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# Using the best of two worlds: A bio-economic stock assessment (BESA) method using catch and price data

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## Abstract

Reliable stock assessments are essential for successful and sustainable fisheries management. Advanced stock assessment methods are expensive, as they require age- or length-structured catch and detailed fishery-independent data, which prevents their widespread use, especially in developing regions. Furthermore, modern fisheries management increasingly includes socio-economic considerations. Integrated ecological-economic advice can be provided by bio-economic models, but this requires the estimation of economic parameters. To improve accuracy of data-limited stock assessment while jointly estimating biological and economic parameters, we propose to use price data, in addition to catches, in a new bio-economic stock assessment ('BESA') approach for de-facto open access stocks. Price data are widely available, also in the Global South. BESA is based on a state-space approach and uncovers biomass dynamics by use of the extended Kalman filter in combination with Bayesian estimation. We show that estimates for biological and economic parameters can be obtained jointly, with reliability gains for the stock assessment from the additional information inherent in price data, compared to alternative assessment methods for data-poor stocks. In a real-world application to Barents Sea shrimp (*Pandalus borealis*, Pandalidae), we show that BESA benchmarks well also against advanced stock assessment results. BESA can thus be both a stand-alone approach for currently unassessed stocks as well as a complement to other available methods by providing bio-economic information for advanced fisheries management.

KEYWORDS
Bayesian estimation, data-poor, Kalman filter, open access, state space modeling

## 1 | INTRODUCTION

Fisheries contribute critically to global food security (FAO, 2018). To make the most of valuable marine resources, it is crucial to maintain stocks at sustainable levels. Careful optimism is spreading: there is evidence that science-based management can enable sustainable fisheries (Fernandes & Cook, 2013; Hilborn & Ovando, 2014; Rosenberg et al., 2018; Zimmermann & Werner, 2019). However, there is also a divergence between scientifically assessed stocks, which are often at healthy levels or rebuilding, and unassessed stocks, which represent the majority of global fish stocks but are frequently unregulated and declining (Costello et al., 2012; Worm et al., 2009). Fisheries stock assessment is described by Maunder and Punt (2004) as 'estimating the parameters of some form of population dynamics model by fitting it to research and monitoring data'. The goal is to quantify the historic development and current status of a stock to guide managers, policy-makers and stakeholders, and to inform bio-economic modelling (e.g. Froese et al., 2011; Lancker, Fricke, & Schmidt, 2019; Nielsen et al., 2018), ultimately contributing to sustainable resource management (Kroetz et al., 2022). However, where insufficient resources for monitoring result in lack of reliable data and stock assessments, continued over-harvesting or inefficient, over-precautionary management may prevail. Both represent a threat to food security and a substantial cost to society, and highlight the need for reliable and affordable stock assessment methods.

Managing fisheries is all about managing people (Hilborn, 2007). Successful fisheries management relies on a combination of information on fish ecology and information on economic incentives that steer fishing activities (Costello et al., 2010; Lubchenco et al., 2016). Ideally, biological and economic parameters are estimated in a coherent framework. However, socio-economic considerations have rarely been included in stock assessments (Chan et al., 2022).

State-of-the-art stock assessment approaches have become increasingly demanding in terms of data and computational power. Based on classic concepts of surplus production (Schaefer, 1954) and age-structured models (Baranov, 1918; Beverton & Holt, 1957), advanced assessment models integrate a wide range of biological and fisheries data (Maunder & Punt, 2013). This includes biological information such as age, length and maturity, requiring data from scientific surveys and observer programs that are costly to obtain. This is a valuable investment, though: monetary investment into assessment and management systems are among the most influential determinants for successful fisheries management (Melnychuk et al., 2017). However, given limited resources and the large number of global fish stocks, it is not everywhere affordable. This includes areas of the world where fisheries resources are particularly important for food security and sustainable livelihoods.

Accordingly, considerable efforts have been made to develop stock assessment methods that can produce stock indicators and reference points from minimal data requirements. Catch time series are routinely collected for many stocks, including in developing countries, and used by most stock assessment methods. Catch-only methods provide a low-cost approach to derive latent stock assessments for data-poor stocks. For example, the CMSY method and its predecessor Catch-MSY (Froese et al., 2017; Martell & Froese, 2013) identify biological parameters from harvest data and parameter priors alone by use of a Monte Carlo approach. In this approach, intrinsic growth rate and carrying capacity combinations are drawn randomly from a given range and combined with harvest observations to produce a biomass time series by iterating forward a surplus production model. Each combination is kept or discarded, based on whether its biomass time series stays within pre-assumed feasible ranges. CMSY and Catch-MSY are widely used for global stock assessments (Costello et al., 2016), were shown to perform reasonably well and to benchmark well against peers such as SSCOM and COMSIR (Thorson et al., 2013; Vasconcellos & Cochrane, 2005), in some cases even against length-based methods (ICES, 2014; Rosenberg et al., 2014).



The information that can be gained from catch data alone remains, however, limited, especially when time series are short or lack contrast. To improve stock estimates and meet objections that methods based on catch data only are prone to inaccurate or biased estimates (Free et al., 2020), many approaches have been proposed that complement catch data with other sources of information, including length frequencies (Hordyk et al., 2014; Kell et al., 2022; Rudd & Thorson, 2018), life-history traits (e.g. Anderson et al., 2017; Branch et al., 2011; Costello et al., 2012; Froese et al., 2017; Martell & Froese, 2013; Thorson et al., 2013), selectivity (Winker et al., 2020) or standardized catch per unit effort (CPUE) (Pedersen & Berg, 2017; Winker et al., 2018). Standardized stock indices, often based on commercial CPUE, also complements catch data in bio-economic state space models (Aeberhard et al., 2018; Auger-Méthé et al., 2021; Ekerhovd & Kvamsdal, 2017; Froese et al., 2017; ICES, 2020; Kvamsdal & Sandal, 2015; Meyer & Millar, 1999; Millar & Meyer, 2000; Winker et al., 2018 provide overviews of these methods). These data-limited assessment methods are valuable avenues to uncover latent information about stock size and parameters, although their performance varies and may depend on the specific stock (Bouch et al., 2020; Pons et al., 2020). Still, the required quantity and quality of data for most of these methods is still substantial, as there are many cases where standardized CPUE or length frequency data are not available or of insufficient quality. Moreover, none of these methods is able to seamlessly provide the economic information required for bio-economic fisheries advice or management strategy evaluation (Nielsen et al., 2018).

In this paper, we present a new bio-economic stock assessment (BESA) approach that utilizes an alternative source of time-series data—namely prices—in addition to catch data. While economists have long studied the relationship between price and resource abundance (Hotelling, 1931), and while the value of price data for inference on stock status has been recognized before (Marvasti & Dakhlia, 2021; Pinnegar et al., 2006; Smith et al., 2017), to the best of our knowledge, no price-reliant stock assessment method is currently used. The paper closest to ours is that of Marvasti and Dakhlia (2021); it shows by use of multivariate time-series analyses that price data, combined with per-trip-landings, is useful to assess biomass development level. Being able to use the additional information inherent in prices may provide an improvement comparable to including standardized indices in an assessment model, producing more reliable stock assessment estimates solely on readily available catch and price data. Furthermore, there is a need for stock assessment methods that integrate biological and economic information and, hence, enable modern fisheries management that takes economic objectives into consideration.

