ICES Journal of Marine Science

ICES Journal of Marine Science (2013), 70(4), 743–754. doi:10.1093/icesjms/fst043

A simulation framework for evaluating fisheries management decisions using environmental information

Dankert W. Skagen[1], Mette Skern-Mauritzen[2]*, Dorothy Dankel[2], Katja Enberg[2], Olav S. Kjesbu[2], and Richard D. M. Nash[2]

[1]*Independent consultant, Fjellveien 96, N-5019 Bergen, Norway*
[2]*Institute of Marine Research, Box 1870 Nordnes, N-5817 Bergen, Norway*

**Corresponding Author: tel: +47 5523 8608; fax: +47 5523 8687; e-mail: mette.mauritzen@imr.no*

Skagen, D. W., Skern-Mauritzen, M., Dankel, D., Enberg, K., Kjesbu, O. S., and Nash, R. D. M. 2013. A simulation framework for evaluating fisheries management decisions using environmental information. – ICES Journal of Marine Science, 70: 743–754.

Received 30 November 2012; accepted 4 March 2013; advance access publication 7 June 2013.

The population dynamics of marine fish stocks are influenced by both physical and biological conditions. Yet, such environmental impacts on stock dynamics, and hence stock production, are rarely included in applied fisheries management. To test the utility of taking ecosystem information into account in management decisions requires efficient tools. We propose a simulation framework for evaluating fisheries management schemes that use environmental information as part of the decision basis. A key feature is to link environmental signals to parameters in functions that define the population dynamics. This allows a direct incorporation of environmental drivers into models of population dynamic processes and emphasizes the need for a quantitative understanding of the influence of environmental drivers on such processes. The utility of the simulation framework is demonstrated through a worked example with different management scenarios, where decisions to increase or decrease the exploitation rely on environmental indicators only, or also on information on stock abundance. In this example, a management that was based on indicators only, without updated measures of the state of the stock itself, failed to respond adequately to changes in stock productivity.

Keywords: ecosystem-based management, environmental indicators, harvest control rules, link functions, management strategy evaluation, population dynamic models, super-individuals.

Introduction

Marine fish stocks are part of ecosystems, influenced by physical conditions and species interactions (Ottersen and Stenseth, 2001; Pörtner *et al.*, 2008; Kjesbu *et al.*, 2010; Stige *et al.*, 2010). Considering the impact of the environment on fish stock productivity, and thereby fisheries, is one of the main pillars of the Ecosystem-based Approach to Fisheries Management (EAF, Bianchi *et al.*, 2008). EAF is ascribed to, and adopted by, many governments and international organizations and agreements (Bianchi *et al.*, 2008). Yet, information about the environmental state, such as e.g. ocean climate, food availability and predator abundance, is rarely included in fisheries management (e.g. ICES, 2010; Brunel *et al.*, 2010). Furthermore, how to incorporate environmental information in practical management is not straightforward or well documented. One approach can be to include this information in the decision basis of management strategies, where the benefits can be tested by simulation (Basson, 1999; Brunel *et al.*, 2010; A'Mar *et al.*, 2009, 2010). For that purpose, we here demonstrate a simulation framework developed to test the performance of management decision rules that take the influence of environmental drivers on stock dynamics into account (Figure 1).

Management of fish stocks relies on information about the state of the stock and its resilience to exploitation. This information may come from an analytical assessment e.g. Virtual Population Analyses (Shepherd and Pope, 2002) or be based on catch statistics and fishery-independent information, from which the current state of the stock, its historical development and its presumed potential for harvestable surplus production can be inferred (Hilborn and Walters, 1992; Hilborn, 2011). The gain of including environmental information into management decisions depends on the *de facto* strength of environmental effects on population processes, the level of process understanding and stock dynamics, as well as the quality of monitoring/prediction of the environment

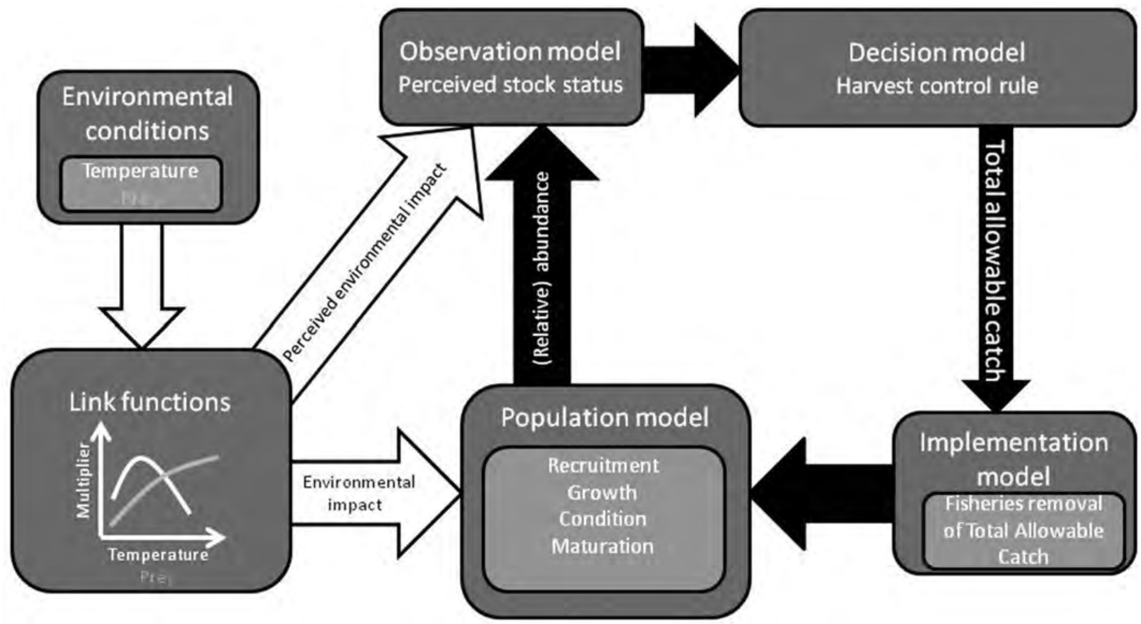

Figure 1. Schematic outline of the simulation tool kit. The boxes are processes; arrows indicate the information flow. Further details are given in the main text.

(Basson, 1999; Walters *et al.*, 2005; Brunel *et al.*, 2010). When an analytical stock assessment is not possible due to restricted data availability, information about the ecosystem may be more rewarding as additional support for managers' decisions than in the case of stocks where analytical assessments are available. For example, reducing an apparently tolerable exploitation may be warranted if there are indications that the external conditions for the stock are deteriorating (Caddy, 2002; Potts *et al.*, 2008). In recent decades, pre-agreed rules for tactical decisions on the permitted catches in the immediate future, commonly called harvest control rules (HCRs), have developed as a key element in fisheries management strategies (Froese *et al.*, 2011). Such rules provide a framework for deciding on the level of removals, for example a total allowable catch (TAC), based on information that typically will come from an analytical assessment, if available. Assuming that environmental factors influence population dynamics, HCRs may be developed to take environmental information into account as part of the decision basis, with or without direct measurements or assessment of the state of the stock itself (Brunel *et al.*, 2010).

