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

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**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

43 1. Introduction

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

58 The EIs serve two purposes in fisheries management, to define decision criteria to
59 trigger management actions and to measure the performance of management strategies
60 (Fulton et al. 2005; Fay et al. 2013), parallel to reference-points approach in
61 single-species management. However, the use of EIs as reference points in
62 decision-making is questionable as their ecological implications may not be
63 straightforward (Rochet and Trenkel 2003). Besides, since the vast majority of
64 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;

87 Jennings and Dulvy 2005).

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

102 The assessment and management of fisheries depend on the quality and quantity
103 of sampling data, yet samples may not be representative of biotic communities due to
104 observation errors and the selectivity of survey gears. This study is focused on the
105 effect of sampling on the ability of EIs to detect changes in fish communities in a
106 manner useful to management. The objectives of this study are to evaluate the
107 relationship between fishing pressure and the observation of EI dynamics; the effects of
108 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 (Δ) 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

130 definition of the EIs were listed in Table 1.

131 *2.2 Size-spectrum model*

132 A multispecies size-spectrum model was used in this study to simulate the effects
133 of fishing and trophic interactions in fish communities. This model was developed by
134 Andersen and Beyer (2006) and formulated by Hartvig et al. (2011) based on the size
135 spectra theory (Sheldon et al. 1972; Sprules et al. 2016), characterized by the explicit
136 consideration of feeding selection and ontogenetic niche shift (Andersen et al., 2009;
137 Andersen et al., 2016). The model assumes that (1) predator–prey relationships are
138 primarily determined by body size ratios; (2) individual-level energy budget is driven
139 by food intake; and (3) physiological processes including metabolism, predation,
140 reproduction are correlated with body size, i.e., the allometric scaling law (Elton 1927;
141 Schmidt-Nielsen 1984; Brown et al. 2004). These assumptions enable the model to
142 formulate biological processes at the individual level. The size-spectrum model has
143 been used to assess fishing impacts (Andersen and Pedersen 2010; Rochet and Benoît
144 2012) and to evaluate management strategies (Jacobsen et al. 2014; Blanchard et al.
145 2014).

146 The size-spectrum model was implemented for the ecosystem of Haizhou Bay,
147 China. Haizhou Bay is an open bay on the continental shelf of Yellow Sea
148 (Supplementary materials, Fig. S1). A total of 22 dominant species that account for 90%
149 of the fish community biomass were included in modelling. Each species was
150 characterized by a set of life-history parameters of growth, predation, mortality, and
151 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

174 arise from sampling methods, such as the selectivity of survey gears, which is
175 considered as systematic bias. Specifically, most fisheries studies are based on trawl
176 survey, which is selective on species distribution, individual age/size and their
177 behavioral responses (Sampson 2013). The trawl sampling data may be biased due to
178 arbitrary mesh sizes, and involve variations from the sampling operation, time and
179 locations. Simulation scenarios are designed to test the effectiveness of EIs with respect
180 to gear selectivity and statistical power. We evaluate the following variables in testing
181 scenarios:

182 (1) Survey selectivity: Different mesh sizes were simulated for the selectivity of
183 scientific surveys. The survey gear was assumed a “knife-edge” selectivity, that is,
184 individuals smaller than the minimum size (knife-edge size) were not sampled. The
185 simulated selection size ranged from 0 to 3 times of Sk_0 (selectivity resulting from the
186 mesh size used in the trawl survey in Haizhou Bay), in which zero implied that all
187 individuals in the simulated fish community were included in sampling.

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

193 (3) Variability of fishing efforts: the variation of survey data may result directly from
194 the fluctuations of fishing efforts, as the fishing pressure would not be constant even in
195 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 (σ_{ob}) and fishing variability (δ_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 Δ (size diversity index).

239 However, the responses may not be consistent regarding the time series, e.g., LFI and Δ
240 decreased before increasing to a stable state in a long term. In addition, the changes in
241 EIs continued after the fishing effort was steady at its new level in both the abrupt and
242 gradual change scenarios (Fig. 1a and b). The time for EIs to reach steady values ranged
243 from 1 to over 10 years after fishing effort stopped changing, and the lag increased with
244 the magnitude of fishing effort changes (Fig. 1c). The LFI took most time to become
245 steady amongst all the EIs, followed by Δ , $\bar{w}$ and B.

246 3.2 Survey selectivity

247 The selectivity of the survey gears could substantially influence the values of EIs.
248 However, their trends were generally consistent when the selection size was less than
249 0.5 times Sk_0 , the characteristic mesh-size of the fishery in Haizhou Bay (Fig. 2).
250 Larger selection size led to stronger changes of B but weaker changes of LFI and $\bar{w}$. The
251 H' and Δ were less responsive to fishing pressure and changes in survey selection sizes.
252 The SL showed constrained response to gear selection but fluctuated greatly once the
253 selection size exceeded $2Sk_0$.