Price data comes with three advantages. First, it is widely available: Many regional fisheries management organizations collect time series, and the FAO provides export prices in its "Global Fisheries and Aquaculture Commodities" dataset for thousands of fisheries world-wide. Second, prices are intensive quantities: A small sample of observations provides reliable information on the entire market, whereas catch is an extensive quantity, such that comprehensive observations are required. Third, prices provide additional information on stock status. Price variation partly comes from exogenous drivers for fish demand, such as income, market access or substitute availability, as well as from integration with global markets (Asche et al., 1999; Bronnmann et al., 2020). This exogenously induced variation constitutes an additional source of information on stock development in open-access settings, where fishers respond to economic profitability. If prices are high, fishers have an incentive to keep up fishing effort even if the stock declines and thus harvesting costs increase. This is the relationship between price and biomass size that we exploit for BESA.

In a nutshell, the method presented here works as follows: BESA essentially relies on a Schaefer (1957) type model in both components, the biological surplus production model with logistic growth and the economic harvesting cost function, which is linear in harvest and inversely proportional to fish population biomass. Using the log-linearized zero profit condition as the measurement equation, we uncover biomass dynamics by use of the extended Kalman filter and Bayesian estimation. Our approach thus integrates economic and ecological aspects of the fishery, based on a most well-known fishery model. We provide the R code necessary for easy implementation alongside this manuscript. A major contribution is that this method allows for simultaneous estimation of both biological and economic parameters. BESA can thus provide the basis not only for maximum sustainable yield management but also inform managers about the maximum economic yield as an alternative management goal. The approach identifies the intrinsic growth rate, the carrying capacity, the cost parameter, as well as the time series of fish stock sizes. We test BESA on simulated data. We find that it provides reliable estimates also in comparison to a catch-data-only state-of-the-art approach, namely CMSY (Froese et al., 2017). Furthermore, we use a rare example of a stock with official stock assessment but without a management plan or total allowable catch—northern shrimp in the Barents Sea (*Pandalus borealis*, Pandalidae)—to benchmark our method in a real-world application. The example code is available at Github: https://github.com/klancker/BESA.git.

## 2 | MODEL

### 2.1 | Data generating processes

Our analysis is based on the classical bio-economic fishery model of Gordon (1954) and Schaefer (1957). It describes the dynamics of fish biomass $B_t$ in discrete time $t$ running from 1 to $T$ (a typical time step from $t$ to $t+1$ is 1 year), depending on biological parameters $r$ (intrinsic growth rate) and $K$ (carrying capacity), and on catches $H_t$. As in reality, fish population dynamics are not deterministic, we include log-normally distributed, unit mean stochastic shocks $\exp(\eta_t)$ on stock biomass in a way that is standard in the bio-economic literature (Costello et al., 2008; Reed, 1979):

$$B_{t+1} = \exp \eta_t \left( B_t + rB_t \left( 1 - \frac{B_t}{K} \right) - H_t \right). \tag{1}$$

The key issue is that biomass $B_t$ is not directly observable. It needs to be estimated from observable data, including observations on total catch $H_t$.

The incentives for fishers to fish depend on revenues, that is price times harvest $P_t H_t$, relative to the costs of harvesting. As in the Gordon-Schaefer framework adopted here, the catch per unit of effort is linear in fish biomass. Furthermore, we adopt the assumption that the cost for an additional unit of effort is constant, such that fishing costs $C_t$ are proportional to the quantity harvested, $H_t$, and inversely proportional to fish biomass $B_t$, as shown in (2). (Under some further standard economic assumptions, the exponent on biomass in the cost function would correspond to the exponent on biomass in a Schaefer type harvest function (Lancker, Fricke, & Schmidt, 2019), where it is often assumed to be unity.) Thus, consistent with the Gordon-Schaefer model, marginal costs per unit of effort are constant (and hence equal to average cost). All else equal, each unit of harvest costs the same amount, and due to search efforts, fishing from a large stock is less costly than fishing from a farther depleted and therefore smaller stock. In addition to this theoretical argument, the inverse relationship between fishing costs and biomass is supported by empirical findings for different species, even though the strength of the relationship seems to depend on schooling behavior (e.g. Bjørndal, 1987; Ekerhovd & Gordon, 2013;

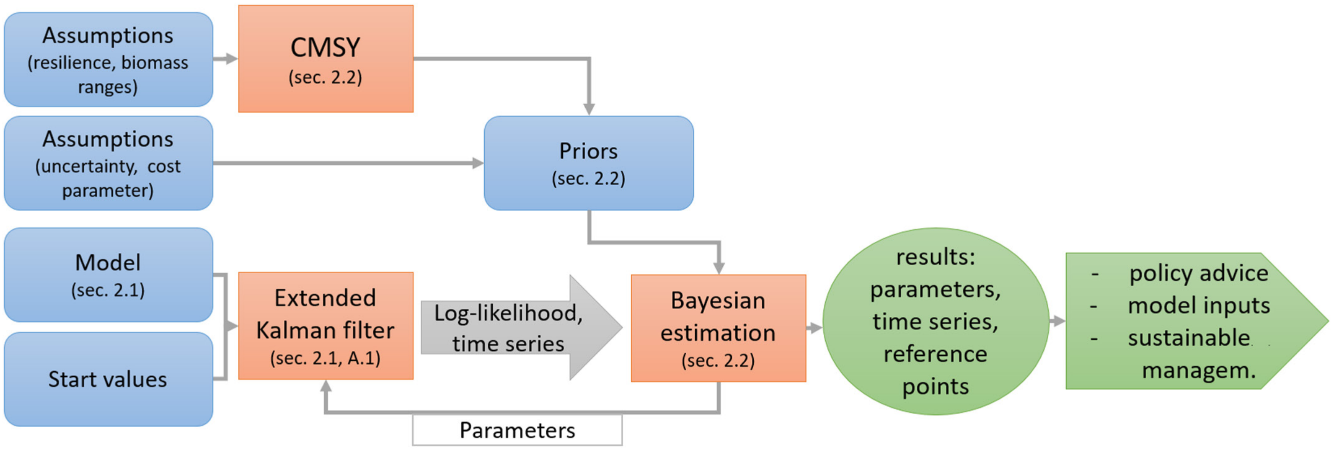


**FIGURE 1** Flow chart illustrating BESA workflow.

Lancker, Fricke, & Schmidt, 2019; Tahvonen et al., 2018). The proportionality constant is composed of two parts, a constant $c > 0$ and a stochastic part $\exp(\epsilon_t)$, which is assumed to be log-normally distributed with unit mean. This stochastic part captures shocks on harvesting costs, for example due to variable weather or economic conditions (Lancker, Deppenmeier, et al., 2019).

Finally, under conditions of open access, profits are driven to zero, which is the case if the price is equal to the marginal cost for harvesting an additional unit of fish as shown in (3),

$$C_t = \frac{\exp(\epsilon_t)\,c}{B_t} H_t, \tag{2}$$

$$P_t = \frac{\exp(\epsilon_t)\,c}{B_t}. \tag{3}$$

Condition (3) captures the feedback of fishing incentives on fish biomass in a commercial fishery (Smith, 1969). It is due to this feedback that fish prices can provide information on fish biology. Under open access, fishers have an incentive to harvest the fish biomass down to the level where the marginal cost is equal to the fish price. We assume that effort adjusts fast enough such that this market equilibrium condition holds in each period. According to Condition (3), the fish price is a signal for biomass, but due to environmental and economic stochasticity, this signal is noisy. By our assumptions on the error term, the distribution of marginal costs (i.e. the right hand side of 5) in levels is right-tailed. In other words, in years where a profit is made, this profit is on average smaller than the loss in loss years. We could for example interpret this as a slightly more sluggish reaction to exit the market than to enter the market or extend fishing activities when profits are above zero.

While prices and biomass result endogenously from the dynamic equations given a harvest time series, the harvest time series itself is generated outside of our model set-up (exogenous), for example given some kind of demand equation. This is intentional: while we use the harvest observations, we do not need to know the data generating process behind the harvest data.

