Evaluation of the potential of harvest control rules based on fishery-independent data to improve fisheries management

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« Des chercheurs qui cherchent, on en trouve
Des chercheurs qui trouvent, on en cherche »

Charles de Gaulle

A Pierre, pour m'avoir tant aidée à aller jusqu'au bout...

Abstract

Most European fish stock assessments are reliant on fisheries dependent data which are subject to potentially high levels of uncertainty. Several recent collapses of important fish stocks have at least in part been attributed to biased stock assessments based on unreliable fishery dependent indices.

The hypothesis evaluated here is that management based on fishery independent data only is less susceptible to bias. This is tested using the example of the North Sea herring fishery by comparing management strategies based on fishery dependent data only, a combination of both types of fishery data and, thirdly, the current management.

The hypothesis was explored using Management Strategy Evaluation (MSE) techniques, by developing a model testing various harvest strategies. The MSE consists of an operating model based on: fishery dependent and fishery independent data, an observation error model, an assessment model considering alternative stock evaluation methods, a harvest control rules model combining both types of fishery data to advise on stock management and allowing for misreporting.

Management procedures based on the simplest rules using fishery-independent data ("model-free rules") provided the best results in terms of robustness. Although the assessments and management strategy currently adopted by the European Union performed fairly well under reasonable levels of misreporting, the simplest rules performed better under high levels of misreporting. These procedures are also robust to changes in the estimations of the biological parameters.

Several new approaches were tested. Management procedures based on total mortality tended to overprotect the stock and led to a decrease of the catch that might not suit requirements of the fishing industry in terms of level and stability in catch. Management procedures using new assessment methods implemented here did not provide acceptable results, for all levels of misreporting, and would likely not suit the requirements of the fishing industry either.

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TERMS AND ABBREVIATIONS

Terms and abbreviations

Term	Definition
Assessment model	Part of the management procedure that uses information derived from the **observation model** in order to provide estimates of the status of the **stock**(s) and **fishery**.
By-catch	Species in the **catch** that are not the main target of the **fishery**. Often the by-catch species are non-commercial and are rejected as **discards**. However, valuable species such as halibut are usually taken also as a by-catch and landed.
Catch	Strictly speaking, this term refers to the total quantity of fish taken by the **fishery**. However, in most cases a proportion of the catch is rejected at sea (**discards**). The fish which are brought ashore constitute the **landings**.
Catchability	The degree to which fish are vulnerable to the fishing gear. The catchability of a species, or of different size classes of the same species, may vary enormously depending on which gear is used. Thus, **pelagic** species such as mackerel have a low catchability in bottom trawls and flatfishes have a low catchability in trawls fished in mid-water.
Cohort	See **year class**.
Conditioning	The process of selecting specifications/parameter values for case-specific trials to ensure that they are not inconsistent with already existing data.
Discards	Organisms that are returned to the sea after capture. Fish may be discarded for several reasons; they may be of non-marketable species, they may be below the minimum legal landing size, current prices may be considered too low, or the quota for a particular species may have been exceeded.
Error (uncertainty)	Differences between the "virtual world" (in the **operating model**) and the perceived one.
Evaluation of management strategy	The process of evaluating (parts of) a **management strategy** against pre-specified **objectives**. The evaluation can consist of simulations of some elements of the management strategy, complemented with analyses of those elements of the strategy which are not amendable to quantitative analysis. The evaluation of **Harvest Control Rules** is a special case of the evaluation of a management.
Fecundity	The total number of eggs spawned by a female during a single spawning season.
Fishery	The term fishery can refer to the sum of all fishing activities on a given resource. It may also refer to the activities of a single type or style of fishing on a particular resource.
Fishery-independent based management procedure	Management procedure for which the harvest control rule is only based on fishery-independent data, whether the rule is **model-free** or **model-based**.
Fishing effort	The total amount of fishing activity on the fishing grounds over a given period of time, often expressed for a specific gear type e.g. number of hours trawled per day, number of hooks set per day or number of hauls of a beach seine per day.
Fishing mortality	Deaths caused by fishing.
Harvest control rule	An algorithm for pre-agreed management actions as a function of variables related to the status of the **stock**.
Implementation error model	Model that represents how implementation of decisions differs from intended ones.
Industrial fishery	A **fishery** that catches fish in bulk for reduction to fish meal and fish oil. The industrial fishery is usually targeted at small, short-lived species which are considered unsuitable for human consumption. However, large quantities of herring may be taken by an industrial fishery.

Initial conditions	The set of conditions (assumptions and events) that result in the historical data that are needed to start the simulations.
Landings	Fish that are brought ashore. See **catch**.
Limit reference point	Benchmarks used to indicate when harvests should be constrained substantially so that the **stock** remains within safe biological limits. The probability of exceeding limits should be low.
Management evaluation framework	A framework for evaluating (parts of) a **management strategy** against pre-specified **objectives**. The evaluation framework can consist of simulations of some elements of the management strategy, complemented with analyses of those elements of the strategy which are not amendable to quantitative analysis.
Management strategy	Management strategies consist of **objectives** with associated performance criteria, the implementation measures (e.g. input or output control) and what is considered a relevant knowledge base for decisions.
Model-free harvest control rule	**Harvest control rule** which does not use results coming from an **assessment model.**
Model-based harvest control rule	**Harvest control rule** which uses results coming from an **assessment model.**
Mortality rate	A measure of the rates at which fish in a given **stock** die during a given time period. Fisheries biologists usually make a distinction between **natural mortality rate** (M) and **fishing mortality rate** (F).
Natural mortality	Deaths due to natural causes, such as disease and predation.
Objective	A target that is actively sought and provides a direction for management action.
Observation model	Part of the **management procedure** that represents the way in which the **operating model** is sampled for fishery-dependent and fishery independent data.
Operating model	A virtual world that is a simplified representation of reality. Its main components are fish and fisheries.
Pelagic	Living mostly off the bottom.
Performance indicator	A specific state, or variable, which can be monitored in a system e.g. a **fishery** to give a measure of the state of the system at any given time. In fisheries management, each performance indicator would be linked to one or more **reference points** and used to track the state of the fishery in relation to those reference points.
Precautionary approach	Implemented in the ICES advice on fisheries management in 1998, consisting of a framework of biological **reference points** related to upper exploitation boundaries. Management decisions for sustainable **fisheries** should restrict the risk that the **spawning biomass** falls below a minimum limit or that the **fishing mortality rate** F becomes too high. A minimum level of spawning stock biomass, or limit biomass (B_{lim}), is defined. Below B_{lim} there is a higher risk that the stock reaches a level where it suffers from severely reduced productivity. In a similar way a limit fishing mortality has been defined (F_{lim}). Management should prevent the spawning stock to decrease below B_{lim}, and avoid an F above F_{lim}. To avoid the risk of the spawning stock to decrease to or below B_{lim} because of uncertainties in the assessment, a higher stock biomass has also be defined, the precautionary biomass (B_{PA}). Similarly, to avoid the fishing mortality to become as high as F_{lim}, a lower level of fishing mortality has been defined, the precautionary fishing mortality (F_{PA}). In general, management advice is aimed at avoiding the risk that the spawning stock falls below B_{PA}, and that fishing mortality rate increases above F_{PA}. For a more detailed explanation of the precautionary approach, see the report of the ICES Advisory Committee for Fisheries Management (ICES SGPA, 2003).
Recruitment	The numbers of new fish which are added to the exploitable portion of the stock resulting from growth or migration of smaller fish.

Reference point	Values of parameters (e.g., B_{MSY}, F_{loss}, F_{PA}) that are useful benchmarks for guiding management decisions. Biological reference points are typically limits that should not be exceeded with significant probability or targets for management. Reference points are an essential element for parameterising **harvest control rules**.
Robustness trials	Trials to examine the robustness of **management procedure** performance to a range of plausible scenarios regarding the dynamics of nature, the adaptation of fishermen, the implementation system and the knowledge production system.
Spawning stock biomass	See **stock**.
Stock	A part of a fish population, usually with a particular migratory pattern, specific spawning grounds and subject to a distinct **fishery**. Total stock refers to both **juveniles** and **adults**, either in numbers or by weight, while **spawning stock (biomass)** refers to the numbers (weights) of individuals which are old enough to reproduce.
Year class (cohort)	A group of fish born in the same year. Thus 1-group fish sampled in 2003, 2-group fish sampled in 2004, and 3-group fish sampled in 2005 are all members of the 2002 year class.

Acronym	Full Name	Description
ADAPT	Adaptive framework	A general approach to fitting **VPA** models. ADAPT is based on minimising the sum of squares over any number of indices of abundance to find best-fit parameters.
B_{lim}	Limit biomass	See **Precautionary Approach**.
B_{PA}	Precautionary biomass	See **Precautionary Approach**.
CEFAS	Centre for Environment, Fisheries and Aquaculture Science	Based in Lowestoft (United Kingdom).
CPUE	Catch per Unit of Effort	
F_{lim}	Limit fishing mortality rate	See **Precautionary Approach**.
F_{PA}	Precautionary fishing mortality rate	See **Precautionary Approach**.
FRS	Fisheries Research Services	Marine Laboratory in Aberdeen, Scotland.
HCR	Harvest Control Rule	See **Harvest control rule**.
IBTS	International Bottom Trawl Survey	
ICA	Integrated Catch-at-age Analysis	Equivalent to **ADAPT**, i.e. using a least squares fit based on **VPA** and auxiliary data, but the standard VPA catch formulation used in ADAPT is replaced by a **separable VPA**.
ICES	International Council for the Exploration of the Sea	Based in Copenhagen (Denmark).
RIVO	Netherlands Institute for Fisheries Research	Based in Ijmuiden (the Netherlands).
SSB	Spawning stock biomass	See **Stock**.
SURBA	Survey-based separable model	
TAC	Total Allowable Catch	Management measure. The total amount of **catch** allowed to be taken from a particular **stock** in a particular year.
VPA	Virtual Population Analysis	A general method to model the progression of a **cohort** through time. VPA became useful when the Baranov catch equation incorporating observed **catches** could be solved sequentially.
XSA	Extended Survivor Analysis	A **VPA** with no catch errors is tuned with age-specific **CPUE** indices. The model is fitted through a specialised robust iteration technique, rather than general least-squares. The procedure includes an iterative weighting of CPUE indices.
YCC	Year Class Curve	A plot of log **CPUE** over age for a single **year-class** of a species

INTRODUCTION

Justification of the study

BACKGROUND TO THE RESEARCH

Everywhere in the world, institutions dealing with fisheries management are beset with negative publicity. A catalogue of poor management results and a growing understanding of the impact of fisheries on marine ecosystems have contributed to this. Examples of this are the collapse of important stocks such as cod in Newfoundland, the publicity surrounding the problem of overfishing and overexploitation (Garcia and Newton, 1997; Mace, 1997), a growing understanding of the large quantity of by-catch generated in many mixed fisheries and the impacts of fishing on the marine environment, such as "fishing down the food web" (Pauly *et al.*, 1998). Particular attention has been given to the impact of fisheries on marine mammals and birds.

In addition to concerns from the general public, institutions have to deal with the fishing industry. The major point of conflict is the conservation of stocks which experience reductions of fishing capacity or fishing levels. One of the most significant problems faced by scientists and managers is to explain the science behind management decisions to all stakeholders (for instance fishermen, the media and environmental organisations) (Smith *et al.*, 1999).

A certain number of stocks in Europe are managed by fisheries quotas which are set to help achieve the objectives of the Common Fisheries Policy for the conservation and sustainable management of fish stocks. The goal of quotas is to control exploitation via Total Allowable Catch (TAC) limitations. The Advisory Committee (ACOM) of the International Council for the Exploration of the Sea (ICES), the umbrella bodyunder which much of the stock assessment of European stocks is carried out, provides management advice based on the current status of the stocks to set the TACs. The current status is determined using assessment methods such as those mentioned in the following paragraphs and explained in more details in the Appendix 2. It is also possible to set TACs using economic considerations through STECF (the Scientific, Technical and Economic Committee for Fisheries). A diagram showing the different steps of the process by which TACs are determined can be found in Figure 1.

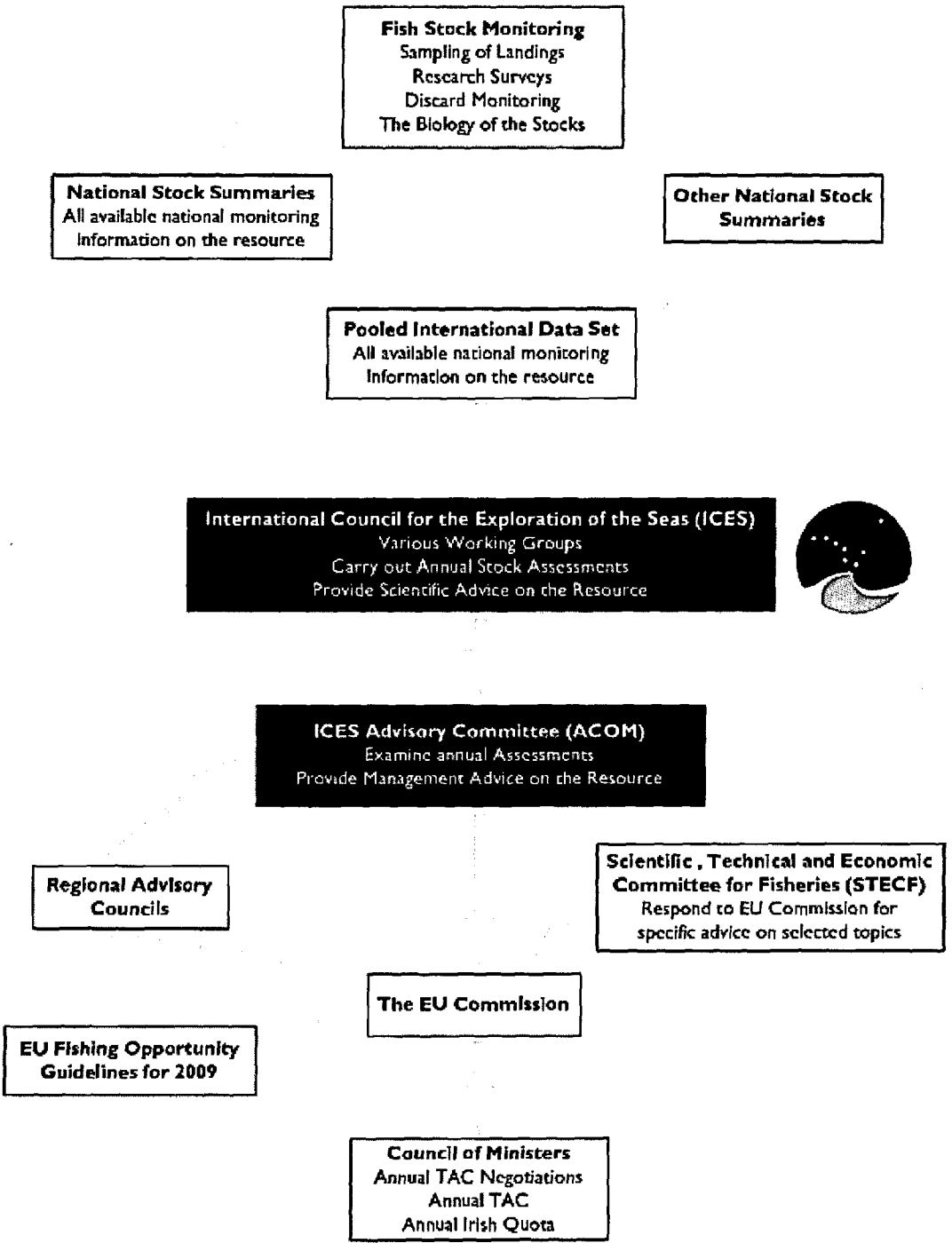


Figure 1: Process by which TACs are determined.
Source: Marine Institute, 2006.

Historically, and more particularly in recent years, important reductions of the biomass in several demersal fish stocks have been observed in ICES areas[1]. This is particularly the case for gadoid stocks in the North Sea, to the West of Scotland and the Irish Sea. These stocks are amongst those that are managed by fisheries quotas. Recent stock

1 A map of the ICES areas can be found in the Appendix 1

biomass declines induced reductions in TAC levels. As a consequence, the motivation for fishermen to discard, misreport or distort catch records increased (Cook, 1997; Anonymous, 2004) so that scientists do not know how many fish have been landed. This leads to negative biases in the catch data, low stock abundance estimates by scientists, and even lower TACs, followed by even more misreporting.

Several stock assessment methods are used for European fisheries. The standard assessment techniques used by the ICES Working Groups are the Extended Survivors Analysis (XSA; Darby and Flatman, 1994), the Integrated Catch-at-age Analysis (ICA; Patterson and Melvin, 1996) and the Time-Series Analysis (TSA; Fryer *et al.*, 1998, 1999). The first two are well established as they have been used for several years and for several stocks. A review of the methods used by ICES experts to assess European fish stocks between 2000 and 2008 has shown that XSA has been used at least once for 49 stocks, a stock defined by a combination of a species and an ICES area, and for 18 of them XSA has been used over the 9 years reviewed. ICA has been used for several herring stocks in Europe and also for the Northeast Atlantic mackerel stock. It has also been used in the past for the anchovy stock in ICES area VIII until a more adapted method was found and applied in the recent years. TSA is used for some major stocks – cod, haddock and whiting – to the west of Scotland but also for whiting in the North Sea. The review also showed that the number of assessment methods has increased in recent years. Most of them are adaptations of previous methods such as SURvey-Based Assessment (SURBA, Appendix 2) which is a recent development of RCRV1A, a method presented by Cook in 1997, and more at the experimental level; Seasonal Extended Survivors Analysis (SXSA) used for sandeel and Norway pout or SAD (Combined Separable VPA /ADAPT) which derives from ICA and ADAPT and is used for the western horse mackerel. Most of these new methods have been implemented to provide a solution to specific issues. For example, the SAD assessment method has been developed to take into account the special characteristics of the catch-at-age data set for the western horse mackerel stock. The stock and catch was dominated by a series of strong cohorts, i.e. the extremely strong 1982 year class and the also strong but much less abundant 1987 year class. In addition, the selection pattern changed greatly over the last decade. The only fishery independent information available for calibration of the population model is a time-series of egg survey estimates of spawning biomass (hence XSA and TSA cannot be used). As no age-disaggregated information is available, an assumption is required that selection at age is constant between years, for years to which

a separable model is fitted. This assumption is valid for recent years in which there are no dominant cohorts but not for those years when the 1982 year class dominated the catch. This need for different structural models for recent and historic periods has been met by the development of the SAD assessment model. The SAD model applies a separable model to recent data and then links to a VPA transformation of historic catch. The standard assessment methods – XSA, ICA and TSA – are heavily reliant on fisheries dependent data, e.g. data on commercial landings and fishing effort (McAllister and Kirchner, 2001; Nielsen and Lewy, 2002; Lewy and Nielsen, 2003; Chen *et al.*, 2004; Cotter *et al.*, 2004). Survey indices are also used in these methods but their role is to "tune" trends in commercial data (Beare *et al.*, 2005). In the standard assessment techniques, the assumptions used in the "Baranov Catch Equation" (Baranov, 1918) are assumed in the estimation of the relationship between total catch and population number. This Baranov Catch Equation is fundamental to much of EU fisheries stock assessment science. The principle is to use mortality signals between age classes along a single cohort and assumes that mortality rates are satisfactorily abridged by the negative exponential relationship. In this process, a substantial part of the information provided by the survey data (e.g., spatial detail) is lost due to the aggregation of data into numbers-at-age indices for given areas. The concern with these methods is the predominance of reported catch-at-age data. In fact, as there is a risk of misreporting and as a consequence of bias in the catch data due to the reduction of TAC levels, the quality of the central data used in the assessments suggests that this type of assessment method might generate misleading scientific advice to fisheries management, with high implications for sustainability, conservation and recovery.

Another issue with stock collapses and problems with standard assessment techniques used by ICES is that some life history information is not taken into consideration. Historically, collapses of important fish stocks have revealed that stock size overestimation is a major risk when commercial catch per effort is used as an abundance trend index, no matter what assessment method is used (Walters and Maguire, 1996). The collapse of the northwest Atlantic cod stock in 1991-92 is a good example. When viewed using a combination of fishery dependent and fishery independent data, i.e., life history information, the collapse seemed sudden (Hutchings and Myers, 1994). After the collapse, an analysis of survey data revealed progressive deteriorating conditions based on population biology indices such as the area occupied by the stock (Myers and Cadigan, 1995; Hutchings, 1996), the population growth rate (Hutchings and Myers,

1994), the maturity-at-age (Longhurst, 1998) and natural mortality rate (Sinclair, 2001). These changes, which could have been detected before the stock collapse, were not included in the population diagnosis at the time and, thus, were not used by scientists to formulate fisheries management advice. At this point in the deterioration of the stock fishery dependent data was becoming less reliable and life history data was becoming more reliable. This same phenomenon may have contributed to the major crisis that is facing EU fish stocks today, and reliable assessments utilising alternative (fishery independent) data are essential to understanding current stock status and progress towards recovery.

The state and behaviour of the "real" fisheries ecosystem and the full impact of human activities (i.e., fisheries and management) on it cannot be known precisely. There are always several sources of uncertainty due to errors and biases in observed data (Kell *et al.*, 2005a). The aim of modelling is to approximate the real system as closely as possible so as to explore the likely impacts of human actions over a range of plausible hypotheses of ecosystem behaviour. Unfortunately, in many cases, only relatively simple models can be applied due to imperfect knowledge, imprecise data and the limited power of computers. Models have to be simplified retaining as much information as possible to provide advice for fisheries management.

The correspondence between advice and the real world is difficult to assess due to the uncertainty in models but also errors in the implementation of management actions (Kell *et al.*, 2007b). One of the main problems with standard fisheries advice is that often it does not explicitly account for important sources of uncertainty. It is generally assumed that:

(1) input data are available and not biased;
(2) stock assessment models faultlessly imitate both population and fisheries dynamics;
(3) management measures are ideally implemented (Cotter *et al.*, 2004; Peterman, 2004; Punt, 2006).

It is widely accepted that many European fish stocks are over-exploited - e.g., western Mediterranean Sea hake (Sardà *et al.*, 2004), North Sea cod (Hutchings, 2005), North Sea mackerel (ICES WGMHSA, 2005) - and the majority of management procedures are based mainly on fishery dependent data, e.g., Norwegian spring spawning herring

(Lillegard *et al.*, 2005), eastern North Atlantic blue whiting (ICES WGNPBW, 2005). Unfortunately this approach may not actively take into account potential bias in observations due to misreporting.

The effective management of fisheries is facing the issue of misreporting of landings in logbooks. In fact, the disparity between real catch and recorded landings of the North Sea cod stock, which led to an overestimation of the stock abundance, is considered as one of the major reasons of the reduced state of the stock. The inappropriate information used by scientists to manage the north western Atlantic cod fishery is supposed to be an important cause in the failure to anticipate the collapse of the stock. There are biases and inaccuracies in stock assessments through the inability to account for all the fish that have been removed from the system implying there is either unaccounted fishing mortality or other unaccounted removals. Although this problem is recurrent and scientists have been striving against it, it has become more critical in recent years. Due to the serious situation, catch forecasts or recommended precautionary catch levels provided by scientists are not longer available. Scientists, managers and other stakeholders are particularly concerned by the tendency of increasing uncertainty in stock assessments and forecasts.

Theoretically, catch controls are the most effective way of adjusting fishing mortality in an effective fisheries management system. However, there are strong incentives for fishermen to fish illegally or misreport landings, especially in a period when quotas are being reduced but economic imperatives remain to maintain catches. Misreporting of catch can occur as a result of several reasons, many of them being legitimate but also a direct requisite of the established management system. In fact, fishermen have been instructed to throw away any fish which does not match the minimum size requirement, if a minimum size restriction is in place for the given stock. Alverson *et al.* (1994) showed that survival rates of discarded fish at sea are low. When discarded fish are not recorded, the official fishing mortality does not include discarded fish, which under-estimates the actual fishing mortality rate. Another source of disparity between real catch and recorded landing is the use of quota and / or trip limitations as a management rule. If fishermen surpass the set quota, they are legally required to discard the excess of catch. However they can illegally land the surplus and sell it through the black market. In both cases, the over-quota catch is not recorded. For some fisheries, the principle of individual quotas has been implemented. This system can also be source of

misreporting. Indeed, fishermen can be tempted by discarding smaller fish to keep the quota for larger and more profitable fish. This process is known as high-grading (Copes, 1986; Anderson, 1994; Arnason, 1994; Pascoe, 1998). Furthermore, misreporting can be explained by the landing and recording in an area of a quantity of fish caught in another area. This distorts the estimation of the stock in both areas. In addition, if fishermen do not manage to reach the set quotas if the stock is in bad condition, they can be tempted to declare more catch than what they actually caught. Indeed, if they do not reach the quota, the latter for the following year might be reduced due to the estimation of the stock biomass. If they declare they have reached the quota, the input of the assessment model will give the impression that the stock is consistent with the estimation made.

If the issue of black market landings is not considered, logbook records reflect a true record of landings but an under-estimation of actual catch. The term "misreporting" is then not, as a direct consequence, based on illegal activity (Pascoe *et al.*, 2004).

The effects of misreporting on the assessment and the management advice are explained in further details in section 4.2.3.

In order to improve advice for stocks where misreporting is felt to be an issue, the European Commission funded a project called FISBOAT (Fisheries Independent Survey Based Operational Assessment Tools). Its purpose is to develop fish stock assessment tools based on fishery independent survey data only (i.e. provided by fisheries research vessels) and evaluate how well these tools perform in producing advice within defined management procedures (FISBOAT, 2003).

FISBOAT PROJECT

The research described in this thesis was undertaken as a contribution to the FISBOAT project, which is part of the sixth framework programme (policy oriented research) funded by the European Commission.

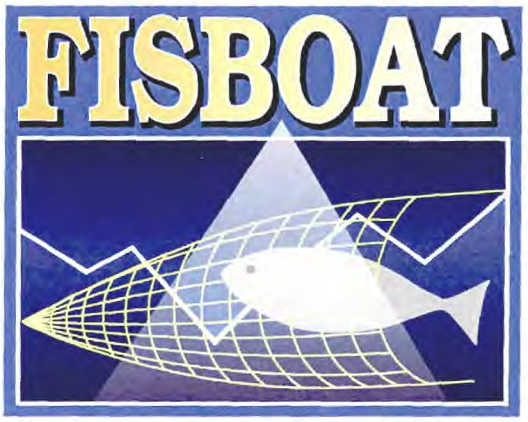


Figure 2: FISBOAT logo. Designed by Sylvie Gros (IFREMER - France)

The objectives of this project in which the thesis research is embedded are to develop research survey-based tools allowing for fishery independent assessments and to evaluate the developed tools in their ability to provide quantitative advice on management options. The case study fisheries in this project include species of different behaviours (demersal and pelagic) and life spans (long or short) that entail different survey types (bottom trawl, hydro-acoustics, pelagic eggs and larvae). Surveys provide indices of population abundance and population biology parameters. With the aim of the FISBOAT project in mind, an evaluation framework was developed that includes the development of several modelling components (a population dynamics model (or "operating model"), an observation error model, an assessment model and a harvest control rules model). The robustness of management procedures based on fisheries-independent data in stock assessment and fisheries management will be evaluated by applying this evaluation framework (FISBOAT, 2003).

I personally took part in the implementation of the generic codes of the models (operating model, observation error model, harvest control rule model) which were then tuned for each case study by the relevant partners. I was in charge of the adaptation of the code to the North Sea herring case study in collaboration with John Simmonds from FRS Aberdeen as he provided the data and the knowledge about the stock and its dynamics. Once the code was implemented, I took part in the selection of the generic performance indices and the one specifically chosen for the herring case study. I also analysed the results obtained and wrote various reports for the project.

What is the originality of the thesis?

The main hypothesis evaluated in this thesis is that fisheries management which utilises methods based on fishery independent data may generate advice that is less susceptible to bias compared with methods utilising a combination of fishery dependent and independent data or on fishery dependent data alone. My PhD research will evaluate the potential usefulness of fishery independent data in fisheries management applied to the North Sea herring (*Clupea harengus*) fishery by comparing advice provided by management strategies based on fishery dependent data only, a combination of fishery dependent and independent data and finally fishery independent data alone. In particular it examines alternative harvest control rules (HCRs) to those currently adopted and explores which are most robust to observation, process and model uncertainties when using fishery dependent or fishery independent methods.

Objectives

The aim of Management Strategy Evaluation (MSE) is to use complex models such as operating models, observation error models, assessment models, and harvest control rules models to evaluate quantitatively the expected performances of management rules prior to implementation. This is done by simulating responses of natural populations to different management actions. Population dynamics models are based on expert knowledge, available data, assumptions and hypotheses. The "real" dynamics cannot be known with accuracy and the aim of MSE is to test the robustness of the strategies based on alternative hypotheses to these "true" dynamics and to meet requirements of the precautionary approach to fisheries management. The link between the "real" and the "observed" systems are observations that are based on outputs of the operating model and the implementation of management actions will act on the "real" system (Food and Agriculture Organisation of the United Nations (FAO), 1996; Kell *et al.*, 2007b). The "real" dynamics and the "observed" data on the system are developed in simulation models. The operating model corresponds to the "real" system. The "observed" one contains three elements: the observation error model, the assessment model and the harvest control rules model. Their links are presented in Figure 3.

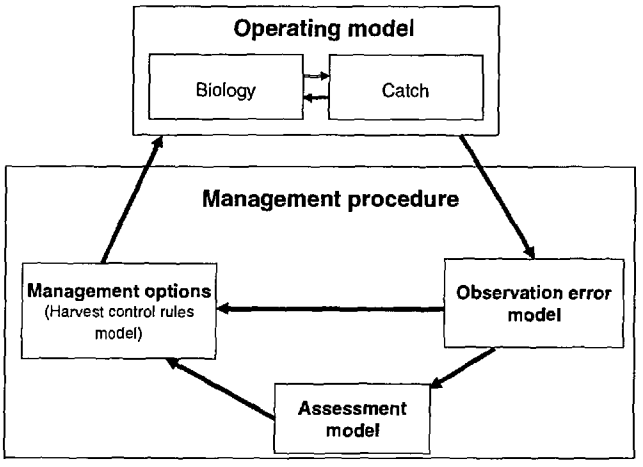


Figure 3: The simulation evaluation platform.

With this in mind, the specific objectives of this project are to develop the four components of the overall evaluation platform, to condition these on data and then to provide a full evaluation of the performance of management procedures based on different combinations of fishery dependent and independent data.

The different steps will be to implement an operating model (age-based population dynamics model) based on fishery dependent and independent data, taking into account potential bias in observations through the observation error model, evaluate the state of the stock through several alternative assessment methods, utilise different combinations of fishery dependent and independent data to give advice for stock management in the harvest control rules model, compare the results of those combinations. The simulation-testing framework will be developed and implemented under FLR (see following section).

In order to develop the platform, an age-structured population dynamics model will be developed (McAllister *et al.*, 1994; Punt *et al.*, 2002b) that allows a realistic representation of the population dynamics of the North Sea herring stock. The operating model will include the following components: age structure, natural mortality rate-at-age, stock-recruit relationship, inter-annual variability in stock-recruit deviates, fraction mature-at-age, weight-at-age and catch biomass per year.

The second component of the evaluation platform is the observation error model that can model, within a Monte Carlo framework, the error structure in the key types of indices that can be derived from fishery dependent and independent surveys of fish

populations (Brooks, 1998; Lewy and Nielsen, 2003) and that may be used in HCRs. Several assessment methods are implemented in this research, some already in existance (ICA, SURBA) and others implemented specifically for the FISBOAT project (YCC) (Appendix 2).

The last component of the simulation evaluation framework is the harvest control rules model. A relatively simple harvest control rules model was generated that incorporated several alternative HCRs (Bell *et al.*, 1998; Stefánsson, 1998b; Cooke, 1999). Two types of HCRs can be considered: model-free and model-based. The first type is based directly on survey data and is relatively simple to understand and to simulate compared to those that are model-based. The latter is based on the results of a stock assessment and provides a smoothing effect by fitting a model to data, which lowers variability when evaluating management controls.

FLR framework as a tool

The models in this research were developed in the FLR (Fisheries Library in R) framework, which is a set of standardised coded modules specifically developed in the programming language R for use in fisheries modelling. One of the principal uses of this framework is the development and evaluation of fisheries management strategies, often referred to as MSE. Butterworth and Punt (1999) have noted that evaluating management strategies without a common framework is a difficult task due to the difficulty of implementing proper operating models. FLR was therefore ideally suited to the tasks in this research.

FLR allows scientists and managers to use already existing models or develop additional models (operating models, observation models, assessment models, harvest control rules models and implementation models) in order to develop and evaluate methods in fisheries management. It can also be used to condition models on available data, to analyse those data and to provide estimates of population parameters based on data but also on assumptions to be used in operating models. All this can be accomplished in a frequentist or Bayesian framework.

FLR is an Open Source framework continuously improved by interested users and more particularly by the FLR developers' team (http://www.flr-project.org). This framework facilitates the implementation, evaluation, validation and utilisation of codes and software between scientists. The key elements included in the development of this software are a diversity of fishery, biological and economical models and combinations of components of those models can afterwards be evaluated for their robustness to uncertainty before implementing management actions in the "real" system (Kell *et al.*, 2007b). The origin of this software is a request from scientists to ICES (ICES WGMG, 2004) which led to the establishment of the European Project FEMS (Framework for the Evaluation of Management Strategies).

In the present research, R version (R 2.3.1) is used since it was the one available when the project started.

Overview of the thesis

This thesis consists of five chapters.

The first chapter provides the background to the case study. It describes the biology and ecology of the herring in the North Sea. It then explains why this study will focus on one specific stock of herring in the North Sea and it relates the history of the North Sea herring stock from the post-war years until today. The chapter concludes by describing the assessment and the management of this stock and the characteristics of the data which are available for assessments.

The second chapter focuses on the first model of the evaluation platform, the operating model. It starts with a description of the structure of the model and particularly the stock-recruitment relationship which a key element of the model. This is followed by a brief description of the Monte Carlo method used to introduce uncertainty in the different models and the characteristics of the parameters specifically applied to the North Sea herring stock.

The third chapter describes the second element of the evaluation platform, the observation error model. The major part of the chapter describes the two types of indices implemented in this research, non age-structured indices and age-structured indices. For each of them, a theoretical explanation is given and an application to the case study is provided.

The fourth chapter describes the implementation of HCRs. Two categories of HCRs are implemented, model-free and model-based. Two elements can be added in the harvest control rules model: a potential implementation error and a limitation of the inter-annual variation in the TAC. These rules are described in detail in the chapter 4.

The fifth chapter starts with an explanation of the concept of Management Strategy Evaluation and its history. This chapter contains the major results of the research, organised in order of increasing complexity of the observation error model and HCRs.

A general conclusion is presented after the final chapter including a summary of the major findings, the scientific contribution of this work and some recommendations for future research.

CASE STUDY:

NORTH SEA HERRING FISHERY

1 Case study: North Sea herring fishery

1.1 Introduction

Herring (*Clupea harengus*) (Figure 4) is one the most important commercial pelagic species taken in the north east Atlantic. Since at least the middle ages it has been the target of inshore fishing using small boats operating at spawning time and was often the mainstay of local economies (Tittler, 1977 in Kelly, NA; De Courcy Ireland, 1981 in Kelly, NA, Poulsen *et al.*, 2007). In the 19th century, herring fisheries grew in importance as major producers of primary protein for urban industrial populations, leading to the development of major processing operations that moved around the coast seasonally following herring spawning times (Devine, 1979; Nadel, 1984). The rapid development of industrial fishing in the middle of the 20th century led to serious overfishing and a collapse of the North Sea stock in the mid 1970s (Burd, 1985; Jennings, 2001; Caddy and Agnew, 2004). This was followed by a four year moratorium of commercial fishing and a substantial recovery over a ten year period. In the 1990s, herring suffered a further decline due to overfishing and high by-catch of juveniles by industrial fisheries targeting sprat (CEFAS, 2007; Simmonds, 2007) (Figure 5).



Figure 4: *Clupea harengus* (Source: Ifremer).

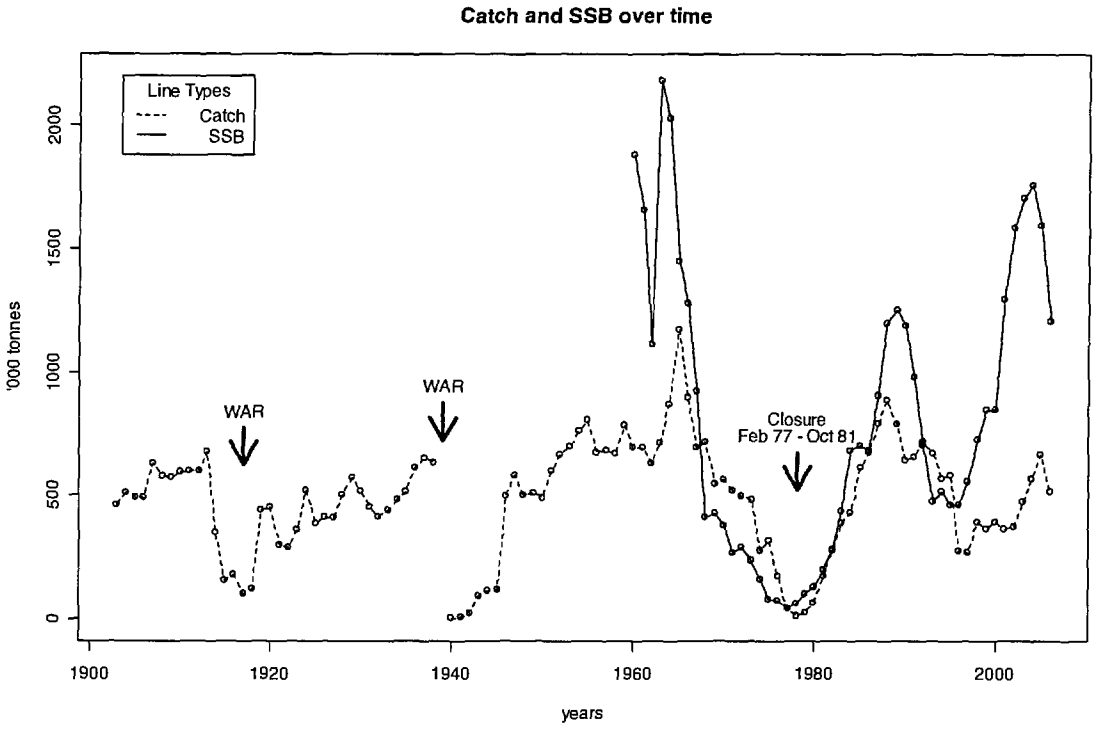


Figure 5: Spawning stock biomass and herring landings from the North Sea.
Solid line: SSB values estimated from ICA between 1960 and 2006 (ICES HAWG, 2007) and dashed line: landings from Dickey-Collas *et al.* (2006).

This chapter consists of three sections. The first describes the biology and the ecology of North Sea herring, and introduces the autumn spawning stock, which is the focus of this research.

The second section relates the history of the herring fishery in the North Sea from the post-war years until today. The third section describes the assessment of the stock, the advice provided by the institutions – i.e. ICES and the Scientific, Technical and Economic Committee for Fisheries (STECF) – and the management applied to maintain the stock at a good level in order to avoid a future decline or collapse of the stock but also to maintain a good level of catch for the fishermen.

1.2 Biology and ecology

The North Sea is a relatively small sea. The edge of the continental shelf, west of Orkney and Shetlands, corresponds to the north-western limit. The north-eastern limit is the Norwegian Deep, a deep-water trench running parallel to the Norwegian coast and

reaching depths of 700 metres. On the eastern edge of the North Sea, the Skagerrak and Kattegat link the North Sea to the Baltic Sea. The last boundary of the North Sea is with the Atlantic Ocean via the English Channel (ICES-FishMap, 2005a).

Herring is a pelagic fish which lives from the surface to the bottom of the sea all over the northern European continental shelf (from the coast to a depth of 200 meters) north of 46°N. Most stocks do not leave the shelf area (Ifremer, 2000). However the most northerly population (Norwegian spring spawning herring) found north of 46°N feeds pelagically in offshore waters between Norway and Iceland (ICES PGNAPES, 2006). Herring are amongst the most spectacular of schooling fish, moving in organised groups of thousands to hundreds of thousands. At the stock scale, schools generally migrate each year between spawning, feeding and nursery grounds (Zimmermann, 2004a). The aim of the schooling behaviour is to improve foraging but also to limit predator efficiency (Partridge, 1982 in Bjørndal, 1989).

Two stocks of herring with different biometric characteristics and spawning seasons are found in the North Sea (Cushing and Bridger, 1966; Ruzzante *et al.*, 2006), commonly referred to as North Sea autumn spawners and western Baltic spring spawners[2].

The autumn-spawning stock comprises several sub-stocks with distinct spawning areas. Orkney and Shetland herring spawn between July and August around the Orkney and Shetland islands, north of Scotland. Buchan herring spawn between August and September off the east coast of Scotland; Banks herring spawn inshore of the Dogger Bank in the central North Sea between September and October and Downs herring, found in eastern part of the English Channel and the south of the North Sea spawn between November and December (Figure 6).

The sites where spring-spawning takes place are around the Danish Islands and along the German Baltic coast (Parmanne *et al.*, 1994) but the main spawning area is around the Rügen Island (Greifswalder Bodden). Depending on the ice coverage the spawning season lasts from around March to May (Zimmermann, 2004c).

[2] Data used in this thesis come from collaboration with John Simmonds and Paul Fernandes from Fisheries Research Services (FRS) Marine Laboratory in Aberdeen. Their database contains data covering ICES divisions IIIa, IVa, IVb, IVc and VIId (c.f. figure 3), known as the North Sea region. This area extends from 49.505 to 62° North and from 2° West to 13° East. As landings of herring are not always available for areas IVc and VIId, those two divisions are combined in the database (Kienzle, 2003).

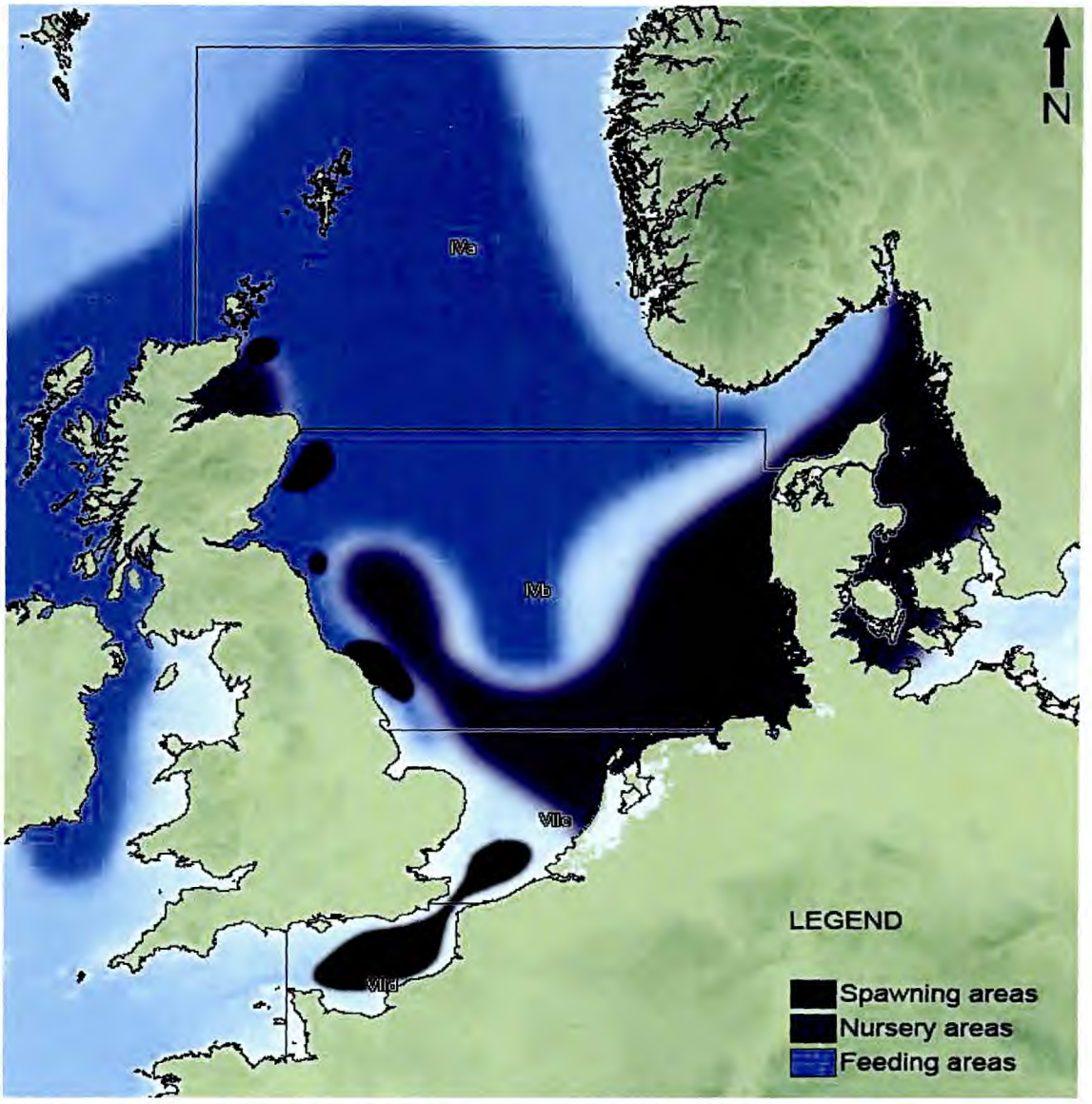


Figure 6: Map of the North Sea with ICES divisions IVa, IVb, IVc and VIId, spawning, nurseries and feeding areas (Source for the base map: iSEA (CEFAS, 2006).

Eggs are demersal, laid in large sticky masses. Larvae hatch after 2 weeks (Quéro and Vayne, 1997) and become pelagic, metamorphosing into juveniles after approximately 6 months (between 3 and 11 months depending on environmental conditions; (Gulf of Maine Research Institute, 2008), at which time they develop their otoliths.

The majority of larvae spawned during the autumn drift during their first winter from the spawning areas on the western side of the North Sea to the nursery areas located on the eastern side (Figure 6). There are smaller nursery areas on the east coast of Scotland and England. Juveniles live in these areas for almost two years before migrating to adult feeding areas. Fish spawned in the autumn of one year are age 0 - according to otolith readings - the following year and age 1 (1-ringers or 1-otolith ring animals) the year

after that following the laying down of the first growth ring. At this point they become vulnerable to juvenile fisheries, although they do not recruit to adult fisheries until age 2.

After spawning, mature herring migrate to feeding areas which are mainly located along the east coast of the UK. Herring coming from the different spawning areas tend to mix in these feeding areas (ICES HAWG, 1964; Ifremer, 2000; Fisheries Research Services, 2007b).

Some density dependence is apparent in herring stock dynamics, and it has often been suggested that this operates at the egg stage since the substrata they require for spawning may be limited in area (Wood, 1981; Zheng, 1996; Iles and Beverton, 2000). When the spawning stock biomass (thereafter SSB) is high, eggs may be deposited in thick layers leading to anoxia and reduced hatching success. This has been demonstrated for Pacific herring (*Clupea harengus pallasii*) but does not appear to be a common occurrence in Atlantic herring (Taylor, 1971 in Fox, 2001; Alderdice and Hourston, 1985; Stratoudakis *et al.*, 1998). Where the extent of the spawning substrate is not limited, it has been shown that it is the extent of the spawning patches which increases with spawning stock size, rather than the thickness of the egg layers (Johannessen, 1986). Herring spawn has been shown to attract predators which may be a mechanism for density dependence (Tibbo *et al.*, 1963 in Fox, 2001; Hempel and Hempel, 1971 in Fox, 2001; Johannessen, 1980; Rankine and Morrison, 1989). Similarly, incoming spawners may cannibalise eggs deposited earlier in the season and this might have more impact when the spawning stock biomass is high (Haegele and Schweigert, 1985; Stocker *et al.*, 1985; Winters and Wheeler, 1987).

In the early 1990s there was an outbreak of *Ichthyophonus* disease in the North Sea herring population. Studies suggest that this had only a relatively small influence on adult mortality and no effect on juvenile mortality (Patterson, 1996; Mellergaard and Spanggaard, 1997). However, coincidentally there was a dramatic drop in the fraction mature of 2 and 3 year old herring. The effect of this outbreak on the development of the stock seems to have been minor (Patterson and Beveridge, 1995).

Spring and autumn spawners can be distinguished using vertebral counts (ICES HAWG, 1990) and more recently by examination of otolith micro-structure (Clausen *et*

al., 2004). One stock of spring spawners is caught in Division IVa (East) close to the Norwegian coast and is managed with a highly variable TAC[3]. The other is located within the Thames Estuary in the southern North Sea. It is managed with a local TAC and landings are quite small (usually less than 100 tonnes) (ICES HAWG, 2007).

This study will focus on the North Sea autumn spawning herring stock, which is the largest stock in the North Sea, rather than considering the other smaller stocks in the area. The autumn spawning herring make up the dominant part of the herring catch in the North Sea, and although there is a mix between spring and autumn spawners in ICES division IIIa, it is negligible when compared to the total autumn spawning population. Similarly, the existing migration between the North Sea and the Baltic Sea will not be taken into consideration.

Since 1971, the autumn spawning herring covering the ICES areas IVa, IVb, IVc and VIId has been managed as a single stock by the ICES Herring Assessment Working Group (HAWG) (Burd, 1985) although management advice is separated by area, for the northern and central North Sea (areas IVa and IVb) area and the southern North Sea and English Channel area (areas IVc and VIId) (ICES HAWG, 2007).

1.3 History of the North Sea herring stock

Fishermen have adapted their methods to the vertical distribution of herring. There are two main types of nets used by herring fisheries: mid-water trawl, meant to capture fish at a given depth where herring have been detected, and purse seine, designed to capture large, dense shoals of fish that swim near the surface (Fisheries Research Services, 2007a). Some inshore fisheries still use drift nets (ICES-FishMap, 2005b). Most catches are made during the summer between June and August, or in the winter in the southern North Sea only.

The exploitation of the North Sea herring stock in the past has been well documented (Burd, 1985; Nichols, 2000; Simmonds, 2007) and offers a good example of the impact of the expansion of commercial fisheries on a single fish stock. During the post-war

[3] Total Allowable Catch

years and until 1960, the annual landings, averaging 650 000 tonnes, were large and stable. When large-scale fishing developed in the 1950s, the herring stock had an estimated SSB of over 2 million tonnes (Zimmermann, 1999) (Figure 5). The rapid decline that followed – the SSB fell by 40% in just over 10 years in the 1970s – was due to a combination of factors: overfishing (unsustainable fishing mortality) caused by the rapid development of industrial fishing (Nichols, 2000) coupled with a loss of important age classes in terms of reproduction, despite an acceptable recruitment. During the late 1960s, the fishing mortality rose drastically leading to removals of more than 70% of fish between 2 and 6 years old. In 1965, 80% of the 1 000 000 tonnes landed were juveniles (less than 2 years old) fish. This was mainly due to the rapid expansion of the industrial fishery[4] for meal and oil, targeting juvenile herring off the Danish coast.

The stock decreased severely in the early 1960s and had collapsed by 1977. The collapse led to a four year moratorium on herring – targeted commercial fishing – although juveniles were still caught as an allowed 10% by-catch in small mesh fisheries targeting other species (Nichols, 2000). Due to this ban and years of good recruitment, the North Sea herring stock recovered. This recovery led to the reopening of the fishery in 1981, but with a restriction: a TAC was implemented to limit future depletion of the stock. This measure was never fully implemented (Simmonds, 2007) and though recovery occurred in the 1980s, management measures proved insufficient and the stock substantially declined throughout the 1990s. Once again, this was due to the increased juvenile mortality as by-catch in sprat fisheries and because TACs for herring-targeted fisheries were exceeded. This inability to keep catches within the TAC has been a consistent feature of the fishery. A drastic reduction of the TAC – 50% of the fishing mortality – was recommended in 1995 by the Herring Assessment Working Group (HAWG) of ICES to rebuild the spawning stock biomass but this suggestion was not followed by managers. The following year, the HAWG reiterated its recommendation which this time was applied (TAC in 1995: 440 000 tonnes, TAC in 1996: 156 000 tonnes for human consumption only) and catch decreased from 501 000 tonnes in 1995 to 228 000 tonnes in 1996. The TAC in 1997 was kept quite low compared with previous years and the excess of landings over TAC was relatively small. Following these two years of low catches, an agreement was made between the European Union

[4] *Industrial fisheries* are defined as all fisheries which target fish not destined to human consumption and which enter an industrial process. Some fish species are used for both industrial purposes and for human consumption (DGR-fish 2004).

and Norway in December 1997 to make efforts to maintain the SSB above the minimum biologically acceptable level of 800 000 tonnes. As the stock started to recover thanks to the drastic reduction of TAC in 1996, the TAC was increased until 1999 when it reached 256 000 tonnes. The slow increase and then constant TAC for four years allowed the stock to recover and it was agreed in 2003 to increase the TAC up to 400 000 tonnes. According to the HAWG estimates of catch for human consumption, catch in 2003 exceeded the set TAC by 38 000 tonnes which was the smallest excess since 1995. TAC was again increased in 2004 and 2005 but due to a low recruitment since 2001, TAC in 2006 was decreased by less than 20% (ICES HAWG, 2007).

1.4 Assessment, advice and management

1.4.1 ASSESSMENT AND ADVICE

Once a year, the ICES HAWG undertakes a North Sea herring assessment. The FAO defines a stock assessment as "the process of collecting and analysing biological and statistical information to determine the changes in the abundance of fishery stocks in response to fishing, and, to the extent possible, to predict future trends of stock abundance. Stock assessments are based on resource surveys; knowledge of the habitat requirements, life history, and behaviour of the species; the use of environmental indices to determine impacts on stocks; and catch statistics. Stock assessments are used as a basis to assess and specify the present and probable future condition of a fishery" (FAO, 2007).

Between 1972 and 1995, assessments were performed using a Virtual Population Analysis (VPA)[5]. Data used to tune the model were larval production estimates and acoustic and trawl surveys (ICES HAWG, 1991). In the early 1990s, larval indices and trawl surveys on the one hand and acoustic surveys on the other hand did not provide the same information on the state of the stock and the assessment became increasingly unreliable. To try to reduce this uncertainty, other assessment methods were examined. At the same time, a reduction in the coverage of the larval surveys in the North Sea led to a deterioration of the quality of this source of information. During the closure of the

[5] More details about VPA can be found in the Appendix 2.

herring fishery in the late 1970s, larval indices had produced a good indicator of the recovery of the stock. They also contributed to a long time series of SSB estimates. In 1993, due to a significant reduction of the spatial and temporal coverage of the larvae surveys, the larvae production estimate was substituted for a multiplicative larval index (MLAI) which could be calculated using the now more limited data set (ICES HAWG, 1996).

Because of the uncertainty in the assessment, the working group switched to an Integrated Catch Analysis (ICA) method (Patterson and Melvin, 1996)[6] in 1995 which is still currently used. The benefits of this method are the possibility to use age-aggregated indices of stock size but also to include potential errors in catch-at-age data and in survey indices (Nichols, 2000). A more precise analysis of VPA, ICA and other assessment methods is provided in Appendix 2 as it is mentioned in the introduction of this thesis.

Once the stock assessment is implemented each year in March by the HAWG, it is evaluated by the ICES Advisory Committee On Management (ICES ACOM) two months later. After potential revisions to the assessment are made, ACOM delivers advice on the state of the stock that incorporates a set of options for fishery managers to examine and serve as a guideline towards defining the TACs for the following year. As there are different types of fleets fishing the North Sea herring stock, the overall estimated allowable catch has to be subdivided between these fleets depending on their different impacts on the stock.

The sub-stock located in the southern North Sea and the English Channel (Divisions IVc and VIId, Downs herring) is reproductively distinct within the North Sea – spawning in the winter, and has in the past been subject to more intense fishing mortality than the rest of the stock. Although the autumn and winter spawners are assessed as a single "autumn-spawning" stock, a specific sub-TAC is set in the current management for this area in order to conserve the Downs sub-stock. In this thesis, no distinction is made between those sub-stocks and they are assumed to correspond to a unit stock.

[6] More details about ICA can be found in the Appendix 2.

1.4.2 MANAGEMENT

Simmonds (2005, 2007) has carried out a thorough analysis of the management of the North Sea herring fishery for the two periods around the closure of the fishery in the late 1970s and its intense decline in the mid 1990s. Between 1903 and 1965, yields were maintained between 300 000 and 1 000 000 tonnes but in the late 1960s, a serious decline of the fishery occurred. The early 1960s were years of intense fishing and growing concerns arose by the mid 1960s. As the stock declined, biologists started to concede that overfishing was occurring but the recognition was slow in coming. The scientific advice was argued and several requirements and propositions were made to improve the science, which managed only to retard decision making. In 1980, Saville and Bailey said "the advice given to the regulatory bodies on management... has tended to be much too optimistic in respect of total allowable catches". The virtual population analysis (VPA) method used to assess the stock, which depends on estimates of the fishing mortality rate overestimated the state of the stock. It appeared that estimated fishing mortality rates were too low, leading to overestimates of the stock biomass and consequently over-optimism about the state of the stock at that time.

The responsibility of the collapse of the North Sea herring stock does not rely only on the stock assessment biologists. It took time to identify the problem but once it was done, the decision makers took even more time to take notice of the scientific advice. Management concentrated on seasonal and areas closures but in spite of indicators showing that the fishing mortality rate was too high and not sustainable, no substantial management action was taken to reduce the fishing mortality rate. In 1970, the stock assessment biologists advised significant reduction of the fishing mortality. In 1974, a total quota was agreed by managers but nothing was imposed before 1977. For the period 1962-1977, no catch limits were set and efforts restrictions were confined to small seasonal closures. Fishing continued and the stock collapsed. Between 1970 when scientists recommended a reduction of the fishing pressure and 1977 when the regulation was finally implemented, the stock declined to less than 200 000 tonnes.

In the 1970s, the Northeast Atlantic Fisheries Commission (NEAFC) strived to attain an accord on a TAC but did not manage to do so because constitutional constraints within NEAFC prevented the early implementation of such a measure. The implementation of

this management tool could only be realised if a sufficient number of national delegates approved it. Unfortunately that was not the case. When the stock was recognised as being in a worrying situation, the constitution was amended and a TAC could be imposed but only if enough delegates agreed. In practice, to avoid economic consequences, only a non-restrictive TAC would be accepted. Short-term economic losses due to catch restrictions were put forward by delegates to refute the suggested catch reductions, without reflecting on long-term biological and economical consequences. When the fishery was closed in 1978, it left no possibility to take into account social and economic issues for potential trade-offs. The losses that would have been incurred in the short-term due to appropriate action were by far outweighed by the medium-term losses consequent to the closure. The opposite happened in the 1990s when short-term restrictions yielded medium-term benefits.

However, in the 1990s there was an underestimation of the true mortality and the assessment did not fully render how changes in management induced modifications in stock and fishery. Although F did not reach its recommended level until 2002, the decline of the SSB was stalled by a reduction of the fishing mortality and thus maintenance of the fishery. Whereas in the 1970s science could not provide evidence to back management decisions, a failing that was constantly used to delay much needed measures, post mid-1990s scientific advice, complemented by more effective management, led to a recovery of the stock in 2003, demonstrating the importance of fisheries science, especially in the light of the late 1970s collapse.

The management of the herring stock in the North Sea has been adequately informed by science from the mid-1990s to the present. Following the two severe declines (up to 1977 and up to 1995), the North Sea herring became the first stock in the North Sea managed through the implementation of the precautionary approach. Following the 1977 collapse, a TAC had been imposed on adults only, but this was seen to be ineffective in conserving the stock when strong fishing pressure on juveniles caused a further decline in 1995. The European Union and Norway adopted a new management agreement in 1997 to limit both juvenile and adult catches when the SSB falls below set reference points (see the extract of the agreement, below). The lower biomass reference point (B_{lim}), below which there is an aggravated risk of low recruitment, is set at 800 000 tonnes and triggers the emergency plan until the upper reference point – B_{PA} set at 1 300 000 tonnes – is reached. Above an SSB of 1 300 000 tonnes, the TAC is fixed at c. 20% for adults ($F_{2\text{-}6}$=0.25) and c. 10% for juveniles ($F_{0\text{-}1}$=0.12).

A by-catch limit for young herring in the small-mesh fisheries – targeted mainly on sprat – is given each year. When the ceiling is reached, some areas are closed to protect both spawning and juvenile herring (Zimmermann, 1999). This encourages a faster rebuilding of the stock, especially as the Danish authorities, in 1996, implemented a new control system to significantly limit by-catches of juvenile herrings.

Extract of the EU-Norway agreement for North Sea herring (Nov. 2004):

"According to the management scheme agreed between the EU and Norway, adopted in December 1997 and last amended in November 2004, efforts should be made to maintain the SSB of North Sea Autumn Spawning herring above 800 000 tonnes. An SSB reference point of 1.3 million has been set (=Bpa) above which the TACs will be based on an F=0.25 for adult herring and F=0.12 for juveniles. If the SSB falls below 1.3 million tonnes, the fishing mortality will have to be linearly reduced. A TAC deviation of more than 15% between two subsequent years should be avoided, however, the TAC might be reduced by more than 15% if the parties consider this appropriate."

Despite some implementation error in TAC management, these errors have never prevented stock recovery. The consistency of the assessment and the scientific advice has been shown by the fact that the harvest control rule performed within the expected range (Simmonds, 2007). The 6 year recovery is the result of a mix of factors: adequate scientific advice, stability in the recommendations coming from the management system, a positive response from industry and management, and sufficient recruitment during the recovery. The crux is that the cost of good scientific advice (2.5% of the landed value in this case) is a small price to pay compared with the benefits it yields: effective management decisions that can prevent stock collapse and maintain a sustained economic gain in the medium- to long-term.

1.4.3 DATA AVAILABLE FOR ASSESSMENTS

Several sources of data are available for herring assessments (Pope, 1982). Total landings and fishing effort data are available from logbooks and routinely collected by member States. Total landings are converted to number of fish landed at age and

maturity using market sampling data. There are additional programmes that examine the species and amounts of discarded fish to better estimate total mortality. Consistency of sampling methods and effort has been implemented since the EU data collection regulation came into force in 2001.

Several fishery independent surveys are carried out annually, using standardised methods so that the results are comparable (ICES-FishMap, 2005c).

1.4.3.1 Herring acoustic survey

In the post-war period, Parish (1953) proposed an "organised echo search" to establish the dispersal of herring in the entire North Sea by developing an acoustic survey. Development of such a system took some time and the first acoustic survey was only carried out a year after the beginning of the moratorium (1979) (ICES HAWG, 1980). The north western and west central North Sea as well as the northern part of Division IVa were surveyed by six vessels. However, in 1980, the spatial coverage by ships was reduced to the Orkney and Shetland area as results from the first survey in 1979 were inconsistent. After 1988, the North Sea was again adequately covered at regular, comparable times by diverse surveys which made possible to obtain a combined estimate (ICES PGAS, 1989). From that date, the international North Sea herring acoustic survey has been conducted every year from late June to early August with the same survey plan and area, involving the United Kingdom (Scotland), the Netherlands, Norway, Germany, Denmark and more recently Sweden (Zimmermann, 2004b).

Methods implemented on herring acoustic surveys (ICES PGHERS, 2007) are based on the concepts developed in Simmonds *et al.* (1992) and later updated in 2005 (Simmonds and MacLennan, 2005). In order to have a consistent index from each survey, the methods employed have been standardised. All vessels use the same type of echo sounder at the same frequency. The process of calibration is identical on all ships and is done on each survey. The distance between two transects cannot exceed 15 nautical miles and the speed of vessels has to be constant – 10 to 12 knots. Transects are only run in daylight hours since herring migrate towards the surface at night where they become undetectable by echo sounders. The composition (species, length, age and maturity) of target echoes is determined by periodic trawl sampling.

Once a year in January, the ICES Planning Group for Herring Surveys (PGHERS) holds a meeting to collate individual survey data – number-at-age, mean weight-at-age and total biomass – to provide a total combined estimate for the North Sea for each parameter. These estimates are then transferred to the HAWG (ICES PGHERS, 2007) which uses them to tune the ICA model and provide the estimate of the total SSB (Zimmermann, 2004b).

1.4.3.2 International Bottom Trawl Survey (ICES IBTSWG)

The International Young Herring Survey (IYHS) was implemented for the first time in 1965 surveying immature herring with the aim of obtaining annual recruitment indices (abundance of 1-ringer on 1st quarter) for the combined North Sea herring stock. During the following years, more countries took part in the survey which was primarily focused only on the southern and central North Sea. Later, the spatial coverage of the survey was extended to the whole of the North Sea so that the survey could supply recruitment indices for other roundfish species such as cod *Gadus morhua*, haddock *Melanogrammus aeglefinus*, whiting *Merlangius merlangus* and Norway pout *Trisopterus esmarki*. The survey was then renamed International Young Fish Survey (IYFS).

Following the moratorium, national groundfish surveys were developed and in 1990 it was agreed to combine all national surveys in a unique international one, the International Bottom Trawl Survey, which was initially implemented four times each year between 1991 and 1996 on the whole of the North Sea. However because it was difficult to maintain such an intense program, it was decided in 1997 to reduce the number of surveys to two per year, one in February and the second in August or September. This frequency has continued since and the survey is coordinated by the ICES International Bottom Trawl Survey Working Group (ICES IBTSWG) (ICES-FishMap, 2005c).

1.4.3.3 Method Isaac Kidd Mid Water Trawl survey (MIK)

The MIK index has been developed to estimate the abundance of autumn-spawned larvae longer than 20 mm (ICES HAWG, 1996). Those larvae are 0 group overwintered fish, and will recruit to the juvenile stock as 1 group the following year, so this survey provides information about recruitment a year before they can be detected through the IBTS (1 group) survey (ICES HAWG, 2007). Samples are taken at night during the IBTS in February each year using a fine-meshed ring net (MIK net).

1.4.3.4 Multiplicative Larval Abundance Index survey (MLAI)

ICES has organised the International Herring Larvae Survey (IHLS) since its beginning in 1967 (Saville, 1968). In 1972, changes were made to the IHLS: it was redefined and standardisation was improved (Anonymous, 1985; Anonymous, 1990). The number of countries participating in the survey increased in the 1970s to a full coverage by 1980 and then declined in the early 1990s from the original eight (Denmark, Germany, England, Ireland, The Netherlands, Norway, Scotland and Sweden) to two – The Netherlands and Germany. As a consequence, the survey coverage and effort has decreased substantially.

Since 1972, the general implementation of surveys has remained the same: several two-week surveys from September to the end of January following a pre-established spatial design. At first, the survey covered most of the western part of the North Sea and the English Channel but following the decline in survey effort in the early 1990s, only the Orkney/Shetland. Buchan, central North Sea and the English Channel areas are now covered (Zimmermann, 2004b).

Larvae sampled with a total length of less than 24 mm are put into length classes defined by 1 mm intervals. Until 1986, only very young larvae measuring less than 10 mm were used to calculate the Larvae Abundance Index (LAI) which, to be reliable, had to be based on a relatively good spatial and temporal coverage as the distribution of larvae is highly patchy. The reduction of country investment in the survey induced the implementation of a new index to compensate for the lack of coverage and so in 1986 the Larvae Production Estimate Index (LPE-index) replaced the LAI (Christensen,

1985; Lassen and Pedersen, 1985; Lough *et al.*, 1985; Christensen, 1989). The calculation of this new index uses the number of larvae measuring less than 17 mm, and a daily hatch rate is calculated for each single mm class of larvae. In 1993, temporal and spatial coverage were further reduced forcing a revision of the analysis method. The resulting Multiplicative Larvae Abundance Index (MLAI) utilises multiple analysis of variance to compensate for temporal and spatial gaps in the survey coverage (Patterson and Beveridge, 1995; Zimmermann, 2004b).

1.5 Conclusion

The North Sea herring stock has always been a key element of North Sea fisheries, having a significant impact on the food security, economy, employment and social structure of coastal communities in the area. For this reason, when the stock declined in the 1970s, managers took measures to rebuild the stock. Biological and commercial data have been recorded for many years, and their quantity and quality have increased with the time. Compared to some other European stocks, scientific surveys to assess the stock have been well established for a number of decades. As time goes by, the number of surveys and their variety has been increased which has improved the quantity of information and its precision. The history of the herring fishery in the North Sea (including as it does an extensive knowledge of the biology and demography of the stocks, assessments covering a 40 year period of variable exploitation and two periods of decline and recovery) offers a substantial knowledge base from which to construct the models required for the investigation of alternative management systems.

Until recently, the weight of catch data in the management procedure of the stock was still important. The improvement of survey data lead to a better use of those data in the choice of management strategies. The herring fishery was therefore an obvious case study for research which aimed to evaluate the relative value of fishery-dependent and fishery-independent assessments in providing for robust management of fish stocks.

The next chapter describes the first component of the evaluation framework implemented in this thesis: the operating model.

A GENERAL OPERATING MODEL

2 A general operating model

2.1 Introduction

In the precedent chapter, I introduced the the North Sea herring case study and briefly presented the rationale for and structure of a simulation evaluation framework. This chapter presents a description of the first component of this simulation evaluation framework: the operating model.

Butterworth *et al.* in 1997 (Butterworth and Punt, 1999; De Oliveira *et al.*, 2007) defined management procedures (MPs) in the form of decision rules for calculating TAC based on available fisheries and survey data and for providing recommendations for management actions. The robustness of those rules is usually tested through simulation in a technique described as management strategy evaluation (MSE). This is a framework within which the relative performance of the rules of an MP can be assessed and evaluated against specified management objectives. The relationship between management procedures and management strategy evaluations has been defined by Rademeyer *et al.* (2007).

MP: Management procedure - the combination of pre-defined data, together with an algorithm to which such data are inputed to provide a value for a TAC or effort control measure; this combination has been demonstrated, through simulation trials, to show robust performance in the presence of uncertainties. Additional rules may be included, for example to spread a TAC spatially to cater for uncertainty about stock structure.

MSE: Management strategy evaluation - the process of testing generic MPs or harvest strategies.

The full MSE for North Sea herring is presented in chapter 5. In this chapter, I describe one of the key components of MSE: the operating model. This aims to represent the true behaviour of the system (of the biology and the fishery) by taking into account all the available knowledge data (Punt *et al.*, 2002b). The quality of the comparisons between the alternative candidate management procedures will depend on the ability of the operating model to mimic reality, taking into account the underlying uncertainty.

The operating model is usually a rather more complex model than other models typically used in stock assessment, which themselves can be a component of the management procedure. It also gives scientists the opportunity to test different assumptions about the population and fishery dynamics and their effects on the actual management of the resource (Punt and Hilborn, 1997; Kell *et al.*, 2007b). Many parameters (e.g. stock weight at age, natural mortality, growth and recruitment) cannot be known exactly, although techniques have been developed which have improved the precision of parameters estimates and for simulating uncertainty around these estimates. These correspond to natural variability, in both space and time, in the dynamics of populations and of fisheries (Hennemuth *et al.*, 1980; Beddington and Cooke, 1983; Polacheck *et al.*, 1993; Megrey *et al.*, 1994; Rosenberg and Restrepo, 1994; Caddy and Mahon, 1995; Fogarty *et al.*, 1996)

This chapter is divided into three sections: Section 1 describes the structure of the operating model including the limitation and assumptions of it, Section 2 lists the model parameters and Section 3 contains the discussion and conclusion.

2.2 Model structure

2.2.1 GENERAL FEATURES OF THE MODEL

The operating model developed in this thesis is based on an age-structured model (McAllister *et al.*, 1994; Punt *et al.*, 2002b). This type of model structures the population into age-groups. The oldest fish can be grouped into a group called "plus group" if, for example, the amount of data for those ages is less numerous than for younger ages. This is usually the case for exploited fish stocks as the oldest animals are less frequent in the stock and, as a consequence, are less likely to be caught. This can imply uncertainties about the old age groups such as the proportion of old fish in the stock, as was the case for North Sea herring. For North Sea herring, fish that are at least 9 years old were grouped into a "9+" age-group. Hence, the population was structured into 10 age groups ranging from 0 to 9+.

The model includes the following components: natural mortality rate at age, fraction mature-at-age, stock-recruitment relationship, weight-at-age in stock and in catch and

total catch biomass per year and selectivity-at-age. Major components - natural mortality-at-age, maturity-at-age and stock-recruitment relationships - are developed in this section. For the other components, the data available are described in section 2.3. Furthermore, a selectivity curve is fitted to the data usig a method described in section 2.3.4.

Stock-recruitment relationships

The Food and Agricultural Organisation (FAO) defines recruitment as the process by which fish enter the exploitable stock and become susceptible to fishing or the number of fish added to the exploitable stock, in the fishing area, each year, through a process of growth - i.e. the fish grow to a size where they become catchable - or migration - i.e. fish of catchable size move into the fishing area (Food and Agriculture Organisation of the United Nations (FAO), 2007). Recruitment depends on many factors such as the abundance and distribution of the mature adult population, the number and viability of eggs produced and the subsequent survival of eggs and larvae.

There is not always a strong relationship between indices of spawning stock size and the recruitment that is observed, or derived from the assessment of the fish stock. However, just because a relationship cannot be observed does not mean one does not exist – after all, without any adult fish, there can be no recruits. In fact, if the number of recruits to a fishery was independent of the adult stock size, collapses might occur less frequently. In 1992, Hilborn and Walters stated that "while recruitment may be largely independent of stock size as a fishery develops, experience has shown that most fisheries will reach a point where recruitment begins to drop due to over-fishing". In 2006, Jennings *et al.* said that "relationships between spawner and recruit abundance are important because they describe the ability of a stock to maintain abundance in response to intensive fishing pressure. If this compensation did not occur, the stock would tend to extinction or an infinite population size, and neither feature is observed in nature on a biological time scale". Reid *et al.* (1999) shown that for the Gulf of Maine area, there was a higher percentage of age 3 Atlantic herring fish mature when the abundance was low. At the beginning of 1983, the recovery of the herring stock was accompanied by a decrease in growth rate and the percentage of fish maturing at age 3. The percent of mature age 3 fish declined from 50-70% in the mid-1980s to 10-30% in 1990-1996.

Where there is intense fishing pressure, fish may increase their spawning to compensate for the depletion due to the fishery's activity. In the case of low fishing pressure, fish may not spawn as intensely as a density dependent effect will occur and the surplus production will be wasted. In fact, Zheng (1996) has shown that survival rates from eggs to recruits decreases as the spawning biomass increases.

Taking into account a stock-recruitment relationship in predictive models of future stock size is important - whatever the projection time. Usually, to predict a state of equilibrium or long-term stock levels, traditional relationships are used such as the Beverton and Holt (1957) (e.g. Touzeau and Gouzé, 1998; Cordue, 2001; Punt *et al.*, 2002b) or the Ricker (1954) functions (e.g. Allen and Miranda, 1998; Roel *et al.*, 2004; Kell *et al.*, 2005c). Another commonly used stock-recruitment relationship is the "hockey-stick" or segmented regression model (e. g. Kolody and Patterson, 1999; Barrowman and Myers, 2000; Glazer and Butterworth, 2006). Recruitment is usually modelled as a stochastic process around a particular stock recruitment relationship which describes how mean recruitment rate varies with stock size (Hilborn and Walters, 1992).

The Beverton-Holt and the Ricker stock-recruitment models are derived from assumptions of density-dependent predation and food limitation. The biological assumption behind the Beverton-Holt stock-recruitment curve is that the mortality rate induced by juvenile competition is linearly dependent on the number of live fish in the cohort at any given time. Mathematically, this translates as:

$$\frac{dN}{dt} = -(q + pN)N \tag{1}$$

where N is the number of live fish in the cohort at time t, q is a density-independent mortality rate and pN is a mortality rate component that is proportional to the density of the cohort at time t. Thus the larger the cohort, the faster individuals are lost (Hilborn and Walters, 1992).

The Beverton-Holt stock-recruitment curve increases steeply toward an asymptotic maximum. The linear relationship between recruitment and spawning stock biomass

implies that the larger the spawning stock the faster the juveniles will die (Haddon, 2001). The density dependence can represent a wide variety of biological phenomena including carrying capacity effects in terms of competition for food and space. It is considered most appropriate for modelling populations characterised by cohort cannibalism or resource competition (Wootton, 1990).

Ricker's model is based on the assumption that the mortality rates of the eggs and juveniles are initial cohort size dependent. Therefore mortality is stock-dependent rather than density-dependent. In order to derive the Ricker curve, the rate of change for cohort size can be written as:

$$\frac{dN}{dt} = -(q + pS)N \tag{2}$$

where N is the cohort size at any time prior to recruitment, S is the initial spawning stock size (proportional to initial cohort size), $q + pS$ is the instantaneous mortality rate for the cohort and q is the density-independent mortality rate.

The Ricker model curve is dome shaped with maximum recruitment occurring at an intermediate level of spawning stock and is based on increasing density dependent mortality at high spawner abundance. There are several possible reasons for obtaining such a shaped recruitment curve: cannibalism of the juveniles by the adults, disease transmission, damage by adults of one another's spawning sites and density-dependent growth coupled with size-dependent predation (Hilborn and Walters, 1992). The Ricker relationship is expected when there is cannibalism of the young by adults or resource competition between parents and progeny, resulting in poor survival of young at high stock sizes (Wootton, 1990).

The last stock-recruitment relationship considered here is the hockey stick whose name comes from its shape. The shape of the hockey stick relationship curve is an intermediate between the Beverton-Holt (constant increase toward an asymptote) and the Ricker (dome shaped) and it is fitted to stock-recruitment data using segmented regression. In this form recruitment increases linearly with the initial abundance to a maximum at a critical value of biomass, after which recruitment is assumed to be

constant. It is appropriate when there is evidence that above a certain spawning stock biomass there is no correlation between the recruitment and the spawning stock biomass. Below a critical spawning stock biomass, recruitment becomes impaired. However, unlike the two other stock-recruitment relationships examined here, the relationship between stock and recruitment below the critical spawning biomass is simply assumed to be linear with a zero intercept.

In 1994, Myers et *al.* showed that the Beverton-Holt model may overestimate the slope at the origin. This can bias the impression of managers about the capacity of fish to recover following a period of intense fishery. Barrowman and Myers showed in 2000 that the Beverton-Holt usually estimates a larger carrying capacity of recruits and a larger maximum reproductive rate than the hockey stick. By contrast, in 1999, Myers *et al.* demonstrated that the Ricker model provides a sensible model for estimating the slope at the origin. But the disadvantage of using this model, or any other parametric spawner recruitment model, is that the slope at the origin is influenced by observations far from the origin (Myers *et al.*, 1997).

This is only partially the case for the hockey stick model. Slopes at the origin are only influenced by the position of the critical spawning biomass and the maximum recruitment. Hockey stick type models are based only on a hypothetical model for mean recruitment given spawner abundance. It is not derived from a more biologically-based model as Beverton-Holt and Ricker models are, but often describes the data more appropriately when there appears to be little relationship between stock and recruitment (Hilborn and Walters, 1992). However, the biologically unrealistic sharp bend on the hockey stick model, representing a change from density-independent to density-dependent pre-recruitment mortality can result in some undesirable properties when fitting the model (Barrowman and Myers, 2000).

As it has been shown, several types of stock-recruitment relationships exist and each corresponds to a specific situation – i.e. increase of the recruitment with the SSB, fixed recruitment above a defined SSB and decrease of the recruitment when the SSB is higher than a determined value. But there is no data set that would match perfectly with any one of them. Data are always spread around a relationship and most of the time so spread that it is not visually possible to guess which stock-recruitment relationship would fit to the data available. There is no stock-recruitment relationship assumed in the

projection of the North Sea herring stock within the actual management procedure. I therefore chose to examine each one to decide on the most appropriate for the operating model. The analysis in section 2.3.5 will show that it was not possible to fit a unique stock-recruitment relationship to the North Sea herring data set and therefore a number of different relationships were used.

The assessment of herring undertaken by ICES assumes a Beverton-Holt stock-recruitment relationship, but only since 1995 when ICA has been chosen as assessment method. Between 1960 and 1994, no stock-recruitment relationship assumed for the assessment. Since 1995, ICA has been used and it is still currently used. The scientists who run the assessment each year can choose to use or not the stock-recruitment relationship in the assessment model. As is explained in the Appendix 2, it is possible to fit a Beverton Holt stock-recruitment relationship to the data and this has been done each year.

2.2.2 RESOURCE DYNAMICS

Abundance at age before recruitment is not modelled and as a consequence could be considered as equal to zero and is given by the equation:

$$N_{y,a} = 0 \qquad a < a_r \quad (3)$$

where $N_{y,a}$ is the number of recruited fish at the start of year y at age a.

Abundance at age of recruitment is given by the equation:

$$N_{y,a} = R \qquad a = a_r \quad (4)$$

where R is the recruitment.

The dynamics of animals of age between age of recruitment a_r plus one and last age group m are governed by the equations:

$$N_{y,a} = N_{y-1,a-1}\left(1-S_{a-1}H_{y-1}\right)e^{-M_{y-1\,a-1}} \qquad a_r < a < m \quad (5)$$

$$N_{y,a} = \left(N_{y-1,a}\left(1-S_aH_{y-1}\right)e^{-M_{y-1,a}}\right)+\left(N_{y-1,a-1}\left(1-S_{a-1}H_{y-1}\right)e^{-M_{y-1,a-1}}\right) \qquad a = m \quad (6)$$

where S_a represents the relative vulnerability to capture of fish at age a, H_y corresponds to the exploitation rate for the year y and $M_{y,a}$ is the natural mortality rate at the start of year y at age a.

S_a is also called selectivity at age and represents the relative vulnerability of fish at age a to capture. This represents the combination of gear selectivity and availability of fish at age in the fish population. In this work, a logistic selectivity ogive is fitted to historical data and the process is explained in section 2.3.4.

The harvest rate is assumed to be perfectly implemented but there is an option of misreporting. This is developed in section 4.2.3.

The reason why harvest rate is used instead of fishing mortality is that it is much easier to estimate as I am adapting TAC and not effort for this case study. The harvest rate is equal catch divided by exploitable stock biomass. To calculate the fishing mortality, I would normally need either effort ($F = qE$) or set a catch C for each age class and solve the Baranov equation:

$$C = \frac{F}{F+M}N\left(1-e^{-F-M}\right) \quad (7)$$

The spawning stock biomass - SSB - is calculated following the equation:

$$SSB_y = \sum_{a=a_r}^{m}\left(N_{y,a} * w_{y,a} * mat_{y,a}\right) \quad (8)$$

where $w_{y,a}$ corresponds to the stock-weight at age a for a given year y and $mat_{y,a}$ is the maturity for the same age and year.

2.2.3 RECRUITMENT

In terms of recruitment, as was explained in section 2.2.1, there are three stock-recruitment functions considered in this work.

The first stock recruitment model is the Beverton-Holt equation:

$$N_{r,y} = \frac{\alpha SSB_{y-1}}{\beta + SSB_{y-1}} e^{\varepsilon_y} \tag{9}$$

where α corresponds to the maximum number of recruits produced and β is the abundance of spawners that give mean recruitment of α/2. The final term, ε_y, is the stochastic recruitment multiplier defined in the following section 2.2.4.

The second one, the Ricker stock recruitment relationship is:

$$N_{r,y} = aSSB_{y-1} e^{-bSSB_{y-1}} e^{\varepsilon_y} \tag{10}$$

where *a* corresponds to the recruits per unit spawners at low stock sizes, *b* captures the density dependence of the relationship and ε_y is the stochastic recruitment multiplier. High *a*, the density-independent parameter, leads to a higher steeper peak in recruitment at a fixed level of spawner abundance, while high b, the density-dependent parameter, decreases the height of the peak and reduces the level of spawner abundance at which the peak occurs. Maximum mean recruitment occurs at spawner abundance $SSB = \frac{1}{b}$.

The last one is the hockey stick equation:

$$\begin{aligned} &if \;\; SSB < S^* \Rightarrow N_{r,y} = \alpha SSB e^{\varepsilon_y} \\ &if \;\; SSB \geq S^* \Rightarrow N_{r,y} = \alpha S^* e^{\varepsilon_y} \end{aligned} \tag{11}$$

where S* corresponds to the level of spawner abundance from which the recruitment becomes constant, α the slope at the origin and ε_y is the stochastic recruitment multiplier.

2.2.4 AUTOCORRELATION IN THE STOCK-RECRUITMENT RELATIONSHIP

There is often a strong possibility of temporal autocorrelation in the recruitment – i.e. means where the residual at time *t* depends on the residual at time *t-1*. Autocorrelation may be suspected if residuals tend to be positive or negative for consecutive years. Thus a realistic operating model may have to include allowance for autocorrelation in recruitment. Indeed, Punt (1997) wrote that that ignoring the consequences of autocorrelation in the recruitment anomalies can lead to overly optimistic appraisals of the ability of management procedures to achieve conservation objectives.

The survival of eggs to recruitment depends on the intensity of environmental pressures. Many of them are assumed to be random as they are not well known but may not be random in reality. If residuals were completely uncorrelated, they would be randomly distributed around zero, depending only on the stochastic term. When it is not the case, it can be assumed that there is, at least, one process that influences the recruitment. Simulating autocorrelation attempts to include a year effect in the observed recruitment residuals as a proxy of several potential underlying processes influencing recruitment.

The potential for autocorrelation in the residuals relating to the predicted and observed recruitment was included in the model, and defined as:

$$\varepsilon_y = \rho\varepsilon_{y-1} + \xi_y \tag{12}$$

where ε_y corresponds to the stochastic recruitment multiplier for the year *y*, ρ is the autocorrelation coefficient for the recruitment deviation and ξ_y is the stochastic term which follows a normal distribution with zero mean and variance $\left[(1-\rho)^2\sigma^2\right]$. The variance of ε_y is σ^2.

To increase the level of autocorrelation, ρ has to be increased. It will reduce the level of noise ξ_y as its variance will decrease. In this work, to increase the level, ρ has been doubled.

2.2.5 MONTE CARLO SIMULATIONS

A way of considering uncertainty in evaluating management strategies is to use the method of Monte Carlo projection. In the absence of uncertainty, each management option would lead to a unique response of the fishery to the evolving state of the stock as it is projected into the future. Introducing uncertainty allows for multiple simulations of a specific management strategy option to be undertaken, each time projecting the stock into the future with its associated parameter uncertainty (in the operating model, for instance in recruitment or weight at age, and the observation error model for instance in the acoustic index of number of fish). For example, for each recruitment trajectory, there is an associated observation. Each of the possible responses of the fishery is a description of how the fishery would evolve as a result of that option. The name "Monte Carlo" implies that there is a random parameter in the implementation of the simulation (Francis and Shotton, 1997; Patterson *et al.*, 2001).

2.2.6 MODEL LIMITATIONS AND ASSUMPTIONS

As explained in section 1.2, there are two herring stocks found in the North Sea but because the objective of this study is to examine the robustness of different management procedures, for simplicity the study will only consider the autumn spawners in the North Sea. Furthermore, the North Sea will be considered as one geographical entity. Movements of fish within the North Sea between spawning, feeding and wintering areas are not taken into consideration. Even if it is known that the herring fishery is not evenly distributed in the North Sea as it follows fish migrations, I will consider it as one fishery with one TAC. Although it would be possible to use smaller time steps, a simple annual time-step was chosen for the model for simplicity.

As explained in the section 1.2, outbreaks of *Ichthyophonus* disease in the North Sea herring population can occur. The phenomenon of cannibalism in herring stocks has also been described. These phenomena were not included explicitly in the operating

model. They are assumed to be subsumed within natural mortality and will not be mentioned and nor discussed later in the present work.

As there is no official stock recruitment relationship for the North Sea herring stock and it has not been proven that there was a change over time of the stock recruitment relationship, one hypothesis is that three of the major stock recruitment relationship are possible and do not switch over time in my simulations.

In order to simplify the model, it is assumed that there are no discards of herring in the past and or in the future. As a consequence, they are considered as equal to zero. Total catches (and catches by age) are equal to the sum of landings and discards, though are assumed to be equal to landings only.

Fishery independent data and fishery dependent data were provided by John Simmonds (from Fisheries Research Services (FRS) Marine Laboratory, Aberdeen, UK). FRS Marine Laboratory maintains a database for the North Sea herring which contains information (national catches of herring and associated biological data) provided by four national and international institutes (Kienzle, 2003). ICA results and ICES working group settings are used as historical data (1960-2006). Even if the data provided by FRS start in 1960, only values after the collapse are taken into account for some parameters in this work. This is due to the fact that values prior to the collapse are mainly guessed or estimated. In the first years after the reopening of the fishery, parameters such as catch weight-at-age or maturity-at-age are routinely monitored, which increases their level of reliability. The first year of use for each set of data is explained in the relevant sections.

2.3 Operating model parameters

Since the operating model developed in this work can be considered as a descriptive model, it is necessary to estimate values for at least some of the model parameters. Parameter estimation involves finding parameter values that provide the best fit between the expectations from the model and the available data. The aim of the operating model is to mimic reality and the simulations for the past should therefore be as close to the

historical data as possible. Fitting a model to a data set implies estimating values for the model's parameters to optimize the agreement between the model's predictions and the fitted data from nature. Haddon (2001) observed that "fitting a model to data only tests how successfully it can *describe* the data and not how well it *explains* the data".

The components of the operating model that are going to be developed in this section are maturity, mortality, weights, selectivity-at-age, stock-recruitment relationships and the autocorrelation in the recruitment.

The population dynamics model starts in 1960 (first year of data provided) and runs to 2006. The operating model was therefore used to reproduce the known current situation (the evolution of the stock from 1960 to 2006) and to project the evolution of the stock into the future. The model therefore needed to be parameterised for both the historic and projected sections of the model.

The database consisted of 12 datasets: proportion of fish mature at age, natural mortality rate at age, stock weight at age, catch weight at age, proportions of fishing mortality at age before spawning and natural mortalities at age before spawning, total catch in weight, catch numbers at age and 4 indices from 4 different surveys. Those datasets are presented briefly in the following paragraphs. For more details, please refer to Appendix 3.

2.3.1 MATURITY

The proportion of fish mature-at-age, or proportion of spawning fish at age, corresponds to the proportion of fish at a given age that are able to spawn and as a consequence to reproduce. The maturity rate at age in the operating model can vary with age and time, which is the case for the North Sea autumn-spawning herring used in this work. For a given year, it varies on a scale of 0 (no fish of a given age are spawning) to 1 (100% of fish for a given age spawn). The variable used here is a relative maturity at age and not fecundity. The percentages of fish mature are estimated from the acoustic survey. The values are determined from samples of herring from the research vessel catches examined for maturity stage and raised by the local abundance. The proportion of mature at age resulting from these surveys is expressed as a matrix by year and by age

covering the period between 1960 and 2006. Although maturity at age was estimated in the early years of the fishery, it was only routinely monitored on an annual basis from 1985.

The proportion of juveniles (0 and 1 year old fish) spawning is null for all years. Adults older than 5 years old are all fully matured so the proportion of fish spawning for ages from 5 to 9+ is always equal to 1. For fish between 2 and 4 years old, proportion of fish spawning is different for each age-group. On average, 75% of two years old are mature. This value increases to more than 95% for 3 years old fish and almost reaches 100% for 4 years old, though some year classes have been known to grow more slowly and mature less rapidly (ICES HAWG, 2007). This is due to the fact that all fish are not matured at the same time. The maturity-at-age over time available from historical data is summarised in Table 1.

Table 1: Maturity-at-age over time.
It is expressed as a proportion of an age group that is mature. The Δ means that the maturity is variable during the years considered.

Age	0	1	2	3	4	5	6	7	8	9+
1960 1971	0	0	1	1	1	1	1	1	1	1
1972 1984	0	0	0.82	1	1	1	1	1	1	1
1985 1987	0	0	Δ	1	1	1	1	1	1	1
1988 2004	0	0	Δ	Δ	1	1	1	1	1	1
2005 2006	0	0	Δ	Δ	Δ	1	1	1	1	1

Many studies have shown that variability in maturity can be influenced by biological and environmental parameters. For example, changes in abundance have an impact on maturity. In fact, at low stock abundance, as the amount of resources available to individuals is large, it has been observed that growth rate is increased and as a consequence, the maturity at young ages rises. This is largely because maturity appears to be related to size of animals as well as externalities such as population density (Jorgensen 1990 in Morgan and Colbourn 1999, Rijnsdorp 1993). In 1995, Sandström *et al.* investigated the effects of temperature on life history variables in perch

(*Perca fluviatilis*). They observed that an increase in temperature lead to an earlier maturity through increased growth. Furthermore, variations in the mortality rate have been associated with changes in maturity rates. Where the mortality rate is high, the chances of a young mature fish surviving to reproduce are higher than for an older fish (Fox, 1994).

The age at 50% maturity for the years when annual estimates have been made (1985 – 2006) is shown in Table 2.

Table 2: Age at 50% maturity for each year between 1985 and 2006.

Year	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Age	1.7	1.7	1.6	1.6	1.6	1.5.	1.6	2	2.1	1.7
Year	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Age	1.7	1.8	1.8	1.8	1.7	1.7	1.6	1.6	2.2	1.7
Year	2005	2006								
Age	1.7	1.8								

The relationship between maturity and biomass is confusing (Figure 7). There are three very high estimates of 50% maturity, which correspond to 1992, 1993 and 2003. As it is explained in chapter 1, there was a dramatic drop in the fraction mature of 2 and 3 years old herring in the early 1990s due to an outbreak of *Ichthyophonus* disease in the North Sea herring population. The first two of these three high estimates correspond to this *Ichthyophonus* outbreak. The last estimate coincides with the samples taken when the population was dominated by the very large 2001 cohort. If these points are removed the relationship is $Age_{50\%} = -0.1054 * SSB + 1.7869$ (n=19, R^2=0.278, p=0.02). This negative slope is counter to the theory outlined above, because it implies that as stock sizes decrease the maturity of younger age groups actually declines in this stock.

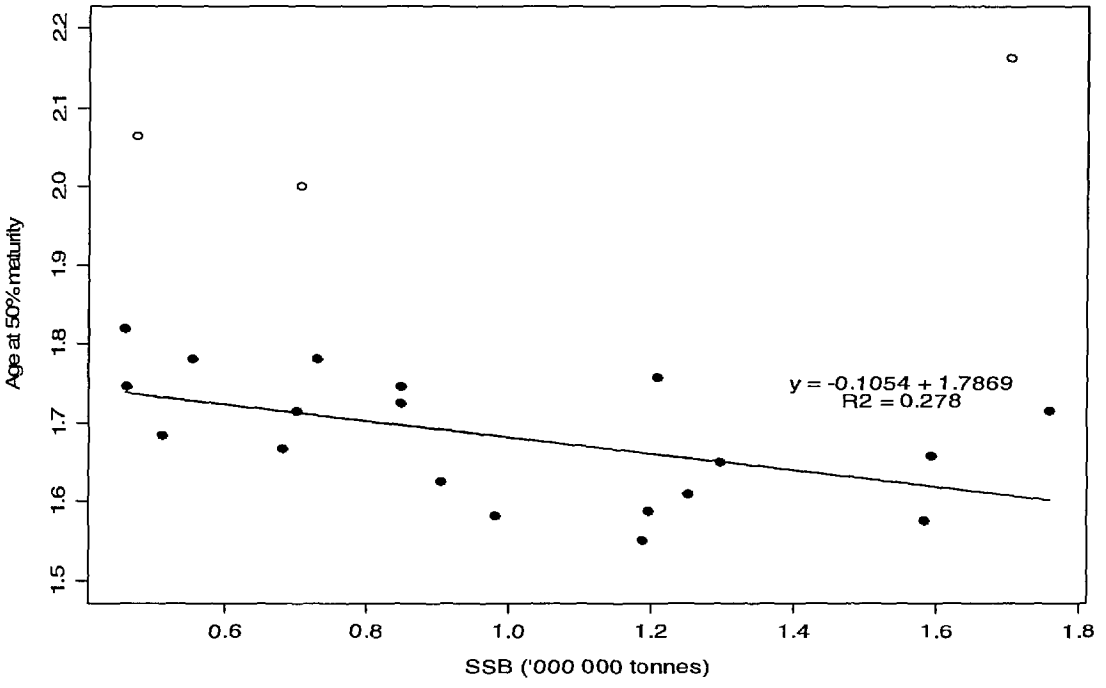


Figure 7: Age at 50% maturity over the spawning stock biomass for all years between 1985 and 2006.

This correlation is only significant when the 2003 data point is removed. This relationship was not included in the general operating model. Instead, the relevant maturity ogive for a particular year of the projection in the operating model was picked at random from the 1985-2006 series. The method follows one used also by Skagen (Pers. Com).

Even so, the possibility of this relationship being an important feature of herring biology cannot be ignored. Accordingly, a sensitivity analysis is explored in Chapter 5 to see if the consideration of the relationship would make a difference in the results of the model and would lead, for example, to a failure of a HCR. For this sensitivity analysis it was necessary to express the relationship seen in Figure 7 in terms of the proportion maturity by age, which is the formulation used in the model rather than $Age_{50\%}$ shown in that figure. Maturity at age 1 is always zero in herring. The following relationships were derived for ages 2 and 3:

$$mat_{age=2} = 0.1139 * SSB + 0.6296 \text{ with a } R^2 = 0.2616 \text{ (n = 19, p = 0.025),} \quad (13)$$

$$mat_{age=3} = -0.0897 * SSB + 1.0238 \text{ with a } R^2 = 0.2122 \text{ (n = 19, p = 0.04)} \quad (14)$$

Since the maturity at age 4 is constant over years except for the last two years of the historical data, the method applied for age 4 in the sensitivity analysis is to take a random proportion mature for age 4.

The values of the maturity-at-age used in the sensitivity analysis were therefore as follows:

- $mat_{age=0:1} = 0$ (15)
- $mat_{age=2} = 0.1139 * SSB + 0.6296$ (16)
- $mat_{age=3} = -0.0897 * SSB + 1.0238$ (17)
- $mat_{age=4} = random\ pick\ from\ historical\ data$ (18)
- $mat_{age=5+} = 1$ (19)

2.3.2 MORTALITY

The natural mortality rate-at-age in the operating model can vary with age and time. The natural mortality rate at age used in this study is based on existing ICES Working Group estimates derived from North Sea Multi Species Virtual Population Analysis (MSVPA[7]) (Pope, 1991). Although these data are sufficient to allow estimation by the MSVPA of age-specific natural mortality, they are not sufficient to allow estimation of different age-specific natural mortality by year. Therefore, this constant natural mortality-at-age was used for all historical and projected years. The mortality ogive can be observed on Figure 8.

[7] MSVPA: Extends the cohort model (VPA: Virtual Population Analysis - a general method to model the progression of a cohort through time) with a model for the natural mortality that includes predator-prey relationships.

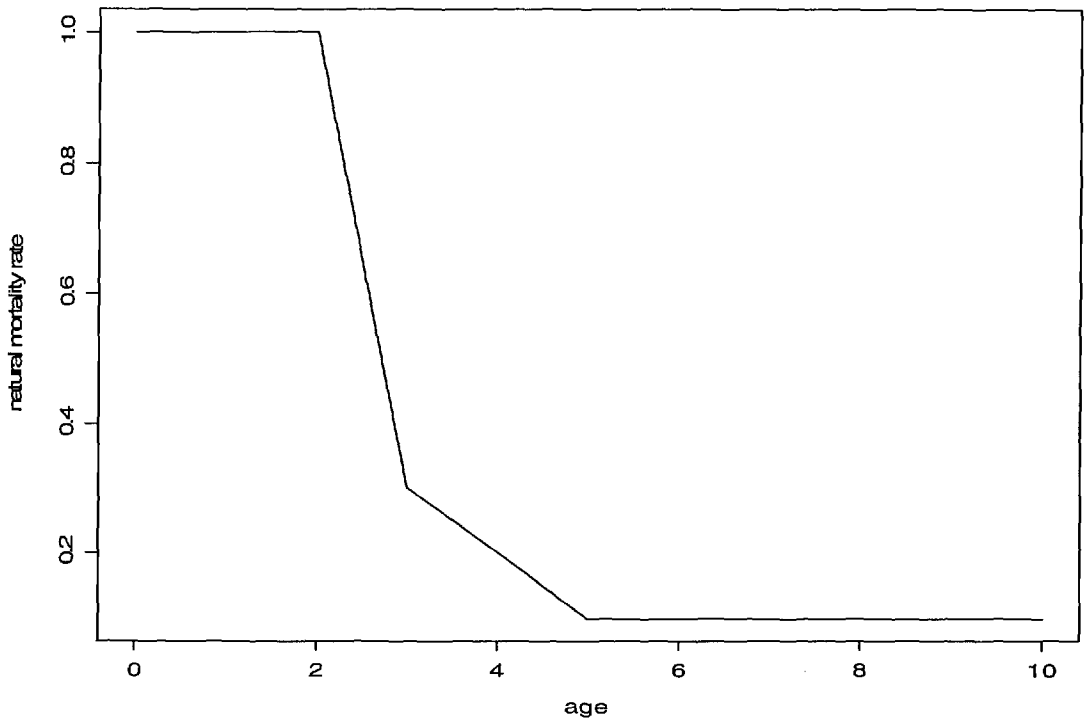


Figure 8: Natural mortality rate at age.

2.3.3 WEIGHTS

Two weights-at-age are considered here: mean weight-at-age in the stock and mean weight-at-age in the catch. Both of them vary by year. Weight at age in the stock values were derived from the North Sea acoustic survey from weighed and aged individuals. Weight-at-age in the catch values were derived from the total international catch-at-age data. Although weight-at-age was estimated in the early years of the fishery, it was only routinely monitored on an annual basis from 1983.

Variation of weight-at-age in stock and catch can be observed on Figure 9 and Figure 10. There appears to have been a decline over time in the mean weight-at-age, although this is more apparent in the stock than in the catch and for older rather than younger fish.

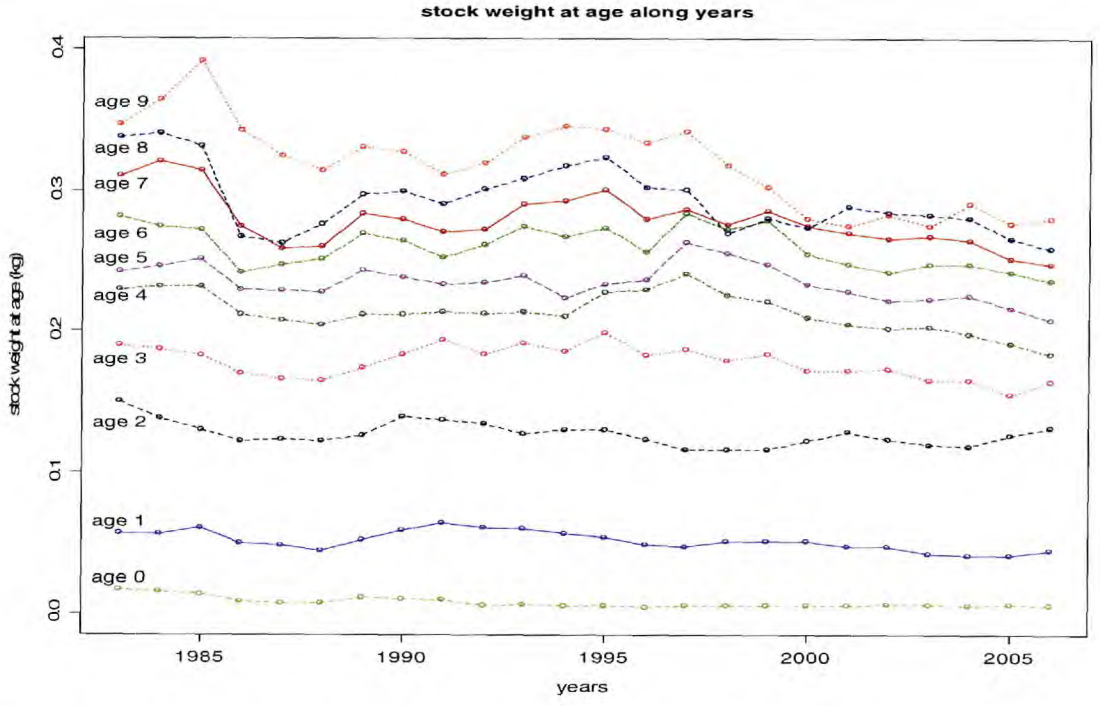


Figure 9: Stock weight at age and spawning stock biomass from 1983 to 2006.

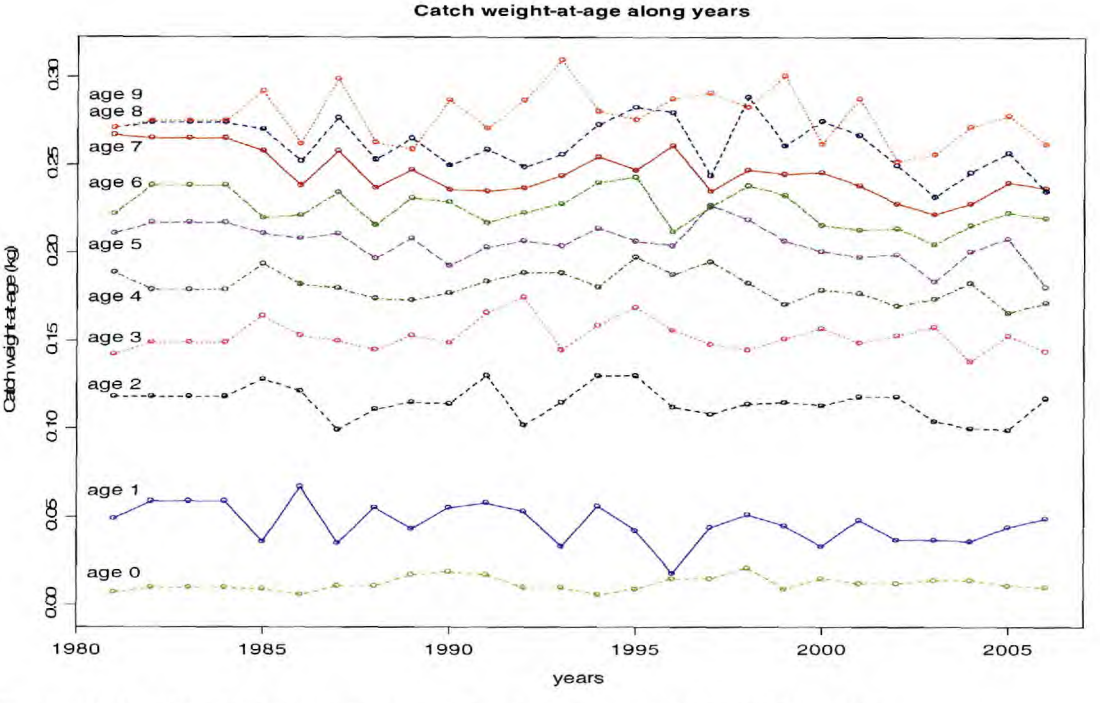
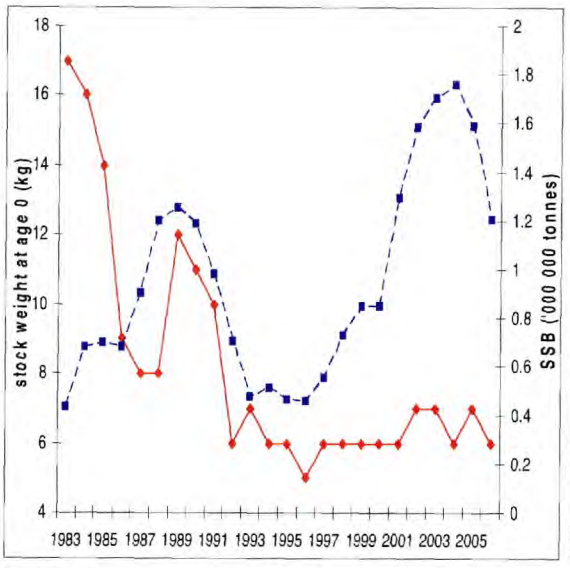
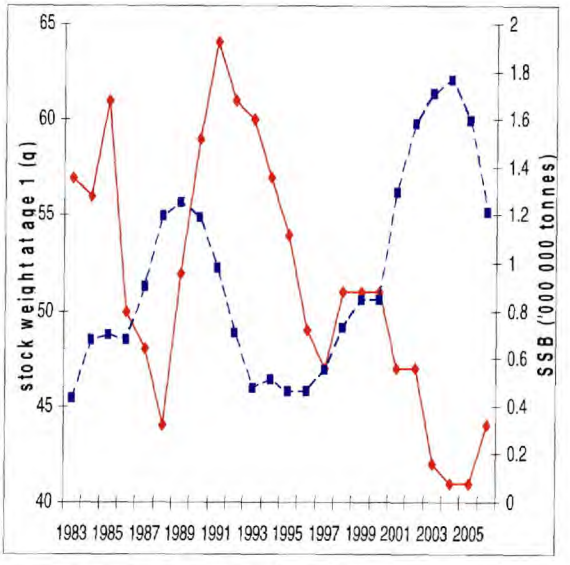
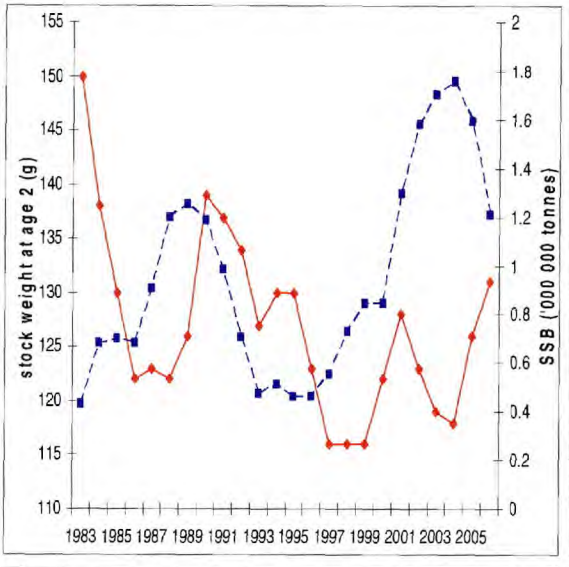


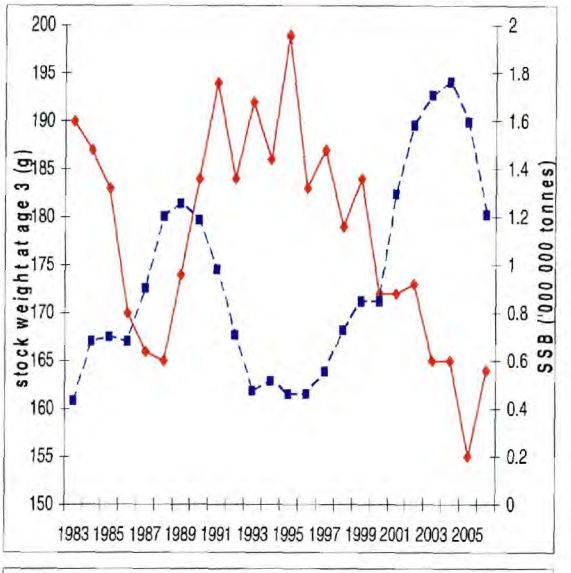
Figure 10: Catch weight at age and spawning stock biomass from 1981 to 2006.

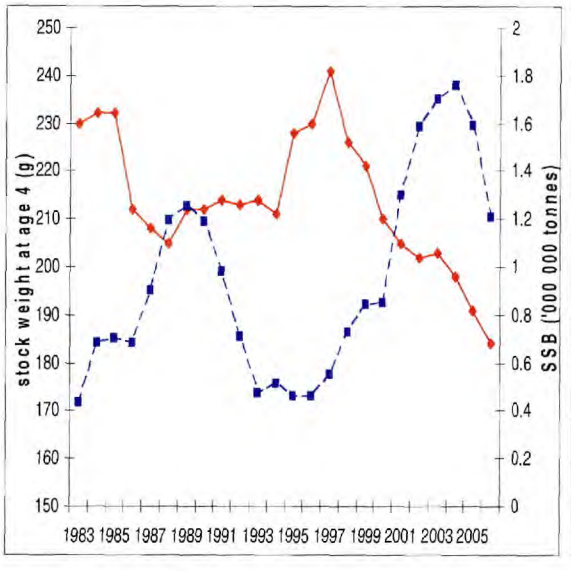
More detailed plots (Figure 11) suggest a negative relationship between mean weight-at-age in the stock and stock biomass. This implies that at low stock sizes animals are able to grow faster, achieving larger weights than at high stock sizes, and is consistent with previously published results (Jorgensen 1990 in Morgan and Colbourn 1999, Rijnsdorp 1993).

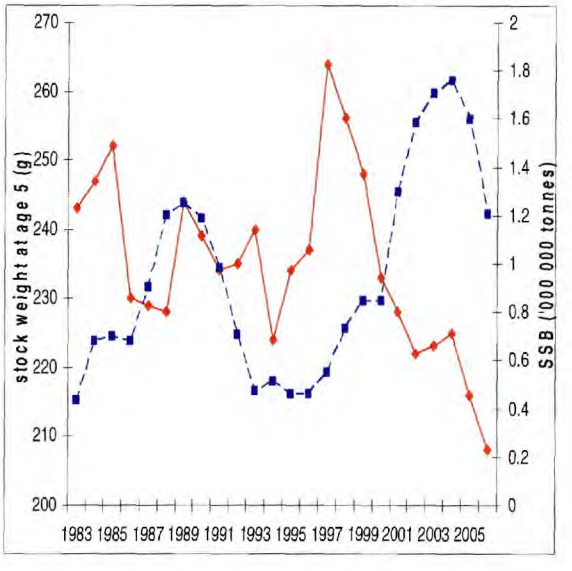

stock weight at age 0 (kg)
SSB ('000 000 tonnes)
1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005


stock weight at age 1 (g)
SSB ('000 000 tonnes)
1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005


stock weight at age 2 (g)
SSB ('000 000 tonnes)
1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005


stock weight at age 3 (g)
SSB ('000 000 tonnes)
1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005


stock weight at age 4 (g)
SSB ('000 000 tonnes)
1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005


stock weight at age 5 (g)
SSB ('000 000 tonnes)
1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005

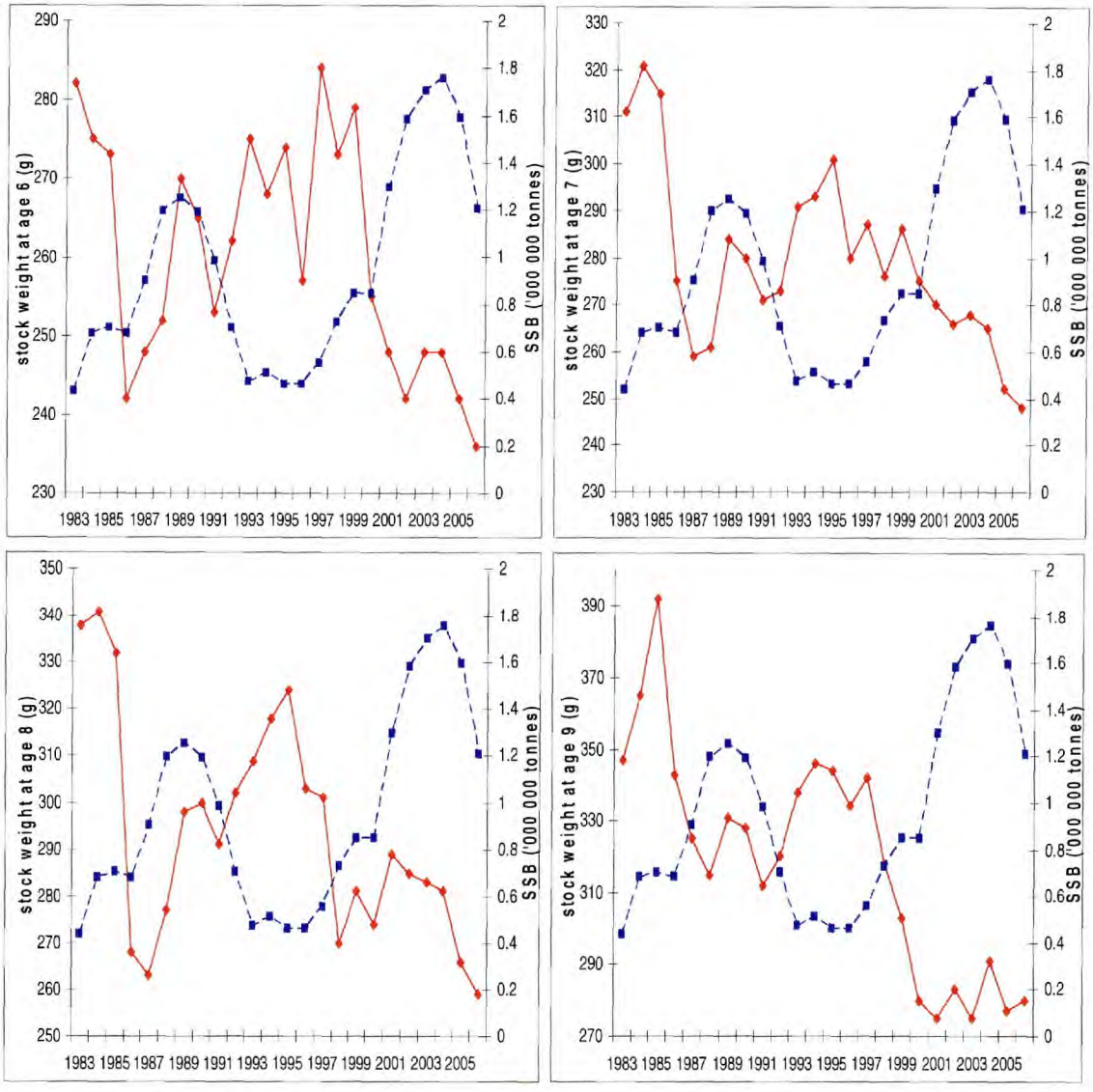


Figure 11: Stock weights-at-age and spawning stock biomass over time.
Stock weight-at-age: solid line, left axis; SSB: dashed line, right axis.

The relationship between stock weight-at-age and the SSB is not obvious for fish younger than 3 years old but is clear for older fish. Parameters of linear regressions between weight-at-age and SSB are shown in the first part of Table 3 where the slope and the intercept are specific to each age.

This relationship was taken into consideration to make the operating model as realistic as possible. To ensure that weights-at-age followed a logical progression in the model, a number of relationships with a single slope and multiple intercepts for the different ages were calculated for fish older than 2 by minimising the combined sums of squares from all relationships by age. The values can be found in the second part of Table 3. For the young fish, as the linear regression did not provide good results, the mean and CV over

historical years between 1983 and 2006 were used in the model. Values for ages 0, 1 and 2 can be found in Table 4.

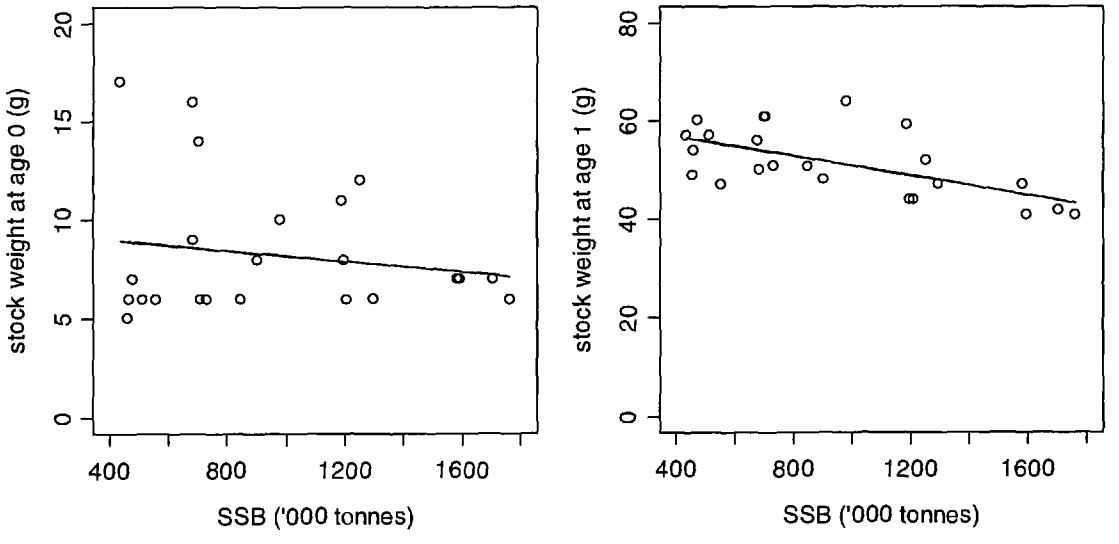
Table 3: Statistics for the Figure 11: slopes, intercepts and R^2 of relationship between stock weight-at-age (g) and SSB (tonnes).
Bold R^2 indicates that it is significantly different from zero with P<0.01.

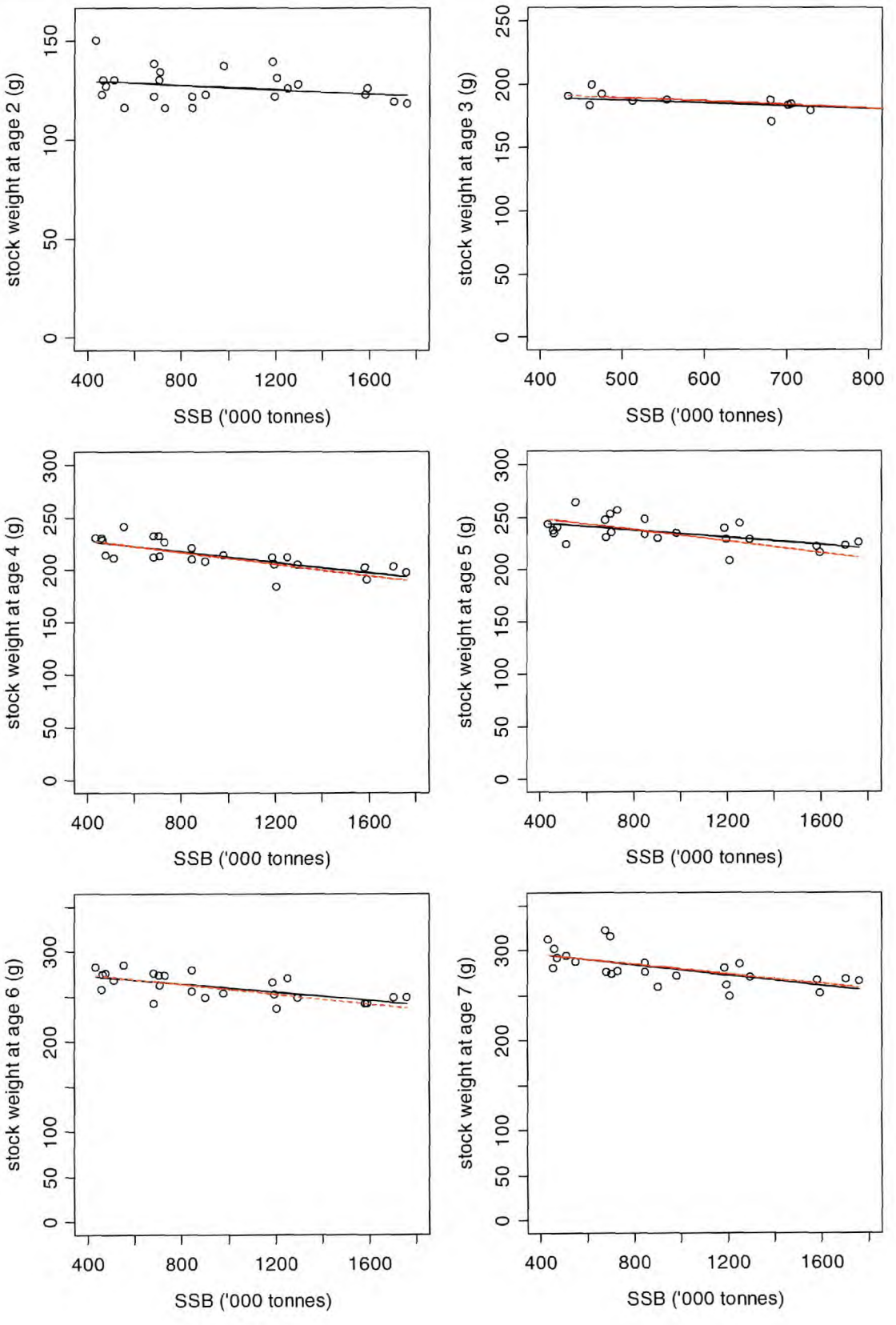
Age	0	1	2	3	4	5	6	7	8	9+
Slope	$-1.78\ 10^{-6}$	$-7.14\ 10^{-6}$	$-2.96\ 10^{-6}$	$-1.68\ 10^{-5}$	$-2.61\ 10^{-5}$	$-1.88\ 10^{-5}$	$-2.24\ 10^{-5}$	$-2.98\ 10^{-5}$	$-2.98\ 10^{-5}$	$-4.97\ 10^{-5}$
Intercept	9.87	57.91	129.61	193.32	237.57	252.02	280.86	306.60	321.01	364.51
Intercept with single slope (-2.76×10^{-5})	/	/	/	203.16	239.03	260.07	285.57	304.62	318.99	344.45
R^2 (n=24)	0.054	**0.214**	0.024	**0.421**	**0.672**	**0.404**	**0.459**	**0.482**	**0.303**	**0.484**

Table 4: Means and coefficient of variation of stock weight for ages 0, 1 and 2.

Age	0	1	2
Mean	8.25	51.42	126.92
CV	0.409	0.132	0.066

Figure 12 shows the linear regressions and, for ages 3 and above, the single estimated slope.




stock weight at age 2 (g)
0
50
100
150
400
800
1200
1600
SSB ('000 tonnes)
stock weight at age 3 (g)
0
50
100
150
200
250
400
500
600
700
800
SSB ('000 tonnes)
stock weight at age 4 (g)
0
50
100
150
200
250
300
400
800
1200
1600
SSB ('000 tonnes)
stock weight at age 5 (g)
0
50
100
150
200
250
300
400
800
1200
1600
SSB ('000 tonnes)
stock weight at age 6 (g)
0
50
100
200
300
400
800
1200
1600
SSB ('000 tonnes)
stock weight at age 7 (g)
0
50
100
200
300
400
800
1200
1600
SSB ('000 tonnes)

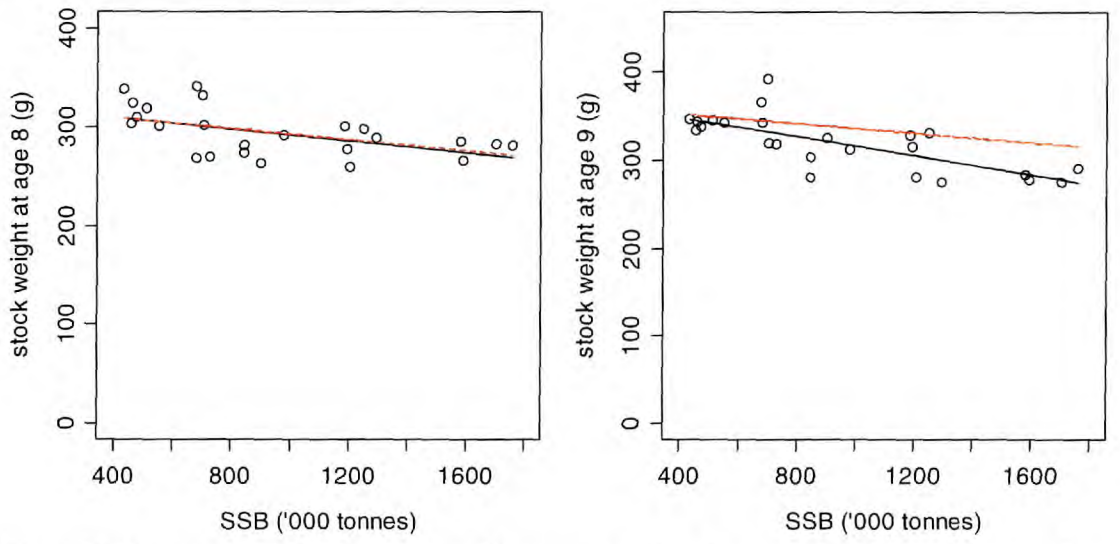
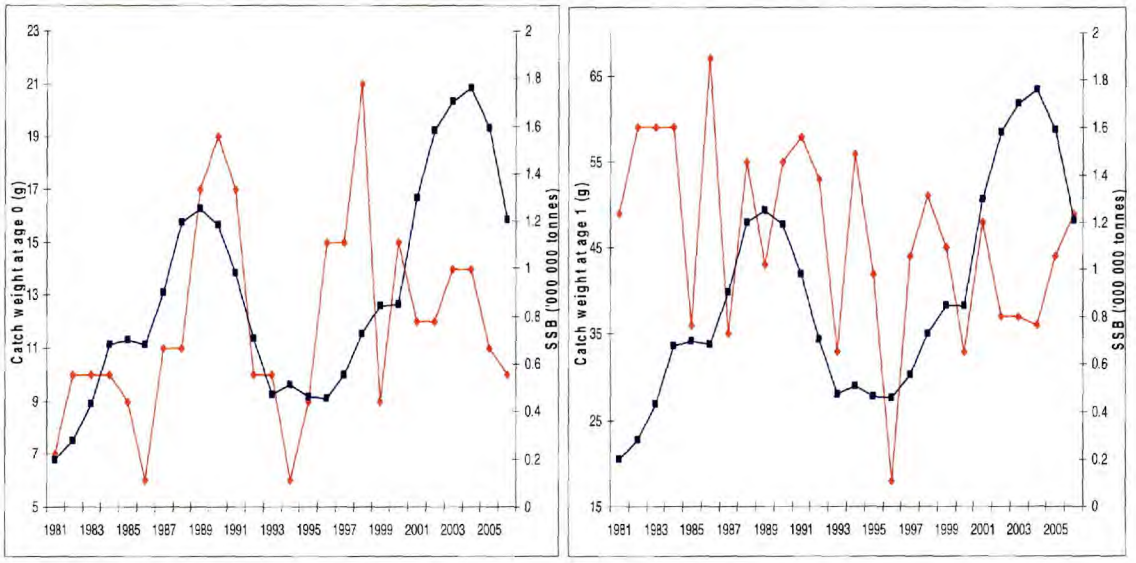
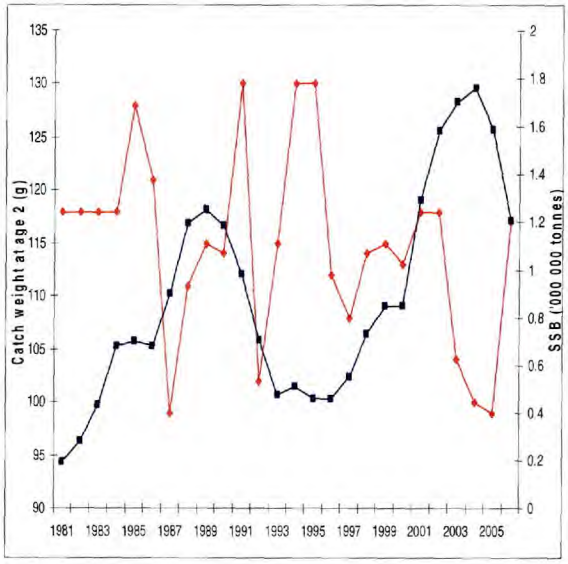
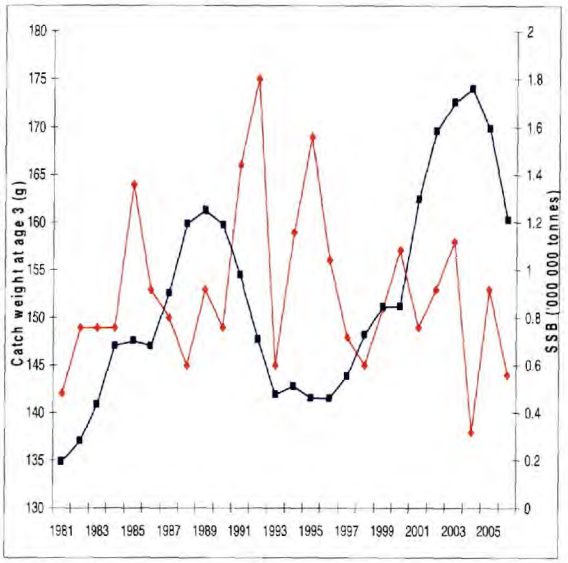


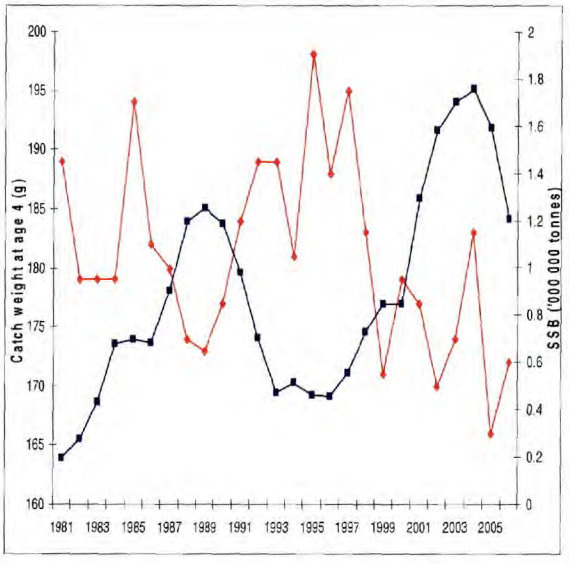
Figure 12: Linear regressions and adjusted linear regressions between stock weight-at-age and spawning stock biomass for each age.
Plain line: linear regression; dashed line: adjusted linear regression.

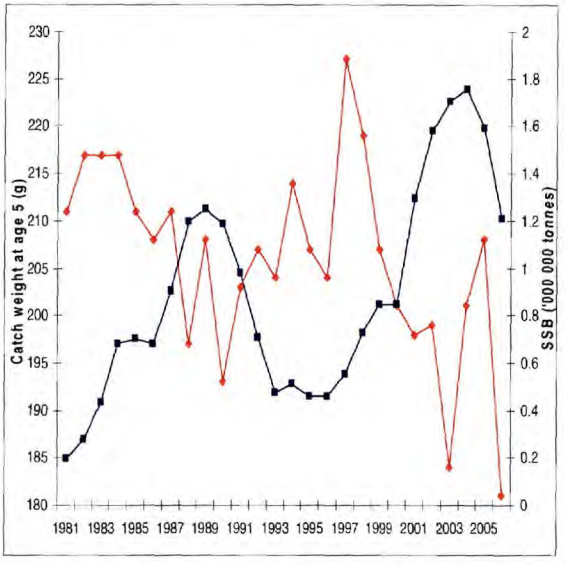
Although the relationship between catch weight-at-age and SSB is not as obvious as for stock weight-at-age, the same analysis was performed. Catch weight shows more variability over time than stock weight but a linear relationship still exists between catch weight-at-age and the SSB for fish older than 3 years old.

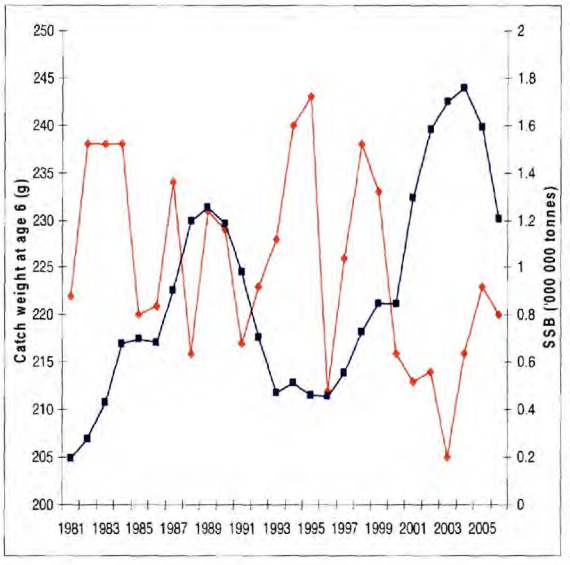


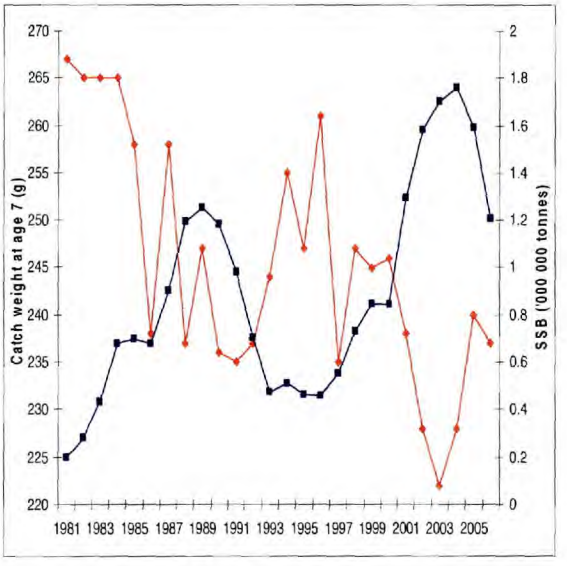

Catch weight at age 2 (g)
SSB ('000 000 tonnes)
135
130
125
120
115
110
105
100
95
90
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005


Catch weight at age 3 (g)
SSB ('000 000 tonnes)
180
175
170
165
160
155
150
145
140
135
130
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005


Catch weight at age 4 (g)
SSB ('000 000 tonnes)
200
195
190
185
180
175
170
165
160
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005


Catch weight at age 5 (g)
SSB ('000 000 tonnes)
230
225
220
215
210
205
200
195
190
185
180
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005


Catch weight at age 6 (g)
SSB ('000 000 tonnes)
250
245
240
235
230
225
220
215
210
205
200
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005


Catch weight at age 7 (g)
SSB ('000 000 tonnes)
270
265
260
255
250
245
240
235
230
225
220
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005

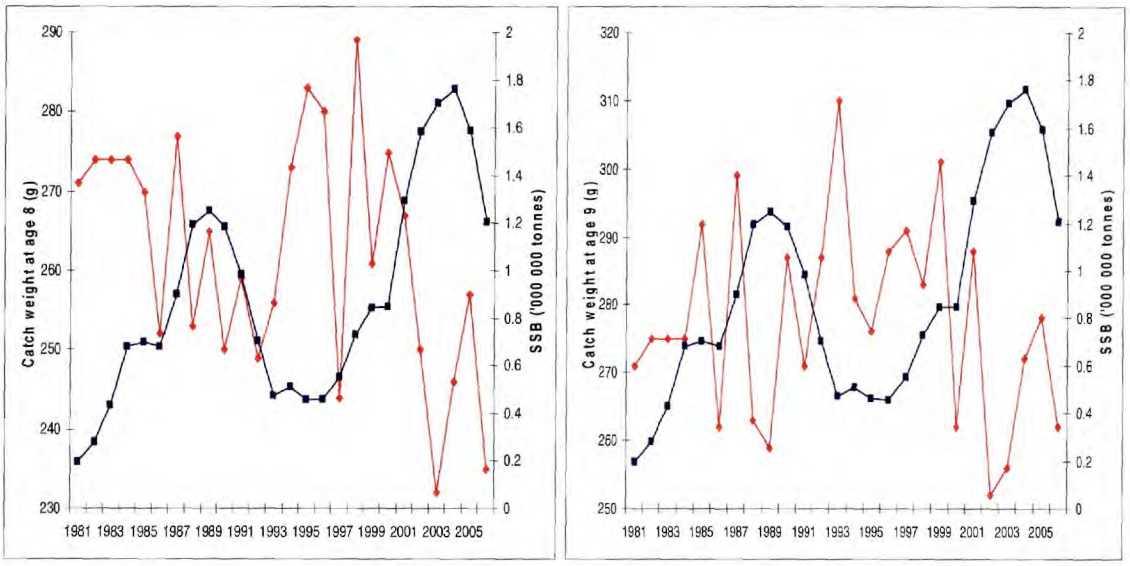


Figure 13: Catch weights-at-age and spawning stock biomass over time.
Catch weight-at-age: solid line, left axis; SSB: dashed line, right axis.

These data were subjected to the same regression analysis as the stock weight-at-age data (Table 5). As for the stock weight-at-age, the linear regression did not suggest a significant correlation existed with young fish (ages 0-3) or for the plus-group. The mean over historical years between 1983 and 2006 and the coefficient of variation was used in modelling. Values found for ages 0, 1, 2, 3 and 9 can be found in Table 6.

Table 5: Regression equations for the relationship between weight-at-age in the catch and SSB; slopes, intercepts and R^2.
Bold R^2 indicates P<0.01 significance, italics indicates P<0.05 significance.

Age	0	1	2	3	4	5	6	7	8	9+
Slope	2.97 10^{-6}	-4.62 10^{-6}	-8.97 10^{-6}	-2.69 10^{-6}	-1.15 10^{-5}	-1.45 10^{-5}	-1.26 10^{-5}	-2.14 10^{-5}	-1.95 10^{-5}	-1.13 10^{-5}
Intercept	9.3	50.3	122.8	155.0	191.2	218.9	236.4	264.6	279.6	287.13
Intercept with common slope of -1.59 10^{-5}	/	/	/	/	193.7	218.7	237.9	258.2	274.9	/
R^2	0.121	0.035	*0.198*	0.020	**0.403**	**0.395**	**0.301**	**0.565**	**0.344**	0.164

Table 6: Means and coefficient of variation of catch weight for ages 0, 1, 2, 3 and 9.

Age	0	1	2	3	9
Mean	11.92	46.19	114.81	152.65	277.54
CV	0.321	0.241	0.079	0.056	0.053

Those two adjusted regression and mean with coefficient of variation for the maturity-at-age and the catch weight-at-age will be used in a sensitivity analysis, developed in sections 5.3.3.1 and 5.3.3.2.

In order to include variability in the model, a random value around the mean, following a log-normal distribution, was picked for each Monte Carlo iteration for the calculation of the stock weight-at-age in the case of young fish and the catch weight-at-age for all ages.

2.3.4 SELECTIVITY

While North Sea herring data contain all the relevant biological information, the operating model has to be seeded. The model requires selectivity information to run. Historical fishing mortality rates at age for all years between 1960 and 2006 are available from the Herring Working Group ICA results, from which selectivity can be obtained by normalising fishing mortality values (Figure 14).

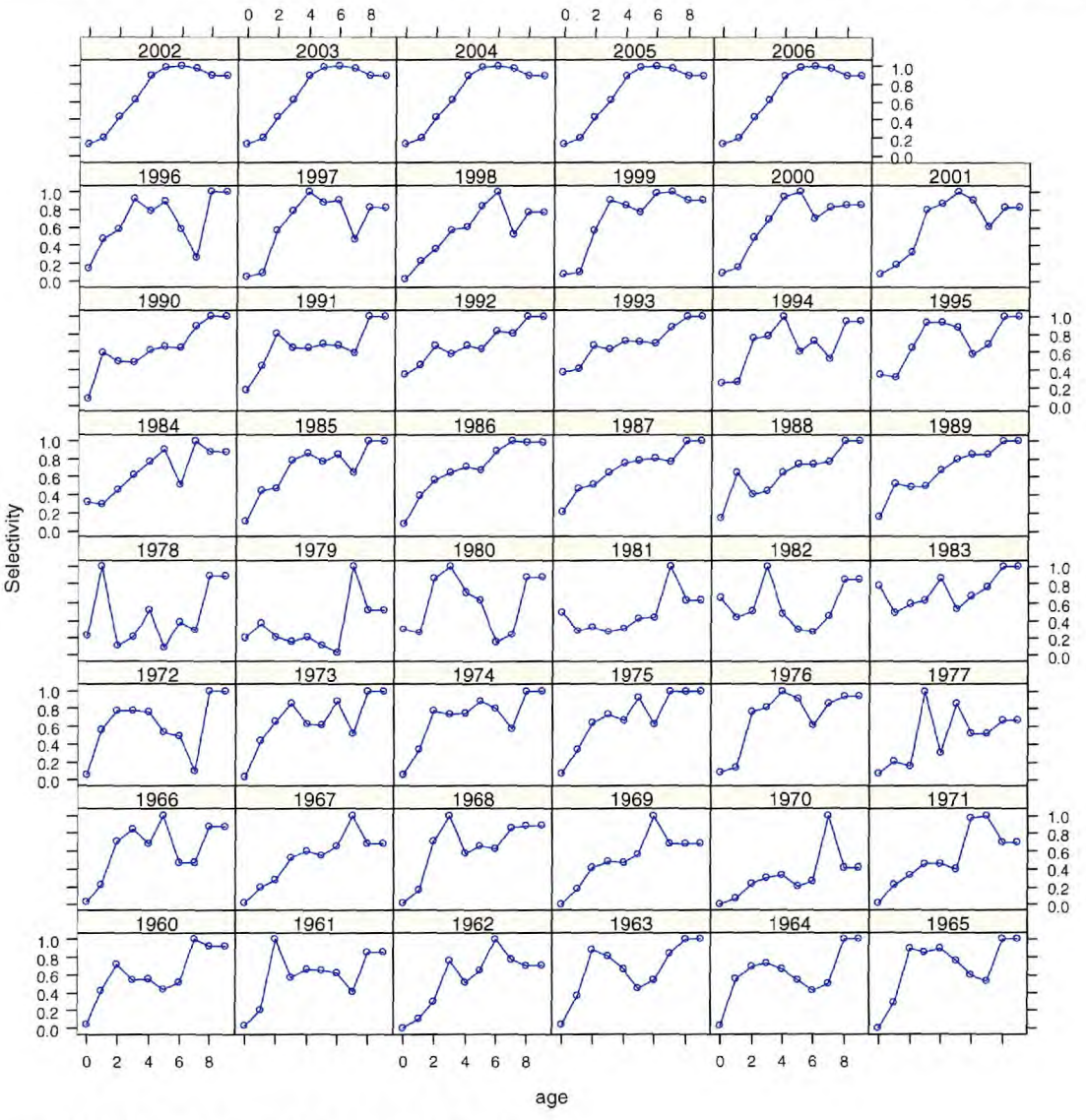


Figure 14: Selectivity at age for each historical year.

The selectivity at age relationship is highly variable between years. Between 1960 and 1972, estimated selectivity ogives are inconsistent over time. Between 1973 and 1976, the selectivity tends to increase until a certain age and then plateau for ages older than this. During the four years of the closure of the fishery, selectivity –at-age ogives were again quite variable. From the reopening of the fishery in 1981 until 1993, the trend was a linear increase with age. From 1994 onwards, the trend is similar to the one observed before the closure of the fishery - an increase with a plateau. Those changes can be explained by modification of the fishing gears used.

There were major changes to fisheries methods in the 1960s', with the traditional drift-net fishery being gradually replaced with a trawl fishery. There has also been a change from bottom trawling to pelagic and semi-pelagic pair- and single-boat trawling. The

introduction of new acoustic fish-finding equipment – i.e. sonar – led to new fishing tactics and to a greater efficiency of fishing effort (ICES HAWG, 1970). But one the most important change was the introduction of the purse-seining technique in 1963 in the north-eastern North Sea and Skagerrak. It was then extended to the Shetland area in 1965. In the 80s, after the reopening of the fishery, adult herring were mainly caught in purse seine fisheries and in pelagic trawl fisheries. Smaller fish – 0-group and 1-group fish - are taken by small mesh bottom trawls but also by purse seine for the large 1-group fish (ICES HAWG, 1986). Those two distinguished types of fisheries are still currently used.

The selectivity values are very similar for the last 5 years (2002-2006) and are consistent with selectivity curves for the time period after 1994. Due to this regular change in the selectivity ogives and the constant pattern in the last years, the selectivity curve was only fitted to the last year. Parameters of the logistic were estimated by using a maximum likelihood estimation method assuming a lognormal likelihood function. The plot of the fitted logistic selectivity ogive can be found on Figure 15.

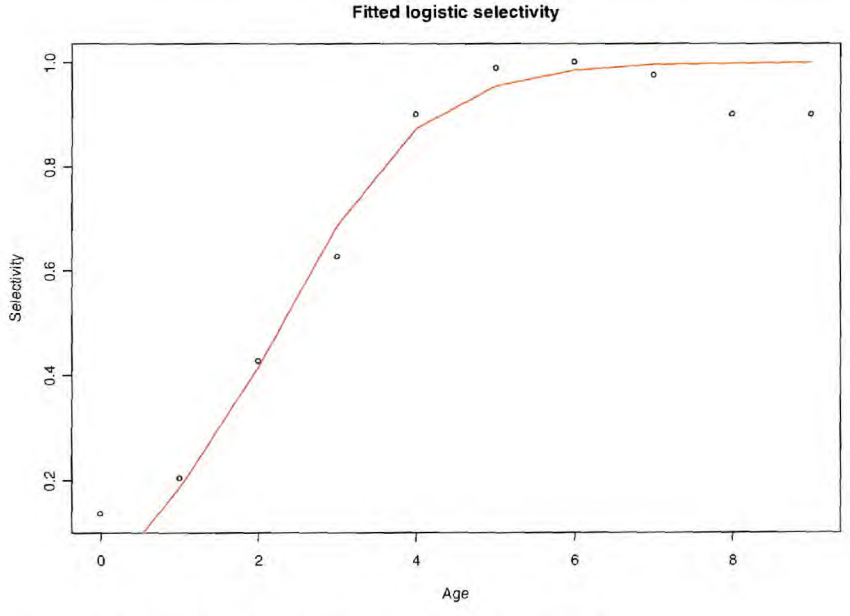


Figure 15: Fitted logistic selectivity on 2006 year's data.

2.3.5 STOCK-RECRUITMENT RELATIONSHIPS

One of the most important parts of the operating model is the stock-recruit relationship. In the case of the North Sea herring stock, the model implemented here and previous stock-recruitment relationship analyses of herring assume density-dependence between SSB/egg production and 0-group animals.

To select a suitable model three alternatives, Beverton-Holt, Ricker and a hockey stick models (c.f. section 2.2.1) were fitted individually to the stock-recruitment data using a maximum likelihood estimation method assuming a lognormal likelihood function. The estimates obtained were:

- For Beverton-Holt: $\alpha = 60.893$ and $\beta = 0.458$
- For Ricker: $\alpha = 120.63$ and $\beta = 0.999$
- For hockey stick: $\alpha = 89.86$ and $S^* = 459\,761$ tonnes

The gradients of the stock-recruitment curve at the origin were

- Beverton-Holt: $\alpha/\beta = 132.95$
- Ricker: $\alpha = 120.63$
- Hockey stick: $\alpha = 89.86$

The gradient is a major productivity parameter. It represents the number of recruits per spawner at low numbers of spawners. Clearly, in a situation of low stock size, the stock will tend to recover faster if the recruitment follows a Beverton-Holt stock-recruitment relationship than a Ricker or a hockey-stick relationship.

The fits of each model to data from the most recent assessment are shown in Figure 16, Figure 17 and Figure 18.

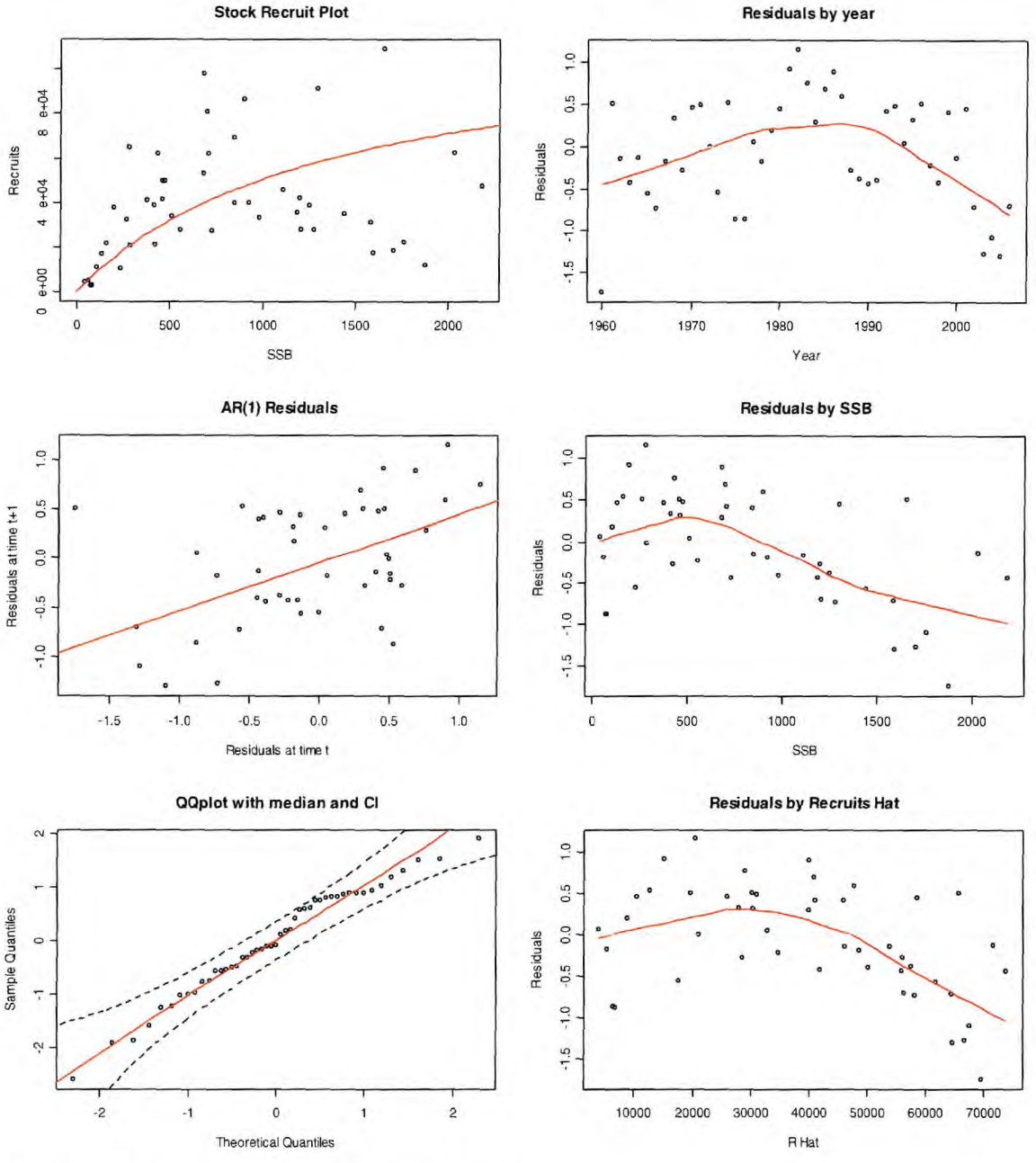


Figure 16: Beverton-Holt stock-recruitment function.
From left to right and from top to bottom: a) stock-recruitment by spawning stock biomass (dots: observed values; line: fitted curve); b) residuals by years (dots: residuals relating to the observed and predicted recruitments; line: smoother); c) AR(1) residuals: residuals at time *t+1* by residuals at time *t* (line: linear trend); d) residuals by spawning stock biomass (line: smoother); e) QQplot with median and confidence interval; f) residuals by recruitment estimated (dots: observed; line: smoother).

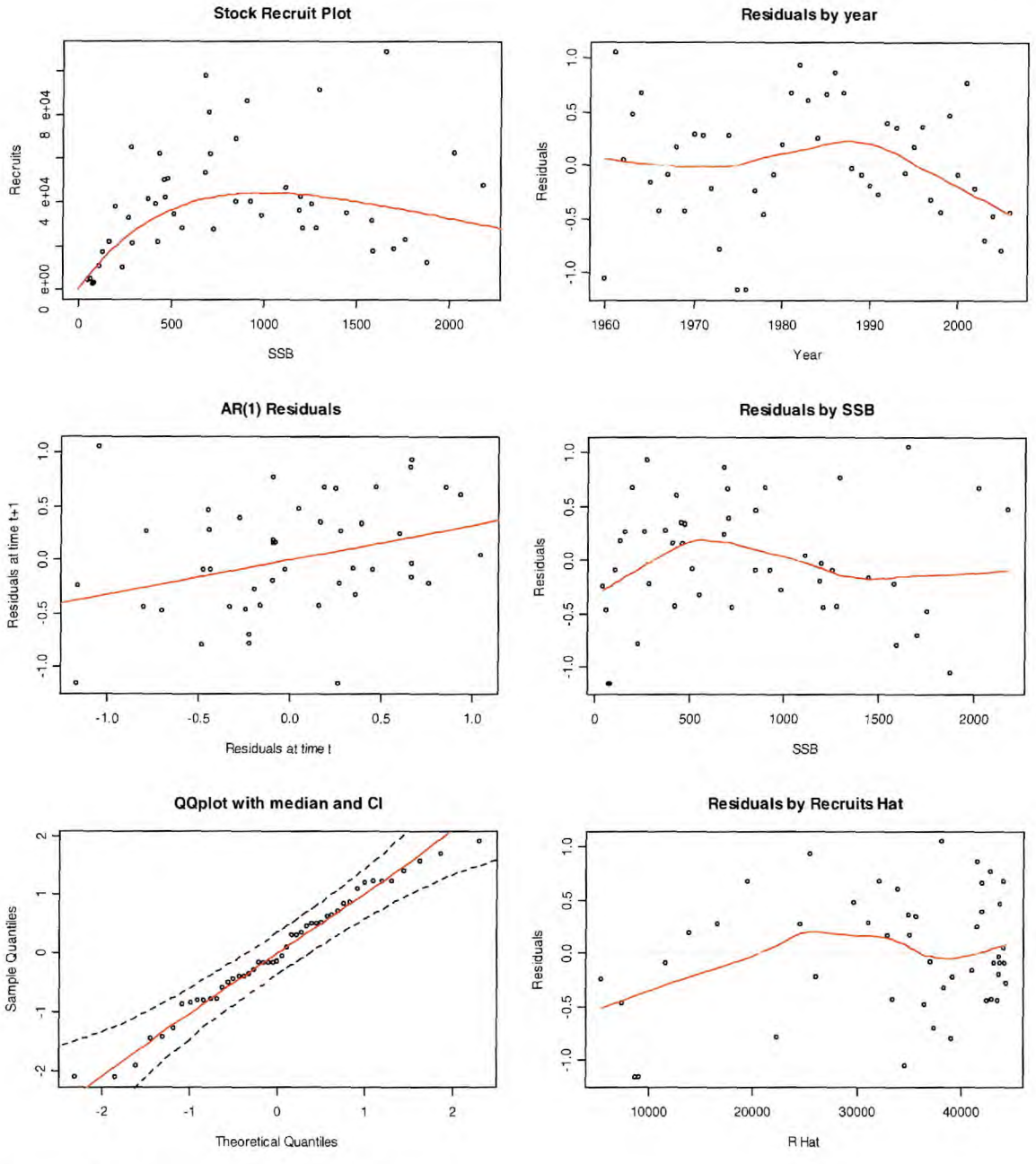


Figure 17: Ricker stock-recruitment function.
From left to right and from top to bottom: a) stock-recruitment by spawning stock biomass (dots: observed values; line: fitted curve); b) residuals by years (dots: residuals relating to the observed and predicted recruitments; line: smoother); c) AR(1) residuals: residuals at time *t+1* by residuals at time *t* (line: linear trend); d) residuals by spawning stock biomass (line: smoother); e) QQplot with median and confidence interval; f) residuals by recruitment estimated (dots: observed; line: smoother).

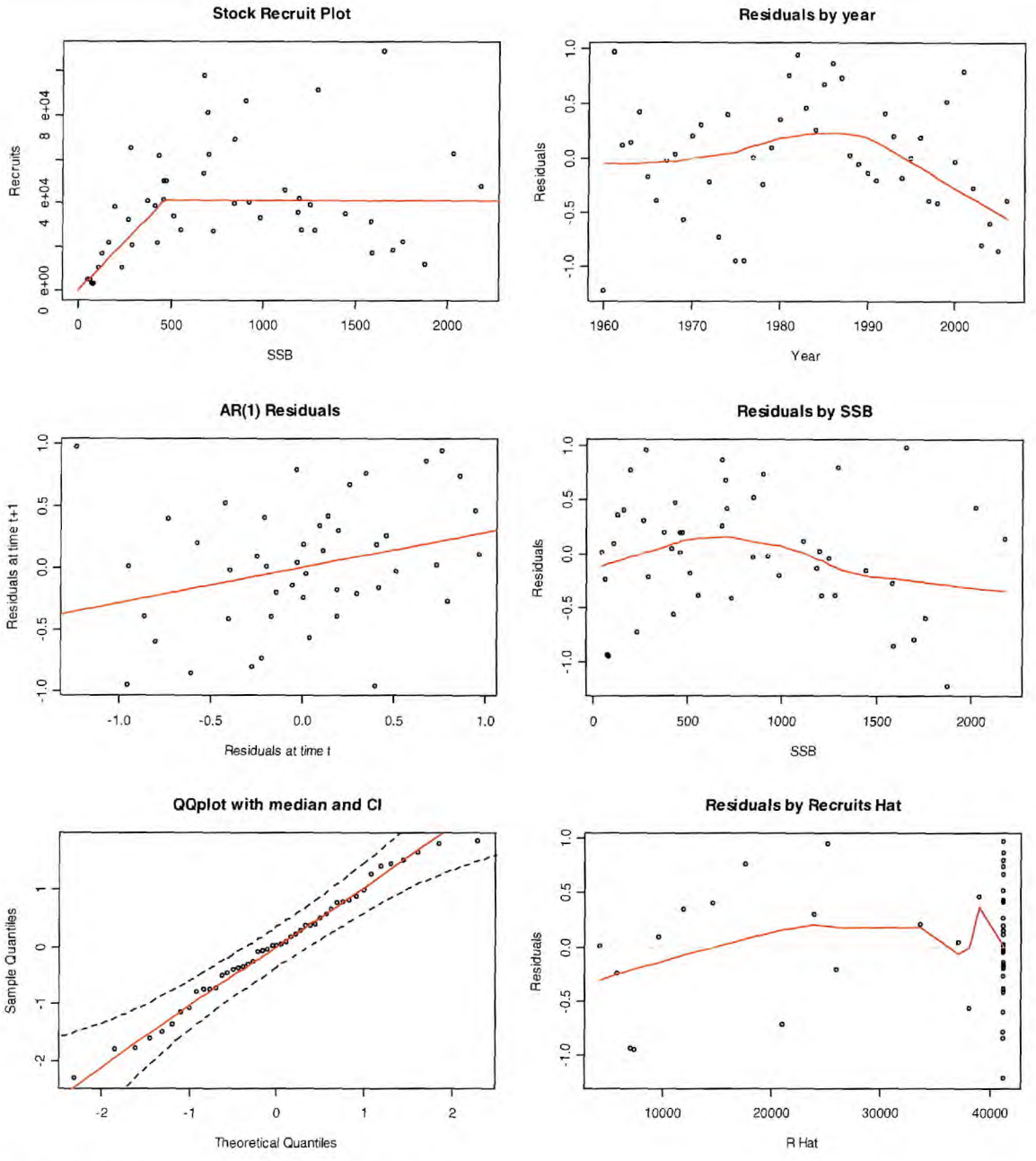


Figure 18: Hockey-stick stock-recruitment function.
From left to right and from top to bottom: a) stock-recruitment by spawning stock biomass (dots: observed values; line: fitted curve); b) residuals by years (dots: residuals relating to the observed and predicted recruitments; line: smoother); c) AR(1) residuals: residuals at time *t+1* by residuals at time *t* (line: linear trend); d) residuals by spawning stock biomass (line: smoother); e) QQplot with median and confidence interval; f) residuals by recruitment estimated (dots: observed; line: smoother).

It is apparent that the Beverton-Holt relationship is a poorer fit to the data than either of the other relationships. This is particularly seen in figures a) and d), where there is a significant trend in the residuals at high stock biomass. On all figures b), it can be seen that the residuals display significant negative residuals in the mid-1970s, when the stock was at a very low level, and that there is a trend to negative residuals again since the

early 1990s. In fact the residuals between 1960 and end of 80s seem to follow a sinusoidal curve starting with a decrease until mid 70s, an increase until early 80s and again a decrease until end of 80s – early 90s.

Figures c) and d) present autocorrelations and density-dependence in the residuals. Autocorrelation is discussed separately below. In respect of density-dependence, the shapes of the smoothers are quite different depending on the stock-recruitment relationship chosen. For the Ricker and the hockey stick models, the smoother is relatively flat, compared with the Beverton-Holt one. This means the first two stock-recruitment relationships seem to take properly into account the effect of density-dependence. With the Beverton-Holt model, from a certain SSB, the higher the biomass is, the higher the absolute value of the residual is. The curve tends to decrease continuously for high SSB. This means the residuals are negative with the effect that recruitment is over estimated.

The figures e) are Q-Q plots. It can be seen that for all stock-recruitment relationships, points are within the confidence intervals and close to the median. This means that the distributions of the observed and estimated recruitments are the same. The choice of a lognormal distribution seems justified.

The figures f) of the Figure 16, Figure 17 and Figure 18 look for density-dependence. With the Beverton-Holt stock-recruitment relationship, as the SSB increases, the recruitment increases. As seen on the figure of the corresponding stock-recruitment relationship, the curve tends to decreases continuously as the estimated recruitment increases. In a similar way to figure d) (residuals by SSB), this shows that the recruitment is over-estimated with this stock-recruitment relationship for high recruitments – or high SSB. The vertical points on the hockey-stick model figure can be explained by the fact that from a certain SSB value, the estimated recruitment is constant but residuals can vary as the observed recruitment is not constant.

For all stock recruit functions, the Akaike Information Criterion (AIC) was calculated. It is a measure of the goodness of fit of an estimated statistical model. The model which minimises this AIC value is the best statistical fit to the data. AIC for Beverton-Holt, Ricker and hockey stick stock recruit functions are equal to 94.87, 79.03 and 76.22

respectively. The third value is the smallest AIC, suggesting that the hockey stick model and Ricker models fit the data best.

Another way to compare stock-recruitment models is to use a measure called Akaike weights. It provides a measure of the strength of evidence for each model, and represent the ratio of delta AIC (Δ_i) values for each model relative to the whole set of R candidate models. The delta AIC is a measure of each model relative to the best model, and is calculated as:

$$Delta\ \ AIC = \Delta_i = AIC_i - \min AIC \tag{20}$$

The Akaike weight can be calculated as follows:

$$w_i = \frac{e^{\frac{\Delta_i}{2}}}{\sum_{y=1}^{R} e^{\frac{\Delta_{yi}}{2}}} \tag{21}$$

In this analysis, the weights calculated for each stock-recruitment relationship are 7.10-5, 0.19 and 0.8 for the Beverton-Holt, Ricker and hockey stick, respectively. In other words, this means that the hockey stick model has 80% chance of being the best-fitting model of the three considered here.

Based on analyses of the figures and the AIC, the Beverton-Holt does not seem to be a suitable stock-recruitment relationship for those data. Future analyses will only focus on the Ricker and the hockey-stick stock-recruitment relationships.

2.3.6 AUTOCORRELATION

The linear trend in Figures 5-7 c) shows the existence and level of autocorrelation in residuals. If the trend is horizontal, there is no autocorrelation. If the trend increases (decreases), there is a positive (negative) autocorrelation and the steeper the line is, the greater the effect. The correlation in figures c) was significant ($n = 46$, $p < 0.05$) for the Ricker model, but not for the hockey-stick model.

It is possible that the change in the trend in residuals from the early 1990s seen in figures b) could be due to changing autocorrelation effects. This was investigated by splitting figures c) into two figures: from 1960 until 1993 and from 1994 until 2006. Following the split none of the correlations was significant, with the conclusion that there was no evidence that autocorrelation had changed during the series. Accordingly, a single autocorrelation relationship was assumed for all years.

2.3.7 OTHER DATA

The model requires several other data: estimated catch and catch at age, and a number of acoustic and net surveys. These are described in chapters 3 and 4.

2.3.8 INITIAL CONDITIONS

Starting conditions for the operating model were set as the output from the most recent herring working group ICA assessment, including predicted numbers at age. The selectivity ogive and the initial harvest rate (derived from maximum initial fishing mortality) were used to initialise the exploitation regime. The initial recruitment value was always defined by the initial recruitment value set by ICA. Finally, the operating model was projected in to the future to see how the stock will evolve following several management strategies developed in the following chapters.

As can be observed in the Figure 5, the stock is in a relatively good condition. The spawning stock biomass in 2006 is just below B_{PA} with a biomass of 1.2 million tonnes, given the stock was assumed to reach almost 1.9 million tonnes in 1960 and has recovered from an important decline of the stock in 1996 (459 665 tonnes) to a maximum of 1.759 million tonnes in 2004. Given the SSB estimated in 2006 and according to the management agreement set in 1997 between EU and Norway, the fishing mortality rate (F) for juveniles should be smaller than 0.12. This was found to be the case. The average F for 0- and 1-year old fish is equal to 0.0758. However, the fishing mortality for adults should be lower than 0.25 - according to the agreement – and this was not found to be the case, as the average fishing mortality rate for 2 year olds and older was 0.354. When the stock was well above B_{PA} in 1960, the fishing mortality for young fish was equal to 0.14, which is not far above the limit set later in

the agreement (F_{0-1} = 0.12 when the SSB > B_{PA}). The fishing mortality rate for older fish was quite similar to the one observed in 2006 (0.336 vs. 0.354). Conversely, in 1996 when the fishing pressure was higher and led to an important decline of the stock, the fishing mortality rate on juveniles was very high considering the estimated SSB that year (459 665 tonnes), which was well below B_{lim} (800 000 tonnes). Indeed, the fishing mortality for juveniles was 0.16 when it should not have been more than 0.04. The adult value of F should have been below 0.1 but was in fact equal to 0.4. Based on these comparisons, it is possible to say that the initial condition of the operating model can be considered as relatively good. In order to test the sensitivity of the model, a sensitivity analysis will be run in section 5.3.3.4 with 1996 as final historical year, year for which the stock was a low level. The fitting of the operating model explained in the previous sections is not modified. The only difference is the starting year.

2.3.9 YIELD-PER-RECRUIT

As supplementary information, a yield-per-recruit analysis has been carried out. Figure 19 shows yield-per-recruit versus harvest rate for some selected years. Data were used for all years available (1960-2006). Curves were plotted for: the first historical year (1960), two years when the fishing pressure was high (1970 and 1990), two years when the fishing pressure was reduced (1975 and 1996) and the final year (2006). For each year selected, the weight-at-age and the selectivity values were used for the given year. It was noticed that the maximum yield was reached for a high harvest rate when the selectivity was high. In 1970, the selectivity was so high that the maximum yield seems to be outside of the graph. This means that increases in harvest rate would not improve the yield and if the rate was in practice increased, the stock could decline and even collapse. And that is what happened. Indeed, the stock collapsed and the fishery was closed in 1977. It is also possible to see that the maximum yield is obtained for a smaller harvest rate in the years when the fishing mortality rate is reduced (1975, 1996). The curve for 2006 shows that increasing the harvest rate above 0.5 is not profitable but the maximum yield would not be much reduced, contrary to the curve for 1975. The situation was such in 1975 that increasing the harvest rate did not seem to be profitable for fishermen and the maintainability of a high harvest rate led to the collapse of the stock and the closure of the fishery 2 years later.

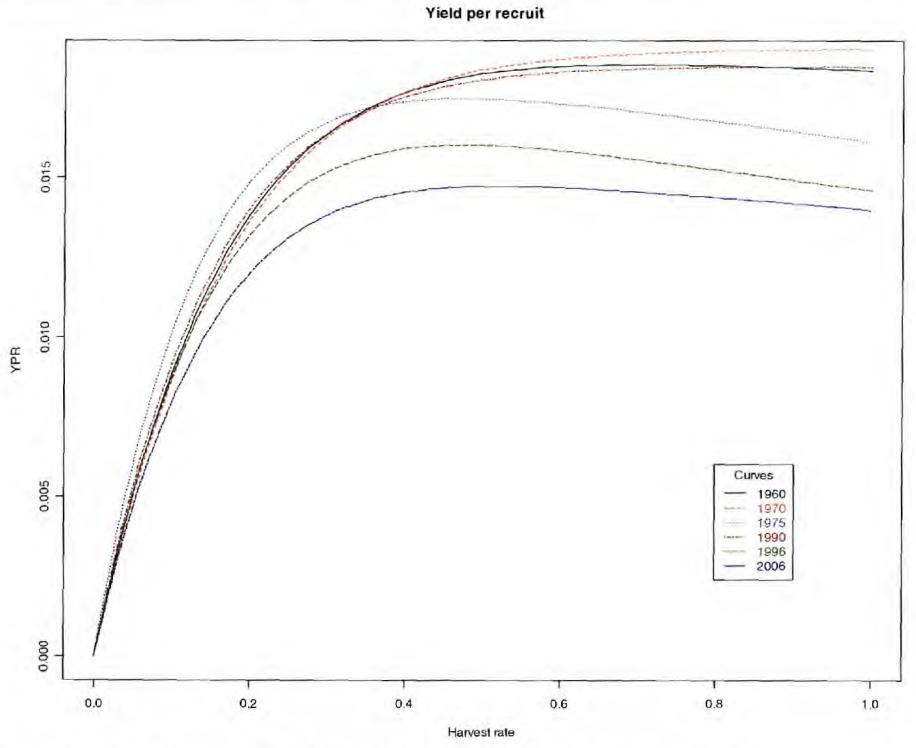


Figure 19: Yield-per-recruit versus harvest rate for several years

2.4 Discussion and conclusion

I have presented several concepts in this chapter and explained the assumptions made in constructing the operating model. The most important building block is the stock-recruitment relationship. Three were initially planned but an analysis of the data showed that only two should be considered further, the Ricker and the hockey stick models. The Beverton-Holt model gave a poorer fit to stock-recruit data.

A logistic selectivity ogive used in the operating model gave a remarkably good fit to the data. The selectivity ogive for herring appears to have stabilised in the last 10 years, primarily because the catch is now taken by a restricted number of very similar vessels operating in the same way with pelagic trawls across the North Sea. Clearly, in projecting the operating model into the future with this selectivity one must assume that the fleet will, in the future, be similar to that which is operating now. There is, however, no reason to doubt that this will be the case, or that there would be a shift back to gears and vessels that were operational in the 1970s. It is possible to observe potential technological advances in the future but this is not considered in the model.

Analysis of a possible autocorrelation effect in the residuals relating to the observed and predicted recruitments showed that there is a significant autocorrelation effect with the Ricker model. The trend in residuals of recruitment with time appears to be related to significant stock effects, notably the decline in the 1970s and the subsequent recovery which produced negative and then positive residuals. The recent decline in residuals is more difficult to explain. It does not appear to be the result of changes to the autocorrelation structure, and may instead be related to regime change.

The method used to assign values-at-age for the natural maturity, stock weight and catch weight is explained above. For the natural maturity, a sensitivity analysis can be found in section 5.3.3.1 to see if the consideration of a linear relationship between maturity and SSB would provide different results that could lead to the failure of a HCR. The relationship found for stock and catch weight-at-age appears to follow the anticipated hypothesis (Brander, 2007) that weight-at-age will be higher when population size is lower. The absence of any observable relationship at very young ages supports this, suggesting that it is only as fish enter the older age groups and recruit to the adult population that stock size induced growth effects become evident.

Once the operating model is implemented and tested, the next step of the development of the simulation evaluation framework is to establish the observation error model which is presented in the following chapter.

CONCEPTUAL FORMULATION OF THE OBSERVATION ERROR MODEL

3 Conceptual formulation of the observation error model

3.1 Introduction

The second main component of the simulation evaluation framework presented in the general introduction is the observation error model. This is the link between the operating model (c.f. Chapter 2) and the management procedure (c.f. Chapter 5).

Although in the simulation we know the real state of the stock, in reality we cannot know this directly. All we have at our disposal is a number of observations. An observation model is therefore needed to interface between the known, simulated, stock and what we might expect to observe. The aim of this model is to simulate data that correspond to the type of data one would monitor from a fish population. This could include fishery-independent data such as known types of survey observations, fishery-dependent data such as catch per unit effort (CPUE) or catch data (Schnute and Richards, 1995; Punt *et al.*, 2002c).

A highly complex model may generate imprecise or biased results if insufficient information is available (Helu *et al.*, 2000). Therefore, in an observation error model it is usually sensible to simulate a number of indices in addition to the conventional catch data or catch per unit effort data. Observations are generally forms of absolute or relative abundance indices which can be age-based or indicative of various subsets of the population. Observations can include tagging data (Patterson, 1999; Punt *et al.*, 2000; Hampton and Fournier, 2001), age composition data (Methot, 2000; Parma, 2001), length-frequency data (Punt and Kennedy, 1997; Helu *et al.*, 2000), length-weight data (Maury and Restrepo, 2002), abundance indices from surveys (Methot, 2000; Cunningham, 2002), stomach content data (Stefánsson, 1998a), etc. By incorporating more information, the accuracy of the results obtained from the model should increase (Punt *et al.*, 2000).

The forms that observations take within a simulation evaluation framework will depend on the methods of data analysis and the HCRs applied. For example, HCRs often use the results of stock assessments based on age-structured data and relative abundance

indices (e.g. Punt and Smith (1999)) but they may also use indices directly (Magnusson and Stefánsson, 1989; Sakuramoto and Tanaka, 1989; Butterworth *et al.*, 1993; De Oliveira *et al.*, 1998b; Geromont *et al.*, 1999). Observations are sometimes assumed to be a perfect representation of the true system, but of course they contain both error and bias. All these features – the different types of indices, and their error and bias – must be simulated in a management strategy evaluation.

The failure to identify and consider uncertainty in population assessments is one of the main reasons of the lack of success of the management of exploited populations (Hilborn and Peterman, 1995). According to the FAO (1995), uncertainty is the incompleteness of knowledge about the states or processes in nature and refers to the estimated amount (or percentage) by which an observed or calculated value may differ from the true value. Several sources of uncertainty can be identified in population assessments. Rosenberg and Restrepo (1994) distinguished five different types of uncertainties: measurement or observation uncertainty, process uncertainty, model uncertainty, estimation uncertainty and implementation uncertainty.

- Measurement or observation error corresponds to the error related to the sampling of the population. It is a combination of measurement error – a consequence of how observations are done (e.g. the choice of sampling strategy or errors in data collection such as errors in measuring landed catches) (Simmonds *et al.*, 1992; Polacheck *et al.*, 1993; Megrey *et al.*, 1994; Rosenberg and Restrepo, 1994) - and estimation error, which is the inaccuracy and imprecision introduced by the method of statistical inference used to estimate system parameters from observations (Harwood and Stokes, 2003). Hilborn (1997) added additional forms of errors to this classification; for example, the uncertainty whether surveys provide absolute or relative indices of abundance, whether there are trends in the catchability of surveys or in the bias of survey results and whether survey catch rate is linearly related to abundance. As an example, the uncertainty whether surveys provide absolute or relative indices is the major source of uncertainty for Cape hake *Merluccius capensis* and *Merluccius paradoxus* off Namibia (Butterworth and Geromont, 1997) and South African sardine *Sardinops sagax* populations (De Oliveira *et al.*, 1998a; De Oliveira *et al.*, 1998b).

- Process uncertainty is "the underlying stochasticity in the population dynamics such as the variability in recruitment" (Caddy and Mahon, 1995, following Rosenberg and Restrepo, 1994). It has also been defined as the "random variation in demographic rates and processes" (Fogarty *et al.*, 1996). This type of uncertainty results from natural variability. The most common example of process uncertainty is the inter-annual variability in recruitment. Beddington and Cooke (1983) catalogued estimates of the extent of this variability for a large number of fish stocks.

- Model uncertainty is the uncertainty in the specification of model parameter values or model structure. It derives from the "lack of complete information on the population and community dynamics of the system" (Fogarty *et al.*, 1996). The term "model" makes reference to the model that fisheries scientists and managers use in the process of making decisions about fish populations and fisheries. Models can be qualitative and then the uncertainties are unquantified (e.g. uncertainties about the location of stock boundaries) but most of the time, they are mathematical. In the latter case, uncertainties correspond to lack of information about the correct structure and parameter values (Francis and Shotton, 1997).

- Estimation uncertainty results from any of the above uncertainties and expresses the uncertainty in the estimated model parameters such as population abundance or mortality rates (Rosenberg and Restrepo, 1994). In a more simplistic way, it could be defined as the sum of the observation error and the process uncertainty.

- Rosenberg and Brault (1993) defined the implementation uncertainty as "the extent to which management policies will be successfully implemented". It results from variability in achieving the target harvest strategy. Rice and Richards (1996) noted that when the objectives of fishery managers and the industry differed significantly, management actions were expected to fail.

Francis and Shotton (1997) mentioned a sixth source of uncertainty: institutional uncertainty. This was defined by O'Boyle (1993) as arising from "problems associated with the integration of the individuals and groups (scientists, economists, fishermen,

etc.) that compose the management process". Stephenson and Lane (1995) asserted that one of the reasons for the failure of fisheries management in the last decades is that "objectives have been broad, ill-defined and in many cases not operationally feasible".

The previous chapter described how process uncertainty has been incorporated into the operating model. Model estimation uncertainty and implementation uncertainty are examined in later chapters (chapters IV and V). This chapter will focus only on observations errors. The observations generated by this module will be used in the survey-based stock assessment methods which are listed in the Appendix 2 and in the survey-based HCRs explained in chapter 4.

The first part of this chapter describes the structure of the observation error model. It includes the types of observations used in this work and the types of indices implemented, based on the observations available. The two sections describing the types of indices contain an explanation of the concept, the equations used and the application to the North Sea herring stock, with respect to the conditioning of the observation error model. The chapter finishes with a discussion and conclusions.

