# An Evaluation of the Robustness of Indices of Productivity Used for the Management of Data Poor and Knowledge Limited Fish Species.

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**Abstract**

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# 1 Introduction

Biological reference points have become central to management following the adoption, by many fisheries organisations, of the precautionary approach (PA, ?). Reference points are used in management as targets to maximise surplus production and limits to minimise the risk of depleting a resource to a level where productivity is compromised. They must integrate dynamic processes such as growth, recruitment, mortality and connectivity into indices for spawning reproductive potential (?) and exploitation level. They are increasingly required for by-caught, threatened, endangered, and protected species where data and knowledge are limited (?), not just for the main commercial stocks, where analytical assessments are available.

In data poor situations life history parameters, such as maximum size and size at first maturity have been used as proxies for productivity (?????). For example in Ecological Risk Assessment (ERA) where the risk of a stock to becoming overfished is evaluated using indices of productivity and susceptibility to fishing (?). Life history attributes are combined and used to rank stocks, populations or species in order of productivity (e.g. ??).

Ranking using a mixture of attributes, however. is sensitive to the choice of attributes, the weights applied when combining them and the methods used in their derivation. Random errors may lead to a switch in rankings, and can influence outcomes considerably (?). Robust rankings, where ranking order is stable, are normally considered to be reliable and trustworthy, and conversely non-robust rankings as unreliable and unstable (?). The robustness of ranking in a composite index, however, may be due to a redundancy of attributes. If so it may make little sense to combine correlated indices (?). Robustness can therefore be both desirable and undesirable simultaneously.

For data poor stocks, where attributes may not be available for all species, a variety of ad-hoc approaches have been used to handle missing data, which may introduce noise and bias (?). An important objective when providing advice is robustness. In statistics, a test is robust if it provides insight despite its assumptions being violated. While in engineering, a robust control system is one that still functions correctly in the presence of uncertainty or stressful environmental conditions (**?**).

A robust index should be both reliable and stable. An index or test has a high reliability if despite uncertainty it provides an accurate result. While an index is stable if despite random error, similar results are produced across multiple trials. To evaluate reliability and stability, and hence robustness, of data poor indices a data rich dataset was first compiled. Then a data poor dataset was created by removing values at random from the reference dataset. Indices were calculated using the data poor set and compared to the population parameters from the reference set, for which they are proxies.

# 2 Material and Methods

Reliability and stability were evaluated by comparing rankings based on the indices of life history attributes from the data poor dataset and the population parameters from the reference set. Spearmans rank correlation coefficient ($\rho$ **?**) was used, $\rho$ is a non-parametric measure of dependence between two variables. A correlation coefficient or +1 or 1 indicates that there is a perfect monotonic relationship between two variables.

## 2.1 Data

The reference set was created by selecting species of the order *teleost* from FishBase where parameters for growth, length at maturity and length/weight parameters were available for several species within a family. The resulting reference set comprised eighteen families, namely *Carangidae, Clupeidae, Cyprinidae, Engraulidae, Gadidae, Lutjanidae, Merlucciidae, Mugilidae, Mullidae, Pleuronectidae, Salmonidae, Sciaenidae, Scombridae, Scophthalmidae, Sebastidae, Serranidae, Soleidae* and *Sparidae*; 139 species in total.

The data poor dataset was then generated by removing a third of the observations from the reference data set at random.

## 2.2 Methods

For each species the life history parameters were used to parameterise a **?** growth curve, a logistic ogive for proportion mature-at-age ogive, natural mortality-at-age (**?**) and a **?** stock recruit relationship. Spawning stock biomass (SSB) was was used as a proxy for stock reproductive potential (SRP **???**). This assumes that fecundity is proportional to the mass-at-age of the sexually mature portion of the population irrespective of the demographic composition of adults (**?**) and that processes such as sexual maturity are simple functions of age (**?**) and independent of gender.

These processes allow an equilibrium per-recruit model combined with a stock recruitment relationship **?** and a Leslie matrix (**?**) to be parameterised.