To derive actual estimation equations, we consider log-biomass $\beta_t = \ln(B_t)$. We follow the literature (Millar & Meyer, 2000; Winker et al., 2018) and formulate the state equation in terms of the depletion rate in logs $\chi_t = \ln(B_t/K_t) = \beta_t - \ln(K)$. The state equation with normal error $\eta_t \left(\eta_t \sim \mathcal{N}\left(0, \sigma_\eta^2\right)\right)$ then reads:

$$\chi_{t+1} = \ln((1+r)\exp(\chi_t) - r\exp(2\chi_t) - H_t/K) + \eta_t \quad \text{(state equation).} \tag{4}$$

We furthermore use the logarithm of the zero profit Condition (3), with normal error $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, as measurement equation. Denoting the log of fish price by $p_t = \ln(P_t)$, we have:

$$p_t = \ln c - \chi_t - \ln(K) + \varepsilon_t \quad \text{(measurement equation).} \tag{5}$$

This model serves as input to the extended Kalman filter as a next step (see Figure 1). In reality, we can observe price $P_t$ and catch $H_t$ time series, but log depletion $\chi_t$ and log biomass $\beta_t$ are unobserved. The means of depletion, denoted by $x_t$, and corresponding variances $Z_t$, can be estimated ("filtered") from the available data by the (extended) Kalman filter (Kalman, 1960). We explain it in detail in the Appendix S1: Section A.1.

## 2.2 | Estimation by means of log-likelihood based Bayesian estimation

As a second step, to estimate the cost parameter $c$, intrinsic growth rate $r$, carrying capacity $K$, process and observation noise standard errors $\sigma_\eta$ and $\sigma_\varepsilon$, the expected starting value for depletion $x_1$, and its variance $Z_1$, we embed the extended Kalman filter and the resulting log-likelihood in a Bayesian estimation framework (see Figure 1). To reduce dimensionality, a 'concentrated log-likelihood' could be used, allowing estimation of the ratio of the error variances ('signal-to-noise-ratio') instead of each error variance separately (Durbin & Koopman, 2012, p. 36). However, we did not observe benefits in the estimation of our model using this alternative. Let $T$ be the number of periods in the dataset, $v_t$ be the residual of the measurement equation, and $F_t$ its variance. Then, the log-likelihood for this model is (Durbin & Koopman, 2012, p. 171):

$$L = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln\left(F_t\right) + \frac{v_t^2}{F_t}\right). \tag{6}$$

We opt for combining the Kalman filter with Bayesian estimation of the parameters. (In theory, the parameters could be estimated via frequentist Maximum Likelihood estimation directly from the Kalman filter. However, we found that maximizing the log likelihood did not lead to stable results—different estimates were obtained when starting from different initial guesses. On the other hand, we found direct Bayesian estimation without the imposed structure granted by the Kalman filter to lead to weak convergence of chains.) We run a Hamiltonian Monte Carlo Markov Chain Monte Carlo sampler using the Stan software (Stan Development Team, 2022b), called from R (version 4.0.4) via the rstan package (Stan Development Team, 2022a). For each stock, we run 8 chains across 20,000 samples, using 6000 iterations for warm up and a thinning parameter of 5. For a better numerical performance, some parameters, such as $K$, are transformed in estimation for a better centring.

We use generic priors for a following synthetic dataset application and as a starting point for real applications of BESA. Naturally, for non-synthetic stocks, our prior assumptions should ideally be replaced by assumptions based on any available prior knowledge, such as from similar fisheries or stocks elsewhere. Priors for $r$ and $K$ are chosen using the CMSY method (Froese et al., 2017). CMSY uses a Monte Carlo approach to obtain a distribution of viable $r$ and $K$ pairs based on the rationale that the correct combination of parameters, in conjunction with observed landings, will lead to a biomass trajectory that starts and ends within applicable ranges and does not go extinct or overshoot. We run CMSY assuming that the resilience class of the stock is known, that starting and mid-year depletion lies between 0.2 and 0.8, and final depletion between 0.2 and 0.6. We then use the distributions of viable $r$ and $K$ combinations to construct means and standard deviations for log-normal $r$ and $K$ priors for BESA, following the methods outlined in Froese et al. (2017). For the starting depletion (in levels), we use prior $\exp\left(x_1\right) \sim \beta(4.56,4.56)$, which gives a symmetric distribution with mean 0.5% and 95% confidence interval limits at 0.2 and 0.8, thus corresponding to our input to CMSY. For $c$, we use a relatively uninformative log-normal prior with a mean constructed from the observation equation at instance 1 inserting the prior means for the other parameters, and standard deviation 1. For process and observation errors, we assume flat normal priors with mean 0.5 and standard deviation 1. Finally, for $Z_1$, we use a log-normal distribution with mean 0.01 and standard deviation 1. We report expected values of log-normal posterior distributions for $c$, $r$, $K$, level depletion and biomass values, and simple means for $\sigma_\varepsilon$, $\sigma_\eta$ and $Z_1$, as well as the 95% highest density Bayesian credible intervals as a measure of variation.

The R code that implements BESA given price and harvest data is provided on Github, together with a synthetic example for easy comprehension and use.

### 2.3 | Computation of reference points

We compute maximum sustainable yield (MSY) and maximum economic yield (MEY) as reference points to explore different uses of BESA in supporting management decisions. For MEY, we compute the maximum yield that can be caught on a sustained basis as $rK/4$. Furthermore, in this study, we use a static version of the maximum economic yield MEY under the constraint that biomass growth equals harvest, that is that this yield can be sustained. The inverse demand function necessary to compute MEY, that is the relationship between the price consumers face and aggregate demand which must equal harvest, can for example be assumed as a log-linear, iso-elastic function. This function can then be estimated from the available harvest and estimated biomass data. The computation is detailed in Appendix S1: Section A.2.

## 3 | DATA

### 3.1 | Generation of simulated data

To test our model under conditions where parameter values are known, we create a simulated data-set of biomass, harvest and price time series. The simulation follows (4) and (5), which describe biomass dynamics and supply. To close the system for the sake of simulating not only price and biomass, but also harvest, we assume that inverse demand is an iso-elastic function of harvest. In logs, the equation reads:

$$p_t = \overline{p} - \nu\ln\left(H_t\right) + \varphi_t, \tag{7}$$

with $\varphi_t \sim \mathcal{N}(0,0.01)$, such that the price ranges with 95% probability between 18% lower and 22% higher than the model value.

We create a dataset which contains a variety of 500 "stocks" with a range of perceivable biological and economic parameters, where one "stock" is made up of a unique parameter combination and time series of harvest, prices and biomass across $T=50$ observations. For biological parameters, we largely follow Froese et al. (2017). We normalize carrying capacity $K$ to 500, and draw from four categories of resilience with category mean and standard deviation for $r$ as given in Table 1. Froese et al. (2017) assume a log-normal error on logistic biomass growth with standard deviation 0.2. For comparability, we choose $\sigma_\eta$ such that the variance of $B_{t+1}$ at maximum sustainable yield equilibrium is approximately the same as in Froese et al. (2017). Since our error acts on period $t+1$ biomass instead of growth, this means that we choose a standard deviation for each resilience scenario corresponding to its mean $r$ (see Table 2) in order to mirror the matching of resilience and standard error size.