3.2 Model structure

This section explains the different components of the observation error model implemented during this work. The first section will list the types of observations used. There are two types of indices developed in this chapter: non-age-structured and age-structured indices which are described in section 3.2.2 and section 3.2.3 respectively. Those two sections will include concepts, equations and applications to the North Sea herring stock.

3.2.1 TYPES OF OBSERVATIONS

This thesis examines the performance of different management strategies when dealing only with fishery-independent data. Therefore, although it would be possible to simulate fishery-dependent indices (observations) in the error model (such as CPUE), the focus

here is on developing appropriate fishery-independent (i.e. survey derived) observations.

The only fishery-dependent observations to be simulated are estimates of catch at age (extractions). I use estimated catch-at-age data, since the assessment used in the actual management of the North Sea herring stock is based on catch-at-age data. Furthermore, one of the tests that is applied in the management strategy evaluation described later in this thesis is a robustness of HCRs to implementation error, in the form of under-reporting in the catch data. The potential for this error being a part of the herring management system is the main reason why fishery-dependent indices such as CPUE are not used in this model.

The Herring Assessment Working Group (HAWG) has collected data from four different surveys: the herring acoustic survey, the International Bottom Trawl Survey (IBTS), the Method Isaac Kidd Mid Water Trawl survey (MIK) and the Multiplicative Larval Abundance Index survey (MLAI). The historical implementation and the principle of those surveys have been explained in section 1.4.3.

For each type of survey, a number of different survey indices could be estimated (e.g. SSB, catch per unit effort, fecundity at age, total biomass). However, here I only generate the indices that are calculated from the real survey observations. The MIK and MLAI surveys produce indices of 0 year group fish and SSB respectively. The IBTS and the acoustic survey produce indices of abundance and age structure in the population. Among the four survey data sets the acoustic survey provides the best information of the abundance and the total mortality rate of the population. A further advantage is that the acoustic survey provides an absolute estimate of the population, rather than a relative index. It also has an excellent spatial coverage and the key ages are covered. The later is not the case for the MIK and MLAI surveys. Also, compared with the IBTS survey data, the mean coefficient of variation is much smaller ($\overline{CV}_{acoustic} = 0.23$ (for 9 ages covered: 1 to 9 years old) and $\overline{CV}_{IBTS} = 1.19$ (for 5 ages covered: 1 to 5 years old)).

To simulate the indices arising from these surveys in a model it is necessary to characterise the functional form and magnitude of the error arising from each source,

the potential correlation between those errors and the bias. The procedure for this is described below in section 3.2.3 for non-age structured indices and 3.2.4 for age-structured indices.

3.2.2 NON AGE-STRUCTURED INDICES

3.2.2.1 Concept

The first type of index developed in this work was a non age-structured index. Non age-structured indices reflect abundance and can correspond to a specific age-class or to a combination of age-groups. They are mainly obtained from scientific surveys but can sometimes come from commercial catch information or tagging experiments (de Pontual *et al.*, 2003; Maunder and Starr, 2003). Abundance indices are usually one of the best sources of information to estimate the actual size and structure of a fish stock but the major problem is the uncertainty in those indices.

Bias can be estimated for absolute or relative indices but also for trends in relative or absolute indices. For each survey index it is necessary to identify and quantify potential sources of bias or trend bias. The quantified biases or bias trend can be directly incorporated into the observation error model.

3.2.2.2 Equations

The key element of this part of the observation error model is the index itself. Any simulated index can be written following this general equation (Cook, 1997; Meyer and Millar, 1999; Chen *et al.*, 2004):

$$\hat{I} = q * I \tag{22}$$

where $\hat{I}$ corresponds to the simulated index, I is the true population variable observed (abundance, recruitment...) and q corresponds to the scaling factor, usually called the catchability coefficient, depending on the index being used.

An observation error can be included in the previous equation. It will be additive or multiplicative depending on the observation error model considered. If the error chosen

is normal, the error parameter is added to the simulated index. If a log-normal or a gamma error is considered, the error parameter is multiplied by the simulated index. For example, if the observation error is assumed to be multiplicative and log normal with a constant coefficient of variation then the relationship between the simulated index and the true population variable observed is:

$$\hat{I} = q * I\left(* \; or \; + \right) \varepsilon \tag{23}$$

where ε is the error. If the error is multiplicative, it follows a log-normal distribution with zero mean and variance σ^2. In the case of additive error, the later follows a normal distribution with mean equal to 1 and variance σ^2.

In the case of a normal or log-normal error, a simple lag-1 correlation effect is possible. Observation bias can also be included (b):

$$\hat{I} = q * I * \varepsilon * b \tag{24}$$

If there is no bias, the value of b is equal to 1. The last parameter that can be included in the calculation of the simulated index is β, also called the index-to-abundance power coefficient. It corresponds to the potential relationship between commercial catch per unit effort – CPUE - and the exploitable stock biomass or number-at-age. The complete equation for the relationship of a simulated index is therefore given as:

$$\hat{I} = q * I^{\beta} * b \left(* \; or \; + \right) \varepsilon \tag{25}$$

This formulation has been used by a number of assessment methods, such as ICA and XSA (ICES AFWG, 2004; Dickey-Collas *et al.*, 2007).

A representation of this relationship can be seen on Figure 20 and demonstrates the effect of β. If $\beta = 1$, there is a linear relationship between the commercial CPUE and the exploitable stock biomass. If $\beta << 1$, the same value of the CPUE will be obtained for a large range of exploitable stock biomass values, including low exploitable stock biomass. In other words, for the same CPUE, it will not be possible to estimate the true

exploitable stock biomass and this situation can easily lead to a collapse of the stock if the exploitable stock biomass level is close to the inflexion point. If $\beta < 1$, the effect will not be as important as for $\beta << 1$ but the index will still overestimate the real exploitable stock biomass. In the case of well designed surveys, β is expected to be equal to 1.

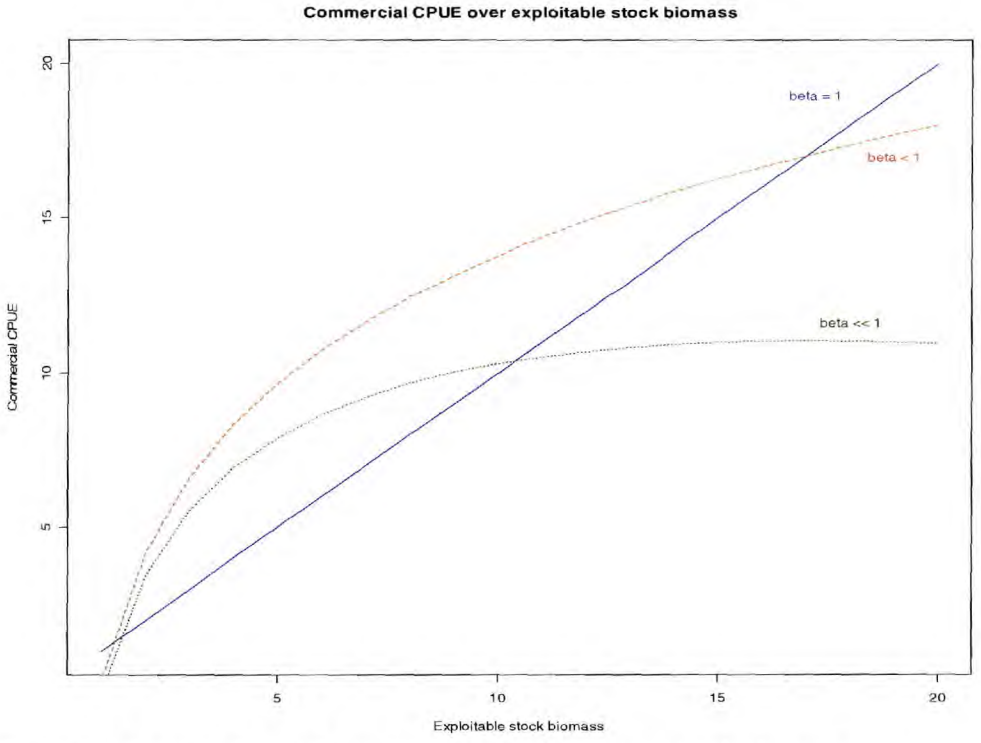


Figure 20: Commercial catch per unit effort over spawning stock biomass. Values on axis are arbitrary.

The behaviour of fish and fishermen is usually not expected to change on a yearly basis. But depending in their age, fish may have a different behaviour. Thus in a general application of equation 24, q, b, ε and β are usually only allowed to vary by age. Even species that are solitary as adults usually school as juveniles as it offers a better protection against predators (Shaw, 1978 in Klimley and Holloway, 1999; Partridge, 1982 in Bjørndal, 1989) leading fishermen to potentially adapt different fishing methods for different ages. Occasionally there may be evidence that q and ε vary by season and other factors over time. Variation of parameters by age, year and season increases the level of temporal variability available and the level of biological precision. The combination of options is sufficient to simulate a quite large diversity of observations and particularly those considered in this work.

3.2.2.3 Application to the North Sea herring stock

The MIK and MLAI surveys were used to simulate non age-structured indices for the North Sea herring stock. These two surveys generate single age-group indices. In the case of MIK, the index is of larval 0-group fish. In the case of MLAI, the survey is used to estimate spawning stock size.

There was no information from which to estimate either bias or the power coefficient of surveys. Surveys follow a pre-defined track and are assumed to be unbiased. Accordingly both bias and power were assumed equal to 1.

Indices of abundance from the two surveys were assumed to be independent with a log-normal error distribution. The coefficient of variation for the MIK survey was 0.27 and for the MLAI survey was 0.22 (from Fisheries Research Services (FRS) Marine Laboratory, Aberdeen, UK). The standard deviation of the log-normal error distribution can be calculated as follows:

$$\sigma = \sqrt{\ln\left(1 + CV^2\right)} \tag{26}$$

where σ is the standard deviation and CV is the coefficient of variation of the surveys.

Indices of abundance were simulated from the known historical trajectory of the herring stock with the appropriate error structure. The results for the MIK survey are shown in Figure 21.

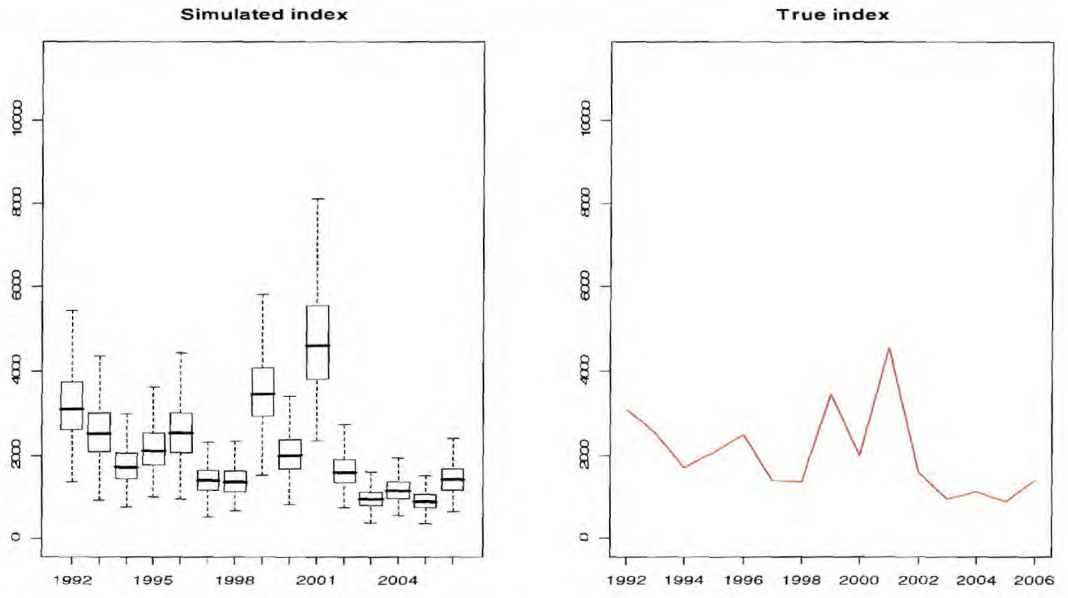


Figure 21: Simulated and true indices of the MIK survey between 1992 and 2006.
Left panel: simulated index. Solid lines: medians of distributions of estimates for each year, boxes: approximate first and third quartiles: whiskers: 95% confidence interval. Right panel: true index.

The simulated observations closely followed the actual trend in number of fish at age 0. As the error follows a lognormal distribution, the value of the median of the simulated index will be equal to the value of the true index. The latter corresponds to the number of fish at age 0 extracted from the historical data.

The results for the MLAI survey are shown in Figure 22:

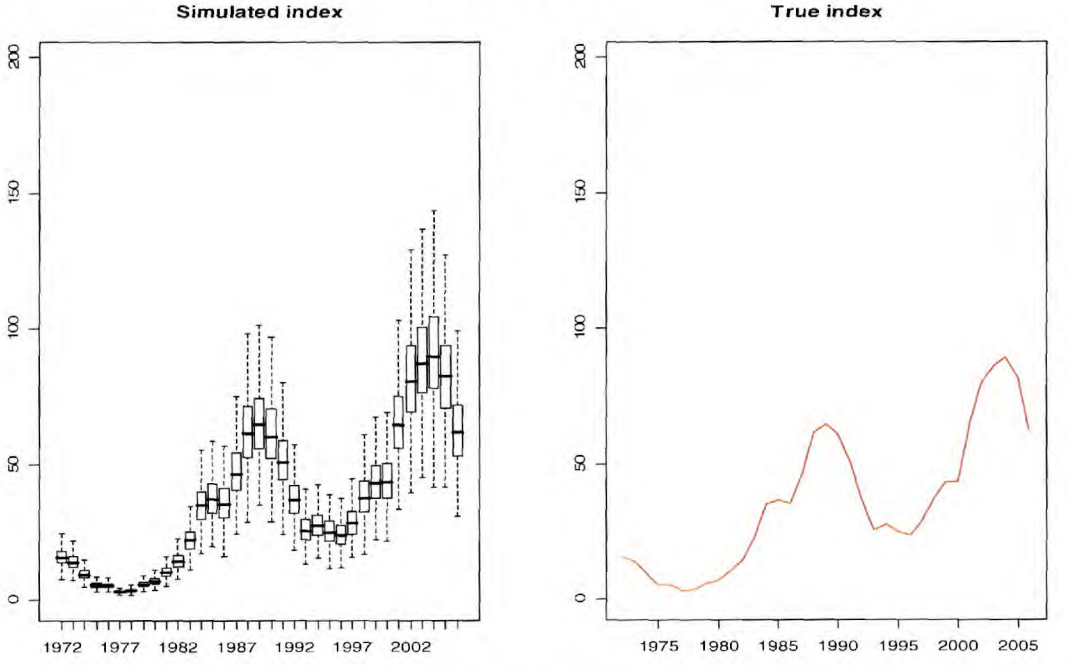


Figure 22: Simulated and true indices of the MLAI survey between 1972 and 2006.
Left panel: simulated index. Solid lines: medians of distributions of estimates for each year, boxes: approximate first and third quartiles, whiskers: 95% confidence interval. Right panel: true index.

Once again, the simulated observations closely follow the actual trend in the SSB. The true index corresponds to the SSB coming from the historical data.

3.2.3 AGE-STRUCTURED INDICES

3.2.3.1 Concept and equations

Age-structured data are often expressed as proportions. Dealing with the error structure of proportional indices is rather more complex than for the simple single-age group indices described above. The primary application of these approaches is simulating ageing error in catch or survey data, but other applications include simulating length reading errors (applicable to deep water fish in particular), as well as correlated year effects in the sampling process. For instance, Van Zwieten *et al.* (2002) described a year effect in the residuals of the catch rates of the industrial pelagic purse-seine fishery of northern Lake Tanganyika. An analysis of the auto-correlation in the residuals of the fit showed that the models were good descriptors of the seasonal pattern. Chen *et al.* (2003) have implemented a stochastic length-based observation-error time series model to represent the dynamics of the New Zealand abalone *Haliotic iris* stock.

Catch-at-age data consist of information on catch and on proportion-at-age derived from sampling of the fishery. Survey data consist of information on the stock and on proportion at age derived from sampling of the surveys. Both are often assumed to be known without error. But proportion-at-age data can be assumed to be sensitive to non-negligible measurement error. In this case, it is important to choose a relevant observation error model for the data-at-age to project the stock and the fishery into the future (Patterson *et al.*, 2001).

A more complex error structure may often be seen with age-sampled data. For example, error is normally correlated across ages to produce an ageing error effect. It is widely known that the ageing of fish is not an exact science and work has already been done to assess (EVARES: Beare *et al.*, 2002) and quantify the magnitude and correlation structure present in the errors that appear in the ageing process. An ageing error usually arises in the reading of the otoliths (Campana and Moksness, 1991; Horn and Sullivan, 1996; Marriott and Mapstone, 2006). This structure of error is rarely taken into consideration in stock assessments, whether based on fishery-dependent or independent

data. The most common assumptions are multinomial error (e.g. Fournier and Archibald, 1982) and lognormal error (e.g. Deriso *et al.*, 1985). The problem with the multinomial error is that it only takes into account negatively correlated errors-at-age. The lognormal error assumes that errors are independent, which may not be the case. Patterson *et al.* (2001) wrote that of these two alternatives, the assumption of multinomial error would seem *a priori* to be the most appropriate, as it accounts for correlations among age groups but nevertheless, the lognormal assumption has been the more common in practice (e.g. Kimura, 1990; Smith and Punt, 1998).

Several steps are required to include ageing errors in simulated data. Raw data need to be converted into proportion data that are then resampled within the relevant strata. These data can then be used in assessments or directly in HCRs.

The first step is to convert data, such as catch-at-age, survey-at-age or survey-at-length data into proportion data. To do this, the historical data are normalised to one along the structural dimension (age, length) following the equation:

$$p_{d,y} = \frac{N_{d,y}}{\sum_{d} N_{d,y}} \tag{27}$$

where d corresponds to the structural dimension, y to the year. $p_{d,y}$ corresponds to the proportion at structural dimension d for the year y of the number of fish $N_{d,y}$ at the same structural dimension and same year.

The second step is to calculate the variance-covariance error matrix that will be used to integrate the structured error in the proportion data. A correlation matrix $cor_{d,d}$ and a coefficient of variation CV_d of the data are needed or have to be estiamted. The coefficient of variation and the mean $\overline{m}$ of the proportion data are used to calculate the standard deviation SD_d as follows:

$$SD_d = CV_d * \overline{m} \tag{28}$$

The latter and the correlation matrix are then used to calculate the variance-covariance matrix $\sigma_{i,j}$.

$$\sigma_{i,j} = cor_{i,j} * SD_i * SD_j \tag{29}$$

where i and j correspond to the two dimensions of the correlation matrix.

The next step is to introduce structured noise to the proportion data. I use a multivariate normal noise to introduce the error, as this allows the consideration of both positively and negatively correlated errors and also dependent errors. The noise can only be structured along one dimension at a time – age, length or year. This is because the noise would then be represented as a matrix and matrix distributional theory is both extremely complicated and not as well developed as vector-based theory. However, multivariate normal noise cannot be applied directly to the proportional data, because the data are not normally distributed, being bounded between 0 and 1. A logit transformation produces transformed data that are assumed normally distributed with unbounded values. This normality in the logit residuals allows the introduction of correlated noise into the system, which is in line with the work that suggests that errors are not independent. A logit function is the inverse of a logistic function, as following:

$$\hat{p} = \ln\left(\frac{p}{1-p}\right) \tag{30}$$

where p are the proportion data obtained in equation 27.

Since we are simulating multivariate normal noise in the logit-transformed proportion data in the simulations, the variance-covariance matrix has to be translated into logit space as well. This is done by using a Delta method, which is a method of approximating the moments of a set of data, under a given transformation (Rice, 1995). This method transforms the moments of a set of data using the partial derivatives of the transformation, evaluated at the mean. Given some differentiable transformation $\phi(p_{y,d})$, the covariance matrix (the variance-covariance matrix in this case) of this transformation $\sigma_{i,j}$ can be expressed as follows:

$$\sigma_{ij}^{\phi} = \frac{\partial \phi}{\partial p_i} * \sigma_{ij} * \frac{\partial \phi}{\partial p_j} \tag{31}$$

where the partial derivatives of $\phi(\ )$, with respect to the proportions, are evaluated at $\overline{m}$. Given the logit transformation presented in equation 29 we have the adjustment of the known variance-covariance matrix σ as follows:

$$\sigma_{ij}^{\log it} = \frac{1}{p_i(1-p_i)} * \sigma_{ij} * \frac{1}{p_j(1-p_j)} \tag{32}$$

where $p_i = \overline{m}_i$.

Once the variance-covariance matrix has been logit-transformed, it is possible to introduce the structured error in the logit transformed proportion data. For each year, given the mean $\overline{m}$ and the variance-covariance matrix $\sigma_{ij}^{\log it}$, the required number of simulations is generated assuming that the new logit proportion data follow a multivariate normal distribution (MNV), as follows:

$$p_{temp} = \log it(p_{new}) = MVN(\overline{m}, \sigma_{ij}^{\log it}) \tag{33}$$

The new data have to be reverse logit-transformed, as follows, in order to be then re-sampled:

$$p_{new} = \frac{e^{P_{temp}}}{1+e^{P_{temp}}} \tag{34}$$

The simulated data are then renormalized, as follows:

$$p_{new} = \frac{p_{new}}{\sum p_{new}} \tag{35}$$

The final step is to regenerate data from the renormalized reverse logit transformed proportion data and the initial raw data as follows:

$$N_{new_{d,y}} = N_{tot,y} * p_{new_{d,y}} \quad (36)$$

Once the newly calculated data are obtained, it is possible to allocate a different inverse variance index for each age.

The newly calculated data can then be used in the assessment or directly in the calculation of HCRs.

3.2.3.2 Application to the North Sea herring stock

In the case of the North Sea herring fishery, two surveys containing non age-aggregated data are available – the acoustic and IBTS surveys - as well as catch-at-age data, the later being used in the actual management and with the assessment called YCC (year class curve). The objective was to convert data into proportion data, resample the proportion data, including the ageing error process, and then regenerate data-at-age that can be used in assessments or directly in HCRs.

For each type of data-at-age, the correlation matrix $cor_{a,a}$ and the coefficient of variation CV_a of the data have been provided by FRS Aberdeen as a result of the ICES SGEHAP and the EU EVARES project (Beare *et al.*, 2002). Values are as follows:

Table 7: Coefficient of variation and correlation matrix for the acoustic survey data.

	1	2	3	4	5	6	7	8	9+
CV	0.186	0.188	0.192	0.217	0.223	0.233	0.245	0.256	0.301

Corr	1	2	3	4	5	6	7	8	9+
1	1	0.042	-0.089	-0.108	-0.108	-0.097	-0.115	-0.104	-0.116
2	0.042	1	0.712	0.542	0.450	0.327	0.307	0.266	0.221
3	-0.089	0.712	1	0.908	0.803	0.713	0.702	0.609	0.583
4	-0.108	0.542	0.908	1	0.923	0.867	0.844	0.753	0.726
5	-0.108	0.450	0.803	0.923	1	0.948	0.889	0.811	0.790
6	-0.097	0.327	0.713	0.867	0.948	1	0.912	0.850	0.836
7	-0.115	0.307	0.702	0.844	0.889	0.912	1	0.918	0.922
8	-0.104	0.266	0.609	0.753	0.811	0.850	0.918	1	0.928
9+	-0.116	0.221	0.583	0.726	0.790	0.836	0.922	0.928	1

Table 8: Coefficient of variation and correlation matrix for the IBTS survey data.

	1	2	3	4	5
CV	0.216	0.282	1.650	2.058	1.761

Corr	1	2	3	4	5
1	1	0.243	0.053	0.026	0.011
2	0.243	1	0.673	0.443	0.328
3	0.053	0.673	1	0.810	0.668
4	0.026	0.443	0.810	1	0.844
5	0.011	0.328	0.668	0.844	1

Table 9: Coefficient of variation and correlation matrix for the catch-at-age sampled data.

	0	1	2	3	4	5	6	7	8	9+
CV	0.127	0.099	0.081	0.070	0.068	0.074	0.088	0.111	0.142	0.181

Corr	0	1	2	3	4	5	6	7	8	9+
0	1	-0.216	-0.049	-0.049	-0.041	0.012	0.047	0.058	0.053	0.076
1	-0.216	1	-0.250	-0.126	-0.051	-0.054	-0.008	-0.011	0.029	0.038
2	-0.049	-0.250	1	-0.035	-0.443	-0.359	-0.325	-0.287	-0.293	-0.321
3	-0.049	-0.126	-0.035	1	-0.104	-0.277	-0.324	-0.236	-0.191	-0.257
4	-0.041	-0.051	-0.443	-0.104	1	0.140	0.052	0.025	0.038	0.002
5	0.012	-0.054	-0.359	-0.277	0.140	1	0.276	0.202	0.083	0.091
6	0.047	-0.008	-0.325	-0.324	0.052	0.276	1	0.205	0.170	0.339
7	0.058	-0.011	-0.287	-0.236	0.025	0.202	0.205	1	0.183	0.403
8	0.053	0.029	-0.293	-0.191	0.038	0.083	0.170	0.183	1	0.237
9+	0.076	0.038	-0.321	-0.257	0.002	0.091	0.339	0.403	0.237	1

For the two age-structured surveys and the catch data the covariance at older ages was positive. This must be taken into account in the formulation of the observation error in the model. The method described and implemented here can deal with this issue, which would not have been the case if a multinomial distribution had been considered.

The variance-covariance matrix was then calculated to include the structured error in the proportion data. The age is the covariate used in the simulation error model and the method developed in the previous section is applied to the three sets of age resolved

data. The structure of the error has been respected in the implementation of the error model.

Indices of abundance were simulated from the known historical trajectory of the herring stock with the appropriate error structure. The results for the acoustic survey are shown in Figure 23 and for the IBTS survey in Figure 24.

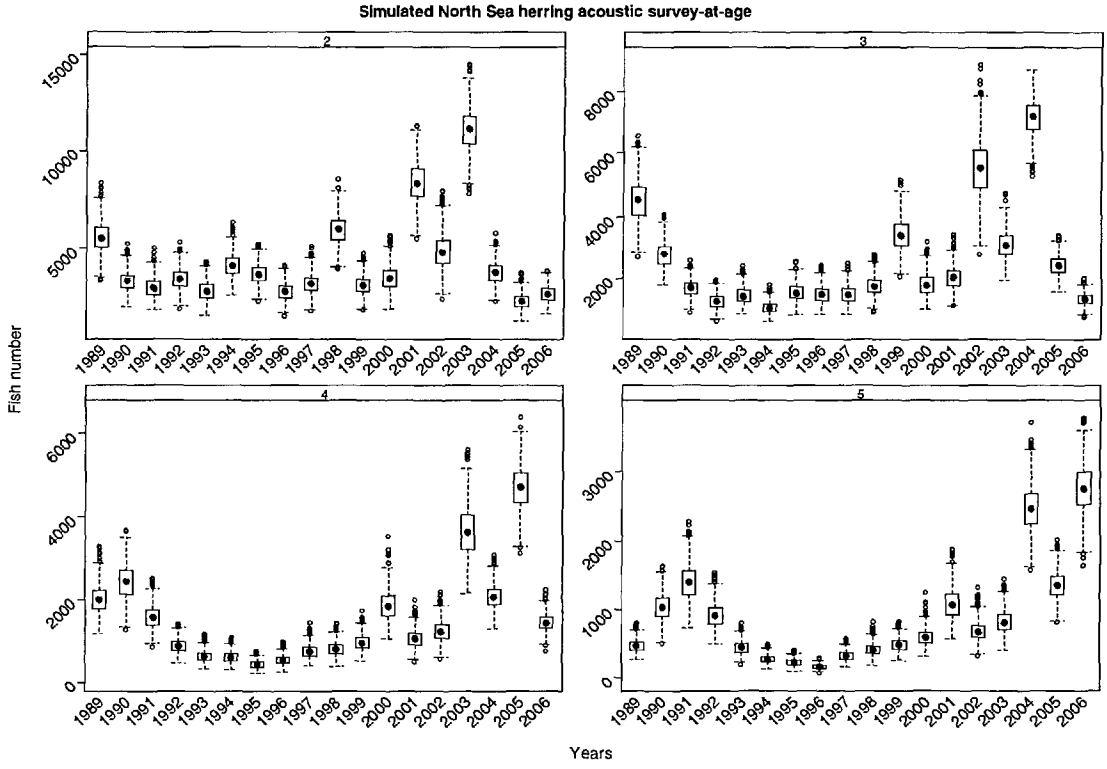


Figure 23: Simulated North Sea herring acoustic survey for ages 2 to 5 between 1989 and 2006. Each panel corresponds to a given age (top, left to right: age 2, age 3; bottom, left to right: age 4, age 5).

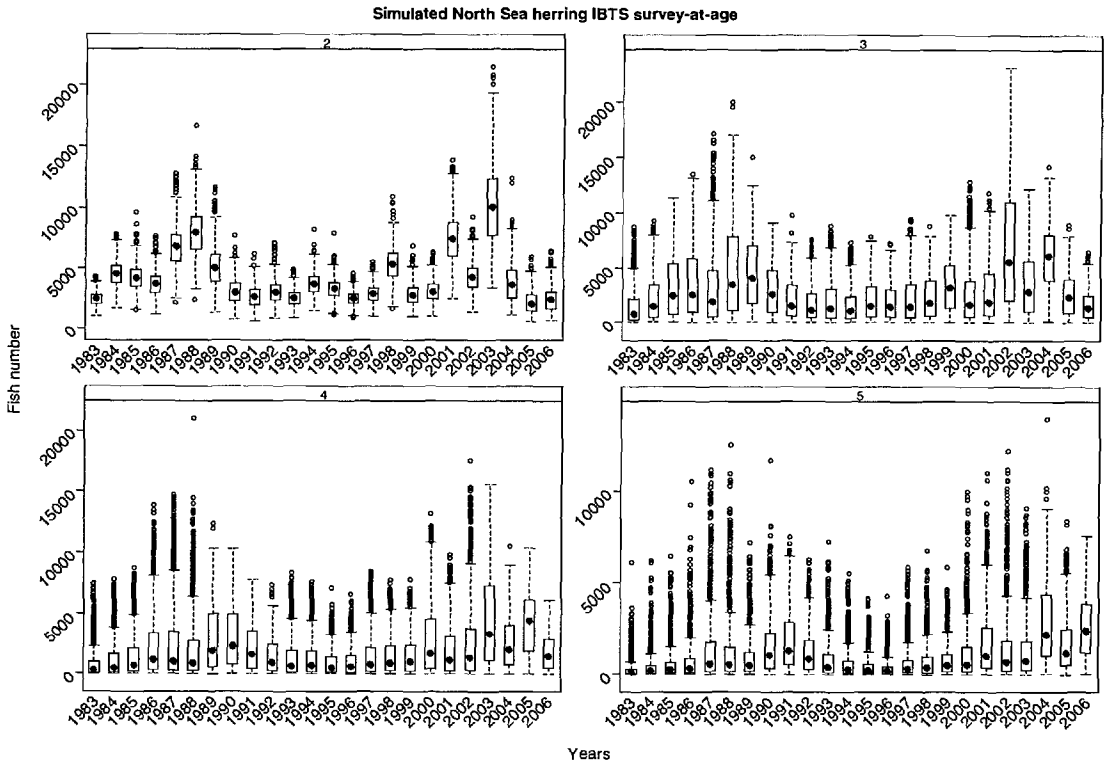


Figure 24: Simulated North Sea herring IBTS survey for ages 2 to 5 between 1983 and 2006. Each panel corresponds to a given age (top, left to right: age 2, age 3; bottom, left to right: age 4, age 5).

These figures show that the medians estimated from the two surveys were relatively close but the spreads of the distributions were larger for the IBTS survey. This is due to the higher level of observation error in this survey.

As explained in the previous section, an inverse variance index can be allocated to each age-group. Young fish (1 and 2 years old) have a very low variance while older fish (3 to 9 years old) have been allocated a much higher variance, the variance increasing with the age. As a consequence, as it is an inverse variance that is allocated to each age-group, this means that information on young fish is assumed to be more reliable. Values come from an analysis of sampling error initially realised by the Study Group on Evaluation of Current Assessment Procedures for North Sea herring (ICES SGEHAP, 2001). The original weighting factors were derived from the survey and catch data by methods given in ICES SGEHAP (2001) and Simmonds (2003). In 2006, a benchmark assessment for North Sea herring was carried out and inverse variance factors have been slightly modified to accommodate the covariance in estimates across ages for each survey (ICES HAWG, 2007).

3.3 Discussion and conclusion

This model simulates different types of observations from the fish population and the fishery and takes into account uncertainty in the observations. Two types of indices have been implemented in this work: age aggregated relative abundance index and an age disaggregated relative abundance index, depending on the data available.

The first index developed is quite simple as the simulated index depends on the true population variable in the operating model (the true index), a catchability coefficient and the error in the observations. Because a lognormal distribution for the error is applied, the simulated index follows the true index because the value of the median of the simulated index is equal to the value of the true index.

The second index implemented is more complex as it takes into account an ageing error process in the observations. In order to include this error in the simulated index, the true index has first to be logit transformed, so that multivariate normal errors can be applied. As was shown in the previous section, the correlations between ages, and particularly older ages, can be quite important. The capacity of the model to take this into account should provide more accurate results as it can reflect the true system in a better way. The method implemented here has this potential. This enables the error model to take into account positive and negative correlations as well as age dependent error, which is not the case with more commonly used indices.

The values for correlation and coefficient of variation used in this model are derived from a previous project, which means that they are estimated and not, as is more usual when developing such error models, simply guessed. This should improve the accuracy of the results.

The choice of index in the implementation of the HCRs will depend on the complexity of the HCR itself. For some HCRs - as is shown on the following chapter - only one index, based on one type of survey, will be considered, for instance the age-structured index based on the acoustic survey. An HCR could, however, combine several indices.

This chapter described the types of observations available in this work and the types of indices that are used in this work, including observation errors. The next chapter explains the concept of HCRs and details the one implemented in this work.

HARVEST CONTROL RULES

MODEL

4 Harvest control rules model

4.1 Introduction

The last component of the evaluation framework developed in this work is the harvest control rules model. A harvest control rule is one element of the management procedure, where a management procedure is defined as the set of rules used to determine management action in which the data, assessment methods or rules used to determine stock status and the HCR used to set management action are pre-defined (Butterworth *et al.*, 1997). The HCR is a set of rules that specify what the exploitation level of the stock (e.g. target levels of fishing mortality, catch or effort) should be depending on the estimated stock status. HCRs are formalisations that translate information simulated in the operating model into a feedback control that adjusts exploitation level (Levontin, 2007). They propose different management procedures and the actions that need to be undertaken based on the comparison of outputs of the model and a pre-determined set of benchmarks to formulate advice (ICES HAWG, 2004). An HCR outputs a management action in the form of a total allowable catch (TAC) or allowable fishing effort (Kell *et al.*, 2006). Moreover, Cooke (1999) refers to an algorithm that yields catch limits, effort limits, season or area limits, or other means of controlling or influencing the level of harvest. The term algorithm presupposes a sufficiently well-defined process to be amenable to computer simulation.

Various HCRs have already been used and are currently used and tested all around the world for different types of fishery and species. Many stocks in Europe are managed with the use of a HCR (e.g. North Sea herring *Clupea harengus*, North Sea cod *Gadus morhua*, Northern hake *Merluccius merluccius*, North Sea plaice *Pleuronectes platessa*, West of Scotland saithe *Pollachius virens*). But this is also the case in South Africa (e.g. West coast rock lobster *Jasus lalandii*, sardine *Sardinops sagax*, anchovy *Engraulis encrasicolus*), in Namibia (seal *Arctocephalus pusillus pusillus*), in Australia (e.g. eastern stock of gemfish *Rexea solandri*, blacklip abalone *Haliotis rubra*), in New-Zealand (hoki *Macruronus novaezelandiae*, orange roughy *Hoplostethus atlanticus*), in Korea (horse mackerel *Trachurus japonicus*) and in Chile (squat lobster *Pleuroncodes monodon*).

In most cases, HCRs are designed to determine the TAC where the target catch is set annually based on the estimated population. In some cases, such as the Northern Australia prawn fishery, fishing effort, rather than a catch limit is set, via controls of the length of the fishing season (Dichmont *et al.*, 2006a). Very simple HCRs such as setting constant catch, constant fishing proportion or fixed escapement can be used (e.g. Getz and Haight, 1989 in De Oliveira *et al.*, 2008; Restrepo and Powers, 1999). More complex rules have also been developed and their use is widespread.

The relationship between catch and population size does not have to be linear. Hilborn and Walters (1992) describe several rules implying curves or lines with inflexion points. A target fishing mortality rate such as $F_{0.1}$ or F_{max} is another possibility regularly used (Rivard and Maguire, 1993).

In order to attain management objectives such as the maximization of yield, the parameters of the HCR can be tuned (e. g. the International Whaling Commission's New Management Procedure, 2005; Butterworth and Best, 1994 in De Oliveira *et al.*, 2008). On the west coast of North America, HCRs dependent on reference points are used for the management of the groundfish fishery (Quinn *et al.*, 1990). The reference points correspond to fractions of the virgin spawning biomass and levels of fishing mortality at which maximum sustainable yield is achieved. Following the development of the concept of the precautionary approach to fisheries management, new reference points have been introduced which aim to keep biomass above pre-defined limit reference points with high probability. Those precautionary reference points are usually related to fishing mortality and spawning-stock biomass.

This Chapter explores the formulation of a number of different HCRs, using different data sources, that will be tested in Chapter 5. The harvest control rule model will consider model-based inputs, survey indices and indices from fishery dependent sources as direct inputs, and also will consider combining indices of population abundance and biology.

All HCRs implemented in this thesis are quite simple rules. The only complex one is that reflecting the actual management applied to the North Sea herring stock. Rules can be grouped into two categories: "model-free" which are based directly on observations and "model-based" which are based on outputs of assessment models.

A number of considerations come into play when deciding which HCRs to explore in a management procedure. One of the key elements in the decision is the availability of long-term series data needed to estimate population parameters. In the case of a large amount of available data, model-based HCRs should perform better in the longer term if estimates of population parameters and reference points are likely to change and there is imprecision in indices of population abundance. On the other hand, if data are of high quality (unbiased and precise) then model-free HCRs are more likely to perform suitably (Rademeyer *et al.*, 2007).

The first section of this chapter (4.2) describes the two categories in which HCRs could be grouped. Section 4.3 lists all the HCRs that have been implemented in this thesis, including the equations. The final section (4.4) corresponds to the discussion and the conclusion of this chapter. It also introduces the final chapter on the evaluation of management strategies.

4.2 Concept and methodology

Different HCRs need to be evaluated before choices can be made regarding which rule to use in a management procedure. It is possible to group HCRs into two categories: "model-free" and "model-based". In the first grouping, the HCR is based directly on observations while in the second one the rule is based on outputs of assessment models (Holland *et al.*, 2005). The following two sections explain these two approaches. The last two sections describe two further extensions that could be added to the HCRs: a potential implementation error and a limitation of the variation of the TAC.

4.2.1 MODEL-FREE HARVEST CONTROL RULES

Although most conventional HCRs use the results of stock assessments as inputs (see next section), this is not compulsory. HCRs can be based directly on observational data (survey or catch data) (Hilborn et al., 2002 in De Oliveira *et al.*, 2008). These rules are easier to understand and to simulate compared to the model-based ones. This simplicity simplifies the computations required in an MSE, and allows for a large number of tests of the robustness of such HCRs. The observed data may be in the form of absolute or

relative abundance data (Magnusson and Stefánsson, 1989; Sakuramoto and Tanaka, 1989; Butterworth *et al.*, 1993; De Oliveira *et al.*, 1998b; Geromont *et al.*, 1999).

These HCRs are usually chosen when either data is precise and unbiased (Rademeyer *et al.*, 2007) or a controversy over stock assessment results exists – e. g. the Namibian hake fishery (Geromont *et al.*, 1999). An assessment may not be necessary when the HCR is only based on abundance data – e.g. a rule may be based on an increasing or decreasing the harvest rate depending on the sign and slope of the average trend in relative abundance over the most recent observations. However, for long-term management, the performance of this type of rule might not be satisfactory, particularly if there are important uncertainties about the stock size and in the type of errors in the data (McAllister, 1995; Geromont *et al.*, 1999).

The model-free approach will perform better if absolute abundance estimates are available on an annual basis (McAllister *et al.*, 1999) and if the associated biases are assumed to be small. This is the case, for example, with the Namibian population of Cape fur seals surveyed by aerial census counts and pup survival (Geromont *et al.*, 1999). Moreover, Magnusson and Stefánsson (1989) found that it was possible to manage changes in abundance and maintain population trends to some level with the model-free HCR they have implemented. Their feedback strategy modifies catch quotas on the basis of the relative slope of the regression line through past CPUE values, applied to a whale stock without specifying the species.

De Oliveira and Butterworth (2004) describe a model-free approach that utilises the fact that the catches of sardines and anchovy in South Africa are linked, since the juveniles of sardines are caught as by-catch in the anchovy adult fishery. A management procedure is used to calculate the combined sardine-anchovy TAC without an assessment but based on abundance estimates from hydro-acoustic surveys of recruitment each May and SSB each November (Plagányi *et al.*, 2007). The TAC for the adult sardine fishery is calculated as a proportion of the one-plus year old biomass estimate from the preceding spawner biomass survey. Precautionary reference points are used to evaluate the level of the population size and adapt the fishing on the stocks. For the South African west coast rock lobster, a management procedure is also used to set the TAC based on commercial CPUE, a fishery independent monitoring survey index of abundance and data on somatic growth rate (Plagányi *et al.*, 2007). The Irish salmon

TAC can be set relative to stock abundance if a number of important values can be estimated: the pre-fishery abundance, the number of fish returning to spawn and the number of fish required to spawn (O Maoileidigh *et al.*, 2004). Finally, Breen *et al.* (2003b) tested several model-free HCRs on the rock lobster (*Jasus edwardsii*) fishery off New Zealand.

4.2.2 MODEL-BASED HARVEST CONTROL RULES

The second category of HCRs is the "model-based" rules. These rules are based on the results of a stock assessment and provide a smoothing effect by fitting a model to data, which lowers variability when evaluating management controls. The International Whaling Commission (1992) and Punt and Smith (1999) have both shown that model-based HCRs may perform better than model-free methods. Harvest control rules that are based on the results of a stock assessment are sometimes more responsive and allow the development of feedback-control systems (McAllister *et al.*, 1999).

Over the long-term, model-based HCRs may perform better than model-free rules, particularly when there are uncertainties about stock size and in the errors in the data. Model-based procedures are often more stable (in terms of the variability of key performance statistics) than model-free HCRs. However, if the models do not describe the real state of the stock properly or are significantly biased, model-based rules may deliver poor management performance (McAllister *et al.*, 1999; Punt and Smith, 1999).

Model-based HCRs model usually control level (Branch, 1998; Cooke, 1999; Geromont *et al.*, 1999; Kell *et al.*, 2006; Kell *et al.*, 2007a; Plagányi *et al.*, 2007) but they can also control fishing effort (Kuikka, 1998; McAllister and Kirkwood, 1998; Punt and Smith, 1999).

A well developed HCR used worldwide is based on biological reference points. Current stock status is assessed against biological reference points and the fishery is manipulated in order to maintain the biomass above a reference level. In most cases, it is the fishing mortality rate that is modified to reach the targets. Reference points can be catch-, biomass- or fishing-mortality-based. For example, in the case of the Norwegian spring spawning herring fishery, two reference points have been defined: B_{lim} (lower

biomass reference point) and B_{PA} (upper reference point). The fishing mortality rate will be adjusted depending on estimates of the level of the SSB to ensure that the SSB will stay above B_{PA} or will recover as quickly as possible if it was estimated to be below this reference level.

The ICES Study Group on the Precautionary Approach to Fisheries Management (ICES SGPAFM, 1998) explained the reason why these reference points have been created and how they have been defined. Initially, fishing mortality reference points have been created. The first reference point implemented is F_{lim} which represents a fishing mortality which must be avoided as it corresponds to a stock collapse. Due to the uncertainties around the estimation of F_{lim} and the current fishing mortality, a precautionary reference point, lower than F_{lim}, called F_{PA}, has been implemented. It has been set such that the probability of being below F_{lim} is high. In other words, the aim of F_{PA} is to make sure that recruitment overfishing does not take place. The choice of F_{lim} and F_{PA} will depend on available information.

F_{lim} is usually only used for calculation to determine F_{PA} and is generally not provided in scientific advice. It might be set with reference to F_{loss} (fishing mortality which corresponds to the lowest observed spawning stock; Cook, 1998), F_{crash} (fishing mortality which results in stock collapse) or F_{med} (sustainable fishing mortality; Sissenwine and Shepherd, 1987). F_{loss} or F_{crash} are set as F_{lim} if one of them is available and values are assumed to be reliable estimates of the corresponding fishing mortality. In the case of unavailability of both of them and the F_{med} is assumed to be correct, the latter can be used as F_{lim}. In case of a fishery not managed according to the precautionary approach and for which the exploitation rate is very high, the current fishing mortality rate could be set as F_{lim}.

F_{PA} has to be set with a high probability of being below F_{lim} due to uncertainties but it also must have a high probability of being sustainable based on the history of the fishery. Another condition for the setting of F_{PA} is that it has to be chosen in a way that when fishing is kept constant at F_{PA}, the corresponding equilibrium biomass is above B_{PA} with a high probability. Fishing mortality rates in excess of F_{PA} will be defined as "overfishing". F_{PA} might be set with reference to F_{med}, F_{lim}, F_{MSY}, $F_{0.1}$, etc. If F_{lim} is available then F_{PA} could be defined through $F_{PA} = F_{lim} e^{-1.645*\sigma}$ (where σ is a measure of

uncertainty in the total F estimate, typically taken as 0.2-0.3) or as F_{lpg} where F_{lpg} corresponds to the fishing mortality value having a 10% probability of giving a replacement line above G_{loss}, G_{loss} being the slope associated with F_{loss}. If F_{lim} is not available and F_{med} goes through a cloud of points which appears to come mostly from the right-hand side of a stock-recruitment relationship, then F_{med} can be used for F_{PA}. If an accepted F_{PA} exists, then this should only be changed if there is a good reason to do so. This methodology gives at the minimum F_{PA}. As a consequence, F_{lim} can be derived from F_{PA} as following: $F_{\lim} = F_{PA} e^{1.645*\sigma}$.

If F_{PA} is properly chosen and adopted as the maximum fishing mortality rate, stocks should remain within safe biological limits. Unfortunately, stocks can decline due to reduced recruitment, even if fishing mortality is kept below F_{PA}. Another issue is the potential difficulty in maintaining the fishing mortality below F_{PA}. As a consequence, the biomass may decrease. To prevent a potential decline to levels where the recruitment is low, a biomass-based constraint can be defined.

B_{PA} is design to ensure that there is a high probability that the spawning stock biomass will not fall below B_{lim}, the level for which the probability of recruitment failure is high or the dynamics of the stock are unknown. The settings of B_{lim} and B_{PA} will depend on available information.

Similarly to F_{lim}, B_{lim} is usually only used for calculation purposes to arrive at B_{PA} as management will make sure that B_{lim} will be avoided. Furthermore, B_{lim} is usually not provided in scientific advice, nor used in management actions. B_{lim} might be set with reference to B_{loss}. If there is no obvious candidate for B_{lim}, a robust estimate of the lowest observed biomass is considered and called B_{loss}. B_{loss} and B_{lim} are used if there is any indication of reduced recruitment at this low biomass or if the stock biomass has varied over a wide range of values.

B_{PA} is the level below which the stock would not be considered as being at a precautionary level, in other words, potentially depleted or overfished. If the biomass is defined as being below B_{PA} then the fishing mortality should be reduced below F_{PA}. B_{PA} has to be set such as B_{lim} will not be reached with high probability. It might be set with reference to B_{loss}, B_{lim} or MBAL (Minimum Biologically Acceptable Level). MBAL

corresponds to the spawning stock biomass below which the, probability of impaired recruitment increases. B_{loss} is used as B_{PA} if there is no indication of recruitment reduction at low biomass. When only B_{lim} is available, B_{PA} has to be chosen so that the probability of being below B_{lim} is as little as possible. Under this circumstance, B_{PA} can be designed as following: $B_{PA} = B_{\lim} e^{1.645*\sigma}$ where σ is a measure of uncertainty in the total biomass estimate, typically taken as 0.2-0.3. This methodology gives at the minimum B_{PA}. As a consequence, B_{lim} can be derived from B_{PA} as following: $B_{\lim} = B_{PA} e^{-1.645*\sigma}$. If an existing MBAL is close to B_{lim} or B_{PA} as defined above, then this might be substituted to maintain consistency and aid communication, so long as its use does not compromise the choice of F_{PA}.

In the case of the Norwegian spring spawning herring fishery described previously, the assessment used is called Triple Instantaneous Separable Virtual Population Analysis (TISVPA) and can represent fishing mortality coefficients as a product of three parameters (ICES WGNPBW, 2007). This HCR is also used for the management of the Northern hake fishery which is widely distributed within the North Atlantic Ocean, the North Sea, the Celtic Sea and the Irish Sea. The assessment method used with this stock is entitled extended survivors analysis (XSA) (ICES WGHMM, 2007). The management of the cod in the North Sea includes as well a HCR based on biological reference points for which an assessment called Virtual Population Analysis (VPA) is done in order to compare the output of the assessment with the reference points (Reeves and Pastoors, 2007).

In European waters, the western horse mackerel TAC is currently adjusted every year based on the analytical assessment performed with the SAD[8] model (Roel and De Oliveira, 2007). The Icelandic cod stock is also managed via a HCR based on an assessment. The TAC for each year is set as 25% of the biomass of cod aged four years and older (Bell *et al.*, 1998). There are no precautionary reference points for this stock and in 2000 the Icelandic government amended the HCR by limiting year-to-year fluctuations in the catches.

[8] SAD model: Separable ADAPT assessment method which combines a separable virtual population analysis (VPA) with an ADAPT model structure (ICES, 2002).

4.2.3 POTENTIAL IMPLEMENTATION ERROR

Implementation uncertainty corresponds to "the extent to which management policies will be successfully implemented" (Rosenberg and Brault, 1993). It is the inability of management to achieve the stated target because of the difficulties of fully monitoring and controlling catch and effort. Factors at the origin of implementation uncertainty include black-market landings, misreporting – the biological composition of the catch is not reported correctly – and discarding.

TAC regulation used in fisheries management can lead fishermen to under-report their catch at landing. Unfortunately, national and international institutions do not have enough resources to control and counteract illegal or over-quota landings (Patterson, 1998b). In spite of this, official data are most of the time used in management procedures, including in stock assessment calculations. The quality of assessments is directly linked to the quality of the fisheries data. Most stock assessments are conditioned on reported catch data, assuming these are known exactly (Pope and Shepherd, 1985; Darby and Flatman, 1994) but also that catch-at-age measurement errors are random and independent (Pope and Shepherd, 1982; Deriso *et al.*, 1985; Gudmundsson, 1986; Patterson and Melvin, 1996). In 2005, ICES expressed great concern over the poor quality of catch and effort data for most of the important fisheries in the ICES areas. One issue is that recorded catch may often be biased for different reasons e.g. - the deficiency of the catch reporting system – i.e. intentional misreporting of catches due to TAC regulations or lack of accessibility to landing harbours. Discarding at sea is another process that can occur. If the level of discarding is high but not corrected in recorded landing data, the latter may not be suitable to use in management of fisheries. The main problem is that if reported catch data are not adjusted given the knowledge of misreporting and discarding, their use in the estimation of stock and fishery components such as stock size or fishing mortality rate may lead to important biases in the estimates (Sinclair *et al.*, 1996; Deriso *et al.*, 1998; Patterson, 1998b). As it is mentioned in the introduction of this work, fishermen can be also tempted to over-report their catch if they have not reached the set quotas to make sure that future quotas will be maintained at a similar level. In both cases of over-reporting and under-reporting, inaccurate catch data can have an important effect on the assessment and as a consequence on the management advice. Indeed, the outputs of the

assessment depend on its input. If the catches are under-reported, the fishing mortality rate will be under-estimated. The assessment will then over-estimate the biomass of the fish stock. The advice following the assessment might provide quotas for the coming year too high and not appropriate to the real state of the stock. In the case of over-reported catches, the principle is slightly different. In fact, if catches did not reach the set quotas and were recorded properly, the assessment would estimate a relatively good state of the stock as the fishing mortality rate would not have been too high. But low catches could have a negative effect on the management decisions. If quotas are not reached, that could mean the stock biomass has been over-estimated. As the precautionary approach tends to be used in European waters, managers might decide to reduce the quotas to limit the risk of causing a decline in the stock. To avoid this perspective, fishermen might over-report their catches. In this case, the assessment will over-estimate the real fishing mortality rate but not for the current year as quotas are virtually reached. The assessment should estimate a biomass according to the expectations and the management advice following this assessment will set quotas similar to the one provided for the current year.
In recent years, it was not possible for ICES to carry out stock assessments for a number of key stocks because of the poor quality of catch data. This is now a very serious problem for the scientific community within ICES.

However, misreporting and implementation error are not necessarily related to each other. Indeed, they can come together but it is also possible to have one without the other. Even if it is not common, it is possible for fishermen to surpass the set quota (implementation error) and declare accurately their overfishing (no misreporting). They can also overfish (implementation error) and not declare the overfishing (misreporting) which is more common than the previous situation. In contrast, fishermen can catch less than the set quotas (implementation error) and declare only their low catches (no misreporting) or over-declare their catch (misreporting). Even if this situation is unlikely to happen, is also possible to misreport catches by fishing in one area and landing the fish in another and at the same time reach the quotas. Finally, it is possible to reach the quota and declare accordingly (no implementation error and no misreporting).

In the case of the North Sea herring fishery, misreporting exists in the form of area misreporting and discards, but its level is unknown and usually under-estimated (ICES HAWG, 2008).

Some studies have investigated implementation uncertainty. For instance, the existence of illegal catches by poachers and discard mortality was used in the evaluation of a management procedure for the rock lobster (*Jasus lalandii*) resource off South Africa's west coast (Johnston and Butterworth, 1997).

4.2.4 POTENTIAL RESTRICTION OF VARIATION OF THE TAC

Except in dramatic cases where the TAC has to be rapidly reduced, or the fishery even closed, to avoid a collapse of a stock, management systems normally experience resistance to rapid variations in the TAC or the harvest rate between successive years due of their effect on the fishing industry. Management systems often therefore impose limits on inter-annual variability in TAC. This is the case for example with the North Sea herring stock management (Appendix 4). It is also described by McAllister and Kirkwood (1998) in their implementation of a Bayesian decision analytic framework for evaluating alternative fishery management procedures that could be applied in a developing fishery. Bell *et al.* (1998) tested different levels of harvesting flexibility, between 25% and 100%, the latter representing no constraints on catch reductions.

4.3 Different management procedures proposed

Seven different HCRs have been implemented in this thesis, some of them being model-free and others model-based. The first one is the actual management applied to the North Sea herring stock. The two following ones are basic tests: no catch and constant catch. The three following are model-free HCRs and the final section corresponds to model-based procedures.

4.3.1 ACTUAL HARVEST CONTROL RULE

The first HCR explained in this part of the chapter corresponds to the actual management of the North Sea herring stock. It is a quite complex management procedure which bases the HCR on outputs of an assessment called ICA (Integrated Catch at Age, Patterson and Melvin, 1996, (Patterson and Melvin, 1996) (Appendix 2). An extract from the European – Norwegian agreement for the North Sea herring stock can be found in Appendix 4. The assessment is undertaken at the annual meeting of the Herring Assessment Working Group (HAWG) which is held in March each year. In the jargon of the Working Group, the current year is called "intermediate year" and the future year is called "assessment year".
The following text describes the procedure used in this thesis to set the TAC according to a model-based HCR that mimicked the procedure used by the HAWG.

Let us assume that the current year is 2007. An assessment was run last year during the annual meeting of the HAWG and provided the "set" TAC for 2007, based on all 2005 data and some data available for the beginning of 2006. In 2007, a new assessment including 2006 data is run as more information is available on what happened in 2006. It is then possible to project forward for the intermediate year (2007) this new assessment using the set TAC. This provides the estimated SSB for the intermediate year. As shown in Appendix 4 and Table 10 the value of the TAC for the "assessment year" depends on the value of the SSB of the intermediate year. The latter is compared with two biological reference points (B_{PA} and B_{lim}). B_{PA} stands for precautionary approach biomass and is fixed at 1.3 million tonnes and B_{lim} corresponds to the limit biomass and the value is agreed to be equal to 800 000 tonnes. The B_{lim} value has been fixed during the closure of the fishery in the late 1970s. It corresponds to the biological criteria for re-opening the herring fishery as it is supposedly the minimum level required to produce average recruitment (ICES HAWG, 1989). The B_{PA} was set within the bilateral agreement between the EU and Norway in 1997. It corresponds to a precautionary level above which the probability of the SSB estimated of being below B_{lim} is low (ICES HAWG, 1999).
As herring are not caught with the same gears and in the same areas (depending upon their age), the HCR distinguishes two age groups: 0-1 ringers and 2-6 ringers. The TAC

or the fishing mortality values for each age-group will follow this rule (Table 10 and Figure 25):

Table 10: Rules to set the TAC for the management of the North Sea herring stock.

SSB and reference points	Age group	Rule
$SSB > B_{PA}$	0-1	$F_{PA,0:1} = 0.12$
	2-6	$F_{PA,2:6} = 0.25$
$B_{PA} > SSB > B_{lim}$	0-1	$F_{0:1} = F_{PA,0:1} - \frac{(F_{PA,0:1} - F_{\lim,0:1})(B_{PA} - SSB)}{B_{PA} - B_{\lim}}$
	2-6	$F_{2:6} = F_{PA,2:6} - \frac{(F_{PA,2:6} - F_{\lim,2:6})(B_{PA} - SSB)}{B_{PA} - B_{\lim}}$
$B_{lim} > SSB$	0-1	$F_{\lim,0:1} = 0.04$
	2-6	$F_{\lim,2:6} = 0.1$

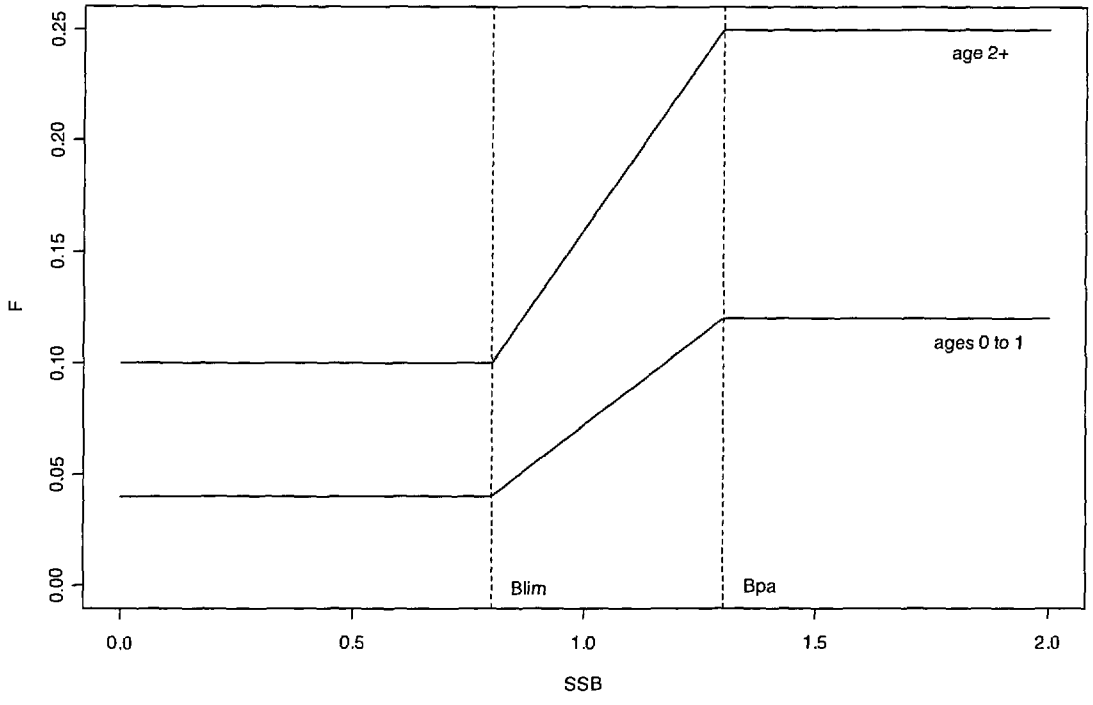


Figure 25: Harvest control rule applied to the North Sea herring stock.
The bottom line corresponds to the age-group 0 to 1 ringer. The top line corresponds to the age-group 2 to 6 ringers. The two vertical lines correspond to the two reference points B_{lim} and B_{PA}.

At the time of the HAWG meeting, values of the IBTS and the MIK surveys are available for the intermediate year. The "new" assessment can be calculated using 2006 data and data from these two surveys. As the MIK index is available for the

intermediate year, it is possible to calculate the recruitment for the projection of the intermediate year. It corresponds to the product of the MIK index of the intermediate year and the *qMIK* for the index. The *qMIK* is calculated as follow:

$$qMIK = \frac{\sum_{y=1992}^{\text{int ermediate year}} true\ recruitment}{\sum_{y=1992}^{\text{int ermediate year}} simulated\ MIK\ index} \tag{37}$$

The recruitment of the assessment year for this new assessment corresponds to the geometric mean of historical recruitments estimated by the assessment. It is assumed that the population is stable and a geometric mean provides the best estimate of the most likely value if the recruitment is assumed to be log normal. There is no assumption of stock-recruitment relationship made for the assessment year.

In undertaking the assessment a weight for each age for the catch-at-age matrix, the aged surveys matrices and the SSB surveys matrices must be defined. Values used in management strategy evaluation of this HCR described in Chapter 5 come from an analysis of the variance of the catch data and particularly an eight year study of international market-sampling data. Values for ages 0 and 1 are arbitrarily down weighted because they are not directly indicatives of year-class strength due to a separate directed fishery.

In evaluating this HCR, error was added to the catch data that are used in the calculation of the assessment. The method used was the same as for the surveys developed in section 3.2.3.1. Values used for the coefficient of variation and correlation matrix are listed in Table 9.

The projection for the intermediate year follows a similar dynamics as the operating model:

$$N_{y+1,a+1} = N_{y,a} e^{-Z_{y,a}} \tag{38}$$

$$N_{y+1,A} = N_{y,A-1} e^{-Z_{y,A-1}} + N_{y,A} e^{-Z_{y,A}} \tag{39}$$

$$C_{y,a} = \frac{F_{y,a}}{F_{y,a} + m_{y,a}} N_{y,a} \left(1 - e^{-(F_{y,a} + m_{y,a})}\right) \quad (40)$$

where Z is the sum of the fishing mortality rate F and the natural mortality m.

Following the benchmark assessment performed in 2006 by the Herring Assessment Working Group, the selection pattern used in the projection was set equal to the mean over the last five years of the fishing mortality, normalised to 1 by the maximum F value. Stock weights and catch weights were determined using the arithmetic mean over the last 3 recent years (a standard ICES approach). In order to define the TAC for the assessment year, the SSB resulting from the projection using the new assessment was compared with the reference points. To use the example taken above, the SSB estimated from the projection - SSB for 2008 - was compared to the reference points to define the TAC for 2008.

As four sets of survey data are available for this stock and are actually used in its management, I will use all of them in its implementation. This is the only HCR for which the four surveys are utilised.

4.3.2 NO CATCHES

The second HCR implemented in the present work is without catch. The purpose of this rule is to test the model. An increase of the SSB is expected, whatever the condition of the stock is, except if the natural mortality rate is not compensated by the new born fish.

$$TAC_{y+1} = 0 \quad (41)$$

where TAC is the total allowable catch in year y+1.

4.3.3 CONSTANT CATCHES

The following HCR is straightforward: constant catch. It is implemented to test the actual level of catch. If the actual catch was too high for the state of the stock, the stock

would collapse. In fact, if the catch and the natural mortality are not compensated by the new recruits, the number of fish would decreases over a number of years.

$$TAC_{y+1} = TAC_y \tag{42}$$

4.3.4 MODEL FREE BASED ON OBSERVATIONS

The first HCR implemented that considers an observation survey index is the following:

$$TAC_{y+1} = TAC_y \left(\frac{I_y}{I_{y-1}} \right) \tag{43}$$

where I is the observation index.

This HCR has already been used by Breen *et al.* (2003b) in a preliminary evaluation of maintenance management procedures for New Zealand rock lobster (*Jasus edwardsii*) fisheries. They developed this simple rule with no parameters, based on the change in the abundance index alone.

The observation index is the output of the observation error model. The value of the TAC for the next year will depend on the TAC of the current year and the ratio of the observation index of the current year and the observation index of the previous year. If the ratio is larger than one this means there is an increase in the observation index which can be interpreted as an increase in the SSB of the stock so catches can be raised proportionally.

The survey used to calculate the index was the acoustic survey. As it was explained in Section 3.2.1, the acoustic survey is the most reliable source of data for the observation error model. The observation index calculated from this survey was:

$$I_y = \sum_a \left(N_{a,y} * w_{a,y} * mat_{a,y} \right) \tag{44}$$

where $N_{a,y}$ is the number of fish at age estimated from the acoustic survey, $w_{a,y}$ is the stock weight at age and $mat_{a,y}$ corresponds to the maturity at age, all of them for the year y.

4.3.5 MODEL FREE BASED ON RELATIVE SSB TREND

The second model-free HCR tested here was based on the relative SSB trend from acoustic survey data: It is an adaptation of that described in section 4.3.4 and as a consequence a generalisation of the one implemented by Breen *et al.* (2003b).

$$TAC_{y+1} = TAC_y \left(\frac{\overline{SSB}_y}{\overline{SSB}_{y-1}} \right) \tag{45}$$

where $\overline{SSB}_y$ is the mean relative spawning stock biomass. SSB trends were calculated for all years from the beginning of the simulated survey (1989 in this study) to the current year of the simulation, y_c:

$$\overline{SSB}_y = \sum_{y=1989}^{y_c} \sum_{a=1}^{9} \left(N_{a,y} mat_{a,y} w_{a,y} e^{-Mspwan_y M_{a,y}} \left(1 - Hspawn_y H_{a,y}\right)\right) \tag{46}$$

where $N_{a,y}$ corresponds to the observed index at age a for the year y coming from the observation error model, $mat_{a,y}$ is the maturity rate at age a for the year y, $w_{a,y}$ stands for stock weight at age a for the year y, $Mspawn_y$ corresponds to the proportion of natural mortality occurring before the spawning during year y, $M_{a,y}$ is the natural mortality rate at age a during the year y, $Hspawn_y$ stands for the harvest rate before spawning for the year y and $H_{a,y}$ corresponds to the harvest rate at age a during year y. The index used in the calculation is the output of the observation error model, the same as the one used in the first HCR. Changes in the TAC of the subsequent year will be proportional to the ratio of the apparent relative SSB trend in the current year and the one of the preceding year.

The major difference between this index and the previous one is that this one is calculated at the end of the simulated year as it takes into account the natural mortality rate and the harvest rate that occurred during the year. Both natural mortality rate and harvest rate distinguish what was removed before and after the spawning time. Another difference is that in the previous HCR, indices were calculated for a given year. With this rule, each index is the sum over years, which means that all historical information is taken into account and influences the future. With the previous HCR, only the last two years were taken into consideration. If there had been an important decline in the stock in the past, it would not have any impact on the projection.

4.3.6 MODEL-FREE BASED ON COMBINED RELATIVE SSB TRENDS

This HCR is similar to the previous one in terms of implementation of the rule (Breen *et al.*, 2003b). The major difference is in the calculation of the index used in the estimation of the SSB. Instead of coming from a single survey, the index is created as a combination of two different surveys. Inverse variance weighting is used, in which weight is allocated to each survey depending on their precision. The two surveys used were the acoustic survey and the MLAI. The MIK survey does not provide information about abundance and the precision of the IBTS survey is not as good as for the acoustic survey. The MLAI is a better indicator of the SSB as it is more precise, assuming it to be unbiased.

The first step in the calculations to apply this HCR was to calculate the SSB from the acoustic survey. This was done by using the same equation as in the previous HCR (4.3.5). The next step was to calculate the coefficient of variation for the SSB estimated from the acoustic survey. As the product of the maturity-at-age matrix by the weight-at-age matrix is an un-normalised weight on the numbers' contribution to the SSB, the coefficient of variation for the SSB could be calculated as follows:

$$weight.survey_{age} = \frac{w_{age} * maturity_{age}}{\sum_{age}\left(w_{age} * maturity_{age}\right)} \tag{47}$$

$$CV.SSB = \sum_{age}\left(weight.survey_{age} * CV_{age}\right) \tag{48}$$

Applying inverse variance weighting required the variance for the SSB estimated from each survey to be calculated. Assuming log-normal errors, the equation is the following:

$$VAR.SSB = \log\left(1 + (CV.SSB)^2\right) \tag{49}$$

Using the two spawning stock biomass indices (SSB.1 from the acoustic survey and SSB.2 from the MLAI survey) with two separate variances (sigma.1 - the *VAR.SSB* calculated previously - and sigma.2 - provided by FRS Aberdeen), the equations for inverse variance weighting were:

$$weight.1 = \frac{\left(\frac{1}{(sigma.1)^2}\right)}{\frac{1}{(sigma.1)^2 + (sigma.2)^2}} \tag{50}$$

$$weight.2 = \frac{\left(\frac{1}{(sigma.2)^2}\right)}{\frac{1}{(sigma.1)^2 + (sigma.2)^2}} \tag{51}$$

The SSB index used in the calculation of the TAC (Equation 44) was the sum of the two weighted indices:

$$\overline{SSB} = SSB.1 * weight.1 + SSB.2 * weight.2 \tag{52}$$

4.3.7 Z-BASED MODEL

The third HCR implemented was, again, model-free. This has been proposed as an HCR by Hillary (Pers. Com.). The reason for developing this rule was to try and mirror aspects of the actual decision rule applied to North Sea herring, but based on total mortality levels on the juvenile and adult sections of the stock.

The structure is different to the two previous HCRs. Two age groups (0 to 1 and 2 to 6) are distinguished in the calculation of the TAC. This implies the use of an age non-aggregated index in the HCR.

$$TAC_{y+1} = TAC_y * \min\left(\frac{Z^{PA}_{[0,1]}}{Z_{y-1,[0,1]}}, \frac{Z^{PA}_{[2,6]}}{Z_{y-1,[2,6]}}\right) \quad (53)$$

Where Z^{PA} and Z_{y-1} are the total mortality associated with maintaining SSB at B_{PA} and the total mortality in the last year, respectively, and [0,1] and [2,6] relate to separate calculations for each of the two age groups, with the minimum of the two ratios being used to set the TAC. Using this equation the TAC of next year will be inversely proportional to changes in total mortality estimated along cohorts from the survey. The abundance index from which the total mortality rate is estimated is the one corresponding to the acoustic survey, for the same reasons as explained in section 4.3.4.

Values of the total mortality rate at age at the precautionary level (Z_{PA}) for each age group derive from other parameter values defined by ICES. The total mortality rate, Z, is the sum of the natural mortality M and the fishing mortality F. For the group 0-1 year old, F_{PA}, defined by ICES, is equal to 0.12 (Appendix 4) and M is estimated as 1 by ICES North Sea MSVPA (Pope, 1991). The combination of both of them gives a value of 1.12 for $Z^{PA}_{[0,1]}$.

For ages 2 to 6, F_{PA} has been fixed at 0.25 by ICES experts and the natural mortality rate is equal to 0.3, 0.2 and 0.1 for ages 2, 3 and 4+ respectively. The combination of the mean of the natural mortality rate at age and F_{PA} gives a value of 0.4 for $Z^{PA}_{[2,6]}$. For each year, both ratios included in Equation 52 are calculated and the minimum value is used to calculate the TAC for the following year. Table 11 shows an example of how it works:

Table 11: Example of calculation of the TAC for the Z based harvest control rule.

$\frac{Z^{PA}_{[0,1]}}{Z_{y-1,[0,1]}}$	$\frac{Z^{PA}_{[2,6]}}{Z_{y-1,[2,6]}}$	TAC_{y+1}
0.98	0.95	- 5%
1.02	1.05	+ 2%
0.98	1.02	- 2%

For example, if both ratios are below 1 (first row), fishing mortality is over the precautionary approach level then the HCR will use the smaller of these two ratios (0.98 and 0.95) and the TAC will be decreased by 5%. On the other hand, if both ratios are above 1, fishing mortality is under the precautionary approach level then the TAC will be increased by the smaller of the two. A last example is when one of the ratios is above 1 and the other one below. As this rule has a conservative behaviour, the smaller ratio will be used, and the TAC then will be decreased by the ratio below one. In all cases, the conservative nature of the rule ensures that the precautionary approach is prioritised.

4.3.8 USING ASSESSMENT METHODS

The last type of HCRs implemented is a model-based as it uses the outputs from stock assessments. Two different assessments are used: YCC and SURBA (Appendix 2). These two assessment methods have recently been suggested as alternative and more simplistic methods within the FISBOAT project (2003) (Fisboat, 2003).

Two types of HCRs were used with these assessments. .The first one is based on the SSB estimated from the output of the assessment and the second one is an adaptation of the Z-based HCR developed in the previous section. The equations for these two rules are as follows:

$$TAC_{y+1} = TAC_y * \frac{SSB.assess_y}{SSB.assess_{y-1}} \tag{54}$$

$$TAC_{y+1} = TAC_y * \min\left(\frac{Z^{PA}_{[0,1]}}{Z^{assess}_{y-1,[0,1]}}, \frac{Z^{PA}_{[2,6]}}{Z^{assess}_{y-1,[2,6]}}\right) \tag{55}$$

The second HCR is quite similar to the previous one (section 4.3.7). The major difference is that the harvest rate is estimated by the assessment and not directly from the survey. It is again a HCR that prioritises the precautionary approach as the variation in the TAC will depend on the smaller of the two ratios.

One of the issues with this second HCR is that due to the noise implemented in the model, it is mathematically possible to obtain negative Z values, something that should not happen in the real world. For this reason, it was initially decided to allocate a 0 value to estimated negative Zs. But based on the simulations run and the fact that the two assessments considered in this work as new methods have been implemented by external authors, in some circumstances it lead to a crash of the simulation. To avoid this problem, it was decided to allocate a very small and positive arbitrarily chosen value (0.001) to estimated negative Z values.

4.3.9 POTENTIAL MISREPORTING AND LIMITATION OF THE TAC

As explained in section 1.3, the substantial decline throughout the 1990s was due to the increased juvenile mortality as by-catch in sprat fisheries but also because TACs for herring-targeted fisheries were exceeded. This inability to keep catches within the TAC has been a consistent feature of the fishery. For all of the HCRs implemented, a potential bias, *bc*, in catches has been included:

$$C' = TAC * bc \tag{56}$$

where C' is the realised catch and TAC is the expected or reported catch. This corresponds to potential misreporting and/or error of implementation of the TAC by fishermen. Three different levels of misreporting were tested: 10, 30 and 80%. 10% corresponds to a reasonably small implementation error and 30% to the levels that are more normally identified by ICES in stocks suffering from unreported catches in European waters (ICES, 2007b). 80% is a very significant level of under-reporting, occasionally but not regularly found in European waters (for instance ICES estimates that the true retained catch of cod in the North Sea was between 70% and 130% times the reported catch in 2003 and 2004; (ICES WGNSSK, 2007)). Although this situation is unlikely to persist for many years, it was included so as to test the robustness of the

model to high uncertainty and examine whether the HCRs defined above would fail in such a situation. Simulations have been run with and without this bias in catch data to see what is the impact of such a bias on the SSB at the end of the projection. For each simulation where a potential misreporting has been included, the level is kept constant all along the projection.

It has been decided to keep the level of misreporting constant over time to simplify the models and see more clearly the effect of including misreporting in the model. Different temporal patterns in the level of misreporting would have affected the assessment and the management in a different way. A constant misreporting over years does not have the same effect on assessment and management as a fluctuating level of misreporting. A constant misreporting will imply a bias in the assessment but trends in the evolution of the total biomass will be consistent with the real changes, even if the assessment might under- or overestimate the biomass. If the misreporting regularly changes, however, firstly it will be difficult to take it into account as it might be difficult to estimate it. Indeed, misreporting data available to scientific community are often qualitative rather than quantitative. Where quantitative estimates exist they tend to be limited in sample size and may not be representative or precise and cannot be used to accurately adjust reported landings. Secondly, the assessment model will have more difficulties to capture the evolution of the stock with a variable misreporting and the estimation of the biomass after a certain number of years might be completely wrong giving rise to poor management choices with severe consequences. By keeping the level of misreporting constant, the value could be assimilated to an average of the different levels of misreporting over time or could represent a limit that should not be exceeded.

As is the case in the actual management of the North Sea herring stock, a limitation upon the inter-annual variation in the TAC has been implemented. The value used in this work is the one set in the EU – Norway agreement and is equal to +/-15%. For each new year projected, the TAC proposed and the TAC corresponding to a variation of 15% are compared and the smaller variation is kept.

In the present work, this limitation is only applied to the actual management. In order to test the effect of this limitation on the final SSB, a sensitivity analysis has been implemented with some of the specific management procedures developed in this work.

This is particularly the case with simple management procedures that do not include assessment methods.

4.4 Discussion and conclusion

A certain number of harvest control rules are implemented in this thesis, based on different types of indices and different levels of complexity. The aim of this thesis is not to find the most relevant harvest control rule for the management of the North Sea herring stock, but to compare the performance of model-based and model-free harvest control rules. As a consequence, the harvest control rules considered are quite simple.
The simple fishery-independent harvest control rule presently implemented (section 4.3.4) might appear overly simple, as it is based on a variation of the spawning stock biomass over two following years. It might be interesting in future work to take into account more years in the calculation of the TAC in order to consider medium term historical impact.

The two harvest control rules based on spawning stock biomass trends (sections 4.3.5 and 4.3.6) should provide smoother outputs than the first harvest control rule due to their incorporation of trends. Any important variation in the estimates due to random noise will be smoothed out by the long term effect of the historical and projected data. An inconvenient factor, however, is that it might not properly reflect the full range of sceniarios in the real system by limiting changes. The harvest control rule combining two indices should provide better results than the one based on a single index, as the index added in the second rule is thought to be a better indicator of the spawning stock biomass.

The conservative aspect of the harvest control rule based on total mortality rate (section 4.3.7) may not be adaptable to any type of fishery or state of stock. In fact, if the stock is in bad condition, this rule might be a good option as it will tend to strongly decrease the TAC to rebuild the stock. If the stock is in good condition, it might not properly reflect the correct level of fishery that could be applied for the relevant stock, as the chances of increasing the TAC are not as high as reducing it.

According to De Oliveira *et al.* (2008), model-free harvest control rules are the most appropriate in situations where data are poor and estimates of the size of the population are not available. Indicators of the state of the stock such as commercial catch per unit effort (CPUE), mean fish weight or size, or spawning level would then be used in the implementation of the harvest control rule. An issue with this type of harvest control rules is its performance when the indices used on the rule do not reflect properly the state of the resource.

When considering actual management, one of the major issues is the consideration of a stock-recruitment relationship in the projection. Until 2003, the mean of the recruitment of the full time series (from 1980 onwards) was used in the projection of the stock in the future. Recently, in the Herring Assessment Working Group, it was thought that recruitment has declined and therefore to be conservative in short-term projections the method used until 2003 was not deemed appropriate anymore. From that year, the mean over the last six years of the perceived current recruitment was used. However, the current situation could not have been predicted three years ago, which explains why the mean is still in use in this work.

In the case of the model-based harvest control rules (section 4.3.8), the format of the rules is similar to the one implemented in sections 4.3.5 and 4.3.7. The differences in terms of results will depend on the quality of the assessment methods - YCC and SURBA – as explained in the Appendix 2.

Consideration of misreporting and limitation of the inter-annual variation of the quotas will give a more realistic aspect to the rules, as both aspects can be implemented in fishery managements. The limitation of the inter-annual variation of the quotas is at present implemented in the management of the North Sea herring stock. As was explained in the section 4.2.4, the aim of the limitation is to limit the effect on the fishing industry of high variations in the TAC between two consecutive years. One of the issues with this element is that its impact will be highly dependent on the state of the stock. In fact, if the stock is declining and the TAC should be reduced to avoid reaching low levels of spawning stock biomass, such a limitation will aggravate the situation (Kell *et al.*, 2002). The lower bound of the limitation will impose a minimum of catch which could be too high for the stock to cope with. In the case where the stock is in

good state, the upper limitation might restrict the catch to a level that will not increase the catch as rapidly as it would otherwise.

The final chapter describes the management procedures implemented in this work, starting with basic testing (no catch and constant catch), followed by the evaluation of strategies without assessment methods and finally those with assessment methods. All results are presented and discussed.

MANAGEMENT STRATEGIES EVALUATION FOR THE NORTH SEA HERRING STOCK

5 Management strategies evaluation for the North Sea herring stock

5.1 Introduction

5.1.1 BACKGROUND

The nature of the advice provided by scientists to institutions dealing with fisheries management has changed with time. Initially it did not clearly take into account uncertainty and advice was often offered as a single recommendation rather than a series of alternative options for different management approaches (Smith *et al.*, 1999). The acceptance of the concept of the precautionary approach to the provision of fisheries management advice (Rio Earth Summit in 1992) and changed the conceptual approach, through its explicit required for the incorporation of uncertainty.

Management Strategy Evaluation was developed as a tool in the 1990s by the Scientific Committee of International Whaling Commission (Kirkwood, 1997; IWC (International Whaling Commission), 1999; Hammond and Donovan, In press). It was further developed for fisheries management in South Africa (Butterworth and Bergh, 1993; Butterworth *et al.*, 1997; Cochrane *et al.*, 1998; Geromont *et al.*, 1999; De Oliveira and Butterworth, 2004; Johnston and Butterworth, 2005) and Australia (Smith, 1993; Punt and Smith, 1999; Punt *et al.*, 2001; Tuck *et al.*, 2003; Campbell and Dowling, 2005; Dichmont *et al.*, 2005; Punt *et al.*, 2005). The use of management procedures is also increasingly widespread as they allow codifying of decisions in the face of often incompatible biological, social and legal objectives (Rademeyer *et al.*, 2007). This approach is under development in Europe because the current fisheries policy in the European Union (Council Regulation No 2371, 2002) requires the use of multi-annual recovery plans to depleted stocks. Such recovery plans are currently implemented using management procedures which are usually subject to MSE in their development.

A major problem of fisheries management is that it has to deal with various and contrary objectives, multiple stakeholders with differing concerns and also high levels of uncertainty about the dynamics of the managed resource. Management strategy evaluation can assist in resolving these issues because it seeks to model both aspects of the problem: imperfect assessment due to imperfect understanding and inherent

uncertainty in the state of nature; and imperfect understanding of fishermen and management response (Smith *et al.*, 1999). One of the most important elements of the management strategy evaluation is that it does not seek to provide an "optimal" strategy or decision. It takes into account uncertainty in the model describing the system and presents the results in a way that highlights the compromise in performance across a span of management objectives (Smith, 1993; Smith, 1994; Punt *et al.*, 2002b). Decision-makers are then free to make their own evaluation of the information provided depending on their own objectives (Kell *et al.*, 2007a).

Smith *et al.* (1999) listed the key ingredients that should be included in the process:

- specifying clear management objectives
- developing quantifiable performance measures for each objective
- identifying alternative management strategies or decision options
- evaluating (using quantitative performance measures) the performance of each strategy or option against the range of objectives, taking suitable account of uncertainty
- communicating the results to decision-makers.

Thus one of the most important uses of MSE is gaining an understanding of the likely outcomes when different decision rules, or management procedures are used. Butterworth *et al.* (1997) describe management procedures as a selection of decision rules used to calculate the TAC based on available fisheries and survey data. The rules are agreed in advance by all interested parties, and specifically state how the TAC is calculated and which data are used to achieve this. Clearly this is advantageous when management procedures or decision rules can be tested before implementation in an MSE framework. However, the validity of comparisons between management procedures depends on the quality of the models used to mimic the fishery and their capacity to represent uncertainties (Butterworth and Punt, 1999).

A management procedure is chosen by using computer simulations to test a set of potential management procedures against a list of plausible future scenarios for the stock (called operating models). The procedures embody uncertainty relating to recruitment variability, sampling error, value of the model parameters such as natural mortality and model assumptions such as the form of the stock-recruitment relationship

(Rosenberg and Restrepo, 1994; De Oliveira *et al.*, 1998a; De Oliveira *et al.*, 1998b; McAllister *et al.*, 1999). The management procedure that will be selected for implementation is the one that shows good performance relating to statistics defined in advance of simulation testing (i.e. high average annual catch and low risk of decline of the managed resource below pre-specified levels). It also has to fulfil the demand of the interested parties but as well demonstrate certain robustness to a range of possible operating models (De Oliveira *et al.*, 2007).

The management strategy evaluation platform implemented in this thesis includes the components described in the previous chapters: an operating model (Chapter 2), an observation error model (Chapter 3), an assessment model (Appendix 2) and a harvest control rule model (Chapter 4). They are all related to each other according to the diagram in Figure 3.

5.1.2 METHODS

The North Sea herring stock is managed according to recommendations by ICES. The precautionary approach used by ICES aims to keep stock and fisheries within safe biological limits. The ICES Advisory Committee on Fishery Management [ACFM] (ICES ACFM, 2001) bases it advice on ensuring that "*there should be a high probability that 1) the spawning stock biomass is above the threshold where recruitment is impaired and that 2) the fishing mortality is below that which will drive the spawning stock to the biomass threshold. The biomass threshold is defined as* B_{lim} (*lim stands for limit) and the fishing mortality threshold as* F_{lim}". Due to the difficulty and uncertainty in estimating F_{lim}, a fishing mortality level below F_{lim} (i.e. F_{PA}) is chosen to in such a way that the probability of biomass falling below B_{lim} is very low (Kell *et al.*, 2005b).

As previously described in Chapter 2 in the operating model used here the ICA results and ICES working group settings are used to define historic levels (1960-2006). The population dynamics model starts in 1960 (the first year of data provided) and runs to 2006. The stock is then projected into the future over a relatively long time horizon. The generation time of North Sea herring is about 10 years, and the recent history of the stock has included two periods of major depletion over the last 40 years (a major crash occurred in the late 1970s and a minor one in the middle 1990s). Based on these

observations, it is assumed that 10 years can be considered as a medium term simulation. In order to provide a strong basis for understanding long-term performance, all simulations were run for 20 years (2 generation times) with 1000 Monte Carlo iterations (unless otherwise noted).

Measures of performance were split into two categories: indices related to stock conservation – i.e. biomass at the end of the simulation with a probability of depleting the stock below a reference point – and indices related to the costs and benefits to the fishing sector – i.e. average catch at the end of the projection and inter-annual variability in catch – (Bergh and Butterworth, 1987; McAllister *et al.*, 1999). Accordingly, the following specific performance criteria were calculated from the results of the simulations:

- Probability of the spawning-stock biomass falling below B_{lim} at least once in the projection.
- Probability of the spawning-stock biomass being below B_{lim} in the final year.
- Probability of the spawning-stock biomass being below B_{PA} in the final year.
- Coefficient of variation in the TAC in final year.

A very basic performance index was also calculated which captures both the final state of the stock and catch. The SSB is compared with B_{PA} as it corresponds to the value above which the SSB should be kept.

$$Perf = (SSB - B_{PA}) + Catch \tag{57}$$

Performance of several simulations can be assessed by comparing performance indices with calculated average of the performance indices of selected scenarios to see which perform best. To do this, a list of selected scenarios is made (Table 12). Performance indices are calculated for each simulation in each selection and the average of the performance indices is calculated. It is furthermore multiplied by 1.1 to fix an even higher average for comparison. This allows selection of the best simulations. Results of comparisons can be found in Appendix 7.

Table 12: Selections for which averages have been calculated.

		Selections														
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Stock recruitment	HS	√	√	√	√	√	√	√								
	Ricker	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
Autocorrelation	Estimated	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
	Higher	√	√	√	√	√	√	√								
Survey	Acoustic	√	√	√			√	√	√	√	√	√	√	√	√	√
	Acoustic + MLAI	√	√	√												
	All				√	√										
Observation error	No	√														
	Yes		√	√	√	√	√	√	√	√	√	√	√	√	√	√
HCR	Obs Index	√	√	√												
	Sngl SSB	√	√	√			√		√		√		√		√	
	Comb SSB	√	√	√												
	Z	√	√	√				√		√		√		√		√
Assessment	None	√	√	√					√	√	√	√	√	√	√	√
	Actual				√	√										
	YCC						√	√								
	SURBA						√	√								
Misreporting	No	√	√		√											
	10, 30 %														√	√
	All			√		√	√	√	√	√	√	√	√	√		
Limitation variation quota	No	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
	Yes				√								√	√		
Sensitivity maturity	No	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
	Yes								√	√						
Sensitivity catch weight	No	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
	Yes										√	√				
Sensitivity initial conditions	No	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
	Yes														√	√

As described in the previous chapters, various options have been implemented to reflect a range of management procedures for testing including several assumptions about the operating model. The entire list of combinations can be found in the Appendix 5. As a summary, all the possibilities can be found in Table 13.

Table 13: Summary of all possible options for the management procedures.

Variable components	Options
Stock-recruitment relationship	Hockey-stick Ricker
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic IBTS MIK MLAI
Observation error in the survey	No Yes
Harvest control rule	None Constant catch Based on direct observation index Based on adjusted observation index Based on a combination of two adjusted observation indices Based on Z Based on F and reference points (actual management)
Assessment	None ICA (actual management) YCC SURBA
Misreporting	0% 10% 30% 80%
Sensitivity analysis	Maturity-at-age Catch weight-at-age Limitation in the variation of the quota Bad initial conditions

The sensitivity analysis described in chapter 2 includes a change in the calculation of the maturity-at-age, in the calculation of the weigh-at-age in the catch, the use of a limitation in the variation of the quota and projections for which the initial conditions of the stock are poor.

Deterministic simulations were run at first in order to test the model. The first run was without catch to check that the spawning-stock biomass would increase immediately, and this was followed with an evaluation with constant TAC, which was set at the recent level recommended by the ICES working group.

Following these tests a number of "families" of models were run:

- Evaluation of the management strategies not using assessments, in which HCRs were model-free (see Chapter 4), with or without observation and implementation error.
- Evaluation of the management strategies using assessments, in which HCRs were dependent upon the assessments.

All results (values and graphs) can be found in the Appendix 6 and Appendix 8 respectively. Due to the very large number of outputs, it is not possible to include all of them in the core of this chapter. Only selected graphs will be included to show different behaviours over time of the stock biomass but also the catch and other variables. On each graph, solid lines give medians of distributions of estimates for each year, boxes show approximate first and third quartiles and dashed vertical lines indicate 95% confidence intervals. Furthermore, an analysis of the end results for each section of this chapter is provided to determine the state of the fishery under 20 years of consistent management.

5.2 Basic validation of the management strategy

The first tests of the management framework are to project the stock without catches and then with constant catches. All simulations have been run for 30 years to verify if the model could reach equilibrium. Simulations were run using 1000 Monte Carlo iterations in order to reduce the variability in the results.

Each graph corresponds to a specific combination of a stock-recruitment relationship with a level of autocorrelation in the recruitment. The one shown in the top left corresponds to a hockey stick stock-recruitment relationship and an estimated level of autocorrelation in the recruitment, the one in the top right to the same stock-recruitment relationship but assuming a higher level of autocorrelation in the recruitment. The bottom left and bottom right correspond to a Ricker stock-recruitment relationship assuming the two previous levels of autocorrelation. On each graph, solid lines give medians of distributions of estimates for each year, boxes show approximate first and third quartiles and dashed vertical lines indicate 95% confidence interval.

5.2.1 NO CATCH

As explained in section 4.3.2, the first test implemented in this study is to run the model without catches. The following figure (Figure 26) shows the results of the simulations.

An increase of the SSB is expected with both the hockey stick and Ricker stock-recruitment relationships and with both levels of autocorrelation in the recruitment. SSB is expected to reach a plateau with the hockey stick stock-recruitment relationship and to decrease when assuming a Ricker stock-recruitment relationship.

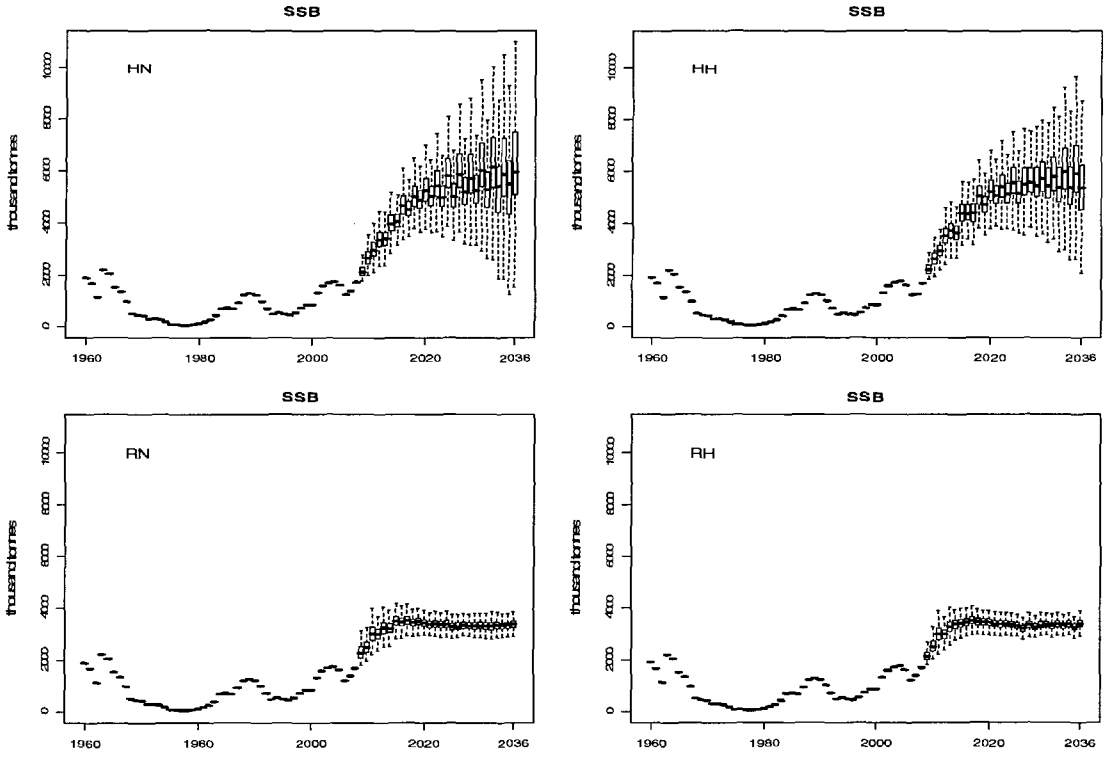


Figure 26: Spawning stock biomass (thousand tonnes) without catch in the projected years. HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation

Figure 26a (top left) and Figure 26b (top right) show that the stock increases continuously with the hockey stick stock-recruitment relationship but cannot reach the expected plateau. It might be reached after more than 30 years of projection. This suggests that even after 30 years, the system has not reach a state of equilibrium. The increase of the uncertainty (the size of the box corresponding to the first and third quartiles and the spread of the outliers) can be explained by the non flexibility of the stock-recruitment relationship from a certain SSB value.

Figure 26c (bottom left) and Figure 26d (bottom right), demonstrate that the stock rapidly increases to a maximum in the first years of the projection and thereafter decreases slowly. This is due to the density-dependence effect that occurs when assuming a Ricker stock-recruitment relationship. The system will tend to reach equilibrium between the natural mortality and the recruitment since catch is assumed to be zero. Figure 26d shows that the equilibrium is reached later when the level of autocorrelation is higher. The existence of autocorrelation means that the residuals in the recruitment for a given year are influenced by the residuals of the previous year.

5.2.2 CONSTANT CATCH

A similar test has been conducted but with constant catch. The aim of this test is to evaluate the set TAC for the final historical year ($512x10^3$ tonnes in 2006). The TAC set for 2006 was defined by the Herring Assessment Working Group at a meeting that took place in March 2005. If the stock is assumed to be in a relatively good condition and well managed and the TAC is fixed over time then the SSB should increase. This can be observed in the following Figure 27.

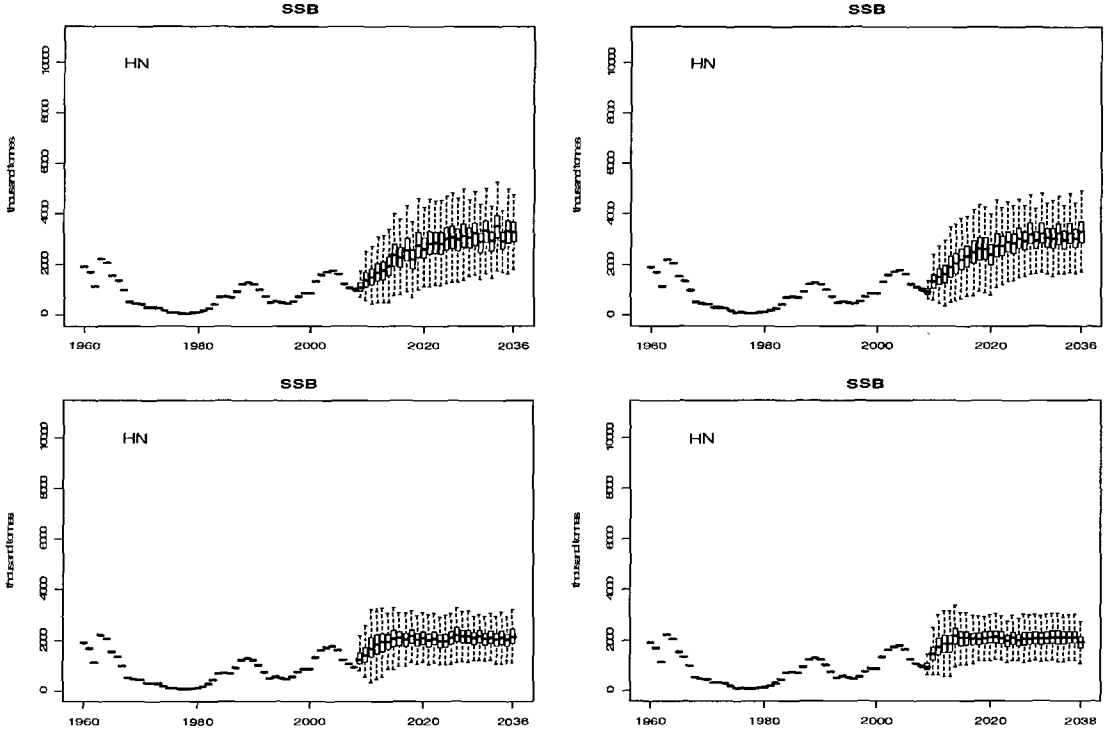


Figure 27: Spawning stock biomass with constant catch in the projected years.
HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation.

For the projection without catches, with the assumption of the Ricker stock-recruitment relationship, the SSB increases rapidly in the first years of the projection until it reaches a plateau. Similarly, simulations assuming a hockey-stick relationship do not reach equilibrium and keep increasing over the 30 years of projection and the incorporation of a TAC necessarily results in a smaller SSB than the previous scenario of zero catches.

The first test shows that the model behaves as expected in absence of catch. The second test shows that the stock under the condition of fixed TAC does not collapse which suggests the level set for 2006 was appropriate for the state of the stock at this time and its assumed behaviour.
The next section provides the results obtained with various HCRs without the use of assessment methods. It also provides results obtained from the sensitivity analysis described in sections 2.3.1, 2.3.3 and 4.3.9.

5.3 Evaluation of the model-free management strategies

This second section describes the results obtained without assessment methods, i.e. using model-free HCRs. This section is divided into three parts. The first one corresponds to the analysis of results obtained for the evaluation of the management strategy with and without observation error and without implementation error. The second section describes those for the evaluation of the management strategies with observation error and implementation error. The final section corresponds to the sensitivity analysis mentioned previously in this work. It includes the evaluation of the change in the maturity-at-age and in the catch weight-at-age but also the effect of limiting the variation of the quota and the result of starting the projection of the stock when initial conditions are poor.

This section covers several options described in chapter 2 on the operating model and in the previous chapter on the HCRs. The two stock-recruitment functions with two levels of autocorrelation are considered as for the operating model. The four HCRs analysed in this part are the model-free based on direct observations (section 4.3.4), model-free based on relative spawning-stock biomass trends (section 4.3.5), model-free based on

combined spawning-stock biomass trends (section 4.3.6) and model-free based on total mortality (section 4.3.7).

A summary of the simulations considered in this section can be found in Table 14:

Table 14: Management procedures options considered in model-free management strategies.

Variable components	Options
Stock-recruitment relationship	Hockey-stick Ricker
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic Combined acoustic + MLAI
Observation error in the survey	No Yes
Harvest control rule	Based on direct observation index Based on adjusted observation index Based on a combination of two adjusted observation indices Based on Z
Assessment	None
Misreporting	0% 10% 30% 80%
Sensitivity	Maturity-at-age Catch weight-at-age Limitation in the variation of the quota Bad initial conditions

An illustration of possible behaviours of stock and fishery over the projection is initially proposed and followed by an analysis of the results in the final year of the projection for combinations of stock-recruitment relationships, levels of autocorrelation and HCRs. After an overview of all graphs (Appendix 8) corresponding to this section, six of them are described here and three added in the sensitivity analysis sub-section corresponding to constraint in the TAC and poor initial conditions. Each graph is illustrative of a different evolution over the projection of the stock and the fishery. The purpose is to examine the various behaviours depending on options chosen for the management procedures. The specific components of the six simulations can be found in Table 15.

Table 15: Selected scenarios illustrating temporal behaviours of model-free management strategies.

Options	Simulation number	21	23	59	67	91	99
Stock-recruitment	Hockey stick	√		√		√	
	Ricker		√		√		√
Autocorrelation	Estimated	√	√	√	√	√	√
Observation error	No	√	√				
	Yes			√	√	√	√
Survey	Acoustic	√	√	√	√	√	√
Harvest control rule	Single SSB trend			√	√		
	Z	√	√			√	√
Assessment	No	√	√	√	√	√	√
Constraint	No	√	√	√	√	√	√
Misreporting	0%	√	√				
	30%			√	√	√	√
Figure		30	31	29	28	32	33

The output of the first simulation presented (no 67) can be seen on Figure 28. This type of output illustrates simulations 9 to 20, 25 to 36, 41 to 88, 193 to 196 and 201 to 204 (Appendix 5) which correspond to the combinations shown in Table 16.

Table 16: Combinations of options illustrated by scenario 67.

Variable components	Options
Stock-recruitment relationship	Hockey-stick Ricker
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic Combined acoustic + MLAI
Observation error in the survey	No Yes
Harvest control rule	Based on direct observation index Based on adjusted observation index Based on a combination of two adjusted observation indices
Assessment	None
Limitation in the variation of the quota	No Yes
Misreporting	0% 10% 30% 80%
Sensitivity	Maturity-at-age Catch weight-at-age

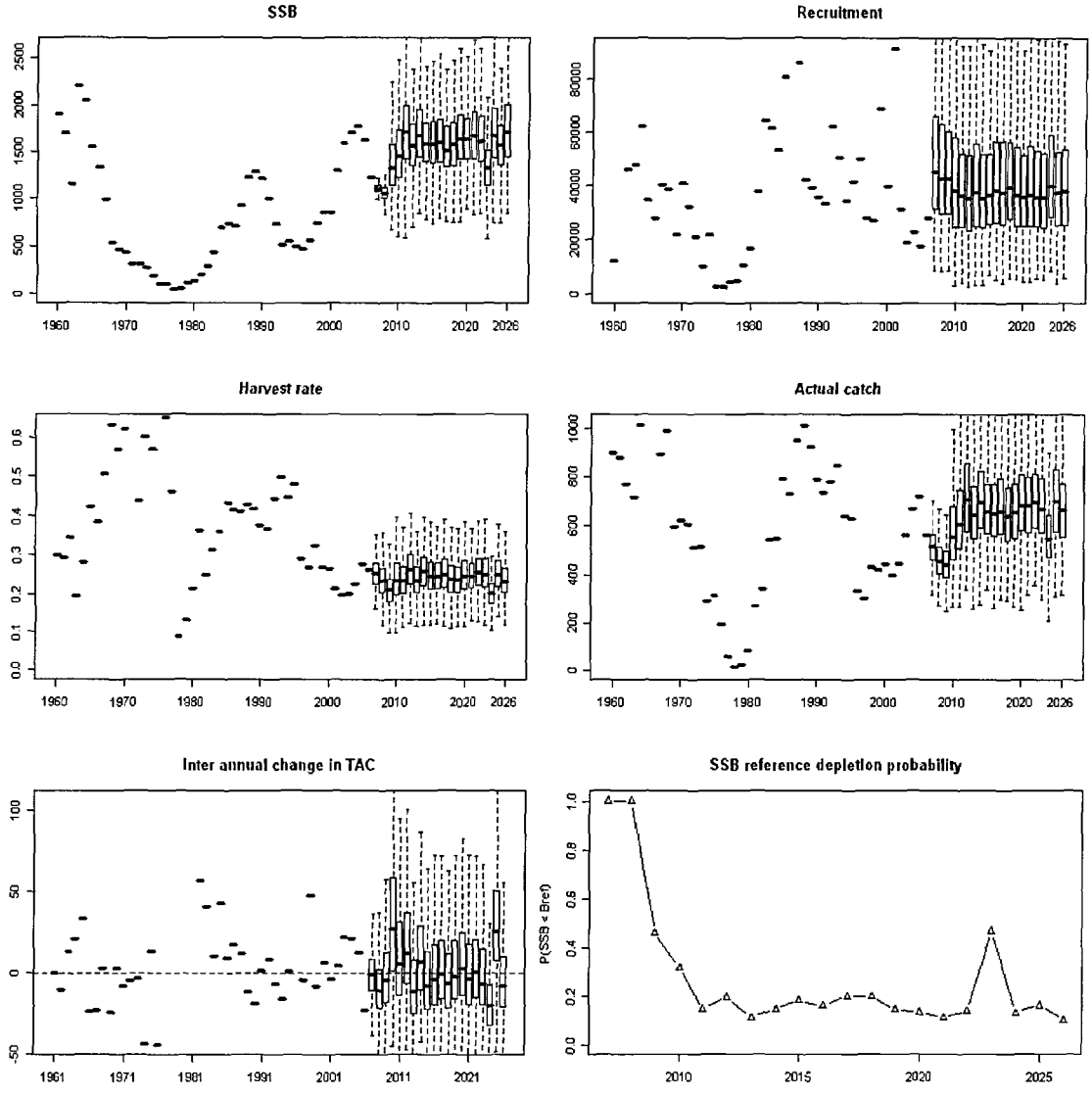


Figure 28: Output of simulation 67.
Stock recruitment: Ricker; autocorrelation: estimated; survey: acoustic with observation error; assessment: none; harvest control rule: Sngl SSB; limitation of variation: none; implementation error: 30%.

Figure 28 shows that the SSB starts by decreasing in the first two years of the projection. This is due to the low levels of recruitment in the last historical years. It then increases for three years until it reaches equilibrium. This is due to the level of catches that have been reduced. In fact, the TAC follows the trend of the SSB with a delay induced by the way TAC is calculated. During the last 15 years of the projections, the SSB is not perfectly constant due to the uncertainty in the parameters such as survey indices. It can be observed that the recruitment starts by decreasing during the first six years of the projection until it reaches equilibrium. The decline is due to the stock-recruitment relationship assumed in the model. In fact, with a Ricker relationship, if the SSB is above a certain value then the recruitment will decrease due to the density-

dependence effect. The harvest rate is kept relatively constant over time with a small decline in the first years of the projection due to the decline of the SSB and the catches. As the latter cannot be perfectly constant over time, the inter-annual change in the TAC is also not constant.

The shape of the curves for the SSB, the recruitment, the harvest rate, the actual catch and the inter-annual change in TAC stays similar if an option of the model is changed, following the list of options short-listed above. The only noticeable difference is when a hockey stick function is assumed for the stock-recruitment relationship. In this case, the recruitment stays constant over the 20 years of projection. Indeed, when the SSB is above the inflection point, the recruitment remains constant whatever the value of the SSB. In the simulations run, the SSB is permanently above the inflection point. This can be observed in the Figure 29 which corresponds to the same options as the previous figure with a hockey stick stock-recruitment relationship.

When the level of misreporting increases from 0 to 80% the estimated average SSB tends to decrease and the average catches and the harvest rate increase. Conversely, the increase of the level of misreporting does not affect the projected recruitment, which is maintained at the same level for all misreporting levels, as does the inter-annual change in TAC. The SSB reference depletion probability increases with the level of misreporting in the 20 years of projection.

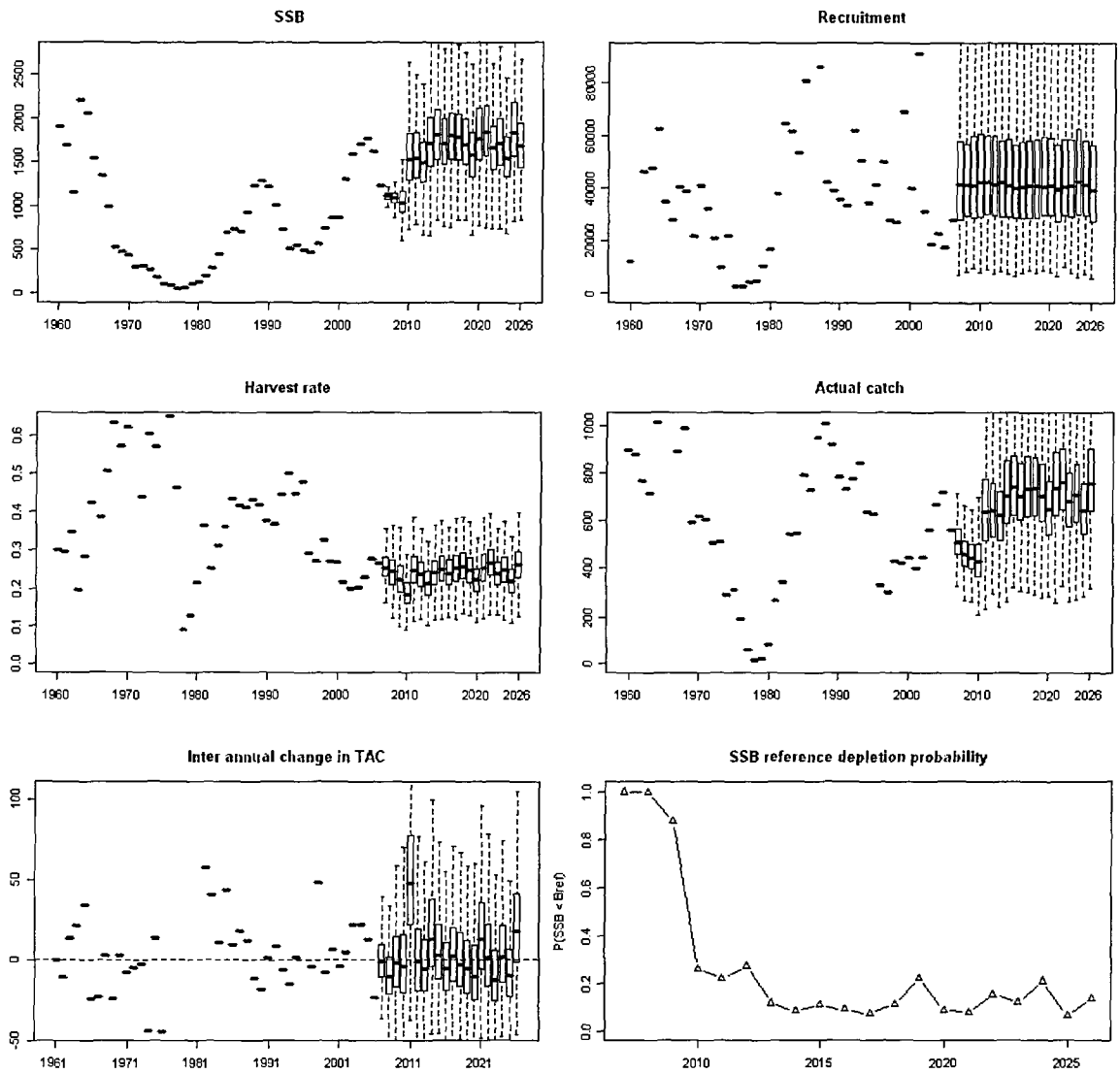


Figure 29: Output of simulation 59.
Stock recruitment: hockey-stick; autocorrelation: estimated; survey: acoustic with observation error; assessment: none; harvest control rule: Sngl SSB; limitation of variation: none; implementation error: 30%.

The output of the simulation 21 can be observed on Figure 30. This type of output illustrates the two simulations (21 and 22, Appendix 5) listed in Table 17.

Table 17: Combinations of options illustrated by scenario 21.

Variable components	Options
Stock-recruitment relationship	Hockey-stick
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic
Observation error in the survey	No
Harvest control rule	Based on Z
Assessment	None
Limitation in the variation of the quota	No
Misreporting	0%

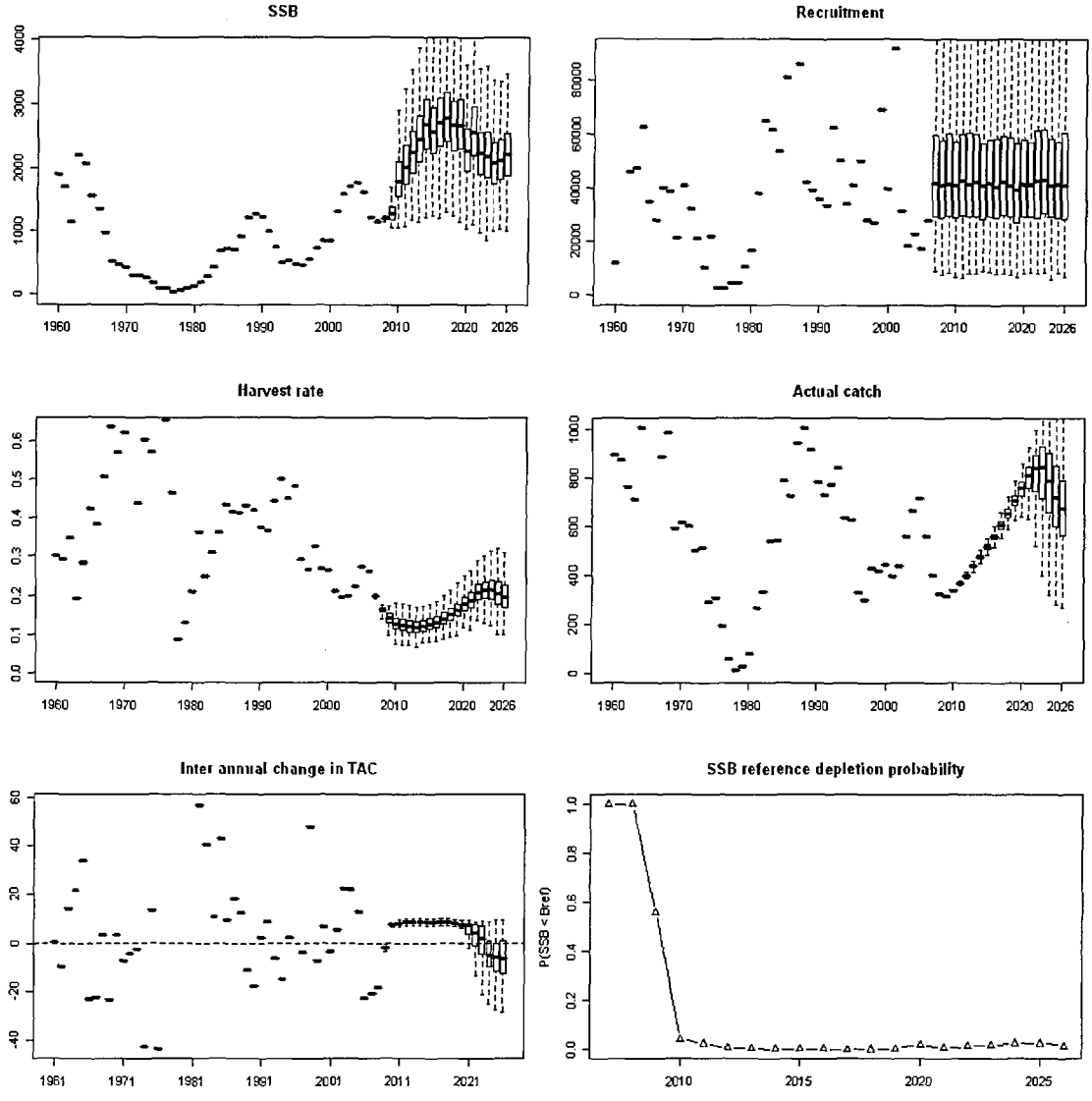


Figure 30: Output of simulation 21.
Stock recruitment: hockey stick; autocorrelation: estimated; survey: acoustic without observation error; assessment: none; harvest control rule: Z; limitation of variation: none; implementation error: 0%.

As it can be observed in Figure 30, the SSB slightly decreases during the first year of the projection, increases for 10 years, decreasing during the following 7 years before increasing for the two final years of the projection. In all years, the SSB is kept well above B_{PA} and the inflection point of the stock-recruitment relationship which implies that the recruitment remains constant over time along the time span of the projection. As this is a Z-based harvest control rule (section 4.3.7) an increase of the TAC can only be explained by the fact that both Z ratios are greater than 1, which means that fishing for each age group is under the precautionary approach level. This situation applies for most of the projection. The decline of the SSB in the final years can be explained by the fact that as fishing pressure becomes too high for the stock, the mortality rate is not

compensated by an increase of the recruitment. Once the catch level is too high, the SSB decreases and subsequently declines, as seen in the final years of the projection. As the catches increase continuously and regularly in the first part of the projection, the inter-annual change in TAC is positive and constant until the catch decrease in the final years and the inter-annual change in TAC decreases and becomes negative.

The output of the simulation 23 can be observed on Figure 31 This type of output illustrates the two simulations (23 and 24, Appendix 5) listed in Table 18.

Table 18: Combinations of options illustrated by scenario 23.

Variable components	Options
Stock-recruitment relationship	Ricker
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic
Observation error in the survey	No
Harvest control rule	Based on Z
Assessment	None
Limitation in the variation of the quota	No
Misreporting	0%

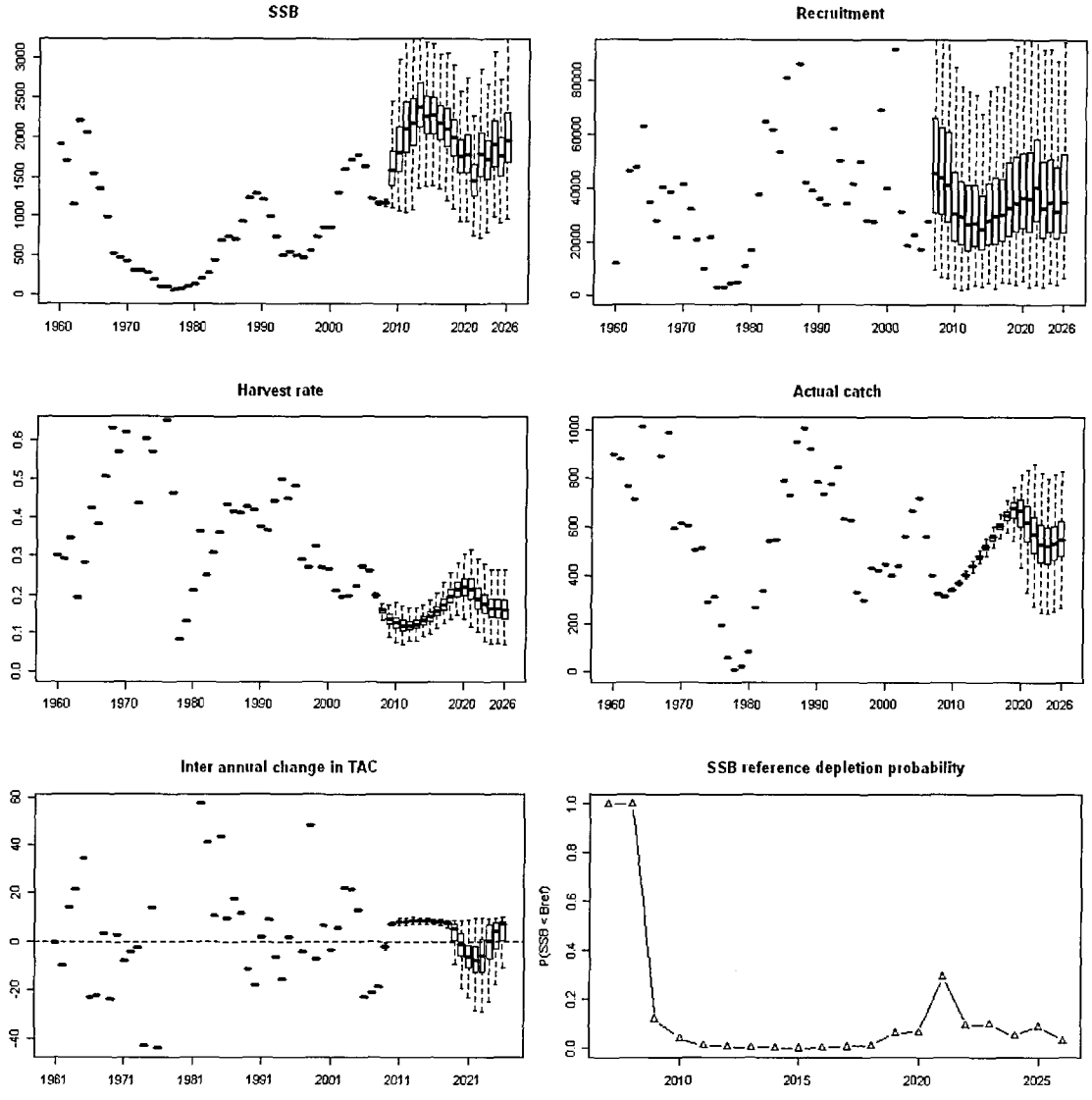


Figure 31: Output of simulation 23.
Stock recruitment: Ricker; Autocorrelation: estimated; Survey: acoustic without observation error; Assessment: none; Harvest control rule: Z; Limitation of variation: none; Implementation error: 0%.

The simulation shown in Figure 31 is similar to the previous one. The only difference is the stock-recruitment relationship assumed: Ricker is considered instead of hockey-stick. The trend in SSB is relatively similar to the previous projection, except an increase of the SSB is evident in the last 5 years of the projection. With a Ricker stock-recruitment relationship, the recruitment varies with the level of SSB which can be observed in the top right graph in the figure. Indeed, the increase of the recruitment in the middle of the projection, linked to the decrease of the SSB, led to an increase of the SSB in the final years. The catch trend is similar to the one observed in the previous figure, except that there is an increase of the catch in the final years. This is due to the increase of the SSB in the last 6 years of the projections. The harvest rate follows the trend of the catch as was already the case in the previous simulation. The inter-annual

change in the TAC stays constant in the first half of the projection and then decreases and increases in the second half. The first half is similar to the situation explained for the previous figure and the decrease and the increase are inversely proportional to the variation in the catch.

The output of the simulation 91 can be observed on Figure 32. This type of output illustrates simulations 37, 38 and 89 to 96 (Appendix 5) and corresponding to the combinations found in Table 19.

Table 19: Combinations of options illustrated by scenario 91.

Variable components	Options
Stock-recruitment relationship	Hockey-stick
Autocorrelation in the recruitment	Estimated level
	Higher level
Survey	Acoustic
Observation error in the survey	Yes
Harvest control rule	Based on Z
Assessment	None
Limitation in the variation of the quota	No
Misreporting	0%
	10%
	30%
	80%

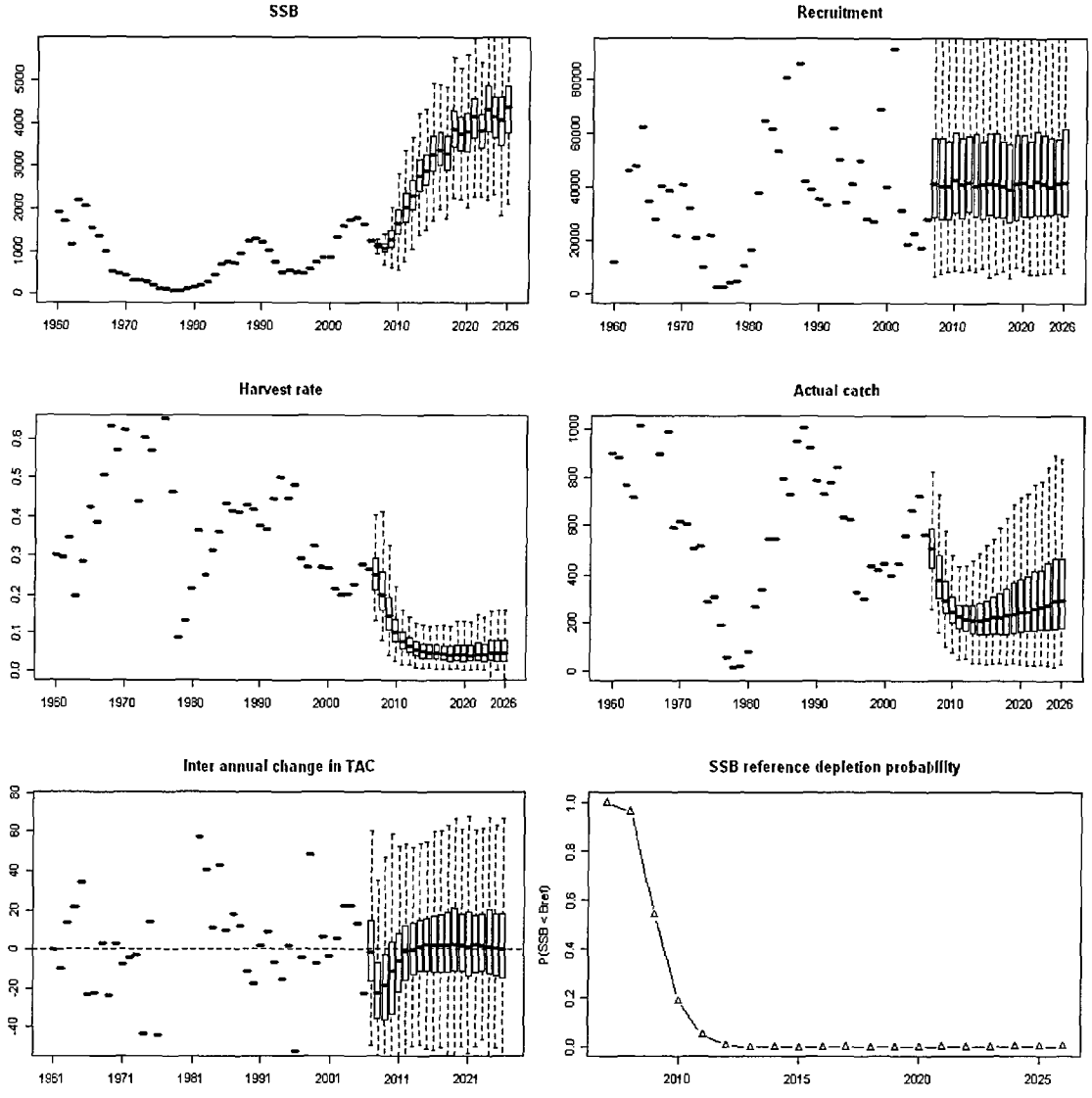


Figure 32: Output of simulation 91.
Stock recruitment: hockey stick; autocorrelation: estimated; survey: acoustic with observation error; assessment: none; harvest control rule: Z; limitation of variation: none; implementation error: 30%.

As can be observed in Figure 32, the SSB increases continuously from the beginning of the projection while the catch decreases rapidly in the first third of the projection and then increases slowly until the end. As this harvest control rule prioritises the precautionary approach - the minimum of both Z-ratios is used in the calculation of the TAC for the following year – and errors are considered in the indices from acoustic surveys, the model tends to increase the SSB. The increase of the SSB is emphasized by the fact that the recruitment cannot be reduced for high levels of SSB and remains constant. The major difference between this and similar simulations and simulation 21 (Figure 30) is the consideration of error in the survey indices. The fact that the catch decreases in the present case means that the Zs coming from the survey indices are

assumed to be higher than the precautionary levels of Z_{PA}. Once the catch has reached a relatively low level, the Zs become smaller than each of the Z_{PA} values and the catch can then increase slowly. The harvest rate trend follows the catch trend. The slowing down of the variation of the harvest rate in the second half of the projection is due to the compensation of the slow increases of SSB and catch, while the intense decrease of the harvest rate at the beginning of the projection is driven by the rapid decline in catch.
An increase of the level of misreporting does not seem to have any noticeable effect on the variables considered here. This is due to the conservative nature of the harvest control rule. The only change is in the spread of the distribution of the variables.

The output of the simulation 99 can be observed on Figure 33. This type of output illustrates simulations 39, 40 and 97 to 104 (Appendix 5) and corresponding to the combinations found in Table 20.

Table 20: Combinations of options illustrated by scenario 99.

Variable components	Options
Stock-recruitment relationship	Ricker
Autocorrelation in the recruitment	Estimated level
	Higher level
Survey	Acoustic
Observation error in the survey	Yes
Harvest control rule	Based on Z
Assessment	None
Limitation in the variation of the quota	No
Misreporting	0%
	10%
	30%
	80%
Sensitivity	Maturity-at-age
	Catch weight-at-age
	Limitation in the variation in the TAC

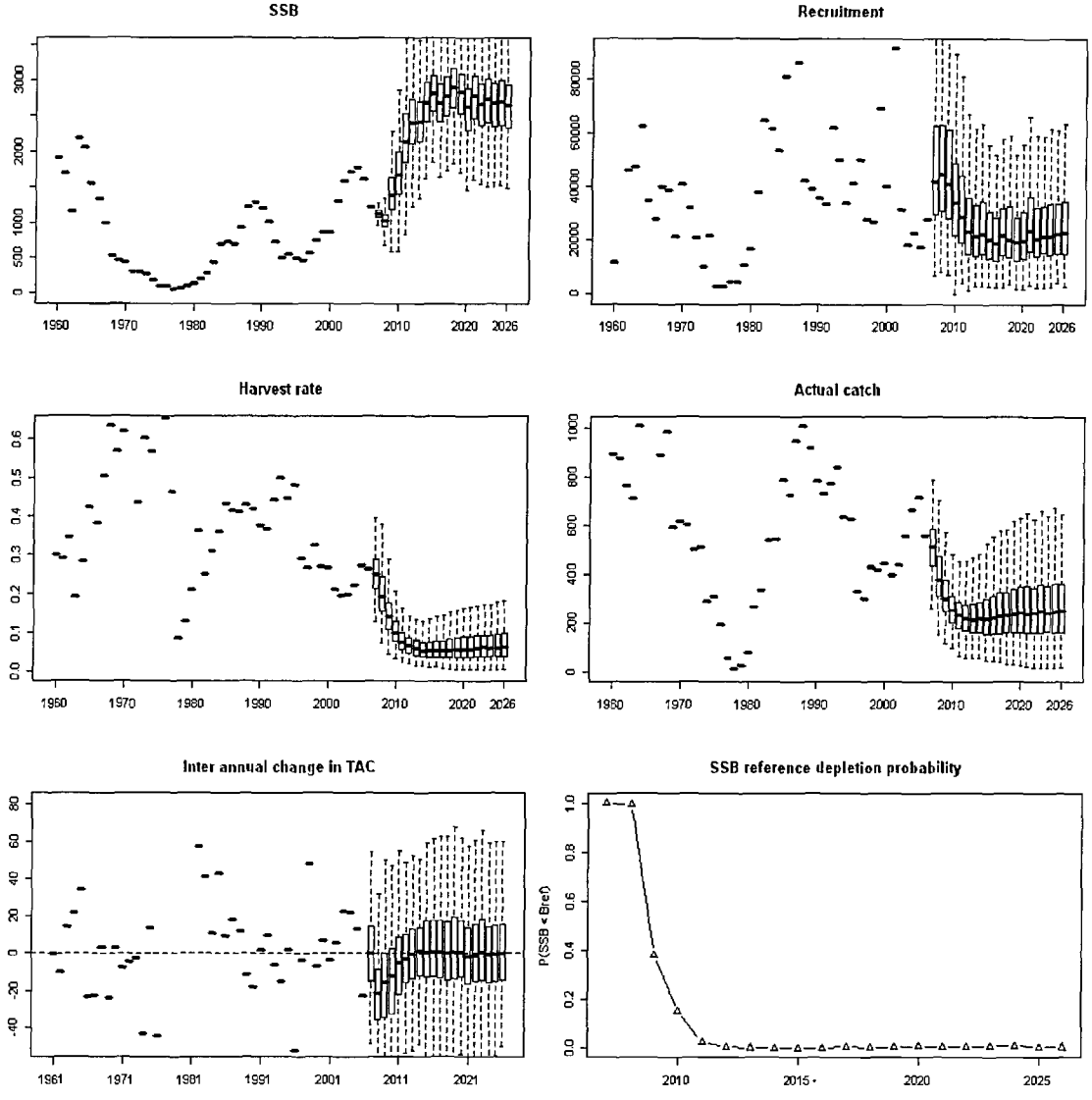


Figure 33: Output of simulation 99.
Stock recruitment: Ricker; autocorrelation: estimated; survey: acoustic with observation error; assessment: none; harvest control rule: Z; limitation of variation: none; implementation error: 30%.

A comparison of Figure 32 and Figure 33 shows that the harvest rate, the catch and the inter-annual change in TAC are similar. The major differences are the SSB and the recruitment. As Ricker is the stock-recruitment relationship assumed here, the recruitment can vary with the SSB. The recruitment reduces as the SSB reaches high values. The decrease of the recruitment observed in the first years of the projection explains the slowing down of the increase of the SSB in the middle of the projection and its slow decrease in the second half of the projection.

An increase in the level of misreporting does not have any noticeable effect on the variables observed here. This is due to the conservative aspect of the harvest control rule.

All figures in section 5.3 are structured as follows: they show either the spawning-stock biomass after the 20 years of projection, the catch in the final year or the CV in the TAC in the final year. Each point corresponds to a combination of a HCR, a stock-recruitment relationship, a level of autocorrelation and a level of under-reporting, when the later is considered.

5.3.1 EVALUATION OF THE MANAGEMENT STRATEGY WITH AND WITHOUT OBSERVATION ERROR AND WITHOUT IMPLEMENTATION ERROR

The aim of the simulations in this section was to test the behaviour of the HCRs in ideal conditions and when observation error was added to the surveys.

Four graphs are plotted. The first two (Figure 34 and Figure 35) show the spawning stock biomass for different management procedures. In the first figure, the observation error in the survey has not been taken into consideration. The second figure shows the effect of considering observation error and superimposes the results. The third figure (Figure 36) shows the catch in the final year and Figure 37 shows the coefficient of variation in the TAC. The 16 scenarios presented in the following figures correspond to the management procedures listed in Table 21.

On each figure, each group of four linked points corresponds to a HCR. The following names are given above the points: Obs Index for Observation index (section 4.3.4), Sngl SSB trend: Relative SSB trend (section 4.3.5), Comb SSB trend: Combined relative SSB trend (section 4.3.6), Z: Z-based (section 4.3.7). Each point of the group corresponds to a combination of stock-recruitment relationship and a level of autocorrelation in this order: HN = hockey-stick and estimated level of autocorrelation, HH = hockey-stick and higher level of autocorrelation, RN = Ricker and estimated level and finally RH = Ricker and higher level of autocorrelation. On all graphs showing the spawning-stock biomass, a horizontal line is drawn indicating the reference level B_{PA} (1 300 thousand tonnes). Another horizontal line is drawn on the figure plotting the catch, corresponding to the TAC set in 2006 (512 000 tonnes). The numbers on the horizontal axis correspond to the number of the simulation that can be found in the Table 21 or Appendix 5.

Table 21: Scenarios used to evaluate management strategies with and without observation error and without implementation error.

		SR		Autocorrelation		Obs error		Survey		HCR				Assessment	Constraint	Misreporting
		HS	Ricker	Est	Dbl	No	Yes	Acoust	SSB	Obs Ind	Sngl SSB	Comb SSB	Z	No	No	No
Simulation number	9	√		√		√		√		√				√	√	√
	10	√			√	√		√		√				√	√	√
	11		√	√		√		√		√				√	√	√
	12		√		√	√		√		√				√	√	√
	13	√		√		√		√			√			√	√	√
	14	√			√	√		√			√			√	√	√
	15		√	√		√		√			√			√	√	√
	16		√		√	√		√			√			√	√	√
	17	√		√		√			√			√		√	√	√
	18	√			√	√			√			√		√	√	√
	19		√	√		√			√			√		√	√	√
	20		√		√	√			√			√		√	√	√
	21	√		√		√		√					√	√	√	√
	22	√			√	√		√					√	√	√	√
	23		√	√		√		√					√	√	√	√
	24		√		√	√		√					√	√	√	√
	25	√		√			√	√		√				√	√	√
	26	√			√		√	√		√				√	√	√
	27		√	√			√	√		√				√	√	√
	28		√		√		√	√		√				√	√	√
	29	√		√			√	√			√			√	√	√
	30	√			√		√	√			√			√	√	√
	31		√	√			√	√			√			√	√	√
	32		√		√		√	√			√			√	√	√
	33	√		√			√		√			√		√	√	√
	34	√			√		√		√			√		√	√	√
	35		√	√			√		√			√		√	√	√
	36		√		√		√		√			√		√	√	√
	37	√		√			√	√					√	√	√	√
	38	√			√		√	√					√	√	√	√
	39		√	√			√	√					√	√	√	√
	40		√		√		√	√					√	√	√	√

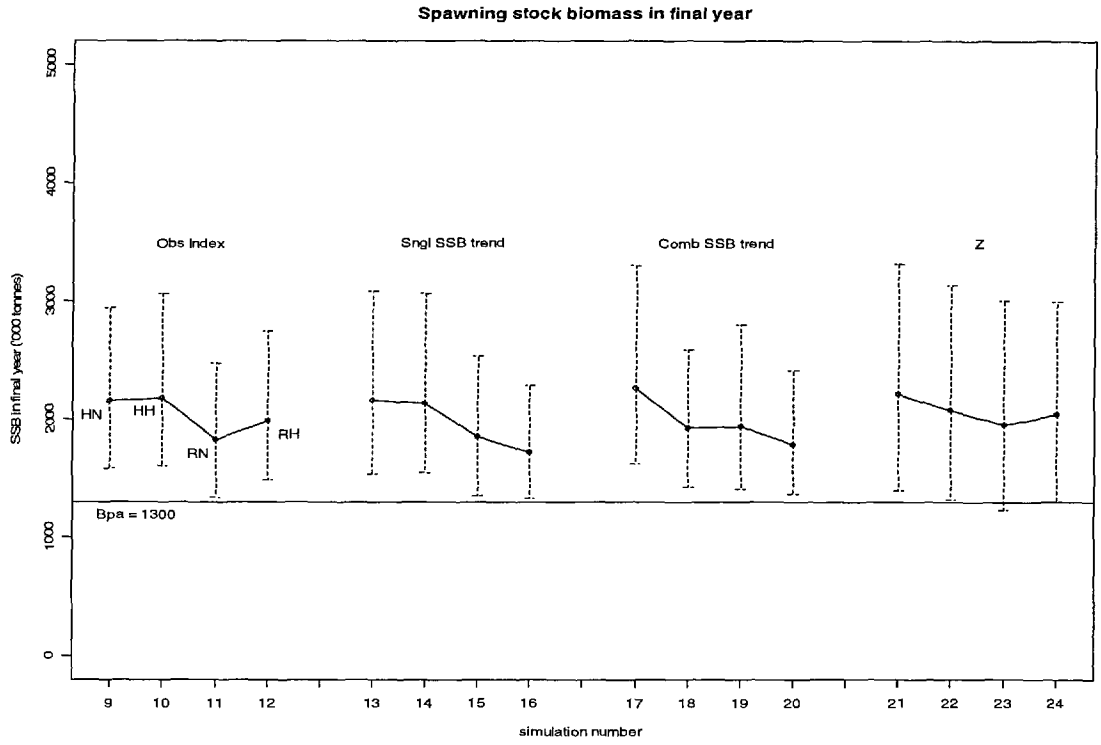


Figure 34: Spawning stock biomass in the final year of the projection.
Each point corresponds to a simulation: cases 9 to 24 in Appendix 5. Unit: thousand tonnes. HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation. Dashed vertical lines correspond to the 95% confidence interval.

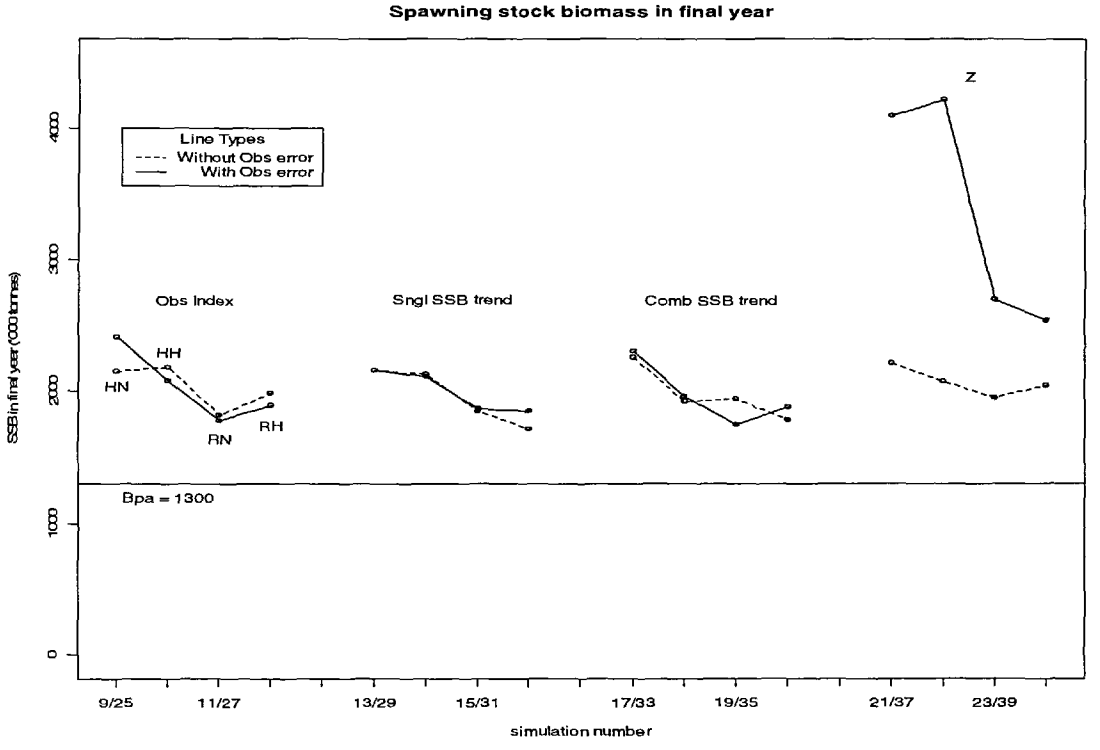


Figure 35: Spawning stock biomass in the final year of the projection.
Each point corresponds to a simulation: cases 9 to 40 in Appendix 5. Unit: thousand tonnes. HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation. Dashed line: without observation error; plain line: with observation error.

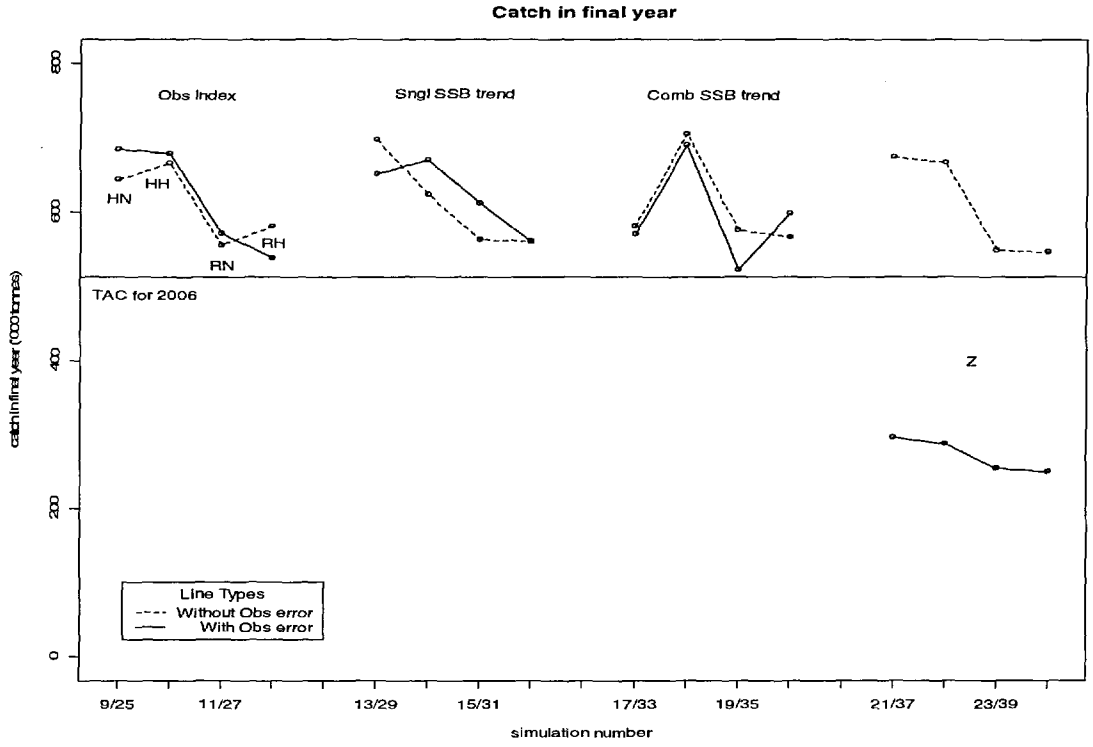


Figure 36: Catch in the final year of the projection.
Each point corresponds to a simulation: cases 9 to 40 in Appendix 5. Unit: thousand tonnes. HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation. Dashed line: without observation error; plain line: with observation error.

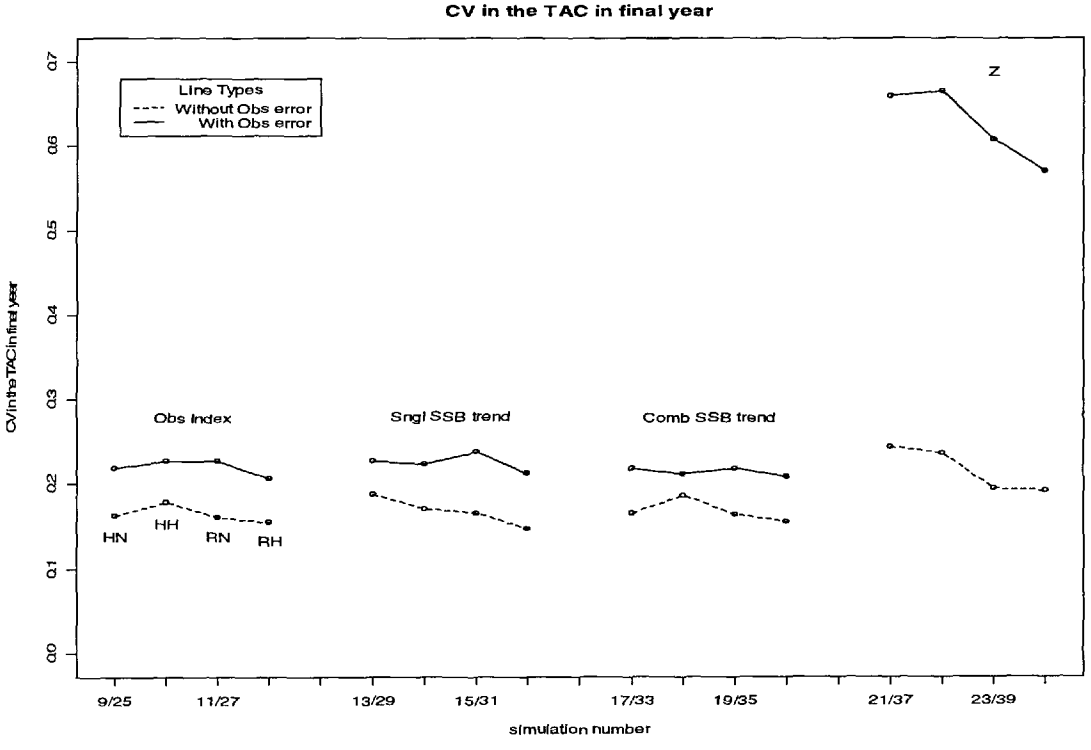


Figure 37: Coefficient of variation in the TAC in the final year of the projection.
Each point corresponds to a simulation: cases 9 to 40 in Appendix 5. HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation.

In all cases the final spawning-stock biomass is well above B_{PA} (1300 thousand tonnes), and the probability of being below B_{lim} (800 000 tonnes) in the final year is negligible or zero. All HCRs except the Z based rule appear to be robust to the introduction of observation error in the surveys, although as expected the CV of the TAC increases with the introduction of observation error.

The change of stock-recruitment relationship or level of autocorrelation has a different effect if the HCR is based on direct observations (first rule) or adjusted observations (second and third rules) and on total mortality rate (forth rule). When a hockey-stick stock-recruitment relationship is considered, an increase of the level of autocorrelation in the recruitment implies a decrease of the final SSB with the first HCRs and an increase with the Z-based one. Conversely, an increase of the level of autocorrelation with a Ricker stock-recruitment relationship implies an increase of the SSB for the SSB-based HCRs and a decrease with the Z-based one. But with all simulations, the final biomass is higher when the hockey-stick relationship is assumed than a Ricker relationship.

The probability of being below B_{PA} in the final year is not zero in most simulations but values are very low. As expected, values are higher with a Ricker stock-recruitment relationship than with a hockey-stick relationship. Note that according to Figure 13 (chapter 1), the optimum recruitment is achieved at a SSB of approximately 1000 thousand tonnes which is captured by the Ricker model but not the hockey-stick model. As the SSB is higher in the final years, the recruitment tends to be reduced with the Ricker model.

The Z-based rule considerably increases biomass and decreases catches when observation error is introduced. As this rule is age-dependent, the simulated error in the precision in the survey has an appreciable effect on the projection of the stock and as a consequence on its conservation and the fishery. However, the rule is a precautionary one. To observe an increase in the TAC, both Zs ($Z_{0:1}$ and $Z_{2:6}$) have to be below Z_{PA}, when a decrease will be observed if at least one of the Zs is above Z_{PA}. This is in accordance with the precautionary nature of this HCR explained in section 4.3.7.

Appendix 6 shows that the probability of being below B_{lim} in the projection was greater under all HCRs when observation error was introduced. In fact, observation errors give

more variable TACs which results in more variable stock sizes and this can lead to more variable recruitment.

Values of the coefficient of variation in the TAC in the final year are quite similar for the three first HCRs when there is no error in the observations considered (Figure 37). Values are higher for the Z-based rule probably as a result of the rule being more reactive to stock changes than the other rules. Although the overall outcomes for the first three rules are generally similar to the case where there was no observation error, the introduction of this error does increase the CV of catches.

Although the Z-based HCR seems to violate some of the industry preferred limitations on the variation in inter-annual TAC, it will be possible to see later that it performs better than the others with respect to detecting stock declines and acting to prevent them.

5.3.2 EVALUATION OF THE MANAGEMENT STRATEGY WITH OBSERVATION ERROR AND IMPLEMENTATION ERROR

European fisheries have been plagued in recent years with considerable mis-reporting and under-reporting of catches. For instance, in 2003 ICES estimated that landings of North Sea and eastern Baltic cod were under-reported by 40-50% and in 2005, 14% of mackerel landings were unreported (ICES, 2007b). The poor record of control in European fisheries has recently been criticised by the European Court of Auditors (Committee on Budgetary Control, 2008) on the control, inspection and sanction systems relating to the rules on conservation of Community fisheries resources). It is extremely important that HCRs intended for use with EU fisheries should be tested for robustness against possible misreporting, and the use of rules that are independent of fishery data holds out considerable hope that this can be achieved.

In this section, the four HCRs already previously used are tested against different levels of misreporting of catches (10, 30 and 80%, levels which span the broad range of mis- and under-reporting levels found in the EU). Management procedures included in this section (scenarios 41 to 104) follow the same structure as the simulations 25 to 40

introduced in the previous section (Table 21) but each of them run for the four levels of misreporting (0 to 80%). All numerical results can be found in Appendix 6.

Results are shown for the final year of the projection to allow for observation of the state of the stock and the fishery after 20 years of constant management. Each figure shows either the spawning-stock biomass after the 20 years of projection (Figure 38), the catch in the final year (Figure 39) or the CV in the TAC in the final year (Figure 40). For the first two figures, to avoid clutter and confusion on the figures, the 95% confidence intervals for each HCR are only shown for one set of runs (the Ricker stock-recruitment relationship and existing autocorrelation in recruitment).

All graphs are structured as follows. Each corresponds to a combination of a HCR, a stock-recruitment relationship, a level of autocorrelation and a level of under-reporting. Each group of four linked points corresponds to a HCR whose name is written above points: Obs Index for Observation index (section 4.3.4), Sngl SSB trend: Relative SSB trend (section 4.3.5), Comb SSB trend: Combined relative SSB trend (section 4.3.6), Z: Z-based (section 4.3.7). Each group of four points linked on the figure corresponds to a given stock-recruitment relationship and a given level of autocorrelation, as before. The numbers on the horizontal axis correspond to the number of the simulation that can be found in the Appendix 5.

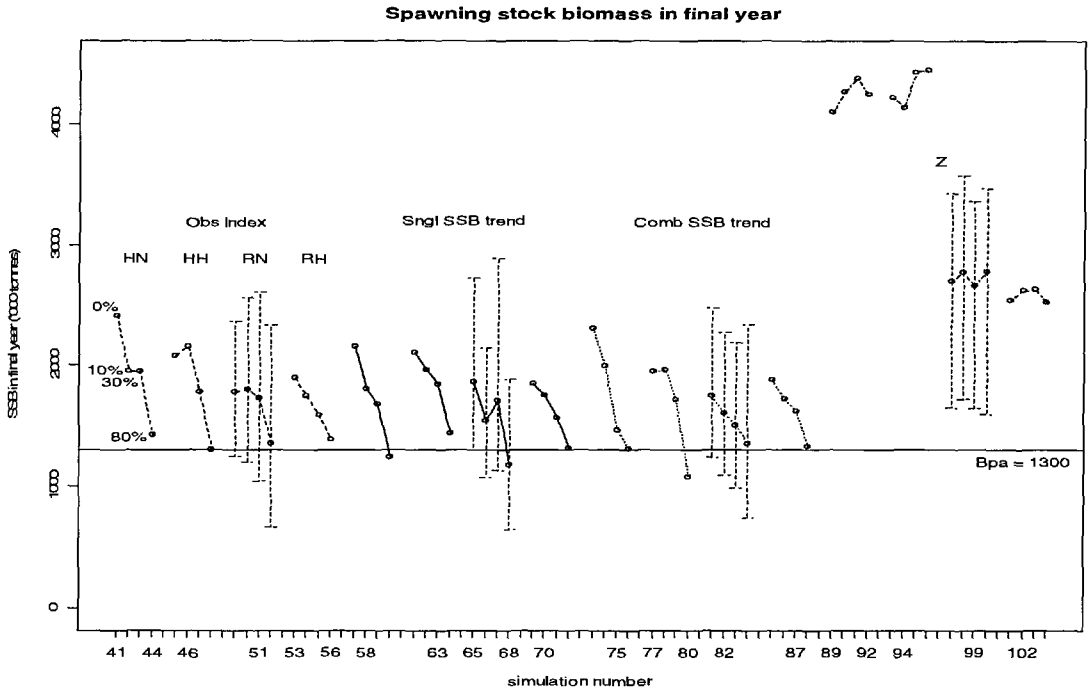


Figure 38: Spawning stock biomass in the final year of the projection.
Each point corresponds to a simulation: cases 41 to 104 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the stock-recruitment relationship / autocorrelation options: HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation. Dashed vertical lines correspond to the 95% confidence interval.

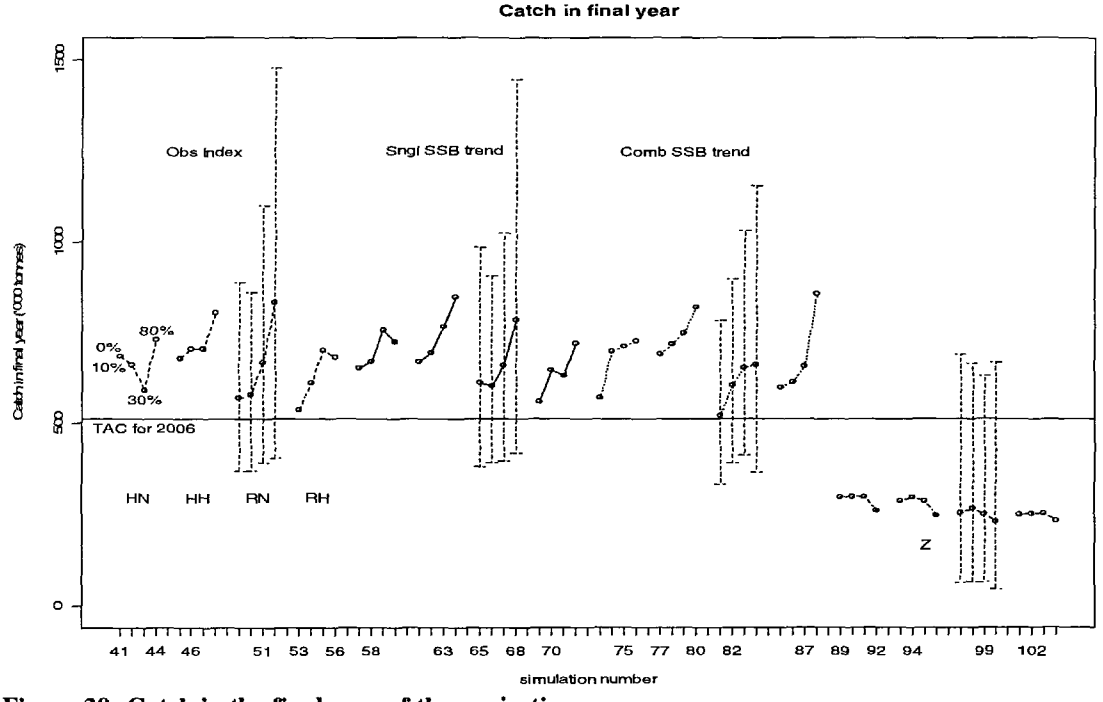


Figure 39: Catch in the final year of the projection.
Each point corresponds to a simulation: cases 41 to 104 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the stock-recruitment relationship / autocorrelation options: HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation. Dashed vertical lines correspond to the 95% confidence interval.

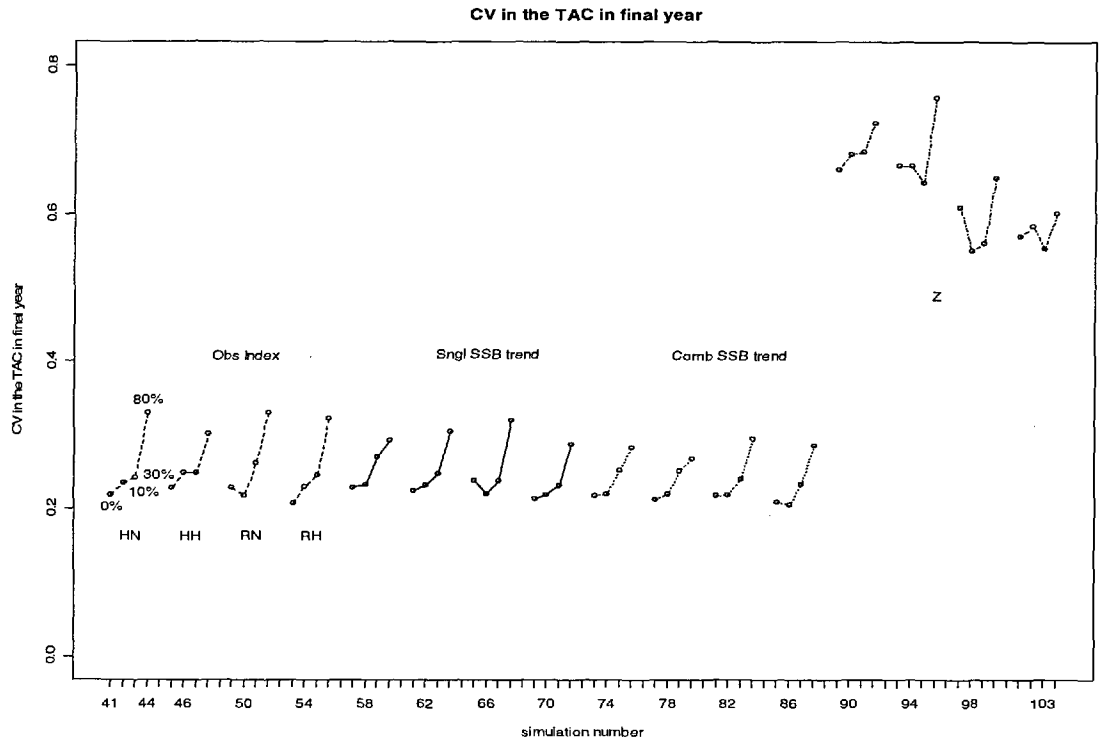


Figure 40: Coefficient of variation in the TAC in the final year of the projection.
Each point corresponds to a simulation: cases 41 to 104 in Appendix 5. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the stock-recruitment relationship / autocorrelation options: HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation.

Once again, the results from HCRs based directly on observations or on spawning stock-biomass trends and on total mortality remain different, whatever the level of under-reporting. On average, the biomass estimated after 20 years with a rule based on total mortality is almost the double of the one estimated with a rule based on direct observations or SSB trends, due once again to the introduction of observation error and the Z-based HCR.

When the level of under-reporting increases, the final spawning stock-biomass decreases sharply with rules based on observations or biomass but, compared with the first rules, does not vary significantly with the rule based on total mortality. This can be explained by the reactivity of the Z-based HCR. The high number of fish removed from the stock due to the under-reporting is reflected in the Z estimate, and compensated for in the rule by the very low TAC estimate, the latter causing an increase of the spawning-stock biomass. This means that the HCR based on total mortality seems to be more robust to a variation in the potential implementation error - although it produces a much reduced total catch. Furthermore, an SSB index is average over many cohorts and will never be able to detect declines as fast as the Z-based HCR.

Another interesting feature is that despite the absence of implementation error, the final biomass is lower if the stock follows a Ricker stock-recruit model instead of a hockey-stick model. This difference appears to be reduced under conditions of high levels of under-reporting. Also, as previously noted, the Z-based HCR does not seem to be robust to different stock-recruitment relationships. This might be attributed to increased changes in recruitment with the Ricker model – these changes in recruitment will result in changes in the $Z_{0:1}$ and $Z_{2:6}$ values which then have a direct influence on the TAC via the HCR. In this set of simulations, a change of the level of autocorrelation in the residuals of the recruitment does not seem to have any noticeable effect of the SSB after 20 years of projection.

Figure 38 shows that the 95% confidence intervals for each HCR seems to be quite similar. Also, an increase in the level of implementation error does not seem to have an effect on the confidence interval.

When the level of under-reporting increases, the probability of being below B_{lim} at least once in the projection increases (from 0% without under-reporting to 0.734 for the highest value with 80% under-reporting) for all control rules except Z (Appendix 6). As the level of under-reporting increases and the SSB in the last historical year is slightly below B_{PA}, the chances of reaching a value below B_{lim} becomes appreciable.
In the final year of projection, the probability of being below B_{lim} and B_{PA} is higher with HCRs based on direct observations and on relative SSB trends as the spawning-stock biomass in the final year is much smaller than with a Z-based HCR (Figure 38).

Rules based on observations or SSB project a total catch at the end of the simulation of between 521 and 857 thousand tonnes (mean = 679 thousand tonnes, CV = 0.12) while the Z-based rule of between 230 and 299 thousand tonnes (mean = 266 thousand tonnes, CV = 0.09). Although this is much lower than the other rules, it is more robust to changes in the level of under-reporting.

It can be observed on Figure 39 that the size of the confidence intervals are relatively similar between HCRs but contrary to the spawning-stock biomass, an increase in the level of implementation error has a noticeable effect on the spread of the interval. For a very high level of misreported catch, the confidence interval is much larger than with ideal implementation. Furthermore, it was observed on Figure 38 that the spread was

larger below the median when the Z-based HCR was considered. It is not the case with the catch. This might be due to the boundary imposed by the model which allocates a zero value to any total mortality estimated as negative.

Under-reporting has an opposite effect on total catch and CV of the TAC to its effect on SSB. Values of CV for the Z-based rule are more than the double of those for the other rules. In the same way as previously, this rule violates some of the industry preferred limitations on variation in inter-annual TAC - although it performs better than the others with respect to detecting stock declines and acting to prevent them.

5.3.3 SENSITIVITY ANALYSIS

This section briefly describes the results obtained for the sensitivity analysis. As was explained in chapter 2 – sections 2.3.1 and 2.3.3 – the way the maturity-at-age and catch weight-at-age are calculated is modified to check if the model is robust to those changes. Furthermore, the effect of the limitation of the variation of the quota is included (section 4.3.9) to test the effect on the final spawning-stock biomass and total catch and the robustness of the management procedures to such a limitation. The impact of the initial conditions is tested in the section 5.3.3.4 in order to see if the management procedures implemented in this work would lead the stock to a collapse.

Eight different management procedures are tested. For all of them, a Ricker stock-recruitment relationship is assumed with the estimated level of autocorrelation predicted by the stock-recruitment data. The Ricker model was chosen because during initial testing without exploitation, SSB reached equilibrium under a Ricker stock-recruitment model, but did not reach equilibrium with the hockey-stick model. The level of autocorrelation in the recruitment was kept at the level estimated in the previous analysis and the increase of level of autocorrelation did not seem to have any noticeable effect. Therefore it was considered appropriate to keep it at an estimated level. Two HCRs were analysed (one based on single SSB trends and one based on total mortality), only the acoustic survey is used. Four levels of misreporting are included in the analysis. The table that summaries the numerical results obtained can be found in the Appendix 6.

Results of the final year are analysed in each of the following sections. All graphs follow the same structure. On the left hand-side, the two lines correspond to the outputs using a single spawning-stock biomass trend as HCR and on the right hand-side, the rule based on total mortality rate. For each HCR, the four points linked on the left hand-side correspond to the output previously obtained and the four on the right to the output obtained with the new calculation. Each point linked corresponds to a level of under-reporting from 0 to 80% from the left to the right.

5.3.3.1 Maturity-at-age

In the previous sections, the maturity ogive applied for a particular year of the projection in the operating model was picked at random from the 1985-2006 series. In this section, a relationship between maturity-at-age and spawning-stock biomass is considered for the relevant ages (see equations 15 to 19). The results obtained for the management procedures considered in this sensitivity analysis can be found in Appendix 6 and Figure 41, Figure 42 and Figure 43. As the figures show, changing the operating model's maturity at age in the projection had a negligible effect on the results.

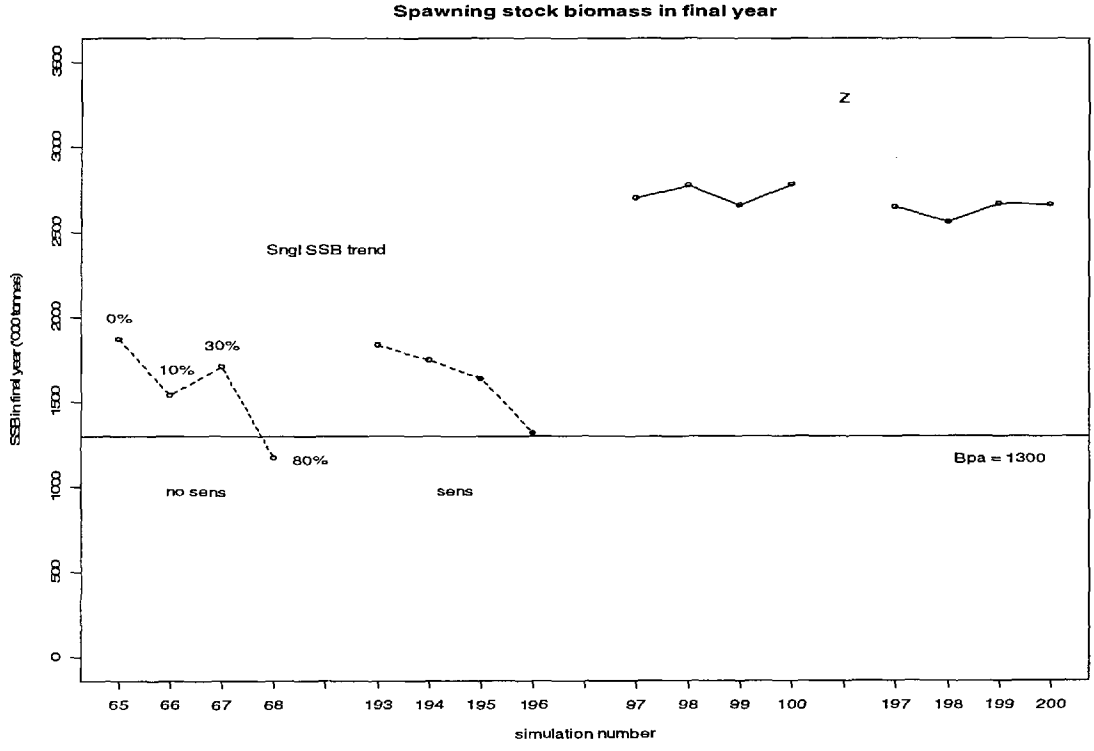


Figure 41: Spawning stock biomass in the final year of the projection.
Each point corresponds to a simulation: cases 65 to 68, 97 to 100 and 193 to 200 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the sensitivity analysis options.

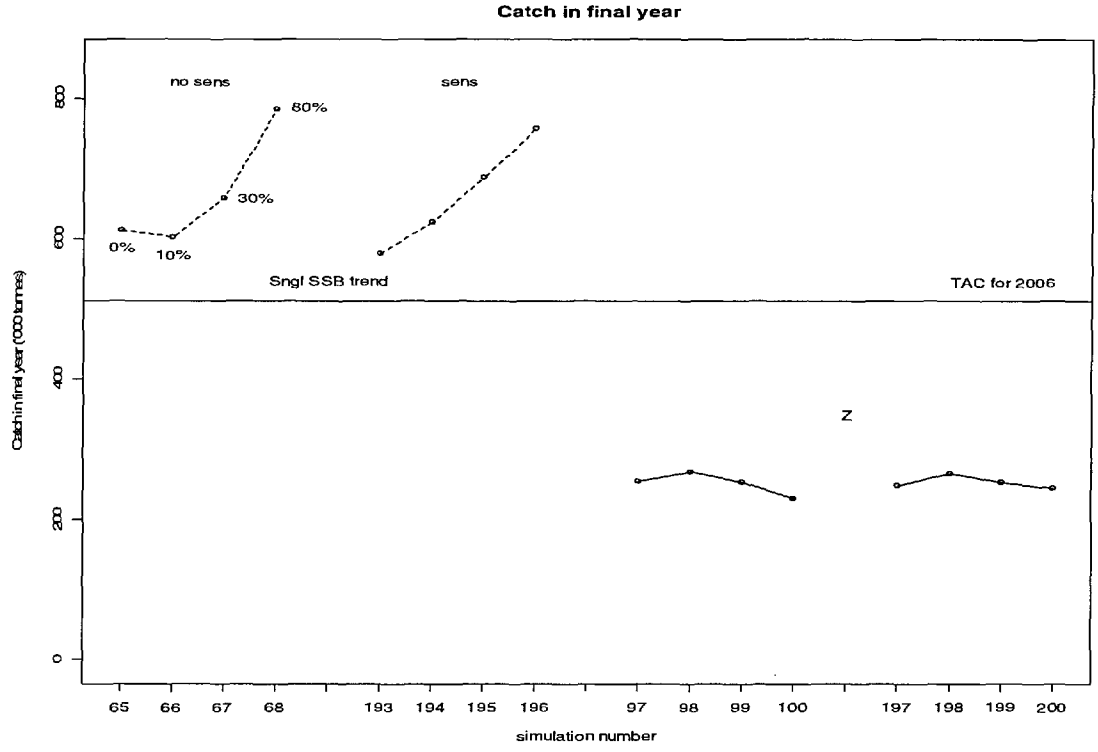


Figure 42: Catch in the final year of the projection.
Each point corresponds to a simulation: cases 65 to 68, 97 to 100 and 193 to 200 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the sensitivity analysis options.

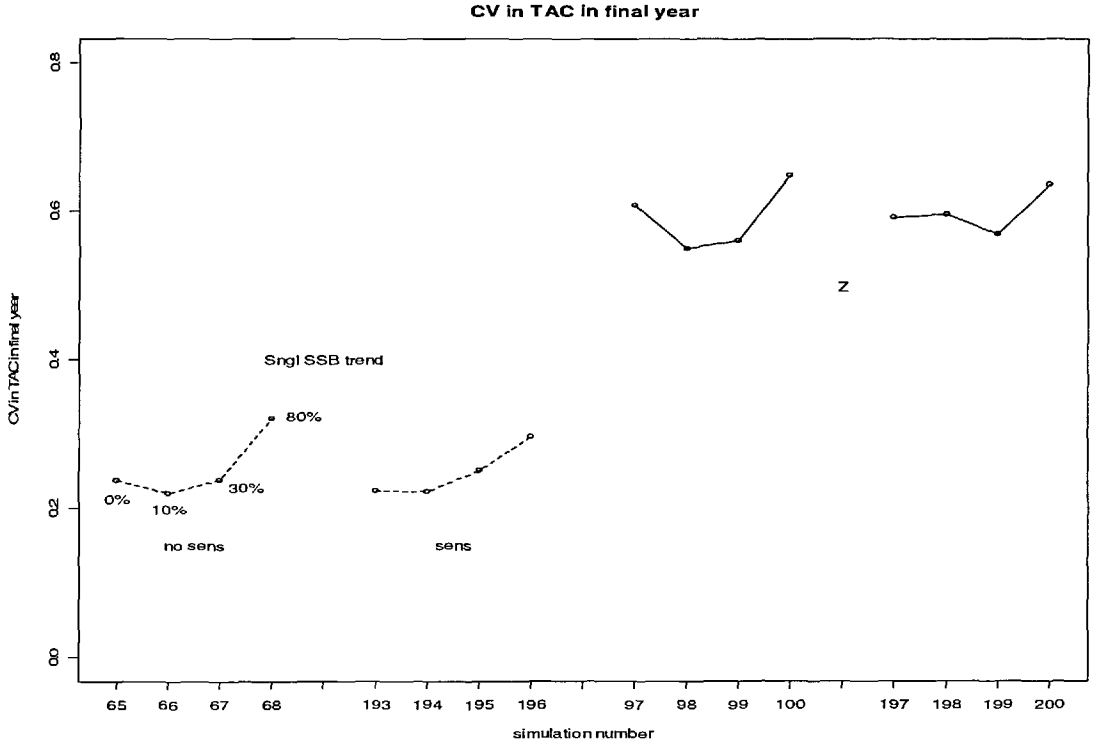


Figure 43: Coefficient of variation in the TAC in the final year of the projection.
Each point corresponds to a simulation: cases 65 to 68, 97 to 100 and 193 to 200 in Appendix 5. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the sensitivity analysis options.

5.3.3.2 Catch weight-at-age

The second point of this sensitivity analysis is the estimation of the weight-at-age in the catch. In the previous simulations, the weight was equal to the mean over historical years between 1983 and 2006 and the coefficient of variation was incorporated in the model. In the sensitivity analysis, a relationship with the spawning-stock biomass in considered, following the one defined in section 2.3.3 and more particularly in Table 5 and Table 6. In the same way as for the maturity-at-age sensitivity analysis, the results obtained for the management procedures can be found in Appendix 6 and Figure 44, Figure 45 and Figure 46. As the figures show, changing the operating model's weight at age in the projection had a negligible effect on the results.

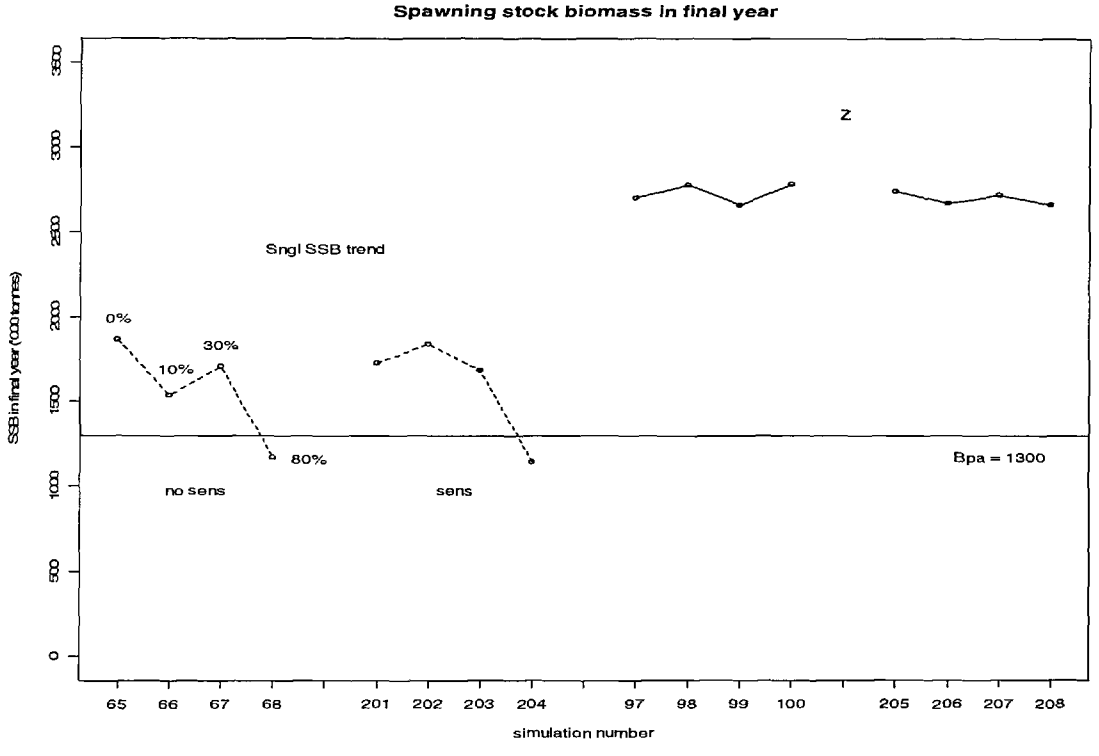


Figure 44: Spawning stock biomass in the final year of the projection.
Each point corresponds to a simulation: cases 65 to 68, 97 to 100 and 201 to 208 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the sensitivity analysis options.

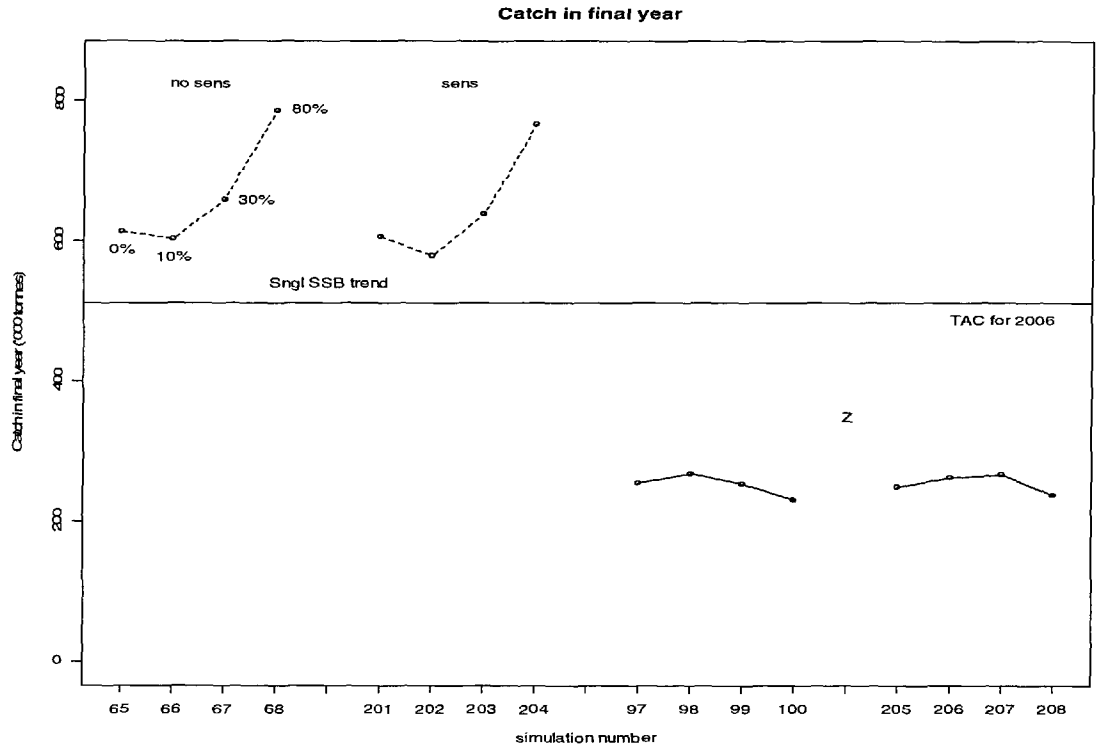


Figure 45: Catch in the final year of the projection.
Each point corresponds to a simulation: cases 65 to 68, 97 to 100 and 201 to 208 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the sensitivity analysis options.

