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ECOTEST PHASE III: SIMULATION TESTING ECOSYSTEM INDICATORS

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SUMMARY

A multi-species, multi-fleet operating model was developed for the North Atlantic longline fishery including two primary species (swordfish and bigeye tuna) and four secondary species (blue shark, shortfin mako shark, white marlin, blue marlin). The operating model was used to generate a wide range of future exploitation scenarios for the various species. Posterior predicted data were generated from data series typically available for secondary species such as length composition data, catch data and recent nominal catch rate data. These data series were processed to generate quantities that could be correlated against known simulated target variables such as spawning biomass relative to MSY levels. Artificial neural networks were trained on posterior predicted data to identify whether the data contain sufficient information to estimate spawning biomass relative to MSY levels. Early evaluations suggest that typical data contain sufficient information to reliably estimate stock status even for secondary species if data types such as catch ratios and catch correlations are provided across multiple species.

RÉSUMÉ

Un modèle opérationnel multi-espèces et multi-flottilles a été développé pour la pêcherie palangrière de l'Atlantique Nord comprenant deux espèces principales (espadon et thon obèse) et quatre espèces secondaires (requin peau bleue, requin-taupe bleu, makaire blanc, makaire bleu). Le modèle opérationnel a été utilisé pour générer un large éventail de scénarios d'exploitation futurs pour les différentes espèces. Les données prédites a posteriori ont été générées à partir de séries de données généralement disponibles pour les espèces secondaires, telles que les données de composition des longueurs, les données de capture et les récentes données sur les taux de capture nominale. Ces séries de données ont été traitées pour générer des quantités pouvant être mises en corrélation avec des variables cibles simulées connues, telles que la biomasse reproductive par rapport aux niveaux de la PME. Des réseaux neuronaux artificiels ont été entraînés sur les données prédites a posteriori afin de déterminer si les données contiennent suffisamment d'informations pour estimer la biomasse reproductive par rapport aux niveaux de la PME. Les premières évaluations suggèrent que les données typiques contiennent suffisamment d'informations pour estimer de manière fiable l'état des stocks, même pour les espèces secondaires, si des types de données tels que les ratios de capture et les corrélations de capture sont fournis pour plusieurs espèces.

RESUMEN

Se desarrolló un modelo operativo multiespecífico y multiflota para la pesquería de palangre del Atlántico norte, que incluye dos especies principales (pez espada y patudo) y cuatro secundarias (tiburón azul, marrajo dientuso, aguja blanca y aguja azul). El modelo operativo se utilizó para generar una amplia gama de escenarios futuros de explotación de las distintas especies. Los datos pronosticados a posteriori se generaron a partir de series de datos habitualmente disponibles para especies secundarias, como datos de composición por tallas, datos de capturas y datos recientes de tasa de capturas nominales. Estas series de datos se procesaron para generar cantidades que pudieran correlacionarse con variables objetivo-simuladas conocidas, como la biomasa reproductora con respecto a los niveles de RMS. Se entrenaron redes neuronales artificiales con datos de predicción a posteriori para identificar si los datos contienen suficiente información para estimar la biomasa reproductora con respecto a los niveles de RMS. Las primeras evaluaciones sugieren que los datos típicos contienen suficiente información para estimar de forma fiable el estado de los stocks, incluso para especies secundarias, si se facilitan tipos de datos como ratios de capturas y correlaciones de capturas de varias especies.

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KEYWORDS

Management strategy evaluation, operating model, management procedure

Introduction

Ecosystem Evaluation

For many regional fisheries management organizations (RFMOs), there is a need for rigorous science to inform decision makers in support of Ecosystem Based Fisheries Management (EBFM). Critical issues include the use of untested ecosystem indicators and the need for tactical advice that accounts for exploitation of bycatch species. Fundamentally, stock assessments of individual species do not usually account for the impact of proposed management strategies for target species on associated bycatch species. These include both non-commercial bycatch species such as birds and turtles, and also commercial species that are avoided by some sectors of the fishery yet targeted in others, such as sharks and billfishes. 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.

In the absence of defensible stock assessments for many bycatch species, ICCAT and other tuna-RFMOs are exploring a system of indicators for EBFM, such as the Ecosystem Report Card. While it can be problematic to assume that indicators such as catch per unit effort (CPUE) are representative of any underlying stock dynamics (Hilborn and Walters 1992), the problems that leads to CPUE being unrepresentative can be even more pronounced in the case of bycatch species or of communities (Maunder *et al*., 2006). Few of these indicators have been tested to ensure that they are expected to be informative and sufficiently responsive to changes in the status and exploitation levels of those species in question.