Furthermore, we vary economic parameters on supply and demand sides (Table 1). Price flexibility $\nu$ is drawn from a beta-distribution, where we choose a median of 0.87 following Costello et al. (2016). We normalize the cost scaling parameter $c$ to 2 across stocks. To obtain different biomass dynamics, we vary the stable static equilibrium biomass $B_{eq}$, where harvest equals biomass growth, by varying demand scaling parameter $\bar{p}$. Furthermore, we vary direction and transition path length. The transition path length $l$ is defined as the percentage difference between zero and the equilibrium biomass for paths approaching from below, and between $K$ and the equilibrium biomass for paths approaching from above. For example, a transition path length $l=0.5$ means that the starting biomass is set at $B_1 = B_{eq} + 0.5(K - B_{eq})$. We let $l$ be equal to −0.75, −0.5, −0.25 and 0 with a 10% probability each and 0.25, 0.5 and 0.75 with a 20% probability each. This means that to be a bit closer to real world fisheries, we let the stock start above $B_{eq}$ with a higher probability than at or below $B_{eq}$. Finally, we (arbitrarily) choose $\sigma_{\varepsilon}=0.05$, such that the 95% error range lies approximately within ±10% of the model value. We explore sensitivities for both observation and process error later in Appendix S1: Section A.6.

Figure 2 summarizes the simulated dataset. The overall average mean (median) fishing mortality lies at 0.24 (0.17).

## 3.2 | Real data for the case study

To benchmark our method, we use a rare example of a fish stock that is regularly assessed but is to date not regulated through a total allowable catch and can be characterized as open access: northern shrimp in the Barents Sea (ICES Subareas 1 and 2; Hvingel & Zimmermann, 2023). We obtain annual data (1977–2021) on catches (in kilotons) and prices (Norwegian Kroner NOK per kg; Norwegian Directorate of Fisheries, 2022), which we deflate using the Norwegian consumer price index (CPI) (Statistisk Sentralbyrå (Statistics Norway), 2022). Prices are ex-vessel unit prices of frozen shrimp landed by the offshore fleets in Norway, obtained as the ratio of values and harvest, which are aggregated over all landing events at landings sites in Norway. Figure 6 in Appendix S1: Section A.3 shows the development of harvest and prices over time. A naive (i.e. ignoring potential simultaneity) linear regression of log price on log harvest shows a negative not significant relationship; the standard deviation of the noise is 0.45, indicating that prices should carry harvest-independent information.

The stock is mainly fished by vessels from Norway, Russia and the EU. Although certain regulations limit parts of the fleet (e.g. bycatch regulations, licensing), there has been no agreed management plan and the fishery overall is not quota limited. Actual harvest has been consistently below estimated maximum sustainable yield and fell short of the scientifically recommended (but unimplemented) total allowable catch in 9 of 10 years between 2011 and 2020. We conclude that the fishery can be characterized as open access fishery.

We compare our results to annual stock size and parameter estimates from the benchmark SPiCT stock assessment, (ICES, 2022) which is based on the same catch data we use, as well as standardized catch per unit effort indices from the Norwegian fleet logbooks and scientific trawl-survey data from Russia and Norway. The assessment has previously been based on a state space framework and Bayesian methods (NAFO/ICES, 2020). In 2022, the stock assessment has been updated to an approach using surplus production model in continuous time (SPiCT) (ICES, 2022; Pedersen & Berg, 2017), which provided the estimates against which BESA was compared.

# 4 | RESULTS

## 4.1 | Synthetic data: Unbiasedness and reliability of BESA

We run BESA for 500 synthetic stocks with 50 observations each using the method described in Section 2. For 6 of the 500 stocks (1.2%), we found convergence issues, as for one or more parameters, $\hat{R}$ is above 1.1. $\hat{R}$ is a convergence diagnostic commonly used to assess convergence. It compares within- and between-chain estimates, and is larger than 1 if they do not harmonize. The value 1.1 is a commonly used threshold. More information can be obtained from the Stan manual. This indicates that chains mixed well for the remaining 494 stocks (98.8% of stocks). The mean number of divergent samples (435) is small relative to the effective sample size (>20,000).

We find that BESA produces reasonably unbiased results for its parameters, as well as for start and end depletion rates, biomass and maximum sustainable yield. To characterize unbiasedness, we use the point estimates' distance (e.g. $\hat{r}$) to the true value (e.g. $r$), known for the synthetic data, relative to the true value (e.g. $(\hat{r} - r) / r$), where a relative distance of 0 indicates that the estimate is accurate. The first row in Table 3 shows the median over BESA's point estimates' relative distance to the true value. The second row reports corresponding CMSY results for comparison. (We implement CMSY with the same information used and settings as described in Section 2.2, for comparability.) Figure 3 reports quantiles of the distribution of relative distance to the true value across 500 stocks (further details in Appendix S1: Section A.4).

| Parameter | $r_{high}$ | $r_{med.}$ | $r_{low}$ | $r_{v.low}$ | $\nu$ | $d$ | $\exp\chi_{eq}$ |
|---|---|---|---|---|---|---|---|
| Mean | 1.05 | 0.5 | 0.275 | 0.0575 | 0.87 | 0.7 | 0.5 |
| SD | 0.15 | 0.1 | 0.075 | 0.0142 | 0.16 | 0.18 | 0.1 |

TABLE 1 Prior distributions to create the simulated data-set for intrinsic growth rate $r$ (four resilience classes), price flexibility $\nu$ and equilibrium depletion $\exp\chi_{eq}$.

We can observe that the median deviations of estimates from true values are close to zero (comparable to CMSY results) for all parameters except $\sigma_\eta$, which is biased upwards. (Problems with correctly estimating process noise have been observed before also for Kalman filter maximum likelihood estimation. It has been suggested to "include additional information [...]" by taking the ratio of process and observation error variances to be known (Millar & Meyer, 2000). However, since we do not see severe spill-overs of this issue towards the estimation of other parameters, and since we do not consider the ratio of process and observation error variances to be reasonably known, we prefer to adhere to the approach at hand. Naturally, we caution against the use of BESA process error estimates in modelling or management.) We investigate systematic dependencies and sensitivities in Sections 4.2 and Appendix S1: Section A.6, and find that this issue is present in all runs, but much weaker for a somewhat larger true process variability and stocks with a higher *r*. It does not noticeably distort other results.

**TABLE 2** Synthetic dataset $\sigma_\eta$ assumptions for different resilience classes.

| High | Medium | Low | Very low |
|---|---|---|---|
| 0.107 | 0.052 | 0.028 | 0.0059 |

We find that BESA produces reliable results as shown in rows 3–6 in Table 3 that report the 5% and 95% quantiles of our relative distance indicator, and in Figure 3. BESA results scatter in a much smaller range around the ideal value of 0 compared to CMSY results, indicating that the additional use of price data leads to a higher probability to obtain results reasonably close to true values. Moreover, on average, 89% of true biomass values along the 50 time steps fall within the estimated 95% highest density Bayesian credible interval, and for 73% of stocks, all true values fall within that range. The true

