



## Selectivity metrics for fisheries management and advice

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# Selectivity metrics for fisheries management and advice

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## Abstract

Fisheries management typically aims at controlling exploitation rate (e.g.,  $F_{bar}$ ) to ensure sustainable levels of stock size in accordance with established reference points (e.g.,  $F_{MSY}$ ,  $B_{MSY}$ ). Population selectivity ("selectivity" hereafter), that is the distribution of fishing mortality over the different demographic components of an exploited fish stock, is also important because it affects both Maximum Sustainable Yield (MSY) and  $F_{MSY}$ , as well as stock resilience to overfishing. The development of an appropriate metric could make selectivity operational as an additional lever for fisheries managers to achieve desirable outcomes. Additionally, such a selectivity metric could inform managers on the uptake by fleets and effects on stocks of various technical measures. Here, we introduce three criteria for selectivity metrics: (a) sensitivity to selectivity changes, (b) robustness to recruitment variability and (c) robustness to changes in  $F_{bar}$ . Subsequently, we test a range of different selectivity metrics against these three criteria to identify the optimal metric. First, we simulate changes in selectivity, recruitment and  $F_{bar}$  on a virtual fish stock to study the metrics under controlled conditions. We then apply two shortlisted selectivity metrics to six European fish stocks with a known history of technical measures to explore the metrics' response in real-world situations. This process identified the ratio of  $F$  of the first recruited age-class to  $F_{bar}$  ( $F_{rec}/F_{bar}$ ) as an informative selectivity metric for fisheries management and advice.

## KEYWORDS

exploitation pattern, fishing mortality, landing obligation, population selectivity, simulation, technical measures

## 1 | INTRODUCTION

All fishing is fundamentally selective. Depending on what fishers want to catch, they choose gear type (e.g., longlines, set nets, trawls), gear specifications (e.g., mesh size, hook size), and the time

and place to deploy these gears. These choices are influenced by the regulatory framework, that is gear regulations, limitations on the catch size and composition, and seasonal and temporal restrictions. Fisheries selectivity relates to desirable species (species selectivity) or sizes (size selectivity). There are three types of size selectivity:

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contact selectivity, which is the differential retention probability of fish that encounter the gear; available selectivity, which is the differential availability of different fish to the gear; and population selectivity, which is the combination of the previous two forms (Millar & Fryer, 1999; Sampson, 2014). Population selectivity is the focus of this study.

Population selectivity (“selectivity” hereafter) describes the differential vulnerability to fishing of the demographic components of an exploited fish population, as a result of the gear used (e.g., choice of mesh size) and availability (e.g., choice of fishing timing and location) (Millar & Fryer, 1999; Quinn & Deriso, 1999; Sampson, 2014; Sampson & Scott, 2012; Scott & Sampson, 2011). Selectivity can be inferred from the age/size composition of the catch (Froese, 2004; Froese, Stern-PirLOT, Winker, & Gascuel, 2008), but in age-structured stock assessment models, it is usually expressed as the standardized vector of age-specific fishing mortalities ( $F$ -at-age) divided by the maximum  $F$  observed for any age-class (Sampson & Scott, 2012; Scott & Sampson, 2011).

Selectivity is of paramount importance for fisheries management. Beverton and Holt (1957) first suggested that for any fixed rate of  $F$ , there is an optimal size/age-at-first-capture at which cohort biomass (i.e., the weight of fish captured from this cohort over its lifetime) is maximized. In the next decades, numerous studies illustrated the benefits in terms of increased yields and lower collapse probability from improving selectivity by adjusting (usually increasing) the size/age-at-first-capture. Such studies have been based mostly on simulations (e.g., Froese et al., 2008; Froese, Winker, Gascuel, Sumaila, & Pauly, 2016; Myers & Mertz, 1998; Prince & Hordyk, 2019; Scott & Sampson, 2011; Vasilakopoulos, O'Neill, & Marshall, 2016), but also on meta-analyses of empirical datasets (Vasilakopoulos, O'Neill, & Marshall, 2011, 2012). The mechanism through which improved selectivity promotes sustainability is by preventing growth overfishing (Beverton & Holt, 1957; Froese et al., 2008), as well as recruitment overfishing (Myers & Barrowman, 1996; Myers & Mertz, 1998). Selectivity studies illustrate that there is a trade-off between  $F$  and selectivity; catching larger fish allows stocks to sustain a higher  $F$  without collapsing, while catching too many small fish can lead to stock depletion even at moderate levels of  $F$  (Prince & Hordyk, 2019; Scott & Sampson, 2011; Vasilakopoulos et al., 2016). Additionally, both Maximum Sustainable Yield ( $MSY$ ) and  $F_{MSY}$  are selectivity-dependent; for most exploited stocks, catching larger fish would lead to a higher  $MSY$  (Froese et al., 2008; Scott & Sampson, 2011; Vasilakopoulos, Maravelias, & Tserpes, 2014; Vasilakopoulos et al., 2016).

The potential gains for a specific fish stock from protecting juveniles can be quantified by checking the interplay between selectivity and  $F$ , and the resulting long-term yield (e.g., Froese et al., 2008; Prince & Hordyk, 2019; Scott & Sampson, 2011; Vasilakopoulos et al., 2016). For the  $F$  levels occurring in the majority of commercial fish stocks (especially demersal ones), an “improved” selectivity would come from a lesser exploitation of juveniles (e.g., Colloca et al., 2013; Froese et al., 2008; Vasilakopoulos et al., 2014; Vasilakopoulos et al., 2016). Accordingly, technical measures typically aim to modify selectivity to protect juveniles (Armstrong, Ferro, MacLennan,

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& Reeves, 1990; European Commission, 2019; Suuronen & Sarda, 2007). Hence, in this study, we refer to “improved selectivity” as the one resulting in a lesser exploitation of juveniles.

Despite the importance of selectivity, fisheries management and the provision of fisheries advice have traditionally focused on the total rate of deaths of fish due to fishing, that is the overall  $F$  (FAO, 2019). This is usually approximated by the average  $F$  of the fully exploited age-classes (i.e.,  $F_{bar}$ ). Regulating  $F_{bar}$  to achieve the maximum sustainable yield ( $F_{MSY}$ ) is a common management objective, while fisheries advice is tailored to the observed levels of  $F_{bar}$  and stock size (usually spawning stock biomass— $SSB$ ) in relation to agreed reference points (Wakeford, Agnew, & Mees, 2009; Worm et al., 2009; ICES, 2018a). The incorporation in fisheries management of a metric summarizing selectivity, analogous to  $F_{bar}$  summarizing fishing mortality, would capture an additional dimension of the exploitation regime, hence allowing an advanced understanding of the exploitation dynamics and potential for higher yields. Such a selectivity metric could be used as an additional lever for fisheries managers to achieve desirable outcomes for both the fishery and the stock through gear regulations and spatio-temporal restrictions of fishing, whose effects would be quantified. In this context, improved selectivity could even allow an increase in  $F_{bar}$  (Froese et al., 2008; Scott & Sampson, 2011; Vasilakopoulos et al., 2014, 2016). A selectivity metric could be also used to track the impact on the stock of the introduction of various regulations, such as technical measures and discard bans,

including the European Union's (EU) recently introduced Landing Obligation (LO) (European Commission, 2013; Guillen et al., 2018). The Scientific, Technical and Economic Committee for Fisheries (STECF) of the EU has repeatedly called for the development of suitable selectivity metrics to track the effect of the LO and of other technical measures on exploited fish stocks (e.g., STECF, 2015; 2016; 2018). The need for selectivity metrics has been also highlighted in the recent EU Regulation 2019/1241 on the conservation of fisheries resources through technical measures (European Commission, 2019).

Previous simulation-based studies of selectivity which have incorporated selectivity metrics (e.g., Froese et al., 2008; Myers & Mertz, 1998; Scott & Sampson, 2011; Vasilakopoulos et al., 2016), have typically focused on the effect of selectivity on equilibrium yield and equilibrium stock size under fixed levels of recruitment and  $F_{bar}$ . However, the response of such selectivity metrics in the face of real-time changes in recruitment and  $F_{bar}$  remains unknown. The investigation of this response is crucial, given that any selectivity metric that is too sensitive to factors unrelated to fishing practices would be of limited use for fisheries managers. Consequently, to assess the utility of any selectivity metric for fisheries management and advice, the following three criteria should be considered:

1. *Ability to track selectivity changes in the fishery.* The metric can clearly capture changes happening in the distribution of  $F$  across the age-classes due to changes in fishing practices (e.g., gear characteristics, spatio-temporal allocation of fishing).
2. *Robustness to recruitment variability.* The metric should not be influenced by changes in the distribution of the population numbers across the different age-classes caused by natural fluctuations, such as recruitment pulses. The utility of a selectivity metric for management relies on its ability to capture changes in selectivity happening due to changes in the fishery, rather than through natural processes.
3. *Robustness to changes in  $F_{bar}$ .* A metric that is highly correlated to  $F_{bar}$  would not fully capture changes in selectivity; hence, it would have limited value.

It should be noted that criteria 2 (robustness to recruitment variability) and 3 (robustness to changes in  $F_{bar}$ ) do not imply that a good selectivity metric must remain always unchanged in the face of recruitment variability and/or changing fishing mortality. Rather, these criteria refer to the correlation between selectivity metrics and recruitment or  $F_{bar}$  while the fishing practices remain unchanged, which may occur due to the numerical configuration of the metrics. However, changing recruitment or  $F_{bar}$  may result in the fishers changing their operation in a way that affects selectivity. For example, recruitment pulses in quota fisheries may affect selectivity due to fishers changing their effort allocation to retain a desirable catch profile while adhering to the quotas. Therefore, a selectivity metric may still respond indirectly to recruitment variability and/or changes in  $F_{bar}$  if these result in fishers changing their differential allocation of  $F$  over the age-classes.

Here, we examine candidate selectivity metrics that can be calculated using standard age-based stock assessments, and test them against the three aforementioned criteria. Seven key metrics are presented in the core text of this study, while seven more are included in the Supporting Information. First, we use simulations to identify those metrics that fulfil our three criteria under controlled conditions. Second, we apply two shortlisted metrics to six fish stocks from the NE Atlantic and the Mediterranean Sea with a known history of technical measures to explore the metrics' response in real-world situations. Combined, this process allowed the identification of the most informative selectivity metrics for fisheries management and advice.

## 2 | MATERIALS AND METHODS

### 2.1 | Selectivity metrics

Seven age-based selectivity metrics have been analysed in the core text of this study (S1–S7; Table 1). These metrics differ in complexity and data requirements but can all be calculated using common stock assessment inputs and outputs with annual resolution, that is age-structured catch,  $F$ , maturity and stock numbers (abundance). Most metrics quantified the relative exploitation of juvenile/undersized fish, given that this is the most common target of selectivity changes. Age-based metrics were preferred here, because most of the stock assessments currently used for management and advice are also age-based. Still, these metrics could also be used with length-based datasets, either by adjusting them to length or by calculating the age from length using appropriate growth equations (as is done here for S2). For all the metrics, lower values indicated an improvement in selectivity, that is less pressure on juveniles, with the exception of S2 and S5 where the opposite was true.

