JOINT ICES-SEAWISE WORKSHOP TO QUALITY ASSURE METHODS TO INCORPORATE ENVIRONMENTAL FACTORS AND QUANTIFYING ECOLOGICAL CONSIDERATIONS IN MANAGEMENT STRATEGY EVALUATION TOOLS (WKECOMSE)

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Contents

i Executive summary

The EU project SEAwise (https://seawiseproject.org/) endeavours to enhance existing multi-stock multi-species Management Strategy Evaluation (MSE) models so that they can be used to define and evaluate fisheries management strategies that address broad Ecosystem-Based Fisheries Management (EBFM) objectives, including in particular identifying Harvest Control Rules (HCRs) that are robust to changes in productivity.

The WKEcoMSE workshop was held to: (1) benchmark the approaches used or developed in the project to develop robust and consistent environment-productivity relationships for commercial stocks across selected case studies and integrate them in MSE models used by the SEAwise project and by ICES; (2) to provide context for those approaches within the general field of "environment-enriched" MSEs; and (3) to draw from the participants collective experience some general guidelines about the integration of environmental impacts on stock productivity in MSE tools.

23 presentations were given, both about the work carried out within SEAwise but also by international colleagues working toward similar objectives, and various topics were discussed over eight sessions designed to accommodate participants spread across Europe and Northern America. "Good practices" to incorporate environmental considerations in MSE modelling were then drafted collectively and have been summarized in the panels below. These rely on the experiences of the WKEcoMSE participants and are not exhaustive.

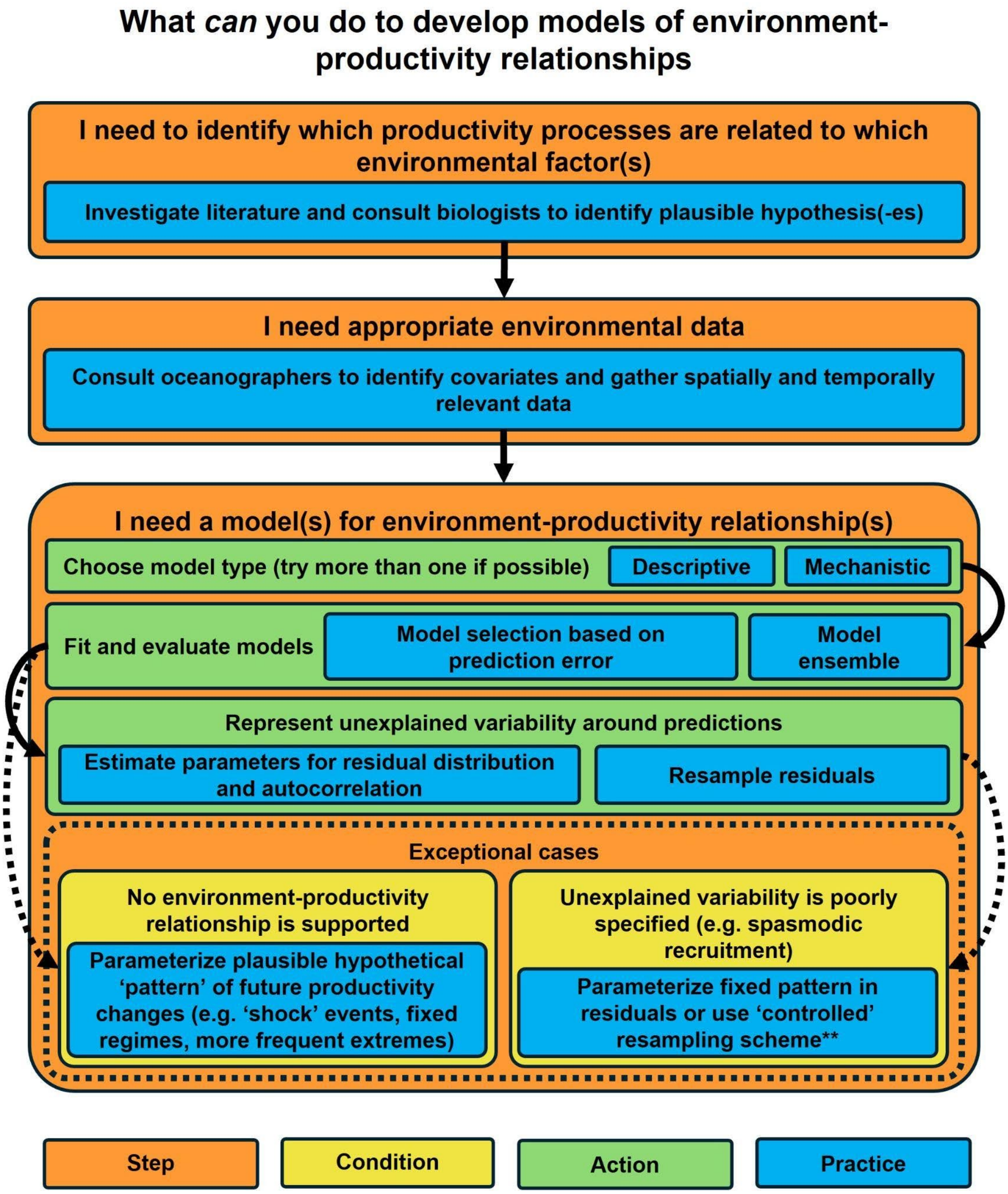

Figure 1: One possible process flow that MSE developers can follow when developing models of environment-productivity relationships to use in MSE. The diagram outlines the typical steps needed (orange), more specific actions within these steps (green), conditions encountered during development (yellow), and the practices one may follow (blue). Where more than one practice (blue) is included within a condition (yellow) or action (green), either or both practices can be done.

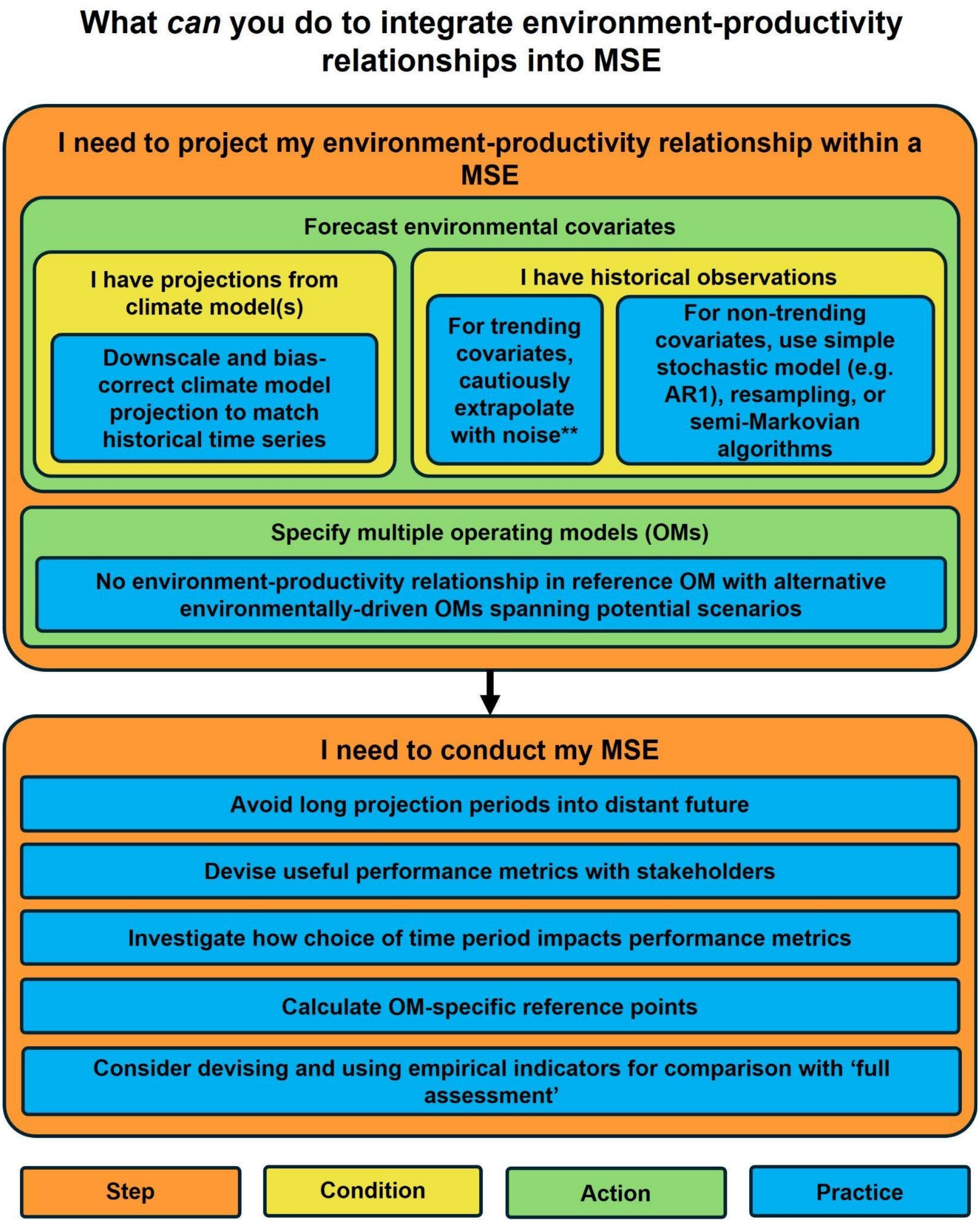

Figure 2: One possible process flow MSE developers can follow when integrating environment-productivity relationships in MSE.

ii Expert group information

Expert group name	Joint ICES-SEAwise Workshop to Quality Assure Methods to Incorporate Environmental Factors and Quantifying Ecological Considerations in Management Strategy Evaluation Tools (WKEcoMSE)
Expert group cycle	Annual
Year cycle started	2024
Reporting year in cycle	1/1
Chair(s)	Marie Savina-Rolland (France)
	Piera Carpi (Norway)
	John Trochta (Norway)
Meeting venue(s) and dates	21-24 May, online, 55 participants

1 Introduction

Management Strategy Evaluations (MSE) are most commonly conducted as single-species analyses but can also address mixed fisheries objectives by using multi-stock and multi-fleet operating models. The EU project, SEAwise (https://seawiseproject.org/), endeavours to advance such multi-stock multi-species models, so that they can be used to define and evaluate fisheries management strategies or procedures that address Ecosystem-Based Fisheries Management (EBFM) objectives, including in particular identifying Harvest Control Rules (HCRs) that are robust to changes in productivity (e.g. in a climate change context).

As a joint SEAwise-ICES initiative, this workshop was held to: (1) benchmark the approaches used or developed in the project to develop robust and consistent environment-productivity relationships for commercial stocks across selected case studies and integrate them into MSE models used by the SEAwise project and by ICES; (2) to provide context for those approaches within the general field of "environment-enhanced" MSEs; and (3) to draw from the participants' collective experience some general guidelines about the integration of environmental impacts on stock productivity in MSE models. The co-chairs and participants acknowledge the existence of a rich documentation on MSE procedures and in particular the three previous ICES workshops WKGMSE, WKGMSE2, and WKGMSE3. The WKEcoMSE group had a fairly focused objective (integrating environment, mainly climate, in multi-species MSE models) and did not undertake a systematic review of all the existing work on this topic.

The meeting was held by videoconference over four days (21-24 May), and was well attended: 55 participants, 18 from SEAwise and 37 outside the project, spread across Europe and the US.

Three topics (predictive models of recruitment, predictive models of growth, integrating environment-productivity relationships in MSE models) were covered by two daily sessions, each including 2-4 presentations and a general discussion. The final day was dedicated to sub-group work on different sections to be included in the report, and to a general discussion on the final diagrams in Section 2.7 (Figures 1 and 2) The full workshop agenda can be found in Annex 3.

S**ection 2** discusses the guidelines outlined above and **Section 3** summarizes all the presentations given during the workshop.

2 Good practices for the integration of environmental impacts on stock productivity in MSE modelling tools

Ecosystem-based fisheries management is becoming more and more important under the current climate change trajectory. Most of the advice currently provided to management is based on single species stock assessments that do not take into account the effect of environment or other ecological processes in the stock dynamics (Skern-Mauritzen *et al.*, 2016); however, ecosystem information is progressively being incorporated in the different steps of management advice (stock assessments, short-term forecasts, Management Strategy Evaluation) (e.g. in the ICES area see Trenkel *et al.*, 2023; and in the U.S. see Dolan *et al.*, 2016). Trenkel *et al.* (2023) estimated that ecosystem trends and/or variability were quantitatively accounted in some form in roughly 50% of MSE analyses surveyed from ICES fishing opportunities advice. Environmental and ecological drivers affect fish productivity through reproduction, recruitment, growth, maturity, and natural mortality. Representation of these life cycle components and population dynamics thus needs to evolve from stationary to non-stationary/dynamic processes and parameters in the models used in MSE.

The wide range of alternative models and approaches available can be overwhelming, and the lack of a standardized framework for model development and model selection makes it difficult to navigate through all the options. Depending on the objectives of the study, the species/stock under examination, the data available, the processes of interest, and the user capacity, some approaches might be recommended over others. Also, the testing and validation methods available might not be conclusive on the most appropriate model to use, and the user experience will play an important role in the model choice.

This report aims to provide some suggestions on the questions and the decisions one needs to correctly set up and evaluate these models. It does not aim to restrict one's choices to what have been described here, but to collect a suite of approaches that have been used in different parts of the world with different objectives, and to highlight some of the main issues and solutions suggested by the workshop participants. In particular, the focus of all approaches listed here was on processes linking environment to growth and reproduction.

In the SEAwise project, multi-species multi-fleet models such as FLBEIA (Garcia *et al.*, 2017) and BEMTOOL (Rossetto *et al.*, 2015; Russo *et al.*, 2017) were used. These are simulation models that take as input externally estimated parameters as opposed to internally estimating them (e.g. as in integrated models used for stock assessment that simultaneously fit multiple data sources). The incorporation of environment-productivity relationship in these simulation models was a 3-step process: (1) fitting one or several environment-productivity relationship(s) outside the operating model (OM); (2) assessing predictive skill of those relationships for model selection; and (3) incorporating the selected one(s) in the existing OM of the MSE modelling framework and running the MSE, over several environment and fishing management scenarios (i.e. the 'mechanistic approach' from Punt *et al.*, 2014). The structure of the guidelines follows this sequence, but alternative approaches are also mentioned (including the 'empirical approach' from Punt *et al.*, 2014).

In the text, an operating model (OM) is a mathematical representation of a given set of processes of stock and/or fisheries dynamics coded in a specific fashion. However, the same term can also be used to differentiate alternative parameterizations of a single productivity process (e.g. stock-recruitment), alternative fixed parameter values for a single parameterization, alternative trajectories of an environmental covariate input to an environment-productivity relationship, or a combination of these. Thus, one OM represents a scenario of the unique combination of stock biology, fishing and environmental assumptions or conditions. In this context, "OM" and "scenario" are either used interchangeably in the text or differentiated where necessary.