Here we suggest a methodological framework for exploring the necessary and sufficient conditions for such HCRs to work. Following the common practice in evaluating HCRs (Butterworth and Punt, 1999; ICES, 2005), we developed a simulation tool designed to assess the likely performance of rules that take environmental information into account. In this tool, the model population is sensitive to environmental drivers. In our framework, we assume that the decision-makers are aware of the environmental drivers and try to take such effects into account, although not necessarily in a correct manner. A simplistic application of this principle would be to recognize that the environment defines the carrying capacity of the relevant part of the ecosystem in question, and assume that the system is autonomous within that constraint. Going beyond that by modelling underlying processes, one may assume that dynamic properties of the stock, i.e. individual growth, recruitment, migration and natural mortality are influenced by the environment on both short, medium and long time-scales (e.g. Ottersen and Loeng, 2000; Mikkelsen and Pedersen, 2004; Hjermann *et al.*, 2004; Fauchald *et al.*, 2006; Klyashtorin *et al.*, 2009). These dynamic population processes are commonly described through well-established equations, for example the von Bertalanffy equation for growth of individuals (von Bertalanffy, 1938). In our simulation framework the influence of environmental drivers is expressed through linking the parameters in well-established population dynamic equations to these drivers. Thus, we included the effects of environmental drivers on the fish stock without disrupting the common process-oriented way of programming population dynamics. Short of a better term, we have used the term "link functions" for expressing the effect of environmental drivers on these parameters (this use of the term should not be confused with link functions in statistical models). For example, temperature effect on growth may be expressed by a link function that describes how the *k*-value in the von Bertalanffy growth equation depends on temperature. In this way, environmental drivers are directly linked to dynamic processes in the simulated population (e.g. Fiksen and Slotte, 2002; Mikkelsen and Pedersen, 2004; Folkvord, 2007; Olsen *et al*. 2011).

Here we present the simulation framework, and demonstrate its application in three management scenarios for a generalized gadoid-like stock where the population dynamics are impacted by environmental drivers (e.g. temperature, prey availability). In these scenarios, management decisions are based on environmental indices only (*Scenario 1*), on environmental and relative stock abundance indices (*Scenario 2*), and finally on an analytical stock assessment (*Scenario 3*). The management performance in each scenario is evaluated by assessing model results for fishing mortality, fisheries catches, spawning stock biomass (SSB) and risk of stock extinction.

Material and methods

Simulation framework

The overall design of the simulation framework, as outlined in Figure 1, generally follows the commonly used template (Basson, 1999; Butterworth and Punt, 1999; Sainsbury *et al.*, 2000; ICES, 2005): A perceived "real world" is created with a stock represented by a forward-projecting population model, in which a fish is born, grows, matures and dies over time. The dynamics of the population are fully described by these processes. They can be represented by well-established parametric standard functions, and we relate the parameters of these functions to environmental drivers through link functions. Decisions on the size of catches are made in a "manager's world". Managers will have information about the environmental drivers and their effects, but only with error (observation model, Figure 1). They may also have information about the state of the stock through some procedures (e.g. stock assessment, survey indices), but again with error. Based on this information, a TAC is decided through a decision rule, representing the HCR to be explored (decision model, Figure 1). An implementation model converts the decided TAC to actual removals from the real stock, assuming that the TAC is taken as decided.

Population model

The population model (Figure 1) projects a population forwards in time, with predefined dynamic elements (recruitment, growth, maturation and mortality) including random terms that are selected to cover a plausible range of realistic representations of the modelled stock. Because we want to cover mechanisms and use information related to length rather than age, we used a population model that was structured by both age and length.

Our population model was designed as a collection of super-individuals, along the lines of individual-based models (IBMs) (e.g. Scheffer *et al.*, 1995). Each super-individual represents a number of fish. This number declines with time due to mortality. The dynamic properties of these super-individuals were expressed through parametric functions, as further described in Table 1. A fixed number of new super-individuals were created annually at recruitment. The number of recruited fish was determined from a parametric stock-recruit function with random terms, and was equally distributed on the new super-individuals. When created, each super-individual was given individual standard values for the parameters in its biological dynamic properties functions (as described in *Recruitment*), drawn according to a specified distribution (lognormal as a standard used in our worked example) with input expectation value and dispersion parameter. We then applied the link functions to convert these standard values into actual parameter values that were explicitly affected by environmental conditions.

The stock was projected forwards in time in seasonal (quarterly) time-steps. To simplify the model we let, in each time-step, the super-individuals first grow and mature and then die according to their length and condition. Since growth only took place between time-steps, the duration of the time-steps had to be small compared to the growth rate. Spawning took place in one defined season, and recruitment in another.

Table 1. Overview of biological dynamic parameters in the population model.

	Function	Parameters	Input values and CV for the worked example
Recruitment	Beverton-Holt	*a*	1000, 0.5
		b	500, 0.0
Length growth	von Bertalanffy	*Linf*	100, 0.1
		k	0.2, 0.2
Individual weight	Fulton	*Condition*	0.000 008, 0.1
		Power	3, 0.0
Maturity	Logistic	*L50*	50, 0.1
		Slope	0.03, 0.0
Natural mortality	Fixed	Value	0.2, 0.1
Selection in fishery	Logistic	*L50*	40, 0.0
		Slope	0.04, 0.05

Except for recruitment, specific values are drawn for each super-individual.

Biological dynamic properties

The model works at two levels: as a collection of super-individuals, and as the internal characteristics of each super-individual. Each super-individual has a set of parameters for its biological dynamic properties, which is updated in each time-step within the population model. Table 1 summarizes the functions and parameters used in the present implementation, including the values that have been applied in the worked example. Each model property is described in detail below.

Recruitment

In our framework, a number of super-individuals enter the population each year in the recruiting season. The total number of recruits, as determined by the recruitment function, was shared evenly between the super-individuals. The stock recruitment function consisted of a deterministic part and a random multiplier. The deterministic stock recruitment functions used standard functions to derive the expected total recruitment as a function of a variable *S*, which could for example be SSB. The framework included several stock recruitment functions. In the worked example the Beverton-Holt function was used:

$$R0 = a^{*}S/(S+b). \tag{1}$$

The stock recruitment function has two parameters *a* and *b*, where *a* is a scaling parameter while *b* is related to the shape of the function. Stochasticity in recruitment was introduced by a random multiplier $\xi(y)$ applied to the total yearly recruitment drawn as a log normally distributed random number with parameters that were input, i.e. $R(y) = R0(S(y))^{*}\,\xi(y)$

Growth

In each time-step *t*, each super-individual *i* grows in length *L* according to the von Bertalanffy growth equation (von Bertalanffy, 1938.) with the parameters *Linf* and *k* which are current for the time-step:

$$L(i, t+1) = L(i, t) + (Linf\,(i, t) - L(i, t))^{*}(1 - \exp(-k(i, t))). \tag{2}$$

The corresponding weight at length is given as

$$W(i, t) = Condition(i, t)^{*}L(i, t)^{3} \tag{3}$$

Maturation

A super-individual can be either sexually immature or mature. The fraction mature at length in the whole population was assumed to follow a logistic function. When projecting the stock forwards, the probability that a still immature super-individual would become mature in the next time-step was derived as:

$$Prob\{Mature\,at\,L \mid Immature\,at\,(L-\Delta L)\} = (Logist(L) - Logist(L-\Delta L))/(1 - Logist(L-\Delta L)), \quad (4)$$

where ΔL was the growth in the time-step and *Logist(L)* the logistic function of length of the form (6) below. Deciding whether the super-individual matured or not was undertaken randomly in each time-step, with the above probability as its success rate.

Mortality

Within each super-individual, the number of fish was reduced by mortality, which is a sum of natural mortality M and fishing mortality F. Mortalities were expressed on a yearly time-scale. Accordingly, the number N of fish represented by a super-individual i was reduced in a time-step of duration Δt as:

$$N(i, t+\Delta t) = N(i,t) * \exp(-(F(i,t) + M(i,t)) * \Delta t) \quad (5)$$

The natural mortality M should be dependent on fluctuating external drives. However, in the worked example, this was not done for simplicity.

