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Black tiger prawn CPUE standardisation and stock assessments

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Contents

List of figures

List of tables

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Executive summary

Historically, Black tiger prawns (*Penaeus monodon*) have not been directly targeted in the Northern Prawn Fishery (NPF). They are retained with the main commercial target species when incidentally captured. Separate from the fishing operations, the development of pond-based aquaculture in recent years has created a broodstock collection targeting live Black tiger prawns in the NPF. The total annual removal of individuals by broodstock collection (retained live catch plus discard mortality) has increased by an average about 68% annually since 2013. During this period, the removal of Black tiger prawns by broodstock collection is about 14% of the total fisheries removals. The broodstock catches have been capped at various levels as there is uncertainty as to setting harvest rates that will not impede the long-term sustainability of the stock. Increasing demand for broodstock has raised the need for an evaluation of the productivity of this stock, and an assessment is required to ensure the species' sustainability.

This report presents the first attempt to conduct quantitative assessments of Black tiger prawns in the NPF. The study includes five major components.

1. CPUE standardisation for the broodstock collection

AFMA has collected and collated eight years of fishery data from the broodstock collection (2005, 2013-2019). A relatively low fishing effort and catch occurred in the first year (2005), while more intensive fishing has continued since 2013. A substantial proportion of Black tiger prawns (over 25%) were discarded in this live-capture fishery. Discards were rarely reported before 2017. Hence, catch-per-unit-effort (CPUE) analysis can only be performed on the most recent three years of data (2017 to 2019).

In this study five CPUE standardisation models were applied to the available data: (i) a generalized linear model (GLM) with a lognormal distribution, (ii) a generalized additive model (GAM) with a lognormal distribution, (iii) a GAM with a negative binomial distribution, (iv) a GAM with a Tweedie distribution (GAM-Tw), and (v) a Bayesian spatial geostatistical model (GSM). Model covariates included live-capture fishery variables, environmental variables, and vessel technical variables.

Cross-validation analysis indicated that GAM-Tw and GSM were more accurate in terms of prediction error so the results of these two models were considered further for CPUE standardisation. However, model fits were poor, even with the best model, in comparison to other co-generic species whereby models were applied for the biennial NPF stock assessment. The standardised CPUE was higher in 2018 and lowest in 2017.

There are several possible reasons for the poor model fits. While it is possible that more relevant and better predictors may have been missed, the data quality is the main concern. Low fishing effort (number of fishing days and shots) and the short time period of available data, as well as many missing values or errors in the fishery data, have increased the difficulties with applying these models. The spatial coverage of the broodstock fishing effort is small compared to both the geographic range of the species and the spatial extent of the commercial fishery. It is possible that within the limited target fishing area for broodstock live-capture, Black tiger prawn distribution and density do not clearly link to any environmental and fishery covariates included in the models.

For the purpose of stock assessment, three years of an abundance index, even if reliable, has little value. It is recommended to continue the collection of accurate live-capture fishery data. In the meantime and in the near future, focusing on data-limited approaches for stock assessment is potentially more beneficial than trying to improve the CPUE standardisation.

2. Standardising CPUE data for the NPF commercial fishery

The NPF commercial logbooks have recorded Black tiger prawn catch since 1998 and the fishing activities extend to the entire NPF region where fishing has targeted common Banana prawns, Grooved tiger prawns, Brown tiger prawns, and Endeavour prawns. However, in fishing grounds (defined by 0.1*0.1 degree spatial grids) where Black tiger prawns have been recorded, more than 98% of the fishing days have recorded zero catch of this species. To deal with this type of data we developed delta-lognormal models for the CPUE analysis. The catch and effort data with excessive zero values were modelled in two parts: a binomial distribution model for modelling the probability of non-zero events, and a log-normal distribution model for modelling the positive catch events. In addition, the extremely low probability of catching Black tiger prawns in many grids and the highly skewed distribution of the positive catch presented a challenge for the reliable standardisation of the CPUE data. Consequently, we conducted additional analyses within two spatially limited levels, not using all the records where black tiger prawns were caught. At Level 1, we excluded grids where the rate of positive catch (fishing days with positive catch divided by the total fishing days in that grid) was smaller than 0.01; and at Level 2, we excluded grids where the rate of positive catch was smaller than 0.1 and had less than 10 fishing days during the 22 years of data that were analysed for the commercial fishery (i.e. 1998 to 2019).

The delta-lognormal models showed a reasonably good fit to the three levels of data, although the standardised index has a high degree of uncertainty. The results indicate an increasing trend of standardized CPUE since 2010 (or abundance if CPUE is related monotonically to abundance). It is difficult to interpret such a trend, because catch also increased during the same period. We hypothesize that one or more combined factors may have caused an increase in CPUE, including (i) possible changes in fishing behaviour and catch reporting over time, (ii) missed important variables that affect fishing power, (iii) heavy depletion of the stock before 1998, and (iv) possible ecosystem changes. Further investigation of the fishery data may be warranted, although it is worth noting that because Black tiger prawns are incidentally captured in the commercial fishing, attempts to standardize CPUE for a bycatch-like species could be fruitless and subject to bias.

As there is not a valid reason for spatially truncating the data, it is recommended that the standardized index from the full dataset be used for stock assessments for the time being. However, caution is needed when interpreting the increasing CPUE trend.

3. Stock assessment of the whole NPF region using a Bayesian state-space biomass dynamics model (BBDM)

The lack of age, size, and life-history information for Black tiger prawns prevented the application of age-structured models for their assessment. Given this restriction, we opted to apply less data demanding models, i.e. a biomass dynamics model (BDM). A Bayesian state-space biomass dynamics model (BBDM) was implemented in the R package JABBA. Since the abundance index from commercial fishing is highly uncertain, we used an informative prior on one of the key parameters—intrinsic population growth rate *r*. We constructed this prior based on the estimated *r* for Grooved and Brown tiger prawns. Various sensitivity tests on the initial depletion level, the intrinsic population growth rate, and the carrying capacity parameters were investigated. In addition to using observed discard mortality rate based on an on-vessel experiment, we tested the model sensitivity to assumed 100% discard mortality rate.

The final model yielded the following estimates for the posterior means (Table ES): (i) unfished biomass *K* of approximately 41.3 tonnes, (ii) F_{msy} of about 0.23 yr^{-1}, (iii) B_{msy} of about 20.7 tonnes, and (iv) MSY of about 4.6 tonnes. The model indicated that the total catches during 2014, 2015, and 2018 were greater than the estimated mean MSY, and that the estimated fishing mortality in 2018 (F_{2018}) was slightly greater than mean F_{msy}, and the estimated mean biomass in all years was above mean B_{msy}. Hence, according to the model estimates the Black tiger prawn stock has not been overfished but overfishing may have occurred in 2018.

Since the Black tiger prawn stock in the NPF region as a single unit is unlikely overfished, and since the total catch continues to increase, the model may have underestimated the carrying capacity and MSY. To detect the full stock size and its production potential, a range of fishing mortality levels (including heavily fished) may better inform the assessment models. It is recommended that the current catch level be maintained for one or two years to see whether the stock can support this level of harvest and to assist the model identifying the maximum potential of production. However, because the total catch may have possibly exceeded the MSY level and fishing mortality exceeded F_{msy} in recent years (noting their high uncertainty), a dramatic increase of catch (e.g. from the live-capture broodstock) should be avoided to prevent severe overfishing. A re-run of the BBDM is warranted in the coming years when new catch (and possibly standardized CPUE) data become available.

4. Stock assessment of the whole stock using catch-only method (COM)

Catch-only models do not require a time series of an abundance index (which is unreliable for Black tiger prawn as described above). The optimized catch-only method (OCOM) used in this study is based on the same biomass dynamics model as used in the Bayesian framework. Again, the *r* prior was constructed from estimated values of Grooved and Brown tiger prawns. The effect of various stock depletion levels was tested by using the BBDM output and an assumed very low level, as a sensitivity test.

The OCOM model estimated median *K* was about 33.2 tonnes, the estimated median MSY about 3.4 tonnes, and the estimated median B_{msy} about 16.6 tonnes (Table ES). These estimates are lower than the BBDM output. The model predictions indicated that the total annual catch was likely greater than model estimated MSY in 2014, 2015, and 2018, and model-estimated fishing mortality was greater than model-estimated F_{msy} in 2018. Nevertheless, the model-estimated median biomass had never been below the median B_{msy} reference point. Hence, the general conclusions that the stock has not been overfished but overfishing may have occurred in recent years concur with the BBDM outputs.

5. Stocks assessments of a putative sub-stock in the broodstock live-capture high fishing effort area

In recent years, the substantial removals of Black tiger prawns by the broodstock collection from relatively small areas compared to the large geographic range of the species has raised concerns over the sustainability of a possible local population if these prawns belong to a separate sub-stock. For this analysis, the assumption is that high live-capture fishing effort has occurred on a sub-stock, and the putative sub-stock area encompasses Cape Van Diemen (CVD) and Joseph Bonaparte Gulf (JBG) as about 98% of the broodstock fishing effort took place in this region. The BBDM and OCOM were applied to data from this region to assess this putative sub-stock.

The BBDM yielded a model-estimated mean unfished biomass *K* of about 12.9 tonnes, a mean B_{msy} of about 6.4 tonnes, and a mean MSY of about 1.5 tonnes (Table ES). The output of the model indicated that the total catch was greater than the model-estimated mean MSY in 2018. Estimated fishing mortality in 2019 (F_{2019}) was slightly greater than the mean F_{msy}, but the mean biomass in all years was above the mean B_{msy}.

The OCOM estimated a lower median carrying capacity about 8.9 tonnes, the median B_{msy} about 4.4 tonnes, and the median MSY about one tonne (Table ES). The total catch was greater than the model-estimated median MSY since 2012 except 2013 and 2017. This model indicates that the median biomass is slightly below median B_{msy} in 2019 and overfishing may have happened in 2018 and 2019.

Overall, the stock assessments using both the BBDM and OCOM approaches demonstrate similar conclusions when the entire NPF was treated as a single stock. Estimated total fishery removals are more than model-estimated MSY in recent years, the stock has not been overfished, but overfishing may have occurred in 2018. However, if we focus on the high broodstock fishing effort areas in CVD and JBG as a sub-stock, the results from the BBDM and OCOM do not fully agree each other. The BBDM indicates that this putative sub-stock has not been overfished, but overfishing may have occurred in 2018. In contrast, the catch-only model suggests that the median biomass in 2019 is slightly below median B_{msy} and overfishing may have happened in both 2018 and 2019. The estimated quantities (Table ES) are highly uncertain, particularly due to the very limited data and questionable CPUE, and partially due to relatively light fishing intensity in the available time series. On the basis of the results herein, it is proposed to keep the catch at the current level for one or two years, which could facilitate the process of acquiring a longer time series and assist models to identify the production potential with lower uncertainty than present assessment. CPUE standardisation is challenging for non-target species and the resulting abundance index is unreliable. The two assessment approaches (i.e. the Bayesian state-space biomass dynamics model and the catch-only method) could be re-run every year in the next couple of years when new catch data become available.

Table ES. Summary of the point estimates for key management parameters for Black tiger prawns. The high effort region includes Cape Van Diemen (CVD) and Joseph Bonaparte Gulf (JBG) with about 98% of fishing effort in broodstock collection. The Bayesian biomass dynamics model (BBDM) is implemented in JABBA package. OCOM (optimized catch-only method) does not use CPUE data.

	Full NPF		High effort region	
Param	BBDM	OCOM	BBDM	OCOM
K	41,341	33,245	12,865	8,855
F_{msy}	0.23	0.21	0.23	0.41
B_{msy}	20,670	16,623	6,432	4,428
MSY	4,624	3,447	1,464	953
B_{2019}/B_{msy}	1.40	1.19	1.35	0.92
F_{2019}/F_{msy}	0.41	0.66	0.75	1.72

1 Introduction

Black tiger prawn (*Penaeus monodon*) is a minor species in the Northern Prawn Fishery (NPF) where the vessels target the main commercial species, i.e., Grooved and Brown tiger prawns, Endeavour prawns and Banana prawns. Recently Black tiger prawn has also become a target for broodstock collection for prawn aquaculture production. The status of the stock is unknown and a quantitative stock assessment is required due to the increasing demand for *P. monodon* spawners. However, it is a challenge to conduct a quantitative stock assessment due to a lack of biological and fisheries data. This report is the first attempt to conduct quantitative analyses of Black tiger prawn abundance and population dynamics in the NPF.

Given the sporadic fishery information, a short-time period of broodstock catch history, and inconsistent data types between years and vessels, it was envisioned that any assessment would be highly uncertain. To increase the likelihood of a useful outcome, multiple approaches were proposed at the onset of this research. Five major analyses are carried out in this study: (1) standardising catch-per-unit-effort (CPUE) data for the broodstock collection; (2) standardising CPUE data for the NPF commercial fishery; (3) a stock assessment of the whole NPF region using a Bayesian state-space biomass dynamics model; (4) a stock assessment of the whole stock using a catch-only method; and (5) stocks assessments of a hypothetical sub-stock in the broodstock collection area where fishing effort is higher.

To provide a relative abundance index over time, standardising CPUE is necessary in many fisheries because catch rate can be affected by many variables beside abundance. The NPF commercial logbooks contain catch and effort data going back to the 1970s with most records reported as daily totals. Boats fishing for broodstock have also collected shot-by-shot catch data in 2005 and since 2013, although there have been considerable inconsistencies in types of data collected and spatial coverage. Information associated with catch data could be used to estimate relative abundance and density distributions. Several models for CPUE standardisation are explored in this study. Since different types of information have been collected in the NPF by both commercial fishing and broodstock collection, CPUE standardisation has to be performed separately for the two datasets (i.e., CPUE standardisation using logbook records and separately CPUE standardisation on broodstock collection fishing trips).

Black tiger prawn is a data-poor species with little targeting by the commercial fishing. The lack of age, size, and life history information restricts any application of mathematically sophisticated age-structured modelling approaches. Thus, the assessments in this study adopt less data demanding methods, the widely used biomass dynamics model (i.e. a surplus production model). This is the initial attempt at applying a quantitative assessment to the Black tiger prawn stock in the Northern Prawn Fishery which potentially could have immediate management implications, as well as provide a baseline analysis for this species for future studies.

2 CPUE standardisation for broodstock catch data

2.1 Materials and methods

2.1.1 Data description

AFMA provided broodstock catch data for all the records which were available in the format of an excel file. The data contain various types of information, including: Vessel ID, Date, Shot No., Depth, Shot Start Time, Location, Latitude, Longitude, Shot End Time, Male (Total No. in shot), Female, Retained, and Discarded. Catch of other species (prawns, bugs, squid, and bycatch species) were occasionally recorded.

The data covered eight years (2005 and 2013 to 2019). Some of the vessels reported daily catch, which was problematic to use together with the majority of the dataset that were shot-by-shot records (e.g., trawling hours varied from 1 to over 14 hours per day and the catch could be either by number or by weight). It was common to have missing (blank) information in many fields, such as location (latitude or longitude), depth, shot-end-time, and vessel code. The most important issue was incomplete records of discards. Fisheries assessment, including CPUE standardisation, requires total catches, that is recorded landed catch plus discards. In this case, total catch = retained + discarded prawns. Unfortunately, discards were not reported in most events (Table 2-1), which would affect CPUE estimation and stock assessment. Records of discards in the eight years (2005 and 2013 to 2019) ranged from 0 to 46% with an annual mean of 16%%. The ratio of the number of discards to the number of retained prawns (when recorded) was substantial (ranging from 0.01 to 0.47 with a mean of 0.23). Attempts to roughly estimate non-reported discards failed because there was no relationship between the number of discards and the number of retained prawns (Figure 2-1). The combined numbers of Male and Female also did not agree well with either Retained or Retained + Discarded (Figure 2-2).

After discussions with AFMA and Industry it was revealed that discards were reported for all shots by all vessels since 2017 so blank cells for discards in 2017 to 2019 implied zero discard. However, before 2017 it is unknown how many blank cells for discards were actually zero discards. For this reason, our analysis focuses on the data from the most recent three years (2017 to 2019).

Fisheries catch rate is a function of abundance and catchability (Campbell, 2015; Campbell *et al.*, 2017). These two variables in turn are affected by many environmental and fishery variables (Maunder and Punt, 2004; Hoyle *et al.*, 2014). We assembled and tested a range of potential covariates which can be grouped into three categories:

- Fishery covariates: vessel_id, year, month, date, season, shot_phase, shot_no, shot.start_time, shot.end_time, shot.hr.
- Geographical covariates: Location, latitude, longitude, stock_region.
- Vessel tech covariates:plotter, pc_sat, echocol, hullg, nav_accg, brdn, d_gps, gps, satnav, plotsoft, dgps, sonar, hullmat, vessel_ length.

2.1.2 Selecting covariates and model building

We used a stepwise variable selection approach as a preliminary step to choose the explanatory variables (covariates) that have potential effect on the catch based on experience in other species (i.e., Grooved tiger prawn fishing power study). The selected variables in this step were validated by the *p*-value of each estimated coefficient. In addition to existing data, we created some new variables. For example we postulated that the time of fishing may affect catchability (or availability) so the "phase of the day" was created from the shot time as:

Phase 1 from 7:00PM to 5:00AM (night),

Phase 2 from 5:00AM to 7:00AM (dawn),

Phase 3 from 7:00 AM to 5:00PM (day),

Phase 4 from 5:00PM to 7:00PM (dusk).

"Phase" here was intended to be a set time period during a 24 hour period. Stock region was based on the common banana prawn stock area. There were four stock regions with records of Black tiger prawns in the broodstock fishery: 1 for CM (Coburg-Melville), 2 for FB (Fog Bay), 3 for JB (Joseph Bonaparte Gulf), and 4 for WA (Weipa).

We attempted to calculate hours trawled in each shot from shot start and end times. However, there were many missing records, with many cases where trawl duration was less than 0.5 hr or greater than 5 hr, indicating possibly errors. We replaced these missing and potentially error values with 1 hr (the average trawling duration from assumed correct records). Unfortunately, models that included trawl duration (including imputed values) were less reliable than models without this variable. Hence, in this analysis catch-per-unit-effort refers to number of prawns captured per shot rather than per hour.

The broodstock fishery has a short time series of eight years (2005, 2013-2019). During this period, especially from 2017 to 2019, we observed that the technology used on fishing vessels remained relative stable, and as such technology variables cannot be used as predictors.

Unlike the NPF commercial fishery, most shots in the broodstock fishery have positive catch of Black tiger prawns as it is the primary target species. Only 13.5% of shots ends up with zero catch. Hence, it is unnecessary to apply zero-inflated models to this dataset (see modelling and issues with excessive zeros in the data in the next chapter).

Generalized linear models and generalized additive models

We first used generalized linear models (GLM) to link catch per shot to various predictors and used a stepwise selection process to select the important influential variables. The general form of the model is:

$$\boldsymbol{\eta_i = g(\mu_i) = \beta_0 + \sum_n \beta_n x_{ni} + \varepsilon_i} \qquad \textbf{Equ 2-1}$$

where mean μ_i is the expected catch (number of prawns) on shot *i* and is linked to the linear predictor η_i, β_0 is the intercept, β_n is a coefficient for the explanatory variable x_n, which is considered a fixed effect, and ε_i is unstructured random error with $N(0, \sigma^2)$. We assumed that the expected catch is log-normally distributed (Figure 2-3). Since some shots have zero catch we added a small value (δ = 0.05) to the recorded catch in each shot to avoid error when taking the log-transformation for these records.

The stepwise regression excluded many insignificant variables. The final GLM has eight predictors:

M1: GLM with lognormal distribution

$$\boldsymbol{\log(CPUE + \delta) = year * stock + vessel + season + month + phase + lat * lon} \qquad \textbf{Equ 2-2}$$

$CPUE \sim LN(\eta, \sigma^2)$, where year and stock region are interaction terms. Since the standardized CPUE is obtained from model prediction (see below), the process is straightforward even when the interaction terms lead to different temporal trends by stock area. All co-variates are treated as categorical variable except lat and lon.

A similar process was used for building the generalized additive models (GAM). We explored three alternative distributions, but all the models have the same covariates. The predictors that made a significant contribution to the model ($p < 0.1$) may differ between models.

M2: GAM-LN with lognormal distribution

$$\log(\boldsymbol{CPUE} + \boldsymbol{\delta}) = \boldsymbol{year} * \boldsymbol{stock} + \boldsymbol{vessel} + \boldsymbol{season} + \boldsymbol{month} + \boldsymbol{phase} + \boldsymbol{te}(\boldsymbol{lon}, \boldsymbol{lat})$$

Equ 2-3

CPUE ~ $LN(\eta, \sigma^2)$.*te* is tensor product smooth function.

M3: GAM-NB with negative binomial distribution

$$\boldsymbol{CPUE} = \boldsymbol{year} * \boldsymbol{stock} + \boldsymbol{vessel} + \boldsymbol{season} + \boldsymbol{month} + \boldsymbol{phase} + \boldsymbol{te}(\boldsymbol{lon}, \boldsymbol{lat}) \qquad \textbf{Equ 2-4}$$

CPUE ~ $NB(\mu, \theta)$, where μ = E(CPUE) (E is expectation), and var[CPUE] $=\mu+\mu^2/\theta$.

M4: GAM-Tw with Tweedie distribution

$$\boldsymbol{CPUE} = \boldsymbol{year} * \boldsymbol{stock} + \boldsymbol{vessel} + \boldsymbol{season} + \boldsymbol{month} + \boldsymbol{phase} + \boldsymbol{te}(\boldsymbol{lon}, \boldsymbol{lat}) \qquad \textbf{Equ 2-5}$$

CPUE ~ $Tw(\mu, \sigma, p)$, where μ = E(CPUE), and var[CPUE] $=\sigma^2\mu^p$.

The catch was over-dispersed (variance to mean ratio was about 27) so it is necessary to use statistical distributions that can deal with over-dispersed data such as negative binomial and Tweedie distributions. The power parameter *p* is estimated in the *tw* function in R package mgcv. Note both the GAM-NB and GAM-Tw can handle zeros so there is no need to include a small value δ.

Geostatistical model (GSM)

In the geostatistical models, the catch at specific location $C(s)$ is a realization of a spatial process characterized by a spatial index *s* which varies continuously in the fixed domain *D* (i.e. the NPF area here). The vector of catches is assumed to follow a multivariate normal distribution with mean $\boldsymbol{\mu} = [\mu(s_1),..., \mu(s_n)]$ and spatially structured covariance matrix $\boldsymbol{\Sigma}$. Such a multidimensional spatial process is called a Gaussian Random Field (GRF) (Blangiardo and Cameletti, 2015). The assumption is that prawn distribution and dynamics are an unobserved latent field, which is partially observed through catch data. Similar to the GAM, the GSM can be expressed as follows:

M5: GSM-NB with negative binomial distribution

$$\boldsymbol{CPUE} = \boldsymbol{year} * \boldsymbol{stock} + \boldsymbol{vessel} + \boldsymbol{season} + \boldsymbol{month} + \boldsymbol{phase} + \boldsymbol{f}(\boldsymbol{lon}, \boldsymbol{lat}) \qquad \textbf{Equ 2-6}$$

CPUE ~ $NB(\mu, \theta)$, where μ = E(CPUE), and var[CPUE] $=\mu+\mu^2/\theta$.

This model differs from GAM Model 3 in that the term *f*(*lon, lat*) is a spatially structured nonlinear smooth function effect of continuous spatial covariates.

The GRF model M5 was implemented in an integrated nested Laplace approximation (INLA) program which handled the continuous GRF by stochastic partial differential equations (SPDEs) and established explicit links between the parameters of each SPDE and the elements of precision matrices for weights in a discrete basis function representation (Lindgren and Rue, 2014).

INLA is a full Bayesian approach where Bayesian geostatistical models require specifying priors for all parameters. In this study we assumed no knowledge about the model parameters so the default priors and hyper-parameters were adopted (Lindgren and Rue, 2014; Zhou *et al.*, 2019). The default vague prior, Normal(0, 10^6), has a large variance so it has little impact on the posteriors, and the results are largely derived from the data. For the random effect component in the GRF model, the prior was specified for the two parameters in the Matérn function, τ and κ, with the default Normal(0, 1).

The first step to implementing the GRF models is to build a spatial "mesh" based on latitude and longitude from all gear set locations in the data. The triangulated mesh provides a base for the GRF models to build spatial representations. The mesh was produced within the defined boundary. An example of the constructed mesh and boundary is shown in Figure 2-4.

Thus, we have five separate models representing various assumptions about the data distributions and the modelling techniques to adapt to the limited data.

2.1.3 Model fitting and model prediction

The five models described above, i.e. GLM, GAM-LN, GAM-NB, GAM-Tw, and GSM-NB, were fitted to the broodstock fishery data, using the R program with packages mgcv and INLA.

The purpose of CPUE standardisation is not only to estimate the expected catch rates in fished locations under various observed conditions, but more importantly to predict the catch rates using the standard predictors in all combinations of *year* and *location*, including those not fished in a particular year. For prediction, unlike during model fitting, variables that affected catch rate were kept constant across all locations and years. Under these circumstances the models predict the catch rate in all years and in all areas within the fishery boundary, with the predicted catch rate representing the latent relative abundance.

To obtain the standardized CPUE we constructed a prediction dataset covering all 0.1*0.1 degree grids fished by the broodstock fleet (Figure 2-5). Each grid and year have the same structure and identical covariates as in Models M1 to M5. As the prediction covered all grids that have been fished while other predictors (except *year*) were fixed at the same value, the five models predicted catch rate and its variance at each location. The annual standardized CPUE was derived by dividing summed annual predicted catch rates by the mean catch rate over the time series considered. Similarly, the total annual variance of the predicted catch rate was the sum of variance over all grids in that year.

2.1.4 Model evaluation and comparison

We examined both fitted catch rate estimates and predicted indices for the five models. Model prediction is often evaluated by predictive information criteria (e.g., AIC, DIC, WAIC, etc.) when the true underlying parameters are unknown. In our case since data and model structures differ among these models (e.g., raw catch vs. log-scaled catch), we cannot use these common statistics for model comparison. Instead, we used cross validation where 90% of data were used for model fitting and the remaining 10% of data were used for model prediction. This was repeated 10 times for each model. Errors (residuals) between the model-fitted catch rates and the observed CPUE for each shot were examined visually and their values compared among the models. Two measurements, the mean squared predictive error $MSPE_M$ and the mean predictive error MPE_M for model M, were used to compare model performance:

$$MSPE_M = \frac{1}{n}\sum_n\left(\widehat{CPUE}_{i,M} - CPUE_i\right)^2, \qquad \text{Equ 2-7}$$

$$MPE_M = \frac{1}{n}\sum_n(\widehat{CPUE}_{i,M} - CPUE_i), \qquad \text{Equ 2-8}$$

where n is the number of shots in the prediction dataset (i.e. 10% of the total records), $\widehat{CPUE}_{i,M}$ is predicted CPUE for shot i by model M, and $CPUE_i$ is the observed catch rate for shot i.

The annual standardized index for model M in year y, $SI_{M,y}$, was scaled so that the mean of the annual index over the time-series considered was equal to 1:

$$SI_{M,y} = \frac{\widehat{CPUE}_{M,y}}{\overline{\widehat{CPUE}_M}}$$ Equ 2-9

2.2 Results

2.2.1 Comparing models using cross validation

The cross-validation using 10% of data and repeated for 10 times reveals varying levels of prediction accuracy amongst the five models (Table 2-2). The GLM (M1) has the highest MSPE and MPE, indicating its poor performance. Within the three GAM models, M2 is only slightly better than the GLM while NB and Tw distributions are similar. The spatial model M5 has the lowest MPE and its MSPE is close to GAM NB and Tw models.

2.2.2 Modelling catch rate

We applied the five models to the shot-by-shot records in the broodstock fishery data. However, since models M1 and M2 performed poorly, we did not focus on these two models. Both GAM-NB and GAM-Tw yielded similar results with GAM-Tw results being slightly better in terms of mean squared predictive error so we presented M4 output only (Table 2-3).

The estimated parameters from M4 indicated that CPUE in 2018 and 2019 was significantly higher than in 2017 while CPUE in 2018 was higher than in 2019 (Table 2-3). Stock region 3 (JB) had a lower catch rate than other regions. The catch rate was highest at dawn (Phase 2, 5 AM – 7 AM) but lowest at dusk (Phase 4, 5 PM – 7 PM). The smooth term of spatial location was significant. However, even with this best model (relative to others) within the GLM and GAM group, it only explained 20.1% of the deviance (adjust R^2 = 0.22). The model diagnosis also showed a lack of fit for the data (Figure 2-6).

The spatial model (GSM-NB M5) yielded similar results. The estimated parameters from M5 also indicated that CPUE in 2018 and 2019 was higher than in 2017 and CPUE in 2018 was higher than in 2019 (Table 2-3). The catch rate was also highest at dawn and lowest at dusk. However, Stock region 4 (WA) had a lower catch rate than other regions. The smooth term of spatial location was significant. Again, although M5 was the best model (relative to others) in the cross validation test, the model diagnosis also showed a lack of fit to the data (Figure 2-7).

2.2.3 Prediction of catch rate (CPUE standardisation)

The prediction of catch rate was estimated for all grids where Black tiger prawns have been captured by the broodstock fishery since 2005, which includes 102 0.1*0.1 degree grids. The standard predictors were chosen as follows. For the categorical variables (e.g. Phase), the most frequent category (the mode) was used. Year, stock region, and location (lon, lat) were always included in the predictors.

The GAM-Tw model (M4) predicted a higher CPUE (Figure 2-8) than the GSM-NB model (M5) (Figure 2-9). However, the relative CPUE over space appeared to be similar. It is worth noting that the predicted CPUE by M5 had much higher uncertainty than M4. The mean values of the standardised indices were similar between the GAM-NB and GSM-NB (Figure 2-10, Table 2-5). However, M4 (GAM-Tw) produced much wider difference between years. GSM-NB also resulted in wider confidence intervals than M3 and M4, probably because it deals better with spatial variation.

We did not focus on the whole time series from 2005 to 2019 because it was known that before 2017 the field data collected from broodstock collection were incorrect due to reporting of discards not being required. However, we included nominal CPUE from 2013 to 2019 in Figure 2-10.