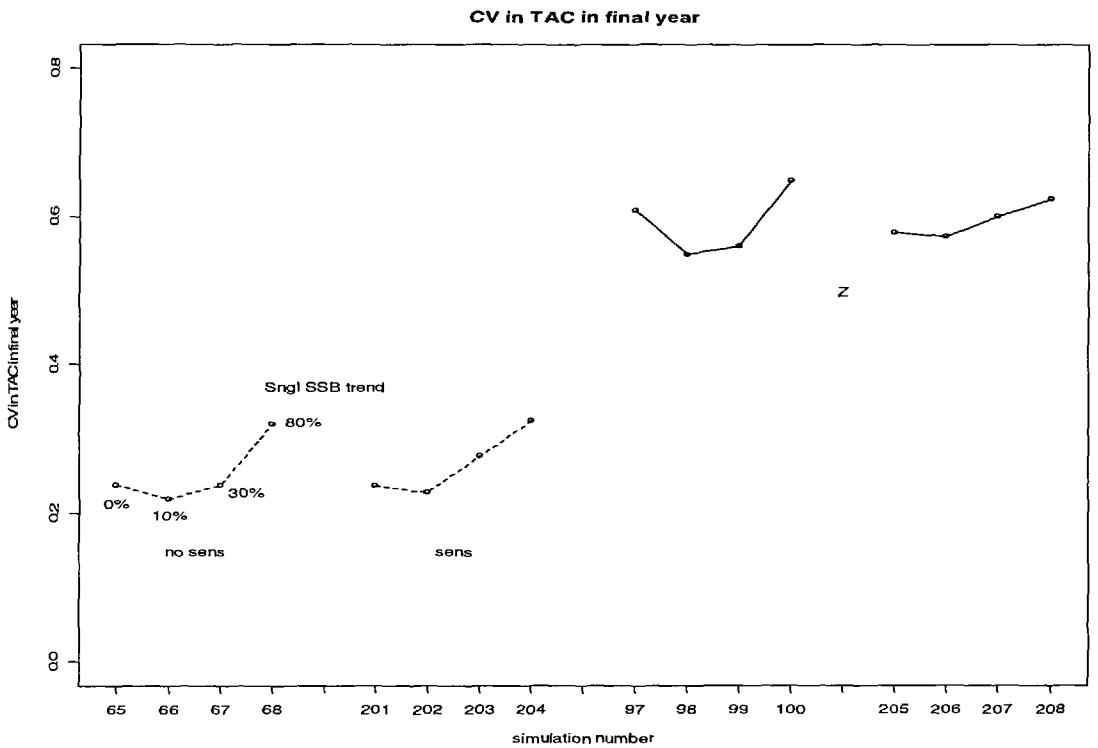


Figure 46: Coefficient of variation in the TAC in the final year of the projection.
Each point corresponds to a simulation: cases 65 to 68, 97 to 100 and 201 to 208 in Appendix 5. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the sensitivity analysis options.

5.3.3.3 Limitation of the variation of the quota

In the third section of the sensitivity analysis, the limitation of the variation of the quota by +/- 15% is tested. As mentioned in section 5.3, some specific scenarios are explained in order to analyse the behaviour of the stock and the fishery over time before an analysis of the results obtained at the end of the projection. They have been selected according to observed trends in the SSB and catch which are different to those presented at the beginning of section 5.3. One illustrates a different behaviour when a constraint in the TAC in considered in some management procedures. Its specific components can be found in Table 22.

Table 22: Selected scenario illustrating the effect of constraint on TAC for model-free management strategies.

	SR	Autocorr	Survey	HCR	Assess	Sensitivity	Misreport
Nb sim	Ricker	Est	Acoust	Sngl SSB Z	No	Lim quota Init cond	30%
211	√	√	√	√	√	√	√

The output of the simulation 211 can be observed on Figure 47. This type of output illustrates simulations 209 to 212 (Appendix 5) and corresponding to the combinations found in Table 23.

Table 23: Combinations of options illustrated by scenario 211.

Variable components	Options
Stock-recruitment relationship	Ricker
Autocorrelation in the recruitment	Estimated level
Survey	Acoustic
Observation error in the survey	Yes
Harvest control rule	Based on adjusted observation index
Assessment	None
Limitation in the variation of the quota	No
Misreporting	0% 30% 30% 80%

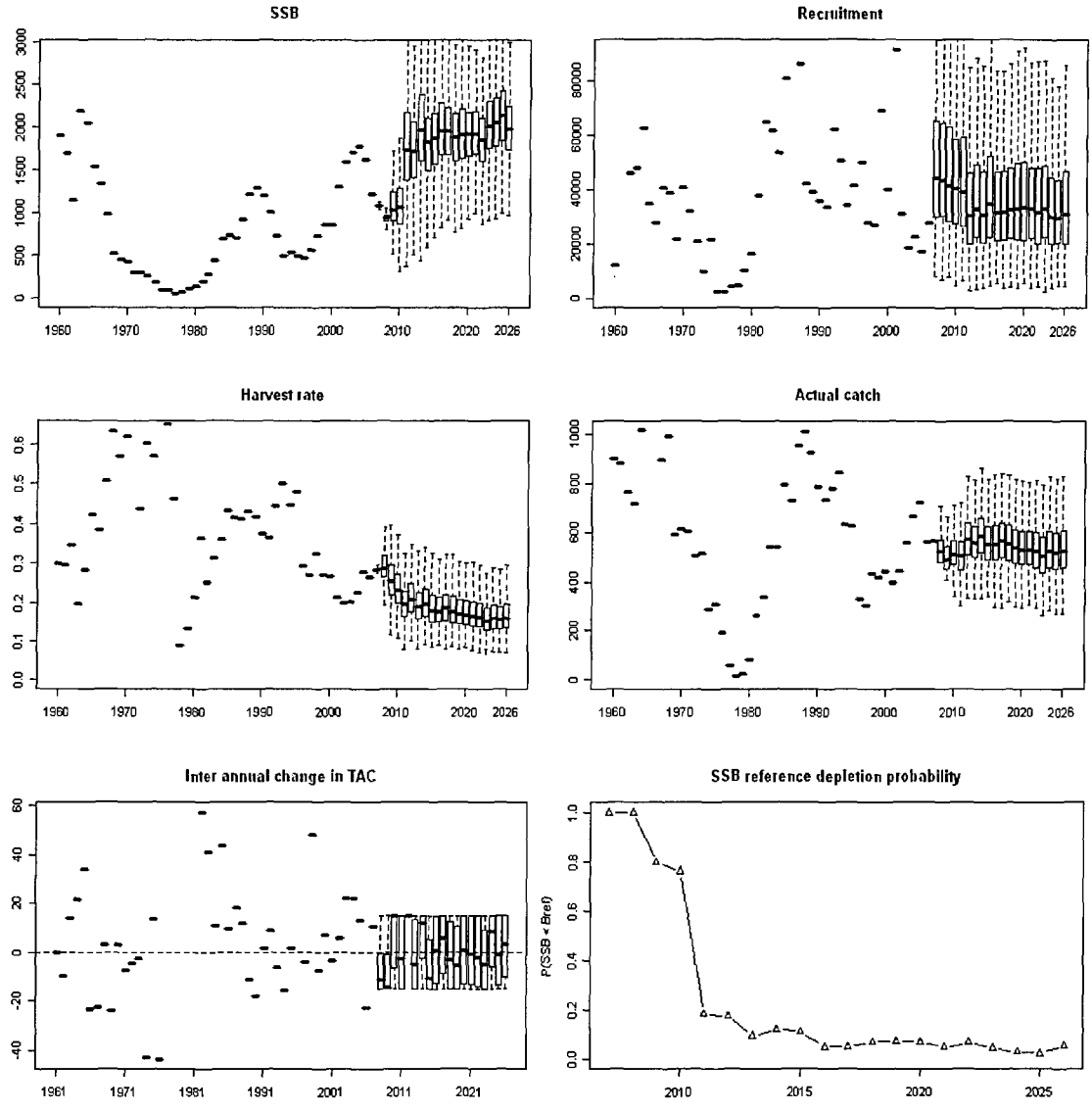


Figure 47: Output of simulation 211.
Stock recruitment: Ricker; autocorrelation: estimated; survey: acoustic with observation error; assessment: none; harvest control rule: Sngl SSB; limitation of variation: yes; implementation error: 30%

This scenario is the same as the first one presented (section 5.3, simulation 67, Figure 28), except that the quota cannot vary by more than 15% from one year to the subsequent. As can be observed in the figure, the SSB increases for the entire span of the projection which was not the case in the Figure 28. Also catches do not increase as much as they did in the Figure 28. This is due to the limitation in the variation of the TAC. Indeed the latter is bounded. This implies that the set TAC cannot be adapted to the real state of the stock. The higher bound can set a TAC too small for the SSB which will tend to increase the SSB to a level that could be more fished. Alternatively, the lower bound can set a TAC insufficiently low enough to protect the stock against significant levels of fishing pressure which could lead to a decline in the stock. It is apparent that catch decreases while the SSB increases. This could be explained by the

fact that there is an initial increase in catch as SSB increases, but it is not particularly high, and certainly not high enough (because of the TAC constraint) to stop SSB from increasing too high and triggering the reduction in recruitment from the Ricker, so that when catches finally reach a high level they encounter a declining recruitment and are necessarily decreased. Another important element to notice is that the limitation of TAC results in wild fluctuations between +/- 15% in the annual TAC - which is clearly unstable behaviour.

Similarly to previous sections, the results obtained in the final year of the projection are plotted and analysed. The scenarios compared in the figures are listed in Table 24.

Table 24: Scenarios used to evaluate the effect of constraint in the TAC on management strategies.

		SR	Aut	Obs error	Survey	HCR		Assess	Misreporting				Constraint	
		Ricker	Est	Yes	Acoustic	Sngl SSB	Z	No	No	10%	30%	80	No	Yes
Simulation numbers	65	√	√	√	√	√		√	√				√	
	66	√	√	√	√	√		√		√			√	
	67	√	√	√	√	√		√			√		√	
	68	√	√	√	√	√		√				√	√	
	209	√	√	√	√	√		√	√					√
	210	√	√	√	√	√		√		√				√
	211	√	√	√	√	√		√			√			√
	212	√	√	√	√	√		√				√		√
	97	√	√	√	√		√	√	√				√	
	98	√	√	√	√		√	√		√			√	
	99	√	√	√	√		√	√			√		√	
	100	√	√	√	√		√	√				√	√	
	213	√	√	√	√		√	√	√					√
	214	√	√	√	√		√	√		√				√
	215	√	√	√	√		√	√			√			√
	216	√	√	√	√		√	√				√		√

Figure 48 shows the spawning-stock biomass obtained after the 20 years of projection, Figure 49 the catch and Figure 50 the coefficient of variation in the TAC.

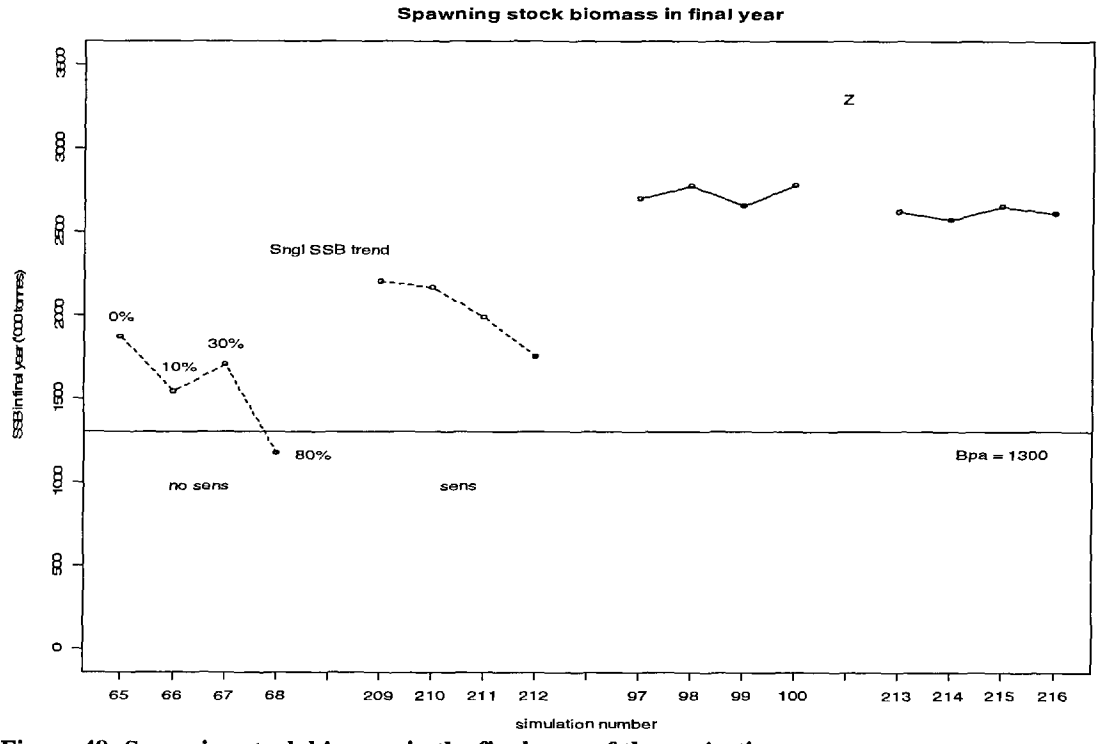


Figure 48: Spawning stock biomass in the final year of the projection.
Each point corresponds to a simulation: cases 65 to 68, 97 to 100 and 209 to 216 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the sensitivity analysis options.

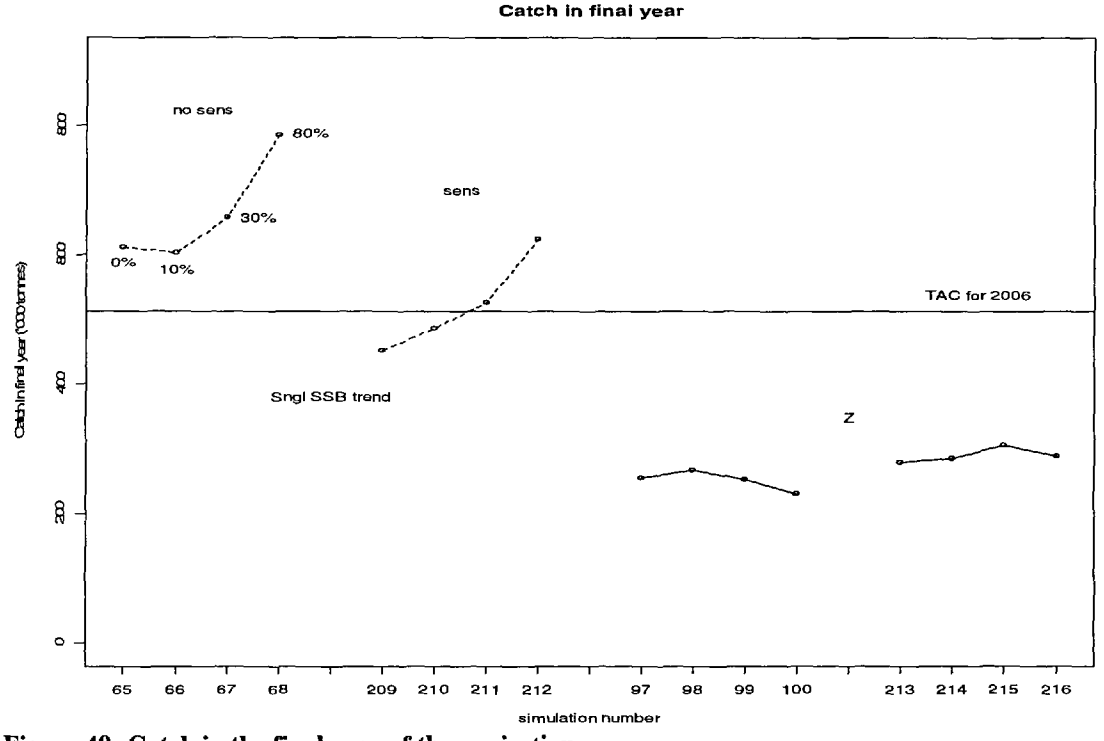


Figure 49: Catch in the final year of the projection.
Each point corresponds to a simulation: cases 65 to 68, 97 to 100 and 209 to 216 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the sensitivity analysis options.

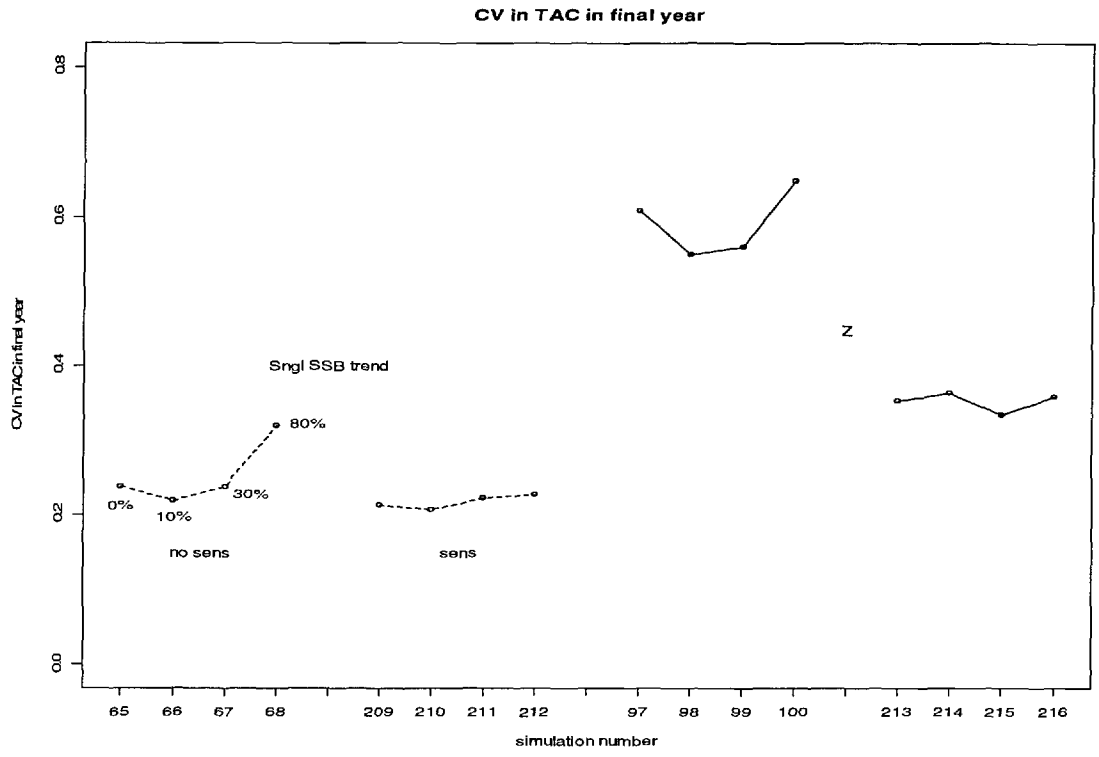


Figure 50: Coefficient of variation in the TAC in the final year of the projection.
Each point corresponds to a simulation: cases 65 to 68, 97 to 100 and 209 to 216 in Appendix 5. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the sensitivity analysis options.

It can be observed in Figure 48 that the limitation of the variation of the quota has a noticeable effect on the spawning-stock biomass at the end of the 20 years of projection. When the HCR used is based on a single spawning-stock biomass trend, values of spawning-stock biomass are higher when the limitation is considered. In fact, when the stock is in relatively good condition, as is the case with the North Sea herring stock, a positive limitation in the variation of the quota can lead to an increase of the spawning-stock biomass which is not compensated by the catch removal. In fact, if the biomass is high, the calculation of the TAC would suggest high removals but the later are limited to a maximum increase of 15%.

On the other side, when a Z-based HCR is utilised in the management procedure, it has the opposite effect. An increase in the level of under-reporting tends to further reduce the TAC in order to compensate for the effects of this increase in fishing pressure. When the variation of the TAC is not limited, it is free to decrease significantly. With the limitation, the rate of decrease in TAC in each year is constrained. In this case, the level of removal can be sufficiently high to decrease the final spawning-stock biomass

when a management procedure not including this limitation would lead to an important decrease of the catch and as a result an increase in the biomass.

As the spawning-stock biomass decreases with the increase in the level of under-reporting when the HCR is based on a spawning-stock biomass trend, the catch increases. That is observed in Figure 49. In Figure 48, the spawning-stock biomass is higher when the limitation is considered which implies that catch will be smaller under this condition (Figure 48). When the rule is based on total mortality, the biomass is quite constant over the levels of implementation error and the catch also tends to stay constant. The effect of the consideration of the limitation in the variation in the quota is more important with the first type of HCR than with the second one.

The final figure of the sensitivity analysis shows the coefficient of variation in the TAC in the final year of the projection. With both HCRs, the coefficient is smaller when the limitation is taken into consideration. This is not surprising considering that is precisely what the limitation is supposed to achieve. This implies that in the absence of limitation, the coefficient of variation can be higher which may make the management procedures less attractive to industry stakeholders. However, it can be observed that the limitation does not have a huge impact on the final catch values for those management procedures.

5.3.3.4 Low biomass as initial conditions

As explained in the section 2.3.8, the initial conditions of the model are relatively good. In order to test the behaviour of the model, I have decided to use the abundant historical data to 1996, when the spawning stock biomass was at the lowest during the second decline of the stock, and then project into the future. It was not realistic to use the historical data prior to 1977, when the stock was close to a collapse, as all the biological data until that year were relatively unreliable.

For this sensitivity analysis, only 4 simulations have been run. The structure of the management procedure is the same as for the previous sensitivity analyses except that only two levels of misreporting have been tested: 0 and 30 %. This is due to the fact that even if fishermen could potentially misreport, this level of misreporting is considered

appropriate even when the stock is known as being in bad condition as was the case in 1996 as the stock was well below B_{lim}.

The evolution over time of two of the four simulations is explained and is followed by an analysis of the results in the final year for the 4 scenarios. The two cases explained correspond to the simulations listed in Table 25.

Table 25: Selected scenario illustrating the evolution of the stock when initial conditions are bad.

	SR	Autocorr	Survey	HCR		Assess	Sens	Limit quota	Misreport
Nb sim	Ricker	Est	Acoust	SnglSSB	Z	No	Init cond	No	30%
218	√	√	√	√		√	√	√	√
220	√	√	√		√	√	√	√	√

Each scenario illustrates simulations with identical options for the two levels of misreporting: 0 and 30%. The output of the simulation 218 can be observed on Figure 51. This type of output illustrates simulations 217 and 218 (Appendix 5). The output of the simulation 220 can be observed on Figure 52. This type of output illustrates simulations 219 and 220 (Appendix 5).

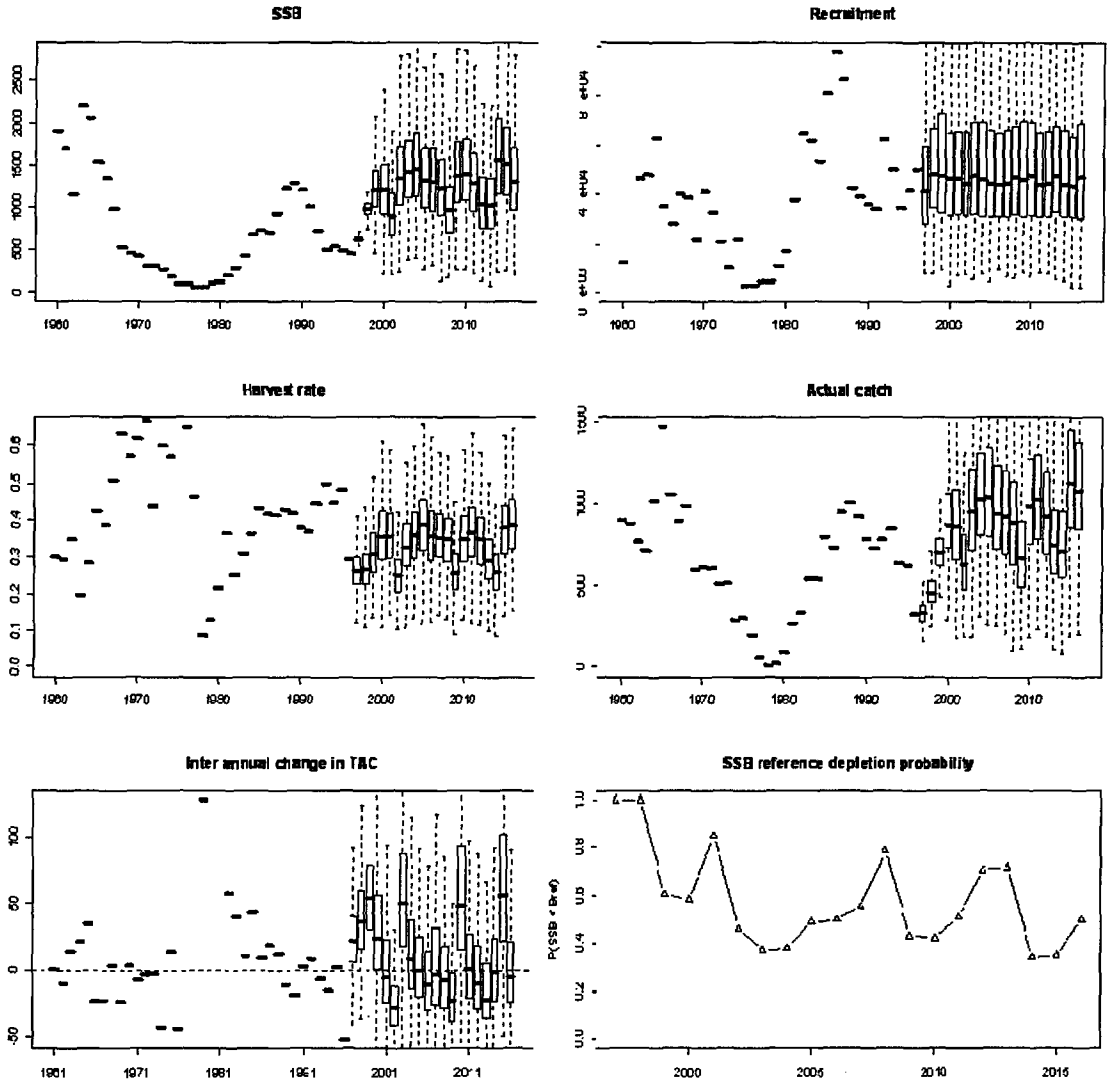


Figure 51: Output of simulation 218.
Stock recruitment: Ricker; autocorrelation: estimated; survey: acoustic with observation error; assessment: none; harvest control rule: Singl SSB; limitation of variation: no; implementation error: 30%.

It is possible to notice in Figure 51 that variables, apart from the recruitment, are quite variable over time compared to what has been observed in previous figures. This variability could be attributed either to a cycling behaviour that is common in Ricker models or by the fact that the biological data used in the model are more guessed values rather than estimated values. This implies that values used might not represent accurately the real stock and as a consequence include bias in the model. The trends observed are relatively similar to the one seen in similar scenarios, i.e. simulation 67 (section 5.3).

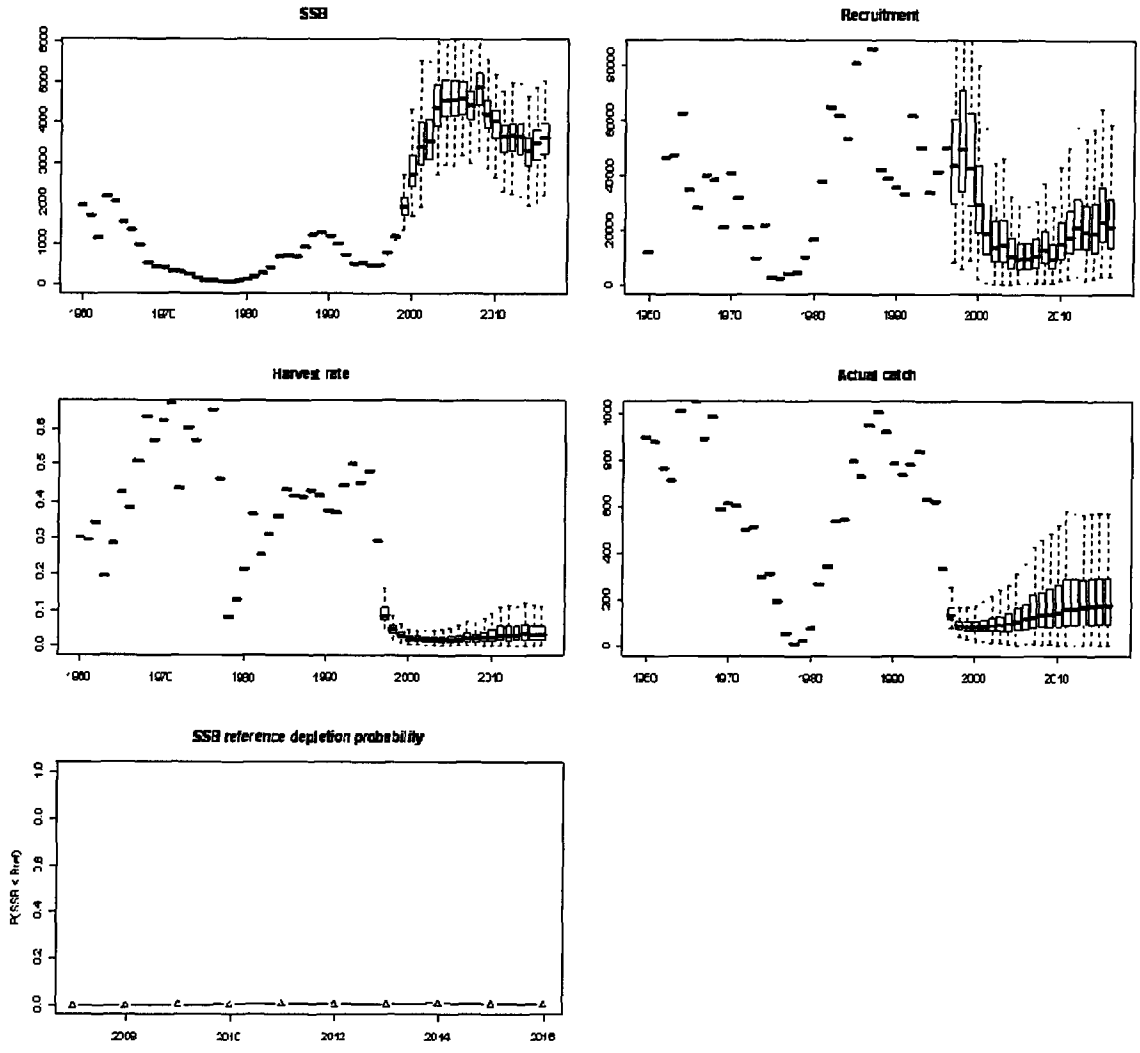


Figure 52: Output of simulation 220.
Stock recruitment: Ricker; autocorrelation: estimated; survey: acoustic with observation error; assessment: none; harvest control rule: Z; limitation of variation: no; implementation error: 30%.

The final figure used to describe behaviour of the fishery over time without assessment method shows an intense and rapid increase of the SSB during the first half of the projection. The marked increase of the SSB can be explained by the nature of the harvest control rule. Indeed, Z acts on Z-values by reacting to the higher values of Z given low stock levels and catches thereby increasing the SSB. As a consequence of the assumed stock-recruitment relationship, the recruitment falls in the first part of the projection due to the high level of the SSB. The catch being reduced intensely by the harvest control rule and the recruitment being low, the SSB finally reach a maximum and decreases in the second part of the projection. As the SSB falls below the inflection point the Ricker stock-recruitment relationship, the recruitment can increase. Furthermore, catch can be slowly increased. The increase of the recruitment in the second half of the projection and the still small catch values, the SSB increases in the last two years of the projection.

As for all sections of this chapter, an analysis of the output in the final year of the projection is provided. The scenarios compared in the figures are listed in.

Table 26: Scenarios used to evaluate the effect of starting in bad conditions.

		SR	Aut	Obs error	Survey	HCR		Assess	Misreport		Initial conditions		Constraint
		Ricker	Est	Yes	Acoustic	Sngl SSB	Z	No	0%	30%			No
Simulation numbers	65	√	√	√	√	√		√	√		√		√
	67	√	√	√	√	√		√		√	√		√
	217	√	√	√	√	√		√	√			√	√
	218	√	√	√	√	√		√		√		√	√
	97	√	√	√	√		√	√	√		√		√
	99	√	√	√	√		√	√		√	√		√
	219	√	√	√	√		√	√	√			√	√
	220	√	√	√	√		√	√		√		√	√

Figure 53 shows the spawning-stock biomass obtained after the 20 years of projection, Figure 54 the catch and Figure 55 the coefficient of variation in the TAC.

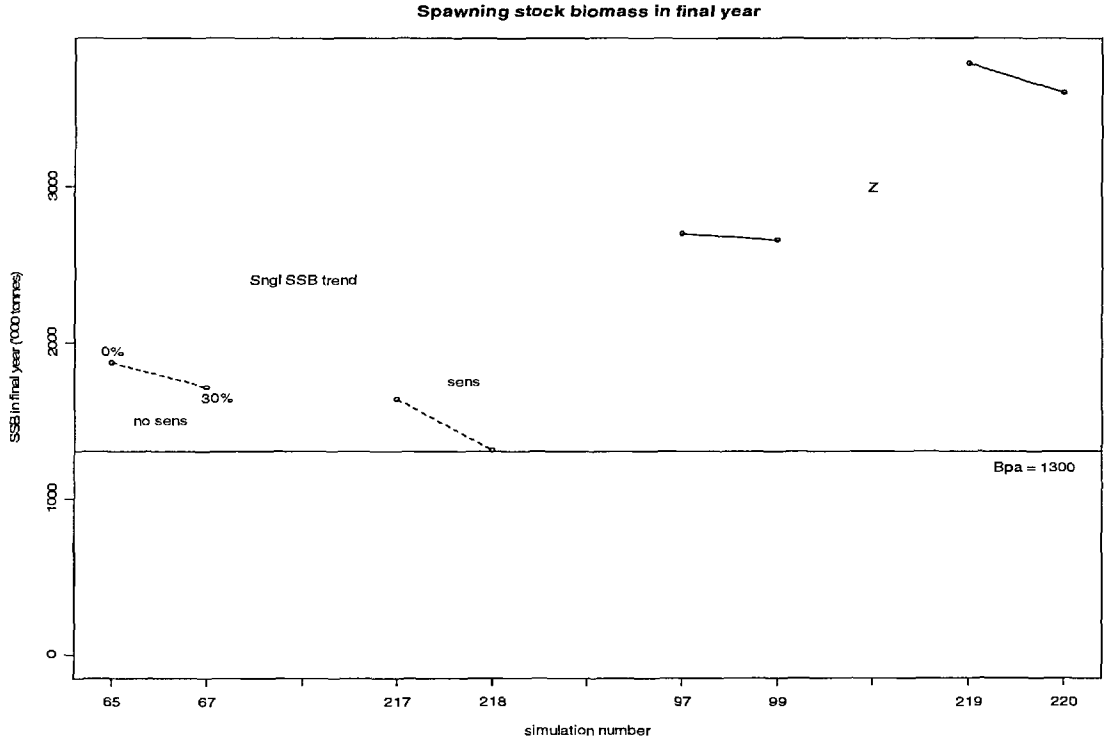


Figure 53: Spawning stock biomass in the final year of the projection.
Each point corresponds to a simulation: cases 65, 67, 97, 99 and 217 to 220 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the sensitivity analysis options.

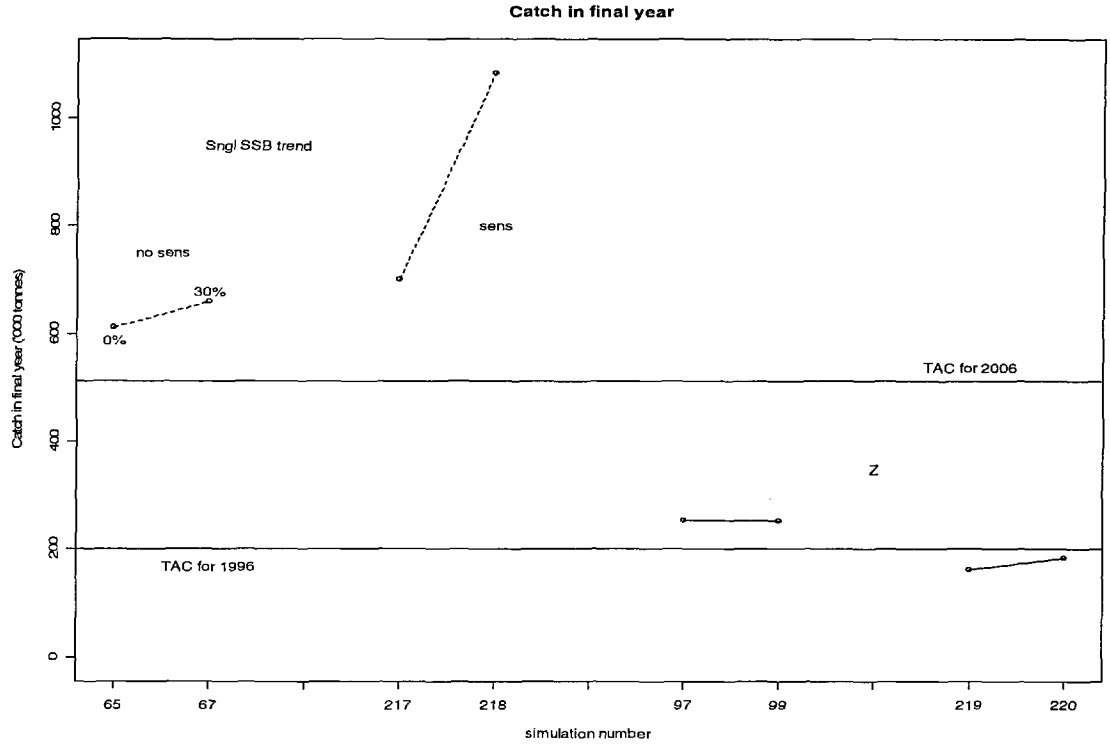


Figure 54: Catch in the final year of the projection.
Each point corresponds to a simulation: cases 65, 67, 97, 99 and 217 to 220 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the sensitivity analysis options.

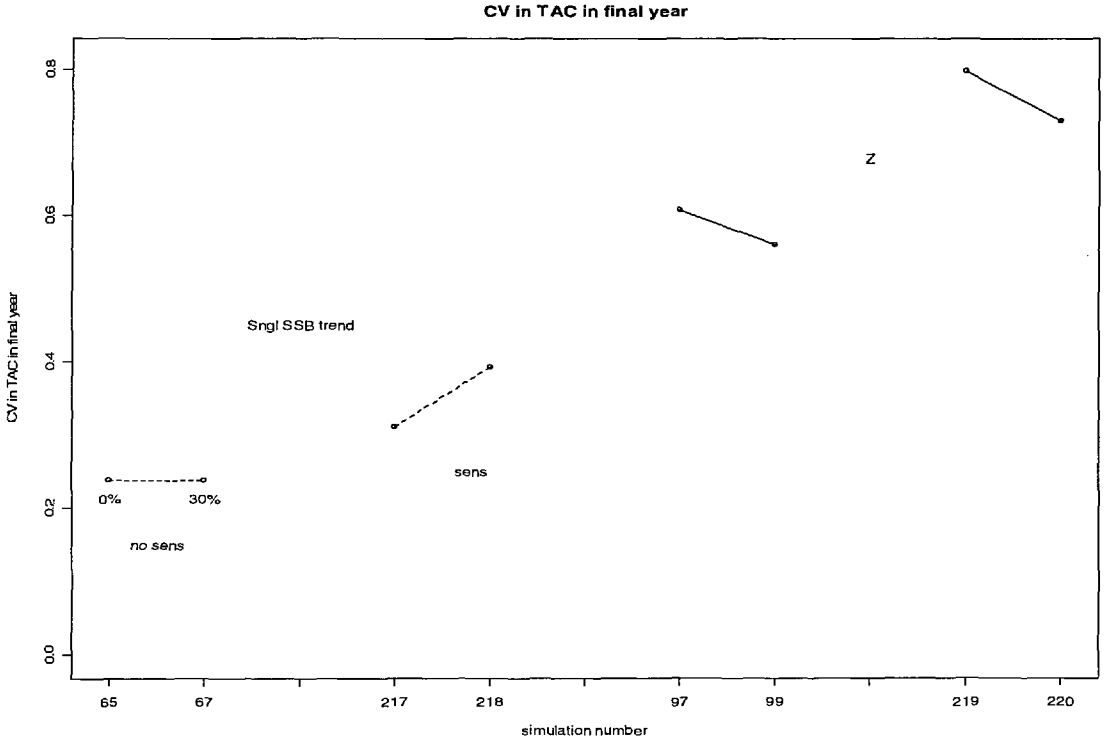


Figure 55: Coefficient of variation in the TAC in the final year of the projection.
Each point corresponds to a simulation: cases 65, 67, 97, 99 and 217 to 220 in Appendix 5. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the sensitivity analysis options.

It can be easily seen in Figure 53 that the consideration of low initial conditions does not have such an important impact of the final state of the stock, particularly when the level of misreporting is increased until a reasonable level. When considering a harvest control rule based on single SSB trend and regardless of the level of misreporting, the final stock biomass is not very different whatever the initial conditions were, and in both cases, the biomass is above B_{PA} after 20 years of projection. As expected, an increase of the level of misreporting implies a decrease of the final biomass. It can be observed that with 30% of misreporting, the final SSB is just above B_{PA}. A larger level of misreporting would lead to a biomass smaller than B_{PA} and maybe smaller than B_{lim} in extreme cases. When the Z-based HCR is considered, the final levels of SSB are relatively different depending on the initial conditions, but do not vary so much with an increase in the level of misreporting. When initial conditions are bad, the conservative effect of the HCR is observable and the management procedure tends to recover the stock as soon as possible and the biomass reaches very high levels before declining to reach a stable level. According to the Figures 219 and 220 in the appendices, the stabilised levels are not yet reached and that could explain the particularly high level of SSB after the 20 years of projection. The equilibrium state could be reached in a reasonable number of years.

The Figure 54 shows that a higher level of misreporting has a very important effect of the final catch when the initial conditions are bad. This could be explained by the unstable state of the population that can be observed in the Figure 218 in the Appendix 7. In fact, the population has not reached the equilibrium state and shows variability in the results. If the projection had been stopped two years before, results would have been completely different. On the opposite, the use of a Z-based HCR does not provide very different catches after the 20 years of projection. In both initial conditions, the final catch is below the TAC set at the beginning of the projection but the difference between the final catch and the set TAC is relatively small when the initial conditions are bad (1996), while it is important when initial conditions are good (2006). This could mean that the stock is close to reach an equilibrium state, whatever the initial conditions were. It can be observed in Figure 55 that the CV in the TAC in the final year is always higher when initial conditions are bad. This can again be explained by the fact that as the stock starts at low level, its first aim is to recover and then balance between the mortality and recruitment.

5.4 Evaluation of the management strategy with assessment method

All simulations analysed up to this point are only based on fishery-independent data. In the next section, depending on the assessment methods utilised, fishery-independent or fishery-dependent data are used. The framework using assessment methods is necessarily more complex than the non-assessment methods.

5.4.1 EVALUATION OF THE ACTUAL MANAGEMENT

In this section, the actual management strategy described in section 4.3.1 and currently being used for North Sea herring was tested. The actual management being more complicated than simpler HCRs without assessment methods, the level of complexity in the MSE was higher than in the previous sections and only 100 Monte Carlo iterations were run for projections. The simulations have been initially run for 20 years but it was observed in some circumstances that the model crashed before reaching the end of the projection. This is was particularly the case with high levels of misreporting (30-80%). The problem with high levels of misreporting is that, with increasing numbers of iterations, it can lead to the disappearance of a cohort when the catch taken can exceed population size. This disappearance then implies an infinite value of fishing mortality which causes ICA to crash given that it works using fishing mortality. As a consequence, I have decided to run the simulations over only 15 years. This does not compromise the quality of the results obtained. Indeed, it is not the quality of the assessment which is the problem but the way the FLR code manages a null harvest rate. Furthermore, three simulations at very high levels of implementation error (80%) created stock collapses and a failure of FLICA very early in the projection; these results could therefore not be included.

This section contains two sub-sections. The first one analyses the effect of limiting the inter-annual variability in the TAC without implementation error. The second describes results obtained without such limitation but under the three levels of implementation error already used previously.

For both stock-recruitment relationships, both levels of autocorrelation in the recruitment and for all levels of misreporting, when available, the trends in the evolution of the stock and the fishery over time are similar and can be observed in Figure 56. It is possible to notice that the SSB increases from the beginning of the projection while the catch start by decreasing and then increase. As the SSB is below B_{PA} in the final historical year, the harvest control rule set a TAC which will reduce catches such that the SSB will increase and reach B_{PA}. The inter-annual variability in the TAC is very high in the first years of the projection due to the intense decrease of the catch due to the fact that the SSB is below B_{PA} at the beginning of the projection. As the SSB is relatively stable over time after the initial increase, the recruitment follows that stability over time.

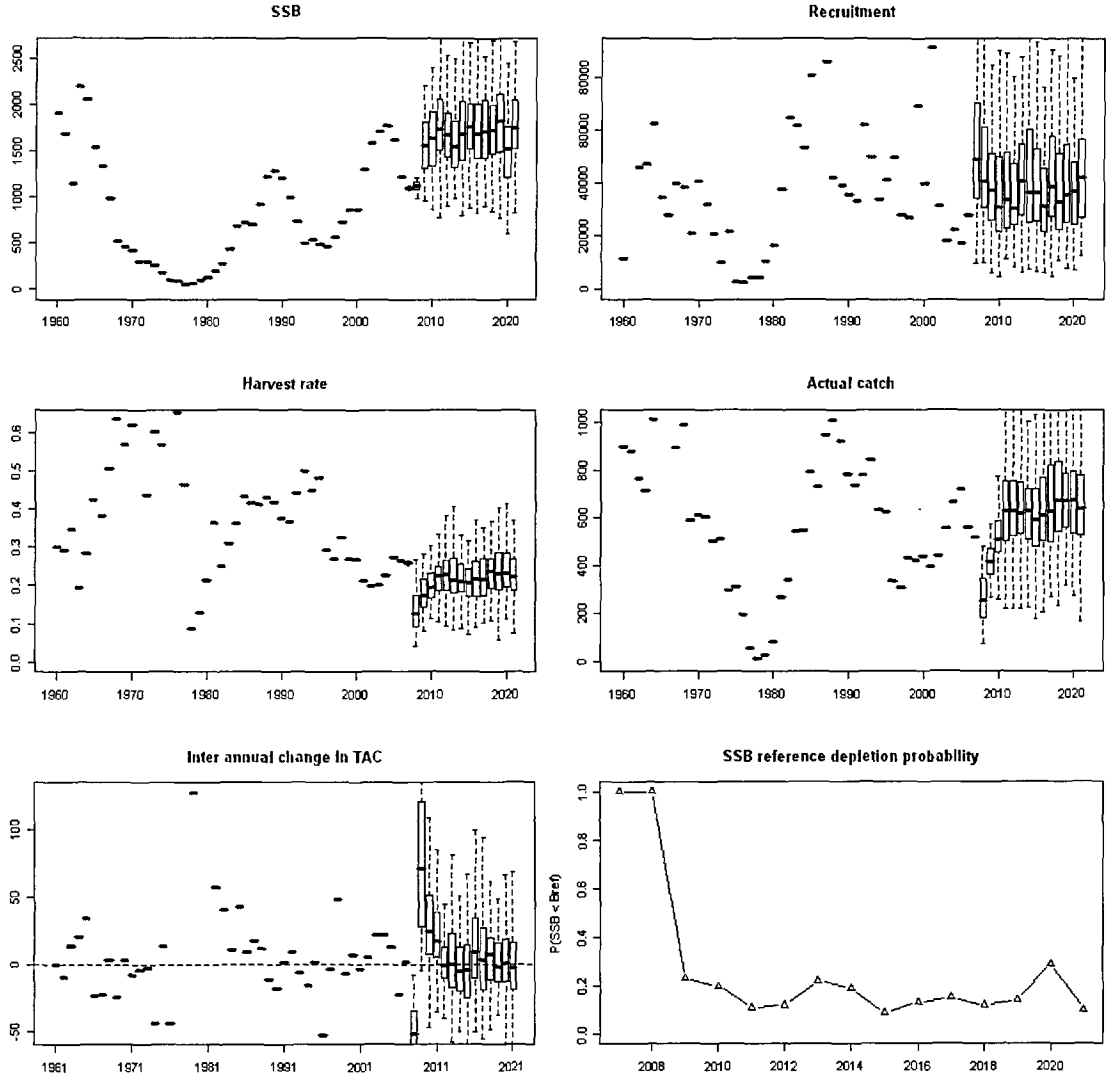


Figure 56: Output of simulation 123.
Stock recruitment: Ricker; autocorrelation: estimated; survey: all; assessment: ICA; harvest control rule: Actual management (F and reference points); limitation of variation: none; implementation error: 30%.

5.4.1.1 Evaluation of the management strategy with limitation of the inter-annual variation in the TAC

The limitation of the inter-annual variation in the TAC, as used in the actual management of the North Sea herring stock is tested here. Four scenarios that include the constraint have been considered and are compared in the following figures with their equivalent scenarios without the constraint. Figure 57 shows the SSB at the end of the 15 years of projection under the conditions of including or not a limitation in the inter-annual change in the TAC. Figure 58 shows the values obtained for the catch at the end of the projection and Figure 59 the coefficient of variation in the TAC in this final year.

The eight scenarios used to make the comparison are listed in Table 27.

Table 27: Scenarios used to evaluate the effect of limiting the inter-annual variation in the TAC.

		Simulations							
		105	106	107	108	109	110	111	112
SR	HS	√	√			√	√		
	Ricker			√	√			√	√
Autocorrelation	Est	√		√		√		√	
	High		√		√		√		√
Obs error	Yes	√	√	√	√	√	√	√	√
Survey	All	√	√	√	√	√	√	√	√
HCR	Actual	√	√	√	√	√	√	√	√
Assessment	ICA	√	√	√	√	√	√	√	√
Misreporting	0%	√	√	√	√	√	√	√	√
Constraint	No	√	√	√	√				
	Yes					√	√	√	√

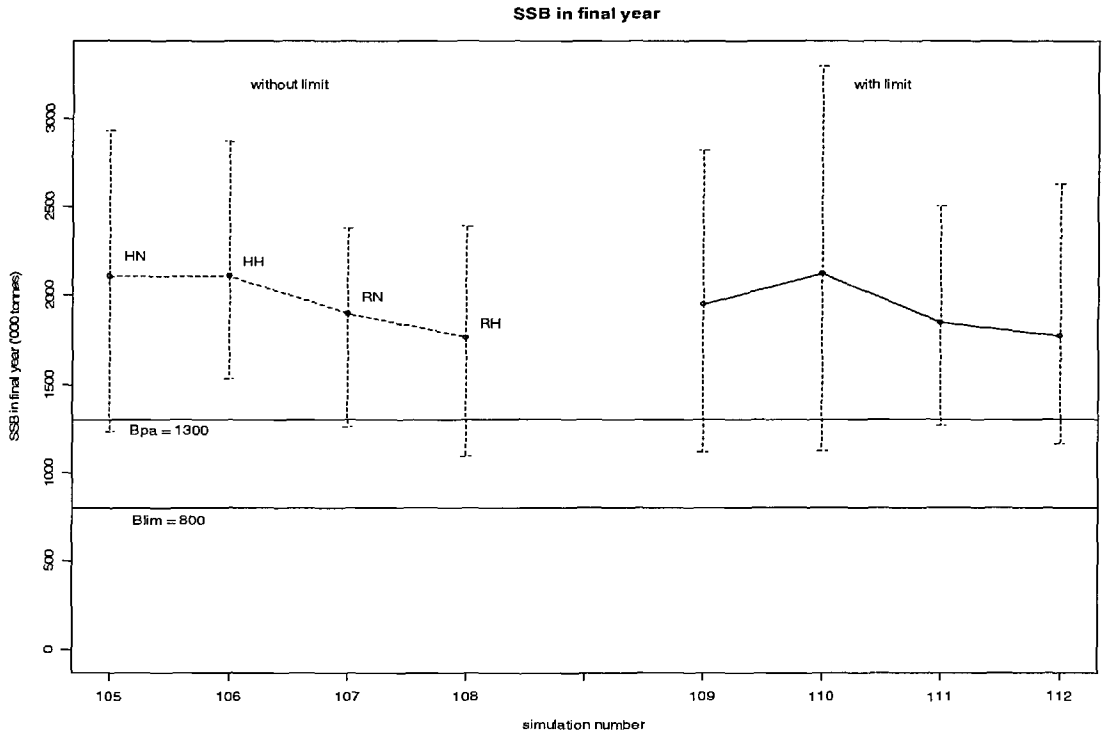


Figure 57: Spawning stock biomass in the final year of the projection.
Each point corresponds to a simulation: cases 105 to 112 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of stock-recruitment relationship / autocorrelation options: HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation. Each group corresponds to a management strategy.

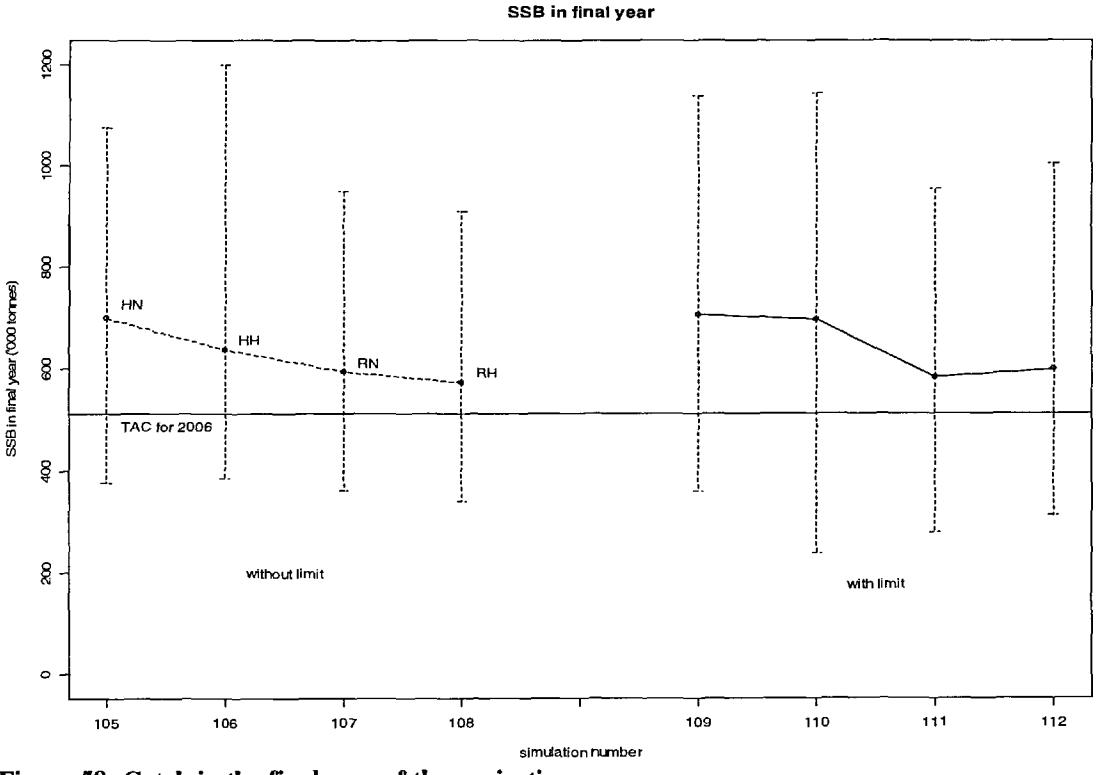


Figure 58: Catch in the final year of the projection.
Each point corresponds to a simulation: cases 105 to 112 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of stock-recruitment relationship / autocorrelation options: HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation. Each group corresponds to a management strategy.

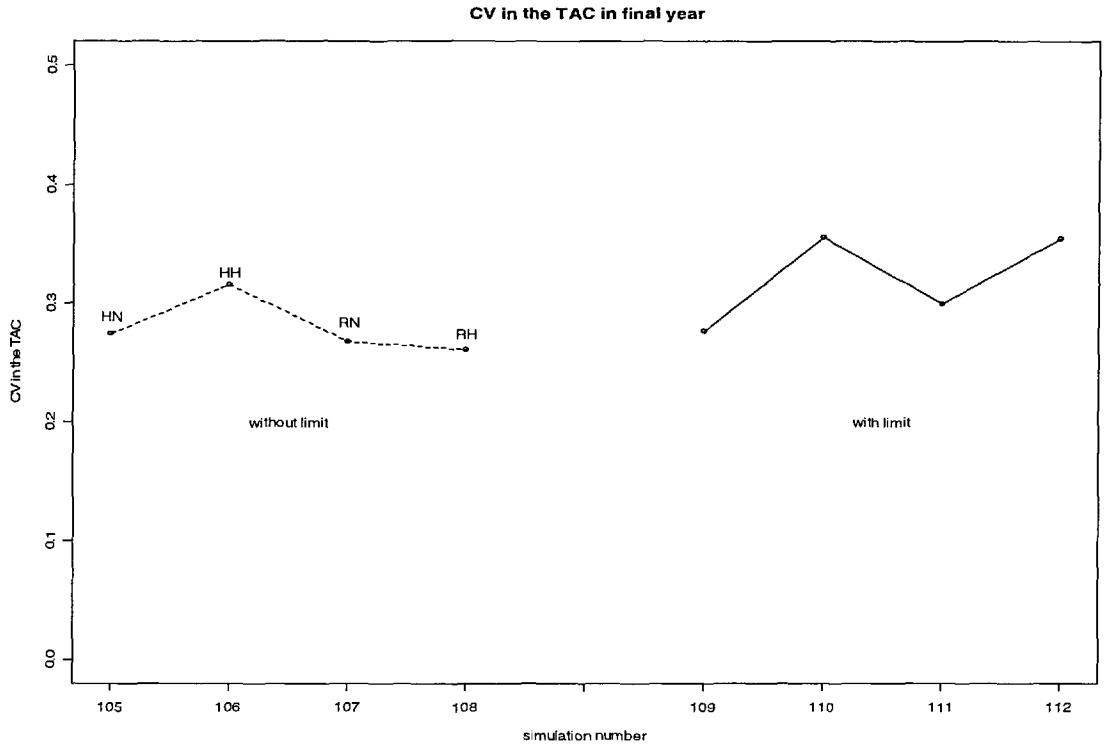


Figure 59: Coefficient of variation in the TAC in the final year of the projection.
Each point corresponds to a simulation: cases 105 to 112 in Appendix 5. Series are arranged in order of stock-recruitment relationship / autocorrelation options: HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation. Each group corresponds to a management strategy.

The HCR currently being used appears to perform equally well with or without the inter-annual TAC constraint. However, there is clearly more variability in TAC with the limitation in place, and this is also reflected in the probability of being below B_{lim} at least once in the projection, and of being below B_{lim} and B_{PA} in the final year, which are always higher with the potential limitation of the variation on the quota. Higher autocorrelation reduces the catch and generally increases the spawning biomass in these results.

The limitation of the variation of the quota does not seem to have a noticeable effect of the catch after 15 years of projection, except perhaps a slightly larger range of values between the use of a hockey-stick stock-recruitment relationship with an estimated level of autocorrelation and the use of the Ricker relationship with a higher level of autocorrelation (82 000 tonnes without limitation vs. 142 000 tonnes with limitation). But that is not what one would expect from the use of the limitation of the variation of the quota under certain conditions. In fact, the limitation should limit the increase or decrease of the catch if the stock was in a very good or bad condition. A very good condition would imply high catch but would be limited by the rule, which would imply

an even higher state of the stock later on. If the stock is in very bad condition, the TAC would be reduced quite a lot to avoid a collapse of the stock. A limitation of the reduction of the quota would lead to a fixed value for the catch (TAC – 15% TAC) if the TAC advised is below the 15% of variation. This would conduct to a collapse of the stock after a certain number of years if the management is not modified.

However in the present case, this difference of values between "without limitation" and "with limitation" means that the stock is in a reasonable state, this situation was apparent following the first tests conducted in this work. This also means that the actual management of the North Sea herring stock seems to be well adapted to the real situation.

In this section, it was possible to see that when there is no implementation error considered, the limitation of the variation of the quota does not have any effect on the final spawning-stock biomass or catch.

5.4.1.2 Evaluation of the management strategy with levels of under-reporting

This section analyses results obtained when using the actual management procedure, including the three levels of implementation error already described but without limitation of the variation of the TAC. The limitation was not taken into consideration for computing purposes.

The scenarios presented in the following figures are listed in Table 28.

Table 28: Scenarios used to evaluate the effect of misreporting on the actual management procedures.

		Simulations												
		113	114	115	116	117	118	119	121	122	123	125	126	127
SR	HS	√	√	√	√	√	√	√						
	Ricker								√	√	√	√	√	√
Autocorrelation	Est	√	√	√	√				√	√	√			
	High					√	√	√				√	√	√
Obs error	Yes	√	√	√	√	√	√	√	√	√	√	√	√	√
Survey	All	√	√	√	√	√	√	√	√	√	√	√	√	√
HCR	Actual	√	√	√	√	√	√	√	√	√	√	√	√	√
Assessment	ICA	√	√	√	√	√	√	√	√	√	√	√	√	√
Misreport	0%	√				√			√			√		
	10%		√				√			√			√	
	30%			√				√			√			√
	80%				√									
Constraint	No	√	√	√	√	√	√	√	√	√	√	√	√	√

The Figure 60 shows the values of the spawning-stock biomass obtained after 15 years of projection, the Figure 61 the final catch and Figure 62 the coefficient of variation in the TAC in the last year of the projection.

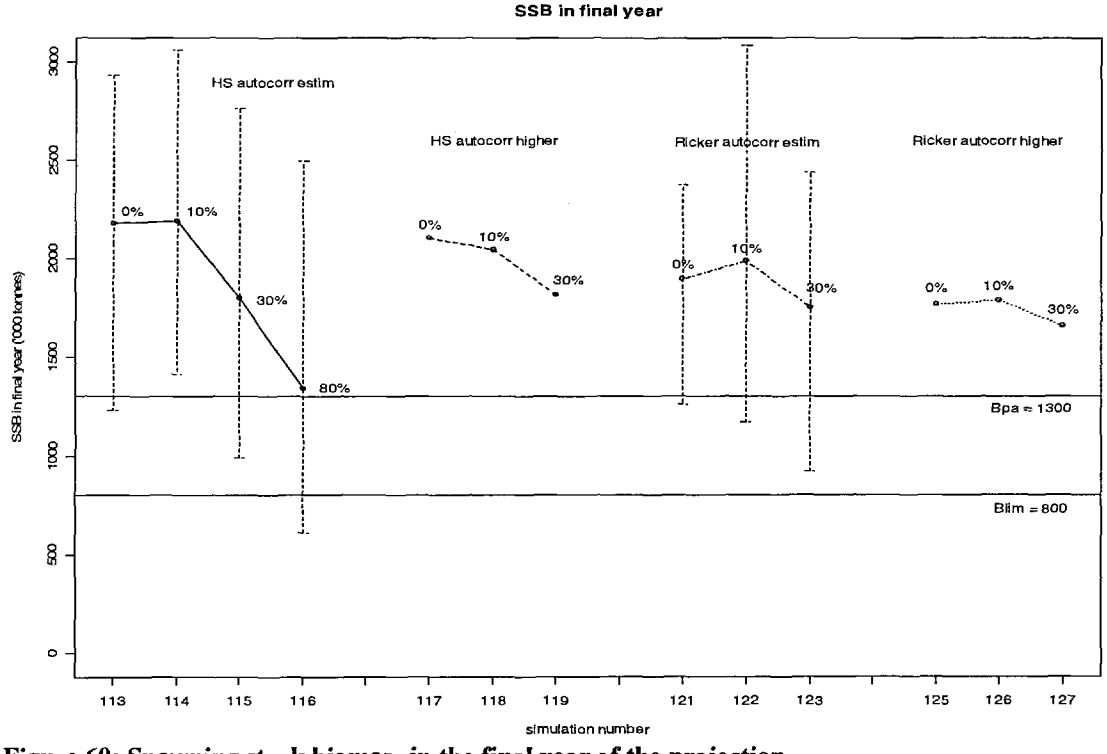


Figure 60: Spawning stock biomass in the final year of the projection.
Each point corresponds to a simulation: cases 113 to 128 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and each group correspond to the stock-recruitment relationship / autocorrelation options: HS = hockey stick. Dashed vertical lines correspond to 95% confidence interval.

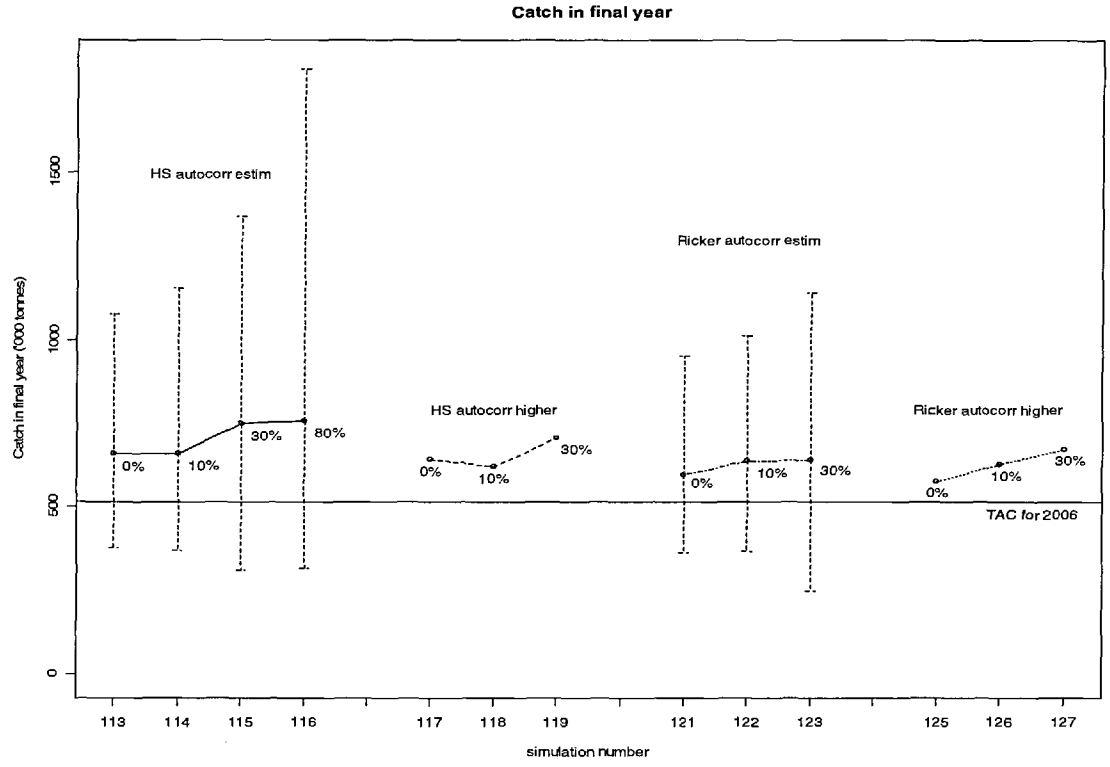


Figure 61: Catch in the final year of the projection.
Each point corresponds to a simulation: cases 113 to 128 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and each group correspond to the stock-recruitment relationship / autocorrelation options: HS = hockey stick. Dashed vertical lines correspond to 95% confidence interval.

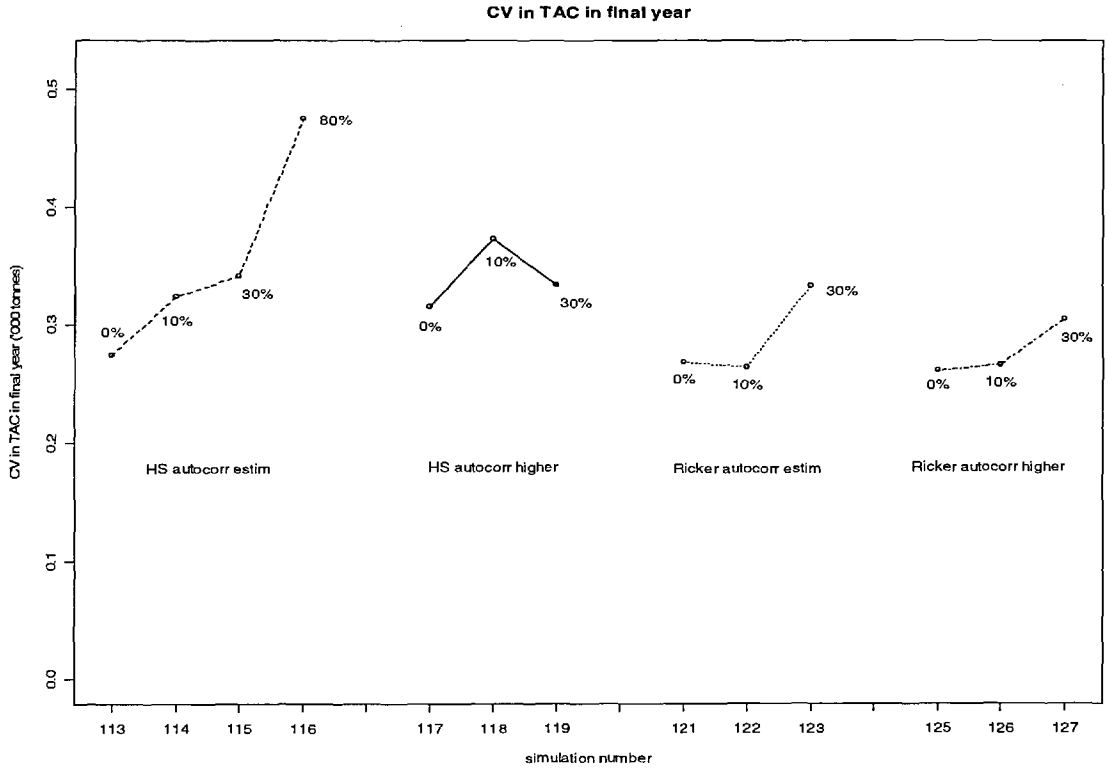


Figure 62: Coefficient of variation in the TAC in the final year of the projection.
Each point corresponds to a simulation: cases 113 to 128 in Appendix 5. Series are arranged in order of increasing implementation error, and each group correspond to the stock-recruitment relationship / autocorrelation options: HS = hockey stick.

The existing HCR performed well, even with a very high level of under-reporting, maintaining SSB above B_{PA} and delivering catches greater than the TAC in 2006. As the level of implementation error increases, the spawning-stock biomass decreases, which is the response expected from the model as there is no limitation in the variation of the quota. Even if the median of SSB values is maintained above B_{PA}, the probability of being below B_{lim} with a high level of implementation error is not unduly high (0.08, see Appendix 6).

In the same way as in previous graphs, final values are smaller when Ricker is considered as stock-recruitment relationship. It is also noticeable that an increase of the level of autocorrelation in the recruitment leads to smaller values of spawning-stock biomass. In fact, when the level is higher, bad years of recruitment are more likely to be followed by bad years.

The three missing simulations are expected to behave similarly as the model provides results consistent with those proposed by the Herring Assessment Working Group. It is important to remember that these simulations have been run over a period of 15 years only. It is feasible to assume that over 20 years, assuming an implementation of 80%, the spawning-stock biomass at the end of the projection would have been even lower, whatever the stock-recruitment relationship and level of autocorrelation assumed.
In general, the coefficient of variation increases with the level of implementation error.

5.4.2 EVALUATION OF THE MANAGEMENT STRATEGY USING NEW ASSESSMENT METHODS

The two assessment methods included in this section are YCC and SURBA. As explained in the previous chapter (Section 4.3.8), for each assessment method, two HCRs are used, one based on SSB and one on total mortality rate Z. All other variables are the same as in section 5.3.

In this section, simulations were run for 20 years and 100 iterations. This smaller number of iterations was necessary due to the computational complexity of including assessments in the simulations, and in order to obtain results in a reasonable amount of time.

Results in this section are organised in a different way to those presented so far. This section is made up of two parts. The first one describes results obtained with the SSB-based HCR for both assessment methods. In the second one, results coming from the use of a Z-based HCR are analysed. In each part, a description of the behaviour of the model over time is presented for some selected scenarios. Furthermore, an analysis of output in the final year is presented, as before, in groups which are labelled in their first appearance. The management strategies considered in this section cover the combinations of options listed in Table 43.

Table 29: Options for management procedures considered in model-based management strategies.

Variable components	Options
Stock-recruitment relationship	Hockey-stick Ricker
Autocorrelation in the recruitment	Estimated level Higher level
Observation error in the survey	Yes
Survey	Acoustic
Harvest control rule	Based on adjusted observation index Based on Z
Assessment	YCC SURBA
Misreporting	0% 10% 30% 80%

5.4.2.1 Evaluation of the management strategy using an SSB-based harvest control rule and an assessment method

This first section on management strategies using new assessment methods will only focus on the procedures using an SSB-based harvest control rule, i.e. single SSB trend. Similarly to previous sections, an analysis of the behaviour of the model over time is proposed. Some scenarios have been selected following changes in the trends in the projection after the change of a variable such as the level of misreporting or the assessment method considered. Four scenarios have been selected to illustrate all simulations for which an SSB-based HCR is considered. Their specificities can be found in Table 30.

Table 30: Selected scenarios illustrating the evolution of the stock when new assessments and SSB-based HCRs are considered.

	SR		Autocorr	Survey	HCR	Assess		Constraint	Misreport		Fig.
Sim nb	HS	Ricker	Est	Acoust	Sngl SSB	YCC	SURBA	No	30%	80%	
131	√		√	√	√	√		√	√		63
132	√		√	√	√	√		√		√	64
139		√	√	√	√	√		√	√		65
155		√	√	√	√		√	√	√		66

The output of the simulation 131 can be observed on Figure 63. This type of output illustrates simulations 129 to 131 and 133 to 135 (Appendix 5) and corresponding to the combinations found in Table 31

Table 31: Combinations of options illustrated by scenario 131.

Variable components	Options
Stock-recruitment relationship	Hockey stick
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic
Observation error in the survey	Yes
Harvest control rule	Based on adjusted observation index
Assessment	YCC
Limitation in the variation of the quota	No
Misreporting	0% 10% 30%

The output of the simulation 132 can be observed on Figure 64. This type of output illustrates simulations 132, 136, 140 and 144 (Appendix 5) and corresponding to the combinations found in Table 43.

Table 32: Combinations of options illustrated by scenario 132.

Variable components	Options
Stock-recruitment relationship	Hockey stick Ricker
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic
Observation error in the survey	Yes
Harvest control rule	Based on adjusted observation index
Assessment	YCC
Limitation in the variation of the quota	No
Misreporting	80%

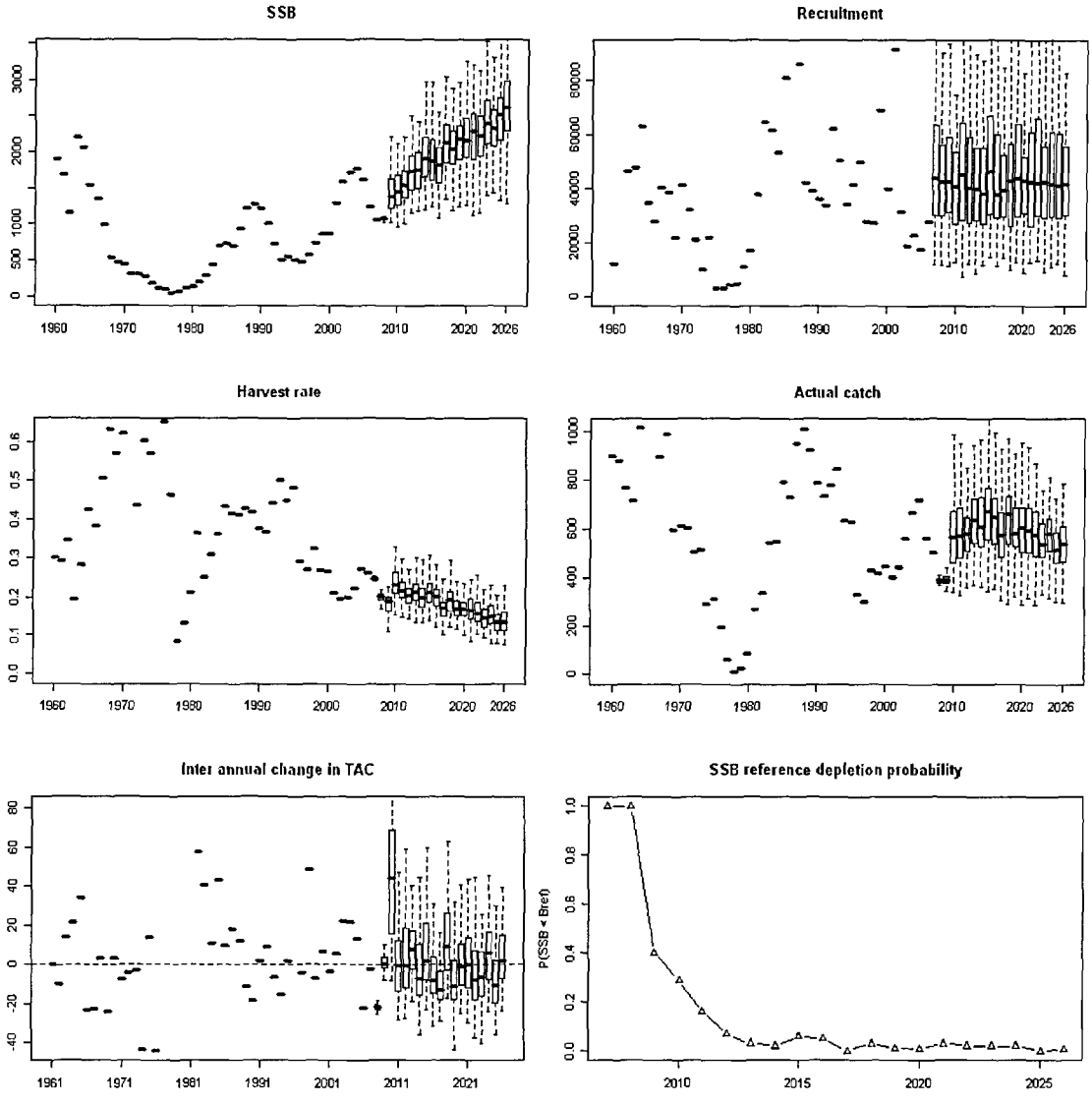


Figure 63: Output of simulation 131.
Stock recruitment: hockey stick; autocorrelation: estimated; survey: acoustic with observation error; assessment: YCC; harvest control rule: Sngl SSB; limitation of variation: none; implementation error: 30%.

It can be observed in Figure 63 that the SSB increases continuously and regularly along the 20 years of the projection for reasonably small levels of misreporting, i.e. between 0 and 30%. At the same time, the harvest rate decreases and the actual catch increase in the first years and then decrease. In Figure 64, the SSB increases in the first years and then decreases rapidly to a very low level when the level of misreporting is high, i.e. 80%. This can be explained by the fact that with YCC, Z is constant over ages and the total mortality is cumulative. As YCC does not estimate an age-dependent Z, a high level of implementation error will have a larger effect on the older ages given differential selection. In fact, in theory, the total mortality-at-age for a given year is equal to the sum of the natural mortality-at-age and the product of the fishing mortality

for this given year and the selectivity-at-age ($Z_{y,a} = M_a + F_y * s_a$). When YCC is used as an assessment method and as the level of implementation error increases, the fishing mortality increases towards a value of 1. As the fishing mortality tends to 1, the total mortality-at-age will become almost independent of the age-structured ($Z_{y,a} \approx Z_y$). As it is explained in the Appendix 2, the YCC assumption is then satisfied and this could explain the results obtained with YCC and high level of implementation error.

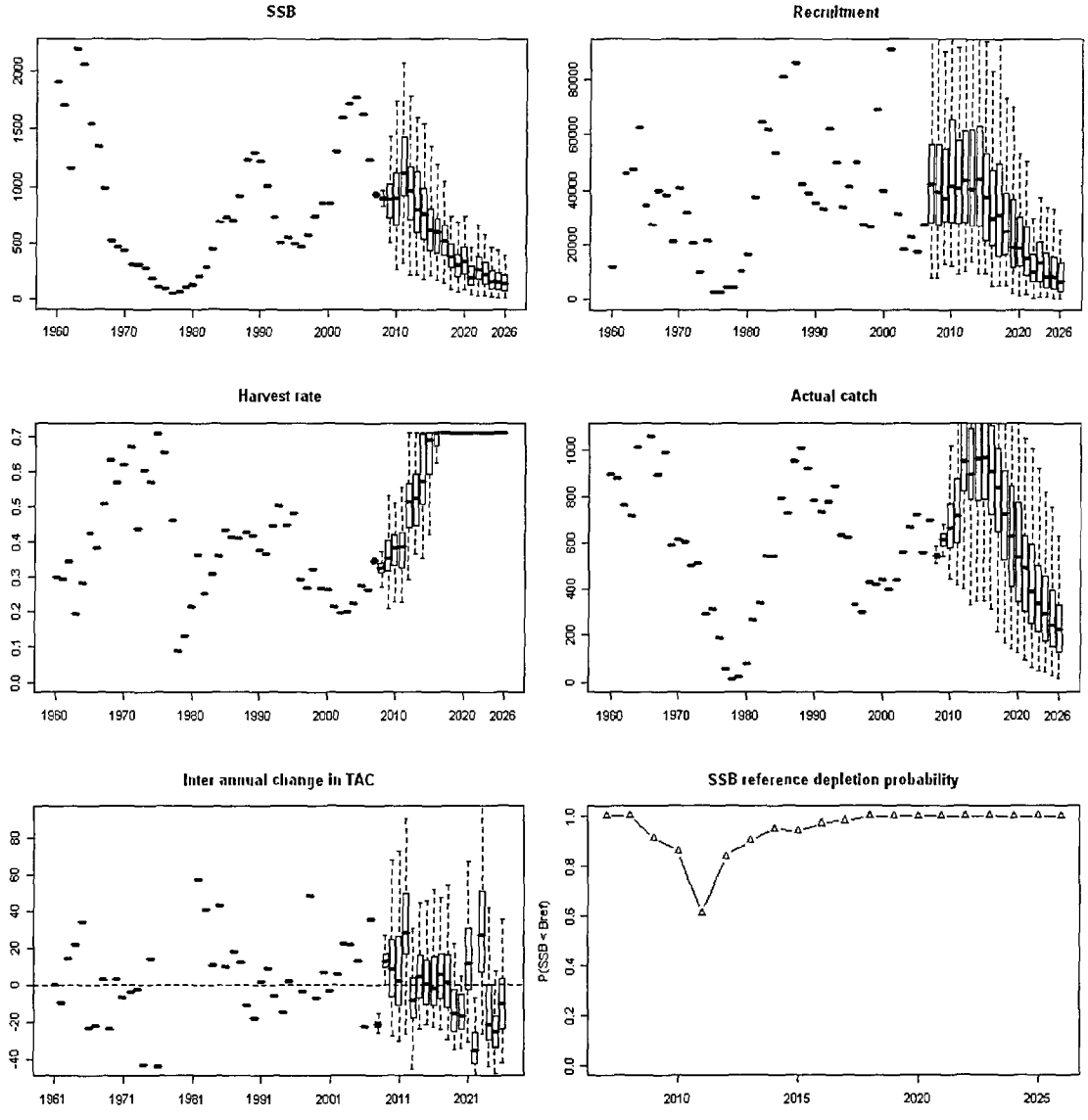


Figure 64: Output of simulation 132.
Stock recruitment: hockey stick; autocorrelation: estimated; survey: acoustic with observation error; assessment: YCC; harvest control rule: Sngl SSB; limitation of variation: none; implementation error: 80%.

In Figure 64, as the SSB decreases due to the high level of misreporting, catches follow this trend and decrease with a two year lag. As the SSB reaches a level smaller than the inflexion point of the stock-recruitment relationship, the recruitment also follows the

trend and declines. The level of misreporting being high, the harvest rate reaches very high levels. The harvest rate level is driven and bounded, as observed in the figure, by the level of misreporting more than by the TAC. As the level of SSB is very low in the final years of the projection, the probability of depletion becomes high relatively quickly in the simulation.

The output of the simulation 139 can be observed on Figure 65. This type of output illustrates simulations 137 to 139 and 141 to 143 (Appendix 5) and corresponding to the combinations found in Table 43.

Table 33: Combinations of options illustrated by scenario 139.

Variable components	Options
Stock-recruitment relationship	Ricker
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic
Observation error in the survey	Yes
Harvest control rule	Based on adjusted observation index
Assessment	YCC
Limitation in the variation of the quota	No
Misreporting	0% 10% 30%

Figure 65 is relatively similar to Figure 63. In fact, the only difference between those two scenarios and the one associated with is the stock-recruitment relationship assumed in the dataset.

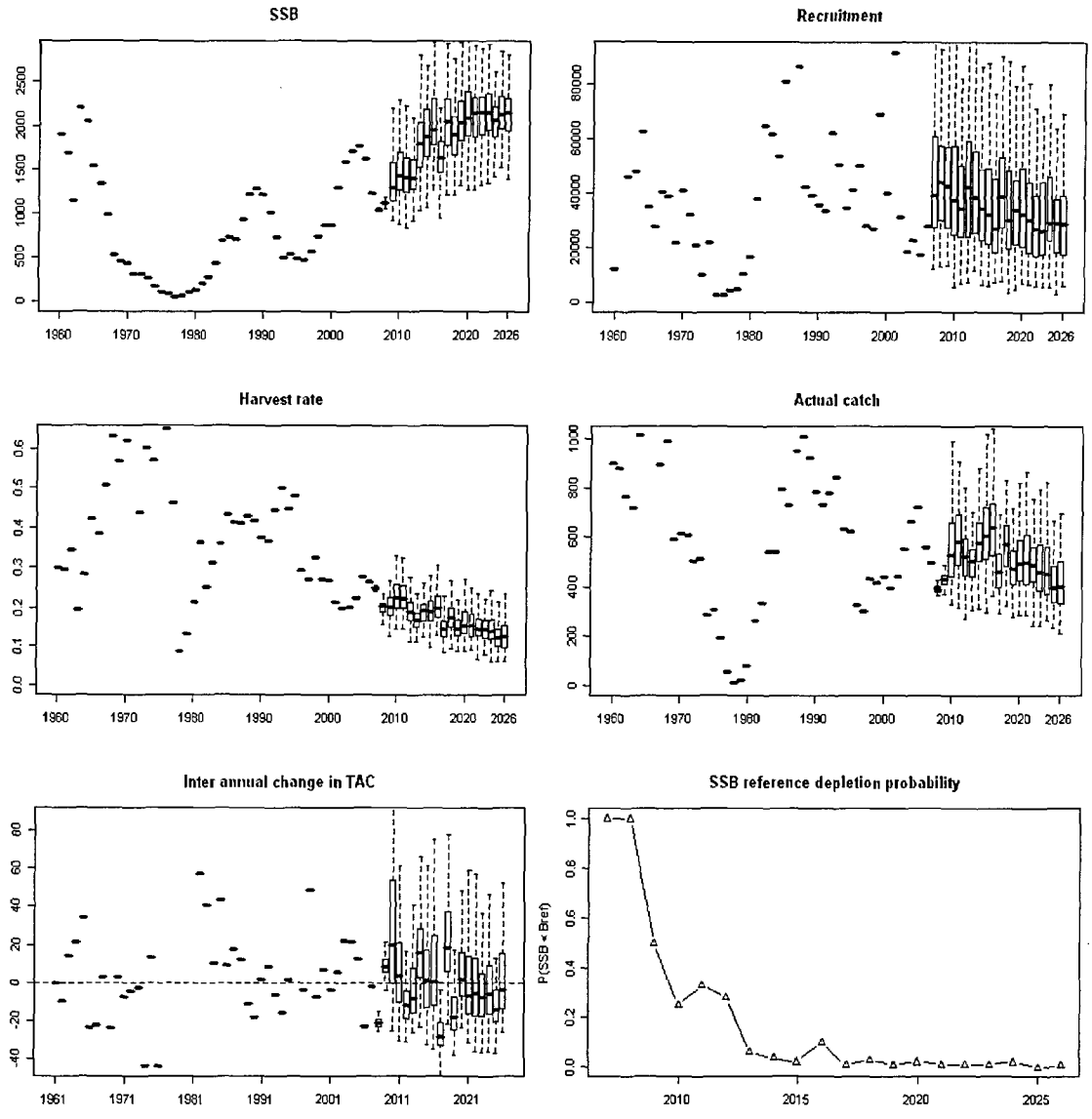


Figure 65: Output of simulation 139.
Stock recruitment: Ricker; autocorrelation: estimated; survey: acoustic with observation error; assessment: YCC; harvest control rule: Sngl SSB; limitation of variation: none; implementation error: 30%.

It is possible to observe in Figure 65 that the increase of the SSB is bounded in the final years of the projection. In fact, in the present case, the stock-recruitment relationship assumed is Ricker. As it was defined in the Chapter 2, when the SSB reaches a certain level, the recruitment decreases due to a density-dependence relationship. As the increase of the SSB is limited, the level of catch is smaller than when a hockey-stick stock-recruitment relationship is assumed.

The final scenario described for its temporal variation corresponds to the simulation 155. The output of this simulation can be observed on Figure 66. This type of output illustrates simulations 145 to 160 (Appendix 5) and corresponding to the combinations

found in Table 34. Those possible scenarios cover all possibilities for which the harvest control rule is based on adjusted observation index and with SURBA as assessment method.

Table 34: Combinations of options illustrated by scenario 155.

Variable components	Options
Stock-recruitment relationship	Hockey stick Ricker
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic
Observation error in the survey	Yes
Harvest control rule	Based on adjusted observation index
Assessment	SURBA
Limitation in the variation of the quota	No
Misreporting	0% 10% 30 80%

For all levels of misreporting, the SSB stays, on average, stable over time. The catch shows more variability over time but remains in the same range of values along the projection. Due to the stability of the SSB over time, the recruitment does not considerably vary. With SURBA, Z is separable by age ($Z_{y,a} = Z_y * s_a$ where s is the selectivity at age and Zy is the total mortality). The effect of a high level of implementation error with SURBA will be limited by its capacity to better estimate Z as it is age-dependent. The selectivity-at-age parameter included in the calculation of Z makes SURBA more efficient at detecting signals coming from the survey data.

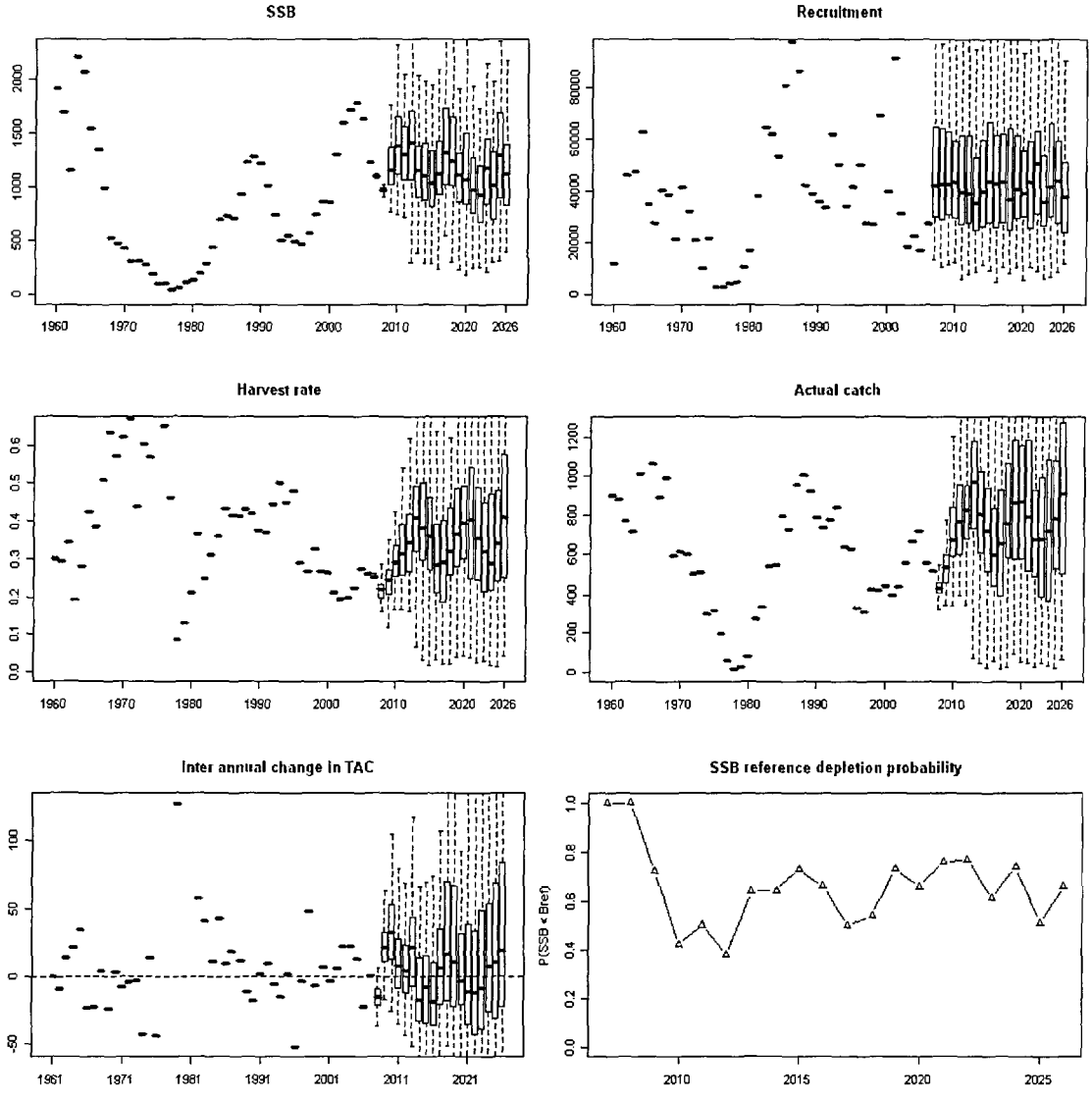


Figure 66: Output of simulation 155.
Stock recruitment: Ricker; autocorrelation: estimated; survey: acoustic with observation error; assessment: SURBA; harvest control rule: Sngl SSB; limitation of variation: none; implementation error: 30%.

Similarly to previous sections and as explained at the beginning of this section, the results obtained in the final year of the projection are analysed. Figure 67, Figure 68 and Figure 69 show output obtained for the spawning-stock biomass, the catch and the coefficient of variation in the TAC in the final year of the projection, each of them with the 95 % confidence interval.

Three graphs are presented here. The first one (Figure 67) show the spawning stock biomass for different management procedures. The second (Figure 68) shows the catch in the final year and Figure 69 the coefficient of variation in the TAC. For the first two figures, to avoid clutter and confusion on the figures, the 95% confidence intervals for

each assessment method are only shown for one set of runs (the Ricker stock-recruitment relationship and existing autocorrelation in recruitment). The 32 scenarios presented in the following figures correspond to the management procedures listed in Table 35.

On each figure, the four groups of linked points on the left hand side correspond to the use of YCC as assessment method and the four groups on the right to the use of SURBA. Each group of linked points corresponds to a combination of stock-recruitment relationship and a level of autocorrelation in this order: HN = hockey-stick and estimated level of autocorrelation, HH = hockey-stick and higher level of autocorrelation, RN = Ricker and estimated level and finally RH = Ricker and higher level of autocorrelation. Within each group of linked points, each point corresponds to the testing of a level of misreporting, i.e. from 0 to 80%. On all graphs showing the spawning-stock biomass, a horizontal line is drawn indicating the reference level B_{PA} (1 300 thousand tonnes) and another one B_{lim} (800 000 tonnes). Another horizontal line is drawn on graph plotting the catch, corresponding to the TAC set in 2006 (512 000 tonnes). The numbers on the horizontal axis correspond to the number of the simulation that can be found in the Table 35 or Appendix 5.

Table 35: Scenarios used to evaluate management strategies using a new assessment method and a SSB-based HCR.

Simulation number	SR		Autocorrelation		Obs err	Survey	HCR	Assessment		Misreporting				Constraint
	HS	Ricker	Est	Dbl	Yes	Acoust	Sngl SSB	YCC	SURBA	0%	10%	30%	80%	No
129	√		√		√	√	√	√		√				√
130	√		√		√	√	√	√			√			√
131	√		√		√	√	√	√				√		√
132	√		√		√	√	√	√					√	√
133	√			√	√	√	√	√		√				√
134	√			√	√	√	√	√			√			√
135	√			√	√	√	√	√				√		√
136	√			√	√	√	√	√					√	√
137		√	√		√	√	√	√		√				√
138		√	√		√	√	√	√			√			√
139		√	√		√	√	√	√				√		√
140		√	√		√	√	√	√					√	√
141		√		√	√	√	√	√		√				√
142		√		√	√	√	√	√			√			√
143		√		√	√	√	√	√				√		√
144		√		√	√	√	√	√					√	√
145	√		√		√	√	√		√	√				√
146	√		√		√	√	√		√		√			√
147	√		√		√	√	√		√			√		√
148	√		√		√	√	√		√				√	√
149	√			√	√	√	√		√	√				√
150	√			√	√	√	√		√		√			√
151	√			√	√	√	√		√			√		√
152	√			√	√	√	√		√				√	√
153		√	√		√	√	√		√	√				√
154		√	√		√	√	√		√		√			√
155		√	√		√	√	√		√			√		√
156		√	√		√	√	√		√				√	√
157		√		√	√	√	√		√	√				√
158		√		√	√	√	√		√		√			√
159		√		√	√	√	√		√			√		√
160		√		√	√	√	√		√				√	√

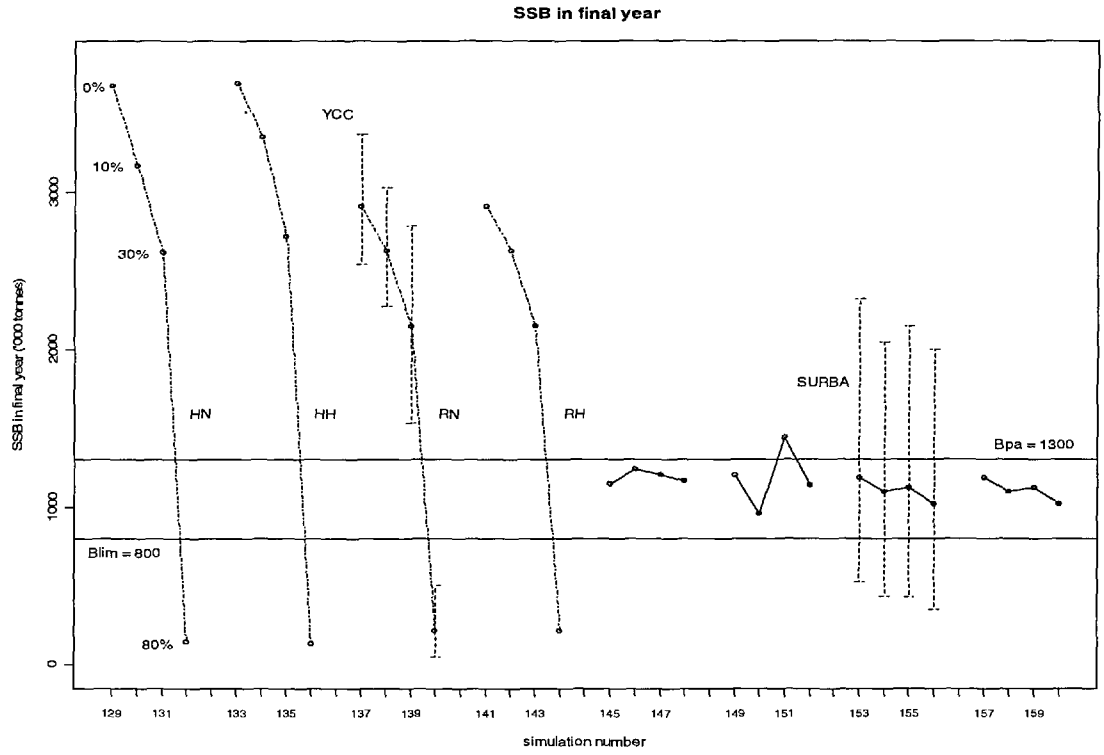


Figure 67: Spawning stock biomass in the final year of the projection.
Each point corresponds to a simulation: cases 129 to 160 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each HCR correspond to the stock-recruitment relationship / autocorrelation options: HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation. Dashed vertical lines: 95% confidence interval.

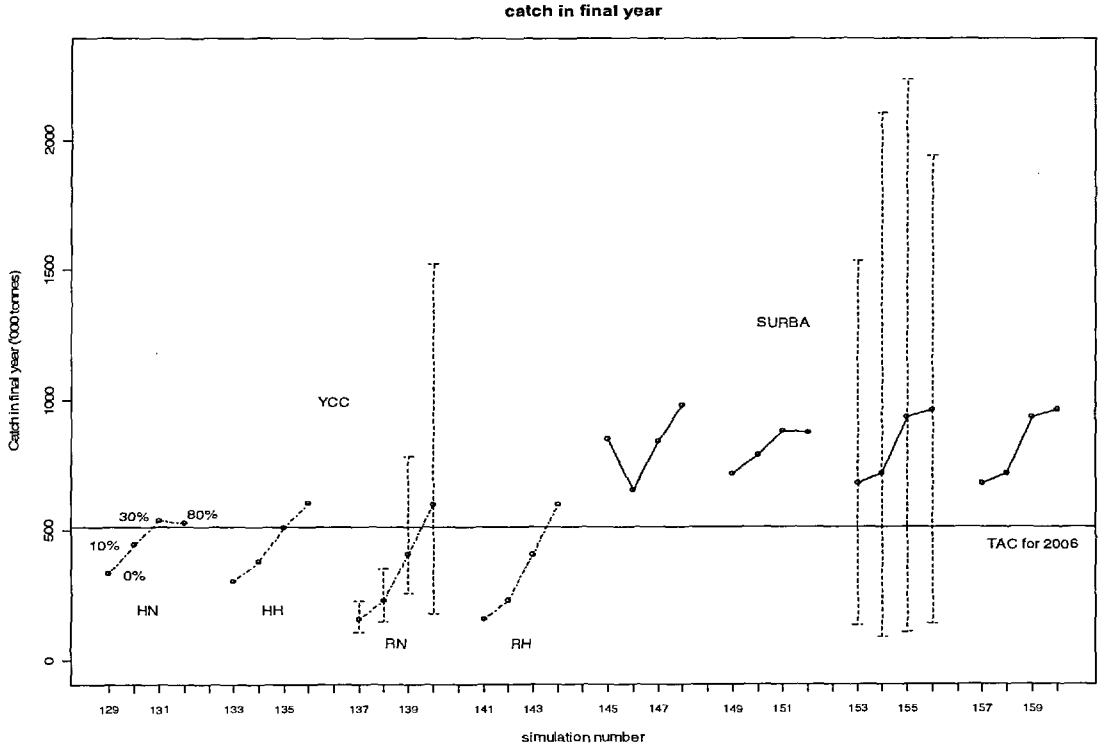


Figure 68: Catch in the final year of the projection.
Each point corresponds to a simulation: cases 129 to 160 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each HCR correspond to the stock-recruitment relationship / autocorrelation options: HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation. Dashed vertical lines: 95% confidence interval.

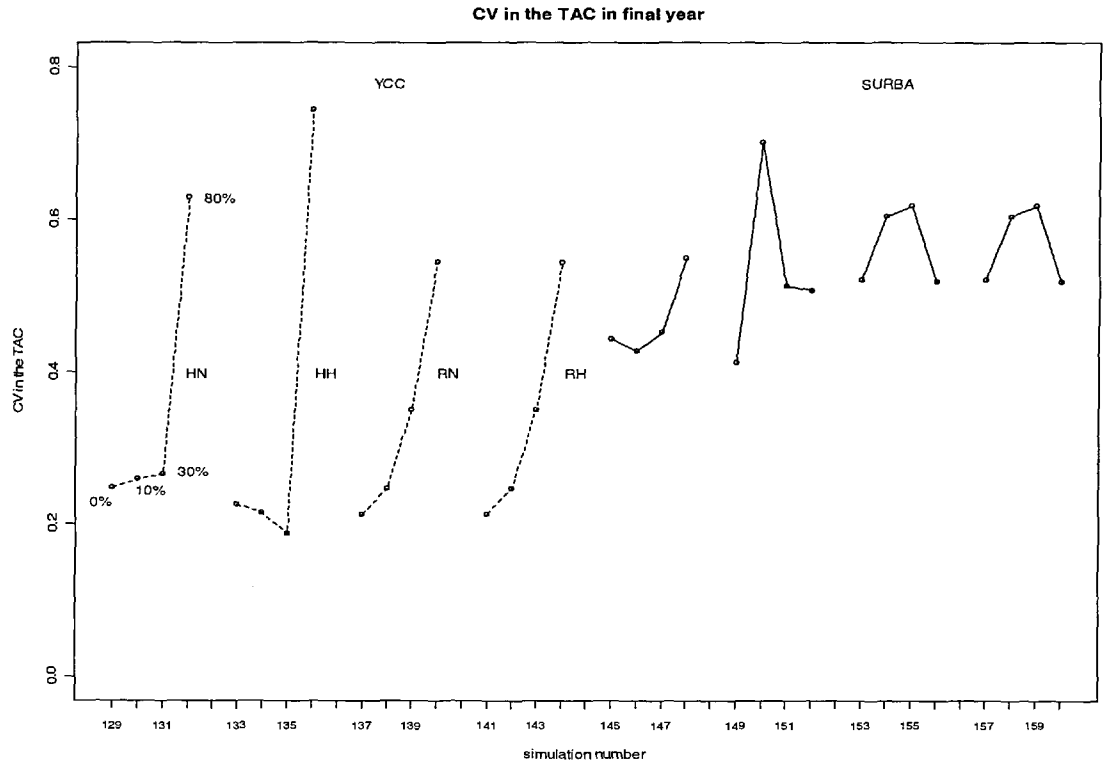


Figure 69: Coefficient of variation in the TAC in the final year of the projection.
Each point corresponds to a simulation: cases 129 to 160 in Appendix 5. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the stock-recruitment relationship / autocorrelation options: HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation.

Figure 67 shows results quite different to those observed in the previous sections. The spawning-stock biomass in the final year is very different depending on the assessment method utilised and the level of implementation error.

When YCC is used as the assessment method, the final spawning-stock biomass at small levels of implementation error is different depending on the stock-recruitment relationship utilised (as has previously been shown for the non-assessment HCRs). At a high level of implementation error, the final values are relatively similar and well below B_{lim} (800 000 tonnes). SSB values for a level of 80% implementation error correspond to on average 5% of the SSB values for simulations without implementation error. With this assessment method and this HCR, the effect of the implementation error could have a dramatic effect on the stock if the catch is not declared accurately or if the TAC is not implemented correctly. On the other hand, SURBA appears to be relatively robust to under-reporting although it performs poorly compared to YCC at low levels of implementation error, since all runs of SURBA resulted in the final biomass being between B_{PA} and B_{lim}.

The difference between the performance of YCC and SURBA can be explained by the way those assessment methods are implemented and their capacity to estimate Z from the survey data. In fact, YCC and SURBA do not estimate Z from the survey following the same method. As it was explained earlier, with YCC, Z is constant over ages and the total mortality is cumulative. With SURBA, Z is separable by age ($Z_{y,a} = Z_y * s_a$ where s is the selectivity at age and Zy is the total mortality). As YCC does not estimate an age-dependent Z, a high level of implementation error will have a larger effect on the older ages given differential selection. In fact, in theory, the total mortality-at-age for a given year is equal to the sum of the natural mortality-at-age and the product of the fishing mortality for this given year and the selectivity-at-age ($Z_{y,a} = M_a + F_y * s_a$). When YCC is used as an assessment method and as the level of implementation increases the fishing mortality increases towards a value of 1. As the fishing mortality tends to 1, the total mortality-at-age will become almost independent of the age-structured ($Z_{y,a} \approx Z_y$). As it is explained in the Appendix 2, the YCC assumption is then satisfied and this could explain the results obtained with YCC and high level of implementation error.

The effect of a high level of implementation error with SURBA will be limited by its capacity to better estimate Z as it is age-dependent. The selectivity-at-age parameter included in the calculation of Z makes SURBA more efficient at detecting signals coming from the survey data.

The change of level of autocorrelation in the recruitment does not have noticeable effect on the spawning-stock biomass projected when YCC is considered but has one with SURBA. Spawning-stock biomass values respond more variably to implementation error at higher levels of autocorrelation.

As it can be observed in Figure 67, the size of the 95% confidence interval is quite different between the results obtained with the two assessment methods. On average, the spread of the interval when SURBA is utilised is on average the double of the one obtained with YCC. This makes the management procedure using YCC and a HCR based on spawning-stock biomass less dependent of the noise present in the model, in the recruitment, the catch data and the survey.

The probability of being below B_{lim} at least once in the 20 years of projection is null for low levels of implementation error when YCC is used (Appendix 6). This is due to the very high spawning-stock biomass values obtained at the end of the projection. But because YCC is not robust to implementation error, at high levels of implementation error the final spawning-stock biomass is below B_{lim}. When SURBA is used, the probability that the final spawning-stock biomass is below B_{lim} is very high at all levels of implementation error and increases with it.

With YCC, at low levels of implementation error, catch is relatively small, compared with the TAC set for 2006 (Figure 68). As the level of implementation error increases, so does the catch. A change in the level of autocorrelation does not show any effect on the catch values after 20 years of projection. With SURBA, catch stays above the TAC set for 2006 and increases in most cases with the level of implementation error.

The first thing that can be observed on Figure 68 is the difference of spread of the confidence intervals between the management procedures and the two assessment methods used. SURBA shows a very large but fairly constant size of confidence interval when the level of implementation error increases. By contrast, when the level of implementation is null, the size of the confidence interval is small when YCC is used. As the level of misreporting increases, the spread of the interval so increases correspondingly and reaches a size close to the one obtained with SURBA and a level of implementation equal to zero. It can be deduced that as the level of implementation error increases, the capacity of the management procedure using YCC as assessment method to estimate a realistic catch decreases. However, for all levels of implementation error, procedures based on SURBA estimate catch with a very large confidence interval.

The coefficient of variation in the TAC is dependent on the level of implementation error, particularly with YCC (Figure 69), but at low levels of implementation error, YCC is much more stable than SURBA.

5.4.2.2 Evaluation of the management strategy using a Z-based harvest control rule and an assessment method

Similarly to previous sections, an analysis of the behaviour of the model over time is presented. Some scenarios have been selected according to changes in the trends in the projection with the changes of a variable such as the level of misreporting or the assessment method considered. Four scenarios have been selected to illustrate all simulations for which a Z-based HCR is considered. Their specifics can be found in Table 46.

Table 36: Selected scenarios illustrating the evolution of the stock when new assessments and Z-based HCRs are considered.

	SR		Autocorr	Survey	HCR	Assess		Constraint	Misreport	
Sim nb	HS	Ricker	Est	Acoust	Z	YCC	SURBA	No	30%	Fig.
163	√		√	√	√	√		√	√	70
171		√	√	√	√	√		√	√	71
179	√		√	√	√		√	√	√	72
187		√	√	√	√		√	√	√	73

The output of simulation 163 can be observed in Figure 70. This type of output illustrates simulations 161 to 168 (Appendix 5) and corresponds to the combinations found in Table 37.

Table 37: Combinations of options illustrated by scenario 163.

Variable components	Options
Stock-recruitment relationship	Hockey stick
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic
Observation error in the survey	Yes
Harvest control rule	Based on Z
Assessment	YCC
Limitation in the variation of the quota	No
Misreporting	0% 10% 30% 80%

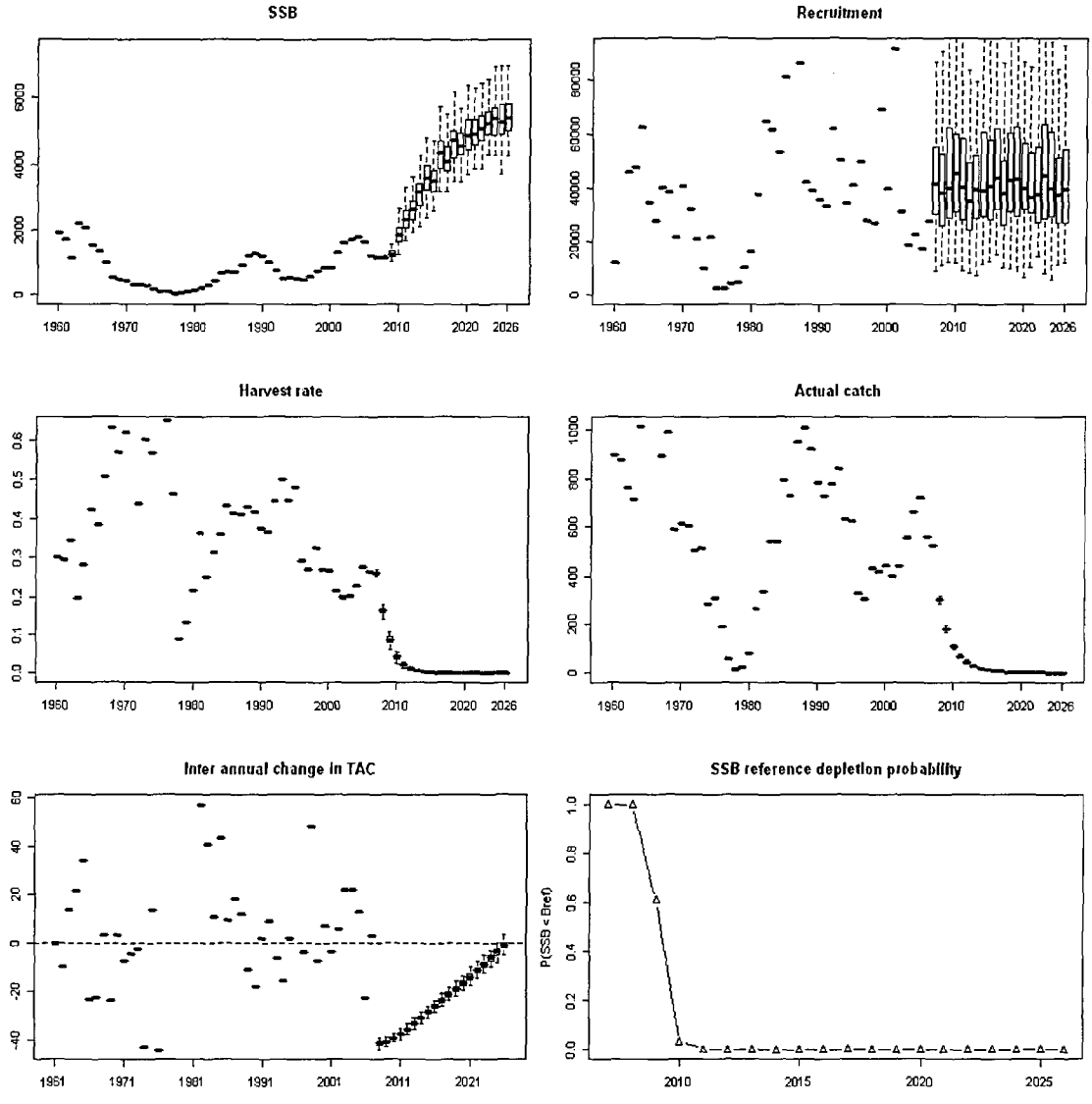


Figure 70: Output of simulation 163.
Stock recruitment: hockey stick; autocorrelation: estimated; survey: acoustic with observation error; assessment: YCC; harvest control rule: Z; limitation of variation: none; implementation error: 30%.

As has been explained previously, the HCR based on Z is generally more conservative than its index or SSB-based counterparts and, as a consequence, the possibility of observing an increase of the TAC is 0.25. Furthermore, as it has been shown in the previous section, these assessment methods may be incapable of fully detecting the signal coming from the survey data in the presence of observation error and given the restrictions in the model structure and estimate parameters. These reasons could explain the behaviour of the model simulations over time. As the SSB is very high, in theory, catch should be possible but this model predicts a collapse of the fishery, i.e. catch almost null.

Due to the stock-recruitment relationship assumed in this scenario, as the SSB is very high, the recruitment is constant over time, which amplifies the increase of the SSB.
The catch being intensely decreased in the first years of the projection, the inter-annual change in TAC is highly negative in the first years and changes become smaller as the decrease of the catch slows down with time.

The output of the simulation 171 can be observed on Figure 71. This type of output illustrates simulations 169 to 176 (Appendix 5) and corresponding to the combinations found in Table 38.

Table 38: Combinations of options illustrated by scenario 171.

Variable components	Options
Stock-recruitment relationship	Ricker
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic
Observation error in the survey	Yes
Harvest control rule	Based on Z
Assessment	YCC
Limitation in the variation of the quota	No
Misreporting	0% 10% 30% 80%

The trends in the catch, harvest rate and inter-annual change in TAC are similar to the one observed on the previous figure. But the choice of the stock-recruitment relationship (Ricker instead of hockey stick) has an important impact of the trend in the SSB. Indeed, a high level of SSB implies a reduction in the recruitment which then bounds the increase of the SSB and limits the explosion of the stock biomass. As always, the use of a harvest control rule based on Z tends to conserve the stock, and in this case over-conserve the stock. In fact, the very high level of SSB could support a certain level of catch but this is not proposed in the projection.

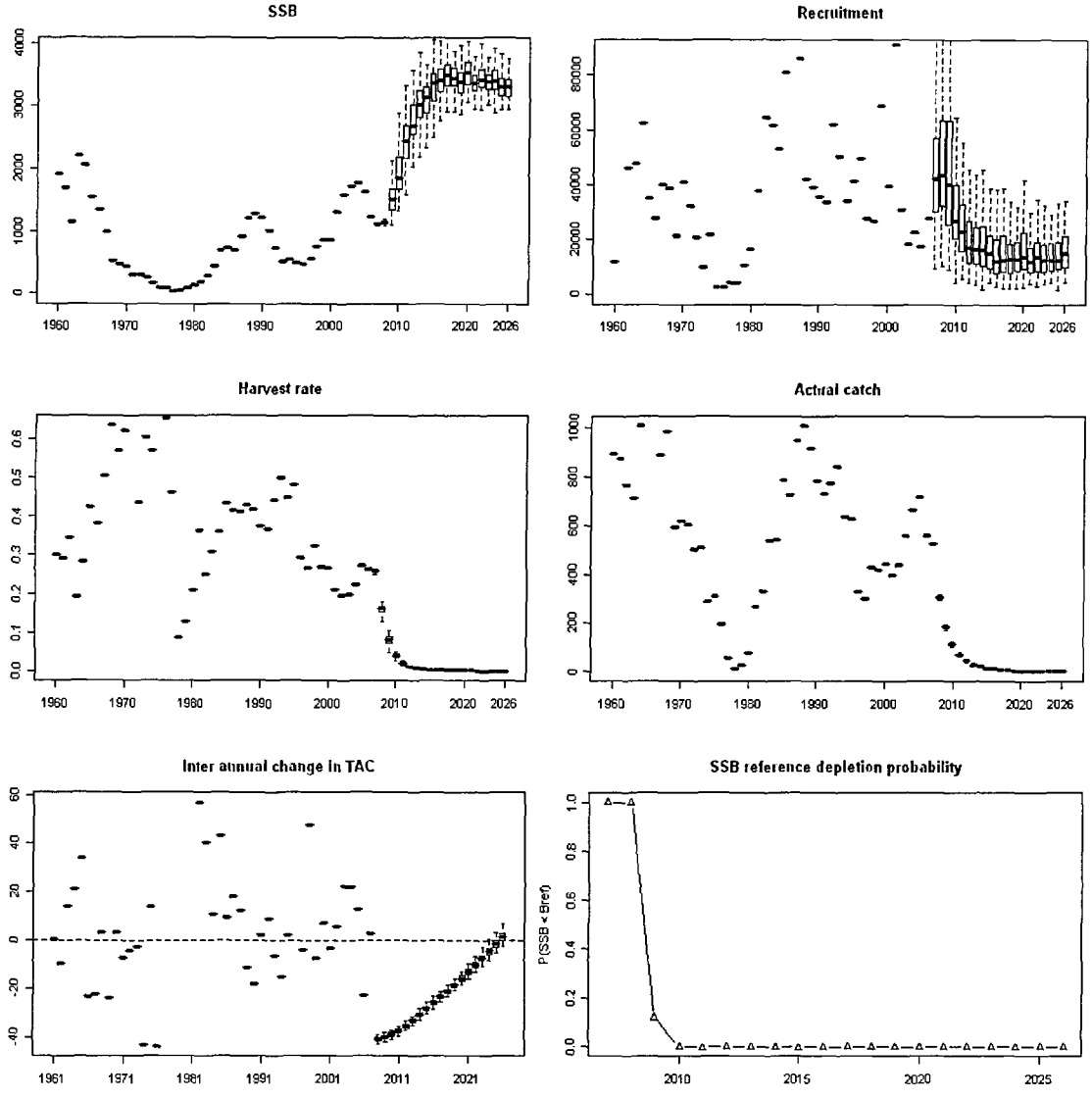


Figure 71: Output of simulation 171.
Stock recruitment: Ricker; autocorrelation: estimated; survey: acoustic with observation error; assessment: YCC; harvest control rule: Z; limitation of variation: none; implementation error: 30%.

The major change between the two previous scenarios and the two following is the assessment method used. Previously, YCC was used while SURBA is the assessment method tested in the following section. The difference between these two new scenarios is the choice in the stock-recruitment relationship. The first one assumes a hockey stick relationship while the second one assumes a Ricker one. Similar to the two previous scenarios, it is possible to observe that the choice of the stock-recruitment relationship has an important impact on the trends in the spawning stock biomass, the recruitment, the catch and the harvest rate.

The output of the simulation 179 can be observed on Figure 72. This type of output illustrates simulations 177 to 184 (Appendix 5) and corresponding to the combinations found in Table 43.

Table 39: Combinations of options illustrated by scenario 179.

Variable components	Options
Stock-recruitment relationship	Hockey stick
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic
Observation error in the survey	Yes
Harvest control rule	Based on Z
Assessment	SURBA
Limitation in the variation of the quota	No
Misreporting	0% 10% 30% 80%

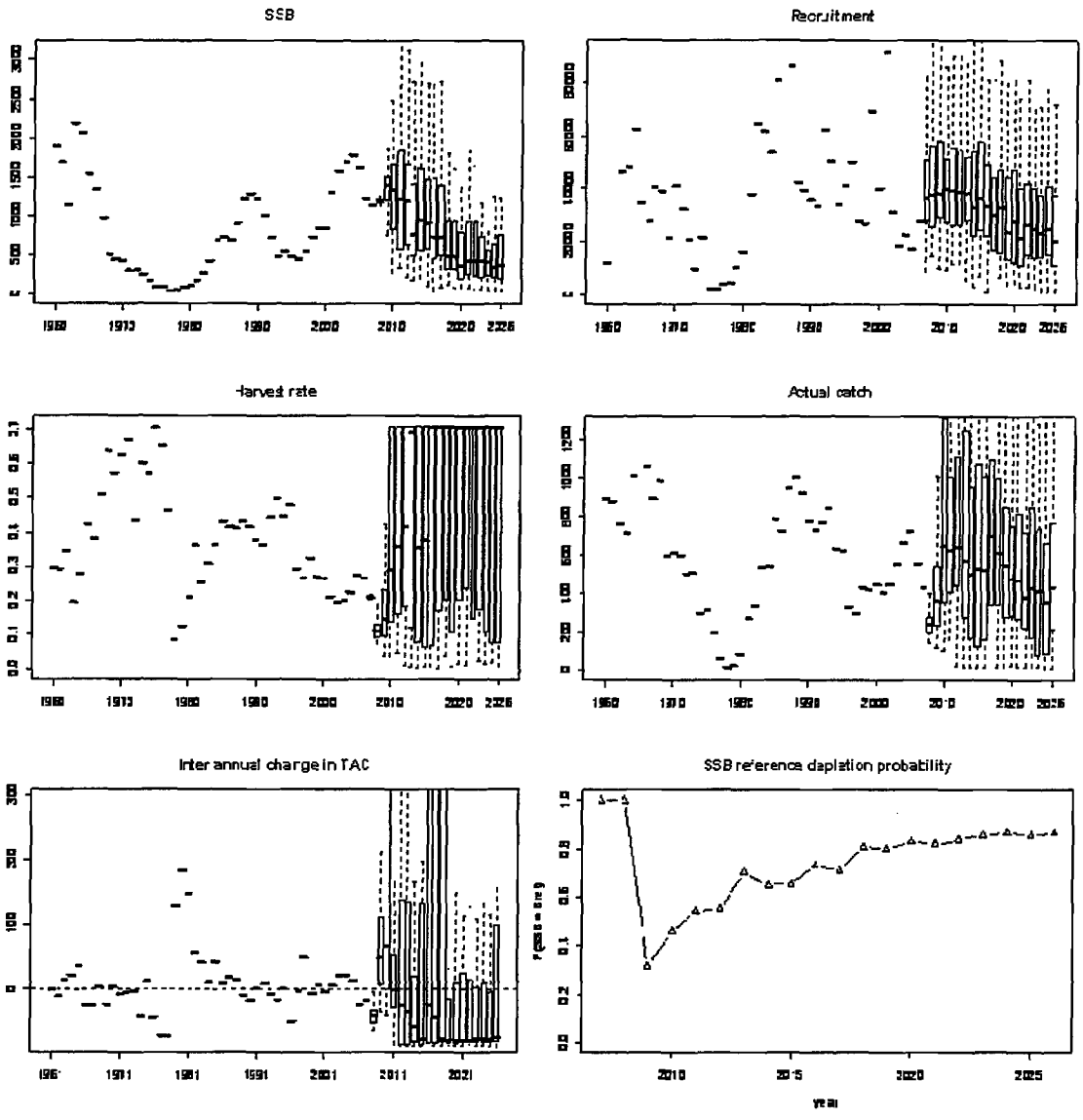


Figure 72: Output of simulation 179.
Stock recruitment: hockey stick; autocorrelation: estimated; survey: acoustic with observation error; assessment: SURBA; harvest control rule: Z; limitation of variation: none; implementation error: 30%.

The trends observed in Figure 72 are completely different to those one observed in the two previous scenarios. Indeed, in the preceding simulations, the SSB tended to increase rapidly and intensely while the catch collapsed. In the present case, it is the opposite. The SSB decreases to a level which is well below B_{lim}. As long as the SSB remains above the inflection point of the stock-recruitment relationship, the recruitment remains constant but decreases when the SSB reaches small values. Catch tend to decrease to a level close to the one observed when TAC was reduced in the 1990s to avoid a second collapse of the stock after the one that occurred in the late 1970s. As the catch do not decrease that much compared to the decline of the SSB, the harvest rate reaches a maximum very early in the projection. It is possible to observe that the inclusion of

SURBA as the assessment method in the model has an important impact of the projection. Indeed, a comparison between Figure 32 and Figure 72 shows that the trends in the SSB are contradictory. The Z-based HCR is by definition conservative but the trend in Figure 72 does not confirm the tendency. This could be explained by the way the assessment method is implemented. In fact, with SURBA, the Z is separable by age ($Z_{y,a} = Z_y * s_a$ where s is the selectivity at age and Zy is the total mortality). The assessment method could estimate higher Zs from the surveys than those estimated directly from the survey without the use of an assessment method. A higher estimation of Zs can lead to a decline of the stock.

It has been noticed that an increase of the level of misreporting does not have a noticeable effect in the trends. This could imply that the assessment method cannot properly account for the increase of the implementation error in the model. In fact, an increase of the misreporting should lead to a decrease of the set TAC to compensate the level of misreporting.

The output of the simulation 187 can be observed on Figure 73. This type of output illustrates simulations 185 to 192 (Appendix 5) and corresponding to the combinations found in Table 40.

Table 40: Combinations of options illustrated by scenario 187.

Variable components	Options
Stock-recruitment relationship	Ricker
Autocorrelation in the recruitment	Estimated level Higher level
Survey	Acoustic
Observation error in the survey	Yes
Harvest control rule	Based on Z
Assessment	SURBA
Limitation in the variation of the quota	No
Misreporting	0% 10% 30% 80%

The only difference between this figure and the previous one is the choice of the stock-recruitment relationship, which means that the choice can have a very important impact on the projection and as a consequence on the advice provided. The trends in the SSB, in the recruitment, in the harvest rate and in the catch are similar to the one observed in

Figure 33 for which the only difference with this scenario is the consideration or not of an assessment method. The final values are not the same but the trends remain similar. Everything is emphasized when SURBA is used in the simulation. The increase of the SSB is more important and the decreases of the recruitment, the harvest rate and the catch are higher. It is possible to notice that one of the six graphs within one figure is not plotted. This is due to the so small level of catch in the simulation. Indeed, the computer cannot calculate the inter-annual variability in the TAC and as a consequence cannot plot it.

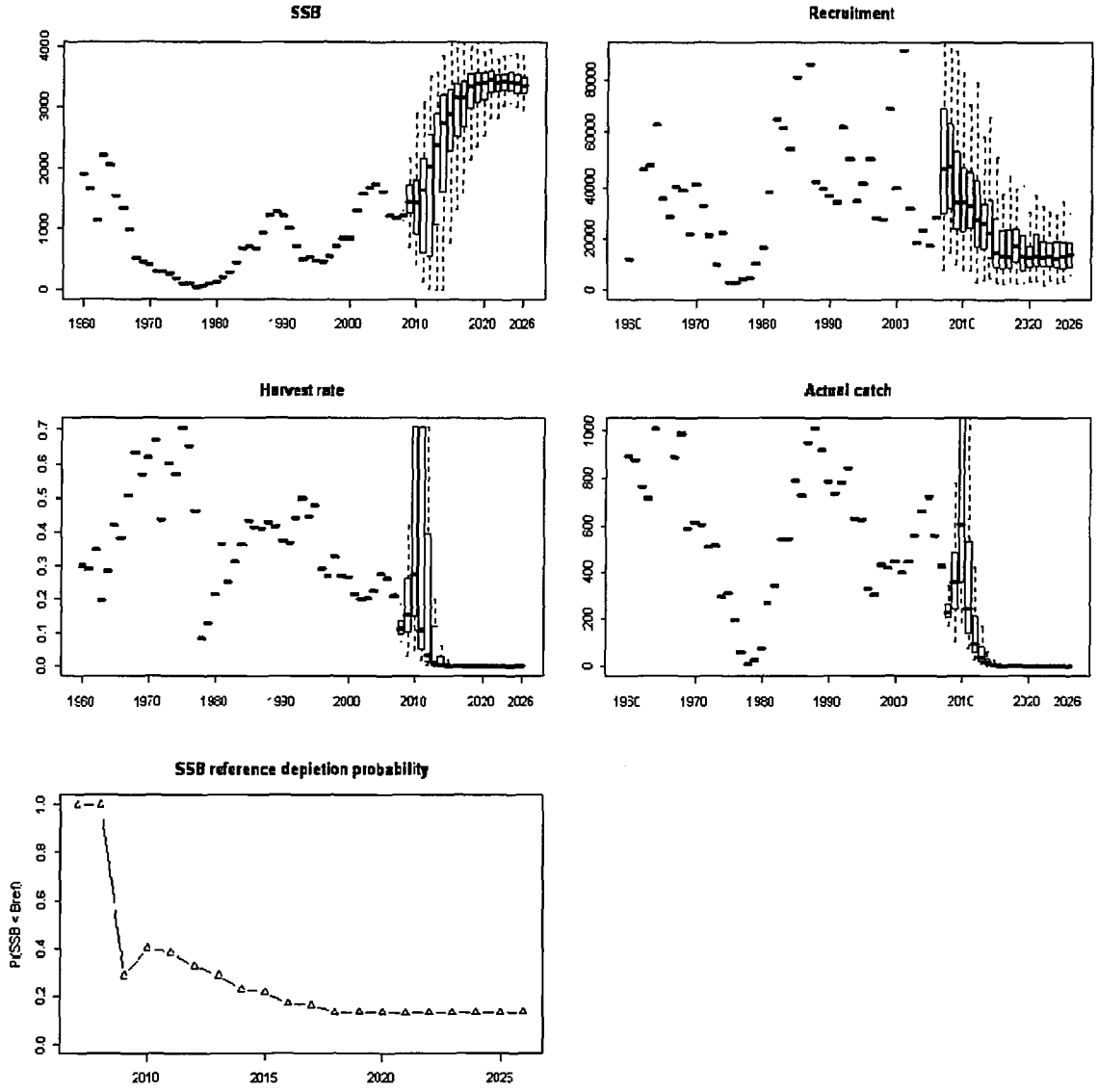


Figure 73: Output of simulation 187.
Stock recruitment: Ricker; autocorrelation: estimated; survey: acoustic with observation error; assessment: SURBA; harvest control rule: Z; limitation of variation: none; implementation error: 30%.

Similarly to previous sections and as explained at the beginning of this one, the results obtained in the final year of the projection are analysed. Figure 74 shows the SSB in the final year of the projection for the two assessment methods considered.

Only one graph is plotted. Figure 74 show the spawning stock biomass for different management procedures. To avoid clutter and confusion on the figure, the 95% confidence intervals for each assessment method are shown only for one set of runs (the Ricker stock-recruitment relationship and existing autocorrelation in recruitment). The 32 scenarios presented in the following figure correspond to the management procedures listed in Table 41.

In the figure, the four groups of linked points on the left hand side correspond to the use of YCC as assessment method and the four one on the right to the use of SURBA. Each group of four linked points corresponds to a combination of stock-recruitment relationship and a level of autocorrelation in this order: HN = hockey-stick and estimated level of autocorrelation, HH = hockey-stick and higher level of autocorrelation, RN = Ricker and estimated level and finally RH = Ricker and higher level of autocorrelation. Within each group of four points linked, each point corresponds to the testing of a level of misreporting, i.e. from 0 to 80%. A horizontal line is drawn indicating the reference level B_{PA} (1 300 thousand tonnes) and another one B_{lim} (800 000 tonnes). The numbers on the horizontal axis correspond to the number of the simulation that can be found in the Table 41 or Appendix 5.

Table 41: Scenarios used to evaluate management strategies using a new assessment method and a Z-based HCR.

Simulation number	SR		Autocorrelation		Obs err	Survey	HCR	Assessment		Misreporting				Constraint
	HS	Ricker	Est	Dbl	Yes	Acoust	Z	YCC	SURBA	0%	10%	30%	80%	No
161	√		√		√	√	√	√		√				√
162	√		√		√	√	√	√			√			√
163	√		√		√	√	√	√				√		√
164	√		√		√	√	√	√					√	√
165	√			√	√	√	√	√		√				√
166	√			√	√	√	√	√			√			√
167	√			√	√	√	√	√				√		√
168	√			√	√	√	√	√					√	√
169		√	√		√	√	√	√		√				√
170		√	√		√	√	√	√			√			√
171		√	√		√	√	√	√				√		√
172		√	√		√	√	√	√					√	√
173		√		√	√	√	√	√		√				√
174		√		√	√	√	√	√			√			√
175		√		√	√	√	√	√				√		√
176		√		√	√	√	√	√					√	√
177	√		√		√	√	√		√	√				√
178	√		√		√	√	√		√		√			√
179	√		√		√	√	√		√			√		√
180	√		√		√	√	√		√				√	√
181	√			√	√	√	√		√	√				√
182	√			√	√	√	√		√		√			√
183	√			√	√	√	√		√			√		√
184	√			√	√	√	√		√				√	√
185		√	√		√	√	√		√	√				√
186		√	√		√	√	√		√		√			√
187		√	√		√	√	√		√			√		√
188		√	√		√	√	√		√				√	√
189		√		√	√	√	√		√	√				√
190		√		√	√	√	√		√		√			√
191		√		√	√	√	√		√			√		√
192		√		√	√	√	√		√				√	√

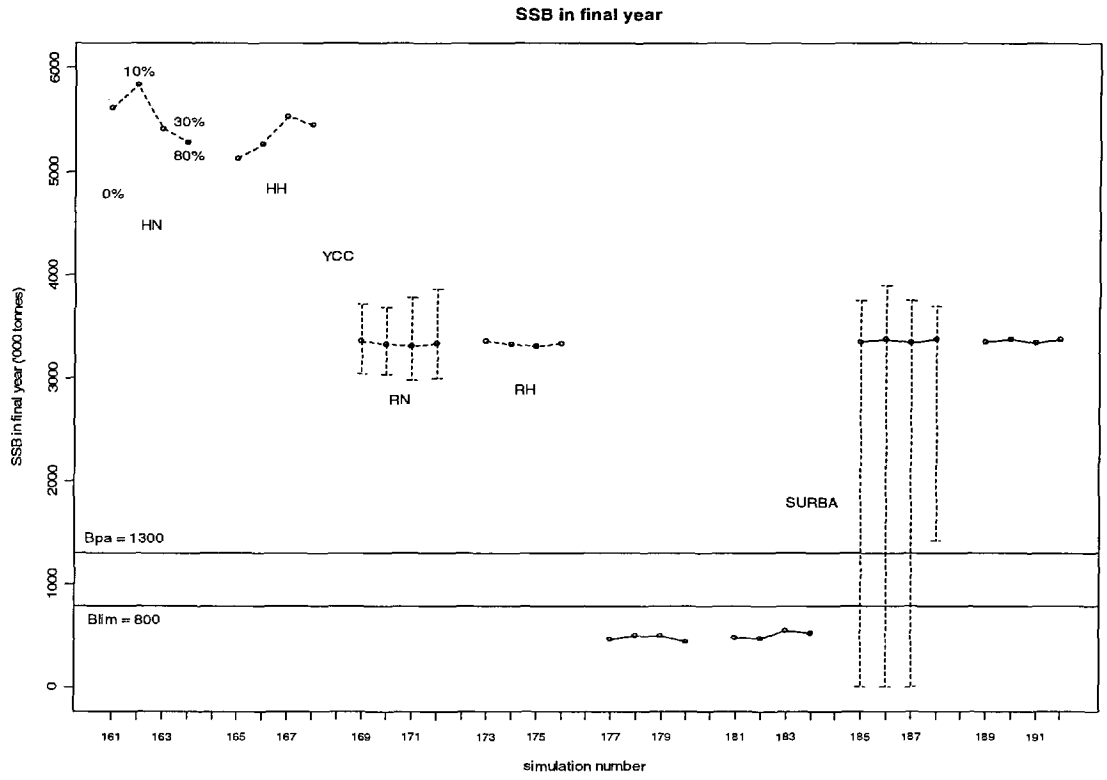


Figure 74: Spawning stock biomass in the final year of the projection.
Each point corresponds to a simulation: cases 161 to 192 in Appendix 5. Unit: thousand tonnes. Series are arranged in order of increasing implementation error, and four groups under each harvest rule correspond to the stock-recruitment relationship / autocorrelation options: HN = hockey stick, normal autocorrelation; HH = hockey stick, high autocorrelation; RN = Ricker, normal autocorrelation; RH = Ricker, high autocorrelation. Dashed vertical lines correspond to the 95% confidence interval.

Both these assessments performed very poorly with Z-based HCRs. The assumed stock recruitment model had a very significant impact on the results. When YCC was used, the assumption of a Ricker model resulted in a final spawning-stock biomass after 20 years of projection on average 40% smaller than with a hockey-stick model. With SURBA the opposite effect was seen, the final SSB with a hockey-stick stock-recruitment relationship being 15% lower than with a Ricker relationship. As a consequence, the spawning-stock biomass with SURBA and a hockey-stick relationship is always below B_{lim}, when in other cases, final values are well above B_{PA}. When a hockey-stick stock-recruitment relationship is considered and SURBA is used as assessment method, the probability of being below B_{lim} at least once is very high: 0.94 on average.

Catch values obtained, as it can be seen in Appendix 6, are extremely different between the two HCRs but also between stock-recruitment relationships when SURBA is used as assessment method. In fact, the highest catch estimated for the final year when a

hockey-stick relationship is assumed, with an estimated level of autocorrelation and 10% of implementation error, is equal to 19 629 thousand tonnes when it is equal to 0.357 tonnes when a Ricker model is used with similar variables and assumptions. For this reason, results are not plotted.

Such large range of values could be explained by the inability of the assessment methods to capture the signal coming from the survey data. Also, the noise around the recruitment could be a source of conflict.

When Ricker is the stock-recruitment relationship with SURBA, catch values are extremely small (0.27 tonnes on average, Appendix 6). Small catch in the final year means reduction of the TAC along years in the projection which implies that at least one of the ratios of the calculation of the TAC is smaller than 1. Catches delivered by YCC, although higher than with SURBA, are two orders of magnitude lower than the 2006 TAC.

In the previous section, SURBA appeared to be most robust to implementation uncertainty when using an SSB-based HCR. Both SURBA and YCC appeared to deliver a robust final stock size with a Z based rule, but this was probably because catches were so low and no firm conclusions can be drawn about this harvest strategy.

5.5 Discussion and conclusion

The work in this chapter has explored the performance of different HCRs in a management strategy evaluation using increasingly complex operating, error and implementation structure. The management procedures are classified in two different ways: model-free versus model-based and fishery-independent based data versus fishery-dependent based data. The "model-free" corresponds to management procedures that do not include assessment methods while "model-based" do. The fishery-independent based management procedures can be model-free or model-based but in both cases, only fishery-independent data are used, even for the assessment model. Those based on fishery-dependent data can use both fishery-dependent and independent data to assess the stock. Table 42 summarises the classification.

Table 42: Summary of the different types of models implemented.

Model / HCRs	Model-free	Model-based	Fishery-independent based	Fishery-dependent based
Observation index	√		√	
Single SSB trend	√		√	
Combined SSB trend	√		√	
Z	√		√	
Current management		√		√
YCC + SSB		√		√
SURBA + SSB		√	√	
YCC + Z		√		√
SURBA + Z		√	√	

In a perfect world, the HCR model behaved as expected. In the absence of exploitation and a stock in a reasonable state, the spawning-stock biomass increases from the first year of the projection until it reaches a maximum determined by the stock-recruitment relationship. As expected, the Ricker stock recruit model depresses recruitment and eventually SSB at high levels of biomass, whereas the hockey-stick model does not. Furthermore, a change in the level of autocorrelation in the recruitment does not appear to have any noticeable effect on the spawning-stock biomass. This parameter does not seem to have a driving effect on the evolution of the stock along time in the case of an unexploited resource. The inclusion of a catch (TAC) fixed at the level set for 2006 demonstrated that this level of catch is sustainable given current assumptions about recruitment.

The main section of this chapter deals with the performance of different decision rules using more realistic operating models (for a Ricker stock-recruitment model, the existing estimated level of autocorrelation, including observation error and the four levels of implementation error) and the results are summarised in Figure 75, Figure 76 and Figure 77 and values can be found in Appendix 7.

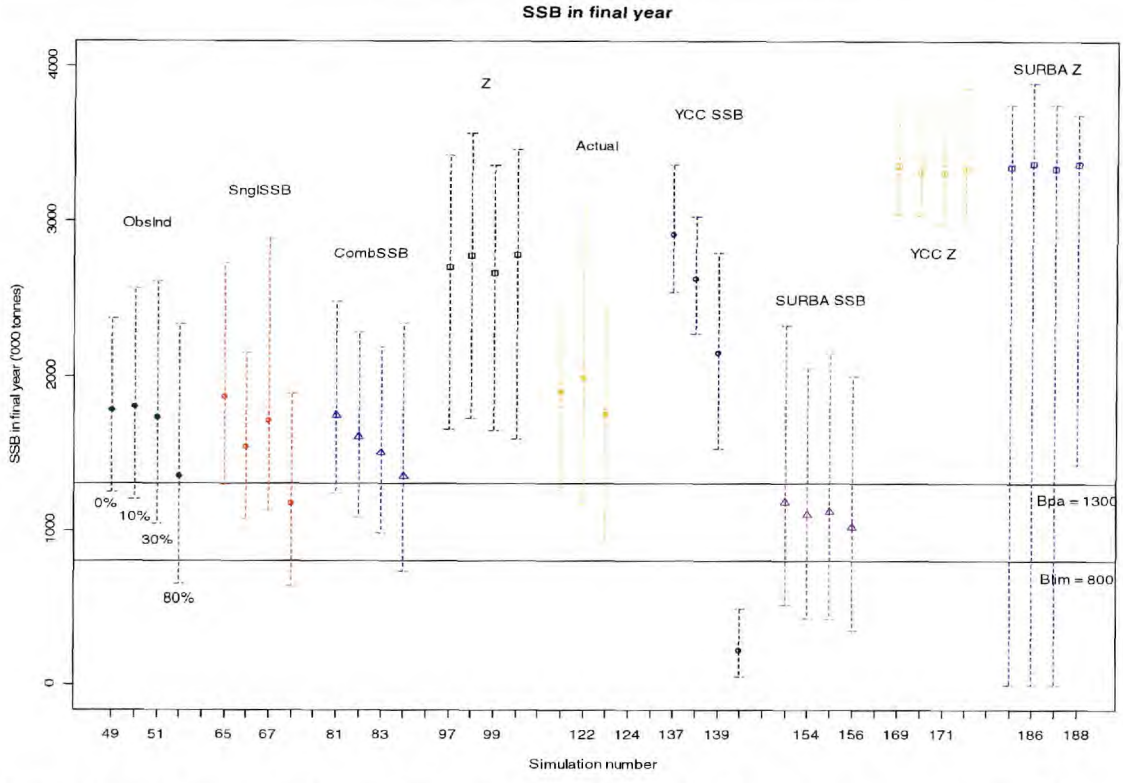


Figure 75: Performance in terms of spawning stock biomass for the nine management procedures. Each point corresponds to a simulation which number is written on the horizontal axis. Each group of four points corresponds to a harvest control rule. Within a group, each point corresponds to a level of misreporting. Whiskers indicate upper and lower 95% limits on the distribution of simulations results.

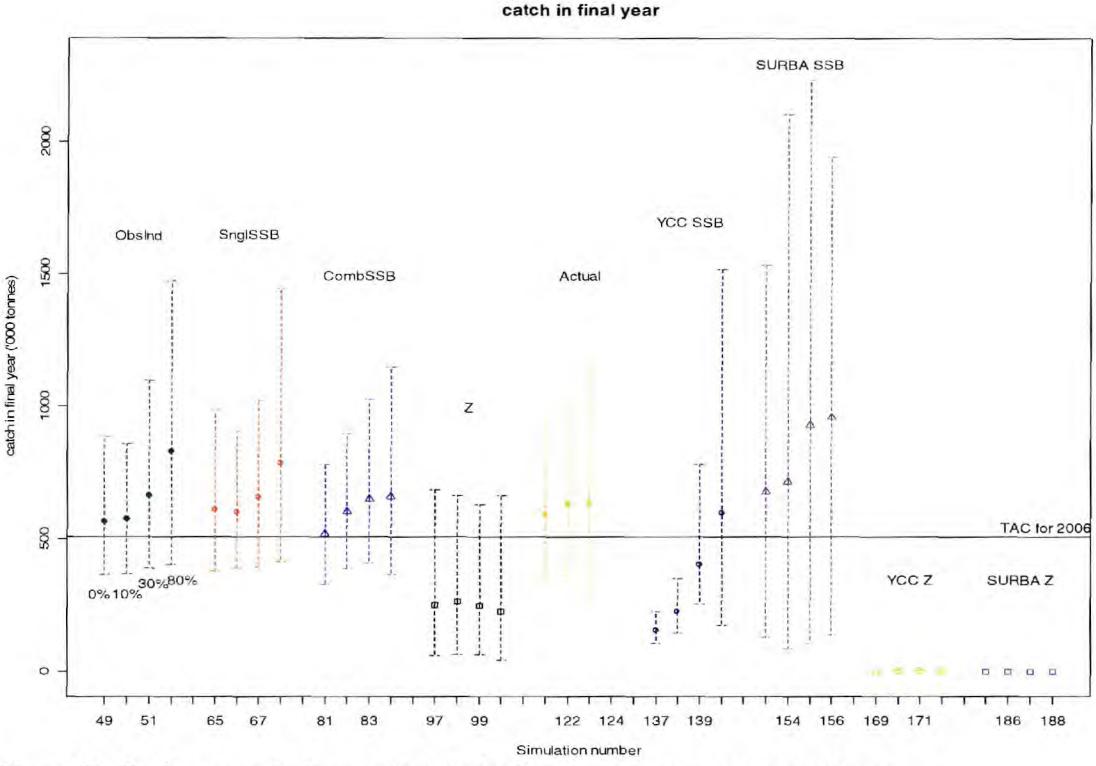


Figure 76: Performance in terms of catch for the nine management procedures.
Each point corresponds to a simulation which number is written on the horizontal axis. Each group of four points corresponds to a harvest control rule. Within a group, each point corresponds to a level of misreporting. Whiskers indicate upper and lower 95% limits on the distribution of simulations results.

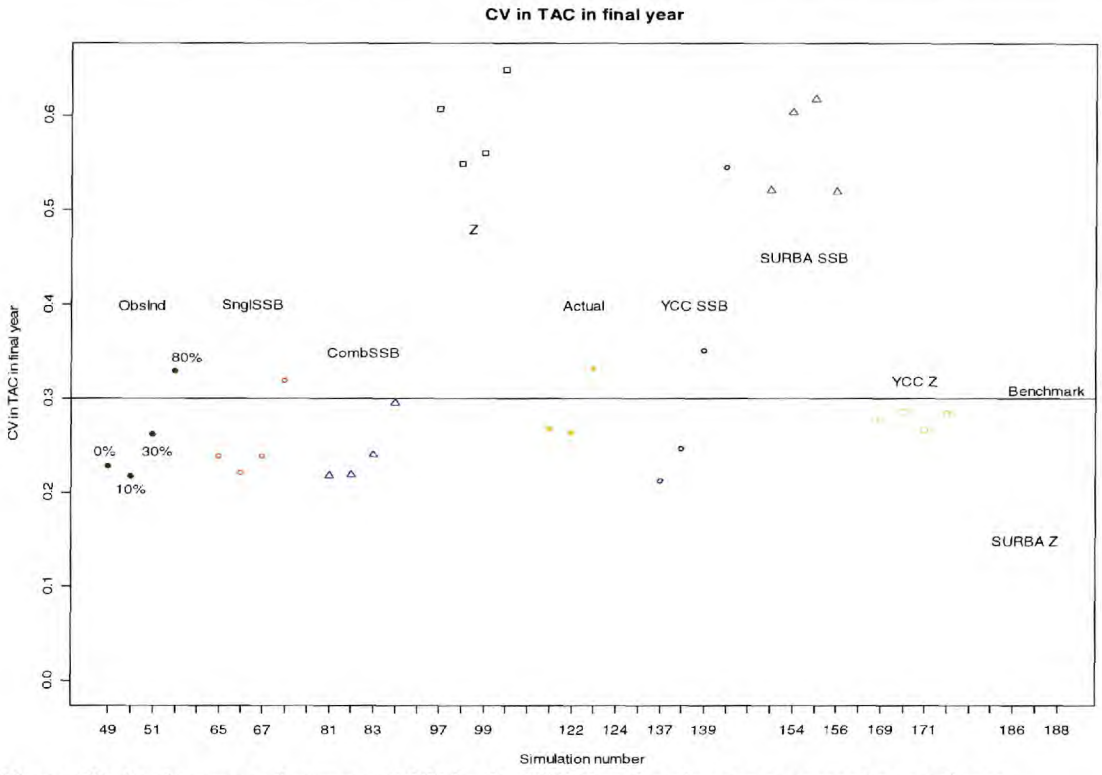


Figure 77: Performance in terms of CV in the TAC for the nine management procedures. Each point corresponds to a simulation which number is written on the horizontal axis. Each group of four points corresponds to a harvest control rule. Within a group, each point corresponds to a level of misreporting. An arbitrary benchmark of 0.3 was chosen for CV in the TAC based on the upper level of that achieved by the actual management strategy adopted by the Commission.

The results of the performance index (equation 56) are presented in Table 43.

Table 43: Performance index results for the nine management procedures. The results in bold and red correspond to results which are below the average of the selected management procedures.

	Performance benchmark: that SSB and catch benchmarks need to be met			
misreporting / MP	0%	10%	30%	80%
Observation index	**1050**	**1081**	**1099**	**883**
Single SSB trend	**1180**	**843**	**1065**	**657**
Combined SSB trend	**968**	**911**	**854**	**709**
Z	1654	1741	1611	1709
Current management	**1192**	**1325**	**1088**	**NA**
YCC + SSB	1767	1554	1252	**-475**
SURBA + SSB	**563**	**515**	**755**	**682**
YCC + Z	2054	2022	2009	2036
SURBA + Z	2048	2070	2037	2068

It can be seen in Figure 75 that most of medians for the simulations are above B_{PA}. Some of them such as the management procedure using a single SSB trend HCR and 80% of misreporting and all simulations using SURBA combined with SSB are below B_{PA} but above B_{lim}. The only management procedure which is below B_{lim} is the one combining YCC with SSB and assuming 80% of misreporting. However, once the upper and lower 95% limits on the distributions are taken into consideration, a large number of simulations have values below B_{PA} which suggests that there is more than 5% probability of being below the reference point. Some scenarios (11 over the 35 plotted) have whiskers below B_{lim} and only five of them have them above B_{PA}. High values of SSB are obtained with four different HCRs: Z-based, the two assessment methods combined with Z and YCC combined with SSB but only for relatively low levels of misreporting for the latter one (0 and 10% misreporting). The two management procedures providing the highest final biomass are the two combining an assessment and the HCR on total mortality rate. Three of the four procedures ending with the highest biomass values use a HCR based on total mortality. This rule has a conservative structure (decreases in TAC require one signal to be higher than Z_{PA}, increases require both signals to be lower) which implies that this rule has more chances than the others of reducing the TAC and as a consequence increase the SSB. In terms of maintaining the stock above reference points - at least above B_{lim}, if not above B_{PA} – all management procedures achieve this target except as mentioned previously the MP combining YCC and SSB at high level of misreporting.

As one would expect, most SSB values are higher when the level of unreported catch is smaller. The greater the difference between two levels of implementation error, the worse the management procedure is able to react to this type of error, primarily due to a delay between observing the problem and reacting to it in the HCR.

An important result from these simulations is that most of the HCRs examined are robust to implementation error of 10%, and it is only with increasing levels of implementation error (30% - 80%) that they become severely challenged. Indeed, a relatively large number of management procedures do not show a noticeable decrease in the SSB when 10% of misreporting is taken into consideration and a fewer when the level of misreporting reaches 30%.

In several cases, catch values are well above the TAC set for 2006. This is not an official reference point but it still gives an idea on the evolution of the stock from its latest historical state. Four management procedures provide catch values below the TAC set for 2006, two of them being extremely low (both assessment methods combined with a total mortality-based HCR). The latter are the two procedures which gave the highest SSB values described in the previous paragraph. Those two procedures violate economic requirements as they propose extremely small catch after 20 years of projection for relatively high values of SSB. The two rules which estimate larger catch but still remain below the set TAC are the one using the rule based on total mortality and the one combining YCC and a HCR based on SSB. Those two rules have already be mentioned in the previous paragraph as they estimated a SSB above 2 000 thousand tonnes after 20 years of projection, which is well above B_{PA} (1 300 thousand tonnes). By contrast, all scenarios that have a median above the TAC set for 2006 have their lower 95% limit below the set TAC. The management strategies based on fishery-independent data and not using assessment methods and the strategy mimicking the actual management have their lower 95% limit not unduly low while the one using assessment methods have very narrow confidence intervals.

In terms of the coefficient of variation in the TAC in the final year, 17 scenarios provide a CV between 0.2 and 0.3, the latter being the arbitrary benchmark fixed in this work. But 13 scenarios give a CV in the TAC above the benchmark value after the 20 years of projection. Between these 17 scenarios, 9 of them are above 0.5 and between them 4 are above 0.6, the maximum being 0.648. For five scenarios, there is no CV provided due to the lack of availability of catch data (actual management with 80% misreporting) or such low catch values that the CVs cannot be calculated (management procedures using SURBA as assessment method combined with a HCR based on SSB). Those available CVs which are below the benchmark occur with management procedures that do not use assessment methods, the actual management and the procedure using YCC as assessment method, all of them for reasonable levels of misreporting (between 0 and 10% for some of them and 0 and 30% for others). The four scenarios giving a CV above 0.3 but within an acceptable range include the two management procedures using an observed SSB index and a single trend in the SSB for very high level of misreporting, the actual management procedure and the procedure combining YCC and SSB, both of them for a medium level of misreporting (30%). The nine very high CVs are observed with management procedures using the Z-based harvest control rule and the one

combining SURBA and the SSB-based HCR. Those high values might violate some of the industry preferred limitations on variation in inter-annual TAC. However the worst situation is for the management procedure combining SURBA and the HCR based on total mortality. In fact, catch values being so small, the coefficient of variation in the TAC is not available. It was already deduced from the previous analysis of the catch projected that this procedure might not fit requests from the fishing industry.
In most cases, the coefficient of variation in the TAC increases in proportions with increases in the estimated level of unreported catch. The increase is slightly higher for the management procedure applying the actual management and the one combining YCC and the HCR based on spawning-stock biomass.

In Table 43 are listed the results of the calculation of the performance indices described in section 5.1.2. Interpretation of this "performance" index should be combined with performance of the HCR against SSB and catch benchmarks. If those failing one or more of these former benchmarks are discounted, the best performing harvest strategies are the current management, the observation index and single SSB trend. As the level of unreported catch increases, the performance of the current management strategy declines, whereas the decision rules based on fishery-independent data perform better.

In this management strategy evaluation management procedures using YCC and SURBA as assessment methods did not perform as well as those using fishery-independent methods and were generally robust to high levels of implementation error. In terms of graph analysis, it is possible to observe that the only combination between assessment method and harvest control rule that produces a controlled development of both SSB and catch is the SURBA-SSB. YCC is uniformly bad, producing extremely unbalanced, wild trajectories. The current management procedure (which uses ICA assessment) performed quite well under low levels of implementation error but not at high levels.

Based on all graphs plotted in this chapter, it is also possible to conclude that a low level of implementation error (10%) does not seem to have a noticeable effect on the state of the stock and its catch after 20 years of projection. This level of error is of a roughly comparable size to the noise already present in the model around the recruitment and the observations from the surveys. With the management procedures based on fishery-independent data and HCRs based on SSB even a level of 30% does

not seem to imply high changes in the projections and the coefficient of variation in the TAC is kept below the benchmark.

Management strategy evaluation enables management decisions to be made while uncertainty is taken into account. In this thesis, sources of uncertainty taken into consideration include alternative stock-recruitment relationships, alternative levels of autocorrelation in the recruitment, alternative error in the acoustic surveys and a possible misreporting in the catch data. Indices of policy performance and median SSB and catch (with 95% probability intervals) allow the alternative management options to be evaluated, taking these uncertainties in the true state of the population into account.

One of the fishery management systems simulated in this work is based on the current management of the North Sea herring stock used by ICES (ICES HAWG, 2008). Thus the currently applied ICA assessment method is included as part of the comparison process although the aim of this work is to evaluate the potential usefulness of harvest control rules based on fishery-independent data to improve fisheries management. A literature review has revealed that such management procedures using harvest control rules based on fishery-independent data has already been implemented in the southern hemisphere. Indeed, for the South African anchovy resource, Butterworth and Berg (1993) have developed such a management procedure in the early 1990s when the previous management system had to be discarded following a series of mistakes in the setting of the TACs. Furthermore, this approach has been used in the interim management procedure developed by Butterworth and Geromont (2001) for the Namibian hake resource, whose aim was to provide TAC recommendations that would perform well (in terms of catch and risk of resource depletion) across the wide range of possible levels of status of the resource argued for at that time.

Change of stock-recruitment relationship

The uncertainty about the true form of the stock-recruitment relationship can be considered as part of the error model (Francis and Shotton, 1997). Model error has been identified as a potentially major, but often overlooked, source of uncertainty when considering management decisions, and particularly the selection of management strategies (Butterworth and Punt, 1999). The form of the relationship has been identified in the past as a factor to which the performance of management strategies has been found to be sensitive. It has been shown in this work that the form of the stock-recruitment relationship had a noticeable effect on the SSB and as a consequence on the

catch, at the end of the 20 years of projection under certain circumstances. A'mar *et al.* (2008) have compared three scenarios: a base scenario in which recruitment is lognormally distributed around a mean value so there is no impact of a reduction in the SSB on the recruitment and two scenarios in which recruitment follows either a Ricker or a Beverton-Holt stock-recruitment relationship. They have shown that the consideration of a density-dependent relationship has an effect on the probability of the stock to fall below a reference point. Indeed, the probability that the stock really drop below the set reference point is lower when a stock-recruitment relationship is considered that for the base scenario. But their study has not shown a difference between the two relationships considered.(Kell *et al.*, 2005a) have evaluated multiple management objectives for Northeast Atlantic flatfish stock and have shown that although the evaluations were performed for a variety of assumptions about the stock-recruitment relationships in the operating model, similar behavioural responses were seen. Based on these observations, the differences observed in the present work could be explained by the fact that some harvest control rules have a more or less important impact on the stock. The model can be extremely sensitive to the form of the stock-recruitment relationship for a given harvest control rule and not so much for another one.

Consideration of autocorrelation error in recruitment

The consideration of autocorrelation in the recruitment is important. Recent work has shown that population models can be affected by autocorrelation with regard to expected risk of extinction (Ripa and Lundberg, 1996; Petchey *et al.*, 1997; Morales, 1999). It may also be of importance in deciding how to manage exploited populations (Koslow, 1989; Walters and Parma, 1996; Spencer, 1997). In 1997, Punt found that a disregard of the consequences of autocorrelation in the recruitment anomalies can lead to unduly confident evaluations of the capacity of management procedures to realise conservation objectives. Furthermore, Poloczanska *et al.* (2004) have shown that introducing autocorrelation in the recruitment residuals decreased mean recruitment. Although a number of studies have taken into consideration the presence of autocorrelation in the residuals in the recruitment (Butterworth *et al.*, 2003; Zheng and Kruse, 2003; Valkeajärvi and Marjomäki, 2004), a literature review has failed to reveal the prior use of several levels of autocorrelation. In this work, two levels of autocorrelation have been tested but it has been shown that an increase of the level of autocorrelation did not have any noticeable effect, neither on the SSB or the catch.

Consideration of error in the observations

An analysis of the effect of taking into account errors in the surveys has been done in the first steps of the global analyse of the evaluation. It has shown that the introduction of errors in the survey data had a noticeable effect on the SSB and catch depending on the harvest control rule considered and always had an impact on the coefficient of variation in the TAC, whatever the HCR. Pelletier and Gros (1991) assessed the impact of sampling error in catch data on estimated yield by three techniques: the delta method, trials form a multinormal distribution of catches (Gaussian approximation) and bootstrap. They concluded that the delta method probably overestimated the variance of the response, Gaussian approximation and bootstrap gave similar values. Butterworth and Geromont (2001) took into consideration several uncertainties in their model to assess candidate interim management procedures performances, including observation error by considering that abundance indices were not uniquely proportional to true abundance but were also subject to observation error. They evaluated the effect of considering this uncertainty on the depletion at the end of the projection and noticed that projected final depletion statistics generally differed little from those when such fluctuations were ignored. Su and Liu (1998) used an observation-error assumption to estimate the parameters of a surplus-production model. They showed that the estimator could provide fuzzy unbiased parameter estimates and have some capacity to withstand the interference of stochastic errors.

Compare the effect of introducing new assessment method

Kolody and Patterson (1999)'s work indicated that different assessment models may provide similar long-term management performance for the North East Atlantic mackerel stock. Conversely, the results presented in this chapter do not show similar trends in the projections when various methods are used. Indeed, the use of SURBA as assessment method combined with a harvest control rule based on single SSB trend estimates low spawning stock biomass after 20 years and very high catch, when YCC combined with the same HCR projects relatively high biomasses and catch far below the TAC set in 2006. But these two assessment methods have shown their limits.

As explained earlier, YCC does not allow an age-dependent mortality rate one was expected. In the present work, YCC did not provide results that would suit the fishing industry expectations. In fact, for both HCRs used with YCC, the model projected very high levels of SSB after 20 years of projections associated with low, if not extremely low, levels of catch. Conversely, Fromentin *et al.* (2007) who estimated total mortality

of Eastern Atlantic bluefin tuna based on year class curved showed that the estimates of Z from the YCC analyses applied on the Spanish trap and Japanese long line fishery data appeared in good or excellent agreement with ADAPT outputs for the same period and same age-classes. Cotter et al. (2007) have also estimated stock parameters from trawl cpue-at-age series using year-class curves and have obtained results consistent with known, age-related, offshore migrations by plaice. In order to use YCC efficiently, it seems to be important to use CPUE data instead of catch to take into account for changes in effort, unless effort has remained constant over time. Effort data were not available in this work and in view of the results obtained in this study, an explanation could be that effort was not constant over time and the use of YCC based on catch was not appropriate.

SURBA being at its preliminary stage, the results obtained are not as good as expected. In fact, SSB results obtained are radically opposite whether the harvest control rule used is based on SSB or Z. Furthermore, this assessment method has been tested by various ICES working groups (ICES HAWG, 2005, 2006, 2007, 2008; ICES WGNSDS, 2006, 2007, 2008; WGBFAS 2004 2005 2006 2007 2008; WGNSSK, 2003, 2004, 2005, 2006, 2007; WGSSDS, 2006, 2007, 2008) and only one, the Working Group on the assessment of Northern Shelf Demersal Stocks (WGNSDS) has decided to keep it as final assessment method for various fish stocks and only for a year or two (cod VIa and VIIa: 1 year, haddock VIa: 1 year, haddock VIIa: 3 years, sole VIIa: 1 year, plaice IIIa: 1 year, whiting VIa: 1 year, whiting VIb: 2 years and Baltic flounder: 2 years). In 2005 and 2006, the ICES Herring Assessment Working Group explored the performance of the survey data using SURBA and noticed that the SURBA run had a higher mean $F_{2\text{-}6}$ and lower SSB in the terminal year than ICA, and showed more between year variability in F in recent years than the other models tested. Furthermore, the ICES Working Group on the Assessment of Southern Shelf Demersal Stocks examined survey data from various surveys using SURBA in 2006. For the French survey, mean standardised survey indices by year class and by year were analysed. Scatter-plots of indices within year classes and catch curves showed poor internal consistency at ages 0-5 in tracking year-classes and there were evidence of some year-effects. For one of the British surveys, results demonstrated inconsistent catch-curves but indices at each age were better correlated with other age classes, demonstrating stronger ability to track strong and weak year-classes. For the other British survey, for which only age 0 and 1 indices are available, analysis showed strong internal consistency between indices at

ages 0 and 1 but catches at age 1 in 2003 and 2004 were particularly low and poorly correlated with indices at age 0.

Change of harvest control rule

In this work, it has been possible to see that the choice of the harvest control rule had a very important impact on the state of the stock and the fishery at the end of the projection. The model-free ones based on spawning stock biomass indices provided results that could suit both fishermen and conservationists. In fact, if results are compared with that obtained using the actual management procedure, even if the latter projections were obtained only for 15 years and not 20, trends are similar and final SSB and catch are relatively close, for various levels of misreporting. Breen *et al.* (2003a) tested several model-free HCRs, issued from the literature or invented for their study, in 100 years stochastic runs to realize a preliminary evaluation of maintenance management procedures for New Zealand rock lobster fisheries. For all sets of run and for all HCRs, the random numbers used in population, observation and implementation randomness were the same, so that differences between rules do not indicate variances in the stochastic environment. By informally experimenting all rules with various parameters for each rule and without tuning, they could eliminate some rules that did not perform adequately. Among the rules tested, one of them is similar to the three SSB-based rules implemented in the present work. The authors showed that their similar rule behaved well without a latent year, although in some cases the scale of fluctuation seems large. It seemed to provide mean biomass close to the set target and good mean catch, all this without crashes.

Although a number of fishery management systems have been modelled using various harvest control rules (e.g. Butterworth and Geromont, 2001; Hilborn *et al.*, 2002; Breen *et al.*, 2003a; Kell *et al.*, 2006; Hobday and Punt, 2007 in De Oliveira *et al.*, 2008; Levontin, 2007), a literature review has failed to reveal the prior use of a harvest control rule based on a ratio of total mortality rates such as the one implemented in the present work (the Z-based rule). The first results, discussed in sections 5.3.2 and 5.5, have shown that this rule responds immediately to change in the stock dynamics. Its conservative aspect might make it interesting in case of rebuilding plans but does not seem to be a good choice when the stock is considered in a good condition as it tends to reduce catch until a level that might violate some of the industry preferred level of catch.

Roel and de Oliveira (2007) tested model-free and model-based HCRs for the Western horse mackerel stock. Results suggested that model-based HCRs are more conservative if the assessment is unbiased or if bias is low. Their results could also be explained by the paucity of fishery-independent data available for this stock. In fact, the only fishery-independent data available is an estimate of egg abundance made every third year. If quantity of data is limited, the variability implied by them can be higher and with good quality survey data.

Although a number of fishery management procedures have been modelled using various assessment methods (Needle, 2006; Porch *et al.*, 2006; Pastoors *et al.*, 2007; Plagányi *et al.*, 2007; Punt and Donovan, 2007), the one implemented in the present work (model-based HCRs) did not provide good results but that might be due to the poor quality of the assessment results, as explained in the previous section. Indeed, the model-free HCRs based on SSB have been shown performing well and the model-free Z-based one behaved as expected by conserving the stock so the extreme results obtained with assessment methods included could be justified by the inefficiency of the assessment methods.

Constraint in the TAC

Constraint in the TAC is at present implemented in the actual management of the North Sea herring stock and has been tested in other management procedures in this work. As explained previously, the consideration of a limitation can have an important impact on the final state of the stock (high SSB) and the fishery (catch maintained at reasonable level) but also on the variability in the inter-annual change in the TAC, which might violate some of the industry preferred limitations on variation in inter-annual TAC. In fact, limitation of TAC makes the annual change in TAC fluctuates wildly between close to +15 to -15% - which is clearly unstable behaviour. The results obtained mirror results also obtained by others (Kell *et al.*, 2006; Kelly, 2006). Indeed, Kell *et al.* examined the effect of applying various levels of symmetric bounds (10%, 20%, 30%, 40% and no constraint) on the annual fluctuation in TAC. They noted that the lower the constraint was (10%), the larger the effect was on the annual change in SSB and yield. Kelly *at al.* tested the effect of introducing a constraint of a maximum year-on-year change in TAC of 15%. Their results showed that the introduction of a 15% limit to the annual changes in TAC resulted in a huge impairment to the likely recovery of the stock, assuming low target fishing mortality. They also tested the effect of combining

the constraint in the TAC with an assumed bias of 20% and random error in the assessment-estimated value of virtual SSB and the actual virtual fishing mortality and an upward implementation bias of 20% in the catch. Results showed that the stock gave the impression to be kept below BPA, regardless of the target fishing mortality.

The need for an inter-annual constraint arose from the desire of industry to have relative stability in catches from one year to the next. Unfortunately, due to the conservative nature of change thus induced it does not let management action respond fast enough in the case of severely depleted stocks, where there is a need to rapidly decrease TACs to effect a recovery, as evidenced by the lack of success of any of the European Union's recovery plans to date. Furthermore, as shown in Figure 47, the limitation on increases of the TAC can create situations where a stock becomes too large too fast, with the consequence that Ricker-like stock recruitment dynamics lead to a decline in recruitment. In its latest communication, the Commission is considering allowing an increase in inter-annual variability in TAC movement to 20% (CEC, 2008). This will go some way to correcting the problems created by the 15% rule: by increasing the upper limit, catch could be more appropriate for the level of the SSB at high stock levels, but for stock in bad conditions, increasing the lower limit of constrain might speed up the recovery of the stock

Effect of increasing misreporting

Overshooting the TAC and misreporting catch are not rare phenomena in actual fisheries but Powers and Restrepo (1998) noticed that the implementation of uncertainty had largely been ignored in the evaluation of management strategies. Leaman and Stanley's (1993) work supports perceptions of stock dynamics and indicate a reduction of the biomass in association with unrestricted fisher, which implies over-exploitation and misreporting. One of the major issues is the uncertainty in the relationship between the TAC recommended by the management procedure and the actual catch (Horwood, 1994). Johnston and Butterworth (1997) have included the impact of catches by poachers and discard mortality in their evaluation of a management procedure for the rock lobster (*Jasus lalandii*) resource off South Africa's west coast. In several studies, a way to implicitly take into account implementation uncertainty was to set lower bounds on the catch. This mirror the reality that even if a management procedure indicates a zero TAC, this is unlikely to be enforced for socio-economic reasons (Cochrane *et al.*, 1998).

Roel and de Oliveira (2007) have tested the effect of overshooting the TAC for model-based and model-free HCRs applied to the Western horse mackerel stock. For both types of HCRs, results showed that the effect of considering a misreporting (mainly area misreporting for this stock) was noticeable. Under some circumstances, the risk of seeing the SBB falling below the threshold was doubled. Dichmont *et al.* (2006b) demonstrated that the extent of implementation error is a key factor affecting performance of management procedures for Gulf of Carpentaria prawn stocks. In fact, the probability for the spawning stock size of being above the spawning stock size at maximum sustainable yield at the end of the projection for the two prawn stocks studied is lower than when other sources of variability are considered (fishing power, catchability coefficient in the operating model and the assessment, spatial autocorrelation in recruitment success and target spawning stock size used in the decision rule). Furthermore, the stability in the catch from one year to the next is increased.

As mentioned in the previous section, Kelly *et al.* (2006) included an upward implementation bias of 20% applied to catches in a management procedure. A comparison of the results obtained with and without this error resulted in lower expected final SSB values, although the difference was not great. it is important to remember that this implementation error was combined with a bias and random error in the assessment-estimated value of virtual SSB and F values. Those studies confirm what has been found in the present work. Nevertheless my simulations largely agree with his results - small levels of implementation error (10% - 30%) may not have significant impacts on the performance of HCRs designed to deal with significant amounts of error and bias in the operating model.

Effect of starting the projection when initial conditions are bad

Miller *et al.* (2007) tested a management strategy evaluation framework for the Greenland halibut fishery in following the report of the inefficiency of the rebuilding plan, in effect since 2003, in initiating any recovery. They evaluated two management strategies: F *status quo* (F_{sq}) and $F_{0.1}$. Given the state of the stock at the beginning of their simulation, the first HCR could be defined as a risk-prone scenario concerning the stock rebuilding considering the extremely high level of the current fishing mortality. The second HCR would have a similar conservative effect to the Z-based HCR implemented in this work as it would lead to an important decrease in fishing mortality

and catch. The first strategy provides higher catch than the second one but values increase very slowly during the projection. The $F_{0.1}$ strategy, conversely, projects a notable decrease of the catch in the first years which then increase steadily during the remaining years to almost reach the level of the F_{sq} strategy at the end of the projection. In terms of SSB, the biomass stays at very low levels under the F_{sq} strategy when with the $F_{0.1}$ strategy it increases consistently and considerably to reach the equivalent of four times the maximum historical level recorded. Punt *et al.* (2002a) derived a similar results, showing that the median of the distribution of the ratio of the spawner biomass at the end of the projection period (20 years) to the corresponding pre-exploitation equilibrium set was always smaller when the initial SSB was lower, for the four stock considered in their work and for various levels of steepness in the recruitment and fishing mortality rate targets.

My results agree with those described above, i.e. bad initial conditions emphasize the effects of the HCRs. Indeed, the conservative HCR (Z-based) tends to decrease the catch more intensely and increase the SSB more considerably under poor conditions than when initial conditions are considered as relatively good. Contrarily, when the HCR does not have such a conservative nature, the increase of the SSB and the decrease of the catch are less important when the initial conditions are not defined as being good.

CONCLUSION

Summary and main findings

One of the current problems is that more and more fish stocks are assessed as being overfished. In 1999, ICES reported that 40 out of 60 major commercial stocks in the North-East Atlantic were outside safe biological limits or, in other words, heavily overfished (OSPAR, 2000). In the same year a scientific assessment of European fish stocks judged that 67% were overfished, 40% depleted, and 37% of species suffered from both problems (CEC, 2000). ICES has also estimated that mature demersal fish had decreased by about 90% between the early 1970s and the late 1990s (CEC, 2001). Such widespread difficulties are likely to lead to reductions of the TAC being necessary in a large number of European stocks over the next decade, which might induce an increase of the levels of misreporting.

As explained in the introduction, most current fisheries management, and particularly stock assessment, is heavily reliant on fisheries dependent data, such as data on commercial landings and fishing effort (Nielsen and Lewy, 2002; Lewy and Nielsen, 2003; Chen *et al.*, 2004; Cotter *et al.*, 2004). One of the major issues that has always undermined assessments is that these data might not be reliable for various reasons, such as biases introduced through the non-random nature of data acquisition or the misreporting of catches. This is the case for example of the North Sea herring stock. During the decline of the resource in the 1990s, the reduction of TACs triggered an immediate decrease in compliance, with fishing exceeding the agreed TACs by an estimated factor of 1.35 (Simmonds, 2007) which had a significant effect on creating a false stock assessment. Another very good example is the North Sea cod stock. Recent ICES assessments based on fishery-independent data show a strong increase in the proportion of unreported catches as the TAC was reduced in the early 2000s, rising to a maximum of 129% in 2003 (ICES WGNSSK, 2007). Estimates made by control authorities confirmed these levels of misreporting (see Scottish Fisheries Protection Authority, Annual Report 2007), but at the time there was sufficient uncertainty about the true level of catches, and this uncertainty had such a significant effect on the assessment, that it was necessary to depart from the use of fishery-dependent data in the mid-2000s to achieve a reliable stock assessment for this stock.

It is therefore important to consider developing a suite of fishery-independent data to supplement fishery-dependent data especially for situations of declining TACs (and when fishermen may not agree with scientists and authorities on the need to reduce catches to preserve stock status). A number of fishery-independent methods of differing complexity currently exist. The main objective of this thesis was to evaluate these different management procedures and see which of the procedures based on fishery-independent data performed best, and whether they would provide more robust outputs to high levels of uncertainty when compared with procedures based primarily on fishery-dependent data, such as those currently used in North Sea herring management.

In order to test this hypothesis, a Management Strategy Evaluation framework was implemented, composed of an operating model (Chapter 2), an observation error model (Chapter 3) and a harvest control rules model (Chapter 4) including assessment methods (Appendix 2), where available and applicable. A thorough analysis of the data available allowed the implementation of the operating model to be as realistic as possible, including the exploration of relationships between some biological factors. Process error was included in the recruitment to take into account the uncertainty about this process which can be highly influenced by environmental factors. The observation error model was based on two types of indices, one of them being non age-structured and the other being age-dependent to account for age/length dependent measurement error which is present in all such fisheries data. Simple Harvest Control Rules (HCRs) were implemented. Various levels of implementation error were included.

The parameterisation of the operating model revealed some relationships between some biological components of the stock. There were potentially important relationships between maturity and spawning stock biomass for young fish – age 2 and 3 – of the herring stock; between catch weight-at-age and spawning stock biomass; and between stock weight-at-age and the spawning stock biomass. The former two were investigated in sensitivity analyses, and the latter was introduced into the model. An analysis of the selectivity over time from the historical data showed that a logistic curve could be fitted to the data and, consequently, this was used in the operating model. Three stock-recruitment relationships were tested (Ricker, Beverton and Holt and hockey-stick) but of these only the hockey-stick and Ricker provided good fits to the historical data. Finally, I have demonstrated the existence of autocorrelation in residuals in the

recruitment, which was incorporated into the operating model, but there appeared to be no change of the level of autocorrelation over time.

Chapter 3 describes the observation errors model. Two types of indices are described and fitted to available data: non age-structured and age-structured indices. The available observations are: herring acoustic survey, International Bottom Trawl Survey (IBTS), Method Isaac Kidd Mid Water Trawl survey (MIK) and Multiplicative Larval Abundance Index survey (MLAI). For each of them, a specific error has been included: a log normal error with a constant coefficient of variation for the first type of indices and an ageing error process for the second type. For each of them, indices of abundance were simulated from the known historical trajectory of the herring stock with the appropriate error structure for each type of survey data available. In all cases, the simulated observations closely followed the actual trends in numbers or spawning stock biomass.

Harvest control rules can be grouped into two categories: model-free and model based. Model free HCRs uses were: based on direct observation, based on relative SSB trends, based on combined relative SSB trends and based on total mortality rate. Model based HCRs were based on relative SSB trends and based on total mortality rate, each of them using each new assessment method: YCC and SURBA. The latter corresponds to the actual management which use ICA as assessment method. Two supplemental elements were used: a management-induced constraint in inter-annual changes in the TAC to $\pm 15\%$, which is implemented in the current management of the North Sea herring stock, and a potential misreporting in the catch data which is assumed to exist in several fisheries in Europe.

The final chapter listed the management procedures based on the elements described in the previous chapters and provided all results of their evaluation.

I found that there were some model-free harvest control rules that used fishery-independent data that did perform as well as the current model-based methods. Under normal conditions they did not out-perform the assessment that is currently used for management of this stock (ICA).

