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On the Assessment of the Northern Shrimp Stock in the Barents Sea

by

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Abstract

The assessment of the Barents Sea shrimp was made on the basis of the "stock-recruitment" logistic function and the Bayesian approach. Calculations were done with different versions of assumptions about possible value of the carrying capacity *K*. Predictive estimates and risk analysis were performed at three eventual exploitation levels: 100, 200 and 300 thousand tons.

Results of investigations revealed that predictive estimates depended on our assumptions about possible value of *K* rather than on actual yield and survey indices. The fishery factor is not a significant factor in the modelled system.

Introduction

Inherently, the Bayesian approach is based on knowledge of four components (Bayesian methods for Ecology, 2007). Prior knowledge (*prior*) and new data (*data*) obtained during the survey and fishery have been integrated by means of a model (*model*) to acquire a posterior knowledge (*posterior*). In our case posterior knowledge means desired values of parameters in the simulated "stock-fishery" system. These four components can be presented in the form of a verbal formula:

$$prior + data \xrightarrow{\text{model}} posterior \quad (1)$$

The influence strength of *prior* and *data* on *posterior* is assigned, by the modeller. Having a high-quality set of *data*, we can reduce the influence of *prior*. And *visa versa*, under low-information conditions prior (preliminary) knowledge of model parameters (*prior*) may affect the parameter estimation to a greater extent. In both cases we can obtain an applicable estimate, for example, for the stock abundance dynamics, calculate the risk of exceeding the reference points of management and provide recommendations for further stock exploitation. However, the researcher has to fully realize whether the results of his/her estimation were based on actual data or expert assumptions that are subjective in many cases.

This paper is an author's attempt to gain insight into the effect of our subjective assumptions on final results of the assessment of the northern shrimp stock state in the Barents Sea.

Method

Modelling framework and state equations

The model was built in a state-space framework (Hvingel, 2007; Hvingel and Kingsley, 2006; Schnute, 1994). Model background, formulation, checking, validation and further details are given in Hvingel and Kingsley (2002).

The basic equation was a generalization of the logistic model of population growth (Schaefer, 1954). Its form is:

$$B_{t+1} = B_t + rB_t\left(1 - \frac{B_t}{K}\right) \quad (1)$$

where B_t is the stock biomass at time *t*, and r is the population growth rate and *K* is the maximum population size for growth to be positive. The equation describing the state transition from time *t* to *t+1* and parameterised in terms of *MSY* (Maximum Sustainable Yield) rather than *r* (intrinsic growth rate) (cf. Fletcher 1978):

$$B_{t+1} = B_t + 4MSY\frac{B_t}{K}\left(1 - \frac{B_t}{K}\right). \quad (2)$$

Data and link functions

The model synthesized information from input priors and three independent series of shrimp biomasses and one series of shrimp catches (Hvingel, 2007; Table 1). The three series of shrimp biomass indices were: a Norwegian standardised series of annual commercial-vessel catch rates for 1980–2006, $CPUE_t$ (Hvingel and Aschan 2006); and two trawl-survey biomass index for 1982–2004, $survR_t$, (Anon. 2005) and 2004-2006, $survE_t$ (Hvingel, 2006). These indices were scaled to 3 true biomass by catchability parameters, q_C, q_R and q_E. Lognormal observation errors, ω, κ and ε were applied, giving:

$$\begin{aligned} CPUE_t &= q_c B_{MSY} P_t \exp(\omega) \\ survR_t &= q_R B_{MSY} P_t \exp(\kappa) \\ survE_t &= q_E B_{MSY} P_t \exp(\varepsilon) \end{aligned} \quad (3)$$

where P_t is the stock biomass relative to biomass at *MSY* ($P_t = B_t/B_{MSY}$) in year *t*. The error terms, ω, κ and ε are normally, independently and identically distributed with mean 0 and variance σ_ω^2, σ_κ^2 and σ_ε^2.
Total reported catch in ICES Div. I and II 1970-2006 was used as yield data (Table 1). The fishery being without major discarding problems or variable misreporting, reported catches were entered into the model as error-free.

Estimation of Parameters (Priors)

According to the equations (2) and (3) prior distributions for parameters P_1, *MSY*, *K*, q_C, q_R, q_E and observation errors should be given to adjust the modelling process. In this paper *priors* were chosen on the basis of an assumption made by Carsten Hvingel and Michel Kingsley when they assessed the northern shrimp stocks off East Greenland, in the Barents and North Seas (Table 2). It is apparent that we do not have today any "external" information on P_1, *MSY*, *K*, q_C, q_R, q_E parameters and observation errors. In this paper *priors* for these parameters were also taken as low-information ones.

