Estimation of population dynamics for the Indian Ocean albacore tuna using state-space production models - ML and Bayesian approaches -

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Abstract

Population dynamics for the Indian Ocean albacore tuna was inferred using state-space age-aggregated surplus production models. For the estimation, both the maximum likelihood (ML) method with a Laplace approximation and Bayesian methods with several MCMC sampling approaches were employed. A total of 12 scenarios were assumed for the state-space models as combinations of [two different surplus production functions: Fox and Pella-Tomlinson]*[two different assumptions for initial depletion: start at 1950 with the assumption of B1950=K and start at 1979 with B1979 = D1979*K < K] *[Assumed extents of sampling CV for CPUE=0, 10% and 20%, in addition to an unknown additional model error]. Furthermore, non-state-space models were run for comparison purposes. In both the ML and Bayesian estimation methods, key parameters in the production function were not well estimated under the Pella-Tomlinson model because of unidentifiability between shape and intrinsic growth rate. As a result, mainly to highlight the impact of presence/absence of process errors (for the comparison of the results in this paper to the ASPIC paper) and to draw attention to the influence of the assumed CV in the CPUE in the estimation process, the results of the Fox production model are shown. These results showed that when estimating the initial depletion level in 1979, the presence/absence of process errors displayed a difference in the population trajectory. Furthermore, the assumed extent of the CV of the CPUE influenced trajectory to some extent, which implied a risk in subjectivity for such assumptions. Regarding the stock status, the results also suggested that the albacore tuna population had not been overfished and had not been subjected to overfishing. One of the main intentions behind the submission of this paper, with a focus on state-space production models, is to compare full assessment results which might be agreed upon in the Working Party with those driven by these simplified models, as is done in this paper. Such simplified models can be used for underlying stock assessment models within model-based management procedures, and therefore it is worth confirming whether there is a consistency between these approaches.

1. Introduction

In the WPTmT in Malaysia in January 2019, several stock assessment models were proposed as candidate stock assessment models. These were divided into two categories: integrated age-structured models and simple age-aggregated models. Of course, if we succeed in conditioning the integrated models with more realistic model configurations, it would contribute greatly not only to the stock assessment of the albacore tuna but also to the management context including the Management Strategy Evaluation of the species.

Here, our primary intention is not to give full stock assessment results using state-space production models, including risk analyses, but to compare full assessment results which might be agreed upon in the Working Party with those derived by such simplified models. The reason for this is that such simplified models can be used for underlying stock assessment models within model-based management procedures and therefore, it is worth confirming if there is a consistency between these approaches.

2. Data

To implement the production model, we used the annual total catch data (Fig 1) and yearly STD CPUE series that were estimated through joint CPUE analyses (see Fig 2). Since CPUE in the regions 3 and 4 may be representative, we chose the joint CPUE (area R3+R4) with vessel effects from 1979 to 2017. Here, no further adjustment for the catchability is considered.

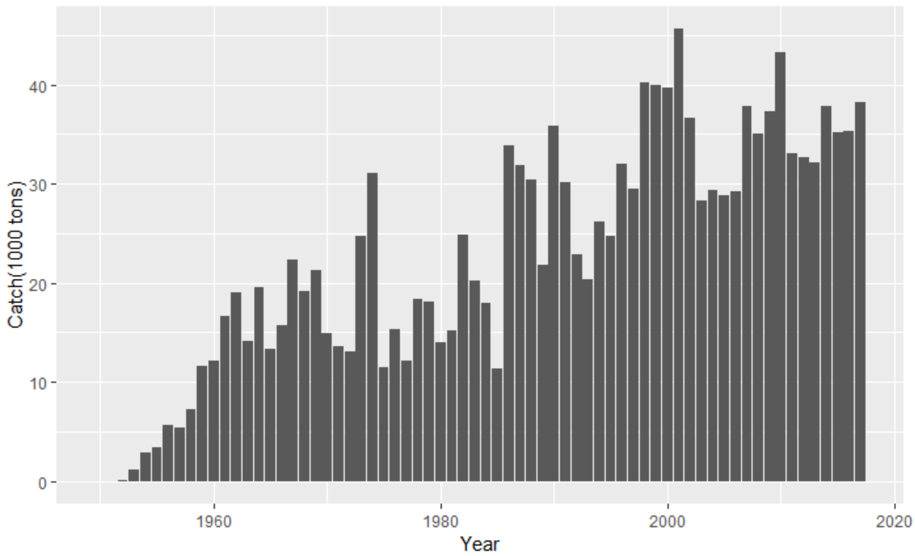


Figure 1. Time series of annual total catch (1000 tons).

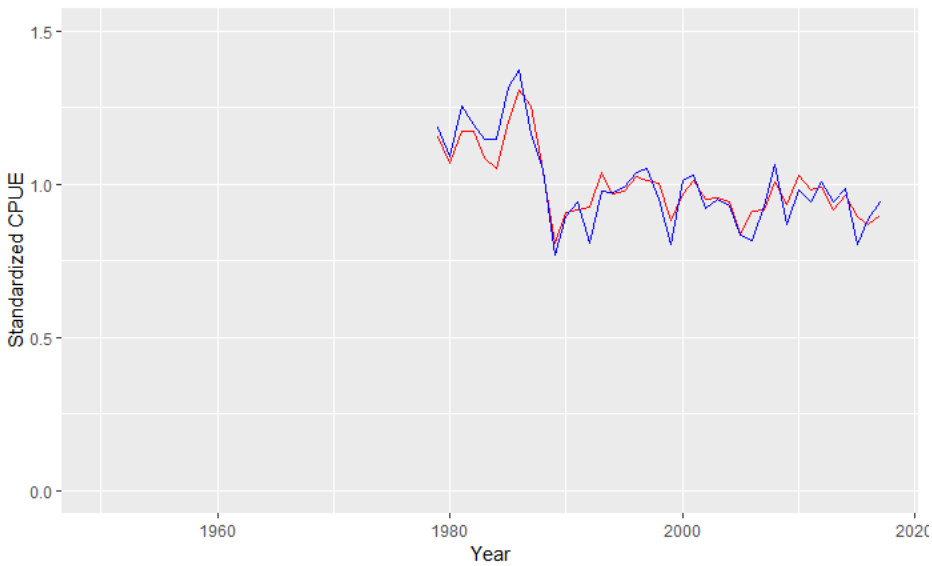


Figure 2. Joint CPUE series for all regions (red) and south regions (R3 & R4).

3. Methods

Population dynamics for the Indian Ocean albacore tuna was inferred using state-space age-aggregated surplus production models.

3.1 State-space production models

In the production model, the population has to be considered as whole biomass of a single species. We thus assumed that albacore tuna in the Indian Ocean is a single stock and cannot provide any estimation related to spawning stock biomass. The general production model equation is:

$$B_{t+1} = B_t + g(B_t) - C_t \tag{1}$$

where B_t is the biomass in year t and C_t is the total catch in year t. It is known that there are 2 types of production models, listed below (Fox and Pella-Tomlinson).

$$g(B) = rB\left(log\frac{K}{B}\right) \tag{2}$$

$$g(B) = rB\left(1 - \left(\frac{B}{K}\right)^z\right) \tag{3}$$

Here, r is the intrinsic growth rate, K is the carrying capacity, and z denotes the shape parameter of Pella-Tomlinson model which controls the model's shape and MSY level.

Table 1. MSY and MSY level for the two production models

Model	MSY	Bmsy
Fox	$\frac{rK}{e}$	$\frac{K}{e}$
Pella-Tomlinson	$rKz(z+1)^{-1-\frac{1}{z}}$	$K(\frac{1}{z+1})^{\frac{1}{z}}$

The observed data are represented by vectors with values for yields and CPUE denoted by C_t and I_t, respectively. The relationship between CPUE and biomass is given by:

$$I_t = qB_t \tag{4}$$

where q is a catchability coefficient. For the model's error structure, we employ a state-space model which assumes the existence of both observation error and process error as follows:

$$\begin{gathered} B_{t+1} = (B_t + g(B_t) - C_t)e^{\varepsilon_t} \\ I_t = qB_t e^{\eta_t} \\ \varepsilon_t \sim N(0, \tau^2) \\ \eta_t \sim N(0, \sigma^2) \end{gathered} \tag{5}$$

where ε_t and η_t are respectively the process and observation errors in year t.

A total of 12 scenarios are assumed for the state-space models as combinations of [two different functions for the surplus production: Fox and Pella-Tomlinson]*[two different assumptions for initial depletion: start at 1950 with the assumption of B1950=K and start at 1979 with B1979 = D1979*K < K] *[Assumed extents of sampling CV for CPUE=0, 10% and 20%, in addition to an unknown additional model error]. In addition, non-state-space models for Models 1-6 were run for the purpose comparison.

Table 1. Model specification for state-space production models.

Model	Production function	Year	Fixed CV for CPUE
1	Fox	1950-2017	0
2	Fox	1950-2017	10
3	Fox	1950-2017	20
4	Fox	1979-2017	0
5	Fox	1979-2017	10
6	Fox	1979-2017	20
7	PT	1950-2017	0
8	PT	1950-2017	10
9	PT	1950-2017	20
10	PT	1979-2017	0
11	PT	1979-2017	10
12	PT	1979-2017	20

3.2 ML estimation via TMB and Bayesian estimation via different MCMC samples using “stan”, “JAGS” and “NIMBLE”

For the estimation process, both the maximum likelihood method with a Laplace approximation and Bayesian methods with several MCMC sampling approaches are employed.

