

Assessing the sensitivity of data-limited methods (DLMs) to the estimation of life-history parameters from length–frequency data

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Abstract: Data-limited methods (DLMs) in stock assessment may provide potential critical information for data-limited stock management. However, the sensitivity of those methods to life-history parameters is largely unknown, resulting in extra uncertainty and consequent risks. In the present study, we designed six parallel workflows (WFs) to incorporate classic and state-of-the-art methods of estimating life-history parameters and examined their influences on the assessment of small yellow croaker (*Larimichthys polyactis*) in Haizhou Bay, China. The sensitivity was evaluated with three objectives: (i) the evaluation of stock status with the spawning potential ratio following different assumptions; (ii) the length-based harvest control rules derived from three management procedures; and (iii) the management performance of these harvest control rules with simulation of management strategy evaluation. The results showed considerable sensitivity regarding the three objectives to the estimations with different WFs, indicating the previous practice of credulously accepting empirical values and indiscriminately selecting references are inadvisable. We also identified the most appropriate WFs used for different purposes with limited data, aiming to provide more reliable inputs for effective fisheries management.

Résumé : Les méthodes de traitement de données limitées (MDL) utilisées dans l'évaluation de stocks peuvent fournir de l'information potentiellement clé pour la gestion de stocks pour lesquels les données sont limitées. La sensibilité de ces méthodes aux paramètres du cycle biologique est généralement inconnue, ce qui se traduit par une incertitude accrue et les risques qui en découlent. Nous avons conçu six flux de travail (FT) parallèles pour incorporer des méthodes classiques et de pointe d'estimation de paramètres du cycle biologique et examiné leur influence sur l'évaluation de la courbine jaune (*Larimichthys polyactis*) dans la baie de Haizhou (Chine). L'évaluation de la sensibilité avait trois objectifs, soit (i) l'évaluation de l'état du stock par l'estimation du rapport du potentiel de frai pour différentes hypothèses; (ii) les règles de contrôle des prises basées sur la longueur découlant de trois procédures de gestion; et (iii) le rendement de la gestion de ces règles de contrôle des prises avec simulation de l'évaluation de stratégies de gestion. Les résultats révèlent une sensibilité considérable concernant ces trois objectifs aux estimations avec différents flux de travail, qui indique que la pratique passée de tenir pour acquises les valeurs empiriques et de choisir des références sans discrimination n'est pas recommandable. Nous avons également cerné les flux de travail les mieux adaptés pour différentes fins en présence de données limitées, dans le but de fournir des données d'entrée plus fiables pour une gestion efficace des pêches. [Traduit par la Rédaction]

Introduction

Over 90% of the fish stocks in the world are managed without formal stock assessment, including the majority of fisheries in the developing countries (Costello et al. 2012). The failure of conducting defensible stock assessment is due to the lack of sufficient data supporting the estimation of reference points and stock status (Pilling et al. 2009). This, in a long term, seriously aggravates the vulnerability of global marine ecosystem, since most of the global production is contributed by the unassessed fisheries (FAO 2016). Data-limited methods (DLMs) are deemed to be feasible approaches to fill the gap of traditional stock assessment methods, and some DLMs are already used for stock management in developed countries (ICES 2012; Hilborn and Ovando 2014; Newman et al. 2014; Edwards 2015; Froese et al. 2011). Their mechanisms were normally less sound, but their performances were often sat-

isfactory compared with the data-rich methods (Carruthers et al. 2016; Chrysafi and Kuparinen 2016; Carruthers et al. 2014). However, since most of DLMs are designed for different data-limited conditions, they should be evaluated for their performances with regards to input data before being implemented for developing management regulations.

For most data-limited fisheries, length–frequency data are among the most readily available (Quinn and Deriso 1999) and are widely used for traditional assessment approaches. Compared with age composition data, length–frequency data do not require tedious work for ageing fishes, but are in many cases equally functional thanks to well-developed length-based methods (e.g., Beverton and Holt 1957; Pauly and Morgan 1987; Gulland and Rosenberg 1992). They can be used for estimating parameters such as asymptotic length (L_{inf}) and growth parameter (K) of the von Bertalanffy growth function (VBGF) (von Bertalanffy 1938).

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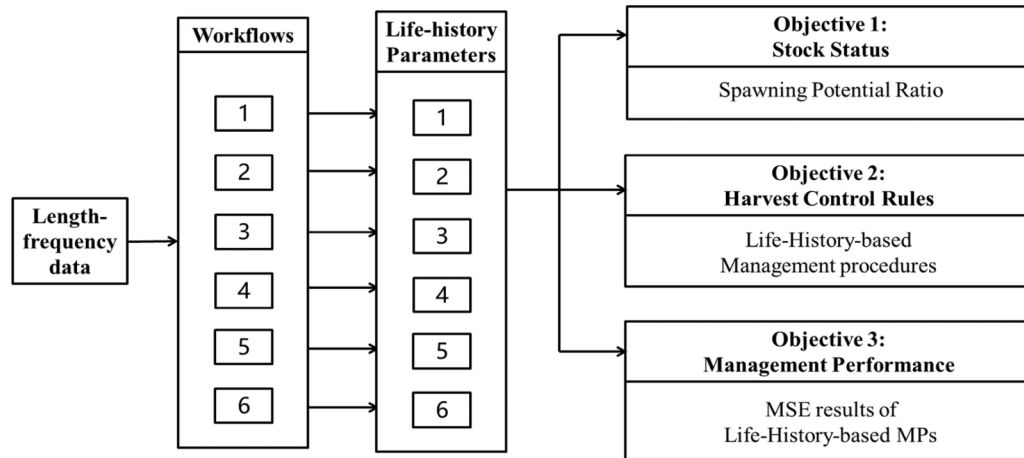
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Fig. 1. Complete schematic of the work design. MSE, management strategy evaluation; MPs, management procedures.



