Update of a projection software to represent a stock-recruitment relationship using flexible assumptions

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Summary
The detailed description of the updated software for stochastic future projection was provided. The newly featured option allows the Beverton-Holt stock-recruitment relationship (BH-SRR) with arbitrary value of steepness (h) and estimated value of unfished recruitment (R_0) for conducting projections, which meet to the request of ISC-PBFWG in 2015. Furthermore, based on the previous results of the stock assessment for PBF in 2014, projections under this option are demonstrated. In this case, it was found that smaller h leads to i) higher estimated value of R_0; ii) upward bias of recruitment in resampling of past deviances; iii) lower level of recruitment and slower rebuilding of SSB in the short terms; and iv) higher risk of decreasing in SSB below the historical lowest level. These conservative results in the short terms indicates that the usage of this option may be beneficial for considering a precautional approach targeted for the stock showing both a higher steepness and bad status.

1. Introduction

In a previous ISC-PBFWG (ISC 2015), the WG agreed to use the future projection software 'ssfuture' in the next stock assessment. This software, distributed as an R-package, has been used for projections of several tuna species and updated in order to replicate management measures, especially in treating Pacific bluefin tuna (*Thunnus orientalis*) (PBF) (Ichinokawa 2012; Takeuchi et al. 2014; Akita et al. 2015). The WG also agreed to conduct several harvesting and recruitment scenarios (details are in ISC-PBFWG 2015 p17-18). The requested recruitment scenarios include a consideration of stock-recruitment relationship (SRR) with steepness = 0.9 while steepness = 0.999 is given in the stock assessment of the base case. The method with this inconsistency is not a standard way to represent SRR for productions and is not implementable in the version used in the last assessment. Therefore, a new option to represent this SRR was introduced into the updated version of this software.

In this document, the detailed description of the updating is provided. Then, based on the previous results of the stock assessment for PBF in 2014, projections under this option are demonstrated. <u>CAVEAT: after the stock assessment for PBF in 2016, the sample data sets and configurations of stock assessment software ('StockSynthesis', Methot & Wetzel 2013; hereinafter called SS) used here for demonstrations should be out of date, thus the demonstrations should only be used to examine competing projection methods but not to infer conclusions regarding the current stock status or future condition of PBF.</u>

2. A new option to represent a stock-recruitment relationship

2.1. Beverton-Holt stock recruitment relationship

In modern stock assessment, the number of recruitment in year t based on the Beverton-Holt stock recruitment relationship (BH-SRR) and its parameterization can be computed as

$$R_t = \bar{R}_t \exp\left[-\frac{\sigma_R^2}{2} + \log R_{\mathrm{dev}}\right], \tag{1}$$

where

$$\bar{R}_t = \frac{4hR_0 \mathrm{SSB}_{t-1}}{B_0(1-h) + \mathrm{SSB}_{t-1}(5h-1)}. \tag{2}$$

The definitions of key symbols in this document are:

Eq. 1

R_t, realized recruitment in year t;
$\bar{R}_t$, expected value of recruitment in year t;
σ_R, standard deviation for recruitment in log space;
$\log R_{\mathrm{dev}}(\sim \mathrm{Norm}(0, \sigma_R^2))$, recruitment deviation in log space;

Eq. 2

h, steepness;
SSB_{t-1}, spawning stock biomass in year $t-1$;
R_0, unfished equilibrium recruitment;
B_0, unfished equilibrium spawning biomass;

Eq. 3

Q_a, maturity at age a;
W_a, weight at age a;
M_a, natural mortality at age a;

Eq. 4

R_t^{data}, estimated recruitment derived from SS output in year t;
SSB_t^{data}, estimated spawning stock biomass derived from SS output in year t;

Others

$\hat{R}_0$, estimated unfished equilibrium recruitment;
R_T, future recruitment in year T;
SSB_T, future spawning stock biomass in year T;
$\tilde{R}_T$, median of future recruitment in year T;
$\widetilde{SSB}_T$, median of future spawning stock biomass in year T;
$\mathrm{B_{loss}}$, historical lowest value of SSB_t^{data}.

Note: R_t^{data} and $\mathrm{SSB}_t^{\mathrm{data}}$ vary with data set from different a bootstrap result.
t and T indicate estimated and projected period of fishing year, respectively.

