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CONDITIONING AN OPERATING MODEL FOR NORTH ATLANTIC ALBACORE

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SUMMARY

When conducting a Management Strategy Evaluation, hypotheses that represent the simulated versions of reality are required for conditioning the Operating Model. There are many alternative ways to do this, one way is to use the the currently-used stock assessment model. Although use of the assessment model as the Operating Model seems to imply that assessment models describe nature almost perfectly, if a Management Procedure cannot perform well when reality is as simple as implied by an assessment model, it is unlikely to perform adequately for more realistic representations of uncertainty. Basing an operating model on the current assessment model also has arguably the lowest demands for knowledge and data. In this paper we summarise an Operating Model developed for North Atlantic albacore conditioned using Multifan-CL.

RÉSUMÉ

Pour réaliser une évaluation de la stratégie de gestion, des hypothèses représentant les versions simulées de la réalité sont requises pour conditionner le modèle opérationnel. Il y a beaucoup d'autres façons de le faire, par exemple en se servant du modèle d'évaluation des stocks actuellement utilisé. Bien que l'utilisation du modèle d'évaluation comme modèle opérationnel semble impliquer que les modèles d'évaluation décrivent la nature presque à la perfection, si une procédure de gestion ne fonctionne pas correctement quand la réalité est aussi simple que celle issue d'un modèle d'évaluation, il est peu probable qu'elle fonctionne correctement avec des représentations de l'incertitude plus réalistes. Faire reposer un modèle opérationnel sur le modèle d'évaluation actuel a aussi sans doute les exigences les plus basses en termes de connaissances et de données. Le présent document contient un résumé du modèle opérationnel élaboré pour le germon de l'Atlantique Nord conditionné au moyen de Multifan CL.

RESUMEN

Al realizar una evaluación de estrategias de ordenación, se requieren hipótesis que representen versiones simuladas de la realidad para condicionar el modelo operativo. Existen varias alternativas para los modos de hacerlo, una forma es utilizar el modelo de evaluación utilizado actualmente como modelo de operativo Aunque el uso del modelo de evaluación como modelo operativo parece implicar que los modelos de evaluación describen la naturaleza casi a la perfección, si un procedimiento de ordenación no funciona bien cuando la realidad es tan simple como se supone en un modelo de evaluación, es poco probable que funcione adecuadamente con representaciones más realistas de la incertidumbre. También puede decirse que basar un modelo operativo en el modelo de evaluación actual implica el nivel más bajo de requisitos en cuanto a conocimientos y datos. En este documento se resume un modelo operativo desarrollado para el atún blanco del Atlántico norte condicionado utilizando Multifan-CL.

KEYWORDS

Albacore, Conditioning, Management Strategy Evaluation, Operating Model, Stock Assessment, Multifan-CL

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Introduction

In this paper we describe a case study to develop an Operating Model (OM) for North Atlantic albacore using the integrated stock assessment Multifan-CL (Fournier *et al.,* 1998). An OM is a mathematical statistical model used to describe the actual resource dynamics in simulation trials and to generate resource monitoring data when projecting forward to simulation test a Management Procedure (MP). While an MP is combination of pre-defined data, together with an algorithm to which such data are input to provide a value for a TAC or effort control measure.

Conducting a Management Strategy Evaluation (MSE) requires six steps (after Punt and Donovan, 2007); namely i) identification of management objectives; ii) selection of hypotheses for the OM; iii) conditioning the OM based on data and knowledge, and possible weighting and rejection of hypotheses; iv) identifying candidate management strategies; v) running the Management Procedure (MP) as a feedback control in order to simulate the long-term impact of management; and then vi) identifying the MPs that robustly meet management objectives.

Developing the OM is mainly concerned with steps ii) and iii); and there are many alternative ways to condition OMs (see Kell *et al*., 2006). The method adopted in this study is to use the currently-used stock assessment model. Although this implies that assessment models describe nature almost perfectly, if a MP cannot perform well when reality is as simple as implied by an assessment model, it is unlikely to perform adequately for more realistic representations of uncertainty. Basing an OM on the current assessment model also has arguably the lowest demands for knowledge and data.

In a stock assessment, the objective is often to find a ‘best‘ model, while when conditioning an OM the objective is to characterise what we don’t know about resource dynamics. As pointed out by Kolody *et al.* (2009) the stock assessment process often appears to involve a haphazard search for a few model specifications which appear to be plausibly, consistent with the data and a priori expectations. When developing an OM many more scenarios need to be run to ensure that the MPs are robust to uncertainty.

Material and Methods

Operating Model

When fitting assessment models there is often insufficient contrast in the data to estimate parameters for important population processes (e.g. Lee *et al*., 2012, 2011; Pepin and Marshall, 2015). Therefore the data may appear equally likely given alternative model assumptions or parameter values (model and parameter uncertainty), while different data sets (CPUE, catch and length distributions) may show conflicting signals. A variety of scenarios therefore need to be run to reflect scepticism about the capacity of the model to estimate key parameters. Scenarios are generally developed by evaluating the effect of fixing some parameters, assuming alternative functional form for processes, or by down weighting some datasets when fitting (Kell and Mosqueira in press).

In the last North Atlantic Multifan-CL assessment (Anon., 2014) 10 scenarios were considered (**Table 1**). The scenarios investigated the impact of the different dataset (size frequency and CPUEs), changing the start and end dates of the model, incorporating tagging data and alternative natural mortality (M) vectors. First the estimated time series and reference points are summarised and then the consequences for the dynamics and the conditioning of the future part of the OM discussed.

Results

Time Series

Time series of recruits, SSB, biomass, F_{bar}, F_{apex}, harvest rate and catch are shown by scenario in **Figure 1**. In general trends are similar across scenarios and quantities. The main differences is seen between the methods used for calculating exploitation; F apex (the highest F by age as used by the SCRS) is much more variable than using F bar (the mean F across reference ages as used by ICES).

Stock Recruitment Relationship

A Beverton and Holt stock recruitment relationship (Beverton and Holt, 1993) was fitted to the recruit and SSB time series. The fit to the Base Case and a suite of diagnostics based on the residuals are shown in **Figure 2**; each plot type is then repeated for all scenarios as a separate figure. The fits to all the scenarios are shown in **Figure 3**; there is little evidence for a reduction in recruitment as population size declines as recruitment quickly saturates as spawning stock biomass (S) increases due to strong density dependence i.e. compensatory dynamics. Next the residuals (on the log scale) are plotted to check for systematic patterns that may suggest that the assumptions are violated.

The residuals are plotted against SSB in **Figure 4** to check for evidence that the Beverton and Holt stock recruitment relationship may not be appropriate and against year in **Figure 5,** i.e. to check for stationarity. Recruitment appears to be highest at medium biomass levels, which could suggest over compensation, however, the plots of residuals against year suggest that there may be a year effect as expected recruitment was higher in the 1960s. It is therefore difficult to say whether recruitment is driven by SSB or environment. The residuals are plotted against the fitted values to check the variance function (**Figure 6**); there is a suggestion that variance may increase with recruitment, i.e. that assuming a log normal error structure may not be appropriate. Therefore quantile-quantile plots are shown in in **Figure 7** to check the assumed error model, while to check for autocorrelation residuals with are plotted with a lag of 1 in **Figure 8**. The residuals appear to be log normally distributed, as they lie along the y=x line with no auto-correlation since the regression of residual t+1 against residual t has a slope near 0.

Production Functions

The assumed biological parameters and the estimated selection patterns are plotted in **Figure 9**; these were combined with the stock recruitment relationships to derive age based equilibrium production curves **Figure 10**. The age based production function for the Base Case are compared with the corresponding Pella-Tomlinson production function, and the stock/yield trajectory, in **Figure 11**. The curves of the two production functions are very similar, although population growth rate at small sizes is slightly underestimated by the biomass function. A simulation using the biomass production function is shown for Base Case in **Figure 12**; harvest rate is capped at 0.3. The production estimated by the function is insufficient to explain the catch at small as the population decreases so the stock collapses. This is due to the large amount of process error, modelled as recruitment variation in Multifan-CL, in the age based model that is ignored by the biomass production function.

Stationarity

Next variability in the time series of recruitment (**Figure 13**) and production (**Figure 14**) is evaluated using a sequential t-test algorithm for regime shifts (the STARS algorithm Rodionov, 2004). The boxes show the means and ±1 standard deviation. For recruitment there appears to be three regimes, with recruitment higher in the middle period. Surplus production is much more variable than recruitment and is driven mainly by strong year classes.

Absolute and relative time series are plotted in **Figures 15** and **16** for estimates quantities, population parameters and reference points. Variability between scenarios is greatest for the absolute estimates, and low for the relative values. The biggest variability across time is seen for F_{MSY}, due to mixing exploitation level and selectivity; the production function parameters derived from the age based parameters (r,k and p) do not change much.

The expected value of surplus production as estimated by the age based model are shown in **Figure 17** (red is the production function with time varying selectivity and recruitment, and black is assuming only time varying recruitment), points are the values by year. The production functions are estimated using a moving average for selection pattern and recruitment (using a 5 year window). Including varying selection has little effect.

The distributions of the estimates annual surplus production are plotted in **Figures 18** and **19**. The latter figure plots the residuals (i.e. observed-expected) and there appears to be a positive bias.

Stock Status

Harvest rate relative to F_{MSY} is plotted in **Figure 20** and stock status in **Figure 21** stock biomass relative to B_{MSY} by scenario. Kobe Phase Plots are shown in **Figure 22** with the 2011 status indicated by the blue point.

Power Spectra

Power spectra are plotted for simulated recruitment, SSB, yield, stock biomass, juvenile biomass and surplus production (**Figures 23, 24, 25, 26, 27** and **28**). For each OM scenario three levels of fishing mortality (F_{MSY} times 0.1, 1 and 2) were simulated. The spectral analysis performed shows even though recruitment is a sequence of serially uncorrelated random variables with zero mean and finite variance (white noise) the time series SSB, yield, stock biomass and juvenile biomass are dominated by low frequencies (i.e. long-term variations) that results from the propagation of stochastic recruitment into the age-classes and lead to a smoothing of the SSB (i.e. cohort resonant effects). The analysis of productivity is different and is dominated by medium frequencies, presumably due to the transient effect of a large recruitment.

Discussion

The scenarios all showed similar trends, estimates of current stock status, production functions and reference points. The dynamics of the time series are also similar, and are driven by variations in recruitment. Although there was no auto-correlation in the recruitment deviates, there is evidence for changes in the mean level of recruitment and large recruitments cause an increase in surplus production. Process error in Multifan-CL is modelled as random recruitment this translates into changes in surplus production and long-term fluctuations in biomass and catches. This will have consequences for the MP, as seen in **Figure 12** since catches can be driven by process error rather than the expected production. Using the stock assessment as the OM helps in ensuring estimates of historical and current stock status are consistent with recent advice. Which in turn makes it easier to make the transition from the Kobe Framework (Kell *et al.*, 2016) based on showing alternative management options to the use of a HCR. Choices still have to be made, however, about simulation of uncertainty into the future and around current status.

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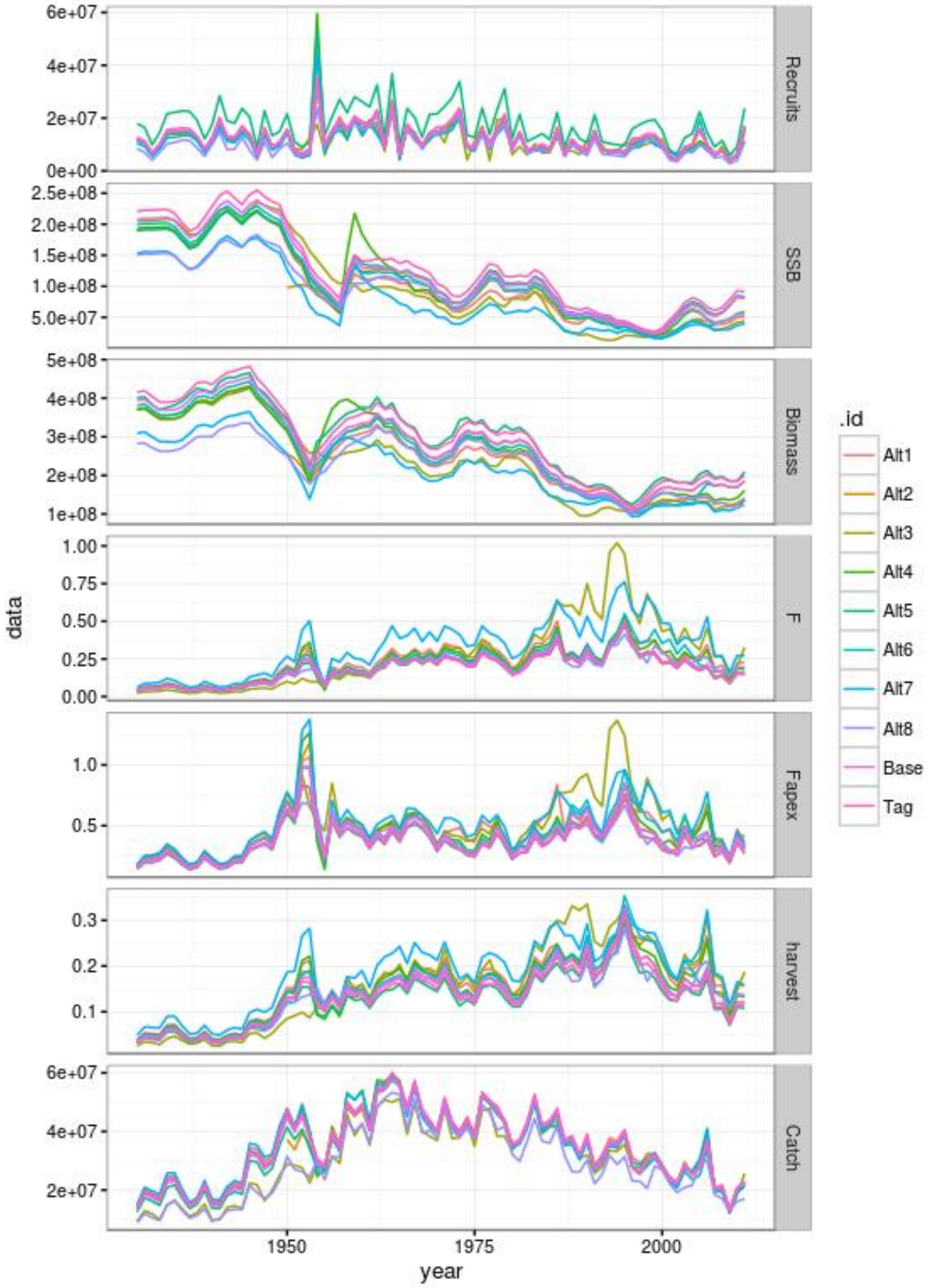

Figure 1. Time series of recruits, SSB, biomass, F_{bar}, F_{apex}, harvest rate and catch by OM scenario.

