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Report of the Workshop on Combining Climatic Scenarios and Medium-Term Predictions for Baltic Herring and Sprat stocks (WKCSMPB)

13–16 October 2009

Ponza, Italy

ICES International Council for the Exploration of the Sea

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Executive summary

The direct and indirect effects of density dependence (i.e. parental stock effects) and climate-induced hydrographic change on five different Baltic herring stocks and on Baltic sprat, investigated by WKHRPB and WKSSRB (ICES 2007b and 2008) to develop stock specific recruitment-environment relationships, were revisited and updated. The predictors to be included in the final recruitment models were selected on the basis of the parsimonious principle, statistical significance of the predictors and the ecological criterion being fulfilled simultaneously (Cardinale *et al.* 2009).

In previous work, temperature was detected to be an important predictor for several stocks of clupeids. Weight at age (WAA) was the major factor explaining recruitment for Main Basin herring (MBH) while spawning stock biomass (SSB) was important for Baltic sprat (BS) and Gulf of Riga herring (GRH). For MBH, food supply was also a significant predictor, suggesting that a part of the changes in climate and hydrographic conditions may affect herring indirectly via prey availability. The best recruitment model for Baltic sprat (BS) linked recruitment success to its spawning stock biomass (SSB), sea surface temperature in August (NASA8), predation mortality by cod (PM), and Bottom Depth Anomaly (BDA) which is a proxy of drift/retention of sprat larvae (ICES 2008).

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).

The results show that in the next 30 years recruitment of herring stocks will generally increase or stay relatively stable at values observed in the last decade for any of the scenarios considered. This is likely to be mainly an effect of a predicted increase in SST. On the other hand, the effect of SSB is small for MBH mainly due to the narrow range of predicted SSB values over the next 3 decades. In the case of GRH, a similar pattern was observed although the increase in recruitment is not as large as for MBH. For sprat, a satisfactory model was not found for predicting recruitment and further analysis are needed.

1 Opening of the meeting and adoption of agenda

2008/2/BCC03 An ICES/BSRP Workshop on Combining Climatic Scenarios and Medium-Term Predictions for Baltic Herring [WKCSMPB] (Chair: M. Cardinale, Sweden and P. Margonski, Poland) will meet in Ponza, Italy from 13–16 October 2009 to:

a) review and validate the developed recruitment models using sensitivity analyses;

b) test different climatic scenarios in the medium-term predictions;

c) explore combining of medium-term predictions of clupeids with density dependent effects and climate scenarios.

WKCSMPB will report by 09 November 2009 for the attention of SCICOM.

The Co-Chairs Max Cardinale and Piotr Margoński welcomed the participants (Annex 1) and introduced the agenda (Annex 2) for the workshop. Main objectives were clearly identified by the Terms of Reference adopted by the Council.

The agenda proposed by the co-chairs was discussed and accepted by the participants. The first day was devoted to presentations provided by participants and plenary discussions on statistical analyses and work plan. Three subgroups were created: data updating and reviewing of the knowledge about the impact of climate change on the Baltic Sea ecosystem, statistical analyses and recruitment modelling, and recruitment prediction with environmental variables and density dependent effects. During the following days participants were working in sub-groups. Plenary sessions were organised daily to present workshop progress and discuss achieved results.

2 Introduction

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 2007b and 2008). A number of hydroclimatic 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 2007b 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 (WAA_{3+}) or SSB remained in the model after the model selection process (i.e. WAA_{3+} 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.

Data for modelling was updated up to 2007. As no satisfactory final model was found for WBH, BSH and BBH stocks (Cardinale *et al.* 2009), the final recruitment models provided by Cardinale *et al.* (2009) were tested with updated data series only for MBH and GRH. Further, as the main aim was to include climatic scenario for recruitment predictions, recruitment was used for all stocks instead of the recruitment success used in the original model. Also, for the Baltic sprat stock, the final model developed during the last workshop (WKSSRB; ICES 2008) was tested using set of explanatory variables selected during WKSSRB, but using recruitment as response variable instead of recruitment success.

3 Presentations given by participants

The presentations given during the first day of the meeting covered (i) Updating of the data used for modelling recruiment and presentation of the plan for the statistical analysis, (ii) presentation and selection of the most relevant climatic scenario for the Baltic Sea (iii) presentation of the BALMAR model as an useful tool for modelling of the stock response to selected climatic scenarios, and (iv) plan of the statistical analyses.

Piotr Margonski presented the terms of reference adopted for the workshop that includes: reviewing and validating the recruitment models developed during the 2008 workshop; a test of the effect of different climatic scenarios for medium-term recruitmentnt predictions; and an exploration of how density dependent effects influence medium-term predictions of clupeids under different climate scenarios. Most of the data series needed for updating and validating the 2008 models were prepared prior to the meeting. To fulfil the term of reference b) a limited number of climatic scenarios will be selected. Based on ther climatic scenario chosen, the explanatory variable (i.e. sea surface temperature; SST) included in the environmentally-sensitive stock recruitment models will be predicted. Changes of sprat and herring SSB due to selected climatic scenarios will be generated by using the BALMAR model (Lindegren *et al.* 2009). There are, however, some variables (e.g.

Bottom Depth Anomaly, BDA) for which predictions will be difficult to obtain and methods of how to deal with these variables were discussed and agreed during the meeting.

Hans Linderholm, in collaboration with David Ryner, University of Gothenburg, presented climate scenarios for the Baltic Sea for the 21st century. When assessing future ecosyetem responses to climate change on a local to regional level, the use of outputs from global climate models (GCMs) are unsuitable. This is due to the low resolution in these large-scale models. To overcome this scale problem, regional climate models (RCMs) are used. These are used to downscale results from GCMs to achieve a higher spatial resolution over a specific region. Thus, using outputs from a Swedish RCM, an extension of Baltic Sea SSTs to 2100 based on two different emission cenarios from the fourth assessment report from IPCC (IPCC 2007); B2 (low emission scenario) and A2 (high emission scenario), were presented. Together with a control scenario (no climate change): These SST series were to be used in modelling of future fish-stock recruitment.

Martin Lindgren presented his work derived from the recent paper (Lindgren *et al.* 2009). Good decision making for fisheries and marine ecosystems requires a capacity to anticipate the consequences of management under different scenarios of climate change. The necessary ecological forecasting requires ecosystem-based models capable of integrating multiple drivers across trophic levels and properly including uncertainty. The methodology presented during the WKCSMPB workshop assesses the combined impacts of climate and fishing on marine food-web dynamics and provides estimates of the confidence envelope of the forecasts. It is applied to cod (*Gadus morhua*) in the Baltic Sea, which is vulnerable to climate-related decline in salinity due to both direct and indirect effects (i.e., through species interactions) on early-life survival. A stochastic food web-model (BALMAR; Lindegren *et al.* 2009) driven by regional climate scenarios (Meier 2006, Meier *et al.* 2006, BACC 2007) is used to produce quantitative forecasts of cod dynamics in the 21st century. The forecasts show how exploitation would have to be adjusted in order to achieve sustainable management under different climate scenarios.

4 Overview of the updated data for fitting recruitment models

4.1 Input data for Main Basin Herring (MBH), gulf of Riga herring (GRH) and 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 section.

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).

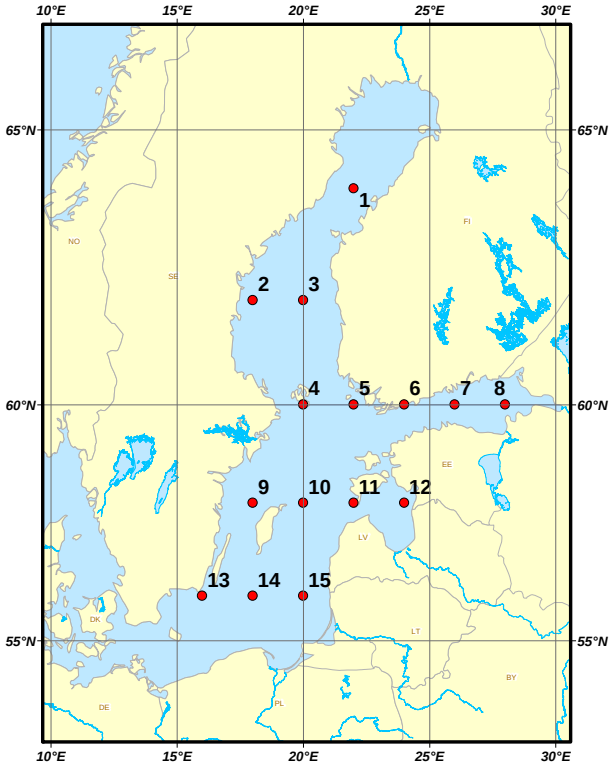


Figure 4.1.1. Central points of 2x2 degree grid of NASA SST measurements used for recruitment analyses (http://www.cdc.noaa.gov/cdc/data.noaa.ersst.html, file: sst.mnmean.nc)

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.).

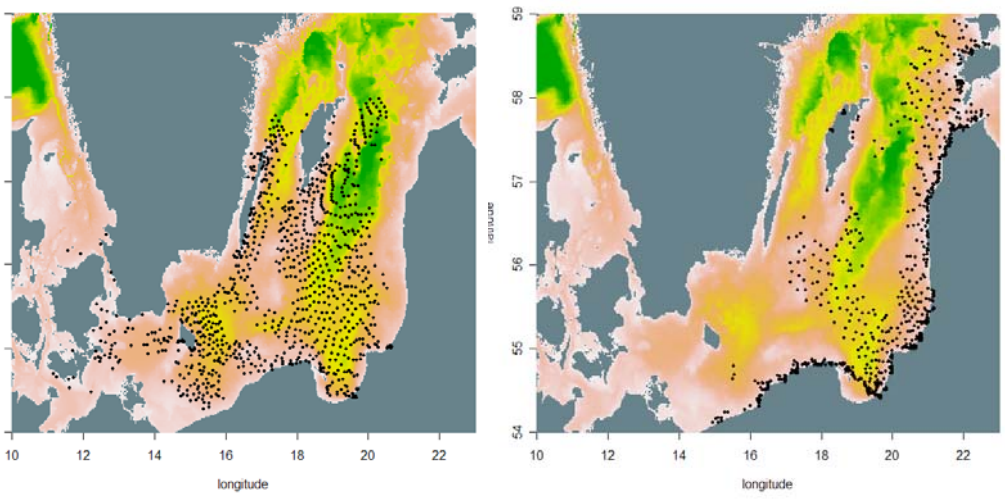


Figure 4.1.2. Two different scenarios of particle drift. Left: retention (2003 data), Right: dispersion (2005 data)

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.

Therefore, a new data series (1999–2007) was calculated using an operational hydrodynamical model operated by the Bundesamt für Seeschifffahrt und Hydrographie (www.bsh.de). It was shown by Baumann *et al.* (2006) that simulations starting at day 190 each year (and lasting 50 days) have the highest correlation to recruitment. Therefore, the same settings were used for calculations of the new data series.

Since, the underlying model changed, some changes in particle tracking had to be implemented. The most important one was the need to reduce the number of drifters released into the model domain (see Figure 4.1.3.). For the new data series, 1000 particles (compared to 2671 in the simulation by Baumann *et al.* (2006)) were distributed over all areas with water depth deeper than 40m and south of 58.12°N.

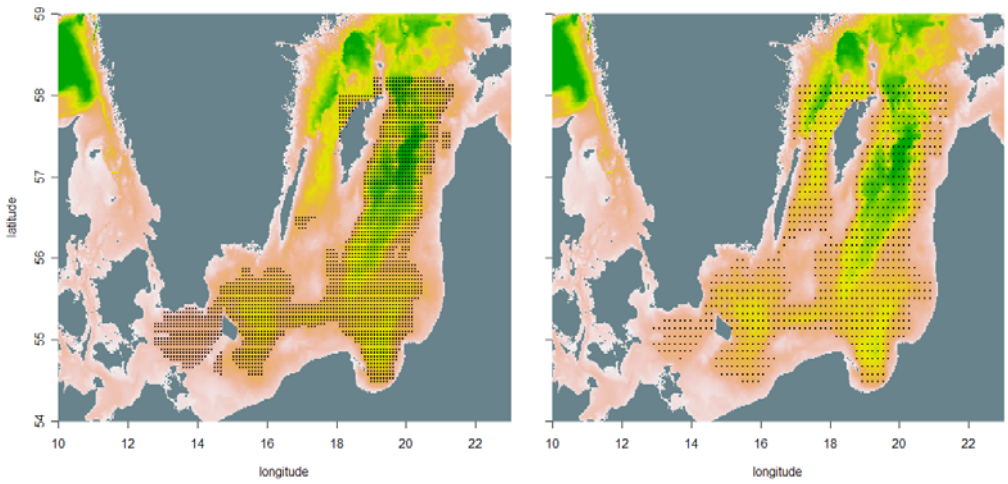


Figure 4.1.3. Comparison of release grid as used by Baumann *et al.* 2006 (left) and the new drift simulations (right)

Slight problems occurred, since the BDA is calculated as index over all model years, which might be somehow tricky when combining two different data series (1976 to 1999 and 2000 to 2007). Nevertheless, both data series were combined by averaging results (mean bottom depth per day of the simulation) of overlapping years prior to the calculation of the BDA.

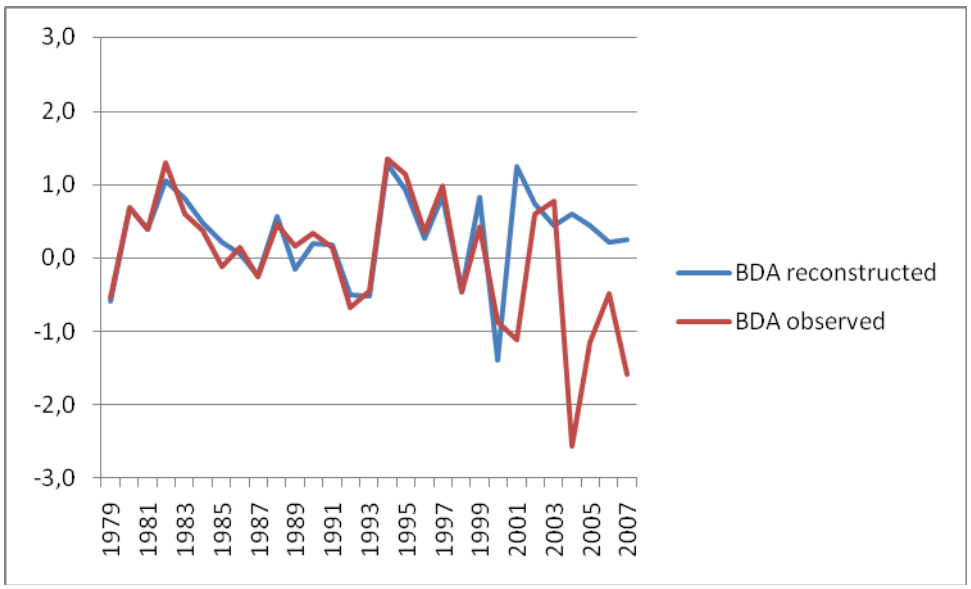


Figure 4.1.4. Comparison between observed (red) and modeled (blue) BDA. The modeled BDA was on a calibrated over the 1979-1999 period.

As explained above, in order to extend the BDA index, a new data series from 1999-2007 was calculated using a operational hydrodynamical model operated by the Bundesamt für Seeschifffahrt und Hyrdographie (www.bsh.de). The two records were combined by averaging results of overlapping years (see ICES 2008). However, a visual inspection of the BDA time series (Figure 4.1.4.) suggests a difference in trend as well as variance from 1999 and onwards. To assess if the time series can be regarded as homogenous, an attempt to reconstruct the BDA from independent data was made. The BDA takes into account the change of bottom depth under modelled drifters and possibly this is related to atmospheric forcing of the surface water. The BDA was compared to a set of regional atmospheric circulation indices developed for the Nordic region by Chen (2000), based on the geostrophic wind and vorticity over a selected area. We used the following three circulation indices: u and v, which are westerly (zonal) and southerly (meridional) components of the geostrophic wind, and ξ that is the total shear vorticity. The geostrophic wind is an ideal surface wind representing transport of heat through air, while the vorticity describes strength of circular movement, i.e. high or low pressure systems. A more detailed definition of these indices is given in Chen (2000).

