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Report of the Workshop on Including Socio-Economic considerations into the Climate-recruitment framework developed for clupeids in the Baltic Sea (WKSECRET)

5–8 October 2010

Ponza, Italy

ICES International Council for the Exploration of the Sea

CIEM Conseil International pour l'Exploration de la Mer

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Executive summary

Recruitment–environment relationships for five distinct Baltic Sea herring stocks inhabiting the areas of the Western Baltic (WBH), the Main Basin (MBH), the Gulf of Riga (GRH), the Bothnian Sea (BSH) and the Bothnian Bay (BBH) and for the Baltic sprat stock (BS) were developed and tested in two previous workshops held in 2007 and 2008 (WKHRPB and WKSSRB; ICES 2007 and 2008) and published in Cardinale *et al*. 2009. A number of hydro-climatic and biological predictors were tested for their effect on recruitment. In previous analyses, temperature was determined to be an important predictor for four of the stocks (MBH, GRH, BSH and BS). However, spawning stock biomass was the major factor explaining recruitment for GRH and BS while weight-at-age of the spawners and spawning stock biomass as those are highly correlated were important predictors of MBH recruitment. For 2 (i.e. MBH and BSH) out of 5 stocks for which complete zooplankton data were available, food supply was also a significant predictor, suggesting that changes in climate and/or food web structure may indirectly affect herring recruitment via prey availability for the recruits or spawners. The results emphasized both similarities and differences in the main regulators of recruitment dynamics for the different stocks that should be taken into consideration in the development of area-specific management strategies thorough the Baltic Sea basin. Further, it calls for a thorough analysis of the effects of climate change on productivity of Baltic herring and sprat stocks in the medium term.

Using GAMs we explored Baltic herring recruitment–environment relationships during a period of prominent change in atmospheric forcing in the Baltic Sea (WKHRPB and WKSSRB; ICES 2007 and 2008). For 4 stocks (MBH, GRH, BSH and BS), temperature was positively correlated with recruitment, i.e. larger year classes were found in years of higher temperature. When condition of the spawners (WAA3+) or SSB remained in the model after the model selection process (i.e. WAA3+ for MBH and SSB for GRH and BS stocks), these were the most important predictors in explaining recruitment variability. Previous workshop results further showed that in the areas where zooplankton time-series were available, zooplankton was a significant predictor for Baltic herring recruitment in 2 out of 4 stocks.

Exploratory analyses clearly showed that climate has the potential to influence clupeid recruitment in MBH, GRH, BSH and BS, via direct changes in temperature, as well as indirectly through changes in the zooplankton food supply influencing larval survival. However, the parental stock characteristics (weight-at age of spawners and spawning biomass) also play a crucial role in the Baltic Sea, being the major regulator in the recruitment dynamics of MBH, GRH and BS stocks. For herring, our results pointed to the importance of considering stock-specific differences in drivers of recruitment dynamics for the different management areas of the Baltic Sea. Those differences are often the results of complex interactions between density dependent (e.g. SSB) and density independent (e.g. SST) factors.

The final recruitment models provided by Cardinale *et al*. (2009) were tested with updated data series only for MBH, GRH and BS as no satisfactory final model was found for the other stocks (Cardinale *et al*. 2009). Further, as the main aim was to include climatic scenarios for recruitment predictions, number of recruits (thereafter referred also as recruitment) was used for all stocks instead of recruitment success. Thus, models developed for MBH, GRH and BS were re-fitted with updated input data and with number of recruits as response variable using both a linear and a GAM

model to allow for medium-term recruitment predictions under different climatic scenarios.

SSB time series were generated using the BALMAR food-web model (Lindegren *et al*. 2009), a linear state-space model based on a theoretical approach for predicting long-term responses of populations to environmental change (Ives 1995; Ives *et al*. 2003). SSB time series were generated assuming two different levels of fishing mortalities (F_{med}, F_{msy} or F_{MP}). Predictions of SST were generated using higher resolution Regional Climate Models (RCMs).

In all the scenarios both spawning stock biomass and recruitment showed a clear relationships with fishing intensity. Marked increase in the estimated abundances of adults and recruits of herring were expected for all the scenarios with more or less accentuated patterns according to the associated climate scenario. The positive effect of sea surface temperature and herring recruitment in the Central Baltic resulted in a moderately positive trend in the herring stock trajectories. However, density-dependent response was evident only for low fishing mortality levels (F_{msy}), when herring population reached large biomasses, indicating that fisheries has a larger effect than climate on the recruitment via the size of the spawners. The herring population oscillated around low values for the whole 40 years projections only in the scenario with combined no climate change and high fishing intensity.

The ecological-economic model used in this study used the same input parameters as the other models used in this workshop, but also included cost and price estimates. The aim was to optimize the net revenue and to investigate which F and SSB would be obtained in the long term. The results of the modeling exercise for MBH show long-term equilibrium F obtaining maximum profits to be slightly below the value currently suggested to be long-term F (ICES 2009a). The actual level of F in this model with environmental sensitive, i.e. mainly temperature, stock-recruit relationship is highly dependent on the temperature development, showing an F of 0.2 or 0.1 if temperature was kept constant at 18°C or at 16°C, respectively. Accordingly, expected climate-driven temperature increase would result in concurrently rising of the optimal F values. The results for GRH show clearly that a density dependent stock-recruit model is needed, as otherwise the SSB would steadily increase.

1 Opening of the meeting, adoption of agenda and workplan

The Co-Chairs, Max Cardinale and Piotr Margoński, welcomed the participants (Annex 1) and introduced the agenda for the workshop (Annex 2).

The agenda was discussed and accepted by the participants. The first day was devoted for discussion on statistical analyses and the work plan. Data series and their sources were identified. The method to include the socio-economic consideration into the existing environmental and climate driven recruitment prediction framework was discussed and decided.

2 Terms of Reference 2009

Main objectives were identified by the Terms of Reference approved by SCICOM:

2009/2/SSGRSP09 A Workshop on Including Socio-Economic considerations into the Climate - recruitment framework developed for clupeids in the Baltic Sea (WKSECRET), chaired by Max Cardinale, Sweden and Piotr Margonski, Poland, will meet in Ponza, Italy, 5–8 October 2010 to:

a) Review and updating the developed recruitment models;

b) Create the successful environmentally sensitive sprat recruitment model;

c) Develop a bioeconomic model to assess the effect of changes in herring recruitment on fleet profitability in the medium and long term under a F_{msy} scenario.

WKSECRET will report by 8 November 2010 (via SSGRSP) for the attention of SCICOM and ACOM.

3 Presentations

Previous years experience and approach used to create the environmental and climate driven recruitment prediction framework was briefly presented.

Jörn Schmidt provided the presentation entitled "Optimal Fisheries Management: accounting for variation in natural mortality: the Baltic sprat and herring case". Age-structured bio-economic models have been developed for Baltic sprat as well as herring. Both models use eight age-classes to meet the standard assessment (ICES 2010) and are parameterized using data from the standard stock assessment. The major assumptions used to ease the interpretation of results are harvest costs independent from stock size and a constant price. The main objective was then to determine the optimal exploitation rates and long term yield for (a) different temperature-dependant stock-recruitment relationships as well as for (b) different states of its main predator (Baltic cod), i.e. including this important species interaction. Temperature has a clearly positive effect on recruitment for both sprat and herring. However the effect on herring was even larger then for sprat. Predation of cod had a clear negative effect on sprat with optimal yield driving the stock to very low levels, whereas the effect on herring was negligible and under optimal yield the herring stock would even increase.

4 Overview of the data used for refitting previous years models

4.1 Input data for Main Basin Herring (MBH), Gulf of Riga herring (GRH) and the Baltic sprat (BS)

Predictors used in the final model of Main Basin Herring (MBH), Gulf of Riga herring (GRH) and Baltic sprat (BS) stock recruitment are showed in the next sections.

4.1.1 Climate data

Sea surface temperature (SST)

NASA data (http://www.cdc.noaa.gov/cdc/data.noaa.ersst.html, 2x2 deg. grid, file: sst.mnmean.nc) were used for all the stocks. Monthly averages of SST calculated from points 1–15; 4–11&13–15; and 12 were used for sprat, CBH, and GRH analyses, respectively (Figure 4.1.1).

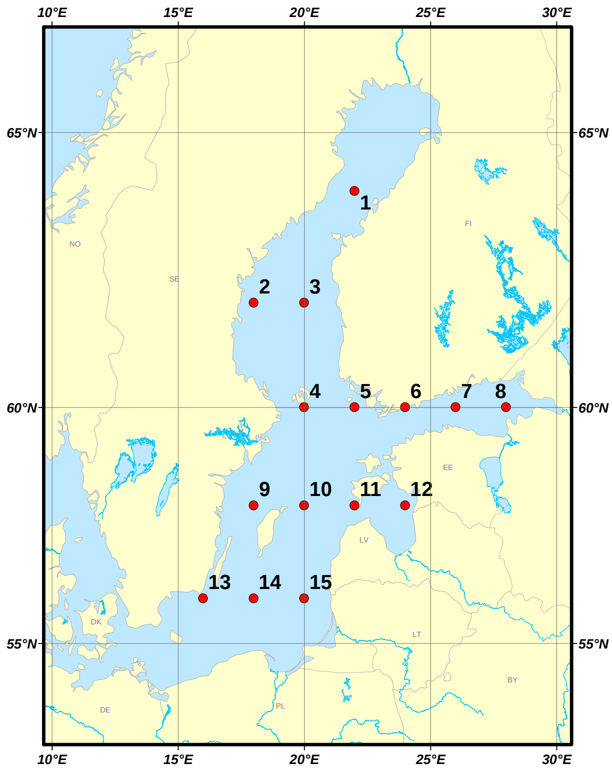


Figure 4.1.1. Central points of 2x2 degree grid of NASA SST measurements used for recruitment analyses (http://www.cdc.noaa.gov/cdc/data.noaa.ersst.html, file: sst.mnmean.nc).

The Bottom Depth Anomaly (BDA) index

Baumann *et al*. (2006) developed an index, which captures the state of larvae drift for sprat stock. This Bottom Depth Anomaly (BDA) takes into account the change in bottom depth under modelled drifters over a given simulation period (see Hinrichsen *et al*. 2005 for a detailed introduction of the hydrodynamical model and the Lagrangian particle tracking method; Figure 4.1.2.).

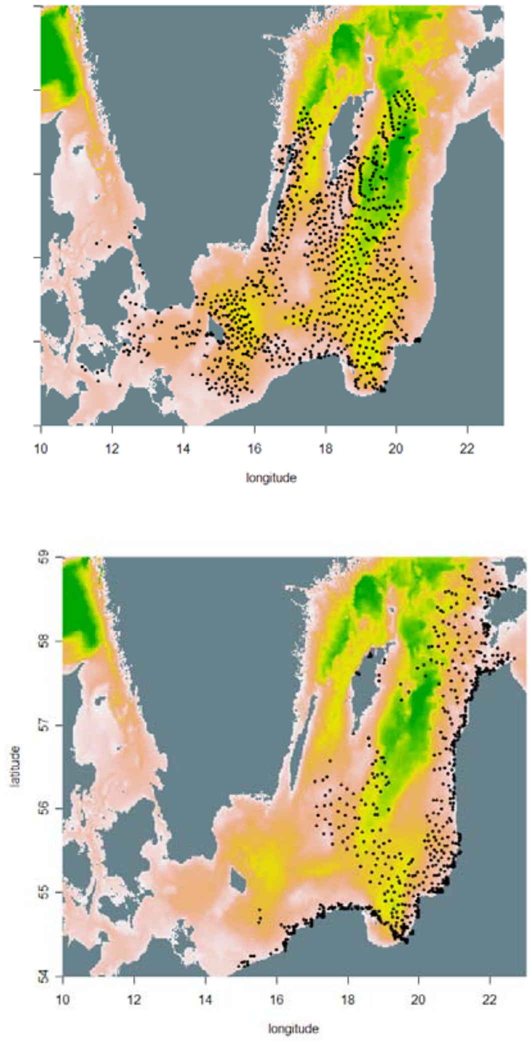


Figure 4.1.2. Two different scenarios of particle drift. Upper: retention (2003 data); Lower: dispersion (2005 data).

This BDA time series was an excellent predictor for sprat recruitment in previous workshops. Therefore, the BDA should be included in environmental sensitive stock-recruitment relationships. In 2010, the original BDA time series (1979–2003) was updated till 2008. Therefore, it was possible to use a consistent BDA data as a sprat recruitment predictor.

4.2 Stock specific data

Gulf of Riga Herring

SSB increased sharply from the mid 1980s and subsequently decreased starting from the mid 1990s. Recruitment of Gulf of Riga herring started to increase from the late 1980s. Average spring sea surface temperature measured in May increased continuously from the beginning of the time series to latest years (Figure 4.2.1.).

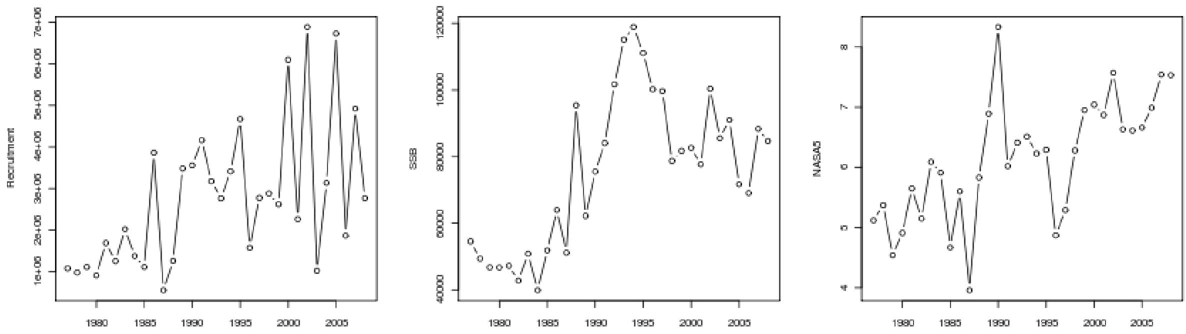


Figure 4.2.1. Biotic and abiotic time-series used in the Gulf of Riga herring final models.

Main Basin Herring (SD25-29&32 excluding Gulf of Riga)

Spawning Stock Biomass (SSB) and recruitment showed a decreasing trend since the mid 1970s, with a slight increase during the last few years while the August sea surface temperature (NASA 8) increased significantly over the last 20 years (Figure 4.2.2.).

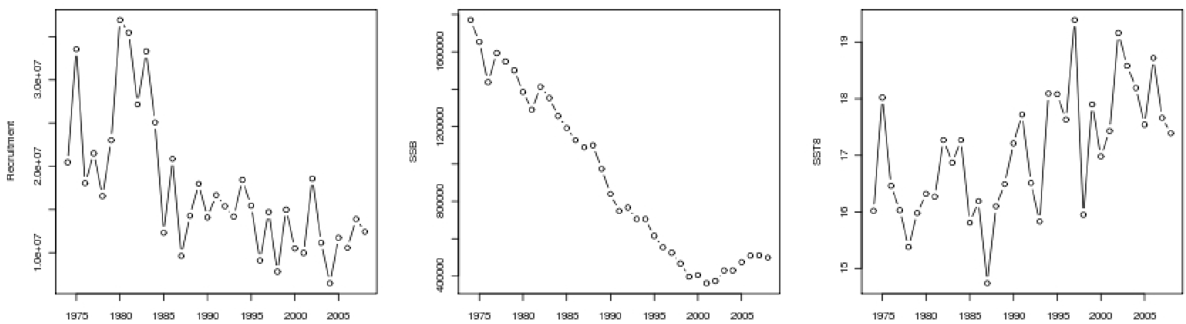


Figure 4.2.2. Biotic and abiotic time-series used in the Main Basin herring final models.

Baltic sprat (SD 22-32)

Time-series used for the final sprat model were presented in Figure 4.2.3. Sprat SSB started to increase dramatically since the beginning of 1990s. Also recruitment was observed at much higher level during that period however a pronounced year to year variability was evident. May sea surface temperatures (NASA5) showed a significant increase since the late 1980s, while BDA is presenting a significant variation with no apparent temporal trend.

