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Peterman's productivity method for estimating dynamic reference points in changing ecosystems

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Target and limit reference points are fundamental management components used to define sustainable harvest strategies. Maximum Sustainable Yield (MSY) and the precautionary principle underpin many reference points. Non-proxy reference points based on MSY in age-based single-species assessments depend on the stock–recruitment (SR) relationship, which can display complex variability. Current reference points ignore persistent dynamic change by assuming that the SR relationship is stationary and with constant recruitment parameters over selected time periods. We highlight Peterman's productivity method (PPM), which is capable of tracking temporal dynamics of recruitment productivity *via* time-varying SR parameters. We show how temporal variability in SR parameters affects fishing mortality and biomass MSY-based reference points. Implementation of PPM allows for integrated dynamic ecosystem influences in tactical management while avoiding overwrought and sometimes ephemeral mechanistic hypotheses tested on small and variable SR datasets. While some of these arguments have been made in individual papers, in our opinion the method has not yet garnered the attention that is due to it.

Keywords: EBFM reference points, non-stationary productivity, scientific fisheries management advice, stochastic processes, stock–recruitment relationship, time-varying parameters.

Introduction

Reference points play a key role in the provision of scientific advice for fisheries management (Garcia, 1996). They provide the basis to define targets and limits that establish operational objectives, necessary for effective fisheries management (Sissenwine and Shepherd, 1987; Schnute and Haigh, 2006; Hilborn *et al.*, 2020). Reference points provide benchmarks to promote the sustainability of the stocks and reliant fisheries (Mace, 1994). By identifying limits that should not be exceeded and targets that should be achieved, they support harvest control rules (HCRs) that guide management decisions (Punt, 2010; Kvamsdal *et al.*, 2016). They have an essential role in current management frameworks, to provide recommendations for fishing strategies and to define tactical management measures, e.g. catch and effort limits, and the design of management plans.

Major paradigms used to define reference points internationally are Maximum Sustainable Yield (MSY) and the precautionary approach (FAO, 1995a). The Food and Agriculture Organization (FAO) of the United Nations defines MSY as: "the highest theoretical equilibrium yield that can be continuously taken (on average) from a stock under existing (average) environmental conditions without affecting significantly the reproduction process". Managing fish stocks under the precautionary approach and MSY has been generally advocated by international agreements (FAO, 1995a; UN, 1995, 2002). The UN Fish Stock Agreement contains guidelines for applying a precautionary approach within an MSY framework. During the World Summit on Sustainable Development, organized by the UN in 2002, it was agreed in the Johannesburg Declaration to, "maintain or restore stocks to levels that can produce the MSY with the aim of achieving these goals for depleted stocks on an urgent basis and where possible not later than 2015" (UN, 2002). These concepts are embraced by intergovernmental organizations and are reflected in important fisheries policies, e.g. Common European Fisheries Policy (EC, 2013) and Magnuson–Stevens Fisheries Conservation and Management (MSA, 2007) in the United States.

While MSY has been criticized from multiple angles (Larkin, 1977), a change in focus, away from MSY as a target catch state towards a target and limit fishing mortality rate at MSY (Mace, 2001), has made it one of the main operational guides for sustainability in global fisheries management (Worm *et al.*, 2009; Marchal *et al.*, 2016). Indeed, given difficulties in establishing economic management objectives, MSY emerges as a default fall-back option (Beverton and Holt, 1993), if not the appropriate economic objective in itself considering all components of the overall fishing sector (Christensen, 2010).

One of the main criticisms of MSY is whether it is possible to take ecological aspects into account (Larkin, 1977; May *et al.*, 1979; Mace, 2001). Studies highlight the challenge of achieving MSY simultaneously for cohabiting species (Mackinson *et al.*, 2009). There is also indication that single-species MSY may need to be adapted when ecological interactions are present—i.e. predation, competition—(May *et al.*, 1979; Gislason, 1999; Collie and Gislason, 2001). Additionally, the growing evidence of regime shifts (Vert-pre *et al.*, 2013; Perälä *et al.*, 2017); and the effect of climate change in fish stocks (Free *et al.*, 2019) emphasize the presence of non-stationary population processes, which mean that reference points will also vary.

The need to adopt a more holistic approach to fisheries management has been globally accepted (FAO, 2003). Thus,

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the ecosystem approach is included in most fisheries' international agreements and policies. Ecosystem-based fisheries management (EBFM) requires comprehension of the broader picture (biophysical interactions, biodiversity, food-web structure, ecological processes, and ecosystem functioning). Therefore, the science for its operationalization and implementation is often considered challenging (Cowan *et al.*, 2012; Dolan *et al.*, 2016). It is crucial to develop reference points as operationally powerful as those currently used in single-species management advice yet in accordance with ecosystem concerns. There is still no agreement on how to evolve the MSY concept and what should be considered targets and limits within EBFM (Rindorf *et al.*, 2017b). The MSY concept applied correctly might be more useful to EBFM than other data-demanding methods (Pauly and Froese, 2021).

There is a "gap" between single-species methods that provide reference points for advice to trigger tactical management and ecosystem-based methods that often do not have clearly defined operative standards for tactical management (Fogarty, 2014). This gap is difficult to bridge because more complex models present greater modelling challenges (Quinn, 2008), making the outcomes less suitable for management. Both methods are needed to support: (a) tactical advice able to make management decisions in an immediate term and (b) strategic advice based on the understanding of the system and the study of ecosystem drivers and their effects. In this article, we focus on how to deal with changing ecosystems within tactical fisheries management. We present a possible bridge to align stock reference points with ecosystem concerns.

In our opinion, the keystone lies in the static assumptions to model recruitment productivity, made in most single-species reference point estimations, which do not reflect non-stationary behaviours shown in fish productivity (Peterman *et al.*, 2000; Minto *et al.*, 2014; Perälä *et al.*, 2017). We briefly review reference point estimation in single-species contexts and highlight how time-varying approaches provide operational objectives for management reflective of a dynamic ecosystem. We believe that the framework for doing this is available, we provide due recognition to the originators—Professor Randall Peterman and his group—, and look to challenges and future developments. We conducted hypothetical numerical simulations to show the role of temporal variability in stock–recruitment (SR) relationship parameters and their impact on reference point estimates. For our example, we chose to explore the commonly applied Beverton–Holt SR model to complement previous research on non-stationary SR relationships, which used the linearized Ricker model. Finally, we propose priority research areas in this field that will improve model development and application.

Status quo of single-species reference points

Globally, there is broad agreement regarding the concepts underlying reference points used to assess the status of fish stocks for management advice. Nevertheless, the interpretation and application of reference points have evolved and differed among regions (Ricard *et al.*, 2012; Hilborn, 2020). We give an overview of the status quo of single-species reference points, focusing on approaches used in areas with advanced fisheries management systems: e.g. the United States and Europe (ICES region). This background provides an entry point for our arguments regarding Peterman's productivity method (PPM).

