Assessing Benthic Impacts of Fish Farming with an Expert System Based on Neural Networks

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Abstract

Geochemical profiles provide valuable data on the benthic impacts of fish farming and other human activities, but the interpretation of these data is a complex process requiring scientific sophistication and understanding of benthic processes. Neural networks were used to simulate the impact-assignment process in an effort to develop an expert system that does the same analysis. This case study reports the use of neural networks to reproduce expert evaluations of data from an investigation of the benthic impact of a fish farm in the Red Sea. Sediment profiles for loss on ignition (LOI) data were used to classify environmental impacts in terms of four fuzzy sets; Nil, Moderate, Severe and Extreme impact. A neural network was trained to produce a set of assessments expressed as fuzzy memberships directly from sediment profile data. The results confirm that a trained neural network is able to come up with results comparable to those of a scientific expert, even in cases of very limited data[1].

Keywords: neural networks, fuzzy logic, expert systems, sediment profiles, benthic impacts.

Introduction

Although biogeochemical effects of benthic organic enrichment arising from aquaculture activities have been identified in site-specific studies, only recently have attempts been made to derive models which link numerous physical, chemical, and biological factors (Hargrave 1994). It is important to measure and quantify environmental impacts of aquaculture so that tools can be developed for licensing authorities to estimate potential impacts of new lease proposals and to calculate the sustainable level of annual production of fish farms (Silvert 1992; Silvert 1994; Silvert and Sowles 1996). Sediment profiles of different physical, chemical, and biological parameters, measured under or near a fish farm, can be used to assess benthic impacts (Hargrave et al. 1995).

Angel et al. (1998) analysed three years of qualitative observations on benthic conditions under a fish farm and found that with fuzzy logic it was possible to quantify the data and obtain a consistent and informative representation of benthic impacts. Because this method proved successful, their earlier analysis was extended by including quantitative measurements, such as sediment profiles obtained from cores under the farm site. In order to convert the different data into a comparable format the findings were assigned the same fuzzy categories that were presented and utilised in Angel et al. (1998). These categories represent the degree of deviation of ecological conditions from those considered normal under undisturbed conditions at the same site and are labelled Nil, Moderate, Severe and Extreme.

Sediment profiles

Sedimentological data are generally expressed as vertical profiles. The interpretation of these profiles is complex and involves some major problems. It is difficult to avoid a

[1] Based on a Master's thesis by M. J. Baptist (1996), *Assessing Benthic Impacts of Fish Farming with an Expert System Based on Neural Networks*, written at the Bedford Institute of Oceanography, Dartmouth, Nova Scotia, Canada, and accepted at the Wageningen Agricultural University, the Netherlands.

degree of ambiguity and subjectivity in the interpretations, although this is a more general problem in the analysis of scientific data than is commonly admitted (Silvert 1997). A typical sediment profile is shown in Figure 1. This type of profile is commonly found for organic carbon and organic matter, and, in the case of hyperenriched sediments, porewater concentrations of nutrients and hydrogen sulphide.

Figure 1 ***A typical sediment profile***

Among the data are profiles for loss-on-ignition (LOI). Organic matter measured by loss-on-ignition was determined by weight loss of the dried sample after 6 hours in a 550°C furnace. The unit of LOI is percentage organic matter. Three variables were identified as significant indicators of past and present benthic conditions:

- Overall organic enrichment
- Thickness of the enriched layer
- Evidence of bioturbation

Each of the three variables above was classified by an expert into several categories. The organic enrichment was classified as *nil, slight, moderate* or *high*, the depth of the enriched layer as *nil, low, moderate* or *high* and the bioturbation as *no, possibly* or *yes*. Each category has partial memberships in the impact classes *nil, moderate, severe* and *extreme* according to Table 1 (Krost & Silvert, pers. comm.). The overall assignment is obtained by the arithmetic mean of three separate assignments.