254 3.3 Statistical powers

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

261 among different fishing mortality scenarios.

262 The inflated variation impaired the statistical powers of EIs, hence a prolonged
263 time was needed in EI monitoring to detect a significant change. For instance, with a
264 median level of sampling errors ($\sigma_{ob}=0.5$), the CUSUM test showed low probabilities
265 (<0.5) to detect trends within a decade for most EIs (Fig. 4), among which the B
266 required the least time to detect trends, followed by $\bar{w}$ and SL, and Δ had substantially
267 lower effectiveness. Both the monitoring efforts before and after fishing effort change
268 were necessary, and there was a prior requirement for the after-event monitoring.

269 In order to detect the trends of EIs with $>95\%$ effectiveness, most EIs needed a
270 decade or less when sampling error or fishing variability was relatively low (σ_{ob} and δ_f
271 <0.2). The minimal number of years for trend detection increased sharply with the
272 noises in data, and most EIs had low powers when $\sigma_{ob} > 0.6$ or $\delta_f > 0.4$ (Fig. 5). The time
273 requirement of B remained low in various levels of sampling errors, followed by $\bar{w}$ and
274 SL. The monitoring time duration were longer to detect significant trends in the
275 scenarios of fishing variability. The Δ required substantially more time to detect trends
276 than other EIs.

277 3.4 Multivariate methods on EIs

278 The information of different EIs were combined using three multivariate methods,
279 PCA, CA and PCoA. In general, the three methods yielded similar results on the
280 statistical powers of EIs (Fig. 5, right column). The PCA method showed slightly better
281 performance, followed by PCoA. The effective monitoring time was substantially
282 reduced compared to the original EIs with sampling error <0.5 and fishing variability

283 <0.4. In particular, the effective monitoring time was less than 5 years when $\sigma_{ob} < 0.2$ or
284 $\delta_f < 0.2$, compared to 10 years using original EIs. However, the required time increased
285 sharply when the data noise increased, and exceeded 50 years in the simulation at a high
286 level of noises, leading to a less desirable effectiveness than some original EIs, such as
287 B and SL.

288 4. Discussion

289 Ecological indicators are supposed to concisely reflect the ecosystem status and
290 trends to support fisheries management (Garcia and Staples 2000; Rochet and Trenkel
291 2003); however, the interpretation of EIs can be greatly complicated by sampling
292 effects. In this study, we used the simulation approach to evaluate the effectiveness of
293 EIs in detecting fishery-induced ecosystem changes regarding a variety of sampling
294 effects. The following conclusions could be drawn from our analyses: (1) The tested
295 EIs show instant responses to the change of fishing efforts, whereas a lag exists
296 between the steady state of EIs and fishing pressure; (2) The selection size of survey
297 gears has slight influences on the relative changes of EIs within a limited range, beyond
298 which the magnitude of changes varies greatly; (3) The variation of EIs increased
299 linearly with sampling and fishing variability, and most EIs had low statistical powers
300 with medium level of noises in data; and (4) Multivariate methods can strengthen the
301 statistical powers of EIs when the levels of noises are relatively low, otherwise this
302 approach may perform no better than the original EIs. These results contribute to the
303 improvement of our understanding of the robustness of EIs regarding sampling

304 uncertainty and should be applicable to a variety of EIs.

305 The lag between the steady state of EIs and fishing pressure suggests that the
306 fishing effects may take time to propagate through the community. The result is
307 consistent with the studies of fish stock recovery from overfishing (Andersen and Rice
308 2010; Frank et al. 2011; Fung et al. 2013), which suggests that the structure of marine
309 communities may take decades to recover from fishing when fishing pressure is
310 substantially reduced or ceased. This pattern may be attributed to the multifaceted
311 effects of fishing. Generally, fishing as a driving force can impose both direct and
312 indirect effects on ecosystems (Nicholson and Jennings 2004; Jennings and Dulvy
313 2005), including (i) removal of large species; (ii) changes of the size and life-history
314 structure within population; (iii) genetic changes; (iv) changes of predator-prey
315 relationships; (v) predation and competition release; and vi) changes in habitat
316 environment, such as damage to the sea bed caused by bottom trawling (Myers and
317 Worm 2003). The size-spectrum model used in the present study is featured by its
318 ability to tackle predator-prey relationships and associated trophic cascades (Andersen
319 and Pedersen 2010). In particular, the food-dependent growth assumption underlying
320 this model may lengthen the response timescales of EIs. In addition, these fishing
321 effects are not isolated. In our case, fishing caused the structural changes of the trophic
322 relationships, which led to a transient status in the community until all the species
323 interactions gradually became stable. The lag and nonlinear relationship between EIs
324 and fishing efforts (Fig. 1) could largely complicate the interpretation of EIs, in
325 addition to climate change and other driving forces of ecosystems. We highlight the

326 fishing-dependent lag for further studies that use EIs to indicate the dynamic of fishing
327 pressure.