Size of initial biomass P_1 is usually assigned large in absence of intensive fishing. In 1970 the shrimp fishery in the Barents Sea took place in costal areas and could not essentially affect the stock dynamics. The size of initial biomass was most likely much above B_{MSY} and ranged from B_{MSY} to *K*. Based on such information we are able to assign the prior normally distributed with median =1.5 and variance σ = 0.26.

Notwithstanding, the initial value of B_1 slightly affects the results of model indices for last years observations provided that observation series is long enough. We have exercised several calculation options with different prior distributions of B_1 but the results of posterior parameters were similar.

The carrying capacity or maximum population abundance K is a key parameter, whose prior distribution has impact on modelling results. In our computations we have used several options of prior distribution of *K*. First of all we applied the principle "let the data speak for themselves" (McAllister and Kirkwood, 1998), i.e we made the distribution limits as great as possible in the range from 0 to 10 million tones. Such a principle is usually applied in the event where results of calculations with minimum impact of prior probabilities for the parameter $p(\theta)$ are to be analyzed with concurrent increasing the impact of function of maximum likelihood In other words, this option of calculation demonstrates how much would our input data informative and how they would affect the calculation results.

For the subsequent calculation options assumptions of possible value of *K* were made. By choosing a prior we based on the principle advanced by Carsten Hvingel and described in Hvingel (2007). A prior for *K* was constructed based on an estimated posterior for this parameter from the West Greenland shrimp stock (Hvingel and Kingsley 2006). This had a median of 728 ktons and 95% of the distribution between 300 and 2500 ktons. The area of the Barents sea is ca. 3.4 times that of the West Greenland area and thus the Greenland estimate of *K* was multiplied by 3.4 to give the *K*-prior for the Barents Sea, i.e. approximated by a lognormal distribution with median of 2500 ktons and 95% confidence limits at 800 and 8000 ktons (Table 2; median *K* = 2500). Such assumptions were used as basis for the option 4 of the calculations.

To investigate the model sensitivity to the parameter *K* the runs were done with a lognormally distributed prior having a median of 625 ktons (option 2 of calculation), 1250 ktons (option 3) and 5000 ktons (option 5) (Table 2).

Risk analysis

Risk analysis was carried out to examine the influence of the prior *K* on predictive indices.
Blim was selected as a reference point for management. It was suggested that a stock was in safe state if risk of its reduction below *Blim* was under 5%. In our paper we applied three possible exploitation rates for the forecast years which were in line with annual catches of 100, 200 and 300 thousand tons.

Results

Simulation runs with five different options for prior *K* were done (Fig.1). By choosing an uniform little informative prior distribution of *K* (Fig. 1A) the model could not be tuned using only input data and give an adequate estimate of its posterior distribution. By choosing an informative prior *K* (Fig. 1 B-E) the estimated results of *K* were extremely similar to its posterior distributions. Because of this, *K* cannot be reliably estimated using input data only; its posterior distribution depends heavily on the chosen prior.

The abundance dynamics has similar trends for all calculation options (Fig. 2). Although the trends agree the biomass absolute values for calculation versions 2 and 3 are lower. When calculating with prior *K* having a median of 2500 thousand tons and over the values of relative biomass *(P*) coincide.

The risk estimation for a one-year period showed a low probability (below 1 %) of stock reduction below *Blim* for estimation options 1-5 with different exploitation rates. The estimation of probability of stock reduction below *Blim* in 5 years is given in Table 3. The value of stock reduction risk depends heavily both on the chosen prior *K* and on the exploitation rate. The results of prognostic risk estimation for a ten-year period at the annual catch of 200 ktons are showed in Figure 3.

The goodness-of fit of input data to properties of the production model can be demonstrated by plot of relationship between the stock size and production surplus calculated directly from observed indices (Figure 4). The results of calculation option 4 with *K*=2500 ktons and MSY= 175 ktons were taken as a basis. Factual indices were applied to compute the biomass size taking due account of catchability factors calculated by the model. The production was calculated by deduction of the biomass in the current year from the next year's biomass, whereupon the removal was added. As shown in Figure 4, the equilibrium curve very approximately describes data, indices and considerable discards which poorly correlate with parabolic dependence of the stock production surplus. The left side of the arc for the lack of input data in this area was calculated using our expert assumptions about K -value.

Discussion

Under conditions of poor information security the estimations for parameters are often found using algorithms based on the Bayes' formula when not only observation data are taken as initial information but also prior (preliminary) knowledge of model parameters. The approach is based on an attempt to start a statistical inference with some initial assumptions (guesses) of probabilistic distribution of unknown parameters. The values of model parameters can be *a priori* assigned on the basis of estimates obtained, for example, for the same species from different areas or for similar species from the same area. With the Bayes's theorem, one can estimate final (posterior) values of parameters with due regard for observation data and preset values of parameters.