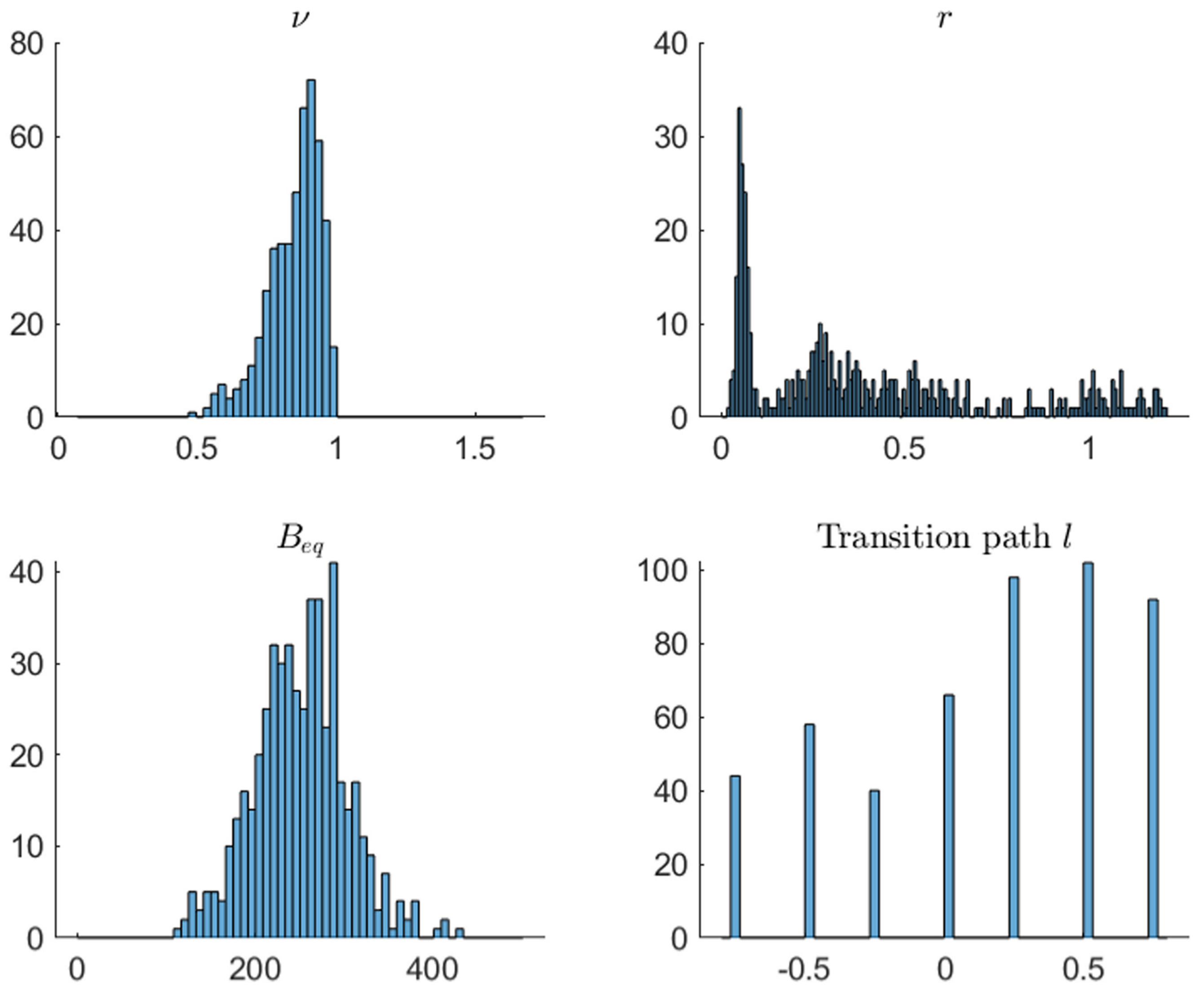


**FIGURE 2** Histograms summarizing the synthetic data-set (500 stocks) according to the main varying parameters demand price elasticity $\nu$, resilience class specific intrinsic growth rate $r$, equilibrium biomass $B_{eq.}$ and transition path length $l$ (negative values indicate a start from below equilibrium biomass).

**TABLE 3** Summary results for the synthetic dataset (500 stocks). The first two rows report the median relative distance of estimates from true values for BESA and CMSY. Rows 3–6 report the associated 5% and 95% quantiles of the relative distance. Rows 7–8 report median relative distance results for data-subsets (very low resilience class, and all other resilience classes). Rows 9–10 report results for the same dataset but based on only 30 observations per stock. Results are reported for cost parameter *c*, intrinsic growth rate *r*, carrying capacity *K*, observation and process standard errors $\sigma_\varepsilon$ and $\sigma_\eta$, start and end biomasses $B_1$ and $B_T$, MSY, MEY and corresponding MEY-biomass $B_{MEY}$.

| | $c$ | $r$ | $K$ | $\sigma_\varepsilon$ | $\sigma_\eta$ | $B_1$ | $B_T$ | MSY | $B_{MEY}$ | MEY |
|---|---|---|---|---|---|---|---|---|---|---|
| BESA, med. dist. | 0.03 | 0.02 | 0.06 | −0.01 | 0.22 | 0.00 | 0.03 | 0.06 | 0.06 | 0.05 |
| CMSY, med. dist. | | 0.04 | 0.05 | | | 0.04 | −0.02 | 0.06 | | |
| BESA, 5% quant. | −0.37 | −0.28 | −0.31 | −0.36 | −0.32 | −0.39 | −0.38 | −0.11 | −0.32 | −0.19 |
| BESA, 95% quant. | 0.84 | 0.53 | 0.62 | 0.33 | 2.08 | 0.87 | 0.80 | 0.30 | 0.58 | 0.36 |
| CMSY, 5% quant. | | −0.33 | −0.41 | | | −0.44 | −.55 | −0.19 | | |
| CMSY, 95% quant. | | 0.64 | 0.95 | | | 2.14 | 0.98 | 0.74 | | |
| Shortened timeframe ($n = 30$) | | | | | | | | | | |
| BESA, med. dist. | 0.03 | 0.04 | 0.07 | 0.00 | 0.34 | 0.01 | 0.02 | 0.08 | 0.07 | 0.05 |
| BESA, 5% quant. | −0.39 | −0.29 | −0.36 | −0.36 | −0.25 | −0.40 | −0.40 | −0.14 | −0.36 | −0.24 |
| BESA, 95% quant. | 0.95 | 0.57 | 0.76 | 0.45 | 3.90 | 0.94 | 0.73 | 0.43 | 0.69 | 0.46 |
| Resilience subgroups | | | | | | | | | | |
| $\text{BESA}_{r<0.1}$, med. dist. | 0.04 | −0.02 | 0.16 | −0.01 | 1.19 | 0.05 | 0.06 | 0.14 | 0.16 | 0.11 |
| $\text{BESA}_{r\geq 0.1}$, med. dist. | 0.03 | 0.03 | 0.04 | −0.01 | 0.08 | −0.02 | 0.01 | 0.05 | 0.04 | 0.03 |

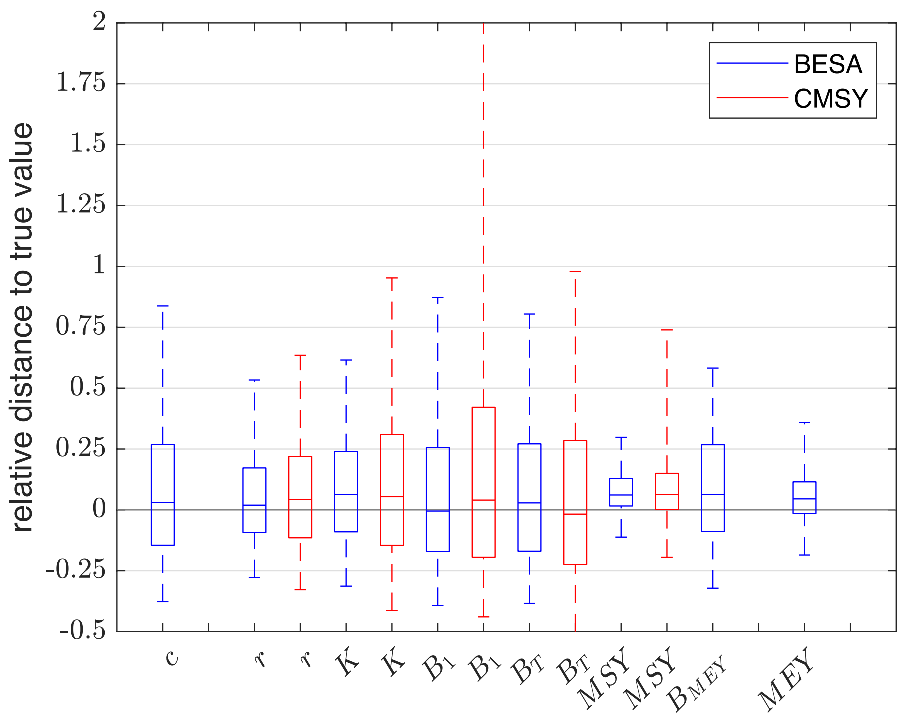


**FIGURE 3** Boxplot showing 5%, 25%, 50%, 75%, 95% quantiles of the relative distance to the true value distribution (shown in Figure 7 in Appendix S1) across 500 stocks, BESA in blue and CMSY in red. For cost parameter *c*, intrinsic growth rate *r*, carrying capacity *K*, start and end biomass $B_1$, $B_T$, maximum sustainable yield (MSY) and maximum economic yield biomass and harvest ($B_{MEY}$, MEY).

