SCRS/2020/047 Collect. Vol. Sci. Pap. ICCAT, 77(x): x-xxx (2020)

VALIDATION OF PRODUCTIVITY ANALYSIS FOR DATA LIMITED STOCKS

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SUMMARY

Regional Fisheries Management Organisations have the responsibility to manage not just the main commercial stocks but also by caught species that may be endangered, threatened or protected and the associated communities. Although ICCAT has over hundred species in its database only 15 stocks have been formally assessed. This is due either to lack of data, capacity or management recommendations. The lack of formal assessments may hamper progress towards Ecosystem Based Fisheries Management. We therefore evaluate estimates of and proxies for productivity for data limited stocks. We do this by evaluating potential methods using data rich stocks as a benchmark.

KEYWORDS

Data Poor; Ecosystem Based Fisheries Management; Ecological Risk Assessment; Productivity; Value-of-Infomation.

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Introduction

ICCAT has recently amended its Convention (PLE_108/2019) to include, inter alia, that the Commission and its Members, in conducting work under this Convention, shall be responsible:

> *for the study of the populations of tuna and tuna-like fishes and elasmobranchs that are oceanic, pelagic, and highly migratory, hereinafter referred to as "ICCAT species", and such other species caught while fishing for ICCAT species*

Regional Fisheries Management Organisations (RFMOs) like ICCAT have increasingly to assess not only the main target species but also bycaught Endangered, Threatened and Protected (ETP) species and the associated ecological communities affected while fishing for the target species. In many cases, however, the data available are insufficient to use traditional stock assessment methods based on catch and age data and indices of abundance. For example, although ICCAT list over a hundred species in its database, currently only 15 tuna and billfish species have been formally assessed. This is due to inefficient processes, lack of data, capacity or management recommendations. This lack of formal assessments may hamper progress towards assessing ETP species.

By-catch is therefore a growing concern for Regional Fisheries Management Organizations (RFMOs). and the fishing fleets who increasingly wish to be Marine Stewardship Council (MSC) certified. For example most of the bycatch of species in the tuna fisheries has never been studied, partly due to the limited data available since a large part of their catches are not recorded (Lucena-Frédou, et al., 2017). Consequently, stock status and life-history characteristics for the majority of these teleosts are largely unknown.

Growing concerns over the impact of the tuna fisheries on bycatch species (King and McFarlane, 2003) have led RFMOs to develop holistic approaches to the assessment and management of all exploited species. Several approaches have been developed, for example to use life history information to rank species according to their intrinsic sensitivities to threats such as fishing (Dulvy et al., 2004, Reynolds et al., 2005). One approach is Productivity and Susceptibility Analysis (PSA; Hobday et al., 2007, 2011) which estimates the vulnerability of a stock based on its biological productivity and susceptibility to fishing. The approach relies on the relationship between the life history characteristics of a stock and its productivity, and its susceptibility to being caught in a fishery.

This study aims to validate methods used to estimate productivity of unassessed, i.e. data poor species, by testing them on data rich stocks where estimates of productivity are available from formal stock assessments.

Material and Methods

We used the RAM legacy database. a compilation of stock assessment results for commercially exploited marine populations from around the world (https://www.ramlegacy.org) to obtain estimates of productivity based on target reference points, i.e. maximum stustainable yield (MSY) and the fishing mortality (F_{MSY}) that would achieve it. The stocks assessment results in the legacy database have been used extensively in management and many global studies have made extensive use of the database (e.g. Hilborn at al., 2020, Rosseau, et al., 2019). We use this well-studied dataset as a benchmark to evaluate the performance of techniques currently used to estimate productivity. This allows the Value-of-Infomation (VoI) to be evaluated, e.g. which is more important for determining bias and precision, the data or expert (prior) knowledge?

A number of life history characteristics have been used as proxies for productivity, i.e. maximum Size (L_{max}) or $L_{infinity}$, the von Bertalanffy growth coefficient (k), size at first maturity (L_{50}), and the ratio L_{50}:$L_{infinity}$. We used life-history parameters from Fish Base, for the data rich stocks in the RAM legacy database and compared these to the estimates H_{MSY} , the harvest rate corresponding to F_{MSY}. Since for data rich stocks F_{MSY} is good estimate of productivity.

We then calculated the population growth rate (r) under a variety of assumptions, corresponding to the steepness of the stock recruitment relationship (h), selection pattern (i.e. logistic dome shaped, or flat) and natural mortality.