Four population parameters were then derived, i.e. i) the ratio of $SSB_{MSY}$ to virgin biomass ($SSB_{MSY}/K$; ii) population growth rate at low population size ($r$); iii) population growth rate at $B_{MSY}$ ($r_{B_{MSY}}$); and iv) the size at which a year-class achieves its maximum biomass $L_{opt}$). $r$ is equivalent to level of exploitation that would drive a population to extinction since a population can not replenish itself if the harvest rate is greater than this, and corresponds to a limit exploitation reference point. $r_{B_{MSY}}$ corresponds to a target exploitation level, since fishing at this level will on average maintained a population at $SSB_{MSY}$. $SSB_{MSY}/K$. $r_{B_{MSY}}$ provides an index of the resilience to recruitment overfishing since if $SSB_{MSY}$ is small compared to $K$ then recruitment levels will be maintained at low stock levels. While $L_{opt}$ is a measure of resilience to growth overfishing.

Reference points and population parameters are highly sensitive to the assumptions about natural mortality-at-age (**?**), vulnerability of age classes to the fisheries (**?**). While the relationship between stock and recruitment is difficult to estimate in practice (e.g. **?????**). Therefore four scenarios (**???**) were considered. Each factors has two levels and were i) the shape of the selection pattern (dome shaped or flat topped), ii) whether juveniles were vulnerable to fishing, iii) M varied by age and iv) steepness of the stock recruitment relationship.

### 2.2.1 Imputation

The data poor dataset was generated by removing a third of the data points for the **?** growth equation parameters $k$ the rate at which the rate of growth in length declines and the asymptotic length $L_\infty$, $L_{50}$ the length at which 50% of individuals attain gonadal maturity for the first time, $L_{50}/L_\infty$ and $b$ the condition factor. This procedure was repeated 100 times and Multiple imputation (MI, **?**) used to fill in the missing entries.

Imputation involves drawing values from a posterior distribution, which reflects the uncertainty surrounding the parameters of the distribution that generated the data. It therefore simulates both the process generating the data and the uncertainty associated with the parameters. **?** showed that if the method to create the imputations is 'proper', then the resulting inferences will be statistically valid. Multiple imputations are said to be proper if the MI estimates $\hat{Q}_{MI}$ are asymptotically normal with mean $\hat{Q}$ and a consistent variancecovariance estimate $B$; and within-imputation variance estimate W is a consistent estimate of the variancecovariance estimate U with variability of a lower order than $Var(\hat{Q}_{MI})$.

Analysis of the imputed data is simpler than the same analysis without imputation since there is no need to bother with missing data. The final step pooling consists of computing statics such as the mean, variance, confidence interval, P value or rank over the simulated data sets.

Analysis was performed on each of the 100 data set singularly before pooling them into the final results. Indices considered were the life history parameters ($k$, $L_{50}$, $L_\infty$, $L_{50}/L_\infty$, $b$); combinations of them i.e. $index_3$ is the rank based on combining the ranks of $k$, $L_{50}$ and $L_\infty$ and $index_3$ based on combining the ranks of $k$, $L_{50}$, $L_\infty$, $L_{50}/L_\infty$ and $b$ and; the first two principal components of the life history parameters.

The benefit of improving the data poor dataset, by targeted studies, was evaluated by creating four datasets by replacing missing values with the values from the reference set for $k$, $L_\infty$, $L_{50}$ and $b$ in turn.

Principal Component Analysis (PCA, **?**) was used to summarise the datasets. PCA assumes that components with larger variance correspond to the interesting dynamics and lower ones to noise. The first principal axis is the one which maximizes the variance, as reflected by its eigenvalue. The second component is orthogonal to the first and maximizes the remaining variance. The first two component should therefore yield a good approximation of the original variables.

# 3 Results

Life history attributes, in the reference set, and the correlations between them are shown in Figure 1. The relationship between life history attributes ($k$, $L_{50}$, $L_\infty$, $L_{50}/L_\infty$ and $b$) is summarised in Figure 2 for the reference set using PCA. 70% of the variance is summarised by the first two components; individual species are shown as points and the ellipses show the 0.95 normal probability density. The first component contrast species that reach a large size ($L_\infty$) with those that are fast growing ($k$) and mature early ($L_{50}/L_\infty$). The second component summarises body shape ($b$). For example *Clupeidae* are fast growing, early maturing and thin; in contrast to *Sebastidae* which are late maturing and slow growing with a compact body shape.

