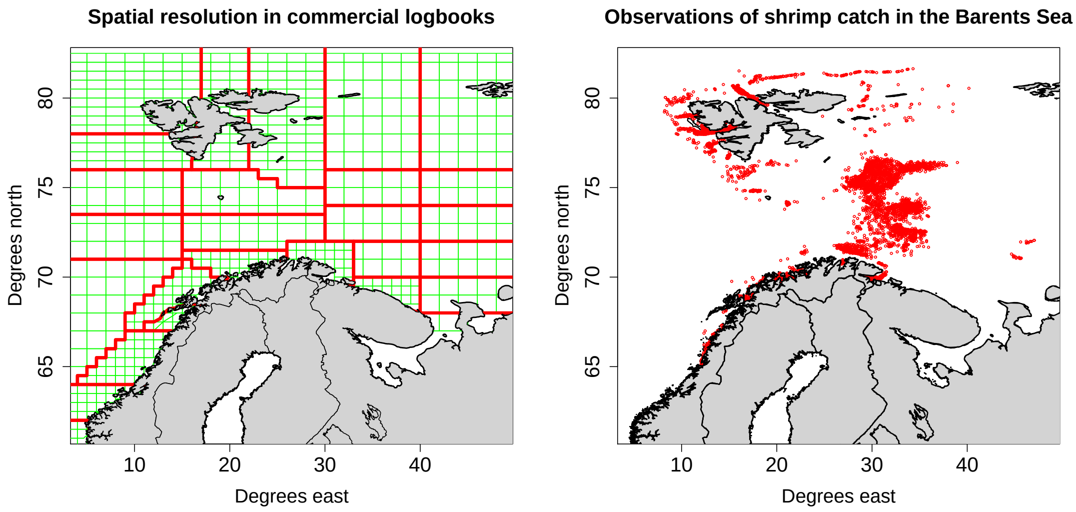
Figure 1 shows the spatial distribution of the data. The left panel shows the spatial resolution of the fishery data (specific locations are not recorded), while the right panel shows the spatial locations of the survey data.

There were reported in total 81,809 commercial shrimp catches during the period 1994 to 2006. Table 1 gives a short summary of possible covariates in the fishery data. Notice that the fishery data consists of daily catches, meaning that if a vessel has made several trawl hauls in the same small-scale spatial unit (see Figure 1) in a single day, this counts as one record.

Data	**Description**
Time	Date of catch (day, month and year)
Location	Which region the catch was taken (see small areas in Figure 1a)
Target catch	Total shrimp catch by one boat in a given area and day (770kg, 13,750kg)
Duration	Hours used to trawl by a boat in a given area and day (7 hours, 22.9 hours)
Number of trawls	The number of trawls varies between (76%), two (23%) or three (1.7%)
Quarter of the year	1st (9.2%), 2nd (42%), 3rd (38%) and 4th (11%)

Table 1: *Summary of fishery data, intervals in parentheses are 90% coverage intervals.*

We used 7,363 observations of shrimp and bycatch of cod from 1994 to 2006 taken by the MSS (the survey data), and provided by the Institute of Marine Research (IMR) in Bergen, Norway, see Table 2 for a short summary of the survey data. There were 18.5% zero-observations of bycatch. The survey observations are collected for regulation purposes and the trawl hauls are conducted using the same equipment as in the commercial fishery. These observations may



(a) (b)

Figure 1: *a) Map of the Barents Sea with small green rectangles describing the spatial resolution of the fishery data. The larger red areas are used when calculating the ratio and effort estimates. b) Map of the Barents Sea with red dots illustrating the survey data.*

Data	**Description**
Target catch	Shrimp catch varied between 2.4 kilogram and 17.7 tons (20, 3,190)
Bycatch cod	The number of cod varied between 0 and 35,775 cod (0, 1,008)
Time	Time of catch down to minutes scale
Location	Catch location (single point) given in longitude and latitude
Open/Closed	Describes if the location was open for commercial fishery or not (83% open)
Duration trawled	The hours used to trawl (1.6 hours, 6 hours)
Number of trawls	The number of trawls varies between one (74%), two (23%) or three (3.0%)
Temperature	Bottom sea temperature (0.17, 9.3)
Depth	Ocean depth at catch location (227, 410)
Quarter of the year	1st (21%), 2nd (35%), 3rd (20%) and 4th (23%)

Table 2: *Summary of data collected by the MSS, intervals in parentheses are 90% coverage intervals.*

either have been taken on board vessels active in the commercial fishery (23%), or by vessels hired by the MSS (77%) for collecting a sufficient amount of observations at selected areas where commercial shrimp trawling occurs.

In addition to the variables in Table 1 we also use total abundance estimates of 0-group cod (juvenile cod less than one year old) in the whole Barents Sea to predict the historical bycatch. These estimates can be found in Jakobsen and Ozhigin (2011, pages 565-567).

3 Methods to estimate historical bycatch

This section gives a brief overview of methods to estimate historical bycatch. Our research focuses on the third method (the model based method).

3.1 The ratio method

The ratio method (Scheaffer et al., 1996, page 204) has been widely used to estimate historical bycatch. The ratio method uses the reported bycatch ratio in the survey data to scale the commercial target catch (here shrimp) to achieve estimates of bycatch, and is defined as

$$\widehat{B}_{A,t}^{\text{ratio}} = \frac{\sum_{i=1}^{n} b_{i,A,t}}{\sum_{i=1}^{n} z_{i,A,t}} Z_{A,t} = \mathrm{R}_{A,t} Z_{A,t}. \tag{1}$$

Here ($z_{i,A,t}$,$b_{i,A,t}$) are the ith observed target catch and bycatch in the survey data in area A and time interval t, $Z_{A,t}$ is the total commercial target catch in area A and time interval t, and $\mathrm{R}_{A,t}$ is the observed bycatch ratio in area A and time interval t. The historical bycatch in several time intervals can then be estimated in the whole Barents Sea as $\sum_A \sum_t \mathrm{R}_{A,t} Z_{A,t}$. We let the areas, A, be the small green rectangles in Figure 1a and each time intervals, t, be quarters of years. The ratio method with these areas and time intervals is currently used as a standard for providing official historical bycatch estimates in the Barents Sea shrimp fishery (Ajiad et al., 2007; Hylen and Jacobsen, 1987).

Equation (1) assumes there exists survey data in each area and time interval where commercial catches occurred. This is not always fulfilled, and in such situations it is a common procedure to expand the area on which the ratio, $\mathrm{R}_{A,t}$, is calculated. In our experiments, we expand the area in the following order: First we use all observations in the larger red area containing the area of interest (Figure 1a) within the given time interval. If there are no observations in this larger area, we use all the observations in the Barents Sea within the given time interval. If there are no observations in the Barents Sea, we use all observations collected one time interval before and after. We also experimented with expanding the time interval before increasing the spatial areas, but this had little effect on the results. Our first expansion step is similar to the one used in Ajiad et al. (2007), but the next expansion steps were not documented in detail in Ajiad et al. (2007). Furthermore, as done in Ajiad et al. (2007), only observations taken at locations open for commercial fishery is used to calculate the bycatch ratio (1).

