

# A neural network approach for predicting stock abundance of the Barents Sea capelin

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## SARSIA



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An artificial neural network (ANN) approach for predicting stock abundance of the Barents Sea capelin (*Mallotus villosus*) is presented. The method is based on training an ANN with a genetic algorithm using input data of ecological importance to the capelin stock. Stock abundance for the coming year is estimated using the trained ANN with the current set of ecological data. Time series of data on cod, herring and capelin abundance, and average weight of capelin for the period 1974-1999 are used to train the ANN. The model was tested for its ability to predict capelin abundance in single years, using the remaining time series for training. The resulting predictions correspond well to observations, and the ANN method gives higher predictive ability than a simple fisheries assessment model. The strength of the ANN method is its ability to predict changes in natural mortality and growth. However, the network is unable to predict the population crashes that took place in the mid 1980s and early 1990s without prior training to similar scenarios. This illustrates the importance of having the full range of ecological interactions represented in the training set. Since the method is simple and relies on data collected by most fisheries institutes, it could easily be applied in calculating stock prognoses.

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## INTRODUCTION

The prominent problem in fisheries assessment is to provide prognoses of fish stock development. This problem is commonly attacked using methods such as the virtual population analysis (VPA) or other techniques that apply fish harvest and estimates of natural mortality and growth to project stock development (e.g. Hilborn & Walters 1991). Whereas harvest data are gathered from commercial catches, natural mortality and growth rates are difficult to estimate. Especially this is a problem when changes in the ecosystem occur, which can alter such rates substantially (Hamre 1994). Here the fisheries assessment problem in general and stock prediction problem of the Barents Sea capelin specifically are attacked using artificial neural networks (ANNs, Rummelhart & al. 1986). ANNs apply principles from neurology to find patterns in complex data and have successfully been used for predicting yields of the Japanese sardine population (Komatsu & al. 1994; Aoki & Komatsu 1997) and African lake fisheries (Laë & al. 1999). Currently the total stock abundance of Barents Sea capelin for the coming year is predicted based on information about cod, herring and capelin abundance, and average weight of two-

year old capelin. These input factors (Table 1) are chosen based on their ecological importance (Gjøsæter 1998). The capelin is a small pelagic planktivorous species that can be very abundant in the Barents Sea. It is harvested for caviar and for fishmeal and oil production (Gjøsæter 1998). Capelin overlaps spatially with cod and herring at different stages of its life history (Fig. 1). Whereas cod is an important predator on adult capelin (Mehl 1989), herring prey on juvenile capelin (Huse & Toresen, in press). When abundant in the Barents Sea, herring often causes recruitment failure and eventually population crashes in the capelin stock (Gjøsæter & Bogstad 1998). Since the biomass of capelin in the coming year will depend on the current one, abundance of capelin may be an important input factor in the ANN. The average weight of the two-year old capelin further indicates the current feeding conditions, which may impact on stock development (Gjøsæter & Loeng 1987).

The advantage of using ANNs is that rather than explicitly determining growth and mortality for the coming year, which are difficult to predict, such relationships are established implicitly in the weights of the adapted ANN. Through training, the ANN learns from patterns in growth and mortality using ecological infor-