The population parameters in the reference set, are summarised in Figure 2, across all scenarios, again 70% of the variance is summarised by the first two components. The first component contrasts population growth rates ($r$ and $r_{B_{MSY}}$) with the shape of the production function ($sk$). Population characteristics are correlated, for example populations with high growth rates are resilient to recruitment overfishing. $L_{opt}$ is orthogonal, i.e. uncorrelated, to the shape of the production function and population growth rate at $B_{MSY}$. Families show a range of characteristic, e.g. *Clupeidae* reach maximum biomass at small and *Merlucciidae* at large size, while *Cyprinidae* show a range of characteristics.

Four factors with two levels each were run as scenarios to evaluate the sensitivity of the results to parameters that are difficult to measure, namely the shape of the selection pattern (dome shaped or flat topped), where juveniles were subjected to fishing mortality, whether M varied by age and steepness. Figure 4 showed that reducing steepness or assuming M varied at age reduced the ratio between Virgin biomass and $B_{MSY}$, while assuming M varied at age resulted in a reduction in $L_{opt}$.

Figure 7 summarises the Spearman rank correlations ($\rho$) between the data poor indices (columns) and the reference set population parameters (rows). A reliable index is one that shows a value of $\rho$ close to 1, while a stable index is one where the variability is small. The boxplot hinges correspond to the inter quartile range , while the whiskers extends from the hinges to the values that are within 1.5 times the interquartile.

- The most reliable index is using $L_\infty$ for $L_{opt}$, it is also stable as variability is small. $L_{50}$ is the next best index, however, when the two attributes are combined as $L_{50}/L_\infty$ the index is a poor proxy.
- For $r$ $k$ is the most reliable.
- While for $r_{B_{MSY}}$ $L_50$, $L_\infty$ and $k$ are equally reliable and $L_{50}$ is the most stable
- Similar results are seen for $sk$, apart from for $k$ which shows low reliability.
- In all case combining all attributes into a single index and $L_{50}/L_\infty$ are not reliable.

An index that is robust to uncertainty about processes will not vary by scenario. There were four scenarios with two factors each, these are shown in Figure 6, all the interactions are shown. The first eight scenarios are for the when it is assumed that the M vector that does not vary by age and the last eight for the Gislason form of M. Odd scenarios are for a steepness of 0.75 and even for a steepness of 0.9.

- For $r$ and $r_{B_{MSY}}$ the assumption about M have a large effect. The indices are more reliable when M varies by age, while the assumption about steepness hase less effect. Vulnerability has no effect on $r$, while $r_{B_{MSY}}$ is affected when juveniles are vulnerability to fishing.
- For $sk$ the form of M has the biggest effect.

The benefit of reducing uncertainty by collecting more data is evaluated in Figure 6, and combines all the scenarios into a single box plot.

- Collecting data on $k$ improved the correlations between $k$ and $r$ and $r_{B_{MSY}}$, improving data on the other traits had little impact.

- That in general collecting more data did not have a large impact shows that the imputation process is robust.

- The variances were less for $L_{opt}$.

# 4 Discussion and Conclusions

**Uncertainty** In fisheries science and management uncertainties are pervasive due to imperfect information, the natural variability of aquatic ecosystems and lack of perfect control over fisheries **?**. To ensure that the risk of failing to meet management objectives is low requires a consideration of uncertainty (**?**).

**Risk** Risk is an uncertainty that matters. What matters depends on management and conservation objectives, and whether objectives are achieved depends on the management framework. Depending on the level of uncertainty different procedures may be used to derive reference points for use in management (**?**).

**Management Frameworks** In data rich cases where an analytical stock assessment is available and a clear relationship between recruitment and spawning stock biomass is evident and growth, natural mortality (M), maturity and selectivity are known then maximum sustainable yield (MSY) based reference may be used. If the stock recruitment relationship is uncertain then per-recruit reference points are used instead. While for information and data poor situations life history attributes are combined in to index and used to rank in order of productivity.

**Robustness** An aim of the study was to evaluate the robustness of productivity indices used in data poor situations. An index is robust if it provides insight despite the assumptions being violated. Therefore to evaluate robustness we generated a data poor dataset from a data rich reference set; alternative data poor indices were then calculated and compared them to reference points and population parameters derived from the reference set. This was done for a range of scenarios to evaluate the sensitivity of the indices to parameters that are difficult to measure such as natural mortality and the relationship between recruitment and stock.