For the Bayesian estimation, a uniform distribution is used as a non-informative prior for all the parameters in the models. The range of the prior distribution was set by trial and error. Checking the results of the posterior distribution of each parameter, we adjusted the range of the prior distribution to be slightly wider than the posterior distribution. We used posterior medians as estimated values for each parameter.

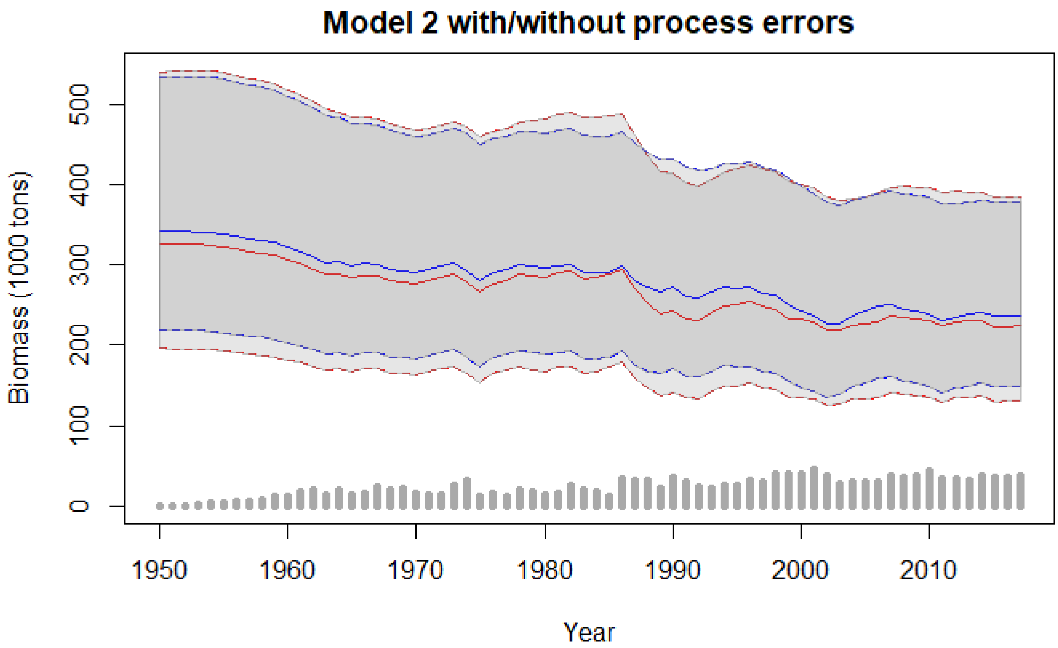
For MCMC sampling, Gibbs sampling (JAGS), Hamiltonian Monte Carlo (Stan) and Metropolis-Hasting algorithm (Nimble) methods are used for comparison.

4. Results and Discussion

4.1 Results of stock assessment by ML estimation via TMB

As a result, mainly to highlight the impact of presence/absence of process errors (for the comparison of the results in this paper to the ASPIC paper) and to draw attention to the influence of the assumed CV in the CPUE in the estimation process, the results of the Fox production model are mainly shown. Table 3 showed results of AIC for model comparison, but just for reference.

These results showed that when estimating the initial depletion level in 1979, the presence/absence of process errors displayed a difference in the population trajectory (see Figure 3). Furthermore, the assumed extent of the CV of the CPUE influenced trajectory to some extent, which implied a risk in subjectivity for such assumptions (see Figure 4).



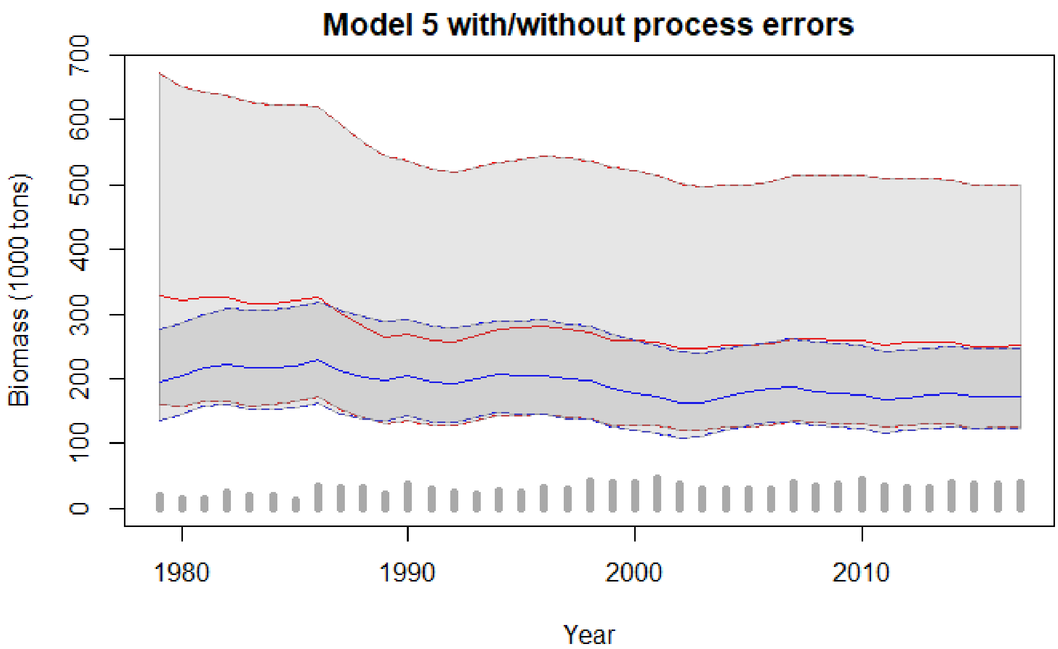


Figure 3. Comparison of biomass trajectories between models with and without process erros for Models 2 and 5.

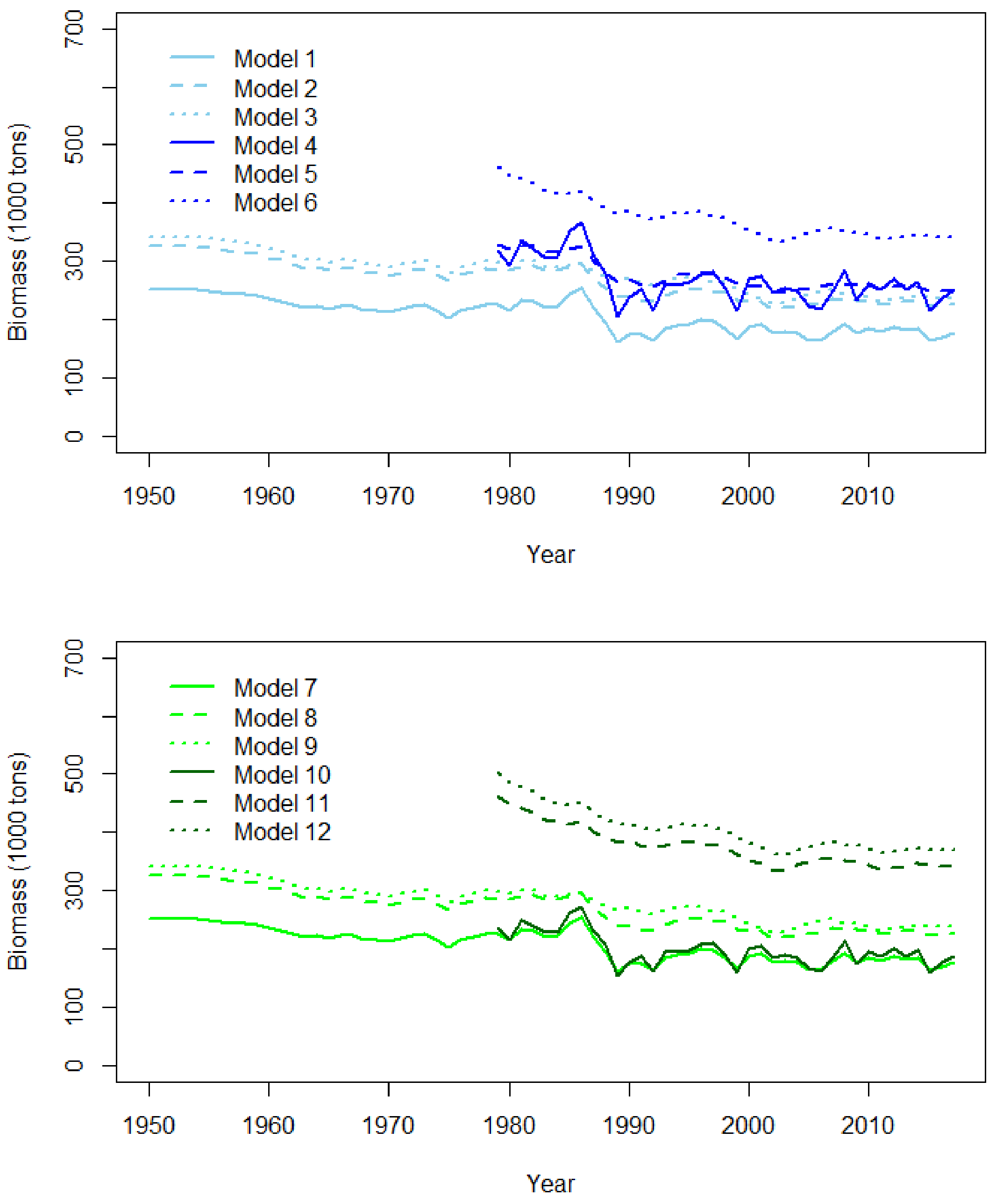


Figure 4. Comparison of biomass trajectories among Models 1-12 estimated by ML method. Note that the results for Model 7-12 are just for illustrative purpose because of non-convergence to reasonable parameter values.

