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THE USE OF MULTIVARIATE STATE-SPACE MODELING FOR UNDERSTANDING THE INFLUENCES OF ENVIRONMENTAL FACTORS ON STOCK DYNAMICS

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SUMMARY

Multivariate state-space methods have been used in finance, physics, and ecology, but have only recently been applied to fisheries. This class of methods allows for analysis of time series in a flexible manner which permits hypothesis testing regarding the nature of relationships between different time series, as well as properties regarding their observation and process variance. As such, the methods are potentially useful for gleaning information on stock dynamics from existing abundance indices at the available political or spatial scales. We showcase the utility of multivariate state-space modeling by applying the methods to swordfish, a species suspected to be influenced by environmental drivers. Alternative models containing assumptions about process error, observation error, stock migrations, and environmental linkages, are compared via an information criterion framework. The most parsimonious model is then used to produce a combined index of abundance for the stock. In addition to informing the issue of combining separate abundance indices, multivariate state-space methods can be used to: estimate commonalities in species' responses to the environment, test for species interactions, identify structural breakpoints, or make one-step-ahead predictions in abundance.

RÉSUMÉ

Des méthodes état-espace à variables multiples sont utilisées dans le domaine de la finance, de la physique et de l'écologie et n'ont été appliquées que très récemment aux pêcheries. Ce type de méthodes permet d'analyser des séries temporelles d'une manière flexible ce qui permet la vérification d'hypothèses au niveau de la nature des relations entre les différentes séries temporelles, ainsi que les propriétés concernant leur observation et la variance du processus. Par conséquent, les méthodes pourraient être utiles pour glaner des informations sur les dynamiques des stocks à partir des indices d'abondance existants aux échelles politiques ou spatiales disponibles. On souligne l'intérêt que revêt la modélisation état-espace à variables multiples en appliquant les méthodes à l'espadon, une espèce soupçonnée d'être influencée par des facteurs environnementaux. D'autres modèles contenant des postulats au sujet de l'erreur de processus, l'erreur d'observation, les migrations des stocks et les interactions environnementales, sont comparés au moyen d'un cadre de critère d'information. Le modèle le plus parcimonieux est ensuite utilisé pour produire un indice combiné d'abondance du stock. Les méthodes état-espace à variables multiples sont utilisées pour documenter la question de la combinaison des indices d'abondance séparés, mais elles peuvent également servir à estimer les points communs des réponses des espèces à l'environnement, à tester les interactions des espèces, à identifier les points de rupture structurels ou encore à formuler des prévisions de l'abondance ayant une longueur d'avance.

RESUMEN

Los métodos de modelación de espacio-estado multivariable se han estado utilizando en estudios financieros, en física y en ecología, y recientemente se están aplicando a las pesquerías. Esta clase de métodos permite analizar series temporales de una manera flexible, lo que permite poner a prueba las hipótesis relativas a la naturaleza de las relaciones entre distintas series temporales, así como las propiedades relativas a su varianza en términos de observación y proceso. En este sentido, los métodos resultan potencialmente útiles para recabar información sobre la dinámica del stock a partir de los índices de abundancia existentes en escalas políticas o espaciales disponibles. En el documento se ejemplifica la

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utilidad potencial del modelo de espacio-estado multivariable aplicando los métodos al pez espada, una especie a la que supuestamente le influyen los factores ambientales. Se comparan modelos alternativos que incluyen supuestos sobre errores de proceso, errores de observación, migraciones del stock y vinculaciones ambientales, a través de un marco de criterio de información. Se utiliza seguidamente el modelo más austero para elaborar un índice combinado de abundancia del stock. Además de para profundizar en la cuestión de cómo combinar índices de abundancia distintos, los métodos de modelación de espacio-estado multivariable pueden emplearse para estimar los elementos comunes en las respuestas de las especies al medio ambiente, contrastar interacciones entre especies, identificar puntos estructurales de ruptura o realizar predicciones sobre la abundancia.