ICCAT's Convention and Resolution 15-11 commit ICCAT to apply the precautionary approach and an ecosystem approach on fisheries management (EAFM). To implement this commitment, ICCAT's Subcommittee of Ecosystems and Bycatch is developing an Ecosystem Report Card (EcoCard) as a tool for monitoring the impacts of ICCAT fisheries (Juan-Jordá *et al.* 2018). It consists of a set of proposed indicators that may be informative with regard to the sustainability of species or stocks and how their fishing impacts on ecosystem structure and function.

A major gap in EAFM implementation where indicator systems are employed is validation to ensure ecosystem indicators are representative and responsive to population dynamics changes. Without such validation, such indicators are impossible to interpret. So, it is important to establish plausible scenarios for ecosystem dynamics to evaluate when indicators detect population dynamics changes and when they are spurious. For example, decreasing bycatch rates may be driven by either declines in the underlying bycatch population size or changes in fleet distribution in search of target species or vice versa. Even if such indicators were validated, ecosystem report cards provide no guidance about an appropriate responsive management strategy. As a result, operationalizing initiatives related to EAFM using indicator systems could prove challenging.

EcoTest Problem Statement

To meet the requirements of the precautionary approach and the ecosystem approach to fisheries management, we require indicators for secondary species that may often be lacking sufficient data or capacity to conduct stock assessments. These indicators must be theoretically sound and be validated empirically.

Aim

Use simulation modelling to identify data and algorithms that can inform stock status of secondary species and then validate these empirically in cases where there have been defensible stock assessments.

Progress and Current Phase

Previous work synthesized the dynamics of six stock assessments (Phase 1) and consolidated those into a single multi-species, multi-fleet operating model (OMs) (Phase 2) (**Figure 1**) (Huynh *et al.* 2022).

Phase 3 focuses on developing scenarios for the operating models, producing posterior predicted data, testing proposed indicators, and identifying new indicators. Posterior predicted data is the Bayesian version of model checking. Here, we document substantial progress in Phase 3 by demonstrating OM projections, synthesizing posterior data, processing those data, and then fitting artificial neural networks to estimate stock status and identify the relative contribution of data types.

Methods

Case study

The North Atlantic longline fishery was selected as a case study on the basis that:

- It has reasonably well documented spatial catch, effort and length composition data for a range of fleets for both primary and secondary species

- Primary target species (e.g. bigeye tuna and swordfish) and several example secondary species (sharks, marlins) have documented stock assessments (**Table 1**, **Figure 1**) that can be used to construct initial operating models

- Several secondary species of similar life history to those with assessments may be of conservation concern.

Further details of the longline case study are provided in Huynh *et al.* (2022).

Target variables

In this context, ecological indicators aim to either provide a classification or estimate a quantity of interest to fishery managers. Possible target variables include:

(quantitative)
- Spawning stock biomass relative to maximum sustainable yield (SSB/SSB_{MSY} or '*Brel'*)
- Spawning stock biomass relative to equilibrium unfished levels (*SSB/SSB0*)
- *Brel* relative to the average *Brel* across species

(qualitative)
- Red (*Brel* < 0.5), Yellow (0.5 < *Brel*< 1), Green (1 < *Brel*)
- Among stocks, this stock has the lowest stock depletion

In this first exploration, we identified *Brel* as the target variable and used the qualitative cut offs of 0.5 and 1 to establish the performance of indicators.

Constructing operating models

The six stock assessments were combined into a single multi-stock, multi-fleet operating model in the OpenMSE (Hordyk *et al*. 2024) framework. From this basis, it is possible to simulate future scenarios for population dynamics (e.g. somatic growth, recruitment), data collection (biases, imprecision), and fishing (correlated, uncorrelated exploitation rates among species, selectivity changes etc). Thus far, constant exploitation rate scenarios have been tested that vary among the species and are uncorrelated. The next step is to simulate correlated (less challenging) / changing exploitation rates (systematic and inter-annual variability which is substantially more challenging) among species. More than 20,000 iterations were run and posterior predicted data were simulated for each species and iteration.

Processing posterior predicted data

For each simulation, a projected year was selected at random. The posterior predicted data up to that 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. All fractions or rates were first log-transformed.

Data types and derived quantities available

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 a spatial range (at the 5x5 Task 2 data resolution) for catch observations. Based on these data streams various derived quantities were calculated for each species (**Tables 2** and **Table 3**, **Figures 3 and 4**).

