SCRS/2022/092 Collect. Vol. Sci. Pap. ICCAT, 79(4): 231-239 (2022)

THE EFFECT OF NON-LINEAR RELATIONSHIPS BETWEEN CPUE AND ABUNDANCE ON THE MANAGEMENT PROCEDURE PERFORMANCE FOR NE PORBEAGLE

N. G. Taylor[1], M. Ortiz[1], A. Kimoto[1], R. Coelho[2], E. Cortés[3] and R. Forselledo[4]

SUMMARY

One potential problem with applying any Management Procedure that requires an index of abundance is that there is only one potential CPUE series, a Spanish longline series that is likely available in the future for management of the eastern Atlantic porbeagle stock. In this fishery, Porbeagle shark are a bycatch species so that there are concerns about the index not being representative of the non-target species. To address this concern, we run a set of simulations across a range of non-linear relationships between CPUE and abundance from hyperstable to hyperdeplete. We test a set of MPs that have previously demonstrated to meet minimum satisficing standards of having a least a 50% change that the stock is above the CITES Appendix 2 threshold of 20% SSB0, at least a 50% chance that the stock is above the level that supports maximum sustained yield, and at least a 50% of chance that fishing mortality is below the fishing mortality that produces maximum sustained yield. We show that for model-free MPs, the effect of hyper stability on MP performance is minimal. For the model-based MPs, performance is adequate provided that there is not excessive hyperstability or excessive hyperdepletion. A key research recommendation for northeast porbeagle is to analyze the Spanish longline index to determine if there is evidence for hyperstability of hyperdepletion, and to see if such effects can be removed through the standardization process.

RÉSUMÉ

L'un des problèmes potentiels liés à l'application d'une procédure de gestion nécessitant un indice d'abondance pour le stock de requin-taupe commun de l'Atlantique Est est qu'il n'existe qu'une série palangrière espagnole où le requin-taupe commun est une espèce rare faisant l'objet de prises accessoires. Par conséquent, on craint que l'indice ne soit pas représentatif. Pour y remédier, nous testons une série de PM dont il a été démontré qu'elles répondent aux normes minimales de satisfaction, à savoir qu'elles ont au moins 50 % de probabilité que le stock soit supérieur au seuil de 20 % de SSB0 de l'annexe 2 de la CITES, au moins 50 % de probabilité que B>BPME et au moins 50 % de chances que F<FPME. Pour les MP sans modèle, l'effet de l'hyperstabilité sur les performances des MP est minime. Pour les MP reposant sur un modèle, les performances sont adéquates s'il n'y a pas d'hyperstabilité ou d'épuisement excessif. Une recommandation clé de recherche consiste à analyser l'indice palangrier espagnol pour déterminer s'il existe une hyperstabilité ou un épuisement excessif, et de voir si ces effets peuvent être éliminés par le processus de standardisation.

RESUMEN

Un posible problema relacionado con la aplicación de un procedimiento de ordenación que requiera un índice de abundancia para el marrajo sardinero del Atlántico este es que solo existe una serie de palangre española en la que el marrajo sardinero es una especie de captura fortuita poco frecuente. En consecuencia, existe cierta inquietud respecto a que el índice no sea representativo. Para abordar este problema, se probó un conjunto de MP que han demostrado previamente cumplir los estándares mínimos de satisfacción de tener al menos un 50 % de

[1] ICCAT Secretariat. Calle Corazón de Maria 8, Madrid Spain 28002.
[2] IPMA - Portuguese Institute for the Ocean and Atmosphere. Av. 5 de Outubro s/n, 8700-305 Olhão, Portugal
[3] NOAA-Fisheries, Southeast Fisheries Science Center, Panama City Laboratory, 3500 Delwood Beach Road, Panama City, Florida
[4] Dirección Nacional de Recursos Acuáticos - DINARA, Laboratorio de Recursos Pelágicos, Constituyente 1497, CP 11200 Montevideo

probabilidad de que el stock se sitúe por encima del umbral del Apéndice 2 de CITES del 20 % de SSB0, al menos un 50 % de probabilidad de que B>B_{RMS} y al menos un 50 % de probabilidad de que F<F_{RMS}. En el caso de los MP no basados en modelos, el efecto de la hiperestabilidad sobre el desempeño de los MP es mínimo. En el caso de los MP basados en modelos, el desempeño es adecuado si no hay una hiperestabilidad o hipermerma excesivas. Una recomendación de investigación clave es analizar el índice de palangre español para determinar si hay hiperestabilidad o hipermerma, y ver si tales efectos pueden eliminarse mediante el proceso de estandarización.

