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Article

Spatially varying catchability for integrating research survey data with other data sources: case studies involving observer samples, industry-cooperative surveys, and predators as samplers

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Abstract

Spatio-temporal models are widely applied to standardise research survey data and are increasingly used to generate density maps and indices from other data sources. We developed a spatio-temporal modelling framework that integrates research survey data (treated as a "reference dataset") and other data sources ("non-reference datasets") while estimating spatially varying catchability for the non-reference datasets. We demonstrated it using two case studies. The first involved bottom trawl survey and observer data for spiny dogfish (*Squalus acanthias*) on the Chatham Rise, New Zealand. The second involved cod predators as samplers of juvenile snow crab (*Chionoecetes opilio*) abundance, integrated with industry-cooperative surveys and a bottom trawl research survey in the eastern Bering Sea. Our integrated models leveraged the strengths of individual data sources (the quality of the reference dataset and the quantity of non-reference data), while downweighting the influence of the non-reference datasets via the estimated spatially varying catchabilities. They allowed for the generation of annual density maps for a longer time-period and for the provision of one single index rather than multiple indices each covering a shorter time-period.

Key words: data integration, spatio-temporal models, density maps, indices of relative abundance

Introduction

Resource management requires information about the dynamics of living marine resources (hereinafter simply "fishes") in space and time. Habitat managers typically need distribution/density maps to designate essential fish habitat (areas that are essential to fish life history) and design marine protected areas (Pennino et al. 2016; Grüss et al. 2021*a*). Fisheries managers very often rely on stock assessments, where population-dynamics models are fitted to multiple sources of information to evaluate the status of a given fish stock and deliver management advice (Methot 2009). Indices of relative abundance or biomass (henceforth simply "indices") are critical components of stock assessments, as they determine the relative abundance trend of the fish stock of interest, thereby having a substantial impact on predicted stock status and management recommendations (Hilborn and Walters 1992; Peterson et al. 2021).

Research surveys, a.k.a. fisheries-independent monitoring programs, are the preferred data source to produce distribution/density maps and indices (Hilborn and Walters 1992). In particular, indices are generally considered more reliable when they are derived from research survey data rather than from fisheries-dependent data such as commercial catch-per-unit effort (CPUE) (National Research Council 1998; Maunder and Punt 2004; Dennis et al. 2015). While research surveys constitute the only source of sampling data for some non-commercial species, there are many instances where distribution/density maps and indices can be generated using other data sources. These other data sources include fisheries-dependent monitoring programs, such as observer programs where scientific observers are placed onboard commercial vessels (Scott-Denton et al. 2012; Storr-Paulsen et al. 2012). Other data sources also include more opportunistic presence-only data coming, inter alia, from citizen science programs, museum records, and tagging studies (Thorson et al. 2014; Pirtle et al. 2019). Predators can also be considered samplers of prey abundance, whereby the stomach contents of predator species are analysed to produce diet-based indices for their prey (Ng et al. 2021; Robertson et al. 2022).

Research surveys typically adopt a stratified sampling design and a well-defined sampling protocol (in terms of methods and effort) (Gunderson 1993; National Research Council 2000; Nielsen 2015). These characteristics allow for a sampling process that can be assumed to be constant in space and time; hence, well-designed research surveys with a consistent sampling protocol can be assumed to have a constant catchability (i.e., to remove a constant proportion of the stock of interest by one unit of effort) (Hilborn and Walters 1992; ICES 2005). With well-designed research surveys with a consistent sampling protocol, the assumption of proportionality between the index derived from sampling data and the true fish stock size is met such that changes in the index reliably reflect true fish abundance trends (Wilberg et al. 2010). However, there are multiple instances where the catchability (a.k.a. detectability) of a given research survey does not remain constant over space and(or) time in which case changes in research survey catch rates likely reflect changes in true fish abundance that are confounded with changes in catchability, and this issue then needs to be addressed (Walters and Maguire 1996; Langseth et al. 2016). Here, we consider three situations: (Situation #1) the research survey has modified its sampling design and(or) protocol over time; (Situation #2) the stock of interest is partly detectable by the gear used in the research survey and the availability of the fish to the gear varies over space and time; and (Situation #3) the research survey area encompasses only a fraction of the spatial distribution area of the stock of interest, and over time, fish move in and out of the area encompassed by the research survey (i.e., spatial availability changes among years).

There are many examples of Situation #1 worldwide, where a given research survey has employed different vessels (e.g., of different sizes and power; Rademeyer and Butterworth 2013) or has modified its sampling design and(or) sampling protocol over time (Wilberg et al. 2010). To illustrate Situation #2, we can mention (1) variation in the catchability of the bottom trawl gear with depth as the bottom trawl changes its shape as more line is let out to reach the bottom, although noting that warp:depth ratios can be standardised to maintain gear parameters (e.g., doorspread and headline height) within consistent ranges regardless of depth (as is done in New Zealand research surveys) and (2) vertical availability in bottom trawl and acoustic research surveys, where the catchability of fishes that exhibit vertical migrations is affected by their position in the water column at the time and location of the bottom trawl or acoustic survey (Godø and Wespestad 1993; Michalsen et al. 1996; Kotwicki et al. 2018). To make optimal use of data in Situation #1 (e.g., exploit the data collected with all research vessels instead of only the best-performing vessel) and Situation #2 (e.g., exploit bottom trawl and acoustic research survey data), fisheries scientists generally resort to "gear calibration" to account for differences in catchability across samples. Gear calibration can be performed via paired sampling in which samples are collected nearly simultaneously using different vessels, gears, or vessel–gear combinations to minimise spatio-temporal variations in catch rates between the vessels, gears, or vessel–gear combinations (Miller 2013; Rademeyer and Butterworth 2013; Delargy et al. 2022). Paired sampling allows for the calculation of fishing-power ratios (e.g., a catchability ratio between a new and old research vessel), which can be employed to calibrate the catches of the different vessels, gears, or vessel–gear combinations against one another so that they are comparable (Cadigan and Dowden 2010; Kotwicki et al. 2017; Delargy et al. 2022). However, paired sampling is costly and often relies on the availability of several vessels. In addition, calculating a fishing-power ratio and using this ratio to adjust data prior to running modelling analyses (e.g., a stock assessment) fails to propagate uncertainty around the fishing-power ratio in the modelling analyses. In recognition of the latter issue, Kotwicki et al. (2018) developed a model combining bottom trawl and acoustic trawl research survey data for eastern Bering Sea (EBS) walleye pollock (*Gadus chalcogrammus*), which employs environmental data to predict the vertical overlap between bottom trawl and acoustic trawl. This model enabled the propagation of uncertainty from the predicted overlap to an index, and this index derived from both bottom trawl and acoustic trawl data was more precise and exhibited less interannual variability than the indices derived from individual data sources (Kotwicki et al. 2018). Yet, the model of Kotwicki et al. (2018) requires that the bottom trawl and acoustic trawl data be collected in the same locales in the same year, thereby limiting the number of years of data useable in analyses.

Changes in spatial availability among years (Situation #3) frequently arise when research surveys are restricted geographically, for logistic or budget reasons, or when research surveys encompass specific jurisdictional boundaries and the distribution areas of the fish stocks of interest extend well beyond these boundaries. To address Situation #3, many studies have developed spatio-temporal models integrating the data collected by different research surveys (e.g., Grüss et al. 2017, 2018; Dolder et al. 2018; Grüss and Thorson 2019; Perretti and Thorson 2019; Maureaud et al. 2021; Monnahan et al. 2021; O'Leary et al. 2022; Thompson et al. 2022). Spatio-temporal models represent spatial variation (long-term unmeasured spatial variation) and, generally, spatio-temporal variation (unmeasured spatial variation that varies among years) at a very fine scale, thereby allowing for the borrowing of information across adjacent locations and time periods (Shelton et al. 2014; Thorson et al. 2015; Ono et al. 2018). Data integration in spatio-temporal models is possible via the inclusion of a research survey catchability factor, which allows for the estimation of fishing-power ratios relative to a reference survey without the need for expensive paired sampling (Grüss and Thorson 2019; Gonzalez et al. 2021; Alglave et al. 2022). Through the sharing of information across years, locations, and research survey datasets, integrated spatio-temporal models can increase the precision of estimates (Grüss and Thorson 2019; Thompson et al. 2022), better characterise how environmental variables shape spatial fish distributions (Pinto et al. 2019), provide valuable insights into spatial distribution patterns in areas where some research surveys contribute very little or no observations (Grüss and Thorson 2019; Thompson et al. 2022), and deliver indices that cover a longer time period with reduced or better characterised uncertainty (O'Leary et al. 2020; Monnahan et al. 2021). Maureaud et al. (2021) and O'Leary et al. (2022) used spatio-temporal models integrating research survey bottom trawl data collected in different jurisdictional areas to track the density of groundfish species across those jurisdictional areas. Monnahan et al. (2021) developed a spatio-temporal model integrating research survey bottom trawl and acoustic data for EBS walleye pollock. With this spatio-temporal model, bottom trawl and acoustic data did not need to cover exactly the same years, the issue of vertical availability was handled through the integration of the two data sources, and the issue of spatial availability was addressed via the estimation of spatial and spatio-temporal variation. Thus, the study of Monnahan et al. (2021) illustrates how spatio-temporal models can correct for any of the causes for varying catchability across research survey observations listed at the end of the second paragraph (i.e., Situations #1, #2, and(or) #3).

Although integrating the data collected by different research surveys is a valuable approach, there are many fish stocks and regions worldwide for which the information provided by the available research surveys remain limited. In those instances, fisheries-dependent monitoring programs (e.g., observer programs) represent an alternative data source to research surveys. Compared to research surveys, fisheries-dependent monitoring programs tend to be less costly, provide data for a longer time period, are generally conducted year-round, and very often encompass much broader geographic areas (Lunn and Dearden 2006; Pennino et al. 2016; Bourdaud et al. 2017; Zhu et al. 2018; Rufener et al. 2021). Their sample size is usually much larger than that of research surveys (Pennino et al. 2016; Rufener et al. 2021; Alglave et al. 2022). However, varying catchability is usually a much more substantial issue with fisheries-dependent monitoring programs than with research surveys (Wilberg et al. 2010). The catchability of fisheries-dependent monitoring programs changes considerably over space and time for multiple complex, and often interacting, reasons. Data collection in fisheries-dependent monitoring programs is reliant on the strategies of fishing vessels, which target specific species, locations, and time periods (Maunder and Punt 2004; Lynch et al. 2012; Grüss et al. 2018). In addition, fishers continuously change fishing methods, gears, and behaviours in response to technological developments, management, and other constraints (Hilborn and Walters 1992; Robins et al. 1998; Marchal et al. 2006; van Oostenbrugge et al. 2008; Oliveira et al. 2009; Abbott et al. 2015). Thus, fisheries-dependent catch rates reflect changes in true fish abundance that are largely confounded with changes in catchability to the extent that fisheries-dependent catch rates often stay elevated while the fish stock of interest is declining (Harley et al. 2001; Wilberg et al. 2010). Consequently, variability in fisheries-dependent catch rates due to variability in catchability needs to be filtered out when predicting densities via a procedure called "CPUE standardisation" (Beverton and Holt 1957, Section 12; Maunder and Punt 2004). CPUE standardisation, in a model designed to produce indices from fisheries-dependent data, accounts for the technical and behavioural characteristics of fishing that influence catchability via catchability covariates (Maunder and Punt 2004; Ye and Dennis 2009). However, the causes of differences in catchability among fishing vessels are numerous, complex, and very often poorly understood such that it is improbable that a CPUE standardisation model will explicitly account for them all (Marchal et al. 2007; Wilberg et al. 2010). For this reason, many CPUE standardisation models include a random vessel effect that represents myriad latent catchability variables not explicitly modelled (Thorson and Ward 2014). The random vessel effect often substitutes any explicit catchability covariates and has revealed to be a critical component for explaining variation in data in CPUE standardisation models fitted to fisheries-dependent data (Xu et al. 2019; Rufener et al. 2021). Varying catchability (detectability) is also an important issue for data other than research survey and fisheries-dependent monitoring data (opportunistic presence-only data and stomach content data). For example, the catchability of a prey species by predators as samplers typically depends on the body length/weight of these predators (Ng et al. 2021).