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 (8 nodes in the first layer, 4 in the second, and therefore 1,897 trainable parameters in total) was the simplest that provided comparable fit to the training and validation datasets. The model was trained to predict the true simulated Brel and the stock specific Brel relative to the mean of the other stocks using 244 derived quantities as inputs (**Tables 2 and 3**). A total of 18,000 simulations were used for training, another 4,000 simulations for validation (a check as the neural network trains, that the fit to the training set is comparable to the validation set - it is not overparameterized) and 1,000 for the completely independent testing dataset.

The neural networks could be trained on various configurations / availability of data types. Two conditions were tested in this initial work: all data inputs (n = 244) and all data inputs excluding the long-term CPUE data and the spatial model (n = 232) (see **Table 4**, input data archetypes, below).

Results

The artificial neural networks trained very rapidly and achieved a very good fit to the simulated Brel data in just 20 epochs obtaining a mean absolute error of less than 0.2 (**Figure 5**).

Given the complete data, the models were remarkably accurate and precise, correctly identifying stock status into three categories: Red (Brel < 0.5), Yellow (0.5 < Brel < 1) and Green (1 < Brel) in between 80% and 95% of simulations (**Figure 6**). Removing the spatial model and the long-term CPUE data reduced this precision (**Figure 6**), but still allowed for high statistical power, correctly identifying 80% of simulations below 50% Brel in the example of blue shark (**Figure 6**).

An Importance Function was developed to calculate the marginal weight of input revealing the information content of each data source independently (**Figure 7**). This can reveal the marginal influence of any single data input, but it does not capture the potentially large influence of an input in combination with levels of other inputs.

Discussion

Research Priority 1: Identify the Target Variable(s) for Ecological Indicators

Without clearly identifying the target variable of an ecological indicator, it is not possible to evaluate the performance of existing indicators or design new indicators. Examples of target variables include spawning biomass relative to MSY levels (Brel: overfished / underfished), slope in spawning biomass (or biomass), stock level relative to other species, fishing mortality rate relative to FMSY (overfishing / underfishing).

Research Priority 2: Identify Levels of Target Variables that are Relevant to Management

It is important to clearly state conditions that are problematic in order to determine the performance of existing or proposed indicators in terms of, for example statistical power and type I error. This forms the fundamental basis for designing / refining / rejecting indicator systems. For example, for spawning biomass relative to MSY levels 40% and 50% are often identified as stock levels of conservation concern below which recruitment may be impaired.

Research Priority 3: Establish Data Archetypes

Secondary species strongly differ in the types of data available and the duration over which such data have been reported. A critical next step is the development of input data archetypes that represent the most likely combinations of available data (e.g. **Table 4**) such that indicators can be developed and performance can be characterised for each data archetype.

Promising Early Results Using Artificial Neural Networks

By simulating the dynamics of two target species and four secondary species, it was possible to generate a wide range of posterior predicted data for the testing of candidate indicators of stock status. Neural networks offer a highly flexible approach for establishing whether, for a given dataset information exists to quantify the target variable. The accuracy and precision of the neural networks varied depending on the input data available to the neural network indicators, but in general they performed very well given only nominal CPUE, catch and length composition data (~80 to 90% classification success rate). This performance is superior to that which can be typically obtained by simulation testing a correctly specified, data-rich stock assessment model. When only catch data and length composition data were available, neural networks were still capable of between 70 and 80% classification success rate.

Stress Tests

The success of the indicators is surprising given that exploitation rates were assumed to be independent among species. Correlations in exploitation rate can be expected to increase the information content of catch ratios with respect to relative stock status ($CPUE_{stock1}$ / $CPUE_{stock2}$ tends to C_{stock1} / C_{stock2} as the common denominator effort, becomes comparable). On the other hand, the exploitation rate scenarios of this demonstration were constant and therefore allowed catch data to inform relative stock level. The neural networks performed similarly well in updated simulations that included time-varying exploitation rate scenarios that have both interannual error in exploitation rate and increasing and decreasing overall trends.

The indicators should also be trained on data arising from changing biological conditions such as systematic changes in somatic growth, natural mortality rate and availability to fishing.

Multivariate Indicators

The sequential neural networks of this research are fitted to the simulated *Brel* for one stock. 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. Investigation of such approaches will come after a full exploration of the data, information and indicator design for a single species and variable.

