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FRDC Project No. 2011/239
March 2014

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FISHERIES RESEARCH & DEVELOPMENT CORPORATION

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Citation

Buckworth, R. C., Venables, W.N., Lawrence, E., Kompas, T., Pascoe, S., Chu, L., Hill, F., Hutton, T. and Rothlisberg, P.C. (2014). Incorporation of predictive models of banana prawn catch for MEY-based harvest strategy development for the Northern Prawn Fishery. Final Report to the Fisheries Research and Development Corporation, Project 2011/239. CSIRO Marine & Atmospheric Research, Brisbane, Australia. 115p.

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National Library of Australia Cataloguing-in-Publication entry

Title:	Incorporation of predictive models of banana prawn catch for MEY-based harvest strategy development for the northern prawn fishery / R. C. Buckworth, W.N. Venables, E. Lawrence, T. Kompas, S. Pascoe, L. Chu, F.G. Hill, T. Hutton, and P.C. Rothlisberg.
ISBN:	978-1-4863-0285-7 (pbk.)
	978-1-4863-0287-1 (CD-ROM)
	978-1-4863-0287-1 (ebook)
Subjects:	Shrimp fisheries--Catch effort--Australia, Northern; Fishery technology--Australia, Northern—Evaluation; Electronic monitoring in fisheries—Australia; Northern—Evaluation; Shrimp industry--Management—Australia; Northern--Evaluation.
Other Authors/Contributors:	Venables, W. N. (William N.), author.; Lawrence, E., author.; Kompas, Tom, author.; Pascoe, Sean. author.; Chu Lai, author.; Hill, F. G., author.; Hutton, T., author.; Rothlisberg, P. C. (Peter C.), 1945- author.
Dewey Number:	639.58

Contents

Figures

Tables

1 Non-Technical Summary

2011/239	**Incorporation of predictive models of banana prawn catch for MEY-based harvest strategy development for the Northern Prawn Fishery**

Project details

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Objectives

1. Investigate the use of robust statistical methods to stabilise and improve the performance of the catch prediction model of Venables *et al.* (2011) against historical catches.
2. Calculate estimates of uncertainty for the catch prediction model.
3. Investigate retrospective and prospective analyses, examining how the predictive models would have performed in recent years, including 2012.
4. Investigate refinements to the spatial scale and other structural aspects of the model.
5. Develop economic indicators of dependence between catch and price, and price elasticity for banana prawns.
6. Develop an MEY analysis for the common banana prawn fishery.

Outcomes achieved to date

The methods developed in this project are a means of predicting potential catch in the White Banana Prawn fishery of the Northern Prawn Fishery catch. This is an essential basis for setting pre-season management controls for the banana prawn fishery that target and deliver Maximum Economic Yield (MEY). A prediction of potential catch is necessary in this fishery to determine either a Total Allowable Catch (TAC) or a catch rate-based trigger, based on a Maximum Economic Yield (MEY) target. Because prawn prices are affected by catch levels, a prediction of potential catch is necessary to both calculations.

The approaches developed here have increased the suite of tools available to improve management performance of fisheries. Many fisheries are subject to large, environmentally-driven fluctuations in the abundance of target species. This study provides an example of the analysis of the response of these fisheries to the environmental drivers. **The outcome of this tool development is that, ultimately, assessments might be developed for such fisheries and, moreover, it might then be also possible to ascertain economic attributes to address MEY targets.**

The outputs from this work were a necessary requirement for a subsequent management strategy evaluation project, to compare the performance of TACs and catch rate triggers set using the current project's outputs, with the existing management controls. **The ultimate outcome from both**

projects will be the improved economic performance of the Northern Prawn Fishery, and concomitant community benefit.

The project has been generally well-accepted by industry and fishery managers, as well as the scientific community.

Non-technical summary

Australian Government fisheries management policy has generated an impetus for output controls for management in the NPF and, consequently, a need to predict potential catch on which to establish annual TACs. Alternative controls include catch rate triggers (the current approach) and a modification of the latter approach, in which catch rate triggers are calculated to achieve an MEY target. The White Banana Prawn, *Penaeus merguiensis*, is a short-lived, fecund, tropical species whose annual catches have varied markedly – around eight-fold – over the history of the fishery. Although fishermen and others associated with prawn fisheries have long known that there is a strong relationship between banana prawn catches and rainfall, description of statistical relationships that are adequate for predictions of catch at the large spatial scale of the Northern Prawn Fishery (NPF) has been elusive. A further constraint, given the short life cycle of *P. merguiensis*, is that the annual opening of the season is around 1 April each year, which follows closely their recruitment to the fishery. Therefore, factors affecting recruitment strength can only be measured up to February in the same year; later influences, or information available later, simply cannot be included.

A feasibility project (Venables *et al.* 2011) built a partially-linear model relating the annual total catches to rainfall indices for each of nine separate common banana prawn stock regions within the Northern Prawn Fishery (NPF). The predicted potential catch for the fishery was simply the sum across predictions for nine individual stock regions. Although successful, the model was unstable and difficult to fit in some regions. In this project, we built upon this earlier work, particularly to make the model more stable and to investigate the uncertainties in the model and its predictions. We developed the economic tools necessary to address MEY goals. These tools enable the prediction of the response of prawn price to landings of banana prawn, and the calculation of catch and effort combinations that represent MEY.

We investigated various methods of making the models more robust with three different forms of the model resulting:

1. The separate regions model (the original form) essentially predicted catches by region based on rainfall. This was altered to reduce the influence of "spikes", of outlying historical rainfall events;
2. A "fixed weight" form used information from across the regions to estimate single (fixed) "early" and "late" distribution of rainfall weights to be applied across all regions; and,
3. A "variable weight" form imposed a link between the parameters for the "early" rainfall distributions for the different regions, and similarly for the parameters for the "late" rainfall distributions. This was a compromise between the first two forms, making use of information across the regions yet adding flexibility to the fixed weights single model approach.

With their additional stability, we consider the fixed weight and variable weight models to be the most viable alternative models. Actual catch and predicted catch trends were closely matched. Individual years were, however, subject to substantial deviation between actual and predicted (potential) catch. While deviations could be due to a variety of reasons, a systematic problem is that the performance of all models is constrained by the requirement that, for the prediction to be timely, only data available by the end of February each year can be used. In years such as 2012, in which there was substantial rainfall in March and April, a marked difference between the prediction and actual catch was anticipated. In 2012, landings had exceeded the prediction of potential catch by roughly 50%, by July 2012.

The project refined the spatial division of the model, to improve the fit, stability, and predictive power. In this work, the Fog Bay region has been separated from the remainder of the Coburg stock region, as it was suspected that the catches of the two parts of the stock region were showing different patterns. The

process requires significant work and care; however, we suggest that further subdivision or re-definition of the regions might enhance stability and predictive power.

To address uncertainty in the models, we measure of goodness of fit, using a Bayesian bootstrapping approach, as well as estimates of uncertainty for predictions. We also initiated retrospective analysis (where the models are built progressively, separately introducing each year's data). We found this approach could not be implemented, as there is only just enough data available to fit the models using the full data set.

An annual survey to monitor recruitment of tiger prawns (*Penaeus esculentus* and *P. semisulcatus*) in the Gulf of Carpentaria has been conducted since 2003. Although the survey design and a number of statistical approaches have attempted to make use of information on *P. merguiensis* abundance from the survey data set, these were not successful. This problem might be resolved through time, as more data and contrast accumulate each year.

Other factors and information could not be captured in the model. Rainfall data from late seasonal rain, for example, cannot be included in the predictions. Some inaccuracy is irreducible. This must be acknowledged and accommodated when management measures are put in place.

We used the predictions of potential catch as a proxy for abundance, to calculate MEY for the *P. merguiensis* fishery. The total of prawn landings also affects the price received – termed 'price flexibility' (and related to demand elasticity). To predict the economic attributes of the fishery, and to address an MEY target, it was thus first necessary to investigate the price flexibility in prawn prices with respect to landings. We supported this requirement in two separate approaches, which were corroborative. This work provides a basis for providing MEY-based TAC or catch-rate trigger predictions for the fishery.

The study also suggests several ways indicated in which further data gathering and analysis will improve the quality of predictions of potential catch. The models presented in this report will, however, enable the managers of the fishery to better comply with Commonwealth fisheries policy by addressing MEY targets, either by using catch-rate triggers or moving to output controls, and so enhance profitability of the fishery. They will contribute and create further opportunities for effective research and the sustainable development of the NPF. The approach and outcomes of this project may also be useful in other Australian fisheries.

KEYWORDS: White banana prawns, *Penaeus merguiensis*, northern Australia, rainfall, environmental correlation, environmental drivers, catch prediction, abundance estimation, partially-linear models, Maximum Economic Yield, price elasticity, bioeconomic model.

2 Acknowledgments

We wish to acknowledge the invaluable input of Scientists and Industry representatives, particularly in the Northern Prawn Management Advisory Committee (NORMAC) and the Northern Prawn Resource Assessment Group (NPRAG), who provided the background information necessary to produce this report.

Cathy Dichmont, Robert Kenyon and Tonya van der Velde provided lengthy discussion on the pertinent operations of the Northern Prawn Fishery as well as their knowledge of the ecology of white banana prawns in northern Australia. Charis Burridge and Tonya van der Velde provided careful reviews of the draft report, while Rachel Harm was especially helpful with editorial production.

Mick Hartcher in CSIRO Ecosystem Sciences arranged acquisition of the rainfall data.

Debbie Vince, Christelle Tait and Rachel Phillips provided much-valued administrative support.

This work received funding support from the Fisheries Research and Development Corporation, CSIRO Wealth from Oceans Flagship, and the Australian Fisheries Management Authority.

3 Background

One of Australia's most valuable fisheries, the Northern Prawn Fishery (NPF) landed catches in 2010-11 valued at $88.8 million (Woodhams 2011). The fishery is essentially two sequential fisheries, one that targets the White Banana Prawn (WBP), *Penaeus merguiensis*, and a mixed species fishery, targetting tiger (*P. esculentus* and *P. semisulcatus*), endeavour (*Metapenaeus endeavouri* and *M. ensis*) prawns, and Red-legged Banana Prawns (*P. indicus*). Although the mixed species fishery has been amenable to assessment and is now closely managed with a bioeconomic model (Punt *et al*. 2011; Dichmont *et al*. 2012), assessment and modelling of the WBP fishery has been less tractable. This fishery comprises an "annual crop", characterised by very high inter-annual variability in recruitment and landings. Landings have ranged from less than 2000 to more than 12000 tonnes. Prawn prices also vary, so that total value of the fishery also varies substantially from year to year. In recent years the WBP fishery has provided around two thirds of the Gross Value of Production (GVP) from the fishery (Woodhams 2011); it has been fully fished since the mid 1970s (Lucas *et al*. 1979; Zhou *et al*. 2007). The large variation has made stock assessment difficult, with the relationship between spawning stock size and recruitment being obscured by the recruitment variation.

An apparent association between environmental factors, particularly rainfall, and banana prawn catches was borne out by statistical analyses (Vance *et al*. 1985). The strength of the relationships between catches and environmental variables, however, were not consistent over time and varied markedly between regions of the fishery (Vance *et al*. 1985, 2003). Environmental factors other than rainfall had variable influence on WBP catches across regions and between years. Confounding between spatial ecological and operational factors also appeared to generate strong variation between regions in the assessments (Vance *et al*. 2003). Clearly, any explanatory or predictive relationship between total catch for the fishery and environmental drivers would need to be based on the fine scale patterns of the catch and the potential environmental drivers.

The impetus for output control-based management in the NPF has generated the need for a mechanism to determine a Total Allowable Catch (TAC) for the WBP. Thus the prediction of a potential catch, rather than the need to explain inter-annual variation as a component of fishery assessment, has driven this further investigation into the statistical relationships between environmental variables and WBP catches. Venables *et al*. (2011) provided a successful feasibility study of catch prediction for the whole WBP fishery, using statistical modelling of catches against fine-scale rainfall information.

Requested by the Northern Prawn Resource Assessment Group (NPRAG; 08/2011), this project continues a long dialogue between the Australian Fisheries Management Authority (AFMA), the Northern Prawn Fishery Management Advisory Committee (NORMAC), NPRAG and industry, as well as valuable prior studies (MRAG 2007; Hutton *et al*. 2009), seeking a satisfactory way to determine TACs for the WBP fishery. This project builds on the collective experience developed in previous projects: Integrating assessment with economics, (Dichmont *et al*. 2008) provided a win-win combination of profitability and sustainability for the tiger prawn fishery, under-pinning TAC-setting methods for the tiger and red-leg banana prawn fisheries suitable for the introduction of output controls (Dichmont *et al*. 2010). However, the lack of a suitable assessment or predictive model for WBP in previous studies (MRAG 2007; Hutton *et al*. 2009) meant that only an empirical approach was available for the WBP fishery, due to the inability to predict WBP abundance and its large variation. The TAC-setting trial in 2010 produced a TAC that was "not appropriate to the scale of catch under inputs"; requiring "urgent revision" (Dichmont *et al*. 2010). Industry and management were justifiably concerned that without a better basis for TAC-setting, a TAC could lead to substantial revenue being foregone - counter to the Commonwealth policy of maximal economic performance.

Reported at NORMAC (06/2011) and NPRAG (08/2011), Venables *et al*. (2011) used rainfall to predict WBP catches. The inception and completion of the current project is recognition by NORMAC and NPRAG of the approach in predicting WBP potential catch. The analysis by Venables *et al*. (2011) demonstrated feasibility, but nevertheless was incomplete, requiring the improvement, testing and evaluation undertaken here. This project addressed statistical stability, and the investigation of uncertainty structures that could not be addressed in a feasibility study. Dichmont *et al*. (2008; 2010; 2012) demonstrated the value of economic tools, rather than proxies, for developing MEY-based TACs. With this experience as a basis, this project incorporated economic analyses addressing Maximum Economic Yield (MEY) goals, thus addressing the management policy of maximal fishery profitability. If output controls are deemed to be unsuitable for the fishery, input controls based on MEY targets, such as catch rate triggers, still require catch and price predictions, as prices respond to the amount of WBP landed. Even under fluctuating conditions and alternative management controls, the project provides a means of setting fishery targets that provide maximal value.

4 Need

Under Commonwealth harvest policy, fisheries are to be managed to maximise economic performance. Most Commonwealth fisheries have/ are developing harvest strategies based on an MEY target and TAC controls. Following Ministerial Direction, the NPF may adopt an ITQ management system from 2014. Alternatively, the fishery for white banana prawns (WBP) may adopt a catch rate-based trigger system that also addresses an MEY target. In both cases, this transition requires: 1, reliable methods for predicting the total sustainable, available catch; and, 2, understanding of the economics of the fishery, providing for setting total allowable catches (TACs) that maximise value rather than catch.

This project addresses these components. Unlike the NPF tiger prawn fishery, the WBP fishery, in which annual catches vary dramatically, has not been amenable to assessment and predictive modelling, as recruitment varies markedly with environmental conditions.

Fishermen have known for many years that banana prawns catches depend upon the amount and timing of rainfall. Considerable research has explored the ecology behind this e.g. relationships between rainfall and catches of WBP, (Vance *et al*. 1985), emigration of WBP from estuaries as salinity decreases (Staples 1980; Staples and Vance 1986; Vance and Staples 1992), temperature and wind (Vance *et al*. 2003) and the effect of fishing effort (Venables and Poloczanska 2006). Venables *et al*. (2011) explored the feasibility of predicting the fishery-wide potential annual catch for WBP. In a manner suitable for TAC-development, it uses information available before the fishery begins each year. The second component follows the successful incorporation of economic objectives into the harvest strategy for tiger and endeavour prawns (Dichmont *et al*. 2008) and would redress the lack of suitable techniques for TAC-setting for WBP, as noted in FRDC 2007-018 (Dichmont *et al*. 2010). The process is relatively simplified in this case, as there is no large interdependence in the fishery and economic modelling entailed.

5 Objectives

1. Investigate the use of robust statistical methods to stabilise and improve the performance of the catch prediction model of Venables *et al*. (2011) against historical catches.
   ***Outcome*: This objective has been achieved.**
2. Calculate estimates of uncertainty for the catch prediction model
   Outcome: This objective has been achieved.
3. Investigate retrospective and prospective analyses, examining how the predictive models would have performed in recent years, including 2012.
   Outcome: This objective has been partially achieved. It was not feasible to undertake the full retrospective analysis because, as we discovered, there is simply insufficient information in available data to do so properly. A prediction has been provided for the 2012 catch, and prediction intervals, indicating the uncertainty in predictions, were also developed;
4. Investigate refinements to the spatial scale and other structural aspects of the model.
   Outcome: This objective has been achieved; Fog Bay is now incorporated as a separate region in the model from Coburg; further refinements could be addressed in future;
5. Develop economic indicators of dependence between catch and price, and price elasticity for banana prawns.
   Outcome: This objective has been achieved. Two distinct methods were applied, providing corroborating analyses.
6. Develop an MEY analysis for the white banana prawn fishery.
   Outcome: This objective was achieved.

6 Methods

6.1 Prediction of “Potential Catch” from Rainfall and Historical Catch

6.1.1 MODELLING STRATEGY

Venables *et al.* (2011) built separate models relating the Annual Total Catch (ATC) to daily rainfall data for each of the nine Banana Prawn stock regions; the technical details of the models described here are provided in Venables *et al.* (2011). In summary, the primary model was a partially-linear model. It also included an intercept and a linear term in “years since 1970” to allow for possible systematic annual proportional increments or decrements in the banana prawn catch. The form of the model was:

$$(1)\quad \log C_y = \gamma_0 + \gamma_1(y - 1970) + \sum_{b\in B}\left\{\delta_b R_b^E(\alpha_1, \beta_1; y) + \theta_b R_b^L(\alpha_2, \beta_2; y)\right\} + \varepsilon_y$$

where:

- B is the set of basins to be used to generate predictors for the particular region
- R_b^E and R_b^L are the rainfall indices for basin *b* for the “early” and “late” season respectively
- $\varepsilon_y = N(0, \sigma^2)$

For any given basin *b*, the rainfall indices are weighted linear combinations of the estimated daily aggregate rainfall for the entire basin. The parameters α and β determine the shape of the weighting, or importance distribution. We assume these are the same for all basins within a stock region, but may vary from stock region to stock region. The “Early” index focuses on the rainfall that occurred prior to the season, with a peak weight typically near September, when a population spawning mode, that corresponds to peak recruitment in the following April, has long been hypothesised to take place (Rothlisberg, Van der Velde and Venables, in prep.). The “Late” index by contrast focuses on the time of year leading up to the opening of the season, but for logistic reasons has to use only rainfall up to the end of February. These importance distributions are also determined by calibration from the catch data, but are non-linear, in contrast to the γ, δ and θ coefficients in model (1) above, which are included linearly.

For reasons both of practicality and parsimony, the estimation of the coefficients in (1) proceeds in a two-stage process:

- Initially the model is fitted by non-linear least squares, using all basins affecting the stock region
- At a second stage, the non-linear parameters α and β, which only determine the focusing weights, are held fixed, and the model is pruned by stepwise methods to remove indices (either early or late, or both for any given basin) which appear not to contribute to the effectiveness of the prediction, again for reasons parsimony.

The model was then refined using stepwise methods, keeping the rainfall indices fixed, to avoid over-fitting that could undermine predictive capacity. An estimate of the mean annual potential catch was calculated using the Finney estimator (Shen and Zhu 2008) to provide an unbiased estimate of the mean catch on the natural scale. Finally, the models were adjusted to incorporate the WBP stock indices from the monitoring surveys, in stock regions where a relevant index was available, using an *ad hoc* process. This was done by fitting a simple linear regression model with log ATC as the response, the estimated mean potential catch (ignoring the survey) as an offset and the log survey index as an explanatory variable. After fitting the models, adjusted estimates of potential catch were then obtained, again using the Finney estimator. The estimate for the potential catch for the total NPF was obtained by summing the estimates, (adjusted where possible), for all nine regions.

The models described by Venables *et al.* (2011) were fitted using both unweighted and weighted least squares approaches. For the weighted version, the case weights used were the nominal WBP effort levels, i.e., the number of boat-days for that year and region for which the imputed target species was WBP. The weighted approach, giving more influence in the model fitting process to the catches where the associated effort was high, was shown to produce the more stable and heuristically reasonable predictions. It also has the advantage, for automatically accounting in the model fitting process for changes in spatial and temporal attributes of the fishery, for example, of closures. It is critical to note that while the model response variable is actual catch, the model predictions are 'potential' catch. In particular we are weighting heavily the regions and years where a high amount of effort was expended, but the model predictions also include potential catch in areas where little or no effort was expended. This is because we are not trying to model what the fishermen caught (if we were, we would include other explanatory variables such as tiger prawn catch, price information etc.), but are attempting to develop a measure of abundance that could be used as one input in a TAC- or target-setting process. It is critical to note that this would not be the only input in such a process.

The SILO data on which the project relies for its rainfall inputs was extensively revised and updated in early March 2012, with some major and unexpected changes. These are described in some detail in the Results and Discussion section. Due to changes in the data, the separate region models built in the previous project were re-built using the updated rainfall data. All of the modelling that has taken place throughout this project has included rainfall data up to 28th February 2012. [1]

The instability of the models fitted in some of the stock regions were a cause for concern during the work by Venables *et al.* (2011). In this project we investigated various methods of making the models more robust, namely:

1. Capping the rainfall weight distribution to prevent "spikes", that is one or a small number of contiguous daily rainfall totals driving the entire rainfall index for that region, and hence forcing the model outcomes to rely unduly on a few capricious historical rainfall events;
2. Severely reducing the number of model parameters by constraining the "early", and the "late", rainfall weight distributions to be the same across all regions; and,
3. Reducing the number of model parameters by imposing a link between the "early" rainfall weight distributions for different regions, while still allowing some flexibility from region to region; the same process is also applied to the "late" rainfall weight distributions.

The statistical methods used are described in the following sections.

6.1.2 MODIFYING THE RAINFALL WEIGHTS

The modelling approach used in Venables *et al.* (2011) resulted in weight distributions for rainfall that would be considered unrealistic, in some regions. Despite the fact that empirically they appeared not to produce particularly unreasonable results, this was considered a potential flaw in the model that could lead to anomalies in future. For example, the effort weighted model for the Mornington region resulted in an "early" rainfall distribution with a weight greater than 0.5 for the first day of the arbitrarily defined "early" rainfall period, (1 June), i.e. any rainfall recorded on the 1st of June, (admittedly a rare event), would nevertheless have received more weight than rainfall recorded on all the other 181 days combined. Similarly the models for the North Groote and Vanderlins regions had particular days associated with estimated daily weights greater than 0.25. As it is highly unlikely that the rainfall on one particular day drives the number of banana prawns caught in the season that follows, in this project the maximum weight is capped at 0.025. If each day were weighted equally, they would each receive a weight of 0.0056 so

[1] Note that catch and effort data is only available up to the end of calendar year, 2011, so estimation of model parameters only relies on rainfall data up to 28th February, 2011; results using rainfall for the period ending 28th February 2012 can only be model predictions.

capping the weight at 0.025 results in no one day being given a weight greater than 4.5 days combined (under the uniform weights case).

This *ad hoc* adjustment of weight distribution was only needed for the separate models, (strategy 1) as listed above. For strategies 2) and 3) the weight distributions were more stable, with fewer spikes, so that capping was not assessed to be needed.

6.1.3 SINGLE MODEL

Fixed weights

Venables *et al.* (2011) fitted a separate model to each of the WBP stock regions. This resulted in a separate rainfall weights distribution for each region and required four degrees of freedom to estimate the associated model parameters (α_1, β_1 defining the shape of the "early" interval weights and α_2, β_2 defining the shape of the "late" period weights for each region). This large number of model parameters, the highly variable nature of the rainfall data and the small sample size led to the models being very unstable and difficult to fit in some regions. This was particularly the case in regions where catch and effort were low or highly variable. To produce credible results, Venables *et al.* (2011) found it necessary to adjust some of the models, including omitting the rainfall data from particular basins in some regions and entire indices from others. This process was fairly ad hoc and time consuming and thus would not be a desirable feature of models that need to be accurate and run quickly in the lead up to setting a TAC. In this project a single model was considered, essentially "borrowing strength" across the regions to estimate a single (fixed) "early" and "late" distribution of rainfall weights to be applied across all regions.

The model is based on a re-parameterisation of the rainfall weights distribution described in Venables *et al.* (2011), where the non-linear parameters estimated by the model are no longer α and β, and instead are η and φ. One advantage is that η and φ are unrestricted, whereas α and β are constrained to be positive.

$$\eta = \log\left(\frac{\mu}{1-\mu}\right) \qquad \text{where} \quad \mu = \frac{\alpha}{\alpha+\beta}, \text{ the mean of the beta distribution}$$

$$\varphi = \log(\alpha+\beta)$$

We note that the parameter μ is included here for illustration of the formal derivation of the parameters. It does not appear in equation 2 below and, more simply,

$$\eta = \log(\alpha/\beta)$$

The model then takes the form:

$$(2)\quad \log C_{y,r} = \gamma_{0,r} + \gamma_{1,r}(y-1970) + \sum_{b\in B}\{\delta_b R_b^E(\eta_1,\varphi_1;y) + \theta_b R_b^L(\eta_2,\varphi_2;y)\} + \varepsilon_{y,r}$$

where:

- B is the set of basins to be used to generate predictors for the particular region,
- R_b^E and R_b^L are the rainfall indices for basin *b* for the "early" and "late" season respectively
- $\varepsilon_{y,r} = N(0,\sigma^2)$

Importantly, η_1, η_2, φ_1 *and* φ_2 are estimated simultaneously across all regions and therefore have the same values regardless of the region.

Variable weights

To incorporate more flexibility into the fixed weights single model approach (Section 1.2.1), whilst maintaining the single model structure, a further modelling approach was investigated. This approach allows η_1 and η_2 to vary by region but maintains a fixed φ_1 and φ_2.

The model then takes the form:

$$(3)\quad \log C_{y,r} = \gamma_{0,r} + \gamma_{1,r}(y-1970) + \sum_{b\in B}\{\delta_b R_b^E(\eta_{1,r},\varphi_1;y) + \theta_b R_b^L(\eta_{2,r},\varphi_2;y)\} + \varepsilon_{y,r}$$

Survey index

The NPF recruitment monitoring survey has only been in operation since 2003. As this time series is so short, it is not possible to include this index in the previously described models in the typical way i.e. to include it, where appropriate, as an extra covariate. Instead we investigated the potential usefulness of including the monitoring surveys information in a number of ways, including:

1. The predictions from the environmental model - 2) and 3) - were used as an offset in a simple linear regression and used the log index as an additional predictor, thereby estimating a coefficient for the log index only.
2. The predictions from the environmental model and the log index were used as predictors, estimating a coefficient for each.
3. Stepwise methods were used in conjunction with 2).

6.1.4 REFINING THE SPATIAL SCALE

The current banana prawn model was developed using the stock regions for Banana Prawns as previously defined (with minor adjustment to exclude the Red-leg Banana Prawn management region). Other regional partitions of the data were not considered in Venables *et al.* (2011), largely due to time constraints. We have now investigated the effect of splitting the Coburg stock region into two sub-regions, namely Fog Bay, the region South of Melville and Bathurst Islands and the remainder, namely the region north of those islands and of the Coburg Peninsula. See Figure 1 below.

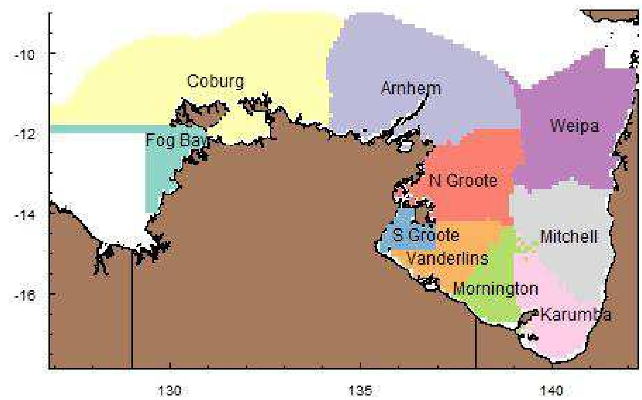

Figure 1. Extended stock regions showing the partition of The Fog Bay sub-region from Coburg.

We have implemented this split for the three modelling approaches described above (separate models with modified weights, single model with fixed weights, and single model with variable weights).

6.1.5 ESTIMATES OF UNCERTAINTY

The Banana Prawn model presented in Venables *et al.* (2011) was not accompanied by estimates of uncertainty. In this project we have produced confidence and prediction intervals for the predicted potential catch for what we consider now to be the most important candidate models. These are the fixed weight and variable weight models, estimated using effort weighting. The uncertainty estimates are generated using a variant on standard bootstrapping, originally due to Rubin, (1981) known as “Bayesian bootstrapping”. We found this more convenient than standard bootstrapping as it ensures that no observation is completely omitted from the re-sampling, which seems to have intuitive advantages.

To calculate Bayesian bootstrap estimates, the models were refitted giving each observation an additional random weight, drawn from an exponential distribution with mean 1. These random weights are then multiplied by the original effort weights and the model re-fitted. Each re-fit then produces an estimate of the mean and variance of the catch on the log scale. These are then converted to estimates of mean catch on the natural scale. This process was carried out 1000 times to produce 1000 bootstrap replicates. The estimate of the mean total catch was calculated for each replicate by summing the estimates for each region within that replicate. The 95% bootstrap confidence intervals were then calculated by taking the 2.5^{th} and 97.5^{th} percentiles of the estimates.

The 95% prediction intervals are generated by an additional step of simulating a notional log-catch for each re-sampling, according to the mean and variance estimate from the re-fit. These notional log-catches are then handled in the same way as the predicted mean catches, to arrive at uncertainty measures that apply to the actual potential catch, as opposed to its mean value. The distinction is important for management purposes, and is further discussed in the Results and Discussion and Further Development sections. Note that this method is somewhat heuristic at this stage, but empirical studies we have undertaken show that it does produce reasonable estimates of uncertainty in the sense of prediction intervals. These estimates of uncertainty only cater for uncertainty in the linear model (that is, in the fixed weight and variable weight models), essentially assuming that $\eta_1,\ \eta_2, \varphi_1\ and\ \ \varphi_2$ are known with certainty, and we emphasise that at this stage, the methods only give an under-estimate of the fully realistic assessment of uncertainty. Extending this to cover the additional uncertainty associated with the estimation of rain weights will require some methodological development and the implications of this are discussed in Further Development.

6.2 MEY and Price Elasticity and for NPF Banana Prawns: Modelling Approach 1

6.2.1 INTRODUCTION AND CAVEATS

Both economic modelling approaches presented here use the measure of 'potential catch' resulting from the statistical model above as a proxy for 'abundance' and calculate Maximum Economic Yield (MEY) for the NPF White Banana Prawn fishery. MEY is the catch or effort level that creates the largest difference between the total revenue and the total cost of fishing. In other words, it is a catch or effort level that equates the marginal revenue and the marginal cost of fishing, ensuring that profits are maximized. To compute this estimate, both revenue and variable cost data are needed, along with measures of the price elasticity of demand and the harvest function. The price elasticity of demand measures the responsiveness of price to harvest, thus determining changes in the total revenue of fishing with a change in catch, and the harvest function specifies the relationship between effort and catch, providing an additional measure of 'abundance'.

There are three important caveats to indicate at the outset:

- The limited amount of available data prevents the use of more elaborate econometric or statistical specifications. As a result, specifications have a limited number of parameters. Data for the estimates of price elasticity are drawn from publically available data provided by ABARES and relevant international datasets. There are 19 observations in total. Although unit-root tests for the order of integration indicate that the series is stationary, the limited number of observations does not allow for more elaborate diagnostic tests. The amount of data used to estimate the harvest function - given the structural change in the fishery after the vessel buyback scheme and the dramatic reduction of the fleet - is also limited. We use several different approaches to estimating the harvest function: a standard 'production function' approach and more a simple function that more adequately captures the convexity in fishing costs (or the relationship between catch and effort).
- The MEY estimates rely on the measure of 'potential catch'. Formally, this enters the analysis as a realization of 'abundance' in the estimated harvest function. The measure of potential catch is different than actual recorded catch in the historical series from 1970 to 2011, and potentially so this is also the case going forward in time. In cases where potential catch is larger than actual catch

this will normally not be a problem for MEY calculations, since given the price elasticity of demand it is generally the case that MEY catch will be lower than potential catch and, in some, if not many cases, actual catch as well. On the other hand, there are 9 years in the overall series where potential catch is less than actual catch, using the ‘effort weighted’ index, and one case where potential catch is less than actual catch, using all of the various measures (i.e., weighted, un-weighted, capped, etc.) of ‘abundance’. Whether this is a problem for MEY estimation depends on the actual measure of profits in that year, compared to MEY forecasts.

- The measure of ‘profit’ in this part of the report is not a measure of actual profit in the fishery, or in any component part of the fishery. There are two reasons for this. First, the data used here are mean-response or average measures of prices and costs. Individual operators may realize different values for the cost of fishing and the price of prawns (when actually sold), and thus actual profits for an individual operator can vary considerably. Second, and more importantly, the MEY measure of profit is based only on variable cost components. Fixed costs (e.g., licence fees) and other administrative costs that clearly affect the ‘bottom-line’ for a fishing operator are excluded. This is at it should be. MEY depends only on variable cost components to determine profit-maximizing catch.

6.2.2 ESTIMATING THE PRICE ELASTICITY/FLEXIBILITY FOR BANANA PRAWNS

The quantity supplied, or in this case, the harvest of prawns brought to market, generally affects the price of prawns. This is almost certainly true in domestic markets, but it can also be the case in international markets, at least if the quantity of product normally supplied is sufficiently large, or there are significant changes in the exchange rate. In the past, with most of NPF prawns destined for large East Asia and Japan markets, it was common to model prices as ‘given’ to Australia by the international market. The MEY forecasts for tiger prawns in the NPF indeed assume that prices are unaffected by harvest in Australia. With the growing reliance on domestic markets for prawns, as well as with dramatic changes in the exchange rate, this is no longer a valid assumption.

To determine the sensitivity of prawn prices to harvest, it is typical for economists to estimate a ‘price elasticity of demand’, or the percentage change in the quantity demanded of a product in response to a one percent change in its price. Price elasticities are almost always negative, since an increase in the quantity brought to market generally results in a fall in price. The important issue is how sensitive is the change in demand to a change in price. The greater is the price elasticity (in absolute value) the more responsive or the larger the effect on the quantity of the good demanded and thus total revenue.

To estimate the elasticity for NPF banana prawns, we use data on catch, prices and nominal revenue from 1992-93 to 2010-11, provided by ABARE. Nominal revenue is converted into 2010-11 Australian dollars to take away the effect of any general inflation on the price of prawns. The choice of the base year is arbitrary, and 2010-11 is simply convenient due to the fact that all cost data in the NPF used here was measured in 2010-11 dollars. The deflator used for this conversion is the annual Australian CPI index.

A formal estimate of demand elasticity requires a statistical procedure, based on a given relationship between price and catch. Due to modest sample size, we use the simple constant-elasticity specification and limit the number of parameters. Specifically, the relationship between the price and the catch of banana prawns in year *i* is specified by the equation:

$$p^i\left(c^i\right) = A^i\left(c^i\right)^{\alpha} \text{ or in the log form } \log\left(p^i\right) = \log A^i + \alpha \log\left(c^i\right)$$

where p^i is the annual average price (in \$A1000/ton, 2010-2011 dollars), c^i is the annual catch (in tonnes), α is the inverse of the price elasticity and A^i captures the effect of factors other than catch in year *i*. The value of α is formally a measure of ‘price flexibility’ or an approximation of the inverse of the usual price or demand elasticity.

With a more substantial data set, the specification above might include the effect of substitute goods, since changes in the price (say) of other fish products may affect the price of prawns, and measures of income.

Changes in the international markets, can also affect the measure of elasticity so that apart from the catch, the price of prawns can be influenced by changes (for example) in Japan's income or inflation rate and the exchange rate between Japanese and Australian currencies. For this reason, we estimate the elasticity in two separate cases, namely one with and without exchange rate effects.

For the purpose of the MEY analysis, we choose a base-scenario (inverse) elasticity of -0.25 (varied later with sensitivity analysis) to build up a demand function for banana prawns, mapping catch to price. In this demand function, to avoid any over-fitting caused by the modest sample size, the coefficient A^i in the demand function is allowed to vary between pre- and post-2004, given the significance of the dummy variable, but not from year to year. These two pre- and post-2004 coefficients are chosen to minimize the sum of squared residuals between the actual and estimated revenues.

6.2.3 ESTIMATING THE HARVEST FUNCTION: A NON-LINEAR APPROACH

The catch-effort relationship for a typical vessel depends on 'abundance'. We first fit the actual weekly data for catch and effort from 2008-2011 (the period since the fishery was "re-structured") to a standard Cobb-Douglas 'production function'. Specifically, the assumed relationship is:

$$c^i(e) = Q\left(S_0^i\right)^{\alpha} e^{\beta} \text{ or in the log-linear form } \log\left(c^i\right) = \log Q + \alpha \log\left(S_0^i\right) + \beta \log e$$

where is the S_0^i index for potential catch (or rainfall) for year *i* = 2008-2011, $c^i(e)$ is the catch in tonnes at year *i* for effort *e* and Q, α, β are the three parameters to be estimated (with $\beta < 1$ implying that an increase in effort will increase catch but at a decreasing rate).

To better capture the convexity in the relationship between actual catch and effort, we also used a nonlinear least-squares model. We denote S_0^i as the 'potential catch' of the prawn in year *i* and $s^i(e)$ as the catch at year *i* after *e* fishing days. If the proportion of the actual to potential catches is denoted as *C(e)* then the harvest function at year *i* will be

$$s^i(e) = S_0^i C(e)$$

The proportion *C(e)* should satisfy the following conditions: (a) if there is no effort, there is no catch; (b) actual catch cannot fall when effort rises; (c) increasing effort will increase catch but at a decreasing rate; and (d) actual catch is bounded by potential catch.

The data used to estimate the harvest function covers three years (*i* = 2009, 2010, 2011), and is given in Appendix 4. For convenience, we choose a non-linear specification that satisfies (a)-(d), or:

$$C(e) = 2\left[\Lambda\left(\beta_0 e^{\beta_1}\right) - 1\right]$$

where

$$\Lambda(x) = \frac{1}{1 + e^{-x}}$$

is the standard logistic function, and β_0 and β_1 are the only two parameters to be estimated. It is straightforward to relax condition (d) with a 'neural network' framework to 'fit' the data.

6.2.4 THE COST OF FISHING FOR WHITE BANANA PRAWNS

The unit cost (for 1 ton) of banana prawns depends on the productivity of boats (as specified by the harvest function) and the cost of one fishing day. The cost of one fishing day, in turn, for an MEY analysis depends on variable cost components, such as labour, fuel, gear and other costs. Fuel costs often play a significant role (Vieira and Perks 2010; Woodhams *et al.* 2011).

For the base-case scenario, we use the estimate for the cost of one fishing day provided in Kompas (2012) which is roughly $A8,800 per day (2010-11 dollars) --- the values for capital, fuel and gear are taken directly from that report, the cost of crew and skipper payments is converted from a per kg measure to a fishing day. These measures are based on survey data provided by industry as given in Barwick (2011, 2012) and Evans (2009).

6.2.5 DETERMINING MEY

Having estimated the cost of one day of fishing for banana prawns, we can further estimate the unit cost for one ton. Specifically, the harvest function determining the relationship between catch and effort allows a mapping between catch and effort in any year as:

$$e = \left[\frac{\log\left(S_0^i + c\right) - \log\left(S_0^i - c\right)}{\beta_0} \right]^{\frac{1}{\beta_1}}$$

Putting together the revenue and total operating costs (effort times the cost of one fishing day), we can derive operating profit in year *i* as a function of the catch as:

$$\pi(c) = p(c) \times c - C \times e = Ac^{1+\alpha} - C\left[\frac{\log\left(S_0^i + c\right) - \log\left(S_0^i - c\right)}{\beta_0} \right]^{\frac{1}{\beta_1}}$$

where A and α are the coefficients and the (inverse) elasticity in the demand function (as described above), β_0 and β_1 are the parameters in the harvest function (as described above) and *C* is the cost of one fishing day (from above).

Given the measure of operating profit, the MEY catch that maximizes profit (contingent on the potential catch S_0^i) will satisfy the first order condition which stipulates that marginal revenue equals marginal cost, or:

$$\pi'(c) = 0 \rightarrow A(1+\alpha)c^{\alpha} = \frac{2CS_0^i}{\beta_0\beta_1\left(S_0^i + c\right)\left(S_0^i - c\right)}\left[\frac{\log\left(S_0^i + c\right) - \log\left(S_0^i - c\right)}{\beta_0} \right]^{\frac{1}{\beta_1}-1}$$

This equation cannot be solved analytically given the estimated parameters. However, numerical solutions can be easily calculated and graphically illustrated, so we have adopted this approach below.

6.3 MEY and Price Elasticity and for NPF Banana Prawns: Modelling Approach 2

6.3.1 BASIC MODEL ASSUMPTIONS

Assume the catch function can be given by $C = qx_0E^{\lambda}$, where q represents the proportion of the stock removed by one unit of effort (a constant) and x_0 is the starting stock size with zero effort. Non-linearity in the relationship between catch and effort is represented by λ, which in economic terms represents the effort elasticity, such that a 1 per cent increase in fishing effort results in a λ per cent change in catch. The value of λ is typically less than or equal to 1 (i.e. $\lambda \trianglelefteq 1$), which implies that more effort will increase catches but at a less than proportional rate. The stock is assumed to become depleted as effort is applied, so that the marginal catch rate declines as effort increases. i.e. $dC/dE = \lambda qx_0E^{\lambda-1}$.

In the case of constant prices, the profit function is given by $\pi = pqx_0 E^{\lambda} - cE$, where *p* is the constant price and *c* is the constant cost per unit effort. Profits are maximised when $\lambda pqx_0 E^{\lambda-1} = c$, which is essentially when the marginal revenue $\left(p\, dC/dE \right)$ is equal to the marginal cost. From this, $E^{\lambda-1} = \dfrac{c}{\lambda pqx_0}$ and $E^{*} = \left(\dfrac{c}{\lambda pqx_0} \right)^{1/(\lambda-1)}$, where E* is the level of effort that maximises profits given c, p, q, x_0 and λ. For a given E*, the optimal catch is given by $C^{*} = qx_0 E^{*\lambda}$

With variable prices, and assuming a constant price flexibility *f*,[2] the profit function becomes $\pi = e^{[\ln p_0 - f \ln(qx_0E^{\lambda})]} qx_0 E^{\lambda} - cE$. Profits to the industry are maximised when

$$
\begin{aligned}
\frac{d\pi}{dE} &= \frac{-f\lambda qx_0 E^{\lambda-1}}{qx_0 E^{\lambda}} e^{\ln(P_o - f\ln(qx_oE^{\lambda}))} qx_0 E^{\lambda} + e^{\ln(P_o - f\ln(qx_oE^{\lambda}))} \lambda qx_0 E^{\lambda-1} - c \\
&= \left(\lambda qx_0 E^{\lambda-1} \right) e^{\ln(P_o - f\ln(qx_oE^{\lambda}))} (1-f) - c
\end{aligned}
$$

from which

$$
\left(E^{\lambda-1} \right) e^{\ln(P_o - f\ln(qx_oE^{\lambda}))} = \frac{c}{\lambda qx_0 (1-f)}
$$

From the above, when *f* is zero (i.e. demand is said to be perfectly elastic and prices perfectly inflexible), this collapses back to the constant price conditions with $p=P_1$.

Given a current quantity (Q_1) and price (P_1), we can approximate price under different quantities as $P = P_1 \left(1 + f \left(Q / Q_1 - 1 \right) \right)$. This is a linear approximation of the logarithmic function above, and is valid for changes in quantities close to the current quantity. Substitution this into the equation above gives

$$
\left(E^{\lambda-1} \right) \left(1 - f \frac{qx_0 E^{\lambda} - Q_1}{Q_1} \right) = \frac{c}{\lambda qx_0 P_1 (1-f)}
$$

Again, when *f*=0 this collapses back to the constant price condition (i.e. $\lambda pqx_0 E^{\lambda-1} = c$).

6.3.2 PRACTICAL BIOECONOMIC MODEL

The above model is highly non-linear and needs to be solved numerically rather than algebraically. It is also relatively restrictive in the assumptions about the relationship between catch and effort. Given this, the approach adopted was to estimate the components of the model separately and optimise profits for the fleet as a whole.

The objective function of the model was given by Max $\pi = P^{*}C - cE$ where P* is the effective price received for the prawns (net of crew share and also marketing costs), C is the catch level (C=f(E, S), where S is the stock index, which is assumed to be exogenously determined independent between years), *c* is the variable cost per unit of effort and E is the level of effort in the fishery. As we are optimising over a single year and are assuming that the fleet size is fixed and hence we are not optimising vessel numbers as well as days fished, we ignore fixed and capital costs. As shown above, the estimated profit is subsequently not a true profit measure, but a measure of revenue less variable costs (i.e. the gross margin). This differs from the NPF tiger prawn model (Punt *et al.* 2011; Dichmont *et al.* 2012), which optimises over time, constraining with lower bounds on profitability (i.e. non-negative profits) in any one year and consequently needs to consider all the costs, not just variable costs.

[2] Price flexibility represents the percentage change in price given a one percent change in quantity landed.

We estimate the effective price as $P^* = P(1-crew) - m$, where P is the prawn price, crew is the crew share of revenue (0.23) and m is the marketing costs ($1.03/kg). The prawn price was estimated as $P = P_1\left(1 + f\left(Q/Q_1 - 1\right)\right)$, where P_1 is the price in the most recently available year (in this case 2011) and Q_1 is the quantity landed in that year (again 2011), and *f* is the price flexibility.

Catch is given by[3]

$$\ln C = \beta_0 + \beta_1 \ln S + \beta_2 \ln E + \beta_3 \ln^2 E + \beta_4 t + \sum_i \delta_i D_i$$

where *t* is a time index to capture technical change (or efficiency change) over time and D_i are a series of year-specific dummy variables that represented major management changes (e.g. buybacks, changes to gear units etc). We allow for a variable λ through the addition of the quadratic effort term, which provides a more flexible functional form than the theoretical basic catch function specified above.

[3] A range of other specifications were also tested, including models with quadratic and cubic time terms, models without the quadratic effort term, models imposing a constant unitary stock elasticity, as well as models with interactions between the stock index, effort and also time. The identified model was the best given the data.

