

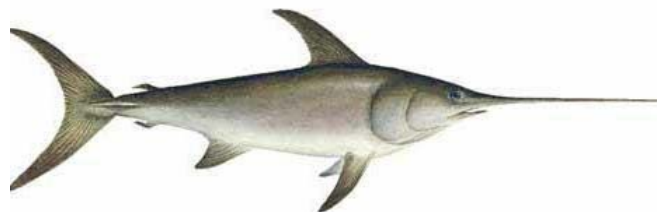
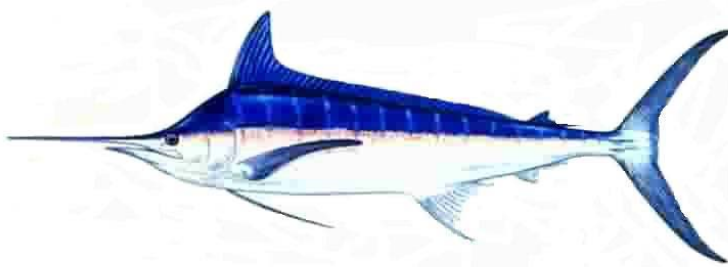


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Model-averaging to account for prior uncertainty in swordfish intrinsic growth rate and carrying capacity

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Abstract

Existing data for the assessment of North Pacific swordfish stocks are limited. The available abundance index and catch data contain little information pertaining to possible population dynamics. Moreover, promised prior information on North Pacific swordfish is not available. Preliminary results of a Bayesian surplus production model of the North Pacific swordfish population suggests that the posterior distributions of means for the intrinsic growth rate and carrying capacity depends on the configurations of the prior distributions. However, the goodness-of-fits given posterior distributions are varied. This study develops a model averaging procedure with Bayesian information criteria (BIC) to account for uncertainties arising from the choice of prior distributions when data contains little information. Our preliminary results suggest the robustness of the BIC weighted parameter estimations and constancy with the Bayesian approach.

Introduction

The primary task of fisheries management is to oversee a decision process regarding the quantity of harvest in a given period, which is based on biological reference points estimated by a fishery stock assessment. In a stock assessment using Bayesian methods, explaining alternative biological reference points with heterogeneous probability distributions is one of the challenges for communicating with fishery managers and resource users (Punt and Hilborn, 1997). As decision makers, fishery resource managers and users prefer to have harvest recommendations of a fixed single number rather than multiple numbers with heterogeneous probabilities. This is particularly true when there is little applied prior information, and posterior probabilities among competing hypotheses are almost indistinguishable.

Fisheries stock assessments are often based on time series data of indices of catch and relative abundance from commercial fisheries, namely catch per unit effort (CPUE). In some cases, these data lack signals with which to verify the model structure and induce distinctively informative posterior distributions.

The North Pacific swordfish occupies the area managed by the northern Committee of the Western and Central Pacific Fishery Commission (WCPFC), and is an economically valuable resource for both commercial and recreational fisheries. The International Scientific Committee for Tuna and Tuna-like Species in the North Pacific Ocean (ISC) is responsible for taking management advice from the

fish stock assessment.

A number of studies for the stock assessment of swordfish have been conducted. As of 2008, three assessments on the North Pacific swordfish stock(s) have been done primarily using catch and CPUE. In 1999, a preliminary surplus production model was applied (Kleiber, 1999). In 2004, Kleiber and Yokawa (2004) conducted MULTIFAN-CL assessment, and Wang et al. (2005; 2007) applied a similar model structure by adding sexual dimorphism data. The latter two studies concluded that there was a little signal in the North Pacific swordfish fishery CPUE data to estimate biological functions and stock status (Courtney et al., 2008)

Brodziak and Ishimura (2009) applied the Bayesian surplus state-space model for the North Pacific swordfish stock assessments by using *WinBUG* (Bayesian inference Using Gibbs Sampling). Their preliminary results suggest that 1) the posterior distributions of means for the intrinsic growth rate and carrying capacity depends on the configurations of the prior distributions and 2) the goodness-of-fits given posterior distributions are distinguishable. This would infer the same conclusions as the previous two stock assessments for the North Pacific swordfish; there is little signal in CPUE data to induce the stable set of posterior distributions of parameters.