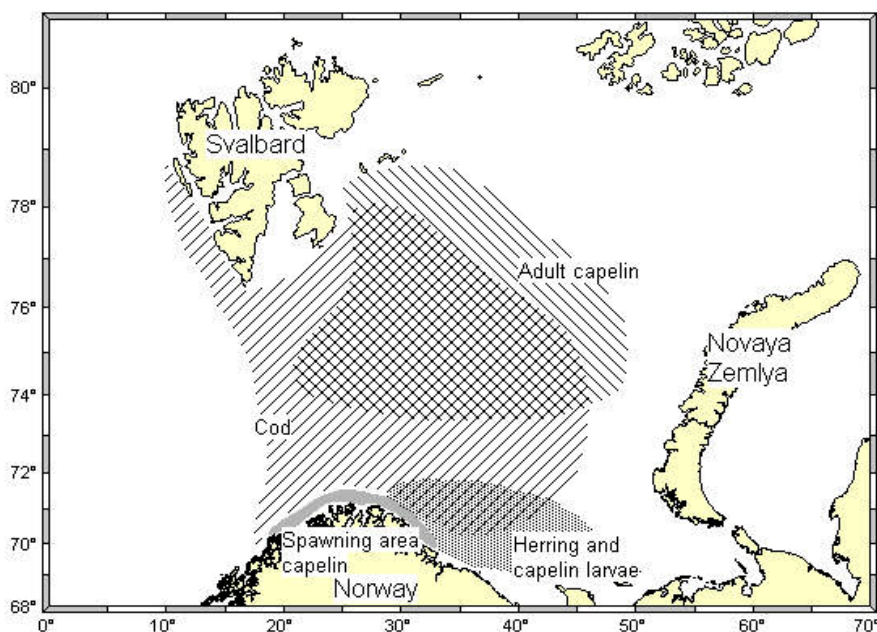


Fig. 1. Map of the Barents Sea with the main features of the distribution of various age groups of capelin as well as cod and herring. Predation by juvenile herring (1-3 years old) on larval capelin seems to have great impact on capelin recruitment at times when herring is abundant in the Barents Sea. Cod predation infers high mortality on the adult capelin, especially during capelin spawning in March.

mation as described above. This knowledge is compiled in the weights and can be used in predictions of future stock development.

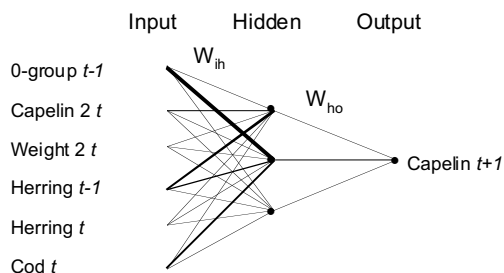


Fig. 2. A schematic drawing of the ANN used in most computer runs. The network is fully connected.  $t$  refers to the year of making the prognosis. The input data are explained in Table 1. The input data are weighted by the connection strength between the input and hidden layers, added together at each hidden node and transformed using Eq 2. The data are then multiplied by the weights of connection between the hidden and output nodes and these sums are added together and transformed at the output node to produce predictions. Differences in thickness of lines illustrate the variation in connection strength between the nodes.

## THE MODEL

ANNs find patterns by differential weighting of input data. The weights of ANNs can be trained using a variety of different techniques, and here the weights are adapted using the genetic algorithm (GA, Holland 1975). The GA applies the Darwinian principle of evolution by natural selection to find good solutions to complex problems, and works by having a population of solutions where each solution is a set of numeric weights in the ANN (Fig. 2). These solutions compete like individuals in a natural population, and the best solutions are continuously reproduced and improved over many generations using the processes of recombination and mutation. A general introduction to GAs is provided by Mitchell (1996), and van Rooij & al. (1995) gives a presentation of how to use the GA to train ANNs.

## NETWORK ARCHITECTURE

The model used here was built by the authors using the programming language FORTRAN 90. For an introduction to ANNs see Anderson (1995), and for ecological and fisheries applications see Saila (1996), Lek & al. (1999) and Huse & Giske (1998). A fully connected feed forward ANN (Rummelhart & al. 1986) was used with input, one hidden and output layers (Fig. 2). Each layer consists of nodes, which are either input data, connec-

tion points where summations and transformations of data occur, or output data (Fig. 2). The input data (Table 1) are standardised between 0 and 1 and multiplied by the weights between the input and hidden layers (Fig. 2):

$$n_h = \sum_{i=1}^m W_{ih} \cdot I_i \quad (1)$$

where  $I_i$  is the input data of input node  $i$  (Table 1),  $W_{ih}$  is the connection weight between input data  $i$  and hidden node  $h$ , and  $n_h$  is the input to hidden node  $h$ . At the hidden node, values ( $n_h$ ) are transformed using the standard sigmoid transformation:

