1 **Data-poor stock assessment of fish stocks co-exploited by commercial and recreational**

2 **fisheries: applications to pike (*Esox lucius*) in the western Baltic Sea**

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14

15 **Abstract**

16 Information on catch and effort of recreational angling in mixed-use fisheries (co-exploited

17 by commercial and recreational fishers) is often scarce, preventing the application of data-

18 rich stock assessments typically performed for industrialized commercial fisheries. Here, we

19 show how data-poor stock assessment methods developed for marine fisheries, particularly

20 a class of models labelled as "catch-only" models (COMs), offer a possible solution. As a case

21 study, we use COMs to assess a northern pike stock around the German Baltic island of

22 Rügen. We fit multiple COMs to a time-series of total pike removals, and use their outputs as

23 explanatory variables in superensemble models. We conclude that the stock is fully exploited

24 and currently declining. Our study highlights the potential for using COMs to determine

25 status of previously-unassessed coastal and freshwater stocks facing recreational fishing

26 pressure, and demonstrates how incorporating recreational removals is crucial for achieving

27 reliable insights into the status of mixed-use stocks.

28

29 **Keywords:** Catch-only models, superensemble models, mixed-use fisheries, stock status,

30 freshwater stocks, coastal stocks.

31

32

33 **Introduction**

34 The management of mixed-use fisheries, i.e., fisheries that are co-exploited by commercial
35 and recreational fishers, poses many challenges. For instance, commercial and recreational
36 fisheries will often have different management objectives (Arlinghaus et al., 2019; Ahrens et
37 al., 2020), and the disparity in aspirations and behaviours increases with the diversity of
38 stakeholders (Mardle et al., 2004; Pascoe et al., 2009). The sustainable management of
39 mixed-use fisheries requires addressing both its commercial and recreational components,
40 because the combined action of both sectors is responsible for the total fishing mortality
41 induced on a stock (Berkes, 1985; Post et al., 2002; Cooke & Cowx, 2004).

42

43 A common precondition for sustainability in fisheries is the existence of regular stock
44 assessments (Melnychuk et al., 2017). Stock assessments employ a variety of methods
45 depending on the data available. The most reliable "data-rich" methods (such as virtual
46 population analysis and statistical catch-at-age models) require data on catch, effort, and the
47 age/length/weight composition, preferably from both the fishery users as well as from
48 independent scientific surveys (Hilborn & Walters, 1992; Hart & Reynolds, 2002). The
49 management of industrial commercial fisheries appears to become increasingly effective due
50 to the presence of frequent and high quality stock assessments, with many assessed stocks
51 showing rebuilding from previously overfished states (Hilborn et al., 2020). However,
52 gathering the required data for such assessments is costly (Mangin et al., 2018), and
53 therefore high quality data to pursue stock assessments are rarely available for many small-
54 scale commercial (Andrew et al., 2007; Graaf et al., 2015; Prince & Hordyk, 2019) and
55 recreational fisheries (Post et al., 2002; Arlinghaus et al., 2019). As a result, mixed-use
56 fisheries can be expected to often face a severe lack of data, preventing the application of
57 standard stock assessment practices common to industrial commercial fisheries.

58

59 When there is insufficient data available for performing a traditional data-rich stock
60 assessment, the fishery is usually referred to as data-poor or data-limited (Prince & Hordyk,
61 2019). Many small-scale commercial and recreational fisheries are characterized as such,
62 with aggregated catch or landings data often being the only form of data available
63 (Vasconcellos & Cochrane, 2005; Newman et al., 2015). An alternative to a stock assessment
64 is to infer stock status from trends in catch data, as is done in stock-status plots (Grainger &

65   Garcia, 1996; Froese & Kesner-Reyes, 2002; Pauly, 2007). However, because catches do not

66   necessarily track changes in underlying biomass, such catch-based methods can result in

67   incorrect conclusions (Branch et al., 2011; Daan et al., 2011; Carruthers et al., 2012). To

68   overcome this problem and still be able to make predictions on stock status using

69   aggregated catch data, more sophisticated models have been developed that either rely on

70   underlying population dynamics models (Vasconcellos & Cochrane, 2005; Martell & Froese,

71   2013), or statistical correlations with data-rich assessed stocks (Costello et al., 2012; Zhou et

72   al., 2017). Here, we call these models catch-only models (COMs).

73

74   COMS designed to estimate stock status time-series can be divided into two broad

75   categories: mechanistic and empirical COMs (Free et al., 2020). Mechanistic COMs fit a

76   population dynamics model to the catch data and make assumptions regarding parameter

77   values to make up for the lack of other data. Mechanistic COMs include models such as

78   CMSY (catch maximum sustainable yield; Froese et al., 2017) and SSCOM (Thorson et al.,

79   2013). Empirical COMs use information from data-rich assessed stocks to find statistical

80   associations between catch, stock status, and other covariates. Empirical COMs include

81   models such as mPRM (Rosenberg et al., 2014) and zBRT (Zhou et al., 2017). COMs are not as

82   accurate in predicting stock status as data-rich statistical catch-at-age models, but they offer

83   a promising alternative when the absence of some data prevents a full data-rich assessment

84   (Free et al., 2020).

85

86   In addition to using quantitative models to determine the status of data-poor stocks,

87   assessments based on traditional ecological knowledge of local residents have been

88   performed as well (Berkes et al., 2000). Individual perceptions can conflict with scientific

89   findings (O'Donnell et al., 2010; Daw et al., 2011), but for many data-poor stocks such local

90   knowledge can be one of the few sources of information on the development of the stock

91   (Johannes, 1998). Furthermore, studies that have compared traditional ecological knowledge

92   with independent stock assessments have often found that model outcomes align with local

93   understanding (Neis et al., 1999; Aswani & Hamilton, 2004) and that local users can

94   approximate scientific understanding of ecological relationships in fish stocks (Aminpour et

95   al., 2020). Thus, the knowledge of local residents can be used to see whether scientific and

96   stakeholder perspectives agree.

97

98   In this study, we explore the usage of COMs to assess the status of a data-poor mixed-use

99   single-species fishery, using a coastal lagoon pike (*Esox lucius*) stock in the western Baltic Sea

100   in Germany as a case study. The pike stock around the island of Rügen is targeted by both

101   recreational and commercial fishers, but regular stock assessments are lacking and disparate

102   perspectives about stock status have emerged among stakeholders that contribute to local

103   conflict (Vogt, 2020). To help solve these issues, we assessed the status of this coastal pike

104   stock using seven different COMs, and used a superensemble model approach to account for

105   individual model biases. We show the importance of using multiple different COMs for

106   assessing stock status, and reveal how including catch data from both its recreational and

107   commercial components is crucial for the assessment of a mixed-use fishery. Furthermore,

108   we show that surveys among local stakeholders can be used to increase the confidence in

109   model results. Using a practically-relevant example of an ongoing management dilemma in a

110   mixed-use coastal fishery, we demonstrate how COMs can be used as an initial method for

111   the assessment of data-poor mixed-use stocks, being aware that it is not a perfect substitute

112   for more data-rich approaches.