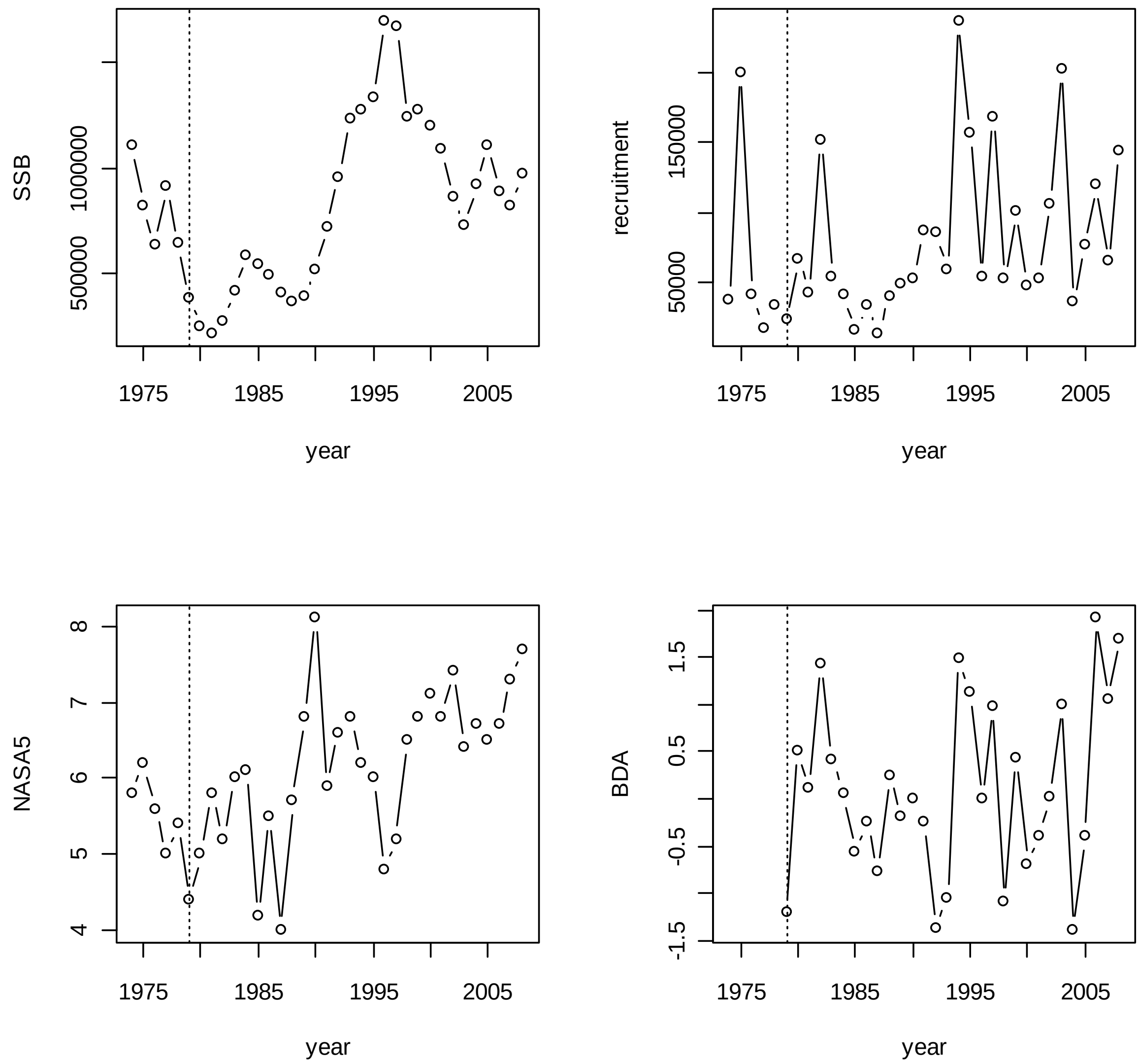
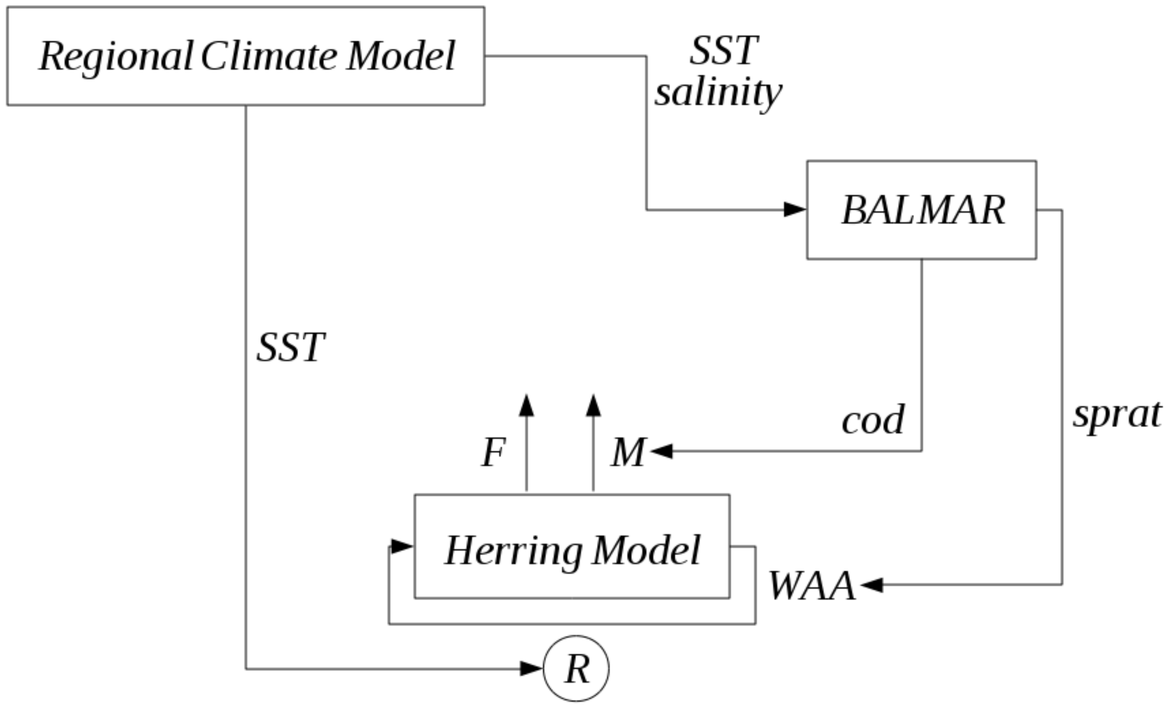


Figure 4.2.3. Sprat recruitment and explanatory variables used in the sprat final GAM model. Model has been built based on data after 1978.

5 Environmentally-sensitive stock-recruitment relationships

5.1 Introduction and results overview

The flowchart summaries the modelling scheme used combining climatic and fishery scenarios to predict herring recruitment in the Baltic. Currently, projections are available for the Main Basin herring stock, for the period from 2010 to 2050 (40 years medium term projections).



5.1.1 Modelling scheme

Biological parameters and data input for BALMAR and recruitment model were derived from MSVPA (Lindegren *et al*. 2009) and VPA (ICES 2009a), respectively.

5.2 The BALMAR food-web model

In order to predict recruitment dynamics of Central Baltic herring and sprat under climate change, forecasted biomasses of both species were modelled using the BALMAR food-web model (Lindegren *et al*. 2009), a linear state-space model based on a theoretical approach for predicting long-term responses of populations to environmental change (Ives 1995; Ives *et al*. 2003). The approach, a first-order multivariate autoregressive model (MAR(1)) applies a statistical framework for modelling food-web interactions at multiple trophic levels (Ives *et al*. 2003) and essentially functions as a set of lagged multiple linear regression equations (one for each species of the food web) solved simultaneously to arrive at the most parsimonious model overall (Hampton & Schindler 2006). Written in state-space form, the MAR(1) model we used is given by:

$$\mathbf{X}(t) = \mathbf{BX}(t-1) + \mathbf{CU}(t-y) + \mathbf{E}(t) \qquad \text{(Eq. 1)}$$

$$\mathbf{Y}(t) = \mathbf{ZX}(t) + \mathbf{V}(t) \qquad \text{(Eq. 2)}$$

where X are spawning stock biomasses (SSB) of cod, sprat and herring derived from multi-species stock assessment (MSVPA) in the Baltic Sea at time t and t_{-1} respectively and B is a 3 x 3 matrix of species interactions, an analogue of the “community matrix” used in food-web theory (May 1972; Pimm 1982). Encompassing the effects of commercial fishing, climate and zooplankton, the covariate vector U contains lagged values of mean annual fishing mortalities (F) and a number of selected climate and zooplankton variables known to affect recruitment of cod, sprat and herring respectively. Consequently, C is a 3 x 9 matrix whose diagonal elements specify the effect of covariates (i.e., fishing, climate and zooplankton) on each species. The process error

E(t) is assumed multivariate normal and temporally uncorrelated. Likewise, the observation error of the covariance matrix of the normal random variable V(t) is assumed independent. Regression parameters were found by maximum likelihood estimation using a Kalman filter (Harvey 1989). The Kalman filter is a recursive estimator that sequentially calculates the unobserved SSB values X(t) from the previous time step (t-1) using the model formula specified in Eq. 1. Predictions from the "hidden" state are then updated using the actual observed SSB values, Y(t) of the "true" observed state (Eq. 2). Model fitting was performed on time series covering the period 1974–2004. Finally, the most parsimonious model in terms of the number of parameters and the explained variance was selected and validated (Lindegren *et al.* 2009). All statistical analyses were conducted using the R software (www.r-project.org).

5.3 Recruitment models

Basically, the models developed by WKCSMPB (ICES 2009b) were re-fitted using the most up-to-date data series. Two different models were prepared: a GAM model and its linear version. Since the main aim was to make recruitment predictions under different climate scenarios, we used recruitment instead of recruitment success for all the models. Moreover, model construction was oriented toward the use of predicting variables for which projections are easily computed or accessible.

For the **Main Basin herring** stock the recruitment model included SSB and sea surface temperature in August (NASA8). The model maintained its elevated performances in terms of ability to predict the intensity of past recruitment events (Dev.expl.=71.6%). The relationships between recruitment and the two predictors maintained the same shape reported in 2009 during WKCSMPB, with a density dependent effect for large values of SSB. Similar predictor effects, and overall model performances (Dev.expl.=68.3%), were obtained in the linear model when second order polynoms were used.

For **Gulf of Riga Herring** stock, the recruitment model included SSB and sea surface temperature in May (NASA5), in agreement with WKCSMPB 2009 results. The occurrence of lower values of SSB during the time period investigated resulted in a linear relationship between recruitment and SSB in the Gulf of Riga, suggesting that density dependent effects are possibly occurring for SSB values larger than those previously observed. GAM and GLM perform similarly, with a deviance explained of 57.6% and 61.0% respectively.

For **Baltic Sprat**, the final model developed during WKCSMPB (ICES 2009b) included SSB, Bottom Depth Anomaly, and sea surface temperature in May. It explained slightly less than 87% of deviance. The model was refitted and no violation of assumptions regarding the independence, homogeneity of variance, and normality of the residuals was observed when checking the autocorrelation graphs and the Shapiro-Wilk normality test of residuals. The refitted model is explaining more than 75% of variance. For details on the model specification, see Appendix 4.

Based on the final GAM model we tried to build the model which is a combination linear and polynomial approach. The relation of SSB (in a log form) with logged recruitment seemed to be very close to linear, while the relation with NASA5 and BDA required a polynomial models of second and third order, respectively. When trying to simplify the initial model, it obtained always a higher AIC score than more simple models, therefore it was decided to regard the initial model as a final one (for details see the Appendix 4). The relationship between recruitment and all the predictors is very similar to that presented by the final GAM model.

5.4 Environmentally-Sensitive Stock-Recruitment final models predicting abilities

GAM models of all the three stocks were used for testing environmentally-sensitive (ES) stock-recruitment models stability and their predicting abilities when compared to the RCT3 predictions provided by the WGBFAS. First, each of the models was re-fitted with shorted VPA data series of preceding years to check if the relationship is stable (see results in Tables 5.4.1, 5.4.2, and 5.4.3). The even and odd years data series were tested as well. Then the predictions calculated by using the environmentally-sensitive models were compared against predictions estimated by the WGBFAS were presented at Figures 5.4.1, 5.4.3, and 5.4.5. Eventually, the accuracy of predictions calculated by using different methods was tested (Figures 5.4.2, 5.4.4, and 5.4.6). The last year VPA recruitment estimates (black circles) are regarded as observed data; previous years VPA estimates of the same year class recruitment are presented as empty circles; WGBFAS and ES predictions are shown as blue and red rhombuses, respectively. Rhombuses closer to the black circle provide better prediction of recruitment.

Central Baltic Herring (SD25–29&32 excl. Gulf of Riga)

gam(R ~ s(SSB, k=4)+s(NASA8), family=Gamma(link="log"))

Model	p	Deviance explained	AdjR^2
Central Baltic Herring			
additive		0.716	0.645
s(SSB)	***		
s(NASA8)	**		

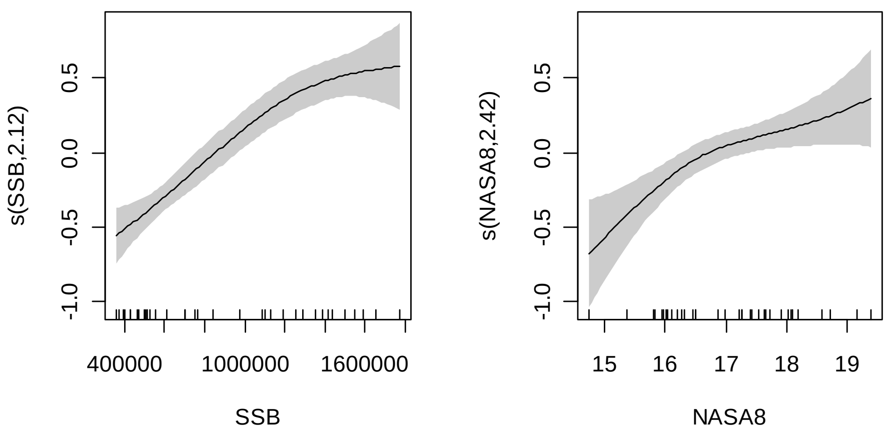


Table 5.4.1. Testing of model stability.

CBH models	*s(* SSB)	s(NASA8)	Dev. Expl	$AdjR^2$	n
1974-2008	***	**	0.716	0.645	35
1974-2007	***	***	0.738	0.666	34
1974-2006	***	***	0.739	0.646	33
1974-2005	***	***	0.686	0.592	32
1974-2004	***	***	0.722	0.620	31
1974-2003	***	***	0.746	0.640	30
even years	***	ns	0.711	0.514	18
odd years	***	*	0.791	0.661	17

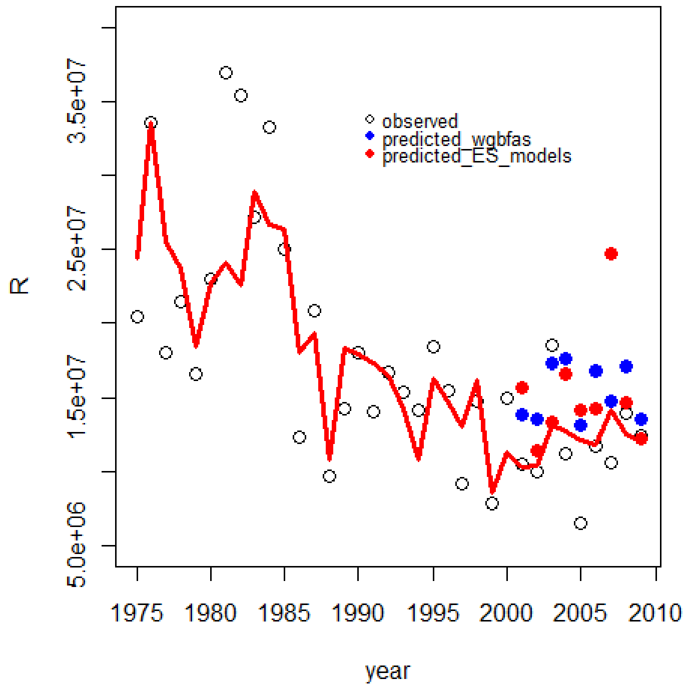


Figure 5.4.1. Comparison of predictions calculated by using the environmentally-sensitive models with predictions estimated by the WGBFAS.

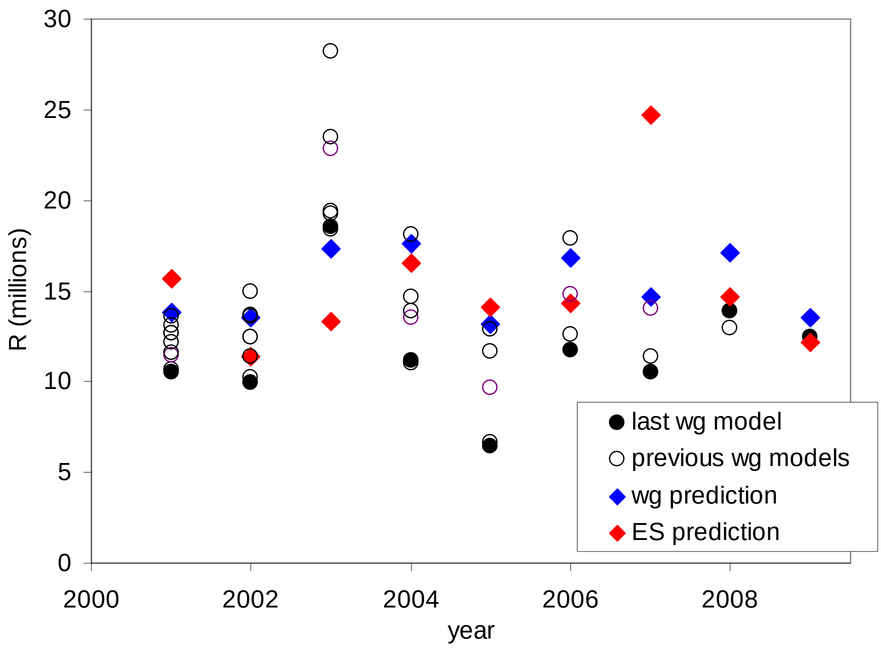


Figure 5.4.2. Accuracy of predictions calculated by using different methods: rhombus closer to the black circle provides better prediction of recruitment.

Gulf of Riga Herring

gam(R ~ s(SSB)+s(NASA5),family=Gamma(link="log"))

Model	p	Deviance explained	AdjR^2
Gulf of Riga Herring			
additive		0.576	0.392
s(SSB)	*		
s(NASA5)	***		

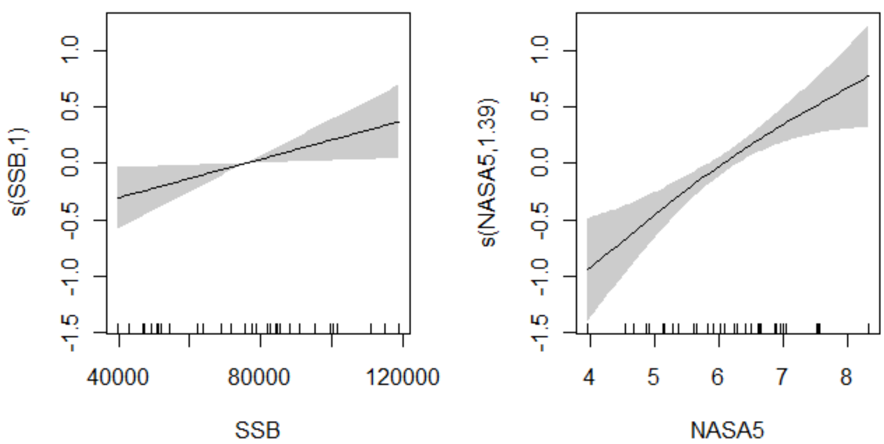


Table 5.4.2. Testing of model stability.