Finally, some of the questions raised during the workshop remained unanswered. We have incorporated these into the report because the participants deemed them as important.

2.1 Stock Data

Two alternative sources of biological data may be used to analyse environmental effects on stock productivity:

Survey data: Includes individual data (i.e. weight-at-age, length-at-age, and weight-at-length) and abundance indices, in particular age 0 or age 1 indices for recruitment estimates. In the case of length-at-age data, these can also be back-calculated through the analysis of otolith growth increments (Presentation P10 in Annex 2). Potential biases include a lack of spatiotemporal representativeness depending on the proportion of the stock covered by the survey(s) and an overestimation of weight-at-age for the individuals of the youngest ages caught (due to gear selectivity). Survey data also allow estimation of individual variability associated with the different biological traits (weight-at-age, length-at-age).

Stock object data: Stock objects are defined here as stock assessment input and end products. These products typically contain observed biological data including information on removals (i.e. catches, landings, and discards), maturity, natural mortality, weight/length-at-age, and the results of an analytical assessment (i.e. estimates of abundance and mortality rates due to removals). Stock objects therefore synthesize management's perception of the stock under structural assumptions with all available inputs considered. The content of stock objects may vary depending on stock assessment groups' procedures and documentation about the parameters, and consequently lack important information for post-hoc analyses. For example, the origin of the data used might not always be documented or easily accessible (e.g. have the catch at age for all-time series been generated using a slicing method, or actual age readings?). Assessment results for multiple stocks can be standardized and centralized within dedicated databases. For example, the RAMS legacy (https://www.ramlegacy.org/) database is an extensive and publicly available resource, and it includes stocks from various parts of the world. However, it mostly only includes a subset of data and estimates from the original stock assessment. Another example is the database associated with the state-space assessment model (SAM) project (https://stockassessment.org) used to conduct assessments for many ICES stocks. It displays stock objects generally closer to those produced by the stock assessment groups, but it is limited to SAM applications.

Ideally, analysis may be performed on both sources of data.

When using stock data to investigate environment-productivity relationships, the number of years available from each source should be considered with respect to the longevity of the studied species. Also, analysing regime shifts requires more data to catch non-linear trend and interpolate step functions.

Useful readings

To navigate between age and length in stock objects: Fisher et al. (2021), *Kell et al.* (2022), *Kell and Kell* (2011)

2.2 Environmental Data

2.2.1 Which environmental data to consider?

A hypothesis-based approach, based on existing literature or preliminary studies, is generally preferred to a grid approach (where you systematically scan any available environmental drivers). In particular, considerations on the spatial and temporal scales (also time lags) of environmental drivers with regards to the biology and ecology of the stock considered helps avoid spurious relationships (for examples see Bartolino *et al.*, 2008; Tolimieri *et al.*, 2018; Henriksen *et al.*, 2021). Also, similar covariates hypothesized to have different biological effects (e.g. surface and bottom temperatures affecting different life stages) might be preserved even if they show collinearity (see for example Morrissey and Ruxton, 2018). If after initial hypothesis-based variable selection there remains a large number of potential candidate variables (especially with different possible timings of the effect of the same covariate, including annual lags and seasonal influences), exploratory approaches such as machine learning can be considered (Kühn *et al.*, 2021). Whichever approach is taken, it is necessary to keep in mind the potential non-stationarity of environment-productivity relationships. Proxies for a known driver may also be used when data about this driver is insufficient.

The availability of data for environmental variables should also be considered before integrating them into the analysis. This includes future availability of the observations, model estimates or projections, which implies the ability to update the environment-productivity relationship should the MSE be used for management on a regular basis, or to explore the impact of climate change in a medium- or long-term perspective.

Investigating relationships suggested by stakeholders can be useful to clarify what is caused by the fishery and what is due to the environment, as well as facilitate communication.

2.2.2 Which type of environmental data to use for estimating environmental-productivity relationships?

Two types of environmental data may be available: observational data (e.g. in-situ, raw or aggregated at different scales, historical or real-time) and forecast/model estimates (e.g. projections from climate models, such as the POLCOMS-ERSEM dataset). Both these types can be combined into composite or reanalysis products (e.g. https://climate.copernicus.eu/reanalysis-qas); such products usually integrate observations for a subset of variables (often when observations are available widely over the study area) and compare predictions to observations for some other variables (at wide or local scale in the study area).

In all cases, these data need to be spatially aggregated, either through simple spatial averaging over the distribution area and bathymetric range of the considered stock, or using more sophisticated dimension reduction methods like EOF/PCA (Empirical Orthogonal Function/Principal Component Analysis) analysis, EOT-analysis (Empirical Orthogonal Teleconnections) or spatial clustering (Kühn *et al.*, 2021). For instance, spatial analyses such as EOF may be helpful to reflect changes affecting specific areas of the stock distribution that are key in the life cycle of the species, hence with implications on the productivity of the stock.

Both types of data (observation and model outputs) have pros and cons. Observational data may require careful scrutinization to make sense from a biological perspective, and model-based aggregation is often still necessary. On the other hand, model predictions can provide useful trends at appropriate time and space scales, but they can fail at capturing important interannual signals at the scale of interest for a given stock, especially when they are not reanalyses or when no data assimilation is performed for the variables of interest within these reanalyses. The appropriateness of the model and specific model run(s) used should be discussed with oceanography modellers.

In order to project such environment-productivity relationships in the future, methods to treat the (sometimes considerable) offset between historical and projected environmental data and climate are available (refer to section 2.5.1).

Useful readings:

Morrissey and Ruxton (2018)

2.3 Fitting statistical environment-productivity models

2.3.1 Models of the productivity process

Two main types of models can be considered, descriptive and mechanistic models. Descriptive models include linear mixed models, generalized additive models, or machine learning, which focus on capturing trends and patterns in data, especially over time. Mechanistic models are derived from ecological theory (e.g. Von Bertalanffy or Gompertz for growth, Ricker or Beverton-Holt for recruitment) and impose strong constraints on predictions from the fitted relationship. For long time series with high contrast, multiple approaches can be applied and compared, while mechanistic approaches might be preferable with shorter time series as they avoid the risk of overfitting to noise and having unreliable estimates. In all cases, descriptive models with shape-constraint (limiting the response complexity by imposing a specific response shape, e.g. concavity; Pya and Wood, 2015; Citores *et al.*, 2020) might still be appropriate as they keep predicted responses close to physiology concepts (e.g. temperature optima), and to avoid predicting outside of the range of the environment covariate on which the models were fitted. Density dependence might be tested systematically in addition to selected environmental covariates (Rindorf *et al.*, 2022).

Estimating individual relationships post hoc can introduce bias and inconsistencies by not fully accounting for the interconnectedness of stock dynamics (e.g. if process error is modelled by recruitment but generated by other processes such as natural mortality). Potential dependency between processes should therefore be explored before to introduce separate environment-productivity process relations in an MSE model. When working with estimation models, the environmental relationship may be fitted directly, which allows for the correlation between life history parameters and the propagation of uncertainty from the data and priors or fixed parameters, through to assessment outputs such as biomass and fishing mortality relative to target and limit reference points. It will also allow goodness of fit diagnostics to be evaluated, providing an objective framework for accepting or rejecting hypothesis, and for assigning weights to models within an ensemble of alternative operating models (see Section 2.6; Haltuch *et al.*, 2019a; Punt *et al.*, 2024).

Generally, a model of the productivity process, especially recruitment, assumes the process is time-invariant. However, changes in productivity function itself have been shown to be common (Vert-pre *et al.*, 2013; Szuwalski *et al.*, 2015, 2019). These changes are interpreted as regime shifts that are environment-driven and may reflect broader ecological shifts. There are a number of methods that can be used to detect regime shifts. They range from change-point detection algorithms (e.g. STARS, Rodionov, 2004; or PELT, Killick *et al.*, 2012) to statistical models like random switching models (Munch and Kottas, 2009), Bayesian change point analyses (Perälä and Kuparinen, 2015; Perälä *et al.*, 2017) or threshold GAMs (Blöcker *et al.*, 2023). Alternatively, time-varying stock-recruitment models can also track gradual changes in recruitment dynamics (Minto *et al.*, 2014; Silvar-Viladomiu *et al.*, 2023).

Note that our focus is on descriptive and mechanistic models, but other models can be employed to project changes in productivity. In particular, individual-based models (IBM) can be used to predict temporal variation in size or recruitment in response to changes in environmental conditions. In the European sea bass IBM developed within the SEAwise project, stock dynamics emerge from the concurrent evolution of a large number of individuals dictated by the dynamic energy budget theory (e.g. growth, fecundity, and survival; Melià *et al.*, 2024). In other words, no explicit relationship between environment and recruitment is modelled, but predictions of recruitment will be the output of the model when forcing it by climate projections.

2.3.2 Models of the uncertainty

The statistical model of the noise should at least incorporate an estimate of process error (e.g. the standard deviation and autocorrelation of recruitment deviates around a stock-recruitment relationship), and ideally measurement error as well (Crone *et al.*, 2019; Maunder and Thorson, 2019). For example, environment-productivity relationships with state-space formulations (Maunder *et al.*, 2015; Miller *et al.*, 2016) or covariates "as data" (Schirripa *et al.*, 2009; Crone *et al.*, 2019) directly incorporated and fitted within stock assessment models not only estimate measurement error, but also integrate this error and all other data inputs to the stock assessment in the estimated environmental effect on productivity. Furthermore, accounting for covariate measurement error is considered good practice when modelling environment-productivity relationships to avoid regression attenuation. For example, a separate likelihood component that "fits" the covariate data with an estimate of that covariate (in a state-space framework; see for example Wildermuth *et al.*, 2023) could be used. Finally, accounting for observation errors in weight/length-at-age should also be considered, depending on the variability of the sample size.

2.3.3 Recruitment-specific considerations

Recruitment variability emerges from multiple mechanisms, all possibly impacted by the environment (e.g. see for example Henriksen et al. 2021; see also Section 2.2.1) and difficult to disentangle.

Comparisons between environment-Stock Recruitment Relationships (SRR) fitted on stock-recruit estimates from stock assessment models (common approach) and SRR produced from integrated assessment models in which environmental relationships are directly incorporated (e.g. SS3, SAM, WHAM) might be useful when possible.

Fisheries reference points are also strongly affected by density-dependent processes. Hence, it is important to incorporate density dependence to provide a more accurate estimation of reference points.

2.3.4 Growth-specific considerations

Changes in size have multiple consequences in the population dynamics of exploited populations, including changes in natural mortality (as bigger fish are thought to have lower M, e.g. Gislason and Lorenzen natural mortality models), reproductive capacity, selectivity at age, and price (when using socioeconomic models).

Testing trends in body condition is a useful addition to studying those in weight-at-age or length-at-age to avoid false conclusions on the impact of one on the other. Similarly, correlations between growth and maturity can be complex and therefore assuming a simple correlation between each other can lead to errors.

Useful readings:

Kell et al. (2016)

2.4 Model evaluation and validation

Detecting relationships between environmental variables and biological responses is extremely difficult due to the multi-dimensionality aspect of ecological systems. Model selection is one method for seeking an understanding of ecological processes. Failing to appropriately evaluate the models developed can lead to the identification of spurious correlations, inaccurate error estimates, poor predictive potential, failure to detect existing relationships, and so on.

One of the key steps before selecting a model is to identify the modelling objectives because there is the risk that assumptions and model specifications which are reasonable for one particular model application are inadequate for another. There are three main objectives that these types of models are used for: (1) exploration; (2) inference; and (3) prediction (Tredennick *et al.*, 2021).

Explorative analyses are useful to describe patterns in the data and generate hypotheses. Usually, explorative analyses cover a wide range of models and correlations with many environmental covariates and bear the risk of encountering spurious relationships (Type I errors).

The goal of inference is to test alternative prior hypotheses about how a system functions, which are formalized as alternative statistical models. In this respect, the prediction skill of the models is then of secondary importance, but validation with independent datasets and across a range of conditions should be performed.

Models that achieve the goals of exploration and inference should produce models that give good predictions, but possibly not the best (see full explanation in Tredennick *et al*. 2021). It is important to highlight the fact that the best model for prediction often cannot be used for inference because, after doing model selection, P-values of terms in the selected model will be artificially low. Also, predictions from the same model with updated data can improve or worsen over time.

Overall, fisheries management prioritizes the goal of prediction because it is key to understanding how the system will behave in the future based on what is known about the past.

Models with the goal of prediction require measures of predictive skill. Prediction skill is typically quantified as the error between the predicted mean (e.g. of a modelled distribution) and observation and can be obtained with hindcast cross-validation, which is closely related to forecast evaluation. There are several types of cross validation, the choice of which primarily depends on the size of the dataset. The k-fold cross validation method is more common for smaller datasets and randomly splits the dataset into multiple (k) groups, where k-1 groups are used for training and the remaining group is used as an independent test dataset. This procedure is repeated so that each group is used as a test set, with the remaining ones for training. The model is fit and selected based on the training data set and then used to make predictions of the test dataset, predictions that are then compared to the actual observations (see details in Hewamalage *et al.*, 2023). Increasing the numbers of folds (i.e. length of the time series you use for training *vs* predictions) too much might inflate the number of accepted variables, so there is a trade-off in the number of folds. In general, the performances of the cross validation depend on the length of the time series. Artificial data sets can help in assessing your predictive skills evaluation method.

How ever the predictive skill of a given model is calculated, it is important to compare this skill against that of a naïve model or forecast. For example, a naïve forecast can be equal to the last observed value (Kell *et al.*, 2021) or to the mean over a range of years. There may be other ways to define "naïve" and the choice should consider how these predictions are used and communicated. Additionally, the number of years to choose for the naïve model should be justified, especially considering the non-stationarity of the system under examination.

If the planned MSE procedure includes only one OM then the model with the highest prediction skill should be preferred, and the uncertainties considered should be relevant to the specific management question investigated. Simulation tests are on the other hand flexible for setting alternative OMs and investigating "what if" scenarios. Note that if a model ensemble is preferred over a single model, this will affect the uncertainty included in the MSE.

Regardless of the model objectives, it is key to make sure that the results are realistic for the stock/species under examination, given what is known about its ecology.

It is also important to consider assessing the full distribution of the predictions and their uncertainty, besides just the error of the predicted mean. It may be that the predicted means are similar across different models, but there exists variability between these models coming from the tails of their distributions.

Finally, there are different types of errors that might affect results and conclusions, and one should be aware of those. Besides Type I (rejecting true hypothesis) and Type II (failing to reject wrong hypothesis) errors, one should be aware of Type III (arrive at the correct conclusion for the wrong reason) and Type IV (explaining your correct conclusion in the wrong way) errors as well. The last two are often overlooked. However, especially when the model is used for management advice or practical decisions, the outcomes could be very different. One way to prevent these is to have a good understanding of the system and of the data available.