A stepwise multiple regression model was chosen to predict BDA (response) using monthly circulation indices (predictors). The criterion used to include an index in the model was the 95% confidence level. If a particular circulation index was not significant at the 95% level according to an F-test, it was excluded. Significant predictors were retained for the final BDA model.

The final model, explaining 91% of the variance of the observed BDA, is:

BDA = 0,40+(0,03*vFeb)-(0,05*ξMar)+(0,03*ξJun)-(0,05*ξJul)–(0,03*ξAug)–(0,06*vNov)+(0,06*vDec)

However, as seen in figure 4.1.4. there is a clear divergence between the records from 2000, which is when the two different BDA data series were previously merged together. Thus, assuming that the reconstructed BDA is plausible throughout the record, it may be concluded that the two records are not fully compatible and that they

may not fully represent the same feature. Provided that the reconstructed BDA is temporarily stable, it may be wiser to extend the old BDA index until the compatibility of the two observed records can be established.

In an attempt to predict the Bottom Depth Anomaly time series into the future according to the selected climatic scenarios, the BDA data were correlated with climate indices for which it might be possible to obtain forward predictions: winter severity index (SI), Baltic Sea Index (BSI), ice cover index (IC) and NASA sea surface temperature monthly averages. No significant correlation was, however, found. Therefore, to resemble the historical range of variability in BDA, future conditions were simulated based on the mean, variance, and autocorrelation structure of the observed time series, using a first order autoregressive (AR(1)) model as described by Ripa and Lundberg (1996).

Nevertheless, due to divergence between the Bottom Depth Anomaly (BDA) index developed by Baumann *et al.* (2006) and extended during WKSSRB to 2007 and the BDA predicted using monthly circulation indices, we decided to use BDA up to 1999 as it represents a homogenous time series in the way the BDA is calculated.

4.2 Stock specific data

Gulf of Riga Herring

SSB increased sharply from the middle of the 1980s and decreased from the end of the 1990s to the latest years. Recruitment of Gulf of Riga herring increased starting from 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.).

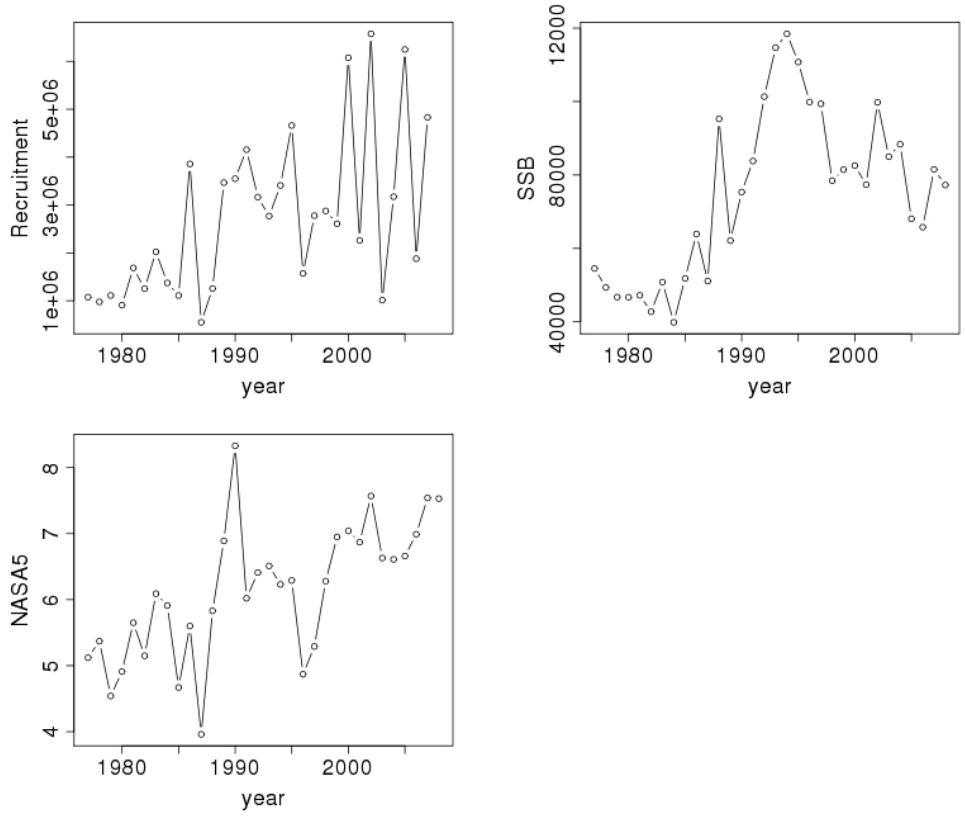


Figure 4.2.1. Biotic and abiotic time-series used in the Gulf of Riga herring final models.

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. The August sea surface temperature (NASA 8) increased significantly over the last 20 years, while winter NAO index did not show any particular trend over the time period considered (Figure 4.2.2.).

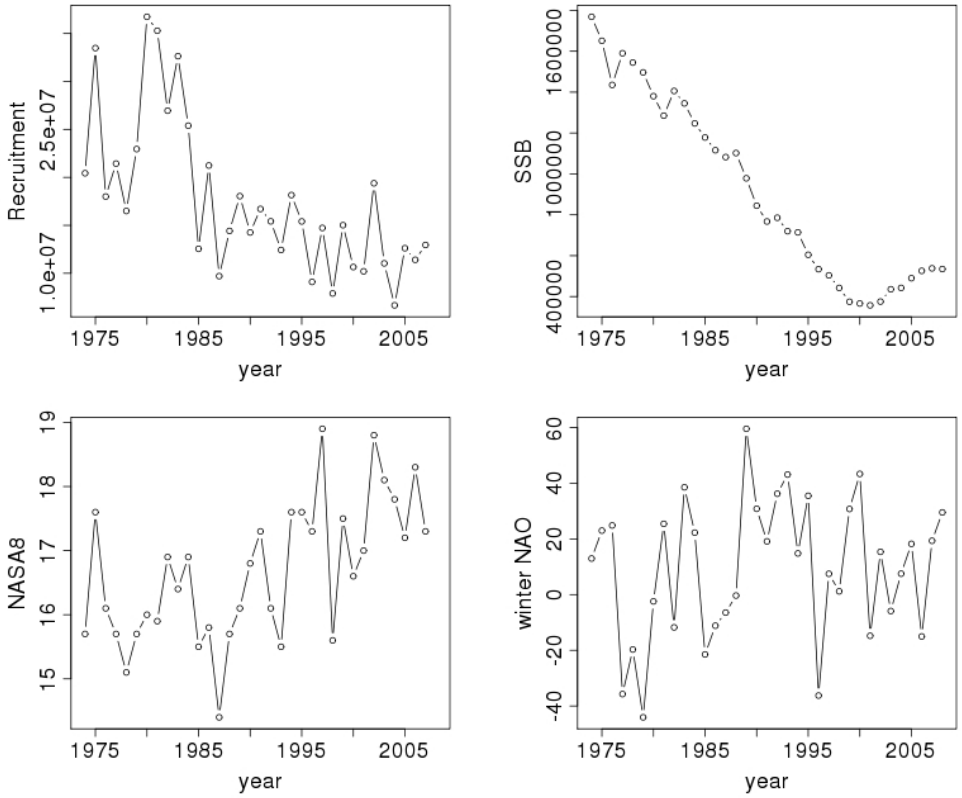


Figure 4.2.2. Biotic and abiotic time-series used in the Main Basin herring final models.

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 showed a decline from 1995 and onwards (Figure 4.2.3.) although the last part of the time series is uncertain as explained above (see chapter 4.1.1).

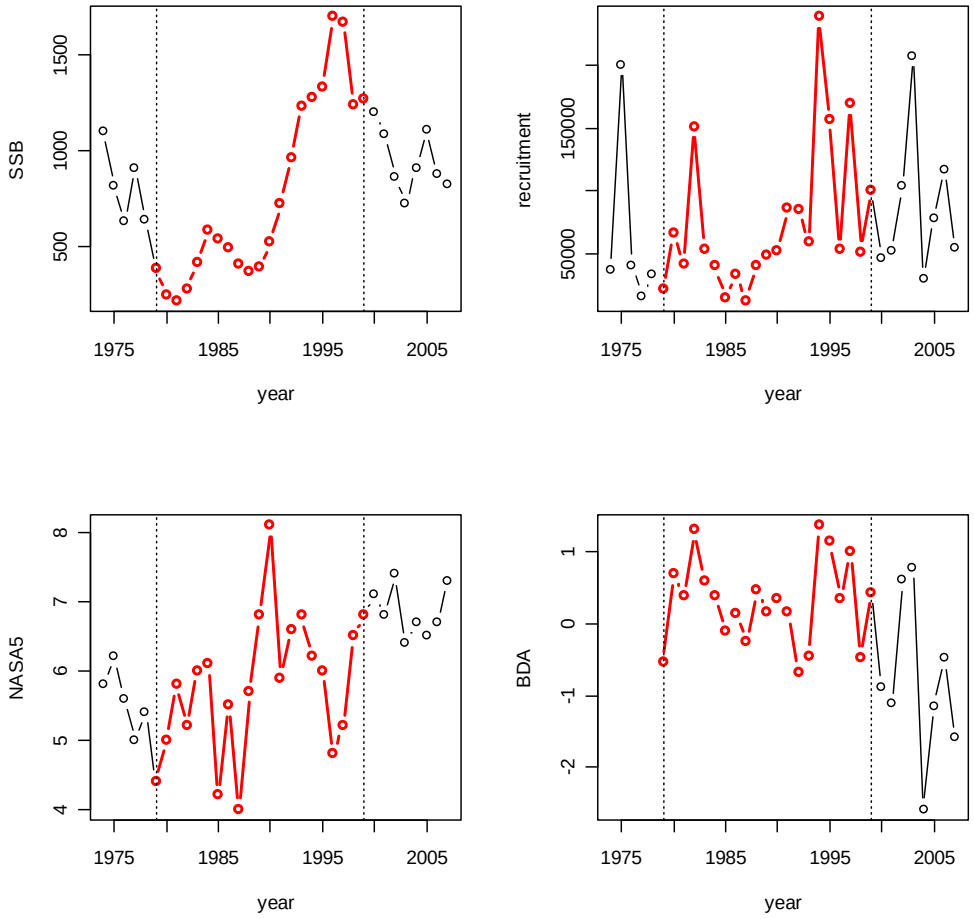
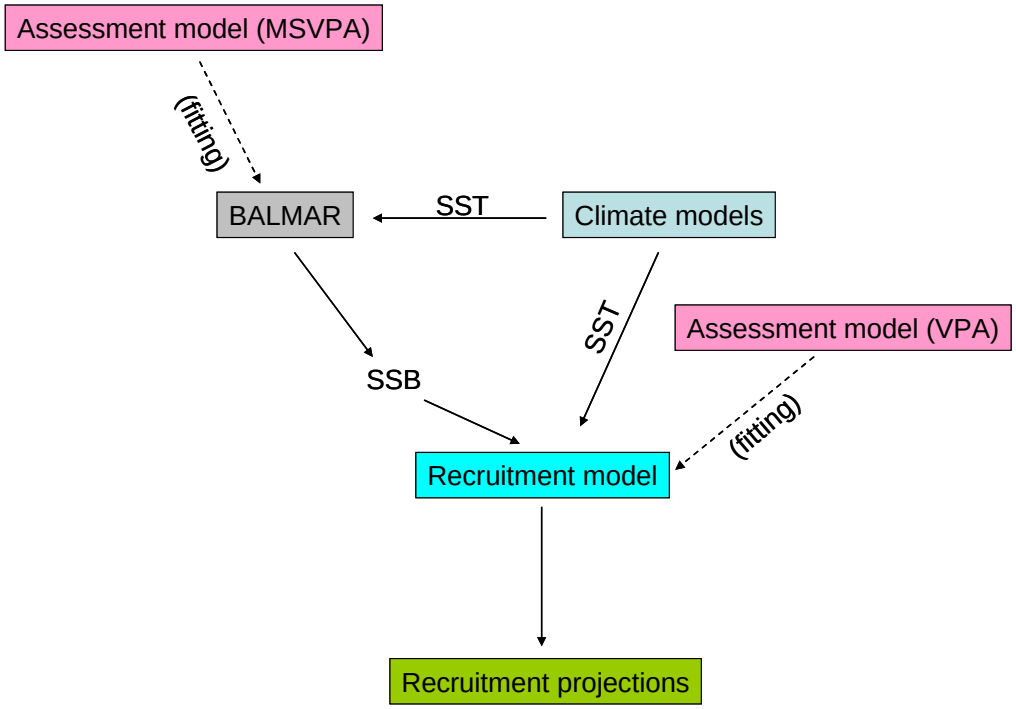


Figure 4.2.3. Sprat recruitment and explanatory variables used in the sprat final GAM model. Model has been built based on data highlighted in red.

5 Environmentally-sensitive stock-recruitment relationships

5.1 Introduction and results overview

The flowchart summarise the modelling scheme used combining climatic and fishery scenarios to predict recruitment of Main Basin herring, Gulf of Riga herring and Baltic sprat during the period from 2007 to 2040 (30 years medium term projections).



5.1.1 Assessment model (VPA and MSVPA)

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

5.1.2 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:

$$\mathbf{X}(t) = \mathbf{B}\mathbf{X}(t-1) + \mathbf{C}\mathbf{U}(t-y) + \mathbf{E}(t) \qquad \text{(Eq. 1)}$$

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

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 respec-

tively. 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).

5.1.3 Recruitment models

Two kind of models were fitted and used to predict recruitment, a GAM model as developed in Cardinale *et al.* (2009) and a linear model for all three stocks. Thus, a new model selection process was performed and final linear models were compared against the GAMs. Biological variables (SSB and recruitment) were log transformed prior to the analyses to meet model linearity assumptions. Since the main aim was to make recruitment predictions under different climate scenarios, we used recruitment instead of recruitment success for all models.

First, we included the predictors selected in the final models developed during two previous workshops (WKHRPB and WKSSRB; ICES 2007b and 2008) and those derived from Cardinale *et al.* (2009) in the initial model and then applied a backward stepwise regression based on statistical significance and generalized cross validation (GCV; Wood 2004) information criterion to find the best possible set of predictors. The least significant variable was excluded at each step of the backward stepwise regression. Further, stepwise selected predictors in the best model were screened using the ecological criterion (see Cardinale & Svedäng 2004 and Casini *et al.* 2006 for a use of the ecological criterion in model selection) as in Cardinale *et al.* (2009).

For the **Main Basin herring stock,** the final GAM model developed during WKSSRB included SSB, Weight at Age 3+ (WAA_{3+}), Baltic Sea Index, August sea surface temperature (NASA8), and spring *Pseudocalanus spp*. biomass. This GAM model explained almost 80% of deviance. Analysis of residuals confirmed no violations of normality and constancy of variance assumptions.

In the updated GAM model, BSI was substituted with winter NAO (thereafter defined as NAO) as it was significantly correlated with BSI (r^2= 0.75; $p<0.01$; n=34) since winter NAO index has the advantage that it is theoretically possible to produce a forecast to be included in future medium-term predictions for recruitment. Also, WAA_{3+} was excluded a priori as it was significantly correlated with SSB (Cardinale *et al.* 2009) and moreover SSB estimations already incorporate variability in WAA of the stock. Thus, the initial model included SSB, NAO, sea surface temperature in August (NASA8) and spring *Pseudocalanaus spp*. biomass. The final GAM model after stepwise selection included only SSB and NASA8 and explained almost 74% of the total deviance. The form of the effect of the final predictors was similar to previous final models developed in Cardinale *et al.* (2009).