Today the assessment of the northern shrimp stock in the Barents Sea by the production model is also based on observation data (catch, survey indices) and preset values for the parameter K. According to Figure 2 the abundance dynamics of the stock depends on abundance indices rather than on possible values of K. With different prior assumptions about possible values of K the character of abundance trends remains unchanged. The application of a relative parameter P_t in studies of abundance dynamics negates any uncertainty about the "catchability» and allows an estimate of the absolute abundance to be ignored.

However, the estimate of K largely influences the biomass absolute abundance (B_t) that in its turn has an effect on the results of calculations when predictive estimation and risk analysis are made. Depending on given possible value of K at annual catches of 200 thousand tons the probability of stock reduction below B_{lim} can increase during 5 years from 3% to 81% (Table 3). The character of risk increase in the course of 10 years may also depend heavily on the chosen prior K (Figure 4).

The production curve may only approximate input data, which is to say that the fishery factor only slightly affect the biomass dynamics of the northern shrimp. Most likely, other factors ignored by the model (e.g. changes in recruitment and natural mortality as well as spatial fluctuations) make a greater impact on the dynamics.

From the foregoing it may be concluded that:

1) Predictive estimates depend on our assumptions about possible value of K to a greater extent than on actual yield and survey indices.
2) The fishery factor is not a significant one in the modelled system.

References

Anon., 2005. Report of the Pandalus assessment working group. *ICES CM 2006/ACFM:10. ref G*. 72 pp.

Fletcher, R.I. 1978. Time-dependent solutions and efficient parameters for stock-production models. Fisheries Bulletin, 76: 377–388.

Hvingel 2006. Research survey information regarding northern shrimp (*Pandalus borealis*) in the Barents Sea. *NAFO SCR Doc. 06/63.*

Hvingel and Aschan 2006. The fishery for northern shrimp (*Pandalus borealis*) in the Barents Sea. *NAFO SCR Doc. 06/65.*

Hvingel, C. and M.C.S. Kingsley, 2002. A framework for the development of management advice on a shrimp stock using a Bayesian approach. *NAFO SCR Doc. 02/158 Serial No. N4787*

Hvingel, C. and M.C.S. Kingsley (2006). A framework to model shrimp (Pandalus borealis) stock dynamics and quantify risk associated with alternative management options, using Bayesian methods. *ICES J. Mar. Sci.* ***63****:68–82.*

McAllister, M. K., Kirkwood G. P. Bayesian Stock assessment: a review and example application using the logistic model. ICES journal of Marine Science, V. 55. – 1998. P. 1031–1060.

Schaefer, M.B. 1954. Some aspects of the dynamics of populations important to the management of the commercial marine fisheries. Bulletin of the Inter-American Tropical Tuna Commission, 1: 27–56.

Schnute, J. 1994. A general framework for developing sequential fisheries models. Canadian Journal of Fisheries and Aquatic Sciences, 51: 1676–1688.

Table 1. Model input data series: Catch by the fishery; three indices of shrimp stock biomass – a standardized catch rate index based on fishery data (CPUE), a research survey index (the "shrimp survey") discontinued in 2004 and the current "Ecosystem survey" started in 2004.

Year	Catch (ktons)	CPUE (index)	Survey1 (ktons)	Survey2 (ktons)
1970	5.5	-	-	-
1971	5.1	-	-	-
1972	6.8	-	-	-
1973	6.9	-	-	-
1974	9	-	-	-
1975	8.2	-	-	-
1976	10.3	-	-	-
1977	24.4	-	-	-
1978	36.3	-	-	-
1979	36.7	-	-	-
1980	46.3	1	-	-
1981	44.6	1.161	-	-
1982	62.8	1.102	327	
1983	104.8	1.257	429	
1984	128.1	1.312	471	
1985	124.5	1.043	246	
1986	65.3	0.629	166	
1987	43.4	0.476	146	
1988	48.7	0.522	181	
1989	62.7	0.681	216	
1990	81.2	0.682	262	
1991	74.9	0.719	321	
1992	68.6	0.828	239	
1993	56.3	0.884	233	
1994	28.3	0.699	161	
1995	25.2	0.615	193	
1996	34.5	0.791	276	
1997	35.7	0.775	300	
1998	55.8	0.934	341	
1999	75.7	0.53	316	
2000	83.2	0.856	247	
2001	57.5	0.859	184	
2002	61.5	0.847	196	
2003	39.2	0.841	212	
2004	40.7	0.752	151	129
2005	40.7	1.096	-	145
2006	29.7	1.254	-	188
2007	28	1.033	-	159

Table 2. Priors used in the model. ~ means "distributed as..", dunif = uniform-, dlnorm = lognormal-, dnorm= normal- and dgamma = gammadistributed. Symbols as in text.