Individual life-history parameters are normally hard to estimate with DLMs. Nadon and Ault (2016) introduced a method to skip the estimation procedure with statistical methods. But in mostly data-limited fisheries, life-history parameters are used collectively with their ratios. Jensen (1996) linked up natural and total mortality (M and Z , respectively) with VBGF parameters by optimizing the trade-off between reproduction and survival and determined the values for Beverton–Holt life-history invariants (BH-LHI): (1) $M \times t_m = 1.65$; (2) $M/K = 1.5$; and (3) $L_m/L_{inf} = 0.67$ (t_m and L_m indicate the age and length at sexual maturity, respectively). The BH-LHI facilitated the development of many DLMs such as potential yield and stock status estimation (Beddington and Kirkwood 2005). Following that, Prince et al. (2015) reconceptualized the BH-LHI as an adaptive framework featuring well-studied species as data sources to support assessment for closely related species. The development of BH-LHI framework was based on the observation that M/K ratio was consistent for fish stocks of similar life histories (Beverton 1992). The decisive role of M/K ratio in the relationship between size and biomass was first proposed by Holt (1958), and its influence on spawning-related measurement was explored and proved to be significant by Hordyk et al. (2015a), indicating that stock can be assessed and managed towards its optimal biomass when the length data are available. F/M ratio is another extensively discussed reference point (e.g., Gulland 1969; Zhou et al. 2012). However, F/M ratio alone does not fully describe the sustainability and therefore is not so recognized as M/K ratio and functions only as one component in DLMs (Walters and Martell 2004; Hordyk et al. 2015b). Recent studies illustrated the computation of spawning potential ratio (SPR), which describes a stock's exploitation status, with length-based data as well as M/K and F/M ratios in a data-limited situation (Hordyk et al. 2015a, 2015b). Additionally, a series of studies have evaluated the BH-LHI-related DLMs to enhance its performance by considering Lee's phenomenon, which highlights the significance of size-dependent mortality and selectivity (Lee 1912; Hordyk et al. 2016).

As DLMs take advantages of limited data, many studies focused on enhancing the robustness of DLMs reference points (Cope and Punt 2009; Brooks et al. 2009); yet the influence of input data was never systematically evaluated. Jennings and Dulvy (2009) and Hordyk et al. (2015b) tested a set of arbitrary values of BH-LHI for DLMs, but did not take the connectivity between life-history estimation and DLMs into consideration. This connectivity was always neglected in actual management because life-history inputs were selected from available literature based on experts' consensus instead of being estimated specifically for DLMs. Unfortunately, such practice relies on substantial studies to reference, and they are normally deficient in developing countries. This is a huge impediment for DLMs implementation in China as well,

where comprehensive life-history studies are limited, generating results neither spatially nor temporally consistent. Similarly, simply implementing BH-LHI can also be biased. The issue highlights the necessity to utilize rationally the limited data to inform management.

In this study, life-history parameters were estimated with the same length–frequency data by six workflows (WF1–WF6) consisting of common length-based methods. The calculation of SPR, the determination of harvest control rules (HCRs) with length-based management procedures (MPs), and management strategy evaluation (MSE) of the HCRs were conducted and investigated for their sensitivities to various input life-history estimations. We expect to demonstrate the importance of life-history estimation methods in a data-limited situation and reveal the consequence of indiscriminate use of life-history information in DLMs.

Materials and methods

The schematic diagram describing the complete work design of the study is presented in Fig. 1. Six WFs were first designed based on their feasibility. They were then adopted to estimate the life-history parameters, which were subsequently used to address the three objectives for their sensitivity to the input data. Other data, such as length–mass relationship parameters, were merely used for parameterization purpose and not contemplated for sensitivity analysis.

Length–frequency data

Length–frequency data of small yellow croaker (*Larimichthys polyactis*) collected in 2011 from Haizhou Bay, China, were used in this study. Small yellow croaker is a pillar commercial species in the region and in urgent need for informative management, which has been suggested by many scientists (Tang et al. 2011; Liu et al. 2012). However, it should be noted that the species has been rarely studied in this region. A total of 923 individuals of small yellow croaker were sampled during five surveys in 2011. Their total lengths were measured and converted to length–frequency data with bin size of 5 mm. In addition, age–length data of the sample individuals were incorporated in a joint analysis in some WFs based on the following two considerations: most captured individuals were of young ages due to overfishing, and they were recognized as being very influential when estimating the VBGF curve (Morgan 1987). Other fundamental biological data were also measured and used, including mass and maturity. All the data utilized in this study were fishery-independent, making it ideal for the implementation of data-limited assessment.

Table 1. Design of workflows (WF1-WF6) to estimate major life-history parameters.

Workflow	L_{inf}	K	M
WF1	ELEFAN	ELEFAN	T_{max} -based
WF2	ELEFAN G.A.	ELEFAN G.A.	T_{max} -based
WF3	Joint analysis	Joint analysis	T_{max} -based
WF4	ELEFAN	ELEFAN	Growth-based
WF5	ELEFAN G.A.	ELEFAN G.A.	Growth-based
WF6	Joint analysis	Joint analysis	Growth-based

Note: Other life-history parameters, including age at zero length and total mortality rates, were estimated with identical approaches and, thus, not presented here. ELEFAN G.A. stands for electronic length frequency analysis optimized with genetic algorithm. L_{inf} , asymptotic total length; K , growth parameter; M , natural mortality rate; T_{max} , maximal age.

Estimation of input life-history parameters

Life-history parameters used in this study were estimated from length–frequency data using six workflows (WF1–WF6) listed in Table 1 (for technical details, see online Supplementary material¹). They consist of different frequently used length-based approaches, which have been widely studied and proved feasible with small yellow croaker (Yan et al. 2006; Liu et al. 2012). The major parameters to estimate were two VBGF parameters, asymptotic total length (L_{inf}) and growth parameter (K), and natural mortality rate (M).