The fishing mortality F is a product of a year/season factor and a selection at length. The year factor Fy was set for each year according to the decided and implemented TAC, and was common to all super-individuals. The selection $(S(L))$ was represented by a logistic function with the general form:

$$Logist(L) = 1/\{(1 + \exp[-4 * slope * (L - L50)]\} \quad (6)$$

with two parameters, $L50$ and *slope,* specific to each super-individual. Hence, $F(i,t,L) = Fy(t)*Logist(i,L)$.

Catches in numbers in a time-step from t to $t+\Delta t$ were derived for each super-individual by the standard Baranov's catch equation (Baranov, 1918), according to the current length L of the super-individual:

$$C(i,t) = N(i,t) * F(i.t, L) * (1 - \exp(-(F(i.t, L)) + M(i)) * \Delta t)/(F(i.t, L)) + M(i)) \quad (7)$$

The corresponding catch in weight was the product of the catch in number and weight-at-length of the super-individual, and the total catch in a time-step was the sum of the catches from all super-individuals.

Link functions

The link functions (Figure 1) describe the relation between environmental drivers and parameters of the biological dynamic property functions of the population. The link functions are in themselves parametric functions of one or more environmental variables. We use the term "link parameters" for the parameters in the link functions. For our purpose, we found it convenient to establish a few building blocks with properties that can be relevant, and to write the link functions by combining such blocks.

Scaled logistic function

The logistic function (6) is used to simulate cases where one may assume an effect that increases with the value of some explanatory variable within some range, but with asymptotic values outside that range. To extend the value space to the range (p_{low}, p_{high}) we used the form:

$$Scalelog(x) = p_{low} + (p_{high} - p_{low})/(1 + \exp(-4^* slope^*(x - x50))). \quad (8)$$

where the link parameters are: p_{low}, p_{high}, and *slope,* and $x50$ and x can be an environmental variable or a population state value. The function can be used for maturity, selection etc., but can also be used to model the effect of an environmental variable on a population property parameter. For example, it can be used as a step function by setting a high slope. It may also be relevant where an effect actually has been demonstrated with a linear model, e.g. by linear regression, but within a quite narrow dynamic range.

An asymmetric bell

In some situations there may be an optimum value of the environmental driver, for example an optimal temperature for the recruitment in a stock. This is represented by an asymmetric bell-shaped function:

$$Abell(x) = y0^* \exp\{-(abs(x - x0)/shape)^{\rho})\}; \quad (9)$$

where the parameter *shape* can have separate values *shape1* and *shape2* for $x > x0$ and $x < x0$. The link parameters are *y0, x0, shape1, shape2, and* ρ, and x represents some environmental variable. An example is shown in Figure 2a, with $y0 = 1$, $x0 = 0$, $shape1 = 7$ for $x < x0$, $shape2 = 5$ for $x > x0$, and $\rho = 3$.

The use of link functions

To illustrate how link functions may be constructed, we have provided some examples. One example related to recruitment is outlined above. For *growth, condition, weight* and *maturity* we used a more elaborate relation that assumed impact by two environmental variables, e.g. temperature (T) and food availability (P). It is derived in multiple steps:

Step 1. Let k in the growth function be dependent on T and on P as a product of a logistic function and an asymmetric bell function:

$$k = kmax^* Abell(T; T0(L), a, \rho)^* Logistic(P; P50, slope) \quad (10)$$

where *kmax* is the k-value at $T = T0$ and P large. We assume that $T0$ is different for small and large fish, and that the a-parameter may be different for $T > T0$ and $T < T0$. An example of this combined asymmetric bell and logistic function is shown in Figure 2b.

Step 2. Let the condition factor *Cond* be dependent on temperature and prey availability, with similar functions as for k, but with different parameter values.

Step 3. Weight per individual is $Cond*L^p$ where p is a fixed parameter, normally near 3.

Step 4. Let maturation be dependent on condition as a step function; below a certain condition level, no further maturation takes place. Above that level, the probability of getting mature is

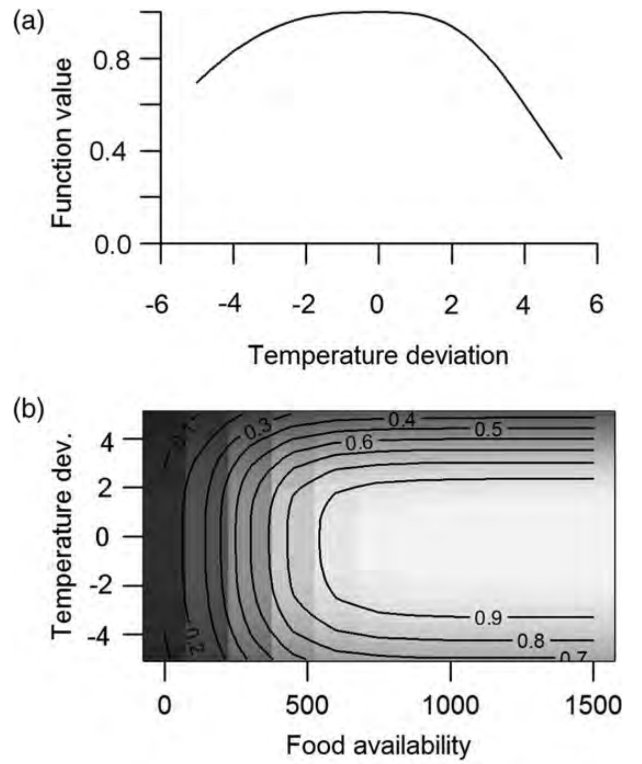

Figure 2. Examples of output from link functions. (a) An example of the asymmetric bell link function (equation 10 in text), with deviation of a temperature indicator from a normal value along the *x*-axis. (b) A link function made by multiplying an asymmetric bell function of temperature deviation from a normal value with a logistic function of an environment indicator, which may represent the food availability (equation 11 in the text). The function is used to model the growth rate *k*, relative to a standard value, in the worked example. The grey shadings and isoclines indicate the relative *k*-values.

derived according to the logistic maturity function (8):

$$Prob\{Mat(t)\,|\,Immat(t-1)\} = (logist(L) - Fract_{mat}(t-1))/(1 - Fract_{mat}(t-1)) \quad (11)$$

if $Cond > Cond\ crit$
$= 0$ if $Cond < Cond\ crit$
In practice, the zero probability can be incorporated by letting the slope in the logistic function equal 0, which would make the probability of maturing zero. This link function is used in the worked example below.

Initializing the population model

To initialize the population model, the model was "primed" by running it for a number of years equal to the maximum number of ages (10) in the model. That generated all the year classes present in the initial year. This was done with random recruitments derived assuming that *R0* equals the *a*-parameter rather than being dependent on the stock biomass. Admittedly, this can imply a higher recruitment in the priming phase than later on, depending on the stock-recruit function. A constant fishing mortality was applied and all other parameters were drawn as described above, but without applying link functions. Thus, the initial population was at stochastic equilibrium without modifications by the environment, and with a fixed exploitation. Link functions to be applied after the priming phase typically have a maximum of 1.0, which implies that the initial input parameters may represent a situation where the environment is absolutely optimal. Therefore, a fixed "environmental multiplier" can be applied to the relevant parameters, to get parameters in the priming phase calibrated to a realistic future level.

Table 2. Example of classification of indicators for management decisions, according to values in the observation model (i.e. expected values given environmental conditions) relative to their reference values.

	Poor	Fair	Good
Recruitment, *a*-parameter	<0.7	0.8 – 1.2	>1.2
k-value	<0.8	0.8 – 1.2	>1.2
Condition	<0.7	0.8 – 1.3	>1.3
Mean length	<0.9	0.8 – 1.1	>1.1
TSB	<0.5	0.5 – 2.0	>2.0

Observation model

We here use the term observation model to describe the collection of models that translate the population model variables and the environmental drivers to the information that is the basis for managers' decisions. Hence, the observation model provides a distorted perception of the stock status, and a distorted perception of the effect of the environmental drivers.

