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Mildenberger, Tobias; Berg, Casper Willestofte; Pedersen, Martin Wæver; Kokkalis, Alexandros; Nielsen, J. Rasmus

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Time-variant productivity in biomass dynamic models on seasonal and long-term scales

Tobias K. Mildenberger

National Institute of Aquatic Resources, Technical University of
Denmark, Kemitorvet, 2800 Kgs. Lyngby, Denmark
t.k.mildenberger@gmail.com

Casper W. Berg

National Institute of Aquatic Resources, Technical University of
Denmark, Kemitorvet, 2800 Kgs. Lyngby, Denmark
cbe@aqua.dtu.dk

Martin W. Pedersen

ENFOR A/S, Lyngsø Allé 3, 2970 Hørsholm, Denmark
National Institute of Aquatic Resources, Technical University of
Denmark, Kemitorvet, 2800 Kgs. Lyngby, Denmark
mawp@dtu.dk

Alexandros Kokkalis

National Institute of Aquatic Resources, Technical University of
Denmark, Kemitorvet, 2800 Kgs. Lyngby, Denmark
alko@aqua.dtu.dk

J. Rasmus Nielsen

National Institute of Aquatic Resources, Technical University of
Denmark, Kemitorvet, 2800 Kgs. Lyngby, Denmark
rn@aqua.dtu.dk

Abstract

The productivity of fish populations varies naturally over time, dependent on integrated effects of abundance, ecological factors, and environmental conditions. These changes can be expressed as gradual or abrupt shifts in productivity as well as fluctuations on any time scale from seasonal oscillations to long-term changes. This study considers three extensions to biomass dynamic models that accommodate time-variant productivity in fish populations. Simulation results reveal that neglecting seasonal changes in productivity can bias derived stock sustainability reference levels and, thus, fisheries management advice. Results highlight the importance of biannual biomass indices and their timing relative to the peaks of the seasonal processes (i.e. recruitment, growth, mortality) for the estimation of seasonally time-variant productivity. The application to real-world data of the Eastern Baltic cod (*Gadus morhua*) stock shows that the model is able to disentangle differences in seasonal fishing mortality as well as seasonal and long-term changes in productivity. The combined model with long-term and seasonally varying productivity performs significantly better than models that neglect time-variant productivity. The model extensions proposed here allow to account for time-variant productivity of fish populations leading to increased reliability of derived reference levels.

Keywords: Eastern Baltic cod (*Gadus morhua*); fisheries management; fish stock assessment; maximum sustainable yield; population dynamics; seasonality; SPiCT; surplus production model

Corresponding author: Tobias K. Mildenerger

Correspondence to: t.k.mildenerger@gmail.com

1 Introduction

Increasing evidence suggests that the productivity of fish populations is time-variant (Hollowed et al., 2013; Petitgas et al., 2013; Hare et al., 2016; Tommasi et al., 2017): Two recent studies using more than 200 stocks from the RAM Legacy Stock Assessment Database (Ricard et al., 2011) and different modelling approaches revealed that around 68% of the assessed fish stocks (230 and 276 respectively) showed significant non-stationary behaviour (Vert-pre et al., 2013; Britten et al., 2017). The productivity of fish populations describes the rate of generation of biomass and is determined by the combined effects of three physiological processes: (i) somatic growth (growth of individuals in weight and length), (ii) recruitment (numbers of individuals recruiting to population), and (iii) the survival rate (number of fish surviving from one point in time to the

next). Time-variant productivity can be attributed to the dependency of the physiological processes and thus productivity on environmental conditions, such as temperature, precipitation, currents, eutrophication, or oxygen conditions (e.g. Pauly, 1980; Brander, 1995; Köster et al., 2005), as well as ecological factors such as predator-prey relationships (e.g. Kempf et al., 2009) or food availability (e.g. Ursin, 1963, 1967; Ross et al., 2018). As environmental conditions are not constant over time (Boyce et al., 2014; Belkin, 2009; Gruber, 2011), neither are the individual physiological processes nor the productivity of a fish population. Variability of productivity is usually described by step-wise shifts between “productivity regimes” or gradual changes in productivity over long time scales such as inter-annual variability (Vert-pre et al., 2013; Peterman et al., 2011; Britten et al., 2017). However, all physiological processes contributing to stock productivity show also within year variability, in particular, in temperate regions, where seasonal differences in environmental conditions are large (e.g. Fretwell, 1972; Pauly, 1980): Seasonal varying growth (e.g. Lambert et al., 2009; Ursin, 1963, 1967; Frisk et al., 2015), maturity (e.g. Lambert et al., 2009), and recruitment (e.g. Pécuchet et al., 2015; Lobón-Cerviá and Bradford, 2014; Kempf et al., 2009; Payne et al., 2009) have been observed and described for many species. Natural mortality is an important parameter in stock assessment, but notoriously difficult to measure and estimate in practice (e.g. Pauly, 1980; Mertz and Myers, 1997; Quinn and Deriso, 1999; Jennings et al., 2009; Curti et al., 2013; Maunder and Punt, 2013). Few studies have shown seasonality of natural mortality (e.g. Carlson et al., 2008; Nielsen et al., 2012).

As the productivity of a stock is directly related to its Maximum Sustainable Yield (MSY; Fletcher, 1978) - an important reference level in fisheries management and advice (Russell, 1931; Graham, 1935; Larkin, 1977; Jennings et al., 2009), seasonal and long-term fluctuations of fish productivity have direct consequences for fisheries management (e.g. Caddy and Gulland, 1983; Jennings et al., 2009, and references therein). Not accounting for time-variant productivity might lead from sub-optimal harvesting and incorrectly specified recovery times to mismanagement and in some cases even stock collapse (Britten et al., 2017; Nesslage and Wilberg, 2019), as the example of Gulf of Maine cod shows (Pershing et al., 2015). In particular, in light of ongoing climate change, accounting for environmentally driven time-variant productivity in stock assessments is crucial. Stock assessment methodologies like Stock Synthesis (Methot and Wetzel, 2013), Gadget (Begley and Howell, 2004), or the state-space assessment model (SAM; Nielsen and Berg, 2014; Berg and Nielsen, 2016) allow for the estimation of time-variant parameters related to catchability, natural mortality, and stock recruitment. Nonetheless, the number of assessments with time-variant parameters is still limited (Britten et al., 2017), which is especially the case for data-limited stock assessment methods. The prevalence of time-invariant parameters in most stock assessments might be attributed to the higher data requirements (quality and quantity) for the estimation of time-variant parameters, in

particular regarding individual physiological processes. Models with a simpler population structure, such as biomass dynamic models (as [Hilborn and Walters \(1992\)](#) coined surplus production models) ease the inclusion of time-variant parameters, in particular considering limited information available, as potentially contrasting non-stationary patterns in the physiological processes do not have to be entangled individually, but are jointly described by the productivity of the population.

Biomass dynamic models are based on the theory of the biomass production of fish populations in relation to population size ([Graham, 1935](#); [Schaefer, 1954](#)) assuming a dome-shaped relationship between surplus production - the net production of biomass per year - and the stock size in biomass (so called production curve). Due to their simplicity (no age or length structure of the stock) and low data requirements (only catch and biomass index time series), this class of models is a commonly used stock assessment model for data-limited and data-moderate stocks.