3.2 The effort method

Another much used method for estimating historical bycatch is the effort method (e.g. Walmsley et al., 2007). The effort method uses reported trawl effort in the commercial fishery to up-scale bycatch estimates from the survey data, and is defined as

$$\widehat{B}_{A,t}^{\text{effort}} = \frac{\sum_{i=1}^{n} b_{i,A,t}}{\sum_{i=1}^{n} \text{time}_{i,A,t}} T_{A,t}. \tag{2}$$

Here $\text{time}_{i,A,t}$ is towing time used when $b_{i,A,t}$ was observed, and $T_{A,t}$ is the total commercial trawl time within area A and time interval t. Note that this method is (at this time) not used for estimating historical bycatch in the Barents Sea shrimp fishery (Ajiad et al., 2007; Hylen and Jacobsen, 1987), but we include it in this research since it is a natural alternative to the ratio method in this fishery.

The effort method (2) also assumes there exists survey data in each area and time interval where commercial catches occurred. When this is not fulfilled, we increase the area, and potentially time, as described for the ratio method. Just as for the ratio method (1), only observations taken at locations open for commercial fishery is used to calculate the effort estimate (2).

3.3 A model-based procedure

A model-based procedure constructs a model for the observed bycatch and uses the model to estimate the unobserved historical bycatch. Let $\mathbf{B}_{\text{C}}$ and $\mathbf{B}_{\text{S}}$ be the bycatch from the fishery data and the survey data, respectively. We know $\mathbf{B}_{\text{S}}$ and want to estimate $\mathbf{B}_{\text{C}}$. Let further $\mathbf{Z} = (\mathbf{Z}_{\text{C}},\mathbf{Z}_{\text{S}})$ be the target catch from both fishery data and the survey data. By using a probabilistic model, M, we can focus on the distribution

$$P(\mathbf{B}_{\mathrm{C}}|\mathbf{B}_{\mathrm{S}}, \mathbf{Z}, M), \tag{3}$$

and use this distribution to construct predictions of historical bycatch with uncertainty.

As opposed to the two previous methods, the model based method (3) does not assume there exist survey data in each area and time interval where commercial catches occur. However, for the model to give realistic predictions, it is crucial that it is able to utilize other sources of information such as relevant explanatory variables and dependence structures. Unlike the ratio (1) and effort method (2), the model-based procedure (3) is able to utilize survey data at locations closed for commercial fishery in order to predict historical bycatch.

4 The model

In this section we introduce our model for historical bycatch (3). The model is a modified version of that introduced in Breivik et al. (2016). Let $B(\mathbf{s},t)$ be the number of juvenile cod caught at time t and location $\mathbf{s}$. We model $B(\mathbf{s},t)$ as zero-inflated negative binomial distributed, that is with density

$$\pi(B(\mathbf{s},t))) = \mathrm{p}(\mu(\mathbf{s},t))\mathrm{I}_{B(\mathbf{s},t)=0} + [1 - \mathrm{p}(\mu(\mathbf{s},t))]\mathrm{NB}(B(\mathbf{s},t); \mu(\mathbf{s},t), \varsigma). \tag{4}$$

Here $p(\mu)$ represent an additional probability for zero, I_{D} is an indicator function which is equal to one if D is true and zero otherwise, and $\mathrm{NB}(\cdot; \mu,\varsigma)$ is the negative binomial density with expectation $\exp(\mu)$ and dispersion parameter ς. The log-expectation, $\mu(\mathbf{s},t)$, of the negative binomial distribution in (4) is modeled as:

$$\mu(\mathbf{s},t) = \mathbf{X}(\mathbf{s},t)^T\boldsymbol{\beta} + \alpha(\mathbf{s}) + \upsilon(t) + \gamma(\mathbf{s},t), \tag{5}$$

where $\mathbf{X}(\mathbf{s},t)$ is a vector of covariates and $\boldsymbol{\beta}$ the vector of corresponding regression coefficients. Three random effect terms are included in the expectation, one spatial, $\alpha(\mathbf{s})$, one temporal, $v(t)$, and one spatio-temporal, $\gamma(\mathbf{s},t)$. These are respectively intended to capture that the bycatch amounts may depend on local features, that bycatch changes between years and that observations close to each other in both space and time are highly correlated. The random effects are modeled as Gaussian random fields.

The additional zero-probability, $p(\mu)$, in (4) is modeled as

$$\mathrm{p}(\mu(\mathbf{s},t)) = 1 - \Big(\frac{\exp(\mu(\mathbf{s},t))}{1+\exp(\mu(\mathbf{s},t))}\Big)^a, \tag{6}$$

where $a > 0$ and adjusts how the zero-probability changes with respect to (5).

4.1 Covariates

The covariates that have been considered are given in Table 3. Notice that shrimp catch is in this setting a given covariate, and differs from the model in Breivik et al. (2016) were the shrimp catch was considered stochastic. In Breivik et al. (2016) the time of the day was also found important for predicting bycatch, but this variable is not given in the fishery data and is therefore not used in this research. We use estimated abundance of 0-group cod in the whole Barents Sea as a covariate. Breivik et al. (2016) tried to utilize the spatial locations of the 0-group estimates as a spatial predictor, but did not find support in the data for such a procedure. Note that the number of trawls used at the same time is included as a categorical variable and not as an offset, this is done since the shape of the trawl may vary with the number of trawls used at the same time.

We use a Fourier series (Lay, 2006, page 456) for the seasonal effect. The Fourier series is given by

$$f(t') = \sum_{i=1}^{r}(c_i \sin(it') + d_i \cos(it')), \tag{7}$$

Covariates	Type	Description
0-group	Continuous	Logarithm of aggregated 0-group abundance of cod
Temperature (standardized)	Continuous	Bottom sea temperature
Depth (standardized)	Continuous	Ocean depth at catch location
Target catch	Continuous	Logarithm of hourly shrimp catch
Number of trawls	Categorical	The number of trawls used at the same time
Seasonal effect	Continuous	Fourier series (7)
Time (scaled to years)	Continuous	Linear covariate of time
Duration	Continuous	Duration of trawl (used as offset)

Table 3: *Covariates considered.*

were $t' \in [0,2\pi]$ is a linear function of time such that $t' = 0$ for 1st January and $t' = 2\pi$ for 31st December. The parameters c_i and d_i in (7) correspond to regression coefficients in (5), and r is the number of harmonics in the Fourier series. As in Breivik et al. (2016), we allow the seasonal effect to be a function of latitude to accommodate for different cod growth ratios which depends on temperature (see Breivik et al. (2016) for details).

4.2 Correlation structure

We assume as in Breivik et al. (2016) that the spatially correlated Gaussian field in (5), $\alpha(\mathbf{s})$, follows a stationary Matern covariance structure:

$$\text{Cov}(\alpha(\mathbf{s}_1),\alpha(\mathbf{s}_2)) = \frac{\sigma_\alpha^2}{2^{\nu-1}\Gamma(\nu)}(\kappa_\alpha||\mathbf{s}_1 - \mathbf{s}_2||)^\nu K_\nu(\kappa_\alpha||\mathbf{s}_1 - \mathbf{s}_2||), \tag{8}$$

where σ_α^2 is the marginal variance, $||\cdot||$ is the Euclidean distance measure in kilometers, ν is a smoothing parameter, κ_α is a spatial scale parameter and $K_\nu(\cdot)$ is the modified Bessel function of the second kind. As in Breivik et al. (2016) we fix $\nu = 1$ since this value is typically poorly identifiable (Blangiardo and Cameletti, 2015, page 194).