The outcome of the observation model was in terms of categorical indices. An example of the classification (used in the worked example) is given in Table 2. Note that "good" mean length means high mean length, which can reflect contrasting situations, such as good growth conditions, poor incoming year classes in the recent past, or low mortality over a long period letting old and big individuals accumulate in the population. The vector of these classification results is the input to the HCR.

The distorted perception of reality was introduced at the classifying stage, by basing the classification on true values multiplied with a random noise factor. The true values were extracted from the population model or from the outcome of the link functions applied to true values for environmental drivers. This design was made to facilitate scaling of the uncertainty in the information that goes into the decision process.

The assumption that the drivers and links are perfectly known to managers can hardly be met in reality. However, the purpose was to mimic a situation where admitting uncertainties leads to a management based on semi-quantitative "indicators". This may be regarded as a simple and pragmatic way of programming an erroneous decision basis in a controlled way.

Decision model

The decision model derives a TAC according to a HCR. For the scenarios in the worked example, only a limited set of rules was constructed. Each of these rules had a set of criteria relating to the categorical evaluations of the indices described above. If all criteria in a set were met, the TAC was changed by a fixed percentage, associated with each set. If not, the current TAC was maintained. The criteria used in the worked example below are presented in Table 3. The rule prescribed percentage changes in TACs. If the previous TAC is zero, it would be impossible to reopen the fishery once it had been closed. The following rule for re-opening

Table 3. Decision rules used in the worked example.

	Increase TAC	Decrease TAC
Recruitment	Fair or good	Poor
k-value	Fair or good	Poor or fair
Condition	Fair or good	Poor or fair
Mean length	Low or fair	Fair or high
TSB	1: Ignored	1: Ignored
	2. Good	2: Poor

If the set of indicators does not fit all entries in any of the criteria sets, the TAC remains unchanged. The criteria for TSB refer to *Scenarios 1* and 2 (please refer to text for further details on the scenarios).

the fishery was therefore defined: if the advice was to increase the TAC and the current TAC is zero, the next TAC would be 10% of the TAC in the first simulation year.

Implementation model

The implementation model translates the TAC decision into actual removals from the stock. The annual TAC was evenly split over the seasons to give four TACs per year, and in the worked example it was assumed that these were taken as exactly the decided amount. A simple forward projection was made with the true stock numbers, and for each season a search was made to find the overall seasonal *F*-factor that gave a total catch as prescribed. The selections and weights for each super-individual were those in the population model, and the individual seasonal *F*s for each super-individual became the individual selection multiplied by the overall *F*-factor. We included rules in the simulations to handle situations if there was not sufficient fish in the stock to take the decided TAC. The primary purpose of these rules was to avoid simulation crashes if the decided TAC exceeds the model stock abundance. The rules are admittedly arbitrary, but may represent a quite likely response to a crisis with a depleted stock. Before searching for an *F* giving the agreed seasonal TAC, the yield was calculated corresponding to a very high *F* (2.0). If this "ceiling TAC" was smaller than the decided seasonal TAC, the TAC for that season and for the remaining seasons that year was set to zero. The TAC for the whole year, which may be needed for reference in the decision model, was set as the sum of the seasonal TACs in the previous seasons that year. The fishery was closed when stock abundance was less than TAC. If this occurred in the first season of the year, the resulting yearly TAC was zero.

Results

A worked example

To illustrate the simulation framework, we provide a worked example. This encompasses a fictitious stock, assuming some environmental influence and a decision rule based on categorical indices representing imperfect knowledge of the environmental influence. We make a brief comparison of the performance of a rule when only environmental information is available, and when that can be supplemented with a semi-quantitative knowledge of the stock abundance. We also compare the result with a management where the stock abundance is known (with some error) and the core of the harvest rule is to apply a fixed harvest rate.

The stock in this example is a gadoid-like stock with medium lifespan. The main parameters determining the stock biology are tabulated in Table 1. The recruitment was according to a Beverton-Holt model with $a = 1000$, $b = 500$, and a lognormal stochastic term with $sigma = 0.5$. Yield and SSB per recruit are shown in Figure 3. The maximum long-term yield (taking the stock recruitment relation into account) was at a harvest rate of 15%, corresponding to an $F = F_{max}$ at approximately 0.175.

We express the environmental conditions as three time-series, one influencing recruitment and two influencing growth (Figure 4). We characterized the environmental conditions as to represent a challenge to managers, starting with good conditions followed by poorer conditions leading to strongly declining growth and recruitment during most of the period, but with some improvement towards the end (Figure 5). The link functions applied were those presented above. All examples were run for 20 years after priming at a fishing mortality of 0.175 (F_{max}), and with 50 super-individuals per year class. Each run is the result of 100 replicas.

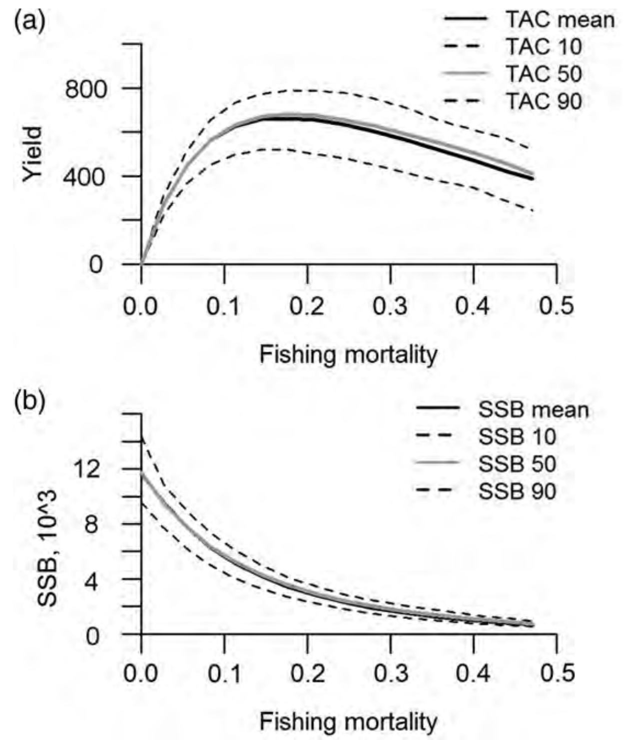

Figure 3. Characteristics of the model population in the worked example. (a) Total allowable catch (TAC), and (b) spawning stock biomass (SSB), as functions of mean fishing mortality after 20 years simulation with constant environmental influence (mean and 10, 50 and 90 percentiles).

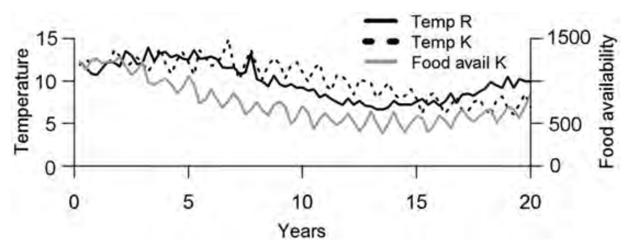

Figure 4. Time-course of environmental variables in the worked example. The variables include temperature associated with recruitment (*Temp R*), temperature (*Temp K*), and food availability associated with growth.