According to a commonly used method, we here assume that recruitment is log-normally distributed and standard deviation of the logarithm of the recruitment residuals (σ_R) is fixed at 0.6 (e.g., summarized in Maunder and Deriso 2003). The term $-\sigma_R^2/2$ in the exponent in Eq.1 is a bias adjustment factor to ensure that $\bar{R}_t$ is equal to the mean recruitment.

If natural mortality, growth, and maturity schedules are known, B_0 is a function with R_0, written by

$$B_0 = \left(\sum_a Q_a W_a \exp\left[-\sum_{a'=0}^{a} M_{a'}\right]\right) R_0, \tag{3}$$

where the term in brackets corresponds to unfished spawning biomass per recruit (SPR). In that case, unknown parameters are h and R_0 in the BH-SRR.

2.2. Future recruitment implemented in the latest software

Under the assumption of the BH-SRR, Eq. 1 can be used for computing future recruitment, although here $\log R_{\mathrm{dev}}$ can be obtained by random resampling of past deviances of recruitment than using the log-normal random errors. There are two extremes as to how the values of parameters (h and R_0) are obtained for the purpose of projection. The first extreme is that the values of parameters are derived from SS output. This choice ensures consistency of the BH-SRR before or after the start of projection but does not allow a flexible setting of parameters, such as choosing a specific value of h. The second extreme is that arbitrary values of parameters are given, implying no relation between the parameter values and time series data of estimated spawner-recruit (denoted by $\mathrm{SSB}_t^{\mathrm{data}}$ and R_t^{data}) which may be far from being efficient use of data.

2.3. Newly featured option: maximum likelihood estimation of R_0 when given arbitrary h

Here, we propose a new method to handle the BH-SRR in projection, which can be considered as a compromise toward the two extreme methods as noted above. Recall that future projections under the given value of h, such as 0.9, are requested by ISC-PBFWG. In order to meet this, maximum likelihood estimation of R_0 from $\mathrm{SSB}_t^{\mathrm{data}}$ and R_t^{data} under arbitrary h is implemented in the software. The method is as follows:

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1. Define the likelihood with a log-normal error structure,

$$L\left(R_0,\sigma | h, R^{\mathrm{data}}, \mathrm{SSB}^{\mathrm{data}}\right) = \prod_t \left(\frac{1}{R_t^{\mathrm{data}}\sqrt{2\pi\sigma^2}} \exp\left[-\left(\log R_t^{\mathrm{data}} - \log \bar{R}_t\right)^2 / (2\sigma^2)\right]\right). \tag{4}$$

2. Set initial values of (R_0,σ) and search the optimum combination of them such that the negative log-likelihood is minimizing by use of function ‘optim’ in R.

3. Estimated value of R_0 (denoted by $\hat{R}_0$) is used for the BH-SRR and future projection.

Note that σ in Eq. 4 is not very interesting here, but it is required for conducting maximum likelihood estimation. Technically speaking, estimated value of recruitment is not corresponding to R_0 but $R_0\exp[-\sigma_R^2/2]$, thus removal of the factor is needed.

2.4. Future projection of PBF based on the BH-SRR

For illustrative purposes, base case data of PBF after the stock assessment in 2014 (ISC-PBFWG 2014) is used for projections including the BH-SRR. Start year (fishing year) of projection is 2012 and recruitment deviation, $\log R_{\text{dev}}$, is resampled from 1953 to 2012. As before, each projection is conducted from three hundred bootstrap replicates followed by twenty stochastic simulations (six thousand runs in total). The setting of projection is the same to the way previously conducted (Fukuda et al. 2015), except the recruitment process.

3. Results

Prior to showing the results of production with the BH-SRR, we check several properties of PBF data set related to the BH-SRR.

3.1. Relationship between h and $\hat{R}_0$

Table 1 summarizes relationships between h and $\hat{R}_0$, and **Figure 1** illustrates data set of base case ($\text{SSB}_t^{\text{data}}$ and R_t^{data}) and fitted curves under various h. The PBF data set supports a clear trend: $\hat{R}_0$ increases with decreasing of h. This is obvious. If $\hat{R}_0$ is fixed and h decreases, a great number of data points around (SSB_t, R_t) = (25000, 10000) would become under estimated; thus maximum likelihood estimation pushes $\hat{R}_0$ up to meet the data.

