Fisheries New Zealand

Tini a Tangaroa

# Integrated estimation of density and catchability parameters from fisheries catch-effort data

New Zealand Fisheries Assessment Report 2021/32

C.T.T. Edwards

ISSN 1179-5352 (online)
ISBN 978-1-99-100931-9 (online)

**June 2021**

New Zealand Government

Requests for further copies should be directed to:

Publications Logistics Officer
Ministry for Primary Industries
PO Box 2526
WELLINGTON 6140

Email: brand@mpi.govt.nz
Telephone: 0800 00 83 33
Facsimile: 04-894 0300

This publication is also available on the Ministry for Primary Industries websites at:
http://www.mpi.govt.nz/news-and-resources/publications
and http://fs.fish.govt.nz (go to Document library/Research reports)

# Table of Contents

# EXECUTIVE SUMMARY

**Edwards, C.T.T. (2021). Integrated estimation of density and catchability parameters from fisheries catch-effort data.**

***New Zealand Fisheries Assessment Report 2021/32.* 32 p.**

Given catch and abundance time series, simple process based models can be used to estimate the biomass and exploitation rate. If these data are of insufficient quality, swept-area methods offer an alternative means for estimating the exploitation rate. A crucial component of swept-area approaches is the catch efficiency (a component of the catchability), which describes the proportion of fish biomass or numbers, within the gear affected area, that are retained by that fishing event. For trawl fisheries, the efficiency is the proportion of fish within the path of the tow that are retained. Multiplication of the effort affected area by the efficiency can approximate the exploitation rate within the region of spatial overlap between the fishery and the population being fished. This approximation can be improved by knowledge of the population's distribution across space, since local exploitation rates can then be aggregated correctly into a global metric. In the current project, a statistical model is proposed to estimate the catch efficiency from catch-effort data for multiple fisheries and gear types operating simultaneously throughout the New Zealand Exclusive Economic Zone. The spatial biomass density for the fished population is co-estimated with the gear efficiency within an integrated framework. Estimation of the relative biomass density allows spatially explicit estimates of the exploitation rate to be combined into a single estimate for the stock. The model was applied to nine fish species and found to provide reasonable fits. Estimates of the catch efficiency for each species and gear type are provided, along with an illustration of how these can be combined with the population density estimates to generate an exploitation rate suitable for management purposes.

# 1 Introduction

Fisheries in New Zealand are tiered according to quality of the data available and rigor of the stock assessments they can support. Tier 1 stocks are high value and typically subjected to fully quantitative assessment methods using process-based models able to estimate the current and projected status. An estimate of status includes both the biomass and and exploitation rate, each relative to its own target reference point. Tier 2 and 3 stocks have a decreasing quality of catch-effort data with which to estimate a time series of relative abundance, whereas Tier 4 have catch data only. For Tiers 2 to 4 no established methods exist for the estimation of stock status. These compromise nearly 80% of all fisheries in New Zealand (by number, Bentley & Stokes 2009), and therefore represent a considerable challenge to implementation of the Harvest Strategy Standard (Ministry of Fisheries 2008, 2011).

The Low Information Stocks Projects (LSP2017-02 and LSP2019-02) were designed to develop methods capable of estimating status for Tier 2 and Tier 3 stocks. These have catch-effort data available of varying qualities, which could in some cases support a simple process-based modelling approach (e.g., McAllister & Edwards 2016). However neither a sufficient time-series nor reliable catches can be assumed, meaning that this approach could not be applied consistently. One class of methods that requires neither a time series nor catch data are known as swept-area methods. They are conceptually based on an estimation of the area of the stock that overlaps with the area covered by a particularly fishery: the larger the overlap the higher the exploitation rate (Edwards 2015). These have a long history of development and are currently applied in both Europe (e.g., Pope et al. 2000, Walker et al. 2019) and the Australian Commonwealth (Zhou & Griffiths 2008, Zhou et al. 2009, 2011, 2014, 2019a). Furthermore, swept-area methods were identified in LSP2017-02 as having scope for potential application in New Zealand (Holmes et al. 2020). This provides motivation for the current work.

## 1.1 Swept area methods

Swept-area approaches are based on a simple assumption that the species in question is distributed homogeneously within spatially defined parts of its range, and fished at random using consistent methods. Central to the derivation is a definition of the catchability $q$, which is equal to the proportion of the area $A$ that is swept by one unit of fishing effort, multiplied by an efficiency term $\pi$ (Paloheimo & Dickie 1964):

$$q_i = \frac{\pi \cdot a_i}{A} \tag{1}$$

For the case of a single area $j$, the local exploitation rate is then simply the proportion of the total area covered by fishing scaled by the efficiency (Daan 1991). Summing across tows $i$:

$$U_j = \frac{\pi \cdot \sum_{i \in j} a_{ij}}{A_j} \tag{2}$$

Unfortunately however, the catchability is hard to estimate, and further problems arise when integrating over the large areas that might enclose the stock being assessed, since the assumption of an homogenous population distribution breaks down. Much of the literature surrounding swept-area approaches has focused on these two issues: non-homogeneity of the population; and, catchability estimation. The assumption of random fishing means that they have typically been developed in the context of bycatch (non-target) fisheries. This report focuses specifically on a method known as SAFE (Sustainability Assessment for Fishing Effects), which has been developed by CSIRO and applied across Australian Commonwealth fisheries (Zhou & Griffiths 2008, Zhou et al. 2009, 2011, 2019a). It has a number of useful properties that have made it a good starting point for methods development in New Zealand. The basic equation for estimating an exploitation rate is the catch, summed over tows $i$, and spatial grids $j$, divided by the exploitable biomass $B_j$ per grid. It is usually written as a function of the density per grid $D_j$:

$$U = \frac{\sum_{ij} q_{ij} \cdot B_j}{\sum_j B_j} = \frac{\pi \cdot \sum_{ij} a_{ij} \cdot D_j}{\sum_j A_j \cdot D_j} \tag{3}$$

If the density is constant across grids then $D_j$ cancels out, and only an estimate of $\pi$ is required to extract an approximate exploitation rate. The basic-SAFE method (Zhou & Griffiths 2008, Zhou et al. 2009, 2011) makes this assumption, and further assumes a range of values for $\pi$ to be applied in an ad-hoc manner depending on the fishing gear. This is the simplest possible approach.

Actual estimation of $\pi$ has proceeded using methods first developed in the ecological literature. It was proposed by Royle (2004) that repeat sampling from multiple non-overlapping sites should allow estimation of both the detectability (analogous to the efficiency) and the abundance, provided that the sampling method and detectability is consistent both within and between sites. Their model was for count data $y_{ij}$, given unknown numbers $N_j$, and can be described as follows:

**Model 1**

$$y_{ij}|N_j \sim Binomial(N_j, \pi) \tag{4a}$$

$$N_j \sim Poisson(\lambda) \tag{4b}$$

The abundance per grid $N_j$, is treated as a nuisance parameter and integrated out of the likelihood during estimation, to be retrieved using an empirical Bayes procedure (Royle 2004). Whether it can be treated as a true abundance depends on whether the detectability term has been estimated correctly. The mean abundance across grids is represented by $\lambda$.

This concept has been extensively developed (e.g., Kéry et al. 2005, Joseph et al. 2009, Dorazio et al. 2013), and was extended to the fisheries literature by Zhou et al. (2014) to estimate the efficiencies for multiple fisheries $k$, repeatedly sampling the same locations. Their model took the form:

**Model 2**

$$y_{ijk}|N_{ij} \sim Binomial(N_{ij}, \pi_k) \tag{5a}$$

$$N_{ij}|\lambda_j \sim Poisson(\lambda_j) \tag{5b}$$

$$\lambda_j \sim NegativeBinomial(r, p) \tag{5c}$$

which notably now models the abundance $N_{ij}$ at the level of the fishing event $i$. This provides an improved fit to highly variably fisheries data but at the expense of a significant computational overhead.

Estimation of the relative catchability between fishing fleets or methods requires them to be fishing at the same time and place. The principal behind the approach is that relative catch rates then give an indication of their differing catchabilities. If this fishing pattern is replicated across space then the relative density distribution across space can also be discerned. A specific pattern of sampling can therefore allow estimation of both the efficiency parameter $\pi_k$, from catch rates within the grid, and the numbers density vector $\mathbf{N}$, from catch rates between the grids.

The difficulty with estimating the catch efficiency $\pi_k$ is that it is never certain whether a zero is a "true zero" (an indicator of the density) or whether the individual is there but not caught (an indicator of the efficiency). Repeat samples at the same location along with an assumption of perfect mixing of the population to some extent alleviates this problem. However, it becomes increasingly difficult at the fringes of either the fishery or the population, where both the fishing effort and positive catches may become too low to separate the parameters. For this reason, Zhou et al. (2014, 2019b) suggest that only a subset of the catch data be used when estimating $\pi_k$, specifically restricting the model to data from well sampled grids with a low variance to mean ratio.

Estimation of $\pi_k$ has been included in the latest version of SAFE, known as enhanced-SAFE (Zhou et al. 2019a). A second addition was to admit that the input density is typically relative, rather than absolute, so that the exploitation rate becomes:

$$U = \frac{\sum_{ijk} \pi_k \cdot a_{ij} \cdot D_j^{rel}}{\sum_j A_j \cdot D_j^{rel}} \tag{6}$$

This idea was first proposed by Pope et al. (2000), who suggested using the local catch rate as a measure of the relative density. Equation 6 can be thought of as a density weighted average of the local exploitation rate given in Equation 2. The enhanced-SAFE approach in particular uses relative density values generated from habitat modelling of the population density surface across space (using a General Additive Model, for example Zhou et al. 2019b), and this is the approach followed by LSP2019-02 (Holmes et al. in prepa).

## 1.2 Shortcomings of the enhanced-SAFE approach

The enhanced-SAFE approach includes three-steps for estimation of the exploitation rate. First, $\pi_k$ is estimated from a localised subset of the catch and effort data. Second, the relative density surface is estimated across the full spatial range of the stock. Third the efficiency $\pi_k$ and the relative density are combined with the areal terms to provide an exploitation rate (Equation 6). Two major shortcomings exist that limit its applicability:

- The methods developed to estimate $\pi_k$ are based on discrete probability distributions, which means they are not suited to a broader fishery setting where data are typically continuous (i.e. records of the biomass per fishing event) or semi-continuous (with a point mass at zero);
- Estimation of the density surface is independent of the estimation of $\pi_k$, and therefore uncertainty in the density distribution layer, which can be considerable, is effectively ignored, although ad-hoc sensitivity tests can be performed.

## 1.3 Estimation of the catch efficiency

Methods development towards estimation of the catch efficiency for New Zealand fisheries were undertaken by Sibanda et al. (2016) and Edwards et al. (2018). This work focused on developing a method for semi-continuous biomass catch data, using the same cross-sampling principle proposed by Zhou et al. (2014), but with different distributional assumptions and with a much greater volume of data. This was further developed by Zhou et al. (2019b) by re-writing the model as a semi-continuous analogue to Model 2:

**Model 3**

$$y_{ij} | y_{ij} > 0 \sim LogNormal(\ln(\pi \cdot a_i \cdot d_j) - \ln(\omega_j) - \sigma^2/2, \sigma^2) \tag{7a}$$

$$I(y_{ij} > 0) \sim Bernoulli(\omega_j) \tag{7b}$$

$$d_j \sim Gamma(\lambda/\theta, \theta) \tag{7c}$$

which includes $d_j$ as a continuously distributed free parameter representing the density per grid, and a mean across grids $\lambda$. The model assumes that the probability of a positive catch per tow $\omega_j$, is independent of the biomass density per grid $d_j$. Making $\omega_j$ a function of $d_j$, and $d_j$ a function of environmental covariates, would be key next steps in model development. Both were shown to be valid avenues for research by Edwards et al. (2018) and are pursued in the current project.

### 1.4 Objectives

Given previous work in developing a swept-area approach for application to fisheries in New Zealand, the current project (SEA2019-12) was developed with the following objectives:

1. Extend and test the hierarchical Bayesian mixture model developed by Edwards et al. (2018) and Zhou et al. (2019b) for estimation of the gear efficiency;
2. Co-estimate fish density distribution within the hierarchical mixture model.

The project ran concurrently with LSP2019-02 (Low Information Stock Status Assessment) and provided interim estimates of $\pi$ for implementation of the e-SAFE methodology (Edwards 2021, Zhou et al. 2021).