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

342 The poor statistical powers of EIs from noisy sampling are consistent with
343 relevant empirical studies (Nicholson and Jennings 2004; Jennings and Dulvy 2005;
344 Blanchard et al. 2010), which suggest that most indicators can hardly detect trends
345 within 5-10 years. The low power implies that EIs are unable to inform fisheries
346 managements within a short time scale. It should be noted that statistical significance in
347 relevant studies did not necessarily imply biological significance, which needs to be

348 better clarified along with ecological reference points in future studies. In addition, the
349 statistical powers of EIs in this study were different from those in Thorpe et al. (2015),
350 which evaluated the signal and noise for some of the EIs and suggested that size
351 spectrum slope was most readily for detecting changes. The divergence may result from
352 the different assumptions of growth rates and fishing selectivity between the two
353 studies. Nevertheless, this study demonstrates that the effectiveness of EIs could be
354 improved by several approaches, including expanding the time-windows of monitoring,
355 reducing the uncertainty of sampling data, and using multivariate methods. However,
356 the implementation of these approaches may be hindered by their feasibility in practice.
357 Specifically, survey data are either short in time series or poor in quality for the most
358 marine areas, and the required sampling precision may not be affordable for developing
359 countries. Besides, our results show that the monitoring before fishing effort changes is
360 not effective in improving statistical powers (Fig. 4), implying that the actual changes
361 can only be confirmed many years after their occurrences even with sufficiently long
362 time series of monitoring data. In addition, the multivariate methods were only useful
363 when the noise in data was relatively low, more so than the single EI cases. This pattern
364 may result from the fact that the multivariate methods rely on the correlations among
365 variables (Legendre and Legendre 1998), which can be substantially undermined by
366 noisy data. Therefore, the effectiveness of multivariate methods needs further
367 validation by including specific data structures. Generally, as the actual level of
368 sampling errors is usually unknown for specific ecosystems, the statistical power of EIs
369 would be uncertain in practice and conclusions should be conservative by using

370 multivariate methods to improve EI performance.

371 The simulation approach has certain advantage over relevant empirical studies in
372 evaluating the effectiveness of EIs, as the causality between fishing pressure and
373 ecosystem status is explicit, and the influences of irrelevant environmental variables
374 can be excluded, assuming that impacts of fishing are much greater than those of
375 environmental changes on the study timescales. In addition, the size-spectrum model
376 used in this study is capable to tackle the complex trophic interactions within marine
377 communities, which makes it suitable to examine ecosystem dynamics under
378 ecological perturbations (Andersen et al. 2016b, 2016a). However, some
379 simplifications of the model and simulation might bias our analyses. For example, the
380 results were derived from an ecosystem-specific model, and the generality of some
381 conclusions should be further examined among marine ecosystems with different
382 fishing regimes for management applications (e.g., the results were compared to that of
383 a “general” ecosystem, shown in the Supplementary Materials). Besides, fisheries
384 survey may be conducted in certain time/season each year, while seasonality is ignored
385 in the structure of the “mizer” model (Scott et al. 2014; Datta and Blanchard 2016). The
386 locations of survey programs may substantially influence the observation of EIs
387 (Adams et al. 2017), which is not accounted for. In addition, our simulations assume
388 species-specific catchability and a knife-edge type of selectivity to approximate the
389 typical sigmoid selectivity of trawls as a result of data limitation, whereas the
390 selectivity curve of trawl may be in different shapes, e.g., the dome selectivity
391 (Sampson and Scott 2012). In this context, our conclusions on fishing variability are

392 constrained to an idealized change of fishing effort, whereas the impact of fishing
393 variability may depend on the nature of the underlying transition as well as the diverse
394 characteristics of fisheries. Moreover, if the fluctuations of environment variables and
395 recruitment variability are taken into account, the effectiveness of EIs may further
396 degrade and the interpretation may be complicated as the different drivers of the
397 ecosystem may lead to the same response (Adams et al. 2017). Therefore, the
398 quantitative results of this study should be used as caveats rather than references in
399 practice. Despite this, we illustrate a baseline of sampling effects, or in other words,
400 suggesting upper limits of detectability that are unlikely to be exceeded in practice.

401

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405 Research in the Public Interest (201303050).

406

407 **Supplementary materials**

408 The supplementary materials briefly introduced the structure and parameterization
409 of the size-spectrum model in Haizhou Bay. In addition, the results of this study were
410 compared to that from a “trait-based” general model with the same simulation
411 processes.