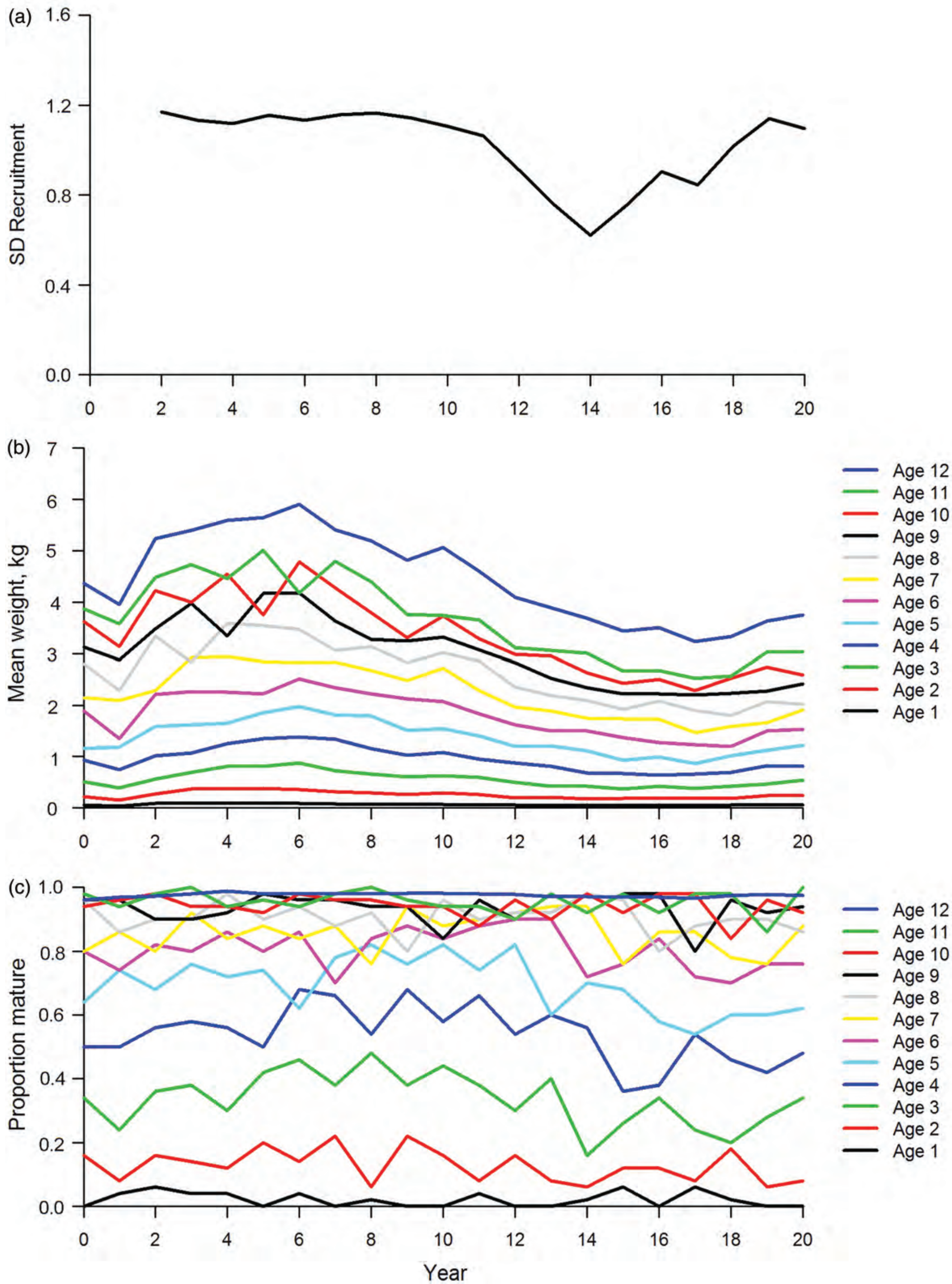

Figure 5. Time-course of stock development and responses to environmental drivers in the worked example. Time-course of (a) mean modelled *a*-parameter in the Beverton-Holt function for recruitment, (b) mean weight at age, and (c) mean proportion mature at age.

Management decision scenarios

We present three scenarios to illustrate the use of the simulation framework and the utility of environmental indicators as the decision basis in this kind of framework. The rules for the different scenarios are presented in Table 3. *Scenario 1*: The rules for the first scenario were made mainly through "common sense"—increase the TAC if the outlook is good and there are no indications that the stock is in trouble, and decrease it if there are indications that the stock may be in trouble and the outlook does not look favorable. The basis for decisions were the semi-quantitative indicators described above, but indicators relating to the stock biomass were ignored. *Scenario 2*: In this scenario the state of the stock is better known, represented by an uncertain measure of the total stock biomass (TSB). The criteria are as in *Scenario 1*, but in addition, a perceived low TSB is required to decrease the TAC and a high perceived TSB is required to increase the TAC. Although the classification here is based on the absolute values of TSB (with error), it may to some extent illustrate the situation where there is some relative measure of the biomass, for example a time-series of CPUE. *Scenario 3*: As a third example we include a simple constant harvest rate rule, where TAC is decided directly as a fraction of an uncertain estimate of TSB. The harvest rate was 0.20, corresponding approximately to $F = 0.25$, and maintained as long as TSB was above the value of 1000 (arbitrary units). Below that, the harvest rate was reduced linearly towards the origin.

In *Scenarios 1* and *2* the initial TAC was the catch at the end of the priming period, which should represent equilibrium at a constant fishing mortality of 0.175. The TAC increase was standardized at 20% and the decrease at 30%. The decisions to increase or decrease the TAC were taken on a year-to-year basis according to the situation in the current year, without considering trends or previous changes.

Scenario outcomes

Summaries of the simulation results are presented in Figure 6. We describe "risk" as the cumulated probability that either the agreed TAC could not be taken or that the SSB was below a low value, indicating stock depletion. This value was set arbitrarily at 400, corresponding to about 3% of the unexploited SSB.

In all scenarios, the stock development reflected trends in the environmental drivers (cf. Figures 4 and 5). Furthermore, the catches generally increased when the SSB stock increased, and decreased when SSB decreased. Relying on only the environmental indicators and the mean length in the catches (*Scenario 1*) allowed for an increase in the catches in the early phase, which sometimes was too strong, but triggered no reduction in the catches sufficiently early to preclude a strong decline in SSB as environmental conditions got worse. With this regime, the cumulated probability of depleting the stock by the end of the simulation period became near 100%, and the fishery was fully or almost stopped in most cases. Including the TSB as an index (*Scenario 2*) improved the performance, as it did not allow for a too strong increase in the catches in the first period. However, during stock decline the fishing mortality and catches were not reduced rapidly enough to prevent stock depletion in a substantial number of cases. With the constant harvest rate (*Scenario 3*) the catches followed the stock abundance quite well, with a relatively stable fishing mortality and no risk of depleting the stock.

Discussion

A simulation model framework for testing the inclusion of environmental information in fisheries management decisions is demonstrated. More specifically, the impact of the environment on the modelled population is studied through functions termed "link functions". The link functions modify the parameters of standard population dynamic functions, for example the growth rate in the von Bertalanffy growth equation (Von Bertalanffy, 1938), or parameters in stock-recruitment functions.

In our framework we used a simple operating model, along the lines advised by Sainsbury *et al.* (2000) and A'Mar *et al.* (2010). We incorporated the effect of environmental drivers by letting them impact multiple dynamic population processes of the fish stock. One challenge in the field of fisheries management is good communication between scientists working in fishery oceanography and in stock assessment and management advice (Ulltang, 2003; Huse *et al.*, 2007). Programming such a framework was a useful and challenging exercise in bridging gaps between branches of science, because it required very specific and detailed formulations of relations and structures, and ambiguities were effectively revealed. Our solution was to establish functional relationships between environmental drivers and parameters in functions describing population dynamics, in terms of the link functions. That made it necessary to develop very precise formulations on how environmental drivers act on population processes. Whereas the scientific literature on environmental impact on dynamic fish population processes is rich and served as input in constructing the link functions (e.g. Ottersen *et al.*, 2001; Fiksen and Slotte, 2002; Hjermann *et al.*, 2004, 2007; Pörtner *et al.*, 2008), the *right* functional forms are rarely identified (e.g. de Oliveira and Butterworth, 2005; Kell *et al.*, 2005). For instance, environmental impacts on fish stocks are often identified as correlations, without clear identification of the underlying processes. The mechanisms are not sufficiently known to claim that the population model in our framework represents reality, but we constructed the environmental effects on the population to represent plausible scenarios. More conceptually, our approach allowed a structured modelling of the environmental impact on the population, where each step can be justified in a logical way as an identifiable process.

