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ECOTEST INDICATOR 2: A GENERAL-PURPOSE STOCK STATUS INDICATOR FOR SHARKS, BILLFISH AND TUNAS

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SUMMARY

EcoTest Indicator 1 was previously developed for the specific case of the multi-species, multi-fleet North Atlantic longline fishery. Those neural networks were trained on historical patterns of exploitation rate and assumed the same life-history parameters specified in the most recent stock assessments. Indicator 1 provided good to excellent predictive ability for the two target species, Swordfish and Bigeye tuna, and the four bycatch species, shortfin mako shark, blue shark, white marlin and blue marlin. The aim of Indicator 2 was to drastically widen the applicability of the A.I. methods: a much larger and broader training data set was simulated including a wide diversity of historical and future fishing dynamics and spanning the life histories of the families Istiophoridae (marlins), Scombridae (mackerels, tunas and bonitos) and Carcharhinidae (requiem sharks). Under a range of data availability conditions (e.g. catch, indices, length and age data) Indicator 2 provided reasonable to good predictive capacity depending on data availability, for example in some cases it was able to correctly identify depleted stocks (below 50% BMSY) in more than 80% of simulations.

RÉSUMÉ

L'indicateur 1 de l'EcoTest a été développé précédemment pour le cas spécifique de la pêche à la palangre multi-espèces et multi-flottilles de l'Atlantique Nord. Ces réseaux neuronaux ont été formés sur la base de modèles historiques de taux d'exploitation et ont postulé les mêmes paramètres du cycle de vie que ceux spécifiés dans les évaluations de stocks les plus récentes. L'indicateur 1 a fourni une capacité de prédiction bonne à excellente pour les deux espèces cibles, l'espadon et le thon obèse, et les quatre espèces faisant l'objet de prises accessoires, le requin-taupe bleu, le requin peau bleue, le makaire blanc et le makaire bleu. L'objectif de l'indicateur 2 était d'élargir considérablement l'applicabilité des méthodes d'intelligence artificielle : un jeu de données d'entraînement beaucoup plus important et plus large a été simulé, comprenant une grande diversité de dynamiques de pêche historiques et futures et couvrant le cycle de vie des familles des Istiophoridae (makaires), Scombridae (maquereaux, thons et bonites) et Carcharhinidae (requins requiem). Dans une série de conditions de disponibilité des données (par exemple, captures, indices, données sur la longueur et l'âge), l'indicateur 2 a fourni une capacité de prévision raisonnable à bonne en fonction de la disponibilité des données ; par exemple, dans certains cas, il a été en mesure d'identifier correctement les stocks épuisés (inférieurs à 50 % de B_{PME}) dans plus de 80 % des simulations.

RESUMEN

El indicador 1 del EcoTest se desarrolló previamente para el caso específico de la pesquería de palangre multiespecies y multiflota del Atlántico norte. Dichas redes neuronales se entrenaron a partir de patrones históricos de la tasa de explotación y asumieron los mismos parámetros del ciclo vital especificados en las evaluaciones más recientes stocks. El Indicador 1 proporcionó una capacidad de predicción de buena a excelente para las dos especies objetivo, el pez espada y el patudo, y las cuatro especies capturadas de forma fortuita, el marrajo dientuso, el tiburón azul, la aguja blanca y la aguja azul. El objetivo del Indicador 2 era ampliar drásticamente la aplicabilidad de los métodos de I.A.: se simuló un conjunto de datos de formación mucho mayor y más amplio que incluía una gran diversidad de dinámicas de pesca históricas y futuras y abarcaba las historias vitales de las familias Istiophoridae (marlines), Scombridae (caballas, atunes y bonitos) y Carcharhinidae (tiburones réquiem). En una serie de condiciones de disponibilidad de datos (por ejemplo, datos de capturas, índices, tallas y edades), el indicador 2 proporcionó una capacidad predictiva entre razonable y buena, dependiendo de la disponibilidad de datos; por ejemplo, en algunos casos fue capaz de identificar correctamente los stocks mermados (por debajo del 50 % de la B_{RMS}) en más del 80 % de las simulaciones.

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KEYWORDS

Ecosystem indicators, artificial intelligence, stock assessment, simulation testing

Introduction

To meet the requirements of the precautionary approach and the ecosystem approach to fisheries management (EBFM), indicators of stock status are needed for secondary species, defined here as those lack sufficient data or capacity to conduct routine stock assessments (see Carruthers et al. 2024 for a detailed problem statement). These indicators must be theoretically sound and be validated empirically. The EcoTest project aims to use simulation modelling to identify data and algorithms that can inform stock status of secondary species and then validate these indicators empirically in cases where there have been defensible stock assessments. A well-documented, defensible and transparent framework is needed to support tactical decision making to move beyond the single species assessment paradigm and make progress towards the essential goals of EBFM.

Previous work synthesized the dynamics of six stock assessments (Phase 1) and consolidated those into a single multi-species, multi-fleet operating model (OM) (Phase 2) (**Figure 1**) (Huynh et al. 2022). In Phase 3, those operating models were used to simulate various future scenarios for fishing and stock dynamics to develop Indicator 1: an indicator system specific to the longline case study that could predict stock status for the 6 species without undergoing a full stock assessment.

The key advance of previous work was to use deep learning to train neural networks on the posterior-predicted data of a large number of simulations. The subject of this paper is the continuation of Phase 3 to develop Indicator 2: a more generic indicator system for a wide range of pelagic highly migratory species that are caught in Atlantic fisheries.

Following feedback from earlier work, these indicators should focus on the prediction of stock status relative to a productive level expressed as spawning stock biomass relative to spawning stock biomass corresponding to MSY levels. This is a key reference level for evaluating stock status for the majority of stock assessed by ICCAT. Expert working groups also confirmed that there is interest in developing indicators that can accommodate various numbers of fleets and stocks, and that these should also apply to varying data availability scenarios with respect to length, age and relative abundance data.