Population Growth Rate

Age structured operating models for the 29 simulated stocks were created using the Fisheries Library in R (FLR, Kell et al., 2007) package FLife (https://github.com/flr/FLife).

Input parameters used were the allometric length-weight parameters (a, b), von Bertalanffy growth parameters L_∞, k and t_0, and the length or age at 50% maturity (L_{50}, a_{50}). These input values are given in Table S1. Table S2 gives further parameters characterising the operating models of the 29 simulated stocks.

Missing input parameters can be estimated by FLife using empirical relationships; namely

$$k = L_\infty^{-0.63}$$

(Gislason et al., 2008) and

$$L_{50} = L_\infty^{0.93}$$

(Beverton, 1992). However, in the present study these equations were not used because empirical estimates were available for each simulated stock.

Growth

Growth was modelled with the von Bertalanffy growth equation

$$L_t = L_\infty\left(1 - e^{-k(t-t_0)}\right)$$

with $1 \leq t \leq a_{max}$.

Natural morality

Natural mortality M was modelled as length dependent according to equation 2 in Gislason et al. (2010):

$$ln(M_L) = 0.55 - 1.61ln(L) + 1.44ln(L_\infty) + ln\ (k)$$

To derive natural mortality at age, the von Bertalanffy growth equation is used.

Maturity

Maturity at age m_t is modelled with a sigmoid function:

$$m_t = \begin{cases} 0, if t < (a_{50} - 5) \\ \frac{t_{sym}}{1+19^{(a_{50}-t)/t_{95}}}, if (a_{50} - 5) \leq t \leq (a_{50} + 5) \\ t_{sym}, if t > (a_{50} + 5) \end{cases}$$

with $t_{sym} = 1$ (maximum maturity value) and $t_{95} = 1$ (steepness of maturity curve).

Selectivity

Fisheries selectivity s_t at age is modelled with a flexible double normal function where the first age with full selectivity is set to a_{50}:

$$s_t = \begin{cases} 2^{-\left(\frac{t-t_1}{sl}\right)^2}, if t < t_1 \\ 2^{-\left(\frac{t-t_1}{sr}\right)^2}, if t \geq t_1 \end{cases}$$

and $t_1 = a_{50} + t_{95}$. The selection pattern was set to an asymptotic selectivity pattern by setting $sr = 5000$ and $sl = 1$

Recruitment

Recruitment (R) is modelled with the Beverton-Holt stock recruitment

$$R = \frac{\alpha S}{\beta + S} \qquad ($$

Reformulated in terms of steepness h (the proportion of expected recruitment produced at 20% virgin spawning-stock biomass S_0 relative to virgin recruitment R_0), this gives

$$R = \frac{0.8 R_0 h S}{0.2 S_0 (1-h) + (h-0.2) S}$$

The population growth rate (r) was estimated from the Leslie Matrix (A), a transition matrix with columns representing age classes (Caswell 1989) i.e

$$N_{t+1} = A N_t$$

where Nt is a vector describing the age composition of the population at time (t). The 1st row of the matrix corresponds to fertility rate by age (f_i), and the sub-diagonal the survival probabilities (s_i) to the end of age i, i.e.

$$\text{A}=\begin{bmatrix} s_0 f_1 & s_0 f_2 & \cdots & s_0 f_{m-1} & s_0 f_m \\ s_1 & 0 & \cdots & 0 & 0 \\ 0 & s_2 & \cdots & 0 & 0 \\ \vdots & \cdots & \ddots & 0 & 0 \\ 0 & 0 & \cdots & s_{m-1} & 0 \end{bmatrix}$$

r can then be derived from λ, the dominant eigenvalue of A:

$$\text{r}=\log(\lambda)$$

For a given value of r the population doubling time is:

$$T_d = log\,(2)/log\,(1 + r)$$

As well as a base case, five scenarios were run to evaluate the sensitivity of the estimates of r to the assumed values of steepness, natural mortality, and selection pattern. The base case assumed a steepness value of 0.9 and that selection pattern was the same as the maturity ogive. The five scenarios were i) steepness = 0.7; ii) flat selection pattern, iii) dome shape selection pattern; iv) higher M; and v) lower M.

Screening

When developing indicators, the total number should be minimised and be complementary and non-redundant (Shin et al. 2010, Kershner et al. 2011). They should also be robust proxies for corresponding ecosystem attributes or pressures (Fulton et al. 2005). They therefore need to be screened using appropriate selection criteria.