Unanswered questions:

How do we assess the validity of a detected relationship? What if different models give contrasting relationships?

What is an acceptable environment-productivity relationship? There are several rules of thumbs that might not necessarily apply. Also, the context within which an MSE is developed might require different scenarios not necessarily supported from a statistical context (depending on how good your data are).

Best practices for the choice of naïve model?
When exploring the impact of environment on productivity processes, a way to define the naïve model could be to consider the model without environmental variables included (e.g. Classical formulations of Beverton and Holt, Ricker SRR, etc…).

2.5 Projection of environment-productivity relationships in MSE

This section presents alternative approaches and methods used for projecting future environmental effects on productivity within a MSE. The projection of environment-productivity relationships has been an integral part of MSE research and development since MSE and similar risk analyses were first formally used for fisheries management. Previously published individual case studies (A'mar *et al.*, 2009; Ianelli *et al.*, 2011; Haltuch *et al.*, 2019b), reviews (Haltuch *et al.*, 2019a; Siple *et al.*, 2021), and guidelines (Punt *et al.*, 2016; ICES, 2019, 2020) have thus set precedents on this topic. The following sub-sections generally reiterate these formerly established practices with more recent examples, while highlighting the common and important considerations and methodologies that may serve as good practices. Two key tasks in MSE development are discussed: (1) projecting environment time series to evaluate environmental impacts on productivity (sections 2.5.1 and 2.5.2) and specifying alternative climate scenarios for projecting these relationships (Section 2.5.2); and (2) designing your operating model depending on the knowledge and data you have available. The latter point is treated with a specific example from a highly mixed fishery which uses a decision tree (Section 2.5.3; Section 3 - Presentation P19) to illustrate the typical choices a MSE developer must make and a potential strategy for making them.

2.5.1 Projecting future environmental time series in the MSE

Generally, perceptions of future environmental conditions for MSE rely on climate change projections. General Circulation Models (GCM) simulate the dynamics of major climate system components (atmosphere, land surface, ocean, and sea ice) at a global scale and provide simulations of various climate evolution scenarios, typically Representative Concentration Pathways (RCP[1]) and Shared Socioeconomic Pathways (SSP[2]) scenarios (e.g. the Geophysical Fluid Dynamics Laboratory (ESM2M), Hadley (HadGEM2-ES), Institut Pierre Simon Laplace (CM5A-MR), European Community Earth system model (EC-EARTH)). For marine ecology and fisheries science purposes, such global climate projections can then be downscaled using Regional Climate Models (RCM), i.e. prediction models forced by specified lateral and ocean conditions from a GCM with a finer resolution and coupled with biogeochemical models (e.g. in Europe: NEMO-MEDUSA, POLCOMS-ERSEM, the 1st acronym being the RCM and the 2nd acronym being the biogeochemical model; in the US: ROMS)).

Impacts of climate change on future stock productivity can thus rely on projections of environmental covariates from one or more RCM. Alternative approaches exist, tailored to the stock- and management-specific scenarios. For example, in Wildermuth *et al*. (2023) climate signals from GCMs were passed to the OM from a model of intermediate complexity (DynaMICE Koenigstein *et al*., 2022), which reflected biological and spatiotemporal detail that could not be accounted for within the MSE modelling framework.

The climate model projection can use a coarser resolution than that of the covariate used to fit the environmental-productivity relationship (e.g. observational time series), which requires the climate projected variable to be downscaled to the appropriate resolution. One may accomplish this statistically, by scaling variance and removing bias between the mean of climate projections and regional observation series. In addition, mean-bias correction (also known as 'delta-correction') or scaling of the entire distribution (e.g. via quantile mapping) over the historical period used to condition the OM is strongly recommended to ensure the scales of historical and projected covariates match (see Figure 3, which was extracted from this tutorial: https://figshare.com/articles/software/Tutorial_-_Ways_to_bias_correct_climate_projections/23514618)

In any case, it is important to ensure the scale of the projected covariate time series derived outside the MSE reasonably matches that of the calibration period used to condition the OM.

[1] https://ar5-syr.ipcc.ch/topic_futurechanges.php

[2] https://www.ipcc.ch/report/ar6/syr/figures/csb-2-figure-1

Additionally, translation between climate projection units and forcing variables in the simulation should be explicitly addressed (e.g. converting modelled mass chlorophyll concentration (mg/m3) https://catalogue.marine.copernicus.eu/documents/PUM/CMEMS-MED-PUM-006-008.pdf) to total chlorophyll-a (kg/m3), https://cds.climate.copernicus.eu/cdsapp#!/dataset/10.24381/cds.dcc9295c?tab=overview).

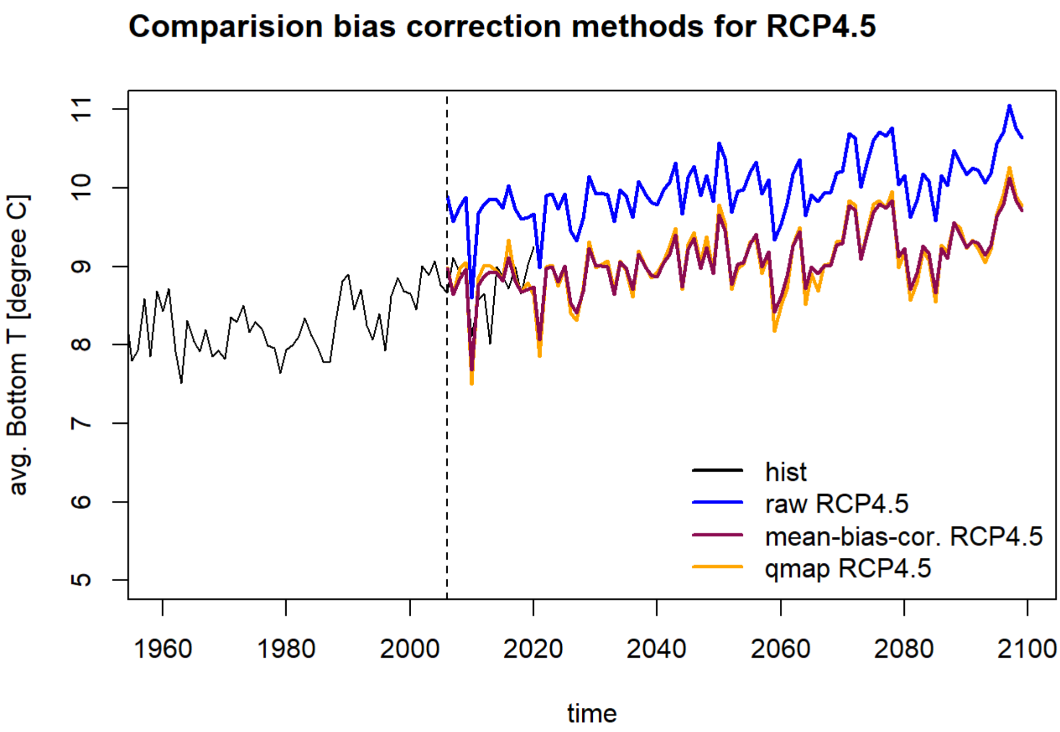

Figure 3 : Bias correction of modelled environmental time series

If a climate model is not readily available, it is still possible to obtain future time series of environmental covariates using different approaches. Several related examples were presented and discussed during the workshop. A MSE analysis for Pacific halibut used a semi-Markovian model (where the next year depends on the current year) to simulate random, decadal changes in a binary environmental regime to mimic the cyclical nature of the Pacific Decadal Oscillation (PDO) and its relationship to average recruitment and movement (Presentation P8 and Section 2.3.4 in Hicks and Stewart, 2022). The probability of changing regime was modelled as a function of the length of the current regime (i.e. the longer the current regime duration, the higher the probability of change), to ensure an average periodicity of approximately 30 years. A similar stochastic regime-shifting approach was used in MSE analyses for Iberian sardine ("two-regime random switching model" in presentations P5 and P13) with unique stock-recruitment models for each regime which, are modulated by the transition probabilities from one regime to the other (Munch and Kottas, 2009).

The use of fixed shifts in recruitment regimes based on stock-recruitment fits to different historical periods was also noted. In a shortcut or desktop MSE analysis for pelagic stocks in the Northeast Atlantic (Presentation P12), shifts between two alternative regimes in the projection period were fixed at years corresponding to the relative timing of regime shifts in the historic period. Similarly, a hindcast MSE can be conducted, where the projection of both stock biology and environment is done over the historical period. A hindcast MSE uses the historical observed environment without making strong assumptions about future environmental conditions or without trying to extrapolate future scenarios. While this does not necessarily test the effectiveness of management strategies under plausible future environmental conditions, it does provide some insights on how new proposed management strategies would have performed under past conditions.

An environmental covariate and fully specified environment-productivity relationship is not necessary to project future environmental effects. In lieu of relying on a model that takes as input a time series of a covariate to predict effects on productivity, the effect is modelled directly in the projection. For example, the demographic variable can be modelled as an autoregressive process (AR-1) if the modelling platform allows random variables to be defined (e.g. the autocorrelated recruitment scenario in Wildermuth et al., 2023). Robustness scenarios of single-year "shocks" can model a short, but extreme event impacting stock productivity, such as a one-off increase in natural mortality to represent a mass mortality event; an example of estimating this effect within a stock assessment model can be found for Pacific herring in Prince William Sound, Alaska (Muradian *et al.*, 2017; Trochta and Branch, 2021). Similarly, extreme values of other productivity processes (e.g. low recruitment or slow growth) can be modelled with increasing frequency during projections. These extreme, or "black swan" events can be modelled statistically with a Student t distribution, which has wider tails in the extremes of the distribution, allowing otherwise unusually large (or small) values to happen with higher probability than a Gaussian distribution (Anderson *et al.*, 2017). If long or continuous historical time series are not available to fit such a distribution, extreme values (either empirical or anecdotal) can be prescribed for one or more years to test the effect of shocks within the context of historical variability (e.g. observations from marine heatwave years, etc.). Some stocks also exhibit 'spasmodic' recruitment, such as Norwegian spring-spawning herring, which are poorly represented by conventional parametric distributions such as the log-normal as the frequency of these year-classes are poorly determined (i.e. too infrequently occurring given the scale of these year-classes) (presentations P7, P12, and P21). In such cases, it is more tractable to understand the impact of different fixed durations between spasmodic year classes across different MSE scenarios.

Some stocks show trends in productivity during the recent historical period, or a modelled productivity process will trend during the projection period of the MSE because of a trending covariate. Caution needs to be exercised when extrapolating trends into the future within MSE. For example, changing the length of the projection period can help constrain a linear trend so that it does not reach unprecedented levels. As mentioned in 2.3.1, using non-linear environmental productivity relationships that force a shape constraint between environment (or time) and productivity parameters can also limit the range of projected productivity changes in MSE (e.g. Smith *et al.*, 2022; Wildermuth *et al.*, 2023). Finally, trending productivity and/or an environmental covariate should be one of multiple scenarios tested in a MSE.

Whether a climate projection from a GCM or alternative method for projecting environmental conditions is used as described above, propagation of uncertainty in the environmental covariates should be accounted for in the projection period. To account for within-model variability of univariate climate projections, time series decomposition and a model of the resulting residuals (e.g. with AR1) may be used to simulate possible future realizations of an environmental time series. For spatial multivariate time series from a climate projection, a combination of a dimensional reduction analysis (e.g. EOF) and multivariate time series model (e.g. Baysian vector autoregression models, or BVAR) fit to dimensionally reduced time series may be used to simulate future realizations of the environment (presentations P1 and P4; also see tutorial at: https://figshare.com/articles/software/Tutorial_-_Capture_uncertainty_of_climate_signals_via_Bayesian_Vector_Autoregression/23546127).

More generally, noise (i.e. generated from a parametric statistical distribution, or resampled from a historical series of estimated errors) could be simulated in the environmental covariate directly (presentations P13 and P15) or as proportional error around the environment-productivity relationship used to link the forcing covariate to system dynamics (e.g. see Presentation P16). This applies to both stationary and non-stationary (e.g. trends) environment-productivity relationships. As mentioned in Section 2.3.2, noise should be ideally incorporated in the form of at least process and ideally observation error too.

2.5.2 Specifying alternative climate scenarios based on available climate projections

In general, researchers should include one or more scenarios to better contextualize the effect of climate change or other environmental covariates on the study system. In addition to different climate change scenarios (e.g. presentations P15 and P16), a null hypothesis OM, in which no climate trend exists, should be included. This can be defined by removing the future trend (median of all realizations) from the time series of the projected climate change scenario, resulting in an environmental time series with the same stationary stochasticity as the climate change run.

For devising scenarios based on climate projections, researchers must be aware of the various models available, how they are used, and differences in their results. As mentioned earlier (Section 2.5.1), two types of climate projections are available, either GCM outputs or RCM. Two series of scenarios are available, the RCP and SSP scenarios. There are seven RCP scenarios of greenhouse gas concentration trajectories. The IPCC currently uses SSP scenarios to characterize the rate and magnitude of future warming, given the socioeconomic circumstances leading to various levels of greenhouse gas emissions. These scenarios replace the previous RCPs but can still be compared to the RCPs through the numbering system identifying each climate scenario (e.g. SSP1-2.6: socioeconomic pathway 1 with radiative forcing of 2.6 W/m^2, or paired with RCP 2.6). Depending on the region of the world, not all the RCP scenarios have been downscaled using RCM, and downscaled SSP are yet to become available, at least in Europe.

Within climate science, it is a standard practice to use model ensembles to project future climate (e.g. a combination of multiple models). Care must be taken to address the structural and scenario uncertainties engrained in these products when using them to project future productivity relationships. Multiple GCM and RCM model structures exist and are used in the global IPCC climate projections, but the magnitudes of change and spatiotemporal pattern of impacts estimated by each GCM may differ at local to regional scales (e.g. Pozo Buil *et al.*, 2021). Spatiotemporal model averages may be a valid method to reduce the number of alternative scenarios, but researchers should be aware of the implications of this simplification for their study region. Alternatively, climate model structures producing contrasting trends in projected variables may be used to explicitly specify alternative OMs that bracket the range of uncertainty in future environmental effects on productivity. Care should be taken to ensure all required physical and biogeochemical variables are available for OM forcing, given alternative climate model structures do not have the same outputs or resolution.