## 2 Data preparation

Commercial catch and effort data were provided by NIWA under project LSP2017-02 (Middleton 2019) for the fishing methods and species listed in Tables 1 and 2. Commercial data were complete for the fishing years 2012/13 to 2017/18 inclusive and consisted of raw event-by-event catch records, with each catch "estimated" by the fisher. The estimated catches are limited to the top five or top eight species caught in an event, meaning that empirical catch rates for any given species will be biased. If missing catch data are discarded, the bias will be towards overestimation of the catch rate. If missing catch data are treated as zero observations, this could lead to underestimation of the catch rate. For this reason, "allocated" catches are typically used for catch rate standardisations and fishery characterisations. Allocated catch data are generated from trip-by-trip landings that are allocated to individual fishing events using the approach of Starr (2007). Unlike estimated catches, most landings data are comprised of measured weights. Although the total catch per trip will be more accurate in the allocated data, it is unsuitable for estimating the catchability, which requires the catches per event. The estimated catches were therefore used in the current analyses. Missing catch data were treated as true zero observations, potentially underestimating the catchability. This implies that when taking an average across events within the strata, and assuming a good model fit, both the observed and predicted catches will be less than the true values. It is also likely that the chance of a catch being not recorded will change depending on the absolute catch. Specifically, high catches are more likely to be in the top species caught, and are therefore more likely to be recorded. Small absolute catches are less likely to be recorded. Observed values may therefore increasingly underestimate the true catch at lower absolute catch values. A better accounting of these biases in the data could prove a useful subject for future work.

**Table 1: Fishing methods included in the LSP2017-02 data (Middleton 2019). Calculations of the gear affected area per fishing event for each gear type are listed (Zhou et al. 2014, 2019b). Distance was in kilometres and time in hours; $w = 1$ in all instances.**

| Method Code | Description | Gear affected area (km$^2$) | Notes |
|---|---|---|---|
| TAN | *Tangaroa* Chatham Rise Survey | $d \cdot h \cdot s$ | $d$ is fishing duration, $h$ is the net wing width, $s$ is tow speed |
| KAH | *Kaharoa* Survey | $d \cdot h \cdot s$ | $d$ is fishing duration, $h$ is the net wing width, $s$ is tow speed |
| BLL | Bottom Long-line | $w \cdot L$ | $w$ is bait attraction distance, $L$ is the length of the line |
| BT | Bottom Trawl | $d \cdot h \cdot s$ | $d$ is fishing duration, $h$ is the net wing width, $s$ is tow speed |
| PRB | Precision bottom trawl | $d \cdot h \cdot s$ | $d$ is fishing duration, $h$ is the net wing width, $s$ is tow speed |
| SN | Set Net | $w \cdot L$ | $w$ is net affected distance, $L$ is the length of the net |
| MW | Mid-water trawl | $d \cdot h \cdot s$ | $d$ is fishing duration, $h$ is the net wing width, $s$ is tow speed |
| CP | Cod pot | $\pi/4 \cdot w$ | $w$ is attraction distance |
| DS | Danish Seine | $\pi \cdot (L/2 \cdot \pi)^2$ | $L$ is the groundrope length of the seine |

Commercial catch and effort data were subjected to the following grooming steps, with the number of records remaining after each step listed in Table S1 (Supplementary Tables):

- Calculate gear affected area using the formulae listed in Table 1.
- Remove records with missing gear area;
- Remove records per fishing method with gear areas outside of the 90% quantiles of the distribution of gear areas (the truncated distribution of gear areas per fishing method is shown in Figure 1);
- Remove records with no positional data;
- Remove records on land;
- Assign to $0.2° \times 0.2°$ grids covering the New Zealand Exclusive Economic Zone (EEZ) and Territorial Sea;
- Remove fishing methods with poor sample coverage (Table S2, retained fishing methods are listed in Table 2);
- Remove records per species and method above the upper 95% quantile of the distribution of catches;
- Select grids that contain 95% of the remaining commercial catch per species (Figures S1 and S2, the number of retained grids is listed in Table 2).

These steps were intended to remove erroneous or missing values, but also to lower the variance to mean ratio in the data. By doing so, it becomes easier to describe the data using standard statistical distributions (Zhou et al. 2014). A substantial proportion of the data were removed (Table S1), and no attempt was made to include these records when predicting the exploitation rate per species. In summary, the grooming process facilitated estimation of the catchabilities, but dependent prediction of the exploitation rate will be substantially underestimated as a result. Further work will be required to groom the data in a manner better suited to prediction of the exploitation rate across all fishing events.

**Table 2: Fish species selected by Fisheries New Zealand, NIWA and other stakeholders for analysis in LSP2019-02. Fishing methods and number of grids retained following data grooming are also listed.**

| Species Code | Common name | Scientific name | Fishing methods | Number of grids |
|---|---|---|---|---|
| ELE | Elephant fish | *Callorhinchus milii* | BT, SN, KAH | 142 |
| GUR | Gurnard | *Chelidonichthys kumu* | BLL, BT, DS, MW, PRB, SN, KAH | 277 |
| HAK | Hake | *Merluccius australis* | BLL, BT, MW, PRB, SN, TAN, KAH | 126 |
| LIN | Ling | *Genypterus blacodes* | BLL, BT, MW, PRB, SN, TAN, KAH | 456 |
| RSK | Rough skate | *Zearaja nasuta* | BLL, BT, PRB, SN, TAN, KAH | 315 |
| SNA | Snapper | *Chrysophrys auratus* | BLL, BT, DS, MW, PRB, SN, KAH | 120 |
| SPE | Sea perch | *Helicolenus* spp. | BLL, BT, PRB, SN, TAN, KAH | 443 |
| STA | Giant stargazer | *Kathetostoma* spp. | BT, SN, MW, TAN, KAH | 202 |
| TAR | Tarakihi | *Nemadactylus* spp. | BLL, BT, DS, MW, PRB, SN, KAH | 308 |

Trawl survey data from the *Tangaroa* Chatham Rise survey and *Kaharoa* were also provided by NIWA. Records with a gear performace score of 1 (excellent) or 2 (satisfactory), and using a gear method of 1 (bottom trawl) or 3 (high opening trawl net), were retained. Gear area was calculated as for the Trawl fishery (Table 1).

# 3 Statistical methods

## 3.1 Background

Fisheries catch rate data typically follow a semi-continuous probability distribution which can be modelled using a two-part model of the form:

$$\omega_i = \text{logit}^{-1}\left(\mathbf{X}_i \cdot \gamma\right)$$

$$\mu_i = \mathbf{X}_i \cdot \beta$$

where $\omega$ is the binomial probability of a positive catch and $\mu$ is the expectation of the log of the positive catches, assuming a log-normal distribution for the positive catch component of the data. Regression coefficients are estimated during the model fit, assuming in this case common covariate design matrices $\mathbf{X}_i$. The expectation is:

$$\mathbb{E}\left[y_i\right] = \omega_i \cdot \exp\left(\mu_i + \sigma^2/2\right)$$

where $y_i$ is the catch per fishing event $i$ and $\sigma$ is the standard error for the log-normal model part. For the current work, a marginalised two-part model is introduced (see Equation 7a and Smith et al. 2014):

$$\omega_i = \text{logit}^{-1}\left(\mathbf{X}_i \cdot \gamma\right)$$

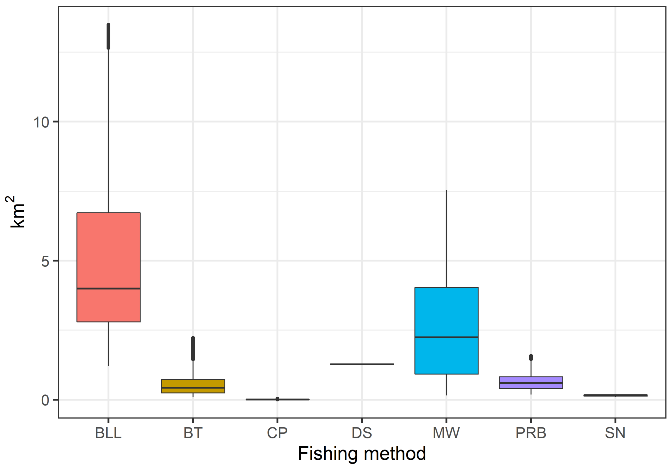



**Figure 1: Distribution of gear affected areas per fishing method following data grooming.**

$$\mu_i = \log(\mathbf{X}_i \cdot \beta) - \log(\omega_i) - \sigma^2/2$$

which has the expectation:

$$\mathbb{E}[y_i] = \mathbf{X}_i \cdot \beta$$

This form of model has the advantage that the expectation is interpretable directly in terms of the estimated $\beta$ coefficients (e.g., Smith et al. 2017, Smith & Preisser 2019). If $\beta$ is the product of a density term and the catch efficiency term $\pi$, and the $\mathbf{X}_i$ covariates represent the gear affected area, then:

$$\mathbb{E}[y_i] = a_i \cdot (\pi \cdot d) \tag{8}$$

meaning that the product $\pi \cdot d$ can be estimated as a predictor of the expected catch per fishing event.

However estimation of an exploitation rate requires both $\pi$ and $\mathbf{d}$ separately (Equation 6). This necessitates a hierarchical model of the form originally proposed by Royle (2004), applied to discrete fisheries data by Zhou et al. (2014) and then to semi-continuous data by Edwards et al. (2018) and Zhou et al. (2019b). Under this model structure the density becomes an estimated parameter across $j$ discrete spatial units:

$$d_j \sim f(\Theta) \tag{9}$$

Given appropriate cross sampling of the data, with repeat sampling both within and across spatial strata using consistent methods, it may be possible to estimate both $\pi$ and $d_j$. However in typical applications the sampling design is insufficient, which can warrant the use of external auxiliary data with which to stabilise estimation of $\pi$ (Barker et al. 2018). This was addressed by Edwards et al. (2018) by including survey data with an informative prior, which was shown through simulation to stabilise the estimation. This substantially lowers the sampling requirements needed for a reliable estimation of the density and opened up the prospect of co-estimating $\pi$ and $\mathbf{d}$ within the same statistical framework. Even if only a relative density can be obtained, given these outputs, an exploitation rate can be immediately calculated.

For this project a hierarchical marginalised two-part model is developed for fisheries data in New Zealand to allow co-estimation of $\pi$ and the density surface $\mathbf{d}$. Successful estimation of both these parameters could provide a framework for future estimation of the exploitation rate using swept area methods (Equation 6). This would represent an advancement of the enhanced-SAFE (and SEFRA, Ministry for Primary Industries 2016) risk assessment approaches, which require external fixed inputs of the biomass or numbers distribution into the model.

## 3.2 Model specifics

The probability density functions used to describe the biomass catch data $y_{ijk}$, can be summarised:

$$y_{ijk} > 0 \sim Bernoulli(\omega_{ijk})$$

$$y_{ijk}|y_{ijk} > 0 \sim logNormal(\mu_{ijk}, \sigma_k^2)$$

with subscripts:

- $i$: fishing event
- $j$: grid
- $k$: fleet or gear type

For the probability of a positive catch, the regression equation is:

$$\omega_{ijk} = 1 - \exp\left(-\gamma_k \cdot a_i \cdot d_{ij}\right) \quad (10a)$$

where $0 \leq \gamma_k \leq 1$ is the "encounter rate". For the conditional catch rate:

$$\mu_{ijk} = \log\left(\pi_k \cdot a_i \cdot d_{ij}\right) - \log\left(\omega_{ijk}\right) - \sigma_k^2/2 \quad (10b)$$

where $0 < \pi_k$ is the "efficiency." These equations give the expected catch per event:

$$\mathbb{E}\left[y_{ijk}\right] = \pi_k \cdot a_i \cdot d_{ij}$$

Rather than treating the biomass density directly as an estimated parameter per grid (Equation 9), it was predicted per event as a function of estimated regression parameters with a grid-specific random effect $\phi_j$:

$$\underbrace{\log\left(d_{ij}\right) \sim \alpha_i + \phi_j}_{\text{density surface}}$$

For the current application:

$$\log\left(d_{ij}\right) = \alpha_0 + \alpha_1 \cdot \log\left(x_i\right) + \alpha_2 \cdot \log\left(x_i\right)^2 + \alpha_3 \cdot z_i + \phi_j$$

where $\log(x_i)$ is the normalised log-latitude per event and $z_i$ is the fishing year. The latitude was selected as the only covariate available in the data provided. No model selection, potentially including different function relationships, was performed.

## 3.3 Prior probabilities and sensitivities

Work carried out by NIWA under LSP2019-02 generated catch efficiency priors for the *Kaharoa* trawl survey through interviews with fishermen (Holmes et al. in prepb). These estimated the proportion of the catch between the trawl doors that would likely be retained. These were converted to catch efficiency priors for the trawl wings using the following assumed gear characteristics:

- Door spread = 70 m

- Wing spread = 16.7 m

$$\underbrace{\text{Efficiency between doors}}_{\theta,\text{ from LSP2019-02}} \times \frac{70}{16.7} = \underbrace{\text{Efficiency between wings}}_{\pi}$$

A Gamma distribution was used to define informed priors for the KAH catch efficiency based on $\theta$ (Table 3).

$$\pi_{KAH} \sim Gamma(0.01, \eta \times 100)$$
$$\implies \mathbb{E}[\pi] = \eta$$

For the remaining fishing methods:

$$\pi_k \sim Gamma(0.1, 1.0)$$

which assumes an expectation of $\mathbb{E}[\pi_k] = 0.1$. For $\gamma_k$ a uniform prior distribution between zero and one was assumed. Sensitivities for the prior on $\pi_{KAH}$ were constructed for ELE and RSK as multiples of $\{0.50, 0.75, 1.25, 1.50\}$ of the reference value (Table 3).