Methods

Simulation design

The OpenMSE framework (Hordyk et al. 2025) was used to simulate 100,000 fisheries consisting of three species exploited by three fleets with exploitation beginning in the period 1955 – 1975 and ending in 2024. These multi-stock, multi-fleet operating models were subject to a wide range of life-history dynamics and exploitation patterns / selectivities. For each simulation, a single future year (2025 – 2074) was sampled and posterior predictive data taken from the operating models subject to observation error. The aim was to encompass a very wide range of scenarios to train a neural network that could predict stock status across diverse life-history and fishery types.

Life history types

A meta-analytic approach was used to sample somatic growth, instantaneous natural mortality rate and length-at-50% maturity for the families *Istiophoridae* (marlins), *Scombridae* (mackerels, tunas and bonitos) and *Carcharhinidae* (requiem sharks) from the data recorded in FishBase (Froese and Pauly 2025). This meta-analytic approach is available via the LH2OM() function of MSEtool (Hordyk et al. 2025). This approach preserves the family-specific correlations among these life-history parameters (Figure 2). No relationship was assumed between these parameters and stock resilience and depletion. Steepness and spawning stock depletion in 2024 were sampled from independent uniform distributions in the ranges of 0.6 – 0.95 and 0.05 – 0.5, respectively (**Figure 2**).

For each simulated fishery, the family of each stock was sampled independently at random such that it was possible to sample any combination of *Istiophoridae, Scombridae* and *Carcharhinidae* including an operating model for three stocks of the same family.

Fleet dynamics

Fishing exploitation patterns included a very wide range of scenarios including underlying trends where exploitation rate could for example, increase to a plateau, show recent declines or exhibit cyclical fishing pressure (**Figure 3**).

These trends were subject to additional interannual variability sampled from a log-normal standard deviation in the range of 0.05 to 0.35 (one sampled standard deviation applied to the entire historical time series). The purpose of including multiple fleets was to allow multiple time series of fleet-specific information to be submitted to the indicator system. These could include catch-at-length, catch-at-age and relative vulnerable biomass information (e.g., an appropriately standardized fishery-dependent catch-per-unit-effort time series). A sufficiently wide range of historical effort patterns were simulated such that they encompassed the historical patterns estimated in stock assessments for the six species of the longline case study (Carruthers et al. 2024) and recent tropical tuna assessments.

The purpose of simulating multiple stocks is to borrow information from species that are co-caught and can be assumed to experience a comparable pattern in fishery exploitation rate. In such situations the ratio of catches, length compositions and indices can reveal relative stock depletion (Carruthers 2018). It follows that among stocks, for the same fleet, effective effort was assumed to be positively correlated (coefficient of 60%, **Figure 5**).

Data types

For most secondary species that are not assessed, the typical data that are available include a catch history, recent nominal catch per unit effort (e.g., numbers per set), recent catch-size data and in some cases catch-age data. Posterior predicted data were simulated assuming that annual catches were observed with an error of 10-30% (CV), indices of vulnerable biomass with an error of 10 – 40% (CV), 100-200 independent lengths per year and 25-50 independent ages per year. Mean length and mean age time series were derived directly from those annual samples of lengths and ages. For each simulation, a projected year was selected at random. The posterior predicted data up to the previous year were then processed to provide data inputs to candidate indicator systems. Data were processed to such that they had mean 0 and standard deviation 1 across simulations. All fractions or rates were first log-transformed. Based on these data streams various derived quantities were calculated for each species (**Tables 1** and **2**, **Figure 6**).

Artificial neural networks

Artificial neural networks provide a flexible and powerful tool for revealing the information content of data inputs and designing indicators that have a suitable statistical power to detect conditions of management concern. Using the R packages Keras, Tensorflow, and Miniconda, sequential artificial neural networks were specified for the purposes of solving regression problems. Various designs (depths and widths of layers) were explored. A model with two hidden layers (4 nodes in the first layer, 2 in the second) was the simplest that provided comparable fit to the training and validation datasets. The model was trained to predict the true simulated spawning stock biomass relative to BMSY using up to 579 inputs (**Table 3**). A total of 80,000 simulations were used for training, another 10,000 simulations for validation (a cross-validation check as the neural network trains, that the fit to the training set is comparable to the validation set - it is not overparameterized) and a further 10,000 for the completely independent testing dataset.

Evaluating neural network performance

The predictive ability of the neural networks was evaluated by the independent testing dataset of 10,000 simulations. Summary statistics included mean absolute error (MAE) in log SSB/SSBMSY, the coefficient of determination (R^2), the rate of true positive detection of stocks below the 0.5 SSBMSY (TP_LRP) and true positive detection of stocks between 0.5 SSBMSY and SSBMSY (TP_R).

Results

The artificial neural networks trained rapidly and in many cases achieved an acceptable fit to the simulated SSB / SSBMSY in just 50 epochs, obtaining mean absolute error values a low as 0.27 (mean absolute error in log(SSB/SSBMSY) (**Table 4**, **Figure 7**).

The results confirmed once again, that fishery catch data alone contain no information about stock status and additional information is required to separate the combined effects of exploitation rate and vulnerable biomass (model #1; R^2 close to zero; **Table 4**, top row; **Figure 7**, top-left panel). In these simulations, declines in catches for example, can be due to reductions in fishing pressure and / or stock level. This rather obvious conclusion has nonetheless been contested at length by proponents of so called 'catch only methods', which is analogous to measuring speed using only distance travelled or evaluating a person's financial health based solely on the magnitude of their expenditures.

For a single stock, including recent age, length and relative abundance information dramatically improved predictive performance (model #8; **Figure 7**, top middle panel) with an 80% probability of detecting a stock below 0.5 SSBMSY (R^2 = 0.596).