MSY reference points

Understanding how population productivity varies with abundance is crucial in determining maximal surpluses and thus defining single-species reference points (Quinn and Deriso, 1999). Reference points are usually expressed in terms of fishing mortality rate (F) and biomass, typically spawning stock biomass (SSB). The scientific concept of MSY was introduced with the aggregated Schaefer model (Schaefer, 1954), which assumes that population growth is density-dependent with a linear decrease in per-capita rate of population growth with increasing abundance, resulting in a logistic population model that is decremented by given catches. The logistic model has production as a quadratic function of abundance. In Schaefer surplus production model (Schaefer, 1954), MSY is obtained at half of the carrying capacity or equilibrium level. Subsequently, (Pella and Tomlinson, 1969) proposed an extension to allow for asymmetric production curves.

For surplus production models, MSY reference points (F_{MSY} and B_{MSY}) are internally estimated as functions of model parameters. These methods, also called biomass dynamic models, focus on population growth and mortality. The productivity of the stock is modelled with a limited set of parameters including the intrinsic growth rate and carrying capacity of the population. Surplus production models are often used for data-limited stocks because they are less data demanding, although Bouch *et al.* (2020) highlight estimation challenges associated with data availability with respect to the stock history.

Age- or length-structured methods allow the cohorts to be followed, and so they use data structured in age or length classes to analyze population changes. These methods provide a more complete analysis of the stock by following the dynamics of individual cohorts. Age- or length-structured methods contain three basic components: growth, mortality, and recruitment (Quinn and Deriso, 1999). In addition to age and length information of the population, the required inputs (which may sometimes be estimated) are biological information including growth parameters, mortality, and maturity. Whereas the majority of contemporary data-rich stock assessments use age-structured models, the choice of model type is usually region-specific (Dichmont *et al.*, 2016). Integrated assessments (Maunder and Punt, 2013), that allow many data types in a single analysis, are becoming more popular, e.g. Stock Synthesis SS3 (Methot and Wetzel, 2013) in the west coast of the United States; as are state–space models such as SAM (Nielsen and Berg, 2014) in the ICES region.

In age-structured assessments, to estimate MSY, the productivity and hence yield from a population is modelled as a function of fishing mortality rate and pattern, and from this, the relationships of yield to biomass and fishing mortality are derived. The age-based MSY has arisen from fundamental population dynamics models based on per-recruit theory (Beverton and Holt, 1957), and is derived from three relationships (see example Figure 1): (i) spawning stock biomass per-recruit (SPR) that models the spawning mass productivity for a given recruit as a function of fishing mortality $SPR(F)$; (ii) SR relationship that models the relationship between the number of recruits to the spawner biomass; and (iii) yield per-recruit that models the mass removed from the population per-recruit by fishing. The per-recruit analysis is related to biological variables (i.e. maturity or fecundity, growth/weight at age, and natural mortality), fishery parameters (i.e. selectivity), and rate of removals. In age-structured methods, MSY-based reference

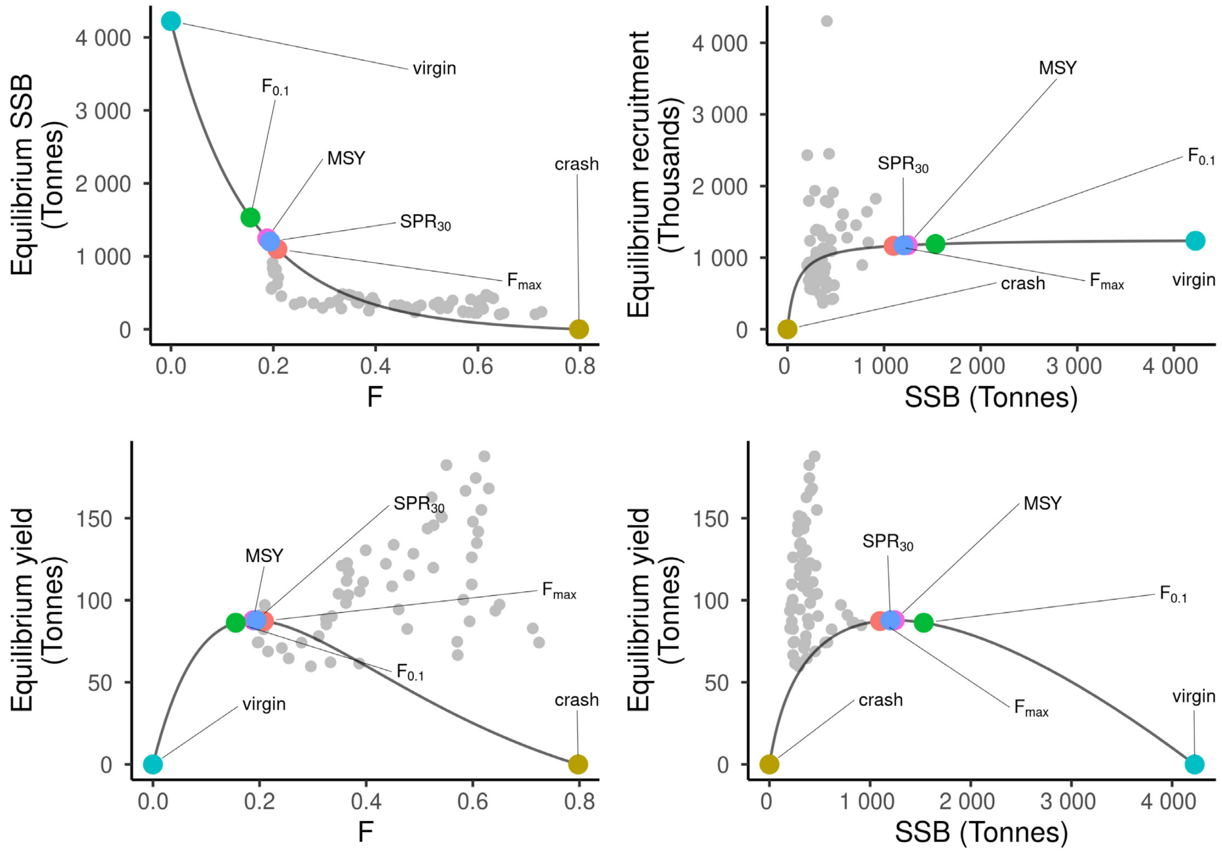

Figure 1. Reference points (virgin, crash, MSY, and per-recruit proxies) and relationships between SSB and F, recruitment and SSB, yield and F, and Yield and SSB at equilibrium with fitted Beverton–Holt functional form for North Sea Skagerrak plaice (Plaice in IV); plots modified from output of FLBRP analysis from FLR package in R (https://flr-project.org/doc/Reference_points_for_fisheries_management_with_FLBRP.html). Grey dots represent data observations for ICES stock Plaice in IV division at the assessment in 2018 (ICES, 2018b), being 2018 the terminal year and the dots observations in preceding years.

points were typically estimated externally to the assessment model. Although integrated assessment methods can estimate reference points internally as functions of model parameters, sometimes fixing parameters of the SR relationship.