The linear model was also built using the same procedure as for the GAM ones. The final linear model included NAO, SSB and SST. The model explained around 65% of the variance and showed similar effect as for the GAM model. No violation of assumptions regarding the independence, homogeneity of variance, and normality of the residuals was observed in the autocorrelation graph and the Shapiro-Wilk normality test of residuals.

For **Gulf of Riga Herring stock,** the final GAM model derived from Cardinale *et al.* 2009 included SSB and May Sea Surface Temperature (SST5). This model explained almost 80% of deviance. In the updated GAM model, May Sea Surface Temperature (SST5) was substituted with May Sea Surface Temperature derived from NASA measurements (NASA5) as in MBH and BS. Thus, the initial model included SSB and sea surface temperature in May (NASA5). The final model after stepwise selection included SSB and sea surface temperature in May (NASA5) as in the initial model and confirmed results obtained in previous workshops. The model explained about 59% of the deviance. Analysis of residuals confirmed no violations of normality and constancy of variance assumptions.

The linear model confirmed the results of the GAM model and it explained about 58% of the variance. No violation of assumptions regarding the independence, homogeneity of variance, and normality of the residuals was observed in the autocorrelation graph and the Shapiro-Wilk normality test of residuals for both models.

For **Baltic Sprat,** the final model developed during WKSSRB (ICES 2008) included SSB, Bottom Depth Anomaly, sea surface temperature in August, and predation mortality by cod. This model explained over 80% of deviance. The analysis of residuals indicated no violations of assumptions. As this model was fitted using recruitment success as response, a new model was developed for recruitment using the final predictors identified in WKSSRB (ICES 2008). Predation mortality by cod was not included as this effect is already accounted for in the BALMAR food-web model to predict changes in SSB. For the purpose of the further analyses, the optimal recruitment GAM model should include SSB, one of the SST time series from May–August period, and other independent variable which enable to explain huge year-to-year variability in sprat recruitment. Based on the previous experience (ICES, 2008) and relevant publications (Baumann *et al.* 2006), the Bottom Depth Anomaly index (BDA) was taken into account. In 2008 the updated BDA time series (1999–2007) was calculated using different hydro-dynamical model (for details see description in ICES, 2008). Unfortunately, the two BDA data series performed in slightly different way and were combined by averaging of overlapping years. This combined data was not significantly correlated with sprat recruitment. Therefore, only original BDA data (period 1979–1999) were used for further analyses. Log transformation was applied for recruitment and SSB. All the explanatory variables correlated positively with log recruitment. Subsequently co-linearity among independent variables was checked using the variance inflation factor. For all the data the VIF values were lower than 5.

There were four temperature time series (May, June, July, and August), and therefore, four different GAM models (with the maximum number of effective degrees of freedom (edf) for smoothers set to 3 and with a Gaussian distribution) were constructed with one temperature data at a time. The model with May temperature has the lowest GCV score and it was selected as the final one. It explains more than 90% of variance. 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.

For details on the model specification, see Appendix 4.

Successful linear model for sprat recruitment was not found and further analyses are needed.

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 the computer programs which are used to simulate the response of the atmosphere and oceans to increasing concentrations of greenhouse gases. However, the spatial resolution of GCMs is too coarse to be used for climate change studies on regional and local scales. This is particularly evident with the Baltic Sea, which most GCMs represent either as a bay (an extension of the North Sea) or as a lake. To overcome the scale problem, higher resolution Regional Climate Models (RCMs) are typically run for smaller areas. Presently, RCM ocean model data in the time-frame required for this project, i.e. covering the first part of the 21st century, are not available. Instead, we use a rapid assessment method, where air temperature from an RCM is used as a proxy for Baltic Sea surface temperature.

6.2 Datasets

RCM monthly-average of minimum air temperature at 2m height scenario data for 2071–2100 were obtained from the PRUDENCE project (The Prediction of Regional scenarios and Uncertainties for Defining European Climate change risks and Effects, web-site http://prudence.dmi.dk. For more details, see e.g. Christensen *et al.* 2007). The outputs we used had been generated using the Max Planck Institute ECHAM4 GCM (Roeckner *et al.*, 1999), downscaled with the Swedish Meteorological and Hydrological Institute (SMHI) RCA2 RCM (Jones *et al.*, 2004). Emission scenarios were derived from the Special Report on Emissions Scenarios (SRES) A2 (considered a high-emissions scenario) and B2 (low scenario), and using SST from 1961–1990 as a control run.

Monthly average SST time-series were derived from the 1º x 1º resolution HadISST gridded observation dataset (Rayner *et al.*, 2003). Time-series were extracted for seven grid cells that are representative of the different Baltic-Sea reaches (see Figure 6.2.1).

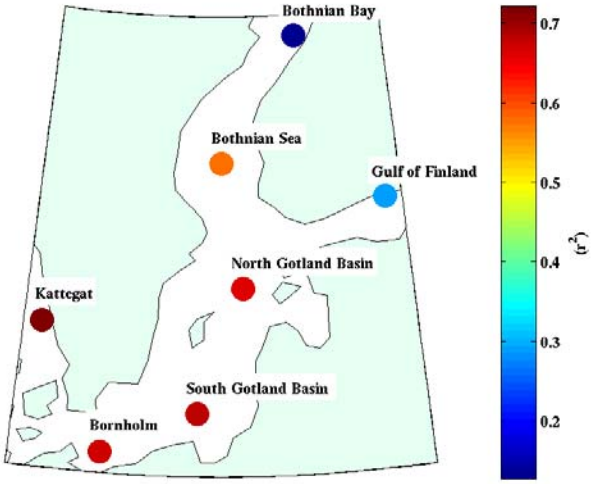


Figure 6.2.1: Correlation between seasonally-detrended SST (HadISST) and monthly average minimum air temperature (NCEP/NCAR Reanalysis).

6.3 Methods

Monthly average minimum air temperature is good proxy for SST over much of the Baltic. The seasonally-detrended correlations between the HadISST SSTs and surface temperature from the NCEP/NCAR reanalysis project are shown in Figure 6.2.1. The correlation 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.

The first step in deriving climate change scenarios was to determine the mean seasonal change in minimum air temperatures between the RCM control run and the scenario runs. The mean changes in temperature are shown in Figure 6.3.1. The changes in air temperature from the RCM were then used to statistically-downscale the observed SST time-series. The procedure was:

1) Detrend the seven HadISST monthly time-series from 1886–2000 by fitting a 3rd order polynomial. Each month-of-year for each station was detrended independently. This provided a time-series of anomalies, representing natural climate variability;

2) Use the detrended SST time-series as the anomalies for the period 1986–2100;

3) Add a linear trend time-series for each location using the change in minimum air temperatures between the RCM control run and the scenario run. For each location, the nearest RCM grid pixel was used. The changes are listed in Tables 6.3.1 and 6.3.2;

4) Adjust the climatology so that the 1986–2006 monthly means of the new time-series match the monthly means of the HadISST time-series for the same period;

5) Join the scenario time-series to the real historical time-series (at 2001), resulting in a temporally-complete time-series from 1870–2100.

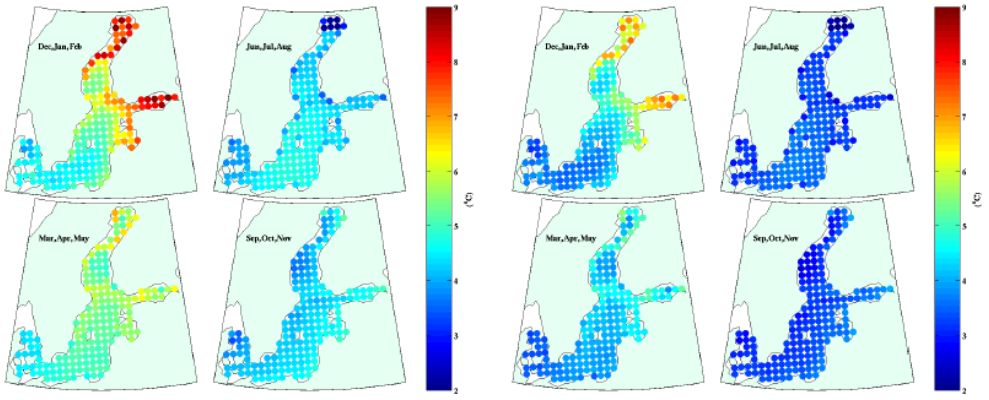


Figure 6.3.1: Change in seasonal minimum temperature 2071-2100 for (left) the SRES A2 scenario and (right) the SRES B2 scenario, relative to the control scenario 1961-1990. Plots also show the RCA2 grid resolution.

The time-series for the resulting two scenarios are shown in Figure 7.3.2.

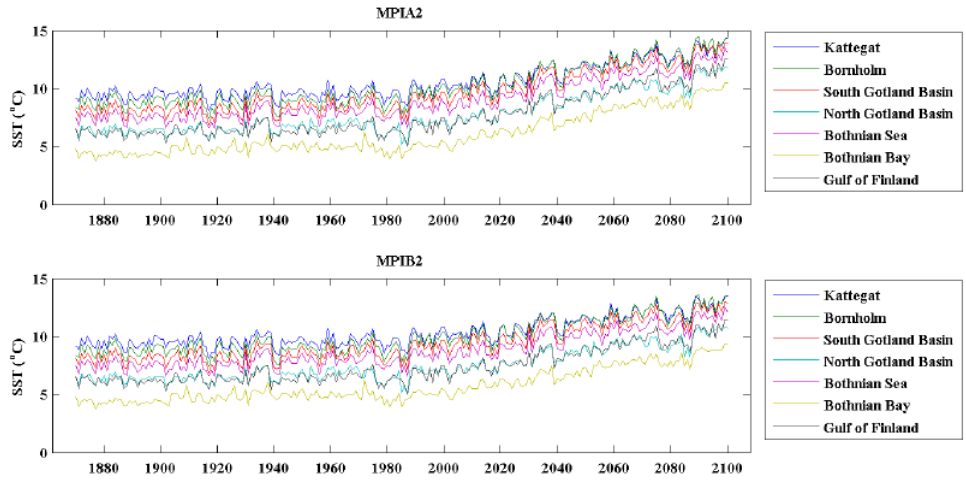


Figure 6.3.2: Downscaled annual SST time-series for the Baltic Sea for (upper) SRES A2 and (lower) SRES B2.

6.4 Discussion

This downscaling method is a simplified version of pattern-scaling (e.g. Christensen *et al.*, 2001), where spatial trends derived from a shorter, potentially high-resolution 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 as usual. However, we then 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 may be inconsistent with time-series from a 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.

Table 6.3.1: Changes in minimum air temperature, 1961–1990–2071–2100, SRES A2

	Dec,Jan,Feb	Mar,Apr,May	Jun,Jul,Aug	Sep,Oct,Nov
Kattegat	**4.1±0.3**	**4.4±0.4**	**3.92±0.22**	**3.5±0.5**
Bornholm	**4.56±0.25**	**4.8±0.3**	**4.6±0.3**	**4.4±0.5**
South Gotland Basin	**4.62±0.23**	**5.1±0.3**	**4.8±0.3**	**4.3±0.5**
North Gotland Basin	**5.15±0.30**	**5.2±0.3**	**4.7±0.4**	**4.3±0.6**
Bothnian Sea	**5.4±0.4**	**5.2±0.4**	**4.4±0.4**	**4.0±0.6**
Bothnian Bay	**7.5±0.4**	**5.2±0.4**	**4.3±0.4**	**4.3±0.7**
Gulf of Finland	**7.8±0.5**	**5.0±0.4**	**4.3±0.4**	**4.7±0.7**

Table 6.3.2: Changes in the minimum air temperature, 1961–1990 - 2071-2100, SRES B2

	Dec,Jan,Feb	Mar,Apr,May	Jun,Jul,Aug	Sep,Oct,Nov
Kattegat	**3.2±0.3**	**3.4±0.4**	**3.15±0.22**	**2.8±0.5**
Bornholm	**3.63±0.26**	**3.8±0.3**	**3.54±0.30**	**3.4±0.5**
South Gotland Basin	**3.63±0.24**	**4.0±0.3**	**3.7±0.3**	**3.3±0.5**
North Gotland Basin	**4.1±0.3**	**4.1±0.4**	**3.5±0.4**	**3.3±0.6**
Bothnian Sea	**4.4±0.4**	**4.0±0.4**	**3.4±0.4**	**3.0±0.6**
Bothnian Bay	**6.1±0.5**	**4.0±0.4**	**3.3±0.4**	**3.2±0.7**
Gulf of Finland	**6.3±0.5**	**3.8±0.4**	**3.3±0.4**	**3.7±0.7**

7 Medium term predictions of recruitment with different climatic scenarios

7.1 Introduction

The BALMAR model was used to generate predictions of SSB from 2008 to 2040 for the Main basin herring and Baltic sprat to be used into medium term predictions of recruitment. SSB predictions were generated with two different scenario of future fishing mortality: with fishing mortality as established in the management plan or F_{pa} (F=0.3, 0.19 and 0.4, for cod, herring and sprat respectively) or using the observed average historical fishing mortality (1974–2004) for each stock (0.91, 0.26, 0.27). Successively, forecast of SST were generated by the Global Climate Models (GCMs) from 2008 to 2040. Therefore, BALMAR model generated an average prediction of SSB with associated uncertainty using GCMs predicted SST. The same SST was then used to generate recruitment values from final recruitment models (both linear and GAM models). The final linear and GAM models for predicting recruitment for all stocks are presented in Appendix 4.

7.2 Results

Main Basin herring

Figures 7.1.1–7.1.7 and figures 7.1.8–7.1.14 show the forecasted recruitment for Main Basin herring stock from 2008 to 2040 using a linear and a GAM model for predicting recruitment, respectively. The SST projections show an increase in recruitment almost regardless of the climatic and fishery scenario analysed here. The reason is because SST is the main driver at the current level of SSB. Comparing the SST projections between the noGlobalWarming and A2 (most extreme) scenario (Figure 1 in Appendix 6) we can see that during the approximately 30 years of recruitment projections the

two SST scenarios are very similar (vertical dotted lines are 2005–2040) while looking on a longer time scale (up to 2100) the two SST scenarios diverge much more. This is linked to the fact that SST will keep increasing even with no further increase in CO2 as an effect of the amount CO2 already in the system. Also, although SSB decreases in A2_Fman while it does not in noCC_Fmean, it is important to note that the range of the SSB projections is rather small compared the SSB values observed between 1974 and 2008 and used to fit the recruitment model (Appendix 6, Figure 3). In conclusion our recruitment projections are driven by SST which trend is not very different across the alternative scenarios. This is not related to the fact that SSB has a small effect on recruitment, but rather by the fact that our SSB projections have a small variability compared the variability observed in the last 34 year (1974–2008). The reduced variability in SSB projections is due to maintaining fishing mortalities at fixed, status-quo levels (F_{mean}, F_{man}) in the future predictions. Given the large historical variability in F levels, future projections of SSB with the same variability in F levels would yield a much larger variability in SSB and consequently also in recruitment predictions for MBH.