Regression parameters $\alpha_0, \alpha_1, \alpha_2, \alpha_3$ were assigned standard normal priors. The density random effect was represented by a multivariate normal distribution:

$$\phi \sim MVN(0, \Sigma)$$

where $\Sigma$ is a covariance matrix with dimensions equal to the number of grids. The grid specific random effect was constrained by representing the multivariate normal distribution as a conditional autoregressive (CAR) prior (Gelfand & Vounatsou 2003, Jin et al. 2005). This parameterises the covariance $\Sigma$ using an estimated correlation term $\rho$ and error $\tau$, such that the prior for $\phi_J$ is informed by the estimates of $\phi_{j \neq J}$ in neighbouring grids.

## 3.4 Estimation

Estimation was performed within a Bayesian framework using rstan (Stan Development Team 2020, R Core Team 2019). For each model fit, two parallel chains were run for 2000 iterations with the first half discarded and convergence assessed visually.

**Table 3: Catch efficiency priors**

| Species | $\theta$ | $\eta$ | Sensitivities |
|---|---|---|---|
| ELE | 0.34 | 1.43 | 0.72, 1.08, 1.79, 2.15 |
| GUR | 0.70 | 2.94 | |
| HAK | – | *1.00 | |
| LIN | – | *1.00 | |
| SNA | 0.29 | 1.23 | |
| SPE | 0.47 | 1.97 | |
| RSK | 0.26 | 1.10 | 0.55, 0.83, 1.38, 1.65 |
| STA | 0.21 | 0.86 | |
| TAR | 0.22 | 0.92 | |

*no prior for KAH survey; assumed $\eta = 1.0$ for TAN

# 4 Results

The model was fitted to groomed catch rate data for the species listed in Table 2. Data were randomly sub-sampled prior to fitting, with 10% of the data retained, so as to reduce the run time and enable testing of the models predictive abilities. Data used to fit the model are referred to as the "insample", whereas data used to test model prediction of the catches is referred to as the "outsample". For each fit, the following diagnostics were implemented:

- Convergence of the estimator: visual inspection of the MCMC chains (Figure 2);
- Fit to catch rate data per grid: predictions of the mean probability of a positive catch and the mean catch rate (kilograms per square kilometre) were plotted against observed values (Figure 3);
- Spatial relationship between available density and the predicted catch rate per grid: predictions of the mean catch rate were compared with the predicted available density (both expressed in kilograms per square kilometre, Figure 4);
- Cross validation: ability of the model to predict the outsample catches (Figure 5).

## 4.1 Diagnostic outputs

Diagnostics demonstrate the model provides a reasonable description of the data. Convergence of the MCMC chains is adequate (Figure 2) despite the short length of the runs, indicating that the model has a structural definition with an appropriate match to the data observation process. The model provides a reasonable fit to the catch rate data when viewed across fishery groups (Figure 3), although the fit per group is sometimes poor (e.g., SN and BLL fisheries for TAR, Figure 3b). The fit is noticeably better for GUR, RSK, and STA, and less good for LIN, SPE, and TAR. This may be due to their respective mobilities or schooling behaviours. Species that are more sedentary and less likely to form schools would be better represented by the model assumptions, and this seems to be the case for RSK and STA.

Spatial diagnostics were constructed to examine internal consistency of the model. Specifically arithmetic means of the catch rate per unit area (CPUA) were obtained from the regression equations (Equation 10) and compared with "available" biomass densities (D), which were calculated directly from the density and catchability parameters:

$$\mathrm{CPUA}_{jk} = \frac{\sum_{i \in jk} \omega_{ijk} \cdot \exp\left(\mu_{ijk} + \sigma_k^2/2\right)}{\sum_{i \in jk} a_i}$$

$$\mathrm{D}_{jk} = \pi_k \cdot \frac{\sum_{i \in jk} d_{ij}}{\sum_{i \in jk} 1}$$

These were shown to correlate well, indicating how the catch rates predicted by the model are determined almost entirely by the catchabilty and density parameters. It is notable that despite this sparse parameterisation of the fisheries catch process, the model is still able to describe the observed data well (Figure 3).

Finally, total predicted catches per fishery were compared to observed values. Catches were predicted using the expected values:

$$\mathrm{Catch}_{jk} = \sum_{i \in jk} \pi_k \cdot a_i \cdot d_{ij}$$

This was repeated for both insample and outsample data to evaluate the ability of the model to predict catch data not used for the model fit. The model is able to provide a good representation of the outsample data (Figure 5), suggesting that it may be suitable for extrapolation of the catches across the fishery, as would be necessary for calculation of an exploitation rate.

## 4.2 Efficiency estimates

Estimates of the catch efficiences per species and fishery group are shown in Figure 6 and listed Table 4. These estimates are ranked in a similar order to the empirical catch rates, which fits with intuition. The fishery groups do not take into account targetting or other differences in fishing behaviour – all vessels with the same gear type are assumed to be equivalent – which may account for some of the small catch efficiencies observed for bottom trawls. This could explain, for example, the higher ELE catch efficiency for SN compared to BT. Relative density maps are shown in Figure 7.

**Table 4: Posterior efficiency ($\pi_k$) estimates for each species and fishing method. The empirical catch per unit area (CPUA; kg per km$^2$), total effort (insample number of fishing events) and $\hat{R}$ convergence diagnostic (Gelman & Rubin 1992) are also shown. For the bottom trawl fisheries (BT/KAH/TAN) efficiency is for the wingspread, with a wingspread efficiency of one equivalent to an efficiency of approximately 25% between the doors.**

| Species | Group | Mean (SE) | Median (95% CI) | CPUA | Effort | $\hat{R}$ |
|---|---|---|---|---|---|---|
| ELE | BT | 0.25 (0.05) | 0.24 (0.16, 0.35) | 46.54 | 9710 | 1.001 |
| | BLL | – | – | – | – | – |
| | MW | – | – | – | – | – |
| | SN | 1.02 (0.21) | 1.00 (0.67, 1.49) | 132.40 | 1652 | 1.002 |
| | DS | – | – | – | – | – |
| | PRB | – | – | – | – | – |
| | KAH | 1.41 (0.12) | 1.40 (1.18, 1.65) | 166.31 | 183 | 1.002 |
| | TAN | – | – | – | – | – |
| GUR | BT | 0.95 (0.12) | 0.94 (0.72, 1.20) | 100.52 | 18346 | 1.014 |
| | BLL | 0.02 (0.00) | 0.02 (0.02, 0.03) | 1.53 | 2606 | 1.016 |
| | MW | 0.04 (0.01) | 0.04 (0.02, 0.08) | 1.11 | 1174 | 1.005 |
| | SN | 0.05 (0.01) | 0.05 (0.04, 0.07) | 6.65 | 1407 | 1.013 |
| | DS | 0.34 (0.05) | 0.34 (0.25, 0.45) | 22.49 | 1074 | 1.012 |
| | PRB | 0.39 (0.06) | 0.39 (0.28, 0.52) | 31.84 | 409 | 1.008 |
| | KAH | 2.94 (0.17) | 2.94 (2.62, 3.28) | 298.58 | 226 | 1.001 |
| | TAN | – | – | – | – | – |
| HAK | BT | 0.61 (0.09) | 0.61 (0.46, 0.80) | 55.68 | 3476 | 1.007 |
| | BLL | 0.01 (0.00) | 0.01 (0.01, 0.01) | 0.98 | 506 | 1.003 |
| | MW | 0.27 (0.04) | 0.27 (0.20, 0.35) | 49.45 | 1705 | 1.006 |
| | SN | 0.09 (0.04) | 0.08 (0.04, 0.19) | 2.63 | 775 | 1.001 |
| | DS | – | – | – | – | – |
| | PRB | 0.49 (0.09) | 0.48 (0.33, 0.69) | 62.30 | 115 | 1.005 |
| | KAH | 0.15 (0.08) | 0.13 (0.05, 0.35) | 7.82 | 35 | 1.001 |
| | TAN | 1.02 (0.10) | 1.02 (0.84, 1.22) | 74.66 | 157 | 1.002 |
| LIN | BT | 0.37 (0.04) | 0.36 (0.30, 0.45) | 73.42 | 11136 | 1.005 |
| | BLL | 0.44 (0.05) | 0.44 (0.36, 0.55) | 82.12 | 2786 | 1.005 |
| | MW | 0.15 (0.02) | 0.15 (0.12, 0.19) | 52.02 | 2143 | 1.005 |
| | SN | 0.18 (0.03) | 0.18 (0.13, 0.24) | 46.26 | 1527 | 1.004 |
| | DS | – | – | – | – | – |
| | PRB | 0.59 (0.08) | 0.58 (0.45, 0.77) | 168.28 | 260 | 1.002 |

*Continued on next page*

**Table 4:** *Continued from previous page*

| Species | Group | Mean (SE) | Median (95% CI) | CPUA | Effort | $\hat{R}$ |
|---|---|---|---|---|---|---|
| | KAH | 0.40 (0.10) | 0.39 (0.25, 0.62) | 67.55 | 84 | 1.000 |
| | TAN | 0.97 (0.09) | 0.97 (0.81, 1.16) | 241.26 | 310 | 1.004 |
| RSK | BT | 0.41 (0.05) | 0.41 (0.32, 0.52) | 27.59 | 21074 | 1.003 |
| | BLL | 0.01 (0.00) | 0.01 (0.01, 0.01) | 0.33 | 2251 | 1.004 |
| | MW | – | – | – | – | – |
| | SN | 0.03 (0.01) | 0.03 (0.02, 0.04) | 5.56 | 2227 | 1.003 |
| | DS | – | – | – | – | – |
| | PRB | 0.41 (0.08) | 0.40 (0.28, 0.57) | 9.42 | 346 | 1.003 |
| | KAH | 1.15 (0.10) | 1.15 (0.97, 1.36) | 103.99 | 288 | 1.004 |
| | TAN | 0.14 (0.07) | 0.12 (0.05, 0.28) | 5.08 | 21 | 1.004 |
| SNA | BT | 0.54 (0.12) | 0.53 (0.34, 0.78) | 158.76 | 7106 | 1.005 |
| | BLL | 0.05 (0.01) | 0.05 (0.03, 0.08) | 52.81 | 2685 | 1.007 |
| | MW | 0.10 (0.10) | 0.07 (0.00, 0.37) | <0.01 | 7 | 1.002 |
| | SN | 0.13 (0.03) | 0.13 (0.08, 0.20) | 83.96 | 604 | 1.002 |
| | DS | 0.17 (0.04) | 0.17 (0.10, 0.25) | 143.32 | 1130 | 1.002 |
| | PRB | 0.59 (0.13) | 0.58 (0.36, 0.87) | 462.49 | 421 | 1.003 |
| | KAH | 1.28 (0.11) | 1.28 (1.07, 1.50) | 392.69 | 15 | 1.001 |
| | TAN | – | – | – | – | – |
| SPE | BT | 0.19 (0.04) | 0.19 (0.13, 0.27) | 18.45 | 11206 | 1.010 |
| | BLL | 0.02 (0.00) | 0.02 (0.01, 0.03) | 1.93 | 3204 | 1.012 |
| | MW | – | – | – | – | – |
| | SN | 0.01 (0.00) | 0.01 (0.00, 0.01) | 1.06 | 1649 | 1.008 |
| | DS | – | – | – | – | – |
| | PRB | 0.54 (0.11) | 0.53 (0.35, 0.79) | 46.79 | 279 | 1.010 |
| | KAH | 1.96 (0.14) | 1.95 (1.70, 2.23) | 151.38 | 170 | 1.001 |
| | TAN | 0.87 (0.17) | 0.86 (0.58, 1.26) | 85.46 | 298 | 1.011 |
| STA | BT | 1.08 (0.30) | 1.05 (0.57, 1.73) | 90.62 | 10294 | 1.007 |
| | BLL | – | – | – | – | – |
| | MW | 0.02 (0.05) | 0.00 (0.00, 0.17) | 0.08 | 1713 | 1.001 |
| | SN | 0.09 (0.03) | 0.09 (0.05, 0.15) | 11.14 | 1467 | 1.008 |
| | DS | – | – | – | – | – |
| | PRB | – | – | – | – | – |
| | KAH | 0.86 (0.09) | 0.85 (0.69, 1.05) | <0.01 | 235 | 0.999 |
| | TAN | 0.10 (0.10) | 0.07 (0.00, 0.39) | <0.01 | 57 | 1.002 |
| TAR | BT | 0.73 (0.17) | 0.72 (0.42, 1.08) | 186.09 | 14207 | 1.001 |
| | BLL | 0.00 (0.00) | 0.00 (0.00, 0.00) | 1.51 | 2458 | 1.000 |
| | MW | 0.04 (0.07) | 0.01 (0.00, 0.24) | 0.01 | 1801 | 1.001 |
| | SN | 0.50 (0.12) | 0.49 (0.29, 0.76) | 168.30 | 1924 | 1.001 |
| | DS | 0.06 (0.02) | 0.05 (0.03, 0.09) | 12.06 | 519 | 1.000 |
| | PRB | 0.53 (0.14) | 0.52 (0.30, 0.82) | 182.80 | 275 | 1.001 |
| | KAH | 0.92 (0.10) | 0.92 (0.73, 1.12) | <0.01 | 200 | 1.003 |
| | TAN | – | – | – | – | – |