Imputation was used to create a database of life history attributes, filling in missing values, before calculating the indices. Imputation is usually the most challenging step since it must account for the process that created the missing data. Namely the data must be missing completely at random. Analysis of the imputed data is simpler than the same analysis without imputation since there is no need to bother with missing data. The final step pooling consists of computing statics. In this case the statistic used was Spearman correlation to compare the reliability of ranks based on the indices and imputation used to evaluate the stability of the ranks.

**Lessons for data poor case studies** Knowledge about the structure is helpful in identify the mechanism which generated the missing data and for aiding in selection of an appropriate imputation method to estimate missing values (**?**). For example estimates of $L_\infty$ and $k$ are often correlated owing to a lack of large old fish in samples, and so only the product of the two can be estimated with reasonable precision (**?**).

**Lessons for data rich case studies** An Understanding of population rynamics is important for stock assessment, since data rich stock assessments often rely upon life history parameters for deriving priors for difficult to estimate population parameters (**????**). Life history parameters are also a major input into ecological risk assessments (ERA) used to prioritise management action (**??**) and ecological models used to help develop an ecosystem based approach to fisheries management (**?**).

https://www.ramas.com/CMdd.htm

# 5 Conclusions

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# 6 Acknowledgement

This study does not necessarily reflect the views of ICCAT and in no way anticipates the Commission's future policy in any area.

# 7 Figures

refLhPairs-1.png

Figure 1: Correlations between life history parameters in the data rich reference dataset.

pcaLh-1.png

Figure 2: Biplots from principle component analysis of life history parameters in the data rich reference dataset.

pcaPop-1.png

Figure 3: Biplots from principle component analysis of life history parameters in the data rich reference dataset by family.

pcaPop2-1.png

Figure 4: Biplots from principle component analysis of productivity metrics in the data rich reference dataset by scenarios.

/home/laurie/MEGAsync/papers/1lifeBalance/tex/stab4-1.png

Figure 5: Spearman rank correlation coefficients between life history parameters and indices and population parameters for the data poor set. The upper and lower boxplot hinges correspond to the first and third quartiles (the $25^{th}$ and $75^{th}$ percentiles), while the whiskers extends from the hinge to the value that is within 1.5 times the interquartile range of the hinge.

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Figure 6: Spearman rank correlation coefficients between life history parameters and indices and population parameters for the data poor set; boxplots by scenarios. The upper and lower boxplot hinges correspond to the first and third quartiles (the $25^{th}$ and $75^{th}$ percentiles), while the whiskers extends from the hinge to the value that is within 1.5 times the interquartile range of the hinge.

Figure 7: Spearman rank correlation coefficients between life history parameters and indices and population parameters for the data poor set; boxplots by augmented dataset. The upper and lower boxplot hinges correspond to the first and third quartiles (the $25^{th}$ and $75^{th}$ percentiles), while the whiskers extends from the hinge to the value that is within 1.5 times the interquartile range of the hinge.

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# 8 Appendix

## 8.1 Population Growth Rate

The maximum theoretical rate of increase of a population in the absence of density-dependent regulation is given by

$$r = \frac{dN}{dt}\frac{1}{N} \tag{1}$$

where the intrinsic population growth rate ($r$) is a function of population size ($N$) and $\frac{dN}{dt}$ the instantaneous rate of increase of the population.

In ecology Leslie matrices (**?**) are widely used to estimate r (**?**) and have been used in fisheries to develop Bayesian priors for r for use in stock assessment (see **?**). The Leslie Matrix ($A$) is a transition matrix that models age dynamics. Each age-class is described by a vector ($B_t$) of length p equal to the terminal age. Entries in the matrix are fecundity ($f_i$) (the quantity of age zero females produced per unit of mature biomass by each age-class) and the survival (and growth if biomass) of an age-class ($s_i$) in each time step $i$, i.e.

$$\begin{aligned}
n_1 &= f_2 n_2 + ... + f_3 n_p \\
n_2 &= s_1 n_1 \\
&... \\
n_p &= s_{p-1} n_{p-1} + s_p n_p
\end{aligned} \tag{2}$$

The matrix of this linear system is

$$\mathbf{A} = \begin{pmatrix} 0 & f_2 & ... & f_p \\ s_1 & 0 & ... & 0 \\ & ... & & \\ 0 & ... & s_{p-1} & s_p \end{pmatrix} \tag{3}$$