113

114   **Materials & Methods**

115

116   ***Study area and data***

117   We studied the pike stock around the German island of Rügen, which is located in the

118   western Baltic Sea (**Error! Reference source not found.**). There are multiple lagoon-type

119   brackish water bodies located around this island, which are connected to the Baltic Sea

120   (Schubert & Telesh, 2017). These lake-like water bodies vary in salinity from nearly fresh to

121   nearly that of the neighboring Baltic Sea (Placke et al., 2018) and exhibit salinities below 14

122   PSU year-round, i.e., mesohaline brackish conditions (Schumann et al., 2006; Schiewer,

123   2008). Although pike is a freshwater fish, the species is able to tolerate the brackish water

124   present in the lagoon waters and is known to successfully spawn and recruit in the brackish

125   conditions around Rügen (Möller et al., 2019).

126

127   The pike stock around the lagoons of Rügen has been exploited by small-scale coastal

128   commercial fishers since at least the late 19th century (Winkler, 1989; Winkler & Debus,

129   2006), and likely long before. For much of the 20th century, the pike was a target for

130   commercial fishers, helped by the guaranteed price per unit weight that was maintained by

131   the East Germany (GDR) government (Döring et al., 2020). However, after the German

132   reunification, the pike has become a bycatch species for most coastal commercial fishing

133   enterprises and is today the primary target for only a small number of dedicated commercial

134   pike fishers. However, the species continues to be captured in gill nets, fyke nets, and with

135   long-lines up to the present day.

136

137   Recreational angling was practiced in the Rügen lagoons during GDR times, and has been

138   increasing in popularity after the German reunification (Figure A5, Appendix A). Pike is a

139   particularly popular fish for recreational fishers around Rügen, especially for non-resident

140   anglers, likely due to its relatively large size in the lagoon ecosystems, but is also a valued

141   target of resident anglers (Weltersbach et al., in press).

142

143   *Catch time-series data*

144   A time-series of annual commercial pike landings from 1976-2018 from the lagoons around

145   Rügen was obtained from the state office for agriculture, food safety, and fisheries (LALLF) of

146   the German state Mecklenburg-Vorpommern (M-V). Furthermore, commercial removals

147   from 1969-1975 and from 1955-1968 were extracted from Winkler (1991) and from records

148   generated from annual official fisheries reports published by the Institut für

149   Hochseefischerei und Fischverarbeitung Rostock of the former GDR, respectively.

150

151   A time-series of recreational removals was not available for the Rügen pike stock, as

152   recreational removals are not actively monitored in the area by public authorities. However,

153   given the popular recreational fishery for Rügen pike, we considered it important to include

154   recreational removals in the time-series of total removals. We reconstructed recreational

155   removals according to the guidelines provided by Zeller *et al.* (2006). We used data from two

156   telephone-diary studies among recreational fishers performed in the region (Dorow &

157   Arlinghaus, 2011; Lucas, 2018; Weltersbach et al., in press) as anchor points. These studies

158   estimated total pike removals in the Rügen area from a random sample of participating

159   recreational fishers for the years 2006/2007 and 2014/2015. From these anchor points, and

160   using additional quantitative data such as proxies for angling effort, we inter- and

161   extrapolated recreational removals for the rest of the time-series.

162

163   The reconstruction of recreational removals of the Rügen pike (detailed in Appendix A) can

164   be summarized as follows. For the year 2007, data were available on resident angler harvest

165   and catch-and-release rate, and the number of angling trips taken in the Rügen area by

166   resident anglers (Dorow & Arlinghaus, 2011). Comparable data were available for 2015, not

167   only for resident but also for tourist anglers (Lucas, 2018; Weltersbach et al., in press). These

168   anchor points were supplemented with time-series data on the annual number of resident

169   fishing licenses issued in M-V as given by LALLF, the annual number of coastal recreational

170   angling licenses issued in M-V as given by LALLF, and the membership numbers of the East

171   German angling association (DAV) prior to the German reunification (VDFF, 1998). We then

172   used the 2007 and 2015 data on resident angling trips together with the time-series on

173   coastal recreational angling licenses to estimate a 1991-2018 time-series on resident angling

174   trips, assuming a linear increase in trips per license for resident anglers between 2007 and

175   2015. Similarly, we used the 2015 data on tourist angler trips together with the time-series

176   on coastal recreational angling licenses to estimate a 1991-2018 time-series on tourist

177   angling trips, assuming a constant number of trips per license for tourist anglers based on

178   the 2015 data. Then, we used DAV membership data to extrapolate this recreational effort

179   time-series back to 1955. Next, using available time-series data on commercial Rügen pike

180   removals and the annual number of commercial fishing vessels registered in the area as

181   given by the European Fleet Register, we estimated a commercial catch-per-unit-effort

182   (CPUE) time-series (landings per boat), assuming a constant commercial effort in the years

183   for which we lacked data (1955-1991). Then, we used this commercial CPUE time-series

184   together with the 2007 and 2015 data on recreational fisher catch rates to estimate a 1991-

185   2018 time-series of recreational catches, assuming constant proportionality between

186   recreational and commercial CPUE for all years. We subsequently estimated resident and

187   tourist removals by accounting for the release rates of 2007 and 2015, assuming a linear

188   decrease in resident release rate between 2007 and 2015 and assuming that tourist release

189   rate remained constant to its 2015 value, and furthermore assuming a release mortality for

190   pike of 7.8% (Hühn & Arlinghaus, 2011). Lastly, we used the reconstructed recreational

191   removals of 1991 to extrapolate recreational removals back to 1955, by assuming a constant

192   proportionality between recreational and commercial CPUE.

193

194   **_Models_**

195   First, we used a suite of different COMs to estimate current status of the Rügen pike stock in

196   an ensemble model approach. We then inserted the results of these models into several

197   different 'trained' statistical models, following the superensemble model approach as

198   described by Anderson _et al._ (2017), providing an estimate of current stock status. Lastly, we

199   used the outcome of the superensemble analysis to assign weights to COM time-series

200   estimates of biomass and fishing mortality, providing an estimate of past stock status. The

201   analysis was performed in R version 3.6.1 (R Core Team, 2019), using the datalimited

202   (Anderson et al., 2016) and datalimited2 (Free, 2018) packages for the COMs, and the

203   randomForest (Liaw & Wiener, 2002) and gbm (Greenwell et al., 2019) packages for the

204   superensemble model.