If recent lengths are available, substantial improvements in predictive performance could be obtained if data from more than one stock are submitted to the neural network. This assumes that those stocks have shared a comparable historical pattern of exploitation rate. For example, model #11 which is trained on catch and length data for 2 stocks and 1 fleet, correctly identified stocks below 50% SSBMSY in 69% of simulations (R^2 = 0.529)

There is evidence that more simulations are required to allow the neural networks to identify the full set of features in the datasets. Adding indices to the example above should provide the same or better predictive performance. For example, model #12 is a version of model #11 with additional index data. However in this case, performance was worse – the indicator could only correctly detect stocks below 0.5 SBBMSY in 62% of simulations with an R^2 of 0.422 (**Figure 7**, bottom right panel). This can only be attributed to either to an insufficiently large training dataset and/or, insufficient training time and/or insufficient neural network complexity.

Given the complete data (e.g., model 62 that includes catches, recent lengths, ages and indices), the models were remarkably accurate and precise, correctly identifying stocks below 50% SSBMSY and above SSBMSY in 81% of simulations (R2 of 0.707, **Figure 7** bottom right panel). These rates are not incomparable to rates achieved by data rich stock assessments give comparable data – a result that should be confirmed in future comparisons of the EcoTest indicator system.

Some neural networks of Indicator 2 failed to train (blank lines of **Table 4**), pointing to a need for an improved system of specifying neural network complexity given the number of data inputs, stock and fleets.

Discussion

By simulating the population dynamics of a wide range of pelagic highly migratory species and varying patterns of exploitation rate, it was possible to generate a predicted dataset for the testing of candidate indicators of stock status of broad generality. Indicator 2 comprises a total of 72 neural networks trained to varying availabilities of data and covariate stocks and fleets. Where new data are submitted, obtaining a status determination from a neural network takes less than a second. These status determinations could include error by empirical resampling approaches such as bootstrapping. Network training took around 30 seconds which means that in principle it might be possible to generate a very large dataset, subset that to a specific pattern of historical exploitation and life-history and retrain an indicator appropriate to the specific data availability of an individual stock.

Artificial neural networks offer a highly flexible approach for establishing whether, for a given dataset, information exists to quantify stock status (e.g., only catches, catches and lengths etc.). The accuracy and precision of the neural networks varied depending on the input data available to the neural network indicators and the number of stocks and fleets for which data were submitted. Unsurprisingly given the much wider range of life-histories and historical effort scenarios, Indicator 2 did not perform as well as Indicator 1 that was tailored to the specific case (and assessed status and histories) of the longline case study and could achieve (e.g. a 90% probability of detecting simulated biomass below 50% SSBMSY).

The indicators established so far underline a missed opportunity in fisheries science relating to the use of multi-stock data. While catch data alone provide no information about stock status, the catches of one stock relative to another can inform relative stock depletion (Carruthers 2018). Across many stocks such ratios provide triangulation that can be further informed by trends in length composition among stocks and fleets. While stock assessments that include multiple stocks struggle to pass peer-review as a basis for management decision making, neural networks can be fitted to such data relative easily, their performance evaluated, and they can then be used as indicators of status for stocks for which routine stock assessments are not possible.

The next step is to conduct evaluation of indicator performance by (1) comparing predictions with those of data-rich stock assessments that are provided with the same simulated data inputs (2) stripping observed time series data to do a retrospective analysis of indicator consistency in inference and (3) applying the indicators to datasets that have been used to conduct defensible stock assessments and compare their estimates.

Phase 4 of EcoTest aims to evaluate the indicators in closed-loop to evaluate their performance within a harvest strategy or as an 'early warning system' that can be used to initiate a stock assessment ahead of schedule. In this MSE-style simulation testing, a key objective is to evaluate the robustness of indicators to systematic changes in biological conditions such as somatic growth, natural mortality rate and availability to fishing.

A key requirement for Phase 4 of EcoTest is to include a useable version of Indicator 1 and 2 in an R package so that users can easily submit data for new species to obtain stock status predictions. In this way EcoTest can provide a quantitative tool to support existing ICCAT approaches such as the Ecosystem Report Card (Juan-Jordá et al. 2018).

There are a number of areas for future development of this indicator approach. The sequential neural networks of this research were fitted to the simulated SSB/SSBMSY for one stock – they have only a single response (dependent) variable. However, it is possible to define multivariate networks that can predict multiple output data simultaneously that could include F/FMSY and those metrics across multiple stocks. An area for future investigation is graph neural networks that may be able to predict stock status based on multiple time series of data (Bing et al., 2018).

Code and data

All code, models and data used in these analyses are available from the public EcoTest GitHub repository: https://github.com/Blue-Matter/EcoTest

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The contents of this paper do not necessarily reflect the point of view of ICCAT or other funders and in no ways anticipate ICCAT future policy in this area.