GoRH models	*s(* SSB)	s(NASA5)	Dev. Expl	AdjR^2	n
1977-2008	*	***	0.576	0.392	32
1977-2007	*	***	0.586	0.413	31
1977-2006	*	***	0.575	0.404	30
1977-2005	ns	***	0.631	0.411	29
1977-2004	**	***	0.685	0.575	28
1977-2003	**	***	0.711	0.576	27
even years	ns	*	0.570	0.418	16
odd years	ns	**	0.571	0.260	16

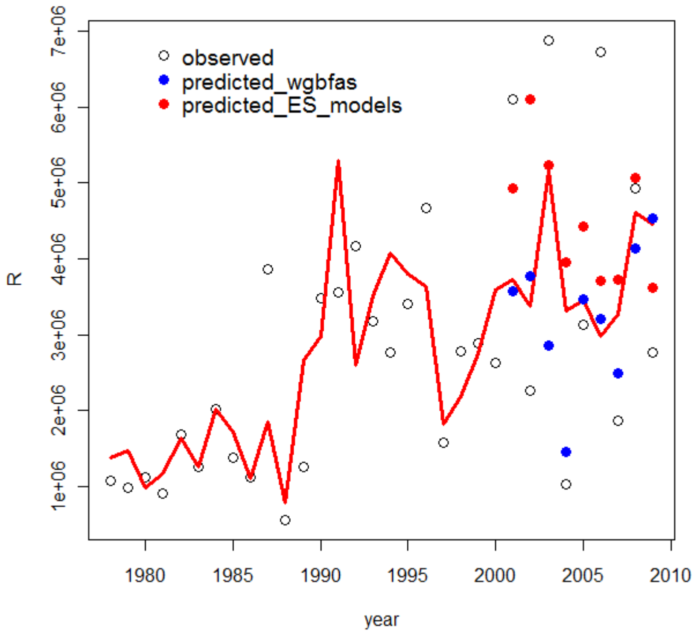


Figure 5.4.3. Comparison of predictions calculated by using the environmentally-sensitive models with predictions estimated by the WGBFAS.

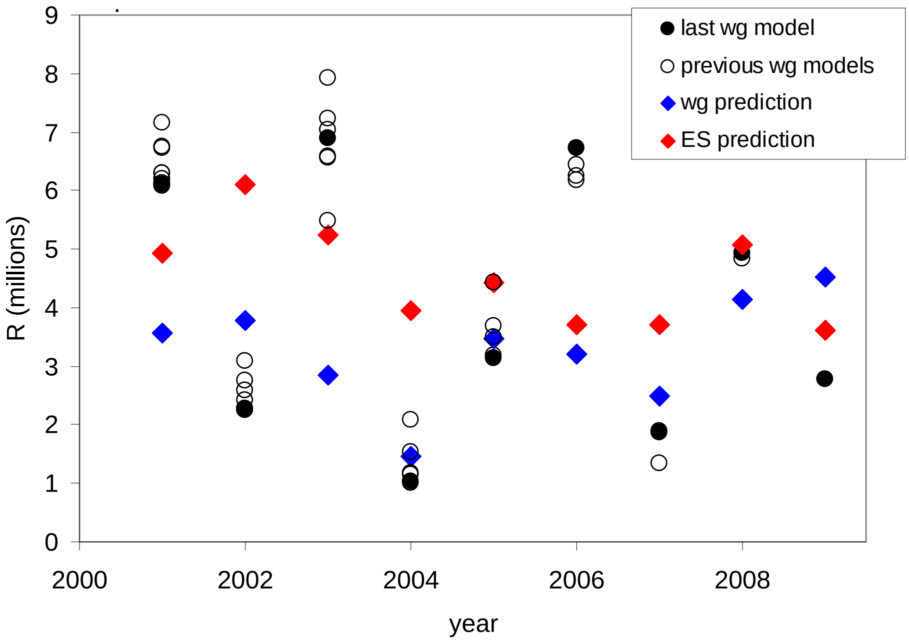


Figure 5.4.4. Accuracy of predictions calculated by using different methods: rhombus closer to the black circle provides better prediction of recruitment.

Sprat (SD 22–32)

gam(R ~ s(SSB, k=4)+s(NASA5, k=4)+s(BDA, k=4),family=Gamma(link="log"))

Model	p	Deviance explained	$AdjR^2$
Sprat			
additive		0.791	0.648
s(SSB)	*		
s (NASA5)	**		
s (BDA)	***		

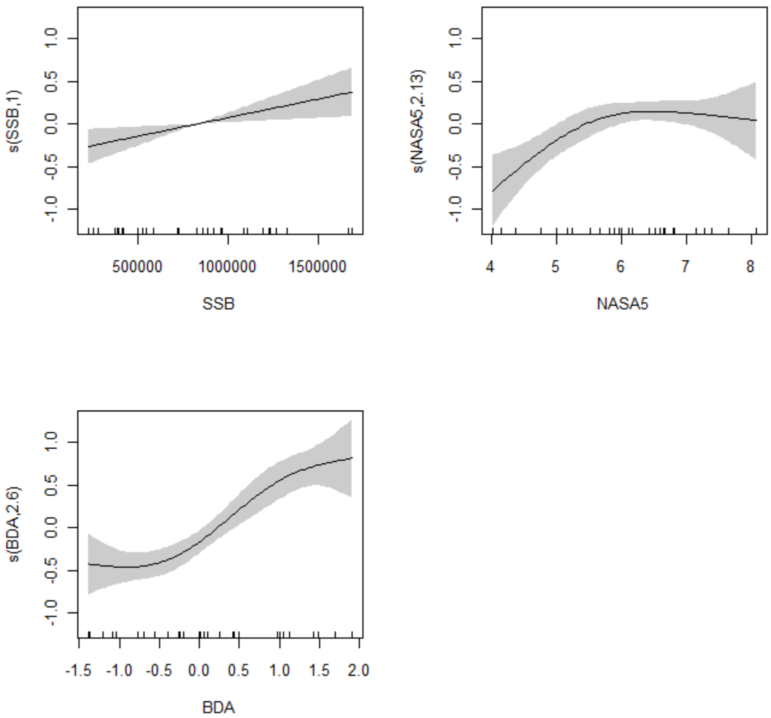


Table 5.4.3. Testing of model stability.

Sprat models	s(SSB)	s(NASA5)	s(BDA)	Dev. Expl	$AdjR^2$	n
1979-2008	*	**	***	0.791	0.648	30
1979-2007	*	**	***	0.763	0.577	29
1979-2006	*	**	***	0.811	0.681	28
1979-2005	*	**	***	0.834	0.745	27
1979-2004	*	**	***	0.870	0.801	26
1979-2003	**	**	***	0.880	0.824	25
even years	ns	ns	**	0.816	0.745	15
odd years	ns	*	*	0.945	0.788	15

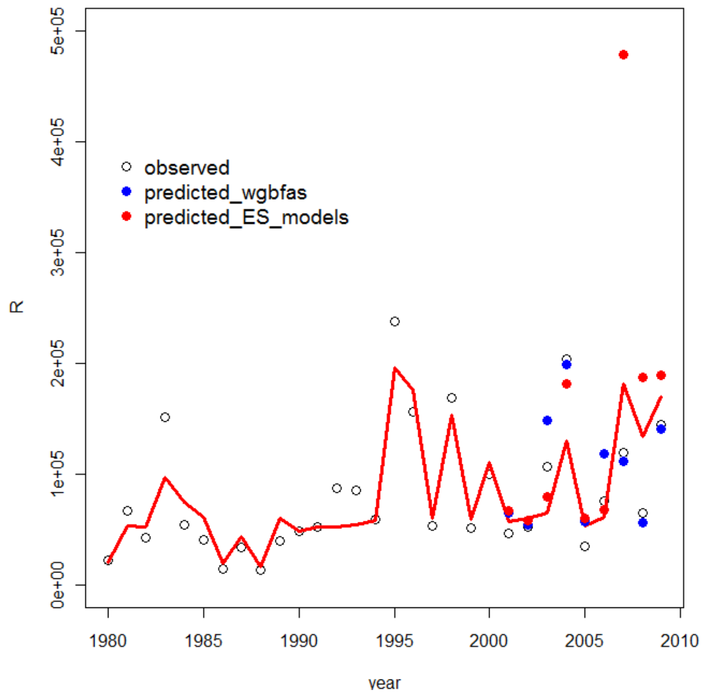


Figure 5.4.5. Comparison of predictions calculated by using the environmentally-sensitive models with predictions estimated by the WGBFAS.

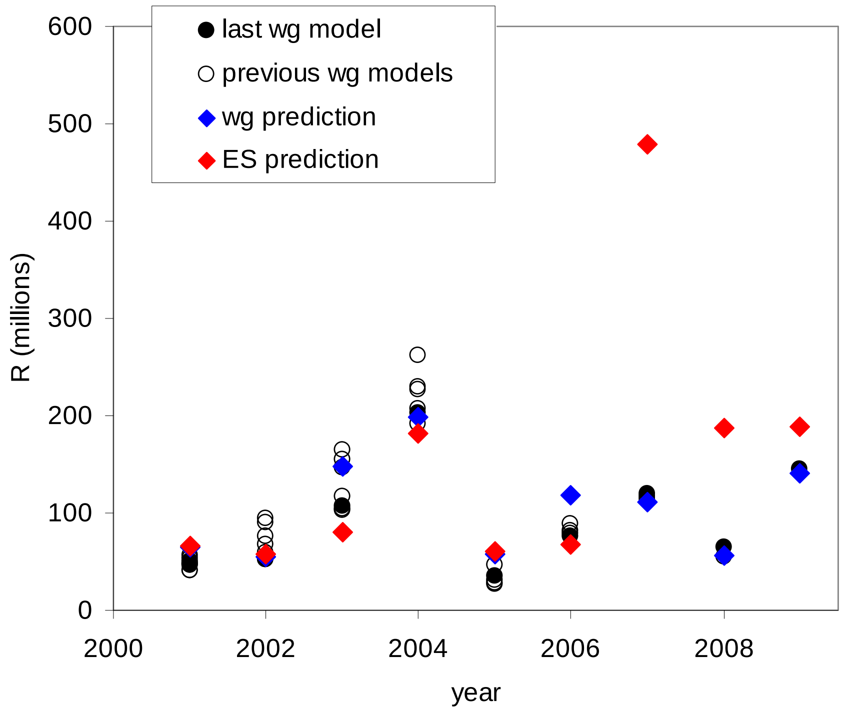


Figure 5.4.6. Accuracy of predictions calculated by using different methods: rhombus closer to the black circle provides better prediction of recruitment.

Recruitment predictions obtained using both methods were then correlated with XSA estimates. RCT3 computer program is used by WGBFAS to predict the recruitment (age group 1 at the beginning of the year) of sprat, Central Baltic Herring and Gulf of

Riga herring. RCT3 program is a type of regression analysis which relates survey data to stock abundance (recruitment). Several survey indices could be used. In RCT3 the estimates of age group 1 which are taken from the latest XSA are regressed against survey indices (predictors).

Central Baltic herring

The acoustic estimates of age group 0 herring from the autumn hydro-acoustic survey in Central Baltic are used as survey indices to obtain recruitment estimates (age group 1) using RCT3 program. Survey indices are available for 1991–2009. The R^2 between XSA estimates and acoustic indices in recent years is rather low, at range of 0.45–0.48 (Figure 5.4.7). Most of the recruitment estimates weight is from XSA estimates (68%). Due to low survey weight the calculated recruitment indices tend towards the long-term average XSA recruitment value. In 2001–2009 RCT3 overestimated the recruitment in the most of the years (except for 2003).

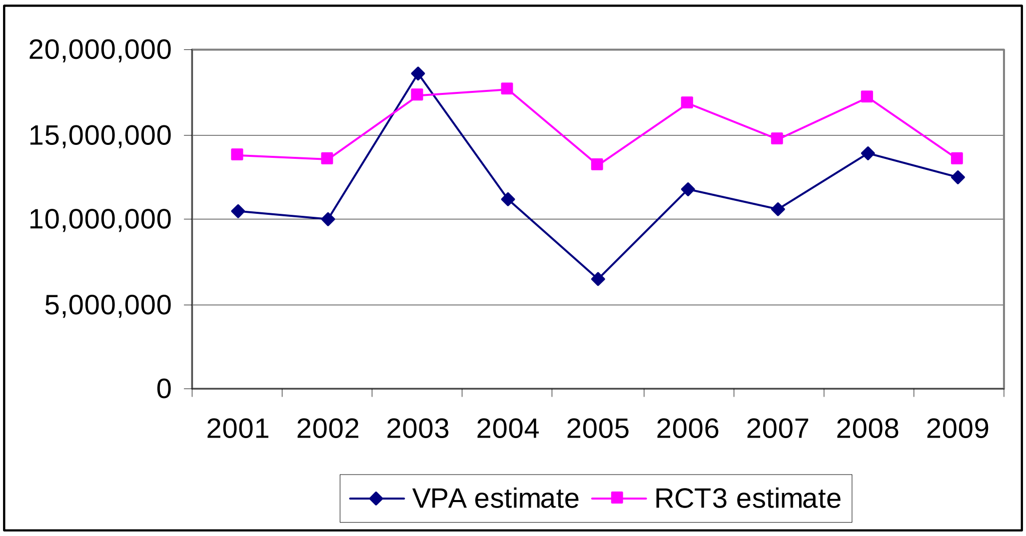


Figure 5.4.7. Central Baltic herring. Comparison of recruitment estimates from RCT3 and XSA (R^2= 0.42 in 2001–2009). The RCT3 estimates are values which were calculated in the year of recruitment prediction (e.g. recruitment in 2004 was predicted by WGBFAS in 2004). The XSA estimates were taken from WGBFAS 2010 report.

The comparison of recruitment estimates from the environmentally-sensitive SR models with XSA estimates is shown in Figure 5.4.8. Practically there is no correlation between XSA and SR models estimates (R^2=0.03 for 2001–2009).

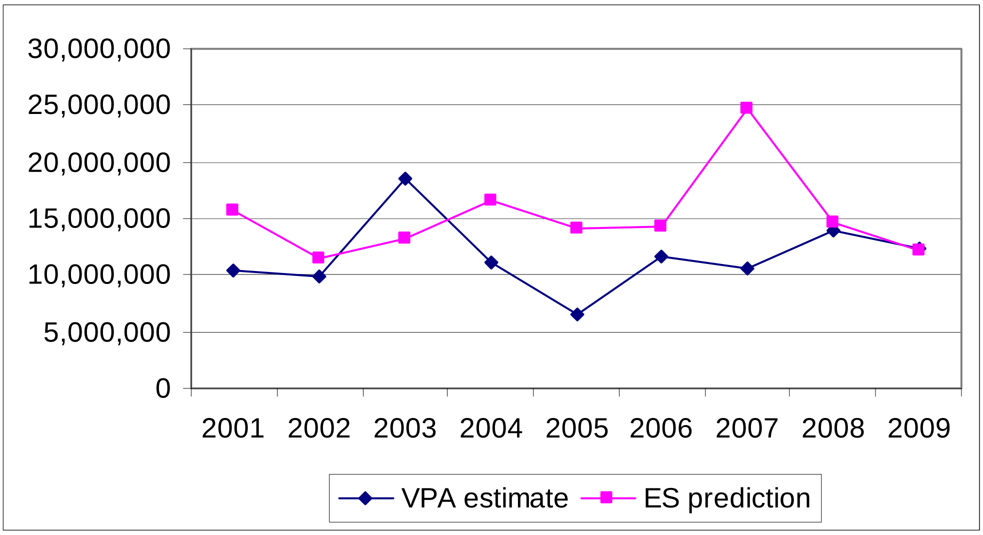


Figure 5.4.8. Central Baltic herring. Comparison of recruitment estimates from XSA and environmentally-sensitive models (R^2= 0.03). The ES model estimates are values which were calculated in the year of recruitment prediction (e.g. recruitment in 2004 was predicted by ES model using data set till 2003). The XSA estimates from WGBFAS 2010.

Gulf of Riga herring

Recruitment prediction of the Gulf of Riga herring is performed in RCT3 using environmental factors which influence the year-class strength of this stock. The mean water temperature of 0–20 m water layer and the biomass of *Eurytemora affinis* in May are used as predictors of the recruitment. The investigations in the Gulf of Riga have shown that the water temperature influences the beginning, length and the course of the spawning. When the water temperature is higher the spawning starts earlier, the spawning period is longer and the spawning grounds are more evenly utilised by herring. *Eurytemora affinis* is the most important food item of herring. Environmental data are available from 1977 onwards. The R^2 between XSA estimates and environmental indices in recent years is in the range of 0.51–0.60 (Figure 5.4.9.). The weight of both indices is rather similar, in the range of 25–36%. The weight of both indices has strongly decreased after the appearance of very rich year-classes in 2000 and 2002 which both were predicted as only slightly above long term average. This could be indicated as the main problem of RCT3 prediction of Gulf of Riga herring recruitment, that it is not able to predict very strong year-classes. In the recruitment estimates the weight from XSA is around 36%.

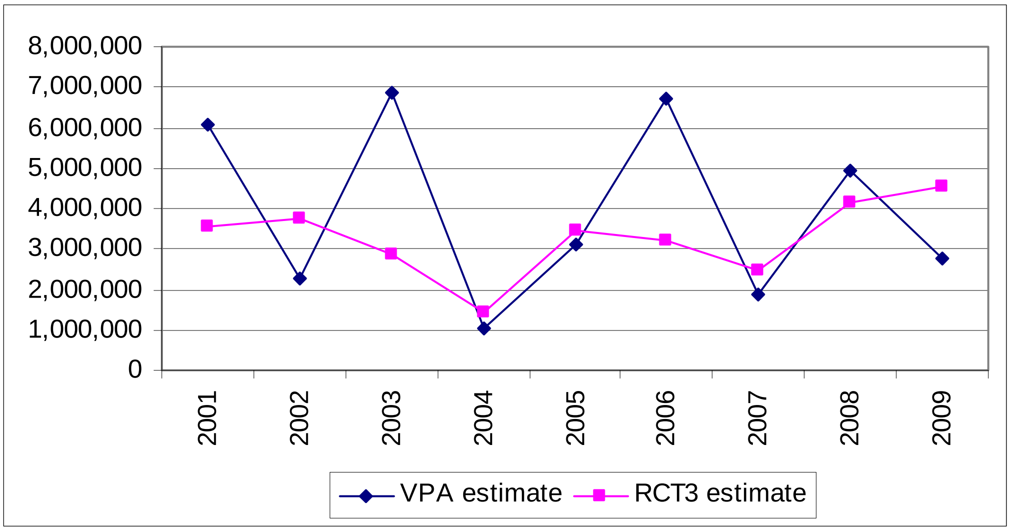


Figure 5.4.9. Gulf of Riga herring. Comparison of recruitment estimates from RCT3 and XSA (R^2= 0.08 in 2001–2009). The RCT3 estimates are values which were calculated in the year of recruitment prediction (e.g. recruitment in 2004 was predicted by WGBFAS in 2004). The XSA estimates from WGBFAS 2010.

