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### Abstract

Sampling effects on the effectiveness of ecological indicators in detecting fishery-induced community changes
Sampling effects on the effectiveness of ecological indicators in
detecting fishery-induced community changes

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Abstract:

Effective ecological indicators (EI) should reflect changes to ecosystem status in a timely manner to guide fishery management; however, the robustness of EIs in the face of sampling uncertainty is not well understood and sampling errors may result in delayed or even unhelpful actions for management. In this study, we use a size-spectrum model to evaluate the effectiveness of EIs in detecting fishery-induced ecosystem changes given various levels of sampling uncertainty. We demonstrate that there is a time-lag exists between changes in fishing pressure and EIs response. The selectivity of survey gears can strongly determine the level of EI responses within certain size ranges. EIs may lost statistical power once sampling errors exceed a certain level, implying that several decades of monitoring data may be needed to be sure of detecting even a large change. Multivariate methods can strengthen the statistical powers of EIs, but only when the level of sampling noises is low. This study suggests the need for considering the impact of sampling uncertainty on the use of ecological indicators in fisheries management.

Key Words: sampling error, size-spectrum model, selectivity, trend test, multivariate analysis
1. Introduction

The concept of “ecosystem-based fisheries management” (EBFM) has been widely accepted in fisheries management with an increased recognition of fishing impacts on marine ecosystems (Hall and Mainprize 2004; Pikitch et al. 2004; Scandol et al. 2005; Link et al. 2011). As a preliminary step towards EBFM, the status and changes of ecosystems should be monitored, in which ecological indicators (EIs) are often used to reflect species diversity, size structure, and trophic structure. A variety of EIs have been proposed based on empirical evidences and ecological theory (Fulton et al. 2004); however, few of them have been adopted by managers in decision-making and formal management actions, mostly due to the insufficient knowledge of their properties. This knowledge gap leads to a remarkable contrast between the long desire for EBFM and the prevalence of single-species approach in tactical fisheries management (Tallis et al. 2010; Skern-Mauritzen et al. 2016). Thus, improving the knowledge of EIs in fisheries management is urgent for promoting the implementation of EBFM.

The EIs serve two purposes in fisheries management, to define decision criteria to trigger management actions and to measure the performance of management strategies (Fulton et al. 2005; Fay et al. 2013), parallel to reference-points approach in single-species management. However, the use of EIs as reference points in decision-making is questionable as their ecological implications may not be straightforward (Rochet and Trenkel 2003). Besides, since the vast majority of worldwide ecosystems have long been subject to exploitation, those reference points...
cannot be justified by comparison with a past “pristine” state. An alternative approach of “reference direction” has drawn more attentions, which measures the relative value or trends of EIs (National Research Council 2000; Jennings and Dulvy 2005). The theoretical reference direction has been well established, as most indicators show relatively consistent responses to fishing (Rochet and Trenkel 2003). For example, species diversity, proportion of large species and individual body weight usually decrease with fishing (Jennings and Kaiser 1998; Hall 1999).

Reference directions need to be extensively validated as they are fundamental for the use of EIs to inform management decision in the absence of a suitable baseline values. Numerous studies have been conducted to examine the temporal trends of EIs in a variety of marine ecosystems to identify the correlations between EIs and fishing pressure (Rochet and Trenkel 2003; Nicholson and Jennings 2004; Jennings and Dulvy 2005; Greenstreet and Rogers 2006; Trenkel and Rochet 2009; Shin et al. 2010b; Blanchard et al. 2010; Kleisner et al. 2015). In general, most EIs are shown to be responsive to fishing and consistent with theoretical reference directions in the long term (Jennings and Kaiser 1998; Rochet and Trenkel 2003), although consistency may be impaired by diverse environment conditions and differences in patterns of fisheries exploitation (Blanchard et al. 2010). It should be noted that the long-term retrospective analyses may not guarantee the valid use of EIs in guiding fishery managements on much shorter time scale (Nicholson and Jennings 2004). On these timescales, the response of EIs may be greatly different from that in long term and may be dominated by stochasticity, giving their low statistical power (Nicholson and Jennings 2004;
Jennings and Dulvy 2005).