KEYWORDS

Simulation, Stock Assessment, Depleted stocks, Shark fisheries, Tuna fisheries, Population dynamics, By catch, Fishery sciences, Fishing effort

1. Introduction

Taylor et al. 2022 SCRS/2022/090 were able to show that there were a number of Management Procedures or MPs (Punt et al. 2016) that could be effective for avoiding CITES appendix 2 limits, keeping the stock at or above the biomass that produces maximum sustainable yield (B_{MSY}), and for keeping fishing mortality below the fishing mortality that produces B_{MSY}, F_{MSY}. Their analysis shows that there are model-free MPs that can meet these criteria across a range of risk thresholds, but that the general pattern was these MPs do so at the expense of yield. MPs that can be used as an estimate of abundance or to estimate depletion tend to have higher yield performance. Because the only remaining index for doing stock assessment and management for northeast porbeagle is the Spanish long line index, where porbeagle sharks are a bycatch, it is not clear that it will be easy to apply a stock-assessment method to northeastern porbeagle for which it will be possible to reliably estimate either abundance or depletion.

One key ingredient for estimating abundance and depletion in traditional stock assessment models is to fit a population dynamics model to an index of abundance (Hilborn and Walters 1992; Quinn T.J. and Deriso 1999; Walters and Martell 2004) or to use the index of abundance as an approximation for the level of depletion (MacCall 2009; Dick and MacCall 2011). The problem with using commercial catch per unit effort, CPUE, as an index of abundance is assuming that it is linearly proportion to abundance. There are two common ways that CPUE can not be proportional to abundance. When CPUE remains high even if the true abundance declines, the index is called hyperstable. Conversely, when CPUE declines faster than abundance, it is called hyperdeplete (Hilborn and Walters 1992; Harley et al. 2001). But in the northeast porbeagle case, the degree of hyperstability or hyperdepletion in the index is not known. There is concern though. One problem with bycatch species is that as effort shifts spatially in pursuit of the target species (and potentially away from bycatch species), then the index can appear to be hyperdeplete (Glazer and Butterworth 2002; Walters 2003). But one could argue the other way, i.e., CPUE series for target species might be hyperstable, as the fishery continues to operate in the core area (where the target species might continue to be abundant), but not in the limits that might get declines faster, so the overall abundance is declining while the CPUE remains stable.

While it is theoretically possible to detect hyperstability or hyperdepletion in catch per unit effort series (Harley et al. 2001; Gaertner and Dreyfus-Leon 2004), there has been no evaluation to see if the Spanish CPUE series used for porbeagle assessment suffers from hyperstability of hyperdepletion. Rather than attempt to determine if there are non-linear relationships between CPUE and abundance for this index, we use a set of closed-loop simulations to examine the effects of hyperstability and hyper depletion of the performance of the 20 MPs that satisficed the minimal criteria defined in Taylor et al. 2022 (SCRS/2022/090). In this way, we can illustrate how different MPs are likely to perform across a range of functional relationships between CPUE and abundance.

2. Methods

The essential elements of the Operating Models (OMs) and the MSE setup are detailed in Taylor et al. (SCRS/2022/090). We explore a set of five of simulations to test effects of non-linear relationships between CPUE and abundance. Following Harley et al. (2001), we model the proportionality between CPUE, and abundance A at time t is

(1) $\mathrm{CPUEt} = \mathrm{q}A_t^{\beta}$

where q is the catchability coefficient. The parameter β determines the degree of hyperstability or hyperdepletion. If β = 1 then catchability changes with A (Figure. 1). When β >1, CPUE declines faster than A i.e., hyperstability. Hyperdepletion occurs if β <1, then CPUE declines slower than A (see Figure 1).

2.1 Simulation Setup

2.1.1 Operating Model Configuration

We test a range of five OMs with β values ranging from 0.25 to 4 as illustrated in Figure 1. For each OM, we test the set of 20 satisficed MPs from Taylor et al. 2022 (2022 SCRS/2022/090). For this preliminary set of simulations, we use the S2 OM configuration (that uses all CPUE indices) from Taylor et al. 2002 as the basis for OMs to test hyperstability and hyperdepletion. To set OMs with hyperstability or hyperdepletion we adjust Obs object's @beta parameter in the OpenMSE R package to values defined in **Table 1**. Apart from changes in β, these OMs were identical to those tested in S2 of Taylor et al 2020 in SCRS/2022/090.

