

A Bayesian analysis of NSW eastern king prawn stocks (*Melicertus plebejus*) using multiple model structures

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Abstract

The eastern king prawn (*Melicertus plebejus*) is a valuable target species for commercial fisheries operating on the Australian east coast. The Bayesian analysis presented here aims to determine the current state and productivity of the NSW component of the eastern king prawn stock and analyse the possible consequences of altering commercial catches in the future. The Bayesian approach is well suited to both these aims, particularly given the significant uncertainty about the true population dynamics of the stock, and the multiple sources of information available. The sampling/importance resampling method was applied as it is numerically robust and straightforward to implement. Various types of uncertainty were incorporated into this analysis including: process and observation error, uncertainty in model structure, and uncertainty associated with the parameter values (captured with prior probability distribution functions). A delay–difference model was used with four different representations of recruitment. Each of the four models examined provided differing results for stock depletion since 1984/1985. Despite this uncertainty, none of the models suggested that the stock has been heavily depleted since 1984/1985. The analysis also identifies 2003/2004 as a particularly poor year for production (as was 1984/1985) but that such events lie within the limits of historically observed variability. Projections of the modelled stock dynamics into future years indicate that the stock does not appear to be at high-risk in the near future. Finally, the results of the decision analysis suggest that significant changes in the future catch are not expected to have a large impact on catch rates or the stock depletion ratio. These results, however, are dependent upon the assumption of continued and robust recruitment from Queensland.

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1. Introduction

The eastern king prawn (*Melicertus plebejus*) is a valuable target species that is harvested by commercial fisheries operating in New South Wales (NSW), Victoria and Queensland (Australia). The combined value of the landed catch in NSW and Queensland is around AUD\$ 70 million per year (wharfside-landed value) (NSW Fisheries, 2001; NSW DPI, 2004; O'Neill et al., 2005), with the majority of prawns caught in Queensland waters. A significant recreational fishery also harvests this species in both states. The commercial and ecological importance of eastern king prawns has encouraged the development of a number of population models (Lucas, 1974; Glaister et al., 1990; Gordon et al., 1995; O'Neill et al., 2005).

Both the fishing industry and fishery managers in NSW have identified the monitoring and assessment of eastern king prawns as a continuing research priority (NSW Fisheries, 2001; NSW DPI, 2004). A dynamic model of the population is an important component of such an assessment and is the subject of the research presented here. An earlier model of the NSW component of the stock published by Gordon et al. (1995) was a spatial extension to the yield-per-recruit analysis presented by Glaister et al. (1990). This deterministic model provided important insights into the trade-offs operating between individual growth, mortality and migration for the fishery along the NSW coast. In contrast, the modelling frameworks developed by O'Neill et al. (2005) used the more standard structures of a delay–difference and a length-structured model. Although O'Neill et al. (2005) considered information from both NSW and Queensland, the emphasis of their study was the Queensland fishery.

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The research presented here has two primary objectives. The first objective is to determine the current state and productivity of the NSW eastern king prawn stock. The second objective is to gain a better understanding of the consequences of alternative management strategies for the stock taking into account the uncertainty regarding the true population dynamics. The Bayesian approach is well suited to both of these objectives, particularly because there is significant uncertainty about how best to model the true population dynamics of the stock (including the model structure and parameter values) and because there exists multiple sources of information that are relevant (such as prior research conducted in Queensland).

The Bayesian approach to stock assessment integrates observations from the stock being examined with population models that contain parameters whose values can have prior information associated with them from other stocks and species (Punt and Hilborn, 1997). Bayes' theorem is employed to combine these different sources of information to generate posterior probability distribution functions (pdf) of the model parameters. A posterior pdf can also be associated with any metrics that are generated by the model, including performance indicators of managerial interest, such as the degree of stock depletion or recovery. Posterior pdfs can therefore be used to provide insights into the consequences of alternative managerial strategies for the fishery (McAllister and Kirkwood, 1998).

The biology and the life history of eastern king prawns has been considered by several researchers (Dall, 1957; Ruello, 1975; Young and Carpenter, 1977; Coles and Greenwood, 1983; Glaister, 1983; Suthers, 1984; Montgomery, 1990; Courtney et al., 1995). Such studies have shown that, although the morphology of the species varies little along the east coast of Australia, the demography of the species can vary considerably. The growth, mortality and recruitment of this species appear to vary greatly both in time and space. Although a lot of research has been conducted on prawn growth and mortality in NSW (Ruello, 1975; Glaister, 1983; Glaister et al., 1987, 1990; Montgomery, 1990; Gordon et al., 1995), other important research into issues such as the species catchability or the efficiency of the fleet (O'Neill et al., 2003, 2005), and reproduction and the stock–recruitment relationship (Young and Carpenter, 1977; Courtney et al., 1995, 1996, 2002; Watson et al., 1996) has, for the most part, been conducted only in Queensland. Dynamic models developed in NSW thus need a systematic method to incorporate information from the Queensland fishery. Although Queensland catch and effort data were not used in this study, the research conducted on the Queensland fishery was drawn upon to develop model structures and informative prior probability distributions.

2. Methods

2.1. Bayesian analysis using sampling/importance resampling

Monte Carlo methods such as Markov Chain Monte Carlo and importance sampling are the most frequently used methods

for Bayesian stock assessment. For the purposes of this study we chose to use the sampling/importance resampling (SIR) method which was numerically robust and straightforward to implement (McAllister et al., 1994).

The SIR algorithm involves two distinct phases. Phase one draws a value from the prior pdf of each of the parameters (a parameter set) and calculates the likelihood of this set given the observations. This process is iterated many times (up to 15 million times in our case), with the parameter set being stored along with the likelihood of this set. Phase two resamples these intermediate results to approximate the posterior pdf of each parameter value. The intermediate results are resampled with replacement using a probability based upon the importance function. In our case, the joint prior pdf was used as the importance function (McAllister et al., 1994; Raftery et al., 1995), which meant that the resampling was proportional to the likelihood of each parameter set. Thus the greater the likelihood of a parameter set the more frequently this set would be resampled and included within the posterior. For a more detailed explanation of Bayesian SIR methods see McAllister et al. (1994) and Punt and Hilborn (1997).

2.2. The alternative population dynamics models

A delay–difference model was the basis of each of the model structures employed in this analysis. The delay–difference model was first developed by Deriso (1980) and later generalised by Schnute (1985). This model has been applied several times for stock assessment (Butler et al., 2003; Dichmont et al., 2003; Vasconcellos, 2003; Pope, 2004) [see Meyer and Millar (1999) for a list of less recent publications]. In terms of complexity, the delay–difference model lies between the simpler surplus production models and the more complex age- or length-structured models, providing some of the advantages of both of these alternatives. Like an age-structured model, the delay–difference model has a sound biological foundation (such as life history), allowing many parameters of biological significance to be estimated directly from observations. The delay–difference model also retains the simpler data requirements of the surplus production model but allows for the representation of time-lags in growth and recruitment. The model also enables predictions of average body weight (and therefore size), which is an important management indicator when age composition data are not available (Walters and Ludwig, 1994). Finally, delay–difference models are numerically efficient; aiding their application within Bayesian analyses, which usually require many millions of iterations.

Delay–difference models are based on a general equation for population biomass that incorporates processes for survival, growth and recruitment. Eq. (1) is the difference equation for biomass used in this study:

$$B_t = (1 + \rho)s_{t-1}B_{t-1} - \rho s_{t-1}s_{t-2}B_{t-2} + w_k R_t \quad (1)$$

where B_t is the exploitable biomass at the beginning of month t for prawns that are aged k months and older (k being the age in months of all juvenile prawns when they recruit to the fishery);

s_t the monthly survival during month t ; w_k the average weight of prawns at age k ; R_t is the number of k month old recruits entering the fishable stock at the beginning of month t . Parameter ρ is the slope of the Ford-Walford growth function under the conditions devised by Deriso (1980) in which the intercept of the Ford-Walford plot is essentially set to zero (see Quinn and Deriso, 1999, p. 212 for more details).

