Fisheries and Oceans Canada's Ecosystem Approach to Fisheries Management Science Methods Toolbox: User Guide

Karen M. Cogliati, Irene Andrushchenko, Hugues Benoît, Alida Bundy, Jackie King, Marten A. Koops, and Mark Simpson

Fisheries and Oceans Canada
Fish Population Science Branch
200 Kent Street
Ottawa, ON
K1A 0E6

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Karen M. Cogliati[1], Irene Andrushchenko[2], Hugues Benoît[3], Alida Bundy[2], Jackie King[4], Marten A. Koops[5], and Mark Simpson[6]

[1] Fisheries and Oceans Canada
Fish Population Science Branch
200 Kent Street
Ottawa, ON
K1A 0E6

[2] Fisheries and Oceans Canada
St. Andrews Biological Station
125 Marine Science Dr
St. Andrews, NB
E5B 0E4

[3] Pêches et Océans Canada
Institut Maurice Lamontagne
850 route de la Mer
Mont-Joli, QC
G5H 3Z4

[4] Fisheries and Oceans Canada
Pacific Biological Station
3190 Hammond Bay Road
Nanaimo, BC
V9T 6N7

[5] Fisheries and Oceans Canada
Great Lakes Laboratory for Fisheries and Aquatic Sciences
867 Lakeshore Road
Burlington, ON
L7S 1A1

[6] Fisheries and Oceans Canada
Northwest Atlantic Fisheries Centre
80 East White Hills Road
St. John’s, NL
A1C 5X1

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TABLE OF CONTENTS

ABSTRACT

Cogliati, K.M., Andrushchenko, I., Benoît, H., Bundy, A., King, J., Koops, M.A., and Simpson, M. 2025. Fisheries and Oceans Canada's Ecosystem Approach to Fisheries Management Science Methods Toolbox: User Guide. Can. Tech. Rep. Fish. Aquat. Sci. 3620: vi + 41 p. https://doi.org/10.60825/77d1-2v87

Fisheries and Oceans Canada's (DFO) national Ecosystem Approach to Fisheries Management (EAFM) Working Group developed a National EAFM Science Methods Toolbox (Toolbox); a compilation of Science methods used by DFO for incorporating ecosystem variables into stock assessments and other assessment-related research activities. This report is the user guide for the Toolbox, which can be downloaded from the Government of Canada's Open Data portal (and found in an appendix of this report).

The Toolbox is a starting point for researchers looking to incorporate ecosystem information in their stock assessment activities, and is not intended to provide an exhaustive list of available analytical tools. Researchers should assess the suitability of any tools in the Toolbox to particular research objectives, as well as investigate the possibility of tools not presently included in the Toolbox (pre-existing or new). It is expected that the Toolbox will remain 'evergreen' with periodic updates to reflect emerging best practices.

RÉSUMÉ

Cogliati, K.M., Andrushchenko, I., Benoît, H., Bundy, A., King, J., Koops, M.A., and Simpson, M. 2025. Fisheries and Oceans Canada's Ecosystem Approach to Fisheries Management Science Methods Toolbox: User Guide. Can. Tech. Rep. Fish. Aquat. Sci. 3620: vi + 41 p. https://doi.org/10.60825/77d1-2v87

Un groupe de travail (GT) national sur l'approche écosystémique de la gestion des pêches (AEGP) de Pêches et Océans Canada (MPO) a élaboré une Boîte à outils nationale de l'approche écosystémique des méthodes scientifiques de gestion des pêches (Boîte à outils). Cette Boîte à outils est une compilation des méthodes scientifiques utilisées par le MPO pour intégrer des variables écosystémiques dans les évaluations des stocks et les autres activités de recherche liées aux évaluations. Ce rapport sert de guide de l'utilisateur pour la Boîte à outils, qui peut être téléchargée à partir du portail de données ouvertes du gouvernement du Canada (et se trouve en annexe du présent rapport).

Il convient de noter que le contenu de la Boîte à outils est destiné à servir de point de départ aux chercheurs qui veulent intégrer l'information écosystémique dans leurs activités d'évaluation des stocks, et non à fournir une liste exhaustive des outils d'analyse disponibles. Les chercheurs sont priés d'évaluer la pertinence des outils de la Boîte à outils pour la recherche en question, ainsi que d'étudier la possibilité d'autres outils (préexistants ou nouveaux) qui ne sont pas actuellement inclus dans la Boîte à outils. La Boîte à outils se veut « évolutive », avec des mises à jour périodiques pour refléter les pratiques exemplaires émergentes.

INTRODUCTION

A national Fisheries and Oceans Canada (DFO) Ecosystem Approach to Fisheries Management (EAFM) Working Group (WG) was established in 2018 to (1) advance the integration of climate, oceanographic and ecological variables into single-species stock assessment and advice to support the further implementation of EAFM; and (2) to identify practical steps to advance the longer-term goal of ecosystem-based fisheries management (EBFM) involving multispecies assessment and advice.

The work plan of the National WG built on the Science Sector's previous initiatives to promote an Ecosystem Approach to Fisheries Management (EAFM) in DFO. For example, the Department's Sustainable Fisheries Framework (SFF) was launched in 2009 and represents the preliminary foundations of an EAFM. While the SFF still provides the policy framework for EAFM at DFO, much work remains to implement an ecosystem approach into the science-management cycle, that is, into stock assessments, the provision of science advice, management recommendations, integrated fishery management plans, other harvest strategies and in the application to fisheries management decision-making.

To better understand the strengths and challenges of current practices across DFO stock assessments and to provide guidance on how to incorporate environmental considerations throughout the data-to-decision process, the National WG established three sub-groups:

The EAFM Case Study Synthesis subgroup: completed an in-depth review of 31 DFO case studies to better understand how ecosystem knowledge has been applied in the science-management cycle and to identify opportunities for, and challenges to, greater integration of ecosystem variables in fisheries decision-making (Pepin et al. 2023).

The FM-Science EAFM Feedback Tool subgroup: reviewed the current DFO advisory cycle (from Science advice to Fisheries Management recommendations) and identified opportunities to strengthen feedback and communication on ecosystem considerations at each step in the process.

The EAFM Science Methods Toolbox subgroup: compiled methods for incorporating ecosystem information into models and analyses including stock assessments and other methods to inform fisheries management (e.g., empirical, statistical, and modelling approaches), based on the National EAFM WG case studies and the related experience of subgroup members.

This document is a product of the third subgroup, providing guidance to researchers looking for methods to incorporate ecosystem variables into individual stock assessments or other assessment-related research activities.

PURPOSE OF THE TOOLBOX

The purpose of the Toolbox is to:

1. Highlight available methods for DFO researchers to incorporate ecosystem variables into stock assessments.
2. Outline factors to consider when selecting a method, such as data availability, staff resources, and types of advice required.
3. Provide guidance on which method(s) might be best suited to a given situation, based on the factors considered.
4. Provide links or references to examples that use these methods to guide researchers in developing their own analyses.

DFO defines EAFM as “a single-stock approach to fisheries management that incorporates ecosystem variables[1] into stock assessments, science advice, management recommendations, integrated fishery management plans or other harvest strategies (i.e., the science-management cycle) to better inform stock and individual fishery-focused decisions”. Accordingly, the Toolbox is primarily focused at this level, although some of the methods included are designed to be applied in a multispecies or ecosystem context.

The scope of the Toolbox includes quantitative and qualitative modelling approaches, single, multispecies and interdisciplinary modelling approaches and non-model based approaches. Most of the methods included were based on methods used or considered for use in the National EAFM WG’s case studies, or from individual subgroup members’ expertise or familiarity. The Toolbox is not intended to be an exhaustive list of all methods available to incorporate ecosystem information into stock assessments (i.e., there are certainly other methods not listed in the Toolbox that could be used and still meet the goal of incorporating ecosystem information), but rather to serve as an accessible entry point that gives users an idea of the types of available methods. Further, given that this is an area of active research, it is expected that new methods will become available over time.

In addition to this technical report, the accompanying Toolbox data spreadsheet will be available through the Government of Canada’s Open Data portal. A Shiny app version is available internally through the DM Apps site. The internal version provides a contact for users to suggest additions or changes to the Toolbox. This section of the User Guide will be updated accordingly, as needed.

USING THE TOOLBOX

Collectively, the Toolbox consists of three components:

- this guidance document, including a description of each of the methods in the Toolbox;
- an accompanying table of methods and considerations to aid in selecting suitable method(s)—see Appendix A, or a more interactive spreadsheet version found on the Government of Canada’s Open Data Portal (https://open.canada.ca/data/en/dataset/5c039538-7605-41f1-a9ba-c3cf82200334); and,
- a user-friendly Shiny app, which can be used in place of the table in Appendix A (DFO Shiny Apps Repository: Ecosystem Approach to Fisheries Management Science Methods Toolbox).

When choosing appropriate methods for incorporating ecosystem variables into stock assessments, there are four main questions to be answered:

1. What are the management (or research) objectives?
2. What outputs are required?
3. What data are available to apply to the question(s)?
4. What resources are required (e.g., staff time and expertise, computing capacity, etc.)?