2.3 Discussion

We have used multiple models, including a GLM, 3 GAM models with alternative assumptions of various statistical distributions, and a geostatistical model, to analyse CPUE in the broodstock collection. We have explored the effect of a range of covariates, from fishery-dependent to geographical factors. Due to the known data paucity and flaws before 2017 (i.e. with regard to discards), the analysis focuses on the most recent three years (2017-2019). Comparison across all models by cross-validation reveals that the spatial geostatistical model has the lowest prediction error. Within the GLM and GAM group, the GAM with a negative binomial distribution or the GAM with a Tweedie distribution outperforms GLM and GAM with a lognormal distribution. The trends of the standardised index are similar between GAM-NB, GAM-Tw, and GSM-NB. However, GSM-NB results in a higher uncertainty than the two GAM models, which appears to be unusual (Zhou *et al.*, 2019).

Even though we are able to derive standardised CPUE, model fitting is poor for all models. Maunder and Punt (2004) noted that when the data are highly disaggregated (e.g. 'tow-by-tow' data), the explanatory power is generally low and can be 'increased' by aggregating the data. It may therefore not be appropriate to compare the level of variation explained among different analyses, and analysts should not base their perceptions about the reliability of their index of abundance on the extent of the variation explained (i.e., 20.1% for M4). We hypothesize several possible reasons for the low model fit:

1. **Best predictors missed.** We have explored a few dozen covariates that are typically used for CPUE standardisation (c.f. Campbell, 2004; Maunder and Punt, 2004; Bishop, 2006; Bishop *et al.*, 2008). Spatial and temporal variables are often sufficient to capture the major pattern in fish distribution and relative density, while vessel characteristics and technical equipment largely affect catchability (Hoyle *et al.*, 2014). It is unlikely that other more important predictors than those we have explored are not included.
2. **Data deficiency.** It is not uncommon to have errors or missing values in fishery data. We have carefully checked the raw data and corrected or excluded records with obvious errors. However, it is challenging to validate data that appear to be suspicious. For example, there are many missing and obviously wrong shot starting time entries and shot ending time entries in the data provided, resulting in about one third of trawling hours not being calculated. Modelling CPUE trends generally requires many observations. The total number of fishing days (687) and shots (6,615) in eight years are regarded as quite low, which increases the challenges with the modelling undertaken in this research.
3. **Random distribution over space and time.** The broodstock fishery targets Black tiger prawns. Fishing takes place in relatively small areas compared to the commercial NPF fishery. Only 78 0.1*0.1 degree grids (or 12 1*1 degree grids) have been fished between 2017 and 2019. It is possible that within these fished areas, Black tiger prawn distribution and density do not clearly link to any of the environmental and fishery covariates that we have examined. If this is the case, few predictors work well.

Considering these potential issues, we believe that the data deficiency is the most concerning. This postulation suggests that the broodstock collection fishery should improve data accuracy, fish a wide range of areas, and have a longer time series. Possible alternative methods could also be applied in the future when a longer time series exists. Several new techniques for CPUE standardisation have appeared in recent years. One of these new techniques is machine learning, which includes a range of methods, e.g., neural networks, regression trees, random forest, and boosted regression trees. The application of machine learning for CPUE studies is still limited (Pons *et al.*, 2009; Adibi *et al.*, 2020). Further research is needed to investigate its advantages and accuracy. Bayesian modelling has been another relatively new approach in CPUE standardisation (Federal *et al.*, 2009; Zhang and Holmes, 2009; Cao *et al.*, 2011). The Bayesian approach has several advantages. Through the specification of prior distributions, the Bayesian method allows the formal inclusion of information from previous studies, expert opinion, or similar studies in other areas and fisheries. From the Bayesian posterior distribution we can obtain the probability of a parameter in relation to certain threshold. However, although the Bayesian approach is very flexible, it has a major drawback – slow computing speed because it generally uses the Markov Chain Monte Carlo (MCMC) technique. In fact, the geostatistical model implemented in INLA is a Bayesian approach. More informative priors may be provided from other studies instead of the default non-informative priors. The first-hand knowledge from fishers about the most likely factors that may affect the catch rate could also be very helpful.

From the stock assessment point of view, a short time series of CPUE, such as only three years in the broodstock case, has little use in population dynamics modelling, even if these CPUEs accurately reflect the abundance trend. This is because a very limited time series of CPUE cannot reveal an abundance trend over time. It is important to continue the collection of accurate fishery data. However, we recommend focusing on data-limited approaches for stock assessment in the time being and in near future until a sufficient period of fishery data become available.

Table 2-1. Summary of broodstock data. Mean catch rate = number of P. monodon per shot; Record% = Percent shots with discards recorded (Non-missing); Ratio = number discards/number retained.

	Retained		Discarded			
Year	No.shot	Mean catch rate	No.shot	Mean catch rate	Record%	Ratio
2005	77	7.3			0%	
2013	344	6.0	41	6.3	12%	0.13
2014	176	6.3			0%	
2015	663	5.9	11	4.9	2%	0.01
2016	1,186	4.7	38	2.0	3%	0.01
2017	1,024	3.5	403	3.3	39%	0.37
2018	893	4.3	195	7.3	22%	0.37
2019	2,188	4.7	1012	4.7	46%	0.47
Mean	819	5.3	283	4.7	16%	0.23

Table 2-2. Ten cross validation tests to compare prediction accuracy for the five models. MSPE: mean squared predictive error; MPE: mean predictive error. M1 = GLM lognormal distribution; M2 = GAM-LN lognormal distribution; M3 = GAM-NB negative binomial distribution; M4 = GAM-Tw Tweedie distribution; M5 = GSM-NB geostatistical model with negative binomial distribution.

Cross	MSPE					MPE				
valid	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
1	39.1	37.0	33.4	36.0	39.2	-2.63	-2.40	-0.14	-0.09	-0.16
2	43.5	41.3	34.2	33.5	31.3	-2.51	-2.38	-0.20	-0.17	0.04
3	36.9	35.7	30.1	29.4	35.1	-2.23	-2.16	0.03	0.04	0.55
4	43.7	41.8	33.3	32.3	42.4	-3.01	-2.83	-0.61	-0.60	-0.34
5	40.6	38.5	32.8	32.1	27.7	-2.28	-2.20	0.04	0.05	0.28
6	46.8	44.8	36.5	35.5	30.3	-2.85	-2.70	-0.48	-0.45	0.08
7	47.1	44.8	35.3	34.1	30.3	-2.84	-2.77	-0.55	-0.50	0.06
8	43.3	41.2	34.0	32.7	34.6	-2.43	-2.41	-0.25	-0.23	-0.04
9	35.9	34.2	28.7	28.4	33.7	-2.33	-2.26	-0.11	-0.09	0.01
10	49.6	48.3	40.8	40.1	31.5	-2.68	-2.65	-0.46	-0.41	-0.12
Mean	42.6	40.8	33.9	33.4	33.6	-2.58	-2.48	-0.27	-0.25	0.04

Table 2-3. Results from fitting GAM model with Tweedie distribution (GAM-Tw, M4).

Param	Estimate	SE	Pr(>|t|)
(Intercept)	2.947	0.700	0.000
year2018	1.337	0.086	< 2e-16
year2019	1.273	0.085	< 2e-16
stockFB	0.000	4.213	1.000
stockJB	-23.803	8.669	0.006
stockWA	76.543	39.645	0.054
season2	-0.598	0.133	< 2e-5
month5	-0.639	0.068	< 2e-16
month6	-0.591	0.079	< 2e-13
month7	0.000	0.131	1.000
month8	0.599	0.127	< 2e-5
month9	0.609	0.123	< 2e-5
month10	0.426	0.125	0.001
month11	0.310	0.120	0.010
month12	-0.603	0.000	< 2e-16
phase2	0.099	0.048	0.037
phase3	-0.082	0.040	0.040
phase4	-0.472	0.075	< 2e-9
vessel_id8643	-0.838	0.071	< 2e-16
vessel_id11609	0.000	0.000	NA
vessel_id12396	-0.994	0.092	< 2e-16
year2018:stockFB	-4.384	0.000	< 2e-16
year2019:stockFB	0.000	0.000	NA
year2018:stockJB	-0.833	0.179	< 2e-5
year2019:stockJB	-1.740	0.174	< 2e-16
year2018:stockWA	0.000	0.000	NA
year2019:stockWA	0.000	0.000	NA

Table 2-4. Results from fitting geostatistical model (GSM-NB, M5).

Param	Mean	SD	2.5%CI	Median	97.5%CI
(Intercept	0.341	0.378	-0.465	0.345	1.162
year2018	0.465	14.142	-27.301	0.464	28.207
year2019	0.352	14.142	-27.414	0.351	28.095
stockID2	-0.701	22.372	-44.625	-0.702	43.186
stockID3	0.047	1.5	-3.626	0.219	2.661
stockID4	-4.614	1.762	-8.544	-4.472	-1.433
vessel_id8643	0.083	14.142	-27.683	0.082	27.826
vessel_id11609	0.778	14.142	-26.988	0.778	28.522
vessel_id12396	-0.045	14.142	-27.811	-0.045	27.698
season2	-0.332	11.952	-23.799	-0.332	23.115
month5	-0.587	0.081	-0.746	-0.587	-0.428
month6	-0.541	0.09	-0.718	-0.541	-0.364
month7	-0.255	11.952	-23.722	-0.256	23.192
month8	0.319	11.952	-23.147	0.319	23.766
month9	0.377	11.952	-23.09	0.376	23.824
month10	0.169	11.952	-23.298	0.168	23.616
month11	-0.016	11.952	-23.483	-0.017	23.431
month12	-0.926	11.953	-24.393	-0.926	22.521
phase2	0.087	0.056	-0.023	0.087	0.198
phase3	-0.089	0.046	-0.179	-0.089	0.001
phase4	-0.433	0.078	-0.586	-0.434	-0.278
year2018:stockID2	-0.701	22.372	-44.625	-0.702	43.186
year2019:stockID2	0	31.623	-62.086	-0.001	62.034
year2018:stockID3	-1.008	0.201	-1.401	-1.009	-0.613
year2019:stockID3	-1.826	0.197	-2.213	-1.826	-1.439
year2018:stockID4	0	31.623	-62.086	-0.001	62.034
year2019:stockID4	0	31.623	-62.086	-0.001	62.034

Table 2-5. CPUE and standardised CPUE (SI, standardised Index). lci = lower confidence interval (i.e., 0.025 quantile), uci = upper confidence interval (i.e., 0.975 quantile).

Year	Nominal	SI	2.5%CI	97.5%CI
GAM-NB, M3				
2017	0.82	0.99	0.42	1.51
2018	1.00	1.06	0.37	1.60
2019	1.17	0.95	0.22	1.50
GAM-Tw, M4				
2017	0.82	0.50	0.17	0.75
2018	1.00	1.38	0.49	2.14
2019	1.17	1.12	0.24	1.87
GSM-NB, M5				
2017	0.82	0.94	0.00	>10
2018	1.00	1.12	0.00	2.38
2019	1.17	0.93	0.00	1.96

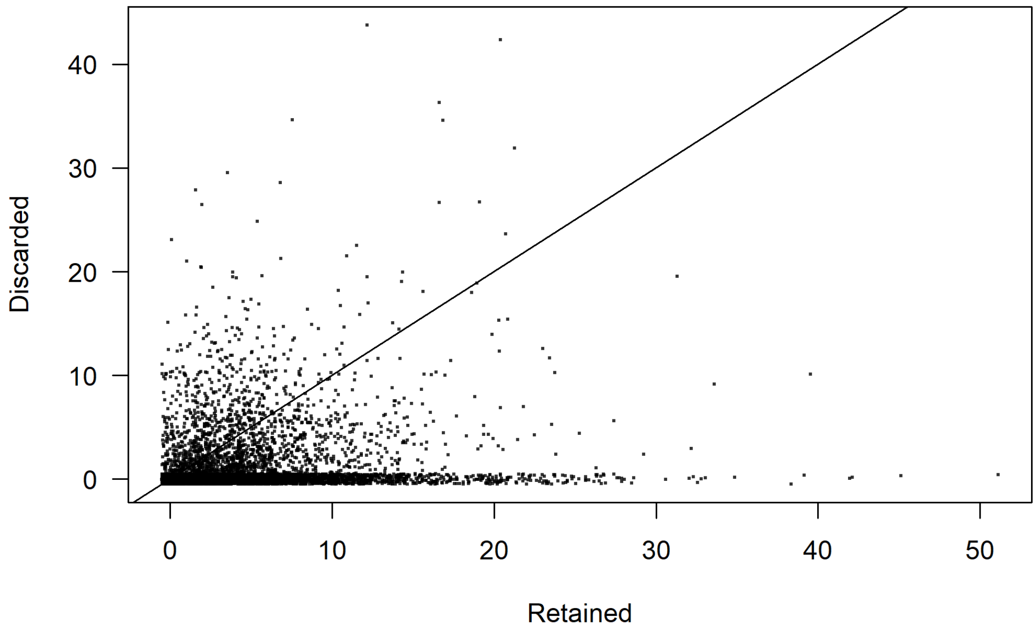

Figure 2-1. A lack of relationship between the number of discards and the number of retained prawns. To avoid overlaying data points, a small random number between [-0.5, 0.5] was added to each data point.

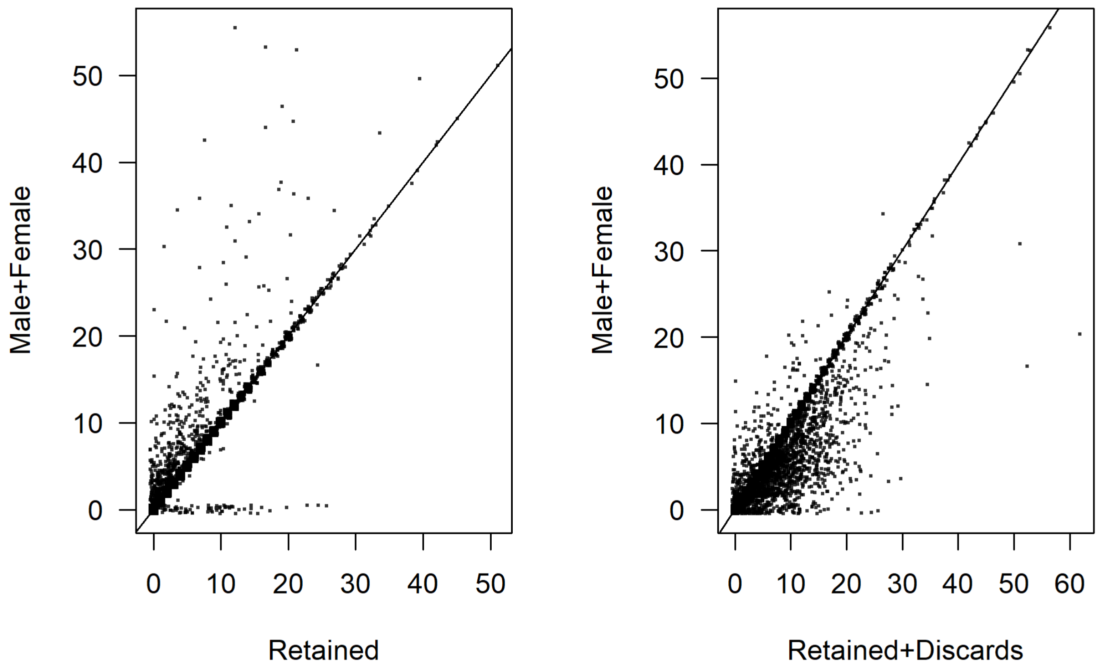

Figure 2-2. Data errors. Ideally, the sum of the recorded male and female should equal the number of retained prawns.

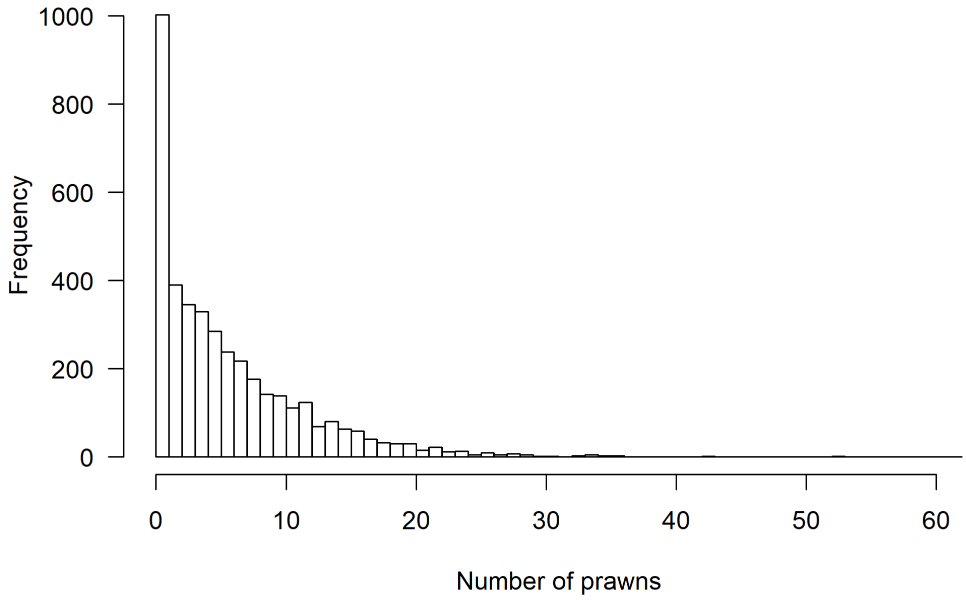

Figure 2-3. Frequency distribution of total catch per shot in 2017-2019.

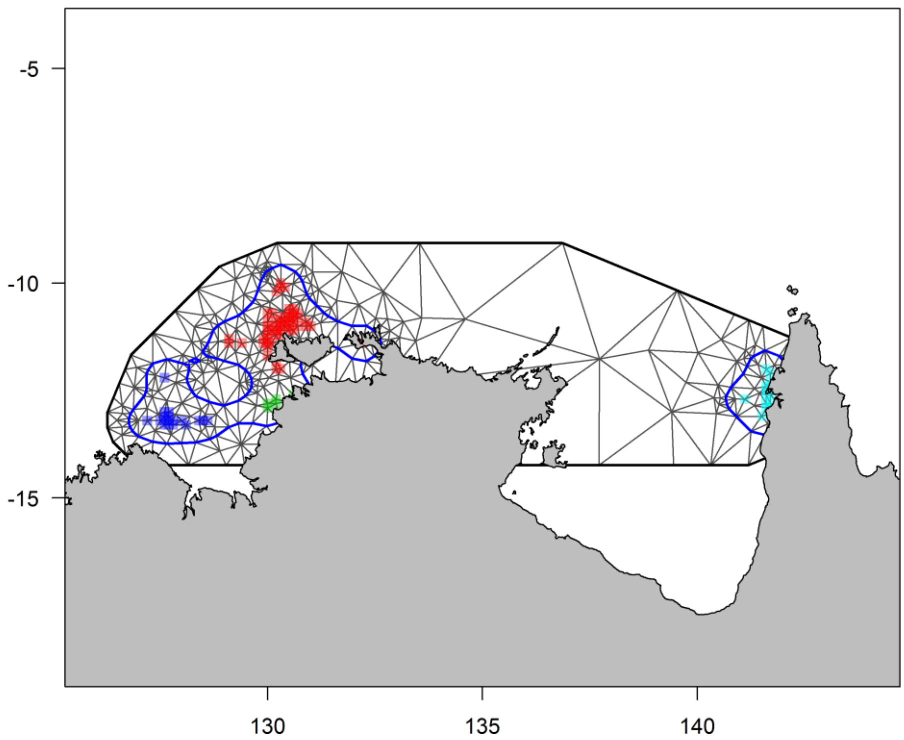

Figure 2-4. Construction of mesh as a base for Gaussian random field models to analyse spatial correlation across the entire region. The colours represent the four stock regions.

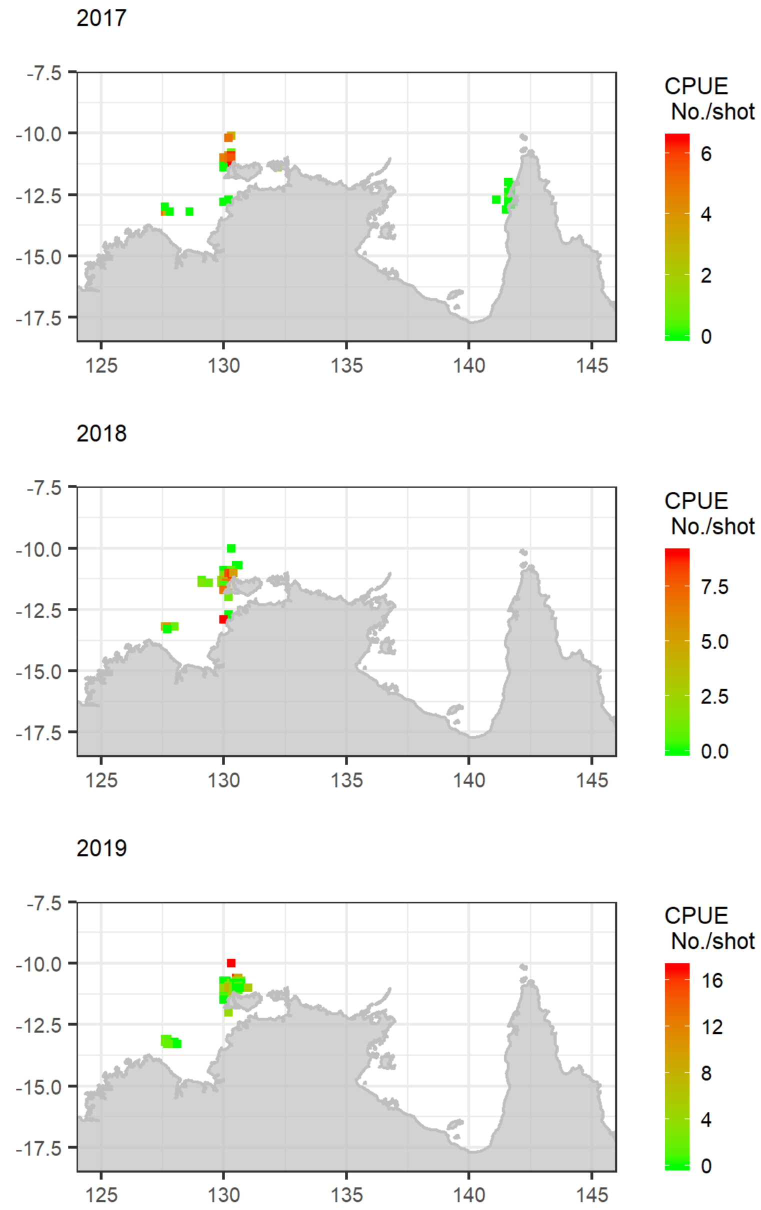

Figure 2-5. Mean observed CPUE from broodstock fishery in 2017-2019.

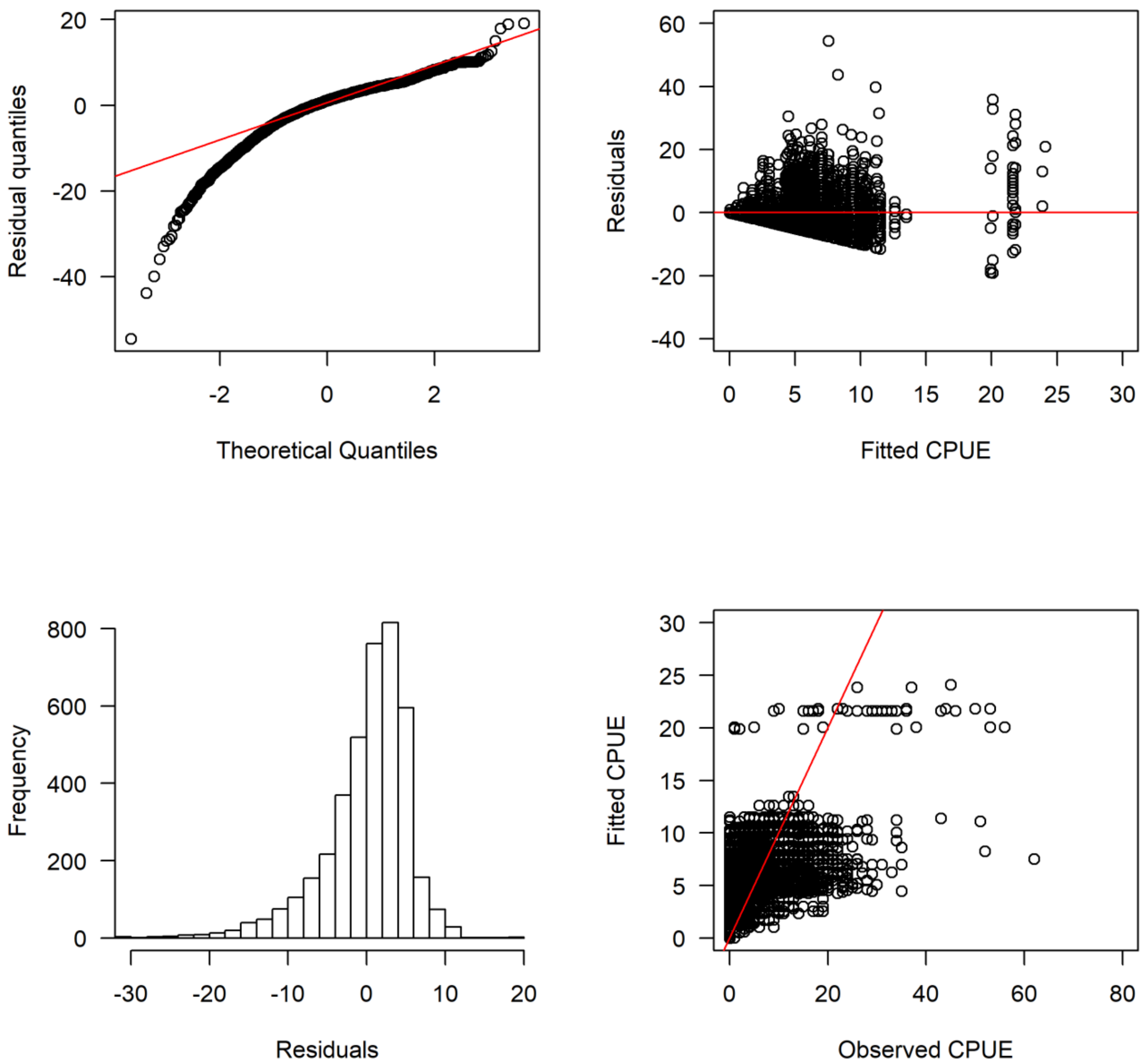

Figure 2-6. Diagnostics for the GAM-Tw model (M4).

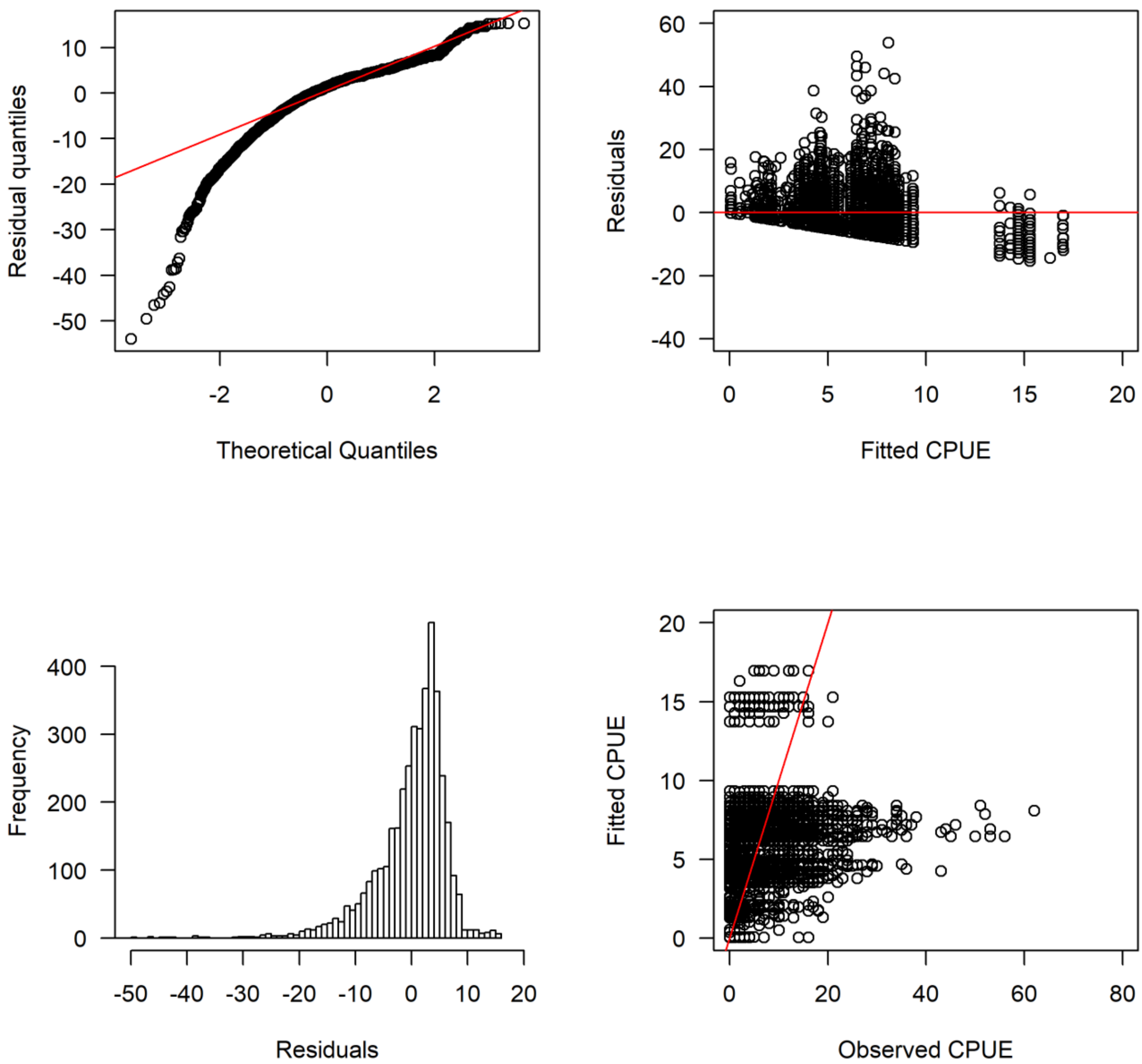

Figure 2-7. Diagnostics for the geostatistical model (GSM-NB M5).