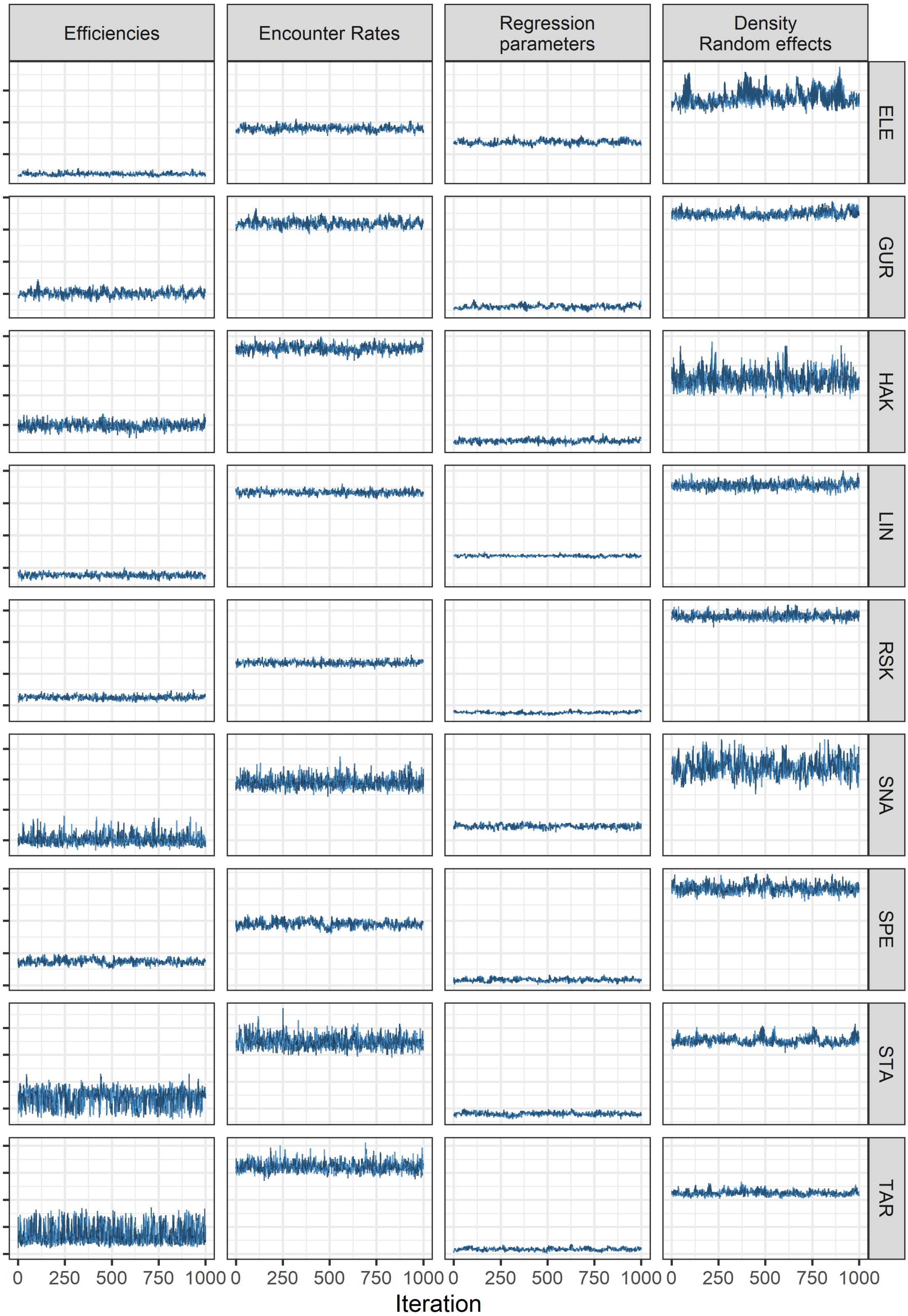
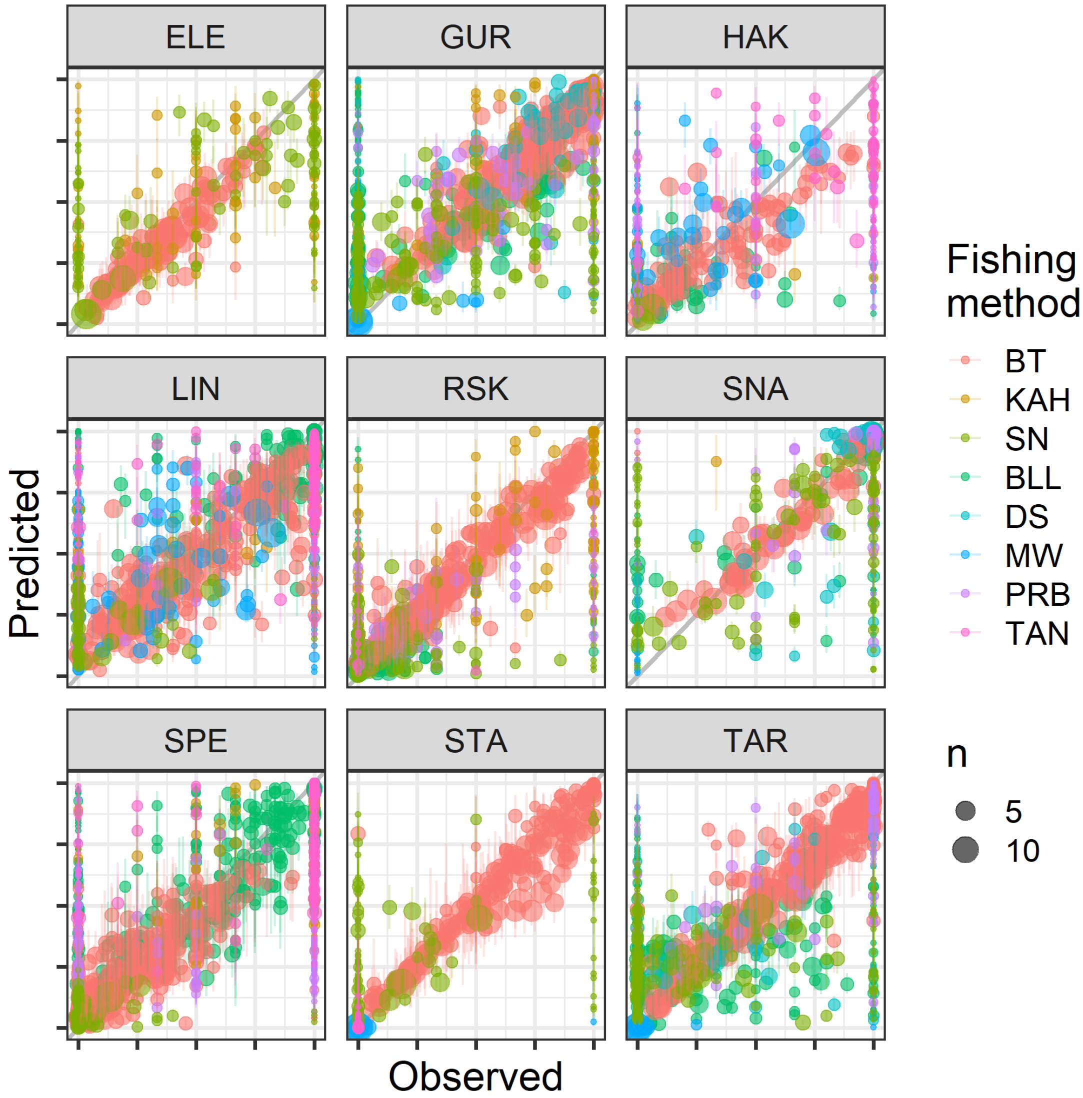
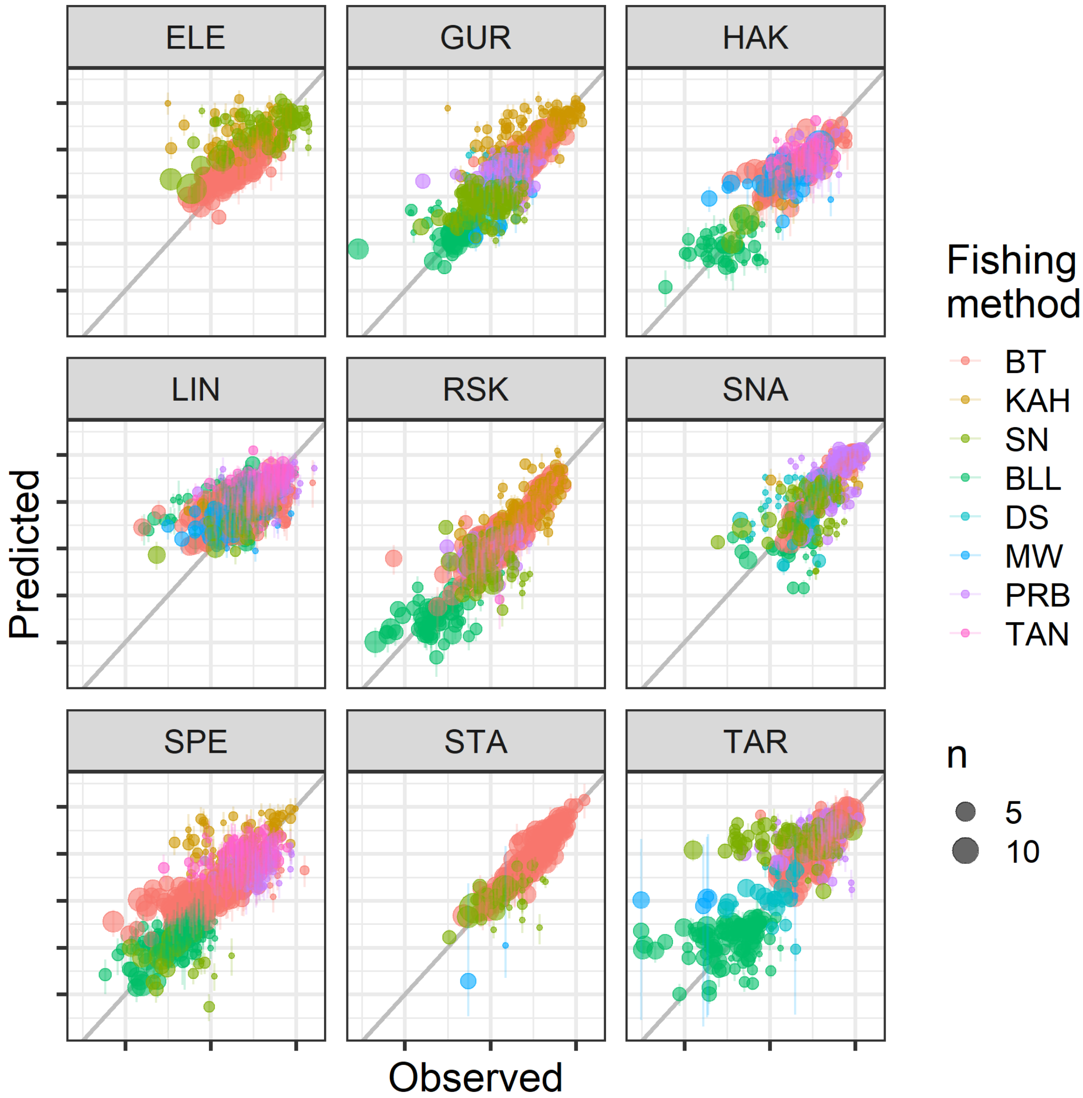



**Figure 2: MCMC trace plots. Each trace represents the Euclidean norm of the parameter vectors of: efficiencies ($||\pi_k||$), encounter rates ($||\gamma_k||$), regression parameters ($||\alpha_0, \alpha_1, \alpha_2, \alpha_3||$) and density random effects ($||\phi_j||$). Two overlapping chains of 1000 iterations are shown in each case for each species.**




**(a)** Fit to the probability of a positive fishing event per species, grid, and fishing method.

**Figure 3: Observed and predicted catch rates. Values are medians of the posterior expectation of the catch rate per grid, with 95% credibility intervals. The size of each point is proportional to the number of data points (fishing events) per fishing method and grid.**