2.2 MPs tested

We tested a set of MPs that have previously been demonstrated to meet minimum satisficing standards of having a least a 50% change that the stock is above the CITES Appendix 2 threshold of 20% SSB0 (P20), at least a 50% chance that the stock is above the level that supports maximum sustained yield (P100), and at least a 50% of chance that fishing mortality is below the fishing mortality that produces maximum sustained yield (PNOF). The MPs are listed in **Table 2**. Before running the full set of simulations (with 135 replicates), we ran an initial check for MP convergence of the OM set to check for convergence of any assessment method. MPs that failed this check were eliminated.

2.3 Summary of MP Performance

To present how MP performance is affected by changes in the functional relationship between CPUE and abundance, we plot MP performance vs β for across different data input classes. We use five different performance metrics (PM) to summary MP performance: the probability of being above 20%SSB0 (the CITES appendix 2 criterion, P20), the probability the stock is above BMSY (P100), the probability that F is lower than FMSY (PNOF) and the probability that the average annual variability in effort is greater than 20% (AAVE).

Since simple stock assessment models like the surplus production models are currently being used to assess the stock, we pay particular attention to those MPs that use stock assessment models that could be applied to the stock in practice. In addition to surplus production models, we include Delay Difference (Deriso 1980; Schnute 1985) models. In the MP set tested, there were three MPs that used surplus production models: SP_4010 which is surplus production model with a 40-10 control rule; SP_75MSY that is surplus production model with a TAC recommendation based on fishing at 75% of F_{MSY}; SP_MSY that is a surplus production model with a TAC recommendation based on fishing at FMSY. For delay difference models there were: DDSS_75MSY which is a state-space delay difference model with a TAC recommendation based on fishing at 75% of FMSY and DDSS_4010 which is a state-space delay difference model with a 40-10 control rule. For these models, we provide a dedicated plot of MP performance vs β.

3. Results and Discussion

3.1 Initial MP Convergence

The OMs with non-linear relationships between CPUE and abundance were more challenging than those tested in SCRS/2022/090. As a result of the violations in the assumptions of the linear relationship between the CPUE and abundance, several MPs could not converge during simulation testing. These MPs are summarized in **Table 3**. These five MPs varied between model-based MPs (Gcontrol, DD40-10 and DD) and index-based MPs (SBT). Note that while the simple delay difference formulation of the delay-difference model failed to converge, the state space variants (DDSS_75MS) and DDSS_4010) did converge.

3.2 Summary of MP Performance

How hyperstability or hyperdepletion affected MP performance differed by data input class (columns **Figure 2**) and the magnitude of β itself. The graphical summary of MP performance is provided in **Figure 2**. In general, MPs were not very sensitive to β except for those MPs that attempt to estimate abundance (first column **Figure 2**). For the catch-based MPs, length, and depletion-based MPs this observation makes sense because there is no feedback from an index of abundance (or fitting to one with an assessment model) that would affect how these MPs performed.

Even for index-based MPs there was small variation in the performance of MPs across changes in β. This observation is paradoxical in that the MPs use indices as the basis for setting MPs. The index-based (model-free) MPs, that we tested in this set of simulations were: ICI, ICI2, and Iratio. The index confidence interval MPs, ICI and ICI2, adjust catch based on the value of the index in the current year relative to the time series mean and standard error as follows:

$TACy=C_{y-1}\alpha$

where the gain parameter α is scaled according to the magnitude of the index compared to the historical time series as follows:

$$\alpha = \begin{bmatrix} d\; if\; It > C \\ u\; if\; It > CI_H \\ 1.\, if\; CI_L \leq I_t \leq CI_H \end{bmatrix}$$

where I_t is the index in the most recent year, d is 0.75 for ICI and ICI2, u is 1.05 and 1.25 for ICI and ICI2 respectively. CI_L and CI_H are the lower and upper bound of the confidence interval of mean historical index. In this way, as long as the index remains between the historical lower and upper confidence interval then α=1 and there is no change in the catch. This means that any changes in catch given by ICI and ICI2 are buffered from any change in the index unless these changes are beyond the historical confidence intervals. This disconnects the catch in the MP somewhat from the hyperstability in the index because unless the changes in the index are very large, the MP returns C_{y-1}.