Within the working groups of the International Council for the Exploration of the Sea (ICES), biomass dynamic models are used to assess the stock status relative to MSY proxy reference levels for data-limited stocks, such as the Eastern Baltic cod stock (ICES Subdivisions 24-32; [ICES, 2018a](#)), hereafter referred to as Baltic cod. With more than 25 thousand metric tonnes in 2017 ([ICES, 2018a](#)), Baltic cod is commercially the most important fish species of the Baltic proper ([Casini et al., 2016](#)). From a stock assessment point of view, Baltic cod is a problematic stock, because age readings seem unreliable (e.g. [ICES, 2018a](#)) and the stock is exposed to very variable environmental conditions (e.g. [Köster et al., 2005](#); [Casini et al., 2016](#)). In the Baltic, cod is distributed according to the salinity tolerance threshold of the species, and the salinity conditions in the different Baltic basins fluctuates extensively due to high periodical variability in inflows of saline Atlantic water to the Baltic proper (e.g. [Köster et al., 2005](#)). The Baltic Sea underwent significant environmental and ecological changes over the last century ([Möllmann et al., 2009](#); [Reusch et al., 2018](#)), such as an increase of seal worm parasites due to increasing seal abundance, shifts in the dominating clupeid species and their spatial distribution patterns, and an increase of hypoxic zones, all of which challenge many Baltic fish stocks and particularly demersal predators such as cod ([Casini et al., 2016](#); [Eero et al., 2015](#)). It has been shown that the nutritional condition of Baltic cod decreased substantially starting in the mid-1990s ([Eero et al., 2015](#); [ICES, 2015](#)). Baltic cod experts hypothesise that somatic growth has decreased and natural mortality has increased based on the decrease in nutritional condition, reduction of maturation size and ecosystem changes, such as higher seal predation, extension of hypoxic areas, cannibalism, and parasite infestation ([ICES, 2017a,b](#)). As claimed already by [Walters \(1987\)](#) and again by [Britten et al. \(2017\)](#), such temporal fluctuations in environmental and ecosystem conditions support the need for assessment models that can integrate between years and within year variability in stock productivity.

Here, we extend a biomass dynamic model to account for time-variant productivity by three different approaches, of which two allow to account for between years variability in productivity, with either step-wise shifts between productivity regimes, or gradual varying productivity, and one allows for within year variability, by a seasonally oscillating productivity. Within a simulation study, we evaluate the precision and accuracy of the models with and without within year variability in productivity under different scenarios. The scenarios focus on the seasonal model since little is understood about the implications and requirements of seasonal oscillating (or within year variability in) productivity in biomass dynamic models. We apply all three models (step-wise, gradual and seasonal) and their combinations to the Baltic cod stock and discuss management implications of the time-variant productivity.

2 Methods

2.1 Stochastic production model in continuous time (SPiCT)

The Stochastic surplus Production model in Continuous Time (SPiCT; [Pedersen and Berg, 2017](#)) is a fully stochastic version of the traditional Pella-Tomlinson biomass dynamic model ([Pella and Tomlinson, 1969](#)). It uses the reparametrisation of [Fletcher \(1978\)](#) and is formulated as a stochastic differential equation (SDE) including process noise:

$$dB_t = \left(\gamma m \frac{B_t}{K} - \gamma m \left[\frac{B_t}{K} \right]^n - F_t B_t \right) dt + \sigma_B B_t dW_t, \quad (1)$$

where $\gamma = n^{n/(n-1)}/(n-1)$, B_t is the exploitable biomass at time t , K is the carrying capacity, m is the productivity parameter and represents the MSY (maximum attainable surplus production [Fletcher, 1978](#)), n determines the shape of the production curve, σ_B is the standard deviation of the process noise, and dW_t is Brownian motion. In SPiCT, the fishing mortality F_t is modelled as a stochastic process:

$$F_t = S_t^{(F)} G_t^{(F)}, \quad (2)$$

where $S_t^{(F)}$ represents the seasonal component, and $G_t^{(F)}$ the diffusion component. The diffusion component follows:

$$d \log(G_t^{(F)}) = \sigma_F dV_t, \quad (3)$$

where σ_F is the standard deviation of the process noise and dV_t is standard Brownian

motion. If seasonal catches are unavailable, $S_t^{(F)} = 1$ and thus $F_t = G_t^{(F)}$. In this study, seasonal fishing mortality was modelled by $S_t^{(F)} = \exp(D_{s(t)})$, representing a cyclic B-spline (de Boor, 1978) with a period of one year with $s(t) \in [0, 1]$ being a mapping from t to the proportion of the current year that has passed. The annual variation allowed by the cyclic B-spline is determined by the number of knots, which must be smaller than or equal to the number of catch observations per year. The values of the cyclic B-spline are defined by the parameter vector ϕ of length equal to the number of knots minus one. Note that the seasonal process represented by the spline ($S_t^{(F)}$) is repeated every year. Pedersen and Berg (2017) implemented an approximation of a seasonal correlation structure in continuous time with a system of coupled SDEs that is known analytically to have oscillatory solutions, i.e. solutions with a sinusoidal repeating signal (Gardiner, 1985). This can accommodate changes in the fishing pattern over time, however using this approach for Baltic cod did not converge to a realistic solution, while significant auto-correlation in the catch residuals was detected when using the cyclic spline (Fig. D13). To circumvent these problems an extension to SPiCT was developed, which adds an auto-correlated (discrete-time) process H on top of the cyclic spline S and the diffusion component G and to equation 2 ($F_t = S_t^{(F)} G_t^{(F)} \exp(H_{j(t)})$).

$$H_{j(t)} = \phi_H H_{j(t-1)} + \varepsilon_{H,j(t)} , \quad (4)$$

where j maps t to a quarter of the year (dependent on the time-resolution of the catch data), ϕ_H is the coefficient of the auto-correlation with the process one year ago (here lag 4 since catches are by quarter), and $\varepsilon_{H,j(t)} \sim N(0, \sigma_H^2)$, with σ_H being the standard deviation of the observation noise term. This represents an important addition to the original SPiCT model, allowing for an alternative way to estimate deviations from a constant seasonal fishing pattern over time. In other words, the H process describes a step function that is constant in time within quarters and auto-correlated with a lag of one year, and may be thought of as deviations from the mean seasonal process described by $S_t^{(F)}$ which can adapt to changes in amplitude and timing (phase) of the real seasonal fishing pattern. The biomass index and catch observations are respectively modelled by:

$$I_t = q B_t \cdot e^{\nu_t} , \quad (5)$$

$$C_t = \int_t^{t+\Delta} F_s B_s ds \cdot e^{\varepsilon_t} , \quad (6)$$

where q is the catchability, $\nu_t \sim N(0, \sigma_I^2)$ and $\varepsilon_t \sim N(0, \sigma_C^2)$, σ_I and σ_C are the standard deviations of the observation noise terms, and Δ is the time-interval for the catch

(typically a year or quarter of a year).

The Pella-Tomlinson biomass dynamic model allows for skewed production curves (see Fig. C7 in the online Supplementary material for two examples) and includes the Schaefer (n=2; Schaefer, 1954) and Fox (n=1; Fox, 1970) models as special cases. The assumptions are 1) the analysed stock is not subject to migration (i.e. closed population), 2) B_t is the exploitable stock biomass, 3) there are no lagged effects in dynamics of B_t , and 4) the catchability in the survey and fishery are constant over the years. Furthermore, fishing gear selectivity and natural mortality are not explicitly modelled.