If the initial population is

$$\mathbf{B}^0 = \begin{pmatrix} n_1 \\ n_2 \\ \dots \\ n_p \end{pmatrix} \tag{4}$$

then after time step i=1 the population is given by

$$\mathbf{B}^i = \mathbf{A}^i \mathbf{B}^0 \tag{5}$$

As $i$ tends to infinity the system reaches equilibrium and the contribution of each age group in the population becomes stable. The population growth rate $r$ is then derived from $\lambda$ the dominant eigenvalue of $A$ (**?**).

To construct the Leslie matrix requires estimates of $f_i$ and $p_i$. In this study these were derived by combining a stock recruitment relationship with a spawner-per-recruit ($S/R$) and yield-per-recruit ($Y/R$) analyses. The life history parameters were used to derive mass ($W$), proportion mature ($Q$), natural mortality ($M$) and fishing mortality ($F$) at age.

$$S/R = \sum_{i=0}^{p-1} e^{\sum\limits_{j=0}^{i-1} -F_j - M_j} W_i Q_i + e^{\sum\limits_{i=0}^{p-1} -F_i - M_i} \frac{W_p Q_p}{1 - e^{-F_p - M_p}} \tag{6}$$

$$Y/R = \sum_{a=r}^{n-1} e^{\sum\limits_{i=r}^{a-1} -F_i - M_i} W_a \frac{F_a}{F_a + M_a} \left(1 - e^{-F_i - M_i}\right) + e^{\sum\limits_{i=r}^{n-1} -F_n - M_n} W_n \frac{F_n}{F_n + M_n} \tag{7}$$

The second term is the plus-group, i.e. the summation of all ages from the last age to infinity.

Growth in length is modelled by the Von Bertalanffy growth equation **?**

$$L = L_\infty (1 - exp(-k(t - t_0)) \tag{8}$$

where $k$ is the rate at which the rate of growth in length declines as length approaches the asymptotic length $L_\infty$ and $t_0$ is the hypothetical time at which an individual is of zero length.

Length is converted to mass using the length-weight relationship

$$W = aL_t^b \tag{9}$$

where $a$ is the condition factor and $b$ is the allometric growth coefficient.

**?** showed that M is significantly related to body length, asymptotic length and k. Temperature is non-significant when k is included, since k itself is correlated with temperature. We therefore model M as

$$M = 0.55L^{1.61}L_\infty^{1.44}k \tag{10}$$

Selection pattern of the fishery was represented by a double normal (see **?**)) with three parameters that describe the age at maximum selection ($a1$), the rate at which the left-hand limb increases ($sl$) and the right-hand limb decreases ($sr$) which allows flat topped or domed shaped selection patterns to be chosen.

$$f(x) = \begin{cases} 0 & \text{if } (a_{50} - x)/a_{95} > 5 \\ a_\infty & \text{if } (a_{50} - x)/a_{95} < -5 \\ \frac{m_\infty}{1.0+19.0^{(a_{50}-x)/_{95})}} & \text{otherwise} \end{cases} \tag{11}$$

The relationship between stock and recruitment was modelled by a Beverton and Holt stock-recruitment relationship (**?**) reformulated in terms of steepness ($h$), virgin biomass ($v$) and $S/R_{F=0}$

$$R = \frac{0.8R_0h}{0.2S/R_{F=0}R_0(1-h) + (h-0.2)S} \tag{12}$$

where steepness is the ratio of recruitment at 20% of virgin biomass to virgin recruitment ($R_0$) and $S/R_{F=0}$ is the spawner per recruit at virgin biomass, i.e. when fishing mortality is zero. Steepness is difficult to estimate from stock assessment data sets as there is often insufficient contrast in biomass levels required for its estimation **?**.

S is spawning stock biomass, the sum of the products of the numbers of females, $N$, proportion mature-at-age, $Q$ and their mean fecundity-at-age, $F$, i.e.

$$S = \sum_{i=0}^{p} N_i Q_i F_i \tag{13}$$

where fecundity-at-age is assumed proportional to biomass and the sex ratio to be 1:1. Proportion mature is 50% at the age that attains a length of $l50$, 0% below this age and 100% above.