From a mechanistic prospective, there are many reasons for the failure of EIs to perform as desired, including: (1) fishing can impose indirect ecological effects through trophic interactions and feedback loops (Jennings and Kaiser 1998; Walters and Kitchell 2001; Gårdmark et al. 2014), and the multiple ecological effects may conceal the relationships between the observed EIs and the driving forces; (2) environmental variability may result in perturbed dynamics of EIs, and it remains challenging to predict the environmental effects on ecosystem structure and functions with regard to the complex trophic networks within marine ecosystems (Maury et al. 2007; Chaalali et al. 2016); (3) observational errors that arise from sampling processes are ubiquitous in ecology studies (Walker et al. 2003; Zhang et al. 2015), which may blur actual changes of ecosystems; and (4) scientific surveys have gear selectivity, and the bias in sampling may result in unrepresentative observations (Jennings and Dulvy 2005). It is therefore challenging to clarify whether observed EIs reflect the actual trends in marine communities.

The assessment and management of fisheries depend on the quality and quantity of sampling data, yet samples may not be representative of biotic communities due to observation errors and the selectivity of survey gears. This study is focused on the effect of sampling on the ability of EIs to detect changes in fish communities in a manner useful to management. The objectives of this study are to evaluate the relationship between fishing pressure and the observation of EI dynamics; the effects of sampling selectivity on the directions of EIs; and the statistical power of EIs with
respect to different levels of sampling errors. We used a size-spectrum model to tackle the trophic interactions within the marine foodweb (Hartvig et al. 2011) and simulate fishing effects on fish communities. A variety of simulation scenarios are developed for evaluating the effects of fishing pressure, survey selectivity and sampling uncertainty on the effectiveness of EIs. Furthermore, individual EI may have constrained statistical power in the presence of sampling errors. We evaluated the use of multivariate approaches to combine a suite of EIs to improve their robustness on sampling errors. The study aims to quantify the effective timescale to detect EI trends and to provide guidance for monitoring program designs for EBFM.

2. Materials and Methods

2.1 Ecological indicators

Six EIs were selected for evaluating the effectiveness of indicators in detecting ecosystem changes, based on their favorable responsiveness, theoretical basis, and measurability (Rice and Rochet 2005; Rossberg et al. 2017). These indicators, including total species biomass ($B$), Shannon-Wiener diversity index ($H'$), large fish index ($LFI$), mean body size ($\bar{w}$), size diversity index ($\Delta$) and the slope of community size spectra (SL), depict the species composition and size structure of marine communities. The reference directions of these indicators were well illustrated (Rochet and Trenkel 2003; Rochet et al. 2005; Rochet and Benoît 2012; Thorpe et al. 2015), and they have been extensively proposed to guide fisheries management (Rochet and Trenkel 2003; Fulton et al. 2005; Shin et al. 2010a; Greenstreet et al. 2011). The
definition of the EIs were listed in Table 1.

2.2 Size-spectrum model

A multispecies size-spectrum model was used in this study to simulate the effects of fishing and trophic interactions in fish communities. This model was developed by Andersen and Beyer (2006) and formulated by Hartvig et al. (2011) based on the size spectra theory (Sheldon et al. 1972; Sprules et al. 2016), characterized by the explicit consideration of feeding selection and ontogenetic niche shift (Andersen et al., 2009; Andersen et al., 2016). The model assumes that (1) predator–prey relationships are primarily determined by body size ratios; (2) individual-level energy budget is driven by food intake; and (3) physiological processes including metabolism, predation, reproduction are correlated with body size, i.e., the allometric scaling law (Elton 1927; Schmidt-Nielsen 1984; Brown et al. 2004). These assumptions enable the model to formulate biological processes at the individual level. The size-spectrum model has been used to assess fishing impacts (Andersen and Pedersen 2010; Rochet and Benoît 2012) and to evaluate management strategies (Jacobsen et al. 2014; Blanchard et al. 2014).

The size-spectrum model was implemented for the ecosystem of Haizhou Bay, China. Haizhou Bay is an open bay on the continental shelf of Yellow Sea (Supplementary materials, Fig. S1). A total of 22 dominant species that account for 90% of the fish community biomass were included in modelling. Each species was characterized by a set of life-history parameters of growth, predation, mortality, and reproduction. The parameters were obtained from FishBase (www.fishbase.org),
previous studies, and the survey data in Haizhou Bay. The model was calibrated to the
species-specific biomass in the survey and the yield of the stow-net fishery. As the
process of model building were explained in a former study (Zhang et al. 2016), the
details of model equations and parameterization are provided in the Supplementary
materials (Tables S1, S2 and S3). The size-spectrum modelling is implemented in R
package “mizer” (Scott et al. 2014).