As stated earlier, the information provided by a combination of different research survey datasets remains in many instances limited, while individual research surveys and other individual data sources (e.g., observer programs) have their strengths and weaknesses. In this context, some recent spatio-temporal modelling studies have employed a combination of research survey data and other data sources to generate distribution/density maps and indices (e.g., Pinto et al. 2019; Gonzalez et al. 2021; Rufener et al. 2021; Alglave et al. 2022). For example, the spatio-temporal model of Rufener et al. (2021) integrated research survey bottom trawl data with observer data collected onboard commercial bottom trawlers for western Baltic cod (*Gadus morhua*). The integrated model of Rufener et al. (2021) included a monitoring program catchability effect and a random vessel effect and also originally accounted for preferential sampling (the likely correlation between sampling locations and fish abundance) for the observer data. However, Rufener et al. (2021) found that accounting for preferential sampling when integrating research survey and observer data did not improve the model nor did it affect parameter estimates, so the preferential sampling component of the model was ultimately dropped.

In this study, we develop and demonstrate a spatio-temporal modelling framework that integrates research survey catch rate data with catch rate data from other sources (observer programs, industry-cooperative surveys, or predator as samplers). Our modelling framework nominates, among different data sources, a given research survey as the reference dataset (i.e., the most reliable dataset) that is treated as having constant catchability, and the catchabilities of the other data sources (non-reference datasets) are estimated as spatially varying variables. Specifically, our spatio-temporal modelling framework estimates a fishing-power ratio for each non-reference dataset relative to the reference dataset using a spatially varying coefficient model (Thorson 2019*a*). By estimating spatially varying catchabilities for non-reference datasets, our modelling framework properly attributes differences in catch rates among data sources to differences in catchability rather than differences in the spatial location of observations (provided that the assumption that the reference dataset has constant catchability over space is true). In the following, we first detail the development, structure, and assumptions of our spatio-temporal modelling framework. Then, we demonstrate our modelling framework using two contrasting case studies. The first case study involves bottom trawl survey data and data collected by observers placed onboard commercial bottom trawlers for spiny dogfish (*Squalus acanthias*) on the Chatham Rise, New Zealand. The second case study involves Pacific cod (*Gadus macrocephalus*) predators as samplers of juvenile snow crab (*Chionoecetes opilio*) abundance, integrated with a small-mesh industry-cooperative survey and a long-term bottom trawl research survey, in the EBS.

Materials and methods

Development of the integrated spatio-temporal model

Spatio-temporal models typically express catch rate d at each site s and in each year t as a function of year intercepts β, spatial variation (long-term unmeasured spatial variation) ω, spatio-temporal variation (unmeasured spatial variation that varies among years) ε, and catchability variables Q (Thorson 2022):

$$g\left(d\left(s_i, t_i\right)\right) = \beta\left(t_i\right) + \omega\left(s_i\right) + \varepsilon\left(s_i, t_i\right) + \sum_{k=1}^{n_k} \lambda\left(k\right) Q\left(i,\ k\right) \tag{1}$$

where i indexes samples; s_i is the location where sample i was collected; t_i is the year in which sample i was collected; $g()$ is a link function (e.g., the log-link function); k indexes catchability covariates; n_k is the number of catchability covariates; and $\lambda(k)$ is the effect of catchability covariate k. The year intercepts β are treated as fixed effects, while the spatial variation ω and the spatio-temporal variation term ε are both treated as random effects and are both specified as Gaussian Markov random fields following a multivariate normal (MVN) distribution (see below). Spatio-temporal models can also include density variables, but we leave this option out of the present paper for simplicity (see the Discussion section). While density covariates can potentially be included in spatio-temporal models to approximate drivers of the true underlying fish density, the catchability variables $Q(i,\ k)$ are nuisance variables included in spatio-temporal models to filter out causes of variation in catch rates due to sampling characteristics (Grüss et al. 2019; Ducharme-Barth et al. 2022; Hsu et al. 2022).

When fitting spatio-temporal models to multiple data sources (integrated data), analysts typically include an additional catchability variable M in the model, which specifies the effect of individual data sources on catch rates to acknowledge catchability differences among the different data sources (Grüss et al. 2017, 2018; Gonzalez et al. 2021; Rufener et al. 2021):

$$g\left(d\left(s_i, t_i\right)\right) = \beta\left(t_i\right) + \omega\left(s_i\right) + \varepsilon\left(s_i, t_i\right) + \sum_{m=1}^{n_m} \delta\left(m\right) M\left(i,\ m\right) + \sum_{k=1}^{n_k} \lambda\left(k\right) Q\left(i,\ k\right) \tag{2}$$

where m indexes data sources; n_m is the number of data sources considered in the spatio-temporal model; $\sum_{m=1}^{n_m} \delta\left(m\right) M\left(i,\ m\right)$ is the effect of data sources on expected catch rates; the design matrix $M(i,\ m)$ is 1 for the data source associated with sample i and 0 otherwise; and the data source effect $\delta(m)$ is set up so that $\delta(m) = 0$ for a "reference dataset", where this constraint is imposed for the identifiability of the year intercepts. In this formulation, the effect of data sources on expected catch rates is treated as a catchability factor, which analysts will prefer to treat as a fixed effect when working with several research surveys to avoid the shrinking of model predictions towards a mean (Grüss and Thorson 2019).

With eq. 2, the analysts need to specify a reference dataset. When the data sources available include only one research survey, the survey should be the reference dataset as it is the most reliable dataset. When working with several research surveys, it is most appropriate to define the research survey with the largest sample size as the reference dataset, unless that particular survey has gone through more changes in sampling design and(or) protocol over time than the other surveys available (Grüss and Thorson 2019; Alglave et al. 2022). Next, the data sources other than the reference dataset are nominated as the "non-reference datasets". Because the data source effect $\delta(m)$ is set to 0 for the reference dataset, it then follows that the specified effect of data sources on expected catch rates enables the estimation of fishing-power ratios relative to the reference dataset for the non-reference datasets within the spatio-temporal model (Monnahan et al. 2021; O'Leary et al. 2022). This property of the spatio-temporal model is valuable as it relieves the analysts from relying on paired sampling experiments, which are expensive and limit the number of years of data useable in analyses. Thus, integrated modelling with spatio-temporal models can allow for "opportunistic paired sampling".

The novelty of the present study consists of specifying the catchability variable M not as a factor that is constant over space as was the case in previous spatio-temporal modelling studies (e.g., Grüss et al. 2017, 2018; Grüss and Thorson 2019; Maureaud et al. 2021; O'Leary et al. 2022; Thompson et al. 2022) but rather as a spatially varying term. We achieve this model feature by employing spatially varying coefficients (SVCs; Thorson 2019*a*). Previously, SVCs have been used to incorporate spatial variation in the response to density covariates in spatio-temporal models (e.g., Thorson 2019*a*; Grüss et al. 2021*b*; Han et al. 2021; Ducharme-Barth et al. 2022). In that setting, density variables were specified to have a zero-centred, spatially varying random effect on fish catch rates, via a Gaussian Markov random field following an MVN distribution with correlation based on the distance between locations (Thorson 2019*a*). In this study, we introduce spatial variation in response to the catchability of non-reference datasets in integrated spatio-temporal models. Thus, with the substitution of the data source catchability factor with SVCs expressing spatially varying catchability for the non-reference datasets, eq. 2 becomes

$$g\left(d\left(s_i, t_i\right)\right) = \beta\left(t_i\right) + \omega\left(s_i\right) + \varepsilon\left(s_i, t_i\right) + \sum_{m=1}^{n_m} \xi\left(s_i, m\right) M\left(i,\ m\right) + \sum_{k=1}^{n_k} \lambda\left(k\right) Q\left(i,\ k\right) \tag{3}$$

where $\xi(s_i, m)$ is the additive, zero-centred, spatially varying impact of data source m at location s_i, and this impact is set to 0 for the reference dataset and is estimated for the non-reference datasets as a random effect following an MVN distribution:

$$\boldsymbol{\xi}(m) \sim \mathrm{MVN}\left(0, \sigma_{\xi}^{2}(m)\,\mathbf{R}(\kappa)\right) \tag{4}$$

where $\mathbf{R}(\kappa)$ is the correlation among locations given an estimated decorrelation distance κ (Thorson et al. 2015); and $\sigma_{\xi}^{2}(m)$ is the estimated pointwise variance of the spatially varying response to non-reference dataset m. With the substitution of the data source catchability factor with spatially varying catchabilities, the definition of the reference dataset becomes even more critical, as one then explicitly assumes that the catchability of the reference dataset is constant over space (as opposed to the catchabilities of non-reference datasets that vary spatially). In other words, spatially varying catchability is not (and cannot be) estimated for the reference dataset, which entails that the assumption that the reference dataset has constant catchability over space is central for utilising our modelling framework. Analyses involving a single dataset typically assume that it has spatially constant catchability (Thorson et al. 2013); our analysis allows us to relax the assumption of constant catchability for all datasets but the reference dataset. Moreover, our modelling framework can work with research surveys whose sampling design and(or) protocol have changed over time as long as those changes are not substantial. Otherwise, research surveys whose sampling design and(or) protocol have changed substantially over time should be split into several survey series, where individual survey series were carried out in similar geographic areas, using similar designs and protocols, and generally shared the same core stratification for the survey design, with consistent vessel and gear throughout.

Because the catch rate datasets that one relies upon in fisheries science typically include many zeros, we implement the integrated spatio-temporal model described by eq. 3 as a two-stage delta (a.k.a hurdle) model (Lo et al. 1992; Stefánsson 1996). To obtain a catch rate d at each site s and in each year t, the delta modelling approach combines the encounter probabilities estimated by a linear predictor, $p(s,t)$, with the positive catch rates estimated by another linear predictor, $r(s,t)$. More precisely, our integrated spatio-temporal model is implemented with the "Poisson-link delta" modelling approach (Thorson 2018), which (1) assumes that groups of fish are randomly distributed in the proximity of sampling such that one can derive encounter probability as a complementary log-log link from the predictions of the first linear predictor of the Poisson-link delta model, n, and (2) expresses positive catch rate r as the product of the first linear predictor of the Poisson-link delta model (n) and the second linear predictor (w), divided by encounter probability. Thus, with the Poisson-link delta model, catch rate d at each site s and in each year t is given by $d(s,t) = p(s,t) \times r(s,t) = n(s,t) \times w(s,t)$. Given the above, our integrated Poisson-link delta spatio-temporal model specifies the probability that the ith sample would yield a density D as

$$f(d(i) = D) = \begin{cases} 1 - p(i) & \text{if } D = 0 \\ p(i) \times h\left(D|r(i);\sigma_r^2\right) & \text{if } D > 0 \end{cases} \tag{5}$$

where $h()$ is the probability density function employed for unexplained variation in positive catch rate $r(i)$; σ_r^2 is residual catch rate variation; and $f(d(i) = D)$ is the data likelihood function. Our spatio-temporal model utilises the Gamma distribution model for $h()$, as recommended in Thorson et al. (2021).

When adapting eq. 3 for the Poisson-link delta modelling approach, (1) the log-link function is used in the two linear predictors, n and w, and (2) SVCs expressing spatially varying catchability for the non-reference datasets are included only in the first linear predictor (Grüss and Thorson 2019):

$$\begin{aligned} \log(n(s_i,t_i)) &= \beta_n(t_i) + \omega_n(s_i) + \varepsilon_n(s_i,t_i) \\ &\quad + \sum_{m=1}^{n_m} \xi(s_i,m)\,M(i,\ m) + \sum_{k1=1}^{n_{k1}} \lambda_n(k1)\,Q_n(i,\ k1) \\ \log(w(s_i,t_i)) &= \beta_w(t_i) + \omega_w(s_i) + \varepsilon_w(s_i,t_i) + \sum_{k2=1}^{n_{k2}} \lambda_w(k2)\,Q_w(i,\ k2) \end{aligned} \tag{6}$$

where $k1$ indexes catchability covariates in the first linear predictor; n_{k1} is the number of catchability covariates in the first linear predictor; and $k2$ and n_{k2} have similar meanings for the second linear predictor.