**(b)** Fit to the mean catch rate (kg per km$^2$) per species, grid, and fishing method.

**Figure 3:** ***continued***

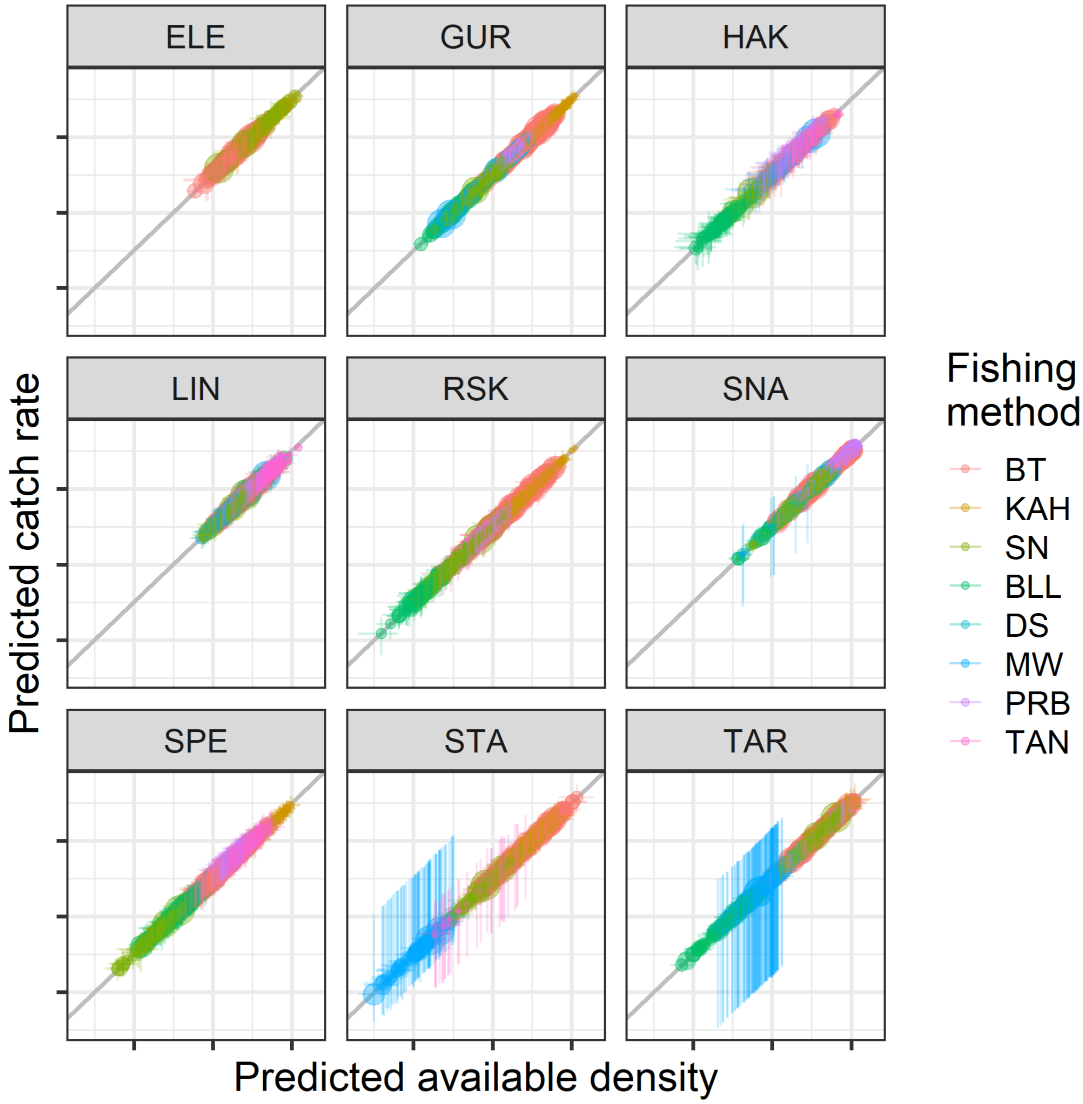



**Figure 4: Relationship between predicted catch rate and the predicted available biomass density.**

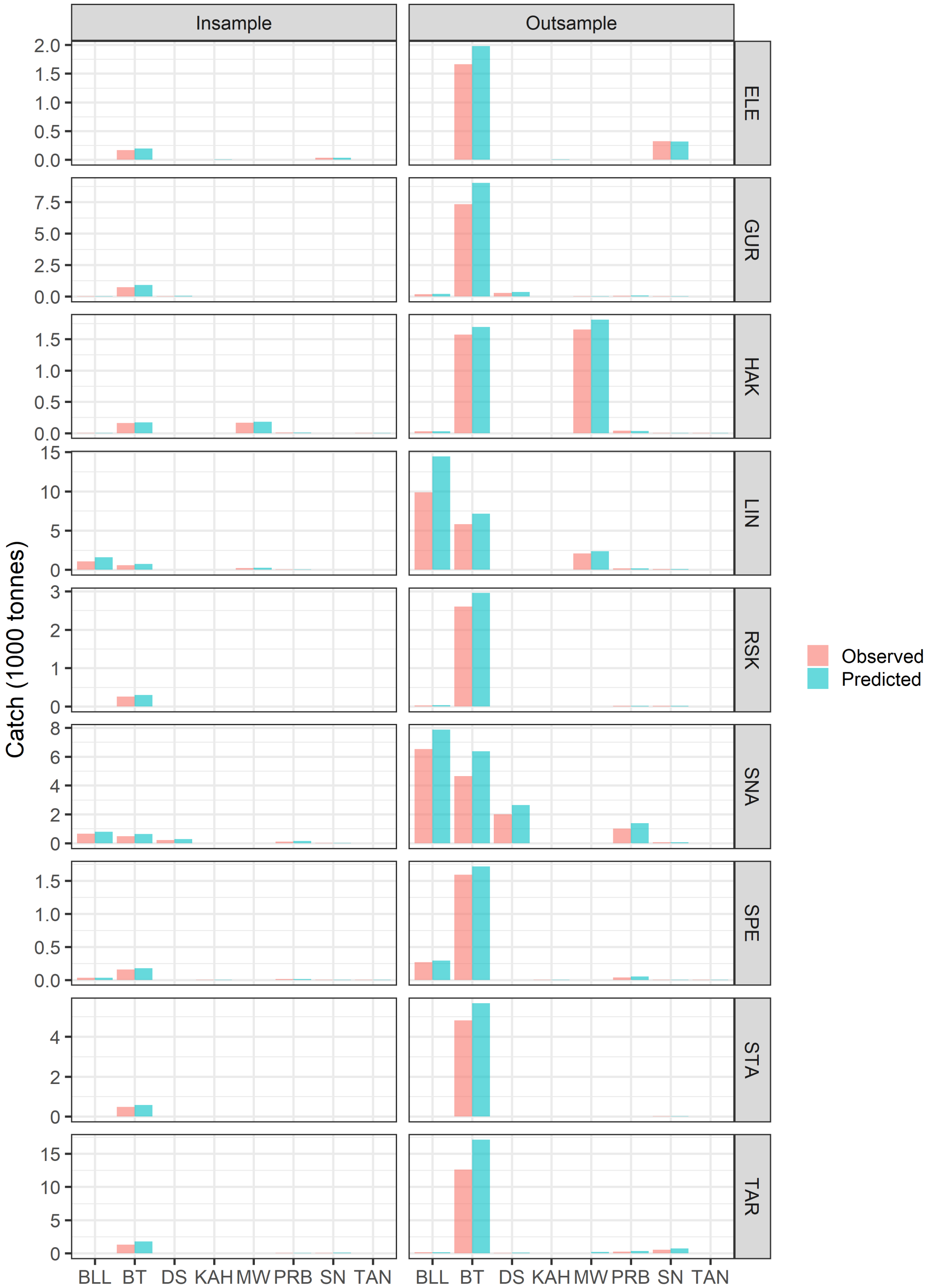



**Figure 5: Fit to total observed catches for the insample and outsample data.**

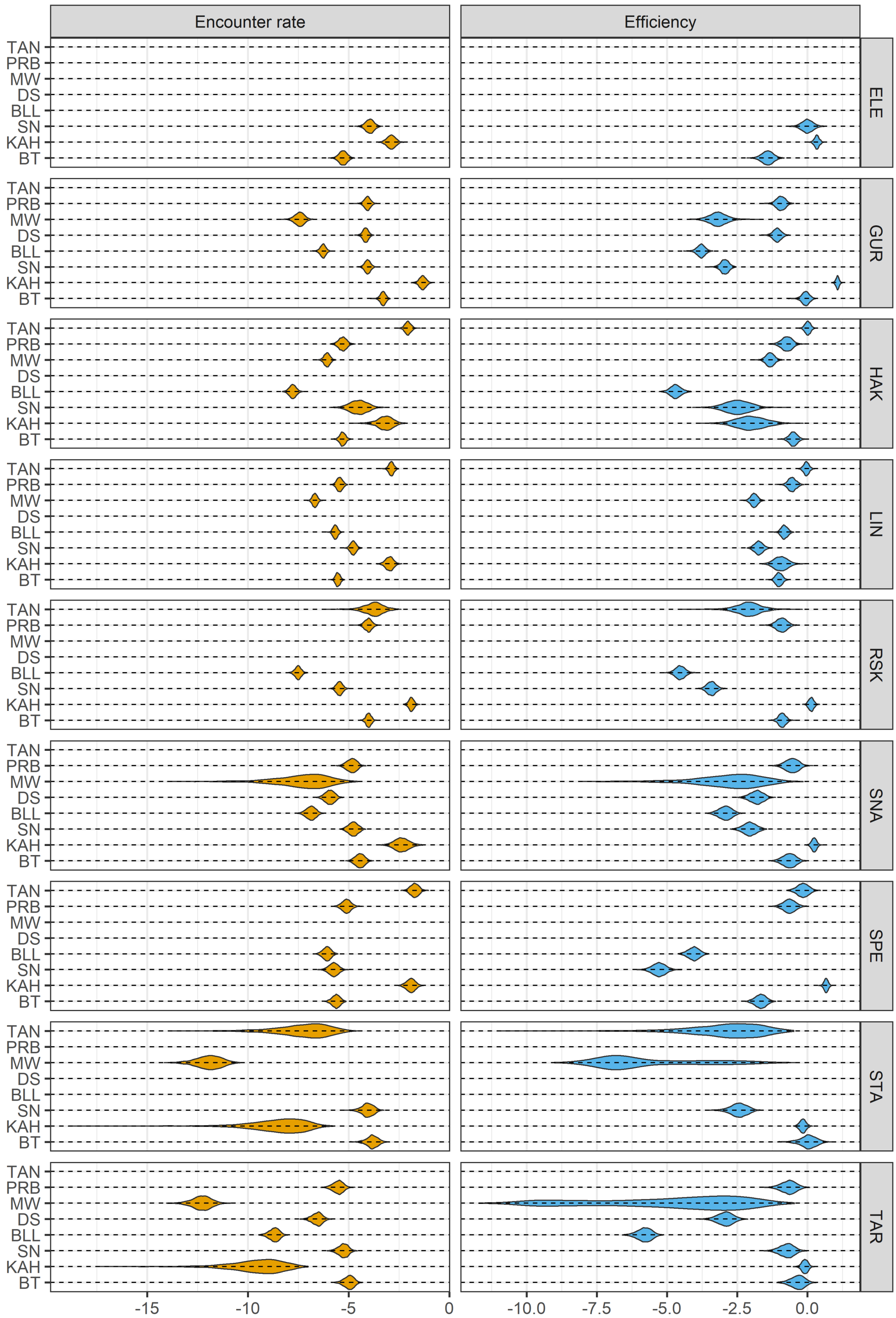



**Figure 6: Posterior distributions for the encounter rate $\gamma_k$ and efficiency $\pi_k$ catchability parameters for each species.**