We assume as in Breivik et al. (2016) the time-dependent zero-mean Gaussian random field, $\upsilon(t)$, to be constant within years while independent between years, with variance σ_υ^2. We further define the first month of the year to be September when we refer to the yearly effect. This is reasonable because the 0-group enters a demersal life stage after September, and thereby starts living on the seabed where shrimp trawling occurs (Jakobsen and Ozhigin, 2011, page 230). Note that this temporal structure comes in addition to possible linear time trend and seasonal effects.

The spatio-temporal interaction term, $\gamma(\mathbf{s},t)$, is modeled with mean zero and a separable stationary exponential covariance structure given by

$$\mathrm{Cov}\Big(\gamma(\mathbf{s}_1,t_1),\gamma(\mathbf{s}_2,t_2)\Big) = \sigma_\gamma^2 \exp\Big(-\frac{||\mathbf{s}_1-\mathbf{s}_2||}{\theta_s} - \frac{|t_1-t_2|}{\theta_t}\Big). \tag{9}$$

Here σ_γ^2 is the marginal variance, $||\cdot||$ is the Euclidean distance measure in kilometers, $|t_1 - t_1|$ is the time difference in days and θ_s and θ_t are range parameters in space and time.

5 Inference and prediction procedure

This section elaborates the inference and prediction procedure, and is divided into two subsection. The first subsection elaborates the inference, while the second subsection elaborates the prediction procedure. Note that only survey data are used for inference, and the fishery data are used combined with the survey data for prediction.

5.1 Inference

Only the survey data are used for inference on models and model parameters. The Bayesian inference is performed with the integrated nested Laplace approximation (INLA) technique (Rue et al., 2009; Martins et al., 2013) with use of the R-package R-INLA (http://www.r-inla.org). The INLA technique is an efficient procedure for fast approximation of the parameters and latent fields in the model. Non-informative priors are used, see appendix A.1, and we refer to Breivik et al. (2016) for more details on the inference procedure.

Which correlation structures to include is first selected with use of all the relevant covariates. The covariates are then selected with a backwards elimination procedure given the selected correlation structure. This ordering for selecting parameters is the same as in Breivik et al. (2016); Zuur (2009, page 121).

We have used the Bayes factor (Gelfand, 1996) for selection of correlation structures and covariates. In Breivik et al. (2016) three other validation criteria were used to evaluate the covariance structure in the model for bycatch of cod. Then all the model selection criteria agreed and we believe it is satisfactory to only use the Bayes factor in this research. The Bayes factor is the ratio of the marginal likelihoods (ML) given by ML $= P(\mathbf{B}_{\mathrm{S}}|M)$. See Rue et al. (2009) on how the ML is calculated within R-INLA. Our model selection procedure has one exception. The 0-group regression parameter is highly confounded with the yearly effect by construction. Because of this the marginal likelihood is not adequate for selection of the 0-group when the yearly effect is included. Just as in Breivik et al. (2016), if the yearly effect is included, the 0-group is included if it has predictive power.

5.2 Historical bycatch prediction

The historical bycatch is predicted by first fitting the selected model from section 5.1 with the survey data using R-INLA, and then, based on the given estimated model, using a prediction procedure which samples from the posterior distribution. This subsection elaborates on the historical bycatch prediction.

Let $\boldsymbol{\varphi} = \{\varphi(\mathbf{s},t)\}$ be the vector of latent fields where

$$\varphi(\mathbf{s},t) = \alpha(\mathbf{s}) + \nu(t) + \gamma(\mathbf{s},t) \tag{10}$$

if all fields are included in the model (5), while some of the terms can be missing in general. Let also $\boldsymbol{\varphi}_{\mathrm{C}}$ and $\boldsymbol{\varphi}_{\mathrm{S}}$ be the subvectors of $\boldsymbol{\varphi}$ corresponding to the commercial bycatch and surveillance bycatch. The latent structure is of the form

$$\begin{pmatrix} \boldsymbol{\varphi}_{\mathrm{C}} \\ \boldsymbol{\varphi}_{\mathrm{S}} \end{pmatrix} \sim N(\mathbf{0}, \boldsymbol{\Sigma}) = N\left(\begin{pmatrix} \mathbf{0} \\ \mathbf{0} \end{pmatrix}, \begin{pmatrix} \boldsymbol{\Sigma}_{CC} & \boldsymbol{\Sigma}_{CS} \\ \boldsymbol{\Sigma}_{SC} & \boldsymbol{\Sigma}_{SS} \end{pmatrix} \right), \tag{11}$$

where $\boldsymbol{\Sigma}$ represents the selected covariance structure with sub-elements $\boldsymbol{\Sigma}_{CC}, \boldsymbol{\Sigma}_{CS}, \boldsymbol{\Sigma}_{SC}$ and $\boldsymbol{\Sigma}_{SS}$ defining respectively the correlation between the commercial bycatch, the cross correlation between the commercial bycatch and the surveillance bycatch and the correlation between the surveillance bycatch. All these terms are derived from the set of latent fields that are included in the model. Note that we do not know the exact locations of the fishery data, $\mathbf{L} = \{(\mathbf{s},t) : (\mathbf{s},t)$ corresponds to fishery data locations$\}$, needed in the covariance structure. To account for the uncertainty in $\mathbf{L}$, we assume for simplicity that the fishery data are independent and uniformly distributed on the areas reported (the green rectangles in Figure 1a).

The distribution of the commercial bycatch given the survey data is given by

$$\pi(\mathbf{B}_{\mathrm{C}}|\mathbf{B}_{\mathrm{S}}) = \int \pi(\mathbf{B}_{\mathrm{C}}|\boldsymbol{\beta},\boldsymbol{\varphi}_{\mathrm{C}},\boldsymbol{\theta})\pi(\boldsymbol{\varphi}_{\mathrm{C}}|\boldsymbol{\theta},\boldsymbol{\varphi}_{\mathrm{S}},\mathbf{L})\pi(\boldsymbol{\theta},\boldsymbol{\beta},\boldsymbol{\varphi}_{\mathrm{S}}|\mathbf{B}_{\mathrm{S}})\pi(\mathbf{L})d\mathbf{L}d\boldsymbol{\theta}d\boldsymbol{\beta}d\boldsymbol{\varphi}_{\mathrm{S}}d\boldsymbol{\varphi}_{\mathrm{C}}. \tag{12}$$

Samples from this distribution can be obtained by the following algorithm:

1. Sample N_1 sets of catch locations $\mathbf{L}$.

2. Sample N_1 sets of hyperparameters, regression coefficients and latent structures, $\boldsymbol{\varphi}_S$, from the posterior distribution $\pi(\boldsymbol{\theta}, \boldsymbol{\beta},\boldsymbol{\varphi}_S|\mathbf{B}_{\mathrm{S}})$ using R-INLA.

3. Use the updating equations:

$$\begin{aligned} \mathrm{E}[\boldsymbol{\varphi}_{\mathrm{C}}|\boldsymbol{\varphi}_{\mathrm{S}}] &= \boldsymbol{\Sigma}_{CS}\boldsymbol{\Sigma}_{SS}^{-1}\boldsymbol{\varphi}_{\mathrm{S}} \\ \mathrm{Var}[\boldsymbol{\varphi}_{\mathrm{C}}|\boldsymbol{\varphi}_{\mathrm{S}}] &= \boldsymbol{\Sigma}_{CC} - \boldsymbol{\Sigma}_{CS}\boldsymbol{\Sigma}_{SS}^{-1}\boldsymbol{\Sigma}_{SC} \end{aligned} \tag{13}$$

   to sample N_2 realizations of $\boldsymbol{\varphi}_{\mathrm{C}}$ given $\boldsymbol{\varphi}_{\mathrm{S}}$ for each set of $(\boldsymbol{\theta}, \boldsymbol{\beta}, \mathbf{L})$.

