FISHBYTE SECTION

Exploring the Use of Neural Networks for Biomass Forecasts in the Peruvian Upwelling Ecosystem

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Abstract

A pilot study was conducted to study the ability of an artificial neural network to predict the biomass of Peruvian anchoveta *Engraulis ringens*, given time series of earlier biomasses, and of environmental parameters (oceanographic data and predator abundances). Acceptable predictions of three months or more appear feasible after thorough scrutiny of the input data set.

Introduction

Ecosystems are determined by a large number of abiotic and biotic factors with manifold interrelations. Experience of the past 25 years has shown that the dynamics of ecosystems can only insufficiently be described by classical mathematical-statistical methods. These deterministic approaches fail particularly with respect to predicting the development of ecosystems.

There are similar problems, e.g., in industry and finances. Here, conviction has spread that such complex systems behave in a deterministic-chaotic manner. Artificial neural networks are being used with great success for modeling purposes, whereas they have so far only found very limited application in marine ecology and fisheries.

We are therefore investigating whether neural networks are suited in principle for ecological or fisheries-oriented modeling, using an extensive dataset from the upwelling ecosystem off northern-central Peru (Pauly and Tsukayama 1987; Pauly et al. 1989). While well structured, upwelling systems are subject to high hydrographical variability, and the strong fluctuations particularly of small pelagics (Fig. 1) have long been subject to scientific debate. The Peruvian system has, at times, been supporting the world's greatest largest fishery for a single species, that for the Peruvian anchoveta *Engraulis ringens*, whose catches are again increasing.

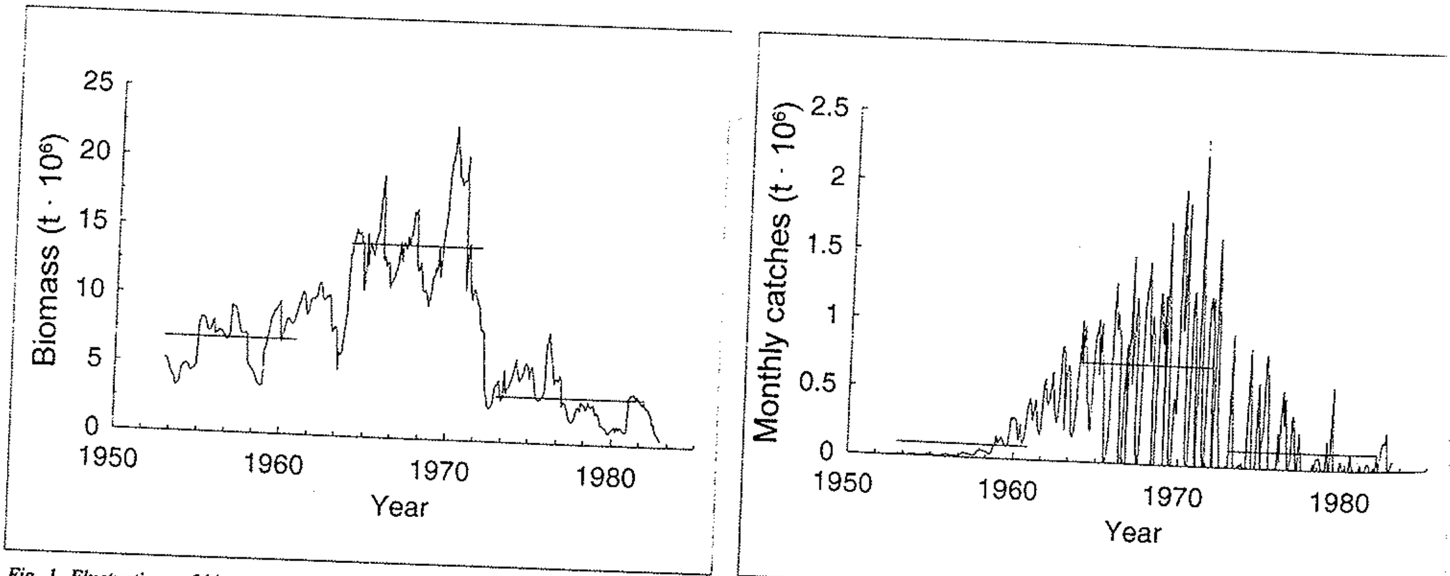

Fig. 1. Fluctuations of biomass and catches of the Peruvian anchoveta. Vertical bars indicate averages under different regimes (adapted from Pauly and Tsukayama 1987 and Jarre-Teichmann 1992).