[1] Ecosystem variables (EVs) represent elements, features and/or processes of an ecosystem that are likely to vary or change, such as those related to climate, oceanography and ecology, which can affect the productivity and/or availability of the stock.

The Toolbox is structured through a series of considerations (Table 1) that correspond to the answers to these four main questions. The considerations are then used to filter the Toolbox to find suitable method(s). Table 1 describes each of the considerations (corresponding to the Toolbox's column headings) and the possible responses to each of the considerations.

Once one or more methods have been identified as potentially applicable, users can obtain further details from the model descriptions in the next section to help narrow down their selection and link to additional resources.

Table 1. Descriptions of the considerations that can be used to filter methods in the Toolbox to find context-specific recommendations, and cross-referenced to the Toolbox tables in Appendix A.

Consideration	**Description**	**Appendix Table**
Method	Method name	All tables
Method Category	There are 4 options to select from: • **Single Species - Age/Size/Stage structured** • **Empirical – Univariate/Multivariate/Other** • **Multispecies** • **Ecosystem**	A1
Type of Approach	There are three options to select from, but most methods can be represented by one or two of the three: **Tactical** – Directed at supporting short-term specific management decisions • **Strategic** – Focused on long-range broad scale assessment of directions and patterns of change, inherently adaptable • **Conceptual** – Aimed at developing an understanding of ecosystem processes (e.g., structure, functioning, interactions)	A1
Has this method been used to provide risk-based advice?	There are 2 options to select from: • **Yes** • **No**	A1
Has this method been used to help set reference points?	There are 3 options to select from: • **Yes** • **No** • **Indirectly**	A1
Spatially explicit?	There are 3 options to select from: • **Yes** • **No** • **Optionally** – it is feasible, but may not have been done, and may be a large step to use as a spatially explicit model.	A2

Consideration	Description	Appendix Table
Statistical or Process?	There are 2 options to select from: • **Statistical** (or empirical) models seek to describe the association between variables; or • **Process** (or mechanical) models which describe a specific assumed form.	A2
Is the process model (e.g., population dynamics) principally fitted or externally parameterized?	There are 2 options to select from: • **Fitted** process models where the estimates of parameters are obtained by fitting the model to data (e.g., fitting assessment models to abundance index and fishery catch data to obtain estimates of various population parameters); or • **Parameterized** process models where estimates for different parameters are derived externally from parameter-specific information (e.g., population parameters inputted to matrix models). Note: By nature, models identified as 'statistical' are 'fitted'.	A2
If the tool can inform total allowable catch advice, what is the nature of this advice?	There are 3 options to select from: • **Quantitative** • **Semi-quantitative** • **Qualitative**	A3
Main model outputs in the context of fishery advice?	Not currently filterable by individual model outputs, but can use text filters to search for one or more of the following terms: **B(N)** Biomass (Abundance) **F(C)** Fishing Mortality (Catch) **Risk**[1] Risk / Probability of Failure **M**[2] Natural Mortality **Sensitivity** Sensitivity to model assumptions **Rmax** Population Growth Rate **K** Carrying Capacity **R** Recruitment **Index** Index of stock status (e.g., of biomass or abundance) **q** Catchability **TL** Trophic Level	A3
Essential data inputs	Not easily filterable, but more to investigate different options after models have been narrowed down from above considerations.	A4

Consideration	Description	Appendix Table
Optional data inputs	Not easily filterable, but more to investigate different options after models have been narrowed down from above considerations.	A4
Data requirements	There are 3 options to select from, in ascending order of data needs: **1** – Low resolution[3] data for single or multiple variables, for fishery dependent and/or fishery independent and/or general life history with general or location-specific information for environmental variable(s) **2** – High resolution[3] data for single or few variables **3** – High resolution[3] data for multiple and diverse components	A4
Time requirements	There are 3 options to select from, related to the time required to do the actual modelling work: **1** – Low: < 6 months **2** – Medium: 6-12 months **3** – High: > 12 months	A4
Expertise requirements	There are 3 options to select from, in ascending order of expertise required: **1** – Low **2** – Medium; requires coding **3** – High Considerations for "Expertise" include: • Subject matter expertise • Programming, statistical, mathematical skills • Model complexity: number of parameters, type of input data, assumptions Software complexity: whether command driven and user-friendly or requiring specific parameterization and coding. • Time required for competent person(s) to learn • Need for interdisciplinary expertise	A4
Computing requirements	There are 3 options to select from, in ascending order of computing intensity: **1** – Standard work computer capable of running model(s) **2** – Need dedicated computer to run model(s); at a minimum, a DFO 'power user' computer needed **3** – High performance computing required	A4
Case Study examples	Examples from the National EAFM WG case studies where more information about the method can be found. Also, see the description of methods later in this report.	A5

Consideration	Description	Appendix Table
Additional resources	Links to websites providing additional details about the method and/or examples demonstrating use of the method.	A5

[1] The risk/probability of failing to meet a stated management objective.
[2] Mortality from ecosystem or biological processes (e.g., predation, starvation, disease) other than fishing.
[3] Resolution refers to the level of spatial and/or temporal detail in which data are measured or represented. Low resolution is considered more coarse or lacking in precision while high resolution is more fine scale and precise.

METHOD DESCRIPTIONS

The model descriptions provided in the sections that follow are high level and intended to aid researchers in identifying potentially applicable methods that incorporate environmental variables (EVs). Researchers will then need to explore more detailed descriptions to fully determine if the proposed model(s) will be suitable for individual circumstances. Additional references are provided for the user to seek more information on how the method(s) may be applied.

Demographically Structured Single Population Models

General Description

These models treat populations structured into classes that represent different developmental or temporal stages and track the progression of cohorts through these stages. In many instances, age is the fundamental class (age-structured models), and the abundance of cohorts is tracked over annual time steps using basic population dynamic equations, beginning from recruitment, and across years until all individuals in a cohort have died. The models can be age-based, when available data are structured by ages, or can be length-based, in which case a growth model is used to translate length-structured observations into age-structured ones. In other instances, populations are structured into two or more developmental stages (stage-based models, including delay-difference models), typically with at least recruit and post-recruit stages, and transition probabilities are used to model the passage of individuals from one stage to the next in an annual time step.

Basic population dynamics equations typically model the recruitment of individual cohorts that enter the population each year (this may represent the birth year, or some fixed number of years following birth), and the annual attrition of those cohorts due to mortality in post-recruitment years. For stocks exposed to fishing, the mortality rate is typically modelled as two components, fishing and other (natural) mortality. Most populations are assumed to be closed, while for others, migration to and from the population is explicitly modelled in the population dynamics equations.

Demographically structured single population models are employed in one of two ways. In analytical stock assessment contexts, the models are ***fitted*** statistically to annual age, length or stage-specific data for fishery catches and for abundance indices (from scientific surveys or fishery catch-per-unit-effort). The objective is to estimate the values of demographic parameters describing recruitment, fishing mortality and natural mortality, and in the case of length or stage-based models, respectively, growth and transition probability parameters. In other applications, often when annual catch and abundance index data are absent, available data and information are used to estimate or calculate values of demographic parameters, and population dynamics are generated using these parameters with matrix algebra or computer simulations (***externally parameterized models***).

Fitted analytical stock assessment models typically include observations equations that link input data to the inferred population dynamics, which is required to obtain statistical fits to the data. These equations generally include “catchability” parameters that scale the input abundance indices to the estimated population absolute abundance. These parameters are typically age, length, or stage specific. Most age-structured catch-at-age (CA) models currently used at DFO are statistical CA (SCA) models in which all observations, survey and fishery catches are fitted statistically. Virtual population analysis (VPA) or sequential population analysis (SPA) models in which fishery catches were assumed known without error and only survey observations were fitted, were commonly used in the past, and were still used in a few recent assessments (e.g., NAFO 3NO cod; Rideout et al. 2021).

<u>Incorporating EVs</u>

The impact of EVs on populations is typically modelled in one of two basic ways: as a time-varying effect on one or more model parameters, or in the case of predation, as age, length, or stage-specific annual removals, much like those from fisheries.

- *EVs as time-varying parameters*

EVs may affect demographic rates of the population or can affect our observations on the population, for instance when an environmental change results in a population shift in distribution relative to surveys, thereby affecting catchability. The effect of EVs can be modelled explicitly by making one or more model parameters a function of the EVs, using some form of regression incorporated into the model (Crone et al. 2019). Alternatively, the effect of environmental change can be modelled indirectly by allowing a model parameter that might otherwise be considered fixed, to vary over time. This has most often been used to model temporal variation in natural mortality (e.g., Swain and Benoît 2015), but also other parameters such as catchability (e.g., Rossi et al. 2019). The estimated trends in the parameters can then be correlated post-hoc with time-variation in candidate EVs to infer the causes (e.g., Regular et al. 2022).