2.2 Time-variant productivity

Time-variant productivity is modelled by the combination of a mean productivity parameter, a seasonal component and an additional component determining the long-term changes in productivity:

$$m_t = \bar{m} \hat{S}_t^{(m)} G_{l(t)}^{(m)}, \quad (7)$$

where \bar{m} is the mean m parameter, $\hat{S}_t^{(m)}$ is the scaled seasonal term, and $G_{l(t)}^{(m)}$ corresponding to the long-term changes. The seasonal productivity is implemented as a yearly repeating seasonal process and is modelled as a sinus curve with a known period of one year.

$$S_t^{(m)} = \exp(A \sin(2\pi t + \phi_S)) \quad (8a)$$

$$\hat{S}_t^{(m)} = \frac{S_t^{(m)}}{E(S_t^{(m)})}, \quad (8b)$$

where A is the amplitude and ϕ_S the phase of the sinus curve. The long-term productivity changes $G_t^{(m)}$ correspond to either one of the following three cases: (i) no long-term changes (Eq. 9), (ii) step-wise changes (Eq. 10), or (iii) gradual changes over time (Eq. 11).

$$G_t^{(m)} = 1, \quad (9)$$

$$\log(G_{l(t)}^{(m)}) = \log(\Delta m_{l(t)}), \quad (10)$$

$$d \log(G_t^{(m)}) = -\psi \log(G_t^{(m)}) dt + \sigma_m dW_t^m, \quad (11)$$

where $\Delta m_{l(t)}$ is the difference in the productivity parameters between regimes with $l(t)$ being a mapping from t to the corresponding regime and ψ is the mean reversion rate, defining the speed with which the process approaches the long-term mean (here 0), σ_m the standard deviation of the Ornstein-Uhlenbeck (OU; Uhlenbeck and Ornstein, 1930) process errors. The gradual model (Eq. 11) corresponds to the OU process, which is a stationary Gauss-Markov process and can be considered the continuous time analogue of the discrete time first order Auto-Regressive process (AR1). The OU process tends to drift towards its long-term mean over time and represents random auto-correlated deviations from the average production \bar{m} . The most likely time point for the regime shift of the step-wise model (Eq. 10) can be determined by minimising the Akaike Information Criterion ($AIC = 2k - 2 \log \hat{L}$, where k is number of estimated parameters and \hat{L} is the maximum value of the likelihood function; Akaike, 1998).

These equations allow to model within year variability in productivity as seasonal (S) changes or as constant (C) and between years variability by the variable step-wise model (Vs), the variable gradual model (Vg), or as constant (C). The combination of these aspects allow to derive the original SPiCT (C-C) and five extensions accounting for time-variant productivity (Table 1). All model extensions are available at the GitHub repository under <https://github.com/tokami/spict/tree/seaprodtvp> and example applications at: <https://github.com/tokami/pubs/tree/master/TVP>.

Table 1: Model extensions regarding time-variant productivity on short and long-term scales based on the original SPiCT.

Model code	Seasonal model	Step-wise model	Gradual model	Equations
C-C				Eq. 9 & $\hat{S}_t^{(m)} = 1$
S-C	✓			Eq. 9 & $\hat{S}_t^{(m)} \neq 1$
C-Vs		✓		Eq. 10 & $\hat{S}_t^{(m)} = 1$
S-Vs	✓	✓		Eq. 10 & $\hat{S}_t^{(m)} \neq 1$
C-Vg			✓	Eq. 11 & $\hat{S}_t^{(m)} = 1$
S-Vg	✓		✓	Eq. 11 & $\hat{S}_t^{(m)} \neq 1$

2.3 Reference levels

SPiCT estimates three reference levels: maximum sustainable yield (MSY), the fishing mortality required to attain MSY (F_{MSY}), and the biomass of the stock if fished at F_{MSY} (B_{MSY}). Traditionally, reference levels are time-invariant, however, the equations for the reference levels (Eq. 12-14 and Appendix A) imply that MSY and F_{MSY} are time-variant if the productivity (in terms of m) is time-variant, but B_{MSY} is not because it does not depend on m . The seasonal component of the productivity is of a lesser interest for fisheries management as the advice is usually based on reference levels representative for a year (or management period). Therefore the seasonal components of m_t and F_t ($\hat{S}_t^{(m)}$ and $S_t^{(F)}$, respectively) are omitted in the estimation of the reference levels.

$$MSY_t = m_t^\zeta \quad (12)$$

$$B_{MSY} = K \left(\frac{1}{n} \right)^{\frac{1}{n-1}} \quad (13)$$

$$F_{MSY_t} = MSY_t / B_{MSY} \quad (14)$$

where m_t^ζ represents the non-seasonal component of m_t ($m_t^\zeta = \bar{m} G_{l(t)}^{(m)}$). These reference levels represent the non-seasonal deterministic reference levels, the non-seasonal stochastic ones can be derived by substituting the corresponding equations in Pedersen and Berg (2017) with above deterministic levels (cf Appendix A). For the step-wise productivity model, this implies a constant MSY and F_{MSY} level for each regime, while for the gradual model, the two reference levels become continuous.

2.4 Simulation study

The simulation study is parametrised according to the results of the SPiCT assessment of the Baltic cod stock with the S-Vg model (Table 4) and allows the evaluation of the seasonal production relative to seasonal patterns, data quality and the non-seasonal SPiCT assessment. Table 2 summarises the parameter values and simulation settings. The framework comprises 500 simulations and extends over a simulation period of 30 years and 4 seasons, which is in line with the occurrent data conditions in the North Sea. Five different scenarios combine seasonal fishing mortality and productivity with variable phases (Fig. 1) and biannual biomass indices with different timing (rugs in Fig. 1; Table 3).

Table 2: Parameters used for the simulation study. Values are based on the results of the SPiCT assessment of the Baltic cod stock with the S-Vg model (Table 4). Values separated by a backslash correspond to different scenarios. SD is the standard deviation and CV the coefficient of variation.

Parameter	Description	Value
dt [year]	Euler time step	$1/16$
K [ktonnes]	Carrying capacity	148.9 (CV=0.1)
m [ktonnes]	Stock productivity	59.78 (CV=0.1)
n	Shape parameter of production curve	0.62 (CV=0.1)
q	Catchability	0.02 - 0.04
bkfrac	Fraction of B/K	0.9 - 1
F_0 [year $^{-1}$]	Initial fishing mortality	0.01
F_{max} [year $^{-1}$]	Maximum fishing mortality	2
σ_B	SD of biomass process error (Eq. 1)	0.1
σ_I	SD of index observation error (Eq. 5)	0.1
σ_F	SD of fishing mortality process error (Eq. 3)	0.1
σ_C	SD of catch observation error (Eq. 6)	0.1
ϕ	Parameter vector of cyclic B-spline of seasonal fishing mortality process (Eq. 2)	1.4, 1, 0.7/ 2.5, 1.2, 0.34/ 0.7, 1, 1.4/ 0.34, 1.2, 2.5
ϕ_S	Phase of seasonal productivity process (Eq. 8)	1.28
A	Amplitude of seasonal productivity process (Eq. 8)	0.73 / 0.25

All models include seasonal fishing mortality (cyclic B spline), but do not include the auto-correlated process H (Eq. 4) nor long-term changes in productivity ($G_t^{(m)} = 1$). The simulation study uses a modified version of the SPiCT simulation model used in Pedersen and Berg (2017). Each scenario is estimated using the models C-C and S-C. Section B