VBGF parameters were estimated following three approaches, including the electronic length frequency analysis (ELEFAN), the ELEFAN optimized with genetic algorithm (ELEFAN G.A.), and joint-analysis (Table 1). The ELEFAN computes L_{inf} and K simultaneously, with ELEFAN based on response surface by fitting multiple growth curves to the length frequency and returning the maximal fitness (Gayaniolo et al. 1988). ELEFAN G.A. is a state-of-the-art optimization approach for VBGF estimation driven by the genetic algorithm, which pursues the maximal fitness with stochastic search process (Scrucca 2013; Taylor and Mildenberger 2017). Its advantage over the basic ELEFAN is that such a process readily models the VBGF growth in light of seasonal oscillation; otherwise, related parameters must be additionally assessed with data-intensive researches. Recent study verified the effectiveness and precision of ELEFAN G.A. (Taylor and Mildenberger 2017). The joint analysis is a combination of ELEFAN and age–length polynomial fitting following the method of Morgan 1987, aiming to optimize the VBGF estimation with updated age–length data. The joint analysis identifies the optimal parameters by maximizing the value of score with

$$(1) \quad \text{Score} = d1 \times \text{ESP/ASP} + d2 \times \text{Pa}$$

where “ESP/ASP” (explained sum of peaks / available sum of peaks) indicates the goodness of fit with ELEFAN (Pauly 1987). “Pa” indicates the proportion of length-at-age data points explained by a fitted growth curve; “d1” and “d2” describe the relative influence of each method; they were both set at 1, being equally important for this study. The value of ESP/ASP was calculated with goodness of ELEFAN (Rn) as

$$(2) \quad \text{ESP/ASP} = \log_{10}(10 \times \text{Rn})$$

The natural mortality rate M was estimated with two methods, following the maximal age- (T_{max}) and the growth-based methods from Then et al. (2015) for WF1–WF3 and WF4–WF6, respectively. T_{max} was recommended as the estimator for M because of its best performance and simplicity (Hoenig 1983; Then et al. 2015). Fitted

with nonlinear least squares as power functions, the equation is given as

$$(3) \quad M = 4.899 \times T_{\text{max}}^{-0.916}$$

The growth-based method was advocated by Then et al. (2015) when T_{max} was not available. The power function was acquired by fitting Pauly’s model with nonlinear least squares, which was given as

$$(4) \quad M = 4.118 \times K^{-0.73} \times L_{\text{inf}}^{-0.33}$$

The estimation methods of other life-history parameters, including the total mortality rate and the age at zero length, were identical for all WFs in subsequent steps. Total mortality rate Z was obtained by linearizing the catch curve to length–frequency data and modeled as (Pauly 1990)

$$(5) \quad \ln(N_t) = \ln(N_0) - Zt$$

where N_t indicates the population size at time t , N_0 indicates recruitment (for plots, see Supplementary Fig. S1¹). Fishing mortality F was obtained by subtracting M from Z . The age at zero length t_0 was calculated with the empirical equation based on L_{inf} and K (Pauly 1983):

$$(6) \quad \log_{10}(-t_0) = -0.3922 - 0.275 \times \log_{10}(L_{\text{inf}}) - 1.038 \times \log_{10}(K)$$

Ratios of life-history parameters, such as M/K and F/M , were calculated with the estimated parameters accordingly.

Sensitivity of objectives

Spawning potential ratio (SPR)

SPR reflects the exploitation status and must be obtained from an age-structured model with multiple age groups in traditional assessment (Hordyk et al. 2015b). SPR is a widely used reference point defining the unfished reproductive potential for exploited stocks, with close to 100% as almost unexploited and close to 0% as almost no spawning (Goodyear 1993). SPR is calculated as

$$(7) \quad \text{SPR} = \frac{\text{total egg production}_{\text{fished}}}{\text{total egg production}_{\text{unfished}}}$$

For comparison purpose, the simplified size-dependent data-rich SPR estimation was conducted. Basically, the two-parameter logistic function was used to model the maturity at length (Mat_l):

$$(8) \quad \text{Mat}_l = \frac{1}{1 + e^{-\ln(19)(l-L_{50})/(L_{95}-L_{50})}}$$

where l indicates length, and L_{50} and L_{95} indicate lengths at 50% and 95% maturity, respectively. Selectivity-at-length (S_a) was also modeled with eq. 8 by replacing L_{50} and L_{95} with LR_{50} and LR_{95} (length of 50% and 95% retention rates). Using an age-structured model considering no uncertainty at length-at-age, the fished and unfished total egg production ($\text{EP}_{\text{fished}}$ and $\text{EP}_{\text{unfished}}$, respectively) was calculated as

$$(9) \quad \text{EP}_{\text{fished}} = \sum \begin{cases} E_a & \text{for } a = 0 \\ e^{-Z_a - t^a E_a} & \text{for } 0 < a \leq a_{\text{max}} \end{cases}$$

¹Supplementary data are available with the article through the journal Web site at <http://nrcresearchpress.com/doi/suppl/10.1139/cjfas-2017-0325>.

Table 2. Length-based management procedures (MPs) implemented as harvest control rules.

MP	Harvest control rule	Calculation of threshold
minlenLopt1	Setting the minimum catch length according to L_{opt}	$LR_{100} = L_{opt} \times (0.7 + \text{buffer})$ $LR_{50} = 0.9 \times LR_{100}$
EtargetLopt	Adjusting effort up or down if mean length above or below L_{opt}	$\text{Effort} = (1 - \text{buffer}) \times (0.5 + 0.5 \times \bar{L}/L_{opt})$
slotlim	Setting the maximum legal length according to L_{inf}	$LR_{100} = 14 + 1.1 \times L_{50}$ $LR_{50} = 0.95 \times L_{50}$ $MLL = LR_{100} + 0.75(L_{inf} - LR_{100})$

Note: The calculation of the threshold follows the equations of Carruthers and Hordyk (2017). “LR₁₀₀” and “LR₅₀” indicate lengths at 100% and 50% retention rates, respectively. The term “buffer” is introduced as a modifier and is set at 0.1. “Effort” indicates the adjusted effort for the next year. “ \bar{L} ” indicates the observed mean length. “MLL” indicates the maximum legal length. “L₅₀” indicates the length at 50% maturity.

and

$$(10) \quad EP_{\text{unfished}} = \sum_a E_a e^{-M_a}$$

where mortality rates were age-dependent and modeled as

$$(11) \quad Z_a = M + S_a \times F$$

Egg production per female and ratio between biomass and egg production should be arbitrarily set because they were eliminated via mathematical manipulation.