4. For each sampled set of $(\boldsymbol{\beta},\boldsymbol{\varphi}_{\mathrm{C}},\boldsymbol{\theta})$ sample one value from $\pi(\mathbf{B}_{\mathrm{C}}|\boldsymbol{\beta},\boldsymbol{\varphi}_{\mathrm{C}},\boldsymbol{\theta})$.

The algorithm above samples N_1N_2 realizations of historical bycatch in the commercial fishery. We selected $N_1 = 100$ and $N_2 = 50$ for the prediction of historical bycatch.

In Breivik et al. (2016) a prediction procedure implemented in R-INLA was used. Such a prediction procedure could also have been used in this research, but then the full precision matrix for the spatio-temporal Gaussian random field is required. We avoided working with this large dense matrix by constructing a prediction procedure outside of R-INLA which only uses sub-matrices of the full covariance matrix $\boldsymbol{\Sigma}$.

6 Prediction of historical bycatch

The object of this research is to predict the historical bycatch, and this result section is divided into two subsections. The first subsection briefly shows the selected covariates and correlation structures, and the second subsection shows the historical bycatch predictions of cod in the Barents Sea shrimp fishery. See appendix A.2 for details regarding the computational features.

6.1 Covariates and correlation

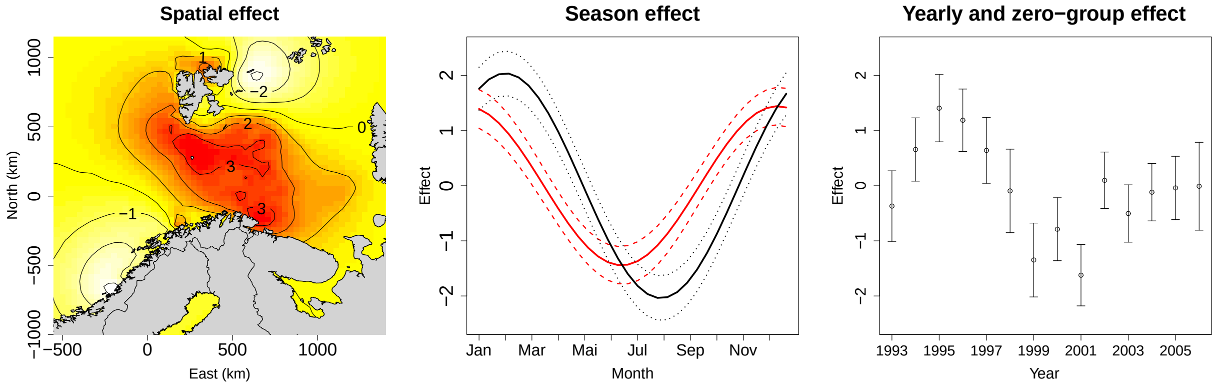
Table 4 lists covariates that were selected for prediction of bycatch. By inspecting the credibility intervals, we found a clear effect of the 0-group. Furthermore, the inclusion of the 0-group halved the variance of the year effect, leading to better predictive power, and is therefore included in the model. As in Breivik et al. (2016), compared to using a single trawl, double trawl was shown to increase bycatch while no effect was found for triple trawl. That triple trawl does not affect the bycatch is intuitively surprising, and may be because only 3% of the survey data are collected with use of triple trawl (see Table 2). Thereby may we not have enough observations to estimate a possible triple trawl effect.

All three random terms in (5) were selected. This selection of random structure is the same as in Breivik et al. (2016). See Table 4 for a summary of the estimated hyperparameters.

Covariates (eq. 5)			**Hyperparametes**		
Parameter	Mean	95% C.I.	Parameter	Mean	95% C.I.
Constant	-0.89	(-3.7,1.1)	ς (eq. 4)	2.09	(1.95,2.23)
depth (standardized)	-0.29	(-0.34,-0.25)	a (eq. 6)	1.70	(1.53,1.88)
0-group	0.49	(0.21,0.76)	σ_α^2 (eq. 8)	5.9	(2.2,14.8)
double trawl	0.43	(0.29,0.58)	κ_α (eq. 8)	0.0050	(0.0027,0.0078)
Shrimp catch (log scale)	0.36	(0.32,0.40)	σ_v^2	0.36	(0.11,0.87)
			σ_γ^2 (eq. 9)	1.9	(1.75,2.08)
			θ_t (eq. 9)	38 (mode)	unknown
			θ_s (eq. 9)	156 (mode)	unknown

Table 4: *Estimates and 95% credibility intervals of the significant regression coefficients and the hyperparameters.*

Figure 2 illustrates the spatial, seasonal and yearly effects for bycatch of cod. By comparing the spatial contribution, $\alpha(\mathbf{s})$ in equation (5), from Figure 2a with the juvenile cod migration pattern in Jakobsen and Ozhigin (2011, page 227) we see a clear overlap. The seasonal effect,



(a) (b) (c)

Figure 2: *a) The spatial effect. b) The seasonal effect at 69 degrees north (red line) and 80 degrees north (black line) with 95% credibility intervals. c) The yearly effects added the zero-group effect with 95% credibility intervals, note that each interval illustrates the effect from 1st September in the denoted year to 31st August in the next year.*

Figure 2b, is included with one harmonic in the Fourier series (7) and depends on latitude. Just as in Breivik et al. (2016), the seasonal effect increases later in autumn in the north compared to in the south, see Figure 2b.

6.2 Prediction

This subsection presents the predicted number of juvenile cod killed as bycatch each year in the Barents Sea shrimp fishery. Our predictions are reported with posterior means and 90% prediction intervals. The predicted yearly historical bycatch (with uncertainty) is shown in Figure 3. The predicted yearly historical bycatch with quarterly predictions are further given in Table 5. There seems to be variation between years, which is reasonable since the fishing intensity and the cod year class strength changes from year to year.

In addition, Figure 3 includes historical bycatch estimates with the ratio method (red crosses) and effort method (green triangles). We see that our method is often in agreement with the ratio and effort methods, but clearly differed from the ratio method in year 1998 and 2004. A main reason why they differ is because of the sensitivity of the ratio method to small shrimp catches. In the fourth quarter of year 2004 there were five observations in the survey data which lead to a bycatch ratio of 38.9 in a specific area north in the Barents Sea. In this area the commercial fishery was 128 times more efficient than the MSS to catch shrimp per hour of

