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Analysis

Up the ante on bioeconomic submodels of marine food webs: A data assimilation-based approach

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ABSTRACT

While economists have discussed ecosystem-based fisheries management and similar concepts, little attention has been devoted to purposeful modeling of food webs. Models of ecosystems or food webs that make economic analysis viable should capture as much as possible of system structure and dynamics while balancing biological and ecological detail against dimensionality and model complexity. Relevant models need strong, empirical content, but data availability may inhibit modeling efforts. Models are bound to be nonlinear, and model and observational uncertainty should be included. To deal with these issues and to improve modeling of ecosystems or food webs for use in ecosystem-based fisheries management analysis, we suggest the data assimilation method ensemble Kalman filtering. To illustrate the method, we model the dynamics of the main, pelagic species in the Norwegian Sea. In order to reduce parameter dimensionality, the species are modeled to rely on a common carrying capacity. We also take further methodological steps to deal with a still high number of parameters. Our best model captures much of the observed dynamics in the fish stocks while the estimated model error is moderate.

1. Introduction

Resource economists should be concerned with building models of marine food webs and ecosystems that readily integrate with frameworks for economic decision analysis. Ecosystem-based fisheries management has been on the agenda for decades (May et al., 1979), but fisheries management is still largely based on single-species approaches (Edwards et al., 2004; Link, 2010; Skern-Mauritzen et al., 2015). The need to incorporate ecological and economic interactions and tradeoffs is pressing, however (Mangel and Levin, 2005; Scheffer et al., 2005; Tschirhart, 2009, and references therein). Further, to provide operationally relevant management advice that is 'straightforward, succinct, and on-point' (Link, 2010, p. 54), we need a unified approach to the decision problem that acknowledges inherent uncertainty and reflects the conflicting societal needs for resources and longevity.

When modeling food webs or ecosystems such that dynamic decision analysis is feasible, we are forced to balance biological and ecological detail against dimensionality and, to some degree, model complexity. While considerable complexity often can be handled, relatively low dimensionality is crucial for, for example, continuous time stochastic optimization. The building of useful models thus relies on our ability to capture as much as possible of the system structure and observed dynamics while limiting dimensionality to a handful of dynamic variables (Link, 2010; Crépin et al., 2011; Levin et al., 2012). Not only do we need to choose our variables with great care, we also need to model their dynamics appropriately. Even though we limit ourselves to just a few variables, the model should still capture key ecological tradeoffs and is bound to become nonlinear, possibly non-convex (Dasgupta and Mäler, 2003), and certainly stochastic. Finally, we need to fit the model to relevant data with methods appropriate for the nonlinearity, stochasticity, and inherent model and observational uncertainty.

As pointed out by many, the complexity and nonlinearity inherent in ecosystem-based fisheries management makes it impossible to provide general analyses and results; each specific case and scenarios require a specific and empirically based analysis (Link, 2010; Crépin et al., 2011; Levin et al., 2012). Of general interest, then, is the methods and conceptual approaches that are found to yield valuable insights in special cases and accordingly have potential when applied to new scenarios. Thus, our present effort to model the Norwegian Sea pelagic complex, while aiming at relevancy for bioeconomic decision analysis, has interest both in the special setting of the Norwegian Sea and in a methodological and conceptual sense.

Our analysis has two elements of particular methodological interest. The first concerns data. Our model is formulated in terms of aggregated biomasses, and relevant 'observations' are then output from stock assessments. The stock level data are maintained and

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published by the International Council for the Exploration of the Sea (ICES, www.ices.dk), which also publishes annual harvest levels. The stock level data are based on stock assessments via virtual population analyses, and recent work shows that the generated data have potential problems with endogeneity (Ekerhovd and Gordon, 2013). Taking care of the problem yields alternative observations that are more statistically coherent for use in, say, catch equations. But the method requires age-structured data and, because of the use of lagged variables, the resulting time series are shorter than the ICES stock level series. When we model the Norwegian Sea pelagic complex (limiting ourselves to Norwegian spring spawning herring, Northeast Atlantic mackerel, and Northeast Atlantic blue whiting; see Skjoldal et al., 2004), the length of the available time series becomes a pressing issue. In some sense, models are only as good as the data used to parameterize them (Mangel and Levin, 2005), and, in applying the Ekerhovd-Gordon approach, we face a tradeoff between time series length and data quality.

The second methodological element of interest is our application of the ensemble Kalman filter (EnKF) to fit the aggregated biomass dynamic model to data on stock and harvest levels. The EnKF is derived from Bayes Law and facilitates simultaneous parameter estimation and model fitting (Evensen, 2003). By fitting the model in an adaptive way, the EnKF allow relatively simple models to capture complex dynamics. It further provides a measure of model error, something that is of particular interest in our context where the model is intended to serve in further stochastic decision analysis. The EnKF uses an ensemble of state vectors to represent the probability density and in that respect resembles particle-based methods. The main motivation for using the EnKF is application to nonlinear models: By avoiding linearization of the model operator, it treats nonlinear models more rigourously than do alternatives such as the extended Kalman filter. EnKF has been widely applied to problems involving chaotic and nonlinear dynamic systems in meteorology, oceanography, and even fish stock assessment (Evensen, 2003). The proven usefulness of EnKF, its familiar, Bayesian features and its ease of implementation make it a valuable and accessible tool for many empirical researchers working with large and volatile systems.