Seven additional selectivity metrics have been examined within the Supporting Information (S8–S14; Table S1). These metrics were variations of the seven metrics included in the core text and had similar performance; hence, it was decided to present them separately so as to reduce the complexity of the core results.

### 2.2 | Simulation analysis

The simulation analysis aimed to test all selectivity metrics against the three criteria described in the Introduction. Accordingly, the selectivity metrics were tested in a controlled environment for their ability to track selectivity changes, as well as their robustness to recruitment pulses and  $F_{bar}$  changes. The simulation analysis was performed within the Fisheries Library in R (FLR) framework (FLR <http://flr-project.org>; Kell et al., 2007) using R v3.5.2 (R Core Team, 2018). The theoretical stocks were generated using packages FLlife and FLasher.

A stock was simulated using the approach developed by Gislason and implemented by FLife (Gislason et al., 2008). The simulated

**TABLE 1** The seven main selectivity metrics investigated in this study

Metric type	Metrics	Description	Formula	Data needed	References
Catch-based	S1	Proportion of juveniles in the catch	$\frac{\sum_{a=rec}^n C_a l_a}{\sum_{a=rec}^n C_a}$	C-at-age Mat-at-age	Froese (2004)
	S2	Proportion of optimal length (converted to optimal age) fish in the catch	$\frac{\sum_{a=opt}^w C_a}{\sum_{a=rec}^n C_a}$	C-at-age Lopt	Froese (2004)
Catch-, N- and F-based	S3	Abundance-weighted catch of juveniles weighted by Fbar	$\frac{\sum_{a=rec}^n C_a l_a}{\frac{\sum_{a=rec}^n N_a l_a}{Fbar}}$	C-at-age Mat-at-age N-at-age Fbar	This study
F-based	S4	F of first recruited age-class divided by Fbar	$\frac{F_{rec}}{Fbar}$	F-at-age	This study
	S5	Difference between age at 50% selection and age at 50% maturity	As50 – Am50	F-at-age Mat-at-age	Vasilakopoulos et al. (2016)
	S6	Fbar of juvenile age-classes	$\frac{\sum_{a=x}^z F_a}{z-x+1}$	F-at-age Mat-at-age	ICES (2014)
F- and N-based	S7	Abundance-weighted F of juveniles divided by the abundance-weighted F of adults	$\frac{\sum_{a=x}^n N_a l_a F_a / \sum_{a=x}^n N_a l_a}{\sum_{a=x}^n N_a M_a F_a / \sum_{a=x}^n M_a l_a}$	F-at-age Mat-at-age N-at-age	Vasilakopoulos, O'Neill, and Marshall (2011)

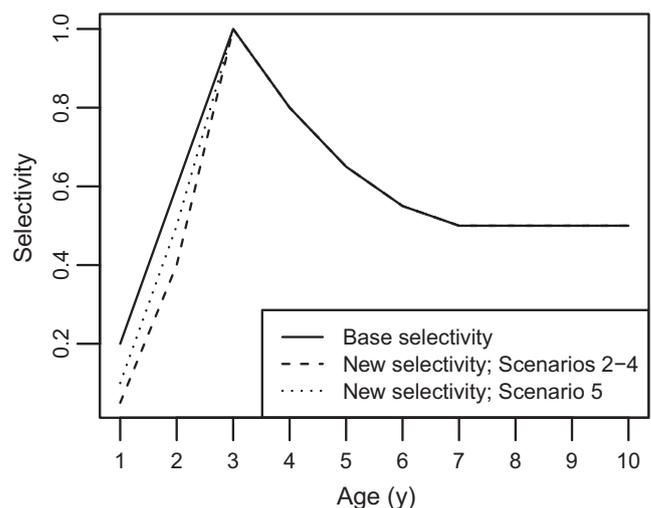
Note: *a*: age; *n*: last age-class; *rec*: first recruited age-class (usually 0 or 1); *z*: last juvenile age-class; *Lopt*: Size at which cohort biomass is maximized; *u*: first age-class falling within the  $0.9 * Lopt - 1.1 * Lopt$  range; *w*: last age-class falling within the  $0.9 * Lopt - 1.1 * Lopt$  range; *C*: Catch; *Mat*: Proportion mature; *l*: Proportion immature ( $1 - Mat$ ); *F*: Fishing mortality; *N*: Stock numbers (abundance); *Fbar*: Average fishing mortality of the fully selected age-classes. *As50*: Age at 50% of selectivity; *Am50*: Age at 50% of maturity.

stock made use of a von Bertalanffy growth model ( $L_{inf} = 90$  cm,  $K = 0.77 \text{ year}^{-1}$ ,  $t_0 = -0.019$  year). The stock was set up to contain 10 age-classes, with the first class being age 1 and the tenth class being a plus group. 50% of the fish were mature at age 2 and all fish were mature from age 4 onwards. Natural mortality was age-dependent using  $M(\text{age}) = 0.2 + 1.64 * \exp(-\text{age})$ , which has an asymptote at  $M = 0.2$  with a much higher juvenile mortality. Recruitment at age 1 was simulated by a Beverton–Holt model; in scenarios with recruitment pulses, the timing and the amplitude of the pulses were fixed across scenarios. The basic recruitment in the absence of recruitment pulses or changes in stock size was set to 154,000 individuals.

The fishery was characterized by a base selectivity, where fish were fully selected at age 3 (Figure 1). In this context, selectivity was the outcome of the fishing activity of all individual fisheries exploiting the stock with their different gears and fishing efforts (F-at-age). *Fbar* was set to a level just above the *Fmsy* reference point ( $Fbar = 1.1 * F_{MSY}$ ) to simulate a stock with a fishing mortality that is not precautionary, that is a state that normally elicits a management response. A total of 200 time steps were simulated, with changes in selectivity occurring around the 100th time step.

To mimic the real-world situation where our perception of the stock comes from a stock assessment rather than the underlying unobservable data, we simulated the deterministic process and added a layer of uncertainty based on a stock assessment fit. For this, an a4a stock assessment model was fitted using Markov chain Monte Carlo (MCMC). a4a is a statistical catch-at-age model implemented in R making use of the FLR platform and using automatic

differentiation implemented in the Automatic Differentiation Model Builder (ADMB) as the optimization engine (Jardim et al., 2014). This process generated both structural uncertainty (through the models chosen for fishing mortality, recruitment and survey catchability) and estimation uncertainty (through the MCMC fit). As a result, the response of the selectivity metrics followed the stock assessment outputs rather than the true unobserved process, as would have happened in a real-world situation. One survey index was used by



**FIGURE 1** Base selectivity (solid line) and the simulated selectivity changes in scenarios 2–4 (dashed line) and scenario 5 (dotted line). Selectivity is F-at-age scaled by the maximum F-at-age

the stock assessment in each time step, and this survey index was generated by applying the survey catchability (same for all age-classes) on the population numbers at age. The survey index's observation error distribution was log-normal with a standard deviation of 0.2. To avoid introducing stock assessment model artefacts associated with the edges of the time series, the first and last fifty time steps were cut off, leaving a time series of 100 years.

In total, five increasingly complex scenarios were tested:

**Scenario 1:** No changes in selectivity,  $F_{bar}$  or recruitment. This scenario was used to check whether selectivity metrics fluctuate in the absence of changes in selectivity, recruitment or  $F_{bar}$ .

**Scenario 2:** Selectivity, taken as the F-at-age scaled by the maximum F-at-age, was reduced at ages 1 (from 0.2 to 0.05) and 2 (from 0.6 to 0.4) (Figure 1) in year 51, while  $F_{bar}$  and recruitment were unchanged. This change in selectivity is a common result of changes in the fishery aiming to protect juveniles (e.g., mesh size increase, protection of nurseries). This scenario aimed to investigate the ability of the metrics to detect a change in selectivity when recruitment and  $F_{bar}$  were kept stable.

**Scenario 3:** The same selectivity change as in scenario 2 occurred in year 68. Seven recruitment pulses and a changing  $F_{bar}$  were added. The recruitment pulses were randomly generated around a 12.5-year mean using a log-normal distribution with a log-sd of 0.3 and occurred at time steps 4, 15, 30, 42, 54, 75, 91. The amplitude of the recruitment pulses was multiplied with deviances generated from a log-normal distribution with a log-sd of 0.6. Fishing mortality followed an up-down trajectory:  $F_{bar}$  gradually increased from  $1.1 \cdot F_{MSY}$  to  $3 \cdot F_{MSY}$  where it remained for 15 years before decreasing again. This scenario was used to test the selectivity metrics against the three criteria (i.e., ability to track selectivity changes, robustness to recruitment variability, robustness to changes in  $F_{bar}$ ) in more realistic conditions, when there is both recruitment variability and changes in  $F_{bar}$ . The improvement in selectivity (i.e., reduced F at ages 1 and 2) occurred while the  $F_{bar}$  was decreasing, to mimic an overfished stock where both overall fishing pressure and selectivity improve in response to management actions.

**Scenario 4:** The same selectivity change as in the previous two scenarios was simulated in year 45. It coincided with a recruitment pulse and occurred while  $F_{bar}$  was high but stable, unlike scenario 3 where the selectivity change occurred while  $F_{bar}$  was also changing. The amplitude of the recruitment pulses was modelled similarly to Scenario 3. This scenario, besides testing the selectivity metrics in the face of recruitment variability and changing  $F_{bar}$ , also aimed to investigate a situation where a recruitment pulse could potentially mask an improvement in selectivity, given that this pulse would result in more juveniles in the catch.

**Scenario 5:** A more subtle selectivity change compared to scenarios 2–4 at ages 1 (from 0.2 to 0.1) and 2 (from 0.6 to 0.5) (Figure 1) was simulated in year 45. As in scenario 4, the selectivity change coincided with a recruitment pulse and occurred while  $F_{bar}$  was

stable. The amplitude of the recruitment pulses was modelled similarly to scenario 3. This scenario aimed to test the differential sensitivity of the selectivity metrics when more subtle selectivity changes occur, while recruitment and  $F_{bar}$  also changed.