Survival rate s_t during month t is determined by the instantaneous natural mortality rate (M) and the instantaneous emigration rate (G) to Queensland, as well as the harvest rate h_t using Eq. (2):

$$s_t = e^{-(M+G)}(1 - h_t) \quad (2)$$

where

$$h_t = \frac{C_t}{B_t} \quad (3)$$

where C_t is the observed landed catch in NSW from all commercial fisheries during month t and B_t is the exploitable biomass at the beginning of month t . This model also assumes that selectivity is uniform across all size classes of prawns and only mature prawns are subject to exploitation. Recent studies into the selectivity of prawn trawls have shown that selectivity of these gears is not knife-edged but can be represented with a logistic relationship (Broadhurst et al., 2004; Macbeth et al., 2005). The assumption of knife-edged selectivity will therefore misrepresent catches marginally above and below the age when 50% of the prawns are vulnerable. Including this additional complexity is not warranted in this study, and knife-edged selectivity is a standard simplifying assumption for a delay-difference model.

In Eqs. (1)–(3), no assertions have yet been made regarding recruitment processes. A number of alternative representations of recruitment resulted in the creation of multiple model structures. Eqs. (1)–(3) are common to all four models presented here.

For the “base model”, the stock–recruitment relationship was based upon the Beverton–Holt model (see Haddon, 2001). The stock–recruitment relationship is as follows:

$$A^{sr} = w_k \left(1 - \frac{z - 0.2}{0.8z} \right) \quad (4)$$

$$B^{sr} = \frac{z - 0.2}{0.8zR_0} \quad (5)$$

$$R_{t+k} = \frac{(B_t - C_t)}{A^{sr} + B^{sr}(B_t - C_t)} \quad (6)$$

The parameter z represents the steepness of the stock–recruitment relationship, and A^{sr} and B^{sr} are the parameters of the Beverton–Holt stock–recruitment relationship where $(B_t - C_t)$ represents the exploitable biomass less catch during time t , R_0 is the initial recruitment, and w_k is the average weight of prawns at age k . This base model therefore assumes that recruitment is related deterministically to exploitable stock size and there is no additional recruitment pattern. The other models explore alternatives to these assumptions.

Bayesian analysis uses a likelihood function to calculate the probability of the data given the model and the current values

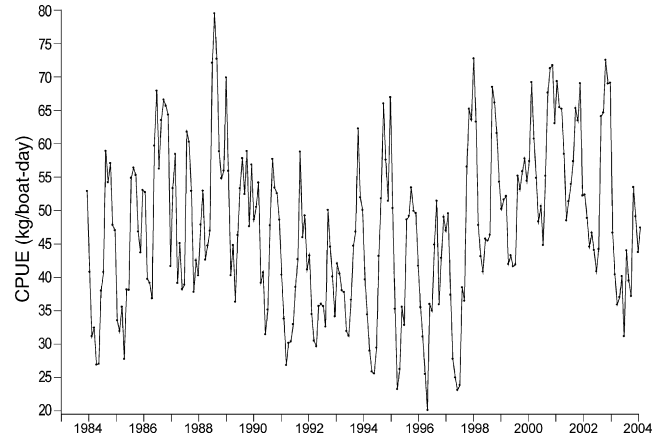


Fig. 1. Observed catch per unit effort (kg/boat-day) of eastern king prawns from the ocean prawn trawling in NSW waters from July 1984 to June 2004. Tick marks indicate the midpoint (June) of the labelled year.

of the model parameters. In this study, the observations used were the monthly catch per unit effort (CPUE or U_t) records of eastern king prawns from the NSW Ocean Trawl Fishery from July 1984 to June 2004 (Fig. 1). This indicator of abundance was estimated with \hat{U}_t which was assumed to be proportional to the exploitable biomass (B_t) and catchability (q_t) at time t , i.e.

$$\hat{U}_t = q_t B_t \quad (7)$$

The likelihood function assumed that the observed CPUE was log-normally distributed about the predicted values with standard deviation σ . Thus the log-likelihood (LL) of the observations given the model was proportional to (McAllister and Kirkwood, 1998):

$$LL = -\frac{1}{2\sigma^2} \sum_{t=1}^{240} \left[\log \left(\frac{U_t}{\hat{U}_t} \right) \right]^2 \quad (8)$$

Seasonal variability was evident in the observed catch rates (see Fig. 1). After exploring various options, it was assumed that this within-year variability was driven by changes to catchability (rather than recruitment) and this seasonality was modelled using the normal distribution function:

$$q_t = q \left(1 + \exp \left(-\frac{((m_t - \mu_q)^2)^{\theta_q}}{2\sigma_q^2} \right) \right) (1 + \delta)^t \quad (9)$$

where m_t is the number of the month ($1, \dots, 12$), and μ_q , θ_q , and σ_q are the mean, slope and variance of the annual catchability pattern, respectively.

The final term δ in Eq. (9) is the change in catchability over time. Catchability is affected by changes in fishing power, such as gear and vessel changes, as well as technological improvements. An extensive study on the changes in fishing power in the east coast prawn fisheries was conducted by O'Neill et al. (2003). This study relied primarily on Queensland catch and effort data and a database of technological changes in the fleet. The authors estimated an increase in catchability for the Queensland ocean trawl fleet, which was used to construct a prior probability distribution of changes to catchability (see Appendix A for more details).

Table 1
Alternative stock recruitment relationships for the four model structures

Model	Stock Recruitment relationship	
Base [Eq. (6)]	$R_{t+k} = \frac{(B_t - C_t)}{A^{sr} + B^{sr}(B_t - C_t)}$	
RE	$R_{t+k,y} = R_{t+k} e^{re_y}$	(10)
MR	$R_{t+k,y} = (\lambda R_{t+k} + (1 - \lambda)R_0) e^{re_y}$	(11)
2C	$R_{t+k} = (\lambda R_{t+k} + (1 - \lambda)R_0) \left(1 + \frac{1}{2} \left[\cos \left(\frac{t}{LRF} - LRP \right) \right]^2 \right)$	(12)

B_t : biomass in month t ; C_t : total catch in month t ; A^{sr} , B^{sr} : Beverton–Holt recruitment parameters; R_{t+k} : recruitment in month $t+k$ where k is the age in months that a juvenile prawn recruits to the fishery; re_y : recruitment error exponent in year y ; $R_{t,y}$: recruitment in month t , year y ; λ : fraction of recruits from NSW; R_0 : initial recruitment from both Queensland and NSW; LRF and LRP are the frequency and phase of the long-run recruitment cycle.

Three additional models were also considered in this study. Each model contained the same underlying delay–difference model (described above) but had different representations of recruitment. These alternative models were developed in response to the patterns found in the residuals of the preliminary model results. The base model did not include any process error (Hilborn and Mangel, 1997) which is likely to be present in prawn recruitment dynamics. Replacing, or amending, the stock–recruitment relationship is the simplest way to improve this representation. Furthermore, the assumption of a simple stock–recruitment relationship, where recruitment is a function of stock size, is likely to be an over-simplification of a system where the majority of the stock biomass is outside of the model domain.

The different stock–recruitment equations for each of the four model structures are provided in Table 1 (including the Beverton–Holt stock recruitment function of the base model). The three alternative models are described in turn. First, the recruitment error model (RE model) incorporates all of the equations of the base model with the addition of Eq. (10) which adds 20 recruitment error parameters to the model, one parameter for each year of the observations. Each error term is exponentiated before being applied to the Beverton–Holt recruitment that is calculated for each month in that year. Thus, the term $\exp(re_y)$ is applied to each calculated recruitment of each month in year y .