To mimic the current level of knowledge available to management, decision makers should have some knowledge of the environmental drivers and an understanding, albeit incomplete and sometimes erroneous, of their effect. Hence, two sets of links between environmental drivers and stock dynamics were included: one for nature, i.e. the population model, and one for managers, i.e. the observation model. The observation model thus has to cover both how well the environmental status is known and how well the effects of environmental influence are understood by managers and their advisors. It would be misleading to restrict the study to the case where the link functions are perfectly understood by managers. Rather, an important aspect should be to explore how far from reality the understanding of environmental effects by managers can be before management fails. Thus, we ran into the paradox that both the operating model representing the "real" world and the observation model for managers' decisions should be based on best knowledge, and still be different. The pragmatic solution here was to introduce errors in the classification step where categorical indices were generated by introducing errors to the true basis for classification.

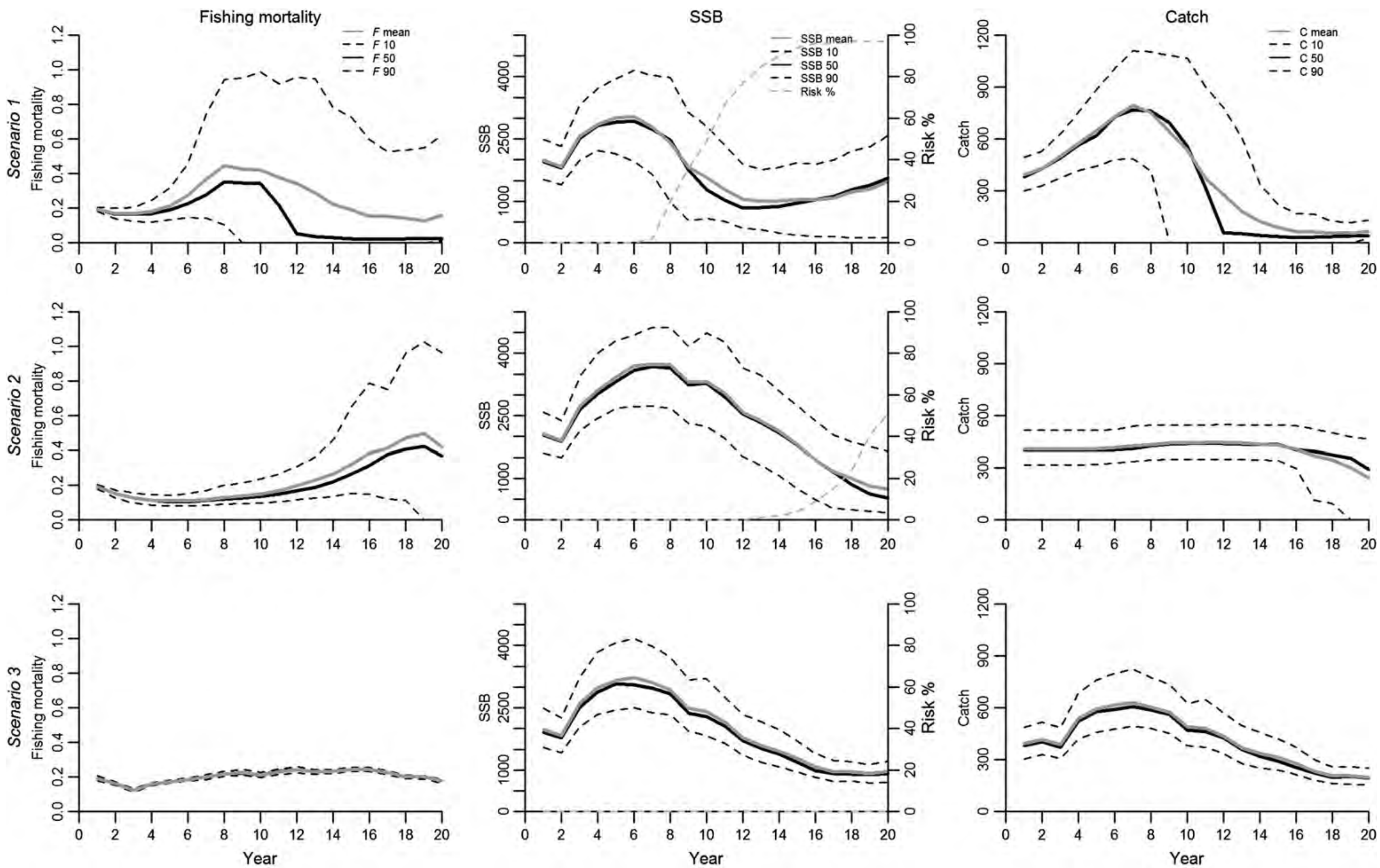

Figure 6. Summary of simulation output of three management regime scenarios for 20 years. Each panel shows the mean and 10, 50 and 90 percentiles by year. Left column: fishing mortality; centre column: spawning stock biomass (SSB) and cumulated risk of stock depletion; right column: catch. Upper row: management regime based on environmental indicators only (*Scenario 1*). Centre row: management regime based on environmental indicators and total stock biomass indicators (*Scenario 2*). Lower row: management regime based on estimated stock abundance and fixed harvest rate (*Scenario 3*). Please refer to text for further definition of decision rules (Table 3) and of risk.

Since we wanted to simulate external influences on not only population abundance, but also on properties such as fish length and maturity at age, a population model that was both age- and length-structured was required. There are several ways of doing that (e.g. Methot, 2000; Frøysa *et al.*, 2001). Our choice was to use IBMs to construct the population as a collection of super-individuals. This was partly motivated by previous experience with such models (Hinrichsen *et al.*, 2011; Hjøllo *et al.*, 2012; Utne *et al.*, 2012). Basic values for all model parameters are primarily given as input, and characterize the kind of population we wanted to simulate. For the population model, each super-individual obtains its own set of basic parameters, by applying random multipliers to the original basic values. Each year, applying the link functions to environmental influence leads to multipliers for the individual basic values that produce the parameter values that are used in the operating model.

There are some advantages with this construction. Giving each super-individual its own growth parameters, allows a realistically broad distribution of lengths at older ages, rather than congestion towards L_{inf}. It also makes some future extensions easier, in particular bringing in the spatial dimension to the simulations. The spatial properties of fish stock distributions, and dynamic spatial responses to environmental variability through e.g. climate changes, influence both the environmental and fisheries impact on stock development (Link *et al.*, 2011; Ciannelli *et al.*, in press). Hence, spatial properties and responses by fish stocks should be included in a Management Strategy Evaluation (MSE) framework (Link *et al.*, 2011; Ciannelli *et al.*, in press). Within the IBM approach it is straightforward to e.g. include migrations and to take the spatial distribution of environmental drivers into account (Hinrichsen *et al.*, 2011; Utne *et al.*, 2012). Likewise, spatial overlap between interacting stocks can be directly modelled (Utne *et al.*, 2012). The most commonly applied alternative, to use state space models of the Markov chain type with transition matrices and functions that are sensitive to environmental drivers, has the disadvantage of lacking memory. Both constructions can become demanding with respect to computing power.