The aim of this paper is to explore the model-averaging technique when a Bayesian approach hardly detects a signal on fish population dynamics from catch and CPUE data. This can be achieved by weighting parameters by the Bayesian information criteria (BIC) of the posterior distributions.

This approach can be considered an analogy of Bayesian decision analysis. First, an equal probability is assigned for each set of candidate prior configurations for the parameters. As a primary condition, the possibility that the prior distributions do not have the same credibility is explicitly excluded. After estimating posterior mode, from a relative value of BIC, the weighting factors of parameters for each posterior distribution are calculated, and applied to the model –averaged parameters.

Methods

Full details of the application of the Bayesian surplus state-space model for the North Pacific swordfish stock assessments are presented in Brodziak and Ishimura (2009).

These authors employed a three-parameterized surplus production model, with the intrinsic growth rate (R), carrying capacity (K) and a production shape parameter (M).

$$(1) B_T = B_{T-1} + R \cdot B_{T-1} \left(1 - \left(\frac{B_{T-1}}{K} \right)^M \right) - C_{T-1}$$

We adapted a statistical package R with *R2WinBUGS* to estimate posterior distributions of parameters which gave us an automatic procedure to test more than one configuration of prior distributions, R and K .

After estimating the posterior mode of parameters for each configuration of the prior distributions, a Markov chain Monte Carlo (MCMC) simulation was applied to numerically sample three chains of length 600,000 from the posterior distribution. Each chain was thinned by 50 to eliminate autocorrelation and the first 5000 thinned iterations were excluded to eliminate potential dependence on initial conditions. Seven thousand iterations were then left for numerical inference using the first chain. Thinned iterations from the second chain were used to assess convergence of the MCMC sampling based on the potential scale reduction factor.

For each configuration of the prior distributions of R and K , the likelihoods of the alternative posterior distributions were compared using the Bayesian information criterion (BIC) to approximate the Bayes factor of each posterior sample. Then, averaging the resulting model probabilities based on the difference between the BIC value for the i th posterior distribution with one with maximized value L for likelihood function, for a Bayesian surplus production state-space model, p parameters (three for our model), and n data points were:

$$(2) \quad BIC_i = -2 \cdot L + p \cdot \log(n)$$

Each model was assigned an equal prior weight of $\Pr(i) = 1/m$, in which m represents the total number of configurations of prior distributions, R and K . The exponential of minus one half times the difference in BIC values between the i th and the best-fitting model with configuration of prior distributions (Θ_0) at the k th iterate ($\Delta_i^{(k)}$) was used to

approximate the Bayes factor ($B_{i,o}^{(k)}$), or the relative odds that model with prior distribution θ_i versus θ_0 has the best fit.

$$(3) \quad B_{i,o}^{(k)} \approx \exp\left(-\frac{1}{2}(BIC_i^{(k)} - BIC_0^{(k)})\right) = -\frac{1}{2}\Delta_i^{(k)}$$

The posterior probability that model was the true model under assessment scenario j ($\Pr(\theta_i | D_j)$) was then calculated from the MCMC samples as

$$(4) \quad \Pr(\theta_i | D_j) = \frac{\Pr(\theta_i) \cdot B_{i,0}}{\sum_m \Pr(\theta_m) \cdot B_{m,0}} \approx \frac{1}{7000} \sum_{k=1}^{7000} \frac{\frac{1}{m} \exp(-0.5\Delta_i^{(k)})}{\sum_{q=1}^m \frac{1}{m} \exp(-0.5\Delta_q^{(k)})}$$

Given the posterior model probabilities, the model-averaged expected values of parameter estimates (K_i or r_i), were computed as the weighted average of the four conditional model expectations:

$$(5) \quad E_M [K_j | D_j] = \sum_{i=1}^m \Pr(\theta_i | D_j) \cdot E_M [K_j | \theta_i, D_j]$$