The third model assumes that recruitment for prawns is partly driven by the local NSW stock and partly by the Queensland stock. This model is based on the work of (Gordon et al., 1995) who suggested that recruitment of eastern king prawn in NSW may be the result of the spawning of both the NSW and Queensland stocks. This mixed recruitment (MR) model combines: a NSW component (using a Beverton–Holt stock recruitment function); a Queensland component, which is represented as constant recruitment (a proportion of R_0 —the initial recruitment); and a stochastic term (the recruitment error exponents used in the RE model). This recruitment model is represented with Eq. (11).

The fourth model is the delay–difference with two cycles (2C) model. This model was based upon an examination of the residuals from the base model that appeared to exhibit a long-run cyclic pattern. This model therefore contains both a short-run seasonal catchability cycle as well as an additional long-run recruitment cycle. The 2C model contains the mixed recruitment equation

and is the same as the MR model except that the 20 recruitment error parameters are replaced with the cyclic recruitment function as shown in Eq. (12). The 1/2 term was employed to constrain the amplitude of the recruitment variation.

The primary management indicator used to evaluate the state of the stock is the biomass depletion ratio. The depletion ratio is the calculated average annual biomass in 2003/2004 (financial year from 1 July 2003 to 30 June 2004) divided by the calculated average annual biomass in 1984/1985, abbreviated as B_{04}/B_{85} .

2.3. Model evaluation

Calculated catch rates were compared with observed catch rates from July 1984 to June 2004 ($20 \times 12 = 240$ months). Due to transient effects in the model, an iterative burn-in process was used to stabilize the model run before comparisons with observations were made. The burn-in process involved running the simulation, using average seasonal catch rates, until the moving average of the biomass (using a 12 month window) changed by less than 0.1%.

The results of each model run were evaluated by the following criteria: the quality of the posterior pdf (see below); a comparison of the prior pdf with the associated marginal posterior pdf; an analysis of sensitivity to alternative priors; an analysis of residuals and the correlations between fitted parameter values; a comparison of estimated biological indicators against observed values; and finally Bayes factors.

Evaluation of each posterior pdf consisted of three diagnostic tests. Firstly, the efficiency of the importance function in the SIR method was estimated using the maximum importance ratio (MIR) (McAllister and Pikitch, 1997). The MIR is equal to the ratio of the maximum of likelihoods to the sum over all likelihoods. McAllister and Pikitch (1997) found that a maximum importance ratio of 0.04 “. . . appeared to provide estimates of posterior pdfs sufficiently precise for stock assessment and decision analysis”. A more conservative value of 0.005 was, however, employed. Another means of improving the posterior pdf is to ensure that a single parameter set is not assigned more than 1% of the total probability (Punt and Hilborn, 1997). Accordingly, the maximum single density (MSD) for each model was calculated which reports the percentage of the posterior that is composed of the dominant parameter set.

Finally, the posterior of the depletion ratio (B_{04}/B_{85}) was evaluated by examining the location of the depletion ratio

associated with the parameter set that achieved the maximum (largest) log-likelihood value. If the values of the maximum likelihood depletion ratio appeared in the tails of the posterior then the importance function may have needed to be reassessed (McAllister and Ianelli, 1997).

The quality of a model as a whole was also judged by the realism of the biological indicators calculated, particularly the average prawn weight. This indicator can be compared directly to observations, so it was used to evaluate whether the models were producing realistic patterns. The average prawn weight could also have been incorporated into a combined likelihood function along with CPUE, but this approach would have required additional coefficients to weight the two resulting likelihood functions. Average stock weight (\bar{w}_t) was calculated as numbers of prawns were tracked in conjunction with biomass (Eqs. (13)–(15)):

$$N_0 = \frac{B_0}{w_k} \quad (13)$$

$$N_t = s_{t-1}N_{t-1} + R_t \quad (14)$$

$$\bar{w}_t = \frac{B_t}{N_t} \quad (15)$$

In Bayesian analysis, the Bayes Factor is regarded as the best criteria for judging the quality of a model (notation and approach adopted from Kass and Raftery, 1995) and is used to compare two alternative models:

$$B_{1,2} = \frac{p(x|M_1)}{p(x|M_2)} \quad (16)$$

where for both models M_i ($i = 1, 2$):

$$p(x|M_i) = \int p(x|\theta_i, M_i)p(\theta_i|M_i)d\theta_i \quad (17)$$

where θ_i are the parameters of model M_i , $p(\theta_i|M_i)$ is the prior density of θ_i in model M_i and $p(x|M_i)$ is the marginal likelihood of the data given model M_i . Because of the integration required in Eq. (17) an exact calculation of Bayes Factors is often not possible. However, various methods are available to estimate Bayes factors and one based on importance sampling is used here. This method estimates the Bayes factor as the harmonic mean of the likelihoods of a sample from the posterior distribution (Newton and Raftery, 1994):

$$\hat{p}(x|M_i) = \left\{ \frac{1}{m} \sum_{j=1}^m p(x|\theta^{(j)}, M_i)^{-1} \right\}^{-1} \quad (18)$$

where $\{\theta^{(j)}: j = 1, \dots, m\}$ are m samples from the posterior distribution of model M_i . The above estimator converges to the correct value as the number of samples increases but is susceptible to any sample, $\theta^{(j)}$, that possesses a small likelihood, which can have a large effect on the final result (Newton and Raftery, 1994). This estimator is, however, relatively easy to compute and in practice appears accurate enough (Kass and Raftery, 1995; Bolton et al., 2003).

The Bayes factors for each of the RE, MR and 2C models was calculated using the base model as M_2 in Eq. (16). The base

model was chosen as the comparative model because it was the simplest model from which all other the models were derived. The calculated Bayes factors were then utilised to produce a Bayes model average (BMA) composite posterior pdf (Hoeting et al., 1999). The BMA composite was generated by resampling the posterior pdfs of each of the RE, MR and 2C models in proportion to the relative Bayes factors for that model divided by the sum of the Bayes factors for all three models (each of the models were given an equal prior probability).

2.4. Assessing the consequences associated with different future catches

Decision makers in fisheries are concerned, *inter alia*, with the consequences of alternative management actions on a fish stock. ‘Decision Analysis’ is an approach that provides a conceptually straightforward procedure for predicting such consequences under various models of uncertainty (Smith, 1988; Hilborn et al., 1994; McAllister et al., 1994; McAllister and Ianelli, 1997; Punt and Hilborn, 1997; McAllister and Kirkwood, 1998; Meyer and Millar, 1999; Hilborn and Punt, 2001). In the Bayesian approach, the model dynamics are projected into the future to determine possible outcomes of alternative management strategies. The probabilities of various outcomes are modelled using the alternative model structures and their associated posterior pdfs.

The eastern king prawn fisheries in NSW are input controlled. The NSW Department of Primary Industries (NSW DPI) manages fishermen’s activities through the number of commercial licences and through restrictions on fishing gears, boat size and engine power, as well as temporal and spatial closures. Rather than attempt to model the effort dynamics in detail, the decision analysis was simplified by only considering the total catch.

Each of the four models was projected forward 60 months (5 years) and included recruitment stochasticity (process error) if it existed in the model. The average annual catch during the calibration period (July 1984 to June 2004) was around 1000 tonnes per annum. Four catch scenarios were evaluated using the models. The first scenario involved reducing annual catch to an average of 250 tonnes per annum (Scenario 1). This scenario was devised to examine the effect of small catches in the fishery. The second scenario involved retaining catches at an average of 1000 tonnes per annum, the third scenario involved increasing catch to an average of 1750 tonnes per annum, and the final scenario involved increasing catch to an average of 4000 tonnes per annum. This last scenario is unlikely to ever occur in reality, but was included to examine how such a large catch would affect the various models.