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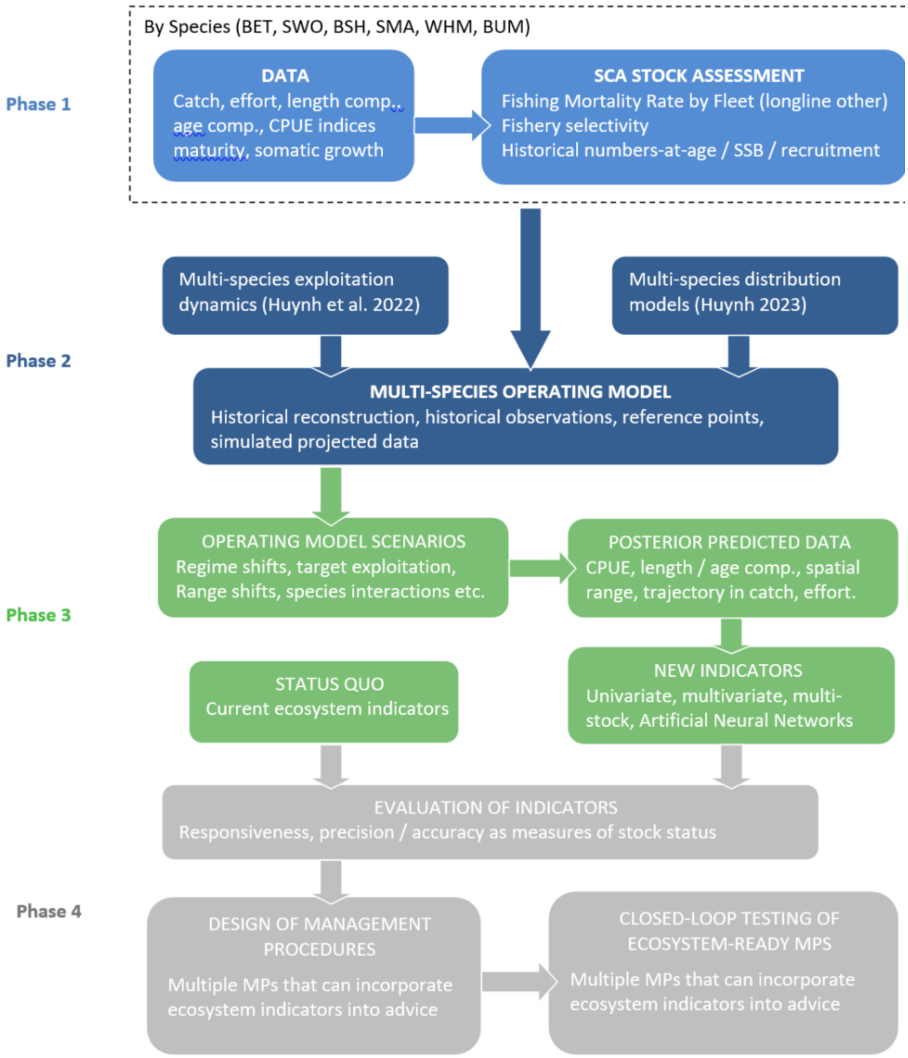

Figure 1. The components and phases of the EcoTest project.

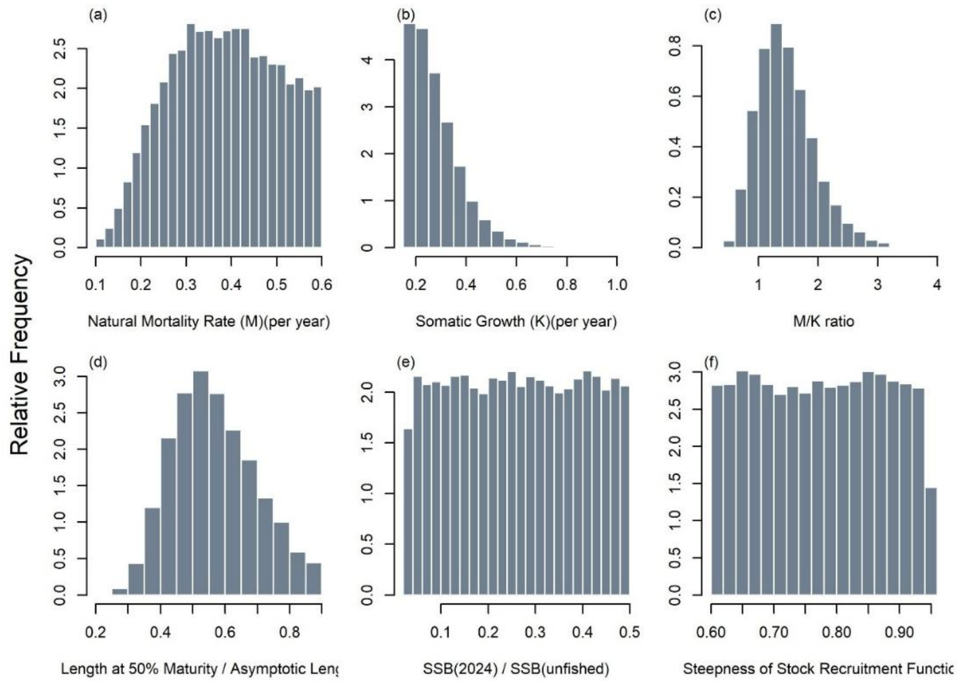

Figure 2. Range of simulated life-histories encompassing the families *Istiophoridae* (marlins), *Scombridae* (mackerels, tunas and bonitos), and *Carcharhinidae* (requiem sharks).