205

206   _Catch-only models (COMs)_

207   We fitted seven individual COMs to the reconstructed removal data of the Rügen pike stock.

208   We used the COMs that had their performance tested by Free et al. (2020). These included

209   five COMs that fit a population dynamics model, and two COMs that find statistical

210   associations using data-rich assessed stocks. Each of the COMs returned an estimate of

211   B/B_{MSY} over the course of the catch time-series, including a 95% confidence interval.

212   Furthermore, parameters and reference points returned by some, but not all, COMs include

213   fishing mortality F, fishing mortality that gives MSY F_{MSY}, biomass B, B_{MSY}, MSY, intrinsic

214   population growth rate r, and population carrying capacity k. The COMs that were used

215   were Catch-MSY (Martell & Froese, 2013), CMSY (Froese et al., 2017), COM-SIR (Vasconcellos

216   & Cochrane, 2005), SSCOM (Thorson et al., 2013), mPRM (Rosenberg et al., 2014), OCOM

217   (Zhou et al., 2018), and zBRT (Zhou et al., 2017). A brief explanation of each model is

218   provided in Appendix B.

219

220   _Superensemble models_

221   The different COMs that we fitted to our data yield different results, owing to their inherent

222   biases due to different methods and assumptions (Free et al., 2020). To try and resolve these

7

223 potential discrepancies, we combined the results of the different COMs in a superensemble
224 model approach. For this, we used the approach described by Anderson et al (2017). Firstly,
225 for each COM, we took the estimated values for mean and slope of B/B_{MSY} and computed
226 an average for the last 5 years of data. Second, we inserted these COM averages as
227 covariates into three different statistical models (here called superensemble models) that
228 were trained on stocks with known status, thereby obtaining a superensemble estimate of
229 the mean and slope of B/B_{MSY} for the last 5 years. The three statistical models that we used
230 for this were a linear model, a random forest, and a boosted regression tree.

231

232 To train the three superensemble models with known data, we used simulated exploitation
233 time-series for 5,760 different hypothetical stocks. For this, we used the exploitation time-
234 series simulated by Rosenberg et al. (2014), which varied in both life-history parameters and
235 fishing regime, and contained both process and observation error. Then, for each
236 hypothetical stock, we fitted each of the seven COMs to its simulated catch time-series,
237 giving seven estimates of a time-series for B/B_{MSY} for each stock. Next, for each of these
238 time-series, we took the mean and slope of B/B_{MSY} and calculated an average over the last
239 5 years of data. Lastly, we trained the statistical models, using either the mean or the slope
240 of recent B/B_{MSY} estimated by the seven COMs for all 5760 simulated stocks as seven
241 independent variables, and the associated true mean or slope of recent B/B_{MSY} of all
242 simulated stocks as the dependent variable. To prevent overfitting of the random forest and
243 boosted regression tree models, we used the caret package (Kuhn, 2020) in R to identify the
244 optimal parameter combination for both the B/B_{MSY} mean and slope model fits. Using a 10-
245 fold cross validation repeated 10 times, optimal parameter combinations were identified as
246 those that resulted in the smallest root-mean-square deviation. Following the results of this
247 tuning procedure (Appendix B), we fitted both random forest models for mean B/B_{MSY} and
248 its slope using 3 randomly selected predictors and 1000 trees, we fitted the boosted
249 regression tree model for mean B/B_{MSY} using 9500 trees, an interaction depth of 10, and a
250 shrinkage of 0.005, and we fitted the boosted regression tree for B/B_{MSY} slope using 7000
251 trees, an interaction depth of 10, and a shrinkage of 0.005, keeping all other parameters to
252 their default setting.

253

254   After the superensemble models have been trained with known data, they were used to

255   estimate the status of the Rügen pike stock. For this we used the outcomes of the seven

256   COMs (estimates of the mean value and mean slope of B/B_{MSY} of the Rügen pike stock over

257   the last 5 years of data) as the independent variables, whilst retaining the values of the

258   regression coefficients estimated in the training of the superensemble models. In this way,

259   each superensemble model provided an estimate of the mean and slope of B/B_{MSY} for the

260   Rügen pike over the last 5 years of data. To study the importance of incorporating

261   recreational removals into the total removals time-series, we repeated this process using

262   only the commercial landings of pike as input to the COMs and the subsequent

263   superensembles.

264

265   *Estimating F and F$_{MSY}$*

266   Aside from a B/B_{MSY} time-series, four mechanistic COMs (Catch-MSY, CMSY, COM-SIR, and

267   OCOM) also estimate F and F_{MSY}. We used these COMs' weighted means of B, B_{MSY}, F, and

268   F_{MSY} to construct a Kobe plot, showing the recent trend in stock status relative to F_{MSY} and

269   B_{MSY}. To construct a weighted mean of each of these variables, we assigned COM-specific

270   weights. These weights were based on each COM's percentage error of its estimate of mean

271   B/B_{MSY} over the last 5 years, compared to the mean of the superensemble estimates.

272   Percentage error p_{error} of COM i was calculated as:

273

$$p_{\mathrm{error},i} = \frac{S_i - S_\mu}{S_\mu} \qquad\qquad 1$$

274

275   where S is the COM estimate of mean B/B_{MSY} over the last 5 years, and S_μ is the mean of the

276   superensemble estimates of mean B/B_{MSY} over the last 5 years. Next, weight w of COM i

277   was calculated as the reciprocal of the absolute value of p_{error}:

278

$$w_i = \frac{1}{|p_{\mathrm{error},i}|} \qquad\qquad 2$$

279

280   Thus, if a COM estimate of B/B_{MSY} had a larger deviance from the superensemble model

281   average, it received a smaller weight. Weights were subsequently normalized according to:

282

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$$w_{\text{norm},i} = \frac{w_i}{\sum w_i} \qquad\qquad 3$$

283

284   Normalized weight w_{norm} of a COM was then used to calculate weighted means of B, B_{MSY},

285   F, and F_{MSY} for each of the COMs that estimated these values.

286

287   *Sensitivity tests*

288   Sensitivity tests were performed to analyze the sensitivity of the models to alternative

289   parameter values, and to test a number of the assumptions made in our reconstruction of

290   recreational removals. The methodology and results of these tests are described in detail in

291   Appendix D. In summary, we first performed an elasticity analysis to test the sensitivity of

292   the model results to changes in COM parameter values. We varied each parameter by 50%,

293   and considered a model sensitive to a given parameter when the model result deviance from

294   its base run estimate was greater than 50%. Second, we looked at the sensitivity of the

295   model results to assumptions made during the reconstruction of the recreational removals.

296   We reconstructed the recreational removals time-series through various alternative

297   methods, ran the COMs and superensemble models with the resulting time-series of total

298   removals, and examined the deviance of each model's result from its base run.