412

413 **References**

- 414 Adams, G.L., Jennings, S., and Reuman, D.C. 2017. Community management
415 indicators can conflate divergent phenomena: two challenges and a
416 decomposition-based solution. *J. Appl. Ecol.* 54(3): 883–893. doi:
417 10.1111/1365-2664.12787.
- 418 Andersen, K.H., and Beyer, J.E. 2006. Asymptotic Size Determines Species
419 Abundance in the Marine Size Spectrum. *Am. Nat.* **168**(1): 54–61. doi:
420 10.1086/504849.
- 421 Andersen, K.H., Beyer, J.E., and Lundberg, P. 2009. Trophic and individual efficiencies
422 of size-structured communities. *Proc. R. Soc. B Biol. Sci.* **276**(1654): 109–114. doi:
423 10.1098/rspb.2008.0951.
- 424 Andersen, K.H., Blanchard, J.L., Fulton, E.A., Gislason, H., Jacobsen, N.S., and van
425 Kooten, T. 2016a. Assumptions behind size-based ecosystem models are realistic.
426 *ICES J. Mar. Sci.* **73**(6): 1651–1655. doi: 10.1093/icesjms/fsv211.
- 427 Andersen, K.H., Jacobsen, N.S., Farnsworth, K.D., and Baum, J. 2016b. The theoretical
428 foundations for size spectrum models of fish communities. *Can. J. Fish. Aquat. Sci.*
429 **73**(4): 575–588. doi: 10.1139/cjfas-2015-0230.
- 430 Andersen, K.H., and Pedersen, M. 2010. Damped trophic cascades driven by fishing in
431 model marine ecosystems. *Proc. R. Soc. B Biol. Sci.* **277**(1682): 795–802. doi:
432 10.1098/rspb.2009.1512.
- 433 Andersen, K.H., and Rice, J.C. 2010. Direct and indirect community effects of
434 rebuilding plans. *ICES J. Mar. Sci.* **67**(9): 1980–1988. doi: 10.1093/icesjms/fsq035.

- 435 Blanchard, J.L., Andersen, K.H., Scott, F., Hintzen, N.T., Piet, G., and Jennings, S.
436 2014. Evaluating targets and trade-offs among fisheries and conservation objectives
437 using a multispecies size spectrum model. *J. Appl. Ecol.* **51**(3): 612–622. doi:
438 10.1111/1365-2664.12238.
- 439 Blanchard, J.L., Coll, M., Trenkel, V.M., Vergnon, R., Yemane, D., Jouffre, D., Link,
440 J.S., and Shin, Y.-J.J. 2010. Trend analysis of indicators: a comparison of recent
441 changes in the status of marine ecosystems around the world. *ICES J. Mar. Sci.* **67**(4):
442 732–744. doi: 10.1093/icesjms/fsp282.
- 443 Brown, J.H., Gillooly, J.F., Allen, A.P., Savage, V.M., and West, G.B. 2004. Toward a
444 metabolic theory of ecology. *Ecology* **85**(7): 1771–1789. doi: 10.1890/03-9000.
- 445 Chaalali, A., Beaugrand, G., Raybaud, V., Lassalle, G., Saint-Béat, B., Le Loc'h, F.,
446 Bopp, L., Tecchio, S., Safi, G., Chifflet, M., Lobry, J., and Niquil, N. 2016. From
447 species distributions to ecosystem structure and function: A methodological
448 perspective. *Ecol. Modell.* **334**: 78–90. doi: 10.1016/j.ecolmodel.2016.04.022.
- 449 Datta, S., and Blanchard, J.L. 2016. The effects of seasonal processes on size spectrum
450 dynamics. *Can. J. Fish. Aquat. Sci.* **73**: 1–48. doi: 10.1139/cjfas-2015-0468.
- 451 Elton, C. 1927. *Animal Ecology*. Macmillan, New York.
- 452 Fay, G., Large, S.I., Link, J.S., and Gamble, R.J. 2013. Testing systemic fishing
453 responses with ecosystem indicators. *Ecol. Modell.* **265**: 45–55. doi:
454 10.1016/j.ecolmodel.2013.05.016.
- 455 Frank, K.T., Petrie, B., Fisher, J.A., and Leggett, W.C. 2011. Transient dynamics of an
456 altered large marine ecosystem. *Nature* **477**(7362): 86–89. doi:

-
- 457 10.1038/nature10285.
- 458 Fryer, R., and Nicholson, M.D. 1993. The power of a contaminant monitoring
459 programme to detect linear trends and incidents. *ICES J. Mar. Sci.* **50**(2): 161–168.
460 doi: 10.1006/jmsc.1993.1017.
- 461 Fulton, E.A., Fuller, M., Smith, A.D.M., and Punt, A.E. 2004. Ecological Indicators of
462 the Ecosystem Effects of Fishing: Final Report. Hobart, Tas.//Canberra, ACT.
- 463 Fulton, E., Smith, A., and Punt, A. 2005. Which ecological indicators can robustly
464 detect effects of fishing? *ICES J. Mar. Sci.* **62**(3): 540–551. doi:
465 10.1016/j.icesjms.2004.12.012.
- 466 Fung, T., Farnsworth, K.D., Shephard, S., Reid, D.G., and Rossberg, A.G. 2013. Why
467 the size structure of marine communities can require decades to recover from fishing.
468 *Mar. Ecol. Prog. Ser.* **484**: 155–171. doi: 10.3354/meps10305.
- 469 Garcia, S.M., and Staples, D.J. 2000. Sustainability reference systems and indicators
470 for responsible marine capture fisheries: a review of concepts and elements for a set
471 of guidelines. *Mar. Freshw. Res.* **51**(5): 385. doi: 10.1071/mf99092.
- 472 Gårdmark, A., Casini, M., Huss, M., Van Leeuwen, A., Hjelm, J., Persson, L., and de
473 Roos, A.M. 2014. Regime shifts in exploited marine food-webs: detecting
474 mechanisms underlying alternative stable states using size structured community
475 dynamics theory. *Philos. Trans. R. Soc. B Biol. Sci.* **370**(1659): 20130262. doi:
476 10.1098/rstb.2013.0262.
- 477 Greenstreet, S., and Rogers, S. 2006. Indicators of the health of the North Sea fish
478 community: identifying reference levels for an ecosystem approach to management.

- 479 ICES J. Mar. Sci. **63**(4): 573–593. doi: 10.1016/j.icesjms.2005.12.009.
- 480 Greenstreet, S.P.R., Rogers, S.I., Rice, J.C., Piet, G.J., Guirey, E.J., Fraser, H.M., and
481 Fryer, R.J. 2011. Development of the EcoQO for the North Sea fish community.
- 482 ICES J. Mar. Sci. **68**(1): 1–11. doi: 10.1093/icesjms/fsq156.
- 483 Hall, S.J. 1999. The effects of fishing on marine ecosystems and communities. *In* Fish
484 biology and aquatic resources serie (1). Blackwell Science, Oxford.
- 485 Hall, S.J., and Mainprize, B. 2004. Towards ecosystem-based fisheries management.
- 486 Fish Fish. **5**(1): 1–20. doi: 10.1111/j.1467-2960.2004.00133.x.
- 487 Hartvig, M., Andersen, K.H., and Beyer, J.E. 2011. Food web framework for
488 size-structured populations. *J. Theor. Biol.* **272**(1): 113–122. doi:
489 10.1016/j.jtbi.2010.12.006.
- 490 Hipel, K., and McLeod, A. 1994. Time series modelling of water resources and
491 environmental systems. Elsevier, Amsterdam, the Netherlands. doi:
492 10.1016/S0167-5648(08)70658-0.
- 493 Jacobsen, N.S., Gislason, H., and Andersen, K.H. 2014. The consequences of balanced
494 harvesting of fish communities. *Proc. R. Soc. B Biol. Sci.* **281**(1775): 20132701. doi:
495 10.1098/rspb.2013.2701.
- 496 Jennings, S., and Dulvy, N.K. 2005. Reference points and reference directions for
497 size-based indicators of community structure. *ICES J. Mar. Sci.* **62**(3): 397–404. doi:
498 10.1016/j.icesjms.2004.07.030.
- 499 Jennings, S., and Kaiser, M.J. 1998. The effects of fishing on marine ecosystems. *Adv.*
500 *Mar. Biol.* **34**(1798): 201–352. doi: 10.1016/S0065-2881(08)60212-6.

-
- 501 Jennings, S., Kaiser, M.J., and Reynolds, J.J.D. 2001. Marine Fisheries Ecology.
502 Wiley-Blackwell. doi: 10.1016/S0022-0981(02)00054-0.
- 503 Kendall, M.G. 1975. Rank correlation methods. *In* 4th edition. Charles Griffin,
504 London, UK.
- 505 Kleisner, K.M., Coll, M., Lynam, C.P., Bundy, A., Shannon, L., Shin, Y.-J., Boldt, J.L.,
506 Maria F., B., Diallo, I., Fox, C., Gascuel, D., Heymans, J.J., Juan Jordá, M.J., Jouffre,
507 D., Large, S.I., Marshall, K.N., Ojaveer, H., Piroddi, C., Tam, J., Torres, M. a.,
508 Travers-Trolet, M., Tsagarakis, K., van der Meeren, G.I., and Zador, S. 2015.
509 Evaluating changes in marine communities that provide ecosystem services through
510 comparative assessments of community indicators. *Ecosyst. Serv.*: 1–17. Elsevier.
511 doi: 10.1016/j.ecoser.2015.02.002.
- 512 Legendre, P., and Legendre, L. 1998. Numerical Ecology, 2nd Edition. Elsevier Science
513 B.V., Amsterdam, the Netherlands.
- 514 Link, J.S., Bundy, A., Overholtz, W.J., Shackell, N., Manderson, J., Duplisea, D., Hare,
515 J., Koen-Alonso, M., and Friedland, K.D. 2011. Ecosystem-based fisheries
516 management in the Northwest Atlantic. *Fish Fish.* **12**(2): 152–170. doi:
517 10.1111/j.1467-2979.2011.00411.x.
- 518 Mann, H.B. 1945. Nonparametric tests against trend. *Econometrica* **13**: 245–259. doi:
519 10.1017/CBO9781107415324.004.
- 520 Maury, O., Shin, Y.J., Faugeras, B., Ben Ari, T., and Marsac, F. 2007. Modeling
521 environmental effects on the size-structured energy flow through marine ecosystems.
522 Part 2: Simulations. *Prog. Oceanogr.* **74**(4): 500–514. doi:

-
- 10.1016/j.pocean.2007.05.001.
- Murawski, S. 2000. Definitions of overfishing from an ecosystem perspective. *ICES J. Mar. Sci.* **57**(3): 649–658. doi: 10.1006/jmsc.2000.0738.
- Myers, R.A., and Worm, B. 2003. Rapid worldwide depletion of predatory fish communities. *Nature* **423**(6937): 280–283. doi: 10.1038/nature01610.
- National Research Council. 2000. *Ecological Indicators for the Nation*. National Academies Press, Washington, D.C. doi: 10.17226/9720.
- Nicholson, M.D., and Jennings, S. 2004. Testing candidate indicators to support ecosystem-based management: the power of monitoring surveys to detect temporal trends in fish community metrics. *ICES J. Mar. Sci.* **61**(1): 35–42. doi: 10.1016/j.icesjms.2003.09.004.
- Page, E.S. 1961. Cumulative Sum Charts. *Technometrics* **3**(1): 1–9. doi: 10.1080/00401706.1961.10489922.
- Pikitch, E.K., Santora, C., Babcock, E.A., Bakun, A., Bonfil, R., Conover, D.O., Dayton, P., Doukakis, P., Fluharty, D., Heneman, B., Houde, E.D., Link, J., Livingston, P.A., Mangel, M., McAllister, M.K., Pope, J., and Sainsbury, K.J. 2004. Ecosystem-based fishery management. *Science* **305**(5682): 346–347. doi: 10.1126/science.1098222.
- Ploberger, W., Krämer, W., and Werner Ploberger, W.K. 1992. The cusum test with OLS residuals. *Econometrica* **60**(2): 271–285. doi: 10.2307/2951597.
- Rice, J., and Gislason, H. 1996. Patterns of change in the size spectra of numbers and diversity of the North Sea fish assemblage, as reflected in surveys and models. *ICES*

-
- 545 J. Mar. Sci. **53**(6): 1214–1225. doi: 10.1006/jmsc.1996.0146.
- 546 Rice, J., and Rochet, M. 2005. A framework for selecting a suite of indicators for
547 fisheries management. ICES J. Mar. Sci. **62**(3): 516–527. doi:
548 10.1016/j.icesjms.2005.01.003.
- 549 Rochet, M.-J., and Benoît, E. 2012. Fishing destabilizes the biomass flow in the marine
550 size spectrum. Proc. R. Soc. B Biol. Sci. **279**(1727): 284–92. doi:
551 10.1098/rspb.2011.0893.
- 552 Rochet, M.-J., and Trenkel, V.M. 2003. Which community indicators can measure the
553 impact of fishing? A review and proposals. Can. J. Fish. Aquat. Sci. **60**(1): 86–99.
554 doi: 10.1139/f02-164.
- 555 Rochet, M.J., Trenkel, V., Bellail, R., Coppin, F., Le Pape, O., Mahé, J.C., Morin, J.,
556 Poulard, J.C., Schlaich, I., Souplet, A., Verin, Y., and Bertrand, J. 2005. Combining
557 indicator trends to assess ongoing changes in exploited fish communities:
558 Diagnostic of communities off the coasts of France. ICES J. Mar. Sci. **62**(8): 1647–
559 1664. doi: 10.1016/j.icesjms.2005.06.009.
- 560 Rossberg, A.G., Uusitalo, L., Berg, T., Zaiko, A., Chenuil, A., Uyarra, M.C., Borja, A.,
561 and Lynam, C.P. 2017. Quantitative criteria for choosing targets and indicators for
562 sustainable use of ecosystems. Ecol. Indic. **72**: 215–224. doi:
563 10.1016/j.ecolind.2016.08.005.
- 564 Sampson, D.B. 2013. Fishery selection and its relevance to stock assessment and
565 fishery management. Fish. Res. **158**: 5–14. doi: 10.1016/j.fishres.2013.10.004.
- 566 Sampson, D.B., and Scott, R.D. 2012. An exploration of the shapes and stability of