$$T_h = \frac{1}{(1 + e^{-(n_h + b_h)})} \quad (2)$$

where  $T_h$  is the transformed value and  $b_h$  is the bias (van Rooij & al. 1995) of hidden node  $h$ . The same procedure is carried out at the output node. The weights ( $W_{ih}$  and  $W_{ho}$ , Fig. 2) are initiated randomly between  $-1$  and  $1$ , but as a result of the training process, weights may move out of this range. The output is transformed using Eq 2, and scaled within the observed biomass interval. The sum of the absolute discrepancies between predicted ( $P_t$ ) and observed ( $O_t$ , column 4 Table 1) capelin biomass over the time series ( $T$ ) is used as a measure of fitness in the GA and referred to as the error ( $E$ ) here:

$$E = \sum_{t=1}^T |P_t - O_t| \quad (3)$$

This error value is then used in the GA to rank the solutions, and the solutions with the lowest  $E$  are selected to be parents for the next generation. The error term is independent of the number of input parameters.

#### THE GENETIC ALGORITHM

A population of weight sets is initiated randomly at generation number 1. This population then evolves using the GA, to seek the best combination of weights for minimising  $E$  (Eq 3). The parameter values used in the GA are given in Table 2. New weight sets are based on the weights of parents, which are the 40 best solutions in each generation. Recombinations with partners, which are selected randomly among the 80 % best solutions,

Table 1. Input data in the ANN model. The 0-group estimate of capelin (Anon. 1999a) is an index for inter annual comparisons. The capelin abundance data for two-year olds and two-year and older (Capelin 2 and Capelin tot., Anon. 1999b) are in mill. metric tons, and are estimated using acoustics during scientific surveys in September-October. Weight of two-year old capelin (Weight 2, g.) is taken from the same survey (Anon. 1999b). Cod (Anon. 1999b) and herring (Gjøsæter & Bogstad 1998) abundance (mill. metric tons) are estimated using VPA (Anon. 1999b). Herring abundance refers to biomass of 1-3 year olds in the Barents Sea.

	0-group	Capelin tot.		Cod		
Year		Capelin 2		Weight 2		Herring
1974	359	3.10	4.80	5.6	3.10	0.00
1975	320	2.50	7.30	6.8	2.50	0.00
1976	281	2.00	5.80	8.2	2.55	0.00
1977	194	1.50	4.20	8.1	2.15	0.00
1978	40	2.50	4.50	6.7	1.80	0.00
1979	660	2.50	4.10	7.4	1.50	0.00
1980	502	1.90	5.50	9.4	1.20	0.00
1981	570	1.80	3.00	9.4	1.20	0.00
1982	393	1.30	2.50	9.0	1.05	0.00
1983	589	1.90	2.60	9.5	0.80	0.00
1984	320	1.40	2.40	7.4	0.85	0.98
1985	110	0.40	0.70	8.2	0.95	1.84
1986	125	0.04	0.08	11.7	1.15	0.26
1987	55	0.02	0.02	12.3	1.00	0.00
1988	187	0.40	0.40	12.2	0.85	0.00
1989	1300	0.20	0.30	12.4	0.90	0.02
1990	324	2.70	3.20	15.3	0.95	0.05
1991	241	5.00	5.60	8.7	1.50	0.49
1992	26	1.70	3.90	8.6	1.85	1.67
1993	43	0.50	0.80	9.0	2.50	1.52
1994	58	0.00	0.10	11.2	2.30	2.86
1995	43	0.10	0.15	13.8	2.00	0.63
1996	291	0.20	0.26	18.6	1.90	0.10
1997	522	0.50	0.49	11.5	1.60	0.01
1998	428	1.00	1.25	13.4	1.60	0.15
1999	650	1.30	2.12	13.6	1.40	0.33

may occur (Table 2). During recombinations, a random portion (on average 50 %) of the weights is taken from the parent and the rest from its partner. Further weight variability may be introduced through mutations. Mutations are performed node-wise by mutating all weights and the bias associated with a hidden node or the output

Table 2. Parameters used during the selection in the GA.

