

1 **Exploring the status of the Indonesian deep demersal fishery using length-based stock**  
2 **assessments**

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23

24 **Abstract**

25 The deep demersal snapper-grouper fishery in Indonesia is a data-poor fisheries resource that  
26 provides food security and a source of income to millions globally. Owing to an ongoing crew-  
27 operated data recording system implemented in Indonesia since 2015, the stocks of this fishery  
28 can now be assessed using length-frequency data and updated life-history parameters. Here,  
29 we use two length-based methods, one that is fishery-specific and another that is more  
30 generalized, to assess the status of Indonesian stocks. Specifically, we develop a literature-based  
31 assessment method based on a patchwork of conventional approaches but tailored to the  
32 studied stocks, and compare it with a newly established and broadly applicable length-based  
33 Bayesian biomass estimation method (LBB). The methods were applied to 16 stocks from 4  
34 Indonesian Fisheries Management Areas and were compared based on simulations, as well as  
35 the convergence of the resulting stock status classification and uncertainty of the results.  
36 Analyzing the effect of using the literature-based species/family-specific life-history parameter  
37 values for asymptotic length ( $L_{inf}$ ) and relative natural mortality ( $M/K$ ) in LBB showed that  
38 different values do affect the estimated biomass indicator. Nevertheless, in more than half the  
39 cases, the stock status classification did not differ between the two methods, while LBB results  
40 became more reliable with narrower confidence limits. Simulations, as well as similar status  
41 indicators between the two models support the value of the literature-based approach as an  
42 assessment methodology for the Indonesian deep demersal fisheries. Narrower confidence  
43 ranges highlight the importance of using fishery-specific information when applying generalized  
44 stock assessment methods. While most catches had few immature fish, half of the assessed  
45 stocks were consistently shown to have low biomass, indicating that important Indonesian  
46 stocks are at high risk of overfishing.

47 **1. Introduction**

48 The Indonesian multispecies deep demersal fishery is a highly productive yet data-poor fishery  
49 in the tropics that is characterized by highly diverse catch composition with hundreds of species  
50 being caught (Bailey et al. 1987). This species complex mainly consists of snappers (Lutjanidae)  
51 and groupers (Epinephelidae) which play a key role as predators in the ecosystem. The snappers  
52 and groupers are of high quality with global demand, which support the livelihoods and food  
53 security of numerous local, small-scale fishing communities (Cesar 1996). The multitude of  
54 species in such tropical fisheries, as well as the lack of historical or current species-specific  
55 catches and no information on fishing effort and baseline population abundances, make  
56 assessments quite challenging, often leaving them under-managed, as in this Indonesian case  
57 study (Stobutzki et al. 2006; Fenner 2012). The deep demersal snapper-grouper fishery is  
58 managed based on total allowable catches (TACs) per species, which limit the number of fishing  
59 licenses per fishery management area (FMA). However, the system faces considerable data and  
60 implementation challenges, hence the characterization of the fishery as under-managed  
61 (Wibisono et al. 2021).

62 The Generic Knowledge Indicator (GKI), that has been developed to evaluate the state  
63 of knowledge of snapper and grouper fisheries around the world, has shown that Indonesia  
64 presents a medium quality of biology/ecology information and fisheries data, while the  
65 knowledge level regarding stock assessments is very low (Amorim et al. 2018). A first step  
66 towards bridging this knowledge gap regarding Indonesian fisheries would be the regular  
67 collection of detailed data that can facilitate the application of stock assessment methods. To  
68 that end, a crew-operated data recording system (CODRS) has been developed and  
69 implemented by Yayasan Konservasi Alam Nusantara Indonesia for the past 6 years for extensive  
70 catch data collection (geo-referenced commercial catch data and length distributions for more  
71 than a hundred species of the snapper-grouper deep demersal fishery) that can support length-

72 based stock assessments aiming to establish harvest control rules (Wibisono et al. 2019).  
73 Recording length-frequency (LF) data from commercial catches onboard, like in the CODRS, or  
74 at landing sites and markets is a cost-effective and straightforward methodology to attain the  
75 types of data required to estimate stock status, especially in data-poor fisheries (Pilling et al.  
76 2008; Mildemberger et al. 2017). The CODRS datasets have so far been used to update life-  
77 history parameters of the top 50 species (Wibisono et al. 2019). Also, to identify factors that  
78 point towards particular locations and combinations of fishing gear and habitat characteristics  
79 linked to catches with immature fishes (Wibisono et al. 2021).

80 The majority of fish stocks, globally and locally, are data-poor and lack the  
81 comprehensive information required to assess biomass and fishing mortality relative to  
82 reference points (Costello et al. 2012; Osio et al. 2015). Thus, the need to assess the numerous  
83 data-poor stocks around the world has led to the development of various catch-based (Cope  
84 2013; Froese et al. 2017), abundance-based (Froese et al. 2020), and length-based (Rudd &  
85 Thorson 2018) methods depending on the available datasets. In the case of Indonesia, the  
86 CODRS length data can be used in length-based models to assess the status of previously  
87 unassessed Indonesian stocks. The published analytical approaches aim to be simple and  
88 generically parameterized based on certain assumptions (e.g., Hordyk et al. 2015b; Ault et al.  
89 2019). Nevertheless, the use of such generic assessment methods requires caution as their  
90 potential out-of-context blanket application may result in erroneous outputs and misinformed  
91 management advice (Dowling et al. 2019). Since each method has its own assumptions and  
92 limitations, local knowledge and expert guidance is required for the appropriate tailoring to  
93 individual stocks or fisheries based on the literature (Pilling et al. 2008; Carruthers et al. 2014).

94 Given that the different stock assessment models have varying data demands and levels  
95 of performance, they may produce alternative perspectives on reference points when applied  
96 to the same data (Bouch et al. 2020; Chong et al. 2020; Pons et al. 2020) and, as a result, a

97 combination of methods to define a range of possible stock status estimates is encouraged for  
98 fisheries management (Chong et al. 2020). Regardless of whether the applied assessment  
99 methods are fishery-specific or more generalized, evaluating model performance can be  
100 challenging since the “true” stock status needs to be known (Cadrin & Dickey-Collas 2015), which  
101 is usually very rare for data-poor stocks (Froese et al. 2018a). In such cases, simulations show  
102 how well a method can reproduce known reference points. On simulated data, state-of-the-art  
103 models can correctly predict ~70% of mean lengths at infinite age and natural mortality relative  
104 to carrying capacity, within 95% confidence limits. Furthermore, they are over 90% accurate at  
105 predicting current stock biomass relative to unexploited stock biomass (Froese et al. 2018b).  
106 Relative biomass prediction can be accurate also on expert-assessed real-stock data (~76%).  
107 However, these models achieve lower performance at predicting other traits - e.g. fishing  
108 mortality relative to natural mortality (~50% accuracy) - also because of the larger discrepancy  
109 between expert estimations of these traits.

110         The present study provides species-specific assessments for 16 previously unassessed  
111 stocks of the Indonesian deep demersal snapper-grouper fishery using length-based life-history  
112 parameters in combination with catch length frequencies from the CODRS dataset. This  
113 particular fishery is used as the base to illustrate the implications of transitioning from  
114 generalized to fishery-specific assessment models. A highly customized length-based approach  
115 using literature studies that each highlight an aspect of the life-history of the studied fish  
116 populations is presented here. This fishery-specific method is then compared to a new more  
117 broadly applicable approach by Froese et al. (2018b) for estimating stock status using LF data  
118 from commercial catches: the length-based Bayesian biomass estimation method (LBB). In the  
119 case of LBB, a parameterization gradient and its effects on the model outcome are also  
120 examined, where we transition from running the model with the generalized default life-history  
121 settings (such as the asymptotic length  $L_{inf}$  and relative natural mortality  $M/K$ ) to incorporating

122 literature-based knowledge about the specific stocks analyzed. We ultimately aim to investigate  
123 whether these two approaches result in the same conclusions for management, and, if not,  
124 whether we can point to the most suitable approach based on simulations. The methods and  
125 assessment results presented here are expected to stimulate discussion among fisheries  
126 scientists on different modeling approaches, as well as among stakeholders in Indonesia  
127 regarding management options and decision-making.

128

## 129 **2. Materials and methods**

### 130 *2.1 Study area and fisheries*

131 Indonesia's demersal fishing grounds have high biodiversity, which is reflected in the  
132 multispecies nature of the catches (Pauly 1979; Wibisono et al. 2019). The Indonesian  
133 multispecies deep demersal fisheries operate in all of Indonesia's 11 fisheries management  
134 areas (FMAs 571, 572, 573, 711, 712, 713, 714, 715, 716, 717, 718) targeting more than a  
135 hundred species of snappers, groupers, emperors and other families at depths from about 50 to  
136 500 m. The most common gear types used by the numerous smaller or larger fishing vessels  
137 (from less than 5 and up to 100 gross tonnage GT; Stobutzki et al. 2006) are droplines, bottom  
138 longlines, or a mix of both gears, while traps and gillnets are far less common and often used in  
139 combination with hook and line gears.

140         The Indonesian deep demersal fisheries are being monitored on a continuous basis since  
141 2015 through the CODRS that collects data on species, catches, length composition, and fishing  
142 location of commercial vessels, aiming to address the existing data gap on the basic  
143 characteristics of the fishery (Wibisono et al. 2019). Approximately 4% (400 out of 10,000 boats)  
144 of the fishery is sampled by CODRS which covers all Indonesian FMAs and has produced over 3.5  
145 million fish images so far (Mous et al. 2020). While this may seem like a small sample, in a huge  
146 archipelagic country like Indonesia, it is not realistic to reach a much higher sample through a

147 privately funded project. Thus, even though we acknowledge the limitations of generalizing the  
148 results of this study, we maintain that this is an important first step to assess the status of  
149 previously unassessed Indonesian fish stocks.