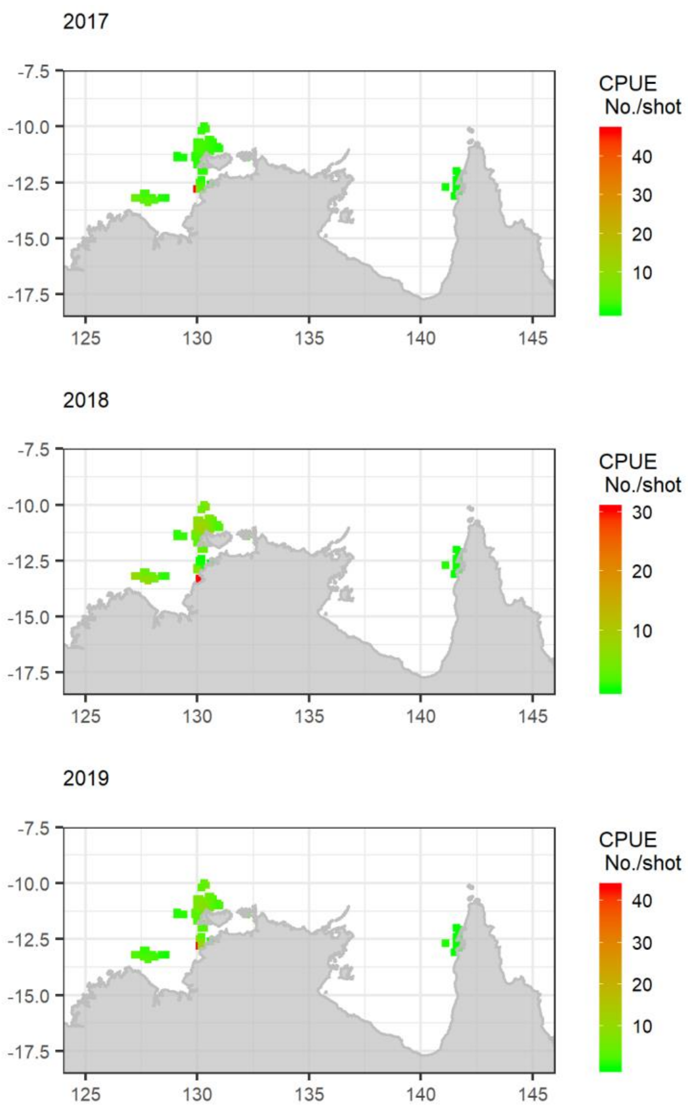

Figure 2-8. Predicted CPUE from GAM-Tw model (M4) for 2017-2019.

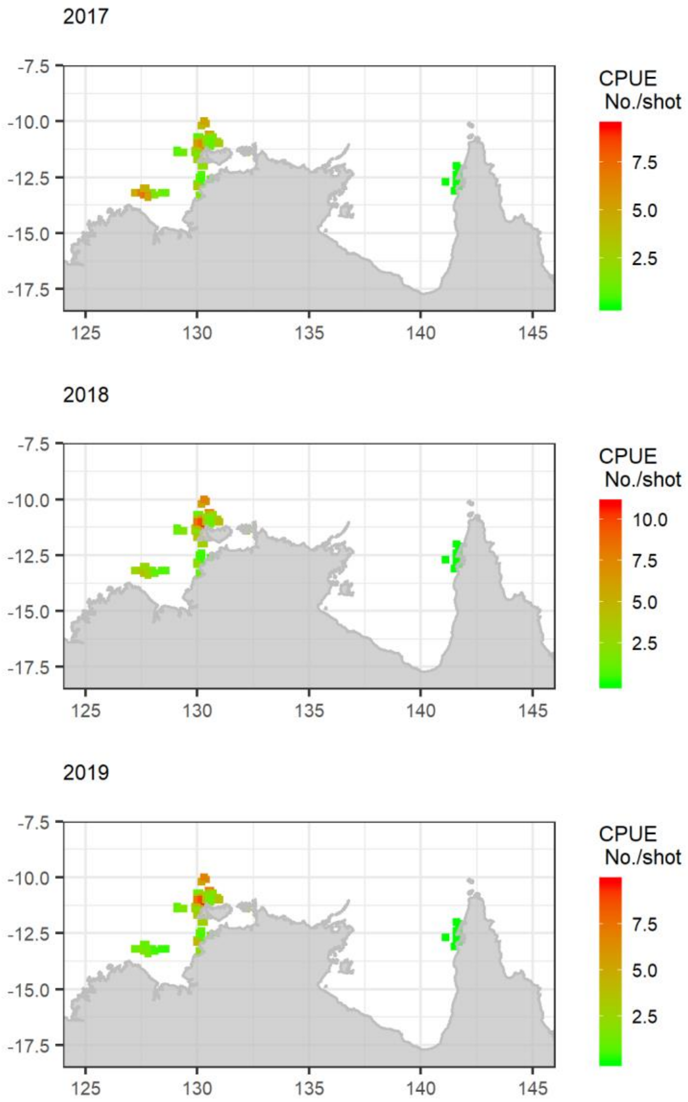

Figure 2-9. Predicted CPUE from spatial GSM-NB model (M5) for 2017-2019.

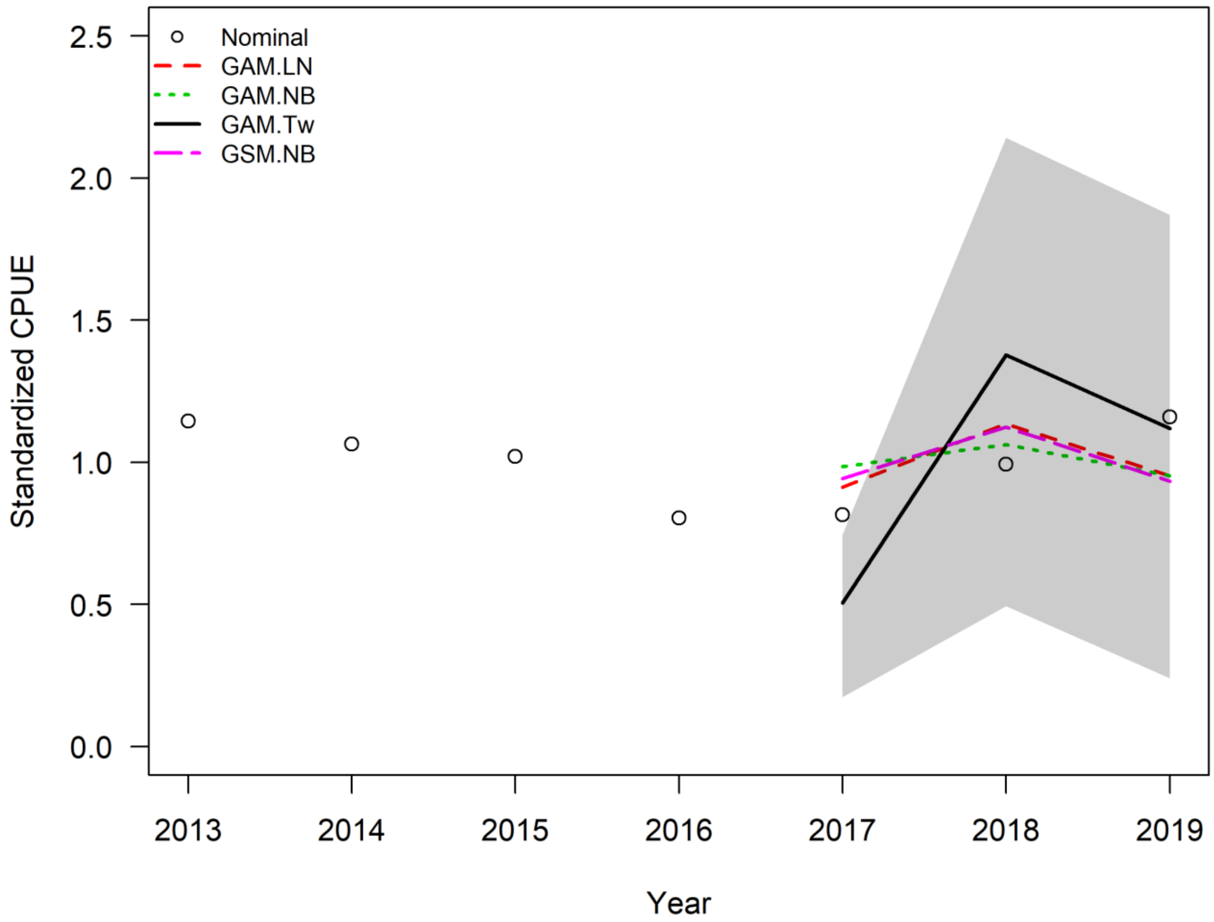

Figure 2-10. Standardised CPUE (number per shot) for Black tiger prawn in broodstock fishery. The grey band is the 95% CI for GAM-Tw model (M4).

3 CPUE standardisation for NPF commercial logbook catch data

3.1 Materials and methods

3.1.1 Data source and description

The NPF logbooks contain catch and effort data going back to the 1970s, with most records reported as daily totals. Black tiger prawn is a minor species in the NPF and is retained and recorded in the logbooks only since 1998.

Black tiger prawn is rarely caught in the NPF commercial fishery not only because of its low abundance but also because it is similar to other by-product species that are incidentally captured by trawls targeting the main prawn species. We limit the logbook data to grids (at a resolution of 0.1 * 0.1 degree) where Black tiger prawns have ever been recorded since 1998, such that we end up with a total of 266 grids (Table 3-1, Figure 3-1). The number of grids with positive catch varies among the common banana (*P. merguiensis*) stock regions. We used common banana stock regions because 78.7% of Black tiger prawns were captured in the banana prawn sub-fishery. As shown in Table 3-1, the mean catch per boat-day in each region (nominal CPUE) is very low, ranging from 0.01 kg/boat-day to 1.19 kg/boat-day with an average of 0.27 kg/boat-day.

We can attribute the low catch mainly to zero catch of Black tiger prawn in more than 98% of fishing days that were recorded (Table 3-2). The average nominal CPUE by year over the entire NPF region is 0.31 kg/boat-day. The probability of catching any Black tiger prawns in a boat-day (= a Fishing day with any positive catch/Total fishing days) is very low, ranging from 0.2% to 7.7%. For those trips with positive catches, the amount of catch is highly variable, ranging from 1 kg to 468 kg (average 19.9 kg) (Table 3-2, Figure 3-2). Note that the catch is recorded as weight rather than in number of prawns unlike the broodstock collection data and the minimum recorded positive catch is 1 kg. It is unclear whether catch that is below 1 kg is recorded as 1 kg or not reported. This approximation will affect the modelling process below, particularly for the probability of non-zero catch events. Fishers indicated that 1 kg Black tiger prawns could be cumulated over several days from a low catch in each haul so it is not necessary a daily catch.

Considerable effort has been devoted to model fishing power in the tiger prawn sub-fishery in the NPF (Bishop, 2006; Bishop *et al.*, 2008). We attempted to use the data from tiger prawn fishing power research. However, the majority of Black tiger prawns are caught during the banana prawn sub-fishery and the specific information collected within the various tiger prawn fishing power research projects is not necessarily adequately applicable to this case. We sought data from various sources including the NPF basic grid data in which the major environmental information for each of the 0.1*0.1 degree grids are stored. Separately we obtained the NPF vessel information (i.e. their technical characteristics) from the fishing power project database. The information listed below is linked to the logbook either by VCODE or Latitude and Longitude. In general, the common vessel information acquired from the fishing power project was extracted and matched with the Black tiger prawn fishery.

We included the following variables in the dataset as potential predictors of changes in relative abundance.

- Fishery covariates: vcode, dd (day of month), month, year, banana (catch), tiger (catch), hours_trawled, stock_region, target, and trygear.
- Geographical covariates: latitude, longitude.

- Vessel technical covariates: plotter, pc_sat, hullg, o_brdn, nav_accg, d_gps, gps, satnav, plotsoft, satig, stress_av, length, and bredth.

3.1.2 Selecting covariates and model building

The logbooks contain over 110,000 boat-day records compared to less than 1,000 boat-days in the broodstock collection fishery (about 164 times greater number of records in magnitude compared to the broodstock data we analysed above). With this amount of data, models that include various covariate interactions, smoothing terms, and spatial random fields take a great deal of computer memory and CPU. The time taken to run these models ranged from several hours to several days. It is impractical to compare models using cross-validation. We opted to build the models in two steps. First, we constructed "full" models by including about 20 variables (covariates) that are likely significant predictors. After model fitting, we excluded those non-significant predictors and kept the significant ones (where $p < 0.1$) for the final model.

The large proportion of zero catch made modelling challenging. Although the Tweedie distribution assumption is flexible and can accommodate excess zeros, the fits to the logbook data were very poor (e.g., negative R-square), perhaps due to >98% of zeros. It became apparent that it is necessary to model the data in two parts: the probability of non-zero catch and the catch rate for trips with positive catch only. We tested a zero-inflated negative binomial distribution, but the results were unrealistic. In addition, the logbooks recorded catch in weight (kg) rather than number of prawns. Strictly, using a model of discrete distribution for continuous data may be questionable. Hence, we opted to use delta-lognormal models to model logbook catch data.

Generalized additive models

We focused on GAM because of its capability to handle non-linear relationship between catch and various predictors. The delta-lognormal model has two components:

$$\Pr(C = c) = \begin{cases} 1 - \pi, c = 0 \\ \pi f(c) c > 0 \end{cases} \qquad \text{Equ 3-1}$$

where π is the probability of positive catch c, and $f(c)$ is the distribution of positive catch, which we assumed to be a lognormal distribution: $log(c) \sim N(\eta, \sigma^2)$ (Figure 3-2). The general form of the model is:

$$\eta_i = g(\mu_i) = \beta_0 + \sum_n \beta_n x_{ni} + \sum_m s(x_{mi}) + \varepsilon_i \qquad \text{Equ 3-2}$$

where mean μ_i is the expected catch (kg of prawns) on boat-day i and is linked to the predictor η_i, β_0 is the intercept, β_n is a coefficient for the linear explanatory variable x_n, which is considered a fixed effect, $s(x_{mi})$ is the smoother function for nonlinear predictor x_{mi}, and ε_i is an error term.

The probability of non-zero catch is modelled as a binomial distribution with a logit link:

$$\log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \sum_n \beta_n x_{ni} + \sum_m s(x_{mi}) + \varepsilon_i \qquad \text{Equ 3-3}$$

The link function for the positive catch subset data is a log function:

$$\log g(c) = \beta_0 + \sum_n \beta_n x_{ni} + \sum_m s(x_{mi}) + \varepsilon_i \qquad \text{Equ 3-4}$$

Geostatistical model (GSM)

We also explored GSM using the INLA program. INLA currently has built-in zero-inflated negative binomial distribution, but the results were unrealistic, similar to the NB distribution in GAM. The extremely large proportion of zeros is likely to be the main problem. In addition, GSM requires high computer power. Regular computers do not have sufficient memory so we used high performing computers. Running one spatial model using CSIRO's super computers took several days to complete. The results were poor and thus are not included in this report, but we report here that the task was undertaken to reflect that it was considered.

3.1.3 Catch prediction and CPUE standardisation

We used two components of the delta-lognormal model to predict the catch rates using the standard predictors. The prediction dataset covered all 0.1*0.1 degree grids where Black tiger prawns have been caught during 1998-2019. Each grid and year had the same structure and identical covariates as in Equ 3-3 and Equ 3-4. Apart from *year* and *location*, other predictors were fixed at the standard values, either the mean or mode of the observed data. The annual standardized CPUE was derived by dividing annual predicted catch rates by the mean catch rate over the 1998-2019 period. The variance of the predicted catch per boat-day was calculated as per other studies(Zhou, 2002; Brodziak and Walsh, 2013):

$$var[CPUE] = var[\pi]c^2 + var[c]\pi^2 \qquad \text{Equ 3-5}$$

The variance of the standardized annual indices was derived from this per boat-day variance in the similar manner and standardising CPUE per se.

3.1.4 Subset data

Modelling the logbook data was challenging due to extremely low positive catch events and highly skewed distribution of the catch data. Many of the 266 0.1*0.1 degree grids have been fished hundreds or over a thousand of boat-days but Black tiger prawns were only encountered a couple of times. Besides using all the data, we investigated an alternative approach by eliminating grids with extremely low occasions of positive catch. We sub-set the logbook data in two levels.

Level 1: We excluded grids where the rate of positive catch was smaller than 0.01 (i.e. one positive catch out of 100 boat-days fished in that grid during 1998-2019). This restriction reduced the number of grids from 266 to 153 (a 42% reduction), and sample size (boat-day) from over 113,000 to 34,389 (a 70% reduction). The average rate of positive catch increased from 1.4% to 3.8%, which is still quite low. The total catch of Black tiger prawns was reduced from 30,716 kg to 27,618 kg (10% reduction), and the positive catch fishing days reduced from 1,540 to 1,310 (a 15% reduction).

Level 2: We excluded grids where the rate of positive catch was smaller than 0.1 (i.e. one positive catch out of 10 boat-days fished in that grid during 1998-2019). In addition, we excluded grids that had been fished less than 10 days during the 22 years. This restriction further reduced the number of grids to 15 (a 94% reduction), and sample size (boat-day) to 1,395 (a 99% reduction). The average probability of positive catch increased to 13.2%. The total catch of Black tiger prawns was reduced from 30,716 kg to 5,688 kg (a 81% reduction), and the positive fishing days was reduced from 1,540 to 184 (a 88% reduction). This level of subset essentially uses data from the highest catch grids for CPUE standardisation.

3.2 Results

3.2.1 Modelling catch rate and CPUE standardisation using data from all grids

Binomial model

The binomial model included following significant covariates:

$$\log\left(\frac{\pi}{1-\pi}\right) = factor(year) * factor(stockID) + factor(season) + factor(gtype) + factor(target) + s(hour.trawled) + te(lon, lat) + s(banana) + s(teger) + factor(pc.sat) + factor(d.gps) \qquad \textbf{Equ 3-6}$$

All covariates were significant at $p \leq 0.05$. The model explained 31.1% of the deviance and the adjusted R^2 was 0.116.

Lognormal model

The model of positive catch ***C*** have some different significant predictors from the binomial model:

$$\log(C) = factor(year) * factor(stockID) + factor(target) + s(hour.trawled) + (banana) + factor(hullg) + factor(o.brdn) + factor(vcode) \qquad \textbf{Equ 3-7}$$

All covariates were significant at $p \leq 0.05$ except hours.trawled which had $p = 0.068$. The model explained 60.9% of the deviance, with an adjusted R^2 of 0.545 which is much better than the binomial component (Figure 3-3).

CPUE standardisation

The fitted binomial model and the lognormal model were applied to create a prediction dataset that included all years and all grids where Black tiger prawns have been captured from 1998 to 2019. The standardised daily catch rates were the product of the two components. This led to the standardized annual abundance index (Table 3-3). The standardised index $SI_{M,y}$ roughly follows the nominal CPUE trend, but is less variable than the nominal CPUE, particularly in the recent years (Figure 3-4).

3.2.2 Modelling catch rate and CPUE standardisation by excluding grids with extremely low probability of positive catch

Level 1 data subset

Binomial model: By excluding grids where the probability of positive catch is smaller than 0.01, we reduced the data from about 113,000 boat-days to about 34,389 boat-days, among which Black tiger prawns were captured in 1,310 boat-days, i.e., about 96% of boat-days ended with zero catch.

Using the Level 1 subset of data, all covariates used in full grids model were significant except gear_type, i.e.:

$$\log\left(\frac{\pi}{1-\pi}\right) = factor(year) * factor(stockID) + factor(season) + factor(target) + s(hour\_trawled) + te(lon, lat) + s(banana) + s(teger) + factor(p\_sat) + factor(d\_gps)$$

Equ 3-8

All predictors were significant at $p \le 0.05$. The model explained 24.9% of the deviance, which is not an improvement over the full dataset.

Lognormal model: The same predictors in the lognormal model applied to the full dataset were included in the model for the reduced dataset. However, hours.trawled was not significant:

$$\log(c) = factor(year) * factor(stockID) + factor(target) + s(banana) + factor(hullg) + factor(o.brdn) + factor(vcode)$$ **Equ 3-9**

The results were nearly identical to the model used for the full dataset. All covariates were significant at $p \le 0.05$ and the model explained 60.6% of the deviance (Figure 3-5). The similar results between the full data model and reduced data model may be due to the similar data: although the full data set was reduced by 70% (from about 113,000 boat-days to 34,389), the total catch of Black tiger prawns was only reduced by 10% (from 30,716 kg to 27,618 kg), and the positive catch fishing days only reduced by 15% (from 1,540 to 1,310).

Standardized index: The standardised abundance index (SI) appears to similar to the SI using the full dataset, but slightly more variable (Figure 3-4). The standard deviation and confidence intervals are relatively narrower than that from the full dataset (Table 3-4).

Level 2 data subset

There is an overall trend of increasing CPUE from both the full dataset and limited areas where the probability of positive catch is greater than 0.01 (Figure 3-4). Since both datasets have a high proportion of zero catches (98.6% and 96.2%, respectively), the catch rate, even after standardisation, may be unreliable. Therefore, we further restrict areas to grids with highest catch rate. However, it is difficult to define and use the "highest catch rate" grids. No single grid has a 100% of probability of positive catch. Focusing on too few grids leads to no data in some years. We opted to restrict grids with the probability of positive catch greater than 10% and the number of positive catch days from 1998 to 2019 to be greater than 10. This condition results in 15 grids. However, there was no catch of Black tiger prawn in these grids in 2008. The nominal CPUE (kg/boat-day) looks flat over the period of 1998-2019 except four years (2000, 2004, 2014, and 2015) whether we used full fishing days or only positive fishing days (Figure 3-7). Experience from CSIRO staff on the monitoring surveys indicated that occasionally the vessel would come across a "patch" of the species.

Binomial model: Level 2 data subset greatly reduced the number of grids, fishing days, and positive catch.

Using the Level 2 subset of data, the binomial model involved the following significant covariates:

$$\log\left(\frac{\pi}{1-\pi}\right) = factor(year) + factor(season) + s(hours.trawled) + s(banana) + factor(d\_gps)$$ **Equ 3-10**

Several covariates were not significant here: stockID, target, longitude and latitude, tiger catch, and pc.sat. The remaining predictors were significant at $p \le 0.05$. The model only explained 10.1% of the deviance, which is worse than the models using the full dataset or Level 1 subset.

Lognormal model: The same predictors in the lognormal model applied to the full dataset were included in the model for the greatly reduced dataset and the significant predictors were as follows:

$$\log(\mathbf{c}) = \boldsymbol{factor(year)} * \boldsymbol{factor(stockID)} + \boldsymbol{factor(hullg)} + \boldsymbol{factor(o.brdn)} + \boldsymbol{factor(d.gps)} + \boldsymbol{factor(nav.accg)} \quad \text{Equ 3-11}$$

The results were very different from the models used for the full dataset or Level 1 subset. All covariates were significant at $p \leq 0.05$ and the model explained 65.9% of the deviance (Figure 3-6).

Standardized index: The standardised abundance index (SI) differed from the SI using the full dataset or Level 1 subset, particularly for years 2000 and 2004 (Figure 3-7). The standard deviation and confidence intervals were much narrower than that from the full dataset or Level 1 subset (Table 3-4). Within such a small area, the nominal CPUE can roughly reflect the standardized CPUE. However, given that so few grids (only 6% of grids where Black tiger prawns have been caught) were analysed, the ability to extrapolate to the entire NPF region is questionable.

3.3 Discussion

3.3.1 Comparison between results of full dataset and reduced dataset

The difference between the three datasets (i.e., full data set and two reduced data sets) was the probability of catching any Black tiger prawn in one boat-day. The full dataset included all grids that have a probability of positive catch greater than zero, and the Level 1 and Level 2 reduction datasets only included grids with a probability of positive catch not smaller than 0.01 (1%) or not smaller than 0.1 (10%), respectively. Although the Level 1 subset excluded a large proportion of grids and logbook records, the proportion of zeros was still very high (96.2%). The slightly increased positive catch events from 1.4% to 3.8% did not substantially improve model fitting. The reduced sample size may also have a negative impact on the binomial and lognormal models. The predicted abundance index trends were similar between the full and the Level 1 subset data. Interestingly, using only 6% of grids that contained 1% of logbook records with the highest catch (Level 2 subset) did not substantially change the CPUE index either, except in two years. We suggest focusing on the result from the full dataset and use this standardized index in stock assessments. However, caution is needed when interpreting the resulting CPUE trend.

Until recently, Black tiger prawns have been a non-targeted by-product over most of the NPF history. Non-targeted fishing behaviour may often miss high abundant areas. In addition, Black tiger prawn is a rare species compared to other prawn species in the NPF. Together, extremely high frequency of zero catches makes CPUE analysis very difficult. The results indicate a general trend of abundance increase, particularly since 2010 (Figure 3-4). There may be four hypotheses for this pattern.

First, the trend results from changes in fishing behaviour (toward targeting Black tiger prawn in recent years) and does not represent a true abundance index for the whole stock (Maunder et al 2006; Quirijns et al. 2008). CPUE standardisation struggles to capture changes in catchability (in regard with the whole stock) when fishers do not try to find the species. If this is the main reason, the standardised CPUE cannot be used as an abundance index.

Second, fishing power has increased over time but not captured by our models. We have examined a range of technological factors and included them as predictors. However, most of these variables did not make a significant contribution to the model fit while others have not changed over time during this period.

Third, Black tiger prawns could have been fished down in early years when their catches were not reported. The increasing trend could be signalling a slow recovery. The CPUE trend appears to mimic the abundance of Grooved and Brown tiger prawns (Hutton *et al.*, 2018). Fishing on the two most studied prawn species started in 1970. Stock assessments show that their spawning biomass rapidly declined from early 1970s to the mid-1980s. The spawning biomass of the two tiger prawns remained approximately stable between the mid-1980s and early 2000s, and a slightly increasing trend was observed since early 2000s. Unfortunately, there are no catch records of Black tiger prawn before 1998 to allow this hypothesis to be investigated. It is therefore unclear whether incidental catch could have led to a substantial decline in stock size in the early years. So far there is not enough information to refute or substantiate this hypothesis. However, stock assessments in the next chapters suggest that even if the stock had been fished down in early years it could have recovered by 2013.

Finally, the ecosystem is changing because of ecological interactions among species and environmental effect. For example, if Black tiger prawn is a competitor with other prawn species (e.g., banana prawns, tiger prawns, and endeavour prawns), a large amount of removal of these other species every year may have reduced competition and led to a greater ecological niche to Black tiger prawns. As a result, environmental carrying capacity for Black tiger prawn may have increased. Testing and proving these hypotheses will require additional data and research. Considering the nominal CPUE trend from the 15 highest catch grids (Figure 3-7), it is more likely that the abundance has remained stable over the 22-year period.

From these hypotheses, further investigation of the fishery data may be warranted. However, because Black tiger prawns have been incidentally captured by vessels targeting other prawn species, attempts to standardize CPUE for such a non-target species could be possibly fruitless. It could be more fruitful to improve and invest in data collection in the targeted fishing (i.e. the broodstock collection) in the future, recognising that broodstock fishing also has limitations (e.g., small spatial coverage).

3.3.2 Comparison between broodstock collection and commercial fishing

The two fisheries have different issues in terms of data quality and quantity. The broodstock fishery has a very small sample size, questionable records of the total catch in many years, missing fishing hours, and limited spatial ranges. On the other hand, the NPF does not target Black tiger prawns when conducting normal fishing practices targeting banana prawns or tiger prawns, thus the logbooks contain extremely large number of zeros, and the positive catches are highly variable. We attempted to overcome these challenges, explored multiple approaches, and produced standardized CPUE indices. However, the results are not ideal compared to analyses for data-rich target species. Having said that, we can give a preliminary comparison of the two index trends. The broodstock collection has reliable catch data from 2017 to 2019, while 2019 data was not available in the NPF logbooks at the time we extracted the data. AFMA provided 2019 data in July 2020 with some correction of earlier data. The results in this report are produced from new model runs using all data including 2019. Hence, there are three common years (2017, 2018 and 2019) in the two sub-fisheries. For the broodstock data, all models indicate that abundance is lowest in 2017 and highest in 2018. For the commercial logbook data, the delta-lognormal models using three alternative datasets (all grids and two levels of reduced grids) also indicate the same pattern: highest index in 2018 and lowest in 2017. However, the commercial collection shows a much large variation in CPUE between years than the broodstock collection, i.e., very high CPUE in 2018. This may be mainly due to a lack of fishing activity overlap (Figure 3-8). The broodstock fleet did not fish in the Weipa region in 2018 and 2019. The logbook records show that this region had a very high catch of Black tiger prawns in 2018. The limited spatial extent of the broodstock fishery is also likely the major cause of the poor model fit. For these reasons, the standardised CPUE index from the commercial logbooks is recommended to be used for the stock assessment, although we acknowledge this is problematic given the non-targeting aspect of this data.

3.3.3 Comparing with the Tiger prawn study

The Tiger prawn sub-fishery targets two species of tiger prawns, *Penaeus esculentus*, the Brown tiger prawn, and *P. semisulcatus*, the Grooved tiger prawn. Extensive research has been conducted to model tiger prawns CPUE and fishing power. The relative fishing power of each vessel is based on the catch rates relative to a hypothetical standard vessel, if all vessels were fishing under controlled availability and abundance conditions (i.e. fixed location, year, month, depth, and moon phase) (Bishop *et al.*, 2008). For Black tiger prawn, a range of models using various covariates have been explored. It was found that realistic values could not always be obtained, because the regression factors were not orthogonal, and data on the presence of technology were sometimes unreliable or systematically incomplete. There was no single best estimation model for CPUE standardisation. Different modelling approaches (e.g., the so-called prediction models and the estimation models) could reveal different trends in relative fishing power and relative abundance. The estimated trends R^2 from the final five models varied between 0.325 and 0.534 (Bishop *et al.*, 2008). Although directly comparison of different studies and species is difficult, looking at the data-rich tiger prawn models, our binary model explained 31.1% of the deviance and the lognormal model explained 60.9% of the deviance, which seem to be within the expected range given the limitations in the data.