As is the case for the spatially varying impact of non-reference datasets (the ξ term), the spatial variation term ω and the spatio-temporal variation term ε are both modelled as Gaussian Markov random fields following an MVN distribution. In addition, for case studies where the spatial distribution of sampling has changed substantially across years, the spatio-temporal variation term ε can also be modelled as a first-order autoregressive process. Thus, in each linear predictor of the Poisson-link delta model, the spatial variation term ω and the spatio-temporal variation term ε are modelled as

$$\begin{aligned} \boldsymbol{\omega} &\sim \mathrm{MVN}\left(\mathbf{0}, \sigma_{\omega}^{2}\mathbf{R}(\kappa)\right) \\ \boldsymbol{\varepsilon}(t) &\sim \begin{cases} \mathrm{MVN}\left(\mathbf{0}, \sigma_{\varepsilon}^{2}\mathbf{R}(\kappa)\right) \ if\, t = t_{\min} \\ \mathrm{MVN}\left(\rho_{\varepsilon}\boldsymbol{\varepsilon}(t-1), \sigma_{\varepsilon}^{2}\mathbf{R}(\kappa)\right) \ if\, t > t_{\min} \end{cases} \end{aligned} \tag{7}$$

where ρ_{ε} is first-order temporal autocorrelation, which is set to 0 if modelling a first-order autoregressive process is not warranted; σ_{ω}^2 is the estimated pointwise variance of spatial variation; σ_{ε}^2 is the estimated pointwise variance of spatio-temporal variation; $t_{\min}$ is the first year in the time series; and ρ_{ε}, κ, σ_{ω}^2, and σ_{ε}^2 are estimated separately for the first and second linear predictors.

Our model is implemented with the vector autoregressive spatio-temporal (VAST) modelling platform using R package *VAST* (Thorson 2019*b*). With the VAST modelling platform, the covariance among locations is estimated separately for the ξ, ω, and ε terms, classically using the "Mesh model". In the Mesh model, (1) the estimated covariances between locations are considered to be stationary and to follow the Matérn distribution presented in Thorson et al. (2015) that accounts for geometric anisotropy; (2) for computational reasons, a predictive approach is followed where a triangulated mesh is constructed around n_x "knots", and covariance is being estimated between those knots (Shelton et al. 2014); and (3) bilinear interpolation is utilised to generate values between knot positions (Grüss et al. 2020*a*). It is now also possible to use a "Barrier model" to estimate covariances among locations with the VAST modelling platform. This option is suited for study regions characterised by the presence of physical barriers (i.e., islands and(or) peninsulas), such as the Chatham Rise. The Barrier model, which was introduced in Bakka et al. (2019), considers the Matérn correlation as an ensemble of paths through a Simultaneous Autoregressive model. Briefly, the Barrier model weakens the dependencies along the paths that cross land to almost zero so that they do not contribute to the estimation of the covariance between locations (Bakka et al. 2019).

Model estimation and evaluation

As is the case with any integrated model, a prerequisite of our modelling framework is that the different data sources integrated in our model result from separate measurements of a common latent (unmeasured) process. Only if the different data sources can be assumed to be statistically independent and to sample the same fish population can the different sources share common parameters and, thus, common likelihood components (Maunder 2004; Grüss and Thorson 2019; Monnahan et al. 2021). Under these circumstances, it is possible to calculate a joint likelihood for the integrated model as the product of the likelihood components for each data source, thereby enabling the estimation of the model from a borrowing of information among the different data sources (Fletcher et al. 2019).

To estimate the parameters of our spatio-temporal model, we employed version 3.10.0 of the VAST modelling platform, whose R code and documentation are publicly available at https://github.com/James-Thorson-NOAA/VAST (see details in Supplementary material A). After model fitting, model convergence is confirmed by checking that the gradient of the marginal log-likelihood is less than 1.10^{-4} for all fixed effects and that the Hessian matrix of secondary derivatives of the negative likelihood is positive-definite. The spatio-temporal model is then evaluated using a procedure relying on R package *DHARMa* (Hartig 2020) that is standard for VAST models (Supplementary material A).

Demonstration #1: spiny dogfish on the Chatham Rise

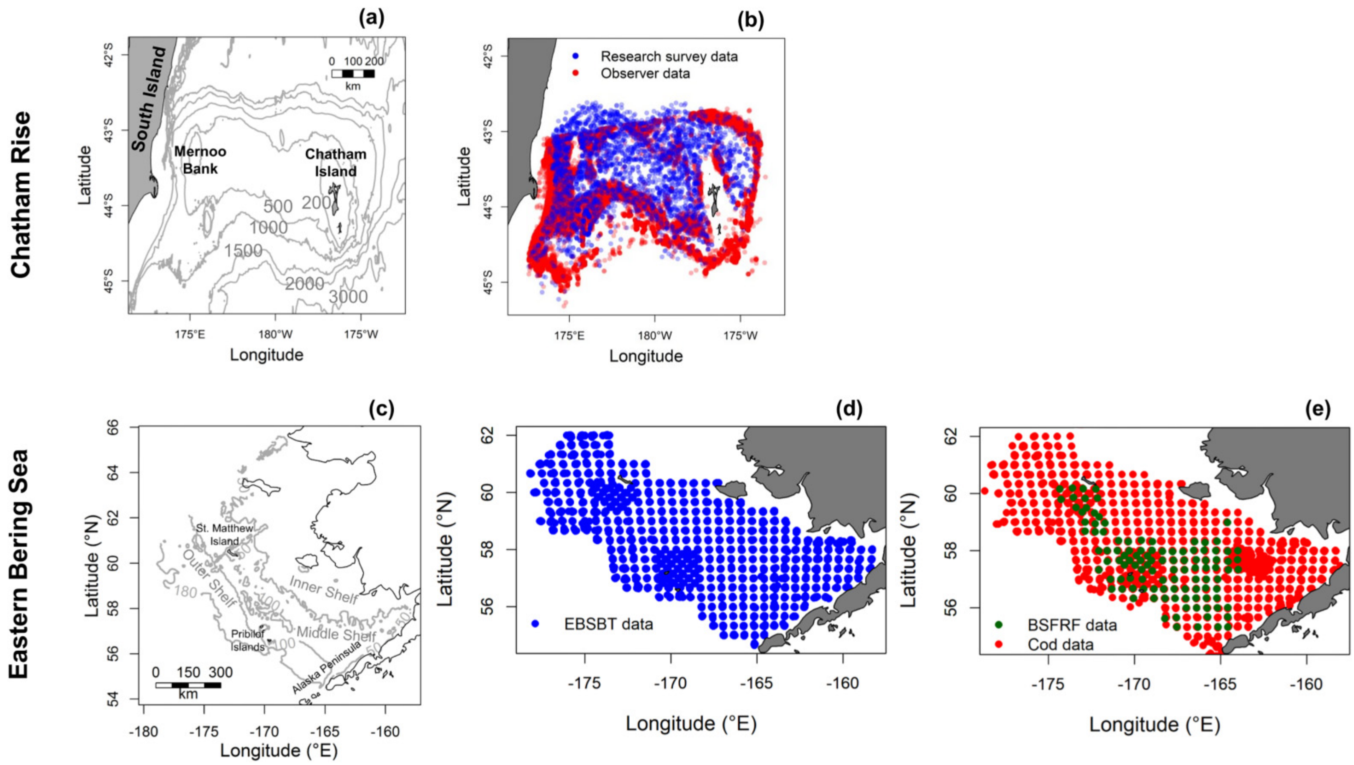
We demonstrated our integrated spatio-temporal modelling framework by applying it to spiny dogfish on the Chatham Rise (Fig. 1*a*). Spiny dogfish is an important bycatch species in New Zealand (NZ) deepwater fisheries (Anderson et al. 2019; Finucci et al. 2019), and there is an interest in NZ in better understanding its biomass trends (Baird and Ballara 2022). For the spiny dogfish case study, the Chatham Rise middle depth bottom trawl (CHAT MD) survey was the reference dataset, and only one non-reference dataset was considered, namely the observer data collected onboard commercial bottom trawlers on the Chatham Rise.

The CHAT MD survey was initiated in 1992 and has been carried out in 27 different years from 1992 to 2022. However, the CHAT MD data for 2022 were unavailable at the time of this study. Therefore, this study relies on 26 years of data, and the last year of CHAT MD data in the present study is 2020. The CHAT MD is conducted with *RV* Tangaroa and provides the most comprehensive time series of relative species abundance at 200–800 m water depths in the NZ exclusive economic zone (EEZ). The CHAT MD survey went through some changes in sampling design in 2010 and 2016. In 2010, the CHAT MD survey was extended to also sample deeper waters (800–1300 m) in the north and the east of the Chatham Rise. In 2016, the duration of the CHAT MD survey was increased by six days to also include deeper strata to the south and the west of the Chatham Rise (Stevens et al. 2021). The CHAT MD survey follows a two-phase random design (Francis 1984) and has used the same bottom trawl over the entire time series (see Hurst and Bagley (1994) for a comprehensive description of the gear). Trawling has followed the standardised procedures described by Hurst et al. (1992) over the entire time series. At each station sampled by the CHAT MD survey, the bottom trawl was usually towed for three nautical miles at a speed over the ground of 3.5 knots (Stevens et al. 2021).

The CHAT MD data were obtained from the Fisheries New Zealand (FNZ) database *trawl* (Mackay 2020). One important detail about the *trawl* database is that not all the records included in that database are valid for biomass estimation (e.g., some bottom trawl hauls were conducted specifically to complement acoustic measurements for a specific species rather than for monitoring multiple species to support stock or habitat assessments). Thus, among the records retrieved from the *trawl* database, we identified those that belonged to the CHAT MD survey series and that were valid for biomass estimation and could, therefore, be retained in our analyses. From the retained records, we extracted biomass catch rate data (in $kg{\cdot}km^{-2}$) for spiny dogfish. We cleaned the survey data using procedures that are standard in NZ (Morrison et al. 2013; Grüss et al. 2023*a*). Ultimately, we had 3152 records in the survey dataset for spiny dogfish (Fig. 1*b*).

The observer data collected onboard commercial trawlers were extracted from the FNZ database *cod* (Sanders and Fisher 2020). The *cod* database gathers the catch information and effort information (including doorspread) for observed commercial fishing vessels collected within the FNZ observer programme since 1986, as well as the age, length, and biological information collated by observers. We cleaned the data collected onboard bottom trawlers over the period 1986–2021, employing procedures that are standard in NZ (Edwards and Mormede 2023; Grüss et al. 2023*a*). Area swept (in km^2) was calculated as the product of doorspread (km) and distance trawled (km), and biomass catch rate was then obtained by dividing catch (in kg) by area swept. Ultimately, we had a total of 39 029 records in the observer dataset for spiny dogfish (Fig. 1*b*). Thus, for the spiny dogfish case study, we had over 12 times more records in the observer dataset than in the survey

Fig. 1. Study regions and spatial distribution of the data for the two case studies. (*a*) Map of the Chatham Rise off New Zealand. Depth contours are labelled at 200, 500, 1000, 1500, 2000, and 3000 m. Important features are also labelled and include New Zealand's South Island and Chatham Island. (*b*) Spatial distribution of the research survey data (blue dots) and observer data (red dots) for the Chatham Rise used in the present study. (*c*) Map of the eastern Bering Sea (EBS) off Alaska. Depth contours are labelled in 50, 100, and 180 m contours. Important features are also labelled and include the Inner Shelf (0–50 m), Middle Shelf (50–100 m), Outer Shelf (100–180 m), the Alaska Peninsula, the Pribilof Islands, and St. Matthew Island. (*d*) Spatial distribution of the research survey (EBSBT) data for EBS juvenile snow crab (*Chionoecetes opilo*) (blue dots). (*e*) Spatial distribution of the data sources other than research survey data for EBS juvenile snow crab, including industry-cooperative survey (BSFRF) data (green dots) and Pacific cod stomach (Cod) data (red dots). In panels (*a*–*b*), shape file data come from https://data.linz.govt.nz/. In panel (*c*), map projection is NAD83/Albers Equal Area.



dataset. Moreover, we had observer data for each individual year of the period 1986–2021, i.e., we had 36 years of data in the observer dataset versus 26 years of data in the survey dataset.