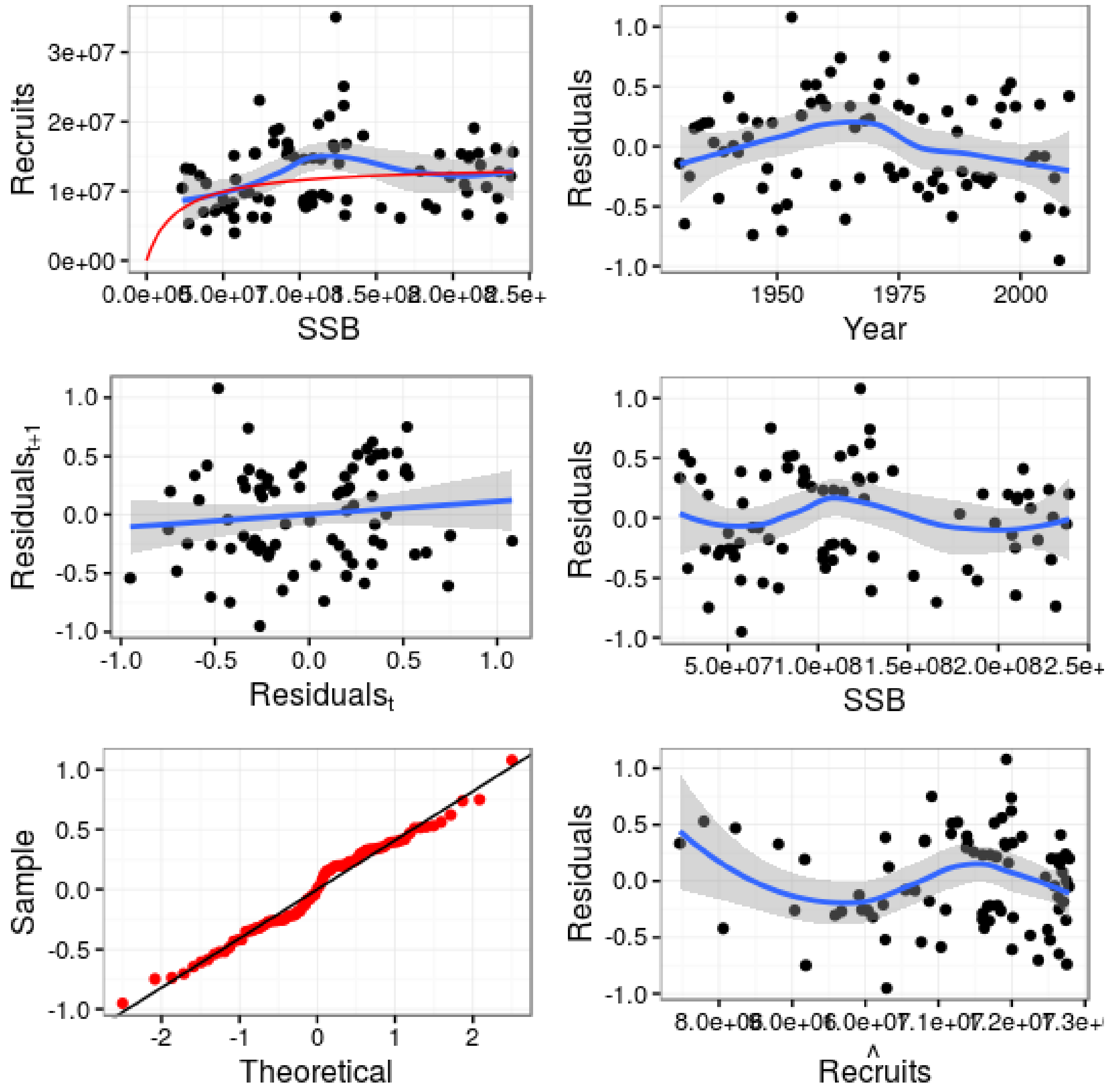

Figure 2. Stock recruitment fit with diagnostics for the Base Case.

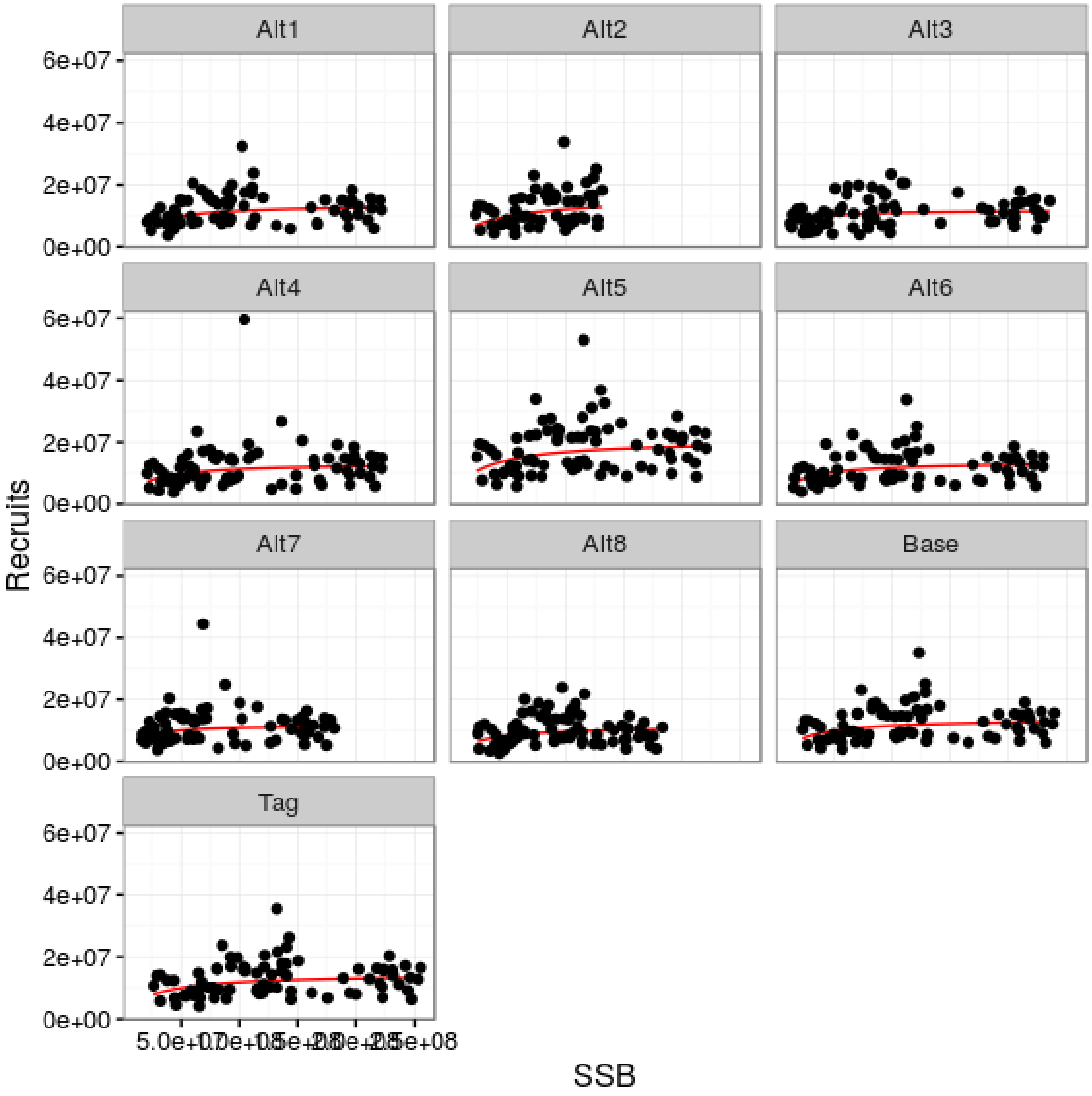

Figure 3. Stock recruitment fits to observations by scenario.

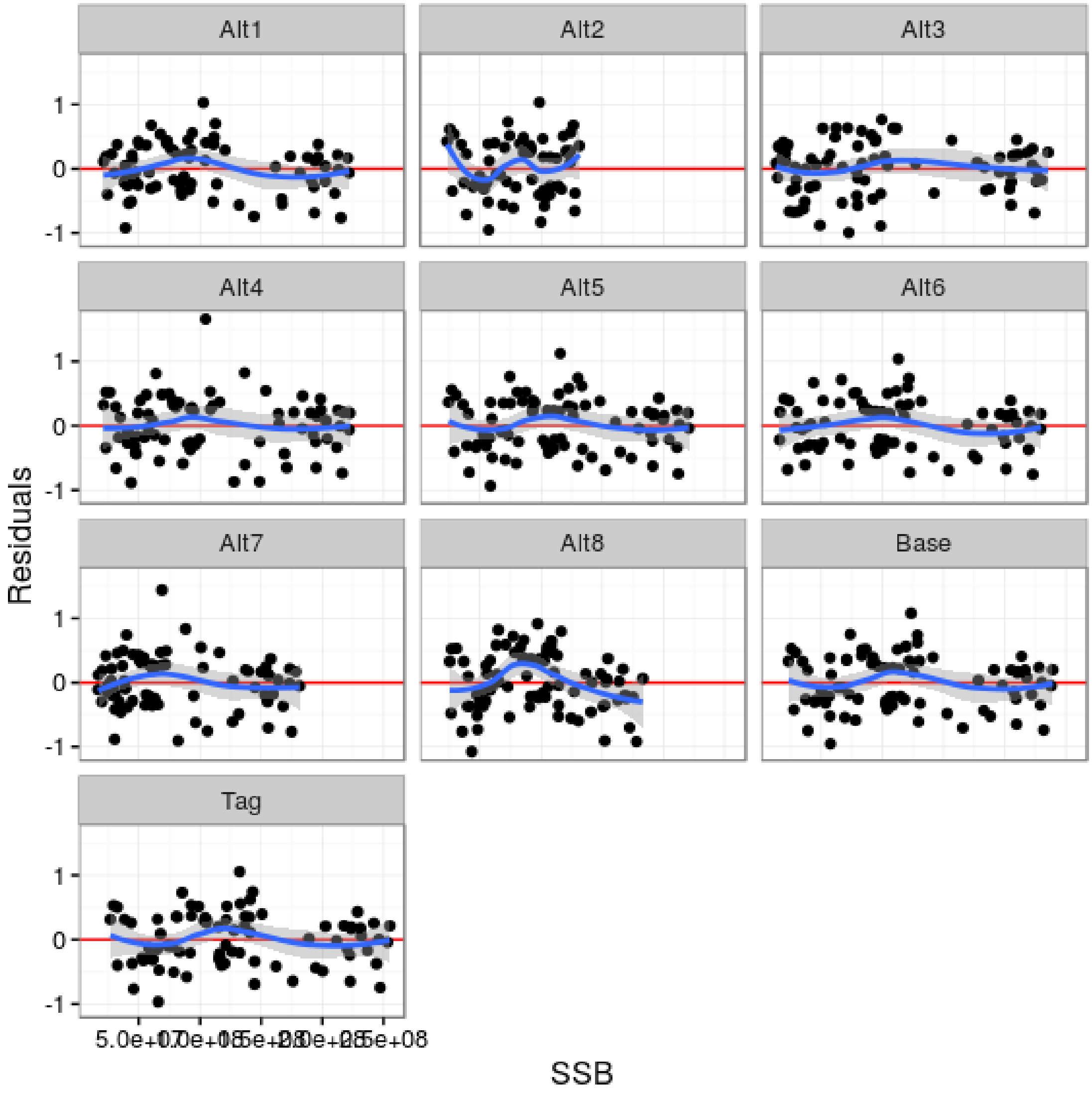

Figure 4. Residuals plotted against SSB by scenario to check for systematic patterns.