Screening potential indicators and reference levels can be performed using Receiver Operating Characteristic or ROC curves (Green and Swets, 1966). A ROC analysis compares the true positive rate (TPR) with the false positive rate (FPR) for different reference levels. Distinguishing between TPR and FPR is important since risks are asymetric, i.e. gains and losses due to failing to act when management action is required are not the same as taking action unneccessarily.

The ROC curve can be thought of as a plot of power as a function of the Type 1 Error of the decision rule. When the probability distributions for both detection and false alarm are known, the ROC curve is generated by plotting the cumulative distribution function (area under the probability distribution of the discrimination threshold) of the detection probability in the y-axis versus the cumulative distribution function of the false-alarm probability on the x-axis. ROC analysis therefore provides a tool to select the best candidate indicators.

An example of a ROC curve is shown in Figure 1, and demonstrates several things: namely

- It shows the trade-off between TPR (or sensitivity) and FPR (or specificity), as any increase in TPR will be accompanied by a decrease in FPR.
- The closer the curve is to the left-hand border and then the top border of the ROC space, the more accurate the test.
- The closer the curve comes to the y=x line of the ROC space, the less accurate is the test.
- The area under the curve is a measure of a test's accuracy. An area of 1 represents a perfect test; an area of .5 represents a worthless test.
- The slope of the tangent line at a cutpoint gives the likelihood ratio (LR) for that value of the test.

To construct ROC curves, we assumed that the objective of the PSA was to identify stocks/species of concern, i.e. those that fell within the lower 10^{th} percentile of productivity estimated by H_{MSY}. The task was then to identify the reference level that when classifying the low productivity stocks would maximise the TPR and minimise the FPR.

Results

Figure 2 shows the relationships between r, H_{MSY}, and the shape of the Pella-Tomlinson production function from data-rich assessments, with data poor estimates of r (r.lh) and the life history parameters $L_{infinty}$, k and L_{50}: $L_{infinty}$. Inspection of the plots and the correlations in the top row show there do appear to be relationships e.g. the correlation between HMSY and k is 0.46, although these are relatively noisy.

The relationship between data poor estimates of population growth rate r under the different scenarios are shown in **Figure 3.** Although the absolute estimates of r change under the different scenarios, the correlations are high and so the rankings of productivity by species are little effected. It appears that the assumed level of M has the biggest impact and that the rankings are robust to uncertainty about steepness and selection pattern.

The ROC curves for life-history parameters and the base case value of r are shown in **Figure 3**. The best classifier is given by the line that contains the point that maximises the TPR and minimses the FPR. The best proxies for productivity are therefore r, rc, L_{50}:$L_{infinity}$ and k. Where rc is the conditional population growth rate (i.e. the growth rate at F_{MSY}).

The ROC curves for different scenarios for estimation of r are shown in **Figure 4.** r is a robust proxy for productivity since despite uncertainly about the actual dynamics classification skill is high and is little effect by uncertainty about the dynamics.

Discussion and Conclusions

- The empirical indicators appear to work well, particularly L_{50}:$L_{infinity}$ and k, and perform nearly as well as those based on r
- r appears to be a robust proxy for productivity.
- A benefit of using a modelled derived quantity is that quantities for use in management can more easily be derived, e.g. population doubling time which could be used as part of a management advice framework.

References

Arrizabalaga, H., Bruyn, P., Diaz, G.A., Murua, H., Chavance, P., Molina, A.D., Gaertner,D., Ariz, J., Ruiz, J., Kell, L.T., 2011. Productivity and susceptibility analysis for species caught in Atlantic tuna fisheries. Aquat. Living Resour. 24, 1–12.

Beverton R.J.H., Holt S.J. 1959. A review of the lifespans and mortality rates of fish in nature and the relation to growth and other physiological characteristics. Ciba Found. Colloq. Ageing 5: 142–177.

Beverton, R.J.H., 1992. Patterns of reproductive strategy parameters in some marine teleost fishes. Journal of Fish Biology, 41: 137–160.

Caswell H. 1989. Matrix population models: construction, analysis, and interpretation Wiley Online Library. Sinauer Associates Inc., Sunderland, MA, 722 pages.