150 In this study, commercial catch length frequencies collected through CODRS from 2016  
151 to the end of 2020 for 11 of the most abundant species (16 stocks, 4 different FMAs) were used  
152 to assess stock status by applying and comparing two computational methods, i.e. a highly  
153 customized length-based approach to stock assessment and a new generally applied approach  
154 by Froese et al. (2018b) for estimating stock status using LF data from commercial catches. While  
155 the comparison cannot identify which method is best, convergence of findings may be  
156 interpreted as robustness and perhaps even accuracy of either method, whereas divergence  
157 may shed a light on the reasons why the same data sometimes lead to different interpretations.  
158 Nevertheless, simulations were also performed to test the consistency and potential biases of  
159 both methods.

160

## 161 *2.2 Fishery-specific length-based approach to stock assessment*

162 The customized approach is based on four length-based life-history parameters: maximum size  
163  $L_{\max}$  (the largest fish observed in the catches of each species measured through the over 3.5  
164 million CODRS images), asymptotic size  $L_{\text{inf}}$  (the mean length in a cohort of infinite age), optimum  
165 harvest size  $L_{\text{opt}}$  (the length class with the highest biomass in an unexploited population) and  
166 size at maturity  $L_{\text{mat}}$  (the length class at which 50% of the individuals are mature). As  
167 documented in detail by Wibisono et al. (2019), the validated (checked for accuracy)  $L_{\max}$  values  
168 in the CODRS dataset for each species were used as the starting point to calculate  $L_{\text{inf}}$ ,  $L_{\text{opt}}$ , and  
169  $L_{\text{mat}}$  from known relationships. For all families, we used  $L_{\text{inf}} = 0.9 * L_{\max}$  based on a recent  
170 simulation approach developed to estimate life-history parameters from a meta-analysis of  
171 published values and relationships between individual parameters (Nadon & Ault 2016). Size at

172 maturity was different for each family, with  $L_{mat} = 0.59 * L_{inf}$  for deep water snappers (Lutjanidae)  
173 and  $L_{mat} = 0.46 * L_{inf}$  for deep water groupers (Epinephelidae: Newman et al. 2016). For emperors  
174 (Lethrinidae) and all other families, we used  $L_{mat} = 0.5 * L_{inf}$  based on the review of published  
175 ranges and meta-analyses (Binohlan & Froese 2009; Grandcourt et al. 2011; Younis et al. 2020).  
176 The values of the life-history parameters were compared with available data from other studies  
177 done in Indonesia and at comparable latitudes before being applied in the length-based  
178 assessments of the fisheries (Wibisono et al. 2019).

179 For the estimation of  $L_{opt}$ , we used the Beverton (1992) estimator:

$$180 \quad L_{opt} = L_{inf} \left( \frac{3}{3 + \frac{M}{K}} \right) \quad [1]$$

181 To obtain family-specific estimates for M and K, we searched the literature for values of M, K,  
182 or M/K (some studies provided M/K as a ratio, without specifying the numerator and the  
183 denominator). We used publications with estimates for M and K values which were based on  
184 ageing studies, or on meta-analyses of such studies (e.g. Aldonov & Druzhinin 1979; Loubens  
185 1980; Matthews & Samuel, 1991; Honebrink 2000; Newman 2002; Newman & Dunk 2003;  
186 Grandcourt et al. 2005; Grandcourt et al. 2006; Fry et al. 2006; Ebisawa & Ozawa 2009; Mehanna  
187 et al. 2012; Newman et al. 2016). The M/K values were compared with the accepted range as  
188 published for Type II Teleosts including tropical snappers (Prince et al. 2015) and with published  
189 values of M/K for specific tropical Indo Pacific species and families (Prince et al. 2019) that are  
190 important in the Indonesian deep demersal fisheries. All the life-history parameter values and  
191 invariants used in this study are presented in Table 1.

192 Stock status was assessed using an indicator for the Spawning Potential Ratio (SPR:  
193 Quinn & Deriso 1999), i.e. the estimated spawning stock biomass (SSB) as a fraction of the SSB  
194 of the pristine population [ratio between the modeled population biomass at estimated fishing  
195 mortality F and the modeled adult population biomass at F = 0 (pristine biomass)] (Meester et



196 al. 2001). A standard, age-based population dynamics model (see Supplement) was applied to  
197 calculate the adult biomass starting from an arbitrary number of recruits. SPR was calculated on  
198 a per-recruit basis from the life-history parameters  $M$  (natural mortality),  $F$ ,  $K$ , and  $L_{inf}$ , as well  
199 as from gear selectivity parameters. The instantaneous total mortality ( $Z = M + F$ ) was estimated  
200 with the equilibrium Beverton-Holt estimator from length data using the Ehrhardt & Ault (1992)  
201 bias-correction. For this estimation, we used the length range of the catch length-frequency  
202 distribution starting with the length that is 5% higher than the modal length and ending with the  
203 99<sup>th</sup> percentile, as it is an accepted practice to disregard the right hand side of the LF that is too  
204 close to  $L_{inf}$  (Sparre & Venema 1998).  $F$  was calculated as the difference between  $Z$  and  $M$ ,  
205 assuming full selectivity for the size range starting at modal length and ending with the largest  
206 fish in the catch. We assumed an S-shaped (logistic) selectivity curve, with 99% selectivity  
207 achieved at modal length, and with the length at 50% selectivity halfway between the first  
208 percentile and modal length of the catch length-frequency distribution.

209 To calculate the length-dependent  $M$  to be used in the SPR calculation, we used an  
210 empirical formula that relates  $M$  to length (from CODRS data) and growth (literature-derived  $K$   
211 and  $L_{inf}$  calculated from the CODRS  $L_{max}$  based on published relationship) characteristics (Gislason  
212 et al. 2010):

$$213 \quad M = \frac{1.733 * K * L_{\infty}^{1.44}}{L^{1.61}} \quad [2]$$

214 (reworked from its original notation as a log-transformed model)

215 Comparison with published values of natural mortality for the main families present in  
216 the tropical deep water demersal fisheries of the Indo-Pacific (Newman et al. 2016) showed that  
217 the relationship by Gislason et al. (2010) resulted in unrealistically high estimates of  $M$  for most  
218 families targeted here, except for Carangidae (jacks). Tropical deep-water snappers, groupers  
219 and emperors in the Indo-Pacific have low natural mortality rates, usually between 0.1 and 0.2

220 per year, and often below 0.15 per year (Newman 2002; Newman & Dunk 2003; Grandcourt et  
221 al. 2006; Newman et al. 2016). Therefore, to correct this, a family-dependent multiplicative  
222 correction factor (CF) was applied to the Gislason et al. (2010) relationship, as follows ( $L_{inf}$  and  $L$   
223 are species-specific from CODRS data, while CF and K are family-specific):

$$224 \quad M = \frac{CF * 1.733 * K * L_{\infty}^{1.44}}{L^{1.61}} \quad [3]$$

225 Most of the studies that we reviewed presented length-independent estimates for  $M$   
226 that were valid for the larger, exploited size range of each species. For the estimation of CF for  
227 each family (Table 1), we assumed that these published estimates for  $M$  applied to  $L_{opt}$ . We  
228 support that this simplification is justifiable, since around  $L_{opt}$ , the Gislason et al. (2010) curve  
229 flattens out, meaning that the dependency between length and mortality is less strong in this  
230 size range. Under the assumption that published values of  $M$  apply to  $L_{opt}$ , and using published  
231 values for  $K$  together with the estimates for  $L_{inf}$  resulting from our CODRS data, we calculated  
232 the values for the CF (Table 1). It should be noted that the introduction of the Correction Factor  
233 did not put the modified Gislason et al. (2010) relation outside its original confidence limits. The  
234 CF values we found average 0.69, ranging between 0.5 and 0.97, whereas the lower confidence  
235 limit for the (back-transformed) confidence limit is 0.56. Hence, with one exception (grunts),  
236 the modified intercept remains within the 95% confidence interval presented by Gislason et al.  
237 (2010).

238 Another complication is that catch curve analysis assumes a constant total mortality ( $Z$ )  
239 over the size range that is used for its estimation, whereas Gislason et al. (2010) demonstrates  
240 that natural mortality varies with size. To work out this inconsistency, we applied the adjusted  
241 Gislason et al. (2010) empirical relationship to the length classes over which we estimated  $Z$ ,  
242 then we calculated the average  $M$  over these size classes, and applied that average to the size

243 range over which we estimated Z. Outside this size range, we assumed a varying M following the  
244 modified Gislason et al. (2010) relation.

245 A set of fishery indicators described below were derived from the literature-based  
246 method to facilitate management advice (Figure 1). A total population biomass B of half the  
247 pristine population biomass  $B_0$  was considered to be the desired reference point for stock size,  
248 minimizing the impact of fishing (Froese et al. 2016). Using the SPR and  $B/B_0$  estimates from our  
249 own data set, this target reference point correlates with an SPR of about 40%, agreeing with  
250 Harford et al. (2019) and not far from but slightly more conservative than the Wallace and  
251 Fletcher (2001) reference point. Therefore, we considered that when SPR is lower than the limit  
252 of 25% ( $0.313 B/B_0$ ) then the stock is at high risk indicating overexploitation that may cause  
253 severe decline of the stock if fishing effort is not reduced. If SPR is equal to or greater than 25%  
254 ( $0.313 B/B_0$ ) and lower than 40% ( $0.5 B/B_0$ ) then the stock is considered to be at medium risk,  
255 while if SPR is equal to or greater than 40% ( $0.5 B/B_0$ ) then the risk that the fishery will cause  
256 further stock decline is small. To facilitate comparison of the two methods' (see section 2.3)  
257 results, we turned SPR to  $B/B_0$  assuming that  $B/B_0 = \text{SPR}/0.8$  (Froese et al. 2019).