In simple simulation models without environmental influences, the basis for decisions, i.e. the observation model, typically estimates stock abundance through an analytical assessment with noisy input data from the population model, or a proxy of a full assessment (Butterworth and Punt, 1999; Sainsbury *et al.*, 2000). Possible environmental influence is incorporated in the population model as stochastic terms (Butterworth and Punt, 1999; Sainsbury *et al.*, 2000). When the basis for management decisions is restricted to an analytical assessment, our approach only differs from the standard framework in that here the population model is explicitly sensitive to environmental drivers. An additional element could be included if the error in deriving input for the assessment (e.g. variations in survey catchability) is influenced by environmental factors (Stoner, 2004). This aspect is not considered here.

We have presented a worked example where the observation model, as well as the HCRs, was made to simulate so-called indicator-based management (Caddy, 2002; Potts *et al.*, 2008; Butterworth *et al.*, 2010; Dichmont and Brown, 2010). Rather than requiring a fully quantitative decision basis and abandoning information that cannot be expressed in a quantitative manner, we sought to utilize all relevant information, even if it is only qualitative (Caddy, 2002; Potts *et al.*, 2008). The present criteria for classification into “poor”, “fair” or “good” (Table 2) were based on how the perceived values of some population properties compare with “standard” values, for pragmatic, programming reasons. Such standard values may not be known in a real setting, although it is likely that there will be some experience that can be used as guidance (e.g. Potts *et al.*, 2008; Butterworth *et al.*, 2010). Such classification schemes should be associated with a relevant precision level of the management regime. An indicator–based management of stocks where there is insufficient information to undertake an analytical assessment may not support smaller, annual quota adjustments, but rather a management regime where quotas remain stable unless indications of altered stock productivity suggest a stepwise reduction or increase in quotas (Caddy, 2002; Potts *et al.*, 2008).

The worked example was included to illustrate how this simulation framework could be designed for practical situations. It was not intended as a demonstration of how to undertake indicator-based management. The decision criteria were derived through trial and error, where the key problem was to strike the balance between incentives to increase and decrease the TAC. In our example the use of environmental information, combined with knowledge on how the environment impacts the stock, did not compensate for the lack of abundance estimates. However, to conclude on the usefulness of including environmental variation and impact in fish stock models, would require extensive studies of opportunities and limitations. The scope of the present work was rather to present a modelling approach that can be used in such studies.

A number of simulation studies have explored the feasibility of incorporating environmental factors in management evaluation procedures. In such studies, the operating models range from simple single-species models with simple environmental parameters impacting on one or a few dynamic population processes (e.g. Basson, 1999; A’Mar *et al.*, 2009, 2010; Brunel *et al.*, 2010; Hurtado-Ferro *et al.*, 2010), to more complex coupled biophysical models (Hinrichsen *et al.*, 2011; Hollowed *et al.*, 2011), multispecies models with dynamic species interactions (Howell and Bogstad, 2010) and comprehensive end-to-end ecosystem models (Fulton *et al.*, 2007; Smith *et al.*, 2007). Collectively, these studies, including the present study, demonstrate that the usefulness of including environmental drivers in fisheries assessment and management depends on a variety of factors, including the strength of environmental impact, the level of process understanding, the life history of the stock, the trends in environmental change, and the responsiveness of the management system.

In summary, we have designed and demonstrated a simulation framework for evaluating fisheries management schemes that uses environmental information as part of the decision basis. A key feature is to link environmental signals to parameters in functions that define population dynamics, like growth functions and stock-recruitment functions. We also provide a worked example that shows some weaknesses in a management that is based solely on environmental indicators as the decision base, to increase and decrease the exploitation, without responding to updated measures of the state of the stock itself. In that sense, this study is a demonstration of the utility of evaluating a harvest rule by simulations and of the utility of the present framework for such studies.

Funding

The authors acknowledge financial support from the Norwegian Research Council through the EcoFish (Grant 17356/i30) and ADMAR (Grant 200497/130) research projects.

References

A'Mar, Z. T., Punt, A. E., and Dorn, M. W. 2009. The evaluation of two management strategies for the Gulf of Alaska walleye pollock fishery under climate change. ICES Journal of Marine Science, 66: 1614–1632.

A'Mar, Z. T., Punt, A. E., and Dorn, M. W. 2010. Incorporating ecosystem forcing through predation into a management strategy evaluation for the Gulf of Alaska walleye pollock (*Theragra chalcogramma*) fishery. Fisheries Research, 102: 98–114.

Baranov, F. I. 1918. On the question of the biological basis of fisheries. Nauchnyi Issledovatelski Ikhtiologicheski Institut Izvestia, 1: 81–128. *In Russian.*

Basson, M. 1999. The importance of environmental factors in the design of management procedures. ICES Journal of Marine Science, 56: 933–942.

Bianchi, G., Sandberg, P., Skjoldal, H. R., and Thórarinsson, K. 2008. The Bergen conference on implementing the ecosystem approach to fisheries (Bergen, Norway, 26-28 September 2006): Summary and main conclusions. *In* The Ecosystem Approach to Fisheries, pp. 1–19. Ed. by G. Bianchi, and H. R. Skjoldal. Food and Agriculture Organization of the United Nations. 363 pp.

Brunel, T., Piet, G. J., van Hal, R., and Rockmann, C. 2010. Performance of harvest control rules in a variable environment. ICES Journal of Marine Science, 67: 1051–1062.

Butterworth, D. S., Johnston, S. J., and Brandao, A. 2010. Pretesting the likely efficacy of suggested management approaches to data-poor fisheries. Marine and Coastal Fisheries, 2: 131–145.

Butterworth, D. S., and Punt, A. E. 1999. Experiences in the evaluation and implementation of management procedures. ICES Journal of Marine Science, 56: 985–998.

Caddy, J. F. 2002. Limit reference points, traffic lights, and holistic approaches to fisheries management with minimal stock assessment input. Fisheries Research, 56: 133–137.

Ciannelli, L., Fisher, J. A. D., Skern-Mauritzen, M., Hunsicker, M., Hidalgo, M., Frank, K., and Bailey, K. M. in press. Theory, consequences and evidence of eroding population spatial structure in harvested marine fishes. Marine Ecology Progress Series, doi: 10.3354/meps10067.

De Oliveira, J. A. A., and Butterworth, D. S. 2005. Limits to the use of environmental indices to reduce risk and/or increase yield in the South African anchovy fishery. African Journal of Marine Science, 27: 191–203.

Dichmont, C. M., and Brown, I. W. 2010. A case study in successful management of a data-poor fishery using simple decision rules: the Queensland spanner crab fishery. Marine and Coastal Fisheries, 2: 1–13.

Fauchald, P., Mauritzen, M., and Gjøsæter, H. 2006. Density-dependent migratory waves in the marine pelagic ecosystem. Ecology, 87: 2915–2924.

Fiksen, O., and Slotte, A. 2002. Stock-environment recruitment models for Norwegian Spring Spawning herring (*Clupea harengus*). Canadian Journal of Fisheries and Aquatic Sciences, 59: 211–217.

Folkvord, A. 2007. Comparison of size-at-age of larval Atlantic cod (*Gadus morhua*) from different populations based on size- and temperature-dependent growth models. Canadian Journal of Fisheries and Aquatic Sciences, 64: 583–585.

Froese, R., Branch, T. A., Proelss, A., Quaas, M., Sainsbury, K., and Zimmermann, C. 2011. Generic harvest control rules for European fisheries. Fish and Fisheries, 12: 340–351.

Frøysa, K. G., Bogstad, B., and Skagen, D. W. 2001. Fleksibest – an age-length structured fish stock assessment tool with application to North-East Arctic cod (*Gadus morhua* L.). Fisheries Research, 55: 87–101.

Fulton, E. A., Smith, A. D. M., and Smith, D. C. 2007. Alternative management strategies for Southeast Australian Commonwealth fisheries. Stage 2: Quantitative Management Strategy Evaluation. CSIRO Marine and Atmospheric Research, Hobart, Tasmania. 405 pp.