The data-rich procedure demands explicit definitions of maturity, mortality, and female abundance at age, which are barely available in data-limited situations. Hordyk et al. (2015a) introduced a data-limited approach based on F/M and M/K ratios:

$$(12) \quad SPR = \frac{\sum (1 - \tilde{L}_x)^{(M/K)(F/M)+1} \tilde{L}_x^b}{\sum (1 - \tilde{L}_x)^{(M/K)} \tilde{L}_x^b}, \quad (x_m \leq x \leq 1)$$

where b is the exponent from the mass-length relationship, x indicates the age standardized to maximum age, x_m indicates the standardized age at maturity, \tilde{L}_x indicates the standardized length at age x . Considering no variance of length-at-age, \tilde{L}_x can be determined with same estimators from eq. 12 as

$$(13) \quad \tilde{L}_x = 1 - P^{[x(K/M)]}$$

where x is the age standardized to maximal age (defined as t/t_{\max}), and P indicates the proportion of individuals that survive to the maximal age class (assumed to be 1%). By assuming knife-edge maturation, full selectivity at all ages, and perfect information on length-at-age, this approach is able to operate with incomplete knowledge of individual parameters by using their ratios. When assuming knife-edge selectivity, the numerator in eq. 12, which represents the EP_{fished} , can be replaced with

$$(14) \quad EP_{\text{fished}} = \sum \begin{cases} (1 - \tilde{L}_x)^{M/K} \tilde{L}_x^b & \text{for } 0 \leq x \leq x_c \\ (1 - \tilde{L}_x)^{M/K+(M/K)F/M} \tilde{L}_x^b & \text{for } x_c < x \leq 1 \end{cases}$$

where x_c indicates the standardized age at L_c . All fish younger than x_c are not subject to fishing mortality under such an assumption, whose value is approximately defined as 2. Values of F/M and M/K can be readily obtained from previous studies and BH-LHI, cost-effectively excluding the influence from any extreme individual values. In the context of poorly studied species with few references, however, the ratios still need to be calculated with individual parameters. Moreover, indiscriminately adopting BH-LHI can be risky. Considering these uncertainties and practical draw-

backs, we found it necessary to test the sensitivity of data-limited SPR estimation approach to our WFs.

Length-based harvest control rules (LB-HCRs)

Three length-based data-limited MPs were implemented as HCRs and presented in Table 2. The MPs “EtargetLopt” and “minlenLopt” were designed based on the optimal length L_{opt} . Froese et al. (2008) pointed out if a cohort was not subject to fisheries, it would reach its theoretical maximal biomass at L_{opt} . The calculation of L_{opt} was revised by Hordyk et al. (2015a) with simple estimators as

$$(15) \quad \tilde{L}_{opt} = \frac{b}{(M/K) + b}$$

where \tilde{L}_{opt} stands for standardized length at L_{opt} . Because L_{opt} could be determined with even minimum data (e.g., as in eqs. 12 and 13 and Hilborn and Walters 2013), it was widely used in modeling growth, informing management, and approximating maturity threshold (Fryer and Iles 1972; Roff 1984; Beverton 1992).

These cost-effective MPs used size and effort controls based on length information to form corresponding HCRs (Table 2): the HCR derived from EtargetLopt adjusted the effort to ensure the mean catch length at L_{opt} level; the HCR derived from minlenLopt prevented individuals from being harvested before reaching a considerable length; the HCR derived from slotlim only allowed for harvest on intermediate size groups to conserve the recruitment and senior spawning groups (Gwinn et al. 2015). Their input length information was estimated with six WFs.

Management performance

The HCRs established in the preceding step were implemented to manage the small yellow croaker stock with MSE. MSE is a simulative framework specializing in testing MPs for their relative performance, compliance of goals, and robustness to uncertainty (De Oliveira et al. 2009). In the present study, MSE was employed to test the sensitivity of three MPs to six groups of input life-history parameters generated by our predesigned WFs. In total, 18 HCRs corresponding to three MPs (coded as “EtargetLopt WF1-6”, “minlenLopt WF1-6”, and “slotlim WF1-6”, respectively) were established and tested in parallel.

The operating model of our MSE was set identically for all HCRs to mimic the population dynamics. Major life-history parameters were parameterized with values sampled from uniform distributions to ensure stochasticity, whose boundaries were defined based on previous literature and extreme estimations (see Supplementary Table S1). The stock was modeled with VBGF growth and subject to size-independent constant natural mortality. Additionally, imprecise and biased behavior of fleet dynamics as well as observation process were also simulated. Fishing intensity was determined by regulations of HCRs. The simulation was operated with 2000 iterations for 30 years.

Simulation performance was measured by three metrics: the relative trade-offs between yield and overfishing, temporal trend of crucial parameters, and the proportion of time the stock spends

Table 3. Life-history parameters, goodness of fit, and length threshold estimated with WF1–WF6.