2.3 Simulation scenarios

The calibrated model was started from low community biomass and run for 100
years to an equilibrium state with a fixed fishing pressure, and the fishing pressure was
changed afterwards to test the effects of fishing on the community (Supplementary
materials, Fig. S2). Both abrupt and gradual changes were implemented to simulate
different patterns of fisheries management. The abrupt changes occurred in one year
and the gradual changes lasted from 2 to 10 years. During the periods, the fishing
pressures increased/decreased to 1.5 or 0.5 times of $F_0$ (1.77year$^{-1}$, the fishing effort in
the calibrated model, described in the Model parameterization in Supplementary
materials section B). Both scenarios were run for an additional 50 years. It should be
noted that this simulation framework implicitly assumed constant environmental
conditions and the evaluation was only valid when the effects of environmental factors
were much less than influences of fishing activity.

We distinguish between sampling uncertainty caused by sampling errors and
sampling bias in this study (Adams et al. 2017). The former may arise from the
variability of sampling operations, which is considered stochastic; and the latter may
arise from sampling methods, such as the selectivity of survey gears, which is considered as systematic bias. Specifically, most fisheries studies are based on trawl survey, which is selective on species distribution, individual age/size and their behavioral responses (Sampson 2013). The trawl sampling data may be biased due to arbitrary mesh sizes, and involve variations from the sampling operation, time and locations. Simulation scenarios are designed to test the effectiveness of EIs with respect to gear selectivity and statistical power. We evaluate the following variables in testing scenarios:

(1) Survey selectivity: Different mesh sizes were simulated for the selectivity of scientific surveys. The survey gear was assumed a “knife-edge” selectivity, that is, individuals smaller than the minimum size (knife-edge size) were not sampled. The simulated selection size ranged from 0 to 3 times of $S_{k_0}$ (selectivity resulting from the mesh size used in the trawl survey in Haizhou Bay), in which zero implied that all individuals in the simulated fish community were included in sampling.

(2) Observation error: the predicted species biomass was manipulated with an error term to simulate the effect of observational errors. The error term was drawn from a log-normal distribution logN(1, $\sigma_{ob}$), in which the standard deviation $\sigma_{ob}$ ranged from 0 to 1. The error terms were multiplied to the size-specific biomass for each species (in the dimension of species × size class).

(3) Variability of fishing efforts: the variation of survey data may result directly from the fluctuations of fishing efforts, as the fishing pressure would not be constant even in well-managed fisheries. A error term following a normal distribution N(0, $\delta_f$) was
added to the preassigned fishing effort to simulate the fishing variability, in which the standard deviation ranged from 0 to 1. The same fishing effort was applied to all species with different catchability in each simulation.

The simulations of observation error and fishing variability were repeated for 1000 times in each scenario to estimate the variation of EIs. The simulation scenarios of this study were summarized in Table 2.

2.4 Trend Detection

We examined the trends of EIs in the simulated time-series and evaluated their effectiveness in trend detection. The EI time-series were chosen to include changes of fishing efforts, with various combinations of monitoring time before and after the changes. The evaluation was conducted under different levels of sampling errors ($\sigma_{ob}$) and fishing variability ($\delta_f$) to evaluate the statistical power of EIs.

The trends of EIs were detected using two approaches, a non-parametric method using the Mann–Kendall trend test (Mann 1945; Kendall 1975; Hipel and McLeod 1994) and a parametric method CUSUM test based on cumulative sums of residuals (Page 1961; Ploberger et al. 1992). The Mann-Kendall test is used to assess a monotonic trend in the time series data, without the requirement for normal distribution or linearity. The CUSUM test measures the cumulative sum of scaled deviations from the mean of a time series, and significant changes could be detected when the cumulative sum exceeds a theoretical boundary. The two methods could account for autocorrelation in the time-series data, and their results were compared with each other. We used a significant level of 0.05 in both MK and CUSUM tests. The procedure of
noise generation and trend test was repeated for 1000 times in each scenario and the proportion of successful detection was used to indicate the effectiveness of EIs (Fryer and Nicholson 1993). Accordingly, the time needed for effective EI monitoring were identified by examining the minimum number of years needed to obtain 95% of successful detections. The trend detection methods were performed using R packages “trend” and “strucchange”, respectively. In addition, three common multivariate methods including PCA (principal component analysis), CA (Correspondence analysis) and PCoA (Principal coordinate analysis) were used to combine the information of different EIs to strengthen their statistical powers. The time series of the six EIs were converted to the ordination scores using the multivariate methods and were tested using the MK and CUSUM methods. The effectiveness of the combined EIs was tested using the same procedure as above. The multivariate methods were performed using R package “vegan.”