Table 3-1. The NPF logbook summary of fished area, fishing effort, catch, and nominal CPUE in each of the common banana prawn stock region since 1998.

Stock ID	No. grids	No. boat-day	Total catch	CPUE
1	47	12,871	3,115	0.242
2	66	18,904	8,040	0.425
3	10	3,616	240	0.066
4	13	17,538	254	0.014
5	8	5,597	179	0.032
6	31	18,941	1,170	0.062
7	19	11,640	920	0.079
8	11	3,295	208	0.063
9	39	9,792	3,771	0.385
10	22	10,740	12,819	1.194
Total	266	112,934	30,716	0.272

Table 3-2. Summary of annual catch, fishing effort, and nominal CPUE in NPF logbooks.

	All fishing days				CPUE in positive catch days			
Year	Total catch	No. boat-day	CPUE	Prob	No. boat-day	Mean	Min	Max
1998	311	9,091	0.03	0.4%	33	9.42	1	14
1999	302	8,030	0.04	0.3%	27	11.19	1	26
2000	530	7,031	0.08	0.2%	16	33.13	10	120
2001	825	7,318	0.11	0.5%	40	20.63	2	200
2002	216	5,849	0.04	0.5%	30	7.20	1	14
2003	376	6,011	0.06	0.7%	44	8.55	1	20
2004	814	5,604	0.15	1.0%	57	14.28	1	96
2005	198	5,210	0.04	0.8%	40	4.95	1	20
2006	1,068	4,708	0.23	1.4%	67	15.94	5	60
2007	292	3,582	0.08	0.4%	16	18.25	5	50
2008	545	4,196	0.13	0.6%	24	22.71	12	50
2009	873	4,112	0.21	0.9%	38	22.97	8	70
2010	421	3,857	0.11	1.0%	40	10.53	2	85
2011	722	4,143	0.17	1.2%	48	15.04	5	54
2012	1,505	4,147	0.36	2.5%	103	14.61	5	65
2013	1,134	3,905	0.29	1.6%	63	18.00	5	80
2014	4,946	4,872	1.02	3.5%	170	29.09	5	260
2015	4,712	3,748	1.26	3.0%	111	42.45	5	468
2016	498	3,899	0.13	0.8%	32	15.56	1	56
2017	544	4,388	0.12	0.9%	39	13.95	5	60
2018	8,402	4,643	1.81	7.7%	357	23.54	5	364
2019	1,482	4,590	0.32	3.2%	145	10.22	1	45
Sum or mean	30,716	112,934	0.31	1.5%	1,540	17.37	3.95	103.50

Table 3-3. Logbook predicted CPUE and standardized abundance index (SI) using all grids where any Black tiger prawns were captured from 1998 to 2019.

Year	Nominal	SI	sd[SI]	5%CI	95%CI
1998	0.11	0.08	0.15	-0.17	0.33
1999	0.12	0.05	0.08	-0.09	0.18
2000	0.24	0.41	0.66	-0.69	1.50
2001	0.37	1.22	2.35	-2.66	5.07
2002	0.12	0.24	0.62	-0.79	1.26
2003	0.20	0.24	0.40	-0.41	0.89
2004	0.47	0.66	1.18	-1.29	2.60
2005	0.12	0.43	0.76	-0.83	1.67
2006	0.74	0.70	1.10	-1.12	2.50
2007	0.26	0.29	0.94	-1.25	1.83
2008	0.42	0.31	0.92	-1.22	1.82
2009	0.69	0.43	1.09	-1.37	2.22
2010	0.35	0.83	1.42	-1.52	3.17
2011	0.56	1.18	1.77	-1.74	4.09
2012	1.18	2.14	3.35	-3.39	7.63
2013	0.94	1.82	2.81	-2.81	6.42
2014	3.29	3.02	4.05	-3.67	9.67
2015	4.08	1.93	5.67	-7.44	11.23
2016	0.41	0.48	0.81	-0.86	1.81
2017	0.40	0.85	1.12	-1.00	2.70
2018	5.87	3.79	4.32	-3.34	10.88
2019	1.05	0.91	1.13	-0.96	2.76

Table 3-4. Logbook predicted CPUE and standardized abundance index (SI) using grids where the probability of catching any Black tiger prawns is greater than or equal to 0.01 from 1998 to 2019.

Year	Nominal	SI	sd[SI]	5%CI	95%CI
1998	0.10	0.07	0.09	-0.08	0.21
1999	0.13	0.05	0.07	-0.06	0.16
2000	0.30	0.35	0.34	-0.22	0.90
2001	0.51	1.19	1.60	-1.45	3.82
2002	0.13	0.21	0.49	-0.59	1.01
2003	0.21	0.18	0.23	-0.20	0.56
2004	0.56	0.53	0.62	-0.48	1.54
2005	0.17	0.34	0.43	-0.37	1.04
2006	0.75	0.55	0.91	-0.96	2.05
2007	0.31	0.18	0.46	-0.59	0.94
2008	0.48	0.24	0.46	-0.53	1.00
2009	0.80	0.37	0.60	-0.61	1.35
2010	0.30	0.69	1.17	-1.24	2.61
2011	0.51	1.06	1.19	-0.90	3.01
2012	1.26	1.93	2.03	-1.43	5.27
2013	0.72	1.09	0.93	-0.45	2.62
2014	3.27	6.17	19.67	-26.28	38.44
2015	4.41	1.89	3.78	-4.36	8.09
2016	0.58	0.45	0.57	-0.48	1.38
2017	0.30	0.54	0.49	-0.27	1.35
2018	5.39	3.22	2.10	-0.26	6.67
2019	0.83	0.70	1.29	-1.42	2.81

Table 3-5. Logbook predicted CPUE and standardized abundance index (SI) using grids where the probability of catching any Black tiger prawns is greater than or equal to 0.1 and the total fishing days is equal to or greater than 10 days during 1998 and 2019.

Year	Nominal	SI	sd[SI]	5%CI	95%CI
1998	0.17	0.34	0.07	0.23	0.45
1999	0.07	0.27	0.05	0.18	0.36
2000	2.98	1.80	0.35	1.22	2.38
2001	0.47	0.59	0.12	0.40	0.78
2002	0.12	0.30	0.07	0.18	0.41
2003	0.16	0.25	0.05	0.17	0.34
2004	2.70	5.03	0.98	3.41	6.63
2005	0.23	0.25	0.05	0.17	0.32
2006	0.32	0.38	0.07	0.26	0.49
2007	0.16	0.11	0.03	0.05	0.16
2008					
2009	0.25	0.22	0.05	0.14	0.30
2010	0.41	0.54	0.26	0.11	0.97
2011	0.56	0.53	0.12	0.33	0.73
2012	0.99	1.66	0.43	0.96	2.36
2013	1.00	1.07	0.18	0.77	1.37
2014	4.22	2.69	1.90	-0.44	5.80
2015	4.04	1.32	0.80	0.00	2.63
2016	0.41	0.49	0.09	0.34	0.63
2017	0.34	0.39	0.11	0.21	0.57
2018	1.97	1.94	0.49	1.12	2.74
2019	0.42	0.84	0.21	0.49	1.19

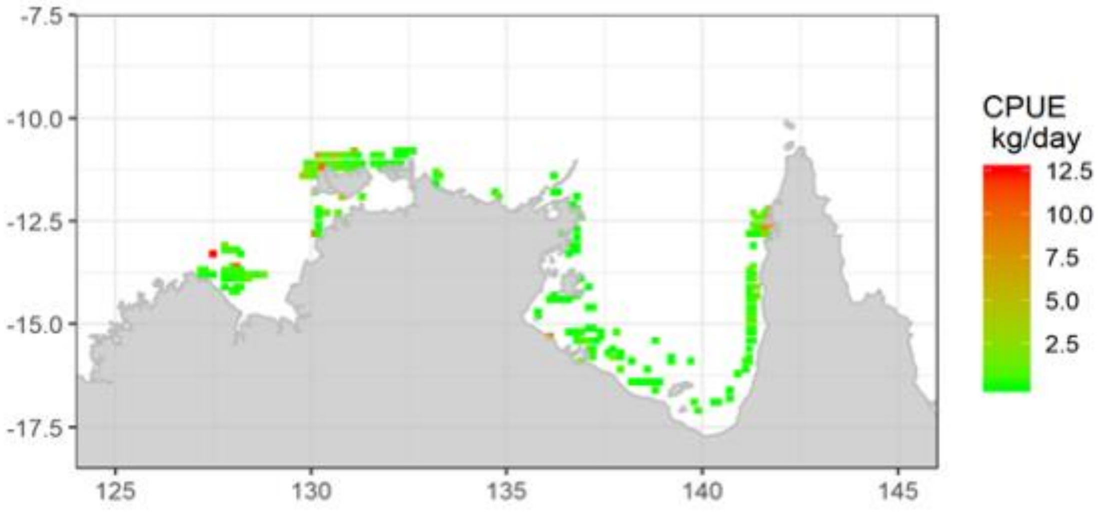

Figure 3-1. Spatial distribution of average Black tiger prawn catch per boat-day in NPF logbooks from 1998 to 2019.

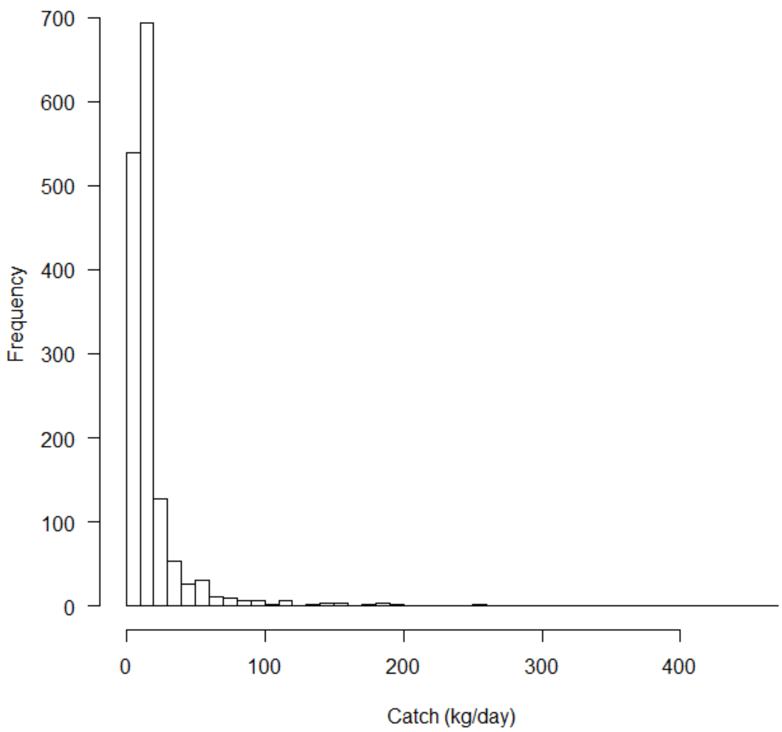

Figure 3-2. Frequency distribution of non-zero catch records in NPF logbooks from 1998 to 2019.

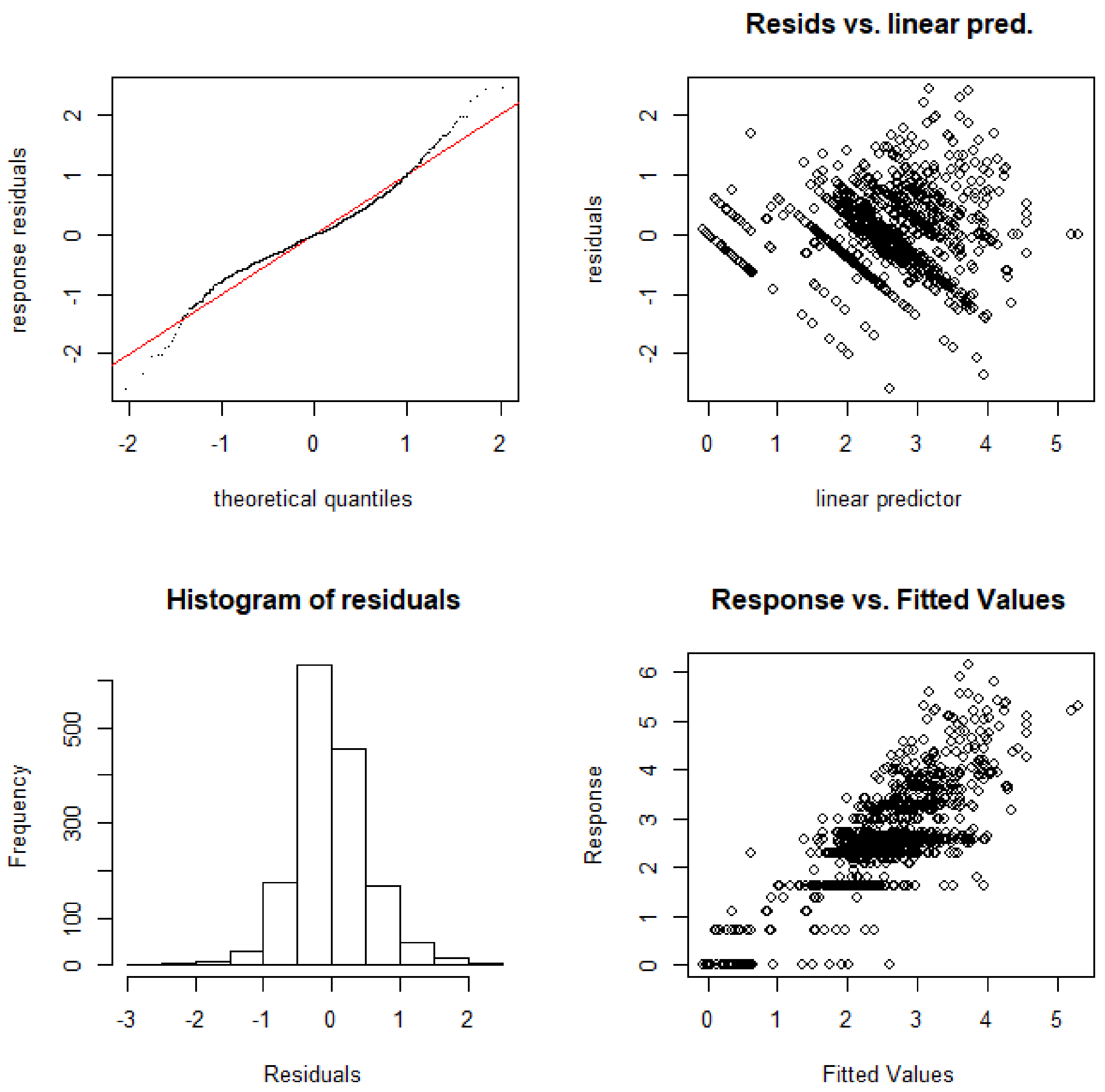

Figure 3-3. Diagnostics of the lognormal model for modelling positive catch using data from all 0.1*0.1 grids that had recorded catch during 1998-2019.

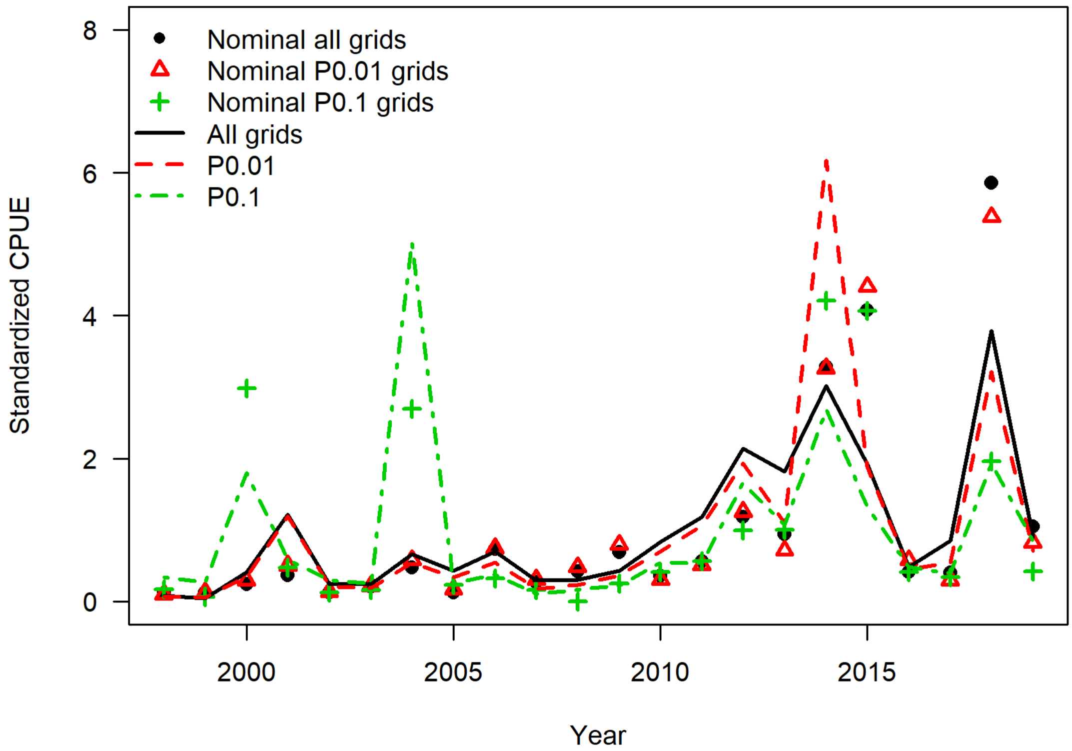

Figure 3-4. Standardized annual abundance index (SI) based on logbook data. All grids refer to all grids in the logbooks where Black tiger prawns were captured during 1998-2019 period. P0.01 and P0.1 grids use data from grids where the probability of positive catch is greater or equal to 0.01 and 0.1, respectively.

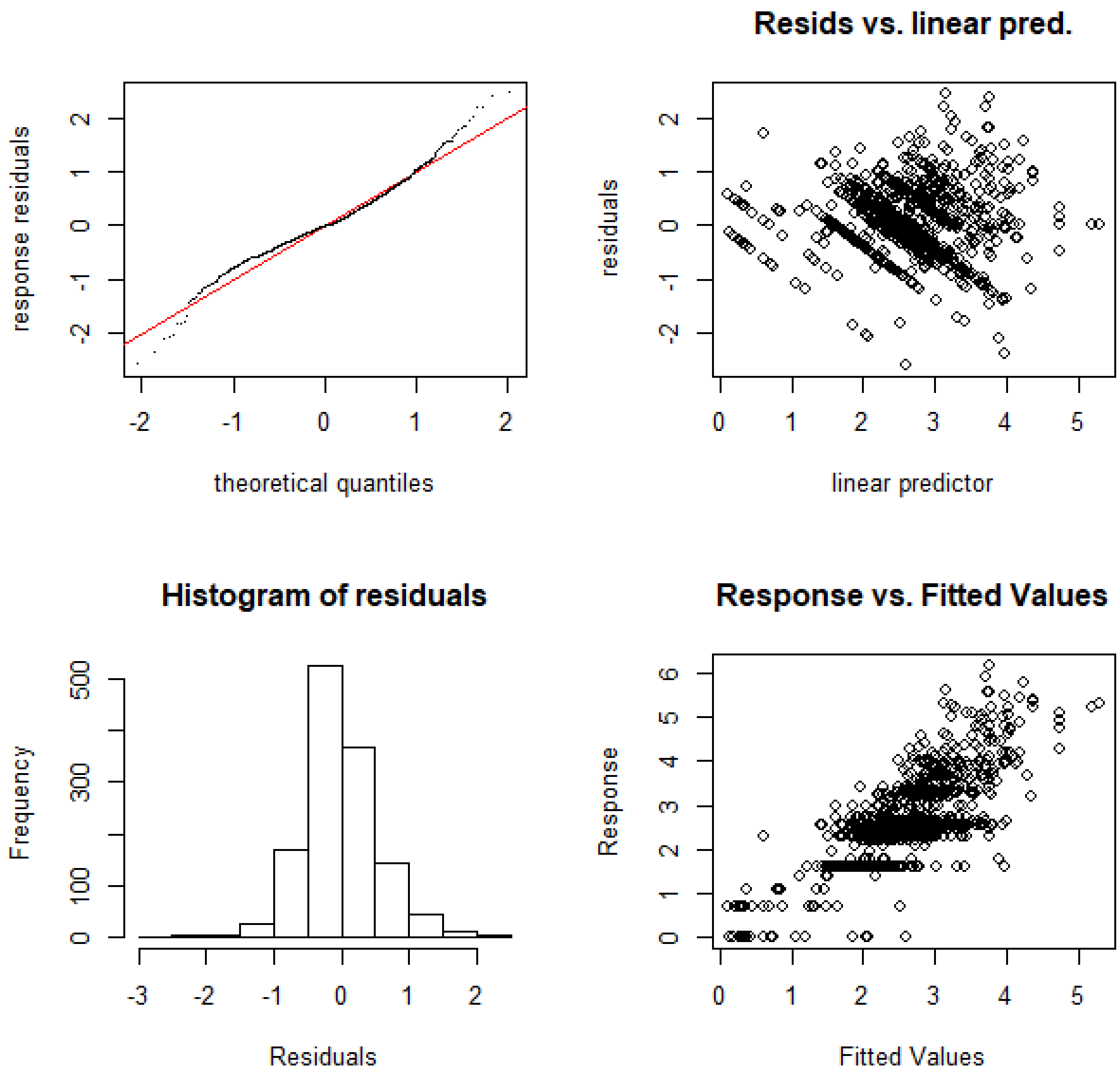

Figure 3-5. Diagnostics of the lognormal model for modelling the positive catch using data from grids that had a probability of positive catch greater or equal to 0.01.

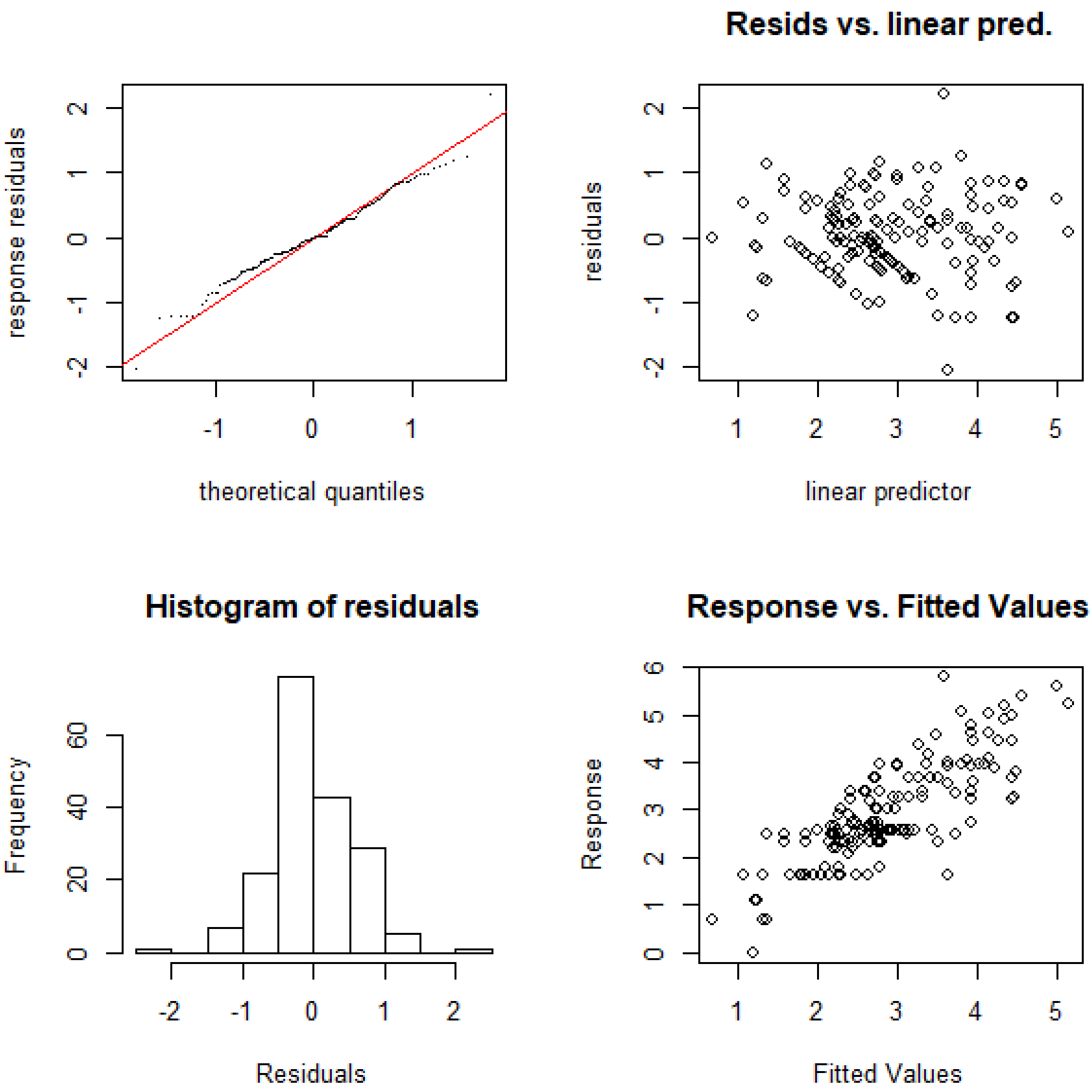

Figure 3-6. Diagnotscis of the lognormal model for modelling the positive catch using data from grids that had a probability of positive catch greater or equal to 0.1 and the total fishing days is greater or equal to 10 days during 1998-2019.

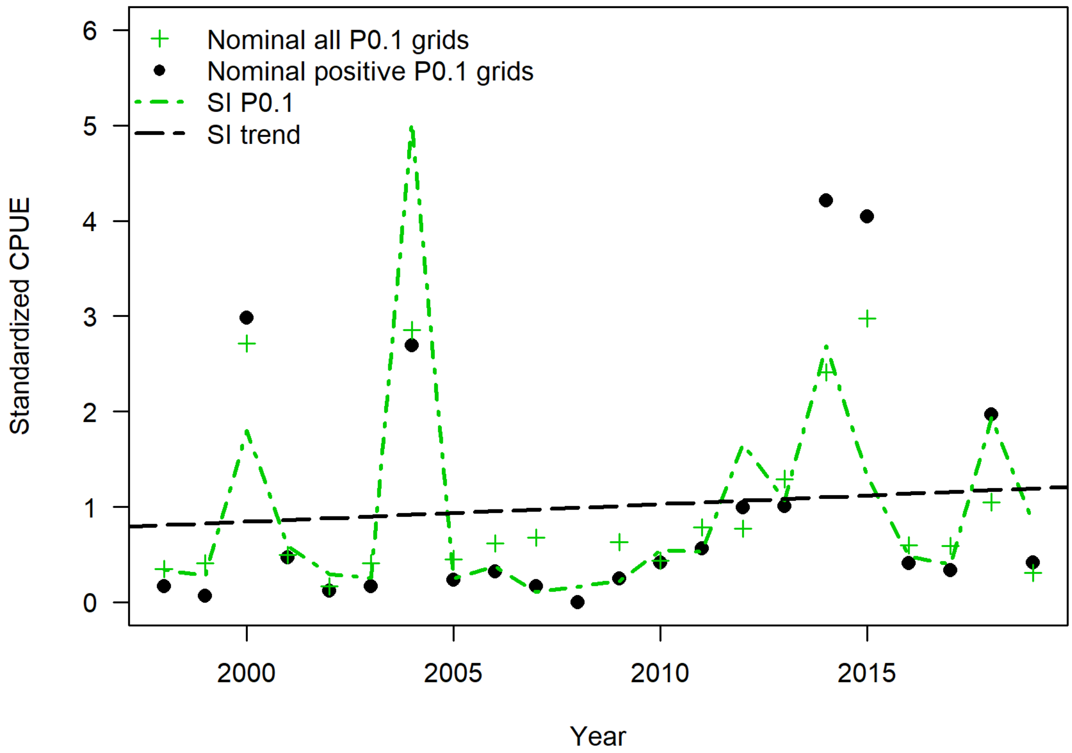

Figure 3-7. CPUE from in highest catch area (15 0.1*0.1 grids) where the probability of positive catch is greater than 0.1 and the total fishing days with positive catch is greater than 10 days between 1998 and 2019.