299

300   **Stakeholder perceptions of stock trends**

301   To gain insight in how different stakeholders perceived the development of the Rügen pike

302   stock, we constructed a short questionnaire and distributed it among the key stakeholder

303   groups (anglers, angling guides, commercial fishers, non-governmental organizations, and

304   fisheries agency staff). Among other things, we specifically asked respondents how they

305   perceived the stock of pike to have changed within the time-frame between today and the

306   first time they fished at the Rügen lagoons. The same question was asked regarding the

307   stock development of pike greater than one meter in length. Responses were measured on a

308   five-point Likert scale from "strong decrease" to "strong increase".

309

310   The survey was administered through a snowball technique to both resident and non-

311   resident anglers as well as angling guides, fishers, and other stakeholders. Data were further

312   collected on an angling exhibition in Rostock in June 2019, and through local angling guides.

313   The total sample size numbered 258 observations. The resulting data are not representative

314   for the population-level perceptions, but allowed us to gather initial insights for the most

315   heavily engaged stakeholders, and to compare stock trends derived from the COMs with

316   stakeholder perspectives.

317

318   **Results**

319   The seven COMs predicted different historic patterns in the B/B_{MSY} trend of the pike stock

320   in the Rügen area (**Error! Reference source not found.**). Notably, zBRT predicted a severely

321   depleted stock status in the 1970s and 1980s, while most other COMs predicted a status of

322   B/B_{MSY} remaining around or above 1 for the majority of the time-series. Similarly, estimates

323   of current B/B_{MSY} varied, with two COMs estimating a current B/B_{MSY} greater than 1, one

324   COM estimating it lower than 1, and four COMs estimating it to be around 1. However, all

325   COMs consistently estimated a decline in B/B_{MSY} in recent years.

326

327   The different superensemble models predicted similar values for mean B/B_{MSY} in the past 5

328   years, and all predicted a negative slope of recent B/B_{MSY} (Table 1). Although all

329   superensemble models predicted a 5-year mean of recent B/B_{MSY} above 1, extrapolating

330   this mean with each superensemble's estimated slope B/B_{MSY} suggested that current

331   B/B_{MSY} of the Rügen pike stock is around or even slightly below 1 (**Error! Reference source**

332   **not found.**). Thus, based on the superensemble model results, the Rügen pike stock is fully

333   exploited, but may also be slightly growth overfished when judged by MSY.

334

335   When recreational removal data was left out of the analysis, and the models were provided

336   with only the commercial catch data, clear differences from the original estimates of the

337   catch-only and superensemble models could be observed (**Error! Reference source not**

338   **found.**). When not considering recreational fishers, the pike stock appeared in a much

339   poorer and highly overfished state than when recreational removals were included.

340

341   The model weights for the calculations of weighted mean values of B, B/B_{MSY}, F, and

342   F/F_{MSY} are given in Table 2. The Catch-MSY model was by far assigned the greatest weight.

343   The resulting weighted averages of B, B/B_{MSY}, F, and F/F_{MSY} were visualized as a Kobe

344   plot (**Error! Reference source not found.**), and indicate that the stock had a healthy status

345   and was not experiencing overfishing up until 2012, after which overfishing gradually

11

346   reduced stock biomass to nearly below B_{MSY}. Thus, the pike stock is currently experiencing

347   overfishing, and is fully exploited. This result contrasts with the results of the superensemble

348   models, which predict a current B state below B_{MSY}. This discrepancy can be attributed to

349   the large weight assigned to the Catch-MSY model, which estimates a current B state above

350   B_{MSY} (**Error! Reference source not found.**). Using the model weights, estimates of current

351   state of the Rügen pike stock, fisheries reference points, and life-history parameters were

352   calculated from their individual COM estimates as summarized in Table 3.

353

354   The various sensitivity analyses showed that the mean of the superensemble model

355   estimates was generally robust to parameter settings and model assumptions (Appendix D).

356   The elasticity test showed that, in general, the models were insensitive to changes in

357   parameter values, with the greatest sensitivity being to changes in the prior of final year

358   biomass range. Next, regarding the assumption of constant commercial effort before 1991,

359   the results remained largely unchanged when different assumptions were made regarding

360   the trend of commercial effort before 1991. Lastly, reconstructing recreational removals in a

361   variety of different ways changed the mean of superensemble estimates of mean B/B_{MSY}

362   over the last 5 years to only a limited degree, with a positive deviance of 20.8% being the

363   highest among all different reconstructions, followed by a positive deviance of 14.2%.

364

365   From the stakeholder survey, when asked about their perceptions of the development of the

366   Rügen pike stock, respondents mostly indicated a perceived decline over time in large pike

367   of the Rügen stock as well as a perceived decline for the Rügen pike stock in general (**Error!**

368   **Reference source not found.**). This perceived decline was greatest among guides and those

369   anglers who were out with a guide when interviewed. Thus, stakeholders agreed with the

370   model results in estimating a recent decline of the pike stock.

371

372   **Discussion**

373   Mixed commercial-recreational fisheries can be challenging to manage because commercial

374   and recreational fisheries typically have divergent management objectives (Arlinghaus et al.,

375   2019; Ahrens et al., 2020). In this context, lack of data can hinder the performance of

376   standard stock assessments, which are an important instrument in the effective and

377   sustainable management of fish stocks (Melnychuk et al., 2017; Hilborn et al., 2020). The

378   application of COMs and superensemble models can be used to deliver insights into stock

379   status when the only fisheries data available are observations of aggregated landings. Here,

380   seven different COMs and three different superensemble models were applied in a case

381   study to assess the status of pike in a German lagoon system. They showed that stock status

382   has been declining in recent years and that current B is around B/B_{MSY}, with the decline

383   being predicted both by individual and ensembled COMs as well as by stakeholders. Our

384   study demonstrates an approach for the data-limited stock assessment of mixed-use

385   fisheries, and complements other recent studies that have shown how marine stock

386   assessment methods can be used in small-scale inland and other small-scale fisheries in

387   transitional waters, such as coastal lagoons (Fitzgerald et al., 2018; Shephard et al., in press).

388   Our work also demonstrates that recreational removals are important to be considered in

389   stock assessments where recreational angling makes up a relevant share of total removals.

390   In our case, neglecting recreational fishing removals lead to an assessment result that

391   indicated a strongly overfished stock due to a long-term decreasing trend in commercial

392   landings. In contrast, by incorporating recreational removals, the total removals time-series

393   trend showed long-term stability of removals up until a recent spike and a subsequent

394   decline, resulting in an assessment that estimates a fully exploited stock status.