3. Results

3.1 Response to fishing

The response pattern of different EIs were generally consistent among scenarios, with different directions between the scenarios of increasing and decreasing fishing efforts. Thus, we showed the scenario of F decrease as an example (Fig. 1). The six EIs showed instant responses to the change of fishing effort, with B (total biomass), LFI (large fish index) and $\bar{w}$ (mean body weight) being more responsive than $H'$ (species diversity index), SL (slope of community size spectrum) and $\Delta$ (size diversity index).
However, the responses may not be consistent regarding the time series, e.g., LFI and $\Delta$ decreased before increasing to a stable state in a long term. In addition, the changes in EIs continued after the fishing effort was steady at its new level in both the abrupt and gradual change scenarios (Fig. 1a and b). The time for EIs to reach steady values ranged from 1 to over 10 years after fishing effort stopped changing, and the lag increased with the magnitude of fishing effort changes (Fig. 1c). The LFI took most time to become steady amongst all the EIs, followed by $\Delta$, $\bar{w}$ and B.

3.2 Survey selectivity

The selectivity of the survey gears could substantially influence the values of EIs. However, their trends were generally consistent when the selection size was less than 0.5 times $S_{k_0}$, the characteristic mesh-size of the fishery in Haizhou Bay (Fig. 2). Larger selection size led to stronger changes of B but weaker changes of LFI and $\bar{w}$. The $H'$ and $\Delta$ were less responsive to fishing pressure and changes in survey selection sizes. The $SL$ showed constrained response to gear selection but fluctuated greatly once the selection size exceeded 2$S_{k_0}$.

3.3 Statistical powers

The coefficient of variation of EIs increased linearly with sampling error, and the relationship with fishing variability was more complex, being linear below 0.4 and increasing more slowly as variability increased further beyond this point (Fig. 3). LFI was most vulnerable to sampling errors, followed by $\bar{w}$ and B. The three EIs were also influenced by fishing variability, among which the B was most vulnerable. $H'$, SL and $\Delta$ were robust to sampling errors and fishing variability. The pattern was consistent
among different fishing mortality scenarios.

The inflated variation impaired the statistical powers of EIs, hence a prolonged time was needed in EI monitoring to detect a significant change. For instance, with a median level of sampling errors ($\sigma_{ob}=0.5$), the CUSUM test showed low probabilities (<0.5) to detect trends within a decade for most EIs (Fig. 4), among which the B required the least time to detect trends, followed by $\bar{w}$ and SL, and $\Delta$ had substantially lower effectiveness. Both the monitoring efforts before and after fishing effort change were necessary, and there was a prior requirement for the after-event monitoring.

In order to detect the trends of EIs with >95% effectiveness, most EIs needed a decade or less when sampling error or fishing variability was relatively low ($\sigma_{ob}$ and $\delta_f$ <0.2). The minimal number of years for trend detection increased sharply with the noises in data, and most EIs had low powers when $\sigma_{ob} > 0.6$ or $\delta_f > 0.4$ (Fig. 5). The time requirement of B remained low in various levels of sampling errors, followed by $\bar{w}$ and SL. The monitoring time duration were longer to detect significant trends in the scenarios of fishing variability. The $\Delta$ required substantially more time to detect trends than other EIs.

3.4 Multivariate methods on EIs

The information of different EIs were combined using three multivariate methods, PCA, CA and PCoA. In general, the three methods yielded similar results on the statistical powers of EIs (Fig. 5, right column). The PCA method showed slightly better performance, followed by PCoA. The effective monitoring time was substantially reduced compared to the original EIs with sampling error <0.5 and fishing variability.
<0.4. In particular, the effective monitoring time was less than 5 years when $\sigma_{ob} < 0.2$ or $\delta_f < 0.2$, compared to 10 years using original EIs. However, the required time increased sharply when the data noise increased, and exceeded 50 years in the simulation at a high level of noises, leading to a less desirable effectiveness than some original EIs, such as B and SL.