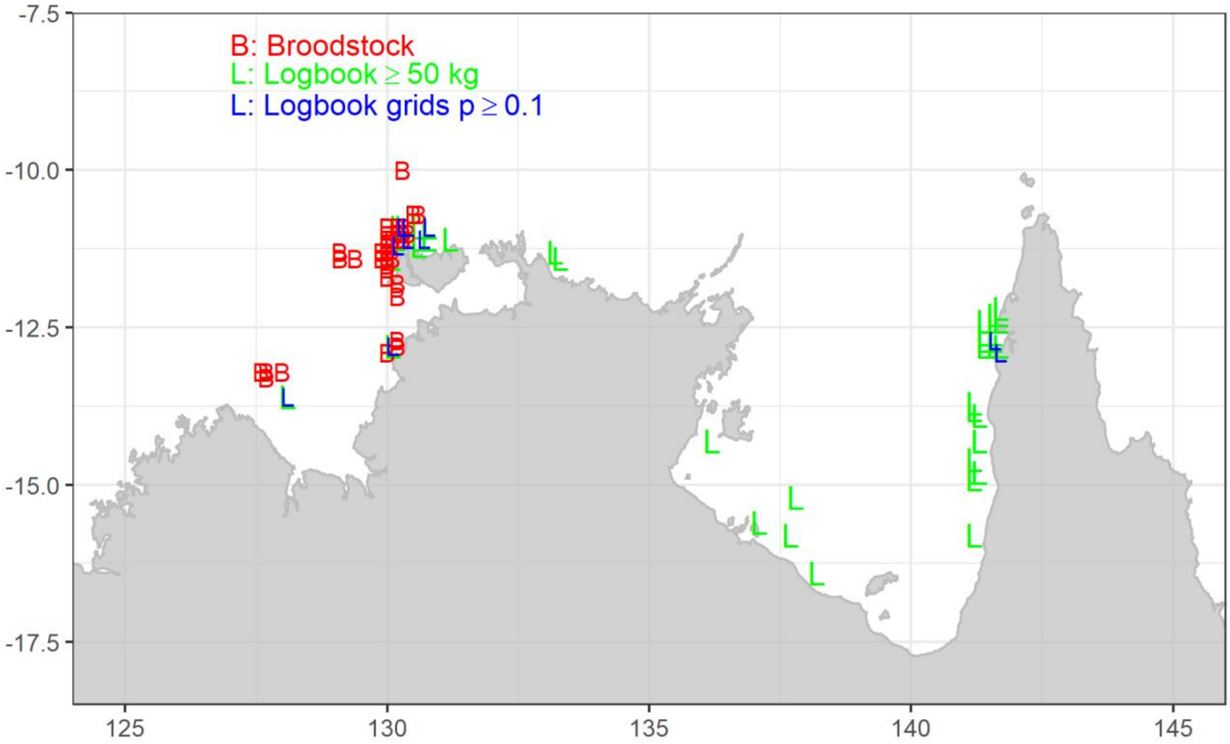

Figure 3-8. Comparison of fishing location in 2018. Red "B" are the grids fished by broodstock collection, green "L" are grids in the commercial logbook with CPUE greater than 50kg (in a single day), and blue "L" are grids in the logbook with probability of positive catch greater than 0.1 between 1998 and 2019.

4 Stock assessment using Bayesian state-space biomass dynamics model

As a rare commercial species in the NPF, Black tiger prawn has very limited data on its biology and population dynamics as well as data from the fishery. In these circumstances it is challenging to apply a size- or age-structured model for stock assessment. We opted to use a less data demanding population model—a biomass dynamics model (BDM, aka surplus production model, SPM). A BDM can estimate key biological and management parameters, including unfished biomass, intrinsic population growth rate, maximum sustainable yield (MSY), biomass and fishing mortality at MSY, current stock status, and time series of biomass and fishing mortality. Although BDMs have several limitations and have been criticised for their simplicity (Maunder, 2003), they are widely used within data-limited and data-moderate fisheries (Dichmont *et al.*, 2016). A major weakness of BDM is its aggregated of age-structure so it does not account for age or size-specific gear selectivity. A BDM also does not specifically model time lagged stock-recruitment relationships. However, for short-lived species, studies show that BDMs can produce nearly identical results as more data-intensive methods (Zhou *et al.*, 2009).

The standardized CPUE, together with catch records, may allow a simple population model, such as biomass dynamics model to be fit. However, the traditional maximum likelihood technique may have difficulties for the species with sporadic low catch data. Consequently, we used a Bayesian state-space model that can handle both observation and process errors and can easily incorporate prior knowledge about the species. The Bayesian state-space formulations of BDMs have been recommended over observation or process error estimators because such formulations are better able to represent uncertainty (Punt *et al.*, 2015).

4.1 Methods and input data

There are several off the shelf software packages that can implement Bayesian production models. We first explored the suitability of JABBA (Just Another Bayesian Biomass Assessment) (Winker *et al.*, 2018). JABBA formulates the surplus production function with the generalized three parameter SPM by Pella and Tomlinson (1969), i.e.:

$$SP_t = \frac{r}{m-1} B_t \left[1 - \left(\frac{B_t}{K}\right)^{m-1}\right] \qquad \text{Equ 4-1}$$

where r is the intrinsic rate of population increase, K is the carrying capacity, B is stock biomass, t is time step, and m is a shape parameter that determines at which B/K ratio maximum surplus production is attained. If the shape parameter $m = 2$, the model reduces to the standard Schaefer production model, with the surplus production (SP) attaining MSY at exactly $K/2$. If $0 < m < 2$, SP attains MSY at biomass levels smaller than $K/2$; the converse applies for values of m greater than 2. A potential problem with this three-parameter model is the difficulty to estimate shape parameter m, particularly for data-limited stocks. As this parameter is close to 2 for most stocks in the RAM legacy database (http://ramlegacy.org), we assume $m = 2$ for Black tiger prawn to avoid the difficulties of estimation. The formulation of the Pella-Tomlinson leads to a rapid increase of surplus production as m decreases for any fixed input values of r and K because of the inclusion of m-1 as the denominator of r. The surplus production model can overestimate biomass growth at lower biomass levels. To avoid this potential issue JABBA provides an option of combining the surplus production with linear growth function when biomass drops below a threshold $P_{lim} = B_{lim}/K$, where P_{lim} ranges of 0.2–0.25, which have been adopted as thresholds for recruitment overfishing (Sainsbury, 2008). We adopted P_{lim} = 0.25 for Black tiger prawns here. JABBA is formulated using the Bayesian state-space estimation framework proposed by Meyer and Millar (1999). The biomass B_t in year t is expressed as a proportion of K (i.e. $P_t=B_t/K$, which is referred to as saturation S_t in this report) to improve the efficiency of the estimation algorithm. The initial biomass in the first year of the time series is scaled by S_0, an assumed initial saturation represented as model parameter φ in JABBA. Note that the commonly called depletion is $d = 1 - S = 1 - B_t/_K$. The stochastic form of the process equation is given by:

$$P_t = \begin{cases} \varphi e^{\varepsilon} & t = 1 \\ \left[P_{t-1} + \frac{r}{m-1} P_{t-1}\left(1 - P_{t-1}^{m-1}\right) - \frac{\sum_f C_{f,t-1}}{K}\right] e^{\varepsilon} & P_{t-1} \geq P_{lim} \\ \left[P_{t-1} + \frac{r}{m-1} P_{t-1}\left(1 - P_{t-1}^{m-1}\right) \frac{P_{t-1}}{P_{lim}} - \frac{\sum_f C_{f,t-1}}{K}\right] e^{\varepsilon} & P_{t-1} < P_{lim} \end{cases} \qquad \text{Equ 4-2}$$

where ε is the process error, with $\varepsilon \sim$ Normal(0, σ_{ε}) and $C_{f,t}$ is catch from fleet f in time t.

The standardised CPUE is considered as “observed data” and the observation model is:

$$I_t = qB_t e^{\epsilon} \qquad \text{Equ 4-3}$$

I_t is the abundance index, a fraction of biomass B_t scaled by catchability q. The random observation error is assumed to be ϵ ~ Normal(0, σ_{ϵ}).

The inputted fishery data included annual catch by fleet f, $C_{f,t}$ and standardised CPUE SI_t. Catch from the NPF commercial fleet are fully retained, but some of the catch in the broodstock fleet are discarded. An on-vessel survival experiment was conducted during a survey in February-March 2020 (G. Fry, CSIRO, *personal communication*). A total of 20 Black tiger prawns (13 males and 7 females) were held in tank for up to 2 hours. At the end of the experiment, 6 prawns were dead while 14 survived and were released, resulting in a survival rate of 0.7. This rate was used to calculate survival rate for the discarded Black tiger prawns in the broodstock fishery.

JABBA can fit to multiple time series of abundance indices from different fleets. We used standardised SI_t for the NPF commercial fleet from the previous chapter, but we did not fit to the CPUE for broodstock fleet because it had only three years of reliable CPUE within the time frame of the available NPF commercial logbook data and the fished areas were small compared to the full geographic range of the fishery.

Bayesian models require prior information. In Equ 4-1 and Equ 4-2, one of the key parameters (hence the major consideration) is the intrinsic rate of population growth r. To our best knowledge, this parameter has not been estimated for Black tiger prawns. This species has similar life-history as Grooved tiger prawn (Gribble *et al.*, 2003). Grooved tiger prawns in the NPF have been assessed using Bayesian state-spatial hierarchical models surplus production models (Zhou *et al.*, 2009). That study demonstrates that simple a BDM implemented in Bayesian state-space formulation can produce nearly identical results as more data-intensive weekly-delay difference model. The technique used for the Grooved tiger prawn is reminiscent of JABBA.

In this chapter, we constructed r prior by borrowing the posterior distribution of the Grooved tiger prawns which has mean r = 0.43 (Table 4-1). For the other parameters, including carrying capacity K and initialsaturation φ, the default priors built in JABBA were used (Table 4-1, Figure 4-1), so this exploration is referred to as the “base case” or “default case”. The default K prior is a lognormal distribution with a mean of 8 times of the maximum catch in the history and a coefficient of variation of 1. The prior for the initial saturation φ was beta(0.9, 0.25), which has a mean about 0.78 and a median about 0.93.

To test the model sensitivity to the assumed priors, several alternations were made to the priors.

To implement the MCMC samples, the model was set up with two chains, 30,000 iterations, saving the results of every 5 iterations and discarding the first 5,000 iterations. The retained 10,000 samples were used to construct the posterior distributions for the parameters and variable of interest.

4.2 Results

4.2.1 Base case

The Bayesian state-space model can be applied without needing further adjustment of priors or initial values. However, the posterior distributions for most of the parameters are quite wide (Figure 4-1). The variability measured by the ratio of posterior CV^2 to prior CV^2 (PPVR) is not much smaller than 1, indicating similar uncertainty between the priors and posteriors. This high uncertainty can also be seen from the numerical output (Table 4-2). The ratios of mean posterior to mean prior value (PPMR) indicate that *r* prior matches its posterior quite closely.

The large variance likely links to the information content of abundance index SI, at least partially. Even with the flexible Bayesian state-space model that takes both process and observation errors into account, the model fails to capture the increasing trend of SI over time (Figure 4-2, CPUE panel at the top left). The posterior abundance index is approximately stable over the entire period from 1998 to 2019.

The results suggest that the total annual catch of Black tiger prawn is below MSY level for most years except in 2018 (Figure 4-2, catch panel at the top right). However, the estimated MSY is highly uncertain, with a 95% CI of 3,773 to 17,083kg (Table 4-2). The total annual catches in 2014, 2015, and 2018 are all larger than the lower MSY credible interval.

The estimated annual fishable biomass is also quite uncertain (Figure 4-2, biomass panel at the middle left). The mean biomass is above the posterior mean B_{msy} in all years, indicating that the stock is not overfished. However, if we take the large variance of B_y and B_{msy} into consideration, the lower 95% CI for biomass trajectory is way below the upper 95% CI for B_{msy}.

The posterior for F_{msy} has a relatively smaller variance compared to that for the other parameters, partially due to informative prior assigned to *r*. The posterior mean annual fishing mortalities (*F*) are below mean F_{msy} (Figure 4-2, fishing mortality panel at the middle right). However, if both uncertainties around the estimated *F* and F_{msy} are considered, overfishing may be occurring in 2014, 2015, and 2018.

Focusing on the point estimates, biomass in all the 22 years are above B_{msy} while the fishing mortality is below F_{msy}, inferring that the stock has never been overfished and overfishing is not occurring (Figure 4-2, surplus production panel at the bottom right). Again, when taking uncertainty into consideration, there is a low probability of overfishing in the most recent years (Figure 4-2, Kobe plot at the bottom left).

It is possible to construct alternative models with different assumption and priors. However, model comparison based on commonly used criteria such as the deviation information criteria, residuals, root mean squared error, etc., can be misleading because of the questionable CPUE data. Sensitivity testing, however, remains a valid approach.

4.2.2 Testing model sensitivity to priors

Several sensitivity tests were performed.

Initial saturation. The increasing biomass at the start of the time series (Figure 4-2, biomass panel at the middle left) suggests that the stock may be recovering from a low level. There were no records of retained Black tiger prawn in logbooks prior to 1998. However, as a non-directed catch species with very low catch from 1998 to 2010, it seems unlikely that the stock was noticeably fished down in the early years. Hence, we first tested the sensitivity to the initial saturation set in the base-case model as φ = *beta*(*a* = 0.9, *b* = 0.25), which has a mean of 0.78 and a median of 0.93. We assumed an alternative prior φ = *beta*(*a* =0.99, *b* = 0.01), i.e. nearly unfished stock (mean φ = 0.99). The change had little effect on the biological and management parameters in Tables 4.2, except for φ itself (posterior mean φ = 0.98) (Table 4-3). This modification removes the slightly uprising biomass trajectories in Figure 4-2, biomass panel at the middle left, so the biomass remains roughly stable until the present.

We further tested the hypothesis that the stock was substantially depleted at the start of 1998. We assumed φ = *beta*(*a* = 0.5, *b* = 0.5), which has a mean and median of 0.5). This scenario led to a large change to the posterior for initial depletion with a mean φ = 0.16 in 1998 (Table 4-3). Biomass increased over the following years because of low annual catch, and recovered to a saturation *S* = 0.94 (i.e., the stock was only depleted by 0.06) in 2013 (Figure 4-3, biomass panel). Increased catch during the most recent years drove the stock to a lower level and the biomass was about 80% of unfished carrying capacity in 2019. However, assuming a low initial depletion again had little effect on other parameters. The stock status (both biomass and fishing mortality) were very similar to the base case.

Intrinsic growth rate. Two alternative models (a classic Graham-Shaefer surplus production model and a modified stock-recruitment model) have been applied to the NPF Grooved tiger prawns in four stock regions, resulting in eight estimates of intrinsic population growth rate *r* (Zhou *et al.*, 2009). The estimated values range from 0.231 to 0.792 (mean = 0.432, sd = 0.136). There is a stock assessment for Torres Strait Brown tiger prawn (*Penaeus esculentus*) (O'Neill and Turnbull, 2006). One of the models used is the Graham-Shaefer surplus production model, which yields three estimates of *r*: 0.448, 0.768, 0.479. The results from the two studies, one on Grooved tiger prawns in the NPF and one in Torres Strait on Brown tiger prawns are comparable.

Instead of using the mean *r* from tiger prawns, we examined effect of this parameter by using the minimum (0.231) and maximum (0.792) values estimated from Grooved and Brown tiger prawns. With these two very different *r* priors, the posteriors for *K*, B_{msy}, S_{2019}, and B_{2019}/B_{msy} remain similar. If Black tiger prawn had a very low productivity, the total annual catch in years 2014, 2015, and 2018 could have been greater than MSY level and F_{2018} could also be above F_{msy} (Figure 4-4). However, the stock biomass had always been above the mean B_{msy} reference point in recent years. In contrast, if Black tiger prawns were very productive, the annual catch would have always been less than mean MSY, biomass greater than mean B_{msy}, and fishing mortality smaller than mean F_{msy} (Figure 4-5).

It is worth noting that the posterior for initial saturation in 1998 was very uncertain even with the same prior. However, the model results were insensitive to this parameter, because even if the estimated φ was very low, biomass can always recover to a high level before 2014 due to low catch between 1998 and 2013.

Carrying capacity. It is very difficult to provide reliable prior for parameter *K* because it is largely determined by a species' habitat and surrounding environment. We tested multiple priors, the mean values of which ranges from the maximum observed catch (meaning all Black tiger prawns could have been harvested), to 10 times the maximum observed catch (approximately 10% of unfished biomass could have been taken in one year). Varying this multiplier from 1 to 10 had clear impact on several key parameters (Figure 4-6). Larger *K* priors led to larger posterior mean for *K*, MSY, saturation, biomass relative to B_{msy} but smaller r and lower F to F_{msy} ratio. In the case of Black tiger prawn, if the unfished biomass is at least 2.5 times of the maximum catch, then the stock is unlikely to be overfished by 2019 and overfishing may have not occurred.

The difference between the prior and posterior distributions decreased and then increased again when *K* prior increased from 1 to 10 times of max(C)(Figure 4-7). To determine a reliable *K* prior, we changed the *K* prior gradually till the mean posterior equals the mean prior. This procedure yielded a mean *K* prior = 4.4*max(C), which was used in the final model. Simulation tests using data-rich stocks in the RAM Legacy Database confirm that this is a feasible approach (results unpublished).

The variance of the *K* prior also has a major effect on the posteriors. We used the similar procedure to determine likely value of the parameter. We changed cv[*K*.prior] from 0.1 to 1 and found that the CV for the K prior was about 0.7 when the mean of the *K* posterior was close to the mean of its prior.

Regardless the values of K prior (mean and CV), i.e., whether using the default values in the JABBA program or the values we chose for the final model, the general conclusions about the stock status remain the same: the point estimates suggest that Black tiger prawn has not been overfished and overfishing didn't occur in 2019.

In addition to the three key model parameters, we also tested model sensitivity to process error and observation error. JABBA allows these two types of errors either to be fixed or estimated. Assuming large errors (e.g., $\sigma = 1$) or letting the model estimate them has little impact on the general conclusions.

4.2.3 Final model and conclusion

The final model used the same priors as in the base case, except that *K*.prior = *LN*(mean = *max*(*C*)*4.4, σ= 0.63) and $\varphi = beta(a = 0.9, b = 0.1)$. Again, the fit of this final model to the standardized index SI was poor (Table 4-4, Figure 4-8). The posterior mean for unfished biomass *K* was about 41.3 tonnes, that for F_{msy} was about 0.23 yr^{-1}, that for B_{msy} about 20.7 tonnes, and that for MSY about 4.6 tonnes (Table 4-5, Table 4-6). The posteriors are quite uncertain. For example, the coefficient of variations (CVs) for *K*, B_{msy}, and MSY are all greater than 60% (Table 4-6). The output of the model indicates that the total catch during 2014, 2015, and 2018 may have been greater than the posterior mean MSY and F_{2018} greater than the posterior mean F_{msy}, but biomass in all years was above B_{msy} (Figure 4-8). Given the assumptions, the model estimates indicate that the stock has never been overfished but overfishing may have occurred in the 2018 (Table 4-5, Table 4-6). Compared to the base case, final model is more conservative.

4.2.4 Sensitivity test of survival rate of discarded prawns in broodstock collection

During the 30 November NPRAG meeting, RAG members questioned the survival rate of discarded Black tiger prawn in the broodstock fishery. The mortality rate of 30% observed on an onboard experiment was considered too low because it did not take into account of potential mortality due to predation after the prawns are returned to the water but before they sink to the bottom. It was recommended that a sensitivity test should be conducted by assuming 100% mortality for the discarded prawns.

This sensitivity test shows that assuming 100% mortality for the discarded prawns has a minor effect on the results (Table 4-7). The relative change ($= \frac{\theta_{100\%} - \theta_{30\%}}{\theta_{30\%}} \times 100$, where $\theta_{100\%}$ and $\theta_{100\%}$ are median parameter values for models assuming a 100% or 30% discard mortality rate) ranges from -4% to 9%. Note that these changes also include the stochastic effect in the Bayesian process. The general conclusion about the stock status, i.e., the stock was not overfished and overfishing did occur in 2019 remains unchanged. The minor effect is expected because discarded prawns only made up between 0 and 16% (mean 5%) of the total catches (broodstock collection and commercial fishing combined). It is also worth noting that discards were not fully reported before 2017.

4.3 Discussion

The Bayesian biomass dynamics models can incorporate various sources of information and types of uncertainties, including prior knowledge, information from other species, measurement error, and process error. It is a flexible tool for assessment of data-poor fisheries. However, even with such a powerful tool the model still cannot track the standardized CPUE well. The model cannot explain the recent increase in CPUE, noting that the CPUE has a very large uncertainty in most years. The increased CPUE in recent years also contradicts the observed catch pattern. If the stock's productivity has not changed substantially, increasing catch would be expected to reduce abundance, which is correctly modelled by the Bayesian biomass dynamics model implemented in JABBA. Assuming very large process error or observation error does not change the point trajectory of posterior biomass.

Although the CPUE data are not informative, the Bayesian model can still produce reasonable results. The success depends on the assumption that Black tiger prawn has an intrinsic productivity similar to that of Grooved tiger prawn or Brown tiger prawn in the Northern Australia. Longevity is the most significant predictor for intrinsic population growth rate (Liu et al., in review). Adult life span of Black tiger prawn ranges from 6 to 24 months (Gribble *et al.*, 2003). The Grooved tiger prawn, *P. semisulcatus*, can live for about 2 years, but a study shows that very few survive beyond 18 months in the north-western Gulf of Carpentaria (Somers and Kirkwood, 1991). The average lifespan of Black tiger prawn in many regions is 2 years (https://animaldiversity.org/accounts/Penaeus_monodon), though it has been suggested that individuals introduced into the Gulf of Mexico have a lifespan closer to 3 years (Dall *et al.*, 1991). Given the similar longevity and life history, the assumption of similar intrinsic population growth rate between the three tiger prawn species (Grooved, Brown, and Black) may be reasonable. We believe that productivity of Black tiger prawn should be at least within the large range that we tested (i.e., between the minimum and maximum r values from the other two tiger prawn species).

All models and sensitivity tests indicate that stock biomass is above B_{msy}. However, the total catch may have been greater than MSY in some years. Fishing mortality may be close or greater than F_{msy} in recent years. Since the increasing catch trend tends to continue upwards and the stock has never been below B_{msy}, the output from this assessment may not hold in the future. To detect the full stock size and its production potential, a range of fishing mortality and biomass levels (including overfished) can better inform the assessment models. It is recommended that the current catch level could be maintained for one or two years to see whether the stock can support this level of production and to assist the model identifying the maximum stock size and potential productivity. However, a dramatic increase of catch should be avoided to prevent severe overfishing. A quick re-run of the Bayesian biomass dynamics model is warranted in the coming years when new catch data become available.

The NPF region is a large area. It is unknown whether Black tiger prawn is a single stock or has multiple sub-stocks in the entire region. The catch varies considerably between Banana prawn stock regions. When more data become available, it is worth analysing the data at the sub-region level to ensure the species is sustainably fished if indeed there exist multiple stocks.

Table 4-1. Input and priors for the base case Bayesian state-space production model. Unit: catch in kg, CPUE in kg/day, r yr^{-1}, K in kg, catchability in day^{-1}. Default refers to the use of the default value in JABBA program.

Variables	Description
Year	1998—2019
Catch	NPF + broodstock[1], CV = 0.1
CPUE	Standardised from NPF commercial logbook
r (based on NPF Grooved tiger)	r.prior = LN(median = 0.432, sd = 0.136, σ = 0.307)
K (default)	K.prior = LN(median = $max(C)$*8 = 81,987, σ= 0.3)
Initial saturation (default)	φ = $beta(a = 0.9, b = 0.25)$
Process error (default)	σ_ε = $unif(sqrt(1/100), sqrt(1/20))$
Observation error (default)	σ_ϵ = $inv\text{-}gamma(0.001, 0.001)$
Catchability (default)	q = $unif(min(\mathrm{SI})/max(C), mean(\mathrm{SI})/max(C))$
Biomass threshold	P_{lim} = 0.25
Shape parameter	m = 2

[1] The broodstock catch are in number of prawns, which includes the retained and discarded prawns. The removal by broodstock collection is total weight in kg where the mean weight per prawn is assumed to be 100g and the mortality rate of 30% for the discards is based on an onboard experiment.

Table 4-2. Results from the base case Bayesian state-space biomass dynamics model for the Black tiger prawn. S_{year} is the stock saturation (= B_{year}/K = 1 – $Depletion_{year}$). Unit: F in yr^{-1}, B and MSY in kg. Units for other parameters are the same as in Table 4-1.

Param	Mean	2.5%	97.5%
K	68,866	39,834	120,072
r	0.46	0.27	0.80
F_{msy}	0.23	0.13	0.40
B_{msy}	34,433	19,917	60,036
MSY	7,877	3,773	17,083
S_{1998}	0.13	0.07	0.30
S_{2019}	0.82	0.59	0.98
B_{2019}/B_{msy}	1.63	1.19	1.97
F_{2019}/F_{msy}	0.21	0.09	0.56

Table 4-3. Posteriors means from the sensitivity tests that vary initial saturation φ and the intrinsic population growth rate *r*. The lowest and highest *r* estimates from the Grooved and Brown tiger prawns studies were assumed for Black tiger prawns. The mean of the *K* prior was assumed to be 8*max[C]. Units are the same as in Tables 4-1 and 4-2.

Param	$\varphi = 0.9$	$\varphi = 0.5$	$r = 0.23$	$r = 0.43$ (base-case)	$r = 0.79$
K	68,720	68,780	71,148	68,866	67,940
r	0.44	0.47	0.28	0.46	0.79
F_{msy}	0.22	0.23	0.14	0.23	0.39
B_{msy}	34,360	34,390	35,574	34,433	33,970
MSY	7,608	8,054	5,050	7,877	13,249
S_{1998}	0.98	0.16	0.16	0.13	0.12
S_{2019}	0.82	0.82	0.75	0.82	0.85
B_{2019}/B_{msy}	1.65	1.65	1.49	1.63	1.70
F_{2019}/F_{msy}	0.21	0.20	0.35	0.21	0.12

Table 4-4. Comparison of standardized index (SI) from commercial logbook and posterior abundance index for the final model.

Year	SI	Estimated	2.50%	97.50%	Residual
1998	0.083	0.280	0.052	1.815	-1.217
1999	0.047	0.297	0.057	1.877	-1.847
2000	0.409	0.314	0.039	2.784	0.265
2001	1.218	0.320	0.002	44.639	1.338
2002	0.242	0.323	0.041	2.730	-0.289
2003	0.242	0.326	0.053	2.194	-0.296
2004	0.661	0.330	0.018	5.648	0.694
2005	0.427	0.327	0.033	3.298	0.268
2006	0.697	0.326	0.023	5.570	0.761
2007	0.291	0.327	0.026	4.033	-0.115
2008	0.305	0.338	0.028	3.925	-0.103
2009	0.432	0.333	0.022	5.524	0.259
2010	0.832	0.323	0.013	9.385	0.946
2011	1.185	0.337	0.007	15.662	1.259
2012	2.137	0.337	0.000	303.263	1.846
2013	1.817	0.334	0.001	93.314	1.693
2014	3.021	0.335	0.000	1176.534	2.199
2015	1.928	0.258	0.000	23776.032	2.013
2016	0.479	0.270	0.025	2.778	0.573
2017	0.854	0.296	0.019	5.141	1.059
2018	3.790	0.309	0.000	1520.398	2.505
2019	0.905	0.227	0.013	3.821	1.385

Table 4-5. Results from the final model with the prior for *r* constructed from the mean and variance of estimated *r* for Grooved tiger prawn, and the prior for *K* constructed using a mean of 4.4 times the maximum catch and a sd of 0.63, and the mean 1998 biomass of about 0.9B_0.

Param	Mean	2.5%	97.5%
K	41,341	19,670	108,302
r	0.45	0.25	0.81
F_{msy}	0.23	0.13	0.40
B_{msy}	20,670	9,835	54,151
MSY	4,624	2,042	13,761
S_{1998}	0.86	0.49	1.04
S_{2019}	0.70	0.29	0.95
B_{2019}/B_{msy}	1.40	0.57	1.89
F_{2019}/F_{msy}	0.41	0.11	2.21

Table 4-6. Key parameters and uncertainty from the final model. σ is the log-scale standard error.

	K	B_{msy}	F_{msy}	MSY
Mean	41,341	20,670	0.23	4,624
σ	0.45	0.45	0.30	0.50
SD	27,693	13,846	0.14	3,174
CV	67%	67%	63%	69%

Table 4-7. Model sensitivity to survival rate of discarded prawns in broodstock collection. All discards are assumed to be dead. Rel change is the relative change between the model that assumes 100% discard mortality and the final model in Table 4-5.

Param	Mean	2.5%	97.5%	Rel change
K	41,926	19,196	121,532	1%
r	0.45	0.25	0.81	0%
F_{msy}	0.23	0.13	0.41	0%
B_{msy}	20,963	9,598	60,766	1%
MSY	4,767	1,922	15,370	3%
S_{1998}	0.83	0.38	1.04	-4%
S_{2019}	0.70	0.21	0.96	1%
B_{2019}/B_{msy}	1.41	0.41	1.92	1%
F_{2019}/F_{msy}	0.45	0.11	3.58	9%

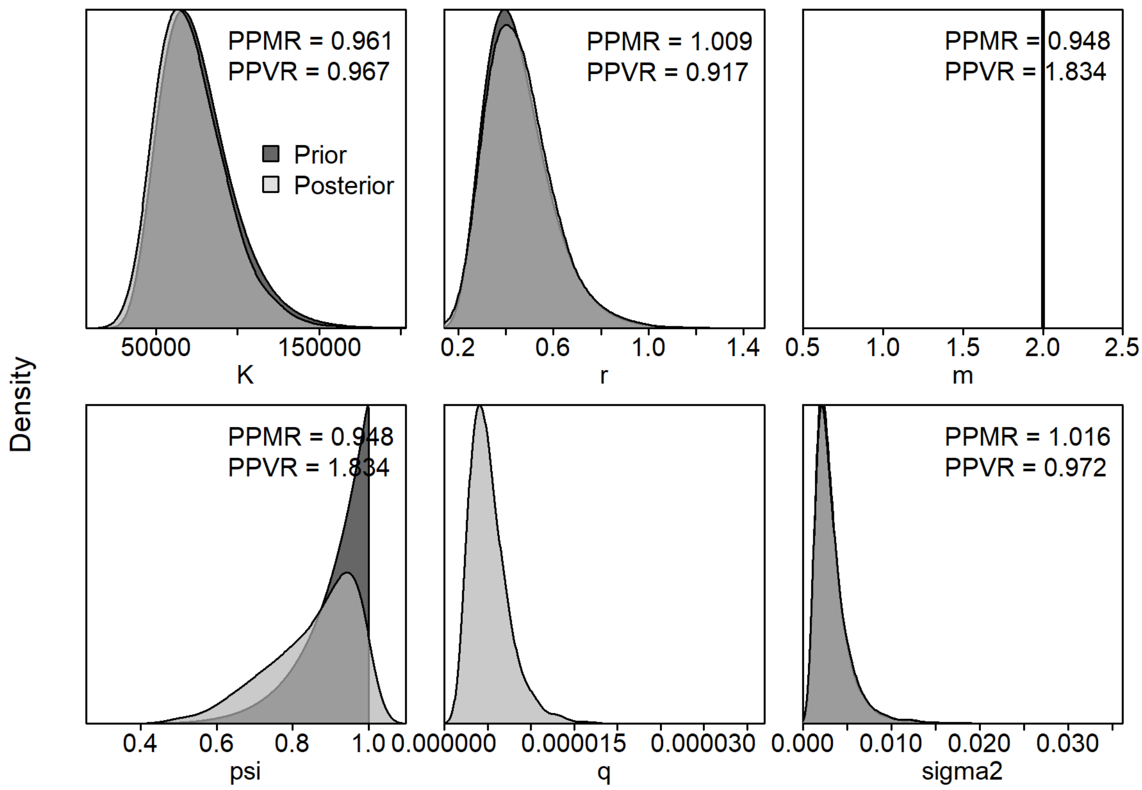

Figure 4-1. Posterior distributions for key parameters for the base case scenario. PPMR: ratio of posterior mean to the prior mean; PPVR: ratio of posterior CV^2 to prior CV^2. Psi is the initial stock saturation S_{1998} (= B_{1998}/K), and sigma2 is the variance of process error σ_{ε}^{2}. Unit for K is kg.