Fisheries-dependent data such as the observer data for spiny dogfish are characterised by very large catchability differences between sampling events because of multiple complex and not well-understood interactions between fish, miscellaneous characteristics of the fishing vessels, and management and other constraints at the time of fishing (Hilborn and Walters 1992; Quinn and Deriso 1999). These catchability differences are so substantial that the observer data may very likely be overdispersed to the extent that the inclusion of catchability covariates Q_n and Q_w in eq. 6 may not be sufficient to remove the variation in the data due to technical and behavioural characteristics of fishing. For this reason, in the spiny dogfish case study, we substituted the Q_n and Q_w terms from eq. 6 with random vessel effects $\eta_n(v_i)$ and $\eta_w(v_i)$, respectively (Xu et al. 2019; Rufener et al. 2021; O'Leary et al. 2022). These random vessel effects followed a normal distribution with a mean of zero and standard deviation estimated (Xu et al. 2019; Bell et al. 2021; Ducharme-Barth et al. 2022; Grüss et al. 2023*b*), and they were fixed at 0 when sample i came from the CHAT MD survey rather than from the observer program.

For the spiny dogfish case study, we developed three different VAST models and compared the predictions of the three models. The three different models were fitted to (1) the data collected by the CHAT MD survey (survey-only data); (2) observer-only data; or (3) both survey and observer data (integrated data). In the models fitted to survey-only and observer-only data, spatially varying catchability was not modelled. In addition, the random vessel effects were not modelled in the model fitted to survey-only data. In the three VAST models (fitted to survey-only, observer-only, or integrated data), the response variable was biomass catch rate in kg·km^{-2}. In all three models, spatio-temporal variation was modelled as a first-order autoregressive process (eq. 7), because the spatial distribution of sampling has changed substantially over time for both the CHAT MD survey and the observer program. Moreover, in all models, we used the Barrier model to estimate covariances among locations because of the presence of islands in the study region. Finally, in all models,

$n_x = 200$ knots were distributed uniformly over a 1×1 km spatial grid for the Chatham Rise, and biomass densities were predicted across 2000 grid cells covering that spatial grid (Grüss et al. 2020*a*). We confirmed that model parameter estimates and predictions were qualitatively similar when specifying more than 200 knots.

We employed the 1×1 km spatial grid for the Chatham Rise to produce density maps from the outputs of the VAST models. In addition, we generated indices for spiny dogfish from the outputs of the VAST models. To obtain indices, we first estimated relative biomasses, $\widehat{B}(t)$, as

$$\begin{aligned}(8)\quad \widehat{B}(t) &= \sum_{j=1}^{n_j} a(j)\,\widehat{n}(j,t)\,\widehat{w}(j,t) \\ &= \sum_{j=1}^{n_j} a(j) \exp\left(\widehat{\beta_n}(t) + \widehat{\omega_n}(j) + \widehat{\varepsilon_n}(j,t)\right) \\ &\qquad \times \exp\left(\widehat{\beta_w}(t) + \widehat{\omega_w}(j) + \widehat{\varepsilon_w}(j,t)\right)\end{aligned}$$

where n_j is the number of knots (200); $a(j)$ is the surface area of knot j (in km^2); $\widehat{\beta_n}(t)$ and $\widehat{\beta_w}(t)$ are fixed effects estimated via maximum likelihood estimation; and $\widehat{\omega_n}(j)$, $\widehat{\omega_w}(j)$, $\widehat{\varepsilon_n}(j,t)$, and $\widehat{\varepsilon_w}(j,t)$ are random effects set to the value maximising the joint likelihood conditional on the estimated fixed effects (Thorson et al. 2015). Indices were then obtained by dividing the indices for each year by the mean value of $\widehat{B_t}$ over the relevant time period (i.e., 1992–2020 in the case of the model fitted to survey-only data and 1986–2021 in the case of the models fitted to observer-only and integrated data). For the three models (fitted to survey-only, observer-only, or integrated data), the VAST indices were compared to the indices computed directly from survey-only data with the *SurvCalc* software (Francis 2009). The SurvCalc indices used in this study came from Stevens et al. (2021). Because the sampling design of the CHAT MD survey changed in 2010 and then again in 2016 with the addition of deeper 800–1300 m strata, SurvCalc indices for the core 200–800 m strata, which have been consistently surveyed in all years, were employed (Stevens et al. 2021).

Demonstration #2: juvenile snow crab in the EBS

We further demonstrated our integrated spatio-temporal modelling framework by applying it to juvenile (0–20 mm carapace width) snow crab in the EBS (Fig. 1*c*). The fishery for snow crab on the EBS has been one of the most valuable shellfish fisheries in the world (Hvingel et al. 2021), although it crashed in 2020–2021 (Szuwalski 2022). In the EBS, snow crab has exhibited pronounced fluctuations in stock size since its monitoring began (Parada et al. 2010; Szuwalski 2019). Production in the EBS snow crab fishery reached a peak at the end of the 1980s, after which snow crab landings have dramatically decreased until the early 2000s. The latest stock assessments indicated that the EBS snow crab stock had been rebuilding, following a series of strong year classes, before crashing in 2020–2021 (Szuwalski 2019, 2022). Predation by Pacific cod is hypothesised to be one of the causes of juvenile snow crab mortality (Livingston 1989; Zheng and Kruse 2006; Burgos et al. 2013). Livingston (1989) also found that snow crab recruitment pulses can be tracked with fluctuations in Pacific cod predation.

In the juvenile snow crab case study, the response variable of the spatio-temporal model was the numerical catch rate in numbers of crabs per km^2. For that case study, the EBS bottom trawl (EBSBT) survey was the reference dataset, and two non-reference datasets were considered: (1) a small-mesh industry-cooperative survey and the Bering Sea Fisheries Research Foundation (BSFRF) survey and (2) juvenile snow crab content in the stomachs of 30–59 cm Pacific cod collected in the EBS. In the second non-reference dataset, which we refer to as the "Cod" dataset, 30–59 cm Pacific cod predators act as samplers of juvenile snow crab.

The EBSBT survey is a standardised bottom trawl survey conducted annually in the EBS by the Alaska Fisheries Science Center (AFSC) (Lauth and Conner 2016). The EBSBT survey takes place during summer, in late May to early August. It employs a fixed-sampling design, where approximately 376 stations on a regularly spaced 20×20 km grid (including higher density "corner stations" in areas with historically high crab abundance) are sampled each year. The EBSBT survey has taken place from 1989 onward but also in 1982–1988 but did not sample as far northward; hence, data for 1982–1988 are not used in this study. Each year, the EBSBT survey begins in the southeast Inner Shelf of the EBS and progresses towards the northwest Outer Shelf. Stations are sampled using an 83–112 eastern otter trawl, towed at a target speed of 1.54 m·s^{-1} for a targeted tow duration of 30 min (Lauth and Conner 2016). The complete description of the gear employed in the EBSBT survey can be found in Stauffer (2004). The EBSBT survey dataset provided us with 11 229 records for juvenile snow crab for the period 1989–2018 (Fig. 1*d*).

The BSFRF survey is an industry-cooperative survey that carried out bottom trawl survey selectivity experiments and generated indices for EBS snow crab and tanner crab (*Chionoecetes bairdi*) during the summers of 2009, 2010, and 2016–2018. When conducting survey selectivity studies, the BSFRF chartered fishing catcher vessels and utilised an experimental trawl to carry out side-by-side tows alongside the vessels used for the EBSBT survey to assess crab selectivity in the centre of specified EBSBT survey stations. The BSFRF survey employed a small-mesh *Nephrops* trawl and towed at a target speed of 1 m·s^{-1} with a targeted tow duration of 5 min with winches locked. Conan et al. (1994) provides a complete description of the gear. BSFRF gear performance was monitored with hydroacoustic sensors for trawl spread and performance. The BSFRF was assumed to capture all crabs in its path. The indices studies were conducted independently from the EBSBT survey, where 2–4 tows were semi-randomly selected in specified EBSBT survey stations. These experiments were continued from 2006 to 2018, focusing on tanner crab. While the focus areas for the 2006–2018 experiments were not fully representative of snow crab grounds (focusing on tanner crab where snow crab densities were lower), opportunistic sampling of snow crab occurred. The BSFRF dataset provided us with 390 records for juvenile snow crab, including 97 records associated with a catch rate of 0 and 293 records associated with a positive catch rate (Fig. 1*e*).

The Cod data originate from samples collected at EBSBT survey stations. Specifically, at each of the stations sampled by the EBSBT survey, species-specific length stratification is utilised to select a fraction of the sampled fish for stomach content analyses, and the results of these stomach content analyses are then entered in the AFSC's Groundfish Trophic Interactions Database (Livingston et al. 2017). For instance, in the case of Pacific cod, three length categories are considered: 1–29, 30–59, and 60+ cm. Because of this sampling stratification, we focus only on a specific Pacific cod length category in this study, namely the 30–59 cm length category, which consumes more snow crab than the 1–29 and 60+ cm length categories (Livingston et al. 2017). The dataset from the AFSC's Groundfish Trophic Interactions Database, which we retrieved from NOAA Fisheries (2021), included stomach content data for a total of 24 146 (30–59 cm) Pacific cod individuals collected in 3978 hauls for the years 1981, 1984–2003, and 2005–2015 (Fig. 1*e*). Some of the Pacific cod individuals had no snow crab in their stomach. We treated these instances as an observation of zero count for snow crab in those hauls. The dataset that we retrieved from NOAA Fisheries (2021) also included predator (Pacific cod) weight data (in kg). We had a total of 24 536 records in the combined BSFRF-Cod dataset, i.e., we had around 2.2 times more records in the combined BSFRF-Cod dataset than in the EBSBT dataset. Also, the time series for the combined BSFRF-Cod dataset started earlier than the time series for the EBSBT data (in 1981 versus 1989 for the EBSBT data) yet did not include any data for the year 2004. Note that we could have treated each tow as the sampling unit and worked with average snow crab counts per tow and average predator weights per tow, as was done in Grüss et al. (2020*b*). When analysing stomach content data, there are rationales for working with average prey counts per tow or non-averaged prey counts. Working with average prey counts per tow may be preferred because stomach samples from the same tow may not be independent (Moriarty et al. 2017; Binion-Rock et al. 2019). On the other hand, the occurrence of prey items in fish stomachs is strongly related to predator length and weight (Livingston et al. 2017; Ng et al. 2021). Thus, analysts may alternatively prefer to work with non-averaged prey counts and include individual predator weight as a covariate in models rather than just averaging prey counts over individual predators with substantially different weights. We elected to treat each individual Pacific cod as a separate sample of snow crab density. Future studies could investigate the impacts of utilising average snow crab counts per tow versus non-averaged snow crab counts in the VAST models, although the results of the present study will remain qualitatively unchanged.

For the juvenile snow crab case study, we developed three different VAST models and compared the predictions of the three models. The three different models were fitted to (1) EBSBT survey data (the reference dataset); (2) the other data sources, i.e., the combined BSFRF-Cod data; or (3) both the EBSBT data and the other data sources (integrated data). In the model fitted to the EBSBT survey data only, spatially varying catchability was not modelled. In the model fitted to the other data sources, the BSFRF dataset was assumed to be more reliable than the Cod dataset; therefore, spatially varying catchability was estimated only for the Cod dataset. In the model fitted to integrated data, spatially varying catchability was estimated for both the BSFRF and the Cod datasets. Moreover, the models fitted to the other data sources and to the integrated data included the effect of Pacific cod weight in the first linear predictor via one catchability term Q_n (eq. 6) to account for the fact that the catchability of juvenile snow crab by Pacific cods as samplers is influenced by the body weight of the Pacific cod predators. In these specific situations, the effect of Pacific cod weight on juvenile snow crab catchability was estimated only for the Cod data in the first linear predictor so that (1) the Q_n term was set to 0 for the EBSBT and BSFRF data and (2) the Q_w term was turned off in the second linear predictor. The effect of Pacific cod weight on juvenile snow crab catchability was modelled as a fixed nonlinear effect using a B-spline with a maximum of two degrees of freedom; specifically, the B-spline basis function *bs* from R package *splines* was employed (R Core Team 2022).

