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Ecological Solutions and Evidence

PRACTICAL TOOLS

smsR: A seasonal assessment model for exploited stocks

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Abstract

1. We present a seasonal stock assessment model, which allows the user to initiate a stochastic age-based model inside the R programming language.
2. The model is currently the official stock assessment model for five small pelagic stocks in the North Sea. The seasonality component enables within year changes in weight, natural mortality and recruitment, which is commonly missing from existing methods.
3. We show through simulation analysis that including seasonality can lead to lower bias in stocks with strong interannual dynamics.
4. We provide a variety of useful functions and applications that let the user perform diagnostics and evaluate the goodness-of-fit of the model. The software contains functions used for catch forecasting and management strategy evaluation. The stock assessment model is written in Template Model Builder (TMB), which enables rapid parameter estimation and the potential to estimate parameters as random effects.
5. *Practical implication*. The model offers a tool for consistent and transparent stock assessments for populations with strong seasonal dynamics.

KEYWORDS
fisheries, R package, seasonality, Stock assessment

1 | INTRODUCTION

Sustainable exploitation of marine resources requires sound and effective management (Hilborn et al., 2020), and at the core of fisheries management is stock assessment, which aims to precisely quantify the abundance and productivity of exploited populations.

Contemporary age-based integrated assessment models use fishery catch, survey data and age compositions to estimate recruitment, stock size and reference points to evaluate the stock status, when that data is available. There are a range of popular stock assessment software and packages used globally to estimate stock status (reviewed in Dichmont et al., 2016; Punt et al., 2020; Cousido-Rocha et al., 2022). Examples of popular packages are the comprehensive Stock Synthesis (Methot & Wetzel, 2013), the SAM package (Nielsen & Berg, 2014) and GADGET (Begley & Howell, 2004); while several software applications also exist for surplus production models, for example, SPiCT (Pedersen & Berg, 2017) and JABBA (Winker et al., 2018). Integrated assessment models featuring age-structured dynamics (Maunder & Punt, 2013) are often considered the gold standard to evaluate stock status and reference points (see, e.g., ICES (2018)), but do, however, require catch-at-age data to determine selectivity, fishing pressure and general demographic dynamics. The availability of such information is pivotal to avoiding biased assessments (Chen et al., 2003; Chrysafi & Kuparinen, 2016) and is often coordinated through long-term data collection programmes, combined with recurring scientific surveys.

Here, we present a new software package—'smsR'—using a single-species version of the Stochastic Multi-Species (SMS) model

(Lewy & Vinther, 2004), which has historically been used as a stock assessment model for small pelagic stocks in the North Sea, that is, sandeel (*Ammodytes* spp.) in areas 1–4, sprat (*Sprattus sprattus*) and previously Norway pout (*Trisopterus esmarkii*) (ICES, 2016). The software is implemented as an open-source R package and is designed for users with only moderate R skills. The underlying stock assessment model is implemented in Template Model Builder (TMB; Kristensen et al., 2016). The model differs from other available packages by implicitly modelling fishing mortality as a separable product that can be divided into seasonal, age-specific and annual components. The model also includes a range of custom options to model parameters as random effects, time-varying mortality and environmentally mediated recruitment.

Seasonality is particularly important for small fast-growing species, as they often demonstrate highly variable growth and mortality (Lindegren et al., 2020) as a result of seasonal environments (Conover, 1992). In addition, the model can account for different timing of surveys. Another issue that may arise without seasons in a stock assessment model is the time lag between advice, the activity of fleets (i.e., disproportionate timing of catches) and biologically important events (e.g., spawning and recruitment). Timing misalignment can cause non-linear effects on the stock (Mildenberger et al., 2020). This can lead to bias in the estimation of recruitment, fishing mortality rate and numbers at age, which may lead to faulty catch advice and an incorrect evaluation of stock status (see, e.g., Collie et al., 2012; Uriarte et al., 2023).

We apply the model to a small benthopelagic stock, sandeel (*Ammodytes marinus*) in the central and southern North Sea (area 1r (ICES, 2022)), which is important for the European industrial fisheries (Dickey-Collas et al., 2014). In addition to seasonal catch-at-age data, the stock assessment uses two surveys taken at different times of year with different durations. We also show how the software provides automated functions to produce diagnostic plots and assess patterns of retrospective bias in the estimates (see diagnostics section).