258 Apart from the SPR, the current status of stocks was expressed through the percentage  
259 of immature and a subset of large mature (mega-spawners: fish larger than 1.1 times the  $L_{opt}$ ;  
260 Froese 2004) fish in the catch. With 0% immature fish in the catch as an ideal target (Froese  
261 2004), a target of 10% or less is considered a reasonable indicator for sustainable (or safe)  
262 harvesting (Fujita et al. 2012; Vasilakopoulos et al. 2011). Zhang et al. (2009) consider 20%  
263 immature fish in the catch as an indicator for a fishery at risk, in their approach to an ecosystem  
264 based fisheries assessment. Results from meta-analyses of multiple fisheries showed stock  
265 status over a range of stocks to fall below precautionary limits at 30% or more immature fish in  
266 the catch (Vasilakopoulos et al. 2011). The fishery is considered at high risk when more than  
267 50% of the fish in the catch are immature (Froese et al. 2016). Hence, if the percentage of

268 immature fish in the catch is equal to or lower than 10%, then the stock is considered here to  
269 be at low risk since at least 90% of the fish in the catch are mature specimens that have spawned  
270 at least once before they were caught. If the immature fish in the catch are greater than 10%  
271 and up to 30%, the risk level is considered to be medium, while more than 30% of immature  
272 individuals indicate that the stock is at high risk of overharvesting of juveniles that have not had  
273 the chance to reproduce before capture. Regarding mega-spawners, if more than 30% of the  
274 catch consists of mega-spawners (and other fisheries do not catch the much smaller fish), it is  
275 indicated that this fish population is in good health (low risk). If more than 20% and less than or  
276 exactly 30% of the population consists of mega-spawners, then the risk level of recruitment  
277 overfishing through over harvesting of the mega spawners is medium, while the risk is high if  
278 20% or less of the population are mega-spawners.

279 Another status indicator used was the “trade limit” length which was derived from the  
280 general buying behavior of processing companies as the minimum size of the fish accepted by  
281 the trade. Comparing the trade limit with  $L_{mat}$  may indicate incentives from traders for either  
282 unsustainable targeting of juveniles or more sustainable targeting of mature fish that have  
283 spawned at least once. We consider a trade limit at 10% below or above  $L_{mat}$  to be significantly  
284 different from it and we consider trade limits to provide incentives for targeting specific sizes of  
285 fish through price differentiation, as it has been shown that the larger individuals of a species  
286 attain higher market prices and are therefore selectively removed because they may yield higher  
287 profit (Tsikliras & Polymeros 2014). If the trade limit for a species is lower than  $0.9 * L_{mat}$  it is  
288 indicated that the trade encourages the capture of immature fish impairing sustainability, and  
289 therefore the risk level is considered high. If the trade limit is above  $1.1 * L_{mat}$  then there seems  
290 to be a low risk for recruitment overfishing. The risk is medium for intermediate values of trade  
291 limit.

292 While this literature-based method was specifically tailored to assess the status of  
293 Indonesian stocks of the deep demersal fishery, we do recognize that it may form a framework  
294 that could be customized to different fisheries and followed by other researchers when the only  
295 available data are length frequency distributions and  $L_{max}$ . The series of steps to be followed to  
296 apply the literature-based assessment framework are presented in Figure 1.

297

### 298 *2.3 Length-based Bayesian biomass estimation method*

299 The Length-based Bayesian biomass estimation method (LBB: Froese et al. 2018b) is an approach  
300 for estimating stock status in data-poor situations using LF data from commercial catches. The  
301 method is outlined below; for a more detailed description, the reader is referred to Froese et al.  
302 (2018b; 2019). The version of the code used (LBB\_33a) can be found online at  
303 <http://oceanrep.geomar.de/43182/>, along with a simple but detailed user guide.

304 In LBB, it is assumed that the fish body grows in length according to the von Bertalanffy  
305 (1938) growth equation, as expressed by Beverton and Holt (1957),

$$306 \quad L_t = L_{inf} [1 - e^{-K(t-t_0)}] \quad [4]$$

307 with  $L_t$  being the length at age  $t$ ,  $L_{inf}$  the asymptotic length,  $K$  the growth rate by which  $L_{inf}$  is  
308 approached and  $t_0$  the theoretical age at zero length.

309 The LBB model uses the annual LF data to simultaneously make an inference for four  
310 parameters over the age range represented in the LF sample with a Bayesian Monte Carlo  
311 Markov Chain approach: (i)  $L_{inf}$ , (ii) the length at first capture at which 50% of the individuals are  
312 retained by the gear ( $L_c$ ), (iii) the mean relative natural mortality ( $M/K$ ), and (iv) fishing mortality  
313 ( $F/K$ ) over the past years. Priors for  $L_{inf}$ , relative total mortality ( $Z/K$ ), and selectivity ( $S_L$ ) are  
314 derived from the aggregated LF samples across years, while the prior for  $M/K$  is assumed to be  
315 around 1.5 (1.2-1.8) which is typical for adults of species that grow throughout their lives  
316 (Hordyk et al. 2015b; Froese et al. 2016). For species that have different life-history strategies

317 with M/K ratios that diverge from the assumed range (Thorson et al. 2017), and if an appropriate  
318  $L_{inf}$  estimate is available from an independent study, then these values can be introduced by the  
319 user to decrease uncertainty in the LBB results. To investigate the uncertainty in the output  
320 biomass indicators associated with the initial estimates of the life-history parameters, we ran  
321 the LBB model four times for each stock using: 1) no user-defined prior as input to the model,  
322 2) user-defined prior as input for  $L_{inf}$  as presented above in Section 2.2, 3) user-defined prior as  
323 input for M/K that was estimated from the customized length-based approach presented above  
324 in Section 2.2, and 4) both  $L_{inf}$  and M/K priors set by the user.

325 When the above parameters are known, current stock status in the form of current stock  
326 biomass B relative to the unexploited stock size  $B_0$  can be estimated from standard fisheries  
327 equations (Beverton & Holt 1957, 1966) and  $L_{c\_opt}$  (i.e. the  $L_c$  value that would result in  $L_{opt}$   
328 becoming the mean length in the catch, with the highest catch and biomass for the respective  
329 fishing mortality and a minimized impact on size structure; Froese et al. 2016) can also be  
330 calculated.

331 If the fish are fully selected by the gear, the curvature of the right side of the catch  
332 samples is a function of Z/K. This curve is expressed by the following equation (Quinn & Deriso  
333 1999),

$$334 \quad N_L = N_{Lstart} \left( \frac{L_{inf} - L}{L_{inf} - L_{start}} \right)^{Z/K} \quad [5]$$

335 for  $L > L_{start}$  and  $L < L_{inf}$  in which  $N_L$  is the number of fish that survive to length L,  $N_{Lstart}$  is the  
336 number of individuals at length  $L_{start}$  with full selection, above which all individuals entering the  
337 gear are retained by the gear, and Z/K is the ratio of the total mortality rate Z to the somatic  
338 growth rate K.

339 The lengths that are partially selected by the gear are a function of gear selectivity (here  
340 assumed to be knife-edged selectivity, i.e. by a trawl or any gear with a trawl-like selection curve)

341 for the species in question, as given by the following ogive (i.e., the curve that represents the  
 342 proportion of individuals being caught by the gear at length) function,

$$343 \quad S_L = \frac{1}{1+e^{-a(L-L_c)}} \quad [6]$$

344 with  $S_L$  being the fraction of fish that are caught by the gear at length  $L$ , and  $a$  describing the  
 345 steepness of the ogive (Sparre & Venema 1998; Quinn & Deriso 1999).

346 The difference equation below is fitted to the whole catch-in-numbers curve to estimate  
 347  $L_{inf}$ ,  $L_c$ ,  $a$ ,  $M/K$ , and  $F/K$  at the same time,

$$348 \quad N_{L_i} = N_{L_{i-1}} \left( \frac{L_{inf} - L_i}{L_{inf} - L_{i-1}} \right)^{\frac{M}{K} + \frac{F}{K} S_{L_i}} \quad [7] \quad \text{and} \quad C_{L_i} = N_{L_i} S_{L_i} \quad [8]$$

349 with  $L_i$  being the number of individual fish at length  $i$ ,  $L_{i-1}$  being the number of fish at the previous  
 350 length, and  $C$  referring to the number of individuals that are vulnerable to the gear and are  
 351 proportionally represented in the catch (Froese et al. 2018b).

352  $L_{opt}$  is calculated using Equation [1] and  $L_{c\_opt}$  can be obtained from,

$$353 \quad L_{c\_opt} = \frac{L_{inf} \left( 2 + 3 \frac{F}{M} \right)}{\left( 1 + \frac{F}{M} \right) \left( 3 + \frac{M}{K} \right)} \quad [9]$$

354 and finally an index of relative biomass depletion for the exploited part of the population  $B/B_0$   
 355 is then calculated from the following equation (Beverton & Holt 1966),

$$356 \quad \frac{B}{B_0} = \frac{\frac{CPUE'}{R}}{\frac{B'_0 > L_c}{R}} \quad [10]$$

357 in which  $CPUE'/R$  is an index of catch per unit of effort that results from an index of yield-per-  
 358 recruit expressed as a function of  $L_c/L_{inf}$ ,  $F/K$ ,  $M/K$ , and relative fishing mortality  $F/M$  and  $B'_0 >$   
 359  $L_c/R$  denotes the relative biomass in the exploited phase of the population if no fishing takes  
 360 place (Froese et al. 2018b).  $B/B_0$  from LBB was used as an indicator of stock status where, in line  
 361 with SPR limits from the fishery-specific method, the stock is considered to be at high risk of  
 362 overexploitation when  $B/B_0 < 0.313$ , at medium risk when  $0.313 \leq B/B_0 < 0.5$ , and at small risk  
 363 when  $B/B_0 > 0.5$  (see also section 2.2).