Similarly, model-averaged variances (V_θ) of derived parameters such as K_i or r_i were computed from the four conditional model variance estimates and expected values as follows:

$$(6) \quad V_\theta [K_j | D_j] = \sum_{i=1}^m \Pr(\theta_i | D_j) \cdot \left\{ V_\theta [K_j | \theta_i, D_j] + (E_\theta [K_j | D_j] - E_\theta [K_j | \theta_i, D_j])^2 \right\}$$

These calculations are applied to see the effects of the model averaging procedure for the Bayesian parameter estimations for each stock scenario.

Results

Arbitrary sets of average K and r for prior distributions are chosen for the model

averaging procedure. The Bayesian parameter estimation of surplus state-space model for the North Pacific swordfish stock assessment were carried. For the single stock scenario, the combinations of $K=75, 100, 125$ and 150 (1000 mt) and $r= 0.5, 0.6, 0.7, 0.8, 0.9, 1.1, 1.2$ and 1.3 are applied for MCMC estimations.

The numeric results of K and r estimations for the single stock scenario are presented in Table 1 and 2 respectively. Estimated K are ranged from 63.90 to 80.06 (1000 mt) and estimated r are ranged from 0.83 to 1.48. Estimated higher K s are matching with lower r s which balance of the tradeoff in two mass increment parameters. This verified that the choice of prior information explicitly influences posterior distributions and a little signal of biomass index in CPUE time series.

The posterior BIC are presented in Table 4. It has narrow ranges from -267.079 to -272.176, but still has differences in fit. Figure 1 shows the weight factor for averaging parameters, which calculated from these BIC values. Prior pairs with higher r and lower K induce high weight factors (shown as %). Finally, table 4 presents model averaged parameters for each scenario.

Concluding remarks

This study is still preliminary and the results suggest our future focus on rather than unduly aggressive management on the swordfish stock assessment in the North Pacific. While application of non-informative or vague priors are often used, this model averaging procedure can be an alternative approach for the Bayesian parameter estimations in the fishery stock assessments.

References

- Brodziak, J. and G.Ishimura. 2009. Development of Bayesian surplus production models for the assessing North Pacific swordfish population. ISC/09/BILLWG-02/02
- Punt, A.E. & R. Hilborn. 1997. Fisheries stock assessment and decision analysis: A review of the Bayesian approach. Rev. Fish. Biol. Fish. 7: 35-63.

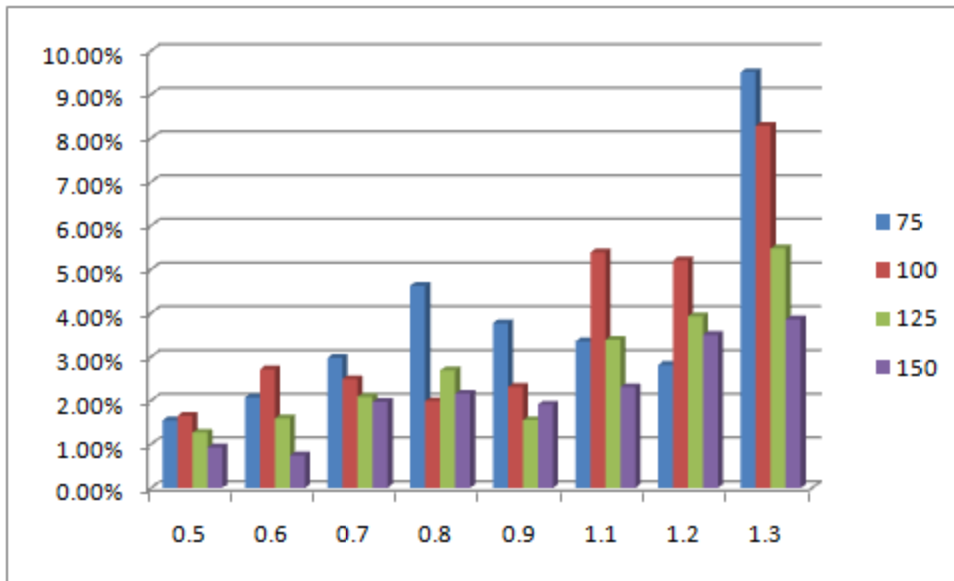


Figure 1. Applied weighting for parameters for the single stock scenario.