Thus, researchers and stakeholders will have to identify the climate model structure and climate scenarios relevant and available for a given study. Combinations of models and scenarios can be selected to provide contrast (e.g. high vs. low emission scenarios), to attempt to represent the most likely outcomes (e.g. only using a model that performs best in the study region), or to assess worst-case scenarios (e.g. only analysing high emissions scenarios as in Wildermuth *et al.*, 2023). Using downscaled model products leads to a much smaller range of available model/scenario combinations. To make up for this, a typical solution would be to use several realizations of the environmental variable and force the simulation model for a series of Monte Carlo simulations (https://figshare.com/articles/software/Tutorial_-_Capture_uncertainty_of_climate_signals_via_Bayesian_Vector_Autoregression/23546127). Alternatively, noise can also be added as a random process, and/or through auto- and cross-correlation.

2.5.3 Example decision tree for devising multi-species OMs with environment-productivity relationships

As implied in the previous sections, determining which OMs to include in the final MSE poses a major challenge for researchers especially because of the trade-off between time and resource constraints, and the need to sufficiently address and/or model the different types of uncertainty. To better illustrate this unavoidable decision process, a decision tree was presented for a MSE for mixed fisheries in the Bay of Biscay (Figure 4 as presented in P19). This tree was built with the goal of projecting climate change effects on all stocks included in the model as much as possible. It can thus be seen as the terminal part, or a subsection of a broader decision tree that may help design the entire MSE. Additionally, this decision tree (and the associated table below) illustrates decisions on how to conduct projections or how to perform extrapolations for one specific trait of a specific stock in our simulations. So, in this example of highly mixed fisheries, this sequence leading to a decision regarding the simulations would be potentially repeated for each trait for each stock for which we want to project climate change impact. Preliminary to that sequence of decisions are hence other decisions. The tree may also allow different applications to be compared, and individual case studies to be summarized.

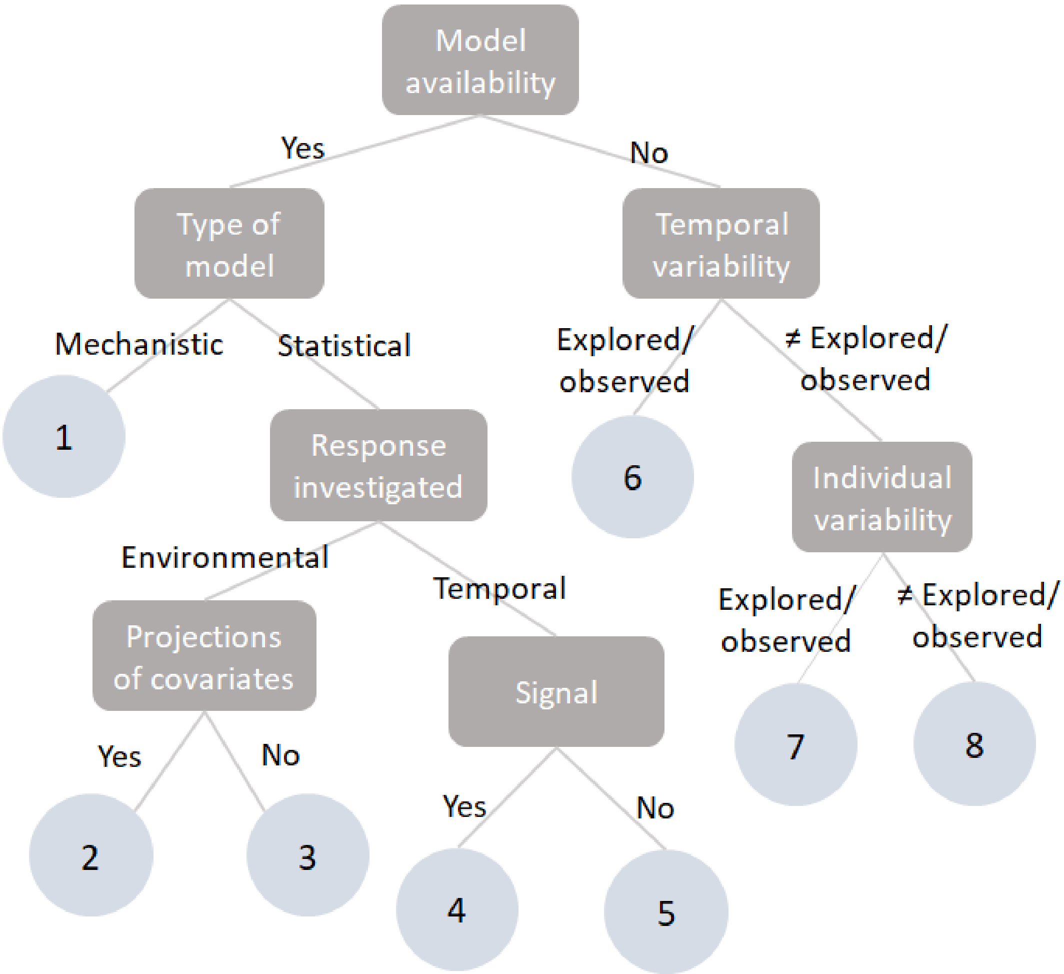

Figure 4 : Decision tree for designing alternative OMs for projecting environmental-productivity relationships (called model in the figure and the table below) in a MSE. Each rectangle is either a condition to address or choice to be made when developing an OM, with the underlying branches representing two alternative outcomes. The circles are end nodes with values identifying a set of potential scenarios to use and how to define them, as shown in Table 1.

Table 1: Cases corresponding to the end nodes of the decision tree in Figure 4, where each case defines a set of scenarios/OMs one may use based on the availability of data, model, and relevant model outputs for an environment-productivity relationship.

Case	Projections or Extrapolation	Source of info for extrap. or proj.	Reference scenario	Least bad case scenario	Worst case scenario	Reference scenario - Option B (maximizing insights)
1	Projec.	Fitted model - future projections	Projected value	Lower/Upper uncertainty bound**	Upper/Lower uncertainty bound**	Projected value
2	Projec.	Fitted model - future projections	Projected value	Lower/Upper uncertainty bound**	Upper/Lower uncertainty bound**	Projected value
3	Extrap.	Fitted model - past predicions	Mean historical value	Lower/Upper historical value*	Upper/Lower historical value*	Mean historical value
4	Extrap.	Fitted model - past predicions	Most recent historical values	Most recent historical values	Prolounged trend	Most recent historical values
5	Extrap.	Fitted model - past predicions	historical / population average	historical / population average	Upper/Lower historical value*	Directional change based on species with similar traits
6	Extrap.	Data	historical / population average	historical / population average	Upper/Lower historical value*	Directional change based on species with similar traits
7	Extrap.	Data	historical / population average	historical / population average	historical / population average	Directional change based on species with similar traits
8	Extrap.	Data	no change	no change	no change	Directional change based on species with similar traits
*	Lower/Historical value choice depends on the expected change given similarities of traits with species for which information is available					
**	Lower/Upper bound choice depends on the direction of the projected change					

2.6 Conducting and presenting MSE analyses with environment-productivity relationships

As noted during the workshop, specific considerations should be made in other aspects of the MSE process when conducting MSE analyses with environment-productivity relationships. General MSE best practices (Punt *et al.*, 2016) and specific guidelines based on experiential knowledge and expert consensus (ICES, 2019, 2020) should be followed as much as possible. This especially includes the process of stakeholder involvement that should occur before, during, and after MSE analyses, for which specific advice is also available (Feeney *et al.*, 2019). The following section generally reiterates existing MSE practices and guidelines, focusing on how they are applied in the context of environment-productivity relationships.

2.6.1 Performance metrics

Performance metrics aim to reflect how well alternative management strategies meet management objectives and their robustness in case of changes in productivity. During the workshop, we mostly focussed on performance metrics related to the status of, and fishing pressure exerted on, managed stocks. Several considerations related to the calculation of performance metrics should be made. As previously noted in Section 2.5.2, reference points used in performance metrics (e.g. virgin or unfished biomass (B_0), biomass at maximum sustainable yield (B_{MSY}), biomass below which recruitment declines (B_{lim})) should be OM/scenario-specific. With trending environmental covariates and/or productivity in the projection period, performance metrics will be sensitive to the choice of time period, particularly with too few years. Choosing a sufficiently long time period should provide a more robust performance metric. Furthermore, including appropriate reference models (without an environmental effect, or "status quo" productivity and possibly fishing mortality; see Section 2.6.2) allows for benchmark performance metrics to be calculated and against which the metrics resulting from environmentally forced OMs may be contextualized (e.g. differentiating the effect of the environment from the effect of different management procedures on performance metrics).

Environmental and especially climate change effects on productivity have implications for fisheries management performance beyond fishing and stock-related objectives. With the aim to operationalize ecosystem-based fisheries management and further considering socio-ecosystems, ecological and socioeconomic objectives will likely become relevant. In particular, a MSE conducted for Atlantic mackerel, used metrics related to nutritional objectives (Presentation P18). MSE frameworks using socio-ecosystem models as OM could explore combined effects of management scenarios and simultaneous productivity changes of multiple stocks on the population status of predators or on revenue distribution among fleet components. These types of objectives and performance metrics should be defined with stakeholders.

2.6.2 Other considerations

In general, many of the MSE analyses presented during the workshop used what are known as desktop or shortcut MSEs (ICES, 2019; Walter III *et al.*, 2023). Shortcut MSEs circumvent the inclusion and fitting of an explicit estimation model (i.e. the stock assessment) within the MSE simulation loop to reduce run-times. Desktop MSEs execute the technical steps of an MSE, but do not involve the collaborative MSE process to incorporate decision-makers in development decisions. It was acknowledged desktop and shortcut MSEs may be useful initially (e.g. running sensitivity tests with MSE, reducing a large set of candidate HCRs, answering research questions), but should always be accompanied by a full MSE process for the final analysis presented to management and stakeholders (ICES, 2019).

Alternatively, we encourage simulation testing of the use of empirical indicators of stock status in management procedures to replace a 'full' estimation model. An empirical indicator is directly computed from a survey(s) as generated by the observation model in a MSE, and subsequently input to the management procedure (e.g. directly into a HCR, Wildermuth et al. 2023). This should be tested alongside the currently used estimation model in a full MSE to compare performance. Furthermore, the implied data needs (and costs) are different between approaches, being simpler for indicators. Researchers and managers may also consider a hybrid-like approach in which a full stock assessment is conducted intermittently (i.e. at intervals determined from species-specific life history) while indicators are used by the management procedure in the interim (Huynh *et al.*, 2020). Researchers should discuss with management about the potential benefits and limitations of using empirical indicators and encourage their inclusion in MSE analyses.

Ideally, an exceptional circumstances protocol would also be defined and can "trigger" a more complex analysis (a full stock assessment, benchmark, and/or OM reconditioning) sooner than in a normal process. It is important to be aware of the mismatch between the complexity of environmentally or ecosystem informed MSEs and management structures (i.e. that are inherently slow to adapt, cannot necessarily provide resources for the continuation of ecosystem information) when communicating outcomes from analyses. Many applications of environmental indices resulted in more precautionary advice (i.e. lower advised catches; e.g. Presentation P21), but these were typically in reference to externally identified reference points which are updated at a slower rate within the management process. The reality may be that if a more responsive management structure is adopted, the advice from environmentally informed assessments may not always be "lose-lose" outcomes. Therefore, when conducting MSEs with environmental or ecosystem information, researchers should clearly communicate the benefits of further investigating environment-productivity links to encourage continued support from management.

The type of model(s) used to project environment-productivity relationships and its role(s) should be clearly communicated to stakeholders and fisheries managers. Modelling tools that account for biosocioeconomic processes (e.g. FLBEIA) or project ecosystem processes and dynamics (e.g. "end-to-end" models such as EwE or Atlantis) are used to understand the emergent outcomes and properties of these processes, set "directions" for research and policy, and are specified by a variety of inputs from different sources instead of conditioned by fitting data directly (i.e. strategic models; FAO, 2008; Plagányi *et al.*, 2014). Models developed more specifically for stock assessment purposes (e.g. SAM, Gadget, SMS, SS3, WHAM) estimate biological and fishing parameters internally from fitting directly to stock-specific data, use statistical diagnostic tools to evaluate model performance, and directly incorporate and estimate uncertainty (i.e. tactical models; FAO, 2008; Plagányi *et al.*, 2014). Each general class of models, and the specific models themselves, have their benefits, limitations, and intended uses that researchers should familiarize themselves with (e.g. all these tools either have publicly available manuals or GitHub repositories with tutorials and examples).

There should also be careful consideration in the characterization of the sources of uncertainties incorporated in MSEs with environment-productivity relationships, and how they are incorporated. Specifically, while MSEs are often used for and communicated as uncertainty analyses, they may also be used as a sensitivity analysis, which focuses on how model outputs change accordingly with changes in different individual inputs. An example sensitivity analysis using a MSE simulation loop was presented for Norwegian spring-spawning herring and explored the impact on performance metrics of different assumptions regarding natural mortality (e.g. fixed M vs time-variant M vs time- and age-variant M; Presentation P21). An uncertainty analysis in contrast propagates through the uncertainty in inputs and assumptions to the modelled outputs, thus providing a more comprehensive understanding of potential management outcomes (e.g. modelling random regime shifts in recruitment between simulations), and thus integrates over this specific uncertainty. However, in fisheries this is seldom possible and so instead a sensitivity analysis is conducted where key parameters, or the assumed model structure, is varied to test its robustness or to prioritize research efforts. The choice between sensitivity and uncertainty analysis depends on the objectives of the study and the nature of the available data.

Non-stationarity in environmental-productivity relationships (e.g. regime shifts in productivity parameters, changes in the link between the environmental covariate and environmental process it is assumed to represent) can never be completely represented in OMs as future changes may (and are likely) not repeat historical changes (i.e. the "unknown unknowns"). This also includes future changes in fishery behaviour, technical interactions, and trophic interactions between multiple species. These uncertainties should be at least addressed in an appropriate exceptional circumstances protocol (Punt *et al.*, 2016).

2.7 Process summary and steps for incorporating environmental factors and quantifying ecological considerations in MSE

The following list presents one process flow a MSE developer may follow when incorporating environment-productivity relationships. The bullets outline the sequence of key decision points developers may likely encounter (primary decision node), the secondary choices likely to be made and questions to answer for each primary decision point (secondary decision node), and suggested actions a developer may take in accordance with the guidelines discussed during the workshop and described in the preceding sections. It is emphasized that while these steps and specific actions are derived from the collective experience of various MSE experts and case studies, they are not "hard" rules as developers may face circumstances not considered here and thus need to adapt their approach accordingly. However, many of these suggested "good" practices should be applicable in a variety of MSE analyses and thus guide developers when needing to account for environment and/or ecosystem effects in their MSE.