In the previous stock assessment of PBF in 2014, h = 0.999 is used and the relational is well documented in Iwata et al. (2012), see also Mangel et al. (2010), although $h \approx 0.93$ minimizes the negative log-likelihood (**Table 1**).

Figure 2 shows the residual plots of recruitment for various h. When h = 0.999, S-R relationship is almost flat among the region with data so that $\text{E}[\log R_{\text{dev}}] \approx 0$ is easily achieved. As h decreases, however, $\text{E}[\log R_{\text{dev}}]$ increases (0.03, 0.07, and 0.13 when h=0.95, 0.9, and 0.85, respectively, as shown in bold lines in **Fig. 2b-d**). This is because, under small h, the degree of freedom of this BH-SRR may be too small to explain the data set (i.e., only R_0 is estimated). This result indicates that recruitment deviances from the past may be biased and there may be a trend toward higher amount of recruitment than expected.

3.2 Future projection

Future projections with the BH-SRR are conducted for various h. **Figure 3a** and **3b** illustrate median of future SSB trajectories (denoted by $\widetilde{SSB}_T$) and median of future recruitment (denoted by $\tilde{R}_T$), respectively. These behaviors can be described as follows:

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1. After projections start, higher h leads to higher $\tilde{R}_T$ and $\widetilde{SSB}_T$ for a while, since $\tilde{R}_T$s with lower h are reduced through the BH-SRR.

2. Then, around 2020, the relationship between h and $\tilde{R}_T$ would change associated with a rebuilding of SSB, although higher h still leads to higher $\widetilde{SSB}_T$.

3. Finally, around 2028, smaller h would come to realize higher $\widetilde{SSB}_T$.

4. Around 2040, $\widetilde{SSB}_T$ with h=0.9 and h=0.85 would be twice and three times as much as with h=0.999, respectively.

In other words, as long as $\widetilde{SSB}_T$ is small, the stronger the BH-SRR, the longer it takes to rebuild the stock. Intriguingly, with our settings (h=0.85~0.999), $\widetilde{SSB}_T$ is not highly dependent on h until the timing that the relationship between h and $\widetilde{SSB}_T$ changes (i.e., around 2028).

3.3 The probability that SSB_T falls below the historical lowest value

Table 2 shows the probability that SSB_T falls below the historical lowest value (denoted by $\mathrm{B}_{\mathrm{loss}}$) at least once for various h. These are calculated using the projections between 2012 and 2022 from six thousand runs. We set $\mathrm{B}_{\mathrm{loss}} = 19000$, which is the historical lowest $\mathrm{SSB}^{\mathrm{data}}$ of base case. The probability increases with decreasing of h. This is because during most of a target period (~2022), smaller h leads to smaller R_T, as illustrated in **Fig. 3b**.

Each bootstrap data set has a specific $\mathrm{B}_{\mathrm{loss}}$. Therefore, the implication of universal use of $\mathrm{B}_{\mathrm{loss}} = 19000$ should be noted. If specific value of $\mathrm{B}_{\mathrm{loss}}$ for each projection is used as a threshold, we found there is no chance (0%) for SSB_T to fall below $\mathrm{B}_{\mathrm{loss}}$ under any assumptions on h, implying that uncertainty of decreasing SSB_T may be principally derived from bootstrap process and not from resampling of past deviances of recruitment.

4. Discussion

In this document, we provided a description of the newly featured option in the software for stochastic projections in future. The option allows the Beverton-Holt stock-recruitment relationship (BH-SRR) with arbitrary value of h and estimated value of R_0 for conducting projections, which meets the request of ISC-PBFWG. Based on PBF data set, we investigated the property of BH-SRR with this method and demonstrated future projections under this option. We believe that following results obtained by the software are general properties especially in species that show environmental-driven recruitment (i.e., not strong relationship between SSB and recruitment). First, as h decreases, $\hat{R}_0$ increases but the fitting accuracy for the data such that $\mathrm{SSB}_t^{\mathrm{data}} < 50000$, which accounts for a substantial fraction of the data, becomes worse (**Table 1** and **Fig. 1**) and thus resampling of past deviances of recruitment tends to upward bias (**Fig. 2**). Second, if current stock status is not very good, the closer h is one, the smaller is the risk of clash of SSB (**Table 2**), and the quicker is its rebuilding in the *short* term (**Fig. 3**)