2 | METHODS

The model is a standard age-based model with all equations described in the appendix. The model estimates age- and season-specific fishing mortality rates, recruitment across past years, recruitment uncertainty, survey catchability and uncertainty in observed catch and survey data. The negative log-likelihood function is based on the following three components: catch-at-age, survey-at-age (can comprise multiple surveys) and a stock-recruitment relationship.

Uncertainty in the numbers-at-age in each separate survey and thus implicitly numbers-at-age in the stock depends on the estimation of age-specific catchability of each survey (i.e., the probability that a fish of a certain age is caught in the survey). However, to reduce the model's degrees of freedom and avoid overfitting, there is an option to group ages and assume that certain sequential ages have the same catchability.

The stock-recruitment (SR) relationship can be assumed to be either a hockey stick, Beverton-Holt or deviants from a mean (Barrowman & Myers, 2000) with an AR1 function. The number of estimated parameters changes based on the chosen function.

Fishing mortality rate is estimated as a product of seasonal, age-based and yearly components,

$$F_{y,a,s} = F_y F_{s,a} F_a$$

where y is year, s is season and a is age. It is common in many fisheries that certain age-groups are excluded from the model, for example, fish that are never caught by the fishery, such as many age-0 fish. If an age group is not caught in specific seasons, then F=0 for that age and season; this may include when the fishery is not active or not targeting an age group. The seasonal component, $F_{s,a}$ has an additional age component such that the selectivity can change between seasons.

For stocks where the data is insufficient to fully estimate the fishing mortality rate, the yearly F contribution can be replaced by nominal effort. In those cases, the fishing mortality is calculated as follows:

$$F_{y,a,s} = E_{y,s} F_{s.b} F_{a,b}$$

where E is the observed nominal effort, standardized to account for technical features of the fishery, which may change across years (see Appendix for description of effort as input). The subscript b denotes any blocks of years in which selectivity can be assumed to be constant across years, which can account for technical changes and differences in catchability over time while keeping model degrees of freedom low to avoid overfitting. The selectivity patterns per age and season are both re-estimated when blocks are modelled.

2.1 | Installing the software

The package can be installed using the following command:

```
remotes::install_github("nissandjac/smsR",
   ref = "main",           # Install main branch
   dependencies = TRUE)    # Installs imports and suggests
```

Then load the package

```
library(smsR)
```

The package includes the 2022 stock assessment for North Sea sandeel in area 1r, and here we use that to show some of the package functionality.

2.2 | Setting up the model

To set up a new model, users need to include the minimal input data required in the model: (1) survey observations (standard as numbers at age, but can also be a biomass index), (2) catch at age in numbers (dimensions of age, year and season, denoted *canum*), (3) weight at age (*weca*), (4) maturity at age (*mat*) (5) natural mortality (*M*). All these need to be organized in arrays with the dimensions listed in Table A3 to make sure they are correctly loaded into *smsR*. The package will send a warning if some dimensions are not correct. Appendix S6 provides a way to give the package data as text files. The simulated data in this example is included as a list called **sim_data** when the package is loaded and can be inspected to help build new models.

The core function in the package is **get_TMB_parameters()**, which turns the input data and settings into a list of objects that form the basis of a stock assessment. The function tests the dimension of the input objects and throws a warning to the user if there are errors in the input data. To illustrate a simple model, we simulate some data (see appendix section 4 to see how the data was simulated) and perform the simplest two-season *smsR* model. Users can compare their input data to the simulated model to start a new assessment. The structure **sim_data** is available in the package, and how it is constructed is provided in the appendix.

```
 # Required input
year <- 1:30
nseason <- 2
mtrx <- list(mat = sim_data$mat,
             M = sim_data$M,
             weca = sim_data$weca,
             west = sim_data$west
             )
Surveyobs <- sim_data$Surveyobs
Catchobs <- sim_data$Catchobs
df.tmb <- get_TMB_parameters(mtrx,
                             Surveyobs, # From a simulated model
                             Catchobs, # From a simulated model
                             years = year,
                             nseason = nseason,
                             ages=0:5,
                             recmodel=3,
                             #randomR=1
)
parms <- getParms(df.tmb)
mps <- getMPS(df.tmb, parms)
sas <- runAssessment(df.tmb, parms, mps = mps)
# Plot the fit
plot(sas)
```

This model converges and fits the simulated data. In the next section, we provide an example of a more advanced model setup using sandel 1r as a case study and show more package functionality. Other recruitment options can be explored; for instance, recmodel = 2 will estimate recruitment as deviations from the mean with an AR1 process.