4.2 Results of stock assessment by Bayesian estimation

Table 3 showed results of WAIC for model comparison. Although the WAIC supported the models with fixed CV of 0%, As in the case of the ML estimation,

Table 3. Results of model selection via AIC with TMB and WAIC in “stan” analysis

	Model	Year	Fixed CV	AIC	Δ AIC	WAIC	Δ WAIC
1	Fox	1950-2017	0%	-60.83	26.24	-97.39	0.0
2	Fox	1950-2017	10%	-57.88	29.19	-65.61	31.8
3	Fox	1950-2017	20%	-33.41	53.66	-38.44	59.0
4	Fox	1979-2017	0%	-87.07	0	-96.73	0.7
5	Fox	1979-2017	10%	-56.39	30.68	-65.43	32.0
6	Fox	1979-2017	20%	-31.65	55.42	-37.74	59.6
7	PT	1950-2017	0%	-58.83	28.24	-88.47	8.9
8	PT	1950-2017	10%	-55.88	31.19	-65.69	31.7
9	PT	1950-2017	20%	-31.41	55.66	-36.12	61.3
10	PT	1979-2017	0%	-85.6	1.47	-88.57	8.8
11	PT	1979-2017	10%%	-54.39	32.68	-65.70	31.7
12	PT	1979-2017	20%	-29.65	57.42	-37.33	60.1

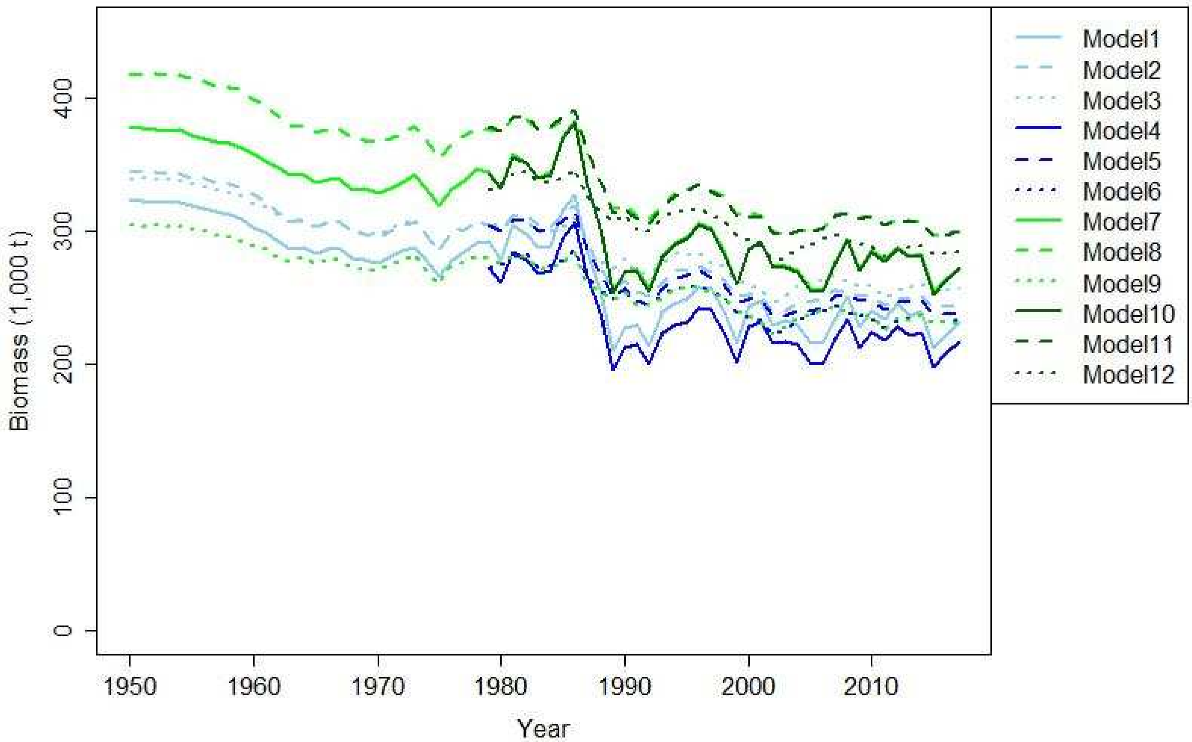


Figure 5. Comparison of biomass trajectories among Models 1-12 estimated by Bayesian method. Note that the results for Model 7-12 are just for illustrative purpose because of non-convergence to reasonable parameter values.

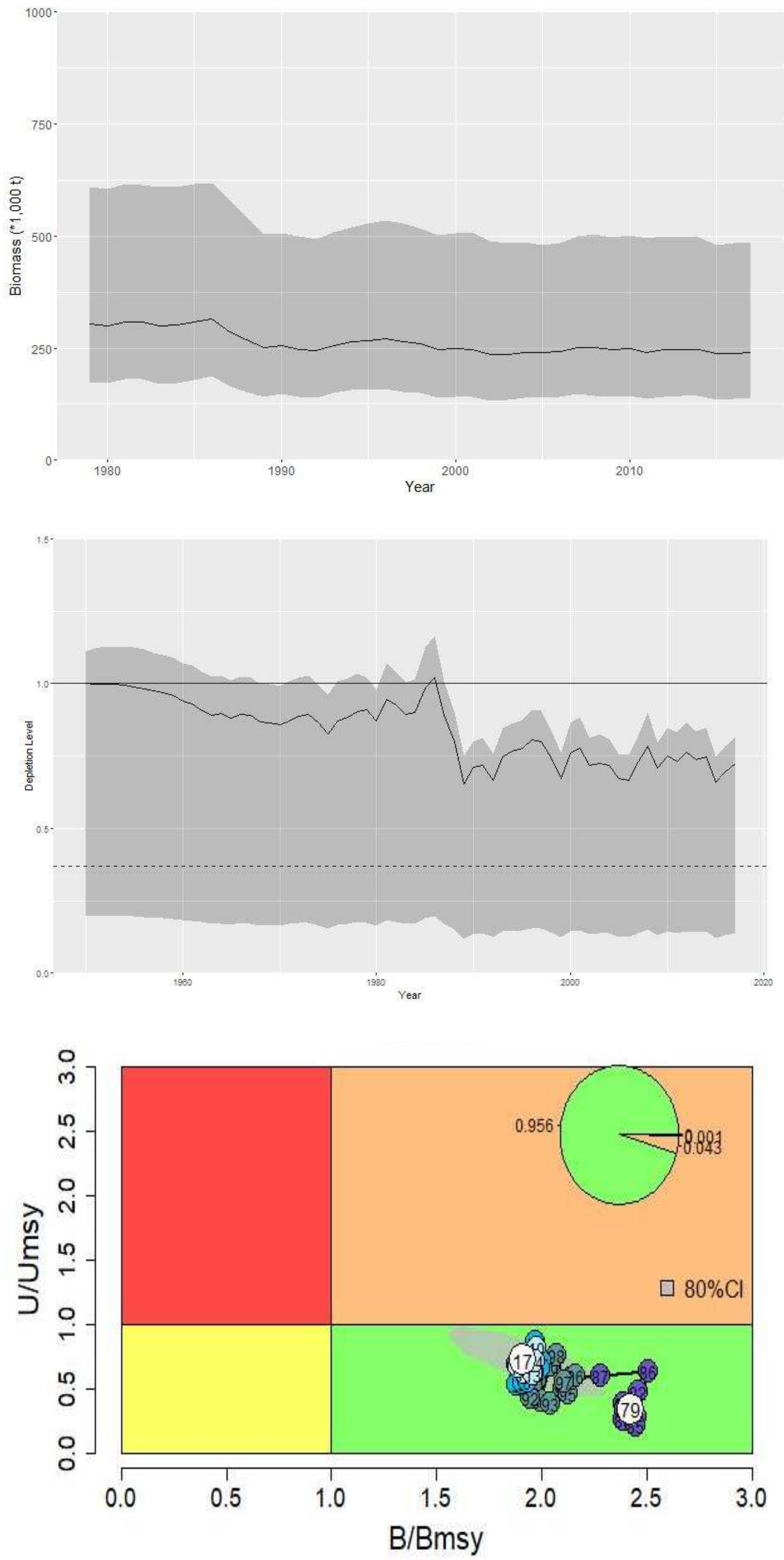


Figure 6. Estimated trajectories for the biomass (B) and depletion level (B/K) with 80%CI and Kobe plot for Model 5.

5. Conclusions

Regarding the stock status, the results based on ML and Bayesian methods suggested that the albacore tuna population had not been overfished and had not been subjected to overfishing.

One of the main intentions behind the submission of this paper, with a focus on state-space production models, is to compare full assessment results which might be agreed upon in the Working Party with those driven by these simplified models, as is done in this paper. Such simplified models can be used for underlying stock assessment models within model-based management procedures, and therefore it is worth confirming whether there is a consistency between these approaches.

Acknowledgement

Authors thank Dr. Hoyle for his kind preparation of annual aggregated joint CPUE series.

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Fox, W. W., Jr. 1974. An overview of production modeling. WTPD-Nantes/74/13, 142-156.

Pella, J.J. and Tomlinson, P.K. 1969. A generalized stock production model. Bull. Inter-Amer. Trop. Tuna. Comm., 13, 421-496.