- *EVs as structured annual removals*

When the annual removals caused by predators can be estimated using data on predator diets, individual consumption rates and abundance, these removals can be directly incorporated in analytical models in the same manner as fishery catches (e.g., O’Boyle and Sinclair 2012). This is sometimes referred to as treating the predator(s) as a fishing fleet. The mortality rate resulting from these removals is estimated as an additional parameter to the annual fishing mortality rate and natural mortality rate parameters.

<u>Types of demographical-structured single population models in an EAFM context:</u>

Delay-difference with EV covariates

Delay-difference models are a form of collapsed age-structured model involving two stages, a recruit stage assumed to not be fished, and a harvested post-recruit stage (e.g., Forrest et al. 2015). These models require annual abundance indices for each stage and annual fishery removal. Recruits are assumed to join the post-recruit stage the following year. The effect of EVs could be modelled via the recruitment estimate, natural mortality in the adult stage or catchability.

Statistical Catch-at-age with EV covariates

In these models the effect of EVs is modelled explicitly by making one or more model parameters a function of the EVs, often using some form of regression incorporated into the model (Crone et al. 2019).

Statistical Catch-at-age with time-varying parameters

In these models the effect of environmental change is modelled indirectly by allowing a model parameter that might otherwise be considered fixed, to vary over time. Estimation employs the use of random-effects modelling, using a random-walk (e.g., Swain and Benoît 2015) or time and age correlated random deviates (e.g., Cadigan 2016).

Statistical Catch-at-age with predators as a fleet

See description above under sub-header “EVs as structured annual removals”.

Matrix population model with EVs

A matrix population model is constructed as a projection matrix that represents a series of linear equations describing survival through classes, transitions to subsequent classes, and reproduction (Caswell 2001, 2019). Classes may be based on age, life stage, or length. Even in the absence of abundance data, a projection matrix can be useful for understanding the dynamics of a population. Based on the projection matrix, there are analytical solutions for calculating the population growth rate (dominant eigenvalue), stable age or stage distribution (right eigenvector), and reproductive value function (left eigenvector). Matrix calculus allows the calculation of sensitivities and elasticities. Sensitivities of population growth rate are measures of the absolute changes in population growth that would result from absolute changes in model vital rates (e.g., juvenile survival). Elasticities of population growth rate are measures of the relative changes in population growth from a relative change in a vital rate, and have the advantage of being additive (e.g., the elasticities of juvenile and adult survival can be added to predict the change to population growth rate from a combined change to juvenile and adult survival).

The population projection matrix can be multiplied by an abundance vector (representing abundance in each class) to predict future abundances. Stochasticity and density-dependence can be added so that the projection matrix is affected by environmental and demographic stochasticity and abundance during model simulations. EV influence can be added to the projection matrix through a relationship between a vital rate and the EV (e.g., Ijima et al. 2019; van der Lee et al. 2022).

Matrix population models are typically constructed as single-population, female-only models; however, two sex and meta-population models can be constructed (e.g., Young and Koops 2014). While matrix population models are typically applied in conservation biology and for population viability analysis (PVA), they are applicable to stock assessment (e.g., Somerville et al. 2014; Hilling et al. 2022). The ‘popbio’ package in R can facilitate the construction and analysis of matrix population models (Stubben and Milligan 2007).

Individual-based models

Individual-based models (IBMs), also known as agent-based models (ABMs), represent a system’s individual components and their behaviours (Railsback and Grimm 2019). In the case of individual-based population models (see the section on multispecies individual-based models for moving beyond single population models), these components may be the actual individuals in a population or may be groups of individuals acting in a coordinated manner (e.g., a school of fish or a cohort). The term individual is simply used in the following description.

The distinguishing feature of an IBM is that each individual exhibits attributes that distinguish it from other individuals (e.g., sex, age, size). While individuals may start with the same attributes and be governed by the same rules, local conditions generate heterogeneity in attributes among individuals. Without some form of heterogeneity among individuals, there is little purpose to applying an IBM versus a simpler mathematical description of the system. Individuals interact with their local environment and other individuals based on rules that can be dependent on local conditions and may change and adapt over the course of a model simulation. Individual behaviours and interactions are often regulated by movements and spatial co-occurrence, with the result that IBMs are often spatially explicit.

Unlike many other modelling approaches that attempt to simplify system dynamics to make them mathematically tractable, IBMs model the rules governing decisions at the individual level with system dynamics as an emergent property of these individual-level dynamics. The emergent system-level dynamics then have the potential to change local conditions that affect individual-level decisions. EVs can be included in IBMs through their influence on the attributes and behaviours of the individuals modelled, or by coupling the IBM with other models that describe EVs (e.g., Hermann et al. 2001; Wang et al. 2013). Due to the inability to mathematically solve an IBM, their dynamics must be simulated, which can be computationally intensive.

While IBMs are not used as an alternative to conventional stock assessments, they have been used to evaluate the population consequences of management strategies (e.g., Boyd et al. 2018; Walker et al. 2020), which may be used in the provision of science advice. Development of IBMs can be facilitated with general programming platforms such as NetLogo (Wilensky 1999) or MASON (Luke 2022).

Single Species – Surplus Production (Biomass Dynamic) Models

General Description

These commonly employed stock assessment models assume simple density-dependent dynamics and pool the various components of production (recruitment, growth, and mortality) into a single production function (Hilborn and Walters 1992; Cousido-Rocha et al. 2022). The population is treated as an undifferentiated aggregate, typically biomass but sometimes numbers. Interannual changes in the population biomass (abundance) are assumed to result from density-dependent processes and removals by fishing. In their simplest form, the production function follows logistic population dynamics defined by an intrinsic rate of increase parameter, *r*, and a carrying capacity parameter, *K*, although asymmetric production functions are also used. These models are fit to one or more indices of population biomass and a time-series of fishery catch or fishing effort. Due to confounding between *r* and *K* parameters, an informative prior on *r* is often derived based on life-history and demographic information (McAllister et al. 2001). A catchability parameter is estimated and scales the biomass index with the estimated population biomass.

Incorporating EVs

There are several means by which EVs are incorporated into surplus-production models.

The first is to model one of the model parameters as a function of EV covariates. The effect of EVs on stock productivity are often incorporated as an effect on the intrinsic rate of increase, *r* (e.g., Mueter and Megrey 2006), but can also be incorporated on the carrying capacity parameter, *K*.

Alternatively, the effect of EVs on the distribution of the stock and its availability to a survey could be modelled on the catchability parameter. An implicit effect of EVs on stock productivity can be incorporated by estimating time variation in the parameter *r*, for instance, by estimating a distinct value for different time stanzas (e.g., Ricard and Swain 2018). The effect of EVs can constitute a direct source of mortality or removals, such as predation. Removals are treated in much the same manner as fishery removals. This approach requires a time series of removals or predation effort (Moustahfid et al. 2009; see also exploration in Yamanaka et al. 2012).

Empirical – Univariate

Linear and additive statistical models

General Description

In the context of an EAFM, univariate statistical models are used to model a response variable as a linear (or linearized) or nonlinear (general additive) function of one or more covariates or factors that include EVs. These statistical models may be directly informative for stock assessment or may provide relationships with EVs that are then factored into other models (e.g., incorporation of fish condition related natural mortality in the assessment for NAFO 3Ps cod; DFO 2022). Applications include:

- modelling the response of population demographic parameters such as recruitment, condition values and natural mortality rates, to biological EVs such as predator or prey abundance indices, or physical EVs such as ocean temperature (e.g., Regular et al. 2022; Brosset et al. 2019; Swain and Sinclair 2000);
- species distribution and spatio-temporal modelling as a function of biological, ecological, and physical EVs (e.g., Swain et al. 2015; Thorson 2015, 2019); and,
- the standardization of fishery-dependent and some fishery-independent catch rate series for factors that affect catchability and that would otherwise lead to confounding between changes in abundance and changes in catchability (Maunder and Punt 2004; Cao et al. 2017). These EVs include variables such as predator presence and ocean temperature (e.g., Chamberland et al. 2022).

These models can be fit in the frequentist paradigm using maximum-likelihood based methods or under the Bayesian paradigm using probability distribution sampling methods such Markov Chain Monte Carlo. Various parametric probability distributions can be assumed for the response, and the linear predictor may include random effects to account for correlation structure in the data such as groups and autocorrelation (spatial or temporal).

Empirical – Multivariate

Gradient Forest Models

General Description

Gradient forest (GF) methods are an extension of the random forest approach (Cutler et al. 2007), integrating random forest analyses over several response variables (Ellis et al. 2012). Random forest analysis is an ensemble regression tree method that fits many decision trees to a data set, and then combines the predictions across trees to provide a mean prediction. Each decision tree splits the ecosystem state (response variables) into two groups at specific values of a pressure; splitting continues until homogeneity of variance within a partition is maximized. While random forest analyses are limited to a single response variable, GF analyses integrate over several response variables and can be used to depict complex relationships between multiple pressures, including environmental and human, and multiple response variables.

Incorporating EVs

Since GF methods provide measures of variable importance, these methods have been applied to identifying relevant ecosystem indices for population response variables (Boldt et al. 2021). The approach has been used to characterize multiple ecosystem variables as cumulative ecosystem responses and define ecosystem-based thresholds to human or environmental pressures (Samhouri et al. 2017; Tam et al. 2017).