In all scenarios, the temporal development of all metrics, recruitment and  $F_{bar}$  were plotted in order to visualize the response of the metrics to change. Furthermore, a linear model was fitted to each selectivity metric ( $S$ , being S1–S7), and the selectivity state ( $Sel$ ; being either base selectivity or new selectivity—see Figure 1), occurrence of selectivity pulse ( $Rec$ ),  $F_{bar}$  ( $F_{bar}$ ) and an interaction term  $Sel:F_{bar}$  as explanatory variables (1):

$$S \sim Sel + Rec + F_{bar} + Sel:F_{bar} \quad (1)$$

$Sel$  and  $Rec$  were modelled as binary variables, while  $F_{bar}$  was modelled as a continuous variable. Modelling  $Rec$  as a binary variable, we aimed to test whether the metrics changed when there was a modelled pulse in recruitment, since our interest was to assess whether the metrics were sensitive to strong recruitment classes. The interaction between  $Sel$  and  $F_{bar}$  was included to ensure that F-at-age being different before and after the selectivity change would not hide the individual effects of  $Sel$  and  $F_{bar}$ . The dataset analysed covered 80 years, 40 prior to the selectivity change and 40 after.

To examine possible lagged effects of  $Rec$  on each selectivity metric, candidate models for each  $S$  with  $Rec$  taken at zero to four lags were constructed. Four lags were chosen as a reasonable limit after visual inspection of the simulated trends. The model with the lag resulting in the lowest AIC was chosen for each metric. The exact recruitment lag with the strongest effect on each metric depends on the specific settings of the simulation and may differ in empirical stocks.

### 2.3 | Analysis of empirical stocks

The results of the simulation analysis refer to a simplified version of reality designed specifically to test the metrics against the three criteria set in the Introduction. Therefore, the simulations should not be considered in isolation, but in combination with an analysis of empirical stocks that entail a much higher level of complexity.

One F-based (S4) and one catch-based (S1) selectivity metric, representing cases with different explanatory power and data requirements, were shortlisted after the simulation analysis. S4 tracked the selectivity change and was robust to changes in recruitment and  $F_{bar}$ , while S1 did not perform very well, but had a simpler calculation and interpretation. The temporal development of these metrics was examined together with that of recruitment and  $F_{bar}$  in six European commercial stocks for which age-structured stock assessments were available. These stocks were selected based on being diverse (six species—four roundfish, one flatfish, one small pelagic), exhibiting different recruitment dynamics, a variety of selection curve shapes, and with different

narratives of technical measures and stock development. Similar to the simulation analysis, selectivity in all stocks examined here was the outcome of the fishing activity of all individual fisheries exploiting the stock with their different gears and fishing efforts. The stocks examined were as follows:

North Sea haddock (*Melanogrammus aeglefinus*, Gadidae): Data for this stock were taken from the latest stock assessment (ICES, 2018b), ranging from 1972 to 2017. Reported age-classes were 0 to 8+ and  $F_{bar}$  was calculated over age-classes 2–4. Over the assessment period, this stock exhibited five strong recruitment pulses, a substantial reduction of  $F_{bar}$  after 2000, and had a well-documented history of technical measures. The timeline of the technical measures and other changes that could have potentially affected the selectivity of this stock is as follows:

- 1983—First EU Technical Measures Regulation established minimum mesh sizes and restrictions on the construction and use of trawl gears. As part of this regulation the mesh size increased from 80 mm in 1983 to 90 mm in 1984.
- 1986—Revised Technical Measures Regulation increased mesh size for gadoid fisheries.
- 2002—Mesh size increased to 110 mm for North Sea gadoid fisheries. Restrictions on gear construction and specific measures for certain fisheries (beam trawls and gillnets).
- 2003—Further increase in mesh size for gadoid fisheries to 120 mm.
- 2004—Introduction of first cod effort management plan, which included a provision to allow increased fishing effort when using selective gears. Limited uptake.
- 2008—First introduction of Conservation Credit Scheme in the United Kingdom (UK) (real-time closures—RTCs) which reduced effort in areas of high concentrations of juveniles. Uptake limited to a small number of Scottish vessels.
- 2009—Introduction of second cod effort management plan which further incentivized the use of selective gears in return for increased effort allocations. Increased uptake particularly in the UK as part of the Conservation Credit Scheme
- 2009—Revised Conservation Credit Scheme in the UK (RTCs). The use of more selective gears was made mandatory for UK vessels in certain fisheries with haddock bycatch.
- 2015—The stock comes under the LO, meaning all haddock must be landed and counted against quota. This introduced an incentive to target larger fish.

West of Scotland whiting (*Merlangius merlangus*, Gadidae): Data for this stock were taken from its latest stock assessment (ICES, 2018c) and ranged from 1981 to 2017. Reported age-classes were 1 to 7+, and  $F_{bar}$  was calculated over age-classes 2–4. This stock was selected because it has been through a recent depletion and is currently rebuilding after going through some emergency technical measures that greatly reduced  $F_{bar}$ . The timeline of the technical measures and other changes that could have potentially affected the selectivity of this stock is as follows:

- 2002—Requirement to increase mesh size (from 80 mm to 100 mm) and use of square mesh panels (90 mm).
- 2004—Introduction of the first cod effort management plan, which linked the use of selective gears to increased effort allocations. Limited uptake.
- 2006—SSB fell to very low levels (only began to increase after 2011).
- 2009—Introduction of the second cod effort management plan which incentivized the use of selective gears in return for increased effort allocations or removal from the effort regime altogether.
- 2009—Introduction of emergency technical measures. Mesh size increased to 120 mm with 120 mm square mesh panels in bottom trawl (TR)1 fisheries (i.e., towed gears with a codend mesh size of greater or equal to 100 mm) and 80 mm plus 120 mm square mesh panels or sorting grid in TR2 fisheries (i.e., towed gears with a codend mesh size in the range of 79–99 mm).
- 2010 onwards— $F_{bar}$  has decreased significantly. Majority of catches now in TR2 fisheries but mostly discarded (undersized). Catches in TR1 fisheries were significantly reduced following the latest mesh size increases.

West Baltic cod (*Gadus morhua*, Gadidae): Data for this stock were taken from its latest stock assessment (ICES, 2018d) and ranged from 1994 to 2017. Reported age-classes were originally 0 to 7+ and  $F_{bar}$  was calculated over age-classes 3–5.  $F_{at-age 0}$  was zero in all years, so prior to quantifying the selectivity metrics, age 0 was trimmed, and age 1 was considered the first recruited age. This stock was selected because of a well-documented history of technical measures, some of which were expected to improve selectivity (e.g., increasing mesh size), while others were expected to deteriorate it (e.g., a reduction in Minimum Conservation Reference Size—MCRS). The timeline of the technical measures and other changes that could have potentially affected the selectivity of this stock is as follows:

- 1986—Minimum Landing Size (MLS) for cod set at 30 cm and codend mesh size at 95 mm.
- 1998—Mesh size increased to 105 mm with an unspecified escape window or 120 mm codend mesh size.
- 2002—Introduction of the option to use either a Bacoma 120 mm or codend mesh size of 130 mm diamond mesh, representing a significant improvement in selectivity. A Bacoma codend is a codend with the upper panel consisting of one large square mesh window.
- 2003—MLS increased from 35 to 38 mm. Emergency closure of the fishery in April 2003.
- 2004—Increase in the codend mesh size to 140 mm (not enforced).
- 2005—Bacoma 110 mm/T90 110 mm codend introduced into the Baltic cod fishery. A T90 codend is a codend where the diamond mesh netting is turned 90° so that the main direction of the run of the netting is parallel to the towing direction.

- 2007—Closed seasons introduced under the Baltic multiannual plan to protect juvenile cod.
- 2010—Increase in the size of the Bacoma window to 120 mm and increase in the length of the Bacoma panel. T90 codend increased to 120 mm.
- 2014—Baltic cod under the LO. MCRS reduced from 38 to 35 cm.
- 2016—Baltic multiannual plan adopted which allows flexibility to introduce additional selectivity measures into the fishery quickly.

North Sea sole (*Solea solea*, Soleidae): Data for this stock were taken from its latest stock assessment (ICES, 2018b) and ranged from 1957 to 2017. Reported age-classes were 1 to 10+ and Fbar was calculated over age-classes 2–6. This stock was selected because of the increasing use of a new type of gear over the past few years, namely the pulse trawl, which has been associated with a spatial shift of the fishing effort. The pulse trawl applies an electrical stimulus to catch flatfish; the electrodes in the pulse trawl replace the tickler chains of the traditional beam trawl that mechanically stimulate flatfish to leave the sea floor (ICES, 2018e). The timeline of the technical measures and other changes that could have potentially affected the selectivity of this stock is as follows:

- 1990–1998—Codend mesh size for sole maintained at 80 mm.
- 2002—Increase in codend mesh size to 120 mm in beam trawl fisheries in the northern North Sea with a continuation of the use of 80 mm in the southern North Sea.
- 2004—Introduction of first cod effort management plan (effort limitations) which included provision to allow increased fishing effort when using selective gears. Limited uptake.
- 2007—Introduction of derogation to allow pulse trawls. Initial observations suggested that pulse trawls had a different gear selectivity than traditional beam trawls.
- 2007—Multiannual plan for sole and plaice (*Pleuronectes platessa*, Pleuronectidae) introduced into the North Sea that aimed to reduce fishing mortality in the 80 mm beam trawl fishery for sole where discards of plaice were significant.
- 2009—Introduction of second cod effort management plan which incentivized the use of selective gears in return for increased effort allocations or removal from the effort regime altogether.
- 2011–2018—Increasing use of the pulse trawl by the Dutch beam trawl fleet with evidence of differences in spatial fishing activity.
- 2015—Sole comes under the LO meaning all sole must be landed and counted against quota.
- 2016—De minimis exemption for sole under the LO in the North Sea linked to use of large mesh panels placed in the bottom part of beam trawls to release undersized sole. This “Flemish panel” in beam trawl fishery was made mandatory for Dutch and Belgium vessels.

North Sea herring (*Clupea harengus*, Clupeidae): Data for this stock were taken from its latest stock assessment (ICES, 2018f) and ranged from 1947 to 2017. Reported age-classes were 0 to 8+ and

Fbar was calculated over age-classes 2–6. This stock was selected because of the high recruitment variability it exhibits, as well as because it has been through a collapse and rebuilt. The timeline of the technical measures and other changes that could have potentially affected the selectivity of this stock is as follows (Dickey-Collas et al., 2010; ICES, 2018f):

- Early 1970s—An industrial fishery developed targeting North Sea sprat (*Sprattus sprattus*, Clupeidae); this fishery occurred to a large extent in areas with juvenile herring.
- 1977–1980—Fishing ban for directed herring fisheries in the North Sea due to stock collapse.
- 1981–1983—Small Total Allowable Catch (TAC) for herring in the southern North Sea and English Channel.
- 1983—Ban on directed fishing for herring lifted.
- 1997—Bycatch regulation enforcement resulted in the sprat fishery having a markedly lower bycatch of juvenile herring.