7 Results/Discussion

7.1 SILO data update

The SILO data set was available in early March 2012. The grid over which the daily rainfall estimates were provided remained the same, but the interpolation methods used to generate the data from the measuring stations were extensively revised. The overall effect of this change in the SILO data is likely to be a considerable improvement in the reliability of the rainfall estimates provided. Small changes are apparent in all rainfall basins bordering the NPF, and in some they appear to be fairly substantial. There have been

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7.2 Separate stock region models

The separate stock region models described in Venables *et al.* (2011) were calibrated using rainfall data up to the 28th February 2011. For this project we have recalibrated the models using the updated SILO data up to 28th February 2012 and the catch and effort from the 2011 season. The results for the total NPF based on the unweighted (UW) and effort weighted (EW) versions of these models are compared to the feasibility models Figure 2. The range of the predictions is truncated above to prevent large predictions from dominating and obscuring the useful part of the scale. Figure 2 shows the actual catch (in black) for the WBP region for 1970-2011, along with predictions from the four models (old and new, UW and EW). The diagram uses black for the recorded catch, open symbols for the models as used in the feasibility study, solid symbols for the revised models, and red for the UW models and blue for the EW models. The fragility of the models, referred to several times above, is clearly apparent, particularly for the earlier years and for the UW models. This effect appears to be less with the new SILO data. The predictions are shown by region for 2011 and 2012 in Table 15 (Appendix 3).

The differences and relative differences between the model predictions (potential catch) and the recorded catch are shown in Figure 3 and Figure 4. These should not be interpreted as typical residuals as we have allowed the model to predict catch in areas where little was taken (according to the model, because little effort was expended). With this in mind, the positive divergences are somewhat expected, while the negative divergences are more of a concern (as potential catch should be larger than actual catch) and indicate where rainfall up to the end of February is not a good predictor of WBP catch. The large negative divergences occur in the years 1971, 1985, 1989 and 2008. The mean divergence is 770 tonnes (29%), although this includes one value of over 10,000 tonnes in 1975. The 2012 value does not appear in the plot as the 2012 season information was not available at the time of the preparation of the report but it is expected that the residual will be large as the catch for the season was already over 4600 tonnes at the end of June 2012, compared to the effort-weighted prediction around 3000 tonnes.

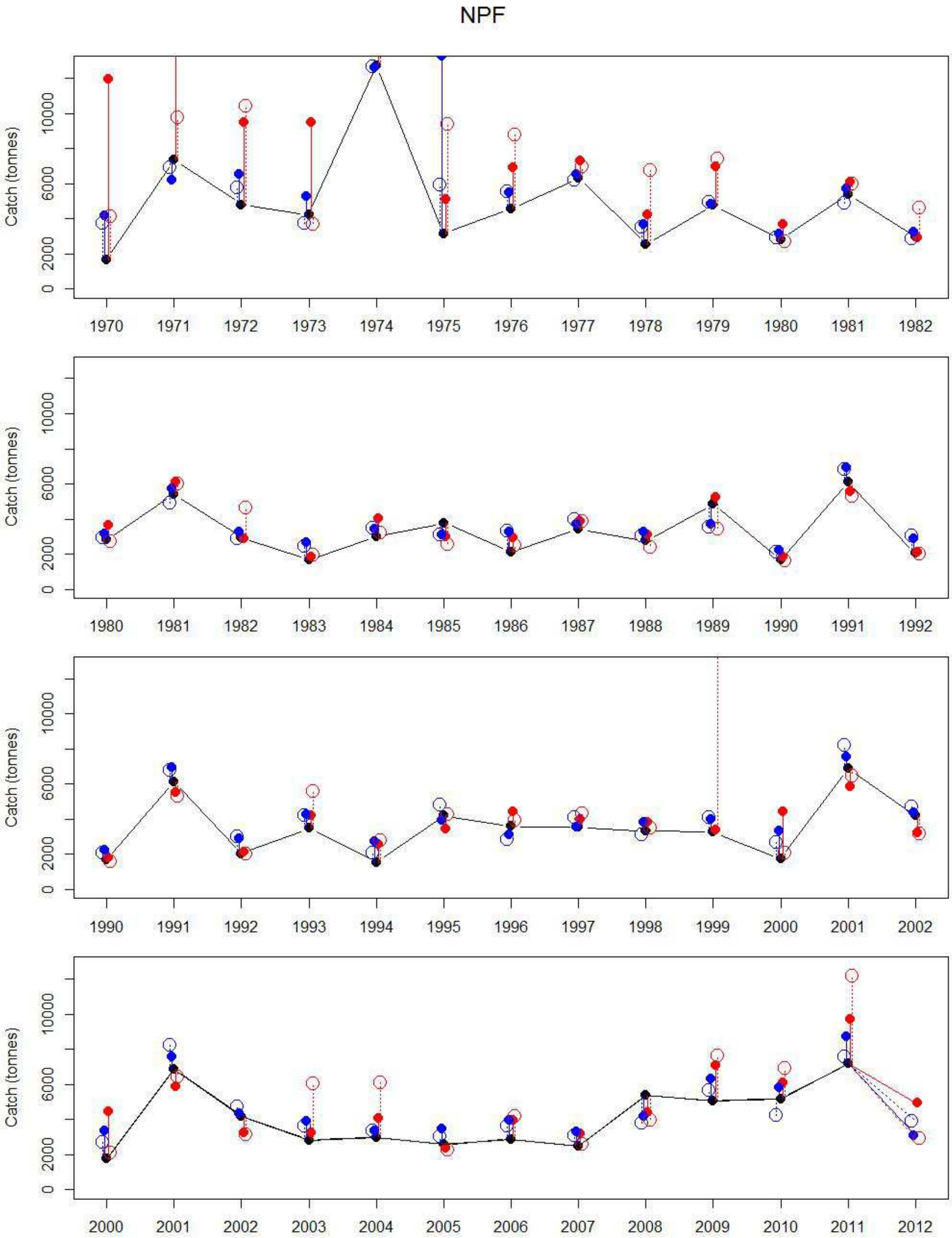

Figure 2. A comparison of recorded Banana Prawn Catch for the TAC region with four predictions.

The recorded catch is shown in black. The blue symbols and lines refer to the EW models and the red to UW models. Solid symbols refer to the new models using updated SILO and catch data. Open symbols refer to the models directly taken from the feasibility study. Each panel covers a 12 year period, with a two year overlap from one panel to the next.

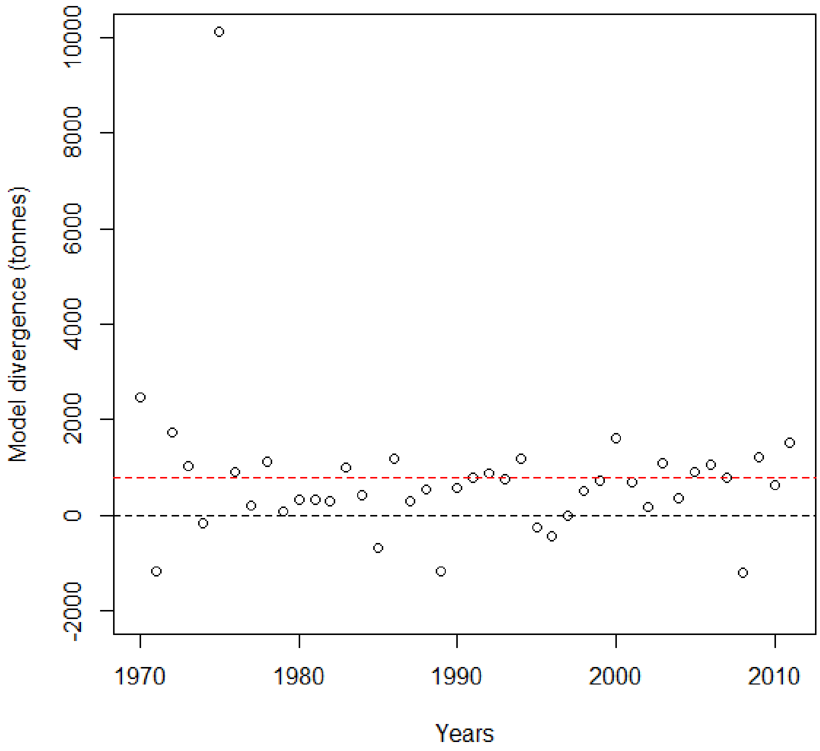

Figure 3. Difference between model predictions (potential catch) and recorded catch taken for the effort weighted, separate stock regions model based on the updated SILO data. The red line shows the mean residual of 770 tonnes.

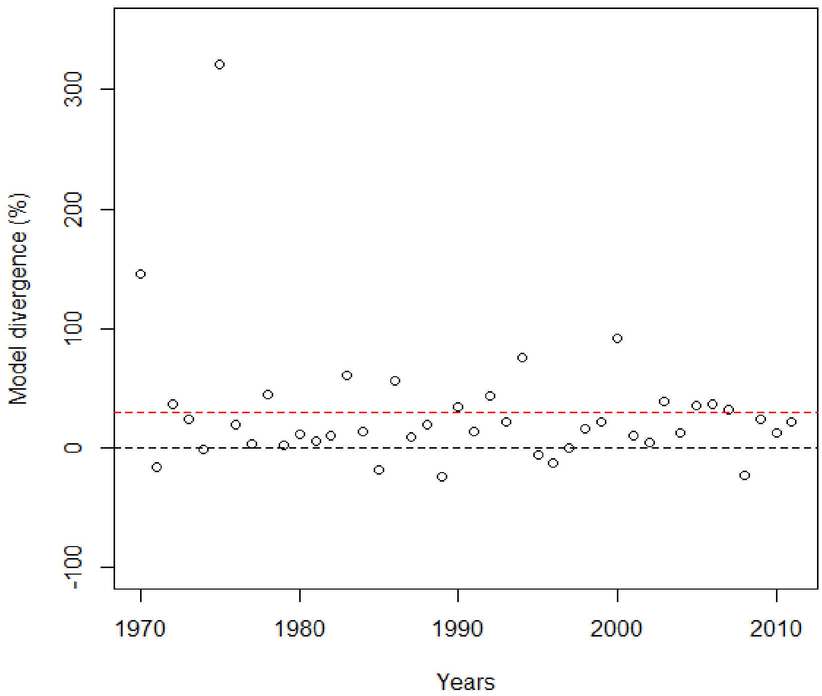

Figure 4. Relative difference between model predictions (potential catch) and actual catch taken for the effort weighted separate stock regions model based on the updated SILO data. The red line shows the mean residual of 29%.

The updated models were refitted restricting the rainfall weights to a maximum value of 0.025. The changes to the distributions of the rainfall weights for North Groote and Vanderlins for the effort weighted models are shown in Figure 5 and Figure 6, as examples of regions that may benefit from restricted weights. The rainfall distributions for all effort weighted and unweighted models are given in Appendix 3.2. In North Groote, a very peaked late rainfall distribution is replaced by a uniform distribution, while in Vanderlins very heavy weights previously allocated to the start of both the early and late seasons are replaced by much lower weights. These distributions are considered much more likely to reflect reality.

The predictions for the total NPF obtained by restricting the weights for the effort weighted and unweighted modelling approaches are compared to the original approach in Figure 7 and Table 16 in Appendix 3.2. While the weight restricted model improved fits in some years for the EW models, it made others worse. However for the effort unweighted models, the weight restriction resulted in a large improvement to the overall model fits. The divergence of the model predictions from the actual catches are shown in Figure 8 and Figure 9. While the large divergence for 1975 that appeared in Figure 3 is no longer apparent, the average divergence is very similar (774 tonnes) due to an increase in the number of positive divergences between 1000 and 3000 tonnes. Again, 2012 will be associated with a large negative divergence based on the Banana prawn catch to date at end June 2012.

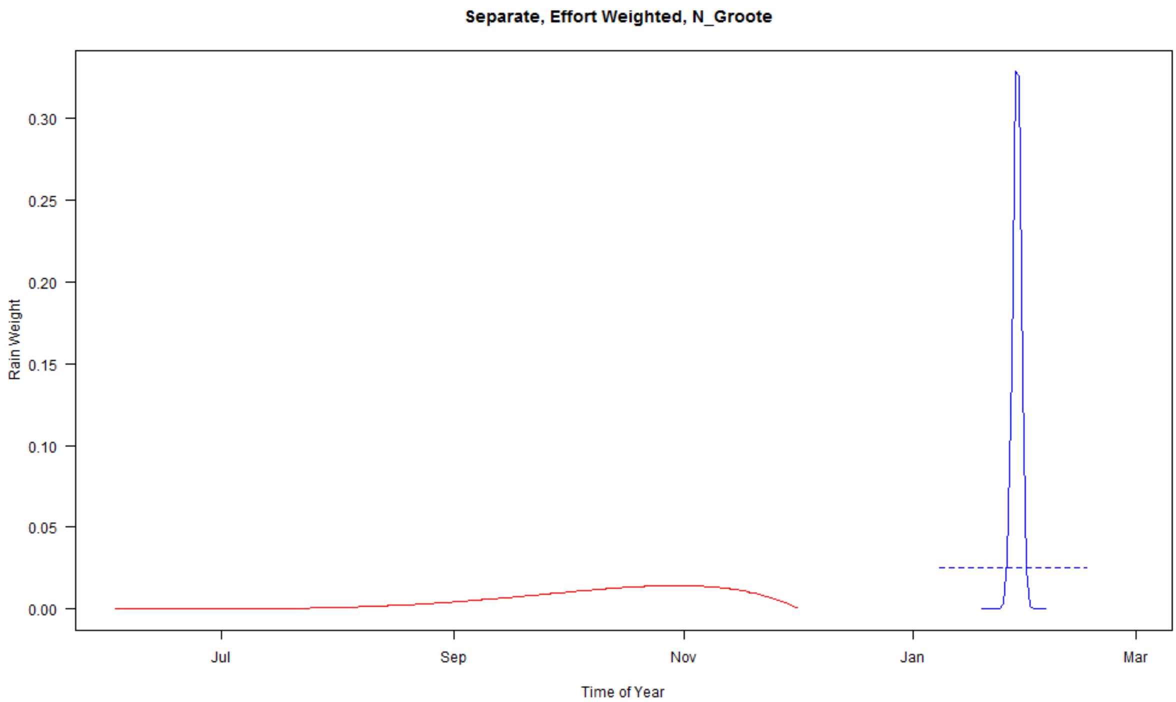

Figure 5. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for North Groote. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

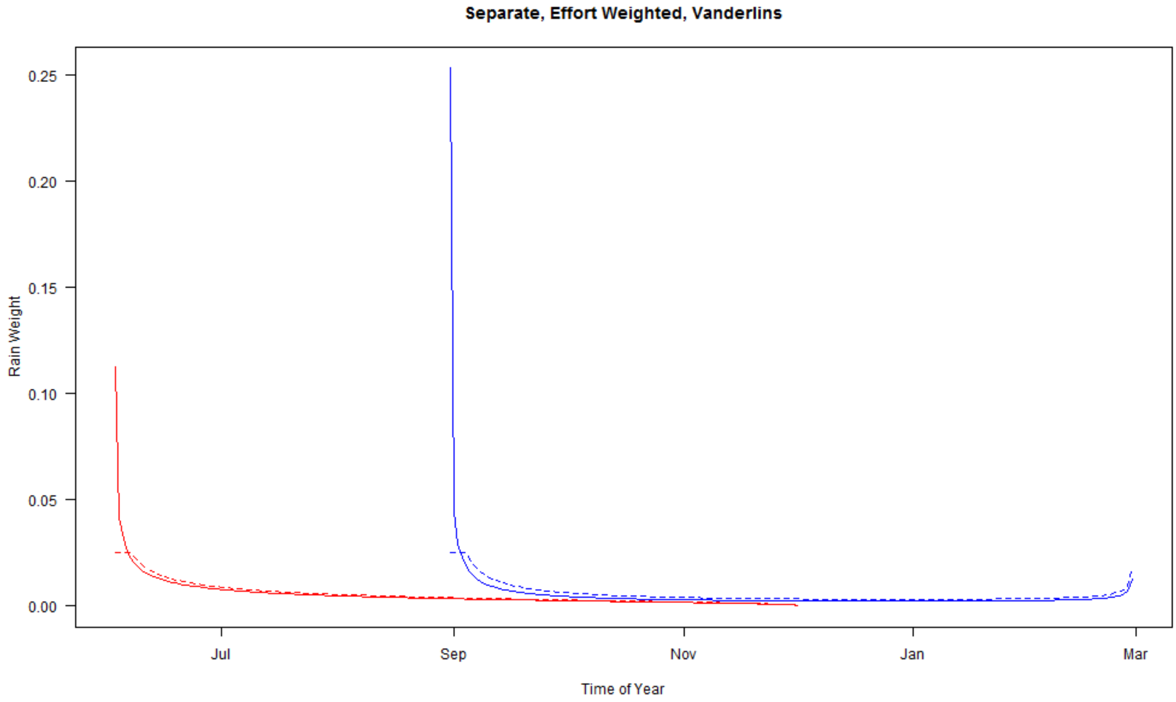

Figure 6. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Vanderlins. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

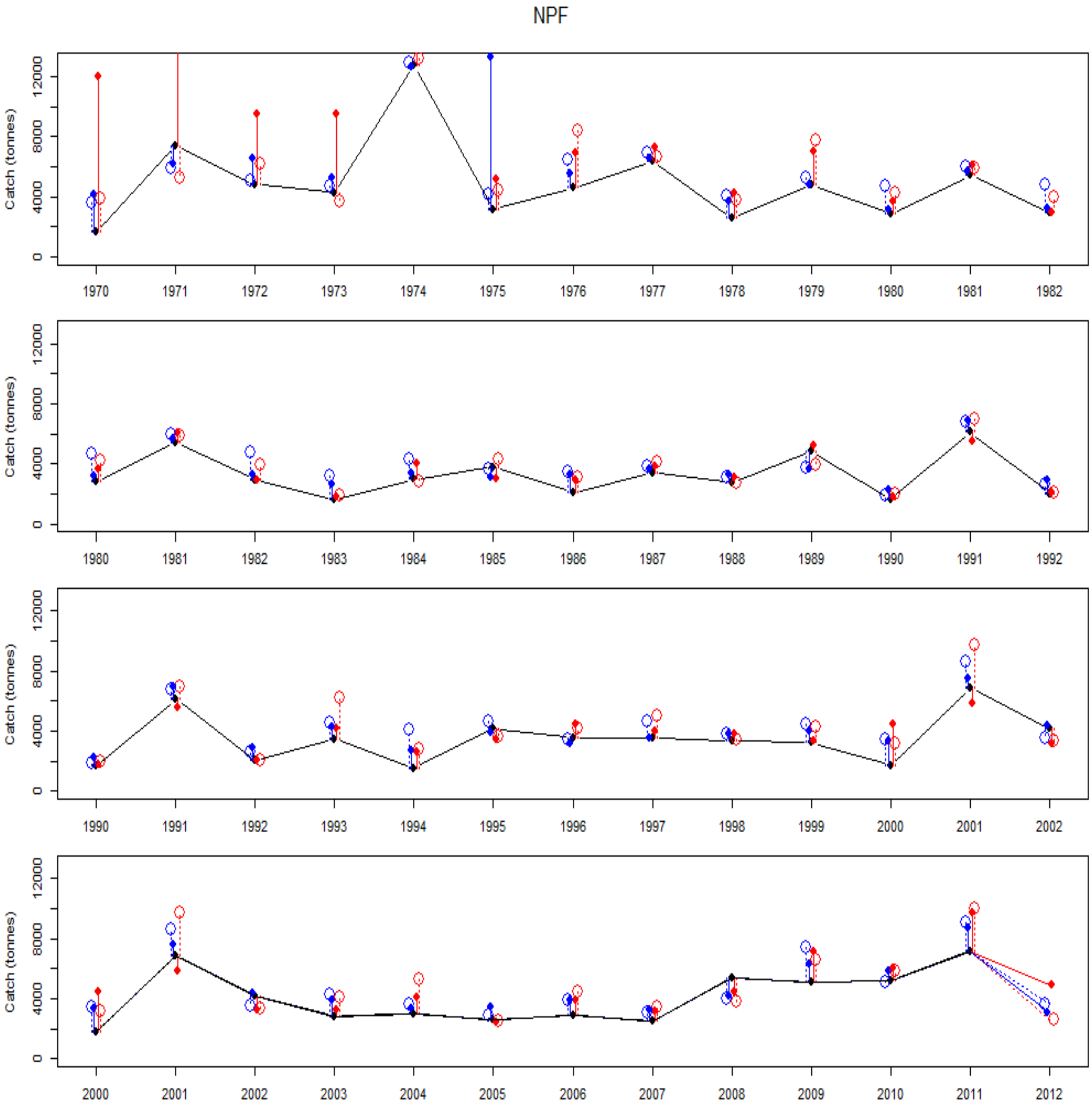

Figure 7. A comparison of recorded Banana Prawn Catch for the TAC region with four predictions. The recorded catch is shown in black. The blue symbols and lines refer to the EW models and the red to UW models. Solid symbols refer to the new models using updated SILO and catch data. Open symbols refer to the models with restricted weights. Each panel covers a 12 year period, with a two year overlap from one panel to the next.

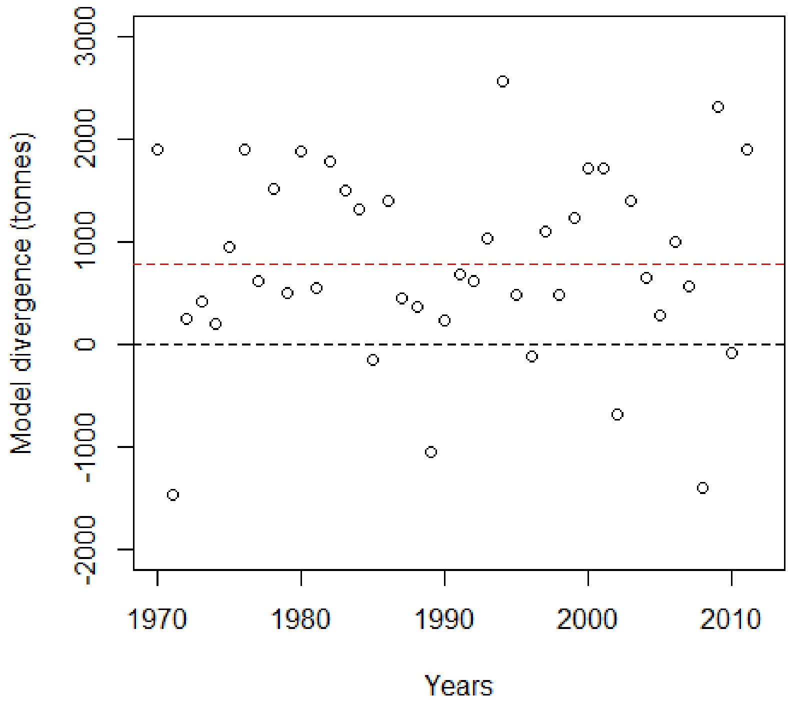

Figure 8. Difference between model predictions (potential catch) and recorded catch taken for the effort weighted model based on the updated SILO data. The red line shows the mean residual of 774 tonnes.

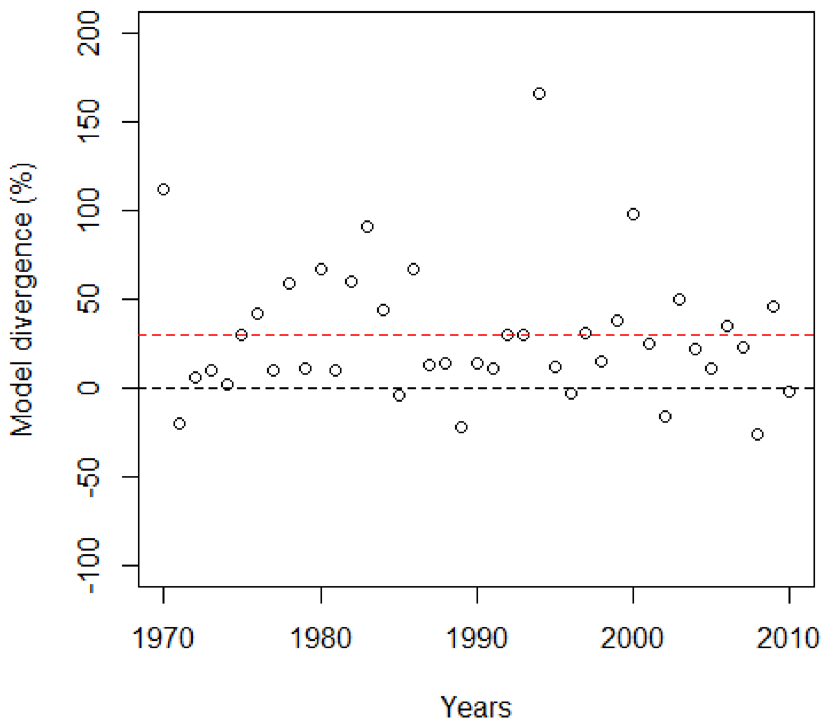

Figure 9. Relative difference between model predictions (potential catch) and recorded catch taken for the effort weighted model based on the updated SILO data. The red line shows the mean residual of 29%.

7.3 Single Model

7.3.1 FIXED WEIGHTS

The catch and predictions for the total NPF banana prawn region using the single model with fixed weights are show in Figure 10. The predictions at the individual stock region level can be found in Appendix 3.3. The effort weighted model (blue circles) provides quite a good fit to the data at the whole of fishery level (black circles), while the unweighted model (red circles) clearly, consistently overestimates the catch. The mean divergence (Figure 11) is around 100 tonnes lower than for the separate region models (Figure 2 and Figure 7), but we note that this is mostly due to an increase in the number of negative divergences.

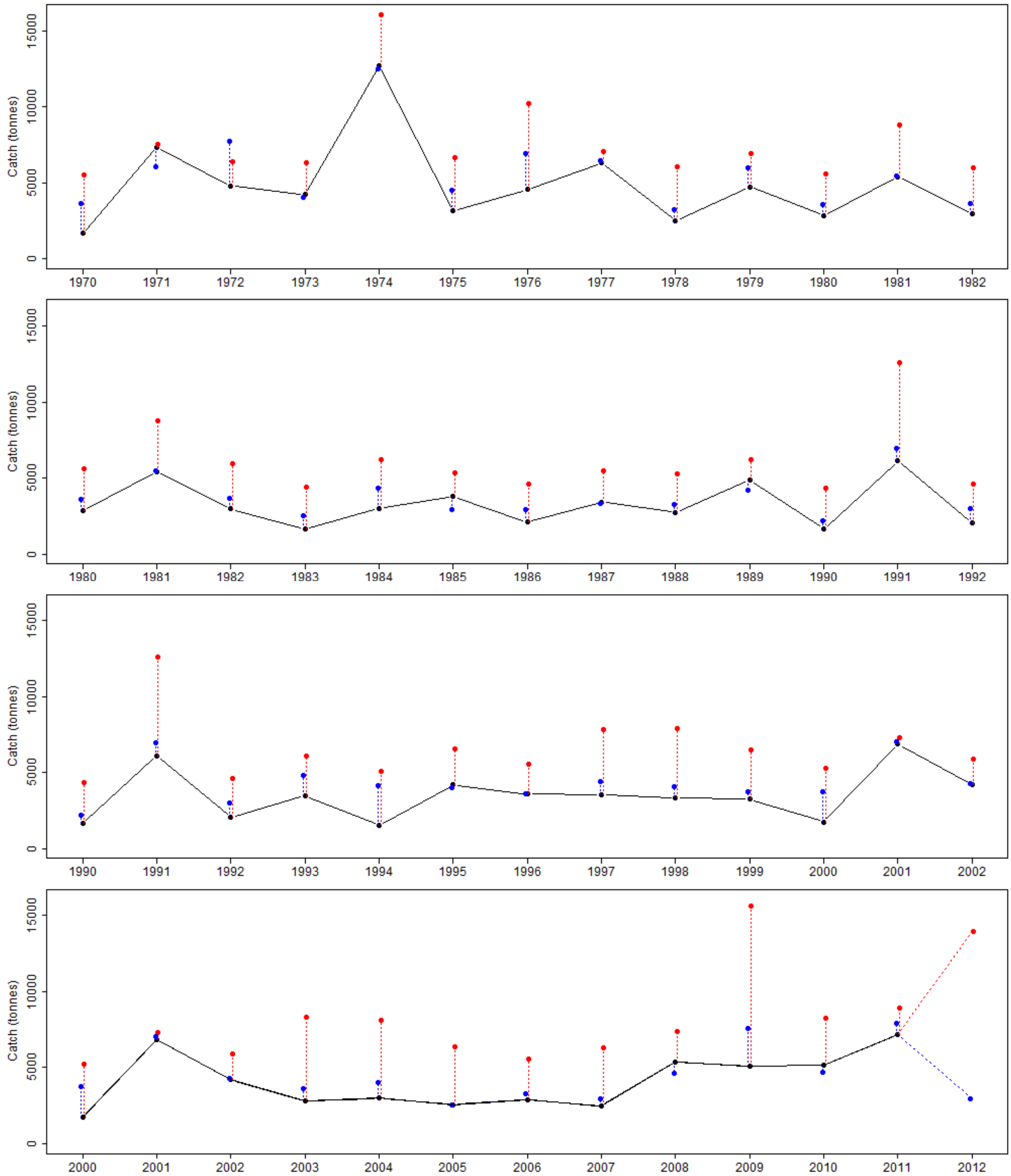

Figure 10. Catch and predictions for NPF region using the single model with fixed weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

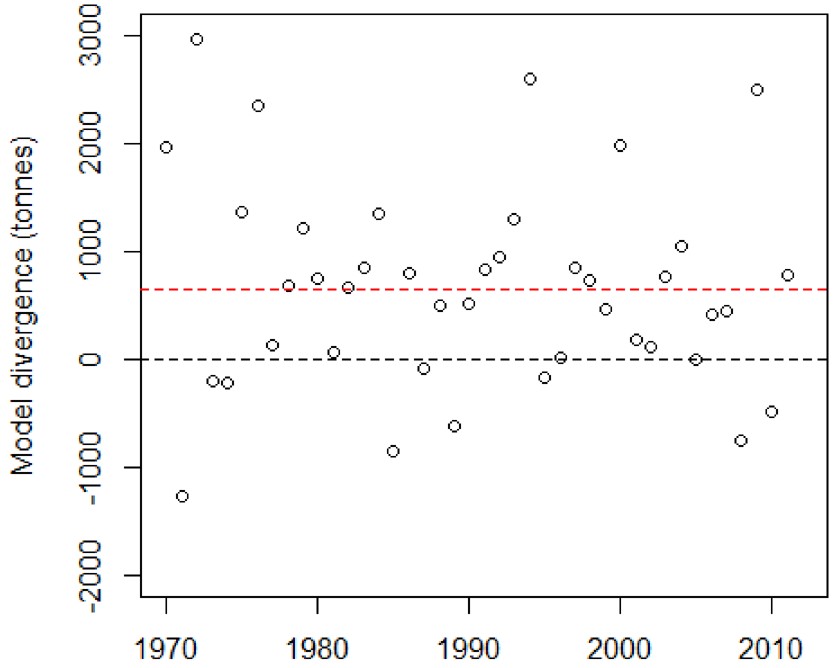

Figure 11. Difference between model predictions (potential catch) and recorded catch taken for the effort weighted single fixed weights model. The red line shows the mean divergence of 654 tonnes.

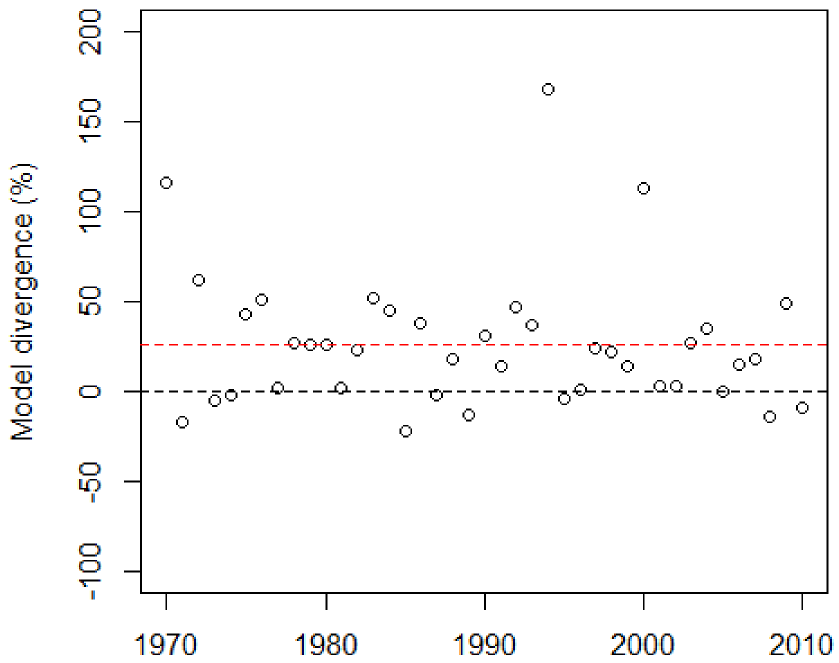

Figure 12. Relative difference between model predictions (potential catch) and recorded catch taken for the effort weighted single fixed weights model. The red line shows the mean divergence of 25%.

7.3.2 VARIABLE WEIGHTS

The catch and predictions for the total NPF banana prawn stock region using the single model with variable weights are shown in Figure 13. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red. The predictions at the individual stock region level can be found in Appendix 3.4. The effort weighted model provides quite a good fit to the data at the whole of fishery level, while the unweighted model clearly consistently overestimates the catch, consistent with the fixed weights model. The effort weighted model fits are similar or slightly better using the variable weights approach in the Coburg, Arnhem, Mornington, Karumba, Mitchell and Weipa. In North and South Groote the variable weights lead to a better fit in some years and worse in others. The variable weights lead to one very large residual in the Vanderlins where the estimate for 1994 is around 2500 tonnes when less than 100 tonnes were caught. The estimated potential catch is also large for the fixed weights case but only around half the size. The variable weights improve the unweighted model fits in many cases; however the fits are still much worse than the effort weighted models. The unweighted models have not been pursued any further in this project due to the evident better predictive capacity of the effort weighted models.

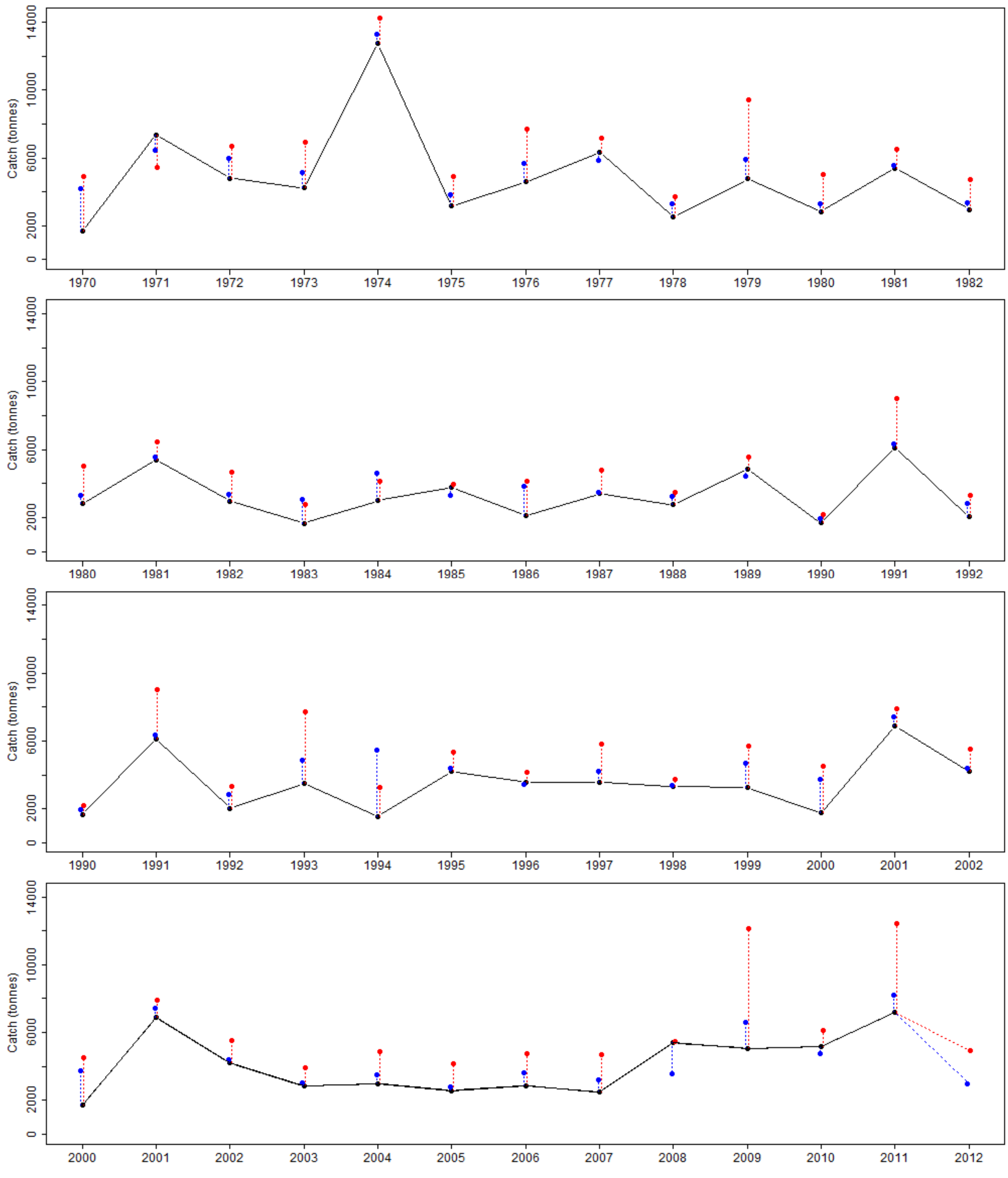

Figure 13. Catch and predictions for NPF region using the single model with variable weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

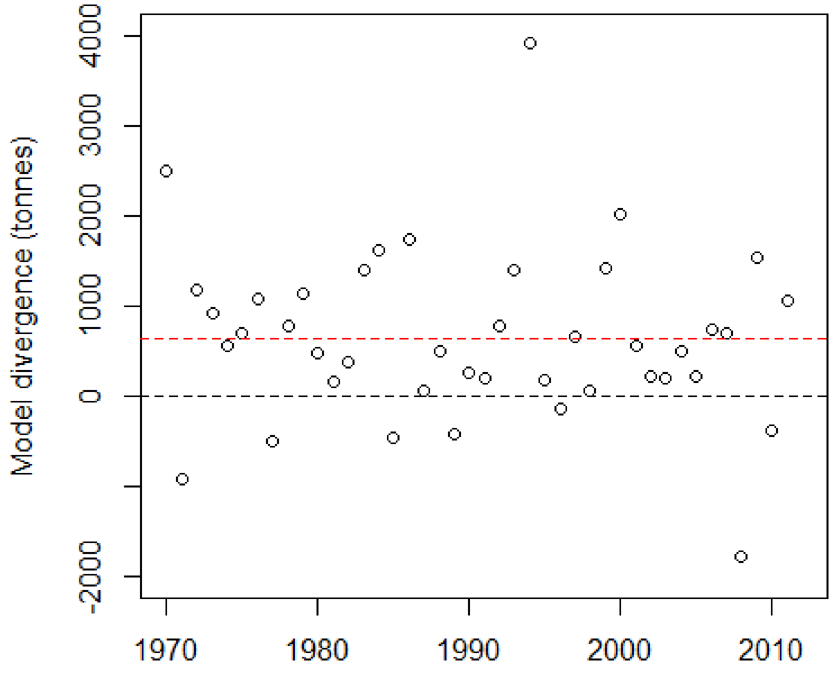

Figure 14. Difference between model predictions (potential catch) and recorded catch taken for the effort weighted single variable weights model. The red line shows the mean divergence of 645 tonnes.

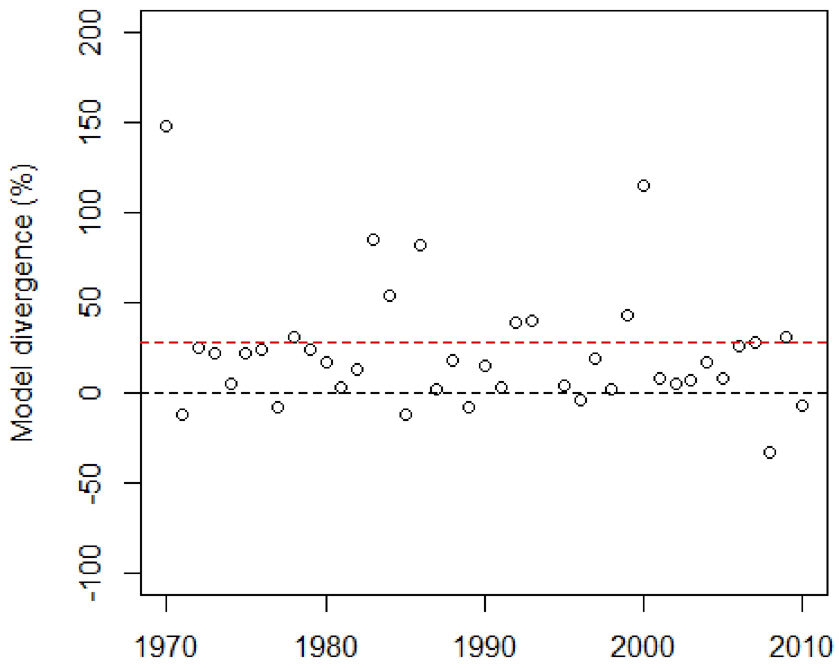

Figure 15. Difference between model predictions (potential catch) and recorded catch taken for the effort weighted single fixed weights model. The red line shows the mean divergence of 28%.

7.3.3 NPF RECRUITMENT MONITORING SURVEY INDEX

None of the exploratory steps proved satisfactory. We feel that the tentative suggestion made in Venables et al. (2011) should no longer be followed, and that the survey information should only be used as an informal ancillary piece of information that could conceivably be used for management purposes at some time in the future.

There are at least three reasons why we are now of this view, namely:

1. The survey is designed specifically to gain a pre-season index of Tiger prawn abundance; information on WBP is only a by-product of the survey;
2. With only nine years of data, any statistical relationship between the survey index and later WBP potential catch cannot be reliably calibrated, statistically; and,
3. On a purely practical level, there can be no guarantee the indices will be available at the time they are needed to use in setting the WBP TAC, since the timing of the survey is linked to moon-phase, which will often mean it takes place well into February.

For completeness, we outline the results of a new investigation into the potential use of the survey indices as an adjustment device, should they be available in time.

Let I be a survey index for a specific stock region. We can in principle transform this into an estimator of potential catch for the region by a scale change, θI. Let C_P be the predicted potential catch for the region using any of the models detailed above. Our task is to combine these two predictors of potential catch optimally into a single predictor. A natural way to do so is to consider a weighted geometric mean, that is, $C = (\theta I)^{\alpha} C_P^{1-\alpha}$ where $0 \le \alpha \le 1$. Taking logs and incorporating sampling errors then leads to an adjustment model of the form

$$\log C = \beta + \alpha(\log I - \log C_P) + \log C_P + \varepsilon$$

where, as before, C is the recorded catch as a proxy for the potential, and α and β $(= \alpha \log \theta)$ are to be estimated. The restriction $0 \le \alpha \le 1$ implies this is a non-linear regression, but we estimate it as a linear regression and check that the restriction applies, as a diagnostic check on the model.

Note that this equation differs from that used in the feasibility study. We consider the present form, though similar to the last, is both statistically more defensible and if anything, slightly more robust than the exploratory version used previously.

The Recruitment Monitoring Survey is confined to the Gulf of Carpentaria and hence provides no reliable information for the 3 regions outside the Gulf. WBP survey indices are provided for 5 survey regions, which only broadly match the 7 WBP stock regions in the Gulf. Stock regions *Vanderlins*, *Mornington*, *Karumba* and *Weipa* all have direct survey indices available. We have use the *Groote* survey index for both *North* and *South Groote* stock regions, and the *Karumba* survey index for the *Mitchell* stock region, also.

The adjustment equations above were also estimated using Effort weights, for reasons similar to those given for the primary prediction models. This weighting makes little difference in most regions, but is quite influential in North and South Groote regions, where there is a wide variation in effort, most likely due to periods of closure.

Table 1 below shows the estimates of the parameter α for the 7 stock regions and for primary predictions from all three modelling strategies. As anticipated, no estimate is larger than 1, and only one, that for *Karumba* with the *Varying* model, is below 0. These estimates give the estimated weight to be given to the survey index in the combined potential catch prediction, with the arithmetical complement going to the initial prediction, $\boldsymbol{C_P}$. The only place where these weights become appreciable is in Weipa, for all three models. This consistency across models suggests that Weipa is a special case and the additional information may well be useful there.

Table 1. Estimates of the α parameter for 7 stock regions and three prediction models.

REGION	FIXED	VARIABLE	SEPARATE
N. Groote	0.1839	0.1891	0.1451
S. Groote	0.2164	0.0136	0.0096
Vanderlins	0.1519	0.1523	0.1455
Mornington	0.2250	0.2298	0.2240
Karumba	0.0174	-0.0959	0.1252
Mitchell	0.2800	0.2200	0.1514
Weipa	0.6832	0.6431	0.7086

To give some indication of the likely effectiveness of the adjustment model, the multiple correlation coefficients for each are shown in Table 2 below. Although these estimates include a bias correction, with only 9 observations and 2 estimated parameters, these must be interpreted with some caution. Again, though, there is some consistency within regions across modelling strategies, with Karumba consistently high near 80% and Weipa around 60%. The other regions are mostly lower.

Table 2. Estimated multiple correlation coefficients for the adjustment models.

REGION	FIXED	VARIABLE	SEPARATE
N. Groote	0.4675	0.3826	0.3698
S. Groote	0.3204	0.3471	0.6148
Vanderlins	0.1951	0.3082	0.3871
Mornington	0.3797	0.3237	0.6872
Karumba	0.8340	0.8477	0.8254
Mitchell	0.4498	0.4612	0.3613
Weipa	0.6350	0.6418	0.6386

Figure 16 below shows the effect of making these survey adjustments in the individual stock regions (where available) and aggregating up to the entire NPF. The black lines and points show the recorded catch (in tonnes), the red dashed lines show the model predictions (Fixed, Variable and Separate models) and the vertical green lines and points show the size and direction of the survey adjustment. In general the effect is usually a small improvement, in the sense of bringing the estimate closer to the actual catch, but overall the effect is insignificant (as well as being statistically non-significant).