A., B., … Primary decision nodes

a., b., … Secondary decision node

i., ii., … Recommended considerations and suggested practices

A. I have a hypothesis and need relevant data

a. Do you know specific productivity processes likely to be affected and how?

i. Yes - obtain historical time series of spatially and temporally relevant environmental covariate representing hypothesis.

ii. No - investigate literature, find likely hypotheses, and look for covariates reflective of variables/processes that may affect stock-specific productivity. Cautionary note: Make sure covariate appropriately scales and co-occurs with productivity process (e.g. at the time and area where juvenile survival is critical when modelling an effect on recruitment).

b. Work with oceanographers to identify data needs

i. Devise method to approve models/variables/relationships

ii. Avoid random investigations and spurious relationships

iii. Identify data needs for the future especially in the context of the existing management procedure (e.g. potential changes in governance structures and support)

B. I need a model(s) for environment-productivity relationship(s)

a. I need to choose model types (try more than one if at all possible)

i. Use a mechanistic model, especially for shorter time series (Growth VB, Gompertz, Recruitment BH and Ricker; i.e. based on life history), as they may be more reliable if trying to extrapolate beyond observed range.

ii. Use a descriptive model, especially for longer time series (GAMMS or LMMs; i.e. based on trends and patterns in data). Cautionary note: Generate predictions with uncertainty from these models and compare against historical; discard model if they are unreasonable (e.g. extend well beyond the range of historical observations).

b. I need to fit and evaluate my model(s)

i. I want to choose reasonably good models and evaluate the strength of each model where the objective is prediction

- Decide on a reasonable naive model for comparison
- Choose between similar models/different covariates using some goodness of fit statistics (e.g. AIC)
- Evaluate prediction skill using hindcast skill, cross validation and/or forecast evaluation

ii. I want to use multiple plausible models weighted by their strength

- Develop model ensemble using an appropriate weighting scheme (Dormann *et al.*, 2018) - especially important for getting the tails/variation right

c. *I need to parameterize/represent/project unexplained variability around my environment-productivity relationship(s)*
   i. Characterize the shape of the distribution of residual errors, which can be the SD of a parametric distribution, resampled residuals or parametrically smoothed residuals. Also account for residual patterns (i.e. estimate autocorrelation or use AR models)
d. *Exceptional cases where alternative practice is needed*
   i. No environmental variable has significant (statistical) or consequential (biological) effect
      - Design plausible hypothetical "patterns" of future climate effect and use in alternative OM, for example, fixed trend, single-year "shocks", more frequent extreme values, or fixed regimes.
   ii. Productivity process exhibits unexplained variability poorly represented by parametric distribution (e.g. spasmodic recruitment that leads to fatter tails in the distribution, but the frequency of spasmodic good years is very poorly determined)
      - Similar technique to exceptional case i.) immediately above. Additionally, a controlled resampling scheme for residuals (e.g. moving block bootstrap) may produce a representative distribution.

C. I need to integrate and project my environment-productivity relationship in my MSE

a. *I need a future realization of my environmental time series to use in MSE*
   i. There is a climate model that projects my time series
      - Pre-process projected time series as for historical data
         - Determine extent of projection time frame and stay within the not-too-distant future to avoid introducing too much uncertainty (keeping in mind the species life span)
         - Downscale (filter and average)
         - Mean-bias correction/QQ mapping
         - Dimension reduction
      - Consider surrogate time series to include uncertainty between models
   ii. There isn't a climate model that projects my time series
      - Is there a pattern in the time-series (trend, cyclic pattern, autocorrelation, …)?
         a. Yes - extrapolate with noise and include as one scenario among others. Use multiple extrapolated timeseries to encapsulate uncertainty in trend. Cautionary note: carefully consider the time horizon of projection to ensure trend does not lead to unreasonable outcomes, and discard if so.
         b. No
            i. Use a simple stochastic model (e.g. AR model) or resample - see above 2.3. for comments on variability between simulations

ii. If interannual environmental effect can simplify to regimes (e.g. "good" and "bad"), a stochastic "shifting" procedure may be used (e.g. Markovian switching algorithm, resampling, or semi-Markovian models)

b. *I need to choose the number of operating models/scenarios to run*
   i. Consider multiple reference models without any environmental-productivity relationship and/or a 'status quo' environmental effect, and OM(s) with environmental effects (to benchmark comparisons)
   ii. Identify representative states of nature for between-model variability of future environmental scenarios.
   iii. If a process is influenced by both environmental data which are available and other data which are not available in projections, the number scenarios will increase a lot, it can be helpful to eliminate very unlikely combinations. Probably the variability within a scenario is not needed as we agreed to stay in the not-too-distant future.
   iv. Derive reference points from each alternative OM/scenario for use in the calculation of performance metrics. These reference points should differ with those used in the MP being tested.

D. I need to run my MSE with environment-productivity relationships

a. *I need useful performance metrics*
   i. Involve stakeholders and managers before MSE development to define objectives
   ii. Consider socioeconomic and ecological performance metrics with stakeholders
   iii. Carefully consider the time period over which metrics are calculated under climate change, as projected environmental conditions may lead to trending performance during projection - do not project into the very distant future, see above - possibly use 3 generations (for multi-stock MSEs, this could be 3 generations of your main target fish or longest-lived one) as in general MSE best practice

b. *What other considerations should I make with my MSE?*
   i. Desktop/shortcut versus full MSE
      - Shortcut MSEs may be useful initially, but should be followed by full MSEs with stakeholder involvement
      - Consider using empirical indicators in the MP instead of shortcut MSE
         - Compare performance with full MSE (i.e. stock assessment as estimation model)
         - Carefully think about what part of population an indicator applies to
         - Consider using indicators as a trigger for a more complex analysis (full assessment, recondition OM) sooner than in normal process
   ii. Pay attention to characterization of uncertainty
      - Clearly communicate whether MSE is used to conduct sensitivity or uncertainty analysis
   iii. Address additional uncertainty due to non-stationarity (in environment, fishery behaviour, or multispecies interactions) not adequately reflected in OMs
      - Develop appropriate exceptional circumstances protocol

iv. Include a model for reference point update procedures (e.g. benchmark processes) in your MSE

v. Account for any management lags in advice (e.g. include intermediate year if stock assessment in the current year results in advice for the following year(s)). Disregarding lags may decrease the accuracy of performance metrics based on predicted catches and Fs.

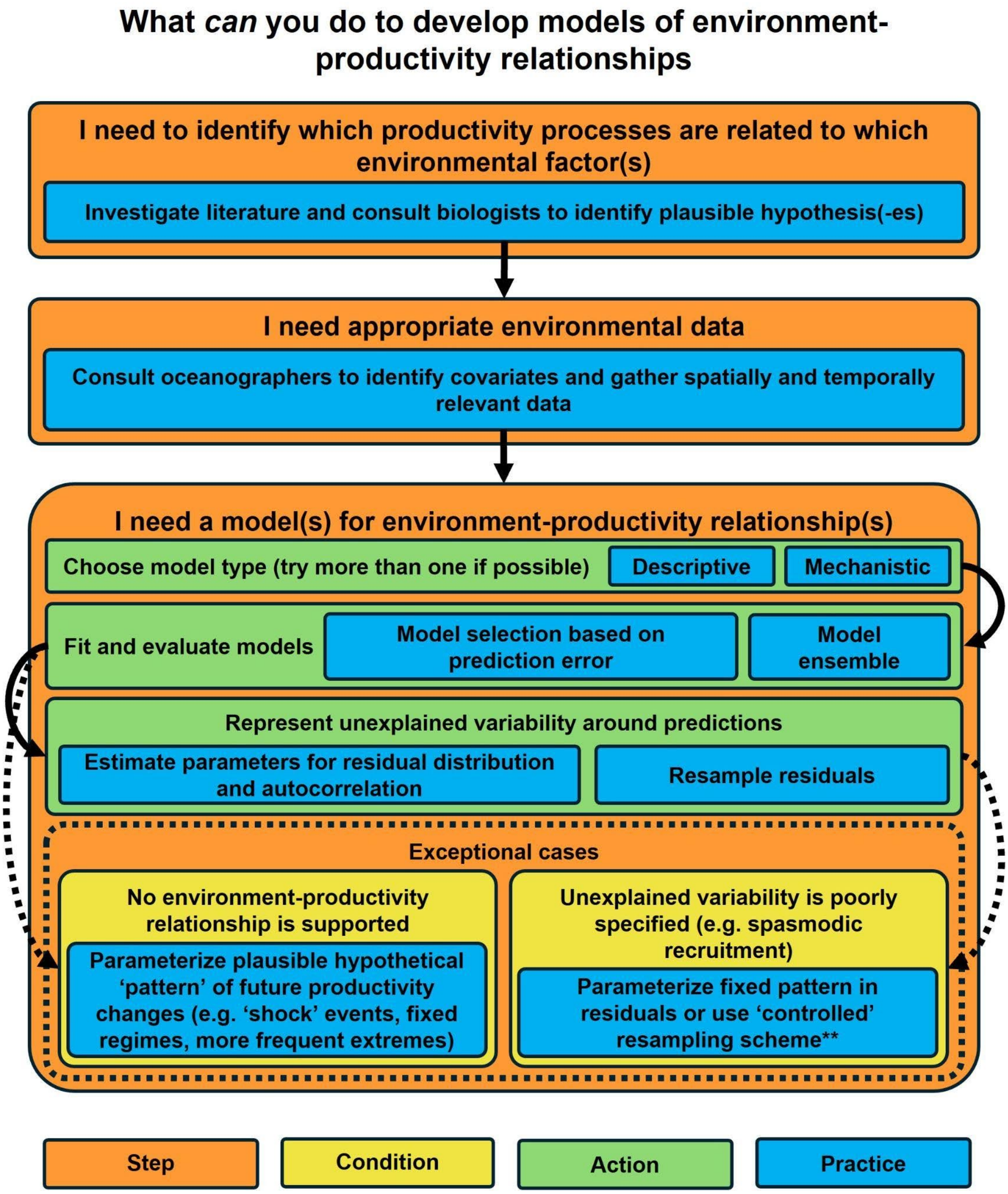

Figure 1: One possible process flow that MSE developers can follow when developing models of environment-productivity relationships to use in MSE. The diagram outlines the typical steps needed (orange), more specific actions within these steps (green), conditions encountered during development (yellow), and the practices one may follow (blue). Where more than one practice (blue) is included within a condition (yellow) or action (green), either or both practices can be done.

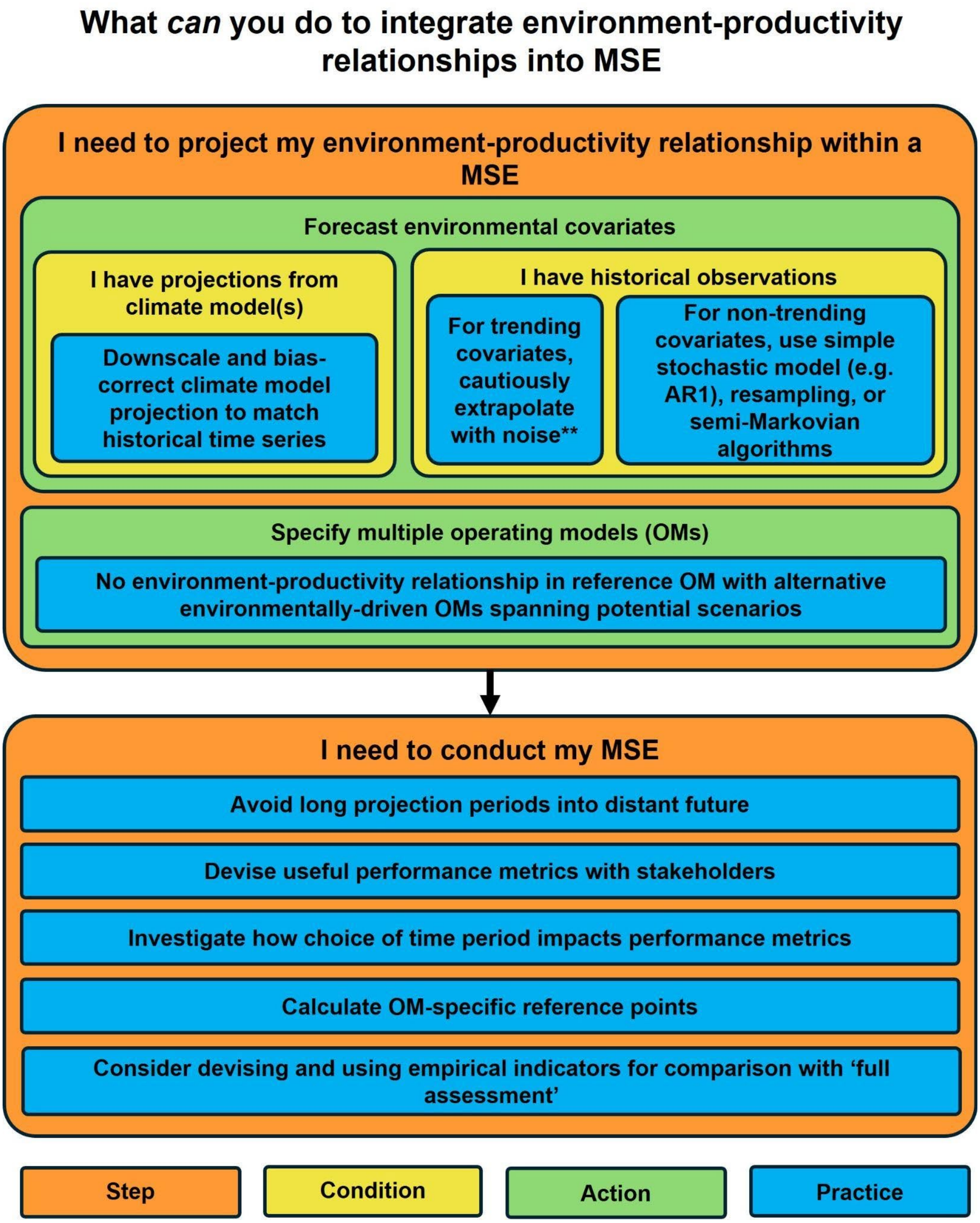

Figure 2: One possible process flow MSE developers can follow when integrating environment-productivity relationships in MSE.