The choice of harvest control rule, as expected, makes a difference in the results obtained. Looking first at model-free HCRs - those that did not rely on an assessment being conducted, the HCR based on total mortality responded rapidly to any change in recruitment and it was highly conservative, giving higher spawning biomass and lower catches than when SSB-based HCRs were used. The current assessment and management HCRs used for North Sea herring provided results which were relatively similar to the ones obtained with the model-free SSB-based harvest control rules. As the current management can be assumed to be a reference, the model-free SSB-based HCRs can be considered as good management procedures.

In contrast, the two new model-based HCRs tested here, YCC and SURBA, did not perform as well as the current assessment method (ICA). I found YCC to be uniformly inappropriate, producing extremely unbalanced trajectories. The reason for this is that it does not allow age-specific Z (total mortality) thus disrupting the model. SURBA, by not being flexible enough, does not properly catch the signal coming from the acoustic survey and does not accurately assess the stock. But SURBA is at its preliminary stage and some improvements should provide better results in the future.

Model free methods performed equally well when compared with the current assessment methods ICA under conditions of low implementation error, and, crucially, they performed marginally better than ICA with high levels of implementation error. ICA crashed and produced erratic management results when misreporting was 80%, and although the performance of model-free HCRs was also affected this was controlled and did not lead to stock collapses.

Management procedures based on the simplest HCRs (SSB-based model-free) provided the best results, in terms of robustness and performance when both the SSB and the catch in the final year were taken into consideration. At relatively low levels of uncertainty, the current management was as robust as the simplest management procedures but as the level of misreporting increased, its relative robustness deteriorated. A misreporting of catch of 80% is not unrealistic, even if it might not be the most common in European fisheries nor perhaps may it last for an extended time (North Sea herring: 13% of the total catch in 2005 (Marine Institute, 2006) with an apparent reduction to approximately 5% in 2006 (Pelagic RAC, 2006); North Sea

mackerel: misreporting of 15 % of the total catch taken in sub-area IV and division IIIa into VIa in 2006 (ICES WGMHSA, 2006)).

I found that management procedures were sensitive to some biological assumptions and various sources of errors. A change in the form of the stock-recruitment relationship had an impact on the predicted final state of the stock. As one would expect, for high levels of spawning stock biomass the recruitment decreases when a Ricker relationship is considered but remains constant when a hockey stick relationship is assumed, which leads to a higher stock level after the 20 years of projection. Conversely, an increase of the level of autocorrelation in the residuals did not seem to have a noticeable effect on the output, whether management procedures were based on fishery-independent or dependent data. The sensitivity analyses regarding maturity-at-age and catch weight-at-age showed that considering relationships between these parameters and the spawning stock biomass did not seem to have any noticeable effect on the final state of the stock. From these points, it is possible to conclude that the management procedures were robust to small changes in the operating model.

The results showed that considering an error in the survey indices could have a non negligible impact on the projections, depending on the harvest control rules chosen. It is then important to consider the ageing error process carefully. The most sensitive and reactive the harvest control rule is, the most the effect of the error will be important. This is especially the case with the model-free Z-based rule.

As mentioned in the previous chapter, the stock is considered as being in relatively good condition at the beginning of the projection, in 2006. In the sensitivity analysis section (5.3.3), the model was tested with bad initial conditions, i.e. low stock size. The fitting of the model to data is similar to the one made under good initial conditions. The only change is the amount of data available as all information posterior to 1996 has been removed. Only two harvest control rules have been tested with different levels of misreporting and in all cases, the stock recovered relatively quickly. Even if this sensitivity analysis is quite simple as the fitting of the operating model has not be modified and only two simple harvest control rules have been tested, it gives a good indication of the potential of the harvest control rules and their behaviour under bad initial conditions.

The constraint in the TAC presently included in the actual management of the North Sea herring resource, has been implemented and tested with model-free management procedures and the current management. It showed that its effect on the current management is good as it does not show any unstable behaviour, although it does constrain the ability of the management procedure to rapidly increase spawning stock biomass when recruitment fails. Conversely, when model-free management procedures were considered, either based on SSB or Z, the inter-annual variation in the TAC was not negligible and the annual change in TAC fluctuated wildly between circa +15 to -15%. This might not suit fishery industry requirements in terms of stability in the catch as this is clearly unstable behaviour.

It is important to remember that the herring fishery is a single species fishery and the results obtained in this thesis might not be applicable to multi-species fisheries. In fact, multi-species fisheries are more complex systems as it is more difficult to anticipate catches and by-catch. In the case of a mixed fishery, by-catch is a significant consideration. Furthermore, the North Sea herring stock is a well known fishery and a wide range of data is available, including information about the observation errors in the four surveys and catch data collected for more than three decades for some surveys. Such quality and quantity of information may not be available for all other stocks on which it would be interesting to test such methods.

Scientific contribution

The main aim of this thesis has been to contribute to the implementation of methodologies that attempt to evaluate management strategies based on fishery-independent data and a combination of fishery-dependent and independent data. It also contributed to the evaluation of their robustness The North Sea herring was used as a case study because of the quantity of high quality data available for this stock, and the fact that it has experienced and recovered from two periods of severe depletion. Methods have been developed and applied to evaluate the consequences of various fisheries management scenarios involving different assumptions and uncertainties.

The scientific contribution of this study consists of five points: implementation of a complex management strategy evaluation framework for a European fishery mainly based on fishery-independent data, implementation of a methodology to include ageing error process in the survey indices, demonstration of the negative effect on stock management of including a constraint in the TAC, demonstration of the undistinguishable effect of a low level of misreporting and demonstration of the robustness of fishery independent management procedures to various biological assumptions and sources of error.

This work is the first attempt to apply such a complex management strategy evaluation framework based on fishery-independent data to a European fishery. The complexity of the framework, which includes an exploration of plausible biological relationships and combines these with explicit characterisation of model error and bias, has proven to be robust within the modelled scenarios. The model performs equally well in simulations of populations starting in healthy and severely depleted situations. With suitable biological re-parameterisation, the model could be used to test other stocks for which fishery-dependent data are thought to be biased or inaccurate.

The most important scientific contribution of this thesis is the demonstration of the robustness of fishery-independent based management procedures to various biological assumptions and sources and levels of errors. Four model-free fishery-independent harvest control rules were implemented (see sections 4.3.4, 4.3.5, 4.3.6 and 4.3.7). The effect of various biological assumptions and sources of errors (form of stock-recruitment relationship, level of autocorrelation in residuals in the recruitment, observation error and implementation error) were tested for model-free management procedures (i.e. those not using a stock assessment analysis) based on fishery independent data, for the current management procedure (which uses fishery dependent data in an assessment called ICA) and procedures based on new assessment methods. The latter were shown to be behaving poorly under some assumptions and particularly when the level of misreporting increased. The model-free based management procedures behaved well and trends and projected values were relatively similar to the one obtained with the actual current assessment and management procedure. When the level of misreporting increased from 10 to 30%, the model-free procedures were robust. Even a high level of misreporting did not induce unrealistic or unacceptable results.

It is widely known that the ageing of fish is not an exact science and error is normally correlated across ages to produce an ageing error effect. A complex method to include ageing errors in simulated data has been implemented and described in Section 3.2.3. The effect of including ageing error process in survey indices has been evaluated in section 5.3.1 and results showed that the intensity of the effect was dependent on the harvest control rule considered. For model-free HCRs based on spawning stock biomass, the consequences of the inclusion of the ageing error process in survey data were minimal. When a Z-based HCR was considered and a hockey-stick stock-recruitment relationship assumed, the spawning stock biomass at the end of the 20 years of projection was doubled when the ageing error process is taken into account. Such error is present in many fisheries and it is important to consider it in management strategy evaluations as this can have important repercussions on the output of the models and the advice provided to managers. Its inclusion makes the model more realistic and should improve the quality of the results. The precision might not be improved as the consideration of a potential error creates a range of possible values for the survey index for each Monte Carlo simulation but each simulation has a high probability of covering the real value of the survey index.

One of the elements of the current management system for the North Sea herring stock is a constraint on the TAC. An upper and a lower limit of 15% for the inter-annual variation in the TAC are set for each year (section 4.3.9). According to the results obtained for the actual management in the present work (5.4.1.1), the inclusion of the constraint does not have any negative effect. This is due to the fact that the inter-annual variation is always smaller than the +/- 15% limit. This is not the case when management procedures are based on fishery-independent data (section 5.3.3.3). Indeed, it has been shown that model-free harvest control rules, and particularly the Z-based one, react very rapidly to any change in the catch. In these situations, the constraint on inter-annual change in TAC fluctuates wildly between close to +15 and -15% which is clearly unstable behaviour and would not suit the requirements of the fishing industry in terms of level and stability in catch.

The final important scientific contribution concerned the behaviour of management procedures under conditions of implementation uncertainty (most particularly, under-reporting of the catch, which is expressed as both uncertainty and bias). TAC regulation used in fisheries management can lead fishermen to under-report their catch.

Unfortunately, national and international institutions rarely have enough resources to control and counteract illegal or over-quota landings, or to estimate their extent accurately. Furthermore, even when such under-reporting is suspected, official data are often still used in assessments and management procedures assume perfect future implementation. In the model, I included three levels of misreporting. The smaller one (10%) had no significant effect on the performance of any management procedure. This is because this low level of bias appeared to be undistinguishable within the MSE from known and assumed errors in the recruitment and in the survey data, particularly ageing error as mentioned earlier. Indeed, in sections 5.3.2, 5.4.1.2, 5.4.2.1 and 5.4.2.2 the two errors mentioned above were taken into consideration in all simulations and the three levels of misreporting were tested and compared to simulations where the data were assumed to be exact (without misreporting). Results obtained for the lowest level of misreporting and situations where there was no misreporting were similar or differences were not noticeable. Differences started to be observed when the level of misreporting increased to at least 30%.

Recommendations for further research

Based on the results obtained in this thesis and in order to carry on and improve the work implemented here, three studies would be recommended.

First of all, it would be interesting to evaluate the management procedures implemented in this work with other stocks for which similar data are available and see if the 10% of misreporting is detectable. It has been shown that such a level of misreporting went unnoticed in the outputs due to the consideration of error in the recruitment and the observations. Some adjustments might have to be made to fit the operating model to the selected stocks. For example, if a density-dependence phenomenon is known or supposed, it would be interesting to test other stock-recruitment relationships than those implemented here. Furthermore, changing the form of the selectivity curve which is fitted to the data set might be another adjustment to make. As the two assessment methods implemented in this work (YCC and SURBA) have been shown to be unreliable, two possibilities can be considered: either improve them – SURBA is

already under improvement – or implement other methods based on fishery dependent and independent data to test the management procedures developed here.

A second research that could be developed, based on the present work, is to distinguish between the two autumn spawning sub-stocks (North of the North Sea and southern North Sea and the English Channel) and conduct separate, parallel analyses for the two sub-stocks. Presently these two sub-stocks are managed by the European Commission with distinct TACs but are assessed by the Herring Assessment Working Group using a single, combined assessment. Whilst the two sub-stocks have been considered as a single stock, as explained in section 1.4.1, they are known to be different. Recent observations have shown a modification of the behaviour of the southern stock (migration season, recruitment period) which might be correlated to the climate change. This could lead to an increase of the differentiation between the sub-stocks. It would therefore be interesting to see if the results obtained for the sub-stocks would follow the same trends. The major issue would be the availability of sufficient data for each sub-stock to efficiently run parallel analyses. A complete data analysis such as the one realized in Chapter 2 would have to be done for each sub-stock. The structure of the management strategy evaluation framework should be kept identical, except for the tuning of parameters such as stock-recruitment parameters or the selectivity curve.

A third interesting analysis would be to redo the evaluation of the management strategies but starting with a stock in bad conditions and with a stock-recruitment that would force a low recruitment and consider various levels of misreporting to see if the procedures implemented in this thesis would still be robust to uncertainties. A preliminary analysis of the robustness of some management procedures, such as model-free SSB- and Z-based HCRs, to bad initial conditions has been carried out in this work. Due to time constraints, it was not possible to tune the operating model. As a consequence, values of parameters fitted in the second chapter were kept the same. The model was fitted to data corresponding to a stock for which SSB has fluctuated highly in the past and which is considered as being in a relatively good condition in 2006. As a consequence, and under the condition of using HCRs showing a reasonable behaviour, it is not easy to verify the robustness of the management procedures implemented to bad initial conditions. By using a stock which is at present assumed to be in bad conditions, starting at a low SSB and forcing a limited renewal of the population, the robustness of the procedures should be easier to observe. Again, two possibilities could be

considered: (i) keep the data of the North Sea herring stock, modify manually the state of the stock, redo the model fitting following the methods developed in the first chapters of this thesis or (ii) use another fish stock which is at present in a bad situation, such as the North Sea cod. If the second case is chosen, similarly to in the previous section, a new data analysis would have to be done to fit the model to data.

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APPENDIX

Appendix 1: ICES Areas

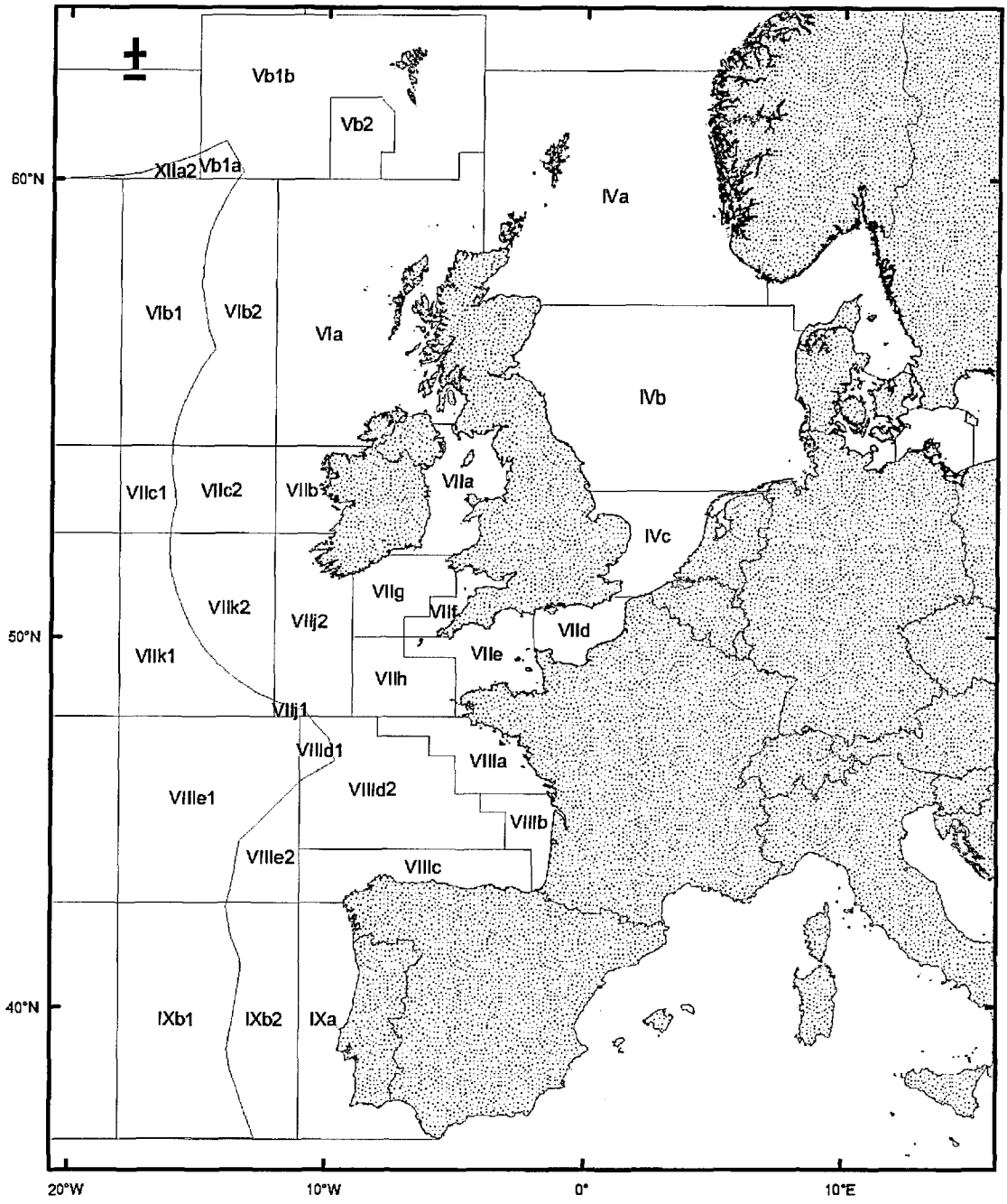


Figure 78: ICES areas of the Western European coast, from Norway to Portugal (ICES Maps).

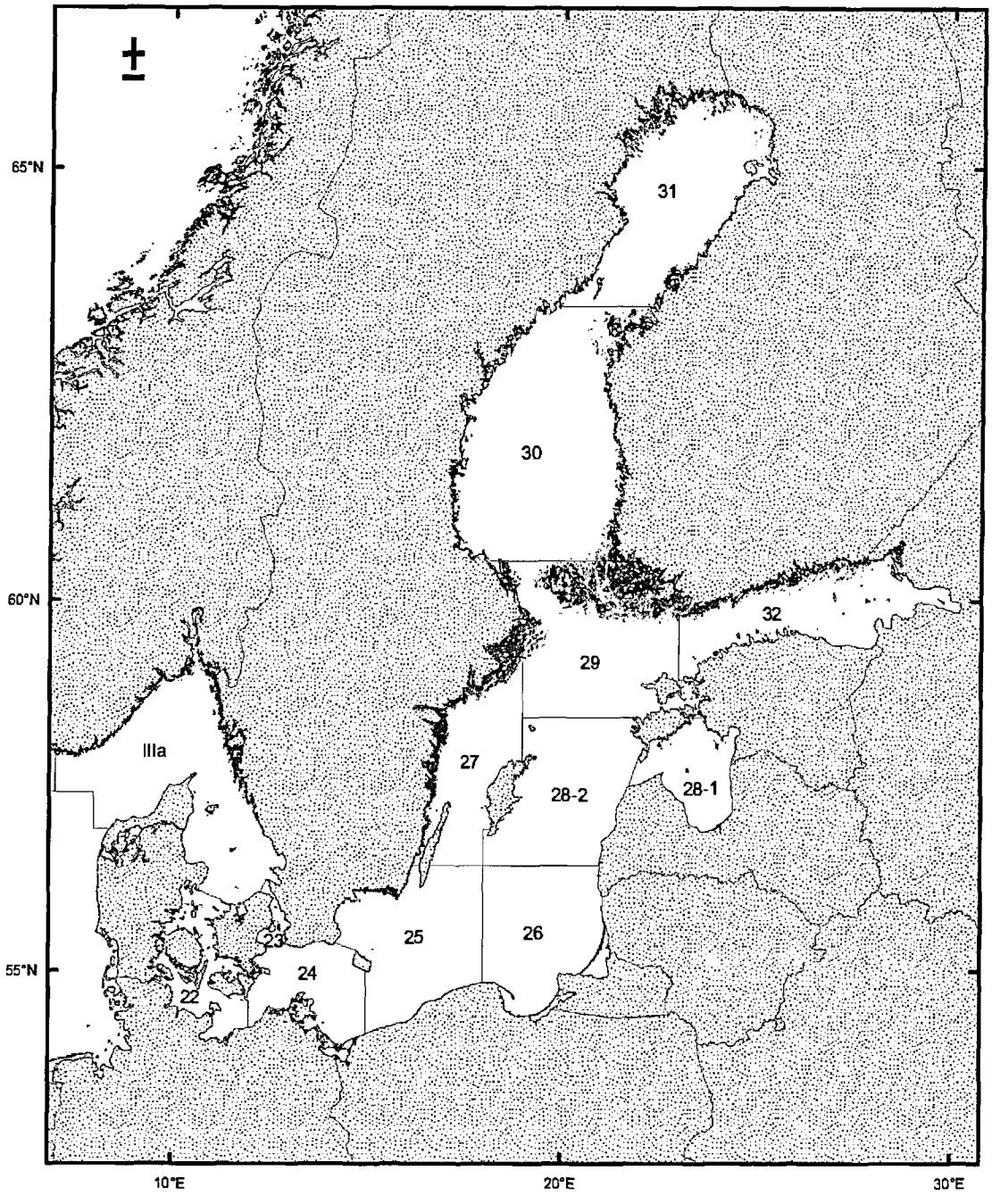


Figure 79: ICES areas of the Baltic Sea (ICES Maps).

Appendix 2: Assessment methods

Introduction

The aim of the assessment model is to estimate stock status from observations and the most important reason to make fisheries stock assessment is to evaluate the potential consequences of alternative management strategies (Punt and Hilborn, 1997). The state of a stock is defined by its abundance at a specific time, together with the mortality and growth that control its development (Lassen and Medley, 2000). Assessment scientists use survey and fishery information in mathematical calculations to estimate the abundance or biomass of the resource considered. Fishery managers use the assessment information about biomass and fishing rates to make decision about the allowable amount of fish that can be caught during the next fishing season. Stock assessment scientists are primarily concerned with variability of the stock.

In the past, a Virtual Population Analysis (VPA) was used to assess the North Sea herring stock. This method is explained in the first section. As this method could not cover all situations, new methods have been developed, deriving from VPA. Some of them are explained in the following sections: Extended Survivors Analysis (XSA), Integrated Catch at Age (ICA), combined separable VPA and ADAPT (SAD), Instantaneous Separable VPA (ISVPA), Assessment Model Combining Information from various sources (AMCI) and Multi Species VPA (MSVPA). ICA is part of the one used in this work with two other: Year-Class-Curves (YCC) and Survey Based Assessment (SURBA) which principles are explained in the following sections. Finally, the last standard assessment method (TSA) used by ICES experts and mentioned in the introduction of this work is explained.

Virtual Population Analysis (VPA)

Haddon (2001) and Jennings *et al.* (2001) explain the principles of the Virtual Population Analysis. VPA is an analytical strategy that relies on the idea that if one has records of the catch-at-age of a set of cohorts until the cohorts all die off, then one should be able to literally back-calculate what the numbers-at-age must have been. In

this way the numbers in the population can be projected backwards until estimates are obtained of the original recruitments. This requires an estimate of the natural mortality and estimates of the fishing mortality by age and year. VPA uses commercial catch data to calculate stock sizes and mortality rates of age-based or length-based cohorts. VPA does not by itself indicate how many individuals can be caught to meet a given objective, nor does it predict the future. In fact, it explains the past. For, if we know the historical age structure of a population, we can then see the consequences of changes in mortality rates, based on methods such as yield-per-recruit calculations.

If we know how many fish from, a given cohort were caught one year, we have a minimum estimate of how many must have been alive the previous year. If we add natural mortality, we have the total mortality for that year and the total number that must have been alive the year before. One can then work backwards, year by year, deriving annual estimates of numbers of survivors and mortality rates. With a good picture of past and present population dynamics, one can then make the forecasts needed to assess management options.

The population model is most often used in a single-species version. It is usually assumed that species interactions do not introduce variation in mortality or growth rates between years (i.e. M is constant from year to year). This assumption is relaxed in multispecies VPA (MSVPA).

VPA methods have been grouped in a number of ways:

- Based on the restrictions imposed in the data model; for example, Extended Survivor Analysis (XSA) does not include biomass indices for tuning the VPA.
- Based on the assumptions imposed, particularly on fishing mortality; for example, the ICA method assumes that the fishing mortality can be decomposed (separated) into an age and a year effect.
- Based on how the calculations are organised. For example, the Virtual Population Analysis (VPA) solves the Baranov equation directly by numerical methods, whereas Cohort Analysis, based on the same data model as VPA, uses an approximate solution to this equation. ADAPT, based on VPA, uses the fishing mortality of the terminal year and of the oldest age as the unknown parameters, whereas the XSA method uses the number of survivors of the each age group as the unknowns.

Children of VPA

EXTENDED SURVIVORS ANALYSIS (XSA)

Dickey-Collas *et al.* (2004) explain in their report the concept of XSA. This is the model used on North Sea cod, sole and plaice. It is based on the basic VPA methods and involves tuning of the recent estimates of fishing mortality (F) with estimates from surveys or commercial CPUE data (Darby and Flatman, 1994; Shepherd, 1999). It was developed from the method of Doubleday (1981). XSA differs from other VPA approaches by using estimates of survivors in the final year to be used in the minimisation process. Most other VPA models just used the numbers of fish on the 1 January of the final year within the analysis. Statistically it uses an iterative re-weighted least squares method.

The basic process is:

1. The abundance of survivors for each cohort is treated as the principle variables to be estimated.
2. Estimate the population abundance for all other ages and years by VPA (Pope, 1972) using the estimated survivors as terminal populations.
3. Calibrate the tuning indices (CPUE or surveys) using the abundance estimates of each tuning fleet and simple catchability models.
4. Use the calibrated abundance indices, for all ages in each cohort as the basis for estimating survivors.

XSA assumes the catch data to be exact, and hence it does not make any assumptions about separability, thus allowing the selectivity pattern of the catch to change by year and age. Shepherd (1999) said that this assumption may be inappropriate where "catch data are poorly sampled or otherwise defective, but where one or more sets of reliable survey data were nevertheless available." It does treat the survey or CPUE fleets as separable and hence determines a selectivity curve for each fleet. It also allows the operator to shrink the most recent estimate of F to a mean value of a chosen number of most recent years. This implies an assumption that the fishery has not changed greatly over the recent time period and gives greater stability to the assessment. However, the use of shrinking F to the recent mean may cause conflict with strong signals in the

surveys, particularly if the catch data are inaccurate and thus a bias towards the mean is introduced (Shepherd, 1999).

The current version of XSA cannot deal with biomass indictors as a tuning index for the assessment. Hence egg or larvae surveys and biomass only acoustic surveys are of no use in an XSA assessment.

XSA calculates the variances of the survey fleets in relation to the catch data and uses them as weighting factors as an integral part of the process and thus it prevents weighting factors being applied manually during the assessment, if so required.

XSA has been heavily scrutinised by ICES and the International community (ICES WGMG, 2003). However the sensitivities of the model to extreme changes in catch or biomass have yet to be assessed. Simulation studies suggest that XSA behaves well, if the assumptions used to create the simulated population are similar to the assumptions underlying XSA. Simulation studies have yet to be carried out on the behaviour of XSA under severe catch limitations.

INTEGRATED CATCH AT AGE (ICA)

In the same report as for XSA (Dickey-Collas *et al.*, 2004), the principle of ICA is described. This is the basic model used on all the herring stocks and NE Atlantic mackerel. In its most basic form it is a separable model for the most recent part of the time series attached to a traditional VPA for the more distant past in the time series. As a separable model, it accepts that the measurements of the catch are not exact and the reduction in the number of parameters estimated improves the precision (ICES WGMG, 2003). In this approach, the fishing mortality $F_{a,y}$ is partitioned into a year effect f_y, which might change with changing fishing effort, and an age effect s_a, which represents how different ages of fish are susceptible to fishing gear in differing degrees. Thus, we can write fishing mortality as $F_{a,y} = s_a * f_y$. This greatly reduces the number of parameters to be estimated and renders tractable the analysis of large datasets, although the assumption of separability may not always be reasonable (Needle, 2000).

A Beverton-Holt stock-recruitment relationship may be imposed on the model fit, with appropriate weighting, and a VPA 'shrunk' to some mean (as in the Lowestoft XSA package, Darby and Flatman, 1994) may be estimated.

Unlike XSA it also gives outputs of the uncertainty in F, due to the fit of the model. Its major weakness is of course the separability assumption, i.e. assuming that the

exploitation pattern (relative F at age) of the fishery on the fish has not changed during the period of separability (Patterson, 1998a). It does allow for two periods of separable constraint to exist, with either an abrupt or gradual change between them.

The minimisation process also requires that selection (relative F) on two ages within the catch at age matrix are fixed and predetermined. One age (usually the first at full exploitation and called the reference age) is set at an exploitation of 1 and the selection at the final true age is then set relative to that value (Patterson, 1998a). This results in part of the exploitation pattern being assumed prior to the assessment and hence it is very important when using ICA that the model fit is widely explored. The selection of the plus group is assumed to be equal to that of the last true age.

The model is based on the work of Deriso *et al.* (1985) and Patterson and Melvin (1996), with additional work by Kimura (1986) and Gudmundsson (1986). The model is fitted in two stages. Firstly a simple iterative procedure (non-linear least squares minimisation) is used to find a conventional separable VPA that fits best to the available survey data. Subsequently a more complicated multidimensional minimisation can be carried out that involves re-weighting the parameters and output functions. Most stock assessments do not use this second stage.

Importantly, Patterson (1998) comments that the underlying assumption of uncorrelated errors in the catch is unrealistic (a common assumption in almost all models), but suggests that there is no alternative at present. Most catch at age matrices will have correlative errors due to age effects, strong cohort effects or other effects.

ICA allows for a choice of relationship between the surveys and the catch at age data. The relationship can be either absolute, linear or a power model. ICA differs from XSA by the surveys being within the objective function of the model. The entire time series of surveys is used to estimate their relationship to the VPA numbers (this relationship is called the catchability coefficient, q) and then this catchability coefficient is used in the separable part of the model to determine terminal Fs.

Apart from offering the re-weighting of the survey and catch data within the model (the second stage described above and not often used), ICA offers the operator the opportunity to weight the importance of the input data manually. This is usually used, and has been very useful in the assessment of North Sea herring, where variances of the surveys were investigated in the project EVARES (Beare *et al.*, 2002). It is important to remember that although the catches are not considered to be exact, the default weighting procedure results in a heavy weighting of the catch over the survey data. This is due to each age in the catch at age matrix getting a weighting of 1, compared to each survey

getting a weighting of 1. So a catch matrix of 9 ages over 25 years would have a weight of 225, an acoustic survey with ages of fish would have a weight of 1 and a biomass survey (e.g. of larvae) would also have a weight of 1. These weightings can be changed but are rarely adjusted to any large degree, hence the catch at age data still dominate the assessment. There are two options for weighting of indices in the separable model: manual, which may be used if either the analyst has some prior information about the variances of each index or all indices are to be weighted equally; and inverse-variance reweighting, in which more precise indices are automatically given greater weight.

Like XSA, ICA also gives the option of shrinking the recent estimates of F to the mean of a selection of years, but unlike XSA this is an extra function and not inherent within the model. Applying a weak level of shrinkage to the F in XSA is advised to maintain the stability of the model, but this is not necessary in ICA.

Finally, there are also two methods of estimating uncertainty in parameters of historical management interest (stock size, fishing mortality, etc): the traditional statistical method using the variance-covariance matrix of the estimated parameters, and a Bayesian method using analysis of the parameter posterior distributions.

There is a worry with many separable models including ICA (ICES WGMG, 2003), which is due to the separable pattern being projected backward through the converged part of the assessment via the plus group and older fish. This is one of the properties of these types of model.

ICA has been widely tested and assessed by ICES and the international community (ICES WGMG, 2003). As with XSA, if the assumptions are not violated, it can be a strong and useful tool for the assessment. However, simulation studies have yet to be carried on the behaviour of ICA under severe catch limitations, such as halving the quota or closing areas.

COMBINED SEPARABLE VPA AND ADAPT (SAD)

The report provided by RIVO (Dickey-Collas *et al.*, 2004) describes the origin and components of the SAD method. This assessment method has been specifically implemented to deal with the unusual characteristics of the western horse mackerel stock. Any assessment model constructed for the western horse mackerel should take into account the special characteristics of the catch at age data set. The stock and catch was dominated by a series of strong cohorts, i.e. the extremely strong 1982 year class

and the also strong but much less abundant 1987 year class. In addition, the selection pattern changed greatly over the last decade. The only fishery independent information available for calibration of the population model is a time-series of egg survey estimates of spawning biomass (hence XSA and TSA cannot be used). As no age-disaggregated information was available, an assumption is required that selection at age is constant between years, for years to which a separable model is fitted. This assumption is valid for recent years in which there are no dominant cohorts but not for those years when the 1982 year class dominated the catch.

This need for different structural models for recent and historic periods has been met by the development of the SAD assessment model. The SAD model applies a separable model to recent data and then links to a VPA transformation of historic catch, as was described for the ICA model. It is developed from the ICA model developed by Patterson and Melvin. (1996) and the ADAPT model which is primarily used in North America. The separable model is fitted to the shortest period possible (3 years), which is the most recent part of the time series. The separable model estimates from the earliest year of the separable period to initiate a historic VPA for the cohorts exploited in that year.

Another effect of the very strong year class is the impact on the plus group. Generally, fishing mortality on the plus group is taken to be equal to that on the oldest true age. However, this is incorrect for years after 1992, as the fishery was still directed at the 1982 year class, which was in the plus group. In order to allow for the directed fishing of the dominant 1982 year class, fishing mortality on this year class at age 10 in 1992 was estimated as a parameter within the model. Estimation is again by non-linear minimisation of the sum of squares.

The parameters estimated are:

1. Fishing mortality on the reference age for the separable model (age 7).
2. The scaling of the fishing mortality for age 10 and the plus group relative to the average of ages 7 – 9.
3. Fishing mortality on the 1982 year class at age 10 in 1992 and the corresponding plus group in later years.

Maturity at age and stock weights at age and the proportions of F and M before spawning, are assumed to be known precisely, as are the catch data in the VPA part of the analysis. The egg survey SSB estimates are considered to be absolute measures of stock abundance. The development of SAD did not deal with the depressed growth caused by the 1982 year class.

Despite all this extra development, the SAD model is still not widely accepted for the assessment of horse mackerel. It has problems reaching a solution and may be over parameterised (ICES WGMG, 2003). ACFM rejected the most recent SAD assessment of horse mackerel because of the sensitivity of the historic biomass estimate to the length of the separable period; a change in separable period from 4 to 5 years gave large differences in the historic VPA converged part of the assessment. This was due to the very different selectivities that were produced by the 4 or 5 year separable period.

The SAD model is a good example of a model that was developed specifically for one stock and its associated problems. This approach is along the lines of AMCI and the North American ADAPT methods. It clearly has strengths, but does require an even greater degree of quality assurance when utilising the model. ICA was developed with specific problems in mind and now appears to be quite a robust tool, but new methods must always be tested and are often not suited for any of purpose other than that for which they were developed.

INSTANTANEOUS SEPARABLE VPA (ISVPA)

This model has been, and is, being developed in Russia (Vasilyev, 2001). It is a separable model that covers the entire assessment period. One separable model can be applied to the whole period, or two different separable models can be applied to two periods, as determined by the user. It is totally different than AMCI, in that it is based on statistical assumptions and approaches, and it searches for model solutions by changing the underlying assumptions. It is not widely used as yet, and has been proposed for the assessment of blue whiting and Atlanto Scandian herring (ICES WGNPBW, 2002). It has proved a useful tool whilst examining the population abundances of herring off Ireland (ICES HAWG, 2003). No stock assessment by ISVPA has been accepted by ACFM as yet.

As with ICA, certain assumptions need to be made about the selection patterns. The selection at the oldest age is equal to that of the previous age; selections are normalized in such a way that their sum across all ages adds up to 1. It does not, however require a reference age, or require assumptions about the shape of the selectivity pattern. As with other separable models the catchabilities of the survey fleets or biomass estimates are estimated within the minimisation of the objective function of the catch data. The plus

group is not modelled, but the abundance is derived from the catch assuming the same mortality as for the oldest true age.

The difference between ISVPA and the other models discussed so far is the wide choice of objective functions that can be used to carry out the analysis. There are 4 possible statistical methods to find a model solution for the catch data and survey data. The method to find a model solution for the SSB surveys is simpler. The different functions are not explained here.

ISVPA offers variance estimates of F and biomass from within the model and also provides the opportunity to bootstrap the populations to obtain ranges on the modelled population, using the determined confidence intervals.

ISVPA offers three different ways to deal with errors in the catch data, one is to be a pure separable model where the catch data are not exact (the effort-controlled version), one acts as a virtual VPA where no errors are assumed (the catch-controlled version) and one offers a mix of the two (the mixed version). The catch controlled version still uses one selectivity pattern and a separable model to arrive at the terminal fishing mortalities. As mentioned above the approach of ISVPA is highly statistical, and with that in mind the model also offers methods and choices for constraining residuals based on catch, mortalities or selection.

This package is still in development and recent experience within RIVO has shown that the minimisation process is still unstable. However the latest version which only arrived at RIVO in late February 2004, may improve this as it allows surveys to be incorporated. In addition some of the stocks for which ISVPA has been proposed as an assessment tool appear to have highly variable selectivity patterns that break some of the assumptions about separability. In a recent study it was shown that ISPVA has problems when selectivity patterns change, even when two periods of separable constraint are used (Eltink, 2004). There might also be a small bias in the estimated selectivity patterns.

ASSESSMENT MODEL COMBINING INFORMATION FROM VARIOUS SOURCES (AMCI)

AMCI was designed to offer flexibility and cope with data coming from different sources and of different quality. The programme was designed to allow for exploration of the data and exploration of combining techniques, as well as stock assessments.

AMCI is a separable assessment model applied to the whole period, but the selectivity pattern can be allowed to slowly change. In the extreme, this means that AMCI can be made to respond as a non-separable VPA type model. The specification of the selectivity is highly flexible and uses a technique of "gain" similar to the Kalman filter of TSA. The data exploration and assessment ability of AMCI is further enhanced by its ability to project forward in time, like a traditional short term prediction. The catchabilities of the surveys can also be allowed to change over time, in a similar way to the selectivity of the catch at age data. Unlike XSA and ICA, the flexibility of the model allows the parameters to be weighted in a manner that the catch data do not dominate.

The developer of AMCI (Dankert Skagen, Marine Institute, Bergen) describes AMCI as less of a "statistical model" than the other catch at age based methods. The models that appear in AMCI are basically functional relationships between model components and between model and observations. This approach was used in recognition that the statistical properties of the data are generally complex and poorly known, and to avoid making the final outcome of the assessment conditional on strong statistical hypothesis.

The main building blocks in AMCI are:

1. A population model which projects the population forwards in time according to specified parameters.
2. Observation models that generate modelled counterparts to observed data.
3. Objective functions that measure the fit of the modelled data to the observations. There is a choice of functions, but the most common is the weighted sum of squared log residuals.
4. Optimisation routines that find the parameter sets that give the best fit of the model to the data.
5. Supporting routines for model specification, data handling, diagnostics, organising bootstrap, retrospective runs, printout etc.

Additional properties are that fish tagging data can be used, and that there are area and fleet components to the assessments. Weighting between variables is decided by the user although there is some internal implicit weighting, which implies that the weights in AMCI are not directly comparable with those in ICA.

AMCI is not widely used at present although comparative runs for mackerel are produced by the assessment working group. AMCI is used to assess Atlanto-Scandian herring and is being used to explore the population dynamics of blue whiting (ICES WGNPBW, 2002). It is relatively new, and as such any major draw backs of the method have yet to be documented and its assumptions fully tested.

MULTISPECIES VPA (MSVPA)

The explanation for this assessment method can be found in a paper written by Sparre in 1991.

Multispecies virtual population analysis (MSVPA) has been developed largely as a joint venture within the ICES Ad hoc Multispecies Working Group (ICES AMAWG, 1984, 1986, 1987). The method integrates the suitability concept of Andersen and Ursin (1977) for describing predator-prey relationships with traditional virtual population analysis (VPA) as developed by Fry (1949) and Gulland (1965). MSVPA takes into account predation among exploited fish populations. MSVPA is a computation technique by which we can calculate the amount of fish there must have been in the sea to account for the observed catches in fisheries and the observed stomach contents of predators. A basic assumption is that suitabilities are constant from year to year.

One principal difference compared to VPA is, of course, that MSVPA deals with several stocks at a time. MSVPA executes a series of parallel linked VPAs.

In single species VPA, each cohort can be treated separately, the results being independent of the results of the other cohorts. The usual procedure is to work backwards in time, starting with the oldest age group and ending with the recruits. For MSVPA, this would not work. All cohorts of all species have to be dealt with simultaneously, as the value of the predation mortality depends on the abundances of the predators and prey. Thus MSVPA works on a "by-year basis" rather than on a "by-cohort basis".

Other assessment methods

YEAR CLASS CURVES (YCC)

Cotter *et al.* (2004) and the help file of FLYCC (FLR package for YCC) describe the assessment method as follows:

The aim of YCC is to fit year class curves to CPUE-at-age by index. It fits a given linear model to estimate (a) the decline of log CPUE over time for each year class, (b) different log catchability factors for each index relative to one treated as the standard.

A 'year-class curve' is a plot of log CPUE over age for a single year-class of a species (in contrast to a 'catch curve' which is fitted to multiple year-classes at one time). When

linear, the intercept estimates the log CPUE at age 0, a measure of year class strength, and the slope estimates average rate of total mortality, Z. FLYCC fits a user-specified linear model for each year-class in the provided set of CPUE-at-age indices using iteratively weighted least squares regression. The weighting, if turned on, is to allow for differing precisions among the different fleets with respect to the given model. This assumes that none is precise purely because of bias, e.g. due to a restricted survey area. The basic YCC function is $\log CPUE \sim -1 + yearclass + age$. Log means natural log (ln). The regression coefficient for age is total mortality, Z per year. Also, a factor is estimated for each observed index except one. This factor is the log catchability factor relative to one of the indices which is treated as the standard. (e.g. year-class curves, residual plots, AIC, or forward prediction errors).

The FLYCC implementation is an abbreviated version of the procedures described by Cotter *et al.* (2004). Re-weightings are not corrected for different degree of freedom associated with each fleet due to estimation of different numbers of parameters, and 'forward validation' is not implemented in FLYCC.

In a more simplistic way, YCC estimates a Z from the survey and catch data. Z is fixed for all ages. From this Z new numbers-at-age will be calculated and will feed the HCR. The Z applied is cumulative. For example, Z for age 3 is 3 times the Z estimated. There is no flexibility.

SURVEY BASED ASSESSMENT (SURBA)

The help file of FLSURBA describes the structure of the assessment method.

The basis of SURBA is a simple survey-based separable model of mortality.

The separable model used in SURBA assumes that total mortality Z(a,y) in age a and year y can be expressed as $Z_{a,y} = s_a * f_y$ where s_a and f_y are respectively the age and year effects of mortality. f_y corresponds to the total fishing mortality (set + overfishing). It is then flexible over year but not over age. Note that this differs from the usual assumption in that total mortality Z is the quantity of interest, rather than fishing mortality F.

The parameters to be estimated when fitting the model are age effects, year effects, and cohort effects. SURBA assumes that at least one age-structured survey index is available: biomass indices are optional. If present, it is assumed that biomass indices are

measured at spawning time, following the convention used in such models as ICA (Patterson and Melvin, 1996).

For the fitting abundance indices (age-structured and biomass) are mean-standardised so that the mean of each index over all ages and years is 1.0. The way SURBA handles age-structured or biomass indices is described in the manual written by Needle (2005).

TIME SERIES ANALYSIS (TSA)

Implementation of the fisheries stock assessment method known as Time-Series Analysis or TSA, has been described in ICES Working Group meeting publications (e.g. Fryer *et al.*, 1998, 1999; ICES 2007a) and is available in Beare *et al.* (2005). Details on the Kalman filter algorithm, which is central to the methodology, are available in the statistical literature (Harvey, 1989; Jones, 1993; Gudmundsson, 1994).

The Kalman filter TSA algorithm is a recursive procedure that represents the variables of interest (stock numbers and fishing mortalities at age) as unobserved state variables that evolve forward over time. Each year, observed catch-at-age data are used to update the estimates of the state variables. Year-class strength is estimated according to a Ricker stock-recruitment model. Model fitting proceeds by examining standardized catch prediction errors (equivalent to model-fit residuals) and inflation of permitted variance on year-age pairs where errors are high. Each estimate of historical mean F_{2-6} and stock numbers is produced with an associated standard error, allowing a statistical evaluation of the uncertainty in the assessment. The model is also able to roll forward and produce estimates for all parameters in the years following the last historical year.

TSA has several advantages over more traditional VPA-based assessment methods (XSA, ICA), which have meant that it has become the standard assessment model for most Northern Shelf and North Sea demersal gadoid stocks. Among these are:

1. Realistic standard errors on model parameter estimates and summary statistics, thus giving an indication of the uncertainty of management population metrics (which may be high, particularly in recent years). Note: the standard errors are realistic because they are based on an accepted statistical technique (Kalman filter), whereas traditional VPA-based techniques are simple recursive numerical data transformations that do not recognize model error (measurement or process) of any sort.

2. Any number of surveys can be included, the catchabilities of each being modelled and allowed to evolve over time via fitted ogives.
3. Landings and discards can be modelled separately, thus allowing for the inherent noisiness of the latter. If this option is taken, discards are expressed by another set of fitted ogives.
4. Entire years of catch-at-age, discard, and survey data can be treated as missing.

The principal disadvantages are:

1. TSA population estimates are driven largely by catch-at-age data, which may become increasingly biased as quotas become more restrictive.
2. There is not yet a robust and general version of the code available, and the knowledge base of practitioners experienced with TSA is very limited.
3. The computer program takes a long time to run on a Personal Computer with a Pentium III processor (>1 h), limiting the potential for hands-on experimentation with model settings.

Appendix 3: Data description

In order to implement the operating model and the observation error model, I use fishery independent data as well as fishery dependent data as the former are insufficient for a good estimation of parameters for the model. A more detailed explanation of the data available is made in this appendix.

Data have been provided by John Simmonds (from Fisheries Research Services (FRS) Marine Laboratory, Aberdeen, UK). They have been collected from different sources. FRS Marine Laboratory maintains a database for the North Sea herring which contains information (national catches of herring and associated biological data) provided by themselves and four national and international institutes: the marine research institutes of Denmark (Danish Institute for Fisheries Research: DIFRES), Norway (Institute of Marine Research: IMR), the Netherlands (The Netherlands Institute for Fisheries Research: RIVO). The International Council for the Exploration of the Sea (ICES) provided the biological information collected during the International Bottom Trawl Surveys (IBTS). Incomplete time series of catches of herring were filled in using data coming from the Herring Assessment Working Group reports (Kienzle, 2003). In fact, catch data have been compiled from the Fisheries Information Network (FIN) database. Total annual catch have been compared with values from HAWG reports and some differences were found. To create the database that is used in this work, the FIN database has been used but values from HAWG reports have been used when a difference occurred. This is due to the fact that catches data declared for an area can have actually occurred in another area. This mistake is corrected by observers but not reported in the FIN database as it is considered as the official one and cannot be modified.

The database utilised in the present work consist of 12 datasets: proportion of fish mature at age, natural mortality rate at age, stock weight at age, catch weight at age, proportions of fishing mortality at age before spawning and natural mortalities at age before spawning, total catch in weight, catch numbers at age and 4 indices from 4 different surveys. Those datasets are presented in the following paragraphs.

The proportion of mature at age is expressed as a matrix by year and by age. The fraction mature at age is variable over age and time for the North Sea herring stock. Values cover the period between 1960 and 2006. For ages 0 and 1, the maturity at age was equal to zero throughout that period of time. Between 1960 and 1971 (the last year before the first survey), the maturity at age was equal to 1 for ages 2 to 9+. From 1972, precision of maturity-at-age values has been improved. Between 1972 and 1984, proportion of mature at age 2 was equal to 0.82 and to 1 for older ages. Finally, from 1985 values vary for ages 2 to 4 and fish older than 4 fully matured. Since 1989, values derive from the North Sea acoustic survey which occurs in July. The proportion of mature herring by age is estimated as the proportion at stage 3 and above on an eight points maturity scale (stages 1 and 2 are assumed not to spawn that year).

Table 44: Maturity-at-age variable over time for each age-group.

years / ages	1960:1971	1972:1984	1985:1986	1987:2004	2004:2006
0:1	0	0	0	0	0
2	1	0.82	Δ	Δ	Δ
3	1	1	1	Δ	Δ
4	1	1	1	1	Δ
5:9+	1	1	1	1	1

Δ: values variable over time for a specific age.

A matrix by year and by age is used to describe the natural mortality rate. Values are based on existing estimates, decrease with age until the last age group and are constant over time for each age group.

Two weights at age are considered: stock and catch weight at age. Both of them vary by year and by age. Weight at age in the catch values derive from the total international catch at age data. In some countries, weight at age is derived from general length-weight relationships, others use direct measurements from market sampling programmes. These programmes are described in detail in the report of the Study Group On Market Sampling Methodology (ICES SGMSM, 2000). Weight at age in the stock values derive from the North Sea acoustic survey (July) from weighed and aged individuals. The surveys are reported annually (see Simmonds *et al.* 2002) and the planning and standard procedures are described in ICES PGHERS (2003).

Catch estimation is based on official landings statistics and augmented by nationally collected information on misreporting and discarding. Discard information is only available for some countries, but nevertheless used in the assessment. Area misreporting is corrected by re-allocating catches from official reported areas to areas where catches were taken, based on additional information. Separation between Baltic Spring spawners and North Sea autumn spawners is difficult, and is now based on otolith microstructure analysis and data has been corrected back to 1996. Some correction of historic data to 1991 has been carried out by fitting otolith microstructure data to vertebrate count data and using the relationship to estimate the earlier years when otolith microstructure data was not available.

Catch at age values are derived from national sampling programmes. Those are highly different by country and sometimes by fishery. Sampling procedures can be divided into separate length and age sampling or representative age sampling. Approximately 300 samples are carried out per year. From those samples, about 11 000 fish are aged and 41 000 are measured.

The proportions of fishing and natural mortalities at age before spawning are constant over years. These are approximate values that come from approximated ideas of when fish spawn and when the fishery is.

International acoustic surveys are carried out in July each year. The surveys are reported by research vessel (between 4 and 5 per year) and a combined report is prepared from estimates by ICES statistical rectangle. Where overlap occurs, the combined estimate is the effort weighted mean of the statistical rectangle estimates. Effort is defined as the number of miles of survey track. Values used here cover the period between 1989 and 2006 for ages 1 to 9. No values are available for age 1 between 1989 and 1996.

International bottom trawl surveys are usually carried out during the 1st and 3rd quarter. Some years, 4 surveys were conducted, one per quarter. Those surveys provide herring indices for 1 to 5+ years old. The survey is described in the reports of the IBTS Working Group (ICES IBTSWG, 2003). Values provided encompass the years 1979 until 1983 for fish aged 1 and then years 1984 until 2007 for ages 1 to 5+.

The MIK index is provided by fine meshed ring net (MIK) hauls carried out during the IBTS 1st quarter survey at night, aimed at catching 0-ringer herring. The procedure is described in the reports of the IBTS Working Group (ICES IBTSWG, 2003). Values are available for all year since 1977.

The MLAI Larval SSB surveys are carried out from September to the end of January by several two-week surveys following a pre-established spatial design. Surveys cover all years from 1972.

Appendix 4: Extract from the European Union - Norway agreement for North Sea herring (November 2004)

According to the EU-Norway agreement (November 2004):

1. Every effort shall be made to maintain a level of Spawning Stock Biomass (SSB) greater than the 800,000 tonnes (Blim).

2. Where the SSB is estimated to be above 1.3 million tonnes the Parties agree to set quotas for the directed fishery and for by-catches in other fisheries, reflecting a fishing mortality rate of no more than 0.25 for 2 ringers and older and no more than 0.12 for 0-1 ringers.

3. Where the SSB is estimated to be below 1.3 million tonnes but above 800,000 tonnes, the Parties agree to set quotas for the direct fishery and for by-catches in other fisheries, reflecting a fishing mortality rate equal to:

   0.25 (0.15*(1,300,000-SSB)/500,000) for 2 ringers and older, and

   0.12 (0.08*(1,300,000-SSB)/500,000) for 0-1 ringers.

4. Where the SSB is estimated to be below 800,000 tonnes the Parties agree to set quotas for the directed fishery and for by-catches in other fisheries, reflecting a fishing mortality rate of less than 0.1 for 2 ringers and older and less than 0.04 for 0-1 ringers.

5. Where the rules in paragraphs 2 and 3 would lead to a TAC which deviates by more than 15% from the TAC of the preceding year the Parties shall fix a TAC that is no more than 15% greater or 15% less than the TAC of the preceding year.

6. Notwithstanding paragraph 5 the Parties may, where considered appropriate, reduce the TAC by more than 15% compared to the TAC of the preceding year.

7. By-catches of herring may only be landed in ports where adequate sampling schemes to effectively monitor the landings have been set up. All catches landed

shall be deducted from the respective quotas set, and the fisheries shall be stopped immediately in the event that the quotas are exhausted.

8. The allocation of TAC for the directed fishery for herring shall be 29% to Norway and 71% to the Community. The by-catch quota for herring shall be allocated to the Community.

9. A review of this arrangement shall take place no later than 31 December 2007.

Appendix 5: Simulations of the management strategy evaluation

- SR: Stock-recruitment relationship; HS: hockey-stick.
- Autocorr: Autocorrelation in the recruitment; Est: estimated; High: higher level.
- Survey; none: no survey considered; no error: no observation error in the surveys; acoust: acoustic; SSB: acoustic + MLAI; all: the 4 surveys available.
- HCR: Harvest control rule; no: no HCR considered; fix: constant catch; Obs Ind: HCR based on direct index; Sngl SSB: HCR based on adjusted spawning-stock biomass; Comb SSB: HCR based on combined indices; Z: HCR based on total mortality; F Ref pt: F and reference points used in the actual management.
- LQ: Limitation in the variation of the TAC.
- Misreporting (MR); 0: 0%; 10: 10%; 30: 30%; 80: 80%.
- OE: Observation error; Sens: Sensitivity analysis.

	SR		Autocorr		Survey					HCR							Assessment				LQ		Misreporting			
Nb sim	HS	Ricker	Est	Dbl	None	No error	acoust	SSB	All	no	fix	Obs Ind	Sngl SSB	Comb SSB	Z	F Ref pt	No	ICA	YCC	SURBA	No	Yes	0	10	30	80
No catch																										
1	√		√		√					√							√				√		√			
2	√			√	√					√							√				√		√			
3		√	√		√					√							√				√		√			
4		√		√	√					√							√				√		√			
Fixed TAC																										
5	√		√		√						√						√				√		√			
6	√			√	√						√						√				√		√			
7		√	√		√						√						√				√		√			
8		√		√	√						√						√				√		√			
No OE																										
9	√		√			√						√					√				√		√			
10	√			√		√						√					√				√		√			
11		√	√			√						√					√				√		√			
12		√		√		√						√					√				√		√			

	SR		Autocorr		Survey				HCR						Assessment				LQ		Misreporting			
Nb sim	HS	Ricker	Est	Dbl	None	No error	acoust	SSB	All	no fix	Obs Ind	Sngl SSB	Comb SSB	Z	F Ref pt	No	ICA	YCC	SURBA	No	Yes	0	10	30	80
13	√		√			√						√				√				√		√			
14	√			√		√						√				√				√		√			
15		√	√			√						√				√				√		√			
16		√		√		√						√				√				√		√			
17	√		√			√							√			√				√		√			
18	√			√		√							√			√				√		√			
19		√	√			√							√			√				√		√			
20		√		√		√							√			√				√		√			
21	√		√			√								√		√				√		√			
22	√			√		√								√		√				√		√			
23		√	√			√								√		√				√		√			
24		√		√		√								√		√				√		√			
OE, no Mr																									
25	√		√				√				√					√				√		√			
26	√			√			√				√					√				√		√			
27		√	√				√				√					√				√		√			
28		√		√			√				√					√				√		√			
29	√		√				√					√				√				√		√			
30	√			√			√					√				√				√		√			
31		√	√				√					√				√				√		√			
32		√		√			√					√				√				√		√			
33	√		√					√					√			√				√		√			
34	√			√				√					√			√				√		√			
35		√	√					√					√			√				√		√			
36		√		√				√					√			√				√		√			

	SR		Autocorr		Survey					HCR							Assessment				LQ		Misreporting			
Nb sim	HS	Ricker	Est	Dbl	None	No error	acoust	SSB	All	no	fix	Obs Ind	Sngl SSB	Comb SSB	Z	F Ref pt	No	ICA	YCC	SURBA	No	Yes	0	10	30	80
37	√		√			√									√		√				√		√			
38	√			√		√									√		√				√		√			
39		√	√			√									√		√				√		√			
40		√		√		√									√		√				√		√			
OE, MR																										
41	√		√			√						√					√				√		√			
42	√		√			√						√					√				√			√		
43	√		√			√						√					√				√				√	
44	√		√			√						√					√				√					√
45	√			√		√						√					√				√		√			
46	√			√		√						√					√				√			√		
47	√			√		√						√					√				√				√	
48	√			√		√						√					√				√					√
49		√	√			√						√					√				√		√			
50		√	√			√						√					√				√			√		
51		√	√			√						√					√				√				√	
52		√	√			√						√					√				√					√
53		√		√		√						√					√				√		√			
54		√		√		√						√					√				√			√		
55		√		√		√						√					√				√				√	
56		√		√		√						√					√				√					√
57	√		√			√							√				√				√		√			
58	√		√			√							√				√				√			√		
59	√		√			√							√				√				√				√	
60	√		√			√							√				√				√					√

	SR		Autocorr		Survey					HCR							Assessment				LQ		Misreporting			
Nb sim	HS	Ricker	Est	Dbl	None	No error	acoust	SSB	All	no	fix	Obs Ind	Sngl SSB	Comb SSB	Z	F Ref pt	No	ICA	YCC	SURBA	No	Yes	0	10	30	80
61	√			√		√							√				√				√		√			
62	√			√		√							√				√				√			√		
63	√			√		√							√				√				√				√	
64	√			√		√							√				√				√					√
65		√	√			√							√				√				√		√			
66		√	√			√							√				√				√			√		
67		√	√			√							√				√				√				√	
68		√	√			√							√				√				√					√
69		√		√		√							√				√				√		√			
70		√		√		√							√				√				√			√		
71		√		√		√							√				√				√				√	
72		√		√		√							√				√				√					√
73	√		√					√						√			√				√		√			
74	√		√					√						√			√				√			√		
75	√		√					√						√			√				√				√	
76	√		√					√						√			√				√					√
77	√			√				√						√			√				√		√			
78	√			√				√						√			√				√			√		
79	√			√				√						√			√				√				√	
80	√			√				√						√			√				√					√
81		√	√					√						√			√				√		√			
82		√	√					√						√			√				√			√		
83		√	√					√						√			√				√				√	
84		√	√					√						√			√				√					√

	SR		Autocorr		Survey					HCR							Assessment				LQ		Misreporting			
Nb sim	HS	Ricker	Est	Dbl	None	No error	acoust	SSB	All	no	fix	Obs Ind	Sngl SSB	Comb SSB	Z	F Ref pt	No	ICA	YCC	SURBA	No	Yes	0	10	30	80
85		√		√				√						√			√				√		√			
86		√		√				√						√			√				√			√		
87		√		√				√						√			√				√				√	
88		√		√				√						√			√				√					√
89	√		√			√									√		√				√		√			
90	√		√			√									√		√				√			√		
91	√		√			√									√		√				√				√	
92	√		√			√									√		√				√					√
93	√			√		√									√		√				√		√			
94	√			√		√									√		√				√			√		
95	√			√		√									√		√				√				√	
96	√			√		√									√		√				√					√
97		√	√			√									√		√				√		√			
98		√	√			√									√		√				√			√		
99		√	√			√									√		√				√				√	
100		√	√			√									√		√				√					√
101		√		√		√									√		√				√		√			
102		√		√		√									√		√				√			√		
103		√		√		√									√		√				√				√	
104		√		√		√									√		√				√					√
Assess																										
105	√		√						√							√		√			√		√			
106	√			√					√							√		√			√		√			
107		√	√						√							√		√			√		√			
108		√		√					√							√		√			√		√			

	SR		Autocorr		Survey					HCR							Assessment				LQ		Misreporting			
Nb sim	HS	Ricker	Est	Dbl	None	No error	acoust	SSB	All	no	fix	Obs Ind	Sngl SSB	Comb SSB	Z	F Ref pt	No	ICA	YCC	SURBA	No	Yes	0	10	30	80
109	√		√						√							√		√				√	√			
110	√			√					√							√		√				√	√			
111		√	√						√							√		√				√	√			
112		√		√					√							√		√				√	√			
113	√		√						√							√		√			√		√			
114	√		√						√							√		√			√			√		
115	√		√						√							√		√			√				√	
116	√		√						√							√		√			√					√
117	√			√					√							√		√			√		√			
118	√			√					√							√		√			√			√		
119	√			√					√							√		√			√				√	
120	√			√					√							√		√			√					√
121		√	√						√							√		√			√		√			
122		√	√						√							√		√			√			√		
123		√	√						√							√		√			√				√	
124		√	√						√							√		√			√					√
125		√		√					√							√		√			√		√			
126		√		√					√							√		√			√			√		
127		√		√					√							√		√			√				√	
128		√		√					√							√		√			√					√
129	√		√			√							√						√		√		√			
130	√		√			√							√						√		√			√		
131	√		√			√							√						√		√				√	
132	√		√			√							√						√		√					√

	SR		Autocorr		Survey					HCR							Assessment				LQ		Misreporting			
Nb sim	HS	Ricker	Est	Dbl	None	No error	acoust	SSB	All	no	fix	Obs Ind	Sngl SSB	Comb SSB	Z	F Ref pt	No	ICA	YCC	SURBA	No	Yes	0	10	30	80
133	√			√		√							√						√		√		√			
134	√			√		√							√						√		√			√		
135	√			√		√							√						√		√				√	
136	√			√		√							√						√		√					√
137		√	√			√							√						√		√		√			
138		√	√			√							√						√		√			√		
139		√	√			√							√						√		√				√	
140		√	√			√							√						√		√					√
141		√		√		√							√						√		√		√			
142		√		√		√							√						√		√			√		
143		√		√		√							√						√		√				√	
144		√		√		√							√						√		√					√
145	√		√			√							√							√	√		√			
146	√		√			√							√							√	√			√		
147	√		√			√							√							√	√				√	
148	√		√			√							√							√	√					√
149	√			√		√							√							√	√		√			
150	√			√		√							√							√	√			√		
151	√			√		√							√							√	√				√	
152	√			√		√							√							√	√					√
153		√	√			√							√							√	√		√			
154		√	√			√							√							√	√			√		
155		√	√			√							√							√	√				√	
156		√	√			√							√							√	√					√

	SR		Autocorr		Survey				HCR						Assessment				LQ		Misreporting			
Nb sim	HS	Ricker	Est	Dbl	None	No error	acoust	SSB	All	no	fix	Obs Ind	Sngl SSB	Comb SSB	Z	F Ref pt	No	ICA	YCC	SURBA	No	Yes	0	10	30	80
157		√		√		√							√							√	√		√			
158		√		√		√							√							√	√			√		
159		√		√		√							√							√	√				√	
160		√		√		√							√							√	√					√
161	√		√			√									√			√			√		√			
162	√		√			√									√			√			√			√		
163	√		√			√									√			√			√				√	
164	√		√			√									√			√			√					√
165	√			√		√									√			√			√		√			
166	√			√		√									√			√			√			√		
167	√			√		√									√			√			√				√	
168	√			√		√									√			√			√					√
169		√	√			√									√			√			√		√			
170		√	√			√									√			√			√			√		
171		√	√			√									√			√			√				√	
172		√	√			√									√			√			√					√
173		√		√		√									√			√			√		√			
174		√		√		√									√			√			√			√		
175		√		√		√									√			√			√				√	
176		√		√		√									√			√			√					√
177	√		√			√									√					√	√		√			
178	√		√			√									√					√	√			√		
179	√		√			√									√					√	√				√	
180	√		√			√									√					√	√					√

	SR		Autocorr		Survey					HCR							Assessment				LQ		Misreporting			
Nb sim	HS	Ricker	Est	Dbl	None	No error	acoust	SSB	All	no	fix	Obs Ind	Sngl SSB	Comb SSB	Z	F Ref pt	No	ICA	YCC	SURBA	No	Yes	0	10	30	80
181	√			√		√									√					√	√		√			
182	√			√		√									√					√	√			√		
183	√			√		√									√					√	√				√	
184	√			√		√									√					√	√					√
185		√	√			√									√					√	√		√			
186		√	√			√									√					√	√			√		
187		√	√			√									√					√	√				√	
188		√	√			√									√					√	√					√
189		√		√		√									√					√	√		√			
190		√		√		√									√					√	√			√		
191		√		√		√									√					√	√				√	
192		√		√		√									√					√	√					√

	SR	Autocorr	Survey	HCR		Assess	Sensitivity		LQ		Misreporting			
Nb sim	Ricker	Est	Acoust	SSB	Z	No	Maturity	Catch weight	No	Yes	0	10	30	80
Sens														
193	√	√	√	√		√	√		√		√			
194	√	√	√	√		√	√		√			√		
195	√	√	√	√		√	√		√				√	
196	√	√	√	√		√	√		√					√
197	√	√	√		√	√	√		√		√			
198	√	√	√		√	√	√		√			√		
199	√	√	√		√	√	√		√				√	
200	√	√	√		√	√	√		√					√
201	√	√	√	√		√		√	√		√			
202	√	√	√	√		√		√	√			√		
203	√	√	√	√		√		√	√				√	
204	√	√	√	√		√		√	√					√
205	√	√	√		√	√		√	√		√			
206	√	√	√		√	√		√	√			√		
207	√	√	√		√	√		√	√				√	
208	√	√	√		√	√		√	√					√
209	√	√	√	√		√				√	√			
210	√	√	√	√		√				√		√		
211	√	√	√	√		√				√			√	
212	√	√	√	√		√				√				√
213	√	√	√		√	√				√	√			
214	√	√	√		√	√				√		√		
215	√	√	√		√	√				√			√	
216	√	√	√		√	√				√				√

	SR	Autocorr	Survey	HCR		Assess	Sensitivity	LQ	Misreporting	
Nb sim	Ricker	Est	Acoust	SSB	Z	No	Initial condition	No	0	30
Sens										
217	√	√	√	√		√	√	√	√	
218	√	√	√	√		√	√	√		√
219	√	√	√		√	√	√	√	√	
220	√	√	√		√	√	√	√		√

Appendix 6: Numerical results of the management strategy evaluation

- X corresponds to the number of year of the projection: 20 years in most cases, 15 for the cases corresponding to the current management (runs 105 to 128).
- Δ means coefficient of variation.
- Orange values correspond to simulations for which performance index is higher than the average of selections of simulations multiplied by 1.1 in order to select the best simulations. Selections are simulations 9 to 24; 25 to 40; 41 to 104; 105 to 112; 113 to 128; 129 to 160; 161 to 176 and 185 to 192; 65 to 68 and 193 to 196; 97 to 100 and 197 to 200; 65 to 68 and 201 to 204; 97 to 100 and 205 to 208; 65 to 68 and 209 to 212; 97 to 100 and 213 to 216; 65, 67, 217 and 218; 97, 99, 219 and 220.

	Once in X years	**In final year**		**Final year**			
Nb sim	P(SSB<Blim)	P(SSB<Blim)	P(SSB<Bpa)	Δ in TAC	SSB	Catch	Performance
No catch							
1	0.01	0.01	0.01	NA	5561	0	/
2	0	0	0	NA	5501	0	/
3	0	0	0	NA	3344	0	/
4	0	0	0	NA	3352	0	/
Fixed TAC							
5	0.06	0	0	0	3274	512	/
6	0.21	0	0.001	0	3323	512	/
7	0.042	0.001	0.008	0	2122	512	/
8	0.13	0.001	0.03	0	1917	512	/
No OE							
9	0	0	0.001	0.163	2154	644	1498
10	0	0	0	0.179	2183	666	1549
11	0	0	0.015	0.161	1821	555	1076
12	0	0	0.001	0.155	1986	581	1267
13	0	0	0.001	0.188	2160	698	1558
14	0	0	0.001	0.171	2132	624	1456
15	0	0	0.004	0.177	1880	614	1194
16	0	0	0.017	0.148	1715	560	975
17	0	0	0.001	0.166	2259	581	1540
18	0	0	0.005	0.186	1921	705	1326
19	0	0	0.004	0.164	1941	575	1216
20	0	0	0.009	0.155	1783	566	1049
21	0	0	0.014	0.244	2213	674	1587
22	0.001	0	0.021	0.236	2074	667	1441
23	0.008	0	0.034	0.195	1955	547	1202
24	0.005	0	0.023	0.192	2042	545	1287
OE, no MR							
25	0.001	0	0.001	0.219	2411	685	1796
26	0	0	0.01	0.228	2082	679	1461
27	0.003	0.001	0.033	0.228	1779	571	1050
28	0.002	0	0.023	0.207	1895	538	1133

	Once in X years	In final year		Final year			
Nb sim	P(SSB<Blim)	P(SSB<Blim)	P(SSB<Bpa)	Δ in TAC	SSB	Catch	Performance
29	0	0	0.009	0.228	2157	652	1509
30	0.001	0	0.008	0.224	2109	670	1479
31	0	0	0.026	0.238	1868	612	1180
32	0	0	0.021	0.213	1853	559	1112
33	0.003	0	0.007	0.218	2306	570	1576
34	0	0	0.025	0.212	1957	690	1347
35	0	0	0.053	0.218	1747	521	968
36	0.004	0	0.016	0.209	1878	598	1176
37	0.006	0.001	0.004	0.66	4094	296	3090
38	0.002	0	0.001	0.665	4214	287	3201
39	0.007	0.001	0.006	0.608	2700	254	1654
40	0.012	0.001	0.01	0.57	2541	249	1490
OE, MR							
41	0.001	0	0.001	0.219	2411	685	1796
42	0.006	0	0.03	0.235	1951	662	1313
43	0.068	0.001	0.066	0.242	1952	592	1244
44	0.726	0.067	0.394	0.33	1420	731	851
45	0	0	0.01	0.228	2082	679	1461
46	0.008	0	0.022	0.249	2156	705	1561
47	0.035	0.001	0.113	0.249	1779	704	1183
48	0.672	0.102	0.508	0.301	1295	804	799
49	0.003	0.001	0.033	0.228	1779	571	1050
50	0.005	0	0.047	0.217	1802	579	1081
51	0.065	0.004	0.125	0.262	1732	667	1099
52	0.739	0.061	0.452	0.329	1351	832	883
53	0.002	0	0.023	0.207	1895	538	1133
54	0.005	0	0.066	0.229	1748	611	1059
55	0.004	0.005	0.17	0.245	1593	701	994
56	0.743	0.068	0.417	0.322	1381	683	764
57	0	0	0.009	0.228	2157	652	1509
58	0.001	0	0.057	0.233	1805	670	1175
59	0.073	0	0.137	0.27	1686	757	1143
60	0.671	0.075	0.57	0.293	1241	724	665
61	0.001	0	0.008	0.224	2109	670	1479
62	0.008	0	0.033	0.231	1960	693	1353
63	0.026	0.001	0.065	0.248	1847	766	1313
64	0.546	0.014	0.345	0.305	1435	847	982
65	0	0	0.026	0.238	1868	612	1180
66	0.004	0	0.182	0.22	1540	603	843
67	0.045	0	0.103	0.238	1707	658	1065
68	0.69	0.094	0.656	0.32	1172	785	657

	Once in X years	In final year		Final year			
Nb sim	P(SSB<Blim)	P(SSB<Blim)	P(SSB<Bpa)	Δ in TAC	SSB	Catch	Performance
69	0	0	0.021	0.213	1853	559	1112
70	0.002	0	0.041	0.219	1756	647	1103
71	0.029	0.005	0.179	0.232	1567	631	898
72	0.534	0.04	0.482	0.288	1313	719	732
73	0.003	0	0.007	0.218	2306	570	1576
74	0.005	0	0.025	0.22	1995	699	1394
75	0.13	0.013	0.294	0.252	1460	710	870
76	0.54	0.041	0.495	0.283	1303	726	729
77	0	0	0.025	0.212	1957	690	1347
78	0.002	0	0.019	0.22	1962	718	1380
79	0.033	0.002	0.097	0.251	1715	748	1163
80	0.673	0.144	0.774	0.268	1075	819	594
81	0	0	0.053	0.218	1747	521	968
82	0.005	0	0.124	0.219	1606	605	911
83	0.06	0.001	0.242	0.24	1501	653	854
84	0.521	0.041	0.44	0.295	1348	661	709
85	0.004	0	0.016	0.209	1878	598	1176
86	0.002	0	0.058	0.205	1722	613	1035
87	0.033	0.001	0.134	0.233	1618	657	975
88	0.627	0.024	0.475	0.285	1323	857	880
89	0.006	0.001	0.004	0.66	4094	296	3090
90	0.019	0.001	0.004	0.68	4255	299	3254
91	0.047	0.001	0.002	0.684	4366	296	3362
92	0.429	0	0.004	0.722	4236	261	3197
93	0.002	0	0.001	0.665	4214	287	3201
94	0.006	0	0	0.665	4135	298	3133
95	0.067	0.001	0.001	0.642	4418	286	3404
96	0.425	0.002	0.002	0.757	4438	248	3386
97	0.007	0.001	0.006	0.608	2700	254	1654
98	0.015	0.002	0.005	0.549	2774	267	1741
99	0.058	0.001	0.006	0.56	2659	252	1611
100	0.509	0.003	0.016	0.648	2779	230	1709
101	0.012	0.001	0.01	0.57	2541	249	1490
102	0.018	0.001	0.009	0.583	2628	251	1579
103	0.087	0	0.008	0.552	2635	253	1588
104	0.364	0.002	0.021	0.601	2531	232	1463
Assess							
105	0	0	0.01	0.316	2177	656	1533
106	0	0	0	0.315	2108	639	1447
107	0	0	0.04	0.268	1898	594	1192
108	0.03	0	0.1	0.261	1766	574	1040

	Once in X years	In final year		Final year			
Nb sim	P(SSB<Blim)	P(SSB<Blim)	P(SSB<Bpa)	Δ in TAC	SSB	Catch	Performance
109	0.02	0	0.07	0.277	1947	708	1355
110	0.01	0	0.07	0.342	2070	635	1405
111	0.01	0.01	0.11	0.33	1793	591	1084
112	0.01	0	0.08	0.331	1904	561	1165
113	0	0	0.01	0.316	2177	656	1533
114	0	0	0.01	0.324	2191	657	1548
115	0.04	0.01	0.12	0.341	1802	747	1249
116	0.31	0.08	0.44	0.475	1342	754	796
117	0	0	0	0.315	2108	639	1447
118	0.01	0	0.02	0.373	2044	618	1362
119	0.04	0.01	0.09	0.334	1816	704	1220
120	/	/	/	/	/	/	/
121	0	0	0.04	0.268	1898	594	1192
122	0	0	0.05	0.264	1991	634	1325
123	0.03	0.01	0.1	0.333	1751	637	1088
124	/	/	/	/	/	/	/
125	0.03	0	0.1	0.261	1766	574	1040
126	0.01	0	0.09	0.266	1787	626	1113
127	0.1	0.02	0.15	0.304	1659	670	1029
128	/	/	/	/	/	/	/
129	0	0	0	0.247	3670	334	2704
130	0	0	0	0.259	3171	444	2315
131	0	0	0.01	0.265	2617	536	1853
132	1	0.99	1	0.629	140	530	-630
133	0	0	0	0.226	3684	303	2687
134	0	0	0	0.213	3345	381	2426
135	0	0	0	0.186	2718	509	1927
136	1	0.98	1	0.744	133	605	-562
137	0	0	0	0.212	2908	159	1767
138	0	0	0	0.246	2626	228	1554
139	0	0	0.01	0.351	2146	406	1252
140	1	0.99	1	0.544	225	600	-475
141	0	0	0	0.25	2733	164	1597
142	0	0	0	0.259	2590	234	1524
143	0	0	0.02	0.252	2133	425	1258
144	1	1	1	0.522	181	638	-481
145	0.7	0.17	0.67	0.443	1149	851	700
146	0.74	0.22	0.55	0.428	1239	655	594
147	0.75	0.16	0.59	0.452	1205	842	747
148	0.97	0.22	0.67	0.549	1161	980	841
149	0.79	0.23	0.64	0.412	1200	716	616
150	0.87	0.3	0.8	0.701	962	788	450
151	0.76	0.07	0.36	0.513	1439	880	1019
152	0.94	0.24	0.62	0.507	1138	876	714

	Once in X years	In final year		Final year			
Nb sim	P(SSB<Blim)	P(SSB<Blim)	P(SSB<Bpa)	Δ in TAC	SSB	Catch	Performance
153	0.64	0.16	0.6	0.521	1183	680	563
154	0.76	0.29	0.65	0.604	1098	717	515
155	0.88	0.22	0.66	0.617	1124	931	755
156	0.98	0.29	0.74	0.519	1022	960	682
157	0.8	0.38	0.81	0.489	943	712	355
158	0.9	0.14	0.57	0.54	1217	621	538
159	0.9	0.21	0.61	0.572	1184	870	754
160	1	0.57	0.92	0.733	749	587	36
161	0.02	0.01	0.01	0.289	5614	0.431	4314
162	0	0	0	0.313	5842	2.91	4545
163	0	0	0	0.3	5414	2.69	4117
164	0.53	0.01	0.01	0.263	5281	2.02	3983
165	0	0	0	0.27	5132	0.416	3832
166	0	0	0	0.248	5266	2.9	3969
167	0.01	0.01	0.01	0.236	5321	2.79	4024
168	0.02	0	0	0.247	5451	2.13	4153
169	0	0	0	0.276	3354	0.438	2054
170	0	0	0	0.286	3319	3.18	2022
171	0	0	0	0.266	3306	3.25	2009
172	0	0	0	0.285	3334	2.33	2036
173	0	0	0	0.276	3233	0.439	1933
174	0	0	0	0.286	3371	3.05	2074
175	0	0	0	0.246	3282	3.04	1985
176	0.05	0	0	0.316	3384	2.22	2086
177	0.96	0.87	0.95	2.55	347	19097	18144
178	0.95	0.85	0.96	3.47	446	19629	18775
179	0.87	0.79	0.87	3.98	394	4407	3501
180	0.97	0.88	0.96	3.56	408	6057	5165
181	0.92	0.74	0.87	3.29	410	3860	2970
182	0.93	0.79	0.91	2.88	356	8007	7063
183	0.9	0.8	0.89	3.62	377	2428	1505
184	0.88	0.82	0.88	2.98	364	1638	702
185	0.48	0.3	0.3	NA	3348	0.00069	2048
186	0.35	0.22	0.22	NA	3370	0.000357	2070
187	0.33	0.13	0.13	NA	3337	0.00032	2037
188	0.15	0.03	0.03	NA	3368	0.000179	2068
189	0.41	0.25	0.25	NA	3258	0.000384	1958
190	0.38	0.16	0.16	NA	3250	0.000367	1950
191	0.32	0.17	0.17	NA	3348	0.000303	2048
192	0.009	0.03	0.03	NA	3300	0.000168	2000

	Once in X years	In final year		Final year			
Nb sim	P(SSB<Blim)	P(SSB<Blim)	P(SSB<Bpa)	Δ in TAC	SSB	Catch	Performance
Sens							
193	0.001	0	0.028	0.224	1833	579	1112
194	0.002	0	0.049	0.223	1746	624	1070
195	0.023	0.002	0.13	0.25	1636	688	1024
196	0.539	0.041	0.479	0.297	1319	758	777
197	0.005	0	0.009	0.591	2648	248	1596
198	0.013	0.002	0.014	0.596	2558	265	1523
199	0.047	0.001	0.012	0.569	2667	252	1619
200	0.447	0	0.007	0.636	2664	245	1609
201	0.001	0	0.056	0.237	1727	606	1033
202	0.01	0	0.036	0.228	1838	578	1116
203	0.041	0.001	0.139	0.277	1682	638	1020
204	0.682	0.103	0.685	0.324	1144	765	609
205	0.015	0.001	0.005	0.578	2736	248	1684
206	0.028	0	0.01	0.573	2666	262	1628
207	0.055	0.001	0.01	0.6	2714	266	1680
208	0.476	0	0.008	0.623	2660	237	1597
209	0.003	0	0.011	0.213	2203	452	1355
210	0.023	0	0.024	0.207	2167	486	1353
211	0.207	0.005	0.054	0.223	1986	526	1212
212	0.999	0.103	0.223	0.227	1754	624	1078
213	0	0	0.002	0.353	2619	279	1598
214	0.03	0	0.003	0.364	2571	285	1556
215	0.117	0	0	0.335	2650	305	1655
216	0.981	0.001	0.002	0.359	2609	288	1597
217	1	0.021	0.25	0.311	1632	700	1032
218	1	0.139	0.498	0.393	1304	1083	1087
219	1	0.001	0.001	0.798	3788	163	2651
220	1	0.002	0.003	0.73	3604	183	2487

Appendix 7: Performance criteria results for the nine management procedures

Table 45: Performance criteria results for the nine management procedures.
Results that did not meet the benchmarks are shown in red. An arbitrary benchmark of 0.3 was chosen for CV in the TAC based on the upper level of that achieved by the actual management strategy adopted by the Commission.

	Performance criteria															
	SSB Benchmarks: B_{PA} 1 300 000 tonnes B_{lim}: 800 000 tonnes				Catch benchmark: TAC_{2006}: 512 000 tonnes				CV in TAC Benchmark: 0.300				Performance Benchmark: that SSB and catch benchmarks need to be met			
misreporting / MP	0 %	10 %	30 %	80 %	0 %	10 %	30 %	80 %	0 %	10 %	30 %	80 %	0 %	10 %	30 %	80 %
Observation index	1779	1802	1732	1351	571	579	667	832	0.228	0.217	0.262	0.329	1050	1081	1099	883
Single SSB trend	1868	1540	1707	1172	612	603	658	785	0.238	0.22	0.238	0.32	1180	843	1065	657
Combined SSB trend	1747	1606	1501	1348	521	605	653	661	0.218	0.219	0.24	0.295	968	911	854	709
Z	2700	2774	2659	2779	254	267	252	230	0.608	0.549	0.56	0.648	1654	1741	1611	1709
Current management	1898	1991	1751	NA	594	634	637	NA	0.268	0.264	0.333	NA	1192	1325	1088	NA
YCC + SSB	2908	2626	2146	225	159	228	406	600	0.212	0.246	0.351	0.544	1767	1554	1252	-475
SURBA + SSB	1183	1098	1124	1022	680	717	931	960	0.521	0.604	0.617	0.519	563	515	755	682
YCC + Z	3354	3319	3306	3334	0.438	3.18	3.25	2.33	0.276	0.286	0.266	0.285	2054	2022	2009	2036
SURBA + Z	3348	3370	3337	3368	6.9e-4	3.57e-4	3.2e-4	1.79e-4	NA	NA	NA	NA	2048	2070	2037	2068

Table 46: Performance criteria results for the nine management procedures.
Upper and lower 95% limits on the distribution of simulations results.

	SSB				Catch			
misreporting / MP	0 %	10 %	30 %	80 %	0 %	10 %	30 %	80 %
Observation index	1247/2371	1201/2565	1042/2606	658/2333	368/889	370/860	393/1099	404/1475
Single SSB trend	1296/2727	1073/2149	1129/2887	638/1886	381/984	392/906	397/1022	418/1445
Combined SSB trend	1236/2479	1086/2277	983/2192	737/2341	332/782	390/896	412/1029	367/1152
Z	1651/3425	1723/3570	1646/3358	1593/3465	63.1/688	64.5/665	65.5/631	44.6/667
Current management	1259/2377	1173/3086	920/2440	NA	361/951	367/1011	248/1141	NA
YCC + SSB	2538/3367	2276/3028	1529/2790	51.4/504	109/228	148/352	258/784	178/1521
SURBA + SSB	525/2322	439/2046	435/2147	361/1998	131/1535	85.4/2106	108/2234	138/1943
YCC + Z	3042/3714	3035/3687	2974/3781	2996/3861	0.288/0.763	2.06/5.36	1.99/5.16	1.37/3.53
SURBA + Z	0/3750	0/3892	0/3752	1419/3690	6.49e-5/Inf	8.16e-5/Inf	8.32e-5/Inf	6.96e-5/ 1.15e-3

Appendix 8: Results of the management strategy evaluation

Each figure is composed of six graphs:

- Spawning stock biomass over historical and projected years
- Recruitment over historical and projected years
- Harvest rate over historical and projected years
- Actual catch over historical and projected years
- Inter-annual change in the TAC over historical and projected years
- SSB reference depletion probability over the projected years

Each figure corresponds to the result of the simulation of a management procedure assuming some specific biological parameters:

- stock-recruitment relationship: hockey-stick or Ricker
- level of autocorrelation: estimated or higher
- consideration or not of a survey and its associated observation error
- consideration or not of an assessment method and its type
- consideration or not of a harvest control rule and its type
- consideration or not of a limitation in the inter-annual variability in the TAC
- consideration or not of an implementation error and its level

The number of the figure corresponds to the corresponding simulation in the Appendix 5.

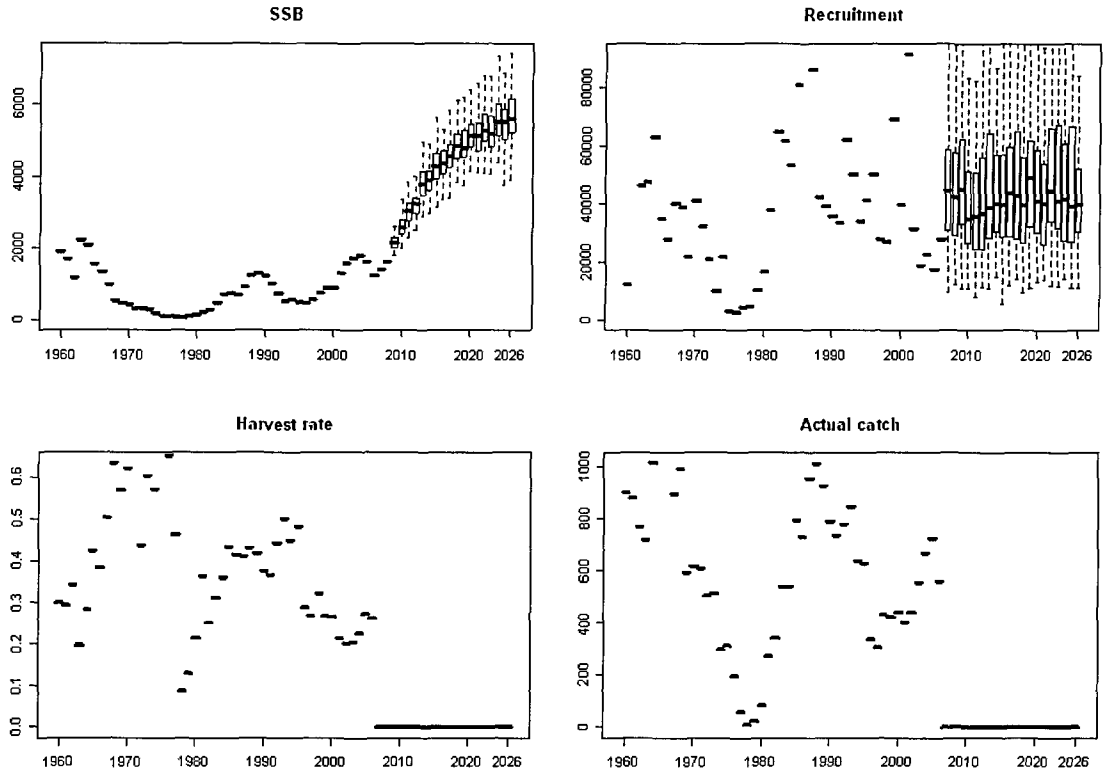


Figure 80: Output of simulation 1.

Stock recruitment: hockey-stick

Autocorrelation: estimated

Survey: none

Assessment: none

Harvest control rule: no catch

Limitation of variation: none

Implementation error: 0%

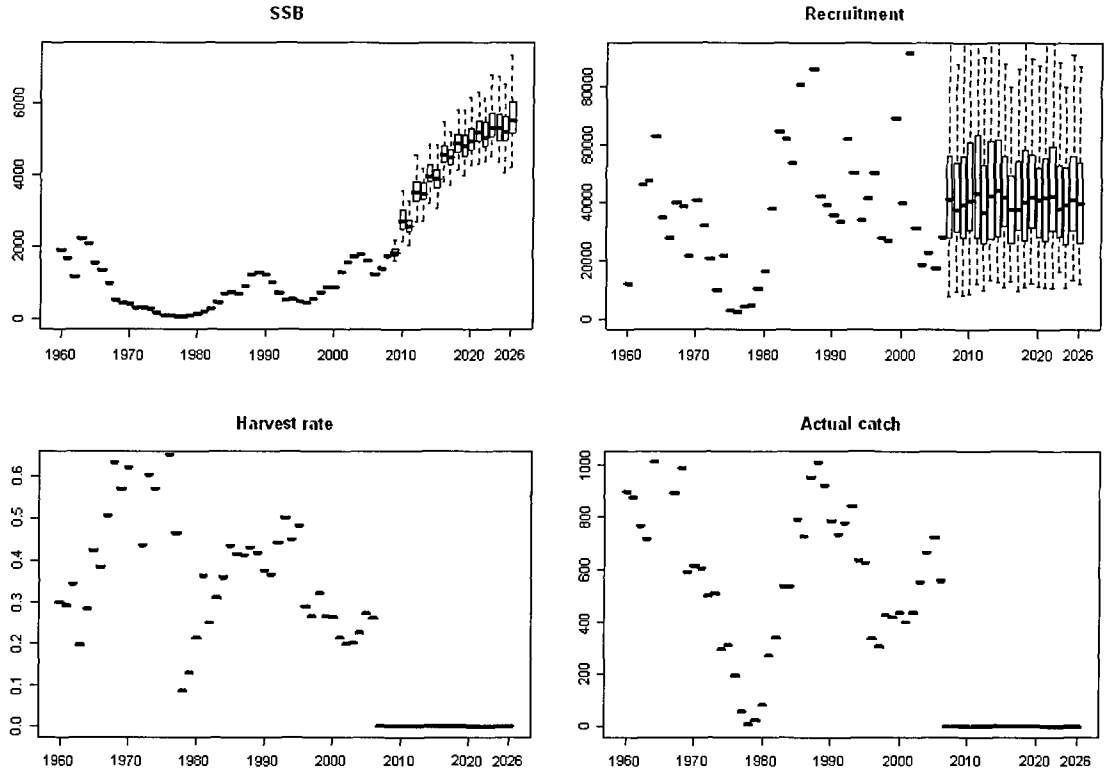


Figure 81: Output of simulation 2.

Stock recruitment: hockey-stick

Autocorrelation: high

Survey: none

Assessment: none

Harvest control rule: no catch

Limitation of variation: none

Implementation error: 0%

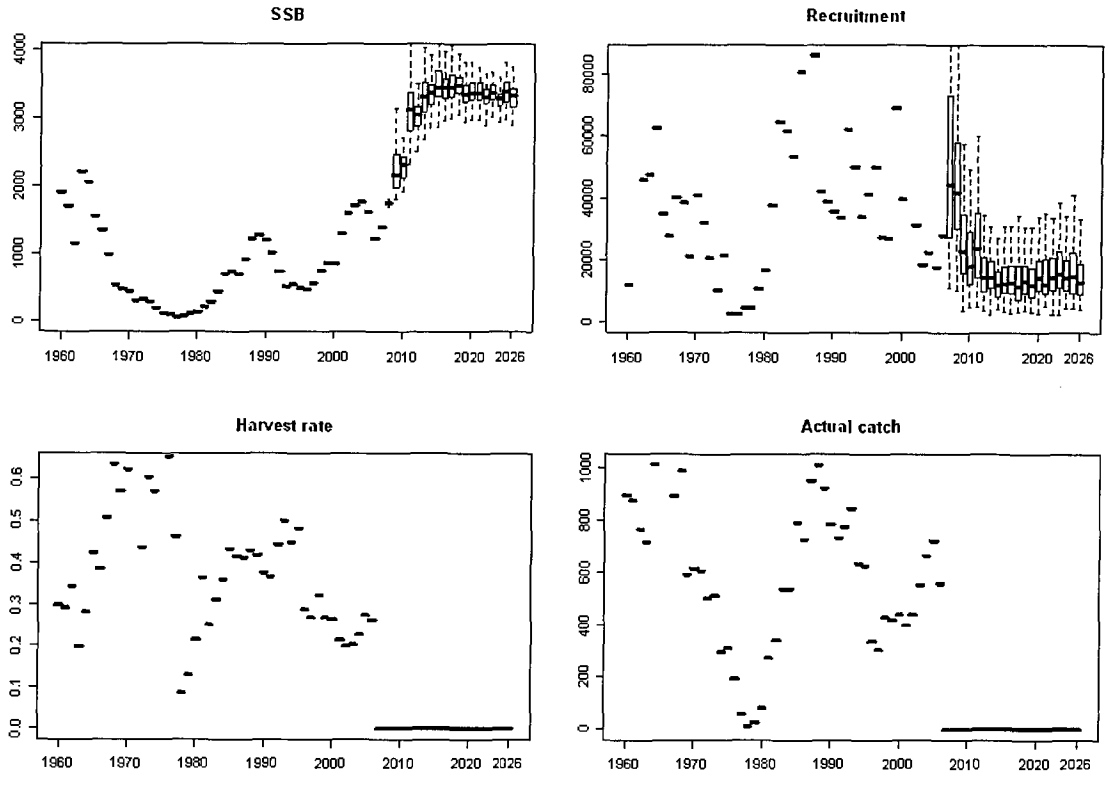


Figure 82: Output of simulation 3.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: none

Assessment: none

Harvest control rule: no catch

Limitation of variation: none

Implementation error: 0%

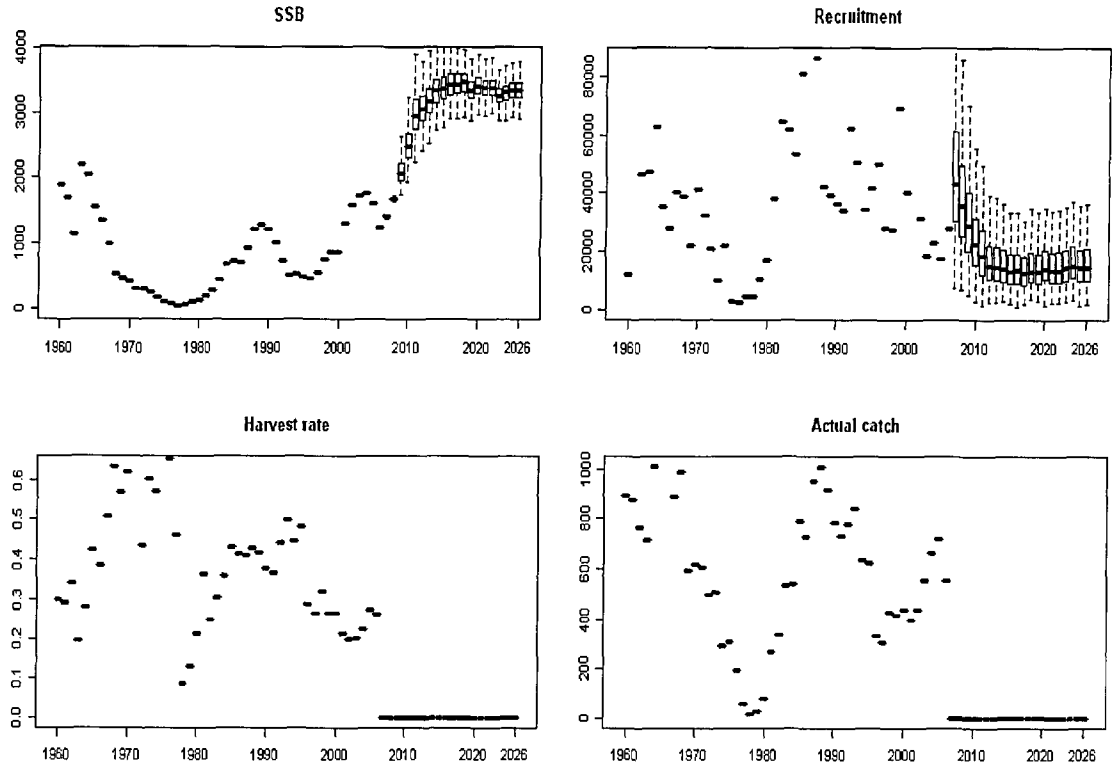


Figure 83: Output of simulation 4.

Stock recruitment: Ricker

Autocorrelation: high

Survey: none

Assessment: none

Harvest control rule: no catch

Limitation of variation: none

Implementation error: 0%

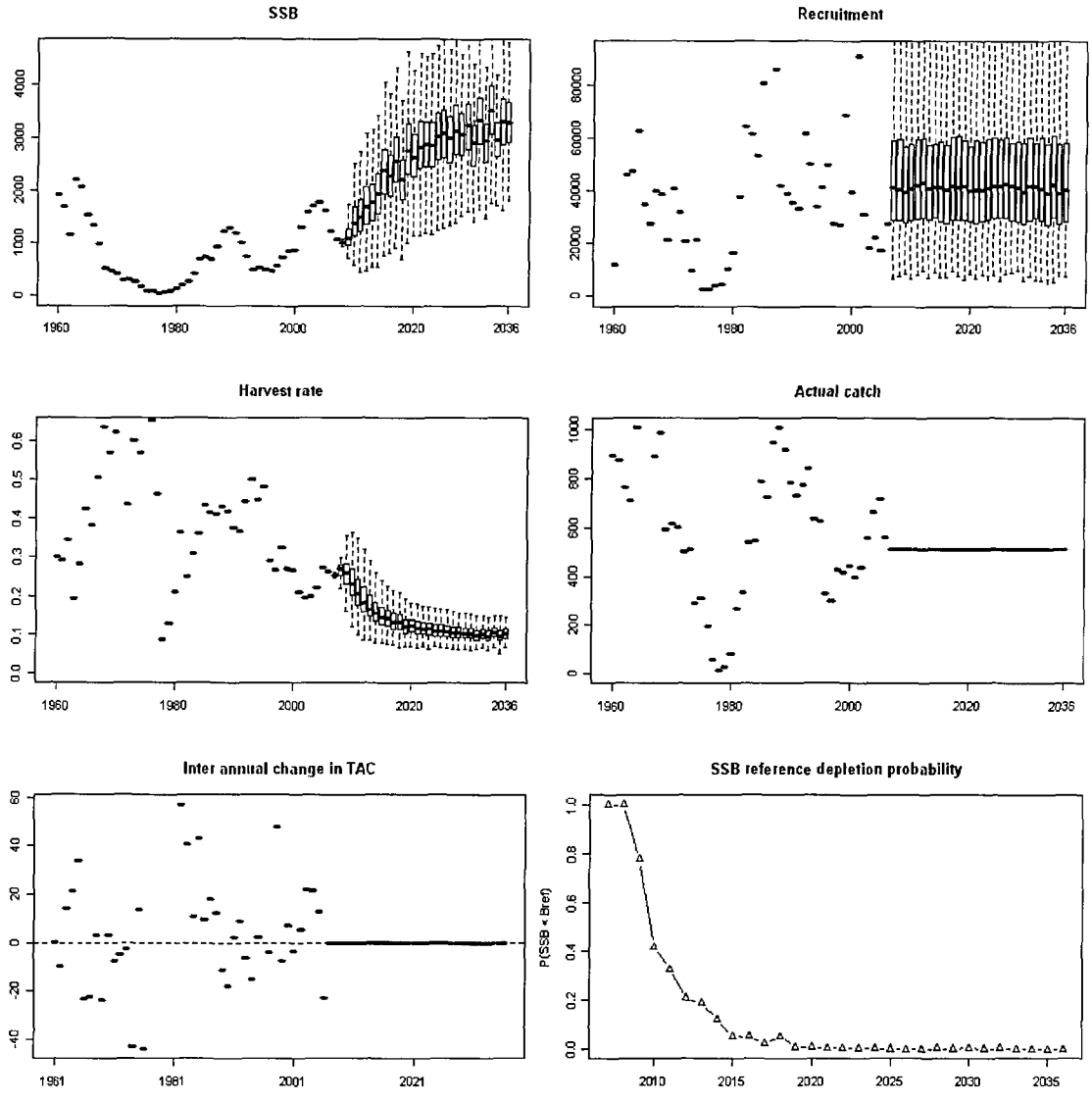


Figure 84: Output of simulation 5.

Stock recruitment: hockey-stick

Autocorrelation: estimated

Survey: none

Assessment: none

Harvest control rule: fixed TAC

Limitation of variation: none

Implementation error: 0%

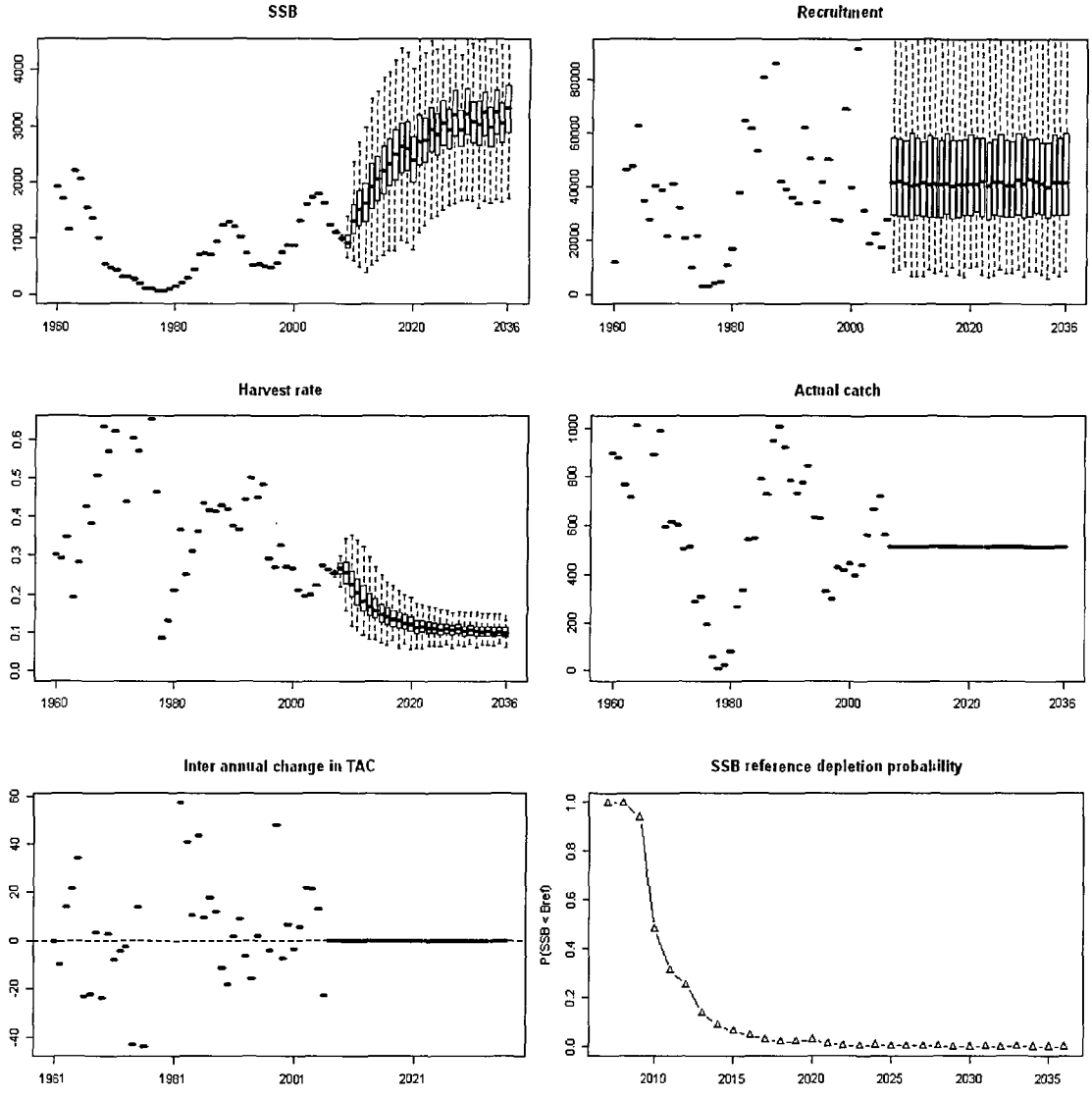


Figure 85: Output of simulation 6.

Stock recruitment: hockey-stick

Autocorrelation: high

Survey: none

Assessment: none

Harvest control rule: fixed TAC

Limitation of variation: none

Implementation error: 0%

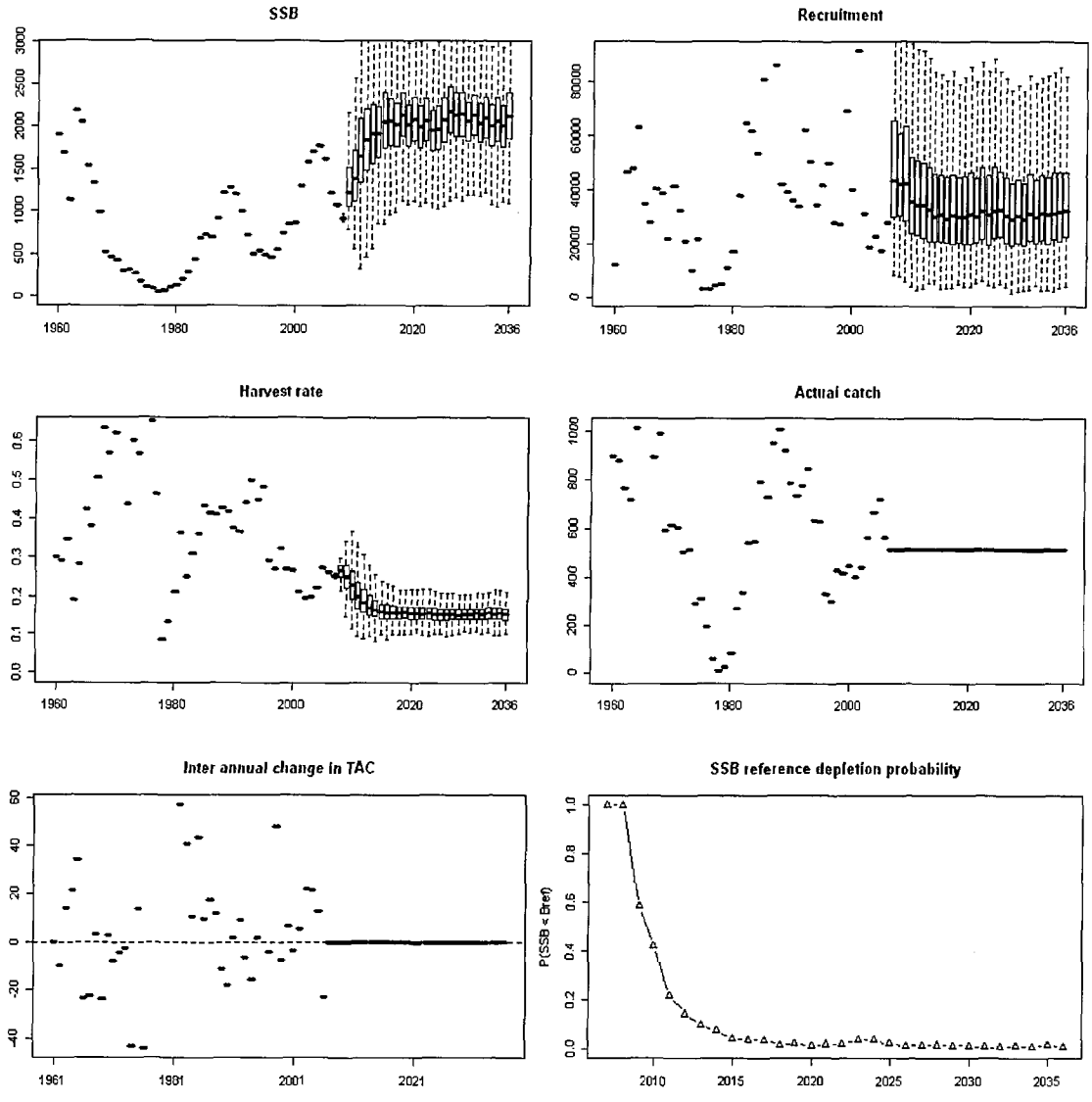


Figure 86: Output of simulation 7.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: none

Assessment: none

Harvest control rule: fixed TAC

Limitation of variation: none

Implementation error: 0%

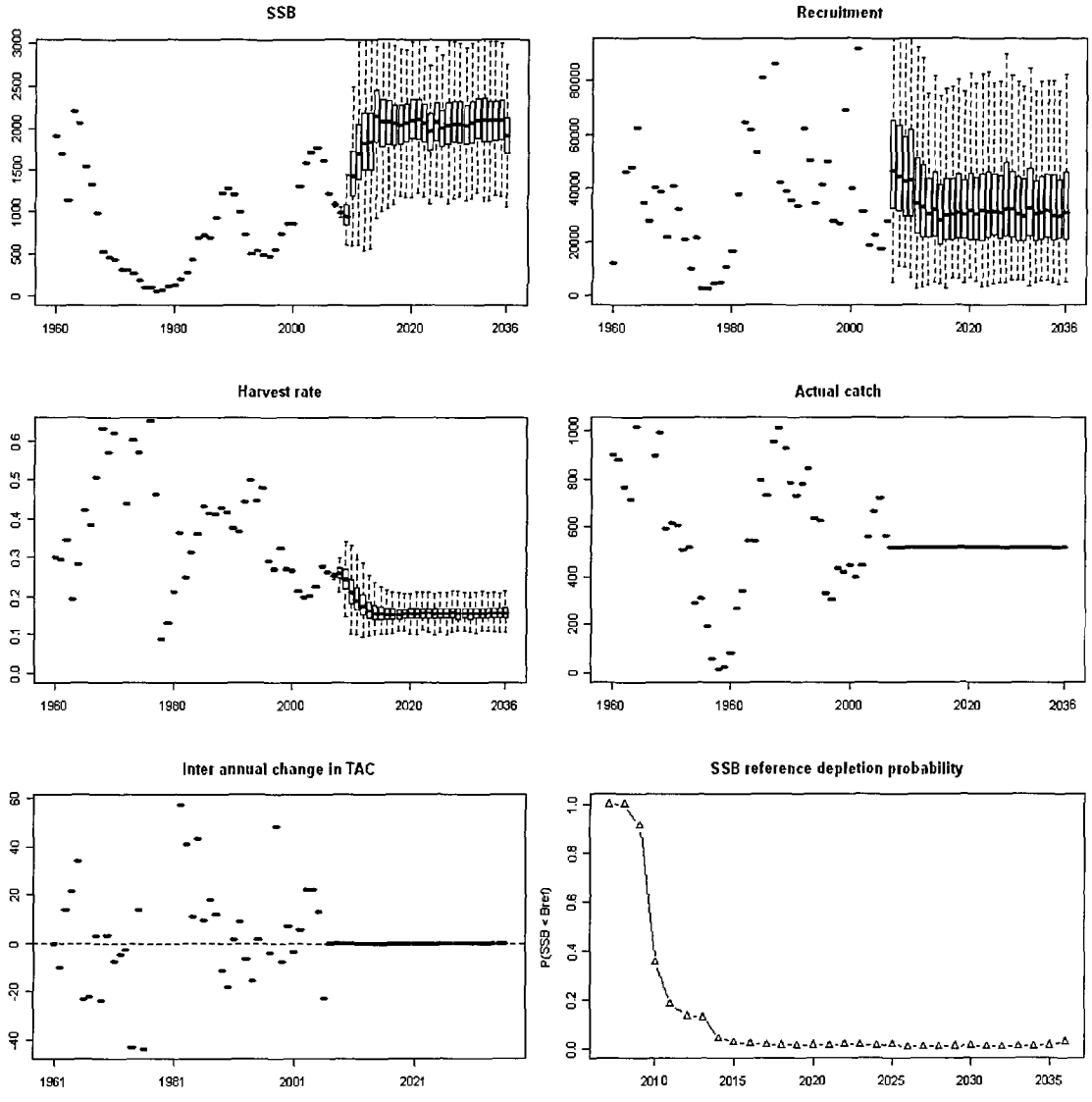


Figure 87: Output of simulation 8.

Stock recruitment: Ricker

Autocorrelation: high

Survey: none

Assessment: none

Harvest control rule: fixed TAC

Limitation of variation: none

Implementation error: 0%

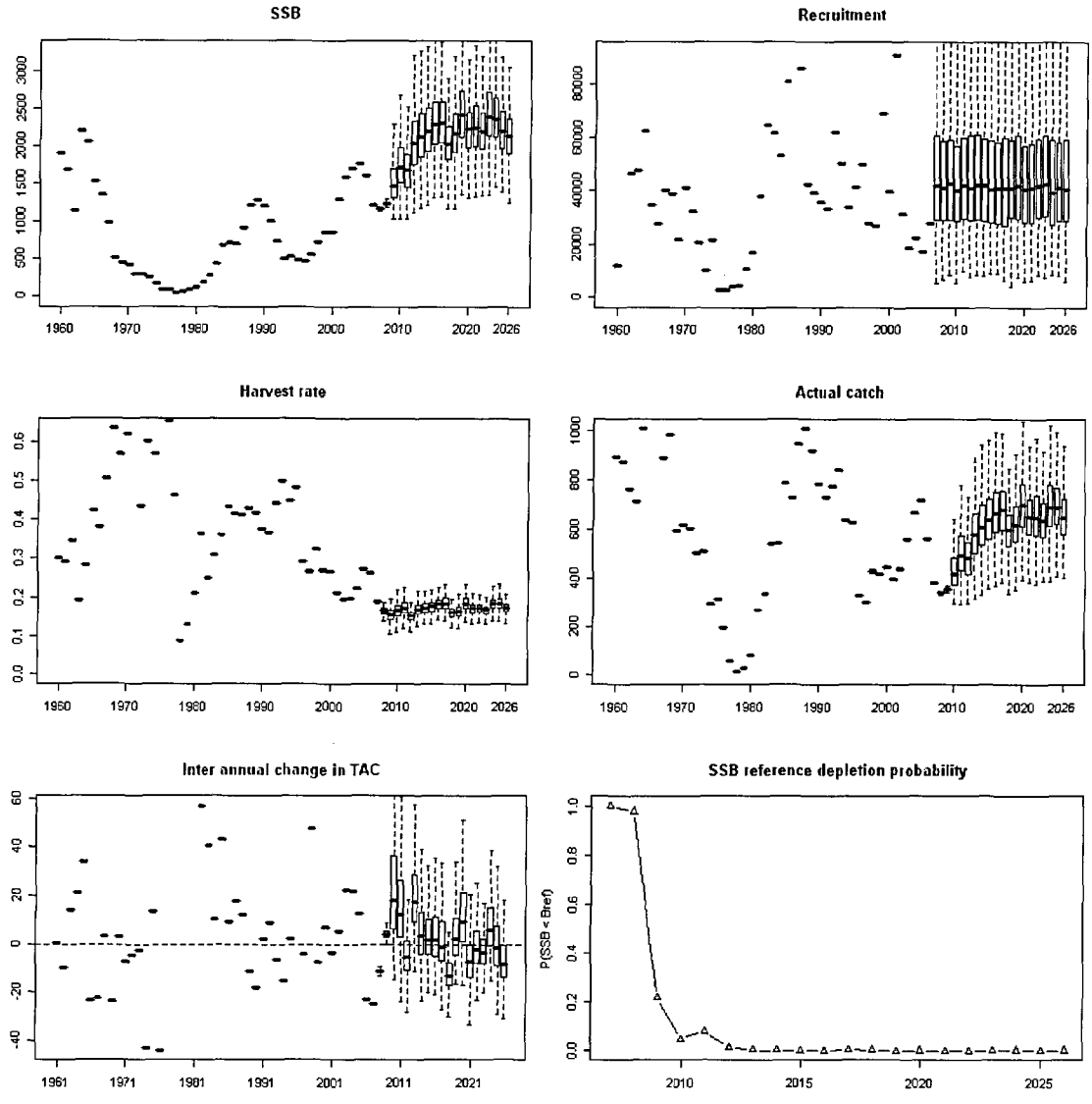


Figure 88: Output of simulation 9.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic without observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 0%

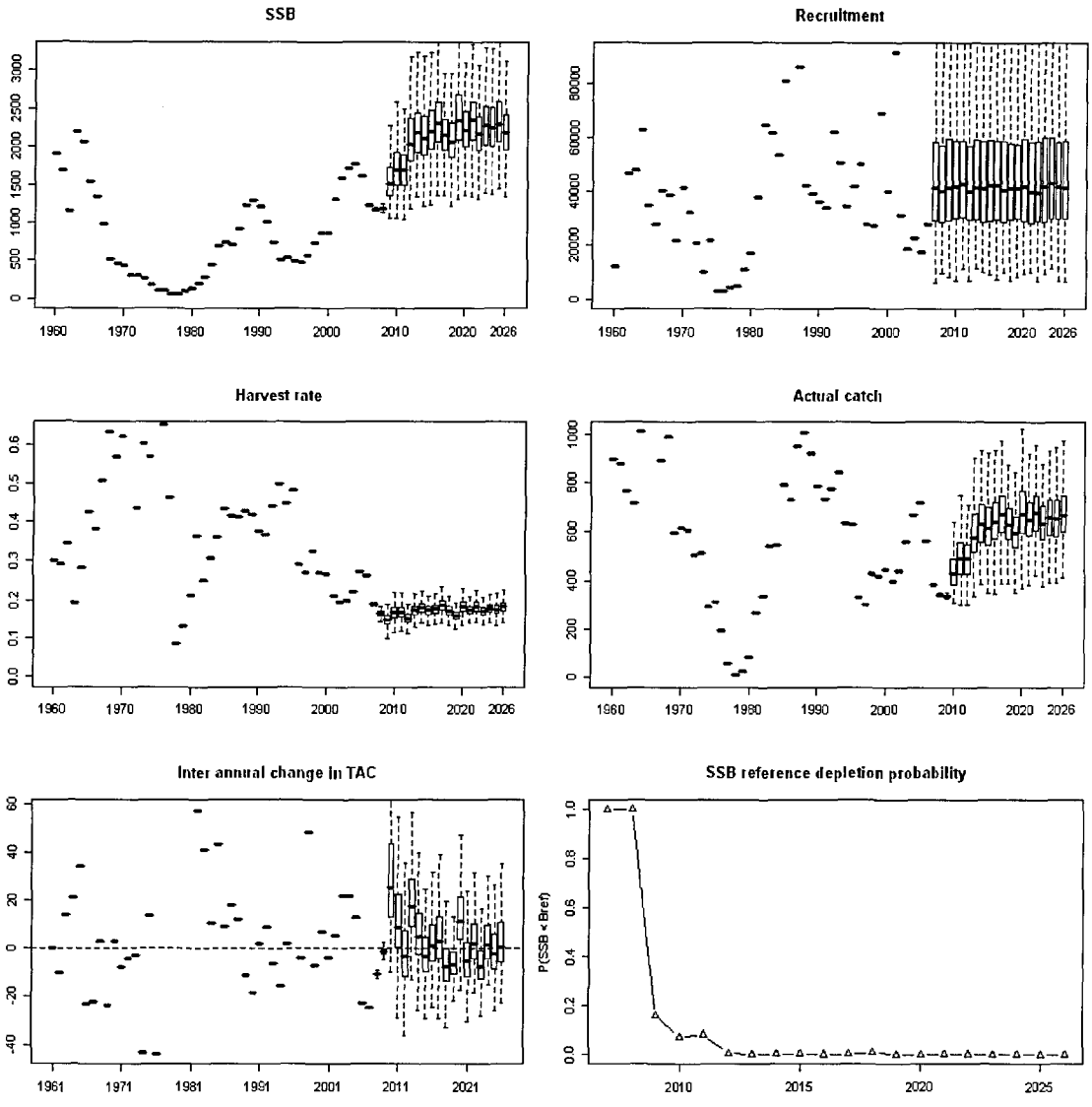


Figure 89: Output of simulation 10.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic without observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 0%

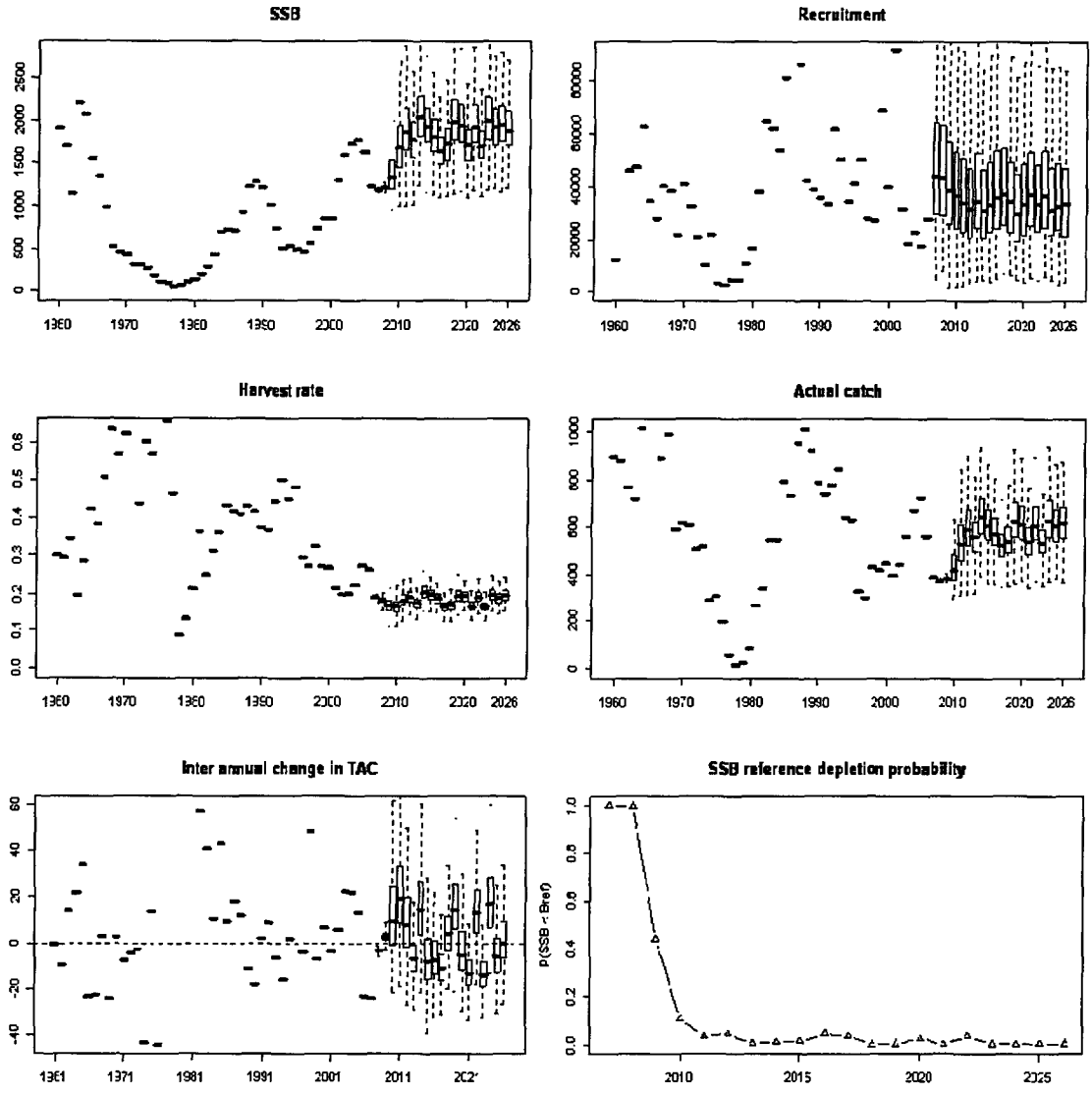


Figure 90: Output of simulation 11.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic without observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 0%

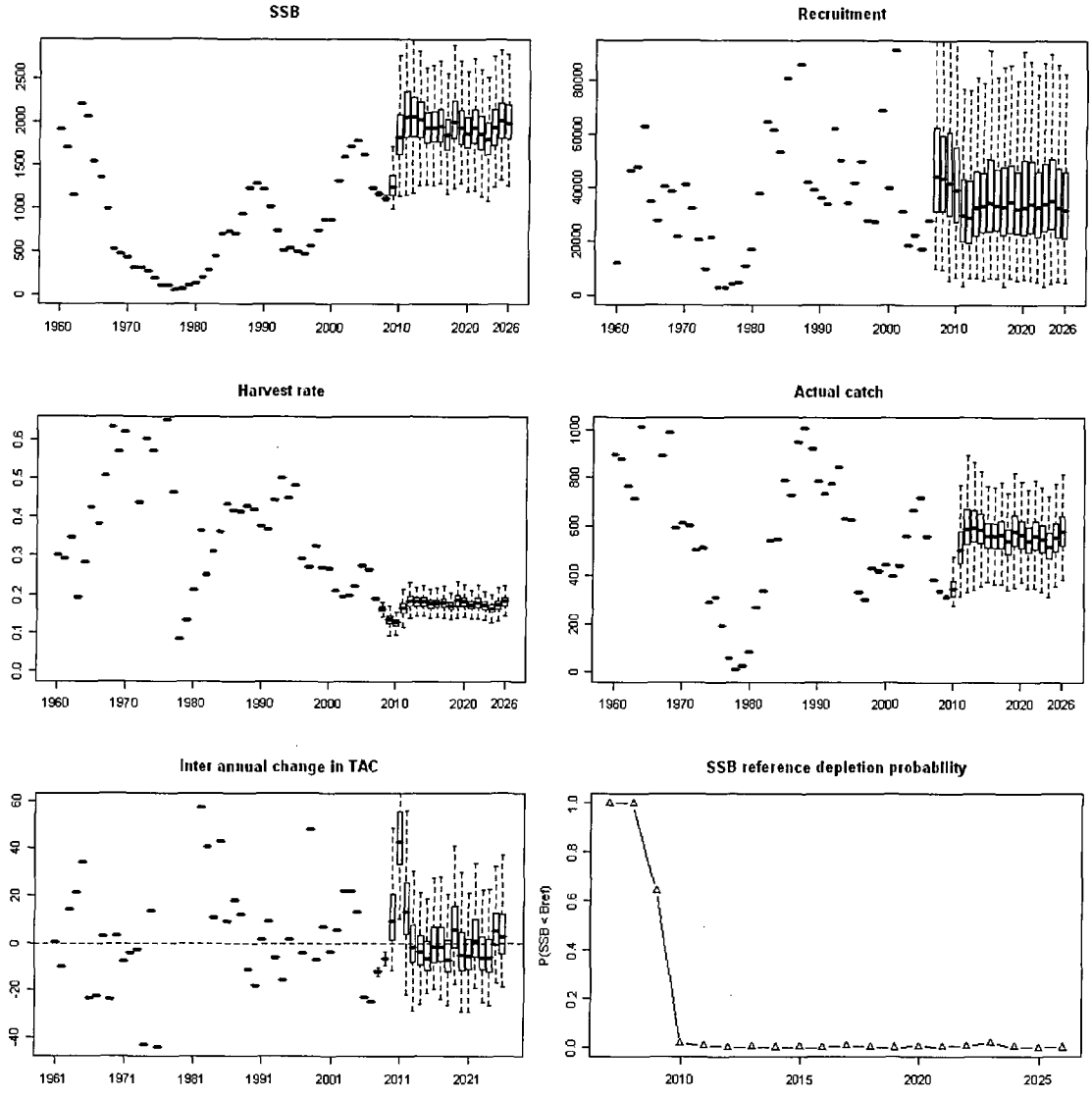


Figure 91: Output of simulation 12.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic without observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 0%

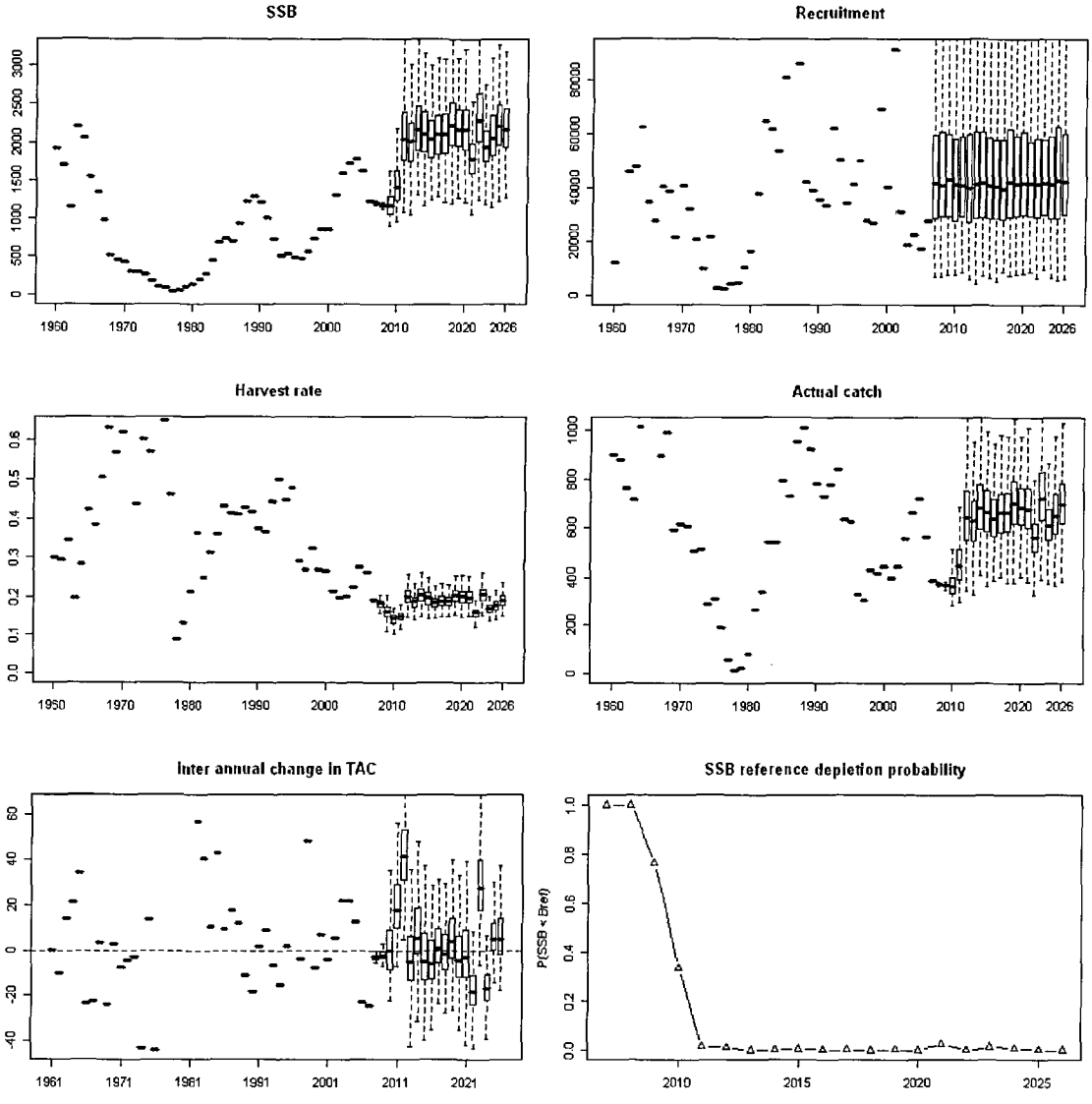


Figure 92: Output of simulation 13.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic without observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

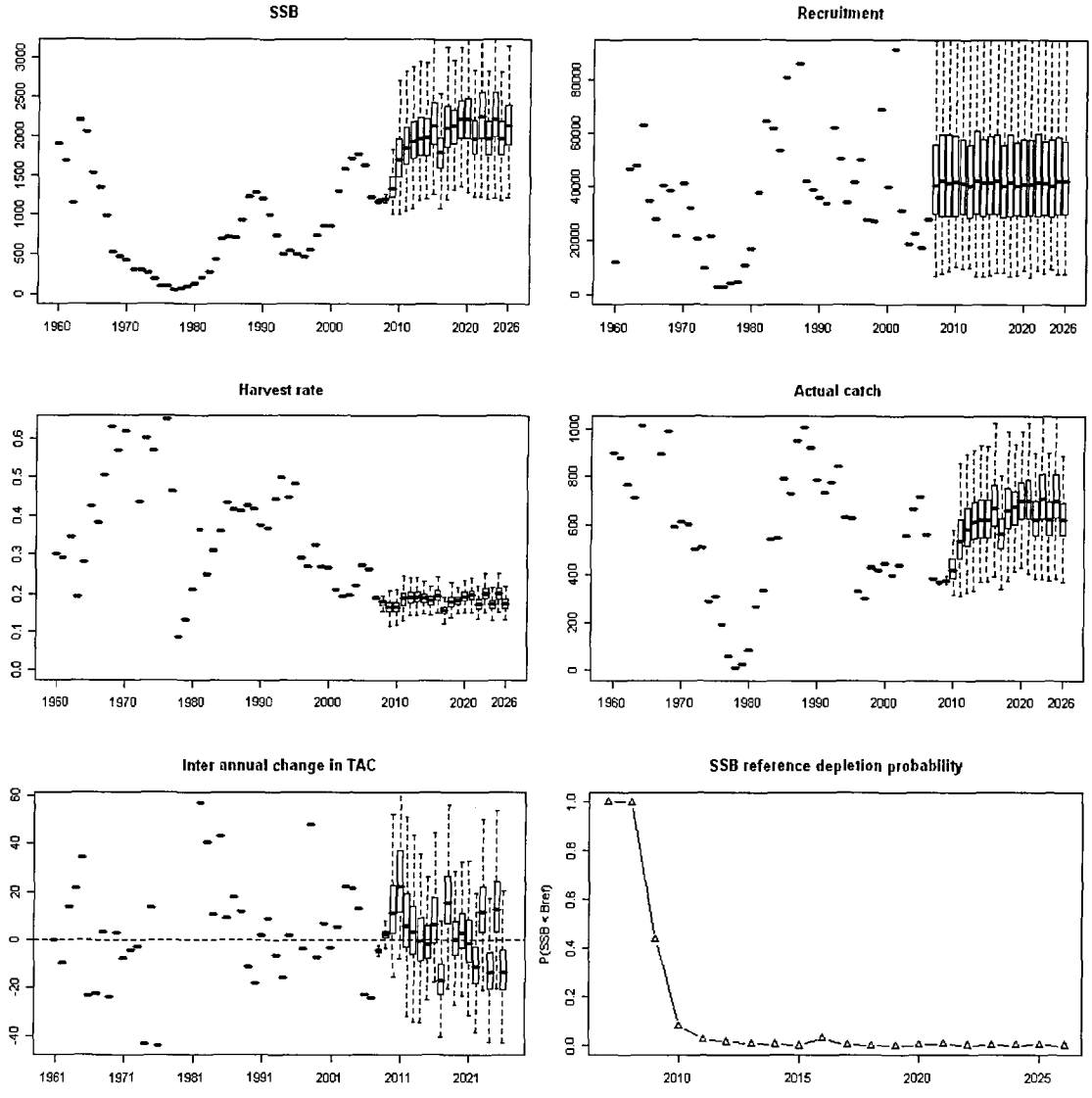


Figure 93: Output of simulation 14.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic without observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

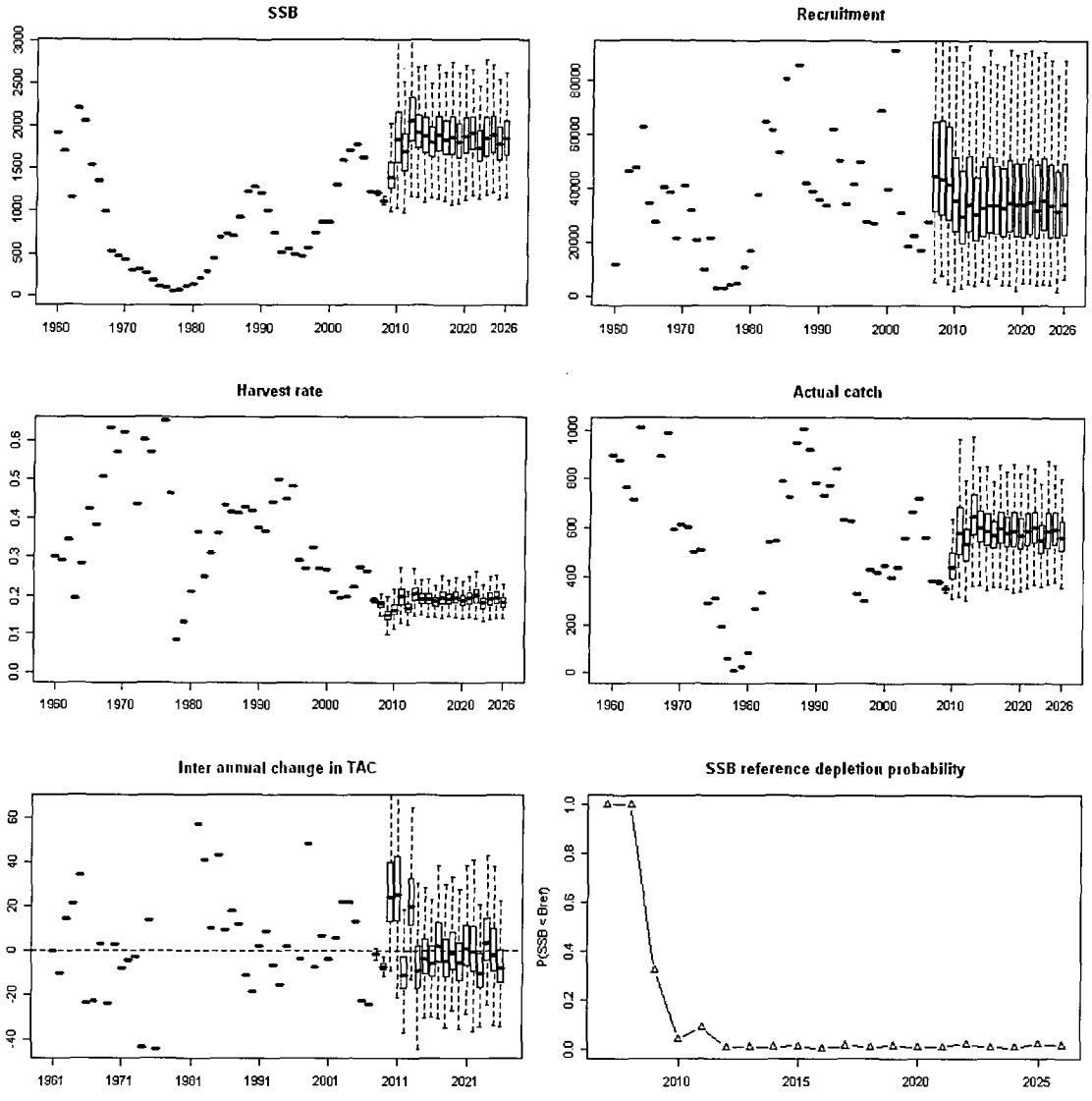


Figure 94: Output of simulation 15.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic without observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

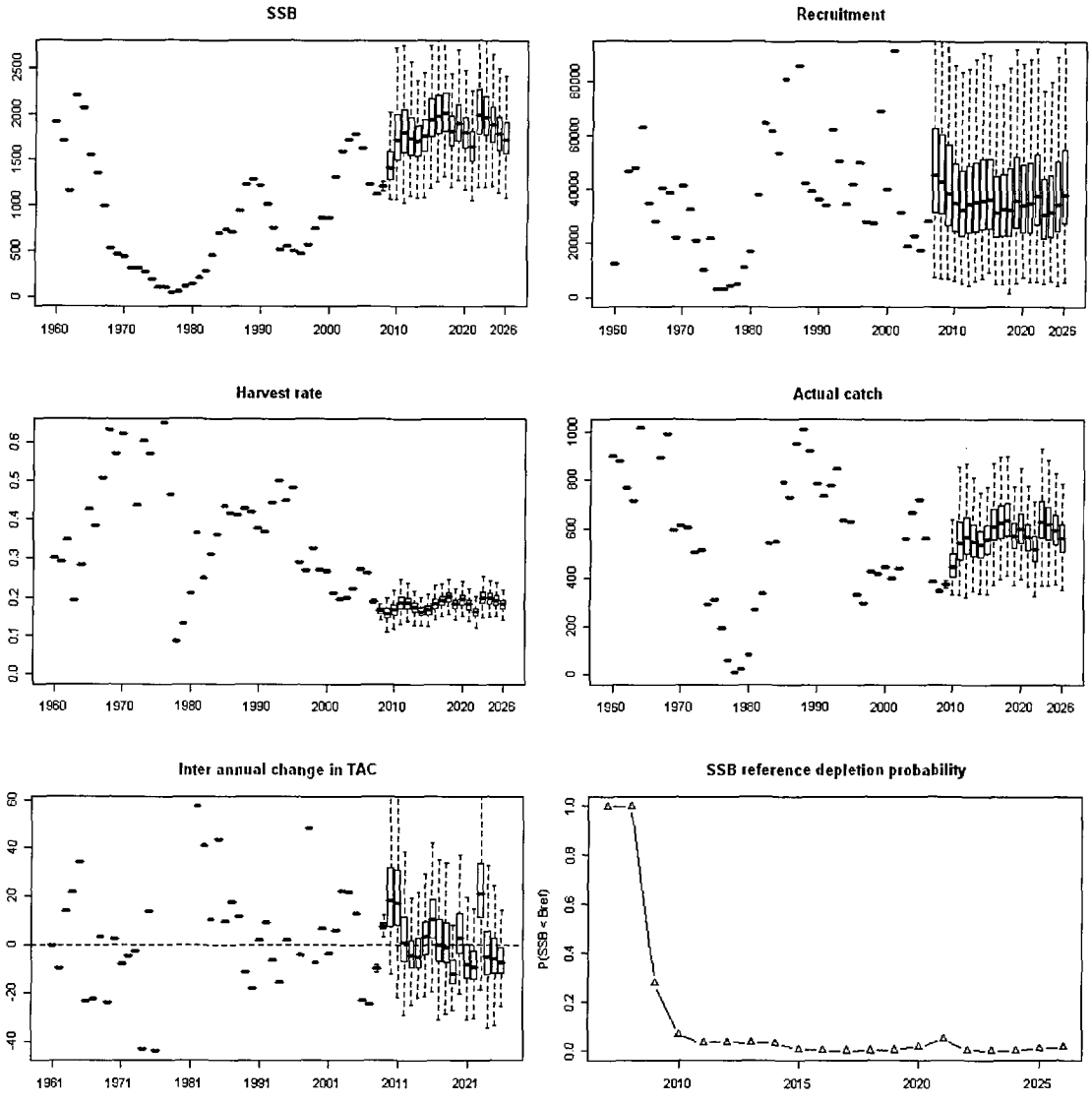


Figure 95: Output of simulation 16.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic without observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

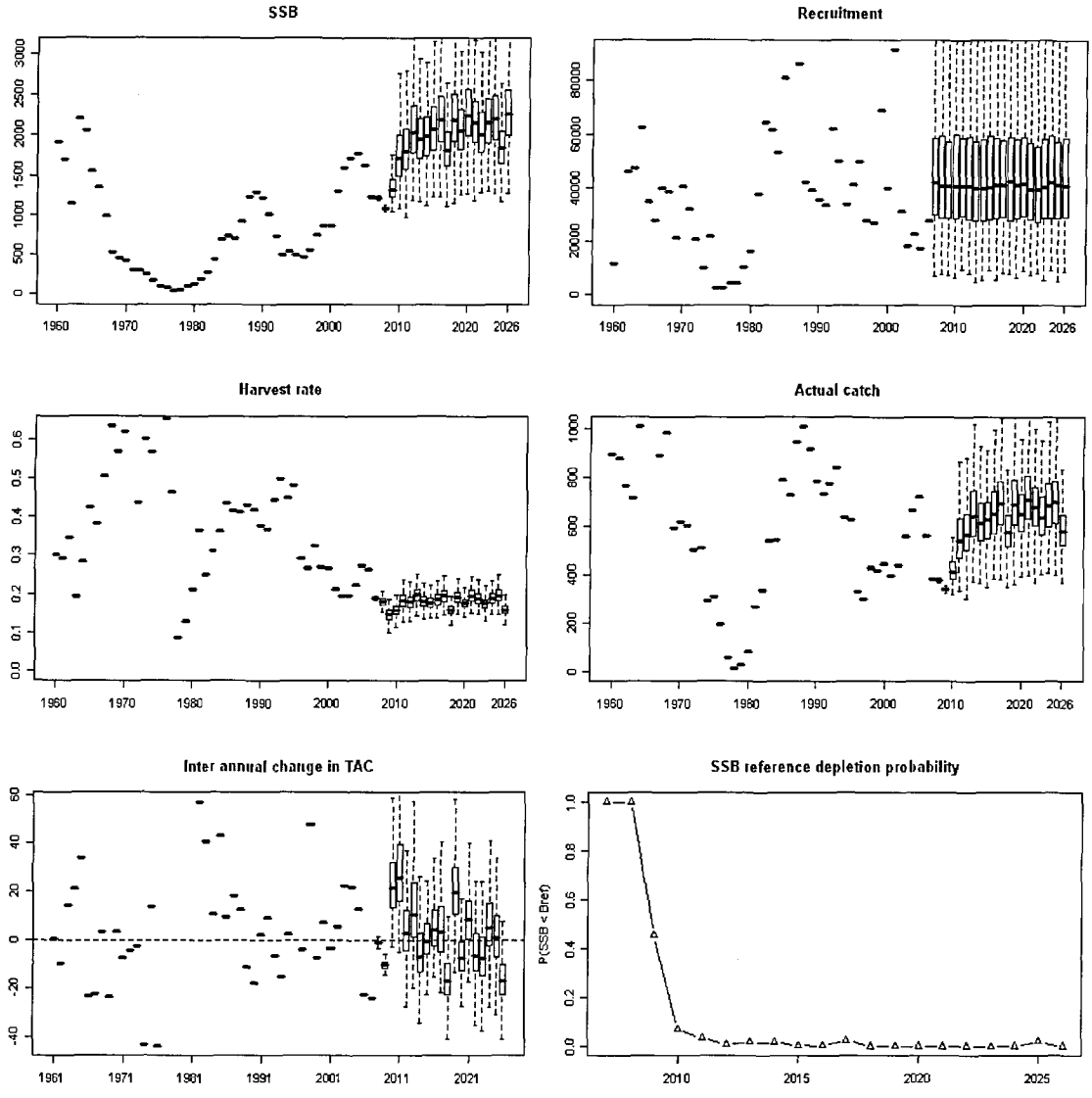


Figure 96: Output of simulation 17.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: combined SSB without observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 0%

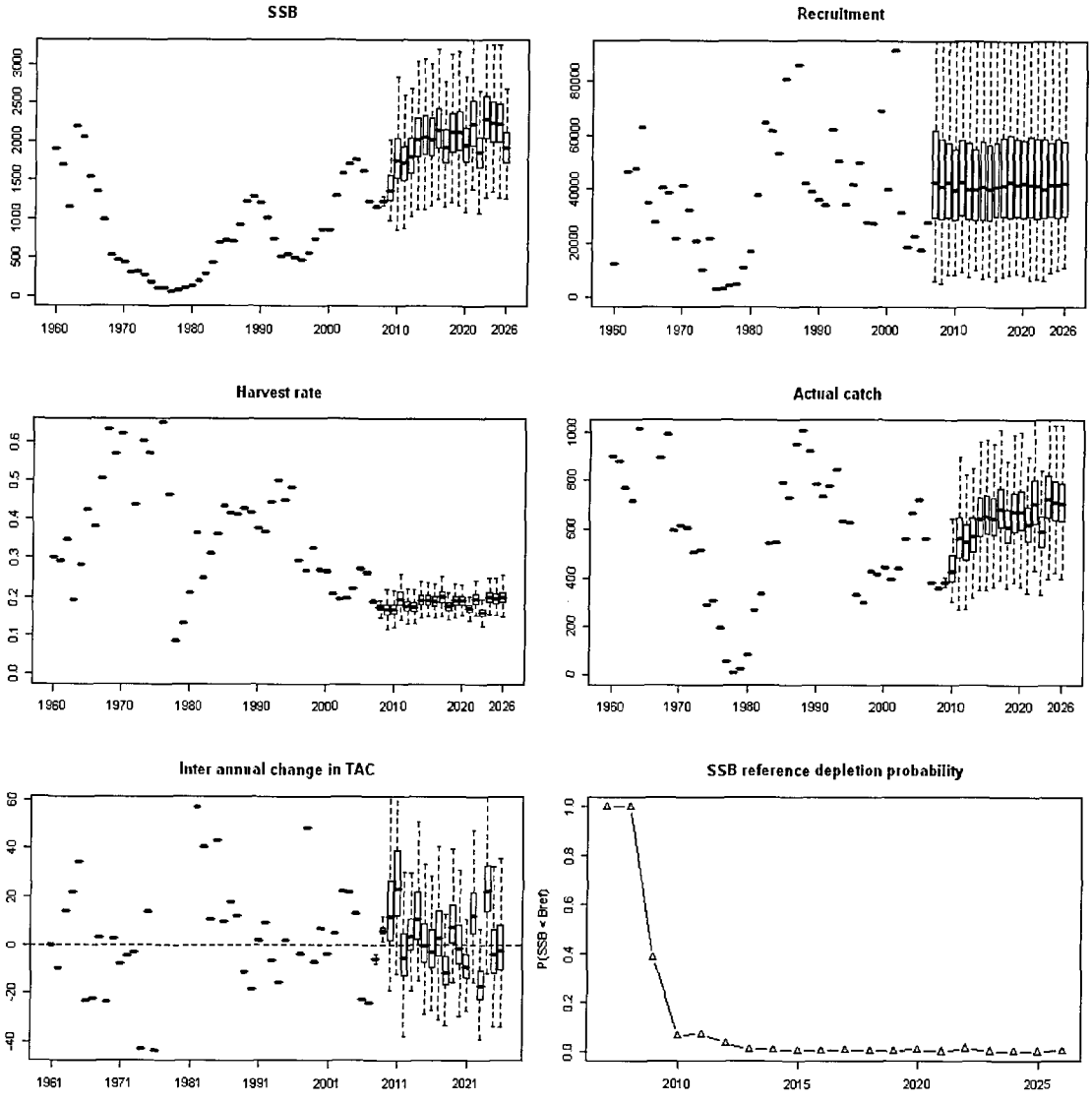


Figure 97: Output of simulation 18.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: combined SSB without observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 0%

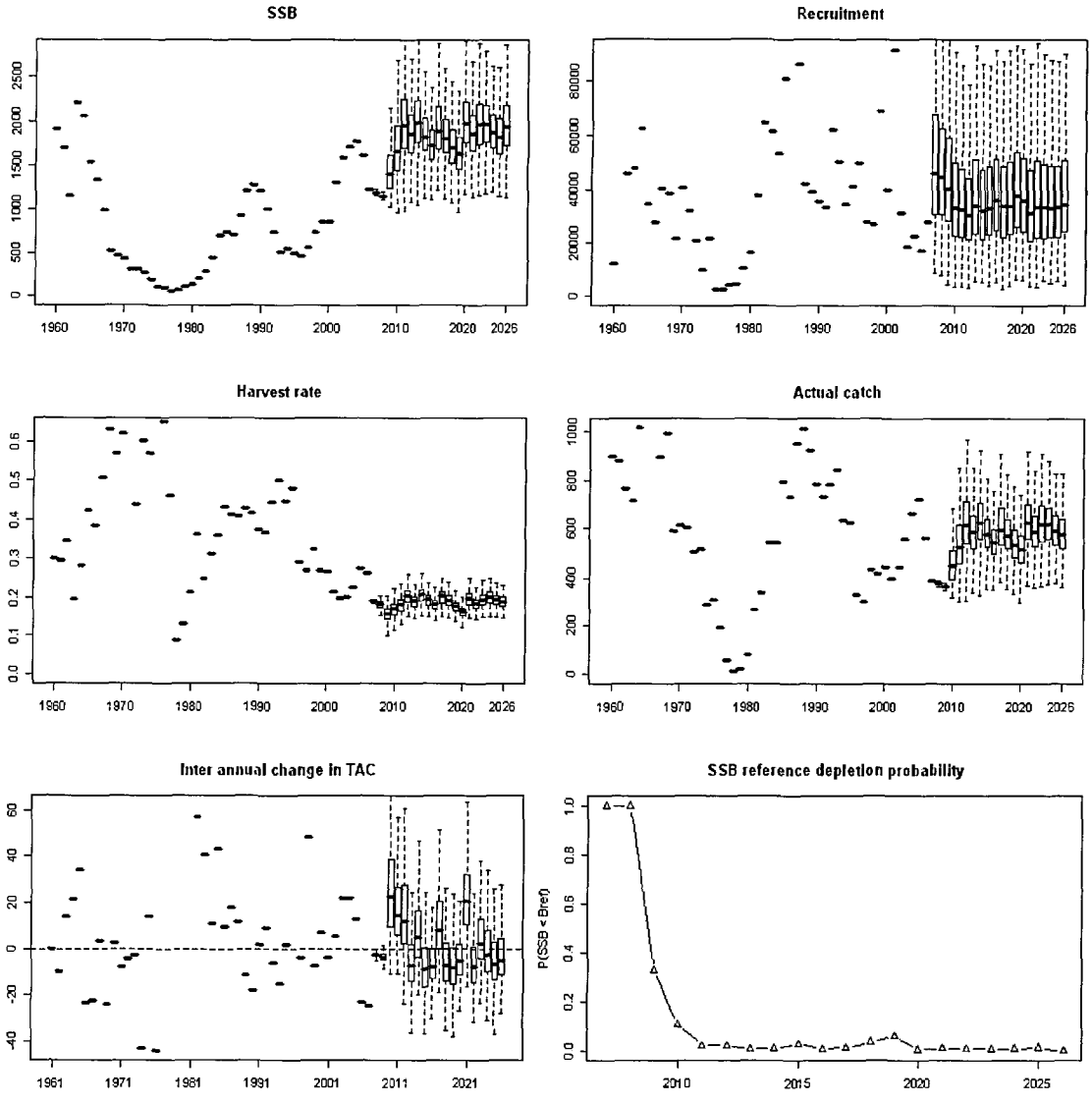


Figure 98: Output of simulation 19.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: combined SSB without observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 0%

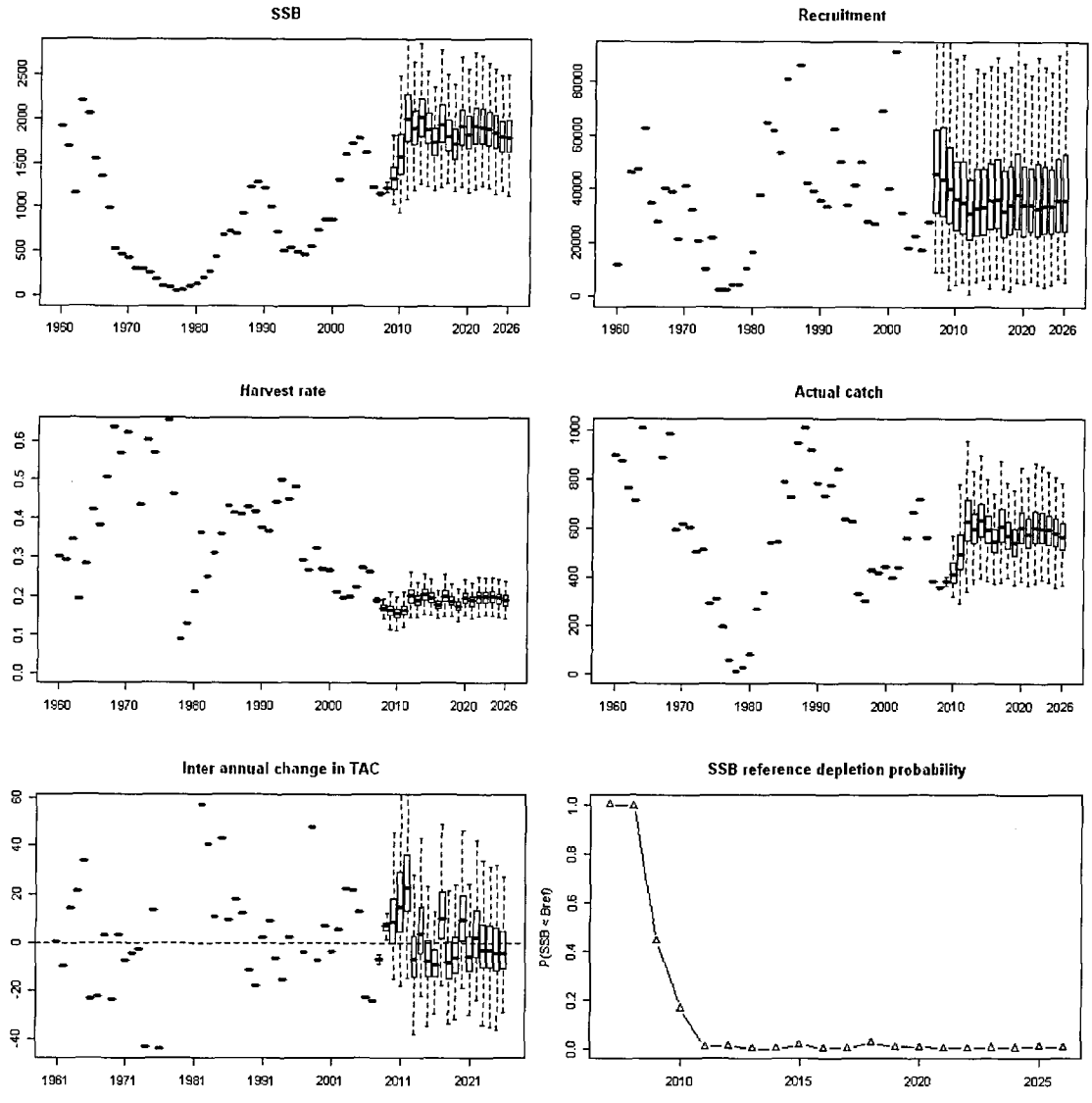


Figure 99: Output of simulation 20.