For reference, the effect of the survey adjustment in each of the 7 stock regions where survey information is available, is shown in a series of similar graphical displays in Figure 80 to Figure 86 (Appendix 3). The effect is most noticeable in Weipa (Figure 86), although it is by no means a uniform improvement. In the case of Weipa, the catch seems to be particularly difficult to predict using rainfall data alone, and while including survey information may offer some improvement, overall the result is very erratic.

Our recommendation is accordingly that the survey information should not be included in any formal way. Informally, such abundance indices may well prove a useful adjunct to the information base to be used when setting the TAC, and as more experience accrues, just how this might best be done may well become more apparent.

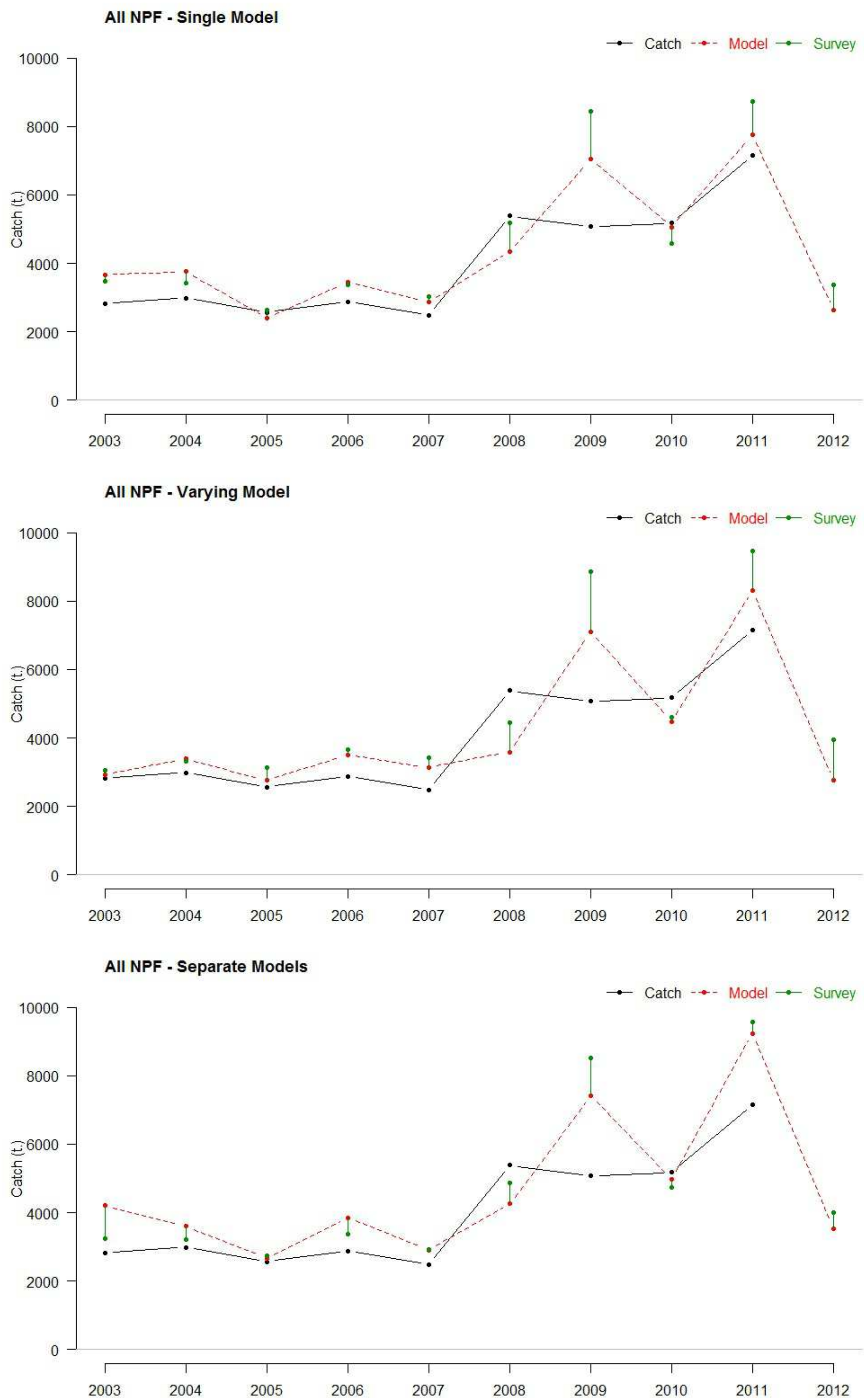

Figure 16. Survey adjustments to model predictions of potential catch aggregated over the entire NPF.

7.4 Refining the spatial scale

7.4.1 SEPARATE REGION MODELS

Separating Fog Bay from the remainder of Coburg and fitting separate region models led to the rainfall weight distributions in Figure 17 and Figure 18. While the Fog Bay distribution (Figure 19) suggests an early peak in August and a late peak in late February, the Coburg distribution (Figure 20) suggests November/December and a much more uniform spread for the later months. The differences between these distributions provide support to separate these areas. The model predictions for Fog Bay, Coburg and the total NPF, are shown in Figure 19, Figure 20 and Figure 21 respectively. The model fits at the region level are reasonable and the fit for the total NPF is similar to Figure 2, which is expected given we have only altered the predictions for one of the original nine stock regions.

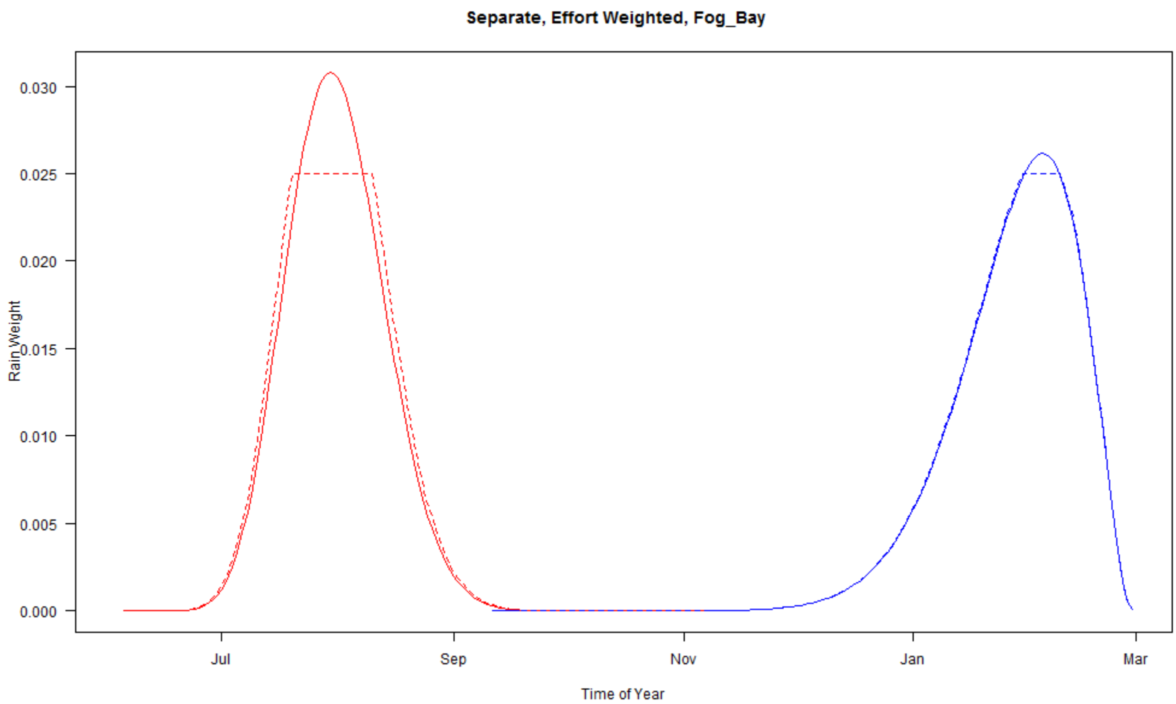

Figure 17. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Fog Bay based on effort weighted model separate region model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

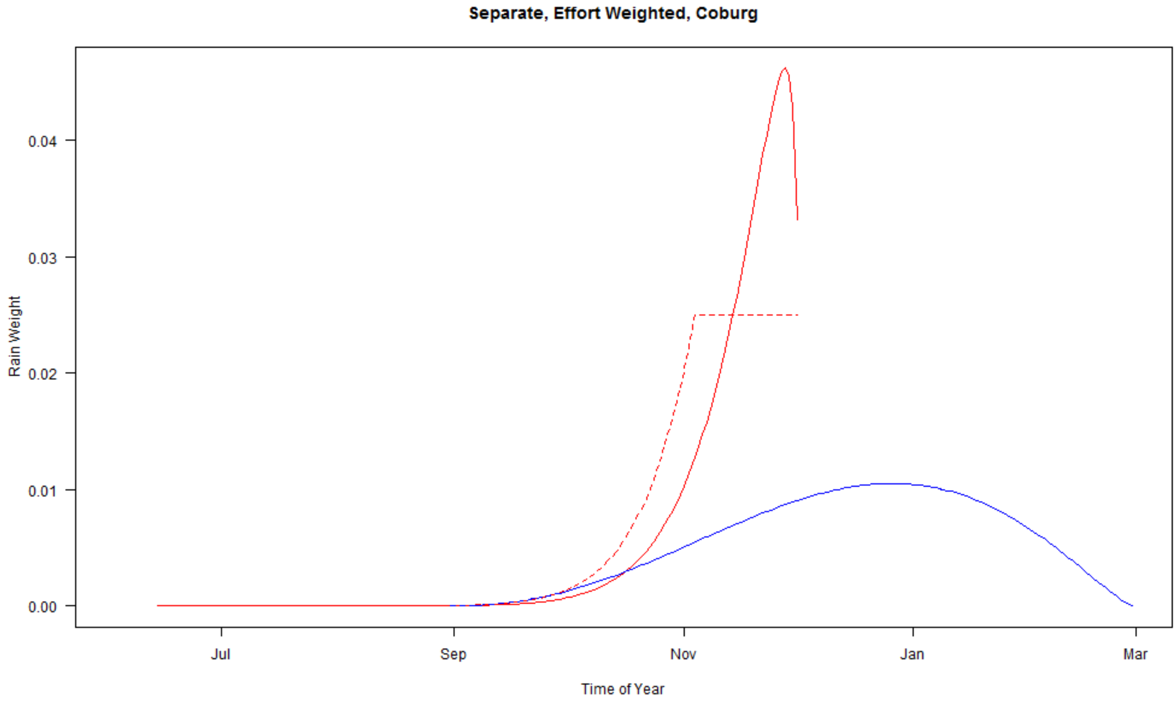

Figure 18. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Coburg (excluding Fog Bay) based on effort weighted model separate region model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

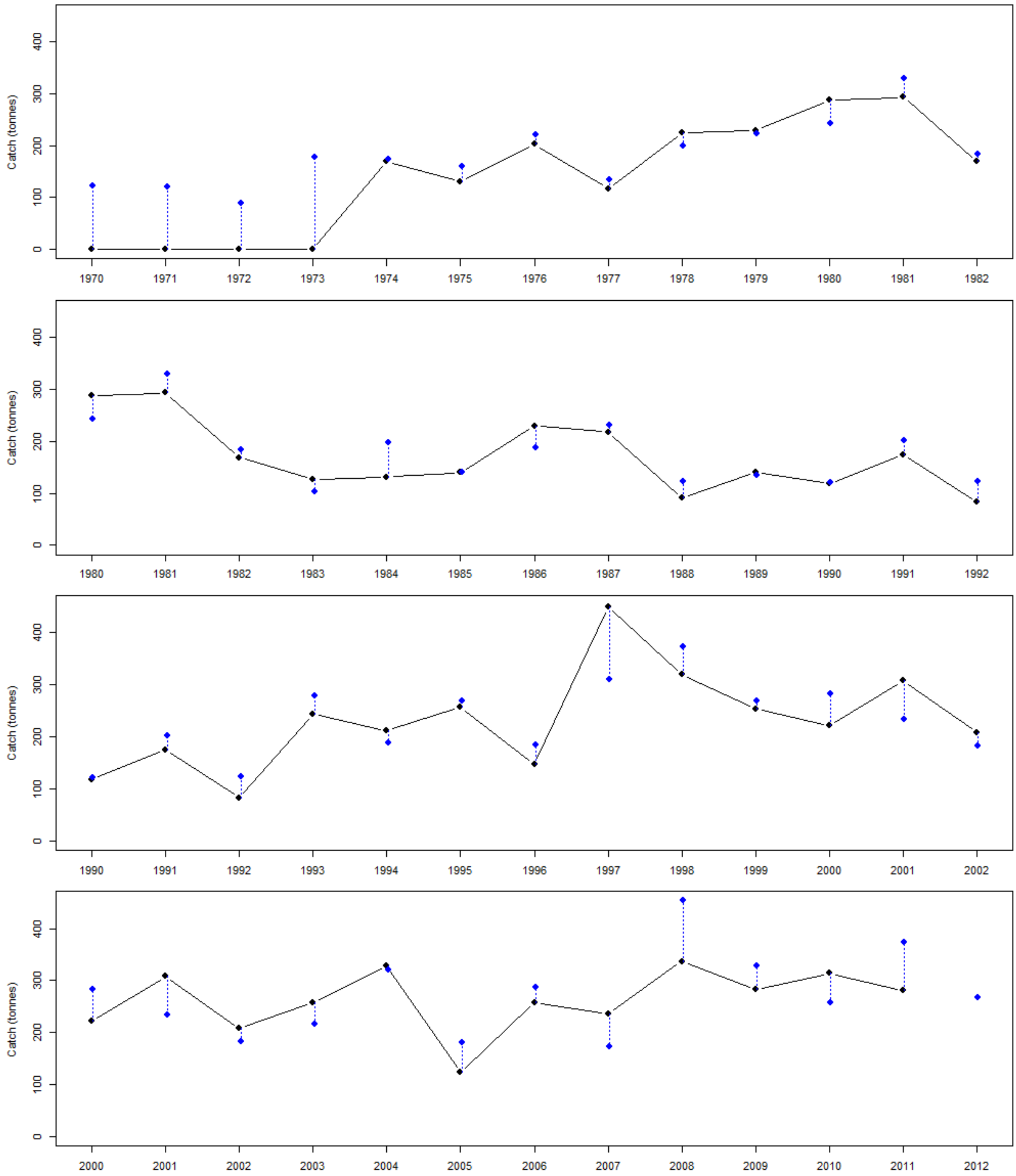

Figure 19. Catch and predictions for Fog Bay region using the effort weighted separate region model. The recorded catch is shown in black and the effort weighted predictions in blue.

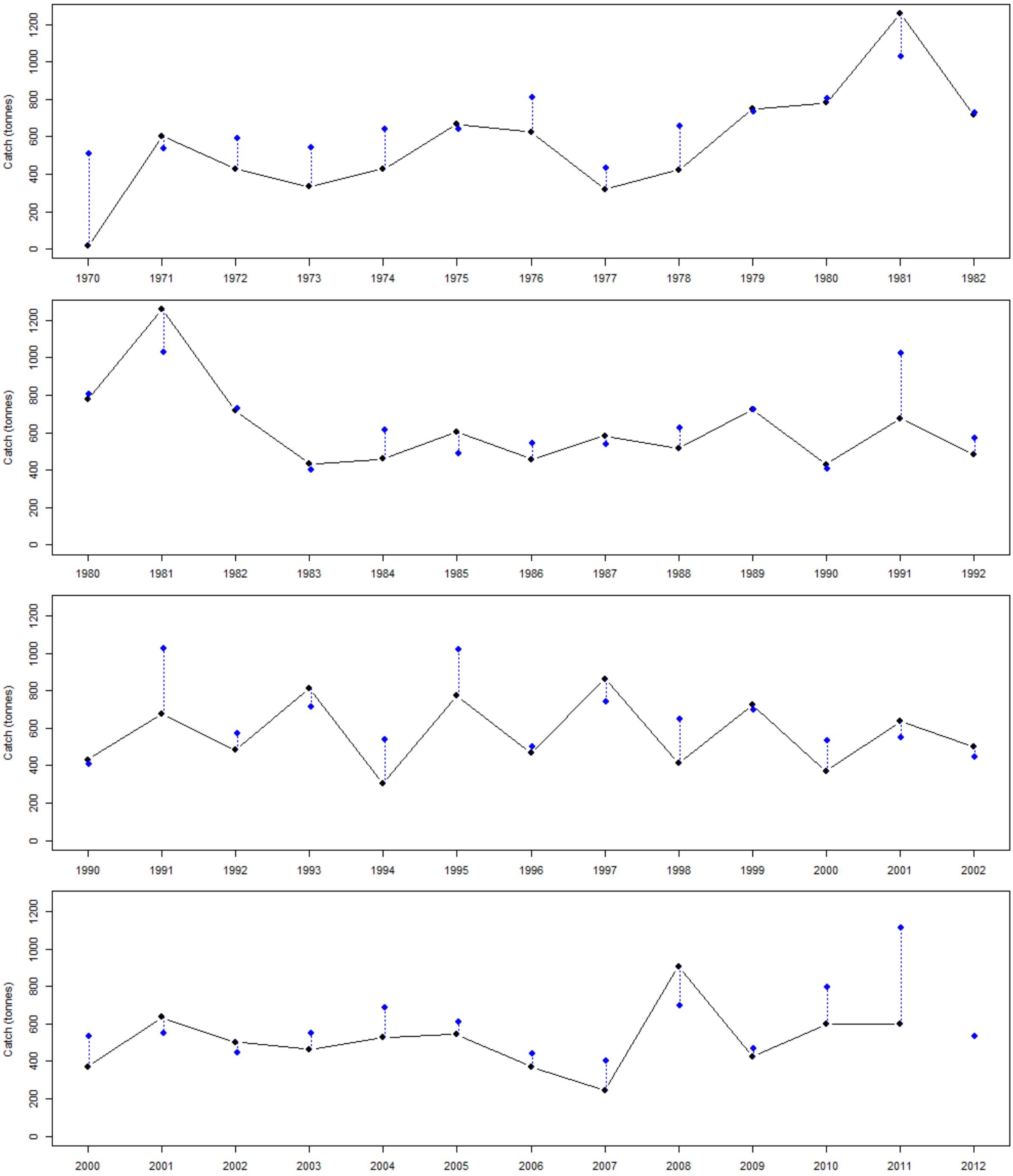

Figure 20. Catch and predictions for Coburg region using the effort weighted separate region model. The recorded catch is shown in black and the effort weighted predictions in blue.

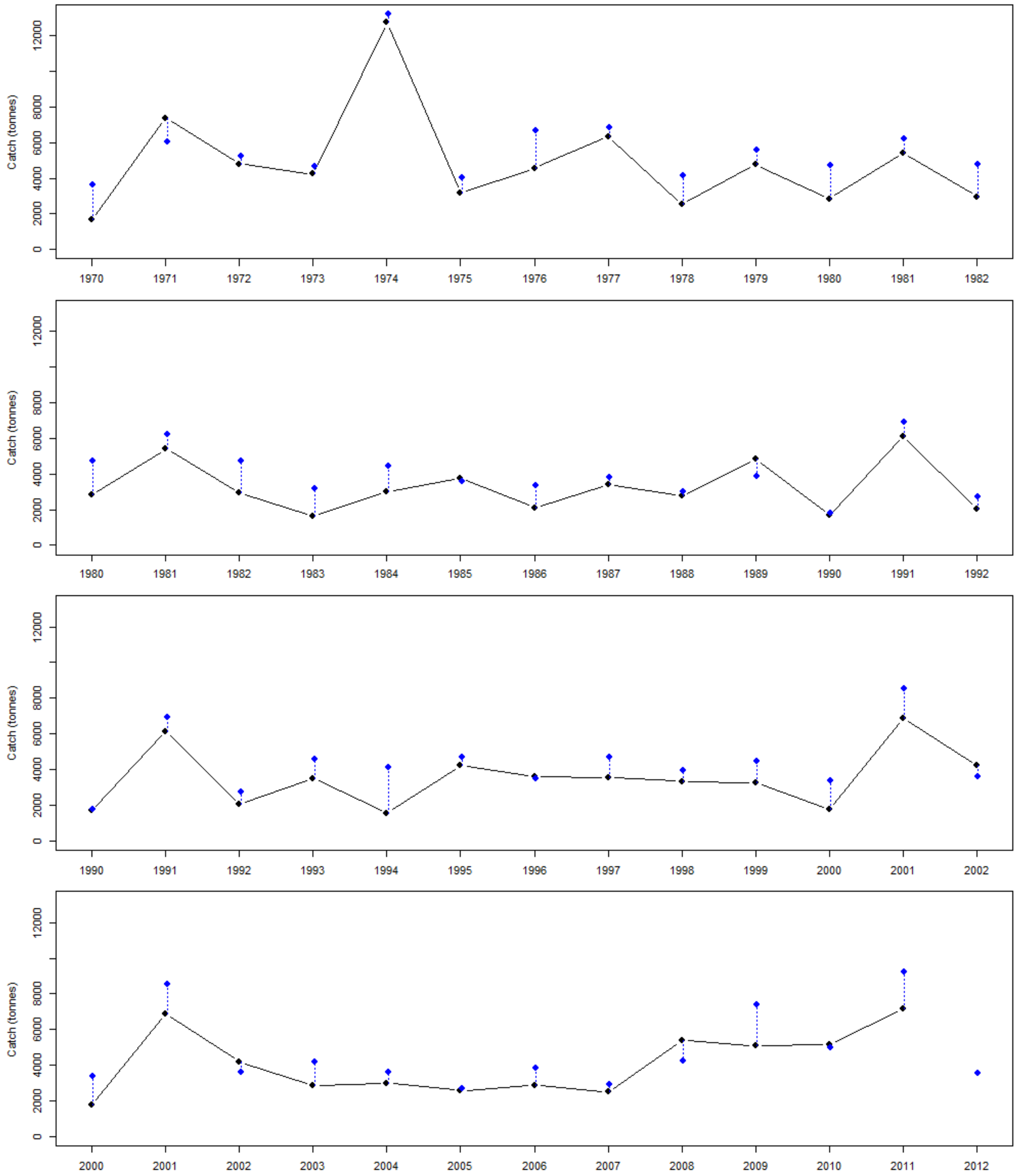

Figure 21. Catch and predictions for the total NPF Banana prawn region using the effort weighted separate region models with separate models for Fog Bay and the rest of Coburg. The recorded catch is shown in black and the effort weighted predictions in blue.

7.4.2 FIXED WEIGHTS

The model predictions and recorded catch for Fog Bay, Coburg and the total NPF using a single fixed weights model (with separate regions for Coburg and Fog Bay) are shown in Figure 22, Figure 23 and Figure 24. In some years this models appears to be a better fit than the separate region models but in others it is worse. The model fitting process is however far more stable and statistically robust. The largest positive divergences occur in 1972 and 1994 (Figure 25 and Figure 26). Of more concern are the large negative divergences in 2008 and 2012, which would have led to an underestimate of the WBP stock available for these seasons. We note that the mean divergence, 817 tonnes (Figure 25) and mean relative divergence, 30% (Figure 26) were a little higher than for previous models, largely because most divergences were positive.

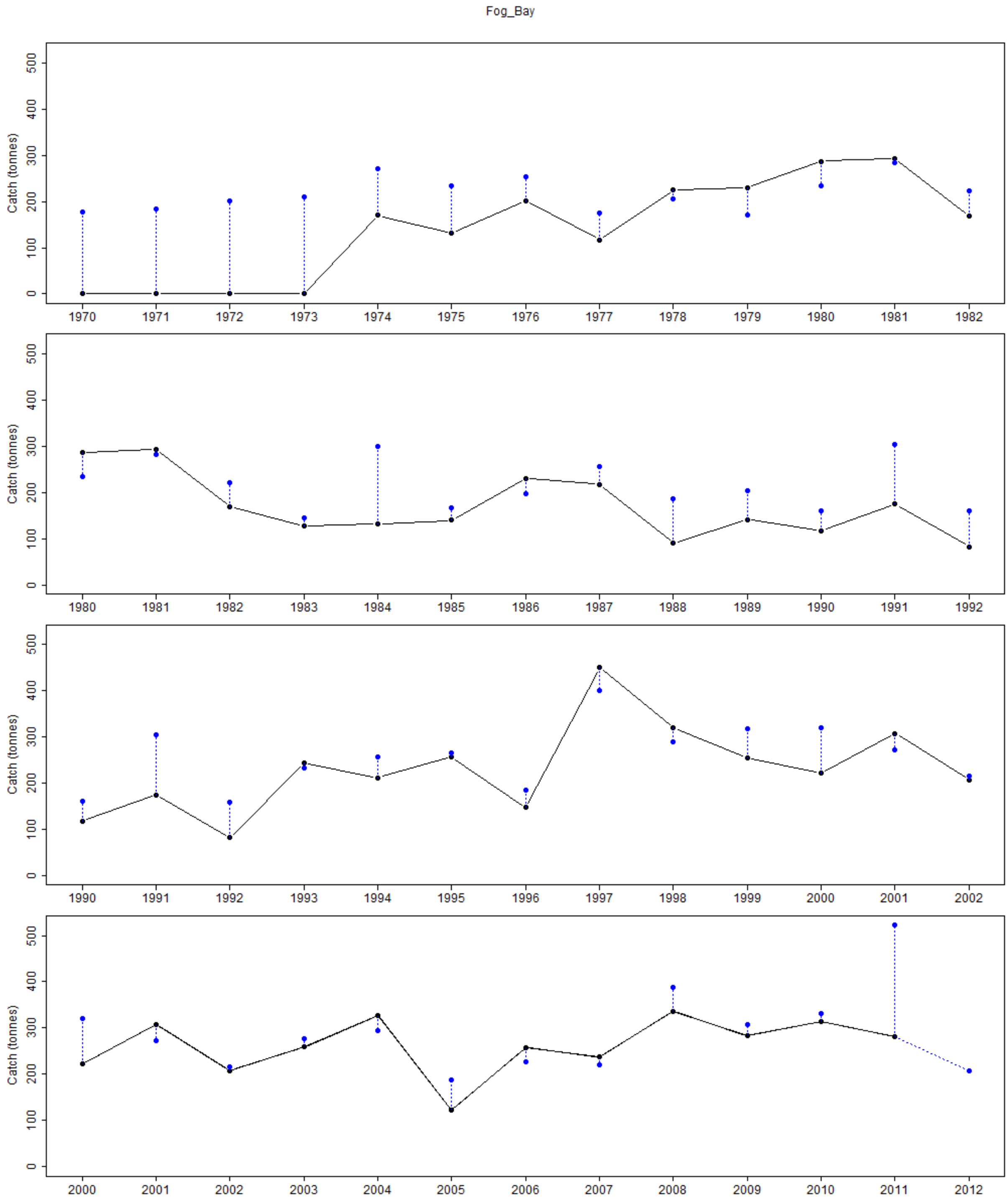

Figure 22. Catch and predictions for the Fog Bay region using the effort weighted fixed weights model with separate regions defined for Fog Bay and the rest of Coburg. The recorded catch is shown in black and the effort weighted predictions in blue.

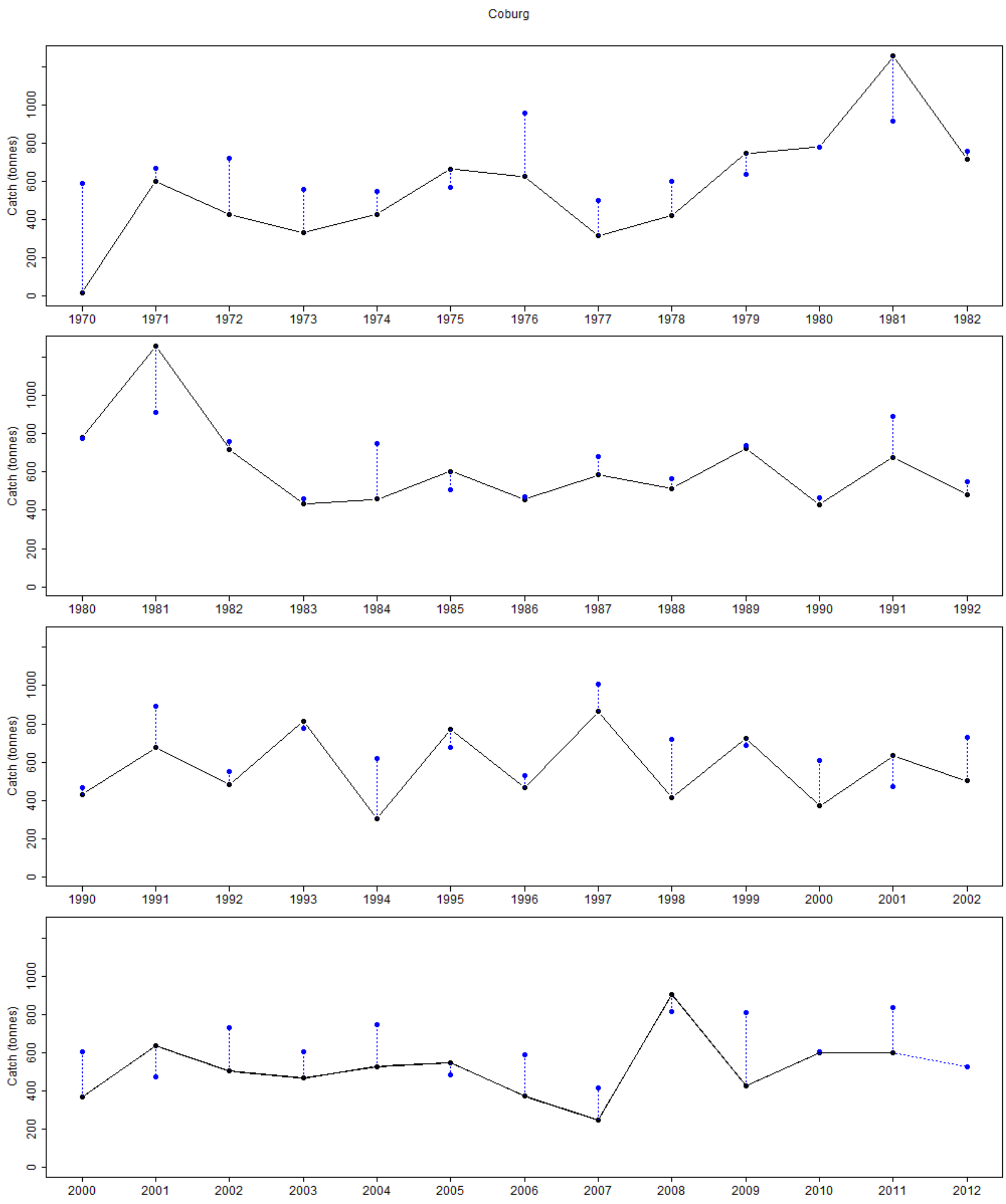

Figure 23. Catch and predictions for the Coburg region using the effort weighted fixed weights model with separate regions defined for Fog Bay and the rest of Coburg. The recorded catch is shown in black and the effort weighted predictions in blue.

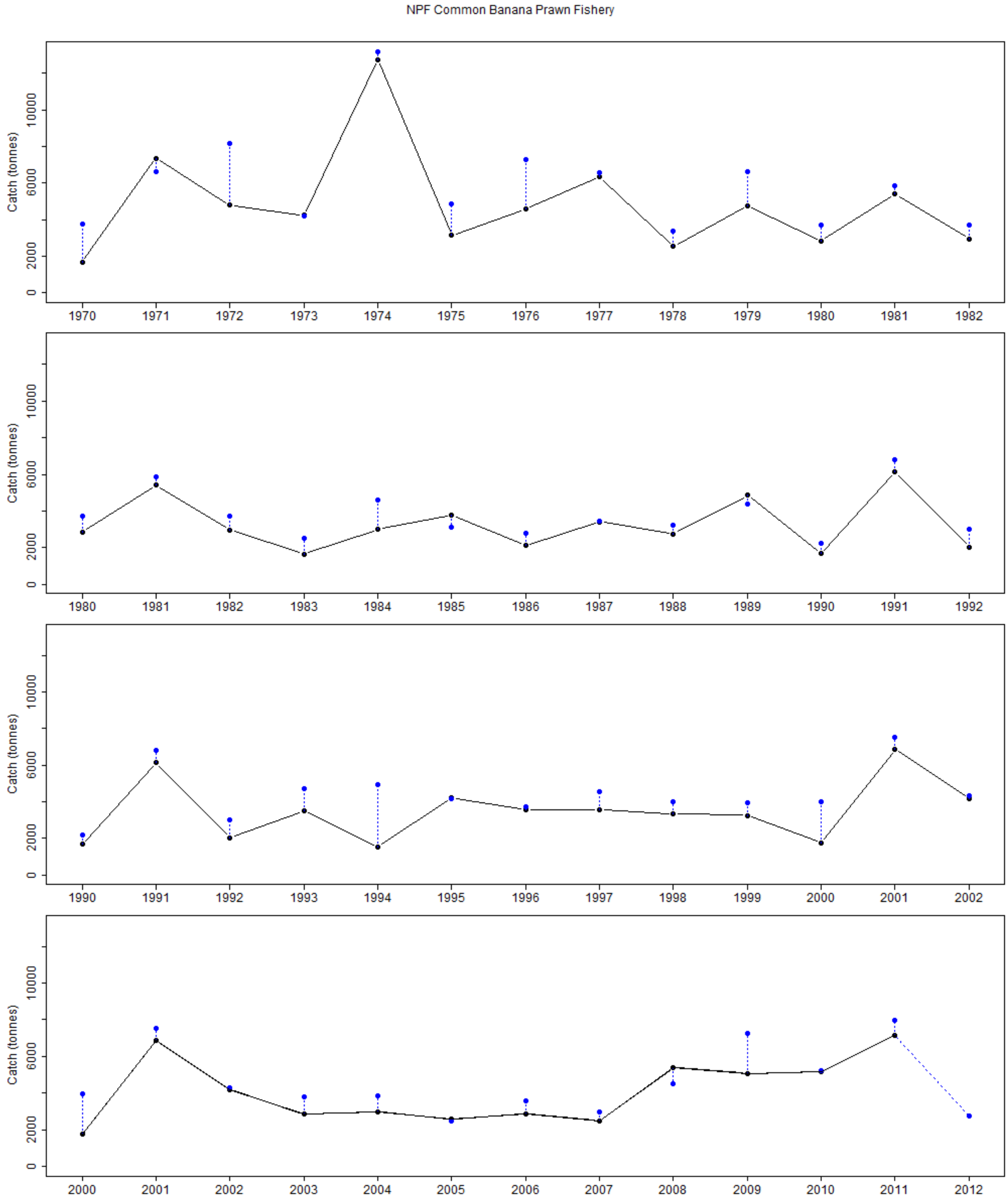

Figure 24. Catch and predictions for the total NPF Banana prawn region using the effort weighted fixed weights model with separate regions defined for Fog Bay and the rest of Coburg. The recorded catch is shown in black and the effort weighted predictions in blue.

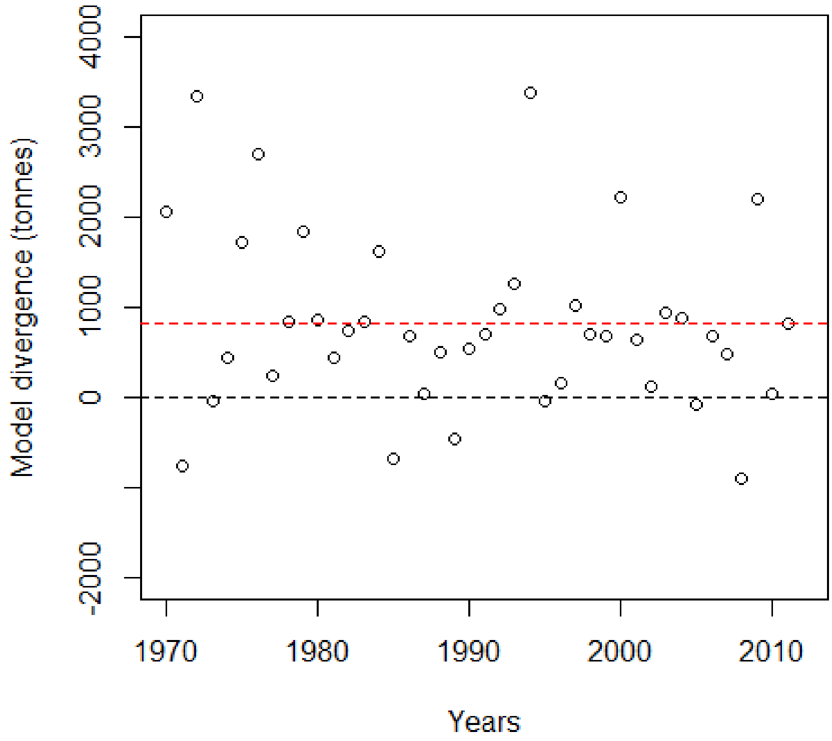

Figure 25. Difference between model predictions (potential catch) and recorded catch taken for the effort weighted single fixed weights model with separate regions defined for Fog Bay and the rest of Coburg. The red line shows the mean divergence of 817 tonnes.

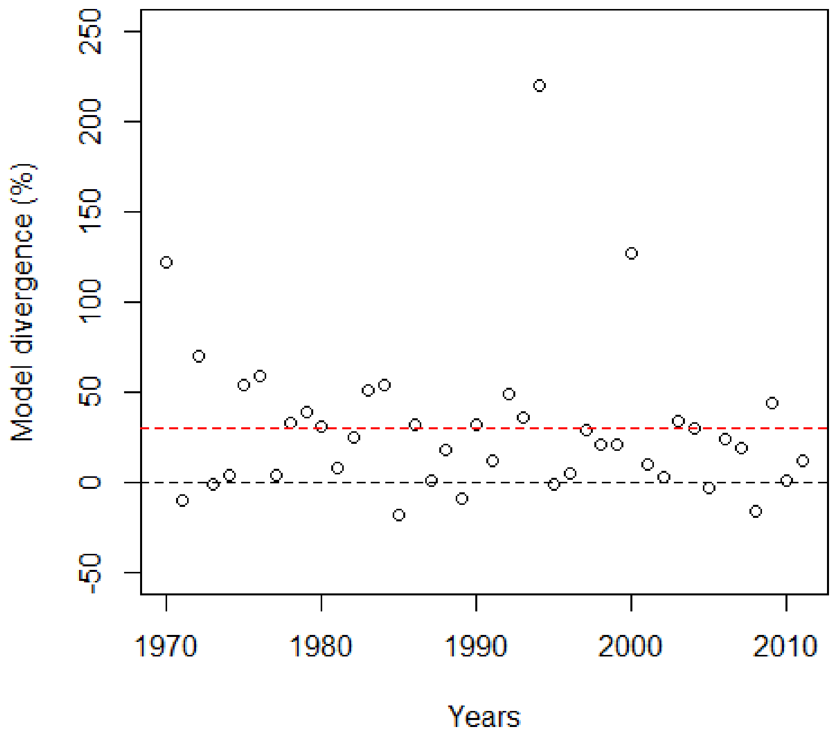

Figure 26. Relative difference between model predictions (potential catch) and recorded catch taken for the effort weighted single fixed weights model with separate regions defined for Fog Bay and the rest of Coburg. The red line shows the mean relative divergence of 30%.

7.4.3 VARIABLE WEIGHTS

The rainfall weights distributions for Fog Bay and Coburg based on the variable weights model are given in Figure 27 and Figure 28. The distributions are very similar and so combining Fog Bay and Coburg would be a reasonable approach to this model. Although the number of model parameters is increased by having an extra region in the model, the sample size is increased through the addition of 42 years of data for Fog Bay through the disaggregation of the catches. In the future the effect of taking this level of disaggregation to a greater extreme (modelling at a much finer scale) could be considered. The model predictions and recorded catch for Fog Bay, Coburg and the total NPF using a variable weights model (with separate regions for Coburg and Fog Bay) are shown in Figure 27, Figure 28 and Figure 29. The model fits are not vastly different to the previous two modelling scenarios.

We recommend this modelling approach as the way forward. It provides some flexibility on a regional level but offers a higher level of stability than modelling each stock region separately.

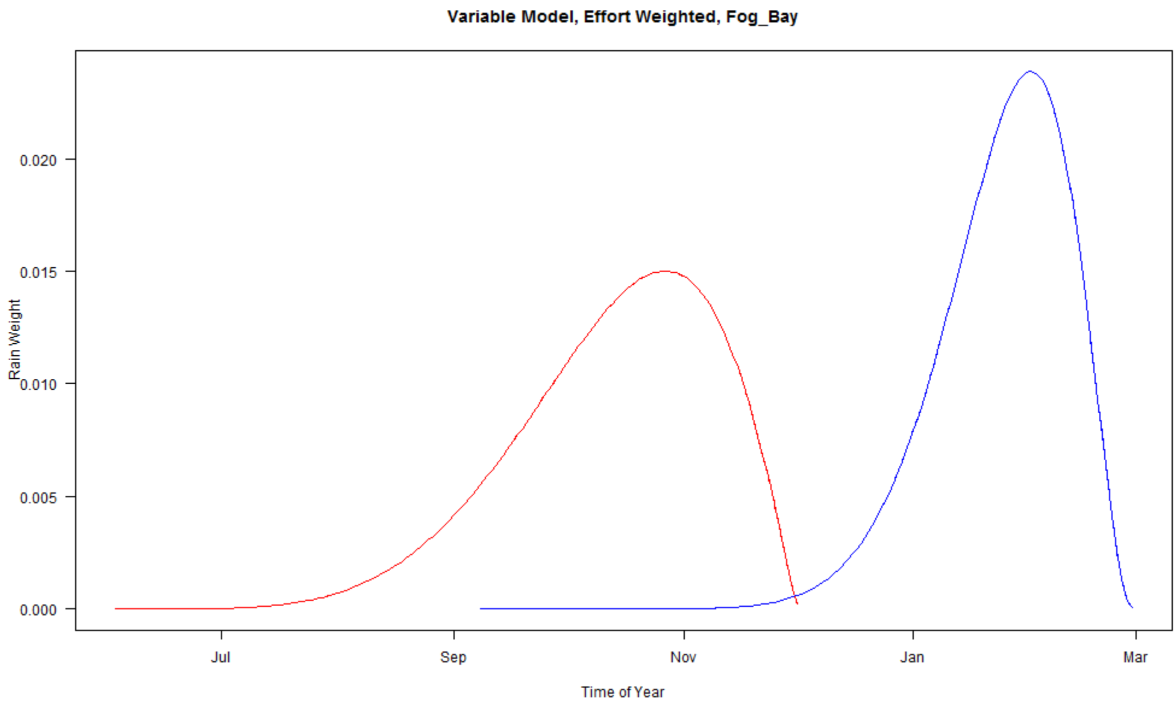

Figure 27. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Fog Bay based on effort weighted model variable weights model.

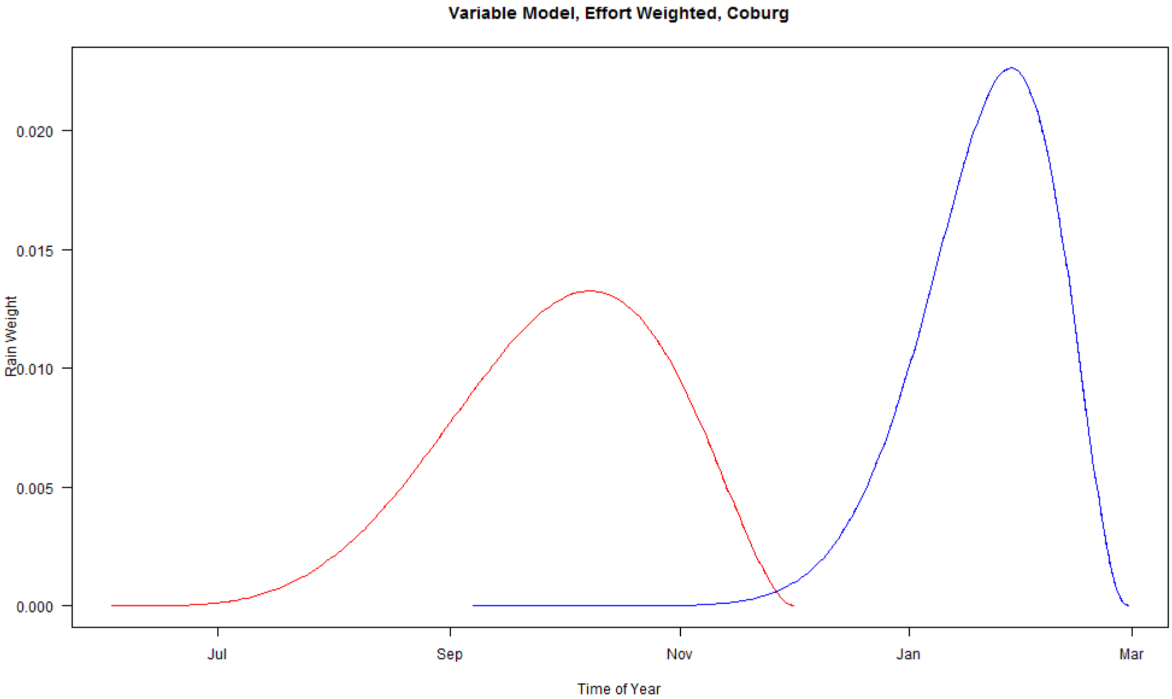

Figure 28. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Coburg based on effort weighted model variable weights model.