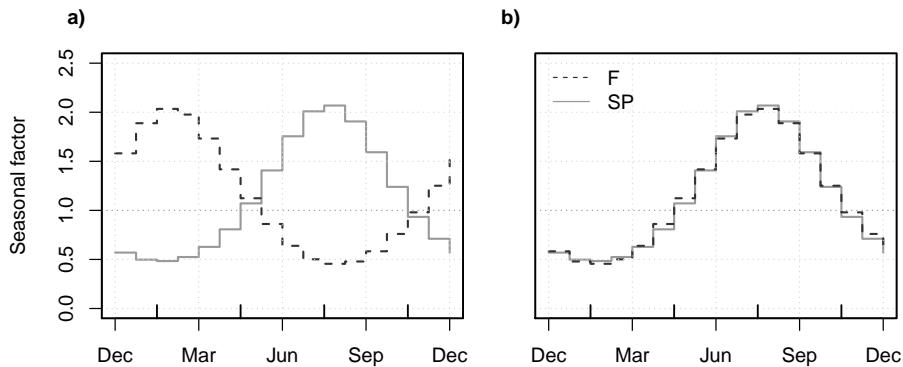


Figure 1: Different scenarios of the seasonal pattern of fishing mortality (dashed) and productivity (solid) with equal amplitudes: a) contrasting pattern of fishing mortality and productivity; b) identical pattern of two seasonal processes. The rugs on the x axis show the timing of the survey indices, where the first and third rug correspond to the survey in the North Sea, the second and fourth to a case where the indices miss the maxima and minima of the seasonal factors, and the first and fourth to the survey in the Baltic Sea.

in the Supplementary material includes more details to the simulations study and ten additional scenarios.

2.5 Performance metrics

The results of the simulations are evaluated based upon several performance metrics, which are estimated for the reference levels and the last observations of the relative biomass and fishing mortality, $(B/B_{MSY})^{last}$ and $(F/F_{MSY})^{last}$, respectively. The relative states in the last year have an important role within stock assessment and management advice. Here, the biomass and fishing mortality values represent the last instances of the baseline trajectories omitting the seasonal factors. The performance metrics are: (i) the proportion of converged model fits, where a model is defined as converged if the optimiser `nlminb` (R Core Team, 2018) reports a successful completion and if confidence intervals (CI) can be estimated and are finite. For converged fits, (ii) the median bias (MB) is estimated by following equation:

$$\text{MB} = \text{median} \left(\frac{\hat{\theta} - \theta}{\theta} \right), \quad (15)$$

where $\hat{\theta}$ is the estimated value and θ the true or target value. Additionally, (iii) the coverage fraction (CF), i.e. the fraction of simulations where the CI includes the true value (target is equal to 95%), and (iv) the coefficient of variation (CV) are estimated.

Table 3: Scenarios of the simulation study with the properties of the simulation framework as well as the number of converged runs for each scenario. All scenarios are estimated with and without the seasonal productivity model. The column “seasonal factors” indicates if the amplitudes of the two seasonal factors (F and P) are equal, or if one or the other outweighs the other and the column $t_{indices}$ indicates the timing of the indices, where NS corresponds to a North Sea like timing (first and third quarter) and X corresponds to a mismatch between indices and the maxima and minima of the seasonal factors (second and fourth quarter; cp. Fig. 1). The first number in the “Converged runs” column represents the values for the seasonal model and the second for the non-seasonal model.

Scenario code	Pattern F vs P	Seasonal factors	Num indices	$t_{indices}$	Converged runs (%)
CE2N	contrasting	equal	2	NS	96.2/99.8
CE2X	contrasting	equal	2	X	50.6/91.4
IE2N	identical	equal	2	NS	100/99.8
IE2X	identical	equal	2	X	95.4/99.8
CE2NX ¹	contrasting	none	2	NS	97.2/99.6

¹ Data simulated without seasonal productivity and estimated with C-C and S-C.

The combination of these metrics allows inference about the precision and accuracy of the different scenarios. The relative errors for the two quantities are compared between the two models (C-C and S-C) and between the scenarios for each model based on the Wilcoxon Signed-Rank test.

2.6 Application to Baltic cod

All six model combinations (Table 1) are fitted to the Baltic cod data: Seasonal catches from all commercial fleets targeting Baltic cod and the biannual (quarter 1 and quarter 4) biomass index from the Baltic International Trawl Survey (BITS) for the years 1991 - 2018 are taken from ICES (ICES, 2018b). All models include the seasonal fishing mortality (cyclic B spline) and the auto-correlated process H (equation 4) and are fitted by a two-step fitting process: First, in order to stabilise the optimiser, the model is fitted using all default priors (n , $\alpha = \sigma_I/\sigma_B$, $\beta = \sigma_C/\sigma_F$ for the Vs models, and additional ψ and σ_m for the Vg models). In the second step the point estimates are used as the initial values for the second fit without any priors. This process stabilises the optimisation and allows to remove the impact of priors on the likelihood of the models and thus the calculation of the likelihood ratio test for nested models.

3 Results

3.1 Simulation study

The simulation study revealed that results of the SPiCT assessment are biased if underlying seasonal productivity is not accounted for (e.g. scenario CE2N; Fig. 2). The median bias of the non-seasonal model is 21% for $(B/B_{MSY})^{last}$ and -10.9% for $(F/F_{MSY})^{last}$ and is significantly higher than of the seasonal model (7.3% and -5.3% , respectively) according to the Wilcoxon Signed-Rank test ($p < 0.001$ and $p < 0.05$ for the two quantities respectively). On the other hand, if no seasonal productivity was simulated, median biases are comparable (scenario CE2NX; Fig. 2) and there is no significant difference between the two models for the two quantities ($p = 0.561$ and $p = 0.708$, respectively), even though the precision of C-C is slightly better than of S-C (Fig. 2).

Overall, the median biases are smallest for MSY and the relative reference levels and higher for B_{MSY} and F_{MSY} (Table B2). Absolute levels, however, vary substantially between the different scenarios and are dependent on the number of indices per year, their timing and the properties of the seasonal processes, one of which is their relative pattern: contrasting vs. identical. While S-C generally outperforms C-C for the contrasting pattern, the C-C model seems to perform better for the identical pattern (Fig. 2). However, the smaller median bias in $(B/B_{MSY})^{last}$ for C-C is the result of highly overestimated B_{MSY} and underestimated biomass (Fig. B4). Additionally, the median bias in $(B/B_{MSY})^{last}$ and $(F/F_{MSY})^{last}$ is comparable between the contrasting and identical pattern for S-C ($p = 0.541$ and $p = 0.767$ for the two quantities respectively), even though, the seasonal productivity process was overestimated to a larger extent in some simulations of the contrasting scenarios in comparison to the identical pattern (Fig. 3). By contrast, C-C shows significant differences between the contrasting and identical pattern of the seasonal processes ($p < 0.001$ for $(B/B_{MSY})^{last}$ and $(F/F_{MSY})^{last}$). The relative strength of the seasonal processes is less important (additional scenarios in Section B of the Supplementary material). Another important factor affecting model performance is the number of indices and their timings. While there is no significant difference in the median bias of $(B/B_{MSY})^{last}$ between 4 and 2 indices ($p = 0.24$ and $p = 0.09$ for the contrasting and identical pattern, respectively; cf. additional scenarios CE4A and IE4A in Fig. B3 and Table B1), the median bias of $(F/F_{MSY})^{last}$ is significantly larger with 2 indices (-5.3%) than with 4 indices (-0.3%) for the contrasting pattern ($p < 0.001$) as well as for the identical pattern with -4% vs 2.5% for 2 and 4 indices, respectively ($p < 0.001$). In addition, the number of simulations overestimating the seasonal productivity pattern is larger for the scenario with 2 indices than for the one with 4 (Fig. B5). If the timing of the indices does not capture any peak of the seasonal processes