4. Discussion

Ecological indicators are supposed to concisely reflect the ecosystem status and trends to support fisheries management (Garcia and Staples 2000; Rochet and Trenkel 2003); however, the interpretation of EIs can be greatly complicated by sampling effects. In this study, we used the simulation approach to evaluate the effectiveness of EIs in detecting fishery-induced ecosystem changes regarding a variety of sampling effects. The following conclusions could be drawn from our analyses: (1) The tested EIs show instant responses to the change of fishing efforts, whereas a lag exists between the steady state of EIs and fishing pressure; (2) The selection size of survey gears has slight influences on the relative changes of EIs within a limited range, beyond which the magnitude of changes varies greatly; (3) The variation of EIs increased linearly with sampling and fishing variability, and most EIs had low statistical powers with medium level of noises in data; and (4) Multivariate methods can strengthen the statistical powers of EIs when the levels of noises are relatively low, otherwise this approach may perform no better than the original EIs. These results contribute to the improvement of our understanding of the robustness of EIs regarding sampling
uncertainty and should be applicable to a variety of EIs.

The lag between the steady state of EIs and fishing pressure suggests that the fishing effects may take time to propagate through the community. The result is consistent with the studies of fish stock recovery from overfishing (Andersen and Rice 2010; Frank et al. 2011; Fung et al. 2013), which suggests that the structure of marine communities may take decades to recover from fishing when fishing pressure is substantially reduced or ceased. This pattern may be attributed to the multifaceted effects of fishing. Generally, fishing as a driving force can impose both direct and indirect effects on ecosystems (Nicholson and Jennings 2004; Jennings and Dulvy 2005), including (i) removal of large species; (ii) changes of the size and life-history structure within population; (iii) genetic changes; (iv) changes of predator-prey relationships; (v) predation and competition release; and vi) changes in habitat environment, such as damage to the sea bed caused by bottom trawling (Myers and Worm 2003). The size-spectrum model used in the present study is featured by its ability to tackle predator-prey relationships and associated trophic cascades (Andersen and Pedersen 2010). In particular, the food-dependent growth assumption underlying this model may lengthen the response timescales of EIs. In addition, these fishing effects are not isolated. In our case, fishing caused the structural changes of the trophic relationships, which led to a transient status in the community until all the species interactions gradually became stable. The lag and nonlinear relationship between EIs and fishing efforts (Fig. 1) could largely complicate the interpretation of EIs, in addition to climate change and other driving forces of ecosystems. We highlight the
fishing-dependent lag for further studies that use EIs to indicate the dynamic of fishing pressure.

The size range included in calculating size-based indicators would influence EI trend and variance (Shin et al. 2005; Jennings and Dulvy 2005). Specifically, EIs including larger fish tend to reflect the direct effects of fishing while EIs including small fish emphasize the indirect effects (Jennings and Dulvy 2005). Therefore, the values of EIs are specific to the use of size range thus incomparable in different surveys or ecosystems. Our results illustrate that the trends of EIs may not be comparable under certain conditions. For instance, $H'$, SL and $\Delta$ showed different signs of changes with the small and large selection sizes. The pattern should be considered in ecosystem evaluation when survey data were mixed from diverse sources. In addition, our result showed that survey gears of a small mesh size might allow the comparison of EI trends among surveys, however, gear selectivity involves more than just body size (Jennings et al. 2001; Sampson 2013), and the increasing noise of sampling data may largely offset the benefit of consistency in using small mesh size. More studies are needed to set criteria for specifying size ranges in the use of EIs.