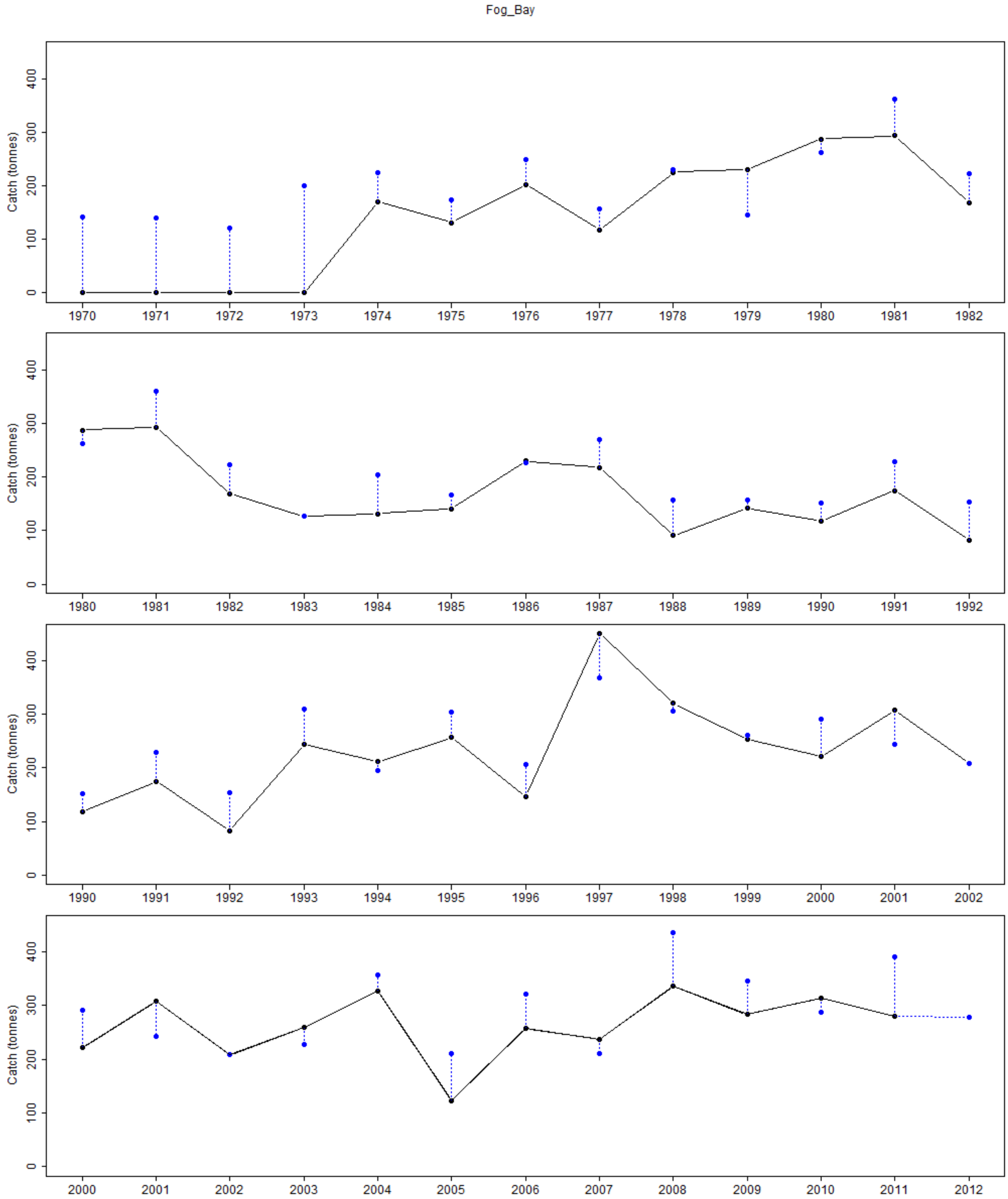

Figure 29. Catch and predictions for the Fog Bay region using the effort weighted variable weights model with separate regions defined for Fog Bay and the rest of Coburg. The recorded catch is shown in black and the effort weighted predictions in blue.

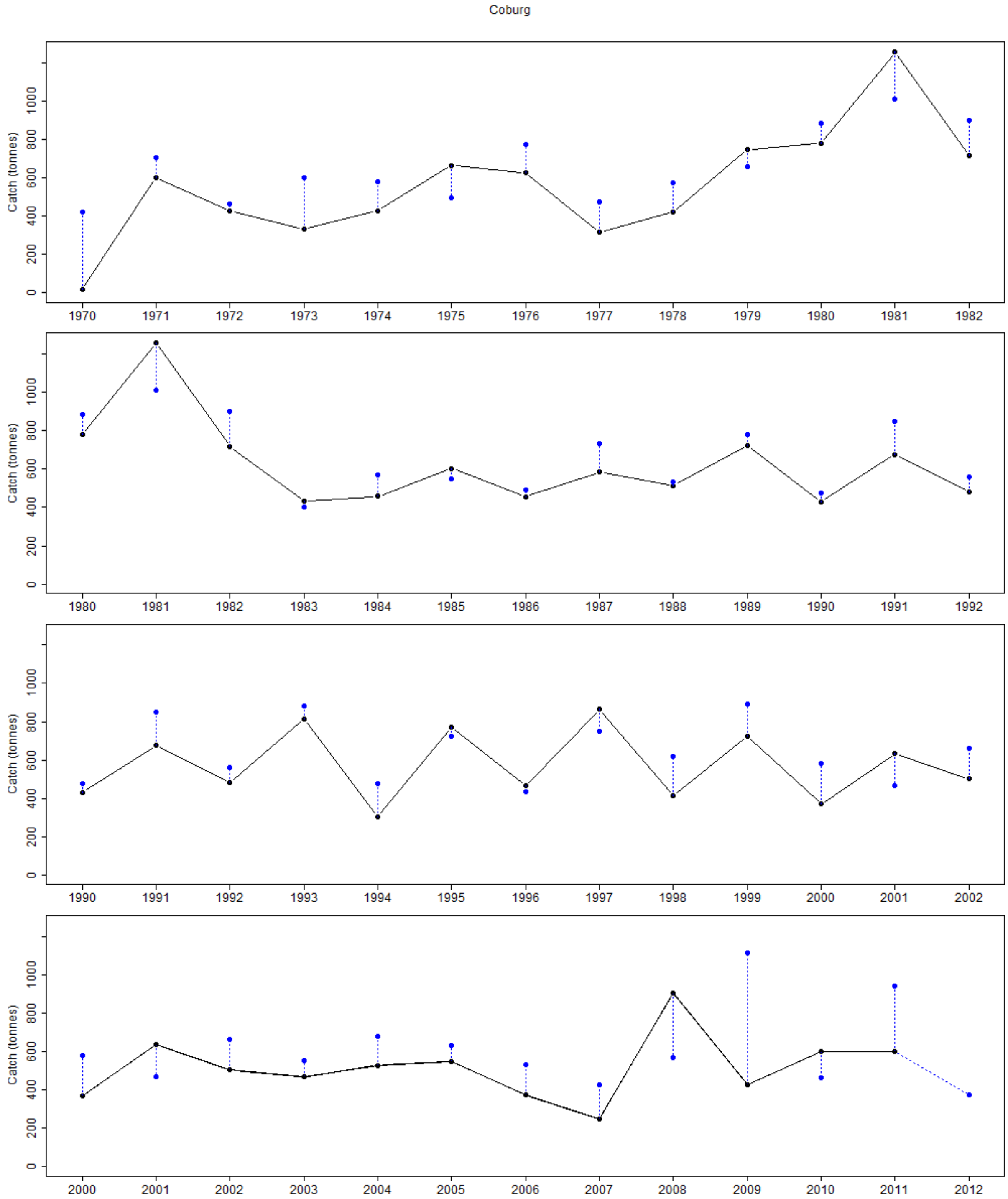

Figure 30. Catch and predictions for the Coburg region using the effort weighted variable weights model with separate regions defined for Fog Bay and the rest of Coburg. The recorded catch is shown in black and the effort weighted predictions in blue.

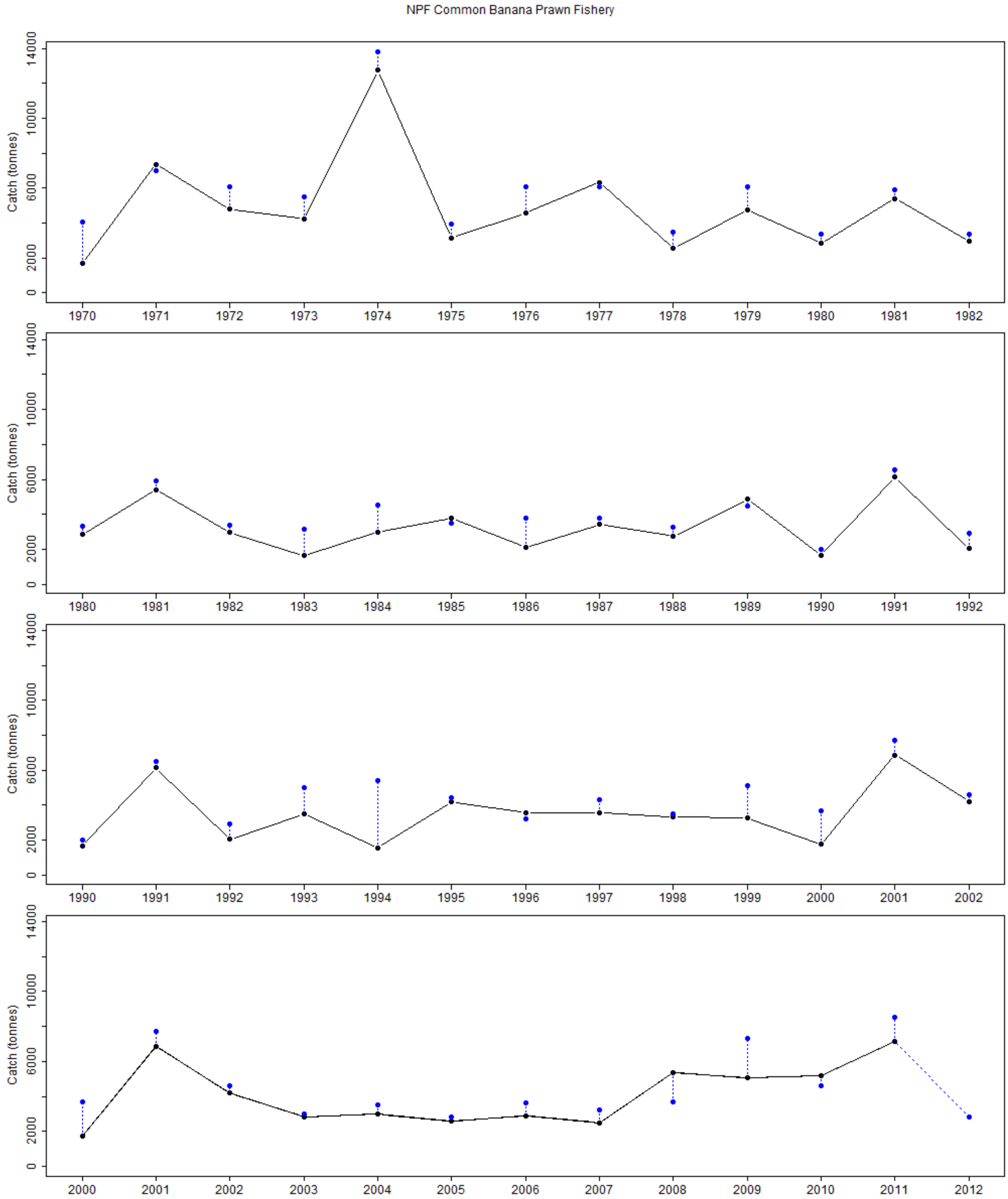

Figure 31. Catch and predictions for the total NPF banana prawn region using the effort weighted variable weights model with separate regions defined for Fog Bay and the rest of Coburg. The recorded catch is shown in black and the effort weighted predictions in blue.

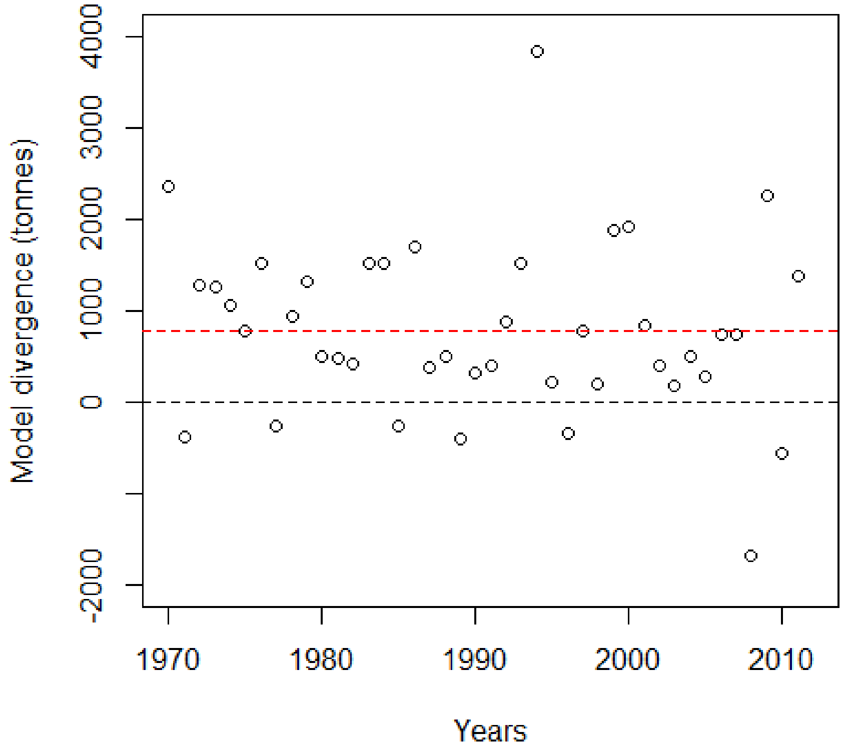

Figure 32. Difference between model predictions (potential catch) and recorded catch taken for the effort weighted single variable weights model with separate regions defined for Fog Bay and the rest of Coburg. The red line shows the mean divergence of 781 tonnes.

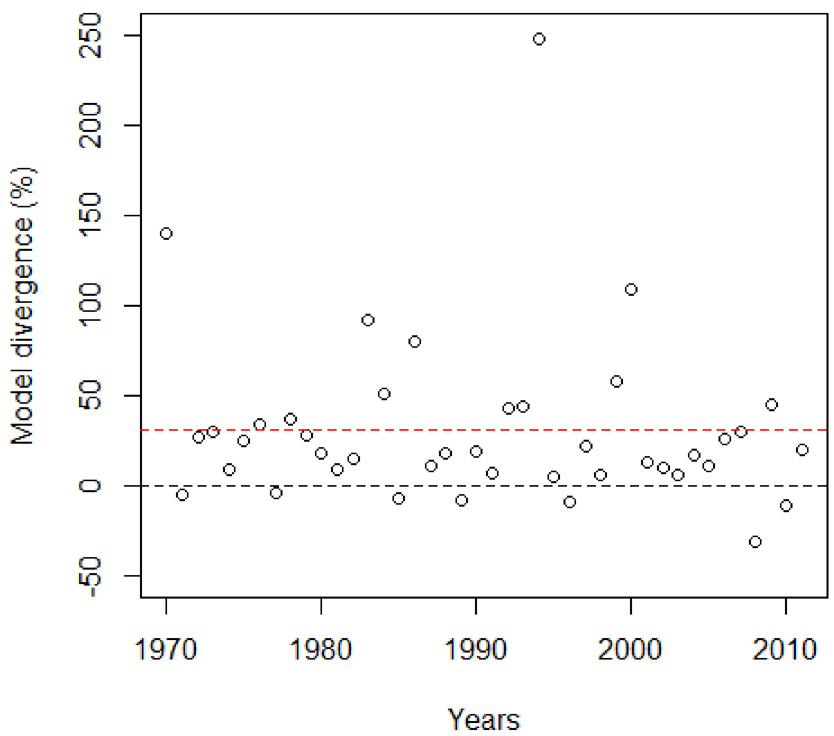

Figure 33. Difference between model predictions (potential catch) and recorded catch taken for the effort weighted single variable weights model with separate regions defined for Fog Bay and the rest of Coburg. The red line shows the mean divergence of 30%.

7.5 Estimates of uncertainty

The confidence and tolerance intervals for the fixed and variable weights effort weighted models are shown in Figure 34, Figure 35 and Appendix 3 (section 15.6). While the confidence intervals indicate the uncertainty around the mean catch value, the tolerance intervals indicate the uncertainty around the potential catch and so by definition are wider. We'd expect the catch for the following year to fall within the tolerance interval 95% of the time. It should be noted though that these intervals do not include any uncertainty associated with the estimation of the non-linear parameters, once this is included (in future model development), the tolerance intervals will be slightly wider.

The intervals indicate a large amount of uncertainty in the fishery in the early years when the fishery was becoming established. The year 1994 is associated with a high amount of uncertainty; however, the actual catch does not fall within the bounds. The bounds are relatively tight in the early 2000's, becoming wider around 2009. The tolerance interval for 2012 is unlikely to contain the total catch for the season. We expect that this is due to the large amount of rainfall falling early in the 2012 season (beyond the cut-off for the late rainfall included in the model).

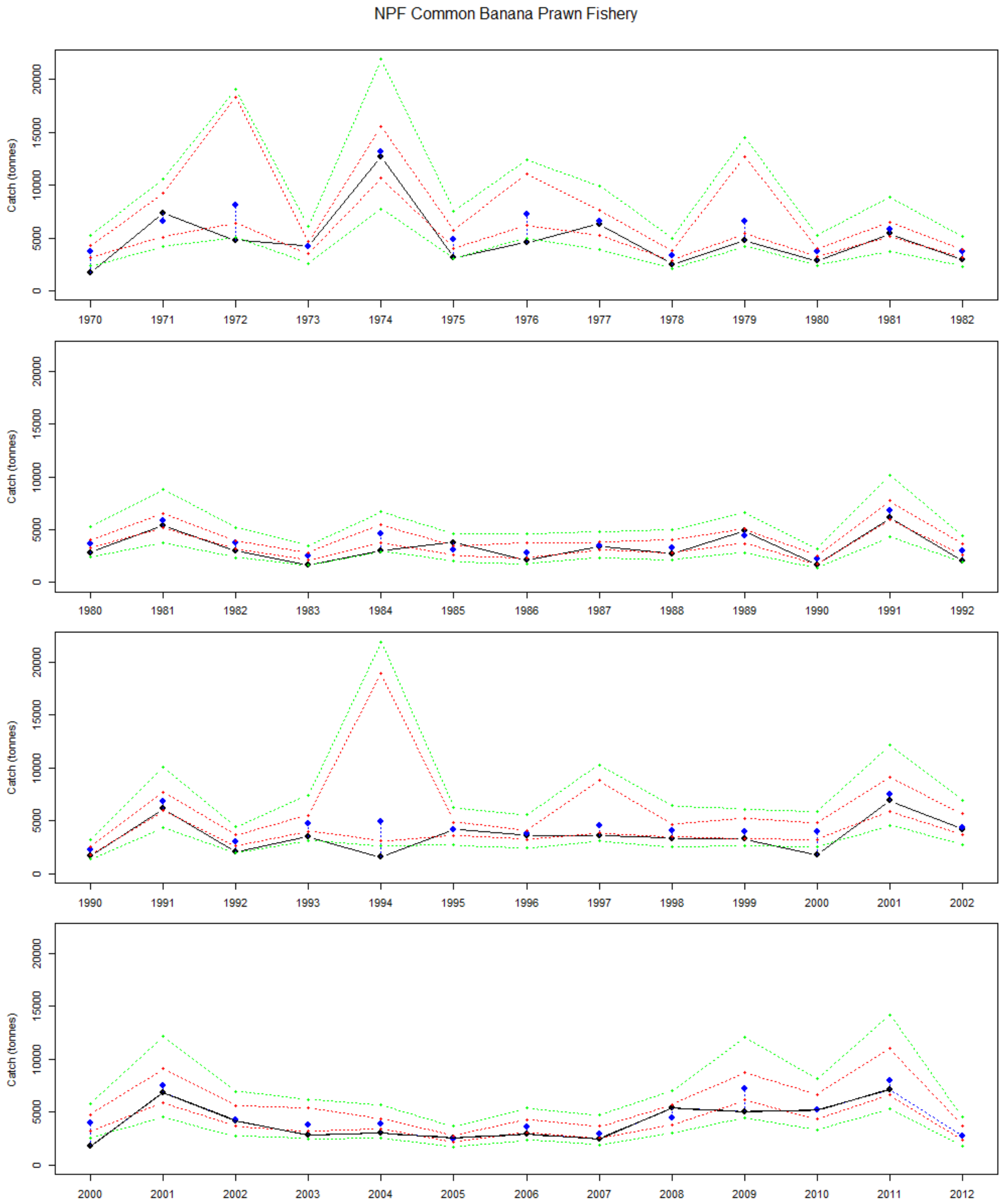

Figure 34. Recorded catch, estimated catch, confidence and tolerance intervals for the NPF banana prawn stock region from 1970-2012. The results are generated using the fixed weights, effort weighted model with 10 regions (Coburg and Fog Bay split). Recorded catch is black, predicted blue, confidence intervals red and tolerance intervals green.

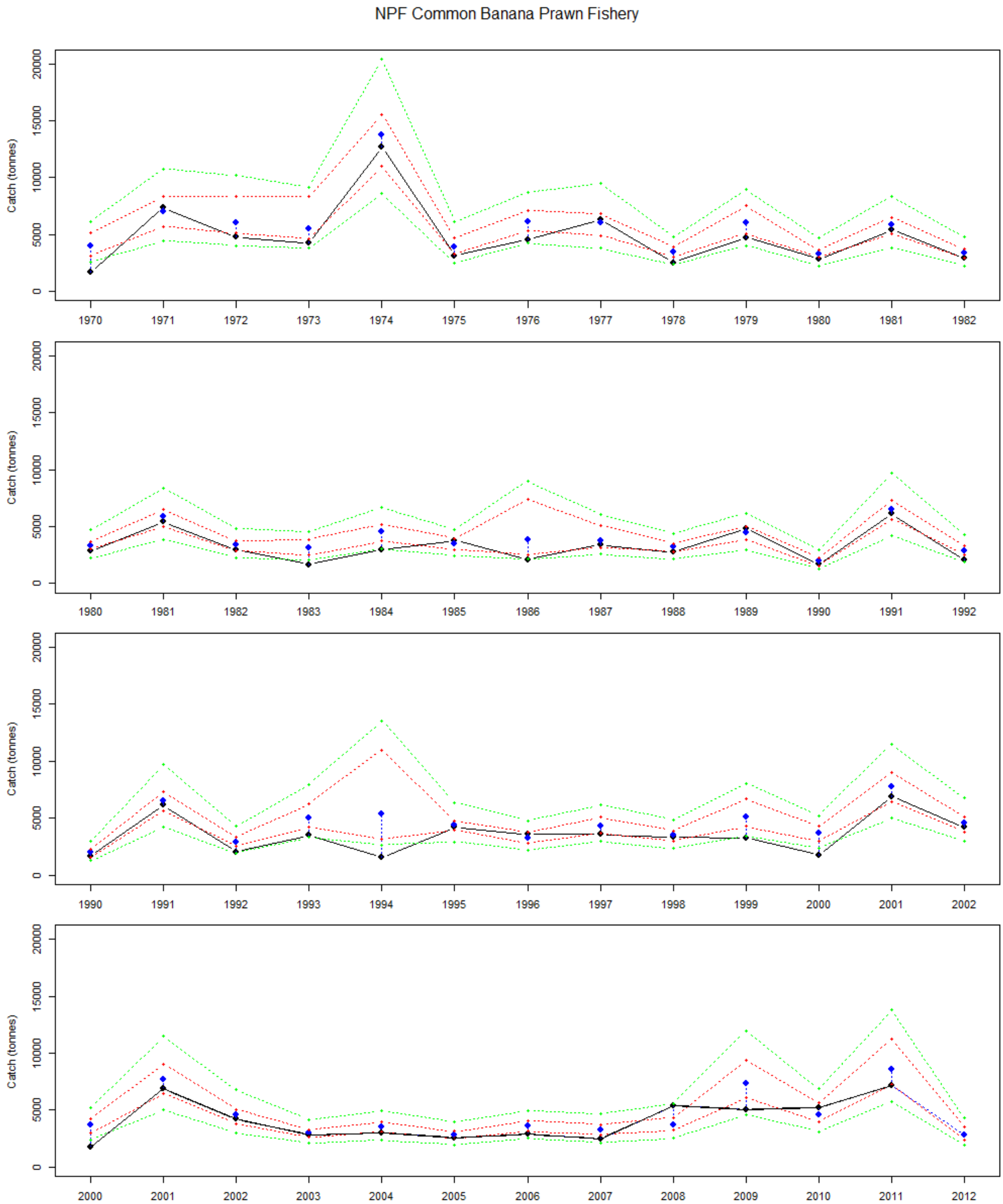

Figure 35. Recorded catch, estimated catch, confidence and tolerance intervals for the NPF banana prawn stock region from 1970-2012. The results are generated using the variable weights, effort weighted model with 10 regions (Coburg and Fog Bay split). Recorded catch is black, predicted blue, confidence intervals red and tolerance intervals green.

7.5.1 RETROSPECTIVE AND PROSPECTIVE ANALYSIS

It was suggested, and captured in the project objectives, that the potential of the models for TAC purposes could be investigated empirically using a 'retrospective analysis' study. That is, by using the data up to year *n* to predict the catch for year *n+1*, for a series of back years. While this suggestion is intuitively appealing, we found it impractical to implement, simply because we found that the models are already at a complexity level where they stretch the capacity of the mere 42 years' data currently available. The non-linear part of the model is particularly sensitive to fit and doing so with a reduced data set, as would be required if the suggestion were to be implemented in full, is not only statistically very sensitive, but computationally very difficult. We note, also, that the rainfall is extremely variable in northern Australia, and one extreme - heavy rainfall or very low-rainfall - year can make an appreciable difference to the model predictions.

7.6 Results of Economic analyses: Modelling Approach 1

7.6.1 PRICE ELASTICITY

To illustrate the attribute of elasticity for banana prawn prices, Figure 36 plots the catch (in tonnes) and the price (in 2010-11 Australian dollars) for banana prawns. The two time series are negatively correlated, and especially so in recent years when more product has been sold domestically.

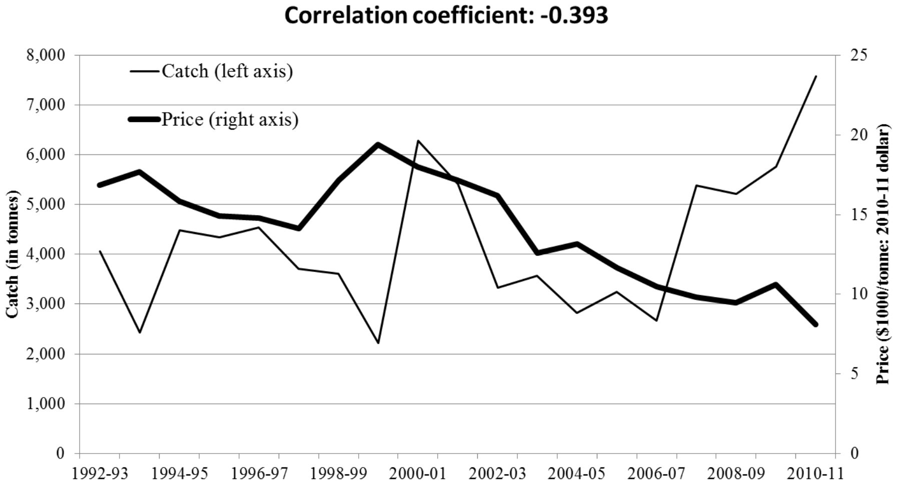

Figure 36. Annual catch and price of banana prawn in 2010-11 dollars.

It turns out that estimates of elasticity with and without exchange rate effects are close, respectively -0.244% and -0.217%. This result implies that if the catch increases by 1%, then the price will fall by 0.244% or 0.217%, thus increasing the revenue by only 0.756% or 0.783%. Details of the estimates are reported in Table 3a, the results of unit-root tests in Table 4 and general goodness-of-fit tests including serial correlation in Table 5. All data used for these estimates are reported in Appendix 4.1.

Table 3. Parameter estimates for demand elasticity, with log(Price) as the dependent variable. Price is $A1000/tonne inflation-adjusted with 2010-11 as the base year. Model A includes an exchange rate term, while model B does not. Both models include predictors log(Annual Catch) and the difference in mean log(Price) between the periods 1992-2003 (12 years) and 2004-2010 (7 years). Significance level (0.1%, 1% or 5%) is indicated by symbols *, **, or * respectively.**

PARAMETER	MODEL	ESTIMATE	STD. ERROR	T VALUE	SIG. LEVEL
Intercept	A	-2.608	0.515	-5.060	***
	B	-2.728	0.622	-4.389	***
Log(Annual Catch)	A	-0.244	0.060	3.935	***
	B	-0.217	0.074	-2.928	***
Difference in mean log(Price) pre- and post-2004	A	0.334	0.050	6.664	***
	B	0.419	0.049	8.558	***
Log(Japan CPI/Exchange Rate)	A	0.594	0.205	2.902	***
	B	n/a	n/a	n/a	n/a

Table 4. ADF unit root tests for the response and predictor series used for modelling demand elasticity over the period 1992-2010 inclusive.

VARIABLE	T VALUE	PROBABILITY
Log(Price)	-1.451	0.808
Log(Annual Catch)	-3.143	0.127
Log(Japan CPI/Exchange Rate)	-2.676	0.250

Table 5. Model fit statistics for modelling demand elasticity over the period 1992-2010 inclusive. Model A includes an exchange rate term, while model B does not.

CRITERION	MODEL A	MODEL B
R-squared	0.904	0.850
Adjusted R-squared	0.885	0.831
DW statistics	2.031	1.411
Probability for AR(2) using BG test:		
F-statistic	0.633	0.627
Chi-square statistic	0.524	0.542

The estimated demand function (used in the MEY analysis) and how the revenues built from this estimate fit with recorded data are presented in Figure 37.

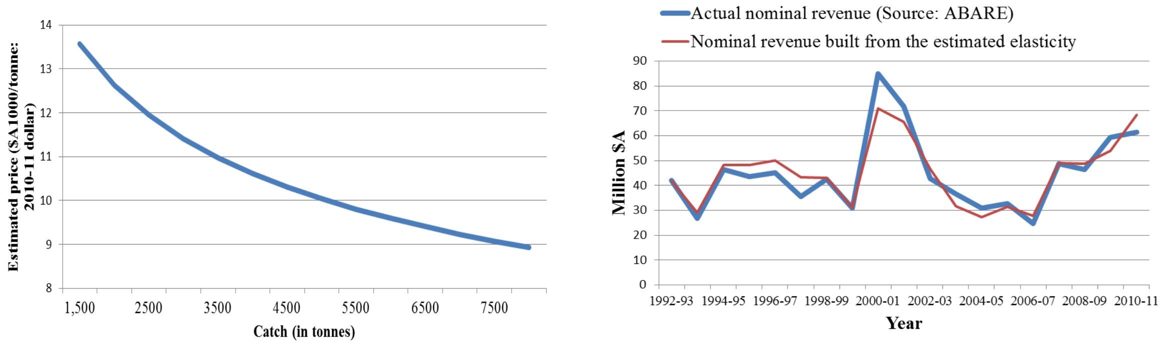

Figure 37. Demand function for banana prawn used for MEY analysis and the comparison of estimated and actual fishing revenue.

7.6.2 ESTIMATION OF THE HARVEST FUNCTION

The estimates for the harvest function based on a standard log-linear production function (model 1) are reported in Table 6, and the dataset is given in Appendix 4. The table shows valid estimates, with an adjusted R-squared value of 0.960 suggesting a good fit. However, when we compare the fitted harvest function to the actual cumulative weekly catch and effort data, it is clear that the specification does not adequately capture the convexity of the actual relationship between catch and effort (see Figure 38), especially for 2008 and 2011. This convexity is important to capture, since it indicates that in the fishery increases in effort produce increases in catch, but at a declining rate.

Table 6. Parameter estimates for the harvest function based on model 1, with log(Cumulative Weekly Catch) as the dependent variable and predictors log(Cumulative Weekly Effort) and log(Annual Abundance Index, S_0). Data are from 2008 to 2011 inclusive (117 records in total). Significance level (0.1%, 1% or 5%) is indicated by symbols *, **, or * respectively.**

PARAMETER	ESTIMATE	STD. ERROR	T VALUE	SIG. LEVEL
Intercept	0.438	0.365	1.323	NS
Log(Cumulative Weekly Effort)	0.765	0.015	52.348	***
Log(Annual Abundance Index)	0.241	0.040	5.966	***

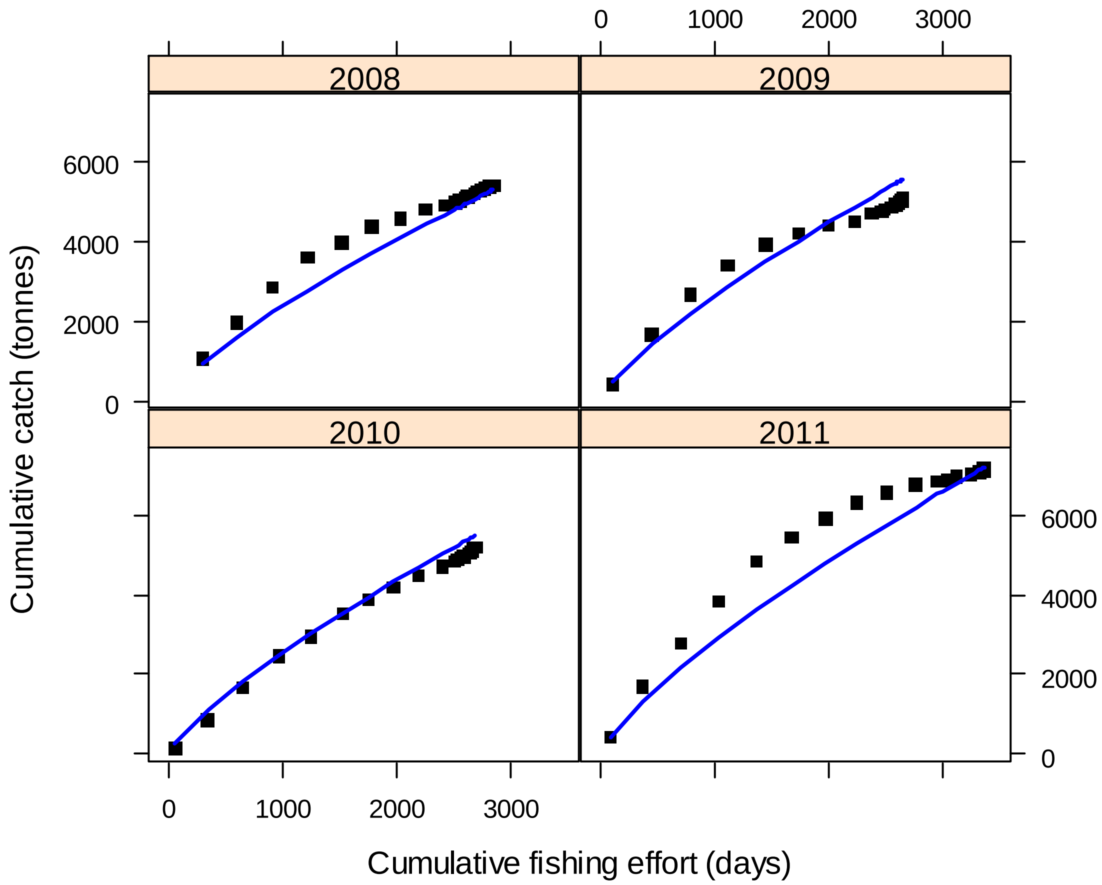

Figure 38. Recorded catch and fitted production function estimates for the harvest function, separately for 2008 to 2011 inclusive. Black solid circles are actual cumulative within-year catch (in tonnes) and effort (in fishing days); red lines are fitted values from model 1.

The estimates for the non-linear parameters of the harvest function based on a half-logistic curve (model 2) are reported in Table 7. The adjusted R-squared value of 0.962 for this model was similar to that of the standard production function (model 1). However, as can be seen in Figure 39, model 2 has more successfully captured the convexity in the relationship between effort and catch for the three years (with different initial measures of 'abundance') than model 1. The figure shows that, as the total quantity of prawns caught rises during the fishing season, so an increasing amount of effort must be expended to catch the next tonne of prawns, and the decline in catch-per-unit-effort is especially marked as the fishery moves closer to the potential catch level. The results allow us to thus specify a harvest function for the banana prawn fishery, using measures of 'abundance' as given realizations in each of the relevant years.

Table 7. Estimates of the two non-linear parameters for the harvest function based on model 2, with Cumulative Weekly Catch as the dependent variable and Cumulative Weekly Effort as the predictor. Annual Abundance Index, S_0, is treated as a known constant. Data are from 2009 to 2011 inclusive (88 records in total). Significance level (0.1%, 1% or 5%) is indicated by symbols *, **, or * respectively.**

PARAMETER	ESTIMATE	STD. ERROR	T VALUE	SIG. LEVEL
β_0	0.0044	0.0011	4.148	***
β_1	0.7838	0.0310	25.274	***

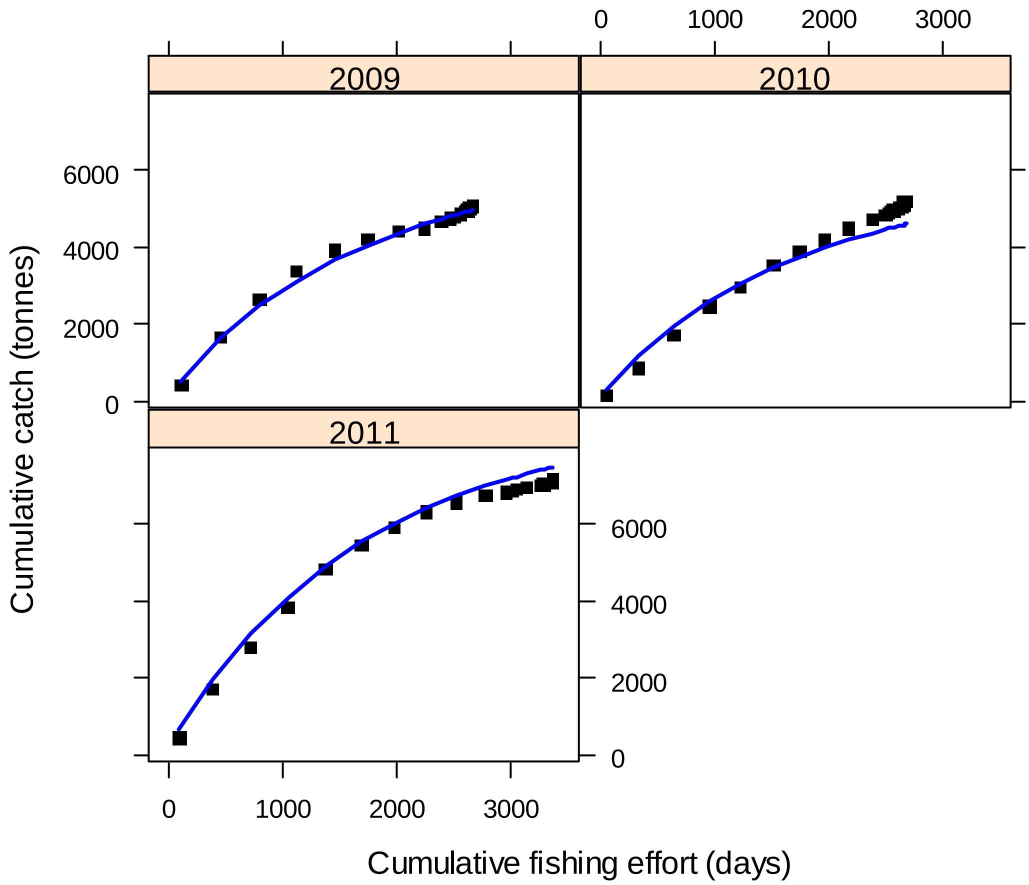

Figure 39. Recorded catch and fitted harvest function from the half-logistic model, separately for 2009 to 2011 inclusive. Black solid circles are actual cumulative within-year catch (in tonnes) and effort (in fishing days); red lines are fitted values from model 2.

7.6.3 FISHING COST INFORMATION

Some of the components of the cost of fishing for banana prawns are reported in Table 8. The ratios of operating cost to income for NPF banana prawns in 2009, 2010 and 2011 are 55%, 45% and 49%, somewhat lower than that of the NPF as a whole (including tiger prawns and other products) during the years 1993-2009 (Vieira and Perks, 2010).

Table 8. Components of the cost of one fishing day (2010-11 dollars). Source: Kompas (2012).

TYPE OF COST	AMOUNT ($)
Capital	2,212
Fuel	3,496
Gear	323
Crew and skipper payments	2,658
Other material and comm. costs	164

7.6.4 ESTIMATION OF MEY

Graphically, the left panel of Figure 40 shows the revenue and the costs estimated for the three years, 2009-2011. The thin unbroken line presents the revenue from catch — which slightly bends downward due to the value of the price elasticity. The upward sloping curves represent the operating costs for the three years — which bend upward given the convexity in the catch and effort relationship — and the gap between the revenue and the cost represents operating profit.

The right panel of Figure 40 shows both marginal revenue and marginal costs, which provide information on the marginal gains and losses with each additional tonne of catch. The intersections of the marginal revenue and the marginal cost curves determine the profit-maximizing catch for each year. The figure shows that the optimal catch varies, relative to the initial value of 'abundance'. Specifically, in year 2011 where the initial stock abundance is relatively higher, the optimal catch is around 6,500 tonnes while it is only 3,869 tonnes in 2010 and 4,303 tonnes in 2009.

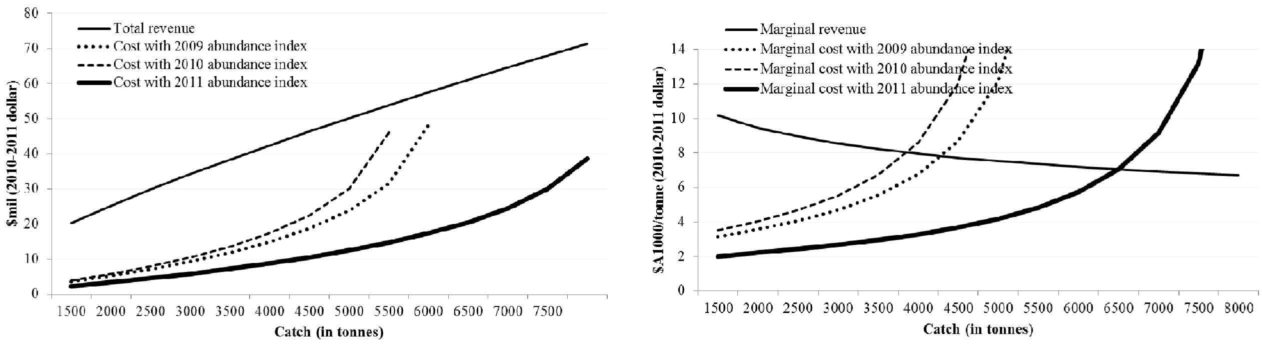

Figure 40. Fishing revenue and costs.

In Table 9, we compare the actual situation and MEY catch and profit. The last column of the table simply calculates actual operating profit from actual catch, price and cost data in the fishery. The table shows that catch should have been less than the actual levels in 2009 and 2011 to obtain higher profits. The reason for this is straightforward, depending on both the effects of the price elasticity and the convexity in the catch and effort relationship, and thus the convexity in marginal costs. Increases in catch both decrease price and revenue and also increase the cost of fishing, at an increasing rate. However, in 2010 the actual profit is higher than what is obtained under MEY.

Table 9. Actual and MEY operating profit.

YEAR	CATCH (TONNES)			OPERATING PROFIT (MILLION 2010-11 DOLLARS)	
	MEY	Recorded	Potential	Estimated from MEY model	Recorded*
2009	4,303	5,214	6,281	27.73	22.20
2010	3,869	5,771	5,794	25.12	33.61
2011	6,500	7,557	8,699	40.60	31.10

* (assuming $A8,800 per fishing day)

The robustness of the MEY estimates depends on the estimates of the price elasticity and the cost of a fishing day. Table 10 provides a sensitivity analysis of MEY in response to the price elasticity. It shows that a higher elasticity will reduce the catch at MEY (keeping other things constant).

Table 10. Changes in MEY catch (in tonnes) in response to changes in price elasticity, where the base case elasticity is 0.25 and fishing cost is fixed at $8,800 per day.

ELASTICITY	2009	2010	2011
-0.15	4,487	4,030	6,781
-0.20	4,439	3,953	6,647
-0.25 (base case)	4,303	3,869	6,500
-0. 30	4,197	3,776	6,336
-0.35	4,081	3,673	6,155

Table 11 provides a sensitivity analysis of the catch at MEY in response to changes in the cost of one fishing day, where the cost varies between ± 20% from the base-case level. The result shows that a lower cost always results in higher catch at MEY (keeping other things constant).

Table 11. Changes in MEY catch (in tonnes) in response to changes in the fishing cost where the base case is $8,800 per day and price elasticity is fixed at -0.25.

COST RELATIVE TO BASE CASE	2009	2010	2011
-20%	4,663	4,217	6,905
-10%	4,481	4,041	6,700
Base case	4,303	3,869	6,500
+10%	4,129	3,701	6,302
+20%	3,959	3,536	6,107

7.7 Results of Economic analyses: Modelling Approach 2

7.7.1 CATCH MODEL RESULTS

The catch model (Table 12) was estimated from daily catch and effort data during the targeted banana prawn season (i.e. excluding banana prawns caught during the tiger prawn season) over the period 1987-2011. The effort weighted (EW) "potential catch" estimated by in the report was taken as the stock proxy.

The coefficient for the potential catch was less than one, indicating that catch did not increase linearly with the estimate of potential catch. That is, higher estimates of potential catch were greater over-estimates of stock abundance than lower estimates. The relationship between catch and effort decreases with increasing effort. Fishers' ability to catch banana prawns increased at an average 1.6% per year over the period examined.[4]

[4] As noted above, quadratic and cubic time trends as well as interaction terms were also considered but the linear model was the most appropriate.

Table 12. Regression results: catch model. The dependent variable is the log of cumulative daily catch over the year. Effort represents the corresponding cumulative boat days fished over the year. EW is the effort-weighted potential catch. Significance level (0.1%, 1% or 5%) is indicated by symbols *, **, or * respectively.**

PARAMETER	ESTIMATE	STD. ERROR	T VALUE	SIG. LEVEL
Intercept	-7.068	0.319	-22.13	***
Log(EW)	0.747	0.013	55.82	***
Log(Effort)	1.717	0.081	21.20	***
$[\text{Log(Effort)}]^2$	-0.078	0.006	-13.68	***
Time	0.016	0.001	20.88	***
Y1994	-1.039	0.018	-59.03	***
Y2000	-0.660	0.021	-31.36	***
Y2006	-0.267	0.022	-12.23	***
Y2007	0.043	0.022	1.91	NS
Y2008	0.455	0.019	23.42	***

The adjusted R-squared was 0.926 for this model. A comparison of the actual and model-estimated catch (based on the observed effort level and the estimated potential catch) is shown in Figure 41. While the estimated catch closely matches the trends in the actual catch, in any one year the estimate may be out by as much as 40 per cent (Figure 42).