Cortés, E., Arocha, F., Beerkircher, L., Carvalho, F., Domingo, A., Heupel, M.,Holtzhausen, H., Santos, M.N., Ribera, M., Simpfendorfer, C., 2009. Ecological risk assessment of pelagic sharks caught in Atlantic pelagic longline fisheries. Aquat. Living Resour. 23, 25–34.

Cortés, E., Brooks, E.N., Shertzer, K.W., 2015. Risk assessment of cartilaginous fish populations. ICES J. Mar. Sci. 72, 1057–1068.

Dulvy, N.K., Jennings, S., Goodwin, N.B., Grant, A., Reynolds, J.D., 2005. Comparison of threat and exploitation status in Northeast Atlantic marine populations. J. Appl. Ecol. 42, 883–891. King, J.R., McFarlane, G.A., 2003. Marine fish life history strategies: applications to fisheries management. Fish. Manag. Ecol. 10, 249–264.

Fulton EA, Smith ADM, Punt AE. 2005. Which ecological indicators can robustly detect effects of fishing? ICES J Mar Sci 62:540–551Hilborn, R., 2011. Future directions in ecosystem based fisheries management: a personal perspective. Fisheries Research, 108(2-3), pp.235-239.

Hilborn, R., Amoroso, R.O., Anderson, C.M., Baum, J.K., Branch, T.A., Costello, C., de Moor, C.L., Faraj, A., Hively, D., Jensen, O.P. and Kurota, H., 2020. Effective fisheries management instrumental in improving fish stock status. Proceedings of the National Academy of Sciences.

Gislason, H., Daan, N., Rice, J. and Pope, J., 2008. Does natural mortality depend on individual size. ICES CM 2008/F:16.

Gislason, H., Daan, N., Rice, J. C., and Pope, J. G. 2010. Size, growth, temperature and the natural mortality of marine fish. Fish and Fisheries, 11: 149–158.

Green, D. M., & Swets, J. A. (1966). Signal detection theory and psychophysics. New York: Wiley

Kell, L. T., Mosqueira, I., Grosjean, P., Fromentin, J.-M., Garcia, D., Hillary, R., Jardim, E., *et al.* 2007. FLR: an open-source framework for the evaluation and development of management strategies. ICES Journal of Marine Science, 64: 640–646.

Kershner J, Samhouri JF, James CA, Levin PS 2011. Selecting indicator portfolios for marine species and food webs: A Puget Sound case study. PLoS One 6:e25248–e25248

Lucena-Frédou, F., Kell, L., Frédou, T., Gaertner, D., Potier, M., Bach, P., Travassos, P., Hazin, F. and Ménard, F., 2017. Vulnerability of teleosts caught by the pelagic tuna longline fleets in South Atlantic and Western Indian Oceans. Deep Sea Research Part II: Topical Studies in Oceanography, 140, pp.230-241.

Reynolds, J.D., Jennings, S., Dulvy, N.K., 2001. Life histories of fishes and population responses to exploitation. In: Reynolds, J.D., Mace, G.M., Redford, K.H., Robinson, J.G. (Eds.), Conservation of exploited species. Cambridge University Press, Cambridge, 147–168.

Rousseau, Y., Watson, R.A., Blanchard, J.L. and Fulton, E.A., 2019. Evolution of global marine fishing fleets and the response of fished resources. Proceedings of the National Academy of Sciences, 116(25), pp.12238-12243.

Shin YJ, Bundy A, Shannon LJ, Simier M, Coll M, Fulton EA, Link JS, Jouffre D, Ojaveer H, MacKinson S, Heymans JJ, Raid T. 2010. Can simple be useful and reliable? Using ecological indicators to represent and compare the states of marine ecosystems. ICES J Mar Sci 67:717–731