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Appendix A: Further information on stock assessment results using the ML method

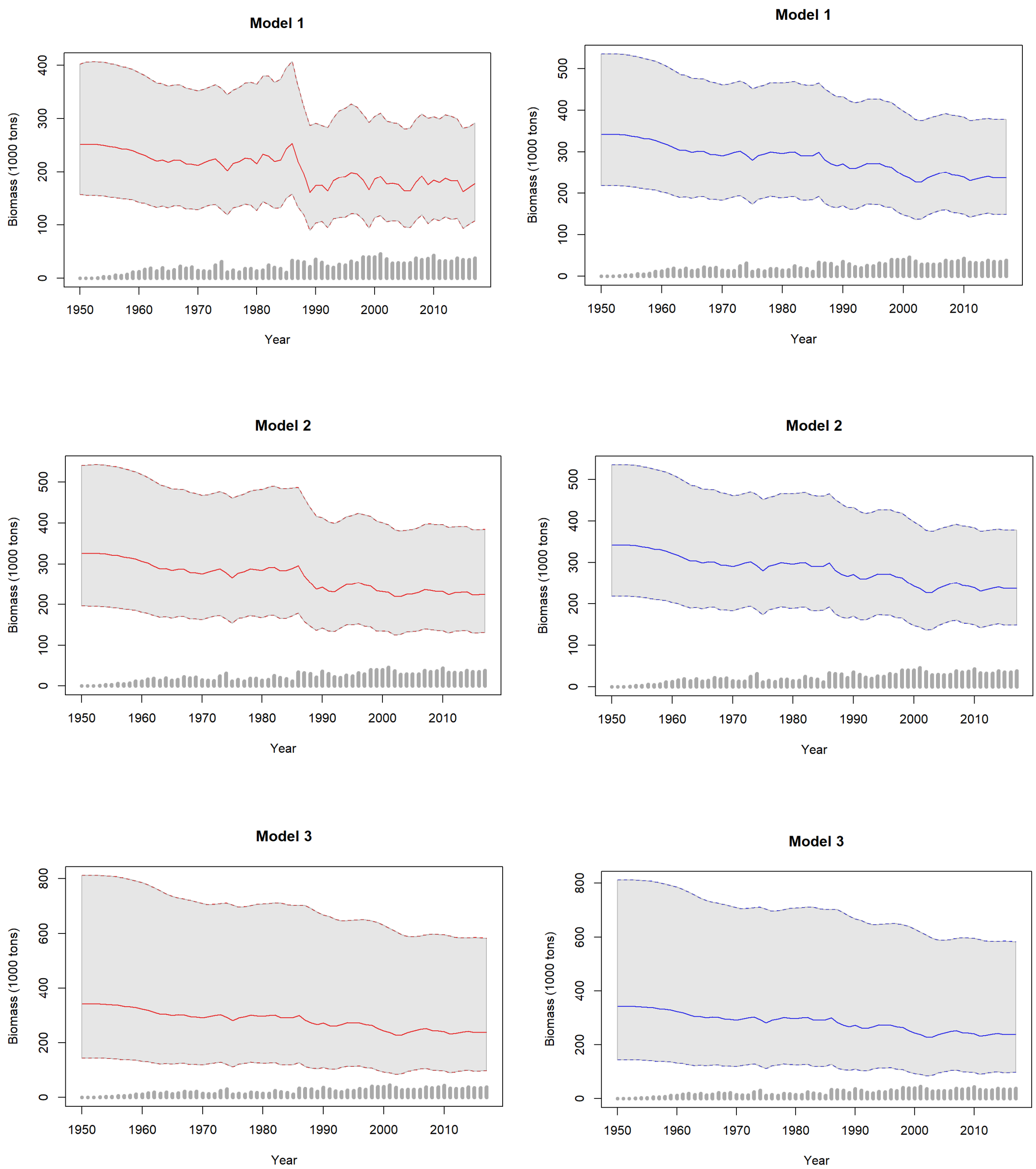

Figure A1. Estimated population trajectories for Models 1-3 with the process errors (left) and without process errors (right). Note that the results for Models 7-9 were similar with the corresponding models but the computation was not converged for all the cases.

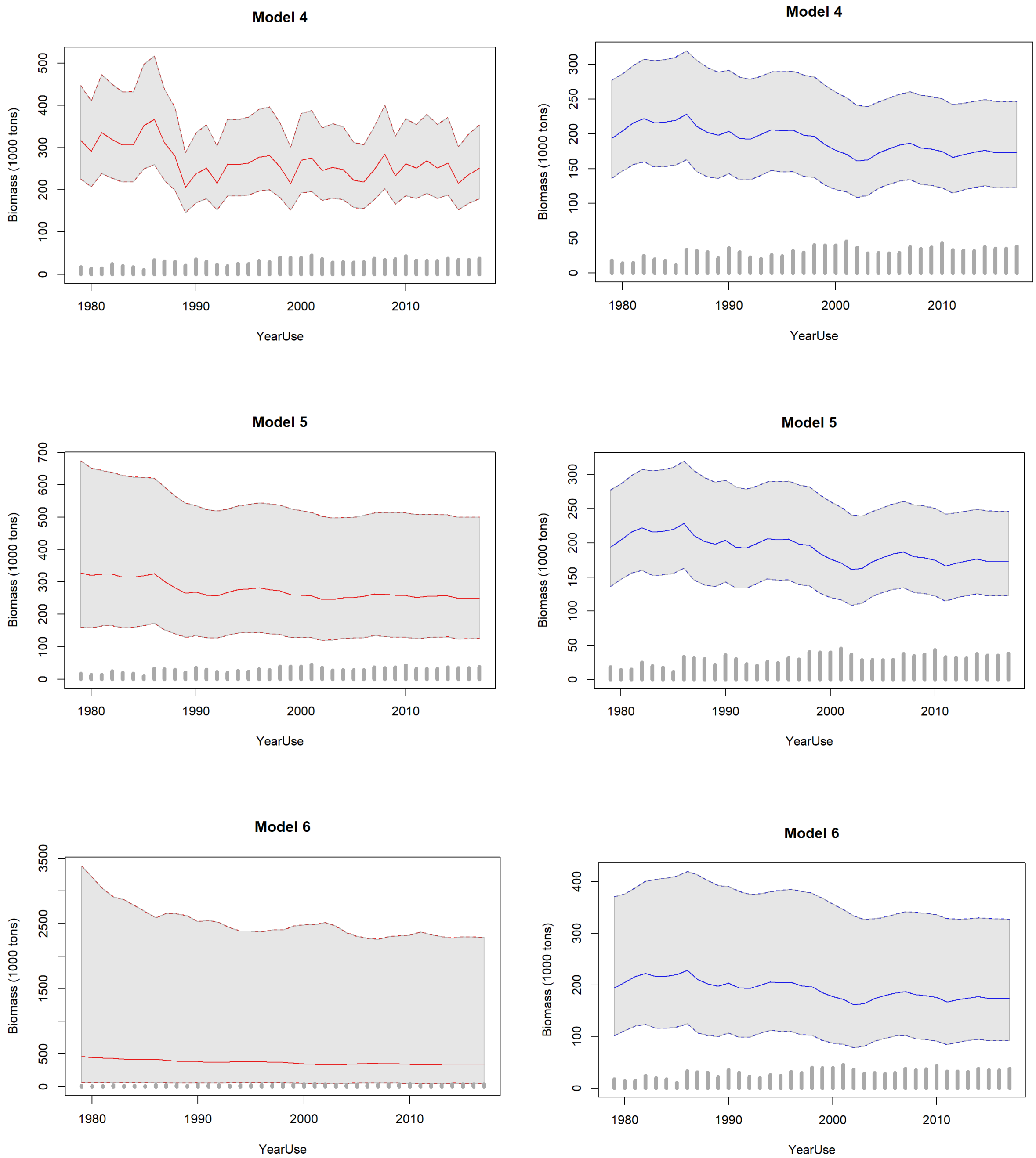

Figure A2. Estimated population trajectories for Models 4-6 with the process errors (left) and without process errors (right). Note that the results for Models 10-12 were similar with the corresponding models but the computation was not converged for all the cases.

Appendix B: Further information on stock assessment results with Bayesian methods – comparison among different MCMC samplers (for Model 5) -

B1. Convergence of MCMC (trace plot)

B1.1. stan

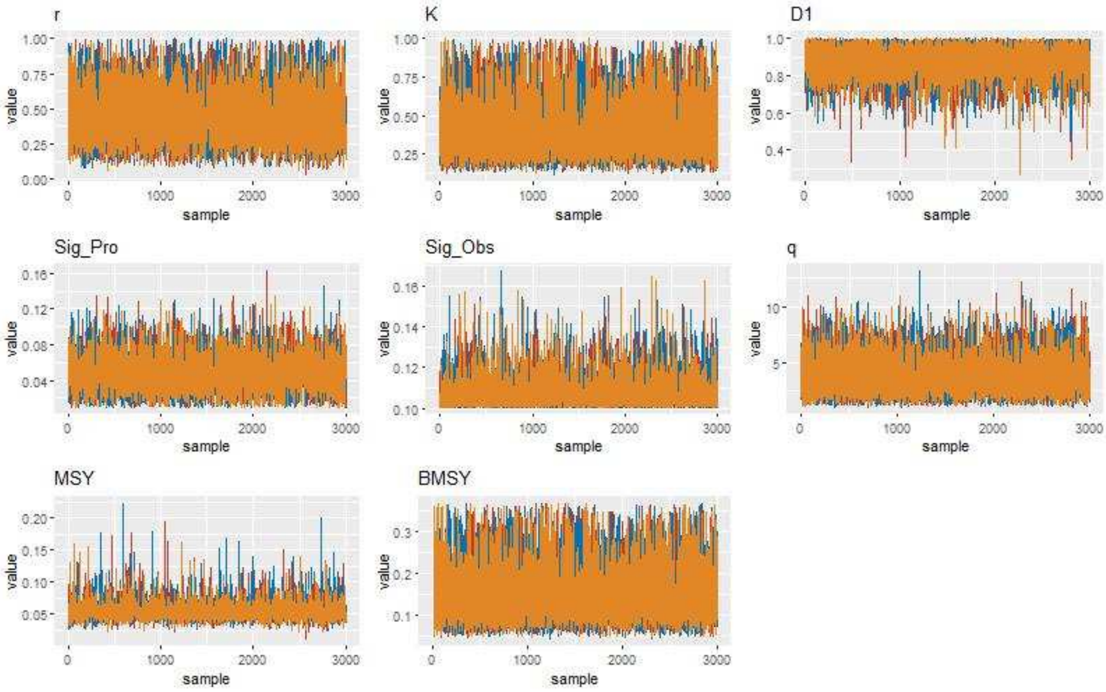

Figure B1-1. Trace plots for each parameter by stan.