The poor statistical powers of EIs from noisy sampling are consistent with relevant empirical studies (Nicholson and Jennings 2004; Jennings and Dulvy 2005; Blanchard et al. 2010), which suggest that most indicators can hardly detect trends within 5-10 years. The low power implies that EIs are unable to inform fisheries managements within a short time scale. It should be noted that statistical significance in relevant studies did not necessarily imply biological significance, which needs to be
better clarified along with ecological reference points in future studies. In addition, the statistical powers of EIs in this study were different from those in Thorpe et al. (2015), which evaluated the signal and noise for some of the EIs and suggested that size spectrum slope was most readily for detecting changes. The divergence may result from the different assumptions of growth rates and fishing selectivity between the two studies. Nevertheless, this study demonstrates that the effectiveness of EIs could be improved by several approaches, including expanding the time-windows of monitoring, reducing the uncertainty of sampling data, and using multivariate methods. However, the implementation of these approaches may be hindered by their feasibility in practice. Specifically, survey data are either short in time series or poor in quality for the most marine areas, and the required sampling precision may not be affordable for developing countries. Besides, our results show that the monitoring before fishing effort changes is not effective in improving statistical powers (Fig. 4), implying that the actual changes can only be confirmed many years after their occurrences even with sufficiently long time series of monitoring data. In addition, the multivariate methods were only useful when the noise in data was relatively low, more so than the single EI cases. This pattern may result from the fact that the multivariate methods rely on the correlations among variables (Legendre and Legendre 1998), which can be substantially undermined by noisy data. Therefore, the effectiveness of multivariate methods needs further validation by including specific data structures. Generally, as the actual level of sampling errors is usually unknown for specific ecosystems, the statistical power of EIs would be uncertain in practice and conclusions should be conservative by using
multivariate methods to improve EI performance.

The simulation approach has certain advantage over relevant empirical studies in evaluating the effectiveness of EIs, as the causality between fishing pressure and ecosystem status is explicit, and the influences of irrelevant environmental variables can be excluded, assuming that impacts of fishing are much greater than those of environmental changes on the study timescales. In addition, the size-spectrum model used in this study is capable to tackle the complex trophic interactions within marine communities, which makes it suitable to examine ecosystem dynamics under ecological perturbations (Andersen et al. 2016b, 2016a). However, some simplifications of the model and simulation might bias our analyses. For example, the results were derived from an ecosystem-specific model, and the generality of some conclusions should be further examined among marine ecosystems with different fishing regimes for management applications (e.g., the results were compared to that of a “general” ecosystem, shown in the Supplementary Materials). Besides, fisheries survey may be conducted in certain time/season each year, while seasonality is ignored in the structure of the “mizer” model (Scott et al. 2014; Datta and Blanchard 2016). The locations of survey programs may substantially influence the observation of EIs (Adams et al. 2017), which is not accounted for. In addition, our simulations assume species-specific catchability and a knife-edge type of selectivity to approximate the typical sigmoid selectivity of trawls as a result of data limitation, whereas the selectivity curve of trawl may be in different shapes, e.g., the dome selectivity (Sampson and Scott 2012). In this context, our conclusions on fishing variability are
constrained to an idealized change of fishing effort, whereas the impact of fishing variability may depend on the nature of the underlying transition as well as the diverse characteristics of fisheries. Moreover, if the fluctuations of environment variables and recruitment variability are taken into account, the effectiveness of EIs may further degrade and the interpretation may be complicated as the different drivers of the ecosystem may lead to the same response (Adams et al. 2017). Therefore, the quantitative results of this study should be used as caveats rather than references in practice. Despite this, we illustrate a baseline of sampling effects, or in other words, suggesting upper limits of detectability that are unlikely to be exceeded in practice.

Acknowledgements

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Supplementary materials

The supplementary materials briefly introduced the structure and parameterization of the size-spectrum model in Haizhou Bay. In addition, the results of this study were compared to that from a “trait-based” general model with the same simulation processes.
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Table 1 The definition of ecological indicators used in this study. The size ranges used for indicator calculation were defined species-specifically according to the actual trawl survey.