Multivariate Dynamic Factor Analyses

General Description

Dynamic Factor Analyses (DFA, Zuur et al. 2003) is a dimension-reducing technique for analysis of multiple stationary time series data. DFA is used to identify underlying common patterns (such as trends, seasonal effects, or cycles) in multiple time series. DFA models time series as linear combinations of common patterns (and can simultaneously estimate the effects of explanatory variables on those patterns). Factor loadings are used to infer which common patterns are important to a particular response variable or group of response variables. Selection of the most appropriate number of common patterns can be based on model selection procedures such as AIC, CAIC, or BIC.

Incorporating EVs

Explanatory variables can obviously include environmental factors, such as sea surface temperature, to explain common trends in fisheries data (Zuur et al. 2003). DFA has been used to elucidate common trends in biomass of Flemish cap groundfish community in relation to fishing pressure, environmental conditions, and predation pressure (Pérez- Rodríguez et al. 2012). Koen-Alonso et al. (2010) used DFA to identify fishing pressure as a detectable influence on Newfoundland-Labrador cod dynamics, and that indirect effects the fishing pressure may be affecting the capacity for cod rebuilding. Boldt et al. (2021) applied DFA to environmental and fishery time series to discern relationships between environmental, ecological, and human pressures and identify overall ecosystem responses to these pressures.

Empirical – Other

Empirical Dynamic Modelling

General Description

Empirical dynamic modelling (EDM) is becoming an increasingly popular method for understanding the dynamics of ecosystems for stock assessments. It avoids specifying a mathematical model of the system being considered and does not require estimation of parameters. Rather, EDM uses only the available data to estimate forecasts. It does this by translating time series of data into a path through multi-dimensional space and making forecasts based on nearest spatial neighbours. A new explanation of EDM is given by Edwards et al. (2024).

Applications of EDM to fish populations have already been widespread, including cod (Sguotti et al. 2020), salmon (Ye et al. 2015), and tuna (Harford et al. 2017). In DFO simulation studies, EDM was found to provide low errors of forecasted fish recruitment (Van Beveren et al. 2021). A new R package developed by DFO researchers, pbsEDM, enhances understanding (by outputting intermediate calculations), gives new options for implementing EDM, and can be applied to new data (Rogers and Edwards 2023).

Incorporating EVs

There are many choices of equations that can be used to model ecological processes such as the influence of temperature on productivity, or the impact of a predator on a prey species (Ye et al. 2015). Since EDM avoids having to prescribe any equations to these processes from the many choices available, there may well be a role for EDM in EAFM. Although there are few existing examples of EDM applications in EAFM-related work, EDM may prove useful as a complementary tool to traditional mechanistic models for producing short-term forecasts for management applications.

Structural Equation Models

General Description

Structural Equation Models (SEM) are statistically an extension of general linear models, but they can incorporate latent variables (referred to as mediators) that might be indicated by multiple responses (Fan et al. 2016). SEM are based on pre-assumed causal relationships between multiple variables, and the model-data fit is used to confirm the structural hypothesis. SEM combines two statistical analyses: path modelling and confirmatory factor analysis. The path model quantifies the causal relationships among variables, including any mediators that can influence an outcome, directly or indirectly through another variable. It estimates multiple regression models simultaneously and allows variables to appear as both predictors and responses, thereby quantifying indirect or cascading effects (Lefcheck 2016). The confirmatory factor analysis estimates the latent variables using covariations in the dataset, i.e., latent factors are hypothesized and verified empirically (Fan et al. 2016).

Incorporating EVs

The causal mechanisms in SEM can include a full suite of environmental variables, from physical oceanography to prey and predator impacts. SEM allows concepts such as ecosystem structure or climate change, which cannot be directly measured, to be defined as a latent variable and apply confirmatory factor analysis to estimate their states from indices (Fan et al. 2016). SEM can be used to identify potential management actions for prey or predators, and to test the impact of fishing while accounting for multiple sources of additional impacts.

Multispecies Models

Bioenergetic Multispecies Models

General Description

Bioenergetic-allometric models can be used to describe the biomass dynamics of a species, a subset of interacting species, or an entire food web. The core tenets of this modelling approach are that biomass dynamics can be represented using basic bioenergetic principles (i.e., energy inputs and outputs), and key vital rates scale allometrically with individual body mass (Yodzis and Innes 1992).

This modelling framework describes the dynamics of a predator-prey system by discriminating between two types of species, basal and consumer species, which are represented using two structurally different equations (Yodzis and Innes 1992). Basal species are those for which there is no explicit representation within the model of the resources being utilized, and hence, their dynamics are modelled using a basic logistic form plus the impact of predation. Consumer species are those for which their prey is explicitly included in the model, and hence, their dynamics are driven by consumption (typically modelled using multispecies functional responses), predation mortality, and density dependence. Both types of species can be subject to fishing.

Basic bioenergetic-allometric models can also accommodate temperature effects on vital rates (Gillooly et al. 2001; Vaseur and McCann 2005), although how best to account for the complexity of temperature effects given the multiple pathways through which temperature can impact species dynamics remains a matter of active investigation.

In a fisheries context, bioenergetic-allometric models have been used to describe entire food webs at equilibrium (i.e., mass-balance) and explore near equilibrium dynamics (Yodzis 1998), temporal dynamics of a subset of interacting species (i.e., minimum-realistic model; Koen-Alonso and Yodzis 2005), and individual species dynamics using prey and/or predator time series as external drivers to test hypotheses on the importance of drivers, and on differences between stocks (Buren et al. 2014; Koen-Alonso et al. 2021).

When this modelling approach is used for describing temporal dynamics, parameters are estimated by fitting the model to time series. The basic data requirements include times series of species biomass indices, removals, and specifications of the key species interactions.

Multispecies Individual-based Models

<u>General Description</u>

As with individual-based population models, a multi-species individual-based model (IBM) represents a system's individual components and behaviours (Railsback and Grimm 2019). In the case of multi-species IBMs, these components may be the individuals in populations of different species, but due to the multiple species included, there are often too many individuals to follow, so the model follows cohorts or super-individuals that represent groupings of individuals with similar attributes (Scheffer et al. 1995). The distinguishing feature of an IBM is that individuals (or super-individuals) exhibit attributes that distinguish it from other individuals (e.g., sex, age, size). Individuals interact with their local environment and other individuals based on rules that can be dependent on local conditions and may change and adapt over the course of a model simulation. Even when individuals start with the same attributes and are governed by the same rules, local conditions generate heterogeneity in attributes among individuals. Behaviours and interactions are often regulated by movements and spatial co-occurrence, with the result that IBMs are often spatially explicit. Unlike many other modelling approaches that attempt to simplify system dynamics to make them mathematically tractable, IBMs model the rules governing decisions at the individual level with system dynamics as an emergent property of these individual-level dynamics. The emergent system-level dynamics then have the potential to change local conditions that affect individual-level decisions. Due to the inability to mathematically solve an IBM, their dynamics must be simulated, which can be computationally intensive. Multi-species IBMs can range from models that consider the interactions of two species (e.g., Rose et al. 1999) to fish communities (e.g., McDermot and Rose 2000; van Nes et al. 2002; Campbell et al. 2011) to IBMs coupled with other models to cover entire ecosystems (e.g., Fietcher et al. 2016).

OSMOSE is a spatially explicit individual-based ecosystem model that accounts for both size-based trophic interactions and whole-lifecycle dynamics of marine species (Shin and Cury 2004). Species included in OSMOSE can be categorized either as focus (typically limited to 10 to 15 for reducing computation intensity) or background species, depending on research or management interest (Fu et al. 2017). Focus and background species together provide a comprehensive and dynamic picture of species interactions within an ecosystem. OSMOSE has been widely applied to support EAFM and EBFM including as an operating model for management strategy evaluation (MSE) and to evaluate the performance of total allowable catch (TAC) strategies (Grüss et al. 2017).

<u>Incorporating EVs</u>

Environmental variables (EVs) can be incorporated into the OSMOSE or other multispecies individual-based models in several ways, by either directly changing mortality or growth parameters of focal species or altering biomass at different trophic levels from lower-trophic-level (LTL) plankton to higher-trophic-level (HTL) species.

Models of Intermediate Complexity for Ecosystem Assessment

General Description

Models of Intermediate Complexity for Ecosystem assessments (MICE) are analytical models intermediate in complexity between traditional single-species stock assessments and whole-ecosystem models (Plagányi 2007; Plagányi et al. 2014). Generally, MICE attempt to describe the underlying ecological processes for a limited group of interacting populations subject to fishing and use standard statistical methods for parameter estimation as in single-species stock assessment. Like some extended single-species stock assessments they can also incorporate the influence of EVs on certain model parameters, and some MICE also include sub-models of human behaviour (e.g., by harvesters and fishery management). MICE intend to address tactical questions such as the estimation of current abundance and fishing mortality rates and can also address more ecosystem-related tactical questions such as the direct and indirect impacts of top predators (e.g., Rossi et al. 2024). In existing MICE, at least one population is modelled as demographically structured (age, length, and stage), while some others might be modelled as demographically aggregated (e.g., biomass dynamics). Functional responses estimated by integrating predation and diet data are used to model predator-prey dynamics, though in some instances the parameters of the functional response are assumed in different model scenarios.