The guidelines presented in McAllister and Kirkwood (1998) were used in the construction of the decision analysis. The results are summarized in a decision table presenting the pdf for the management indicator, in our case the depletion ratio (B_{09}/B_{85}), partitioned over the alternative models with the expected consequences for each scenario presented. The seasonality in catch was included in the projections by partitioning the annual catch in proportion to the average monthly catch during the model calibration period. Management scenarios were chosen such that

their consequences would be noticeably different under each model, demonstrating the influence of the different model structures (McAllister and Kirkwood, 1998).

3. Results

A summary of the results from the Bayesian analysis is provided in Table 2. The table presents the quartiles of the prior and marginal posterior pdfs for the model parameters where prior

pdfs were defined (q , δ , z , $M + G$, and ρ). Quartiles are also presented for the posterior pdfs of the calculated biomass at the end of financial year 2003/2004 (i.e. B_{04}); the biomass depletion ratio (B_{04}/B_{85}); the ratio of average fishing mortality to total mortality (F/Z); and the average prawn weight (\bar{w}_{04}) at the end of 2003/2004.

Table 2 also provides the diagnostics that are used to evaluate the quality of the model's posterior pdfs including the maximum importance ratio (MIR), the maximum single density (MSD), the

Table 2

Quartiles of the prior and posterior probability distribution functions (pdf) for the models considered along with other diagnostic results

Parameter	Quartile	Prior pdfs	Base model posterior pdfs	RE model posterior pdfs	MR model posterior pdfs	2C model posterior pdfs	BMA posterior pdfs
q ($\times 10^{-6}$)	1	0.6	2.6	2.5	1.2	1.5	1.4
	2	3.1	3.5	3.4	1.8	2.0	1.9
	3	18.0	4.8	4.8	2.9	2.9	2.9
δ ($\times 10^{-4}$)	1	1.3	2.6	1.5	2.7	1.2	1.9
	2	3.0	4.1	3.0	4.3	2.8	3.6
	3	4.7	5.8	4.7	5.9	4.4	5.3
z^a	1	0.81/0.40	0.81	0.81	0.38	0.51	0.44
	2	0.87/0.60	0.87	0.87	0.58	0.72	0.65
	3	0.94/0.80	0.94	0.94	0.79	0.88	0.84
$M + G$ (month $^{-1}$)	1	0.17	0.36	0.34	0.37	0.43	0.40
	2	0.21	0.41	0.39	0.42	0.49	0.45
	3	0.27	0.47	0.44	0.48	0.56	0.52
ρ (month $^{-1}$)	1	1.03	1.03	1.03	1.03	1.02	1.02
	2	1.05	1.05	1.05	1.05	1.05	1.05
	3	1.08	1.08	1.08	1.08	1.07	1.07
λ (%)	1	25	N/A	N/A	26	14	19
	2	50	N/A	N/A	51	34	43
	3	75	N/A	N/A	76	62	71
B_0 (tonnes)	1	5700	12600	10600	8400	8900	8600
	2	10500	15600	14000	12500	12700	12600
	3	15300	17900	17100	16300	16100	16200
B_{04} (tonnes)	1		5300	4600	7200	7600	7400
	2		7100	6400	11100	10900	10900
	3		9600	8700	16700	14800	15500
B_{04}/B_{85}	1		1.01	0.93	0.93	1.12	0.95
	2		1.01	0.94	0.95	1.16	1.02
	3		1.01	0.97	0.97	1.21	1.16
F/Z	1		0.22	0.24	0.13	0.12	0.13
	2		0.25	0.29	0.17	0.15	0.16
	3		0.30	0.35	0.24	0.20	0.22
\bar{w}_{04} (g)	1		28.2	25.0	30.3	26.1	27.8
	2		32.3	28.9	34.6	29.5	31.7
	3		37.4	33.7	39.8	33.0	36.3
MIR			0.0001	0.0002	0.0001	0.0004	
MSD			0.06%	0.12%	0.05%	0.12%	
MaxLL B_{04}/B_{85}			1.00	0.96	0.92	1.15	
Bayes Factors				0.0002	1.0198	1.0042	
BMA (%)				0.0%	50.4%	49.6%	

Parameters include: q , catchability (fleet efficiency); δ , annual growth in catchability (fleet efficiency); z , steepness of the Beverton–Holt stock–recruitment relationship; M , instantaneous monthly natural mortality; G , instantaneous monthly emigration rate; ρ , slope of Ford–Walford growth function; λ , fraction of recruits from NSW; B_0 , initial biomass; B_{04} , calculated biomass in 2003/2004; \bar{w}_{04} , average prawn weight in 2003/2004; B_{04}/B_{85} , stock depletion ratio of (2003/2004)–(1984/1985); MIR, maximum importance ratio; MSD, maximum single density of B_{04}/B_{85} posterior; Max LL B_{04}/B_{85} , the value of B_{04}/B_{85} produced by the simulation that achieved the maximum likelihood.

^a Note: The two pairs of values shown in the prior pdfs column for the parameter z are the values for the priors used for the base and RE model followed by the values used for the MR and 2C models.

maximum log-likelihood estimate of the depletion ratio ($\max LL B_{04}/B_{85}$), the Bayes factors for the RE, MR and 2C models and the percentage of each model used to produce the BMA composite.

Table 2 indicates that for the model parameter ρ (the slope of Ford-Walford growth function) the posteriors do not differ greatly from the priors. For other parameters, such as $M+G$ (natural mortality plus emigration), q (the catchability), and B_0 (the initial biomass) there is a significant contrast between the prior and posterior pdfs. This is the result of the models using the parameters $M+G$, q and B_0 as the primary means of calibrating the calculated catch rates to the observed catch rates. This is evidenced by the fact that the medians of the posteriors of $M+G$ for all models are consistently greater than the medians of the priors, and that the base and RE models have higher values for q but lower values for B_0 . Such results suggest that there is a lack of contrasting information in the observed catch rates to specify all of the model parameters (which is not surprising). The posterior pdfs for the parameter z (the slope of the Beverton Holt stock–recruitment relationship) and λ (the percentage of recruitment originating from NSW) appear to suggest a somewhat stronger recruitment from NSW in the MR model when compared to the 2C model.

The management indicators produced by each of the models (B_{04} , B_{04}/B_{85} , F/Z , and \bar{w}_{04}) suggest some interesting differences between the models. The RE model shows the highest exploitation rate (F/Z) due possibly to its relatively lower natural mortality and emigration rate ($M+G$). The estimated natural mortality and emigration rate ($M+G$) is largest for the 2C model which is somewhat surprising since it displays the highest depletion ratio values (B_{04}/B_{85}). However, the 2C model estimates a lower absolute biomass (B_{04}) and also estimates a lower annual growth in fleet efficiency (δ). The average stock weight value (\bar{w}_{04}) for all models lies within the expected range of around 0.03 kg (30 g) (Glaister et al., 1990).