B1.2 JAGS

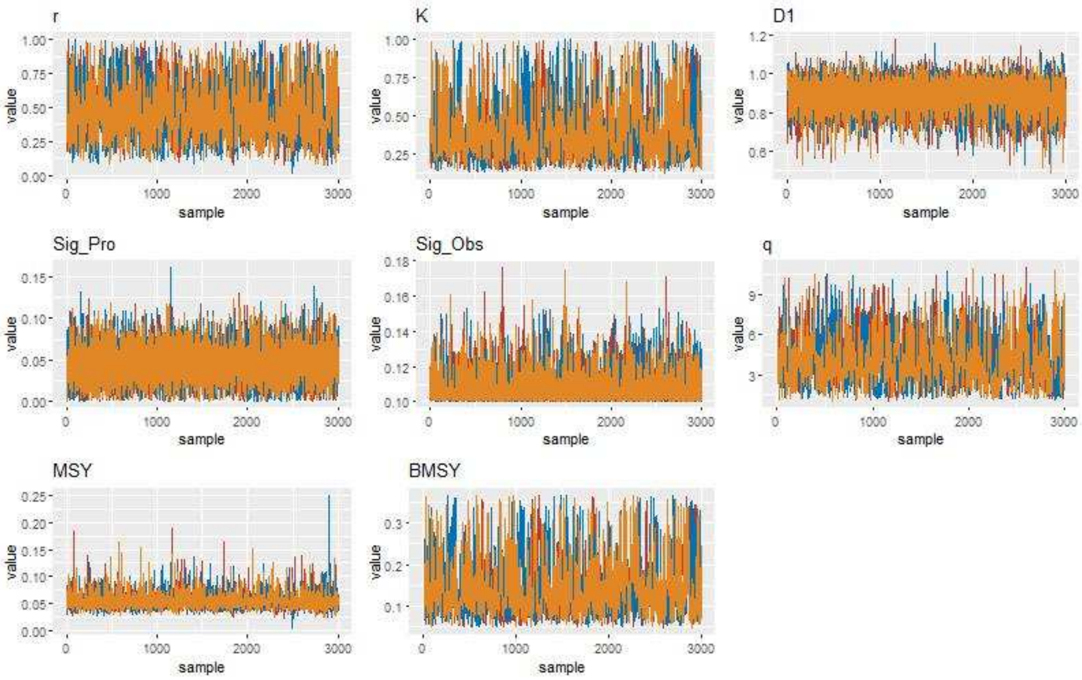

Figure B1-2. Trace plots for each parameter by JAGS.

B1.3 NIMBLE

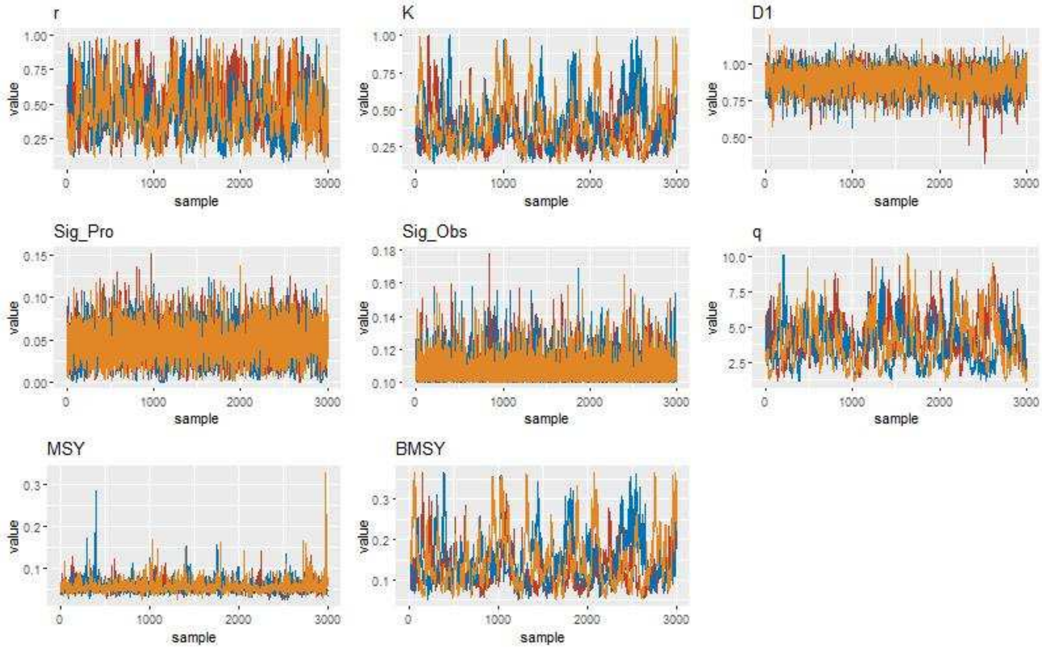

Figure B1-3. Trace plots for each parameter by NIMBLE.

B2. Posterior distribution

B2.1 Stan

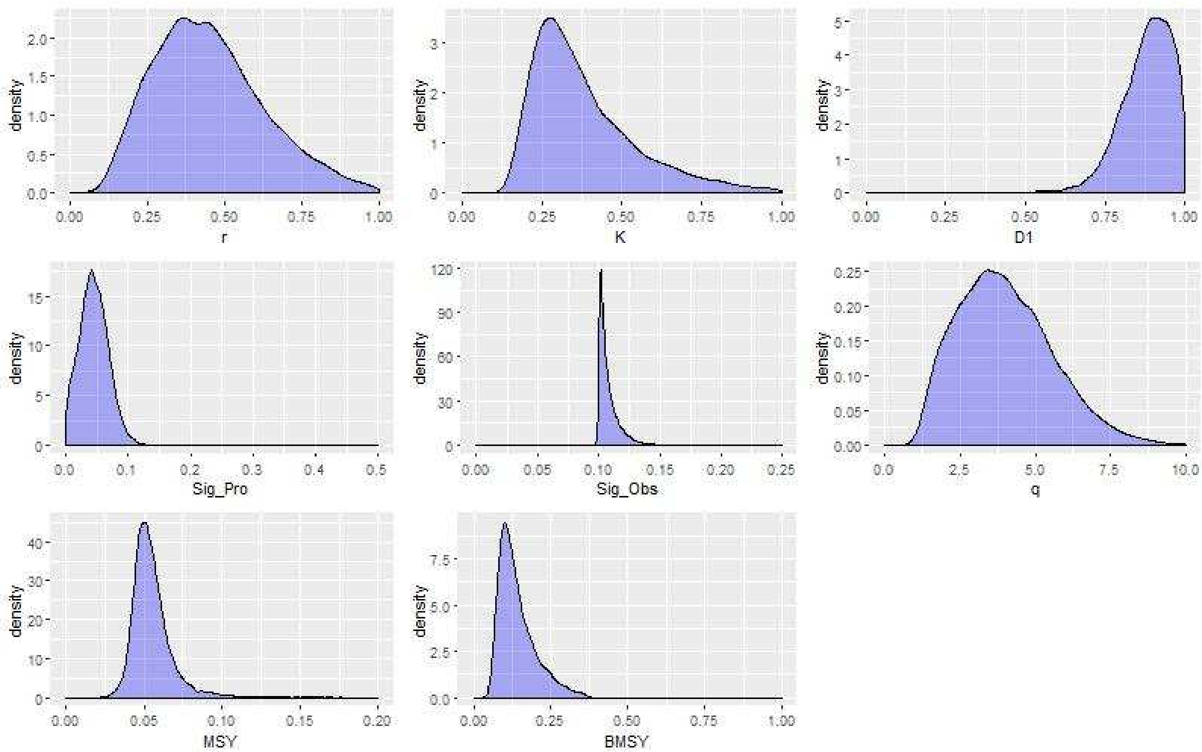

Figure B2-1. Posterior distribution for each parameter by stan.