Table 1 ***Partial memberships of classifications***

Neural networks for LOI data

The LOI data consist of measurements at eleven different depths of 0.5 cm, 1.0 cm and every centimetre up to 10.0 cm. The neural network for this problem has one layer of eleven input neurons (one for each depth), one layer of four output neurons (the four fuzzy sets) and one layer with several hidden neurons. The neural network was trained with a set of sediment profiles and the corresponding four grades of membership. A different set of sediment profiles and memberships was used to test the results. The sediment profiles were chosen from the larger set of profiles for different dates and their replicates. Figures number 2 to 5 give the results of the neural network (NN) output assignments compared to the expert assignments. The left-hand side of the figures give the training set and the right-hand side the test set. The neural network was able to fit the training sets almost perfectly, and although there are some discrepancies in the comparison between the NN output and the test assignments, it appears capable of assigning memberships that come reasonably close to the expert assignments. This neural net consists of eleven input neurons, eleven hidden neurons, four output neurons, and has

165 synapses. Thus the degrees of freedom in this network are certainly sufficient to make a good fit, compared to the number of samples.

Analysis of the strength of the synapses suggests that the form of the LOI curve in the top 4-5 cm is, perhaps, the predominant indicator of the status of the sediment. The experts distinguish several patterns and corresponding benthic impacts (Angel, pers. comm.). After training, the neural network succeeded well in recognising these patterns and giving the correct assignments as output.

Figures 2, 3, 4 and 5 here

Fourier Transforms

During training a neural network adaptively learns the position of hyperplanes that act as discriminants. This process is a *black box* sort of procedure which cannot readily be tuned by the researcher. When an expert assigns memberships to different profiles, he makes use of discriminants too, although of a more subjective nature. For example, the overall level of enrichment discriminates between a high benthic impact or a low benthic impact. High surface values discriminate in favour of a high benthic impact, and the evidence of bioturbation is a discriminant for high nil scores.

It might simplify the neural network lay-out and speed the training process if the data are preprocessed and expert-based discriminants are used as input to the neural network. One way to do this is to transform the data with orthogonal functions, such as Fourier transforms. Fourier transforms tend to distinguish particular patterns, and at least for the lower-frequency transforms each fourier component emphasises a specific part of the profile and might serve as a discriminant.

To carry out the Fourier transform analysis, the interval over which the LOI profile was measured is decomposed into a finite number of subintervals in each of which the profile is represented by a linear function of the form *f(x) = a + bx* in between each two measured depths. For each of the ten intervals a different set of coefficients a and b are defined. The Fourier transforms of *f(x)* can then be calculated as:

$$C_n = \frac{2}{T}\int_0^T f(x)\cos nx\, dx$$

$$S_n = \frac{2}{T}\int_0^T f(x)\sin nx\, dx$$

where T is the depth of the profile and n is an integer. Only the first five fourier components were considered, namely C_0, C_1, S_1, C_2 and S_2 (S_0 is zero by definition). Because the experts placed more emphasis on the topmost 6 centimetres, T = 6 cm was chosen as the period , data from deeper depths was discarded.

The C_0 component is a measure of the surface area under the profile and indicates the level of overall enrichment. The other two cosine components have high values if the

LOI profile has high surface values and falls off to lower background levels, since high surface values are multiplied by a cosine function with values near one at surface depths. The integral of this product is thus large and positive. The sine components distinguish patterns of high LOI values at a depth below the surface, because the sine function is large and positive at those depths.

This way, the fourier components distinguish particular patterns in the LOI profiles. Furthermore, the number of input neurons can be reduced to five for example, when the C_0, C_1, S_1, C_2 and S_2 components are used.

These five fourier components were used as input to a neural network. This is a very small number of components, too few to provide a very good representation of f(x), but the goal was to get an idea of the shape of the pattern with a minimum number of input neurons. It turns out however that these fourier components are very sensitive to variations in the LOI values, which makes this method less useful, and leading to significant discrepancies between the interpretation of replicate profiles.

Despite this problem, we trained a neural network with five fourier components as input, five hidden neurons, and the four assignments as output. The same profiles were used for training and test sets as those used to train a neural network with raw LOI data. The results were comparable with those of the raw LOI profiles, which, given the sensitivity of the fourier components to small variations in the LOI values, suggests that a more robust transform technique might be useful.