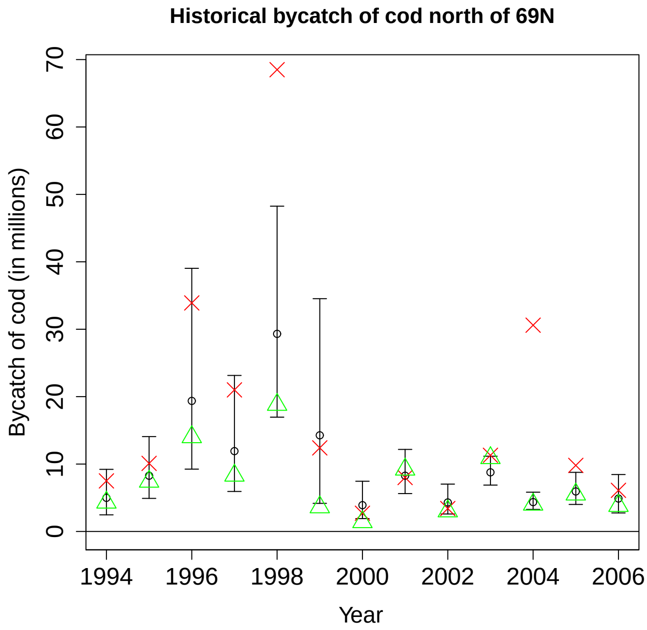


Figure 3: *Posterior means of yearly historical bycatch with 90% prediction intervals. The red crosses are the ratio estimates (1) and the green triangles are the effort estimates (2).*

trawl, which implies that the ratio estimate was not representative for the commercial fishery. Removing these five observations resulted in a ratio method estimate of 3.9 million instead of 30.6 million cod in year 2004, which is much more in agreement with our model-based approach. The difference in year 1998 can be explained likewise, and is omitted for brevity. The effort method (2) is not sensitive to small shrimp catches since it neglects the target catch, but is however sensitive to short trawl hauls.

Note that depth is included as a covariate in the prediction procedure, while not given in the fishery data (see Table 1). The depth at the commercial catch location is in this research extrapolated to be the same as the depth at the closest surveillance observation in space for prediction. The survey data are concentrated where commercial shrimp trawling occurs, and we therefore assume this approximation is sufficient.

7 Validation

In this section we validate the models ability to produce reliable bycatch predictions with uncertainty. This validation section is divided into three subsections. The first subsection validates predictions and uncertainty estimates of aggregated bycatch. The second subsection validates

Year	Total	1st quarter	2nd quarter	3rd quarter	4th quarter	Shrimp catch
1994	5.0 (2.5,9.2)	2.5 (0.8,5.7)	0.7 (0.3,1.3)	0.9 (0.2,2.5)	0.9 (0.3,1.9)	18900 tons
1995	8.3 (4.9,14.1)	2.9 (1.3,6.1)	2.5 (1.6,3.7)	1.7 (0.4,4.8)	1.2 (0.2,3.4)	15600 tons
1996	19.4 (9.2,39.0)	6.4 (1.0,19.3)	8.0 (3.5,17.1)	4.2 (2.2,7.6)	0.7 (0.2,1.7)	20500 tons
1997	11.9 (5.9,23.1)	2.6 (0.7,6.6)	4.8 (2.2,10.4)	3.5 (1.0,9.1)	1.0 (0.3,2.6)	25600 tons
1998	29.3 (17.0,48.3)	17.7 (8.4,32.9)	7.6 (4.0,13.0)	2.6 (0.6,6.8)	1.5 (0.3,4.0)	41200 tons
1999	14.3 (4.2,34.5)	7.5 (1.3,21.7)	4.4 (1.0,12.0)	2.0 (0.4,5.4)	0.3 (0.1,0.5)	48400 tons
2000	3.9 (1.9,7.4)	1.9 (0.5,5.0)	0.6 (0.3,1.0)	0.8 (0.3,2.0)	0.5 (0.2,1.3)	52000 tons
2001	8.3 (5.6,12.2)	2.8 (1.6,4.8)	2.7 (1.5,4.7)	1.2 (0.4,2.8)	1.5 (0.9,2.5)	42200 tons
2002	4.3 (2.6,7.0)	2.3 (0.8,4.8)	1.1 (0.7,1.7)	0.2 (0.1,0.4)	0.7 (0.4,1.2)	49500 tons
2003	8.8 (6.9,11.2)	0.7 (0.3,1.2)	5.0 (3.6,6.9)	2.8 (2.0,4.0)	0.3 (0.1,0.7)	33200 tons
2004	4.4 (3.3,5.8)	1.4 (0.8,2.2)	1.8 (1.2,2.5)	0.7 (0.4,1.1)	0.5 (0.3,0.9)	35000 tons
2005	5.9 (4.0,8.8)	1.4 (0.8,2.5)	2.2 (1.3,3.6)	1.8 (0.9,3.2)	0.5 (0.2,1.2)	34000 tons
2006	4.9 (2.7,8.4)	1.5 (0.4,4.0)	2.5 (1.3,4.4)	0.3 (0.2,0.6)	0.5 (0.1,1.5)	27900 tons

Table 5: *Yearly and quarterly historical bycatch predictions of cod with 90% prediction intervals (in millions), and yearly aggregated Norwegian commercial shrimp catch.*

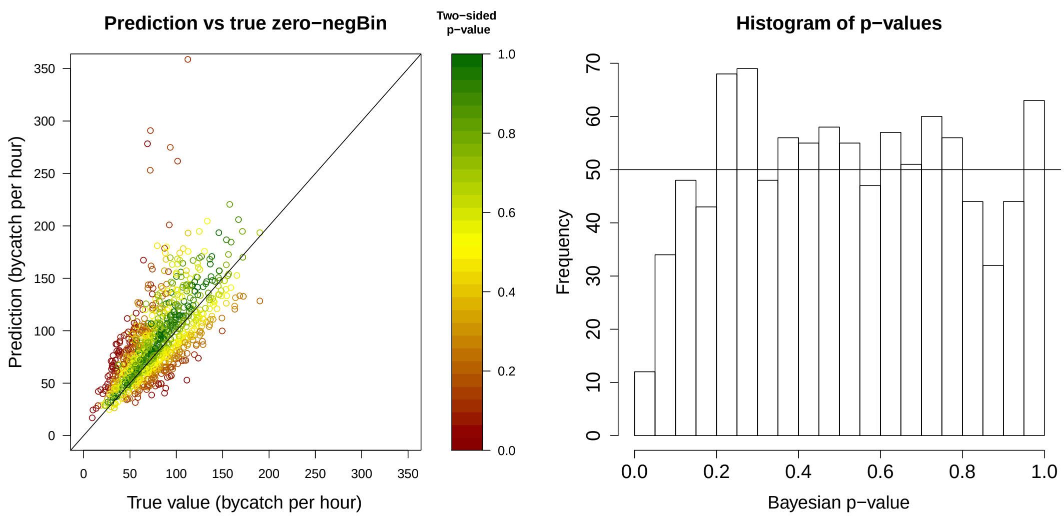
model assumptions. The third section investigates prediction bias and power using a simulation study. Due to the computational cost of integrating out the uncertainty in the hyperparameters, validation is performed with empirical Bayes, i.e. using posterior mode of hyperparameters. We have observed that the bycatch predictions are typically little affected by using the posterior mode of the hyperparameters, which indicates that this procedure does not strongly influence the validation.

7.1 Validation of predictions

This subsection validates the predictions, and shows that the model is able to give realistic predictions and uncertainty measures. The fishery and survey data are typically clustered in space and time. Therefore, to make the validation representative for the prediction purpose, the survey data are divided into clustered training and test sets. The clustering is accomplished by first dividing the survey data into *fishing trips*. A fishing trip is here defined as the largest set of observations taken by one distinct boat such that every time gap between two observations next to each other in chronological order is less than 3 days. The clustered test sets are then constructed with the same reasoning as in Hastie et al. (2009, page 241) by uniformly dividing the fishing trips into ten groups with equally many fishing trips within each group. Each group is then used as a test set and the others as the training set. This procedure is repeated 100 times leading to in total 1000 test and training sets. Note that we only use the survey data for validation of predictions since we know the true observed bycatch in the survey data, and can thereby compare the predictions with the truth.