Novel point of this option is that user can apply the different value of h from the stock assessment to projections, while R_0 is obtained by maximum likelihood estimation (recall the BH-SRR can be determined by h and R_0). One might think that the difference of h used in the stock assessment and the projection requires the change of the species' environment or life-history before and after the start of projection. In practice, however, assuming a smaller value of h may be important for a precautional approach because the handling of steepness is still an open issue even in modern stock assessment.

Currently, this option cannot reflect environmental effects to recruitment, although the process error is considered. For example, ISC-PBFWG assumed low level of recruitment in relation to periodic effects in environment. Implementation of this effect is one of our plans for updating the software.

References

Akita, T., Turuoka, I., Fukuda, H., and Oshima, K. 2015. Update of R packages 'ssfuture' for stochastic projections in future. ISC/15/PBFWG-2/14rev.

Fukuda, H., Turuoka, I., and Oshima, K. 2015. Updates of recruitment and harvesting scenario for the future projection of Pacific bluefin tuna. ISC/15/PBFWG-1/10.

Ichinokawa, M. 2012. Operating manual and detailed algorithms for conducting stochastic future projections with R packages of 'ssfuture'. Nat. Res. Inst. Far Seas Fish., Shimizu, Shizuoka, Japan, Available at: http://cse.fra.affrc.go.jp/ichimomo/Tuna/projection_manual_v0.4.pdf

ISC-PBFWG. 2014. Stock Assessment of Bluefin Tuna in the Pacific Ocean in 2014.

ISC-PBFWG. 2015. Pacific Bluefin Tuna Working Group Intersessional Workshop. November 18-25, 2015.

Iwata, S. 2012. Estimate the frequency distribution of steepness for PBF. ISC/12/PBFWG-3/01.

Mangel, M., Brodziak, J., and DiNardo, G. 2010. Reproductive ecology and scientific inference of steepness: a fundamental metric of population dynamics and strategic fisheries management. Fish and Fisheries 11, 89–104.

Maunder, M., N., and Deriso, R., B. 2003. Estimation of recruitment in catch-at-age models. Can. J. Fish. Aquat. Sci. 60, 1204–1216.

Methot Jr., R.D., Wetzel, C.R. 2013. Stock synthesis: A biological and statistical framework for fish stock assessment and fishery management. Fisheries Research 142, 86–99.

Takeuchi, Y., Tei, Y., Tsuruoka, I., and Ichinokawa, M., 2014. Updated future projections of Pacific bluefin tuna with draft results to answer the requests from NC9. ISC/15/PBFWG-1/10rev.

Table 1: Relationship between h and $\hat{R}_0$.

h	Negative Log-Likelihood	$\hat{R}_0$	$\hat{B}_0$
1.000	48.97	15337	646187
0.999	48.93	15387	648299
0.990	48.59	15843	667505
0.980	48.26	16381	690158
0.970	47.98	16954	714325
0.960	47.77	17568	740163
0.950	47.61	18225	767853
0.940	47.53	18931	797606
0.930	47.50	19692	829670
0.920	47.55	20515	864337
0.910	47.68	21408	901951
0.900	47.87	22380	942925
0.850	49.93	28957	1220003
0.800	53.66	41244	1737695

Note: Unit of $\hat{R}_0$ and $\hat{B}_0$ is 1000 fish and mt, respectively.
$\hat{B}_0$ is calculated from $\hat{R}_0$ (Eq. 3).