In the three different VAST models (fitted to EBSBT survey data, other data sources, or integrated data), spatio-temporal variation was not modelled as a first-order autoregressive process, i.e., the ρ_ε term from eq. 7 was set to 0. Moreover, in all three models, we used the Mesh model to estimate covariances among locations. Finally, in all models, $n_x = 100$ knots were distributed uniformly over a 20×20 km spatial grid for the EBS, and numerical densities were predicted across 2000 grid cells covering that spatial grid (Grüss et al. 2020*a*). We confirmed that model parameter estimates and predictions were qualitatively similar when specifying more than 100 knots.

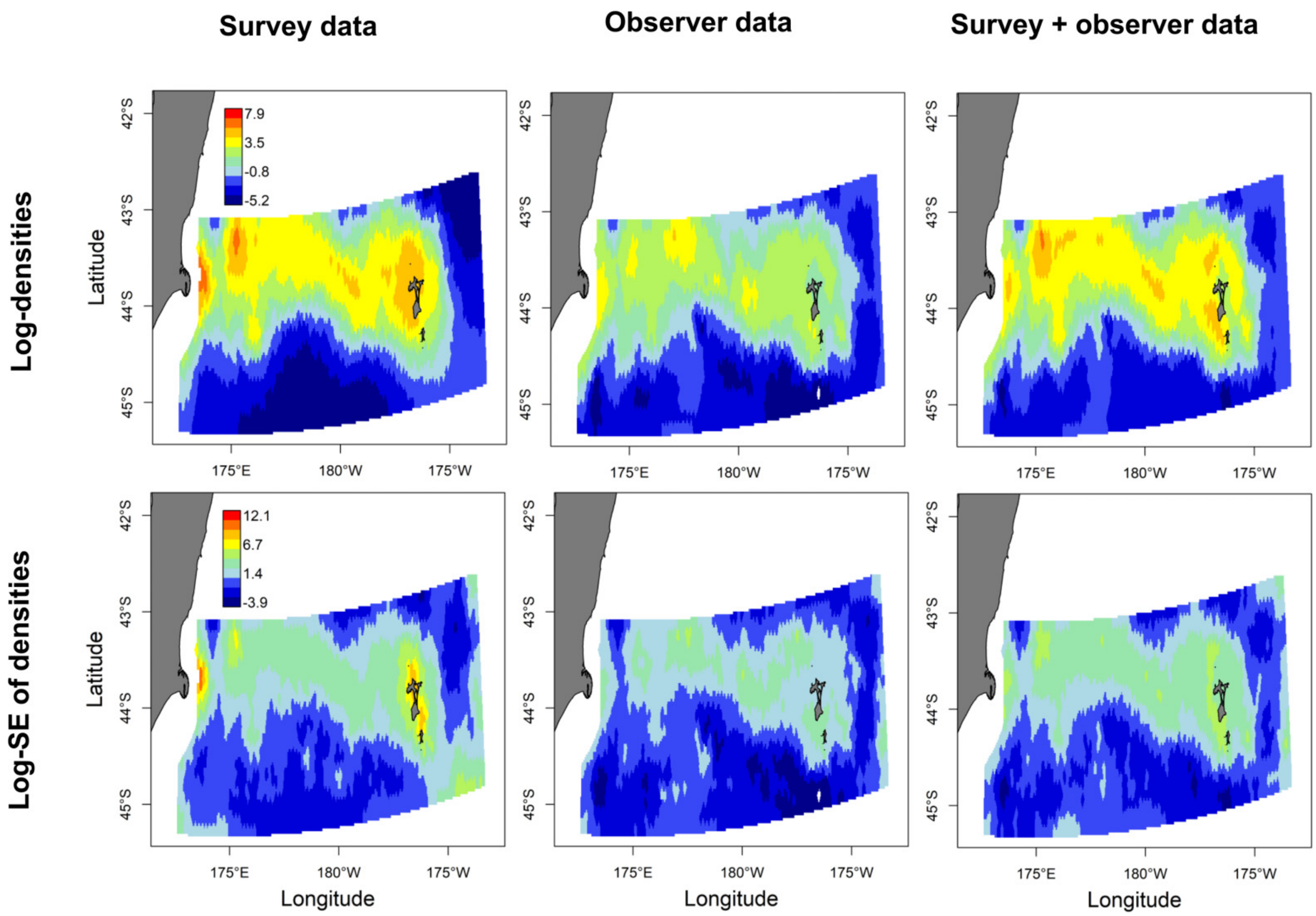
From the outputs of the VAST models for juvenile snow crab, we produced density maps using the 20×20 km spatial grid for the EBS, as well as indices (eq. 8). For the three models (fitted to EBSBT survey data, other data sources, or integrated data), the VAST indices were compared to the total recruitment time series estimated by the 2019 EBS snow crab assessment model (Szuwalski 2019).

Results

Demonstration #1: spiny dogfish on the Chatham Rise

In the spiny dogfish case study, the model fitted to survey-only data predicted density to be highest in those areas of the Chatham Rise where bottom depth is less than 500 m, particularly in the area close to NZ South Island (Figs. 2 and 3). The spatial density patterns of spiny dogfish predicted by the model fitted to observer-only data were quite different. Specifically, with the model fitted to observer-only data, high-density areas were predicted to occupy a smaller surface area and to be located mainly on Mernoo Bank. By contrast, the spatial density patterns of spiny dogfish predicted by the model fitted to integrated data were very similar to those predicted by the model fitted to survey-only data (Figs. 2 and 3). Regarding the predictions made by the model fitted

Fig. 2. Mean spatial patterns of spiny dogfish (*Squalus acanthias*) log-density over the period 1986–2021 (in log-kg·km^{-2}) on the Chatham Rise and their associated standard errors (SEs), predicted by the vector autoregressive spatio-temporal (VAST) models fitted to research survey data (left panels), observer data (middle panels), or both research survey and observer data (right panels). In all panels, shape file data come from https://data.linz.govt.nz/.

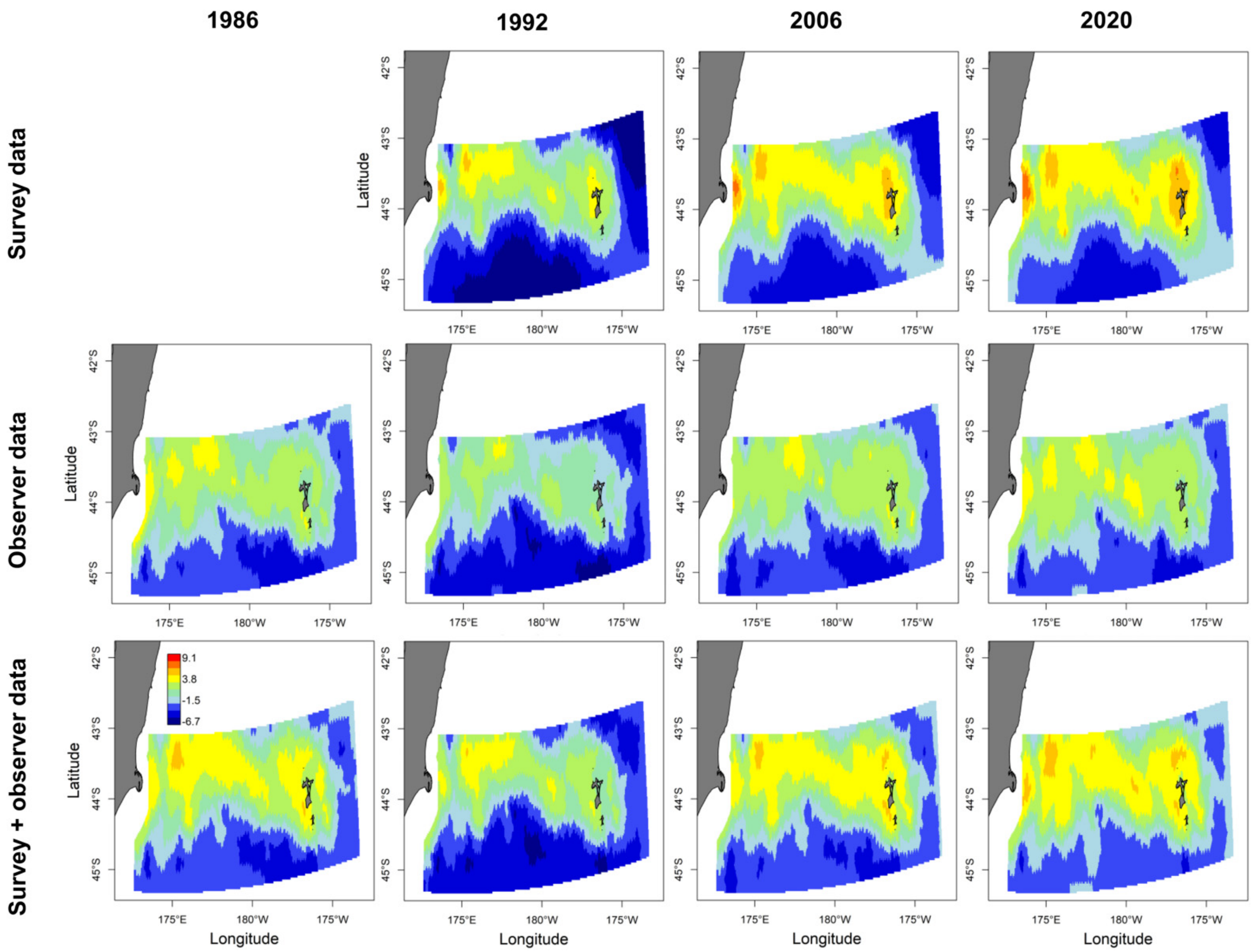


to integrated data for individual years, we can distinguish between two situations: (Situation #1) observations were provided by both the survey and the observer dataset (years 1992–2014, 2016, 2018, and 2020) and (Situation #2) observations were provided by the observer dataset only (years 1986–1990, 2015, 2017, 2019, and 2021). In Situation #1, the spatial density patterns predicted by the integrated model were very similar to those predicted by the model fitted to survey-only data (Fig. 3). In Situation #2, even in the absence of survey observations, there were clear differences between the predictions of the integrated model and those of the model fitted to the observer-only data, and the predictions of the integrated model appeared like the predictions that one would expect with the model fitted to survey-only data (Fig. 3).

In the model fitted to integrated data, the spatially varying catchability of the observer program data was estimated (Fig. 4). The catchability from the observer program data was predicted to be lowest around Chatham Island, as well as on Mernoo Bank. It was predicted to be highest in the northern part of the Chatham Rise, excluding Mernoo Bank, and in the southwestern corner of the Chatham Rise (Fig. 4).

The three spatio-temporal models (fitted to survey-only, observer-only, or integrated data) predicted an increase in spiny dogfish density on the Chatham Rise over time (Fig. 3). As a result, all three models predicted that the index of spiny dogfish increased over time (Fig. 5). However, the model fitted to observer-only data and, consequently, the model fitted to integrated data provided an index for spiny dogfish for a longer time period. Compared to the index derived from survey-only data, the index derived from observer-only data agreed less with the SurvCalc index, was more uncertain, and displayed more interannual variability. The integration of survey and observer data resulted in an index that, compared to the index derived from observer-only data, agreed more with the SurvCalc index, was less uncertain, and exhibited smaller and more reasonable interannual variability. The degrees of uncertainty around the indices derived from survey-only and integrated data were comparable (Fig. 5). Note that post 2015, spatio-temporal model indices were always larger than SurvCalc indices, likely because the CHAT MD survey expanded to deeper strata to the south and the west of the Chatham Rise in 2016, but we used SurvCalc indices for the core strata of the CHAT MD survey.

Fig. 3. Spatial patterns of spiny dogfish (*Squalus acanthias*) log-density (in log-kg·km^{-2}) in select years on the Chatham Rise, predicted by the vector autoregressive spatio-temporal (VAST) models fitted to research survey data (top panels), observer data (middle panels), or both research survey and observer data (bottom panels). Note that data were for a shorter time period when using survey-only data, hence the absence of map in the top-left panel. In all panels, shape file data come from https://data.linz.govt.nz/.

