Fisheries Research 207 (2018) 95–109

Contents lists available at ScienceDirect

Fisheries Research

journal homepage: www.elsevier.com/locate/fishres

Pushing the limits of a data challenged stock: A size- and age-structured assessment of ling (*Molva molva*) in Icelandic waters using Gadget

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ARTICLE INFO

Handled by A.E. Punt

Keywords:
Stock-assessment
Uncertainty
Bootstrap
Database
Gadget
Fish population dynamics
Nonlinear models
Correlated data
Bootstrapping
Data-limited species

ABSTRACT

In recent years a greater emphasis has been placed on developing management strategies that prevent overexploitation. Harvest control rules (HCRs) have therefore, in many places, been developed and implemented. Commonly these HCRs are developed for stocks that are assessed using age-structured models, and various platforms exist to evaluate their performance and analyze various sources of bias for that particular class of models. Many stocks, however, cannot be assessed reliably using classical age-structured methods due to data limitations (gaps in data series, unreliable age readings, etc.). One such stock is the common ling (*Molva molva*) in Icelandic waters. Availability of data on the stock dynamics, in particular age data for both survey and commercial samples, has been a limiting factor when assessing the stock. When modeling stocks such as this, data limitations need to be considered, and how associated uncertainty is propagated both through the assessment and into the advice. In this study, ling was assessed using the size- and age-structured model Gadget after synthesizing all available data. Having limited age data available causes high uncertainty in the model fitting process, especially in estimating growth. However, including this key uncertainty in the assessment allowed the subsequent management strategy evaluation to take it into account directly while deriving common management reference points and estimating uncertainties in stock status and other derived quantities. Uncertainty was estimated using a specialized bootstrap for disparate data sets that mimics the sampling process. The process of assimilating data for the assessment model and the bootstrap procedure was performed using a specialized database program, MFDB, ensuring that the whole process is reproducible.

1. Introduction

In recent years there has been a call for sustainable management of fisheries. This is reflected in a number of common multinational resolutions on the governance of marine ecosystems (e.g. UN, 2002; Parliament, 2008). In particular the European Union has stipulated that all fish stock should be managed according to maximum sustainable yield principle (Anon, 2002a,b). To ensure that these objectives are reached, management plans that restrict fishing effort have been proposed and implemented (e.g. see Annex 1 of ICES, 2013b). Typically these plans include some form of a harvest control rule (HCR) based on the available data (e.g. see Baldursson et al., 1996; Butterworth and Punt, 1999).

Evaluating fisheries management plans is not a trivial undertaking. The HCR is often simulation tested using an operating model which is based on knowledge of the population dynamics (discussed by Butterworth and Punt, 1999, and references therein) and industry governance. ICES (2013a) provides guidelines on how to conduct these simulations, and ICES (2017b) specifically describes how to derive management reference points necessary to implement an HCR in European waters. For many species, the information typically needed for traditional age-based assessments is lacking, leaving little data available to inform general productivity and stock structure. This is true for many of the stocks assessed by multinational bodies such as ICES (e.g. see ICES, 2014a). For example, some age-based methods do not allow for years of missing data (e.g. Shepherd, 1999, and other VPA-based methods). According to ICES, the lack of data to produce an assessment, and subsequently quantitative forecasts, warrants a classification as data limited (ICES, 2012). Without age composition data, variants of the surplus production model (as described by Pella and Tomlinson, 1969) are commonly applied (Carruthers et al., 2014). These approaches allow for the analytical estimation of reference points while being based on fairly limited data. For example, a popular expansion of this approach was developed by Pedersen and Berg (2017), which has been rapidly applied in a variety of cases (e.g., ICES, 2017a). Surplus production methods, however, are known to fail in situations where

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https://doi.org/10.1016/j.fishres.2018.06.005
Received 8 March 2018; Received in revised form 6 June 2018; Accepted 7 June 2018
0165-7836/

little contrast is available in the survey and catch time series or such contrast is only exhibited as a constant decrease (i.e., "one-way trip"). In contrast, age-structured models are still able to capture some information from such scenarios (Magnusson and Hilborn, 2007) as there is contrast in cohort strength.

Age-based methods are therefore preferred, and considered a standard in stock assessment the advisory process, because age transfers important information into a stock assessment model: it allows for inference of the time scale on which population dynamics occur, by supplying information on the growth of individuals and how it translates into growth of the population. Age in combination with weight- and maturity-at age is used to calculate the rate at which spawning stock biomass is generated, which can in turn be used to detect recruitment impairment due to low spawning stock biomass within a stock–recruitment relationship. At the same time, however, inclusion of faulty age-related information can lead to bias. Age-based methods assume that age is known perfectly with no error, a false assumption in many cases (Reeves, 2003; Yule et al., 2008; Treble et al., 2008). Ageing error can then cause bias in a number of age-based processes within age-based stock assessment methods, since a variety of data included are a discretized by age (e.g., numbers-, catch-, maturity-, selectivity- and weight-at age). Quite often the age determination involves the processing of sagital otoliths and/or a study of length distributions to infer a cohort structure (as discussed by Jobling, 2002 and references therein). The ageing process is for many species, such as cod (*Gadus morhua*) and haddock (*Melanogrammus aeglefinus*), fairly straightforward. Both species are highly abundant, many facets of their life cycle well known and they are of considerable commercial value. However, even for highly studied data-rich species, inconsistencies in ageing can bias stock assessments (e.g., Baltic cod among other species Bertignac and De Pontual, 2007; Koenigs et al., 2013; Henríquez et al., 2016; Hüssy et al., 2016), as can undetected changes in growth rates over time (e.g., Icelandic haddock ICES, 2017c). Fishing-induced changes in growth can also bias age-based assessments, spurring the development of "platoons" in age-structured models (Taylor and Methot, 2013; Akselrud et al., 2017). Finally, for many species, information on age is simply hard to obtain. This may be due to lack of hard parts that show year rings, inconclusive otolith readings, or difficulties/inconsistencies in age data collection (Treble et al., 2008). As a result, even when otoliths are available, translating continuously deposited bone tissue (i.e., rings) into discrete annual growth measures (i.e., age) typically require sound and validated methods.