Additional options for the function call include the potential to model some of the parameters as random effects. Specifically, setting *randomR* = *1* or *randomF* = *1*. The former enables estimating recruitment as random effects, specifically by modelling the parameters as deviations from the stock recruitment relationship with mean = 0. *randomF* enables estimating F_y as a random walk, shrunk by the deviations from year-to-year changes with mean = 0. The model then estimates selectivity (F_a and F_s) as fixed effects. The last option is to set *randomM* = *1*, which enables estimating natural mortality as a random walk. Note that this option requires a strong signal in the survey and catch data and can often lead to non-converged models.

2.3 | Case study: Sandeel area 1r

For a more complex model setup, we here showcase sandeel in the North Sea. The data used in the model are catch at age divided into two seasons (half-year) and two surveys describing numbers at age. The dredge survey is conducted at the end of the year, targeting fish of ages 0 and 1 (see also details in Henriksen et al., 2021). The real-time monitoring survey (RTM), which contains observed age composition of the catch, is an index that can be used to dynamically adjust the total allowable catch (TAC) in the season. This data is being sampled by commercial vessels at the beginning of the season, but technically it is being used as an independent survey in the model. Below, we present code and output from our R script and do the stock assessment for sandeel in area 1r to show some of the functionality in smsR. The data is available as a list named **sandeel_1r**.

2.3.1 | Running the assessment

First, we set up some crucial settings, such as the number of age groups, years that correspond to the catch data and some information about the surveys (two in this case):

We can use the function **get_TMB_parameters()** to prepare the data for the stock assessment model. The function initializes all the settings for the assessment model, and we can start to prepare the assessment settings by using the following call. Settings should be carefully tailored to each specific application, as each decision changes the estimated parameters based on the corresponding assumptions

```
df.tmb <- get_TMB_parameters(
   mtrx = sandeel_1r$lhs, # List that contains M, mat, west, weca
   Surveyobs = sandeel_1r$survey, # Survey observations
   Catchobs = sandeel_1r$Catch, # Catch observations
   years=1983:2021, # Years to include in model
   nseason=2, # Number of seasons
   useEffort = TRUE, # Use effort to calculate F
   ages=0:4, # Ages of the population
   recseason=2, # Season when recruitment occurs

   recmodel=1, # Hockey stick recruitment model
   CminageSeason = c(1,1), # Minimum catch age by season
   Fmaxage=3, # Age with maximum fishing mortality
   Qminage = c(0,1),# Minimum age by survey
   Qmaxage = c(1,3), # Max age by survey
   Fbarage = c(1,2), # Min and max age used to calculate Fbar
   effort = sandeel_1r$effort, # Effort input
   blocks = c(1983,1999), # Breakpoints of blocks for selectivity
   nocatch = sandeel_1r$nocatch, # (Binary) non-zero catch by year and season
   surveyStart = c(0.75,0), # Portion of season elapsed at start of survey
   surveyEnd =  c(1,0), # Portion of season elapsed at end of survey
   surveySeason = c(2,1), # Season in which each survey occurs
   surveySD =  list(c(0,1),c(1,2)), # Survey age groupings for SD estimates
   catchSD = list(c(1,3), c(1,3)), # Catch age groupings for SD estimates
   estSD = c(0,2,0), # Flags for how to handle SDs for 1) survey, 2) catch, 3)
Stock recruitment relationship
   beta=105809, # Assumed hockey stick break point (SSB),
   nllfactor = c(1,1,0.05) # Manual weighting of 3 log-likelihood components
)
```