Gulf of Lion hake (*Merluccius merluccius*, Merlucciidae): Data for this stock were taken from its latest stock assessment by the General Fisheries Commission for the Mediterranean (GFCM, 2017) and ranged from 1998 to 2016. Reported age-classes were 0 to 5+ and Fbar was originally calculated over age-classes 0–2. Because Fbar included the first recruited age (0), the age-classes of Fbar were changed here to 1–3. This stock was selected as a typical example of demersal Mediterranean fisheries (Colloca et al., 2013; Vasilakopoulos et al., 2014); it is highly overexploited, without catch limits, and with substantial catches of juvenile fish. The timeline of the technical measures and other changes that could have potentially affected the selectivity of this stock is as follows (GFCM, 2017):

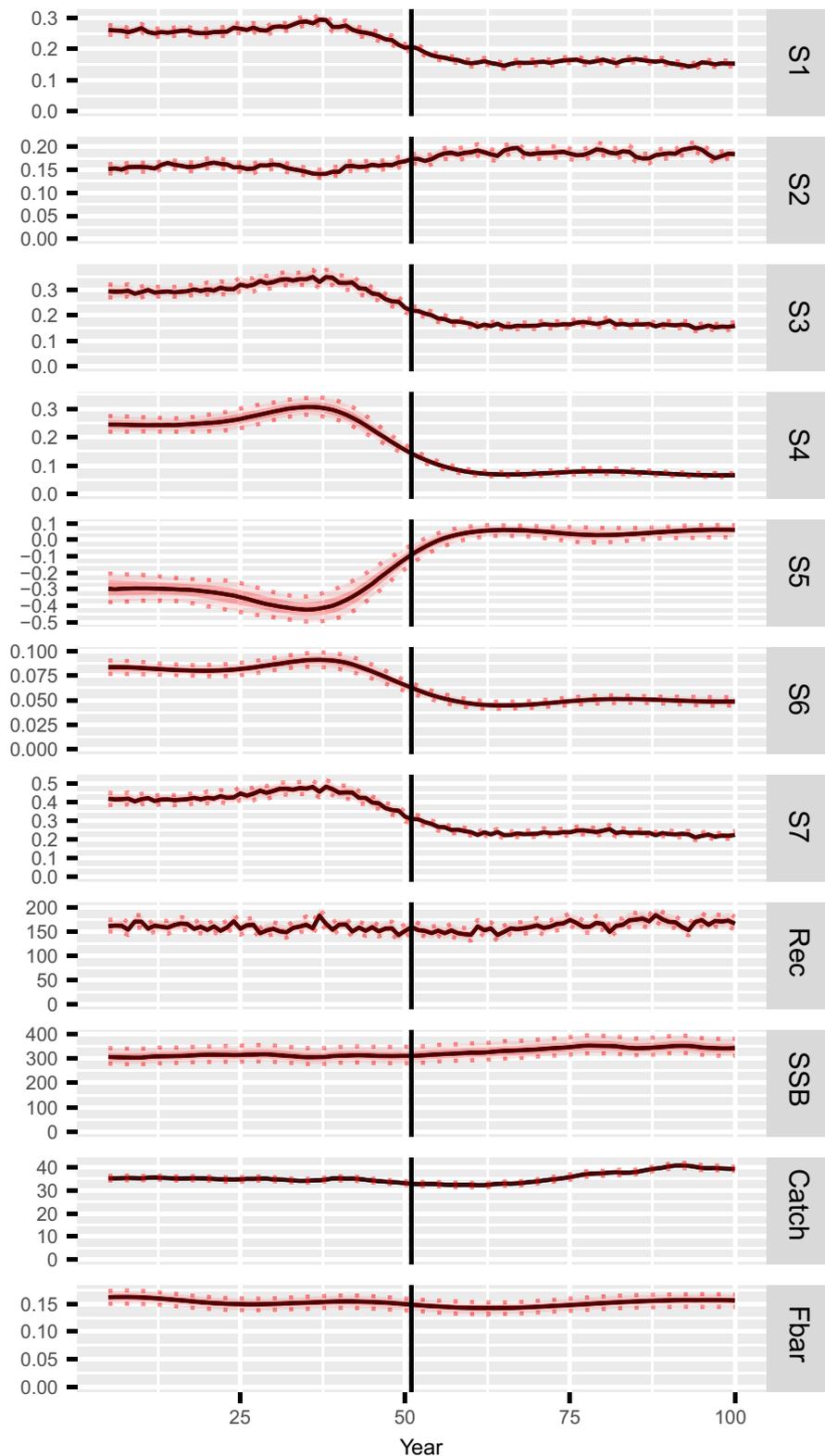
- 1998–2016: The number of French trawlers, which were responsible for most of juvenile hake catches in the area, decreased by 50%.
- 2009—Due to the large decline of the small pelagic fish species in the area, the trawlers targeting small pelagics shifted their effort to demersal species.
- 2010—New mesh size regulation for trawlers (from 40 mm diamond to 40 mm square or 50 mm diamond). This new regulation has not been fully implemented by the French trawlers.

## 3 | RESULTS

### 3.1 | Simulation analysis

For scenarios 2–5, the temporal development of seven selectivity metrics (S1–S7) is presented here (Figures 2–5), while the temporal development of all 14 metrics in all scenarios is presented in the Supporting Information (Figures S1–S5).

Scenario 1, featuring no changes in selectivity, Fbar and recruitment, confirmed that when Fbar and recruitment were stable, the



**FIGURE 2** The temporal development of seven selectivity metrics (S1–S7), Recruitment (Rec), SSB, Catch and Fbar for the simulated stock of scenario 2. Vertical lines indicate the point in time when the selectivity change happened. Dotted lines indicate the confidence intervals [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

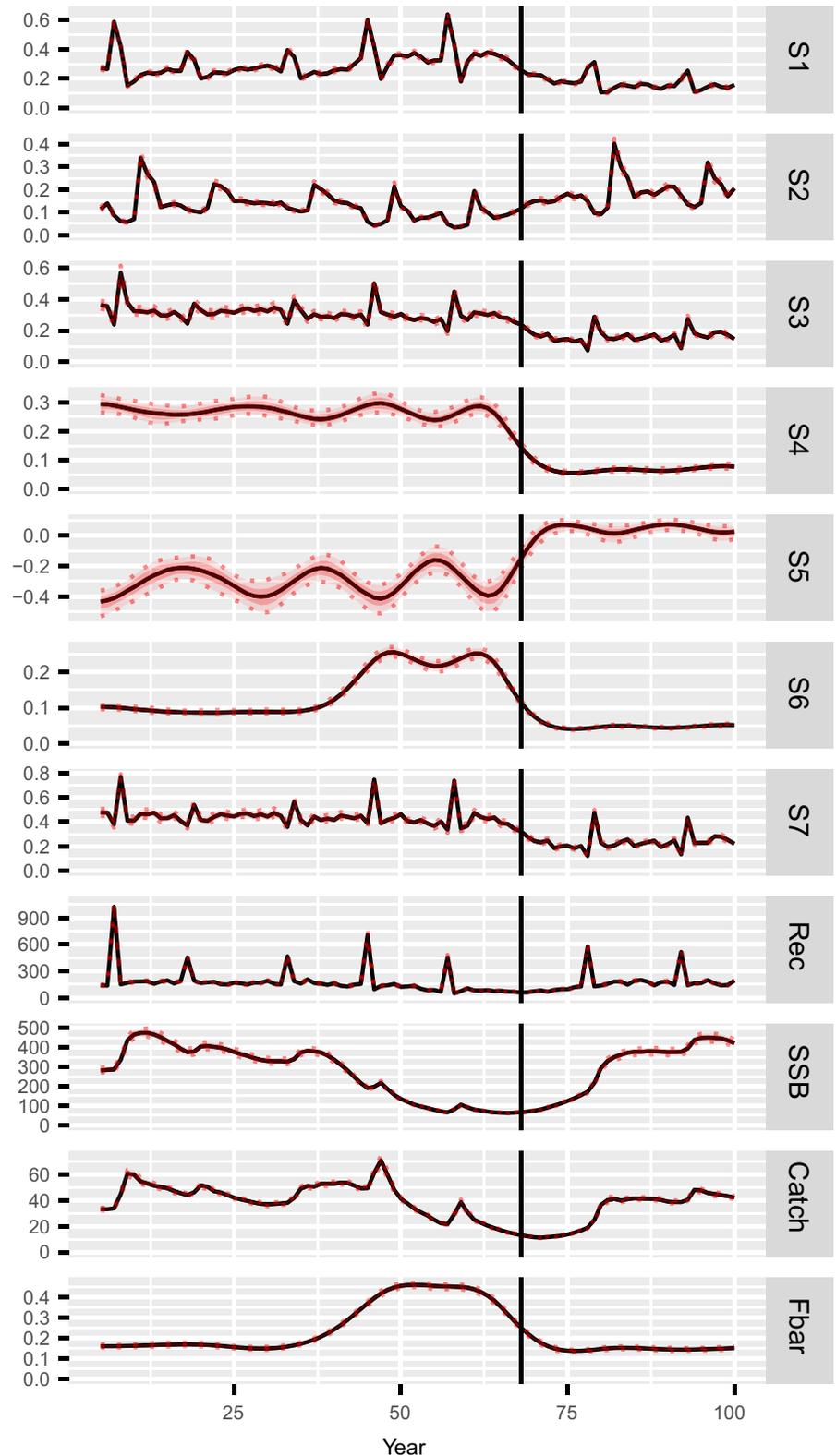
selectivity metrics did not pick up any change in selectivity (Figure S1).

Scenario 2, where selectivity changed while Fbar and recruitment were stable, suggested that all metrics were able to track changes in selectivity when Fbar and recruitment were kept stable (Figure 2; Figure S2). However, there were certain metrics with higher contrast

before and after the selectivity change than others (e.g., S4 and S5; Figure 2). The seemingly earlier onset of the selectivity change captured by the tested metrics came from the smoothing introduced by the stock assessment fitting process.