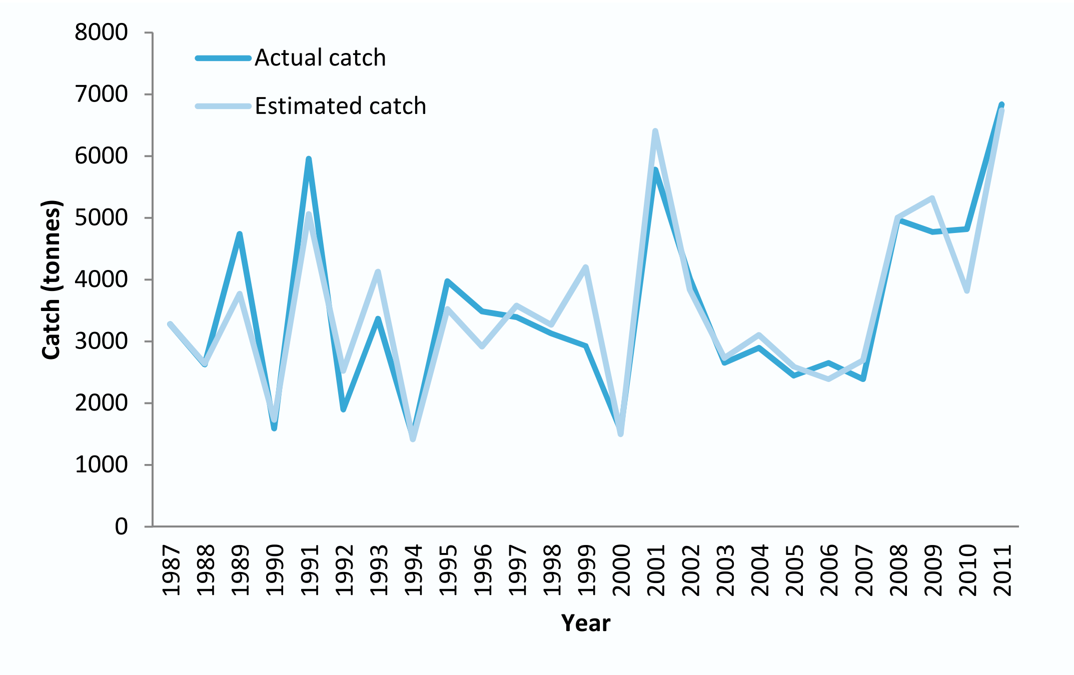

Figure 41. Comparison of estimated and actual banana prawn catch.

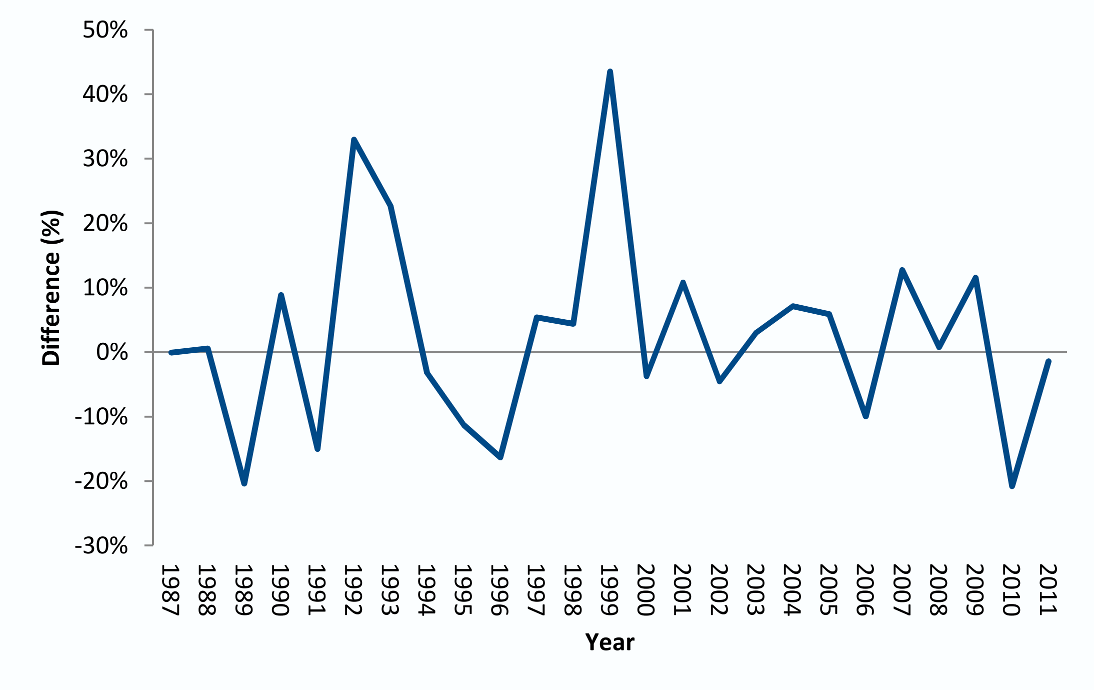

Figure 42. Percentage error between estimated and recorded banana prawn catch.

7.7.2 ESTIMATES OF MEY

MEY was estimated for each year between 1987 and 2011 given the recent estimates of cost and price conditions. As these parameters were held constant, variations in MEY were due solely to changes in the initial estimate of 'potential catch'.[5] The key parameters used in the analysis are given in Table 13. The prices and costs were also those used in the analysis of Section 7.6 above, to provide a direct comparison of results, although some costs are implemented differently in the models.

Table 13. Parameters used in the analysis for economic Modelling Approach 2.

PARAMETER	UNIT	VALUE
P_1	$/tonne	8,000
q_1	tonnes	6,835
f		-0.3
C	$/day	3,819
Crew	%	23
Marketing	$/tonne	1,030

The resultant MEY effort and catch, and the underlying 'potential catch' (effort weighted, or EW) are shown in Figure 43. As would be expected, the variability in optimal catch is greater than the variability in optimal effort. As would be expected, optimal catch also closely follows the estimate of the potential catch.

[5] Incorporating year-specific costs and prices would add greater variability to the analysis and additional confusion as to the extent that estimates of the 'potential catch' has on optimal catch and effort.

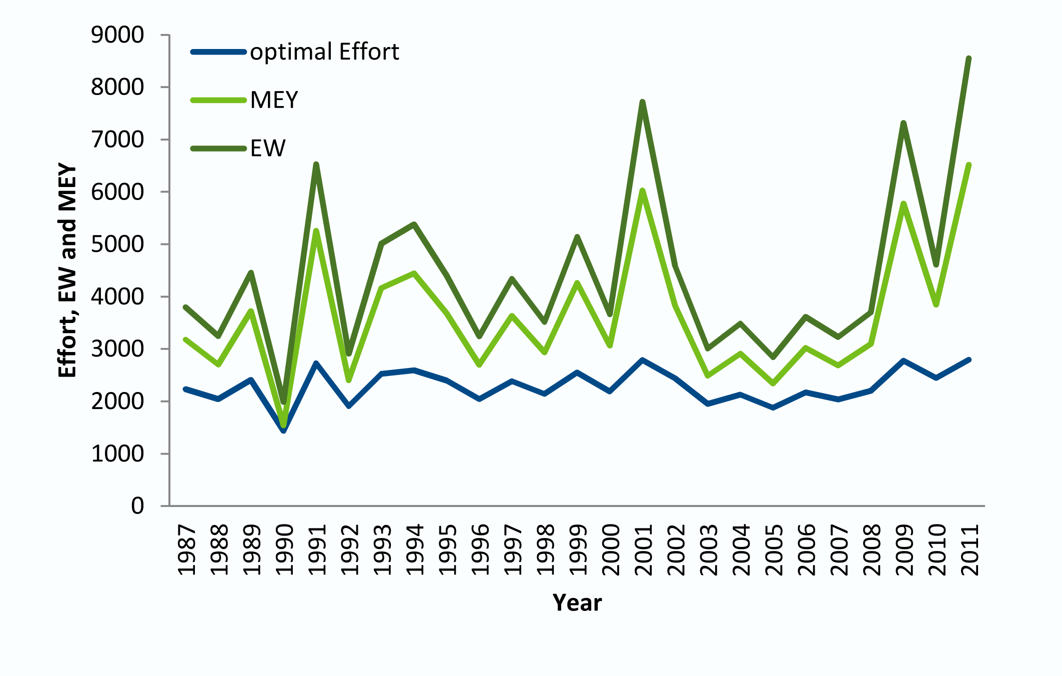

Figure 43. Optimal effort and catch with current prices and costs. Effort is in total boat days. EW and MEY are in tonnes.

A comparison of the MEY estimates from Section 7.6 and this approach is given in Table 14. The estimates correspond almost identically for 2010 and 2011, but diverge for 2009. There were differences in the estimate of potential catch underlying each of the models, although adjusting for these made only a small difference. Other key differences in methodology include capital costs (included in the analysis in Section 7.6 but excluded from the analysis in this section) and the treatment of crew and other costs. A fixed amount per day was assumed in Section 7.6, while in this section these costs varied based on output per day. Further, the catch model used in this analysis was based on a longer time series of data than that of Section 7.6, with the time trend and dummy variables incorporated to capture technical change and significant management changes.

Table 14. Comparison of model results from Sections 7.6 and 7.7 for MEY catch

YEAR	ESTIMATED MEY (TONNES)	
	Section 7.6 model	Section 7.7 model
2009	4,303	5,776
2010	3,869	3,844
2011	6,500	6,514

8 Benefits and Adoption

The direct beneficiaries of this research are industry and management associated with the Northern Prawn Fishery:

1. The Northern Prawn Fishery;
2. The Australian Fisheries Management Authority (AFMA); and
3. The Department of Agriculture, Fisheries and Forestry (DAFF), Australian Government.

Aspects of the research might also have benefit for industry and management of other fisheries that experience large variation due to environmental drivers, including fisheries for prawns and other crustaceans, and some finfish fisheries.

The research provided a number of potential benefits.

The prediction of potential catch:

1. Is a basis on which management might set TAC values that are comparable with the catch that would have been available in the status quo input control system; and
2. Provides prior information on the likely size of landings, for potential application in industry marketing, and so improve planning and profitability.

The economic analyses provide the means to improve the economic performance of the NPF's WBP fishery, by either:

1. Adjusting TACs (determined using the "potential catch" from the model), to TAC_{MEY}, i.e. choose TACs that are close to the economic optimum; and
2. In an input control context, as the basis to calculate a catch rate trigger, that accounts for price flexibility with landings volume (so using the "potential catch" calculation) and that would address an MEY target (and so using the economic analyses undertaken here).

These alternatives are currently under consideration by the management of the fishery, with elaboration via the related, AFMA-funded project *Comparison of TAC and current management for the White Banana Prawn fishery of the Northern Prawn Fishery* (Buckworth *et al.* 2013). Linkage between the projects was via the Principal Investigator and other team members common between the projects. It is noted that both projects were conducted with support of NORMAC and NPRAG. It is likely that either the TAC_{MEY} strategy or the MEY-trigger approach will be adopted, so that the management of the fishery is able to address an MEY-based harvest strategy for the WBP fishery. These outcomes both depend upon the direct outputs of this project.

The modelling system is a new tool which also:

1. Can be incorporated in future simulations of the WBP fishery;
2. Could be adapted to other fisheries driven by environmental variation; and
3. Could be used in assessments of the fishery that accommodate the variance that has hitherto prevented the development of a reliable population model and assessment for the fishery.

The effect of these tools and potential management actions are difficult to predict in terms of effects on profits or stability of the fishery. They will, however, enable the managers of the fishery to better comply with Commonwealth fisheries policy, which requires that Maximum Economic Yield (MEY) targets are addressed, and so enhance profitability. They will contribute and create further opportunities for further research and development in the NPF by providing better understanding and quantification of the variance in catches that is attributable to environmental drivers, particularly rainfall. Additionally, as a model approach and methodology, the project may also provide additional opportunities for other Australian prawn fisheries.

Benefits and beneficiaries described here are in agreement with those described in the original application for this work. There has been continual feedback to the main beneficiaries of the work – industry and management – via reports and presentations to NORMAC and NPRAG and we have endeavoured to ensure incorporation of any feedback that these groups have provided. To further disseminate the work and engender scientific feedback and peer review, seminars on aspects of this project were presented at the Australian Society for Fish Biology Conference in July 2012, to AFMA staff in June 2013, and to the International Environmetrics Society Conference in Anchorage, Alaska in June 2013.

9 Further Development

There are a number of aspects of the White Banana Prawn prediction model that should be developed further if the model and economic analyses are to be used to predict potential annual catch in time to set a TAC or catch rate trigger for the upcoming season. These include:

- Putting systems and protocols in place to ensure that the SILO data can be downloaded automatically, in the correct format, in or before the first week of March each year, so providing sufficient time for analysis, and advice to management of the fishery. This should include ensuring that CSIRO always has an up-to-date SILO data licence in place and allowing for flexibility around the data download process to accommodate changes in data schemes.
- Investigate the potential of performing mid-season updates based on catches taken during the first few weeks of the season.
- Develop methods to account for the uncertainty in non-linear model parameters and extend the confidence and prediction intervals to account for this uncertainty. This will have a relatively minor impact on the confidence and prediction intervals but should be undertaken to demonstrate the true model uncertainty.
- Further investigate the spatial scale of the model. To date we have accepted the banana prawn stock regions as given with the exception of splitting Fog Bay from the remainder of Coburg. Separating a few more logically and visually separate regions with high banana prawn fishing intensities will increase the degrees of freedom and may improve the performance of the model.
- Further exploration of the use of the survey data: potentially we could apply a Bayesian update process as a means of including recruitment survey information.
- Develop ways to cope with future “censored data”. By this we mean that if, in the future, the catch is dictated by a TAC or other mechanism that depends strongly on the model, then the model would not be receiving new information on “potential catch”, so that the model would not be updated and not be able to accommodate new information. We suggest as a possible approach, using the catch from the first 3-4 weeks of the season versus rainfall would remove some of the effect of having a TAC system. Even so, the predicted changes in efficiency and behaviour that might arise with a TAC-based system are not known and might also need to be accommodated.
- Timing of the survey, and so availability of the survey index, could be of issue in some years – assuming that the survey index in future provides greater utility to the prediction model than it currently does.
- If there were a TAC system in place, a default TAC would need to be decided if rainfall data were unavailable; alternatively, there needs to be a means of deciding what might be an appropriate rainfall proxy.

We also suggest incorporating the rainfall relationships in future assessments, combining it perhaps with the depletion approach developed by Zhou *et al.* (2007) and as applied in Buckworth *et al.* (2013). This could also include or incorporate a fishing power analysis for banana prawns.

10 Planned Outcomes

The principal outputs of the project are the prediction of potential catch, and economic tools for calculation of MEY-based management controls.

Prediction of potential catch:

1. Is a basis on which management might set TAC or catch rate trigger values that are comparable with the catch that would have been available in the status quo input control system; and
2. Provides prior information on the likely size of landings, for potential application in industry marketing, and so improve planning and profitability.

The economic analyses provide the means to improve the economic performance of the NPF's WBP fishery, by either:

1. Adjusting TACs (determined using the "potential catch" from the model), to TACMEY, i.e. choose TACs that are close to the economic optimum, MEY; and
2. In an input control context, calculate a catch rate trigger, that accounts for price flexibility with the volume of landings (so using the "potential catch" calculation) and that would address an MEY target (and so using the economic analyses undertaken here).

These alternatives are currently under consideration by the management of the fishery, with elaboration via the related, AFMA-funded project *Comparison of TAC and current management for the White Banana Prawn fishery of the Northern Prawn Fishery*. It is likely that either the TAC_{MEY} strategy or the MEY-trigger approach will be adopted, so that the management of the fishery are able to address an MEY-based harvest strategy for the WBP fishery. These options, both dependent upon the direct outputs of this project, are consistent with the Commonwealth Harvest Strategy Policy; the benefit of an appropriate strategy will be maximisation of the annual economic performance of the fishery.

11 Conclusion

Describing the prediction of potential catch for the NPF's banana prawn fishery, and developing economic tools required to address an MEY target for the fishery, the principal applications of the outputs of this project are in development of a MEY-based Total Allowable Catch (TAC) or a catch rate trigger for the fishery.

The project successfully extended the methods of Venables *et al.* (2011), applying several approaches to improve the stability and accuracy of the model (objective 1). It would be feasible to apply (not re-fit) the different approaches each year; however, we recommend the "variable weights" model as a structural compromise that promotes stability, yet allows regional flexibility. We caution that the models are unable to make predictions that incorporate rainfall occurring after February each year – a reason for some major deviations. Additionally, we offer that the models are built on a data set of just 42 years – there will be future rainfall patterns and quantities outside the "experience" of the model that will potentially engender strong deviations between predicted and actual catches. At the same time, each new year may provide extra information and thus opportunities to include that information in updated models, or will see experience accrued as to which modelling approach is the more reliable or useful in different contexts.

We developed methods to calculate both the uncertainties associated with estimation and prediction, so achieving project objective 2. We found that these measures were valuable in conveying to stakeholders the degree of uncertainty in the predictions. They also have utility in simulation of the management of the fishery and have already been applied in the management strategy evaluation of the WBP fishery by Buckworth *et al*. (2013).

Investigating retrospective and prospective analyses, we found that there was simply insufficient data (there was not sufficient information to ensure that the models were sufficiently stable). This means that objective 3 was only partially met; nevertheless, a prediction was provided for the 2012 catch, and prediction intervals, indicating the uncertainty in predictions, were also developed.

We incorporated Fog Bay as a separate region from Coburg in the model. Our investigations indicated quite distinct rainfall weights for the two putative regions, so the separation was considered appropriate (objective 4). Further refinements addressing the spatial scale of the models could be addressed, in a similar manner, with each similar adjustment providing greater utilisation of available data and thus potentially providing models with greater descriptive and predictive power.

Although inclusion of the data from the annual NPF recruitment monitoring program was not successful, we believe that with the accumulation of more data and perhaps different techniques, an effective means to incorporate the survey information might be developed.

Analysing the response of banana prawn prices to the size of the annual catches, the relationships between potential catch and economic variables, we were able to develop predictive relationships between catches, effort, prices and costs (objective 5) which, in turn enabled development of a MEY analysis for the fishery (objective 6).

By developing and applying economic analyses, the project is a quantitative base on which a prediction of potential catch can be utilise to provide either a TAC, or a catch rate trigger, to address MEY for the banana prawn fishery. The project also demonstrates a set of statistical modelling approaches with application to other fisheries, particularly prawn fisheries, which are similarly subject to environmental drivers.

12 References

Barwick, M. (2011). Northern Prawn Fishery Data Summary 2010. NPF Industry Pty Ltd, Australia.

Barwick, M. (2012). Northern Prawn Fishery Data Summary 2012. NPF Industry Pty Ltd, Australia.

Buckworth, R. C., Ellis, N., Zhou, S., Pascoe, S., Deng, R. A., Hill, F. G., and O'Brien, M. (2013). Comparison of TAC and current management for the White Banana Prawn fishery of the Northern Prawn Fishery. . *Final Report to the Australian Fisheries Management Authority. CSIRO Marine & Atmospheric Research, Brisbane Australia.*

Dichmont, C. M., Deng, A., Punt, A. E., Venables, W. N., Ellis, N., Kompas, T., Ye, Y., Zhou, S., Bishop, J., and Che, N., Gooday, P. (2008). Bringing economic analysis and stock assessment together in the NPF: a framework for a biological and economically sustainable fishery. *Final Report to Fisheries Research and Development Corporation Project 2004/022. CSIRO Marine & Atmospheric Research, Brisbane, Australia.*

Dichmont, C. M., Deng, R., Punt, A. E., Venables, W. N., Pascoe, S., Zhou, S., Kompas, T., Kenyon, R., Bishop, J., van der Velde, T., Kienzle, M., Hutton, T., Plagányi, É., Miller, M., Donovan, A., Ye, Y., and (2010). Developing techniques to estimate total allowable catches for the NPF major prawn species. *Final Report to Fisheries Research and Development Corporation, Project 2007/018. CSIRO Marine & Atmospheric Research, Brisbane, Australia*

Dichmont, C. M., Deng, R. A., Punt, A. E., Venables, W. N., and Hutton, T. (2012). From input to output controls in a short-lived species: the case of Australia's Northern Prawn Fishery. *Marine and Freshwater Research* **63**, 727-739. doi:10.1071/mf12068

Evans, S. K. (2010). Northern Prawn Fishery Data Summary 2009. NPF Industry Pty Ltd, Australia.

Kompas, T. (2012). Economic Data and Price Forecasts for the Northern Prawn Fishery. Australian National University, Canberra.

Kompas T., Dichmont, C., Punt, A., Deng, A., Che, N., Bishop, J., Gooday, P., Ye, Y., and Zhou, S. (2010) Maximizing profits and conserving stocks in the Australian Northern Prawn Fishery, Australian Journal of Agricultural and Resource Economics, 54: 281-99.

Hutton, T., Dichmont, C., and Pascoe, S. (2009). Banana Prawns and TAC. *Section 6, in Kompas, T. and Grafton, R.Q. (eds.) "A Cost-Benefit Analysis of Alternative Management Options for the Australian Northern Prawn Fishery". Unpublished Report, Sustainable Environment Group*, 100.

Lucas, C., Kirkwood, G., and Somers, I. (1979). Assessment of the stocks of the banana prawn *Penaeus merguiensis* in the Gulf of Carpentaria. *Australian Journal of Marine and Freshwater Research* **30**, 639-652.

MRAG (2007). Assessment of alternative approaches to implementing Individual Transferable Quotas (ITQs) in the Australian Northern Prawn Fishery (NPF) and identification of the impacts on the fishery of those approaches. *Final Report to AFMA and NORMAC*, 112.

Punt, A. E., Deng, R., Pascoe, S., Dichmont, C. M., Zhou, S. J., Plaganyi, E. E., Hutton, T., Venables, W. N., Kenyon, R., and van der Velde, T. (2011). Calculating optimal effort and catch trajectories for multiple species modelled using a mix of size-structured, delay-difference and biomass dynamics models. *Fisheries Research* **109**, 201-211. doi:10.1016/j.fishres.2011.02.006

SEG (Sustainable Environment Group) (2009) A Cost-Benefit Analysis of Alternative Management Options for the Australian Northern Prawn Fishery, Report to AFMA, Canberra.

Staples, D. J. (1980). Ecology of juvenile and adolescent banana prawns, *Penaeus-merguiensis*, in a mangrove estuary and adjacent off-shore area of the Gulf of Carpentaria .1. Immigration and settlement of post-larvae. *Australian Journal of Marine and Freshwater Research* **31**, 635-652.

Staples, D. J., and Vance, D. J. (1986). Emigration of juvenile banana prawns *Penaeus merguiensis* from a mangrove estuary and recruitment to offshore areas in the wet-dry tropics of the Gulf of Carpentaria, AUSTRALIA. *Marine Ecology-Progress Series* **27**, 239-252. doi:10.3354/meps027239

Vance, D. J., Bishop, J., Dichmont, C. M., Hall, N., McInnes, K., and Taylor, B. R. (2003). Management of common banana prawn stocks of theGulf of Carpentaria: separating the effects of fishing fromthe environment. *Final Report to the Australian Fisheries Management Authority, Project No. 98/0716.*, 116.

Vance, D. J., and Staples, D. J. (1992). Catchability and sampling of 3 species of juvenile penaeid prawns in the Embley River, Gulf of Carpentaria, Australia. *Marine Ecology-Progress Series* **87**, 201-213.

Vance, D. J., Staples, D. J., and Kerr, J. D. (1985). Factors affecting year-to-year variation in the catch of banana prawns (*Penaeus merguiensis*) in the Gulf of Carpentaria, Australia. *Journal Du Conseil* **42**, 83-97.

Venables, W., Hutton, T., Lawrence, E., Rothlisberg, P., Buckworth, R., Hartcher, M., and Kenyon, R. (2011). Prediction of Common Banana Prawn Potential Catch in Australia's Northern Prawn Fishery. . *Unpublished Report to the Australian Fisheries Management Authority.*

Vieira, S. and Perks, C. (2010) Australian fisheries surveys report 2009: Survey results for selected fisheries, 2006-07 and 2007-08, preliminary estimates for 2008-09, ABARE report to the Fisheries Resources Research Fund, Canberra.

Vieira, S., Perks, C., Mazur, K., Curtotti, R. and Li, M. (2010) Impact of the structural adjustment package on the profitability of Commonwealth fisheries, ABARE research report 10.01, ABARE, Canberra.

Woodhams, J., Larcombe, J., and Geoge, D. (2011). Northern Prawn Fishery. Woodhams, J, Stobutzki, I, Vieira, S, Curtotti, R and Begg G.A. (eds) 2011, Fishery status reports 2010: status of fish stocks and fisheries managed by the Australian Government, Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra. Chapter 5, 69-89.

Zhou, S. J., Dichmont, C., Burridge, C. Y., Venables, W. N., Toscas, P. J., and Vance, D. (2007). Is catchability density-dependent for schooling prawns? *Fisheries Research* **85**, 23-36. doi:10.1016/j.fishres.2006.11.034

13 Appendix 1: Intellectual Property

The research is for the public domain. The report and any resulting manuscripts are intended for wide dissemination and promotion. All data and statistics presented conform to confidentiality arrangements.

14 Appendix 2: Staff

Staff involved in the project were:

TEAM MEMBER	ORGANISATION	FUNDING
R. Buckworth	CSIRO	FRDC and in-kind
L. Chu	ANU	In-kind
M. Hartcher	CSIRO	In-kind
F. Hill	AFMA	In-kind
T. Hutton	CSIRO	FRDC and in-kind
T. Kompas	ANU	FRDC and in-kind
E. Lawrence	CSIRO	FRDC and in-kind
S. Pascoe	CSIRO	In-kind
P. Rothlisberg	CSIRO	In-kind
W. Venables	CSIRO	In-kind

15 Appendix 3: Modelling Potential Catch

15.1 Modelling Individual stock regions

The following table shows the Catch for 2011 and predictions for 2011 and 2012 for each stock region and the NPF TAC region as a whole. Table 15 shows the results for individual stock region models, using both EW and UW versions, based on the updated SILO data/inclusion of 2011 (new) and the models from Venables *et al.* (2011).

Table 15. Catch and predictions, in tonnes, for four models, 2011 and 2012, using individual stock region models and aggregating. The EW and UW models are re-built using data up to 2011 for their calibration; the (old) versions use the models from the feasibility study without change.

	CATCH	EW(NEW)	UW(NEW)	EW (OLD)	UW (OLD)
2011					
Coburg	879.9	1206.8	1213.6	1415.0	2353.6
Arnhem	338.9	420.3	376.9	857.2	729.9
N_Groote	158.9	166.4	955.5	2094.0	5219.6
S_Groote	102.0	107.5	333.2	2.5	1994.1
Vanderlins	148.6	166.2	193.0	23.9	91.7
Mornington	917.1	902.6	2162.5	206.2	627.8
Karumba	2818.3	3633.3	2784.4	211.7	264.7
Mitchell	1045.5	1304.0	898.7	1921.0	406.5
Weipa	757.2	791.5	776.5	821.8	476.6
NPF	**7166.5**	**8698.5**	**9694.3**	**7553.3**	**12164.5**
2012					
Coburg		831.8	770.6	700.5	680.9
Arnhem		173.0	92.7	195.2	93.8
N_Groote		50.2	55.0	320.0	94.2
S_Groote		11.0	947.4	51.7	253.3
Vanderlins		167.8	0.5	73.0	9.2
Mornington		217.7	223.0	232.7	111.9
Karumba		635.4	1876.3	1125.9	843.4
Mitchell		796.0	802.7	1034.9	730.3
Weipa		216.3	166.9	146.7	111.1
NPF		**3099.2**	**4935.1**	**3880.6**	**2928.1**

15.2 Restricting rainfall weight distributions

Table 16. Comparison of predictions ('000 tonnes) for the total NPF obtained by restricting weights (cap) for the effort weighted (EW) and unweighted (UW) modelling approaches using updated SILO data (to 29 February 2012).

YEAR	TOTAL	TOTAL_EW_12	TOTAL_UW_12	TOTAL_EW_12_CAP	TOTAL_UW_12_CAP
1970	1690	4154	11974	3587	3891
1971	7365	6200	65831	5895	5206
1972	4805	6548	9478	5060	6130
1973	4239	5259	9472	4653	3702
1974	12742	12588	14259	12938	13203
1975	3156	13280	5123	4109	4430
1976	4579	5485	6901	6484	8342
1977	6329	6521	7291	6950	6613
1978	2544	3672	4227	4054	3749
1979	4757	4834	6974	5261	7723
1980	2837	3160	3672	4722	4209
1981	5410	5737	6090	5960	5897
1982	2964	3262	2905	4749	3948
1983	1653	2650	1823	3158	1884
1984	2993	3407	4023	4306	2857
1985	3779	3086	3013	3622	4328
1986	2116	3290	2922	3524	3154
1987	3416	3706	3861	3863	4127
1988	2752	3275	3120	3123	2705
1989	4855	3693	5221	3796	3960
1990	1675	2248	1819	1903	1968
1991	6127	6923	5544	6815	7007
1992	2036	2909	2110	2649	2077
1993	3492	4257	4203	4530	6242
1994	1544	2711	2593	4113	2838
1995	4197	3946	3461	4682	3685
1996	3585	3137	4443	3473	4202
1997	3557	3538	4006	4661	5047
1998	3326	3843	3823	3814	3469
1999	3257	3969	3378	4484	4313
2000	1749	3360	4459	3468	3155
2001	6874	7551	5849	8590	9708

YEAR	TOTAL	TOTAL_EW_12	TOTAL_UW_12	TOTAL_EW_12_CAP	TOTAL_UW_12_CAP
2002	4195	4362	3223	3515	3349
2003	2831	3920	3236	4234	4089
2004	2990	3347	4044	3642	5254
2005	2566	3469	2384	2840	2511
2006	2879	3930	3941	3877	4446
2007	2489	3283	3189	3046	3470
2008	5385	4163	4406	3985	3827
2009	5067	6281	7101	7380	6594
2010	5173	5794	6064	5083	5862
2011	7167	8699	9694	9062	10018
2012	NA	3099	4935	3641	2638

The rainfall weight distributions for the separate region models (effort weighted and unweighted) with restricted rainfall weights and unrestricted rainfall weights are shown in the Figures below.

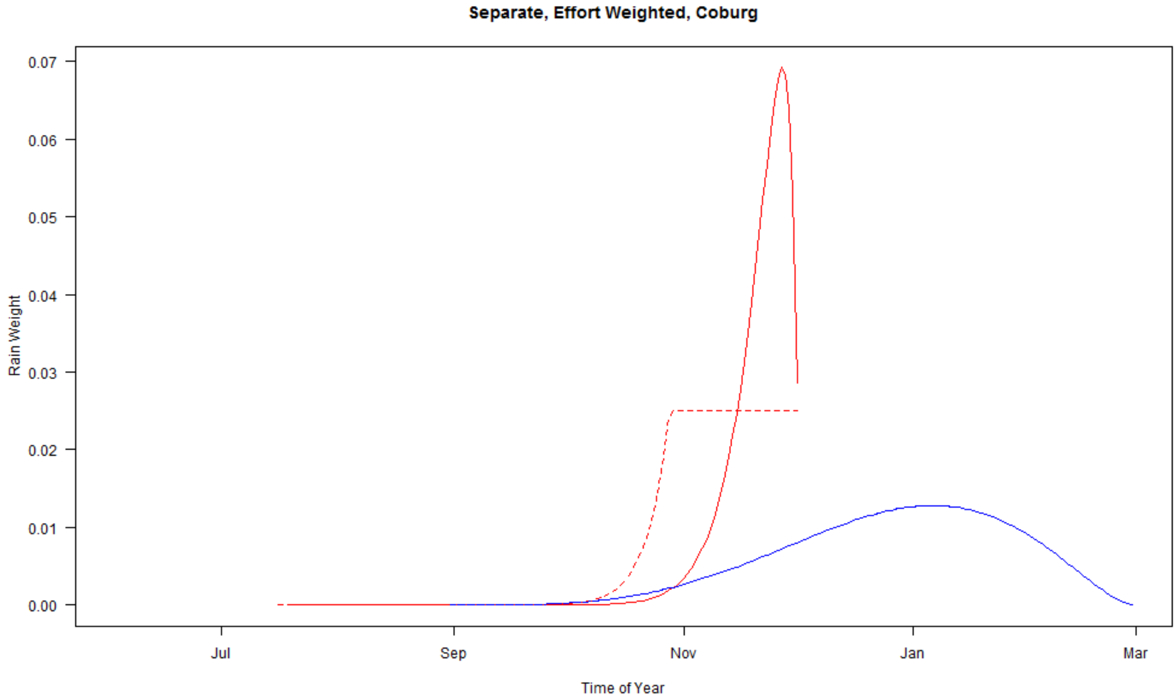

Figure 44. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Coburg for the effort weighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

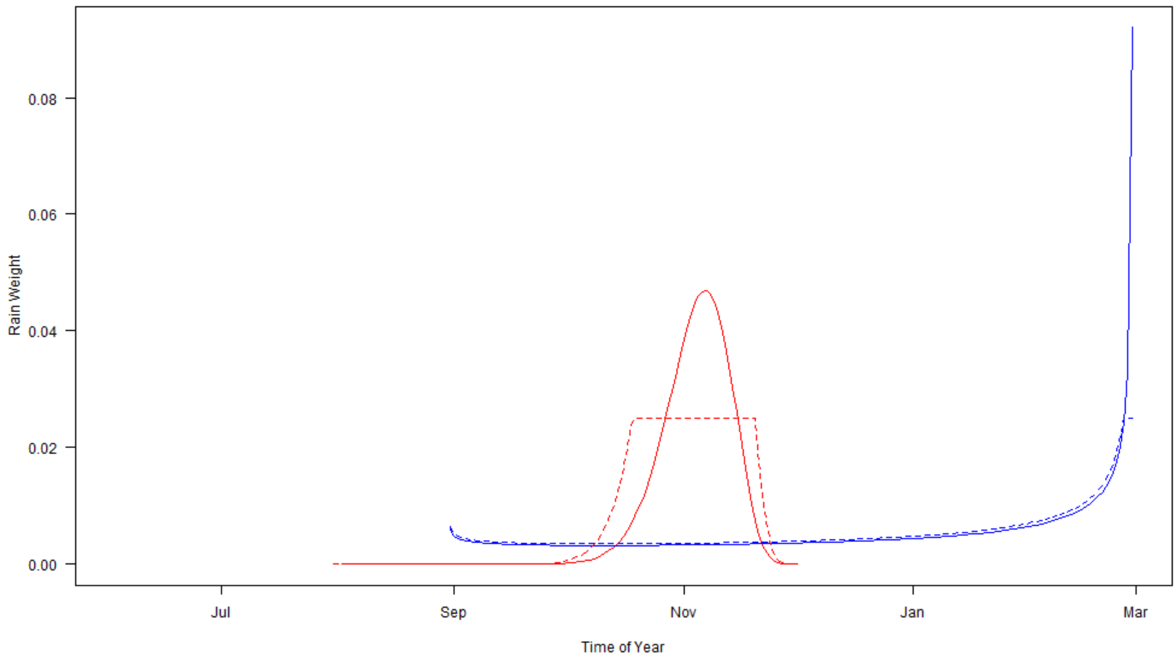

Figure 45. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Arnhem for the effort weighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

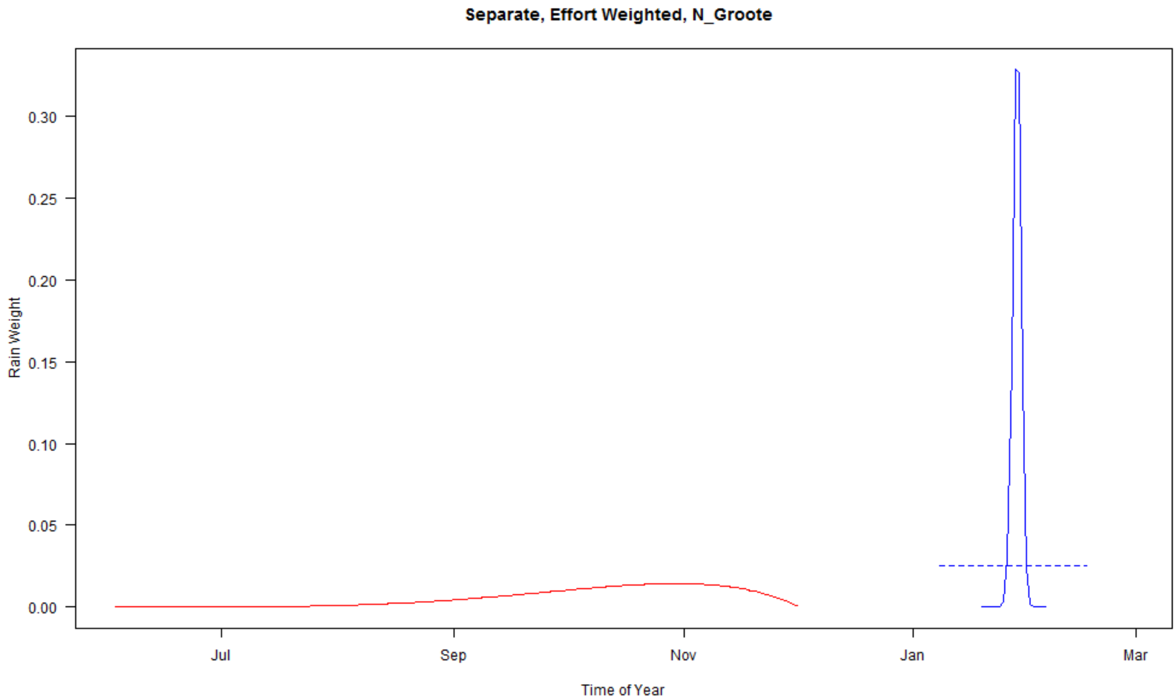

Figure 46. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for North Groote for the effort weighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

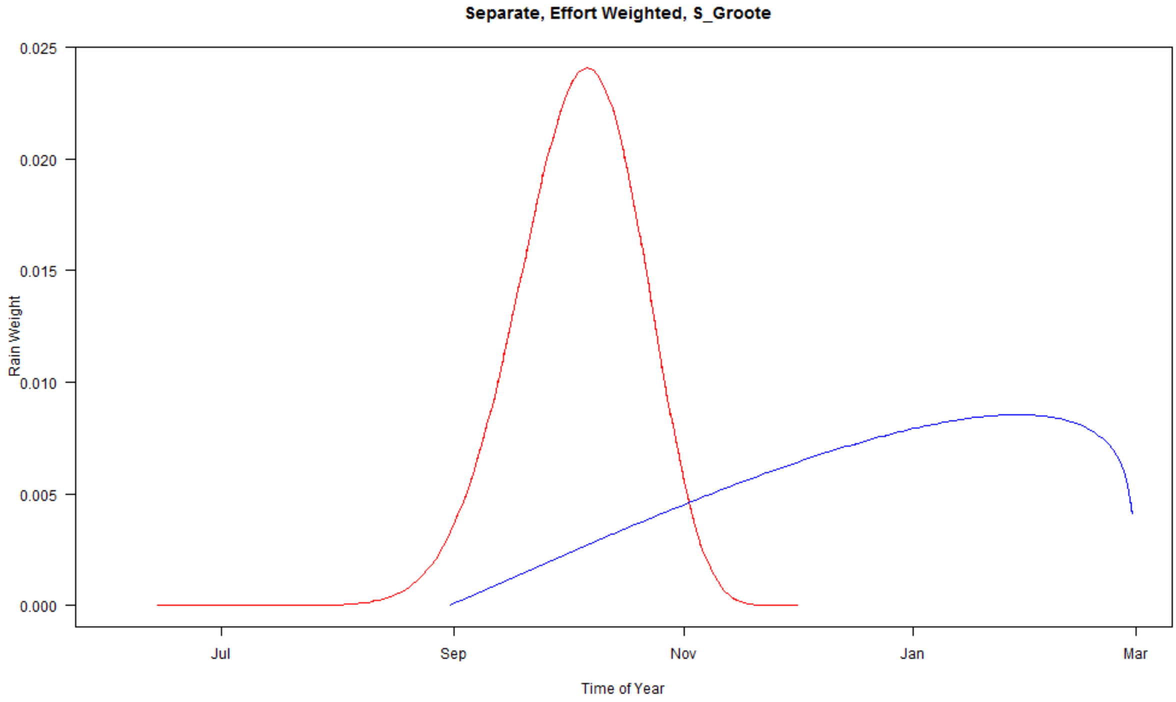

Figure 47. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for South Groote for the effort weighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

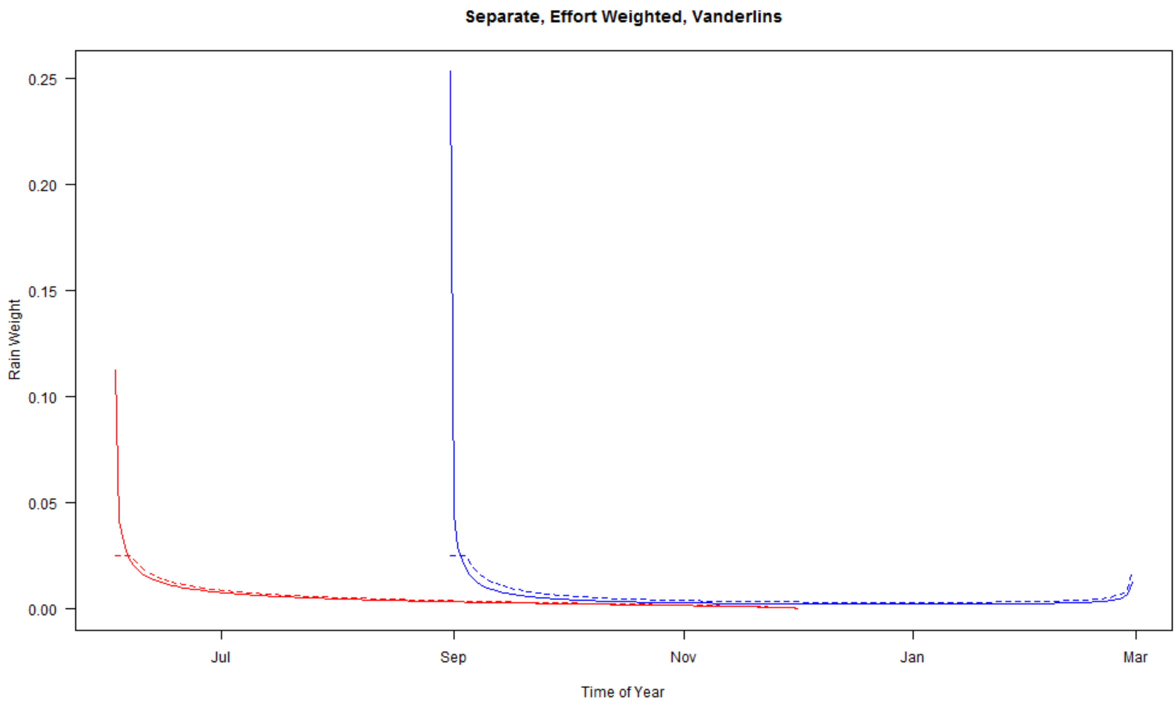

Figure 48. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Vanderlins for the effort weighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

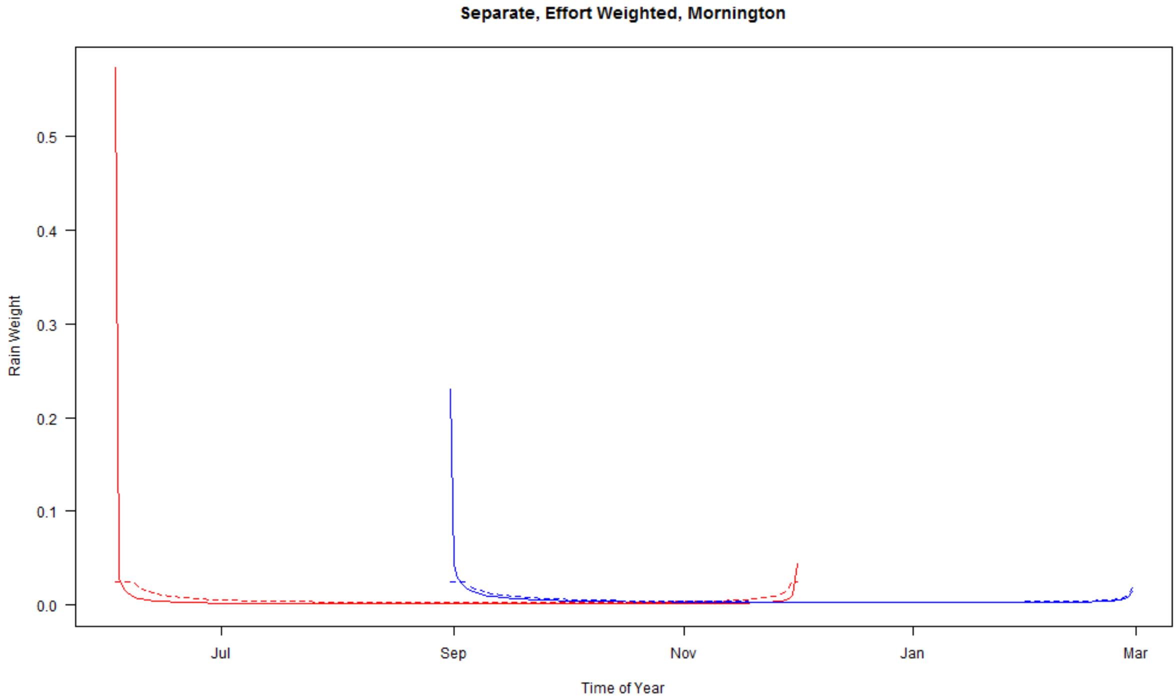

Figure 49. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Mornington for the effort weighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