Figure 4 shows predicted aggregated bycatch in the test sets versus the true observation with Bayesian p-values (Gelman et al., 2003, page 162). We see from Figure 4a that our model has predictive power, and by inspection of the Bayesian p-values in Figure 4b we observe that the model is able to give reasonable uncertainty estimates (since the p-values are roughly uniformly distributed). The relatively few small Bayesian p-values in Figure 4b indicates that the upper bound of the prediction intervals of historical bycatch in Figure 3 and in Table 5 might be slightly overestimated. Figure 7 illustrates the Bayesian p-values if we neglect parts of the random effects in the model (5), and we observe that the random effects are crucial for estimating the uncertainty, properly.

Coverage of bycatch predictions in the test sets in three common prediction interval levels are given in Table 6. Just as in Figure 4b, we observe that our model typically overestimate the upper bound of the prediction intervals.



(a) (b)

Figure 4: *a) Plot of predicted bycatch versus observed bycatch per hour trawl in the test sets, with color code illustrating the two sided p-values. b) Histogram of the Bayesian p-values. The horizontal line show the expected frequency of p-values if the model was correct.*

The accuracy of the prediction procedures is investigated with the mean absolute *relative error*

P.I. level	Inside P.I.	Under P.I.	over P.I.
90%	92.4%	6.2%	1.3%
95%	95.6%	4.0%	0.4%
99%	98.4%	1.2%	0.2%

Table 6: *Coverage of our model in three common prediction interval levels.*

of aggregated bycatch in the test sets. The relative error is defined as

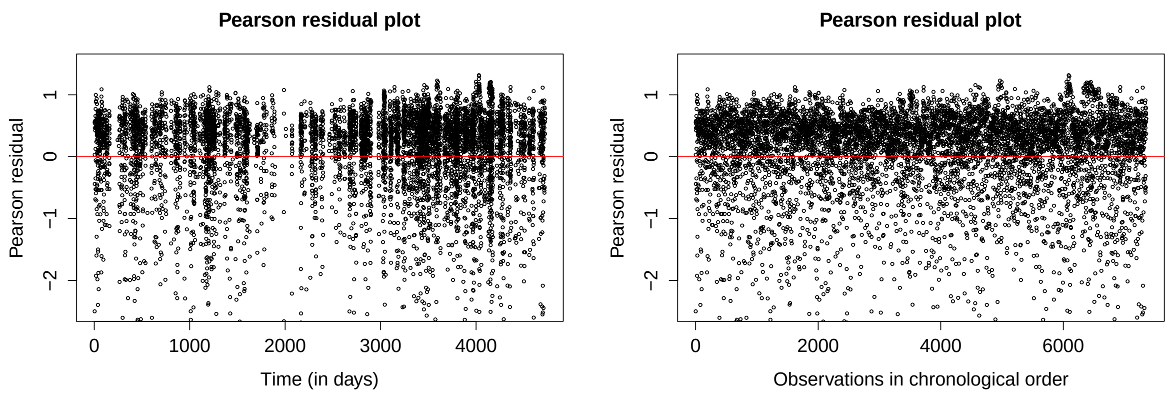
$$\text{relative error} = \frac{\text{prediction} - \text{true value}}{\text{true value}}. \tag{14}$$

With the ratio method, effort method and our model based approach the mean absolute relative error is equal to 0.51, 0.34 and 0.32 respectively. This indicates that our prediction procedure is more accurate than the ratio method which is currently in use for providing official historical bycatch estimates in the Barents Sea shrimp fishery.

The two range parameters in the spatio-temporal interaction (9) are estimated with all the survey data (that is both the training and test set) when predicting bycatch in the test sets. This was done due to the computational cost of estimating these parameters. We have observed that the posterior mode of the range parameters in the spatio-temporal interaction is approximately unchanged when estimated with several different training sets, which indicates that this procedure does not influence the validation of prediction.

7.2 Validation of model assumptions

Model assumptions are investigated using Pearson type residuals (McCullagh and Nelder, 1989, page 37) as recommended in Zuur and Ieno (2016). The residuals are calculated by sequentially leaving out every tenth surveillance observations and predicting them. Plots of Pearson residuals versus time and space coordinates and versus explanatory variables are investigated for correlation structures and for evidence of non-linearity in (5), and no clear violations are observed. All these plots are given in the online supplementary information. We also include Pearson residuals plotted against the order of each continuous variable, these are included to make clustered Pearson residuals easier to validate visually. As an example, Figure 5 shows



(a) (b)

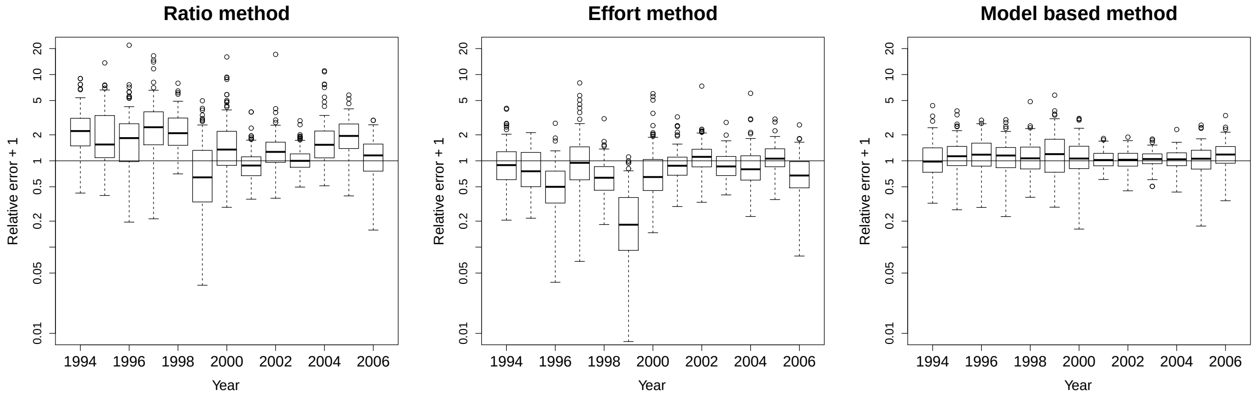
Figure 5: *a) Pearson residuals versus time. b) Pearson residuals in chronological order.*

Pearson residuals plotted against time. Variogram and autocorrelation plots are included in the online supplementary information, and give no indication of violations.

7.3 Validation through a simulation study

In this subsection we investigate the bias of historical bycatch predictions when assuming our model describes the underlying stochastic structure of the bycatch observations. The ratio and effort method are observed to be typically biased, while no such structure is observed for the model-based procedure. The validation is conducted by first simulating bycatch conditioned on the observed shrimp catch (only 10% of the fishery data from each year, chosen at random, is used due to computation time). See appendix A.3 for a description of the joint simulation of $\mathbf{B}_{\mathrm{C}}$ and $\mathbf{B}_{\mathrm{S}}$. The bias is then investigated through the distribution of the relative error (14) of the aggregated simulated commercial bycatch.