parameters *c*, *r* and *K* lie within the estimated 95% credible intervals in 90%, 80% and 77% of the cases. These numbers are lower compared with 84% (*r*) and 92% (*K*) for CMSY, but CMSY also relies on larger confidence intervals: For *r* (*K*), the average BESA confidence interval spans 0.19 (344) units, compared with 0.30 (743) for CMSY, again indicating a better efficiency gained by the additional use of price data.

There are economic parameter estimates that BESA can provide that do not find their CMSY counterpart in Figure 3. Foremost, we are able to estimate cost parameter *c* reliably.

Identification of parameter $c$ constitutes an important advantage when parameterizing bio-economic models for further prediction and scenario analysis. Moreover, it allows for the integration of socio-economic considerations in management. For example, it is possible to compute biomass and harvest producing maximum economic yield ($B_{MEY}$ and MEY) by use of BESA estimates, complemented with an estimate for the demand function, which we obtain by use of the BESA estimated biomass time series (see Section 2.3). The unbiased and very accurate estimate of MEY (see Figure 3 and Table 3) can be used to inform about contrast between the more biological MSY management approach and the more economic MEY approach, which also considers stock size effects on fishing costs.

We explore sensitivities concerning the robustness of unbiasedness and reliability concerning changes in error sizes in Appendix S1: Section A.6, and concerning a non-unity stock elasticity of harvesting costs with respect to biomass in Appendix S1: Section A.7. To explore unbiasedness of BESA for a lower number of observations, we run BESA over the original dataset, using only the first 30 instead of the full 50 observations. Results in rows 7–9 of Table 3, as well as the corresponding box-plot of relative distance from true value in Figure 8 (Appendix S1: Section A.5), show that results remain robust, even though the scattering range becomes wider.

Finally, we are interested in whether results depend systematically on certain parameter choices. Anecdotally, we find for our main synthetic dataset that results for the group of stocks with very low resilience differ from the results across all other groups (see rows 10–11 in Table 3), in particular concerning $K$ and $\sigma_\eta$.

## 4.2 | Synthetic data: Systematic dependencies

To analyze particular strengths or weaknesses with respect to certain stock characteristics, we explore visually how key results depend on the true intrinsic growth rate $r$, inverse demand elasticity $v$, and the ratio of starting to equilibrium biomass ($B_1/B_{eq}$). For the sake of this investigation, we draw a new set of 500 stocks following the previous procedure, except that for the respective variable of interest, we use a linear set of 5 values and draw 100 stocks for each value. We then use boxplots to visualize results. Varying $r$ linearly between 0.04 and 1.24, we find a tendency of CMSY to overestimate $MSY = rK/4$ for low resilience stocks (i.e. low $r$), which is partly inherited by BESA, though the bias is substantially reduced. Regarding the separate identification of $r$ and $K$, we do not find a monotonous relationship to resilience. Biases may stem from a tendency of CMSY to estimate $r$ towards the resilience class centres, as the bias is positive where $r$ values lie below the respective resilience class center, and vice versa. We do observe that biases in $r$ or $K$ from the CMSY procedure are inherited by BESA through priors, though they are dampened (see Figure 4). To observe absolute differences between true and estimated $r$, please consult the scatter plot in Figure 10 in Appendix S1: Section A.8.

We furthermore observe for very low $r$ values that MEY is overestimated and that variation in estimation accuracy is high. Finally, BESA's tendency to overestimate the process error standard deviation $\sigma_\eta$ seems strongly linked to a the estimation error for stocks with a low $r$. Hence, it is evident that BESA should not be used for stocks where the user suspects a very low intrinsic growth rate, such as certain sharks and rays. However, we presume that the share of the lowest resilience class in actual fisheries is smaller than in our main synthetic dataset (about 25%, following Froese et al. (2017)), and that most fished species have an intrinsic growth rate above $r = 0.1$. We conclude that use of BESA is valid for the typical area of application.

For $v$, we do not observe strong systematic dependencies (see Figure 11 in Appendix S1: Section A.8). The method seems well suited both for stocks with stronger or weaker price endogeneity. Concerning transition paths (see Figure 12 in Appendix S1: Section A.8), we observe a slight trend towards estimating a lower $K$ and a higher $r$ for stocks approaching $B_{eq.}$ from below as opposed to above. It is likely that certain patterns in biomass dynamics hamper BESA's ability to identify the two cleanly from each other, which is a common and known problem in surplus production models. We also observe a related positive tendency for MEY, and as we do not find a similar systematic tendency in demand function parameter estimates, we conclude that the systematic dependency in MEY likely results from that in $K$.

## 4.3 | Case study: Barents Sea shrimp

We report BESA results for Barents Sea shrimp, based on mean priors $r = 0.28$ and $K = 1{,}596$ created from CMSY with the assumption of resilience class 2 (low) (results where we input resilience class 3 (medium) instead are provided in Appendix S1: Section A.11), where in contrast to the synthetic runs, we use 0.5 and 0.95 as limits for start, end and intermediate biomass, based on expert knowledge. For the Stan run, we then use a corresponding prior for starting biomass. For prior and posterior density plots, please consult Figure 13 in Appendix S1: Section A.9. Table 4 shows that results between BESA and the SPiCT assessment are relatively close. BESA estimates a slightly larger MSY and a larger $K$ than under the SPiCT assessment, but confidence intervals overlap broadly. Uncertainty is high for carrying capacity estimates. Figure 5 shows that except for early years, BESA estimates similar stock sizes to the SPiCT assessment results. With a correlation coefficient between BESA and SPiCT estimates of 0.36, there is a positive though relatively weak correlation. Biomass is estimated to be slightly higher given the higher estimate for $K$ in most years. However, the difference is small relative to the typical size of uncertainty present in stock assessment estimates, and also visible in Figure 5. We show the development of depletion rates in Figure 14 in Appendix S1: Section A.10. The substantially larger uncertainty in biomass estimates compared to depletion estimates is attributable to uncertainty in the carrying capacity estimate, which is large also in SPiCT assessments. The