3 Presentations

3.1 Input data

P1 - Available climate data and various aspects relating to preparing climate data for statistical model fitting and forecasting within the MSE

Bernhard Kühn and Marc Taylor - Thünen institute - SEAWise

In order to explicitly integrate environmental data into MSE simulations different choices and pre-processing steps need to be done beforehand. The talk addresses several questions of what kind of data to use for the history and the future projections, trying to highlight the different properties of the data (ability to capture interannual trends vs. longterm climatological mean). An overview is given on ways to aggregate environmental data spanning the range of utilising simple spatial averages vs. dimension reduction algorithms, with their own pros and cons. As a further step in climate projection pre-processing, two ways of bias correction are presented, which are needed to correct for an offset or change in variance when dealing with historical and future data of different sources. Furthermore, the question is raised on how to incorporate variability of the climate projection as uncertainty in the MSE run and a way presented utilising Bayesian Vector Autoregressive Models (BVARs). Examples are given based on own past experiences with data handling within the North Sea case study in SEAwise. For the bias correction, as a tool to join data of different sources, a tutorial was prepared that summarises the steps done in R: https://figshare.com/articles/software/Tutorial_-_Ways_to_bias_correct_climate_projections/23514618 Additionally, a similar tutorial is available to fit a BVAR-model to spatio-temporal data, that allows to generate artificial time series with the same trend, autocorrelation and cross-correlation to other variables for the use in fisheries management projections: https://figshare.com/articles/software/Tutorial_-_Capture_uncertainty_of_climate_signals_via_Bayesian_Vector_Autoregression/23546127

3.2 Predictive models of recruitment

P2 - Recruitment of European hake, red mullet, and various shrimps in the Adriatic and western Ionian Seas

Isabella Bitetto, Walter Zupa and Maria Teresa Spedicato - Fondazione COISPA ETS - SEAwise

Exploring the processes that influence the recruitment of fish species is a challenging issue in fisheries science, especially in the Mediterranean Sea, where the time series of spawning stocks and recruitments are generally short and poorly contrasted. In the case study of Adriatic and Western Ionian Seas (GSAs17-18-19), the influence of the environmental covariates on the recruitment process was explored on the key demersal stock of the GFCM Multi-Annual Management Plan for demersal fisheries (European hake, red mullet, deep-water rose shrimp, giant red shrimp and blue and red shrimp). Sea surface temperature, bottom temperature, salinity, bottom salinity and net primary production were integrated in the Beverton-Holt, Ricker and hockey stick traditional parametric stock–recruitment formulations. For this purpose, the last stock assessment results were used. In all cases, the inclusion of the environmental variables improved the precision or the prediction power of the models. In all the cases, the environmentally mediated stock-recruitment relationship allowed to reduce the prediction error and improved the relative quality of the stock-recruitment model with respect to the formulation without environmental covariates. Recruitment projections were carried out under RCP4.5 and RCP8.5 climate change scenarios.

P3 - Environmental processes affecting fish recruitment in the North Sea

Bernhard Kühn, Alexander Kempf and Marc Taylor - Thünen institute - SEAwise

The North Sea as a highly productive fishing ground for several commercially important demersal stocks, is also expected to change strongly under climate change. After an era of overexploitation, successful fisheries management allowed various stocks to recover. Still the effects of climate change provide a challenge for future management, as productivity declines for some of the boreal demersal stocks in the North Sea are expected. Impacts of climate change are believed to affect the abiotic environment and the ecosystem of the North Sea through all trophic levels, which will eventually change how much yield fishermen can sustainably harvest. Incorporating explicit environmental influences on productivity could help to understand how the mixed demersal fisheries of the North Sea are affected and what alternative management rules might work in the face of climate change. Therefore, we fitted environmentally-mediated stock recruitment relationships (EMSRRs) to eight commercially important stocks in the North Sea. We investigated the effects of temperature, salinity, currents, chlorophyll and zooplankton on recruitment of cod, haddock, saithe, whiting, plaice, sole, sprat and herring using a semi-automated, machine learning framework. Using a cross-validation setting and an additional holdout period at the end of the time series, should allow the testing and evaluation of predictive capability to only allow models to be used in the MSE that showed some skill on the leftout data. Overall, the incorporation of environmental effects in stock-recruitment relationships improved recruitment predictions in five out of eight stocks.

P4 - Dynamic factor analysis applied to 6 demersal stocks in the Celtic Seas

Klaas Sys - ILVO

In this work, we looked at the dynamics of stock recruitment relationships from a multivariate perspective which may be beneficial in the context of multi stock MSEs. A dynamic factor model was used to analyse trends in the stock recruitment relationships of 6 demersal fish stocks in the Celtic Sea ecoregion. For each of the stocks, a stock recruitment relationship was determined, either Beverton Holt or Ricker, and changes in productivity were described by the contribution of two dynamic factors. The results showed that the stock recruitment dynamics of the roundfish stocks were correlated, as well as those of the flatfish stocks considered in the model. The dynamic factor model does not allow to identify environmental drivers, but based on the trends of the factors, the model suggests that temperature and zooplankton abundance are the main drivers of recruitment. In addition, the dynamic factor model showed better forecast skills compared to the stock recruitment models fitted to single species data.

P5 - Environment-driven stock recruitment models in Western Waters

Leire Ibaibarriaga, Andrés Uriarte, Leire Citores, Ixak Sarasua, Almudena Fontán, Sonia Sánchez-Maroño, Ane López de Gamiz and Dorleta Garcia - AZTI - SEAwise

In this work we have studied the impact of environmental conditions in stock-recruitment models for twelve stocks in the Western Waters. For the Bay of Biscay anchovy, we have revisited past stock-recruitment-environment models and we have tested its validity with the inclusion of new observations. The results indicated that the upwelling and the turbulence indices remained as important predictive variables for anchovy recruitment. For the Iberian sardine, we have studied a variety of non-stationary stock-recruitment models, including models that accounted for abrupt regime shifts or models that have parameters smoothly changing along time. Although the underlying mechanism and model assumptions were different, all the models confirmed the low productivity regime of Iberian sardine since 2006 onwards. Additional regime shifts, though of less intensity, were also identified around 1993 and 2015. All the selected models had better prediction skills than the naïve model based on the average of the time series, indicating potential to be transferred to WP6. For the other 10 stocks, we have explored the potential inclusion of environmental variables such as temperature, salinity, or general circulation pattern indices into their stock-recruitment models. The results indicated that for the Bay of Biscay sardine the minimum value of NAO index improved the initial stock-recruitment model; for black-bellied anglerfish the AMO index in the first quarter and the salinity; for northern hake the NAO index in the third quarter; for sole the minimum value of AMO index; for mackerel the AMO index in the first quarter non-linearly; and for blue whiting the maximum value of EA index. These models were considered as preliminary and need to be further studied.

P6 - Ocean-climate effect on recruitment in blue whiting in the NE Atlantic

Costanza Cappelli and Brian MacKenzie - DTUAqua

Blue whiting, Micromesistius poutassou, is a key prey and predator in northeast Atlantic food webs and supports one of the largest commercial fisheries in the Atlantic Ocean (2024 quota = 1.5 million tonnes). Production and survival of new juveniles (recruitment) varies up to 10-fold across years for unknown reasons, creating challenges for forecasting and sustainable management. Here we focus on a key atmospheric driver of ocean variability, the wind stress curl (WSC), which may affect recruitment through several mechanisms, including meridional transport, vertical mixing, and frontal positions. The location of the transition zone between cyclonic and anticyclonic WSC in the Rockall region is a center of action of this atmospheric driver, and it coincides with the location of the largest known blue whiting spawning area. We hypothesize that WSC variability affects environmental conditions (e. g., temperature, salinity) and drift patterns experienced by eggs and larvae, and ultimately regulates survival. Coupling spawner biomass-recruit relationships to indices of WSC variability significantly increases explanatory power (up to ~42%) over a 40-year period, especially if recruit survival is lagged one year behind WSC variations. The one-year lag is consistent with a literature-reported ca. one year response time of several ocean properties to WSC variations in this region. Model forecast skill with retrospective out-of-sample data had similar explanatory power. Major recruitment variations can now be predicted sooner and more reliably than previously possible. This linkage suggests an underlying mechanistic driver that can potentially inform sustainable and ecosystem-based management practices for this important fishery resource.

P7 – Mackerel predation effect on Norwegian spring-spawning herring recruitment with a simple overlap factor

John Trochta - IMR

Recruitment variability of Norwegian spring-spawning stock of Atlantic herring (Clupea harengus) has been previously associated with several environmental and ecosystem factors. A more recent potential factor is consumption by Atlantic mackerel (Scomber scrombrus), as supported by observed localized predation and increased spatiotemporal overlap with herring larvae in part due to the northward range expansion of mackerel. The impact of mackerel predation on herring recruitment has been noted as a research priority for herring management in Norway (Huse et al. 2018). A MSE framework has been developed that tests the existing herring HCR against alternative models of reduced herring recruitment, with and without an explicit effect of mackerel. The first model considers a regime shift in recruitment, specifically a stepwise reduction in average recruitment, to explain less frequent strong cohorts and generally lower numbers since the mid-2000s. The strong herring cohorts result in a recruitment distribution with a fatter upper tail, so these cohorts are explicitly modelled as a multiplicative factor on average recruitment with all remaining variability captured by random lognormal variation. For MSE projections, this reduction in average recruitment is modelled in the last 40 years of an 80-year projection period, and the timing of strong cohorts is fixed according to the historical timing (i.e. using the same sequence of durations between historical strong cohorts). The second model considers both effects of mackerel biomass and larval drift. Specifically, a multiple linear regression is used to combine an effect of the difference between mackerel spawning biomass and herring larvae latitudinal centers-of-gravity (CoGs) with an effect of meridional drift velocities, and that are estimated with historical time series of these variables (recruitment variability explained was R^2=0.66). For MSE projections, mackerel CoG is a function of mackerel SSB that is projected under the current mackerel HCR, while herring larvae CoG and drift use the historical values (i.e. as in a hindcast projection). Simulations shown that the HCR configuration currently used for herring management was risky under both recruitment models; however, alternative and similar configurations (i.e. Btrigger and Ftarget combinations in the ICES hockey-stick rule) were less risky under a stepwise reduction in recruitment while all alternatives still shown high risk with the explicit mackerel effect accounting for overlap. More generally, the relatively more complex model with a simple factor accounting for predator-prey overlap shown very different MSE results from the simpler recruitment model. This work demonstrates the importance of testing alternative and increasingly complex OMs.

Huse, G., Skern-Mauritzen, M., Bogstad, B., Sandberg, P., Ottemo, T., Veim, A. K., Sørdahl, E., et al. 2018. Muligheter og prioriteringer for flerbestandsforvaltning i norske fiskerier. Fisken og havet. Havforskningsinstituttet.

P8 - Impact of the PDO on halibut's recruitment: developing environmental relationships and incorporating uncertainty

Allan Hicks and Ian Stewart - IPHC

The Pacific halibut (Hippoglossus stenolepis) stock in the Northeast Pacific Ocean shows high variation in many life-history attributes, including recruitment. Past studies have found that the Pacific Decadal Oscillation (PDO) is a stronger predictor of recruitment than the spawning biomass. It is clear that historically, average recruitment is higher in periods of a positive PDO, and the current stock assessment estimates a difference of approximately 1.5 times. Studies of egg and larval movement show considerable advection of larvae away from spawning grounds, but a clear mechanism has not been determined. An MSE framework for Pacific halibut has been developed and integrated over many different sources of variability. Recruitment variability is introduced through random lognormal variation around average recruitment, and average recruitment dependent on simulated positive and negative PDO regimes. A semi-Markovian model is used to simulate cyclical PDO regimes where the probability of switching regime is an increasing logistic function based on the length of the current regime. It was found with longer PDO regimes (i.e. a lower probability of switching regime), 100-year simulations had not converged to equilibrium, and the PDO regime was not fully integrated into an equilibrium state. With recent observations suggesting the potential for shorter PDO regimes, the probability of switching PDO regime was increased to encourage regimes typically between 10 and 30 years. This has resulted in a full integration of high and low PDO regimes which fully describes the uncertainty in average recruitment. Additionally, it is possible to examine simulation outcomes assuming persistent low PDO (i.e. low productivity) or persistent high PDO (i.e. high productivity), which are useful to understand the effect of the environment but are not used to explicitly evaluate management procedures.

3.3 Predictive models of growth

P9 - Stock growth analysis in Baltic Sea, North Sea and Western Waters

Mollie Brooks (DTUaqua), Luke Batts, Jochen Depestele, Leire Ibaibarriaga, Bernhard Kühn, Marie Savina, Klaas Sys, Marc Taylor, Morgane Travers - SEAwise

We collected observed average cohort weights at age by year from FLStock objects and checked which were time-varying so that they would be appropriate to model. We omitted the plus-group because the age composition varies by year. We also extracted the estimates of SSB from the FLStock objects. We also collected ORAS5 data averaged over each stock area, including temperature (surface or bottom depending on the stock) and salinity.

Our growth models looked at each cohort's weight in the next year dependent on its weight in the current year and the environment (abiotic and biotic). We tried mechanistic models of length at age (Gompertz and Von Bertalanffy) by converting weights to lengths using coefficients from the FishBase website. In addition to mechanistic models, we used linear mixed models (LMMs) and generalized addative mixed models (GAMMs) because they are more flexible than mechanistic models and make it easier to test the effects of multiple environmental variables. All mixed models (LMMs and GAMMs) included random efects of cohort and year to reduce the chance of selecting models containing spurious patterns. The global models of the LMMs which was then reduced was

log(wt+1) ~ log(wt) + age + age^2 + age^3 + log(wt):age +

salinity + SSB + temperature + temperature^2 +

log(wt):salinity + log(wt):SSB + log(wt): temperature

However, this was later changed to omit the age^3 term. The global model for the LMMs was either (1) fit using the R package glmmTMB and reduced by AICc or (2) fit by glmmLASSO and reduced by L1 penalization. In method (2), the penalization parameter was chosen either via K-fold cross validation (https://github.com/mebrooks/cv.glmmLasso) or via BIC (https://github.com/bbolker/lmmen). When doing cross validation in method (2), we tried both 10-fold and 5-fold.

The global formula of the GAMMs which was reduced via AICc model selection was

log(wt+1) ~ log(wt) + s(age, k=3) + log(wt):age +

salinity + SSB + s(temperature, k=3) +

log(wt):salinity + log(wt):SSB + log(wt): temperature +

(1 | cohortf) + (1 | yearf)

We conducted a large forecast evaluation on each of the modelling methods described above. First, we partitioned each stock's data into a training set and a validation set, perfomed the model selection method on the training data, and compared observations to predictions for the validation data. We repeated this procedure 15 times for each data set, so that the validation data set was all lengths 1 to 15. For each partition, we made predictions for the entire validation dataset. For each method and stock combination, we calculated prediction skill as the mean squared error of all the predictions. We compared the prediction skill of our modelling methods to a naïve average of the last 3 years in the training data (a benchmark based on what might be done in a short-term forecast for setting an allowable catch). As we were not sure which time horizon would best summarise our needs, we looked at the prediction skill in three ranges: short horizons (1-3 years), long horizons (5-10 years), and the entire 15-year horizon.

We found that 15 out of 27 stocks had at least one method with better prediction skill than the naive 3-year average (i.e. forecast potential). For had.27.7a, sol.27.7e, and whg.27.47d, only the mechanistic models had forecast potential. For had.27.7b-k, sol.27.20-24, and whg.27.7b-ce-k, all methods had forecast potential. Results varied widely across stocks, with no single method standing out as the best. For some LMMs, the effect of SSB was estimated to be positive (the opposite of that hypothesized). It would be difficut to constrain the coefficient on SSB while automatically doing model selection, so future models will omit that term.