The relationship between stock size and recruitment defines the reproductive productivity of the stock and is, therefore, key to the estimation of non-proxy reference points. Understanding the SR relationship is crucial for MSY-based reference point estimation (Shepherd, 1982; Conn *et al.*, 2010). The inverse of the equilibrium *SPR(F)* provides a slope that intersects with the SR function at the equilibrium level of recruitment (Figure 1). The most popular functions developed to understand the SR relationship are: Beverton–Holt model (Equation (1); Beverton and Holt, 1957), Ricker model (Ricker, 1954), and hockey-stick segmented regression (Barrowman and Myers, 2000; Mesnil and Rochet, 2010). These models determine the density-dependent form and hence the compensation of the stock before recruitment. The parameters of the SR model relate to the reproductive potential of the stock and the rate at which recruitment changes with increasing eggs or abundance. For example, in the commonly used Beverton–Holt equation,

$$R = \frac{\alpha SSB}{\beta + SSB}, \tag{1}$$

where recruitment increases towards an asymptote as spawning stock increases, α is the maximum number of recruits produced, and β is the spawning stock needed to produce (on average) recruitment equal to $\alpha/2$. The SR relationship is typically modelled as stationary (parameters are averages across time) and so assumed constant over time (Hilborn and Walters, 1992).

Despite its importance, the SR relationship is challenging to model for many stocks because of insufficient contrast and a high degree of variability. For stocks where recruitment information is lacking or there is high recruitment variability, per-recruit analysis can offer proxies to use as reference points (Gabriel and Mace, 1999). The validity of per recruit levels as proxies for MSY reference points is highly dependent on the life history characteristics of the stock (Mace, 1994). It is recommended to support the choice of appropriate proxy with the SR information available (Cadrin 2012). Spawner per-recruit levels are commonly used as proxies for MSY-based reference points in the US (Maunder and Deriso, 2014; Wetzel and Punt, 2017), where they are developed for individual stocks and designed to work in a precautionary sense.

Biomass limit reference points

Limit reference points are critically important for defining HCRs. HCRs are a structured framework for providing scientific management advice (Punt, 2010) and are considered a key component of the precautionary approach to fisheries management (FAO, 1995b). In HCRs, biomass limit reference points are used to indicate the level of biomass below which

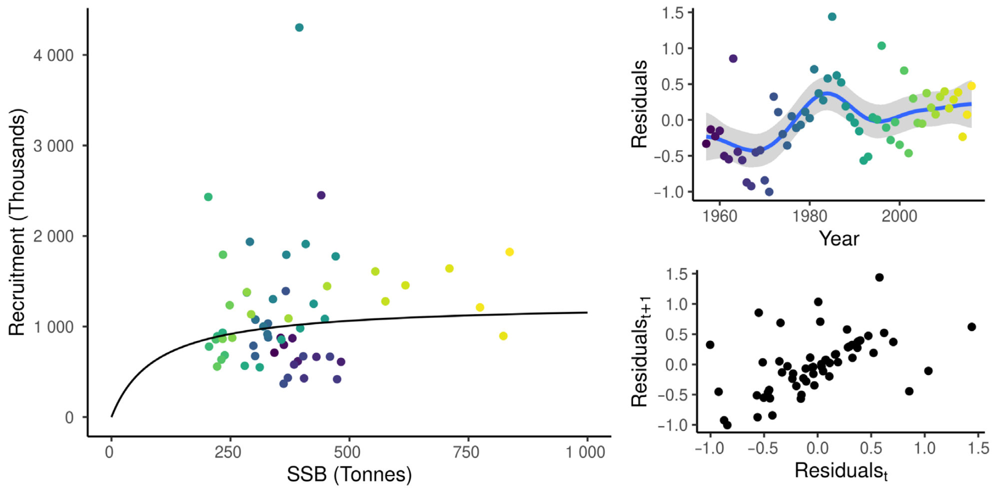

Figure 2. SR relationship of the North Sea and Skagerrak plaice. Left panel shows the relationship between SSB and recruitment with fitted Beverton–Holt functional form; right panel shows the temporal evolution of residuals of the SR relationship (top), and the relationship between residuals at year *t* with residuals at year *t+1* (bottom). Dots represent data observations, colour scale represents the assessment year, and the blue line is a gam model of the residuals with a first-order penalty.

reproductive potential is impacted to avoid recruitment overfishing; typically interpreted as the SSB under which recruitment declines. There are several ways to set biomass limit reference points (Punt *et al.*, 2014b) depending on the HCRs in which they are to be used. The approach chosen to estimate biomass limit reference points impacts both the level and the amount of uncertainty associated (Deurs *et al.*, 2021). In the United States, a percentage of B_{MSY} is typically used to define limit biomass reference points. In situations when the SR relationship is not well understood, a fraction of the unfished biomass (B_0) can be used to define the biomass limit reference point and occasionally also as a proxy for MSY biomass reference point. In ICES, the key biomass reference point is B_{lim}, which is defined as the deterministic limit of biomass below which a stock is considered to have reduced reproductive capacity. This reference point is determined following SR typology rules that account for how stock biomass relates to recruitment at the window of data available (ICES, 2017a). A commonly used biomass limit reference point is the lowest observed biomass (B_{loss}) for stocks with no clear relation between stock and recruitment. The biomass limit reference point is the basis of all precautionary reference points in the ICES advice rule used to estimate other precautionary reference points.

Stochastic MSY

Initial static and deterministic interpretations of equilibrium MSY were thought to be inappropriate because they ignore the fact that fish populations fluctuate in abundance (Mace, 2001). Most current MSY interpretations aim to deal with those dynamics and account for sources of uncertainty. The processes for taking into account uncertainty in reference point vary; different methods to assess stocks deal with including variance and uncertainty differently (Patterson *et al.*, 2001; Dichmont *et al.*, 2016).

In assessments, biological information (growth, mortality, and maturity) vary by age structure and can vary over time (Methot and Wetzel, 2013; Nielsen and Berg, 2014; Dichmont *et al.*, 2016). To derive reference points when biological variables vary over time, a typical approach is to estimate their average value and account for temporal variability with parametric bootstrap or random sampling methods. A temporal window of biological information time series might be used, e.g. ICES guidelines state to use a 10-year time window (ICES, 2017a) unless temporal patterns are found, in which case the time-window is shortened.