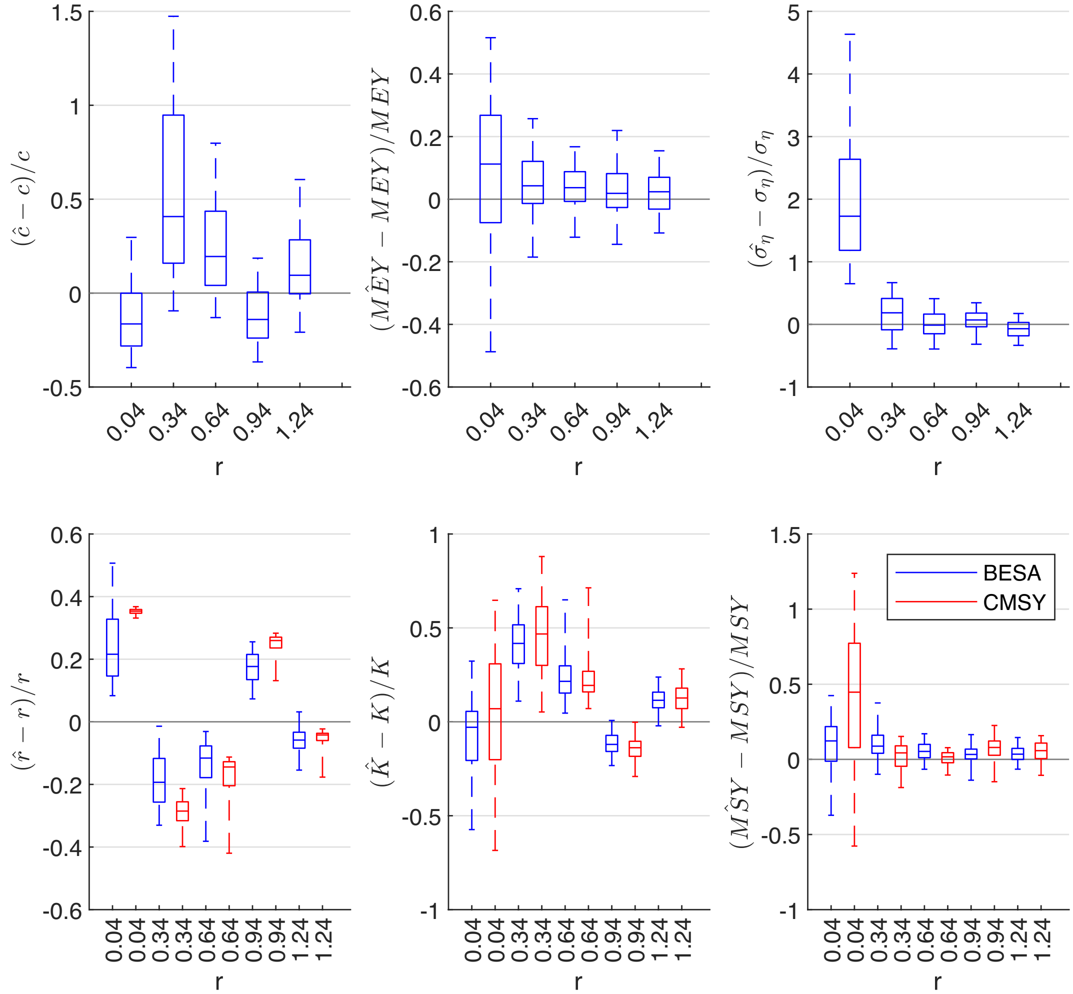


FIGURE 4 Boxplots showing the median relative distance to true value for synthetic stocks with variation in *r*. For cost parameter *c*, maximum economic yield (MEY), process error standard deviation $\sigma_\eta$, intrinsic growth rate *r*, carrying capacity *K* and maximum sustainable yield (MSY).

TABLE 4 BESA results for Barents Sea shrimp ($n=45$) compared with SPiCT results for intrinsic growth rate *r*, carrying capacity *K*, MSY and cost parameter *c*.

| | BESA, priors from CMSY[a] | SPiCT[b] |
|---|---|---|
| *r* | 0.25 (0.14, 0.37) | 0.26 (0.11, 0.60) |
| *K* (kt) | 1875 (997, 2865) | 1653 (507, 5388) |
| MSY (kt) | 116 (52, 194) | 106 (32, 357) |
| *c* (1E+9 NOK) | 29.5 (13.7, 47.5) | |
| MEY (kt) | 37.40 (−7.35, 81.14) | |

[a]95% highest density Bayesian credible interval in parentheses.
[b]95% confidence interval in parentheses.

early years constitute a formative period for the fishery, which may be one reason for the difference in assessments, for example if the zero profit condition is violated due to sluggish early investment in the fishery, or because by-catch still played a larger role prior to the introduction of sorting grids. Results for time series shortened by 5–10 years remain similar for parameter estimates. Results are available upon request. Since we find neither a significant relationship between harvest and biomass, nor between price and harvest, and since expert advice indicates that Barents Sea Shrimps are traded on world markets, we calculate maximum economic yield based on a constant price, operationalized as the mean over 45 years of deflated prices (19.09 NOK/kg). We find $B_{MEY}$ to be 1710kt and MEY as 37kt, meaning that economically, a much larger biomass and a much smaller sustainable harvest might be optimal compared to MSY management. Among the 22,400 samples output by BESA, there are some where biomass overshoots carrying capacity. If this happens often enough, then the 95% highest density interval can include cases where $B_{MEY}$ is larger than *K* and MEY negative. It is possible to rule out overshooting paths from the viable set of samples after running BESA. However, depending on the area of application, overshooting may be considered realistic behavior, and we therefore leave this decision to the individual user and as a possible avenue of future research.

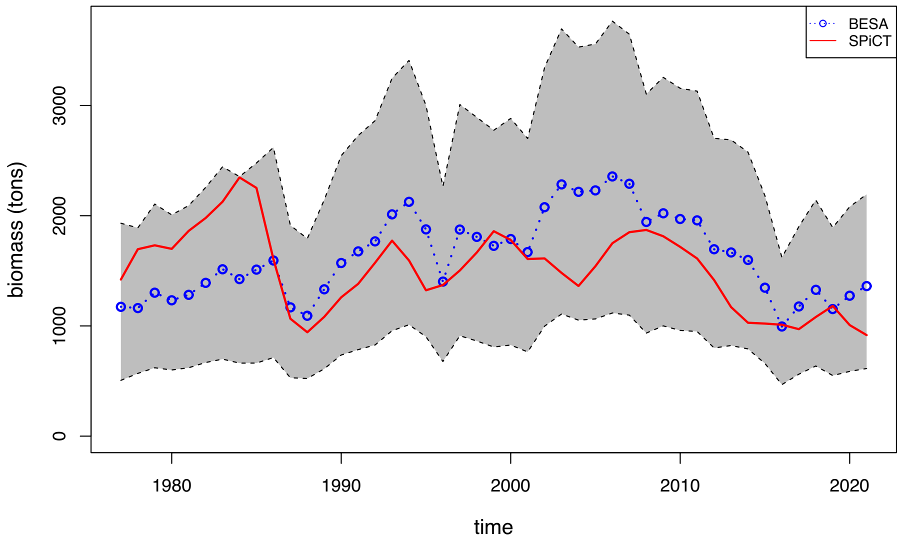


FIGURE 5 Stock size results BESA ($n = 45$) versus SPiCT assessment (95% highest density Bayesian credible intervals in grey).

## 5 | DISCUSSION

We present a bio-economic stock assessment (BESA) method to obtain reliable stock assessment estimates for data-poor open-access settings. The method relies on observed time series of harvest and prices, which are frequently available from FAO or national fisheries agencies. It is thus widely applicable to stocks around the world, and the R code we provide ensures easy implementation for researchers and practitioners. We show that the method provides unbiased reference point estimates for simulated data. Exploiting the additional information inherent in price data leads to accuracy gains compared to harvest-only methods like CMSY. It provides an improvement comparable to including standardized indices in an assessment model.

Our investigation of systematic dependencies reveals that BESA provides reliable estimates for a typical application area to stocks with $0.1 \leq r < 1.5$. Similar to many stock assessment models, BESA has difficulty in assessing stocks of very low resilience. As visible in Figure 4, separate identification of $r$ and $K$ remains a challenge. Moreover, BESA tends to estimate higher carrying capacity $K$ and MEY for stocks that start from above their equilibrium biomass as opposed to stocks that approach from below.