For the Iratio MP, the TAC is calculated as:

$TAC_y=\mu C_{y-1}$

where C_{y-1} is the catch from the previous year, and μ is the ratio of the mean index in the most recent two years of the time series and the mean index in years from *t-3* to *t-5*. Like ICI and IC2 where α buffers how much the TAC varies with the index, the Iratio MP annual changes in the TAC with a pseudo Kalman gain (Walters 2004) parameter μ that implements lagged changes TAC with changes in the index. Finally, there is one more factor in these simulations that limits how much these MPs are affected by hyperstability or hyperdepletion: both MPs start the projection period with low C_y at the start of the projection period so that the catch is 15-20% of the reference yield (**Figure 2**). In other words, because the index MPs are harvesting well below potential yield, the stock size is relatively high so that the difference between the “true” relative abundance (β=1) and those where β≠1 is smaller than it would be at intermediate values (**Figure 1**).

For MPs that estimate abundance, how performance varied with β depended on the MP itself. Part of the explanation for this difference is the categorization of these MPs into a bin called “abundance based”. But even within this bin, MPs that estimate abundance do not necessarily involve using an index of abundance to fit a stock assessment. Instead, the input of the harvest control rule is an estimate of abundance. Indeed, two of the Simple Stock Synthesis variants (SSS_4010 and SSS_75MSY) do not use an index of abundance at all. Rather, the depletion of the stock in the last conditioning year is fixed to 0.4. Selectivity is fixed to the maturity ogive and the sole parameter estimated is R0 (unfished recruitment), with no process error. Accordingly, it makes sense that the Simple Stock Synthesis variants do not respond to changes in β of an index that they do not use.

The effect of changes in β on MP performance was pronounced for MPs that do estimate abundance with an index of abundance. For all performance statistics, those MPs that used a surplus production model i.e., SP_4010, SP_75MSY, and SP_MSY showed a quasi-parabolic functional form with the β parameter producing the best performance (the highest value of the performance metric) when β is near or at unit, i.e., that the index is neither hyperstable nor hyperdeplete. But delay difference models did not necessarily follow the same pattern for performance with respect to β. DDSS and DDSS_4010 AAVE tended to decline as β increased (tending toward hyperdepletion see **Figure 3**). For the remaining P20, P100, PNOF and P40 performance statistics, the tendency was for DDSS and DDSS_4010 to have optimal performance when β was near 2 except for the Yield statistic where for DDSS_4010, the optimal performance is where β=1.

So, what does all this mean for stock assessment and management of the northeast porbeagle stock? First if being above the CITES threshold is the primary concern, then some MPs like SP_75MSY and SP_MSY are robust to hyperstability or hyperdepletion provided that β is neither too big nor too small i.e,, $0.5 \geq \beta \geq 2$. In such cases, the probability of being above the CITES threshold is consistently greater than 75% for all the surplus production models that we tested. But this pattern does not hold for all MPs. What is clear however is that the magnitude of potential hyperstability matters for the conservation and yield of performance of the stock so developing a set of hypotheses to define a reasonable range of β for the Spanish CPUE index should be a priority. In addition, in this case and in Taylor et al. 2022 (2022 SCRS/2022/090), we did not test MP performance across a broad range of hypothesis about the stock. To get a sense of how robust any of these MPs might be to alternative states of nature these could include the status of the stock, different selectivity assumptions, and different implementation models.

References

Deriso, R.B. 1980. Harvesting strategies and parameter estimation for an age-structured model. Can. J. Fish. Aquat. Sci. **37**: 268–282.

Dick, E.J., and MacCall, A.D. 2011. Depletion-Based Stock Reduction Analysis: A catch-based method for determining sustainable yields for data-poor fish stocks. Fish. Res. **110**(2): 331–341. Elsevier B.V. doi:10.1016/j.fishres.2011.05.007.

Gaertner, D., and Dreyfus-Leon, M. 2004. Analysis of non-linear relationships between catch per unit effort and abundance in a tuna purse-seine fishery simulated with artificial neural networks. ICES J. Mar. Sci. **61**(5): 812–820. doi:10.1016/j.icesjms.2004.05.002.

Glazer, J.P., and Butterworth, D.S. 2002. GLM-based standardization of the catch per unit effort series for South African west coast hake, focusing on adjustments for targeting other species. South African J. Mar. Sci. Tydskr. Vir Seewetenskap **24**: 323–339.