The comparison of recruitment estimates from the environmentally-sensitive SR models with XSA estimates is shown in Figure 5.4.10. In 2001–2009 the ES models predict only rich or above average recruitment, while there were also two poor year classes in 2003 and 2006. In general there is poor correlation between XSA and ES models estimates (R^2=0.04 for 2001–2009).

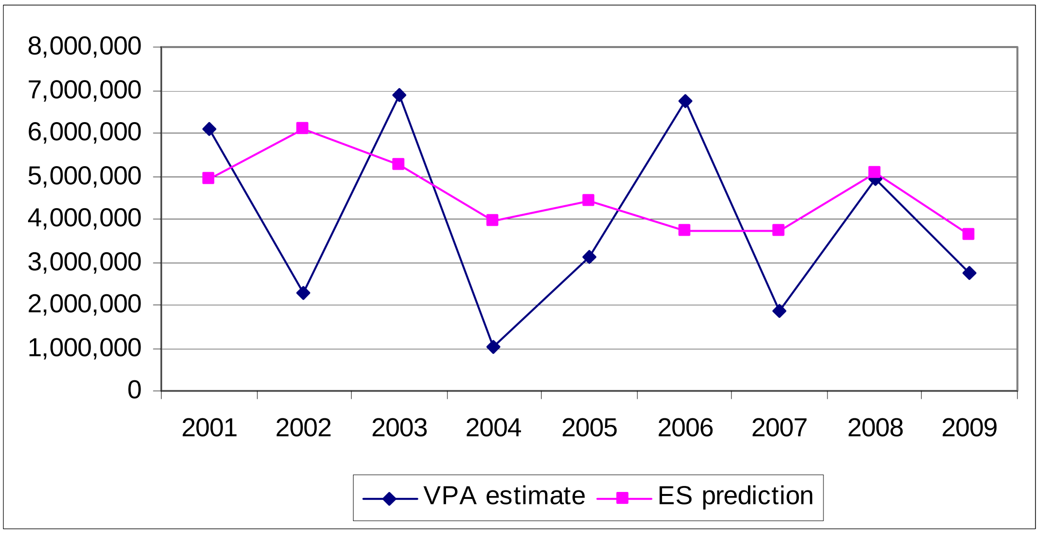


Figure 5.4.10. Gulf of Riga herring. Comparison of recruitment estimates from XSA and environmentally-sensitive models (R^2= 0.04 in 2001–2009). The ES model estimates are values which were calculated in the year of recruitment prediction (e.g. recruitment in 2004 was predicted by ES model using data set till 2003). The XSA estimates from WGBFAS 2010.

Baltic sprat

The acoustic estimates on age group 0 sprat in Sub-divisions 26+28 are used as survey indices to obtain recruitment estimates (age group 1) using RCT3 program. Survey indices are available for 1991–2009. The R^2 between XSA estimates and acoustic indices is high, generally at range of 0.75–0.80 (Figure 5.4.11.). Most of the recruitment estimates weight is from survey (around 65%).

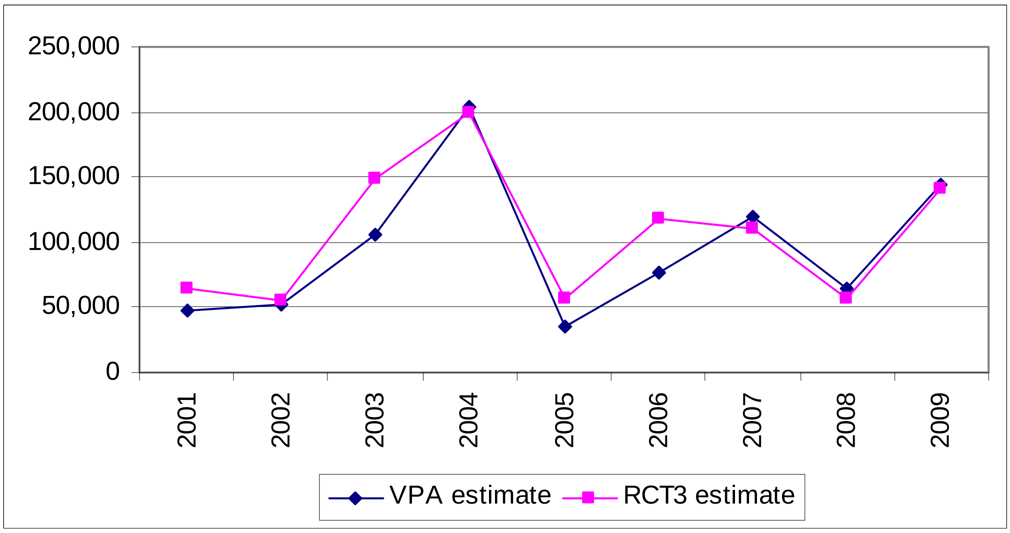


Figure 5.4.11. Baltic sprat. Comparison of recruitment estimates from RCT3 and XSA (R^2= 0.86 in 2001–2009). The RCT3 estimates are values which were calculated in the year of recruitment prediction (e.g. recruitment in 2004 was predicted by WGBFAS in 2004). The XSA estimates from WGBFAS 2010.

The comparison of recruitment estimates from the environmentally-sensitive SR models with XSA estimates is shown in Figure 5.4.12. SR models estimates are close to XSA estimates in 2001–2006, however in the latest three years SR models overestimate the recruitment, the difference is especially high in 2007. This makes the relationship between XSA and SR estimates rather poor (R^2=0.20 for 2001–2009).

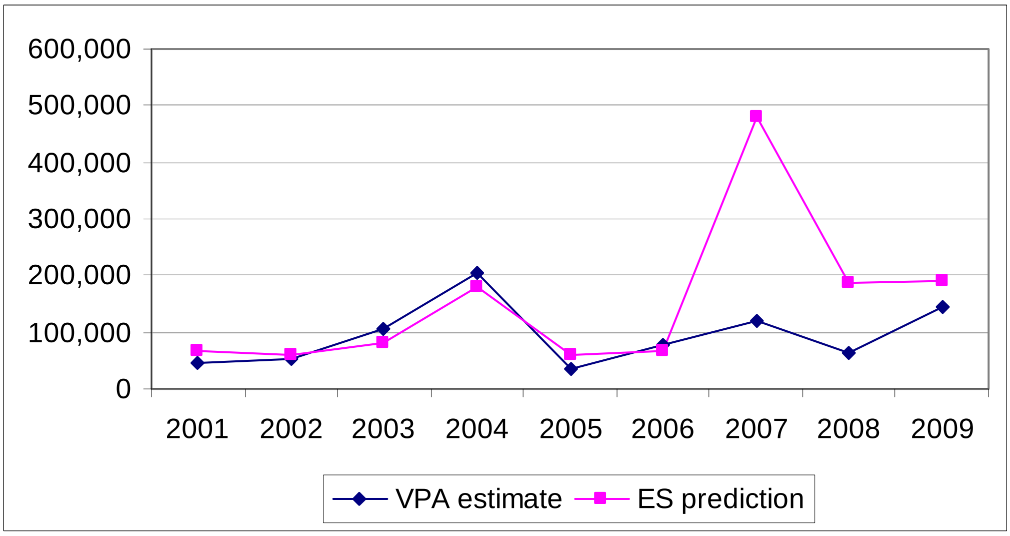


Figure 5.4.12. Baltic sprat. Comparison of recruitment estimates from XSA and environmentally-sensitive models (R^2= 0.20). The ES model estimates are values which were calculated in the year of recruitment prediction (e.g. recruitment in 2004 was predicted by ES model using data set till 2003). The XSA estimates from WGBFAS 2010.

Concluding, the predicting abilities of the current year recruitment using the environmentally-sensitive stock-recruitment models were, on average, poorer when compared with RCT3 models which are mostly based on the previous autumn 0 group acoustic estimates. Therefore, in that sense, our models cannot be treated as an alternative for the regular RCT3 estimates. However, they might provide a "second opinion" whenever the RCT3 estimates seems to be unrealistic or e.g. when acoustic observations are not available.

However, it should be stressed that the environmentally-sensitive stock-recruitment models are essential tool for testing hypothesis in the medium and long-term perspective (when RCT3 models cannot be used) and to incorporate climate change and socio-economic impact into biological models.

6 Climate change scenarios for the Baltic Sea using a rapid assessment method: Forecasted sea surface temperature (SST) for the period 2008–2100

6.1 Introduction

Global Climate Models (GCMs) are used to simulate the response of the atmosphere and oceans to increasing concentrations of greenhouse gases. However, when regional studies are concerned, the spatial resolution, usually around 3º, of GCMs is too coarse to be used for climate change studies. This particularly applies to the Baltic Sea, which most GCMs represent either as a bay (an extension of the North Sea) or as a lake. To make more realistic simulations of climate over smaller areas, e.g. Northern Europe, higher resolution (around 10 km) Regional Climate Models (RCMs) are used. However, since RCM ocean model data for the studied region covering the entire 21st century were not available, we used RCM air temperature from two periods to estimate Baltic Sea surface temperatures for the entire twenty-first century. The method is briefly described below, for more information we refer to ICES 2009b.

6.2 Data and methods

Monthly averages of minimum air temperature at 2m height scenario RCM data for 2071–2100 were obtained from the PRUDENCE project, since minimum air temperature is good proxy for SST over much of the Baltic. Two SRES emission scenarios were used: A2 (considered a high-emissions scenario) and B2 (low scenario). We used RCM SST from 1961–1990 as a control run. Observational time-series were derived from the 1º x 1º resolution HadISST gridded dataset (Rayner *et al.*, 2003). The time-series were extracted for seven grid cells representative of the different Baltic-Sea reaches (see Figure 6.2.1).

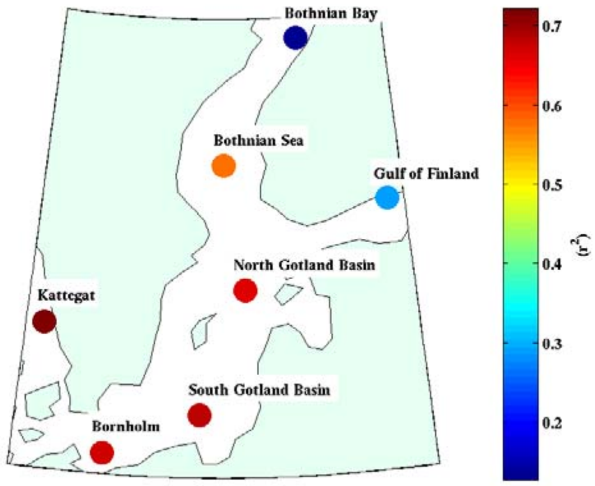


Figure 6.2.1. Correlation between seasonally-detrended SST (HadISST) and monthly average minimum air temperature (from NCEP/NCAR Reanalysis).

Correlation between seasonally-detrended HadISST SSTs and minimum air temperature showed that the agreement is poor for the Bothnian Bay and Gulf of Finland, presumably because sea-ice coverage decouples the SST from the overlying air. Thus, the climate change scenarios for these regions should be treated with caution.

To obtain climate change scenarios, first the mean seasonal change in minimum air temperatures between 1961–1990 and 2071–2100 (A2 and B2 scenarios) was determined (Figure 6.2.2). The changes in air temperature from the RCM were then used to statistically-downscale the observed SST time-series. In brief the procedure was as follows. The observed SSTs were detrended over 1886–2000 to provide anomalies representing natural climate variability. The detrended time series were then used as anomalies for the 1986–2100 period, top which a linear trend, representing change from the RCM control run and the two scenarios, was added. After adjustment of the new time series to the HADISST one, the scenario time series were added to the observed historical time series, resulting in temporally complete time series (Figure 6.2.3, for further details see ICES 2009b).

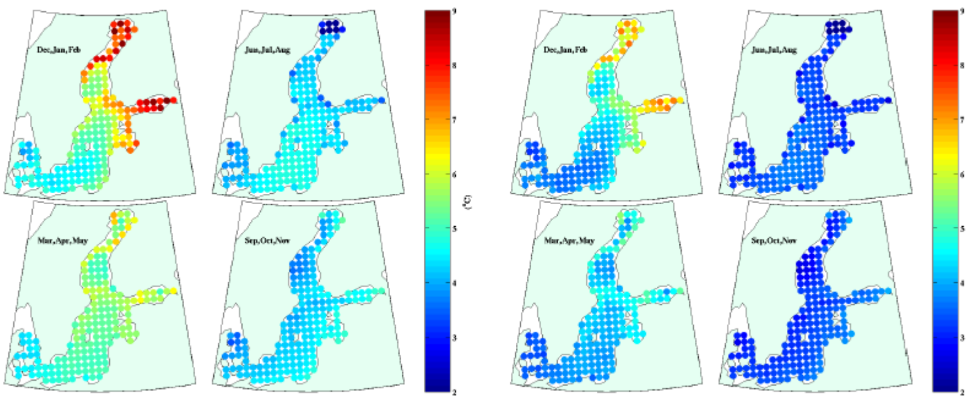


Figure 6.2.2. Change in seasonal minimum temperature 2071–2100 for (left) the SRES A2 scenario and (right) the SRES B2 scenario, relative to the control scenario 1961–1990. Plots also show the RCA2 grid resolution.

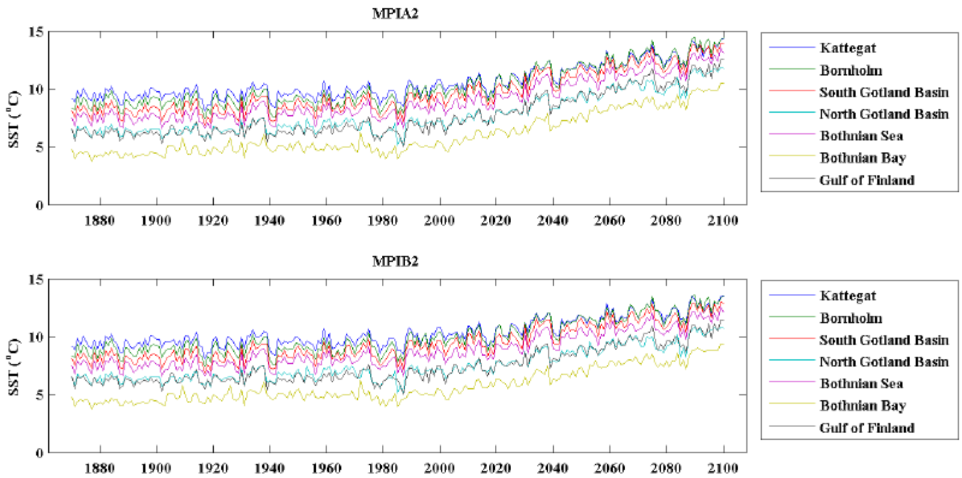


Figure 6.2.3. Downscaled annual SST time-series for the Baltic Sea for (upper) SRES A2 and (lower) SRES B2.

6.3 Discussion

This downscaling method is a simplified version of pattern-scaling (e.g. Christensen *et al*., 2001), where spatial trends derived from shorter model runs are multiplied by global warming factors from another model. In our downscaling algorithm, we derived the spatial pattern of change from a RCM (Figure 6.2.2.), but then we used a linear trend combined with past historical variability to create the scenarios, rather than global warming factors from another GCM. As a result, although the overall warming trend in our downscaled scenarios is consistent with the SRES A2 and B2 parent scenarios, the development of the trend from 2000–2100 is likely to be inconsistent with time-series from a transient GCM run with these emission scenarios. For example, the B2 scenario show an initial increase in emissions, which flatten from around 2050. The A2 scenario shows continually increasing emissions throughout the 21st century. In our downscaled scenarios, however, temperature rises follow linear trends, and in order to more reliably capture the decadal variability, transient RCM model runs are needed.

7 Medium term predictions of recruitment with different climatic scenarios

7.1 Introduction

SST projections were generated from the Global Climate Models (GCMs) for the period 2010–2050. These projections had an associated uncertainty that was generated maintaining SST temporal autocorrelation structure from the last century observations and adding a random noise. Consequently, the effects of different SST scenarios and their associated uncertainty were propagated into BALMAR and the herring age-structure model.

The BALMAR model was used to generate predictions of cod and sprat SSB from 2010 to 2050 for the Main basin. Predicted cod and sprat from BALMAR affected herring dynamics via predation (*M~f(COD)*) and competition (*WAA~f(SPRAT)*), respectively. Predictions from both BALMAR and the herring model were generated with two different scenarios of future fishing mortality. In the first case fishing mortality was fixed to F_{msy} values as estimated for the management plan (F=0.30, 0.19 and 0.32, for cod, herring and sprat, respectively). In the second case fishing mortality for herring (F_{high}) was increased to 0.34, the average values observed between 1993 and 2002 (this period is characterized by the highest fishing level observed during the last three decades in the Central Baltic).

7.2 Results

Main Basin herring

In all the scenarios both spawning stock biomass and recruitment showed a clear relationships with fishing intensity. Marked increase in the estimated abundances of adults and recruits of herring were expected for all the scenarios with more or less accentuated patterns according to the associated climate scenario. The positive effect of sea surface temperature and herring recruitment in the Central Baltic resulted in a moderately positive trend in the herring stock trajectories also under elevated fishing mortality. However, density-dependent response was evident only for low fishing mortality levels (F_{msy}), when herring population reached large biomasses. The herring population oscillated around low values for the whole 40 years projections only in the scenario with combined no climate change and high fishing intensity.

As expected recruitment showed wider variations and lower temporal autocorrelation than adult herring biomass. As expected, propagation of the uncertainty associated to the water temperature projections into the herring dynamics, resulted in an increasing predicted variance.