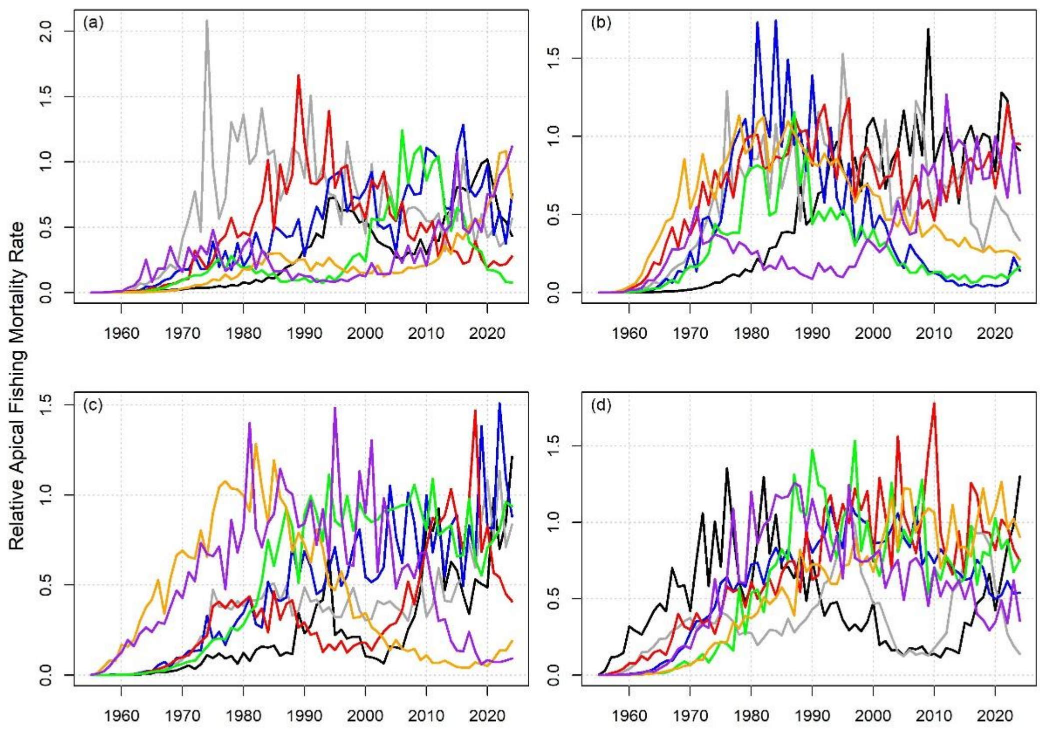

Figure 3. Simulated relative effort for 28 simulations (7 simulations per panel).

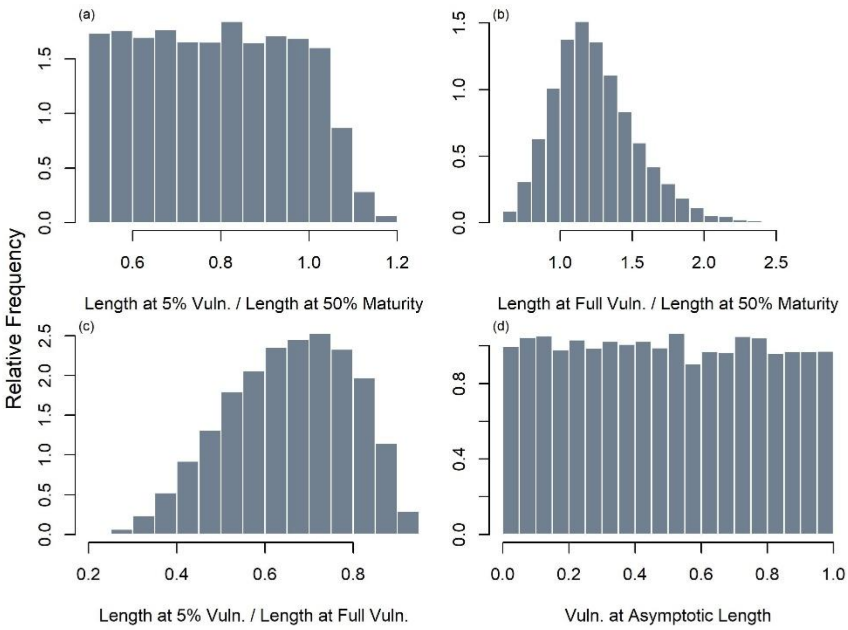

Figure 4. Sampled parameters controlling fleet selectivity.

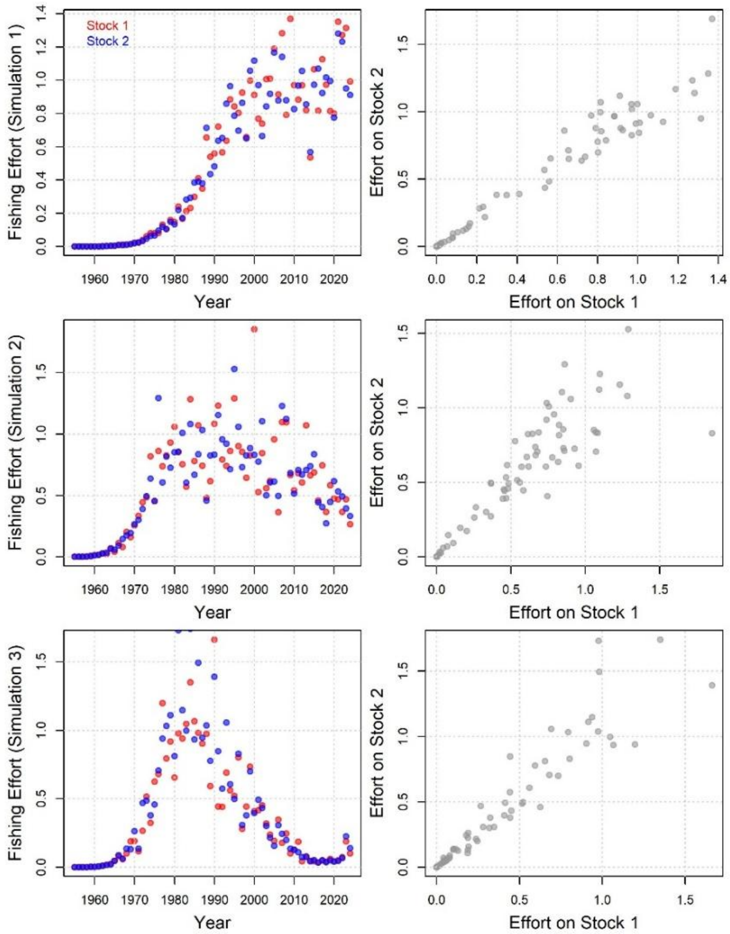

Figure 5. Correlated historical fishing effort among stocks (three simulations, each row of panels is a simulation).