Minimum Realistic Models (MRM; e.g., Punt and Butterworth 1995) predated MICE and while the terms have previously been used interchangeably, they are considered by some to be a special case of MICE in that they also focus on the limited number of species most likely to have important interactions with a target species of interest, but in the present definition do not intend to also address tactical questions (e.g., abundance and fishing mortality estimation). MRMs include various forms of multispecies virtual population analysis (VPA) and statistical catch at age modelling (SCA) (e.g., Magnússon 1995), as well as models such as multi-species surplus production and bioenergetic-allometric.

Multispecies Size-Based Models (e.g., Mizer, LeMaRns)

General Description

Size-based models are used to model a size-structured population based on prey consumption and growth across life stages as represented by size, typically weight. These models focus on growth and maturation as dependent on prey and are formulated with varying complexity. At one end, community size-based models assume constant reproduction and only growth and mortality are modelled based on energy flow determined by predation (Benoît and Rochet 2004). Individuals are not modelled, but instead are grouped into size bins across species. Next in complexity, are trait-based models that instead of aggregating all species separates the model into species groups representing the range of asymptotic sizes. The trait-based model relies on asymptotic size to estimate model parameters, for example size-at-maturation is a fixed fraction of asymptotic size. The most complex models are multispecies size-based models where each species is modelled individually with distinct life history, feeding, growth and reproduction parameters. Multispecies size-based models can incorporate size as weight (e.g., 'mizer', Scott et al. 2014) or as length (e.g., 'LeMaRns', Hall et al. 2006; Spence et al. 2020).

Incorporating EVs

At the foundation of size-based models is the transfer of energy via predation, so these models incorporate prey availability and predation as the ecosystem pressures on a population. These models simulate population dynamics and can assess the impacts of fishing (*F*) on biomass estimates especially for mixed-fisheries analysis (Hall et al. 2006). The models can simulate a range of exploitation strategies and management options.

Multispecies Surplus Production Models

General Description

Two types of multi-species surplus production models have been defined, one that incorporates multi-species ecological interactions (hereafter Ecological multi-species) and a second that jointly models the dynamics of single species harvested in mixed fisheries (hereafter Technical multi-species).

Ecological multi-species surplus production models are a multiple species (n≥2) extension of single species production models that follow a generalized Lotka-Volterra dynamics in which the production function for each species includes a density-dependent component and a component resulting from interactions with other species (e.g., Gamble and Link 2009; Gaichas et al. 2012). An interactions matrix specifies the per capita effect of each modelled species on every other species. For instance, a given predator species will be associated with a negative interaction term for each of its prey species (predation effect), while the prey species will be associated with a positive interaction term for the predator species (benefit to that predator of consuming its prey). In this manner, community dynamics subjected to species-specific fishing are modelled. In practice these models have been used as simulation tools to evaluate multispecies trade-offs and references points in a multi-species context. Results of this simulation work showed that failure to account for such considerations by applying management frameworks based on single-species maximum sustainable yield consideration only, risks failing to meet both single species and biodiversity conservation objectives, including the anticipated loss of certain species or functional groups (~~,~~e.g., Walters et al. 2005; Gaichas et al. 2012). Consequently, results of multi-species surplus production modelling could be used to set reference points and harvest strategies in a multi-species context, or to inform the use of buffers or corrections for precautionary approach frameworks derived initially from single species considerations only. In principle these models can be fitted to abundance indices, fishery catch series and prior knowledge of species interactions based on diet studies although this is unlikely to be straight-forward.

Technical multi-species surplus production models aim to model technical interactions in mixed fisheries, but do not model multispecies dynamics (Johnson and Cox 2021). They employ a hierarchical (across species) modelling structure to model single species dynamics and are readily fitted to data. These models are used to provide science advice in support of multi-species fisheries management aiming to balance harvests of target and non-target species that vary in abundance, productivity, and degree of technical interaction.

Ecosystem Models

Atlantis

General Description

The text below is drawn from the Atlantis webpage[2] and Link et al. (2010).

Atlantis is an explicit 3D spatial ecosystem model that encompasses the biophysical, economic and social components of aquatic ecosystems and was originally intended for use in management strategy evaluation (Fulton et al. 2004a, 2004b, 2004c, 2011; Link et al. 2010 and references therein). It is a deterministic biogeochemical whole of ecosystem model and has been applied to multiple marine systems at multiple spatial scales (Fulton et al. 2011). Further details and descriptions can be found in Fulton et al. (2004a, 2004b, 2004c, 2004d, 2011) and Brand et al. (2007).

[2] https://research.csiro.au/atlantis/

The overall structure of Atlantis is based on a Management Strategy Evaluation (MSE) approach, with multiple alternative sub-models to represent each step in the management strategy and adaptive management cycles. It therefore includes both operating (biophysical and fisheries sub-models) and assessment sub-models (so that the efficacy of monitoring and assessment models can be considered together with any management strategies). At the core of Atlantis is a deterministic biophysical sub-model, coarsely spatially resolved in three dimensions, which tracks nutrients (usually nitrogen and silica) flows through the main biological groups in the system. The primary ecological processes modelled are consumption, production, waste production, migration, predation, recruitment, habitat dependency, and mortality. The trophic resolution is typically at the functional group level. Invertebrates are typically represented as biomass pools, while vertebrates are represented using an explicit age-structured formulation. The physical environment is also represented explicitly, via a set of polygons matched to the major geographical and bioregional features of the simulated ecosystem. Biological model components are replicated in each depth layer of each of these polygons. Movement between the polygons is by advective transfer or by directed movements depending on the variable in question.

Atlantis also includes a detailed exploitation sub-model focused on the dynamics of fishing fleets, but which can also include the impact of pollution, coastal development, and broad-scale environmental (e.g., climate) change. It allows for multiple fleets, each with its own characteristics of gear selectivity, habitat association, targeting, effort allocation and management structures. At its most complex, it includes explicit handling of economics, compliance decisions, exploratory fishing, and other complicated real-world concerns such as quota trading. All forms of fishing may be represented, including recreational fishing (which is based on the dynamically changing human population in the area). Ports are also considered in a spatial context as part of the fleet dynamics when weighing distance to travel against realized catch-per-unit-effort (CPUE) for targeted functional groups.

Incorporating EVs

Atlantis models typically include biophysical environmental data, predator-prey linkages and can include economic and social data.

Ecopath with Ecosim (EwE)

General Description

The Ecopath with Ecosim (EwE) modelling approach was primarily developed as a toolbox to explore ‘what if’ questions about ecosystem functioning, impacts of fishing and development of policy that could not be addressed with single-species assessment models (Pauly et al. 2000; Christensen and Walters 2004, 2011). EwE has three main components: *Ecopath,* a static, mass-balanced snapshot of the living resources in an ecosystem and their interactions, represented by trophically linked functional groups; *Ecosim*, a time dynamic simulation module; and *Ecospace*, a spatial and temporal dynamic module. Since its original development in the early 1980s (Polovina 1984), EwE has been widely applied to inform ecosystem-based management (e.g., Christensen and Walters 2011; Coll and Libralato 2012; Coll et al. 2009; Bundy and Fanning 2005; Guenette et al. 2014; Blukacz-Richards and Koops 2012; Colléter et al. 2015; Heymans et al. 2016).

Ecopath, the core mass balance model, represents the entire food web, from primary producers to top predators (Pauly et al. 2000; Christensen and Walters 2004; Christensen et al. 2005). Its roots are in classic ecology where functional groups are linked through trophic interactions. Functional groups may be species, groups of species with ecological similarities or ontogenetic fractions of a species, e.g., a group may be split into larvae, juveniles, and spawners. Ecopath data requirements are relatively simple, and generally readily available from stock assessments, ecological studies, or literature. Basic data requirements for each group include biomass estimates, total mortality estimates (or a production to biomass, P/B, ratio), consumption estimates, diet compositions, and fishery catches. Each group is represented by two equations: one that relates a group's productivity to its losses that include fishing and predation, and the second that balances energy flows within a group by balancing consumption with production and respiration. Once the initial model parameters are estimated, they are then adjusted to achieve mass balance across the specified food web based on these two equations.

Ecopath forms the base model from which temporal and spatial dynamic simulations can be developed (Walters et al. 1997, 1999; Christensen and Walters 2004). The trophodynamic simulation model Ecosim (Walters et al. 1997; Christensen et al. 2005) introduced the capability to conduct dynamic multispecies simulations to explore the impact of fishing, policy exploration and more. Ecospace (Walters et al. 1999; Christensen et al. 2005) is the dynamic spatially explicit ecosystem module of EwE that enables simulation of both temporal and spatial dynamics using the spatial-temporal-framework and the habitat foraging capacity model (Christensen et al. 2014).