Fig. 2 presents the marginal posterior probability distributions of the depletion ratio for the four models using the informative prior pdfs summarized in Table 2 (with details provided in Appendix A). Also illustrated on Fig. 2 is the Bayes model averaging (BMA) composite posterior, which is, for intents and purposes, evenly divided between the MR and 2C models (actual percentages are given in Table 2). Note how the differing representation of recruitment of these two models causes greater divergence in the depletion ratio than the variability in the parameter estimates within any one particu-

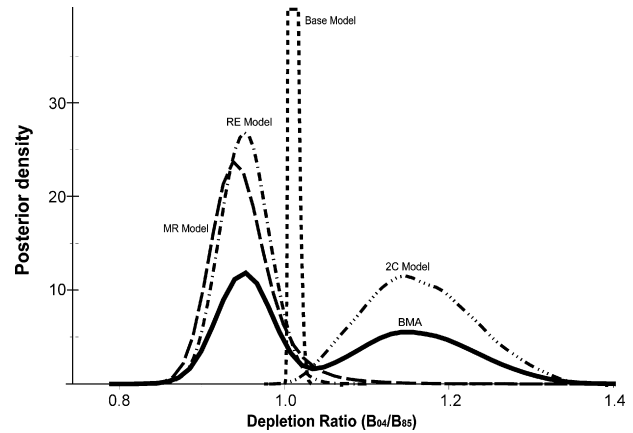


Fig. 2. Comparison of the posterior probability distributions of the stock depletion ratio (B_{04}/B_{85}) for the four models considered as well as the Bayesian model average composite.

lar model. This uncertainty in the model structure is represented in the width of the BMA posterior of the depletion ratio which ranges from around 0.85–1.40, indicating a much larger uncertainty compared to the amount reported by any single model structure. Fig. 3 provides a graphical representation of the prior and posterior pdfs of some of the key parameters and indicators from Table 2 for the BMA composite, showing the extent of our uncertainty in their estimated values.

The small variability of the posterior for the base model was a consequence of the poor model fit (note the relatively thin depletion ratio posterior pdf for this model as seen in Fig. 2). Only the RE, MR and 2C models gave a satisfactory fit to the data, as can be seen by the residual plots shown in Fig. 4. This figure presents the residual plots for each of these models for the parameter set with the greatest likelihood. Included in each residual plot is a smoother to indicate any possible pattern in the residuals. Fig. 4 (base) illustrates the longer-term patterns in the residuals which are indicative of an inadequate model; whilst Fig. 4 (RE) and (MR) shows that the 20 annual recruitment error terms (process error) allow these models to adjust to fit the pattern in the residuals. Fig. 4 (2C) illustrates the residuals for the optimal 2C simulation that used a long-run cycle of recruitment to fit the patterns within the residuals observed in Fig. 4 (base).

The decision analysis was conducted by projecting the results presented in Table 2 into the future. Each of the models was projected forward 5 years and the posteriors of the management indicators were calculated (see Table 3). The median value of the

Table 3
Results of the decision analysis for the calculated depletion ratio given four alternative scenarios of future annual catch levels in tonnes per annum (t.p.a), over a 5-year period from July 2004 to June 2009

Model	Projected catch			
	Scenario 1, 250 t.p.a	Scenario 2, 1000 t.p.a	Scenario 3, 1750 t.p.a	Scenario 4, 4000 t.p.a
Base	1.03 (1.03, 1.04)	1.00 (1.00, 1.00)	0.96 (0.95, 0.97)	0.84 (0.80, 0.87)
RE	1.05 (0.94, 1.16)	1.00 (0.90, 1.12)	0.96 (0.85, 1.07)	0.82 (0.70, 0.94)
MR	1.03 (0.93, 1.15)	1.00 (0.90, 1.12)	0.97 (0.87, 1.09)	0.89 (0.78, 1.02)
2C	1.24 (1.18, 1.30)	1.21 (1.15, 1.27)	1.19 (1.13, 1.24)	1.11 (1.04, 1.17)
BMA	1.17 (1.03, 1.26)	1.14 (1.00, 1.24)	1.11 (0.98, 1.21)	1.03 (0.88, 1.13)

Values given are the median depletion ratio B_{09}/B_{85} with the first and third quartiles in parentheses.

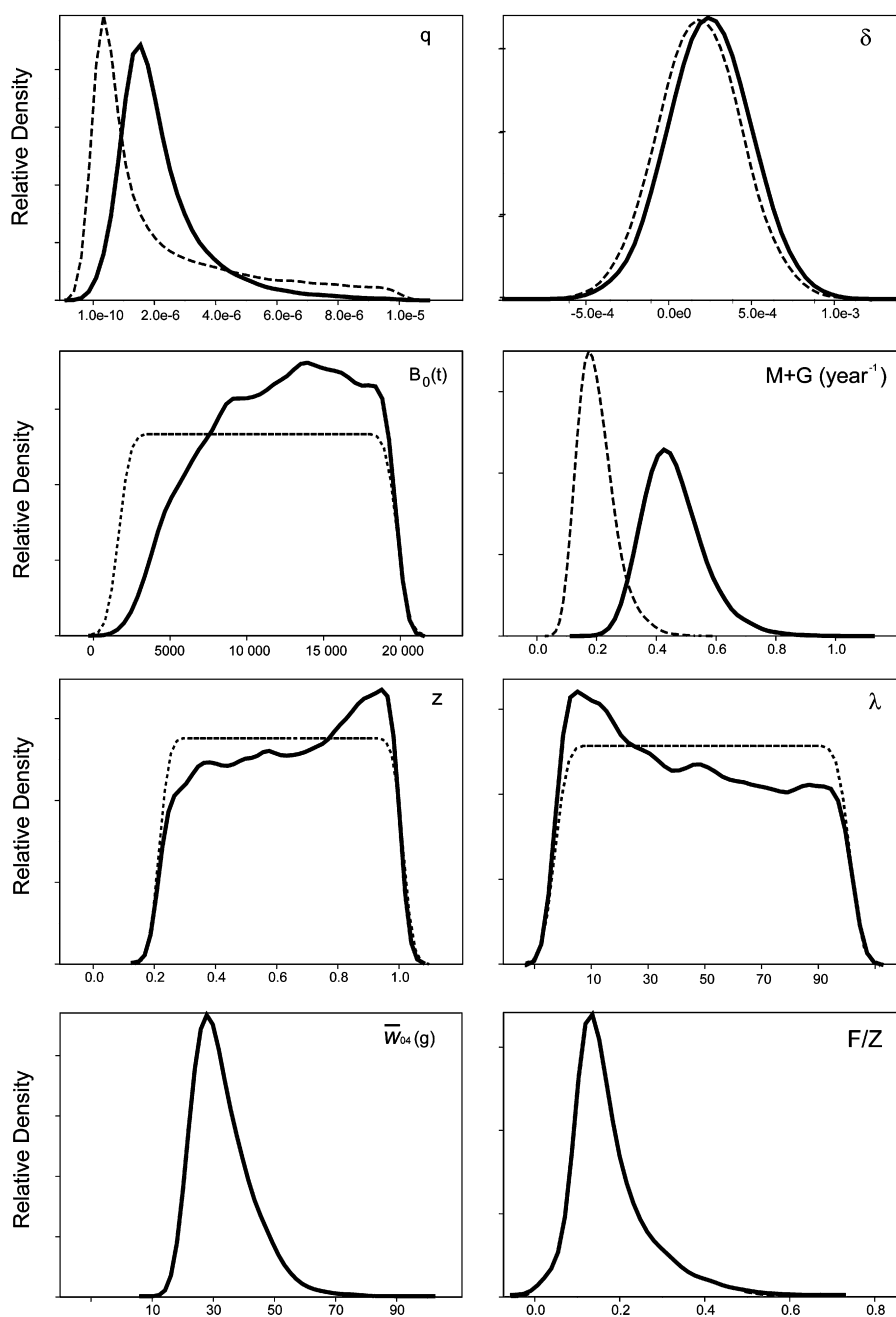


Fig. 3. Density plots of the prior (dashed line) and posterior (unbroken line) probability distributions of parameters and indicators from the Bayesian model average composite. The parameter or indicator represented is annotated in each sub-figure.

marginal posterior pdf for each indicator is given along with the first and third quartiles. Scenarios 1 and 2 show that all models predict stability in stock levels if catch levels are maintained at or below current levels. Scenarios 3 and 4 indicate that increasing catch above current levels could lead to depletion of the stock within 5 years.

