Recovery of European fish stocks and the Reform of the Common Fisheries Policy

Annex I & II:

I – Material and Methods

II – List of fish stocks and model parameters

I - Material and Methods following Neubauer et al. 2013 – Science 340, 347-349

Definitions

We used the following operational definitions of depletion, recovery, and recovered. A stock was classified as depleted when its biomass (spawning stock or total biomass) fell below half of its MSY reference point, B_{MSY}. We considered a stock to be recovered once its biomass exceeded B_{MSY}. Recovery is then the demographic process of population growth between the time of depletion, $B < 0.5B_{MSY}$, and the time when the biomass first exceeds B_{MSY}. Note that according to these definitions a stock may be classified as overfished more than once throughout its exploitation history and we term each such event a depletion event.

Data

Our analyses are based upon Version 1.0 of the Ram Legacy Stock Assessment Database (Ricard et al. 2012), with European stock assessments conducted by International Council for the Exploration of the Seas (ICES) updated to assessment available in September 2011. For each stock, we obtained time series of estimated biomass B (spawning stock or total biomass, in order of preference) and fishing mortality F, as well as the corresponding reference points B_{MSY} and F_{MSY}, the biomass and fishing mortality estimated to lead to the maximum sustainable yield (MSY). Only time-series with at least 10 years of data were retained for analysis. We used MSY reference points directly from the assessments, where available, and estimated them using surplus production model fits to stocks' biomass and catch time series for the remaining stocks. Of the 253 stocks for which these data were available, 153 stocks, comprising 85 different species, were depleted at some point, and several were depleted multiple times, resulting in a total of 184 depletion events.

Modeling recovery

Our approach to modeling the recovery process is motivated by the underlying population dynamics of recovering stocks, which can be represented using a stochastic differential equation model for stock biomass dynamics:

$$dB_t = \varphi_t B_t dt + \sigma B_t dW_t \qquad (1)$$

where B_t is the biomass at time t, the function φ_t, which represents the deterministic component of the biomass dynamics (e.g., survival and reproduction), models the rate of increase of the population, and could, for example take the form of an exponential or logistic growth model with variable fishing mortality (e.g., a Graham-Schaefer surplus production model). W_t is a Wiener process with mean 0 and variance coefficient σ. This continuous-time stochastic process is commonly used

to model Brownian motion, and here represents the stochasticity of the biomass dynamics. Thus, model (1) is a stochastic version of a continuous biomass dynamics models (Lewy & Nielsen 2003), in which the recovery target is approached at a recovery rate determined by φ_t. Use of this model directly, however, would necessitate specifying the form of φ_t and thus determining *a priori* which (and how) covariates influence the biomass dynamics. This is, however, exactly what we seek to determine empirically, and imposing a particular model for φ_t may therefore bias our inference. Rather than specifying a specific model for biomass dynamics, our aim is to estimate the importance of covariates that influence these dynamics and the associated stochasticity, and therefore determine the time to recovery. Thus, instead of modeling the time-series themselves, we can model the time to recovery directly by taking the time to recovery as the response variable. Under the assumption that the a stochastic component of the time-series can be reasonably described by a Wiener process, the time from depletion to recovery follows an inverse-Gaussian (IG) distribution with density

$$f_{IG}(t) = \frac{c'}{\sigma\sqrt{2\pi}}\, t^{-3/2}\exp\left[-\frac{(c'-v't)^2}{2\sigma^2 t}\right] \tag{2}$$

where c'=-log(B_d) is a function of the initial biomass at depletion, B_d, v' is a function of φ_t , and coefficient σ is the Wiener process variance (Aalen & Gjessing 2001). Regardless of the precise model for the biomass, the parameters c' and v' can be interpreted as influencing the 'distance' to the recovery target and the 'recovery rate', respectively. Both parameters are relative to the stochasticity of the biomass dynamics, such that, for instance, the same biomass for highly stochastic dynamics will represent a lower distance from the recovery target since a recovery due to a stochastic event is more likely. f_{IG} thus depends on σ through $c'/\sigma = c$ and $v'/\sigma = v$ (i.e., there are only two free parameters, and we can set σ=1 without loss of generality (Aalen & Gjessing 2001)), and we may then investigate the importance of covariates in determining the recovery rate and distance from recovery relative to the stochasticity in the time series by placing a regression formulation on each of c and v (Aalen & Gjessing 2001). This means that regression covariates can in theory influence the time to recovery either directly by influencing c' or v' , or by modifying the amount of stochasticity σ.