Feature	Value
Mutation probability per node	0.2
Mutation effect in weights and biases	randomly, max $\pm 1$ change
Recombination probability	0.2
Number of offspring per parent	5
Parent selection	400 best individuals
Partner selection	among 80 % of best individuals
Generations per run	500
Population size	2000
Number of replicate runs	10

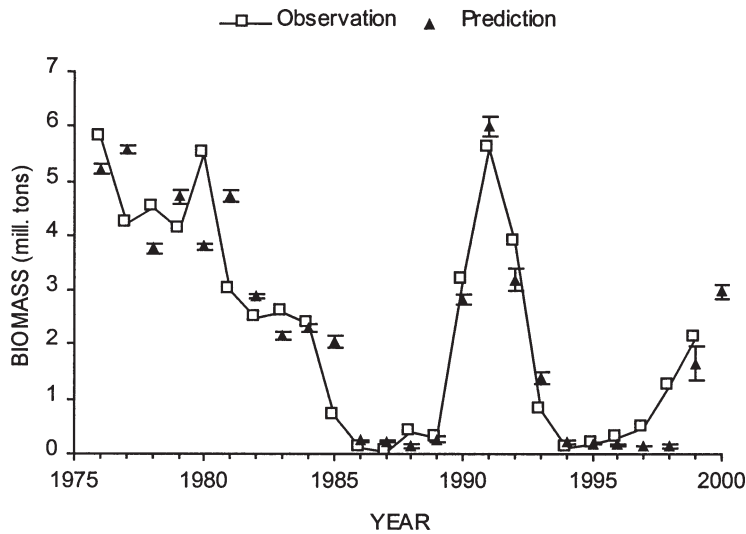


Fig. 3. The observed biomass of two-years and older capelin for 1976-1999 and corresponding predictions made by the trained ANN. ANN predictions ( $\pm$  SE) are based on single years as test sets and the remaining time series as the training set.

node at the same time (Montana 1991). The new generation is then put through the test described above, and once again the best ones are selected to reproduce. By carrying out this GA procedure over many generations, increasingly better solutions to the problem will emerge. To avoid over-training (Geman & al. 1992), the number of hidden nodes was limited to 3 and the number of generations was kept at 500.

SIMPLE FISHERIES ASSESSMENT PROGNOSIS

ANN predictions were compared with simple fisheries assessment prognoses to enable an evaluation of the new approach. The conventional prognoses for the biomass of three-years-old and older capelin next year were made for each of the age groups separately, and in two steps. First, a forecast of the number of fish in age group  $a+1$  in year  $y+1$  was made based on the number of immature fish in age group  $a$  in year  $y$ , applying the equation:

$$N_{y+1,a+1} = N_{y,a} \cdot e^{-(F+M)} \quad (4)$$

where the fishing mortality rate  $F$  was calculated based on number-at-age in the catches during the period, and the natural mortality rate  $M$  was set equal to the estimated  $M$  from the acoustic surveys in year  $y-1$  and year  $y$  (ICES 1999). Only the immature part of age group  $a$  is used as basis for the forecast, since all capelin is assumed to die after spawning. The next step was to multiply the estimated number in age group  $a+1$  in year  $y+1$  by the average weight in age group  $a+1$  in year  $y$ , and sum the results. The reason why the one-year olds were excluded from the analysis was that the acoustic estimates of this age group in the period before 1980 is considered unreliable (Gjøsæter & al. 1998).

ANALYSIS OF INPUT DATA

Initially the different input data were tested individually for their ability to predict the observed capelin dynamics. In all analyses regardless of the number of input nodes, three hidden nodes and one output node were applied. The abundance of two-year old capelin was the

Table 3. Results of runs with different input data. In the upper rows, results using single input (one input node) are shown in the upper row, and in the lower row the results from accumulating the input data from the top row are shown, so that 1 is abundance of two-year old capelin only, 1-2 is capelin and herring as input and so forth. Herring-1 is the herring abundance in the previous year. The  $E$  is the discrepancy between the predicted and observed biomasses (Eq 3).