Stock recruitment: Ricker

Autocorrelation: high

Survey: combined SSB without observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 0%

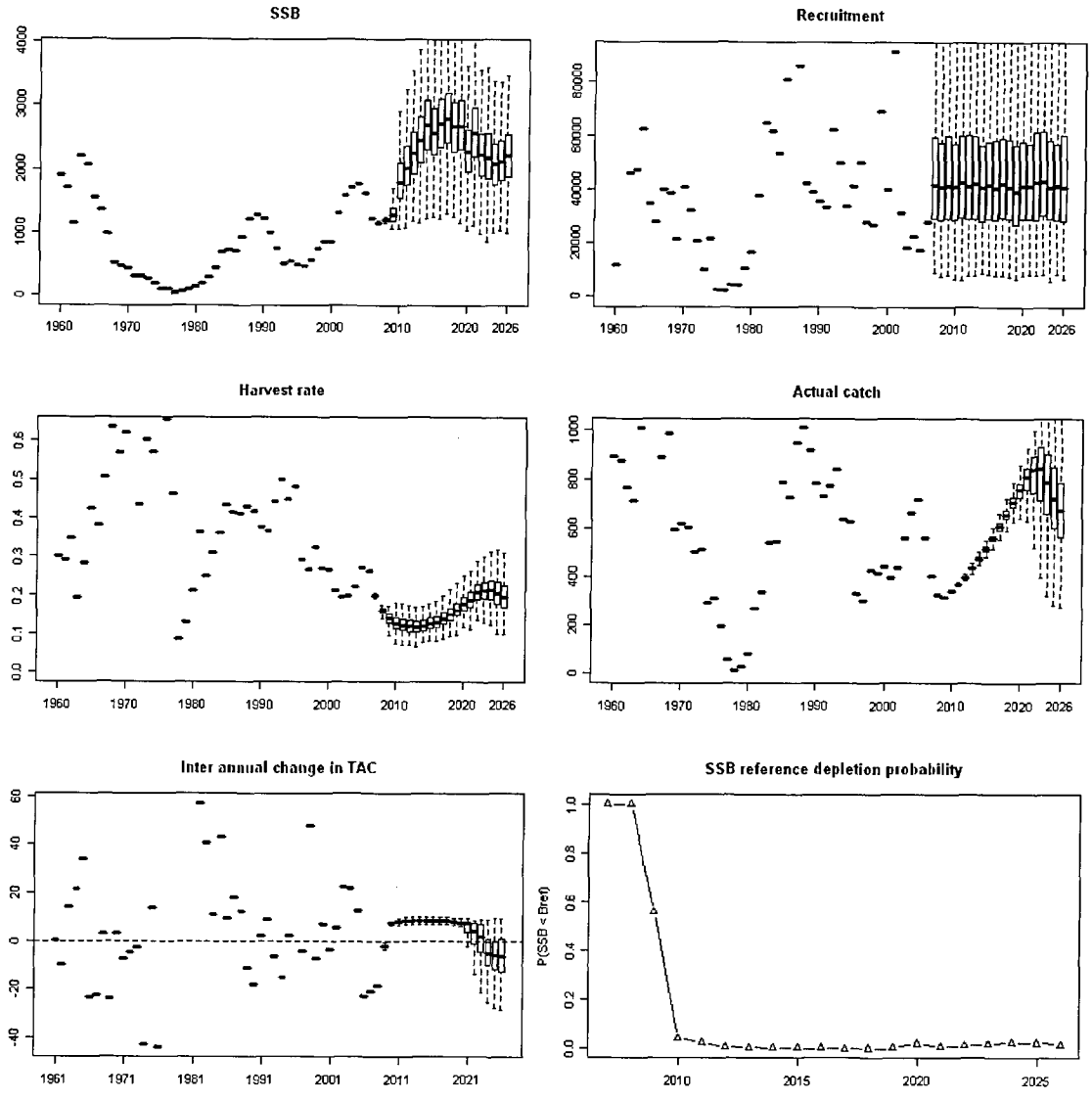


Figure 100: Output of simulation 21.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic without observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

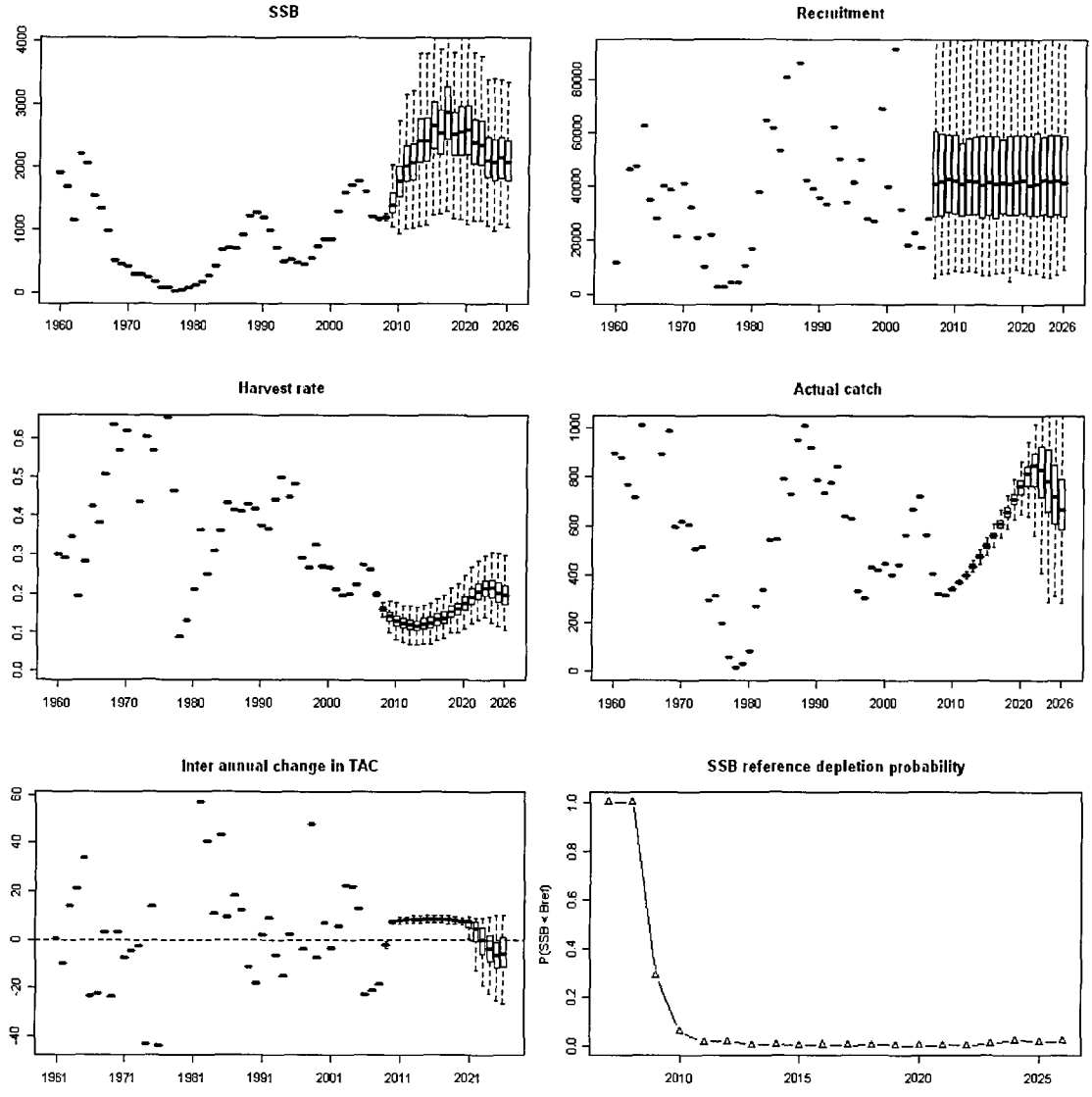


Figure 101: Output of simulation 22.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic without observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

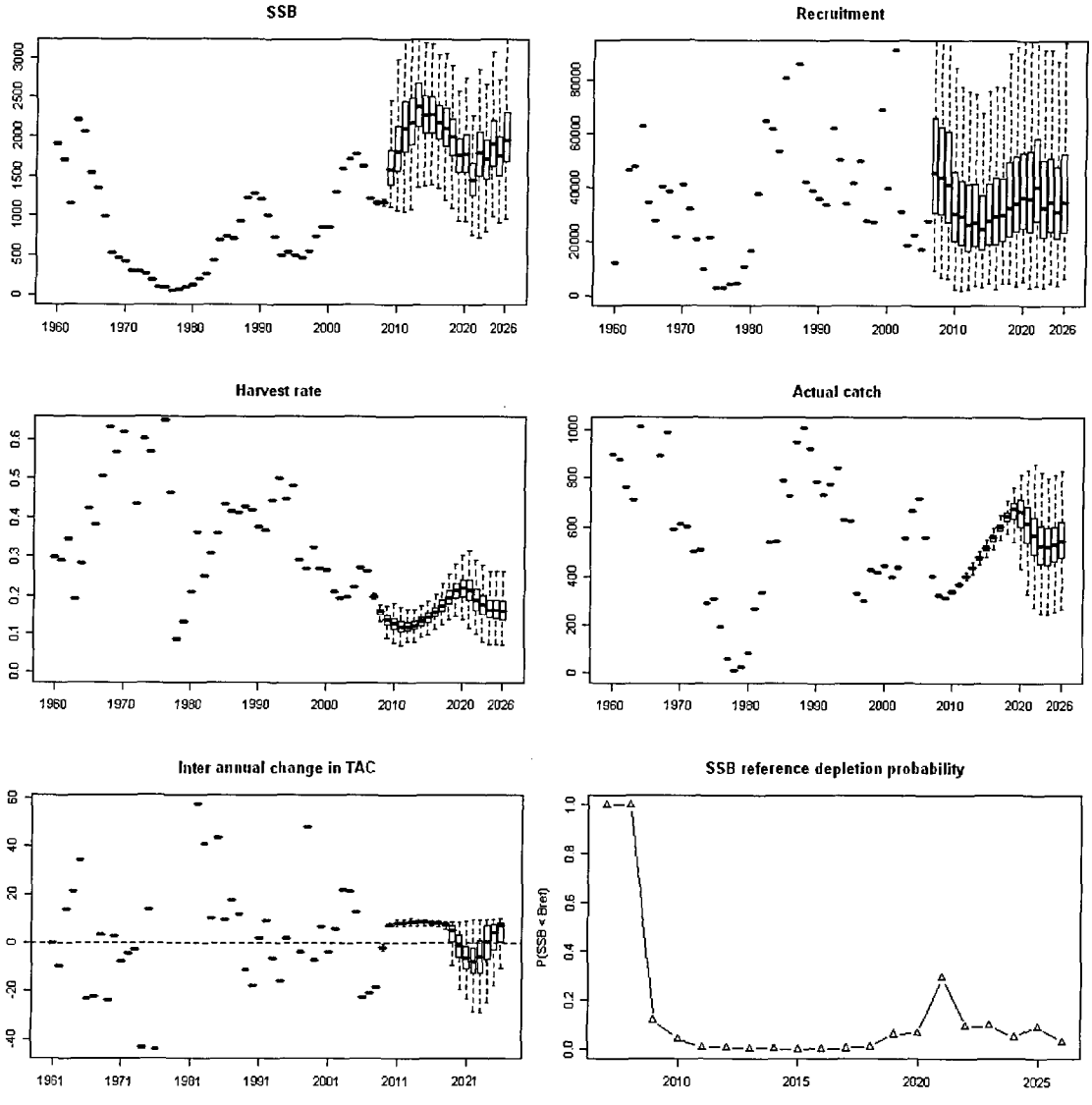


Figure 102: Output of simulation 23.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic without observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

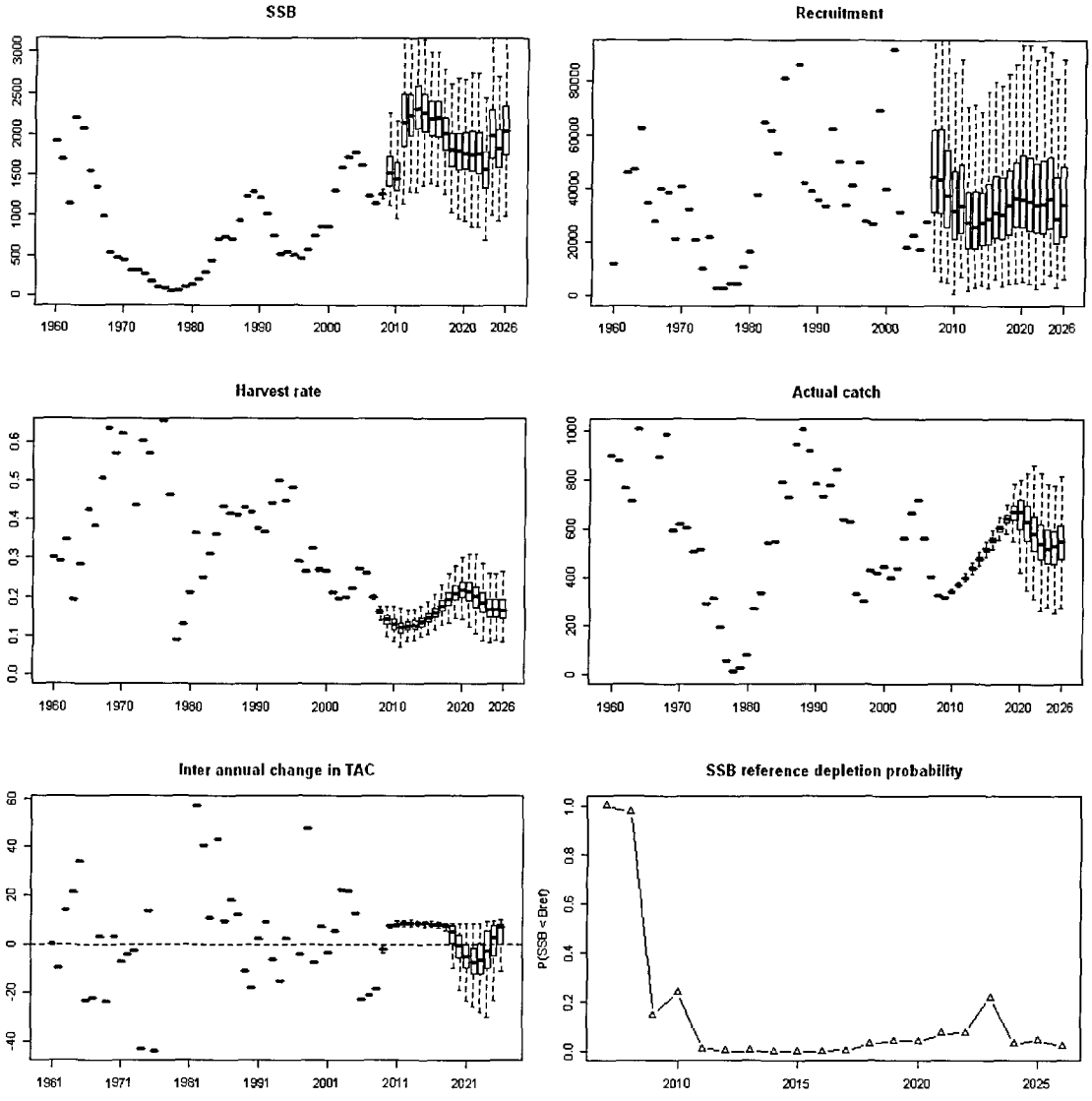


Figure 103: Output of simulation 24.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic without observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

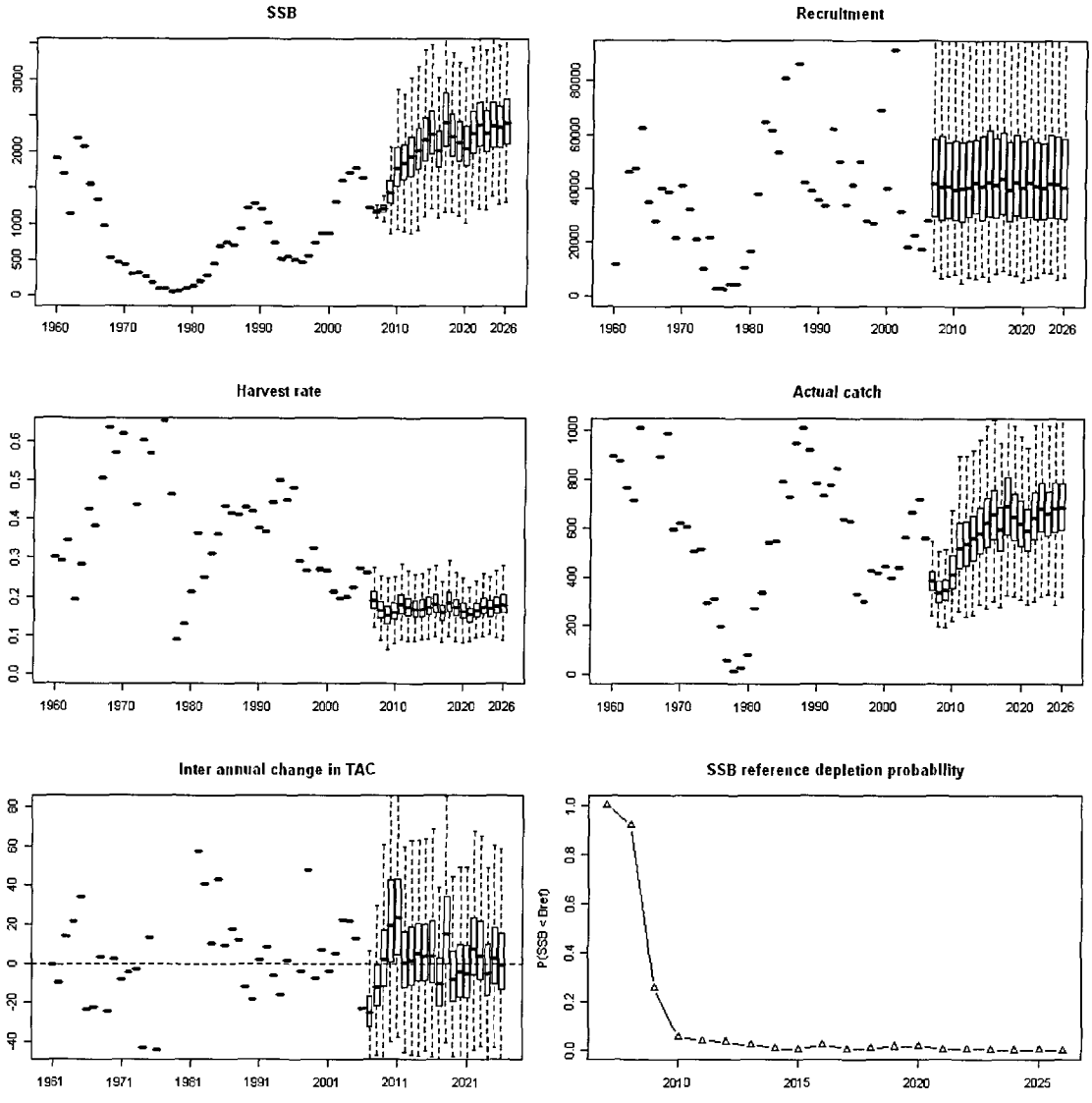


Figure 104: Output of simulation 25.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 0%

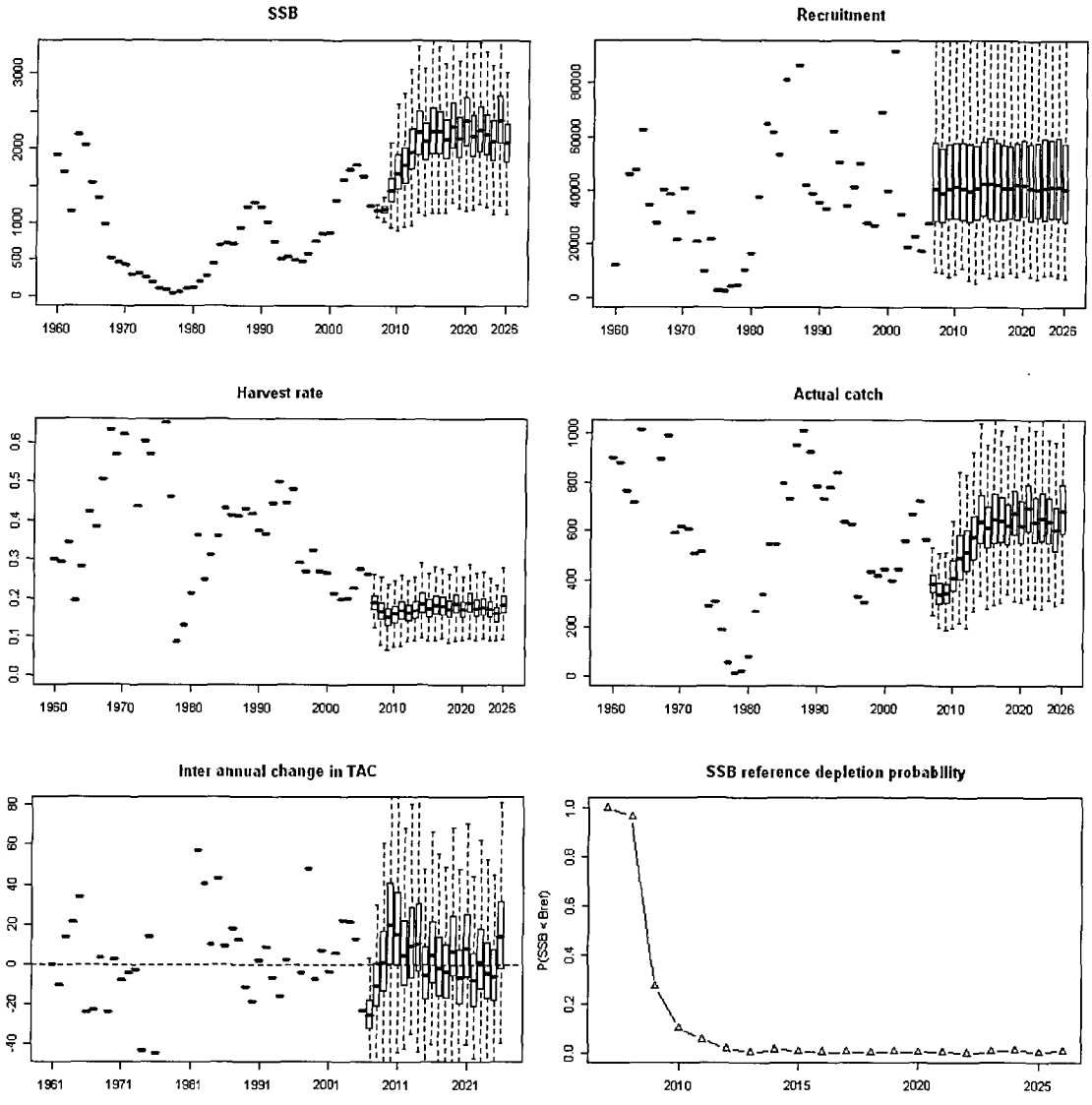


Figure 105: Output of simulation 26.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 0%

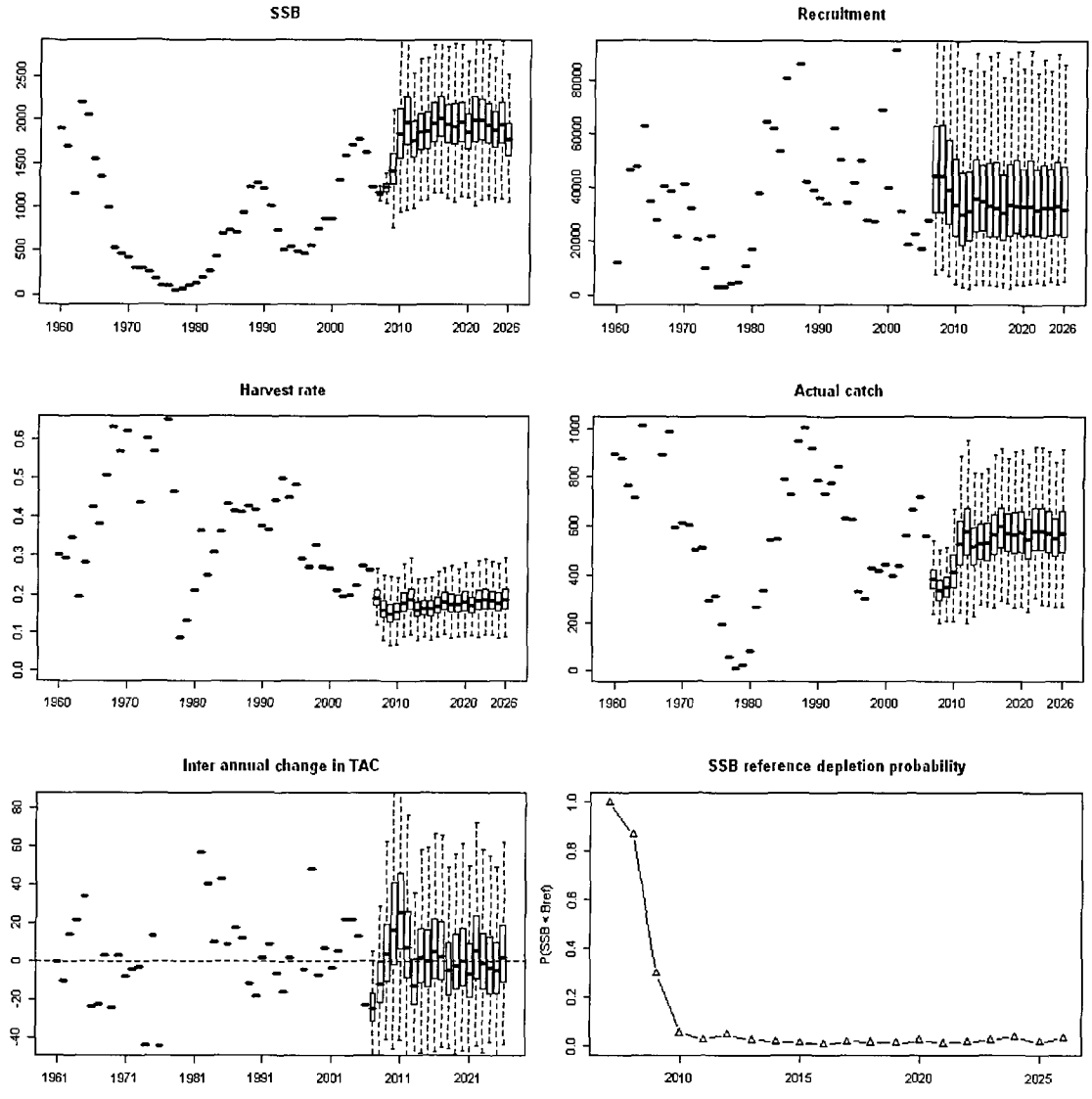


Figure 106: Output of simulation 27.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 0%

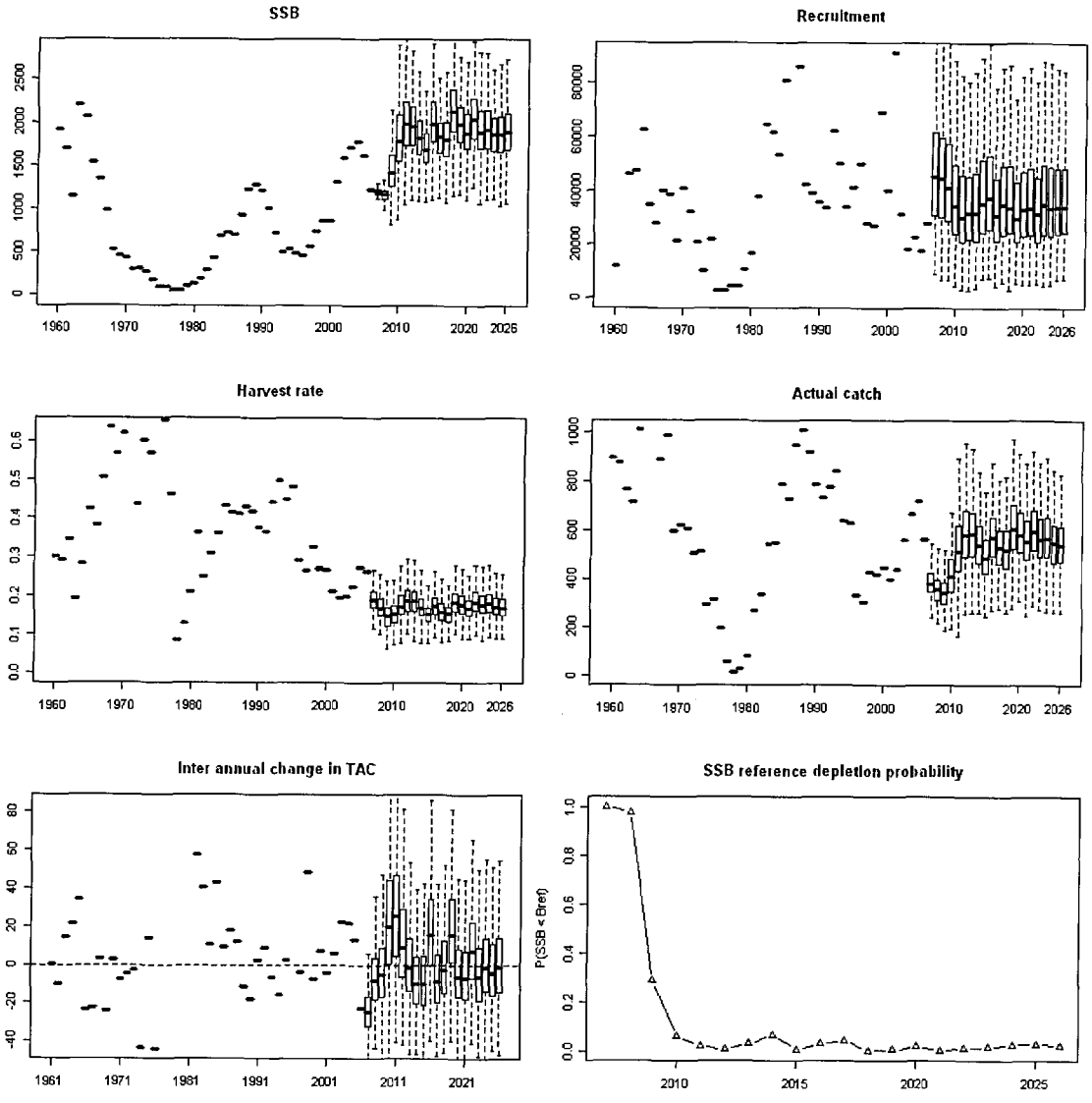


Figure 107: Output of simulation 28.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 0%

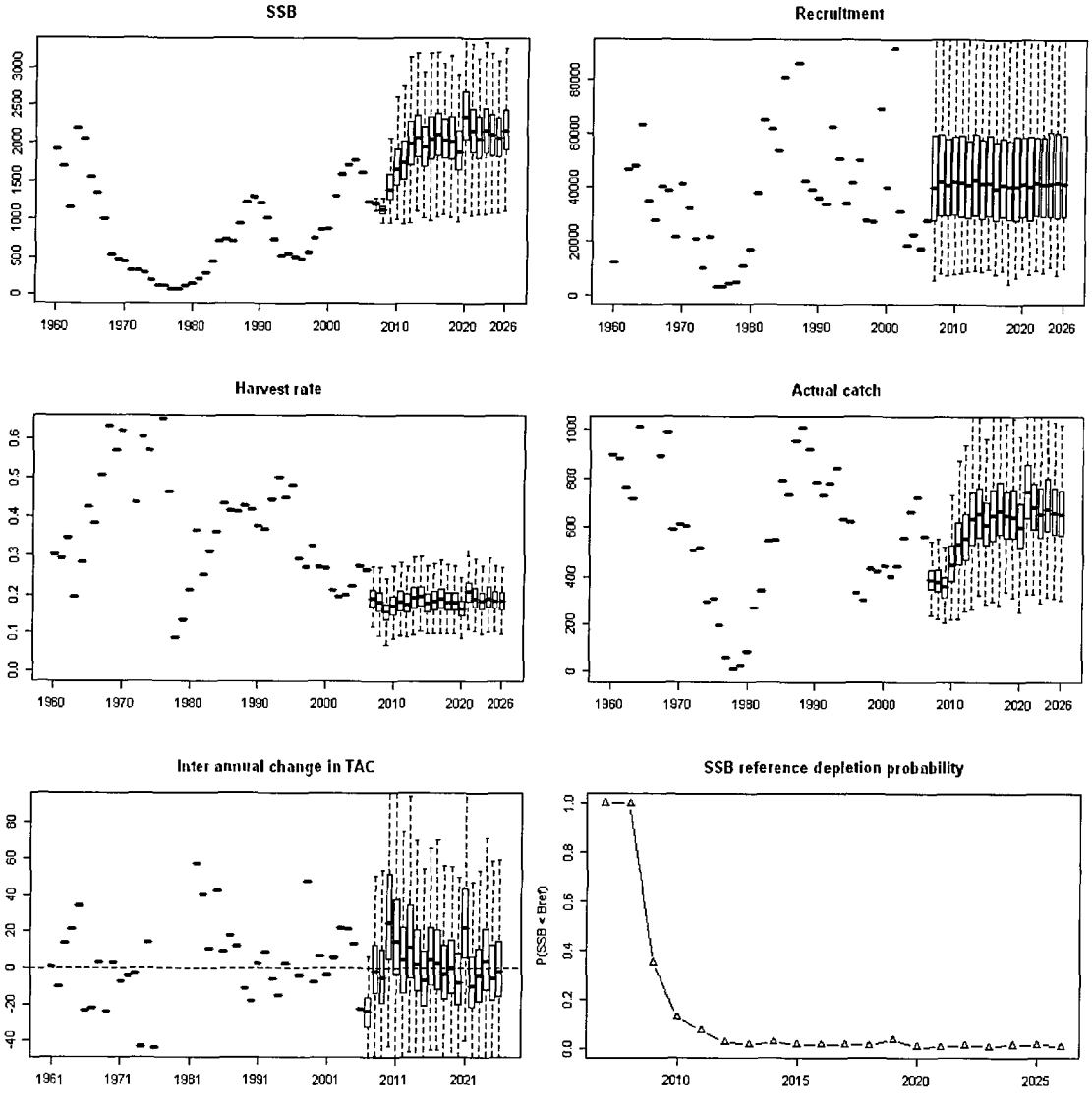


Figure 108: Output of simulation 29.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

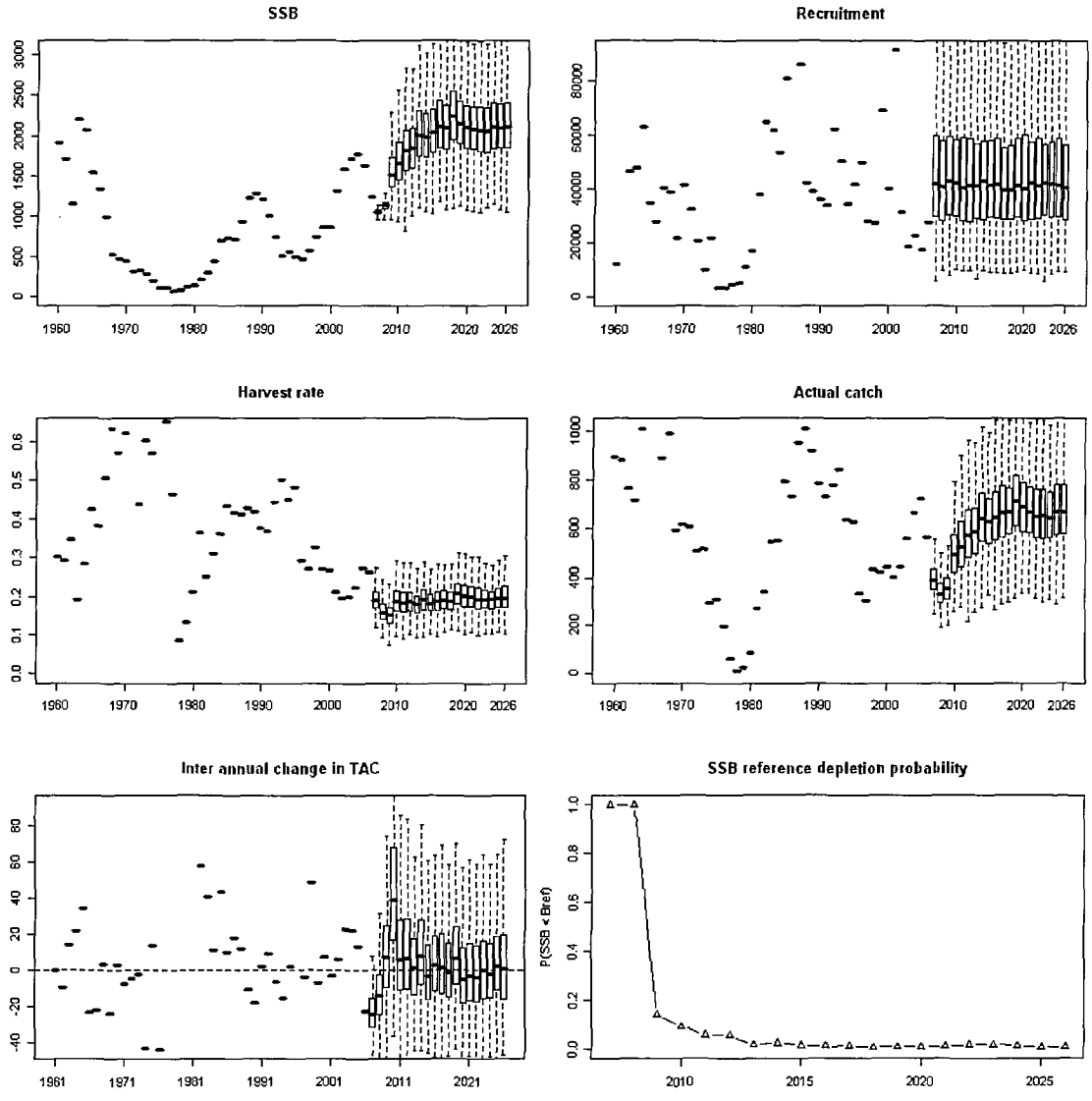


Figure 109: Output of simulation 30.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

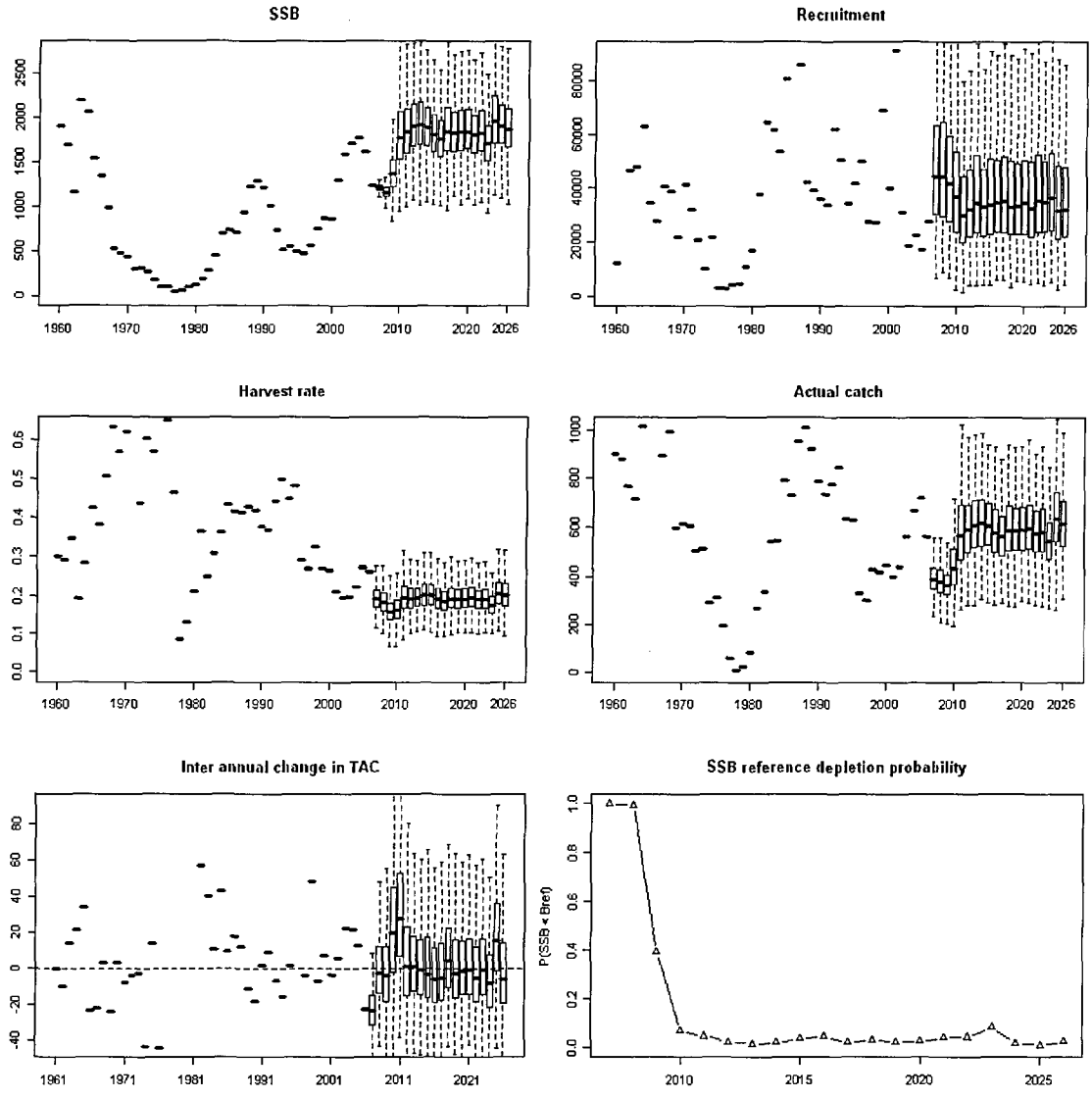


Figure 110: Output of simulation 31.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

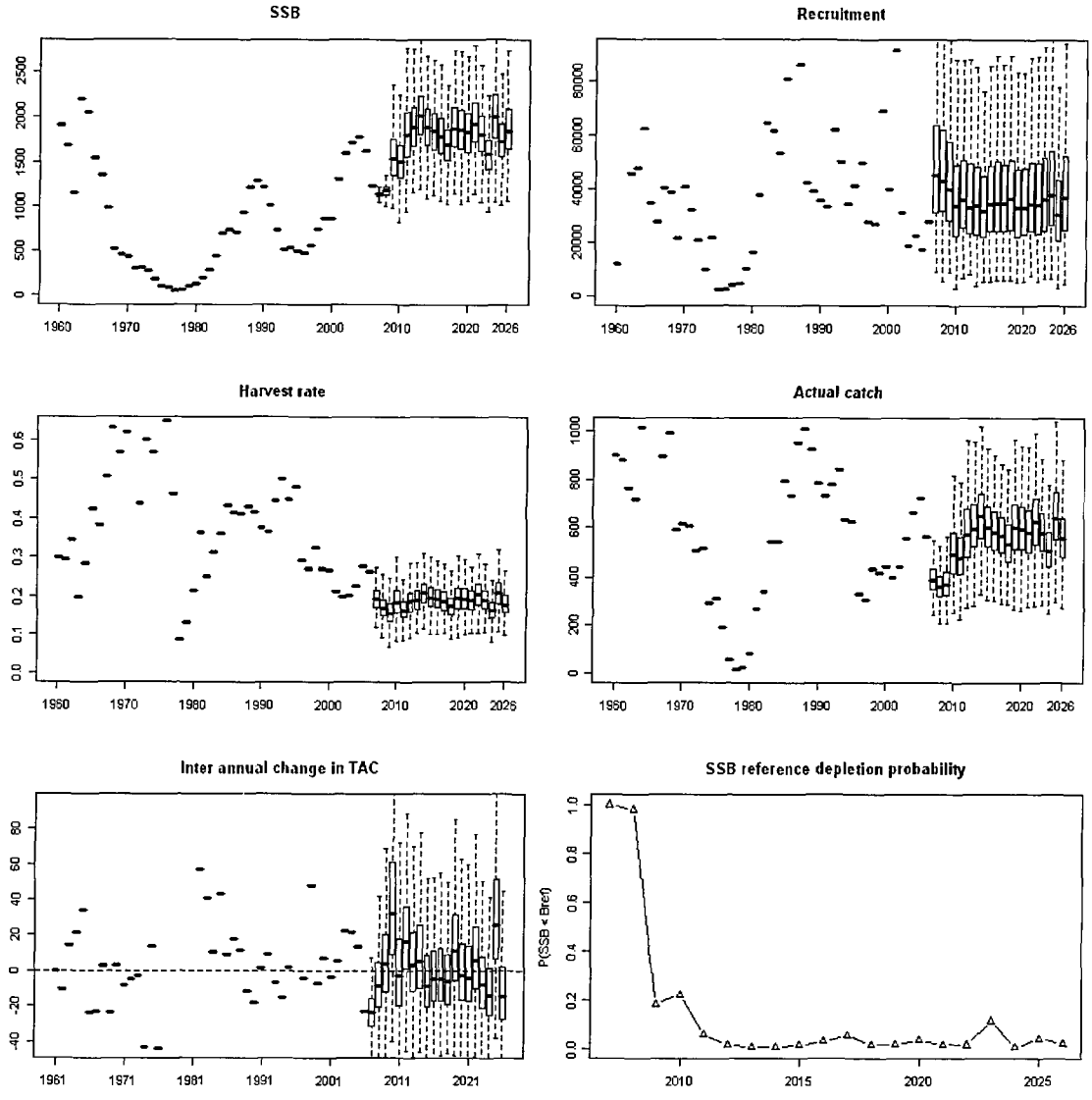


Figure 111: Output of simulation 32.
Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

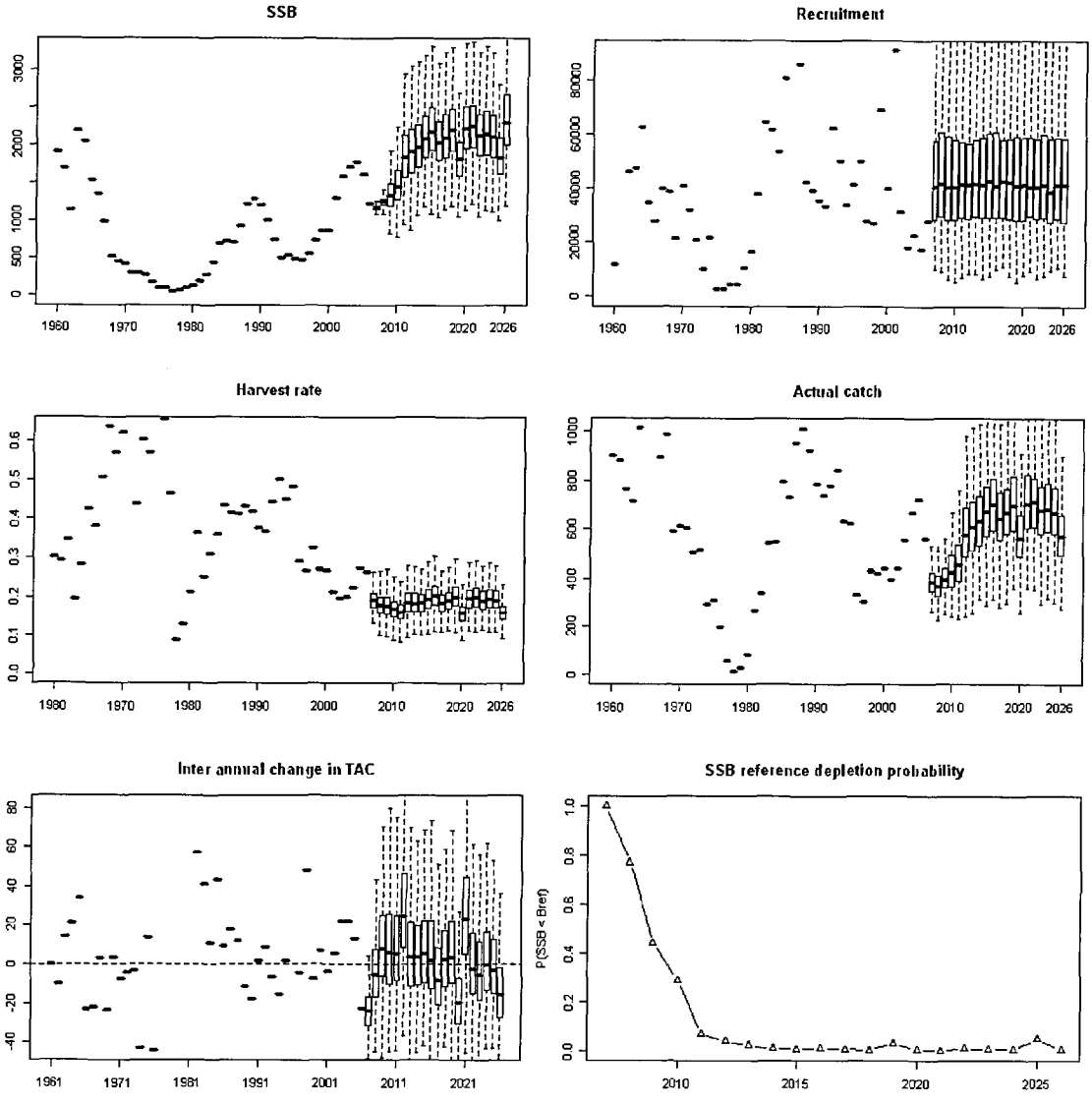


Figure 112: Output of simulation 33.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 0%

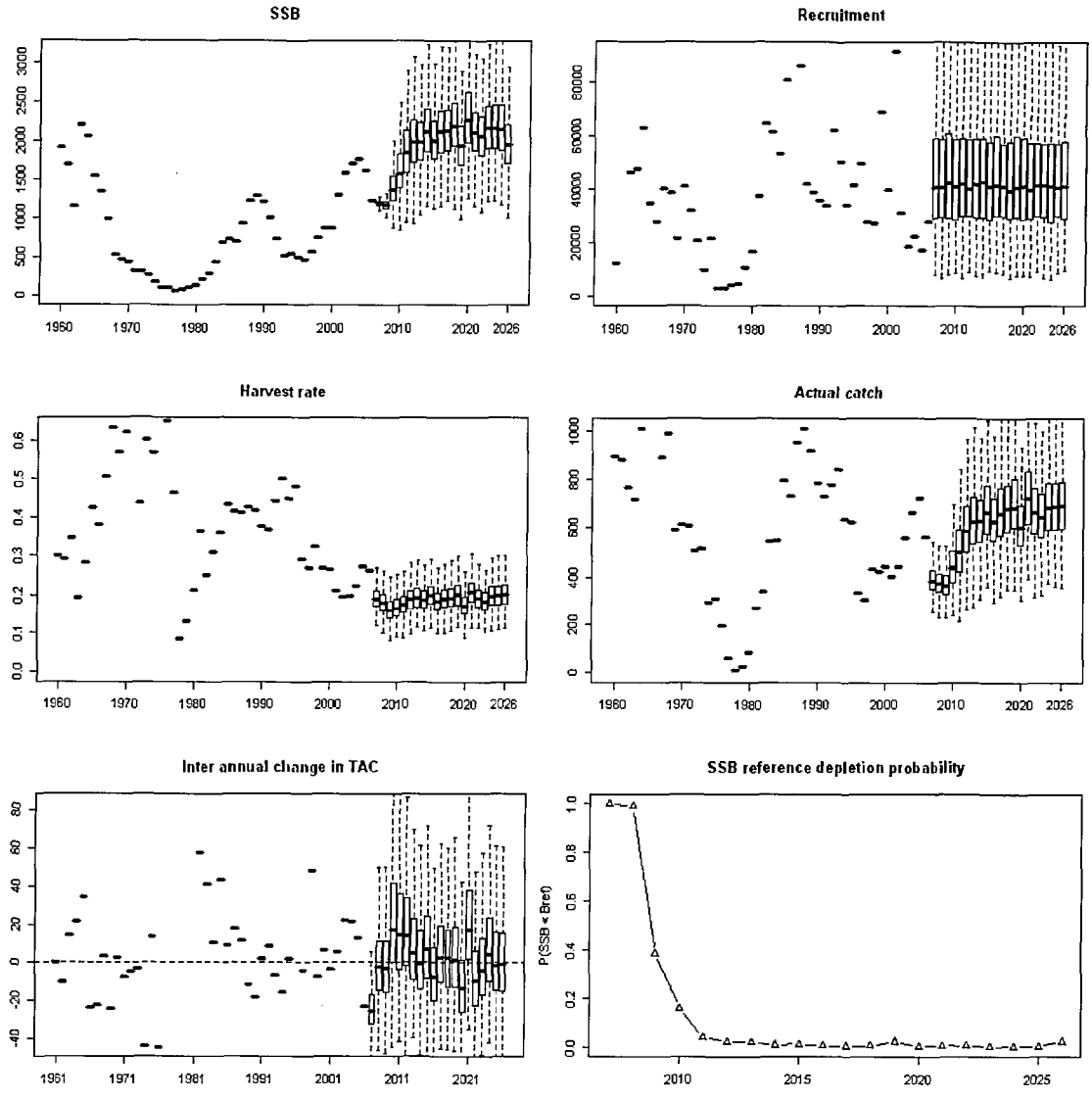


Figure 113: Output of simulation 34.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 0%

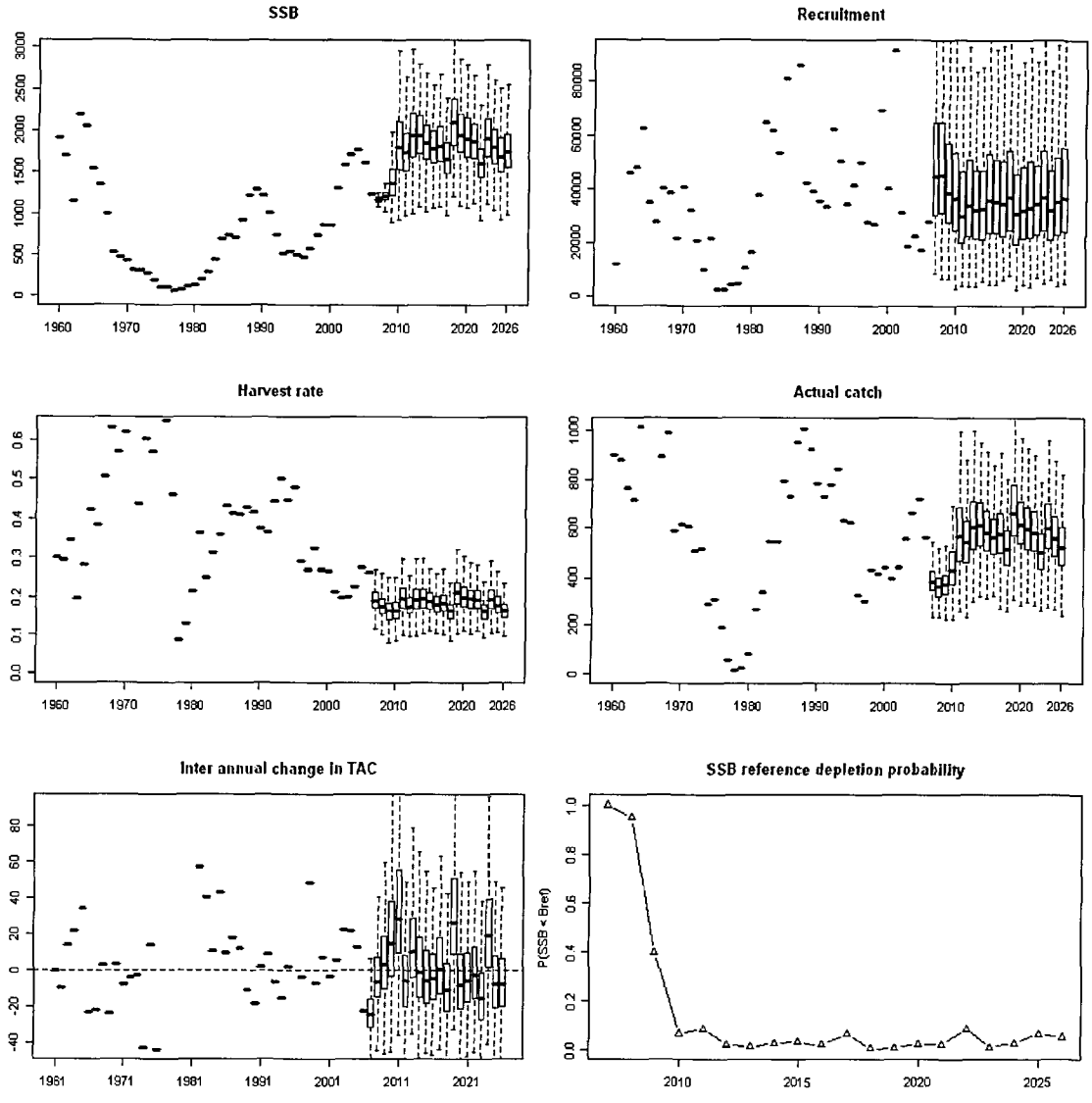


Figure 114: Output of simulation 35.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 0%

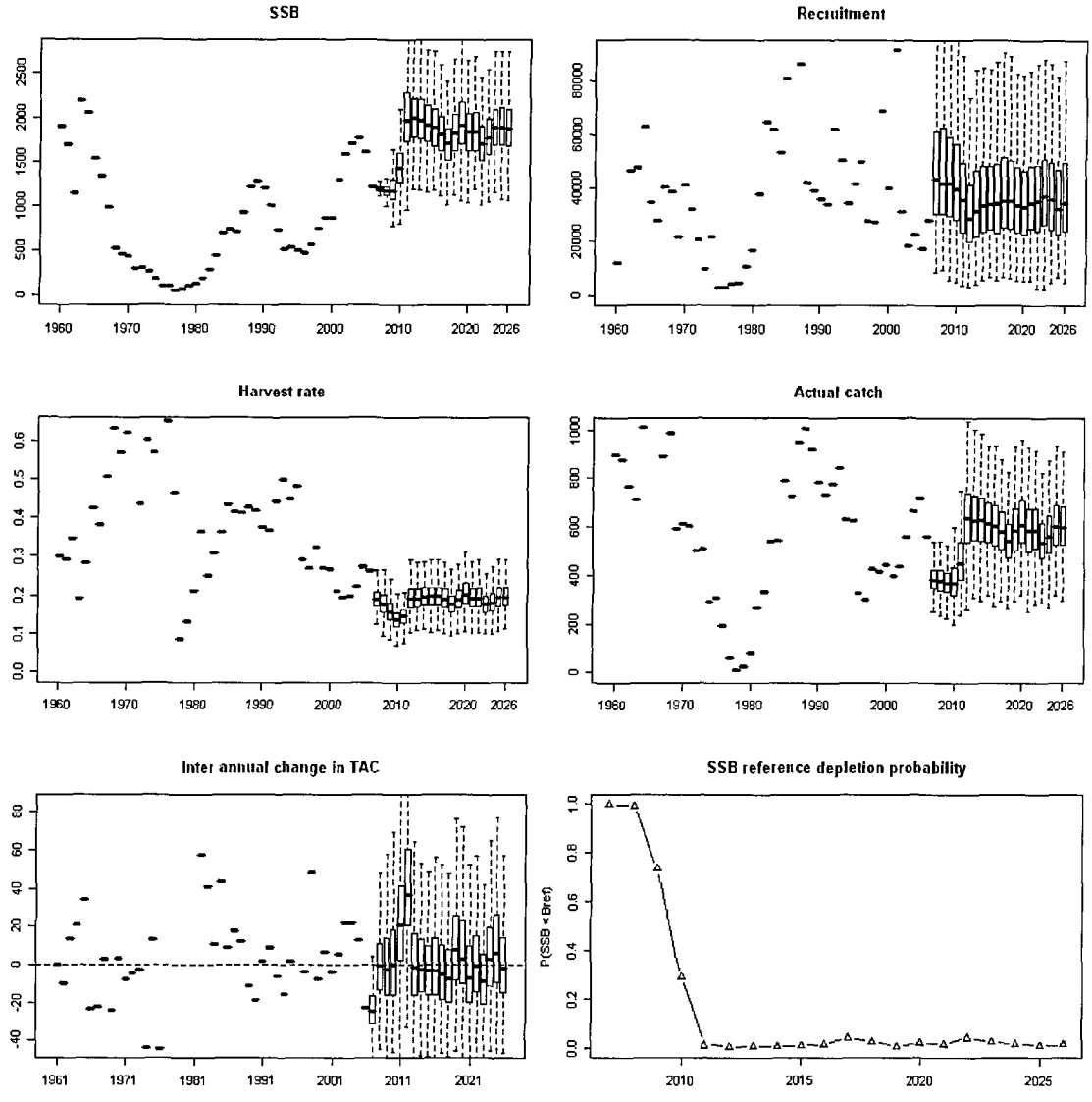


Figure 115: Output of simulation 36.

Stock recruitment: Ricker

Autocorrelation: high

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 0%

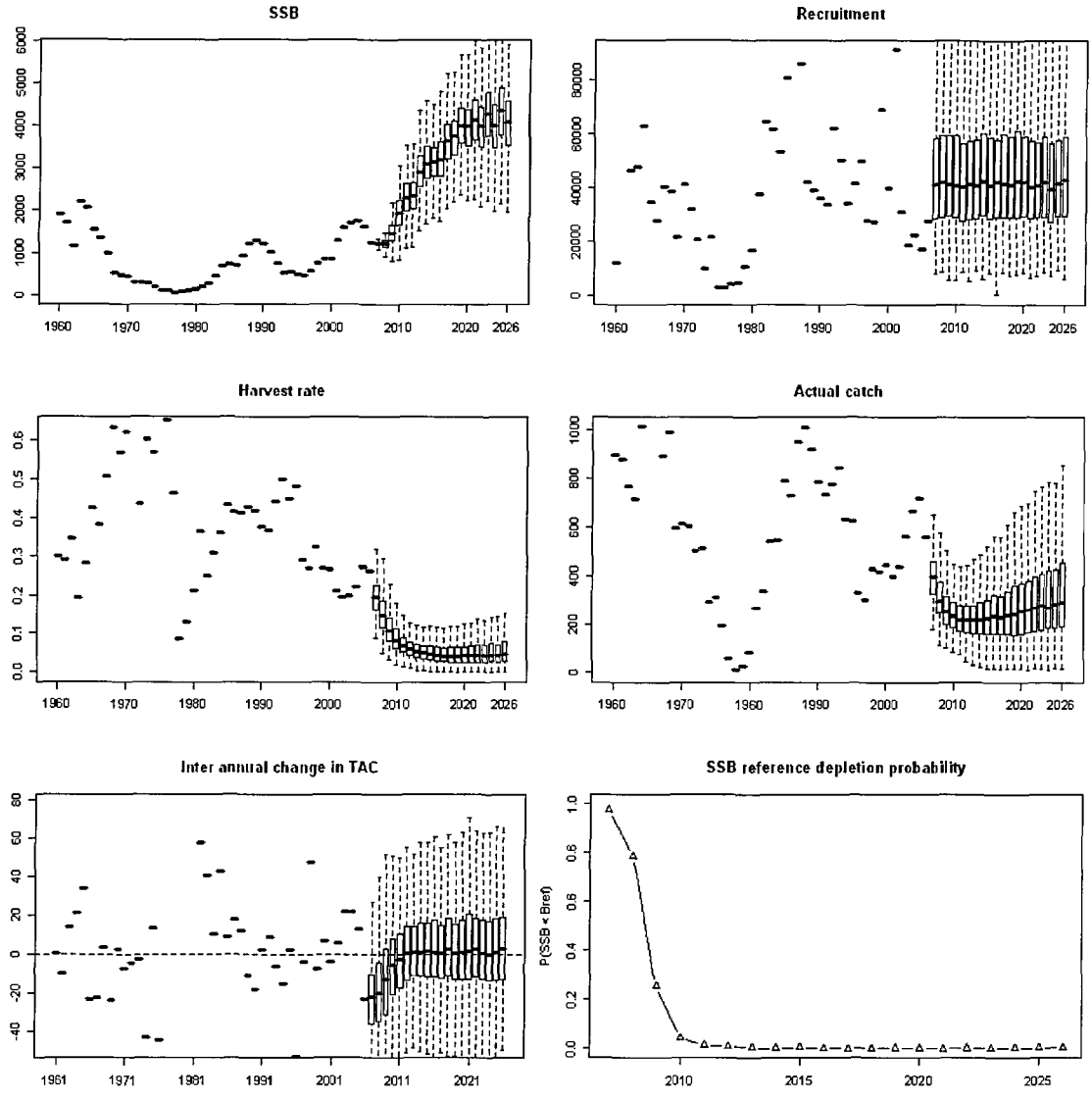


Figure 116: Output of simulation 37.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

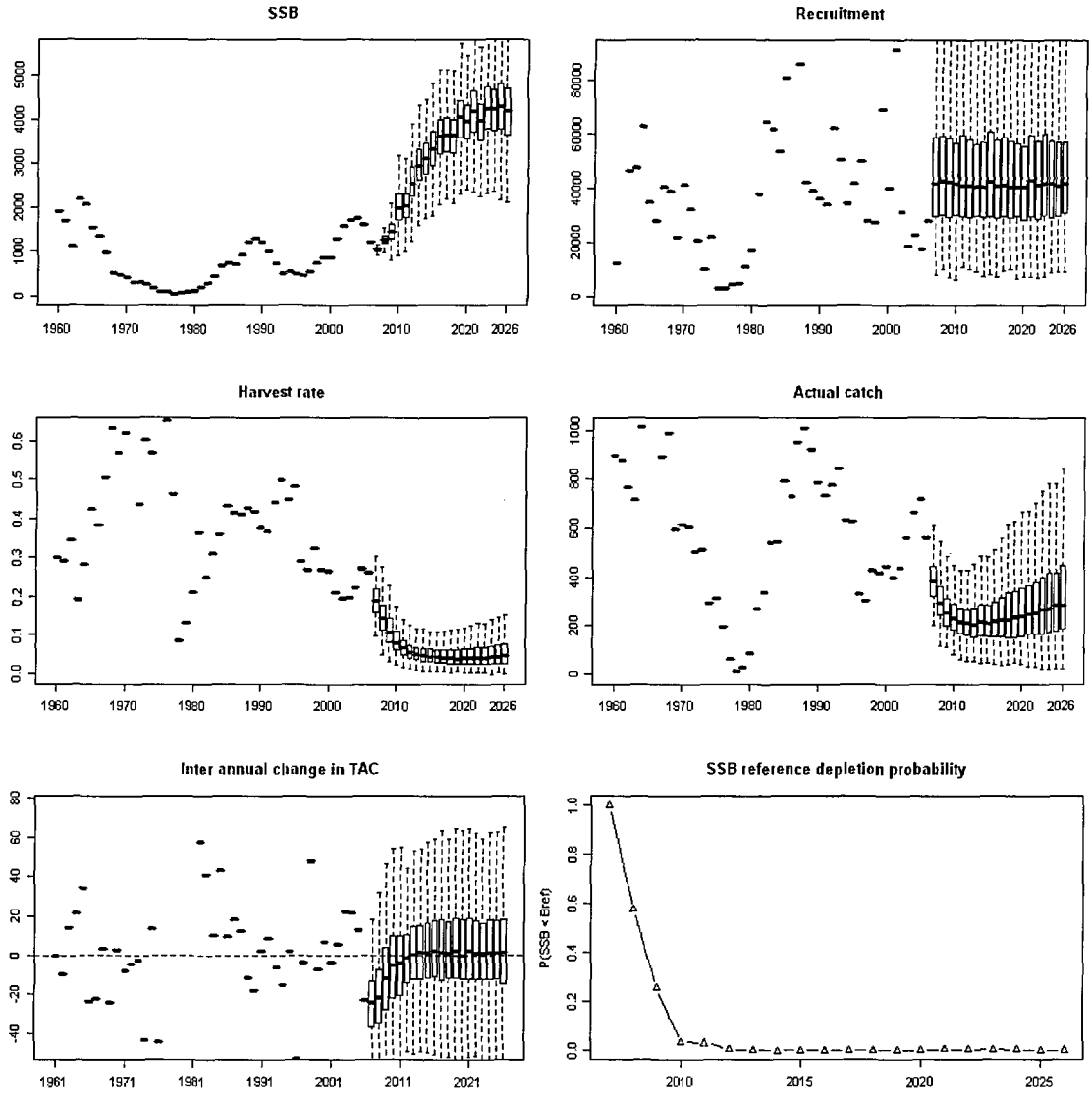


Figure 117: Output of simulation 38.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

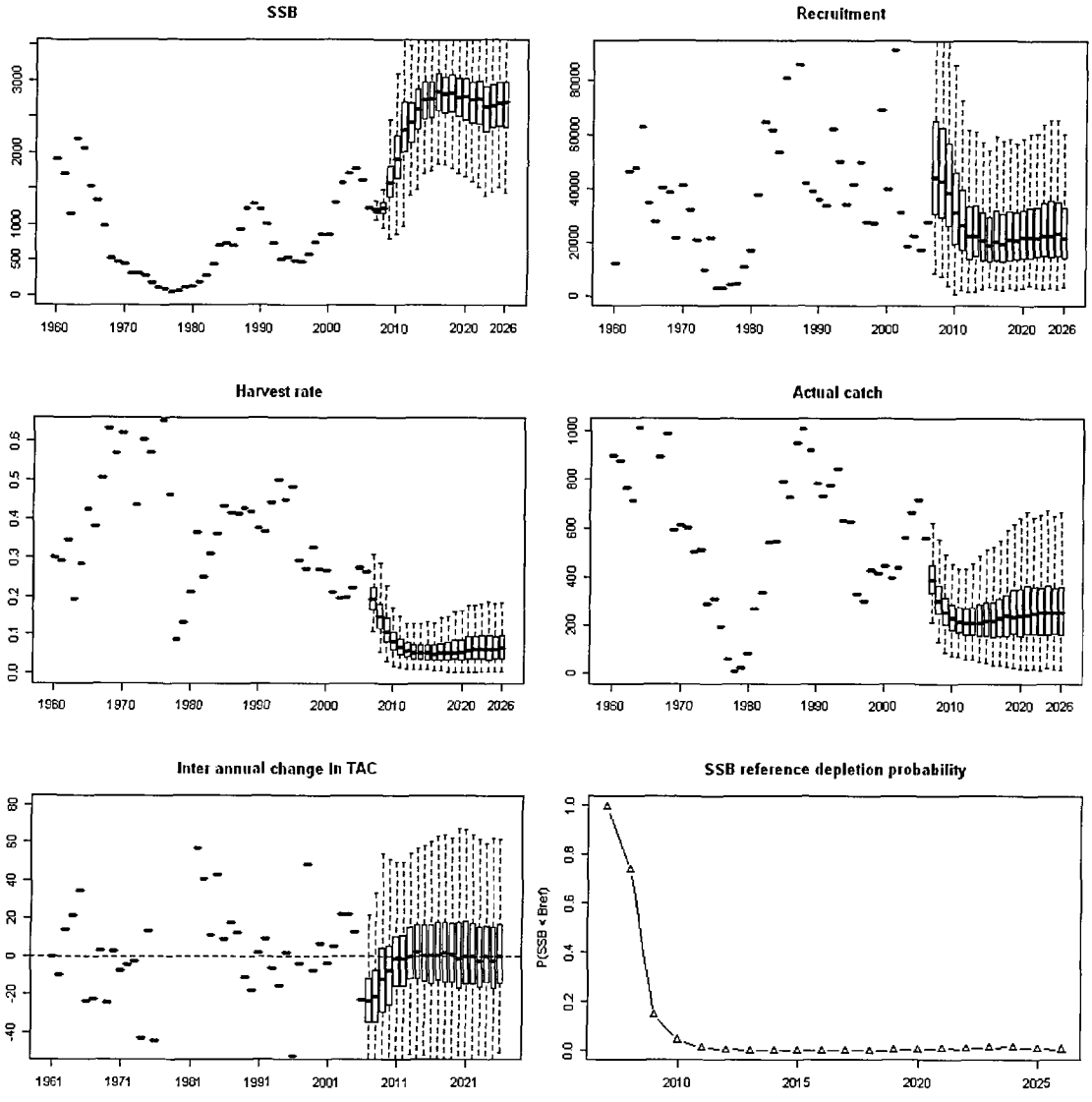


Figure 118: Output of simulation 39.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

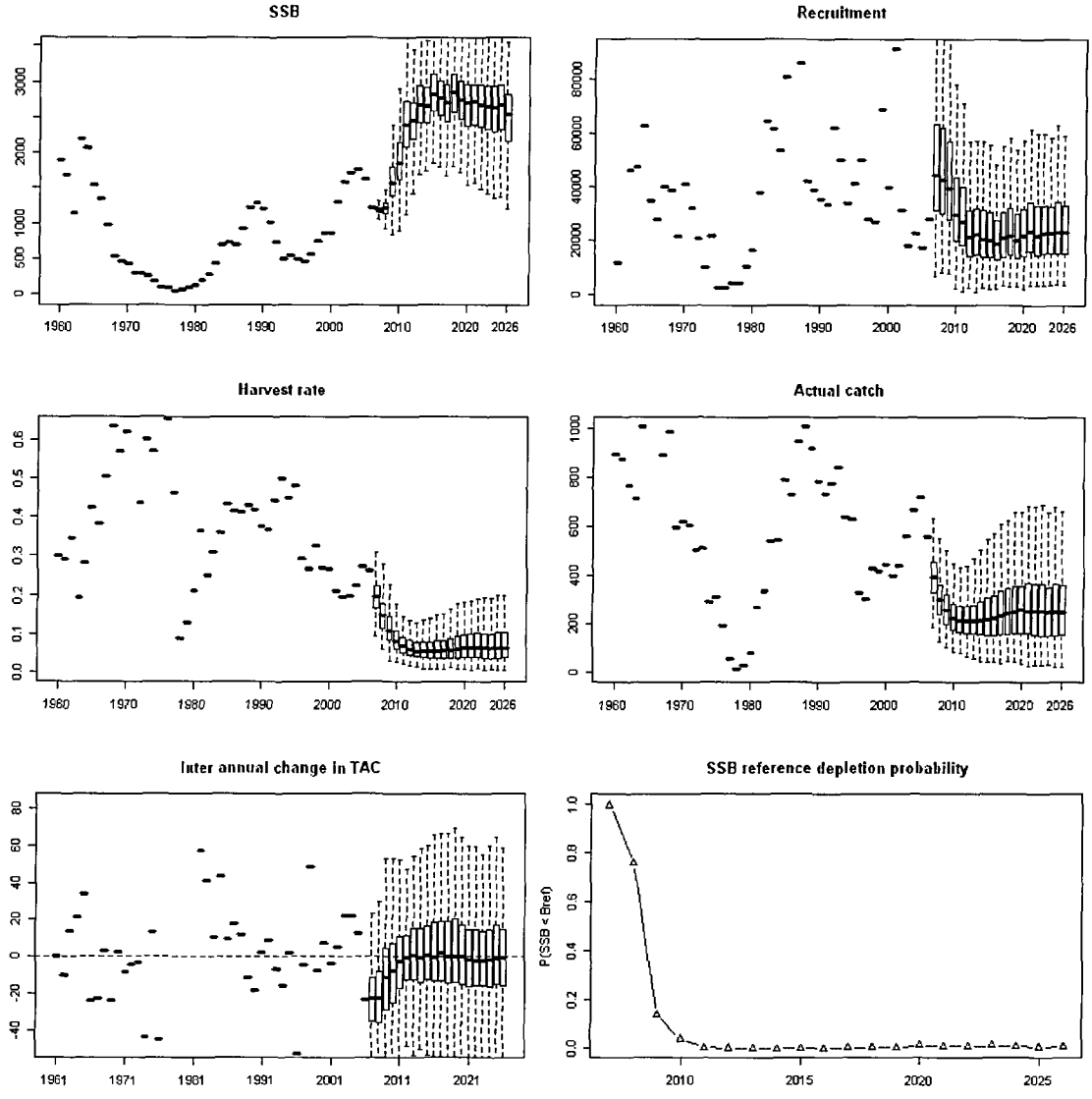


Figure 119: Output of simulation 40.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

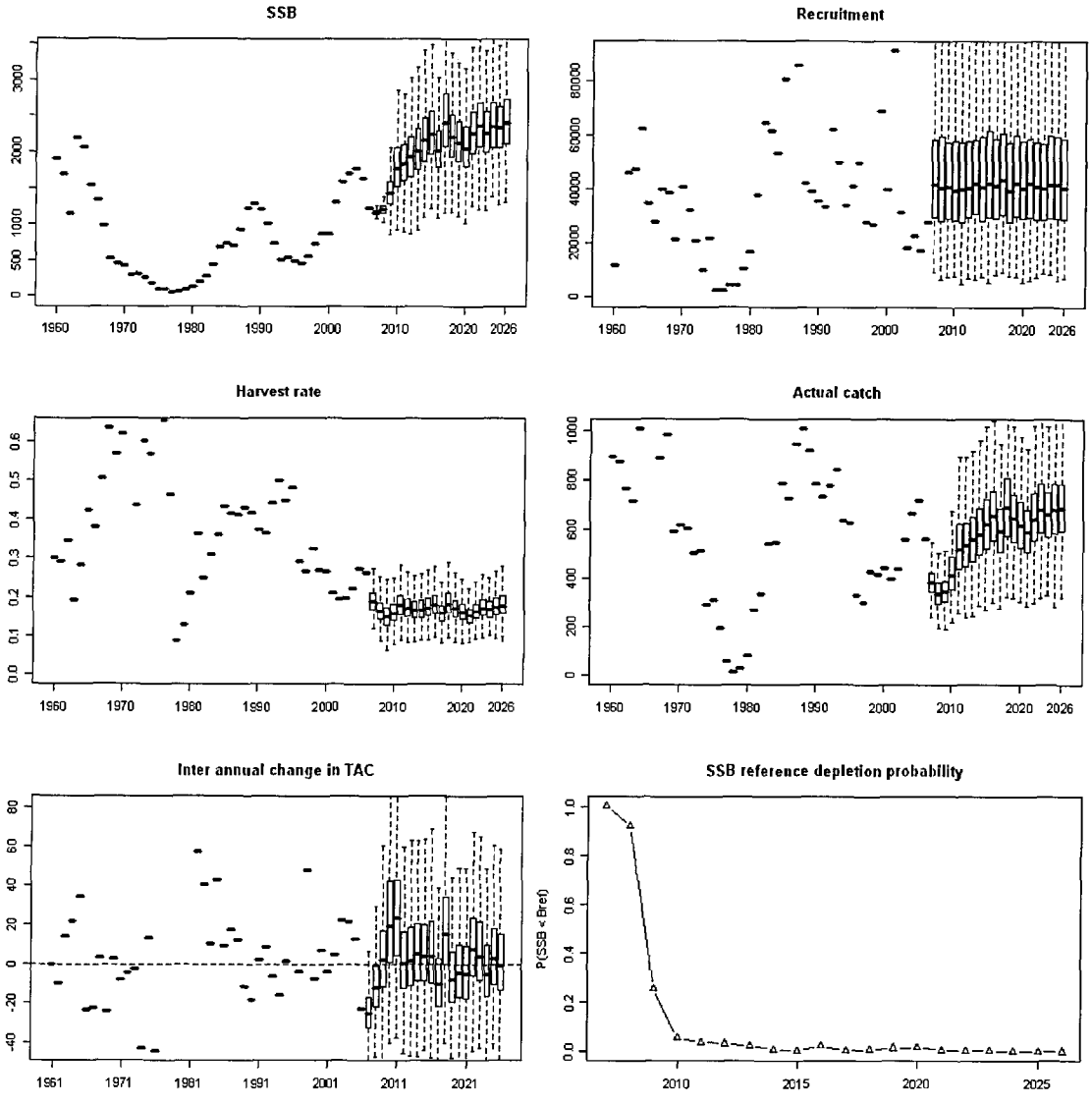


Figure 120: Output of simulation 41.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 0%

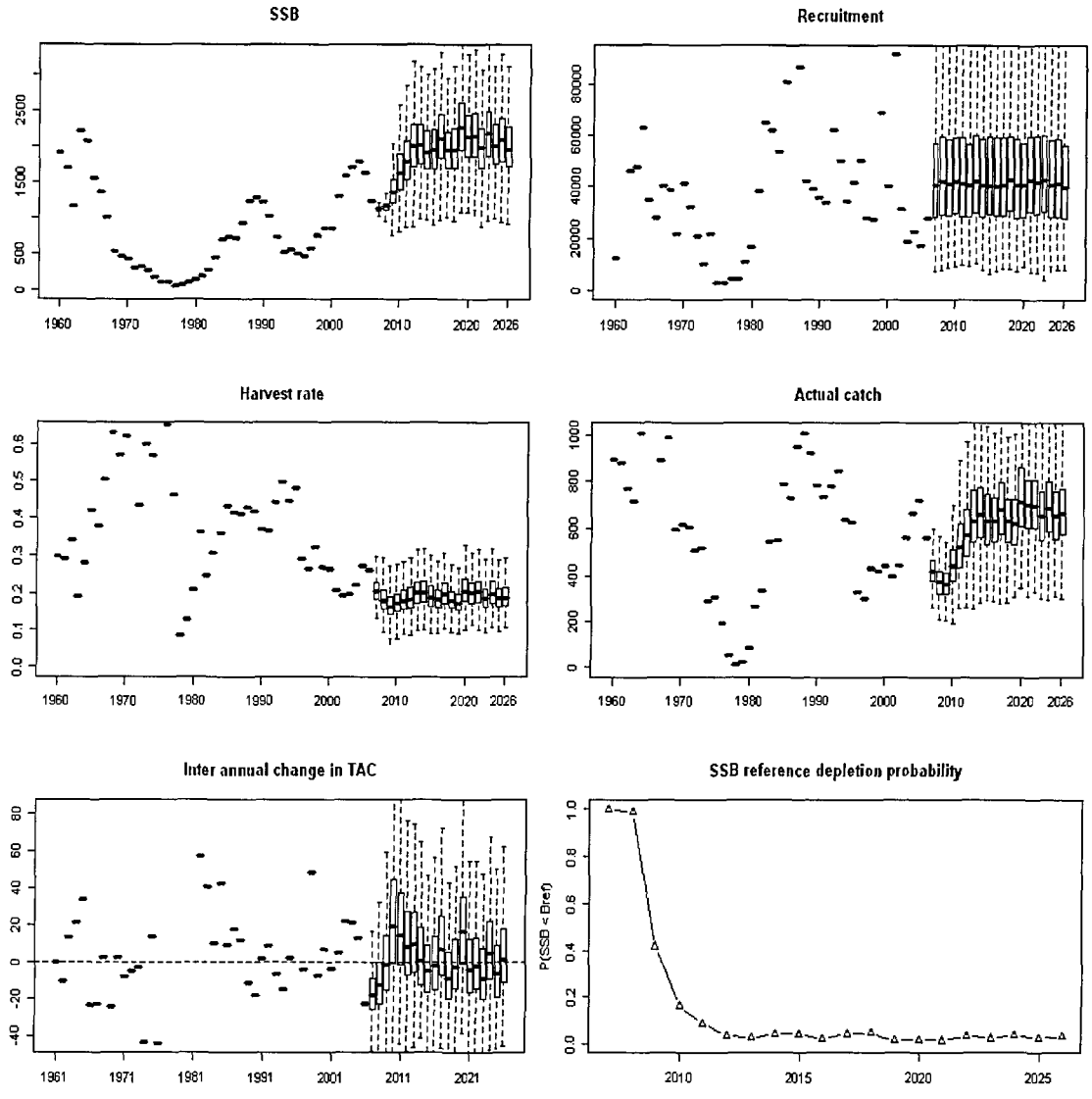


Figure 121: Output of simulation 42.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 10%

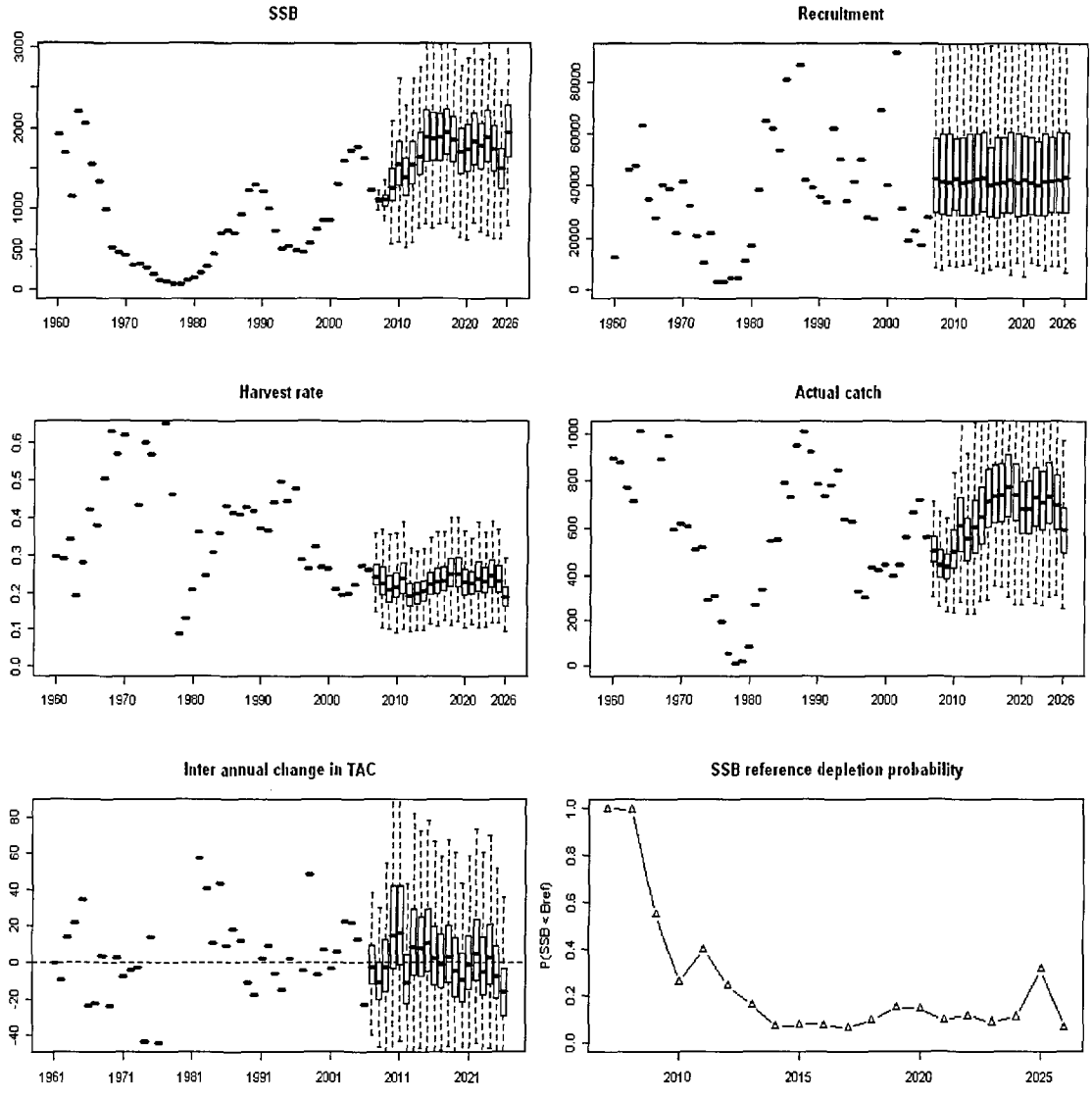


Figure 122: Output of simulation 43.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 30%

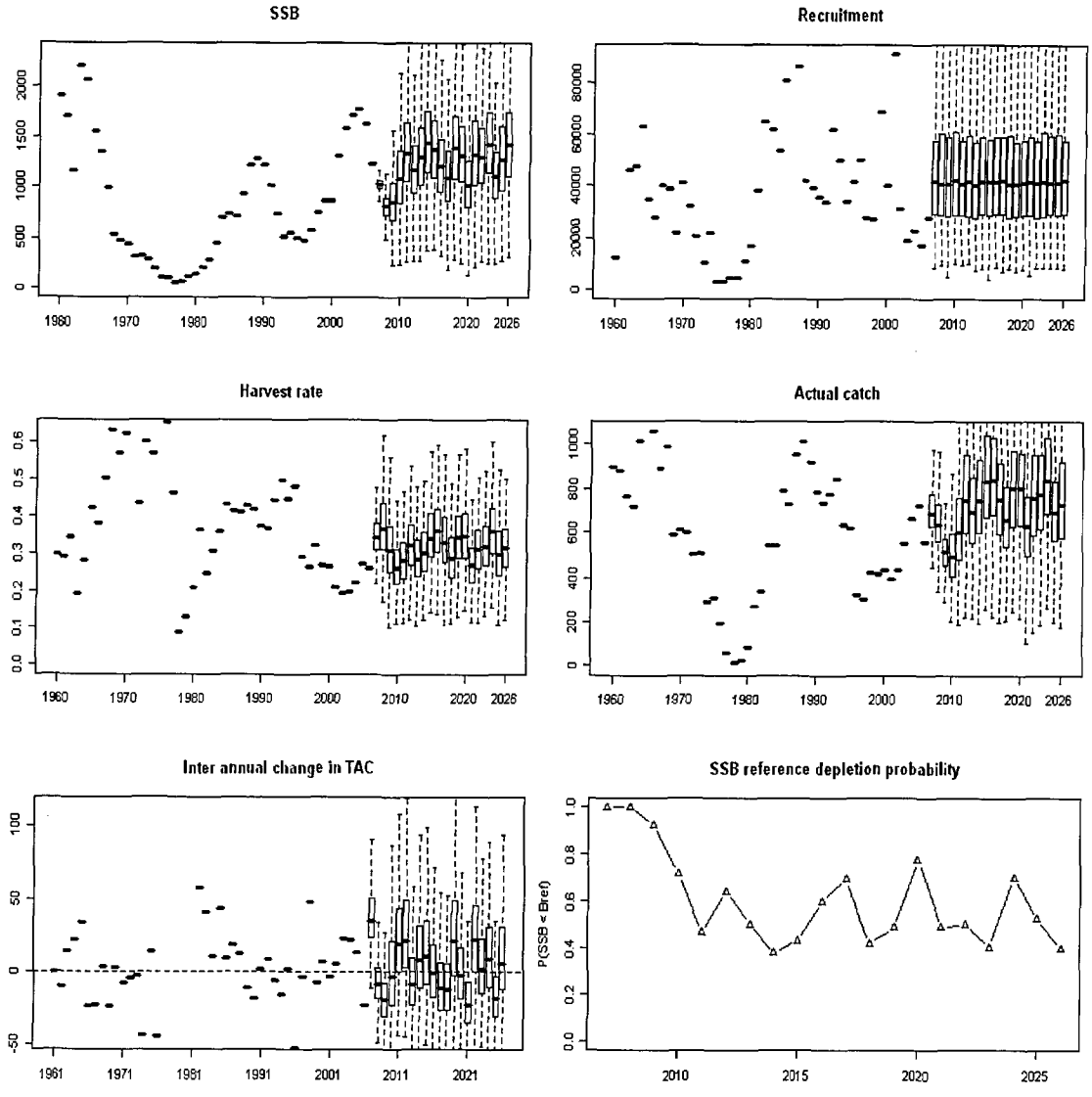


Figure 123: Output of simulation 44.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 80%

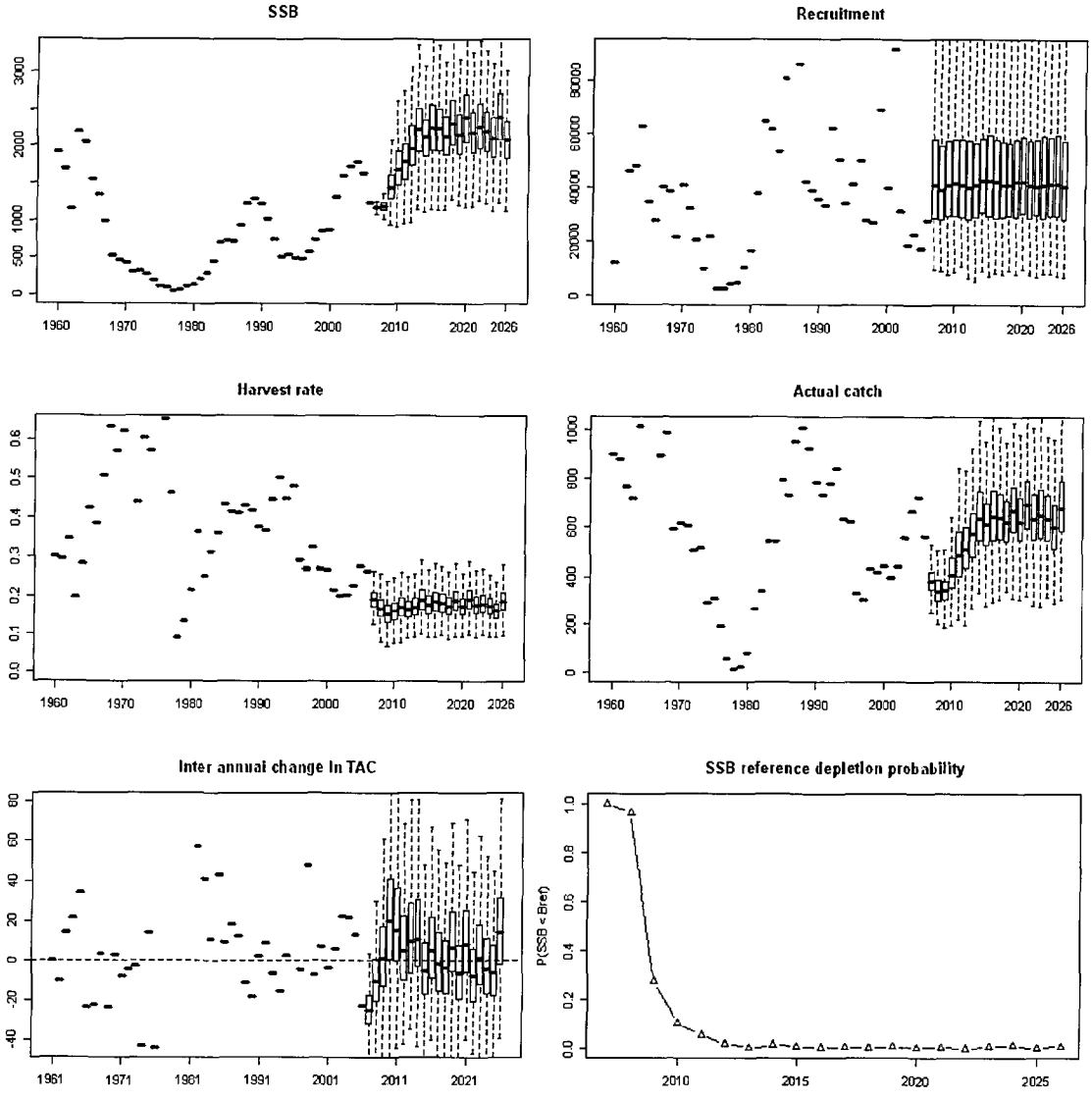


Figure 124: Output of simulation 45.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 0%

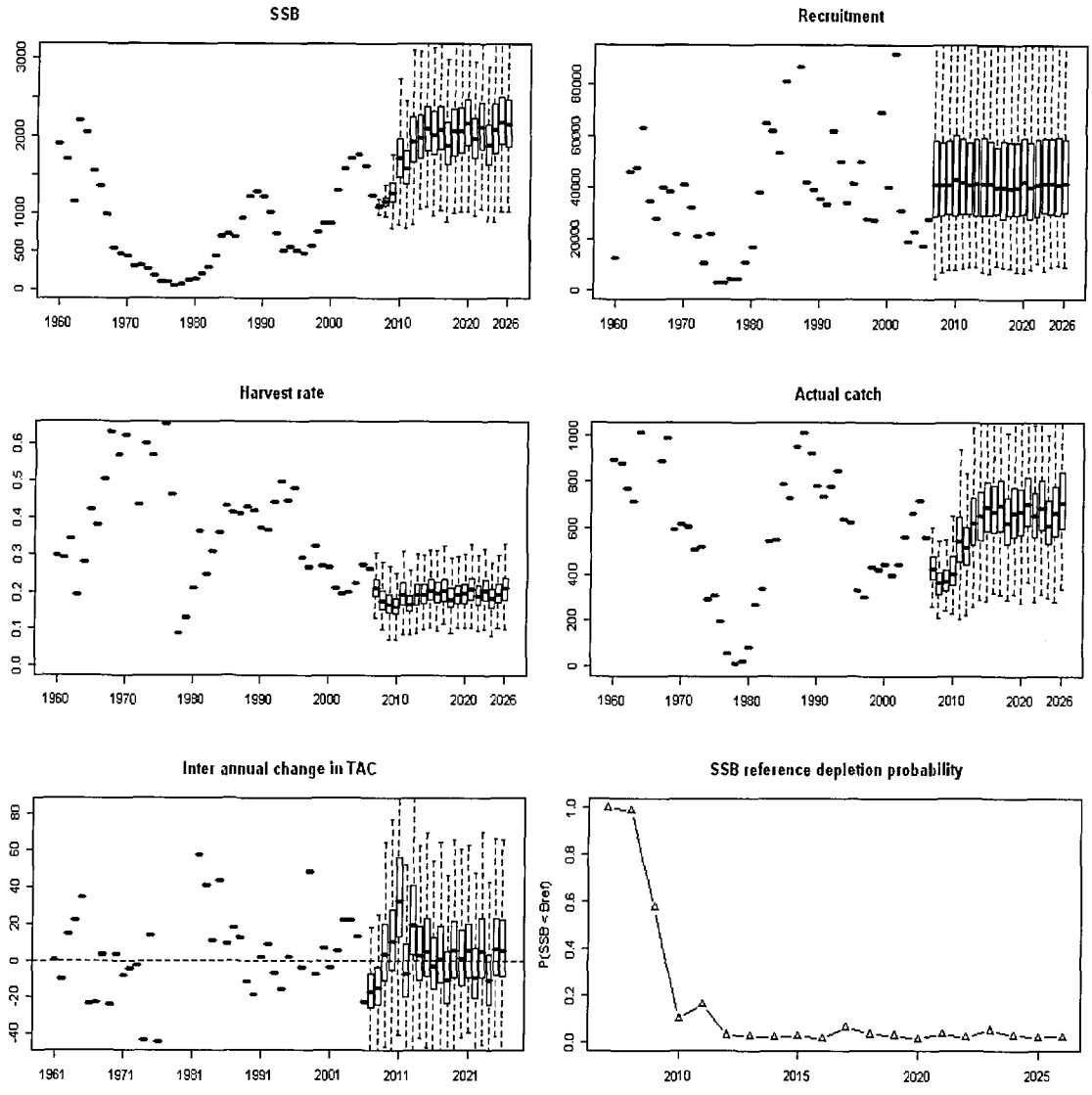


Figure 125: Output of simulation 46.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 10%

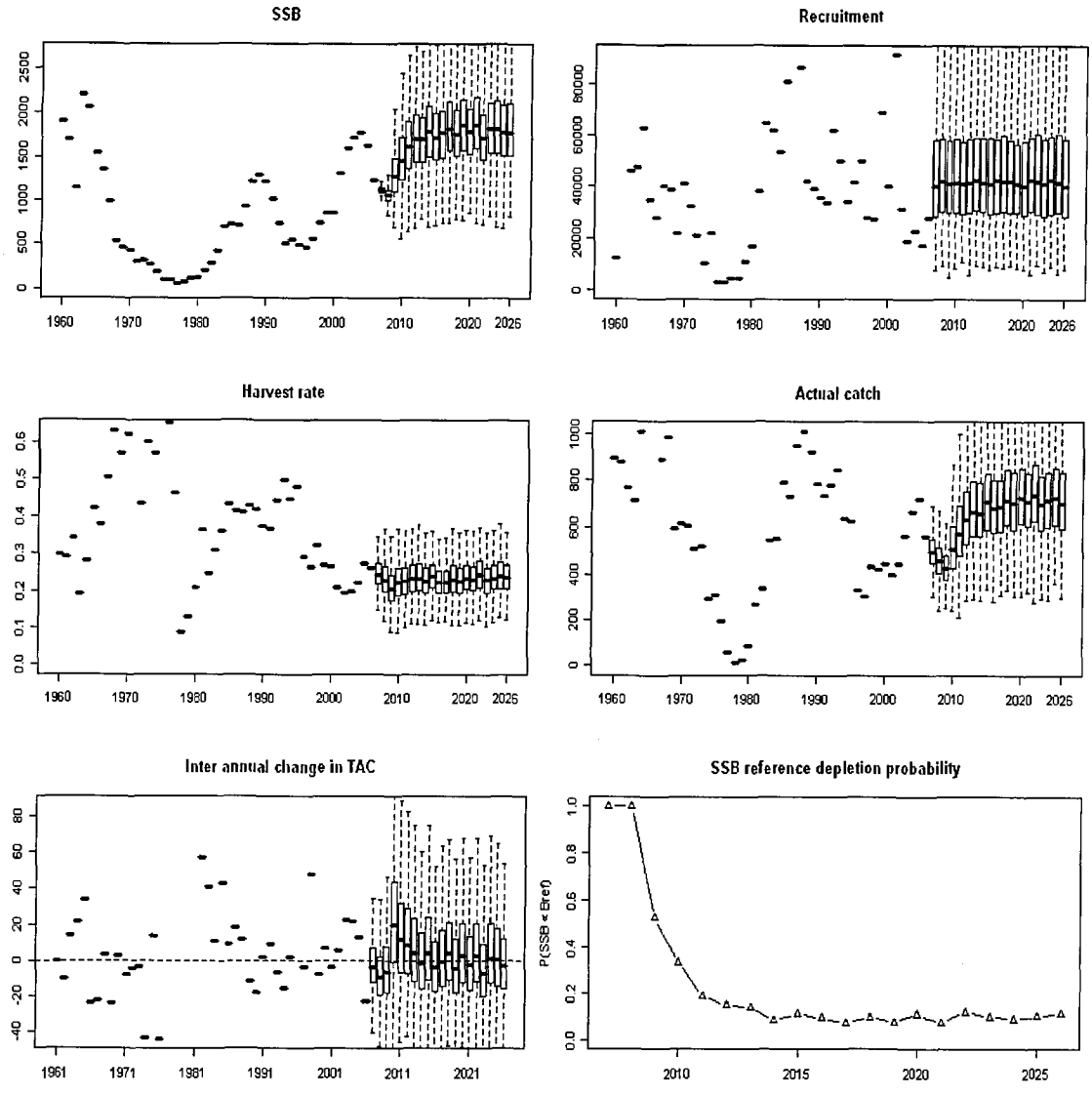


Figure 126: Output of simulation 47.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 30%

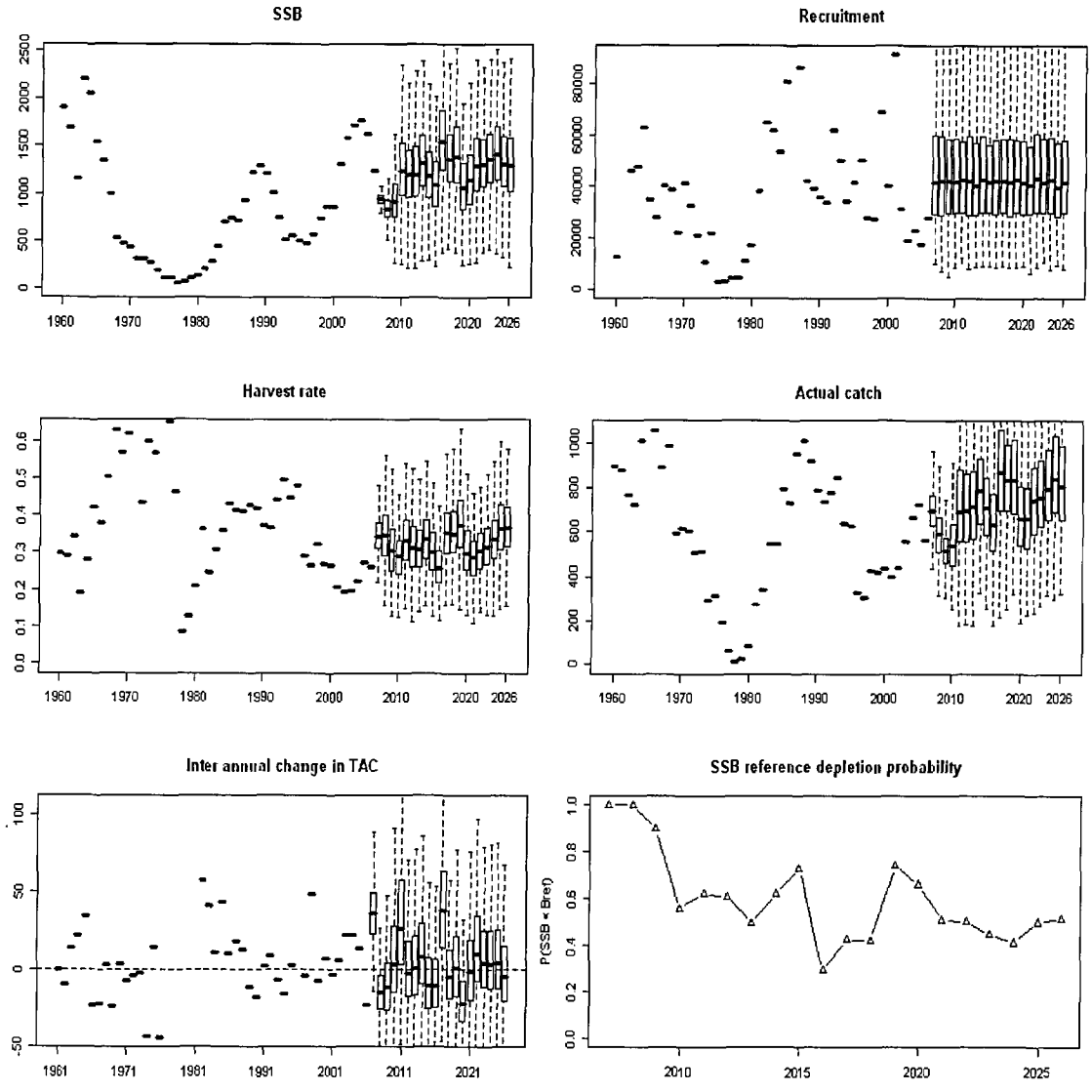


Figure 127: Output of simulation 48.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 80%

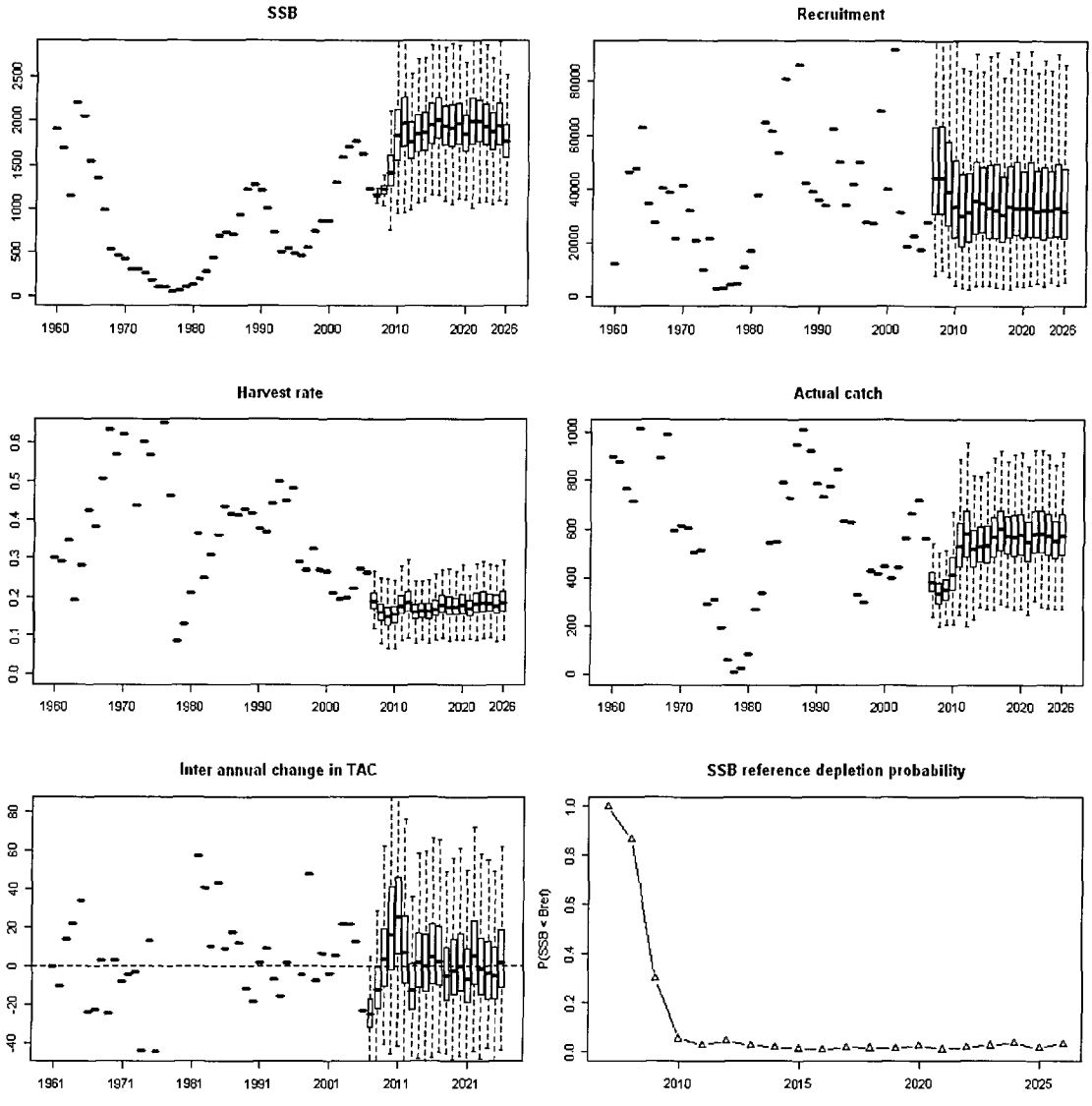


Figure 128: Output of simulation 49.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 0%

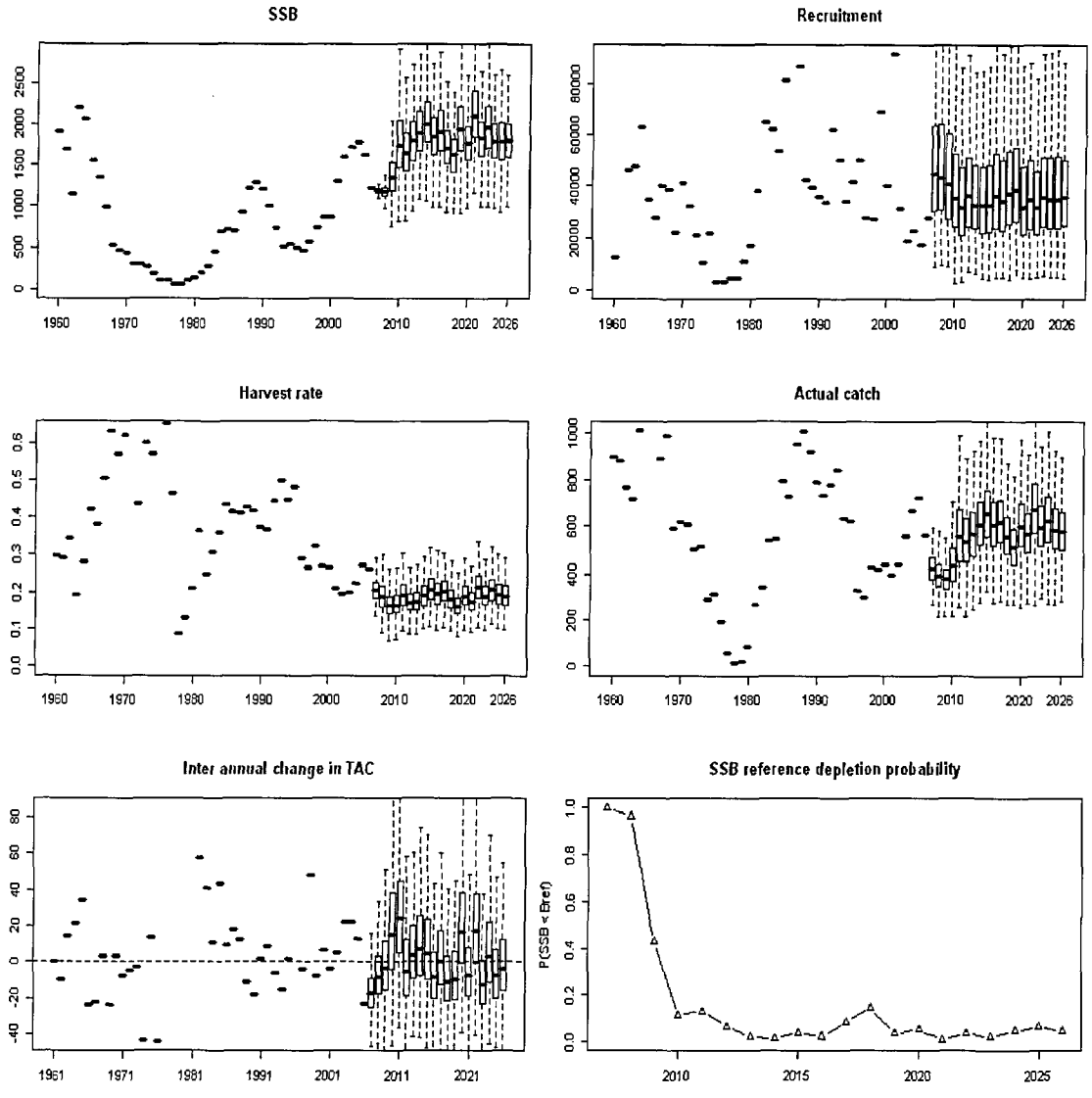


Figure 129: Output of simulation 50.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 10%

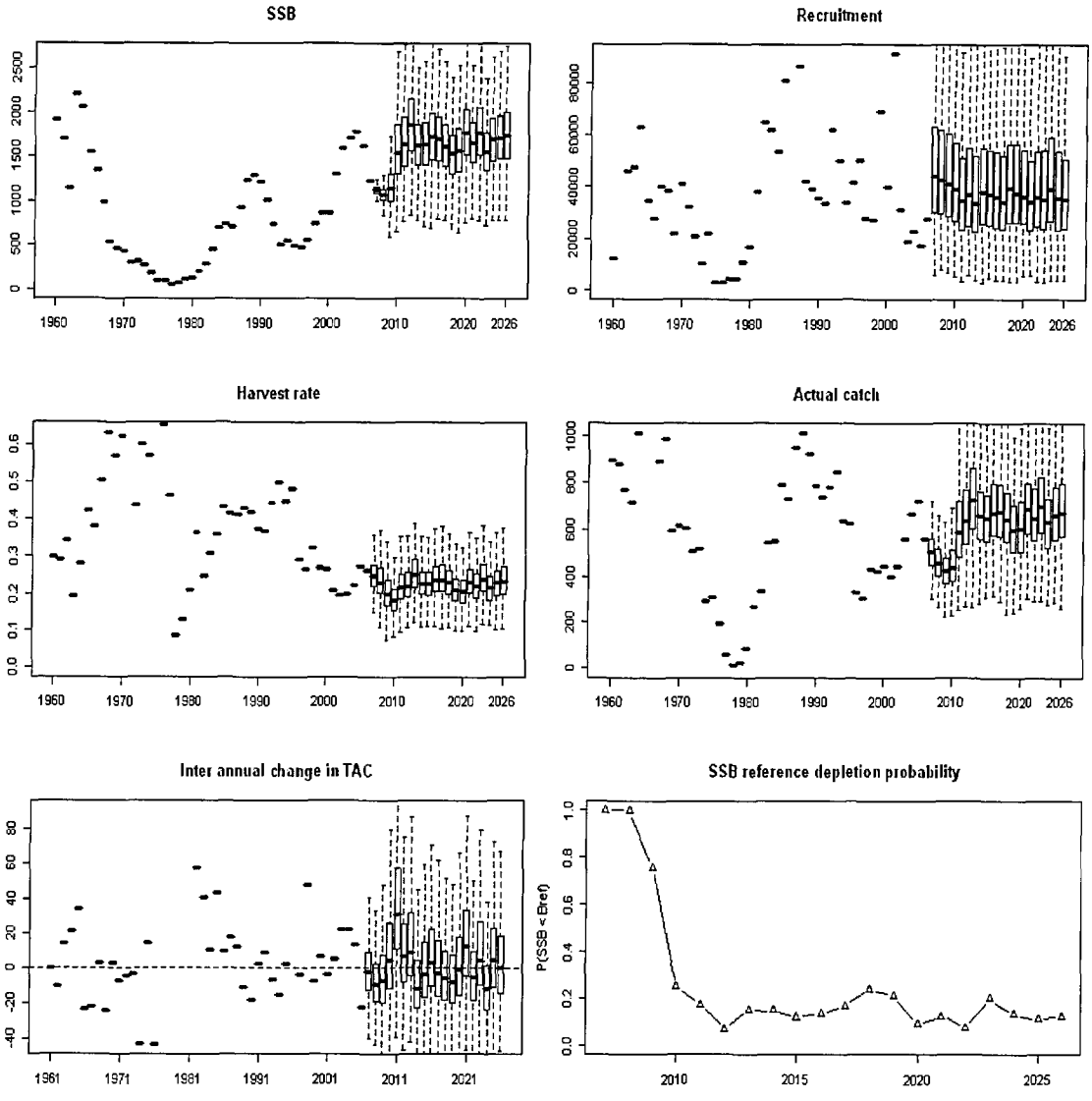


Figure 130: Output of simulation 51.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 30%

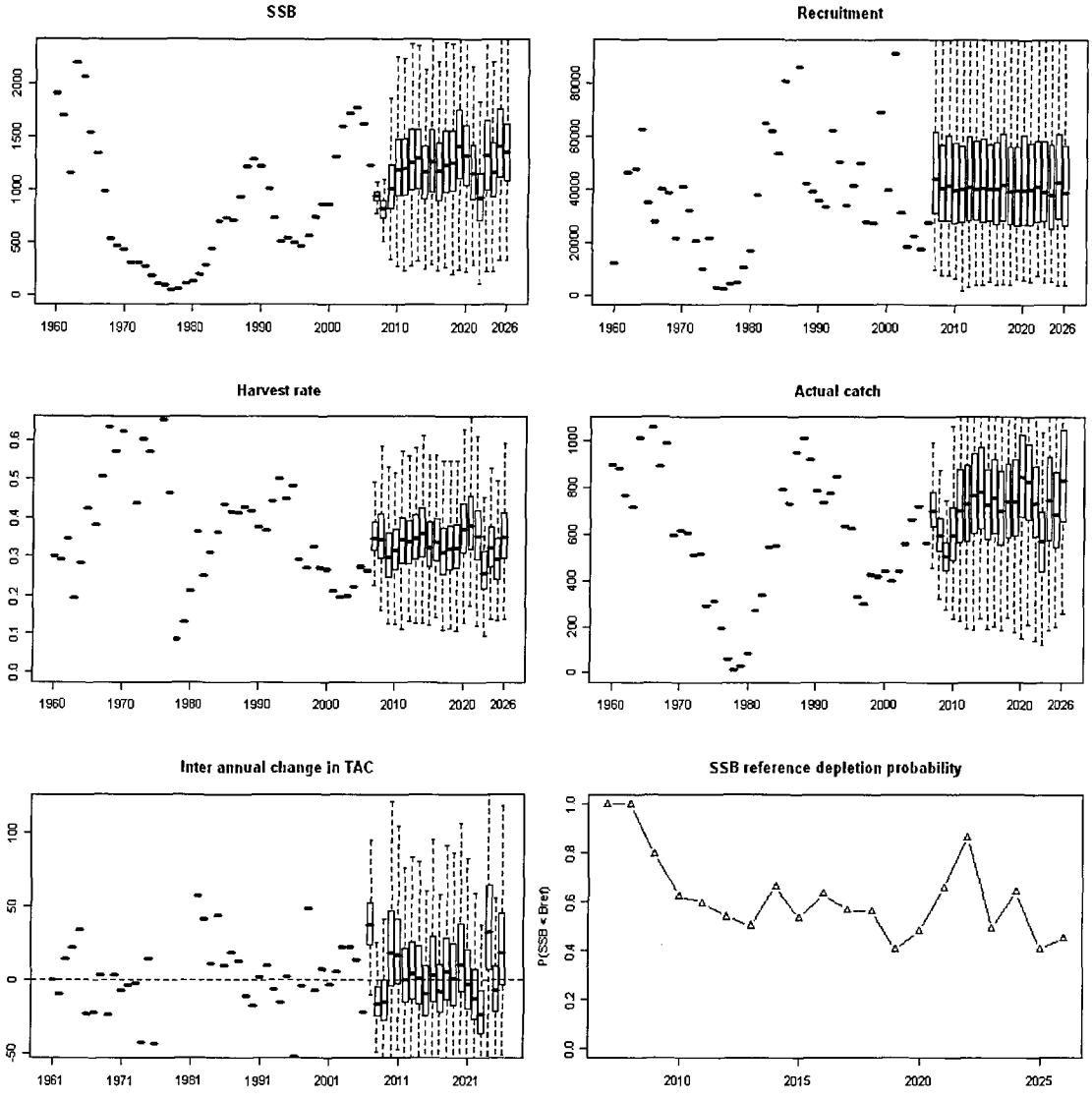


Figure 131: Output of simulation 52.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 80%

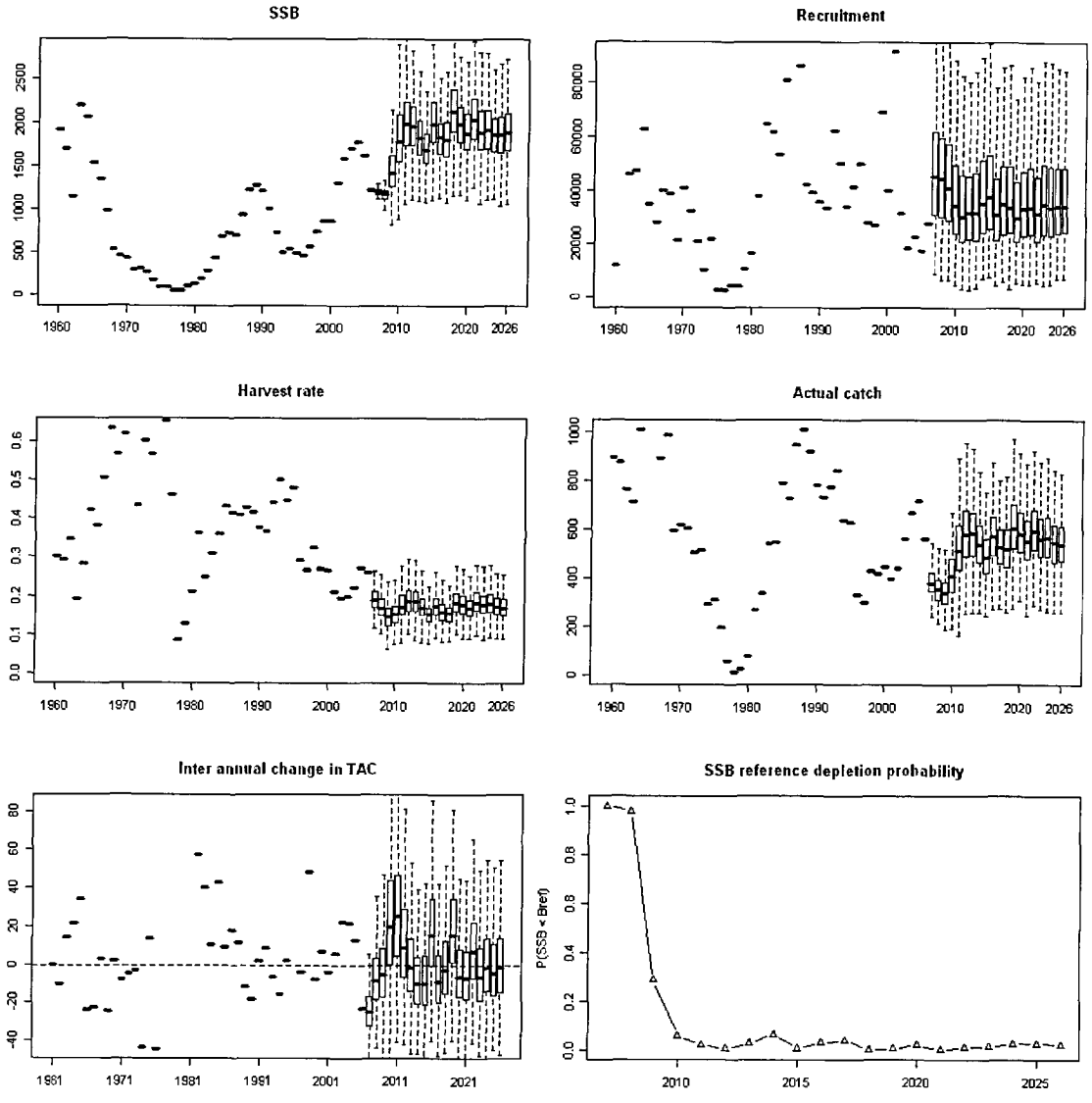


Figure 132: Output of simulation 53.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 0%

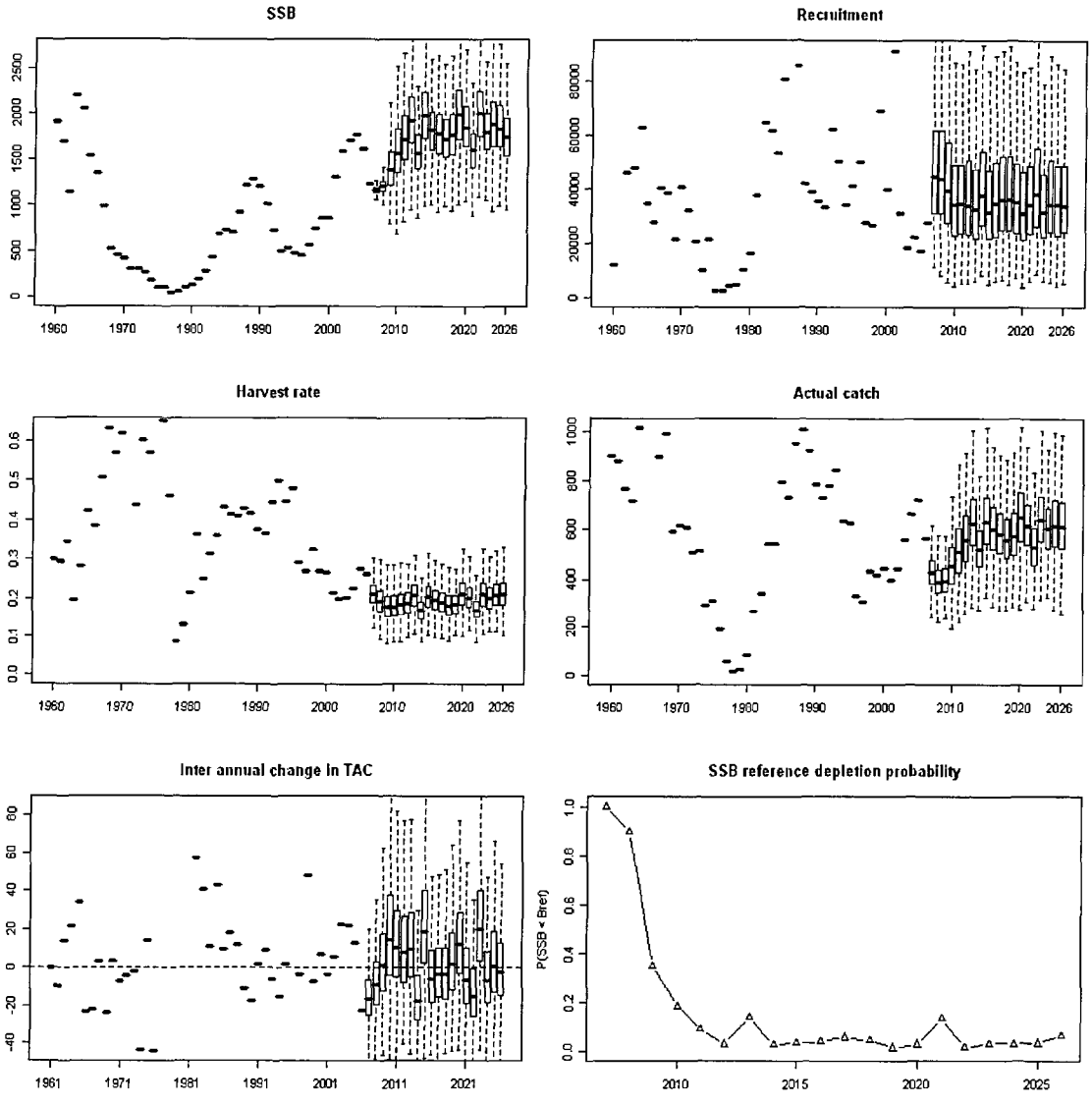


Figure 133: Output of simulation 54.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 10%

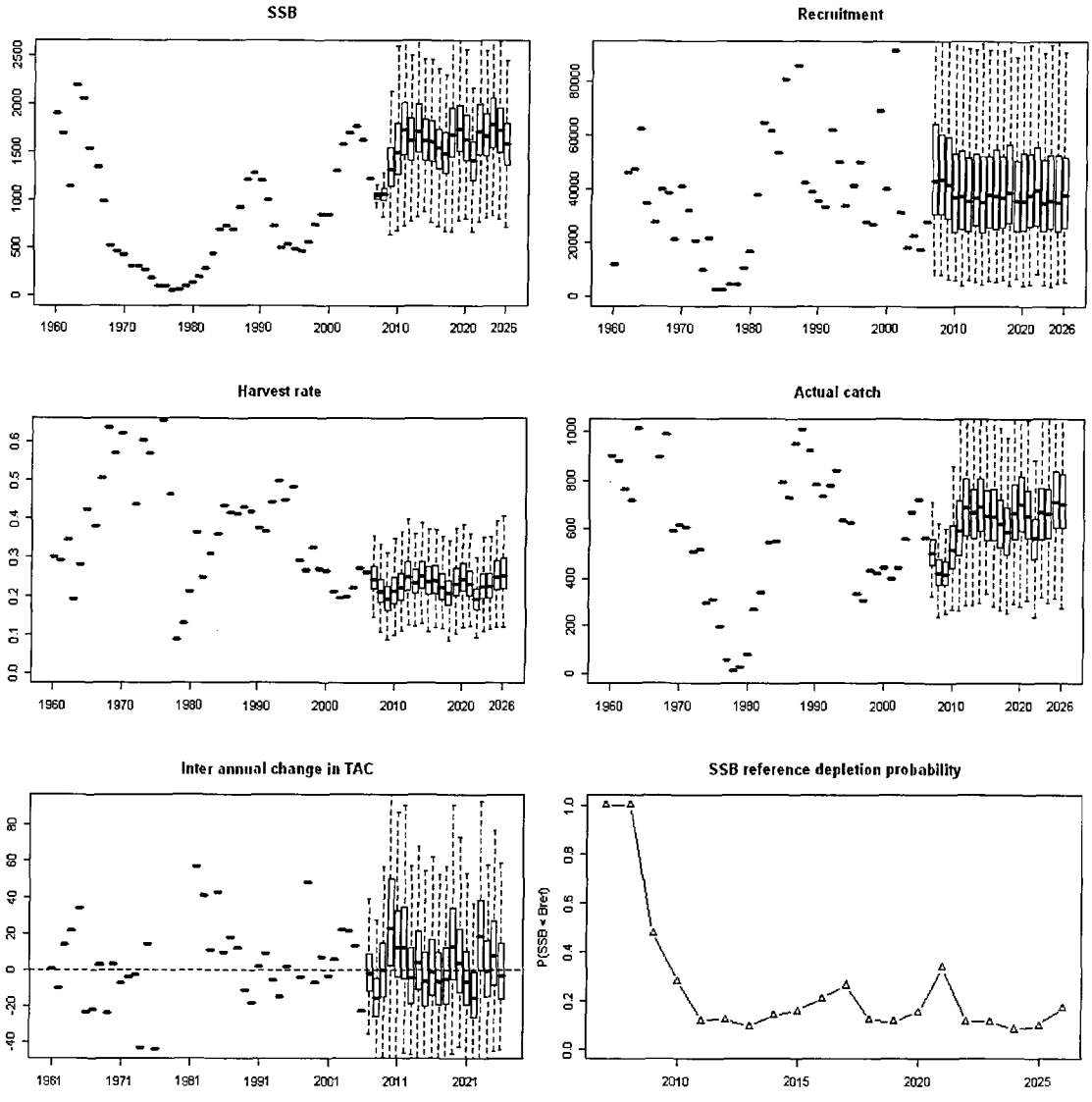


Figure 134: Output of simulation 55.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 30%

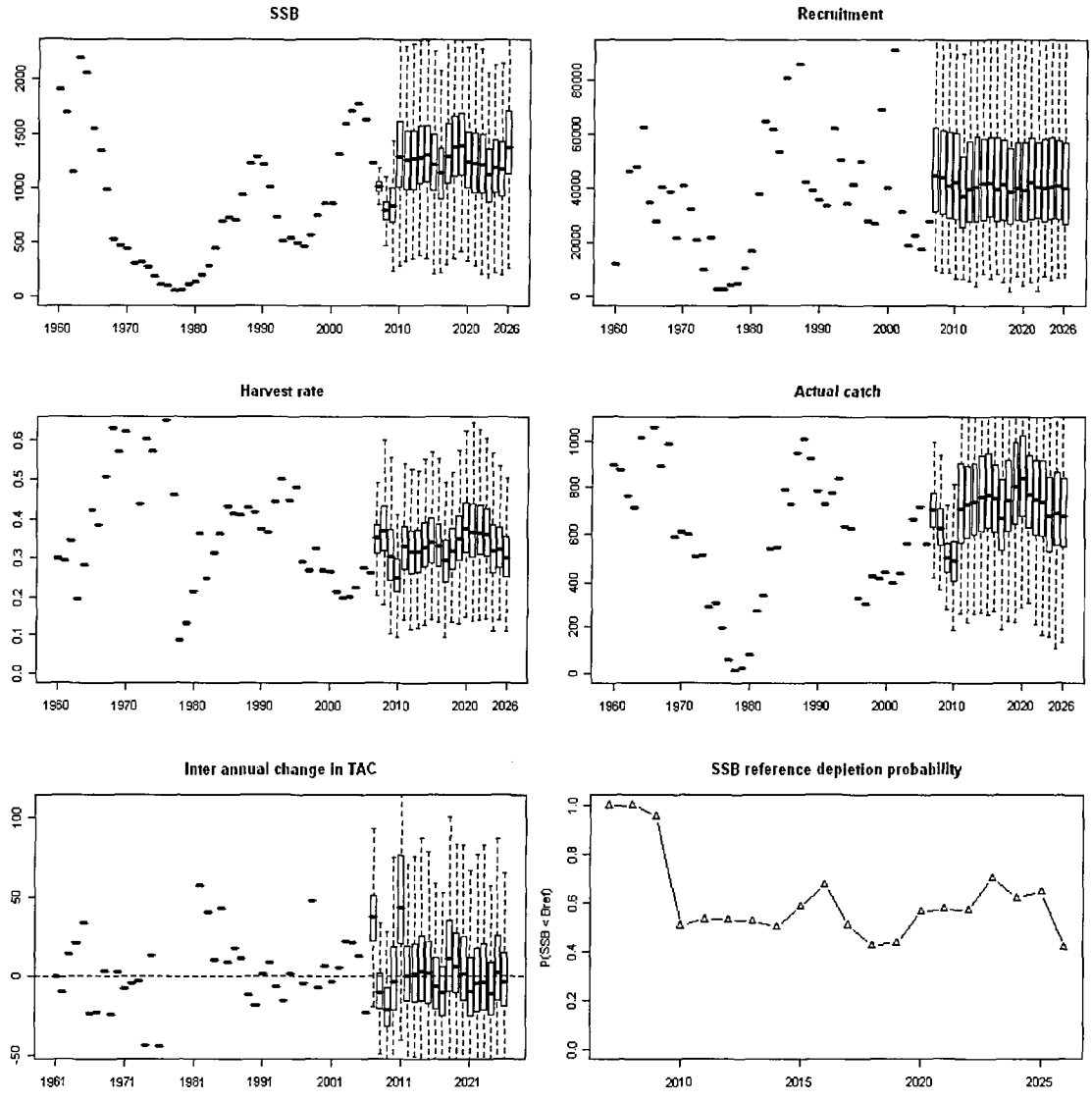


Figure 135: Output of simulation 56.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Obs Index

Limitation of variation: none

Implementation error: 80%

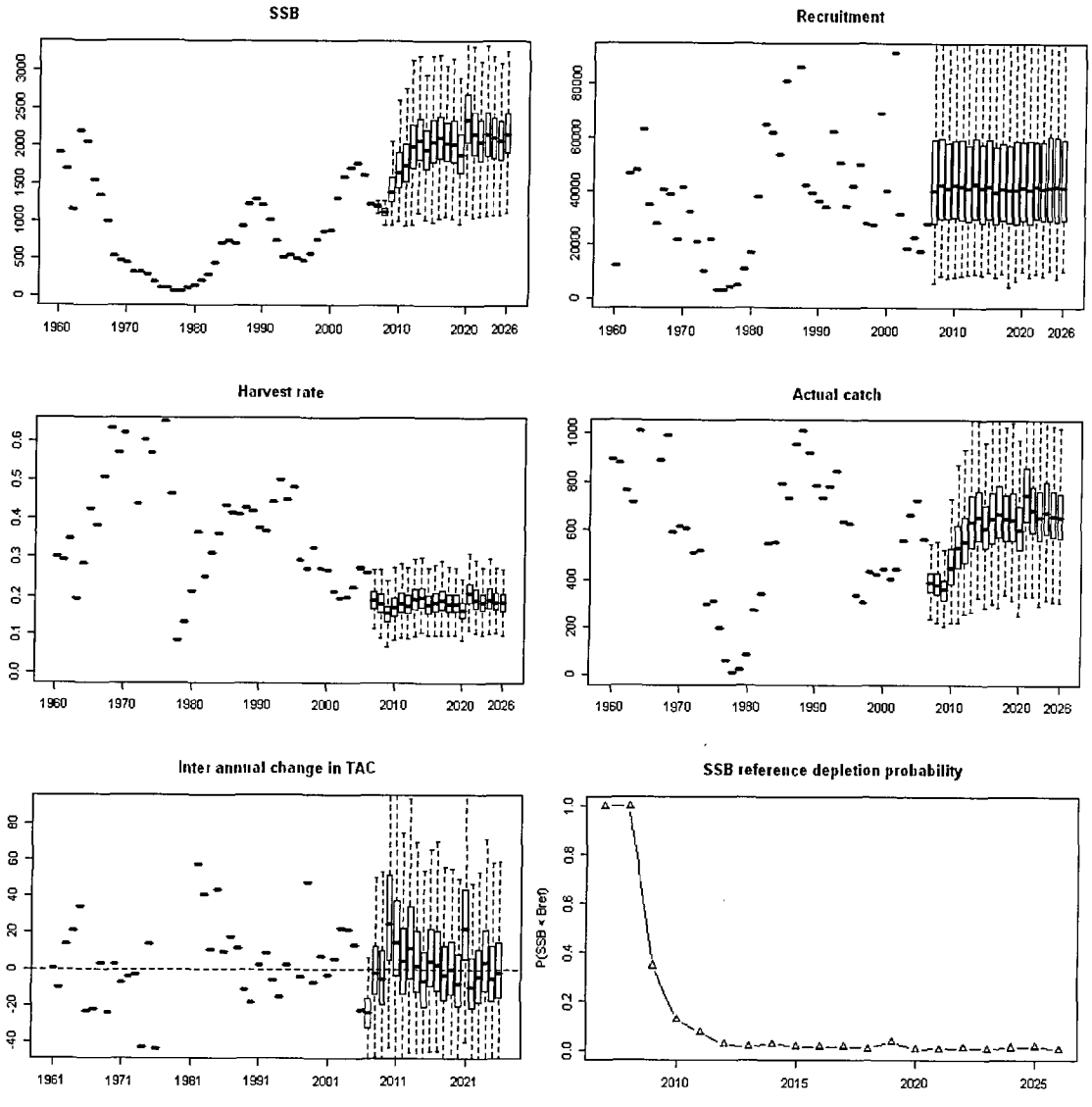


Figure 136: Output of simulation 57.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

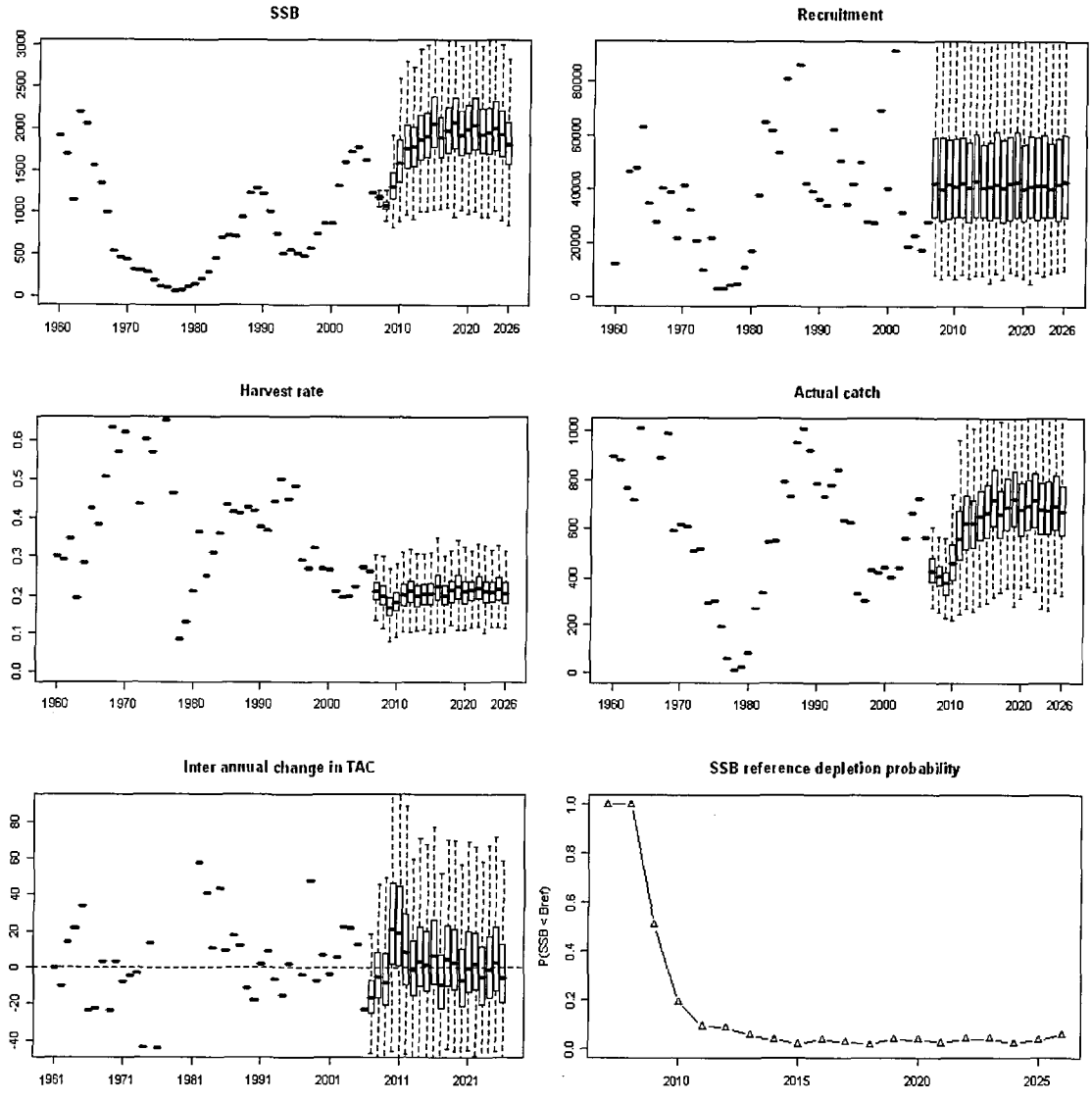


Figure 137: Output of simulation 58.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

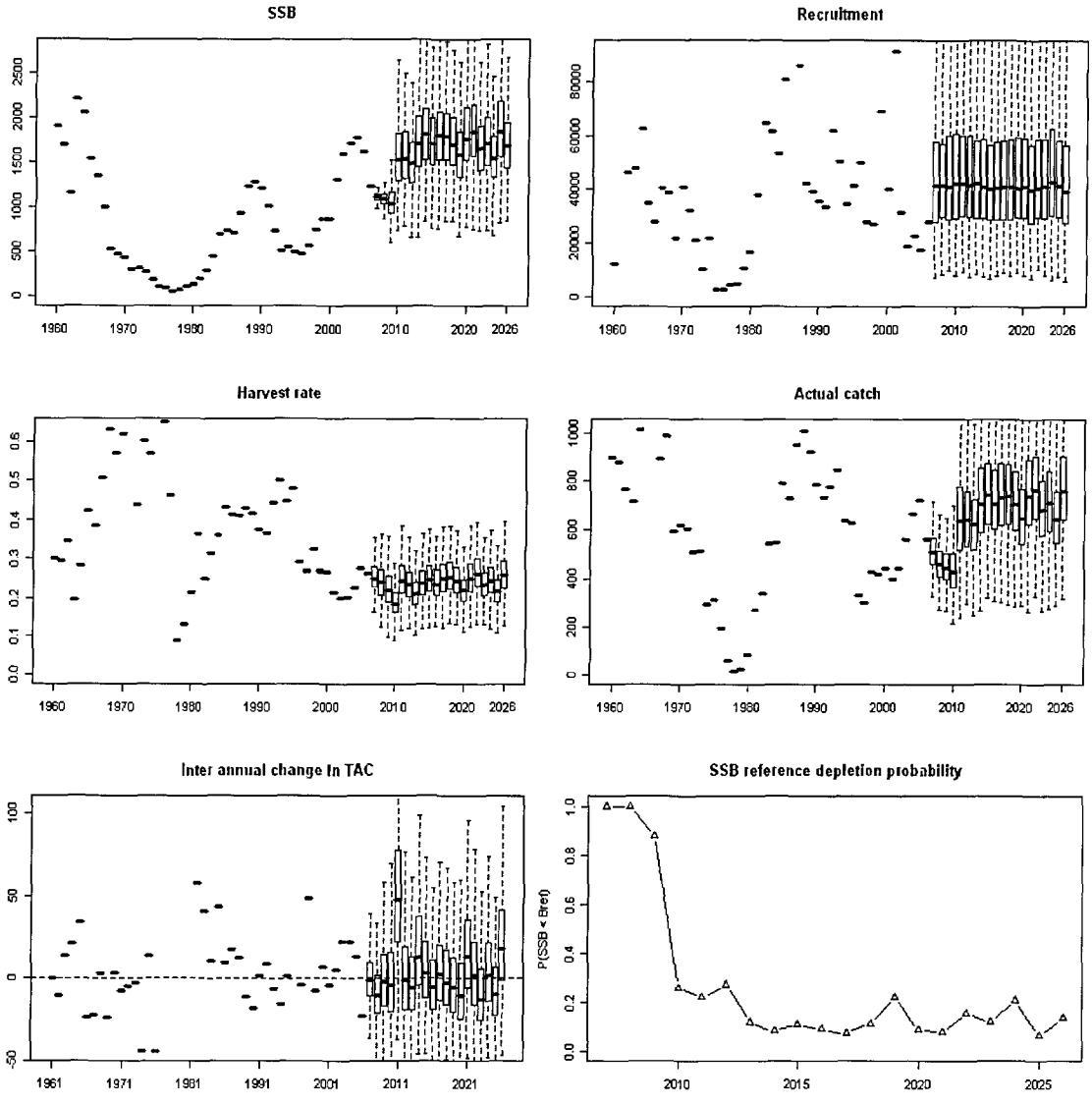


Figure 138: Output of simulation 59.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

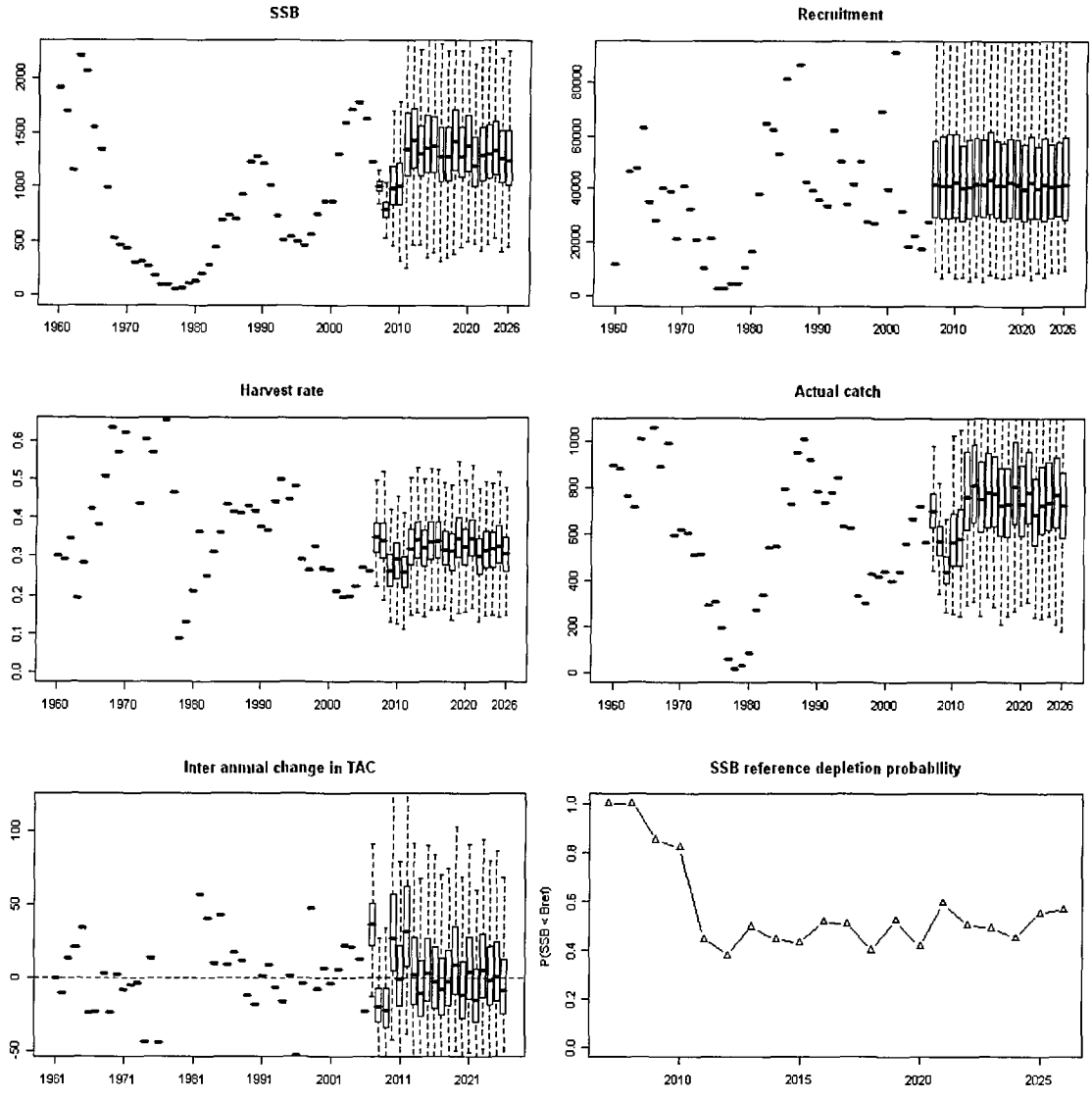


Figure 139: Output of simulation 60.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

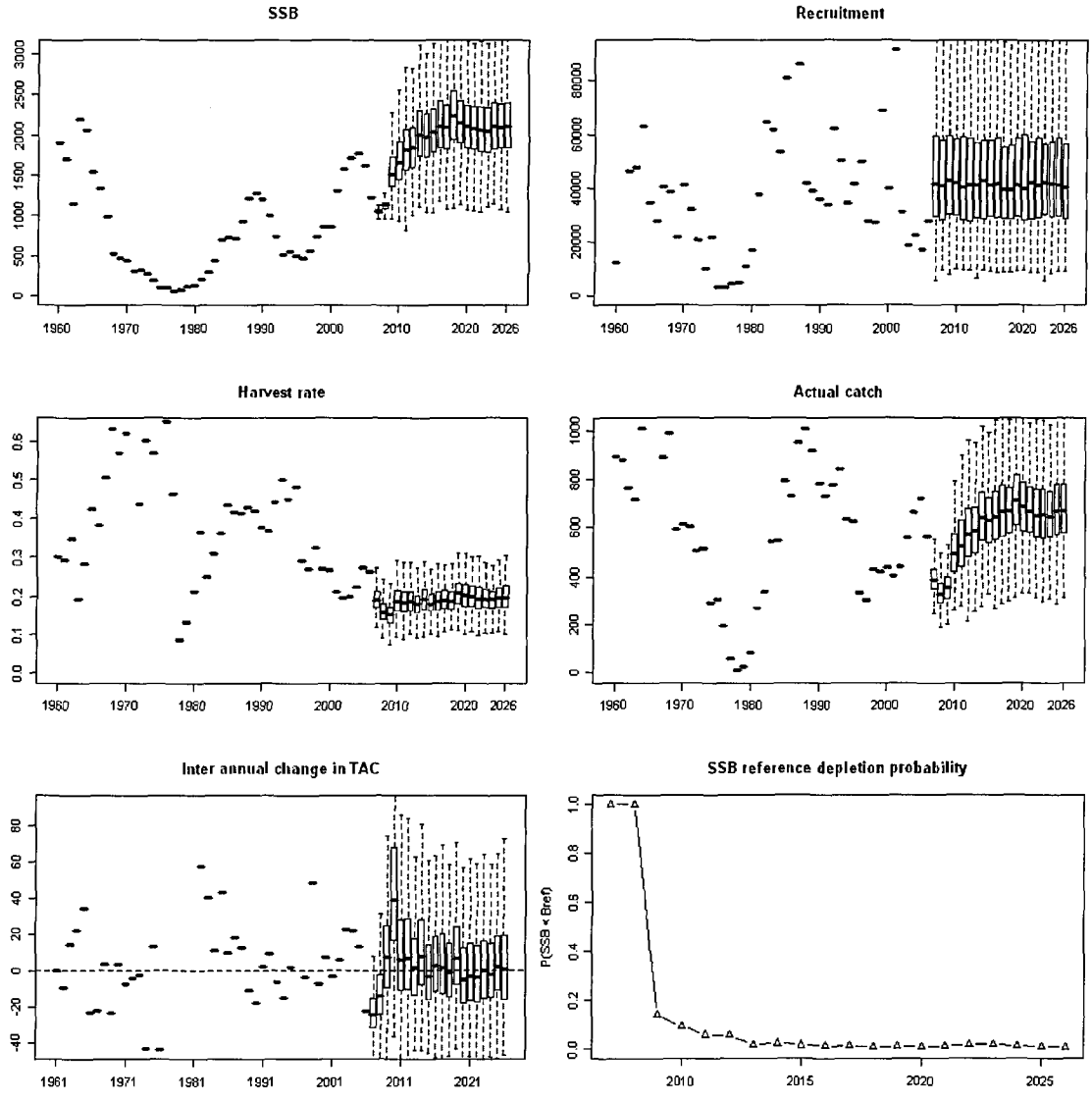


Figure 140: Output of simulation 61.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

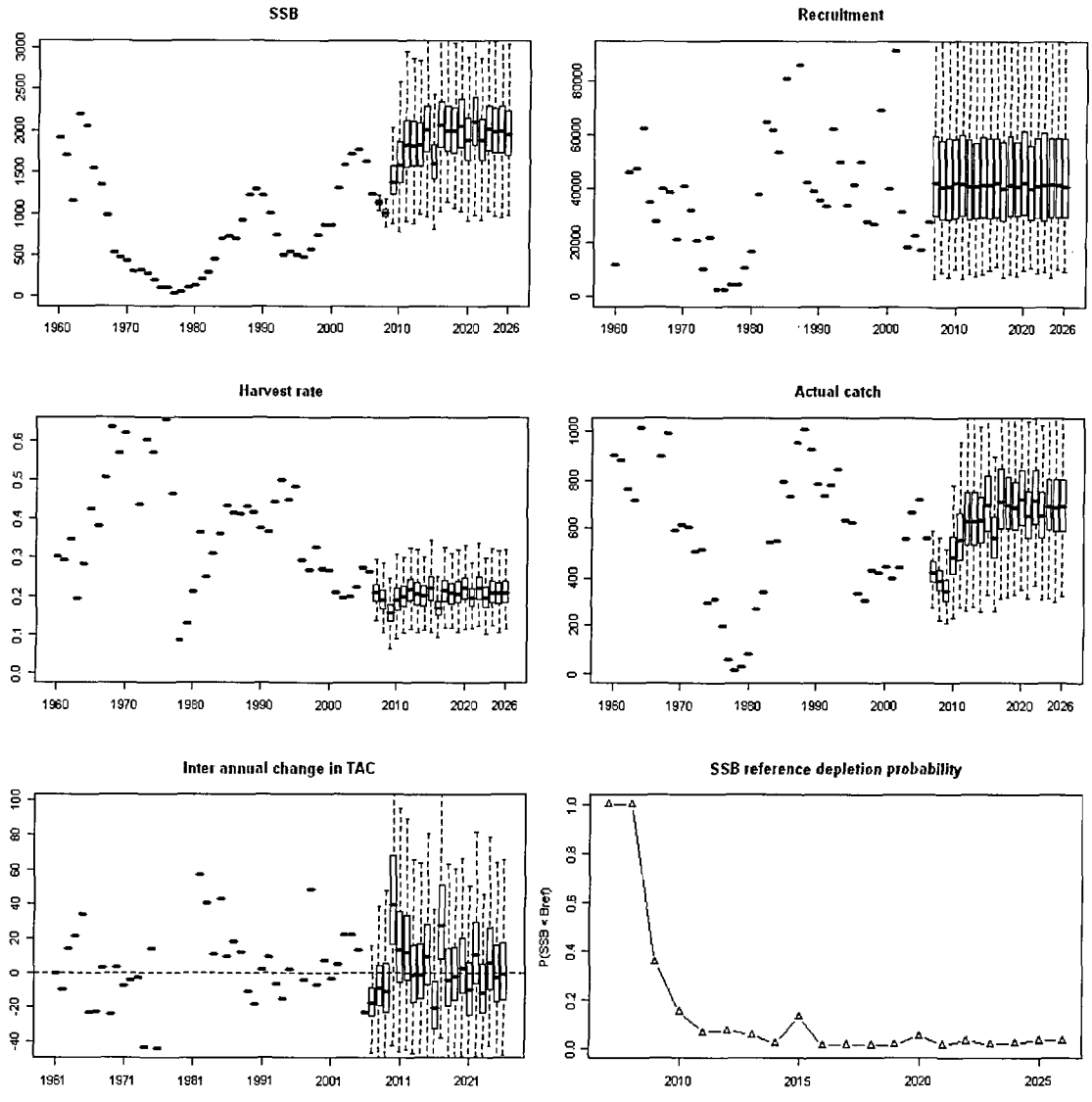


Figure 141: Output of simulation 62.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

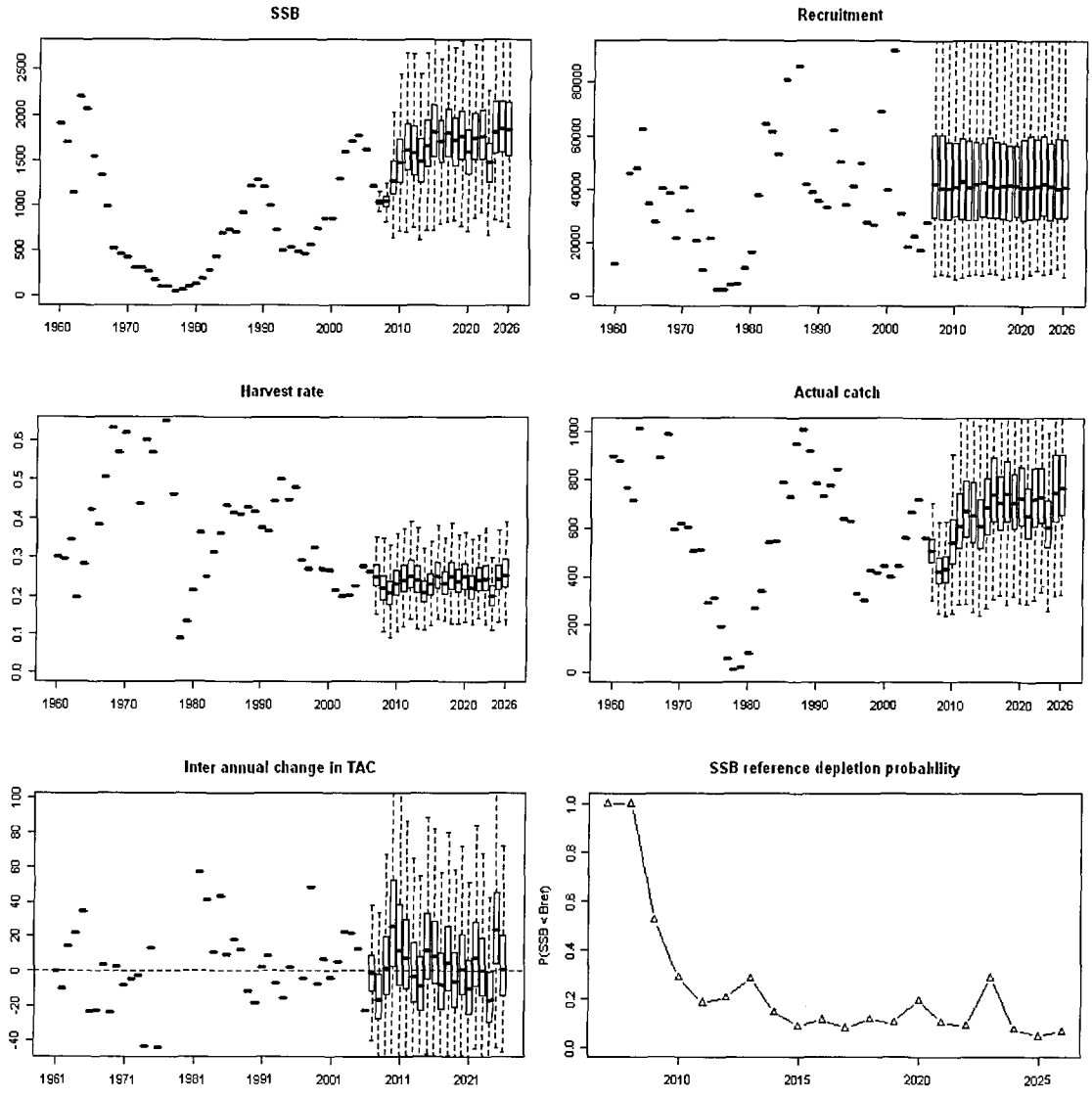


Figure 142: Output of simulation 63.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

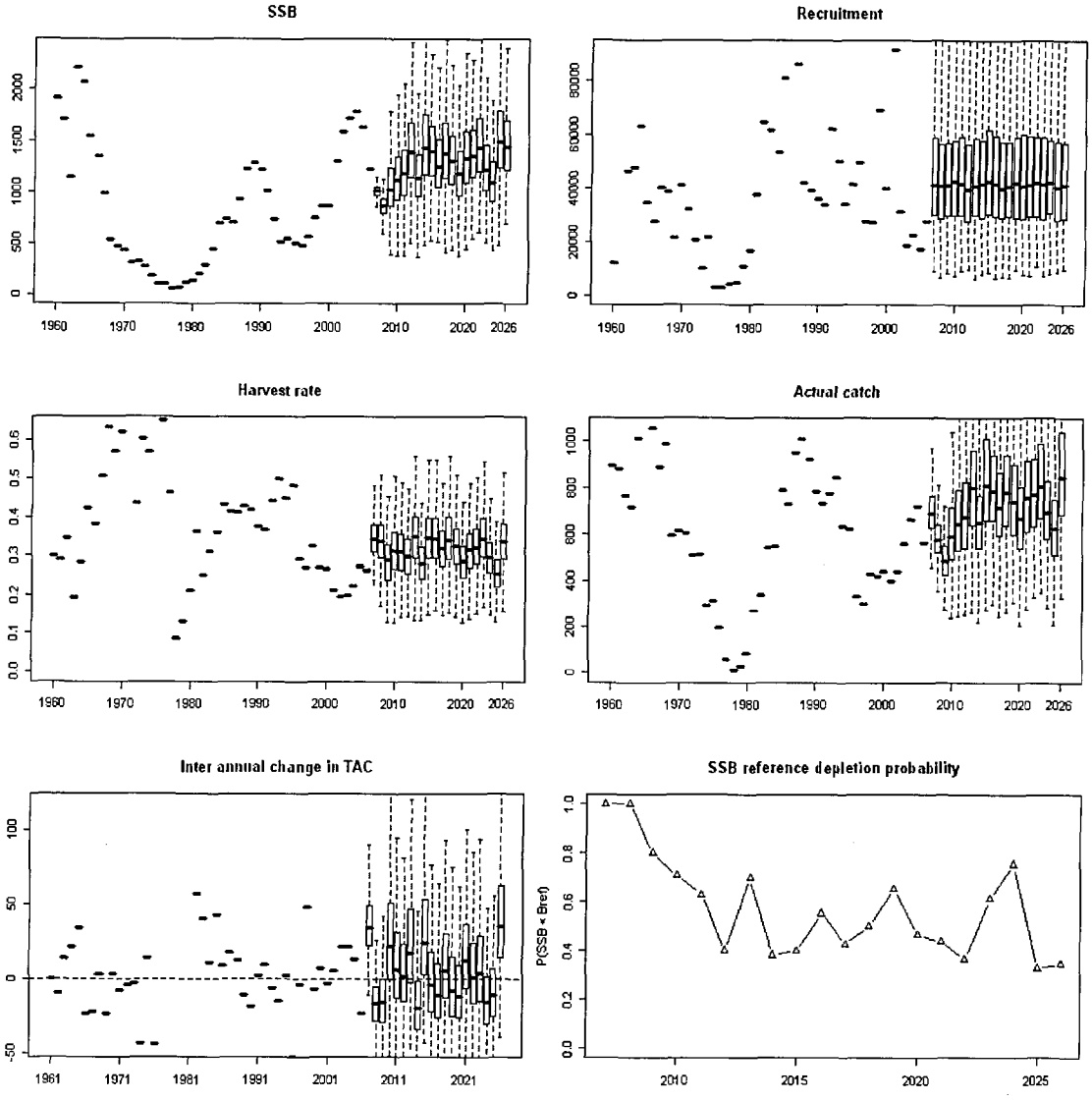


Figure 143: Output of simulation 64.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

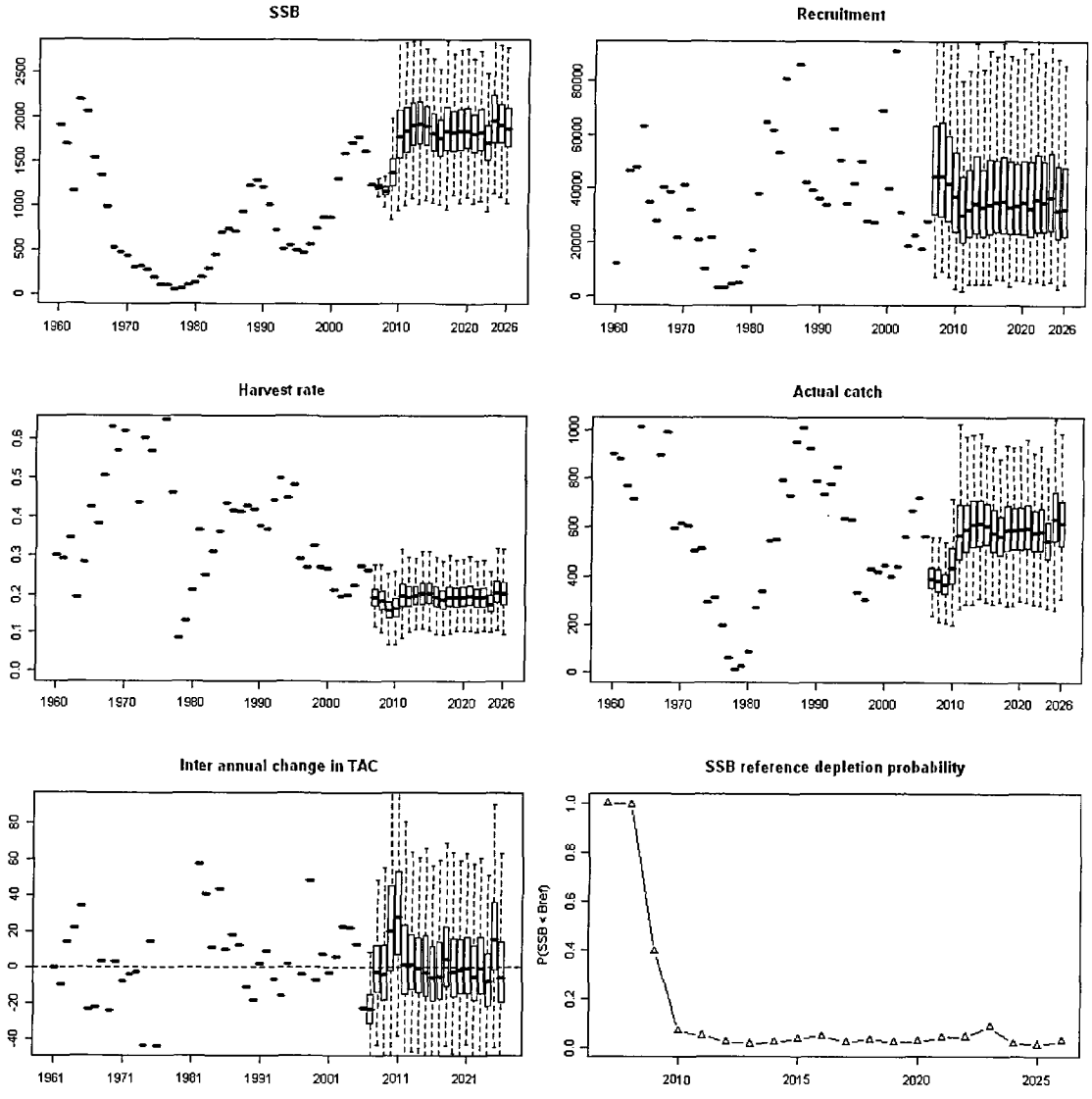


Figure 144: Output of simulation 65.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

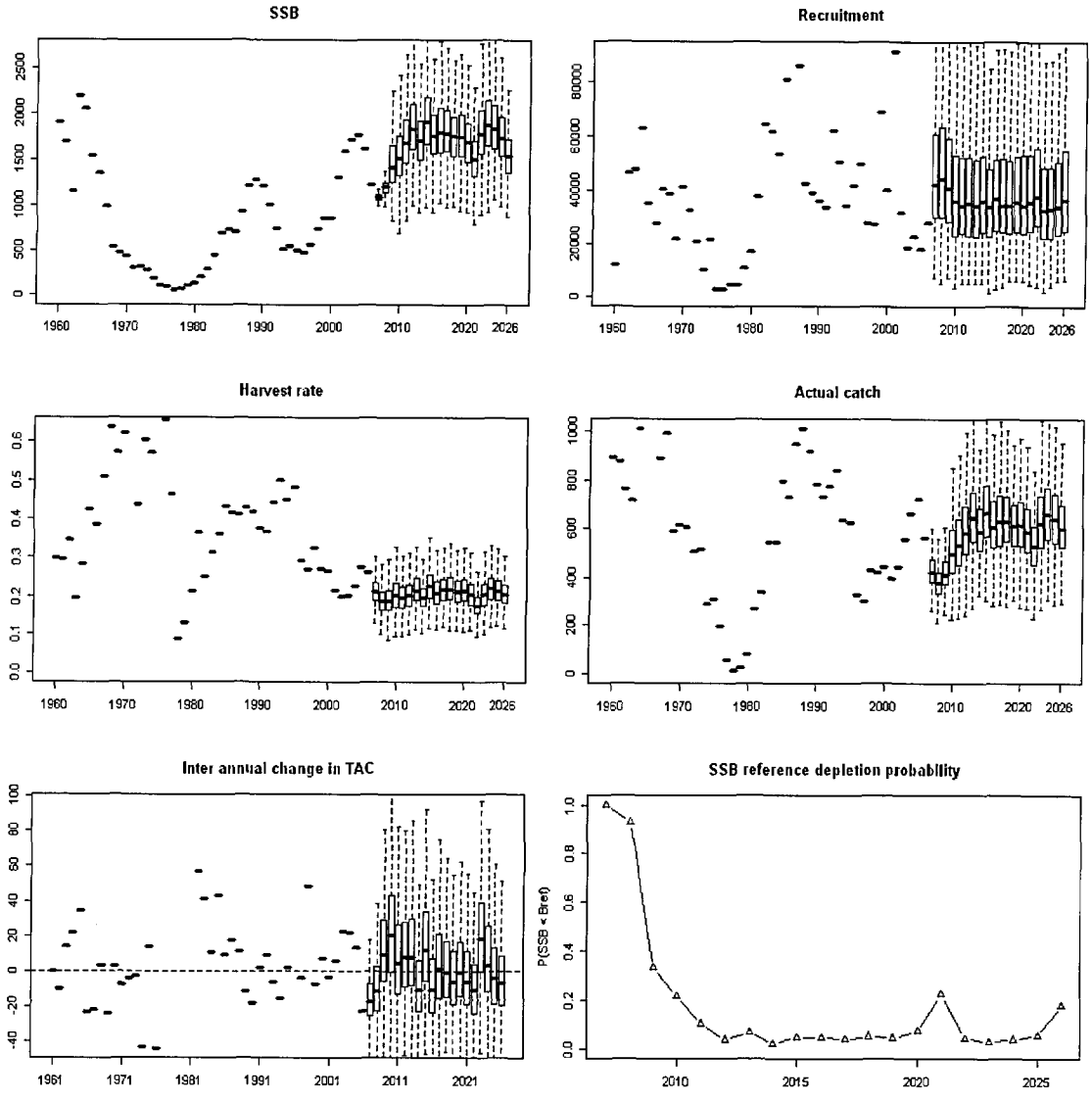


Figure 145: Output of simulation 66.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

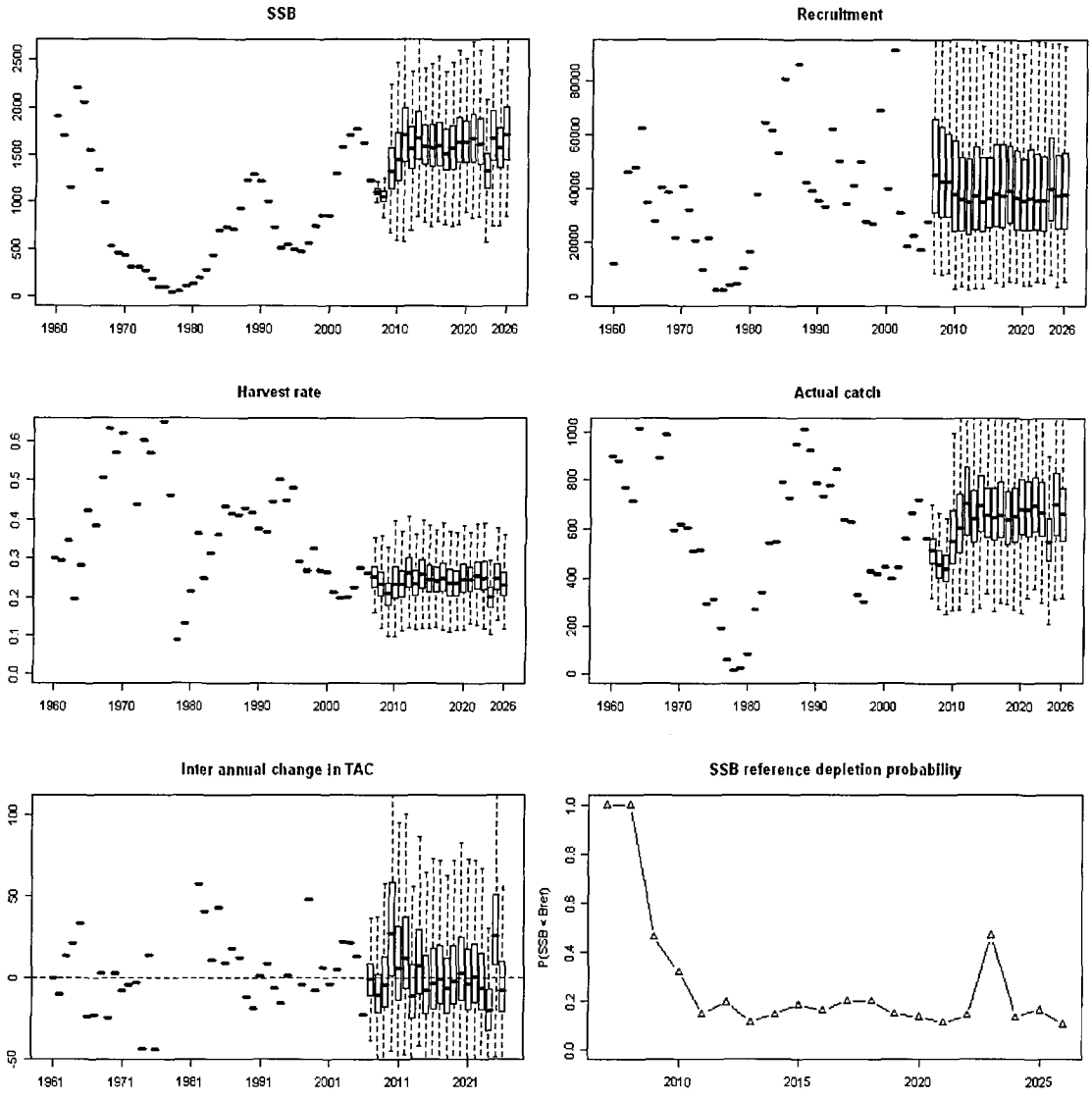


Figure 146: Output of simulation 67.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

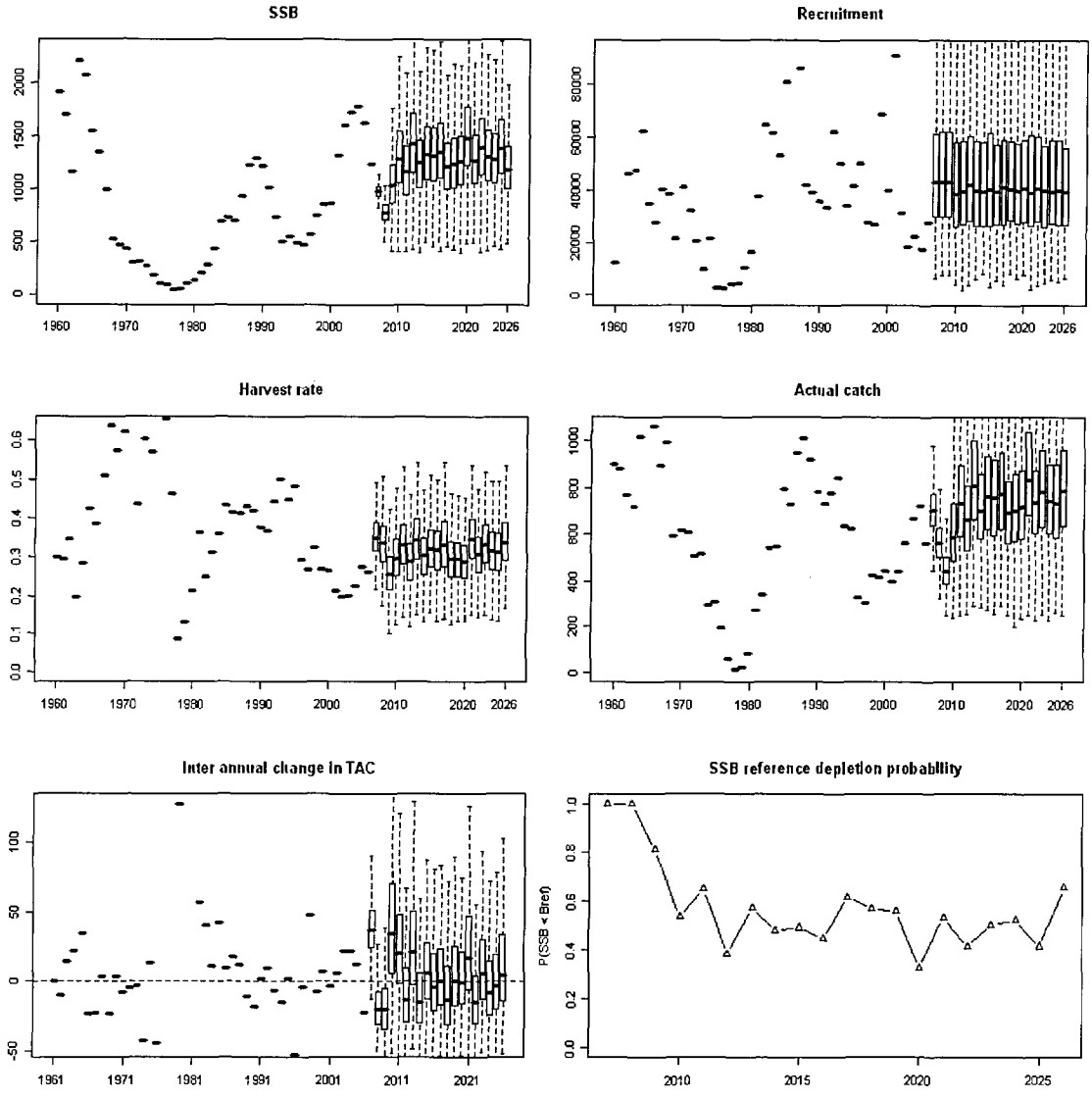


Figure 147: Output of simulation 68.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

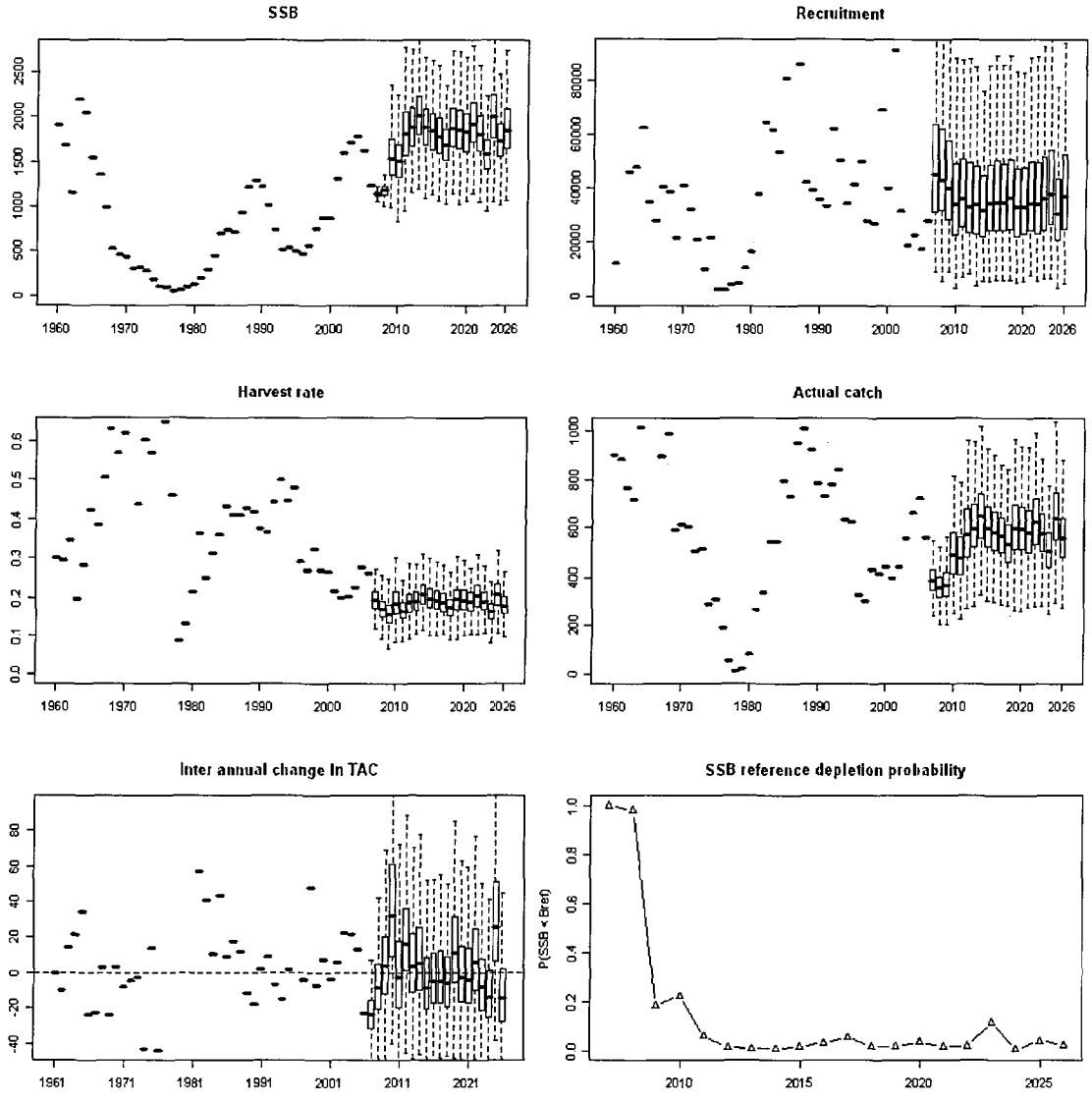


Figure 148: Output of simulation 69.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

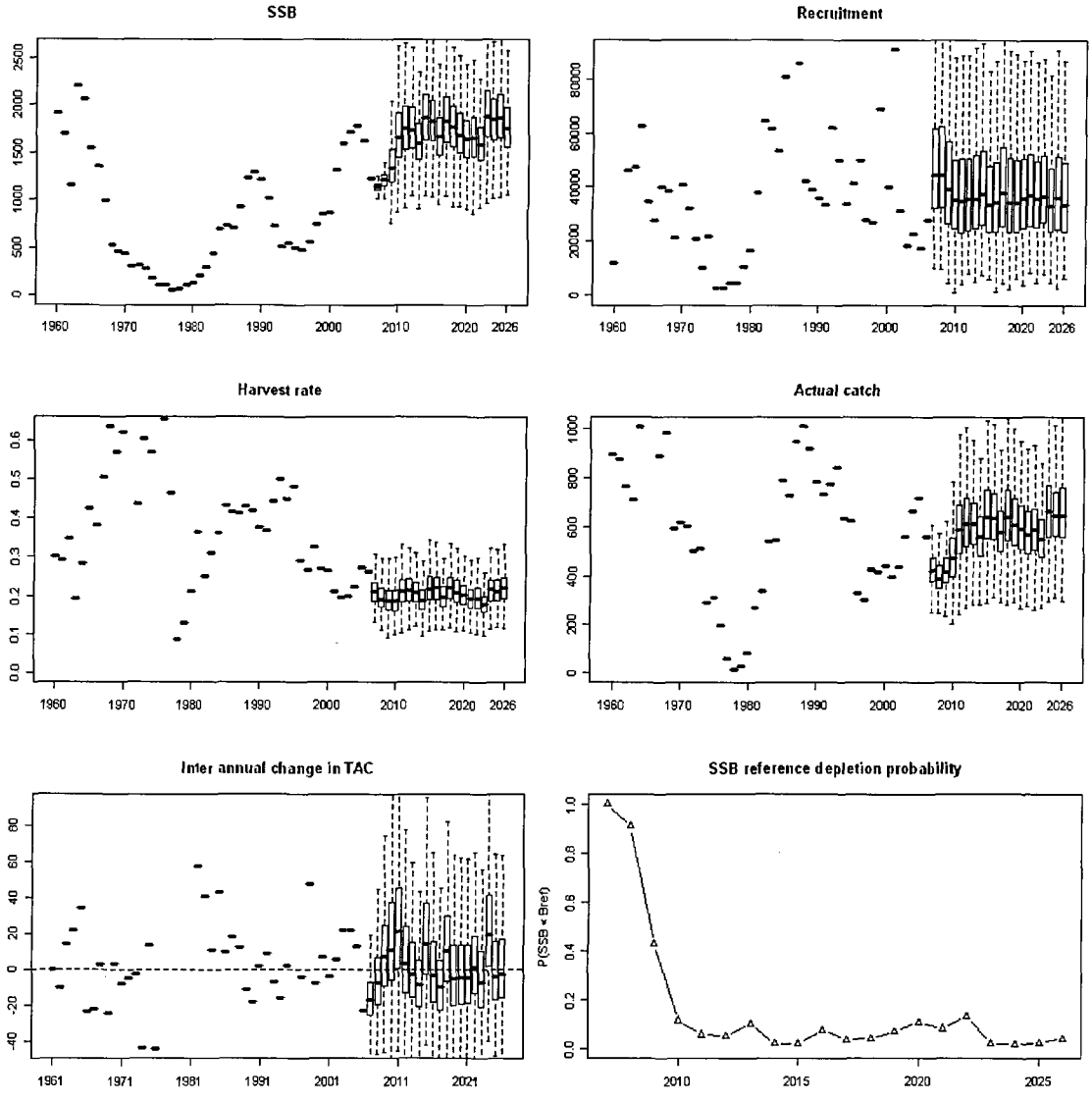


Figure 149: Output of simulation 70.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

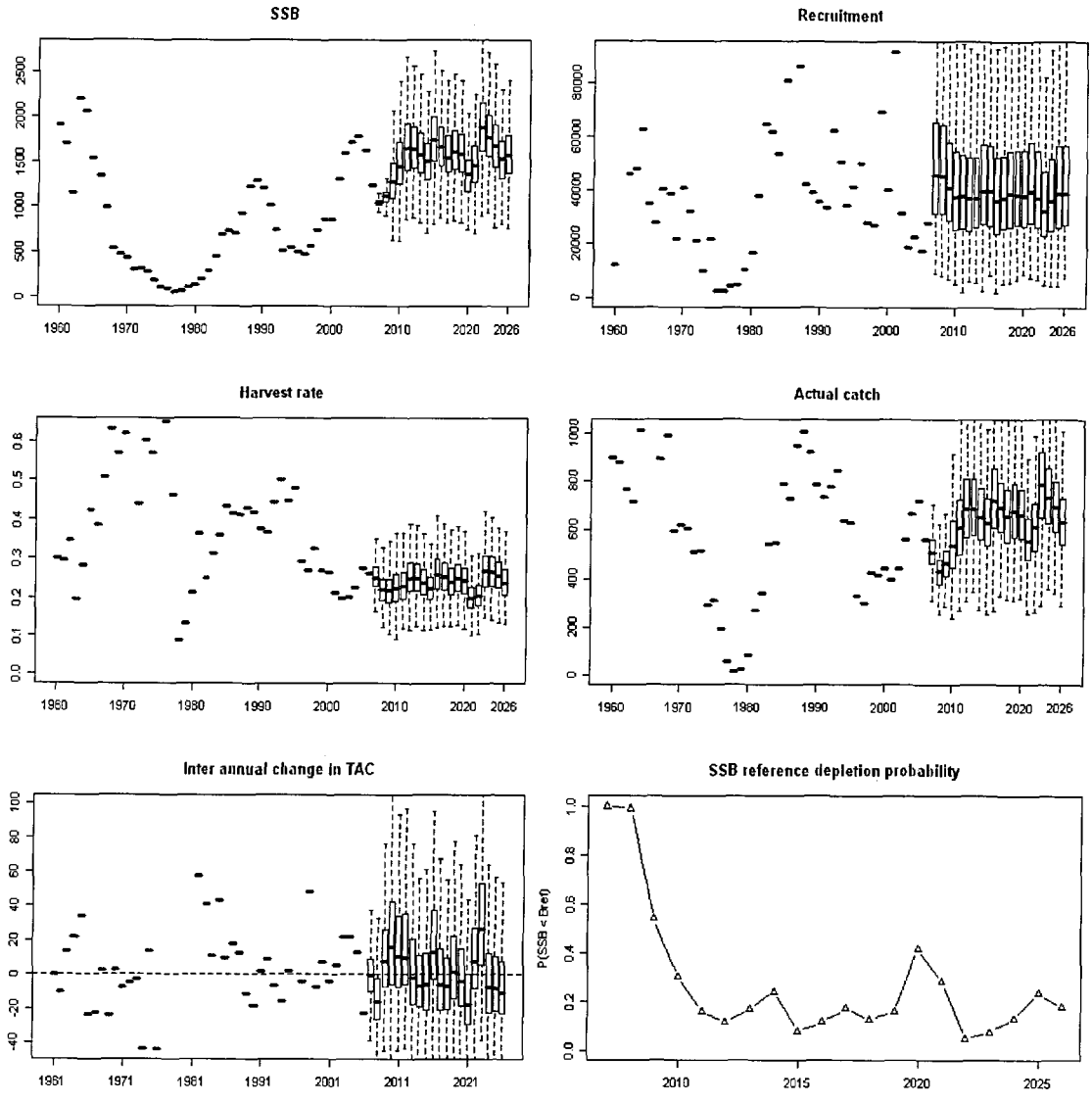


Figure 150: Output of simulation 71.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

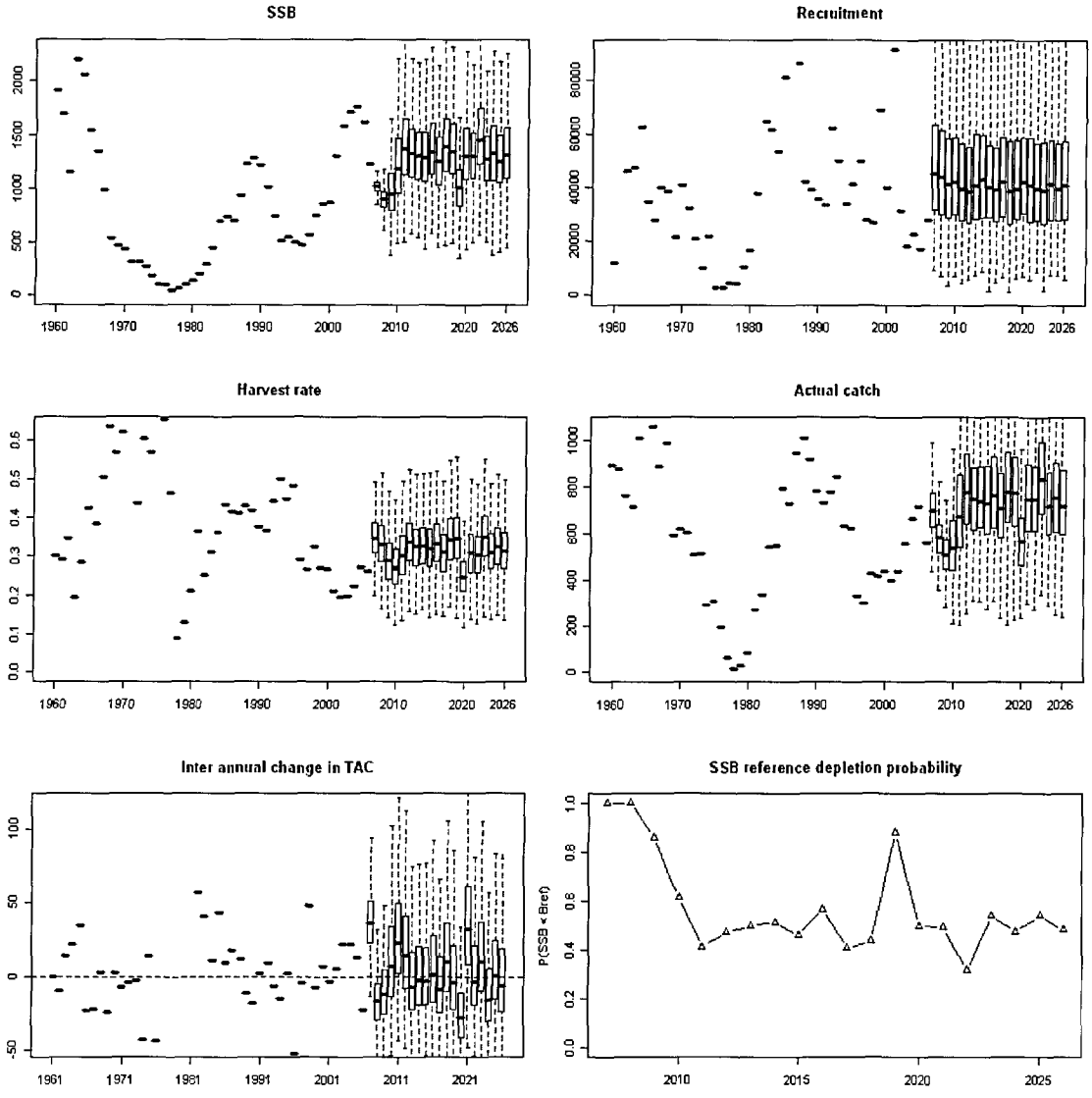


Figure 151: Output of simulation 72.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

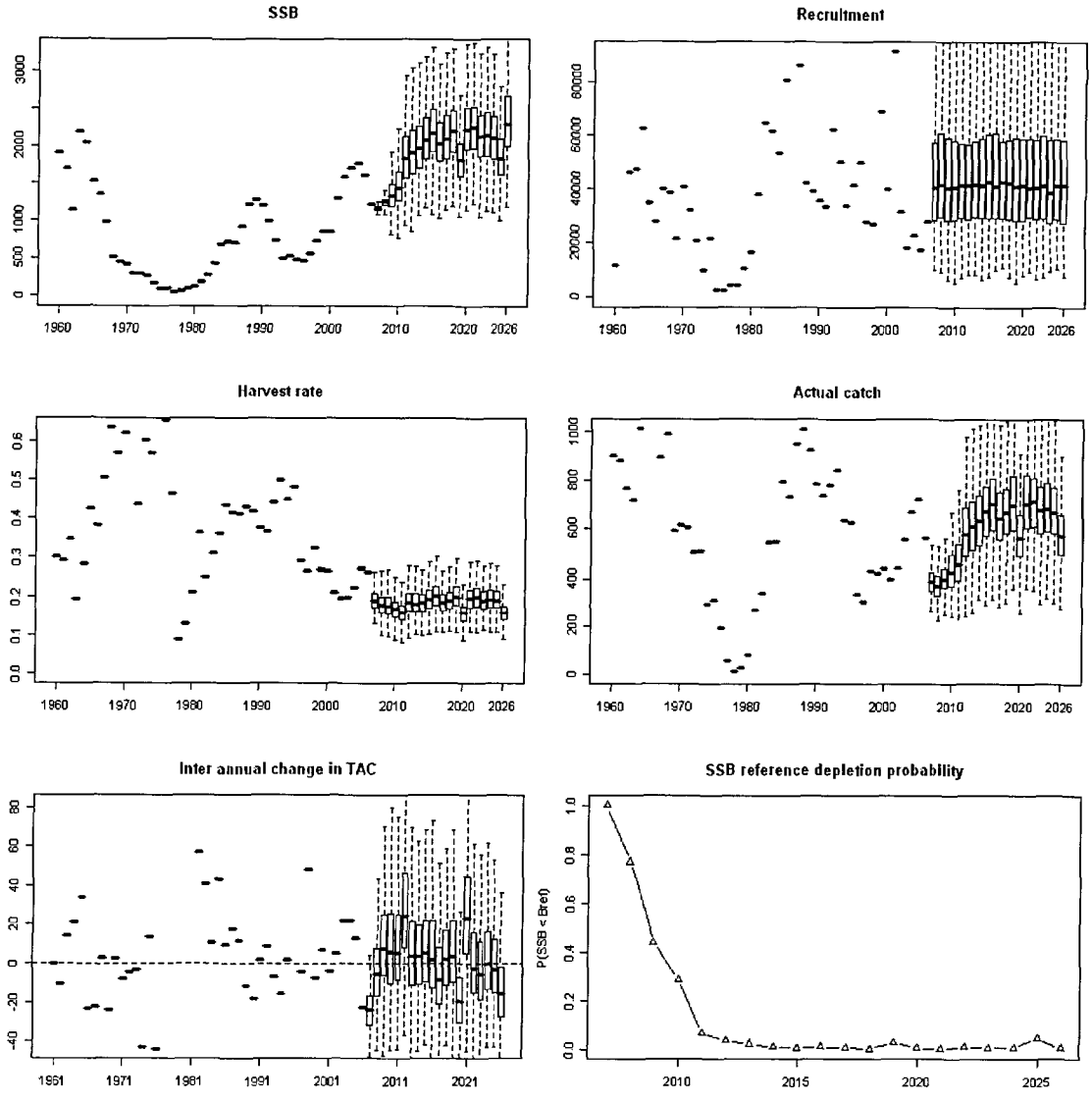


Figure 152: Output of simulation 73.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 0%

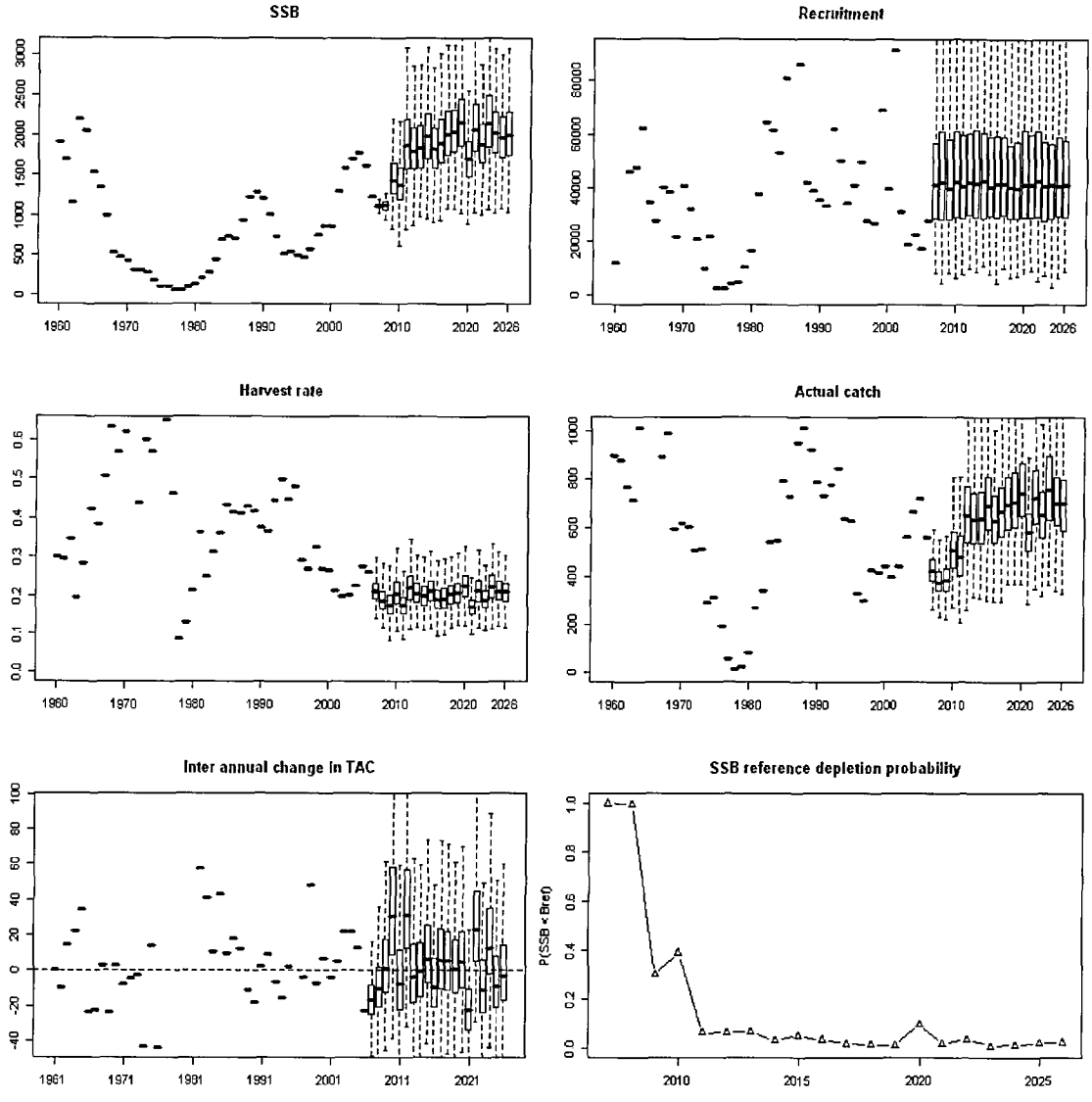


Figure 153: Output of simulation 74.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 10%