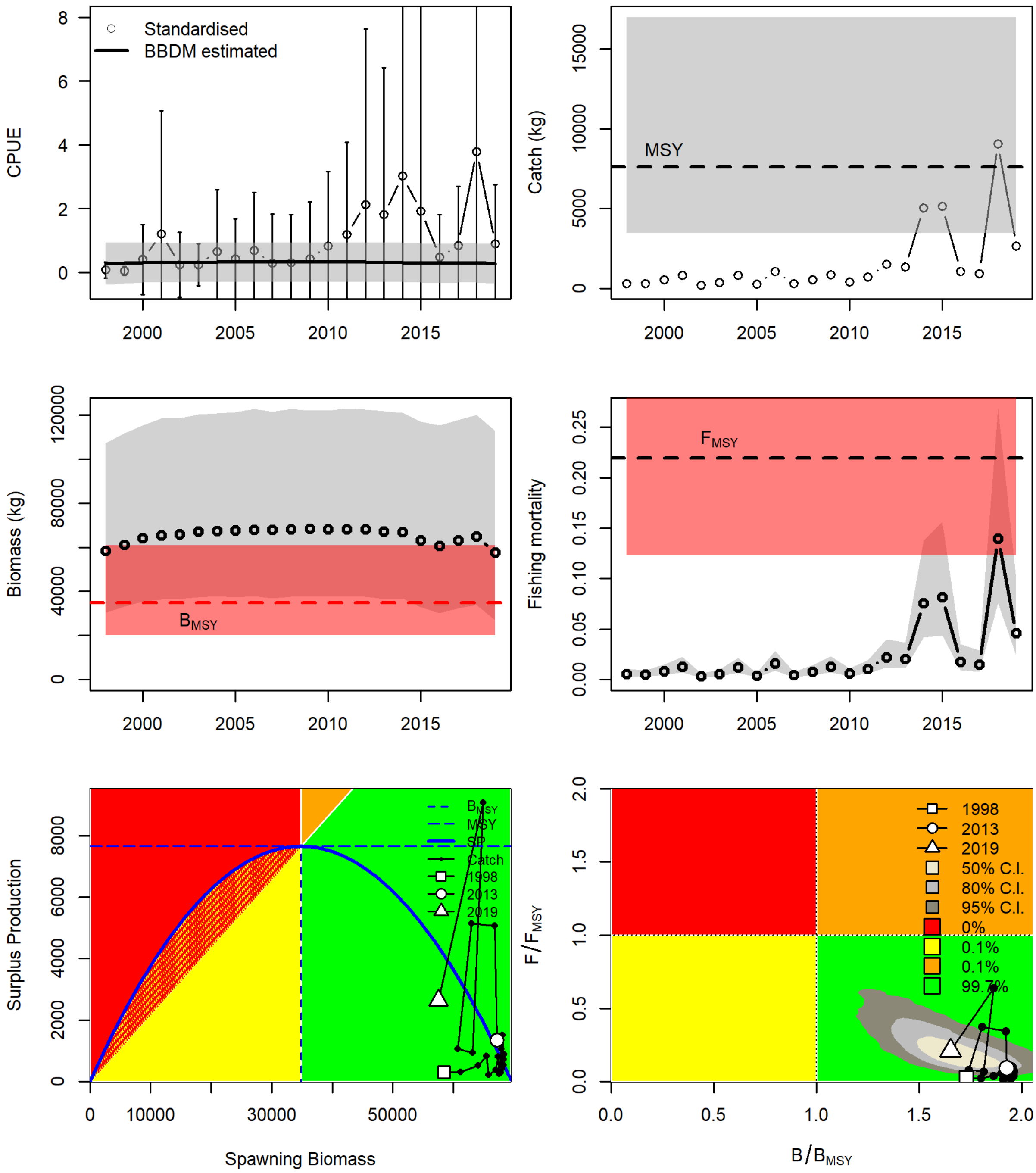

Figure 4-2. Output from the base case Bayesian state-space surplus production model (JABBA) for the Black tiger prawns. The y-axis labels denote the posteriors in each panel. The error bars and the grey or red bands are 95% credible intervals while three levels of CIs are shown in the Kobe plot.

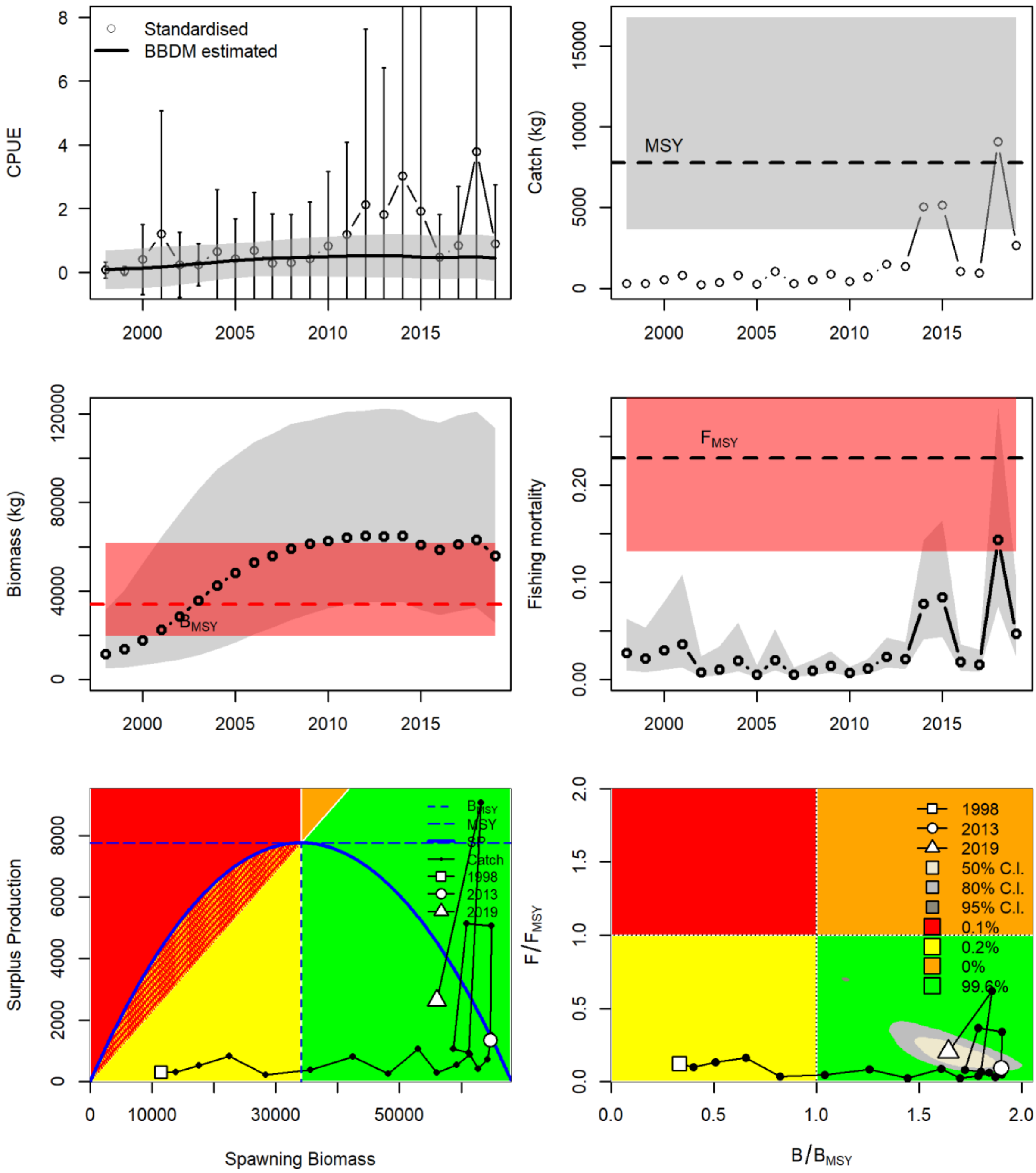

Figure 4-3. Sensitivity to the initial saturation in 1998 with an assumed prior mean for φ of 0.5. Other priors remain the same as in the base case. The error bars and the grey or red bands are 95% credible intervals while three levels of CIs are shown in the Kobe plot.

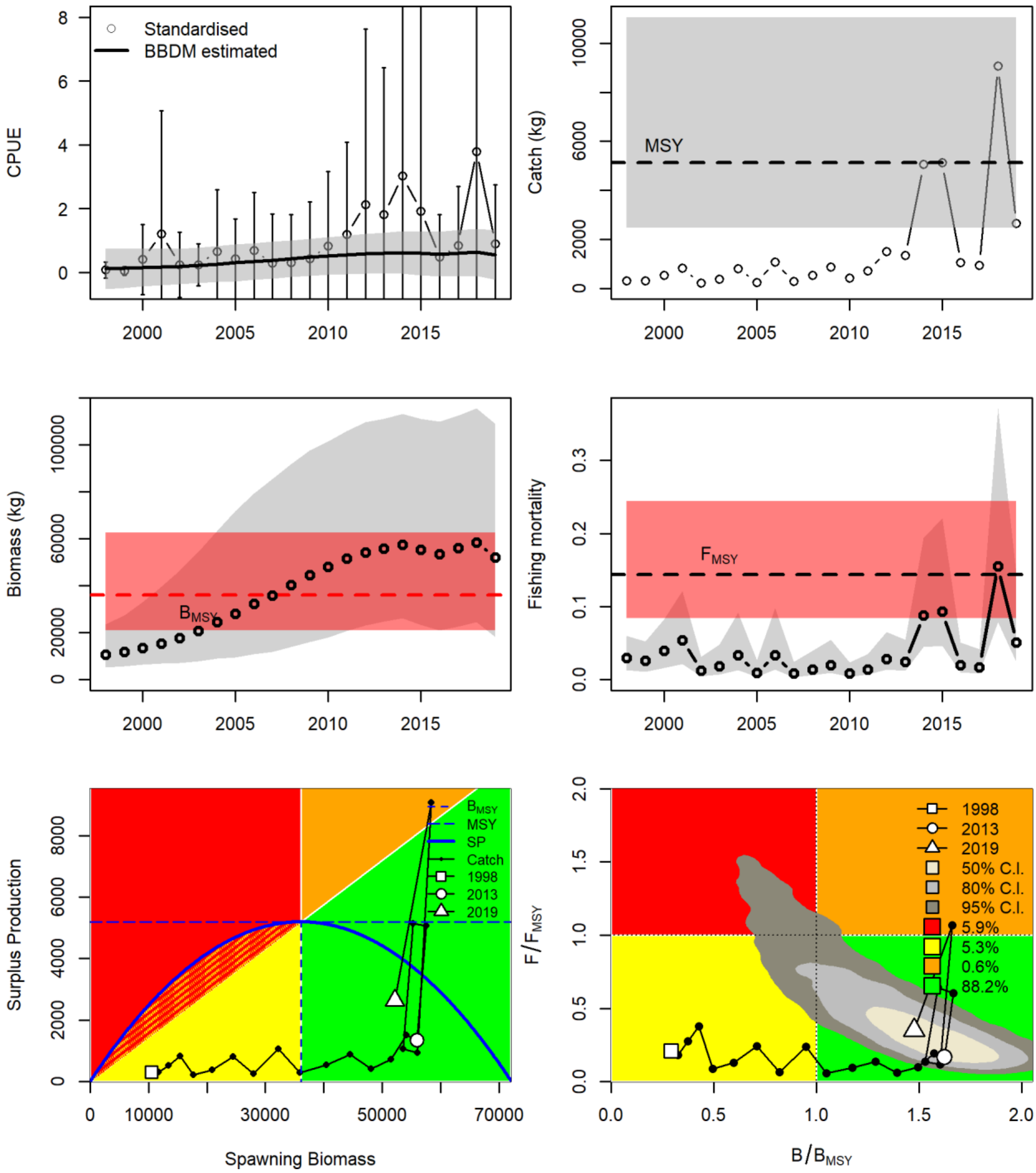

Figure 4-4. Sensitivity to setting the mean of the prior for *r* to the minimum estimate of *r* for Grooved and Brown tiger prawns (*r* = 0.231). The prior for initial biomass B_{1998} was set to Beta(0.9, 0.25). The error bars and the grey or red bands are 95% credible intervals while three levels of CIs are shown in the Kobe plot.

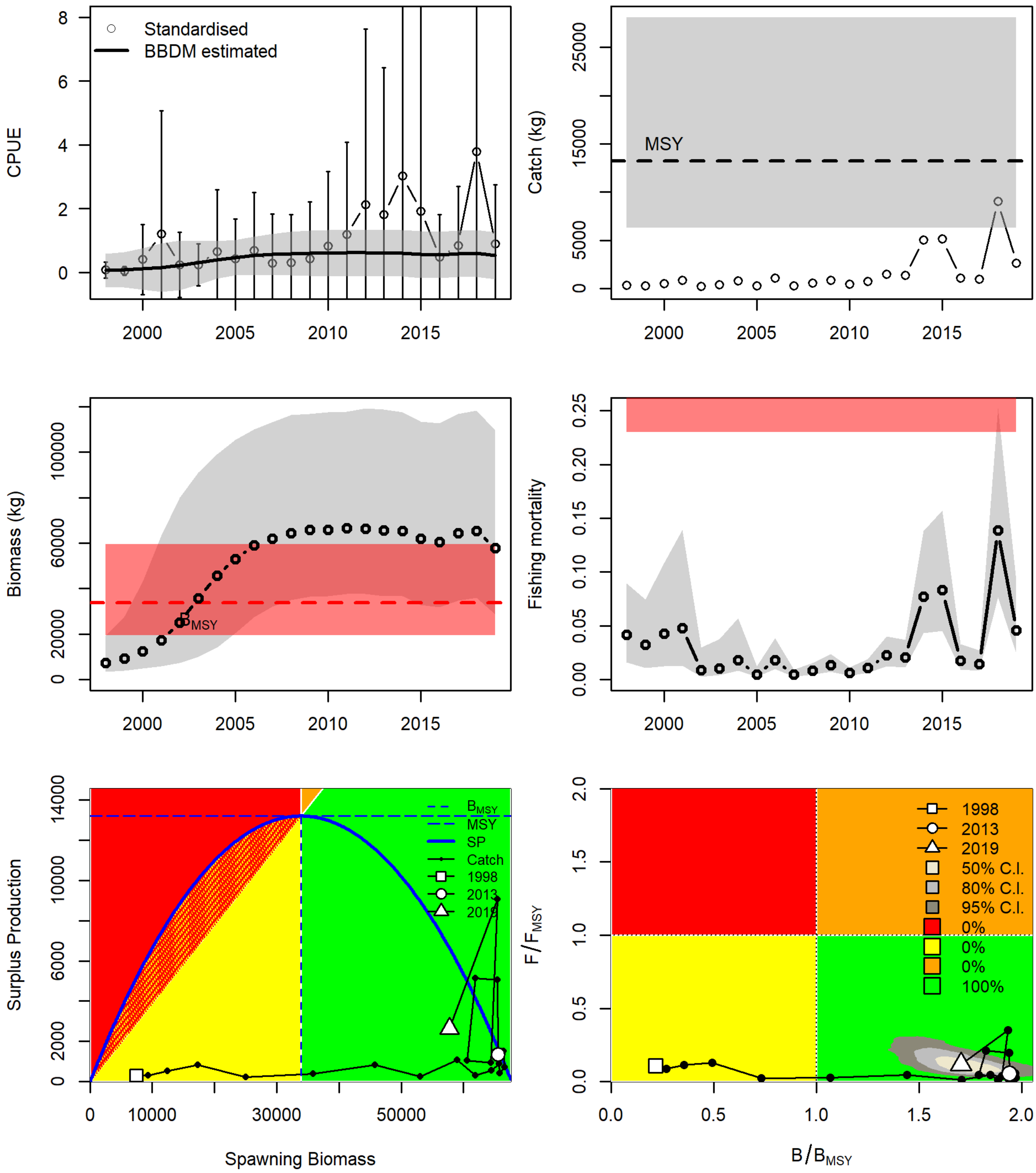

Figure 4-5. Sensitivity to setting the mean of the prior for *r* to the maximum estimate of r for Grooved and Brown tiger prawns (*r* = 0.792). The prior for initial biomass B_{1998} was set to Beta(0.9, 0.25). The error bars and the grey or red bands are 95% credible intervals while three levels of CIs are shown in the Kobe plot.

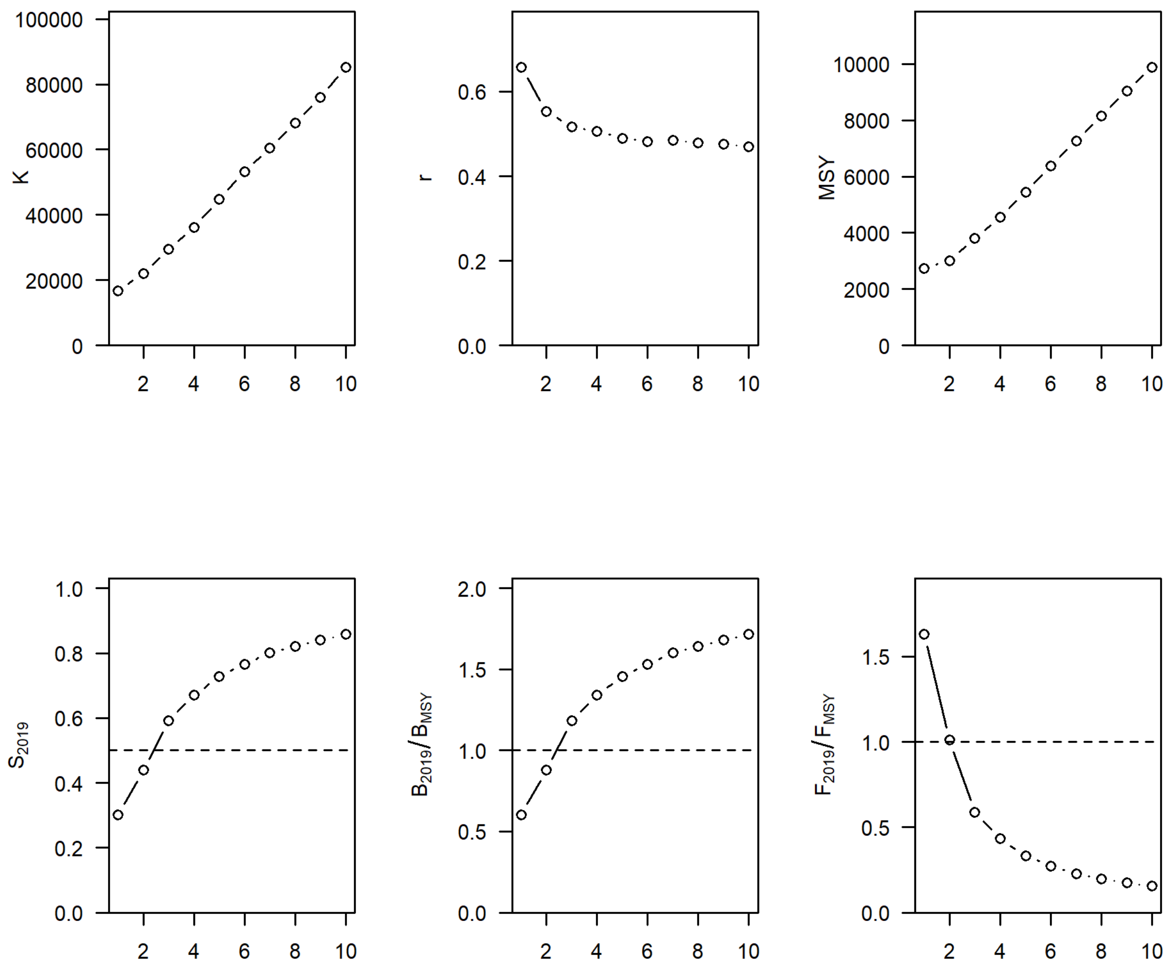

Figure 4-6. Sensitivity of key parameters to the prior for *K*. The plot in each panel is the posterior means. The x-axis is the multiplier to the maximum catch max(*C*), i.e., from 1 to 10 time of the maximum catch.

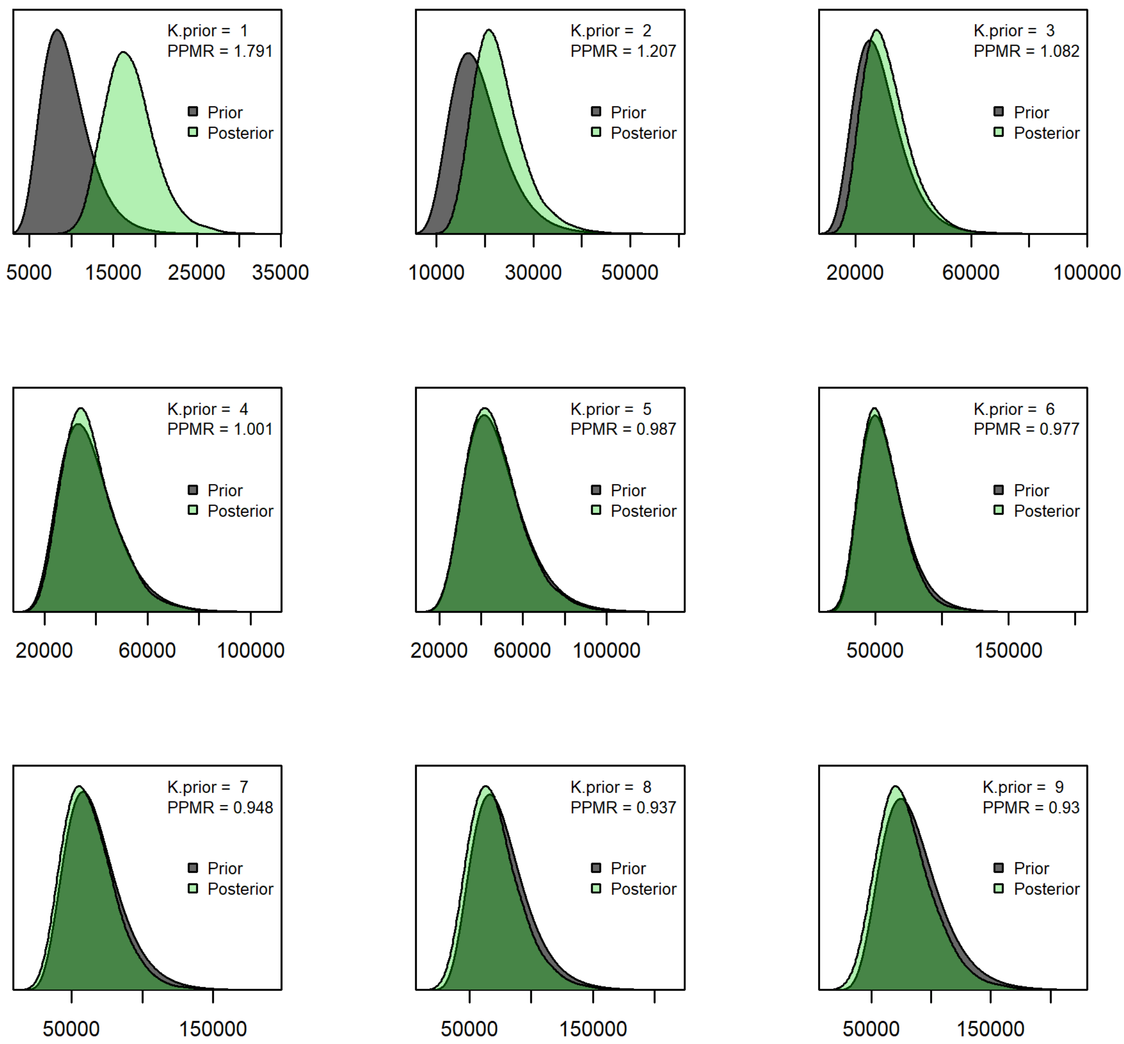

Figure 4-7. Prior and posterior *K* density distributions for four *K* priors: mean *K* from 1 to 9 times of max(*C*) and sd = 0.3. The prior *r* was based on mean for Grooved and Brown tiger prawns (r = 0.432). The prior for initial biomass B_{1998} was assumed to be Beta(0.9, 0.25).

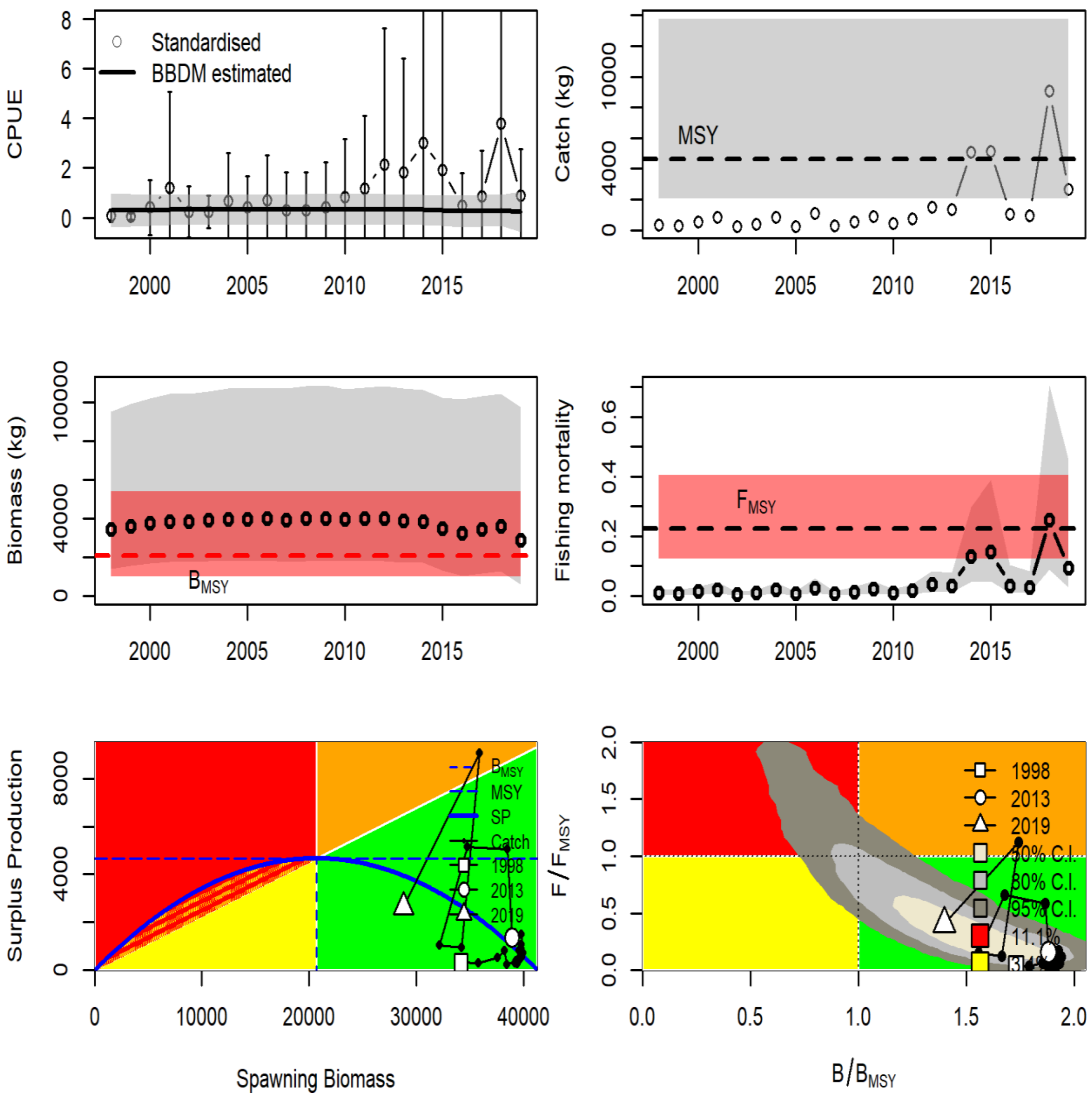

Figure 4-8. Results of the final model. Priors used: *K* ~ LN(4.4*max(*C*), 0.63); *r* ~ LN(0.432, 0.31); initial saturation φ ~ beta(0.9, 0.1). The error bars and the grey or red bands are 95% credible intervals while three levels of CIs are shown in the Kobe plot.

5 Stock assessment using catch-only methods

The standardized NPF commercial fleet CPUE exhibits an increase over time, especially during recent years. This unexpected pattern can be hard to interpret based on biological and population dynamics theory. Analysis using a Bayesian state-space surplus production model further substantiates the dilemma of using this index. Since Black tiger prawn is not a major target species in the NPF, CPUE data, even after standardisation, may not fully represent the trends in abundance. As discussed in the previous chapters, catchability and availability may have changed due to unknown variables not included in the model (such as a shift in targeting behaviour), leading to an increase in CPUE. Stock assessment based on such a distorted index can be misleading.

Compared to using CPUE as abundance index, catch data are more accurate and reliable, noting that there are reporting issues, particularly during the early years. It is useful to apply catch-only methods to compare and validate the model fitting approach (i.e., the Bayesian biomass dynamics model).