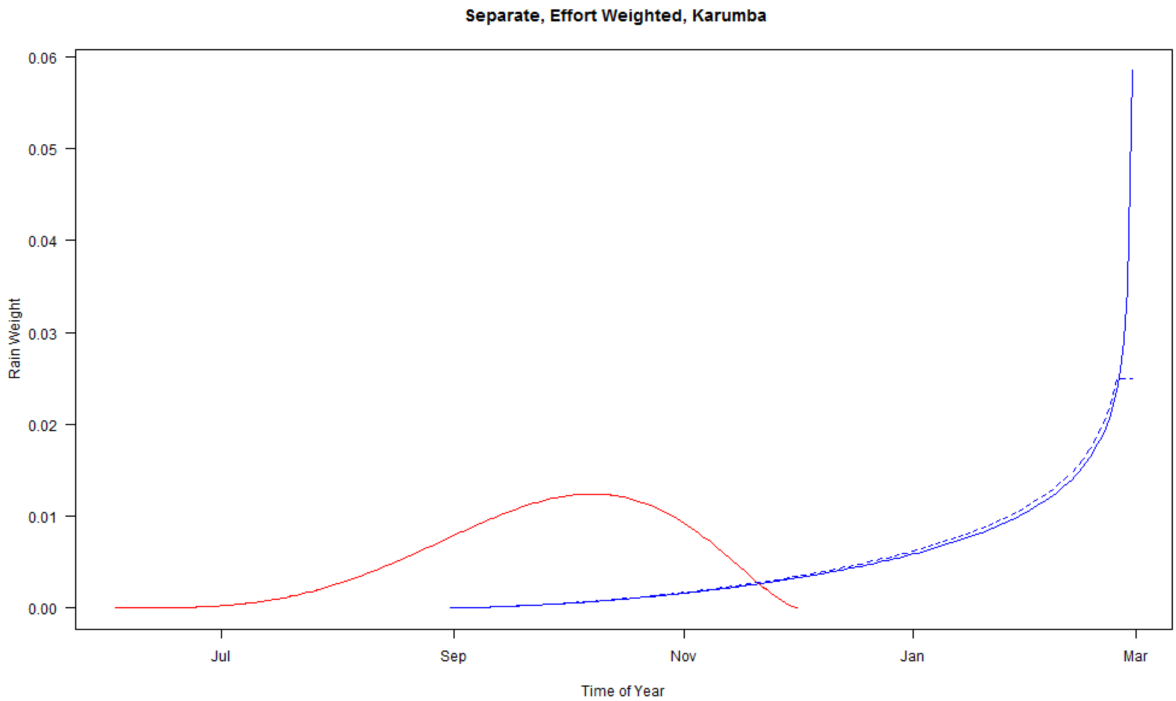

Figure 50. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Karumba for the effort weighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

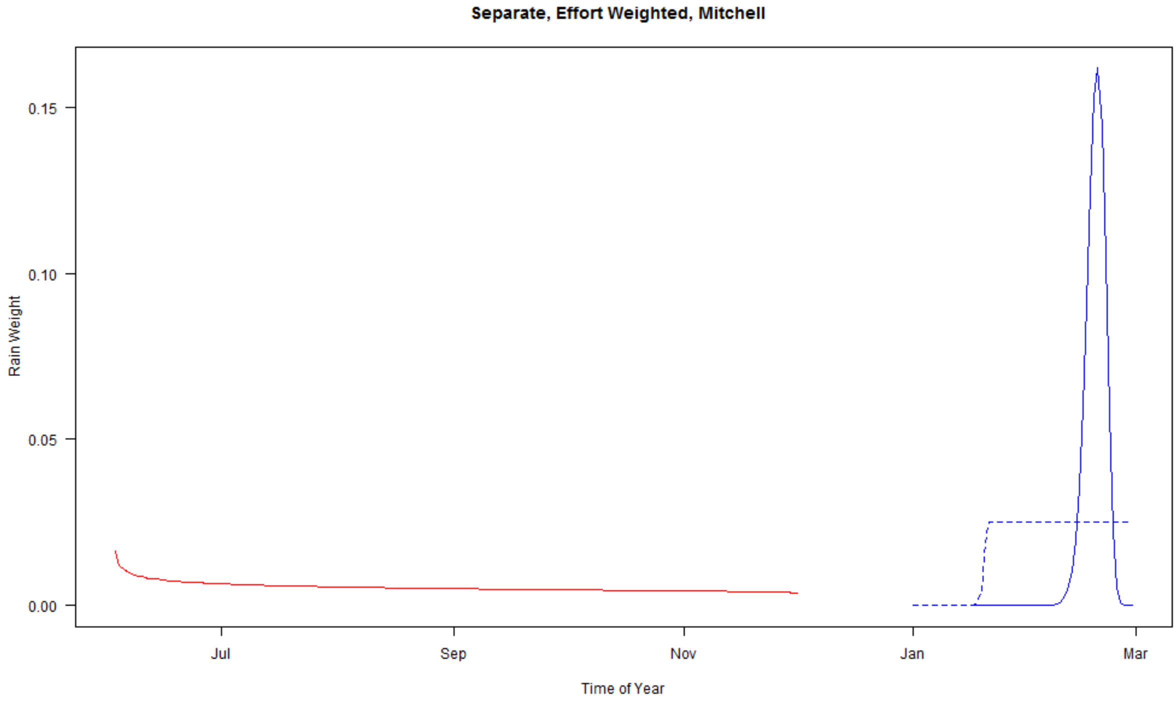

Figure 51. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Mitchell for the effort weighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

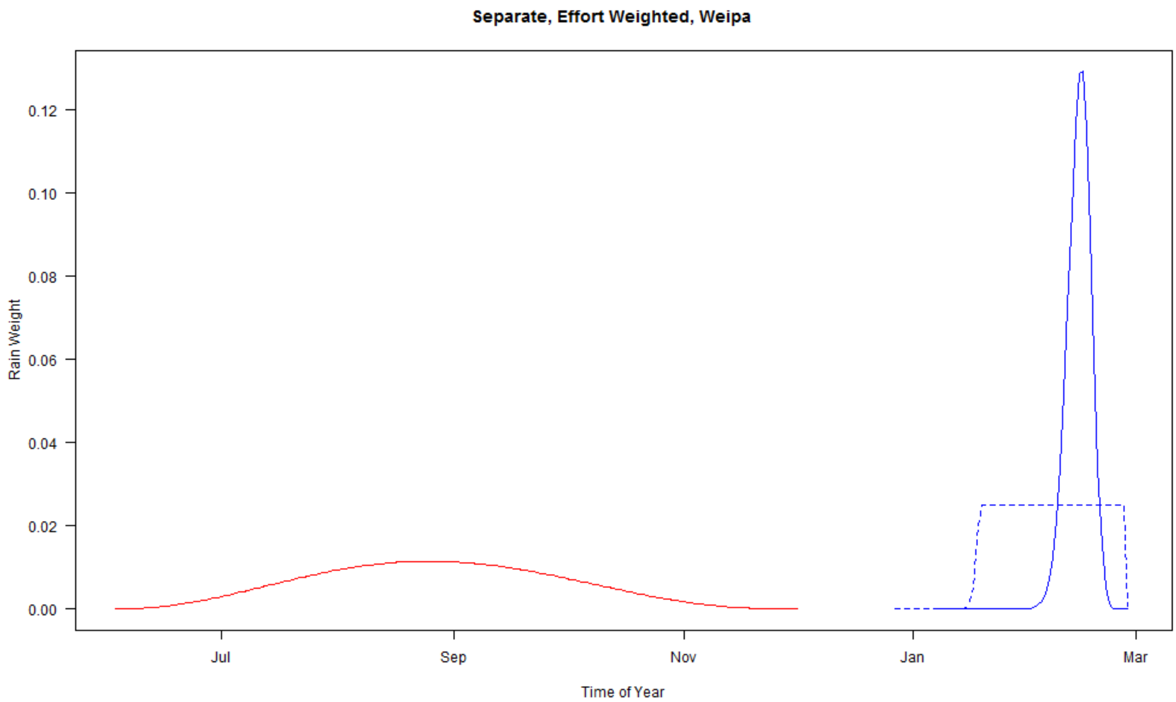

Figure 52. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Weipa for the effort weighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

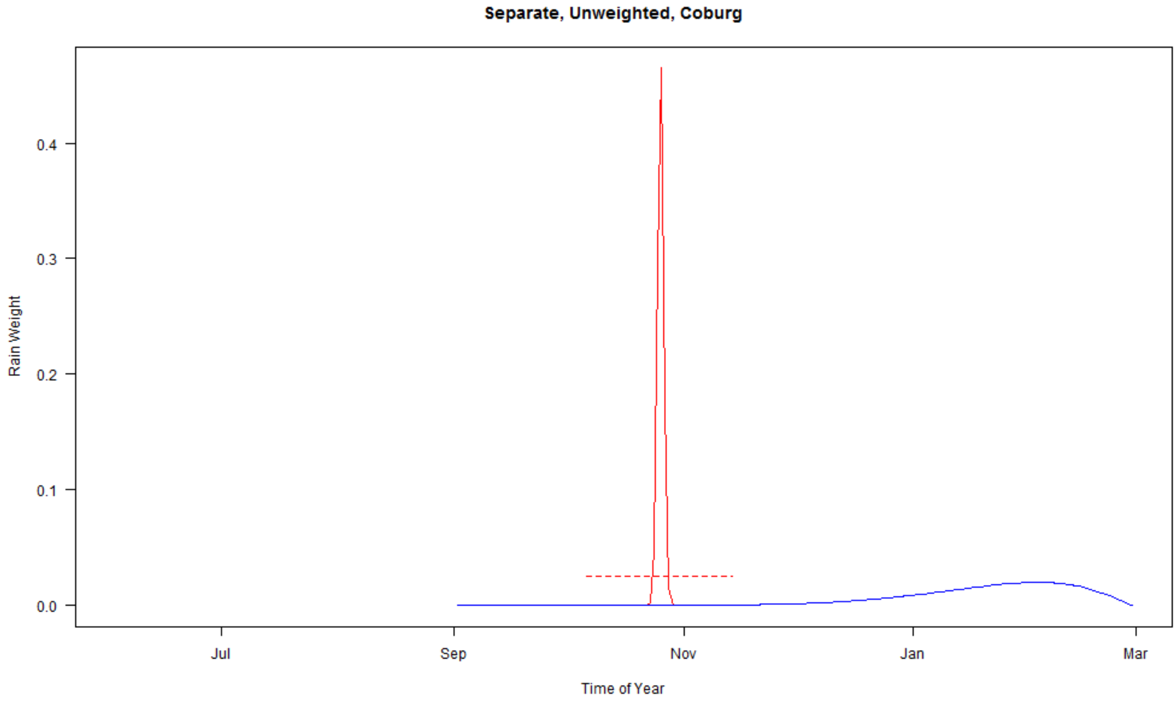

Figure 53. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Coburg for the unweighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

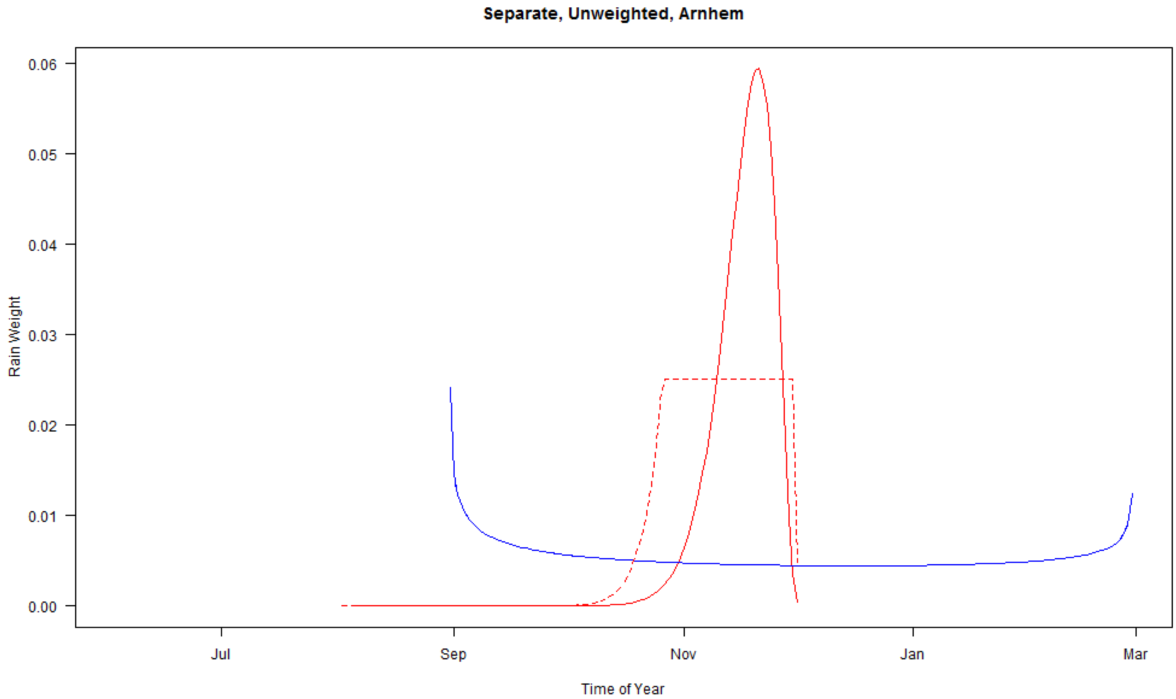

Figure 54. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Arnhem for the unweighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

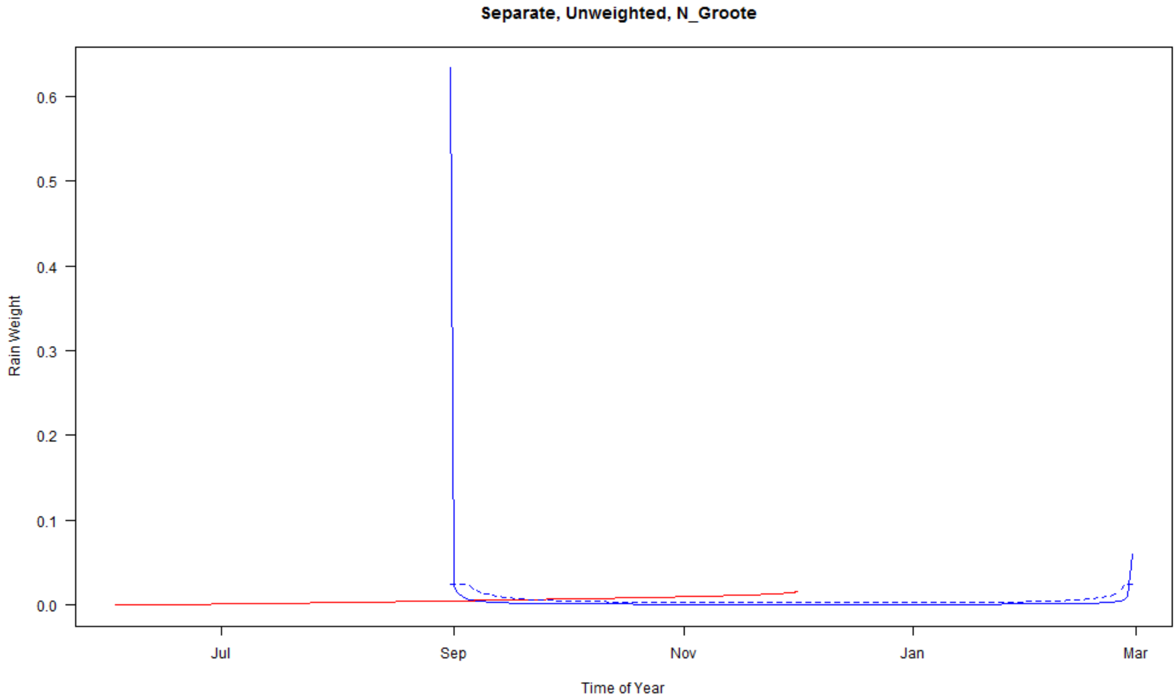

Figure 55. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for North Groote for the unweighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

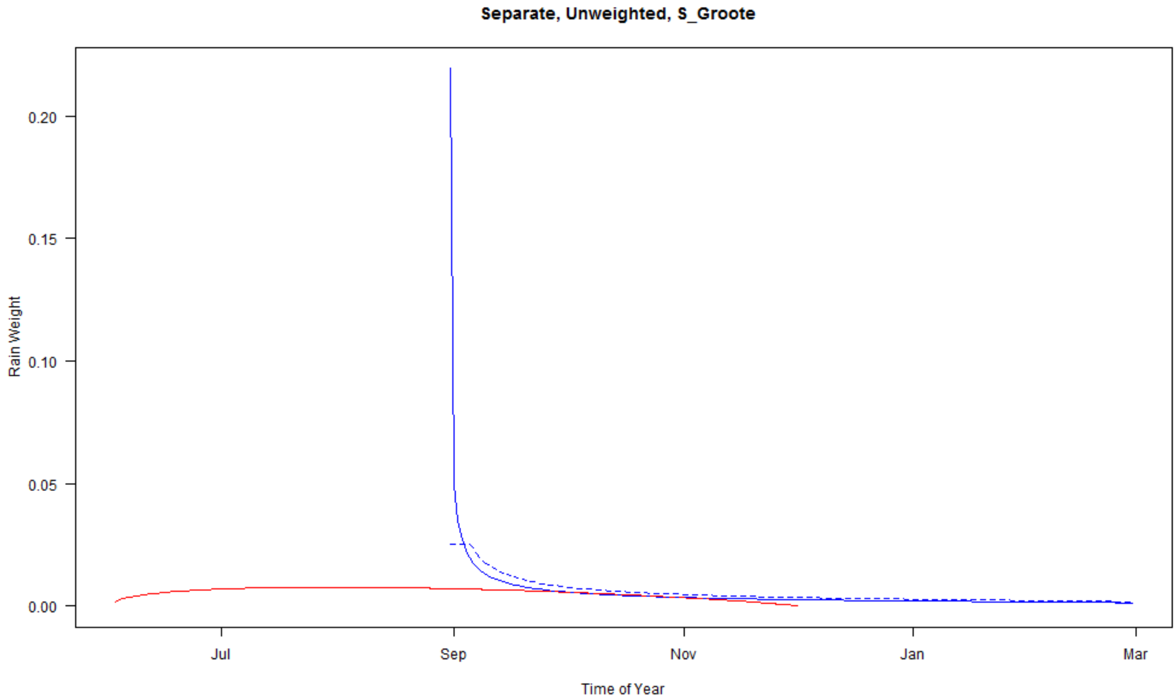

Figure 56. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for South Groote for the unweighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

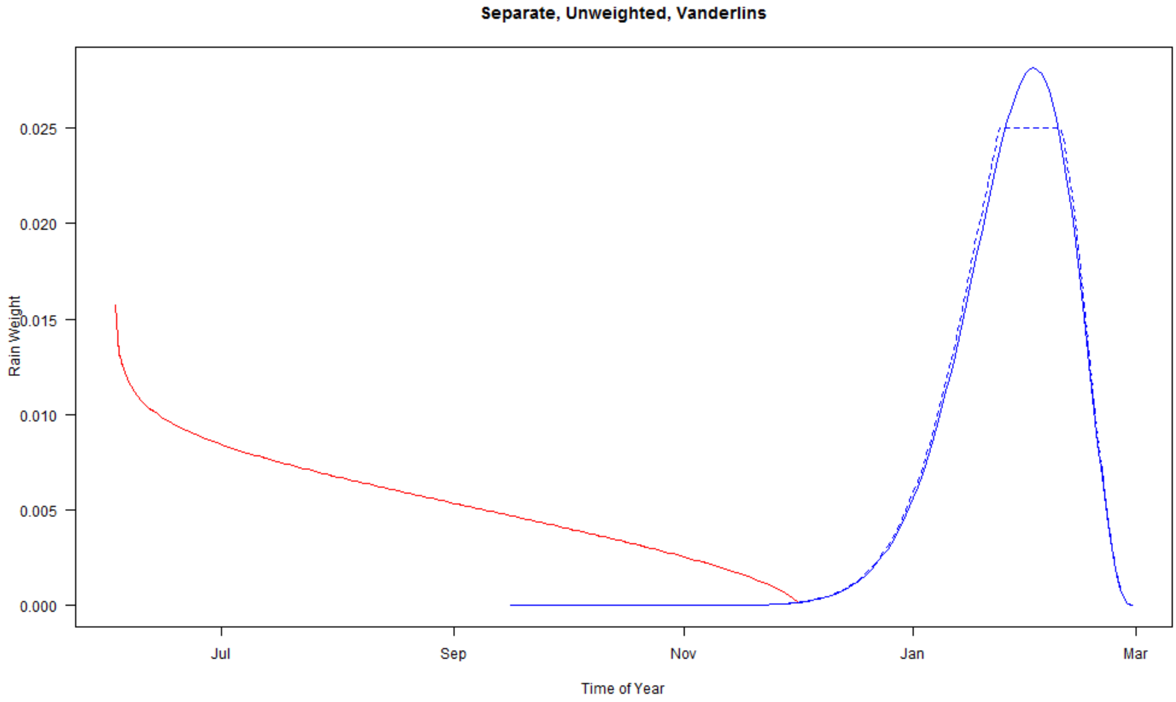

Figure 57. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Vanderlins for the unweighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

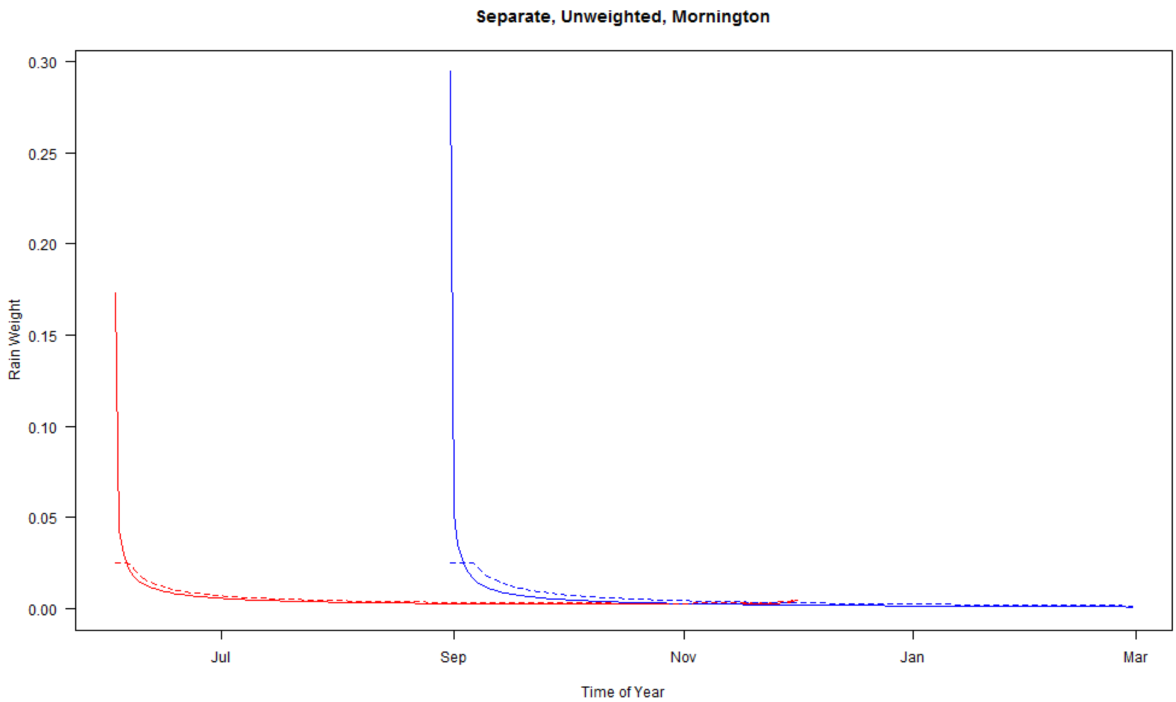

Figure 58. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Mornington for the unweighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

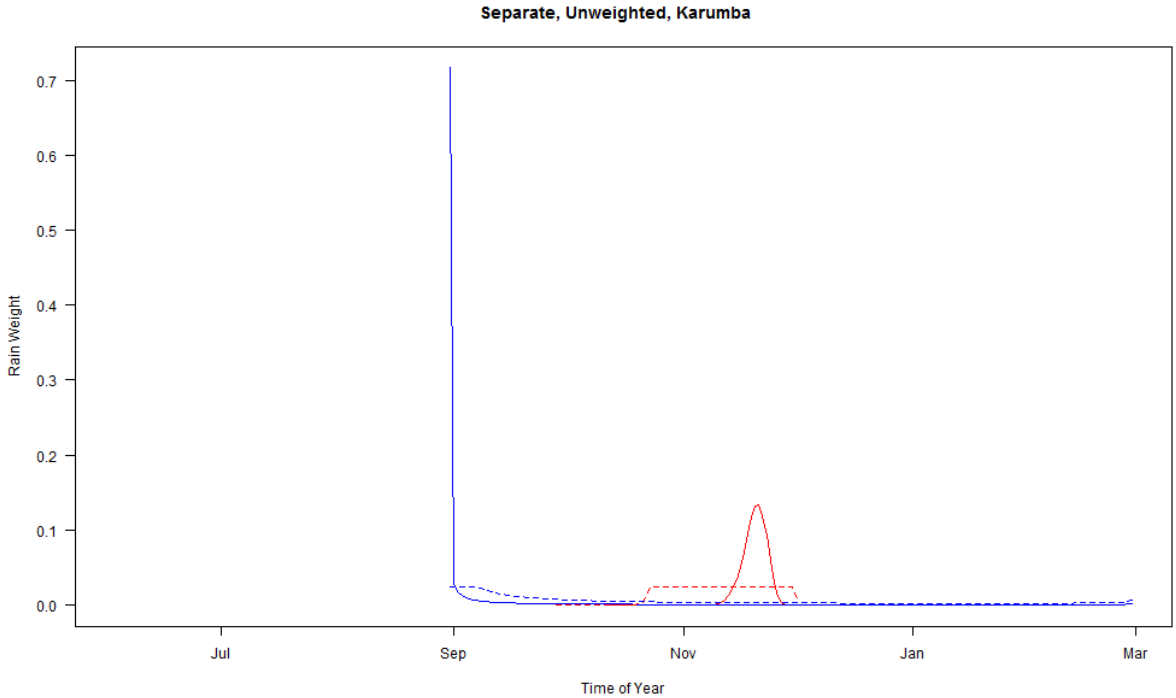

Figure 59. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Karumba for the unweighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

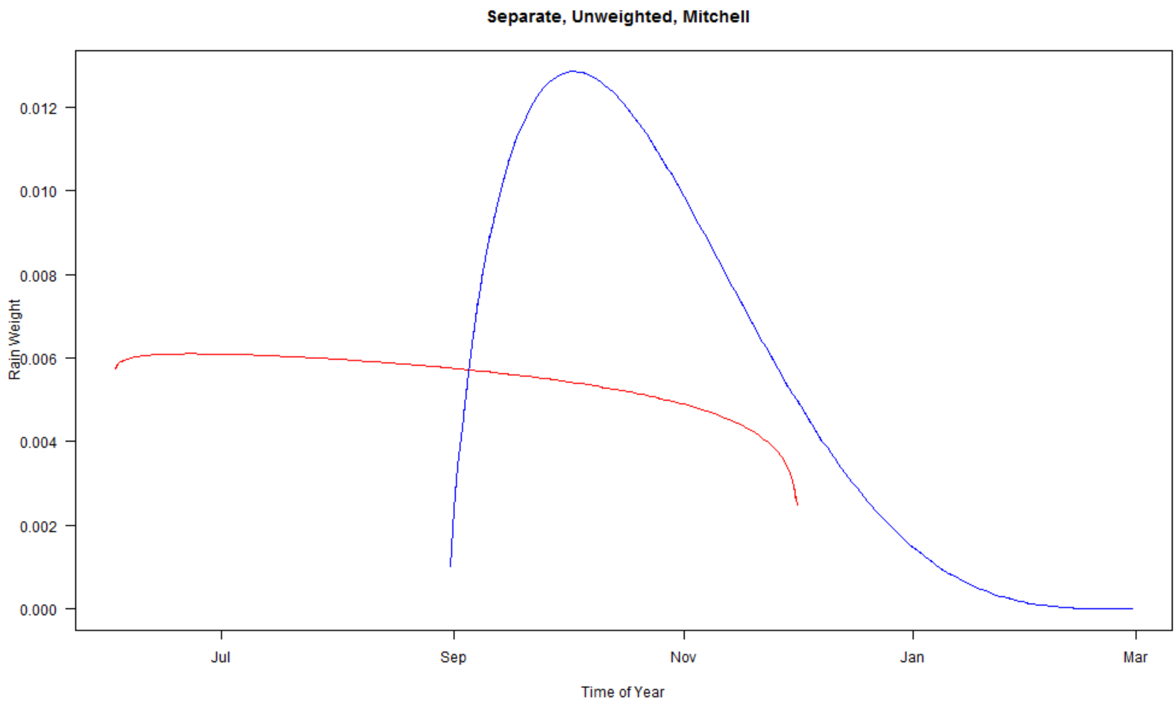

Figure 60. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Mitchell for the unweighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

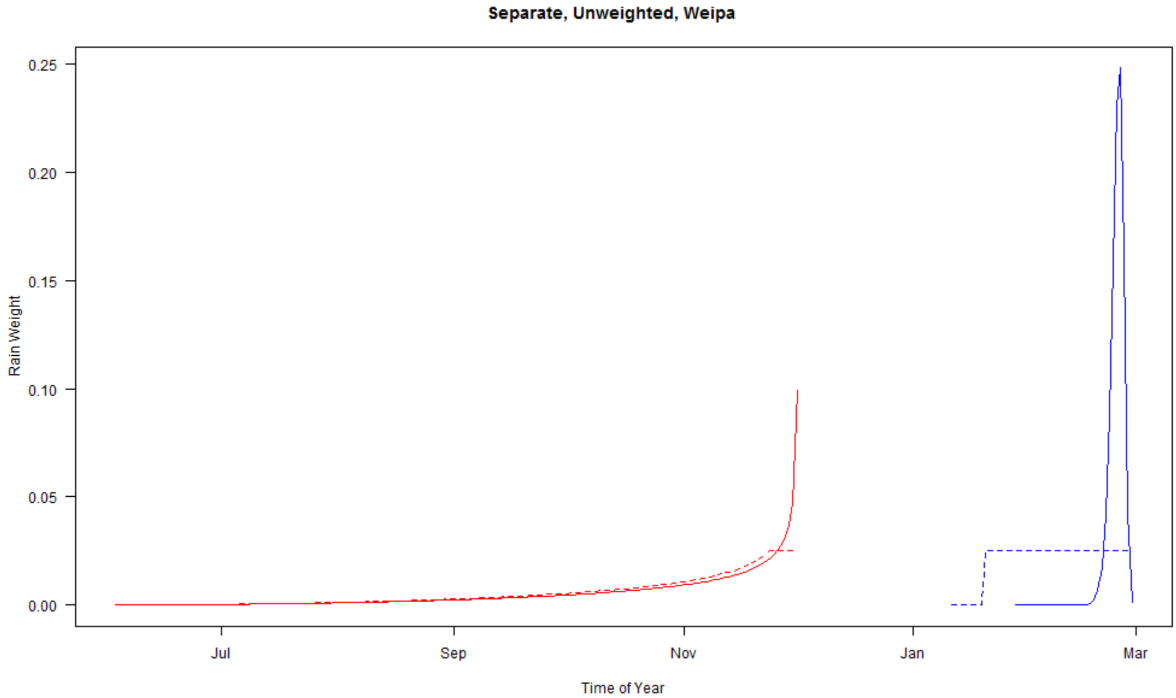

Figure 61. Distribution of rainfall weights for "early" (red) and "late" (blue) rainfall seasons for Weipa for the unweighted model. Solid line is the original model, dotted line is the model where weights are capped to 0.025.

15.3 Regional predictions for fixed weight model

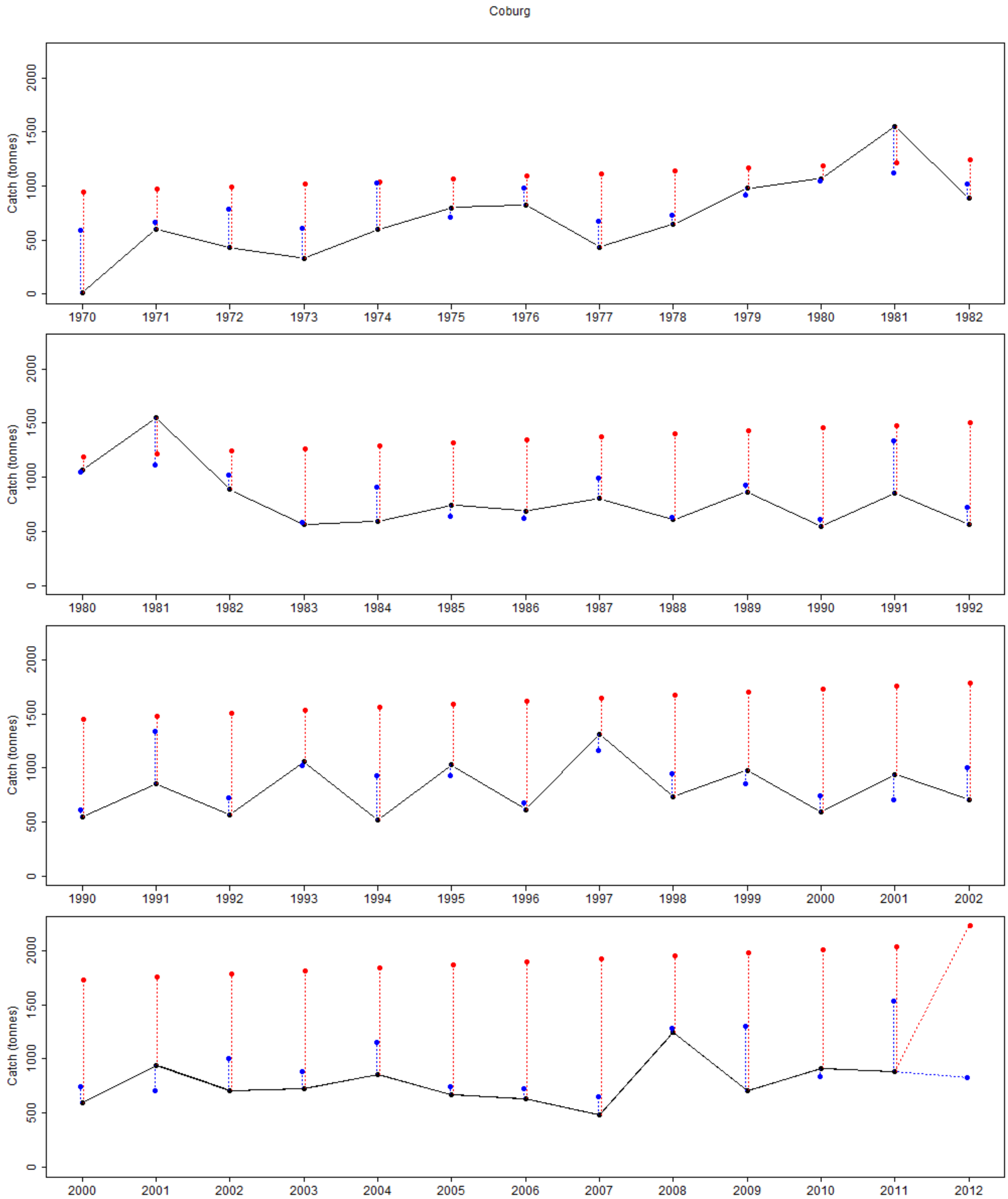

Figure 62. Catch and predictions for Coburg region using the single model with fixed weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

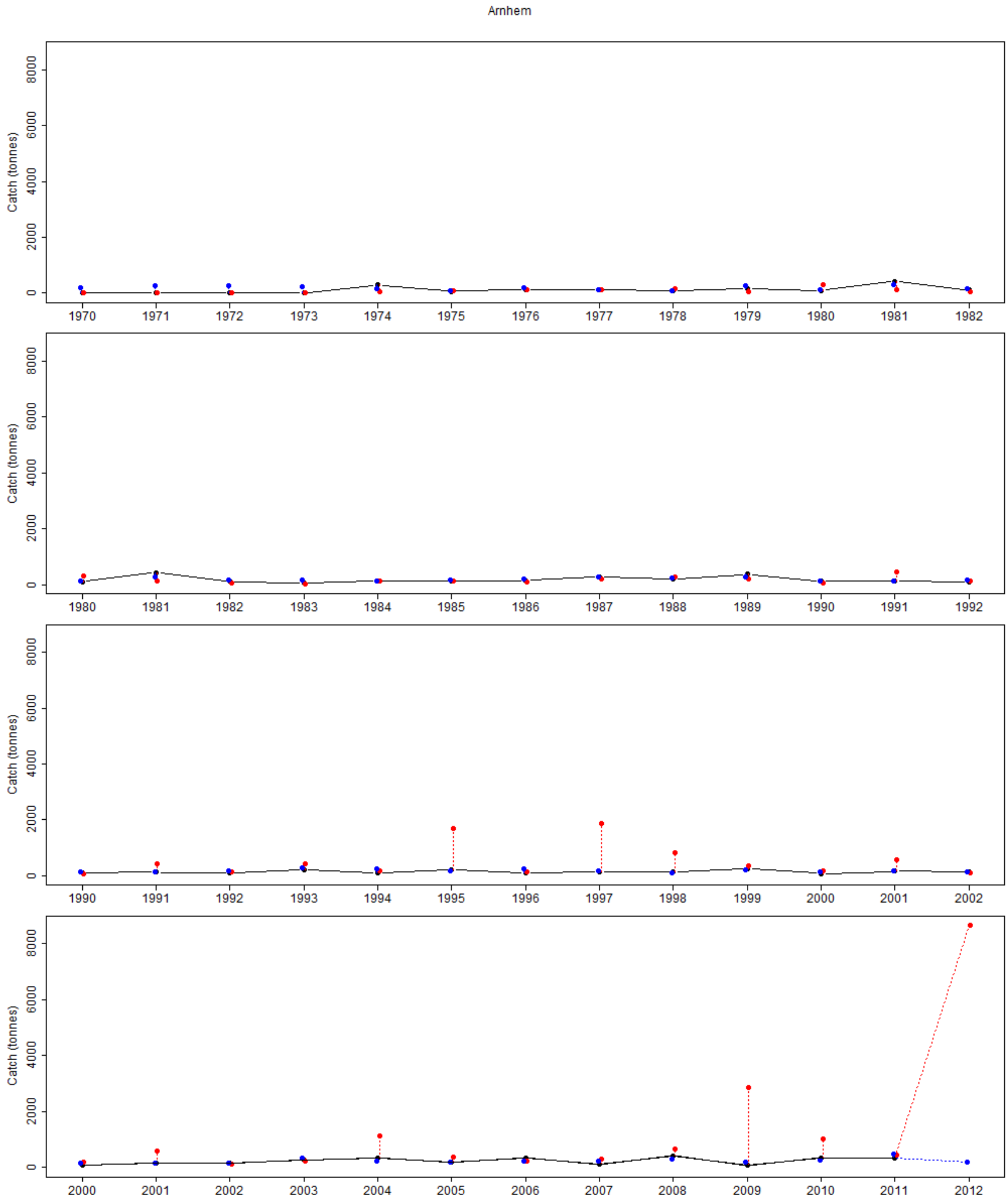

Figure 63. Catch and predictions for Arnhem region using the single model with fixed weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

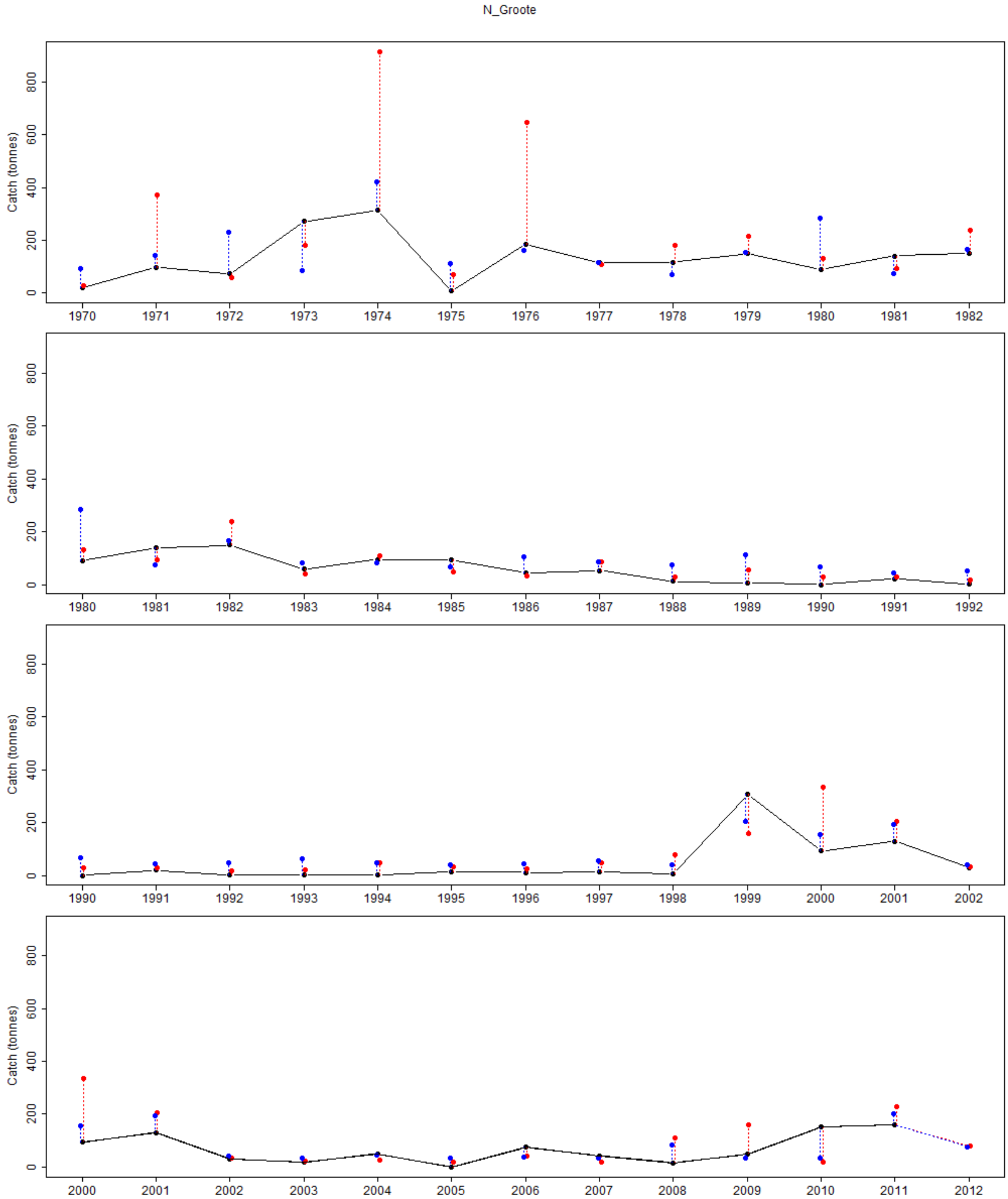

Figure 64. Catch and predictions for North Groote region using the single model with fixed weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

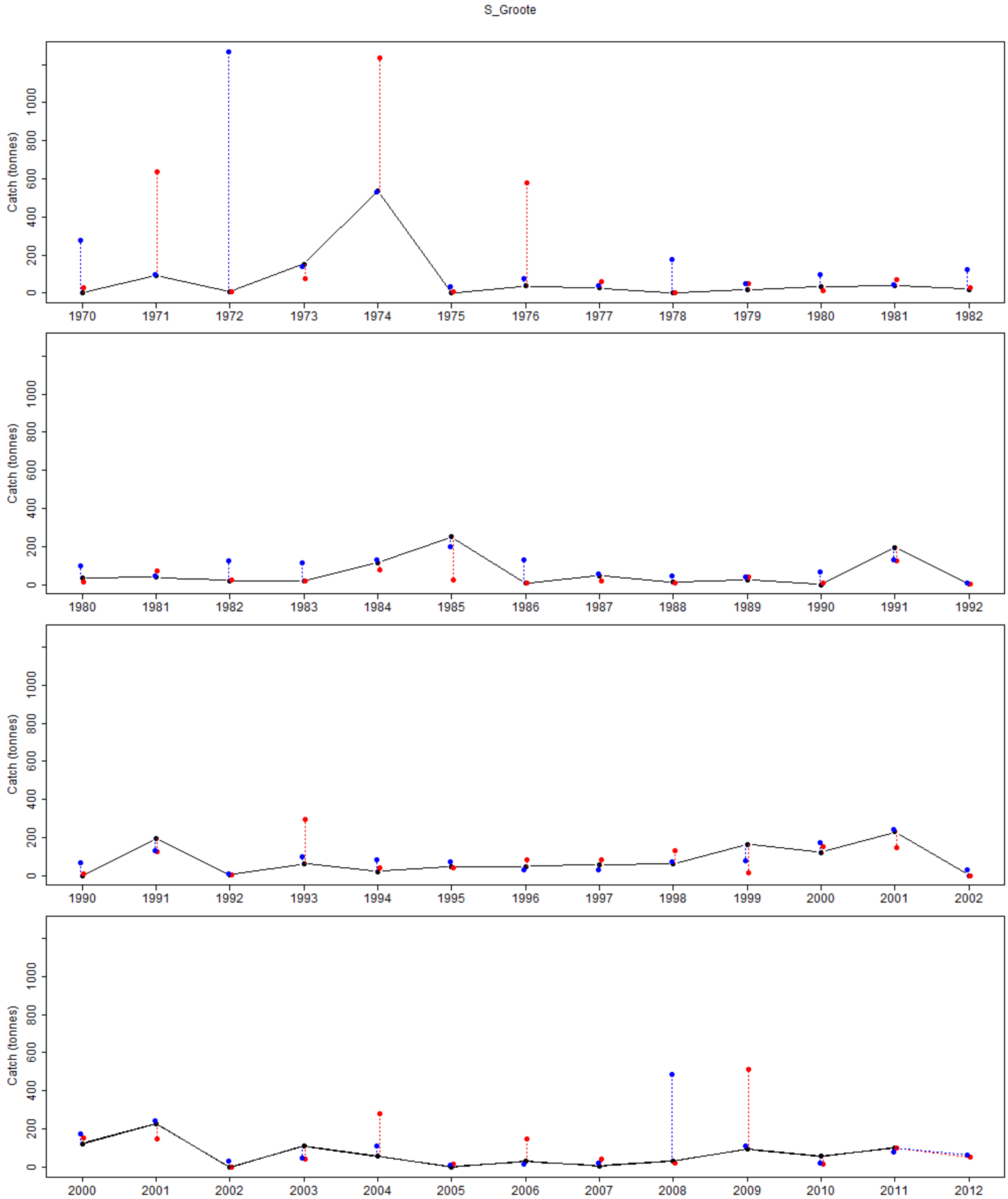

Figure 65. Catch and predictions for South Groote region using the single model with fixed weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