4. Discussion

The analysis presented here is relatively optimistic in regards to the state of the eastern king prawn stocks in NSW. Although each of the four models examined provided differing results for

the stock depletion ratio since 1984/1985, none of the models, or the results from the Bayes model average, suggested that the stock has been heavily depleted since 1984/1985. This result can be contrasted with O'Neill et al. (2003) who, using non-Bayesian maximum likelihood methods and a similar delay–difference model on the combined Queensland and NSW stock, obtained somewhat different results. Under a range of assumptions for varying fishing power and natural mortality rates, O'Neill et al. (2003) suggested a median depletion ratio of 0.3–0.7, with 90% confidence intervals encompassing the range 0.1–1.0. Rather than using informative priors, O'Neill et al. (2003) used additional penalty functions on the likelihood function to prevent

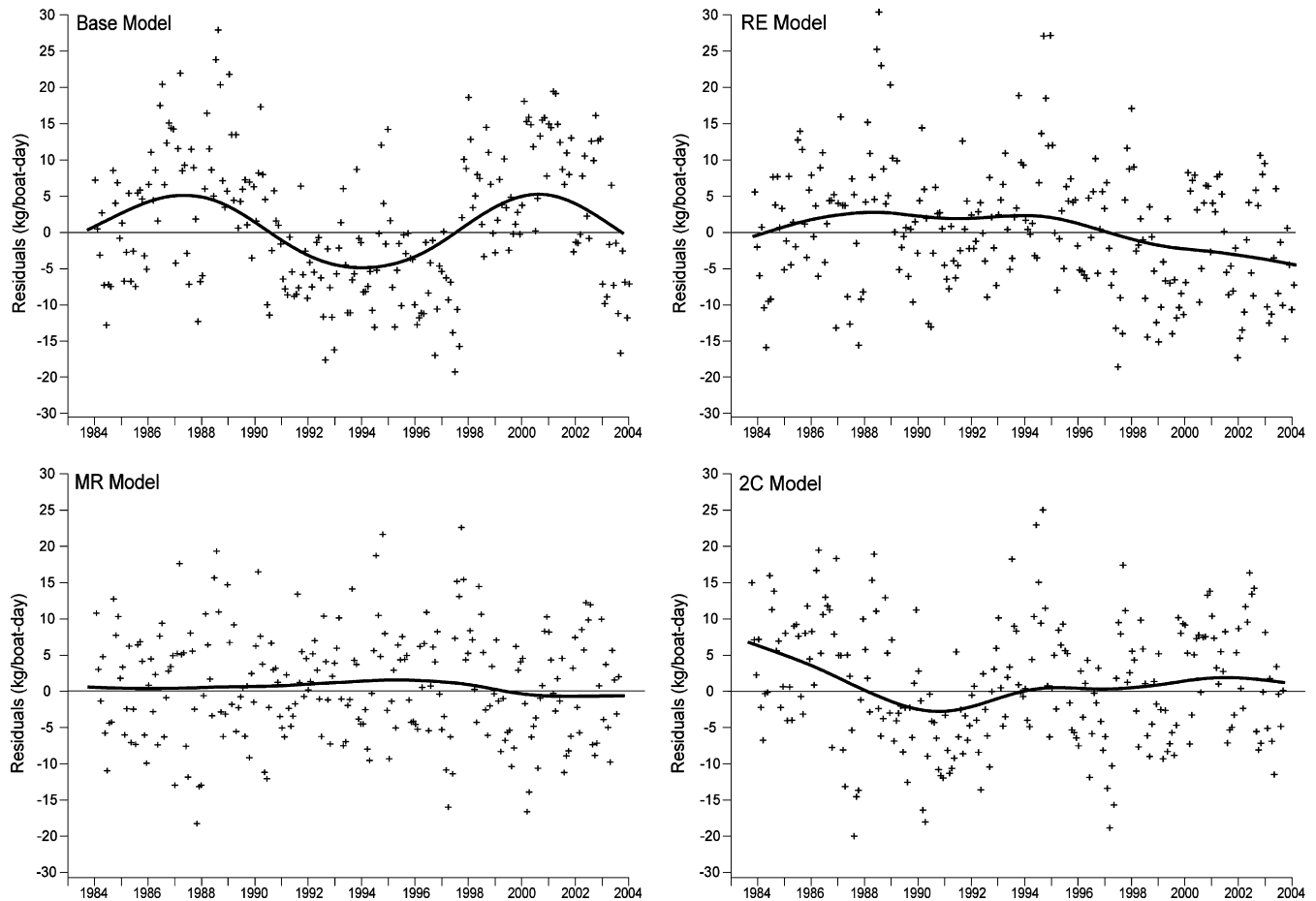


Fig. 4. Plots of the residual values between the observed and calculated CPUE values for each of the four models evaluated: base model; RE model; MR model; 2C model. In all cases, residuals from the simulation that resulted in the maximum log-likelihood are illustrated. Each residual plot also includes a cubic B -spline smoother with 5 degrees of freedom. Tick marks indicate the midpoint (June) of the labelled year.

extremely small or large harvest rates. Both modelling projects indicated significant uncertainties in the calculated biomass and, in both cases, the lack of effective contrast in the catch and effort data was responsible.

The results of the decision analysis also appear positive. The calculated biomass ratio between the years 2008/2009 and 1984/1985 is around 1.0 for scenarios 1–3. If, however, the depletion ratio (B_{04}/B_{85}) posterior pdfs are compared with the posterior pdfs resulting from the projections used in the decision analysis it can be seen that the posteriors for the MR and RE models are considerably wider in the later projections. The posterior pdf for B_{04}/B_{85} lies within the lower half of estimated future depletion ratio B_{09}/B_{85} . That is, 2003/2004 appears to have been a particularly poor year for the stock (as was the year 1984/1985 or B_{85}) but such low values still lie within the range of historical variability.

Although these modelling results suggest that stock levels do not appear to be at high-risk in the near future, lower than average catch rates (such as those experienced in 2003/2004), are possible. Also, if the 2C model has any credibility, the catch rates may get worse before they improve as the long-run cycle is yet to reach its lowest point. Finally, the results of the decision analysis suggest that significant changes in the catch are not

expected to have a large impact on the NSW catch rates or the depletion ratio. This result must, however, be traced back to the assumption of strong ongoing recruitment from Queensland. A change to the representation of recruitment has a significant effect on this model.

This analysis presents a straightforward application of Bayesian methods for stock assessment and decision analysis for a penaeid fishery. The results illustrate a number of strengths and weaknesses of the approach. The primary strength was the flexibility of being able to define and calibrate models with both observation and process error. The primary weakness of Bayesian analysis for this case study was the necessity of using informative prior probability distributions to get usable results. Solutions were only found for our models using informative priors that did not fully reflect our uncertainty about these parameters. In particular, for the SR and RE models we had to provide the recruitment error terms with informative priors that were based upon an iterative process (Smith et al., 1987) (explained in more detail in Appendix A). As this iterative process essentially re-uses data, it is likely that the results underestimate the variance of the posterior pdfs.

In summary, the lack of contrast in the catch and effort observations forced us to point our Bayesian model in the “right

direction” (using informative priors) to obtain a credible fit of the models to the observations. Increasing the number of iterations used in the SIR algorithm could, in theory, ameliorate this issue, but computational limitations prevented us from calculating more than 15 million replicates. Although we employed the method of managing sampled parameter sets by storing only the random number seeds (McAllister and Ianelli, 1997), the models still caused us to run into computational constraints using a fast Pentium computer with 3 GB of random access memory. This can be viewed as a limitation of the SIR methodology, and in our case, the use of joint prior pdfs as the importance function. This result has practical implications for the use of such models in fisheries management when there is so little effective contrast in the observations.