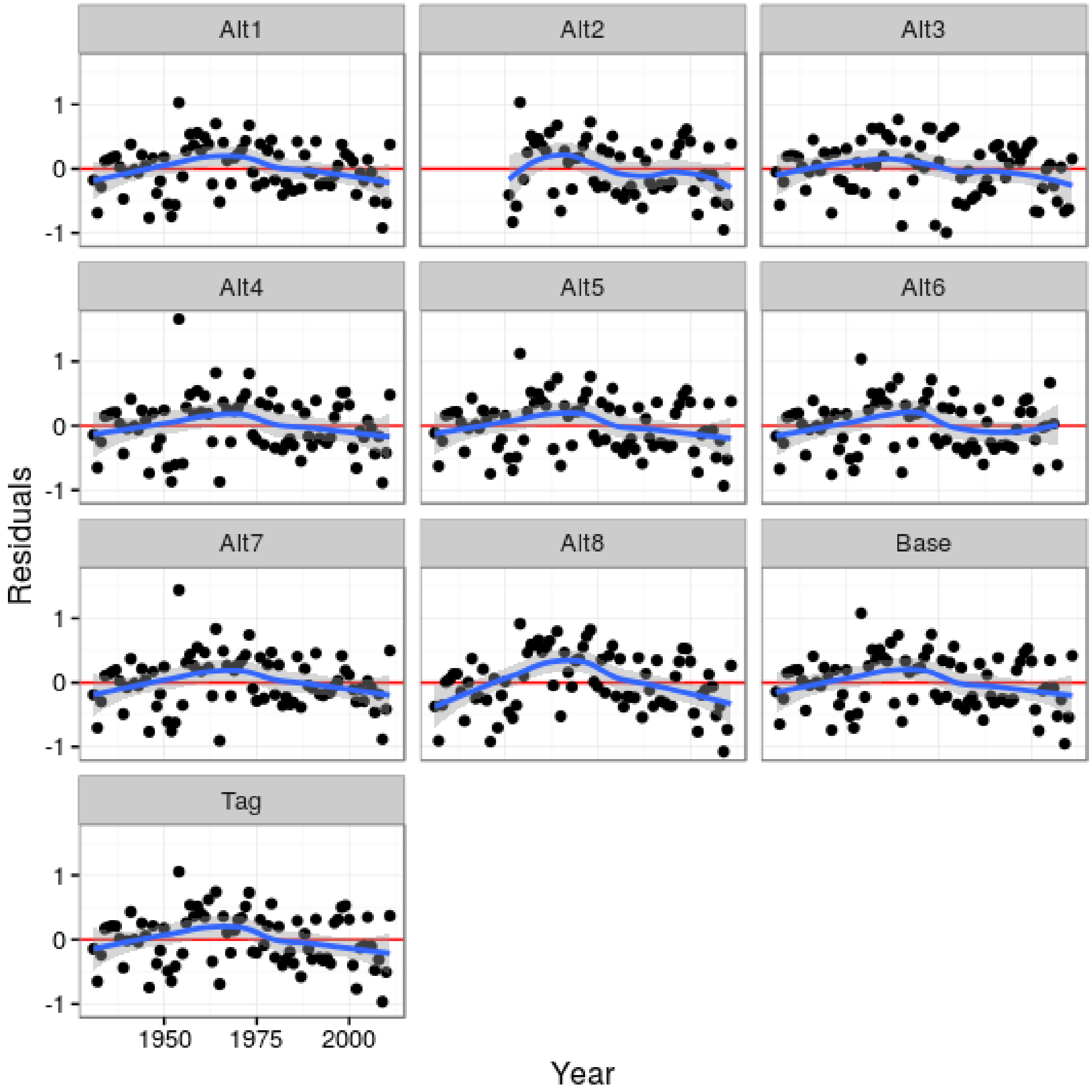

Figure 5. Residuals plotted against year by scenario to check for systematic patterns.

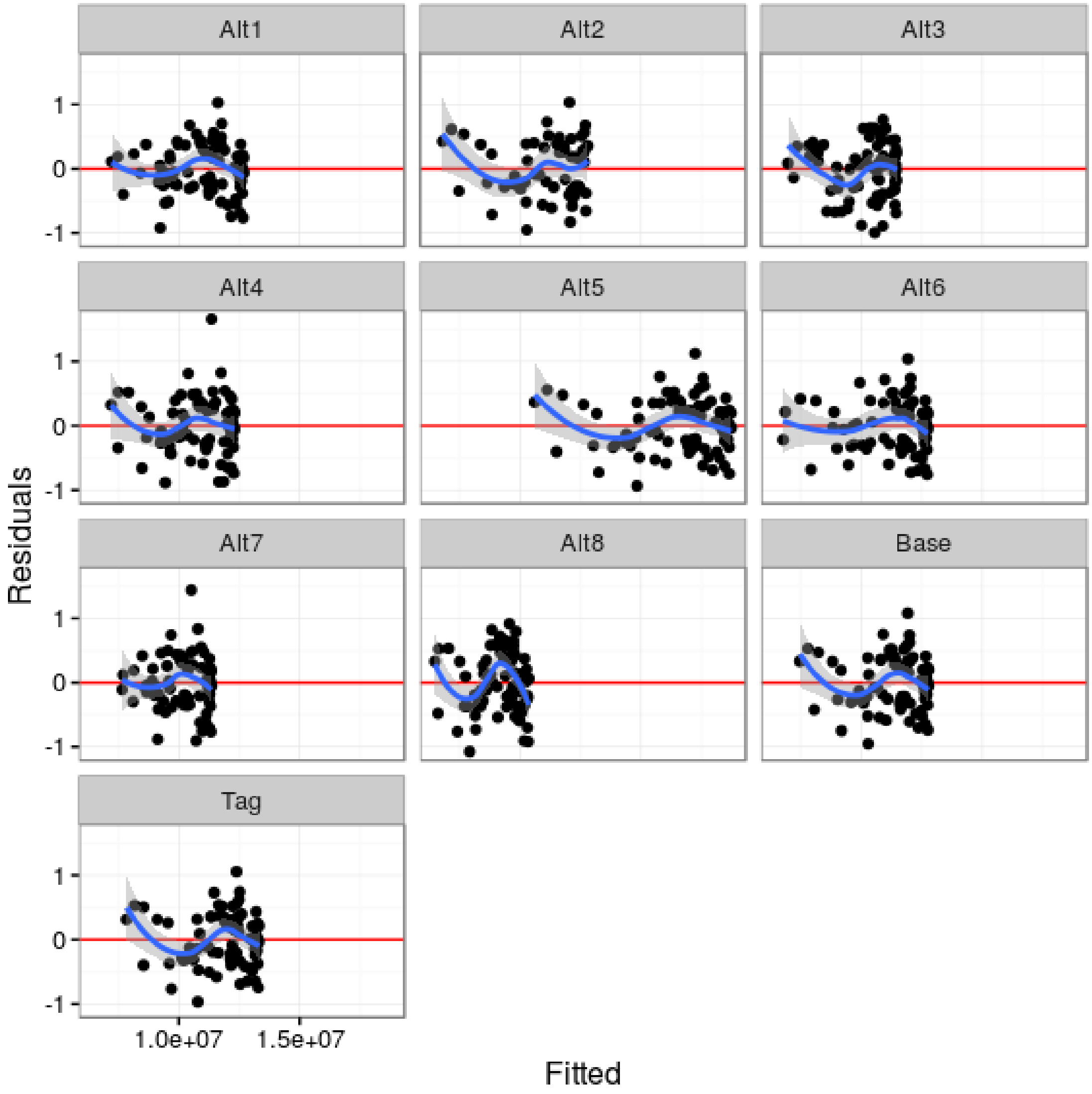

Figure 6. Residuals plotted against fitted by scenario to check variance function.

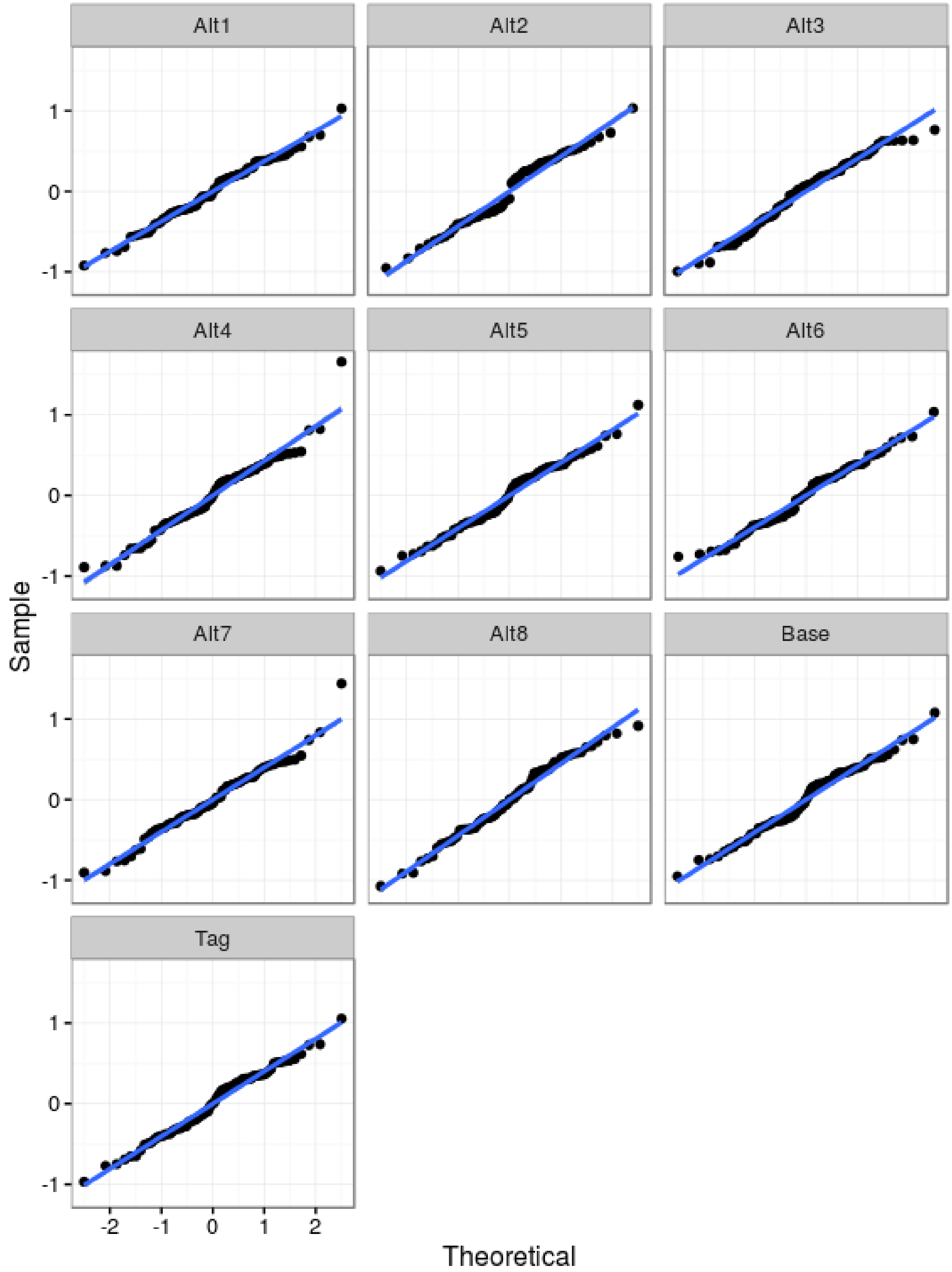

Figure 7. Quantile-quantile plot by scenario to check error model.

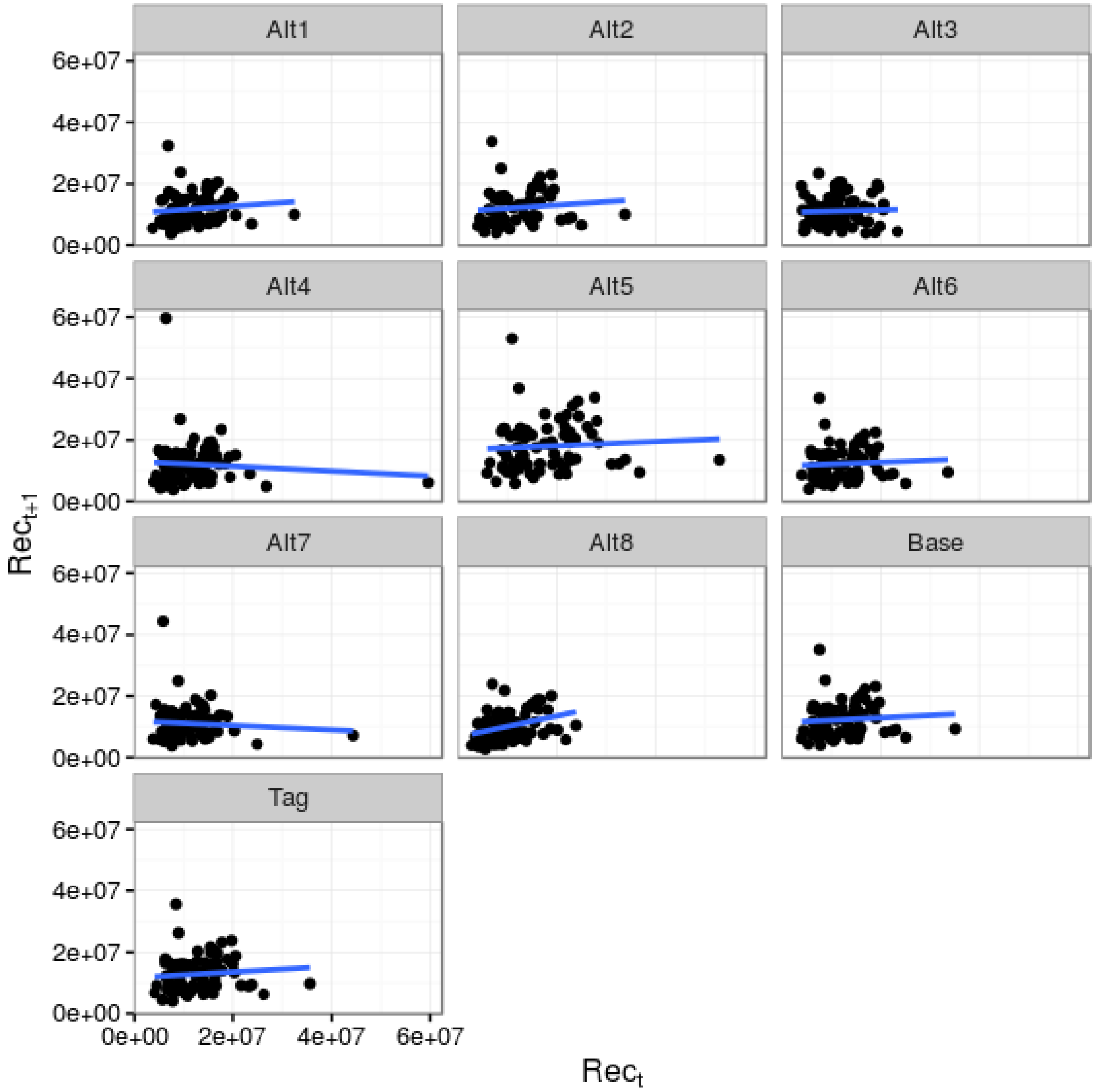

Figure 8. Plot of lagged recruitment residuals by scenario to check auto-correlation.