KEYWORDS

Time series analysis, Population dynamics,
Fishery statistics, Environmental effects, Stochastic processes

1. Introduction

While the effect of the physical environment on the dynamics of pelagic fish stocks has long been recognized, the methods for integrating these influences in the assessment of our stocks still remain largely unexplored. Generally environmental influences are introduced into a stock assessment in one of two ways: either during the catch-per-unit-effort (CPUE) standardization process, or linked to a process within the assessment model itself. In CPUE standardization, a year * area interaction variable is often used, which essentially absorbs any large-scale environmental variability without explicitly accounting for it; for example, in a case where a stock migrates to a certain area only during years with specific environmental conditions. Environmental variables can also be added to the standardization process when available at spatial and temporal level of the fishing activity, to model the case where catchability is modulated by the environment (e.g. Lauretta *et al.* 2014). Depending on the flexibility of the stock assessment model used, environmental parameters can be linked to different aspects of the stock (Schirripa *et al.* 2009) ; however, such options may be limited, and increasing the complexity of an integrated assessment model can lead to problems with parameter confounding or model misspecification (Maunder and Punt 2013). In sum, environmental effects can be incorporated into the stock assessment process in a number of ways; however, they may not be directly comparable from a hypothesis-testing perspective, and they are limited in the ways in which they can model effects of environment on the stock.

A number of statistical approaches have been developed to analyze time series data such as CPUE indices or other fisheries data. One class of models, the multivariate autoregressive state-space models, are well-developed and have been used in the study of finance, economics, psychology, and ecology, but remain relatively unused in the fisheries realm. Following Holmes *et al.* (2014), a multivariate state-space model can be written as a "state process" and an "observation process" as follows:

$$x_t = B_t X_{t-1} + u_t + C_t c_t + w_t;\ w_t \sim MVN(0, Q_t)$$
$$y_t = Z_t X_t + a_t + D_t d_t + v_t;\ v_t \sim MVN(0, R_t)$$

where all elements are matrices, *x* is a state variable and *y* is the actual time series observation at time *t*. We describe the other parameters in the model in reference to the case where the observations *y* are indices of abundance and the states *x* are the underlying abundances. In the state equation, the matrix *B* is a parameter that represents the interactions between different states or subpopulations with separate abundance patterns. The parameter *u* is a scaling parameter, and the parameter *c* can represent environmental drivers whose effects map to the states according to matrix *C*. The matrix *w* represents the process errors. In the observation equation, *Z* is a matrix which maps the time series data to their respective states *x*, a is again a scaling parameter and *d* can represent environmental drivers whose effects map to the time series observations according to matrix *D*. Finally, *v* represents the observation errors. Further details on model structure can be found in Holmes et al. (2014) and in the extensive reference list within.

This class of models is extremely flexible in that any of the terms above can be omitted, treated as known, or parametrized as a function of another unknown variable. The equations can be modified to represent a number of more commonly used statistical techniques; a simple linear regression, for example, can be expressed in matrix form by excluding the state process and diluting the observation equation to $y_t = a + Dd_t + v_t$. The multivariate state space form thus represents a highly flexible framework which should be useful for testing hypotheses regarding different assumptions about a given set of time series observations. The equations can be solved using a relatively new, well-developed R package (MARSS (Multivariate Auto-Regressive State-Space); Holmes et al. 2014). This package is particularly useful in that it has implemented an algorithm robust to missing values, as well as a bias-corrected information criterion metric which can be used in model selection.

Here we present a preliminary application of multivariate state space models to test hypotheses regarding a set of CPUE time series. We use swordfish (*Xiphias gladias*) as an example, as this species is thought to be influenced by the environment and was subject to a recent discussion on how to best capture these influences in a stock assessment (Schirripa 2014). Schirripa (2014) noted that these environmental drivers could potentially affect catchability, migration patterns, stock expansion, or a change in food availability, among other possibilities or combinations of the above. The goal is to test various assumptions about the relationships between different abundance indices, and also the effects of suspected drivers on stock dynamics. We focus on three different sets of hypotheses: 1) regarding the relationships of observation error and process error among fleets, 2) regarding environmental drivers, and the aspects of stock dynamics that these drivers affect, and 3) regarding interactions between the fractions of the stock targeted by different fleets. The intent of this paper is not to be conclusive regarding the effects of the environment on Atlantic swordfish, nor do we expect that we have captured the full range of plausible hypotheses. The paper is simply meant to serve as an introduction to the methods and their application to analysis of fishery abundance indices, and to serve as a jumping-off point for further study in this regard. We do not explore detailed model diagnostics in this paper, but recognize that this is an essential step before taking the methods further; thus the results herein thus should be interpreted with caution.