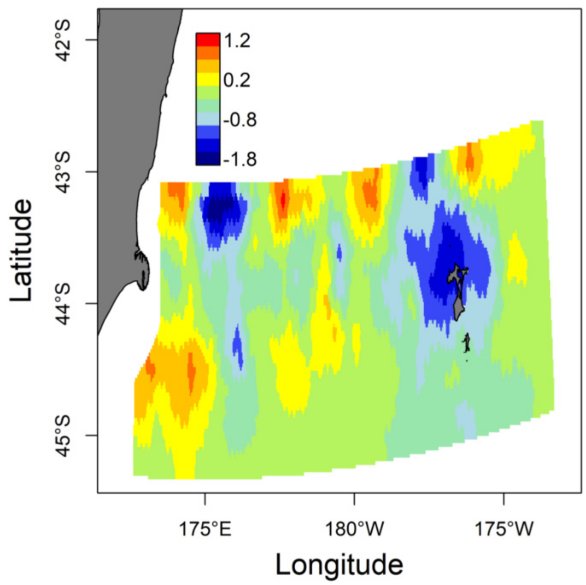


Demonstration #2: juvenile snow crab in the EBS

In the juvenile snow crab case study, it was necessary to turn off the spatio-temporal variation term in the second linear predictor for the model fitted to the combined BSFRF-Cod dataset to allow for the convergence of this model. On the other hand, the model fitted to EBSBT data and the model fitted to integrated data both converged without any problems.

The model fitted to EBSBT data predicted that long-term average density of juvenile snow crab was highest in the northern part of the EBS Middle and Outer Shelves, particularly north of St. Matthew Island (Fig. 6). The annual densities predicted by the model fitted to EBSBT data were, in general, similar to the long-term average density predicted by the model (Fig. 7). Exceptions to this general pattern included years such as 2004, where high-density areas were also predicted in the central part of the EBS Middle and Outer Shelves between St. Matthew Island and Pribilof Islands. The model fitted to the combined BSFRF-Cod dataset predicted that the density of juvenile snow crab was highest in the central part of the EBS Middle and Outer Shelves between St. Matthew Island and Pribilof Islands, both on average over all years and in individual years (Figs. 6 and 7). The long-term average spatial density patterns of juvenile snow crab predicted by the model fitted to integrated data were very similar to those predicted by the model fitted to EBSBT data only (Fig. 6). Regarding the predictions made by the model fitted to integrated data for individual years, we can distinguish between two situations: (Situation #1) observations were provided only by the EBSBT dataset (year 2004) or by both the EBSBT dataset and the combined BSFRF-Cod dataset (years 1989–2003 and 2005–2018) and (Situation #2) observations were provided by the combined BSFRF-Cod dataset only (years 1981 and 1984–1988). In Situation #1, the spatial density patterns predicted by the integrated model were very similar to those predicted by the model fitted to EBSBT data only (Fig. 7). In Situation #2, even in the absence of EBSBT observations, there were clear differences between the predictions of the integrated model and

Fig. 4. Spatially varying catchability effect of the observer program estimated by the vector autoregressive spatio-temporal (VAST) model for spiny dogfish (*Squalus acanthias*) fitted to both research survey and observer data. Shape file data come from https://data.linz.govt.nz/.



those of the model fitted to the combined BSFRF-Cod dataset, and the predictions of the integrated model appeared like the predictions that one would expect with the model fitted to EBSBT data only. For example, in 1981, the integrated model predicted that the density of juvenile snow crab was highest in the northern part of the EBS Middle and Outer Shelves (Fig. 7).

In the model fitted to the combined BSFRF-Cod dataset, the spatially varying catchability of the Cod dataset was estimated to be highest in the northern part of the EBS Outer Shelf and around Pribilof Islands (Fig. 8*a*). The spatially varying catchability of the Cod dataset estimated by the integrated model was very different (Fig. 8*b*). Specifically, in the integrated model, the spatially varying catchability of the Cod dataset was estimated to be highest in the central part of the EBS Outer Shelf and along the Alaska Peninsula (Fig. 8*b*). Moreover, the integrated model estimated the spatially varying catchability of the BSFRF dataset was highest in the central part of the EBS Middle and Inner Shelves and in the southern part of the EBS Outer Shelf (Fig. 8*c*).

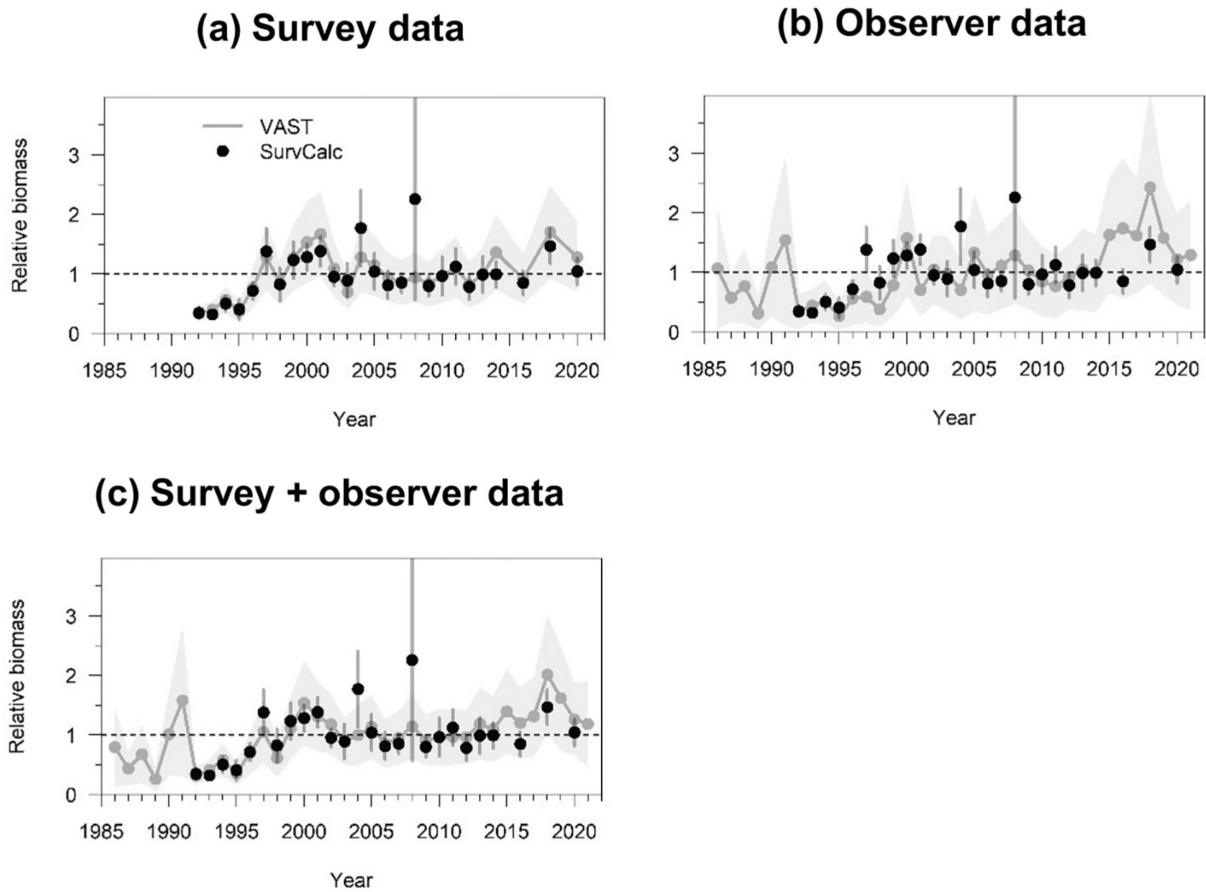
The three spatio-temporal models (fitted to EBSBT data, the combined BSFRF-Cod dataset, or integrated data), all predicted that the index of juvenile snow crab fluctuated widely over time (Fig. 9). The indices estimated by the models fitted to EBSBT data and integrated data were very similar, and both differed markedly from the index estimated by the model fitted to the combined BSFRF-Cod dataset. For example, over the period 2008–2018, (1) the models fitted to EBSBT data and integrated data predicted a large increase in the index until 2017 followed by a massive drop in the index in 2018, while (2) the model fitted to the combined BSFRF-Cod dataset predicted low index values until 2012, a slight increase in the index between 2013 and 2015, and a drop to low index values afterwards. The index estimated by the model fitted to the combined BSFRF-Cod dataset was also more uncertain than the indices estimated by the models fitted to EBSBT data and integrated data. While the index derived from EBSBT data and the index derived from integrated data were very similar, the primary advantage of the index derived from integrated data was that it covered a longer time period, which extended back to 1981. There appeared to be a better-lagged correlation between the indices derived from EBSBT and integrated data and total recruitment estimated by the snow crab assessment model than between the index derived from the combined Cod-BSFRF dataset and total recruitment from the assessment model (Fig. 9).

Discussion

In the present study, we developed a spatio-temporal modelling framework that integrates research survey data (treated as a "reference dataset") and other data sources (treated as "non-reference datasets") while estimating spatially varying catchability for the non-reference datasets. This framework enables estimating a fishing-power ratio for each non-reference dataset relative to the reference dataset, whose variation over space is estimated using SVCs (Thorson 2019*a*). By expressing the fishing-power ratio of non-reference datasets as a function of multiple unmeasured (latent) variables, SVCs allow our spatio-temporal modelling framework to attribute some of the residual variance to spatial processes, thereby improving model predictive performance (Finley 2011).

The two demonstrations provided in this study (spiny dogfish and juvenile snow crab) showed that the estimated spatially varying catchabilities act to substantially downweight the influence of the non-reference datasets on model predictions (Figs. 4 and 8). Other methods have addressed conflicts between multiple data sources and have similarly sought to downweight the influence of non-reference (least reliable or least critical) datasets, including reweighting methods for stock assessment models (Francis et al. 2003) and dynamic factor analysis (DFA; Zhu et al. 2018; Peterson et al. 2021). By attributing a larger variance to the indices derived from non-reference datasets, reweighting methods are useful to downweight the importance of the non-reference datasets within a stock assessment, yet these methods are ad hoc and sometimes produce unsatisfactory results (Wilberg et al. 2010). DFA combines multiple indices into a single "consensus" index before the stock assessment model is implemented (Peterson et al. 2021). DFA does have downsides. First, with DFA, it is necessary to give some implicit weight to the different indices and often constituent indices that represent small or large areas are assigned the same weight. Secondly, residual variance in constituent indices is not considered, precluding the propagation of uncertainty from the constituent indices to the consensus index. Our integrated spatio-temporal model reconciles reference and non-reference datasets without the drawbacks of reweighting methods and DFA. Nevertheless, there may be situations where retaining an index estimated by a spatio-temporal model fitted to research survey

Fig. 5. Indices of relative biomass for the Chatham Rise middle depth (CHAT MD) area predicted by the vector autoregressive spatio-temporal (VAST) models for spiny dogfish (*Squalus acanthias*) fitted to (*a*) research survey data, (*b*) observer data, or (*c*) both research survey and observer data. Also shown in all panels are the SurvCalc indices of relative biomass obtained from trawl survey data (not for all years of the period 1992–2021 contrary to the VAST indices of relative biomass), which come from Stevens et al. (2021). In all panels, the shaded areas represent 95% confidence intervals around VAST predictions, while vertical bars represent 95% confidence intervals around SurvCalc indices of relative biomass.