Table 2: Probability that SSB falls below SSB_{loss} (=19000 mt) at least once between 2012 and 2022 from six thousand runs. These demonstrations should only be used to examine competing projection methods but not to infer conclusions regarding the current stock status or future condition of PBF.

h	$Pr[SSB_t < SSB_{loss}]$
0.999	15%
0.950	17%
0.900	20%
0.850	24%

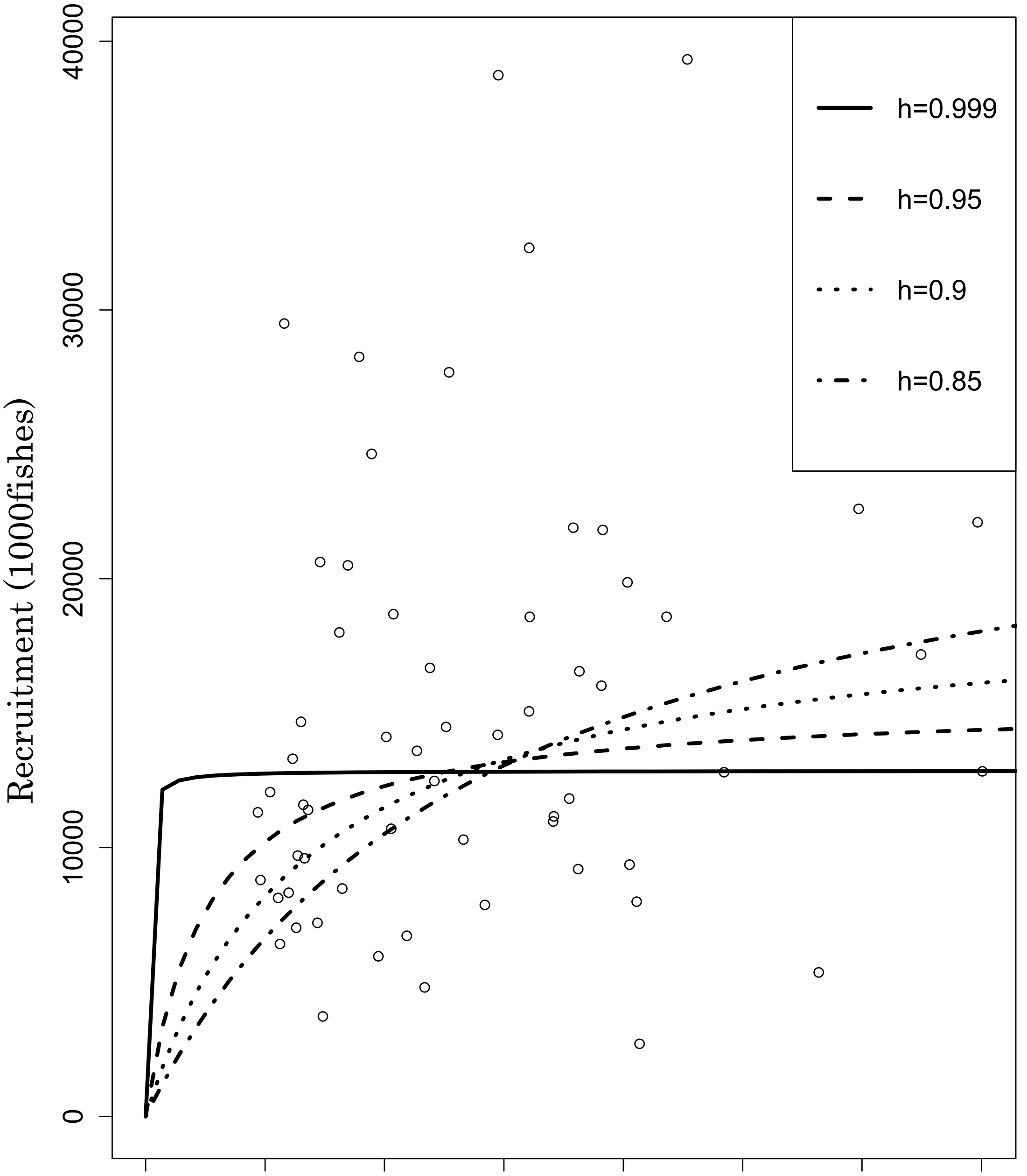

Figure 1: The Beverton-Holt stock recruitment relationship. Fitting curves are obtained by maximum likelihood estimation for various h. Data set is derived from the base case result of PBF in 2014. Note the curves reflect a bias adjustment factor and thus $\lim_{\mathrm{SSB}\to\mathrm{B0}} R_t = R_0 \exp[-\sigma_R^2/2]$.