2. Methods

The last North Atlantic swordfish assessment included CPUE time series from 5 different fleets: Canada, Portugal, Spain, Japan, and the United States. The United States index was split in 2004 due to the introduction of new gear which was thought to significantly change catchability. Note that an abundance index from Morocco was also available; this was excluded due to the short time series as we wished to keep the number of missing values limited for initial exploration. For this reason, we also limited our preliminary analysis to the data-rich 1986 – 2011 period. Biomass time series in were taken from the 2013 stock assessment report (Anon 2013; **Table 3**). Schirripa (2014) hypothesized a number of drivers that were thought to potentially affect the stock: the Atlantic Multidecadal Oscillation, the North Atlantic Oscillation, and the Atlantic Warm Pool. Indices for these environmental drivers were taken from the Gulf of Mexico Ecosystem Status Report (Karnauskas *et al.* 2013). In this preliminary exploration we tested various hypotheses under the logic that follows.

The first hypotheses dealt solely with the spatial nature of the abundance indices from different fleets, disregarding for the moment any effects of the environment. The general form of the MARSS equations for this set of hypotheses is as follows:

$$x_t = x_{t-1} + u + w_t;\ w_t \sim N(0, q)$$
$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix}_t = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} x_t + \begin{bmatrix} 0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{bmatrix} + \begin{bmatrix} v_{1,t} \\ v_{2,t} \\ v_{3,t} \\ v_{4,t} \\ v_{5,t} \\ v_{5,t} \end{bmatrix};\ v_t \sim MVN\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} r_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & r_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & r_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & r_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & r_5 & 0 \\ 0 & 0 & 0 & 0 & 0 & r_5 \end{bmatrix} \right)$$

In the simplest case (hypothesis H_{0A}), a single abundance state is assumed to exist, and we estimate a single state scaling parameter *u*, a set of observation scaling parameters *a* (which are meaningless as the indices are relative), a single process error *q*, a set of independent observation errors *r*, and finally a time series of states x_t which represent the underlying abundance trend. Note that the last two observation errors are estimated to be the same value because they both represent indices from the United States; we assume that while the gear has changed, and thus the scaling parameters a_4 and a_5 should differ, the level of observation error has stayed the same. Other plausible hypotheses are also proposed as follows:

> H_{1A}: Each time series of observations represents a separate abundance state, and process errors are equal among states.

H_{2A}: Each time series of observations represents a separate abundance state, and the process errors differ among states.
H_{3A}: Each time series of observations represents a separate abundance state, except for the two indices from the USA which were mapped to a single state process, and separate process errors and covariances among process errors are estimated. (Note that the full 6-state model did not converge so we limited the number of states to 5, assuming the process error of the two United States observations was similar).
H_{4A}: Based on the patterns in covariance of process errors from H_{3A}, the observation time series are grouped and mapped to a smaller number of different underlying states.

The second set of hypotheses involves testing environmental covariates as influencing either the observation process or the state process. The base model is the same configuration as above, with the addition of a covariate linked to the state variable:

$$x_t = x_{t-1} + u + C_t c_t + w_t;\ w_t \sim N(0, q)$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix}_t = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} x_t + \begin{bmatrix} 0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{bmatrix} + \begin{bmatrix} v_{1,t} \\ v_{2,t} \\ v_{3,t} \\ v_{4,t} \\ v_{5,t} \\ v_{5,t} \end{bmatrix};\ v_t \sim MVN\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} r_1\ 0\ 0\ 0\ 0\ 0 \\ 0\ r_2\ 0\ 0\ 0\ 0 \\ 0\ 0\ r_3\ 0\ 0\ 0 \\ 0\ 0\ 0\ r_4\ 0\ 0 \\ 0\ 0\ 0\ 0\ r_5\ 0 \\ 0\ 0\ 0\ 0\ 0\ r_5 \end{bmatrix} \right)$$

The hypotheses tested were as follows:

H_{0B}: Six time series observations with independent observation error linked to a single underlying state, with the environmental variable (Atlantic Multidecadal Oscillation) affecting the abundance state.
H_{1B}: Six time series observations with independent observation error linked to a single underlying state, with the environmental variable (Atlantic Multidecadal Oscillation) affecting the observation states (with a different effect measured for each observation time series). Note that the environmental effect $D_t d_t$is included in the observation state and the $C_t c_t$ term is dropped.
H_{2B}: Six time series observations with independent observation error linked to a single underlying state, with the environmental variable (Atlantic Warm Pool mean annual size) affecting the abundance state.
H_{3B}: Six time series observations with independent observation error linked to a single underlying state, with the environmental variable (North Atlantic Oscillation) affecting the abundance state.
H_{4B}: Six time series observations grouped and mapped to three underlying states (using the same optimal configuration used in H_{4A}) with the environmental variable (Atlantic Multidecadal Oscillation) affecting the observation states. The process errors of the three underlying states, and all of their covariances, are estimated. The effect of the environmental variable is independently estimated for each of the three states.

The final set of models was set up to test hypotheses concerning potential interactions among the identified subpopulations (using, as above, the optimal configuration determined in H_{4A}), as well as the potential environmental influences on individual subpopulations. We use the term "subpopulation" not to suggest that there are distinct, genetically separate subpopulations within the overall Atlantic stock, but rather to refer to fractions of the population that display differing dynamics (as suggested by the data), which are represented by the three different state variables. To understand the interactions between these "subpopulations," we are interested in estimating the matrix parameter *B*; however, to avoid a model with infinite solutions this requires us to set other parameters as fixed. The parameter *B* is well known to be confounded with the scaling parameter u, and thus we fixed u to zero (Holmes *et al.* 2014). Additionally, model convergence was somewhat problematic for models where the process error was allowed to vary, so we estimated only a single process error variance which was equal for all subpopulations. The model structure for this set of hypotheses was thus:

$$\begin{bmatrix} x_c \\ x_s \\ x_u \end{bmatrix}_t = \begin{bmatrix} B_{c,c}\ B_{c,s}\ B_{c,u} \\ B_{s,c}\ B_{s,s}\ B_{s,u} \\ B_{u,c}\ B_{u,s}\ B_{u,u} \end{bmatrix} \begin{bmatrix} x_c \\ x_s \\ x_u \end{bmatrix}_{t-1} + \begin{bmatrix} C_c \\ C_s \\ C_u \end{bmatrix} [env_t] + \begin{bmatrix} w_{c,t} \\ w_{s,t} \\ w_{u,t} \end{bmatrix};\ \begin{bmatrix} w_{c,t} \\ w_{s,t} \\ w_{u,t} \end{bmatrix} \sim MVN\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} q\ 0\ 0 \\ 0\ q\ 0 \\ 0\ 0\ q \end{bmatrix} \right)$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix}_t = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{t,1} \\ x_{t,2} \\ x_{t,3} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ a_1 \\ a_2 \\ 0 \\ a_3 \end{bmatrix} + \begin{bmatrix} v_{1,t} \\ v_{2,t} \\ v_{3,t} \\ v_{4,t} \\ v_{5,t} \\ v_{5,t} \end{bmatrix} \; ; \; v_t \sim MVN\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} r_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & r_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & r_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & r_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & r_5 & 0 \\ 0 & 0 & 0 & 0 & 0 & r_5 \end{bmatrix} \right)$$

Note that the Z matrix maps different observation time series y to their respective states x. The subscripts c, s, and u refer to Canada, Spain/Portugal/ Japan, and the United States, as these subpopulation groups were derived from the first set of hypotheses (see ***Results*** below). In each of these models, the six time series were mapped to the three states as shown above, and the observation error was allowed to vary by fleet. Additionally, we used only the single environmental covariate that obtained the best statistical support from the second set of hypotheses.

H_{0C}: No environmental effect on the state processes of the subpopulations.
H_{1C}: The environmental covariate is linked only to the x_u state process
H_{2C}: The environmental covariate is linked only to the x_c state process
H_{1C}: The environmental covariate is linked only to the x_s state process
H_{1C}: The environmental covariate is linked to the x_c and x_u state processes in the same manner (a single parameter estimated for the combined effect).
H_{1C}: The environmental covariate is linked to the x_s and x_u state processes in the same manner (a single parameter estimated for the combined effect).
H_{1C}: The environmental covariate is linked to the x_c and x_s state processes in the same manner (a single parameter estimated for the combined effect).