The final model for time to recovery for all $i = 1 \ldots N$ depletion events can be expressed hierarchically as:

$$t_i | v_{i,j}, c_i \sim IG(v_{i,j}, c_i)$$
$$v_{i,j} = \beta' X_i + \epsilon_j$$
$$c_i = -\log(B_d) * \exp(\gamma' \Xi_i)$$
$$\epsilon_j \sim N(0, \xi)$$

where, X_i and Ξ_i are regression covariates influencing the relative recovery rate and the relative distance to recovery, respectively. For the latter, a multiplicative regression formulation assures that the distance remains positive, but is decreased by negative effects of covariates. To circumvent pseudo-replication in stocks with more than one depletion event, we introduce a random effect ϵ_j for the recovery rate of stock j. The probability $\varphi(t)$ that a stock will take at least a time T (e.g., 10 years) to recover is then $F(t) = 1 - P_{IG}(T \leq t)$, where P_{IG} is the inverse Gaussian cumulative distribution function at T integrated over the random effect (see below).

Importantly, this model form allows for the possibility that some stocks may not recover. Recovery will be increasingly unlikely with an increasingly negative recovery rate and increasing distance from the recovery target (relative to the stochastic component in the time series). This probability can be directly quantified for our model, and can thus be investigated in terms of regression covariates (see below).

Survival analysis for stock recoveries
Models of 'time-to-recovery' often involve censored (i.e., incomplete) data. Specifically, data are censored for each stock that was already depleted at the beginning of its time series (i.e., year of depletion unknown) or was not yet recovered in the final year of its time series (i.e., year of recovery unknown). For such populations, we know the minimum time t of the depletion event, but not the full time of recovery T (which is infinite for populations that never recover). Thus $T > t$ for such depletion events, while $T = t$ for recovered populations in which the full depletion duration is known. These data are most appropriately modeled in a statistical 'time-to-event' framework, which takes into account their incompleteness(Zens & Peart 2003).

To estimate parameters in our model, we need to be able to write the likelihood for all non-censored and censored data. The inverse Gaussian density of time to recovery (2) can be decomposed into the probability of recovering in the time interval $t + \Delta t$ with $\Delta t \to 0$ given that recovery hasn't taken place up to that point, times the probability that recovery hasn't taken place up to that point. For censored observations, we know only that the depletion event lasted at least time t. We

thus only have a partial likelihood for these data points. As above, the probability F_{IG} that a stock will take at least a time t to recover is

$$F_{IG}(t) = 1 - P_{IG}(T \leq t) = \Phi\left(\frac{c - vt}{\sqrt{t}}\right) - \exp(2cv)\Phi\left(\frac{-c - vt}{\sqrt{t}}\right).$$

The total likelihood is then

$$L(t) = \prod_{i \epsilon n} F_{IG}(t)^{1-I} f_{IG}(t)^I,$$

where I is an indicator taking value 1 for complete and 0 for censored observations.
To make predictions about the statistical population of stocks, we integrate with respect to the random effect, which yields (Aalen & Gjessing 2001)

$$\begin{aligned}
F_U(t) &= 1 - P_U(T \leq t) \\
&= \Phi\left(\frac{c - vt}{\sqrt{t^2\xi^2 + t}}\right) \\
&\quad - \exp(2cv + 2c^2\xi^2)\Phi\left(\frac{-c - 2ct\xi^2 - vt}{\sqrt{t^2\xi^2 + t}}\right) \quad\quad (2)
\end{aligned}$$

where the U in the subscript indicates that this quantity is now unconditional, that is, not conditional on the random effect of a particular stock.