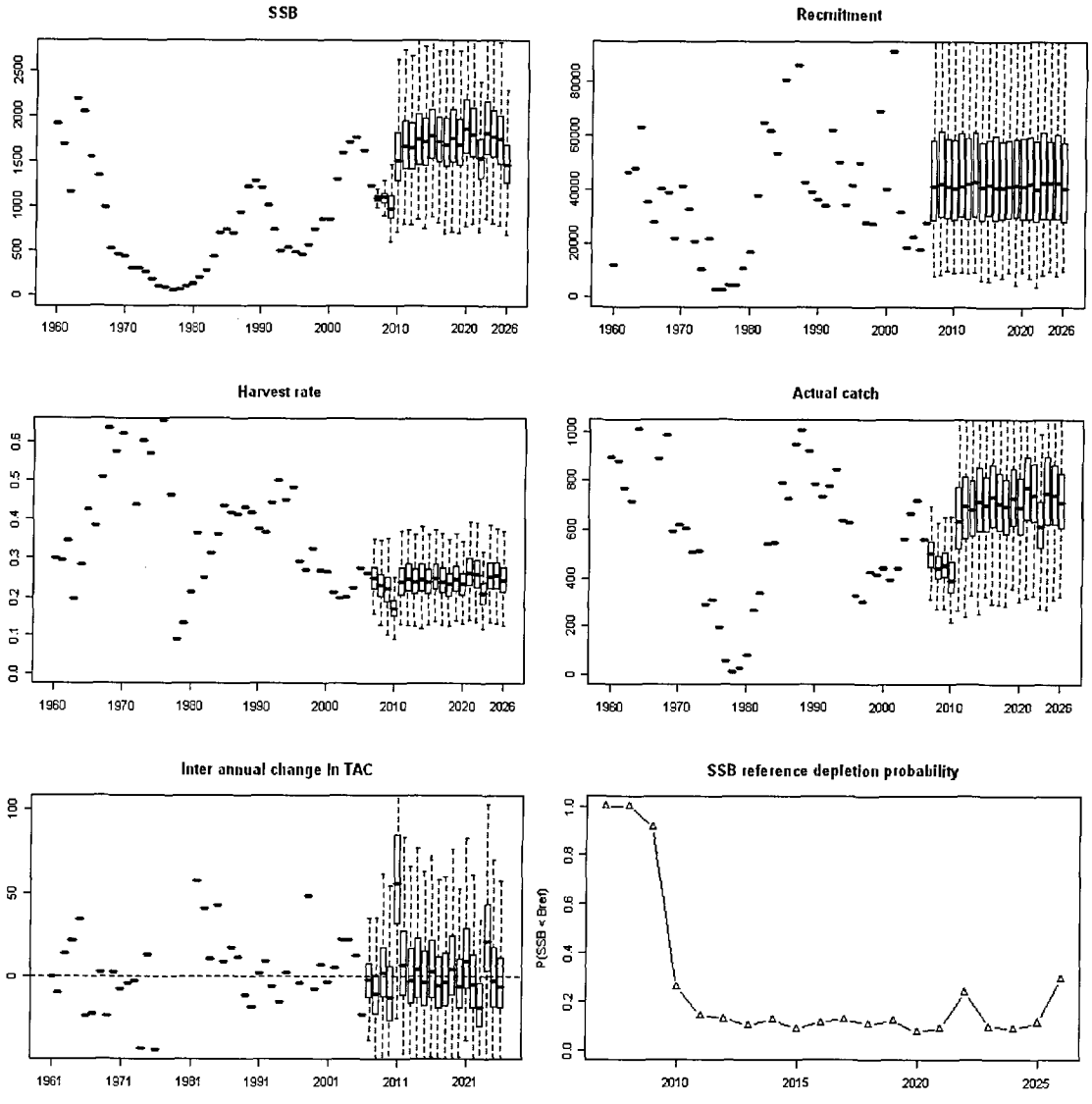


Figure 154: Output of simulation 75.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 30%

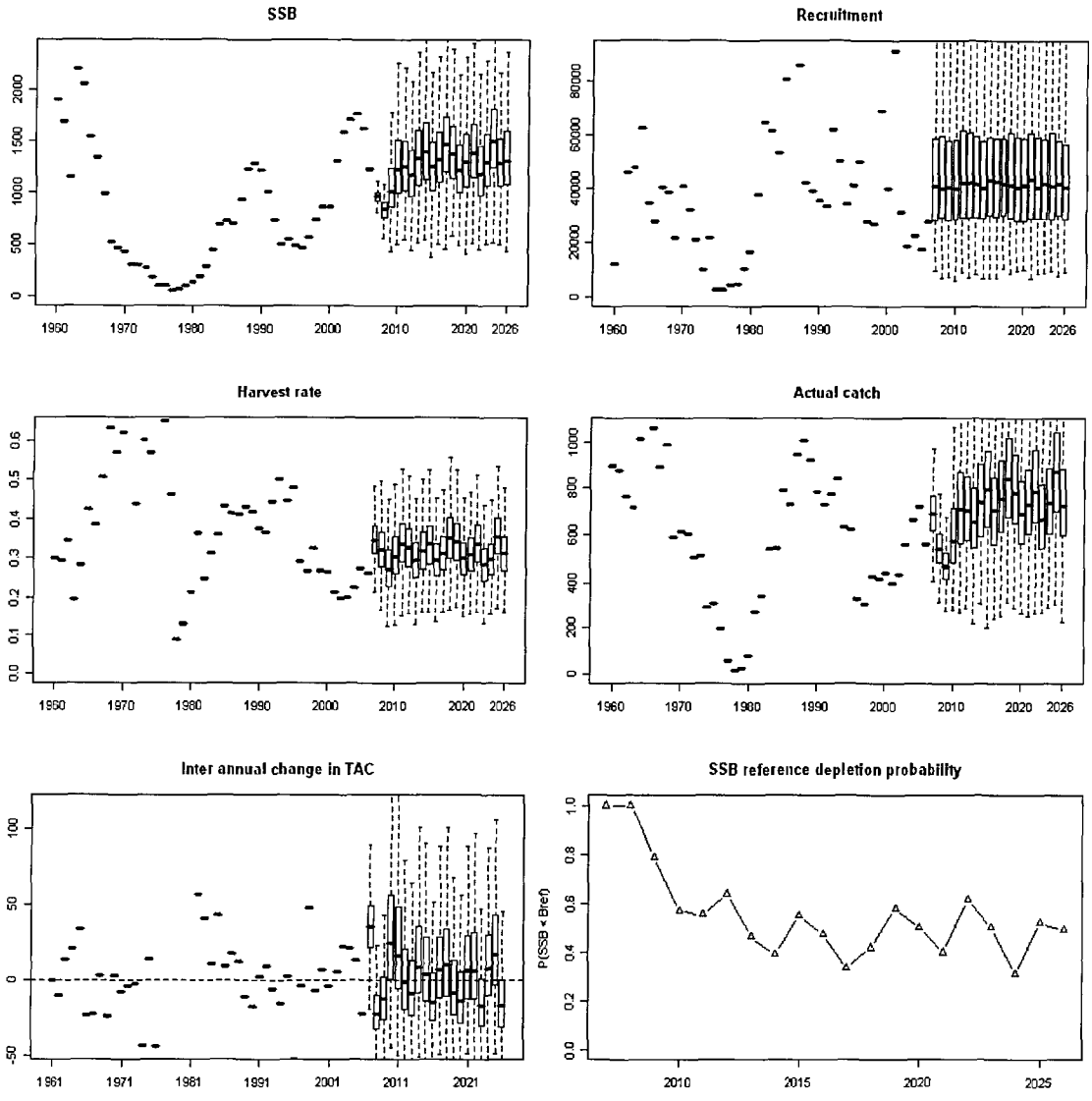


Figure 155: Output of simulation 76.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 80%

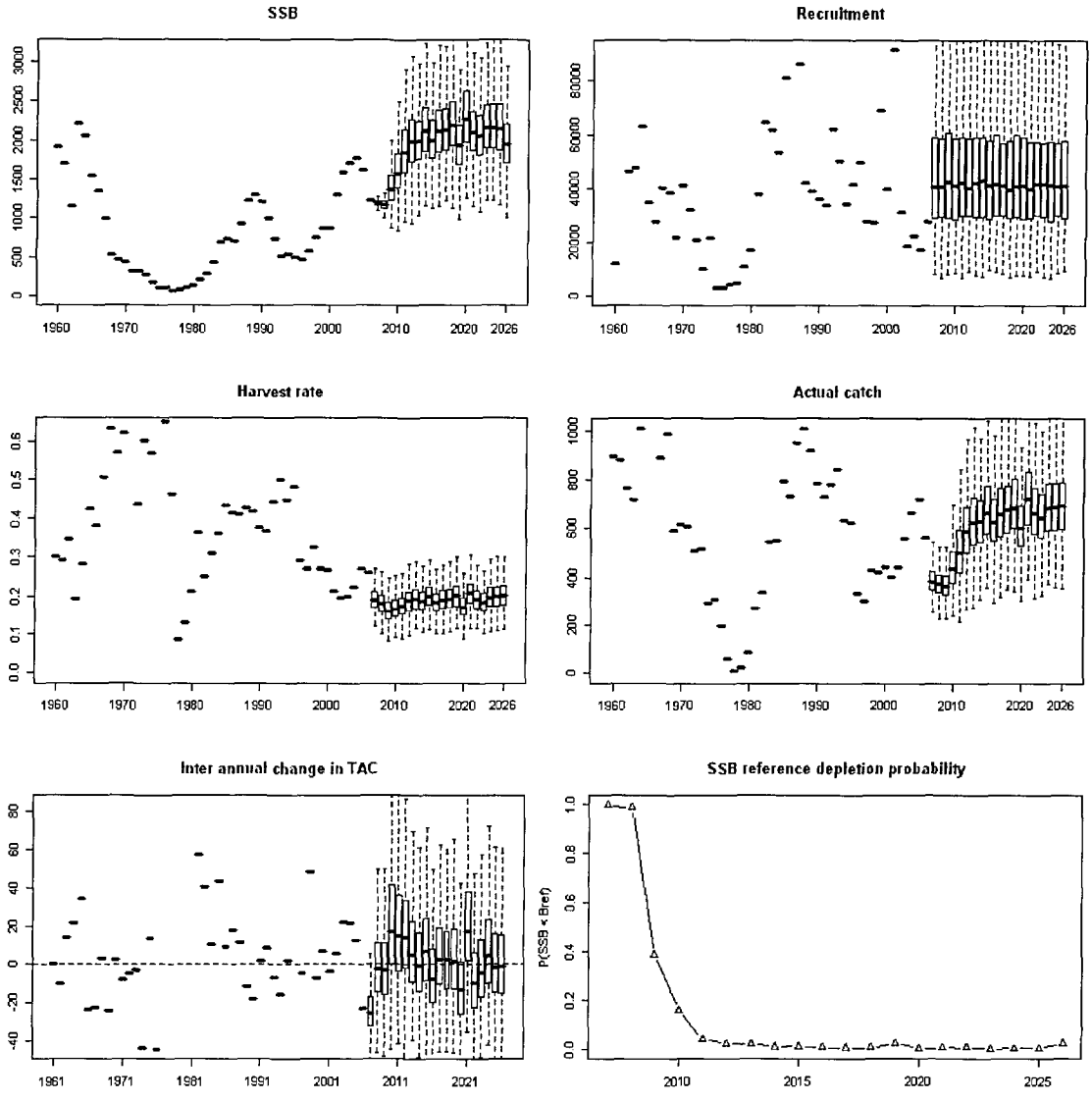


Figure 156: Output of simulation 77.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 0%

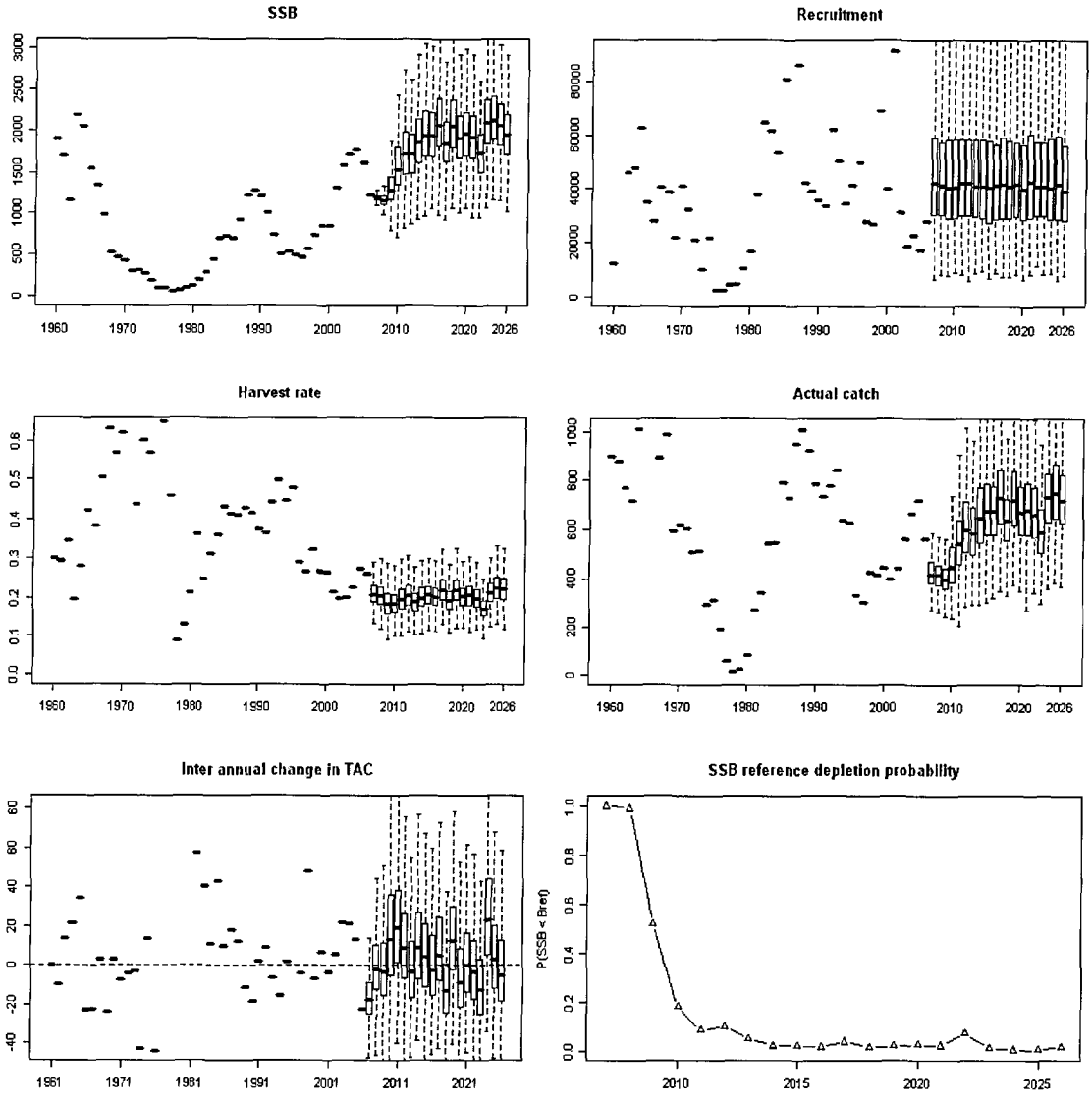


Figure 157: Output of simulation 78.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 10%

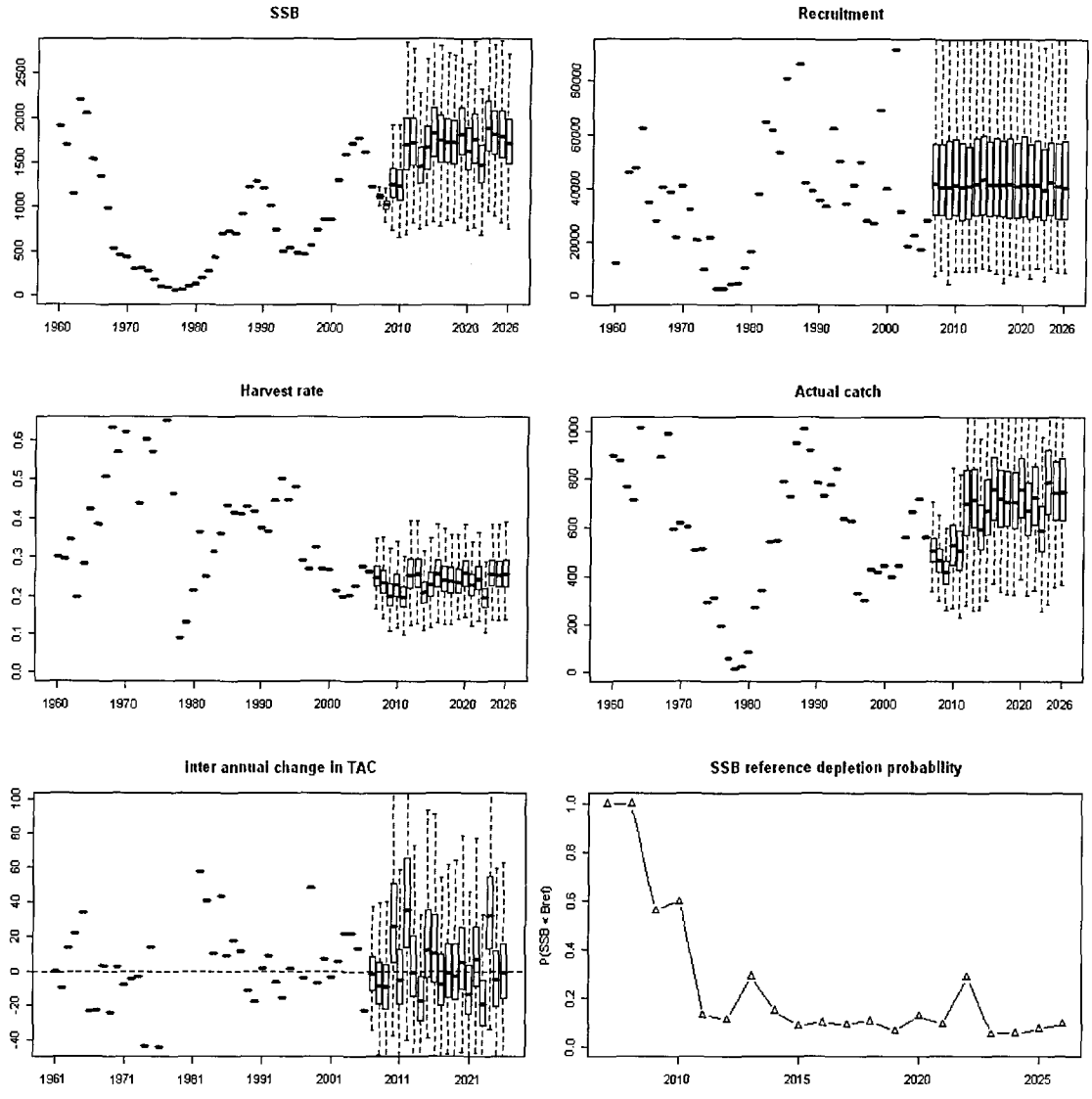


Figure 158: Output of simulation 79.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 30%

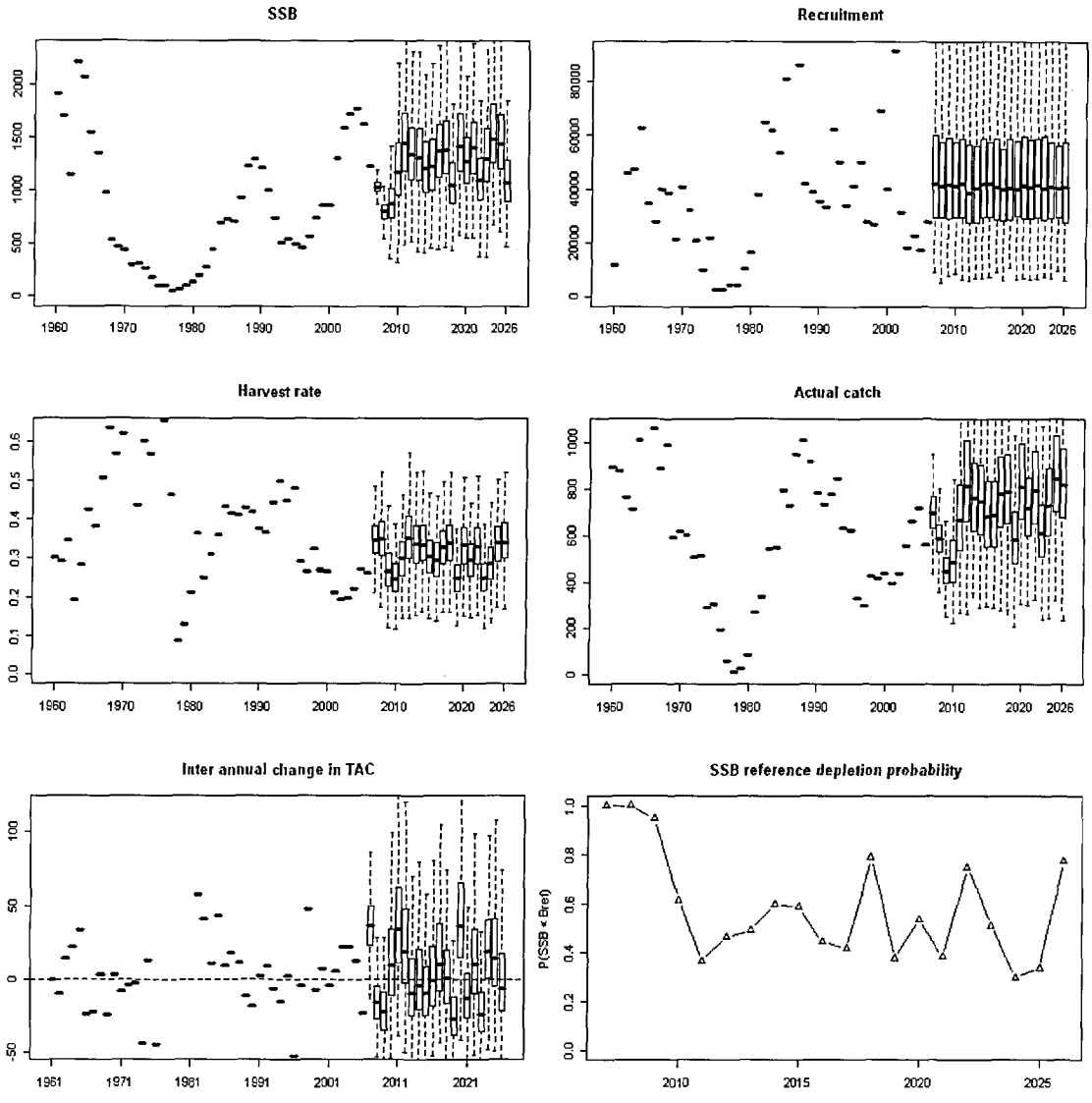


Figure 159: Output of simulation 80.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 80%

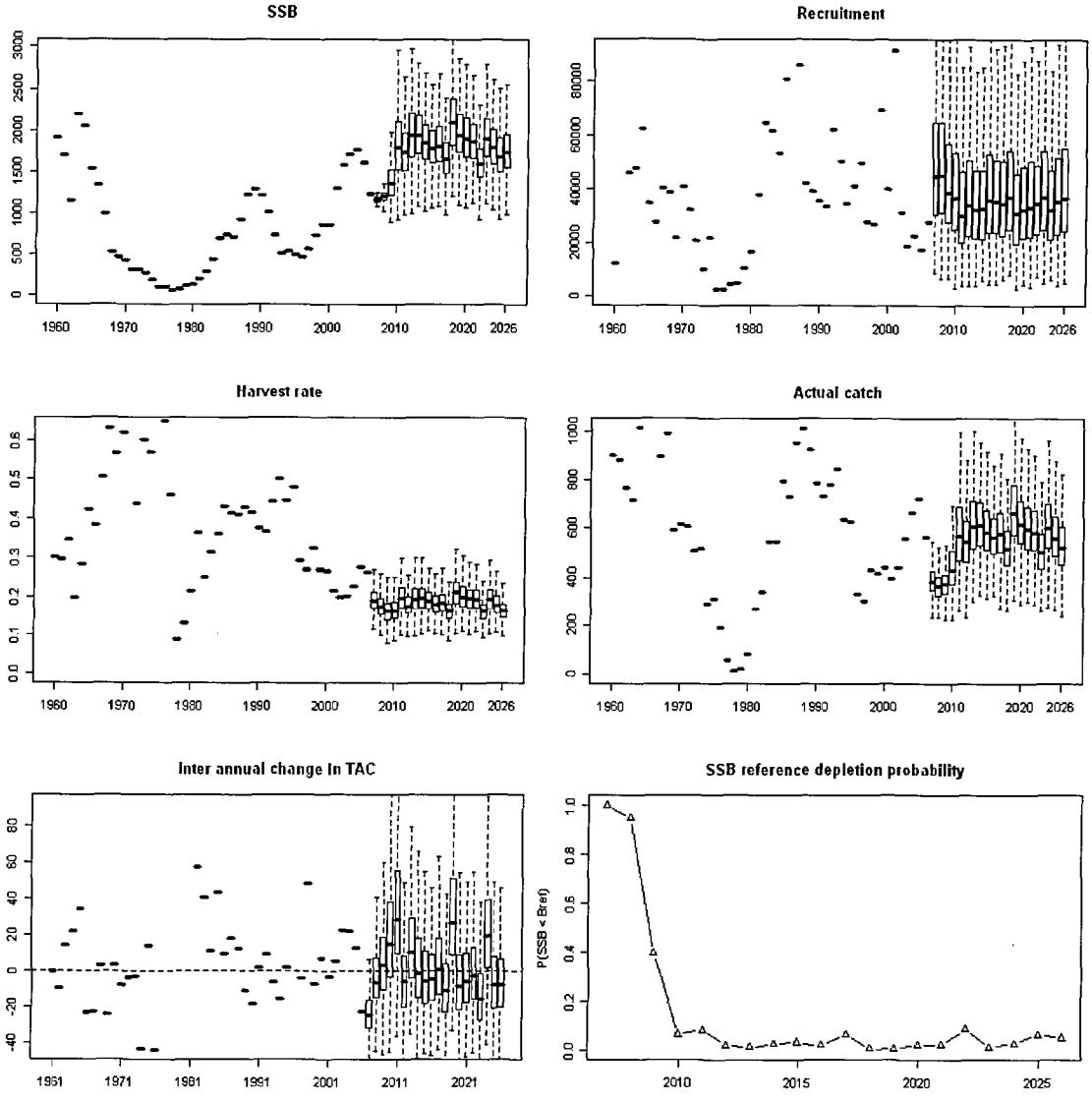


Figure 160: Output of simulation 81.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 0%

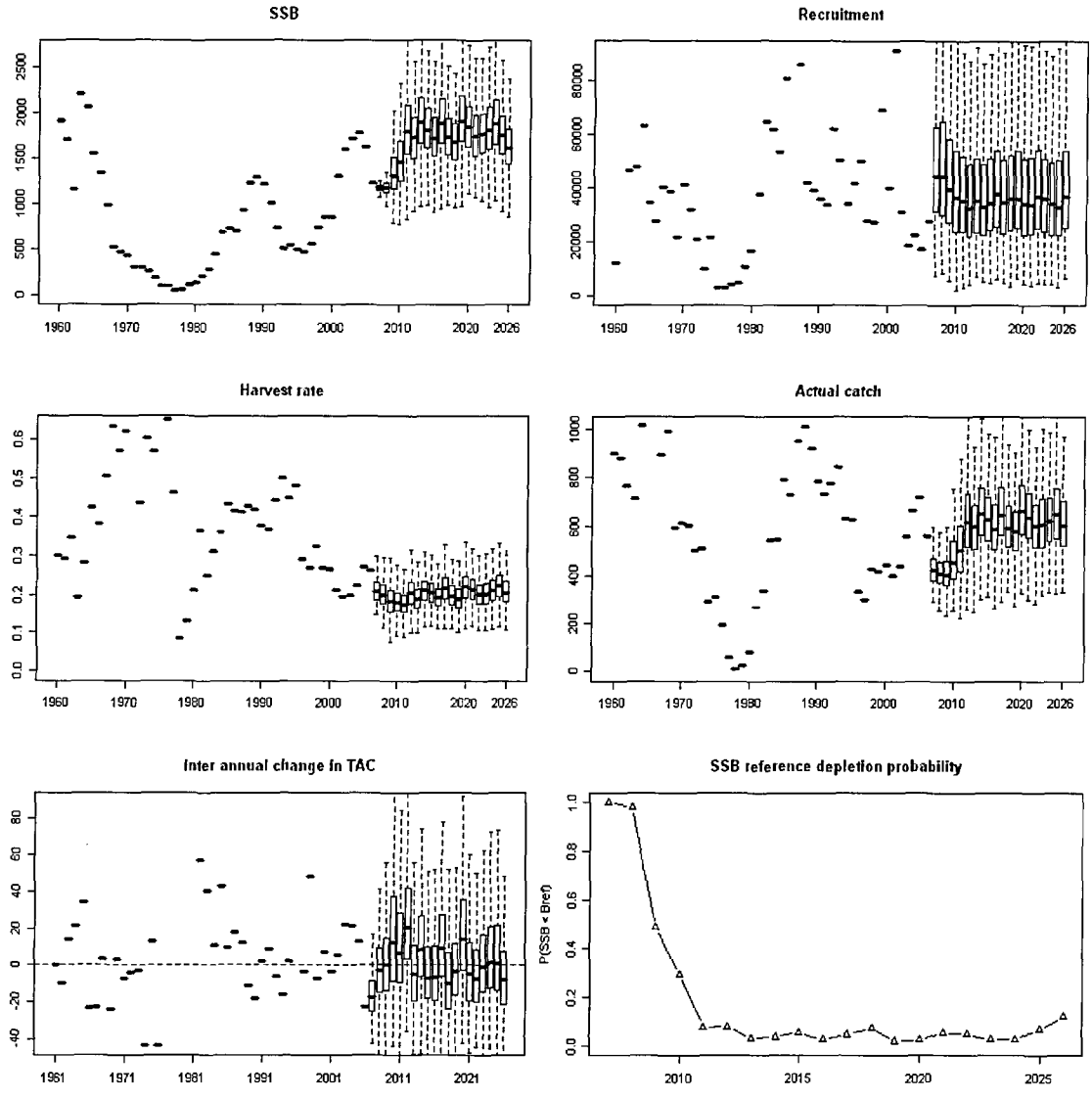


Figure 161: Output of simulation 82.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 10%

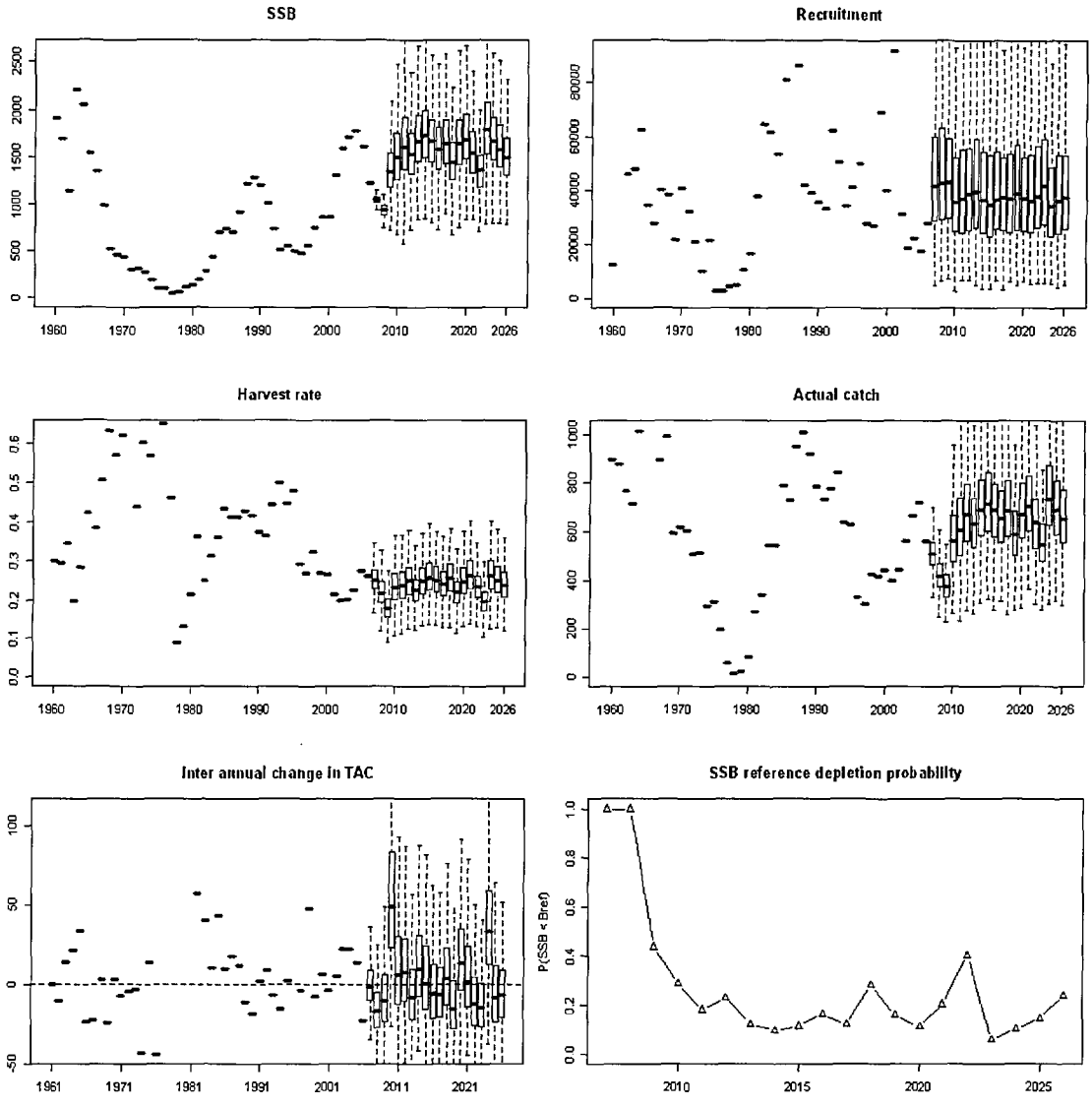


Figure 162: Output of simulation 83.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 30%

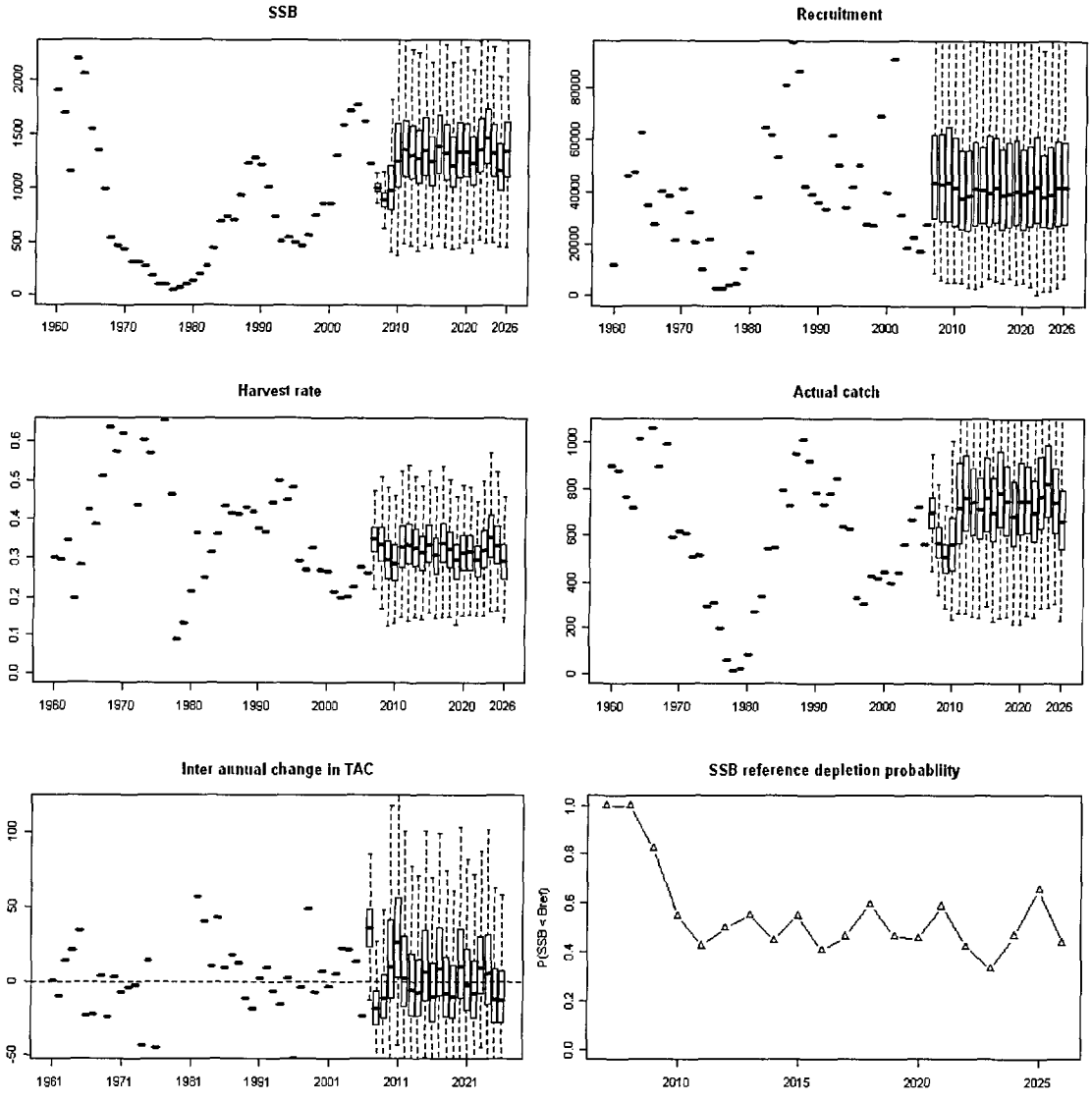


Figure 163: Output of simulation 84.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 80%

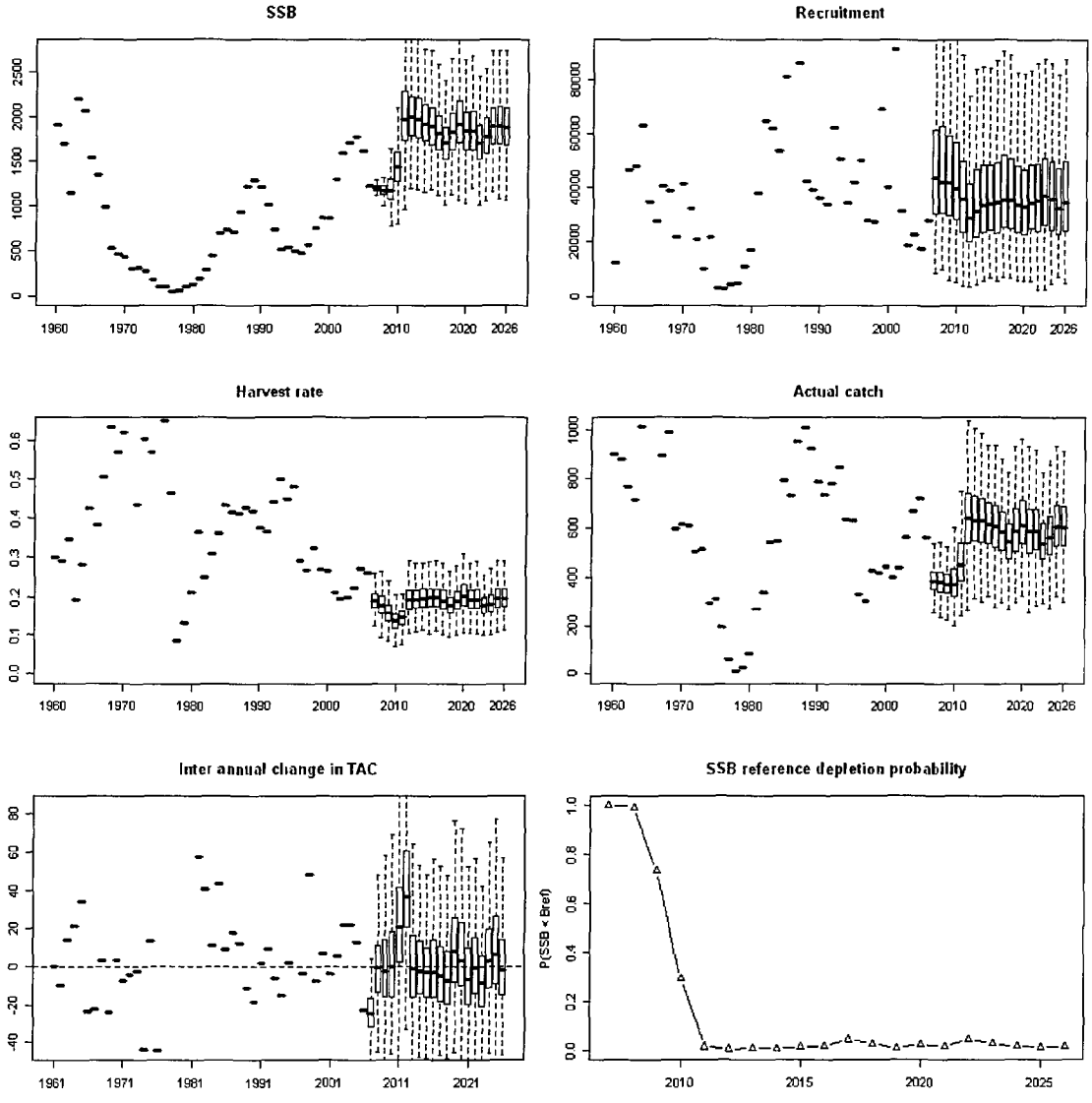


Figure 164: Output of simulation 85.

Stock recruitment: Ricker

Autocorrelation: high

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 0%

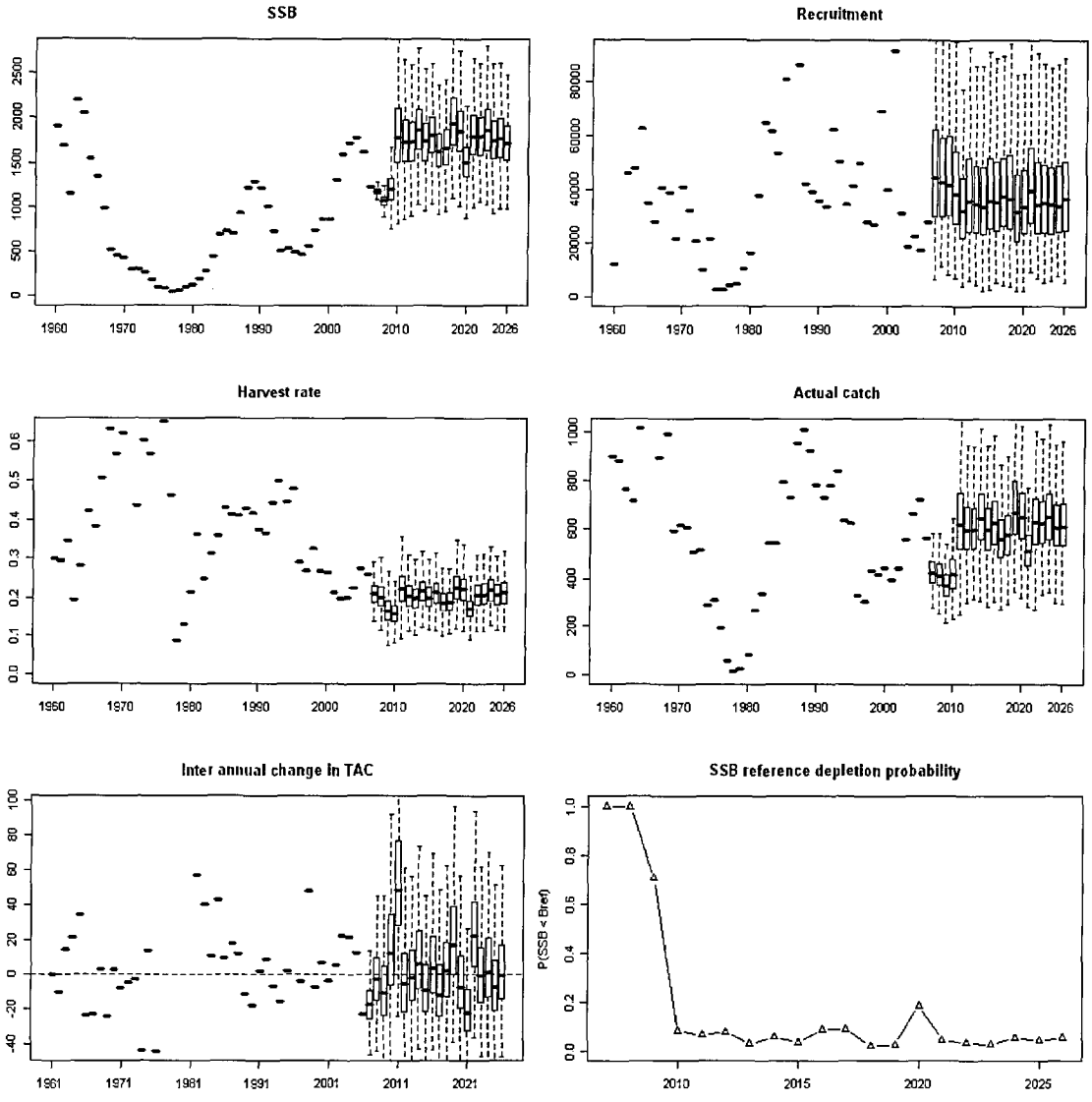


Figure 165: Output of simulation 86.

Stock recruitment: Ricker

Autocorrelation: high

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 10%

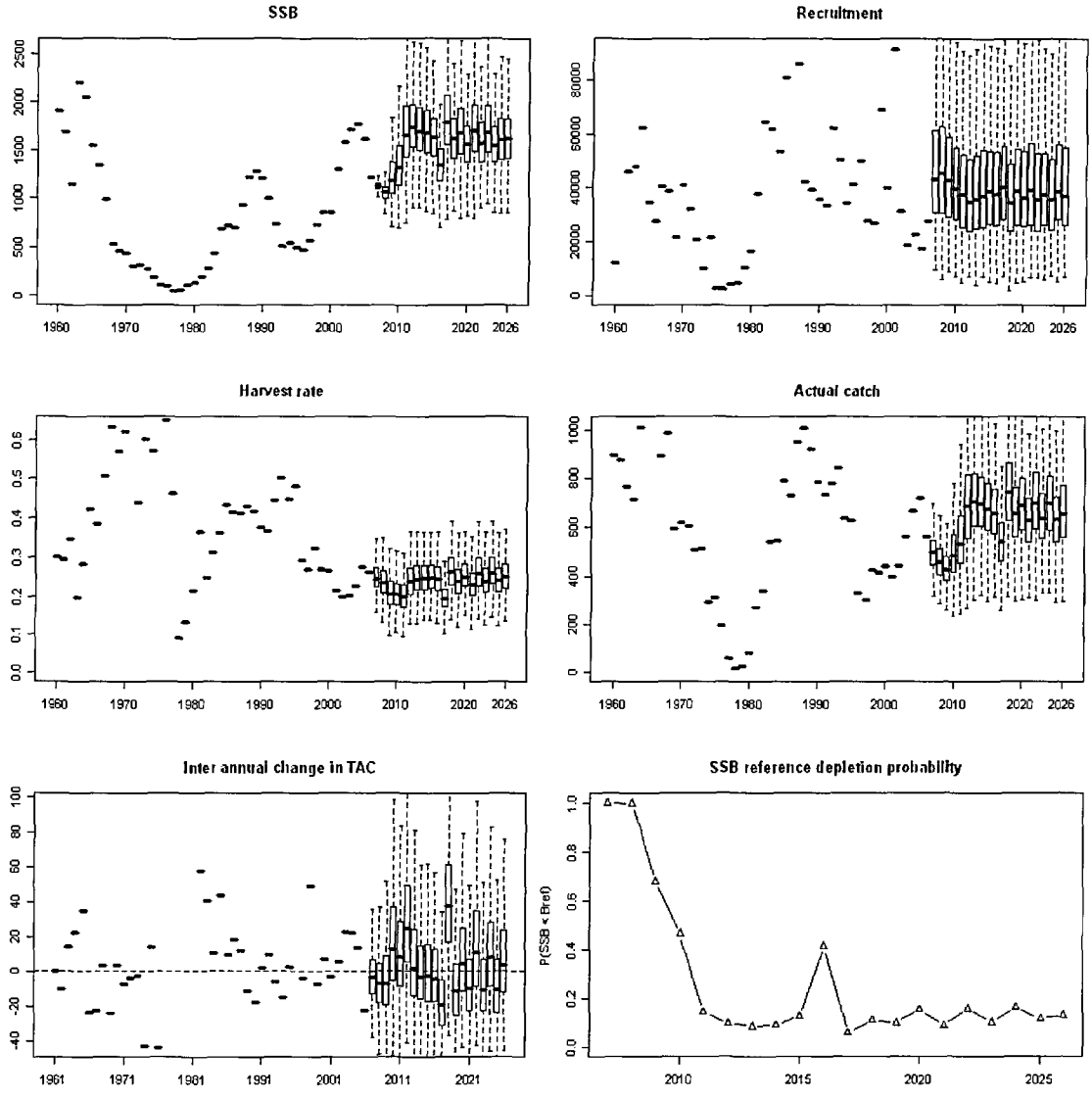


Figure 166: Output of simulation 87.

Stock recruitment: Ricker

Autocorrelation: high

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 30%

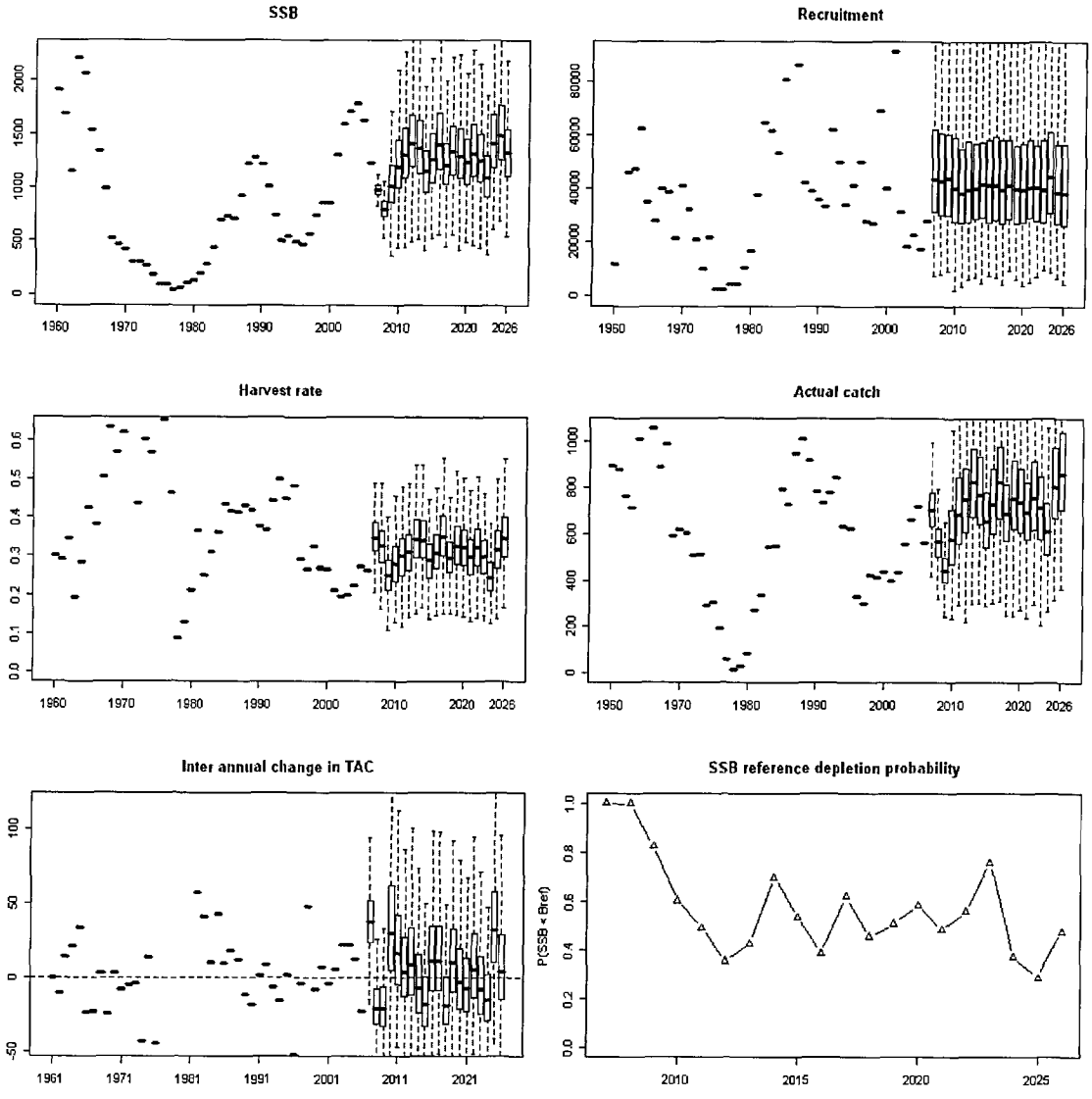


Figure 167: Output of simulation 88.

Stock recruitment: Ricker

Autocorrelation: high

Survey: combined SSB with observation error

Assessment: none

Harvest control rule: Comb SSB

Limitation of variation: none

Implementation error: 80%

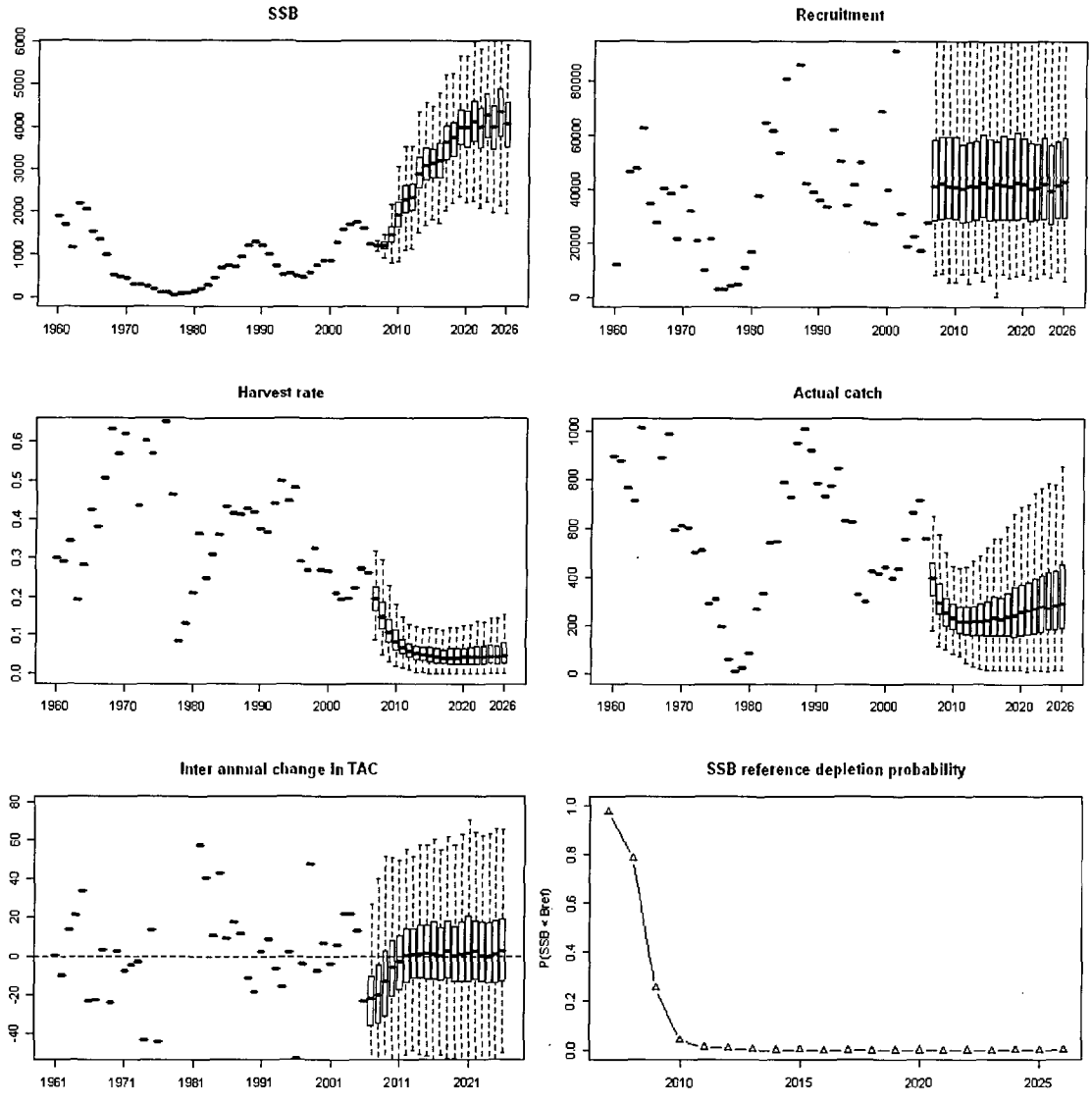


Figure 168: Output of simulation 89.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

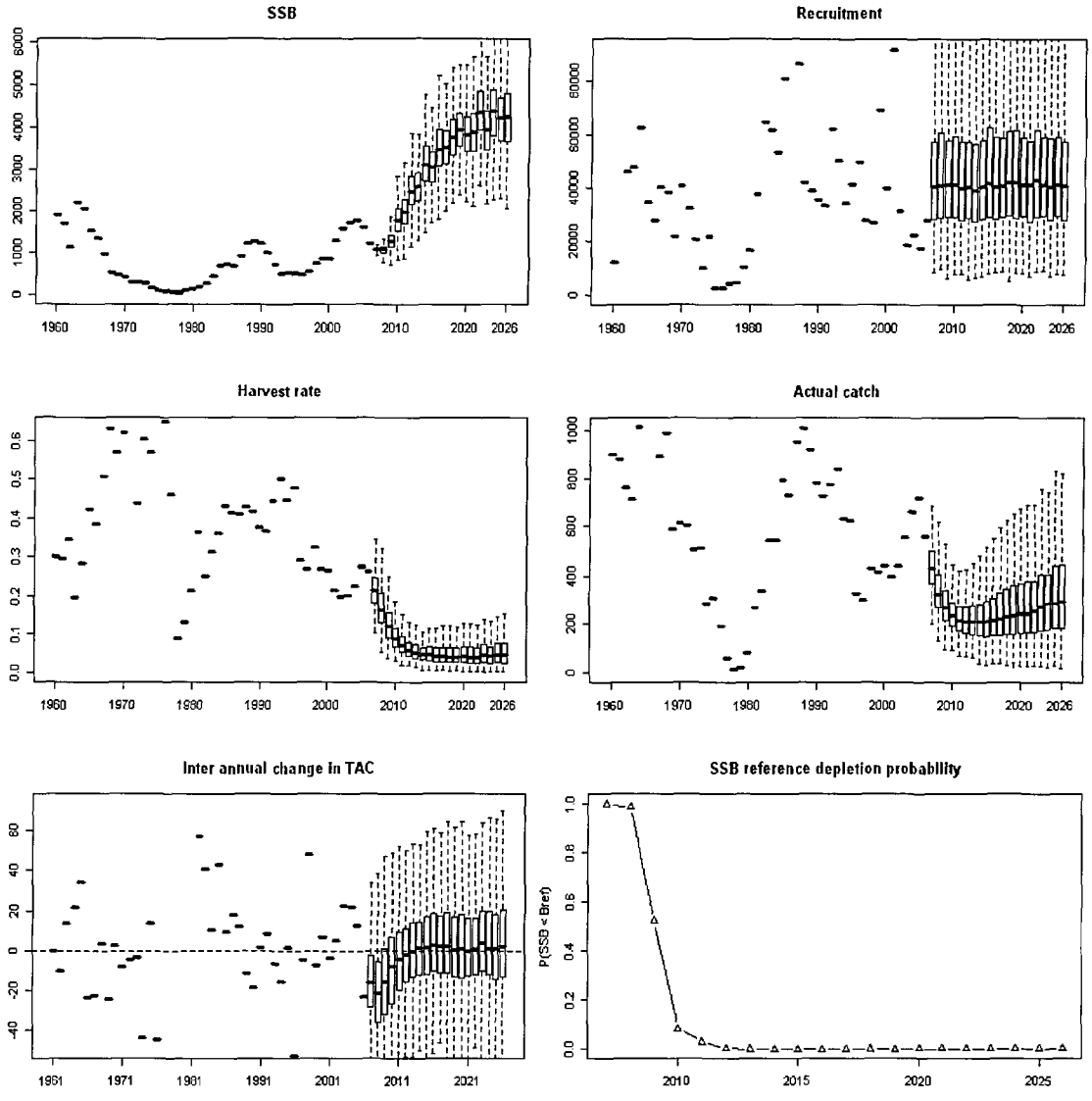


Figure 169: Output of simulation 90.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

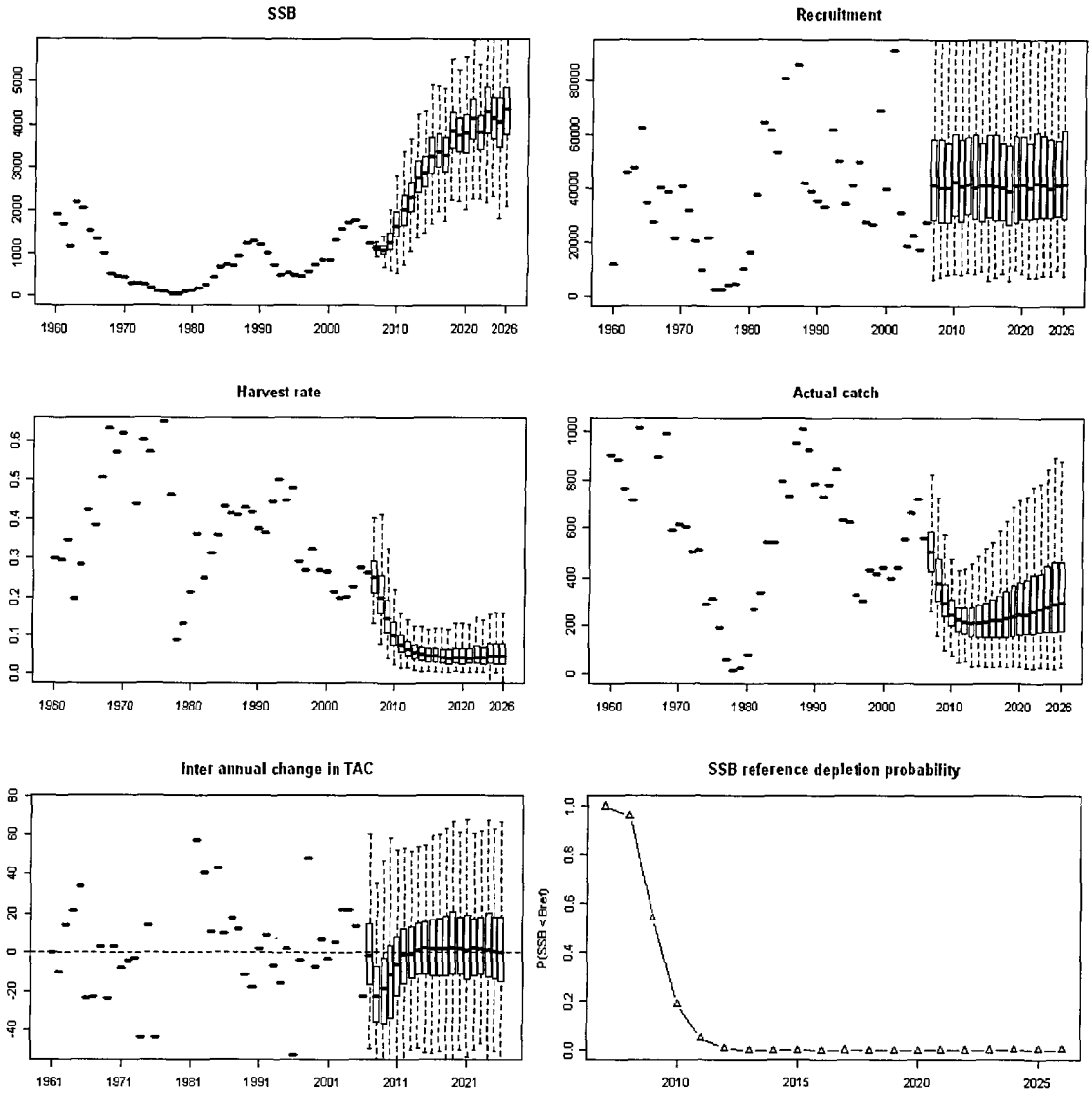


Figure 170: Output of simulation 91.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

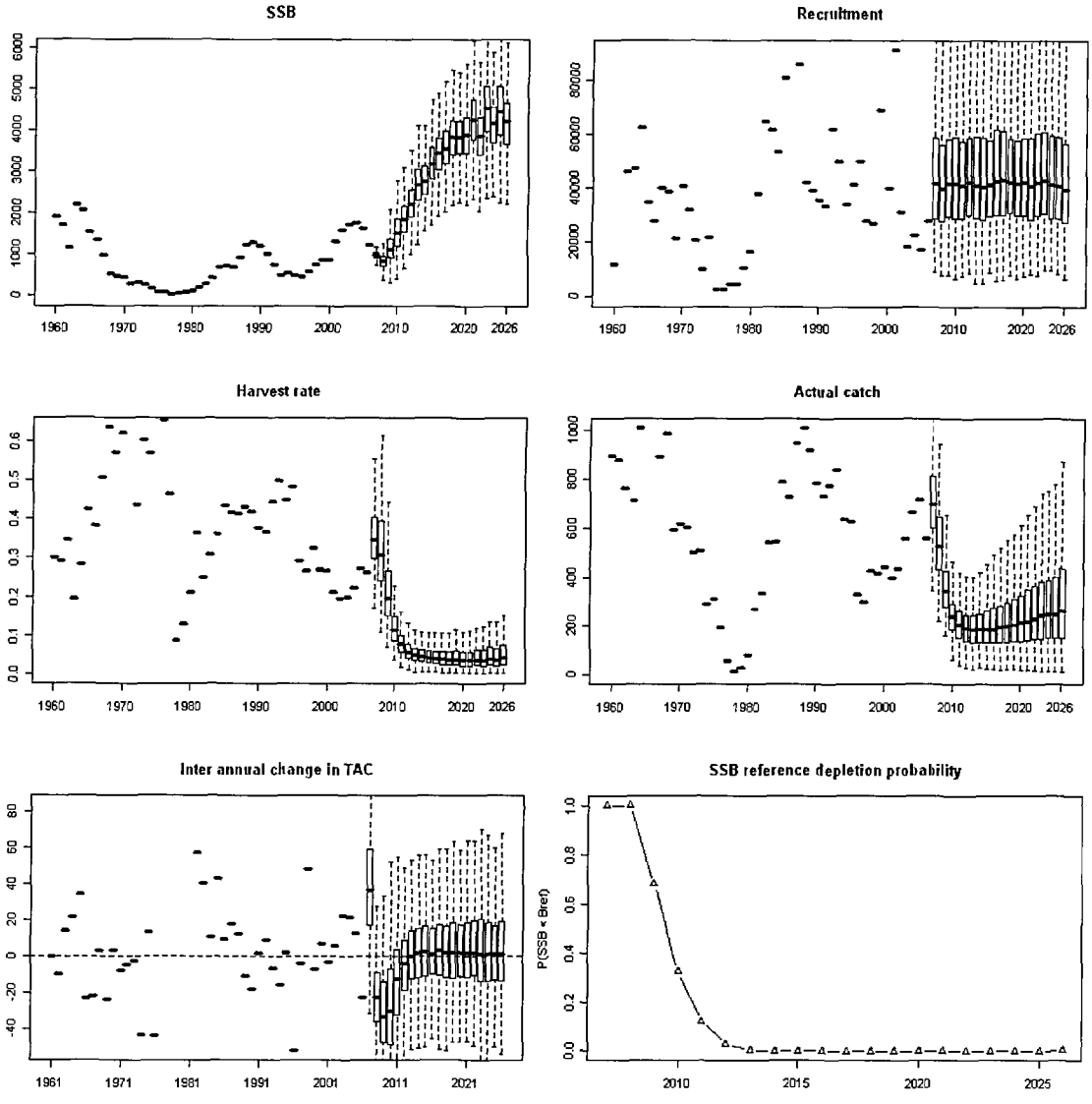


Figure 171: Output of simulation 92.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

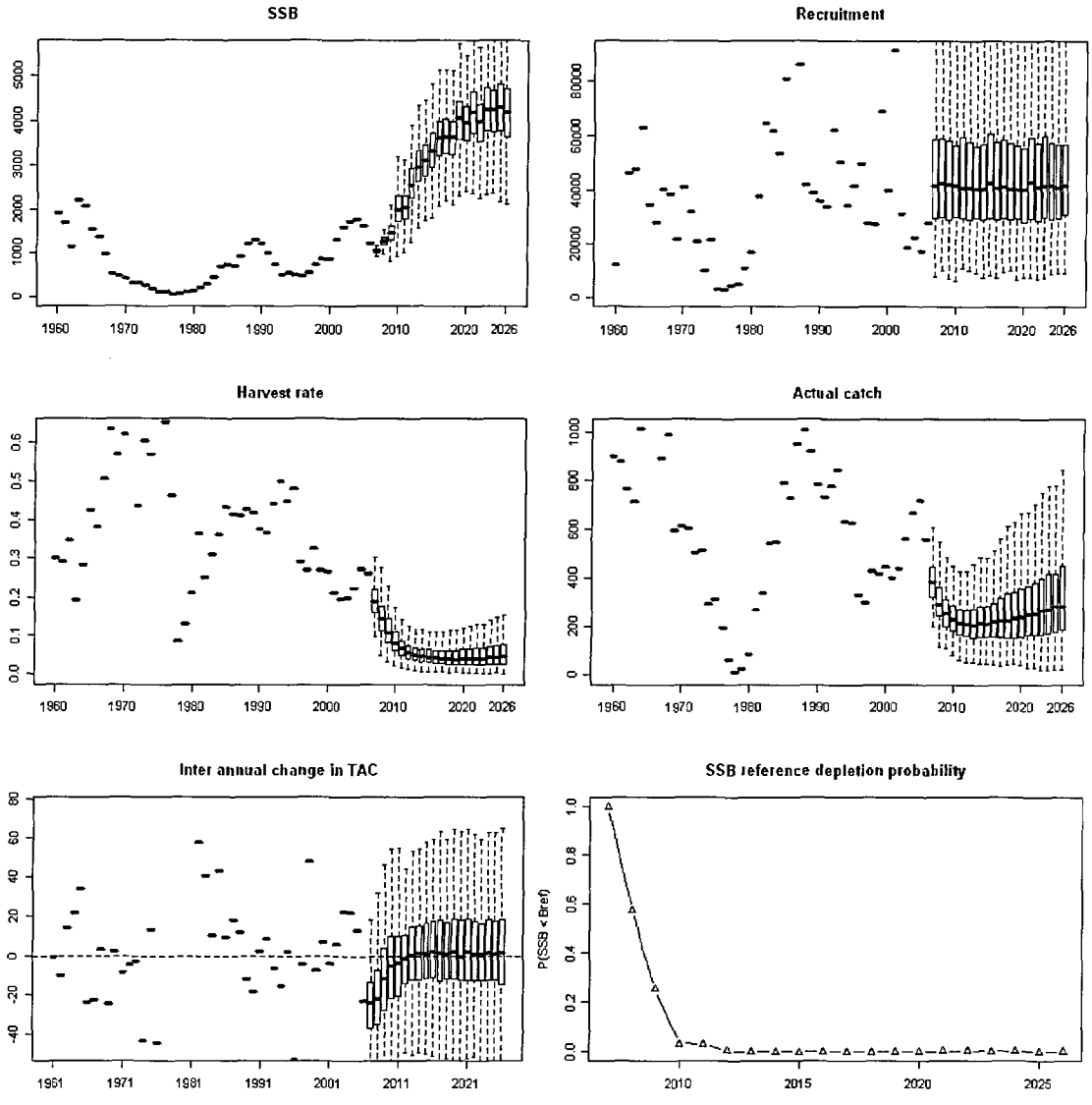


Figure 172: Output of simulation 93.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

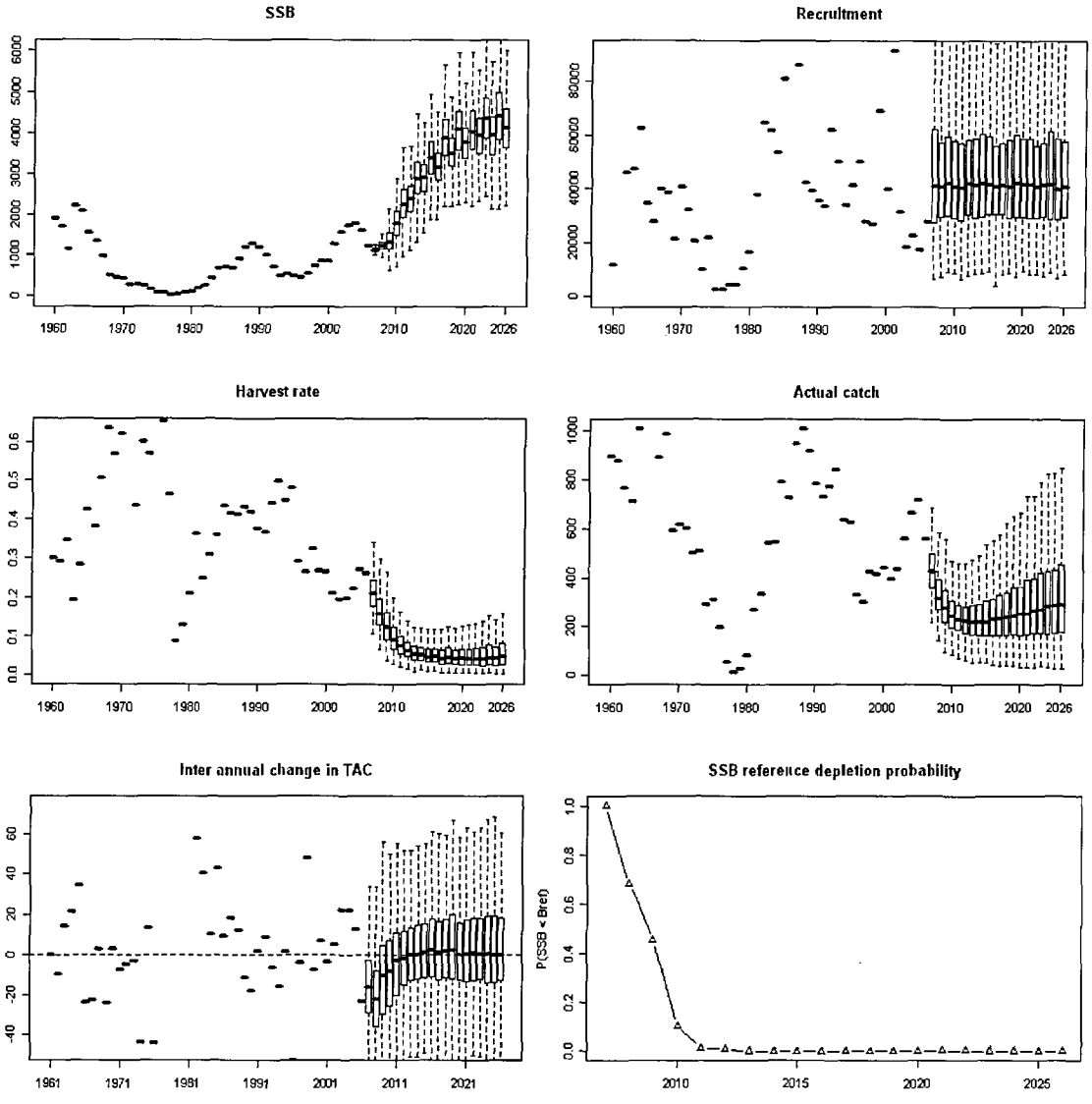


Figure 173: Output of simulation 94.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

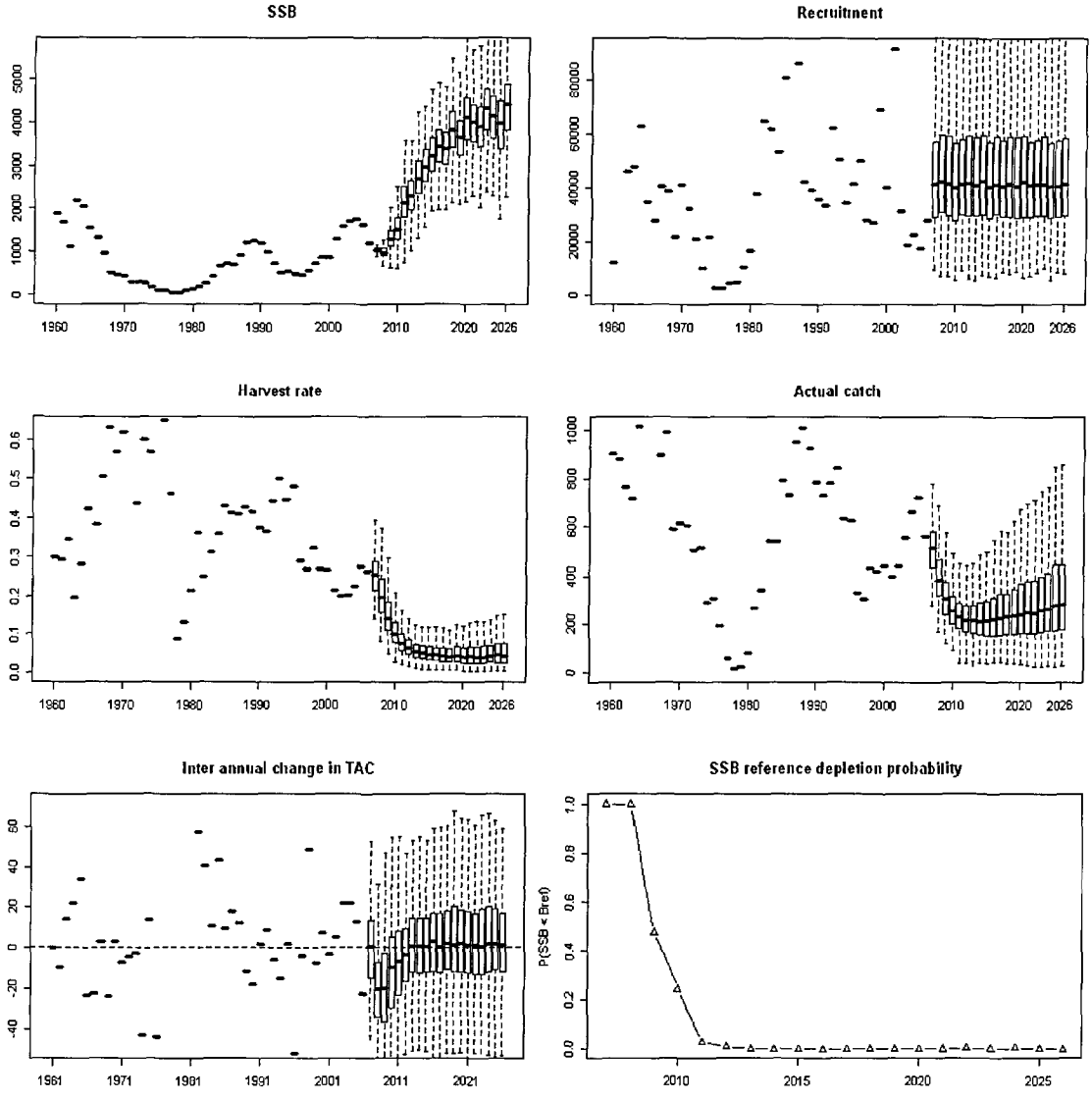


Figure 174: Output of simulation 95.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

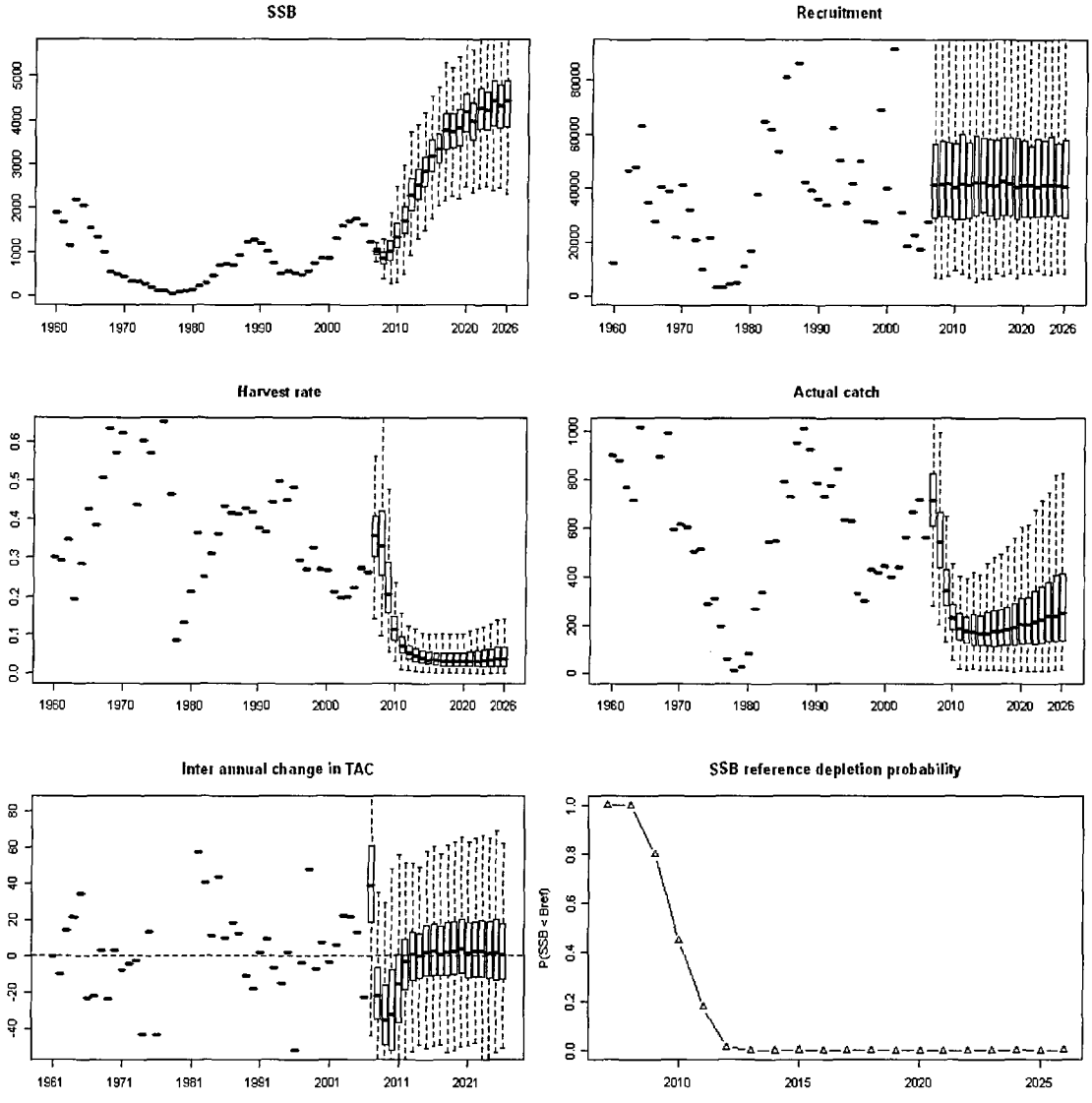


Figure 175: Output of simulation 96.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

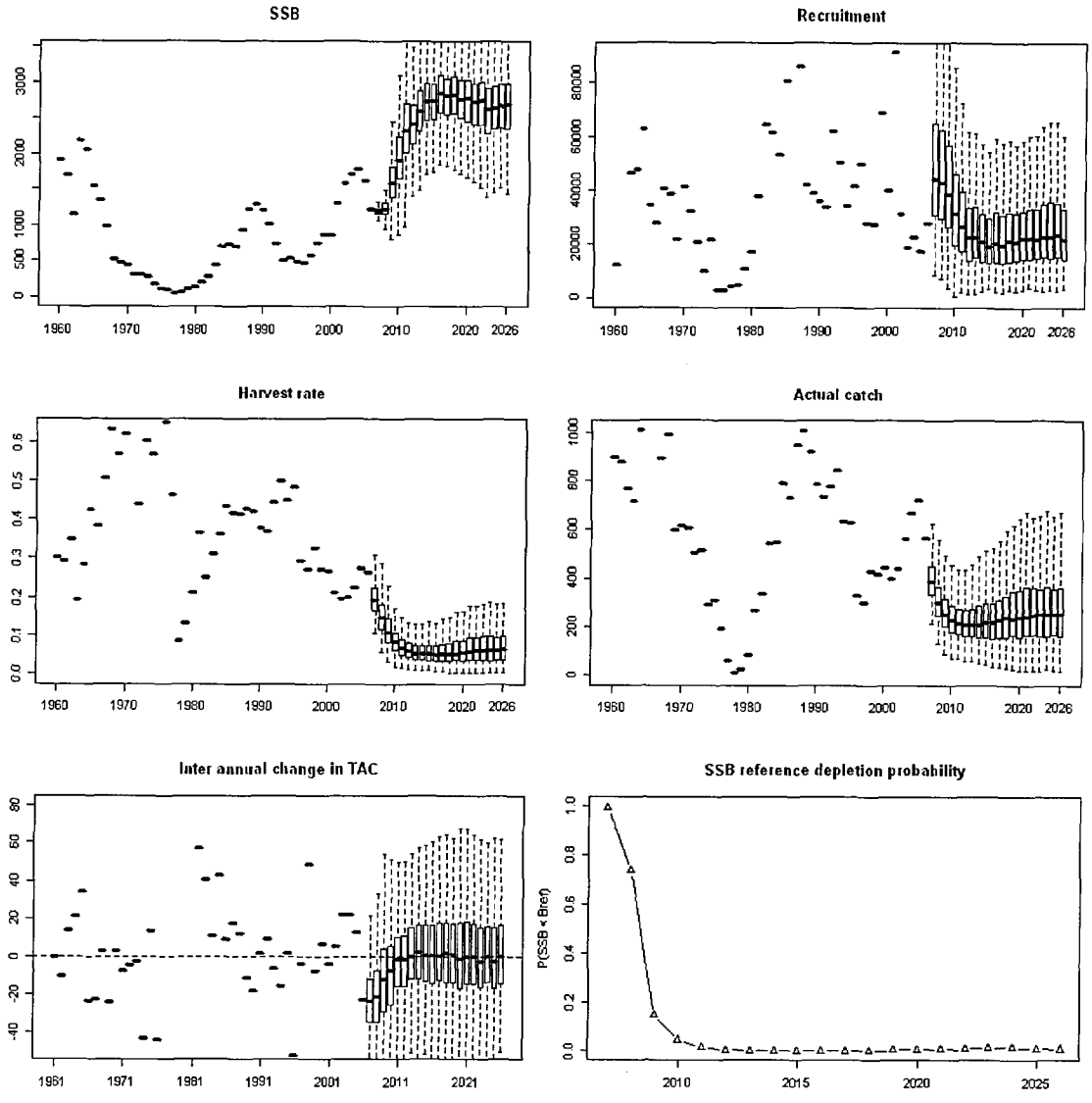


Figure 176: Output of simulation 97.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

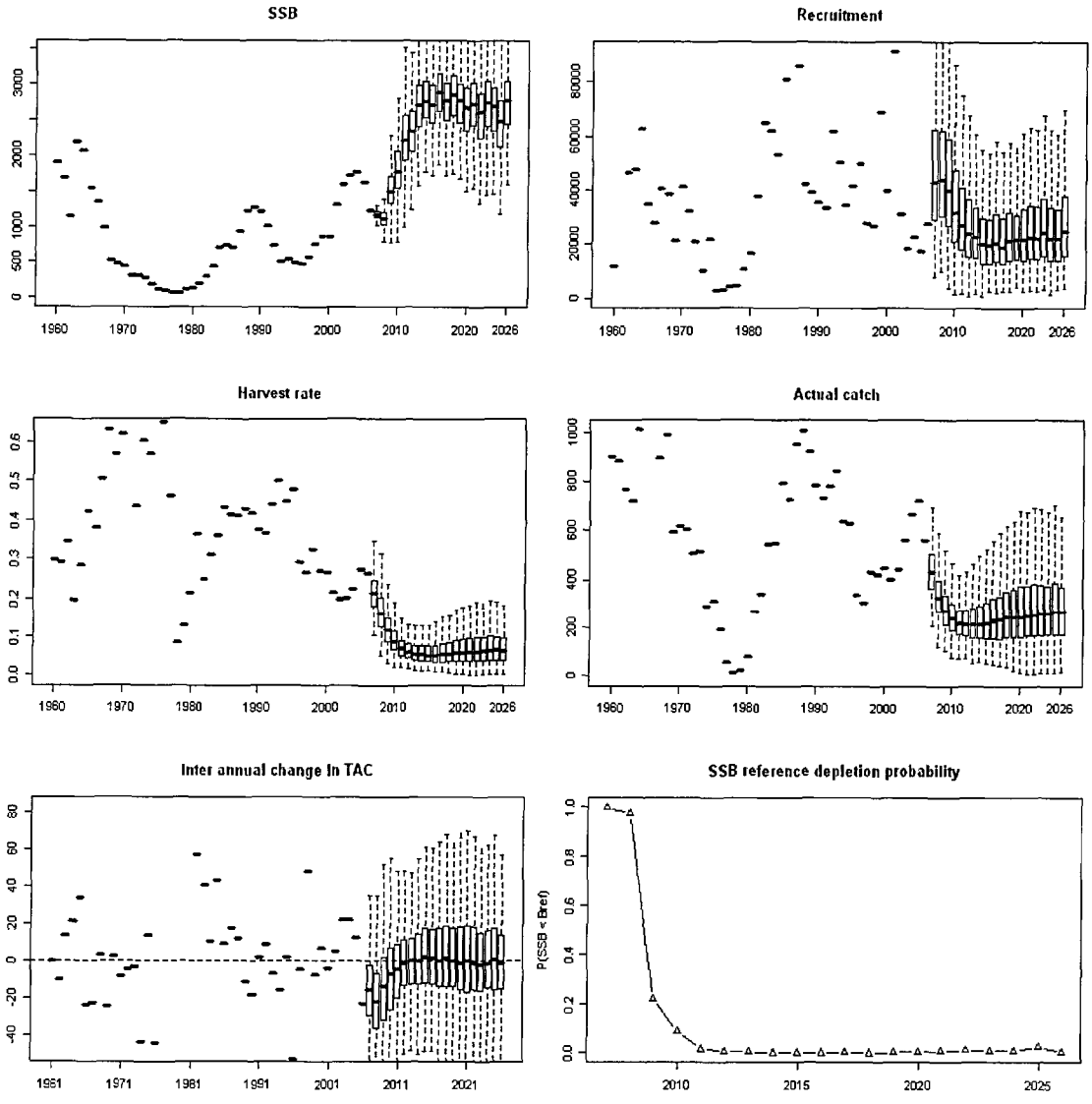


Figure 177: Output of simulation 98.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

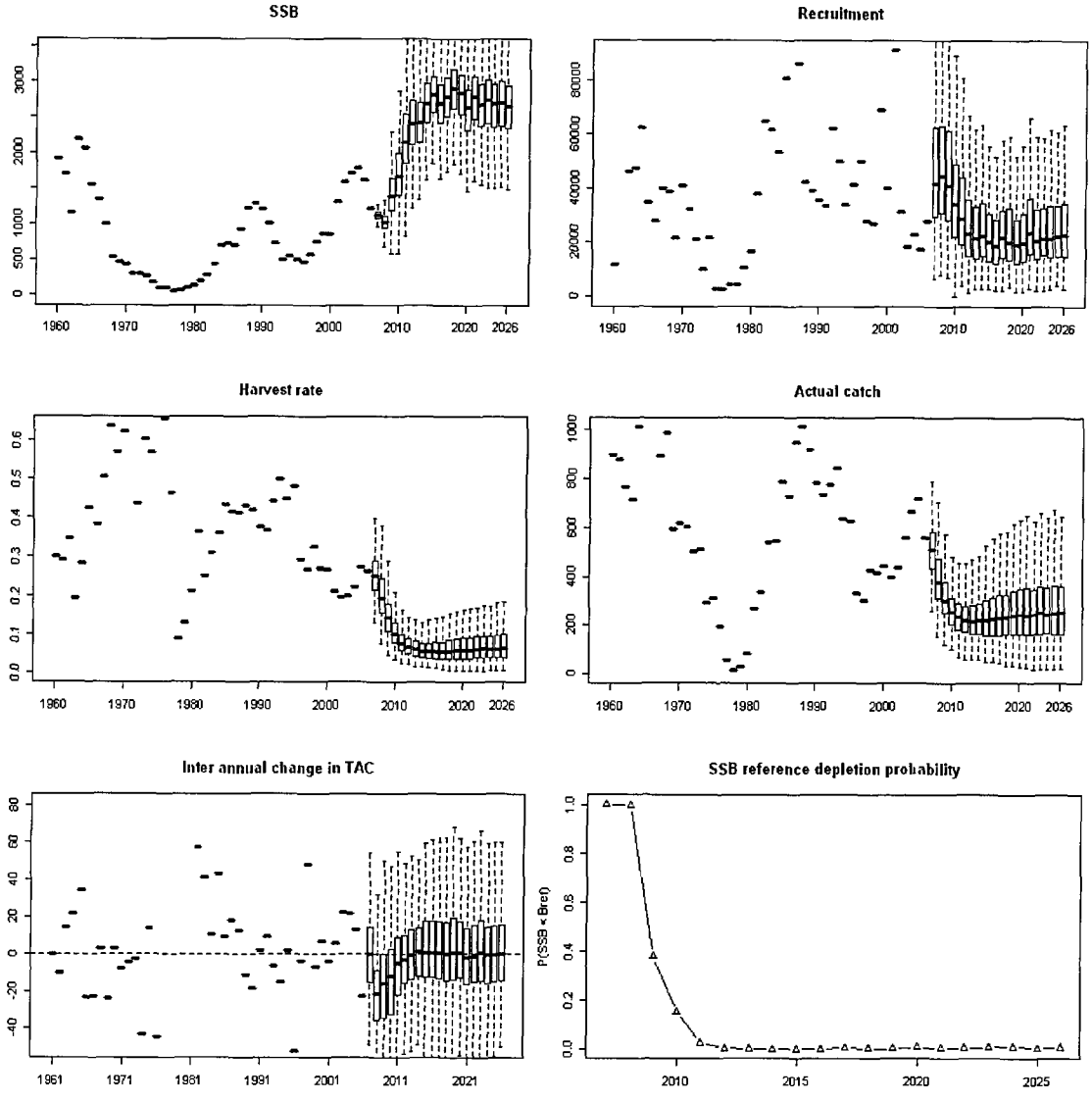


Figure 178: Output of simulation 99.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

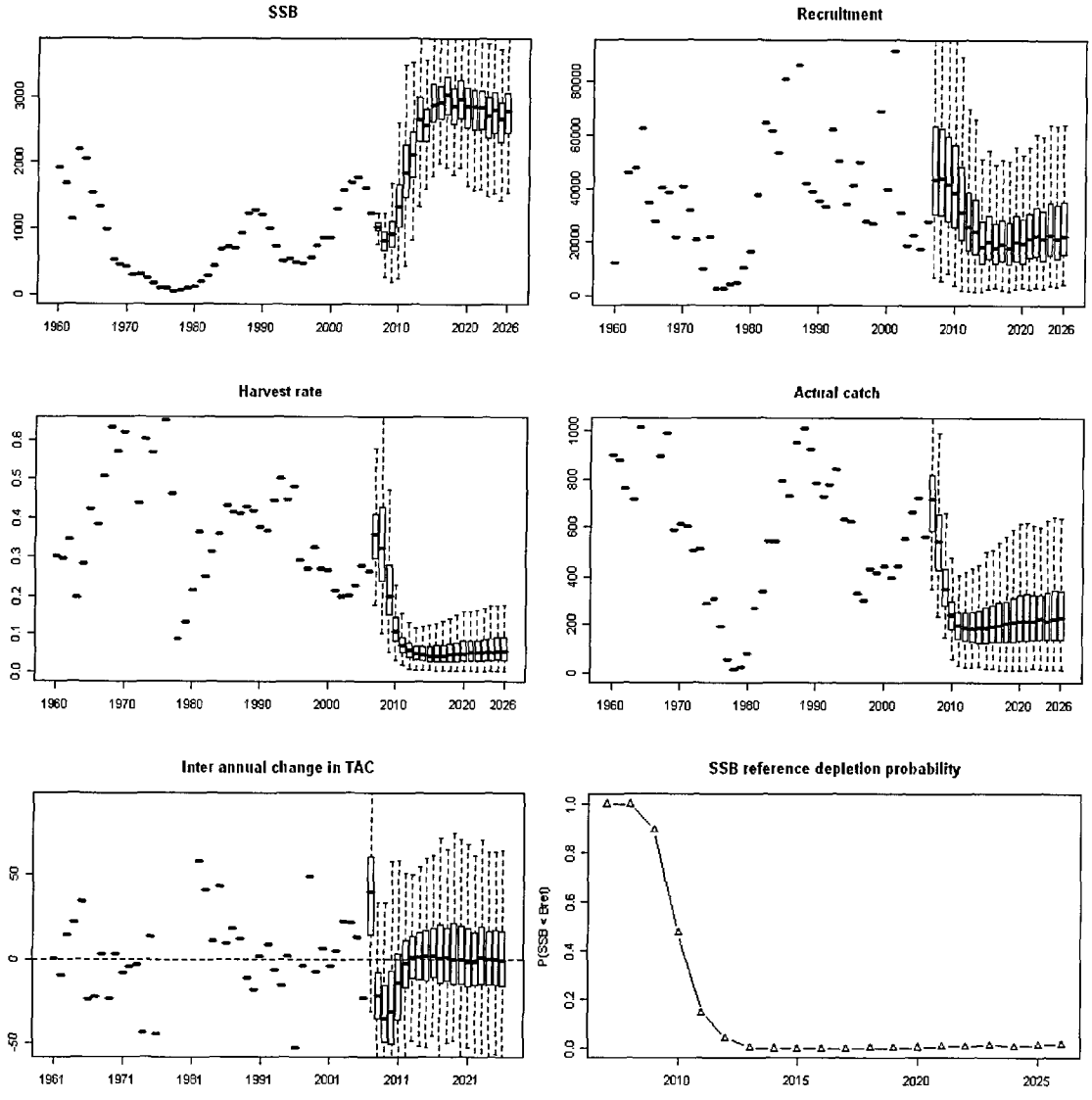


Figure 179: Output of simulation 100.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

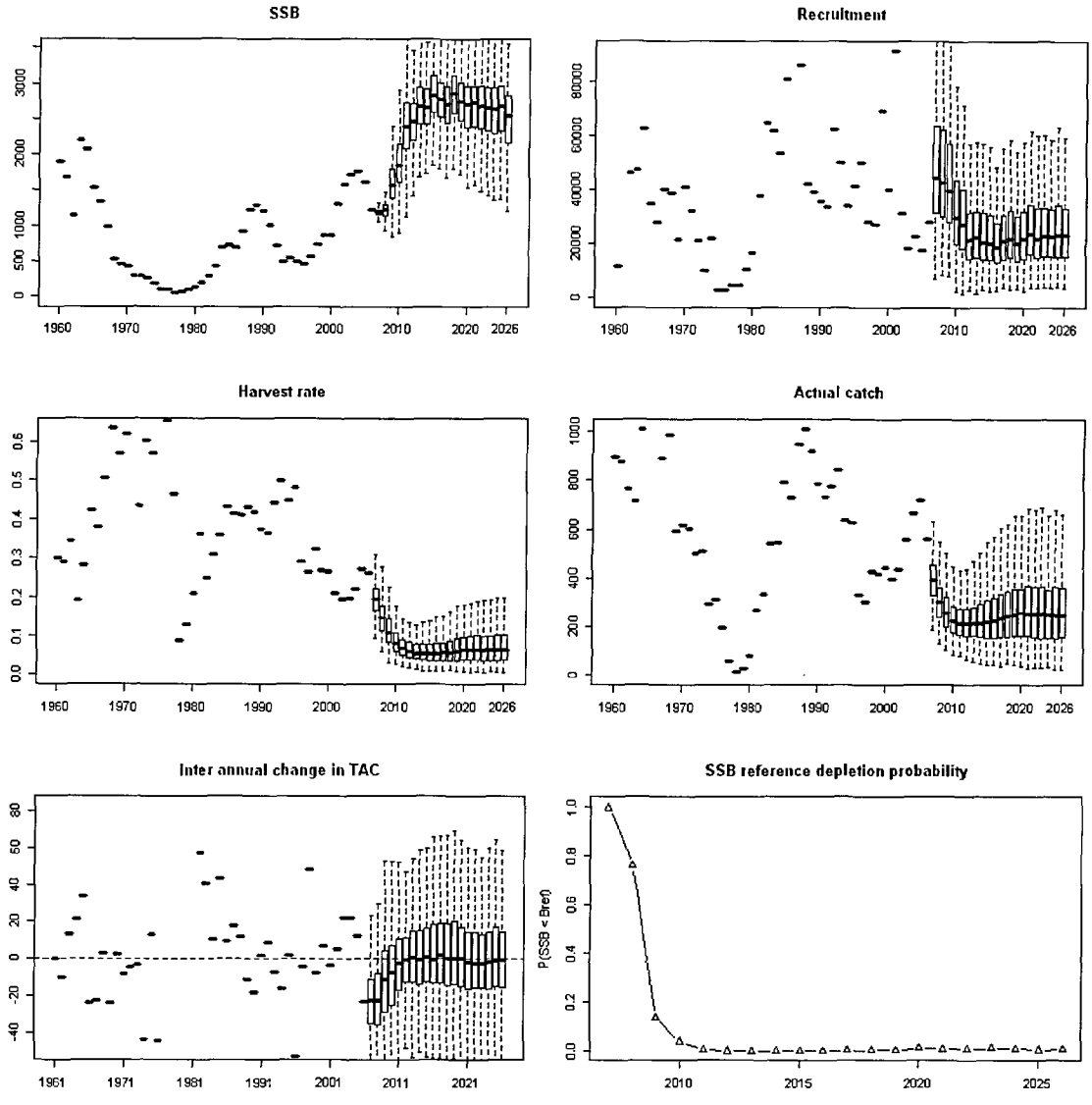


Figure 180: Output of simulation 101.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

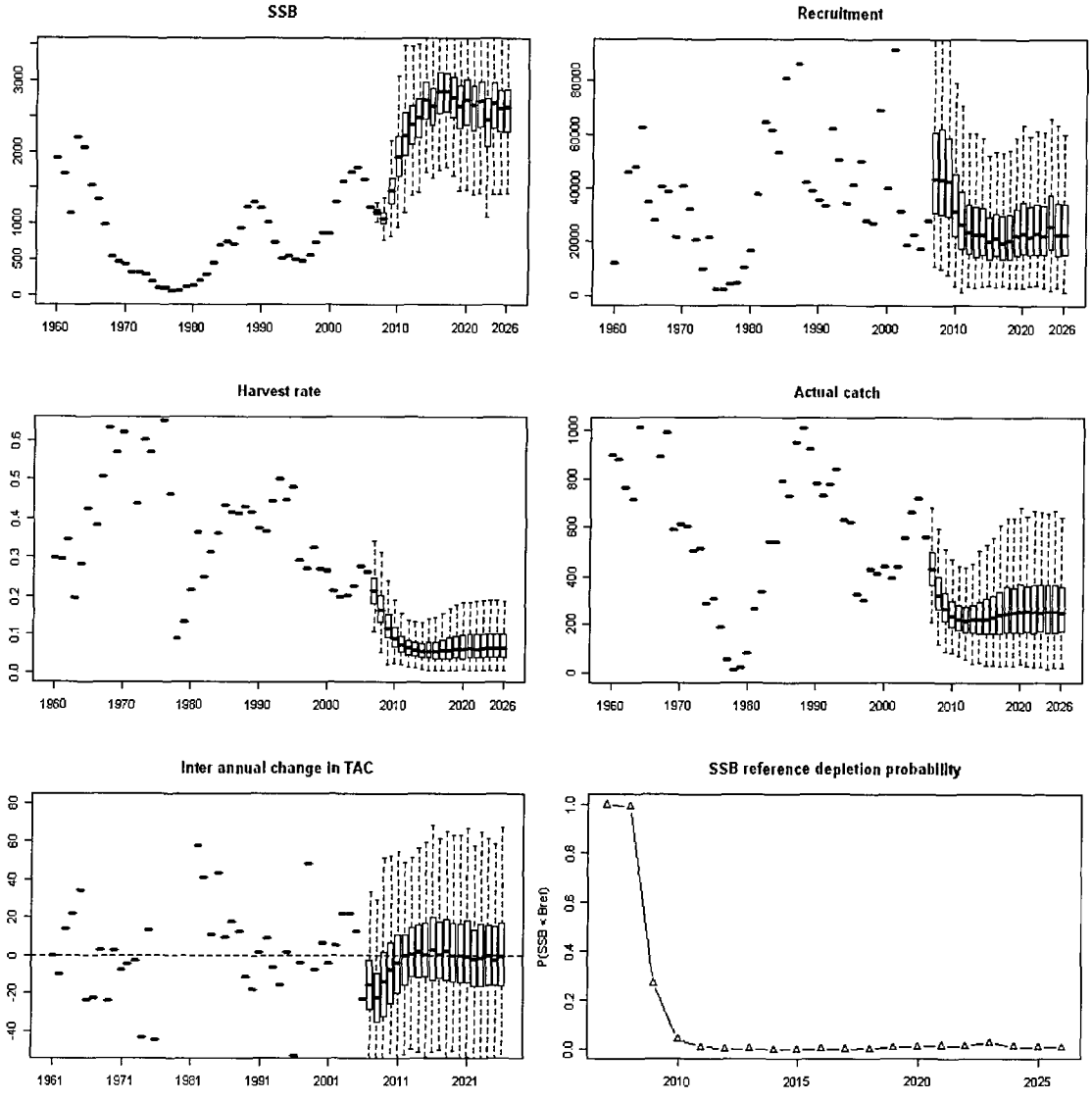


Figure 181: Output of simulation 102.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

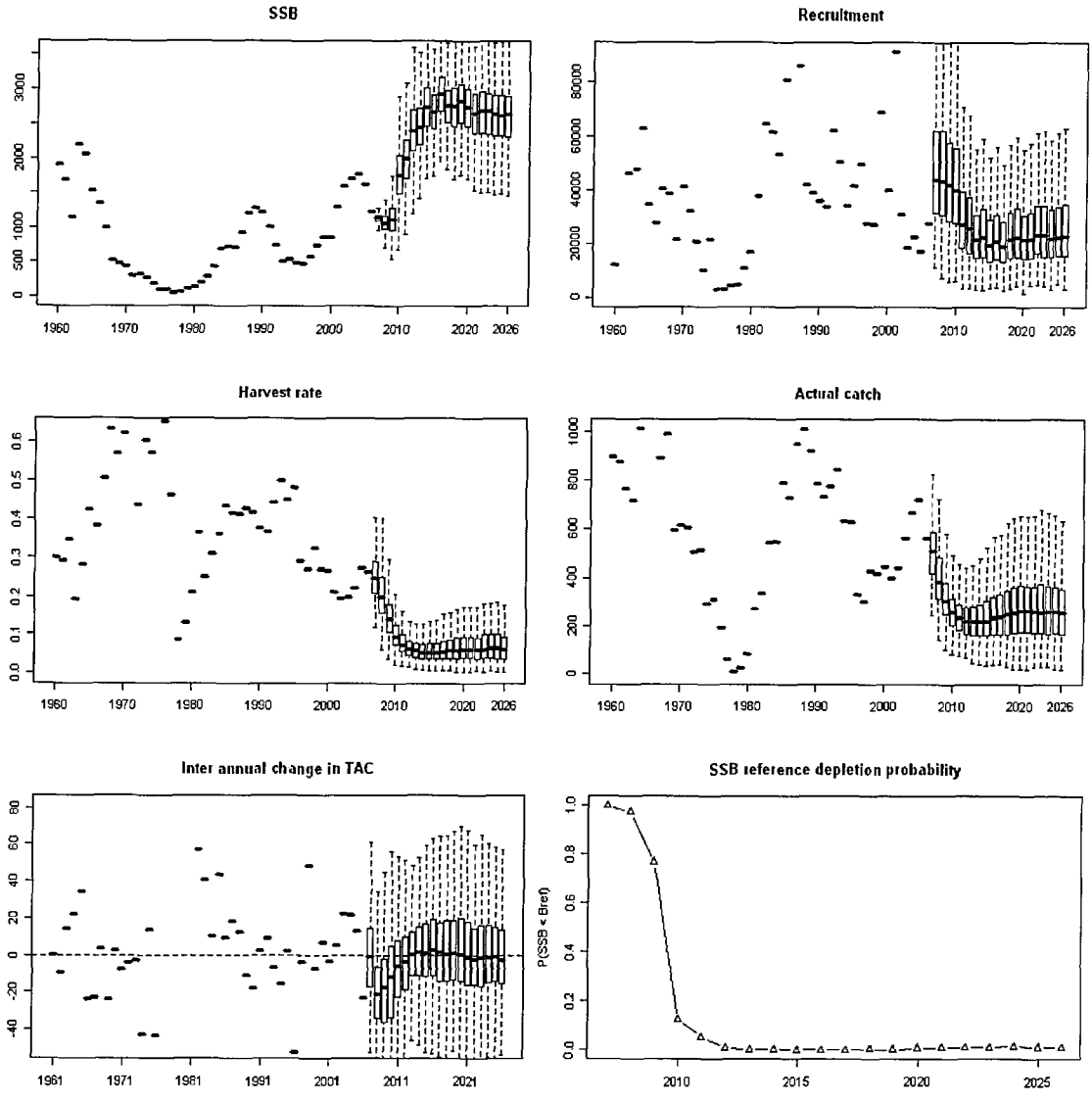


Figure 182: Output of simulation 103.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

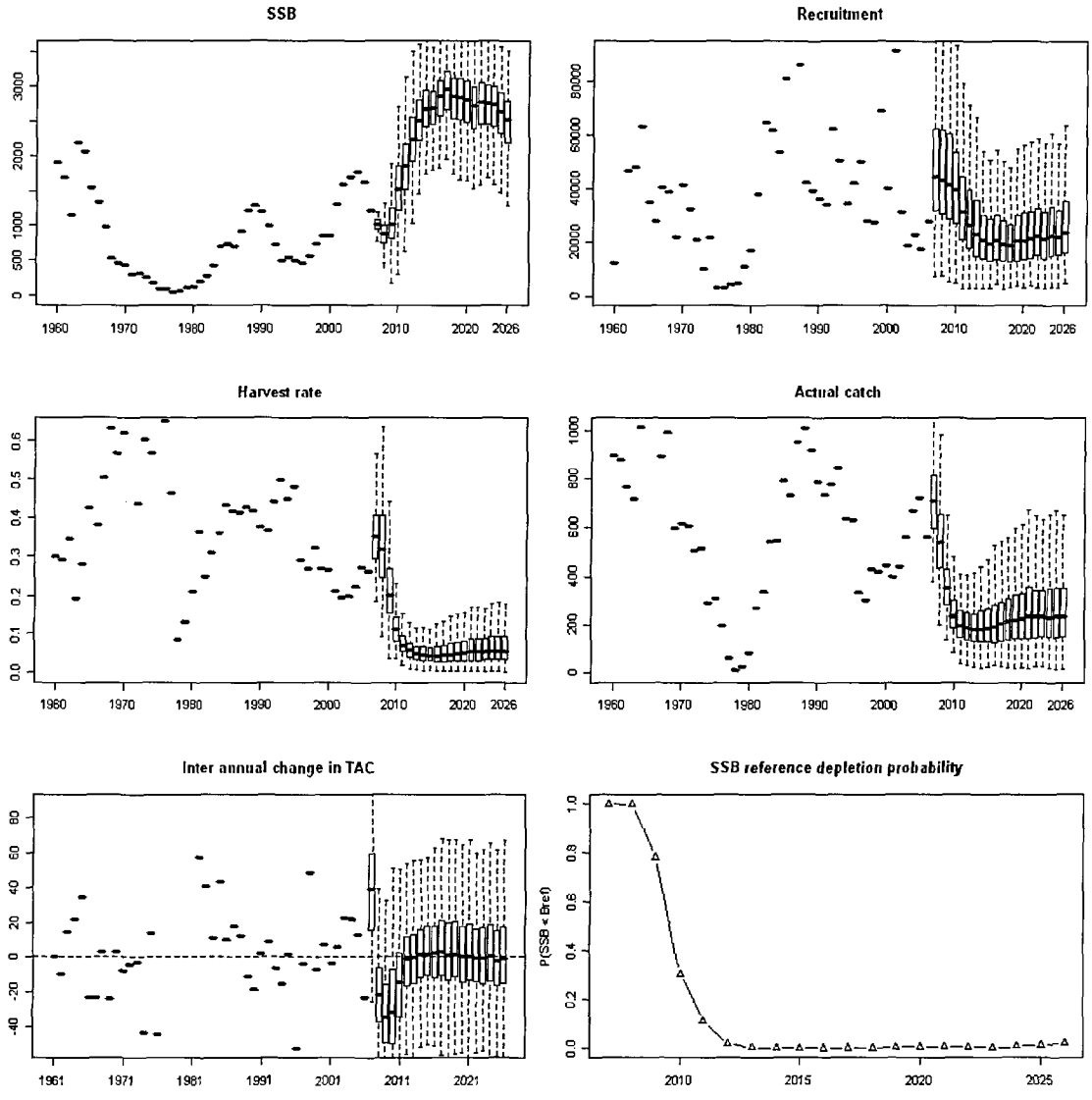


Figure 183: Output of simulation 104.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

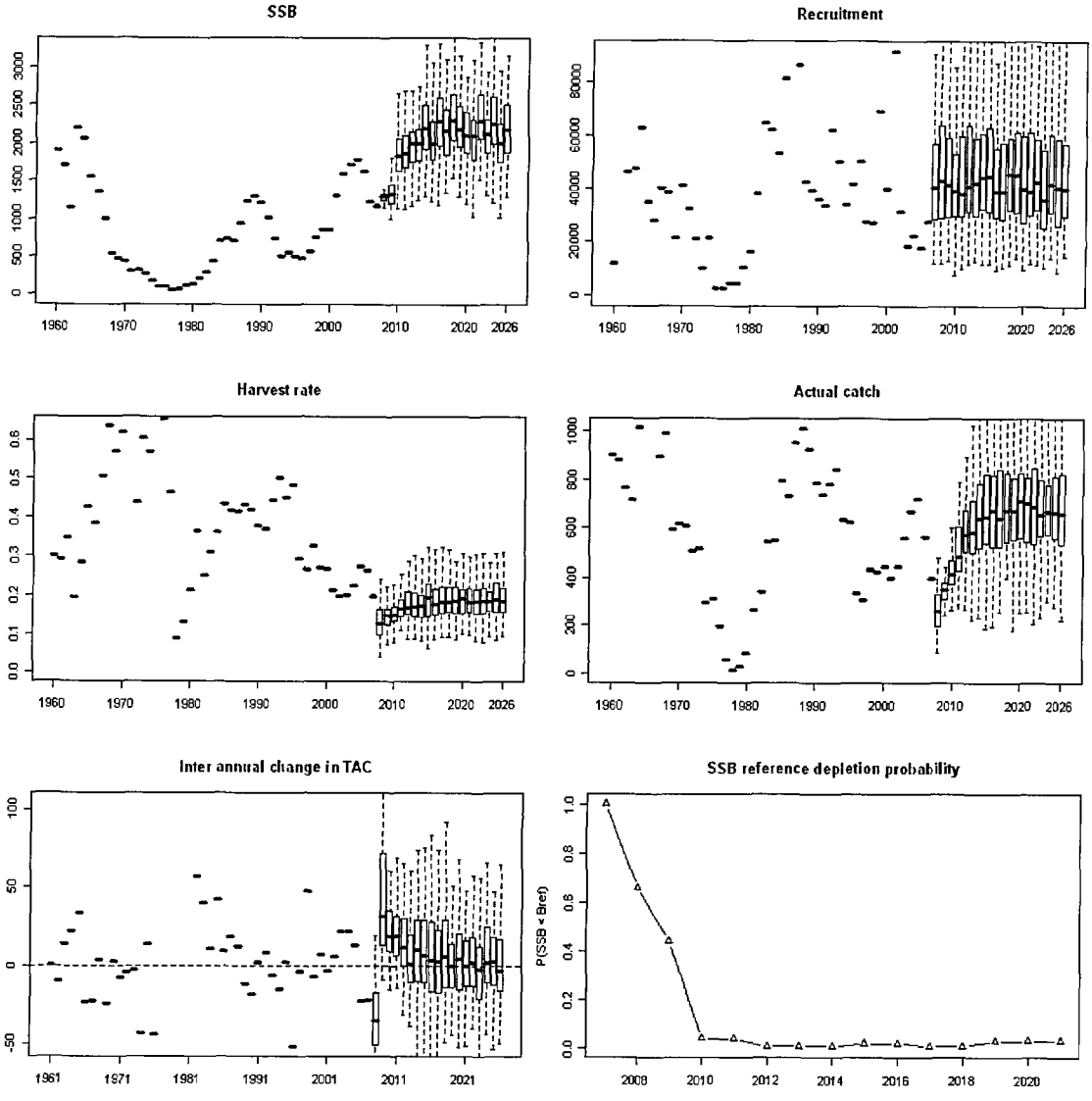


Figure 184: Output of simulation 105.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 0%

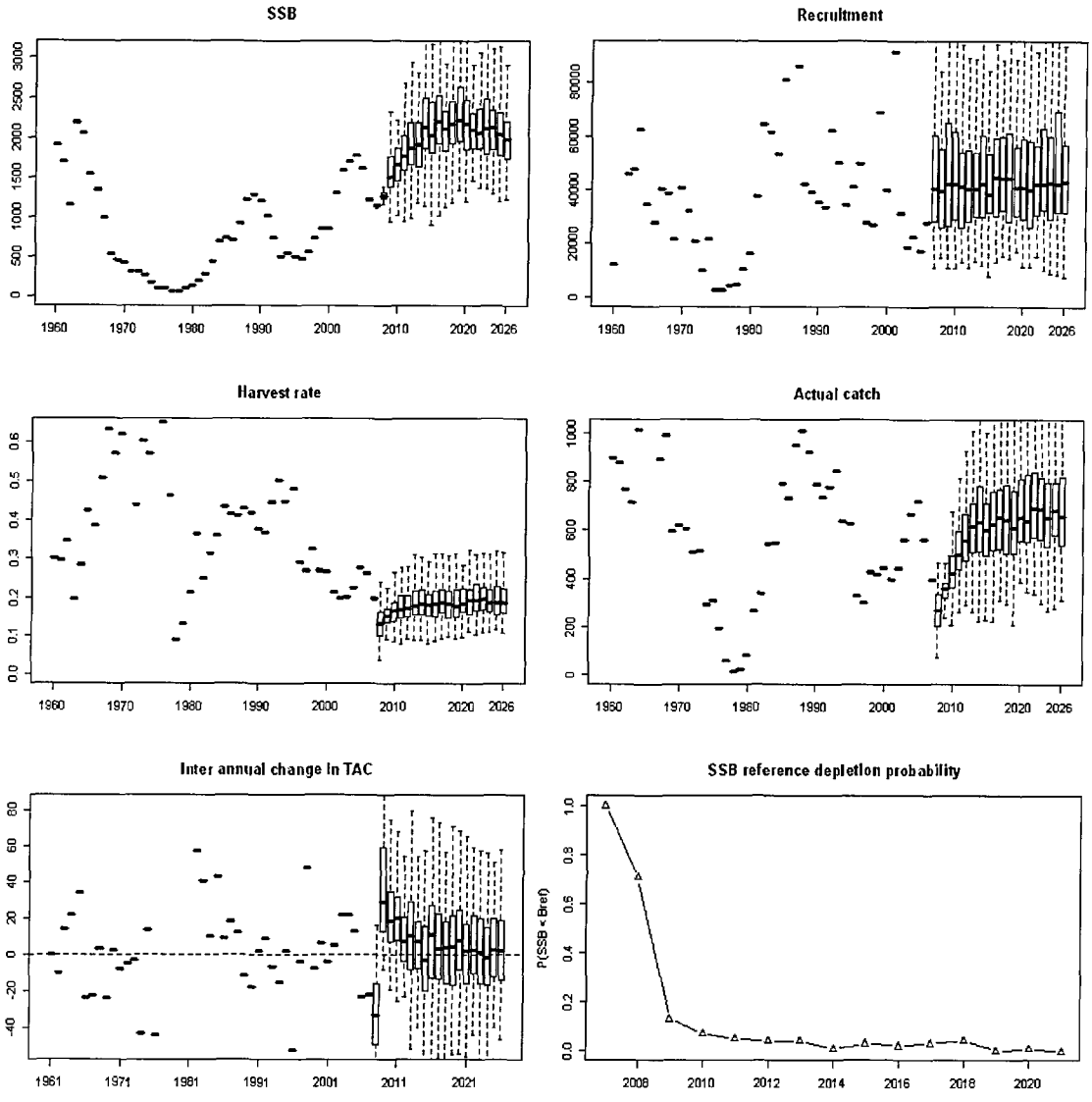


Figure 185: Output of simulation 106.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 0%

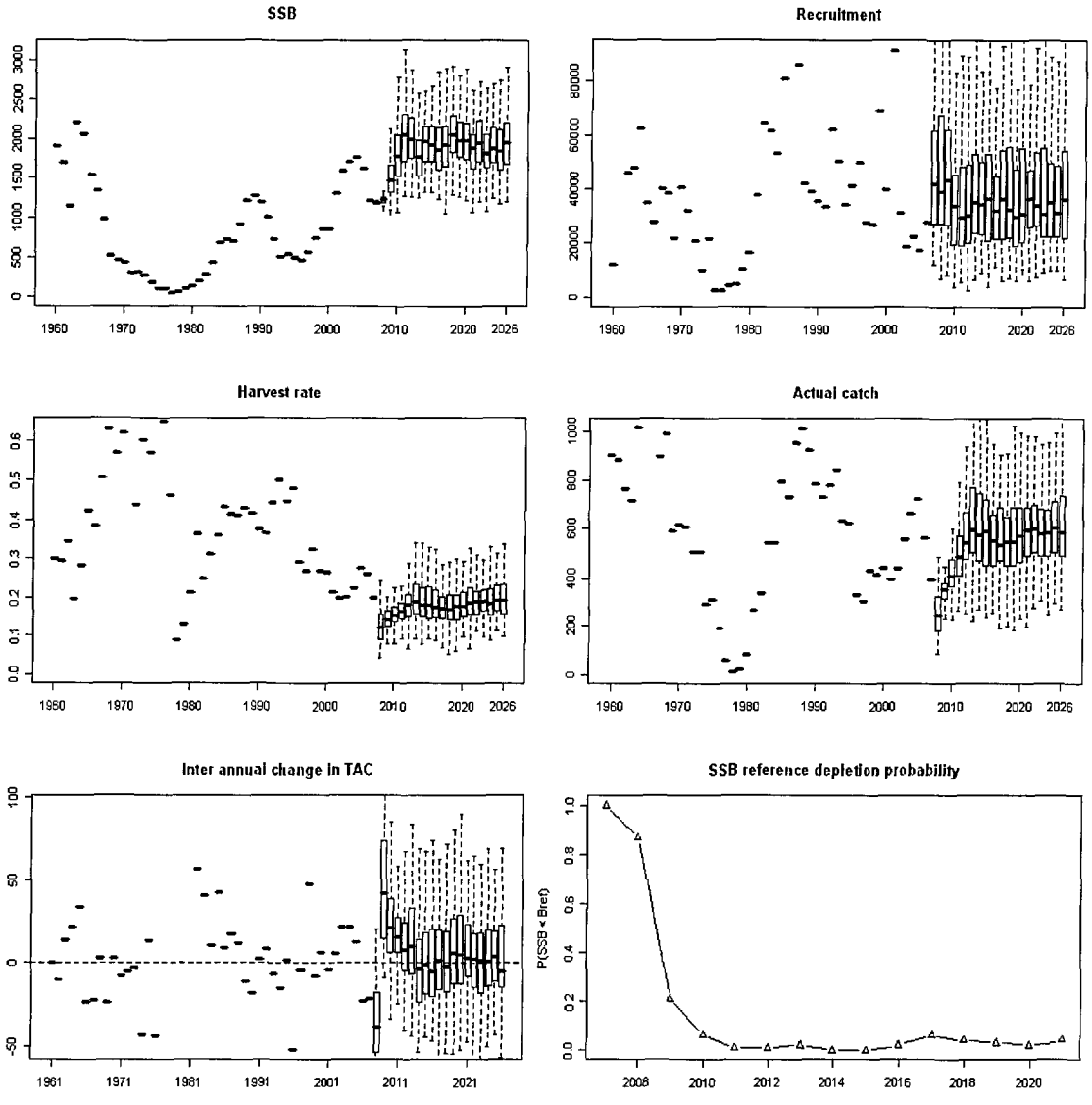


Figure 186: Output of simulation 107.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 0%

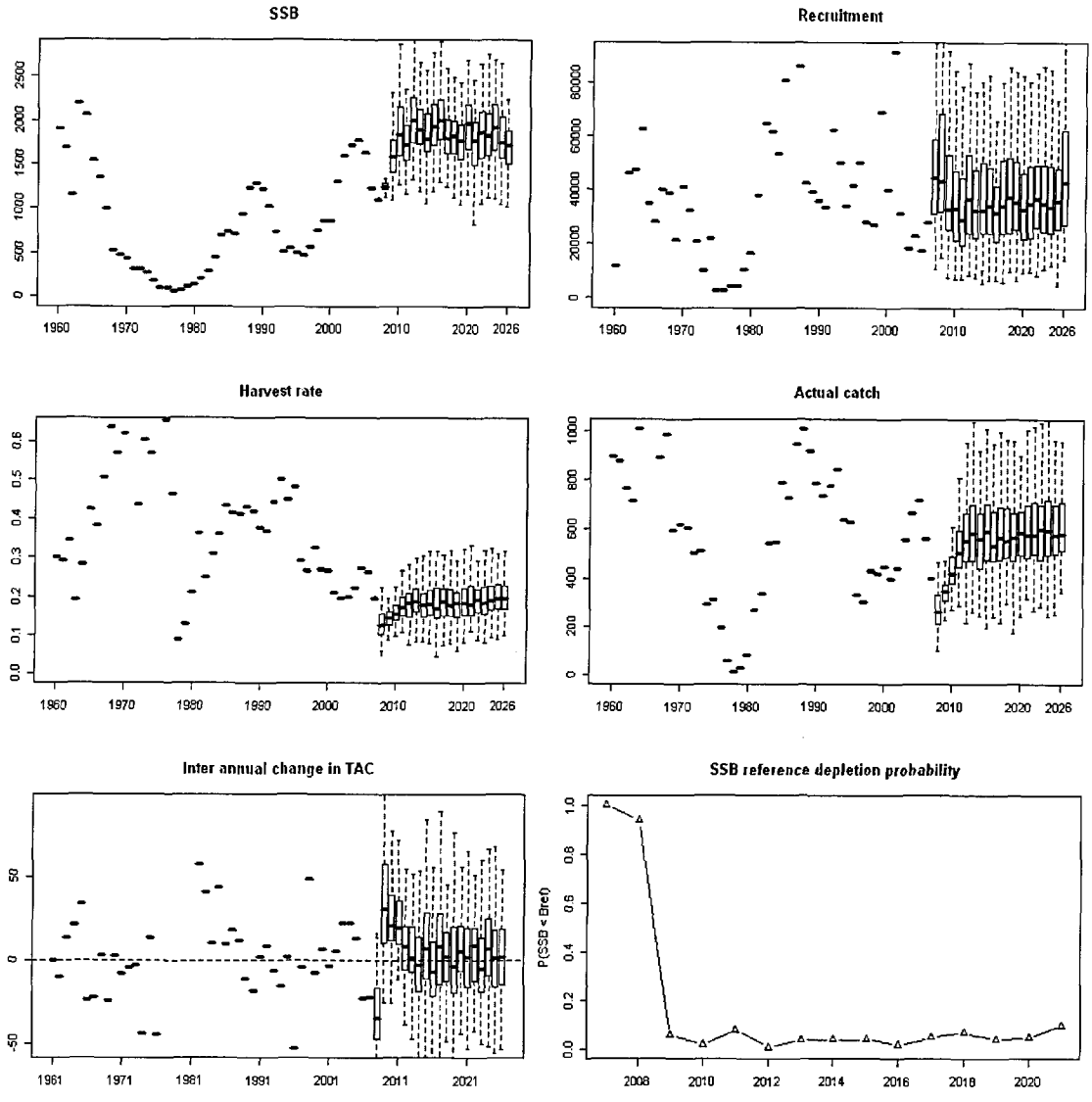


Figure 187: Output of simulation 108.

Stock recruitment: Ricker

Autocorrelation: high

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 0%

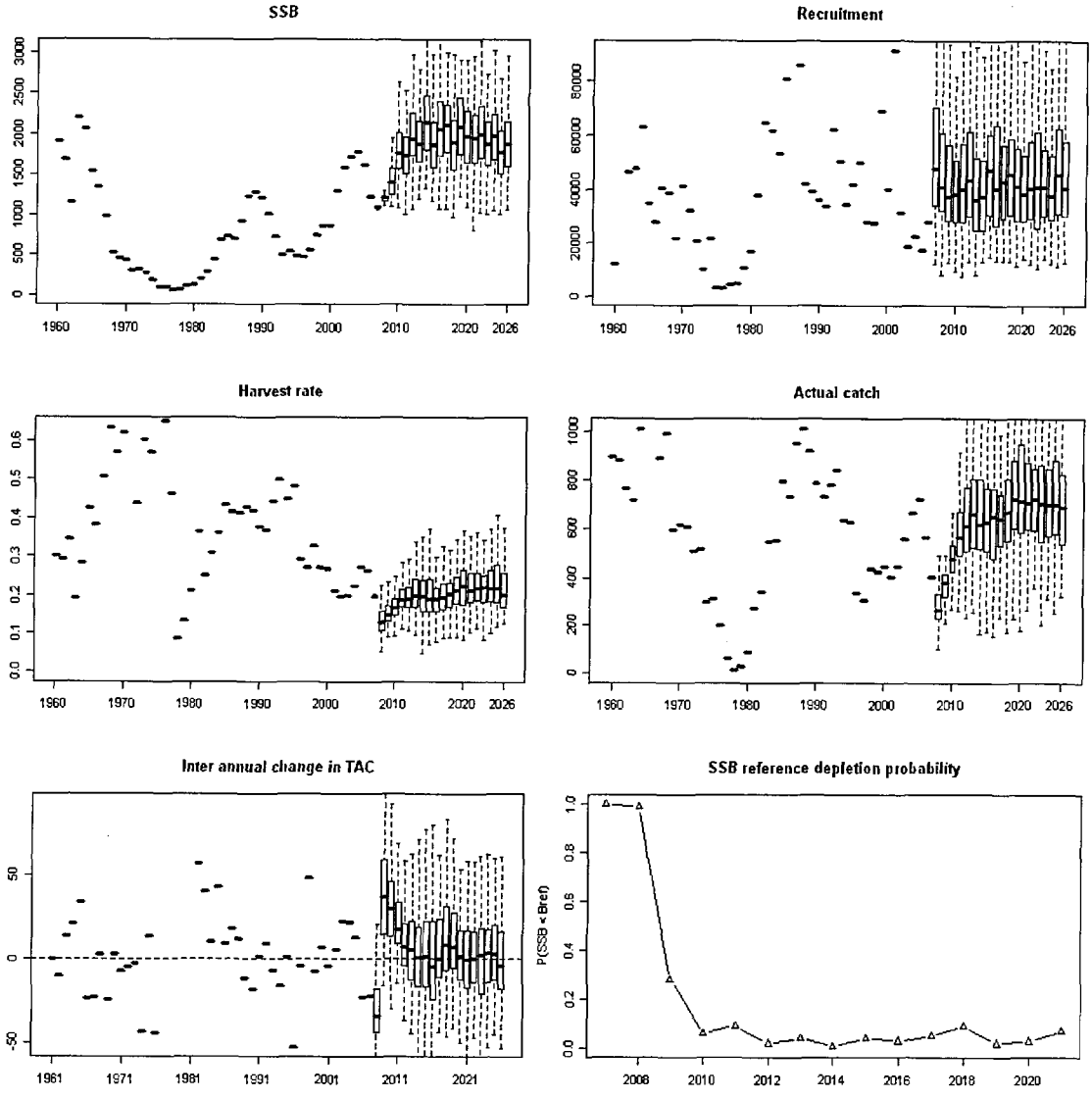


Figure 188: Output of simulation 109.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: +/- 15%

Implementation error: 0%

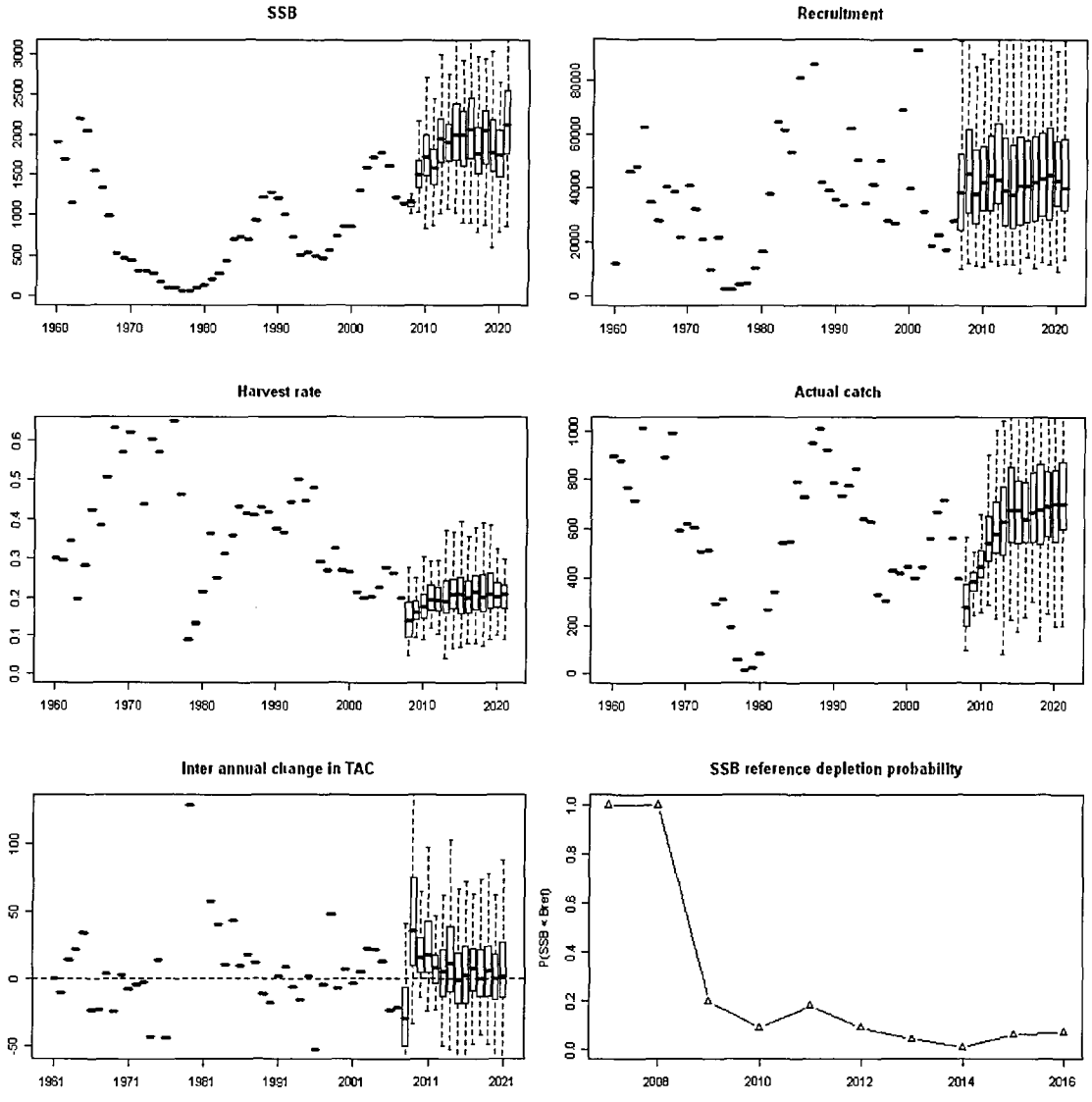


Figure 189: Output of simulation 110.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: +/- 15%

Implementation error: 0%

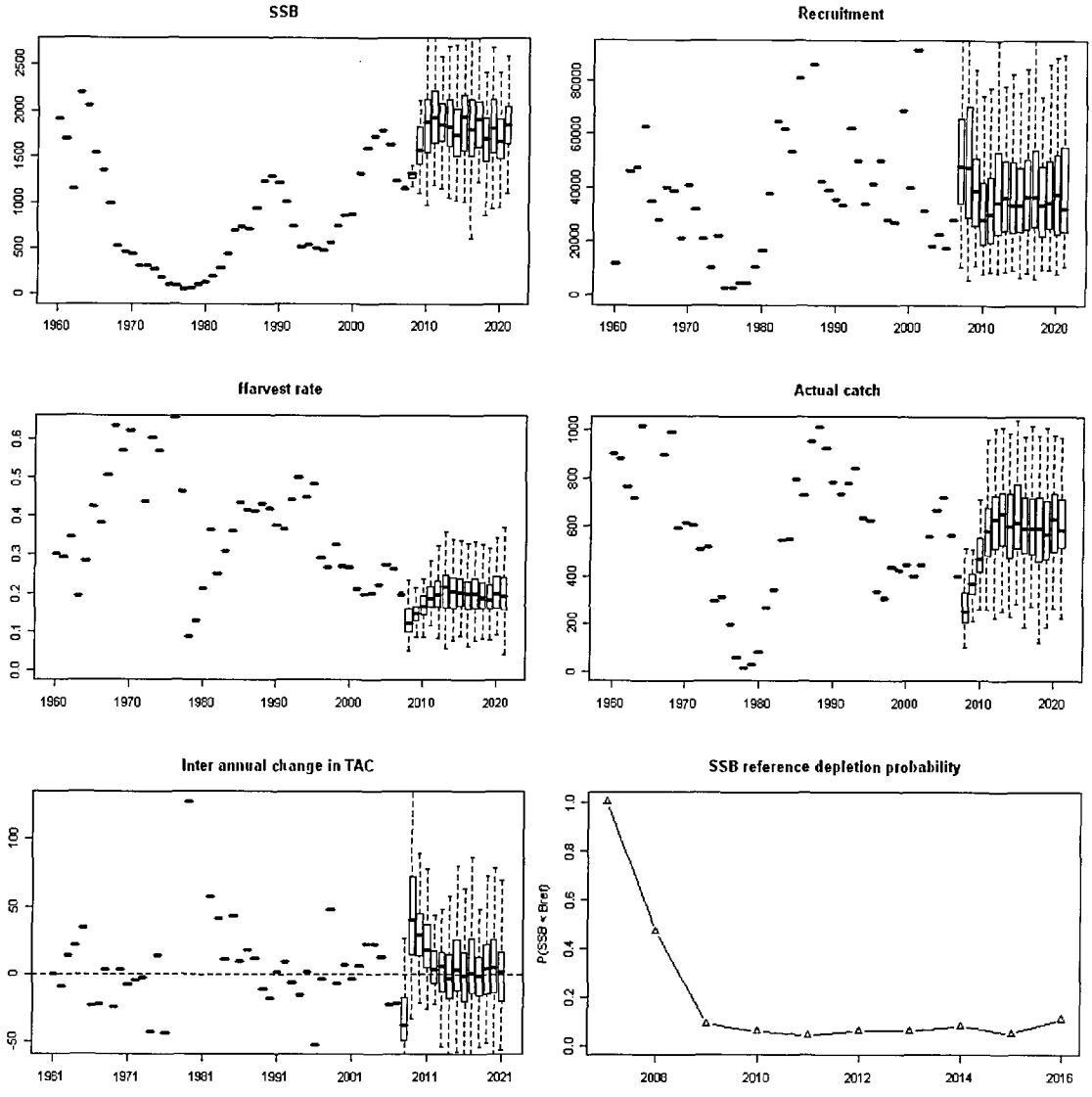


Figure 190: Output of simulation 111.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: +/- 15%

Implementation error: 0%

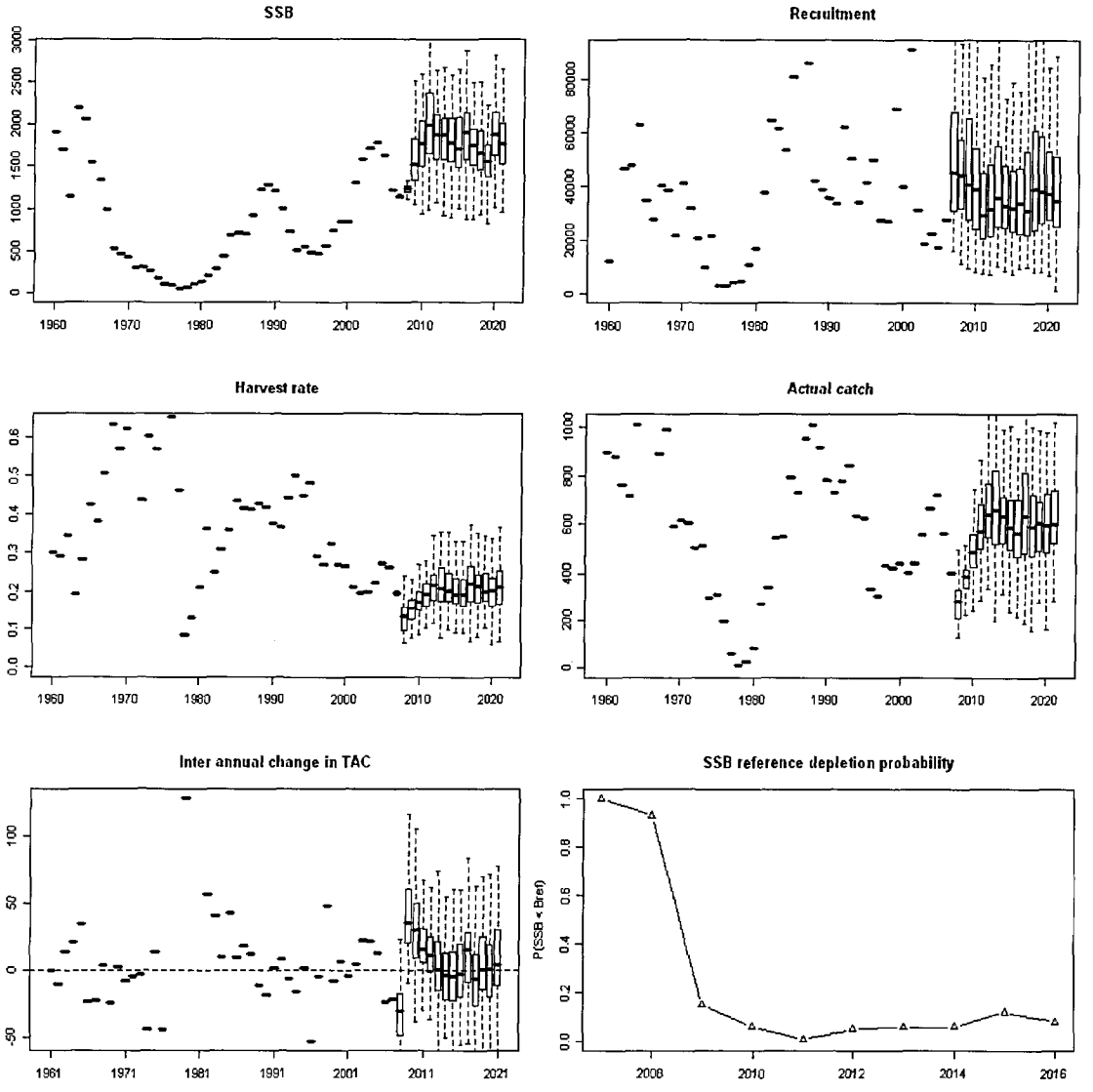


Figure 191: Output of simulation 112.

Stock recruitment: Ricker

Autocorrelation: high

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: +/- 15%

Implementation error: 0%

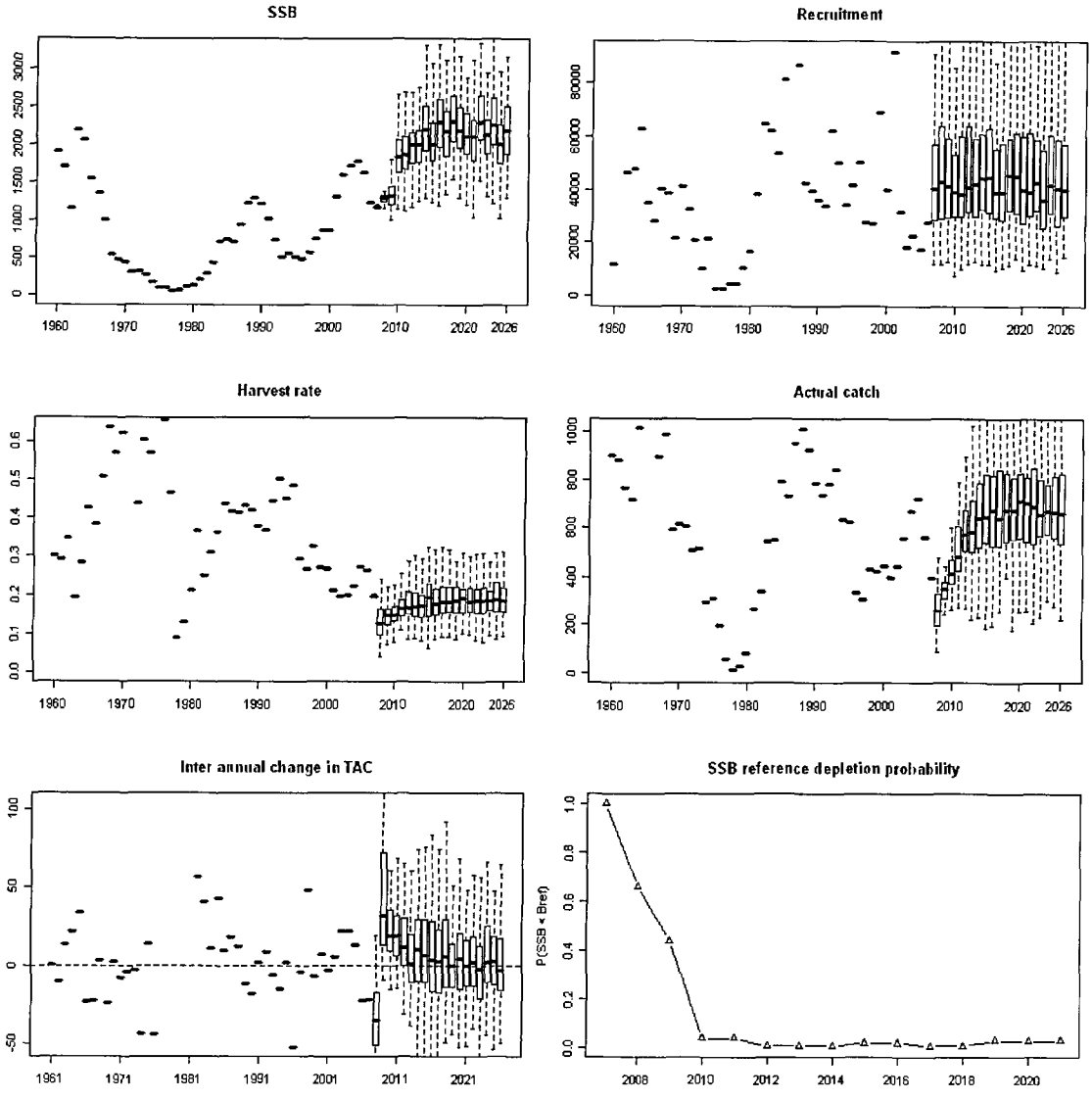


Figure 192: Output of simulation 113.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 0%

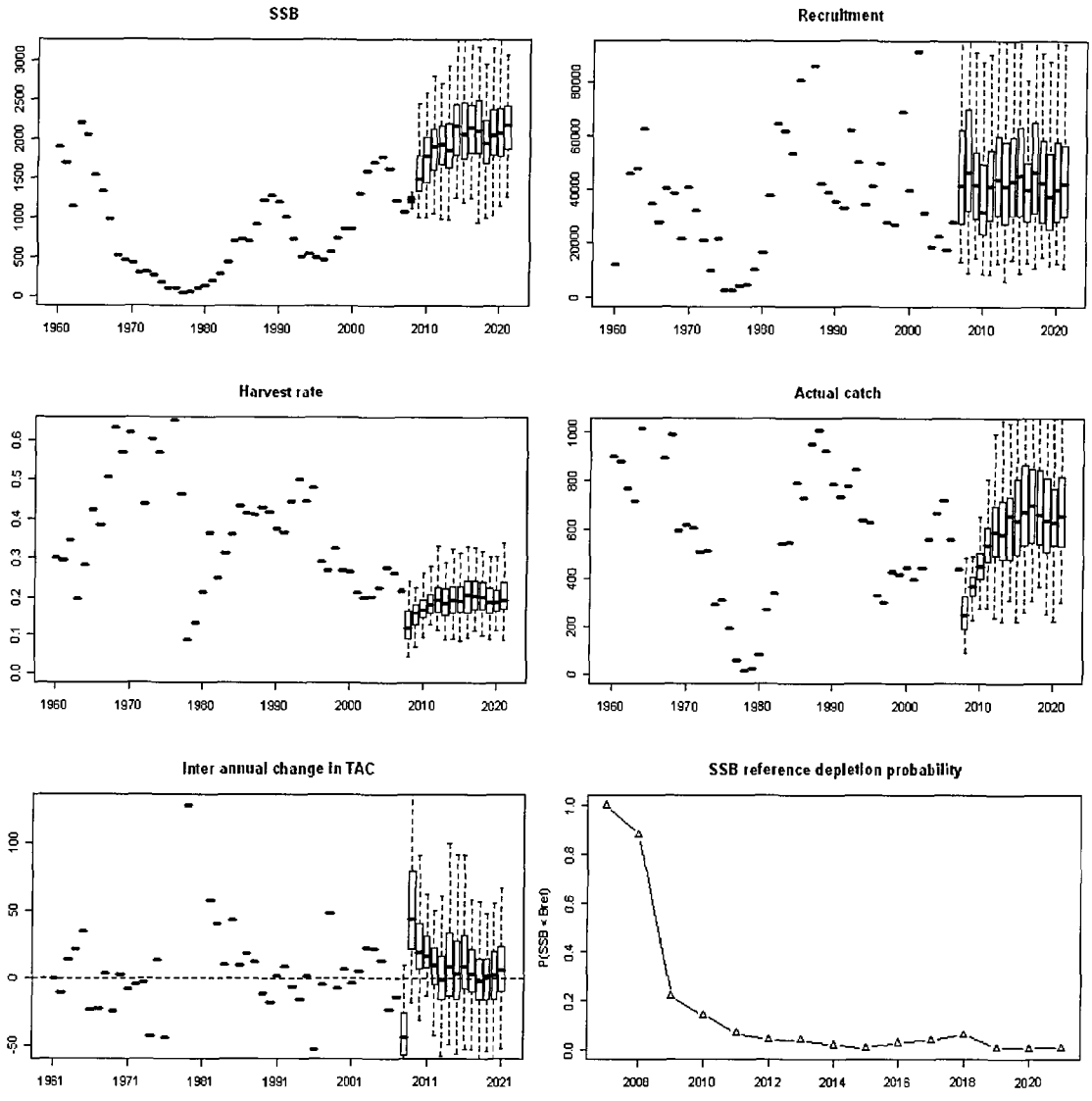


Figure 193: Output of simulation 114.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 10%

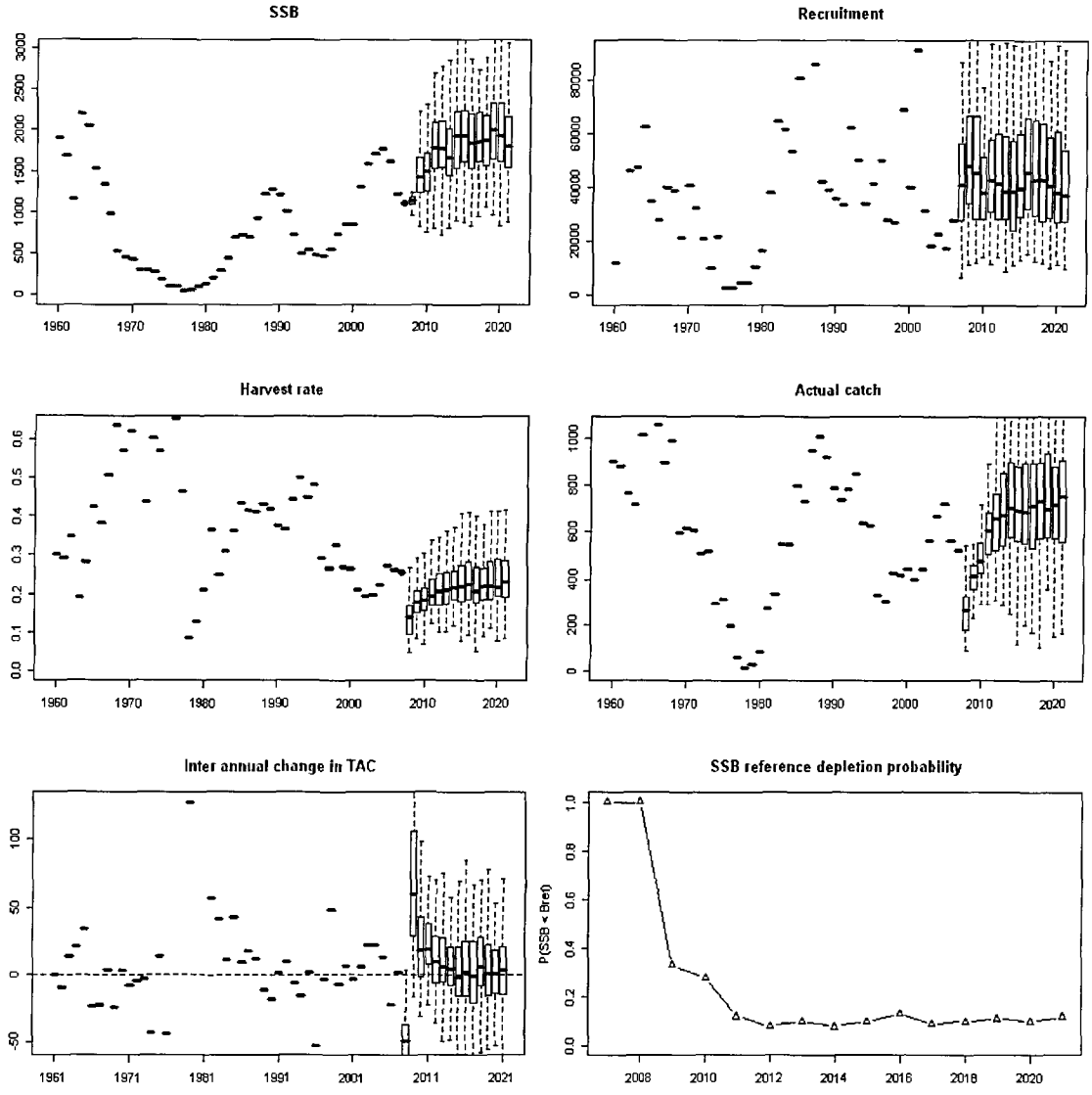


Figure 194: Output of simulation 115.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 30%

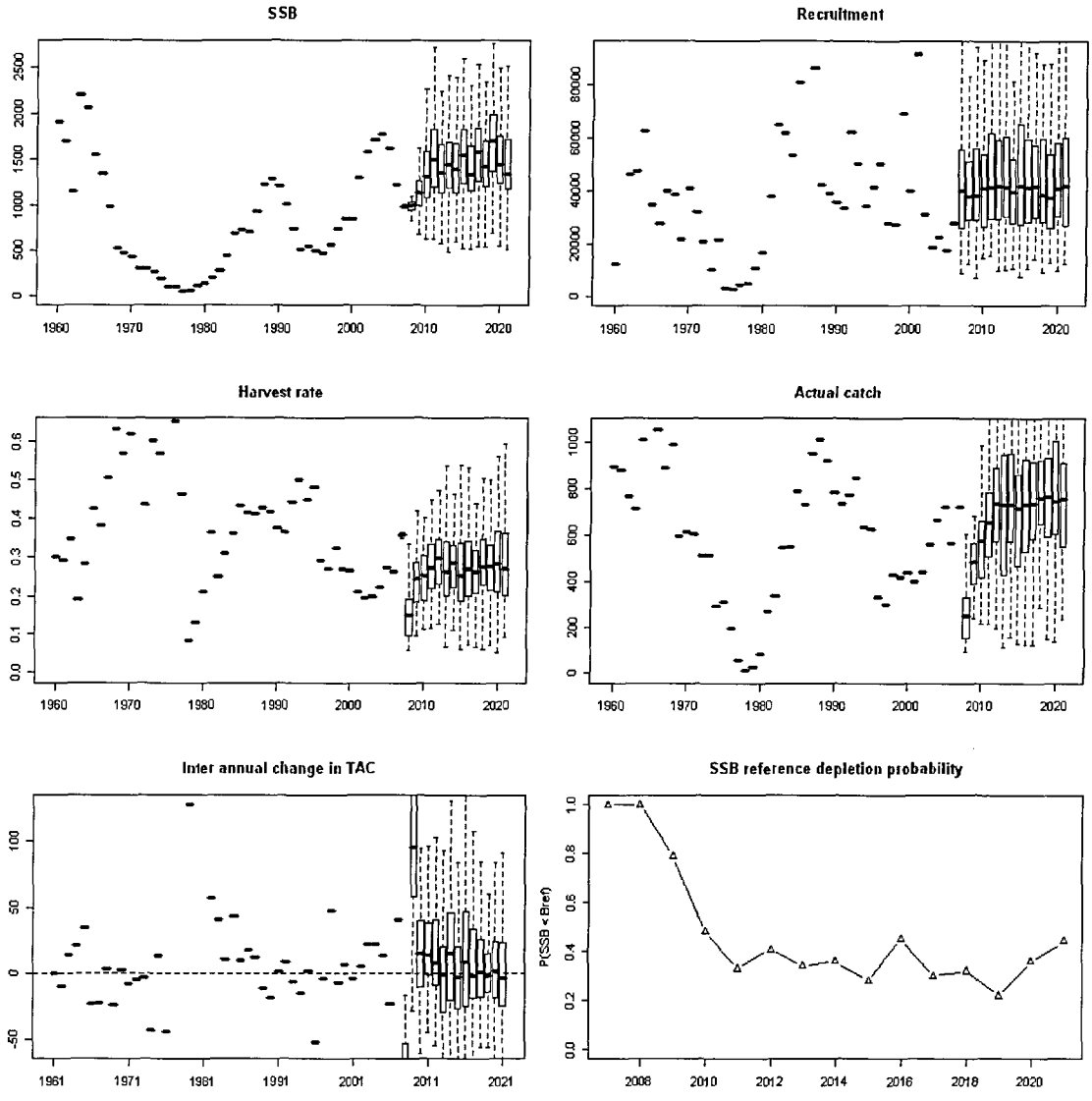


Figure 195: Output of simulation 116.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 80%

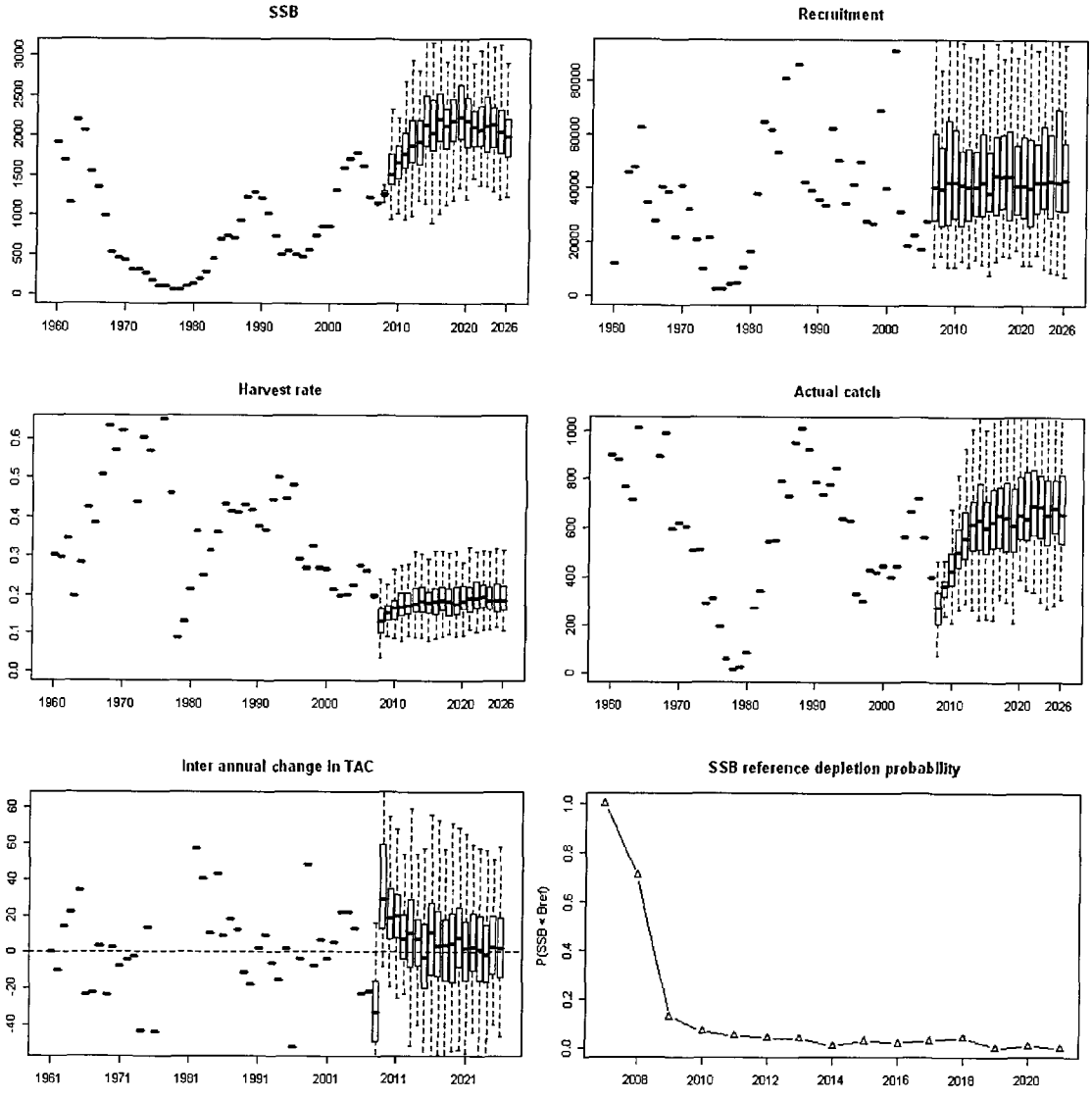


Figure 196: Output of simulation 117.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 0%

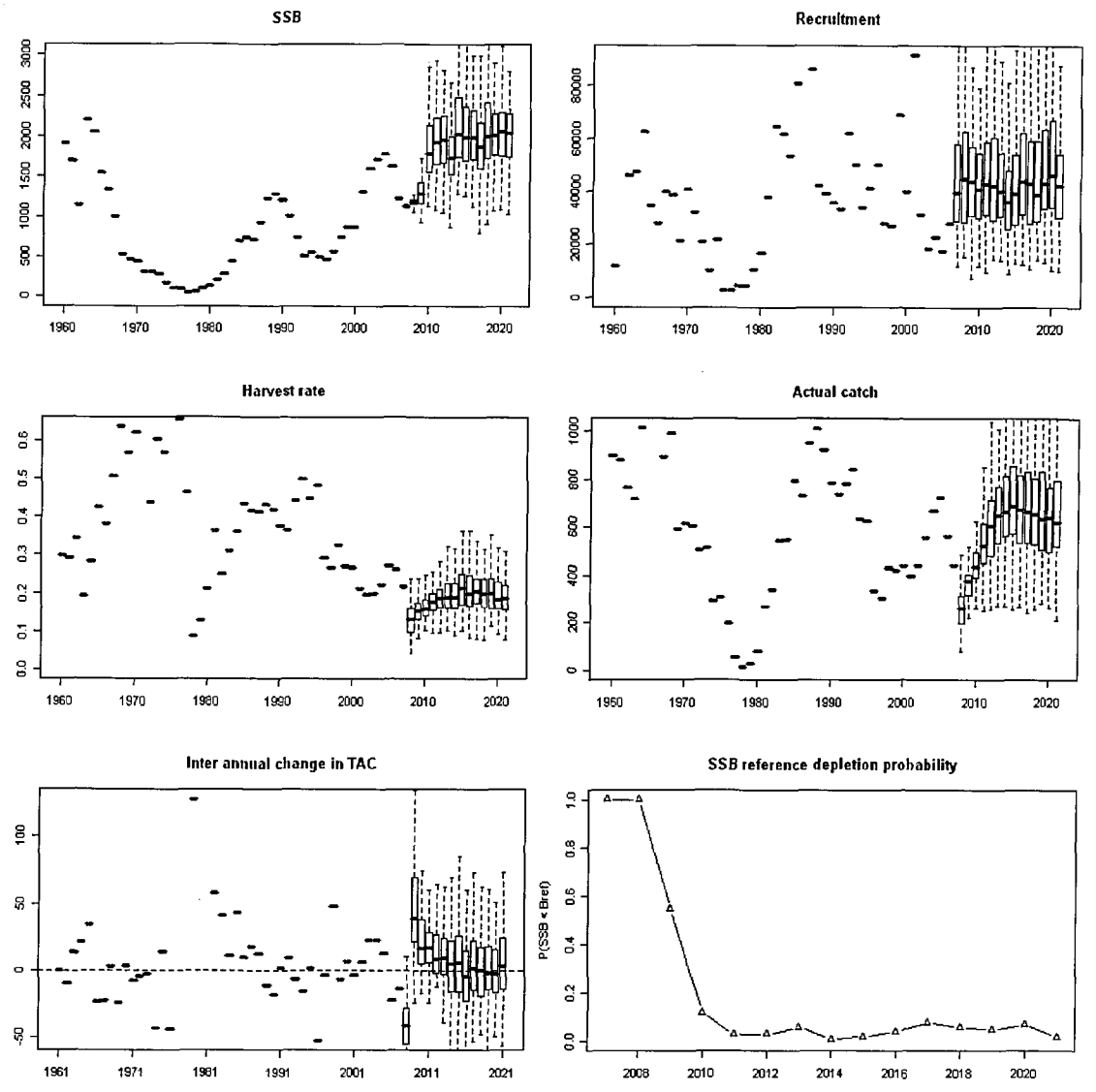


Figure 197: Output of simulation 118.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 10%

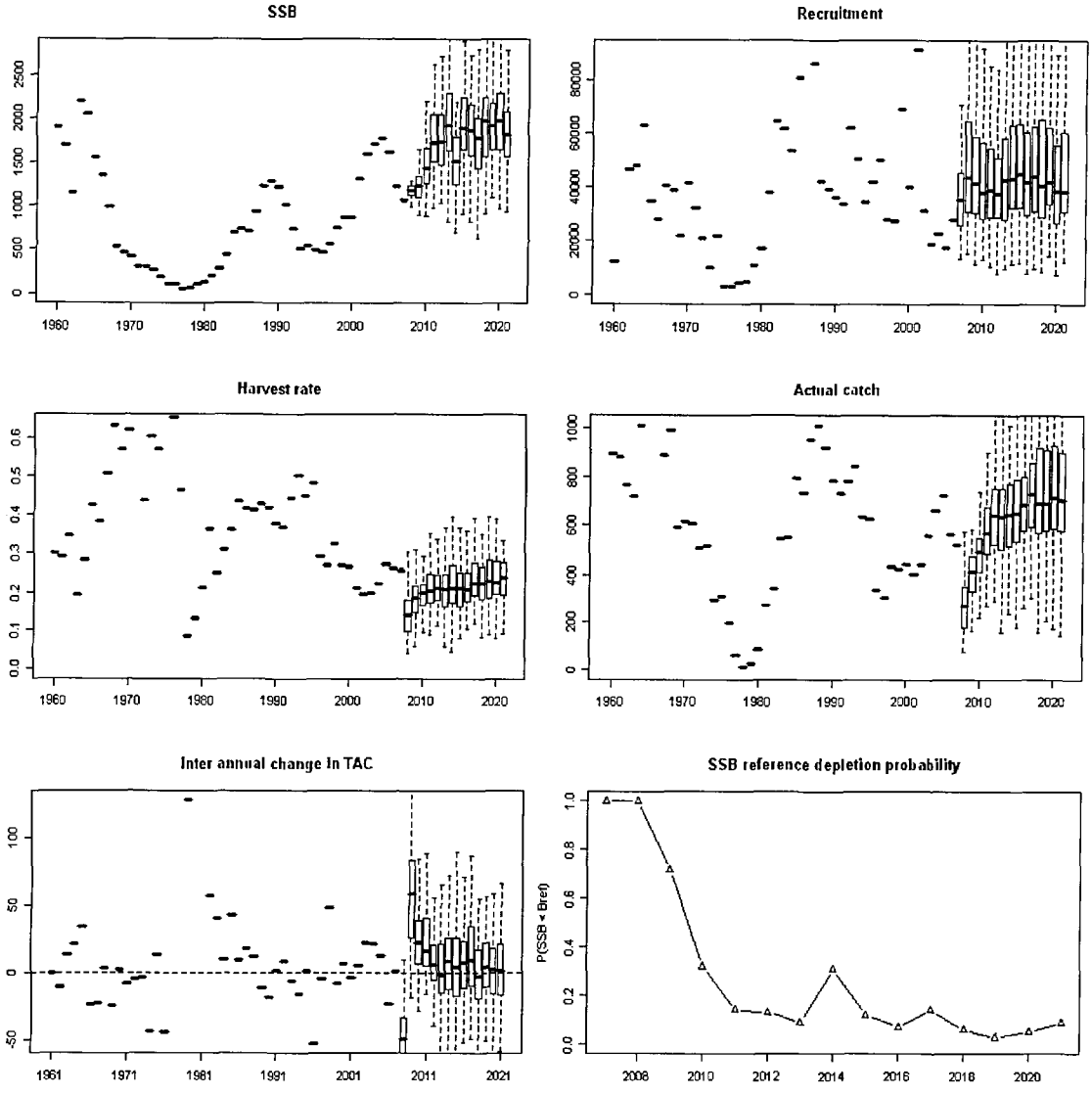


Figure 198: Output of simulation 119.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 30%

NOT AVAILABLE

Figure 199: Output of simulation 120.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 80%

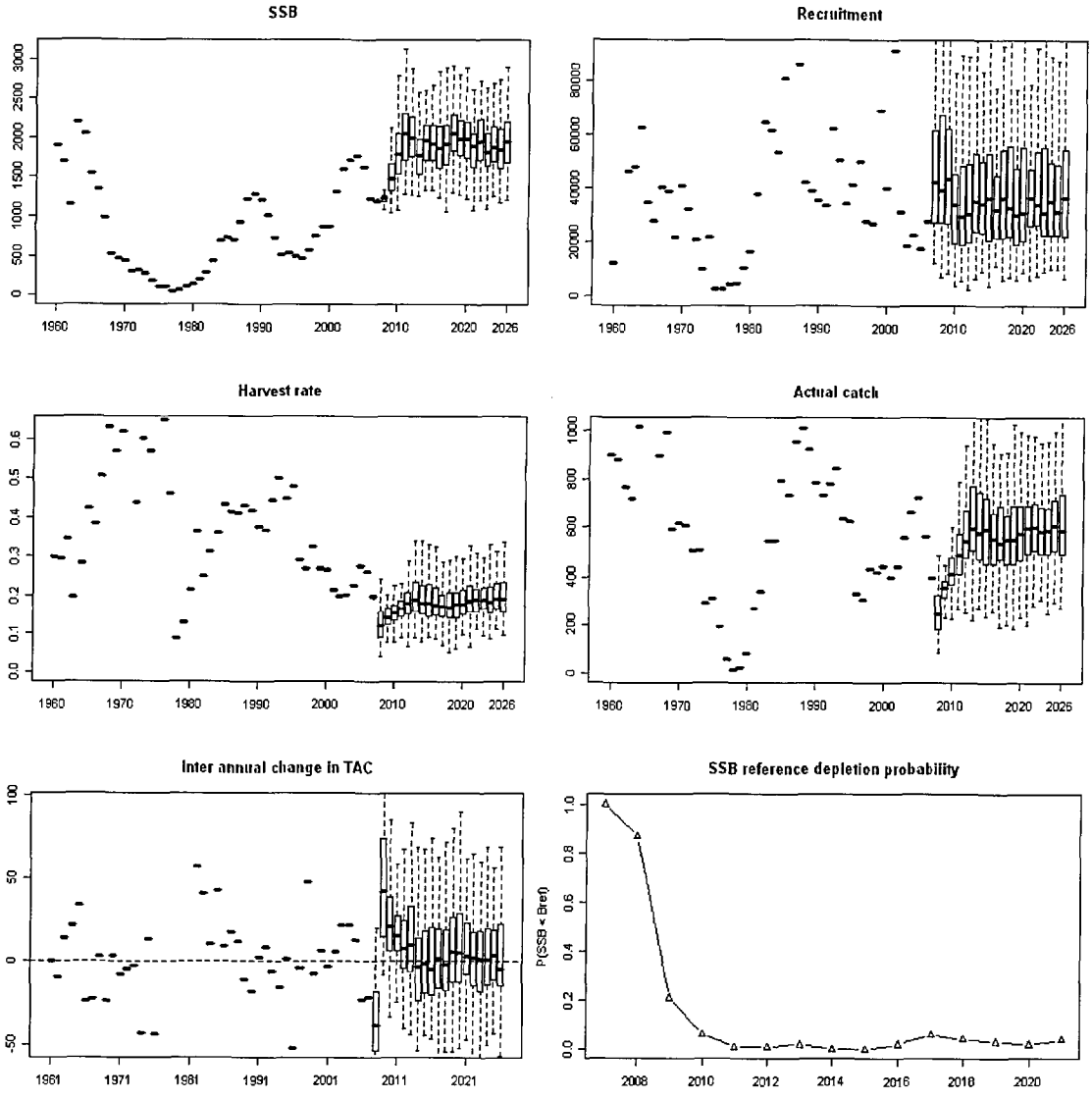


Figure 200: Output of simulation 121.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 0%

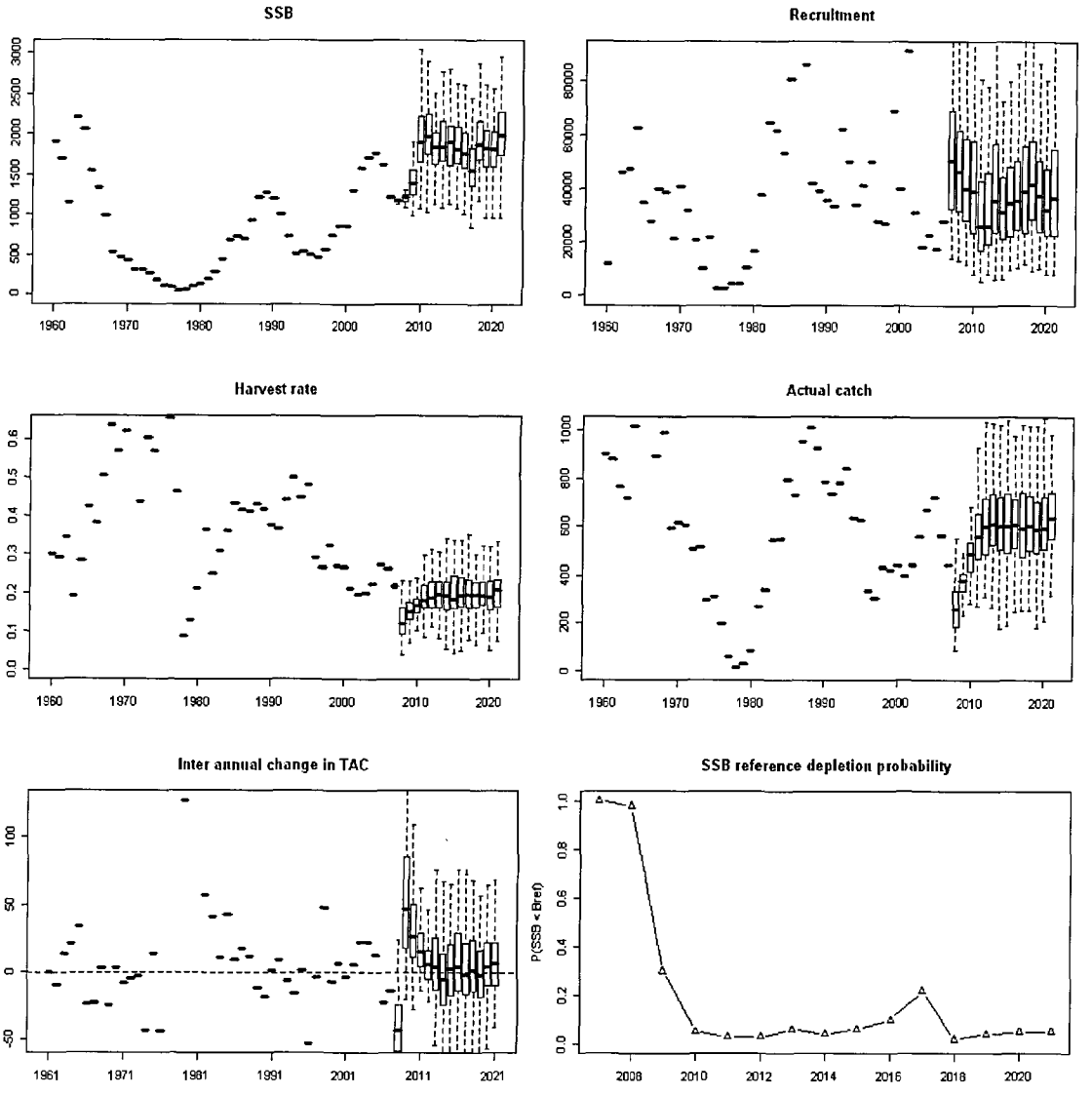


Figure 201: Output of simulation 122.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 10%

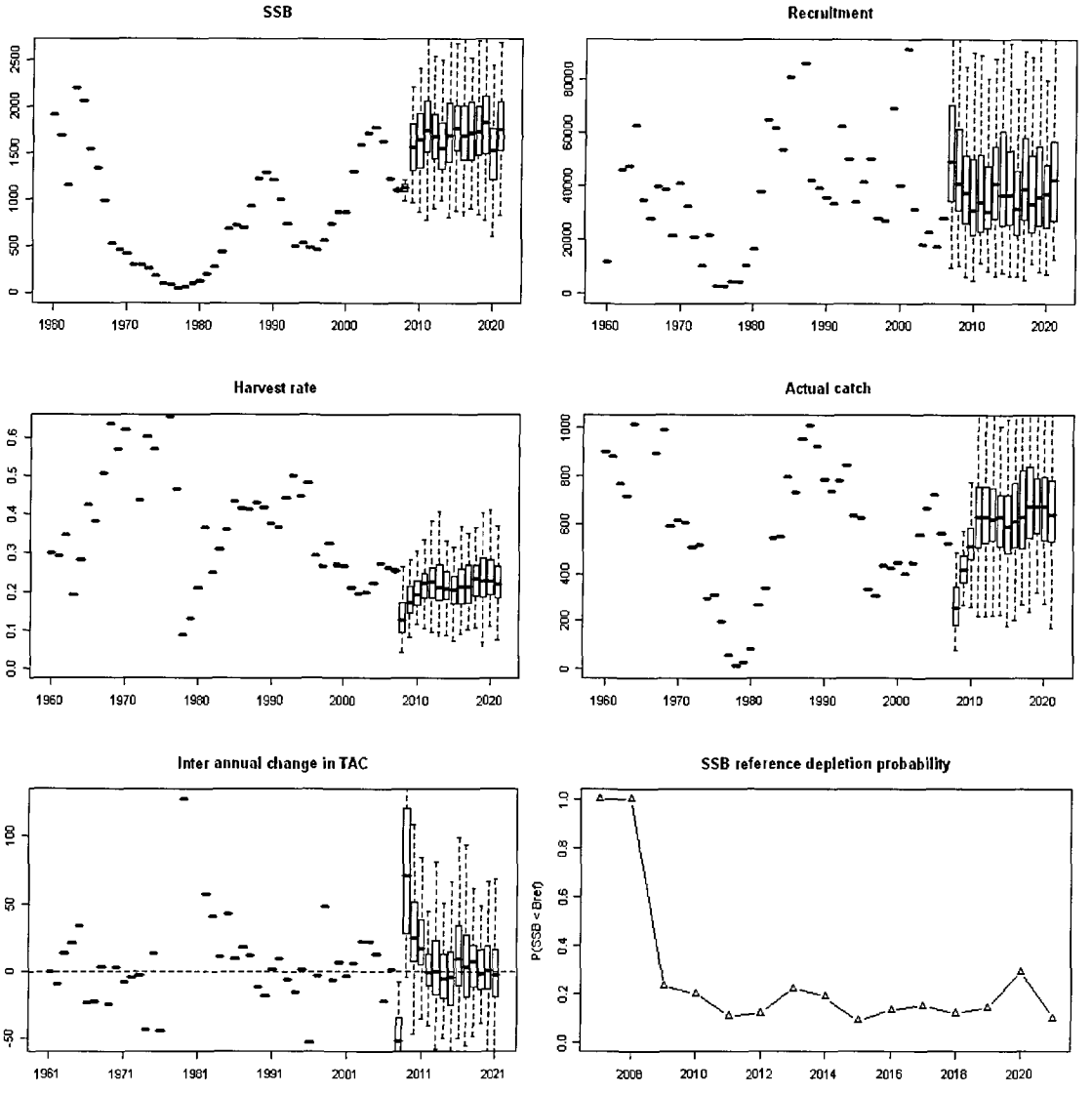


Figure 202: Output of simulation 123.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 30%

NOT AVAILABLE

Figure 203: Output of simulation 124.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 80%

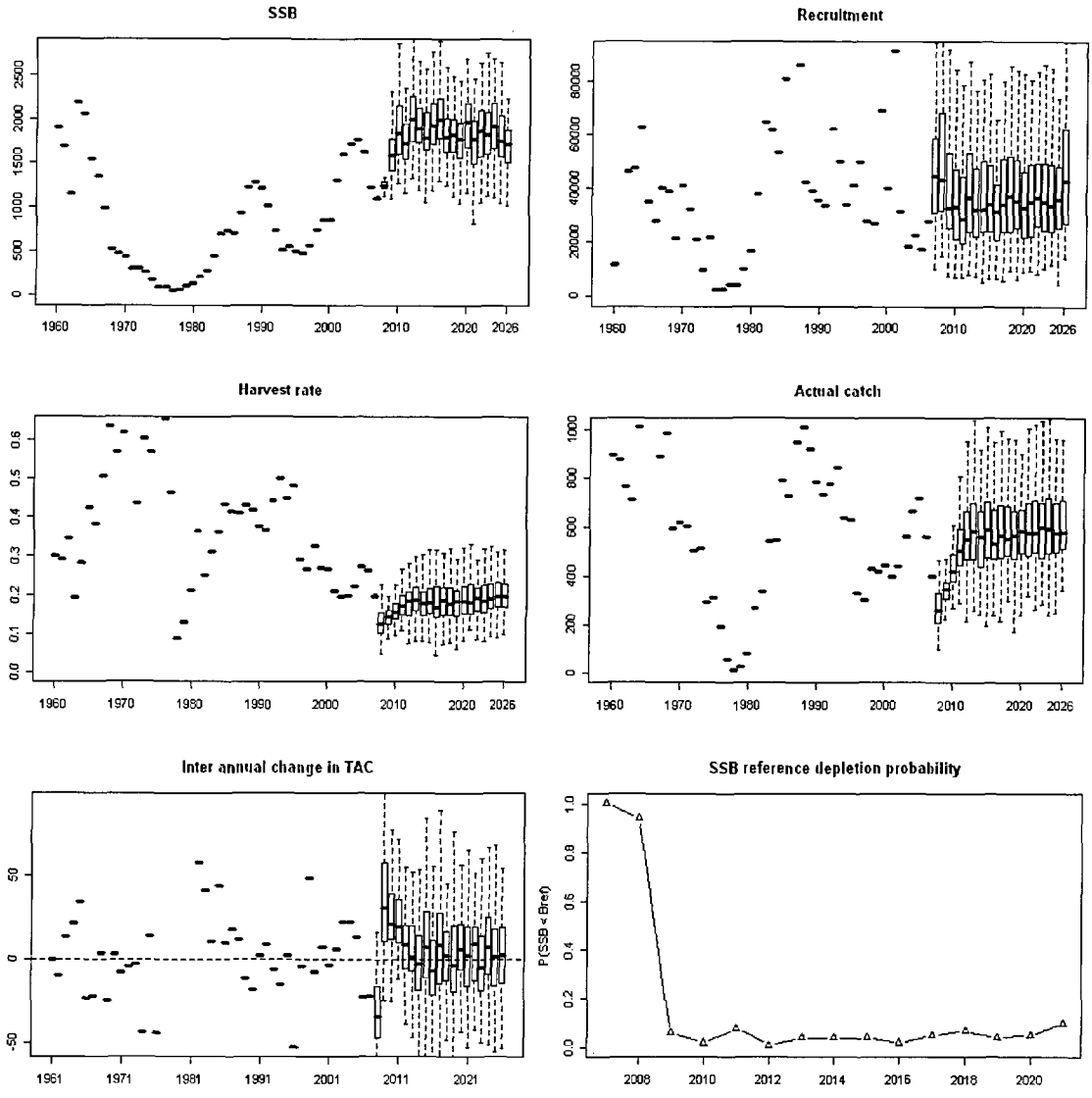


Figure 204: Output of simulation 125.