All analyses were run using R version 2.3.1 (R Core Development Team, 2015) and using the MARSS package (Holmes et al. 2012). All indices and covariates were scaled to a mean of zero and standard deviation of 1 in order to simplify the analysis by limiting the number of necessary parameters to be estimated and improve model convergence. The Expectation-Maximization algorithm (Holmes 2012) was used for model fitting. Each model was run until a tolerance value (the slope of the log parameter versus the log iteration) of 0.1 had been achieved.

3. Results

We report results in **Table 1** which reiterates the model number, assumptions used, and the bias-corrected AIC (AICc). A lower AICc indicates a more parsimonious model fit. For the first set of hypotheses, regarding stock structure, models assuming a single underlying abundance trend were clearly inferior to models incorporating some sort of spatial fleet structure. When the process error term was left fully unconstrained and thus all variances and covariances estimated by the model, logical relationships between fleets emerged (**Table 2**). Covarying process errors (i.e., "high" years and "low" years of abundance) were found for fleets that generally overlap in space. Process errors from the Portuguese, Spanish, and Japanese fleets were all highly correlated ($R > 0.70$). Process errors from the Canadian fleet were somewhat correlated with Spain and Portugal, but not with Japan. Process errors from the United States fleet were not correlated or were strongly negatively correlated with other fleets. Based on the process error structure, further hypothesis testing was developed around an assumption of three different underlying states whose dynamics were represented by 1) the Canadian fleet, 2) Spanish, Portuguese, and Japanese fleets (referred to as the "Spanish subgroup"), and 3) the United States fleet.

Results from the second set of hypotheses elucidated the potential environmental drivers affecting stock dynamics. Generally, the data seemed to most strongly support the Atlantic Multidecadal Oscillation (AMO) as the most influential driver, and there was more statistical support for a model linking the environmental effects to the state process than to the observation process. A model assuming a single underlying abundance state, driven by the AMO, was only slightly less-supported than a model assuming three abundance states, each with separately estimated AMO effects (H_{0B} vs. H_{4B}, $\Delta AIC = 1.76$). In the latter model, the AMO effect was estimated to be positive for the Canadian fleet and Spanish subgroup (0.19 and 0.17 respectively), and negative for the United States fleet (-0.20).

The third set of hypotheses generated information regarding the interactions between subpopulations. Note again that the term "subpopulation" is used here not to denote a genetically different or independent stock, but to describe an observed portion of the stock whose dynamics follow a particular abundance trend. The model results indicated that clearly, interaction effects were important, and support the idea that these subpopulations belong to a single, mixed population with certain migrating sectors. Even the model with no environmental effect, but assuming subpopulation interaction (H_{0C}) was superior to all the models from sections 1 and 2 which did not assume interactions. Addition of an environmental covariate (the AMO) provided further insight to the dynamics of the stock. Of all the hypotheses considered in the entire study, the most parsimonious was that which considered interaction effects, and an AMO effect that was common to both the Canadian and United States subpopulations. This contrasts the estimation of the AMO effect in the previous section (where subpopulation interactions were not included) and the AMO effect on the United States was estimated to be opposite that of the effect on the Canadian subpopulation. Thus, the introduction of migratory dynamics into the model suggested that the nature of the environmental effect was more East-West in nature than North-South.

Analyzing the estimated *B* matrix from the model lends insight into the nature of the dynamics of the stock and its subcomponents (**Table 3**). The diagonals of the matrix denote the level of density-dependence within stock subunits, with values close to 1 indicating low density dependence. The model estimates suggest that density dependence is low in the area of the Canadian and European fleets, but high in the area fished by the United States. The off-diagonal components indicate the effect of the fleet in a column on the corresponding fleet in a row. In other words, the value of $B_{i,j}$ gives the effect of subpopulation *j* on subpopulation *i*. Based on the model estimates, we can see that the Canadian subpopulation has a small positive effect on the combined Spanish subpopulation, but a large positive effect on the United States subpopulation. The combined Spanish subpopulation, in turn, has no effect on the Canadian subpopulation, and a very large negative effect on the United States population. Finally, the United States population has little effect on other subpopulations. Overall, the matrix seems to suggest a somewhat distinct subpopulation targeted by the United States fleet, whose dynamics do not highly influence abundance trends in other regions. However, when CPUE of the Spanish subpopulation is high, it has a large negative effect on the United States, indicating that perhaps swordfish are migrating from the southwest Atlantic to the northeast Atlantic. When CPUE is high in the Canadian subpopulation, it is also high in other areas, which seems to suggest that years of high CPUE are caused by an expansion of the stock across the Atlantic, rather than a migration out of one area and into another.