364

#### 365 *2.4 Simulations*

366 For verification purposes in the absence of knowing “true” stock status, simulated LF data with  
367 known underlying parameter values were used to run both models and compare the results.  
368 Simulated data were used to assess model performance and validate the consistency between  
369 the two methods, following the practice reported in Froese et al. (2018b). These data were  
370 produced using equation [5] and assuming that the number of survivors per length followed a  
371 standard dynamic for full net selectivity (Quinn & Deriso 1999). Parameter values were set to  
372 simulate 3 hypothetical stocks representing full exploitation, with length at first capture ranging  
373 from 18 to 35 cm and with similar life histories to the Indonesian deep demersal stocks ( $L_{inf}$  from  
374 35 to 120 cm and  $M/K$  from 1.33 to 1.6). The two stock assessment methods analyzed here,  
375 were checked to produce comparable results for the estimates of  $B/B_0$  and  $SPR$  turned to  $B/B_0$   
376 (Table S1).

377

### 378 **3. Results**

379 In total, 16 stocks of the Indonesian deep demersal fisheries were analyzed with two different  
380 length-based assessment methods. The stocks belonged to 11 snapper, grouper, and croaker  
381 species of 4 fisheries management areas (FMAs) of the Indonesian waters: 573 Savu and Timor  
382 Sea, 712 Java Sea, 713 Makassar Strait, and 718 Arafura Sea. Figures 2-3 show the catch length  
383 frequency distributions for the CODRS samples collected in 2020 and life-history parameters  
384 ( $L_{mat}$ ,  $L_{opt}$ ,  $L_{inf}$ ,  $L_{max}$ ) as estimated with the customized length-based approach for the 16 analyzed  
385 Indonesian stocks. Table 2 shows the literature-based species/family-specific  $L_{inf}$  and  $M/K$  values  
386 that were used as input (priors) to the LBB model, as well as the resulting parameter values  
387 (median and ~95% confidence limits).



388           Based on the fishery-specific length-based approach presented here (Table 3), 9/16  
389 (56%) stocks were in a poor state with spawning potential ratio (SPR) values below 0.25, while  
390 4/16 (25%) stocks were in a medium state with SPR values between 0.25 and 0.39, and only 3/16  
391 (19%) stocks were in a good state with SPR values at or over 0.40. A low percentage ( $\leq 10\%$ ) of  
392 immature individuals was found in the catch of 10/16 (63%) stocks, while for 3/16 (19%) stocks  
393 the percentage of immatures was 11-30% or over 30%. Most of the stocks (14/16, 88%) had a  
394 very low number of mega-spawners ( $\leq 20\%$ ), while the catches of only two stocks consisted of  
395 over 20 and 30% of very large mature fish. Based on the species-specific trade limit results, 5/11  
396 (45%) species seemed to run a high risk of unsustainable exploitation of immature individuals,  
397 while 2/11 (18%) and 4/11 (36%) species ran a medium and low risk, respectively.

398           According to the LBB model run without user-defined priors (LBB  $B/B_0$ , Table 3), 10/16  
399 (63%) stocks had poor relative biomass status with  $B/B_0$  values below 0.313, 3/16 (19%) stocks  
400 were in moderate biomass state (between 0.313 and 0.49), and another 3/16 (19%) could be  
401 considered healthy with  $B/B_0$  values at or over 0.5. Running the LBB model using a prior for  $L_{inf}$   
402 as estimated from the customized length-based approach gave different results in some cases,  
403 with 8/16 (50%) stocks being in a poor state, 3/16 (19%) as medium status, and 5/16 (31%) in a  
404 healthy state. Informing the LBB model with an M/K prior that was estimated with the tailored  
405 length-based approach resulted in all of the analyzed stocks (100%) shown to have very low  
406 biomass levels compared to the pristine population biomass. Finally, when running LBB with  
407 both the  $L_{inf}$  and M/K priors from the customized length-based approach (Table 3; Figure 4),  
408 12/16 (75%) stocks were shown to have unhealthy biomass levels, while 2/16 (13%) seemed to  
409 be in a medium (the snappers *Lutjanus russelli* and *Paracaesio gonzalesi*) and good (the grouper  
410 *Epinephelus areolatus* and the snapper *Lutjanus vitta*) biomass status. Based on the range of the  
411 confidence limits (Table 3), it was evident that the uncertainty in the LBB  $B/B_0$  estimates was by  
412 far the highest when the model was run using the  $L_{inf}$  from the customized length-based

413 approach as a user-defined prior, followed by running LBB with no set priors and then by using  
414 both  $L_{inf}$  and M/K priors. Uncertainty was reduced the most when running LBB with an M/K prior  
415 derived from the highly customized length-based approach. All results of the LBB analyses are  
416 given in the supplement (Figures S1-S136).

417 The four independent LBB runs resulted in the same poor status categorization for 7 out  
418 of the 16 (44%) analyzed stocks (LBB  $B/B_0$ , Table 3). For the remaining 9 stocks, the LBB runs  
419 resulted in two (4/16 stocks, 25%) or three (5/16 stocks, 31%) different status classifications for  
420 each stock. The highest agreement (but with quite high uncertainty) of the current method and  
421 the LBB model regarding biomass status, SPR, and  $B/B_0$  respectively, was when LBB was run  
422 without any user-defined priors (11/16 stocks, 69%). Out of these 11 stocks whose biomass  
423 status were in agreement with both methods, 8/11 (73%) were shown to have low biomass,  
424 2/11 (18%) had medium biomass levels, and only 1/11 (9% - the snapper *Paracaesio gonzalesi*)  
425 seemed to be healthy. Using the M/K prior and both  $L_{inf}$  and M/K resulted in the same status  
426 categorization for 9/16 (56%) stocks (with low and moderate uncertainty, respectively), while  
427 using only the  $L_{inf}$  prior showed an agreement of the two methods in 7/16 (44%) stocks (with the  
428 highest uncertainty).

429 Half of the studied stocks (8/16) were consistently categorized as having a poor biomass  
430 status, meaning that the current method and at least 3 out of the 4 LBB runs resulted in a low  
431 biomass indicators. These stocks were the orange croaker *Atro Bucca brevis*, banded grouper  
432 *Epinephelus amblycephalus*, Malabar blood snapper *Lutjanus malabaricus* (in all three studied  
433 FMAs), emperor red snapper *L. sebae*, brownstripe, red snapper *L. vitta*, and pinjalo *Pinjalo*  
434 *pinjalo*. No stocks were consistently shown to have healthy biomass levels using the assessment  
435 methods tested here.

436

437 **4. Discussion**

438 In multispecies fisheries, like the deep demersal snapper-grouper fishery in Indonesia, the high  
439 diversity of species that share common morphological characteristics and life-history traits  
440 makes the identification and reporting at the species level challenging. This results in poor  
441 resolution of official catch statistics, hindering the application of stock assessment methods.  
442 Using the species-specific data collected through the CODRS over the past five years, as well as  
443 the estimated life-history characteristics for the main target species (Wibisono et al. 2019), it is  
444 now possible to apply length-based stock assessment methods to this fishery. This study  
445 explored the stock status results derived from two methods, a simple customized literature-  
446 based assessment framework based on conventional approaches (Figure 1), and a more  
447 generally applicable model (LBB: Froese et al. 2018b) for the analysis of length frequency  
448 distributions from commercial catches. The transition from a fishery-specific to a generalized  
449 method was examined and different parameterization levels of the latter method were tested,  
450 ranging from running LBB with the generalized default life-history settings to using literature-  
451 based values tailored to the analyzed stocks. The performance of both methods was tested with  
452 simulated stocks, showing that LBB gave biomass estimates close to the “true” simulation values  
453 and within the 95% confidence limits in all three simulated stocks (100%), while the fishery-  
454 specific method was accurate in two stocks (67%). In two out of the three simulated stocks, LBB  
455 overestimated biomass, whereas the fishery-specific method underestimated biomass in all  
456 three stocks which makes it a more precautionary approach. The results are expected to  
457 stimulate a focused discussion among stakeholders on the different methodologies, as well as  
458 the status of the fisheries.

459           The highly customized length-based assessment approach described here is the product  
460 of working with Indonesian species-specific CODRS datasets, cross-checking references to obtain  
461 family-specific life-history parameters that apply to Indo-Pacific species, and tweaking published  
462 methods (e.g., Gislason et al. 2010) to incorporate insights of others. The aim has been to

463 develop a literature-based model that can be used specifically to assess the stock status of  
464 Indonesian deep demersal fisheries. Ultimately, as illustrated in Figure 1, this assessment  
465 framework can be followed by other researchers when the only available information is length  
466 data and  $L_{max}$ . For comparison and to discuss the transition from a fishery-specific to a  
467 generalized method and vice versa, we decided to also include LBB, i.e. the Length-based  
468 Bayesian biomass estimation method of Froese et al. (2018b). LBB is a more broadly applicable  
469 model that can nevertheless be tailored to the studied stocks when the user chooses to specify  
470 priors for known parameters, such as the asymptotic length  $L_{inf}$  and relative natural mortality  
471  $M/K$ . It has been suggested, and it is confirmed here, that carefully tuning generic assessment  
472 approaches to the examined stocks using species-specific parameters may enhance their  
473 reliability (Dowling et al. 2019). LBB has been increasingly applied to Asian fisheries (Ju et al.  
474 2020; Liang et al. 2020; Wang et al. 2020; Zhang et al. 2020; Kindong et al. 2020; Yue et al. 2021)  
475 and it has been gaining consideration as a plausible method in international commissions like  
476 the International Commission for the Conservation of Atlantic Tunas ICCAT. However, as it is a  
477 recently developed assessment method, this is among the first published comparisons of LBB  
478 with other length-based methods (Pons et al. 2020).