The function prepares all the settings for the stock assessment model in the `df.tmb` object. There are some uncommon options used here that are specific to sandeel; the 'blocks' argument determines that there are two blocks of years (1983–1998 and 1999 to 2021), wherein fishery selectivity is assumed to be constant. The ages assumed to have equal standard deviation for catch and surveys are given as lists `surveySD and catchSD`. surveySD = list(c(0,1),c(1,2)) have c(0,1) for the first survey, which assumes that age 0 and age 1 have separate SDs and c(1,2) for the second survey, which assumes a separate SD for age 1 and one for all ages above and including 2. Refer to the help file for the function to see a description of all possible settings. The input *beta* is the hockey stick break point of a stock recruitment relationship, which (for this stock) is defined as the lowest SSB that gave a high recruitment (above median) in a previous assessment. Specifically, for sandeel, the stock recruitment relationship is considered to be weak, so the SR likelihood is manually reduced in the 'nllfactor' call. A weak SR relationship is expected for many short-lived forage fish stocks (Hilborn et al., 2017; Somarakis et al., 2019; van Deurs et al., 2020). Fbarrage defines the subset of age groups over which to calculate the average annual fishing mortality for reporting, F_{BAR}. Finally, the stock has an input file called 'nocatch', which includes year-season combinations with zero catches and are not included in the likelihood.

The vector estSD controls how observation and process standard deviations are treated in the model. Each element specifies whether the corresponding standard deviation is estimated as a free parameter or computed internally by the model. A value of 0 indicates that the standard deviation is estimated as a free parameter, while a value of 2 indicates that the standard deviation is calculated internally from the log-scale differences between observed data and model predictions. The vector must have length three and corresponds, in order, to the survey observations, catch observations and the stock–recruitment relationship. In the sandeel configuration, the catch standard deviation is calculated internally rather than estimated as a free parameter, as fishing mortality is driven by effort. However, we recommend keeping the standard settings of 0 when possible.

The list created by **get_TMB_parameters()** can then be used to automatically prepare the parameters required for that assessment model.

```
parms <- getParms(df.tmb)
```

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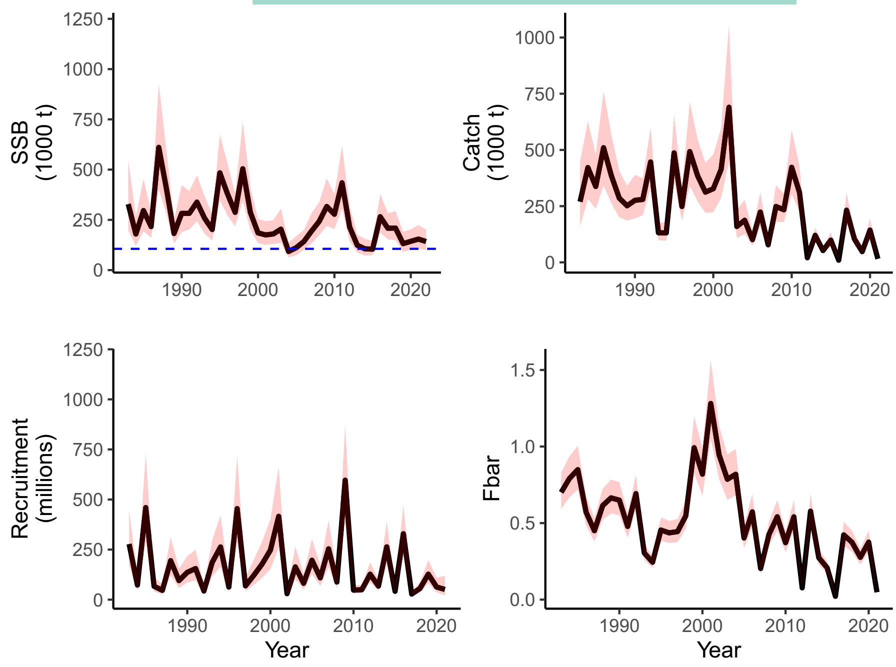

FIGURE 1 Spawning stock biomass, total catch, recruitment and fishing mortality (F_{bar}) of sandeel in area 1r. Red shading indicates the 95th confidence region. See?plotDiagnostics for additional options and overview over standard plots. The dashed line on the SSB plot represents B_{lim}.