B2.2 JAGS

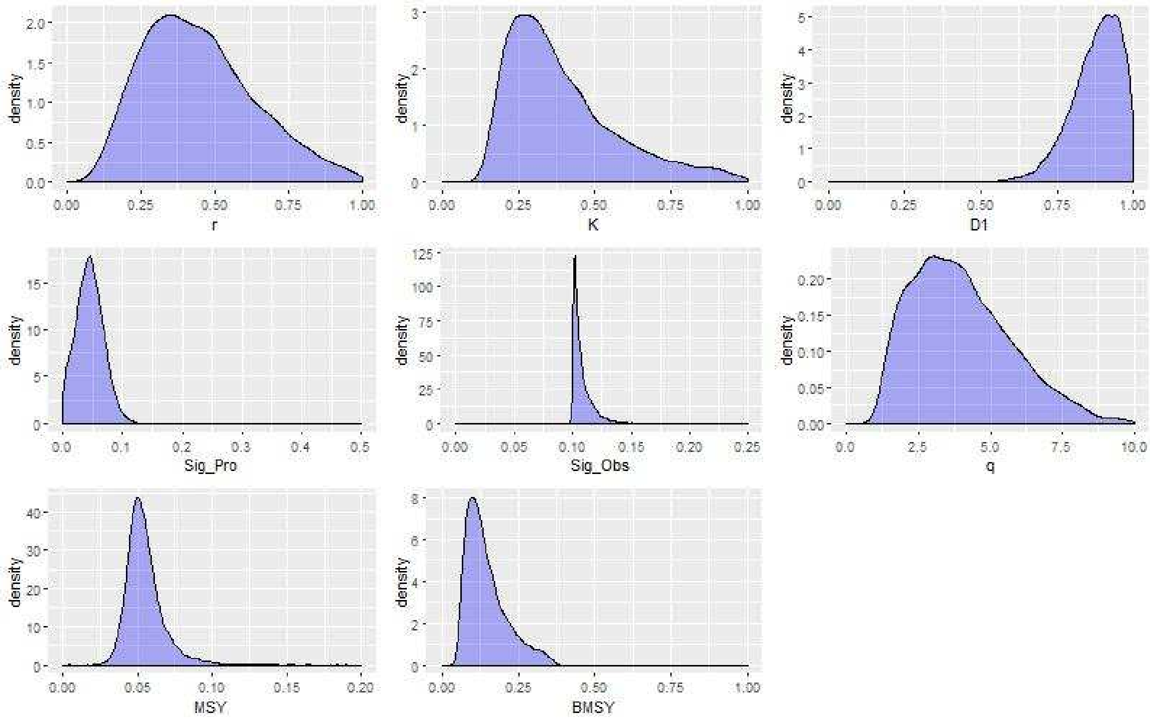

Figure B2-2. Posterior distribution for each parameter by JAGS.

B2.3 NIMBLE

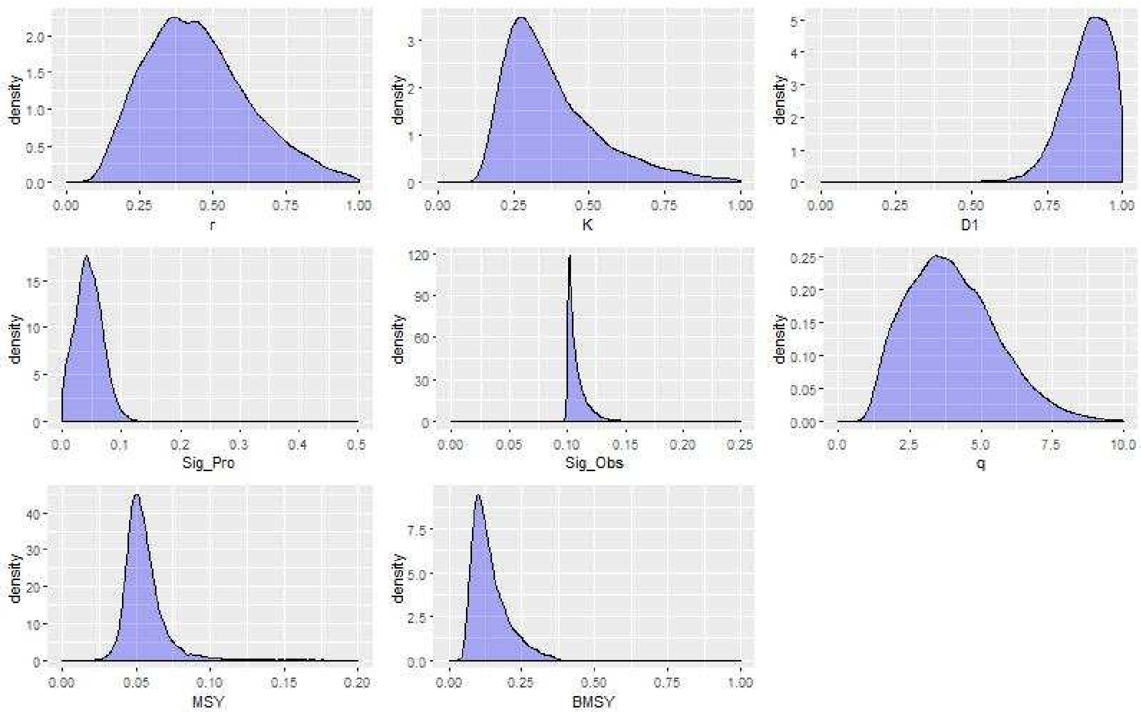

Figure B2-3. Posterior distribution for each parameter by NIMBLE.

B3. Estimation values and 80% credible interval

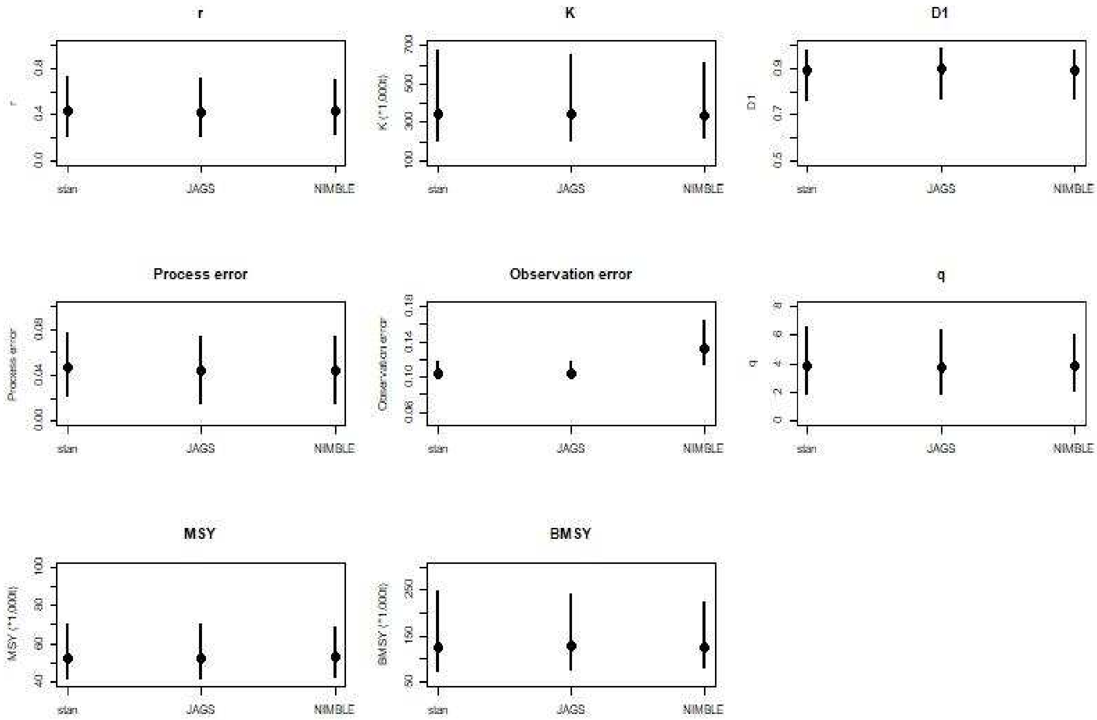

Figure B3. Point estimates and 80% credible intervals for each parameter for the stan, JAGS and NIMBLE.

B4. Population dynamics

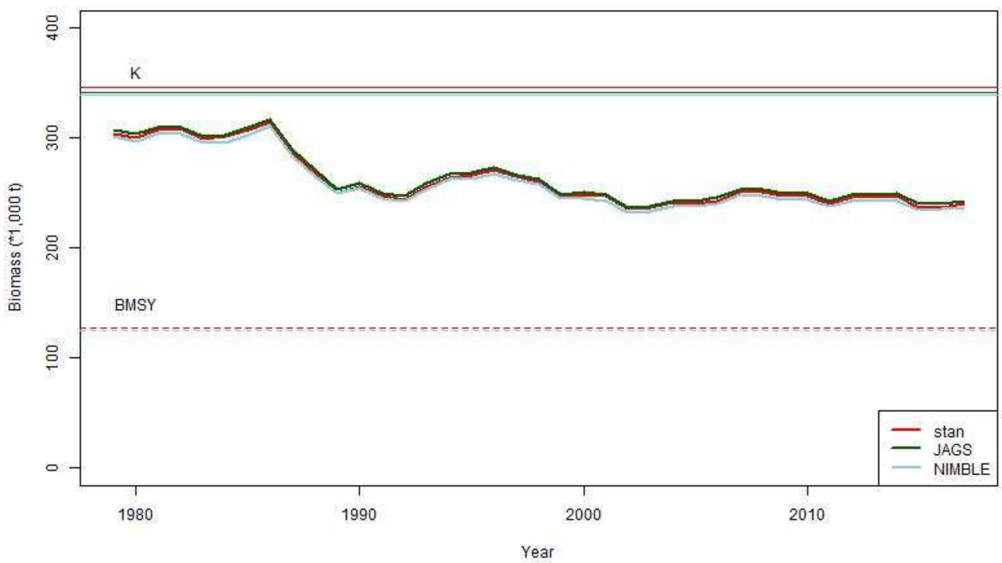

Figure B4. Comparison of median trajectories of population biomass among the stan, JAGS and NIMBLE.