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<th>Indicators</th>
<th>Symbol</th>
<th>Definition</th>
<th>Sources</th>
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<tr>
<td>Total species biomass</td>
<td>$B$</td>
<td>The sum of species biomass in the fish community</td>
<td>Murawski 2000; Fulton, Smith and Punt 2005</td>
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<tr>
<td>Shannon-Wiener diversity index</td>
<td>$H'$</td>
<td>$H' = \sum_{i} p_i \ln(p_i)$, where $p_i$ is the proportion of species $i$ in the fish community by biomass.</td>
<td>Shannon 1948</td>
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<td>Large fish indicator</td>
<td>$LFI$</td>
<td>$LFI = \frac{\sum_{w} B(w &gt; wt)}{\sum_{w} B}$, the proportion of fish above a threshold of $wt$ by biomass. $wt=100g$ in this study.</td>
<td>Greenstreet et al., 2011</td>
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<td>Mean body weight</td>
<td>$\bar{w}$</td>
<td>$\bar{w} = \frac{\sum_{w} w N(w)}{\sum_{w} N(w)}$, mean body weight of all fishes in the community. $N(w)$ is the abundance of all individuals with body size $w.$</td>
<td>Rochet and Trenkel, 2003</td>
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<tr>
<td>Size diversity index</td>
<td>$\Delta$</td>
<td>$\Delta = \frac{\sum_{w_1} \sum_{w_2} d(w_1, w_2) B(w_1) B(w_2)}{\sum_{w_1} \sum_{w_2} B(w_1) B(w_2)}$, where $w_1$ and $w_2$ are the size bins; and $d(w_1, w_2) = 1 - e^{-\frac{\log(w_1) - \log(w_2)}{\delta}}$ is a ‘V-shaped’ distance metric between size $w_1$ and $w_2$ where $\delta = 2\ln(10).$</td>
<td>Rochet and Benoît, 2012</td>
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<td>Slope of community size spectrum</td>
<td>$SL$</td>
<td>$\log(D(w)) = \alpha + SL \log(w)$, the slope of a linear regression between the abundance density $(D(w))$ and body weight $(w)$ in log-log scale.</td>
<td>Rice and Gislason, 1996</td>
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Table 2 Summary of simulation scenarios in this study. The $F_0$ and $Sk_0$ refer to the fishing effort and gear selection size in the calibrated model.

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<th>Values</th>
<th>Notes</th>
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</thead>
<tbody>
<tr>
<td>Fishing pressure</td>
<td>$F$</td>
<td>0.5-1.5$F_0$</td>
<td>The changes of fishing effort include abrupt and gradual changes. The latter means a linear changes in a period ranging from 2 to 10 years (see Supplementary material)</td>
</tr>
<tr>
<td>Survey selectivity</td>
<td>$Sk$</td>
<td>0-3$Sk_0$</td>
<td>Gear selection size is used in a knife-edge selectivity curve, in which 0 means sampling all individuals of the community</td>
</tr>
<tr>
<td>Observation errors</td>
<td>$\sigma_{ob}$</td>
<td>0-1</td>
<td>The standard deviation of the error term $logN(1, \sigma_{ob})$ in observational errors</td>
</tr>
<tr>
<td>Fishing variability</td>
<td>$\delta_f$</td>
<td>0-1</td>
<td>The standard deviation of the error term $N(0, \delta_f)$ in the variation of fishing pressure</td>
</tr>
</tbody>
</table>
Fig. 1 The response of ecological indicators to the change of fishing efforts (a decrease to 0.5 $F_0$) in (a) abrupt changes and (b) gradual changes. The dash lines denote the year when fishing effort is steady. Panel (c) shows the time lag between EIs and fishing efforts regarding different levels of fishing pressure. The time lag is measured as the differences in time that fishing pressure and EIs reach steady values.

Fig. 2 The effect of survey selectivity on the observed trends of EIs. The colored lines represent the different levels of relative fishing efforts to $F_0$. The values of EIs are relative to the equilibrium values when fishing effort is at the baseline level, and the selection size is the simulated mesh size of survey gears relative to the actual trawl survey.

Fig. 3 The coefficients of variance (CV) of EIs resulting from sampling error ($\sigma$) and fishing variability ($\delta$). The two columns exemplify the results from the increase and decrease of fishing effort, respectively (0.5 and 1.5 times of $F_0$).

Fig. 4 The monitoring time needed to detect significant changes in the time series of EIs. T1 and T2 were the time before and after the change in fishing effort, respectively. The colors denote the probability of detecting significant trends using CUSUM test
(p<0.05). The results are derived for the scenarios of observational errors $\sigma_{ob}=0.5$ with
an increasing fishing effort (1.5$F_0$).

Fig. 5 The effective time of EI monitoring with respect to data noises from sampling
errors and fishing variability. The required time is defined as the number of years
needed to obtain >95% effectiveness for trend detection. The significance of trends is
tested using Mann-Kendall test (MK) and CUSUM test, respectively. The statistical
power of original EIs and combined EIs with multivariate methods are shown in the left
and right columns, respectively. The truncated lines indicate that the required time
exceeds 50 years at the specific level of sampling error or fishing variability. The results
are derived for the scenarios with an increasing fishing effort (1.5$F_0$).