Parameter		Options	Prior	
Name	Symbol		Type	Distribution
Carrying capacity	*K*	*1*	reference	~dunif(0,10000)
		2	informative (median = 625kt)	~dlnorm(6.475,3)
		3	informative (median = 1250kt)	~dlnorm(7.127,3)
		4	informative (median = 2500kt)	~dlnorm(7.82,3)
		5	informative (median = 5000kt)	~dlnorm(7.515,3)
Maximal Suatainable Yield	*MSY*	*1-5*	reference	~dunif(1,1000)
Catchability survey 1	q_R	*1-5*	reference	ln(qR)~dunif(-10,1)
Catchability survey 2	q_E	*1-5*	reference	ln(qE)~dunif(-10,1)
Catchability CPUE	q_C	*1-5*	reference	ln(qC)~dunif(-10,1)
Initial biomass ratio	P_1	*1-5*	informative	~dnorm(1.5,15)
Precision survey 1	$1/\sigma_R^2$	*1-5*	reference	~dgamma(4,0.1125)
Precision survey 2	$1/\sigma_E^2$	*1-5*	reference	~dgamma(4,0.1125)
Precision CPUE	$1/\sigma_C^2$	*1-5*	reference	~dgamma(4,0.1125)
Precision model	$1/\sigma_P^2$	*1-5*	reference	~dgamma(0.1,0.1)

Table 3. Risk of falling bellow *Blim* within a five-years perspective and associated with three optional catch level given different *K* options

Prior *K* option		Catch option (ktons)		
		100	200	300
1	reference (~dunif(0,10000))	1.0	3.1	7.7
2	informative (median = 625kt)	11.2	81.0	92.5
3	informative (median = 1250kt)	2.2	37.3	64.4
4	informative (median = 2500kt)	2.2	8.6	19.1
5	informative (median = 5000kt)	1.3	3.0	5.8

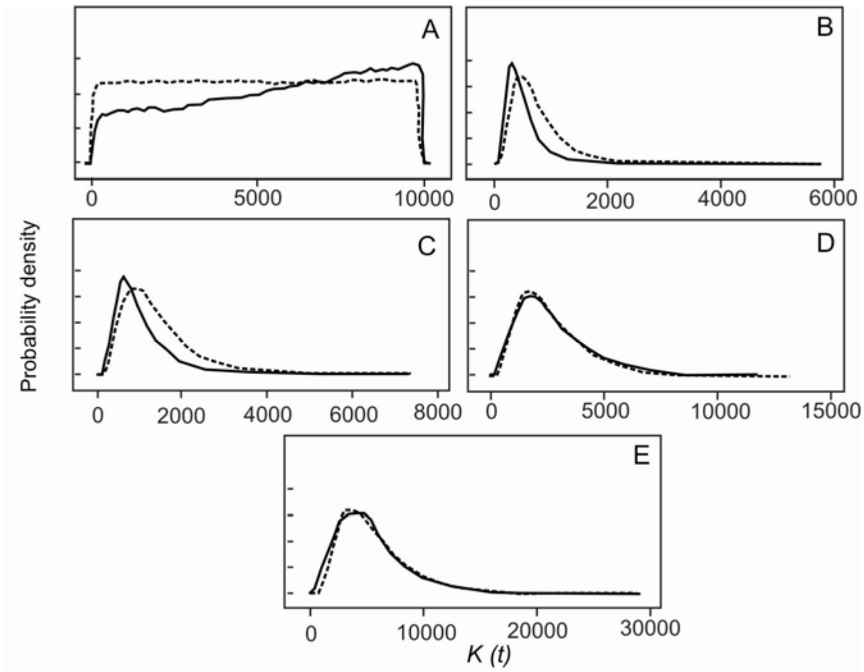

Fig. 1. Probability density distributions of carrying capacity (K): posterior (solid line) and prior (broken line) distributions (A – K ~dunif(0,10000); B – *median* K = 625kt; C – *median* K = 1250kt; D – *median* K = 2500kt; E – *median* K = 5000kt).