Figures

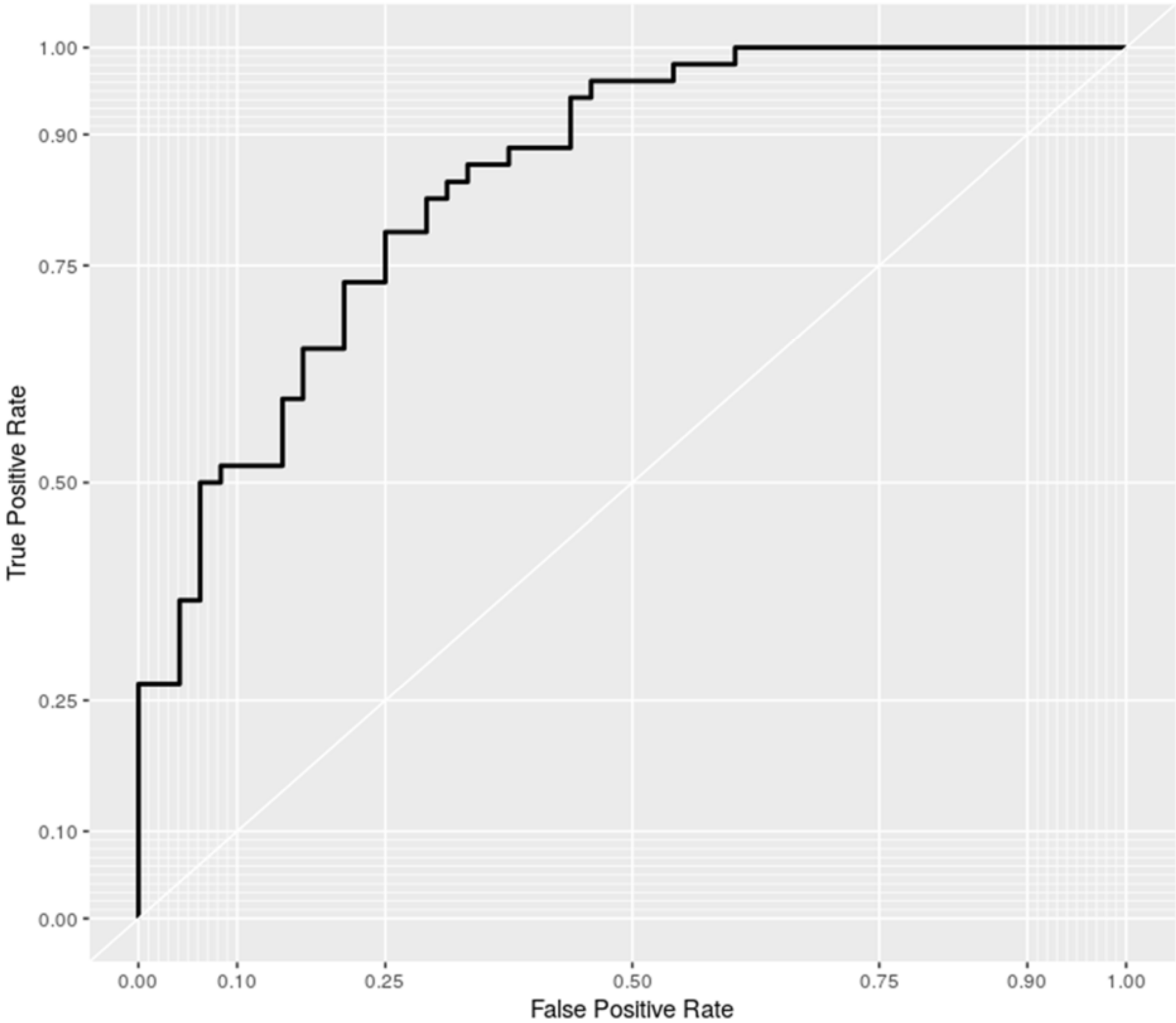

Figure 1. Reciever Operator Characteristic curve, showing an example of a classifier, the y=x line represents a model with no skill.