B5. KOBE plot

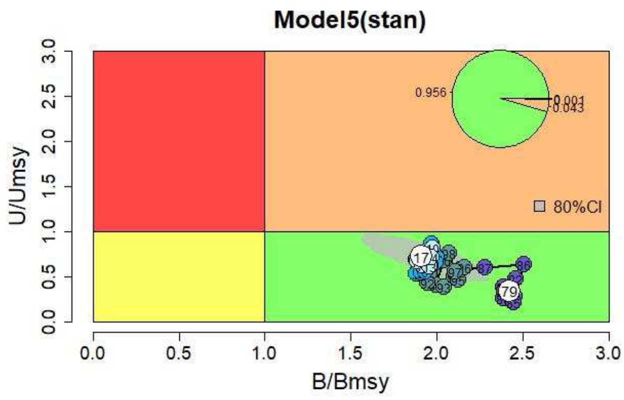

Figure B5-1. Kobe-plot by Stan.

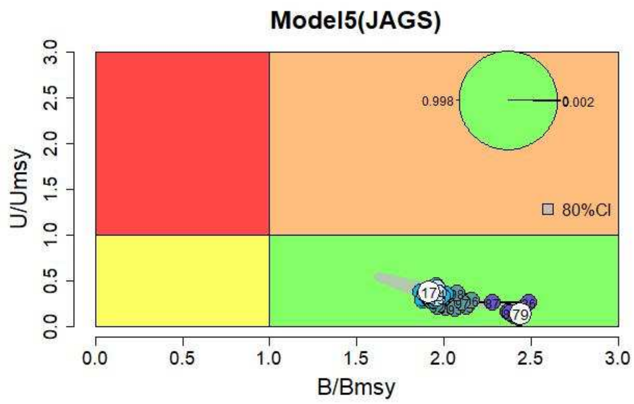

Figure B5-2. Kobe-plot by JAGS

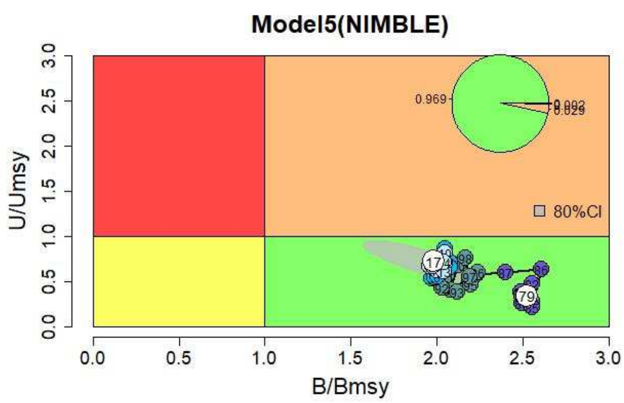

Figure B5-3. Kobe-plot by NIMBLE.

Appendix C: Further information on stock assessment using Bayesian methods – comparison of

results over 12 models based on stan analysis –

C1. Population dynamics

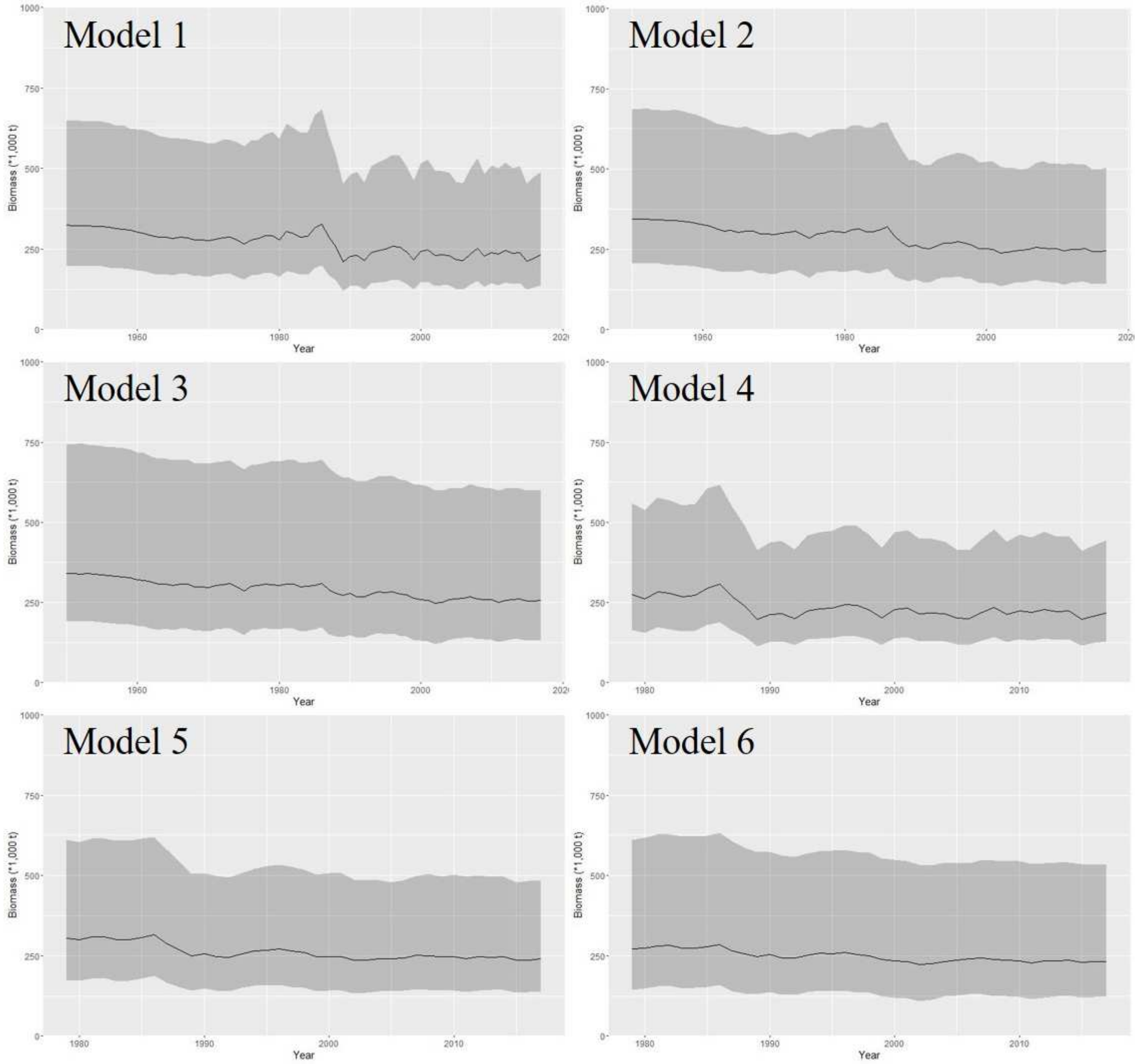

Figure C1-1. Median biomass trajectories with 80% CI for Models 1-6.