Recruitment typically fluctuates considerably, reflecting that this is often the most variable component in assessments (Maunder and Thorson, 2019). Complete time series of recruitment are typically used to derive reference points unless regime shifts are detected. The SR relationship is modelled as a stationary process with some variability (Figure 2). Fluctuations in recruitment are commonly treated as a random process (e.g. log-normal) around an assumed relationship between stock size and recruits. Reference points are based on the long-term mean SR relationship (fixed parameters of the functional form chosen), and independent or mean-reverting autocorrelated process errors. Commonly no process error in the parameters is incorporated (i.e. process uncertainty of the model structure reflecting the natural variability of the processes affecting the dynamics). The residuals of the fitting frequently have temporal patterns with autocorrelation of residuals sometimes being stronger than the SR relationship itself (e.g. North Sea and Skagerrak plaice, Figure 2). The stochastic equilibrium software for MSY modelling has been developed by ICES to implement stochasticity in reference point estimation (Eqsim, https://github.com/ices-tools-prod/msy). Eqsim performs random sampling of the biological and fishery variables and samples from the predictive recruitment distribution. Simulated autocorrelation in recruitment can be included if shown to be important. Eqsim can also deal with structural uncertainty of the SR functional form by applying the averaging of a combination of models (ICES, 2017b).

Simulations of the entire system in Management Strategy Evaluation frameworks (MSE; Punt *et al.*, 2016) play a key role in identifying sources of uncertainty and stochastic elements, and in testing the precautionary criteria (Kell *et al.*, 2005). In an MSE, the whole management system is modelled in the operating model (reality system or true state) and the management procedure (perceived state). The MSEs have become crucial to evaluate reference points and the performance of HCRs relative to agreed management goals (De Oliveira *et al.*, 2009). Development of MSEs is impacting the choice of reference points, which to be precautionary must consider uncertainty in both the science (stock assessment and reference point estimation) and the management process. A present focus of MSE is evaluating the ICES precautionary criteria, specifically, if advised reference points ensure the populations are maintained within safe biological limits under given uncertainties (ICES, 2017a).

Reference points for changing ecosystems

Ecosystems are non-stationary, often presenting complex dynamical behaviour (Sugihara *et al.*, 2012; Fogarty *et al.*, 2016). Globally, the productivity of assessed fish stocks has been observed to fluctuate in a non-stationary manner (Vert-pre *et al.*, 2013; Perälä *et al.*, 2017; Britten *et al.*, 2017). Changes in productivity constitute a challenge for defining management reference points. A major limitation of single-species management is that interactions with ecosystem drivers are usually not accounted for. An important element in transitioning to EBFM would be to include these ecosystem concerns in the estimation of single-species reference points. In this section, we address approaches to deal with changing ecosystems in the calculation of reference points.

Ecosystem concerns

Tools for EBFM comprise a heterogeneous group of models, used for multiple objectives (see Geary *et al.*, 2020 for a complete overview on ecosystem models). Each marine ecosystem has its own features and functional responses with spatial and temporal scales that are still relatively unknown (Hunsicker *et al.*, 2011). Modelling tools that include ecosystem considerations increase in complexity to incorporate ecological interactions, environmental drivers, and human impact (Collie *et al.*, 2016). When complexity increases it also increases the knowledge needed to build the models, the parameters to estimate, and the uncertainty propagated (Hollowed *et al.*, 2011). Therefore, complexity translates to an increase in data demand and a potential decrease in predictive ability (Geary *et al.*, 2020). Despite this, ecosystem models have developed substantially in the last decades and have proved fundamental for strategic management advice (Nielsen *et al.*, 2018), offering a key holistic view of the system (Benson and Stephenson, 2017). Including ecosystem concerns, while balancing complexity, e.g. Models of Intermediate Complexity for Ecosystems (MICE models), helps improve understanding of the processes and disentangle important ecological components (Plagányi *et al.*, 2014). Studies on empirical reference points from multispecies and ecosystem approaches, i.e. multispecies MSY (Gislason, 1999; Collie and Gislason, 2001; Moffitt *et al.*, 2016), aggregate biomass MSY (Gaichas *et al.*, 2012), ecosystem global MSY (Trenkel, 2018), have shown intriguing mismatches with single-species reference points. Although generally not used for tactical management, these studies emphasize that incorporating ecosystem effects does alter MSY-based reference points.

In the United States, a food web ecosystem model of intermediate complexity was used to estimate ecological reference points for Atlantic Menhaden (Chagaris *et al.*, 2020). In this way, information on ecosystem drivers and predator–prey interactions were incorporated into the assessment and management. To our knowledge, this is the only case where an ecosystem model was used to set an alternative ecological reference point. Additionally, ecosystem model information was proposed as guidance within the ICES stock advice framework. In the EU, where several stocks and fleets share the same space, reference ranges—developed from the concept of Pretty Good Yield (Hilborn, 2010)—are used to give flexibility around fishing mortality at MSY in mixed fishery contexts (Kempf *et al.*, 2016; Rindorf *et al.*, 2017a). The ICES working group WKIRISH (ICES, 2020) has suggested that indicators from an ecosystem model can be used to provide information on ecosystem conditions and make recommendations regarding where in the precautionary F ranges we should be setting fishing mortality from an ecosystem point of view, so called F_{eco} (Bentley *et al.*, 2021; Howell *et al.*, 2021). In these cases, the ecological drivers selected depend on the stock interaction with the ecosystem studied.

Incorporation of holistic ecosystem considerations can be done at the simulation level to evaluate alternative management strategies. If there is an ecosystem model developed for the region, MSE can incorporate that ecosystem model as the operating model (see Perryman *et al.*, 2021 review). Higher complexity and descriptive properties of the ecosystem model as the operating model provides the capacity to evaluate the performance of an HCR taking into account ecosystem considerations (Lucey *et al.*, 2021). For example, the end-to-end ecosystem model, Atlantis, has been used in an MSE for the Southeast Australian fisheries (Fulton *et al.*, 2014).

Inclusion of mechanistic drivers

A huge array of factors (biological interactions, climatic forcing, maternal effects, climate change, and so on) can influence stock productivity. Inclusion of ecosystem drivers in an explicit mechanistic way requires a significant expansion of assessment frameworks to enable a more data and time-intensive assessment approach (Burgess *et al.*, 2017). These ecosystem considerations are currently seldom included in stock assessment or at the HCR level. Skern-Mauritzen *et al.* (2016) found a diversity of ecosystem drivers and approaches based mainly on expert knowledge and specific to a certain fishery. Most cases were identified among US and ICES stocks. But in general, these were rarely included in operational management advice. Their inclusion is limited by the high level of understanding required, and the complexity of the interactions, relationships, and their stability, which can be ephemeral (Myers, 1998; Sugihara *et al.*, 2012).