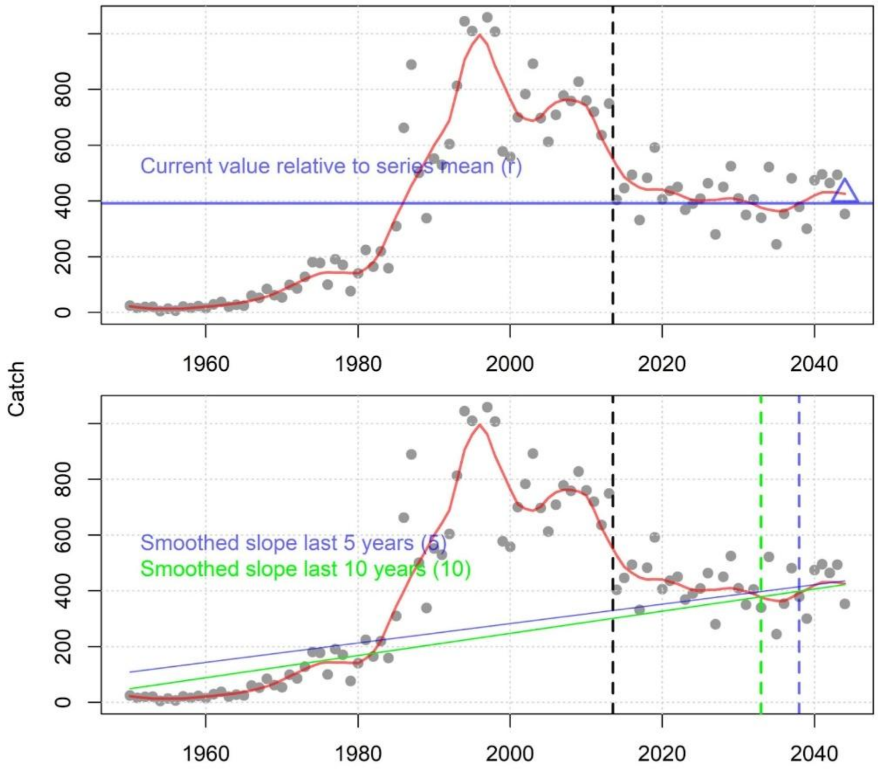

Figure 6. An example of a time series of annual catch observations (grey points), a smoothed trend line (red) and current smoothed level (blue triangle) relative to series mean (horizontal blue line), and mean slope in the smoothed line over the last 5 (blue vertical dashed line) and 10 (green vertical dashed line) years. The vertical dashed black line demarks the end of the historical assessed period and the start of the closed-loop projections that were used to train indicators range of scenarios for population and fishing dynamics.

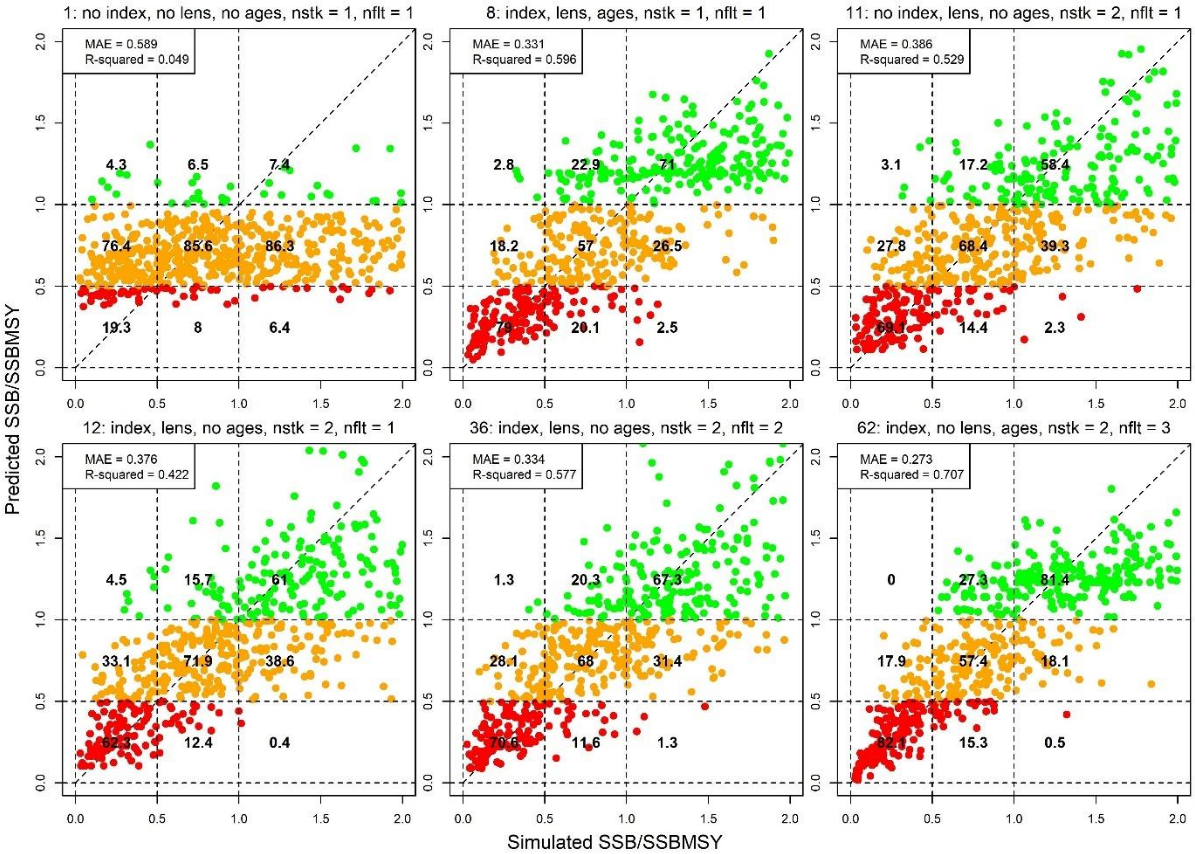

Figure 7. Predictive ability of 6 of the 72 neural networks (Table 4) for 1000 simulations of the independent testing dataset. Each point is a simulation. Simulations are color-coded according to the neural network prediction of stock status (green is above SSBMSY, orange between SSBMSY and 50% SSBMSY, red are predictions below 50% BMSY). The numbers represent the percentage of predicted values across each simulated range (i.e. values sum to 1 vertically) providing an indication of the expected error rates in classifying stocks. For example, neural network #62 (bottom right panel) which was trained on index and age data for two stocks and three fleets correctly identified a heavily depleted stock below 50% of SSBMSY in 82.1% of simulations

Table 1. Time series data per fleet, from which derived quantities are calculated for use in indicators. Across 3 species, 12 data streams, 5 derived quantities and three fleets, this includes up to 540 data inputs (depending on number of stocks, fleet and data availability (see **Table 3**).