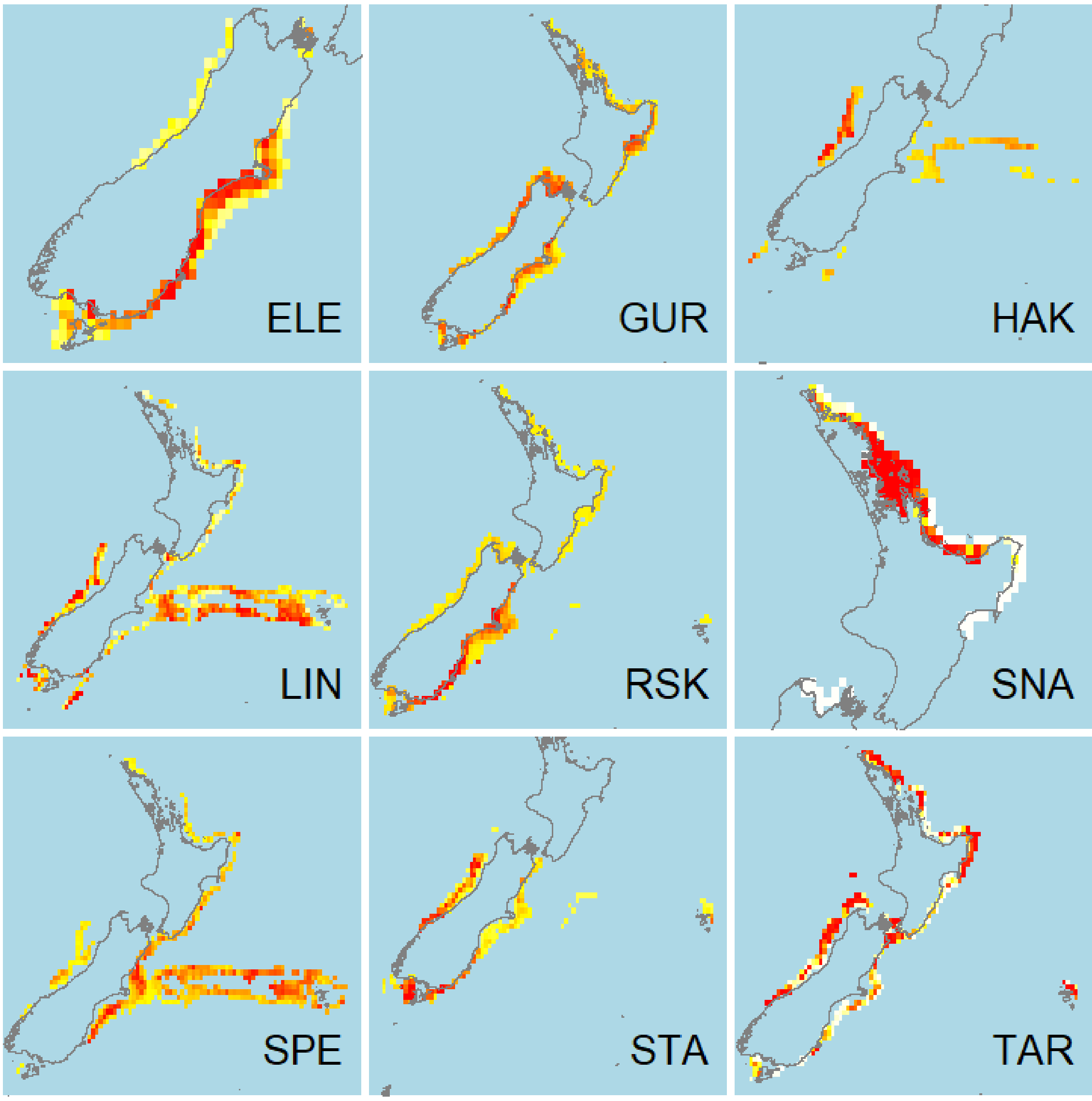



**Figure 7: Estimated density heat maps, showing the posterior median of the expected density per grid following each model fit. The expectation per grid was calculated as an arithmetic average of $d_{ij}$ across fishing events.**

## 4.3 Sensitivities

The model takes as input a single informative prior, namely catch efficiency for the trawl survey; usually for the KAH (Table 3). Alternative runs were performed to examine the influence of this prior on model estimates of the catch efficiencies and densities. Posterior estimates of the catch efficiency are sensitive to the input prior, which has an inverse relationship to the mean density (Figure 8). Intuitively, given the expected catch equation $\mathbb{E}\left[y_{ijk}\right] = \pi_k \cdot a_i \cdot d_{ij}$, higher values for $\pi_k$ imply lower values for $d_{ij}$ and *vice versa*.

# 5 Discussion

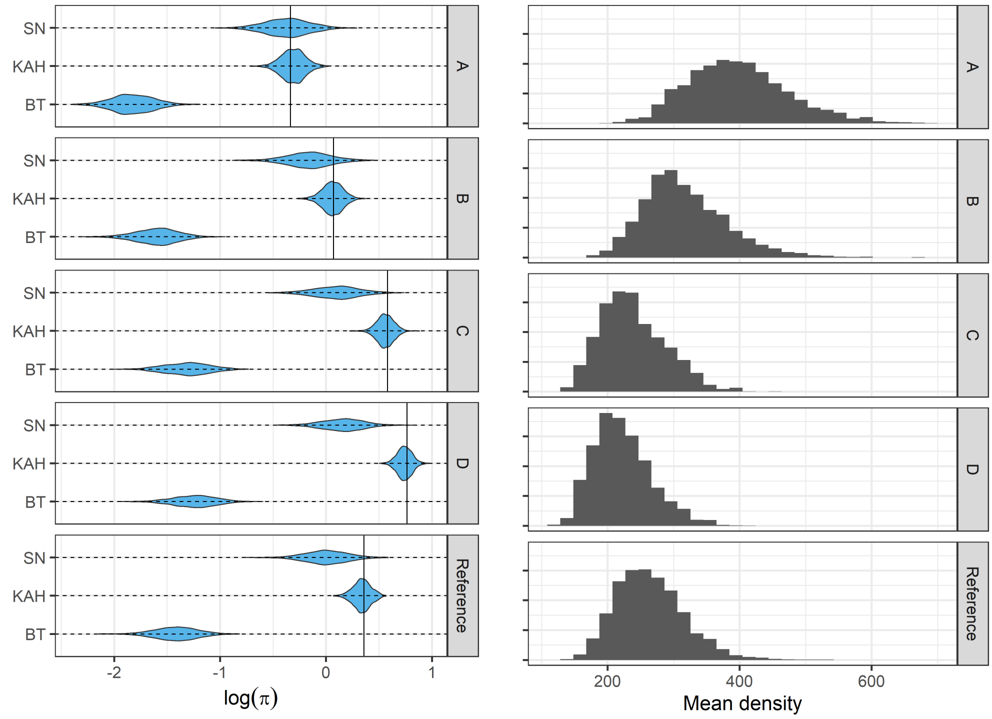
## 5.1 Summary and Conclusions

The statistical methods developed in the current project are able to represent a spatial, semi-continuous catch process across multiple fishing fleets operating simultaneously throughout the New Zealand EEZ and Territorial Sea. The catch process itself requires only two parameters per fleet ($\gamma_k$ and $\pi_k$), indicating how strongly the catch rates are driven by the underlying density distribution, which is also estimated by the model.

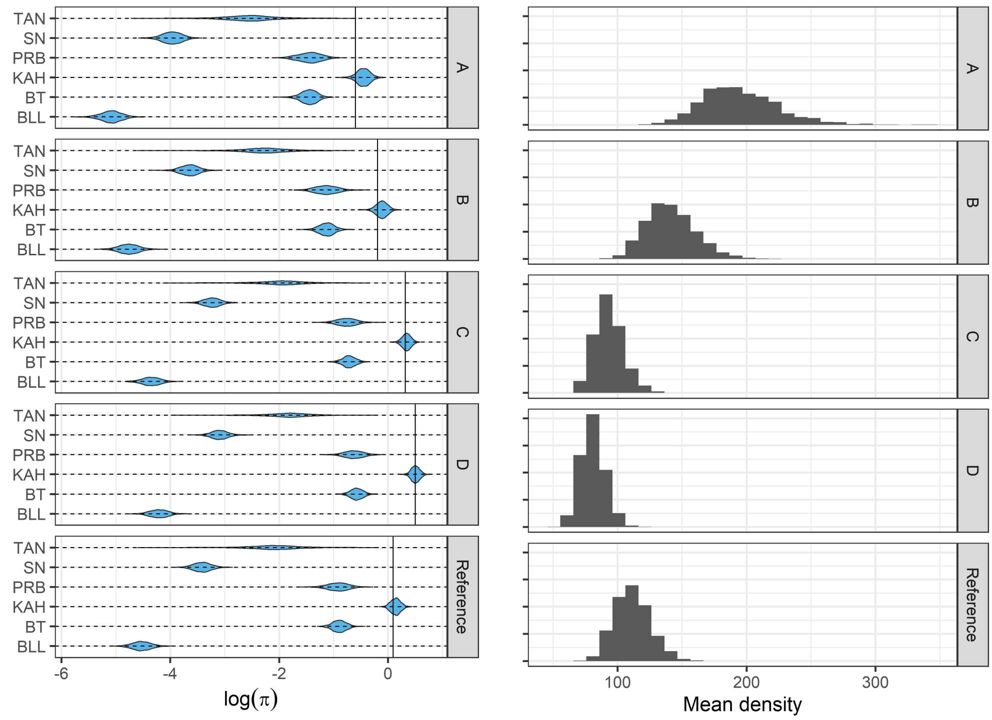
The basic framework is applicable across multiple fish species, although the quality of the fits varies (Figure 3). A more informed representation of $\pi_k$ and $d_j$, potentially including more covariates or a higher resolution definition of the fisheries, could improve these results. Depth and seasonal affects for example, could prove useful predictors of the density. Fisheries could also be defined so as to better represent their likely targetting behaviour. But even with better fishery group definitions, poor fits may result from statistical distributions that are too conservative for aggregating species, and more highly skewed descriptions of the conditional catch process are needed. This may also increase the quantity of data that can be included in the model.

The grooming procedures were developed by Zhou et al. (2019b) to limit the extreme variances in the data, and thereby ensure more stable estimations of the catch efficiencies using standard statistical distributions. However, over 30% of the data were discarded due to errors in the positional or gear area calculations (Table S1). Extreme catch records represented a much smaller subset of data removed, with the biggest loss due to the removal of low catch grids per species. The data retained were therefore only a small subset of the total commercial fishing effort. Improvements to the data preparation would be important if the method is to be applied across the full set of commercial fishing effort to estimate an exploitation rate of catches across entire fisheries. This may include effort for which there are no catch records. In some deepwater fisheries for example, bycatch is recorded by observers on only a subset of the effort. In these instances the observer data would be needed to fit the model and to predict catches across the unobserved proportion, as is done routinely for bycatch estimation (e.g., Anderson & Edwards 2018, Anderson et al. 2019, Finucci et al. 2019). Results presented here, showing good prediction of the outsample catches (Figure 5), indicate that the model may be suited for this type of application.

The model framework is ultimately intended to generate an exploitation rate that can be resolved as necessary across space, years, and fisheries. An exploitation rate per species can be calculated using Equation 6, by summing across the outsample effort data. Because only a small subset of the effort data were retained (see Table S1), only illustrative exploitation rates could be calculated in the current application (Figure S3). These are nevertheless indicative of how the model framework could be used in future applications. The model includes uncertainty in both the underlying density distribution and catch process, with recognisable diagnostics for evaluation of model performance.




**(a)** ELE. Prior expected values for $\pi_{KAH}$ are Reference = 1.430; A = 0.715, B = 1.073, C = 1.788, D = 2.145 (Table 3).




**(b)** RSK. Prior expected values for $\pi_{KAH}$ are Reference = 1.100; A = 0.550, B = 0.825, C = 1.375, D = 1.650 (Table 3).

**Figure 8: Sensitivity test results showing posterior distributions for the efficiency parameters $\pi_k$ and mean density (kg per km$^2$) across grids. The prior mean for $\pi_{KAH}$ is shown as a vertical line.**

Requiring only catch and effort data, with catch only needed for a subset of the effort, improved curation of the data could allow the method to be applied to estimate an exploitation rate across a wide range of bycatch and mixed species fisheries.

### 5.2 Improvements and further work

- Data grooming: discarding of data during the grooming steps could be replaced by more detailed imputation of missing or likely erroneous values. A more complete set of effort data will improve spatial and temporal coverage of the fisheries and translate into more reliable estimates of the exploitation rate.
- Population density covariates: estimation of the population density surface will likely be improved by additional environmental covariates or proxies, for example, depth and seasonal changes.
- Fishing behaviour covariates: commercial catchability parameters are currently defined according to a single fixed effect, namely the gear method. Further covariates could be added to improve fits to the data, for example, targetting behaviour or vessel effects. These could explain additional variation in the catch data, in a manner similar to how fishing-related covariates are used in catch-per-unit-effort standardisations.
- Statistical modelling: refinement of the assumed statistical distributions may improve fits to highly skewed catch data and allow better representation of the inflated variance characteristic of catch data from aggregating species.
- Catchability priors: refinement of the catchability priors for the *Kaharoa*, and the development of priors for the *Tangaroa*, will improve confidence in the exploitation rates ultimately estimated by the model.

Collection of data through the Electronic Reporting System may improve both data quality and the availability of covariates, facilitating future applications of the proposed framework.

## 6 Acknowledgements

I am grateful to Shijie Zhou (CSIRO, Brisbane, Australia) and Nokuthaba Sibanda (Victoria University Wellington, New Zealand) for useful discussions concerning development of the methods presented here. Rosemary Hurst (NIWA, Wellington, New Zealand) assisted with interpretation of survey priors for the *Kaharoa* that were generated as part of LSP2019-02. Formatted commercial catch-effort data were provided by Steven Holmes (NIWA, Wellington, New Zealand) under LSP2017-02, with additional data from the *Kaharoa* and *Tangaroa* trawl surveys provided for this project.

The work was funded by Fisheries New Zealand under project code SEA2019-12. Previous developmental work had been conducted under project codes: LSP2017-02, SEA2016-19, and SEA2015-13.

This report received helpful reviews from Pamela Mace and Susan Jane Baird (Fisheries New Zealand, Wellington, New Zealand).

## References


Anderson, O.A.; Edwards, C.T.T. (2018). Fish and invertebrate bycatch and discards in New Zealand arrow squid and scampi trawl fisheries from 2002–03 until 2015–16. *New Zealand Aquatic Environment and Biodiversity Report No. 199.* 135 p.

Anderson, O.A.; Edwards, C.T.T.; Ballara, S. (2019). Non-target fish and invertebrate catch and discards in New Zealand hoki, hake, ling, silver warehou, and white warehou trawl fisheries from 1990–91 to 2016–17. *New Zealand Aquatic Environment and Biodiversity Report No. 220.* 117 p.