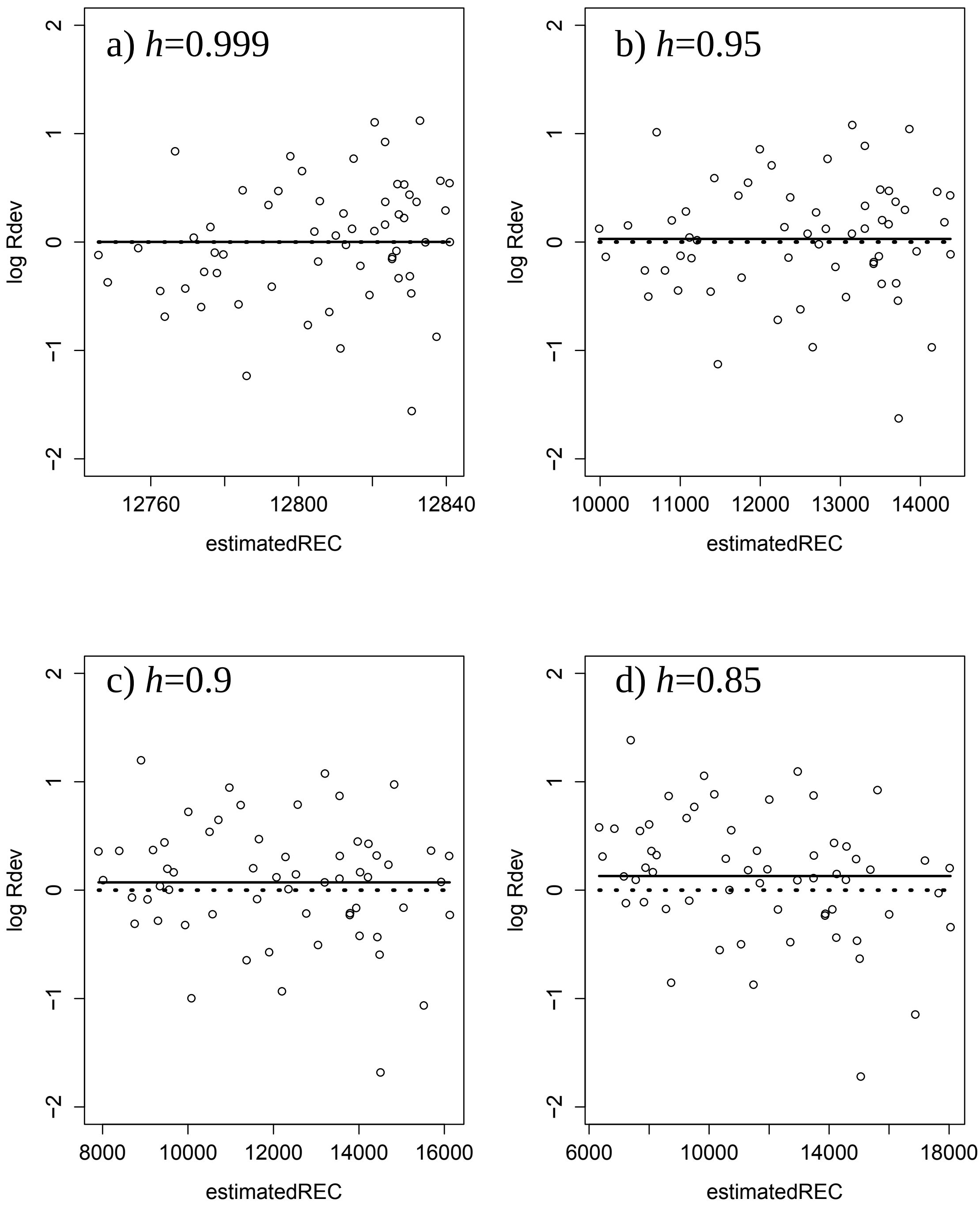

Figure 2: Estimated recruitment, $\bar{R}_t \exp[-\sigma_R^2/2]$, vs. $\log R_{\text{dev}} (= \log[R_t^{\text{data}}/\bar{R}_t])$. Bold line indicates the mean value of $\log R_{\text{dev}}$. Note that the scale of horizontal axis differs among these plots.