Predicted commercial catches showed higher initial catches for those scenarios characterized by elevated fishing mortality (F_{high}) than for those scenarios with F_{msy}. Despite this, after only 7–8 years the application of F_{msy} instead of F_{high} allowed to build larger SSB with a positive effect for the stock and the consequent catches. Before 2020, all the scenarios with F_{msy} produced higher catches than those with F_{high}. In combination with increasing water temperature (e.g., climate scenarios A2 and B2) F_{msy} produced the most pronounced increase in commercial catches. After approximately 25 years (2035) catches reached a plateau level >2.5 times larger than the initial value.

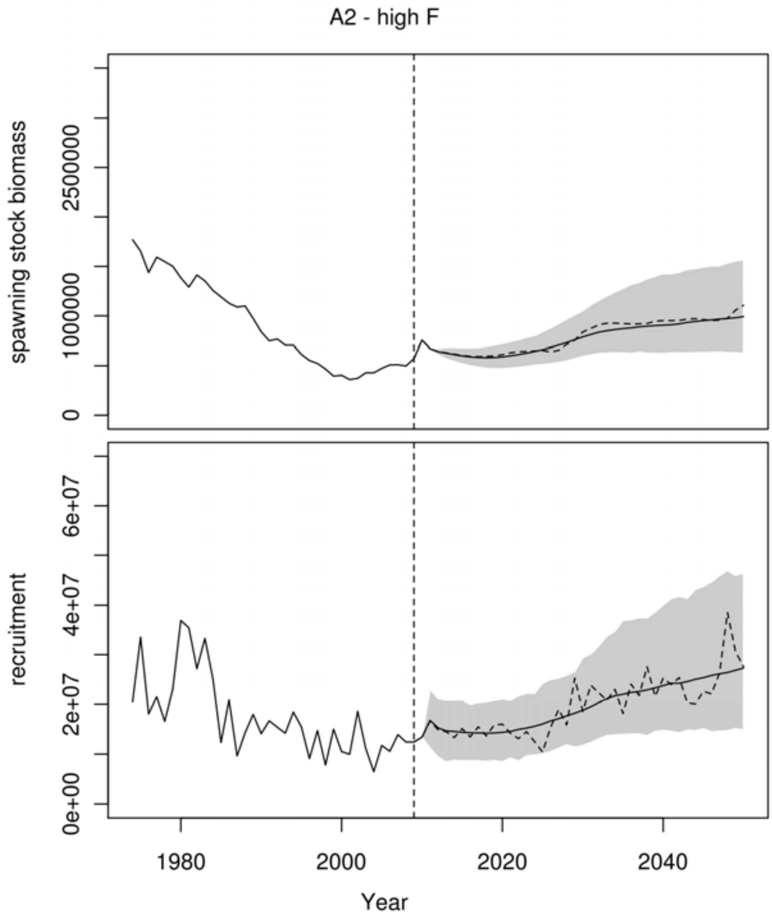


Figure 7.1.1. Herring annual spawning stock biomass and recruitment year class for MBH as predicted from 2010 to 2050 under A2 climate scenario and high fishing effort. Mean prediction as continuous line, 95 percentiles from 1000 temperature replicates as shaded area, and one of the potential trajectories as dotted line. The vertical line in 2009 separates spawning stock biomass estimated by the assessment VPA (upper plot) and recruitment estimated by fitting GAM (lower plot) from their forecasts in the herring model.

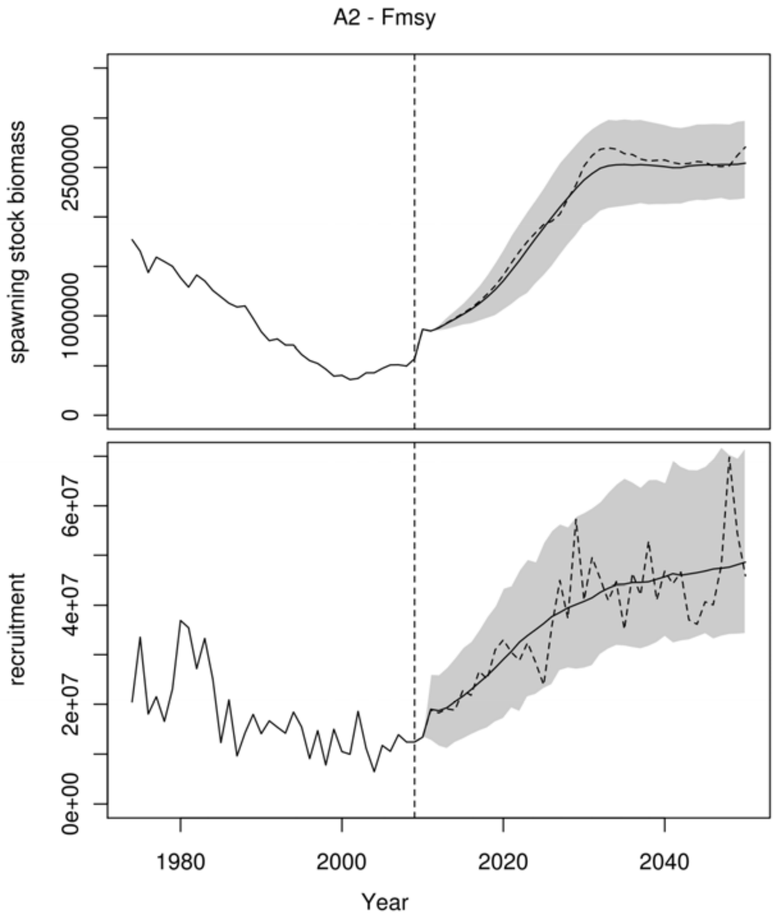


Figure 7.1.2. Herring annual spawning stock biomass and recruitment year class for MBH as predicted from 2010 to 2050 under A2 climate scenario and F_{msy}. Mean prediction as continuous line, 95 percentiles from 1000 temperature replicates as shaded area, and one of the potential trajectories as dotted line. The vertical line in 2009 separates spawning stock biomass estimated by the assessment VPA (upper plot) and recruitment estimated by fitting GAM (lower plot) from their forecasts by the herring model.

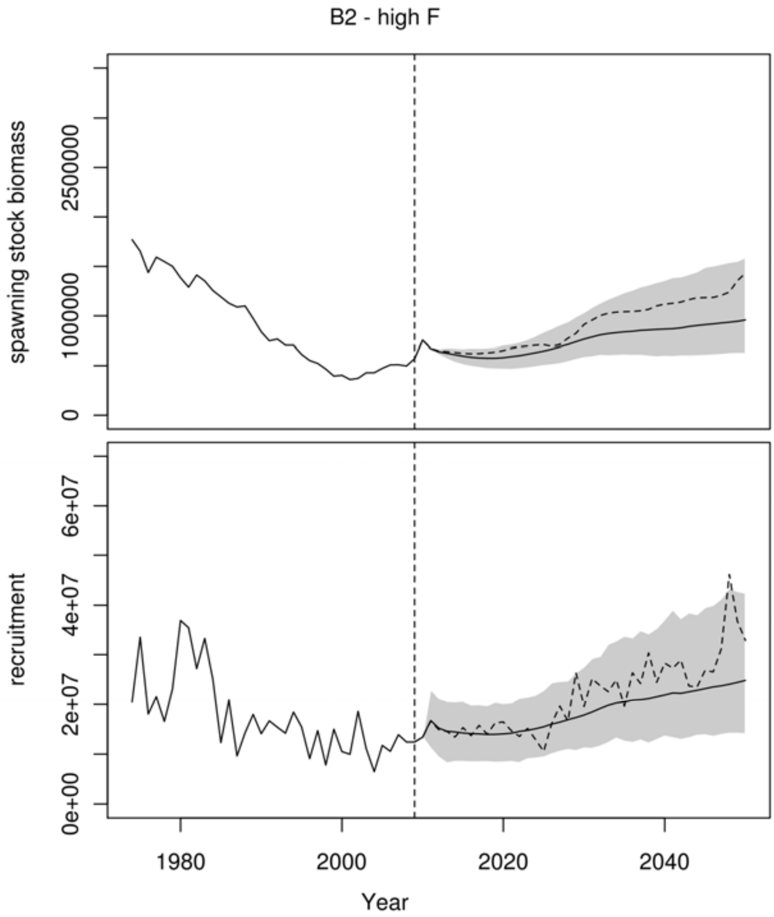


Figure 7.1.3. Herring annual spawning stock biomass and recruitment year class for MBH as predicted from 2010 to 2050 under B2 climate scenario and high fishing effort. Mean prediction as continuous line, 95 percentiles from 1000 temperature replicates as shaded area, and one of the potential trajectories as dotted line. The vertical line in 2009 separates spawning stock biomass estimated by the assessment VPA (upper plot) and recruitment estimated by fitting GAM (lower plot) from their forecasts by the herring model.

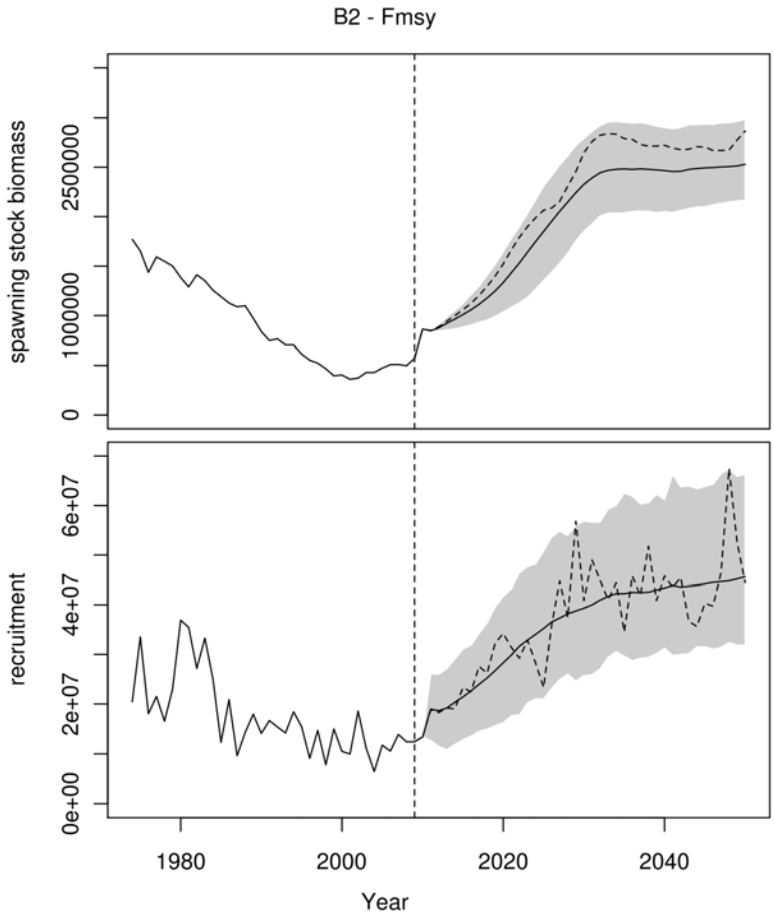


Figure 7.1.4. Herring annual spawning stock biomass and recruitment year class for MBH as predicted from 2010 to 2050 under B2 climate scenario and F_{msy}. Mean prediction as continuous line, 95 percentiles from 1000 temperature replicates as shaded area, and one of the potential trajectories as dotted line. The vertical line in 2009 separates spawning stock biomass estimated by the assessment VPA (upper plot) and recruitment estimated by fitting GAM (lower plot) from their forecasts by the herring model.

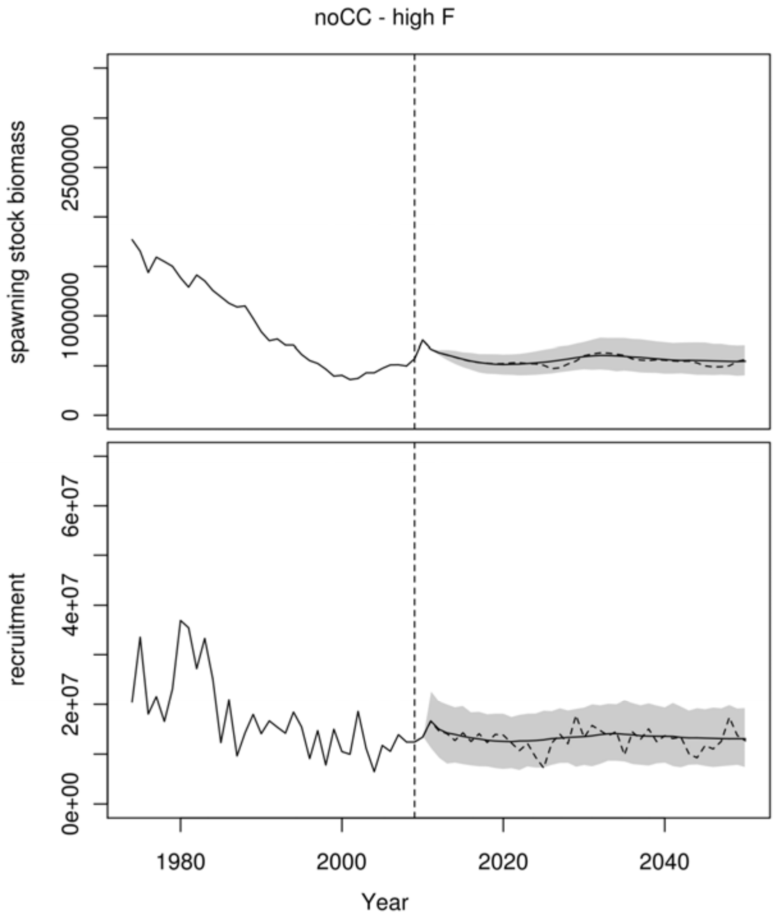


Figure 7.1.5. Herring annual spawning stock biomass and recruitment year class for MBH as predicted from 2010 to 2050 under no climate change scenario and high fishing effort. Mean prediction as continuous line, 95 percentiles from 1000 temperature replicates as shaded area, and one of the potential trajectories as dotted line. The vertical line in 2009 separates spawning stock biomass estimated by the assessment VPA (upper plot) and recruitment estimated by fitting GAM (lower plot) from their forecasts by the herring model.

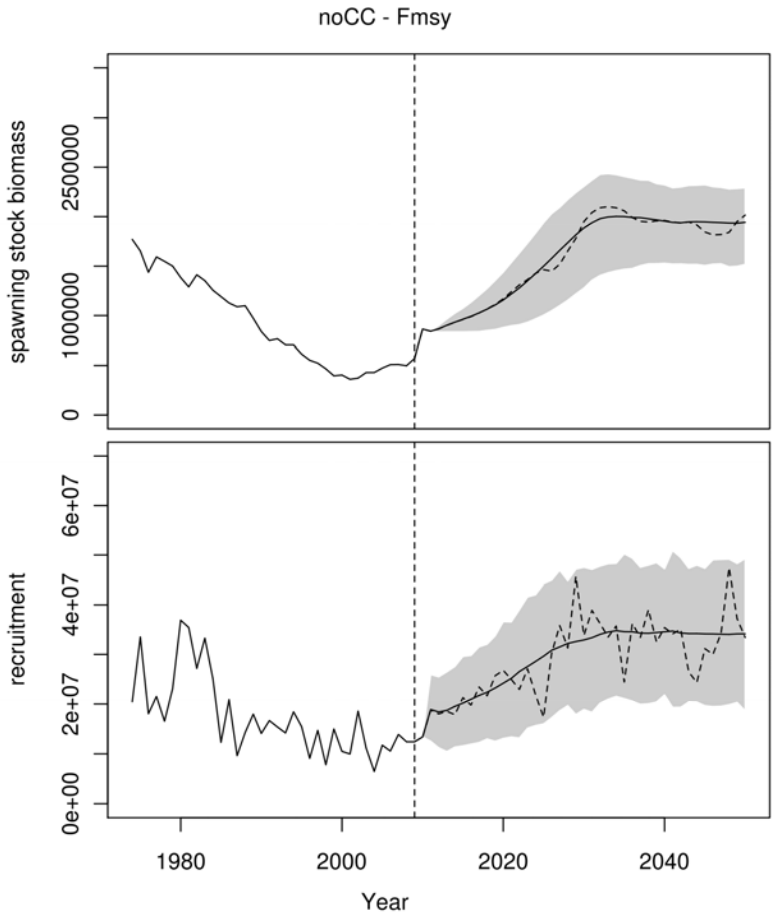


Figure 7.1.6. Herring annual spawning stock biomass and recruitment year class for MBH as predicted from 2010 to 2050 under no climate change scenario and F_{msy}. Mean prediction as continuous line, 95 percentiles from 1000 temperature replicates as shaded area, and one of the potential trajectories as dotted line. The vertical line in 2009 separates spawning stock biomass estimated by the assessment VPA (upper plot) and recruitment estimated by fitting GAM (lower plot), from their forecasts by the herring model.

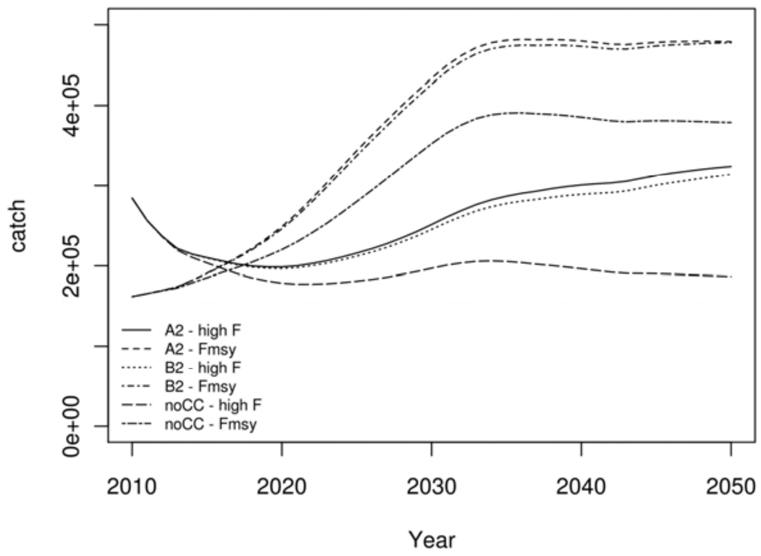


Figure 7.1.7. Herring annual commercial catch for MBH as predicted from 2010 to 2050 under different combination of climate and fishing intensity scenarios.