In a real world application to Barents Sea shrimp, we show that our method benchmarks well against official, more advanced stock assessment results, underlining that BESA can be both an important lone-standing approach to establish stock assessments for data-poor stocks as well as a valuable complement to other available methods. Validating multiple assessment methods against each other can increase confidence in stock estimates, and as shown by Rosenberg et al. (2018) in a super-ensemble approach, the use of several assessment methods in conjunction can substantially improve individual model predictions.

BESA estimates biological and economic parameters simultaneously in a coherent framework from one model and dataset. This makes estimates consistent and highly useful for bio-economic modeling predictions and policy advice. It also constitutes a substantial step towards contrasting MSY-management with alternatives. In addition to biological parameters, it identifies the cost parameter $c$. The cost parameter scales both overall costs and the impact of stock size on fishing costs. Identification of $c$ is an important step towards incorporating economic objectives in management Clark (1990); Punt et al. (2013). A recent report by NOAA (National Oceanic and Atmospheric Administration, US) states that “Additional data on costs of fishery operations would be required for implementing MEY in U.S. fisheries[…]” (Chan et al., 2022, p. 7). We showcase this opportunity by computing static maximum economic yield (MEY) from our results as example.

BESA is applicable whenever the zero-profit condition holds and commercial interests are behind a major part of harvests. This can for example be the case if a stock is unregulated, or de-facto open-access, where harvest is not constrained by output regulation such as a TAC, but rather through economic limitations. This includes stocks where TACs are set, but do not actually restrict fishing activity. This is the case for many fisheries, including European stocks (Quaas et al., 2012). This does not mean that the zero profit condition has to hold for the whole fishery. It is sufficient if a significant commercial fleet segment is operating under zero profits, as for this fleet segment the price data provides information about stock status. As long as cumulative harvest is known, and prices adjust sufficiently for the commercial fleet segment(s) to stay in the market continuously, price data for this segment are sufficient to identify the cost parameter for that fleet segment. For example, with a commercial and a subsistence fleet segment, BESA can be applied to the commercial price data in the measurement equation.(With data available for multiple fleet segments, one measurement equation per fleet segment can be used akin to the case of Bayesian assessment with catch per unit effort data Winker et al. (2018). For BESA, one would then expand the Kalman filter to vector form (Kalman, 1960).) Moreover, BESA relies on the assumption that fleet size adjustment is fast enough that the zero profit condition holds in each period. Therefore, if the temporal resolution of data is fine, for example weeks or months, one should explicitly model effort dynamics, as for example in Smith (1969), and include a corresponding extra state equation.

It is for open-access stocks that simple and cost effective stock assessment methods, such as BESA, can be most valuable: Any stock that incurs positive profits is likely already subject to effective management, and therefore in most cases already reliably assessed. Under certain conditions, BESA could also be used for constantly managed stocks: If the profit margin is constant over time, it simply adds to the cost constant. Alternatively, if data on the profit margin are available, the model can also be applied to manage stocks more generally.

Because the true state of a stock is unknown, careful evaluation of the underlying assumptions and model performance is crucial to validate BESA in a real-word application, using procedures recommended for every stock assessment method (Kell et al., 2021). Importantly, BESA works on the assumption that the price data adequately reflects the fishers' (variations in) incentives to fish. It is not necessary that prices follow supply incentives, for example that prices directly react to the state of the biomass and ensuing supply quantities. By contrast, we exploit the feedback of fishing incentives on fish biomass. As long as fishers are price takers, it is of no consequence what causes fluctuations in incentives. For example, a shift in consumer preferences, rising consumer incomes or changes in the final product destination might all alter the price offered to fishers, and thus incentives to fish. Ex-vessel prices should best reflect these incentives, and are therefore preferable. However, prices observed farther along the value chain, such as wholesale or export prices (as provided by FAO, for example), are also of use, as long as price transmission is strong enough and ideally symmetric (Tveterås et al., 2012). In mathematical terms, with sufficiently strong price transmission, all of this variation enters the left hand side of the measurement Equation (5), contributing to exogenous stochastic variation that helps us identify the biomass signal. A counter-indication might for example be upstream prices that include strongly variable transport costs. If transport costs are included in the price calculation of the observed price time series, the observed variation in prices may not translate into incentive variation for fishers (weak price transmission). If price transmission is weak, incentives are mis-measured.

In our main model for BESA, we follow the classic Schaefer model in assuming that costs are inversely proportional to stock size, which corresponds to the traditional assumption of a unit stock elasticity. This assumption is shared with all other state space model approaches that regularly set the Schaefer stock elasticity equal to unity, but is not present for example in CMSY. We relax this assumption in Appendix S1: Section A.7 and show that BESA still works well for non-unity stock elasticity, as long as the stock elasticity is known. While the stock elasticity of unassessed stocks is unlikely to be known exactly, it can be guessed (with associated sensitivity analysis) based on schooling behaviour, as schooling is considered a major determinant of the stock elasticity (Bjørndal, 1987). In theory, the stock elasticity can be identified in the Kalman filter when the model is supplemented by a second observation equation that describes demand. However, our runs with synthetic data indicate that the higher number of parameters renders reliable estimation infeasible given the number of observations that can reasonably be expected. Further research should keep searching for ways to obtain reliable estimates for the stock elasticity. It is an important parameter governing stock effect as well as bio-economic coupling in terms of economic reactions to declining stock size.

Some limitations apply and constitute interesting opportunities for future work. It is an advantage that price time series need no standardization for technological change, like CPUE time series. However, prices need to be deflated and the choice of the adequate deflation rate may not be obvious. Furthermore, in areas with a weak market integration, the regional variation in prices may be a strong confounder, when fishers from different regions are subject to different prices. Aggregation of price data across different market segments is a well-known challenge: a singular price time series should continuously reflect changing incentives to fishers. This is possible if markets are sufficiently integrated that price variation across segments is correlated due to arbitrage, or if the fleet(s) in question primarily serve one observable market segment. Similarly, ignoring the importance of demographic structure (Hixon et al., 2014) in surplus production models is not only a limiting simplification for population dynamics but also prices, because they may vary due to consumer preferences for, for example specific sizes (Zimmermann & Heino, 2013).

Further avenues for future research include the practical application of BESA to yet unassessed stocks, as well as incorporating price data into more data-rich methods, for example CPUE based state space models, in order to make the most of this valuable data source. Extensions of BESA towards different formulations—such as a Pella-Tomlinson growth function or a non-linear cost function—should provide possibilities in tailoring BESA to specific applications.

BESA offers a simple-to-implement, data-limited method for fisheries stock assessment. It can help improve stock assessments for many fish stocks in industrial countries that are not assessed or managed due to lower economic relevance, but whose overall stock health should nonetheless be monitored to sustain ecosystem health, income opportunities and cultural values. Perhaps even more importantly, it can be used for countries of the Global South, who less often afford the substantial investment necessary for advanced stock assessments, and who often cannot resort to long historical time series collected for the purpose of stock assessment (Melnychuk et al., 2017; Mora et al., 2009). In those cases, BESA can play a role in reducing geographic inequalities and thus contribute to sustainable development in terms of zero hunger, reduced inequalities and sustainable life below water.

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## CONFLICT OF INTEREST STATEMENT

There are no conflicts of interest for any of the authors.

## DATA AVAILABILITY STATEMENT

All data are openly available: The synthetic dataset is available upon request from the corresponding author. Price data are available from the Fisheries Directorate of Norway (Landings- and sales slips register, https://www.fiskeridir.no/Tall-og-analyse/AApne-data/Fangstdata-seddel-koblet-med-fartoeydata), stock assessment data from the International Council of the Exploration of the Sea (ICES) (ICES, 2021, 2022).

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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