Empirical Testing and Ground Truthing

After using the simulation model to identify indicators that are theoretically informative, there are a number of approaches for testing indicators against assessment models and subject to observed data:

(1) test the performance of the indicators against data-rich stock assessments that are provided with the same simulated data inputs.

(2) Strip observed time data to do a retrospective analysis of indicator consistency in inference

(3) Apply the indicators to datasets that have been used to conduct defensible stock assessments and compare their estimates.

All of these steps can also be conducted for any reproducible indicator that has been proposed in the literature.

Large, Generic Simulation

Depending on the success of the indicators for the longline case study, it may be possible to conduct a very large fishery simulation exercise to identify generic indicator systems that can operate for a wide range of secondary species such as turtles and sea birds. Such systems would require inputs that allow for differences in the biology, ecology and fishery interactions among such species and fisheries. If such an indicator can be established it may be possible (data permitting) to apply it to a very wide range of species in both the Atlantic and other oceans.

Management Strategy Evaluation of MPs Incorporating Indicators

Ultimately it would be desirable to incorporate the neural network indicators in management procedures that can be tested for the provision of management advice. These MPs could be tested for robustness to a wide range of changing ecosystem conditions.

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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Table 1. Documented stock assessments (Stock Synthesis 3) used as the basis for constructing preliminary multi-stock, multi-fleet operating models for the North Atlantic longline case study (Huynh *et al.* 2022).

Stock	Reference	Description
Primary		
Bigeye tuna (BET) 1948 - 2020	Anonymous (2021)	M = 0.2 and steepness = 0.8
North Atlantic swordfish (SWO) 1948 – 2017	Schirripa and Hordyk (2020)	Base Model (M = 0.2 and steepness = 0.75)
Secondary		
Blue shark (BSH) 1969 - 2013	Courtney (2016)	Run 6 (Best convergence diagnostics, less weight to the length composition likelihood)
Shortfin mako (SMA) 1948 – 2016	Anonymous (2017), Courtney et al. (2017)	Run 1, steepness = 0.354
White marlin (WHM) 1954 - 2018	Anonymous (2020), Schirripa (2020)	Model 6 (Use all CPUE indices except EU_Spain longline, without a catch multiplier, with variance reweighting)
Blue marlin (BUM) 1954 - 2016	Anonymous (2018), Schirripa (2018)	Base Model (M = 0.122 and steepness = 0.50)

Table 2. Time series data from which derived quantities are calculated for use in indicators. Across 6 species, 20 data streams and 5 derived quantities, approximately 226 derived quantities are available.

Species (n = 6)		Data Stream (n = 20)		Derived quantities (n = 5)
Bigeye tuna		Catches		Current level / ref. point (e.g. muL / Linf)
N. Atl. swordfish		Nominal CPUE		Current level / time series mean
Blue shark		Mean length (muL)		Slope over last 5 years
Shortfin mako shark		Fraction mature		Slope over last 10 years
Blue marlin		Variability length		Slope over last 20 years
White marlin		Catch ratio: Spec. 1 / Spec. 2		
		Catch ratio: Spec. 1 / 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)		
		…		

Table 3. Additional species attributes/ derived metrics that may be submitted to the neural network.

Metric	Description
M/K ratio	The ratio of natural mortality rate to von Bertalanffy growth parameter K.
Maximum age	The oldest age reliably observed in the population
Lc / L50	Length at first capture relative to length at 50% mature
LFS / L50	Length at full selection relative to length at 50% mature
L50 / Linf	Length at 50% mature relative to asymptotic length
Spatial models	A model that approximates the relationship between stock level and the spatial coverage of catch or nominal catch per unit effort data.

Table 4. Examples of four data input archetypes.

	Archetype			
Data stream	**Full**	**No spatial**	**Recent CPUE**	**Only catch and recent composition**
Catch data				
Recent length composition				
Historical length composition				
Recent CPUE				
Historical CPUE				
Spatial model(s)				