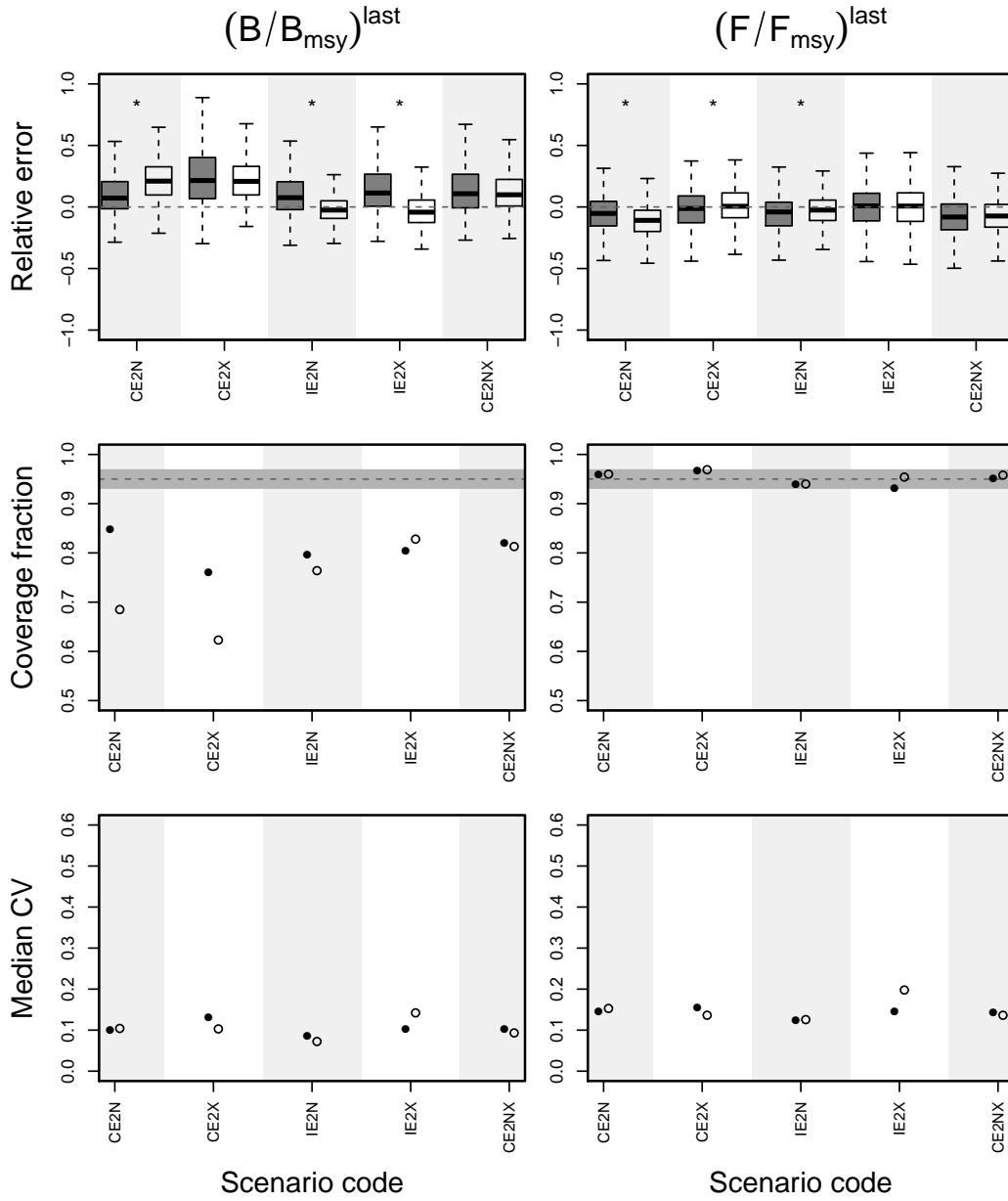


Figure 2: Results of the simulation study for the two quantities $(B/B_{MSY})^{last}$ and $(F/F_{MSY})^{last}$ for all scenarios. Dark filled bars and circles represent seasonal model (S-C), while white bars and circles represent the non-seasonal model (C-C). The boxplots do not include outliers. The second row shows the coverage fraction, where the horizontal line represents the reference line for the 95% confidence intervals at 0.95 with expected uncertainty for the reference line dependent on the number of simulations as the shaded area. The stars above the boxplots in the first row indicates for which scenario the differences between the two models (C-C and S-C) are significant based on the Signed-Rank Wilcoxon test (Table B2).

(scenarios CE2X and IE2X), the median bias in both quantities is significantly higher than if both peaks of the seasonal processes are captured (scenarios CE2N and IE2N in Fig. 2) or when at least one peak is captured (cf. additional scenarios CE2B and IE2B in Fig. B3 and Table B1). Although the bias in $(F/F_{MSY})^{last}$ for scenarios CE2X and IE2X is smaller than the other scenarios (Fig. 2), Figure B4 reveals that the bias in the individual reference levels is highest for these scenarios and the resulting median bias in $(F/F_{MSY})^{last}$ is only the consequence of a highly overestimated F_{MSY} and underestimated F .

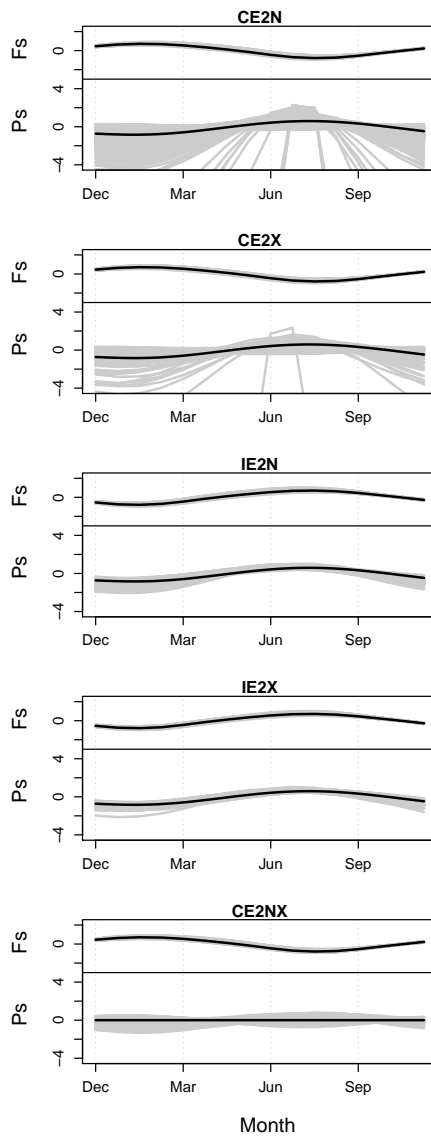


Figure 3: Estimated and true seasonal processes. The black line represents the true seasonal pattern used in the simulation and the grey lines represent the estimated patterns for each simulation. Fs indicates the seasonal F process and Ps the seasonal productivity process.

Across all scenarios, between 90 and 100% of all simulations converged, except for scenario CE2X, which shows a high proportion (50.6%) of non-converged runs for the seasonal model (Table 3). Also C-C shows convergence problems for this scenario but the convergence ratio was substantially higher (91.4%). Overall, the proportion of converged non-seasonal fits is higher than the seasonal fits (Table 3). The coverage fraction is generally quite high with values around 80% for B/B_{MSY} and around 95% for F/F_{MSY} for most scenarios (Fig. 2). The coefficient of variation is around or below 0.1 and 0.2 for B/B_{MSY} and F/F_{MSY} , respectively and similar across all scenarios and C-C and S-C (Fig. 2). Figure 3 shows that the seasonal pattern was generally well estimated, albeit with some outlying simulations, in particular for the scenarios with contrasting seasonal patterns. For CE2NX, the amplitude of the seasonal process (parameter A in Eq. 8) was with 0.2 (median over all simulations) estimated to be much smaller than for the comparative scenario CE2N (0.73).