395

396   Our case study results indicate that the Rügen pike stock is currently fully exploited, but may

397   experience first signs of growth overfishing ($F > F_{MSY}$). Accordingly, current biomass trends

398   are showing a decline. Commercial and recreational fishing mortality are both relevant

399   factors, and removals from recreational fishing are currently outweighing commercial fisher

400   removals, despite recent catch-and-release rates of pike in Rügen by recreational fishers

401   exceeding 60% (Lucas, 2018). Additionally, environmental changes unrelated to fishing may

402   also contribute to this decline. Previous work on recreational use of pike in inland lakes in

403   the USA has revealed ample variation in recreational fishing-induced pike exploitation rates

404   (Pierce et al., 1995), but the current fishing mortality rate estimated for Rügen pike (F = 0.18

405   yr^{-1}) is high when compared with those found in lake studies from the USA (Pierce et al.,

406   1995). Specifically for Germany, roughly 20% of lentic pike stocks have been found to

407   experience fishing mortality rates that are larger than F_{MSY} (Arlinghaus et al., 2018), and the

408   Rügen stock thus compares with intensively fished lake stocks.

409

13

410   We assessed the status of the Rügen pike stock using MSY-derived metrics. However, when

411   it comes to mixed-use fisheries, a core question is whether MSY represents the optimal

412   measure for defining stock status (Arlinghaus et al., 2019). For commercial fishers, it has

413   often been suggested that maximum economic yield (MEY) rather than MSY would be a

414   more suitable measure for defining stock status, for two main reasons. Firstly, a stock that is

415   fished at a level that returns MEY instead of MSY would be more desirable from most

416   commercial fishers' point of view (Norman-López & Pascoe, 2011), whilst secondly the stock

417   would also have a higher overall biomass (Grafton et al., 2007). For recreational fishers,

418   measures of optimal fish status relate more to individual fish size and abundance, rather

419   than maximum biomass yield, and the benefits of a fish stock to recreational fishers are thus

420   usually maximized at lower fishing mortality rates than those that produce MSY (Radomski

421   et al., 2001; Ahrens et al., 2020). For instance, size truncation reduces the satisfaction of

422   those recreational fishers that prefer large pike in the catch (Arlinghaus et al., 2014;

423   Beardmore et al., 2015). Current biomass trends of the Rügen pike are negative and around

424   B_{MSY}, meaning the stock status is size-overfished and thus may be far from optimal from a

425   recreational fishing point-of-view. In this study we have used MSY as a reference for defining

426   stock status due to its widespread acceptance in fisheries literature as a reference by which

427   stock status should be compared, but acknowledge that this is likely an unsuitable measure

428   of stock status particularly for recreational fishers. We therefore encourage the use of

429   alternative measures by which stock status, and more generally fishery quality, can be

430   quantified in mixed-use fisheries.

431

432   The models we have used to derive biomass trends of the Rügen pike stock assumed a

433   constant natural environment. However, this has not been the case in the waters around

434   Rügen. Nutrient load greatly increased from the 1950s to the 1980s (Munkes, 2005), after

435   which it has been steadily declining again (LUNG, 2013). Furthermore, submerged

436   macrophyte coverage has greatly deceased in the Greifswalder lagoon and in the Darss-

437   Zingster lagoons (Kanstinger et al., 2018; Pankow & Wasmund, 1994). Although submerged

438   macrophyte coverage has remained roughly constant over time in the Westrügen lagoons

439   when compared with 1932, it has changed in species composition since then (Blindow et al.,

440   2016). These environmental changes could have affected the productivity of the pike stock,

441   thereby changing the relationship between population abundance and productivity (Vert-Pre

442   et al., 2013), and thus potentially impacting the values of both B and B_{MSY} over the years

443   (Rose, 2004; Jensen, 2005). In the Darss-Zingster lagoons for instance, increased

444   eutrophication has been thought to be responsible for a decline in pike in favour of

445   pikeperch in the late 1960s (Winkler, 2002). Thus, unaccounted environmental or habitat-

446   driven changes in stock productivity that happened throughout a time-series of landings

447   generally affect stock assessment outcomes and create relevant uncertainty in assessment

448   results (Brown et al., 2019). However, more complex and data-rich age-structured

449   assessment models face a similar issue.

450

451   Multiple different COMs have been developed over the years to estimate stock status under

452   data-limited conditions. To be able to run with limited data, these COMs make a variety of

453   simplifying assumptions, increasing the chances for bias and uncertainty of their estimate

454   (Rosenberg et al., 2014; Free et al., 2020). Therefore, using only a single COM for assessing

455   stock status increases the risk of producing a flawed or biased status estimate. This is

456   supported by the results of our case study, which showed a large spread in individual COM

457   predictions. Thus, using only a single COM to estimate stock status should be avoided.

458   Instead, the use of multiple different models in an ensemble approach, with the final

459   estimated value either being the average of all models or the product of some weighting

460   procedure, is expected to increase the robustness of the result (Bates & Granger, 1969).

461

462   Although a simple model averaging approach could improve estimates of stock status, it will

463   not incorporate that some models perform better or worse under certain conditions. A

464   superensemble model, on the other hand, allows for exploiting the covariance between

465   individual COM predictions (Anderson et al., 2017), allowing for a better accounting of

466   individual model biases. In our case study, we applied three different types of

467   superensemble models and found their estimates of recent biomass status were relatively

468   similar, increasing our confidence in their results. However, Free et al. (2020) found that

469   superensemble models of COMs generally produce a negatively-biased estimate of stock

470   status for lightly-exploited stocks. Thus, it is possible that the pike stock in our case study is

471   actually in a better shape than suggested by the superensemble models.

472

473   Furthermore, the predominant reliance of COMs on landings time-series means that it is
474   important that these data are reliable and of high quality. For many mixed-use fisheries this
475   is rarely the case, with data on recreational removals often missing or being incomplete
476   (Arlinghaus et al., 2019). Commercial landings statistics may also suffer from illegal and
477   unreported catch (Agnew et al., 2009). In our case study, we reconstructed a time-series of
478   recreational removals using two local scientific studies as anchor points, and using various
479   other forms of time-series data to interpolate between and extrapolate from these points.
480   Such reconstructions should be paired with rigorous sensitivity analyses. Even though we
481   tested the sensitivity of the model results to various alternative reconstruction approaches
482   and found limited impact, we cannot exclude the possibility that our reconstruction of
483   recreational removals contained uncertainty. Nevertheless, our results showed that it is
484   advisable to reconstruct recreational fishing removals, even when uncertain, instead of
485   solely relying on commercial landings data. Thus, in the absence of sufficient data to perform
486   more sophisticated assessments that incorporate age data, COMs may provide
487   approximations of stock status, as long as uncertainties are recognized and explored. We
488   tested several sensitivities and found our results to be largely robust, and additionally
489   mirrored by stakeholder perceptions.