Parameter	WF1	WF2	WF3	WF4	WF5	WF6
Life-history parameters						
L_{inf} (mm)	250.90	253.24	259.90	250.90	253.24	259.90
K (year ⁻¹)	0.27	0.26	0.37	0.27	0.26	0.37
t_0	-0.58	-0.60	-0.41	-0.58	-0.60	-0.41
M	0.44	0.44	0.44	0.26	0.25	0.32
Z	1.04	1.04	1.25	1.04	1.04	1.25
F	0.60	0.60	0.81	0.78	0.79	0.93
M/K	1.63	1.69	1.19	0.96	0.96	0.86
F/M	1.36	1.36	1.84	3.00	3.16	2.91
Goodness of fit						
Rn	0.83	0.76	0.3	0.83	0.76	0.3
ESP/ASP ^a	0.92	0.88	0.47	0.92	0.88	0.47
Pa ^b	— ^c	—	0.87	—	—	0.87
Score ^d	—	—	1.34	—	—	1.34
Z C.I. ^e	0.85–1.22	0.87–1.22	0.96–1.55	0.85–1.22	0.87–1.22	0.96–1.55
Length threshold						
x_m^f	2.70	2.76	1.86	2.70	2.76	1.86
L_{opt} (mm)	161.36	160.66	184.99	188.95	190.98	200.77
LR ₁₀₀ (mm)	129.09	128.53	147.99	151.16	152.62	160.62
LR ₅₀ (mm)	116.18	115.68	133.19	136.04	137.36	144.56
MLL ^g (mm)	232.24	233.99	238.99	232.24	233.99	238.99

^aESP/ASP (explained sum of peaks / available sum of peaks) is converted from Rn with eq. 2.

^bPa indicates the goodness of fitting with age–length approach.

^cA dash (—) indicates the value cannot be directly estimated with corresponding WF.

^dScore indicates the weighted sum of Pa and ESP/ASP.

^eZ C.I. indicates the confidence interval of total mortality rates estimated with length-converted catch curve method.

^f x_m indicates the age of full maturity assuming knife-edge maturity (need to be standardized in eq. 12).

^gMLL indicates the maximum legal length regulated by the MP “slotlim”.

in different states. Reference level of these metrics was defined with the maximum sustainable yield (MSY) reference point, which was identified as the highest long-term yield. The influence of different input parameters estimated with WFs was evaluated based on comparison with each other for optimistic or conservative results.

The open source programming language R (version 3.4.0) was used in this study (R Core Team 2017). The life-history parameters were estimated with R package “TropFishR” (version 1.1.4; Mildenerberger et al. 2017). The implementation of DLMs and MSE was performed with the “Data-Limited Methods Toolkit” (DLMtool, version 4.1.0; Carruthers and Hordyk 2017). Visualization of the simulation results was achieved with R package “ggplot2” (version 2.2.1; Wickham 2009) and DLMtool.

Results

Life-history parameters

Life-history parameters were estimated using the six WFs and are presented in Table 3. In general, high sensitivity to methodology was demonstrated. Individual values estimated by WF1, WF2, WF4, and WF5 were consistent besides M . The values of VBGF parameters increased significantly when age–length data were incorporated with WF3 and WF6. Such a change in individual estimations resulted in highly diverse values for M/K and F/M , ranging from 0.86 to 1.69 and 1.36 to 3.16, respectively. Notably, only the values obtained with WF1 and WF2 approximated the values of BH-LHI implemented in most data-limited management, although all the values were within feasible ranges for DLMs (Hordyk et al. 2015a).

SPR

The results of both the data-limited and the data-rich estimations are presented in Table 4. Estimations of the data-rich SPR under both assumptions were under 20%, indicating severe depletion of the stock. The data-rich approach was less sensitive to

Table 4. Spawning potential ratio (SPR, %) derived from WF1–WF6.

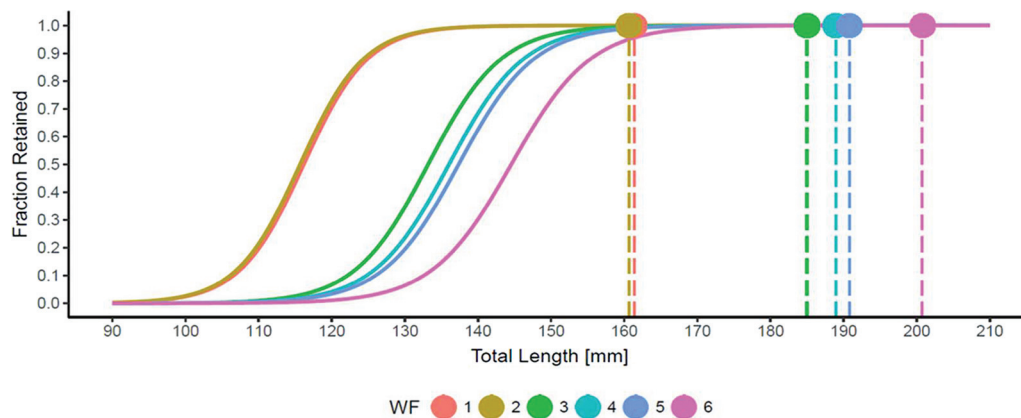
Workflow	Knife-edge selectivity		Full selectivity	
	Data-limited	Data-rich	Data-limited	Data-rich
WF1	10.9%	8.7%	8.1%	6.5%
WF2	10.6%	8.5%	7.9%	6.3%
WF3	8.2%	14.4%	6.5%	5.2%
WF4	4.7%	8.3%	1.2%	2.0%
WF5	4.4%	8.0%	1.2%	1.8%
WF6	5.5%	9.7%	2.7%	2.7%

various WFs than the DLM. The DLM demonstrated consistent underestimation of SPR with WF1, WF2, and WF3 and consistent overestimation with WF4, WF5, and WF6, regardless of selectivity assumption. The bias was caused mainly due to different estimation approaches for M . Using inputs from WF1 and WF2, the data-limited approach tended to generate the most precise estimation, despite that they were slightly more optimistic. In contrast, results from WF4 and WF5 were too conservative to be true under full selectivity assumption (1.2%), because a stock was barely possible to support a fishery with such low reproduction potential.