Linear model

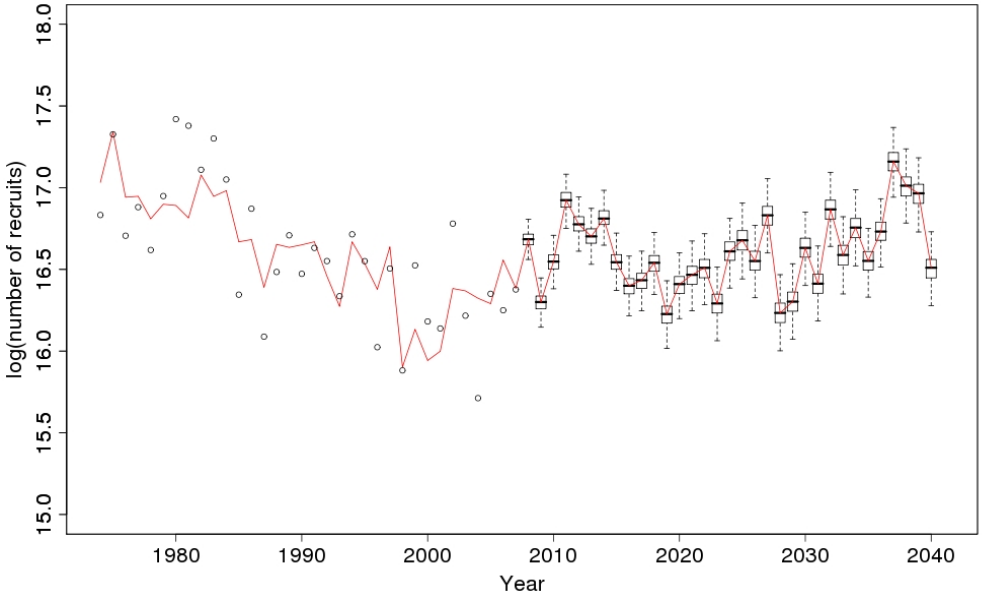


Figure 7.1.1. Recruitment (year class) medium term predictions for MBH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with BALMAR model using F as agreed in the management plans for cod, sprat and herring and assuming no increase in sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

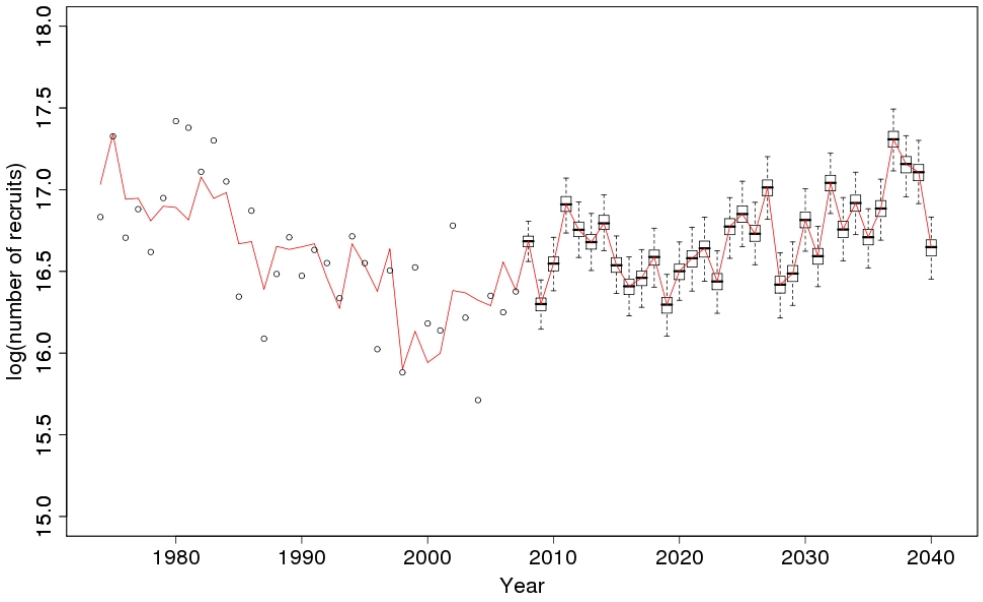


Figure 7.1.2. Recruitment (year class) medium term predictions for MBH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with BALMAR model using average historical F for cod, sprat and herring and assuming no increase in sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

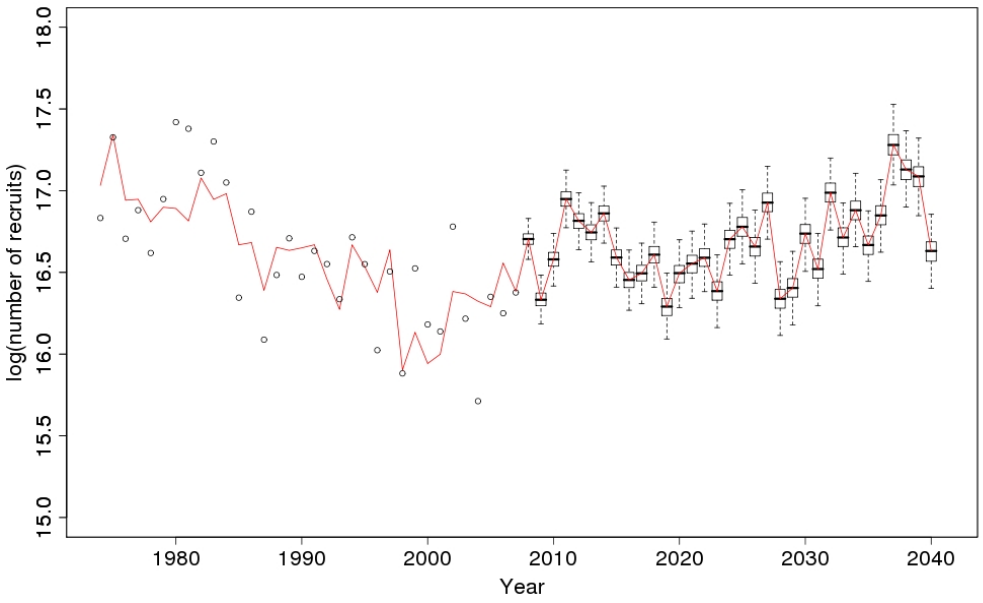


Figure 7.1.3. Recruitment (year class) medium term predictions for MBH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with BALMAR model using F as agreed in the management plans for cod, sprat and herring and assuming B2 scenario for sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

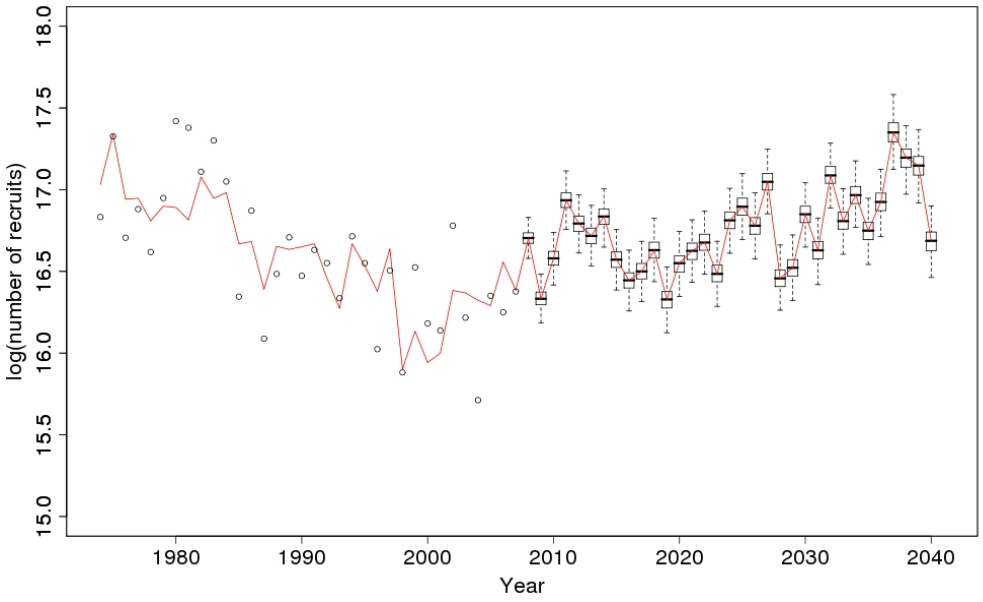


Figure 7.1.4. Recruitment (year class) medium term predictions for MBH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with BALMAR model using average historical F for cod, sprat and herring and assuming B2 scenario for sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

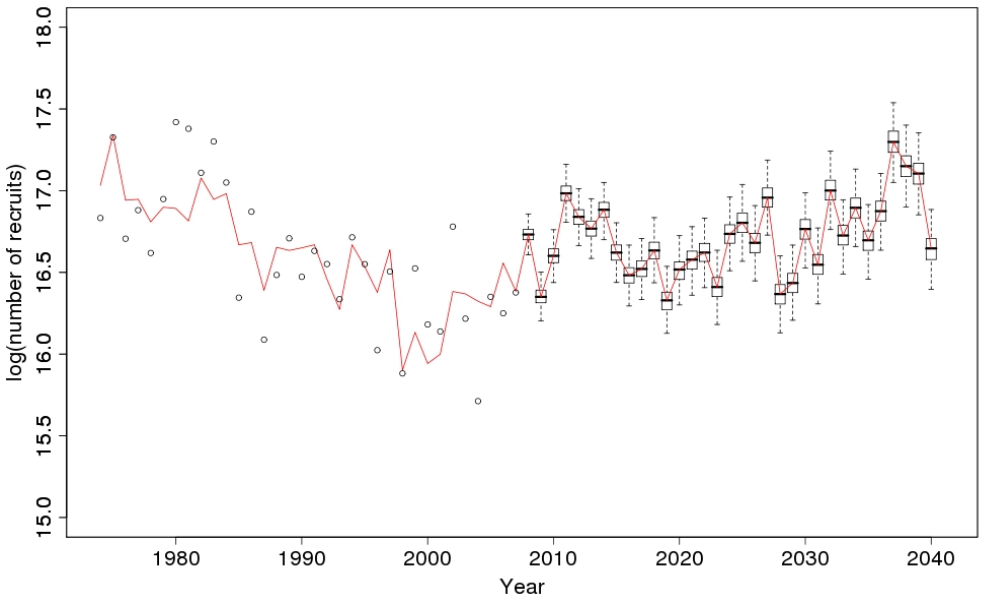


Figure 7.1.5. Recruitment (year class) medium term predictions for MBH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with BALMAR model using F as agreed in the management plans for cod, sprat and herring and assuming A2 scenario for sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

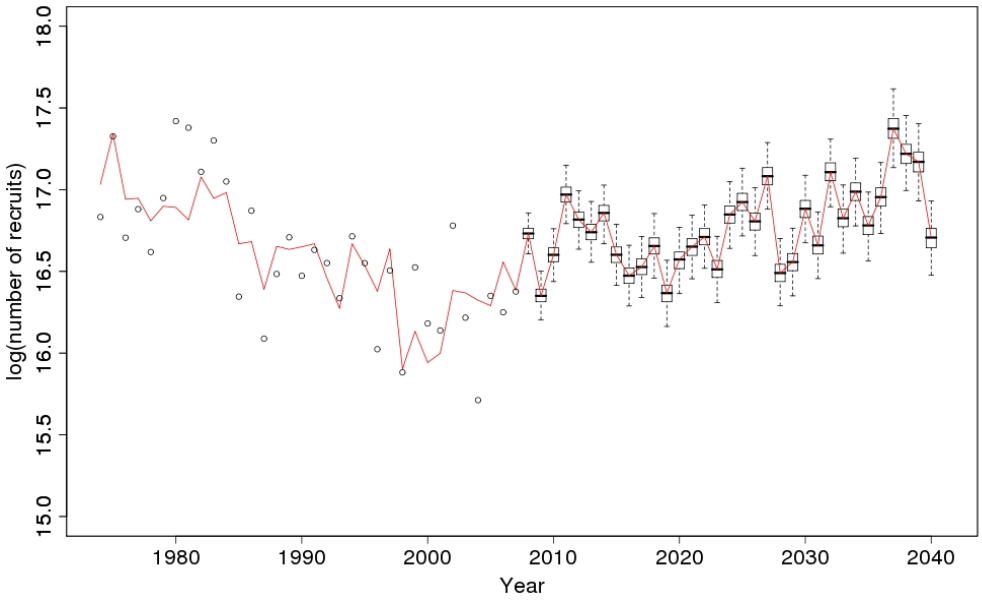


Figure 7.1.6. Recruitment (year class) medium term predictions for MBH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with BALMAR model using average historical F for cod, sprat and herring and assuming A2 scenario for sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

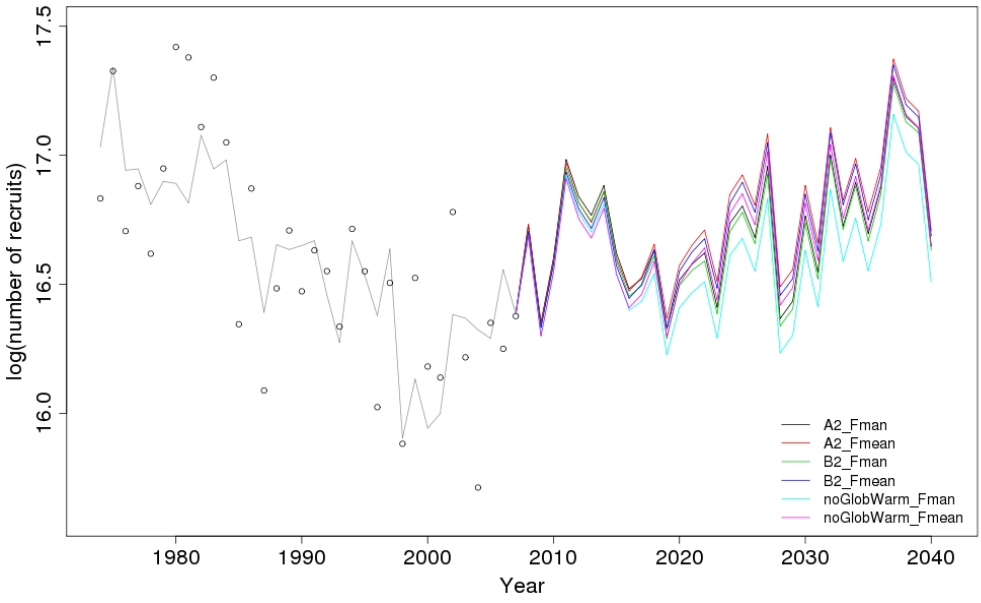


Figure 7.1.7. Recruitment (year class) medium term predictions for MBH (median values) derived from SSB estimated with BALMAR model using average historical F or F as agreed in the management plans for cod, sprat and herring and assuming different scenario for sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

GAM model

The results from the GAM model (7.1.7–7.1.13) showed the same pattern as for the linear model. The results are not surprising as the two models gives similar results within the range of SSB predicted by the BALMAR. The differences arise at larger

values of SSB, where the GAM model predicts a decrease in recruitment as likely an effect of density dependent mechanisms.

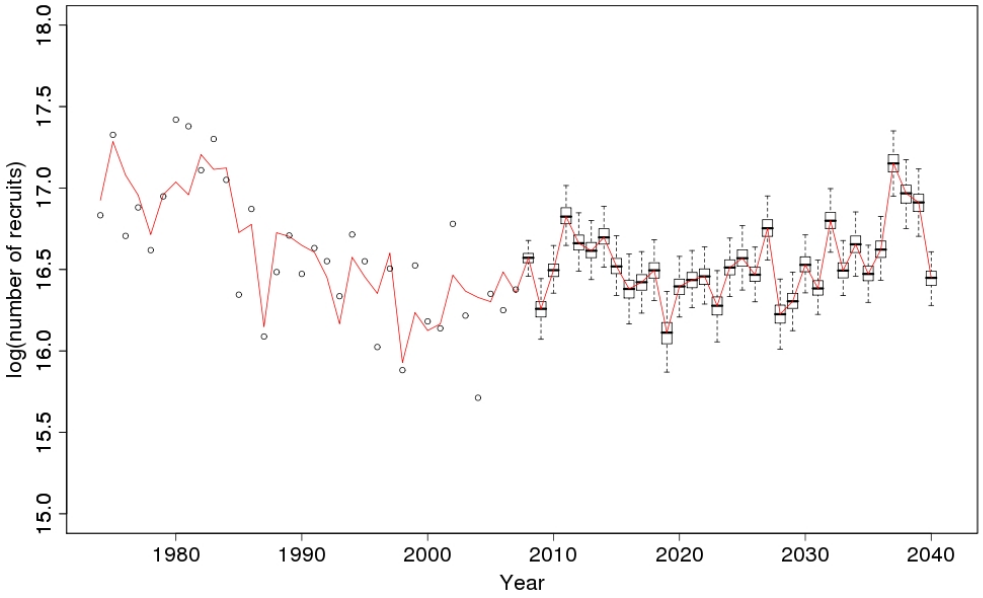


Figure 7.1.8. Recruitment (year class) medium term predictions for MBH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with BALMAR model using F as agreed in the management plans for cod, sprat and herring and assuming no increase in sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the GAM model predictions of the observed historical recruitment (i.e. white open dots).