Barker, R.J.; Schofield, M.R.; Link, W.A.; Sauer, J.R. (2018). On the Reliability of N-Mixture Models for Count Data. *Biometrics 74*: 369–377.

Bentley, N.; Stokes, K. (2009). Contrasting Paradigms for Fisheries Management Decision Making: How Well Do They Serve Data-Poor Fisheries? *Marine and Coastal Fisheries 1* (*1*): 391–401.

Daan, N. (1991). A theoretical approach to the evaluation of ecosystem effects offishing in respect of North Sea benthos. *ICES CM 1991/L*: 27.

Dorazio, R.M.; Martin, J.; Edwards, H.H. (2013). Estimating abundance while accounting for rarity, correlated behavior, and other sources of variation in counts. *Ecology 94* (*7*): 1472–1478.

Edwards, C.T.T. (2015). Review of data-poor assessment methods for New Zealand fisheries. *New Zealand Fisheries Assessment Report 2015/27.* 24 p.

Edwards, C.T.T. (2021). Updated estimates of catchability parameters for prediction of the exploitation rate using e-SAFE. (Unpublished CEscape Report prepared for NIWA for Fisheries New Zealand project SEA2019-12 and held by Fisheries New Zealand, Wellington.)

Edwards, C.T.T.; Sibanda, N.; Roux, M.J.; Sharp, B. (2018). Estimating capture and retention efficiency for nontarget fish species in commercial trawl fisheries. (Unpublished Final Research Report prepared for MPI project SEA2016-19 and held by Fisheries New Zealand, Wellington.)

Finucci, B.; Edwards, C.T.T.; Anderson, O.A.; Ballara, S. (2019). Fish and invertebrate bycatch in New Zealand deepwater fisheries from 1990–91 until 2016–17. *New Zealand Aquatic Environment and Biodiversity Report No. 210.* 77 p.

Gelfand, A.E.; Vounatsou, P. (2003). Proper multivariate conditional autoregressive models for spatial data analysis. *Biostatistics 4* (*1*): 11–15.

Gelman, A.; Rubin, D.B. (1992). Inference from Iterative Simulation Using Multiple Sequences. *Statistical Science 7* (*4*): 457–472.

Holmes, S.; Arnold, R.; ; Doonan, I.; Dunn, A.; Dunn, M.; Edwards, C.; Hamill, J.; Hurst, R.; Langley, A.; McGregor, V.; Zhou, S. (in prepa). Low Information Stock Status Assessment. Draft New Zealand Fisheries Assessment Report.

Holmes, S.; Arnold, R.; Clendon, G.; Doonan, I.; Edwards, C.; Goeden, Z.; Langley, A.; Liu, I.; MacGibbon, D.; McMillan, L.; Middleton, D.; Stephenson, F.; Webber, D.; Zhou, S.; Dunn, M. (2020). Low information stock status assessment. *New Zealand Fisheries Assessment Report 2020/05.* 206 p.

Holmes, S.; Hurst, R.; Hamill, J. (in prepb). Estimation of catchability of key species on R.V. *Kaharoa* South Island trawl surveys. Draft New Zealand Fisheries Assessment Report.

Jin, X.; Carlin, B.P.; Banerjee, S. (2005). Generalized hierarchical multivariate car models for areal data. *Biometrics 61* (*4*): 950–961.

Joseph, L.N.; Elkin, C.; Martin, T.G.; Possingham, H.P. (2009). Modeling abundance using N-mixture models: the importance of considering ecological mechanisms. *Ecological Applications 19* (*3*): 631–642.

Kéry, M.; Royle, J.A.; Schmid, H. (2005). Modeling avian abundance from replicated counts using binomial mixture models. *Ecological Applications 15* (*4*): 1450–1461.

McAllister, M.K.; Edwards, C.T.T. (2016). Applications of a Bayesian surplus production model to New Zealand fish stocks. *New Zealand Fisheries Assessment Report 2016/52*. 79 p.

Middleton, D. (2019). Low Information Stock Status Assessment: data preparation. (Unpublished report prepared by Trident Systems for Fisheries New Zealand project LSP2017-02 and held by Fisheries New Zealand, Wellington.)

Ministry for Primary Industries (2016). Spatially explicit fisheries risk assessment (SEFRA): A framework for quantifying and managing incidental commercial fisheries impacts on non-target species, pp. 18–55. *In*: Aquatic Environment and Biodiversity Annual Review, 790 p.

Ministry of Fisheries (2008). *Harvest Strategy Standard for New Zealand Fisheries*. Ministry of Fisheries, New Zealand, 25 p.

Ministry of Fisheries (2011). Operational Guidelines for New Zealand's Harvest Strategy Standard Rev. 1. Ministry of Fisheries, New Zealand, 78 p.

Paloheimo, J.E.; Dickie, L.M. (1964). Abundance and fishing success. *Rapports et Proces-Verbaux des Reunions, Conseil International pour L'exploration de la Mer 155*: 152–163.

Pope, J.G.; Macdonald, D.S.; Daan, N.; Reynolds, J.D.; Jennings, S. (2000). Gauging the impact of fishing mortality on non-target species. *ICES Journal of Marine Science 57* (*3*): 689–696.

R Core Team (2019). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria

Royle, J.A. (2004). N-mixture models for estimating population size from spatially replicated counts. *Biometrics 60* (*1*): 108–115.

Sibanda, N.; Edwards, C.T.T.; Roux, M.J.; Dunn, A. (2016). Estimating gear efficiency for non-target species. (Unpublished Final Research Report prepared for MPI project SEA2015-13 and held by Fisheries New Zealand, Wellington.)

Smith, V.A.; Neelon, B.; Preisser, J.S.; Maciejewski, M.L. (2017). A marginalized two-part model for longitudinal semicontinuous data. *Statistical Methods in Medical Research 26* (*4*): 1949–1968.

Smith, V.A.; Preisser, J.S. (2019). A marginalized two-part model with heterogeneous variance for semicontinuous data. *Statistical Methods in Medical Research 28* (*5*): 1412–1426.

Smith, V.A.; Preisser, J.S.; Neelon, B.; Maciejewski, M.L. (2014). A marginalized two-part model for semicontinuous data. *Statistics in Medicine 33* (*28*): 4891–4903.

Stan Development Team (2020). RStan: the R interface to Stan. R package version 2.19.3

Starr, P. (2007). Procedure for merging MFish landing and effort data. v2.0. (Unpublished report prepared for MPI project AMPWG 07/04 and held by Fisheries New Zealand, Wellington.)

Walker, N.D.; García-Carreras, B.; Le Quesne, W.J.F.; Maxwell, D.L.; Jennings, S. (2019). A data-limited approach for estimating fishing mortality rates and exploitation status of diverse target and non-target fish species impacted by mixed multispecies fisheries. *ICES Journal of Marine Science 76* (*4*): 824–836.

Zhou, S.; Daley, R.M.; Fuller, M.; Bulman, C.M.; Hobday, A.J. (2019a). A data-limited method for assessing cumulative fishing risk on bycatch. *ICES Journal of Marine Science 76* (*4*): 837–847.

Zhou, S.; Deng, R.; Edwards, C.T.T.; Holmes, S.; Dunn, M. (2021). eSAFE assessment of fishing mortality status for nine New Zealand low information finfish stocks. (Unpublished CSIRO Report prepared for NIWA for Fisheries New Zealand Project LSP2019-02 and held by Fisheries New Zealand, Wellington.) 35 p.

Zhou, S.; Edwards, C.T.T.; Holmes, S.; Dunn, M. (2019b). Assessment of fishing mortality status for New Zealand's low information finfish stocks. (Unpublished CSIRO Report prepared for NIWA for Fisheries New Zealand Project LSP2017-02 and held by Fisheries New Zealand, Wellington.) 36 p.

Zhou, S.; Griffiths, S.P. (2008). Sustainability Assessment for Fishing Effects (SAFE): A new quantitative ecological risk assessment method and its application to elasmobranch bycatch in an Australian trawl fishery. *Fisheries Research 91* (*1*): 56–68.

Zhou, S.; Griffiths, S.P.; Miller, M. (2009). Sustainability assessment for fishing effects (SAFE) on highly diverse and data-limited fish bycatch in a tropical prawn trawl fishery. *Marine and Freshwater Research 60* (*6*): 563–570.

Zhou, S.; Klaer, N.L.; Daley, R.M.; Zhu, Z.; Fuller, M.; Smith, A.D.M. (2014). Modelling multiple fishing gear efficiencies and abundance for aggregated populations using fishery or survey data. *ICES Journal of Marine Science 71* (*9*): 2436–2447.

Zhou, S.; Smith, A.D.; Fuller, M. (2011). Quantitative ecological risk assessment for fishing effects on diverse data-poor non-target species in a multi-sector and multi-gear fishery. *Fisheries Research 112* (*3*): 168–178.

## Supplementary Tables

**Table S1: Data cleaning steps for combined commercial fisheries. The number of fishing events following each cleaning step is listed per species. The initial cleaning steps are commmon to all species. The percentage of fishing events relative to the initial data extract is shown in parentheses.**

| Description | All | ELE |
|---|---|---|
| Initial | 640852 (100.0%) | |
| Missing gear area | 608010 (94.9%) | |
| Extreme gear area | 543180 (84.8%) | |
| Missing positional data | 451547 (70.5%) | |
| Records on land | 447132 (69.8%) | |
| Poorly sampled methods | | 7333169 (52.0%) |
| Extreme catches | | 328609 (51.3%) |
| Low catch grids | | 112533 (17.6%) |
| | RSK | GUR |
| Poorly sampled methods | 404735 (63.2%) | 446974 (69.7%) |
| Extreme catches | 394242 (61.5%) | 425133 (66.3%) |
| Low catch grids | 254818 (39.8%) | 245815 (38.4%) |
| | SPE | SNA |
| Poorly sampled methods | 404735 (63.2%) | 446974 (69.7%) |
| Extreme catches | 399011 (62.3%) | 434968 (67.9%) |
| Low catch grids | 157804 (24.6%) | 116931 (18.2%) |
| | STA | TAR |
| Poorly sampled methods | 363155 (56.7%) | 446974 (69.7%) |
| Extreme catches | 355059 (55.4%) | 433119 (67.6%) |
| Low catch grids | 132886 (20.7%) | 206366 (32.2%) |
| | HAK | LIN |
| Poorly sampled methods | 434721 (67.8%) | 434721 (67.8%) |
| Extreme catches | 431941 (67.4%) | 421685 (65.8%) |
| Low catch grids | 63552 (9.9%) | 171791 (26.8%) |

**Table S2: Total catch, number of grids occupied and number of records, per species and fishing method. These were used to justify removal of selected fishing methods during the data grooming procedure.**

| Species | Method | Total Catch | Number Grids | Number Records | Remove? |
|---|---|---|---|---|---|
| ELE | BLL | 591 | 1065 | 66042 | TRUE |
| | BT | 5464804.6 | 1444 | 303883 | FALSE |
| | CP | 0 | 25 | 158 | TRUE |
| | DS | 0 | 126 | 12253 | TRUE |
| | KAH | 22557.5 | 151 | 367 | FALSE |
| | MW | 200 | 397 | 29986 | TRUE |
| | PRB | 0 | 343 | 5524 | TRUE |
| | SN | 793132 | 542 | 29286 | FALSE |
| | TAN | 144.7 | 325 | 568 | TRUE |
| RSK | BLL | 92548 | 1065 | 66042 | FALSE |
| | BT | 5046437.65 | 1444 | 303883 | FALSE |
| | CP | 0 | 25 | 158 | TRUE |
| | DS | 3100 | 126 | 12253 | TRUE |
| | KAH | 5564.2 | 151 | 367 | FALSE |
| | MW | 1566 | 397 | 29986 | TRUE |
| | PRB | 33068 | 343 | 5524 | FALSE |
| | SN | 35348 | 542 | 29286 | FALSE |
| | TAN | 460.5 | 325 | 568 | FALSE |
| GUR | BLL | 412888.75 | 1065 | 66042 | FALSE |
| | BT | 13937776 | 1444 | 303883 | FALSE |
| | CP | 0 | 25 | 158 | TRUE |
| | DS | 510952.8 | 126 | 12253 | FALSE |
| | KAH | 13403.7 | 151 | 367 | FALSE |
| | MW | 44085 | 397 | 29986 | FALSE |
| | PRB | 110490 | 343 | 5524 | FALSE |
| | SN | 41003.3 | 542 | 29286 | FALSE |
| | TAN | 137.3 | 325 | 568 | TRUE |
| SPE | BLL | 591671.15 | 1065 | 66042 | FALSE |
| | BT | 3941228.3 | 1444 | 303883 | FALSE |
| | CP | 145 | 25 | 158 | TRUE |
| | DS | 71 | 126 | 12253 | TRUE |
| | KAH | 14610.5 | 151 | 367 | FALSE |
| | MW | 2742 | 397 | 29986 | TRUE |
| | PRB | 76168 | 343 | 5524 | FALSE |
| | SN | 7580.2 | 542 | 29286 | FALSE |
| | TAN | 8667.7 | 325 | 568 | FALSE |
| SNA | BLL | 9192317.5 | 1065 | 66042 | FALSE |
| | BT | 10012322.5 | 1444 | 303883 | FALSE |
| | CP | 0 | 25 | 158 | TRUE |
| | DS | 3829842.5 | 126 | 12253 | FALSE |
| | KAH | 1675.8 | 151 | 367 | FALSE |
| | MW | 24304 | 397 | 29986 | FALSE |
| | PRB | 1695904 | 343 | 5524 | FALSE |
| | SN | 154909.75 | 542 | 29286 | FALSE |
| | TAN | 0 | 325 | 568 | TRUE |
| STA | BLL | 158 | 1065 | 66042 | TRUE |
| | BT | 11156121.13 | 1444 | 303883 | FALSE |
| | CP | 0 | 25 | 158 | TRUE |