A boxplot summary of 100 simulated relative errors of aggregated yearly bycatch in the commercial fishery is shown in Figure 6. We see that there is a tendency to overestimate bycatch when using the ratio method (Figure 6a), and a tendency to underestimate when using the effort method (Figure 6b). This bias can be explained by that the commercial fishery focuses on areas with high density of shrimps, while survey data are relatively random located were shrimp trawling occurs. Our research indicates (Table 4) that a doubling of shrimp catch (given unchanged trawling effort) imply a bycatch increase of approximately 28%, while the ratio (1) and effort (2) methods on the other hand assumes 100% and 0% increase respectively. Given that the commercial fishery catches shrimps more effectively than the MSS, this indicates that the ratio method typically overestimates while the effort method typically underestimates historical bycatch.



(a) (b) (c)

Figure 6: *Illustration of relative error with the ratio method (a), with the effort method (b) and with our model based approach (c). Note that the y-axis is on logarithmic scale.*

Figure 6c illustrates the relative error when using our model based approach. Given that our model represents the true underlying stochastic structure, we observe that it gives reasonable unbiased predictions and thereby has predictive power.

"When simulating data from the model, the simulated data should be comparable to the original data. If not, the model needs improvement" (Zuur and Ieno, 2016). By investigating the simulations with the true observed bycatch, with respect to number of zeros, maximum value, total bycatch, median bycatch and visual inspection, we observed that they are comparable (see online supplementary information for details).

8 Discussion

The object of this research has been to predict historical bycatch in commercial fishery by using a Bayesian spatio-temporal latent Gaussian model. This discussion is divided in three parts. First we discuss the importance of random effects in our model. Secondly we discuss the observation model used. Thirdly we compare the historical bycatch with abundance estimates of cod.

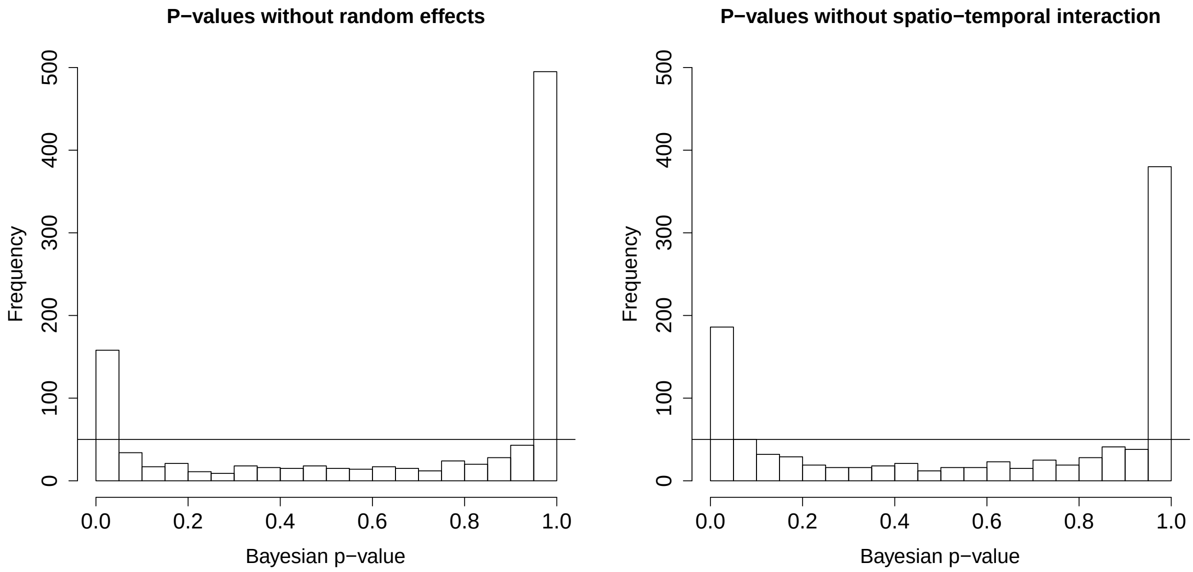
8.1 The importance of random effects

Predictions of bycatch using model-based procedures has been conducted earlier. Murray (2005) used a generalized additive model to predict the total bycatch of loggerhead turtles in the Atlantic Sea scallop dredge fishery without random effects. Pennino et al. (2014) investigated a spatio-temporal model for bycatch without the spatio-temporal interaction. Figure 7 shows the estimated p-value of aggregated bycatch in the test sets if we use no random effect or a spatio-temporal structure without spatio-temporal interaction respectively. By comparing Figure 7 with Figure 4b we see that the model including all selected random effects much better estimates the uncertainty since the Bayesian p-values are more uniformly distributed.

Cosandey-Godin et al. (2014); Ward et al. (2015) investigated spatio-temporal models for bycatch with a separable spatio-temporal interaction function that discretizes time and uses an autocorrelated structure of order one in time and a Matern correlation structure in space. Such a discretized spatio-temporal structure was also considered with the survey data in Breivik et al. (2016), but the continuous correlation function (9) was favored and therefore used in this research. A problem encountered with the spatio-temporal correlation function in Cosandey-Godin et al. (2014) is that our data are unstructured and a coarse grid in both space and time is needed for the model to be computationally feasible due to the large imposed grid structure in space and time (Cameletti et al., 2013). We have predicted the historical bycatch in several years with use of the spatio-temporal interaction function in Cosandey-Godin et al. (2014) (with time discretized in 30 days, and with spatial locations more then 80 km from each other in the spatial grid) and the predictions were similar to ours most of the years (not shown). Some years however were predicted different, but by using finer temporal discretization (20 days), the predictions were more similar. This is not surprising since a relatively fine temporal and spatial discretization results in that the spatio-temporal interaction structure in Cosandey-Godin et al. (2014) is approximately similar to the one used in this research (Breivik et al., 2016).

8.2 Survey data compared with fishery data

This research utilizes two data sources, survey data and fishery data, and it is assumed that the survey data are representative for the fishery data for predicting bycatch *given shrimp catch*. In fisheries research it is commonly assumed that expected catch is expressed as a product of



(a) (b)

Figure 7: *Bayesian p-values of hourly bycatch in the test sets without using random effects (a) and with spatial and temporal random effects but without the spatio-temporal interaction (b). The horizontal line show the expected frequency of p-values if the model was correct.*

the catchability and the local density of the species (Thorson et al., 2016). The survey data are collected using the same type of equipment as used in the commercial fishery. Thereby, we argue that the assumption of representative catchability is reasonable. The density of bycatch is indifferent of the purpose of the trawl. However, some of the survey observations are taken due to expected high bycatch ratios of a commercial fish species or of undersized shrimps, e.g. due to seasonal effects or information received by the fishery (MSS, pers. comm.). The commercial fishery may also behave differently when an observer is on board, e.g. to avoid high bycatch ratios for saving time and fuel needed to leave a closed area. The presence of observations taken due to information not included in the analysis (e.g. the fisheries knowledge about the spatio-temporal interaction effect for cod) may introduce a bias in the predictions. This possible bias is assumed to be small, and is neglected in our analysis. Note that the MSS regulates with respect to several other fish species, as described in section 1. These species have different juvenile migration patterns compared to cod (Jakobsen and Ozhigin, 2011), which is an argument for why such a possible bias introduced should be small. We want to emphasis that the procedure used in this research should be generalized to other fisheries with caution if there are reasons to question the assumption of representative survey data.

The exact spatial locations of the fishery data are not given, which differs from the survey data.