8 Economic models

We applied an age-structured economic-ecological model, including cost- and price functions, to investigate optimal Baltic herring management (in terms of profit) under different climate change scenarios. We analyzed two Baltic herring stocks: The central Baltic herring (MBH) and the Gulf of Riga herring (GRH). The MBH model includes major species-interaction aspects by using a natural mortality function, depending on cod stock biomass (the major predator on juvenile herring). Interaction between the two clupeid stocks, i.e. herring and sprat, can also be included using a function for herring weight as depending on sprat stock size. We analyzed 2 future climate scenarios: A2, and B2. Additionally, we analyzed 3 constant temperature scenarios for central Baltic herring: mean current temperature as well as ±1°C to show the sensitivity of results on the impact of temperature.

We used X_{at} to denote the stock (in numbers) of age class $a = 1,\ldots,A$ in year $t = 0,1,\ldots$. We considered eight age classes, i.e. we set $A = 8$ as in the ICES standard assessment (ICES, 2010). Further, we used H_{at} to denote harvest of age class a in year t. The equations of motion describing the population dynamics of the age-structured fish stock are given by:

$$
\begin{aligned}
X_{1,t+1} &= r\left(\sum_{a=1}^{A} c_a w_a X_{at}\right) \equiv r\left(X_{0t}\right), \\
X_{a+1,t+1} &= b_a\left(1-\varphi_a E_t\right) X_{at}, \qquad a = 1,\ldots,A-2, \qquad (1) \\
X_{A,t+1} &= b_{A-1}\left(1-\varphi_{A-1} E_t\right) X_{A-1,t} + b_A\left(1-\varphi_A E_t\right) X_{At},
\end{aligned}
$$

where $b_a, a = 1,\ldots,A$ are age-specific survival rates, c_a, $a = 1,\ldots,A$ are the age-specific maturities, φ_a, $a = 1,\ldots,A$ are age-specific catchabilities and *r* is a recruitment function (see below). Age-specific survival rates ($b_a = \exp(-M2_a)$) were dependant on cod stock size and estimated for different trajectories of Baltic cod stock development (see below). Age-specific maturity (c_a) was taken from single-species standard assessment (ICES, 2010). Age-specific catchability (φ_a) was estimated based on mean age-specific fishing mortalities for the years 2007–2009 (Fbar 07-09) as reported in ICES (2010) with φ_a =1 for the oldest age class by normalization. The age-specific weights (w_a) are taken from standard single-species assessment (ICES, 2010).

We used E_t to denote fishing effort in year *t*. The spawning stock biomass was given by $X_{0t} = \sum_{a=1}^{A} c_a w_a X_{at}$.

(2)

Cost functions were derived using the general approach of Nostbakken and Bjorndal (2003) for North Sea Herring. The Cost functions for the two Baltic stocks investigated here were weighted according to their carrying capacity (2.9 million tonnes for MBH and 175 000 tonnes for GRH). Prices for different market categories of Baltic Herring were taken from Finnish Statistics Yearbooks (Producer Prices for Fish 2004–2009) and averaged for the years 2004 to 2009. Market categories were allocated to the 8 age classes of the model (Table 8.1).

Table 8.1. Price data for central Baltic herring (MBH) and Gulf of Riga herring (GRH).

Market class	Definition (n/kg)	Age MBH	Age GRH	€ per kg						
				2004	2005	2006	2007	2008	2009	average
00	12-17	8	-	0.34	0.35	0.34	0.46	0.52	0.50	0.42
0	18-24	7	-	0.34	0.38	0.38	0.46	0.50	0.33	0.40
1	25-32	5,6	-	0.21	0.20	0.24	0.26	0.26	0.25	0.24
2	33-44	3,4	5-6	0.12	0.12	0.13	0.14	0.15	0.14	0.13
3	45-60	1,2	1-4	0.12	0.08	0.14	0.13	0.14	0.14	0.12

In the standard setting we used an interest rate of 7%, with a interest rate $\delta > 0$, the discount factor is defined as $\rho = 1/(1+\delta)$. The necessary conditions for the optimal harvesting of the age-structured herring stock were obtained by applying the Lagrangian method with appropriate Kuhn-Tucker conditions. Let us consider the interior solutions where harvest and number of fish in each age classes remain nonzero. Let H_t denote the period *t* total harvest. With λ_{at}, $a = 1,\ldots,A$, $t = 0,1,\ldots$ as the Lagrangian multipliers the Lagrangian (*L*) function and the first order necessary conditions for optimal solutions where:

$$L = \sum_{t=0}^{\infty} \rho^t \left\{ \begin{aligned} & \frac{1}{1-\eta} H_t^{1-\eta} + \lambda_{1t}\left[r(X_{0t}) - X_{0,t+1} \right] \\ & + \sum_{a=1}^{A-2} \lambda_{a+1,t} \left[b_a (1-\varphi_a E_t) X_{at} - X_{a+1,t+1} \right] \\ & + \lambda_{At} \left[b_{A-1}(1-\varphi_{A-1}E_t) X_{A-1,t} + b_A (1-\varphi_A E_t) X_{At} - X_{A,t+1} \right] \end{aligned} \right\}, \tag{3}$$

$$\frac{\rho^{-t}\partial L}{\partial E_t} = H_t^{1-\eta} E_t^{-1} - \sum_{a=1}^{A-1} \lambda_{a+1,t} b_a \varphi_a X_{a,t} - \lambda_{At} b_A \varphi_A X_{At} = 0 \tag{4a}$$

$$\frac{\rho^{-t}\partial L}{\partial X_{1,t+1}} = \rho\left[H_{t+1}^{\;\;1-\eta} X_{1,t+1}^{\;\;-1} + \lambda_{1,t+1} r'(X_{0,t+1}) + \lambda_{2,t+1} b_1 (1-\varphi_1 E_t)\right] = \lambda_{1t}, \tag{4b}$$

$$\frac{\rho^{-t}\partial L}{\partial X_{a+1,t+1}} = \rho\begin{bmatrix} H_{t+1}^{\;\;1-\eta} X_{a+1,t+1}^{\;\;-1} + \lambda_{1,t+1} r'(X_{0,t+1}) \\ +\lambda_{a+2,t+1} b_{a+1}(1-\varphi_{a+1} E_{t+1}) \end{bmatrix} = \lambda_{a+1,t},\ a = 1,\ldots,A-2 \tag{4c}$$

$$\frac{\rho^{-t}\partial L}{\partial X_{A,t+1}} = \rho\begin{bmatrix} H_{t+1}^{\;\;1-\eta} X_{A,t+1}^{\;\;-1} + \lambda_{1,t+1} r'(X_{0,t+1}) \\ +\lambda_{A,t+1} b_A (1-\varphi_A E_{t+1}) \end{bmatrix} = \lambda_{A,t}, \tag{4d}$$

Equation (4a) states that for an optimal effort level, marginal net benefits of applying the effort level must equal the aggregate opportunity cost of decreasing the stock. These were obtained by calculating the aggregate marginal effect of increasing effort on the age-structured stock valued at shadow prices λ_{at}. The rest three equations show that the shadow value of a fish in each age class is composed of each period marginal utility from harvest, the positive effect on recruitment and the positive effect of the number of fish in the next age class.

Natural mortality of herring is not constant, but mainly influenced by the size of the cod stock, which is the major predator on juvenile herring. To account for fluctuations in the abundance of the cod stock, we used a linear regression of natural mortality on cod stock size (for each herring age-class separately) to predict natural mortality from future trajectories of cod stock development. Scenarios of future cod stock fate were taken from BALMAR predictions (Lindegren *et al*. 2009) using $F_{Management}$-Scenarios.

Competition with the sprat stock was modelled by including a herring weight-at-age function being dependant on sprat stock size (optional). Sprat stock size was also taken from BALMAR predictions as used for cod biomass. The relationship was estimated by a simple linear regression for each herring age-class (Casini *et al*., 2006), resulting in decreasing herring weights at increasing sprat stock size.

We used temperature-dependant stock-recruitment functions as estimated in this meeting (central Baltic herring) and derived from Cardinale *et al*. 2009. For Gulf of Riga herring, SSB and sea surface temperature in May was used as predictors in a non-density dependent model, while SSB and surface temperature in August was used in a density-dependent recruitment model of central Baltic herring.

Optimal management was calculated for 2 future climate scenarios: A2 and B2. During the meeting of WKCSMPB (ICES 2009b) 1000 trajectories of sea surface temperature in August were calculated for each climate scenario. These temperature trajectories are the same used as input in the BALMAR predictions, which delivered cod and sprat biomass time-series used as input in our modelling approach. We used the mean of these 1000 iterations as input in the optimization model. Input parameters for the two herring stocks investigated are given in Table 8.2 and 8.3.

Table 8.2. Input data for central Baltic herring (MBH), average values for 2000–2009 were calculated from values taken from the 2010 Assessment report (ICES 2010); price data was taken from Finnish Statistics Yearbooks (Producer Prices for Fish 2004–2009).

Parameter	Unit								
		Age1	Age2	Age3	Age4	Age5	Age6	Age7	Age8
weight-at-age	Kg	0.012	0.020	0.026	0.030	0.035	0.040	0.045	0.052
catchabilities		0.27	0.48	0.67	0.89	0.97	1.00	1.00	1.00
Proportion mature		0.00	0.70	0.90	1.00	1.00	1.00	1.00	1.00
price	€*kg^{-1}	0.12	0.12	0.13	0.13	0.24	0.24	0.40	0.42
Initial stock numbers	10^6	12425	9610	5315	3663	1253	1646	1591	773

Table 8.3. Input data for Gulf of Riga herring (GOR), average values for 2000–2009 were calculated from values taken from the 2010 Assessment report (ICES 2010), price data was taken from Finnish Statistics Yearbooks (Producer Prices for Fish 2004–2009).

Parameter	Unit								
		Age1	Age2	Age3	Age4	Age5	Age6	Age7	Age8
Natural mortality		0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
weight-at-age	kg	0.010	0.014	0.018	0.021	0.024	0.025	0.028	0.029
catchabilities		0.29	0.66	0.82	0.93	0.98	1.00	1.00	1.00
Proportion mature		0.00	0.93	0.98	0.98	1.00	1.00	1.00	1.00
price	€ *kg^{-1}	0.125	0.125	0.125	0.125	0.133	0.133	0.133	0.133
Initial stock numbers	10^6	2767	3488	716	1726	377	59	286	82

In order to determine the optimal management of Baltic herring, we numerically solved the optimization problem for each setting. The dynamic optimization was performed using the interior-point algorithm of the Knitro (version 6.0) optimization software with Matlab and AMPL.

Results - Central Baltic Herring (MBH)

Figures 8.1 to 8.6 show results from the ecological-economic model for Central Baltic Herring. A common pattern for all presented scenarios is an initial drop in F to values well below the current state (as estimated by the official assessment) and a subsequent increase. The main reason for this pattern is the currently low level of the stock. Thus it is more beneficial to wait with the harvest until the stock has recovered. Within the model, the objective function is non-linear. Thus the model is adverse against large year-to-year changes in catch, and a zero catch for the initial years, which would be intuitive, is avoided.

Another general pattern is that for most scenarios a relatively stable equilibrium in F, SSB, yield, and profit is reached about the year 2020. However, under climate change scenarios, all values show a slightly increasing tendency even after 2020. This is due to the fact that the stock-recruit relationship used is strongly temperature driven: Recruitment and associated stock growth is positively correlated to the temperature and thus anticipated temperature increase in the climate change scenarios is expected to support stock productivity.

Optimal catch depends on the discount rate. As reference case for MBH, the A2 climate scenario and a reasonable interest rate of 7% was chosen (Figure 8.1). Over the period of 2008–2033 the SSB of MBH grows from roughly 600 thousand tonnes to nearly 1.5 million tonnes. Accordingly, the profits increase from near zero to ~ 40 million Euros. Please be aware of the fact that the profit is dependent on the price and costs within the model. At the moment we used the best available data, but still the numbers should be seen as qualitative indicators rather than absolute quantitative values. A low interest rate (in this case 0%; Figure 8.2) will lead to lower catch in the beginning of the predictions and higher recovery of the stock (~1.7 million tons SSB). Medium-term profits will, however, not be lower. The opposite will happen if the interest rate is higher (14%; Figure 8.3). At even higher interest rates it will become more and more rational to fish as much as possible today, as the interest rate will be higher than the growth potential of the stock. Overall, the results are relatively stable concerning variations in interest rate in a reasonable range of values.

Temperature increase is less in the climate scenario B2 compared to A2. Accordingly, optimal fishing mortality, SSB, yield, recruitment and profit are somewhat lower (Figure 8.4).

In the model setups discussed so far, weight-at-age of herring is <u>not</u> dependant on sprat stock biomass. However, Casini *et al*. (2006) have shown that there is a string density dependence effect of sprat biomass on herring growth. When implementing their functional relationship for herring weight-at-age being dependant on sprat stock biomass, model results are considerably higher in terms of herring SSB (~2 million tons), and associated recruitment, yield and profit (~80 million Euro; Figure 8.5).

A sensitivity analysis concerning the impact of different constant temperatures on optimal herring management is presented in Figures 8.7–8.9. Optimal management outcomes range from decreasing trends in SSB, yield and profit (Figure 8.7) to increasing trends (Figure 8.9) over a temperature range of only 2°C (sea surface temperature in August).

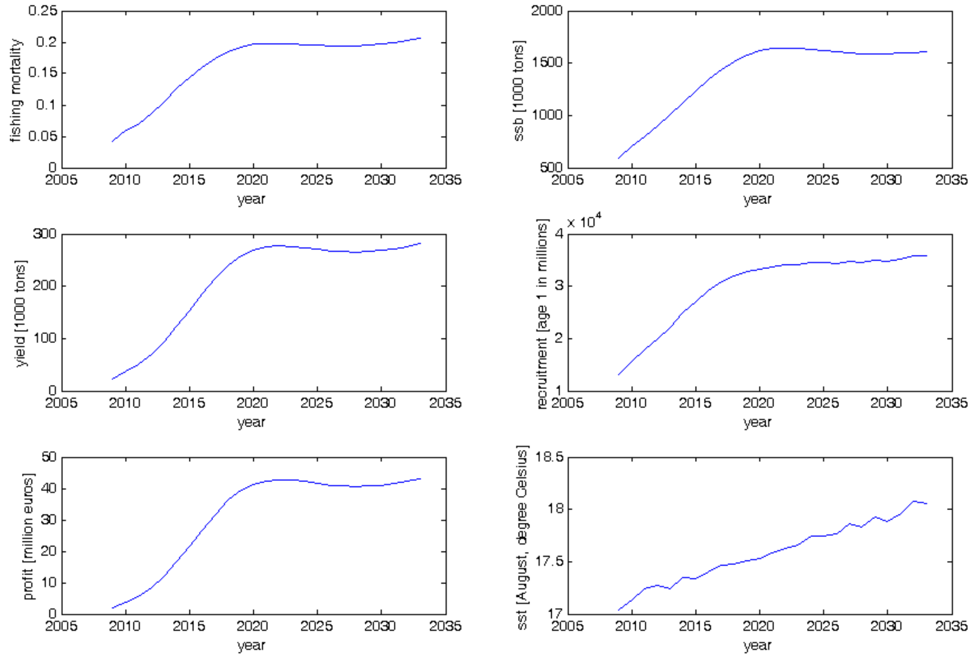


Figure 8.1. Main Baltic Herring (MBH), temperature scenario A2, 7% discount rate.

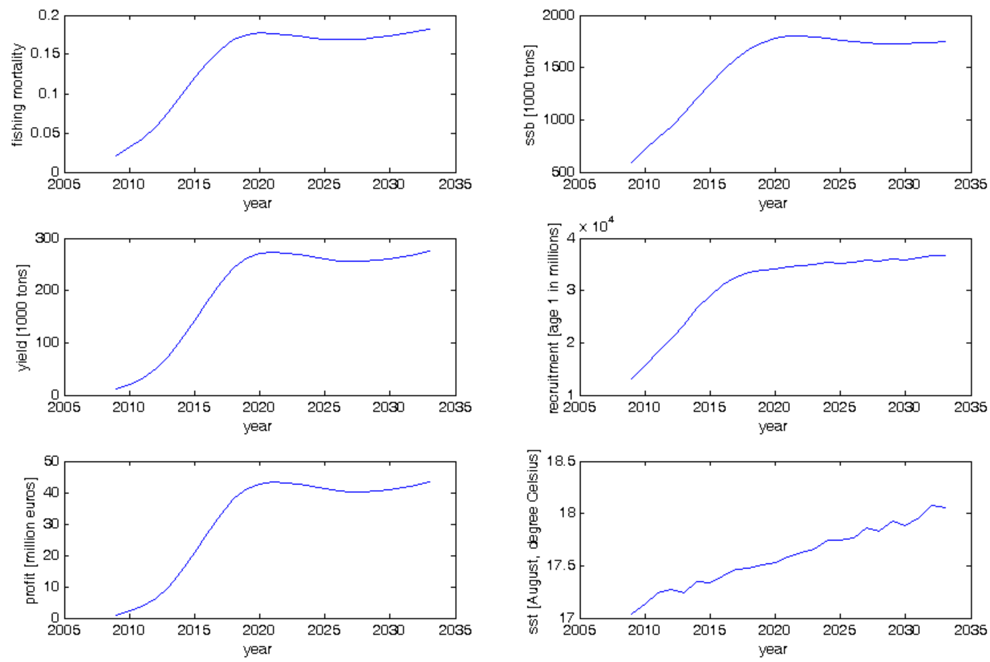


Figure 8.2. Main Baltic Herring (MBH), temperature scenario A2, 0% discount rate.