Hilborn, R. 2011. Future directions in ecosystem based fisheries management: a personal perspective. Fisheries Research, 108: 235–239.

Hilborn, R., and Walters, C. J. 1992. Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty. Chapman and Hall, New York. 570 pp.

Hinrichsen, H. H., Dickey-Collas, M., Huret, M., Peck, M. A., and Vikebø, F. B. 2011. Evaluating the suitability of coupled biophysical models for fishery management. ICES Journal of Marine Science, 68: 1478–1487.

Hjermann, D. O., Bogstad, B., Eikeset, A. M., Ottersen, G., Gjøsæter, H., and Stenseth, N. C. 2007. Food web dynamics affect Northeast Arctic cod recruitment. Proceedings of the Royal Society of London. Series B, Biological Sciences, 274: 661–669.

Hjermann, D. O., Stenseth, N. C., and Ottersen, G. 2004. Indirect climatic forcing of the Barents Sea capelin: a cohort effect. Marine Ecology Progress Series, 273: 229–238.

Hjøllo, S. S., Huse, G., Skogen, M. D., and Melle, W. 2012. Modeling secondary production in the Norwegian Sea with a fully coupled physical/primary production/individual-based *Calanus finmarchicus* model system. Marine Biology Research, 8: 508–526.

Hollowed, A. B., Aydin, K. Y., Essington, T. E., Ianelli, J. N., Megrey, B. A., Punt, A. E., and Smith, A. D. M. 2011. Experience with quantitative ecosystem assessment tools in the northeast Pacific. Fish and Fisheries, 12: 189–208.

Howell, D., and Bogstad, B. 2010. A combined Gadget/FLR model for management strategy evaluations of the Barents Sea fisheries. ICES Journal of Marine Science, 67: 1998–2004.

Hurtado-Ferro, F., Hiramatsu, K., and Shirakihara, K. 2010. Allowing for environmental effects in a management strategy evaluation for Japanese sardine. ICES Journal of Marine Science, 67: 2012–2017.

Huse, G., Bogstad, B., Hiis, Hauge K., Korsbrekke, K., Loeng, H., Michalsen, K., Skagen, D., *et al.* 2007. Environmental information for stock evaluation and management advice purposes. Fisken og Havet, Report No. 4. 35 pp.

ICES. 2005. Report of the Study Group on Management Strategies (SGMAS), 31 January–3 February 2005, ICES Headquarters. ICES Document CM 2005/ACFM: 09. 157 pp.

ICES. 2010. Report of the ICES Advisory Committee 2010. ICES Advice, 1–11. 1928 pp.

Kell, L. T., Pilling, G. M., and O'Brien, C. A. 2005. Implications of climate change for the management of North Sea cod (*Gadus morhua*). ICES Journal of Marine Science, 62: 1483–1491.

Kjesbu, O. S., Righton, D., Kruger-Johnsen, M., Thorsen, A., Michalsen, K., Fonn, M., and Witthames, P. R. 2010. Thermal dynamics of ovarian maturation in Atlantic cod (*Gadus morhua*). Canadian Journal of Fisheries and Aquatic Sciences, 67: 605–625.

Klyashtorin, L., Borisov, V., and Lyubushin, A. 2009. Cyclic changes of climate and major commercial stocks of the Barents Sea. Marine Biology Research, 5: 4–17.

Link, J. S., Nye, J. A., and Hare, J. A. 2011. Guidelines for incorporating fish distribution shifts into a fisheries management context. Fish and Fisheries, 12: 461–469.

Methot, R. D. 2000. Technical description of the stock synthesis assessment program. U.S. Dept. Commer. NOAA Technical Memorandum NMFS-NWFSC-43. 46 pp.

Mikkelsen, N., and Pedersen, T. 2004. How can the stock recruitment relationship of the Barents Sea capelin (*Mallotus villosus*) be improved by incorporating biotic and abiotic factors? Polar Research, 23: 19–26.

Olsen, E. M., Ottersen, G., Llope, M., Chan, K. S., Beaugrand, G., and Stenseth, N. C. 2011. Spawning stock and recruitment in North Sea cod shaped by food and climate. Proceedings of the Royal Society of London. Series B, Biological Sciences, 278: 504–510.

Ottersen, G., and Loeng, H. 2000. Covariability in early growth and year-class strength of Barents Sea cod, haddock, and herring: the environmental link. ICES Journal of Marine Science, 57: 339–348.

Ottersen, G., Planque, B., Belgrano, A., Post, E., Reid, P. C., and Stenseth, N. C. 2001. Ecological effects of the North Atlantic Oscillation. Oecologia, 128: 1–14.

Ottersen, G., and Stenseth, N. C. 2001. Atlantic climate governs oceanographic and ecological variability in the Barents Sea. Limnology and Oceanography, 46: 1774–1780.

Pörtner, H. O., Bock, C., Knust, R., Lannig, G., Lucassen, M., Mark, F. C., and Sartoris, F. J. 2008. Cod and climate in a latitudinal cline: physiological analyses of climate effects in marine fishes. Climate Research, 37: 253–270.

Potts, W. M., Sauer, W. H. H., Childs, A. R., and Duarte, A. D. C. 2008. Using baseline biological and ecological information to design a Traffic Light Precautionary Management Framework for leerfish *Lichia amia* (Linnaeus 1758) in southern Angola. African Journal of Marine Science, 30: 113–121.

Sainsbury, K. J., Punt, A. E., and Smith, A. D. M. 2000. Design of operational management strategies for achieving fishery ecosystem objectives. ICES Journal of Marine Science, 57: 731–741.

Scheffer, M., Baveco, J. M., Deangelis, D. L., Rose, K. A., and Vannes, E. H. 1995. Super-individuals. A simple solution for modeling large populations on an individual basis. Ecological Modeling, 80: 161–170.

Shepherd, J. G., and Pope, J. G. 2002. Dynamic pool models I: interpreting the past using Virtual Population Analysis. *In* Handbook of Fish Biology and Fisheries, 2, pp. 127–136. Ed. by P. J. B. Hart, and J. D. Reynolds. Blackwell Science, Oxford, UK. 432 pp.

Smith, A. D. M., Fulton, E. J., Hobday, A. J., Smith, D. C., and Shoulder, P. 2007. Scientific tools to support the practical implementation of ecosystem-based fisheries management. ICES Journal of Marine Science, 64: 633–639.

Stige, L. C., Ottersen, G., Dalpadado, P., Chan, K. S., Hjermann, D. O., Lajus, D. L., Yaragina, N. A., and Stenseth, N. C. 2010. Direct and indirect climate forcing in a multi-species marine system. Proceedings of the Royal Society of London. Series B, Biological Sciences, 277: 3411–3420.

Stoner, A. W. 2004. Effects of environmental variables on fish feeding ecology: implications for the performance of baited fishing gear and stock assessment. Journal of Fish Biology, 65: 1445–1471.

Ulltang, Ø. 2003. Fish stock assessment and predictions: integrating relevant knowledge. An overview. Scientia Marina, 67(Suppl. 1): 5–12.

Utne, K. R., Hjøllo, S. S., Huse, G., and Skogen, M. 2012. Estimating the consumption of *Calanus finmarchicus* by planktivorous fish in the Norwegian Sea using a fully coupled 3D model system. Marine Biology Research, 8: 527–547.

Von Bertalanffy, L. 1938. A quantitative theory of organic growth. Human Biology, 10: 181–213.

Walters, C. J., Christensen, V., Martell, S. J., and Kitchell, J. F. 2005. Possible ecosystem impacts of applying MSY policies from single-species assessment. ICES Journal of Marine Science, 62: 558–568.

Handling editor: Jason Link