Not all the parameters in this list are necessarily estimated. The precise number of estimated values depends on the specific settings applied to the initial assessment model. The prepared data and parameters can then be used to call the assessment model using `runAssessment()`.

```
sas <- runAssessment(df.tmb, parms = parms)
Congrats, your model converged.
```

The software indicates whether the model has converged properly. Non-convergence will give a warning or error and specify where the problem can be fixed (e.g., data file, parameter specification). The object `sas` includes many estimated objects from the stock assessment that can be used for exploration, plotting and analysis. However, it is recommended to utilize the built-in functions in the package. For instance, one can extract observed and predicted data from a model using `smsR::get-function`.

For example, here we extract spawning stock biomass (SSB) and recruitment.

```
SSB <- getSSB(df.tmb, sas) # Extract SSB
R <- getR(df.tmb, sas) # Extract recruitment
```

2.3.2 | Plotting and standard output

The smsR package also includes some plotting functions using ggplot2 as an underlying package, generating standard output commonly used in stock assessments for evaluating the stock status (Figure 1).

```
plot(sas)
```

2.3.3 | Diagnostics

The data for exploring the diagnostics can be accessed by the function `smsR::get (getCatchSD, getSurveySD and getSummaryCVs)`. A range of standard diagnostic plots can additionally be extracted by the function `plotDiagnostics()`.

Another useful diagnostic method is to fit the model with surveys individually removed (in case an assessment has more than one survey) to get an overview of their individual contributions to the assessment (Figure 2). This is done via the call.

```
removeSurvey(sas)
```

2.3.4 | Retrospective patterns

The model also has an automated function to calculate retrospective patterns using the Mohns rho metric (Mohn, 1999). Mohns rho compares values for SSB, recruitment and F_{BAR} to a stock assessment where a specified range of years is removed from the end of the time series, also called a peel. This metric can be useful to check the consistency of the model when adding another year of data (Deroba, 2014). In the example provided here, 5 peels (i.e., omitting the last 5, 4, 3, 2 and 1 years) are calculated from the stock assessment (Figure 3).

```
mr <- mohns_rho(df.tmb, peels=5, parms)
```

2.3.5 | Forecasting

In addition to performing the stock assessment, there are functions available to perform forecasts to give advice on TAC. Sandeel stocks

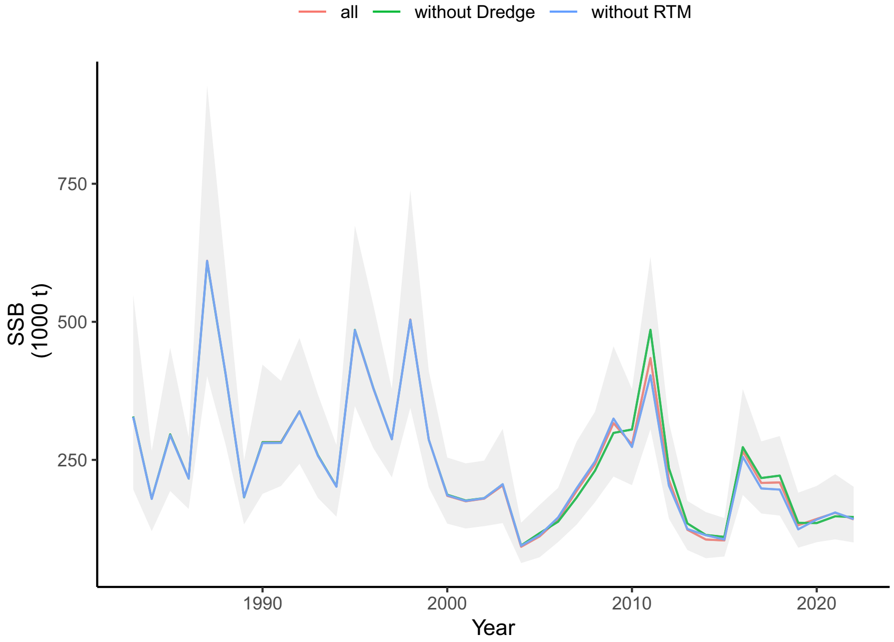

FIGURE 2 SSB when removing surveys one after one. The grey shading indicates the 95th confidence region of the model with all surveys included. RTM refers to the 'Real Time Monitoring' survey used in the assessment.