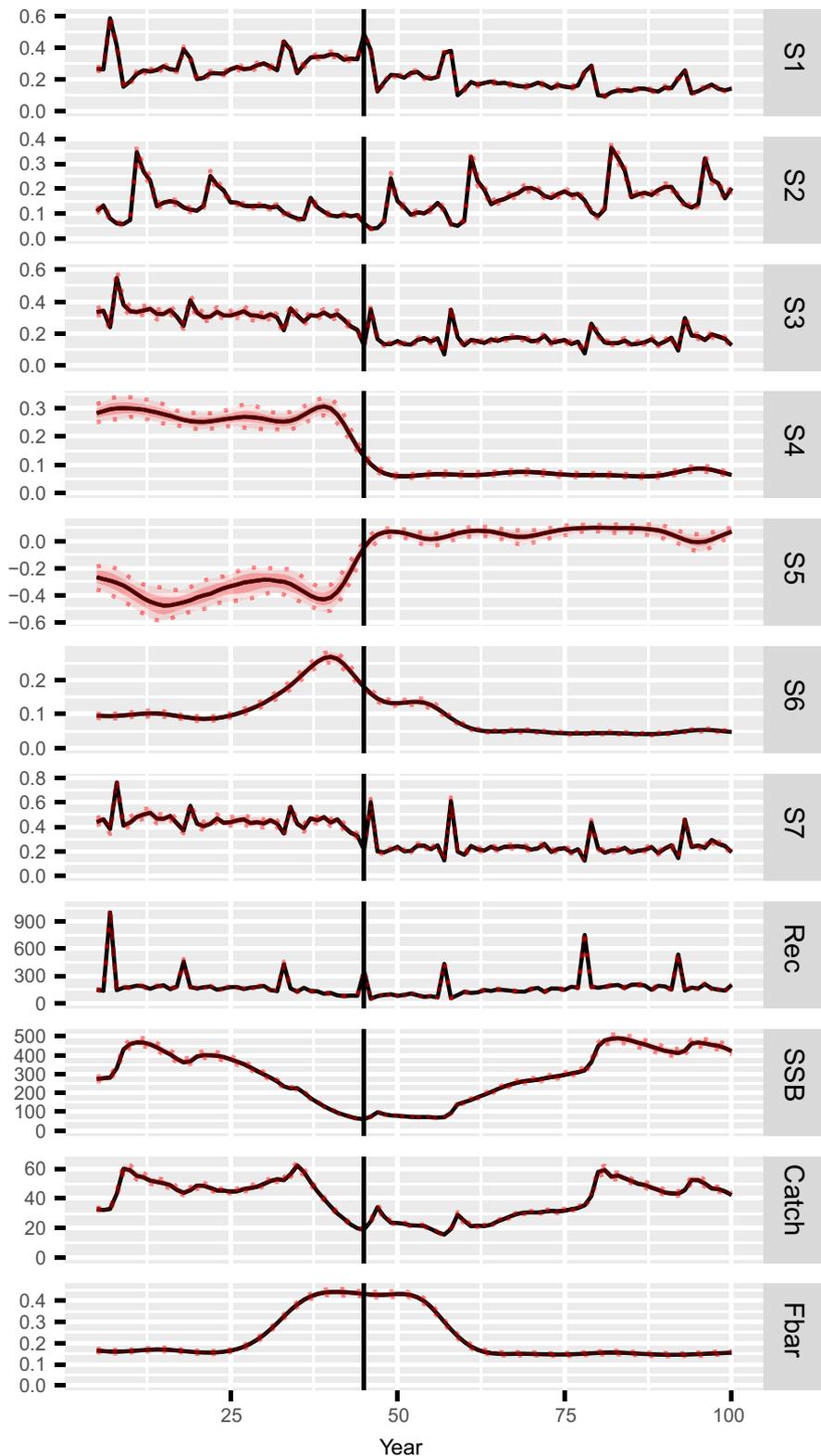
In scenario 3, where selectivity changed while Fbar and recruitment were fluctuating, the differences in performance between

**FIGURE 3** The temporal development of seven selectivity metrics (S1–S7), Recruitment (Rec), SSB, Catch and Fbar for the simulated stock of scenario 3. Vertical lines indicate the point in time when the selectivity change happened. Dotted lines indicate the confidence intervals [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]



metrics became more apparent. Visual inspection of the metrics' trends suggested that while most metrics responded to the selectivity change, the F-based metrics S4 and S5 performed the best with regards to their robustness to changing Fbar and recruitment (Figure 3). F-based metrics similar to S4 (S11–S13) exhibited similarly good performance (Figure S3). Metrics incorporating catch

and/or abundance data (S1, S2, S3 and S7), exhibited trends with abrupt changes of various magnitudes in response to the modelled recruitment pulses (Figure 3). Notably S3, which was both catch- and N-based, responded to recruitment pulses with a dip on the year of the pulse followed by an increase the year after (Figure 3). This was because the high abundance of juveniles in the

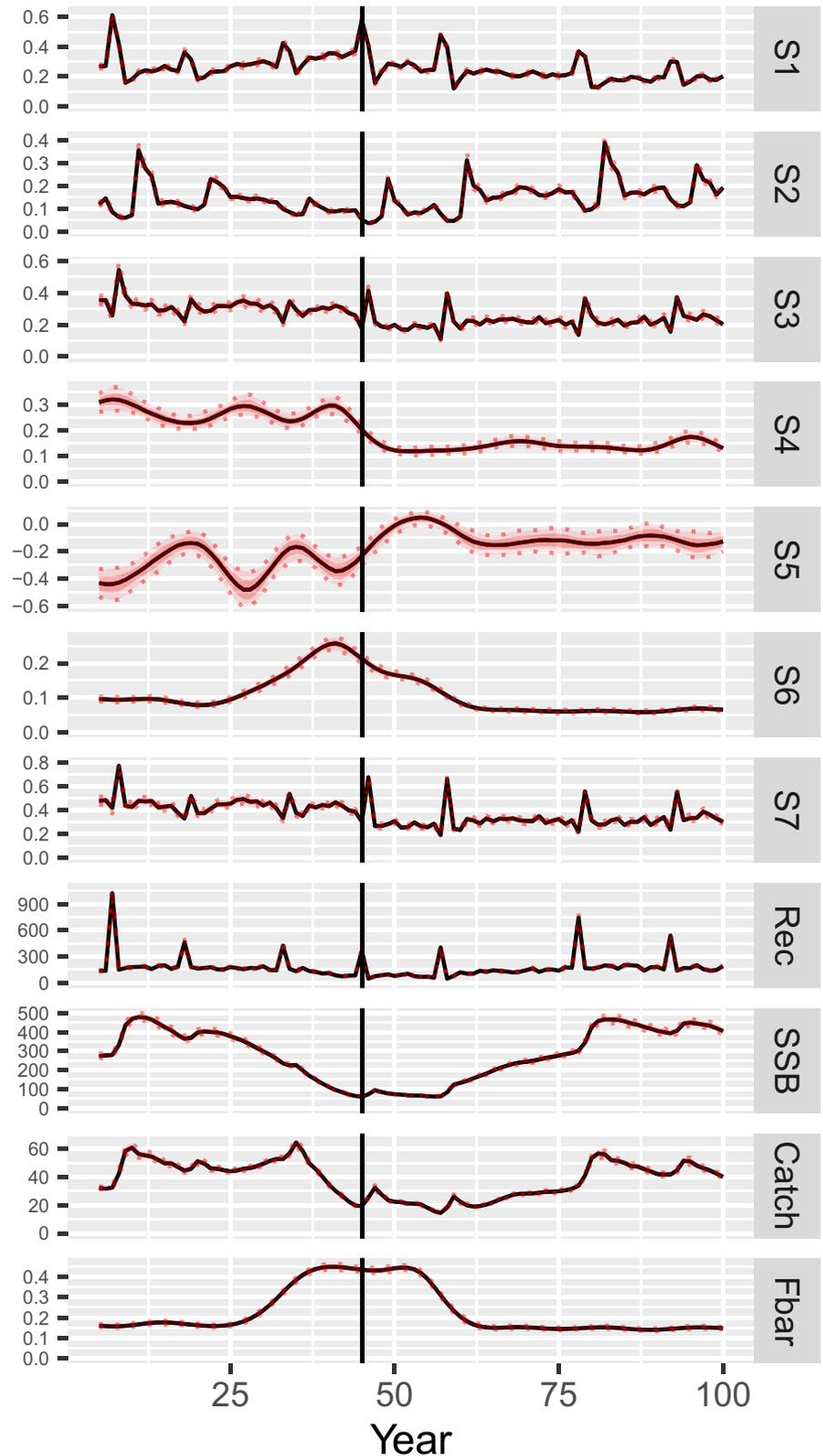


**FIGURE 4** The temporal development of seven selectivity metrics (S1–S7), Recruitment (Rec), SSB, Catch and Fbar for the simulated stock of scenario 4. Vertical lines indicate the point in time when the selectivity change happened. Dotted lines indicate the confidence intervals [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

sea generated by a recruitment pulse gave a signal of “good” selectivity in the same year followed by a signal of “bad” selectivity the year after, when many fish from the previous year’s pulse were caught. Regarding the effect of the changing Fbar, S6 mistook the increase of Fbar as worsening selectivity (i.e., higher targeting of juveniles) (Figure 3).

In scenario 4, Fbar and recruitment were fluctuating and the selectivity changes coincided with a recruitment pulse. As in scenario 3, F-based metrics such as S4 exhibited a better performance than the others (Figure 4). Notably, the synchronization of the selectivity change with a recruitment pulse led to the perception of a worsening selectivity in the same year by S1, a year later by S3 and S7, and four

**FIGURE 5** The temporal development of seven selectivity metrics (S1–S7), Recruitment (Rec), SSB, Catch and  $F_{bar}$  for the simulated stock of scenario 5. Vertical lines indicate the point in time when the selectivity change happened. Dotted lines indicate the confidence intervals [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]



years later by S2 (Figure 4). Fitting multiple linear regressions to the relationships of each selectivity metric against  $Sel$ ,  $F_{bar}$  and  $Rec$  (see Figures S6–S12 for the diagnostic plots) confirmed that while the selectivity change had a statistically significant effect on most metrics, only metrics S4 and S5 were found to be independent from both  $F_{bar}$

and  $Rec$  (Table 2). Both  $F_{bar}$  and  $Rec$  had a statistically significant effect on all other metrics, except S7 where only  $Rec$  had a significant effect and S6 where only  $F_{bar}$  had a significant effect (Table 2).

In scenario 5, where a more subtle change in selectivity was modelled compared to scenario 4, the simple catch-based selectivity

Scenario	Variable	Metrics						
		S1	S2	S3	S4	S5	S6	S7
4	<i>Sel</i>	***	*	***	***	***	*	***
	<i>Fbar</i>	***	**	**	-	-	***	-
	<i>Rec</i>	***	***	***	-	-	-	***
	<i>Rec lag</i> in best model	0	4	1	0-4 <sup>a</sup>	0-4 <sup>a</sup>	0-4 <sup>a</sup>	1
	Adj. <i>R</i> <sup>2</sup> of best model	.66	.54	.87	.96	.93	.98	.88
5	<i>Sel</i>	-	-	***	***	***	-	***
	<i>Fbar</i>	***	**	*	-	-	***	-
	<i>Rec</i>	***	***	***	-	-	-	***
	<i>Rec lag</i> in best model	0	4	1	0-4 <sup>a</sup>	0-4 <sup>a</sup>	0-4 <sup>a</sup>	1
	Adj. <i>R</i> <sup>2</sup> of best model	.59	.54	.75	.88	.61	.97	.78

Note: The *Rec lag* of the model for each metric with the lowest AIC is also noted. See Figures S6-S19 for the diagnostic plots.

Coefficient significance levels:  $-p > .05$ ;  $*.01 < p < .05$ ;  $**.001 < p < .01$ ;  $***p < .001$ .