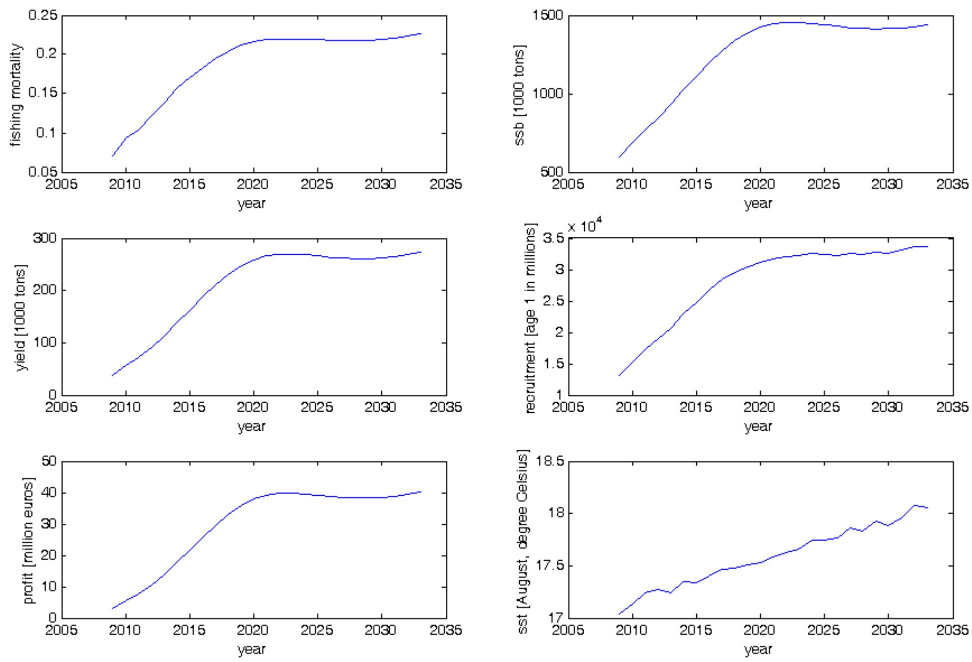


Figure 8.3. Main Baltic Herring (MBH), temperature scenario A2, 14% discount rate.

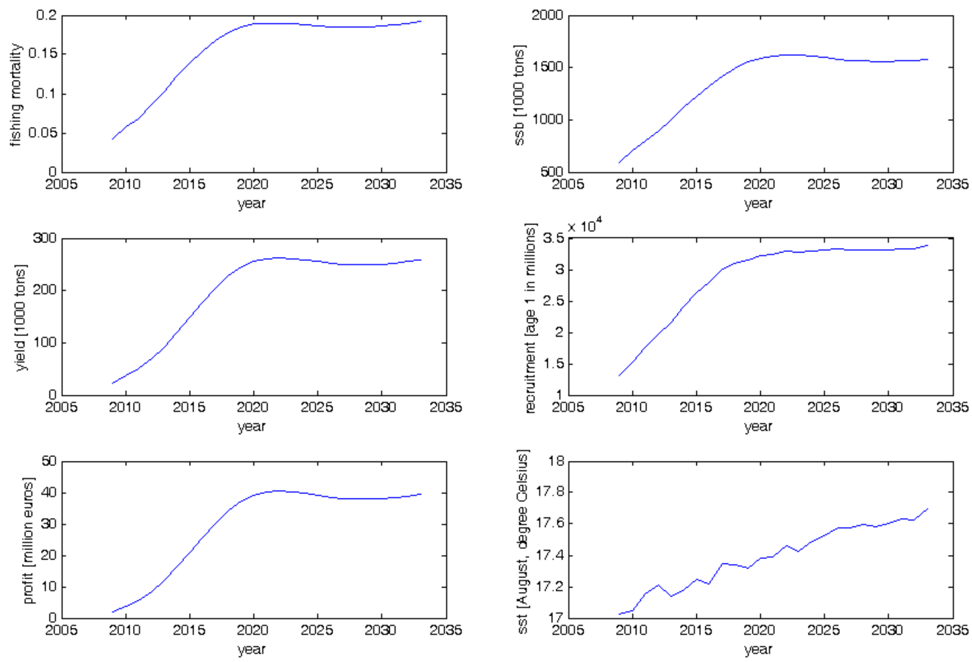


Figure 8.4. Main Baltic Herring (MBH), temperature scenario B2, 7% discount rate.

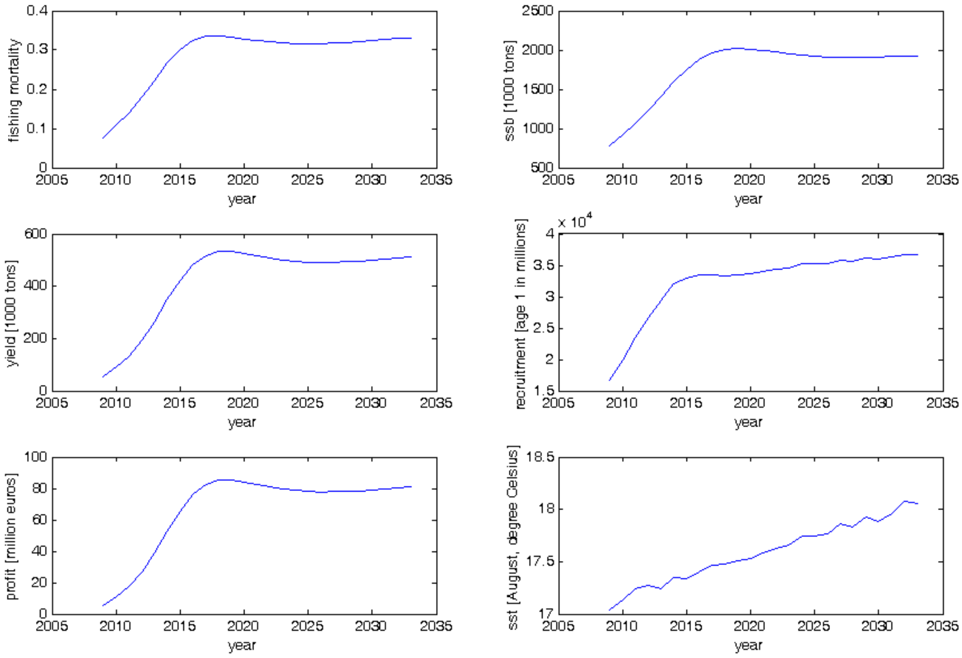


Figure 8.5. Main Baltic Herring (MBH), temperature scenario A2, 7% discount rate, herring weight-at-age dependant on sprat stock.

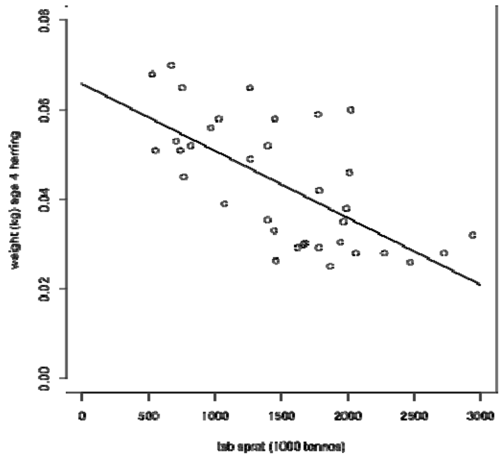


Figure 8.6. Weight of age 4 herring vs. Sprat stock biomass from 1974–2009, r^2=0.43.

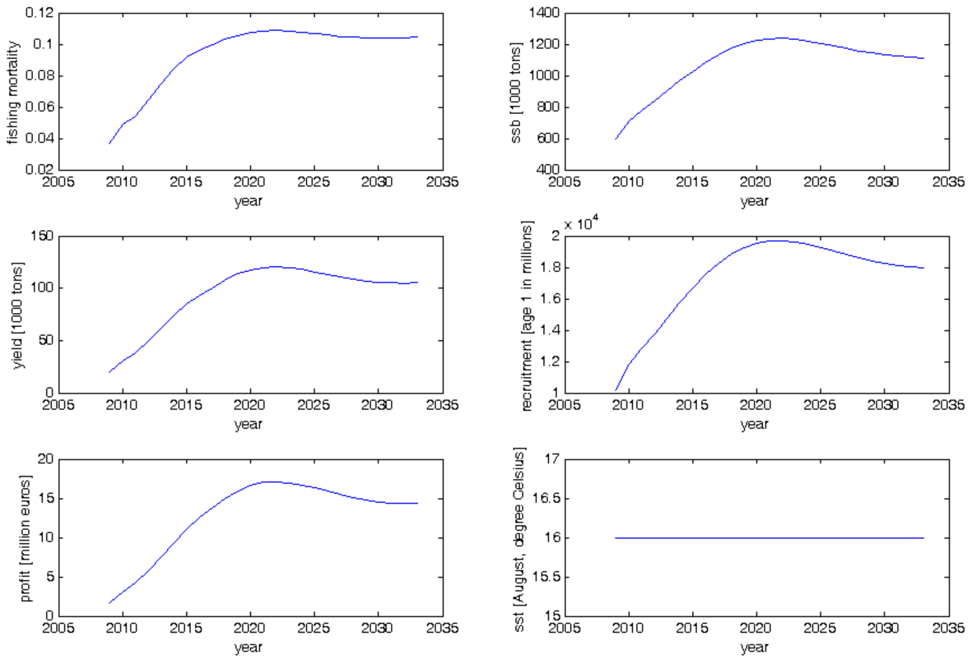


Figure 8.7. Main Baltic Herring (MBH), constant temperature 16°C, 7% discount rate.

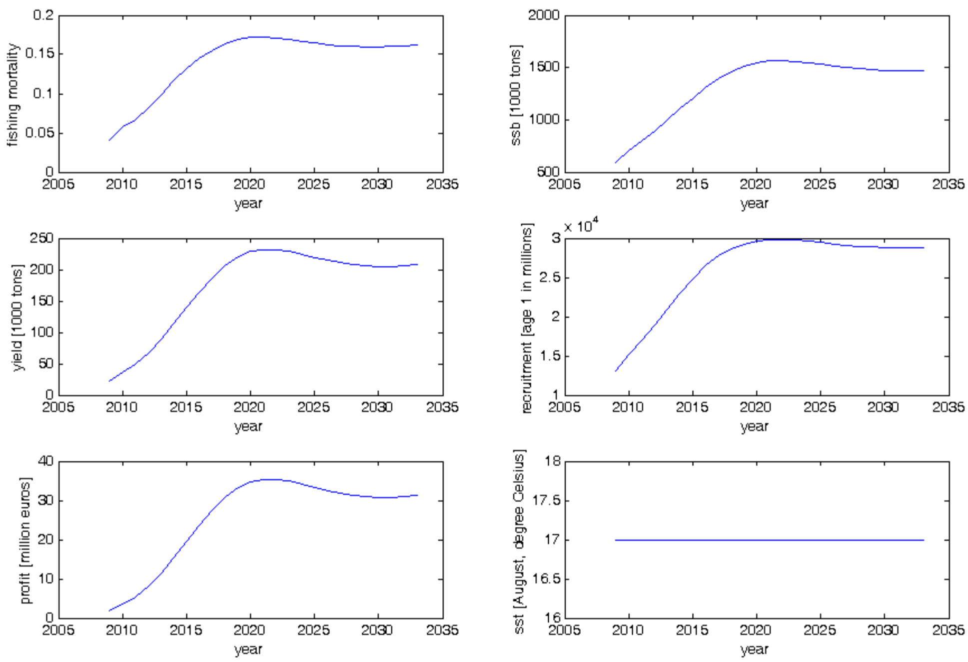


Figure 8.8. Main Baltic Herring (MBH), constant temperature 17°C, 7% discount rate.

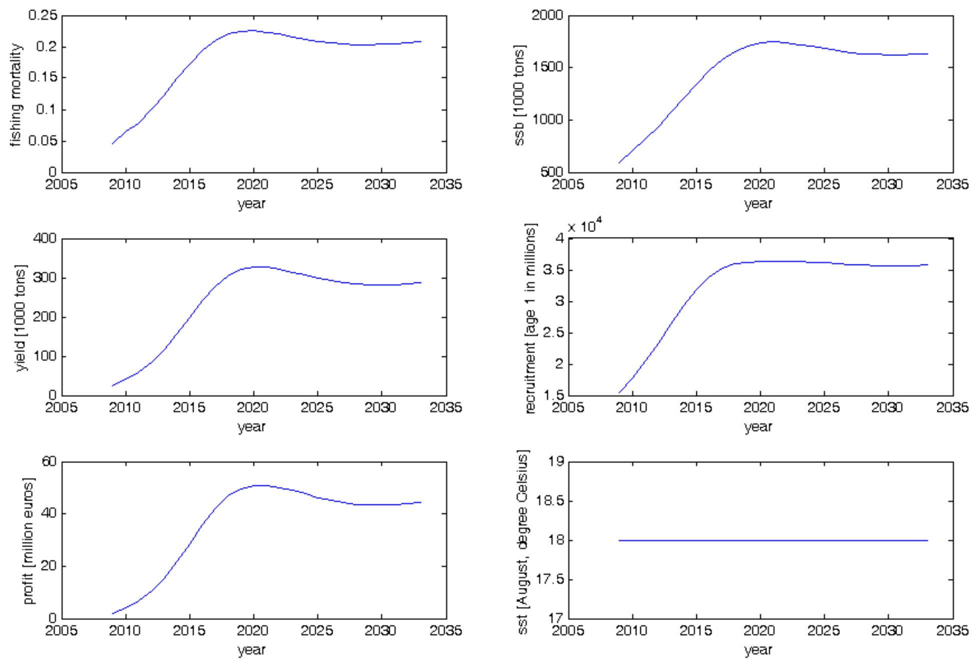


Figure 8.9. Main Baltic Herring (MBH), constant temperature 18°C, 7% discount rate.

Results - Gulf of Riga Herring (GRH)

Figures 8.10 to 8.13 show results from the ecological-economic model for Gulf of Riga Herring. As for MBH, a common pattern for all presented scenarios is the initial drop in F and the subsequent increase. The main reason for this pattern is the non-density dependent S/R-relationship. Under such an assumption, it will in most cases (i.e. for any reasonable rate of interest) be more beneficial to build up the stock and benefit from constantly increasing recruitment numbers. The non-linear objective function leads to non-zero catches for the initial years, which would otherwise be intuitive.

Another general pattern seen is that no equilibrium in the biomass is reached. This is due to the fact that the stock-recruit relationship used has no density- dependence. Thus it is economically optimal to let the stock grow to produce higher recruitment each year. Stock growth (driven by recruitment) is positively correlated to the temperature and thus anticipated temperature increase in the climate change scenarios is expected to support this trend.

Recruitment is even stronger improved under a high temperature regime. This leads to increasing biomass even under high interest rate scenarios. The terminal spawning stock biomass is higher than the expected carrying capacity for GRH (used here: 180 000 tonnes). These results are expected to be highly unrealistic and illustrate the need to incorporate density-dependence in stock-recruitment models, even if the model fit to historical data might be somewhat lower.

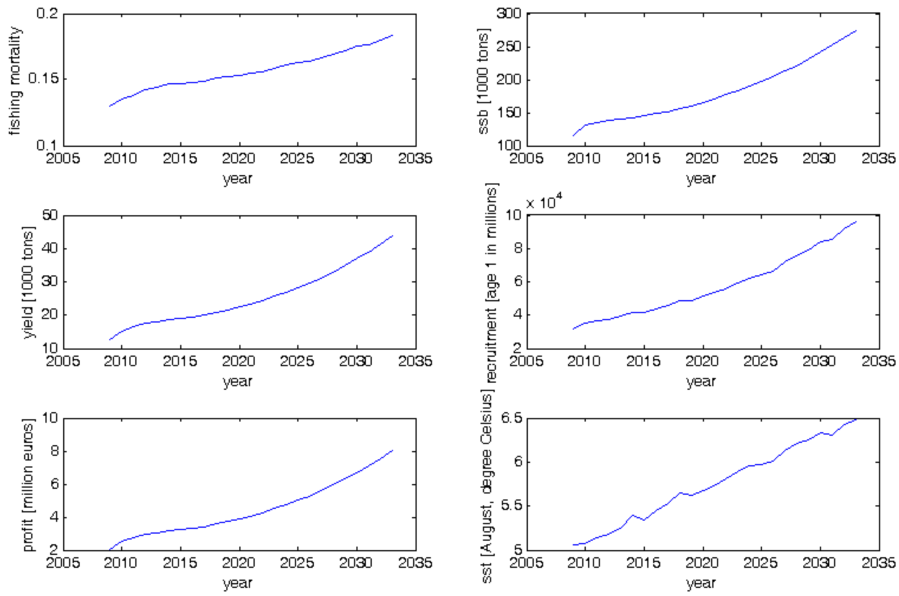


Figure 8.10. Gulf of Riga Herring (GRH), temperature scenario A2, 7% discount rate.

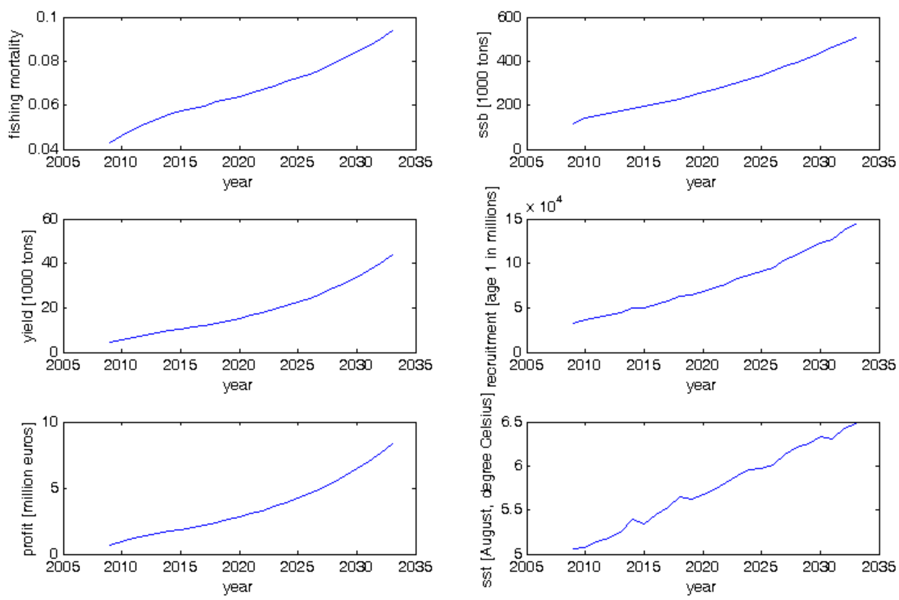


Figure 8.11. Gulf of Riga Herring (GRH), temperature scenario A2, 0% discount rate.