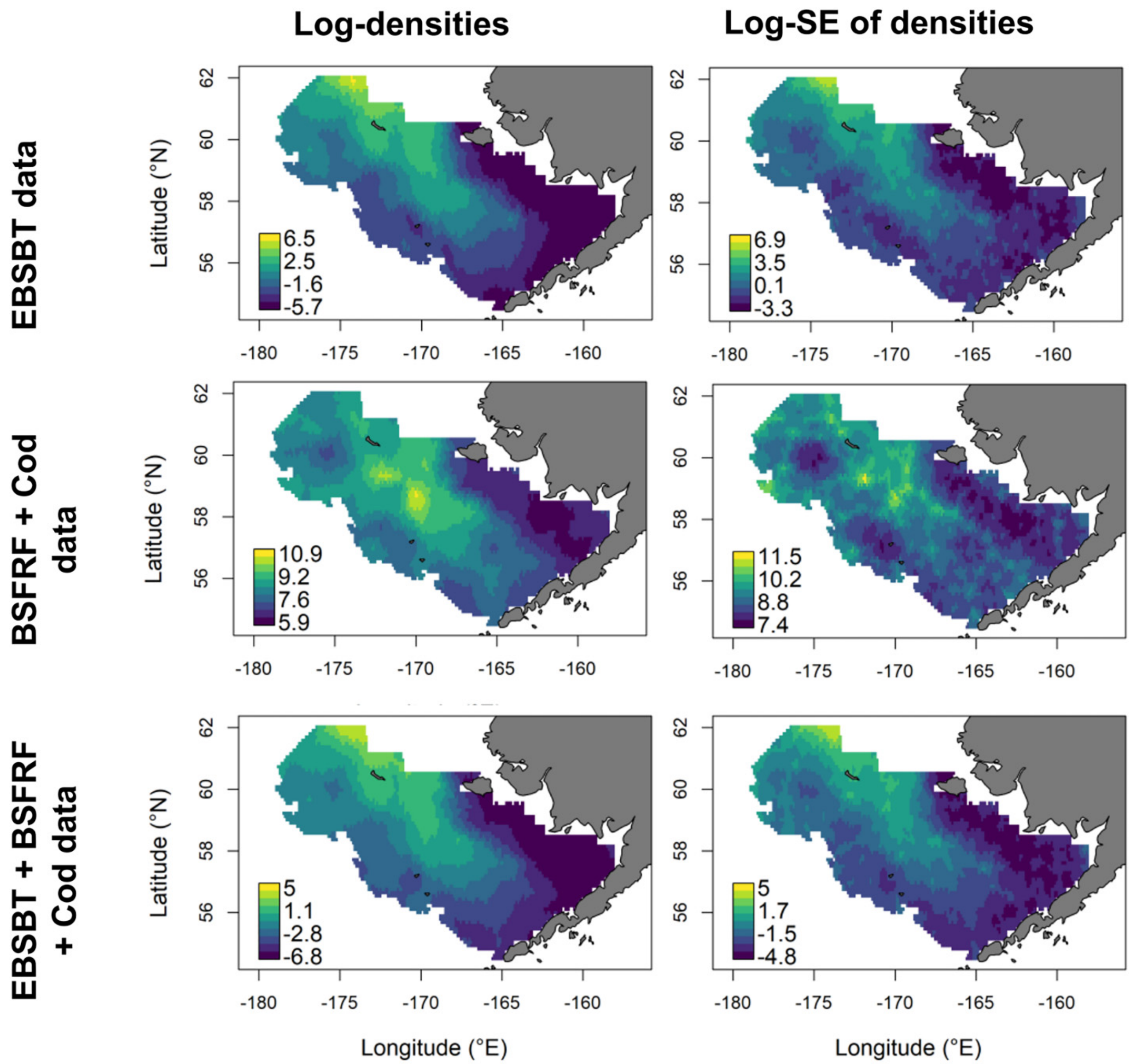


data is preferable to opting for an index estimated by a spatio-temporal model fitted to integrated data (e.g., because the index derived from research survey data displays much less interannual variability and(or) uncertainty). Therefore, in situations where enough research survey data are available, we recommend that fisheries analysts (1) develop both a spatio-temporal model fitted to research survey data and a model fitted to integrated data, examine the resulting indices, and retain the most plausible one according to experts of the fish stock of interest and (2) when planning to employ an index derived from integrated data in a stock assessment model, run sensitivity analyses to compare the impacts of using multiple indices derived from different data sources versus one single index derived from integrated data in the stock assessment model (Adkison 2009; Peterson et al. 2021).

In our two case studies (spiny dogfish and juvenile snow crab), the density maps predicted by the models fitted to the reference dataset and the integrated data were similar, and all density maps concurred with the literature. Anderson et al. (1998) reported that within NZ waters, spiny dogfish are generally encountered at depths shallower than 500 m. Bull et al. (2001) studied fish communities on the Chatham Rise and found that spiny dogfish preferred depths less than 350 m. Regarding EBS snow crab, the stock was reported to be primarily found in the northern part of the EBS Middle and Outer Shelves, where juveniles tend to occupy shallower waters to the north of the adults (Zheng et al. 2001; Liu 2019). Orensanz et al. (2004) found that Pacific cod predation on snow crab largely controlled the southern boundary of snow crab distribution areas in the central part of the EBS Middle and Outer Shelves. In our two case studies, the model fitted to non-reference datasets only (observer-only data in the former case and the combined BSFRF-Cod dataset in the latter case) provided incomplete insights into the spatial density patterns of the study species.

While both the integrated model and the model fitted to the reference dataset delivered accurate density maps, the integrated model had the advantages of providing annual density maps and an index for a longer time-period in both case studies. For both spiny dogfish and juvenile snow crab, for the years with no observations in the reference dataset, the spatio-temporal model fitted to integrated data

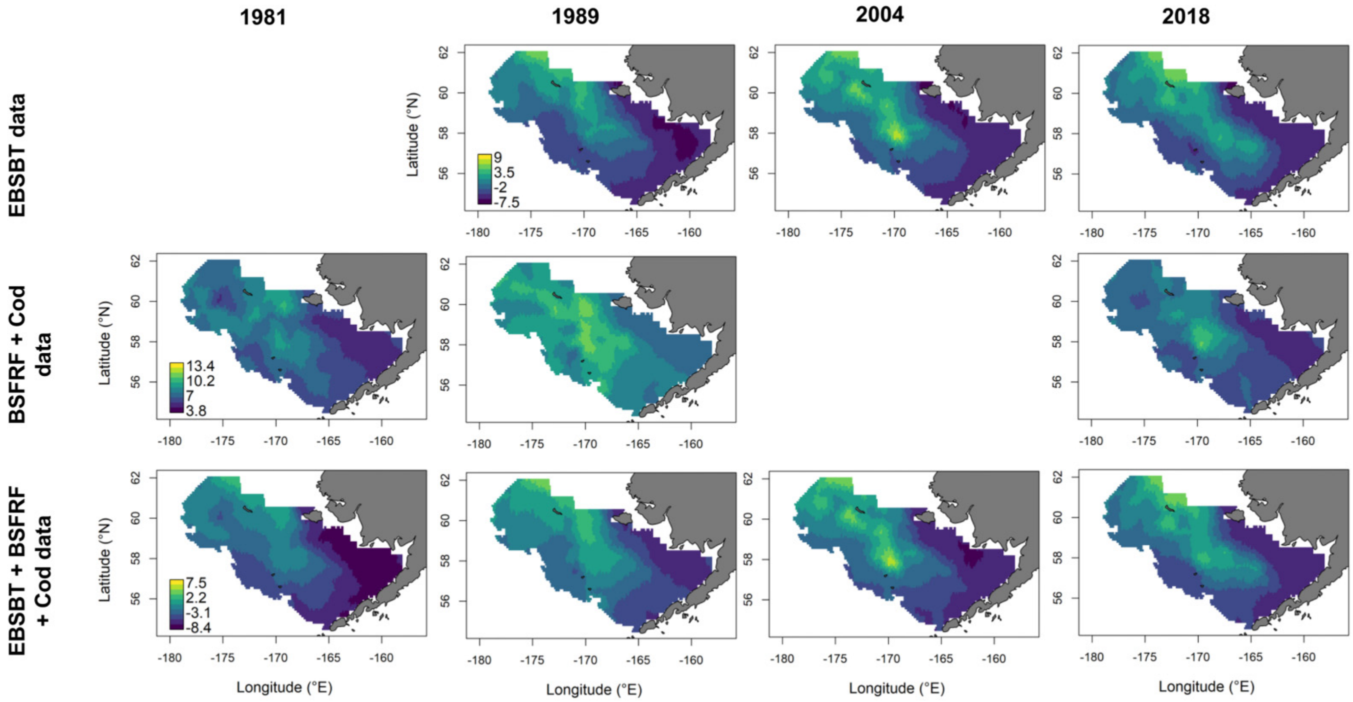
Fig. 6. Mean spatial patterns of juvenile snow crab (*Chionoecetes opilo*) density over the period 1981–2018 (in number of fish per km^2) and their associated standard errors (SEs) predicted by the vector autoregressive spatio-temporal (VAST) models fitted to research survey (EBSBT) data (top panels); industry-cooperative survey (BSFRF) data and Pacific cod stomach (Cod) data (middle panels); or EBSBT, BSFRF, and Cod data (bottom panels).



predicted spatial density patterns that resembled the spatial density patterns that one would have expected had the model been fitted only to reference data (Figs. 3 and 7). This result stems from the fact that, in the integrated model, information is shared between locations, years, and data sources, while the influence of the non-reference datasets is largely downweighted via their estimated spatially varying catchabilities. Moreover, in both case studies, the integrated model estimated indices that displayed less uncertainty and less interannual variability and agreed more with indices estimated with other tools than the model fitted to non-reference datasets. Therefore, the present study concurs with many other previous studies demonstrating the value of integrated spatio-temporal models to leverage the strengths of several data sources while correcting as much as possible for the weaknesses of the individual data sources (e.g., Grüss and Thorson 2019; Pinto et al. 2019; O'Leary et al. 2020, 2022; Monnahan et al. 2021; Rufener et al. 2021; Thompson et al. 2022).

In the juvenile snow crab case study, convergence was possible for the spatio-temporal model fitted to the combined BSFRF-Cod dataset only when the spatio-temporal variation term in the second linear predictor was turned off. This result is because in the model fitted to the BSFRF-Cod dataset, the BSFRF dataset is defined as the reference dataset (in the absence of EBSBT survey data), but the BSFRF dataset includes around 62 times fewer observations than the Cod dataset (390 versus 24 146). With such a great imbalance of observations between the BSFRF and Cod datasets, the spatio-temporal model struggled to estimate a fishing-power ratio for the Cod

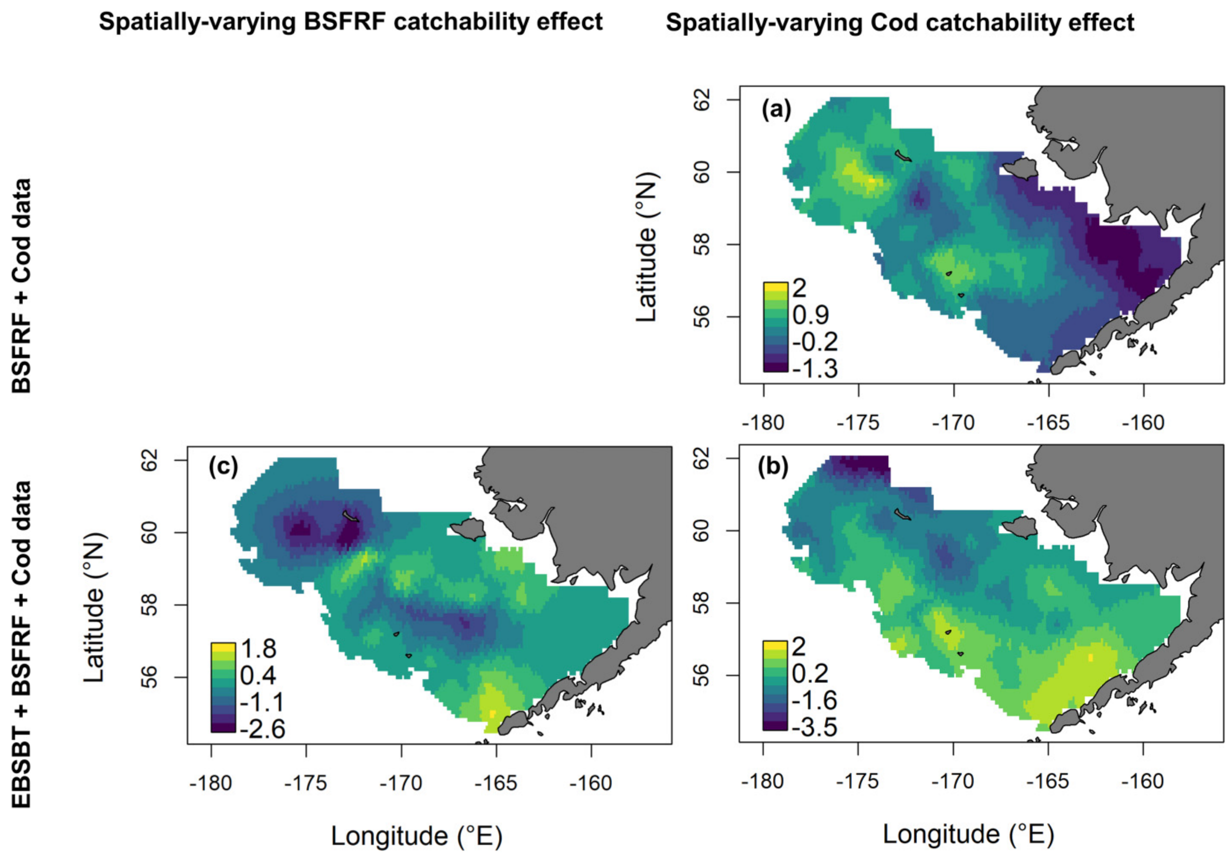
Fig. 7. Spatial patterns of juvenile snow crab (*Chionoecetes opilo*) density (in number of fish per km^2) in select years predicted by the vector autoregressive spatio-temporal (VAST) models fitted to research survey (EBSBT) data (top panels); industry-cooperative survey (BSFRF) data and Pacific cod stomach (Cod) data (middle panels); or EBSBT, BSFRF, and Cod data (bottom panels). Note that data were for a shorter time-period when using EBSBT data only, while there were no BSFRF or Cod data for 2004, hence the absence of map in some panels.