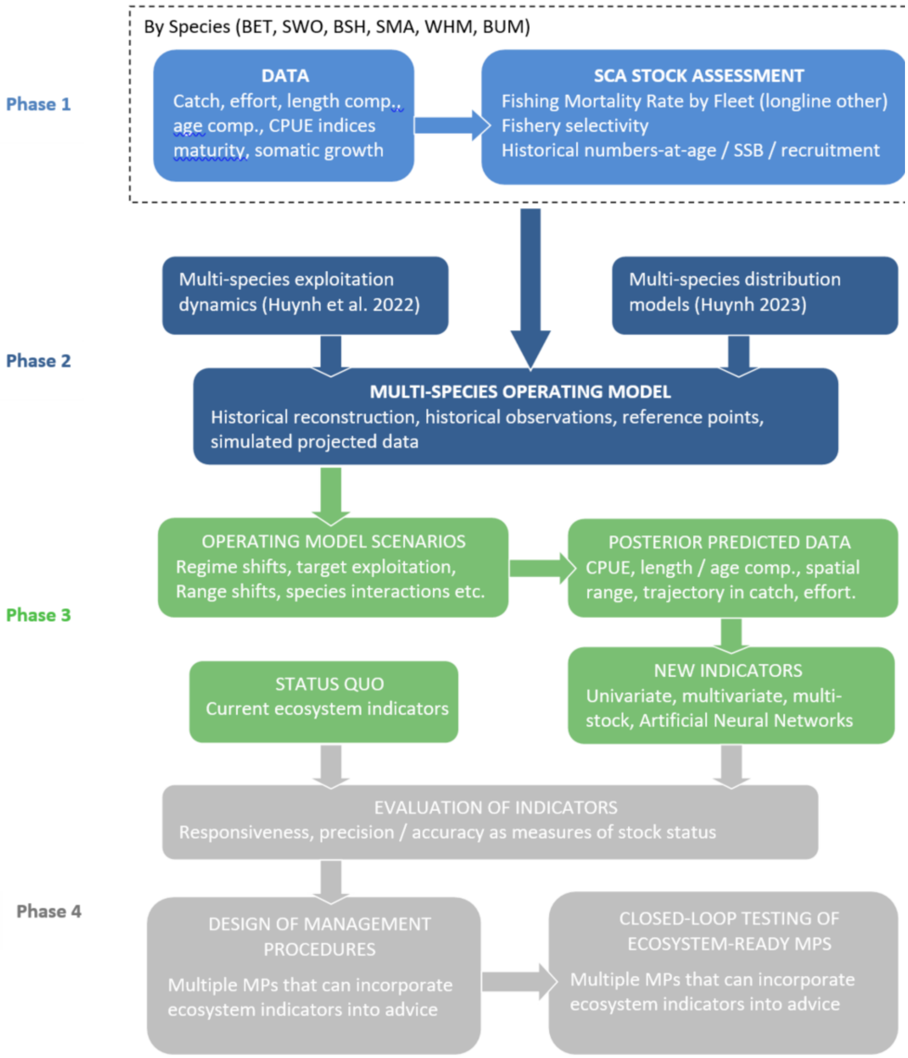

Figure 1. The components and phases of the EcoTest project.

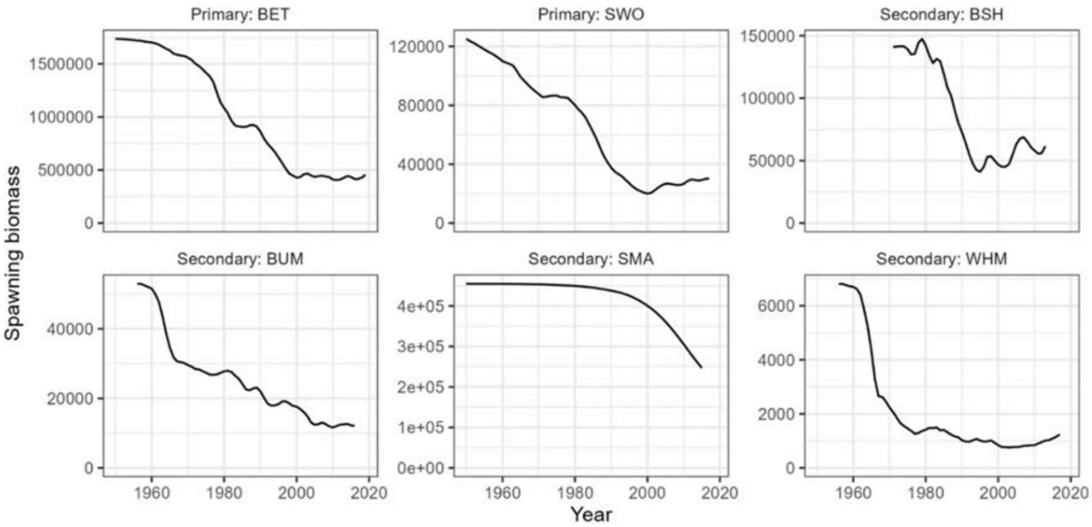

Figure 2. The maximum likelihood estimates of spawning biomass (kg) for the two primary and four secondary species caught in the North Atlantic longline case study.