One of the unavoidable issues resulting from the low contrast in the catch and effort data in this model was the inability of any of the models to provide a credible estimate of absolute biomass. The apparently tight posterior for B_{04} presented in Table 2 is a result of the restricted prior placed on B_0 . This can be seen in the high density in the right tail of the posterior for B_0 shown in Fig. 3. Furthermore, the estimates of absolute biomass were highly correlated with the estimates of catchability; reducing our confidence in both of these parameter estimates. The inability to estimate absolute biomass is a problem for many fish stocks, even those rich in observations, and has led to a number of scientists cautioning against decisions or decision-making frameworks that require absolute estimates of biomass (Hilborn, 2002). These results have shown that the level of uncertainty surrounding management indicators based on relative biomass levels, such as the depletion ratio, is much less than that associated with an estimate of the absolute exploitable biomass.

The depletion ratio however is not without its problems as a management indicator. The depletion ratio provides insights into the sustainability of the species being examined but does not address the sustainability of by-catch species that are also affected by the fishery. This is a problem shared with other single-species reference points such as maximum sustainable yield (MSY) (Mace, 2001; Punt and Smith, 2001). As is the case with reference points such as MSY, the depletion ratio is also susceptible to natural fluctuations in stock size. The fact that the 2C model suggests that 2004/2005 biomass levels are well above 1984/1985 levels is an anomaly of the structure of the model. This model has a long-run phase of around 11 years. Therefore, in order to compare two similar years, such as when using a depletion ratio, these two chosen years would have to be 11 or 22 years apart. This suggests a possible weakness in the use of such a ratio for models with any long-run cyclic trends in recruitment.

Although the long-term recruitment cycle used in the 2C model has not been the subject of specific research for eastern king prawns, such long-run patterns in recruitment or ‘regime shifts’ have been suggested for other fisheries (McAllister et al., 2001). There is evidence for a relationship between prawn catchability and short-term rainfall events (Ruello, 1973; Glaister, 1978, 1983) as well as prawn growth and water temperature (Somers, 1975 as cited in Glaister, 1983). This suggests the pos-

sibility that long-term climatic patterns could explain some of the long-run patterns found in catch records for this species—a possible avenue for future investigation.

The Bayesian approach appears to have been appropriate for this study because the method allows the use of prior pdfs for model parameters. This enables existing research on the species to be incorporated into the model calibration process. Such information not only provides evidence for parameter values but also captures the uncertainty or variability in these parameter values. Bayesian methods also present us with a framework in which to compare multiple model structures allowing us to deal with the important issue of model uncertainty (Hilborn and Punt, 2001). The research presented here aimed to determine the current state and productivity of the NSW component of the eastern king prawn stock and analyse the consequences of varying commercial catches into the future. To varying degrees of success, both of these aims were achieved, but only after significant limitations of the modelling approach and underlying data were identified.

The sampling importance/resampling (SIR) algorithm applied here is a relatively simple and versatile Monte Carlo method for use in fisheries assessment. However, the relatively simple models used in our study uncovered some of the limits of the SIR algorithm, as evidenced by our difficulty in finding acceptable posteriors for the MR and RE models due to the recruitment errors. The most obvious explanation for our difficulties was that our importance function, the joint model priors, was inefficient (Chen et al., 2000). According to McAllister (1997) this importance function works best when the data are not very informative and the model is fairly simple—as was the case with the base and 2C models. A number of alternative approaches could have been employed including the use of other importance functions, such as the multivariate t -distribution (McAllister and Ianelli, 1997), or using alternative sampling methods, such as adaptive importance sampling (Oh and Berger, 1992). Modifications to the maximum likelihood estimation could also be applied (Chen and Andrew, 1998). Finally, SIR could be replaced with Markov Chain Monte Carlo (MCMC) methods which are more robust for large numbers of parameters (Gelman et al., 2004). Inclusion of spatial processes and the length structure of the prawn population could increase the biological resolution of the models, but at the expense of an increase in the number of parameters. Incorporating the Queensland fishery would eliminate the need for an emigration term and may justify specification of a stock recruitment relationship (if it exists).

There are also a number of avenues for further research into alternative management strategies for this stock. For example, simulation modelling could be utilised to evaluate the most efficient avenues for further research, such as whether research into biological parameters would bear more fruit than conducting independent surveys to provide an alternative index of abundance. The model could also be expanded to include socio-economic components to consider the possible consequences of alternative management strategies on the individuals and industries dependent upon the prawn stock. The recently published work of Holland et al. (2005) demonstrates the value of cou-

pling such economic components to a Bayesian stock assessment model.

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Appendix A. Prior probability distribution functions

A number of distributions were used for prior pdfs. An explanation for each is given below:

$LN(\mu, \sigma)$ —*Log normal pdf*: A lognormal distribution with mean μ and standard deviation σ .

$LU(\min, \max)$ —*Log uniform pdf*: A distribution which is uniform in a log scale between the minimum and maximum values. For example, for the prior $q \sim LU(1 \times 10^{-7}, 1 \times 10^{-5})$ $p(q)$ is uniform on $\log q$ from 1×10^{-7} to 1×10^{-5} .

$N(\mu, \sigma)$ —*Normal pdf*: A normal distribution with a given mean (μ) and standard deviation (σ).

$U(\min, \max)$ —*Uniform pdf*: All values greater than or equal to the minimum and less than or equal to the maximum value have an equal probability.

Prior probability distributions for the parameters used in the models

B_0 —Initial biomass

From annual catch levels we can be confident that the initial biomass is at least greater than the highest annual catch recorded since 1984—around 1000 tonnes. A maximum catch level was set at 20,000 tonnes which is about 20 times the largest recorded catch value, i.e. $B_0 \sim U(1000, 20,000)$. Note that the burn-in phase, which can take up to 240 monthly time-steps, occurs between B_0 and B_{85} .

δ —Monthly change in catchability

This term represents the monthly change in average relative catchability or fishing power. Based on the work of O'Neill (2003, Table 6.4.4) fishing power in the east coast deep water prawn trawl industry in Queensland has grown around 5.1% over the 11 years of 1989–1999 with a 95% confidence interval from -0.9 to 11.0% . Converting this annual change to a monthly timescale and converting the rate into the form used in Eq. (9), this change in catchability is represented by a δ value of 3.0×10^{-4} . The prior applied to this parameter was normal with mean monthly catchability growth rate of 4.0×10^{-4} and

standard deviation of 3×10^{-4} that coincides with the confidence intervals estimated in O'Neill et al. (2005). The estimates from the O'Neill et al. (2005) study were used as this fishery most closely resembled the NSW eastern king prawn fishery, but the estimates from other penaeid prawn fisheries (Wang and Die, 1996; O'Neill et al., 2003) were also considered in the sensitivity analysis $\delta \sim N(4.0 \times 10^{-4}, 3 \times 10^{-4})$.

G —Emigration to Queensland

Although a number of tagging studies have demonstrated that the NSW stock emigrates to Queensland in significant quantities (Lucas, 1974; Ruello, 1975; Glaister et al., 1987; Montgomery, 1990; Gordon et al., 1995) very little information exists to provide a prior for this parameter. The only estimate that could be found was from Lucas (1974) which estimated the instantaneous emigration rate out of Moreton Bay in Queensland at 0.168 week^{-1} . An uninformative prior of $U(0.01, 1)$ was problematic for this parameter as such a prior could skew the results in this study given that G and M play a similar role in all four models. The prior for this parameter was based on the tagging studies and subsequent compartmental model for eastern king prawns developed by Gordon et al. (1995) which estimated emigration up the NSW coast based on alternative values for M . The prior for G was set accordingly at $G \sim LN(0.2, 0.3)$ with the mean value translating into approximately 25% of the prawns migrating out of NSW waters each month.

k —Recruitment delay (months)

According to Gordon et al. (1995) eastern king prawns recruit at 9–12 months, into the ocean fishery. Initially a discrete uniform prior between 9 and 12 months was used, but this parameter was found to have very little impact so was reduced to a constant value of 9 months for simplicity (i.e. $k=9$).