The idea of conducting stock assessments using primarily catch data is not new. This type of analysis was called Stock Reduction Analysis (SRA) and first explored in the 1980s (Kimura and Tagart, 1982; Kimura *et al.*, 1984). There has been an increased development of SRA-type methods in recent years and several methods based on this concept have be developed (Walters *et al.*, 2006; MacCall, 2009; Dick and MacCall, 2011; Martell and Froese, 2013; Froese *et al.*, 2017).

The optimized catch-only method (OCOM) belongs to the SRA class of methods (Zhou *et al.*, 2018). It uses an optimization algorithm rather than stochastic “thread the needle” approaches as in other SRAs and can be more efficient in finding feasible parameters. OCOM focuses on catch data and does not need information required by classic stock assessment models (e.g., age, length, sex, maturity, gear selectivity, fishing effort). The OCOM method can be enhanced by incorporating limited CPUE data to improve model performance.

5.1 Catch-only method and input data

The optimized catch-only method is based on the Graham-Schaefer surplus production model, which simplifies the Pella-Tomlinson (1969) 3-parameter generic production model (Equ 4-1) to a simple population dynamics model with only two parameters:

$$\boldsymbol{B_{t+1} = B_t + rB_t\left(1 - \frac{B_t}{K}\right) - \sum_f C_{f,t}} \qquad \textbf{Equ 5-1}$$

Catch-only methods do not try to “fit” a model to the data. Hence, there is no need to scale the biomass by *K* as in Equ 4-2. OCOM requires priors on *r* and stock saturation $S_{last} = B_{last}/K$ at the end of the catch time series. When information on *r* is not available, OCOM derives a prior distribution for *r* from life-history parameters such as natural mortality (*M*) and maximum lifespan (T_{max}), which in turn can be estimated from other life-history parameters. The prior distribution for the saturation parameter S_{last} is derived from the catch trend over the history of the fishery (Zhou *et al.*, 2017). With these two priors, *K* in equation 5-1 can be solved for by using an optimisation algorithm. Note that the so-called “prior” for *r* and *S* here is essentially the range or distribution of possible values and it differs from the prior in Bayesian models.

For the prior of the stock saturation level at the end of the time series, the existing OCOM uses skewed normal distributions separately for two ranges of estimated saturation from boosted regression tree (BRT) models, $S_{BRT,last} \leq 0.5$ and $S_{BRT,last} > 0.5$. The BRT model uses the RAM Legacy database and correlates depletion with a range of predictors calculated from catch data. The most important predictors are catch trends obtained from linear regressions of scaled catch on time, including regression coefficients for the whole catch time series, the sub-series before and after the maximum catch, and that for recent years. This model is used to predict $S_{BRT,last}$ for new fisheries such as Black tiger prawn in this report. Additional analysis has shown that using two skewed normal distributions does not necessary improve accuracy for most species tested (study unpublished). Hence, in this report, the prior for the saturation in the final year is modelled as beta distribution: $S_{prior,2019}$ ~ beta(α, β), where parameters α and β are estimated such that the mean of $S_{prior,2019}$ equals $S_{BRT,2019}$ from the BRT model and the variance of $S_{prior,2019}$ equals the variance of predicted S_{BRT} from the RAMLD, which is 0.18^2 (Table 5-1). The beta distribution ensure non-negative samples, the S prior is constrained within the range of [0, 1], and the distribution is skewed toward left when $S_{BRT,2019} < 0.5$ but skewed toward right when $S_{BRT,2019} > 0.5$ (similar to the result based on RAM Legacy Database).

Total annual catch data were the primary input required by OCOM. Again, the survival rate assumed for discarded prawns was based on an on-vessel experiment, which resulted in a mortality rate of 30%. CPUE can be included, but contrast between its increasing trend and the expected decreasing biomass due to fishing, prevents the model from converging. As such, the standardised index was not used in the final analyses. We again constructed the r prior by borrowing the estimate from the NPF Grooved tiger prawn assessment (Zhou *et al.*, 2009).

Implementation of the surplus production model (Equ 5-1) in the OCOM approach was efficient. Specifically, model implementation involved: (i) drawing a large number (e.g. n = 10,000 in this study) of values for r and S_{2019} from their priors; (ii) deriving K (from equation 5-1) by solving $B_{last}/K = S$ using an optimization algorithm (function “optimize” in R), and (iii) computing any output quantities of interest such as reference points F_{msy}, B_{msy}, and the time series of B_t and F_t.

To test the model sensitivity to the prior for saturation level based on $S_{BRT,2019}$, we explored two alternative priors: (i) based on S_{2019} estimated by JABBA in the previous chapter, i.e., $S_{prior,2019}$ ~ unif(0.29, 0.95), (ii) assuming the stock was severely depleted, i.e., $S_{prior,2019}$ ~ unif(0, 0.1). The former test was to see whether using the same input should lead to the same results, while the latter test was a worst case, which would reveal the worst possible stock status.

5.2 Results

Implementing OCOM using catch data only (without CPUE) was straightforward. Data-poor assessments often produces highly variable results so we included a 60% confidence interval (20% and 80% fractals; Figure 5-1). The median estimated K was about 33,245 kg, MSY 3,447 kg, B_{msy} 16,623 kg, and F_{msy} 0.21 yr^{-1} Table 5-1, Table 5-2). There were three years (2014, 2015, and 2018) where the total annual catch was greater than estimated MSY reference point (Figure 5-1, catch panel at the top left). The viable r-K pairs were widespread (Figure 5-1, top right panel), mainly due to highly uncertain depletion level particularly at the upper S range. For example, if the stock was lightly depleted (large S_{2019}), carrying capacity K could be very high. This skewed uncertainty can also be observed in the estimated biomass trajectories (Figure 5-1, biomass panel at the middle left). Nevertheless, this model indicated that the estimated median biomass had never been below the median B_{msy} reference point, and the lower 20% confidence interval for biomass was slightly below the B_{msy} during the last four years. The estimated fishing mortality rate mimicked the catch trend (Figure 5-1, middle right panel). Fishing mortality during 2018 was very high, but declined in 2019 with a median ratio $F_{2019}/F_{msy} = 0.66$. The Kobe plot (Figure 5-1, bottom left) suggested that Black tiger prawn was not overfished but overfishing occurred during 2018.

Stock depletion status is a leading indicator of sustainability and of primary interest in fishery management. However, depletion level is difficult to quantify even for many data-rich stocks. OCOM estimated that Black tiger had a median saturation of 59% in 2019, slightly larger than the BRT predicted 37%. The 80% confidence intervals of saturation ranged between 34% and 83% (Table 5-1, Table 5-2). The estimate was based on BRT model prediction from the catch history.

To some extent, OCOM allows the likelihood of the estimated depletion to be validated. To investigate the reliability of the results, we manually provided $S_{prior,2019}$ based on JABBA output. Comparing Table 4-5 with Table 5-3, and Figure 4-8 with Figure 5-2, we can see that the results from the two methods were similar in terms of the stock status.

We further assumed the stock was highly depleted and set $S_{\text{prior},2019}$ = c(0, 0.1), a clearly unlikely assumption. OCOM searched *K* values that minimized the squared error between the BDM estimated final year S_{2019}, given the known catch history and the *r* prior and *S* prior. The unrealistic *S* prior resulted in more pessimistic outcomes than those using BRT predicted saturation (Figure 5-3). The most obvious difference was the linear viable *r*-*K* pairs. This was because each viable *K* resulted from a random *r* and a *S* closest to the range of [0, 0.1]. The estimated parameters were very conservative. The estimated fishing mortality in 2019 was 3.1 times of F_{msy}, a seriously case of overfishing. The stock was below B_{msy} level. In fact, when $S_{\text{prior},2019}$ was set to such low level, the estimated 80% CI of S_{2019} ranged from 0.20 to 0.23 with a median of 0.21. These values suggested that in the worst scenario Black tiger stock was unlikely to have been depleted below 20% of its unfished level, if their productivity was similar to Grooved or Brown tiger prawns (Figure 5-4).

A sensitivity test was also carried out on the survival rate of discarded prawns in broodstock collection. Similar to the test using JABBA, we assumed a 100% mortality for the discarded prawns instead of the observed 30% mortality. The OCOM results confirm that assuming 100% mortality for the discarded prawns has a minor effect (Table 5-5). The relative change ($= \frac{\theta_{100\%}-\theta_{30\%}}{\theta_{30\%}} \times 100$) ranges from 0 to 7%. OCOM involves stochastic process so these changes also include the stochastic effect in modelling process. Again, the general conclusion about the stock status (i.e., the stock was not overfished and overfishing did occur in 2019) remains unchanged.

5.3 Discussion

Compared to the Bayesian state-space model, the catch-only method produces more conservative results. The estimated median carrying capacity is lower (33.2 tonnes vs. 41.3 tonnes), which also leads to a lower MSY (3.4 tonnes vs. 4.6 tonnes). However, the overall conclusions about the stock status are similar between the two assessment methods. Both models concur that the median biomass has always been above the B_{msy} level, and overfishing may have taken place in 2018. Again, to detect the maximum stock size and production potential, a stock has to be overfished in some years. We have not seen this in the available time series. It is worth noting that the total fishery removal (catch plus discard mortality) in 2019 is lower than in 2018. Whether this is due to a reduced abundance or due to commercial fishing simply not catching this species has a significant consequence on stock status. It is very important to vigilantly monitor both the broodstock collection and commercial fishing in the next one or two years.

Table 5-1. Input and priors for the optimized catch-only method.

Variables	Description
Year	1998—2019
Catch	NPF + broodstock
CPUE	NPF commercial logbook
r (based on NPF Grooved tiger)	*r*.prior = *LN*(median = 0.432, sd = 0.136, sigma = 0.307)
K range (required by optimization function)	max(*C*) to max(C)*80
Initial saturation	$S_0 = 1$
Saturation prior	$S_{prior} = Beta\left(\begin{array}{c} \alpha = \frac{(1-S_{BRT})S_{BRT}^2}{0.18^2} - S_{BRT}, \\ \beta = \left[\frac{(1-S_{BRT})S_{BRT}^2}{0.18^2} - S_{BRT}\right]\frac{1-S_{BRT}}{S_{BRT}} \end{array}\right)$
Biomass threshold	$B_{lim} = 0.25\ K$

Table 5-2. Key biological and management parameters estimated by OCOM. Saturation $S_{prior,2019}$ is based on BRT model prediction. The %s are the percentiles of the 10,000 stochastic samples. Parameter units are the same as in Table 4-1.

Param	10%	20%	50%	80%	90%
K	21,212	24,082	**33,245**	52,234	71,439
r	0.28	0.32	**0.42**	0.54	0.62
MSY	2,207	2,524	**3,447**	5,475	7,569
S_{2019}	0.34	0.43	**0.59**	0.75	0.83
B_{msy}	10,606	12,041	**16,623**	26,117	35,719
F_{msy}	0.14	0.16	**0.21**	0.27	0.31
B_{2019}	7,398	10,347	**19,597**	38,995	58,403
F_{2019}	0.05	0.07	**0.13**	0.26	0.36
B_{2019}/B_{msy}	0.69	0.86	**1.19**	1.51	1.65
F_{2019}/F_{msy}	0.21	0.33	**0.66**	1.23	1.70

Table 5-3. Sensitivity of the OCOM results to setting the prior for saturation $S_{prior,2019}$ from JABBA output of 95%CI (i.e., 0.29—0.95). 50% is the median value of the 10,000 stochastic samples.

Param	10%	20%	**50%**	80%	90%
K	21,992	24,719	**35,379**	68,750	109,866
r	0.28	0.32	**0.41**	0.53	0.61
MSY	2,248	2,546	**3,647**	7,177	11,062
S_{2019}	0.36	0.43	**0.62**	0.82	0.88
B_{msy}	10,996	12,360	**17,689**	34,375	54,933
F_{msy}	0.14	0.16	**0.21**	0.27	0.31
B_{2019}	8,046	10,495	**21,799**	56,605	96,577
F_{2019}	0.03	0.05	**0.12**	0.25	0.33
B_{2019}/B_{msy}	0.72	0.85	**1.24**	1.64	1.77
F_{2019}/F_{msy}	0.14	0.22	**0.59**	1.23	1.60

Table 5-4. Testing worst scenario by assuming unrealistically low saturation $S_{prior,2019}$ of [0, 0.1], a highly depleted status.

Param	10%	20%	**50%**	80%	90%
K	16,381	17,401	**19,535**	21,569	22,566
r	0.28	0.32	**0.41**	0.54	0.61
MSY	1,585	1,717	**2,009**	2,342	2,510
S_{2019}	0.20	0.20	**0.21**	0.22	0.23
B_{msy}	8,191	8,700	**9,767**	10,785	11,283
F_{msy}	0.14	0.16	**0.21**	0.27	0.31
B_{2019}	3,702	3,857	**4,149**	4,386	4,487
F_{2019}	0.59	0.60	**0.64**	0.69	0.71
B_{2019}/B_{msy}	0.40	0.41	**0.42**	0.44	0.45
F_{2019}/F_{msy}	2.33	2.55	**3.10**	3.79	4.20

Table 5-5. Model sensitivity to survival rate of discarded prawns in broodstock collection. All discards are assumed to be dead. Rel change is the relative change between the model that assumes 100% discard mortality and the OCOM model in Table 5-2.

Param	10%	20%	**50%**	80%	90%	Rel change
K	21,961	24,854	**34,233**	54,658	75,180	3%
r	0.28	0.32	**0.42**	0.54	0.61	0%
MSY	2,232	2,586	**3,549**	5,688	7,725	3%
S_{2019}	0.35	0.44	**0.60**	0.76	0.83	2%
B_{msy}	10,981	12,427	**17,116**	27,329	37,590	3%
F_{msy}	0.14	0.16	**0.21**	0.27	0.31	0%
B_{2019}	7,868	10,865	**20,603**	41,409	62,005	5%
F_{2019}	0.05	0.07	**0.14**	0.27	0.38	7%
B_{2019}/B_{msy}	0.71	0.87	**1.21**	1.52	1.66	2%
F_{2019}/F_{msy}	0.23	0.35	**0.70**	1.31	1.87	7%

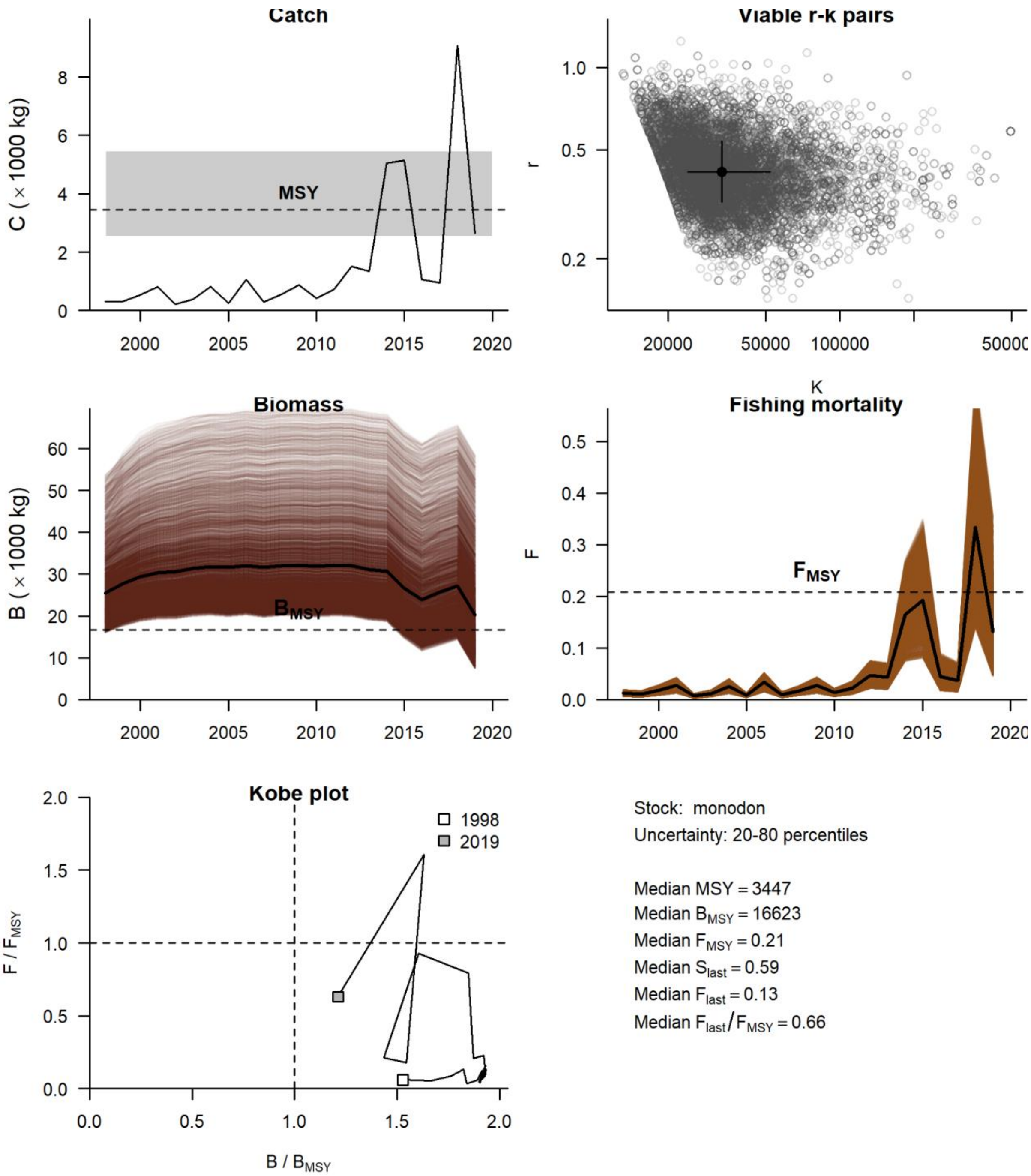

Figure 5-1. Output from the optimized catch-only method. The *$S_{prior,2019}$* is derived from BRT model prediction.

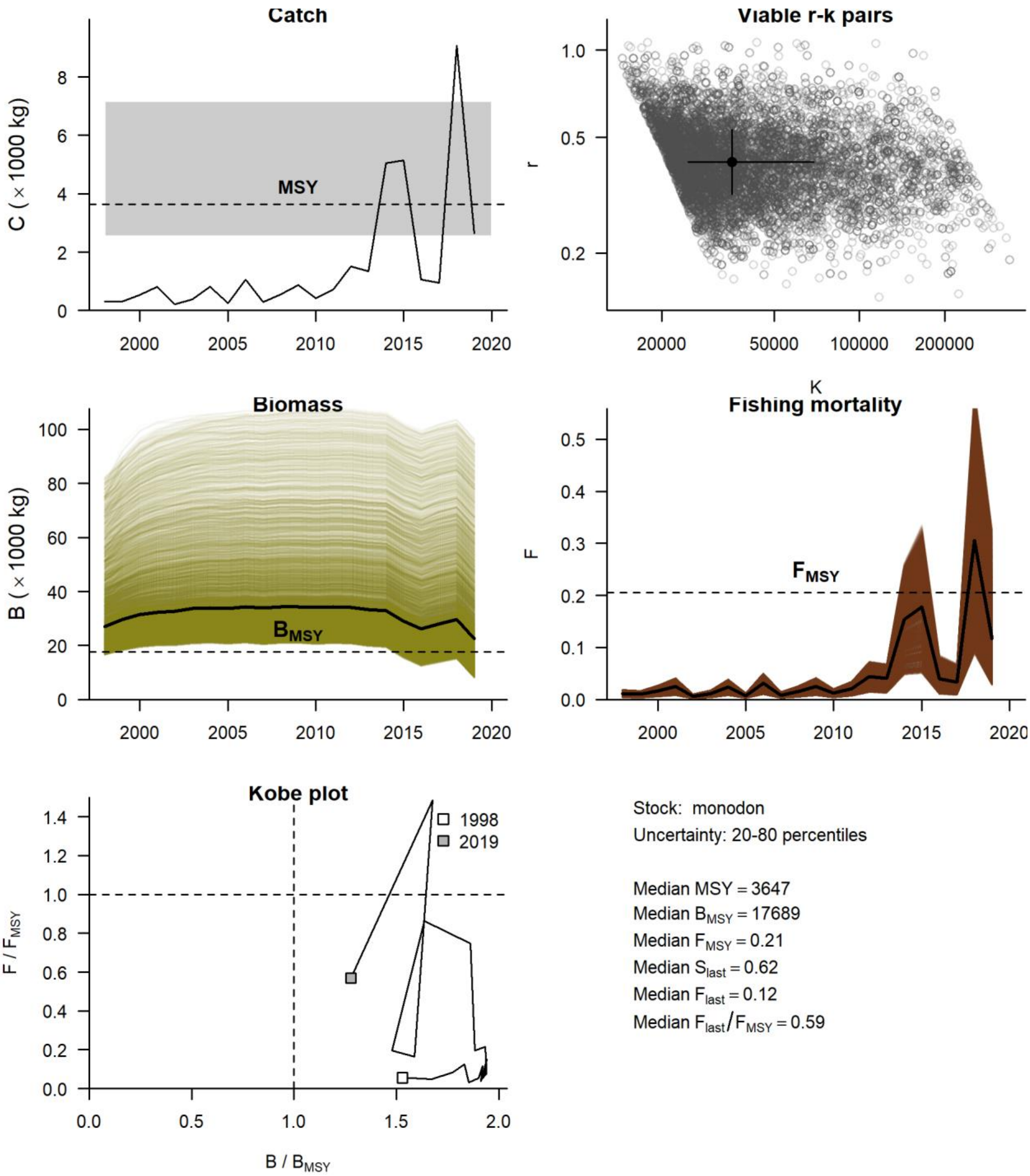

Figure 5-2. Sensitivity of the application of the optimized catch-only method to the Black tiger prawn by using $S_{prior,2019}$ from JABBA output (S_{2019} = 0.29-0.95).

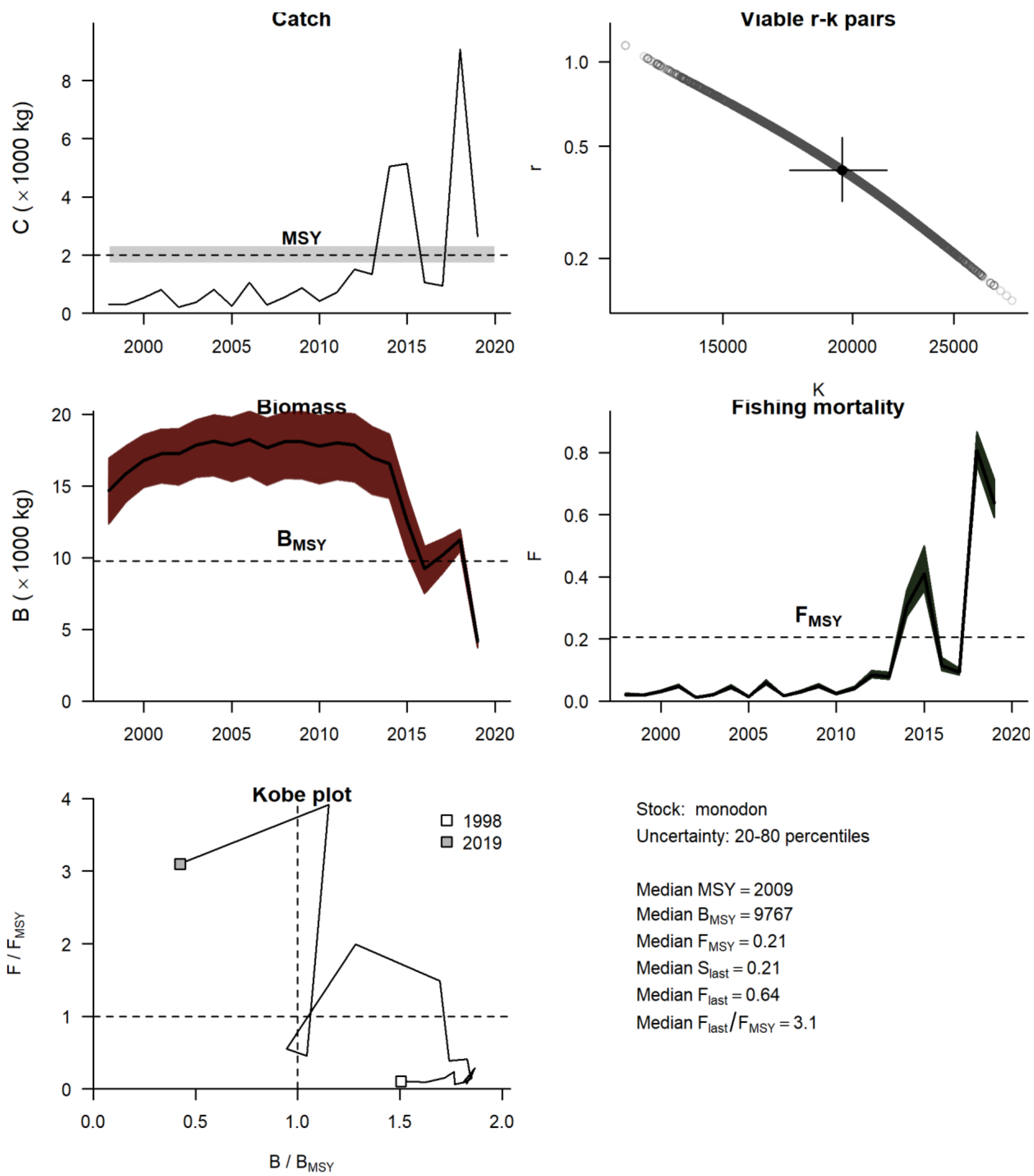

Figure 5-3. Testing the worse scenario by assuming that $S_{prior,2019}$ is unrealistically low, i.e., between 0 and 0.1.

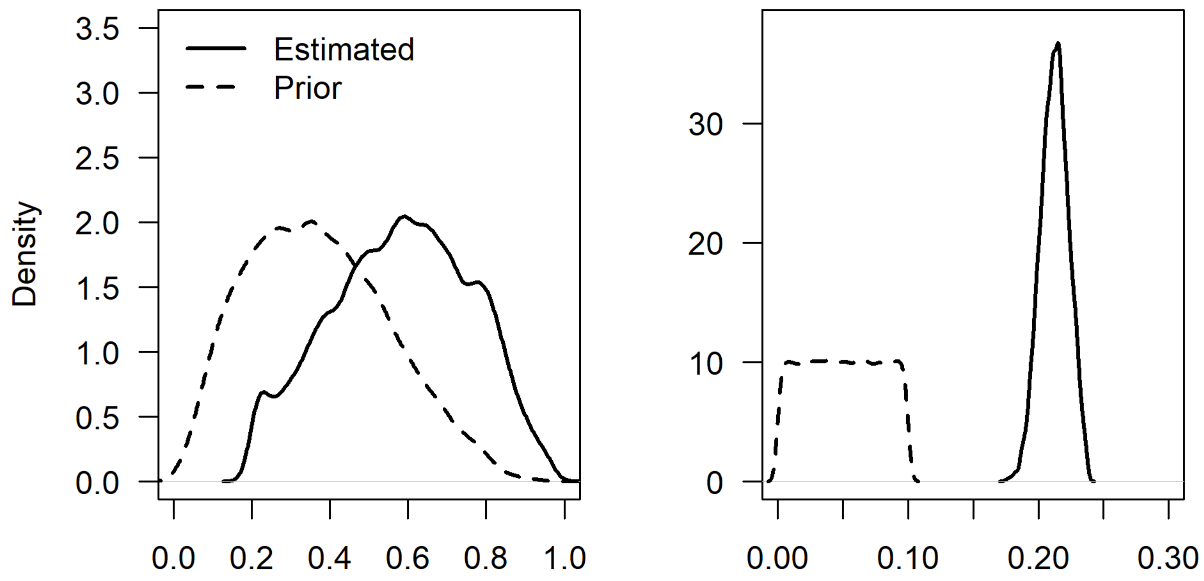

Figure 5-4. Comparison of saturation distribution between priors based on BRT prediction and assumed low values. Left panel: prior based on BRT model prediction; right panel: assuming $S_{prior,2019}$ range between 0 and 0.1 (highly depleted stock).

6 Stock assessment of high broodstock fishing effort area

The total removal of Black tiger prawns by the broodstock collection (retained catch plus dead discards) has increased by an average about 68% annually since 2013. During 2013-2019, the removal of Black tiger prawns by broodstock collection is about 14% of the total fisheries removals. Fishing effort in the broodstock collection has been concentrated off Cape Van Dieme (about 66% of the total tows) and the JBG (about 33% of the total tows). The dramatic increase of catch and constrained fishing area (i.e. localised) have become a concern for the sustainability of the local population if these prawns belong to a separate sub-stock. In this chapter, we assumed that the population in the broodstock high fishing effort area is a unique sub-stock and conducted stock assessments for this sub-stock.

6.1 Defining high fishing effort area

Between 2005 and 2019 approximately 98% of fishing effort in the broodstock collection took place in two stock regions: Cape Van Diemen (CVD) and the Joseph Bonaparte Gulf (JBG). The total catch (including discards) in these two stock regions summed to almost all of the total catch over all regions (69.7% from CVD and 29.9% from JBG). Although CVD had a highest effort and catch, it may be inappropriate to exclude the JBG. In addition, these two regions are relatively close to each other, compared to the Gulf of Carpentaria. Hence, we considered the populations in the two areas as potentially a single stock.

We first considered the grids where broodstock fishing effort was greater than the mean fishing effort across all grids fished by the broodstock collection (green box in Figure 6-1). We then examined all grids in the CVD and JBG fished by the broodstock collection. The area covering all these grids (box with the black line in Figure 6-1) wasn't much larger than the green box. We chose this large box as the hypothetic sub-stock region, which avoids the potential high catch by the commercial fishing outside the green box but within the black box. This larger box is defined by latitude between -13.6 and -10.0, and longitude between 127.2 and 132.2. The data are all fisheries removals within this box, including retained catch and dead discards in the broodstock collection and catch in the commercial fishery.

This hypothetic sub-stock area contained over 98% of black tiger prawns removal by the broodstock collection. The fraction of catch by the commercial fishing in this stock area ranged from 0 to 80% from 1989 to 2019 with a mean of 41.2%.