Harley, S.J., Myers, R.A., and Dunn, A. 2001. Is catch-per-unit-effort proportional to abundance? Can. J Fish. Aquat. Sci. **58**(9): 1760–1772.

Hilborn, R., and Walters, C.J. 1992. Quantitative Fisheries Stock Assessment Choice, Dynamics and Uncertainty. Routledge, Chapman and Hall.

MacCall, A.D. 2009. Depletion-corrected average catch: A simple formula for estimating sustainable yields in data-poor situations. ICES J. Mar. Sci. **66**(10): 2267–2271. doi:10.1093/icesjms/fsp209.

Punt, A.E., Butterworth, D.S., de Moor, C.L., De Oliveira, J.A.A., and Haddon, M. 2016. Management strategy evaluation: Best practices. Fish Fish. **17**(2): 303–334. doi:10.1111/faf.12104.

Quinn T.J., J., and Deriso, R.B. 1999. Quantitative Fish Dynamics. Oxford University Press, New York.

Schnute, J.T. 1985. A general theory for the analysis of catch and effort data. Can. J. Fish. Aquat. Sci **42**(3): 414–429.

Walters, C. 2003. Folly and fantasy in the analysis of spatial catch rate data. Can. J. Fish. Aquat. Sci. **60**: 1433–1436.

Walters, C.J. 2004. Simple representation of the dynamics of biomass error propagation for stock assessment models. Can. J. Fish. Aquat. Sci. **61**: 1061–1065.

Walters, C.J., and Martell, S.J.D. 2004. Fisheries Ecology and Management. Princeton University Press, Princeton, NJ.

Table 1. Beta parameter (β) values for Operating Models (OM) that define the hyperstability and hyperdepletion scenarios.

OM	β
S2.B025	0.25
S2.B050	0.4
S2.B10	1
S2.B20	2
S2.B40	4

Table 2. Satisficed MPs used for testing MP performance.

MP	MPInputClass
SP_75MSY	Abundance-based
SP_4010	Abundance-based
DD	Abundance-based
SP_MSY	Abundance-based
DD4010	Abundance-based
DCAC_ML	Length based
SSS_75MSY	Abundance-based
DCACs	Depletion-based
DCAC_40	Depletion-based
DCAC4010	Depletion-based
DDSS_4010	Abundance-based
SPSRA	Depletion-based
DDSS_75MSY	Abundance-based
SSS_4010	Abundance-based
MCD4010	Depletion-based
SPMSY	Catch based
ICI2	Index based
YPR_ML	Length based
BK_ML	Length based
SBT1	Index based
Fratio_ML	Length based
Iratio	Index based
ICI	Index based
SPslope	Abundance-based
Gcontrol	Index based

Table 3. MPs that failed to converge in initial testing.