dataset and, therefore, needed to be simplified. We faced similar issues in a recent unpublished study for the NZ EEZ. In that unpublished study, we attempted to fit a spatio-temporal model to 12 different bottom trawl research survey datasets and the observer program, the CHAT MD survey dataset was defined as the reference dataset, and a fishing-power ratio was estimated for the 11 other research survey datasets and the observer dataset. There were around 40 times fewer observations in the CHAT MD survey dataset than in all non-reference datasets combined, and the integrated model (that included both spatial and spatio-temporal variation terms in the two linear predictors) did not converge (results not shown here and not published). We recommend that future studies seek ways to make integrated models converge when there is a substantial imbalance between the reference and non-reference datasets.

The main novelty of the present study consisted of accounting for multiple data sources in an integrated spatio-temporal model via the estimation of spatially varying catchabilities for the non-reference datasets rather than a monitoring program catchability factor. It would be useful for future studies to further evaluate our integrated spatio-temporal modelling framework with a simulation experiment. This simulation experiment would allow for an understanding of the performance of our integrated spatio-temporal modelling framework in terms of accuracy, error, and confidence interval coverage (Grüss and Thorson 2019; Grüss et al. 2019; Ducharme-Barth et al. 2022; Charsley et al. 2023). In addition, future studies should run comparisons of integrated spatio-temporal models, including spatially varying catchability terms versus a monitoring program catchability factor. Such comparisons would identify the situations where the use of spatially varying catchability terms is feasible (i.e., allows for a converged model) and leads to increased model performance (in terms of precision, accuracy, and(or) confidence interval coverage). It will be particularly important to understand whether the use of spatially varying catchability terms results in better confidence interval coverage, as a recent spatio-temporal modelling study reported no improvement in confidence interval coverage with an integrated model accounting for multiple data sources via a monitoring program catchability factor (Grüss and Thorson 2019). Future studies could also investigate the consequences of defining alternative data sources (e.g., alternative research surveys and(or) observer programs) as the reference dataset in our integrated modelling framework to better understand the downweighting at play with the estimated spatially varying catchabilities (Alglave et al. 2022). Moreover, our spatio-temporal models included a spatially varying catchability term only in the first linear predictor, as our modelling framework is an expansion of the modelling framework developed in Grüss and Thorson (2019), which includes a monitoring program catchability factor only in the first linear predictor. In addition, preliminary analyses revealed that the inclusion of a spatially varying catchability term in both the first and second linear predictors resulted in a net spatially varying catchability effect (the sum of the spatially varying catchability effects for the first and second

Fig. 8. Spatially varying catchability effects estimated by the vector autoregressive spatio-temporal (VAST) models for juvenile snow crab (*Chionoecetes opilo*) fitted to (*a*) a combination of industry-cooperative survey (BSFRF) and Pacific cod stomach (Cod) data or (*b*–*c*) a combination of research survey (EBSBT), BSFRF, and Cod data.

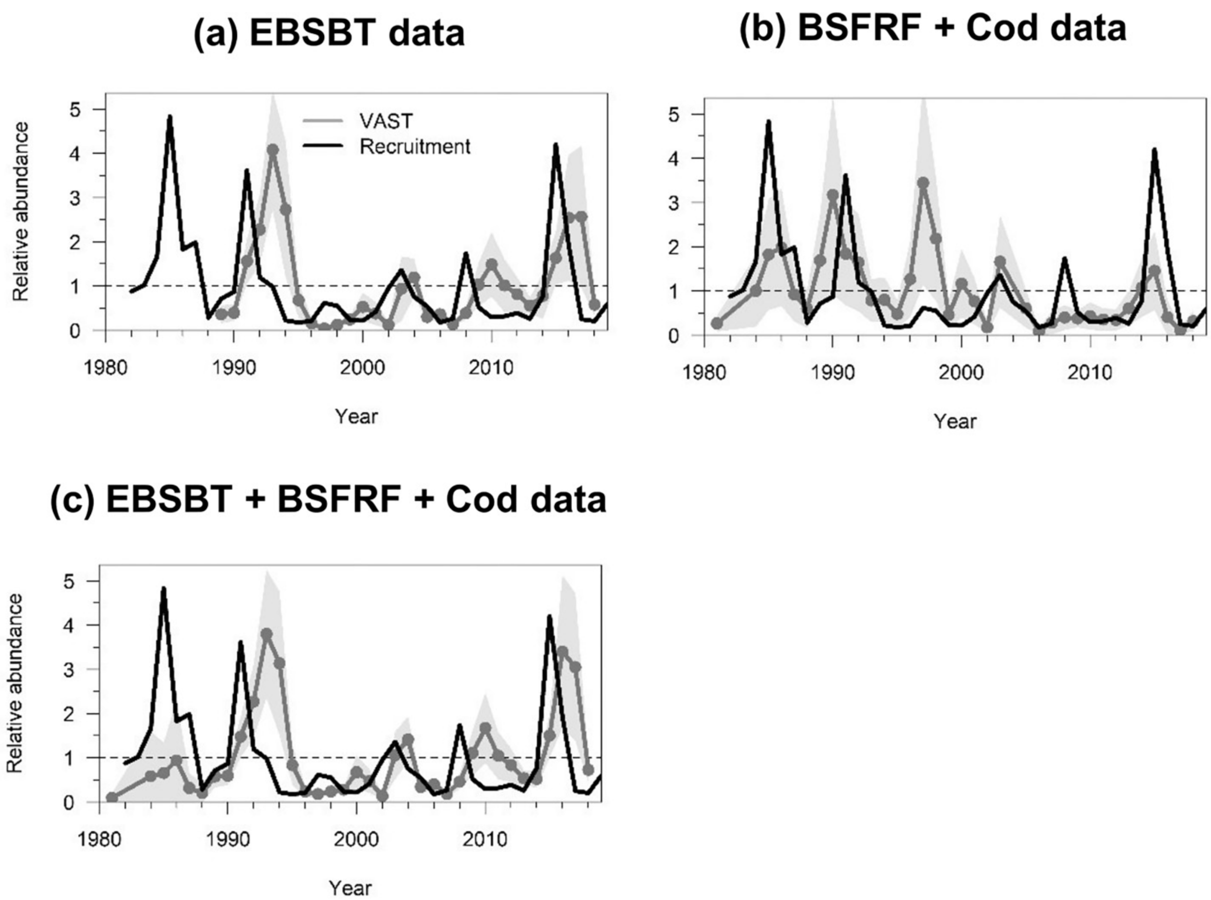


linear predictors) that was virtually similar to the spatially varying catchability effect for the first linear predictor (results not shown). That being said, future studies could further investigate the impacts of including a spatially varying catchability term in both the first and second linear predictors. Finally, while Rufener et al. (2021) found that accounting for preferential sampling had negligible impacts on the predictions of their integrated spatio-temporal models, two other studies (Pennino et al. 2019; Alglave et al. 2022) found that modelling preferential sampling was warranted when integrating research survey data and fisheries-dependent data (e.g., spatially referenced logbook data). Therefore, we recommend further research regarding the representation of preferential sampling in integrated spatio-temporal models.

The integrated spatio-temporal models implemented in this study did not include any environmental or other density covariates. However, the spatial and spatio-temporal variation terms of spatio-temporal models account for various unmeasured processes that influence fish densities (Shelton et al. 2014; Thorson et al. 2015; Ono et al. 2018). Future studies could evaluate the impacts of including alternative environmental covariates (e.g., bottom temperature, bottom dissolved oxygen concentration) in our integrated modelling framework on the accuracy and precision of spatial predictions (Pacifici et al. 2017; Simmonds et al. 2020; O'Leary et al. 2022). This future research would be particularly interesting for snow crab, as it was found that snow crab prefer the coldest parts of the EBS Middle and Outer Shelves and that in warm years shifts in the distribution of Pacific cod to those specific areas of the EBS enhances snow crab predation mortality (Liu 2019). Future versions of our integrated modelling framework, including environmental covariates, would also be useful to better understand distribution shifts in fish stocks in relation to environmental changes. Studies investigating distribution shifts have typically relied on data collected by one specific monitoring program (e.g., Dulvy et al. 2008; Nye et al. 2009; Thorson et al. 2017). Data permitting and revisiting these studies using multiple data sources may result in more accurate and more precise information for habitat managers.

In conclusion, we developed an integrated spatio-temporal model that, by estimating spatially varying catchabilities for the least reliable data sources (the non-reference datasets), downweights their influence in model inferences. Integrated models allow for the generation of annual density maps for a longer time-period and for the provision of one single index to stock assessments rather than multiple indices (each usually covering a shorter time period). When fisheries analysts fit a model to integrated data, we recommend that they also fit another model to survey-only data, provided that enough research survey data are available, and evaluate the indices

Fig. 9. Indices of relative abundance for juvenile snow crab (*Chionoecetes opilo*) predicted by the vector autoregressive spatio-temporal (VAST) models fitted to (*a*) research survey (EBSBT) data, (*b*) industry-cooperative survey (BSFRF) data and Pacific cod stomach (Cod) data, or (*c*) EBSBT, BSFRF, and Cod data. Also shown in all panels is the total recruitment time series estimated by the 2019 eastern Bering Sea snow crab assessment model (Szuwalski 2019).



resulting from the two models to retain the most plausible one according to experts' opinion. We also recommend that future research keep exploring the potential and performance of the integrated modelling framework developed in this study, particularly by running comparisons with simpler integrated models, including a monitoring program catchability factor in lieu of the spatially varying catchability terms. Finally, we encourage future applications of our integrated modelling framework to seek to integrate research survey data with commercial CPUE data, as well as to leverage more predators as samplers in integrated models, which currently constitute a fairly untapped data source in fisheries science studies (Hatch and Sanger 1992; Ng et al. 2021).

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Data availability
The research survey data for the Chatham Rise case study are the property of Fisheries New Zealand and can be obtained via an email to rdm.sharedrdm@mpi.govt.nz.
The observer data for the Chatham Rise case study are confidential and, therefore, cannot be shared.
The research survey data for the eastern Bering Sea (EBS) case study can be obtained via an email to james.thorson@noaa.gov.
The Bering Sea Fisheries Research Foundation (BSFRF) data used in the EBS case study can be obtained via an email to sgoodman@nrccorp.com.
Finally, the stomach content data (Cod data) used in the EBS case study are available for download at https://access.afsc.noaa.gov/REEM/WebDietData/DietDataIntro.php.

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Supplementary material

Supplementary data are available with the article at https://doi.org/10.1139/cjfas-2023-0051.

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