1. *Inclusion of trophic interactions*. The most typical trophic interaction included in assessments is the predator–prey relationship, which can be incorporated in parameters of natural mortality and growth rate. Predation mortality rates can be estimated from stomach-content analysis with multispecies models. Multispecies dynamic models are extensions of single-species assessment models that integrate trophic predator–prey interactions with the mortality caused by the predator derived from the predator diet data (Trijoulet *et al.*, 2019). Addition of mechanistic trophic interactions has been observed to greatly impact reference points (Gislason, 1999; Trijoulet *et al.*, 2020). In some cases, parameter estimates from multispecies models are thought to be more realistic than estimates from single-species approaches

(Hollowed, 2000). Hence, natural mortality parameters from multispecies models are occasionally used in stock assessments. For example, several North Atlantic stocks assessed by ICES use the natural mortality estimates from a Stochastic Multi Species model (SMS; Lewy and Vinther, 2004) in the single-species assessment to provide management advice (ICES, 2018a). Predation also impacts and can be incorporated into the SR relationship to help understand trophic interactions in recruitment dynamics (Swain and Sinclair, 2000; Minto and Worm, 2012; Collie *et al.,* 2013).

2. *Inclusion of environmental and ecological variables.* Environmental and ecological variables have shown a strong impact on population dynamics. Examples of environmental drivers include temperature (e.g. sea surface temperature), hydrodynamics, precipitation, wind-mixing energy, North Atlantic Oscillation index, upwelling index, and river input. Other influential ecological drivers might be zooplankton, chl *a* (hence primary productivity), and eutrophication. The environment is considered to primarily affect recruitment dynamics showing relatively rapid responses, especially for short-lived species (Clausen *et al.,* 2018). Apart from stock responses to these variables being specific to species and systems, ecosystems are non-stationary, and therefore, different states may have different influential drivers (Skern-Mauritzen *et al.,* 2016). Resulting in the inclusion of environmental drivers being challenging (see Crone *et al.,* 2019 for good practices). Including environmental variables in the SR model has often failed, which might be due to non-stationary relationships or because multiple variables were tested without correcting for multiple tests (Myers, 1998; King *et al.,* 2015). Besides, the link between SR and environmental drivers might not be linear (Subbey *et al.,* 2014). Several assessment models can include environmental drivers, but in practice, their inclusion results in little improvement with respect to management performance (Punt *et al.,* 2014a; Haltuch *et al.,* 2019). Therefore, environmental driver inclusion remains rare and most reference points and HCRs do not explicitly incorporate those relationships (Haltuch *et al.,* 2019).

Re-estimation of reference points

Currently, reference points reflect average ecological and environmental conditions over the time period of the data. By definition, MSY-based reference points are estimated given prevailing average environmental conditions (MSA, 2007; EC, 2013). Average fishery and population dynamics of a stock along with environmental conditions are inherently included in their estimation (integrated in the average SR, growth, post-recruit mortality, and maturity parameters). The FAO Fish stock assessment manual establishes that reference points must be regularly updated, taking into consideration possible changes in the biological parameters or exploitation patterns (FAO, 2003). If reference points are not changed once established, they will not reflect the dynamic nature of the ecosystem (Kell *et al.,* 2016). Hence, reference points are usually re-evaluated in the light of environmentally and stock density induced changes in stock productivity and changes in species interactions (ICES, 2021a). In theory, the faster the dynamics evolve, the more often reference points would need to be updated (Burgess *et al.,* 2017).

Typically, reference points are revised with varying regularity. ICES considers reference points to be valid only in the medium term (5–10 years), and therefore, they should be updated according to new population and fishery information, and process understanding (ICES, 2021b). During assessment benchmarks, data and parameters (biological, fishery, and SR relationship) are revised and observed changes are taken into account. In the ICES region, reference points have been observed to change frequently impacting the perception of sustainability status (Silvar-Viladomiu *et al.,* 2021). The ICES working group WKRPCHANGE (ICES, 2021a) identified several reference points that are allowed to vary according to prevailing conditions. In the United States, the National Standards guidelines state that because MSY is a long-term average, it does not need to be estimated annually, but should be re-estimated as required by changes in long-term environmental or ecological conditions, fishery technological characteristics, or new scientific information (NOAA Fisheries, 2016). Even so, certain agencies update reference points with each assessment, e.g. North Pacific Fisheries Management Council (check SMART tool; NOAA Fisheries, 2021).

In updating reference points, changes in productivity or regime shifts are generally taken into account by the revision of the time series used for their derivation. Regime shifts or trends present can be identified *ad hoc* or through regime detection algorithm (e.g. STARS; Rodionov, 2004). Some approaches to deal with regime-shifts and changes in productivity are: (i) moving window, which includes modelling recruitment from a specified number of years (King *et al.,* 2015); (ii) use of a detection algorithm to select the data with which to base reference points (Punt *et al.,* 2014a); and (iii) tailoring or truncation of the data series to a temporal window after a shift has been detected (Szuwalski and Punt, 2013). A common difficulty, however, is how to decide which time period to choose as representative of present dynamics. Estimation of reference points might become unreliable as the time series is reduced (Deurs *et al.,* 2021). Particularly, where one parameter (e.g. density-dependent asymptotic recruitment) may not be updated at all given recent ranges of the stock but the slope at the origin might be. Truncating data in this case risks losing relevant partial information from earlier periods.

Dynamic proxy reference points

A reference point that takes into account shifts in the underlying productivity of the stock has been proposed for the virgin biomass. In the United States, where the virgin biomass reference point is extensively used for HCRs, a time-varying approach called dynamic virgin biomass was developed—dynamic B_0 (A'Mar *et al.,* 2009; Field *et al.,* 2010). Contrary to the static virgin biomass, which is an equilibrium-based measure, dynamic virgin biomass is a reference population state representing the biomass that would have resulted across time in the absence of fishing. The dynamic B_0 approach uses the values of the parameters estimated in the assessment to project the population over time with no fishing, obtaining a time series of B_0. The biomass varies in time because of the estimated recruitment deviations and time-varying growth and natural mortality. The population is simulated typically under the assumption of a stationary SR relationship or driven by a separable function of environmental drivers and stock size.

Dynamic B_0 is increasingly being used because it can track population productivity over time if fishing had not occurred (Punt *et al.,* 2014a), but explicit mechanisms involved in the change in productivity do not need to be identified. A'Mar *et al.* (2009) evaluated a management strategy with dynamic virgin biomass and showed that management and estimation performance was improved by adjusting the exploitation rate based on recent recruitment. Dynamic B_0 performs better than static B_0 when stock productivity shifts directionally (Berger, 2019). The Inter-American Tropical Tuna Commission (IATTC) recommends the use of dynamic virgin biomass when trends in productivity or regime shifts are detected (Maunder and Deriso, 2014).

PPM: dynamic recruitment productivity

Methods capable of modelling dynamic processes and detecting process variation over time are increasingly used (Auger-Méthé *et al.,* 2021). Dynamic state–space models to fit time-series data have been implemented both within age-based assessment models (Aeberhard *et al.,* 2018) and for the estimation of population biomass dynamics and productivity (Walters, 1986; Pella, 1993; Schnute and Richards, 1995; Millar and Meyer, 2000). State–space models allow simultaneous estimation of variability in ecological dynamics and measurements (Thorson and Minto 2015). Several estimation methods have been developed to fit state–space models: the Kalman filter and non-linear extensions, ADMB (Automatic Differentiation Model Builder) Laplace and higher-order quadrature approximations, TMB (Template model Builder) approximations, EM (Expectation-maximization algorithm), particle filters, and MCMC (Markov chain Monte Carlo methods). The well-known Kalman filter is an optimal linear Gaussian estimation and forecasting method designed to extract signals from noisy data.