Drivers of recovery
We tested a suite of covariates hypothesized to influence recovery. Most obvious is the fishing mortality, F, relative to F_{MSY} during the recovery period; here we used the mean F/F_{MSY} during recovery as a potential predictor of the recovery rate. The minimum biomass reached during the depletion may also have an important effect on recovery times, both via density dependent effects on the recovery rate as well as by providing additional information about the distance from the recovery target. High sustained fishing mortality can lead to a number of (potentially hereditary) changes in the demography and physiology of exploited stocks that may be directly related to fishing pressure and may limit or enhance the ability of a stock to recover. To account for potential adaptive and evolutionary effects of high and sustained fishing mortality we included the historic fishing intensity as well as the exploitation time as covariates for both the recovery rate and the relative distance. We defined exploitation time as the number of years from the development year, taken as the time from which catches first exceed 20% of the maximum catch, or the first record in the assessment database if the former was not available, until the year of depletion, and historic fishing intensity as the mean F/F_{MSY} over this period. We hypothesized stocks with long exploitation histories prior to depletion would be more strongly affected by historic fishing intensity, and thus included first order interaction terms of historic fishing intensity with exploitation time (termed 'exploitation history'). All covariates were centered, such that the main effects describe influences at the mean covariate values, and the interaction term describes deviations from mean effects.
We also included the intrinsic rate of increase, r, as a covariate to control for 'fast' versus 'slow' life histories in determining the recovery rate. The intrinsic rate of increase was estimated for each of these stocks in a taxonomically hierarchical meta-analysis of surplus production model r estimates. We included a binary habitat category for pelagic and demersal species as a predictor of both the recovery rate and relative distance, since the demersal species are often caught in multi-species fishery, where continued bycatch mortality may prolong recoveries. To make effects sizes comparable among continuous and categorical variables, we divided all covariates by twice their standard deviation. Lastly, we included species' trophic level (from Fishbase (Froese & Pauly 2009)) in both regressions to account for potentially differential recovery regimes at different levels of the food web.

Analysis step specific to prediction of rebuilding time for stocks with characteristics of currently depleted stocks under EU legislation.

To make specific inferences regarding a statistical population of stocks with life-history and depletion characteristics resembling those of currently depleted European stocks, we examined model predictions, calculating times τ at which a proportion p of 0.50, 0.75 and 0.90 of stocks with these characteristics would be recovered with a cumulative posterior recovery probability of 0.75. For

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this, unconditional recovery times (see above) were predicted using (2), and integrated to marginalize over stock characteristics. This was done by numerically integrating and solving

$$\int_0^\tau \int P(p(t \leq T) = K | X_{EU}, \Xi_{EU}) \, d(X_{EU}, \Xi_{EU}) d\tau$$

for τ, such that the outer integral (the cumulative posterior probability) is numerically equal to 0.75. $K = 0.5, 0.75$ and 0.9 are the proportion of stocks, and X_{EU}, Ξ_{EU} are covariates for European stocks described in Table 1.

Annex II – List of Fish stocks and model parameters

Table 1: Stock description, binomial species names and variables used for the recovery analysis. Missing cases indicate that this information was not available from the assessments and was put (predicted) in the analysis using the posterior predictive distribution for the variable.