P10 - Impact of environmental drivers on the growth and reproduction traits of several species in the south Adriatic Sea and North West Ionian Sea

Pierluigi Carbonara, Walter Zupa, Matteo Chiarini, Neglia Cosmidano, Isabella Bitetto, Loredana Casciaro, Palmisano Michele - Fondazione COISPA ETS - SEAwise

In order to investigate the impact of the environmental drivers on the growth and reproduction traits, they were analysed in the study areas (South Adriatic Sea GSA 18 and North West Ionian Sea GSA 19) size at first maturity (L_{50}), condition factor (CF) and the otolith growth increment (OI). The environmental variables used are: Sea Surface Temperature (SST), bottom temperature (botT), salinity in water column (so), bottom salinity (botso) and net primary production (nppv). The data collected within the Data Collection Framework (DCF) was the main source of information on maturation and growth for hake (Merluccius merluccius), red mullet (Mullus barbatus), deep-water rose shrimp (Parapenaeus longirostris), giant red shrimp (Aristeomorpha foliacea) and blue and red shrimp (Aristeus antennatus) in GSAs 18-19.

In the study area (South Adriatic Sea GSA 18 and North West Ionian Sea GSA 19) has been highlighted a significant impact of some environmental drivers (e.g. sst, botT, botso, nnpv) on the growth and reproduction traits, in term of size at first maturity (L_{50}), condition factor (CF) and the otolith growth increment (OI). For the L_{50} was observed a decrease effect of the botT in deep rose shrimps and red mullet. For the CF was observed a decrease effect of the sst in red mullet. For the OI an increase effects of environmental variables (sst, botT, nnpv) for hake and red mullet.

The growth pattern observed at individual level is the result of an interaction between potential growth defined by the genotype and the environmental conditions under which each individual fish lives. The otolith of red mullet (Mullus barbatus) from three areas of South Adriatic and Ionian Sea are used to assess the presence of spatial difference in red mullet growth. Several environmental parameters and years were considered in the analysis. Moreover, the Representative Concentration Pathways (RCP8.5) climate model scenario was used, in order to assess the changing of the red mullet growth pattern in medium (2048) and long term (2098).

The results show that red mullet growth pattern display difference in the studies areas analysed (West South Adriatic [WestGSA18], East South Adriatic [EastGSA18], Ionian [GSA19]), with the East side of the South Adriatic Sea (GSA 18) and the north part of the West GSA18 that they show a higher red mullet growth pattern. The environmental covariate, among those analyzed (sea surface temperature, bottom oxygen, net primary production, bottom temperature, bottom salinity), that explains much of the variability is the temperature (bottom and surface).

Using climate change projections (RCP8.5) it was possible to analyze the changes in the growth pattern for red mullet in the three areas analysed (West South Adriatic, East South Adriatic, Ionian). The relative changes compared to the hindcast show an increase in the growth pattern in the medium term (2048) in different areas, while in the long term (2098) a generalized decrease is observed.

P11 - Shrinking body size of European anchovy in the Bay of Biscay

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Abstract (from the published paper): Decreased body size is often cited as a major response to ocean warming. Available evidence, however, questions the actual emergence of shrinking trends and the prevalence of temperature-driven changes in size over alternative drivers. In marine fish, changes in food availability or fluctuations in abundance, including those due to size-selective fishing, provide compelling mechanisms to explain changes in body size. Here, based on three decades of scientific survey data (1990–2021), we report a decline in the average body size—length and weight—of anchovy, Engraulis encrasicolus L., in the Bay of Biscay. Shrinking was evident in all age classes, from juveniles to adults. Allometric adjustment indicated slightly more pronounced declines in weight than in total length, which is consistent with a change toward a slender body shape. Trends in adult weight were nonlinear, with rates accelerating to an average decline of up to 25% decade−1 during the last two decades. We found a strong association between higher anchovy abundance and reduced juvenile size. The effect of density dependence was less clear later in life, and temperature became the best predictor of declines in adult size. Theoretical analyses based on a strategic model further suggested that observed patterns are consistent with a simultaneous, opposing effect of rising temperatures on accelerating early growth and decreasing adult size as predicted by the temperature-size rule. Macroecological assessment of ecogeographical—Bergmann's and James'—rules in anchovy size suggested that the observed decline largely exceeds intraspecific variation and might be the result of selection. Limitations inherent in the observational nature of the study recommend caution and a continued assessment and exploration of alternative drivers. Additional evidence of a climate-driven regime shift in the region suggests, however, that shrinking anchovy sizes may signal a longlasting change in the structure and functioning of the Bay of Biscay ecosystem.

P12 - Growth analysis and MSE models for pelagic stocks off Norway

John Trochta – IMR

Density-dependence is prevalent in the growth dynamics of various fish stocks. Evidence for strong density dependent growth has been found for the three major pelagic stocks in the Northeast Atlantic, Atlantic mackerel (Scomber scrombrus), blue whiting (Micromesistius poutassou), and Norwegian spring-spawning herring (Clupea harengus). Because of the feeding dynamics of these stocks, density-dependent growth may be influenced by interspecific competition as well as intraspecific competition, and by different age groups within species because of changes in overlap throughout their life history. In this analysis, these different potential effects are uniquely specified in each species' growth-condition model and evaluated for use in multi-species MSE projections to account for interspecific competition. The effect of density-dependence, represented as the aggregate abundance of a specific age group(s) within or across species, is modelled as a linear function on either the von Bertalannffy growth rate for each cohort, and/or the multiplicative factor in the allometric equation that converts length to mass. These models also estimate the variance of random effects by year and cohort and are fit to each species average mass-at-age. Across all species, model fitting and selection shown that average mass-at-age was best predicted by the model with only intraspecific density effects, not interspecific densities. Furthermore, the model-selected effects were separated by age-groups: a cohort effect on the growth rate of the abundance at the age of recruitment and age immediately after, and a year effect on the multiplicative factor in the length-mass conversion of the abundance of all post-recruitment ages. These density-dependent growth models were paired with alternative recruitment scenarios (one with variability matching historical patterns, and one with variability matching periods of low average recruitment) in MSE projections. Simulations shown that impacts of density-dependent growth on reference points were largely controlled by the assumptions about recruitment variability (e.g. assuming lower recruitment weakened density-dependent growth impacts).

3.4 Integrating environment-productivity relationships in MSE models

P13 - Integration of environment-productivity relationships for anchovy and sardine in FLBEIA - Bay of Biscay

Sonia Sánchez-Maroño, Leire Ibaibarriaga, Dorleta García, Leire Citores and Marga Andrés - AZTI - SEAWise

Aimed at moving towards the ecosystem-based fisheries management (EBFM), we have worked on incorporating information on environmental impacts on stocks productivity for several fish stocks. Specifically, we have analysed the effect of abiotic and biotic variables for the recruitment and growth processes of anchovy in the Bay of Biscay and for the recruitment of Iberian sardine. Recruitment for anchovy was modelled as a Ricker stock-recruitment model including an upwelling index and a non-parametric term for turbulence in the third quarter of the year. Recruitment for sardine was modelled as a two-regime random switching model (Munch and Kottas, 2009). This consists in two different Ricker stock-recruitment models for low and high productivity regimes, where the annual regime is defined by the transition probabilities from the low to the high and from the high to the low regimes. The weight-at-age for anchovy in the Bay of Biscay were based on the work by Taboada et al. (2023), where weight-at-age 0 was modelled as a function of the SSB, whereas weight-at-ages 1, 2 and 3+ depended on SSB and surface temperature.

This information was then incorporated into FLBEIA (Garcia et al., 2017) to evaluate the impact of the climate change on the inshore pelagic fisheries in the Bay of Biscay given the management strategies currently in place. From the three environmental indices included in the simulations (surface temperature, upwelling index and turbulence), only the temperature for the projection period was obtained from the POLCOMS-ERSEM model and from NEMO-MEDUSA model (Kay, 2020; Yool et al., 2015; results are only summarised here for POLCOMS-ERSEM RCP 8.5) for different IPCC representative concentration pathways (RCP) scenarios. The time-series of the projection period were bias-corrected using the quantile mapping approach as described by Kühn (2023). Alternatively, the upwelling index and turbulence for the simulation period were based on a time-series surrogate that accounted for the linear trend and the periodicity observed in the past. Uncertainty was not included in none of the environmental time-series.

The impact of considering environmentally driven stock productivity models varied between stocks and fleets. For sardine, the incorporation of switching recruitment regimes led to higher abundance and increased mean age. While environmentally dependent growth led to similar or slightly higher biomass levels for the anchovy, the environmentally driven recruitment resulted into a faster reduction in the mean age when compared to the non-environmentally driven assumptions.

When including the environment-driven productivity models for both species at the same time, impacts on sardine were the same as observed when doing it in isolation, while the negative impacts on anchovy due to the environmental influence on recruitment were mitigated when also including the impacts on weights at age. In all the cases, the risks of stock collapse and overfishing were higher for the scenarios where the environmental drivers were incorporated than when not taking them into account, and the economic indicators were worse for all the modelled fleets. However, the percentage of revenues from vessels of less than 24 m increased.

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P14 - Integration of environment-productivity relationships for hake and red mullet in FLBEIA in the Eastern Ionian Sea

Stavroula Tsoukali, Vasiliki Sgardeli, Marianna Giannoulaki, Georgia Papantoniou, Konstantinos Tsagarakis, Vassiliki Vassilopoulou - HCMR - SEAwise

The integration of environment-productivity relationships was investigated for European hake and red mullet in the Eastern Ionian Sea, by exploring how the relationship of spawning stock biomass and recruitment is affected by environmental variables. Regressions were implemented with modified Stock-Recruitment models (Ricker, Beverton-Holt) as well as GAMs, investigating the effect of one or two environmental covariates. The SSB and recruitment data were retrieved from officially validated stock assessments, while the environmental data are derived from work performed within the CERES project (CERES, 2018) and were initially analysed in Task 3.2 of SEAWISE. The selection procedure ended up in an environmentally modified Ricker including microphytoplankton Chl, (in mg/m3) for both stocks. These were integrated in FLBEIA in order to improve the baseline FLBEIA model, which was developed during the WP6 of SEAWISE for the demersal fishery of the Eastern Ionian Sea. The baseline FLBEIA describes a demersal fishery that includes 2 fleets (Large Scale and Small Scale Fishery), and 5 main stocks (2 age-structured: HKE, MUT and 3 biomass dynamic: DPS, MUR and Others). A set of management scenarios were applied, where the constant effort was adjusted to achieve the respective F target of the management scenario. Three climatic scenarios (noCC, RCP4.5, RCP8.5) were integrated in FLBEIA to investigate whether the environmental changes affect the dynamics of the stocks in future projections. Finally, the uncertainty of stock assessments and of stock-recruitment was integrated in the FLBEIA projections through 300 iterations in a MC setting. Hake stock status appears to be affected by climatic changes (scenarios RCP4.5, RCP8.5), but further exploration of the effect of microphytoplankton Chl is needed. Under management scenarios that assume reduction of the biomass (SQ, PGY, Fcomb, compared to F01), the effect of the environment is more pronounced for HKE. When HKE biomass increases (F01, reduced fishing effort) the internal dynamics (density-dependence) of the population appear to drive the stock status. Regarding red mullet, all management scenarios result in higher SSB compared to the Status Quo, while there was no evidence that red mullet is affected upon climatic changes (RCP4.5, RCP8.5), across all management scenarios.

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P15 - Integration of environment-productivity relationships for various demersal stocks in FLBEIA in the North Sea

Bernhard Kühn, Marc Taylor, and Alexander Kempf - Thünen institute - SEAwise

Impacts of climate change are believed to affect the abiotic environment and the ecosystem of the North Sea through all trophic levels, which will eventually change how much yield fishermen can sustainably harvest. Understanding and modelling these productivity changes of the ecosystem and in particular on the most commonly exploited stocks is therefore crucial to inform management and allow the fishery to adapt to potential future changes. To test different management routines, we conducted a short-cut MSE simulation with the bioeconomic modelling framework FLBEIA applied to the demersal mixed fisheries of the North Sea. Productivity changes for four stocks (Cod, Saithe, Plaice and Whiting) were modelled explicitly incorporating climate effects from a regionally-downscaled ocean model POLCOMS-ERSEM under the Representative Concentration Pathways RCP4.5 and RCP8.5 via an environmentally-driven stock-recruitment relationship (EMSRR). Two different baseline runs, representing the current situation were caried forward – one representing the ICES benchmark implementation (bench.), the other one a noCC climate scenario with a detrended RCP4.5 run. Various harvest control rules were tested representing different degrees of implementation of the EU landing obligation, trying to capture the current imperfect implementation (Case Study scenario), a strict implementation (FMSY-Min) and a middle-way, where choking effects are somewhat relaxed allowing fishing in the upper FMSY-range if stocks are within sustainable limits (PGY-Min). A Status quo effort scenario was simulated as a baseline with no management. Results point towards decreasing recruitment for the gadoids Cod and Saithe, mixed results for Plaice and slight increases for Whiting, compared to the noCC baseline. Performance of management point showed tradeoffs, with PGY-Min presenting a middle-way of sustaining high biomass, while allowing for increased catch. Remaining at the status quo effort for the whole simulation resulted in increased risk of falling below Blim, exacerbated by climate change for saithe. Additionally, we highlight that a reasonable choice of the baseline runs (e.g. noCC vs. bench.) is crucial for a meaningful comparison of scenario performance. In a short-term perspective, benchmark scenarios with a status quo perception of recruitment (SRR fitted to the recent historical period) provide a reasonable, conservative estimate of future stock development under climate change.

P16 - Integration of environment-productivity relationships for various stocks in BEMTOOL in the Adriatic and western Ionian Sea

Isabella Bitetto and Maria Teresa Spedicato - Fondazione COISPA ETS - SEAwise

Under SEAwise a case study was developed on demersal fisheries operating in Adriatic and western Ionian Sea.The BEMTOOL bio-economic model, integrating the environmentally mediated stock-recruitment relationship (EMSRR), is used to investigate the biological and socio-economic impact of management measures under different climate change scenarios (No Climate Change, RCP4.5, RCP8.5). The alternative scenarios explored are the Fmsy (for the target stocks of the GFCM Multi-Annual management Plan, Rec.GFCM/43/2019/5) and a combined Fmsy used as proxy for PGY. According to the results, the projections of the stocks under the 3 management and the 3 climate change scenarios would not fall below the biomass reference point, when they are available. The integration of environmental variables in BEMTOOL highlighted for all considered stocks a decrease, less or more pronounced according to the stock, in productivity due to forecasted climate change. Among the investigated management measures, Fmsy scenario represents a valid option to mitigate the impact of climate change on stock productivity, allowing to reduce, for the overexploited stock (e.g European hake), the risk to fall below the reference point. On the other hand, considering that there are stocks in Adriatic and Western Ionian Seas that are exploited below or close to Fmsy, PGY scenario can represent an option to reduce the underutilization of these resources, activating possible compensation mechanisms for the fleets.