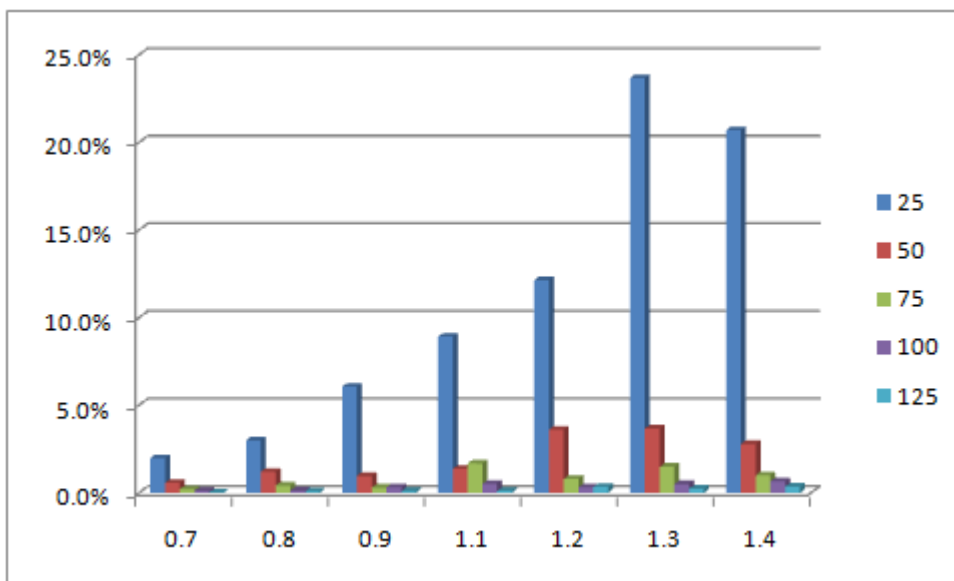


Figure 2. Applied weighting for parameters for Northern stock of the two stock scenario.

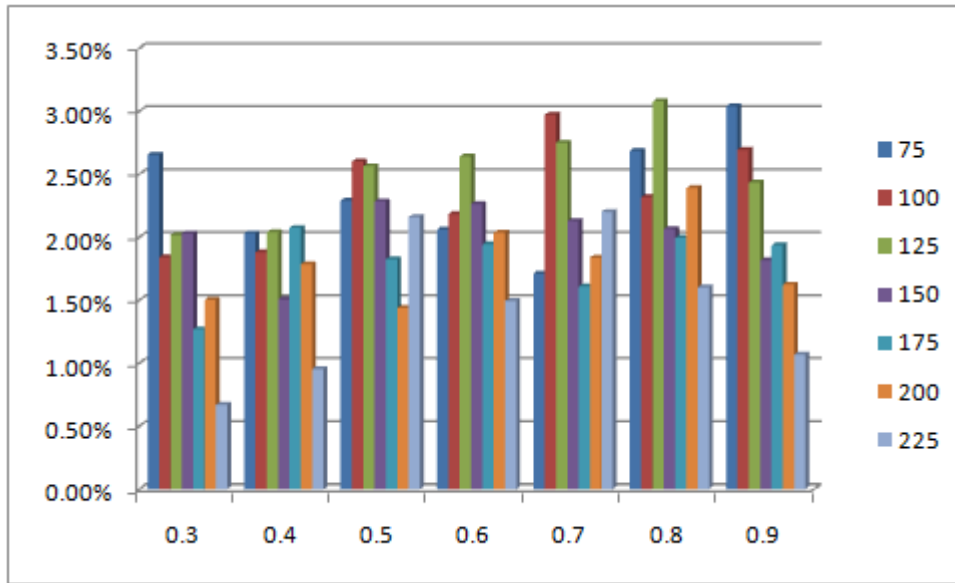


Figure 3. Applied weighting for parameters for Eastern stock of the two stock scenario.