Peterman *et al.* (2000) first introduced the use of the Kalman filter to identify temporal patterns in recruitment productivity parameters. This method was built on earlier applications of the Kalman filter in fisheries (Walters, 1986; Sullivan, 1992; Pella, 1993; Gudmundsson, 1994; Schnute, 1994), though these were not explicitly implemented on SR parameters. The entry of new recruits into the population modelled by the SR relationship is a fundamental part of stock productivity. Recruitment productivity represents the most important and largest source of variation in population processes (Quinn and Collie, 2005). Randall Peterman and colleagues modelled the SR relationship as a dynamic process by allowing process variation in the parameter governing recruitment productivity.

In this article, we assign the term *Peterman's productivity method* (PPM) to estimation, filtering and smoothing methods, based in the first instance on the Kalman filter, where SR parameters are part of the dynamic state process, and thus allowed to vary over time (Peterman *et al.,* 2000). The method enables recruitment productivity to be modelled as a dynamic process with temporal dimension, by allowing the process signal to be absorbed by the time-varying parameters. These parameters track the variability of productivity dynamics and reconstruct estimates of stock productivity in the past, allowing us to better predict recovery times based on present productivity (Peterman *et al.,* 2003).

Minto *et al.* (2014) extended the PPM to a multi-stock setting and studied the variation in the maximum reproductive rate parameter of the SR relationship for North Atlantic cod stocks. They showed that recruitment productivity of North Atlantic cod populations has varied markedly over time and that populations go through long periods of both high and low productivity. Multivariate developments on PPM enable the strength of the correlation between the populations to be estimated within the model. Thus, providing increased understanding of the similarity or dissimilarity of productivity dynamics inter- and intra-species within and across regions. Tableau *et al.* (2019) expanded the methodology exploring links with environmental variables and evaluating differences between species and areas in the Northwest Atlantic. The number of estimated parameters were reduced because they assumed a common signal to noise ratio among stocks. The multi-stock estimation allows us to disentangle and account for the different sources of uncertainty (i.e. measurement and process) and increases the robustness of the estimates even with limited length of the data time-series. Links with environmental drivers can be easily incorporated in the PPM. Nevertheless, prior work found relatively few relationships between productivity and the selected covariates (Tableau *et al.,* 2019). Adjacent stocks of the same species exhibited similar productivity patterns with the strength of covariation declining over distance, which shows that the method is powerful for detecting coherent ecological signals rather than tracking noise.

The PPM enables us to model a stochastic process on some or all parameters of the SR relationship, and in theory separate signal from noise in the recruitment productivity process. But, how sensitive are management reference points to changing recruitment productivity? Either the density-dependent or density-independent parameters, or both, can vary in time and impact biomass or fishing mortality reference points differently. To visualize the effects of changes in either parameter in MSY-based reference points, we ran a simulation example based on the North Sea and Skagerrak plaice stock. We projected the stock forward 50 years under a hypothetical random walk on either parameter with a process variation of 0.2 on the annual deviations and estimated the resulting dynamic reference points. We chose a random walk over an explicit mechanism for illustration. When, in a Beverton–Holt SR functional form [Equation (1)], the α parameter varies in time we found that it has a strong impact on the biomass MSY reference point. Being the maximum recruitment, the α parameter affects mainly density-dependent regulation of the population (Figure 3a). Time-varying β parameter, which is mainly related to density-independent processes, caused strong impact on the fishing mortality reference point because it affects the slope at the origin of the SR relationship (Figure 3b). Note that in this common formulation of the Beverton–Holt density-independent and density-dependent processes are present in both parameters (Beverton and Holt 1957) but dominate as above. Dynamic reference points estimated with PPM, which incorporate the integrated signal on recruitment, are fundamentally different approach to dynamic B_0. In dynamic B_0, temporal changes in stock dynamics and underlying productivity are accounted for by implementing stochasticity through variability in recruitment deviations assuming a static SR relationship. Modelling time-varying SR parameters also differs from projecting a population forward under a mean-reverting autocorrelated process that assumes deviations return to the expected static form.

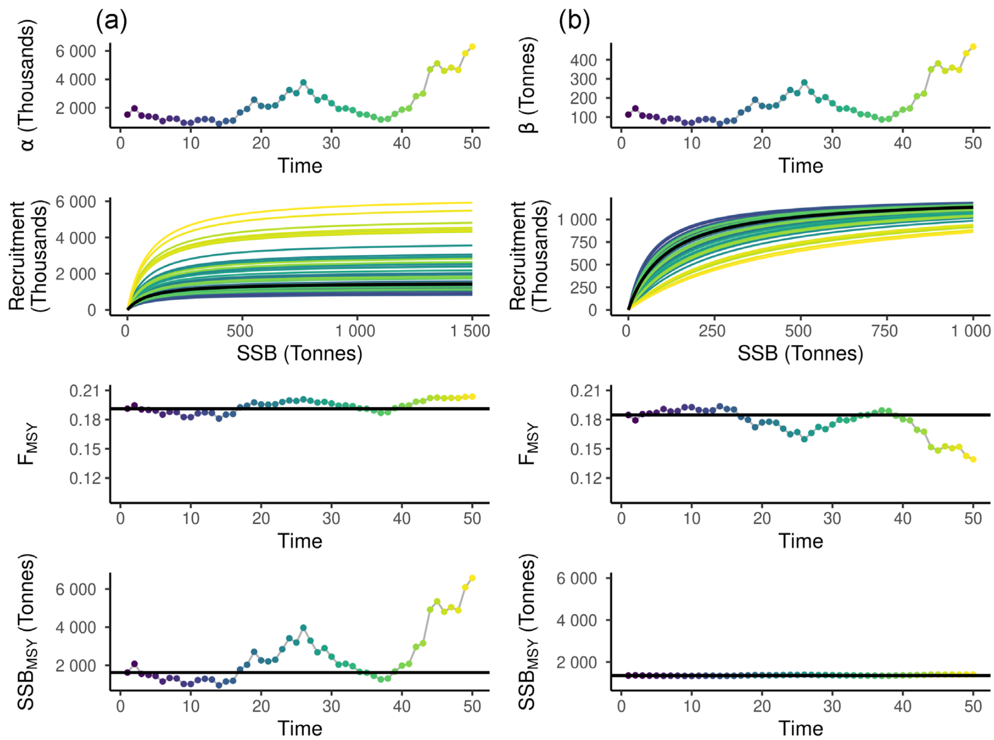

Figure 3. Impact on reference points of SR parameter temporal dynamics. Simulated projections of time-varying parameter α (a, left) and parameter β (b, right); and below the impact in estimated recruitment productivity, and fishing mortality and spawning biomass MSY-based reference points. Black line represents static reference points. Simulations are based on Plaice in IV data (ICES, 2018b) (ICES, 2018b) with Beverton–Holt SR model, using for reference point calculation FLBRP from FLR R software (starting values: $\alpha_0 = 12\,633$ thousands, $\beta_0 = 93\,995$). Both parameters are allowed to vary according to a random walk on the log scale with deviations from a normal distribution with mean zero and a standard deviation of 0.2. Colour scale represents the assessment year.