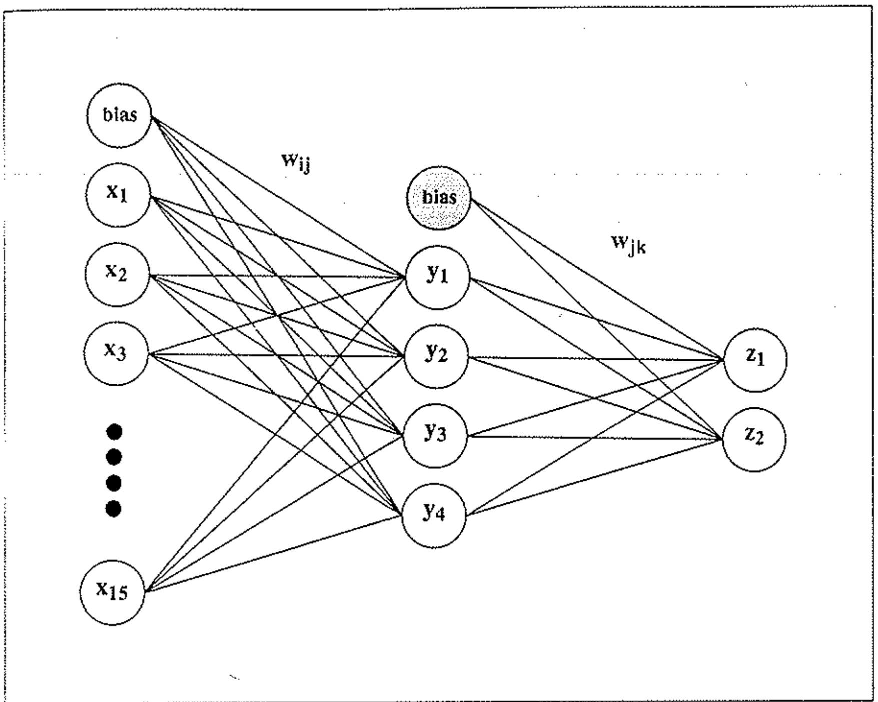

Fig. 2. Scheme of an artificial neural network, composed of an input layer with 15 parameters (x), one hidden layer with four processing elements (y) and an output layer with two elements (z). W_{ij}, W_{jk} indicate the weighted connections between different processing elements (from Simpson et al. 1992).

Neural Networks

Artificial neural networks are a family of computer algorithms which, in a strongly simplified manner, simulate the functioning of biological neurons and the processing of information in the brain. The basic element of an artificial neural network is the processing element, i.e., the functional model of a neuron (Fig. 2). Its task is to receive signals from other processing elements, to weight them, and to summarize the various inputs to a new input quantity which determines its state of activity. By transformation with a specific transfer function, the output of each processing element is computed and forwarded to other processing elements. Processing elements are arranged in layers, the components of which are connected with one or more processing elements in other layers. After having passed the network, the activity of the processing elements in the output layer determines the network's solution for the given problem.

In order to deal with a specific problem, neural networks must be trained from a set of examples of the problem and their results. During the training process, the weights of each processing element are adjusted to minimize the deviation of the computed (estimated) vs. the desired (observed) output. Therefore, the network must, for each weight, compute how the error changes if the weights are slightly increased or decreased. The backpropagation-algorithm is the most widely used method to achieve this goal.

Materials and Methods

For the pilot study presented here, a subset of ten parameters considered highly relevant for anchoveta biomass was used from the database on the Peruvian ecosystem (see Palomares et al. 1989 for details), 4-14°S, January 1953 - December 1982, i.e., sea surface temperature at three points of the Peruvian coast (Callao, Chimbote and Pto. Chicama), coastal upwelling off Callao, anchoveta biomass, anchoveta nominal catch, anchoveta egg numbers, and the abundance of three of its predators, mackerel, horse mackerel and hake.

The Professional Works II+ software (Version 5.1) of NeuralWare was used for the construction of the backpropagation networks. The data were linearly transformed to fit into a consistent numerical range. Usually, all available months were used, but in some cases, years in which El Niño occurred (see, e.g., Arntz and Fahrbach 1991 for an extensive background on this subject), were analyzed separately from non-El Niño years. About 10-20% of the data were used for testing the networks.

Different networks were designed to forecast anchoveta biomass one to three months ahead, exploring a suitable set of input parameters, as well as the impact of different numbers of processing elements, transfer functions and learning schedules. One experiment was conducted to forecast the anchoveta biomass for the following 12 months.

Results and Discussion

Most networks learnt the data surprisingly well (Fig. 3), including the considerable fluctuations of anchoveta biomass during El Niño conditions or regime shifts. Forecasts of 2-3 months yielded quite satisfactory results, but forecasts for a longer period tended to be too conservative in view of the high variability in the system.

From the parameter set used, anchoveta egg numbers turned out to be of little relevance to the prediction of anchoveta biomasses. The best result of the pilot study was obtained using historical information (in this case, from the past three months) of all nine remaining parameters for forecasting. Using only oceanographic data or only data on anchoveta yielded poorer results, indicating that the predator field must be considered in future studies on the prediction of anchoveta biomasses.