An EwE model must represent the main species and trophic levels that are present in the modelled ecosystem and are of relevance for the policy or research questions. The time frame and spatial extent of the EwE model depends on the questions to be addressed, as well as data availability. The modelled ecosystem should, as a rule, include the whole habitat area of the main species of concern.

Building an EwE model requires the collection, compilation, and harmonization of diverse types of information: descriptive data on species abundance, diet composition and catch; computed data on species production, consumption, and ecosystem properties; and simulation data on species biomass trends, after applying alternate scenarios (Christensen et al. 2008). By summarizing all available knowledge on the modelled ecosystems and deriving various system properties, EwE models help understanding the structure and functioning of ecosystems (Walters et al. 1997).

Details on the core principles and equations of EwE can be found in the EwE user guide available online (Christensen et al. 2008). The EwE software is user-friendly, free (under the terms of the GNU General Public License) and downloadable online (www.ecopath.org). It is also available as an R Package (https://noaa-edab.github.io/Rpath/, Lucey et al. 2020).

Incorporating EVs

Predator-prey trophic interactions are the core of the EwE modelling approach. In addition, other EVs can be introduced into the modelling framework through forcing functions, mediating factors in Ecosim and spatial EV data (e.g., temperature, oxygen, salinity, and pH) are required for the habitat suitability model of Ecospace.

Network Models (topological or qualitative models)

General Description

Network models represent systematically developed conceptual models. Conceptual models are defined as any abstract representation of static or dynamic processes between model elements (or nodes, components, or objects). Network models use systematic rules, or parameters, to define model components and linkages. These relationships or connections can be either qualitative or fuzzy-qualitative but can be based on quantitative or causal relationships. There are a variety of analytical methods to explore perturbations in network models that use qualitative or fuzzy-qualitative information to define linkages between model nodes (Reum et al. 2021).

Network models can be used to qualitatively examine the impacts of any pressure variable (or group of pressure variables) on model components (e.g., fish stock productivity). This translates to a risk measure or likelihood of the pressure(s) onto a model component.

Incorporating EVs

(For examples, see Pourfaraj et al. 2022a, 2022b)

Network models are a useful tool to incorporate EVs into a biological, ecological, or social-ecological systems. EVs can be included as model elements that drive other model elements in the system. Network models can also be developed in real-time, including Rightsholders, stakeholders, and experts, with models then being refined and developed further as an iterative product.

Types of network models in an EAFM context

There are several types of network model, which are briefly described below.

- ***Qualitative Network Models or Loop Analyses***

(For examples, see Reum et al. 2021; Melbourne-Thomas et al. 2012; Wildermuth et al. 2018; Pittman et al. 2020; Dambacher et al. 2009).

Network models for both Qualitative Network Models (QNMs) or Loop Analysis consist of model elements and directed ties denoting positive or negative influence on one another, which are typically abstracted as directed, unweighted, signed digraphs. QNMs and Loop Analysis require only a qualitative understanding of how variables interact. The interaction between model components may or may not be linear, but there is an assumed overall linear interaction based on the given model structure. QNM and Loop analysis are mathematical models in which perturbations can be assessed for their qualitative impact on the given system (sustained marginal increase/decrease in one or more model components).

- ***Fuzzy Cognitive Mapping***

(For examples, see Kosko 1986; Özesmi and Özesmi 2004; Papageorgiou and Salmeron 2013; Baker et al. 2018).

In Fuzzy Cognitive Mapping (FCM), the magnitude of the effect or degree of causality is designated according to linguistic categories (e.g., weak, moderate, strong; rarely, sometimes, usually, etc.) and fuzzy causal algebra is used to propagate causal relationships and infer the system-wide effects of perturbation scenarios. The use of linguistic categories captures uncertainty or fuzziness in the nature of the relationships and is easily understood using human reasoning. To propagate causal relationships, linguistic categories are first converted to real numbers on the interval [−1, 1] based on fuzzy set theory or, alternatively, designation of linguistic categories can be bypassed, and causal weights specified directly.

- ***Bayesian Belief Networks***

(For examples, see Reum et al. 2021; Renken and Mumby 2009; Landuyt et al. 2013).

There are two structural components required for Bayesian Belief Networks (BBNs): 1) a directed acyclic graph (DAG) and 2) a conditional probability table (CPT). These directed dependence relationships flow from at least one model component to another without creating cycles (no feedbacks). The linkages represent the strength of the dependence relationships in the DAG and denote the likelihood of the model element (“child” element) being influenced from another (“parent” element). Values composing the tables can be constructed from empirical data where available or assigned based on expert judgment. Outcomes correspond to equilibrium conditions and do not represent temporal dynamics.

Ecosystem Individual-based Models

Refer to the Multispecies Individual-based Models section for details on OSMOSE and other individual-based models.

Other Approaches

Risk Equivalence

General Description

When stock assessment advice is produced, it is essentially an evaluation of risk to the stock. That is, there are objectives that are implicit if not stated directly, and the advice represents some kind of evaluation of harvest relative to achieving the objectives. Fisheries management is likewise risk management that uses the scientific risk evaluation as a basis for evidence-based decisions. Consistent risk management in fisheries therefore attempts to make decisions that are consistent with respect to risk, but not necessarily consistent with respect to catch. Climate and ecosystem change can alter the risk associated with making a decision, all else being equal in the system. Therefore, a risk-equivalent management action in a changing ecosystem will account for this climate or ecosystem forcing. If we accept that risk and risk equivalence is an effective way to provide consistent management of fish stocks, then Science can serve management well by evaluating the impacts of climate and ecosystem change on the advice and provide risk equivalent options.

Provision of risk equivalent advice that accounts for climate and ecosystem change is, however, not always straight-forward to produce. Understanding how these forces change stock productivity over the advice period (say 1-10 years) often involves strong assumptions and correlational effects that may be somewhat ephemeral. Nevertheless, it is important to inform management with the best available science given the time and resource constraints on the science-management system as a decision will be made regardless, with or without advice. Therefore, a risk equivalence approach may incorporate ‘solid’ methods to study the impacts of ecosystem or climate change on stocks while it may also incorporate more speculative methods when other options are not available given constraints. The updating of advice as information arrives becomes more important when these mechanisms are used. Risk equivalence is therefore not a tool like say a statistical catch at age model is a tool, it is simply a means of creating risk-consistent advice in a changing ecosystem. Any number of tools could be used to provide it and therefore the concept is generic and applicable over a wide range of situations where advice is provided.

The main advantage of a risk and risk equivalence approach is that it tries to align evaluation of stocks and fisheries and the management actions taken relative to the risk of not achieving objectives and not just catch. Risk equivalence can be used to alter advice according to the evaluation of climate and ecosystem impacts on the stock and provides a tool to inform management of risk-consistent decisions. This is applicable between years, across stocks and across regions.

For more information, see Duplisea et al. (2020, 2021), Roux et al. (2022) or the following websites:

https://climateconditioned.org/

https://github.com/duplisea/ccca

Literature review and expert interviews

General Description

A weight of evidence approach is a general method for decision-making that involves consideration of multiple sources of information and lines of evidence (Government of Canada 2022). The process involves:

- generating a suite of possible hypotheses for the phenomenon under study,
- gathering available and relevant information related to these hypotheses from various sources (e.g., published information, novel data analysis, stakeholder interviews, expert opinion),
- critically assessing the quality of the individual studies or pieces of information,
- assessing the relative evidence for each hypothesis in light of the available information,
- combining the lines of evidence to characterize risk and reach an assessment conclusion, taking into account the strength and relevance of available information. This combination may be derived formally using quantitative or semi-quantitative methods, or informally based on the perceived evidence.

In the context of an ecosystem approach to fisheries, the weight of evidence approach has been applied, for instance, to improving the understanding of the factors affecting the productivity of cod stocks in the Baltic Sea, Kattegat and Skagerrak (Bryhn et al. 2022) and to understanding the possible causes of elevated natural mortality in a Canadian cod stock (Swain et al. 2011).

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APPENDIX 1: EAFM METHODS TOOLBOX

See Table 1 on page 3 for descriptions of the table headers.