3.2 Baltic cod

Beside S-C, all models applied to Baltic cod converged and resulted in reasonable parameter estimates (Section D3 in the Supplementary material) and derived quantities (Table 4). However, estimated confidence intervals for derived quantities (Table 4) of the models C-C, S-C, and C-Vg span up to 5 orders of magnitude, indicating that there is very little information in the data about these quantities. The remaining 3 models C-Vs, S-Vs, and S-Vg gave reasonable confidence intervals (maximum difference between upper and lower CI limits of 1 order of magnitude) and show similar biomass and fishing mortality trajectories (Fig. 4) and the same stock perception (Table 4): over-fishing in terms of biomass ($B/B_{MSY} < 0.5$) and fishing mortality ($F/F_{MSY} > 2$) at the last assessment time point.

The optimum break point of the Vs models was estimated based on model comparison with different break points (Fig. D14), resulting in two productivity regimes: (i) 1991-2009 and (ii) 2010-2017. The MSY of the first productivity regime (~ 91 ktonnes) is more than two times higher than the second regime (~ 40 ktonnes) for both models. The average productivity parameter of the Vg models is ~ 70 ktonnes, however, decreased from ~ 100 ktonnes in 1995 to ~ 40 ktonnes in 2018 (Fig. 4f). The uncertainty of the biomass and fishing mortality trajectories in the S-Vg model are higher than in the S-Vs model (Fig. 4). For the step-wise models, the seasonal and non-seasonal gave similar point estimates and CIs. For the gradual models, however, the model without seasonality did not give reasonable results (cf. Section D7) and indicates the opposite stock perception than of the S-Vg. Although the trajectory of the MSY of the S-Vs and the

Table 4: Results of the Baltic cod assessment. Bold numbers represent point estimates with the respective 95% confidence intervals below. For the Vg models, values for the time-variant MSY and F_{MSY} represent averages over the whole time period. For Vs models, the estimates and CIs of both regimes are presented. The last row shows the results of the likelihood ratio test for each model pair. The grey columns highlight the most suitable models.

Quantity	Models					
	C-C	S-C	C-Vs	S-Vs	C-Vg	S-Vg
B_{MSY}	14.09 0.01 – > $1e^3$	68.39 11.43 – 409.13	72.06 40.06 – 129.63	65.38 38.1 – 112.18	3.58 < 0.01 – > $1e^3$	42.35 18.11 – 99.02
F_{MSY}^1	6.34 < 0.01 – > $1e^3$	0.66 0.11 – 4.04	1.29 0.73 – 2.27	1.4 0.8 – 2.44	19.83 < 0.01 – > $1e^3$	1.68 0.71 – 3.95
F_{MSY}^2			0.55 0.28 – 1.09	0.64 0.34 – 1.21		
MSY^1	89.29 47.31 – 168.54	45.32 35.24 – 58.27	92.66 80.3 – 106.93	91.13 78.81 – 105.36	70.92 49.47 – 101.67	71.03 61.21 – 82.43
MSY^2			39.42 31.2 – 49.81	41.86 33.89 – 51.72		
$(B/B_{MSY})^{last}$	3.61 < 0.01 – > $1e^3$	0.68 0.07 – 6.54	0.38 0.25 – 0.59	0.31 0.22 – 0.45	4.47 < 0.01 – > $1e^3$	0.28 0.15 – 0.52
$(F/F_{MSY})^{last}$	0.09 < 0.01 – 280.54	0.83 0.08 – 8.64	2.13 1.17 – 3.87	2.1 1.28 – 3.47	0.25 < 0.01 – 787.69	2.61 1.33 – 5.13
	$LR(2) = 15.05, p < 0.001$		$LR(2) = 14.02, p < 0.001$		$LR(2) = 11.28, p < 0.001$	

¹ Corresponds to the first productivity regime (1991-2009) for the Vs models.

² Corresponds to the second productivity regime (2010-2017) for the Vs models.

S-Vg models are different, the absolute value in the last assessment year of both models is close: 42 and 37.4 tonnes, respectively.

The likelihood ratio test indicates that for all nested models the addition of the two parameters of the seasonal model improves the model fit significantly (Table 4). All models estimated a similar seasonal fishing mortality pattern, with a maximum between April and May and minimum around August (Fig. 5a, b). Also the seasonal productivity pattern is similar between the S-Vs and S-Vg, with the maximum around May-June and the minimum between November and December (Fig. 5c, d). The slight difference in timing of maxima and minima between models is also shown in the phase parameter: -0.36 and -0.09 for S-Vs and S-Vg, respectively. The amplitude of the seasonal productivity is 1.55 and 0.92 for the step-wise and gradual model, respectively. The uncertainty of the seasonal production factors estimated with S-Vs is almost twice as high as for the gradual model. The C-Vg model gives comparable results to S-Vg if a vague prior for the reversion rate (ψ) is used.