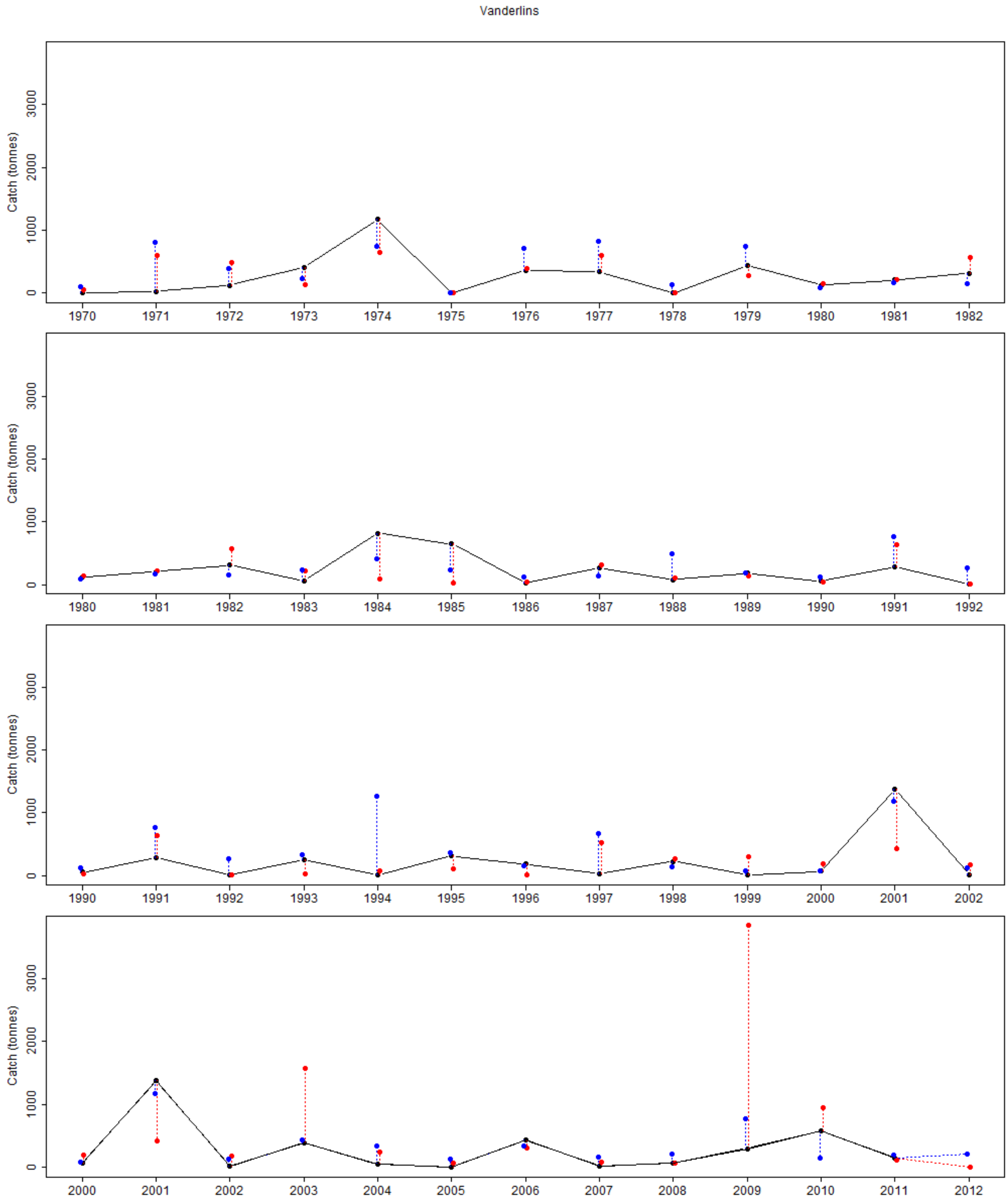

Figure 66. Catch and predictions for Vanderlins region using the single model with fixed weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

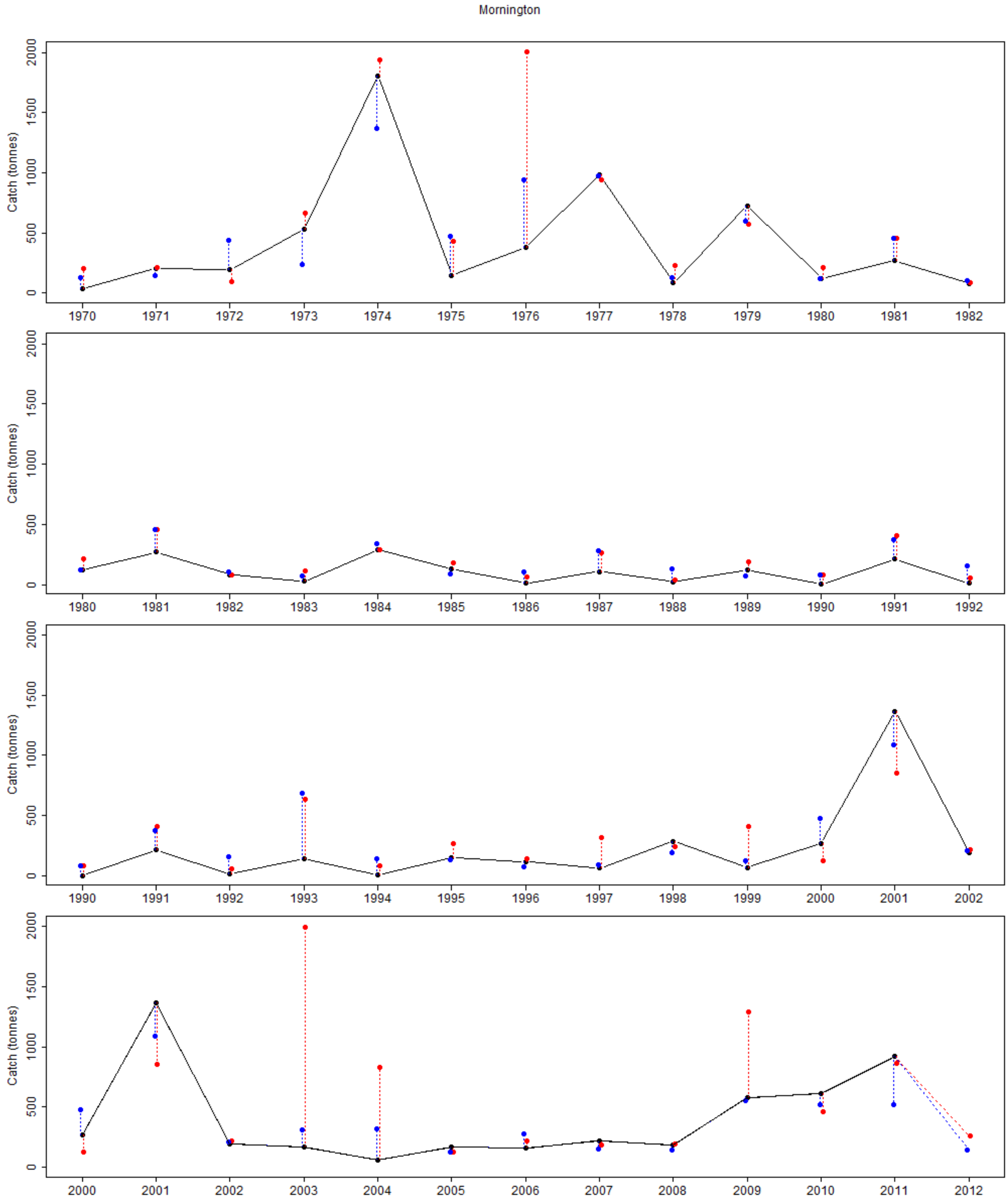

Figure 67. Catch and predictions for Mornington region using the single model with fixed weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

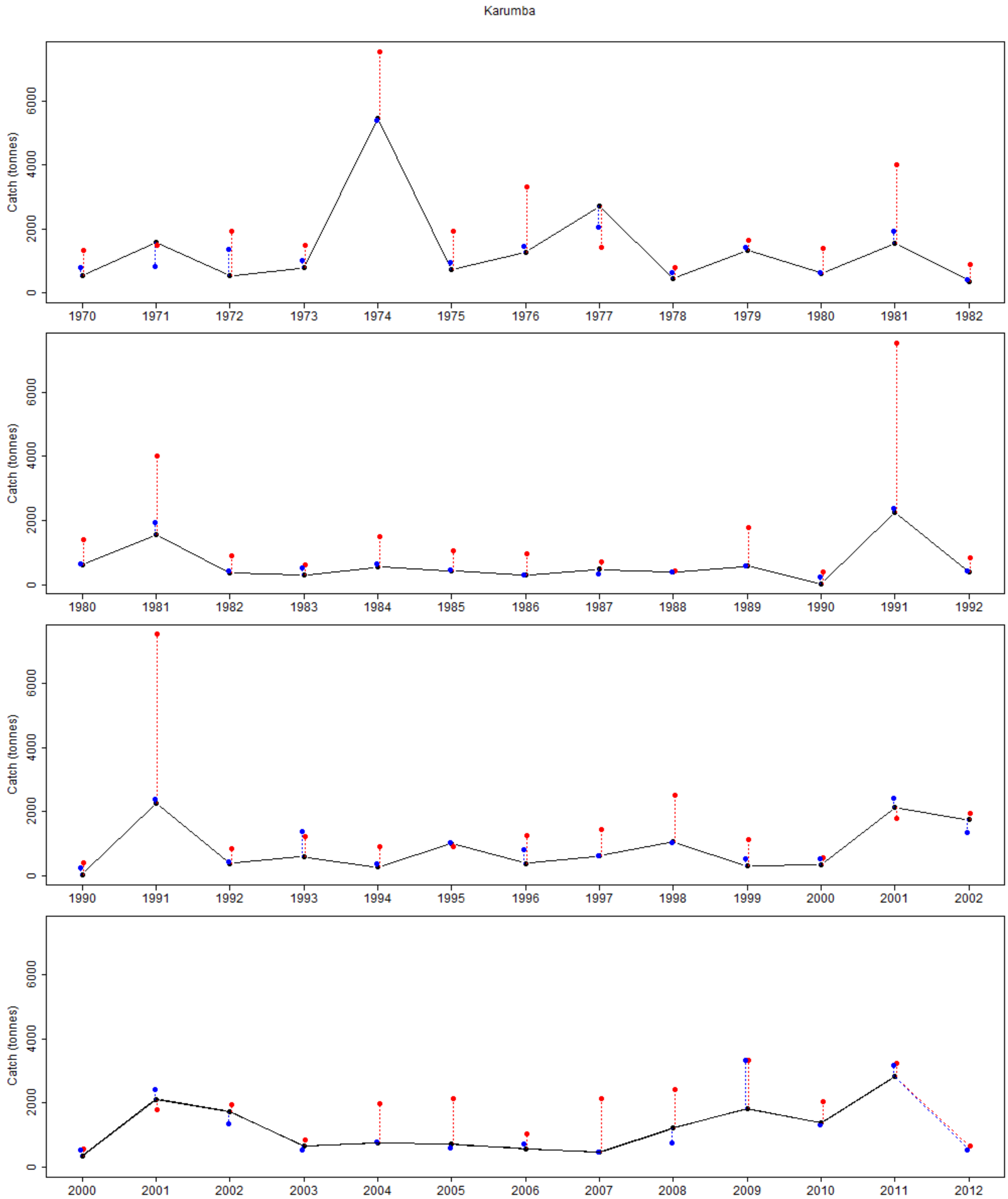

Figure 68. Catch and predictions for Karumba region using the single model with fixed weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

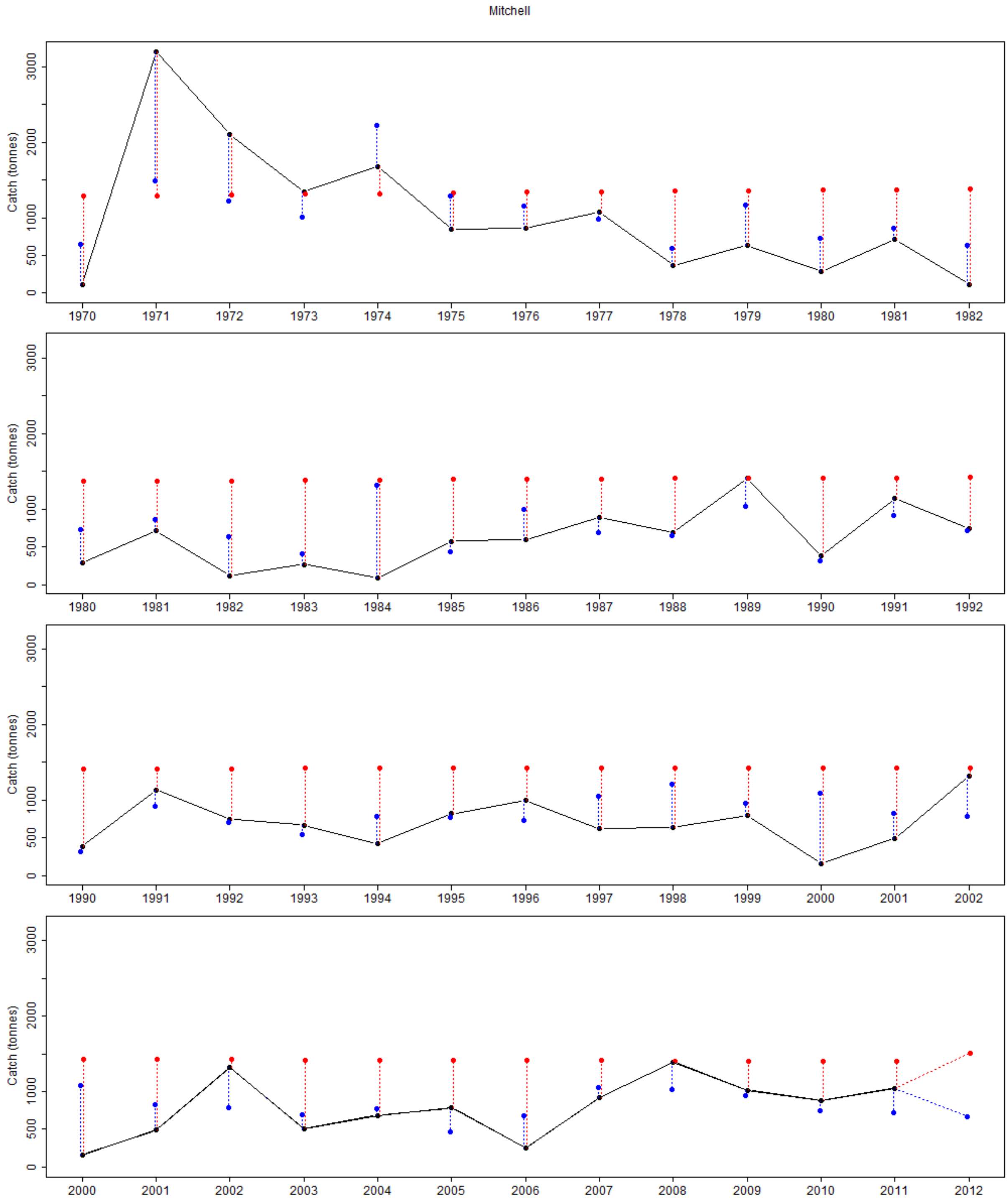

Figure 69. Catch and predictions for Mitchell region using the single model with fixed weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

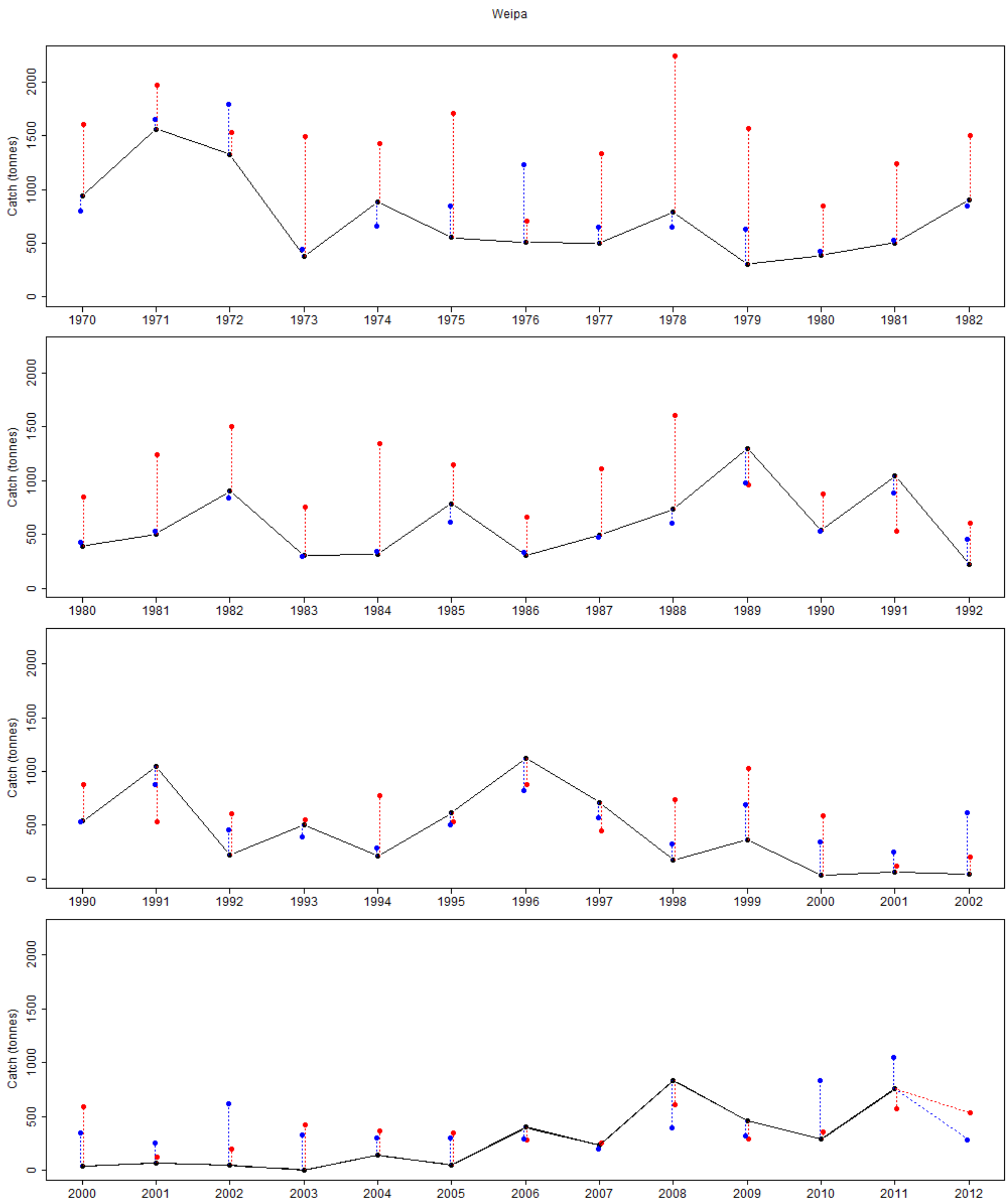

Figure 70. Catch and predictions for Weipa region using the single model with fixed weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

15.4 Regional predictions for variable weight model

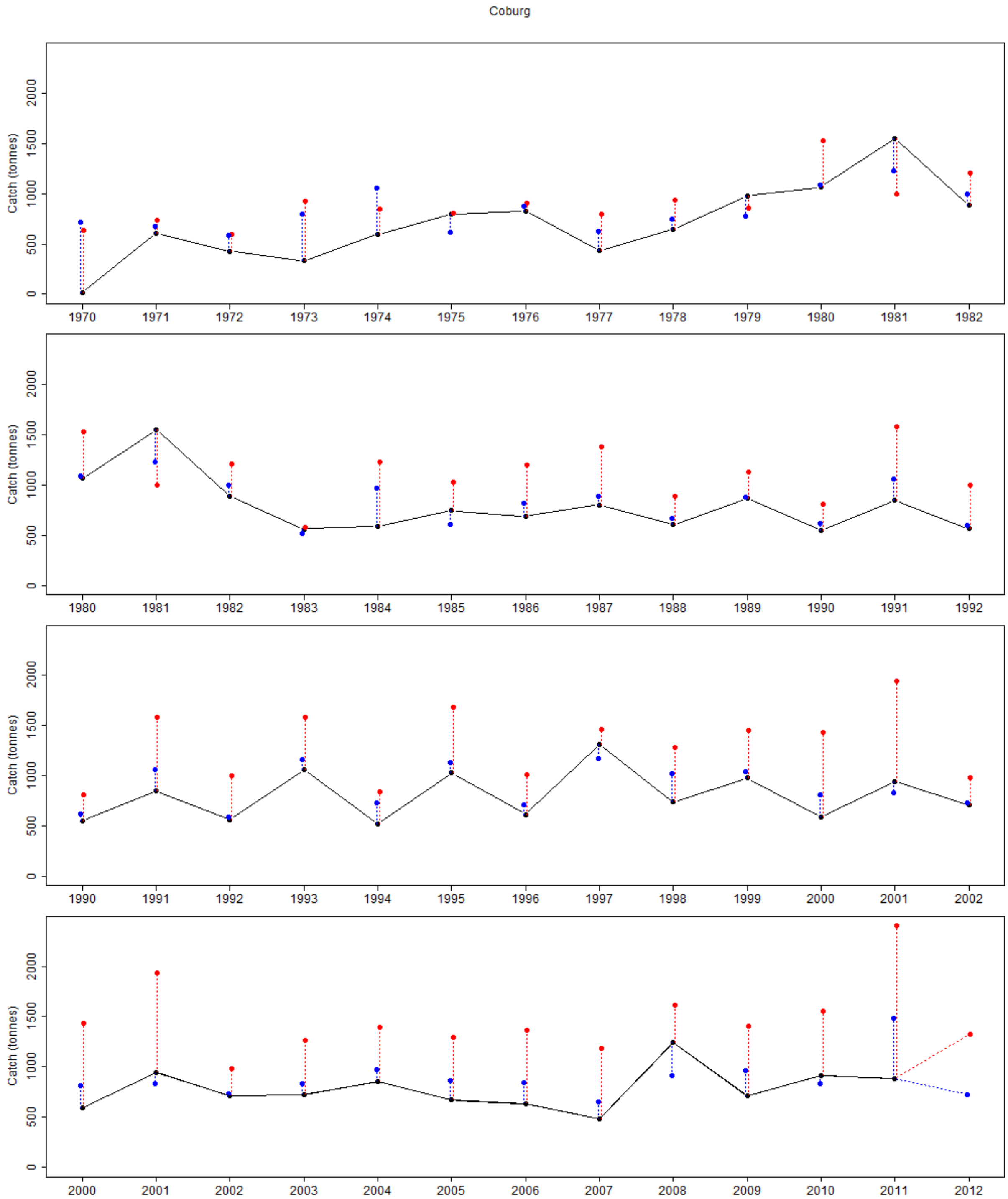

Figure 71. Catch and predictions for Coburg region using the single model with variable weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

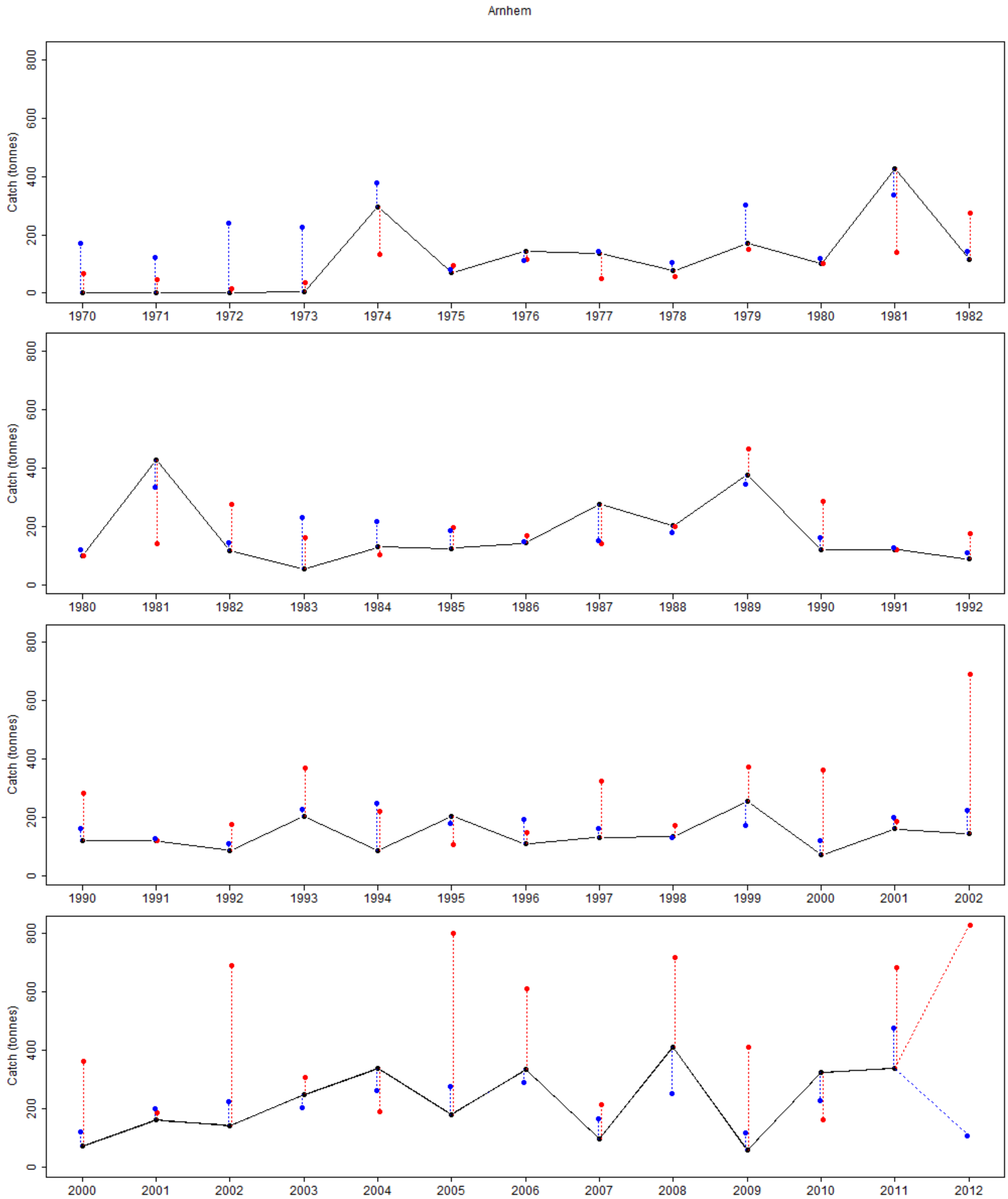

Figure 72. Catch and predictions for Arnhem region using the single model with variable weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

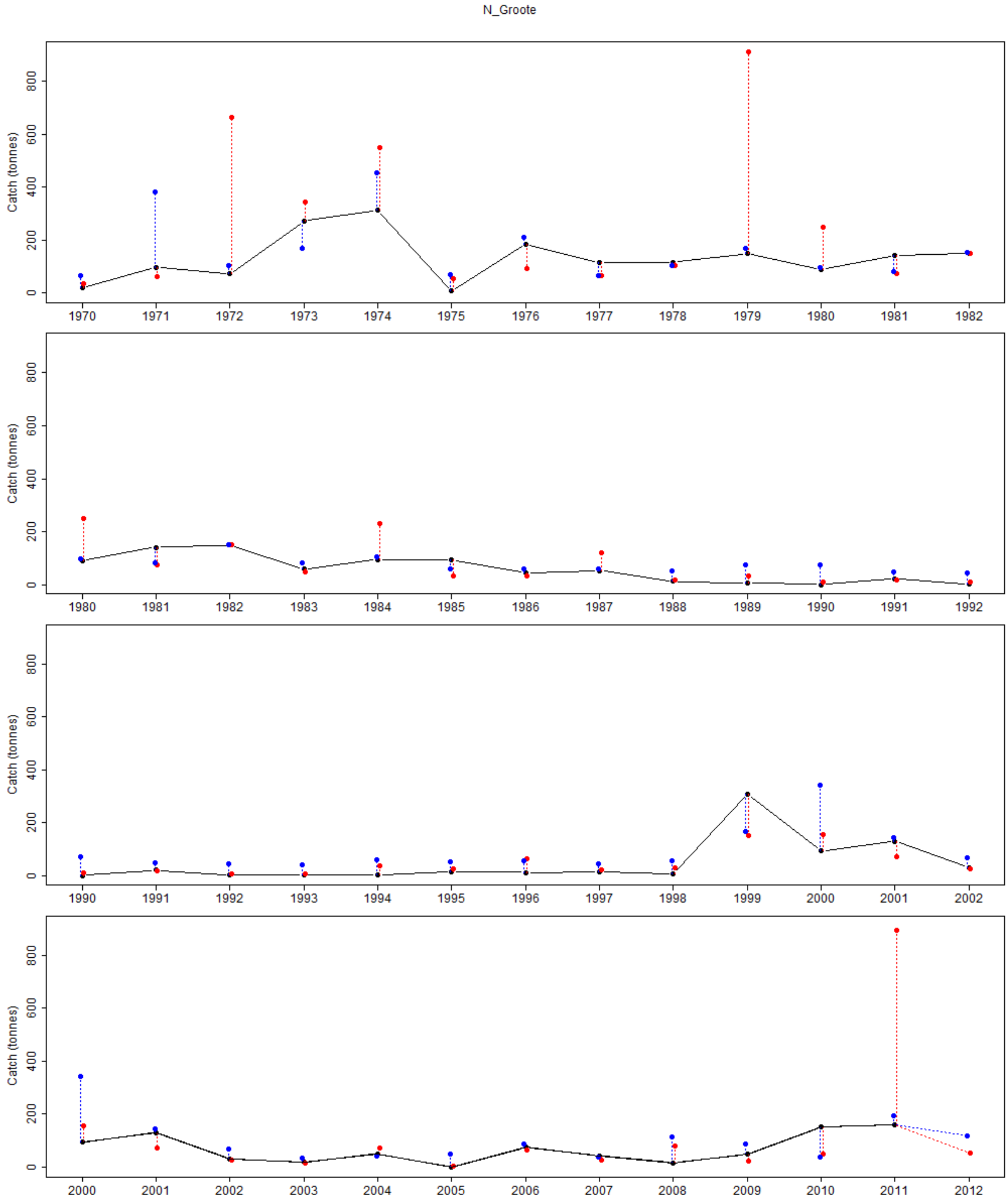

Figure 73. Catch and predictions for North Groote region using the single model with variable weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

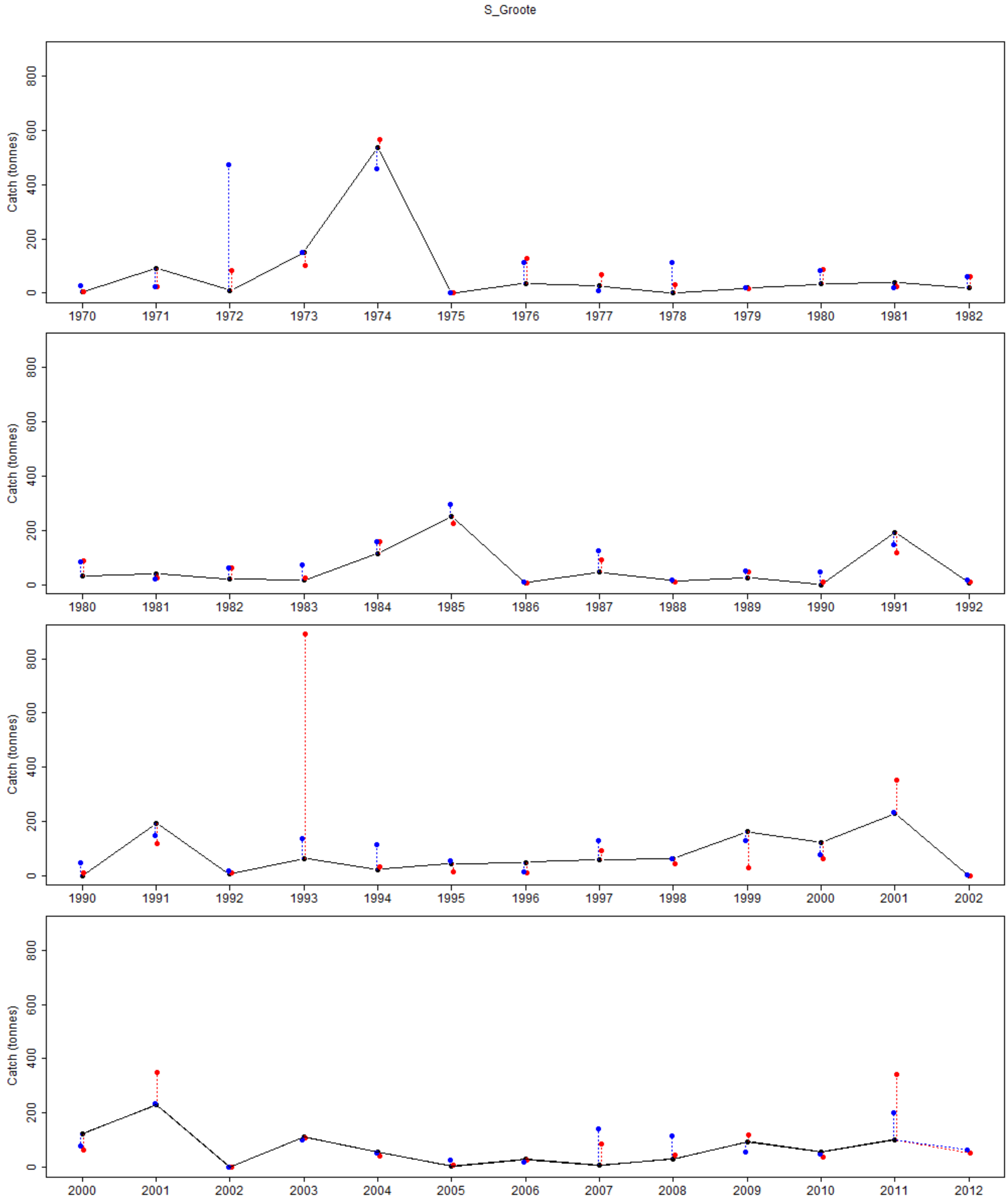

Figure 74. Catch and predictions for South Groote region using the single model with variable weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

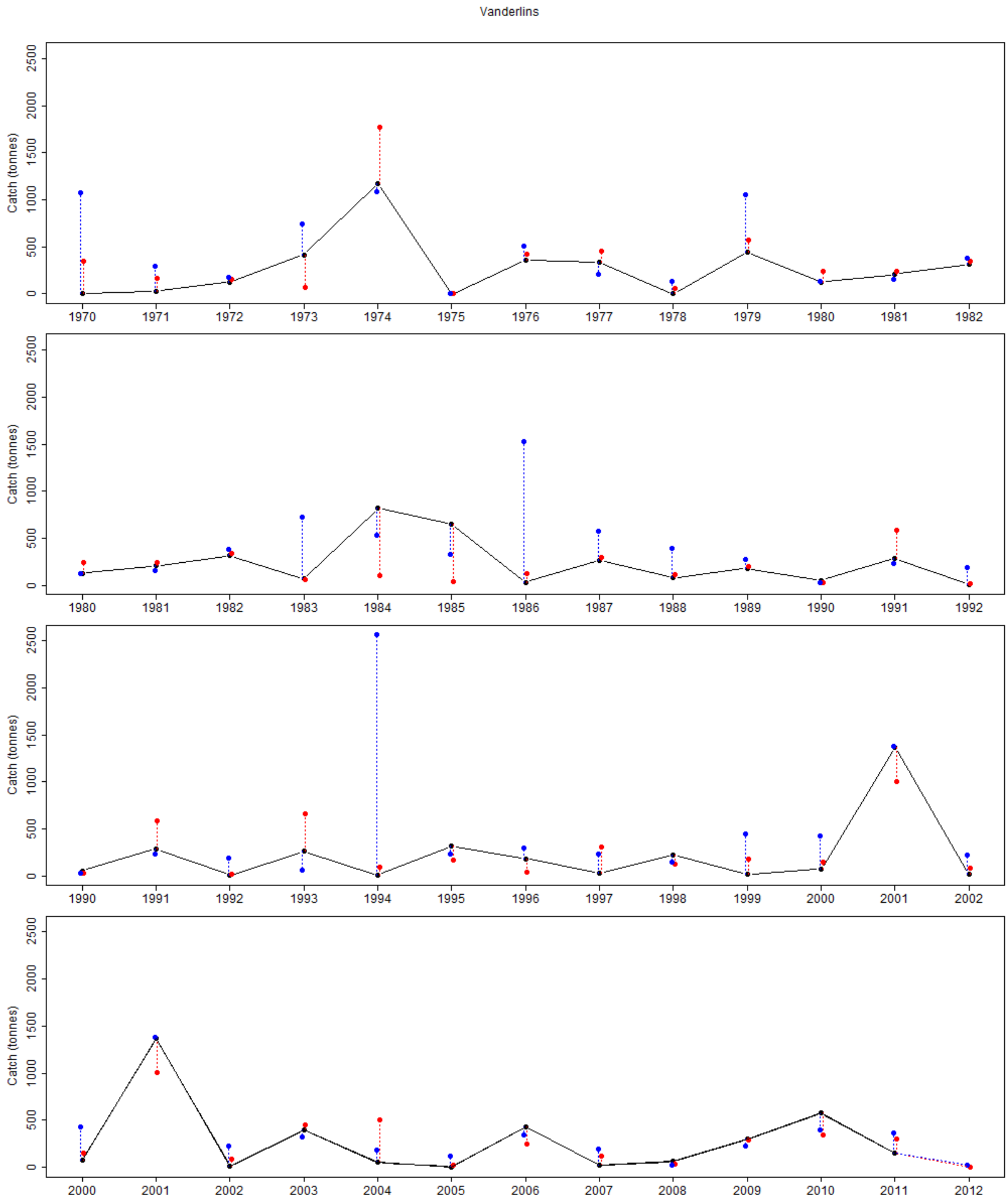

Figure 75. Catch and predictions for Vanderlins region using the single model with variable weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

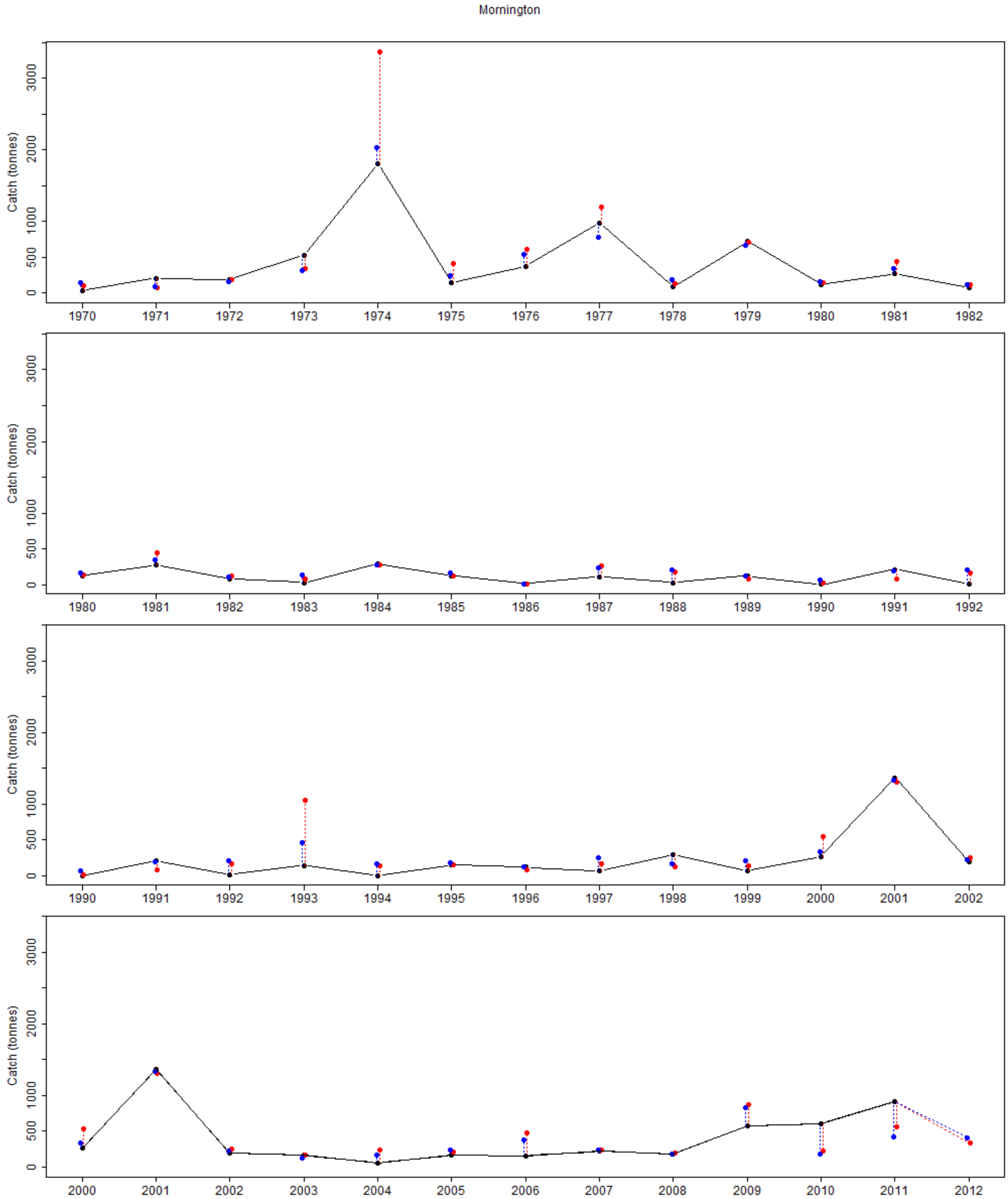

Figure 76. Catch and predictions for Mornington region using the single model with variable weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

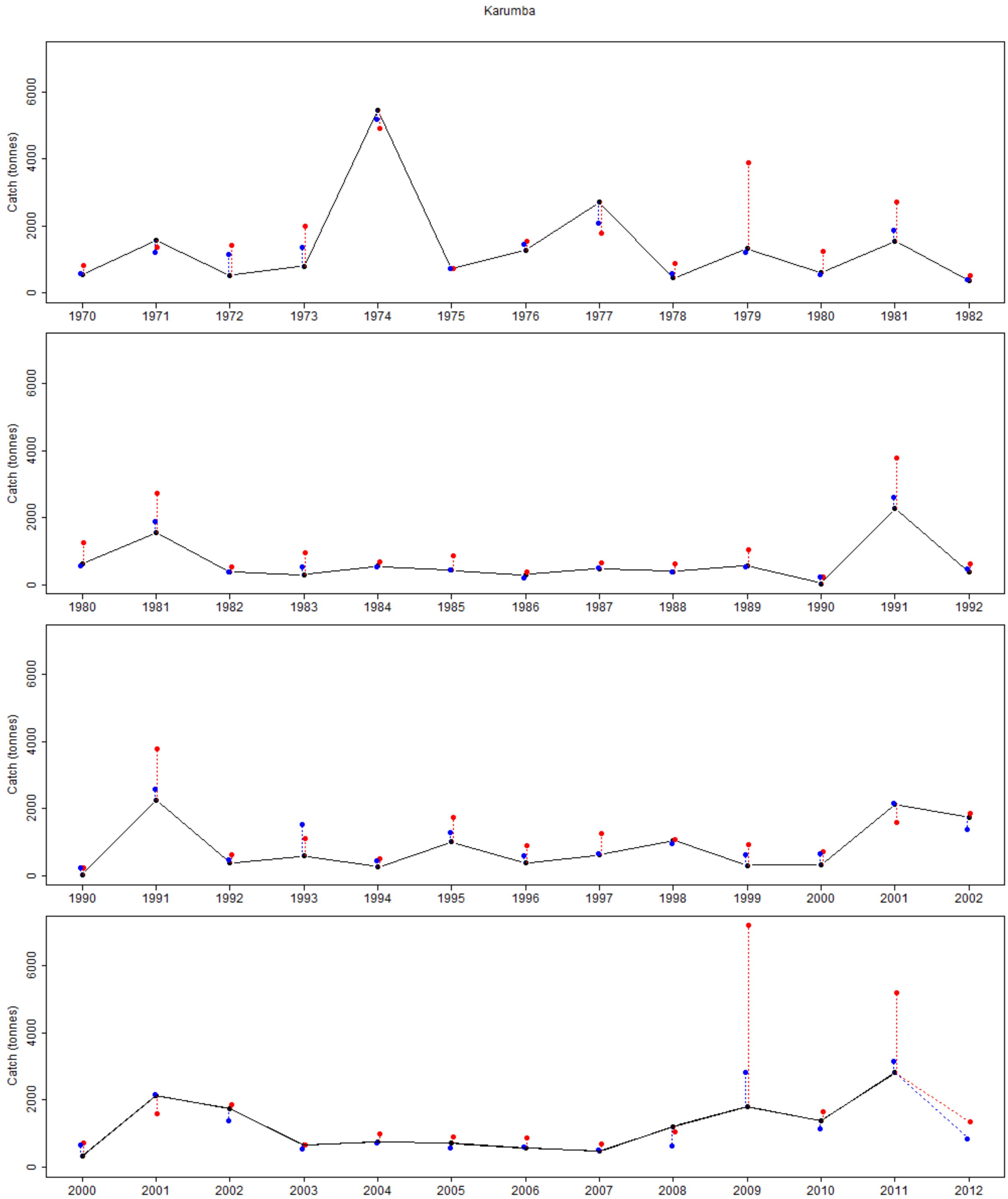

Figure 77. Catch and predictions for Karumba region using the single model with variable weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