We show that including time-varying productivity parameters can impact biomass and fishing mortality reference point estimates. Being able to track these changes in time can provide substantive improvements when biological or fisheries conditions are changing. In which case, estimated reference points using time-varying SR parameters are less biased (Holt and Michielsens, 2020). The PPM not only allows us to estimate present productivity and historical trends but also to capture the underlying change in recruitment productivity. These dynamic reference points can be used in harvest policies based on dynamic productivity forecasts to provide catch advice; applications of dynamic HCRs result in higher catches and reduced risk (Collie *et al.,* 2012) and are more robust to climate change impacts (Collie *et al.,* 2021).

The PPM does not explicitly model measurement error in *SSB* (Peterman *et al.,* 2003). Although recruitment and SSB are the best estimates currently available, there is inherent uncertainty associated with them (Brooks and Deroba 2015). This uncertainty from the previous model can potentially be propagated in the subsequent analysis. Uncertainty propagation could be implemented by drawing from the estimator of SR parameters either by assuming multivariate normality using the estimated Hessian matrix or by using MCMC to sample from the posterior distribution. It may also be possible to directly use the covariance matrix in the estimation likelihood in TMB as a known measurement error component (Thorson *et al.*, 2015).

Towards a dynamic future

Status quo reference points include stochasticity, yet assume that fluctuation in biological parameters (growth and mortality), the SR relationship, and the resulting stock productivity are centred on a stationary mean at a given harvest rate. Reference points are subject to updates but regime shifts are notably difficult to predict and defining time windows can be difficult. In stochastic implementations of MSY, random variability is usually added as an error around average expected recruitment; but this is unlikely to completely capture the dynamics of the process in time (Kell *et al.*, 2016). Marine ecosystems are not stationary; long-term trends are present, including those induced by climate change (Szuwalski and Hollowed, 2016). Population dynamics have multiple complex interactions with the ecosystem (top panel Figure 4), and dynamics thereof (Deyle *et al.*, 2013). Beyond direct influence of environmental drivers and direct trophic effects, population dynamics are affected indirectly by changes in food-web structure, composition, and processes within the food-web, e.g. trophic cascades (Frank *et al.*, 2005; Casini *et al.*, 2008). The relationship between early life history (recruitment) and stock size, which has strong influence on population dynamics, has shown marked variation over time for many stocks (Minto *et al.*, 2014; Britten *et al.*, 2016; Perälä *et al.*, 2017; Szuwalski *et al.*, 2019; Tableau *et al.*, 2019). The challenge is to manage fisheries to sustainability in light of scientific uncertainty, natural variability, and changing ecosystems. Current advice

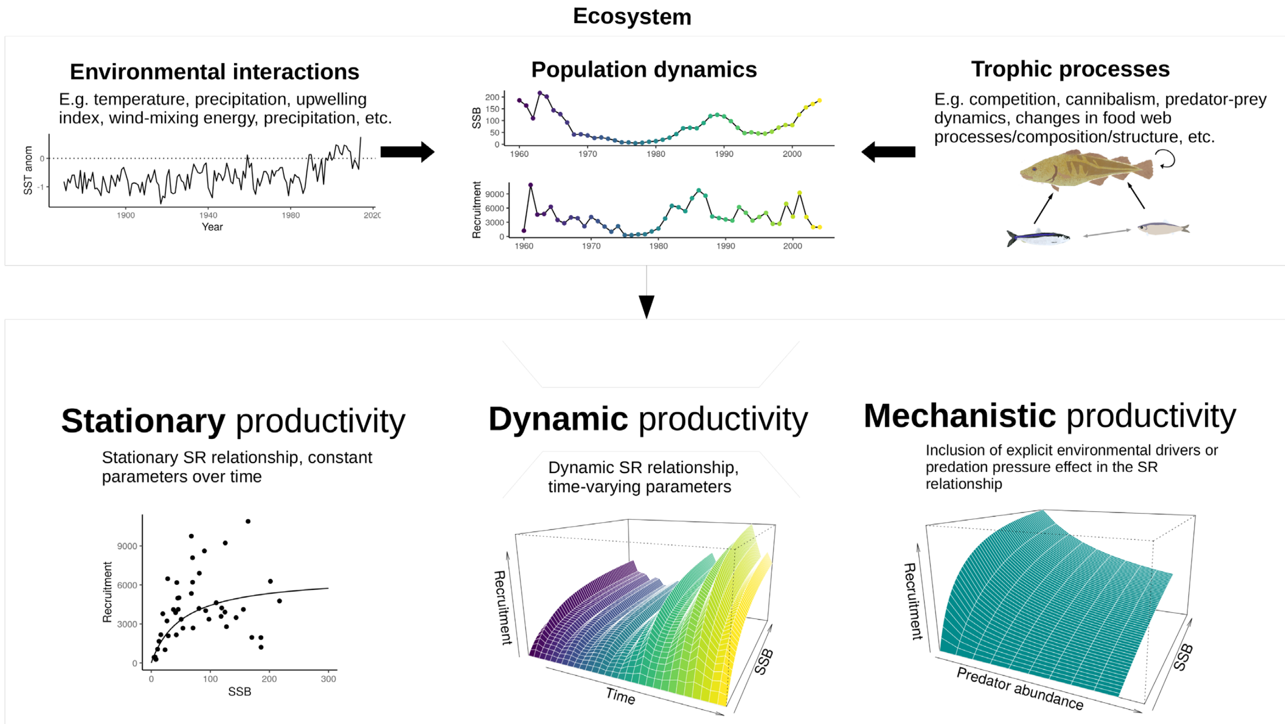

Figure 4. In reality, many ecosystem drivers influence population dynamics (top panel). We argue that time-varying parameters as available *via* PPM provide a bridge between stationary and mechanistic modelling of recruitment productivity.

frameworks may not sufficiently address the dynamic nature of MSY and reference points (Sissenwine *et al.*, 2014). So far, pretty good yield ranges have been proposed in the EU to allow flexibility around MSY fishing mortality reference points in mixed fisheries contexts (Rindorf *et al.*, 2017a).