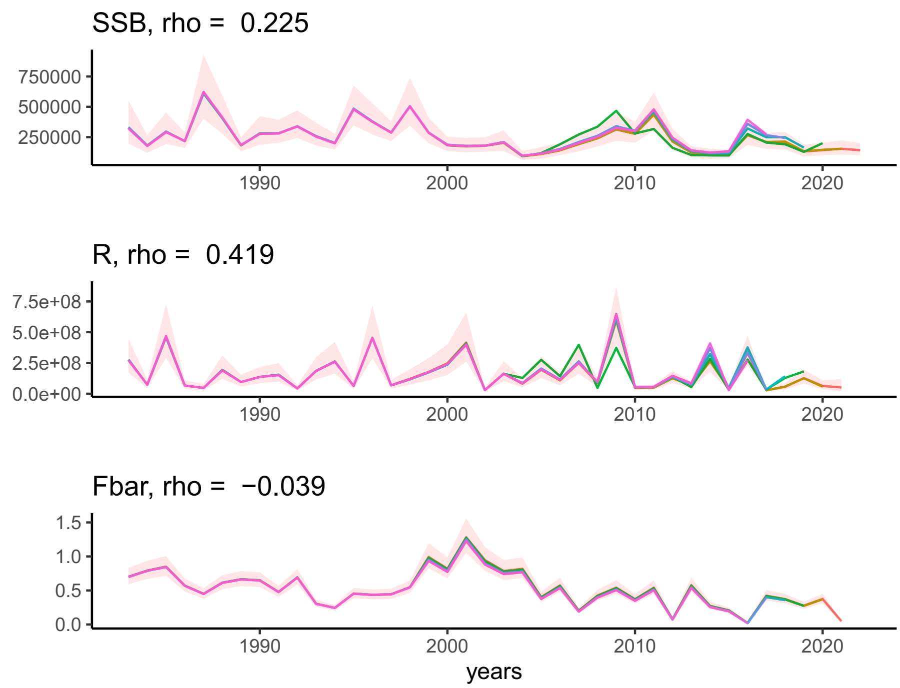

FIGURE 3 Mohns rho calculation for SSB, R and F_{bar} for sandeel area 1r. Line colour indicates the five peels, and the red shade indicates the confidence interval from the final assessment.

TABLE 1 A forecast table as used in standard ICES advice sheets run in 2022.

Basis	Total catch (2022)	*F* (2022)	SSB (2023)	SSB change %	TAC change %
Bescapement (Fcap)	16448.25	0.07	140824.0	−1	−86
$F=0$	0.00	0.00	149177.0	5	−100
Bescapement (no cap)	16448.25	0.07	140824.0	−1	−86
B_{lim}	86524.64	0.39	105809.0	−26	−28
$F=F$ 2021	12315.78	0.05	142918.4	0	−90
Obs TAC	5000.00	0.02	146620.4	3	−96

Note: Fcap is the maximum allowed fishing mortality for the stock, and Bescapement is the desired biomass target (i.e., Bpa).