Species (n = 3)	Data Streams (n = 12) per stock and fleet	Derived quantities (n = 5)
A tuna, mackerel, bonito, shark, marlin	Catches	Current level / ref. point (e.g. muL / Linf)
A tuna, mackerel, bonito, shark, marlin	Nominal CPUE	Current level / time series mean
A tuna, mackerel, bonito, shark, marlin	Mean length	Slope over last 5 years
	Fraction mature	Slope over last 10 years
	Variability length	Slope over last 20 years
	Mean age	
	Catch ratio: Spec. 1 / Spec. 2	
	Catch ratio: Spec. 1 / Spec. 3	
	Catch ratio: Spec. 2 / Spec. 3	
	Residual correlation between detrended catch Spec. 1 and Spec. 2 (F correlation)	
	Residual correlation between detrended catch Spec. 1 and Spec. 3 (F correlation)	
	Residual correlation between detrended catch Spec. 2 and Spec. 3 (F correlation)	

Table 2. Additional species attributes / derived metrics that may be submitted to the neural network.

Metric	**Description**	**Type**
M/K ratio	The ratio of natural mortality rate to von Bertalanffy growth parameter K.	Stock-specific
Maximum age	The oldest age reliably observed in the population	Stock-specific
L50 / Linf	Length at 50% mature relative to asymptotic length	Stock-specific
Lc / L50	Length at first capture relative to length at 50% mature	Fleet-specific
LFS / L50	Length at full selection relative to length at 50% mature	Fleet-specific
Vmaxlen	Vulnerability of asymptotic length	Fleet-specific

Table 3. The 72 neural networks that comprise Indicator 2. These allow for varying numbers of stocks and fleets and data availabilities and as such range in their number of data inputs (size of input layer) from just 12 data sources to 579. The table at the top shows the neural network numbering, the table below shows the size of the input layer (number of data types) on which the neural networks were trained.

	Has age composition:	**N**	**N**	**N**	**N**	**Y**	**Y**	**Y**	**Y**
	Has length composition:	**N**	**N**	**Y**	**Y**	**N**	**N**	**Y**	**Y**
	Has recent Rel. Abund. Index:	**N**	**Y**	**N**	**Y**	**N**	**Y**	**N**	**Y**
No. Fleets	**No. stocks**								
1	**1**	NN #1	NN #2	NN#3	…				
1	**2**	NN #9	NN #10	…					
1	**3**	NN #17	…						
2	**1**	…							
2	**2**								
2	**3**								…
3	**1**							…	NN #56
3	**2**						…	NN #63	NN #64
3	**3**					…	NN #70	NN #71	NN #72

	Has age composition:	**N**	**N**	**N**	**N**	**Y**	**Y**	**Y**	**Y**
	Has length composition:	**N**	**N**	**Y**	**Y**	**N**	**N**	**Y**	**Y**
	Has recent Rel. Abund. Index:	**N**	**Y**	**N**	**Y**	**N**	**Y**	**N**	**Y**
No. Fleets	**No. stocks**								
1	**1**	12	17	27	32	17	22	32	37
1	**2**	44	54	74	84	54	64	84	94
1	**3**	126	141	171	186	141	156	186	201
2	**1**	20	30	50	60	30	40	60	70
2	**2**	80	100	140	160	100	120	160	180
2	**3**	240	270	330	360	270	300	360	390
3	**1**	28	43	73	88	43	58	88	103
3	**2**	116	146	206	236	146	176	236	266
3	**3**	354	399	489	534	399	444	534	579

Table 4. Neural network estimation performance according to data availability. Ind, Length and Age denote whether relative vulnerable biomass indices, length composition and age composition data are available, respectively. S and F refer to the number of stocks and fleets for which data were provided for neural network training. R_sq is the r-squared statistic. MAE is the mean absolute error in estimates of log SSB(2024)/SSBMSY. TP_LRP (true positive - limit reference point) is the probability of correctly detecting biomass below the 50% BMSY limit reference point. TP_R (true positive - rebuilding) is the probability of correctly detecting biomass levels between 50% SSBMSY and SSBMSY. R_sq, MAE and TP_LRP are shaded such that better values (higher, lower and higher, respectively) are shaded green. Certain data combinations are highlighted in grey (only catch and length data) and blue (only catch, index and length data). Neural networks that failed to train do not have values.