490

491   There is still an active debate among fisheries scientists on whether catch-only methods
492   should be used at all for assessing fish stock status. Some argue that catch data represents
493   the only data available for many data-limited fish stocks, and that using catch-only methods
494   provides the only option of getting an indication of the status of those stocks, even if they
495   are less precise than data-rich stock assessments (Froese et al., 2012; Pauly et al., 2013).
496   Others argue that it is better not to use catch-only methods when they may be wrong, and
497   that instead the focus should be on collecting and including additional data (Branch et al.,
498   2011; FAO, 2019). Explicitly accounting for the higher levels of uncertainty of data-limited
499   methods by including precautionary management measures or buffers may resolve some of
500   this debate (Dowling et al., 2019). For instance, Walsh et al. (2018) found that using
501   superensembles of catch-only models to inform fisheries management could reduce the risk
502   of overfishing, but only when combined with a precautionary harvest control rule, which in
503   turn might result in poor yields. Thus, the usage of COMs and superensembles in the
504   management of mixed-use fisheries should be combined with a precautionary approach, and

16

505 whenever possible additional data should be collected to allow for more data-rich
506 assessments. For instance, we added survey data from stakeholders to increase our
507 confidence in the assessment outcomes. Although stakeholder perspectives present their
508 own biases (O'Donnell et al., 2010), the alignment of stakeholder perceptions and COM
509 predictions support the conclusion that pike biomass has declined in recent years.

510

511 **Conclusion**

512 We have used a combination of individual and ensembled COMs and stakeholder surveys to
513 assess the status of a data-poor coastal pike stock that is exploited by both commercial and
514 recreational fishers. We conclude that the pike stock is fully exploited, currently declining,
515 and may be experiencing growth overfishing. Thus, reductions in fishing mortality may be
516 advisable. Our study has shown the benefits of using multiple different models and including
517 stakeholder surveys when assessing stock status through data-limited methods, and has also
518 demonstrated the importance of including recreational removals when assessing the status
519 of a stock that is co-exploited by commercial and recreational fisheries.

520

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527

528 **References**

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753 **Tables**

754
755 Table 1: COM and superensemble model estimates of the mean value of B/B_{MSY} in the last 5 years of data, and the
756 average slope of B/B_{MSY} in the last 5 years of data. Shown in bold are the averages of all COMs and all
757 superensemble models, respectively.

Model	Mean	Slope
COM		
Catch-MSY	1.13	-0.0622
CMSY	0.784	-0.121
COM-SIR	1.63	-0.000620
mPRM	1.30	-0.147
OCOM	1.02	-0.0762
SSCOM	1.69	-0.105
zBRT	1.18	-0.100
COM average	**1.21**	**-0.0875**
Superensemble		
Boosted regression	1.16	-0.144
Linear model	1.18	-0.123
Random forest	1.15	-0.155
Superensemble average	**1.16**	**-0.141**

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761 **Table 2: Weights assigned to the listed COMs, used to calculate time-series of the weighted means of B, B/B_{MSY}, F,**
762 **and F/F_{MSY}, as well as estimates of current state of the Rügen pike stock, fisheries reference points, and life-history**
763 **parameters.**

Model	Normalized weight
Catch-MSY	0.737
CMSY	0.0587
COM-SIR	0.0198
OCOM	0.0783

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766 **Table 3: Estimates of the 2018 state of the Rügen pike stock, fisheries reference points, and life-history parameters,**
767 **including 95% confidence limits. Estimates are calculated as a weighted mean of four COMs: Catch-MSY, CMSY,**
768 **COM-SIR, and OCOM.**

Estimate	Value	Lower limit	Upper limit
2018 F (yr^{-1})	0.18	0.084	0.52
2018 B (t)	2217	592	6914
MSY (t)	356	205	597
F_{MSY} (yr^{-1})	0.17	0.055	0.35
B_{MSY} (t)	2154	1103	4734
r (yr^{-1})	0.347	0.109	0.699
k (t)	4308	2207	9468