Single input	Cap 2	Herring	Herring-1	Weight 2	0-group	Cod
$E$	18.5	22.5	23.2	30.4	37.2	40.0
Accumulated input	1	1-2	1-3	1-4	1-5	1-6
$E$	18.5	16.4	16.3	16.0	10.7	8.3

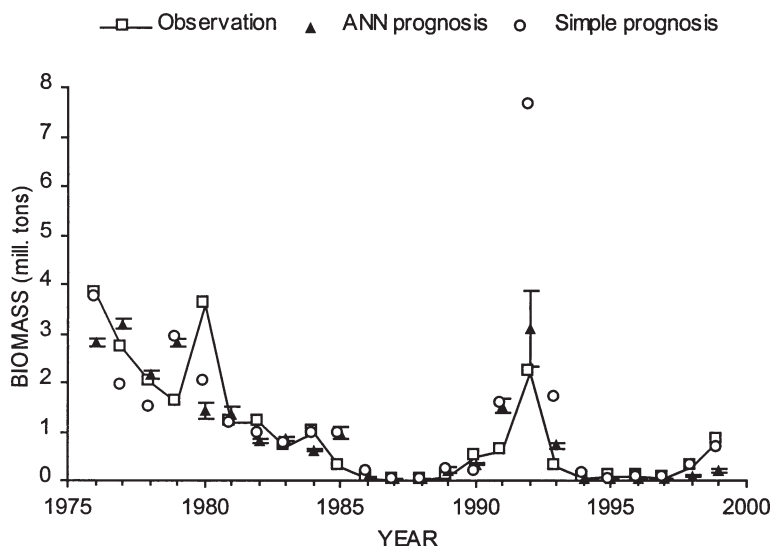


Fig. 4. Observed capelin biomass for three-year and older fish and predictions ( $\pm 2$  SE) made by the simple stock projection method and by the ANN method. ANN predictions are based on single years as test sets and the remaining time series as the training set.

most important variable explaining the biomass of capelin in the following year (Table 3). Next was the current ( $t$ ) and previous ( $t-1$ ) abundance of herring in the Barents Sea. The analysis was extended to include combinations of the different input variables. The error associated with the single input networks was much higher than for the networks containing more input data (Table 3). However, the error is at its lowest level when all the 6 factors are included in the model ( $R^2 = 0.925$ ), and all the six input data were consequently used in generating model predictions. There is no simple additive effect of the increase in number of input nodes and drops in  $E$  occur as a combined effect of the input data (Table 3). The part of the time series used during training are referred to as the training set while the data for which predictions are being made are called the test set.

#### EVALUATION PROCEDURE

The model was tested for its ability to predict abundances in single years, by leaving out one year of the time series during training and predicting the biomass in this year. Such prognoses were compared with the simple fisheries assessment prognosis. Next the training sets were reduced to investigate the impact on the predictive ability of the network. This was carried out by dividing the time series in two with the periods 1976-1983 and 1984-1999 as training sets. Also a reduced time series based on every other year from the time series 1976-1999 was performed to investigate effects of different time periods. Since the results of a computer run depends to some extent on the random number generator, ten replicate trials were performed for all computer runs, and the aver-

age values of these runs with a variance measure (standard error, SE) is presented here.

#### RESULTS

##### SINGLE YEAR PROGNoses

The predictive ability of the model was tested using one year of the time series as the test set and the remaining time series as the training set (Fig. 3). There are some discrepancies, such as in 1980 and 1981, but in general the total abundance of capelin is well predicted by the model with a high degree of correlation ( $R^2 = 0.85$ ). An increase in stock biomass to about 3.1 million tons is predicted for year 2000. The ANN model also provides a better fit with observations than the simple assessment model (Figs 4 and 5A). For stable periods with relatively constant growth and natural mortality the simple assessment model has good predictive abilities, but when changes occur the conventional technique performs poorly. This is illustrated by the outlier point 1992, a year when herring predation led to collapse in the capelin stock (Figs 4 and 5B).