Discussion

Probability density function

Training of neural networks is a procedure of minimising the error between desired and actual output by adjusting the weights and biases in the network. The neural network estimates the probability density functions $p(x_k)$, $p(y_i)$ and the joint probability function $p(x_k,y_i)$ for the patterns x_k and the output classes y_i. The function $p(x)$ denotes the probability of a pattern to belong to a group of similar patterns. These are used to classify the patterns through the use of discriminants based on the joint probability function. After training a neural network recognises a new pattern in the test set by using the estimated probability density function $p(x)$. The implicit assumption is that the probability function of the training set is similar to that of the test set. This may be true for certain fields of pattern recognition, but it may not be the case with environmental impact assessment, since the probability distribution for data from impacted areas may not be the same as the original data used to calibrate the model. In environmental impact assessment, a network can be trained to recognise certain environmental patterns, LOI profiles for example, and classify them just as an expert would do. The neural network identifies these patterns as belonging to a class of patterns it already knows using the estimation for the probability density function $p(x)$. The function $p(x)$ introduces a bias, since each new pattern is interpolated in the direction of a high probability density region of $p(x)$, so the outputs are biased according to the most frequent patterns. The assignments thus tend to have values nearer to the mean scores than the extreme scores.

Dataset

The results of this study must be qualified by the observation that there were not enough profiles to train the network thoroughly in relation to the number of degrees of freedom. This reflects a general problem with neural networks, in that the number of separate parameters is very large and requires a large quantity of data to estimate reliably.

The original dataset of LOI profiles contains several replicate samples taken on the same day. Because of errors made during sampling and analysing, and of natural differences between separate samples these profiles give different results. An implicit assumption of our analysis is that each profile can be assessed independently. However, when the experts made the assignments they used a mental averaging of the replicate profiles, so the assignments were in most cases the same. This makes the use of these replicates for training and testing not as useful as we had hoped.

Expert Systems

Neural networks are useful for developing an expert system. It is very hard to grasp the way a human being thinks, other than by trying to imitate the mapping between stimulus (input) and response (output). A neural network provides a generic model for this mapping procedure without any prior assumptions. But experts undergo a continuous process of changing and rechanging their thoughts, based on new ideas and insights. The trained neural network as an expert system therefore, does not always agree with the way experts explain their decision process. The expert system that can think instead of imitate has yet to be invented.

Conclusions

It can be concluded that it is realistically possible and perhaps even useful to train a neural network to analyse sediment profiles in a standard way. Even with a limited number of LOI profiles a fairly good expert system was developed, one that was able to come up with results comparable to those of scientific experts. Furthermore, the development and preliminary results of this expert system gave feedback to the experts, that caused the experts to explain their way of thinking and look at the data very carefully in cases where the neural network pointed out inconsistencies and omissions.

We also found that it might be useful to preprocess (transform) the data before it is fed into a neural network, as it can reduce the number of input neurons and also may help to understand the processes inside a neural network (Silvert and Baptist, subm.).

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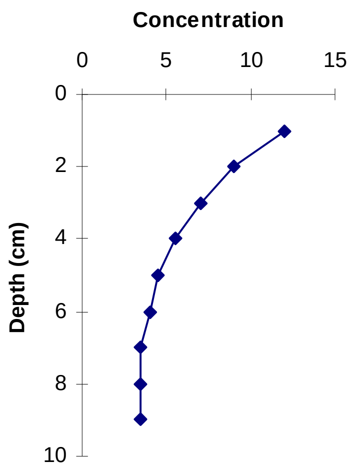

Figure 1 ***A typical sediment profile***

Organic enrichment	nil	slight	moderate	high	
	0.80	0.20	0.10	0.00	nil
	0.20	0.50	0.50	0.10	mod
	0.00	0.30	0.30	0.30	sev
	0.00	0.00	0.10	0.60	extr
Depth of enriched layer	nil	low	moderate	hi(deep)	
	0.70	0.20	0.10	0.00	nil
	0.30	0.50	0.50	0.10	mod
	0.00	0.30	0.30	0.30	sev
	0.00	0.00	0.10	0.60	extr
Bioturbation	yes	possibly	no		
	0.60	0.25	0.00		nil
	0.30	0.25	0.20		mod
	0.10	0.25	0.30		sev
	0.00	0.25	0.50		extr