In response to the common need for stock assessment models to both handle data limitations as well as propagate error appropriately throughout the assessment by integrating various steps of analysis into a single stock assessment model, integrated stock assessment models, such as the Gadget model presented here, have increased in popularity over the last decades (Maunder and Punt, 2013). The ICES classification of data-limited is often a misnomer as there may be a wealth of other information, such as size composition data, on the species than that which is directly applicable to standard assessment models. Were a stock to be evaluated under alternate criteria, it may not be considered data limited due to the existence of at least some compositional data in addition to survey indices and catch (Ralston et al., 2011; Berkson and Thorson, 2014; Carruthers et al., 2014). For example, the lack of reliable age data on ling in Icelandic waters is reminiscent of assessments of many invertebrate stocks (e.g. see Punt et al., 2013, 2016, and similar papers). The stock assessment of ling in Icelandic waters presented here is therefore more analogous to size-structured assessments, as historically little information has been collected from commercial samples, particularly on age.

Size-structured models that also track age, so that data on growth may be used to supplement them, are commonly referred to as size- and age-structured models (Punt et al., 2017), and are most commonly implemented as integrated models. In size- and age-structured models, the data and model predictions have two attributes: a length-group bin and an age-group bin. As a result, when parameterized such that growth, maturation, and selection processes are only dependent on size, size-structured models are a special case of size- and age-structured models. However, common implementations of age-based models (e.g., Stock Synthesis Methot, 2013 or MULTIFAN-CL Fournier et al., 1998) are often not a special case of size- and age-structured models, due to the need to apply a summarised effect of growth, maturity, and/or selectivity (when these are size-based processes) to all individuals (regardless of length) within an age bin (see Punt et al., 2017, for an example). Size- and age-based models, such as those developed using Gadget (Begley and Howell, 2004) or CASAL2 (Doonan et al., 2016), offer alternative methods to assess the stock status combining compositional data if and when available.

The trade-off for using size- and age-structured models comes in the form of a reduction in computational efficiency, due to the higher dimensionality of the model (Punt et al., 2017). But in the case of data limited species, the resulting benefits may be well worth the cost. Even if there is little or no information available on age, other size-structured biological information may be available that can provide insights into the stock dynamics. In terms of management, the inclusion of even very limited length data may improve estimate on how much the stock can reasonably be harvested without severely depleting the stock (Wetzel and Punt, 2011).

The goal of this study is to demonstrate how a size- and age-based model (i.e., Gadget) can be suitable for stock assessment by providing an appropriate means to propagate error, especially age-related error, into a management strategy evaluation of harvest control rules. This framework is especially valuable where data are limited, such as in the case for ling (*Molva molva*) in Icelandic waters, as standard age-based methods are likely to misrepresent age-related uncertainty. Gadget is a statistical modelling and simulation framework that allows the creation of a multi–species, multi–fleet, multi–stock, size- and age-structured simulation model. Originally outlined by Stefansson and Palsson (1998) Gadget is a conceptual continuation of the work described by Gavaris (1988) and Bogstad et al. (1997) and is implemented as a computer program (Begley, 2005). We present simulations where observation uncertainty (and to a certain extent structural error) is projected forward using a specialised spatial bootstrap approach described by Elvarsson et al. (2014). Robust data handling is also essential for this line of work; therefore, a specialised database system, MFDB (Lentin, 2014), is also presented which builds upon concepts of database design that particularly suit the needs of stock assessment and ecosystem studies, as described by Kupca (2006). This database procedure is used in conjunction with a specialised R package, Rgadget (Elvarsson and Lentin, 2018), that allow rapid and reproducible model building within the Gadget framework. Although the simulation procedure described here is applied to a single-species assessment, it can be generalized to a wider set of models, e.g. multi-species, multi-stock, or multi-fleet models, as implemented in the Gadget framework.

2. Materials and methods

The first step of this study details a data challenged stock assessment using Gadget, after synthesizing the available data on the population dynamics of ling. The second step extends the assessment model by setting up a projection model in which precautionary biomass reference points were derived (first set of projections). In the final step, the projection model was used as the operating model on which a management strategy evaluation (MSE) was based, in which the application of simple harvest control rule was simulated (second set of projections).

2.1. Ling in Icelandic waters

Ling (*Molva molva*) is a demersal fish found in the Northeast Atlantic, with the main spawning grounds observed south of Iceland, by the Faroe islands and in the Norway Sea, representing different stocks