The estimates of the underlying state variables are shown for a select number of the hypotheses considered. To illustrate the effect of the environmental covariate on the abundance, we plot the estimated state from hypothesis H_{0B} against the estimated state from H_{0A} (**Figure 1**). Overall, the inclusion of the AMO as linked to the state process does not greatly change the estimated trend in population abundance over time. We also plot the three state processes for the most parsimonious model, H_{4C} (**Figure 2**). As was shown by the inspection of model parameter estimates, the United States subpopulation ('state 3') is distinct and shows a trend of fluctuating but stable abundance over time. The Canadian and Spanish subpopulations (states 1 and 2, respectively) show similar trends until about the year 2000, at which point they diverge.

4. Discussion

This preliminary exploration of the application of multivariate state space models to fishery abundance indices is intended to showcase potential utility of the methods, and understand whether reasonable model results can be obtained with the typical fisheries data which tend to have high observation error and many missing values. The results presented here suggest that this framework could be useful for further exploration, as we obtained results consistent with our general knowledge of the test species. Among the suite of hypotheses that we considered, which are clearly not inclusive of all the possibilities, we show that the most parsimonious model of stock dynamics is that there exist three, highly interactive subpopulations, and that movements among these subpopulations are driven by an environmental factor, the Atlantic Multidecadal Oscillation. This model appears to fit well with our current understanding that Atlantic swordfish is a single, highly migratory stock and that divergent trends in CPUE across fleets are probably due to variable migratory patterns depending on environmental conditions. However, further hypothesis testing and model diagnostics are needed, before any definitive conclusions can be drawn from these analyses.

Importantly, this analysis focused on fleet-specific abundance indices which are likely not the most suitable for exploring spatial dynamics of the stock. Ideally, area-specific combined CPUEs, such as those proposed by Lauretta *et al.* (2015) could be obtained. If combined area CPUEs are not available, the year * area interaction least squares parameter estimates could similarly be used to represent trends in abundance specific to smaller areas. A similar analysis, carried out on time series with higher spatial resolution, would likely yield further insights into the interactions among space, time, and environment. It would also be worthwhile to consider nominal CPUE trends by area, since the process of feeding the data through a generalized linear model may remove some of the environmental signal which could be informative to the process error component of the state space model.

Notable features of the MARSS R package implementation of these methods is that it easily handles extended periods of missing values in the data inputs, and information can easily be "borrowed" by parameterizing some unknowns as functions of other unknowns. The framework therefore may be promising for issues such as combining CPUE indices from multiple sources, which usually contain different years of data or different levels of detail. The state estimates produced from these models are theoretically representative of the underlying population trends after accounting for process error, observation error, environmental dynamics, and any other processes parameterized in the model. As such, they could represent an alternative to the traditional method of using generalized linear models to estimate combined abundance indices, particularly as the latter are somewhat limited as to how the error structures and environmental drivers can be accounted for. Beyond the application to abundance indices, these highly flexible models may be useful for analysis of other types of data frequently encountered in fisheries. An extensive discussion of potential applications appears in Holmes *et al*. (2014) and includes: analysis of animal tracking data, identification of species interactions, or forecasting of short-term dynamics. We suggest that, given the extensive sets of time series data that we deal with in the fisheries realm, this flexible class of models may be worth further exploration.

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Table 1. List of hypotheses tested in this study. Note the observation error structure was consistent across all models (independently estimated by fleet with no covariances estimated).