List of Acronyms

BDM	Biomass Dynamic Model
DFA	Dynamic Factor Analyses
EDM	Empirical Dynamic Modelling
EV	Ecosystem Variable
EwE	Ecopath with Ecosim
GAM	Generalized Additive Model
GLM	Generalized Linear Model
GF	Gradient Forest
IBM	Individual-based Model
LM	Linear Model
LMM	Linear Mixed Model
MICE	Models of Intermediate Complexity for Ecosystem
MSE	Management Strategy Evaluation
NPZD	Nutrient-phytoplankton-zooplankton-detritus (model)
OSMOSE	‘**O**bject-oriented **S**imulator of **M**arine ec**OS**yst**E**ms’
PVA	Population Viability Analysis
SCA	Statistical catch-at-age
SEM	Structural Equation Models
SP	Surplus Production

Table A1 – Method Overview

Method No.	Method	Method Category	Type of Approach	Used to provide risk-based advice?	Used to help set reference points?
1	Delay-difference with EV covariates	Single Species - Age/Size/Stage	Tactical / Strategic	Yes	Yes
2	SCA with EV covariates	Single Species - Age/Size/Stage	Tactical / Strategic	Yes	Yes
3	SCA with time-varying parameters	Single Species - Age/Size/Stage	Tactical / Strategic	Yes	Yes
4	SCA with predators as a fleet	Single Species - Age/Size/Stage	Tactical / Strategic	Yes	Yes
5	Matrix Population Model with EV	Single Species - Age/Size/Stage	Tactical / Strategic	Yes	Yes
6	Individual-based Models (IBM)	Single Species - Age/Size/Stage	Conceptual / Strategic	No	No
7	Surplus Production	Single Species - SP/BDM	Tactical / Strategic	Yes	Yes
8	Linear Models (e.g., GLM, LMM, linear regression, Bayesian LMs)	Empirical - Univariate	Tactical / Strategic	No	Indirectly
9	Generalized Additive Models (e.g., mixed effects, Bayesian GAM)	Empirical - Univariate	Tactical / Strategic	No	Indirectly
10	Gradient Forest Models	Empirical - Multivariate	Conceptual / Strategic	No	Yes (ecosystem)
11	Multivariate Dynamic Factor Analyses	Empirical - Multivariate	Conceptual / Strategic	No	No
12	Empirical Dynamic Modelling	Empirical - Other	Tactical / Strategic	No	No
13	Structural Equation Models	Empirical - Other	Conceptual / Strategic	No	No
14	Bioenergetic Multispecies Models	Multispecies	Conceptual / Strategic	No	No
15	Individual-based Models (IBM)	Multispecies	Conceptual / Strategic	No	No
16	Models of Intermediate Complexity for Ecosystem Assessment (e.g., MICE, SCA)	Multispecies	Tactical / Strategic	Yes	Yes
17	Multispecies Size-Based Models (e.g., Mizer, LeMaRns)	Multispecies	Conceptual / Strategic	No	No
18	Multispecies Surplus Production Models	Multispecies	Conceptual / Strategic	Yes	Yes
19	Atlantis	Ecosystem	Conceptual / Strategic	Yes	unclear
20	Ecopath with Ecosim	Ecosystem	Conceptual / Strategic	Yes	Yes
21	Network models (topological or qualitative models)	Ecosystem	Conceptual	No	No
22	Ecosystem Individual-based Models (e.g., OSMOSE and other IBMs)	Ecosystem	Conceptual / Strategic	Yes	unclear
23	Risk Equivalency	Other - Empirical	Strategic	Yes	No
24	Literature review and expert interviews	Other - Weight of Evidence	Conceptual / Strategic	No	No

Table A2 – Method Details

Method No.	Method	Spatially explicit?	Statistical or Process?	Is the process model principally fitted or externally parameterized?
1	Delay-difference with EV covariates	Optionally	Process	Fitted
2	SCA with EV covariates	Optionally	Process	Fitted
3	SCA with time-varying parameters	Optionally	Process	Fitted
4	SCA with predators as a fleet	Optionally	Process	Fitted
5	Matrix Population Model with EV	Optionally	Process	Parameterized
6	Individual-based Models (IBM)	Optionally	Process	Parameterized
7	Surplus Production	Optionally	Process	Fitted
8	Linear Models (e.g., GLM, LMM, linear regression, Bayesian LMs)	Optionally	Statistical	Fitted
9	Generalized Additive Models (e.g., mixed effects, Bayesian GAM)	Optionally	Statistical	Fitted
10	Gradient Forest Models	Optionally	Statistical	Fitted
11	Multivariate Dynamic Factor Analyses	No	Statistical	Fitted
12	Empirical Dynamic Modelling	No	Statistical	Fitted
13	Structural Equation Models	No	Statistical	Fitted
14	Bioenergetic Multispecies Models	Optionally	Process	Fitted
15	Individual-based Models (IBM)	Optionally	Process	Parameterized
16	Models of Intermediate Complexity for Ecosystem Assessment (e.g., MICE, SCA)	Optionally	Process	Fitted
17	Multispecies Size-Based Models (e.g., Mizer, LeMaRns)	No	Process	Parameterized
18	Multispecies Surplus Production Models	Optionally	Process	Fitted
19	Atlantis	Yes	Process	Parameterized
20	Ecopath with Ecosim	Optionally	Process	Parameterized
21	Network models (topological or qualitative models)	No	Process	Parameterized
22	Ecosystem Individual-based Models (e.g., OSMOSE and other IBMs)	Yes	Process	Parameterized
23	Risk Equivalency	No	Statistical	Fitted
24	Literature review and expert interviews	Optionally	Process	N/A

Table A3 – Fishery Advice Outputs

Method No.	Method	If the tool can inform total allowable catch advice, what is the nature of this advice?	Main model outputs in the context of fishery advice?
1	Delay-difference with EV covariates	Quantitative	B(N), F(C), R, K, Rmax ; [M]
2	SCA with EV covariates	Quantitative	Age-specific B(N), F(C), R, Risk, Rmax; [M]
3	SCA with time-varying parameters	Quantitative	Age-specific B(N), F(C), R, Risk, Rmax, M or q
4	SCA with predators as a fleet	Quantitative	Age-specific B(N), F(C), R, Risk, Rmax, M or q
5	Matrix Population Model with EV	Quantitative	B(N), Rmax, Risk, Sensitivity, F(C)
6	Individual-based Models (IBM)	Semi-Quantitative	Many possible, including: B(N), M, F(C), movement
7	Surplus Production	Quantitative	B(N), F(C), R, K
8	Linear Models (e.g., GLM, LMM, linear regression, Bayesian LMs)	N/A	Index, relationships between demographic parameters and EVs
9	Generalized Additive Models (e.g., mixed effects, Bayesian GAM)	N/A	Index, relationships between demographic parameters and EVs
10	Gradient Forest Models	N/A	Thresholds
11	Multivariate Dynamic Factor Analyses	Semi-Quantitative	Time series patterns
12	Empirical Dynamic Modelling	N/A	Time series patterns
13	Structural Equation Models	N/A	Sensitivity
14	Bioenergetic Multispecies Models	Semi-Quantitative	B(N), F(C), R, K, M
15	Individual-based Models (IBM)	Semi-Quantitative	Many possible, including: B(N), M, F(C), movement
16	Models of Intermediate Complexity for Ecosystem Assessment (e.g., MICE, SCA)	Quantitative	Age-specific B(N), F(C), R, Risk, Rmax, M
17	Multispecies Size-Based Models (e.g., Mizer, LeMaRns)	Semi-Quantitative	B(N), M, F(C)
18	Multispecies Surplus Production Models	Quantitative	B(N), F(C), R, K
19	Atlantis	Semi-Quantitative	B(N), F(C), R, M, TL, →MSE
20	Ecopath with Ecosim	Semi-Quantitative	B(N), F(C), R, M, TL, →MSE
21	Network models (topological or qualitative models)	Qualitative	Consensus building and development of priorities
22	Ecosystem Individual-based Models (e.g., OSMOSE and other IBMs)	Semi-Quantitative	Age/size -specific B(N), F(C), R, M, TL, →MSE
23	Risk Equivalency	Semi-Quantitative	Risk assessment, sensitivity
24	Literature review and expert interviews	Qualitative	Various

Table A4 – Method Inputs & Requirements

Method No.	Method	Essential data inputs	Optional data inputs	Requirements			
				Data	Time	Expertise	Computing
1	Delay-difference with EV covariates	Biomass index, recruitment index, removals series, EV(s)	Informed priors for certain model parameters	1	1	2	1
2	SCA with EV covariates	Age-specific abundance index, removal series, weights, EV(s)	Informed priors for certain model parameters, tagging data	2	2	3	2
3	SCA with time-varying parameters	Age-specific abundance index, removal series, weights	Informed priors for certain model parameters, tagging data	1	2	2	1
4	SCA with predators as a fleet	Age-specific abundance index, removal series, weights, removals from predators	Informed priors for certain model parameters, tagging data	1	2	2	2
5	Matrix Population Model with EV	vital rates (mortality, fecundity, maturity, longevity)	abundance time series	2	2	3	2
6	Individual-based Models (IBM)	individual heterogeneity, vital rates (mortality, fecundity, maturity, longevity)	spatial data and species distributions	1	2	2	1
7	Surplus Production	Biomass index, removals series, EV(s)	Informed priors for certain model parameters	1	1	1	1
8	Linear Models (e.g., GLM, LMM, linear regression, Bayesian LMs)	Could include fisheries dependent or independent abundance indices, EVs		1	1	1	1
9	Generalized Additive Models (e.g., mixed effects, Bayesian GAM)	Could include fisheries dependent or independent abundance indices, EVs		1	1	1	1
10	Gradient Forest Models	abundance index		2	1	1	1
11	Multivariate Dynamic Factor Analyses	time series for multiple component		1	1	1	1
12	Empirical Dynamic Modelling	time series		1	1	2	1
13	Structural Equation Models	time series for multiple components, EV(s), plausible system states		1	2	2	1