P17 - Estimation and integration of time-varying reference points in MSE

Marc Taylor, Bernhard Kühn, and Alexander Kempf - Thünen Institute - SEAwise

The presentation outlined an approach for estimating future reference points given changes in environmentally mediated productivity. The motivation of this work is to simulate the periodic updating of reference points within the management procedure (e.g. benchmark assessments within ICES). The approach showed how time series of projected environmental covariates could be transformed to reflect changes over distinct periods of time, via detrending and offset, which could then be used to estimate equilibrium reference points over the full time series. Preliminary results from MSEs integrating environmentally-mediated stock recruitment relationships for four demersal stocks of the North Sea (cod, saithe, plaice and whiting) were presented, showing changes in reference points (e.g. Fmsy, MSY, Bmsy, Btrigger) over time. Finally, the presentation raised the question about how to address variables that may be influenced by the environmentally-mediated process, which may also need to be updated; e.g. modelled weight-at-age changes are likely to affect mortality- and selectivity-at-age.

P18 - Comparative Evaluation of Model-Based and Empirical Indicators under Climate Change Scenarios for Ecosystem-Based Fisheries Management

Laurence Kell (Sea++), Massimiliano Cardinale, Iago Mosqueira, Christopher Griffiths

This talk gave an overview of fundamental MSE concepts and practices, and proceeded with stock-specific examples of environmental and socioecological considerations in the various parts of the MSE, and not just the OM. Examples were provided in how the management procedure can incorporate such considerations (risk equivalence and Feco) and calculation of performance metrics (e.g. related to nutrition).The flexibility of the Fisheries Library in R (FLR) framework is important for modelling climate change impacts and conducting MSE. FLR's modular design allows for the integration of various data types and modelling approaches. FLR supports the development and testing of management strategies under different climate scenarios, facilitating robust decision-making processes. By enabling the incorporation of ecosystem-based management principles and accommodating the uncertainties associated with climate change, FLR enhances the resilience and sustainability of fisheries management practices.

P19 - Isis Fish in the Bay of Biscay

Pierre-Yves Hernvann (IFREMER), Sigrid Lehuta, Stéphanie Mahévas, Ian Pellet, Marie Savina-Rolland, Morgane Travers-Trollet, Antoine Ricouard, Jean-Baptiste Lecomte, Louis Maillard, Audric Vigier, Olivier Le Pape - SEAwise

By coupling stock assessment models with operating models that can integrate environment, and species or fleet interactions, management strategy evaluation (MSE) is a key tool for transitioning towards an operational ecosystem-based fisheries management. In the Bay of Biscay (BoB), the sustainable management of the demersal fisheries is challenged by their highly mixed aspect, and even more in a context of climate change, which is expected to unequally affect the productivity of exploited stocks. Therefore, we adopted the fisheries spatially-explicit simulation model ISIS-Fish as the operating model of a climate-informed MSE in the BoB. The population, finely-resolved fleet and flexible management modules of ISIS-Fish make it particularly pertinent for testing management strategies while accounting for technical interactions in multistock, multigear fisheries. Due to the heterogeneity in the material available for our study, our MSE framework was designed to implement either shortcut MSE or closed MSE loops. The closed loop was tested for common sole in the BoB, a commercially important and emblematic stock whose sustainable exploitation is challenged by both the highly mixed nature of demersal fisheries and changes in stock productivity over recent decades. The loop connects ISIS-Fish (operating model) to the BoB sole stock assessment model used by the WGBIE. In particular, ISIS-Fish represents the environmental control on sole recruitment via a nursery habitat capacity model based on river flow. To investigate management procedures performing better than the MSY approach in a changing environment and mixed-fisheries context, we simulated over the historical period the effect of alternative management procedures incorporating environmental information at different steps of the management cycle: in the stock assessment or in the harvest control rule using its output. In the former, the nursery habitat capacity model predicts next years' recruitment from recent river flow measurements, then integrated into the short-term projections required for the advice; in the second, the harvest control rules use measurements of recent changes in river flows to scale up or down the total allowable catch based from the MSY approach. Our preliminary work highlighted the efficiency of environmentally-informed procedures to rebuild the stock of sole but also the need to account for their implications on mixed fisheries, especially regarding the variability in their revenue. In the next steps of this work, our MSE framework, which is developed within the SEAWise project, will integrate environment-productivity relationships for other species and test the robustness of various multispecies management procedures within the MSE closed loop or shortcut framework, according to various scenarios of climate change.

P20 - Accounting for environmental drivers of Pacific sardine recruitment through multivariate analysis and MSE simulation testing

R Wildermuth (University of California), Desiree Tommasi, Peter Kuriyama, Isaac Kaplan, James Smith, Charles Hinchliffe, Stefan Koenigstein, Andrew Thompson, Noelle Bowlin, Mercedes Pozo Buil, Michael G. Jacox, Steven J. Bograd, and Barbara Muhling

Climate-driven changes in ocean temperatures, currents, or plankton dynamics may disrupt pelagic forage fish recruitment. Being responsive to such impacts enables fisheries management to ensure continued sustainable harvest of forage species. We conducted a management strategy evaluation to assess the robustness of current and alternative Pacific sardine harvest control rules under a variety of recruitment scenarios representing potential projections of future climate conditions in the California Current. The current environmentally-informed control rule modifies the harvest rate for the northern sardine subpopulation based on average sea surface temperatures measured during California Cooperative Oceanic Fisheries Investigations (CalCOFI) field cruises. This rule prioritizes catch at intermediate biomass levels but may increase variability in catch and closure frequency compared to alternative control rules, especially if recruitment is unrelated to ocean temperatures. Fishing at maximum sustainable yield and using dynamically estimated reference points reduced the frequency of biomass falling below 150,000 mt by up to 17%, while using survey index-based biomass estimates resulted in a 14% higher risk of delayed fishery closure during stock declines than when using assessment-based estimates.

P21 - Including temporal variability in natural mortality of the Norwegian spring spawning herring in a MSE

Jessica Tengvall, Fabian Zimmermann, Katja Enberg, Anders F. Opdal, John T. Trochta - IMR

Ignoring or oversimplifying important processes that determine stock dynamics, notably natural mortality and density-dependence, may increase the risk of inadequate fisheries management, as it can mean overlooking important population fluctuations. Here, we tested the sensitivity of the currently used ICES harvest control rule (current HCR) for Norwegian spring-spawning herring (NSS herring) under alternative population models using a short-cut management strategy evaluation (MSE). We configured a base scenario with age-dependent natural mortality (SCbase) similarly to the ICES MSE for NSS herring. The alternative population scenarios included a) density-dependent growth and maturity (SC1), included in most alternative population scenarios, b) random-walk natural (SC2), c) increasing trend in natural mortality over 30 years (SC3), d) length-based natural mortality (SC4), e) indirect density-dependent effect in length-based natural mortality (SC5), f) direct density-dependent effect in age-based natural mortality (SC6). A grid of possible HCR control parameters (Ftarget and Btrigger) was tested for each scenario. Performance was evaluated according to risk of SSB falling below an absolute B_{lim} and relative B_{lim} values based on the pristine biomass per scenario alongside interannual variability (IAV) in median catch and median catch. Results show that the current HCR is sensitive to the added biological complexity, particularly an increasing rate of natural mortality. However, the level of risk depends on the definition of B_{lim}. A lower Ftarget and a higher Btrigger demonstrated lower risk without compromising catch compared to the current HCR across most population scenarios. Shortcut MSEs offer a more efficient initial exploration of sustainable long-term management of various population scenarios against several HCRs, facilitating a more comprehensive evaluation of management performance before conducting a full MSE.

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Annex 2: Terms of Reference

A joint ICES - SEAwise workshop to quality assure methods to incorporate environmental factors and quantifying ecological considerations in Management Strategy Evaluation tools (WKEcoMSE)

The Workshop to quality assure methods to incorporate environmental factors and quantifying ecological considerations in Management Strategy Evaluation tools (WKEcoMSE) will meet on 21- 24 May 2024 online chaired by John Trochta CHAIR (Norway), Marie SAVINA-ROLLAND (France) and Piera Carpi (Norway).

The WKEcoMSE will work to provide a powerful set of tools for scientists to develop harvest control options that align with management objectives. Most commonly conducted as single-species analyses, MSEs can also address mixed fisheries objectives by using multi-stock and multi-fleet operating models. The EU project, SEAwise, endeavours to develop such multi-stock multi-species models further so that they can be used to define and evaluate fisheries management strategies that address broad Ecosystem Based Fisheries Management (EBFM) objectives, including identifying HCRs that are robust to changes in productivity. As such, a key deliverable of this workshop is to develop robust and consistent environment◎productivity relationships for commercial stocks across selected case studies, which potentially can be integrated in models used by ICES and the SEAwise project. The methods put forward in the workshop will be peer-reviewed to ensure that they are scientifically robust and fit-for-purpose for the advisory frameworks, policy, and management needs in FAO areas 27 and 37 (the ICES area (i.e. North Atlantic) and the Mediterranean Sea).

Terms of reference

1. Methods for consideration by the WK will be proposed by workshop participants, including those methods specifically examined by the SEAwise project.

2. Review the proposed methods regarding their capacity to incorporate the impact of environmental factors on the productivity of commercial stocks in the Fisheries Management Strategy Evaluation tools.

3. Evaluate the guidelines for each of the different processes controlling productivity, i.e. recruitment, growth and maturity, and survival, including: a. the biological and environmental datasets to be used and potential pre-processing procedures; b. the statistical models to use; c. methods and metrics to assess the predictive capacity of the statistical models developed; and, d. procedures to assess the uncertainty added to the considered management tool.

4. Review the proposed approaches and make recommendations to end users on whether the studied environment-productivity relationships should be considered or not. Recommend alternative, more generic approaches if the targeted approach is inconclusive

Annex 3: Agenda

Day 1 (21st May)

Morning (Europe 9:30 to 12:30)

Introduction - Marie Savina – 20 mn

Input data

Presentations

Available climate data and various aspects relating to preparing climate data for statistical model fitting and forecasting within the MSE- Bernhard Kühn and Marc Taylor - 20 min

Session 1: Predictive models of recruitment

Presentations

Recruitment of European hake, red mullet, and various shrimps in the Adriatic and western Ionian Seas - Isabella Bitetto and Maria Teresa Spedicato – 20 min

Environmental processes affecting fish recruitment in the North Sea - Bernhard Kühn and Marc Taylor – 20 min

Dynamic factor analysis applied to 5 demersal stocks in the Celtic Seas – Klaas Sys – 15 min

Structured discussion about the guidelines (facilitation : Piera Carpi and Ole Henriksen)

Afternoon (US West 7:30-10:30 am / US East 10:30 - 1:30 pm / Europe 4:30 - 7:30pm)

Introduction and summary of the first session (30 min)

Session 1: Predictive models of recruitment (cont)

Presentations

Environment-driven stock recruitment models in Western Waters – Leire Ibaibarriaga – 15 min

Ocean-climate effect on recruitment in blue whiting in the NE Atlantic – Costanza Capelli and Brian Mackenzie – 15 min

Mackerel predation effect on Norwegian spring-spawning herring recruitment with a simple overlap factor - John Trochta – 15 min

Impact of the PDO on halibut’s recruitment: developing environmental relationships and incorporating uncertainty – Allan Hicks – 15 min

Structured discussion about the guidelines (facilitation Piera Carpi)

Day 2 (22nd May)

Morning (Europe 9:30 to 12:30)

Summary of the recruitment discussions and way forward – Piera Carpi – 10 min

Session 2: Predictive models of growth

Presentations

Stock growth analysis in Baltic Sea, North Sea and Western Waters- Mollie Brooks – 40 min

Impact of environmental drivers on the growth and reproduction traits of several species in the south Adriatic Sea and North West Ionian Sea – Perluigi Carbonara- 20 min

Shrinking body size of European anchovy in the Bay of Biscay– Leire Ibaibarriaga – 20 min

Structured discussion about the guidelines (facilitation: Marie Savina and Leire Ibaibarriaga)

Afternoon (US West 7:30-10:30 am / US East 10:30 - 1:30 pm / Europe 4:30 - 7:30pm)

Session 2: Predictive models of growth (cont.)

Summary of the first session – Marie Savina or Leire Ibaibarriaga – 10 mn

Presentations

Growth analysis and MSE models for pelagic stocks off Norway - John Trochta – 25 min

Structured discussion about the guidelines (facilitation: Marie Savina and Leire Ibaibarriaga)

Day 3 (23rd May)

Morning (Europe 9:30 to 12:30)

Summary of the growth discussions and way forward – Marie Savina – 10 min

Session 3: Integrating environment-productivity relationships in MSE models

Presentations

Integration of environment-productivity relationships for anchovy and sardine in FLBEIA - Bay of Biscay -– Leire Ibaibarriaga – 20 min

Integration of environment-productivity relationships for hake and red mullet in FLBEIA – Eastern Ionian Sea– Stavroula Tsoukali -20 min

Integration of environment-productivity relationships for various demersal stocks in FLBEIA – North Sea – Bernhard Kühn and Marc Taylor– 20 min

Integration of environment-productivity relationships for various stocks in BEMTOOL – Adriatic and western Ionian Sea – Isabella Bitetto – 20 min

Structured discussion about the guidelines (facilitation: John Trochta and Marc Taylor)

Afternoon (US West 7:30-10:30 am / US East 10:30 - 1:30 pm / Europe 4:30 - 7:30pm)

Summary of the first session – John Trochta – 10 min

Session 3: Integrating environment-productivity relationships in MSE models (cont.)

Presentations

Reference point estimation Food for thoughts - Bernhard Kühn and Marc Taylor -15 min

FLR functionalities to integrate environment in FLR-based mse models – Laurie Kell – 15 min

Session 4: Accounting for environment-related changes in productivity in MSE models

Presentations

Isis Fish in the Bay of Biscay – PY Hernvann – 20 min

Accounting for environmental drivers of Pacific sardine recruitment through multivariate and MSE simulation testing– R Wildermuth – 20 min

Including temporal variability in natural mortality of the Norwegian spring spawning herring in a MSE– Jessica Tengvall – 10 min

Structured discussion about the guidelines (facilitation J Trochta and Marc Taylor)

Day 4 (24th May)

Morning (Europe 9:30 to 12:30)

Summary of MSE discussions and way forward – John Trochta – 15 min

Session 4: Accounting for environment-related changes in productivity in MSE models (cont.)

Structured discussion about the guidelines –work in subgroups – 3 co-chairs

Afternoon (US West 7:30-10:30 am / US East 10:30 - 1:30 pm / Europe 4:30 - 7:30pm)

Summary of discussions and way forward – 3 co-chairs

Structured discussion about the guidelines –work in subgroups – 3 co-chairs