6.2 Assessment approaches

The two stock assessment methods applied to the whole NPF region were applied to the hypothetical sub-stock. As before, we assumed that the intrinsic population growth rate is similar to that for Grooved and Brown tiger prawns. The methodology, both the Bayesian state-space model and the optimized catch-only method were the same as described in the previous chapter. The main difference from the whole NPF assessment was the catch data in the limited area (Table 6-1).

6.3 Results

6.3.1 Bayesian state-space biomass dynamics model

We used the same technique to find the proper *K* prior, i.e., by varying the value of *K* prior and then comparing the posterior and prior distributions. This led to the median *K* prior of 4.9 times the maximum catch. Sensitivity tests showed that although changing the median of *K* prior from 3*max(*C*) (= 8,438 kg) to 10*max(*C*) (= 28,13 kg) had an effect on some key management parameters, it did not change the overall conclusion on stock status (Figure 6-2).

The final model used the following priors: *K*.prior = *LN*(mean = *max*(*C*)*4.4, σ= 0.63), φ = *beta*(*a* = 0.9, *b* = 0.1), and *r*.prior = *LN*(mean = 0.432, σ= 0.306), which are consistent with the models used for the whole NPF. One obvious difference from the whole NPF region assessment was the lower catch in this sub-stock region in 2014, 2015, and 2018 (Figure 6-3). However, the total removal in 2018 (about 2,813 kg) was still the highest during the 22 years, which is above the estimated MSY level. The high catch in 2018 was the direct driver for the high fishing mortality rate F_{2018}, which is above the mean F_{msy} (Figure 6-3). The posterior mean for unfished biomass *K* in this area was about 12.9 tonnes, F_{msy} about 0.23 yr^{-1}, B_{msy} 6.4 tonnes, and MSY 1.5 tonnes (Table 6-2). The output of the model indicated that since 2014 the total annual catch were greater than the lower 95% CI for MSY. Mean fishing mortality F_{2018} was greater than mean F_{msy}, but mean biomass in all years was above mean B_{msy} (Figure 6-3). The sub-stock may have not been overfished but overfishing may have occurred in 2018 (Table 6-2).

As requested by the NPRAG in November 2020, we conducted additional sensitivity test on discard survival rate in broodstock collection in CVD and JBG regions. Assuming 100% mortality for discarded prawns leads to a relative change between -2% and 11% for the key parameters (Table 6-5). The overall conclusion about the stock status remains the same (i.e., not overfished and no overfishing in 2019), in spite of the relative larger proportion of discards in the total catch within this confined region (between 0 and 26%, with mean of 8%).

6.3.2 Optimized catch-only method

OCOM does not require CPUE data and can use catch data only. The median estimated carrying capacity in the broodstock high fishing effort area was about 8.9 tonnes and the median MSY about 1 tonne (Table 6-3). The total annual catch in this area was greater than the median MSY in 2014, 2015, 2018 and 2019 (Figure 6-4, catch panel at the top left). The estimated *K* values were highly uncertain (Figure 6-4, top right panel), mainly due to highly uncertain depletion level particularly at the upper *S* range (if the stock is lightly depleted, carrying capacity *K* can be very large). OCOM estimates that Black tiger in the high fishing effort region has a median saturation of 46% in 2019, which translates to B_{2019}/B_{msy} = 0.92 (Table 6-3). The estimated fishing mortality rate mimics the catch trend (Figure 6-4, middle right panel). Fishing mortality in the last two years was very high and their median values were greater than median F_{msy}. The Kobe plot (Figure 6-4, bottom left) suggests that Black tiger prawn has been slightly overfished and overfishing may have also occurred in 2018 and 2019.

To investigate the reliability of the depletion estimate and the worst scenario, we assumed the stock was highly depleted and set $S_{prior,2019}$ = c(0, 0.1). This unrealistic *S* prior resulted in a median S_{2019} = 0.31 (Table 6-4, Figure 6-5). This means that given the continuously increasing catch trend, it is possible that the population in the high fishing effort area could have been overfished (biomass below the B_{msy} level). Under this unrealistic assumption, fishing mortality rates in 2018 and 2019 were very high – about 3 times F_{msy}. The total annual removal of Black tiger was greater than MSY since 2012 except 2013 and 2017 (Figure 6-5). These results were for sensitivity test only and should not be considered as likely status.

We also used OCOM to conduct a sensitivity test on discard survival rate in broodstock collection in CVD and JBG regions. Assuming 100% mortality for discarded prawns results in a relative change between -1% and 19% for the key parameters (Table 6-6). The relative changes are larger than BBDM but the overall conclusion about the stock status remains the same (i.e., slightly overfished and overfishing occurred in 2019).

6.4 Discussion

In this chapter we aim to address management concerns about the high fishing effort and catch by the broodstock collection in the recent years. Nearly 99% of broodstock fishing has taken place in Cape Van Dieme and Joseph Bonaparte Gulf areas. The total catch (including discard mortality) from this high effort region was over 2,800 kg in 2018 and over 1,400 kg in 2019. Is such a high fishing intensity sustainable if the population in this region is a unique stock? To answer this question, we assume that the population in this region is independent from other areas and developed a population dynamics model for this sub-stock only. We used both a Bayesian state-space production model and catch-only method. The results are somewhat different. The BBDM indicates that the mean biomass for this putative sub-stock has always been greater than B_{msy} level (i.e., not overfished). However, the catch-only model suggests that the median biomass in 2019 is slightly below median B_{msy} (i.e., possibly overfished). The BBDM suggests the fishing mortality may have been greater than F_{msy} in 2018, but COM indicates overfishing may have happened in both 2018 and 2019. Catch status is similar between the two methods, both suggesting that the total removal by broodstock collection and commercial fishing may have been higher than MSY level in 2018 and 2019.

Given the short life span (adult 6 month to 2 years, Gribble *et al.*, 2003) and the continuous increase of catch, fishery data so far may have not revealed the true production potential in this enclosed region, if the population inside is indeed a separate sub-stock. It is well-known that to find out the maximum potential stock size and productivity, the data should include some years when the exploited stock was overfished.

Since both models suggest that the total catch has been higher than MSY and fishing mortality may have been higher than F_{msy} in recent years, it is prudent not to increase catch substantially in the next couple of years. Ideally, the catch level in 2019 (about 1,500 kg) could be maintained for two years to see if this sub-stock can support this level of production before increasing catch further. The rationale is that all catch is made up by recruits spawned within two years. If this level of catch can be maintained for three consecutive years, it indicates that the number of spawners left after fishing can produce enough recruits. However, if the stock cannot support such a level of harvest, recruitment overfishing will occur and catch will decline in the next one or two years. As such fishery removals should be reduced immediately.

Table 6-1. Catch of black tiger prawns in the hypothetical sub-stock area. The Retained and Discarded catch from the broodstock collection are numbers of prawns, and the Removal is total weight in kg where the mean weight per prawn is assumed to be 100g and the mortality rate for the discards is assumed to be 30%.

	Logbook	Broodstock			
Year	Catch(kg)	Retain(N)	Discard(N)	Dead(kg)	Total(kg)
1998	175				175
1999	153				153
2000	396				396
2001	214				214
2002	127				127
2003	250				250
2004	460				460
2005	138	561		56	194
2006	41				41
2007	-				-
2008	25				25
2009	34				34
2010	213				213
2011	185				185
2012	984				984
2013	378	2,065	259	214	592
2014	1,268	1,104		110	1,378
2015	770	3,931	54	395	1,165
2016	369	5,533	75	556	925
2017	272	3,597	1,318	399	671
2018	2,169	6,011	1,415	644	2,813
2019	311	10,189	4,785	1,162	1,473

Table 6-2. Posteriors for the putative sub-stock in broodstock high fishing effort area. The *r* prior was constructed from the mean and variance of estimated *r* for Grooved tiger prawn, the *K* prior was constructed using a mean of 4.4 times of maximum catch and a sd of 0.63, and the mean of the prior for the biomass in 1998 was about 0.9B_0. The units for each parameter are the same as in Table 4-1.

Param	Mean	2.5%	97.5%
K	12,865	6,243	33,028
r	0.46	0.25	0.82
F_{msy}	0.23	0.13	0.41
B_{msy}	6,432	3,121	16,514
MSY	1,464	651	4,145
S_{1998}	0.86	0.47	1.04
S_{2019}	0.67	0.26	0.93
B_{2019}/B_{msy}	1.35	0.51	1.85
F_{2019}/F_{msy}	0.75	0.20	4.26

Table 6-3. Key biological and management parameters estimated by OCOM for sub-stock in the broodstock high fishing effort area. The prior for saturation $S_{prior,2019}$ is based on BRT model prediction.

Param	10%	20%	**50%**	80%	90%
K	6,674	7,302	**8,855**	12,565	15,695
r	0.28	0.32	**0.42**	0.54	0.63
MSY	681	758	**953**	1,305	1,622
S_{2019}	0.31	0.33	**0.46**	0.63	0.71
B_{msy}	3,337	3,651	**4,428**	6,282	7,847
F_{msy}	0.14	0.16	**0.21**	0.27	0.31
B_{2019}	2,229	2,378	**3,986**	7,825	11,136
F_{2019}	0.13	0.19	**0.37**	0.62	0.66
B_{2019}/B_{msy}	0.62	0.66	**0.92**	1.26	1.42
F_{2019}/F_{msy}	0.65	0.91	**1.72**	2.78	3.34

Table 6-4. Key biological and management parameters estimated by OCOM for the sub-stock in the broodstock high fishing effort area. The prior for saturation $S_{prior,2019}$ is based on an assumed very low prior of [0, 0.1].

Param	10%	20%	50%	80%	90%
K	6,136	6,560	7,314	8,046	8,452
r	0.28	0.32	0.42	0.54	0.62
MSY	595	651	761	881	953
S_{2019}	0.29	0.30	0.31	0.33	0.34
B_{msy}	3,068	3,280	3,657	4,023	4,226
F_{msy}	0.14	0.16	0.21	0.27	0.31
B_{2019}	2,091	2,167	2,292	2,401	2,456
F_{2019}	0.60	0.61	0.64	0.68	0.70
B_{2019}/B_{msy}	0.58	0.60	0.63	0.66	0.68
F_{2019}/F_{msy}	2.27	2.53	3.09	3.79	4.26

Table 6-5. BBDM sensitivity to survival rate of discarded prawns in broodstock high fishing effort area. All discards are assumed to be dead. Rel change is the relative change between the model that assumes 100% discard mortality and the model in Table 6-2.

Param	Mean	2.5%	97.5%	Rel change
K	14,095	7,247	34,324	10%
r	0.45	0.24	0.81	-2%
F_{msy}	0.22	0.12	0.40	-2%
B_{msy}	7,048	3,624	17,162	10%
MSY	1,571	703	4,343	7%
S_{1998}	0.85	0.39	1.04	-1%
S_{2019}	0.69	0.32	0.93	3%
B_{2019}/B_{msy}	1.38	0.65	1.85	3%
F_{2019}/F_{msy}	0.83	0.24	3.72	11%

Table 6-6. OCOM sensitivity to survival rate of discarded prawns in broodstock high fishing effort area. All discards are assumed to be dead. Rel change is the relative change between the model that assumes 100% discard mortality and the model in Table 6-3.

Param	10%	20%	**50%**	80%	90%	Rel change
K	7,184	7,793	**9,226**	12,670	15,934	4%
r	0.28	0.32	**0.42**	0.54	0.61	-1%
MSY	723	798	**991**	1,316	1,619	4%
S_{2019}	0.35	0.37	**0.46**	0.62	0.70	-1%
B_{msy}	3,592	3,896	**4,613**	6,335	7,967	4%
F_{msy}	0.14	0.16	**0.21**	0.27	0.31	-1%
B_{2019}	2,746	2,876	**4,110**	7,689	11,017	3%
F_{2019}	0.16	0.24	**0.44**	0.63	0.66	19%
B_{2019}/B_{msy}	0.70	0.73	**0.92**	1.25	1.40	-1%
F_{2019}/F_{msy}	0.81	1.13	**2.04**	2.99	3.47	19%

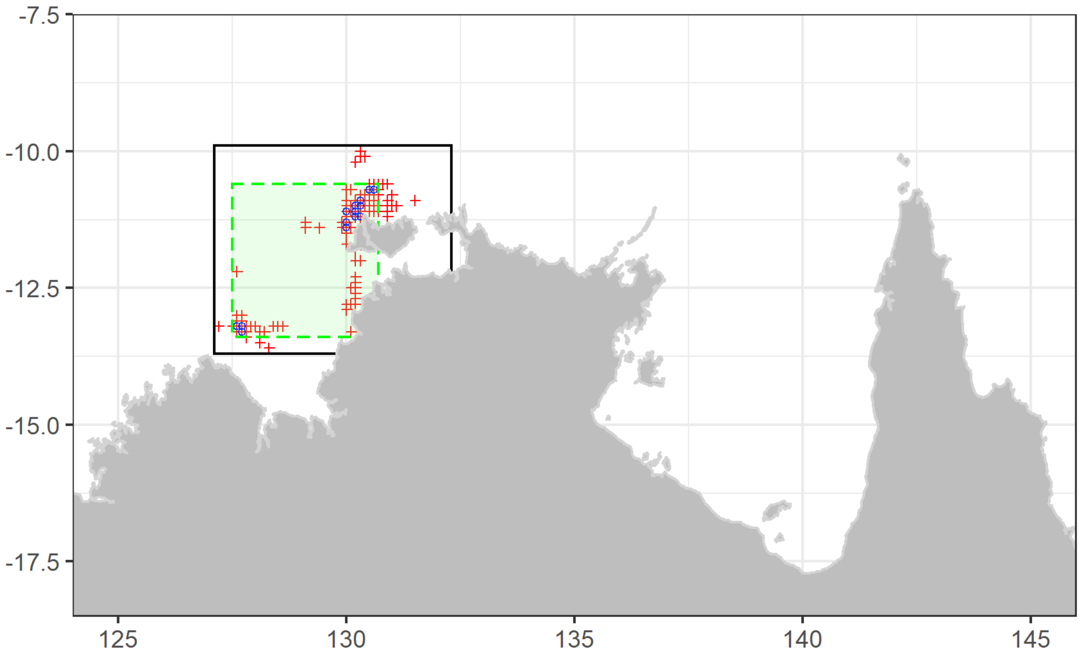

Figure 6-1. Broodstock collection concentrated fishing locations (2005 to 2019). The blue circles are grids with fishing effort (number of tows) greater than the average, which is enveloped within the green box. The red crosses are all effort covered by the black-lined box.

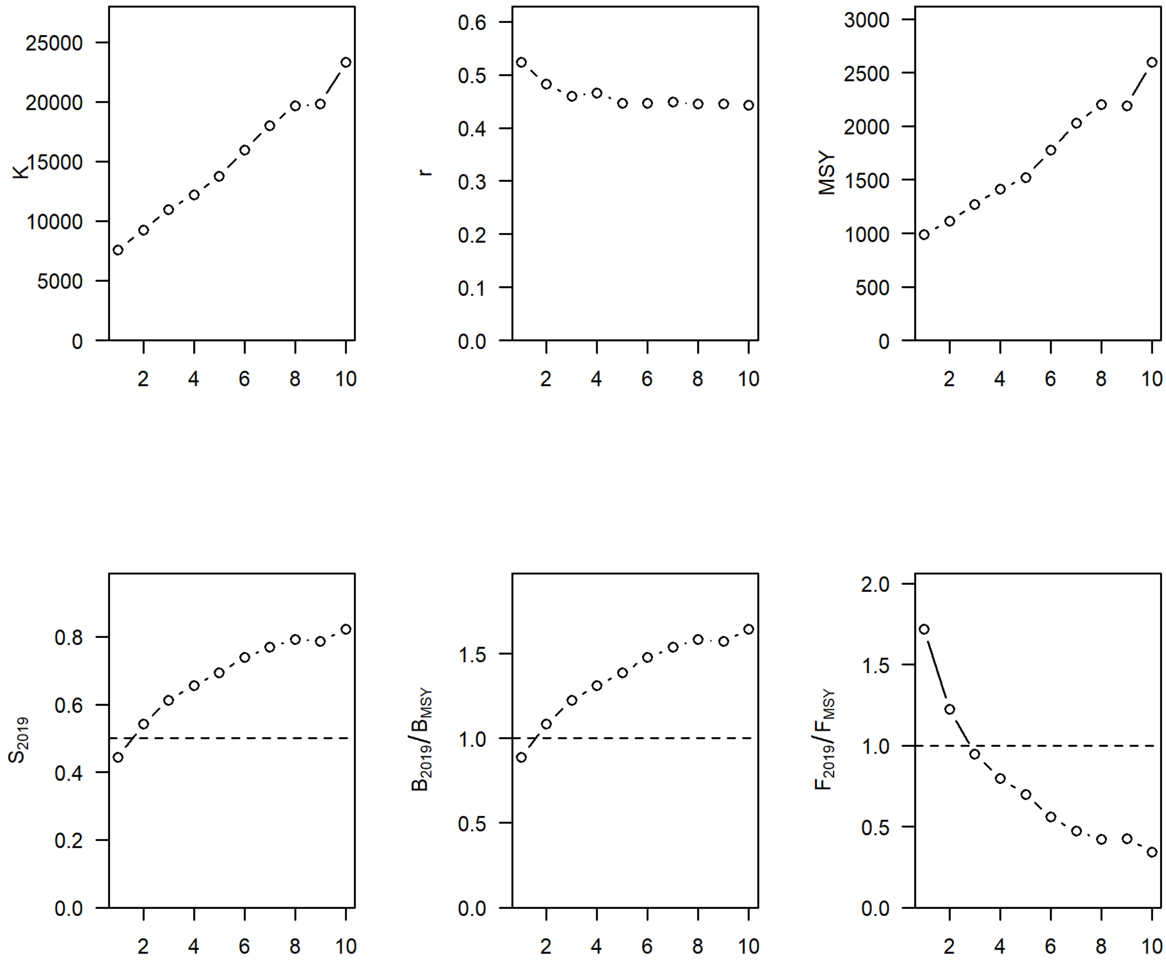

Figure 6-2. Effect of varying the median of *K* prior values on key management quantities. The plot in each panel is the posterior mean from JABBA. The x-axis values are the multipliers on the maximum catch over 1989-2019 period.

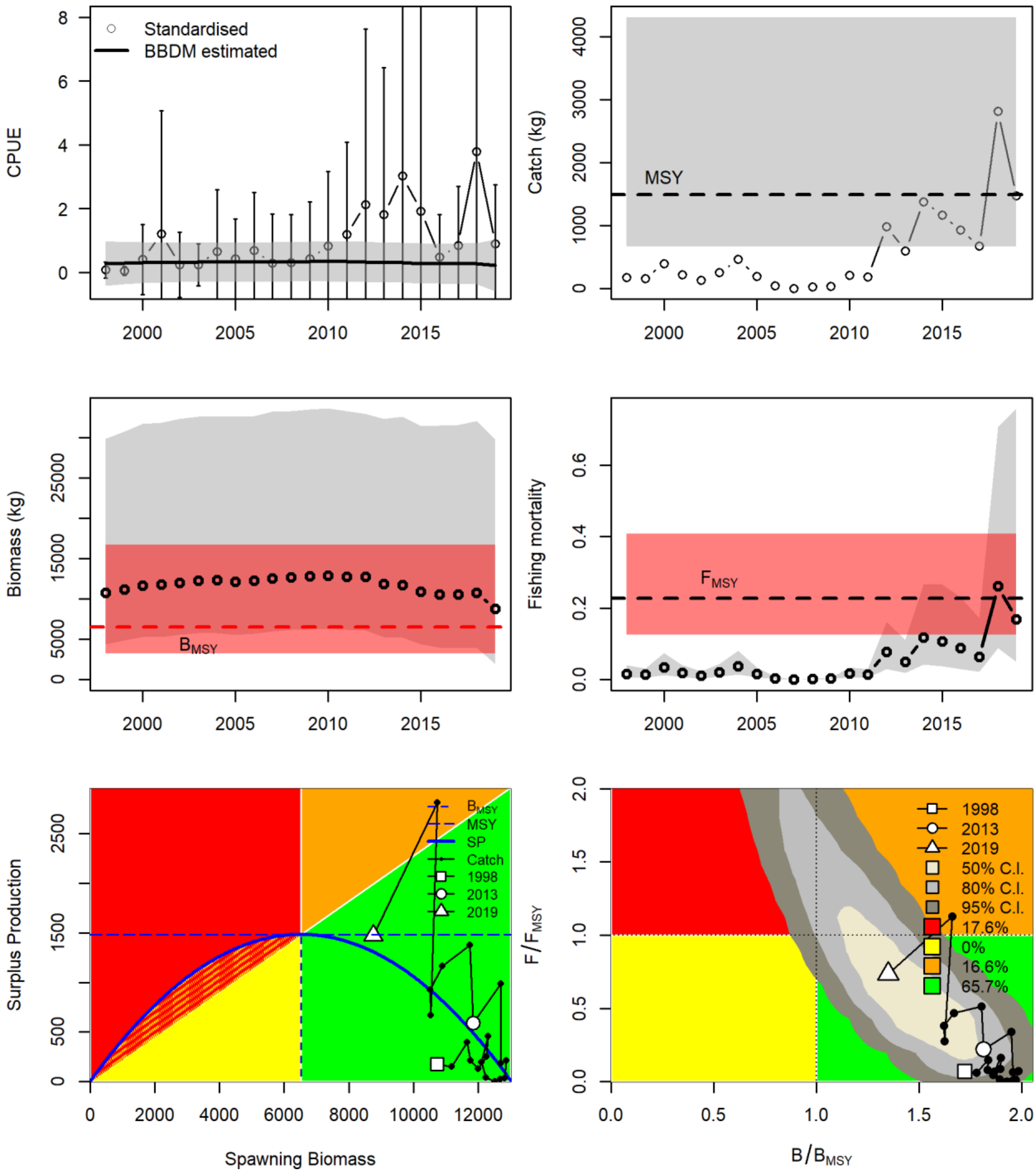

Figure 6-3. Bayesian biomass dynamics model results for the putative sub-stock in the broodstock high fishing effort area. Priors used: *K* ~ LN(4.4*max(*C*), 0.63); *r* ~ LN(0.432, 0.31); initial saturation φ ~ beta(0.9, 0.1). The error bars and the grey or red bands are 95% credible intervals while three levels of CIs are shown in the Kobe plot.

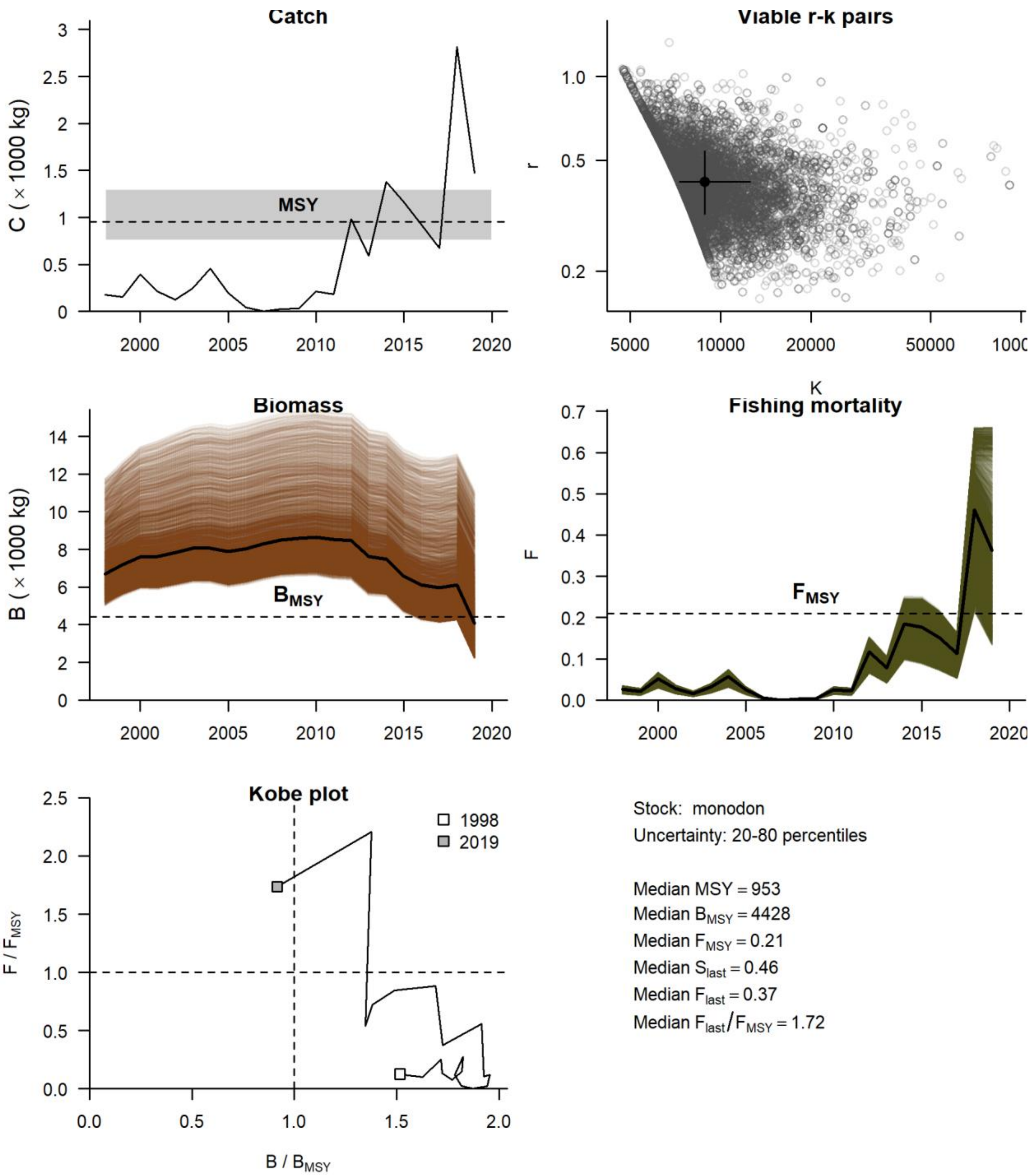

Figure 6-4. Output from the optimized catch-only method for the putative sub-stock in broodstock high fishing effort area. The $S_{prior,2019}$ is derived from BRT model prediction.

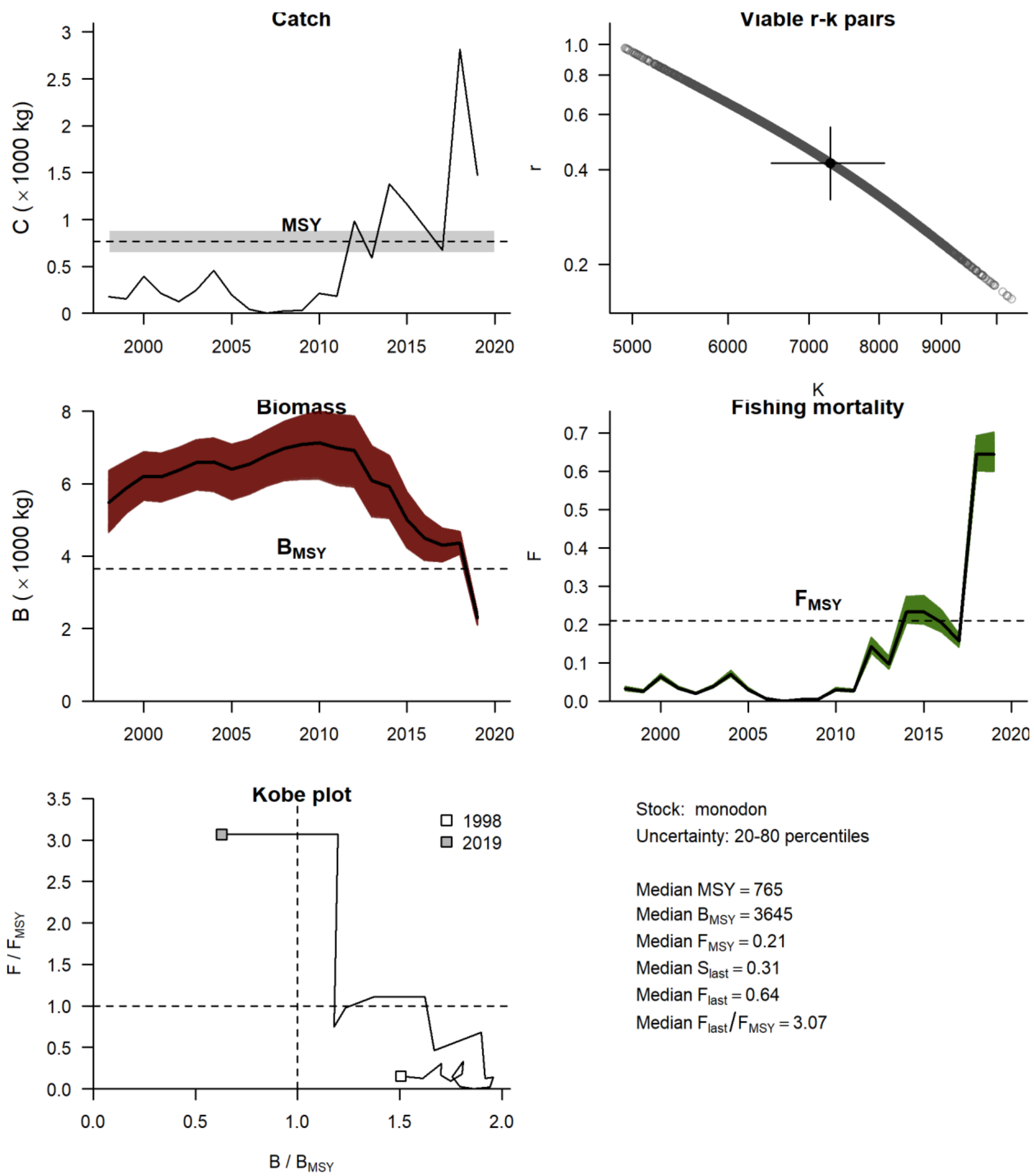

Figure 6-5. Worst case scenario for the putative sub-stock in the broodstock high fishing effort area. The $S_{prior,2019}$ is assumed to be between 0 and 0.1.

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