##### REDUCED TRAINING SETS

When the ANN was trained only using the time series from 1976-1983, the predictive ability for the following period was very poor (Fig. 6A). Also the variance between replicate runs was greatly increased. When a training set for the period 1984-1999 was applied, the predictive ability of the previous period was decreased (Fig. 6B), but not as much as in the previous case. These results are due to the differences in the ecological system



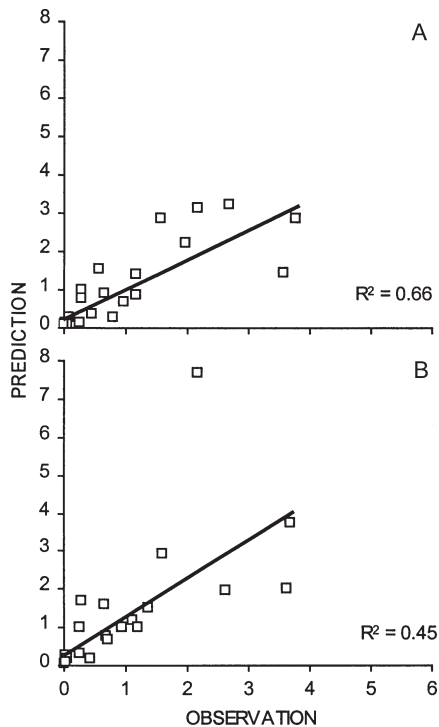


Fig. 5. Observed vs. predicted abundances (in mill. tons) of three-year and older capelin during the period 1976-1999 for the ANN model (A), and the simple assessment model (B).

of the Barents Sea with the capelin population dynamics being influenced by herring predation in the mid 1980s and 1990s, but not in the 1970s and early 1980s. Herring has a great influence on population dynamics of capelin (Hamre 1994), and must be accounted for in the training set. This is illustrated by the relatively good predictive ability of the ANN when only every other year in the time series 1976-1999 is in the training set (Fig. 6C). Even though the training set in the previous run (Fig. 6B) is greater, the performance of the every other network (Fig. 6C) is better since a greater range of ecological factors are included.

## DISCUSSION

The current ANN model shows promising abilities in predicting fish stock development. Especially the single year prognoses, which are relevant for fisheries assessment purposes, were in good accordance with observed data. For the Barents Sea capelin, the ecological factors controlling population dynamics are relatively well known but still difficult to quantify (Hamre 1994; Gjøsæter 1998). It was therefore easy to intuitively provide the input data necessary for fitting the model. In

other cases it may be productive to analyse the impact of many data types including environmental data and indices of climatic conditions to see which are best able to predict the observed population dynamics (Aoki & al. 1999). The analysis of input data and use of limited data sets showed that herring abundance is essential in understanding capelin population dynamics, which supports former studies (Hamre 1994; Gjøsæter & Bogstad 1998; Hamre & Hatlebakk 1998). Aoki & Komatsu (1997) analysed hidden node weights in order to better understand the relationship between the input data and the predictions made by an ANN model. Such an analysis was considered outside of the scope of the current paper, but can be a valuable tool, especially if the behaviour of the model is difficult to understand.

During the process of choosing the appropriate input factors, different temperature time series were tested. Even though temperature affects capelin growth (Gjøsæter & Loeng 1987), it is difficult to find time series of temperature that correlates well with the ambient water temperature of capelin. Our data set therefore only contained biological data. Hamre & Hatlebakk (1998) use shifts to warmer climate as a proxy for good herring recruitment in a system model containing the major Barents Sea fish species. In this case temperature becomes an important factor in explaining capelin dynamics.

If the acoustic estimates of the capelin stock each year and the reported catches by age is taken to be correct, the simple forecasting technique used relies solely on the  $M$  and mean fish weight applied. If there is no variation in these quantities from year to year, the prognosis will match next year's acoustic estimates exactly. However, when these quantities change, the prognoses will differ from the true values. If  $M$  and mean fish weight change gradually, the prognosticated values will "lag behind" the true values. Typically the prognoses will be too low when the stock increases in size and too high when the stock decreases. This problem can largely be solved using the ANN, since the network is able to learn from previous experience and the ANN is therefore able to provide better estimates of mortality and growth when changes in the ecosystem occur. Such changes, triggered by strong herring recruitment, took place in the Barents Sea during the mid 1980s and early 1990s (Hamre 1994). When trained to similar events (see Fig. 6C), the ANN was able to predict crashes in abundance not accounted for by the network trained using the data up to 1983. When many ecological scenarios are represented in the training set, the ANN is good at combining them and predicting the combined effect.