SC-ECO

Productivity Analysis

L Kell
10 April, 2020

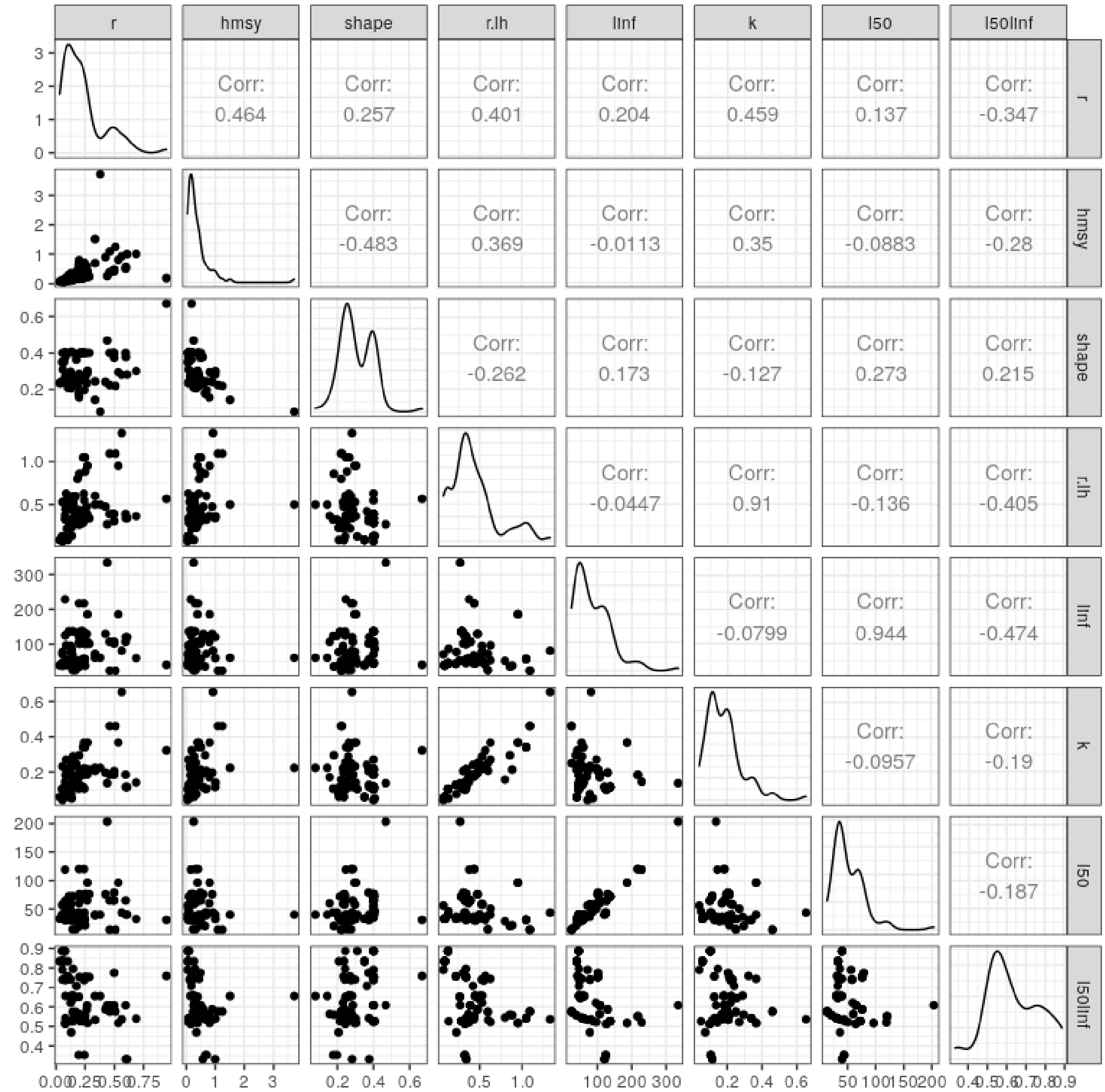

Figure 2 Relationships between r, H_{MSY}, and the shape of the Pella-Tomlinson production function from data rich assessments, with data poor estimates of r (r.lh) and life history parameters $L_{\nfty}$, k and L_{50}/L_{∞}.