479         As observed in this study, it is to be anticipated that the performance of various  
480 compared methods may be different and often result in opposing status estimations based on  
481 the tested fishing intensity trends, depletion levels, data availability and resolution, and life-  
482 histories (Rosenberg et al. 2018; Pons et al. 2020; Bouch et al. 2020). The snapper and grouper  
483 stocks that are mostly included here (as well as a croaker species), cover a broad spectrum of  
484 depletion, and generally have small differences in their life-histories. As it has been previously  
485 shown, the biggest source of uncertainty in stock status estimates is the uncertainty in life-  
486 history parameters (Babcock et al. 2013; Mannini et al. 2020). Fundamental linkages between  
487 life-history parameters have long been identified in fishes (Beverton & Holt 1959; Beverton

488 1963). The ratio of natural mortality over growth rate ( $M/K$ ) is one of these so called Beverton-  
489 Holt invariants (Charnov 1993). In species whose LF distributions contain only few individuals  
490 that survive to approximate  $L_{inf}$ ,  $M/K$  is typically close to 1.5 as assumed by default for the  $M/K$   
491 prior in the LBB model (Froese et al. 2018b; Froese et al. 2019). Nevertheless, this invariant, that  
492 has probably been conserved through natural selection (Beverton & Holt 1959), may in fact be  
493 quite different among taxonomic groups based on their life-history strategies and would be  
494 better defined on a taxon level as we have outlined here in the customized length-based  
495 approach (Prince et al. 2015; Thornson et al. 2017).

496         Users of the LBB approach are encouraged to replace the default setting of  $M/K$  with  
497 their own informed values when they have strong evidence that  $M/K$  lies outside the assumed  
498 default range of 1.2-1.8 for the analyzed stock (Froese et al. 2018b; Froese et al. 2019). Using  
499 default priors is understandable in truly data-poor situations when available data cannot  
500 support the implementation of data-rich assessment methods, but when some parameters  
501 specific to the analyzed stocks are known, then their use is highly encouraged (Bouch et al.  
502 2020). In the present study, we followed this advice to use informed family-specific  $M/K$  values  
503 ( $\sim 0.8$ ) that were based on  $M$  and  $K$  information from various sources and reflected the low  
504 natural mortality and slow/modest growth rates of the deep-water tropical demersal snappers  
505 and groupers (e.g. Prince et al. 2015; Newman et al. 2016). We then tested the effect of this  
506 tweak on the results of the model and particularly the estimated relative biomass, which is the  
507 main target output of LBB (Table 1). Natural mortality ( $M$ ) may affect stock assessment derived  
508 reference points and consequently management advice. Biased  $M$  values impact the  
509 information contained in the biomass index, since higher  $M$  for the same total mortality ( $Z$ ) will  
510 correspond to lower fishing mortality ( $F$ ) given the catch, and ultimately higher biomass (Punt  
511 et al. 2021). Indeed, based on model sensitivity, when the lower  $M/K$  values were used as priors,  
512 LBB estimated a higher relative fishing mortality and a lower stock status, albeit with

513 considerably lower uncertainty, hence more reliable results, which is the goal of using informed  
514 user-defined priors. In more than half of the cases in our study that did not cause a change in  
515 the stock status classification. Thus, the use of literature-based species/family-specific life-  
516 history parameters is encouraged, as it is shown that when setting M/K within this range of  
517 values, the influence on the estimation of relative biomass, which is the main target output of  
518 LBB, is minor (Froese et al. 2018b), while the reliability of the results is greatly increased.

519 Asymptotic length is also a critical parameter for reliable estimates of fishing mortality  
520 and SPR (Hordyk et al. 2016), with higher values of it leading to an overestimation of exploitation  
521 rate and a subsequent underestimation of stock status, and vice versa. Indeed, based on model  
522 sensitivity, using lower  $L_{inf}$  priors from the customized length-based approach as an input to LBB  
523 consistently resulted in higher relative biomass for all stocks. The same pattern was also found  
524 by Nadon & Ault (2016). However, although  $L_{inf}$  is estimated from  $L_{max}$ , which is the most  
525 observable parameter in the set of life-history parameters, the LBB results with a literature-  
526 based  $L_{inf}$  prior were highly uncertain, mostly owing to the Malabar red snapper *Lutjanus*  
527 *malabaricus* (FMA 718), Russell's snapper *L. russelli* (FMA 718), and Vanuatu snapper *Paracaesio*  
528 *gonzalesi* (FMA 573). In these three cases, the literature-based  $L_{inf}$  prior that was inserted in LBB  
529 was so much lower than what LBB would have calculated using the default prior settings (Table  
530 2), that the right hand side of the length distribution was truncated (Figures S58, S67, S113). This  
531 seems to be causing the high uncertainty or in some cases completely stopping the LBB  
532 calculations.  $L_{inf}$  is derived from  $L_{max}$  in both methods compared here as  $L_{max}$  has been shown to  
533 be a reasonable predictor of  $L_{inf}$  (Froese et al. 2019). However, the customized length-based  
534 approach calculates asymptotic length as  $L_{inf} = 0.9 * L_{max}$ , while LBB estimates  $L_{inf}$  from the  
535 available data, while considering a prior that, if not provided by the user, is derived from  
536 aggregated LF data within the range of  $0.9 * \text{median } L_{max} - 1.2 * \text{median } L_{max}$  (Froese et al. 2018b;  
537 Froese et al. 2019). This might explain why running LBB with  $L_{inf}$  priors results in the lowest

538 agreement between the two methods, as well as high uncertainty. For example, for the Malabar  
539 blood snapper *L. malabaricus* in FMA 712, the median  $L_{max}$  was 89 cm, so LBB picked a prior of  
540 80.1-106.8 (that is 103; Figures S47, S48) when no user-defined prior was provided to the model,  
541 while for *L. malabaricus* in FMA 713, the median  $L_{max}$  was 90.5 cm, so LBB picked a prior of 81.45-  
542 108.6 (that is 104; Figures S56, S57). However, the literature-based  $L_{inf}$  value for this species was  
543 85 cm, i.e.  $0.9 * L_{max}$  ( $L_{max}=94$  cm), and when this was inserted as a prior to LBB, the resulting  
544  $B/B_0$  estimates were more uncertain. Both lower ( $\leq 85$  cm) and higher (up to 105.4 cm)  $L_{inf}$   
545 estimates have been reported for this species in the west Pacific Ocean (Martinez-Andrade  
546 2003).

547 On the other hand, running LBB with an M/K prior alone, or both  $L_{inf}$  and M/K priors  
548 estimated with the customized length-based approach, provided more reliable results with  
549 higher agreement between the two methods and low uncertainty. Inserting no priors into LBB  
550 had the highest agreement across assessment scores, but with quite high uncertainty, and  
551 therefore it would better be avoided when fishery-specific information is available like in this  
552 study. Consequently, when both agreement of the two methods and uncertainty of indicators  
553 are to be considered as performance criteria, and when species/family/stock-specific values are  
554 available, then the best approach is to run LBB using as priors the tailored and customized M/K  
555 values, or both  $L_{inf}$  and M/K. Communicating to managers the uncertainty in fisheries scientific  
556 advice that stems from uncertainty in the estimated parameters owing to measurement,  
557 process, or model errors, may allow them to evaluate trade-offs between different management  
558 strategies (Rosenberg & Restrepo 1994).

559 LBB simulation testing highlighted that the uncertainty in estimated  $B/B_0$  values that are  
560 compatible with the LF pattern was considerably higher in lightly exploited stocks (Froese et al.  
561 2018b), which was also the case with the Russell's snapper *Lutjanus russelli*, and brownstripe  
562 red snapper *L. vitta* (FMAs 712 and 718) in the present study (see Supplement). The biomass

563 estimates of these stocks, along with the Vanuatu snapper *Paracaesio gonzalesi* and areolate  
564 grouper *Epinephelus areolatus*, were highly uncertain and thus presented the most  
565 contradicting results between the two methods and the different LBB runs. The observed  
566 discrepancies between the two methods could also be linked to the fact that  $B/B_0$  was estimated  
567 for the exploited length range, while SPR used SSB. As pointed out by Froese et al. (2018b), “...if  
568  $L_c$  is significantly larger than mean length at first maturity, the depletion of biomass in the  
569 exploited length range may be much stronger than the depletion of spawning biomass...”. In any  
570 case, these stocks would benefit from further assessment possibly with longer time-series data  
571 and/or species- and area-specific life-history studies. Although longer time-series do not  
572 necessarily guarantee better estimates, it has been shown that ten years of length data may  
573 result in greater accuracy and precision of biomass estimates by length-based methods,  
574 especially for species that are medium or longer-lived (Rudd & Thorson 2018). The highest  
575 consensus between the methods and among LBB runs was reached in stocks that had low  
576 relative biomass. This could be related to the finding of Pons et al. (2020) who demonstrated  
577 that LBB performed better in cases of stocks that have relatively low to medium stock sizes.

578         Regarding stock status, various studies have investigated the levels of SPR to be used as  
579 target reference points, and it is generally accepted that an SPR value of approximately 40% is  
580 sustainable for most species (Hordyk et al. 2015a and references therein). Based on the biomass  
581 indicators ( $B/B_0$  and SPR), half of the examined stocks were consistently shown to be fished at  
582 unsustainable levels, while none of the 16 stocks could be unanimously considered as healthy  
583 using both methods. Only the Vanuatu snapper *Paracaesio gonzalesi* was found to have a  
584 healthy biomass by the customized length-based approach and two of the four LBB runs.  
585 Babcock et al. (2013) also tested the sensitivity of length-based indicator results for the spear  
586 gun fishery of groupers and snappers in Belize and suggested that when stocks are shown to be  
587 overfished or experiencing overfishing across a range of plausible life-history parameters, then



588 improved management with enforced size or catch limits would be recommended. This finding  
589 is worrying about the future of the most abundant stocks of the deep demersal fisheries in  
590 Indonesia and highlights the need for effective management, with potential enforcement of  
591 science-based harvest control rules that determine how much fishing can take place, based on  
592 indicators of the targeted stock status (Bellido et al. 2020). Such actions may contribute to  
593 ensuring the long-term sustainability of these vital resources of high commercial value which  
594 support the livelihoods and food security of numerous local communities. Although much like  
595 biomass estimations, the trade limit and mega-spawners indicators were not encouraging for  
596 the Indonesian deep demersal fisheries, the percentage of immature individuals in the catch  
597 was overall low, indicating that from this aspect the fishery seemed to be at lower risk (Froese  
598 et al. 2016). Nevertheless, attention should be paid to FMAs 712 and 713 where a high  
599 proportion of immature Malabar red snapper and pinjalo individuals seem to be getting caught.  
600 These areas, i.e. the Java Sea – Makassar Strait, have been identified by Wibisono et al. (2021)  
601 as juvenile hotspots and were therefore suggested to be prioritized in fisheries management  
602 plans as they overlap with common fishing grounds.