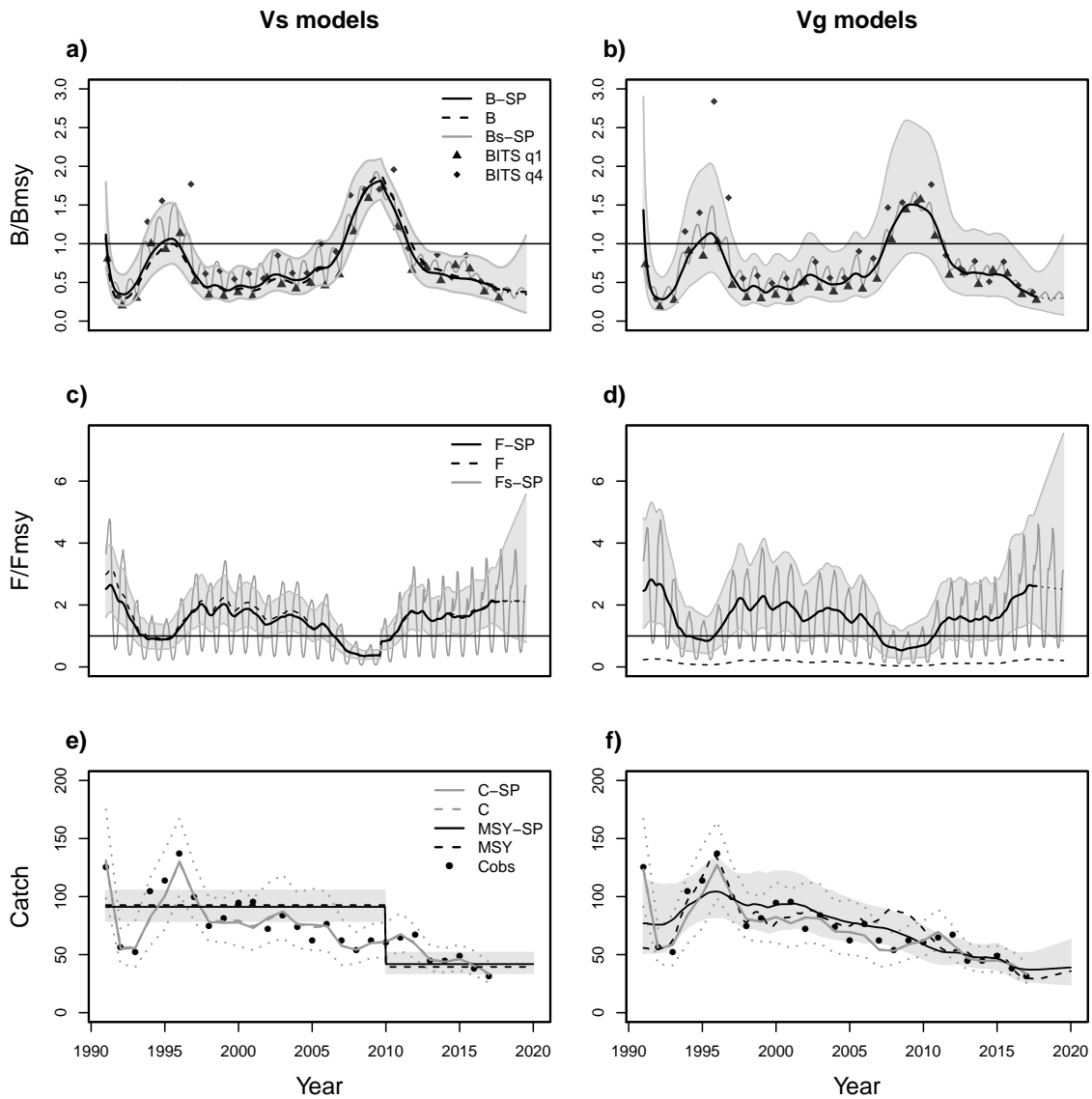


Figure 4: Bold black lines in the two top rows represent the relative mean biomass and fishing mortality from the seasonal models, respectively, while the grey lines include the seasonal processes. Dashed lines represent estimated trajectories from non-seasonal models. Shaded areas represent the 95% CIs of the relative mean trajectories of the seasonal models (without seasonality). The relative biomass trajectory of C-Vg is outside of the plotting region with an average value of 8.4. The third row shows catch trajectories and estimated MSY of the seasonal models (solid grey and solid black lines, respectively) and of the non-seasonal model (dashed grey and dashed black lines, respectively). The different symbols represent the observations of the two surveys and catches, respectively.

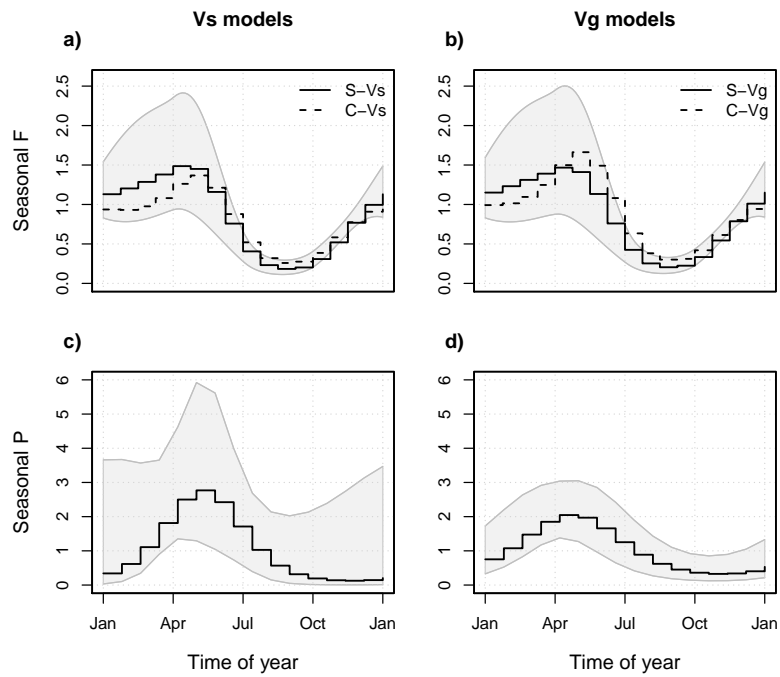


Figure 5: Seasonal processes of the Baltic cod assessment: The first column shows the seasonal processes for the regime-shift model and the second column for the gradual model. Shaded areas represent the 95% CIs. The first row includes the seasonal fishing mortality process for the non-seasonal models (dashed lines).

4 Discussion

Productivity is not constant over time, but shows time dependent variability due to intra-specific and ecological processes, and environmental conditions (Caddy and Gul-land, 1983; Mullon et al., 2005; Vert-pre et al., 2013; Britten et al., 2016, 2017; Peterman et al., 2011). The proposed extensions to a biomass dynamic model allow to account for time-variant productivity both within and between years, i.e. on both short-term seasonal and long-term inter-annual basis. The new models (S-C, C-Vs, S-Vs, C-Vg, S-Vg) were simulation tested (Section C in the Supplementary material) and did not reveal any error or dependence on life-history traits, showing expected declining error and confidence intervals with increasing length of the time series (Fig. C8 - C12).

4.1 Simulation study

The simulation study reveals that reference levels are not only biased when neglecting seasonal productivity but that the biases depend on the properties of the seasonal processes quantitatively and qualitatively. Thus, not accounting for within year variability in productivity might have similar negative effects on management as it was shown for between years variability in productivity (Peterman et al., 2011; Britten et al., 2017; Nesslage and Wilberg, 2019). Furthermore, the simulation study shows how unaccounted seasonal productivity can lead to large biases in absolute reference levels (B_{MSY} and F_{MSY}) and states (B and F), while the bias in MSY and relative reference levels (B/B_{MSY} and F/F_{MSY}) is relatively small, e.g. for scenario I2EN. This underpins the recommendation of using the relative reference levels for fisheries management (Pedersen and Berg, 2017) as they are the least biased quantities even if seasonal productivity is not accounted for.

Overall, the biases are smaller with the identical pattern in comparison to the contrasting pattern. This can be attributed to the fact that the two seasonal processes are overlapping and that the effect on biomass (and thus on the observed indices) is multiplicative. It appears that it is more complicated for the model to resolve the seasonal trends in catch and biomass and allocate them correctly to the seasonal productivity when the patterns are contrasting (more deviations from the true seasonal productivity curve for the contrasting scenarios in comparison to the identical patterns in Figure 3). While two indices can be sufficient for the estimation of seasonal productivity, the simulation study revealed the importance of the timing of the indices relative to the peaks of the seasonal processes. Scenarios with the timing close to at least one peak of the seasonal productivity process perform better than if the timing is in between peaks. In this case, the biomass index can not inform the model about the amplitude or phase of the seasonal productivity process.

Although, the biases in derived quantities for the best informed scenario (CE4A, see Sec-

tion B in the Supplementary material) are small and the distributions include zero, the coverage fraction for all quantities (except F/F_{MSY}) is smaller than the nominal 95%. The small biases and low coverage fraction can be attributed to the differences of the fishing mortality process in the simulation and estimation and/or data limitations. The simulated roller-coaster pattern for the fishing mortality violates the assumptions of the random walk model used in the estimation procedure. The maximum likelihood estimator and Laplace approximation might introduce a bias, in particular for short time series. A time series of 30 years is far from the asymptotic limit (cf. Figures C8 and C9 in this study and Fig. S5 in Pedersen and Berg (2017)) and thus, might be insufficient in regard to the complexity of the model additions.

This study contributes to a growing body of research demonstrating how time-variant parameters in surplus production models can improve model performance (Prager, 1994; Vert-pre et al., 2013; Nakayama et al., 2017; Nesslage and Wilberg, 2019), however, this study is the first to model time-variant parameters of surplus production models with the Fletcher parametrisation (Fletcher, 1978) rather than the original parametrisations (Graham, 1935; Schaefer, 1954; Pella and Tomlinson, 1969) and particularly quantifying short-term seasonal productivity fluctuations. As previous studies, we considered time dependent variability in the intrinsic population growth rate (or its analogue 'm' in the Fletcher parametrisation) rather than the carrying capacity K. While processes affecting the carrying capacity of fish populations take place (e.g. habitat contraction; Orensanz et al., 2005; Worm and Tittensor, 2011), they are more difficult to detect based on a biomass index time series alone and due to the weak dynamical connection between biomass and carrying capacity when biomass is low (Britten et al., 2017).