SBT1
Gcontrol
DD4010
DD
SPslope

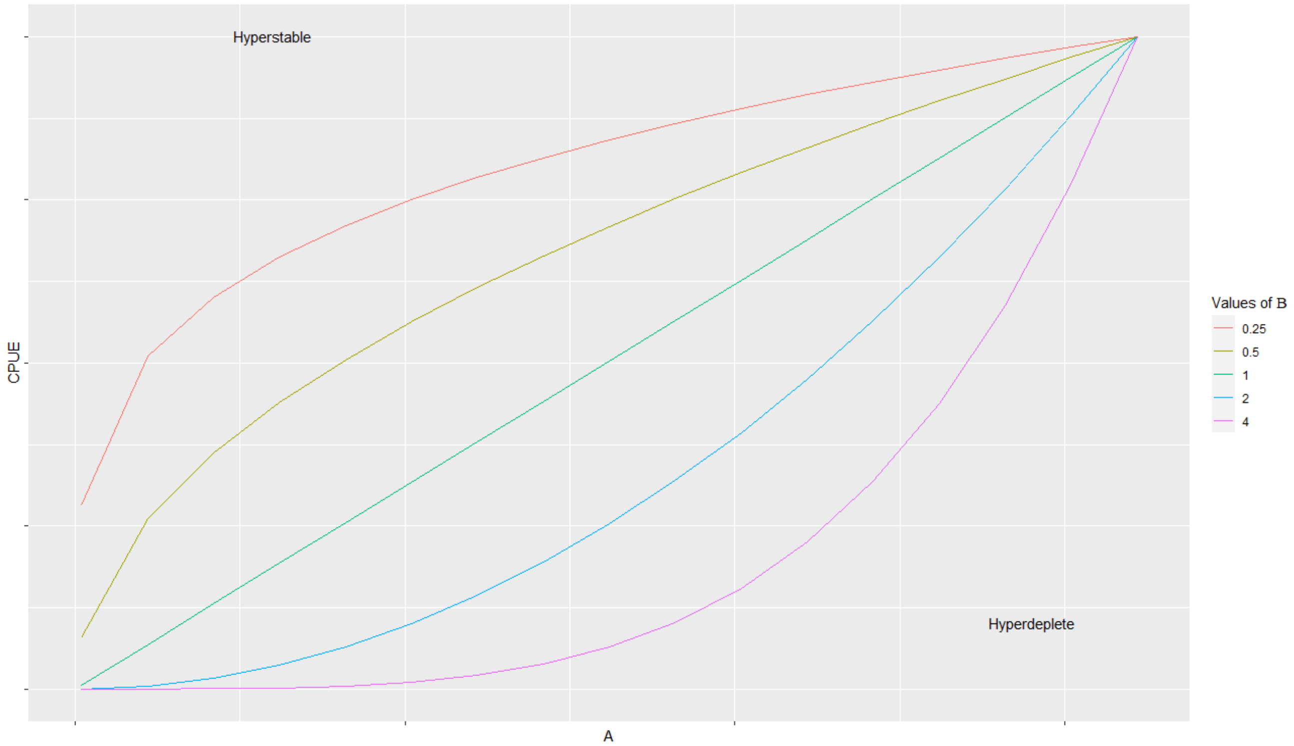

Figure 1. The relationship between normalized CPUE and abundance across.