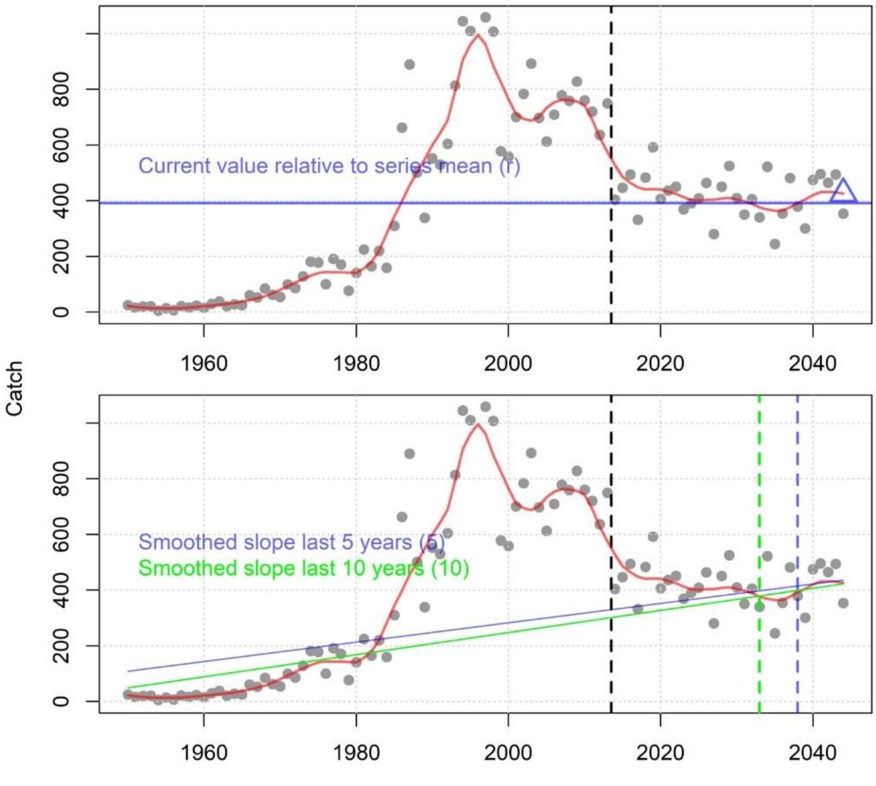

Figure 3. An example of a time series of annual catch observations (grey points), a smoothed trend line (red) and current smoothed level (blue triangle) relative to series mean (horizontal blue line), and mean slope in the smoothed line over the last 5 (blue vertical dashed line) and 10 (green vertical 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 test indicator performance over a range of future scenarios for population and fishing dynamics.