<sup>a</sup>Models with all four *Rec lags* provided similarly good fits (AIC values within two units).

metrics (S1-S2), as well as S6, were no longer able to pick up the selectivity change (Table 2) (see Figures S13-S19 for the diagnostic plots). In other words, these metrics responded with a false negative signal to the selectivity change. This was because the effects of recruitment pulses and changes in *Fbar* were more pronounced than the effect of the selectivity change (Figure 5). By contrast, S4 and S5 were still able to pick up the effect of the selectivity change, without being affected by changes in *Fbar* and *Rec* (Table 2).

The simulation analysis indicated that metrics based on catch and/or abundance data (S1, S2, S3 and S7), can be representative of selectivity, but they are also sensitive to fluctuations in *Fbar* and/or recruitment (Table 2). Moreover, the simple catch-based metrics S1 (i.e., proportion of juveniles in the catch) and S2 (i.e., proportional of fish at optimal length in the catch) were able to track the pronounced selectivity change in scenario 4, but not the more subtle one in scenario 5 (Table 2). This means that S1, S2, S3 and S7 fail at least one of the three criteria set in the Introduction; hence, they are sub-optimal for use in empirical fish stocks. S4 met all three criteria as it was able to track selectivity changes, and it was also robust to changes in recruitment and *Fbar* (Table 2). F-based metrics similar to S4, had also similarly good performance (S11-S13; Figures S4-S5). Therefore, these types of metrics are the most suitable to be further examined in empirical stocks. S5 (i.e., difference between A50 of selectivity and A50 of maturity) also performed well, while S6 (i.e., *Fbar* of juveniles) was sensitive to fluctuations in *Fbar* and could track only the pronounced selectivity change (Table 2).

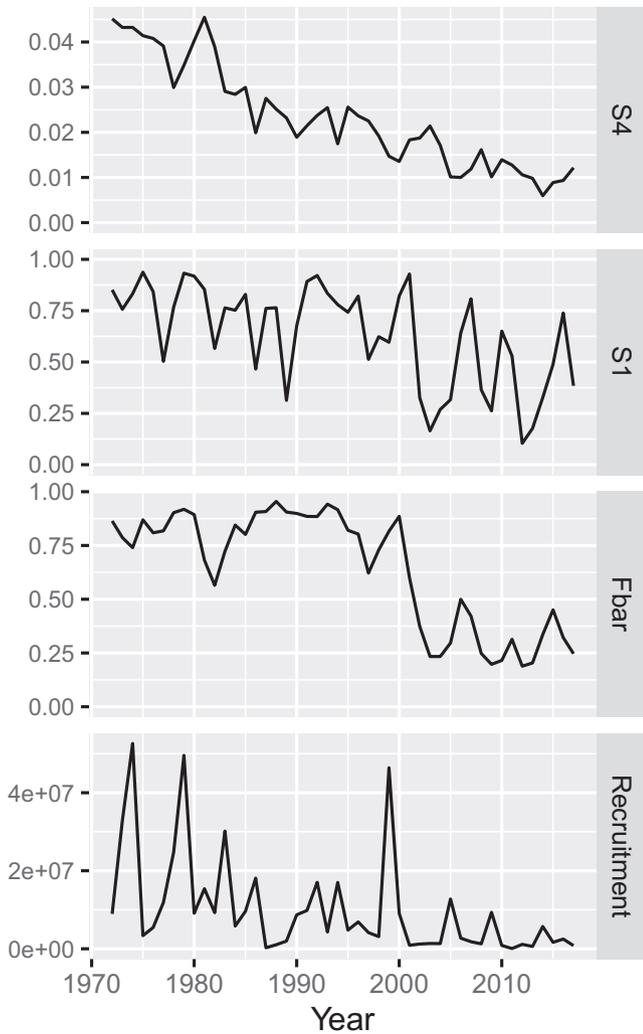
Based on the results of the simulation analysis, two metrics were shortlisted to be tested on empirical stocks. These were S4 and S1. S4 (i.e., *Frec/Fbar*) was chosen as representative of the group of best performing F-based metrics (S4, S11-S13) which all tracked the selectivity change and were robust to changes in recruitment and *Fbar*. S4 was considered to have the most straightforward calculation and interpretation

**TABLE 2** Summary of the multiple linear regression models for the seven selectivity metrics (S1-S7) against *Sel*, *Fbar* and *Rec* (zero to four lags) in scenario 4 (big selectivity change) and scenario 5 (small selectivity change)

among these metrics expressing different ratios of F of recruits (*Frec*) to some measure of F of non-recruits, given that *Fbar* is the most common measure of overall fishing pressure. S5 (i.e., difference between A50 of selectivity and A50 of maturity) was not shortlisted because it is known to be unsuitable for saddle-shaped or multi-peak selectivity curves that make the calculation of A50 problematic (Vasilakopoulos et al., 2016). S1 (i.e., proportion of juveniles in the catch) was shortlisted mainly to provide a contrast to S4 in the sense of exhibiting how a sub-optimal selectivity metric performs. In addition, S1 was chosen because it may be an option for data-limited fisheries (i.e., those without an analytical stock assessment), given that its calculation only requires data on catch and maturity (Table 1). S1 has been suggested as a useful indicator in data-rich stocks as well (Froese, 2004).

### 3.2 | North Sea haddock: A case of recruitment pulses

The shape of the selectivity curve in this stock ranged from asymptotic to domed, with the highest selection (i.e., highest F) occurring typically at age 3, 4 or 5 (Figure S20). North Sea haddock had a history of strong recruitment pulses and a big *Fbar* reduction after 2000. This resulted in the catch-based selectivity metric (S1) to exhibit a rather unstable trend (Figure 6). This was to be expected from the results of the simulation analysis that indicated a sensitivity of this metric to both recruitment pulses and *Fbar*. S1 ranged from 10% to 94%, and recruitment pulses were associated with high values of S1 within 0-2 years. Meanwhile, S4 had a relatively smooth decreasing trend (Figure 6). This trend of S4 indicated an improving selectivity, which agreed with the relevant consecutive technical measures implemented from 1980 onwards. Nevertheless, there was not an exact synchrony between specific

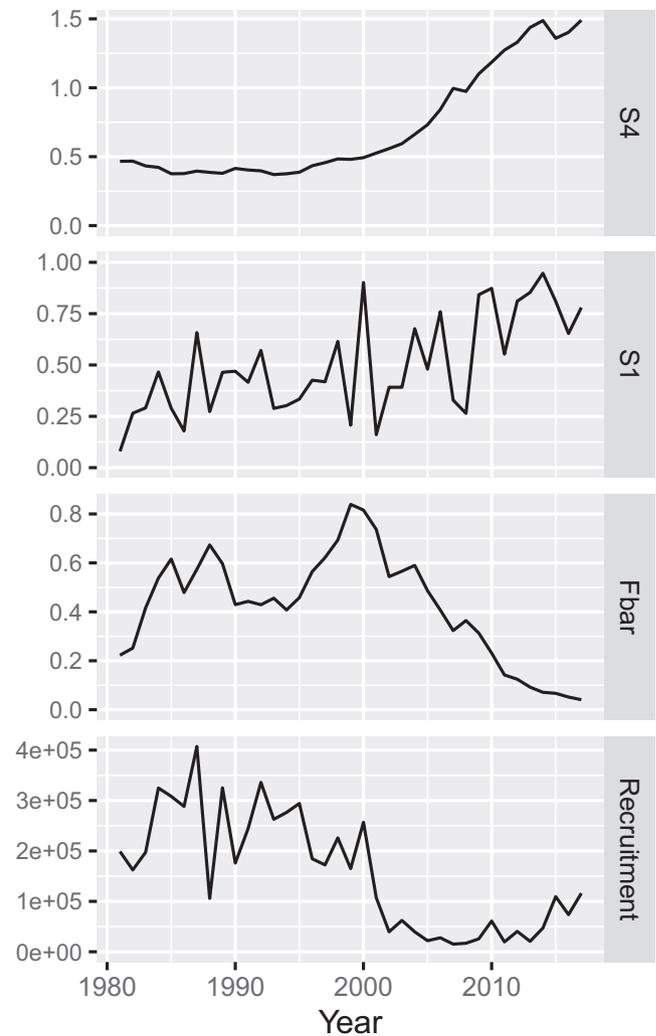


**FIGURE 6** The temporal development of selectivity metrics S4 and S1, Fbar and Recruitment (thousands) in North Sea haddock

technical measures and improvements in selectivity, possibly due to the gradual implementation of the technical measures by the fishing fleets.

### 3.3 | West of Scotland whiting: A case of stock depletion

The shape of the selectivity curve in this stock was asymptotic, with the highest selection (i.e., highest  $F$ ) occurring at age 4–6, with the exception of the last five years of the time series when selection peaked at age 1 (Figure S21). West of Scotland whiting went through a period of very low SSB and recruitment in the early 2000s. As in the case of North Sea haddock, S4 exhibited a much smoother trend than S1 (Figure 7). Up until the early 2000s, peaks in recruitment were associated with peaks in S1, but not in S4 (Figure 7), in agreement with the findings of the simulation analysis. S1 continued to exhibit high variability after the early 2000s when recruitment was more stable, owing to high variability in catches at age 1. From 1995 onwards, a slow deteriorating trend in selectivity (i.e., higher targeting of juveniles) was captured by S4, which was further accelerated

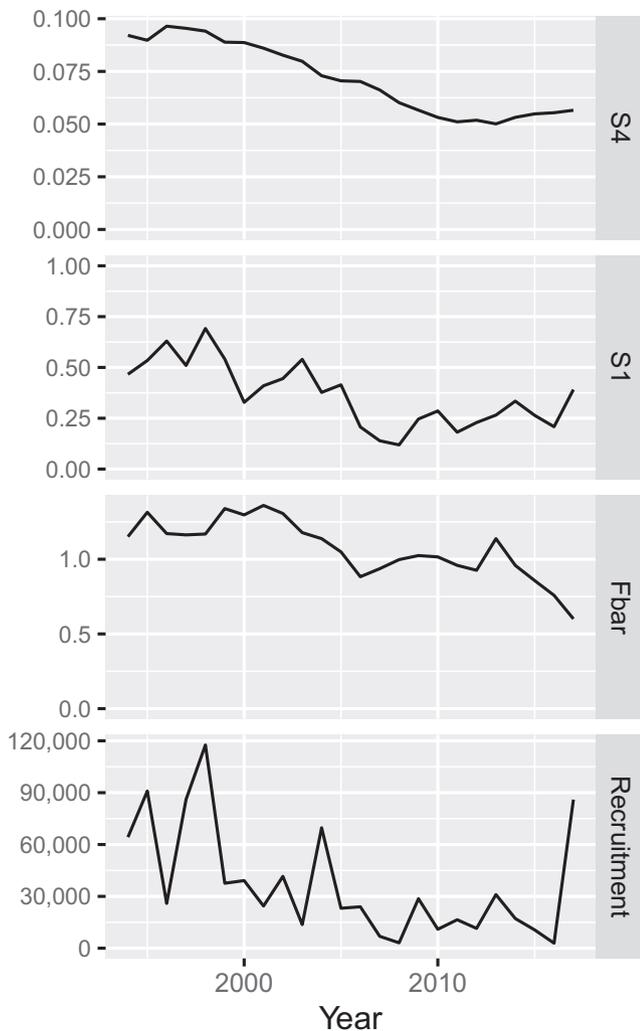


**FIGURE 7** The temporal development of selectivity metrics S4 and S1, Fbar and Recruitment (thousands) in West of Scotland whiting

from the early 2000s onwards, when the SSB was depleted. This was because technical measures taken from 2002 onwards aimed to reduce the catch of whiting by the TR1 fisheries (gadoid fisheries), which targets adult whiting. As a result, Fbar gradually decreased. However, there was little change in the bycatch of juvenile whiting by the TR2 fishery (small mesh fishery for *Nephrops*). This led to a perception of deteriorating selectivity picked up by S4, and less so by S1.