603 Tailoring assessment methods to the specific life-histories of the analyzed stocks and  
604 taking into account data quality and model assumptions is expected to increase the reliability of  
605 the results. To that end, a length-based approach to stock assessment that is especially tailored  
606 to the Indonesian deep demersal snapper-grouper fishery but can also be modified for other  
607 fisheries was presented here, along with the more broadly applicable LBB method of Froese et  
608 al. (2018b) for comparison. The results of the customized method agreed in most cases with  
609 LBB, while using the literature-based species/family-specific  $L_{inf}$  and  $M/K$  values in LBB improved  
610 the certainty of the stock status estimates, thus supporting the value of the customized method  
611 presented here as a tailored assessment framework especially for Indonesian fisheries. Both  
612 methods told the same story for at least half of the examined stocks pointing out that, in terms

613 of biomass, important stocks of this fishery are at high risk and would need to be managed at  
614 more sustainable levels. It is important to continue collecting data through the CODRS to be able  
615 to monitor status and trends over time. After all, “[m]anaging a stock without knowing its  
616 condition might be like driving with a windshield blacked out; crashes can be expected” (Fenner  
617 2012).

618

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626

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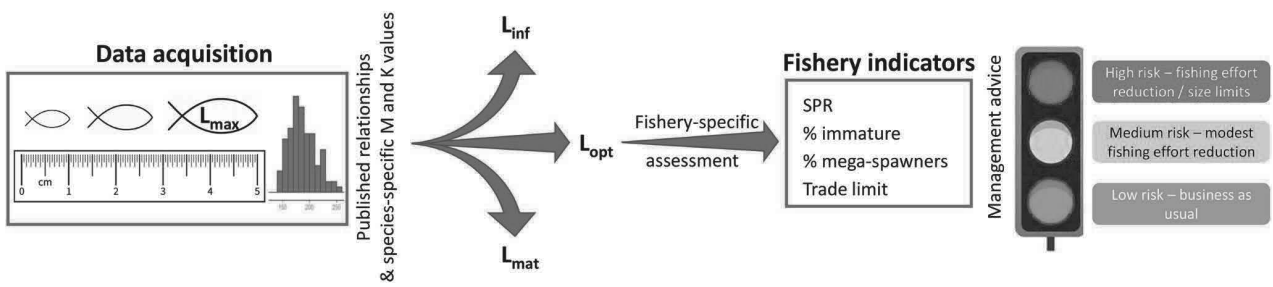
839 **Figure legends**

840 **Figure 1.** Schematic of the different steps to be followed to apply the literature-based method  
841 to assess stock status with only available information the maximum length ( $L_{max}$ ) and length-  
842 frequency distribution.  $L_{inf}$ : asymptotic size,  $L_{opt}$ : optimum harvest size,  $L_{mat}$ : size at maturity,  
843 SPR: spawning potential ratio.

844 **Figure 2.** Catch length frequency distributions, life-history parameters and reference points as  
845 estimated with the highly customized length-based approach presented here for orange  
846 croaker *Atrubucca brevis* (FMA 718), banded grouper *Epinephelus amblycephalus* (FMA 718),  
847 areolate grouper *E. areolatus* (FMAs 712 and 718), crimson snapper *Lutjanus erythropterus*  
848 (FMA 573), and Malabar red snapper *L. malabaricus* (FMAs 712, 713, 718). Fish photos are  
849 from the crew-operated data recording system (CODRS; Wibisono et al. 2019). SPR: spawning  
850 potential ratio.  $L_x-codrs = L_{max}$ , i.e. the largest specimen in the CODRS database.

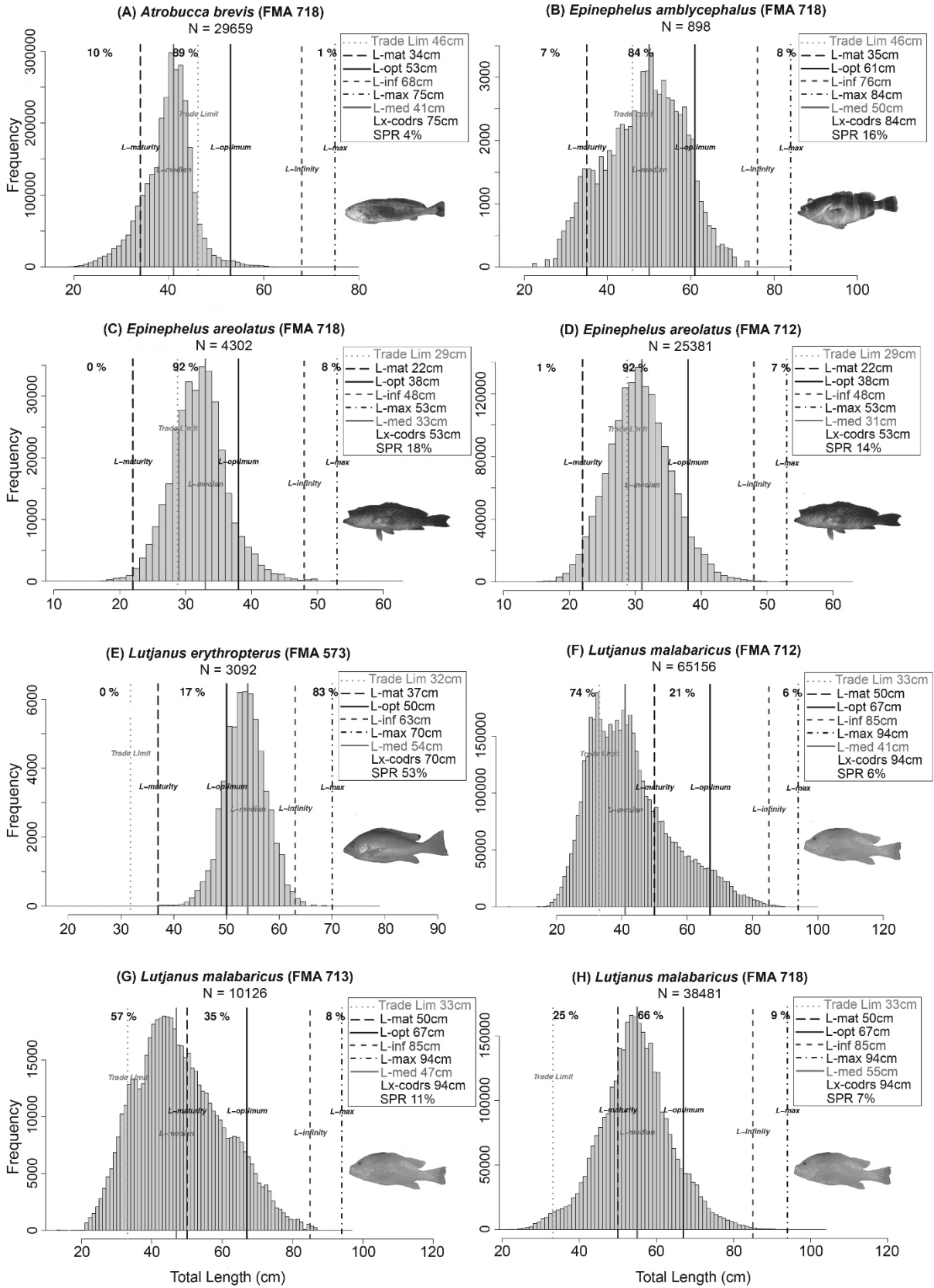
851 **Figure 3.** Catch length frequency distributions, life-history parameters and reference points as  
852 estimated with the highly customized length-based approach presented here for Russell's  
853 snapper *Lutjanus russelli* (FMA 718), emperor red snapper *L. sebae* (FMA 718), brownstripe red  
854 snapper *L. vitta* (FMAs 712, 713, 718), Vanuatu snapper *Paracaesio gonzalesi* (FMA 573),  
855 slender pinjalo *Pinjalo lewisi* (FMA 573), and pinjalo *Pinjalo pinjalo* (FMA 712). Fish photos are  
856 from the crew-operated data recording system (CODRS; Wibisono et al. 2019). SPR: spawning  
857 potential ratio.  $L_x-codrs = L_{max}$ , i.e. the largest specimen in the CODRS database.

858 **Figure 4.** The relative biomass  $B/B_0$  (black curve) with approximate 95% confidence limits  
859 (shaded grey area) for each of the 16 analyzed stocks (LBB runs using literature-based  $L_{inf}$  and  
860  $M/K$  priors), with indication of a proxy for the biomass that can deliver the maximum  
861 sustainable yield  $B_{msy}$  (green dashed line) and a proxy for  $0.5 B_{msy}$  (red dotted line). The  
862 number in the parenthesis indicates the Fisheries Management Area of the stock.