- 567 population-selection curves. *Fish Fish.* **13**(1): 89–104. doi:
568 10.1111/j.1467-2979.2011.00417.x.
- 569 Scandol, J.P., Holloway, M.G., Gibbs, P.J., and Astles, K.L. 2005. Ecosystem-based
570 fisheries management: An Australian perspective. *Aquat. Living Resour.* **18**(3):
571 261–273. doi: 10.1051/alr:2005031.
- 572 Schmidt-Nielsen, K. 1984. *Scaling: Why is Animal Size so Important?* Cambridge
573 University Press, Cambridge, UK.
- 574 Scott, F., Blanchard, J.L., and Andersen, K.H. 2014. mizer : an R package for
575 multispecies, trait-based and community size spectrum ecological modelling.
576 *Methods Ecol. Evol.* **5**(10): 1121–1125. doi: 10.1111/2041-210X.12256.
- 577 Shannon, C.E. 1948. A mathematical theory of communication. *Bell Syst. Tech. J.* **27**:
578 379–423. doi: 10.1145/584091.584093.
- 579 Sheldon, R.W., Prakash, A., and Sutcliffe, W.H. 1972. The size distribution of particles
580 in the ocean. *Limnol. Oceanogr.* **17**(3): 327–340. doi: 10.4319/lo.1972.17.3.0327.
- 581 Shin, Y., Rochet, M., Jennings, S., Field, J., and Gislason, H. 2005. Using size-based
582 indicators to evaluate the ecosystem effects of fishing. *ICES J. Mar. Sci.* **62**(3): 384–
583 396. doi: 10.1016/j.icesjms.2005.01.004.
- 584 Shin, Y.J., Bundy, A., Shannon, L.J., Simier, M., Coll, M., Fulton, E.A., Link, J.S.,
585 Jouffre, D., Ojaveer, H., Mackinson, S., Heymans, J.J., and Raid, T. 2010a. Can
586 simple be useful and reliable? Using ecological indicators to represent and compare
587 the states of marine ecosystems. *ICES J. Mar. Sci.* **67**(4): 717–731. doi:
588 10.1093/icesjms/fsp287.

- 589 Shin, Y.J., Shannon, L.J., Bundy, A., Coll, M., Aydin, K., Bez, N., Blanchard, J.L.,
590 Borges, M. d F., Diallo, I., Diaz, E., Heymans, J.J., Hill, L., Johannesen, E., Jouffre,
591 D., Kifani, S., Labrosse, P., Link, J.S., Mackinson, S., Masski, H., Mollmann, C.,
592 Neira, S., Ojaveer, H., ould Mohammed Abdallahi, K., Perry, I., Thiao, D., Yemane,
593 D., and Cury, P.M. 2010b. Using indicators for evaluating, comparing, and
594 communicating the ecological status of exploited marine ecosystems. 2. Setting the
595 scene. *ICES J. Mar. Sci.* **67**(4): 692–716. doi: 10.1093/icesjms/fsp294.
- 596 Skern-Mauritzen, M., Ottersen, G., Handegard, N.O., Huse, G., Dingsør, G.E., Stenseth,
597 N.C., and Kjesbu, O.S. 2016. Ecosystem processes are rarely included in tactical
598 fisheries management. *Fish Fish.* **17**(1): 165–175. doi: 10.1111/faf.12111.
- 599 Sprules, W.G., Barth, L.E., and Giacomini, H. 2016. Surfing the biomass size spectrum:
600 some remarks on history, theory, and application. *Can. J. Fish. Aquat. Sci.* **73**(4):
601 477–495. doi: 10.1139/cjfas-2015-0115.
- 602 Tallis, H., Levin, P.S., Ruckelshaus, M., Lester, S.E., McLeod, K.L., Fluharty, D.L., and
603 Halpern, B.S. 2010. The many faces of ecosystem-based management: Making the
604 process work today in real places. *Mar. Policy* **34**(2): 340–348. doi:
605 10.1016/j.marpol.2009.08.003.
- 606 Thorpe, R.B., Le Quesne, W.J.F., Luxford, F., Collie, J.S., and Jennings, S. 2015.
607 Evaluation and management implications of uncertainty in a multispecies
608 size-structured model of population and community responses to fishing. *Methods*
609 *Ecol. Evol.* **6**(1): 49–58. doi: 10.1111/2041-210X.12292.
- 610 Trenkel, V.M., and Rochet, M.J. 2009. Intersection-union tests for characterising recent