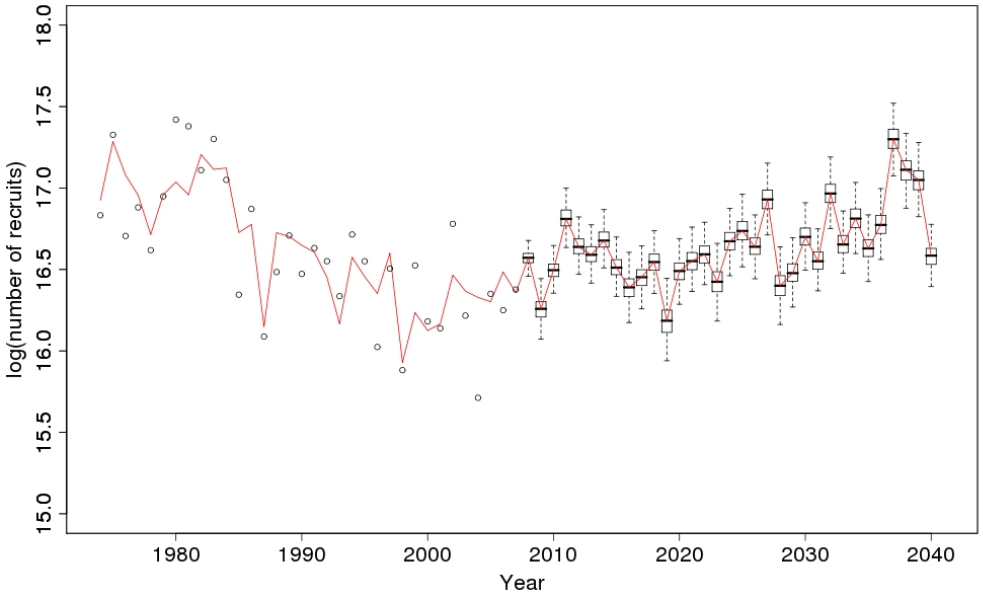


Figure 7.1.9. Recruitment (year class) medium term predictions for MBH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with BALMAR model using average historical F for cod, sprat and herring and assuming no increase in sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the GAM model predictions of the observed historical recruitment (i.e. white open dots).

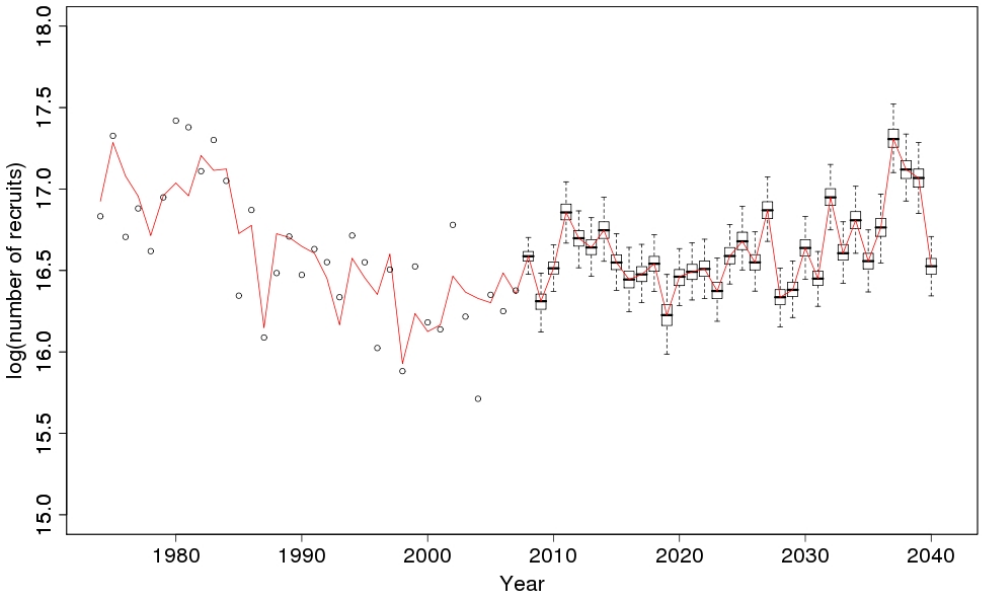


Figure 7.1.10. Recruitment (year class) medium term predictions for MBH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with BALMAR model using F as agreed in the management plans for cod, sprat and herring and assuming B2 scenario for sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the GAM model predictions of the observed historical recruitment (i.e. white open dots).

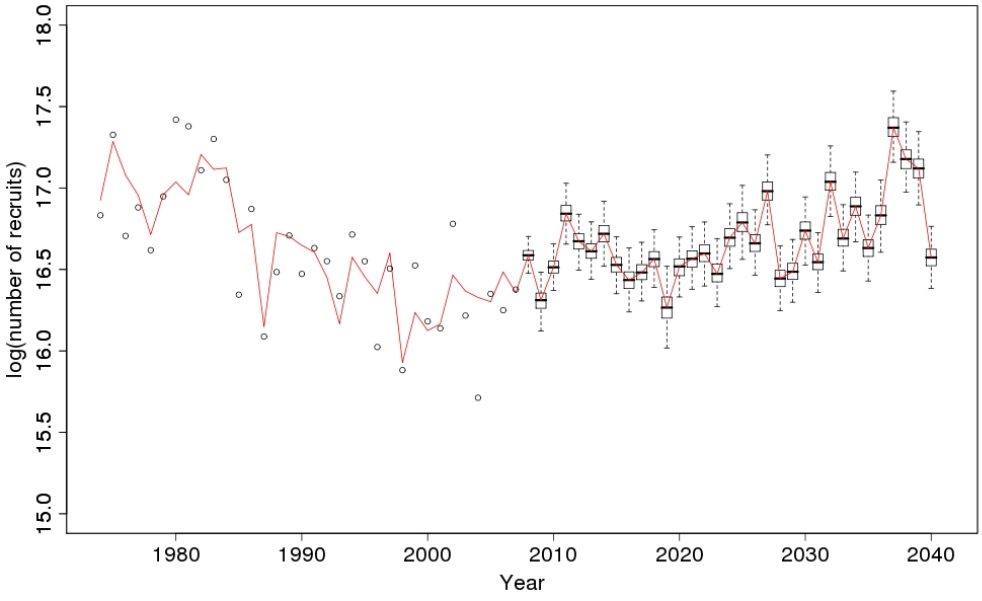


Figure 7.1.11. Recruitment (year class) medium term predictions for MBH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with BALMAR model using average historical F for cod, sprat and herring and assuming B2 scenario for sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the GAM model predictions of the observed historical recruitment (i.e. white open dots).

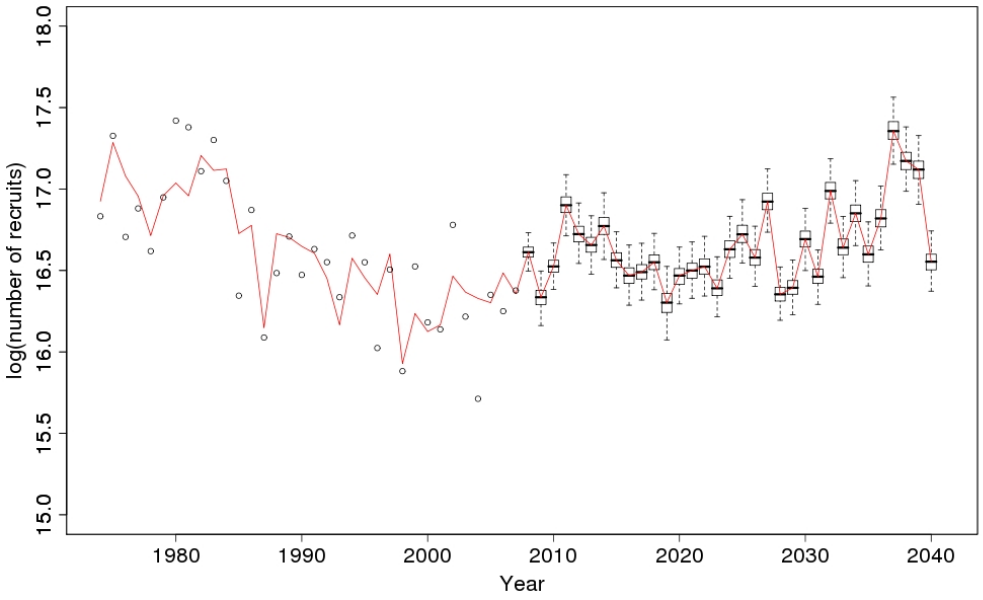


Figure 7.1.12. Recruitment (year class) medium term predictions for MBH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with BALMAR model using F as agreed in the management plans for cod, sprat and herring and assuming A2 scenario for sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the GAM model predictions of the observed historical recruitment (i.e. white open dots).

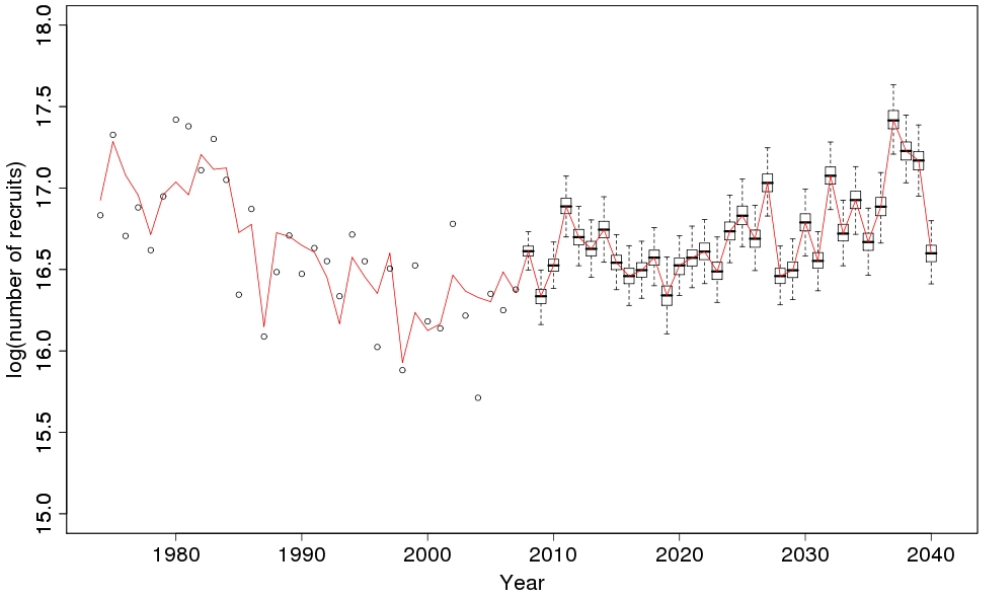


Figure 7.1.13. Recruitment (year class) medium term predictions for MBH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with BALMAR model using average historical F for cod, sprat and herring and assuming A2 scenario for sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the GAM model predictions of the observed historical recruitment (i.e. white open dots).

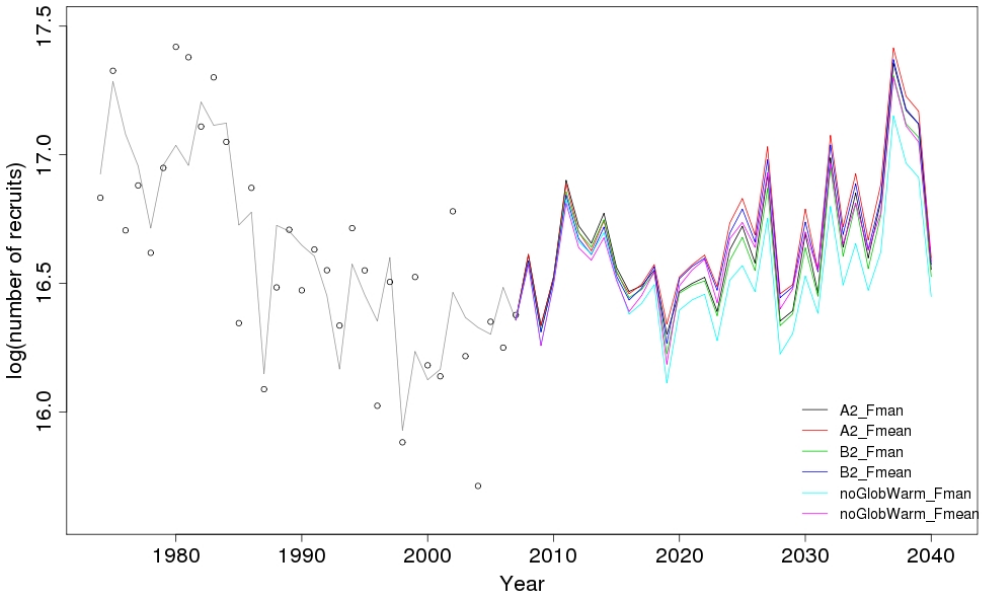


Figure 7.1.14. Recruitment (year class) medium term predictions for MBH (median values) derived from SSB estimated with BALMAR model using average historical F or F as agreed in the management plans for cod, sprat and herring and assuming different scenario for sea surface temperature of the Central Baltic Sea from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

Gulf of Riga herring

Figures 7.1.15–7.1.21 shows the forecasted recruitment for Gulf of Riga herring stock from 2008 to 2040 using a linear model for predicting recruitment. Results from the GAM model were very similar are not showed here. Differently from herring, we used a age based medium term forecast model, with M, weight at age and maturity at age as in ICES latest working group report (2009). As the effects of both the GAM and the linear model did not show a density dependent effect of SSB on R, we deliberately chosen to use a hockey-stick kind of models in those cases SSB will increase over the maximum observed values used to fit the R models. The model did not assume any uncertainty around the R estimates. This assumed a maximum recruitment of around 3 000000 (at 6 degrees of SST in May) for SSB larger than 120 000 tonnes. The different scenario showed that recruitment will slightly increase or stay at the level observed in the last decade during the period analysed for all scenarios (i.e. predicted trends in SST are presented in Figure 2 in Appendix 6). Variability estimate for the period 2008–2040 is similar to that observed during the last years of the time series.