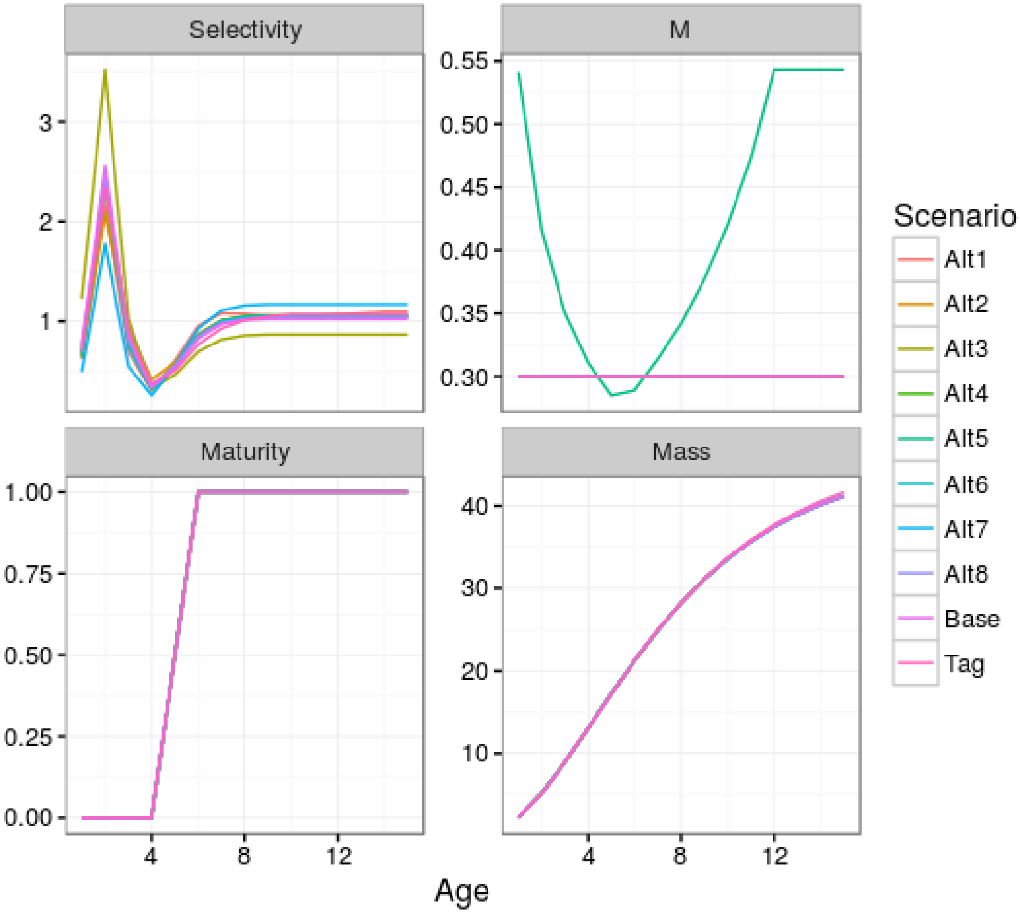

Figure 9. Biological parameters by scenario.

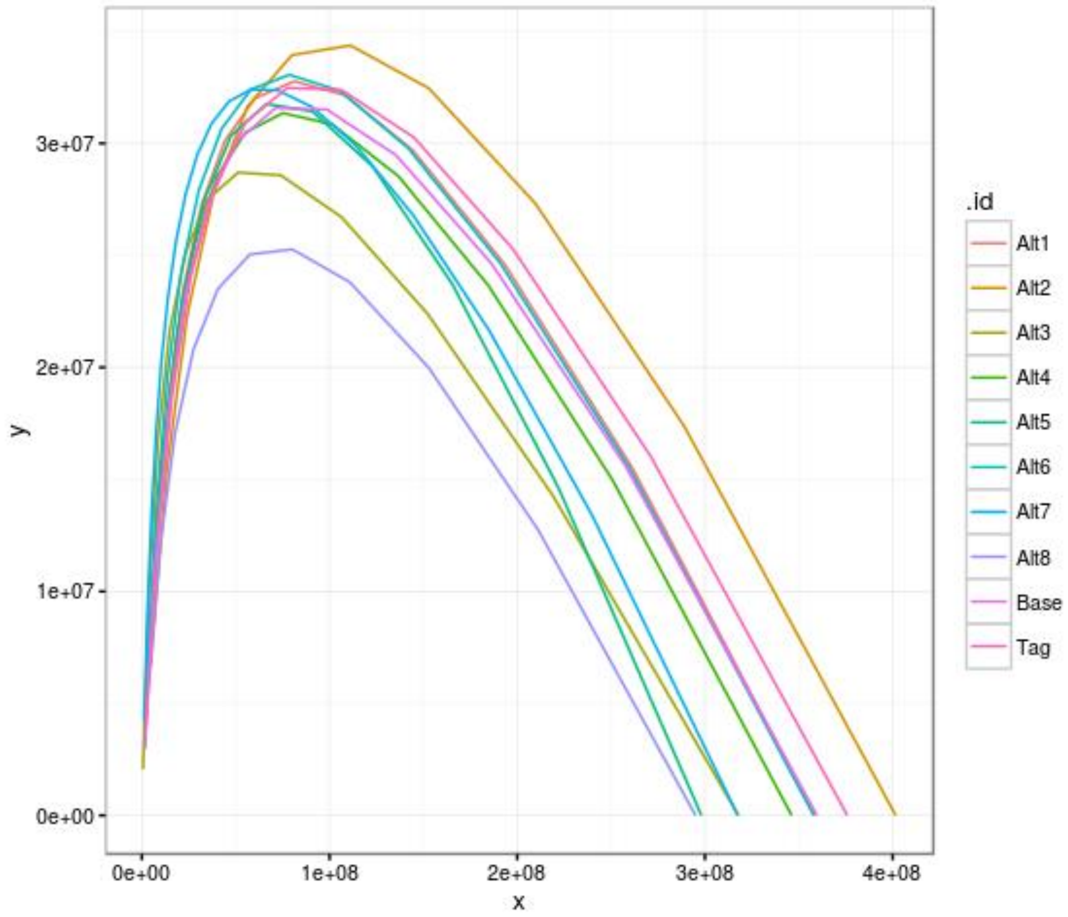

Figure 10. Equilibrium curves derived from stock recruitment relationships and per recruit analysis.

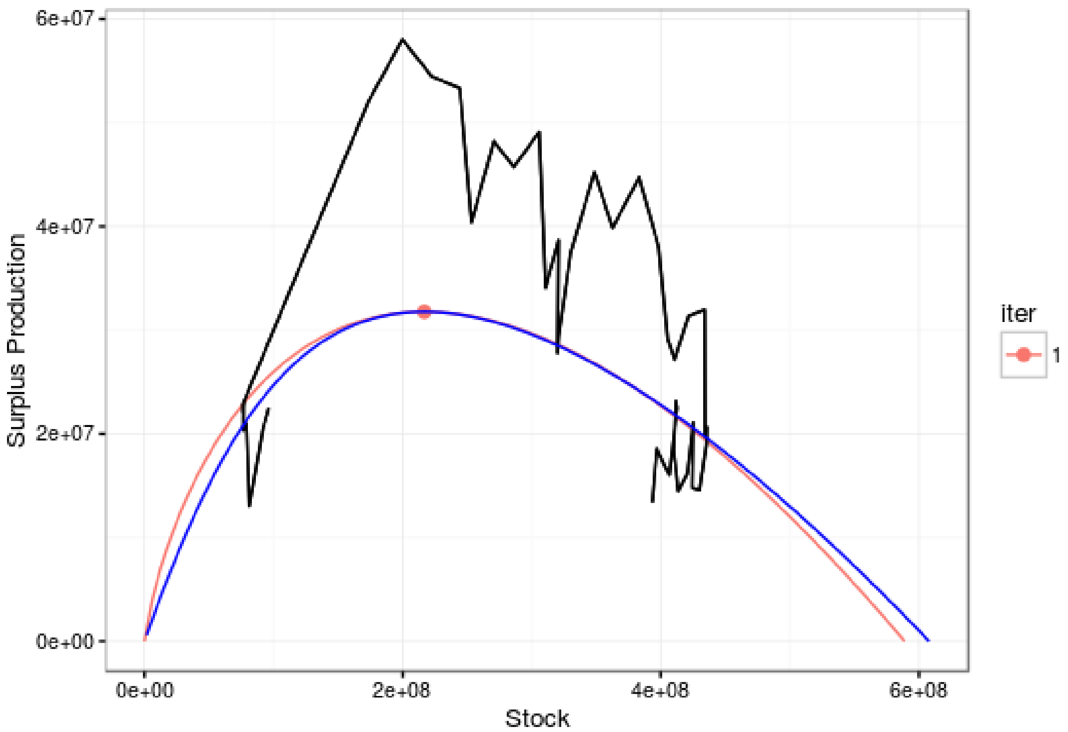

Figure 11. Comparison of age and biomass based production functions for the Base Case, the track is the estimated stock yield trajectory.

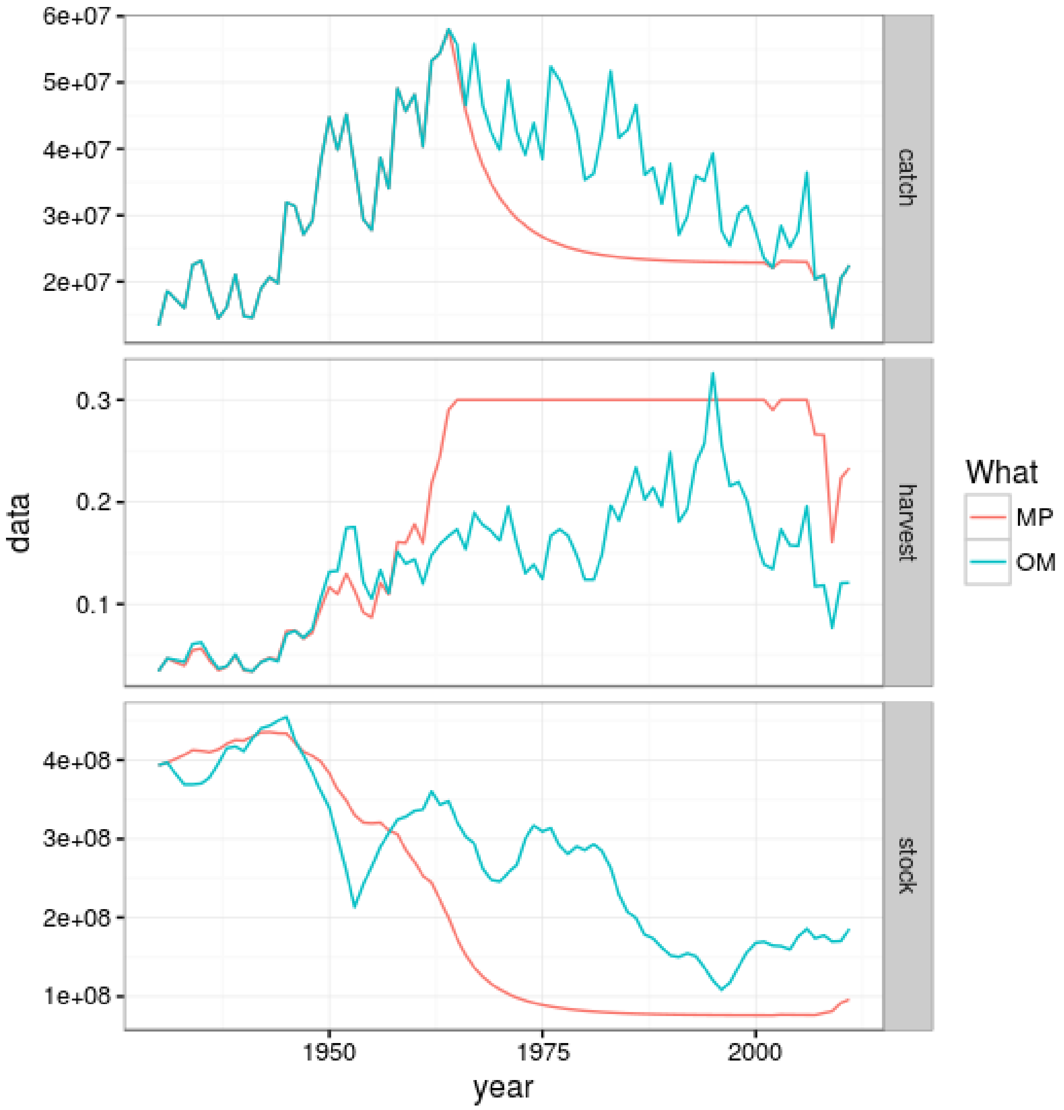

Figure 12. Simulation of biomass production function with parameters (r, K and shape) equivalent to OM Base Case; harvest rate capped at 0.3.