*Continued on next page*

**Table S2:** *Continued from previous page*

| Species | Method | Total Catch | Number Grids | Number Records | Remove? |
|---|---|---|---|---|---|
| | DS | 4 | 126 | 12253 | TRUE |
| | KAH | 0 | 151 | 367 | FALSE |
| | MW | 3494 | 397 | 29986 | FALSE |
| | PRB | 4481 | 343 | 5524 | TRUE |
| | SN | 95657.1 | 542 | 29286 | FALSE |
| | TAN | 0 | 325 | 568 | FALSE |
| TAR | BLL | 630168.4 | 1065 | 66042 | FALSE |
| | BT | 24257133.41 | 1444 | 303883 | FALSE |
| | CP | 0 | 25 | 158 | TRUE |
| | DS | 193916 | 126 | 12253 | FALSE |
| | KAH | 0 | 151 | 367 | FALSE |
| | MW | 21202 | 397 | 29986 | FALSE |
| | PRB | 554532 | 343 | 5524 | FALSE |
| | SN | 989141 | 542 | 29286 | FALSE |
| | TAN | 0 | 325 | 568 | TRUE |
| HAK | BLL | 165801.15 | 1065 | 66042 | FALSE |
| | BT | 4644812.8 | 1444 | 303883 | FALSE |
| | CP | 0 | 25 | 158 | TRUE |
| | DS | 0 | 126 | 12253 | TRUE |
| | KAH | 237.2 | 151 | 367 | FALSE |
| | MW | 3709180 | 397 | 29986 | FALSE |
| | PRB | 67765 | 343 | 5524 | FALSE |
| | SN | 4537 | 542 | 29286 | FALSE |
| | TAN | 5496 | 325 | 568 | FALSE |
| LIN | BLL | 17635311.478 | 1065 | 66042 | FALSE |
| | BT | 18369242.9 | 1444 | 303883 | FALSE |
| | CP | 572 | 25 | 158 | TRUE |
| | DS | 2162 | 126 | 12253 | TRUE |
| | KAH | 3742.1 | 151 | 367 | FALSE |
| | MW | 3574623.75 | 397 | 29986 | FALSE |
| | PRB | 284335 | 343 | 5524 | FALSE |
| | SN | 194235 | 542 | 29286 | FALSE |
| | TAN | 22825.9 | 325 | 568 | FALSE |

## Supplementary Figures

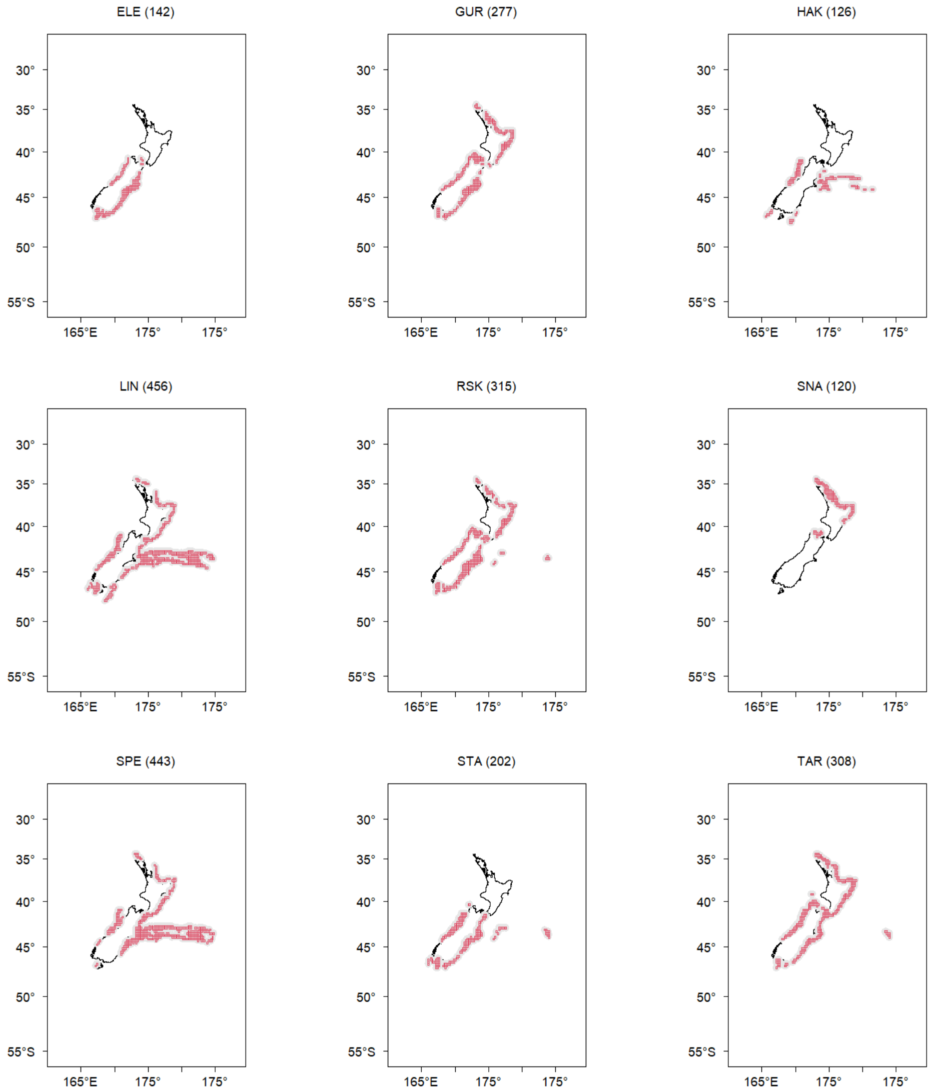



**Figure S1: Grid definitions for each species following data grooming. The number of grids per species is shown in parentheses.**

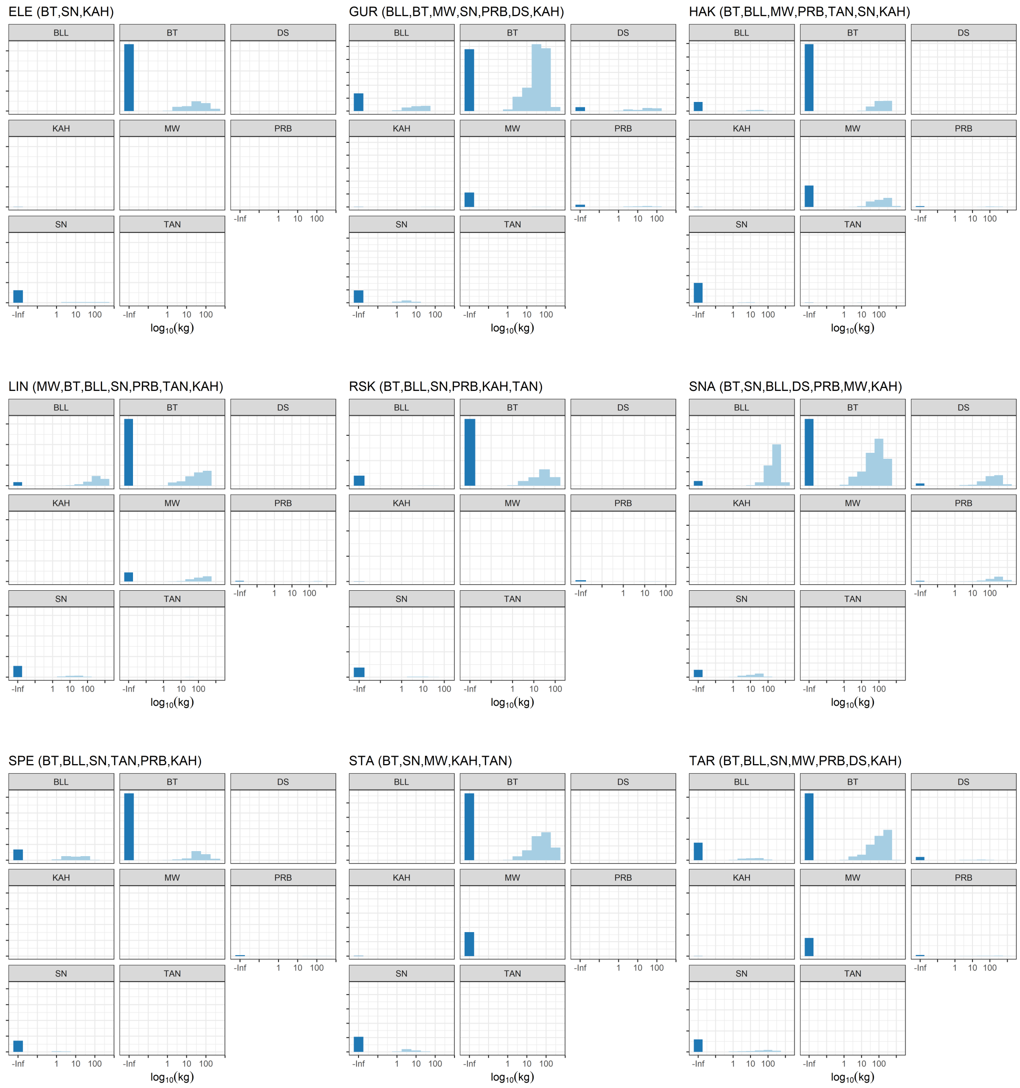



**Figure S2: Empirical distribution of catches per fishing event per species following data grooming. Fishing methods retained in the analysis are shown in parentheses for each species. Catches are shown on a log10-scale, with zero values plotted at negative infinity.**

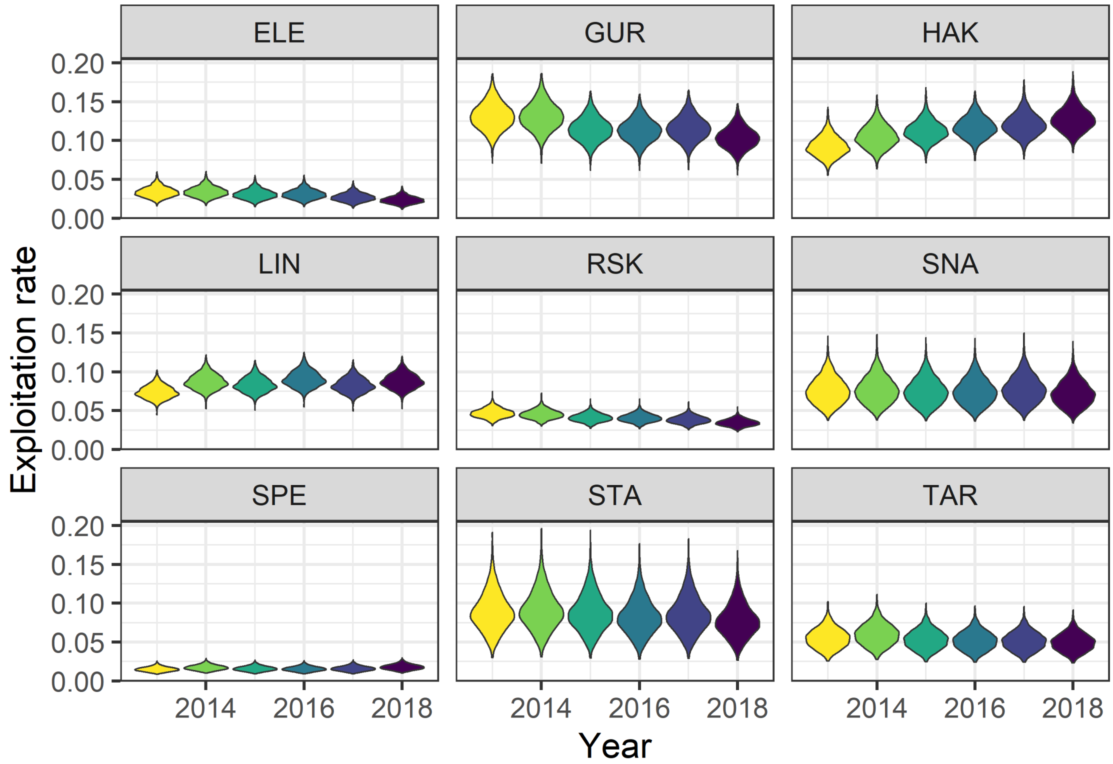



**Figure S3: Illustrative exploitation rates per year and species calculated using Equation 6.**