Common Name	Stock	ICES Region	Latin name	Development Year	Historic mean F/FMSY	Year of Depletion	mean F/FMSY since depletion	B/BMSY	Intrinsic Growth Rate	Trophic Level	Habitat
Sand lance	North Sea	IIIa & sub area IV	Ammodytes marinus	1962	1,26	2003	1,11	0,92	0,92	2,71	demersal
Herring	Celtic Sea	VIa & VII b, c	Clupea harengus	1950	2,00	2000	2,95	0,50	0,34	3,23	pelagic
Herring	Baltic Sea, Bothnian Sea	Sub area 31	Clupea harengus	1950	2,89	1994	3,41	0,29	0,26	3,23	pelagic
Herring	Irish Sea	VIIa North	Clupea harengus	1950	2,68	1978	2,31	0,32	0,35	3,23	pelagic
Herring	Central Baltic Sea	sub areas 25-32	Clupea harengus	1950	2,43	1996	2,97	0,43	0,27	3,23	pelagic
Herring	Iceland (Summer spawne	Va	Clupea harengus	1950	2,02	1989	1,66	0,62	0,34	3,23	pelagic
Atlantic cod	Kattegat	IIIa East	Gadus morhua	1950	3,02	1982	3,24	0,04	0,68	4,42	demersal
Atlantic cod	Irish Sea	VIIa	Gadus morhua	1950	3,31	1978	4,00	0,17	0,65	4,42	demersal
Atlantic cod	Faroe Plateau	Vb	Gadus morhua	1946	1,87	2004	1,81	0,79	0,53	4,42	demersal
Atlantic cod	Norwegian Sea	sub areas I & II	Gadus morhua	1946	2,67	2005	2,31	0,51	0,31	4,42	demersal
Atlantic cod	Central Baltic Sea	sub areas 25-32	Gadus morhua	1950	3,65	1987	3,50	0,32	0,52	4,42	demersal
Atlantic cod	West of Scotland	VIa	Gadus morhua	1950	2,65	1990	2,66	0,22	0,63	4,42	demersal
Atlantic cod	North Sea	IV	Gadus morhua	1950	2,36	1989	2,41	0,22	0,63	4,42	demersal
Atlantic cod	Iceland	IIa & sub areas V, XIV	Gadus morhua	1946	2,40	1991	2,43	0,66	0,50	4,42	demersal
Atlantic cod	Baltic Sea	sub areas 22-24	Gadus morhua	1950	2,92	1986	2,85	0,43	0,75	4,42	demersal
Megrim	Biscaya & Atlantic-Iberian Waters	VIIIc & IXa	Lepidorhombus boscii	1950	1,85	1994	1,52	0,32	0,31	3,91	demersal
Fourspotted megrim	Biscaya & Atlantic-Iberian Waters	VIIIc & IXa	Lepidorhombus whiffiagonis	1986	1,92	2000	1,66	0,67	0,37	3,66	demersal
Capelin	Iceland	Va	Mallotus villosus	1970	-	2005	-	0,49	0,65	3,15	pelagic
Capelin	Barents Sea	sub areas I & II	Mallotus villosus	1970	-	1993	-	0,17	0,52	3,15	pelagic
Haddock	Faroe Plateau	Vb	Melanogrammus aeglefinus	1950	1,84	2008	1,26	0,31	0,42	4,09	demersal
Haddock	North Sea & Skagerrak	sub area IV & IIIa West	Melanogrammus aeglefinus	1950	3,60	2010	1,11	0,38	0,44	4,09	demersal
Haddock	Iceland	Va	Melanogrammus aeglefinus	1950	2,11	1983	2,02	0,48	0,56	4,09	demersal
Whiting	Celtic Sea & West of Scotla	VIIe-k	Merlangius merlangus	1951	3,01	2006	2,76	0,91	0,52	4,33	demersal
Hake	Northern Stock	IIIa, sub areas IV, VI, VII & VIII a, b, d	Merluccius merluccius	1950	3,60	1981	3,47	0,75	0,46	4,42	demersal
Blue whiting	North-East Atlantic	I-IX, XII & XIV	Micromesistius poutassou	1979	2,26	2007	-	0,41	0,36	4,01	demersal
European Plaice	Celtic Sea	VIIf,g	Pleuronectes platessa	1950	1,84	2002	1,89	0,65	0,67	3,26	demersal
Pollock	North Sea	IIIa & sub area IV	Pollachius virens	1950	2,28	1967	2,03	0,30	0,44	4,38	pelagic
Greenland halibut	North-East Artic	sub areas I & II	Reinhardtius hippoglossoides	1964	2,25	1975	1,92	0,68	0,27	4,48	demersal
common European sole	Irish Sea	VIIa	Solea solea	1950	1,97	2004	1,53	0,25	0,45	3,17	demersal
common European sole	Western Channel	VIIe	Solea solea	1950	0,85	1969	1,74	0,48	0,32	3,17	demersal

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