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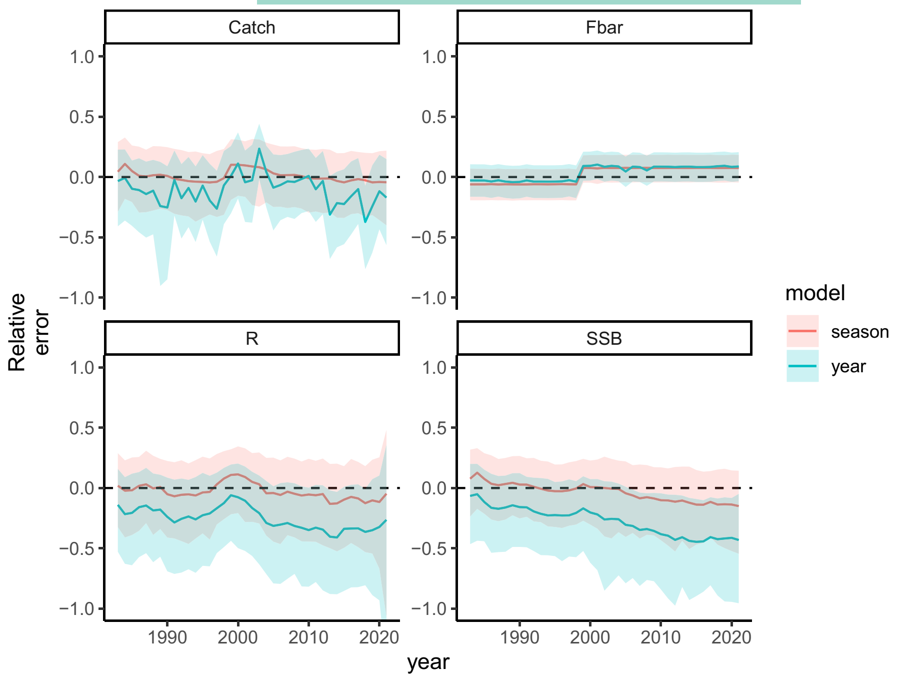

FIGURE 4 Relative error $((x_{true} - x_{estimated})/x_{true})$, where x represents either Catch, F_{bar}, recruitment (R) and spawning biomass (SSB) when fitting a yearly (blue) and seasonal model (red) to a seasonal operating model. The lines represent the median of 1000 runs, and the shading represents the 95th and 5th percentile.

in the North Sea use a $B_{escapement}$ strategy that aims to always keep the projected biomass at a certain level where recruitment is not impaired (ICES, 2022). This can be capped by an additional threshold reference point on fishing mortality, known as F_{cap}. However, there are also options to run a standard F_{MSY} forecast in the model, by adding *HCR = 'Fmsy'* into either **getForecastTable()** or **getTAC()** (Table 1). In that case the user has to provide F_{MSY}. F_{MSY} is the fishing mortality that provides the long term maximum sustainable yield and can potentially also be calculated with the function getFmsy(). Here, $B_{escapement}$ is 140,824 tonnes, meaning that we aim to leave that amount of SSB in the stock after the TAC is taken. The TAC here is compared to last year's TAC of 120,428 tonnes, including an 'observation TAC' of 5000 tonnes. The observation TAC is used in case of fisheries closure to obtain biological samples and inform the assessment.

```
getForecastTable(df.tmb, sas, Btarget=140824,
Flimit=0.36, TACold=120428, TACtarget=5000)
```

The model used in the forecast is the same as the model described in the appendix and optimizes the fishing mortality required to get to B_{pa}. The forecast model uses the same number of seasons as the assessment model.

2.4 | Seasonality

To show the impact of seasonality on the assessment, we simulated 1000 replicates from the sandeel area 1 stock with recruitment being randomly sampled every year and log-normal error on the survey and catch estimates (see appendix for specifics). We fitted the model itself to evaluate the potential bias of not including seasonality. We ran a seasonal and a yearly model. The seasonal model was run with the original two seasons. Natural mortality was summed across seasons. In the annual model, we summed the number of effort days to inform the fishing mortality. We used the weight at age and maturity in the season where SSB was calculated in both the annual and the seasonal models. The annual model tended to overestimate R and SSB, particularly in the later period after the year 2000 (Figure 4). The small change in fishing mortality in the year 1999 is due to a change in selectivity in the operating model.

3 | PERSPECTIVES AND CONCLUSIONS

The *smsR* package is a modern development of a tested stock assessment model that has been used for small pelagic stocks across Europe for almost two decades. The **smsR** model is a single-species formulation of the SMS multispecies model (Lewy & Vinther, 2004). SMS excels by having a seasonally separable fishing mortality formulation. This is of great advantage when a stock assessor needs to account for varying catch rates, important life history timing and different time series of data that are sampled throughout the year. The opportunity to incorporate time-steps into the model can align any varying fishing mortalities, weight fluctuations and survey estimates and avoid issues and bias in the estimation of stock parameters. Furthermore, the model can also assume annual time-steps like more traditional stock assessment models if that suits the data available. The breadth of functions available are not fully covered in this paper, and the package is under continuous development to support stock assessments and navigate towards sustainable fisheries.