LB-HCRs

The estimated length thresholds implemented in HCRs are presented in Table 3. The estimations of L_{opt} were observed for great disparity among WFs, ranging from 160.36 to 200.77 mm. Such disparity consequently lead to different control measures for the MPs. The specific retention ogives utilized for HCRs following minlen_{opt} are illustrated in Fig. 2. The ogives and values of L_{opt} were approximately the same for WF1 and WF2, whose estimations were more optimistic than other WFs, resulting in more intense harvest on younger individuals. For example, fish of 130 mm total length showed less than 50% of probability to be caught with HCRs derived from WF3–WF6, while they would be

Fig. 2. Fraction of individual fish retained at different total lengths constructed following the MP “minlenLopt1” derived from WF1–WF6 estimations. The curves are the length control measures of corresponding harvest control rules. The selectivity curves are characterized by LR_{100} and LR_{50} (i.e., length at 100% and 50% retention rates, respectively). The points indicate the corresponding values for optimal length L_{opt} . [Colour online.]



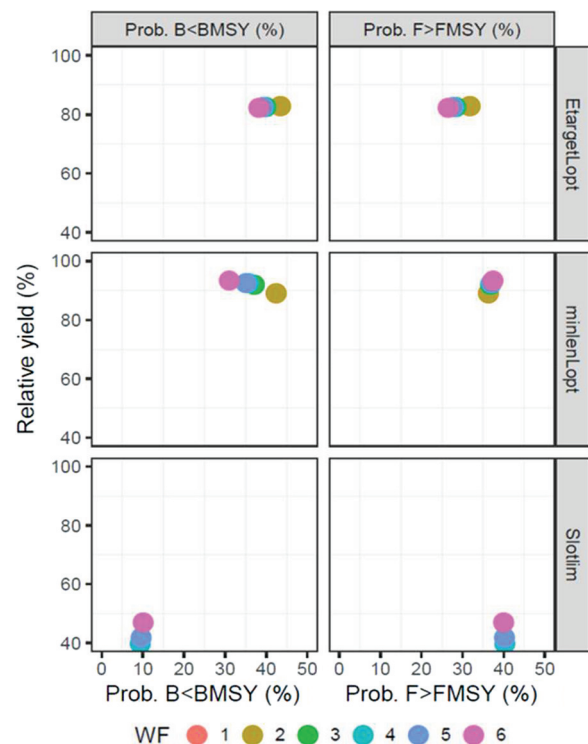
already fully selected with WF1 and WF2. This substantial variation could be mainly attributed to the lower M/K ratios estimated with WF1 and WF2 (Table 4). The most conservative length control was observed with WF6, whose fully selected length was exceedingly high. Nevertheless, the age at full maturity under knife-edge assumption (x_m) of WF6, as well as for WF3, were the lowest among all WFs, indicating the data-limited SPR estimation approach was more sensitive to life-history ratios instead of the age interval over which it was calculated. The other length threshold, maximum legal length of the MP “slotlim”, was quite consistent among the WFs.

Performance of MPs

MSE simulation was conducted to better understand the influence of diverse HCRs. The stock reached equilibrium at the end of the simulation period (30 years). Simulation of the last 10 years was selected for sensitivity examination. The trade-offs between the relative long-term yield and risk of overfishing were first compared (Fig. 3). The best trade-off was achieved with the HCRs derived from WF6 for three MPs, which displayed not only the lowest risk of overfishing ($F > F_{MSY}$) and overfished ($B < B_{MSY}$), but also the highest relative yield compared with other WFs. Variations of locations of the points were not significant, except for the overfishing probability for the MP minlenLopt, ranging from 30% to 45%. HCRs established with WF6 also outperform other WFs in terms of annual catch, spawning stock biomass, and avoiding overfishing, although the advantage was not great (Fig. 4). The MP slotlim illustrated the lowest catch and the highest spawning stock biomass level among three MPs. However, it performed poorly in restraining fishing mortality, which indicated it was specifically targeting certain size groups following a slot control design.

In addition to the equilibrium stage, we also contemplated the complete simulation period for the stocks developments under different states (Fig. 5). The proportion for the stock staying in the safe state (not overfished and no overfishing) was significantly enhanced when managed with estimations from WF6, increasing from 47% to 51.3% and 48.7% to 54.5% for the MPs minlenLopt and EtargetLopt, respectively. HCRs based on WF6 also reduced the possibility of falling in the worst state (being overfished and overfishing occurring) by up to 5.7% and 4.8% for the two MPs. The MP slotlim, in contrast, was quite insensitive to the input data regarding this performance.