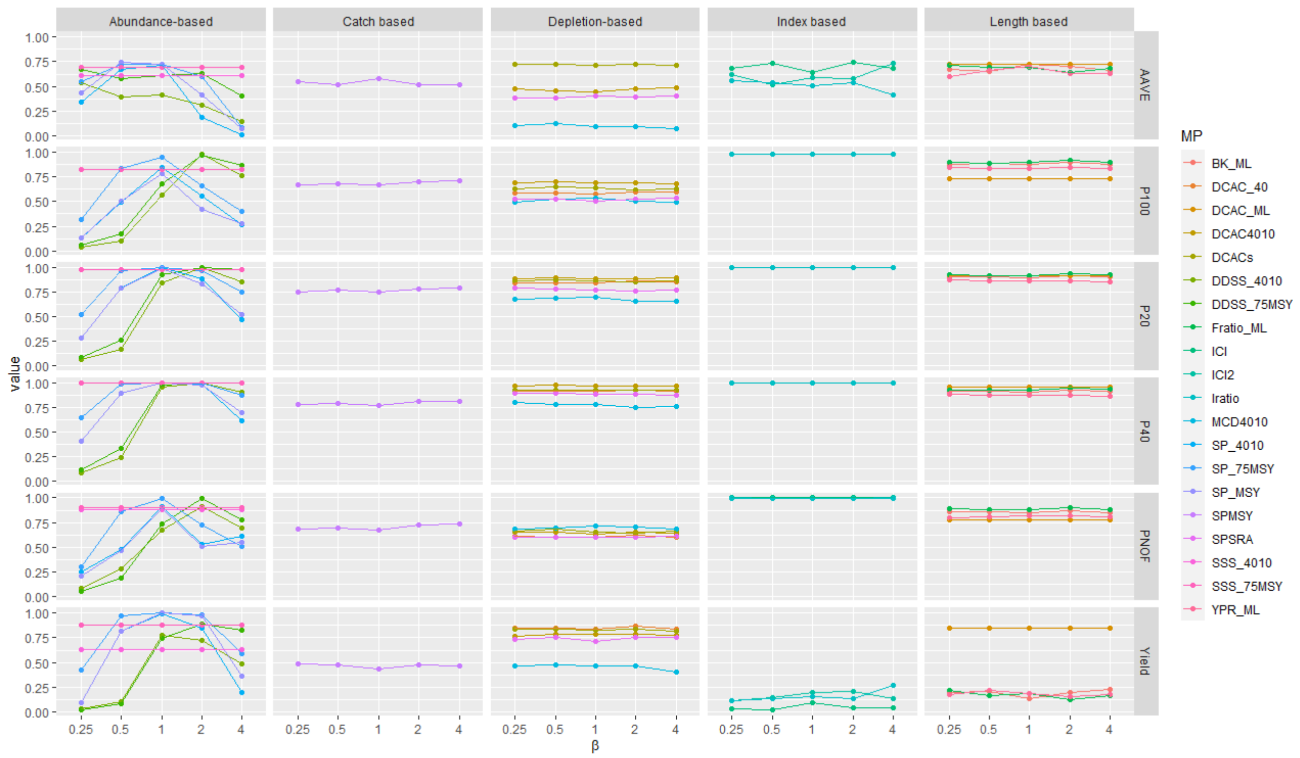

Figure 2. Performance metric values (y) vs β by different data input classes (columns) and by Performance Metric (rows). P20 is the probability of being above 20%SSB0 (the CITES appendix 2 criterion). P100 is the probability the stock is above BMSY, PNOF is the probability that F is greater than FMSY and AAVE is the probability that the average annual variability in effort is greater than 20%.

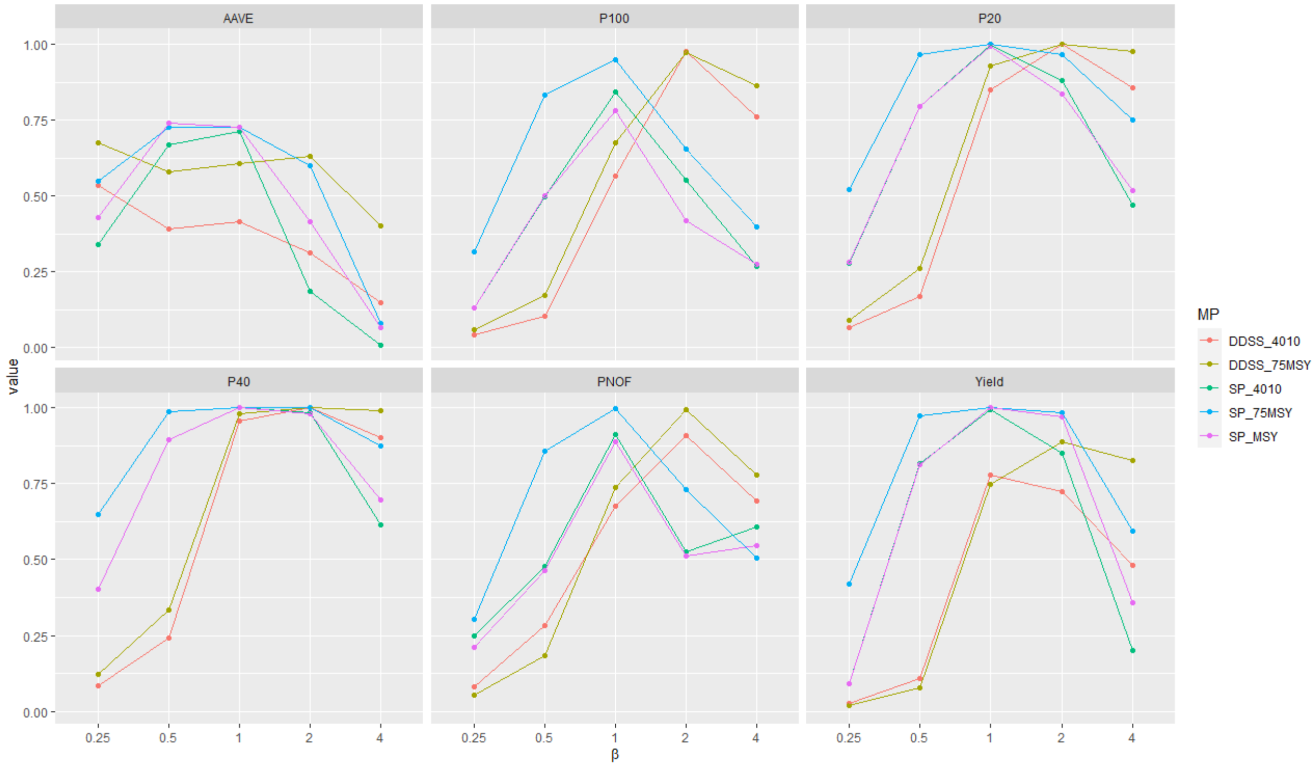

Figure 3. Summary of MP performance for delay difference and surplus production models. P100 is the probability the stock is above BMSY, PNOF is the probability that F is greater than FMSY and AAVE is the probability that the average annual variability in effort is greater than 20%.