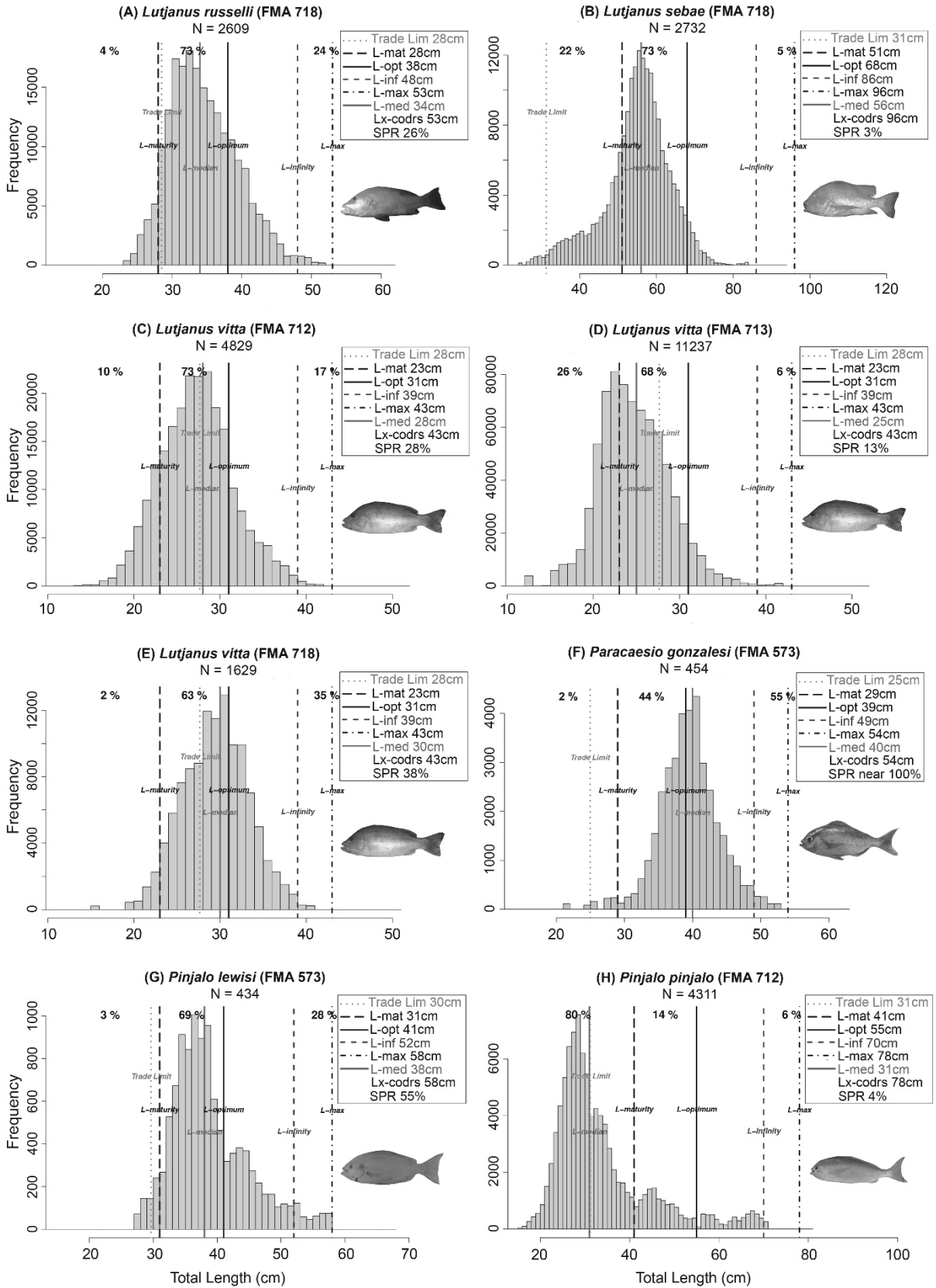
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864 Figure 1. Dimarchopoulou et al.



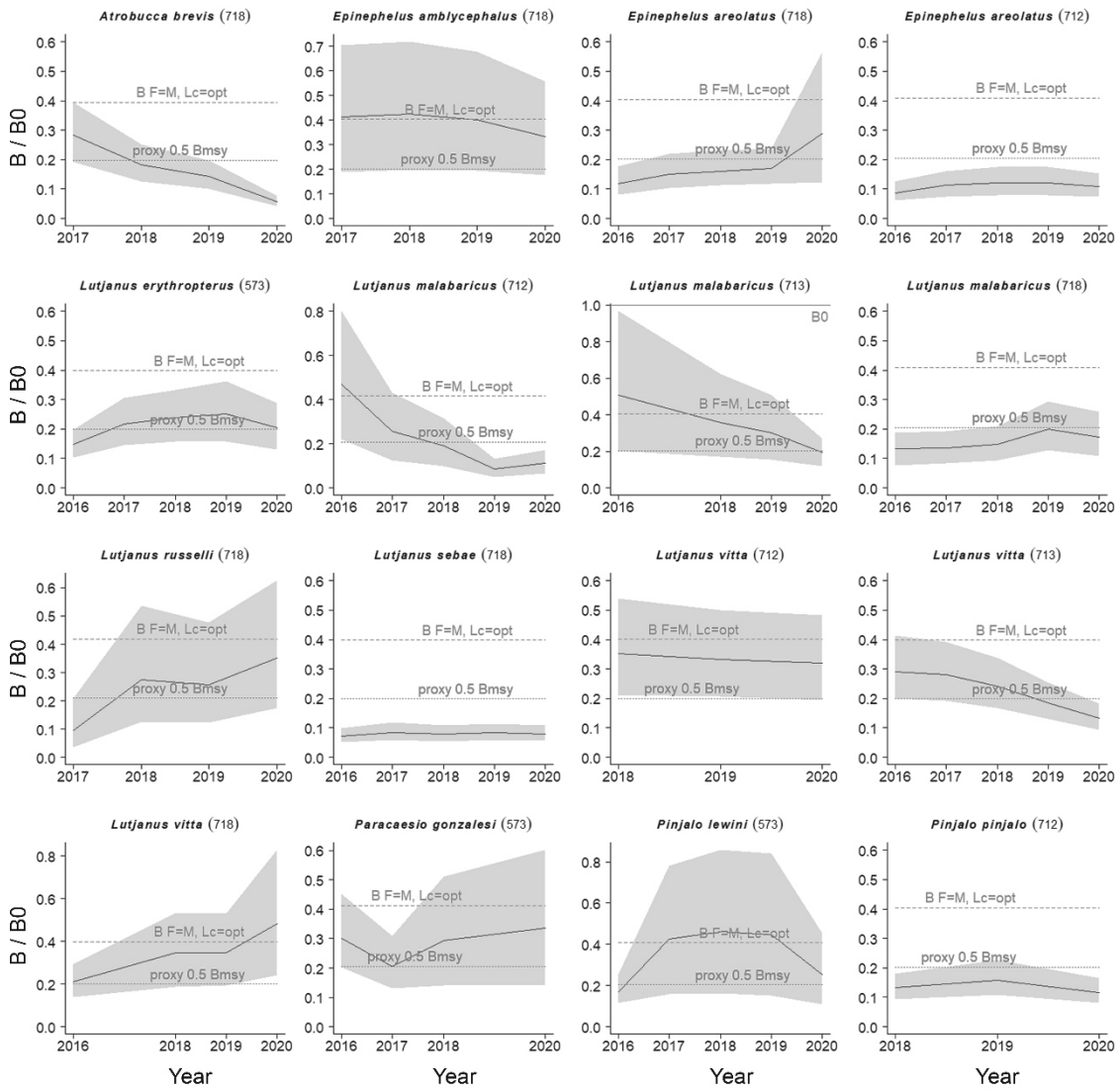
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866 Figure 2. Dimarchopoulou et al.



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Figure 3. Dimarchopoulou et al.



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871 **Figure 4. Dimarchopoulou et al.**

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873



874 **Table 1.** Life-history parameter values and invariables, and a correction factor (CF) to adjust  
 875 length-dependent natural mortality M (Gislason et al. 2010) to estimated M at optimum harvest  
 876 size  $L_{opt}$ .

Deep Demersal Target Families	$L_{inf}/L_{max}$	Mortality		Growth		Life-history Invariant values		
		M ( $L_{opt}$ )	CF	K	$(M/K)_{opt}$	$L_{opt}/L_{inf}$	$L_{mat}/L_{opt}$	$L_{mat}/L_{inf}$
<u>Snappers</u>	0.90	0.18	0.67	0.23	0.79	0.79	0.75	0.59
<u>Groupers</u>	0.90	0.12	0.71	0.16	0.75	0.80	0.58	0.46
<u>Emperors</u>	0.90	0.15	0.60	0.21	0.70	0.81	0.62	0.50
<u>Grunts</u>	0.90	0.13	0.50	0.24	0.54	0.85	0.59	0.50
<u>Jacks</u>	0.90	0.35	0.97	0.22	1.61	0.65	0.77	0.50
<u>Others</u>	0.90	0.18	0.69	0.21	0.88	0.77	0.66	0.50

877

878 **Table 2.** Input and output life-history parameters for 16 species of the Indonesian deep demersal fisheries, analyzed with a highly customized length-  
879 based approach presented in this study (current method) and also with the LBB model (four independent runs: a. no user-defined priors set, b. an  $L_{inf}$   
880 prior as estimated with the customized length-based approach was inserted into the model, c. an M/K prior as estimated with the customized length-  
881 based approach was inserted into the model, d. both informed priors were inserted into the model: Froese et al. 2018b). The literature-based  $L_{inf}$  and  
882 M/K values of the customized length-based approach were used an input (priors) to LBB runs b, c, and d. The resulting median estimated parameter  
883 values of the LBB model are presented along with their ~95% confidence limits of the Monte Carlo estimates in parentheses. FMA: Fisheries  
884 Management Area.  $L_{inf}$ : asymptotic length. M/K: natural mortality over growth rate.