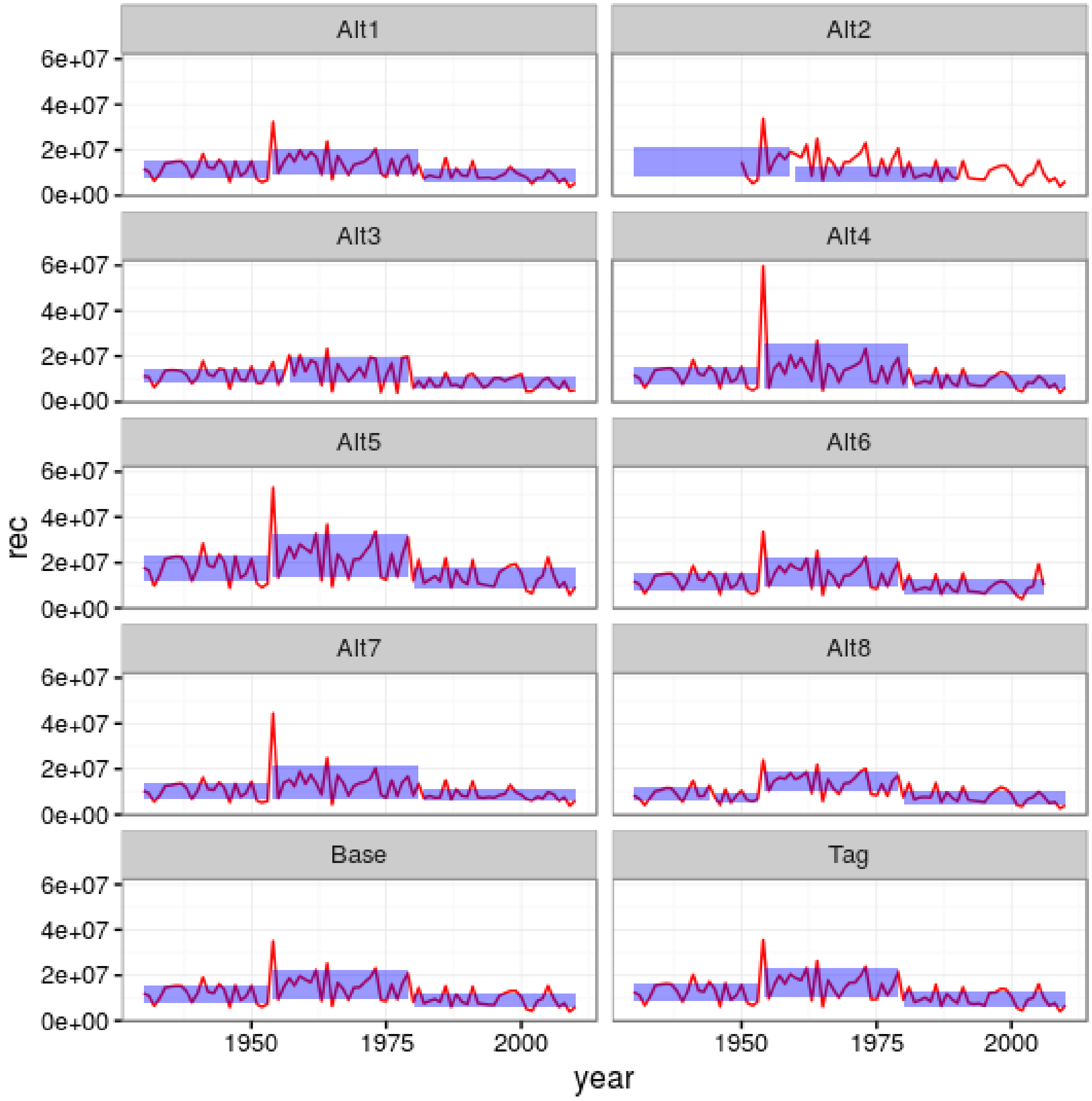

Figure 13. Time series of recruitment by scenario, with means and standard deviations as estimated by the STARS algorithm.

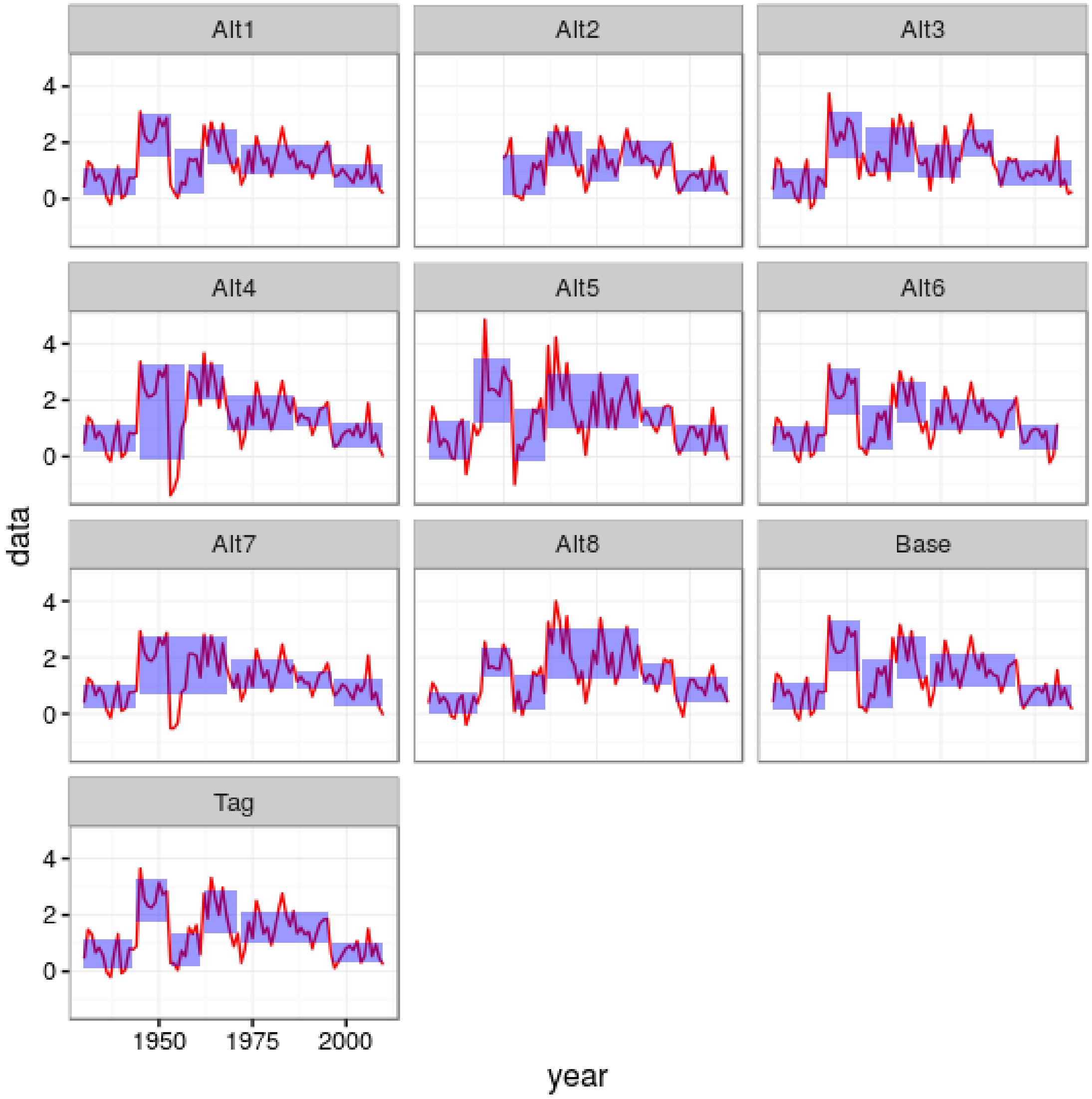

Figure 14. Time series of production by scenario, with means and standard deviations as estimated by the STARS algorithm.

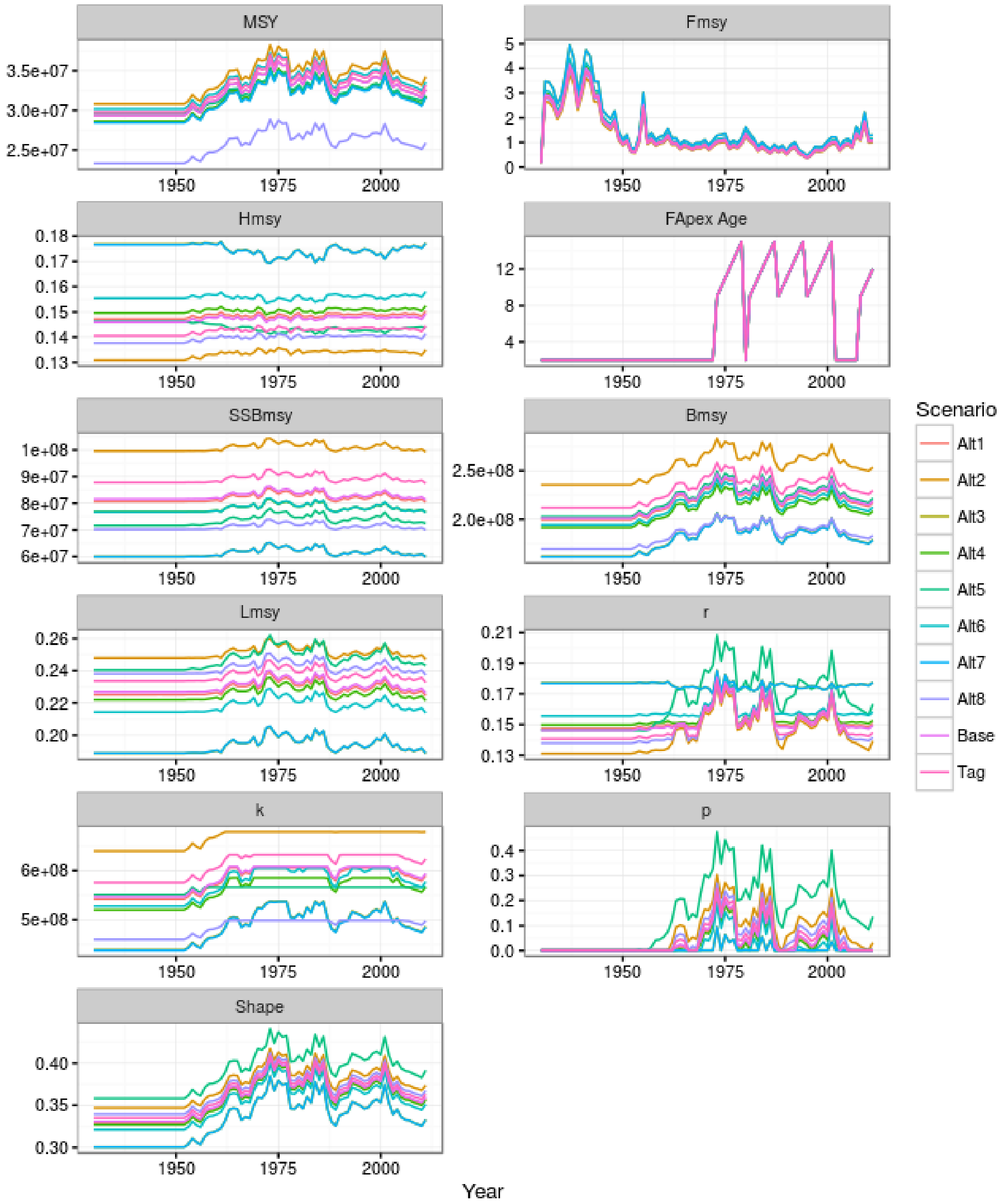

Figure 15. Time series of derived quantities, population parameters and reference points for all scenarios.

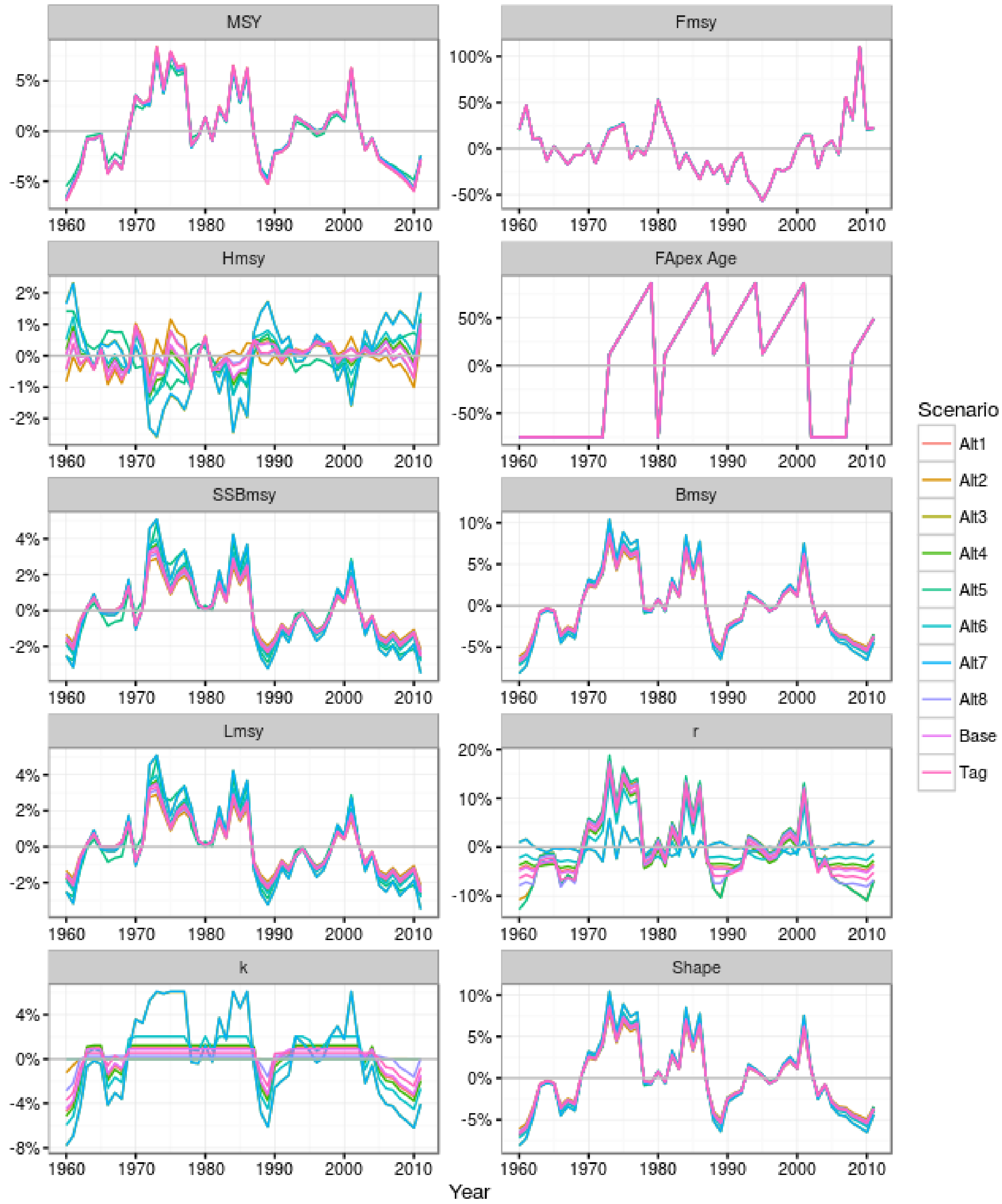

Figure 16. Time series scaled by means within a scenario of derived quantities, population parameters and reference points.