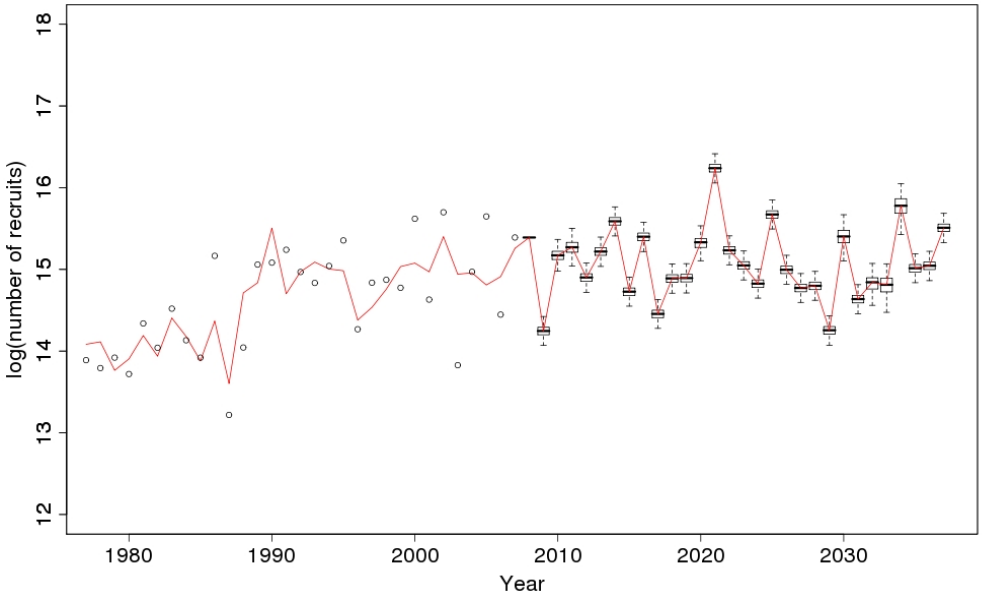


Figure 7.1.15. Recruitment (year class) medium term predictions for GRH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with an age based model using F equal to F01 (0.25) and assuming no increase in sea surface temperature in the Gulf of Riga from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

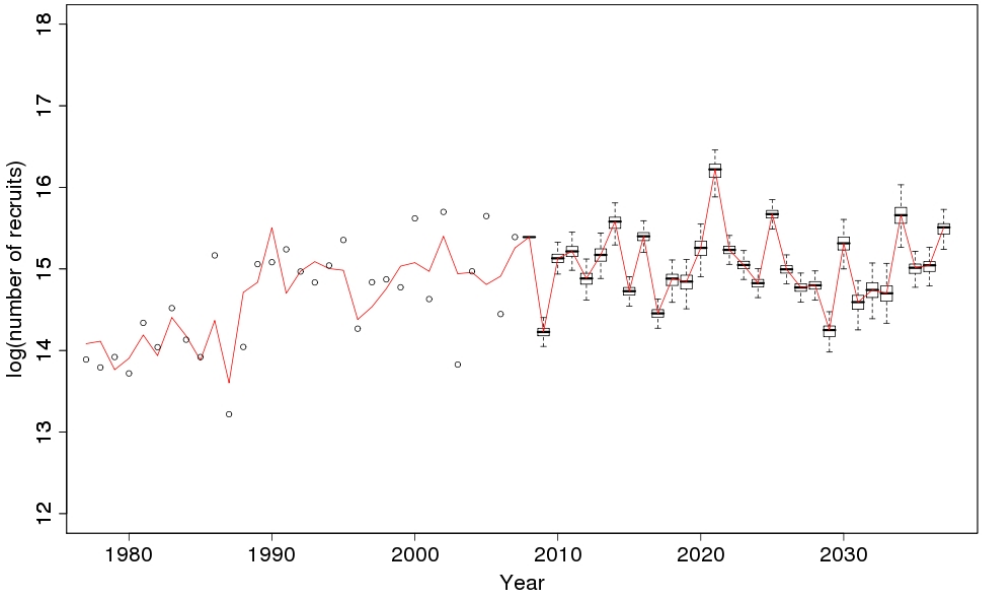


Figure 7.1.16. Recruitment (year class) medium term predictions for GRH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with an age based model using average historical F (0.29) and assuming no increase in sea surface temperature in the Gulf of Riga from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

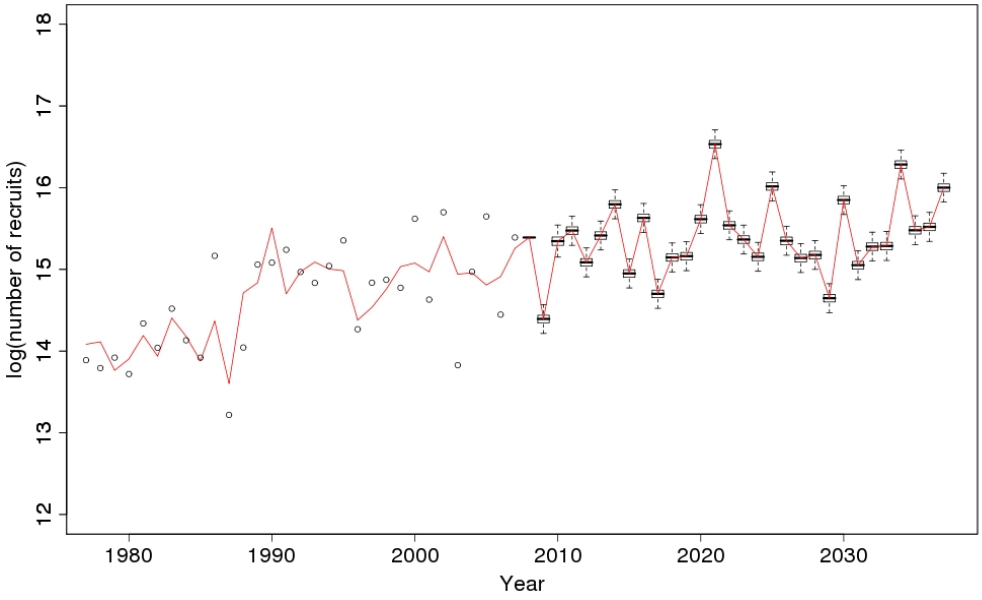


Figure 7.1.17. Recruitment (year class) medium term predictions for GRH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with an age based model using F equal to F01 (0.25) and assuming B2 scenario for sea surface temperature in the Gulf of Riga from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

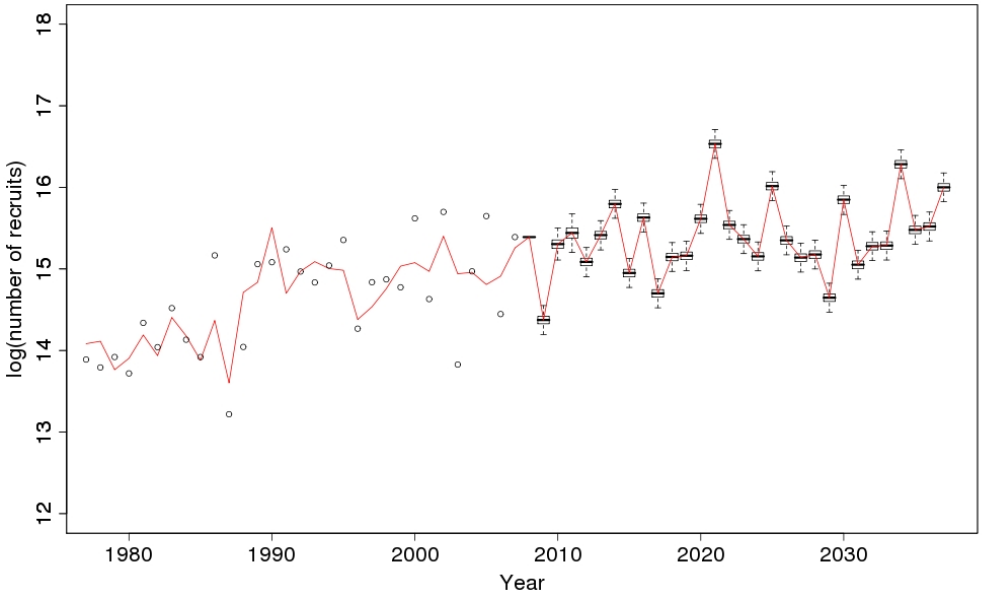


Figure 7.1.18. Recruitment (year class) medium term predictions for GRH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with an age based model using average historical F (0.29) and assuming B2 scenario for sea surface temperature in the Gulf of Riga from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

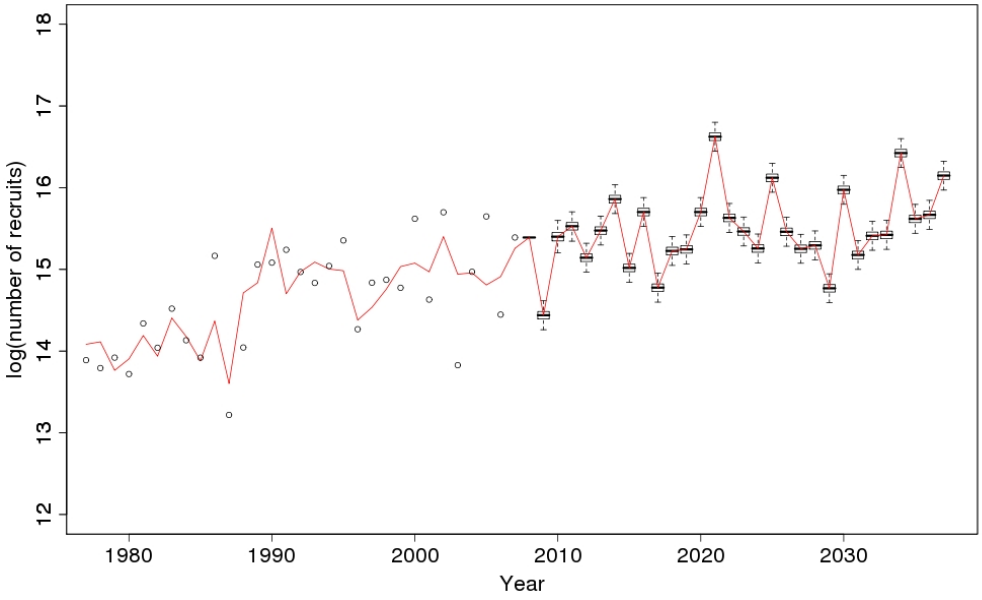


Figure 7.1.19. Recruitment (year class) medium term predictions for GRH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with an age based model using F equal to F01 (0.25) and assuming A2 scenario for sea surface temperature in the Gulf of Riga from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

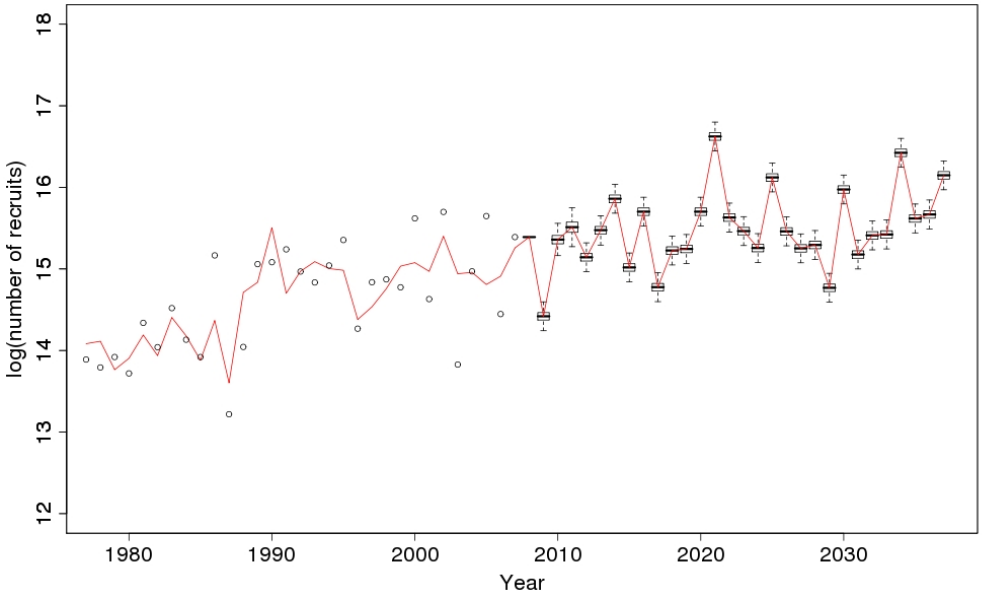


Figure 7.1.20. Recruitment (year class) medium term predictions for GRH (median, 1st and 3th quartiles and ± 95% percentiles) derived from SSB estimated with an age based model using average historical F (0.29) and assuming A2 scenario for sea surface temperature in the Gulf of Riga from 2007 to 2040. The red line from 1974 to 2007 indicates the linear model predictions of the observed historical recruitment (i.e. white open dots).

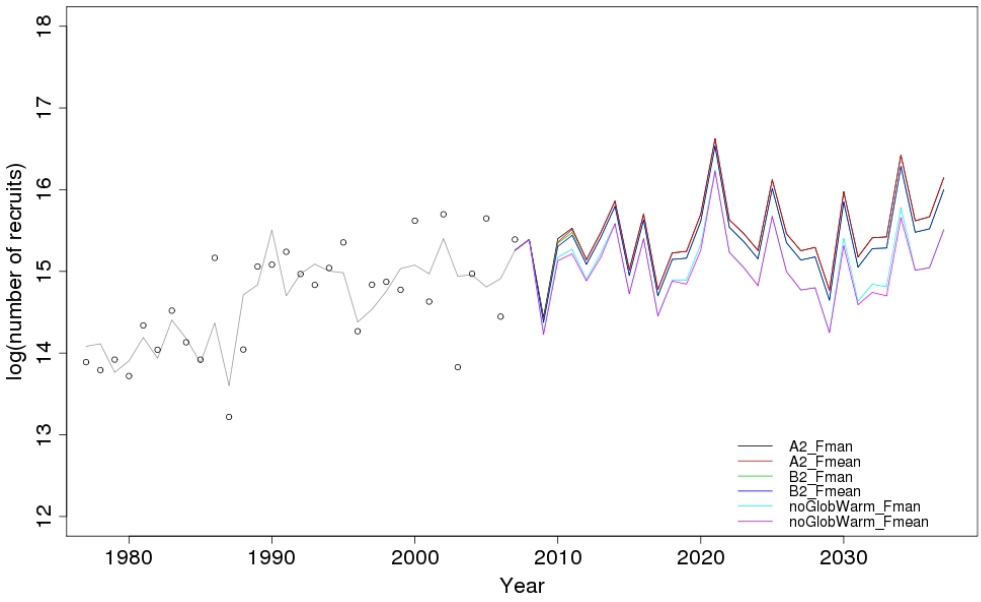


Figure 7.1.21. Recruitment (year class) medium term predictions for GRH (median values) derived from SSB estimated with an age based model using F equal to F_{01} (0.25) or average historical F (0.29) and assuming different scenario for sea surface temperature in the Gulf of Riga from 2007 to 2040.

Baltic sprat

The successful linear model for sprat recruitment was not found. The final GAM model included the original Bottom Depth Anomalies data series from 1979–1999. Due to the BDA data inconsistency described in the chapter 4.1.1 it was not possible to use more extended time series. The calculated GAM model showed no violation of assumptions regarding the independence, homogeneity of variance, and normality of the residuals but it has some problems with prediction of sprat recruitment starting from the beginning of 1990s. As using the BDA as a predictor of sprat recruitment is scientifically justified by relevant publications (Baumann *et al.* 2004, Baumann *et al.* 2006) and by our own group experience with constructing the sprat recruitment success GAM model (ICES 2008) the urgent need arise to update the BDA time series using the same hydro-dynamical model (the applied 3-dimensional, baroclinic circulation model adapted to the Baltic Sea) as described in detail by Lehmann (1995) and Lehmann and Hinrichsen (2000). However, it was not possible during the workshop meeting and this task need to be fulfilled in future workshops.

8 Conclusions and Recommendations

The outcomes of our analyses showed clearly that management of fishing pressure should take into account multispecies interactions in a climate changing framework instead of single species approach with a constant climate assumption. The results indicated that it is possible to build a robust framework for predictions of how the different climatic scenarios will affect the recruitment of pelagic fish stocks in the Baltic. A further step will be to apply the same methodologies developed here to the other herring stock in the Baltic Sea. However, similar analyses for the other Baltic herring stocks will be possible when existing fisheries assessment for herring stocks in the Bothnian Sea and Bothnian Bay is accepted by ICES and additional environmental datasets (e.g. zooplankton time series) are available for successful model(s) of the Western Baltic Herring stock.

A further development would be to include socio-economic considerations into our climate-recruitment framework and investigate which are the socio-economic implications of the changes in stock productivity linked to predicted climate trends in the next 3 or 4 decades. This should be addressed by a specific workshop build on the results obtained in the previous WKHRPB and WKSSRB (ICES 2007b and 2008) and methodologies and results described in this report.