### 3.4 | West Baltic cod: A case of technical measures reversal

The shape of the selectivity curve in this stock was asymptotic, with the highest selection (i.e., highest  $F$ ) occurring at age 5 (Figure S22). West Baltic cod went through a series of technical measures from 1998 onwards aiming to reduce the catch of small fish; however, in 2014 MCRS was reduced, allowing the capture of smaller fish. S4 proved to be sensitive to these technical measures, capturing a gradual improvement in selectivity during 1998–2013, followed by a

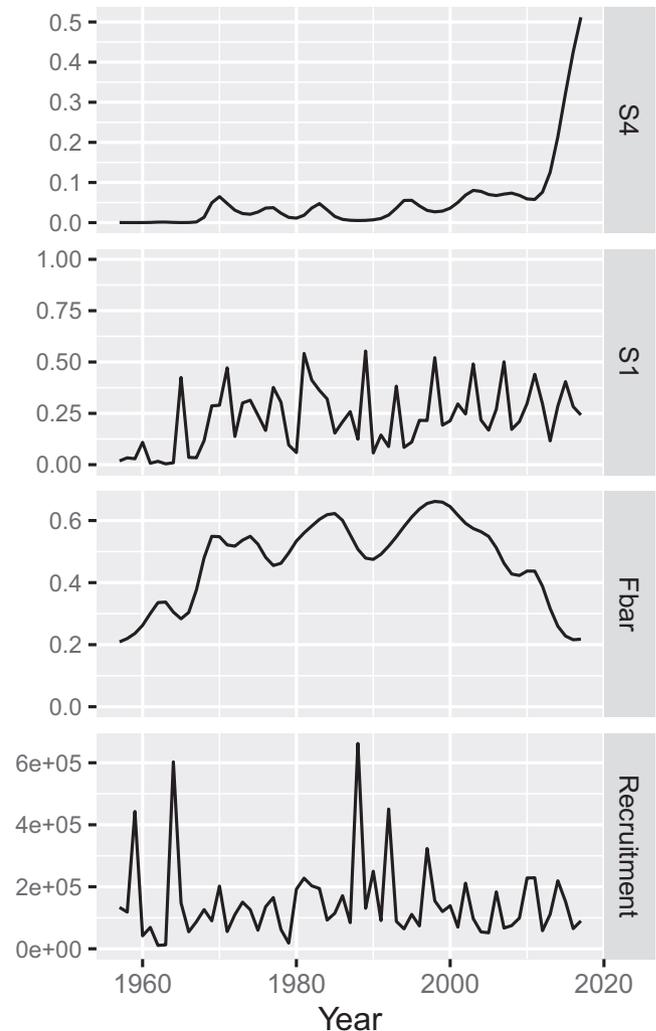


**FIGURE 8** The temporal development of selectivity metrics S4 and S1, Fbar and Recruitment (thousands) in West Baltic cod

deterioration of selectivity from 2014 onwards (Figure 8). The signals coming from S1 were more obscure, as S1 tended to follow recruitment fluctuations within 0–1 year, in agreement with the findings of the simulation analysis. Notably, the large recruitment pulse in the last year of the time series had a clear impact on S1, but not S4 (Figure 8).

### 3.5 | North Sea sole: A case of introducing a new gear

The selectivity curve in this stock was domed, with the highest selection (i.e., highest  $F$ ) occurring typically at age 3, 4 or 5 (Figure S23). Selectivity of North Sea sole, as captured by S4, remained rather stable in the 1960s, 1970s and 1980s, and deteriorated slightly during the 1990s and 2000s (Figure 9). However, the analysis indicated that the most significant deterioration in selectivity started after 2011, particularly in the period 2014–2017. This rapid deterioration of selectivity coincided with the expansion of pulse trawling for sole in the North Sea. The pulse trawl is a much more efficient gear for in catching sole than the conventional beam trawl, and it can operate in areas with

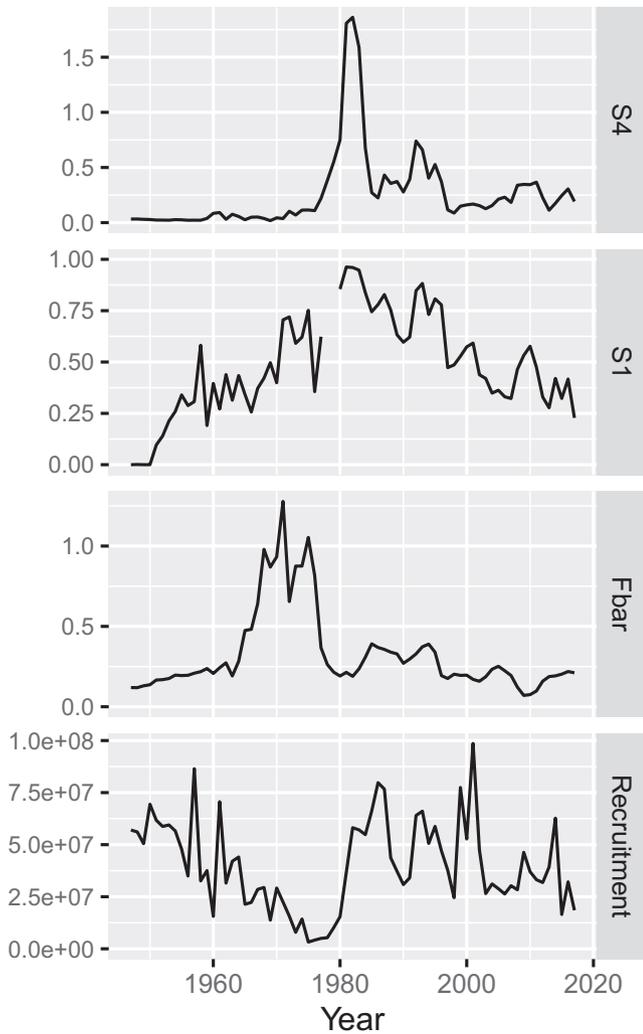


**FIGURE 9** The temporal development of selectivity metrics S4 and S1, Fbar and Recruitment (thousands) in North Sea sole

high sole concentrations where the beam trawl cannot (ICES, 2018e). Notably, S1 did not pick up this signal of deteriorating selectivity (i.e., higher targeting of juveniles) at the end of the time series and exhibited high variability (Figure 9). S1 tended to follow recruitment pulses, in agreement with the findings of the simulation analysis, with one year lag (Figure 9). The increasing use of pulse trawl did not translate into a higher Fbar in 2011–2017, despite the higher efficiency of that gear, because fishing effort decreased during the same period (ICES, 2018b).

### 3.6 | North Sea herring: A case of collapse and rebuilt

North Sea herring was the stock with the longest time series among the ones examined (1947–2017). During this time it went through a stock collapse and a rebuilt. The shape of the selectivity curve in this stock was highly variable from year to year, with the highest selection (i.e., highest  $F$ ) occurring anywhere between age 1 and age 7 (Figure S24). Selectivity, as captured by S4, started deteriorating (i.e., increasing targeting of juveniles) in the early 1970s (Figure 10), coinciding with

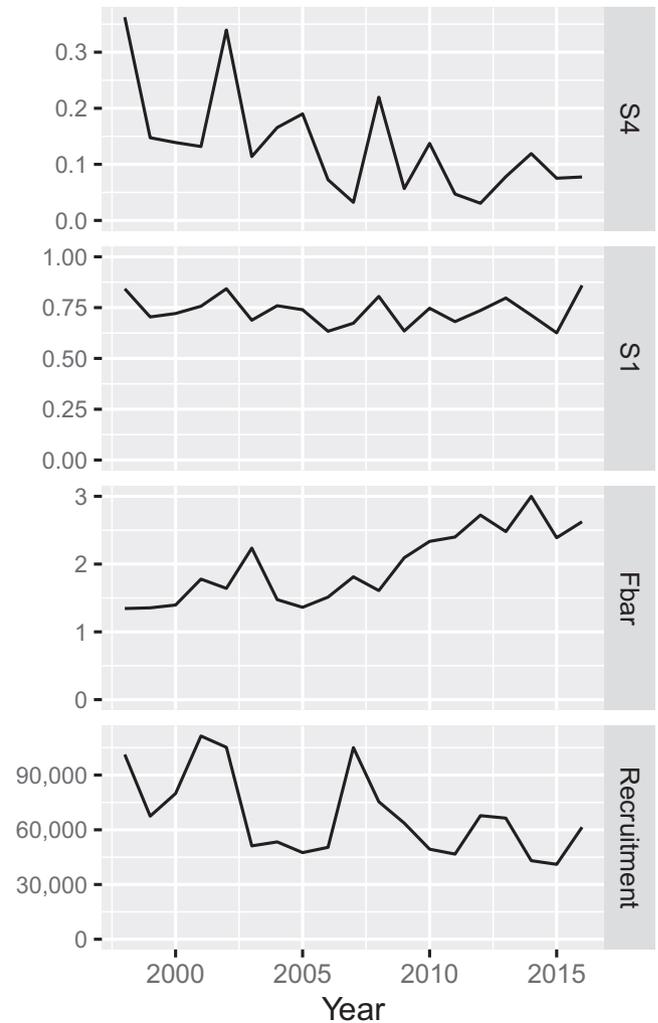


**FIGURE 10** The temporal development of selectivity metrics S4 and S1, Fbar and Recruitment (thousands) in North Sea herring. S1 values in 1978 and 1979 could not be calculated due to the lack of catch-at-age data

the development of the sprat fishery which caught juvenile herring. In the late 1970s the herring stock collapsed and the directed fishery for herring stopped, resulting in a decrease in Fbar and a perceived deterioration of selectivity because juvenile herring was being caught as bycatch. In 1981–1982 there was a peak in both S4 and S1 (Figure 10), corresponding to the highest proportional representation of age 0 herring in the catch over the entire time series (ICES, 2018f). This was due to the opening of the fishery in these years only in the southern North Sea areas, which host more juveniles than the central and northern ones. Both S4 and S1 also captured a selectivity improvement in the late 1990s (Figure 10), coinciding with the bycatch regulation enforcement that reduced the bycatch of juvenile herring by the sprat fishery.