4.2 Baltic cod

The models fitted to Baltic cod show a consistent and clear pattern of long-term changes in stock productivity, with either a continuously decreasing productivity pattern or a high and subsequent low productivity regime and none of the models with constant long-term productivity converged without problems. The estimated long-term productivity changes of Baltic cod correlate well with observed changes in the condition of Baltic cod that started in the mid-1990s (Eero et al., 2015; ICES, 2015). The decreasing condition and productivity of Baltic cod can be explained by the individual processes contributing to stock productivity (somatic growth, recruitment and survival): The peak of the continuous productivity (and the high first productivity regime) fits to the peak abundance of sprat in the Baltic Sea in the mid-1990s (Casini et al., 2016), which was the most abundant pelagic prey in the stomachs of Baltic cod (Uzars et al., 2000; Neuenfeldt

and Beyer, 2003). Although the subsequent decline of sprat abundance does not have the same reduction rate as the decrease in modelled productivity, the increased spatial mismatch between the core sprat and cod distribution areas in the Baltic poses another cause for productivity decrease (Casini et al., 2016). Similarly, the sharp decline of the productivity of the Northwest Atlantic cod (*Gadus morhua*) stocks at levels of high stock density in 1985 was attributed mainly to the decline of available forage fish (Hilborn and Litzinger, 2009; Rothschild, 2007; Shelton et al., 2006). In addition, according to Casini et al. (2016) the increase in hypoxic zones in the Baltic Sea since the 1990s (Conley et al., 2011) has affected cod productivity negatively due to physiological stress, benthos productivity decrease, and habitat compression. Also the increasing seal abundance and, thus, the increase in seal parasites which affect the somatic growth and survival of Baltic cod negatively increased over the last two decades (Mehrdana et al., 2014).

As for long-term changes in productivity, seasonal variations result from seasonal patterns in somatic growth, recruitment, and/or survival. The feeding level of Baltic cod peaks in the 3rd and 4th quarter (Baranov and Uzars, 1986). However, the maximum feeding level does not correspond to the maximum somatic growth rate, as the individuals have an energy deficit after spawning which has to be balanced out before energy can be allocated to somatic growth. The peak in somatic growth is, thus, delayed and to be expected in the first quarter (Dr Stefan Neuenfeldt, DTU Aqua, personal communication), fitting well to the estimated pattern in seasonal productivity. Also the low lipid content of the main pelagic prey species (sprat and herring) from November to March (Røjbek et al., 2014) matches the pattern of the seasonal productivity. The second individual-level process, recruitment and, thus, spawning also shows a seasonal tendency for Baltic cod: Although, Baltic cod has a prolonged spawning period from February to November, spawning peaks in May-August (Wieland, 2000; Bleil et al., 2009), which is expressed in the estimated seasonal productivity pattern in two ways: (i) individuals recruiting to the fishery in May in the third year after spawning (biomass in SPiCT corresponds to exploitable biomass), and (ii) weight-loss after peak spawning in May-August (Dr Stefan Neuenfeldt, DTU Aqua, personal communication). Less is known about the third component, seasonal patterns of the survival of Baltic cod, but the natural mortality of Baltic cod might be high right after spawning (Dr Karin Hüsey, DTU Aqua, personal communication).

The assumption of the SPiCT assessment that the Baltic cod stock is not subject to migration is likely violated as individuals are not only migrating within the Baltic Sea and mixing with the western Baltic cod stock (particularly in the Arkona Basin; Aro, 1989; Nielsen et al., 2013), but the migration rate also varies over time (Hüsey et al., 2016). Furthermore, we made the assumption that the seasonal productivity pattern is constant over time although some inter-annual variability has been observed (Wieland, 2000; Bleil et al., 2009). This should be seen as an assumption necessary to facilitate the

analysis rather than representing the truth, since we are approaching the limit of what can be estimated from the data. Random deviations from a constant pattern would likely increase the uncertainty but not introduce bias, whereas systematic trends are likely to introduce biases in the assessment. Extending the model to allow the seasonal productivity pattern to change over time is an avenue for future research.

According to the assessments with reasonable fits and uncertainties (C-Vs, S-Vs, S-Vg), the Baltic cod stock is depleted ($B < B_{MSY}$) and subject to over-fishing ($F > 2F_{MSY}$). The models with seasonal productivity are significantly better at describing the data compared to models without seasonality, although the estimates of $(B/B_{MSY})^{last}$ and $(F/F_{MSY})^{last}$ are almost identical. However, the simulation study showed that this may not be the case in other cases. The time-variant reference levels (MSY and F_{MSY}) do not affect the classification of the stock in terms of these relative states historically or in the current year. Taking assessment uncertainty into account, useful management advice can be given based on the relative states in the last time step ($(B/B_{MSY})^{last}$ and $(F/F_{MSY})^{last}$) as demonstrated for the original SPiCT (ICES, 2018a).

5 Conclusion

This study introduces a novel approach to incorporate environmental change into stock assessments without the need of complex and data-demanding (ecosystem) models and defines time-variant reference levels for fisheries management and advice. Although the extensions of biomass dynamic models introduced here, increase requirements for data quality and quantity (seasonal catches and biannual survey indices required), accounting for time-variant productivity is important as stocks in low-productivity regimes cannot support the same yield as stocks in high-production regimes and neglecting seasonality might severely bias estimated reference levels and relative states and, therefore, management advice. Accounting for a combination of time-variant productivity on seasonal and long-term scales improves the assessment of the Baltic cod stock significantly.

6 Supplementary material

Further details on the settings and results of the simulation study, the simulation study for the validation of the model additions, and additional results regarding the Baltic cod assessment are available at ICESJMS online.

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A Estimation of the non-seasonal stochastic reference levels and relative states

The non-seasonal stochastic reference levels can be derived by substituting the corresponding equations in [Pedersen and Berg \(2017\)](#) with the deterministic reference levels (Eq. [12 - 14](#)), resulting in:

$$MSY_t^s = MSY_t^d \left(1 - \frac{n/2}{1 - (1 - F_{MSY_t}^d)^2} \sigma_B^2\right) \quad (16)$$

$$B_{MSY_t}^s = B_{MSY}^d \left(1 - \frac{1 + F_{MSY_t}^d (n-2)/2}{F_{MSY_t}^d (2 - F_{MSY_t}^d)^2} \sigma_B^2\right) \quad (17)$$

$$F_{MSY_t}^s = F_{MSY_t}^d - \frac{(n-1)(1 - F_{MSY_t}^d)}{(2 - F_{MSY_t}^d)^2} \sigma_B^2 \quad (18)$$

where the superscript d refers to the deterministic reference levels as defined in [Section 2.3](#) and σ_B refers to the standard deviation of the biomass process noise. Similarly, in the estimation of the relative states (B_t/B_{MSY} and F_t/F_{MSY}), the seasonal part of the biomass and fishing mortality is omitted as otherwise the quantities were strongly dependent on the time of the year one chooses to evaluate them. These relative states are estimated by removing the seasonal components of m_t and F_t ($\hat{S}_t^{(m)}$ and $S_t^{(F)}$, respectively) in [equation 1](#) and [2](#).