Method No.	Method	Essential data inputs	Optional data inputs	Requirements			
				Data	Time	Expertise	Computing
14	Bioenergetic Multispecies Models	Biomass indices, removals series, species interaction information, bioenergetic allometry		1	3	3	2
15	Individual-based Models (IBM)	individual heterogeneity, vital rates (mortality, fecundity, maturity, longevity), behavioural or interaction rules	spatial data and species distributions	1	2	2	2
16	Models of Intermediate Complexity for Ecosystem Assessment (e.g., MICE, SCA)	Age-specific abundance indices, removal series, weights, species interaction information	Informed priors for certain model parameters, tagging data	3	3	2	2
17	Multispecies Size-Based Models (e.g., Mizer, LeMaRns)	body size, biomass indices, size/species specific removals	predator-prey interactions, species mortality, growth maturity, reproduction, gear selectivity and catchability, fishing effort, resource carrying capacity and birth rate	1	2	3	1
18	Multispecies Surplus Production Models	Biomass indices, removals series, EV(s), species interaction information	Informed priors for certain model parameters	1	2	2	1
19	Atlantis	EV, bathymetry, hydrodynamic forcing, physics, biomass, catch, dispersal, diet data, economic data,	Social data	3	3	2	3
20	Ecopath with Ecosim	B, P/B, Q/B, diet, catch, size/age structure	biomass time series, harvest time series, spatial distribution maps, physical/ oceanographic and biogeochemical/NPZD models, economic and social data	3	3	2	1
21	Network models (topological or qualitative models)	network nodes (e.g., species), connections among nodes, species interactions matrix	knowledge of relative interaction strengths for some nodes	1	1	1	1

Method No.	Method	Essential data inputs	Optional data inputs	Requirements			
				Data	Time	Expertise	Computing
22	Ecosystem Individual-based Models (e.g., OSMOSE and other IBMs)	Growth, reproduction, mortality rates, spatial distribution maps	physical/oceanographic and biogeochemical/ NPZD models	3	3	2	3
23	Risk Equivalency	B(N) time series, EVs		1	2	2	1
24	Literature review and expert interviews	Various		N/A	2	1	1

Table A5 – Method Examples & Additional Resources

Method No.	Method	EAFM WG Case Study examples	Additional Resources
1	Delay-difference with EV covariates	MAR - Scallop	• https://openmse.com/features-assessment-models/1-dd/ • https://link.springer.com/chapter/10.1007/978-1-4615-3598-0_9
2	SCA with EV covariates	MAR – Halibut QUE - Cod-Seal NL - Harp Seal	• https://openmse.com/features-assessment-models/2-sca/
3	SCA with time-varying parameters	MAR - 4X5Y Cod QUE - Cod-Seal PAC - Haida Gwaii Herring PAC - Spot Prawn NL - Cod Gulf - Cod-Seal Gulf - 4T Herring	• https://vlab.noaa.gov/web/stock-synthesis
4	SCA with predators as a fleet		
5	Matrix Population Model with EV	O&P - Lake Sturgeon	• https://cran.r-project.org/web/packages/popdemo/vignettes/popdemo.html • https://www.whoi.edu/cms/files/mpm2e_tableofcontents_116984.pdf
6	Individual-based Models (IBM)		• https://noaa-fisheries-integrated-toolbox.github.io/VPA • https://flr-project.org/doc/Stock_assessment_using_eXtended_Survivors_Analysis_with_FLXSA.html
7	Surplus Production	MAR - Shrimp NL - SFA 4-7 Northern Shrimp NL - Cod Arctic - Cumberland Sound Beluga Arctic - Walrus	• https://www.mhprager.com/aspic.html • https://github.com/DTUAqua/spict?tab=readme-ov-file#readme • https://openmse.com/features-assessment-models/3-sp/

Method No.	Method	EAFM WG Case Study examples	Additional Resources
8	Linear Models (e.g., GLM, LMM, linear regression, Bayesian LMs)	MAR - Scallop QUE - Snow crab QUE - Shrimp PAC - Haida Gwaii Herring PAC - Fraser River Sockeye MSE PAC - Fraser River Sockeye RPA NL - Snow Crab NL - Capelin Gulf - Snow crab	
9	Generalized Additive Models (e.g., mixed effects, Bayesian GAM)	MAR - Lobster QUE - 4RST Turbot QUE - GSL Northern Shrimp QUE - Capelin PAC - Northern abalone PAC - Haida Gwaii Herring Gulf - Snow Crab	• https://github.com/jabbamodel/JABBA
10	Gradient Forest Models	PAC - Haida Gwaii Herring	• https://onlinelibrary.wiley.com/doi/full/10.1111/ddi.12787 • https://doi.org/10.1080/00288330.2019.1660384 • www.sustainableseaschallenge.co.nz/tools-and-resources/filling-gaps-in-marine-data-using-gradient-forest-models/
11	Multivariate Dynamic Factor Analyses	PAC - Haida Gwaii Herring	• https://search.r-project.org/CRAN/refmans/MARSS/html/MARSS_dfa.html
12	Empirical Dynamic Modelling	PAC - Fraser River Sockeye EDM	
13	Structural Equation Models	MAR - Lobster	
14	Bioenergetic Multispecies Models		
15	Individual-based Models (IBM)		
16	Models of Intermediate Complexity for Ecosystem Assessment (e.g., MICE, SCA)	QUE - Cod-Seal Gulf - Cod-Seal	
17	Multispecies Size-Based Models (e.g., Mizer, LeMaRns)		• https://cran.r-project.org/web/packages/LeMaRns/vignettes/lemarns.html • https://sizespectrum.org/mizer/index.html • https://cran.r-project.org/web/packages/LeMaRns/vignettes/lemarns.html

Method No.	Method	EAFM WG Case Study examples	Additional Resources
18	Multispecies Surplus Production Models		• https://cdnsciencepub.com/doi/full/10.1139/cjfas-2012-0229
19	Atlantis		• https://research.csiro.au/atlantis/
20	Ecopath with Ecosim		• https://ecopath.org/
21	Network models (topological or qualitative models)	QUE - Capelin QUE - GSL Northern Shrimp	
22	Ecosystem Individual-based Models (e.g., OSMOSE and other IBMs)		• https://osmose-model.org/
23	Risk Equivalency		• https://climateconditioned.org/ • https://github.com/duplisea/ccca
24	Literature review and expert interviews	Gulf - Atlantic Salmon	

APPENDIX 2: EAFM SCIENCE METHODS TOOLBOX SHINY APP

There are three tabs along the top of the application window:

- User Guide - The first (default tab) hosts this user guide, which can be downloaded as a pdf.
- Walk through the Toolbox – the user can walk through the Toolbox based on the filters selected for all or some of the considerations. The user should see a column with the filterable considerations on the left, descriptions of these considerations on the right (same descriptions as in Table 1), and below these two columns, one will see the methods table that will be updated based on considerations selected.
- Exploring the Toolbox - allows a user to filter the Toolbox on their own, like one would a spreadsheet. The Excel spreadsheet can also be downloaded through this tab.

In the Shiny app, the considerations can be filtered in any order, but they have been provided in a logical order based on the four main questions (see below) and the order presented in Table 1. Not all considerations need to be filtered for the table to update.

As a reminder, the four main questions that should be considered when choosing appropriate methods for incorporating ecosystem variables into stock assessments are:

1. What are the management (or research) objectives?
2. What outputs are required?
3. What data are available to apply to the question(s)?
4. What resources are required (e.g., staff time and expertise, computing capacity, etc.)?

APPENDIX 3: ADDITIONAL RESOURCES

The following websites provide links to other toolboxes and/or provide general information about additional stock assessment tools relevant to EAFM.

Title	Link
NOAA Stock Assessment Model Descriptions	• https://www.fisheries.noaa.gov/insight/stock-assessment-model-descriptions
NOAA Fisheries Integrated Toolbox	• https://noaa-fisheries-integrated-toolbox.github.io/
Ecosystem Modelling Overview	• https://www.sciencedirect.com/topics/earth-and-planetary-sciences/ecosystem-modeling
FAO Guidance	• https://www.fao.org/4/Y2787E/y2787e07.htm • https://www.fao.org/3/I0151E/i0151e.pdf
FAO EAFnet	• https://www.fao.org/fishery/en/eaf-net
Gadget – A toolbox for fisheries stock assessments	• https://gadget-framework.github.io/gadget2/
Paradigm for Novel Dynamic Oceanic Resource Assessments (PANDORA) Toolbox	• https://www.ices.dk/PANDORA/Pages/default.aspx • https://www.ices.dk/PANDORA/Pages/assessment.aspx
Data Limited Methods Toolkit (DLMtool)	• https://www.datalimitedtoolkit.org/
Stock Assessment Methods Toolkit (SAMtool)	• https://openmse.com/features-assessment-models/
Stock Assessment Software Catalogue, *hosted by the International Commission for the Conservation of Atlantic Tunas* (ICCAT)	• https://github.com/ICCAT/software/wiki • https://www.iccat.int/en/AssessCatalog.html