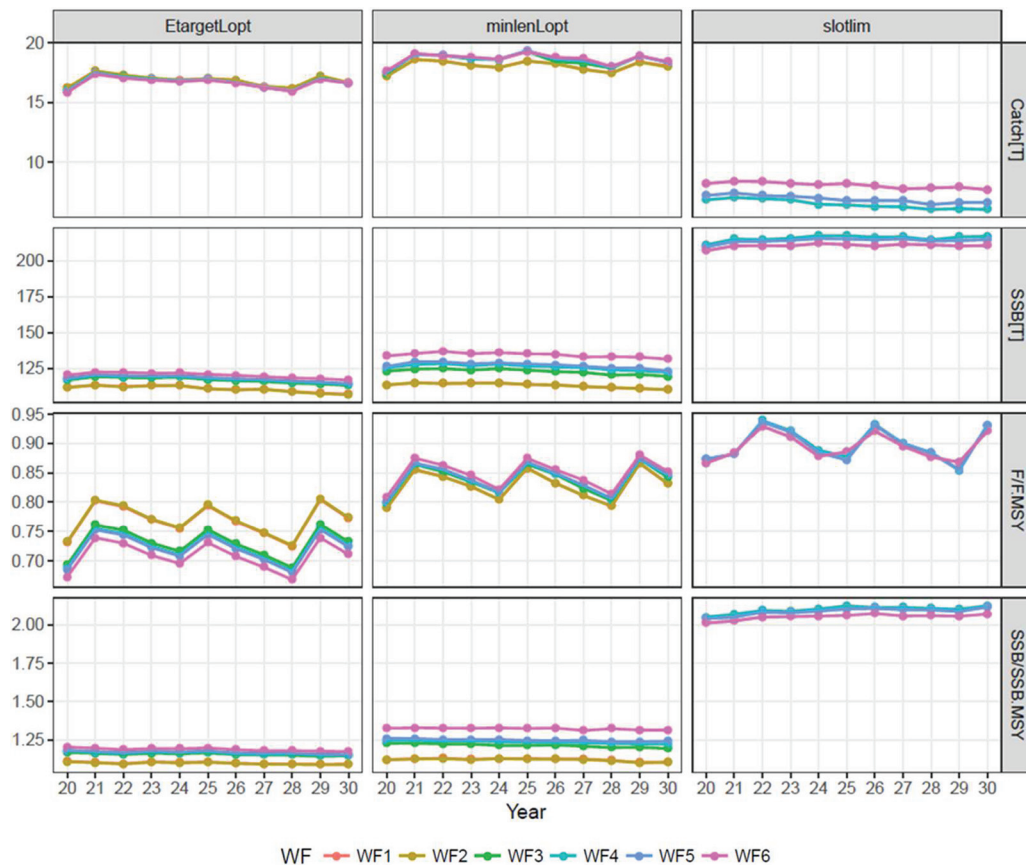
Fig. 3. Relative trade-offs distribution for harvest control rules (HCRs) derived from WF1–WF6 estimations. The coordinates of the points are the median value of 2000 iterations and indicate the trade-offs between the relative long-term yield and the probability of overfishing, as well as the probability of being overfished. Because of the same length control measures (Table 3), results of WF1, WF2, and WF3 were identical to those of WF4, WF5, and WF6, respectively, for the MP “slotlim”. [Colour online.]



Discussion

This study is dedicated to reveal the sensitivity of data-limited assessment to systematic estimation of length-based input life-history data, which is a problem not comprehensively answered previously. Assessment approaches, especially with DLMs, are consistently modified for better methodology designs, but the uncertainty from input data are seldom addressed, which is essen-

Fig. 4. The temporal trend of annual catch, spawning stock biomass (SSB), F/F_{MSY} , and SSB/SSB_{MSY} for HCRs derived from WF1–WF6 estimations. The dots are the median values of the 200 iterations and indicate the values of the parameters at each year. Dots are connected with lines to illustrate the trend for each WF. Because of the same length control measures (Table 3), results of WF1, WF2, and WF3 were identical to those of WF4, WF5, and WF6, respectively, for the MP “slotlim”. [Colour online.]



tially the primary cause of repeated management failures (Walters and Martell 2004). Although some innovative models, such as the Length-based Integrated Mixed Effects Model (Rudd and Thorson 2018), address the problem of data by accounting for variation in several life-history parameters, the generic problem of indiscriminate use of life history in DLMs still remains ubiquitous. The risk of the inadvertence merits more seriously examination to prevent further failures in actual management.

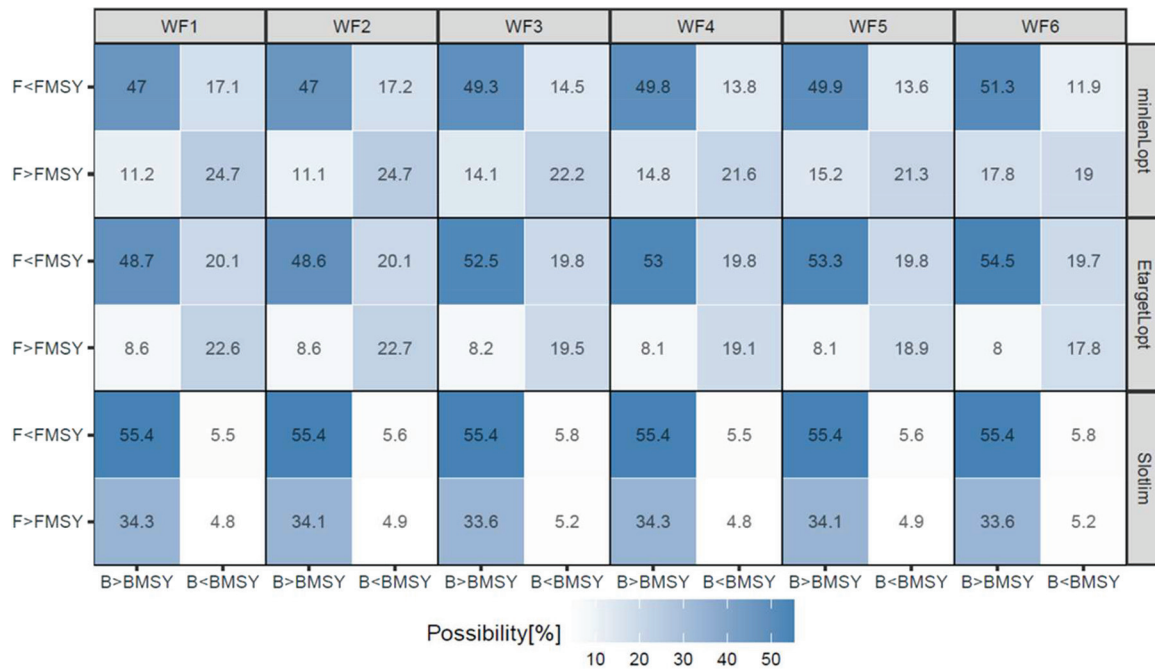
By testing the sensitivity of three objectives with DLMs in the present study, we came to the conclusion that the influence of input life-history parameters estimated with different WFs is of great importance. We observe misjudgment on the stock status based on SPR with different WFs (Table 4), discrepant length control measures with HCRs (Table 3; Fig. 2), and dissimilar management performance (Figs. 3, 4, and 5). According to the results, we recommend using WF1 or WF2 to support SPR estimation thanks to their precision. WF6 should be implemented when age reading data are available to support HCR establishment thanks to their excellent balance of productivity and sustainability; otherwise WF5 is the best option.