For each network, a specific set of transfer functions and a number of processing in the hidden layer had to be identified (by trial and error),

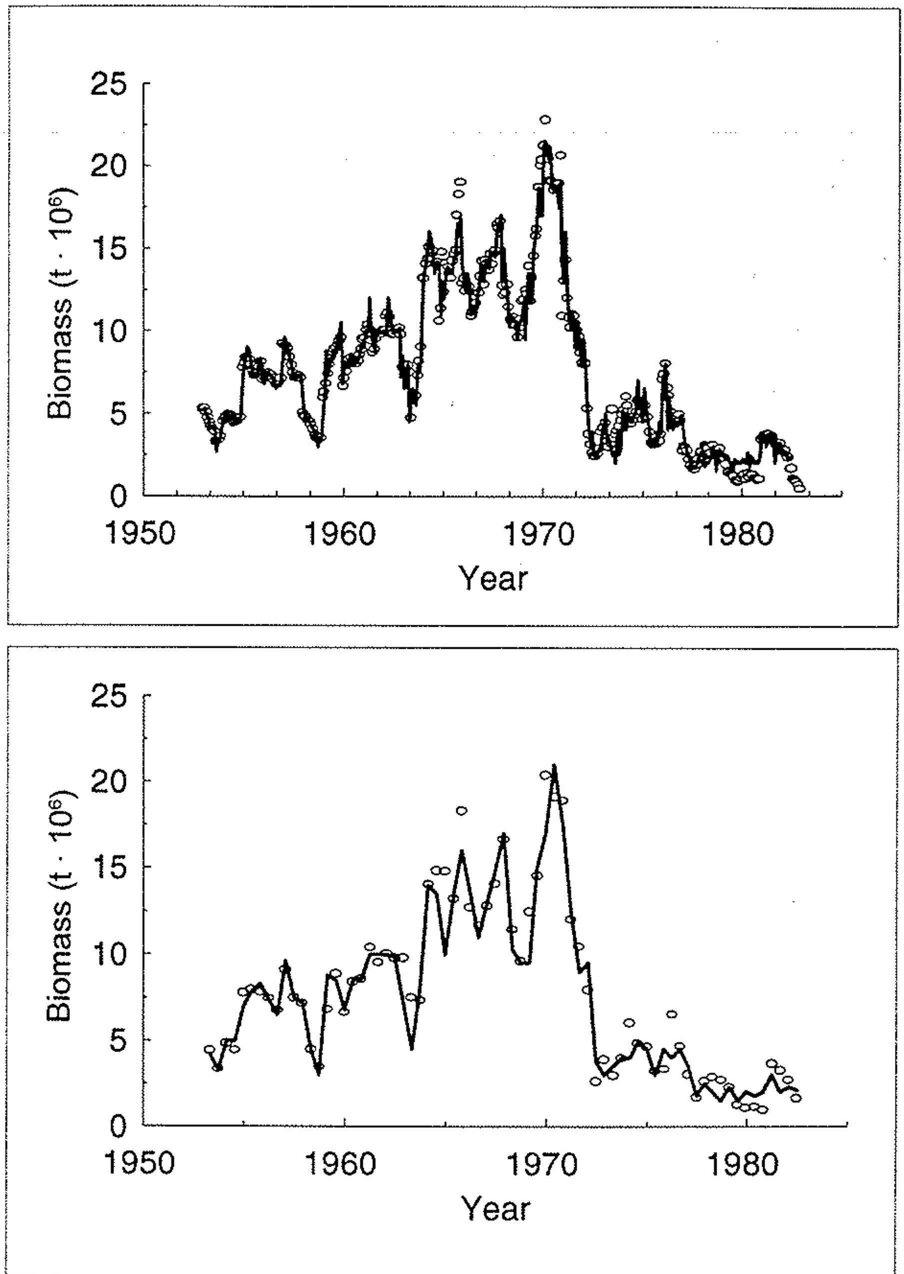

Fig. 3. First results of biomass forecasts of Peruvian anchoveta, developed by the participants of a seminar-project "Forecast techniques" at the University of Bremerhaven. A. Back propagation network with training cycles of three months, recall with learning data. B. The same network, testing with 71 months previously omitted from the training series.

where a lower number of processing elements in the hidden layer sometimes outperformed a higher one. The networks generally appeared to be sensitive to the selection of training and testing datasets. Their ability to extrapolate, e.g., to deal with regime shifts, could therefore be limited.

Not quite unexpectedly, the variability of the anchoveta biomass forecast years without El Niño events was smaller than in those years in which El Niño occurred, because the intensity of the anomaly determines the degree of disturbance of the ecosystem. Unsurprisingly, it is thus easier to predict anchoveta in non-El Niño years.

Based on the experience from this pilot study, the parameter set used as inputs for neural networks will be extended with the aim of maximizing the period for which forecasts can be made. In order to achieve this goal, it is expected that some of the time series available need to be re-estimated based on more recent findings on the Peruvian upwelling ecosystem. Also, different parameter transformations will be explored. If results show that acceptable forecasts can be made for a period of at least three months, we will attempt to minimize the number of parameters necessary for the predictions, in order to focus future sampling efforts.

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