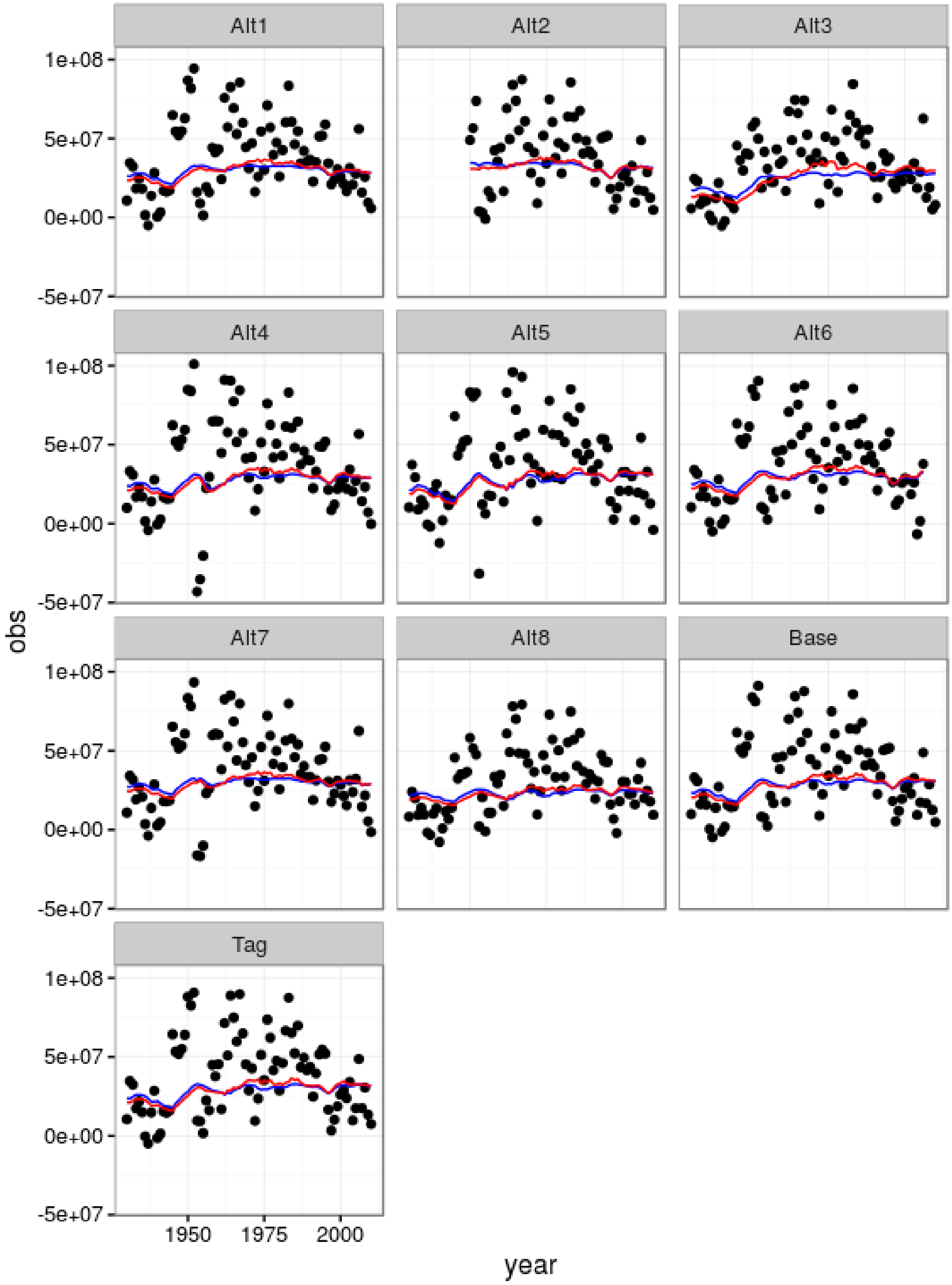

Figure 17. Surplus production as estimated by age based model, lines are expected values, red is the production function allowing for change in selection pattern.

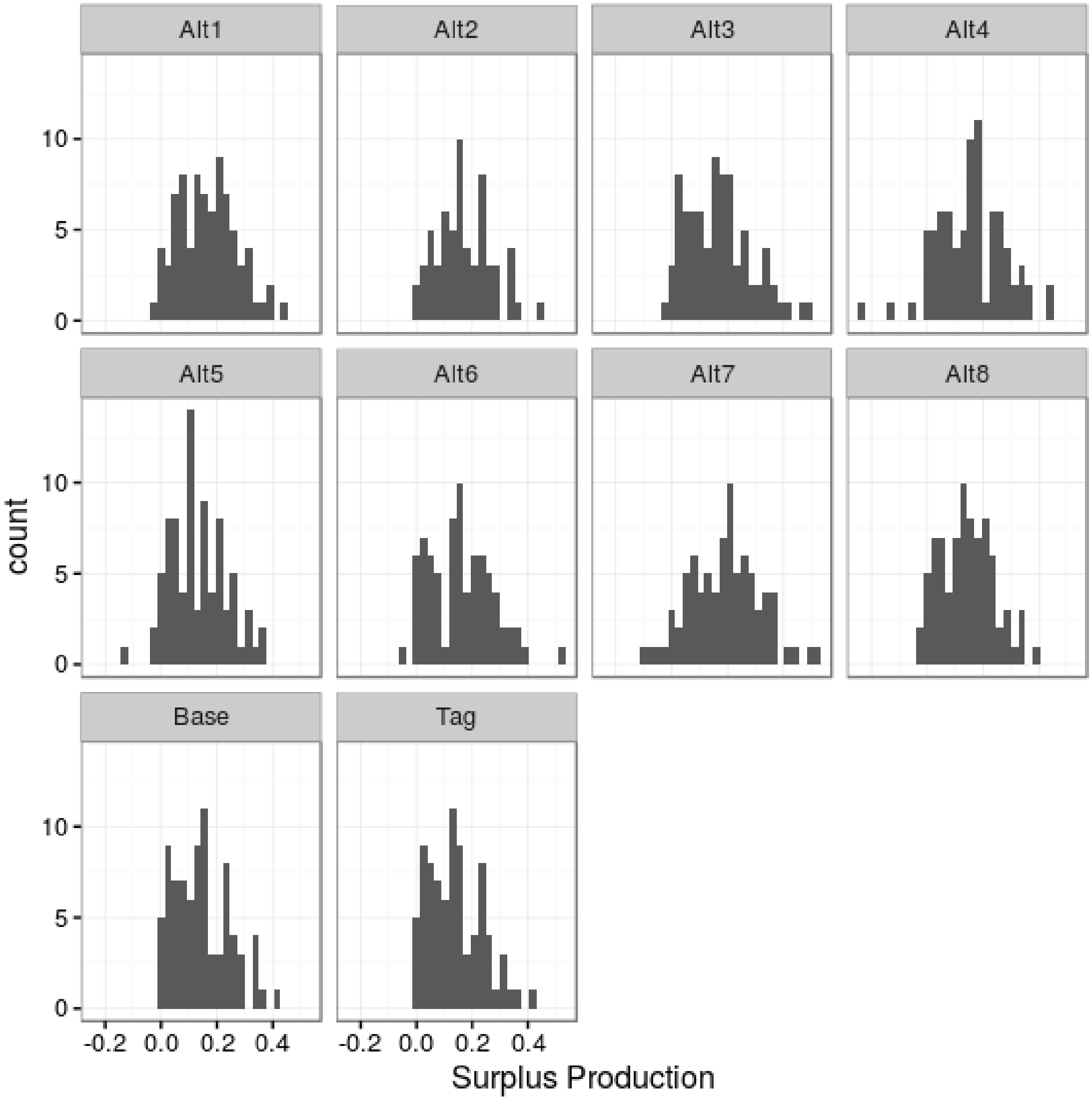

Figure 18. Conditional population growth rate distributions by scenario.

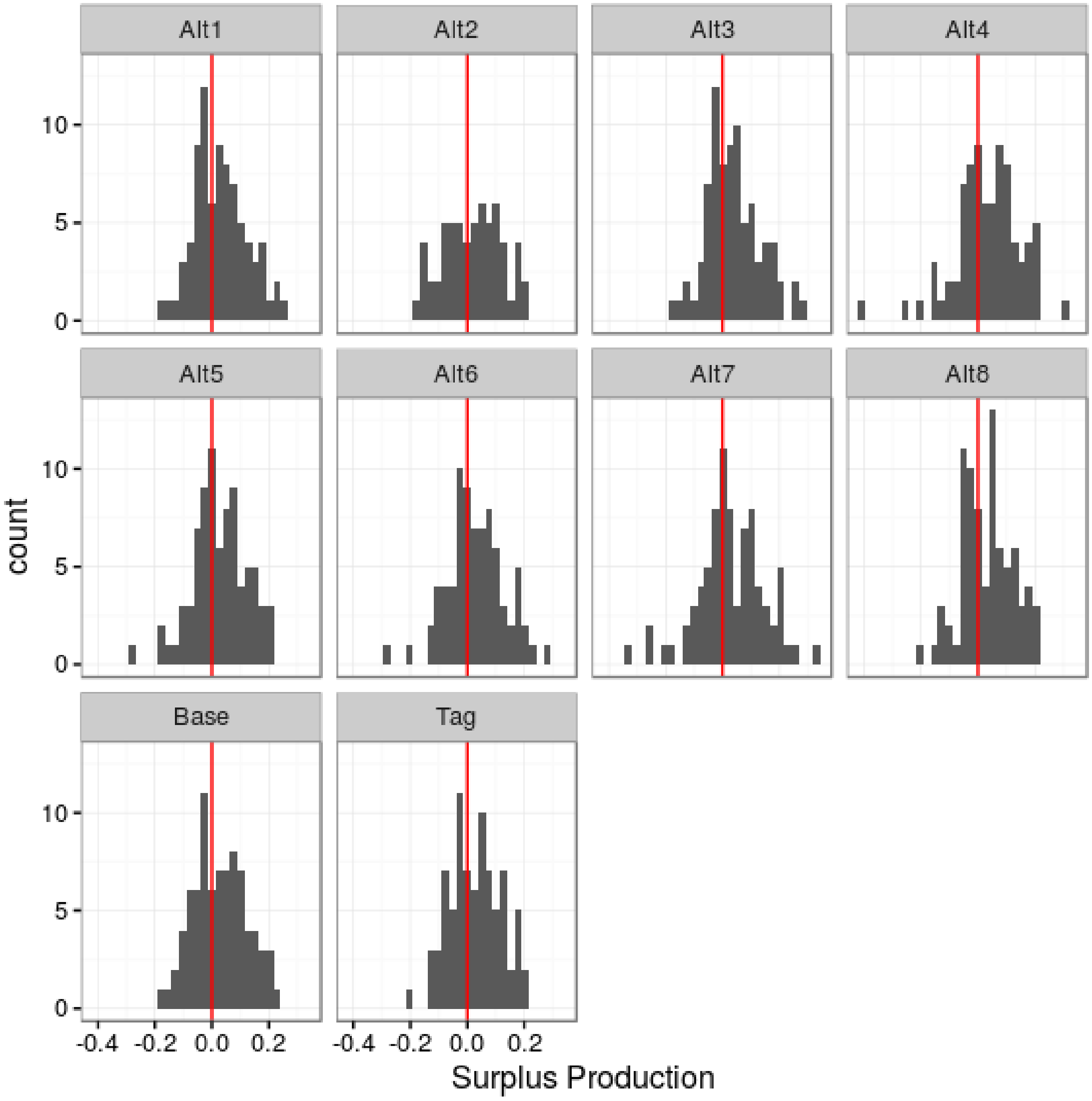

Figure 19. Condition population growth rate residuals (observed-expected) by scenario.

Figure 20. Harvest rate relative to F_{MSY} by scenario.