The Norwegian Sea harbors some of the world's largest stocks of herring, mackerel, and blue whiting, often collectively referred to as the pelagic complex of the Norwegian Sea (Huse et al., 2012). The related fisheries are of considerable commercial interest, which leads to conflict of interest among neighboring fishing nations (Bjørndal and Ekerhovd, 2014). Further, because the Norwegian Sea is very deep, with an average depth of more than 5500 ft, there are no (significant) demersal predators such as cod present. Thus, at least from a commercial perspective, there are no species at higher trophic levels of interest. Similarly, at lower trophic levels, the main species is the zooplankton species *Calanus finmarchicus*, also of limited commercial interest. *Calanus* is, however, the main food source for the pelagic complex for large parts of the year (Utne et al., 2012a). In other words, the particular geographical and ecological structure of the Norwegian Sea gives rise to a rather simple foodweb where the pelagic complex relies, to a large extent, on a common food base. In an admittedly simplified perspective, we model the Norwegian Sea pelagic complex as three species at the same trophic level that compete for food and, in model-speak, share a common carrying capacity. Modeling of competition in ecological models has seen little use in practice (Link, 2010, p. 100), but we find the approach appropriate and useful for the Norwegian Sea pelagic complex. Thus, establishing models for economic analysis in the Norwegian Sea setting should be of both scientific and industrial interest.

We think there is a need for an explicit focus on modeling of biology and ecology that provides relevant structures for further economic analysis (*sensu* Sandal and Steinshamn, 2010; Poudel et al., 2012; Ekerhovd and Steinshamn, 2016). Such model structures seldom arise within the fields of biology and ecology because such models and relevant data typically abstract from details that are of fundamental interest in these fields. Thus, economists that are concerned with these models need to engage with biologists and ecologists to create and enhance this focus. Moreover, the existing understanding of ecological-economic interactions in marine food webs is far from complete (Peck et al., 2014), which further underlines the need for research into ecological-economic models. As we commit to such modeling, we gain a broader view on the interdisciplinary nature of our work, which provides us with a more unified perspective on ecosystem-based management. We also think such modeling is necessary to support better economic decisions because decision makers need good measures of how the underlying, interconnected systems respond to different management regimes.

2. Data and Method

Fig. 1 displays the aggregated stock level estimates (dashed curves) and annual harvest levels (circled points) for Norwegian spring spawning herring, Northeast Atlantic mackerel, and Northeast Atlantic blue whiting that are published by ICES. The full time series for herring and mackerel go back to 1972, while the blue whiting series go back to 1977, but the figure only shows years where full age-structured information is available. As discussed in great detail by Ekerhovd and Gordon (2013), when the ICES stock level estimates are used in the type of equations we use below, they likely introduce a bias because of endogeneity between stock and catch variables (see Gordon, 2015, for further discussion of the endogeneity problem and related issues in fisheries). Ekerhovd and Gordon (2013) find a valid instrument for the catch variable in a lagged catch variable. We implement the Ekerhovd-Gordon approach to obtain statistically coherent stock estimates for the stocks of interest. Some details on the procedure are provided in Appendix A; see Ekerhovd and Gordon (2013) for the full account.

The Ekerhovd-Gordon approach leads to revised stock estimates, which we present in Fig. 1 (solid curves). The revisions are at times substantial. Two particular features are worth noting: (i) The herring stock levels in the late 1980s are revised heavily downwards, which implies that the subsequent buildup was more rapid. (ii) The spike in blue whiting after 2000 is essentially non-existent in the revised stock estimates and implies less volatile stock dynamics. Let us hasten to add that the Ekerhovd-Gordon revisions are not necessarily improvements to the stock estimates: The ICES-estimates are likely the best reflection of the stock developments. But for use in the type of empirical equations we use below, the Ekerhovd-Gordon approach addresses a potential bias, and the revisions do therefore have implications for the estimated stock dynamics.

Because the Ekerhovd-Gordon approach relies on lagged variables and the availability of age-structured data, revised estimates are only available from 1988 for herring, 1982 for mackerel, and 1981 for blue whiting. Because the approach uses lagged variables as instruments, some year classes are consumed in the process. We guesstimate levels for the missing year classes by adopting adjustment factors (that is, the relationship between the original ICES estimate and the revised estimate) for neighboring year classes. The effect of this procedure on the total stock estimates is minor and within the observation error we assume below.

When we fit a model to the stock levels in Fig. 1, we only use observations for the years where all stocks are observed (1988–2013). It is technically feasible to fit a model with missing observations, but the fitted model is hard to interpret when the missing observations are at the beginning of the time series. (Another alternative is to use the observations in Fig. 1, with increased observation error, when Ekerhovd-Gordon estimates are missing.) For the balance of this work, however, we limit ourselves to the observations in Fig. 1 with 10% observation uncertainty.