model	*# states*	*process error*	*B matrix*	*U*	*environmental effect*	*AICc*	*ΔAIC*
H_{0A}	1	one combined	set to identity	estimated	none	263.43	31.18
H_{1A}	6	shared across fleets	set to identity	estimated	none	258.20	25.96
H_{2A}	6	independent by fleet	set to identity	estimated	none	263.68	31.43
H_{3A}	5	fully unconstrained	set to identity	estimated	none	267.81	35.56
H_{4A}	3	independent by fleet	set to identity	estimated	none	257.13	24.88
H_{0B}	1	one combined	set to identity	estimated	AMO linked to state process	248.18	15.93
H_{1B}	1	one combined	set to identity	estimated	AMO linked to observation process	265.35	33.10
H_{2B}	1	one combined	set to identity	estimated	AWP linked to state process	257.20	24.95
H_{3B}	1	one combined	set to identity	estimated	NAO linked to state process	263.58	31.33
H_{4B}	3	shared across fleets	set to identity	estimated	AMO linked to each of 3 processes	246.42	14.17
H_{0C}	3	shared across fleets	estimated	set to zero	none	244.58	12.33
H_{1C}	3	shared across fleets	estimated	set to zero	AMO linked to only X_u state process	248.64	16.39
H_{2C}	3	shared across fleets	estimated	set to zero	AMO linked to only X_c state process	235.27	3.02
H_{3C}	3	shared across fleets	estimated	set to zero	AMO linked to only X_s state process	247.55	15.30
H_{4C}	3	shared across fleets	estimated	set to zero	AMO linked to X_c and X_u state	232.25	0.00
H_{5C}	3	shared across fleets	estimated	set to zero	AMO linked to X_s and X_u state	247.73	15.48
H_{6C}	3	shared across fleets	estimated	set to zero	AMO linked to X_c and X_s state	241.25	9.00

Table 2. Correlation matrix of process errors from each fleet, as estimated by model H_{3A}. Correlations of R > 0.70 appear in shaded boxes.

	CAN	*POR*	*SPA*	*JAP*	*USA*
CAN	1.00				
POR	0.62	1.00			
SPA	0.47	0.73	1.00		
JAP	0.12	0.84	0.52	1.00	
USA	0.18	-0.45	0.14	-0.77	1.00

Table 3. B matrix estimated from model H_{0C}, showing interactions between subpopulations.

		effect of this subpopulation		
		CAN	*SPA/POR/JAP*	*USA*
on this subpopulation	***CAN***	0.98	0.00	0.11
	SPA/POR/JAP	0.16	0.88	0.18
	USA	1.58	-2.20	-0.11