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Annex 1: List of participants

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Annex 2: Agenda

ICES Workshop on Combining Climatic Scenarios and Medium-Term Predictions for Baltic Herring [WKCSMPB]

Ponza, Italy, 13 to 16 October 2009

Monday 12/10/09

Arrival and arrangements in the Hotel Ortensia

Tusday 13/10/09

0930 – 1030 Practical information, Introduction to the Workshop and Discussion of the Agenda (*Piotr Margonski & Max Cardinale*)

1030 – 1100 Coffee & Tea

1100 – 1300 Presentations:

1) Updating of the stock assessment data (*Piotr Margoński*)
2) Climatic scenario for the Baltic Sea (*Hans Linderholm*)
3) Modelling climatic scenario (*Martin*)

1300 – 1430 Lunch

1430 – 1600 Discussion of group work and forming of sub-groups

Potential sub-groups

1) Reviewing the knowledge on the impact of climate change on the Baltic Sea ecosystem (Hans, Max, Håkan)
2) Statistical analyses and modelling (Martin, Piotr, Valerio)
3) Prediction with environmental variables and density dependence (Martin, Piotr, Valerio)

1600 – 1630 Coffee & Tea

1630 – 1900 Work in subgroups cont.

2000 - Dinner

Wednesday 14/10/09

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 15/10/09

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 16/10/09

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
SD 22-32	BS	Sea Surface Temperature July	NASA7	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.
SD 25-29 & 32 exl.GOR	MBH	Spawning stock biomass	SSB	ICES 2009
Gulf of Riga ICES SD 28.1	GRH	Spawning stock biomass	SSB	ICES 2009
SD 22-32	BS	Spawning stock biomass	SSB	ICES 2009
ICES SD 25-29 & 32 exl.GOR	MBH	Recruitment age at 1	R1	ICES 2009
Gulf of Riga ICES SD 28.1	GRH	Recruitment age at 1	R1	ICES 2009
SD 22-32	BS	Recruitment age at 1	R1	ICES 2009

Annex 4: Statistical output of the recruitment models

Gulf of Riga Herring

Linear model

Initial model

```
Call:
lm(formula = log(RECR) ~ log(SSB) + NASA5, data = dat)

Residuals:
     Min       1Q   Median       3Q      Max
-1.11308 -0.25713  0.03783  0.18896  0.83906

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.09984    2.84585   1.792 0.083943 .
log(SSB)     0.64634    0.27381   2.361 0.025448 *
NASA5        0.37779    0.08858   4.265 0.000206 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4253 on 28 degrees of freedom
  (1 observation deleted due to missing value)
Multiple R-squared: 0.6042,   Adjusted R-squared: 0.5759
F-statistic: 21.37 on 2 and 28 DF, p-value: 2.315e-06
```

Final model

```
Call:
lm(formula = log(RECR) ~ log(SSB) + NASA5, data = dat)

Residuals:
     Min       1Q   Median       3Q      Max
-1.11308 -0.25713  0.03783  0.18896  0.83906

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.09984    2.84585   1.792 0.083943 .
log(SSB)     0.64634    0.27381   2.361 0.025448 *
NASA5        0.37779    0.08858   4.265 0.000206 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4253 on 28 degrees of freedom
  (1 observation deleted due to missing value)
Multiple R-squared: 0.6042,   Adjusted R-squared: 0.5759
F-statistic: 21.37 on 2 and 28 DF, p-value: 2.315e-06
```

GAM model

Initial model

```
Family: Gamma
Link function: log

Formula:
RECR ~ s(SSB) + s(NASA5)

Parametric coefficients:
```

```
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 14.70150    0.07592   193.7   <2e-16 ***
---

Approximate significance of smooth terms:
           edf Est.rank     F p-value
s(SSB)   1.000        1 5.206  0.0304 *
s(NASA5) 1.159        3 8.373  0.0004 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.413   Deviance explained = 58.6%
GCV score = 0.19893   Scale est. = 0.17866   n = 31
```

Final model

```
Family: Gamma
Link function: log

Formula:
RECR ~ s(SSB) + s(NASA5)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 14.70150    0.07592   193.7   <2e-16 ***
---

Approximate significance of smooth terms:
           edf Est.rank     F p-value
s(SSB)   1.000        1 5.206  0.0304 *
s(NASA5) 1.159        3 8.373  0.0004 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.413   Deviance explained = 58.6%

GCV score = 0.19893   Scale est. = 0.17866   n = 31
```

Central Baltic Herring (SD25-29&32 exl. Gulf of Riga)

Linear model

Initial model

```
Call:
lm(formula = log(RECR) ~ log(SSB) + log(PSE) + NASA8 + NAO_DJF,
    data = dat)

Residuals:
      Min        1Q    Median        3Q       Max
-0.554384 -0.156527 -0.008039  0.153757  0.481124

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.379791   2.201034   1.536  0.13549
log(SSB)    0.721652   0.129146   5.588 4.96e-06 ***
log(PSE)    0.111631   0.083764   1.333  0.19301
NASA8       0.177889   0.050846   3.499  0.00153 **
```

```
NAO_DJF     0.004468   0.001843   2.424  0.02182 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2501 on 29 degrees of freedom
  (1 observation deleted due to missing value)
Multiple R-squared: 0.6982,   Adjusted R-squared: 0.6565
F-statistic: 16.77 on 4 and 29 DF, p-value: 3.181e-07
```

Final model

```
Call:
lm(formula = log(RECR) ~ log(SSB) + NASA8 + NAO_DJF, data =
dat)

Residuals:
     Min       1Q   Median       3Q      Max
-0.58613 -0.14072 -0.05177  0.12013  0.55548

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.269445   2.063431   1.100  0.28015
log(SSB)    0.823156   0.105636   7.792 1.08e-08 ***
NASA8       0.185376   0.051184   3.622  0.00107 **
NAO_DJF     0.003739   0.001783   2.097  0.04450 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2533 on 30 degrees of freedom
  (1 observation deleted due to missing value)
Multiple R-squared: 0.6797,   Adjusted R-squared: 0.6477
F-statistic: 21.22 on 3 and 30 DF, p-value: 1.435e-07
```

GAM model

Initial model

```
Family: Gamma
Link function: log

Formula:
RECR ~ s(SSB, k = 4) + s(PSE) + s(NASA8) + s(NAO_DJF)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 16.61308    0.03631   457.5   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
             edf Est.rank      F  p-value
s(SSB)     2.735        3 19.220 9.24e-07 ***
s(PSE)     2.430        5  1.540 0.212183
s(NASA8)   1.000        1 19.431 0.000162 ***
s(NAO_DJF) 1.000        1  8.572 0.007034 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


R-sq.(adj) =   0.75   Deviance explained =   81%
```

```
GCV score = 0.059005   Scale est. = 0.044835, n = 34Family:
```

Final model

```
Family: Gamma
Link function: log

Formula:
RECR ~ s(SSB, k = 4) + s(NASA8)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  16.6191     0.0407   408.3   <2e-16 ***
---

Approximate significance of smooth terms:
           edf Est.rank      F  p-value
s(SSB)   2.515        3 22.368 1.41e-07 ***
s(NASA8) 2.635        6  4.716  0.00198 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.666   Deviance explained = 74.3%
GCV score = 0.06877   Scale est. = 0.056331, n = 34
```

Sprat (SD 22-32)

Linear model

No successful model for sprat recruitment was found.

GAM model

The recruitment GAM model included SSB, one of the SST time series from May – August period, and the Bottom Depth Anomaly index (only original BDA data from the 1979-1999 period were used). There were four temperature time series (May, June, July, and August), and therefore, four different GAM models were constructed with one temperature data at a time. The model with May temperature has the lowest GCV score and it was selected as the final one.

Final model

```
Family: gaussian        Link function: identity

Formula:
LN_R ~ s(NASA5, k = 4) + s(LN_SSB, k = 4) + s(BDA, k = 4)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 10.97052    0.05959   184.1   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
            edf Est.rank      F  p-value
s(NASA5)  2.101        3  8.434  0.00184 **
s(LN_SSB) 1.523        3  4.651  0.01833 *
```

```
s(BDA)    2.200        3 18.718 3.37e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.868   Deviance explained = 90.7%
GCV score = 0.11048   Scale est. = 0.074575  n = 21
```

Annex 5: Statistical output of the BALMAR model used in the medium term predictions of recruitment

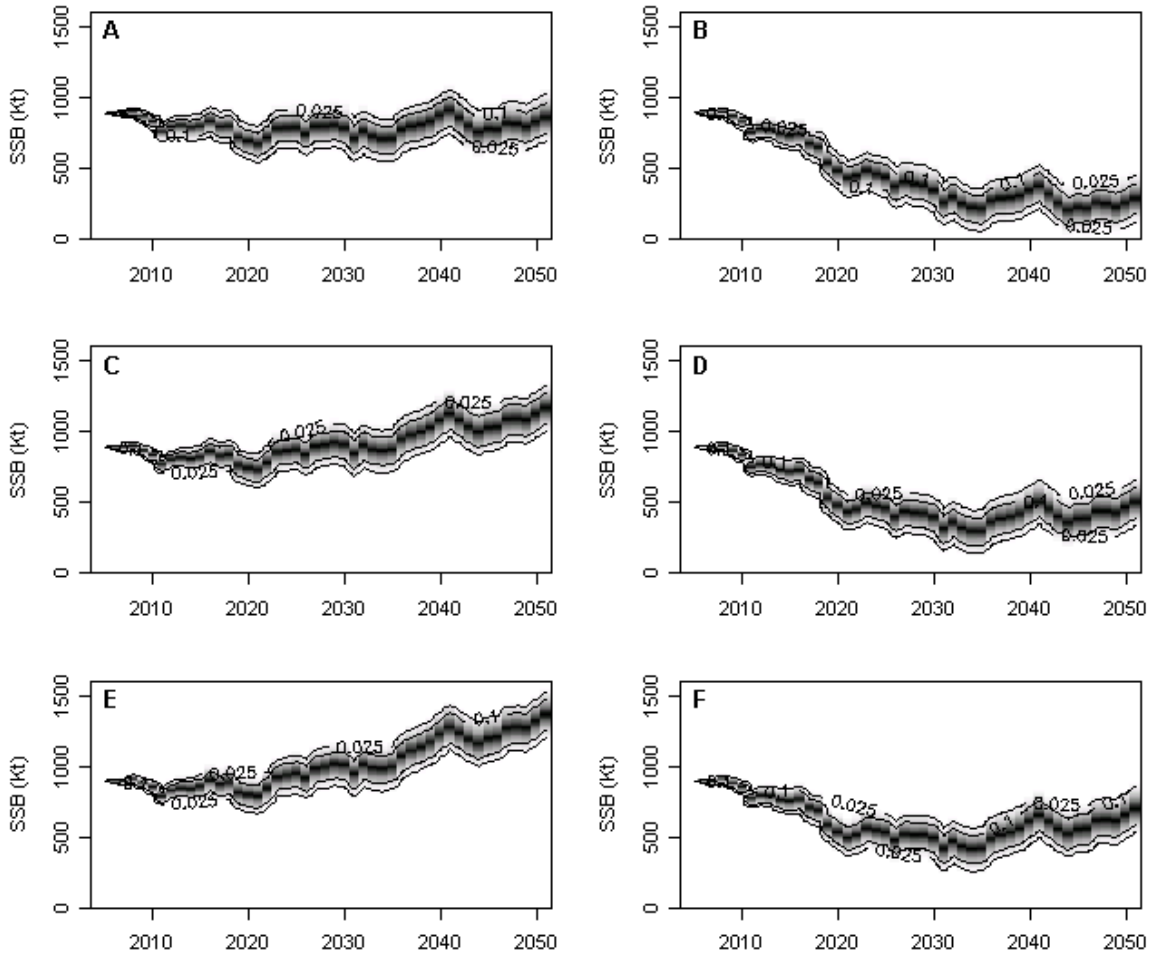

Figure 1.

Forecasted spawning stock biomasses (SSB) of sprat (i.e., using the BALMAR food-web model) from 2004–2050 under different climate- and management scenarios. (A) A status-quo scenario with F levels and climate conditions (i.e., SST and salinity) maintained at mean historical levels (1974–2004), hence at a "no climate change" scenario. (B) As in (A) but with F levels set according to recommended management plans for Baltic cod, sprat and herring (i.e., F_{cod}= 0.3, $F_{herring}$= 0.19, F_{sprat}= 0.40). In (C) and (D), a projected increase in Baltic Sea SST, as predicted by the IPCC B2-emission scenario, is combined with mean F and recommended management F levels respectively. The two last scenarios (E, F) include a more pronounced increase in SST, as predicted by the IPCC A2-emission scenario (IPCC 2007), and is combined with mean F and recommended management F levels respectively. In order to represent the uncertainty in forecasted SST during the period, multiple simulations (i.e., 1000 runs) were performed, each simulations representing a random draw from within the confidence range of forecasted SST (i.e., following a Gaussian distribution). Black contour lines show the 90% and 95% prediction intervals of the future probability distribution of Baltic sprat.

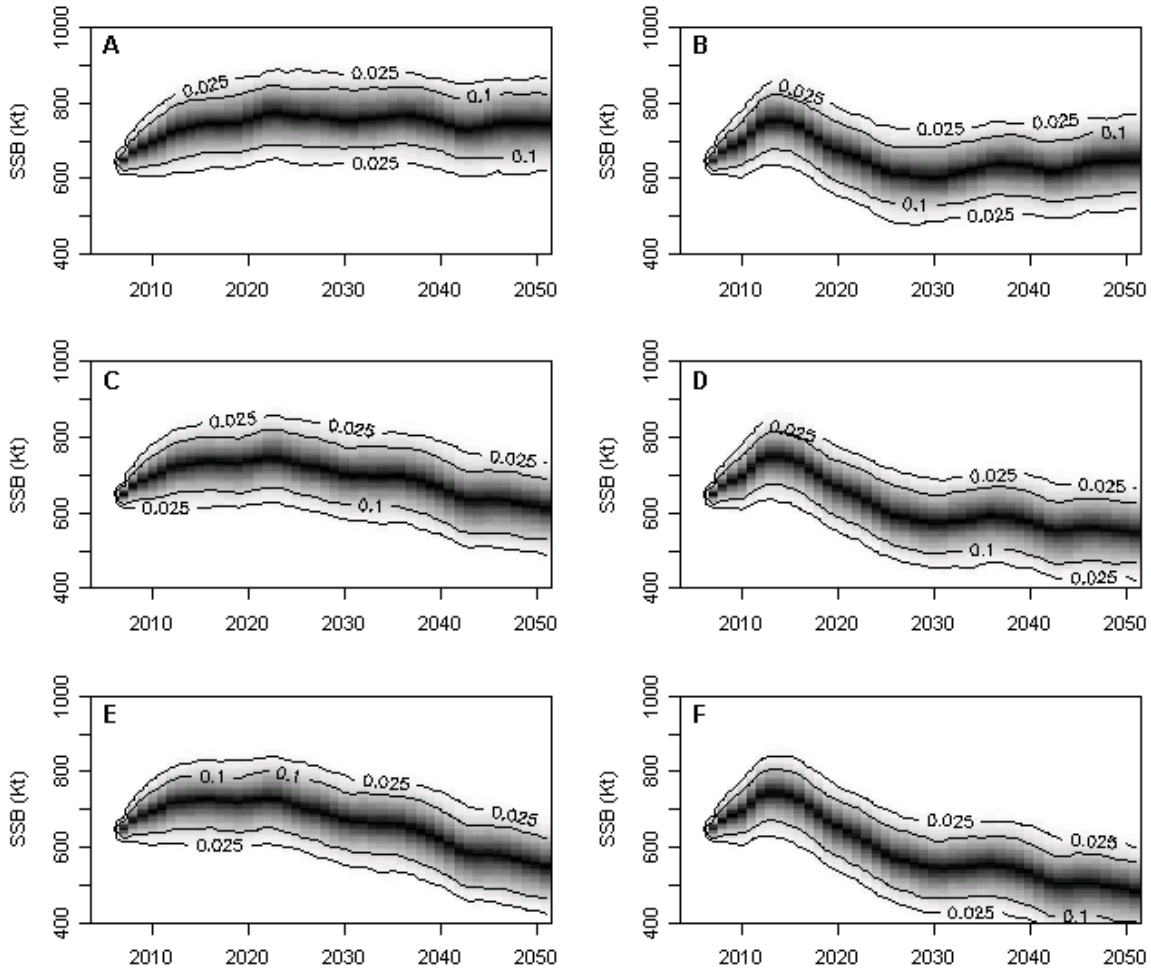

Figure 2.