Table 1: Average K for the single stock scenario for r and K prior sets.

		r							
		0.5	0.6	0.7	0.8	0.9	1.1	1.2	1.3
K	75	71.39	68.66	68.63	67.26	66.79	64.83	63.75	63.90
	100	74.17	72.29	71.38	71.00	69.13	67.49	67.17	66.31
	125	78.13	75.28	75.39	74.89	73.13	71.81	69.83	70.02
	150	80.06	78.25	78.80	76.60	75.04	73.50	71.84	72.60

Table 2. Average r for the single stock scenario for r and K prior sets..

		r							
		0.5	0.6	0.7	0.8	0.9	1.1	1.2	1.3
K	75	0.90	1.00	1.05	1.12	1.20	1.32	1.40	1.48
	100	0.87	0.96	1.03	1.08	1.16	1.31	1.38	1.44
	125	0.85	0.94	0.99	1.05	1.14	1.25	1.35	1.40
	150	0.83	0.91	0.97	1.05	1.11	1.25	1.34	1.38

Table 4. BIC for the single stock scenario. for r and K prior sets.

		r							
		0.5	0.6	0.7	0.8	0.9	1.1	1.2	1.3
K	75	-268.542	-269.127	-269.853	-270.732	-270.323	-270.089	-269.738	-272.176
	100	-268.672	-269.668	-269.493	-269.042	-269.344	-271.04	-270.97	-271.899
	125	-268.137	-268.598	-269.14	-269.649	-268.546	-270.11	-270.405	-271.073
	150	-267.515	-267.079	-269.022	-269.206	-268.96	-269.341	-270.175	-270.37

Table 5; Summary of model averaged parameters for the North Pacific swordfish.

Model Averaged Parameters	Single Stock	Two Stock NPO	Two Stock EPO
Average K	69.70	62.97	74.99
Average r	1.23	1.26	0.49
Average M	0.99	0.86	0.63
S.D. K	5.55	5.71	10.79
S.D. r	0.70	0.70	0.49
S.D. M	0.68	0.65	0.64
BMSY	34.76	30.62	34.51
HMSY	0.61	0.58	0.19
MSY	21.29	17.80	6.56
PMSY	0.50	0.49	0.46
FMSY	0.41	0.38	0.09

Appendix

Table 1. Average K for the single stock scenario for r and K prior sets.

		r							
		0.5	0.6	0.7	0.8	0.9	1.1	1.2	1.3
K	75	71.39	68.66	68.63	67.26	66.79	64.83	63.75	63.90
	100	74.17	72.29	71.38	71.00	69.13	67.49	67.17	66.31
	125	78.13	75.28	75.39	74.89	73.13	71.81	69.83	70.02
	150	80.06	78.25	78.80	76.60	75.04	73.50	71.84	72.60

Table 2. Average r for the single stock scenario for r and K prior sets..

		r							
		0.5	0.6	0.7	0.8	0.9	1.1	1.2	1.3
K	75	0.90	1.00	1.05	1.12	1.20	1.32	1.40	1.48
	100	0.87	0.96	1.03	1.08	1.16	1.31	1.38	1.44
	125	0.85	0.94	0.99	1.05	1.14	1.25	1.35	1.40
	150	0.83	0.91	0.97	1.05	1.11	1.25	1.34	1.38

Table 3. Average M for the single stock scenario for r and K prior sets..

		r							
		0.5	0.6	0.7	0.8	0.9	1.1	1.2	1.3
K	75	1.35	1.25	1.19	1.11	1.05	0.96	0.92	0.85
	100	1.34	1.22	1.14	1.10	1.04	0.92	0.88	0.85
	125	1.31	1.22	1.14	1.06	0.99	0.91	0.87	0.83
	150	1.29	1.19	1.12	1.04	1.00	0.89	0.84	0.81