To accommodate for the uncertainty in location, the commercial catch locations are sampled uniformly within the areas reported (see green rectangles in Figure 1). It is reasonable that the catch locations are clustered in both time and space, which typically increases the uncertainty of the predictions through the spatio-temporal interaction. However, we assume that this effect is small and neglect it in our analysis. Note further that the commercial catches are reported as daily catches, meaning that two separate catches are treated as *one* if they are caught the same day and in the same area. This differs from the survey data, where each catch is distinctly given. That the commercial bycatch is modeled with daily catches may introduce an overestimation of the uncertainty.

8.3 Observation models

Breivik et al. (2016) models bycatch with use of a log-Gaussian observation model. However, O'hara and Kotze (2010); Warton et al. (2016) make a strong case that counting data should be modeled with a counting distribution rather than a log-Gaussian. After a comment from a reviewer, a zero-inflated negative binomial observation model was therefore investigated in this research. By comparing the predictions of aggregated bycatch in the test sets in section 7.1, the zero-inflated negative binomial model was favored due to a clear observed underestimation by the log-Gaussian model. The removal of this underestimation is a main reason for modifying the model in Breivik et al. (2016) to a zero-altered negative binomial model. Since we use the user-friendly R-package R-INLA, such a change of data distribution is easily achieved by only changing a few lines in the R-code. However, the non-Gaussian data distribution results in a more complex and time consuming inference of the latent structure, especially when utilizing the uncertainty in the hyperparameters (Rue et al., 2009).

8.4 The impact of bycatch on the cod population

This subsection compares estimated abundance of one year old cod with the predicted historical bycatch. Figure 8 shows the total historical bycatch of cod in each year as a percentage of the estimated aggregated abundance of one year old cod obtained from (ICES, 2015). This figure might give a rough indication on how much bycatch is caught compared with aggregated abundance estimated in the beginning of the year. Note, however, that the uncertainty in the

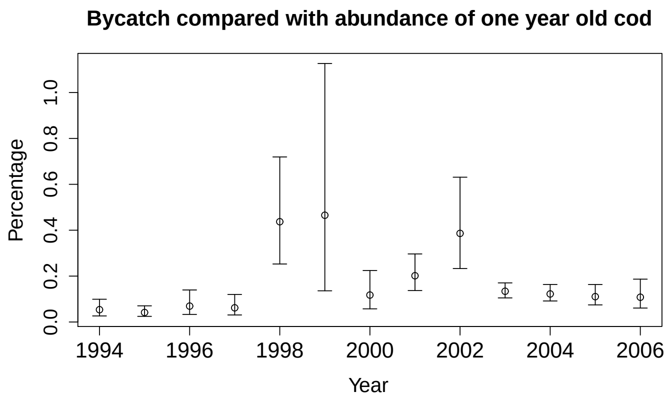


Figure 8: *Historical bycatch as percentage of the estimated aggregated abundance of one year old cod (ICES, 2015) in the Barents Sea. The intervals represent 90% prediction intervals when neglecting the uncertainty in the abundance estimates.*

abundance estimates are not given in ICES (2015), and therefore should the prediction intervals given in Figure 8 be wider (these are only based on uncertainty in the bycatch predictions). Note further that there is a regulation regime in the Barents Sea which closes areas when high bycatch ratios are observed, and without the regulation regime the historical predictions could have been larger. The relative low total bycatch may hence illustrate the success of the current regulation regime.

9 Conclusions and further work

We conclude that the model-based procedure produces reliable predictions (including uncertainty measures) of historical cod bycatch in the Barents Sea shrimp fishery, see section 7.1. We further make a strong case that the Bayesian spatio-temporal model based method outperforms both the ratio and effort methods for prediction of historical bycatch. This argument is based on the following observations elaborated in the article:

- The ratio and effort methods are sensitive to small shrimp catches and short trawl hauls respectively, see section 6.2.
- The model based method produces reliable predictions with uncertainty estimates, see section 7.1.
- The shrimp catch is positively correlated with bycatch (Table 4), indicating that both the

ratio and effort methods are biased, see section 7.3.

Further work is desirable on prediction of historical bycatch for other species and in other fisheries to investigate the generality of the model based approach. We strongly believe similar spatio-temporal models are useful for bycatch predictions of other species and in other fisheries. The R-code used for predicting bycatch is available upon request.

Acknowledgments

The authors want to thank Ida Scheel for valuable discussion on the model. The authors are also very thankful for constructive discussion with several employees at the Norwegian Institute of Marine Research and the Norwegian Directorate of Fisheries Monitoring and Surveillance Service. The authors are also grateful to Alain Zuur, James Thorson and two anonymous reviewers who gave constructive comments and suggestions which improved the article.

Appendix

A.1 Priors

The priors for the hyperparameters used in this research are given in Table A.1. These are constructed to be relatively non-informative. The gamma distribution used has the parametrization:

$$\pi(x|\alpha,\beta) = \frac{\beta^\alpha}{\Gamma(\alpha)}\tau^{\alpha-1}\exp(-\beta x). \tag{A.1}$$

R-INLA by default uses an improper prior for the intercept regression coefficient and a $N(0,1000)$ distribution for the other regression coefficients.

Parameter	Prior	Parameter	Prior
$\log(\sigma_\alpha^2)$	N(0,10)	$1/\sigma_\nu^2$	gamma(1,0.00005)
$\log(\kappa)$	N(0,10)	$1/\sigma_\gamma^2$	gamma(1,0.00005)
$\log(\varsigma)$	N(1,1)	θ_t and θ_s	$\propto 1$
$\log(a)$	N(2,1)		

Table A.1: *Prior distributions.*

A.2 Computational features

The first step of our historical bycatch prediction procedure is to estimate the parameters in the model given the survey data. This took approximately 1.4 hours on an Intel Core i5-2500 CPU 3.30GHz $\times$ 4 processor (with good starting values of the Newton method used to find posterior mode of the hyperparameters within R-INLA and after the posterior mode of the range parameters in the spatio-temporal interaction was found). The second part of the predicting procedure of historical bycatch is done on a cluster of computers. Notice the parallel structure caused by the independent simulation of catches. We used 20 cores each with 32 gigabyte memory and 2.20GHz. This second part took 1.5 hour to 5 hours for each year, depending on the number of daily catches.

A.3 Joint simulation of $\mathbf{B}_\mathbf{C}$ and $\mathbf{B}_\mathbf{S}$

This section elaborates the joint simulation procedure for commercial bycatch and bycatch in survey data. The simulation is done with the following algorithm:

1. Find the posterior mode of the hyperparameters, $\hat{\boldsymbol{\theta}}$, given $\mathbf{B}_\mathrm{S}$.

2. Sample $\boldsymbol{\beta}^*$ and $\boldsymbol{\alpha}^* = \{\alpha^*(\mathbf{s})\}$ from $\pi(\boldsymbol{\beta},\boldsymbol{\alpha}|\mathbf{B}_\mathrm{S},\hat{\boldsymbol{\theta}})$.

3. Sample $\mathbf{B}_\mathrm{C}^*$ and $\mathbf{B}_\mathrm{S}^*$ from $\pi(\mathbf{B}_\mathrm{C},\mathbf{B}_\mathrm{S}|\hat{\boldsymbol{\theta}},\boldsymbol{\beta}^*,\boldsymbol{\alpha}^*)$.

Notice that we use the full posterior distribution of the regression coefficients and the spatial effect while we only use the posterior mode of the hyperparameters.

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