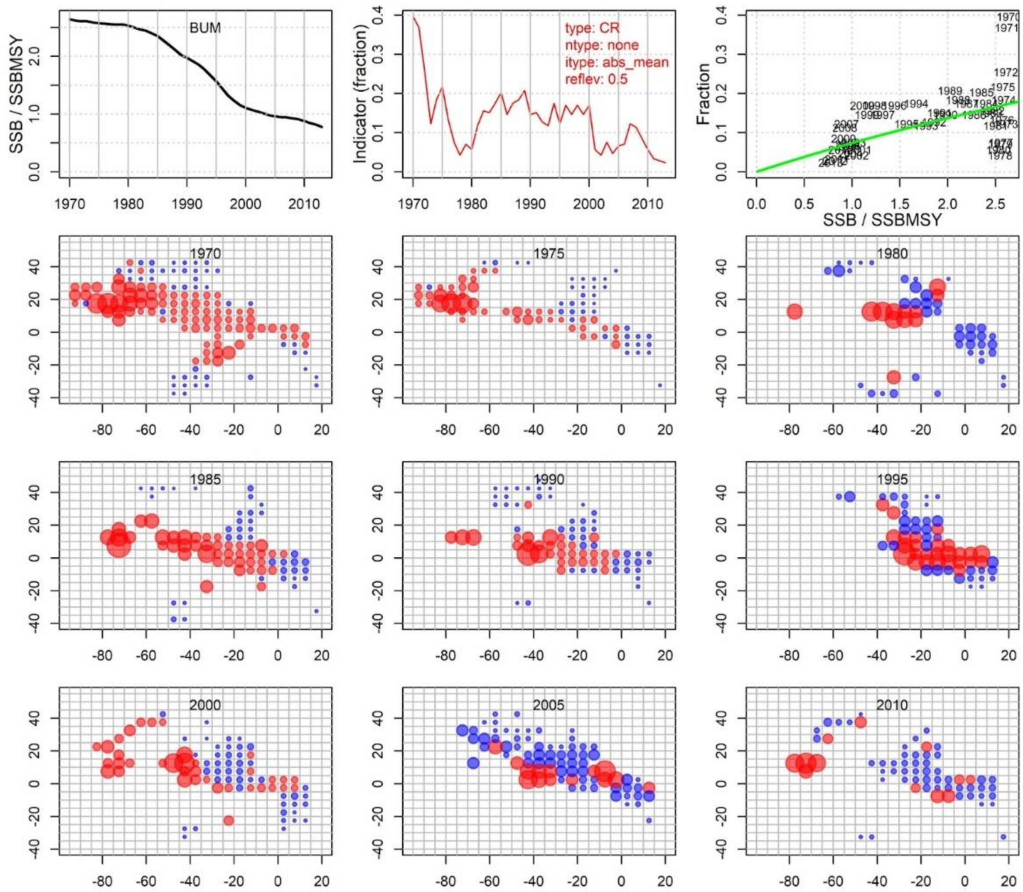

Figure 4. Task 2 nominal catch per unit effort for the Japanese longline fleet from 1970 - 2013. The top left panel is the maximum likelihood estimate of the spawning stock biomass relative to MSY levels from the stock synthesis assessment. The top middle panel shows the fraction of spatial cells that are above half the time series mean (the fraction of circles in each plot / year, which are shaded red). The top right panel shows the correlation among the assessment SSB/SSBMSY and the fraction of cells above half the time series mean, including a fitted logistic regression model (green line). Optionally, these spatial models and their prediction of the spatial fraction, can be added as covariates to the simulated data.

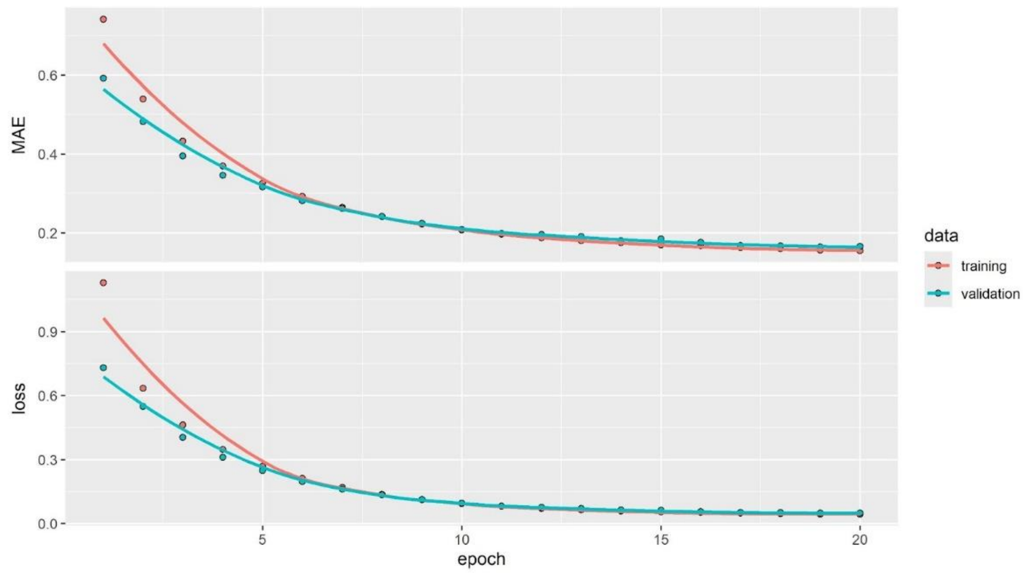

Figure 5. Progression of the neural network training across 20 epochs (passes of the back propagation algorithm through the neural network to numerically optimize for network weights) for the full blue shark data set (including CPUE and spatial model data). The top panel shows the mean absolute error (MAE) in simulated vs neural-network-predicted stock status (SSB/SSBMSY). The bottom panel shows the loss function (mean squared error) which was used to train the neural network.