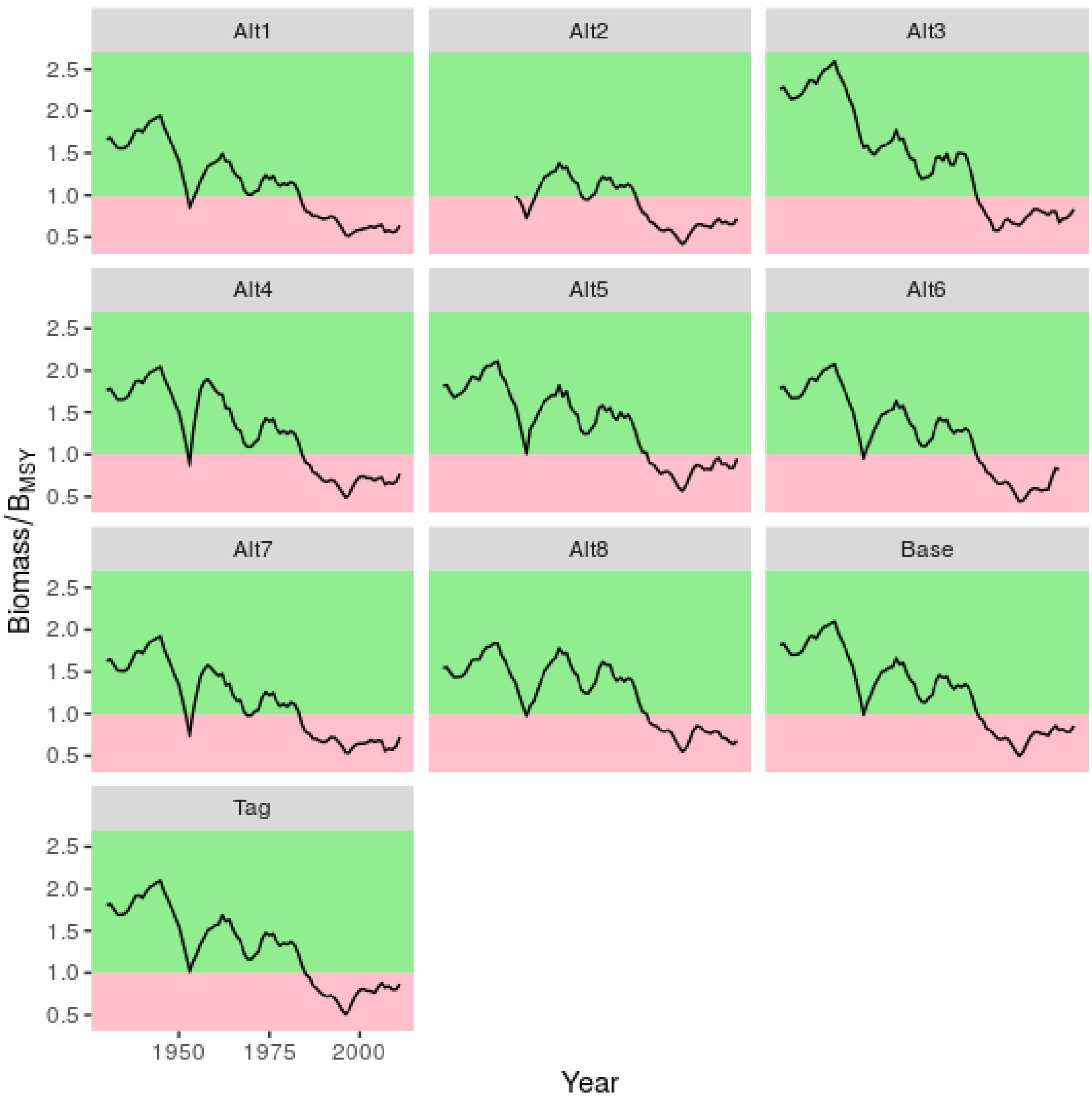

Figure 21. Stock biomass relative to B_{MSY} by scenario.

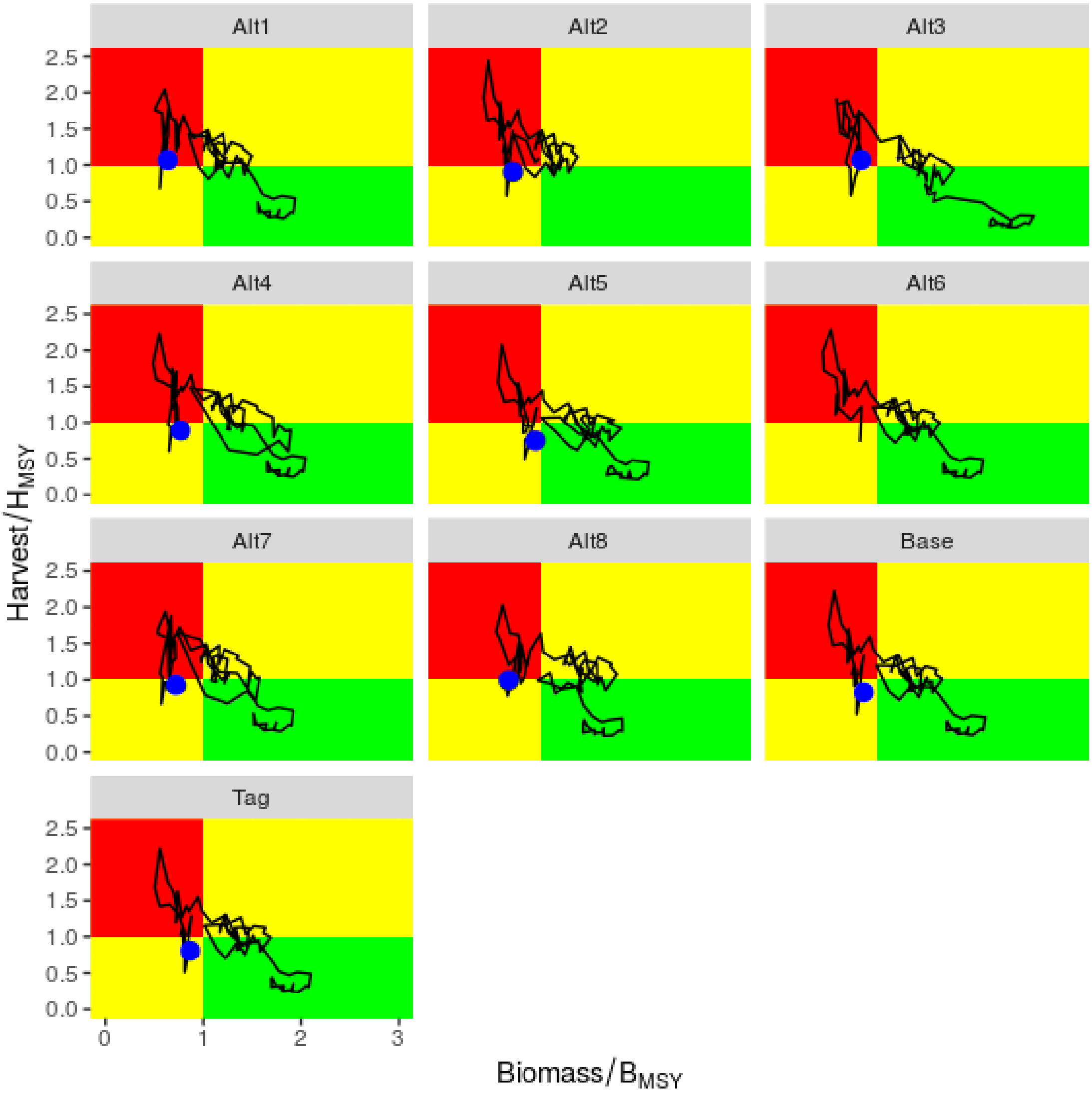

Figure 22. Kobe Phase Plots, with 2011 status (blue point) by scenario.

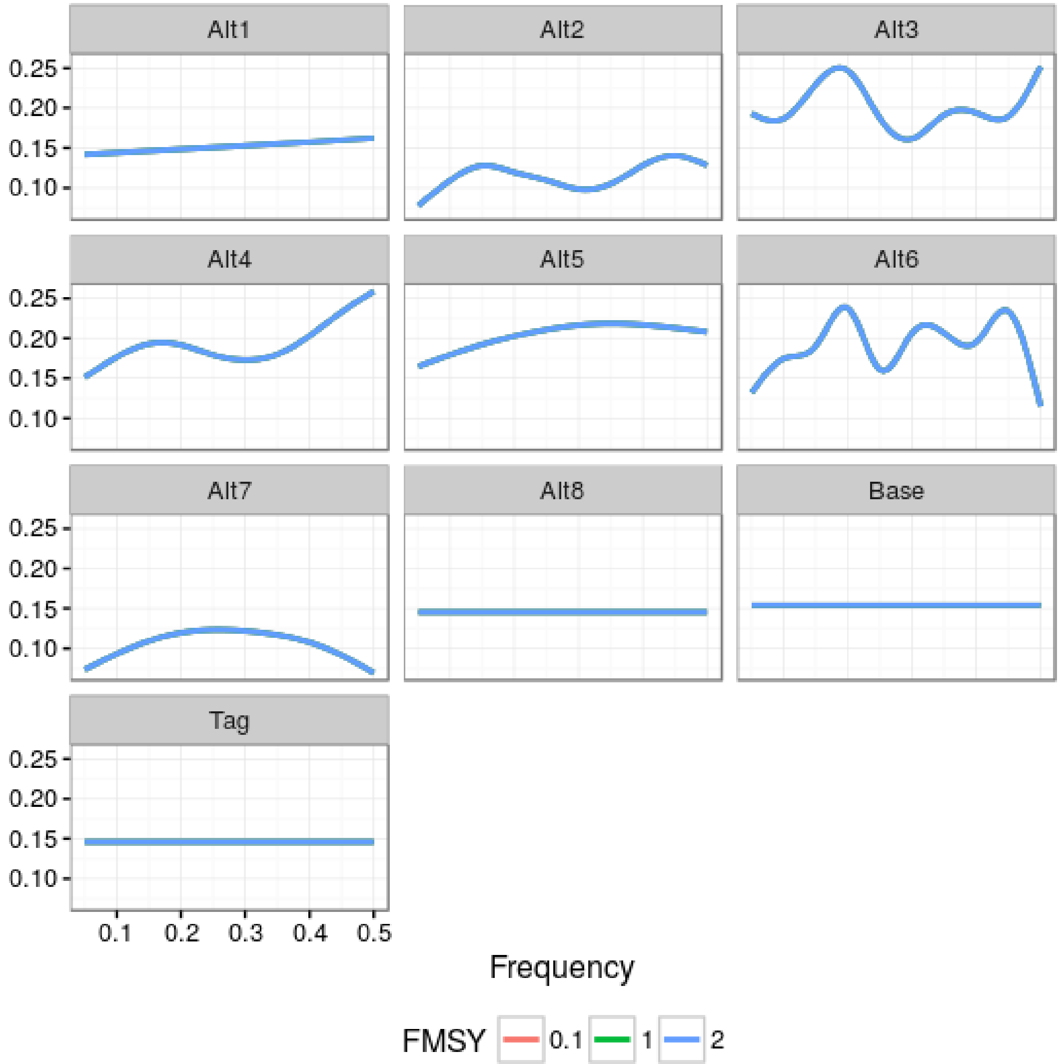

Figure 23. Power spectra of recruitment; simulations for each Operating Model scenario and three levels of fishing mortality (F_{MSY} times 0.1, 1 and 2).

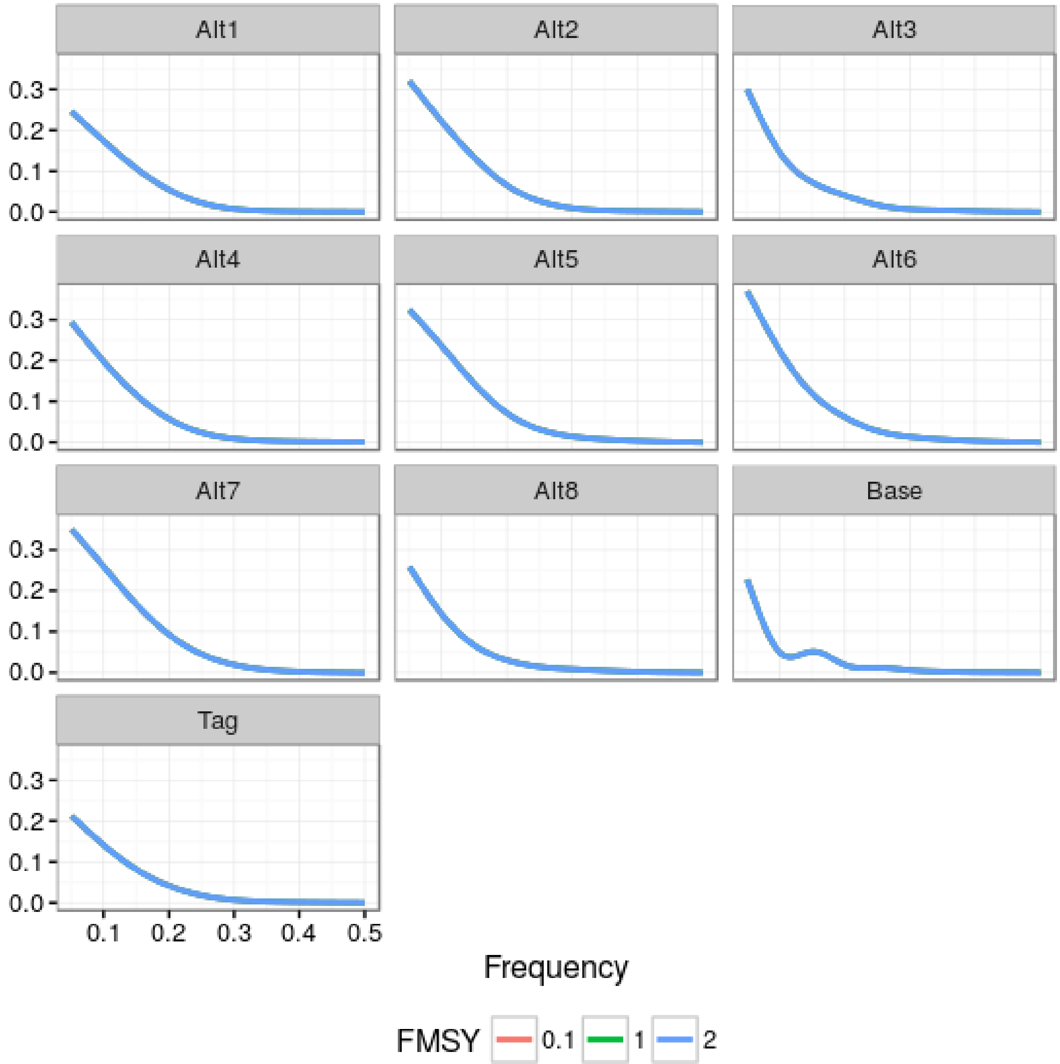

Figure 24. Power spectra of SSB; simulations for each Operating Model scenario and three levels of fishing mortality (F_{MSY} times 0.1, 1 and 2).