How can we bridge the gap between current MSY reference points and EBFM? On the one hand, current advice is based on the assumption that SR is stationary (left bottom panel Figure 4). On the other hand, the dynamics created by the ecosystem are complex and manifold and so it can be difficult to use direct ecosystem process information to inform management decisions. Mechanistic inclusion of drivers in the SR relationship (right bottom panel Figure 4) is risky because effects might be direct or indirect, linear or non-linear, and multiple ecological factors may interact and vary over time. We argue that modelling dynamic productivity using PPM might bridge the gap and ultimately reconcile the MSY concept and EBFM (centre bottom panel Figure 4). Dynamic parameter models have demonstrated potential to implicitly incorporate the response of the stock to ecosystem change without specifying the exact driver or functional mechanism involved (Minto *et al.*, 2014; Nesslage and Wilberg, 2019). Dynamic parameters applied to the SR relationship enable estimation of MSY-based reference points that take into account temporal changes in recruitment productivity. Several studies have shown that in the presence of temporal variability in stock productivity, dynamic processes should be accounted for to estimate reliable reference points (Berger, 2019; Mildenberger *et al.*, 2019; Zhang *et al.*, 2021). Given that productivity is non-stationary, rather than reference points based on past average productivity, PPM provides a more informative picture of the present productivity and its dynamics and therefore enables the estimation of reference points in tune with the current state of the ecosystem (Britten *et al.*, 2017; Tableau *et al.*, 2019).

While EBFM comprises broader concerns than recruitment productivity in fisheries management, we believe that using PPM has an important role to include the influence of changing ecosystems on current fish stock management. It would be very valuable for managers and assessment scientists to fully understand the ecosystem processes and ecological mechanisms causing these dynamics. That is not always possible, but this should not stop us considering the implications of these processes, even if they are not completely understood. The main advantage of this method for immediate application in management is that it can be applied without understanding the process that caused the change in stock productivity. Presently, time-varying productivity relationships may be where we have the greatest opportunity to empirically deliver on some of the requirements of EBFM in tactical fisheries management (Minto *et al.*, 2014). Sustainable harvest depends critically on compensatory processes such as the SR relationship. Application of PPM in the SR relationship to estimate dynamic reference points might be a first step towards accounting for changing ecosystems in a MSY management goal. Previous studies have demonstrated the strengths of PPM in capturing complex dynamics in recruitment productivity, improving recruitment forecast, and enabling sustainable dynamic harvest practices (Peterman *et al.*, 2000; Collie *et al.*, 2012; Minto *et al.*, 2014; Britten *et al.*, 2016; Tableau *et al.*, 2019; Holt and Michielsens, 2020). Also, reference points from PPM within HCRs have recently been shown to provide resilience to climate-induced effects (Collie *et al.*, 2021).

Incorporating ecosystem variability in reference points could make communication with stakeholders more challenging. Usually the more complicated the modelling approach the more difficult it becomes to communicate, particularly when those lead to a reduction in fishing opportunities. As we develop more complex models we also have to think harder about how we communicate these models so that social license is not lost. It is important to encourage engagement in participatory science for management, e.g. stakeholders should be aware of why it is important to include productivity dynamics. Social license is not only obtained with simple models, social license is also obtained by including elements that are relevant to include. For instance, by not accounting for ecosystem concerns in reference points social license might be removed. The work developed in WKIrish (ICES, 2020) is an example of where a more complex understanding of the system improved social license. In that project, fishers and stakeholders were recognized as knowledge experts of the system, and so their understanding of the system was included. By the end, fishers and stakeholders had a very good understanding of the complex analysis performed.

While PPM has much potential, important issues remain on how to manage stocks with dynamic reference points. As to *Quo Vadimus*—we propose the following four priority research areas to further PPM:

1. Estimability—can time-varying SR parameters be reliably estimated? Does PPM have the ability to detect change where there is change and reject it where there is no change? Estimated covariation from independent assessments (Minto *et al.*, 2014; Tableau *et al.*, 2019) suggests that real ecological changes are tracked. But state–space models are difficult to estimate (Auger-Méthé *et al.*, 2016), time series length can be constraining, and some convergence issues were found when both parameters of the SR relationships were allowed to vary over time (Szuwalski *et al.*, 2019).
2. Uncertainty propagation—we use estimated recruitment and SSB that have associated uncertainties and covariations (Dickey-Collas *et al.*, 2014; Brooks and Deroba, 2015). We disagree that these outputs should not be considered "data" (Brooks and Deroba, 2015), however, as we consider "data" in a broad information context rather than restricted to raw observations. Many stock assessments use model-derived indices as "data" input. A main goal of stock assessments is to estimate abundance state and exploitation rate, often fitting and tracking independent survey-derived recruitment indices. We argue that in the context of much ecosystem uncertainty, estimated recruitment is some of the best information we have on productivity dynamics. We certainly need to propagate uncertainty correctly but the message that these data should only be used with extreme caution could hamper enormous potential for delivering on EBFM. With respect to the stock assessment model, comparisons of external and internally estimated signals would help guide practitioners. Stock-assessment free methods, such as (Perälä *et al.*, 2017) also have great potential to inform the debate on what is signal and what is post-assessment artifact.
3. What are the consequences of poorly estimated time-varying reference points vs. well-estimated static relationships? Juxtaposing the relative risks of managing under the presumption of no change when there is change and *vice versa*. So far, estimators of the model quality, e.g. AIC, have been used to compare time-varying models and static approaches. Statistical inference for these models is an active area of research such as prediction error variance. In addition, time-varying approaches can be evaluated with MSE or stochastic programming methods (Collie *et al.*, 2021). Generally, evaluation within MSE is recommended before using these reference points to inform management decisions (Holt and Michielsens, 2020).
4. Nature of change—the Kalman filter is restricted to linear Gaussian processes. Available integration methods for latent variables such as Laplace approximation (TMB) or MCMC enable a great variety of stochastic processes (including regimes, hidden Markov states, HMM filter, extended Kalman filter, unscented Kalman filter, Kim filter, and continuous processes in non-linear systems) to be considered and compared. These methods can be applied to time-varying parameters under different recruitment model structures (e.g. Beverton–Holt model). Of particular importance is where change happens more abruptly than the process expects it to and takes more time to adjust, essentially the Kalman filter smooths over an abrupt jump (Peterman *et al.*, 2000). Perälä *et al.* (2017) addressed this with a Bayesian change point model with stationary processes within each regime. While the nature of the process and estimation method may change we believe that using the term "Peterman's productivity method", applies for all settings where the SR parameters evolve in time and recognizes the originator for a set of methods that will broaden from the original Kalman filter.

Finally, we note that by using PPM we may gain an understanding of how productivity has changed, but without knowledge of the mechanism, we cannot predict where it is going (in the medium to long term). While we may track productivity and manage accordingly, we must recognize the need for continual mechanistic insights at broader levels to inform strategic management. All the while, we rest on the feedback nature of HCRs to compensate for our ignorance (Collie *et al.*, 2021).

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Data availability

No new data were generated or analyzed in support of this research.

Authors' contribution

All authors contributed to the conceptualization, design, draft, and revision of the manuscript. PSV and CM performed the simulation and created the figures.

Competing interest

Authors declare no competing interests.

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