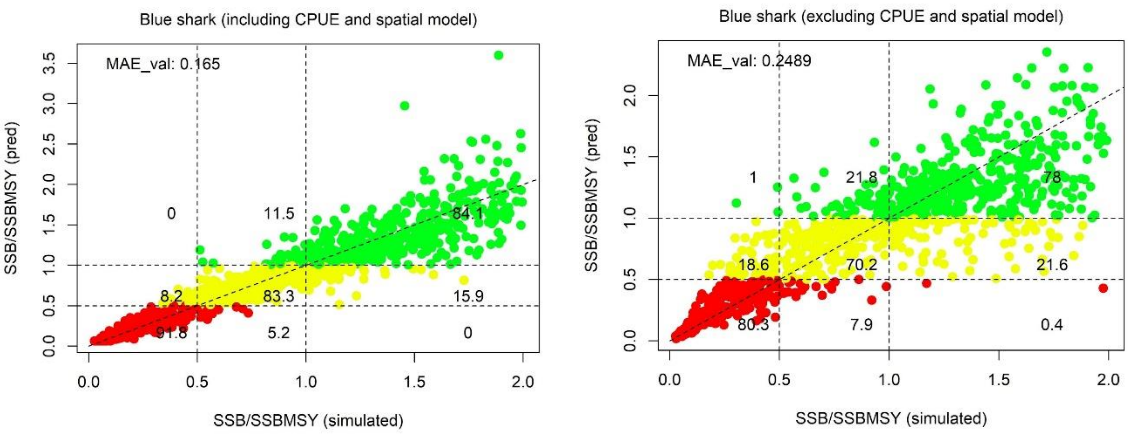

Figure 6. Predictive performance of a preliminary neural network fitted to true stock status (SSB / SSBMSY) using all data inputs (left panel) and all data inputs except CPUE time series and the spatial model (right panel). The plotted data are for a completely independent testing dataset of 1000 data points. The mean absolute error of the validation dataset is included in the top left of each panel. Plotted points are color coded according to the predicted categorical stock status defined by the horizontal lines at 0.5 and 1 SSB / SSBMSY. The numbers plotted on the chart indicate how the neural network assigned stocks status categories given each simulated category. The numbers are the % predicted in each stock level given a simulated stock level (values sum to 100% in each simulated level). The success rate is the number in the positive diagonal.

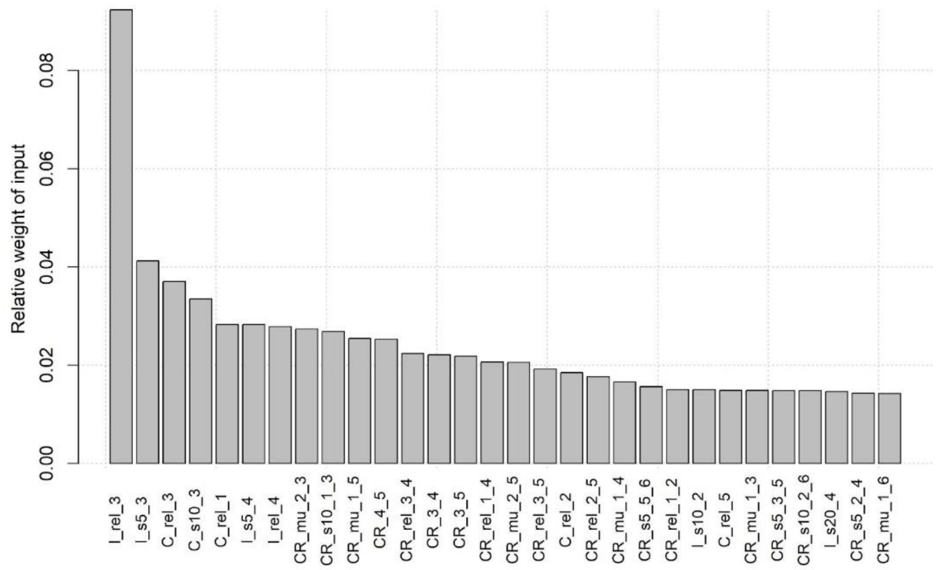

Figure 7. The relative importance (weight) of the 30 most influential data inputs, for the neural network predicting blue shark (BSH) stock status. I, C, CR, ML refer to time series of nominal CPUE, catches, catch ratios and mean length, respectively. '_rel' refers to the current level relative to the series mean. _s5 and _s10 refer to slope over the most recent 5 and 10 years, respectively. The numbers (e.g. _4) refer to stocks in the order of BET, SWO, BSH, SMA, BUM, WHM. Thus the most influential input for the full dataset for SHK was current (smoothed) CPUE today relative to the mean of the series (see top panel of **Figure 2**).