#	Ind.	Length	Age	S	F	R_sq	MAE	TP_LPR	TP_R
1	FALSE	FALSE	FALSE	1	1	0.05	0.59	0.193	0.86
2	TRUE	FALSE	FALSE	1	1	0.15	0.56	0.303	0.77
3	FALSE	TRUE	FALSE	1	1				
4	TRUE	TRUE	FALSE	1	1	0.49	0.39	0.712	0.55
5	FALSE	FALSE	TRUE	1	1	0.56	0.37	0.725	0.57
6	TRUE	FALSE	TRUE	1	1	0.58	0.35	0.702	0.64
7	FALSE	TRUE	TRUE	1	1	0.56	0.35	0.747	0.61
8	TRUE	TRUE	TRUE	1	1	0.6	0.33	0.79	0.57
9	FALSE	FALSE	FALSE	2	1	0.25	0.53	0.217	0.72
10	TRUE	FALSE	FALSE	2	1	0.25	0.53	0.391	0.85
11	FALSE	TRUE	FALSE	2	1	0.53	0.39	0.691	0.68
12	TRUE	TRUE	FALSE	2	1	0.42	0.38	0.623	0.72
13	FALSE	FALSE	TRUE	2	1	0.6	0.35	0.747	0.56
14	TRUE	FALSE	TRUE	2	1	0.63	0.33	0.73	0.6
15	FALSE	TRUE	TRUE	2	1	0.57	0.33	0.723	0.52
16	TRUE	TRUE	TRUE	2	1	0.64	0.32	0.749	0.64
17	FALSE	FALSE	FALSE	3	1	0.22	0.51	0.431	0.82
18	TRUE	FALSE	FALSE	3	1	0.2	0.5	0.404	0.73
19	FALSE	TRUE	FALSE	3	1	0.44	0.37	0.667	0.49
20	TRUE	TRUE	FALSE	3	1	0.51	0.36	0.645	0.51
21	FALSE	FALSE	TRUE	3	1	0.53	0.35	0.742	0.43
22	TRUE	FALSE	TRUE	3	1	0.01	0.34	0.653	0.61
23	FALSE	TRUE	TRUE	3	1				
24	TRUE	TRUE	TRUE	3	1	0.62	0.33	0.75	0.57
25	FALSE	FALSE	FALSE	1	2	0.21	0.51	0.405	0.71
26	TRUE	FALSE	FALSE	1	2	0.29	0.49	0.487	0.56
27	FALSE	TRUE	FALSE	1	2	0.62	0.34	0.718	0.66
28	TRUE	TRUE	FALSE	1	2	0.53	0.33	0.716	0.61
29	FALSE	FALSE	TRUE	1	2	0.63	0.31	0.748	0.56
30	TRUE	FALSE	TRUE	1	2	0.61	0.3	0.804	0.46
31	FALSE	TRUE	TRUE	1	2	0.66	0.31	0.724	0.57
32	TRUE	TRUE	TRUE	1	2	0.62	0.3	0.727	0.54
33	FALSE	FALSE	FALSE	2	2	0.3	0.45	0.506	0.72
34	TRUE	FALSE	FALSE	2	2	0.34	0.44	0.621	0.57
35	FALSE	TRUE	FALSE	2	2	0.61	0.33	0.687	0.61
36	TRUE	TRUE	FALSE	2	2	0.58	0.33	0.706	0.68
37	FALSE	FALSE	TRUE	2	2	0.65	0.31	0.763	0.58
38	TRUE	FALSE	TRUE	2	2	0.67	0.3	0.789	0.51
39	FALSE	TRUE	TRUE	2	2	0.66	0.31	0.787	0.64
40	TRUE	TRUE	TRUE	2	2				
41	FALSE	FALSE	FALSE	3	2	0.34	0.45	0.447	0.68
42	TRUE	FALSE	FALSE	3	2	0.38	0.44	0.559	0.69
43	FALSE	TRUE	FALSE	3	2				
44	TRUE	TRUE	FALSE	3	2				
45	FALSE	FALSE	TRUE	3	2	0.62	0.3	0.828	0.56
46	TRUE	FALSE	TRUE	3	2	0.63	0.31	0.734	0.58
47	FALSE	TRUE	TRUE	3	2				
48	TRUE	TRUE	TRUE	3	2				
49	FALSE	FALSE	FALSE	1	3	0.34	0.44	0.542	0.71
50	TRUE	FALSE	FALSE	1	3	0.37	0.43	0.597	0.66
51	FALSE	TRUE	FALSE	1	3	0.61	0.33	0.739	0.54
52	TRUE	TRUE	FALSE	1	3	0.56	0.32	0.783	0.6
53	FALSE	FALSE	TRUE	1	3	0.66	0.27	0.842	0.56
54	TRUE	FALSE	TRUE	1	3	0.66	0.28	0.733	0.63
55	FALSE	TRUE	TRUE	1	3	0.71	0.28	0.778	0.64
56	TRUE	TRUE	TRUE	1	3	0.65	0.29	0.688	0.63
57	FALSE	FALSE	FALSE	2	3	0.38	0.43	0.534	0.71
58	TRUE	FALSE	FALSE	2	3	0.42	0.4	0.604	0.61
59	FALSE	TRUE	FALSE	2	3	0.64	0.31	0.83	0.6
60	TRUE	TRUE	FALSE	2	3	0.6	0.31	0.809	0.65
61	FALSE	FALSE	TRUE	2	3	0.64	0.29	0.764	0.65
62	TRUE	FALSE	TRUE	2	3	0.71	0.27	0.821	0.57
63	FALSE	TRUE	TRUE	2	3	0.64	0.29	0.723	0.58
64	TRUE	TRUE	TRUE	2	3	0.71	0.28	0.788	0.67
65	FALSE	FALSE	FALSE	3	3	0.34	0.42	0.449	0.63
66	TRUE	FALSE	FALSE	3	3	0.38	0.42	0.563	0.62
67	FALSE	TRUE	FALSE	3	3	0.56	0.32	0.73	0.62
68	TRUE	TRUE	FALSE	3	3	0.59	0.3	0.726	0.63
69	FALSE	FALSE	TRUE	3	3	0.62	0.28	0.753	0.6
70	TRUE	FALSE	TRUE	3	3	0.68	0.29	0.682	0.68
71	FALSE	TRUE	TRUE	3	3	0.66	0.28	0.759	0.49
72	TRUE	TRUE	TRUE	3	3	0.63	0.3	0.748	0.6