The standard state-space formulation used in models such as SAM includes process error on both survival and fishing mortality (Nielsen & Berg, 2014). For stocks exhibiting substantial inherent process variability—arising, for example, from misspecified natural mortality—this structure can help absorb unmodeled natural variation and improve the separation of process and observation error. However, the opposite effect may also occur: shrinkage induced by the process-error formulation can overly constrain year-to-year variability, producing population and fishing-mortality trajectories that are smoother than the true underlying dynamics. In such cases, genuine temporal variation may be partially suppressed, potentially biasing inference and management advice.

One of the current developments in stock assessment methodology is the inclusion of time-varying processes into the estimation procedure of stock assessment models. Examples of these are temporal changes in natural mortality (Jacobsen et al., 2019; Johnson et al., 2015), environmental effects on recruitment or mortality (Wang et al., 2020), or time-varying selectivity for fisheries (Nielsen & Berg, 2014) or survey (Wilberg et al., 2010). Other options include the so-called MICE models (Models of Intermediate Complexity for Ecosystem assessment) that include, for example, an index of predator abundance to calculate natural mortality (Plagányi et al., 2014). Compositional data is treated either as numbers at age or through a Dirichlet multinomial (Thorson et al., 2017). However, other approaches exist, such as the multivariate Tweedie (Thorson et al., 2023). Compositional data, MICE models and time-varying processes are either already working or in development in *smsR*.

The stock assessment model is particularly useful for short-lived stocks, such as many small pelagics, where inter-annual variability can have a large influence on the sub-annual dynamics (e.g., a species might change its maturity ogive quite significantly within a year). Additionally, there can be several fisheries on a stock that may operate in different seasons, or a stock that moves between areas in seasons and experiences variable fisheries selectivity and catchability (O'Boyle et al., 2016). The framework provided here can account for this with the seasonal component of *F*.

smsR differs from SAM and SS3 in that it is formulated as a single-species, seasonally resolved model designed for flexibility rather than standardization. There are options in smsR to run both as a state-space model and resolving parameters as fixed effects, like in SS3. Unlike SAM, which typically operates on an annual time step with fixed structural assumptions for routine assessments, smsR explicitly resolves within-year dynamics, allowing fishing mortality, natural mortality, recruitment and observation processes to vary by season. Compared to SS3, which is highly configurable but generally emphasizes age–length structure within an annual framework, smsR prioritizes transparent experimentation with seasonal processes, alternative mortality and recruitment formulations, and model structure itself. Flexibility and parameter estimation speed (due to the TMB implementation) make smsR particularly suited for process-oriented analyses and management strategy evaluation, where seasonal dynamics and structural uncertainty are central, rather than for producing a single operational assessment.

As in many assessment models, a successful fit is indicated by both good diagnostics (e.g. survey residuals not autocorrelated, reasonably low Mohn's rho values) as well as complete parameter convergence. For many stocks, this might require some tuning of model settings, such as CV groupings and the assumed stock recruitment relationship. Any user applying a model framework like this to their stock should familiarize themselves with each of the standard settings to ensure a thorough understanding of the assumptions they are using to give advice. We recommend using the smsR model for small pelagic stocks, as the inclusion of inter-annual variability in weight and mortality is paramount for eliminating bias in the assessments of these fisheries. The fishing mortality formulation distinguishes the model from other existing frameworks and can be useful for species with strong intra-annual dynamics. For more in-depth use and alternative applications, we refer to the package help files.

AUTHOR CONTRIBUTIONS

Nis sand Jacobsen (NSJ) conceived the ideas and designed the core software package. NSJ and Mollie E Brooks (MEB) contributed code to the package development. NSJ, MEB, Ole Henriksen (OH) and Mikael van Deurs (MvD) tested the package. NSJ led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1002/2688-8319.70261.

DATA AVAILABILITY STATEMENT

All data used in the paper are included in the software package and are available at https://doi.org/10.5281/zenodo.20019876 (Jacobsen & Brooks, 2026).

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SUPPORTING INFORMATION

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

Appendix S1. Mathematical description and implementation guide for smsR.

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