Results of our study highlight the necessity of an active use of up-to-date data and reasonable choice of the method for individual parameter estimation. Their biases are originally believed to be successfully reduced by using the ratios of parameters. However, their results are still more or less determined by individual components' values. We implemented the ELEFAN G.A. for VBGF parameters, which is an improvement of the traditional ELEFAN. Individual parameters estimated with optimized ELEFAN G.A. in WF2 and WF4 were slightly different from the traditional ap-

proach in WF1 and WF3, which leads to small variation in the calculation of ratios and further measures. Nevertheless, the computational process as well as the declaration of complex initial input is much released (Scrucca 2013; Taylor and Mildenberger 2017). Considering the overall behavior of their consequences and the effort, we highly recommend using the ELEFAN G.A., instead of the traditional ELEFN, to support length-based DLMs. When the age-length data are incorporated with WF3 and WF6, the VBGF estimations diverge greatly, especially in the estimation of growth parameter K , which is in accordance with the results of Morgan (1987). In our case, a possible biological explanation is fishery-induced evolution, since small yellow croaker is known to be long-lived and has a moderate growth rate (Lin et al. 2004; Heino et al. 2013); however, current captured individuals are mostly of young age groups and demonstrate higher growth rates (Zhang et al. 2010; Liu et al. 2012). Estimation of natural mortality, which is generically tricky, is realized with longevity- and VBGF-based approaches (Then et al. 2015). Neither of the approaches is versatile concerning our objectives: the longevity-based method generates higher M , resulting in more similar M/K ratios to the BH-LHI of 1.5 and better precision with SPR estimation; the VBGF-based methods generate lower M , resulting in extreme M/K ratios and better performance with HCRs and MSE.

SPR estimation is dependent on a variety of factors with DLMs. Basically, our results indicate that SPR estimation declines when F/M ratio increases, which is identical to the results from Hordyk et al. (2015a). This theory is reasonable because an increase in F/M ratio means the stock is exposed to a more intensive fishing mortality than natural mortality and loses more spawning individu-

Fig. 5. The proportions of time the stock spends in different states. Cells are formed with MPs and input estimation WFs. The values are calculated as the proportion of the 2000 iterations. Each cell is then divided into four quadrants, representing the state of safe ($B/B_{MSY} > 1$ and $F/F_{MSY} < 1$), overfishing occurring but not overfished ($B/B_{MSY} > 1$ and $F/F_{MSY} > 1$), overfished but no overfishing ($B/B_{MSY} < 1$ and $F/F_{MSY} < 1$), and overfished and overfishing occurring ($B/B_{MSY} < 1$ and $F/F_{MSY} > 1$). A spectrum of transparency is used to represent the percentage of time spent in that state, which is noted as well. Owing to the same length control measures (Table 3), results of WF1, WF2, and WF3 were identical to those of WF4, WF5, and WF6, respectively, for the MP “slotlim”. [Colour online.]



als. It is pronounced by the conclusion of Goodyear (1993) that SPR estimation is sensitive to F when F/M is at a low level. Another crucial issue with SPR estimation is the choice of assumptions. Inappropriate choices for selectivity patterns can severely undermine the reliability of the assessment (Walters and Martell 2004; Punt et al. 2014). A formal selection test cannot be conducted in a data-limited situation; therefore, both knife-edge and full selectivity are examined with SPR estimation. Although the absolute estimations are not consistent following two assumptions, the patterns of sensitivity are identical. This indicates our conclusion concerning sensitivity is reliable.

The population dynamics of the operating model from our MSE is parameterized with all possible values from uniform distribution because of two factors: (i) results from available references are various, and (ii) population dynamics is naturally subject to intrinsic–extrinsic uncertainties. The former is a seriously neglected issue with data-limited fisheries management as discussed above. In our study, it is considered and unraveled with our HCRs. The latter, fortunately, has been considered and elaborated; for example, Hilborn and Walters (2013) pointed out the uncertainty in models parameters could impair the robustness of fishery analysis and effective management. The influence of uncertainty is hard to be fully interpreted with population model based on a single-species context (Hollowed et al. 2000). To account for these uncertainties and prevent DLMs from being unreliable, future management with limited data should be considered with ecosystem perspective for interactive mechanism (Pikitch et al. 2004).

By following a tangible scheme based on the raw data, this study puts more effort in the investigation and elaboration of the systematical connection between life-history information and the DLMs. This complete design is more enlightening than simple sensitivity analysis, which simply tested if the methods were robust given different scenarios with regards to its assumptions (e.g., Hordyk et al. 2015b; Kokkalis et al. 2017). Additionally, our

perspective is informative to practical management supported by purely fishery-independent data.

In practical data-limited management, input data are likely to be chosen from current researches or empirical invariants. But with limited literature and little knowledge of target stocks, the choice can be risky due to the temporal and spatial variations, demonstrating strong localized characteristics. Data scarcity of our studied species is unique. As with most of the commercial fisheries in China, the only available data for small yellowtail croaker were short-term fishery-independent data. In contrast, data-limited stocks are defined as those with only fishery-dependent data (or simply catch) in most parts of the world, and DLMs based on catch data are therefore well-developed (Thorson et al. 2013; Kokkalis et al. 2015).

Given the issues analyzed and discussed in this study, fisheries management with DLMs should take caveats in adopting input life-history data estimation, selecting assumption, and meeting localized demands. Future research should focus on continually enhancing the DLMs to account for more uncertainties to warrant the management to be robust and effective.

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