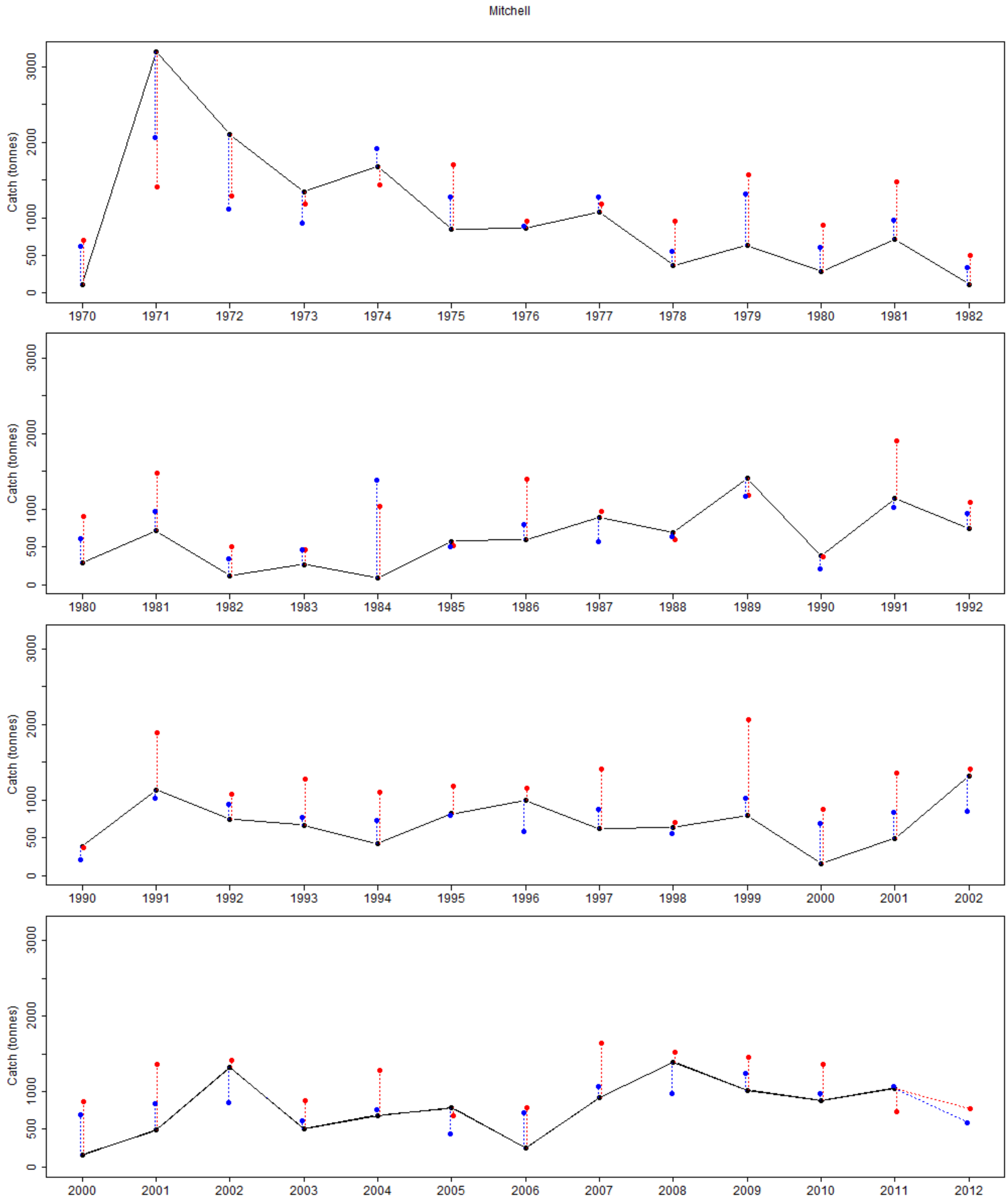

Figure 78. Catch and predictions for Mitchell region using the single model with variable weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

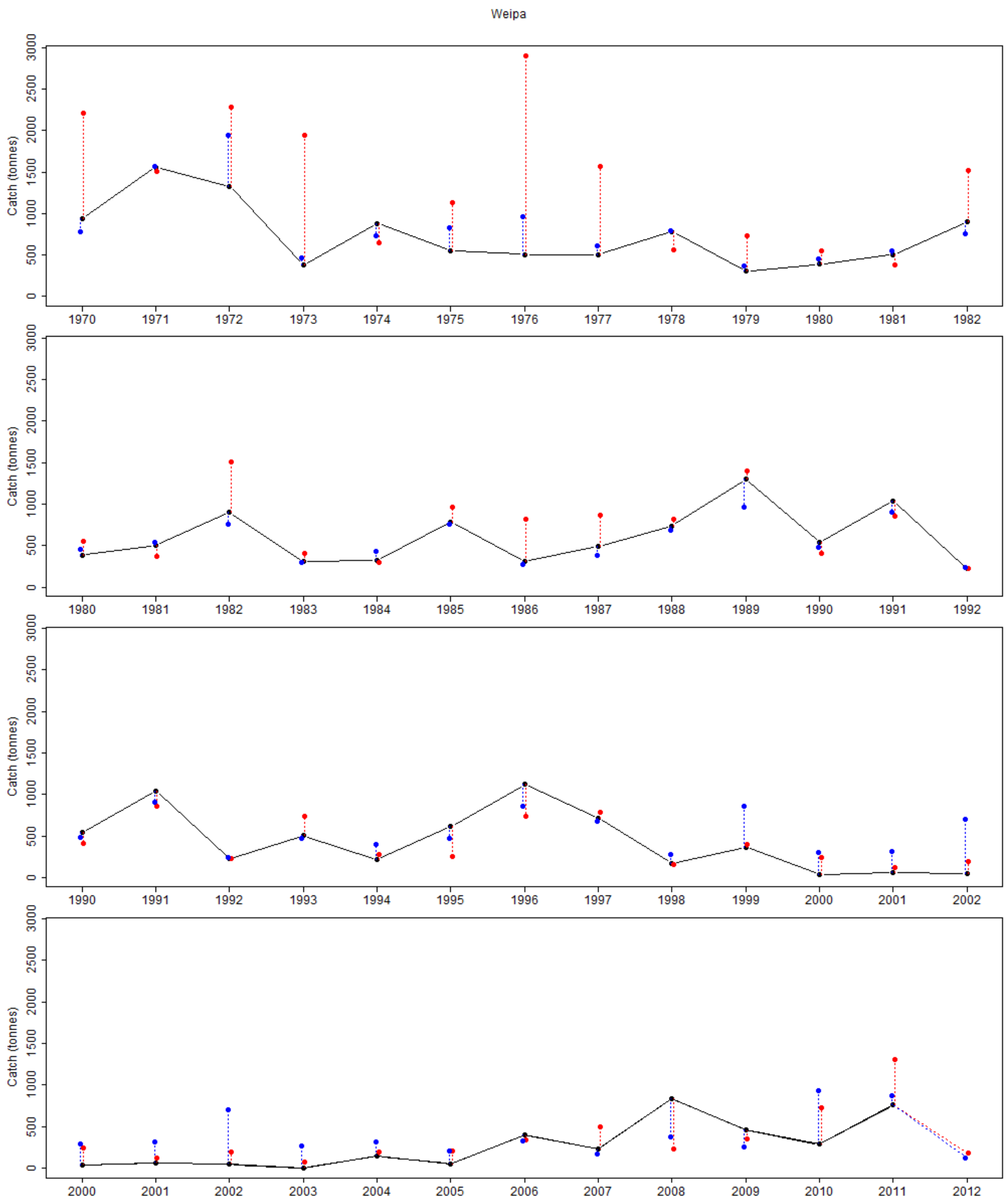

Figure 79. Catch and predictions for Weipa region using the single model with variable weights. The recorded catch is shown in black, the effort weighted predictions in blue and the unweighted predictions in red.

15.5 The effects of the survey adjustment on catch predictions in individual regions

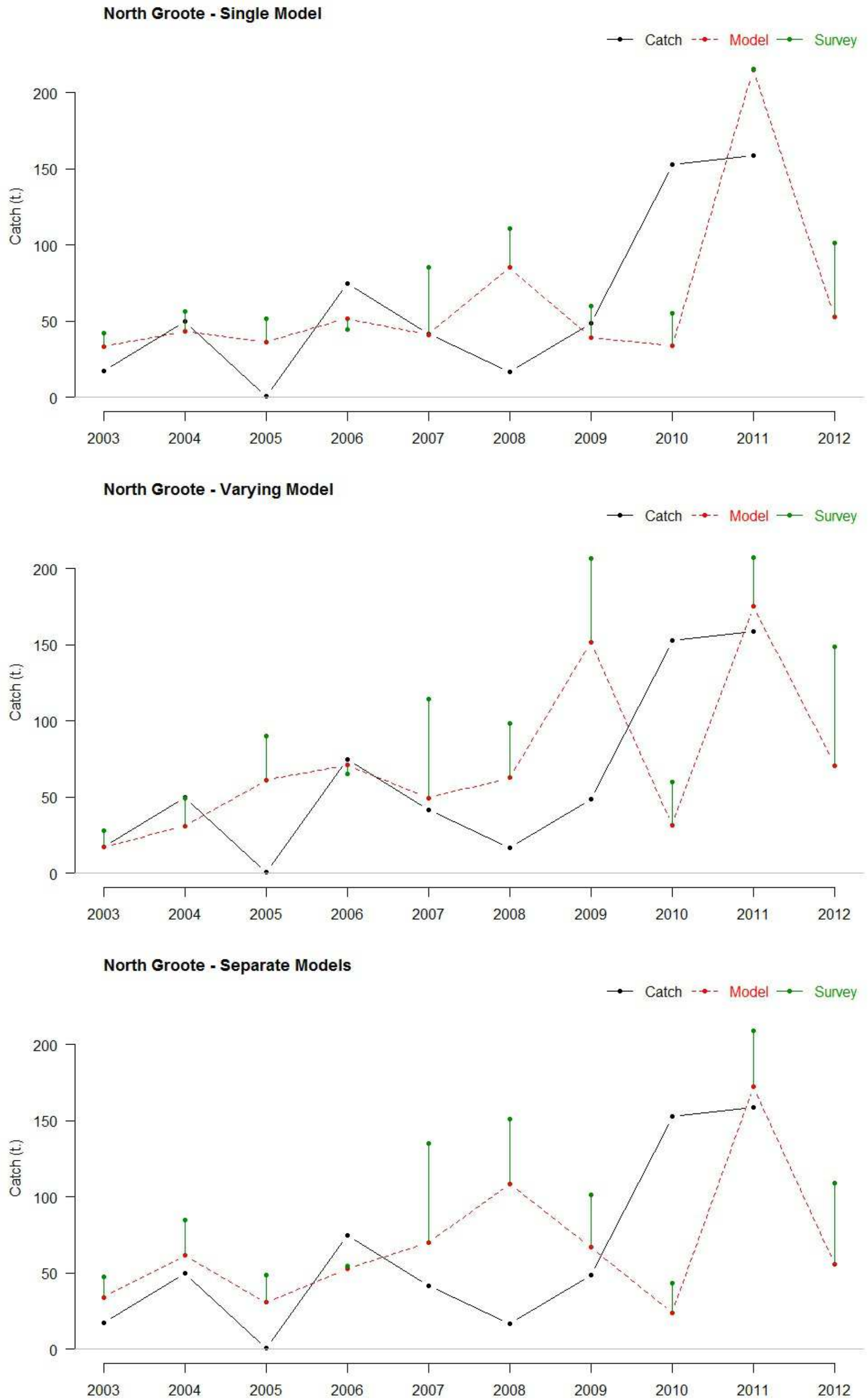

Figure 80. The effect of the survey adjustment on the predicted catch for North Groote.

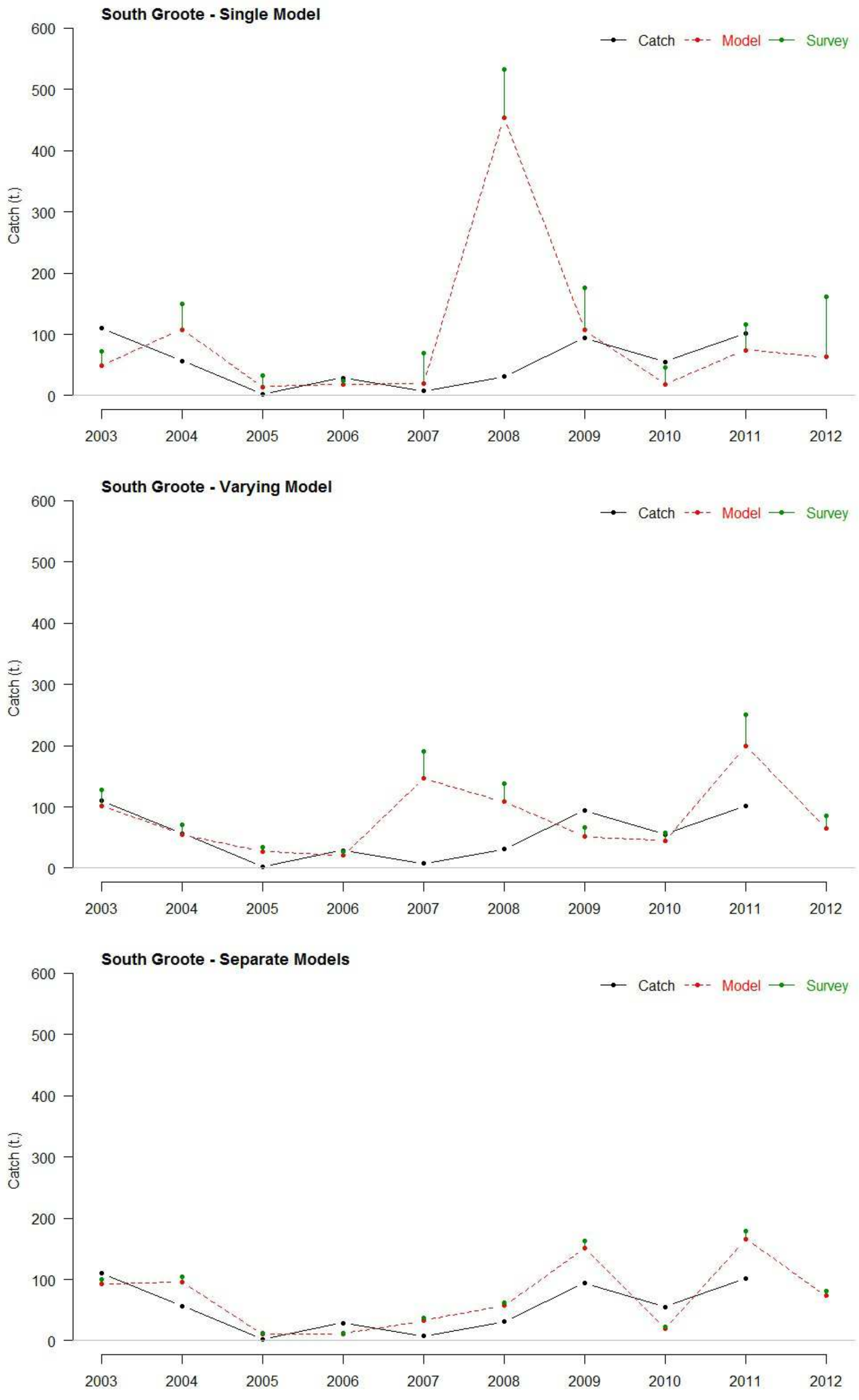

Figure 81. The effect of the survey adjustment on the predicted catch for South Groote.

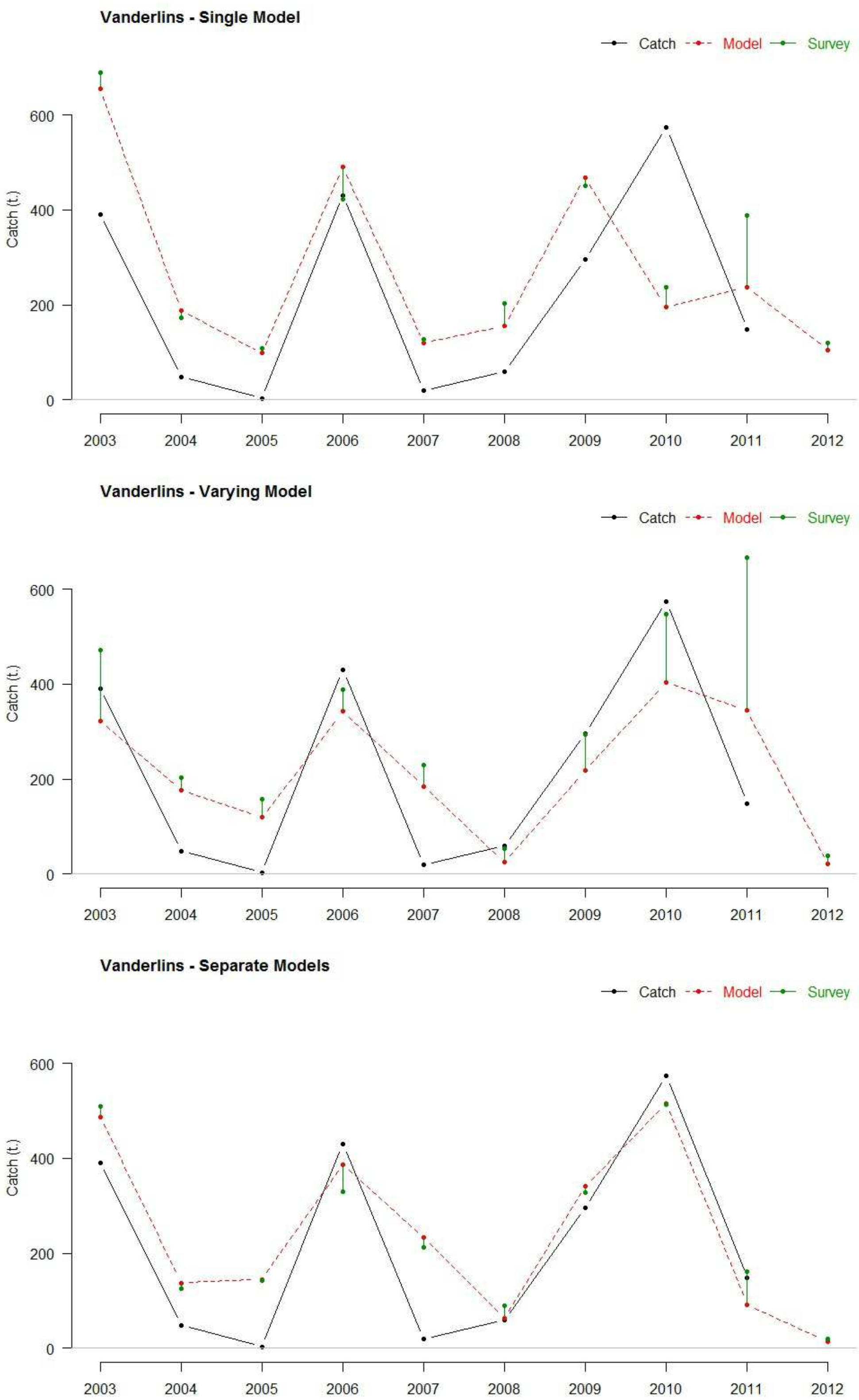

Figure 82. The effect of the survey adjustment on the predicted catch for Vanderlins.

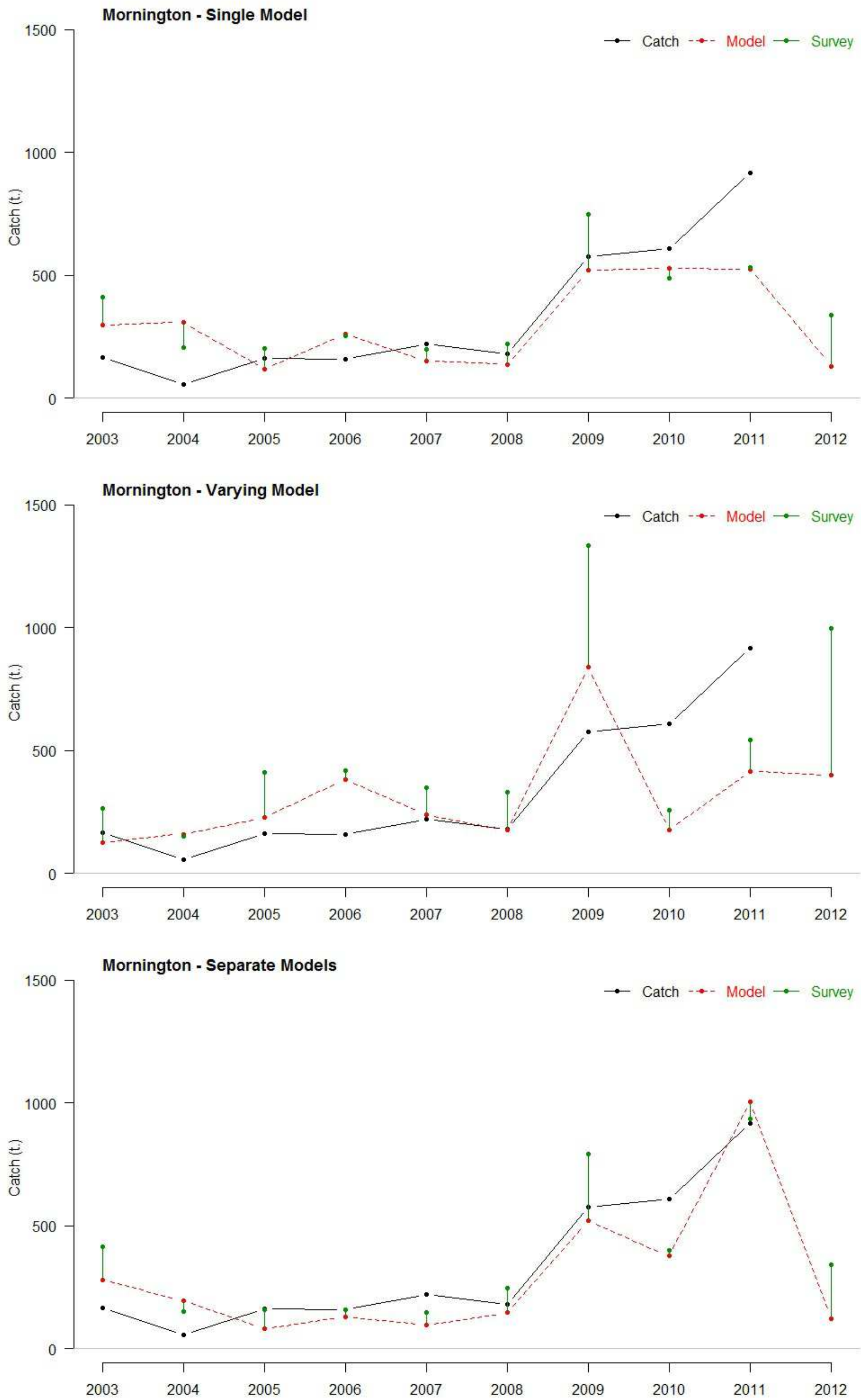

Figure 83. The effect of the survey adjustment on the predicted catch for Mornington.

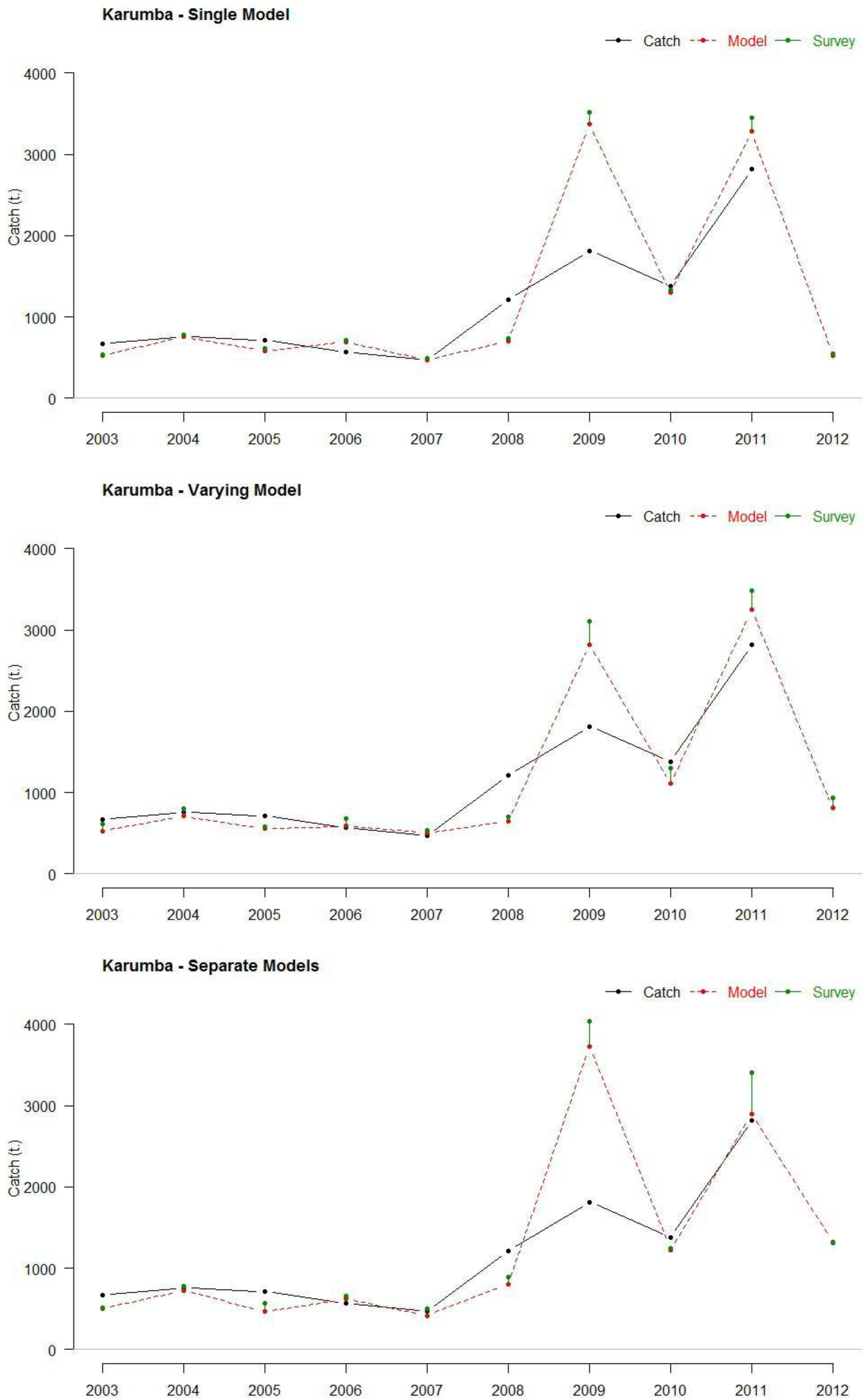

Figure 84. The effect of the survey adjustment on the predicted catch for Karumba.

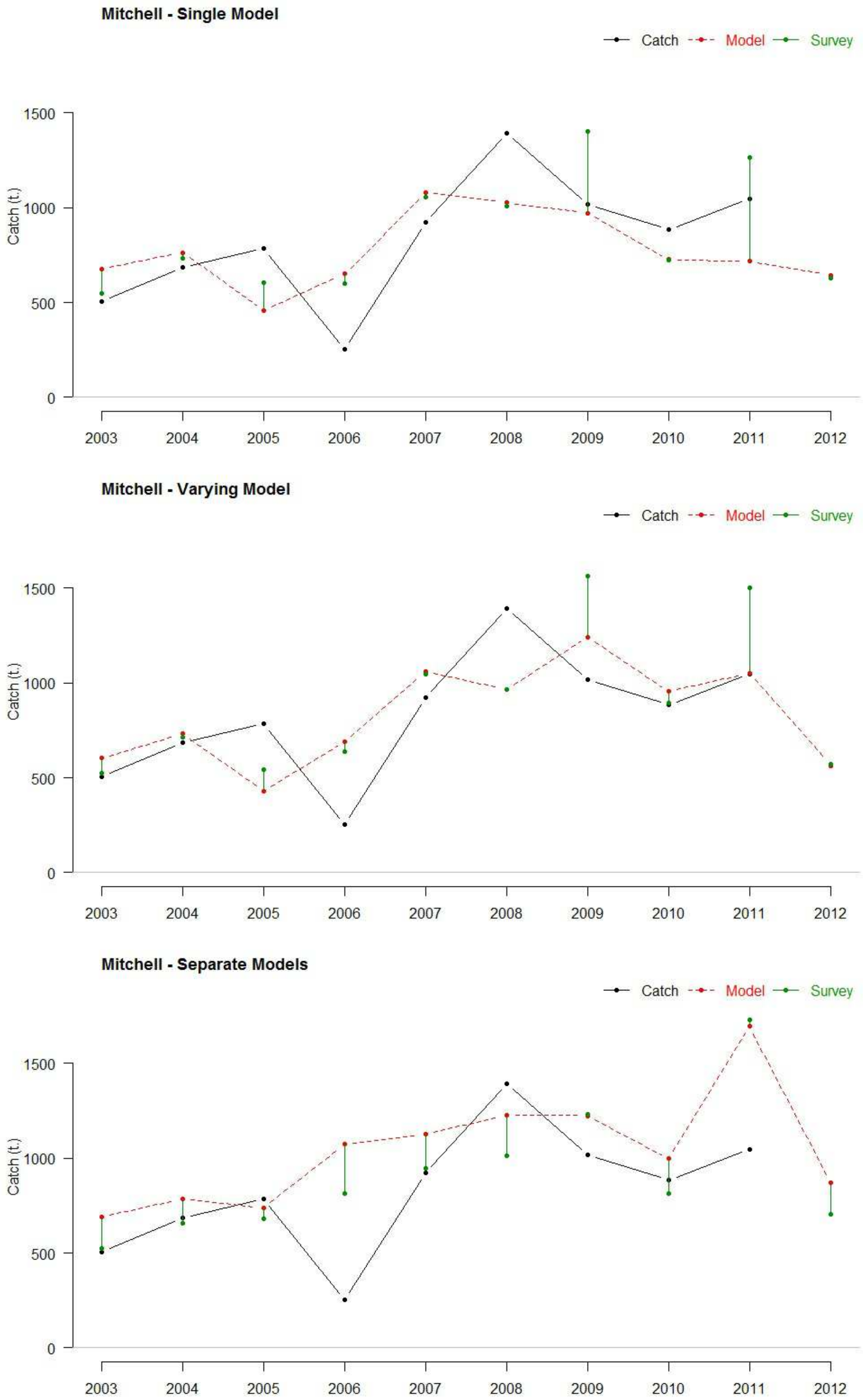

Figure 85. The effect of the survey adjustment on the predicted catch for Mitchell.

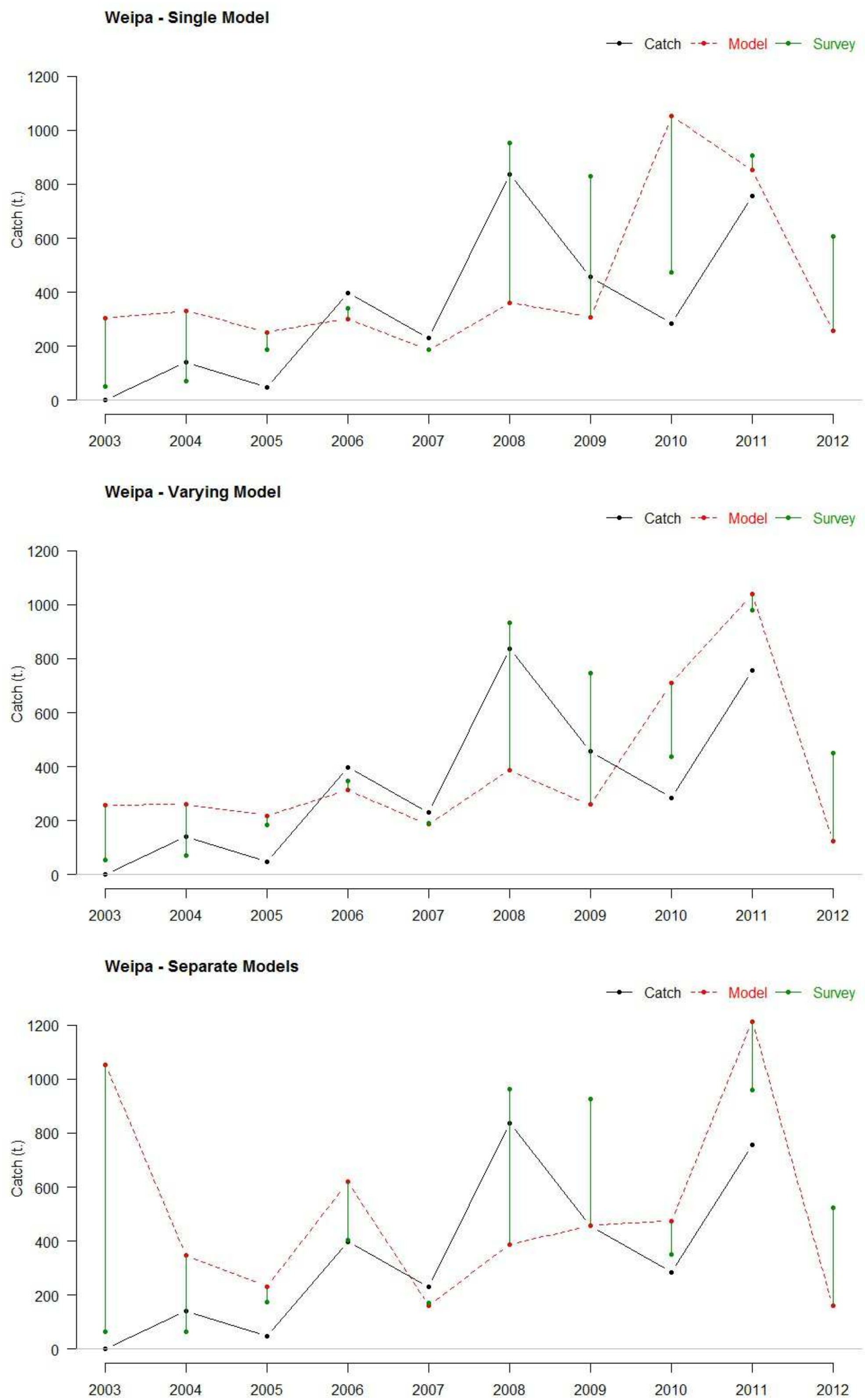

Figure 86. The effect of the survey adjustment on the predicted catch for Weipa.

15.6 Estimates of Uncertainty

Table 17. Recorded catch, estimated catch, confidence and tolerance intervals for the NPF banana prawn stock region from 1970-2012. The results are generated using the fixed weights, effort weighted model with 10 regions (Coburg and Fog Bay split).

YEAR	CATCH	ESTIMATE	LOWER CONFIDENCE INTERVAL	UPPER CONFIDENCE INTERVAL	LOWER TOLERANCE INTERVAL	UPPER TOLERANCE INTERVAL
1970	1690	3753	3145	4266	2358	5290
1971	7365	6604	5105	9258	4223	10612
1972	4805	8157	6447	18368	5072	19047
1973	4239	4203	3545	4672	2638	6156
1974	12742	13175	10670	15589	7790	21952
1975	3156	4867	4054	5762	3101	7601
1976	4579	7272	6204	11070	5023	12417
1977	6329	6568	5298	7622	3890	9966
1978	2544	3383	2918	3809	2152	4986
1979	4757	6607	5415	12680	4239	14537
1980	2837	3701	3279	4055	2443	5242
1981	5410	5844	5174	6526	3780	8845
1982	2964	3709	3213	3949	2346	5205
1983	1653	2489	2111	2828	1621	3506
1984	2993	4613	3796	5475	2931	6712
1985	3779	3099	2568	3462	2011	4621
1986	2116	2797	2335	3735	1766	4640
1987	3416	3456	3081	3807	2365	4835
1988	2752	3245	2820	4026	2127	4969
1989	4855	4390	3703	5044	2831	6641
1990	1675	2212	1723	2551	1373	3230
1991	6127	6826	5928	7720	4320	10106
1992	2036	3021	2591	3643	1928	4402
1993	3492	4744	3992	5525	3133	7416
1994	1544	4936	3091	18943	2578	21920
1995	4197	4144	3603	4847	2696	6234
1996	3585	3748	3214	4102	2403	5545
1997	3557	4577	3847	8790	3076	10273
1998	3327	4022	3457	4660	2484	6393
1999	3257	3925	3320	5225	2641	6105

YEAR	CATCH	ESTIMATE	LOWER CONFIDENCE INTERVAL	UPPER CONFIDENCE INTERVAL	LOWER TOLERANCE INTERVAL	UPPER TOLERANCE INTERVAL
2000	1749	3976	3218	4771	2537	5834
2001	6874	7521	5873	9113	4550	12140
2002	4195	4308	3659	5634	2717	6956
2003	2831	3776	3215	5366	2490	6166
2004	2990	3868	3383	4363	2552	5689
2005	2566	2475	2165	2772	1681	3660
2006	2879	3548	3053	4286	2364	5363
2007	2489	2960	2502	3649	1912	4700
2008	5385	4483	3813	5717	2976	7000
2009	5067	7260	6122	8697	4437	12107
2010	5173	5217	4343	6664	3311	8124
2011	7167	7987	6626	11030	5276	14168
2012	NA	2726	2350	3681	1815	4517

Table 18. Recorded catch, estimated catch, confidence and tolerance intervals for the NPF banana prawn stock region from 1970-2012. The results are generated using the variable weights, effort weighted model with 10 regions (Coburg and Fog Bay split).

YEAR	CATCH	ESTIMATE	LOWER CONFIDENCE INTERVAL	UPPER CONFIDENCE INTERVAL	LOWER TOLERANCE INTERVAL	UPPER TOLERANCE INTERVAL
1970	1690	4054	3168	5177	2600	6167
1971	7365	6984	5740	8344	4447	10789
1972	4805	6084	5133	8345	4042	10202
1973	4239	5507	4655	8382	3799	9191
1974	12742	13806	10998	15539	8596	20418
1975	3156	3929	3288	4693	2494	6118
1976	4579	6107	5339	7118	4271	8752
1977	6329	6067	4927	6808	3819	9478
1978	2544	3473	3064	3947	2381	4813
1979	4757	6077	5114	7518	4051	8963
1980	2837	3342	3021	3664	2244	4704
1981	5410	5896	5035	6508	3863	8357
1982	2964	3388	2911	3723	2246	4839
1983	1653	3166	2484	3883	2096	4545
1984	2993	4514	3715	5211	3013	6706
1985	3779	3514	2970	3961	2444	4773

YEAR	CATCH	ESTIMATE	LOWER CONFIDENCE INTERVAL	UPPER CONFIDENCE INTERVAL	LOWER TOLERANCE INTERVAL	UPPER TOLERANCE INTERVAL
1986	2116	3806	2557	7438	2137	8995
1987	3416	3795	3154	5111	2568	6066
1988	2752	3248	2820	3504	2160	4413
1989	4855	4456	3822	5018	2961	6185
1990	1675	1988	1561	2251	1265	2950
1991	6127	6528	5647	7302	4184	9691
1992	2036	2911	2536	3319	1928	4276
1993	3492	5014	4200	6243	3313	7978
1994	1544	5380	3141	10995	2655	13562
1995	4197	4404	3933	4741	2919	6353
1996	3585	3241	2773	3772	2160	4787
1997	3557	4339	3662	5066	2954	6148
1998	3327	3514	3005	3904	2340	4877
1999	3257	5140	4268	6663	3429	8049
2000	1749	3662	2985	4266	2380	5230
2001	6874	7721	6468	9033	4989	11486
2002	4195	4584	3795	5062	3009	6759
2003	2831	3006	2596	3251	2075	4168
2004	2990	3486	3077	3960	2350	4951
2005	2566	2844	2501	3122	1959	3930
2006	2879	3610	3146	4062	2534	4943
2007	2489	3226	2838	3735	2130	4676
2008	5385	3696	3222	4344	2533	5568
2009	5067	7318	6099	9411	4586	11966
2010	5173	4606	3978	5671	3110	6849
2011	7167	8552	7273	11232	5734	13821
2012	NA	2847	2399	3496	1931	4298

16 Appendix 4: Economic Data

Table 19. Data used for estimating price elasticity.

YEAR	CATCH (TONNES)	NOMINAL VALUE (MIL $A)	EXCHANGE RATE AUD/JPY	JAPAN'S INFLATION INDEX (2005=100)	AUSTRALIAN INFLATION INDEX (2005=100)
	ABARE			IFS database, IMF	
1992-93	4,058	42.0038	75.563822	100.124	73.453
1993-94	2,433	26.8822	74.695368	100.813	74.845
1994-95	4,490	46.5219	69.67748	100.689	78.316
1995-96	4,347	43.5535	85.1871	100.822	80.362
1996-97	4,546	45.1700	89.955579	102.598	80.563
1997-98	3,711	35.5467	82.30019	103.278	81.251
1998-99	3,608	42.6154	73.448615	102.938	82.442
1999-00	2,222	31.0097	62.619716	102.266	86.131
2000-01	6,286	84.8545	62.869723	101.444	89.904
2001-02	5,419	71.9099	68.064903	100.531	92.604
2002-03	3,325	42.7968	75.660444	100.282	95.170
2003-04	3,572	36.6157	79.552911	100.274	97.401
2004-05	2,827	31.0568	83.823183	100.000	100.000
2005-06	3,247	32.7986	87.636987	100.241	103.538
2006-07	2,674	24.7621	98.714384	100.299	105.953
2007-08	5,380	48.6583	88.716097	101.676	110.565
2008-09	5,214	46.4932	73.976122	100.307	112.578
2009-10	5,771	59.2867	80.628023	99.585	115.781
2010-11	7,577	61.3720	82.593331	99.303	119.705

Table 20. Data used for estimated the harvest functions

YEAR	POTENTIAL CATCH	CATCH (C) IN TONS	EFFORT (E) IN DAYS
2008	4163	1050.833	288
2008	4163	1950.168	589
2008	4163	2825.182	909
2008	4163	3569.443	1209
2008	4163	3958.212	1514
2008	4163	4350.267	1773
2008	4163	4553.971	2029
2008	4163	4787.882	2251
2008	4163	4894.945	2411
2008	4163	4959.806	2506
2008	4163	4965.942	2517
2008	4163	5019.695	2548
2008	4163	5073.941	2593
2008	4163	5119.17	2617
2008	4163	5198.82	2683
2008	4163	5245.343	2708
2008	4163	5265.7	2727
2008	4163	5288.178	2739
2008	4163	5304.53	2766
2008	4163	5322.198	2779
2008	4163	5363.564	2809
2008	4163	5377.214	2818
2008	4163	5381.05	2820
2008	4163	5382.949	2827
2008	4163	5384.36	2834
2008	4163	5384.453	2841
2008	4163	5384.516	2843
2008	4163	5384.612	2845
2008	4163	5384.68	2845
2009	6281	405.574	104
2009	6281	1657.424	452
2009	6281	2648.816	789
2009	6281	3379.241	1116

YEAR	POTENTIAL CATCH	CATCH (C) IN TONS	EFFORT (E) IN DAYS
2009	6281	3909.811	1449
2009	6281	4195.4	1740
2009	6281	4392.329	2008
2009	6281	4494.6	2239
2009	6281	4681.87	2386
2009	6281	4741.855	2471
2009	6281	4769.958	2501
2009	6281	4848.771	2557
2009	6281	4913.249	2594
2009	6281	4935.064	2605
2009	6281	4942.661	2611
2009	6281	4960.886	2617
2009	6281	4991.638	2634
2009	6281	4997.158	2635
2009	6281	4999.923	2643
2009	6281	5010.893	2646
2009	6281	5032.111	2654
2009	6281	5035.627	2654
2009	6281	5038.918	2656
2009	6281	5039.358	2659
2009	6281	5040.707	2659
2009	6281	5050.338	2659
2009	6281	5062.003	2659
2009	6281	5066.952	2661
2009	6281	5066.975	2661
2010	5794	155.296	51
2010	5794	852.733	334
2010	5794	1685.543	645
2010	5794	2449.931	960
2010	5794	2951.342	1234
2010	5794	3526.082	1522
2010	5794	3884.69	1751
2010	5794	4172.365	1967
2010	5794	4477.074	2185
2010	5794	4704.532	2394

YEAR	POTENTIAL CATCH	CATCH (C) IN TONS	EFFORT (E) IN DAYS
2010	5794	4819.852	2503
2010	5794	4862.497	2530
2010	5794	4938.002	2558
2010	5794	4960.401	2580
2010	5794	5014.692	2622
2010	5794	5038.205	2641
2010	5794	5066.622	2656
2010	5794	5081.652	2660
2010	5794	5100.041	2662
2010	5794	5110.714	2666
2010	5794	5116.327	2666
2010	5794	5125.666	2666
2010	5794	5134.311	2666
2010	5794	5135.114	2666
2010	5794	5148.231	2666
2010	5794	5165.469	2666
2010	5794	5172.296	2671
2010	5794	5172.776	2681
2010	5794	5172.922	2686
2011	8699	418.401	86
2011	8699	1706.41	376
2011	8699	2780.388	711
2011	8699	3825.482	1040
2011	8699	4811.712	1371
2011	8699	5423.853	1683
2011	8699	5908.831	1977
2011	8699	6293.96	2255
2011	8699	6559.18	2517
2011	8699	6748.019	2773
2011	8699	6819.245	2962
2011	8699	6835.427	3005
2011	8699	6835.427	3006
2011	8699	6879.587	3044
2011	8699	6943.529	3134
2011	8699	7005.52	3257

YEAR	POTENTIAL CATCH	CATCH (C) IN TONS	EFFORT (E) IN DAYS
2011	8699	7024.688	3288
2011	8699	7053.073	3331
2011	8699	7054.467	3339
2011	8699	7072.201	3359
2011	8699	7074.215	3359
2011	8699	7081.838	3361
2011	8699	7082.282	3362
2011	8699	7090.746	3363
2011	8699	7095.651	3364
2011	8699	7118.141	3364
2011	8699	7144.271	3364
2011	8699	7163.61	3364
2011	8699	7165.793	3368
2011	8699	7166.549	3369

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