Table 4. BIC for the single stock scenario. for r and K prior sets.

		r							
		0.5	0.6	0.7	0.8	0.9	1.1	1.2	1.3
K	75	-268.542	-269.127	-269.853	-270.732	-270.323	-270.089	-269.738	-272.176
	100	-268.672	-269.668	-269.493	-269.042	-269.344	-271.04	-270.97	-271.899
	125	-268.137	-268.598	-269.14	-269.649	-268.546	-270.11	-270.405	-271.073
	150	-267.515	-267.079	-269.022	-269.206	-268.96	-269.341	-270.175	-270.37

Table 5. Parameter weight calculated from BIC for the single stock scenario. for r and K prior sets.

		r							
		0.5	0.6	0.7	0.8	0.9	1.1	1.2	1.3
K	75	1.55%	2.07%	2.98%	4.62%	3.77%	3.35%	2.81%	9.51%
	100	1.65%	2.71%	2.49%	1.99%	2.31%	5.39%	5.20%	8.28%
	125	1.26%	1.59%	2.08%	2.69%	1.55%	3.39%	3.92%	5.48%
	150	0.93%	0.74%	1.97%	2.16%	1.91%	2.31%	3.50%	3.86%

Table 6. Average K for the two stock – Northern stock scenario for r and K prior sets.

		r						
		0.7	0.8	0.9	1.1	1.2	1.3	1.4
K	25	63.00	62.15	62.09	61.12	60.53	60.91	59.46
	50	70.69	69.63	68.97	67.78	67.59	66.97	67.99
	75	76.10	74.30	73.96	72.11	72.05	71.94	71.51
	100	78.43	77.81	77.60	76.06	75.95	74.88	74.86
	125	82.27	81.97	80.05	79.61	78.47	77.87	78.83

Table 7. Average r for the two stock – Northern stock scenario for r and K prior sets.

		r						
		0.7	0.8	0.9	1.1	1.2	1.3	1.4
K	25	0.95	1.02	1.09	1.20	1.25	1.33	1.39
	50	0.90	0.96	1.02	1.15	1.19	1.28	1.31
	75	0.87	0.92	0.99	1.12	1.17	1.23	1.31
	100	0.84	0.90	0.96	1.08	1.15	1.23	1.28
	125	0.82	0.89	0.95	1.06	1.14	1.18	1.27

Table 8. Average M for the two stock – Northern stock scenario for r and K prior sets.

		r						
		0.7	0.8	0.9	1.1	1.2	1.3	1.4
K	25	1.18	1.10	1.01	0.93	0.91	0.82	0.80
	50	1.08	1.02	0.97	0.86	0.83	0.78	0.73
	75	1.04	0.99	0.93	0.82	0.78	0.75	0.70
	100	1.03	0.96	0.90	0.81	0.76	0.72	0.69
	125	1.00	0.93	0.88	0.78	0.73	0.72	0.65

Table 9. BIC for the two stock – Northern stock scenario for r and K prior sets.

		r						
		0.7	0.8	0.9	1.1	1.2	1.3	1.4
K	25	-275.582	-276.42	-277.835	-278.608	-279.226	-280.562	-280.294
	50	-273.097	-274.585	-274.13	-274.86	-276.794	-276.829	-276.281
	75	-270.95	-272.435	-271.716	-275.261	-273.776	-275.024	-274.224
	100	-269.783	-269.931	-271.865	-272.854	-271.841	-272.827	-273.354
	125	-266.717	-269.09	-269.431	-269.799	-272.021	-271.317	-272.112

Table 10. Parameter weight calculated from BIC for the two stock – Northern stock scenario for r and K prior sets.

		r						
		0.7	0.8	0.9	1.1	1.2	1.3	1.4
K	25	2.0%	3.0%	6.1%	8.9%	12.1%	23.7%	20.7%
	50	0.6%	1.2%	0.9%	1.4%	3.6%	3.7%	2.8%
	75	0.2%	0.4%	0.3%	1.7%	0.8%	1.5%	1.0%
	100	0.1%	0.1%	0.3%	0.5%	0.3%	0.5%	0.6%
	125	0.0%	0.1%	0.1%	0.1%	0.3%	0.2%	0.3%