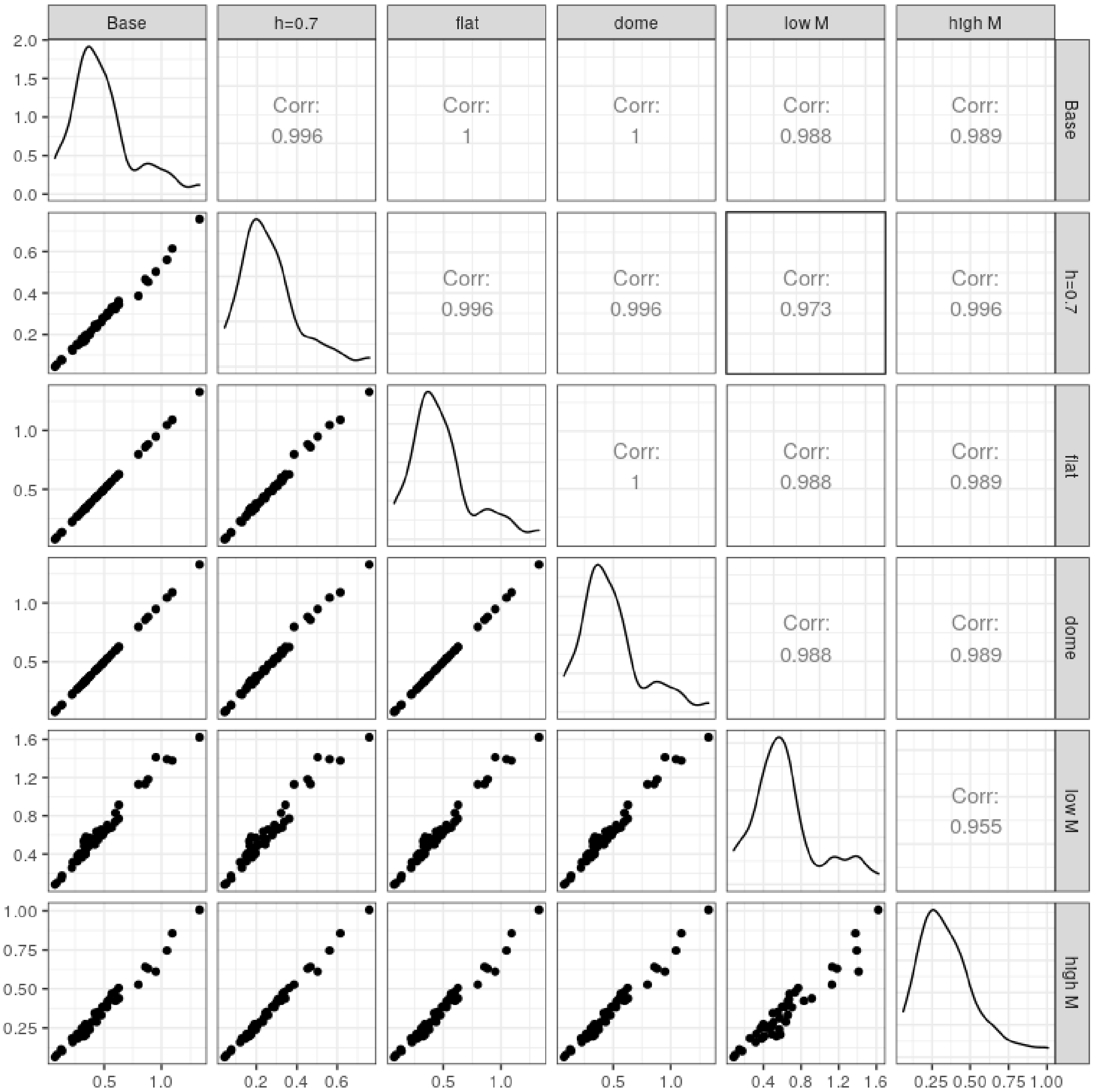

Figure 3 Relationship between data poor estimates population growth rate (r) under the different scenarios.