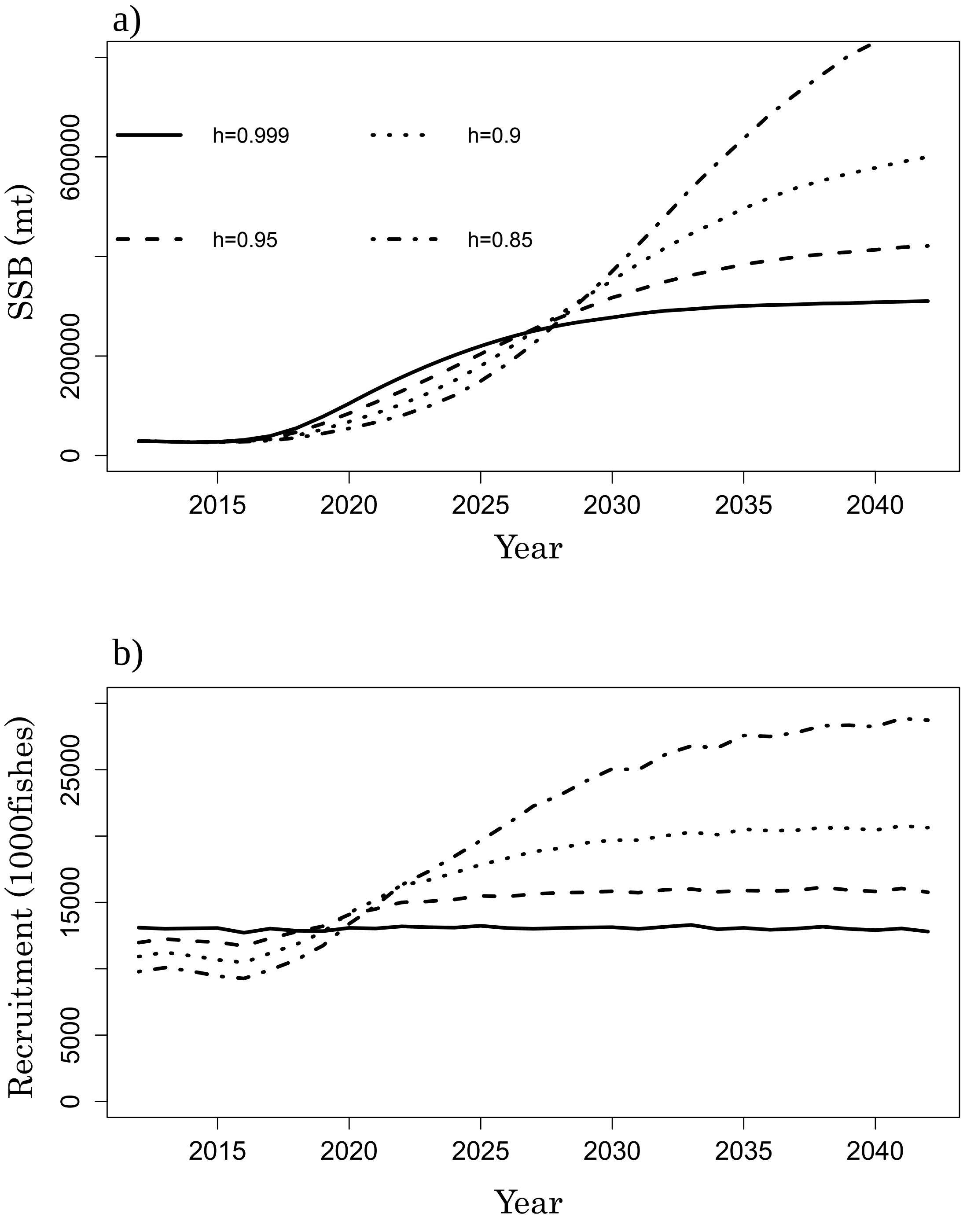

Figure 3: Future projections of SSB (a) and recruitment (b) for various h. Median of each projection is shown. <u>These demonstrations should only be used to examine competing projection methods but not to infer conclusions regarding the current stock status or future condition of PBF.</u>