Table 11. Average K for the two stock – Eastern stock scenario for r and K prior sets.

		r						
		0.3	0.4	0.5	0.6	0.7	0.8	0.9
K	75	64.15	61.33	61.23	60.80	59.26	59.55	59.35
	100	70.56	68.49	67.29	68.12	66.72	65.85	65.21
	125	76.60	73.65	72.42	71.25	70.94	70.51	70.86
	150	81.12	78.09	76.79	75.77	76.52	75.72	76.14
	175	85.22	83.95	80.97	80.04	83.80	80.34	79.43
	200	93.15	87.38	88.77	84.56	84.21	83.65	84.51
	225	94.82	92.69	89.67	91.96	88.23	86.99	92.21

Table 12. Average r for the two stock – Eastern stock scenario for r and K prior sets.

		r						
		0.3	0.4	0.5	0.6	0.7	0.8	0.9
K	75	0.30	0.38	0.43	0.49	0.56	0.62	0.69
	100	0.29	0.36	0.43	0.48	0.56	0.61	0.68
	125	0.29	0.36	0.42	0.49	0.55	0.61	0.67
	150	0.28	0.35	0.42	0.48	0.54	0.61	0.67
	175	0.28	0.35	0.41	0.47	0.55	0.61	0.66
	200	0.27	0.35	0.40	0.48	0.54	0.60	0.65
	225	0.27	0.34	0.41	0.47	0.54	0.60	0.66

Table 13. Average M for the two stock – Eastern stock scenario for r and K prior sets.

		r						
		0.3	0.4	0.5	0.6	0.7	0.8	0.9
K	75	0.98	0.86	0.75	0.67	0.60	0.55	0.49
	100	0.95	0.83	0.71	0.63	0.57	0.52	0.48
	125	0.93	0.79	0.69	0.60	0.55	0.50	0.46
	150	0.90	0.77	0.66	0.61	0.54	0.48	0.45
	175	0.87	0.75	0.66	0.60	0.50	0.47	0.44
	200	0.86	0.74	0.64	0.57	0.51	0.46	0.42
	225	0.85	0.72	0.62	0.54	0.50	0.45	0.40

Table 14. BIC for the two stock – Eastern stock scenario for r and K prior sets.

		r						
		0.3	0.4	0.5	0.6	0.7	0.8	0.9
K	75	-107.41	-106.87	-107.11	-106.90	-106.53	-107.43	-107.68
	100	-106.68	-106.72	-107.37	-107.02	-107.63	-107.14	-107.44
	125	-106.86	-106.88	-107.34	-107.40	-107.48	-107.70	-107.23
	150	-106.87	-106.28	-107.11	-107.09	-106.97	-106.91	-106.65
	175	-105.93	-106.91	-106.66	-106.78	-106.41	-106.84	-106.78
	200	-106.27	-106.61	-106.18	-106.88	-106.67	-107.20	-106.43
	225	-104.65	-105.36	-107.00	-106.26	-107.03	-106.40	-105.59

Table 15. Parameter weight calculated from BIC for the two stock – Eastern stock scenario for r and K prior sets.

		r						
		0.3	0.4	0.5	0.6	0.7	0.8	0.9
K	75	2.65%	2.03%	2.29%	2.06%	1.71%	2.69%	3.04%
	100	1.84%	1.88%	2.60%	2.18%	2.97%	2.32%	2.69%
	125	2.02%	2.04%	2.56%	2.64%	2.75%	3.08%	2.43%
	150	2.03%	1.51%	2.29%	2.26%	2.13%	2.07%	1.82%
	175	1.27%	2.07%	1.82%	1.94%	1.61%	2.00%	1.94%
	200	1.50%	1.78%	1.44%	2.04%	1.84%	2.39%	1.62%
	225	0.67%	0.95%	2.16%	1.49%	2.20%	1.60%	1.07%