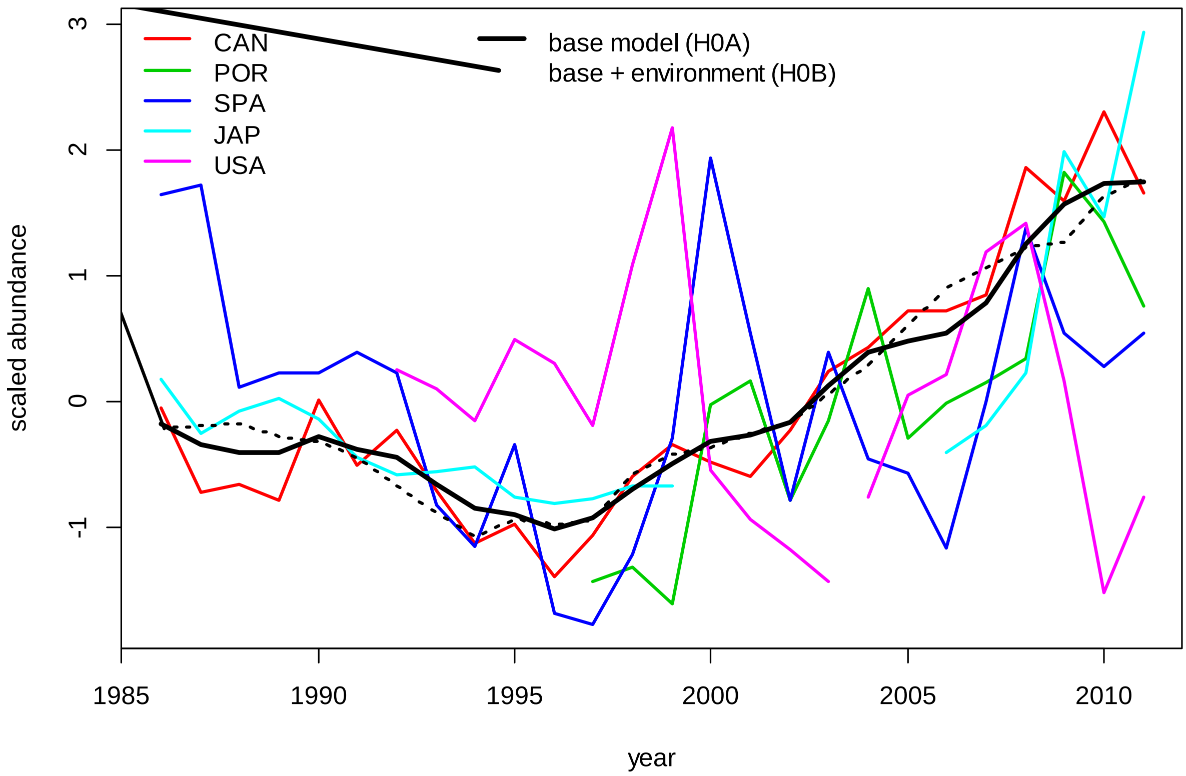

Figure 1. Estimated state process for a single combined Atlantic swordfish population, with and without the effect of the environmental covariate.

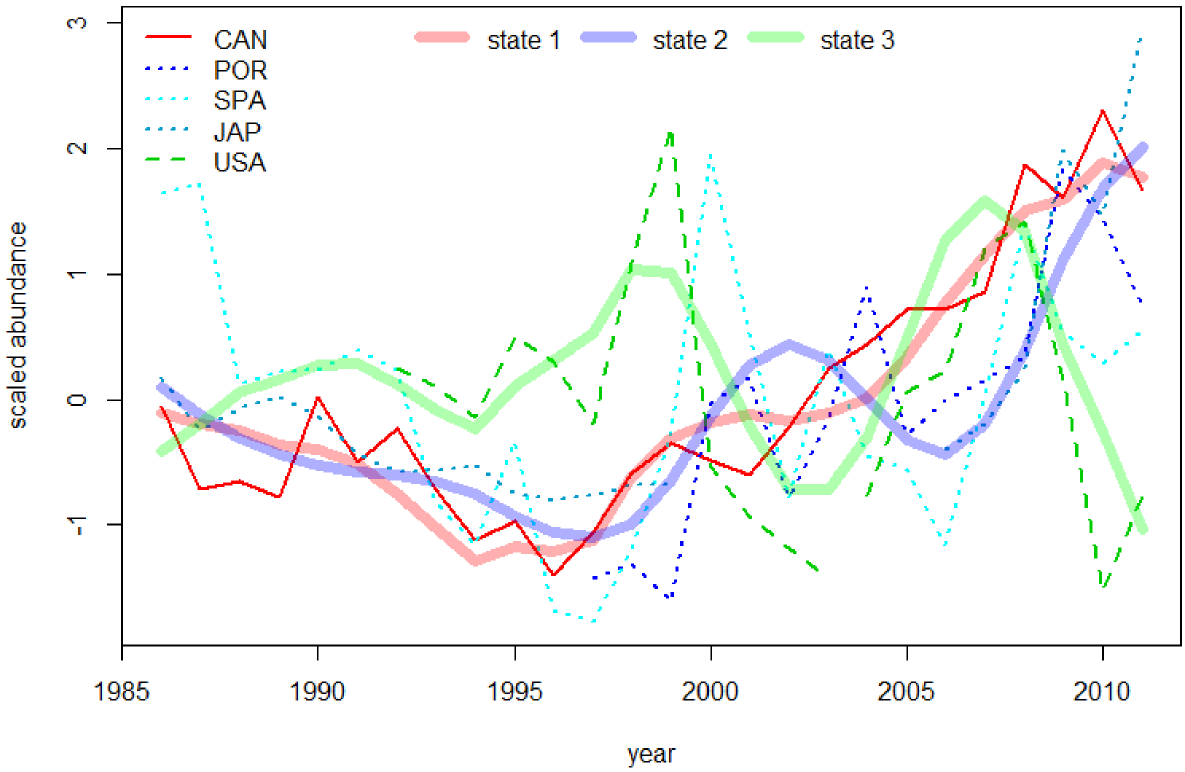

Figure 2. Estimated state processes from the most parsimonious model of the set considered in the study (H_{4C}). State 1 is observed by the Canadian fleet, state 2 is observed by the Portuguese, Spanish, and Japanese fleet, and state 3 is observed by the United States fleet.