Stock recruitment: Ricker

Autocorrelation: high

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 0%

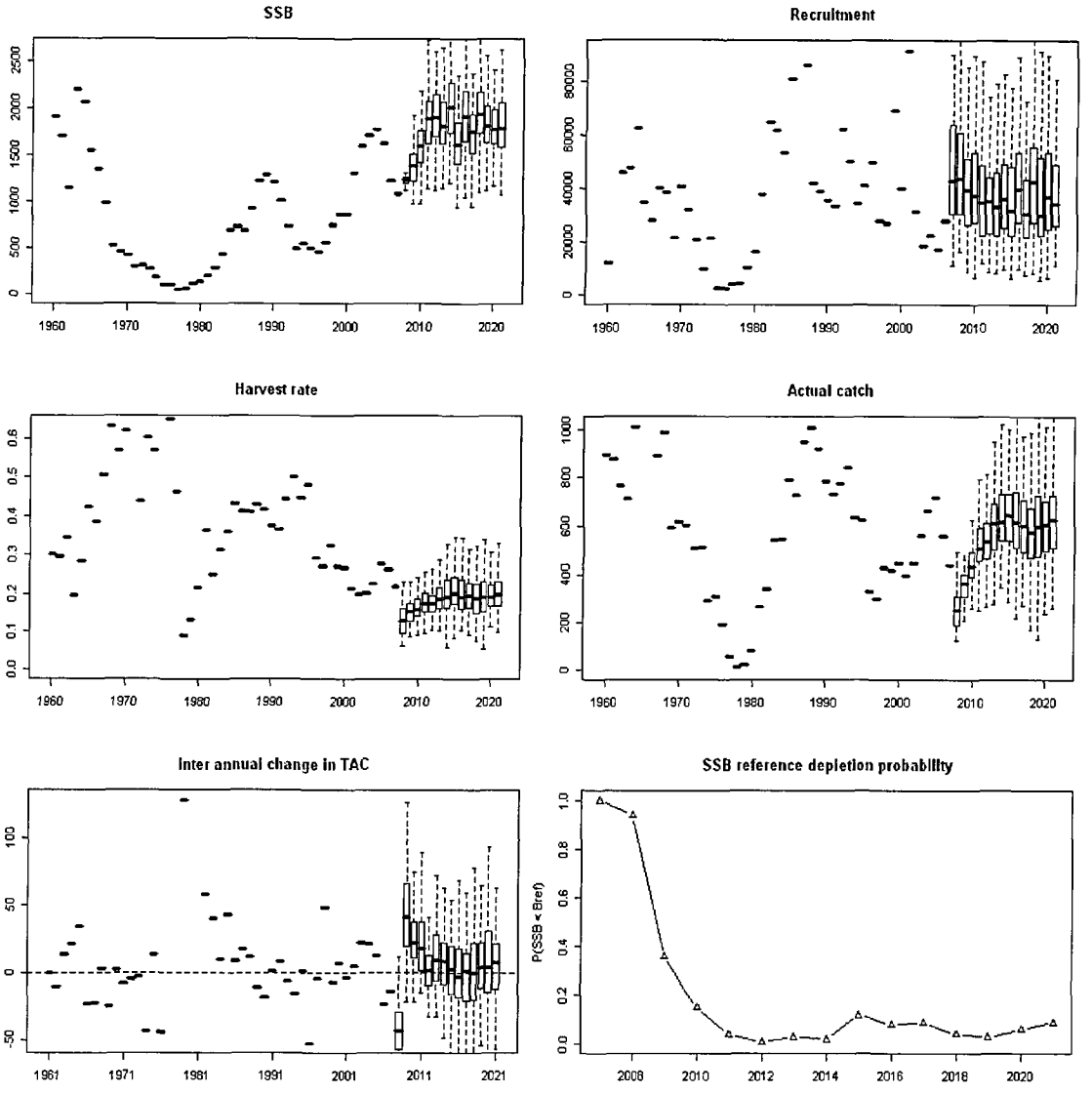


Figure 205: Output of simulation 126.

Stock recruitment: Ricker

Autocorrelation: high

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 10%

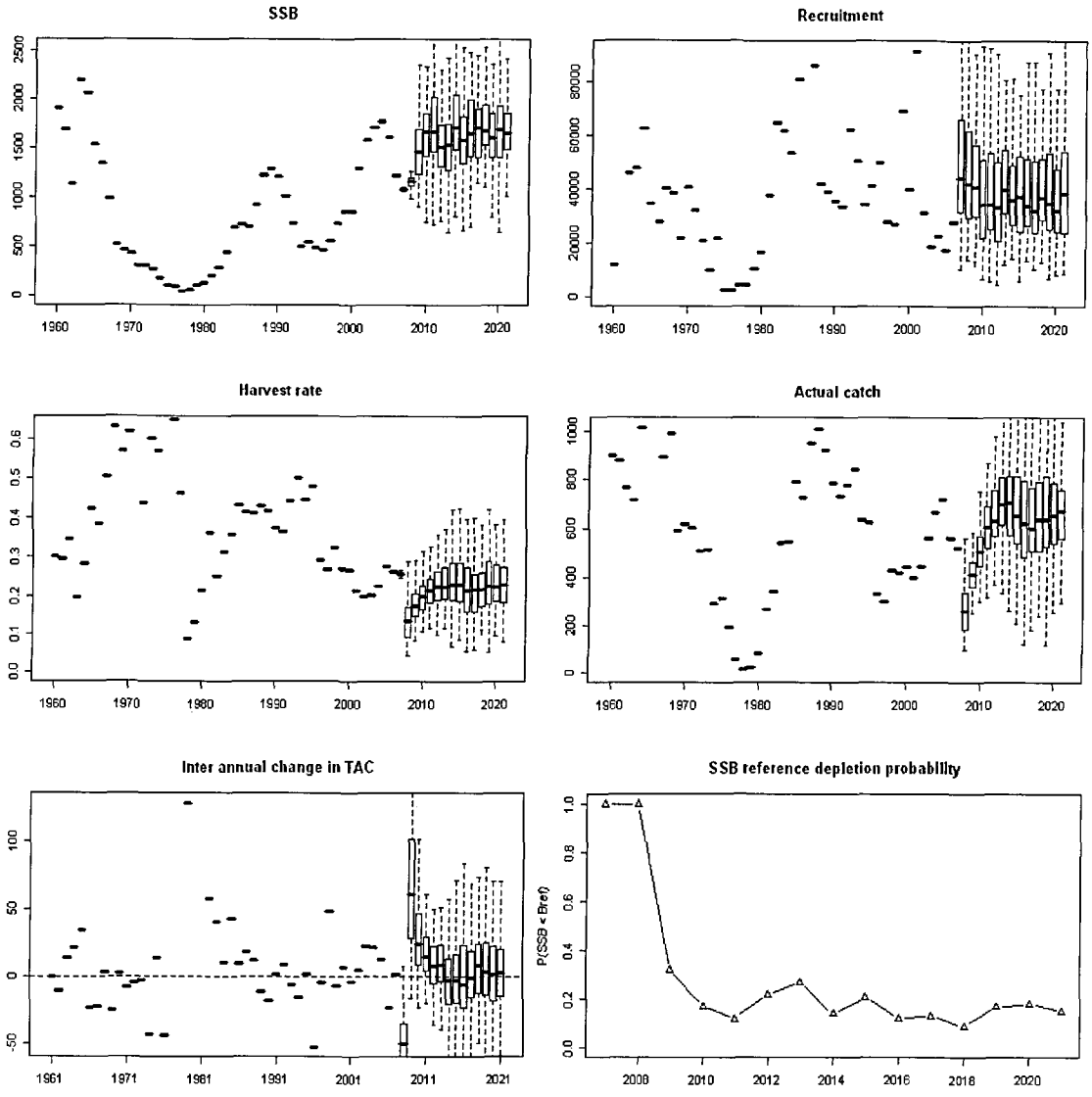


Figure 206: Output of simulation 127.

Stock recruitment: Ricker

Autocorrelation: high

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 30%

NOT AVAILABLE

Figure 207: Output of simulation 128.

Stock recruitment: Ricker

Autocorrelation: high

Survey: all

Assessment: ICA

Harvest control rule: Actual management (F and reference points)

Limitation of variation: none

Implementation error: 80%

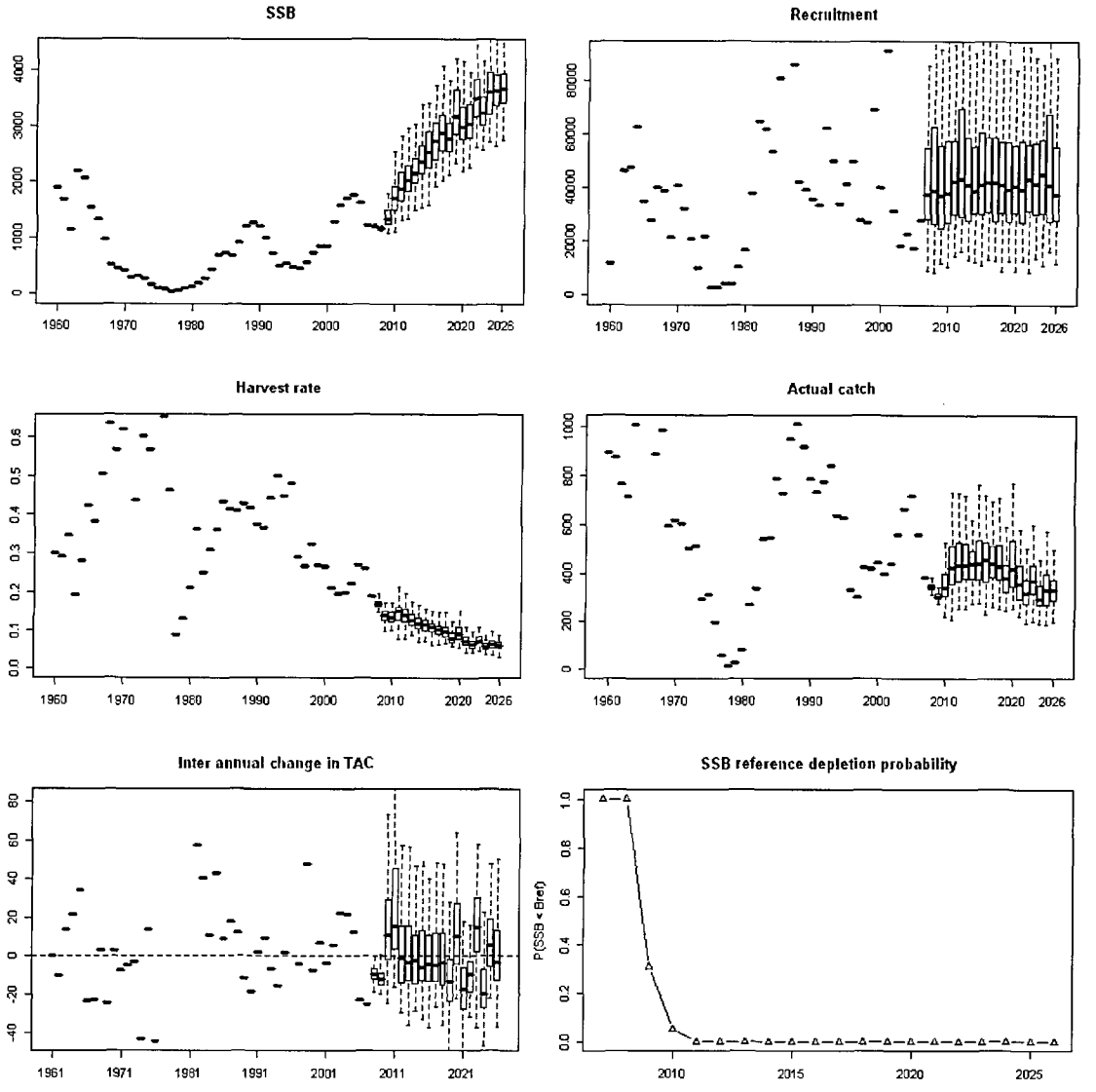


Figure 208: Output of simulation 129.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

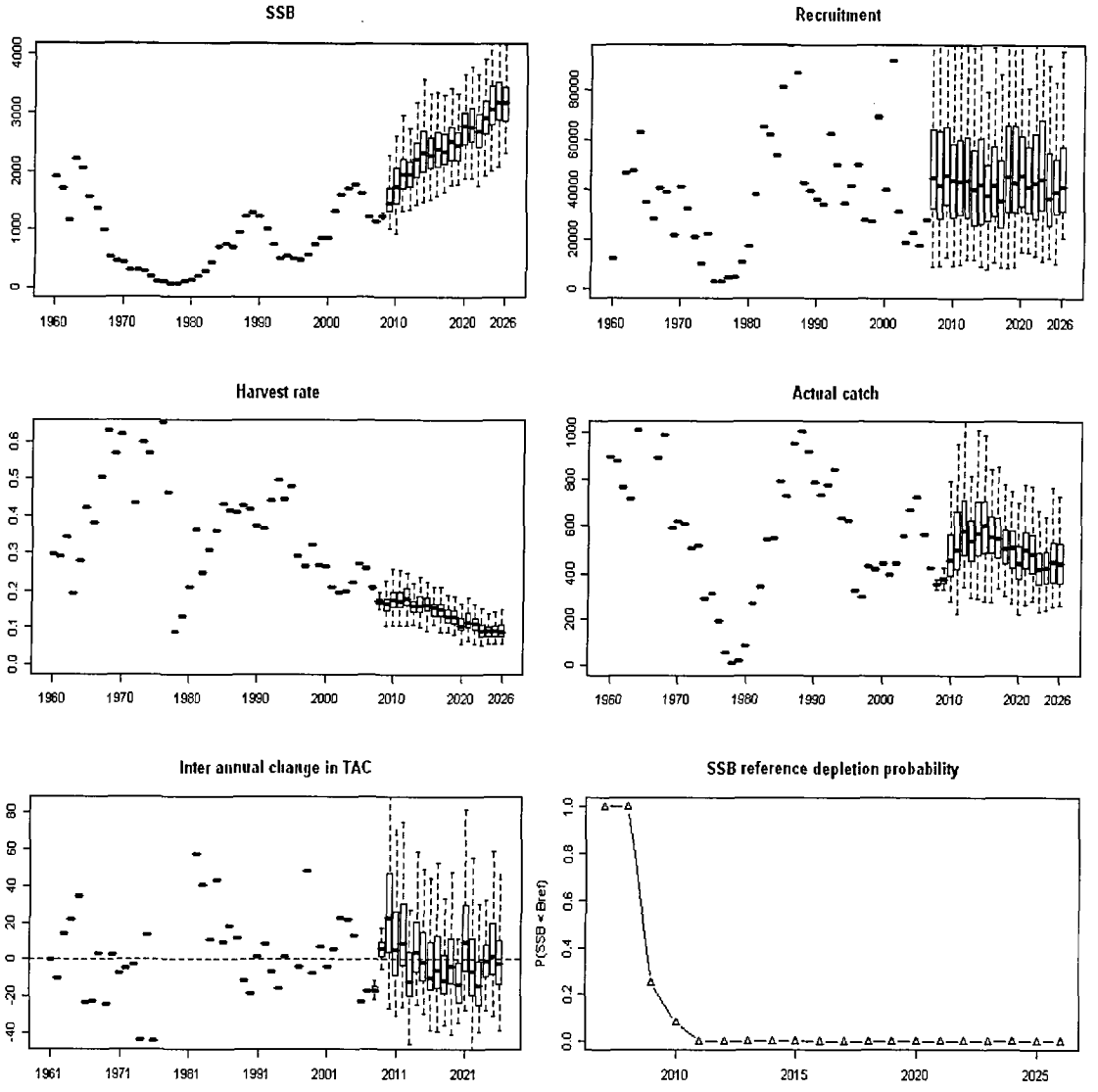


Figure 209: Output of simulation 130.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

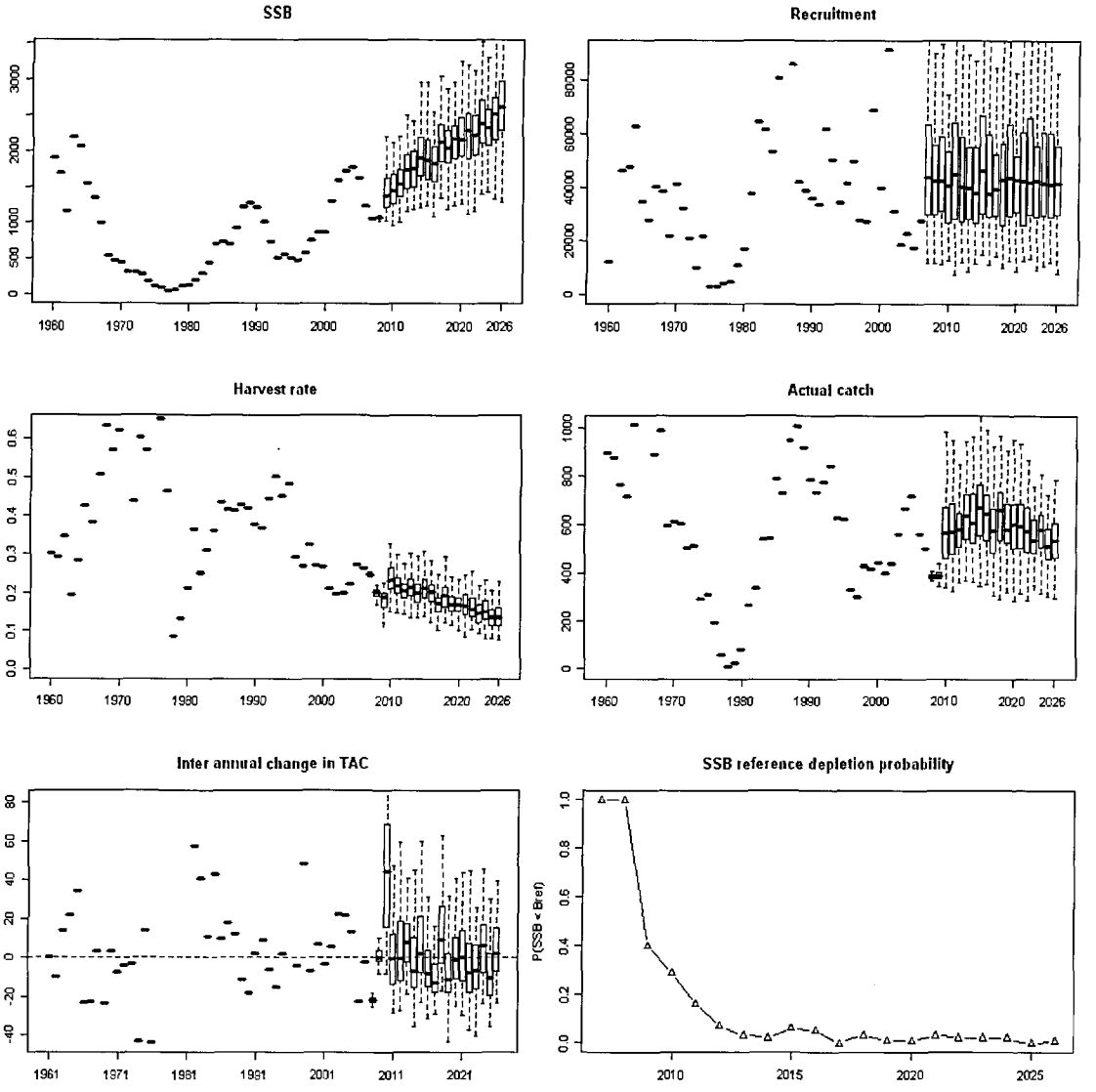


Figure 210: Output of simulation 131.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

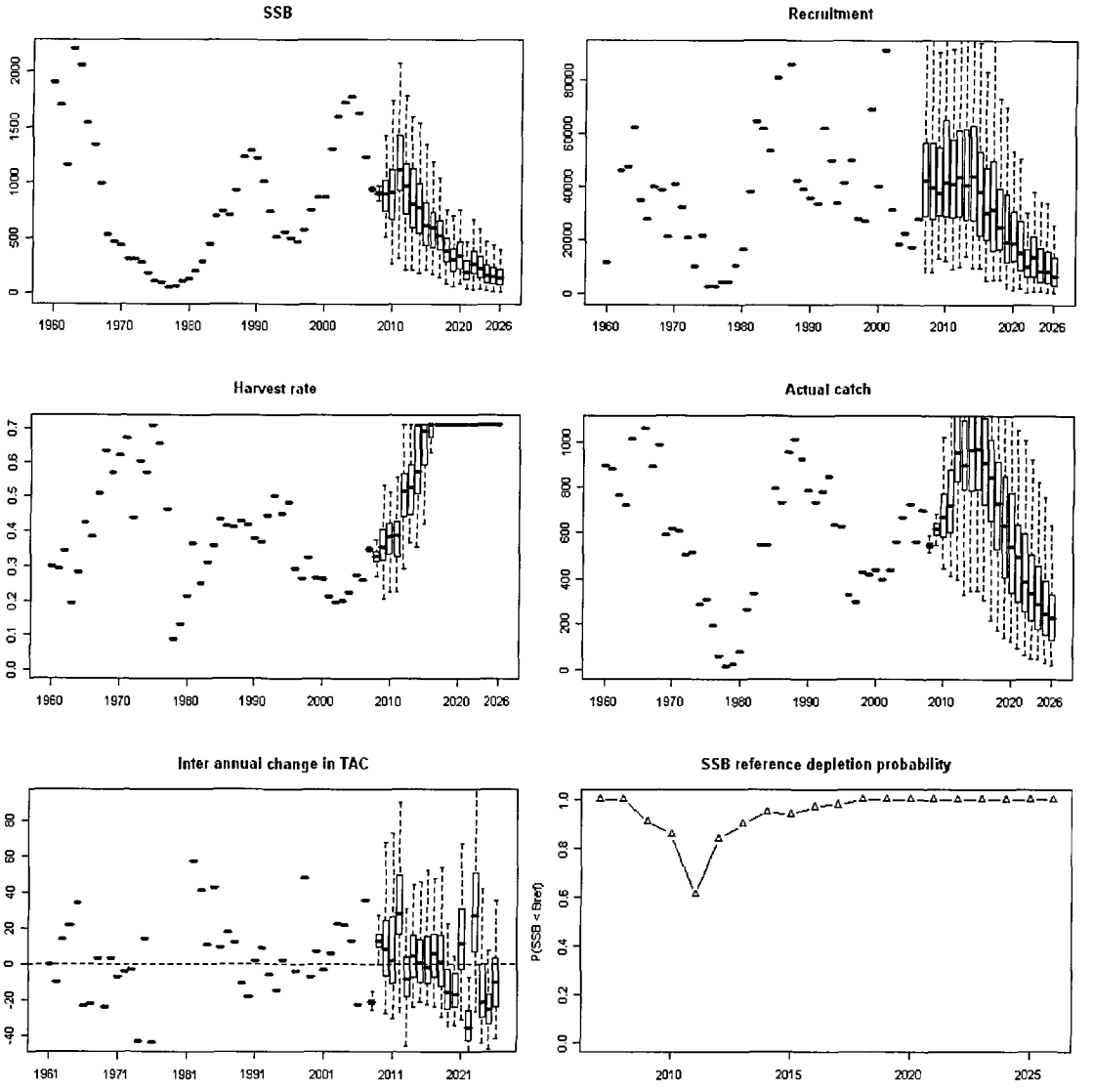


Figure 211: Output of simulation 132.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

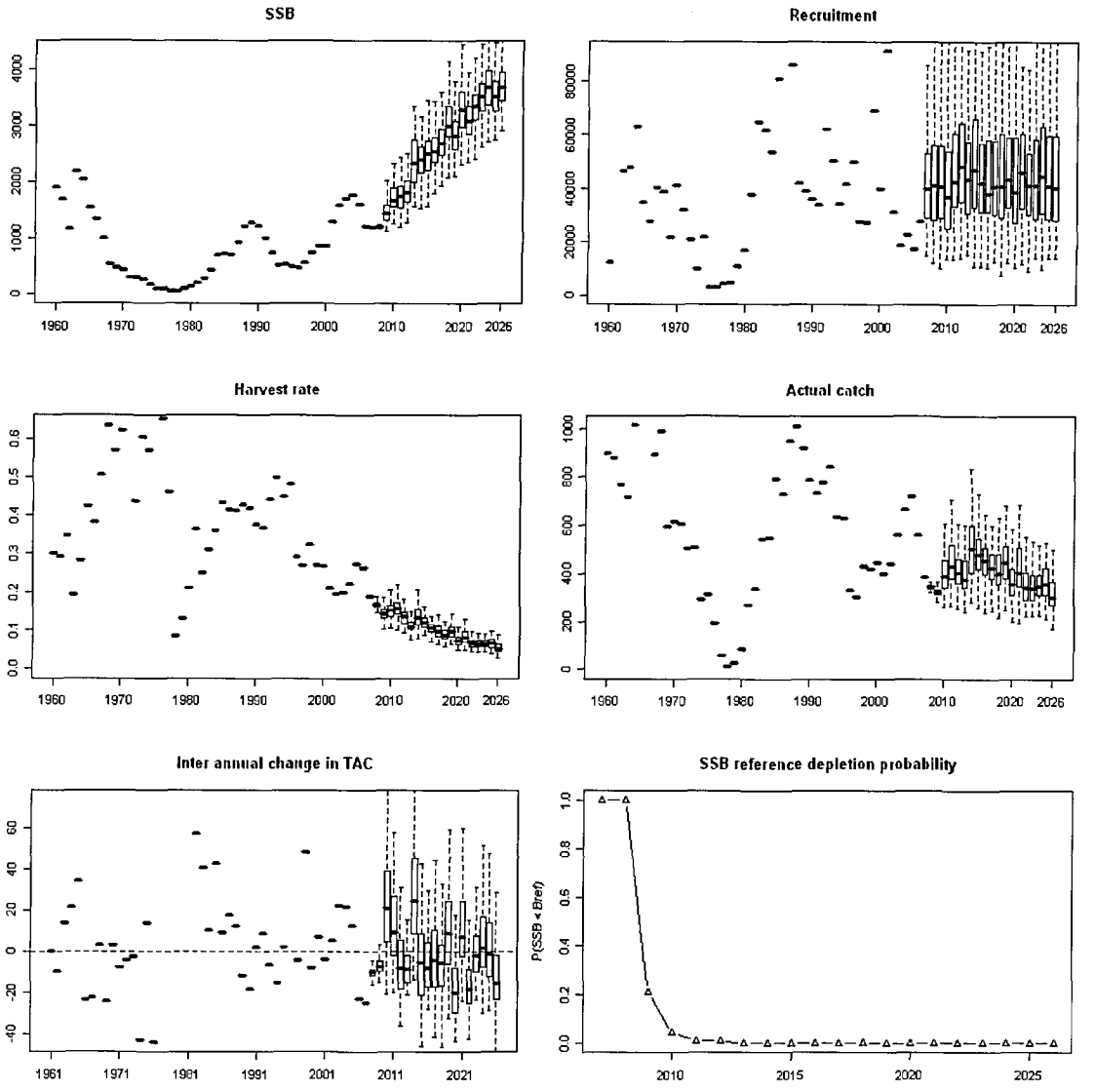


Figure 212: Output of simulation 133.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

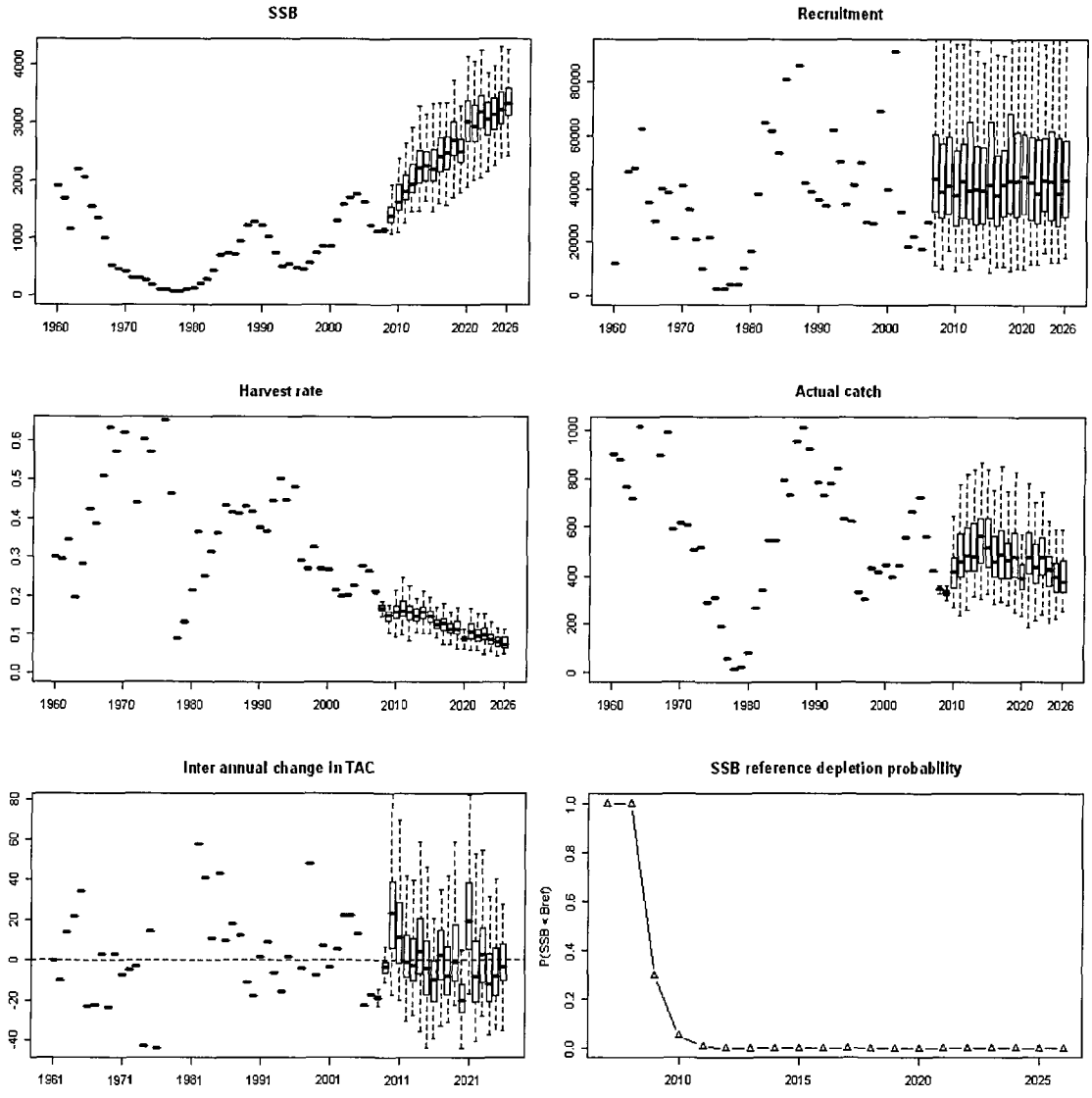


Figure 213: Output of simulation 134.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

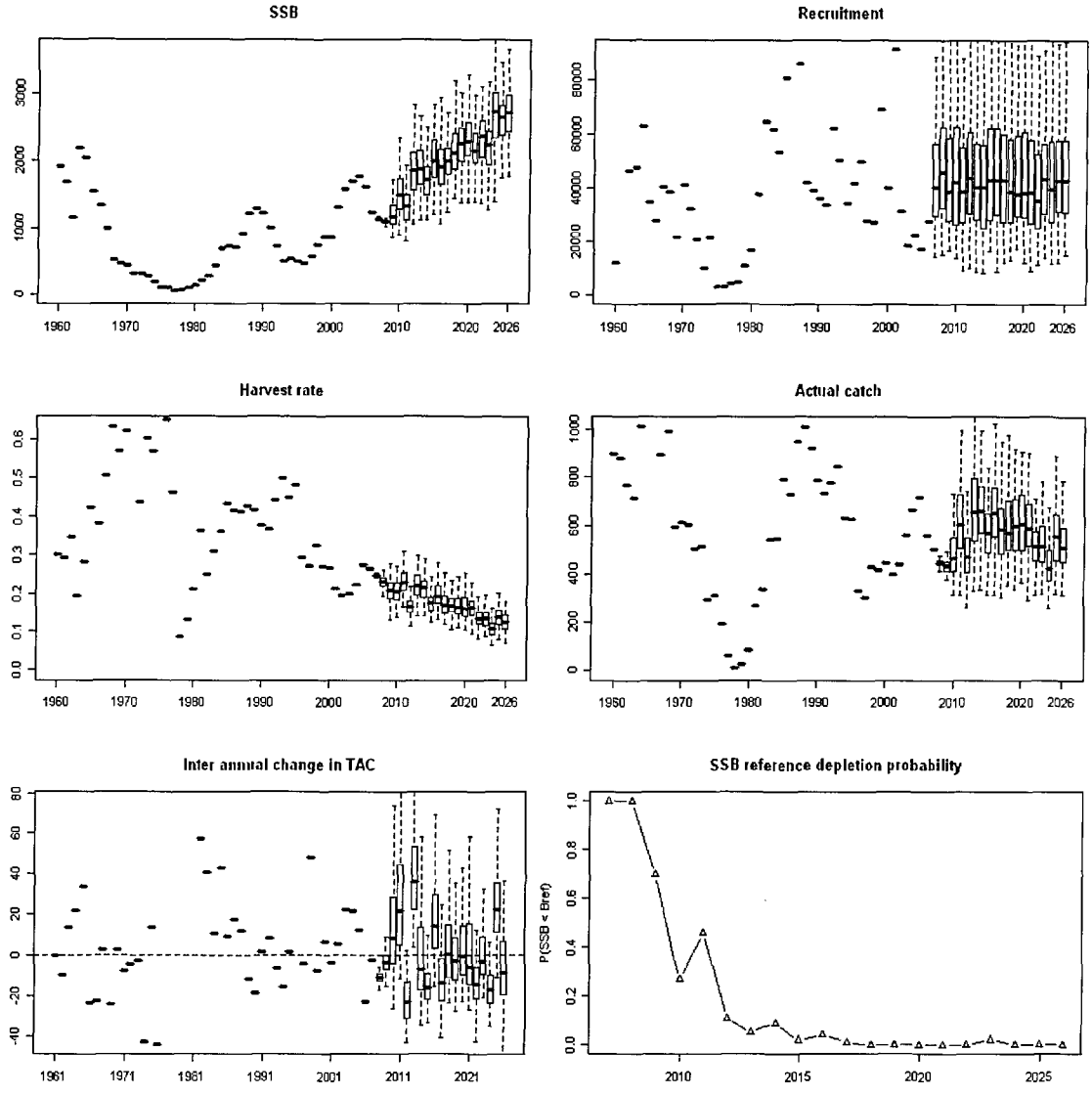


Figure 214: Output of simulation 135.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 3%

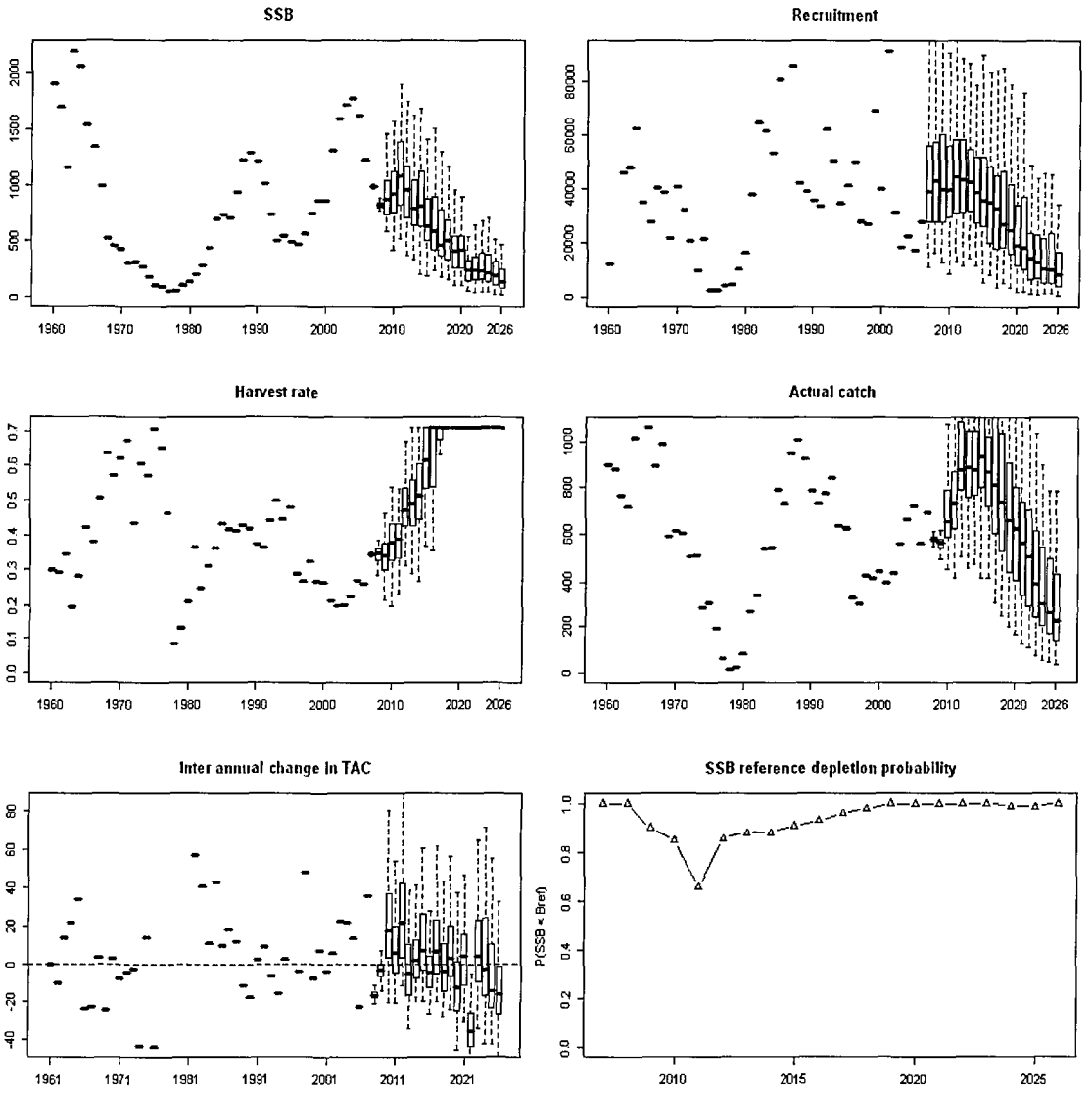


Figure 215: Output of simulation 136.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

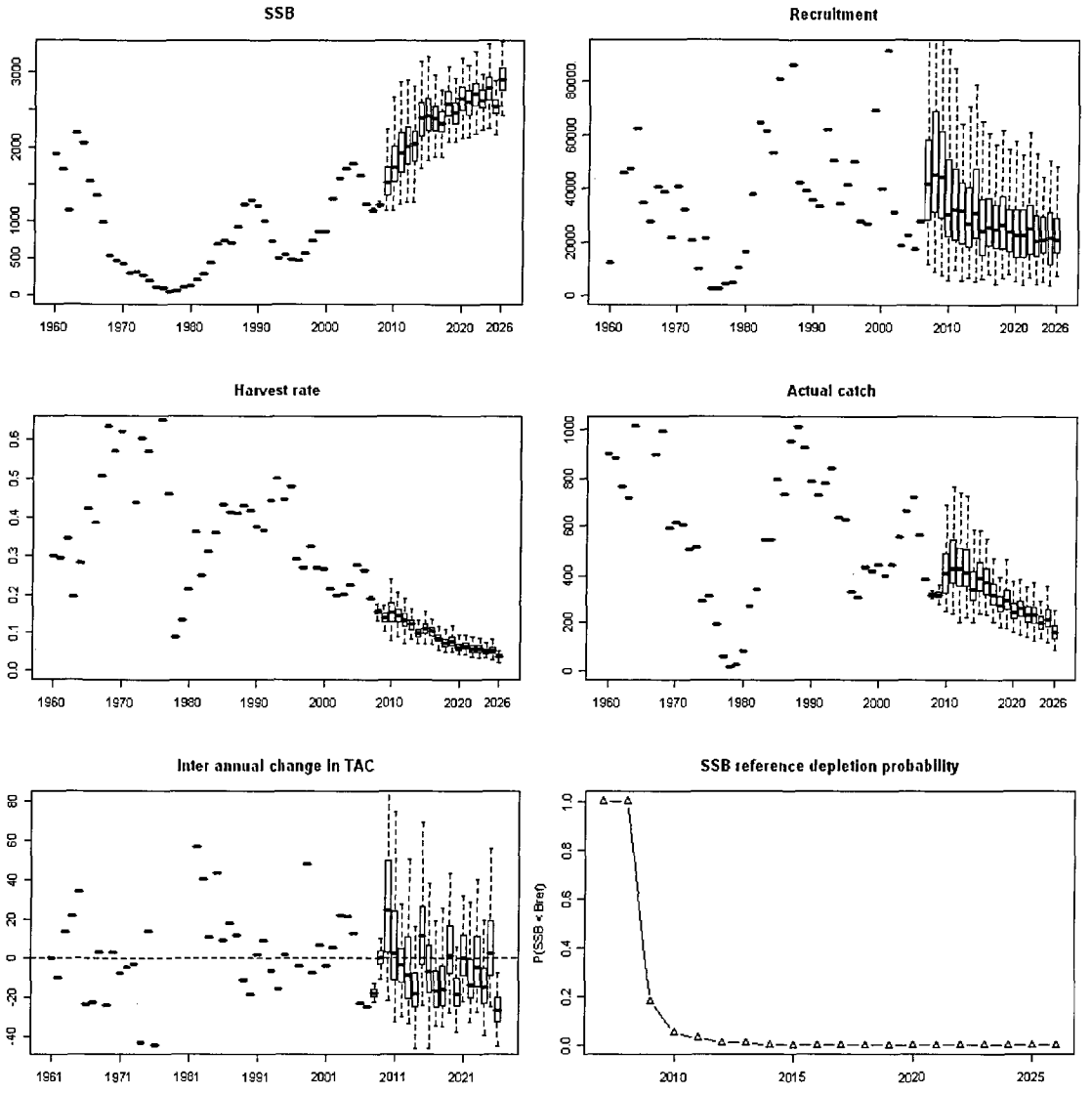


Figure 216: Output of simulation 137.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

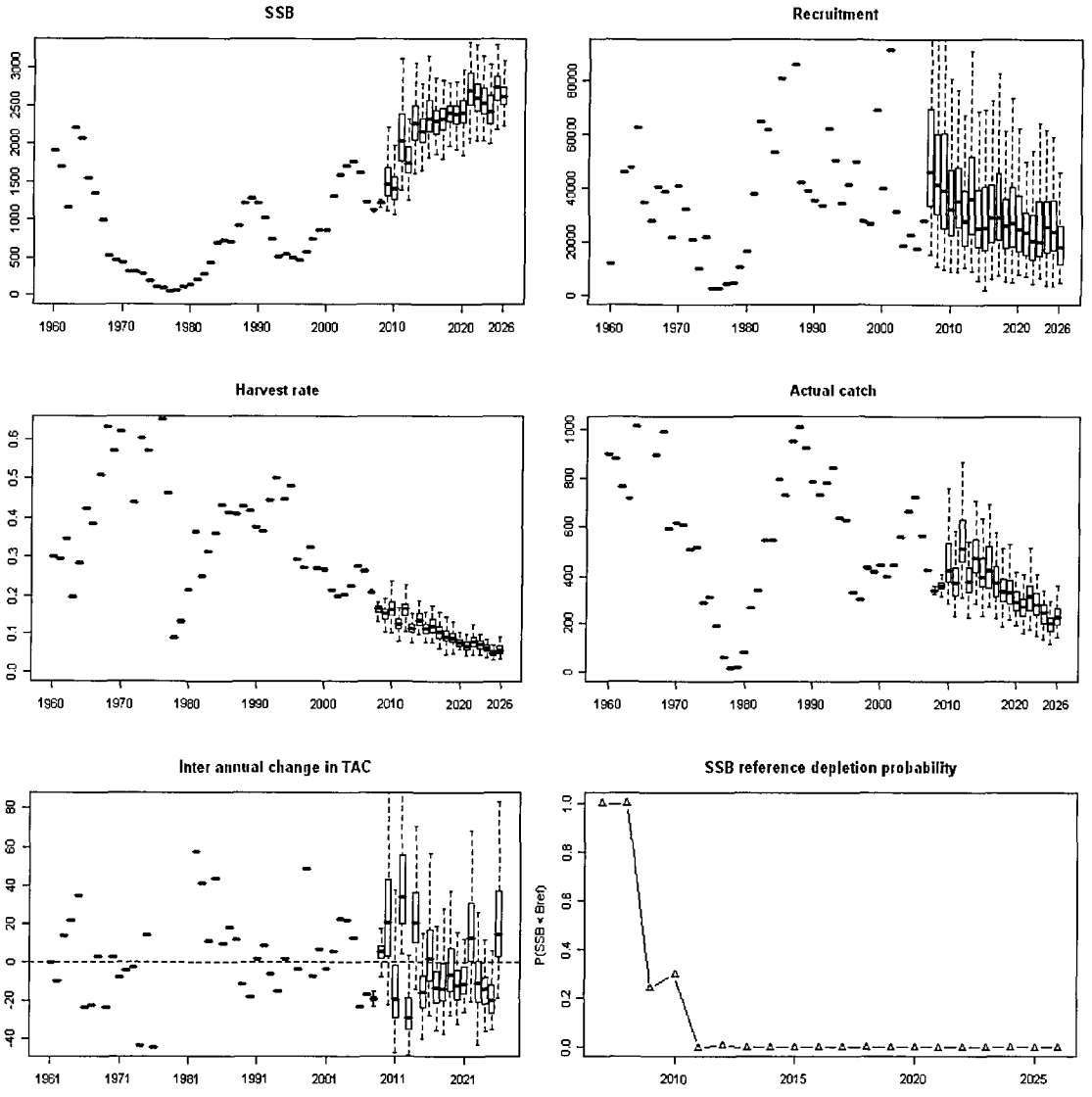


Figure 217: Output of simulation 138.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

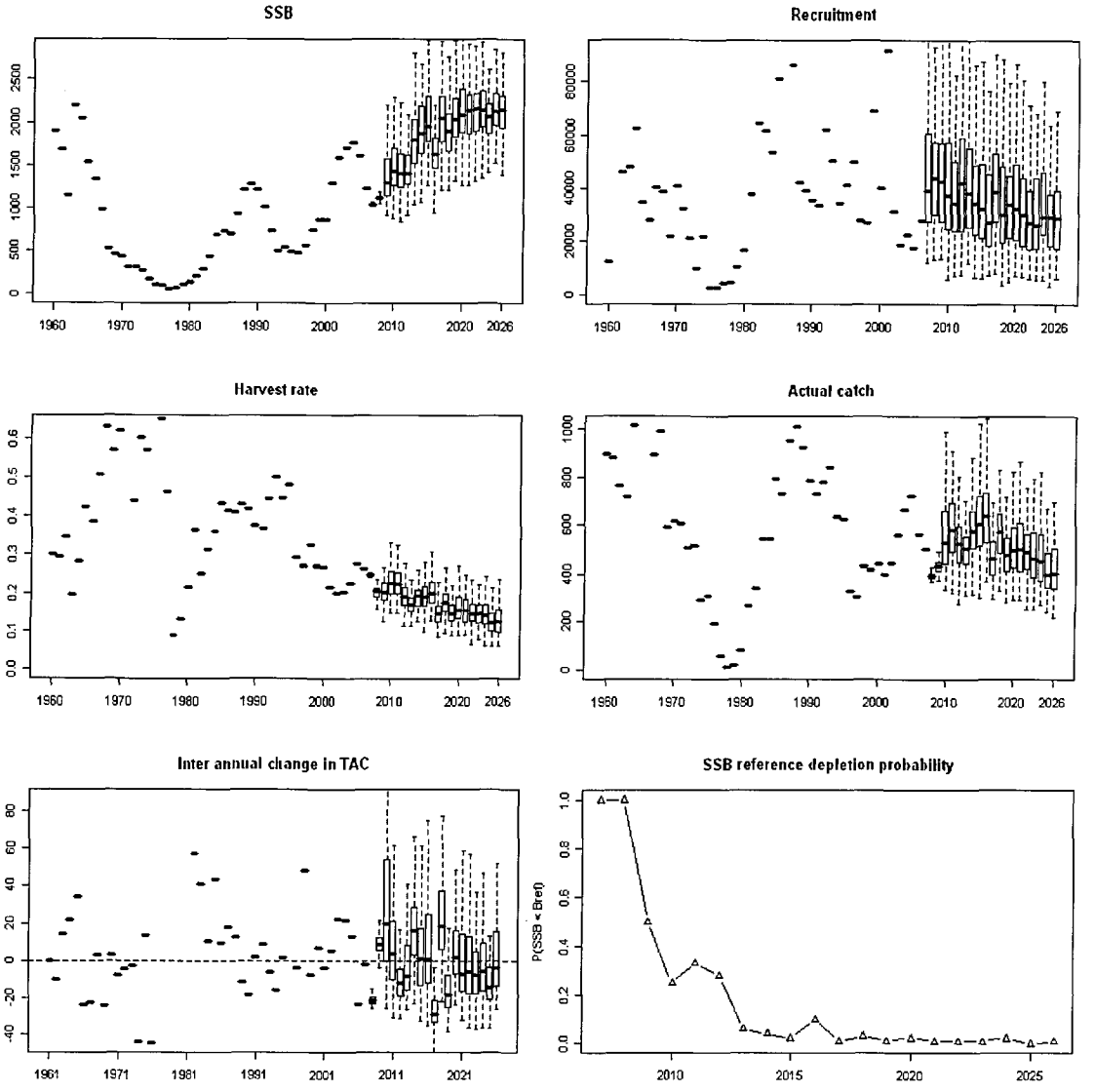


Figure 218: Output of simulation 139.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

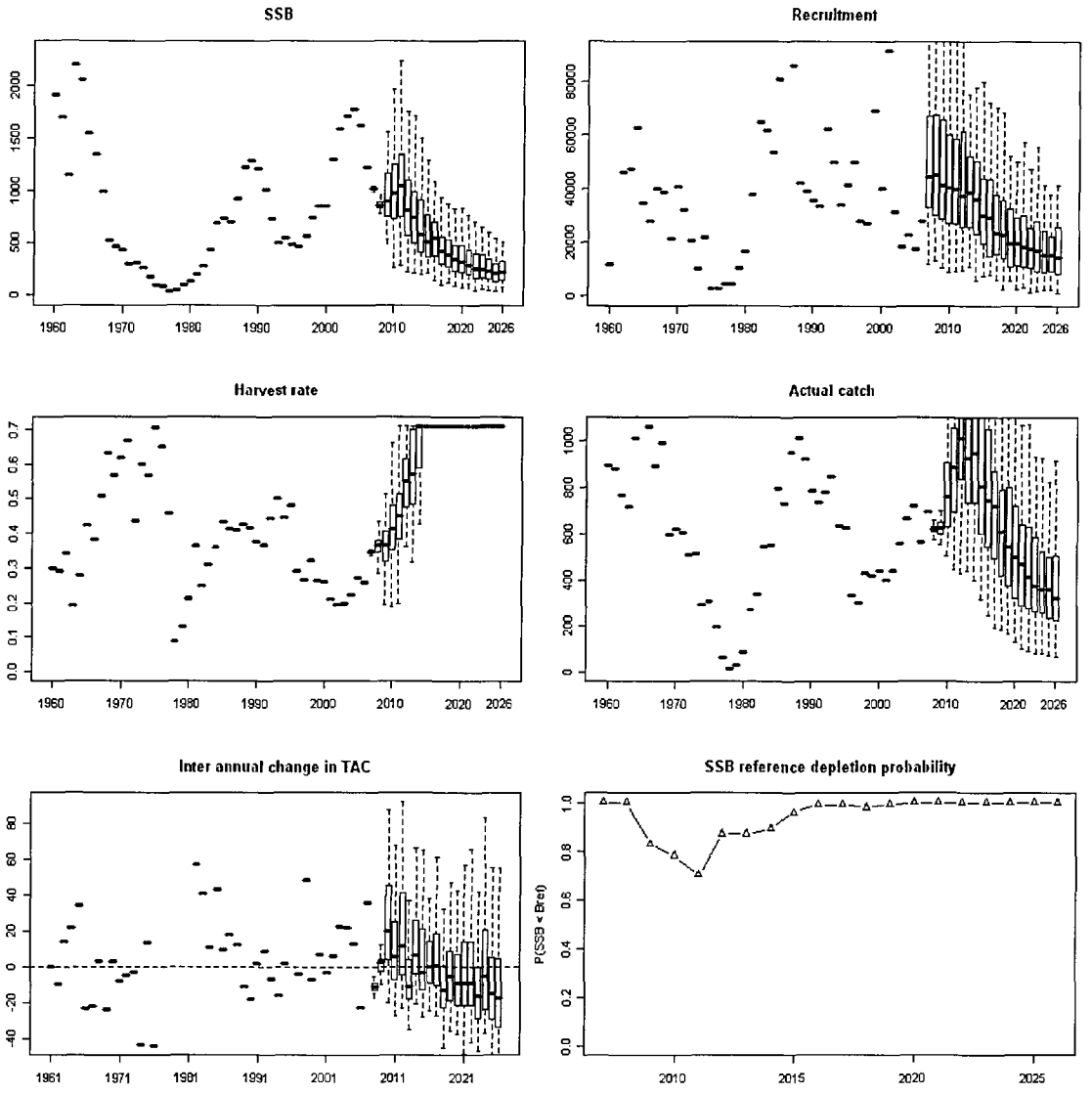


Figure 219: Output of simulation 140.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

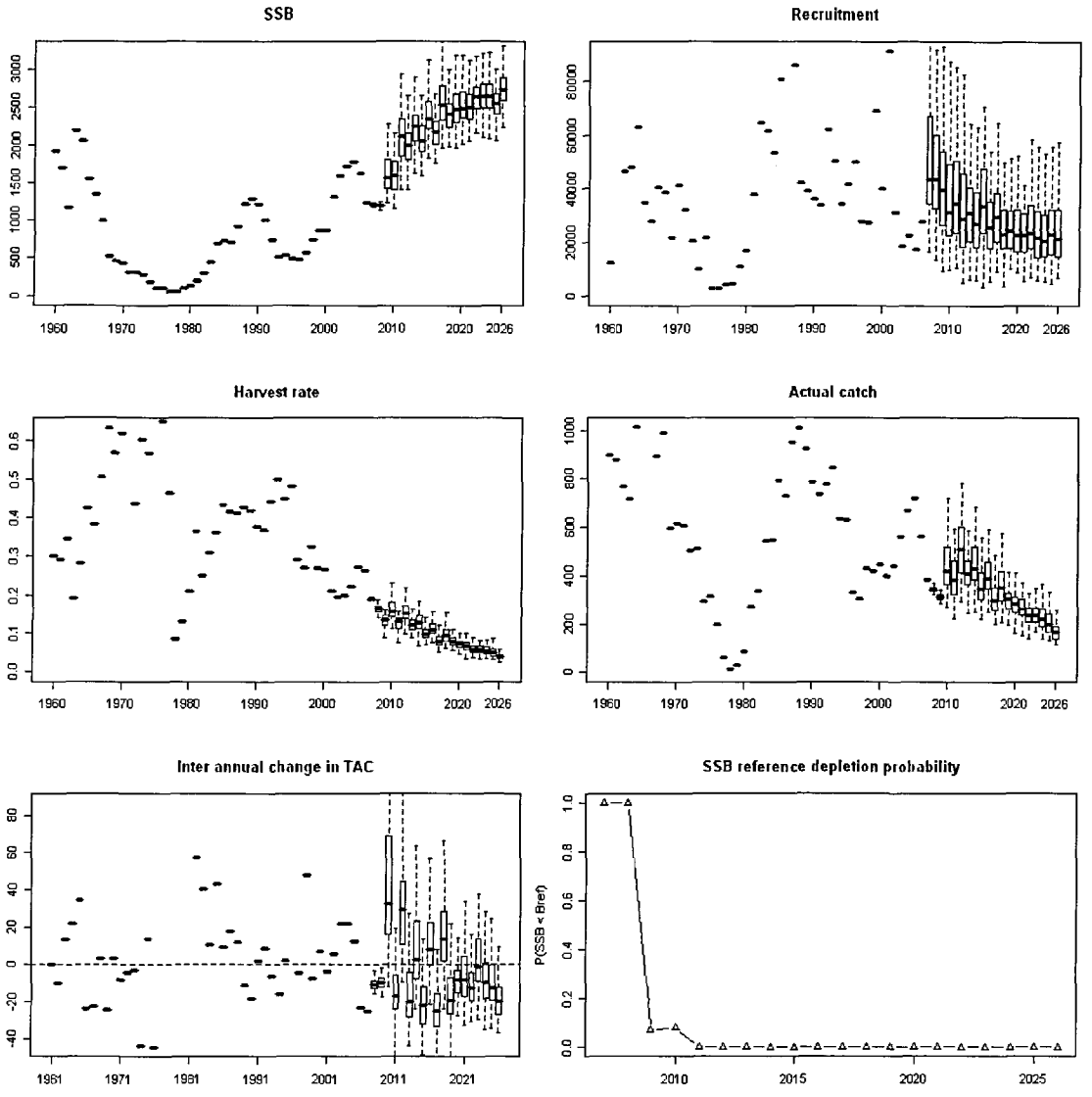


Figure 220: Output of simulation 141.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

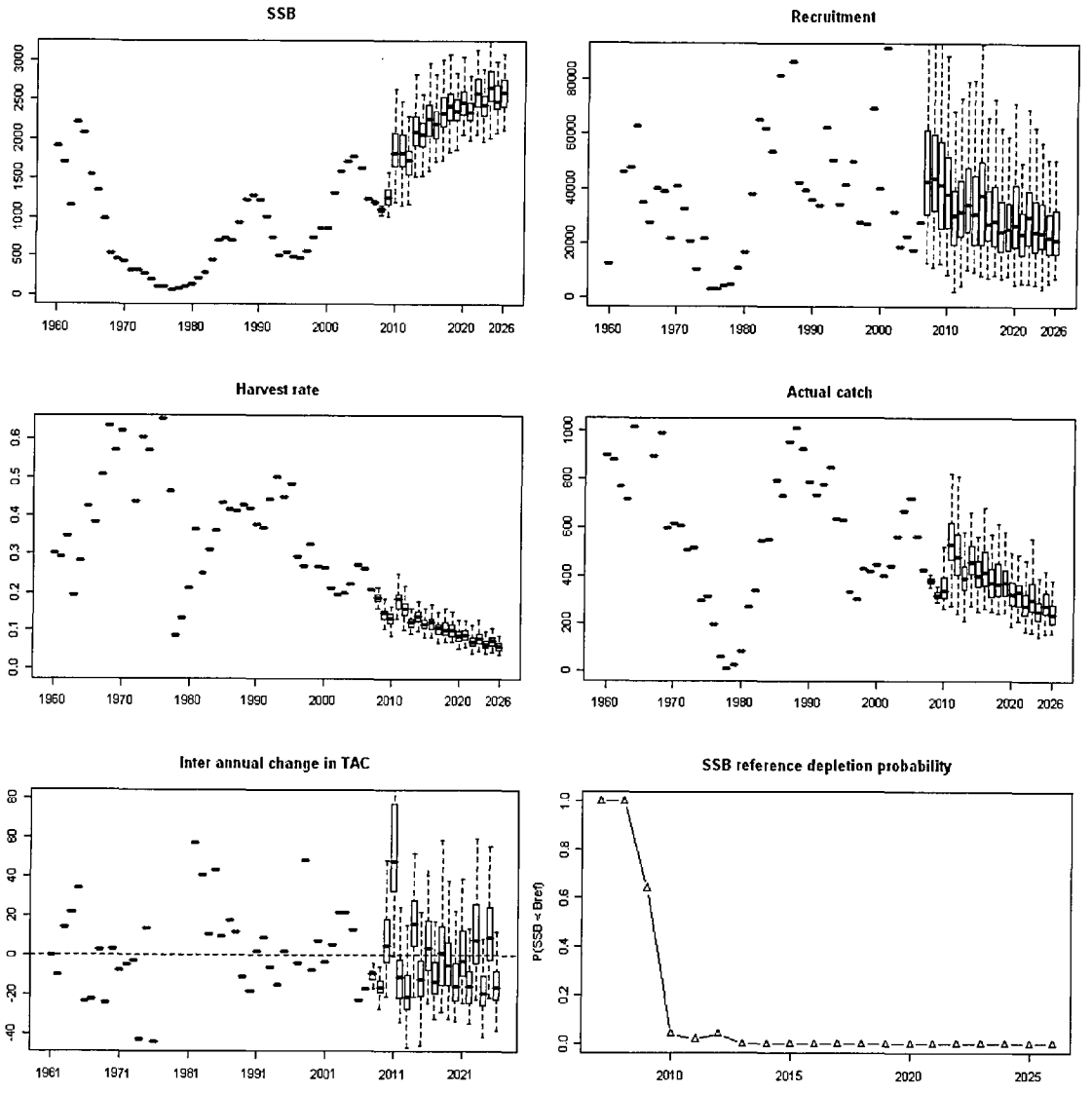


Figure 221: Output of simulation 142.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

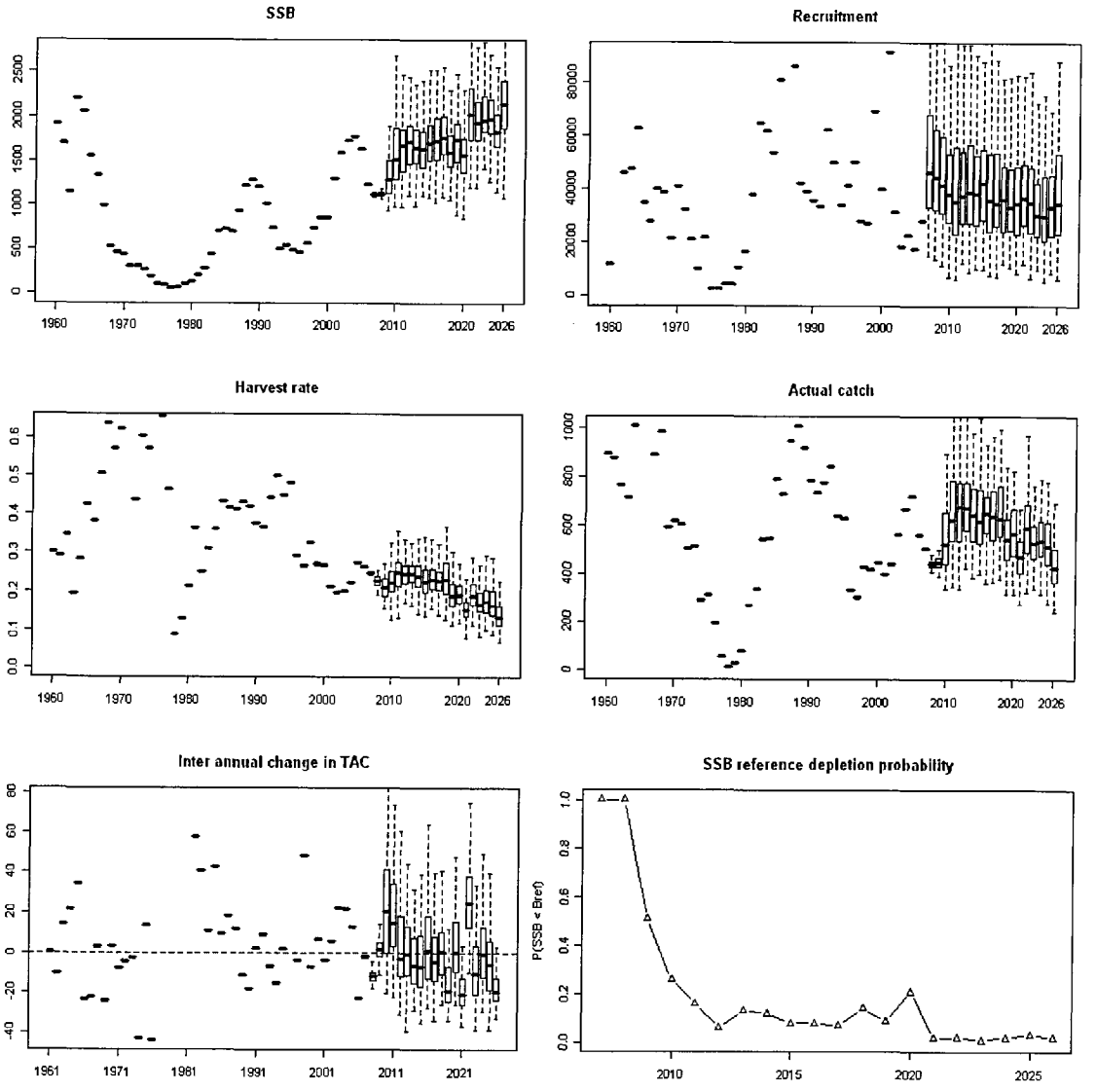


Figure 222: Output of simulation 143.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

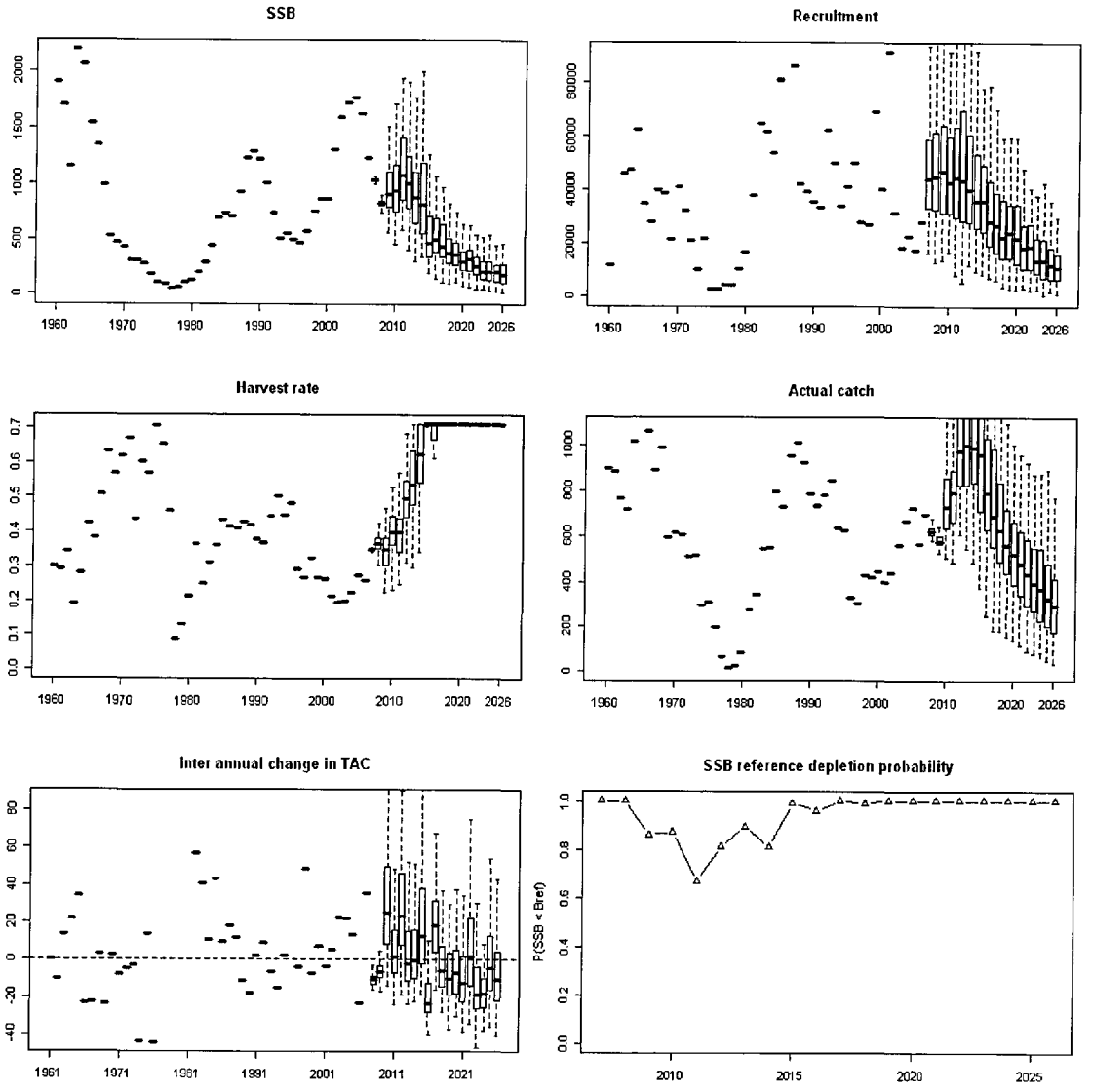


Figure 223: Output of simulation 144.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

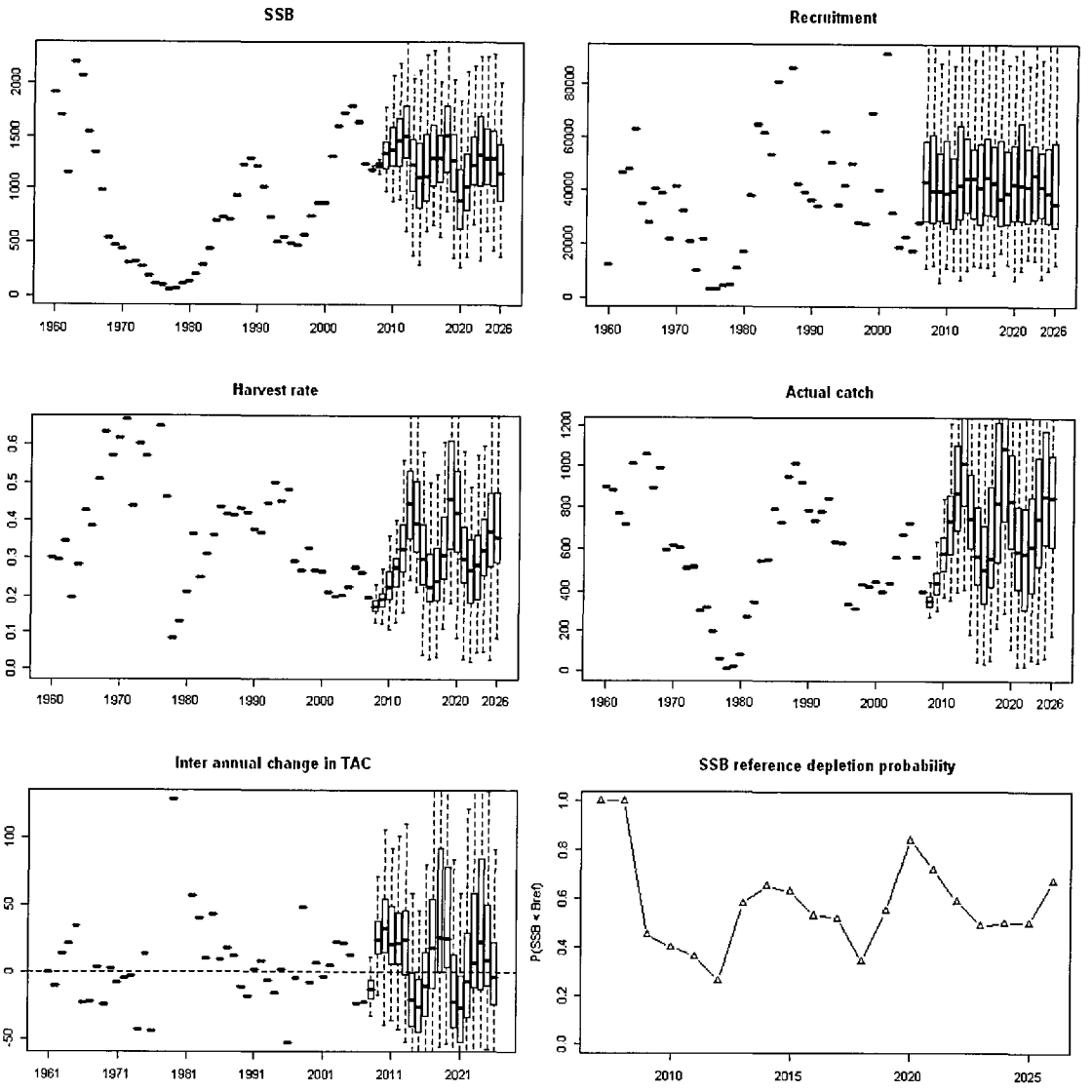


Figure 224: Output of simulation 145.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

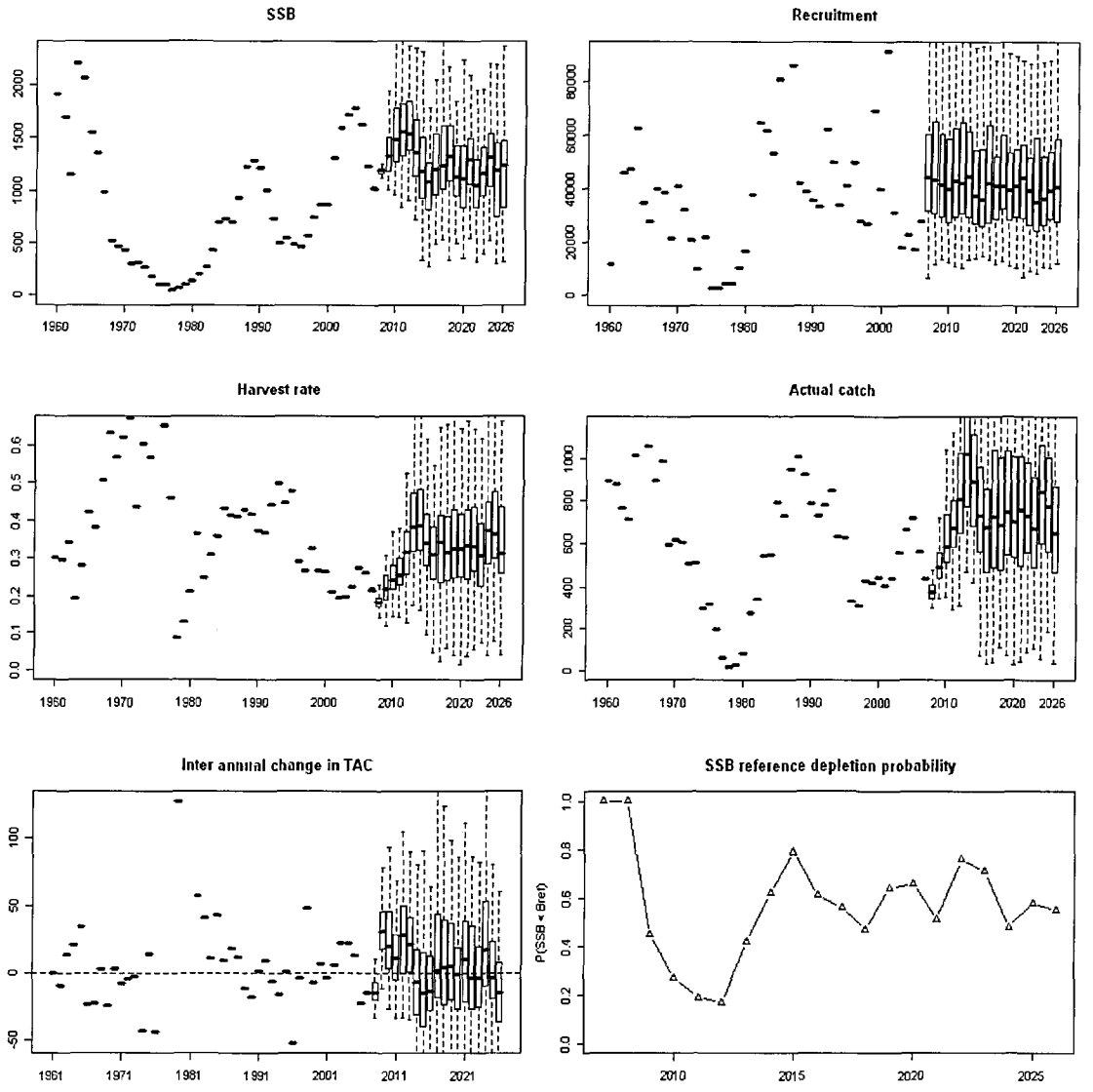


Figure 225: Output of simulation 146.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

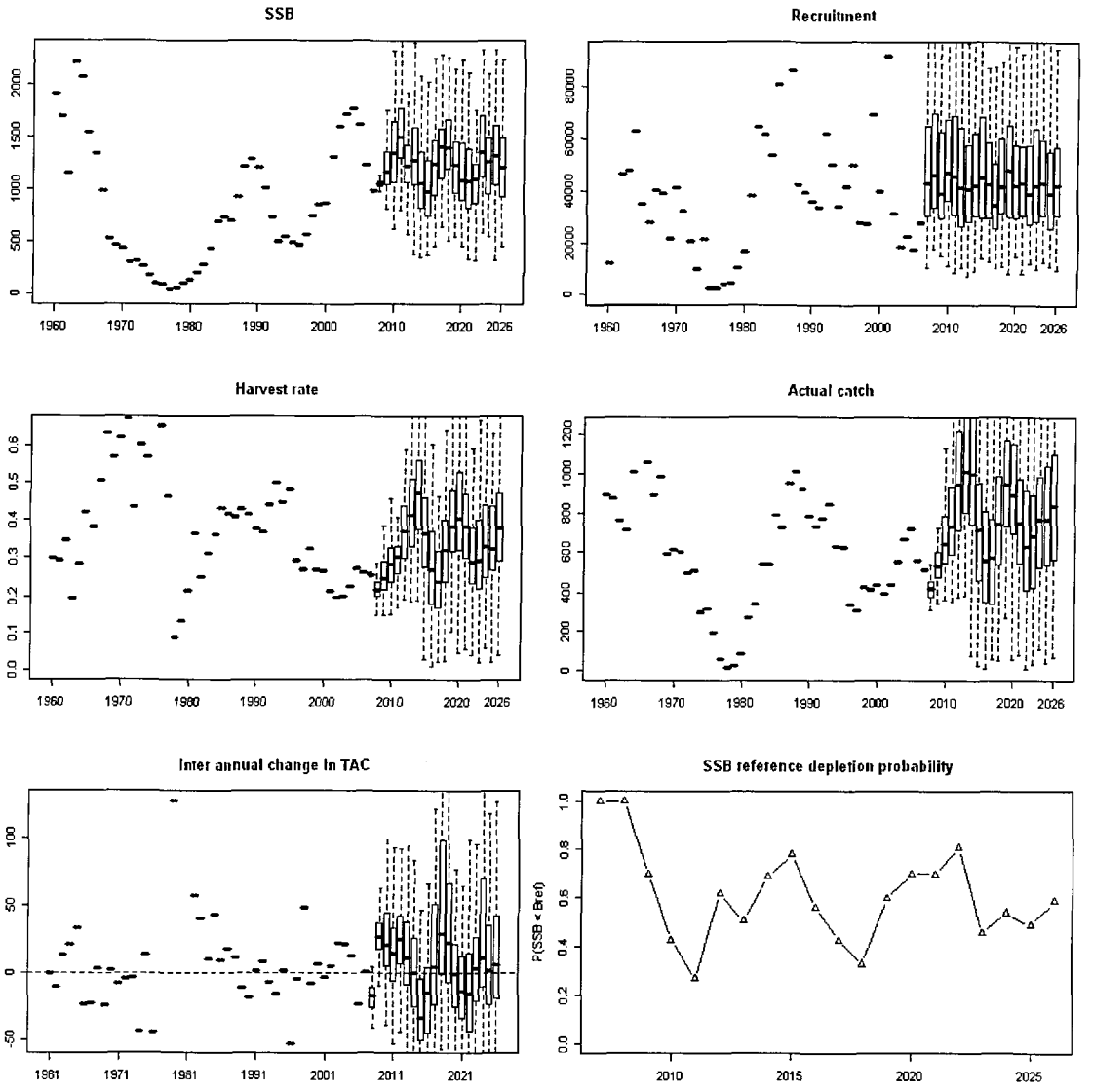


Figure 226: Output of simulation 147.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

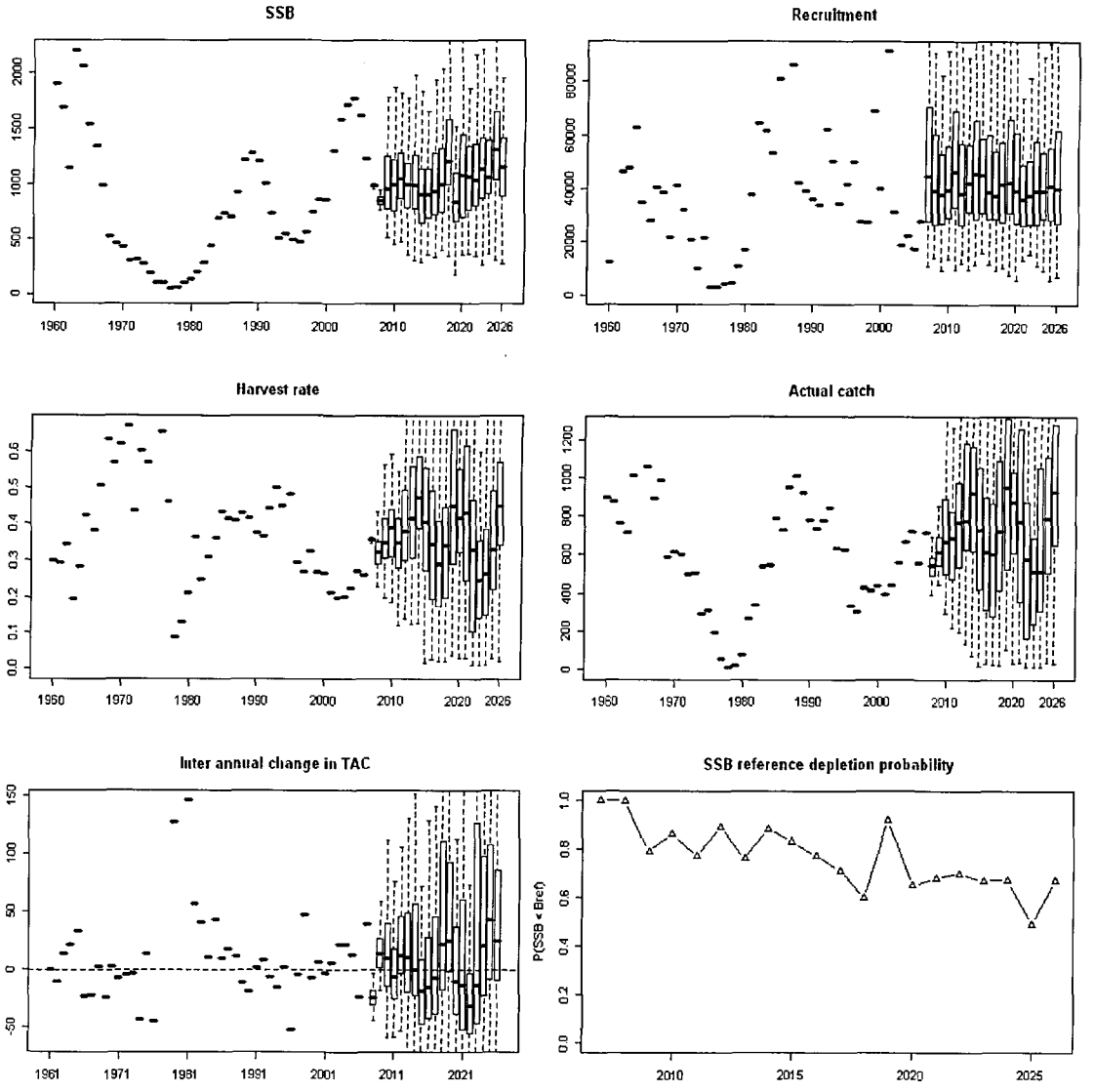


Figure 227: Output of simulation 148.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

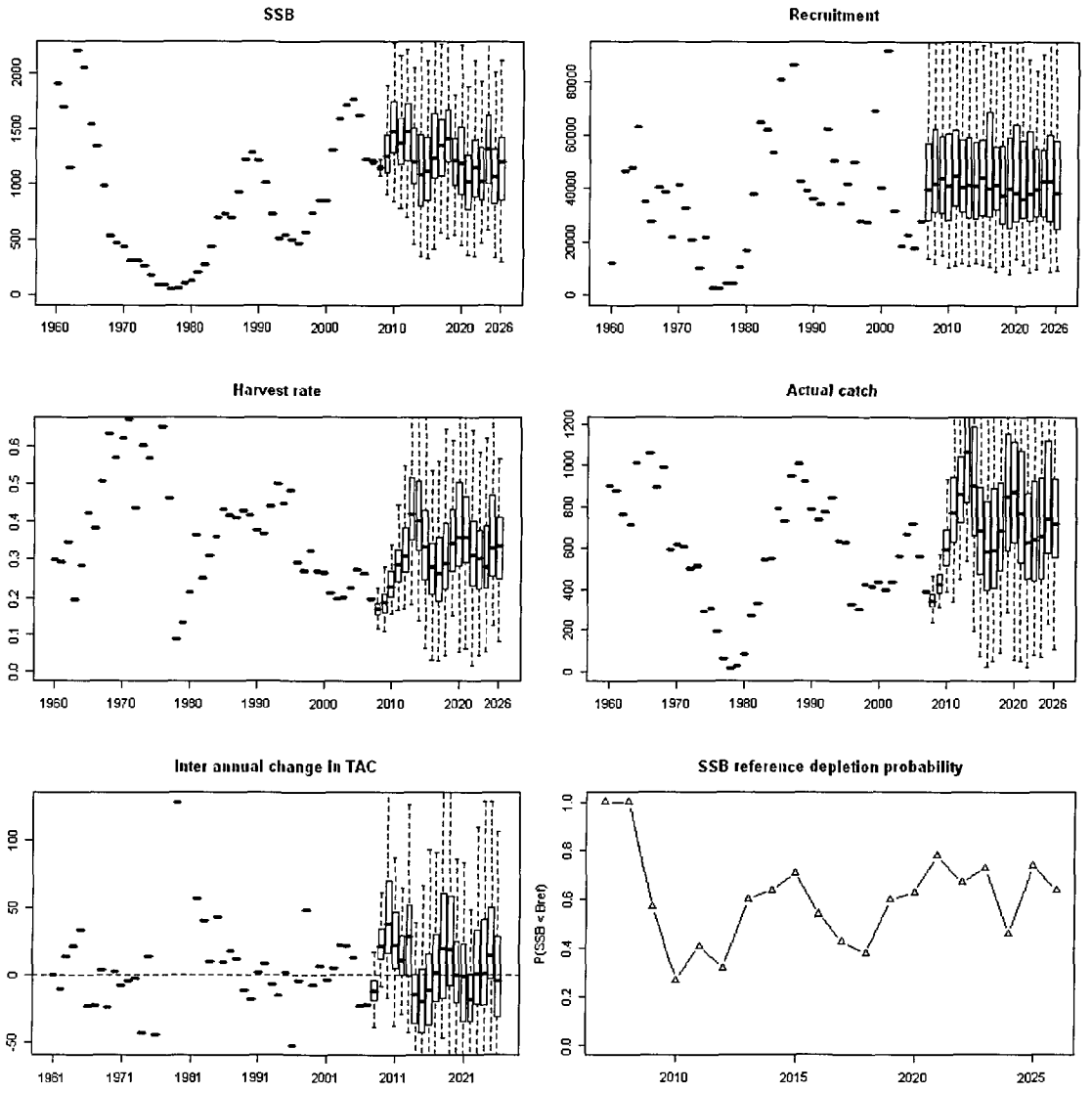


Figure 228: Output of simulation 149.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

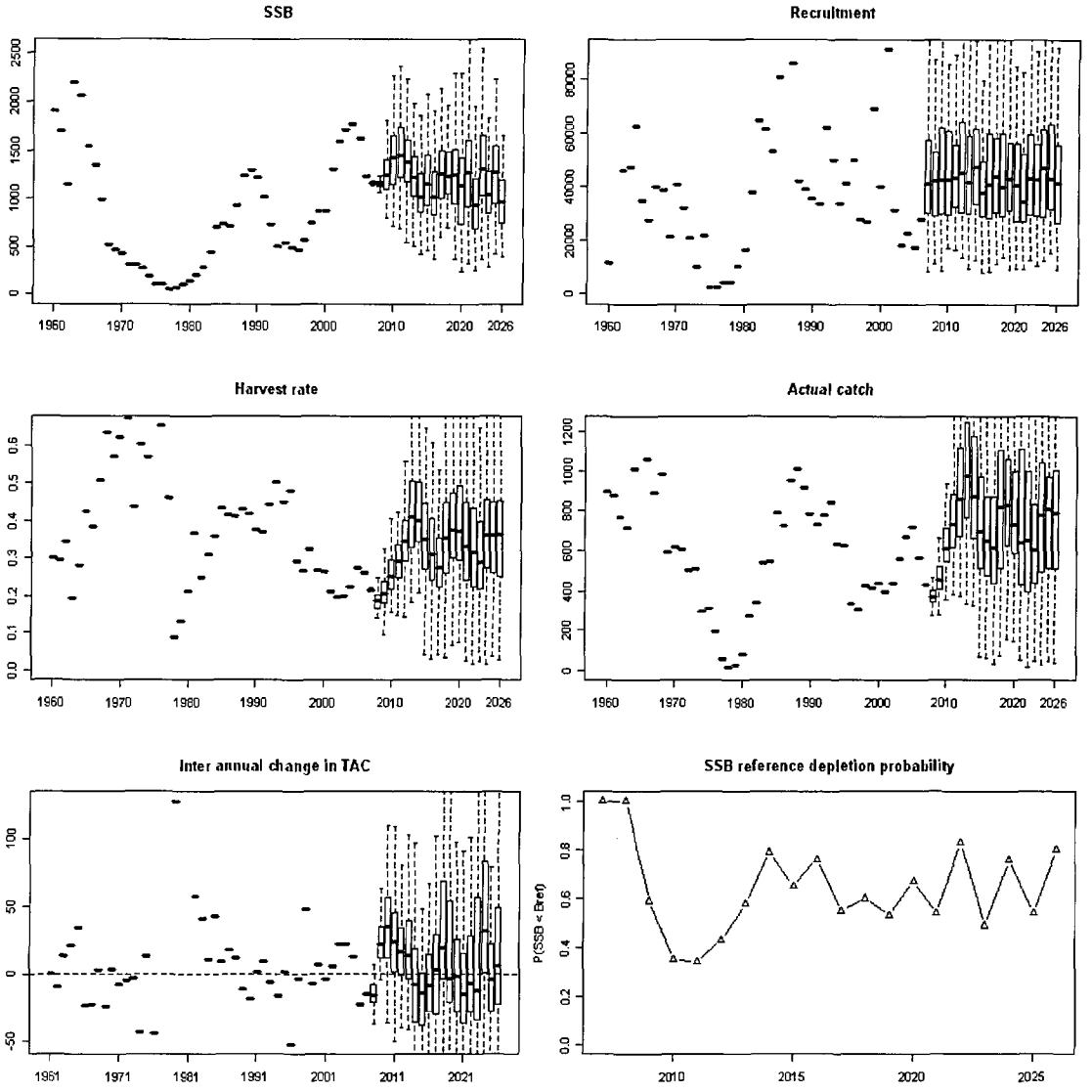


Figure 229: Output of simulation 150.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

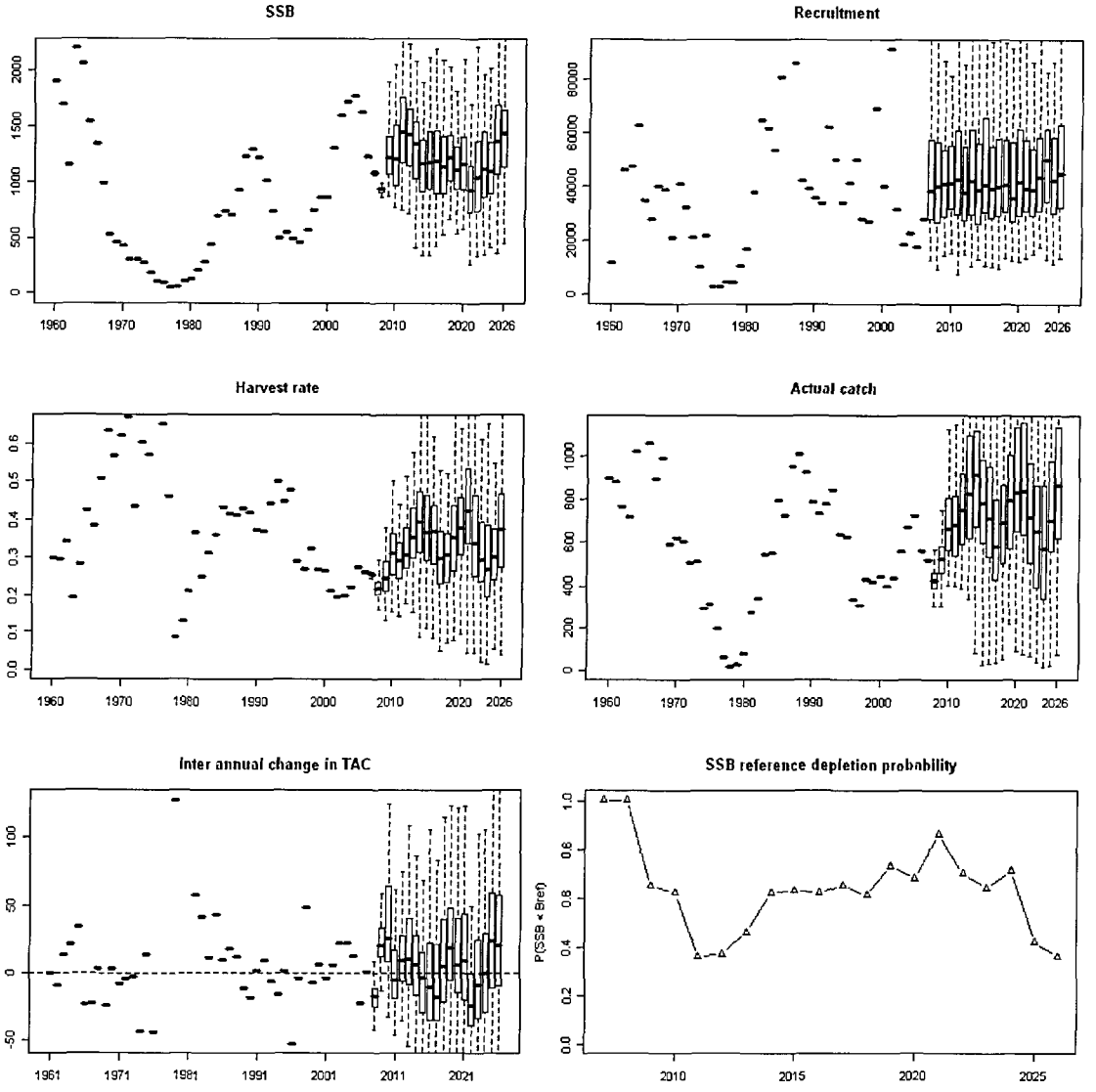


Figure 230: Output of simulation 151.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

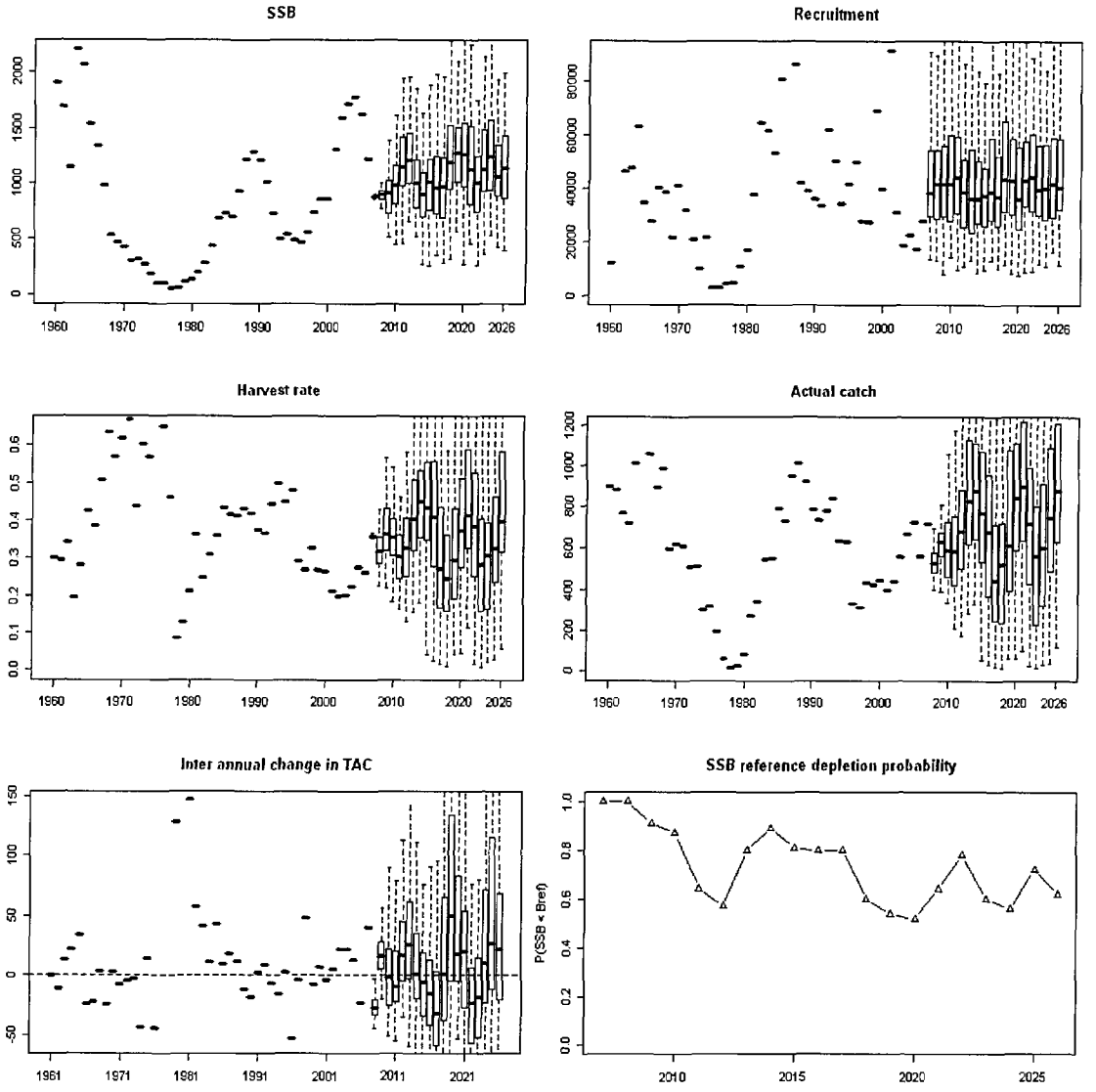


Figure 231: Output of simulation 152.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

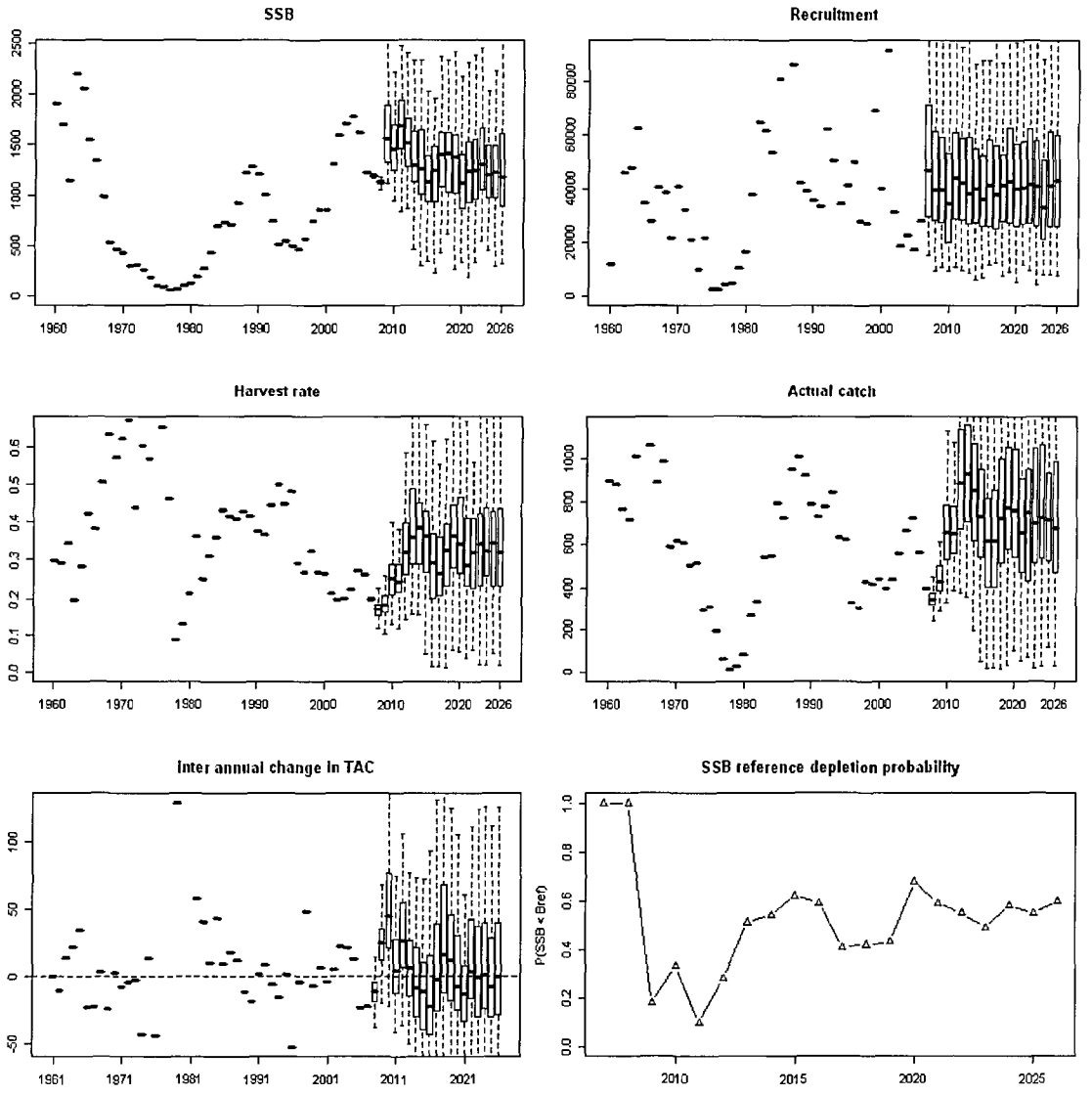


Figure 232: Output of simulation 153.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

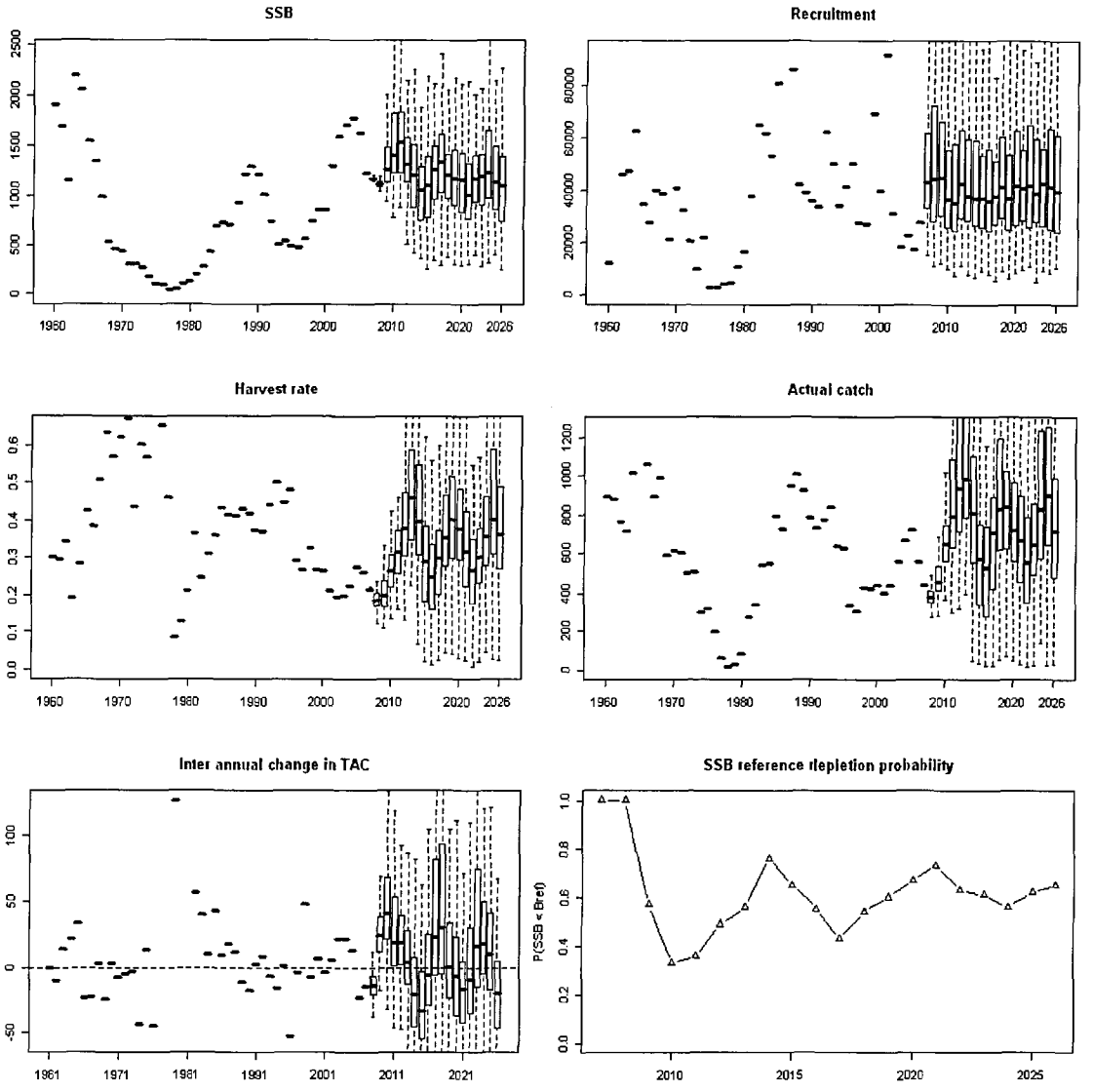


Figure 233: Output of simulation 154.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

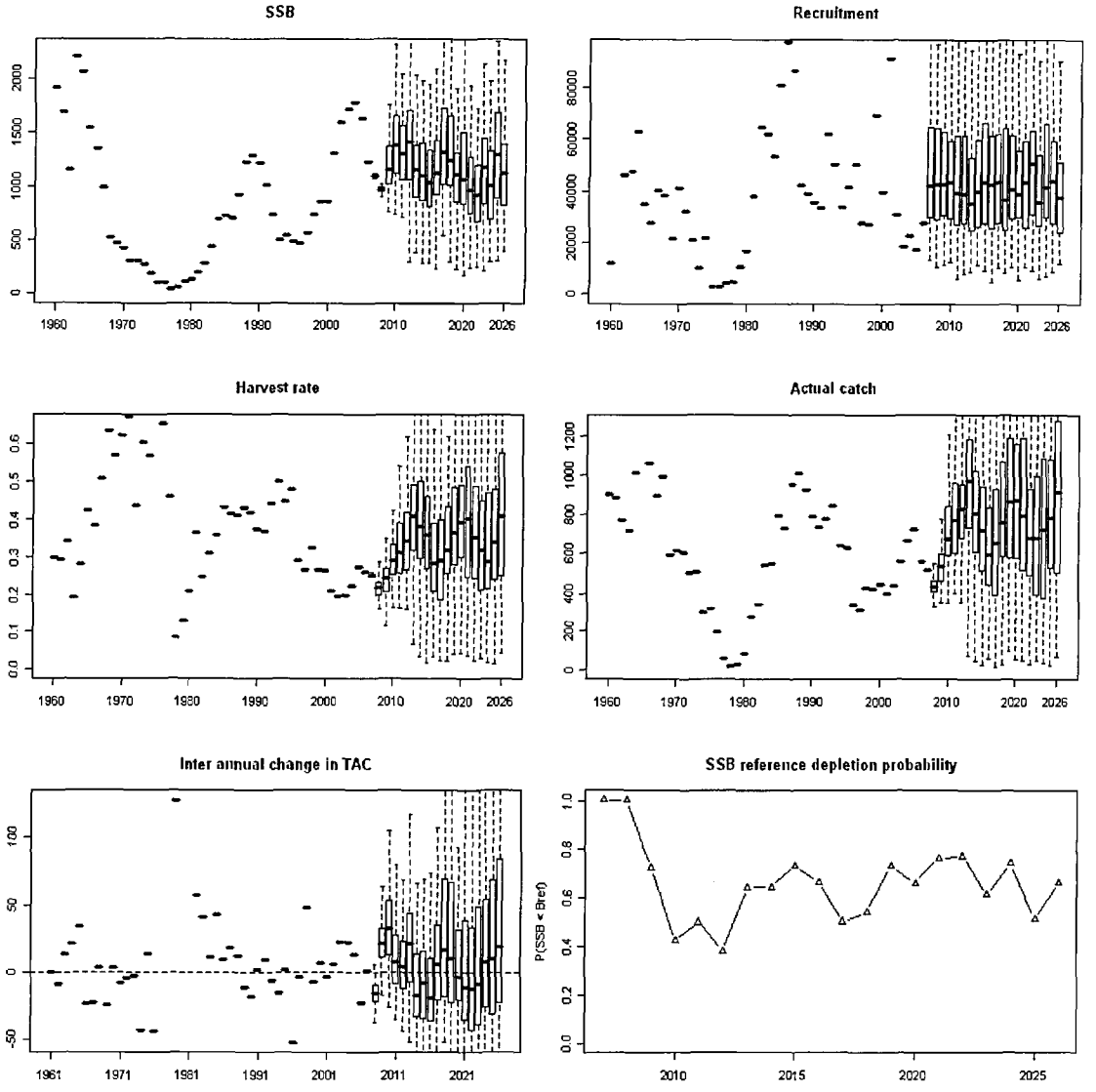


Figure 234: Output of simulation 155.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

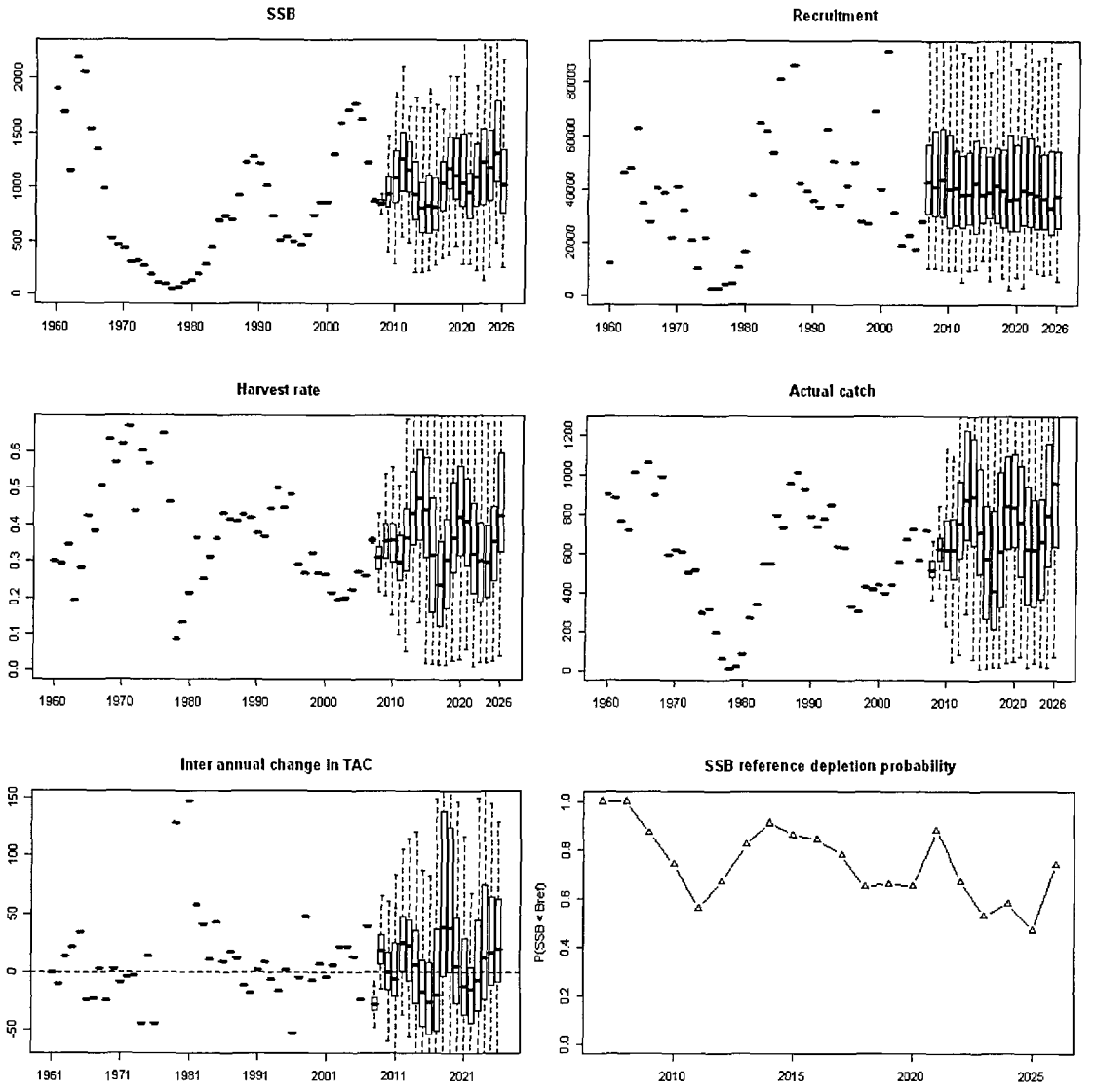


Figure 235: Output of simulation 156.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

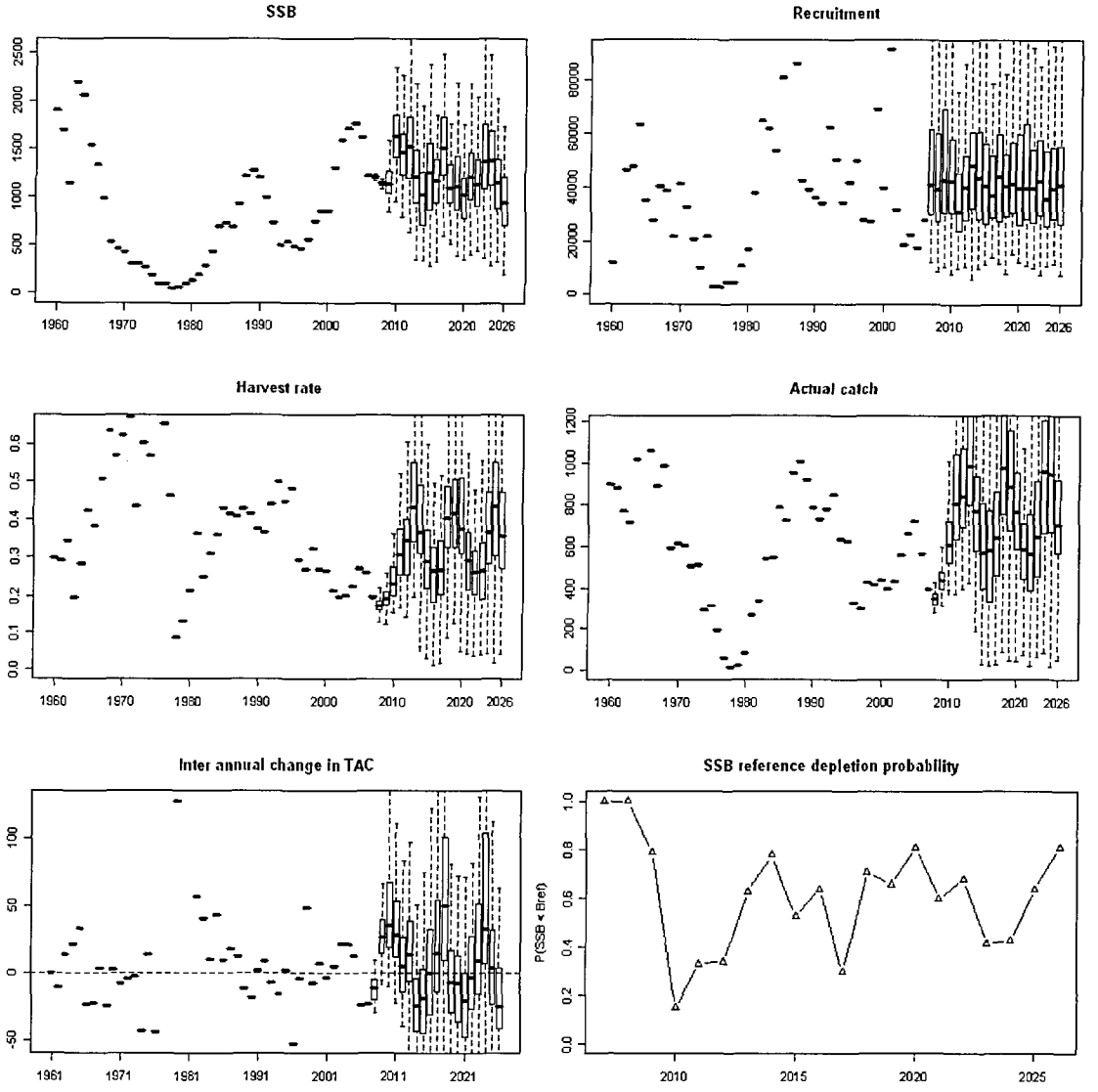


Figure 236: Output of simulation 157.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

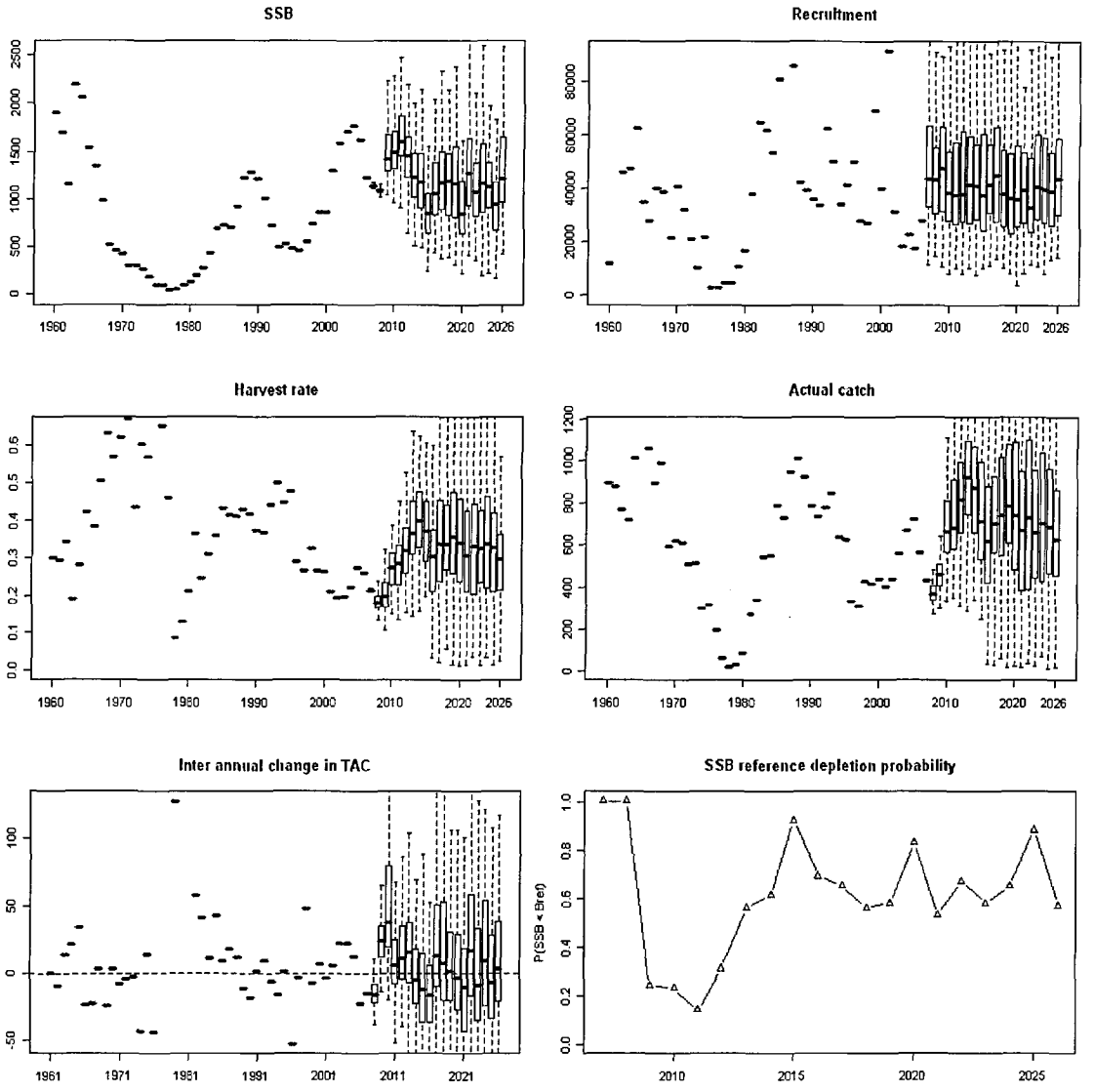


Figure 237: Output of simulation 158.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

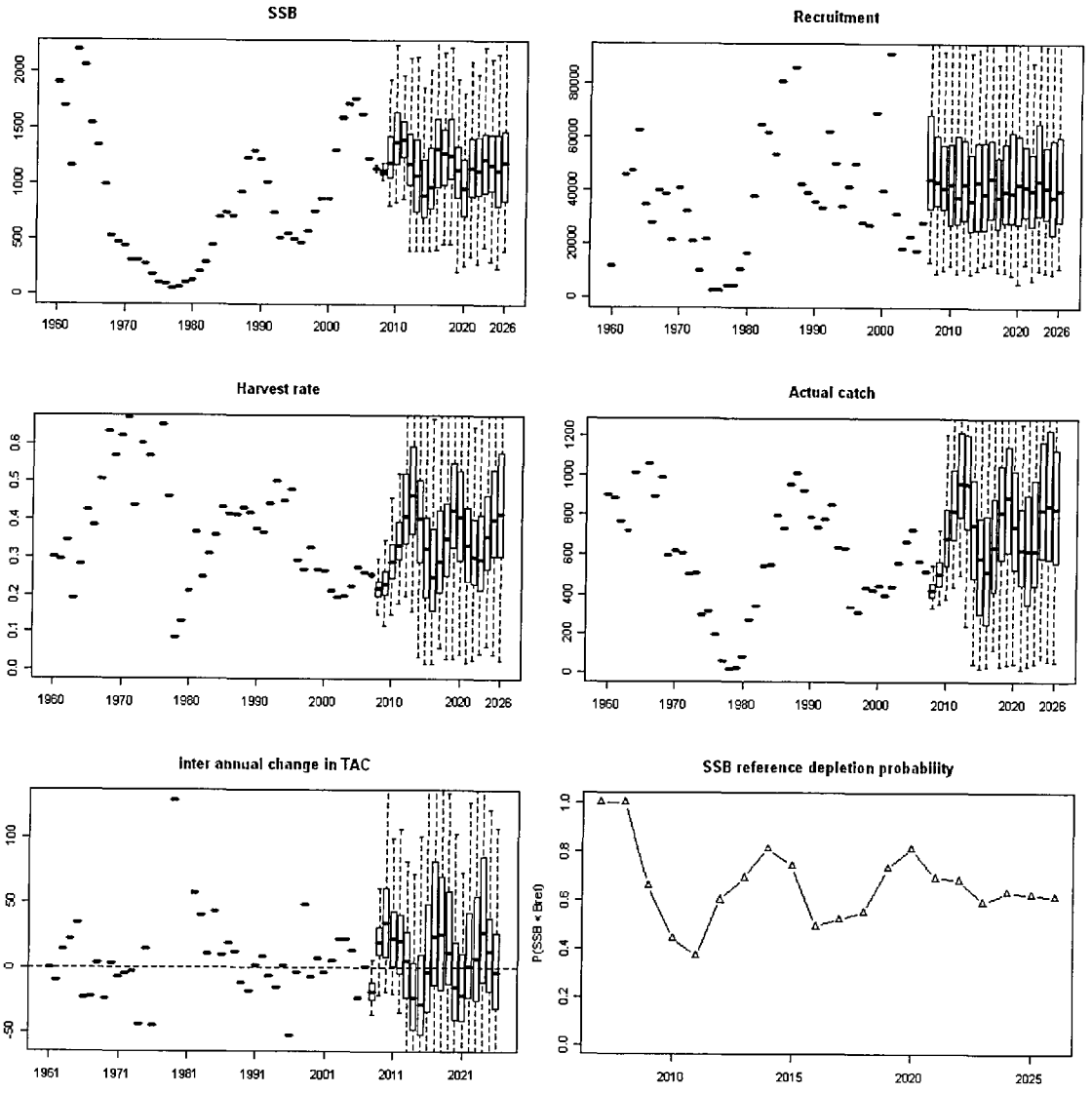


Figure 238: Output of simulation 159.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

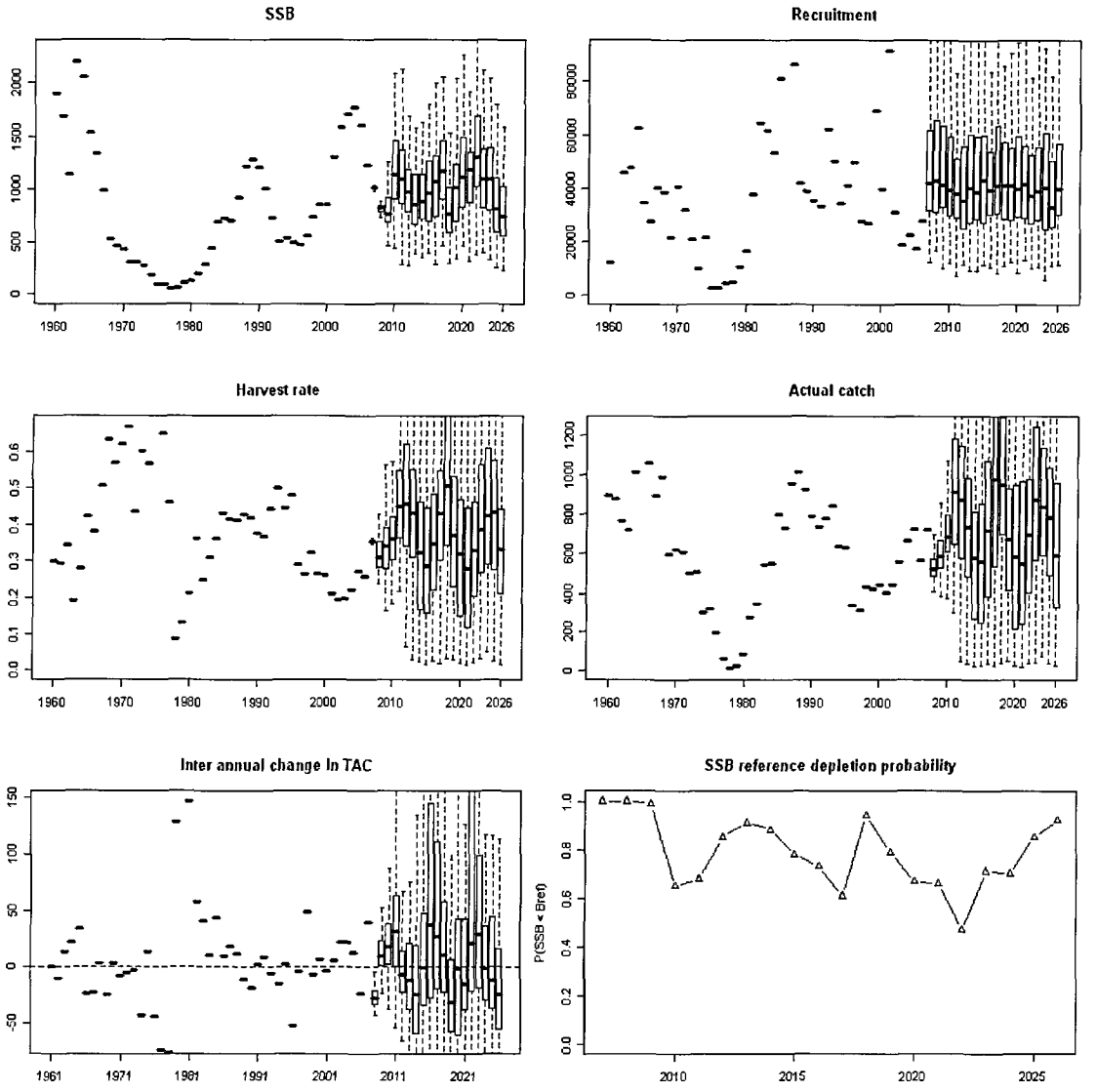


Figure 239: Output of simulation 160.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

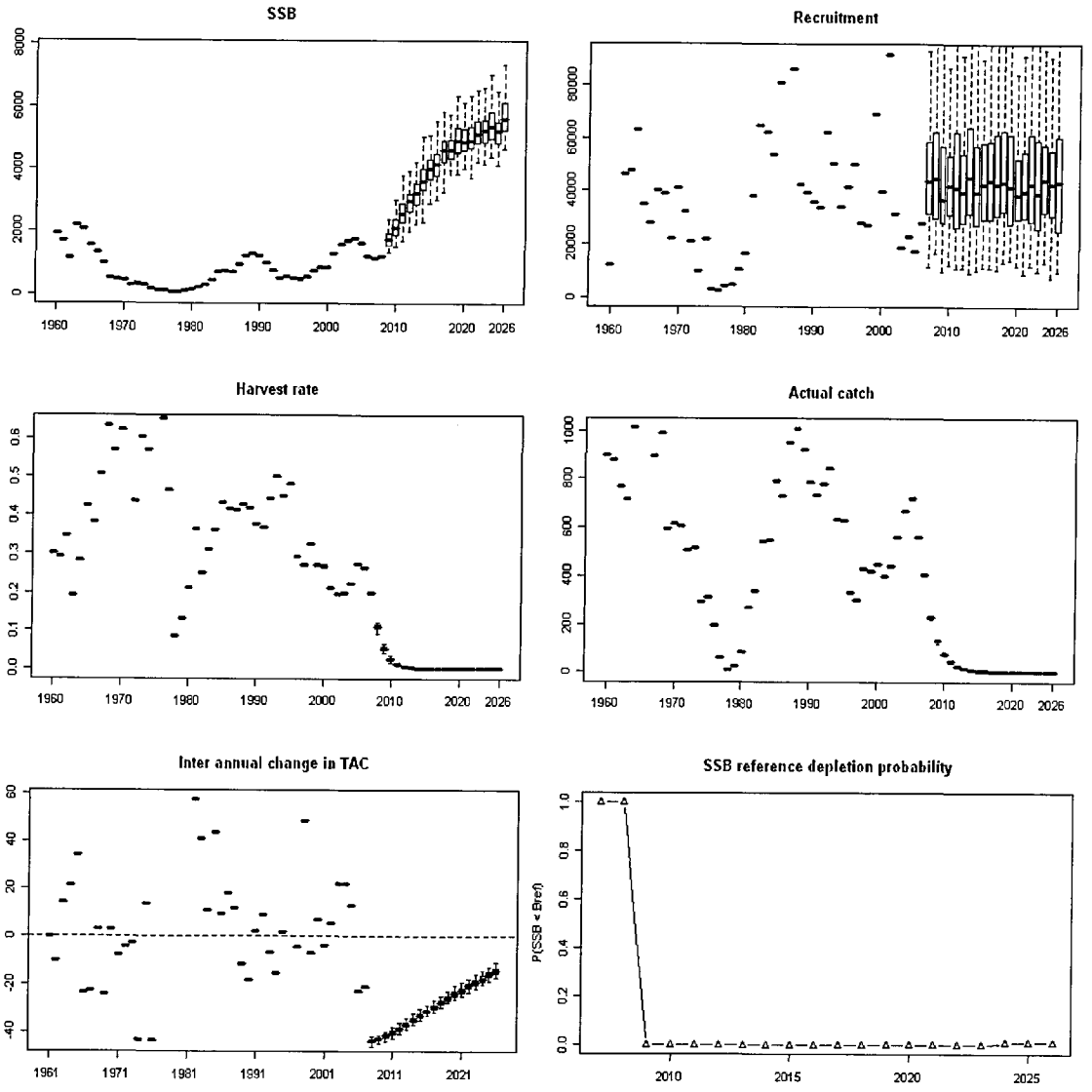


Figure 240: Output of simulation 161.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

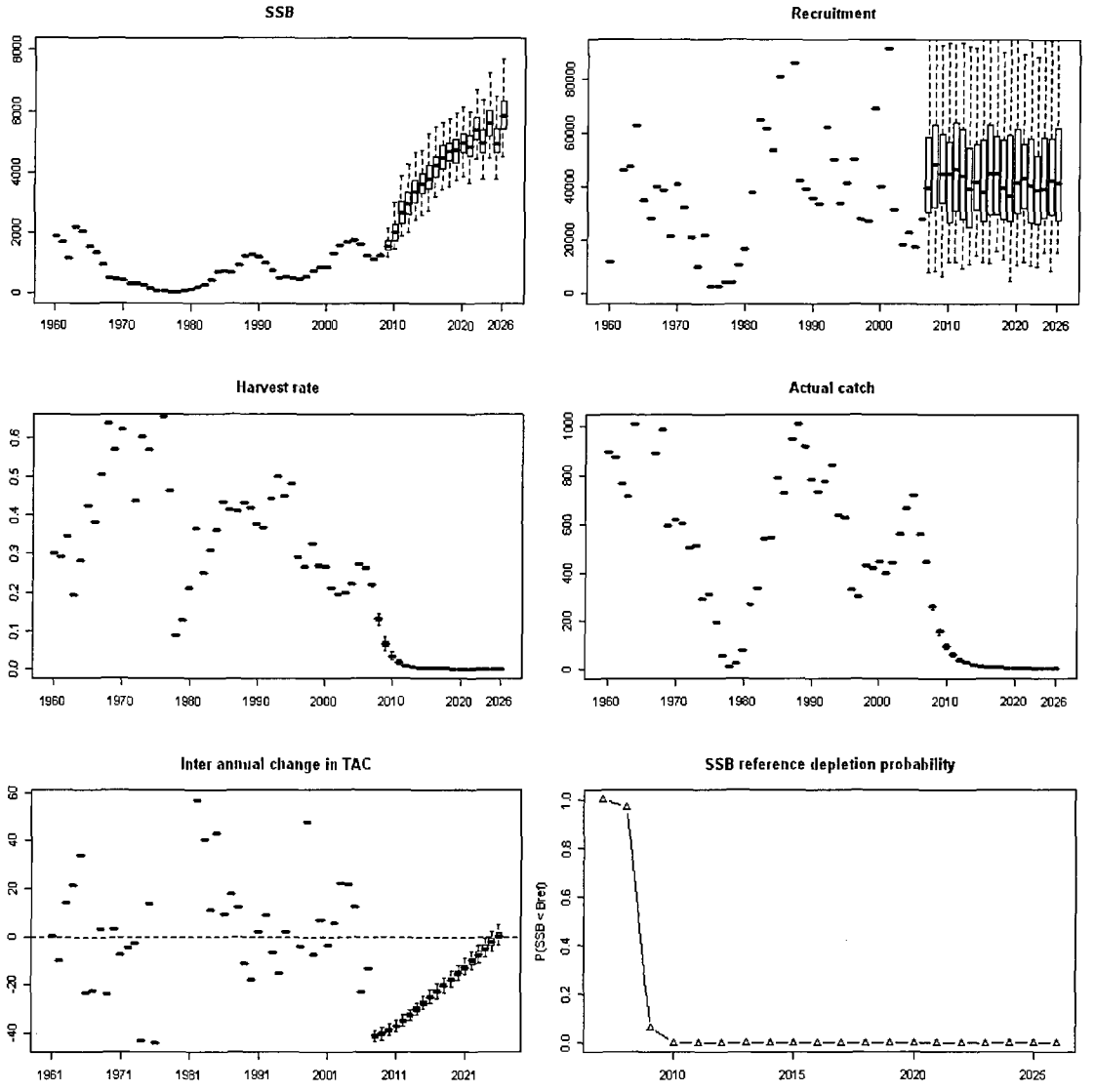


Figure 241: Output of simulation 162.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

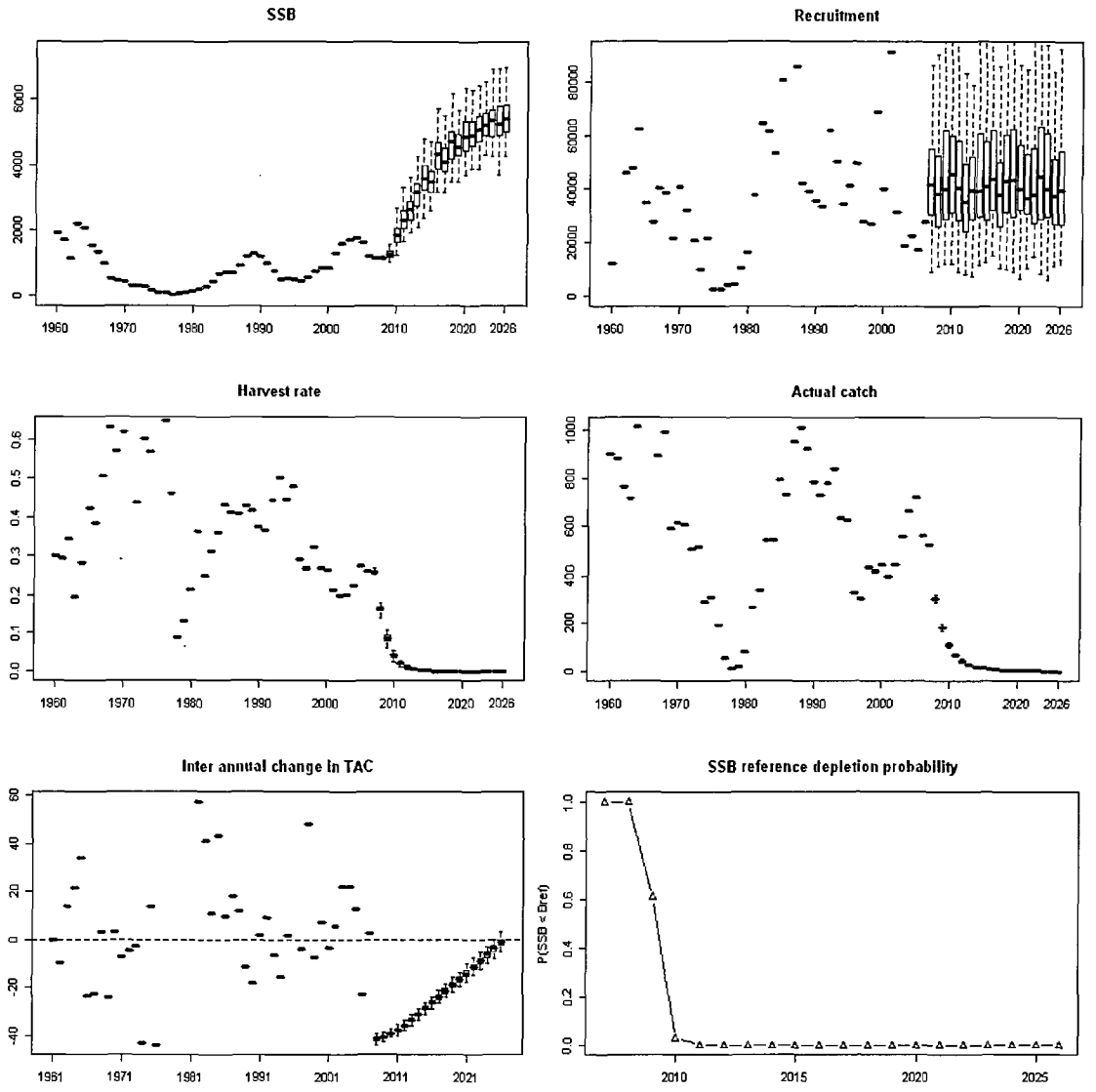


Figure 242: Output of simulation 163.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

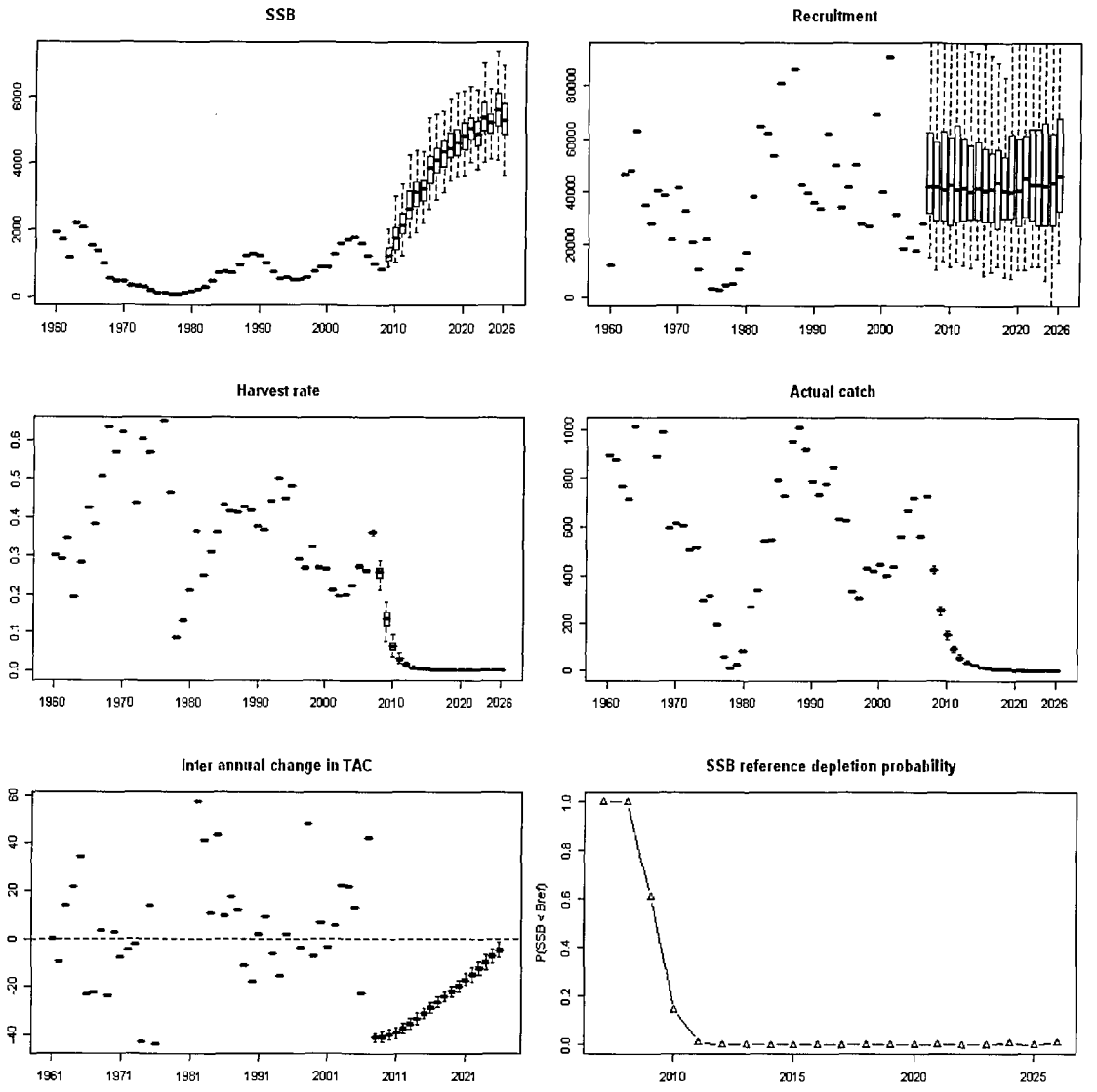


Figure 243: Output of simulation 164.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

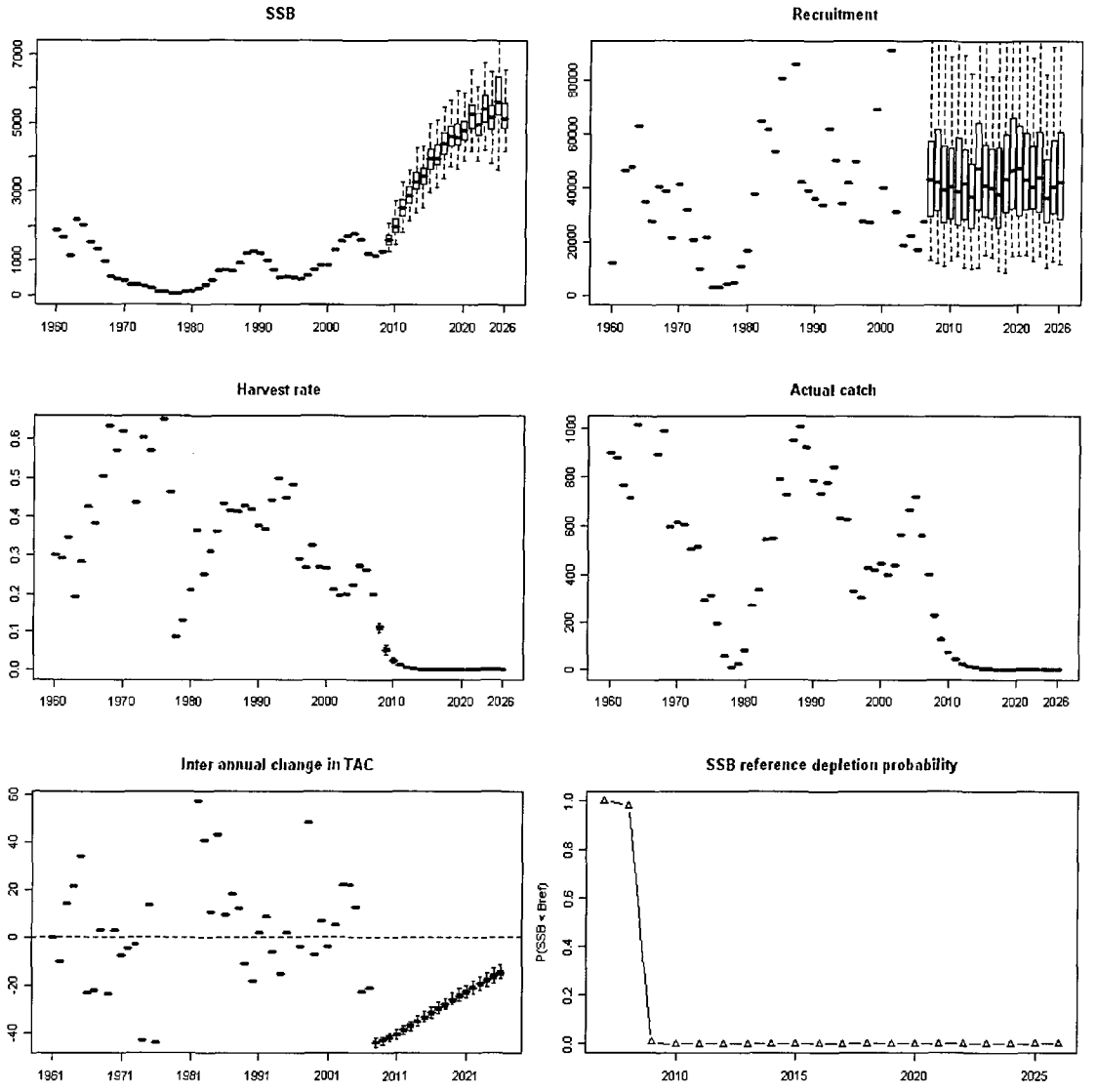


Figure 244: Output of simulation 165.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

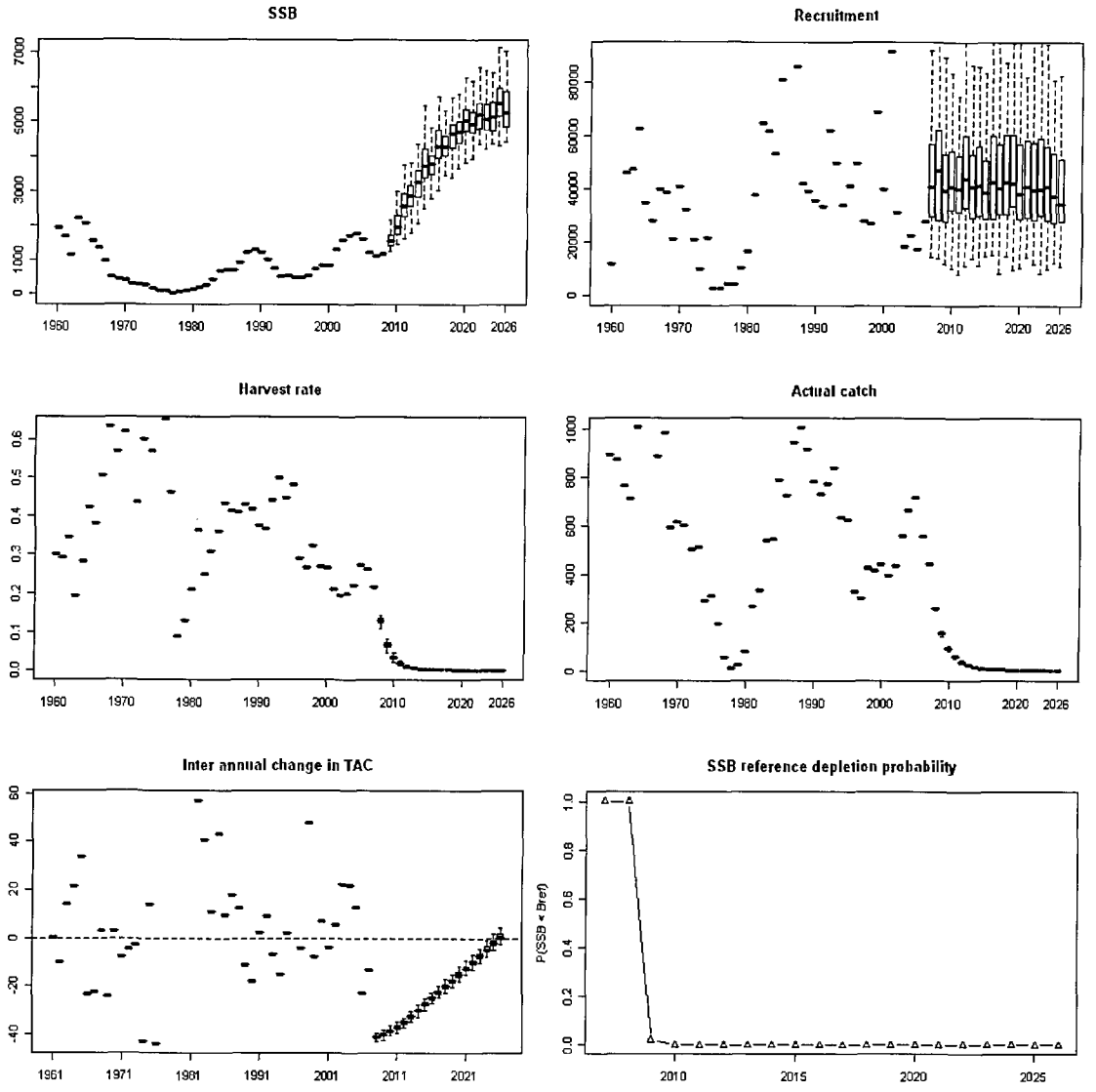


Figure 245: Output of simulation 166.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

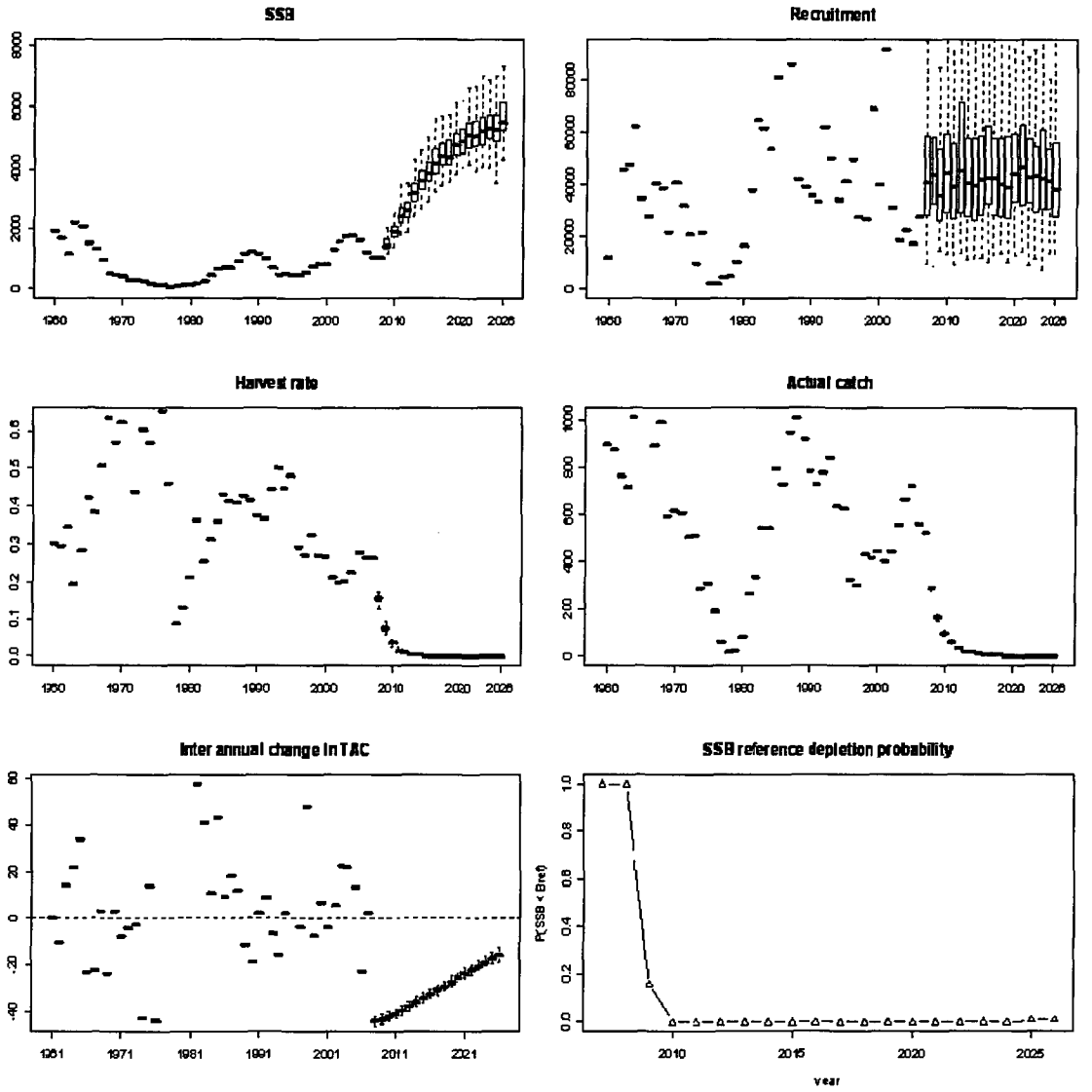


Figure 246: Output of simulation 167.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

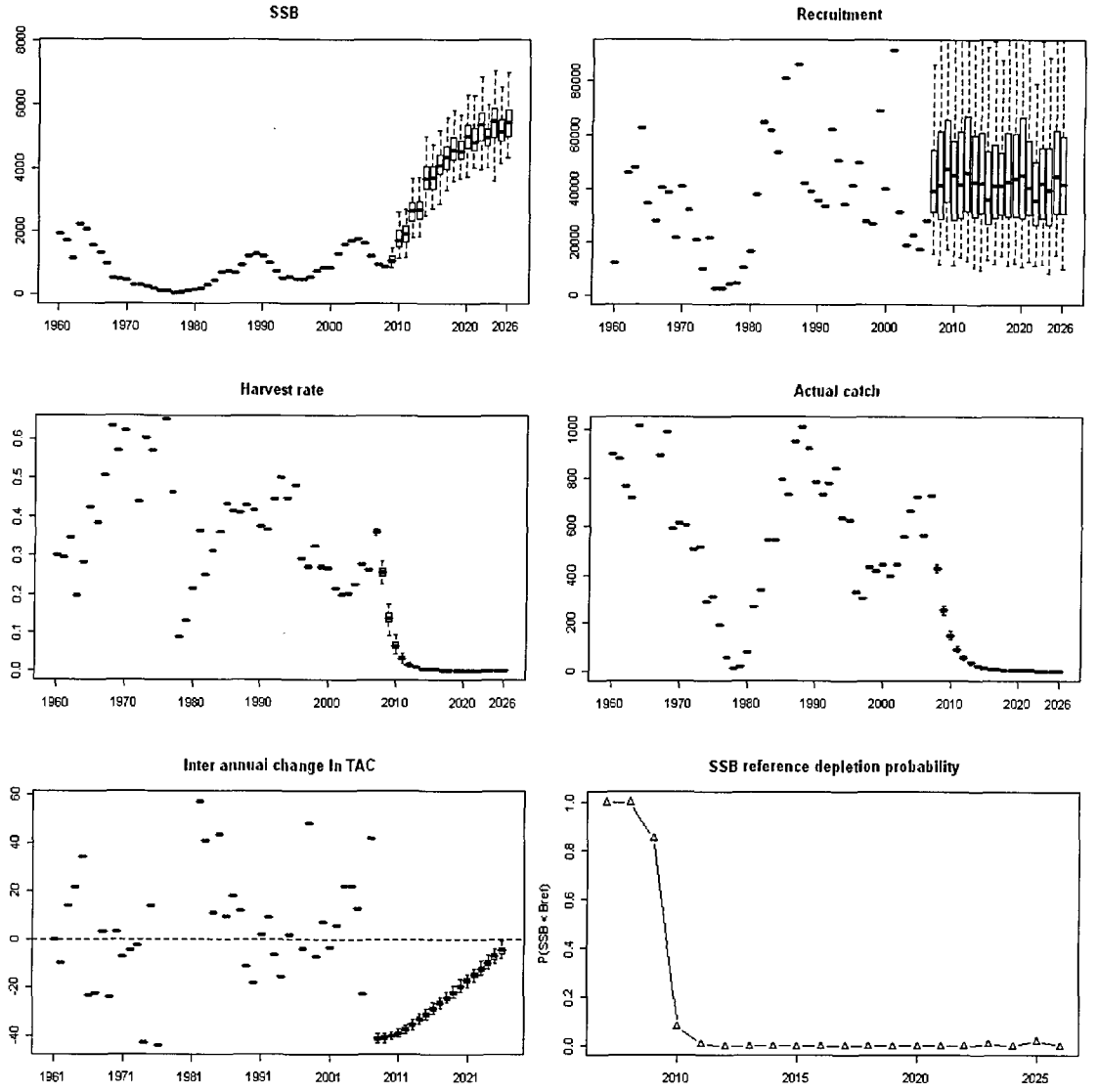


Figure 247: Output of simulation 168.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

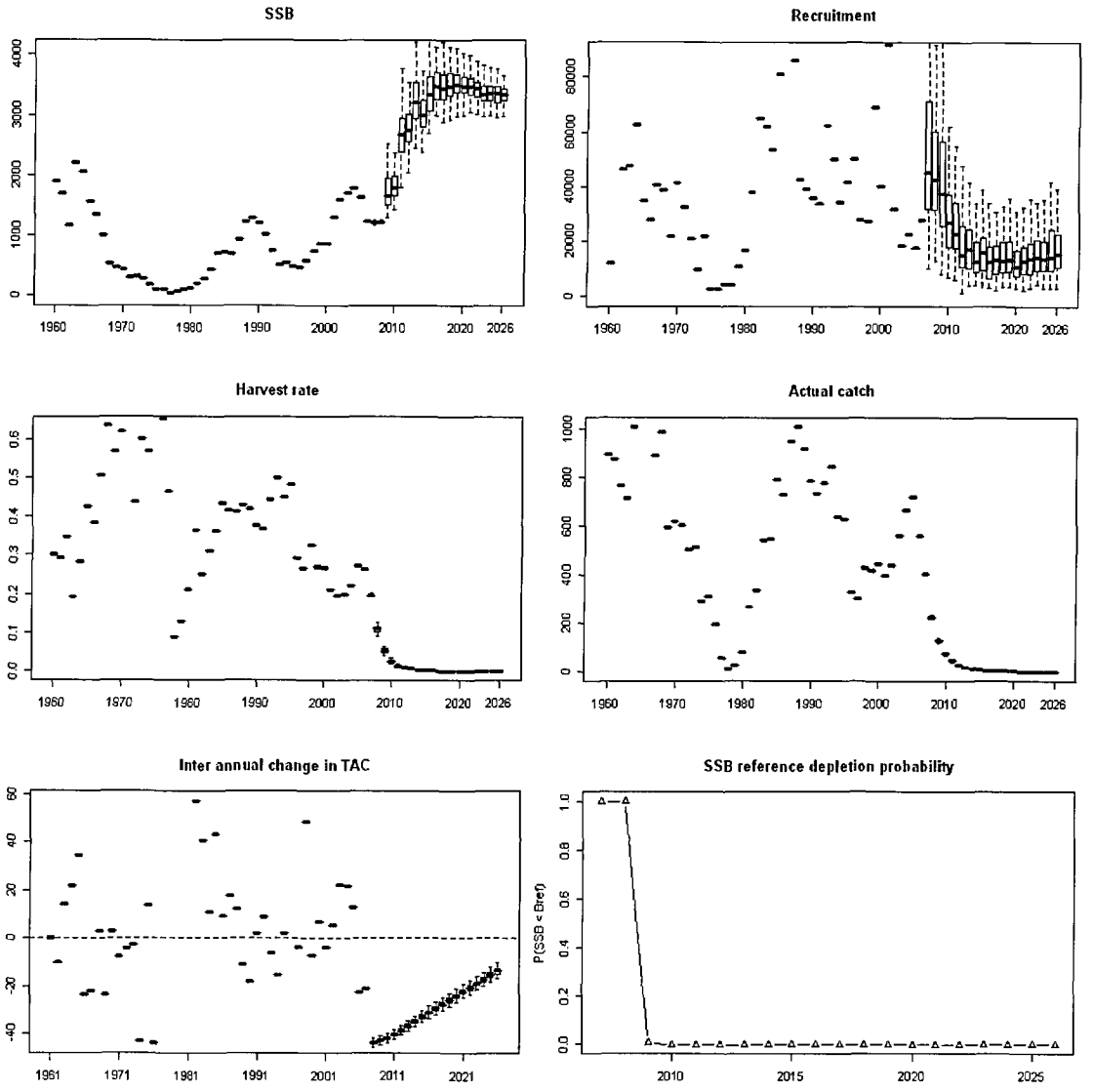


Figure 248: Output of simulation 169.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

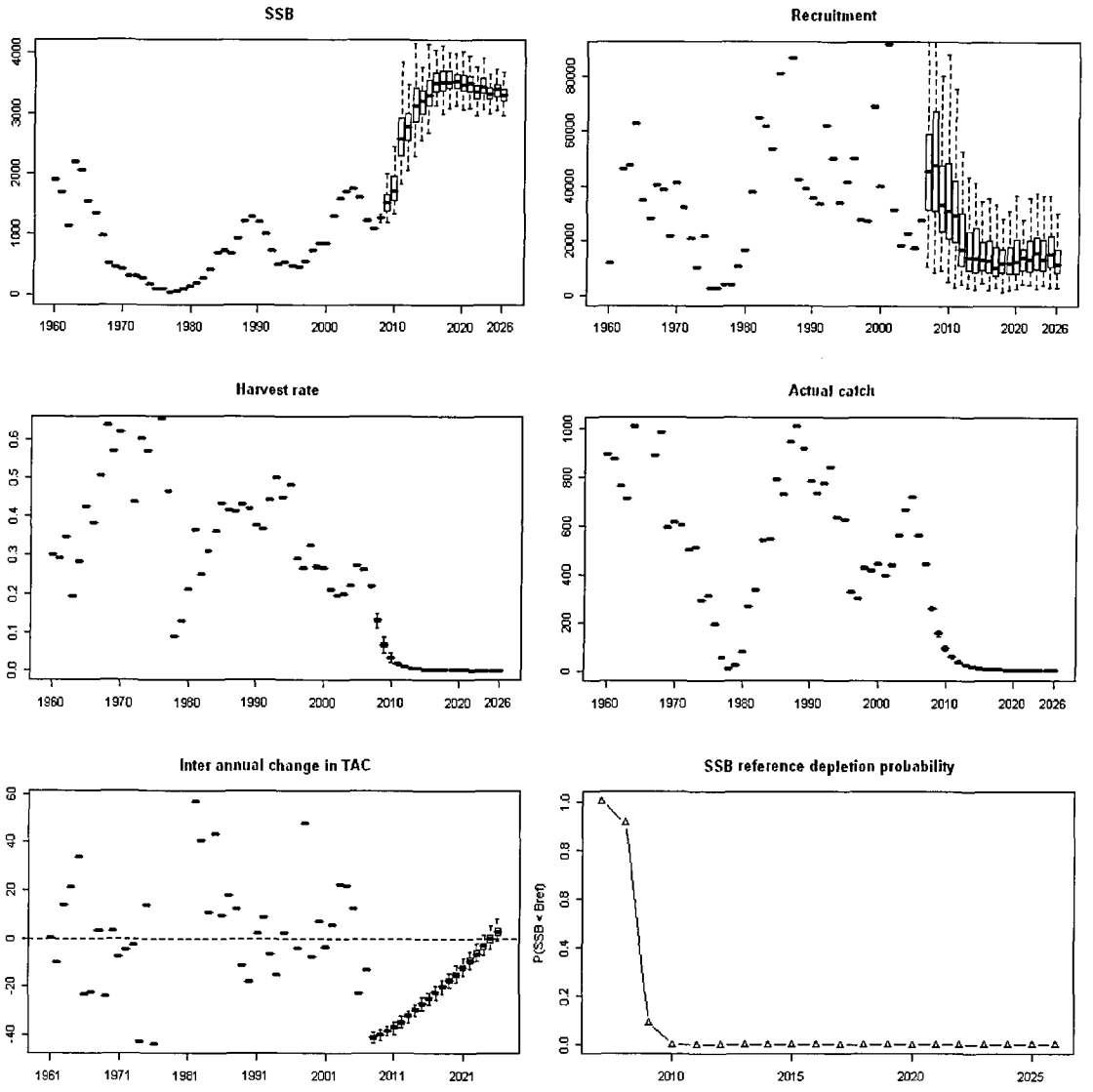


Figure 249: Output of simulation 170.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

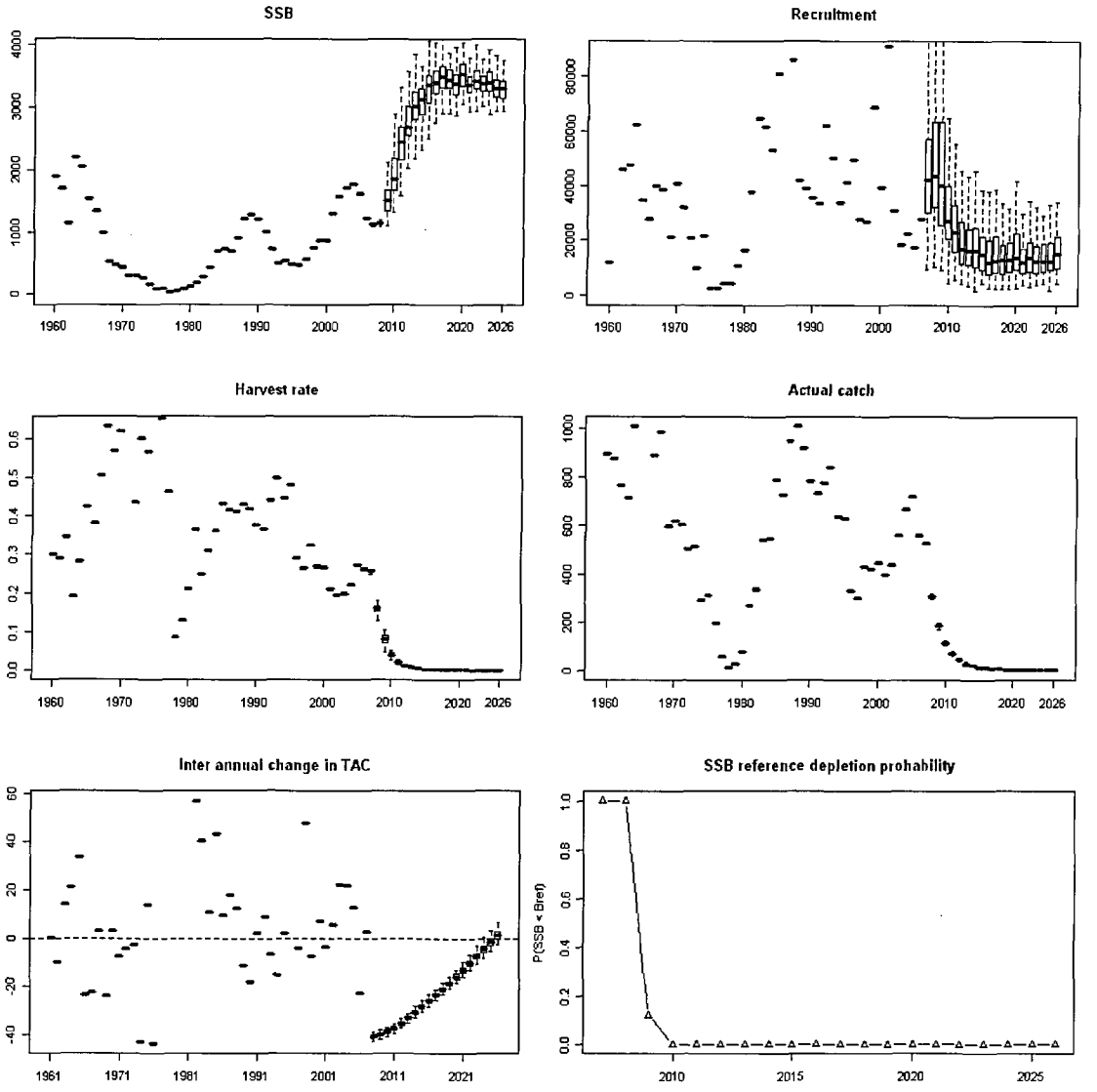


Figure 250: Output of simulation 171.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

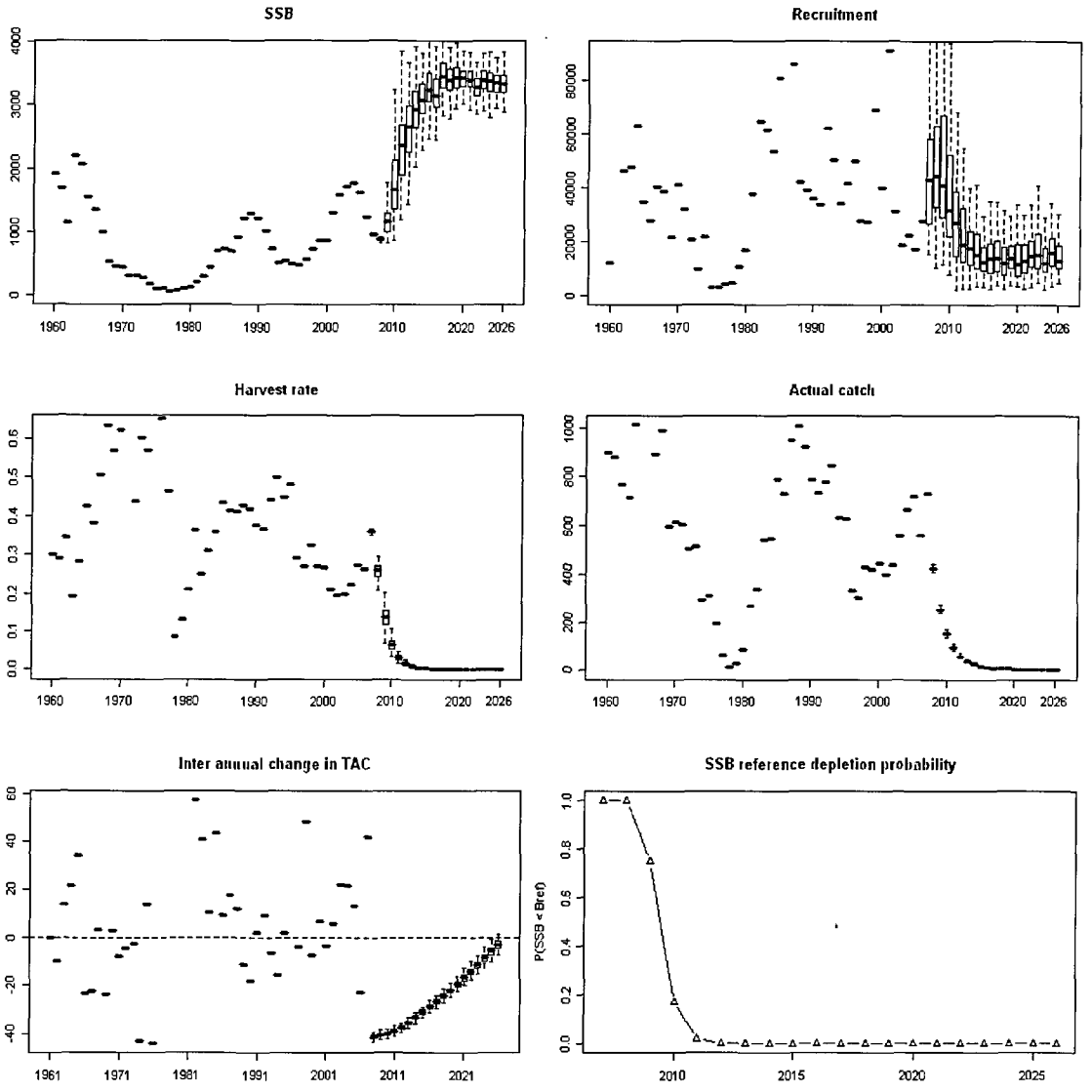


Figure 251: Output of simulation 172.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