Species	Family	FMA	Customized length-based approach		LBB $L_{inf}$				LBB M/K			
			$L_{inf}$	M/K	No user-defined priors	$L_{inf}$ prior	M/K prior	$L_{inf}$ & M/K priors	No user-defined priors	$L_{inf}$ prior	M/K prior	$L_{inf}$ & M/K priors
<i>Atrobucca brevis</i>	croaker	718	68	0.88	69.5 (68.5-70.6)	68.7 (67.6-69.8)	69.6 (68.6-70.7)	68.8 (67.9-70)	1.48 (1.2-1.73)	1.51 (1.26-1.72)	0.903 (0.73-1.02)	0.898 (0.75-1.02)
<i>Epinephelus amblycephalus</i>	grouper	718	76	0.75	73.5 (72.4-74.7)	75.6 (74.5-76.3)	72.7 (71.4-74)	74.4 (72.9-76.1)	1.41 (1.22-1.64)	1.85 (1.67-2.03)	0.772 (0.62-0.92)	0.778 (0.64-0.91)
<i>Epinephelus areolatus</i>	grouper	718	48		49.4 (48.9-50.1)	48.6 (48-49.3)	49.5 (49-50.2)	48.6 (48-49.3)	1.45 (1.18-1.72)	1.4 (1.11-1.69)	0.739 (0.6-0.89)	0.757 (0.6-0.89)
		712			48.7 (48.2-49.1)	47.7 (47.2-48.2)	48.7 (48.1-49.4)	47.7 (47.2-48.3)	1.18 (0.98-1.43)	1.13 (0.88-1.38)	0.682 (0.55-0.81)	0.686 (0.55-0.81)
<i>Lutjanus erythropterus</i>	snapper	573			70	65.6 (65.2-66)	68 (67.3-69.4)	65.4 (65.1-65.9)	68.6 (67.2-70.1)	1.61 (1.4-1.86)	1.76 (1.55-2.03)	0.877 (0.76-1)
<i>Lutjanus malabaricus</i>	snapper	712	85	0.79	103 (101-105)	86.4 (85.4-87.1)	103 (101-105)	86.4 (85.2-87.4)	1.07 (0.85-1.35)	0.71 (0.49-0.1)	0.704 (0.56-0.82)	0.613 (0.49-0.75)
		713			104 (102-106)	86.8 (85.8-87.8)	104 (102-106)	87 (85.8-88)	1.32 (1.05-1.63)	1.28 (1.1-1.47)	0.747 (0.62-0.91)	0.731 (0.6-0.86)

		718		95.2 (93.4-96.8)	88.2 *(87.3-89.3)	95.9 (94.3-97.4)	88.2 (87-89.1)	1.18 (0.83-1.4)	1.39 *(1.12-1.72)	0.734 (0.6-0.87)	0.695 (0.55-0.86)
<i>Lutjanus russelli</i>	snapper	718	48	52 (51.6-52.5)	48.8 (48.3-49.3)	52.3 (51.8-52.8)	48.7 (48.3-49.3)	1.33 (1.16-1.46)	1 (0.88-1.14)	0.626 (0.48-0.76)	0.592 (0.45-0.73)
<i>Lutjanus sebae</i>	snapper	718	86	87.7 (86.1-89.2)	87.6 (86.4-89.2)	87.9 (86.6-89.3)	88.3 (86.7-89.5)	1.75 (1.44-2.01)	1.75 (1.49-1.98)	0.842 (0.69-0.98)	0.852 (0.71-1.01)
<i>Lutjanus vitta</i>	snapper	712	39	42.7 (42.1-43.1)	40.2 (39.7-40.6)	42.7 (42.1-43.5)	40.1 (39.6-40.7)	1.59 (1.42-1.86)	1.48 (1.31-1.69)	0.811 (0.65-0.91)	0.814 (0.69-0.97)
		713		44.1 (43.4-44.8)	40.2 (39.7-40.8)	44.2 (43.5-44.9)	40.3 (39.7-40.8)	1.65 (1.44-1.96)	1.69 (1.42-1.93)	0.84 (0.71-0.79)	0.856 (0.72-0.99)
		718		45.9 (44.9-46.7)	40.3 (39.8-40.8)	45.9 (44.9-46.9)	40 (39.7-40.5)	1.61 (1.35-1.81)	1.45 (1.25-1.63)	0.804 (0.68-0.96)	0.841 (0.68-0.96)
<i>Paracaesio gonzalesi</i>	snapper	573	49	51.6 (50.9-52.3)	48 (47-48.6)	51.7 (50.8-52.6)	48.3 (47.4-49.1)	1.11 (0.87-1.37)	0.979 (0.7-1.11)	0.706 (0.58-0.87)	0.652 (0.5-0.76)
<i>Pinjalo lewisi</i>	snapper	573	52	59.9 (58.9-61.3)	53 (52.2-53.9)	60 (58.8-61.1)	52.7 (52-53.6)	1.68 (1.41-1.93)	1.6 (1.29-1.85)	0.802 (0.67-0.95)	0.719 (0.58-0.82)
<i>Pinjalo pinjalo</i>	snapper	712	70	70.9 (70.2-72.2)	71 (70.1-71.9)	71.1 (70.1-72)	71.1 (70.1-72)	1.52 (1.2-1.79)	1.4 (1.13-1.67)	0.76 (0.62-0.87)	0.756 (0.64-0.89)

885

886 **Table 3.** Results of the length-based assessments for 16 species of the Indonesian deep demersal fisheries. The data were analyzed with a highly  
887 customized length-based approach presented in this study (current method) and also with the LBB model (four independent runs: a. no user-defined  
888 priors set, b. an  $L_{inf}$  prior as estimated with the customized length-based approach was inserted into the model, c. an M/K prior as estimated with the  
889 customized length-based approach was inserted into the model, d. both informed priors were inserted into the model: Froese et al. 2018b). Presented  
890 values refer to the year 2020 (exceptions in which values are for 2019 are shown with an asterisk). Median estimated parameter values of the LBB  
891 model are presented along with their ~95% confidence limits of the Monte Carlo estimates in parentheses. FMA: Fisheries Management Area.  $B/B_0$ :  
892 current stock biomass relative to pristine population biomass.  $L_{max}$ : maximum recorded length in the dataset (cm).  $L_{inf}$ : asymptotic length. M/K: natural  
893 mortality over growth rate. SPR: Spawning Potential Ratio. Red values indicate poor stock status, orange values show medium status and green values  
894 represent good status. For details see the Materials and Methods section.

Species	Family	FMA	Customized length-based approach						LBB $B/B_0$			
			Immatures (%)	Mega-spawners (%)	Trade limit (cm)	$L_{max}$	SPR	SPR to $B/B_0$	No user-defined priors	$L_{inf}$ prior	M/K prior	$L_{inf}$ & M/K priors
<i>Atrobucca brevis</i>	croaker	718	10	0	46	75	0.04	0.05	0.06 (0.04-0.08)	0.06 (0.05-0.08)	0.02 (0.01-0.03)	0.02 (0.02-0.03)
<i>Epinephelus amblycephalus</i>	grouper	718	7	2	46	84	0.16	0.2	0.53 (0.1-1)	0.13 (0.02-0.51)	0.26 (0.12-0.4)	0.21 (0.13-0.35)
<i>Epinephelus areolatus</i>	grouper	718	0	3	29	53	0.18	0.23	0.28 (0.13-0.43)	0.49 (0.2-1.14)	0.19 (0.09-0.31)	0.53 (0.14-1.24)
		712	1	2			0.28	0.35	0.18 (0.14-0.24)	0.19 (0.12-0.29)	0.09 (0.06-0.13)	0.1 (0.07-0.13)
<i>Lutjanus erythropterus</i>	snapper	573	0	34	32	70	0.53	0.66	0.45 (0.25-0.71)	0.35 (0.22-0.5)	0.18 (0.11-0.24)	0.14 (0.1-0.19)
<i>Lutjanus malabaricus</i>	snapper	712	74	2	33	94	0.06	0.08	0.11 (0.06-0.19)	0.25 (0.12-0.41)	0.05 (0.03-0.07)	0.12 (0.07-0.18)
		713	57	3			0.11	0.14	0.13	0.39	0.06	0.18

		718	25	3					(0.07-0.24)	(0.1-0.8)	(0.04-0.1)	(0.1-0.26)
							0.07	0.09	0.01 (0-0.3)	0.9 *(0.09-3.1)	0.04 (0.02-0.08)	0.05 (0.03-0.09)
<i>Lutjanus russelli</i>	snapper	718	4	10	28	53	0.26	0.33	0.82 (0.23-1.72)	0.86 (0.24-2.28)	0.23 (0.15-0.34)	0.38 (0.19-0.65)
<i>Lutjanus sebae</i>	snapper	718	22	1	31	96	0.03	0.04	0.31 (0.19-0.44)	0.31 (0.21-0.42)	0.08 (0.06-0.11)	0.09 (0.06-0.12)
<i>Lutjanus vitta</i>	snapper	712	10	7			0.28	0.35	0.48 (0.23-0.78)	0.74 (0.1-1.75)	0.19 (0.14-0.27)	0.29 (0.17-0.45)
		713	26	2	28	43	0.13	0.16	0.17 (0.12-0.23)	0.3 (0.17-0.5)	0.07 (0.05-0.09)	0.12 (0.08-0.16)
		718	2	11			0.38	0.48	0.43 (0.21-0.63)	0.88 (0.29-1.88)	0.16 (0.11-0.23)	0.62 (0.27-1.19)
<i>Paracaesio gonzalesi</i>	snapper	573	1	23	25	54	~1	1.25	0.53 (0.16-1)	0.82 (0.002-4)	0.29 (0.18-0.49)	0.43 (0.2-0.72)
<i>Pinjalo lewisi</i>	snapper	573	3	15	30	58	0.55	0.69	0.12 (0.08-0.16)	0.26 (0.18-0.37)	0.04 (0.03-0.05)	0.11 (0.08-0.15)
<i>Pinjalo pinjalo</i>	snapper	712	80	4	31	78	0.04	0.05	0.09 (0.06-0.14)	0.09 (0.06-0.13)	0.03 (0.02-0.04)	0.03 (0.02-0.04)



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