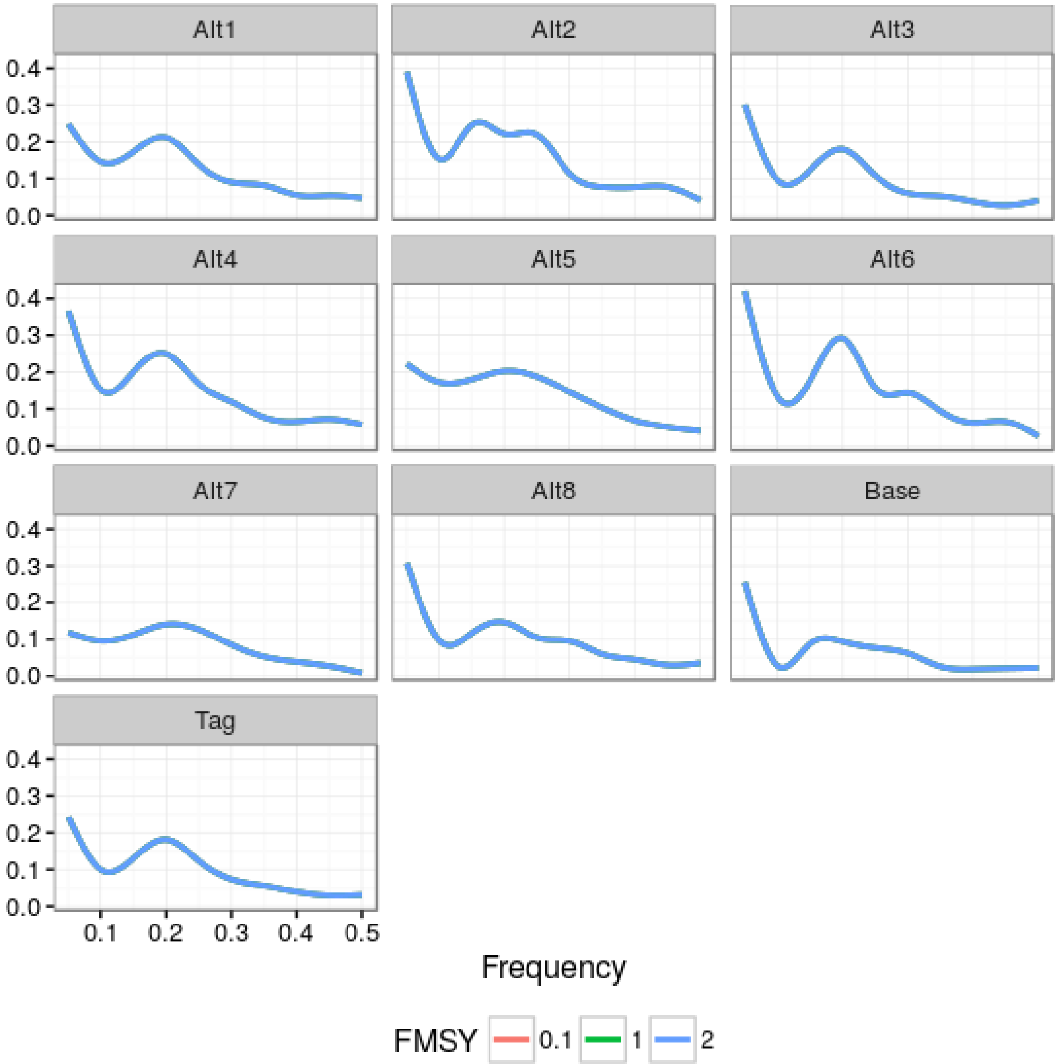

Figure 25. Power spectra of yield; simulations for each Operating Model scenario and three levels of fishing mortality (F_{MSY} times 0.1, 1 and 2).

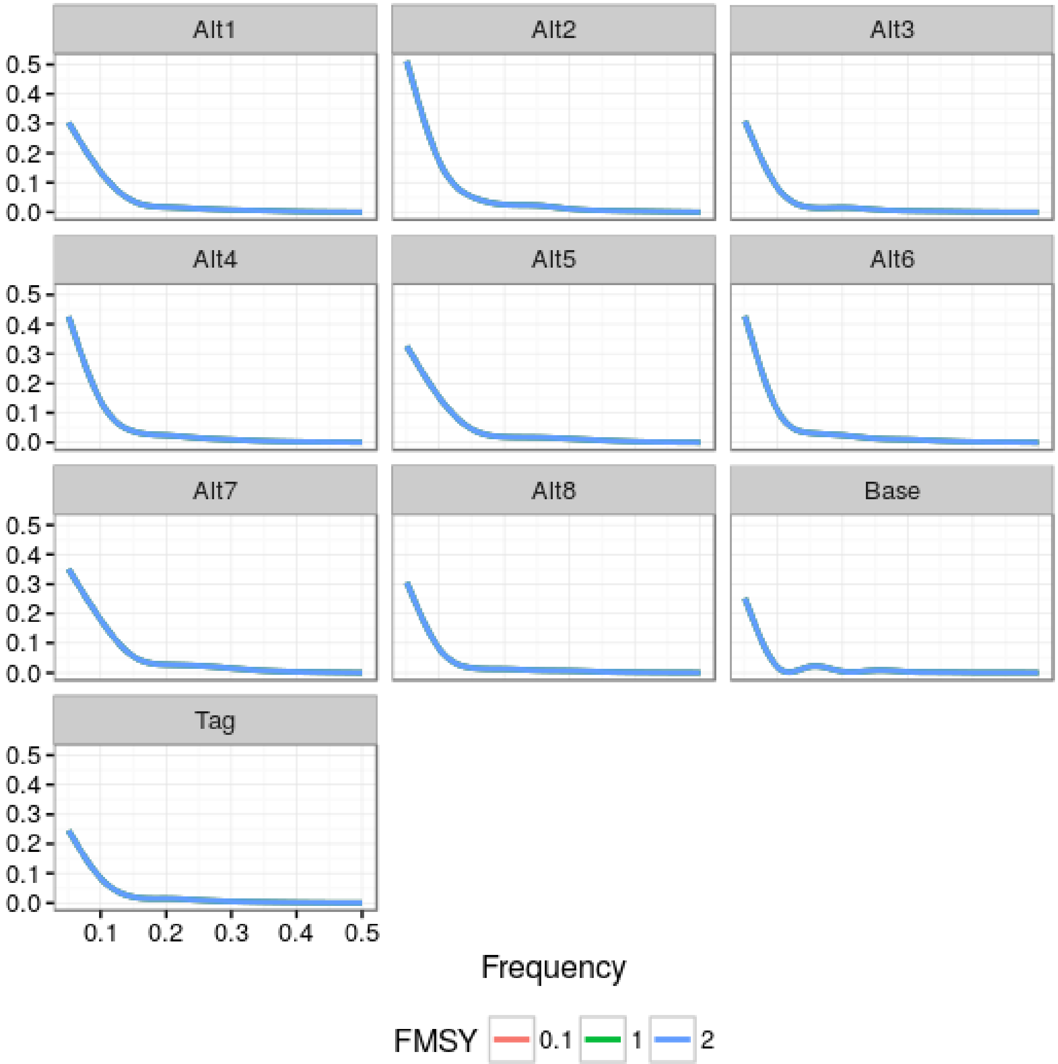

Figure 26. Power spectra of stock biomass; simulations for each Operating Model scenario and three levels of fishing mortality (F_{MSY} times 0.1, 1 and 2).

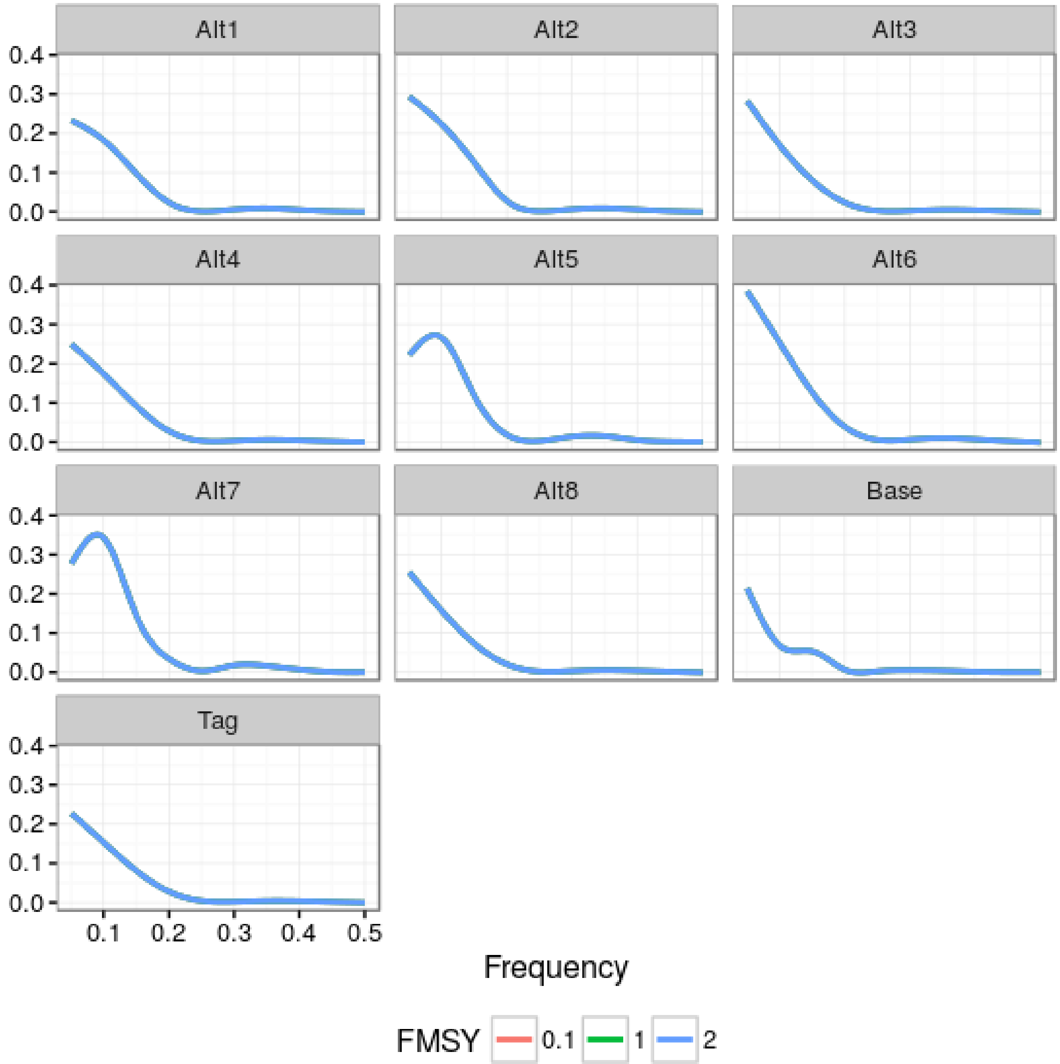

Figure 27. Power spectra of juvenile biomass; simulations for each Operating Model scenario and three levels of fishing mortality (F_{MSY} times 0.1, 1 and 2).

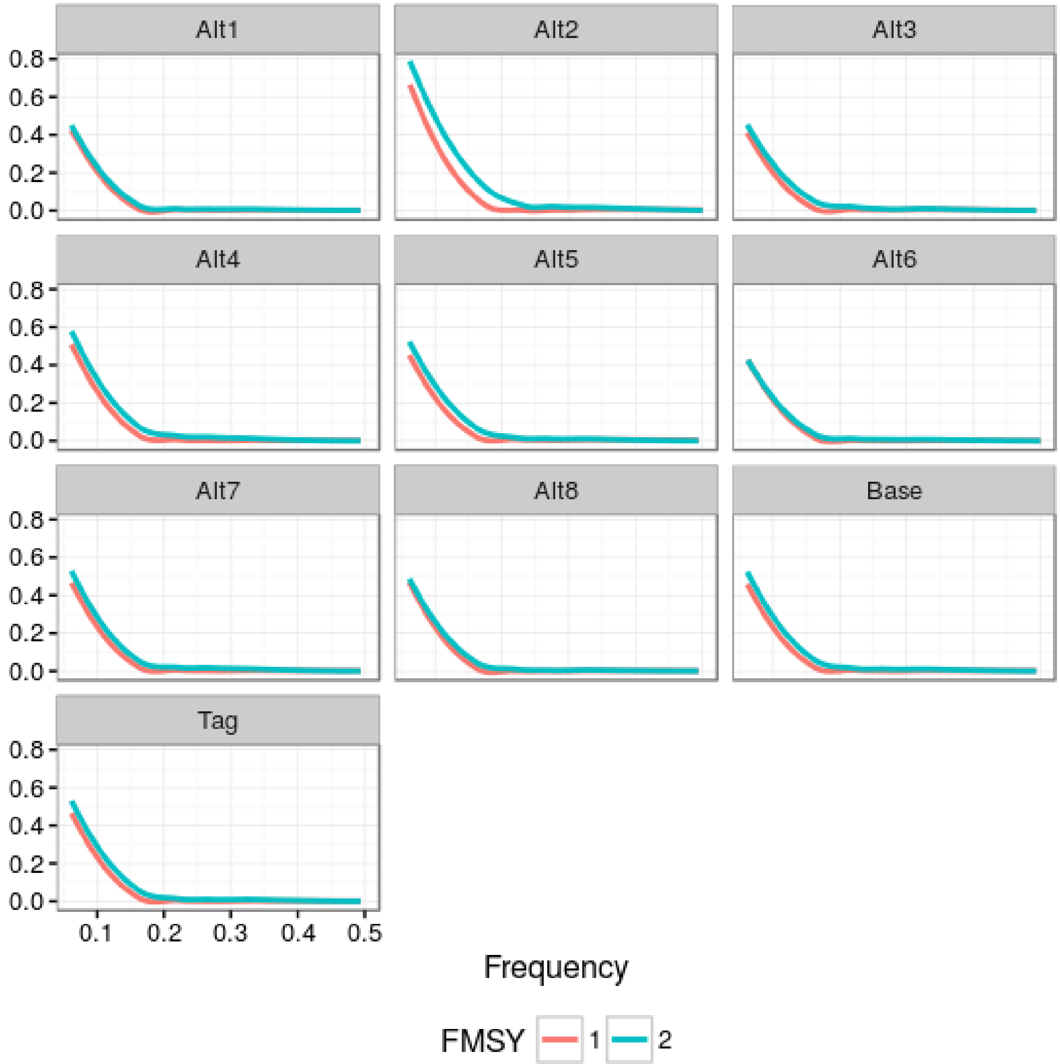

Figure 28. Power spectra of surplus production; simulations for each Operating Model scenario and three levels of fishing mortality (F_{MSY} times 0.1, 1 and 2).