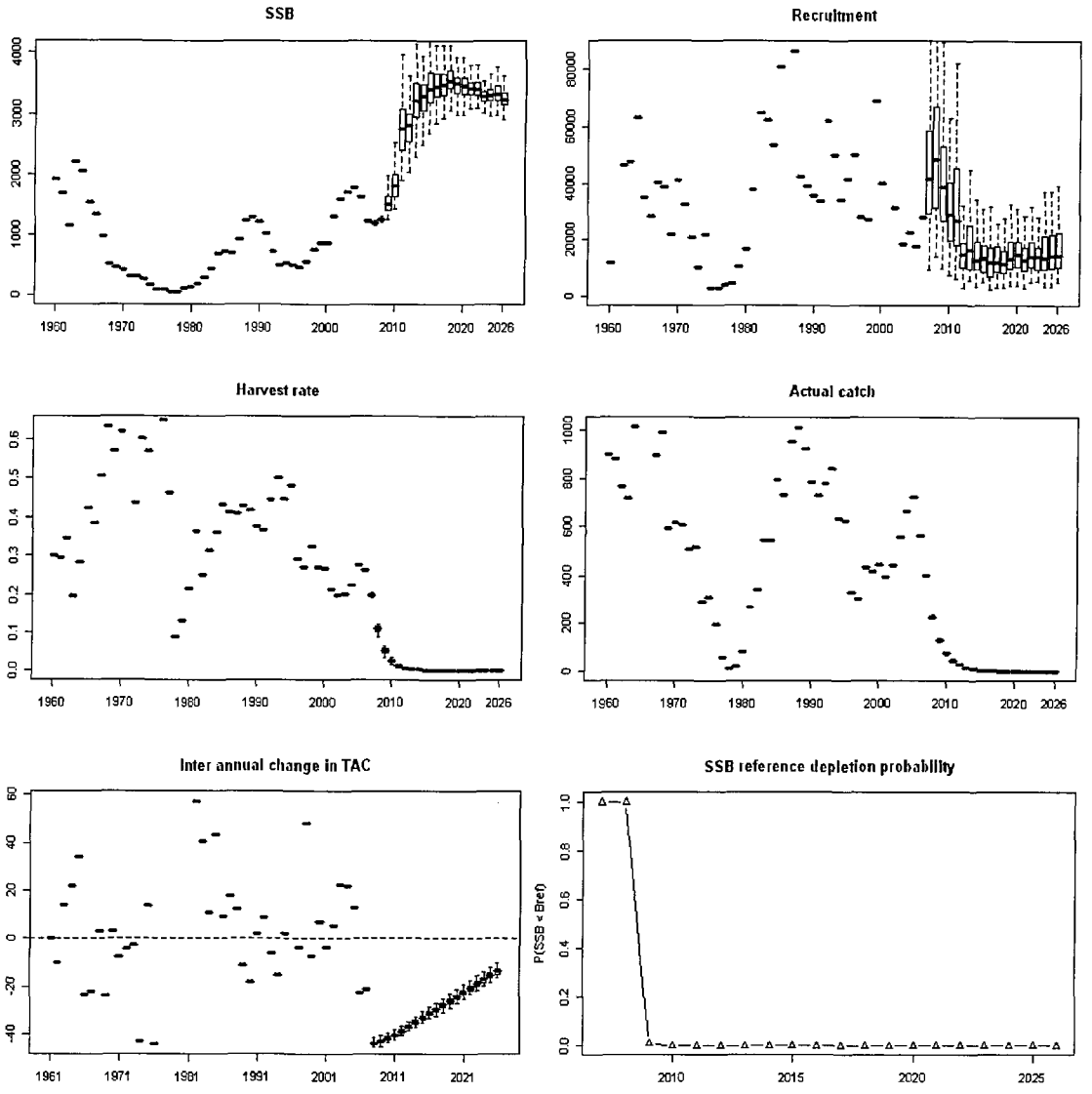


Figure 252: Output of simulation 173.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

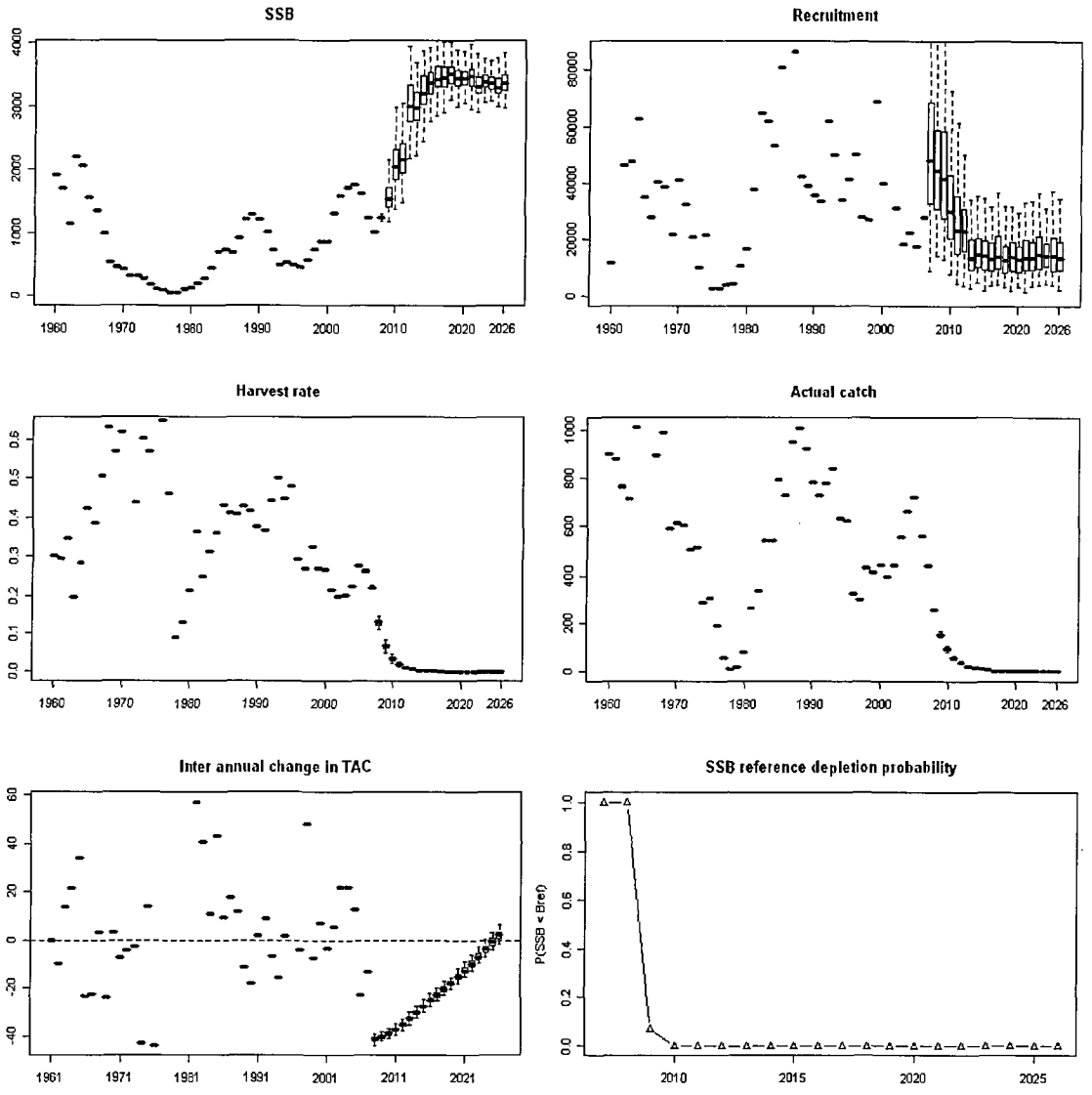


Figure 253: Output of simulation 174.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

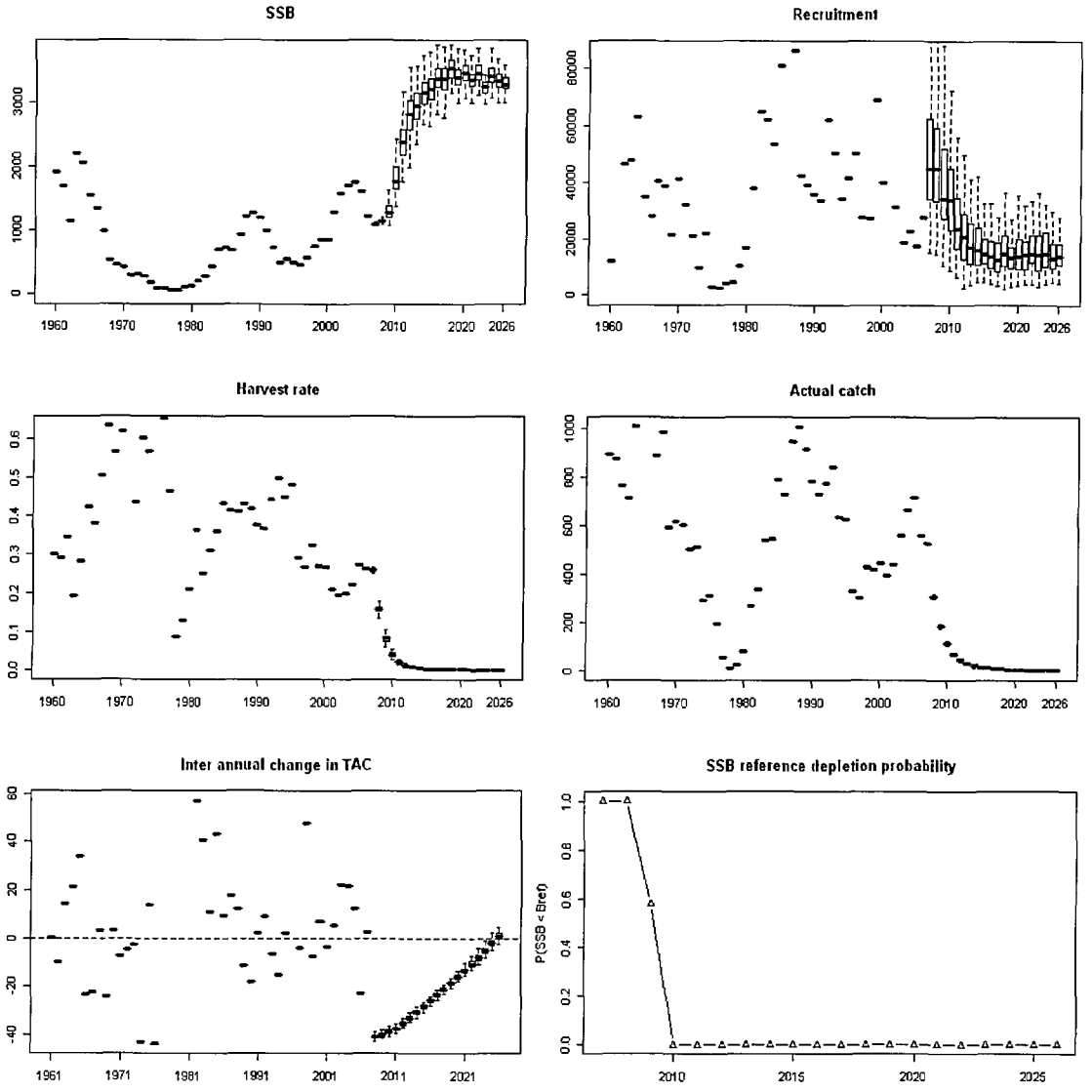


Figure 254: Output of simulation 175.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

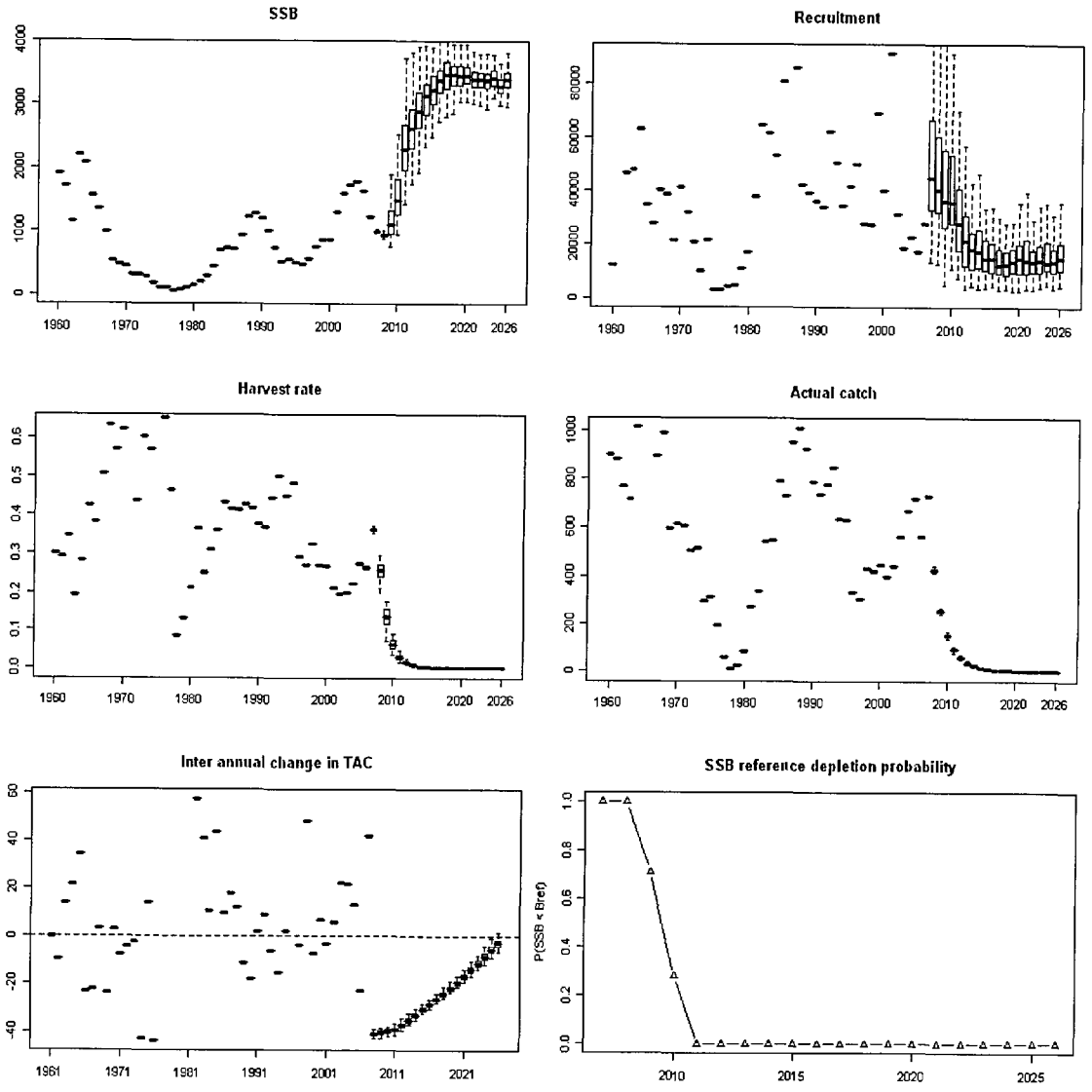


Figure 255: Output of simulation 176.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: YCC

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

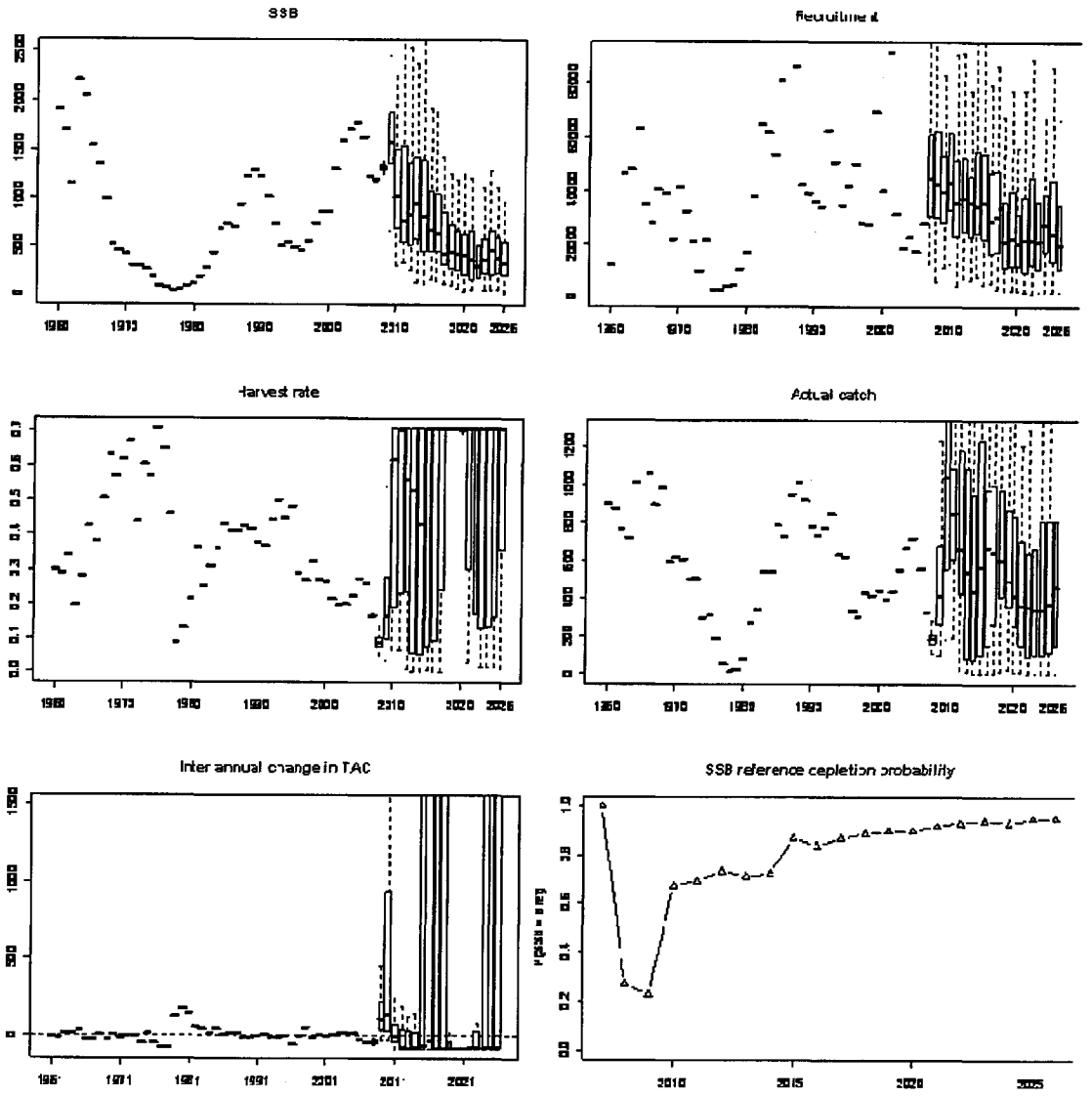


Figure 256: Output of simulation 177.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

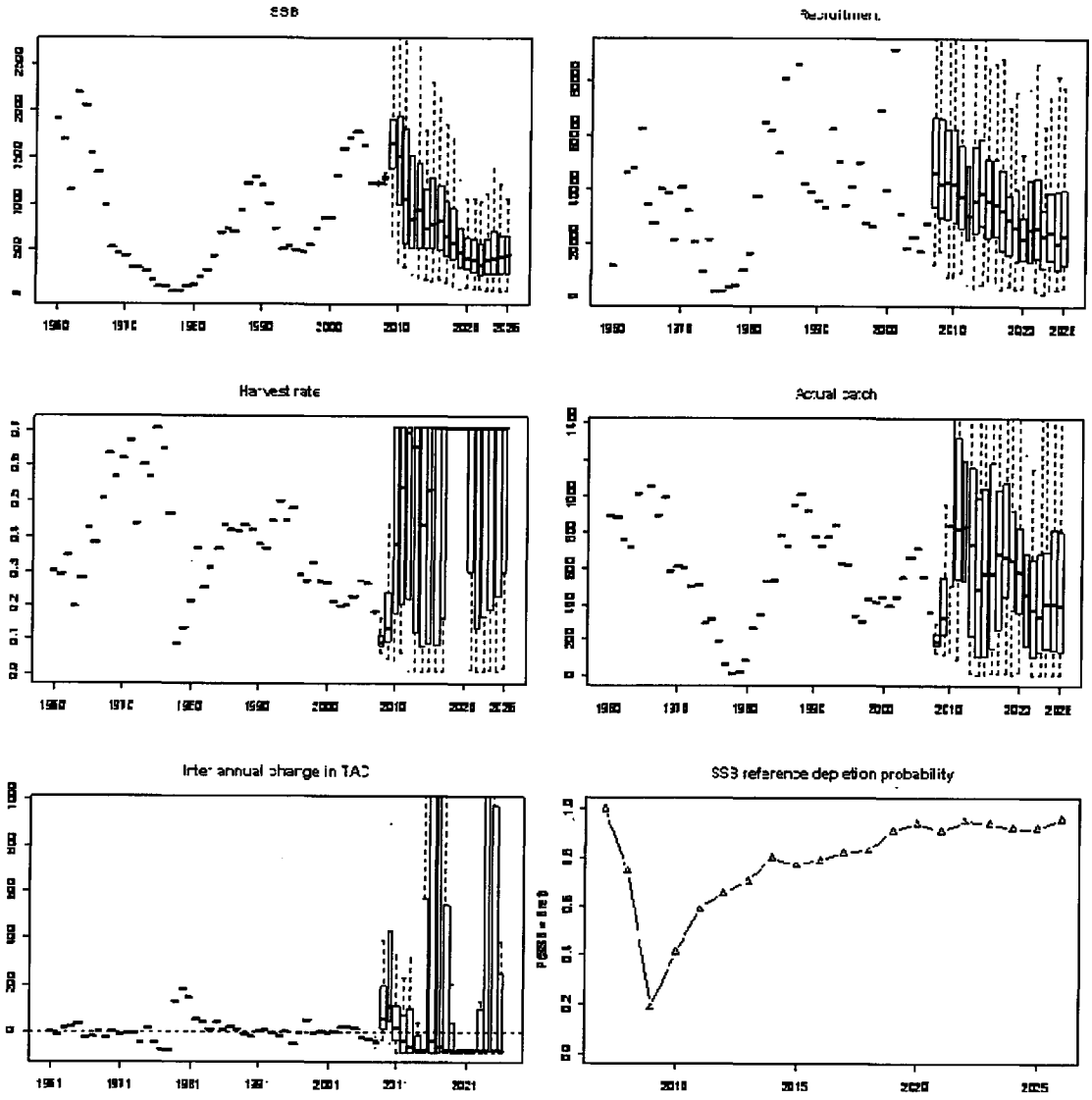


Figure 257: Output of simulation 178.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

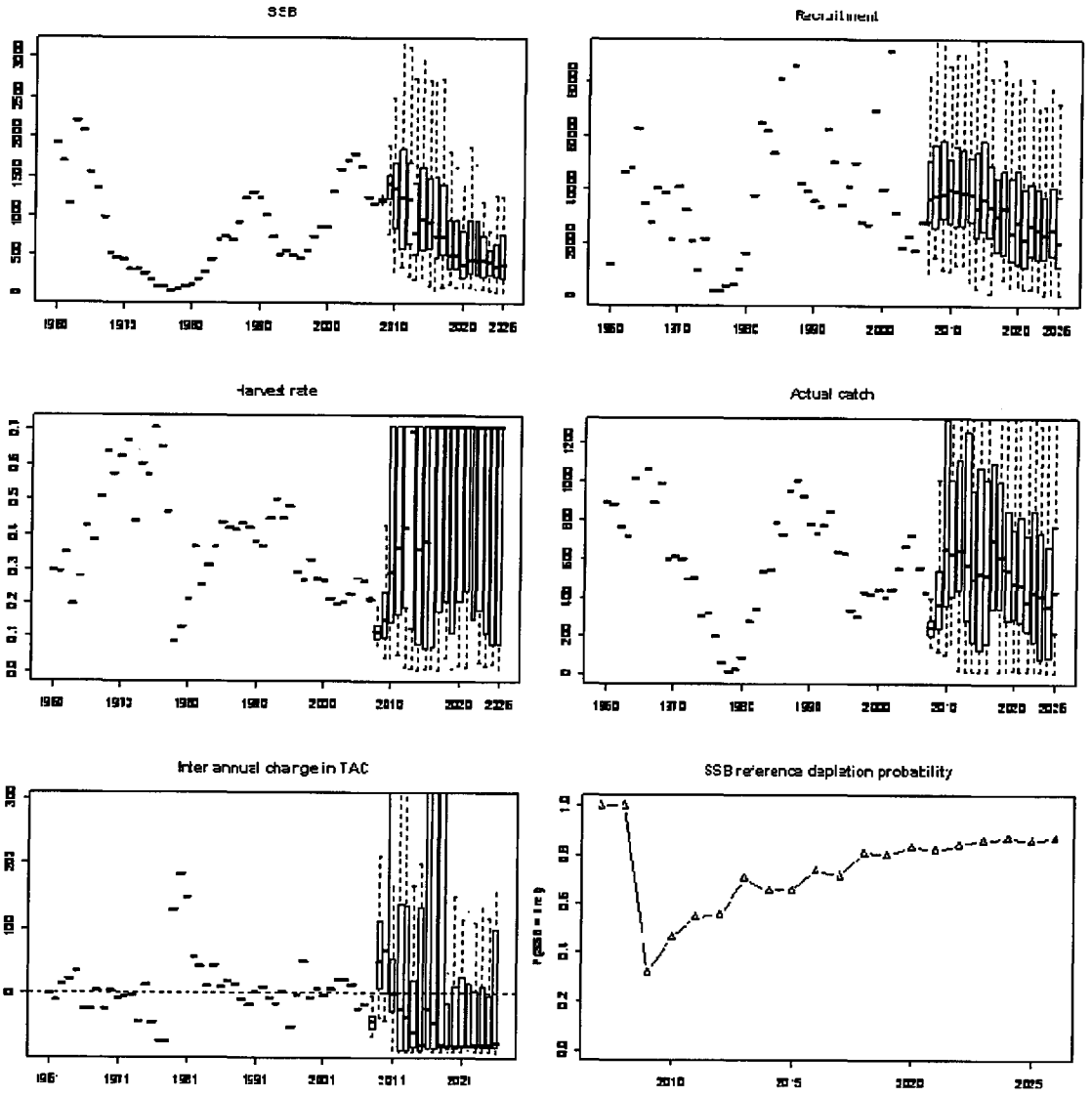


Figure 258: Output of simulation 179.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

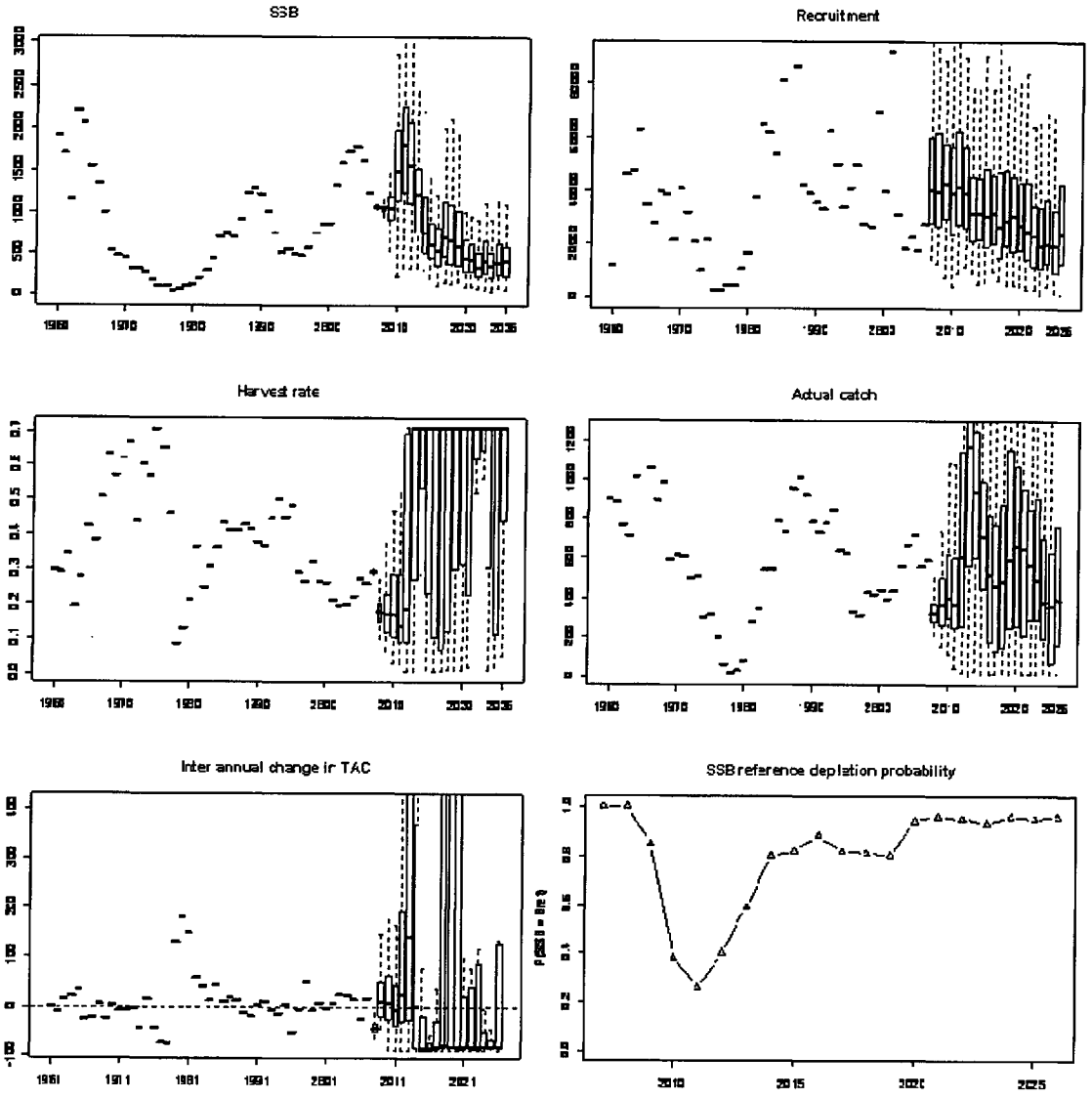


Figure 259: Output of simulation 180.

Stock recruitment: hockey stick

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

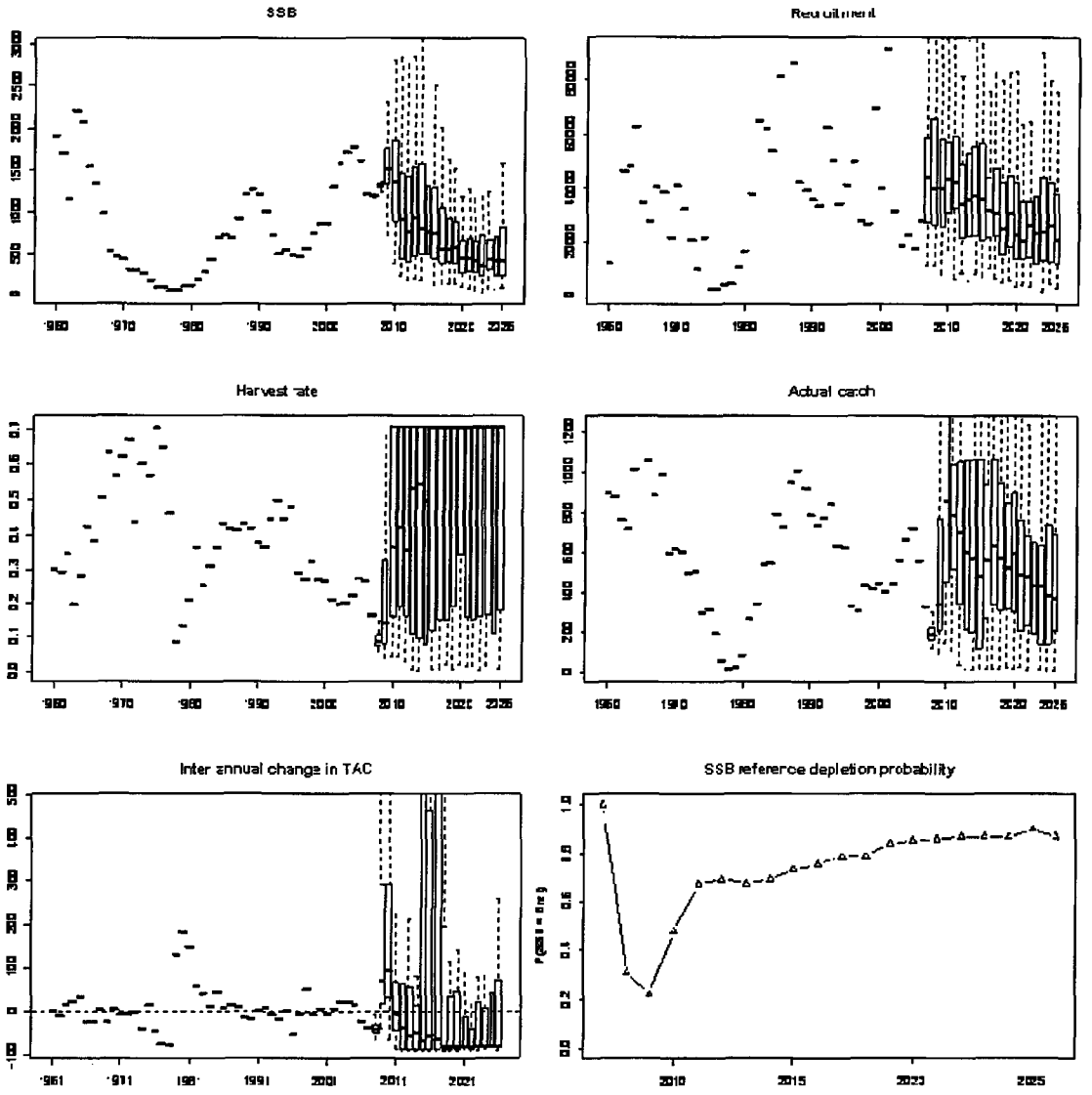


Figure 260: Output of simulation 181.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

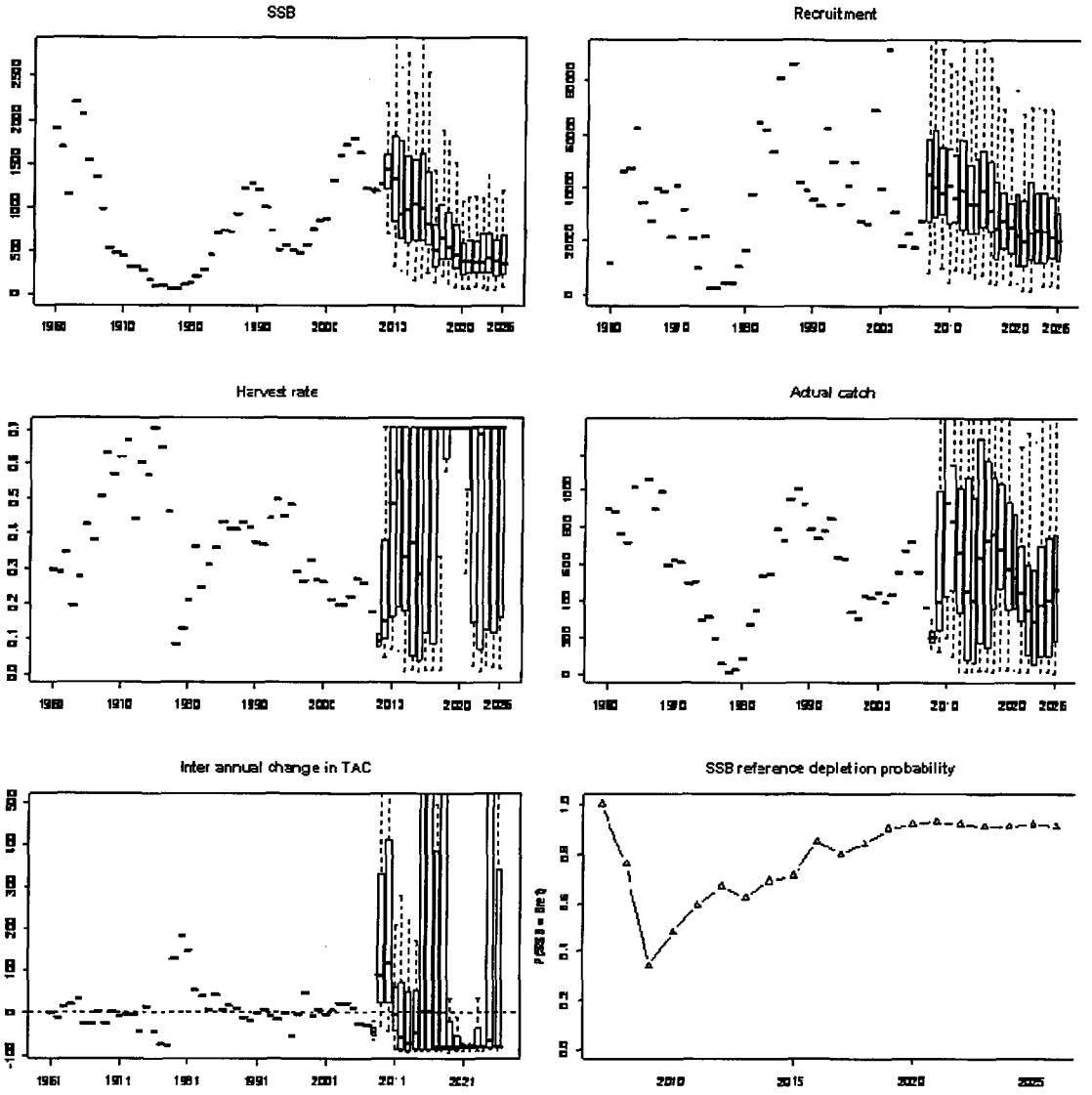


Figure 261: Output of simulation 182.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

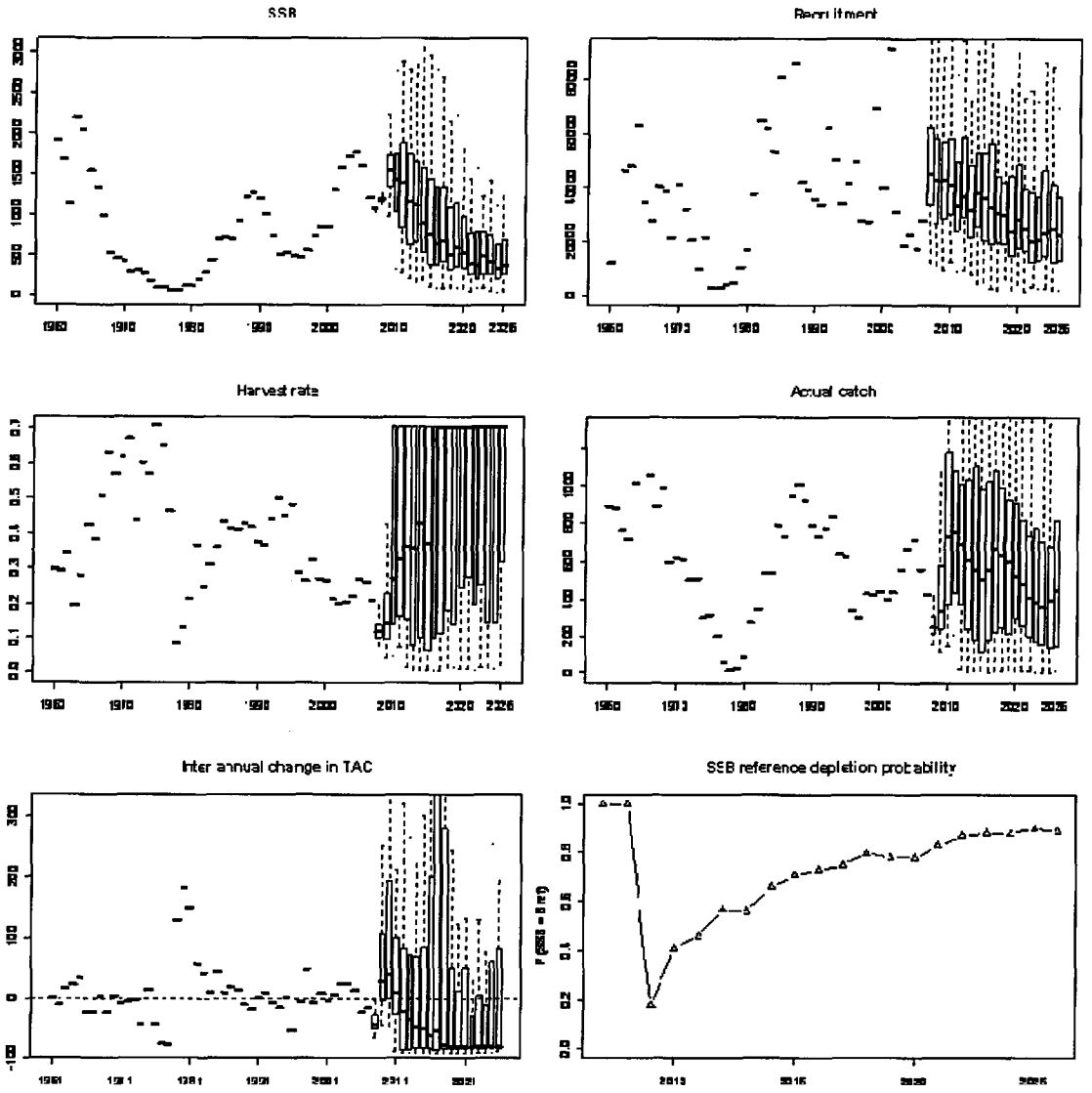


Figure 262: Output of simulation 183.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

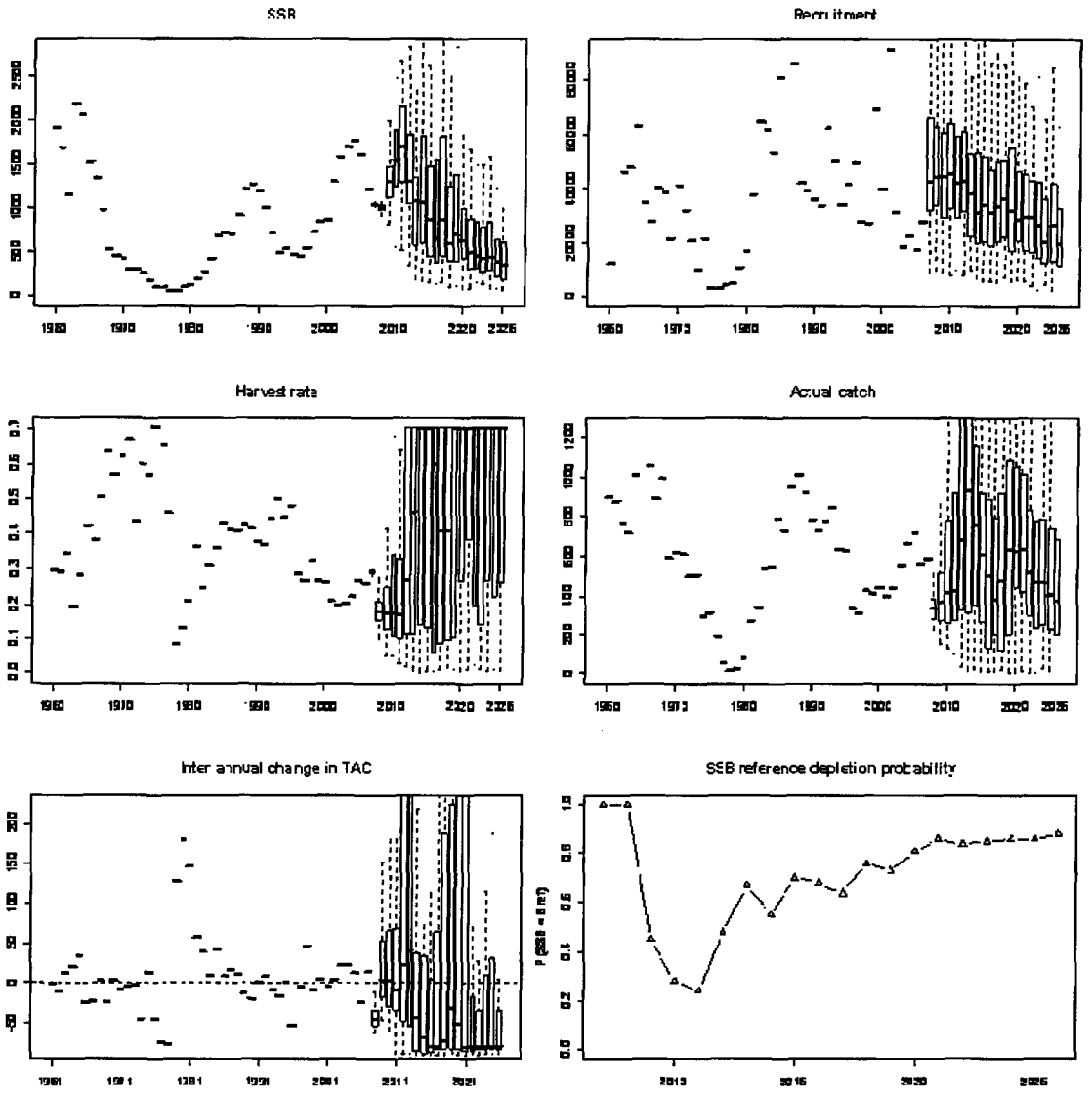


Figure 263: Output of simulation 184.

Stock recruitment: hockey stick

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

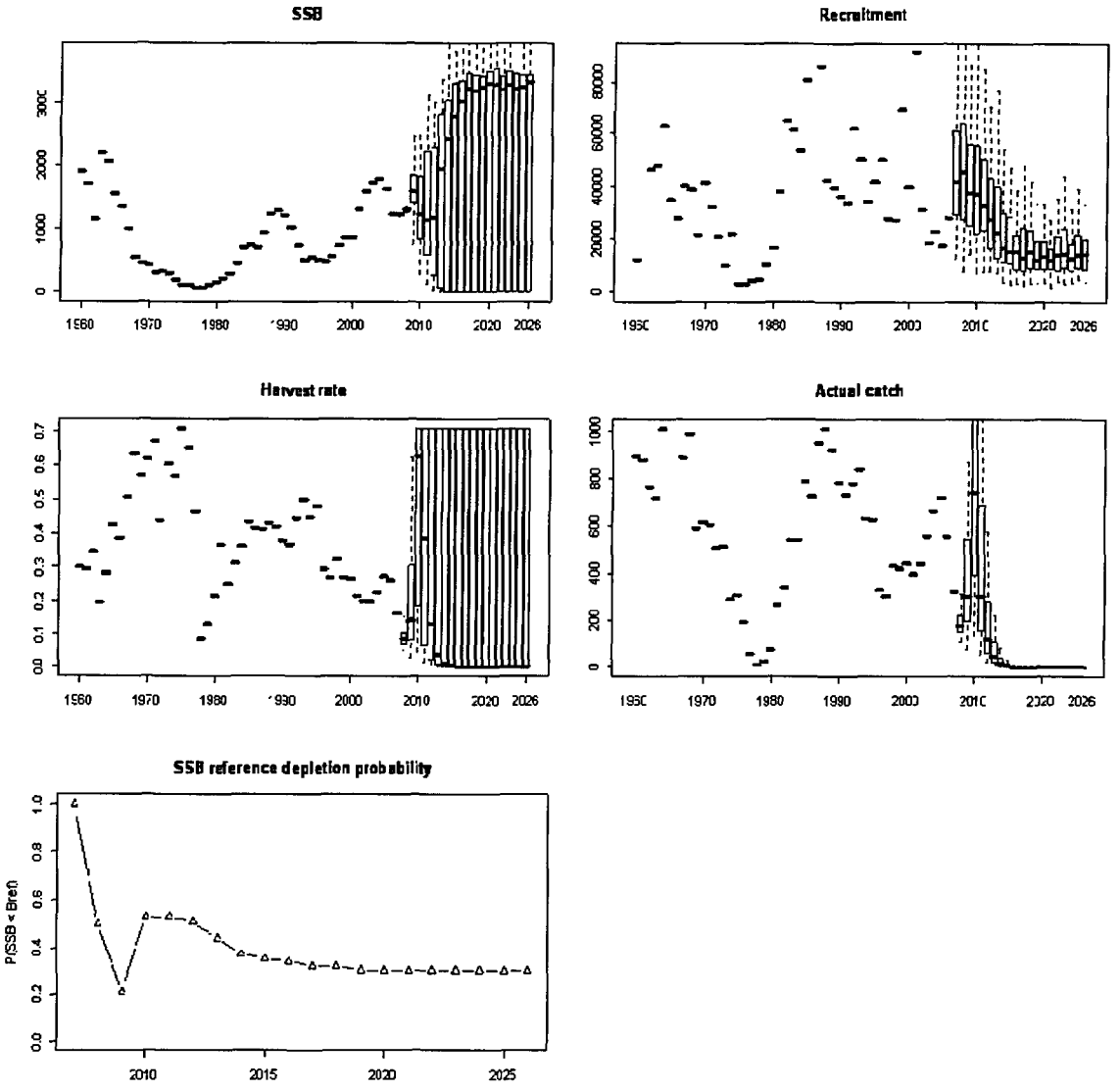


Figure 264: Output of simulation 185.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

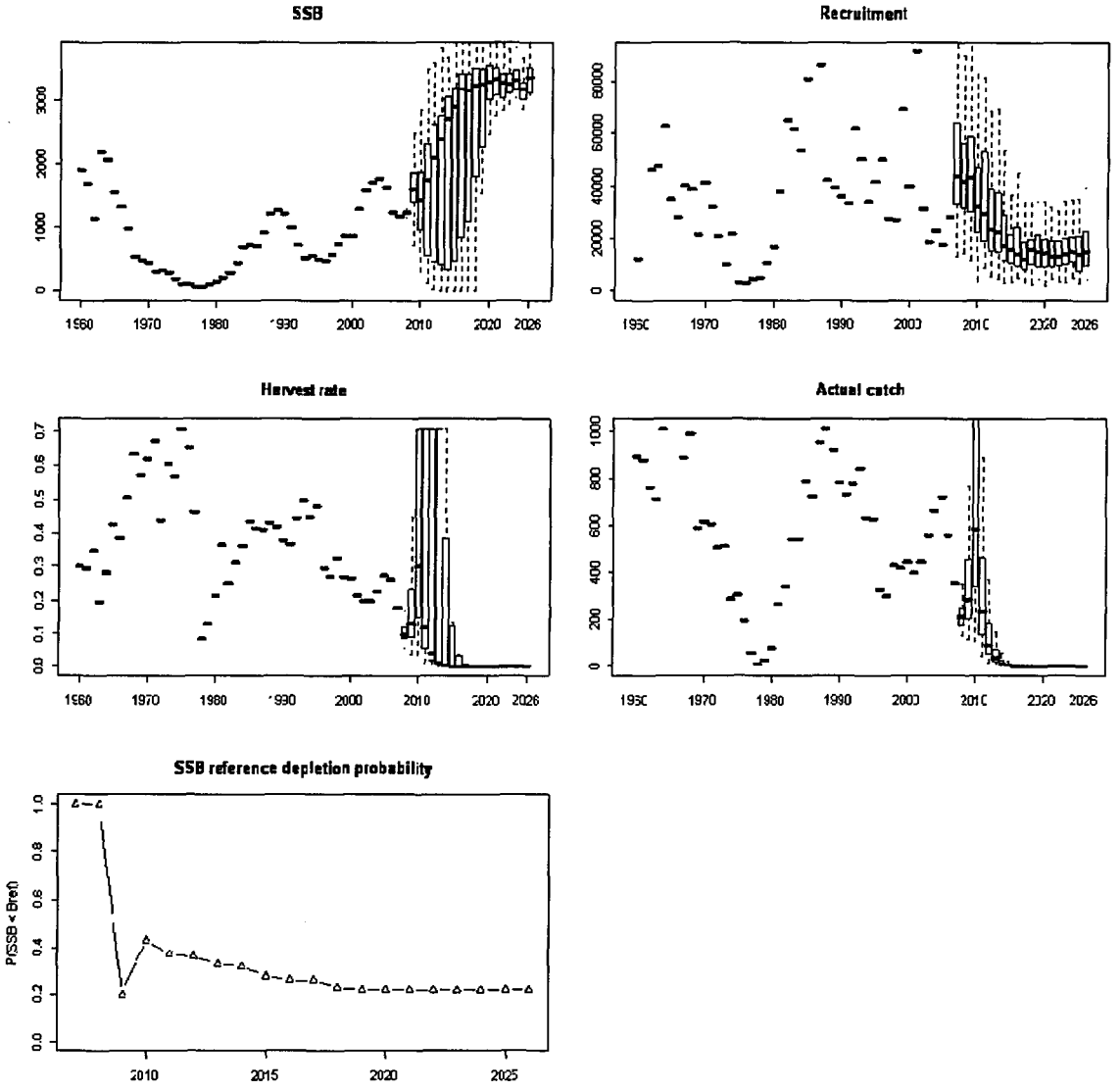


Figure 265: Output of simulation 186.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

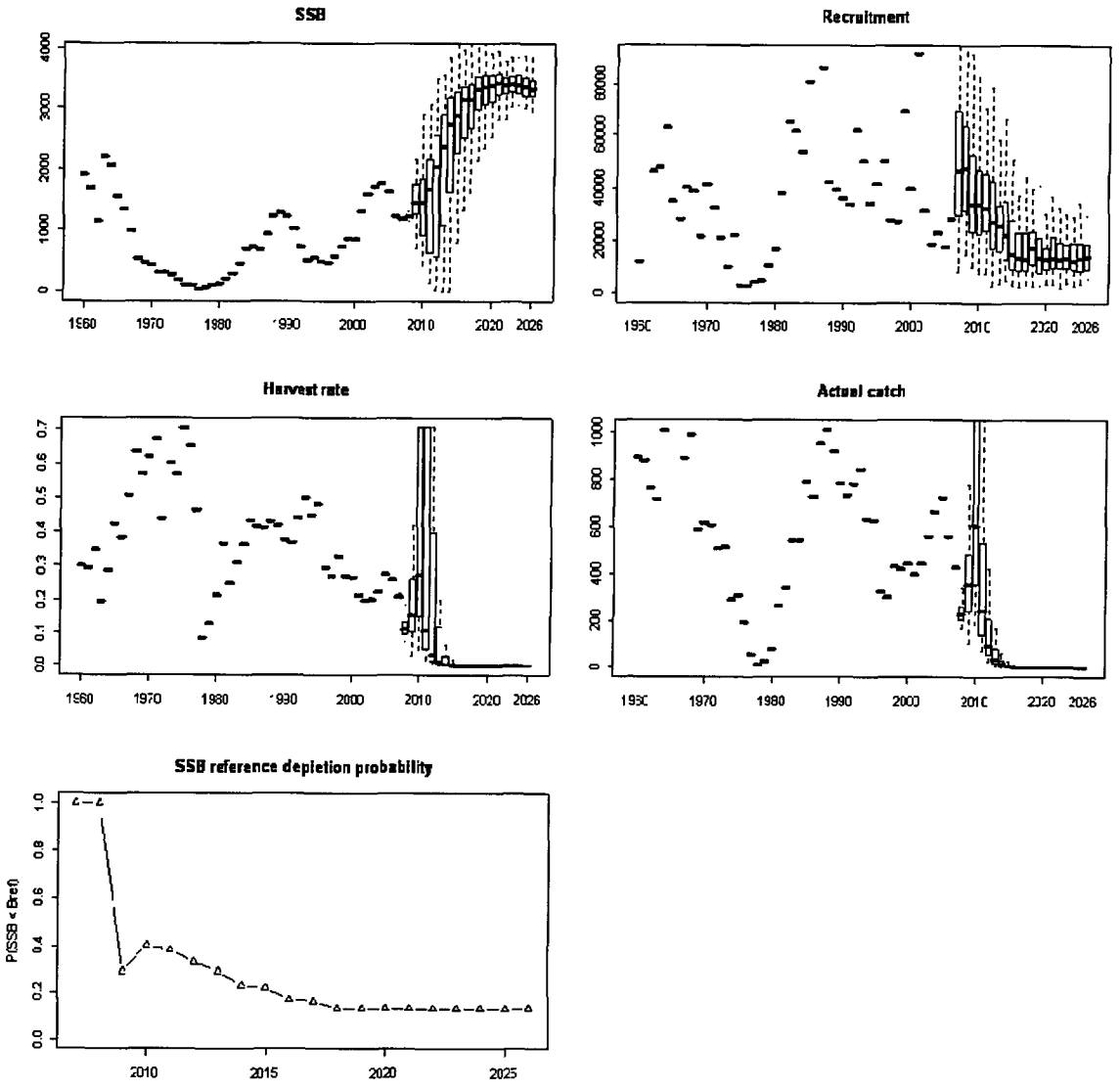


Figure 266: Output of simulation 187.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

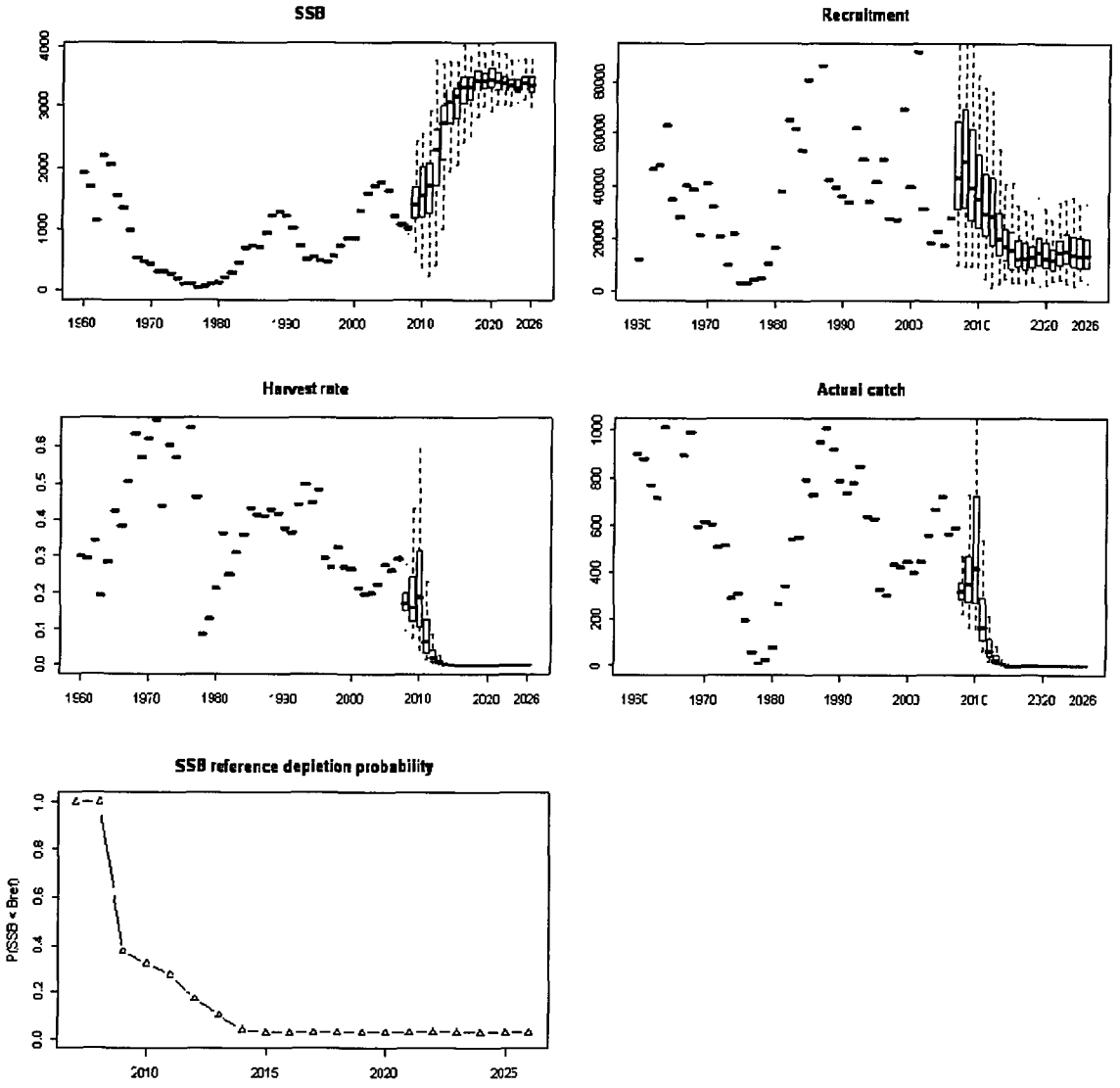


Figure 267: Output of simulation 188.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

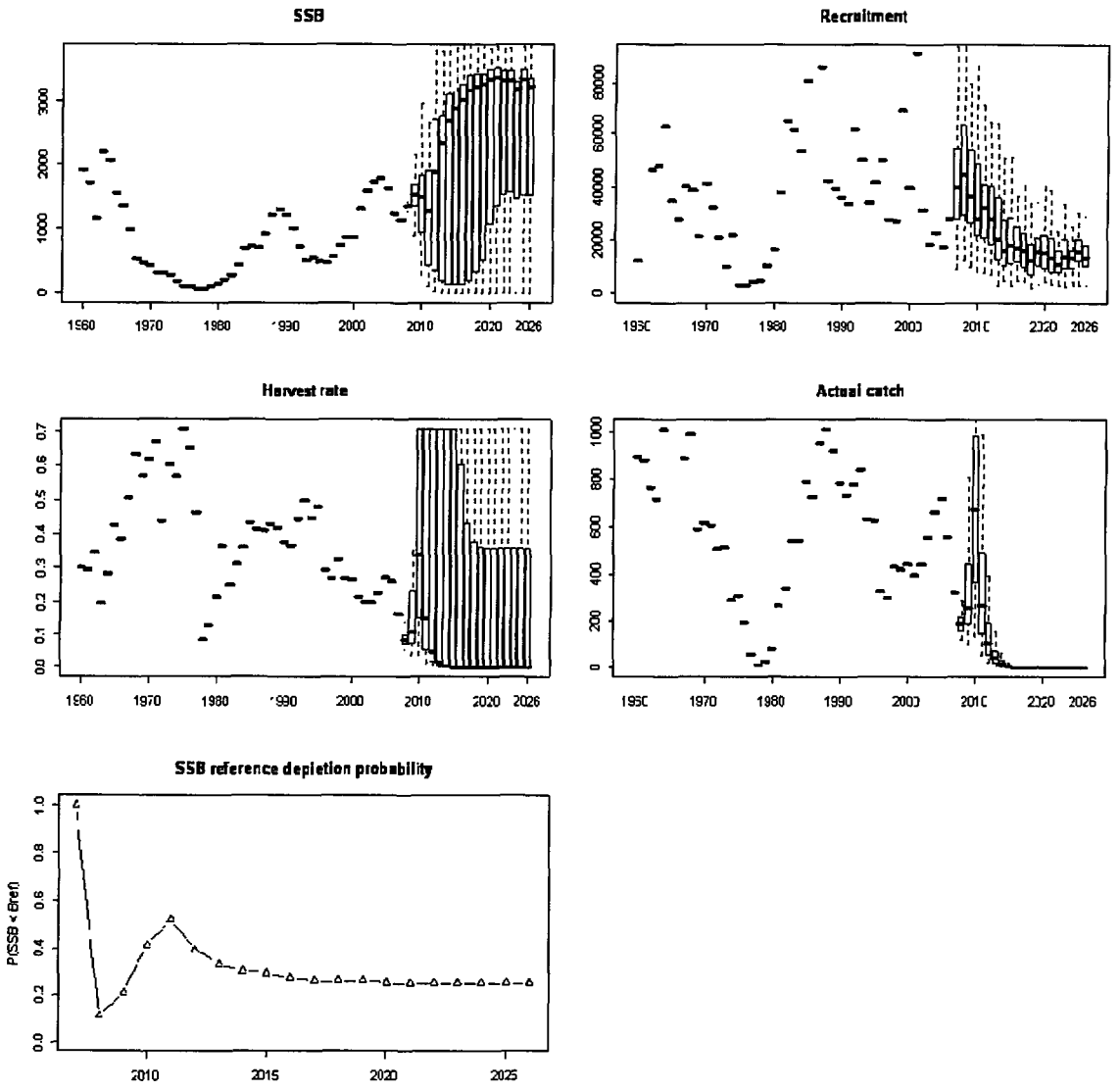


Figure 268: Output of simulation 189.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

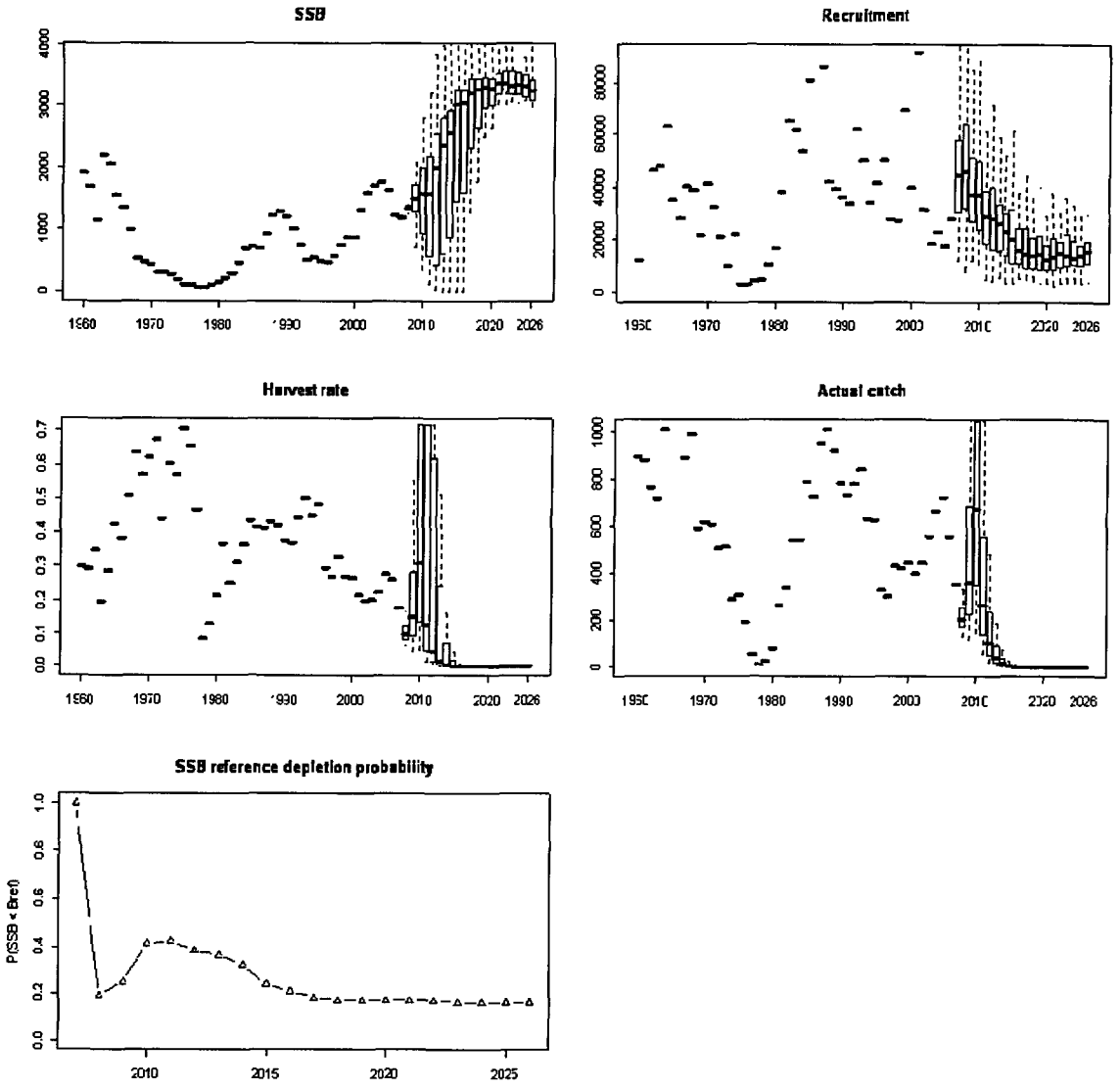


Figure 269: Output of simulation 190.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

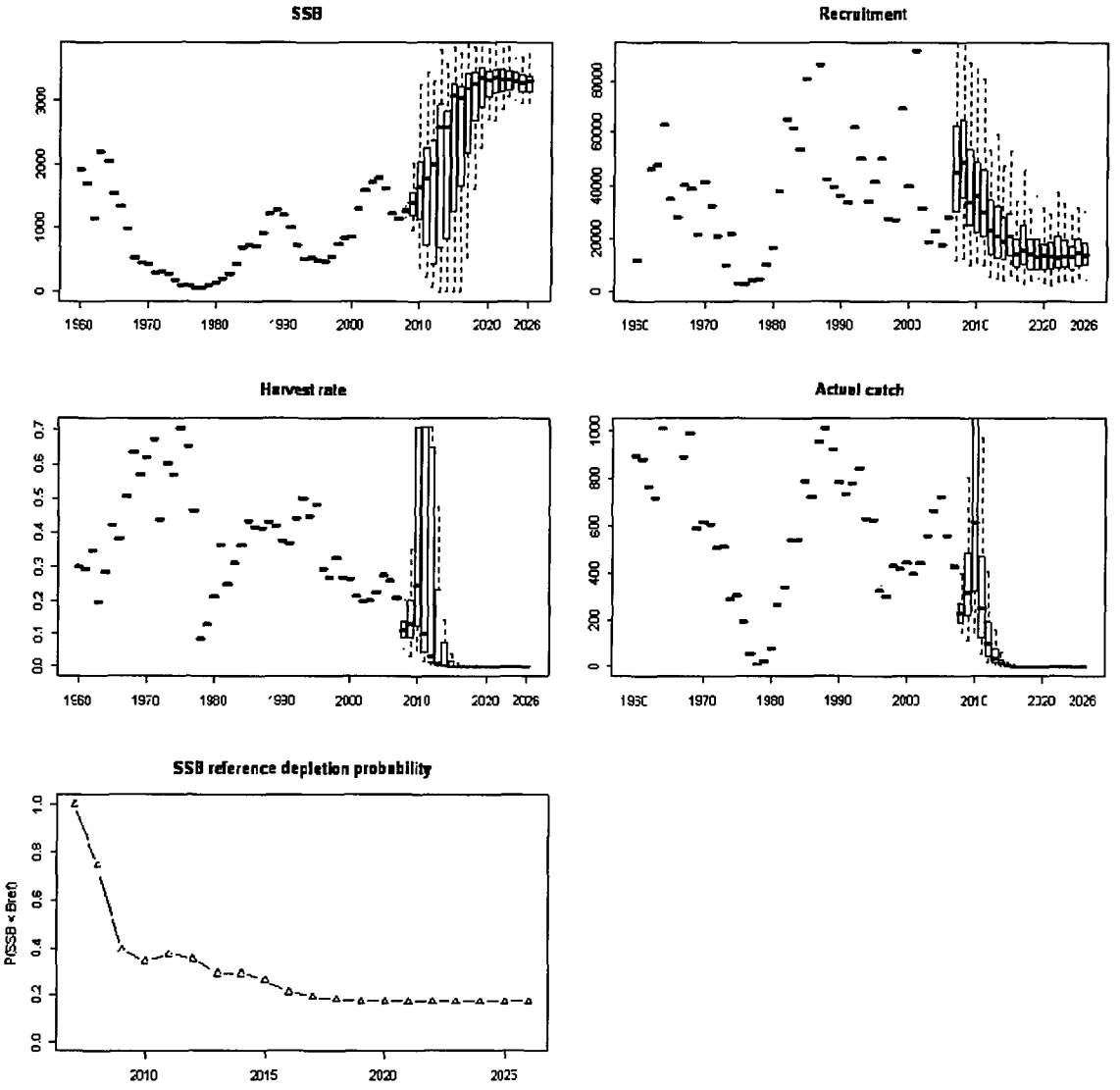


Figure 270: Output of simulation 191.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

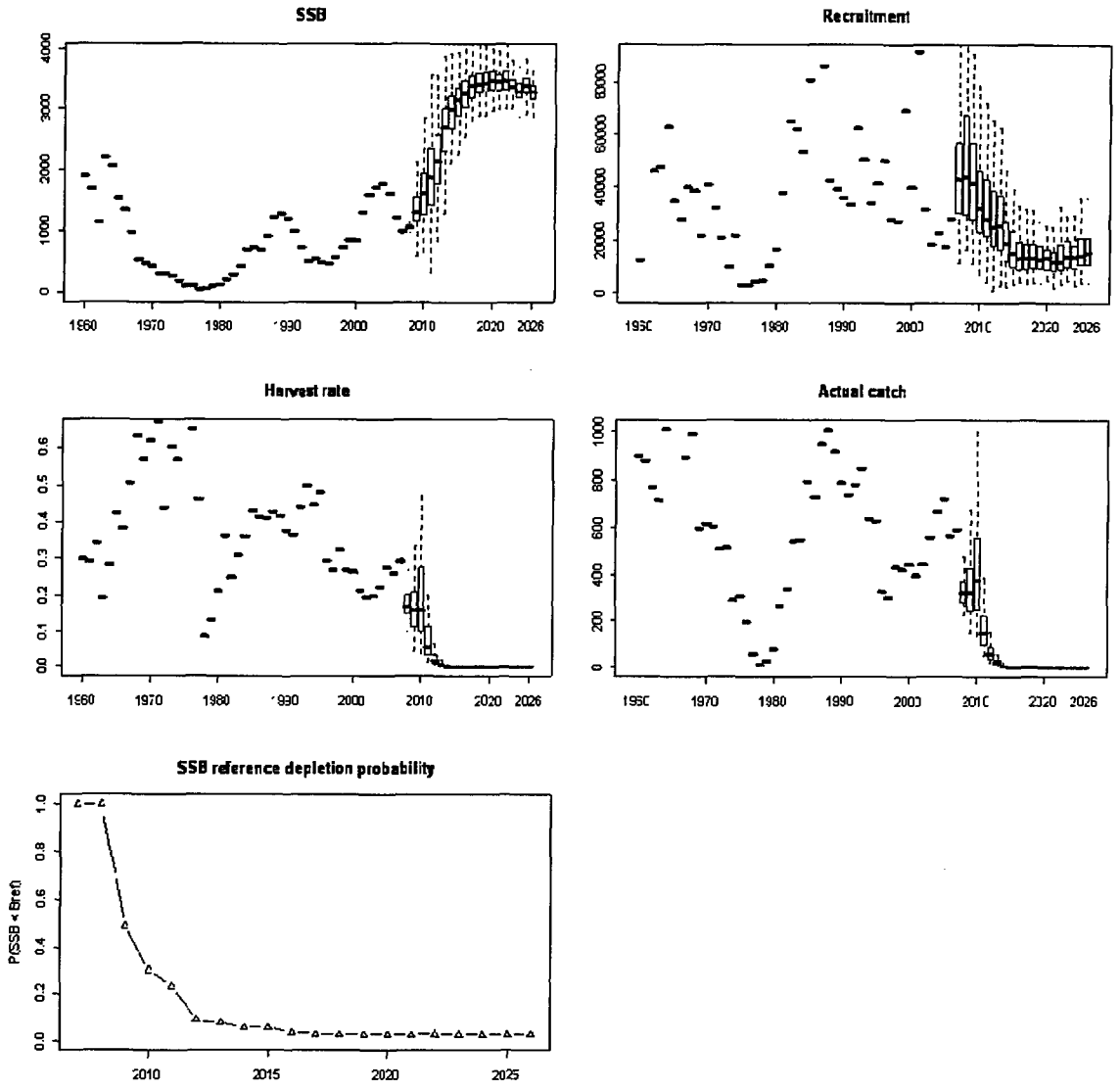


Figure 271: Output of simulation 192.

Stock recruitment: Ricker

Autocorrelation: high

Survey: acoustic with observation error

Assessment: SURBA

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

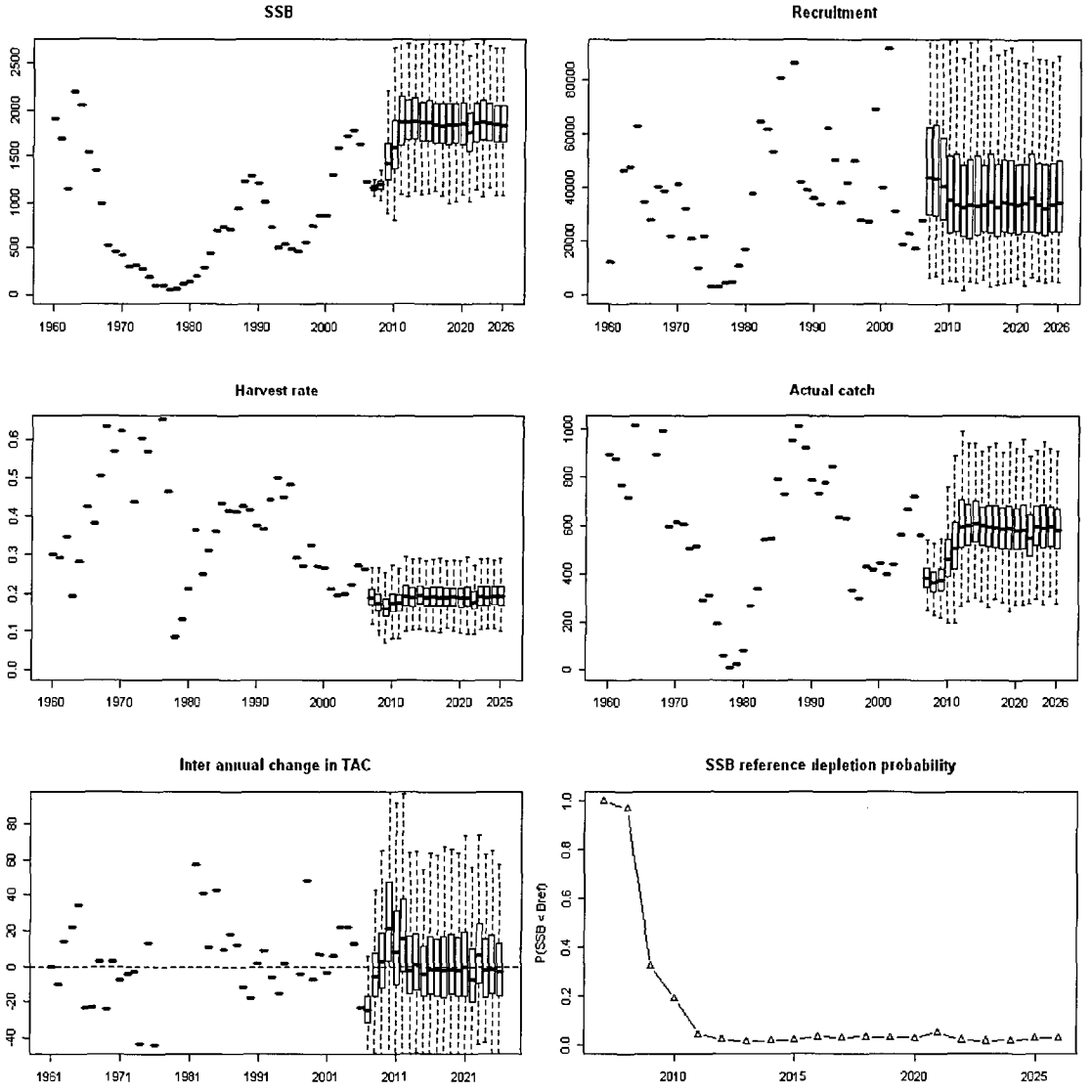


Figure 272: Output of simulation 193.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

Sensitivity analysis: Maturity-at-age

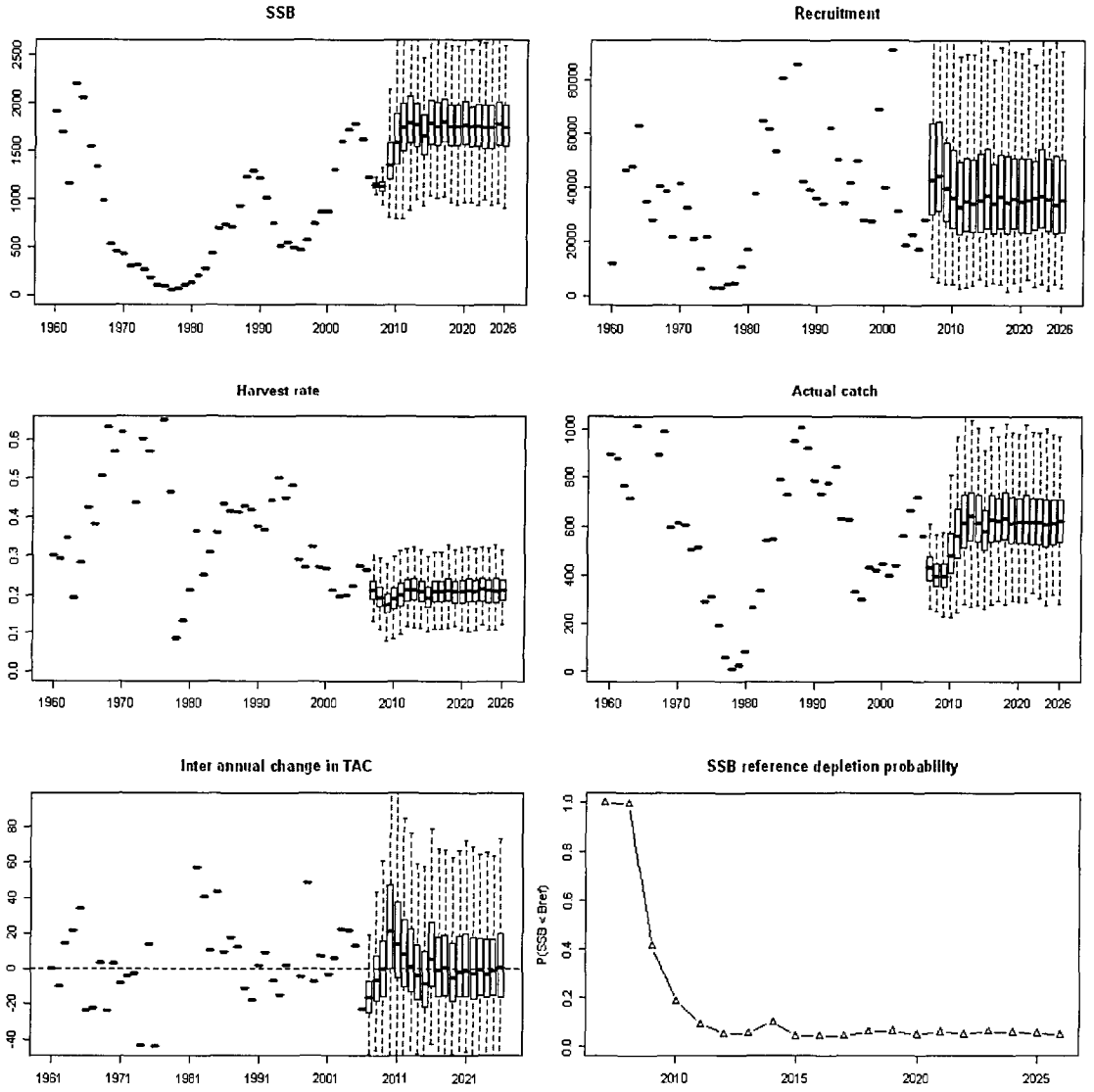


Figure 273: Output of simulation 194.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

Sensitivity analysis: Maturity-at-age

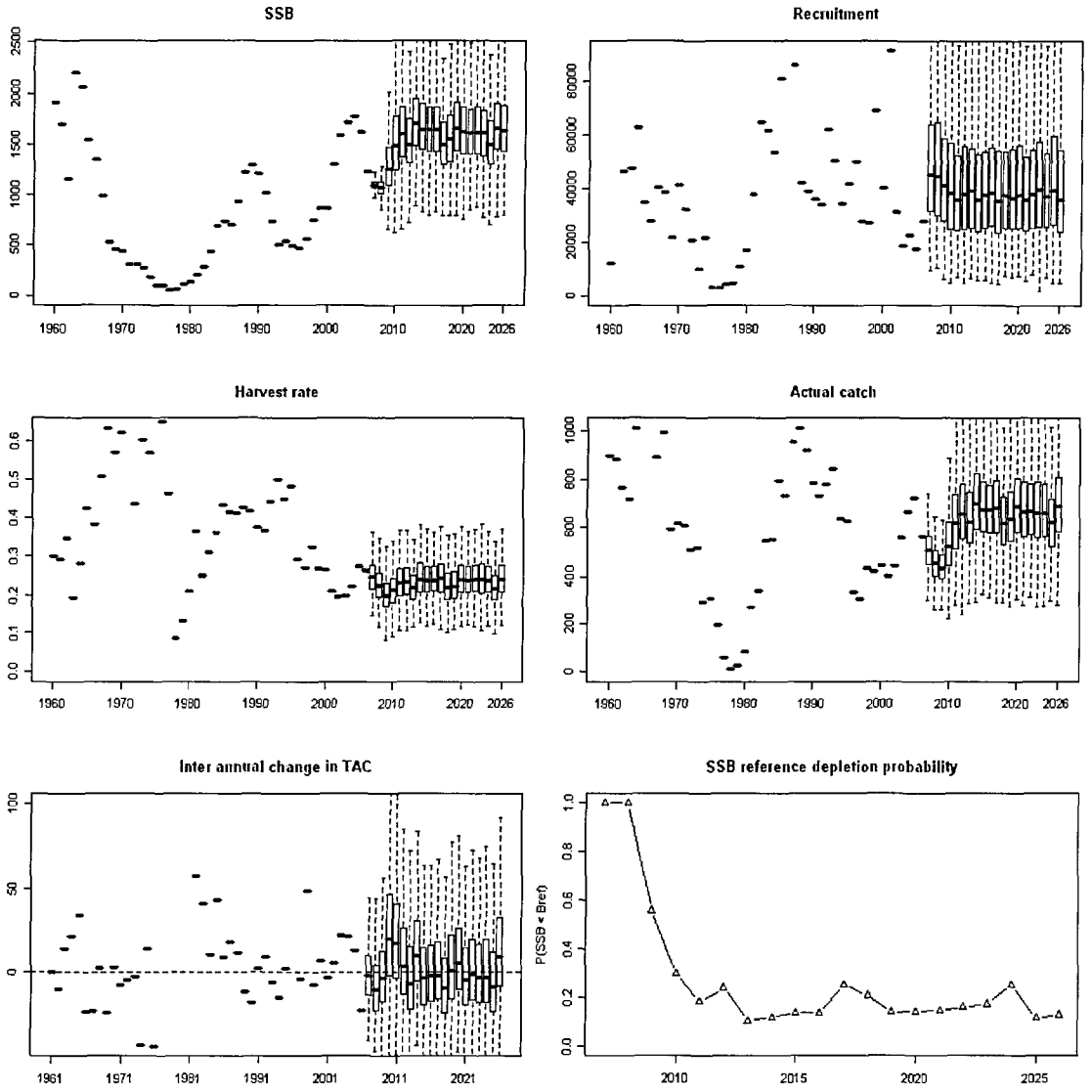


Figure 274: Output of simulation 195.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

Sensitivity analysis: Maturity-at-age

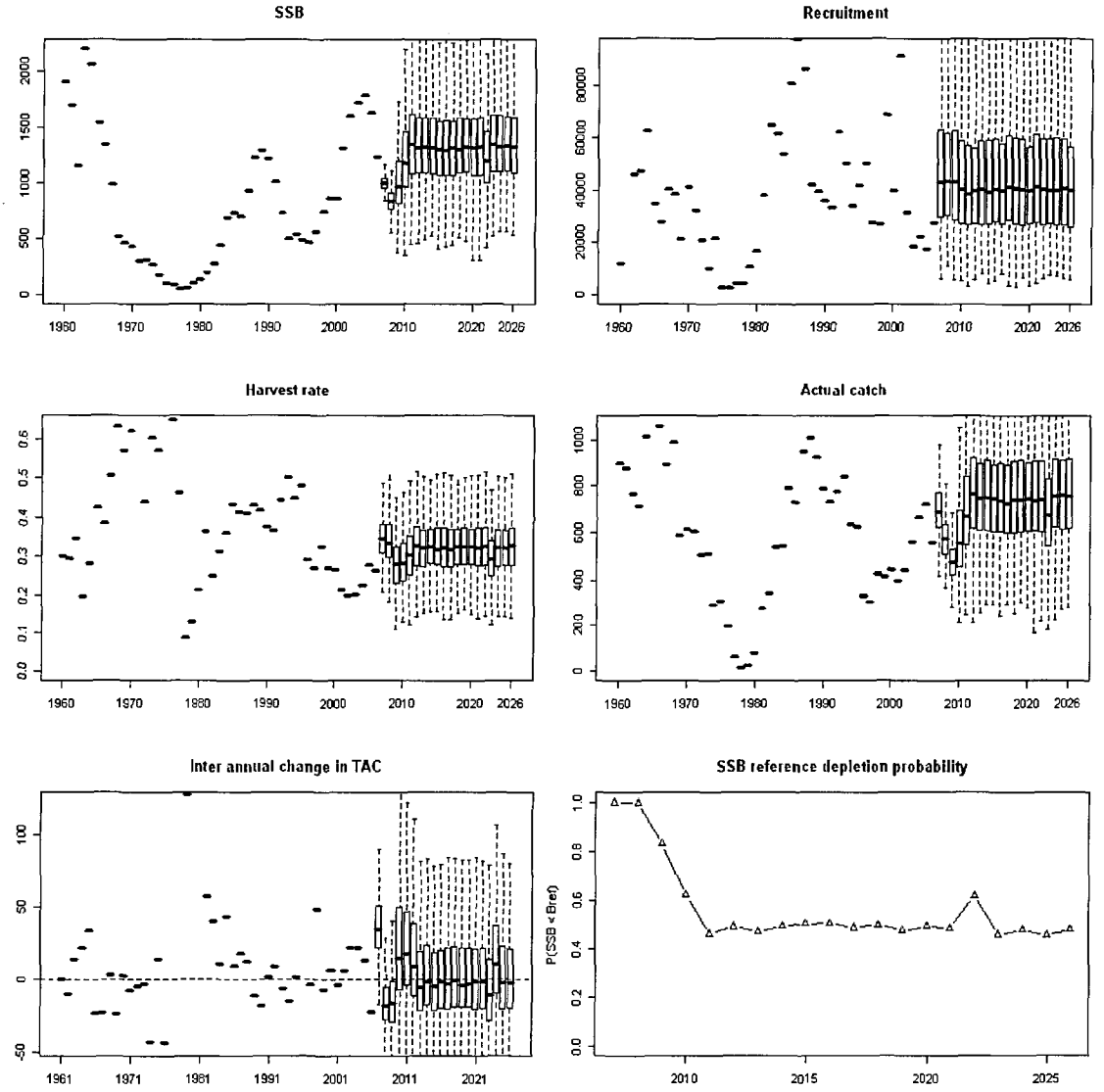


Figure 275: Output of simulation 196.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

Sensitivity analysis: Maturity-at-age

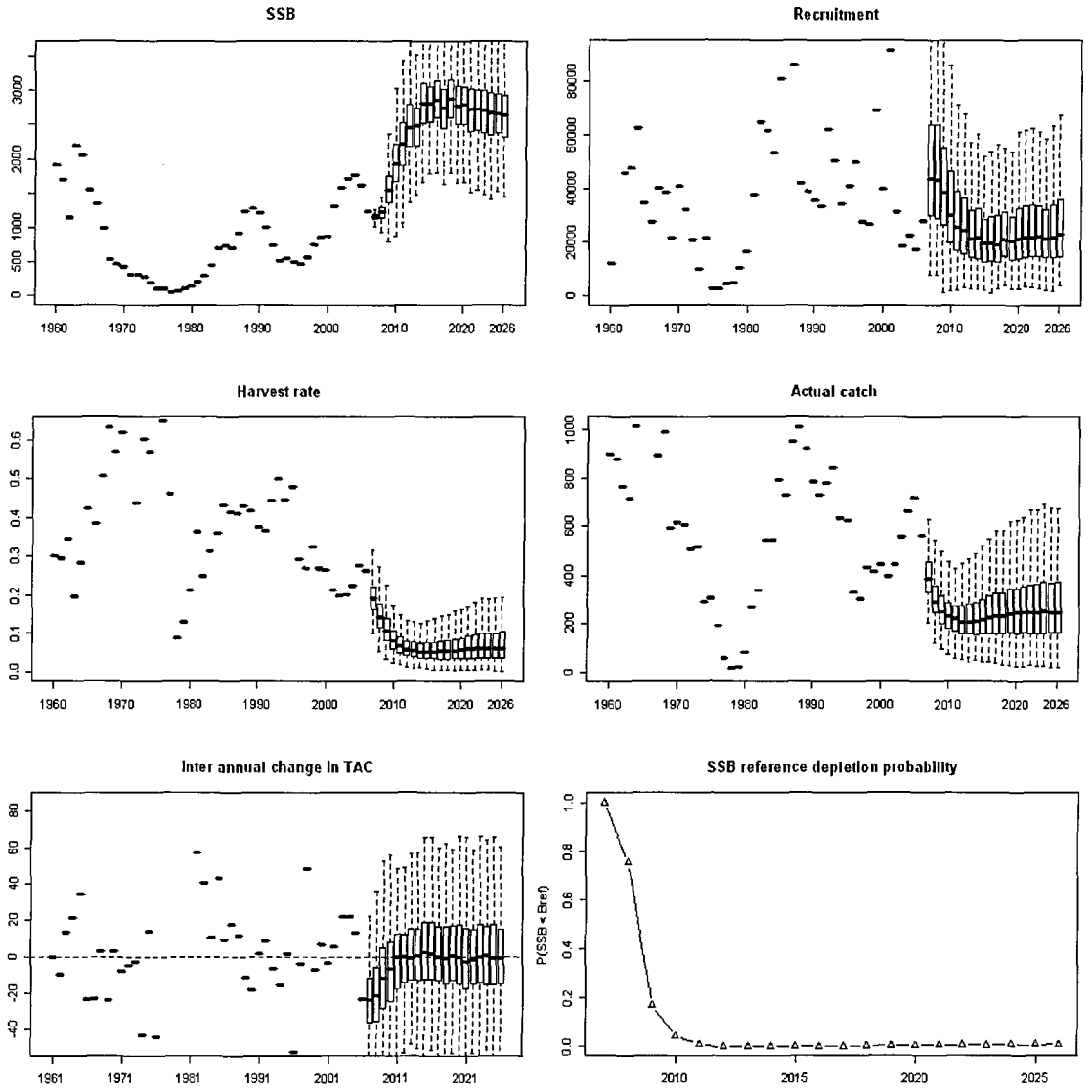


Figure 276: Output of simulation 197.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

Sensitivity analysis: Maturity-at-age

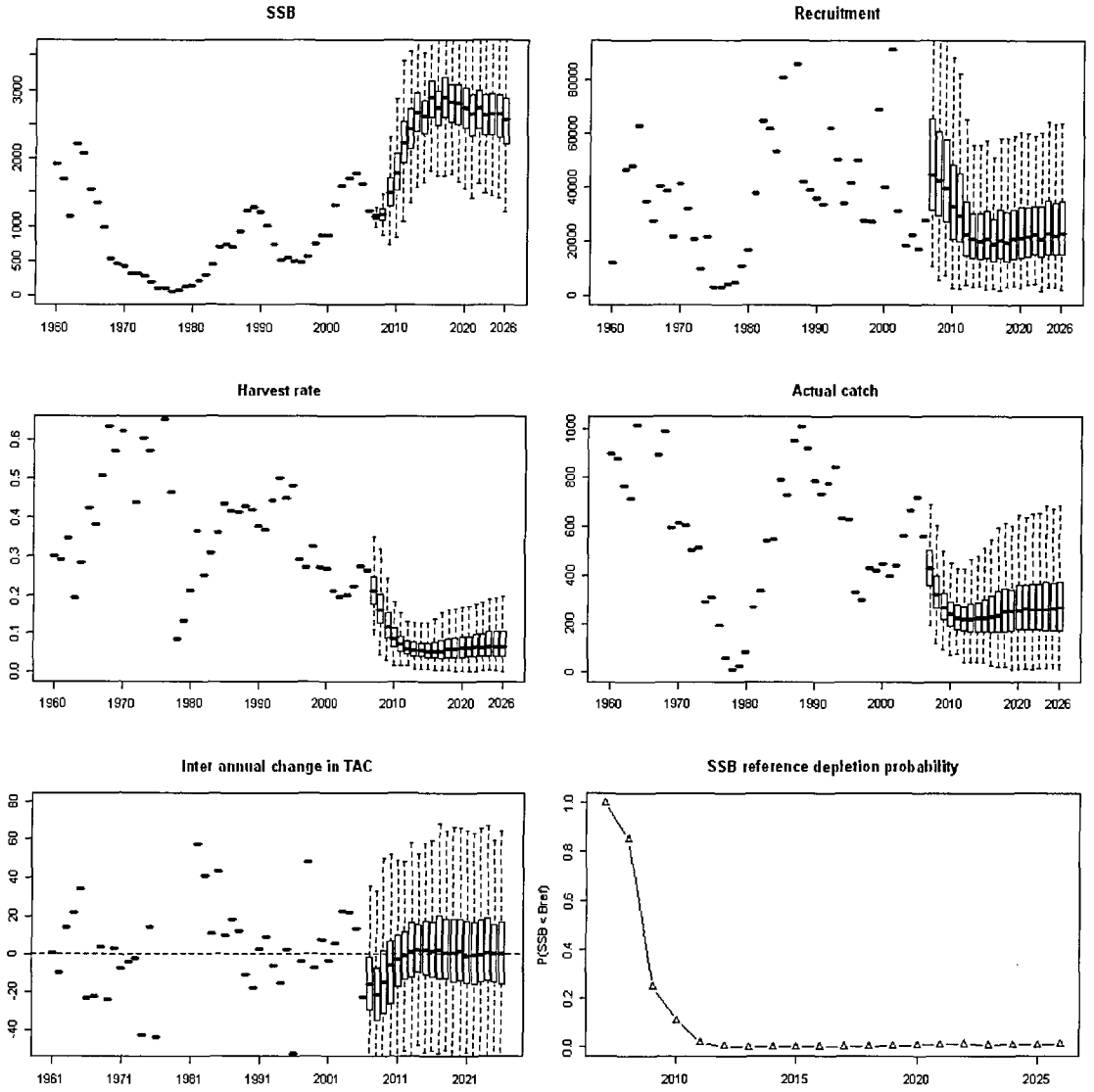


Figure 277: Output of simulation 198.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

Sensitivity analysis: Maturity-at-age

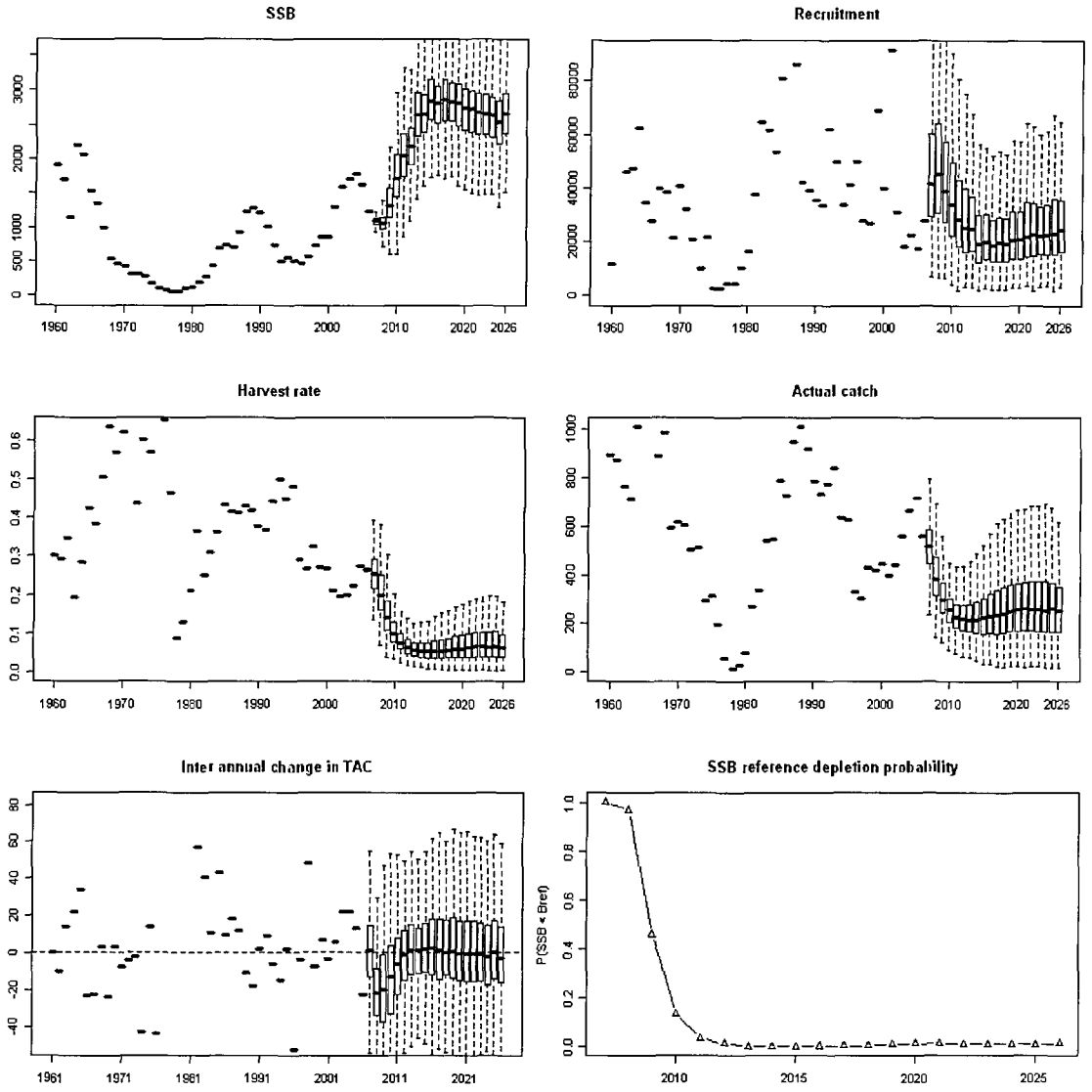


Figure 278: Output of simulation 199.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

Sensitivity analysis: Maturity-at-age

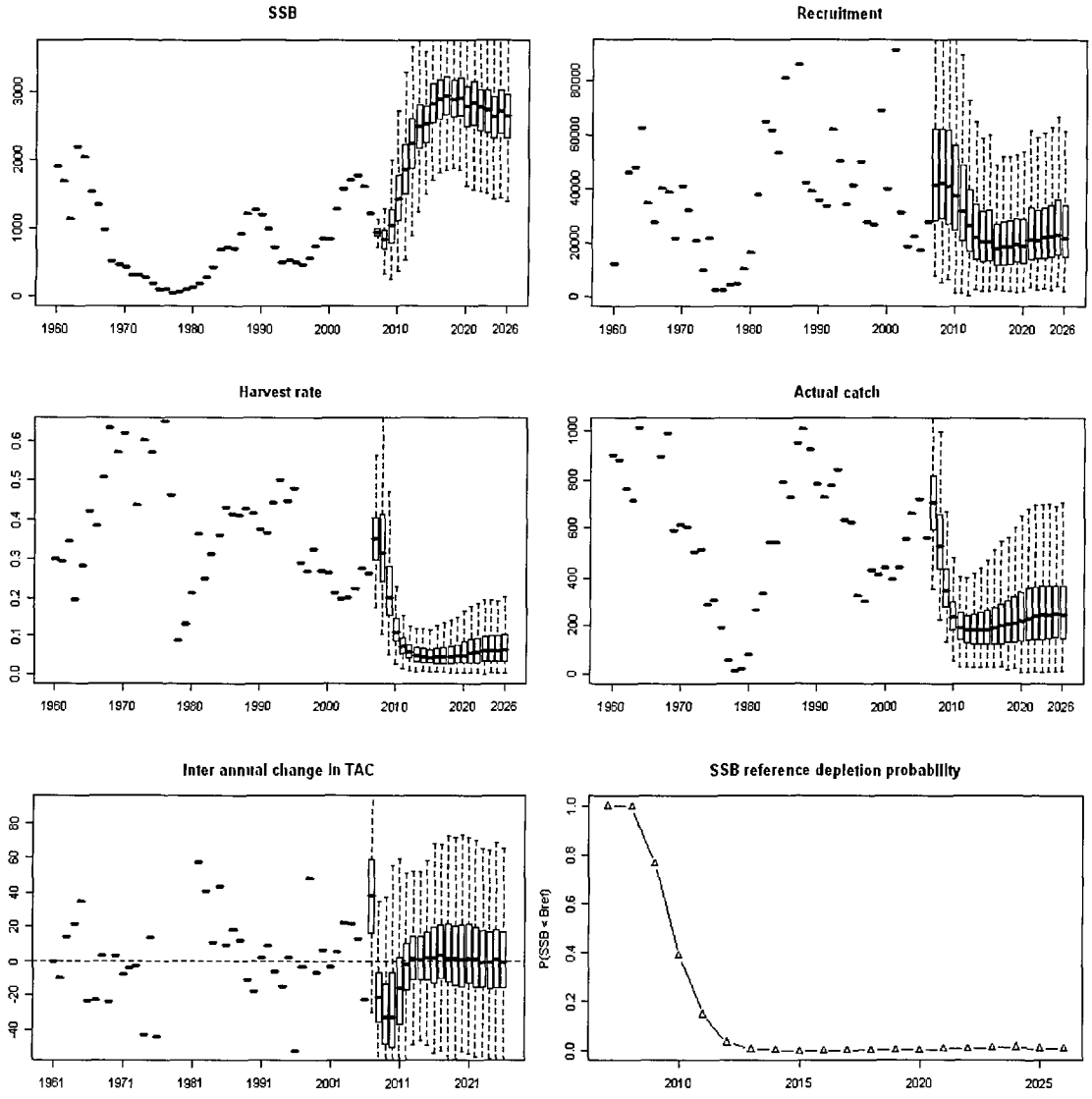


Figure 279: Output of simulation 200.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

Sensitivity analysis: Maturity-at-age

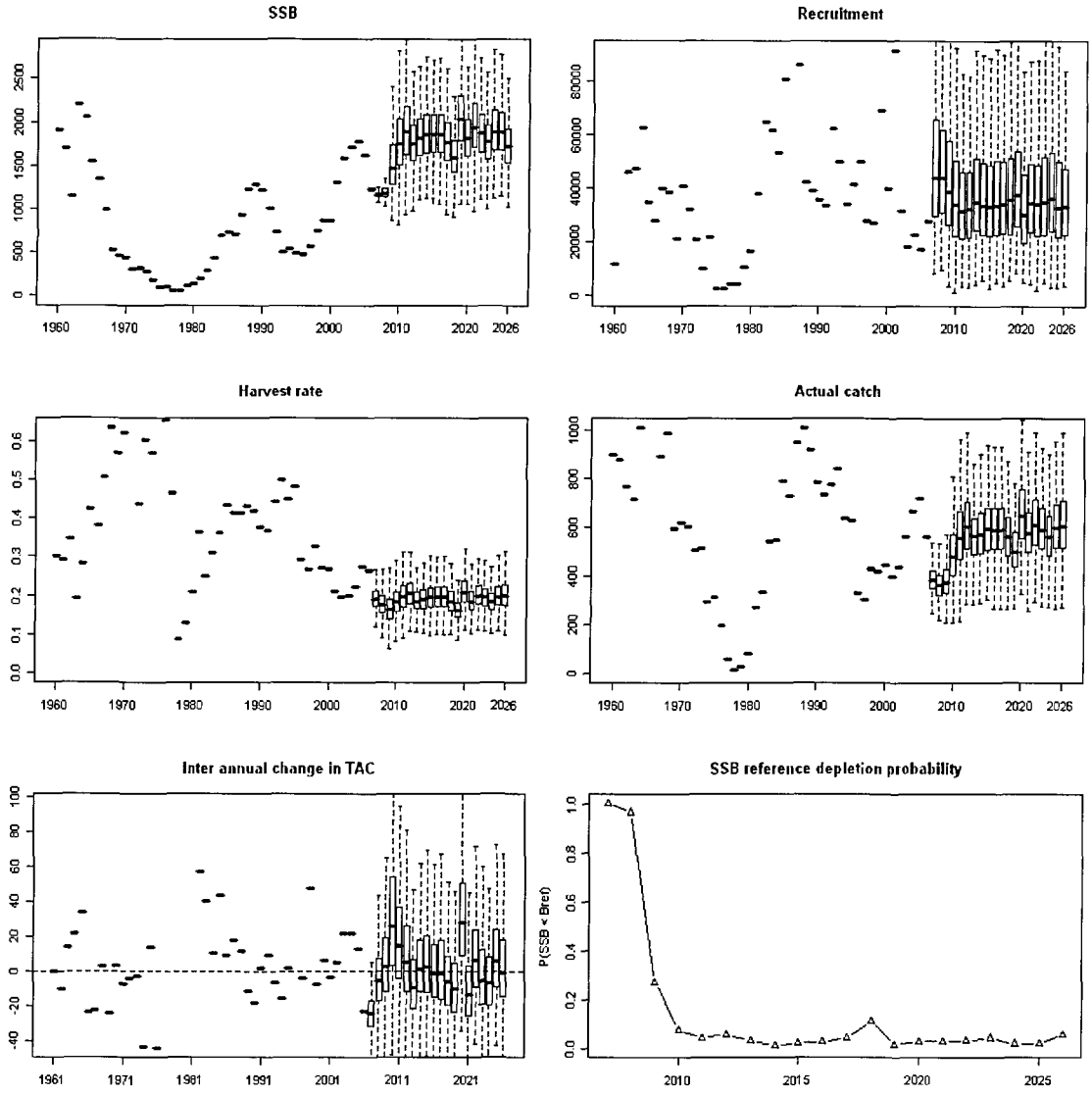


Figure 280: Output of simulation 201.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 0%

Sensitivity analysis: Catch weight-at-age

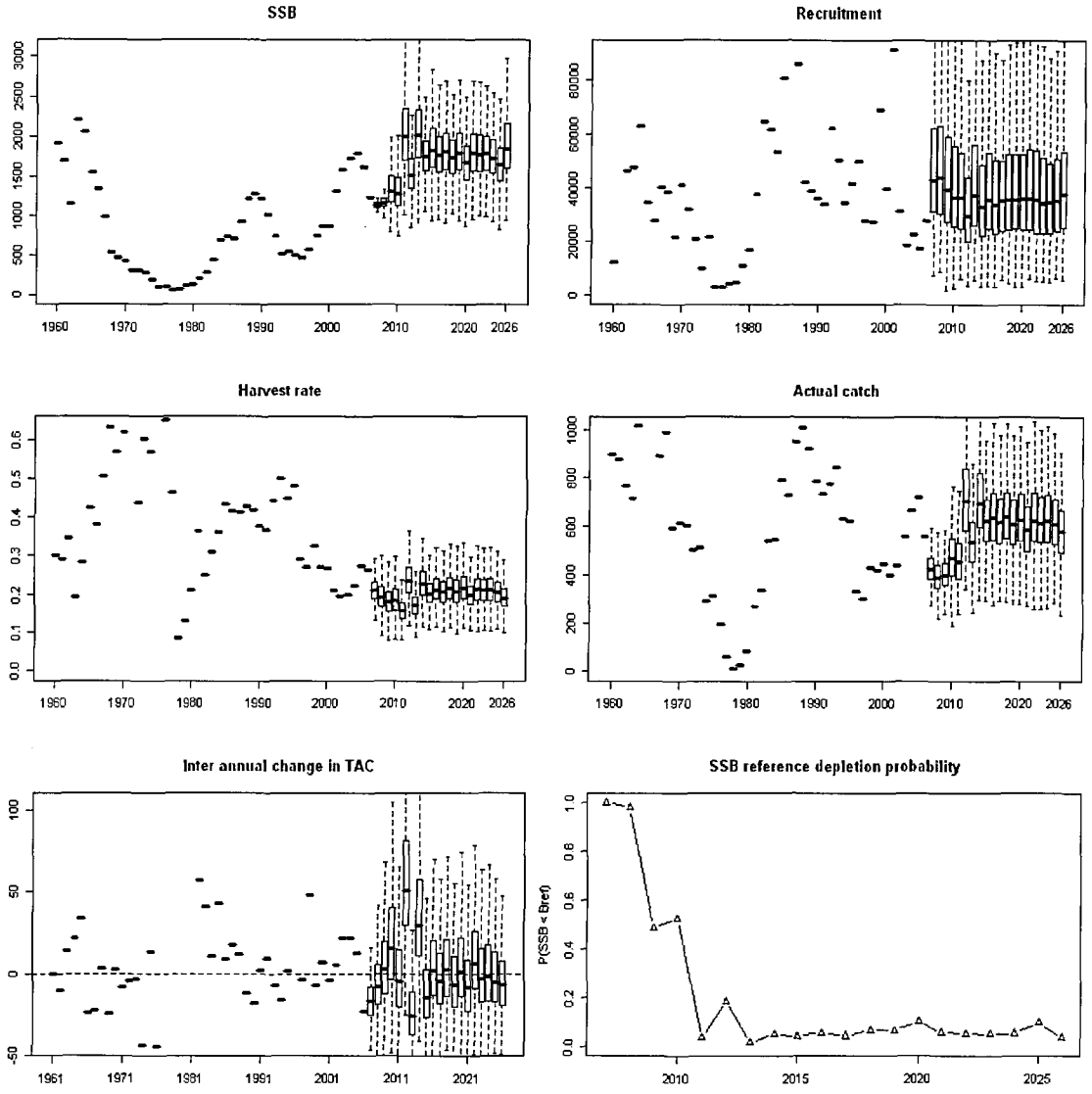


Figure 281: Output of simulation 202.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 10%

Sensitivity analysis: Catch weight-at-age

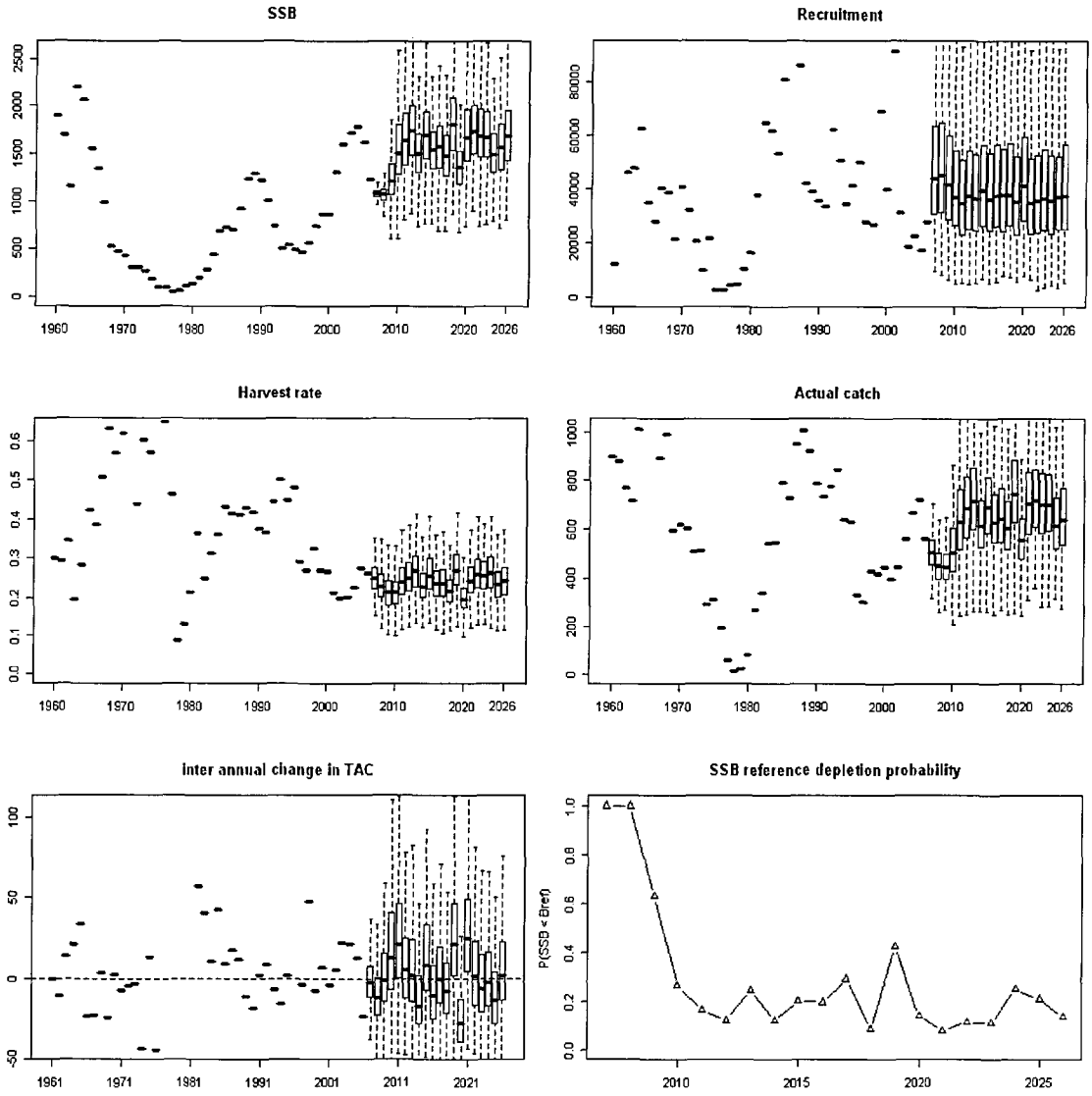


Figure 282: Output of simulation 203.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 30%

Sensitivity analysis: Catch weight-at-age

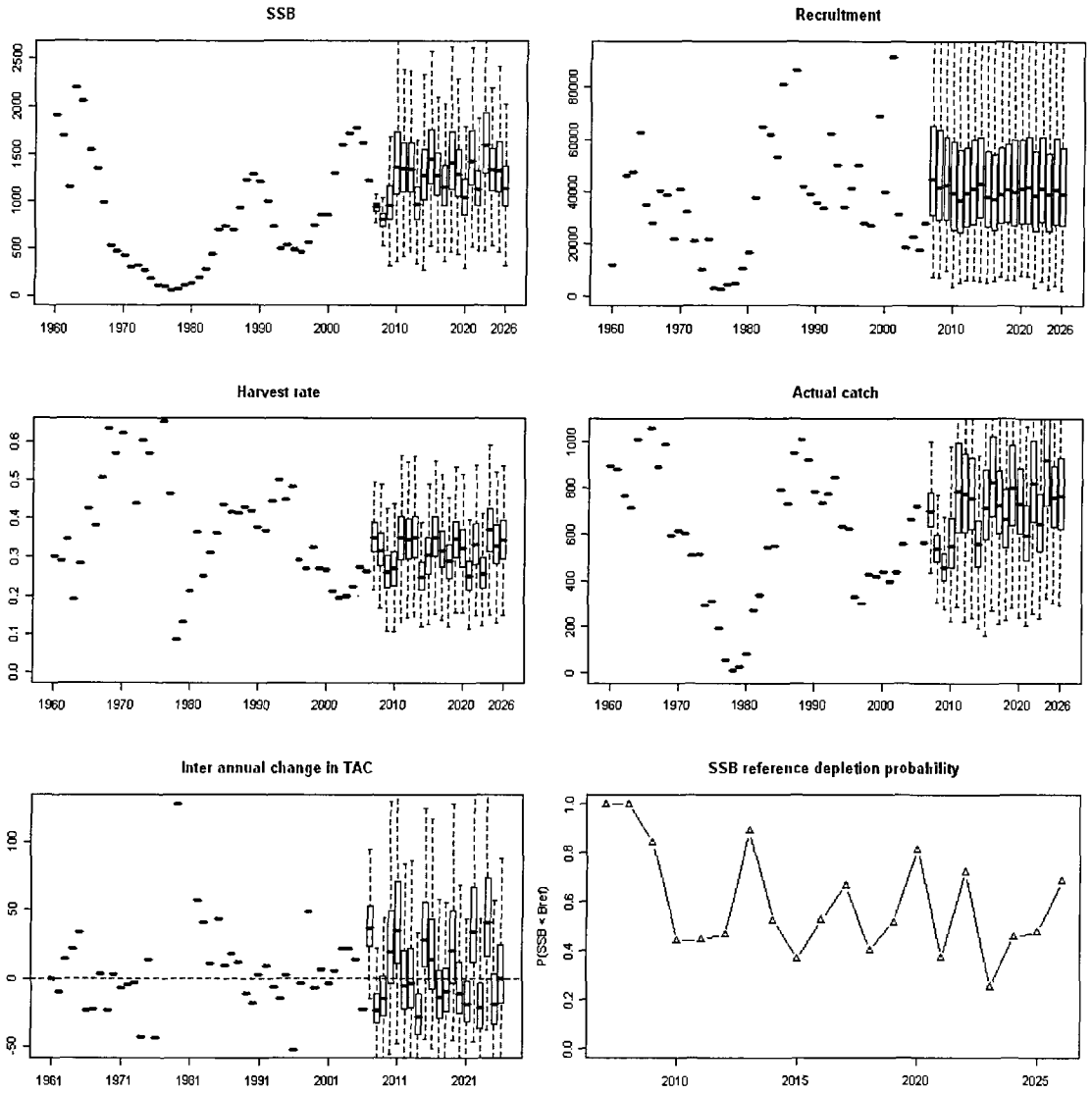


Figure 283: Output of simulation 204.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: none

Implementation error: 80%

Sensitivity analysis: Catch weight-at-age

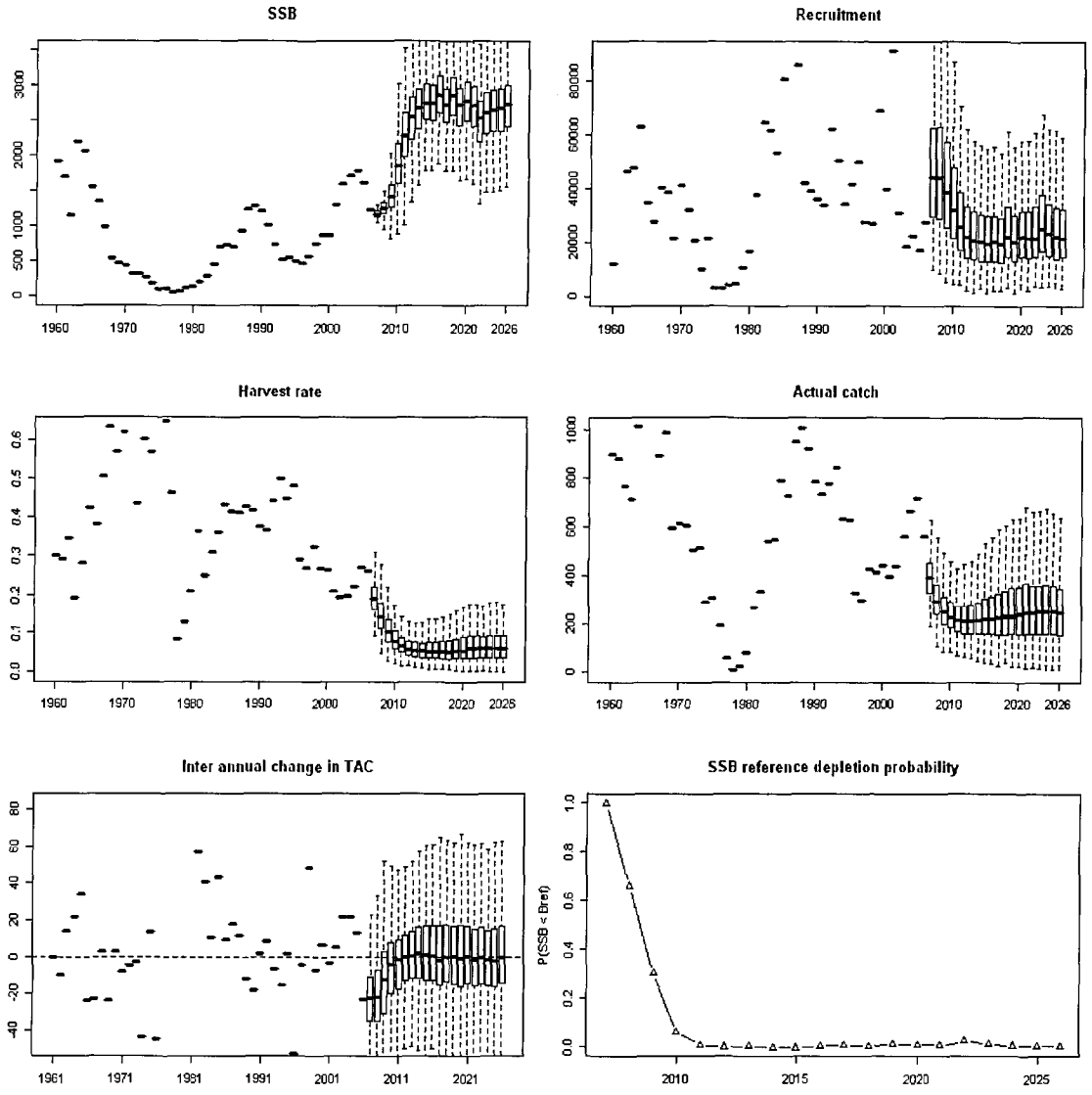


Figure 284: Output of simulation 205.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 0%

Sensitivity analysis: Catch weight-at-age

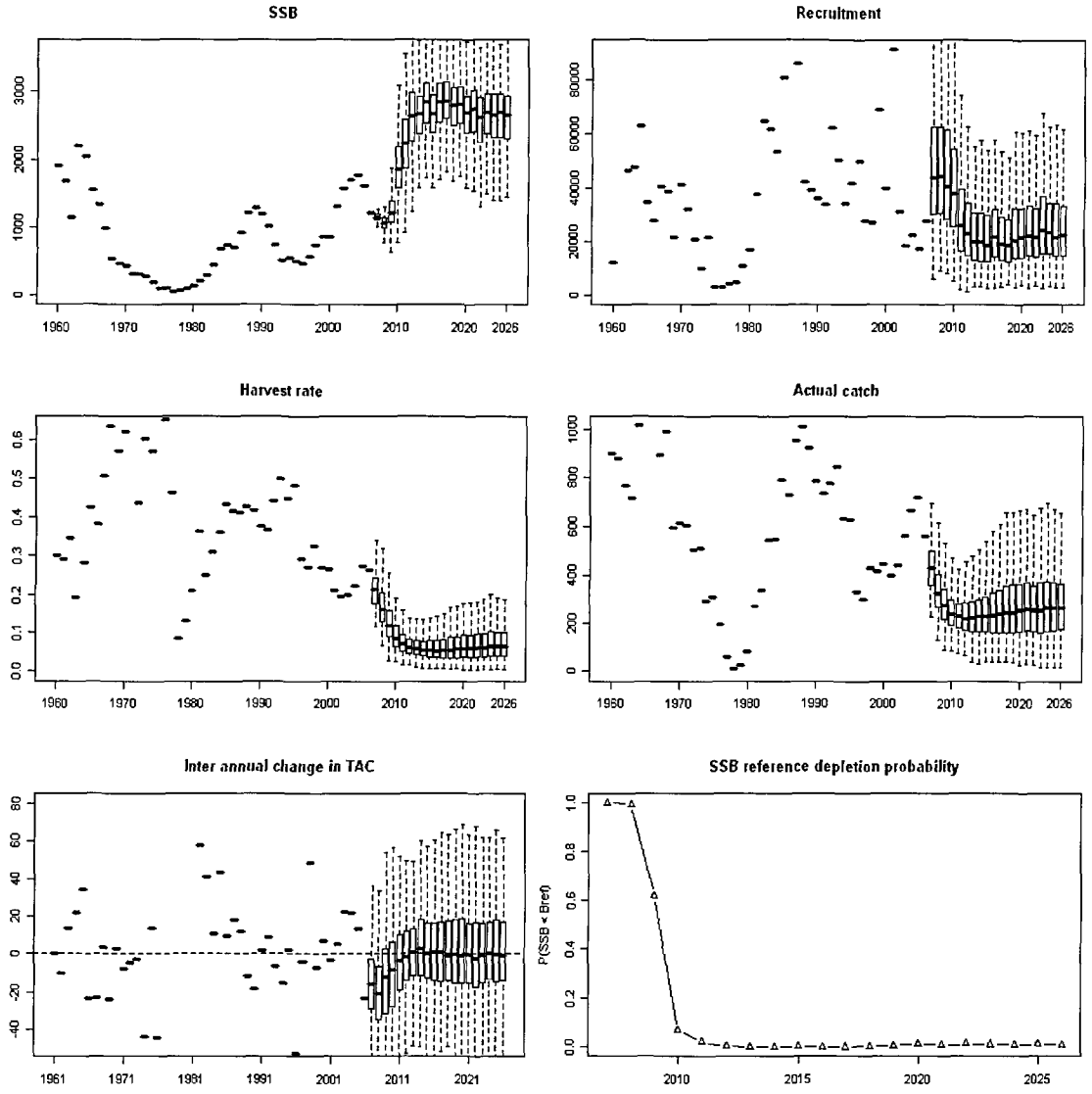


Figure 285: Output of simulation 206.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 10%

Sensitivity analysis: Catch weight-at-age

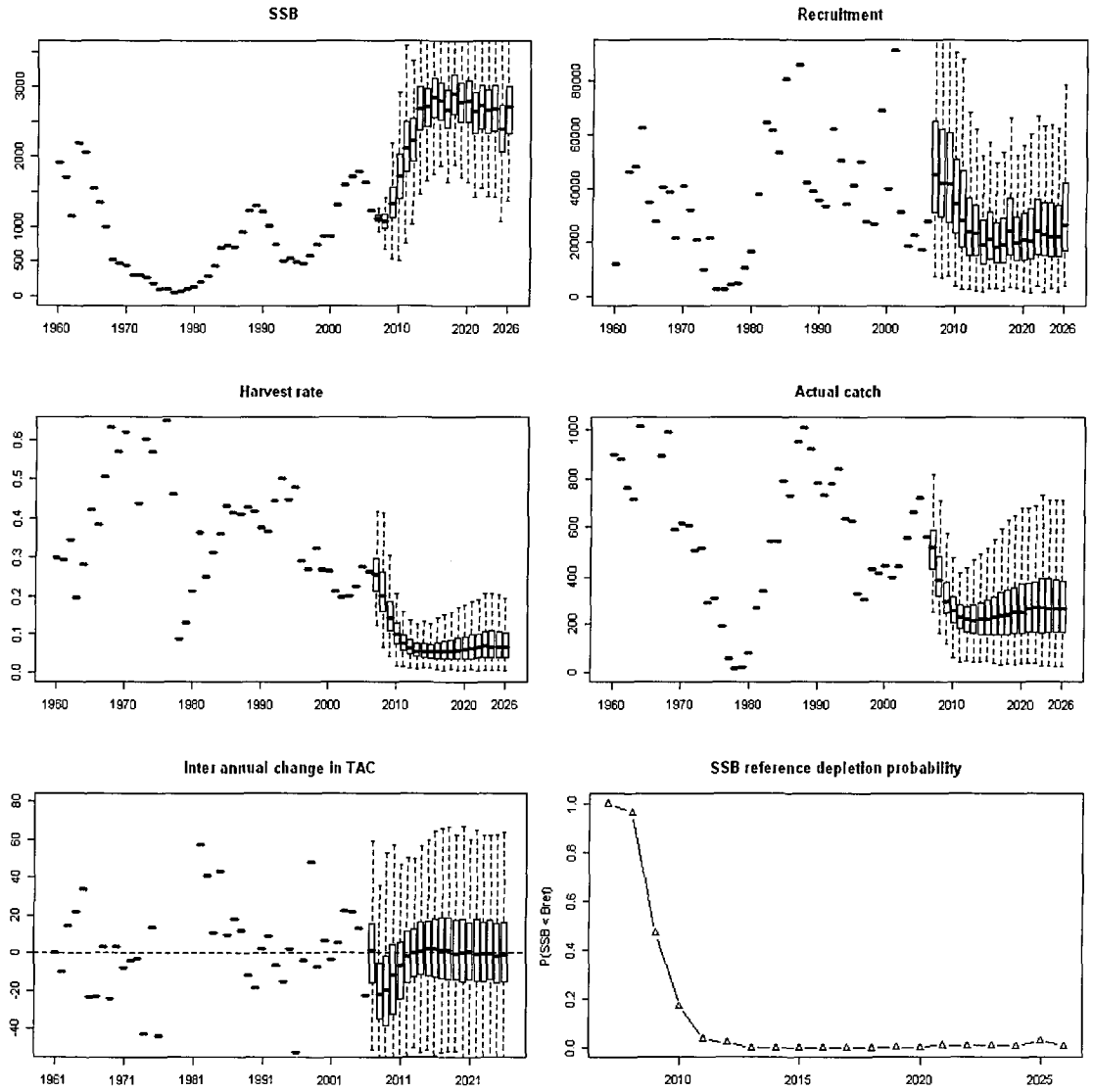


Figure 286: Output of simulation 207.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 30%

Sensitivity analysis: Catch weight-at-age

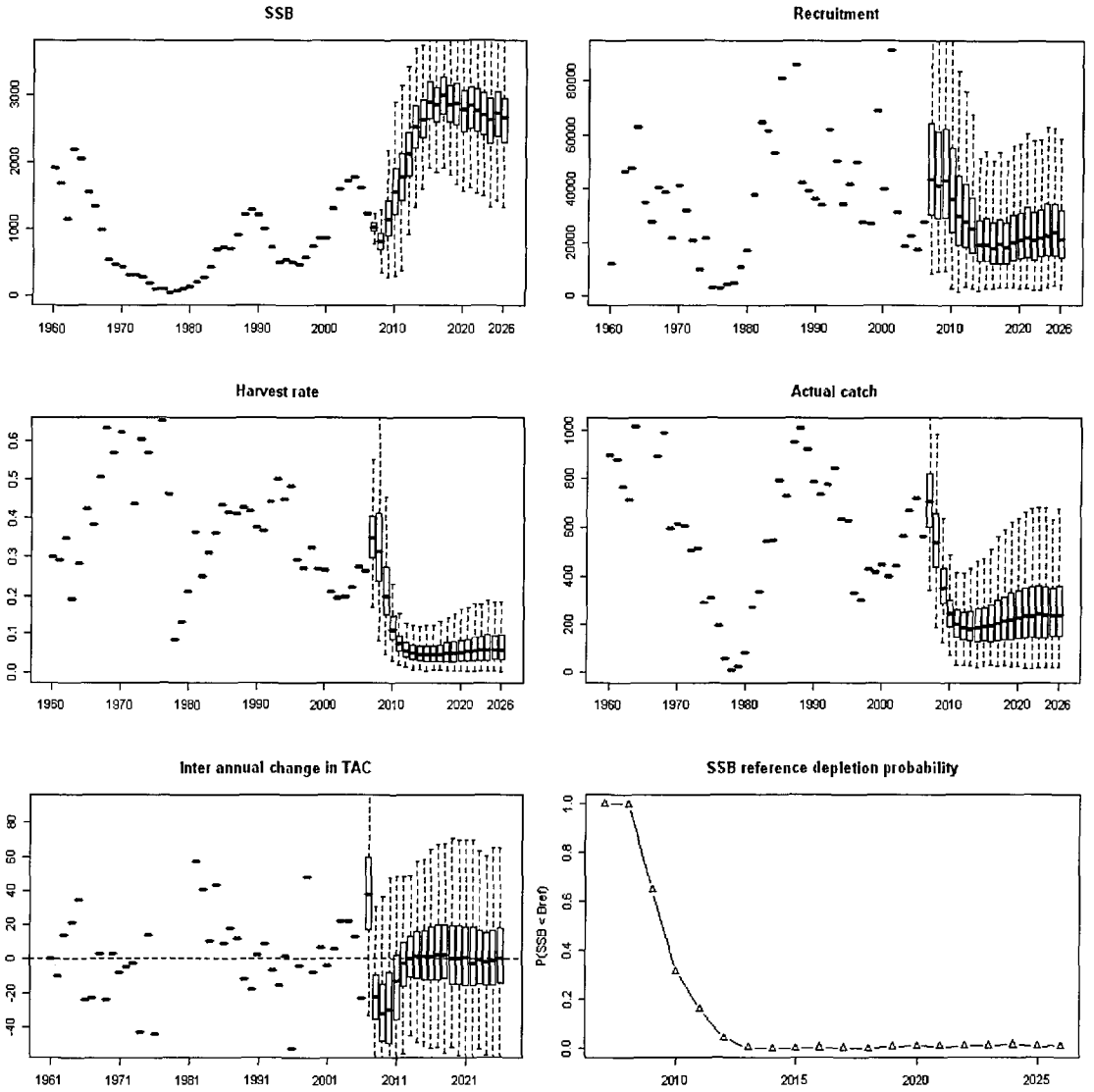


Figure 287: Output of simulation 208.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: none

Implementation error: 80%

Sensitivity analysis: Catch weight-at-age

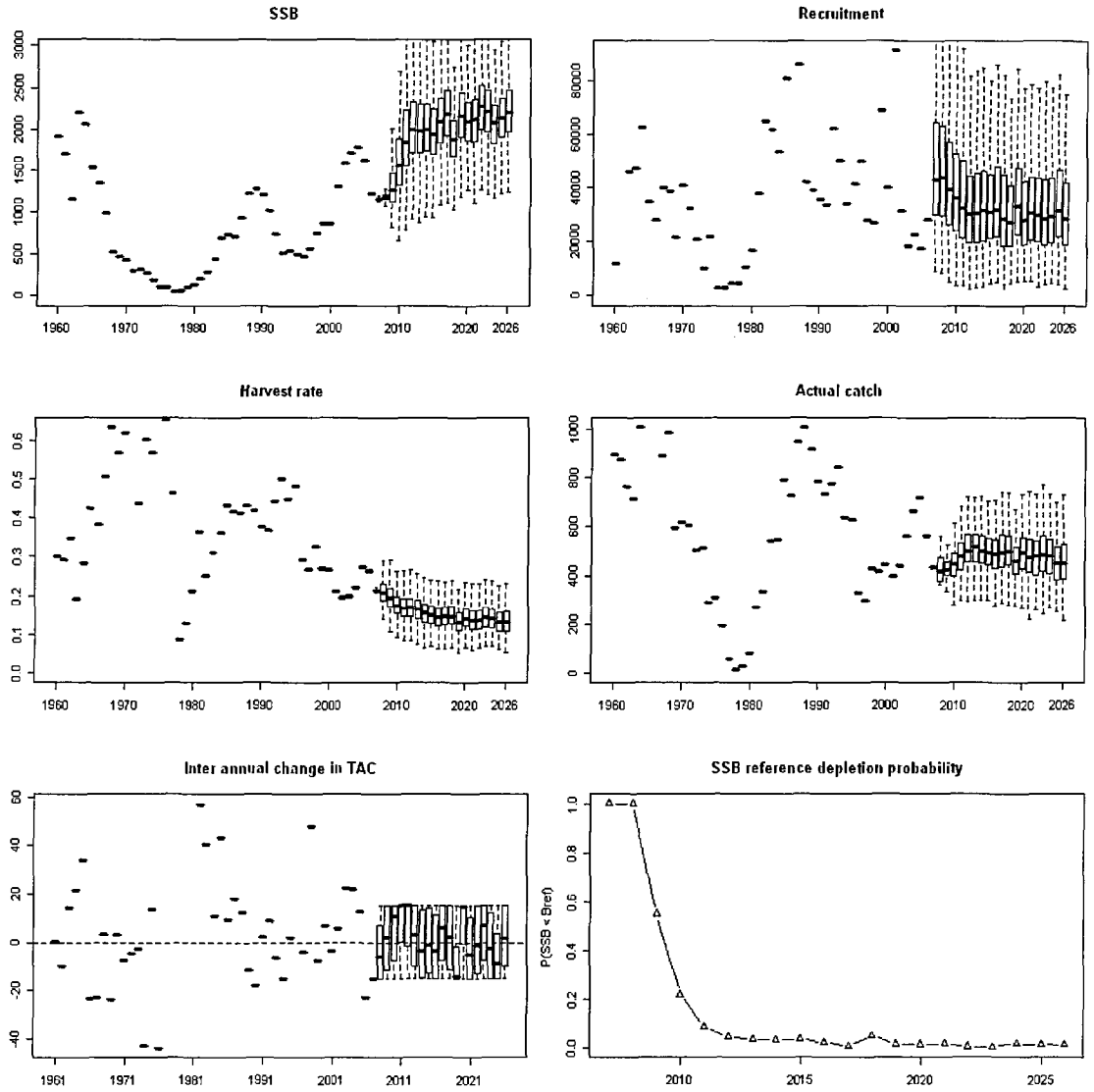


Figure 288: Output of simulation 209.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: yes

Implementation error: 0%

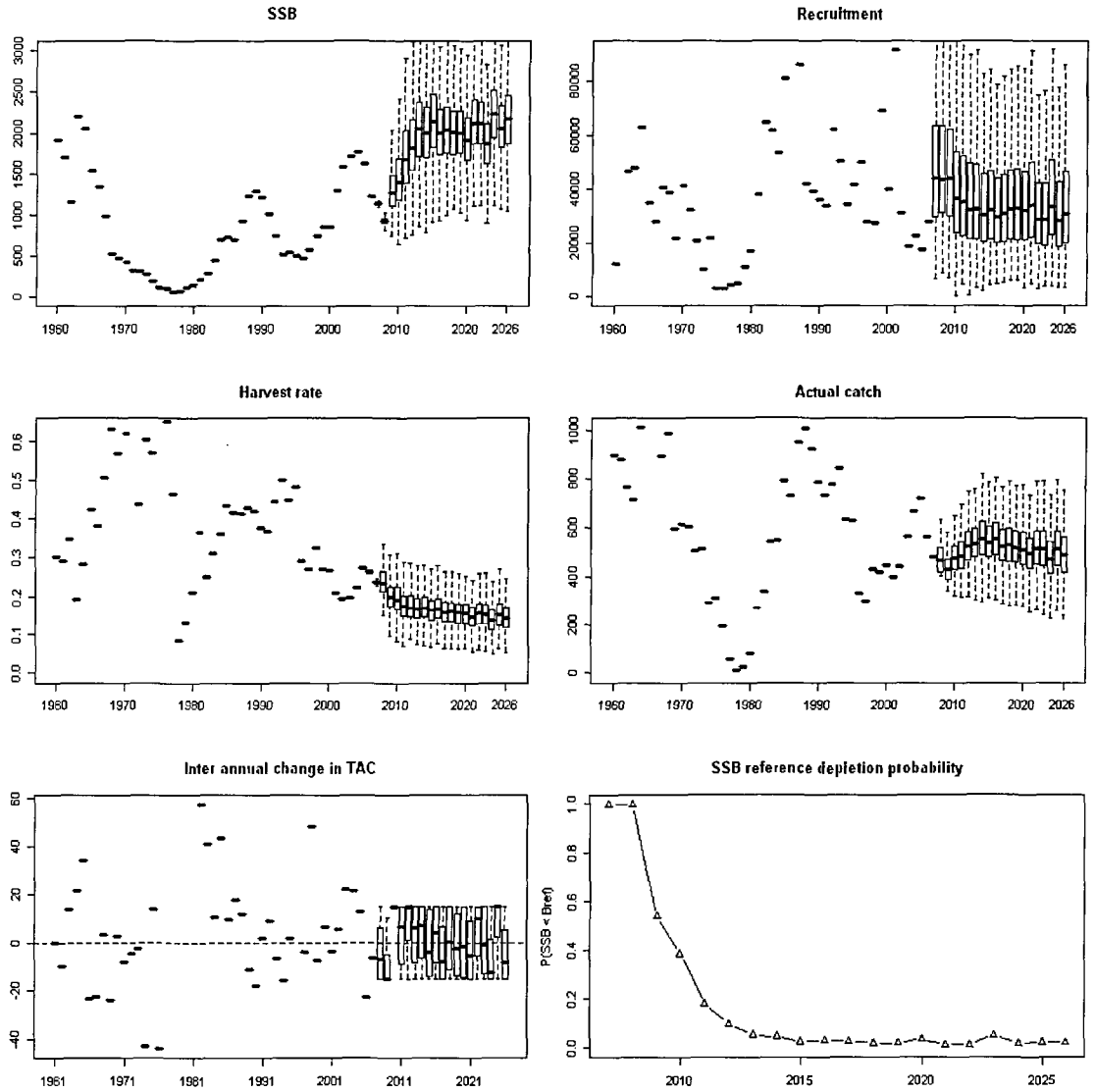


Figure 289: Output of simulation 210.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: yes

Implementation error: 10%

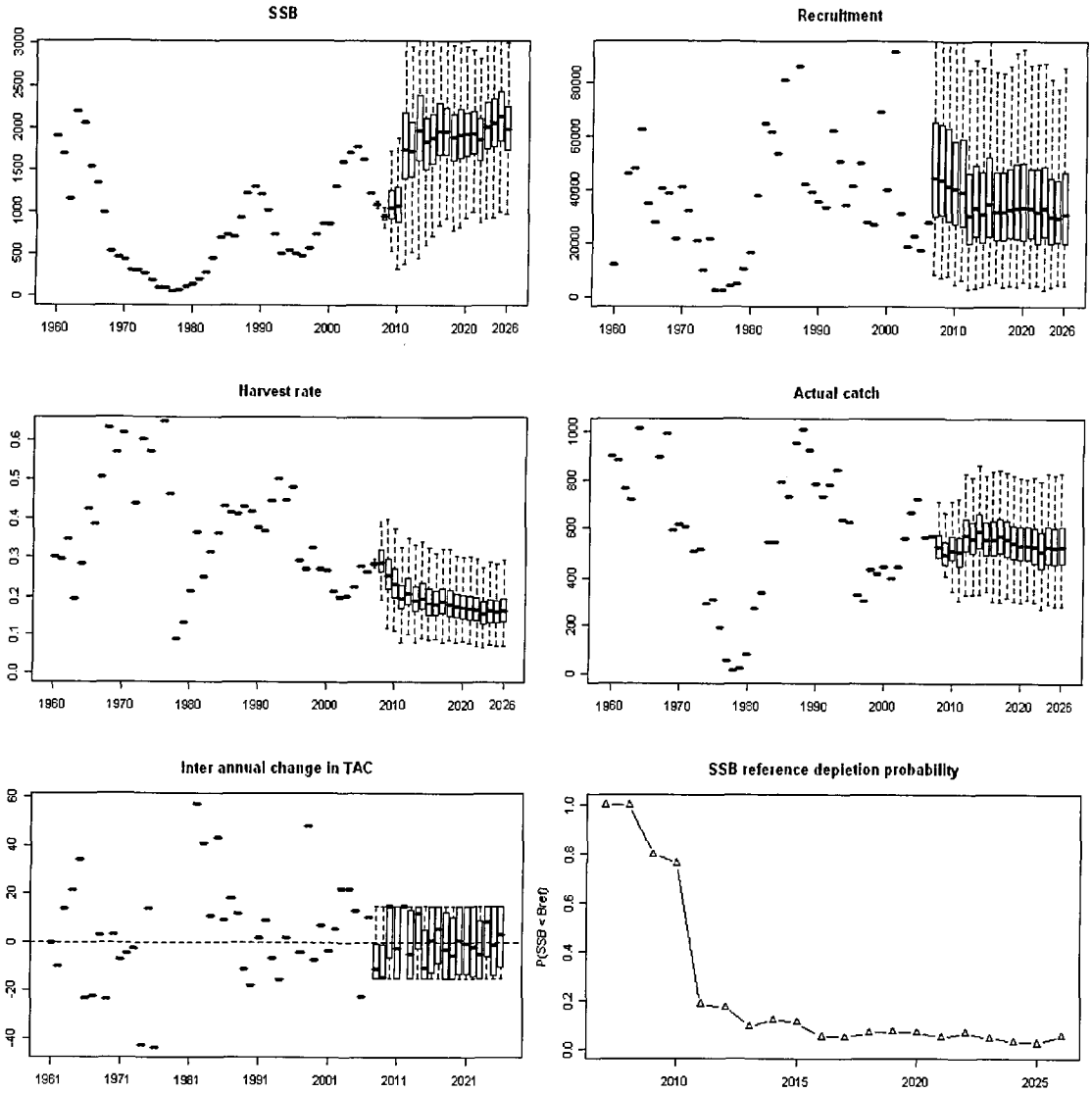


Figure 290: Output of simulation 211.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: yes

Implementation error: 30%

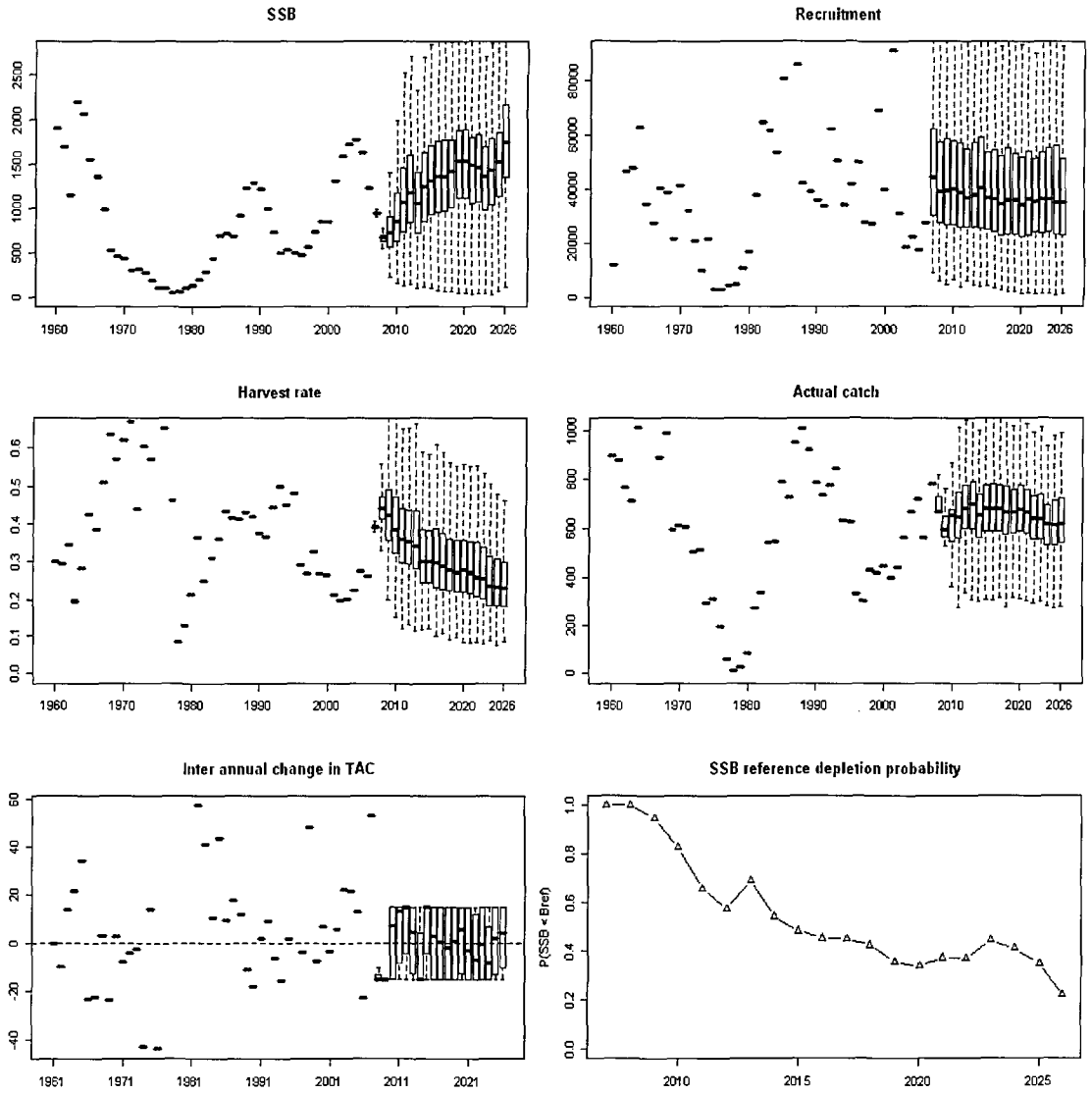


Figure 291: Output of simulation 212.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Sngl SSB

Limitation of variation: yes

Implementation error: 80%

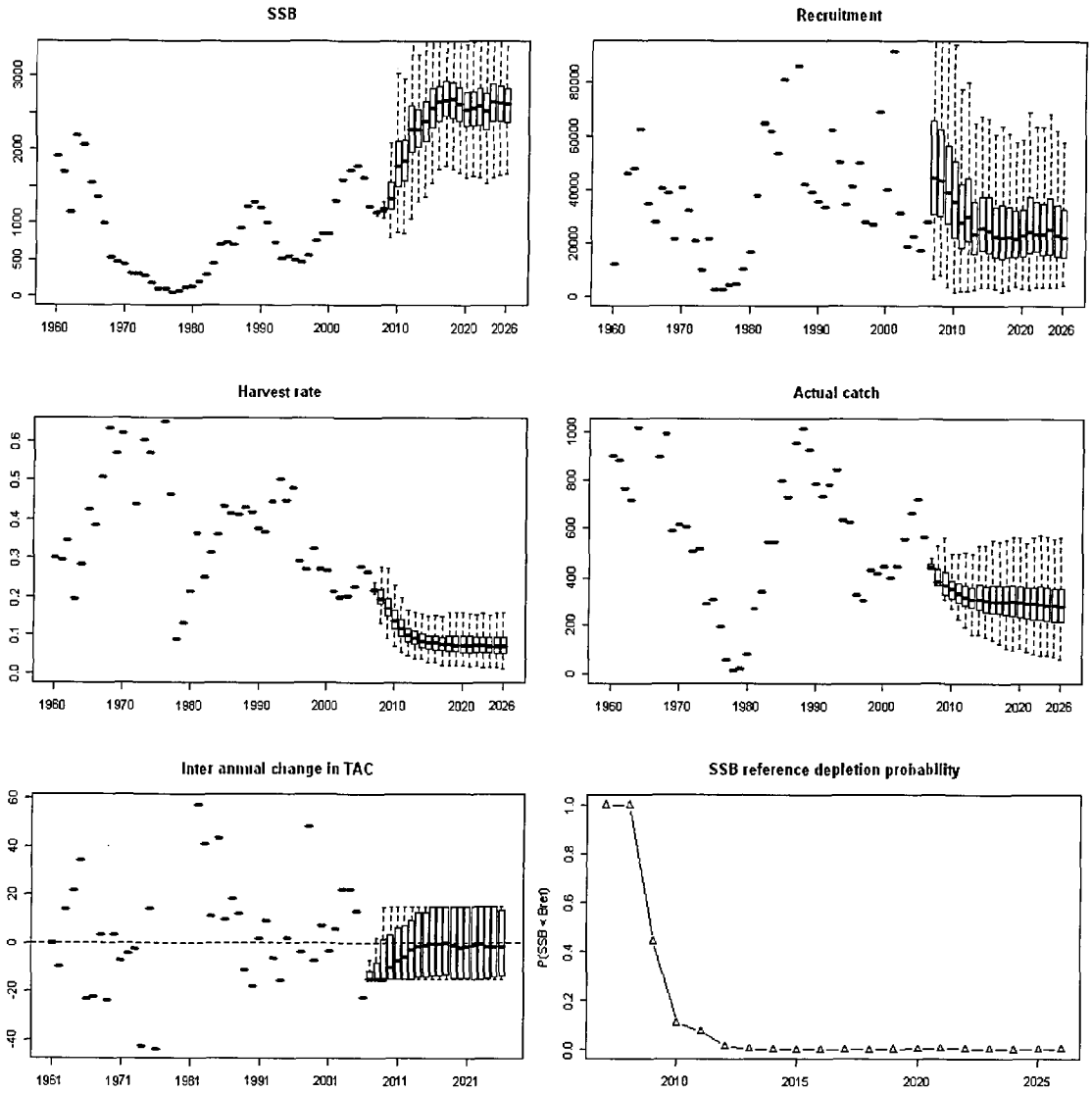


Figure 292: Output of simulation 213.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: yes

Implementation error: 0%

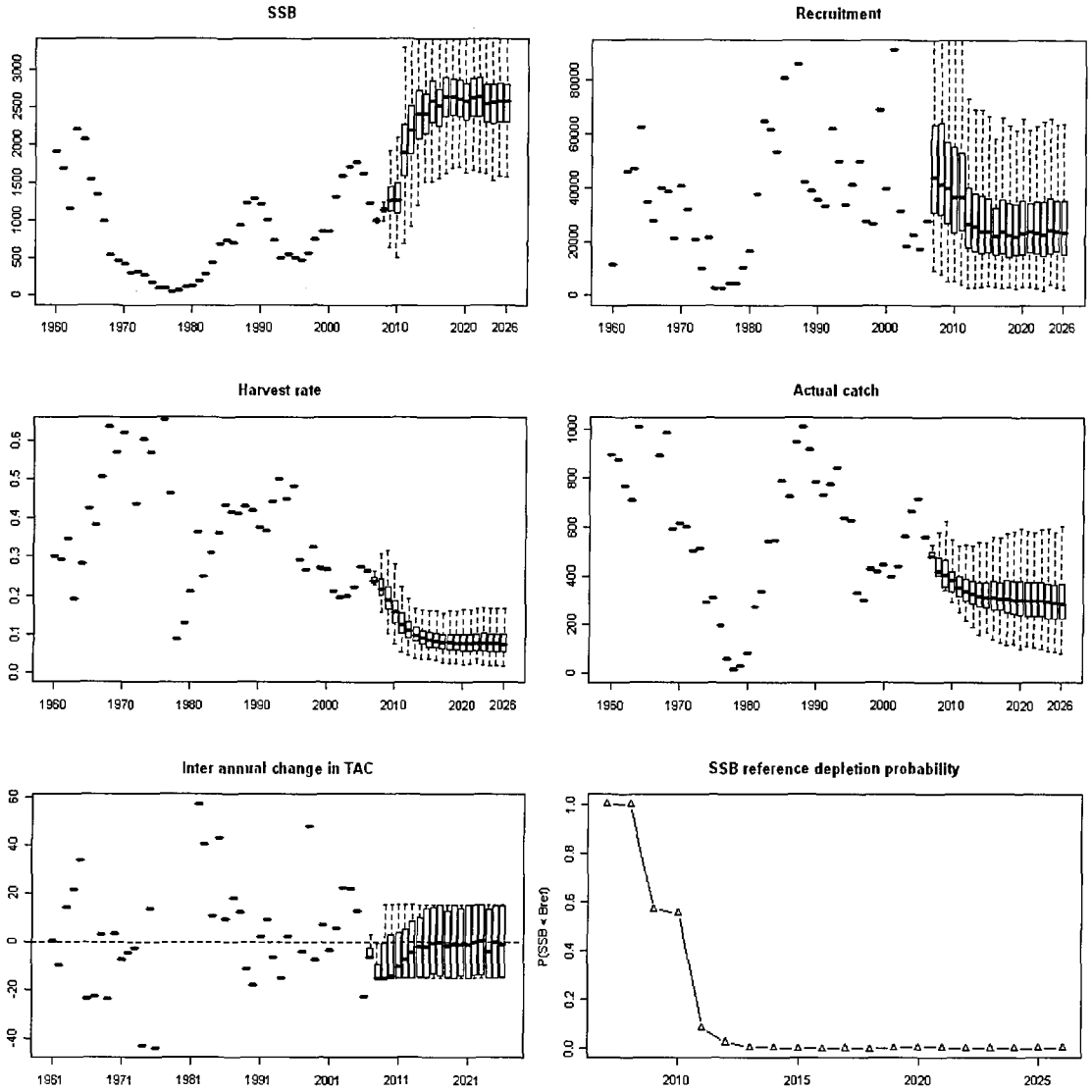


Figure 293: Output of simulation 214.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: yes

Implementation error: 10%

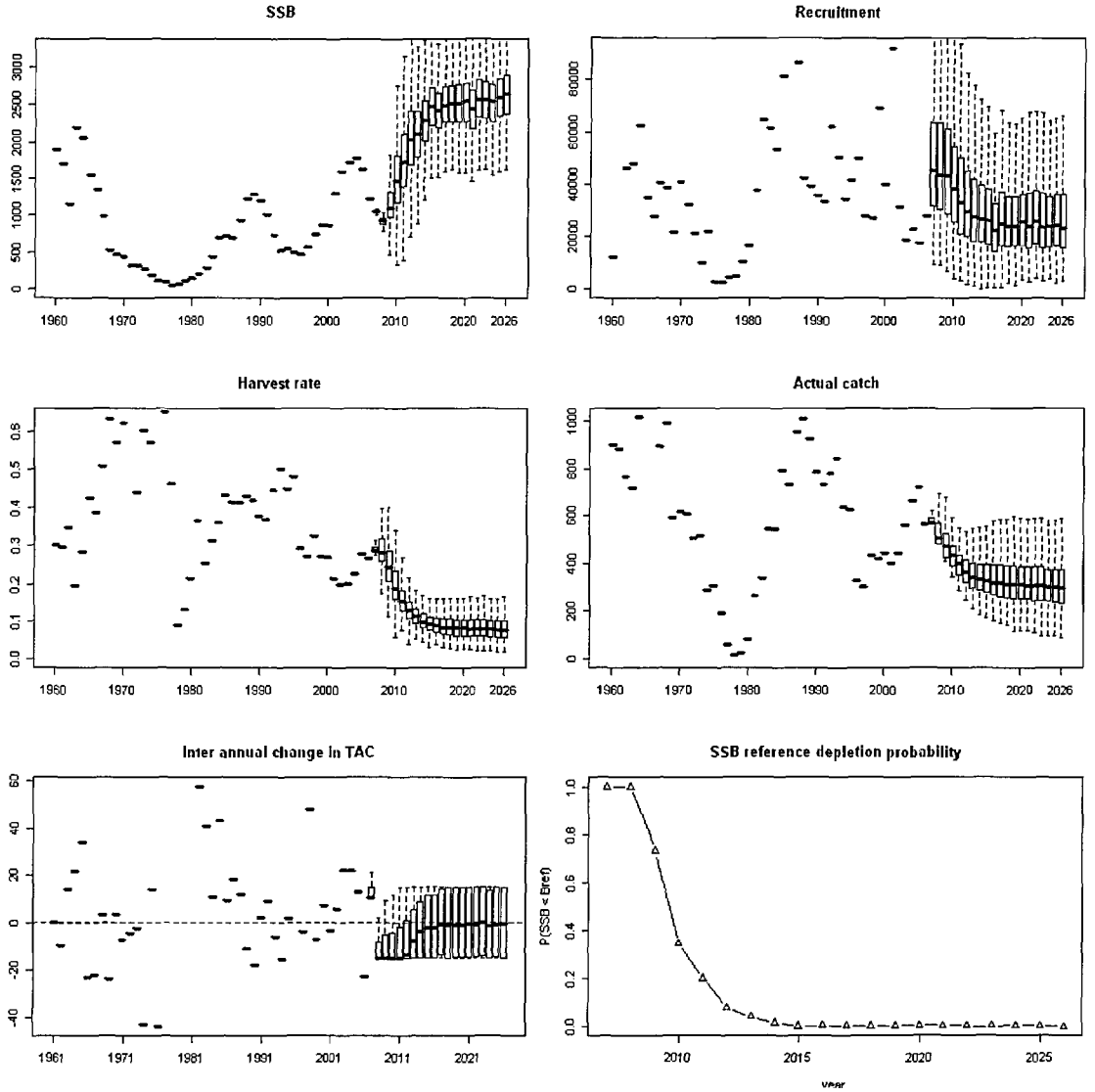


Figure 294: Output of simulation 215.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: yes

Implementation error: 30%

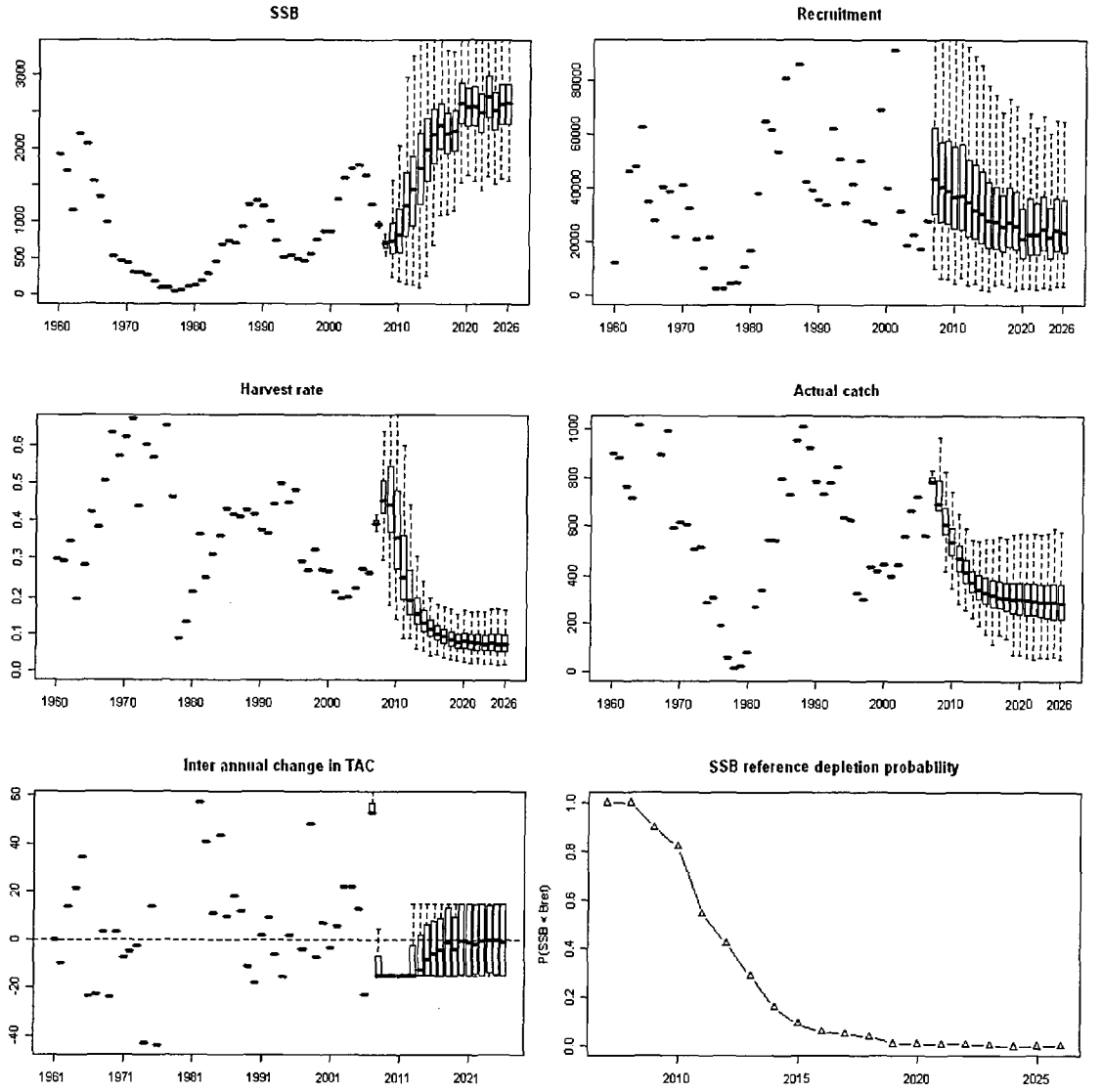


Figure 295: Output of simulation 216.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: yes

Implementation error: 80%

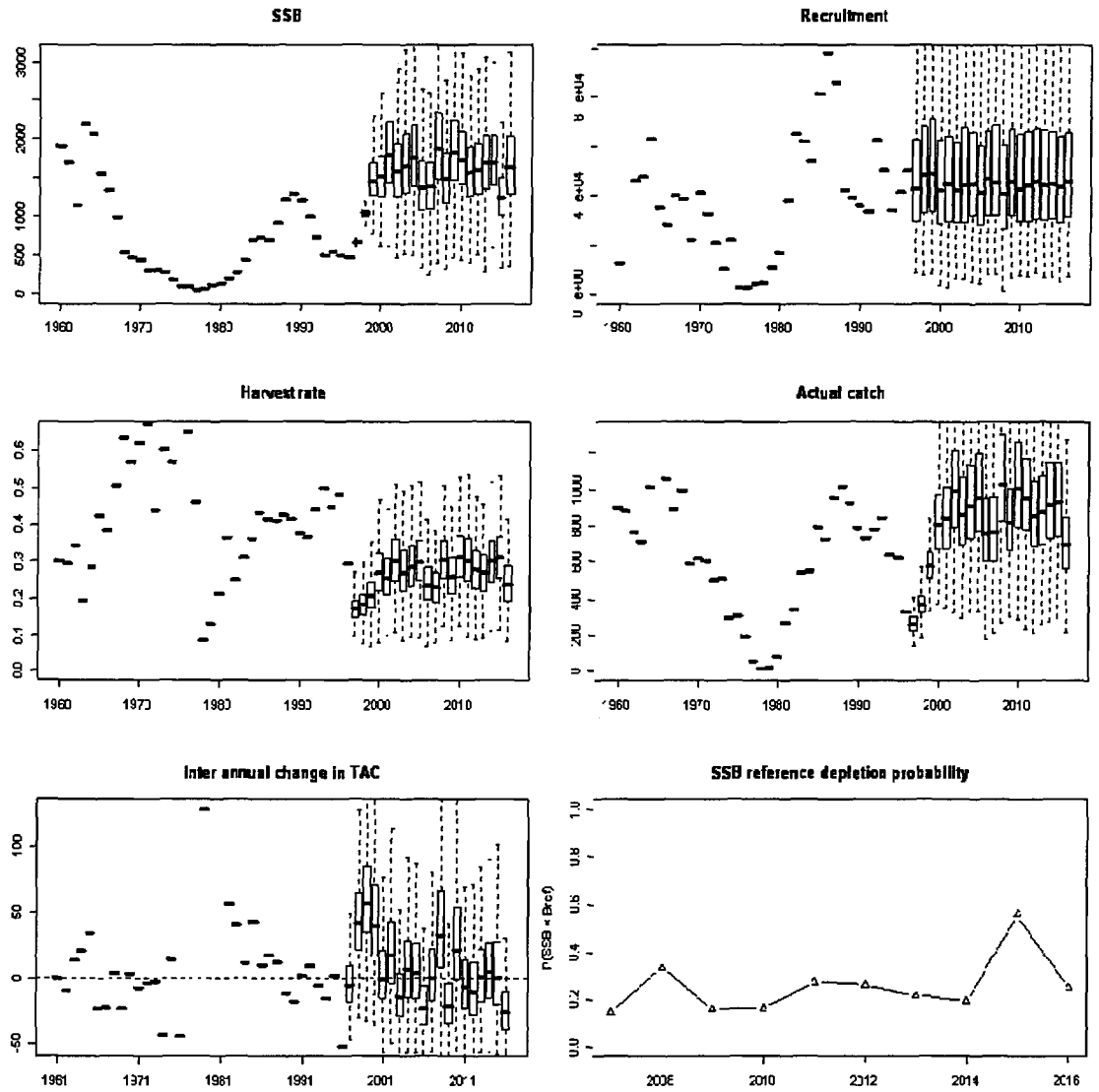


Figure 296: Output of simulation 217.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Singl SSB

Limitation of variation: no

Implementation error: 0%

Sensitivity analysis: bad initial conditions

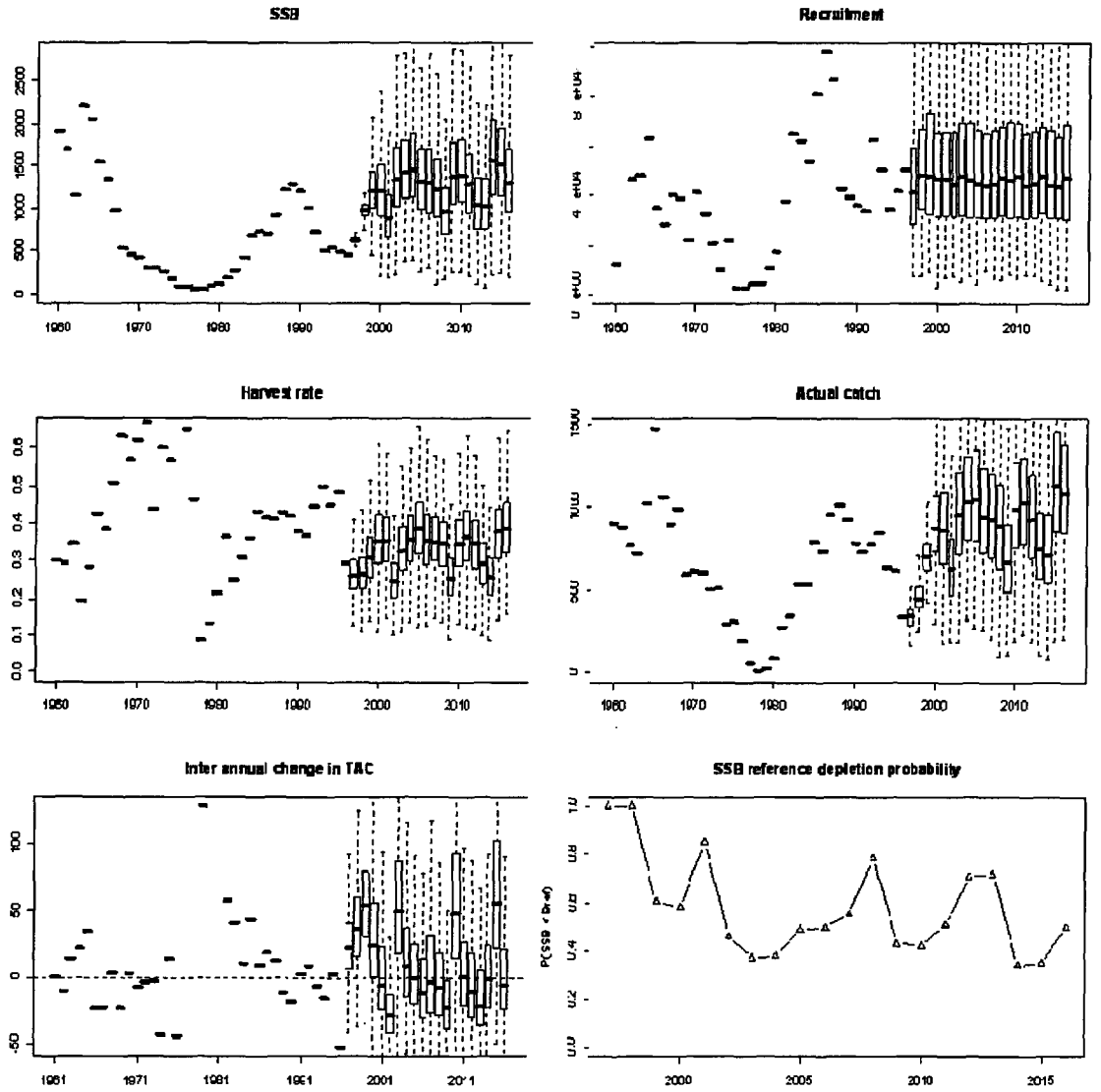


Figure 297: Output of simulation 218.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Singl SSB

Limitation of variation: no

Implementation error: 30%

Sensitivity analysis: bad initial conditions

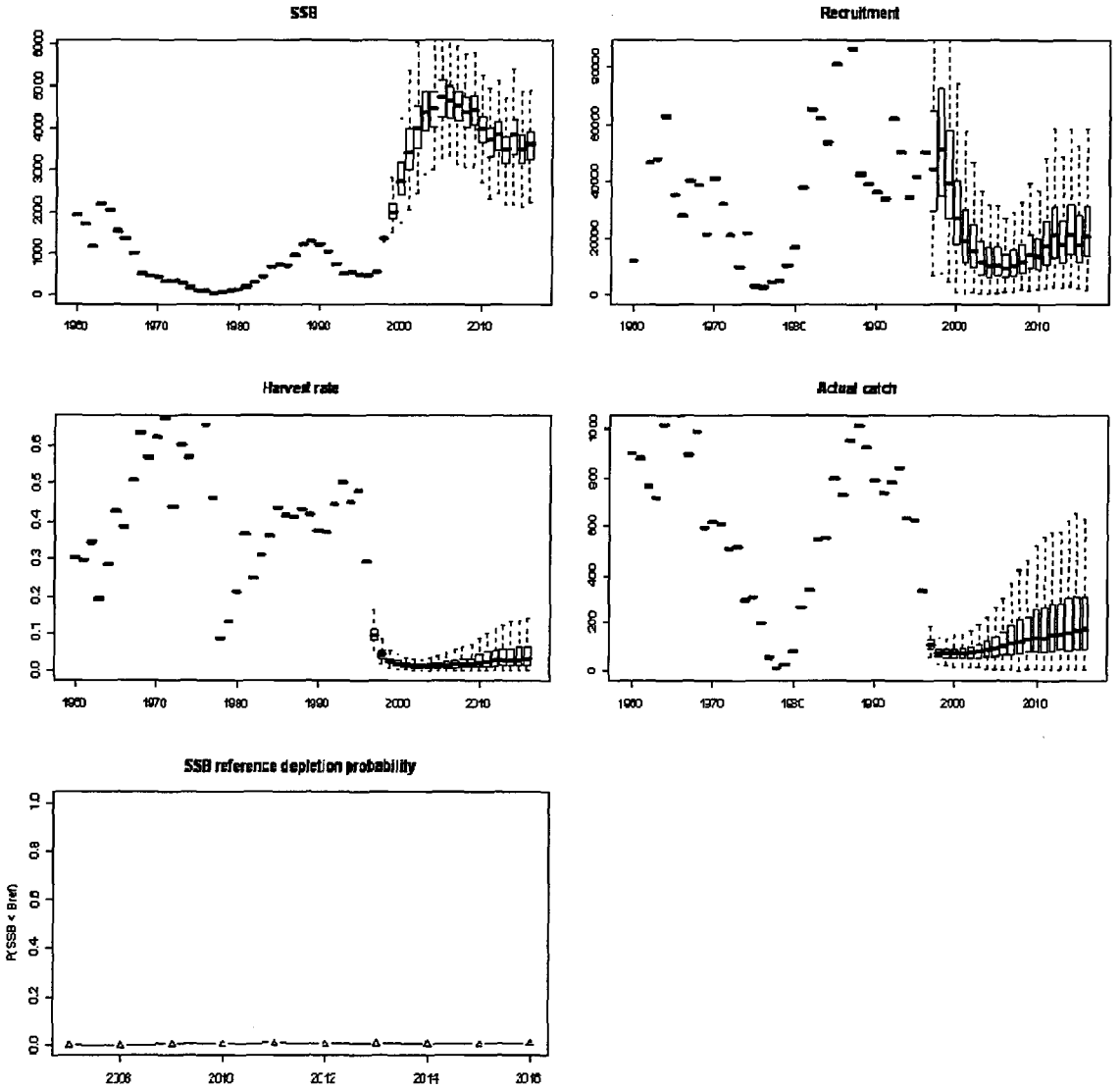


Figure 298: Output of simulation 219.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: no

Implementation error: 0%

Sensitivity analysis: bad initial conditions

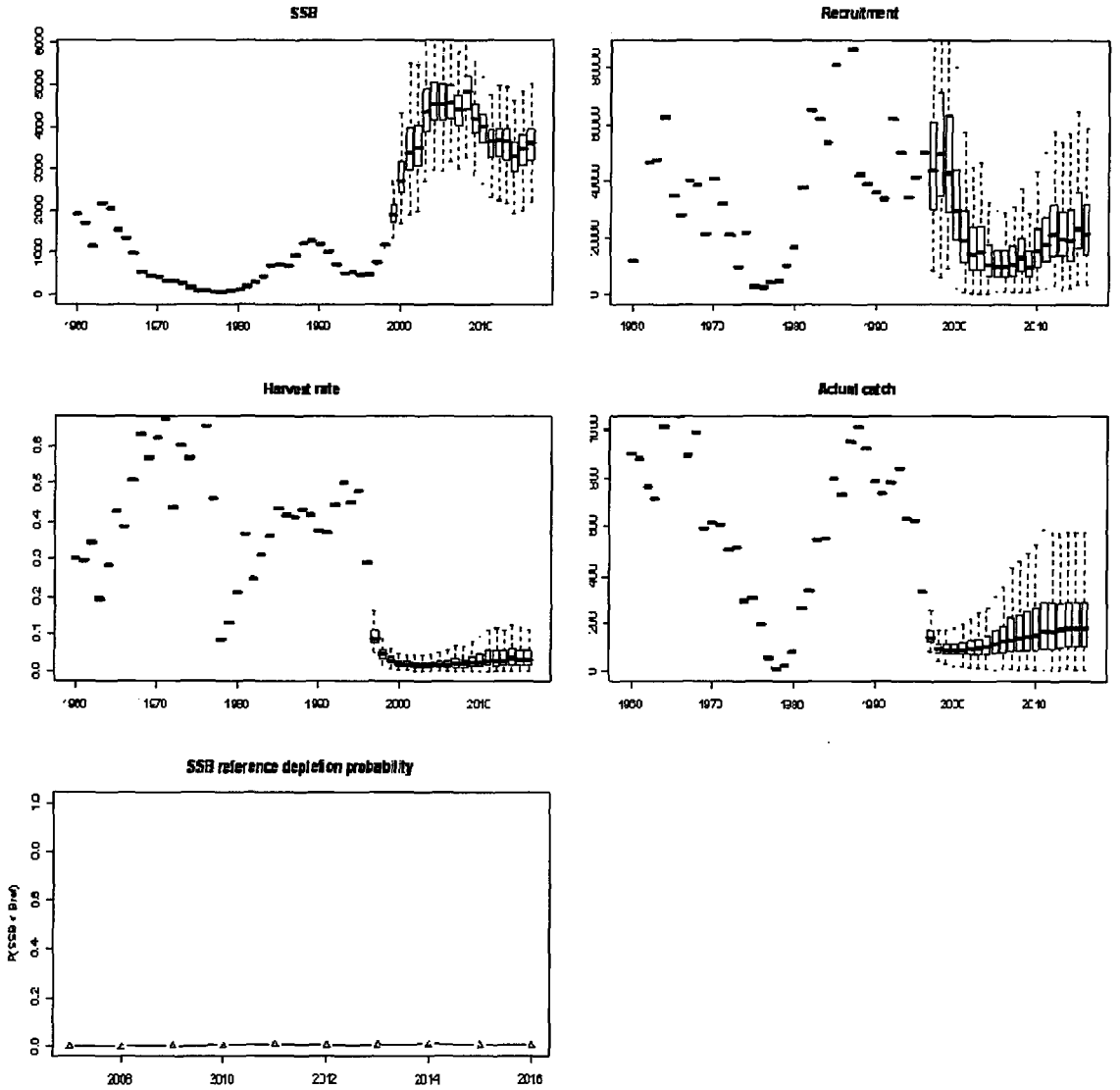


Figure 299: Output of simulation 220.

Stock recruitment: Ricker

Autocorrelation: estimated

Survey: acoustic with observation error

Assessment: none

Harvest control rule: Z

Limitation of variation: no

Implementation error: 30%

Sensitivity analysis: bad initial conditions