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Figures
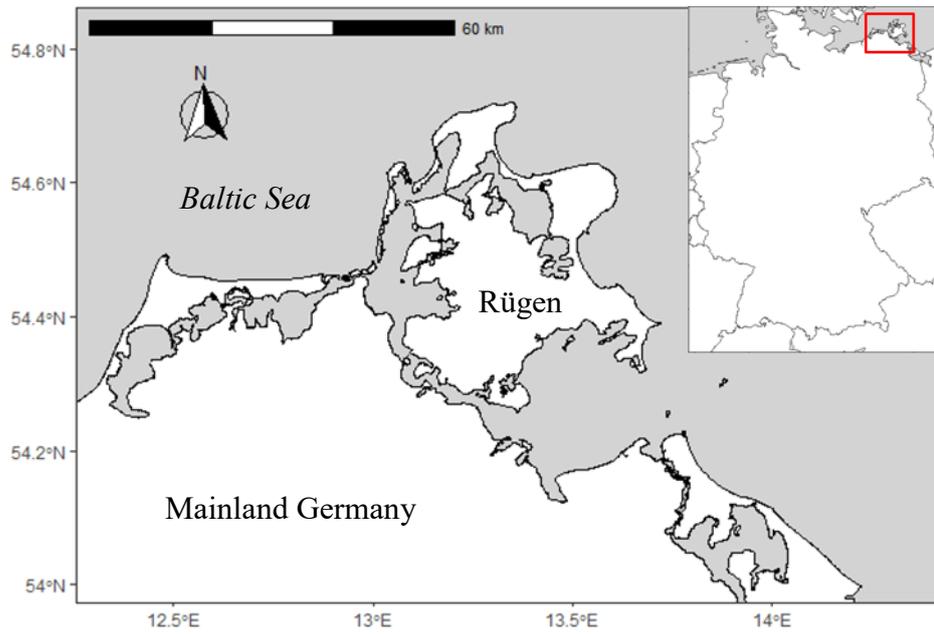
Figure 1: A map of the German Baltic island of Rügen, also indicating its location within Germany.
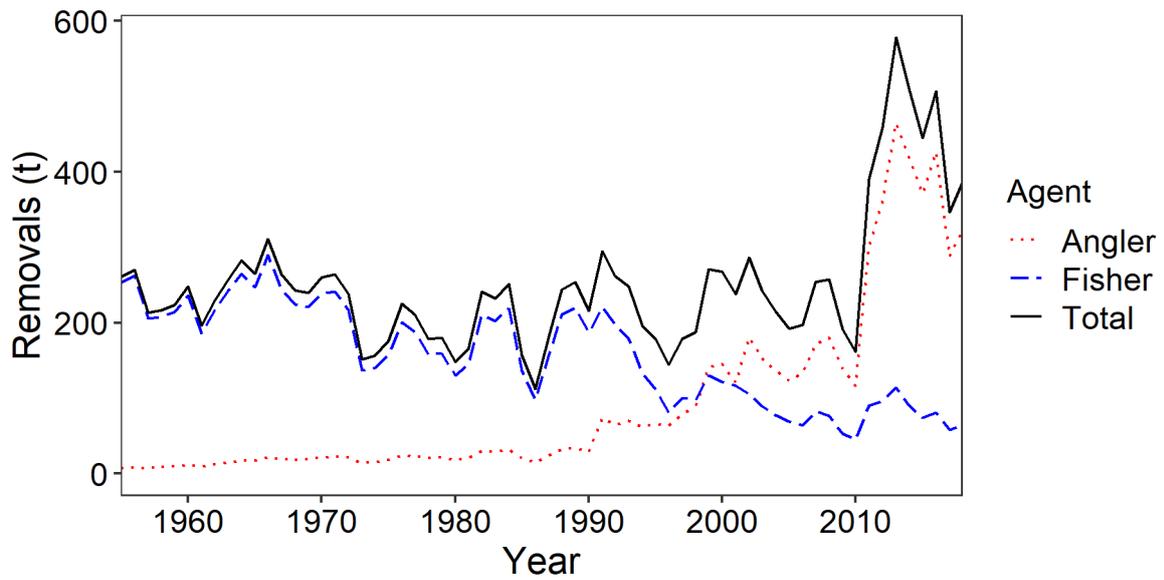
Figure 2: Total removals by both commercial and recreational fishers in the Rügen area over time (solid black). Shown too are removals by commercial fisheries over time (dashed blue) and reconstructed removals by recreational fishers over time (dotted red).
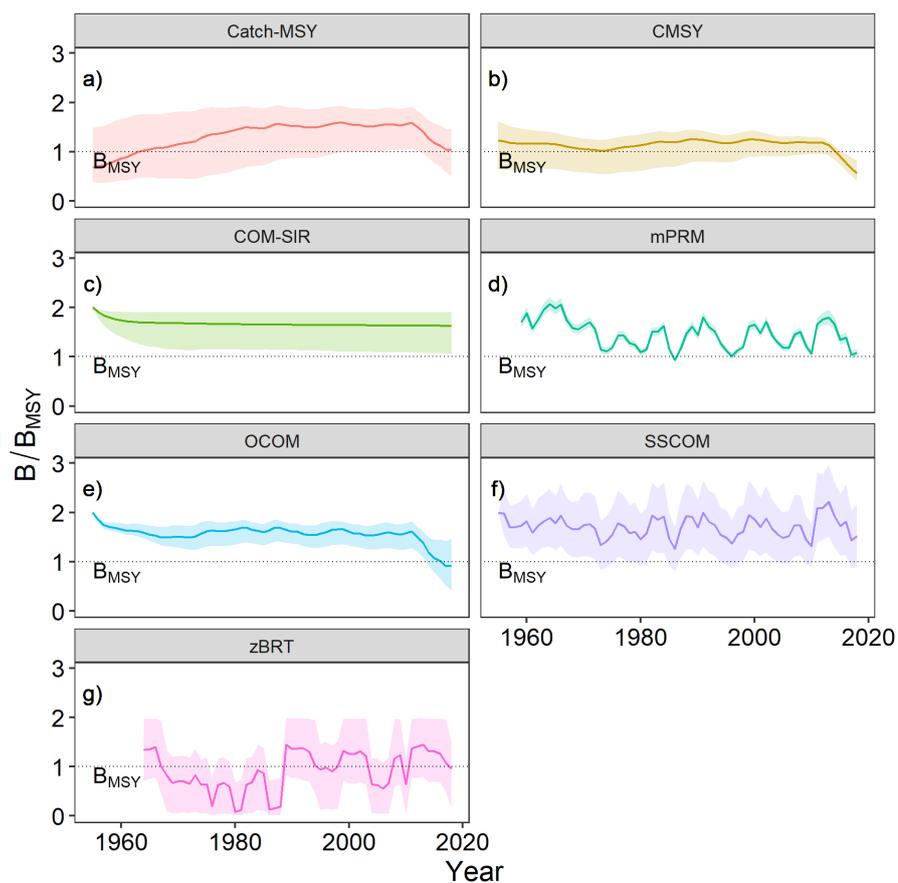
Figure 3: B/B_{MSY} **trends as estimated by seven individual COMs: Catch-MSY (a), CMSY (b), COM-SIR (c), mPRM (d), OCOM (e), SSCOM (f), and zBRT (g) . Shaded areas indicate 95% confidence intervals, the dotted line indicates B_{MSY}.**
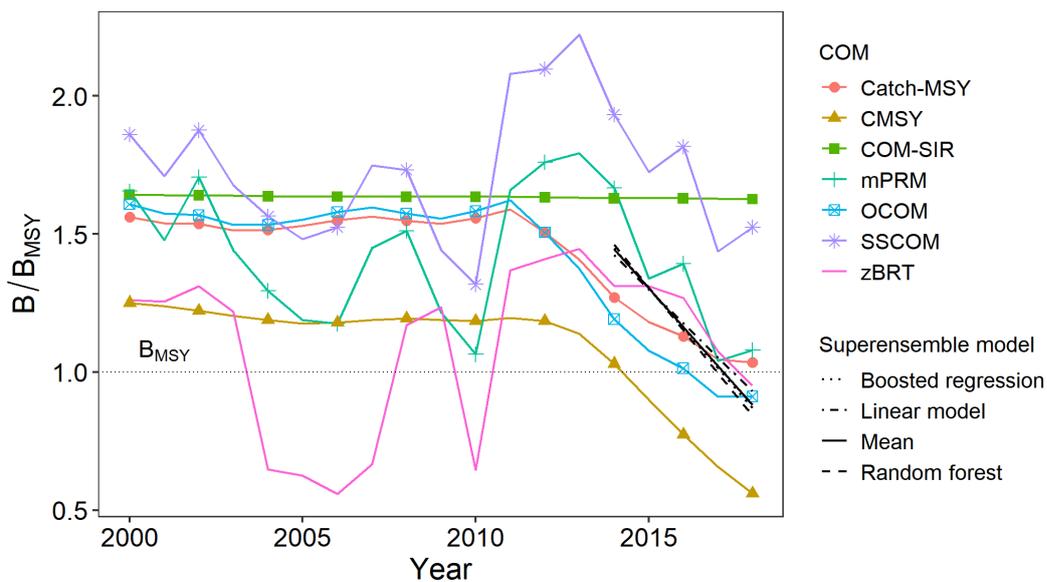
Figure 4: Results of the superensemble model estimates of mean and slope of B/B_{MSY} over the last 5 years of data, including their overall mean, overlaid on a truncated time-series of individual COM results. The horizontal dotted line indicates B_{MSY}.