Forecasted spawning stock biomasses (SSB) of Central Baltic herring (i.e., using the BALMAR food-web model) from 2004–2050 under different climate- and management scenarios. (A) A status-quo scenario with F levels and climate conditions (i.e., SST and salinity) maintained at mean historical levels (1974–2004), hence at a "no climate change" scenario. (B) As in (A) but with F levels set according to recommended management plans for Baltic cod, sprat and herring (i.e., F_{cod}= 0.3, $F_{herring}$= 0.19, F_{sprat}= 0.40). In (C) and (D), a projected increase in Baltic Sea SST, as predicted by the IPCC B2-emission scenario, is combined with mean F and recommended management F levels respectively. In order to reflect the projected change in Baltic Sea salinity (Meier 2006, Meier *et al.* 2006, BACC 2007), a gradual decrease in future salinities were modelled based on the actual mean, variance and autocorrelation of the historical time series (i.e., using an AR(1) climate model by Ripa and Lundberg 1996). The two last scenarios (E, F) include a more pronounced increase in SST, as predicted by the IPCC A2-emission scenario (IPCC 2007), and is combined with mean F and recommended management F levels respectively. In order to represent the uncertainty in forecasted SST (i.e., and salinity levels) during the period, multiple simulations (i.e., 1000 runs) were performed, each simulations representing a random draw from within the confidence range of forecasted SST (i.e., following a Gaussian distribution). Black contour lines show the 90% and 95% prediction intervals of the future probability distribution of Central Baltic herring.

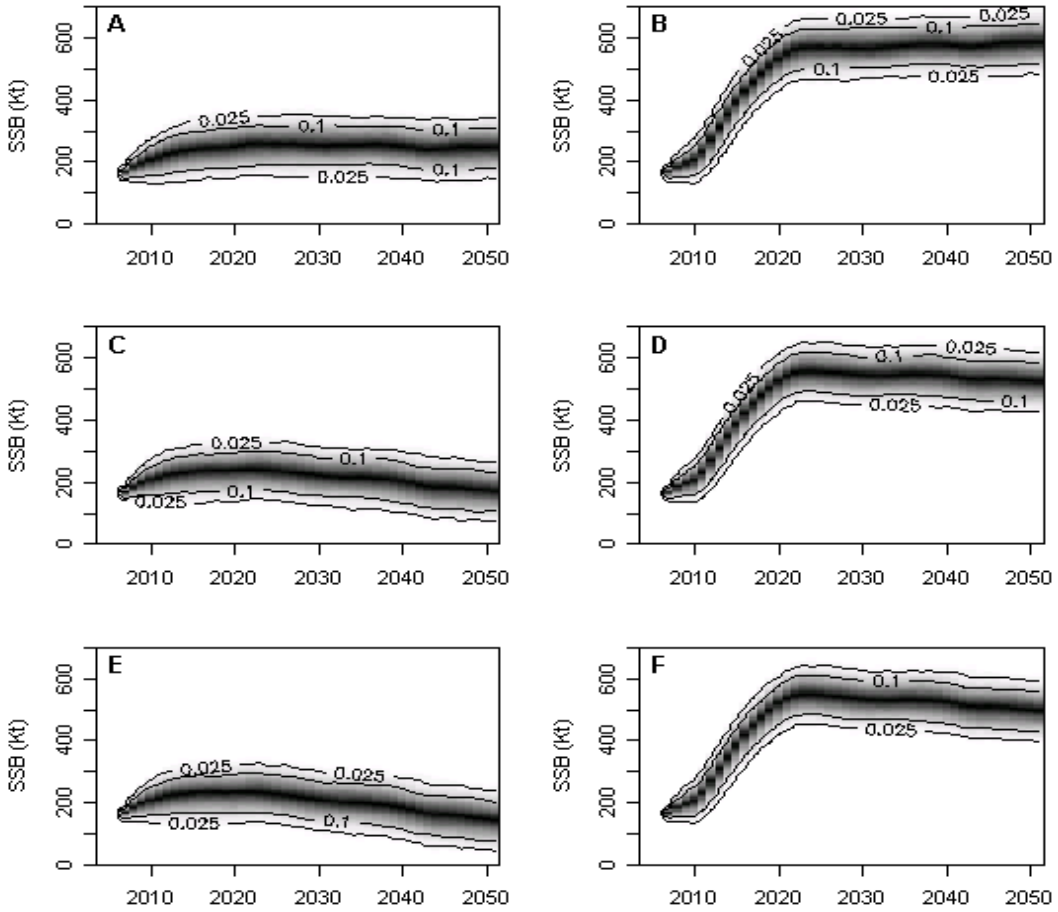

Figure 3.

Forecasted spawning stock biomasses (SSB) of Eastern Baltic cod (i.e., using the BALMAR food-web model) from 2004–2050 under different climate- and management scenarios. (A) A status-quo scenario with F levels and climate conditions (i.e., SST and salinity) maintained at mean historical levels (1974–2004), hence at a "no climate change" scenario. (B) As in (A) but with F levels set according to recommended management plans for Baltic cod, sprat and herring (i.e., F_{cod}= 0.3, $F_{herring}$= 0.19, F_{sprat}= 0.40). In (C) and (D), a projected increase in Baltic Sea SST, as predicted by the IPCC B2-emission scenario, is combined with mean F and recommended management F levels respectively. In order to reflect the projected change in Baltic Sea salinity (Meier 2006, Meier *et al.* 2006, BACC 2007), a gradual decrease in future salinities were modelled based on the actual mean, variance and autocorrelation of the historical time series (i.e., using an AR(1) climate model by Ripa and Lundberg 1996). The two last scenarios (E, F) include a more pronounced increase in SST, as predicted by the IPCC A2-emission scenario (IPCC 2007), and is combined with mean F and recommended management F levels respectively. In order to represent the uncertainty in forecasted SST (i.e., and salinity levels) during the period, multiple simulations (i.e., 1000 runs) were performed, each simulations representing a random draw from within the confidence range of forecasted SST (i.e., following a Gaussian distribution). Black contour lines show the 90% and 95% prediction intervals of the future probability distribution of Eastern Baltic cod.

Annex 6: SST scenarios and stock and recruitment relationships

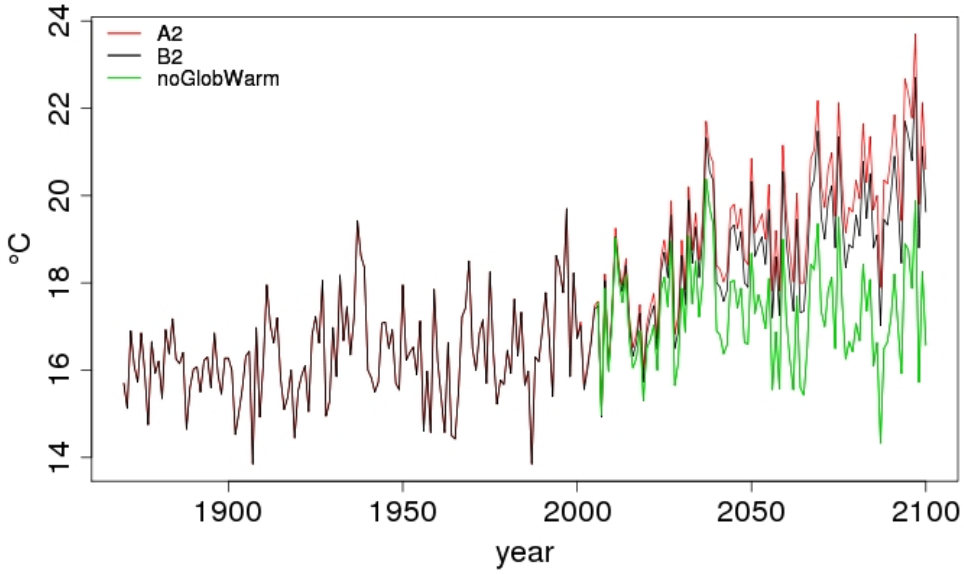

Figure 1. Estimated trend in SST for the Central Baltic herring and sprat with different global warming scenarios (see text for details).

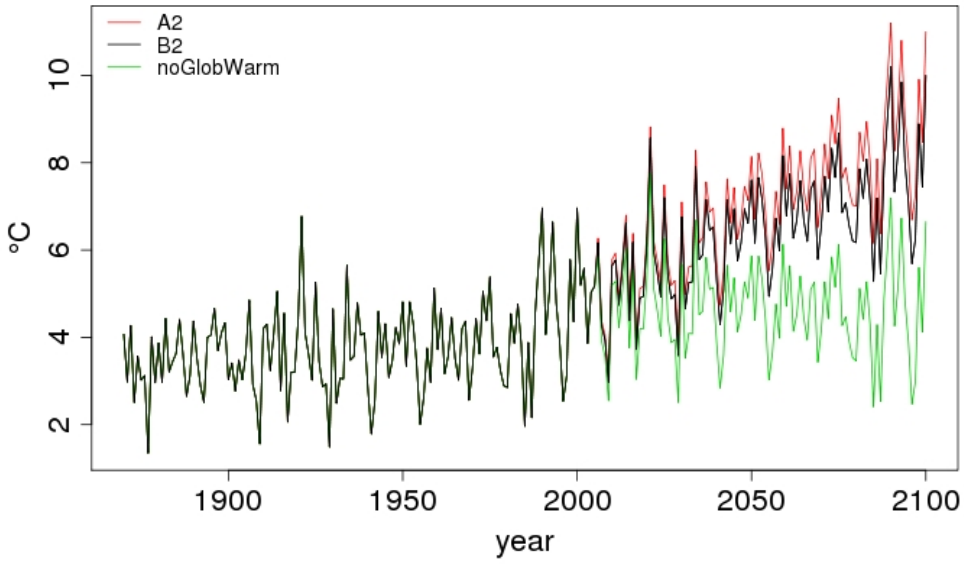

Figure 2. Estimated trend in SST for the Gulf of Riga herring with different global warming scenarios (see text for details).

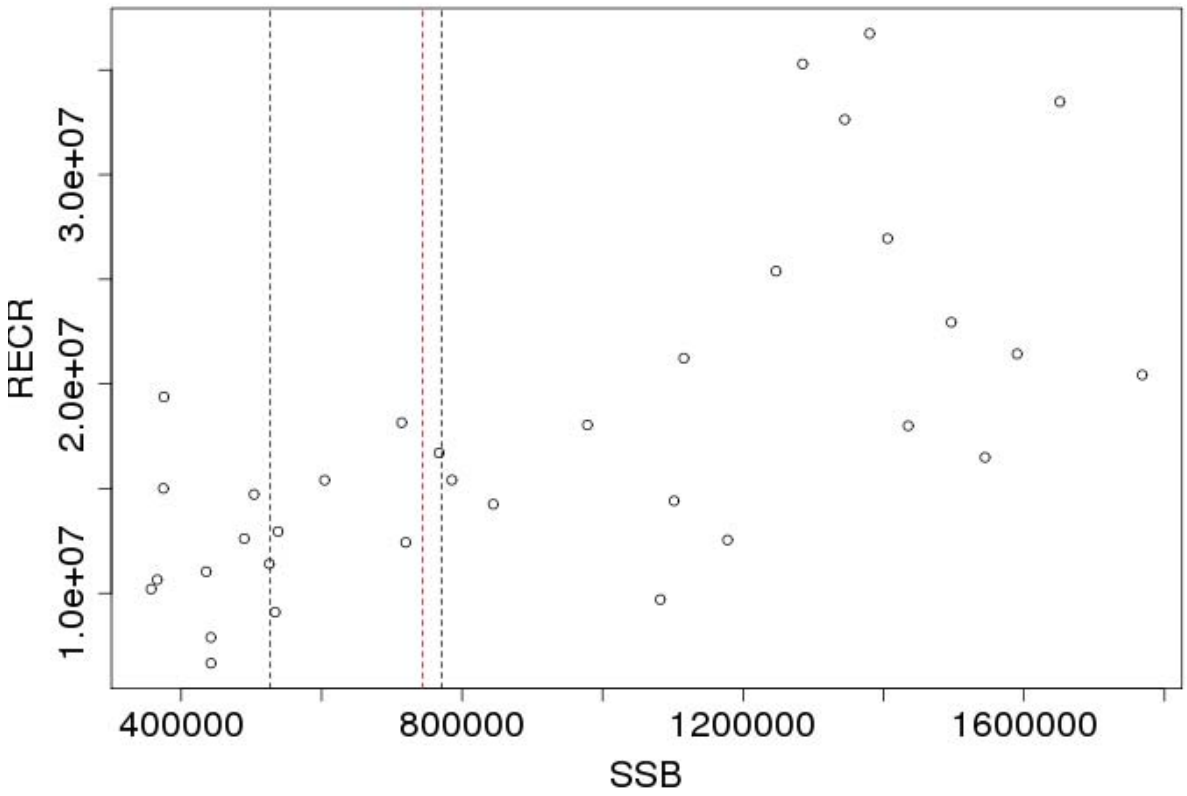

Figure 3. Stock and recruitment for the Central Baltic herring with indicated the range (dashed lines are the min e max mean annual SSB projected by BALMAR until 2050) of SSB values used in the predictions (see text for details).

Annex 7: Draft resolution for a workshop in 2010

A Workshop on Including Socio-Economic considerations into the Climate-recruitment framework developed for clupeids in the Baltic Sea (WKSECRET), chaired by M. 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) include bio-economic consideration into the environmental and climate driven recruitment predictions.

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

Supporting information

Priority	This Workshop will explore the possibility of including socio-economic considerations into the climate-recruitment framework developed for clupeids in the Baltic Sea
Scientific justification	The Workshop contributes to Actions 1.1, 1.2, 1.3, 1.6, 1.7, 1.12, 3.1, 3.2, 3.5, 3.12, 3.15, 4.11, 4.15, 5.3 of the ICES Action Plan.Herring is an essential component of the Baltic ecosystem, being a food item for cod and exerting predation pressure on zooplankton populations. The different populations are of considerable commercial value for the countries bordering the Baltic. Recruitment trends drive a large proportion of the dynamics of the different stocks, which are partly of opposite direction. The work of WKHRPB, WKSSRB and WKCSMPB has shown that these trends in recruitment are due to direct (e.g. temperature) and indirect effects (e.g. food availability) of climate. Reliably predicting recruitment is essential for proper stock management and environmentally-sensitive stock recruitment relationships are essential for implementing precautionary and ecosystem approaches. The WKCSMPB results indicated that it is possible to build a robust framework for predictions of how the different climatic scenarios will affect the recruitment of pelagic fish stocks in the Baltic. The workshop will built on the result of previous ones and include socio-economic considrations into developed climate-recruitment models. Also, the workshop will develop stock-specific strategies for including environmental information into the work of WGBFAS.
Resource requirements	Assistance of the secretariat in maintaining and exchanging information and data to potential participants.
Participants	This Workshop is expected to attract 10–15 participants working on Baltic herring and sprat stocks, contributing data and expertise. Further, experts from other areas should be encouraged to participate. Climate change and fisheries socio-economy experts should also be encouraged to participate,
Secretariat facilities:	None
Financial:	No financial implications.
Linkages to advisory committees	ACOM
Linkages to other committees or groups	SCICOM, Expert Groups related to Baltic Sea issues, WGIAB
Linkages to other organizations	HELCOM