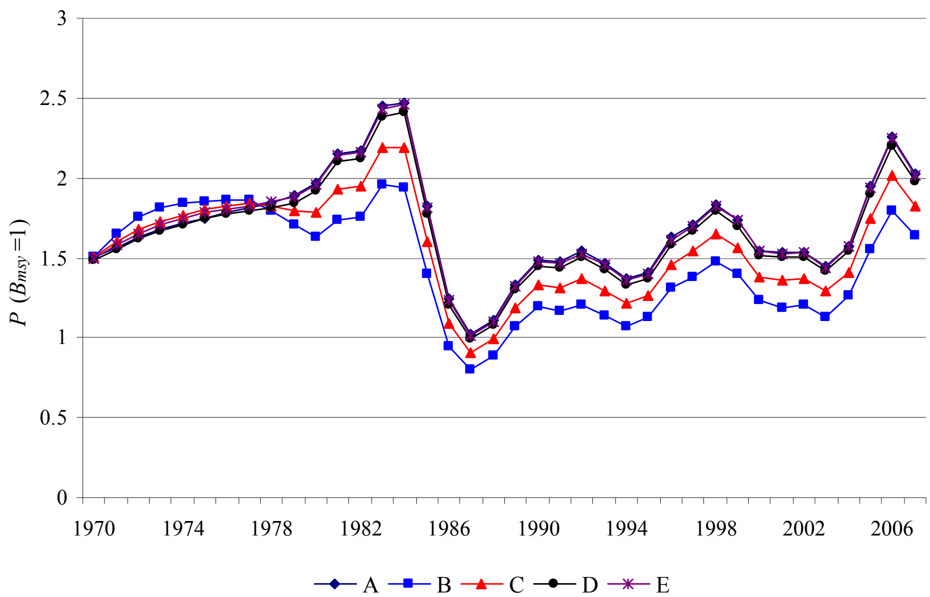

Fig.2. Estimated median biomass trajectories 1970-2007 given different K options (A – K ~dunif(0,10000); B – *median* K = 625kt; C – *median* K = 1250kt; D – *median* K = 2500kt; E – *median* K = 5000kt).

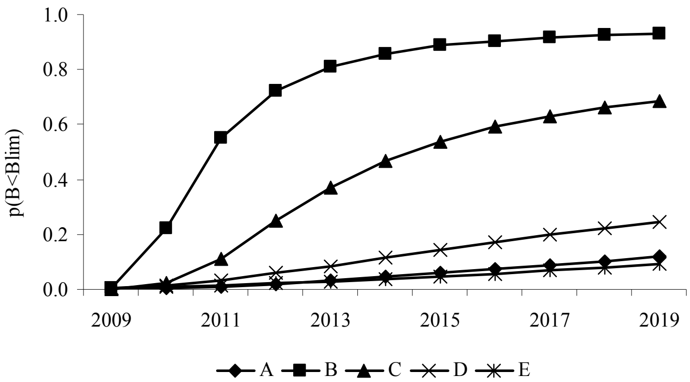

Fig.3. Risk of going below *Blim* 1970-2007 given 200 kt catch level and different *K* options (A – *K* ~dunif(0,10000); B – *median K* = 625kt; C – *median K* = 1250kt; D – *median K* = 2500kt; E – *median K* = 5000kt).

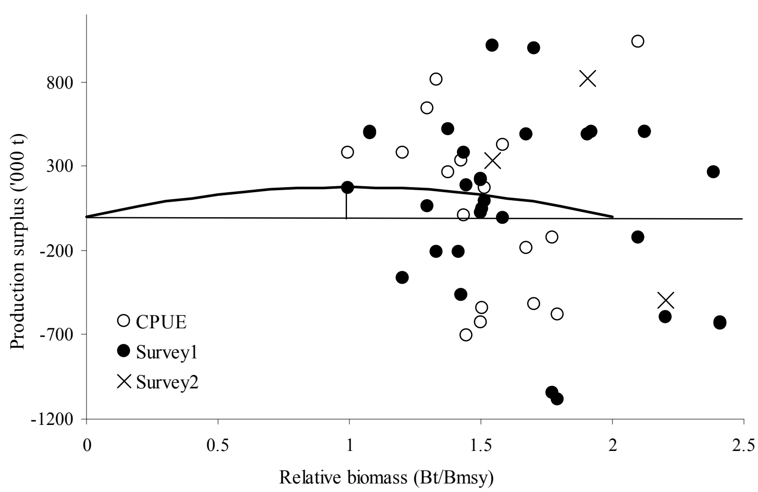

Fig. 4. Ability of model to define the stock-production curve: annual stock size estimates calculated directly by applying the estimated catchabilities to the actual index values, and the corresponding production calculated by subtracting biomass in the current year from biomass in the next, then adding catch. The generalized stock-recruitment curve shown was based on the median of the posteriors of the parameter *MSY*.