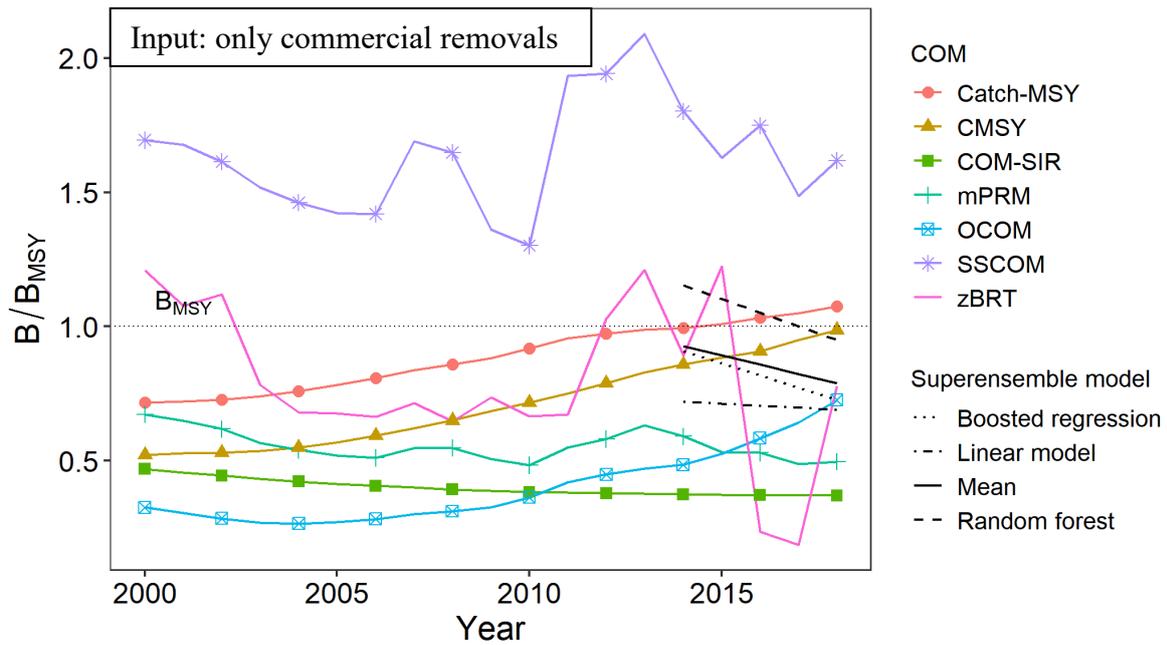
Figure 5: Model output when only the commercial removals time-series is used as input, and the recreational removals time-series is left out. Shown are the subsequent results of the superensemble model estimates of mean and slope of B/B_{MSY} over the last 5 years of data, including their overall mean, overlaid on a truncated time-series of individual COM results. The horizontal dotted line indicates B_{MSY}.
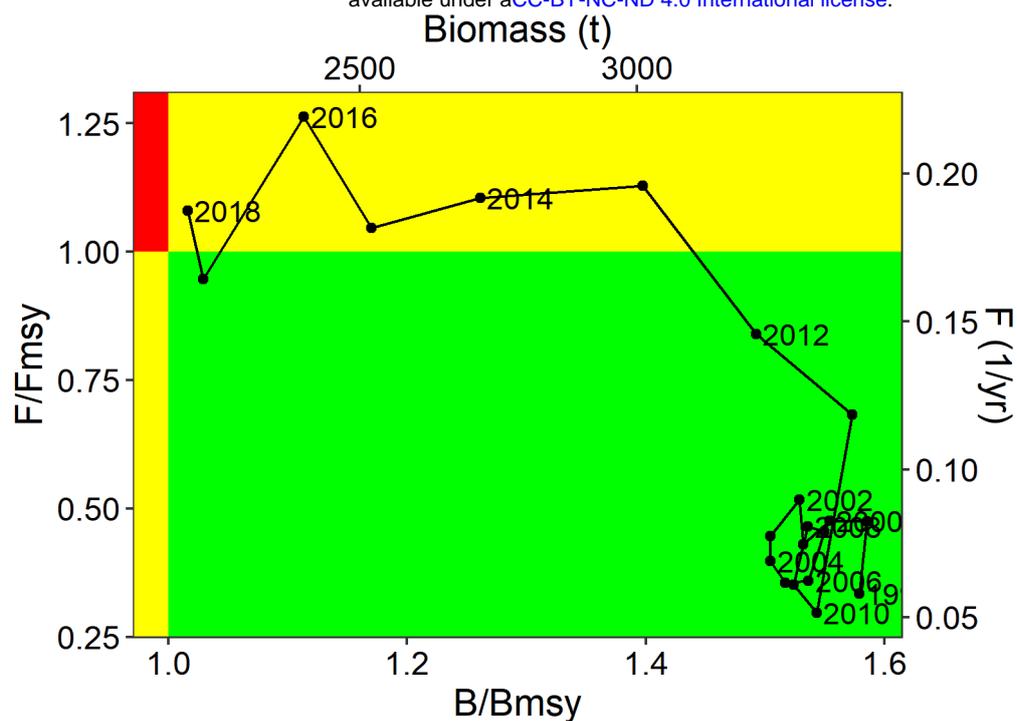
Figure 6: Kobe plot showing the weighted averages of B, B/B_{MSY}, F, and F/F_{MSY} for the years 1998 to 2018. The green area indicates healthy stock status, the yellow areas indicate that the stock is either overfished ($B/B_{\mathrm{MSY}} < 1$) or subject to overfishing ($F/F_{\mathrm{MSY}} > 1$), and the red area indicates that the stock is both overfished and subject to overfishing.
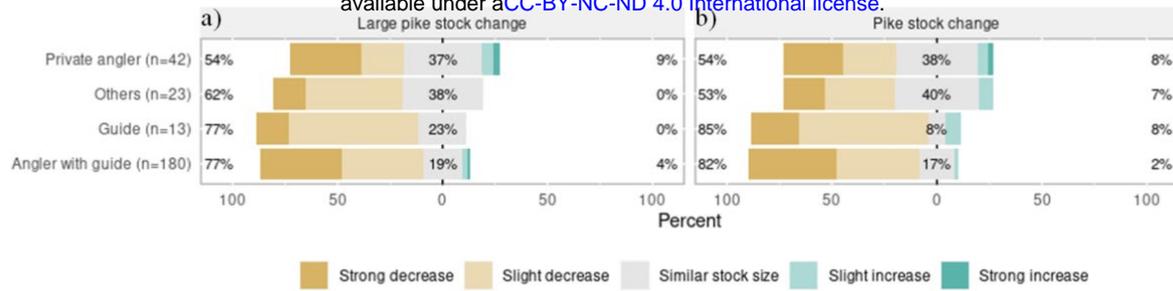
Figure 7: Stakeholder perceptions regarding the recent trends in the number of large pike of the Rügen stock (a) and the total size of the Rügen pike stock (b).