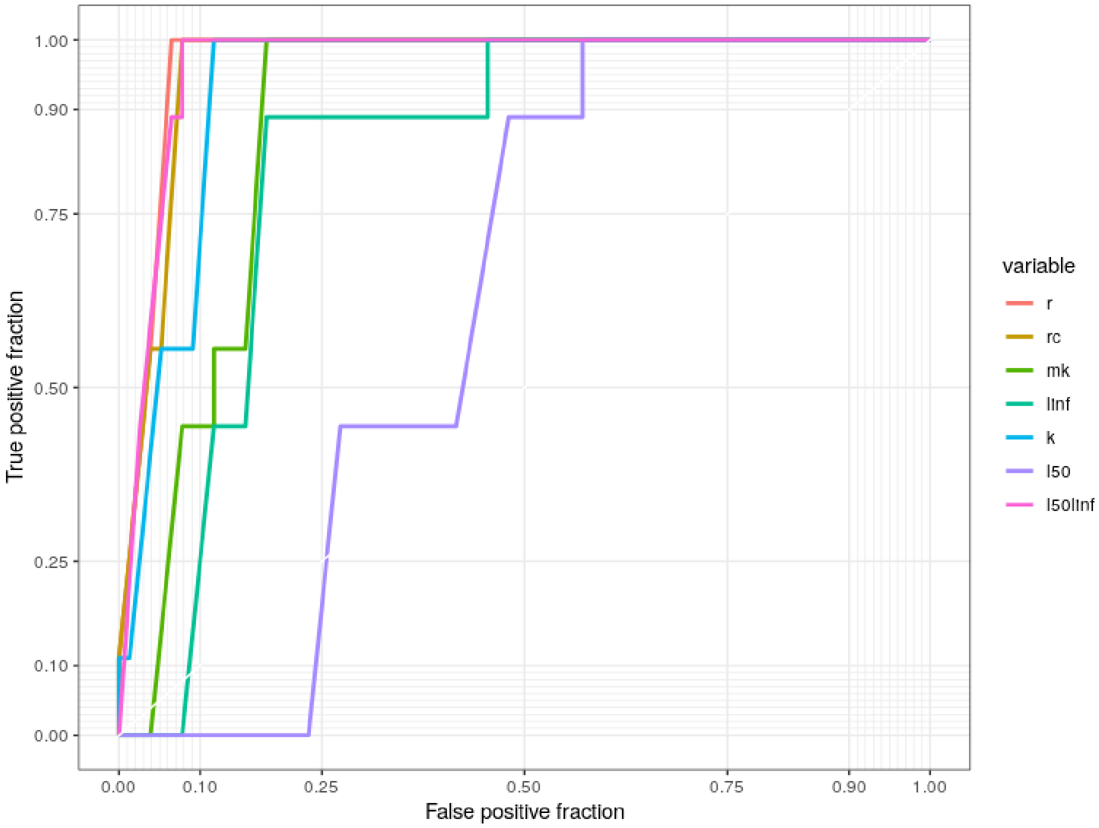

Figure 4 ROC curves for life history parameters and derived quantities.

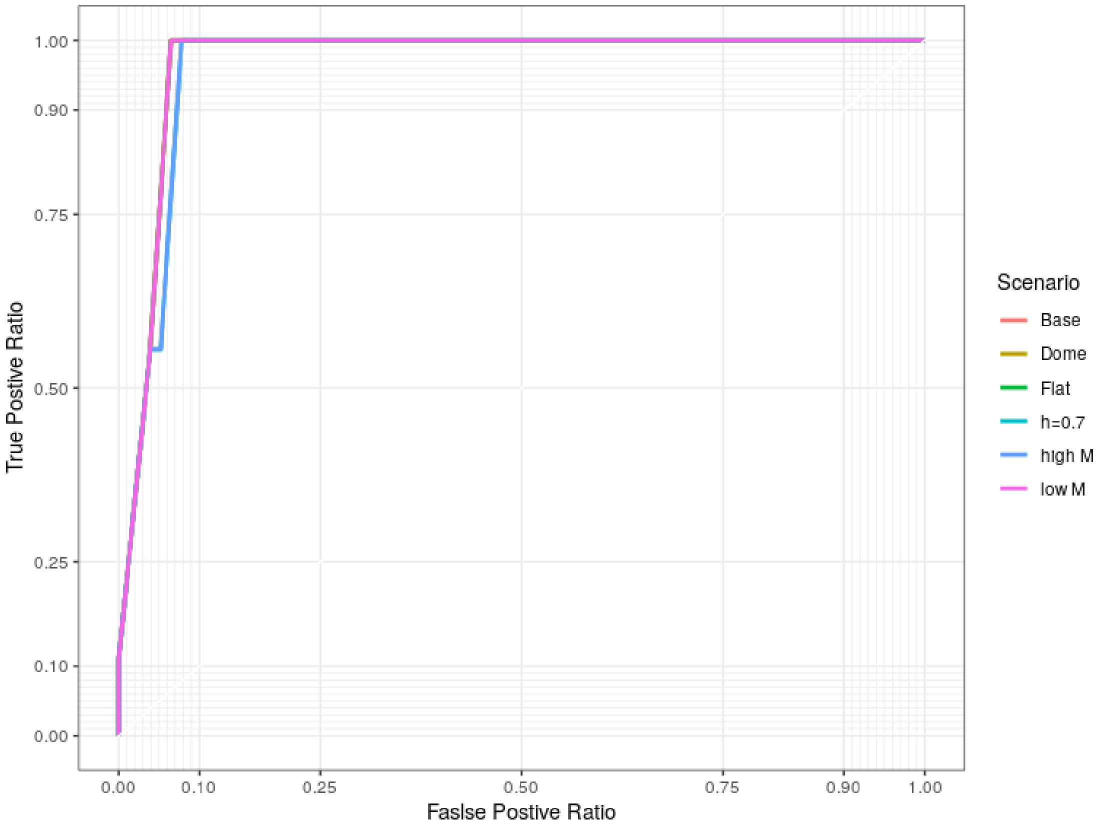

Figure 5 ROC curves for different scenarios for estimation of r