The conventional projection model was only applied for the three-year and older fish since the acoustic estimate of one-year olds is unreliable. An estimate of one-

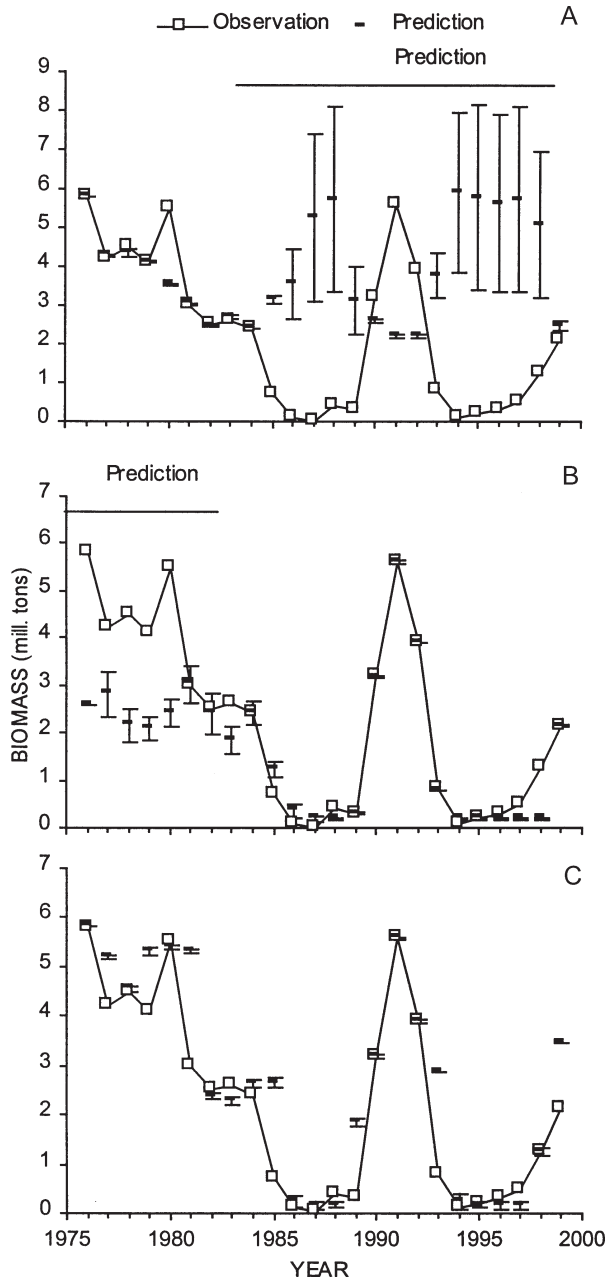


Fig. 6. Model predictions ( $\pm 2$  SE) with limited training sets. Training of the ANN was performed using data from periods 1976-1983 (A), 1984-1999 (B), every other year between 1976 and 1999 (C), while predictions are made for the entire data set.

year olds could have been modelled based on the 0-group index. However, this would have made the assessment model much more complex and we therefore chose to compare the predictions of three-year and older fish, which could be based on the acoustic estimate of two-year olds. The relatively poorer fit between observations

and predictions for the three-year and older fish compared with the two-year and older fish may be due to that the input data were chosen based on predicting the total biomass of capelin rather than the biomass of the oldest individuals (3+). If the input data had been chosen for predicting three-year and older individuals, the



predictive ability would probably have been improved.

The current way of using the ANN has many similarities with multiple regression. Nevertheless, ANNs have been shown to perform better than multiple regression under ecological scenarios similar to the current (Brey & al. 1996; Laë & al. 1999). ANNs are good at sorting out non-linear relations, which are common in fish population dynamics. The approach is general and can be applied to any fish stock where relevant data can be obtained. We therefore conclude that the proposed method can provide fisheries managers with a fruitful tool for

making prognoses about stock developments. Since the method is simple and relies on data collected by most fisheries institutes, it could easily be implemented in fisheries assessment.

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