M —Monthly instantaneous natural mortality

Natural mortality includes all sources of mortality except recorded fishing mortality, but excludes emigration from the system. Numerous studies have attempted to evaluate the natural mortality rate for eastern king prawns. The most extensive work being Glaister (1983) who compiled estimations based on catch rates, tagging studies, and even a meta-analysis of mortality rates of other penaeid species. Table A.1 provides a listing of the estimates from each of the studies. These estimates were pooled with greater weight given to estimates based on eastern king prawn, particularly in NSW waters. An informative prior was generated in the following form: $M \sim LN(0.25, 0.3)$.

q —Catchability

Informative bounds on this prior can be defined by recalling $U=qB$ and using the observed values of U and the mean of the prior pdf for B_0 . The work of McAllister and Kirkwood (1998) and Punt and Hilborn (1997) suggested that a uniform

Table A.1

Estimates of the instantaneous natural mortality rate (M) of eastern king prawns (*Melicertus plebejus*)

Source	M (month ⁻¹)	Estimation method
Glaister (1983)	0.13	Applied Pauly (1978) approach
Lucas (1974)	0.22	Evaluation of South East Queensland stock from tagging study
O'Neill et al. (2003)	0.2	From Lucas (1974) and Garcia (1985)
Glaister (1983)	LN(0.2, 0.5)	Meta-analysis from other penaeid species
Glaister et al. (1990)	0.27	Tagging study (1979) in NSW waters
Glaister et al. (1990)	0.35	Tagging study (1980) in NSW waters
Gordon et al. (1995)	0.29	Tagging study (1991, 1992) in NSW waters

prior for q will bias initial biomass values due to the correlation between q and B_0 . Each author suggested that a more appropriate prior for q is uniform on $\log(q)$, i.e. $q \sim \text{LU}(1 \times 10^{-7}, 1 \times 10^{-5})$.

re_y —recruitment error for year y

Each of the 20 recruitment error terms were initially given a normal distribution with mean of 0 and standard deviation of 0.2. Unfortunately, the RE and MR models that both use the recruitment error terms were unable to produce posterior distributions that met our posterior quality standards (in particular $\text{MIR} < 0.005$ and $\text{MSD} < 1\%$). We therefore employed an iterative process similar to that suggested by Smith et al. (1987). A full run (10 million iterations) of the SIR process was employed, following which the mean of the posterior pdfs for each of the recruitment error parameters was used as the prior for another full run of the SIR process, with the standard deviations of the recruitment error terms halved. The priors for each of the other model parameters were kept the same as they were in the first full run, with the only change between each full run being the changes to the recruitment error priors. Four full model runs were completed at which point the quality of the posterior was found to meet our posterior quality requirements. To test the validity of this approach we examined the effect of the multiple runs on the posterior of the non-recruitment error parameters. We found that the posteriors for the non-recruitment error parameters were not significantly altered (reduced) through the four full model runs. Thus the initial priors for each of the recruitment error parameters was $re_y \sim N(0, 0.2)$ followed by $re_y \sim N(\text{run 1 } re_y \text{ posterior mean}, 0.1)$, $re_y \sim N(\text{run 2 } re_y \text{ posterior mean}, 0.05)$, and $re_y \sim N(\text{run 3 } re_y \text{ posterior mean}, 0.025)$.

ρ —Ford-Walford plot slope

Using the age–length and length–weight relationships developed by Glaister (1983) averaged over both sexes and fitted to a Ford-Walford plot gave a range of $\rho \sim U(1.0, 1.1)$.

σ —Standard deviation of observation error

The SIR algorithm could not find a satisfactory approximation for the posterior pdf of σ . Walters and Ludwig (1994) presented an analytical method for calculating the marginal likelihood of σ but this was not applied in this study. A simpler option was used, where this parameter was treated as known and set to a value of 0.4 (which is the approximate maximum likelihood estimate given the range of calculated and observed catch rates in our study). A similar approach was adopted by McAllister and Kirkwood (1998) as a posterior for σ is rarely needed.

\bar{w}_k —Average prawn weight at recruitment

For the purposes of this study, recruitment into the fishery occurs when the prawns recruit to the ocean fishery. According to Gordon et al. (1995) this occurs when the eastern king prawn are around 25 mm carapace length, which is when the prawns are around 0.01 kg (using the age–length and length–weight relationships developed by Glaister, 1983). Accordingly we chose an informative log normal prior with a mean of 0.01 kg and a coefficient of variation of 20%, i.e. $\bar{w}_k \sim \text{LN}(0.01, 0.002)$.

z —Steepness of Beverton–Holt stock recruitment relationship

The steepness of Beverton–Holt stock recruitment relationship, z , represents the proportion of virgin stock recruitment levels that will recruit if the current stock is at 20% of virgin stock levels (Hilborn et al., 1994). A value of z closer to 1 means that recruitment levels are determined less by the current stock size and more by environmental conditions (or virgin recruitment capacity). According to Glaister (1983) there appears to be little or no evidence of a strong stock–recruitment relationship for the eastern king prawn. This is possibly the case for many crustacean species that are highly fecund and spawn in areas where their larvae are dispersed over a large area of coastline habitat (Schnute, 1985; Walters and Ludwig, 1994). In this case, the stock recruitment relationship is also compromised because of the likely southerly advection of larvae from Queensland. Consequently for the base model and the RE model, both of which rely on local recruitment, we used an informed prior for z between 0.75 and 1 reflecting a belief that environmental conditions play a large role in recruitment levels, i.e. $z \sim U(0.75, 1)$. For the MR model and the 2C model where recruitment from Queensland is regarded as a separate process error a prior that allows z to take on any value over the allowable range was used, i.e. $z \sim U(0.2, 1.0)$.

μ_q, θ_q and σ_q —Mean, slope and variance of the short-run (seasonal) catchability pattern

Based on an analysis of the seasonal cycle seen in the CPUE data and the explanation of recruitment cycles by Glaister (1983) and O'Neill et al. (2005) the short-run (seasonal) catchability cycle occurs regularly over a 12-month period. The mean μ_q ,

which determines the lowest point for the pattern, was found to be the month of July (7) for the NSW eastern king prawns. The priors for the slope θ_q and variance σ_q were then chosen to cover ranges that provided an acceptable correspondence to the observed data. In summary: $\mu_q = 7$, $\theta_q \sim U(1.45, 1.75)$ and $\sigma_q \sim U(6, 7)$.

LRf and LRp—Long-run (seasonal) recruitment cycle frequency (LRf) and phase (LRp)

Based on an analysis of the long-run cycle seen in the CPUE data the long-run recruitment was given an uninformative prior for the phase of between 0 and π and a prior for the frequency of between 40 and 45 month⁻¹, which equates to a full long-run cycle of between 10 and 12 years. In summary: LRp $\sim U(0, \pi)$; LRF $\sim U(40, 45)$.

Sensitivity of results to informative priors

A sensitivity analysis was conducted on both the MR and 2C models to examine the consequences on the results of altering the informative priors for the parameters as described in Appendix A. Parameter priors were altered one at a time and the impact on the depletion ratio posterior pdf examined. In some cases the quality of the posterior was reduced (based on the criteria discussed in Section 2). As expected, widening the priors on the parameter B_0 (initial biomass) had a significant effect on B_{04} but did not greatly affect the depletion ratio. Widening the priors of other significant parameters such as G (emigration), M (natural mortality), q (catchability), and δ (annual catchability growth) similarly did not significantly impact the depletion ratio but did affect the quality of the posterior (higher MIR and MSD values). Increasing the mean for δ to the highest levels reported by O'Neill et al. (2003) decreased the depletion ratio but only by around 5%. Altering \bar{w}_k (average weight at recruitment) appeared to directly affect the posteriors of the average stock weight, mortality and emigration but not the depletion ratio.

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