### 3.7 | Gulf of Lion hake: A case of a Mediterranean demersal fishery

Gulf of Lion hake has been chronically overexploited, as is the case for most Mediterranean hake stocks (Vasilakopoulos et al., 2014). The



**FIGURE 11** The temporal development of selectivity metrics S4 and S1, Fbar and Recruitment (thousands) in Gulf of Lion hake

shape of the selectivity curve in this stock ranged from asymptotic to domed, with the highest selection (i.e., highest F) occurring typically at age 2 or 3 (Figure S25). Fbar levels have been high and they even exhibited an increasing trend during the studied time period (Figure 11). S1 did not exhibit any particular trend, but S4 indicated an improvement in selectivity over time coinciding with the reduction in the number of French trawlers, which are mostly responsible for the catches of juvenile hake. However, this decreasing trend of S4 stopped after 2010 (Figure 11), possibly reflecting the pelagic trawlers switching to demersal trawling due to the crash of the small pelagic stocks (GFCM, 2017).

## 4 | DISCUSSION

This study offers a comprehensive analysis of selectivity metrics, with a focus on their utility for fisheries management and advice. The simulation analysis suggested that F-based metrics provide more adequate quantifications of selectivity than metrics incorporating catch and/or abundance data. The latter may track selectivity changes but they are also sensitive to changes in recruitment and Fbar, meaning that they are not suitable to use as representative measures of

fisheries selectivity in real-world fisheries. Selectivity metrics using only  $F$  data, such as the ratio of the  $F$  of recruits to  $F_{bar}$  ( $F_{rec}/F_{bar}-S4$ ) respond clearly to selectivity changes, while they are also robust to both recruitment variability and changes in fishing pressure. Testing  $F_{rec}/F_{bar}$  on real data, illustrated the metric's ability to track the effects of technical measures and other changes on the selectivity of commercial fish stocks. Therefore, this metric could be used to identify and monitor changes in selectivity that may arise from current and future technical measures, such as the Landing Obligation in Europe (European Commission, 2013; 2019).

The  $F_{rec}/F_{bar}$  selectivity metric needs to be tailored to the specific characteristics of a given fish stock. The age-class chosen to calculate  $F_{rec}$  needs to be the first age-class for which some non-negligible harvest occurs (first recruited age-class), which is not necessarily the first age-class in the stock assessment. For example, in the case of West Baltic cod,  $F_{rec}$  had to be calculated at age-class 1 rather than age-class 0 which was the first available age-class in the assessment data. Additionally, the age-classes of  $F_{bar}$  need to exclude the first recruited age-class, to avoid duplicating information in both the numerator and denominator of the  $F_{rec}/F_{bar}$  ratio. For example,  $F_{bar}$  in the case of Gulf of Lion hake, which was originally calculated over age-classes 0–2, had to be recalculated over age-classes 1–3. Other adjustments may also be useful depending on stock-specific needs:  $F_{rec}$  could be assigned to any juvenile age-class, if that age-class is the focus of a specific management measure, or it could even be taken as the average of multiple age-classes in the case of stocks with many juvenile age-classes (e.g., NE Arctic cod).

This study focused on data-rich stocks with age-structured analytical assessments. In this context, only two metrics were examined that can be calculated without the requirement of a stock assessment, namely  $S1$  (i.e., proportion of juveniles in the catch) and  $S2$  (i.e., proportion of fish at optimal length— $L_{opt}$ —in the catch).  $F$ -based selectivity metrics were found to work much better than these simple catch-based metrics. The latter tend to be more “noisy” and sensitive to changes in population structure, because when there are more juveniles in the sea, there tend to be more juveniles in the catch. Also, simple catch-based metrics, respond strongly to variability in the catch of juveniles compared to  $F$ -based ones. Nevertheless, in some of the empirical stocks (North Sea haddock, West Baltic cod, West of Scotland whiting, North Sea herring),  $S1$  (i.e., proportion of juveniles in the catch) was able to track some of the selectivity changes similarly to  $F_{rec}/F_{bar}$ , albeit with much higher inter-annual variability. In other cases (North Sea sole, Gulf of Lion hake),  $S1$  failed to do so. Consequently, simple catch-based selectivity metrics should be avoided if  $F$ -at-age is available. In data-limited situations where  $F$ -at-age is absent, simple catch-based selectivity metrics such as  $S1$  and  $S2$  could potentially be used as an indication of selectivity if  $F_{bar}$  and recruitment are assumed to be stable. Still, as indicated by the simulation analysis of strong versus subtle changes in selectivity, these sub-optimal catch-based metrics would be useful only if strong changes in selectivity have occurred. Nevertheless, selectivity-based management, whereby minimum fish size limits and size selectivity of fishing gears are set above the mean size at maturity, is

considered a sound strategy in data-limited fisheries (e.g., Prince & Hordyk, 2019; Vasilakopoulos & Maravelias, 2016). In other words, even in the absence of information on  $F$ , minimizing the catches of juveniles while increasing the catches of fish at  $L_{opt}$  is a good rule of thumb (Froese, 2004; Froese et al., 2008, 2016).

This study highlights how the use of an appropriate selectivity metric such as  $F_{rec}/F_{bar}$  can reveal mismatches between the observed population selectivity and expectations from changes in gear selectivity. Population selectivity is the combination of gear selectivity and availability; hence, the effect from changes in gear selectivity leading to the capture of larger fish can be cancelled out by changes in the spatio-temporal allocation of fishing effort that makes juveniles more available to fishing. In the case of North Sea sole, despite the pulse trawl having better selectivity for juvenile sole than the conventional beam trawl (van Marlen, Wiegerinck, Os-Koomen, & Barneveld, 2014), population selectivity rapidly deteriorated in 2014–2017 as pulse trawlers replaced beam trawlers. This is presumably due to the ability of pulse trawlers to fish over substrate types where the beam trawlers cannot operate (Soetaert, Decostere, Polet, Verschueren, & Chiers, 2015), and because of the freedom of pulse trawlers to fish in more coastal areas where conventional beam trawling is prohibited (Haasnoot, Kraan, & Bush, 2016). Indeed, recent research has shown that pulse trawlers prefer different fishing grounds than the conventional beam trawlers, and that pulse trawlers discard more sole than beam trawlers (ICES, 2018e).

Most selectivity metrics tested here ( $S3$ – $S7$ ), including  $F_{rec}/F_{bar}$ , are derived from stock assessments; hence, they are sensitive to the stock assessment model type and specifications. A mis-specified stock assessment model, or the calculation of  $F_{bar}$  over not fully selected age-classes, could result in a distorted perception of selectivity, as it is also the case for the perception of  $F_{bar}$  and  $SSB$ . Stock assessment specifications may also lead to selectivity changes not being exactly synchronized with changes in the selectivity metric, as is the case in the simulation analysis here. Some delay between the legislation of technical measures and the response of a selectivity metric may also be due to the gradual implementation of the technical measures by the fishing fleets.

While our investigation of selectivity metrics has been quite exhaustive here, the existence of additional good selectivity metrics cannot be ruled out. Protecting juveniles is a major priority for European fisheries management, but other selectivity concerns may exist in different fisheries around the world, for example related to the protection of other age-classes, or related to changing the shape of the selectivity curve. In such cases, other selectivity metrics may need to be developed. Some of these metrics could be constructed by modifying metrics tested here. For example, in any particular case where managers want to track changes in the relative exploitation of an adult population component (e.g., big old fish), the  $F$  of the relevant age-class(es) could be used as numerator in the  $F_{rec}/F_{bar}$  metric. In any case, any alternative selectivity metrics should satisfy the three criteria proposed in this study: ability to track selectivity changes, robustness to recruitment variability, and robustness to changing  $F_{bar}$ .

Improving selectivity, albeit important, it is not a panacea. Within the ranges of selectivity and  $F_{bar}$  commonly observed in

commercial fish stocks, the latter is the most important driver of stock status (Vasilakopoulos, O'Neill, & Marshall, 2011, 2012). Also, to fully understand the effects of selectivity on stock size and fisheries yield, selectivity and  $F_{bar}$  need to be considered together (Froese et al., 2008; Prince & Hordyk, 2019; Vasilakopoulos et al., 2016). Therefore, a deteriorating selectivity (i.e., higher targeting of juveniles) does not necessarily need to be alarming. For example, in the cases of West of Scotland whiting and North Sea sole, selectivity has been deteriorating in recent years but  $F_{bar}$  has been decreasing and SSB has been increasing (ICES, 2018b; 2018c). Conversely, selectivity has been slightly improving in the Gulf of Lion hake due to the trawling effort reduction, but the stock is still severely depleted due to a very high  $F_{bar}$  (GFCM, 2017).

A robust selectivity metric, such as  $F_{rec}/F_{bar}$ , with a proven ability to track selectivity changes in response to technical measures could be a powerful tool for managers to promote fisheries sustainability. For example, by breaking down  $F$  into partial  $F$ -at-ages from different fleet segments and using them to infer partial selectivity, managers could identify the fleet segments that are fishing less sustainably than others and focus on improving them. Additionally, by calculating partial selectivities, managers would be able to identify the fleet segments that are affected or should have been affected by specific management measures, such as the Landing Obligation. A lower-than-expected selectivity improvement of a fleet segment could either mean a limited uptake of the management measure, or changes in fleet behaviour to circumvent the effects of that management measure. In both cases, managers could use the selectivity metric as an objective measure of fleet performance.

Quantifying selectivity not only allows to track the effect of management measures, but also enables the systematic exploration of the stock-specific potential for higher sustainable yields which have been predicted by simulation studies (e.g., Froese et al., 2008; Froese et al., 2016; Prince & Hordyk, 2019; Scott & Sampson, 2011; Vasilakopoulos et al., 2014; Vasilakopoulos et al., 2016). The latter is an area where future research needs to focus; the expected yields from different combinations of  $F$  and selectivity needs to be studied on a stock-by-stock basis. Subsequently, to integrate fully selectivity into fisheries management and advice, stock-specific selectivity reference points analogous to  $F_{MSY}$  and  $B_{MSY}$  need to be investigated. This would operationalize selectivity as a second lever, complementary to  $F_{bar}$ , for managers to achieve desirable states and outcomes for exploited fisheries resources.

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## CONFLICT OF INTERESTS

The authors confirm that there is no conflict of interest to declare in this paper.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study were derived from the following resources available in the public domain: the International Council for the Exploration of the Sea [<https://www.ices.dk/community/Pages/default.aspx>] and the General Fisheries Commission for the Mediterranean Sea [<http://www.fao.org/gfcm/activities/fisheries/stock-assessment/en/>].

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## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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