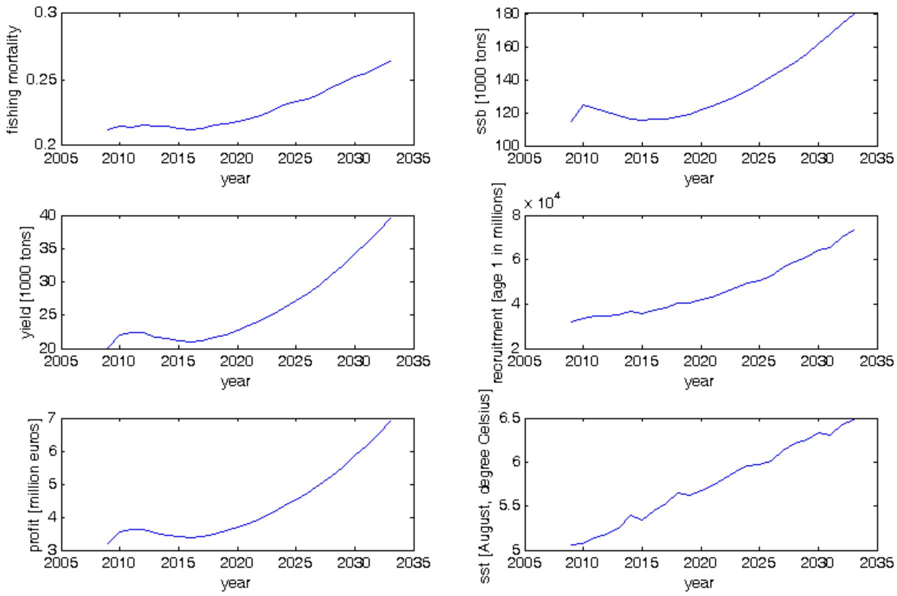


Figure 8.12. Gulf of Riga Herring (GRH), temperature scenario A2, 14% discount rate.

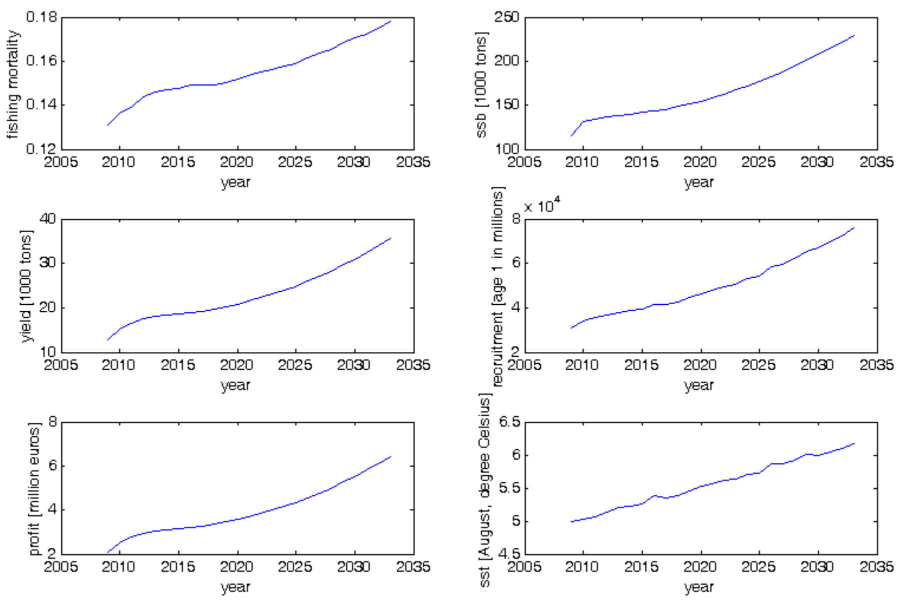


Figure 8.13. Gulf of Riga Herring (GRH), temperature scenario B2, 7% discount rate.

Outlook

Modelling approaches like the one presented here obviously can be improved. The ecologically most important advancement would be to formulate a density-dependant, environmentally-sensitive stock-recruitment relationship for the Gulf of Riga stock. Results on unrealistic high optimal stock sizes are mainly triggered by the absence of such density dependence, and biological sensible carrying capacities should be agreed for the different herring stocks. Furthermore, analysis of additional regional herring stocks would be worthwhile. Basic biological input data is available, but environmentally-sensitive stock-recruitment relationships are missing, e.g. for western Baltic herring or the stock inhabiting the Bothnian Sea.

From the economic point of view, better cost and price data are needed. Prices are so far not dependant on catch levels, which is to some degree unrealistic. Specific cost functions would be needed for different fleets (or metiers) targeting the herring stocks. This would enable us to perform better impact assessments, even on a regional scale. Unfortunately, such data is currently not available.

9 Conclusions and recommendations

In all the scenarios both spawning stock biomass and recruitment showed a clear relationships with fishing intensity. Marked increase in the estimated abundances of adults and recruits of herring were expected for all the scenarios with more or less accentuated patterns according to the associated climate scenario. The positive effect of sea surface temperature and herring recruitment in the Central Baltic resulted in a moderately positive trend in the herring stock trajectories also under elevated fishing mortality. However, density-dependent response was evident only for low fishing mortality levels (F_{msy}), when herring population reached large biomasses. The herring population oscillated around low values for the whole 40 years projections only in the scenario with combined no climate change and high fishing intensity.

The ecological-economic model used in this study used the same input parameters as the other models used in this workshop, but also included cost and price estimates. The aim was to optimize the net revenue and to see which F and SSB would be obtained in the long run. The results of the modeling exercise for MBH show long-term equilibrium F obtaining maximum profits to be slightly below the value currently suggested to be long-term F (ICES 2009a). The actual level of F in this model with environmental sensitive, i.e. mainly temperature, stock-recruit relationship is highly dependent on the temperature development, showing a drop of 0.1 from 0.2 to 0.1 in F if temperature was kept constant at 18°C and 16°C respectively. Accordingly, expected climate-driven temperature increase would result in concurrently rising optimal F values. The results for GRH show clearly that a density dependent stock-recruit model is needed, as otherwise the SSB would steadily increase.

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Annex 2: Agenda

Ponza, Italy, 5 to 8 October 2010

Monday 4/10/10

Arrival and arrangements in the Hotel Ortensia

Tusday 5/10/10

0930 – 1030	Practical information, Introduction to the Workshop and Discussion of the Agenda (*Piotr Margonski & Max Cardinale*)
1030 – 1100	Coffee & Tea
1100 – 1300	Presentations:
	Updating of the stock assessment data (*Jörn*)
1300 – 1430	Lunch
1430 – 1600	Discussion of group work and forming of sub-groups

Potential sub-groups

1) Reviewing and updating the developed recruitment models (*Valerio, Piotr*)

2) Creating the successful environmentally-sensitive sprat recruitment model (*Piotr, George*)

3) Including bio-economic consideration into the environmental and climate driven recruitment predictions (*Jörn, Max*)

1600 – 1630	Coffee & Tea
1630 – 1900	Work in subgroups cont.
2000 -	Dinner

Wednesday 6/10/10

0900 – 1045	Work in subgroups
1045 – 1100	Coffee & Tea
1100 – 1300	Work in subgroups cont.
1300 – 1415	Lunch
1415 – 1530	Plenary: 1st summary of the state of the sub-groups
1530 – 1600	Coffee & Tea
1600 – 1700	Work in subgroups cont.

Thursday 7/10/10

0900 – 1045	Plenary: Review of the statistical analyses and the forecast modelling
1045 – 1100	Coffee & Tea
1100 – 1300	Work in subgroups cont
1300 – 1415	Lunch
1415 – 1530	Plenary: Summarizing results of subgroups; decision on structure and contents of the report

1530 – 1600	Coffee & Tea
1600 – 1700	report writing and (if needed) additional work in subgroups

Friday 8/10/10

0900 – 1045	Plenary: Wash-up
1045 – 1100	Coffee & Tea
1100 – 1300	Report writing
1300	closure of workshop
1400	Transport to the harbour for those catching the 1430 ferry to Formia

Annex 3: Overview table on data series used in the final recruitment models

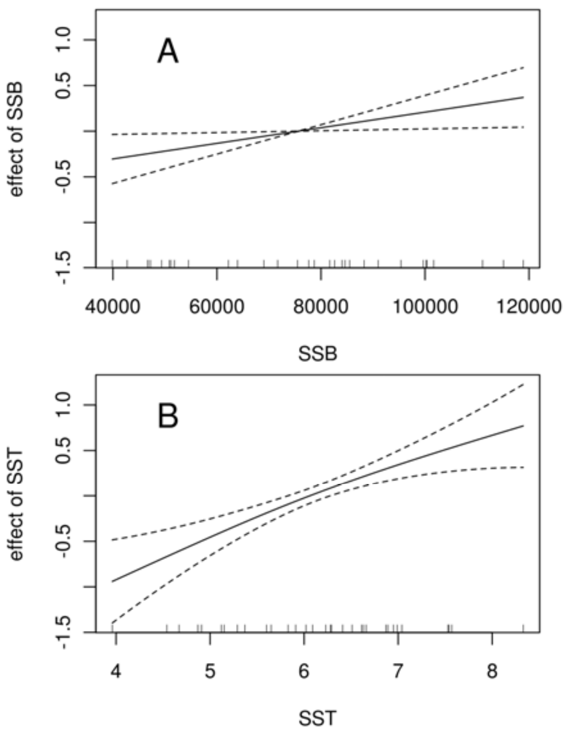
Stock area	Stock acronymous	Variable	Variable acronymus	Source
ICES SD 25-29 & 32 exl.GOR	MBH	Sea Surface Temperature August	NASA8	www.cdc.noaa.gov
Gulf of Riga ICES SD 28.1	GRH	Sea Surface Temperature May	NASA5	www.cdc.noaa.gov
SD 22-32	BS	Baltic depth anomaly	BDA	Baumann et al. 2006
SD 25-29 & 32 exl.GOR	MBH	Spawning stock biomass	SSB	ICES 2010
Gulf of Riga ICES SD 28.1	GRH	Spawning stock biomass	SSB	ICES 2010
SD 22-32	BS	Spawning stock biomass	SSB	ICES 2010
ICES SD 25-29 & 32 exl.GOR	MBH	Recruitment age at 1	R1	ICES 2010
Gulf of Riga ICES SD 28.1	GRH	Recruitment age at 1	R1	ICES 2010
SD 22-32	BS	Recruitment age at 1	R1	ICES 2010

Annex 4: Statistical output of the final recruitment models

Gulf of Riga Herring

GAM model

```
Family: Gamma         Link function: log
Formula: RECR ~ s(SSB) + s(NASA5)
Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 14.71492    0.07576   194.2   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Approximate significance of smooth terms:
           edf Ref.df      F  p-value
s(SSB)   1.000  1.000  5.143 0.031067 *
s(NASA5) 1.389  1.691 13.485 0.000151 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.392   Deviance explained = 57.6%
GCV score = 0.20544  Scale est. = 0.18368   n = 32
```



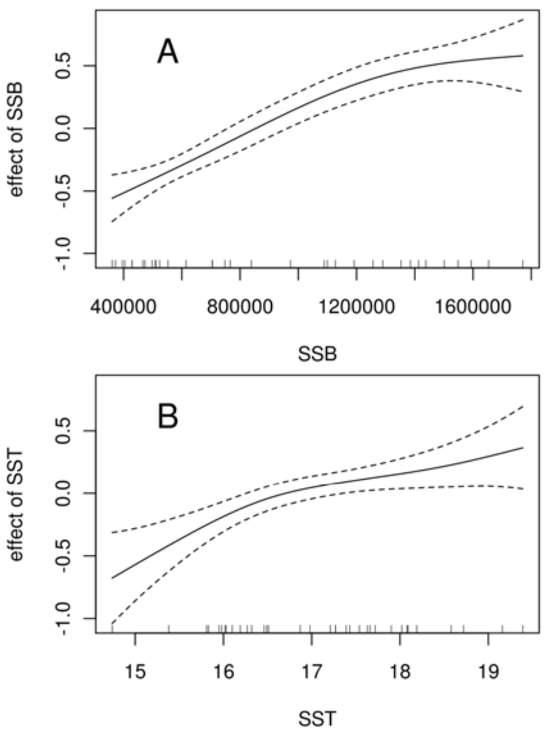
Linear model

```
Call:
glm(formula = RECR ~ SSB + SSB.sq + NASA5 + NASA5.sq,
family = Gamma(link = "log"), data = dat)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.06216  -0.25523  -0.09497   0.14935   0.79451

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  7.152e+00  2.469e+00   2.897  0.00738 **
SSB          3.743e-05  2.773e-05   1.350  0.18832
SSB.sq      -1.867e-10  1.740e-10  -1.073  0.29283
NASA5        1.607e+00  7.623e-01   2.108  0.04447 *
NASA5.sq    -1.027e-01  6.185e-02  -1.661  0.10828
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
(Dispersion parameter for Gamma family taken to be
0.1696257)
    Null deviance: 12.3935  on 31  degrees of freedom
Residual deviance:  4.8351  on 27  degrees of freedom
AIC: 979.64
Number of Fisher Scoring iterations: 6
```

Central Baltic Herring (SD25–29&32 excl. Gulf of Riga)

GAM model

```
Family: Gamma   Link function: log
Formula:   RECR ~ s(SSB, k = 4) + s(NASA8)
Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 16.61208    0.04187   396.7   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
           edf Ref.df      F  p-value
s(SSB)   2.119  2.519 23.691 1.69e-07 ***
s(NASA8) 2.421  3.044  5.915  0.00266 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.645   Deviance explained = 71.6%
GCV score = 0.072903  Scale est. = 0.061363  n = 35
```



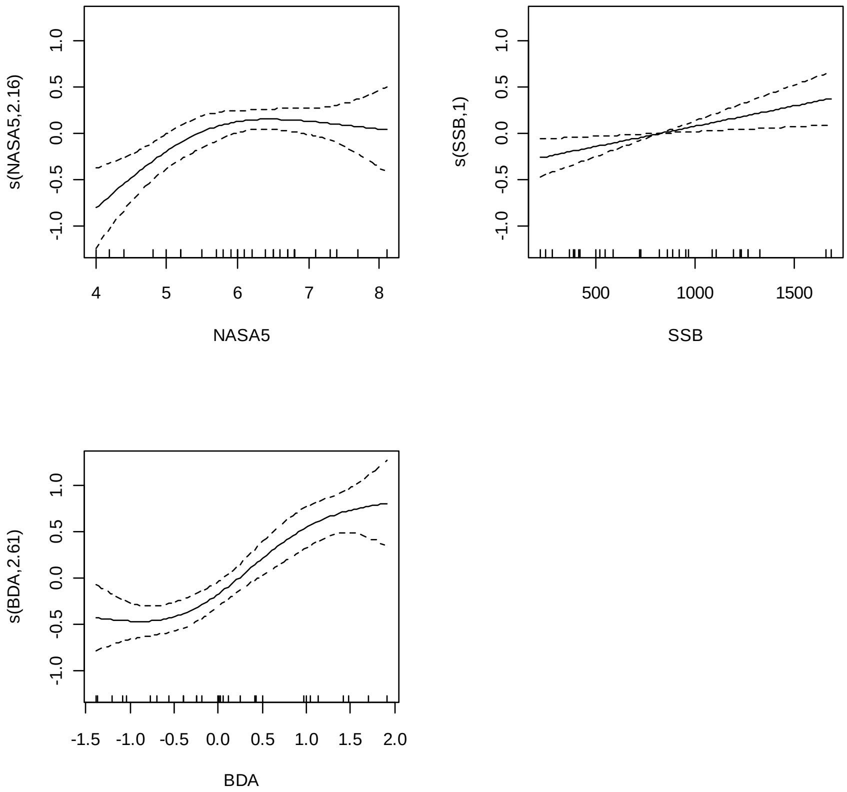
Linear model

```
Call:
glm(formula = RECR ~ SSB + SSB.sq + NASA8 + NASA8.sq,
family = Gamma(link = "log"), data = dat)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.57608  -0.13425  -0.02777   0.06598   0.52998

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.045e+00  9.547e+00  -0.110   0.9135
SSB          2.056e-06  6.840e-07   3.006   0.0053 **
SSB.sq      -5.621e-13  3.276e-13  -1.716   0.0965 .
NASA8        1.721e+00  1.117e+00   1.541   0.1339
NASA8.sq    -4.446e-02  3.260e-02  -1.364   0.1827
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1

(Dispersion parameter for Gamma family taken to be
0.07070321)

    Null deviance: 6.3564  on 34  degrees of freedom
Residual deviance: 2.0118  on 30  degrees of freedom
AIC: 1172.7

Number of Fisher Scoring iterations: 5
```

Sprat (SD 22–32)

GAM model

```
Family: Gamma     Link function: log

Formula: R ~ s(NASA5, k = 4) + s(SSB, k = 4) + s(BDA, k = 4)

Parametric coefficients:

            Estimate Std. Error t value Pr(>|t|)
(Intercept) 11.11957    0.06431   172.9   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:

           edf Ref.df      F  p-value
s(NASA5) 2.155  2.524  6.166  0.00447 **
s(SSB)   1.000  1.000  6.844  0.01537 *
s(BDA)   2.608  2.879 14.598 1.76e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.651   Deviance explained = 79.2%
GCV score = 0.16017  Scale est. = 0.12406   n = 30
```



Linear model

```
Call:
lm(formula = LN_R ~ LN_SSB + NASA5 + I(NASA5^2) + BDA +
I(BDA^2) +
    I(BDA^3), data = dat2)
Residuals:
     Min       1Q   Median       3Q      Max
-0.77629 -0.18887 -0.03867  0.20543  0.52011
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.97721    1.99651   1.491 0.149495
LN_SSB       0.32454    0.12686   2.558 0.017573 *
NASA5        1.82463    0.67564   2.701 0.012762 *
I(NASA5^2)  -0.13928    0.05608  -2.483 0.020740 *
BDA          0.78993    0.17204   4.592 0.000129 ***
I(BDA^2)     0.18415    0.09072   2.030 0.054104 .
I(BDA^3)    -0.20218    0.09073  -2.228 0.035912 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.3529 on 23 degrees of freedom
Multiple R-squared: 0.8048,     Adjusted R-squared: 0.7539
F-statistic: 15.81 on 6 and 23 DF,  p-value: 3.934e-07
```