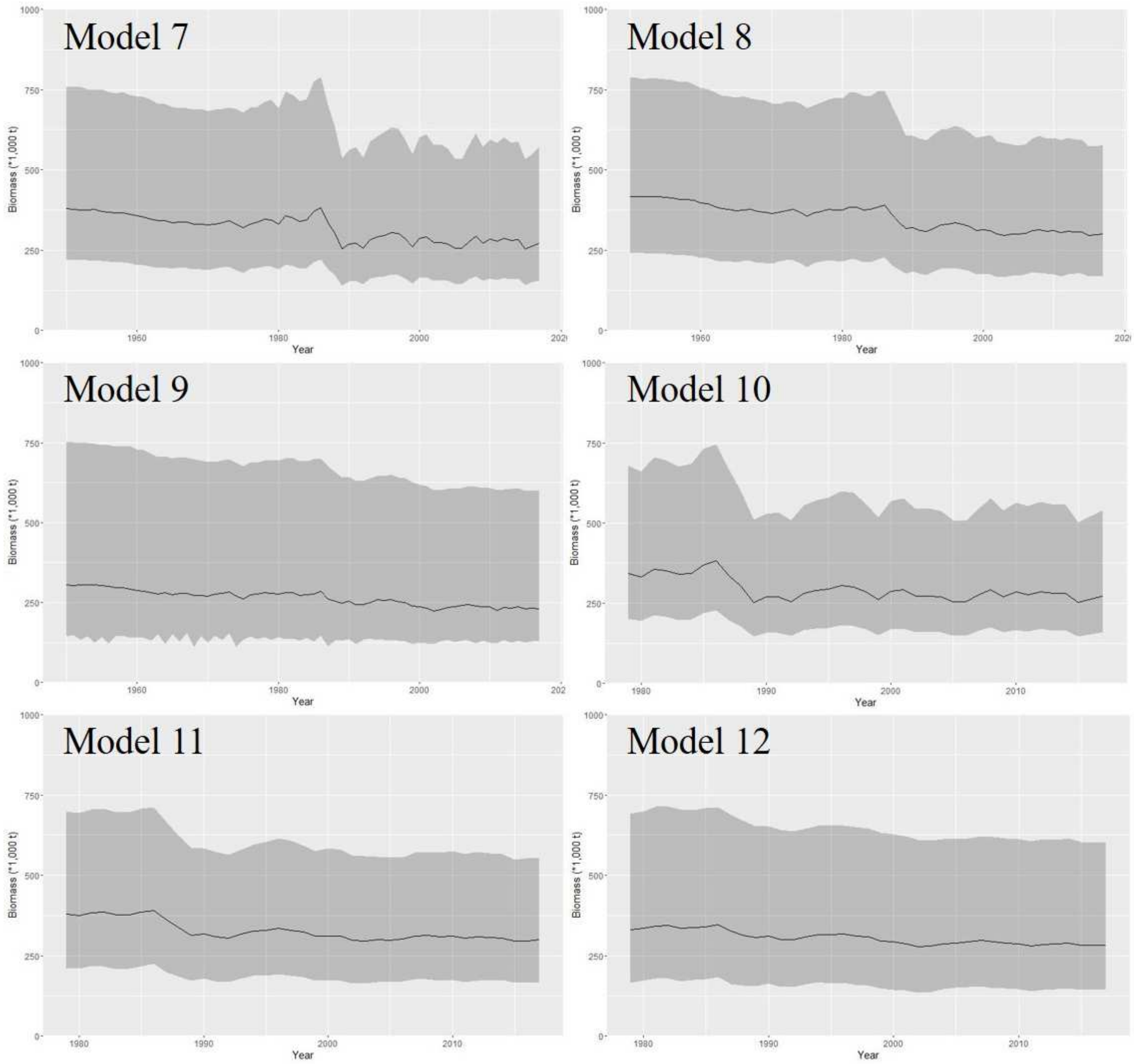

Figure C1-2. Median biomass trajectories with 80% CI for Models 1-6.

C2. KOBE plot

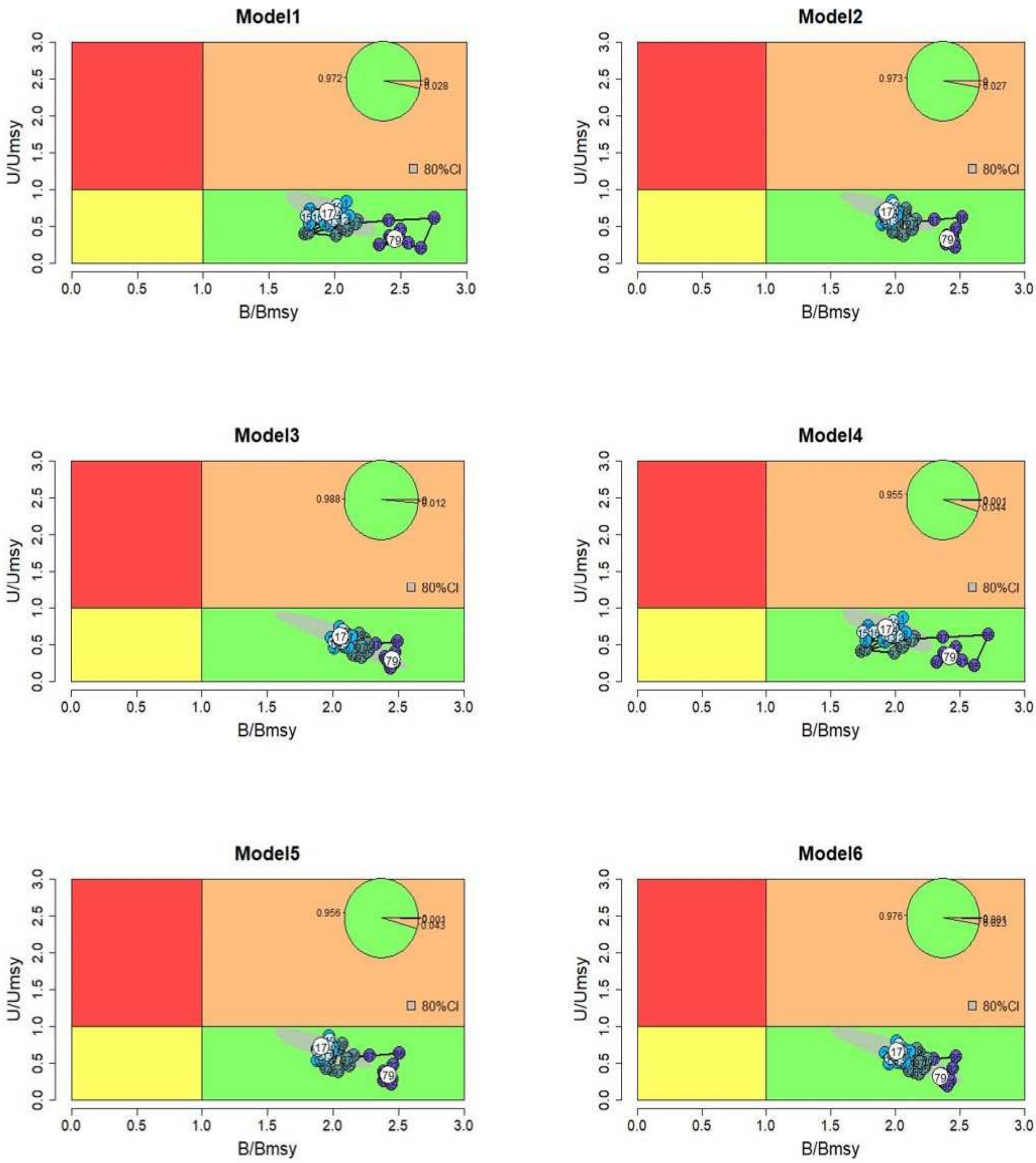

Figure C2-1. Kobe plots for Models 1-6.

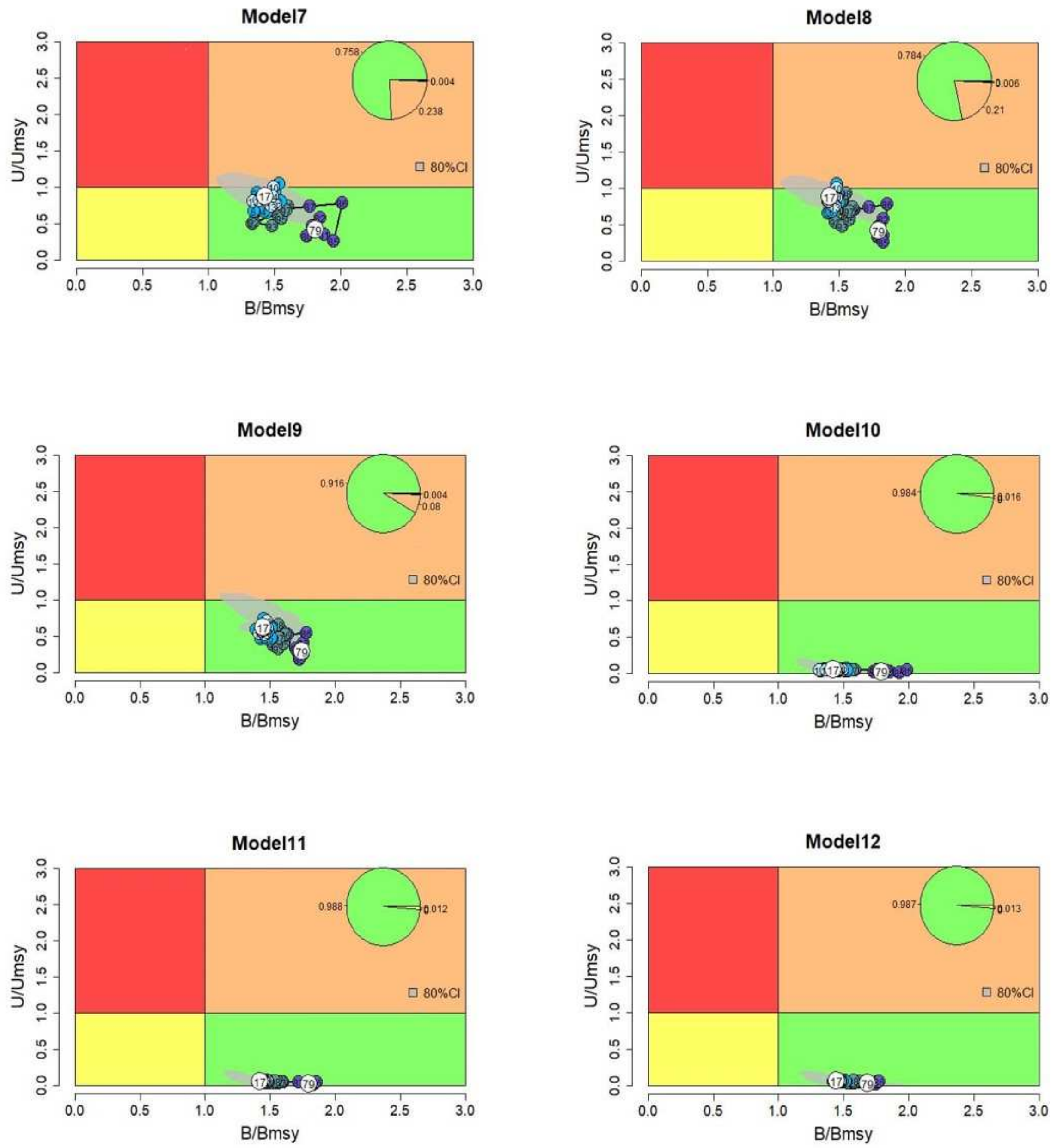

Figure C2-2. Kobe plots for Models 7-12.