- 611 changes in smoothed indicator time series. *Ecol. Indic.* **9**(4): 732–739. doi:
612 10.1016/j.ecolind.2008.09.005.
- 613 Walker, W.E., Harremoës, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B.A.,
614 Janssen, P., and Kreyer von Krauss, M.P. 2003. Defining uncertainty: a conceptual
615 basis for uncertainty management in model-based decision support. *Integr. Assess.*
616 **4**(1): 5–17. doi: 10.1076/iaij.4.1.5.16466.
- 617 Walters, C., and Kitchell, J.F. 2001. Cultivation/depensation effects on juvenile
618 survival and recruitment: implications for the theory of fishing. *Can. J. Fish. Aquat.*
619 *Sci.* **58**(1): 39–50. doi: 10.1139/f00-160.
- 620 Zhang, C., Chen, Y., and Ren, Y. 2015. Assessing uncertainty of a multispecies
621 size-spectrum model resulting from process and observation errors. *ICES J. Mar. Sci.*
622 **72**(8): 2223–2233. doi: 10.1093/icesjms/fsv086.
- 623 Zhang, C., Chen, Y., Thompson, K., and Ren, Y. 2016. Implementing a multispecies
624 size-spectrum model in a data-poor ecosystem. *Acta Oceanol. Sin.* **35**(4): 63–73. doi:
625 10.1007/s13131-016-0822-0.
- 626

627 Table 1 The definition of ecological indicators used in this study. The size ranges used
 628 for indicator calculation were defined species-specifically according to the actual trawl
 629 survey.

Indicators	Symbol	Definition	Sources
Total species biomass	B	The sum of species biomass in the fish community	Murawski 2000; Fulton, Smith and Punt 2005
Shannon-Wiener diversity index	H'	$H' = -\sum_i p_i \ln(p_i)$, where p_i is the proportion of species i in the fish community by biomass.	Shannon 1948
Large fish indicator	LFI	$LFI = \frac{\sum_w B(w > wt)}{\sum_w B}$, the proportion of fish above a threshold of wt by biomass. $wt = 100$ g in this study.	Greenstreet et al., 2011
Mean body weight	$\bar{w}$	$\bar{w} = \frac{\sum_w w N(w)}{\sum_w N(w)}$, mean body weight of all fishes in the community. $N(w)$ is the abundance of all individuals with body size w .	Rochet and Trenkel, 2003
Size diversity index	Δ	$\Delta = \frac{\sum_{w_1} \sum_{w_2} d(w_1, w_2) B(w_1) B(w_2)}{\sum_{w_1} \sum_{w_2} B(w_1) B(w_2)}$, 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 $\delta = 2\ln(10)$.	Rochet and Benoît, 2012
Slope of community size spectrum	SL	$\log(D(w)) = \alpha + SL \log(w)$, the slope of a linear regression between the abundance density ($D(w)$) and body weight (w) in log-log scale.	Rice and Gislason, 1996

630

631 Table 2 Summary of simulation scenarios in this study. The $F0$ and $Sk0$ refer to the
632 fishing effort and gear selection size in the calibrated model.

Scenarios	Variables	Values	Notes
Fishing pressure	F	$0.5-1.5F0$	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)
Survey selectivity	Sk	$0-3Sk0$	Gear selection size is used in a knife-edge selectivity curve, in which 0 means sampling all individuals of the community
Observation errors	σ_{ob}	0-1	The standard deviation of the error term $\log N(1, \sigma_{ob})$ in observational errors
Fishing variability	δ_f	0-1	The standard deviation of the error term $N(0, \delta_f)$ in the variation of fishing pressure

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635 Fig. 1 The response of ecological indicators to the change of fishing efforts (a decrease
636 to $0.5 F_0$) in (a) abrupt changes and (b) gradual changes. The dash lines denote the year
637 when fishing effort is steady. Panel (c) shows the time lag between EIs and fishing
638 efforts regarding different levels of fishing pressure. The time lag is measured as the
639 differences in time that fishing pressure and EIs reach steady values.

640

641

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

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648

649 Fig. 3 The coefficients of variance (CV) of EIs resulting from sampling error (σ) and
650 fishing variability (δ). The two columns exemplify the results from the increase and
651 decrease of fishing effort, respectively (0.5 and 1.5 times of F_0).

652

653

654 Fig. 4 The monitoring time needed to detect significant changes in the time series of EIs.
655 T_1 and T_2 were the time before and after the change in fishing effort, respectively. The
656 colors denote the probability of detecting significant trends using CUSUM test

657 (p<0.05). The results are derived for the scenarios of observational errors $\sigma_{ob}=0.5$ with
658 an increasing fishing effort ($1.5F_0$).
659
660
661 Fig. 5 The effective time of EI monitoring with respect to data noises from sampling
662 errors and fishing variability. The required time is defined as the number of years
663 needed to obtain >95% effectiveness for trend detection. The significance of trends is
664 tested using Mann-Kendall test (MK) and CUSUM test, respectively. The statistical
665 power of original EIs and combined EIs with multivariate methods are shown in the left
666 and right columns, respectively. The truncated lines indicate that the required time
667 exceeds 50 years at the specific level of sampling error or fishing variability. The results
668 are derived for the scenarios with an increasing fishing effort ($1.5F_0$).
669

a

b

c

Time before F changes (T1 year)

Time before F changes (T1 year)

Time before F changes (T1 year)

Time before F changes (T1 year)

Time before F changes (T1 year)

Time before F changes (T1 year)