Table 1 ***Partial memberships of classifications***

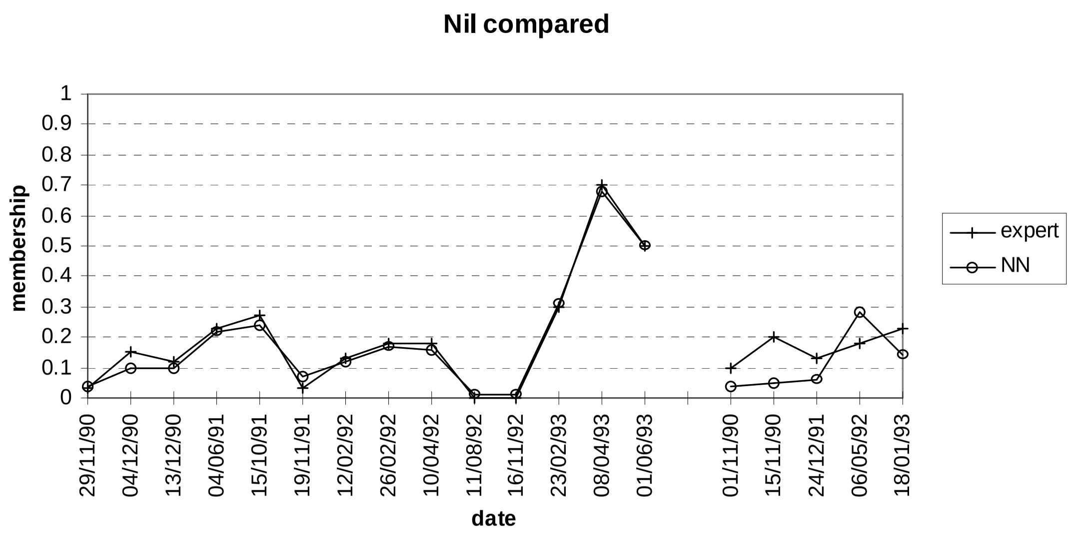

Figure 2 ***Comparison of expert NIL assignments with NN assignments***

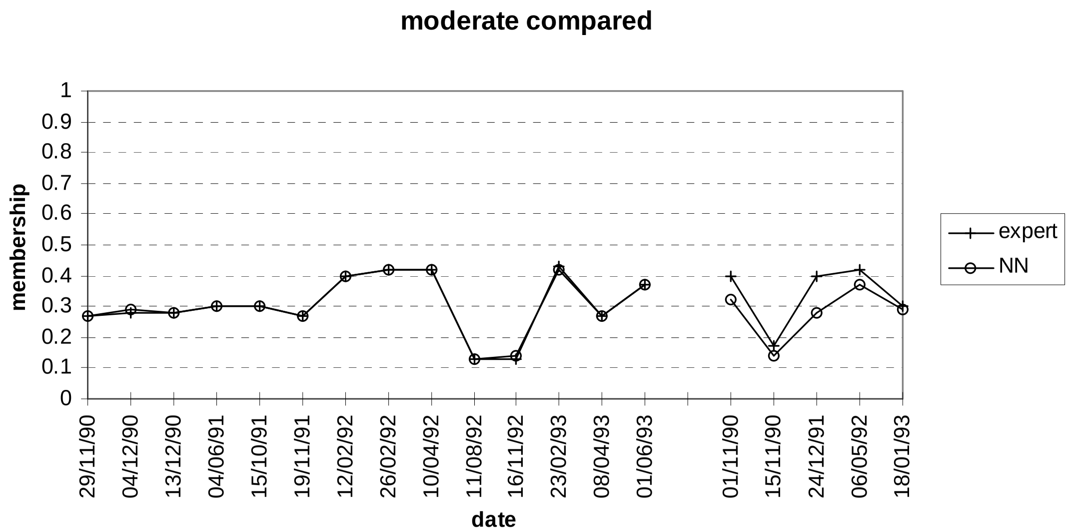

Figure 3 ***Comparison of expert MODERATE assignments with NN assignments***

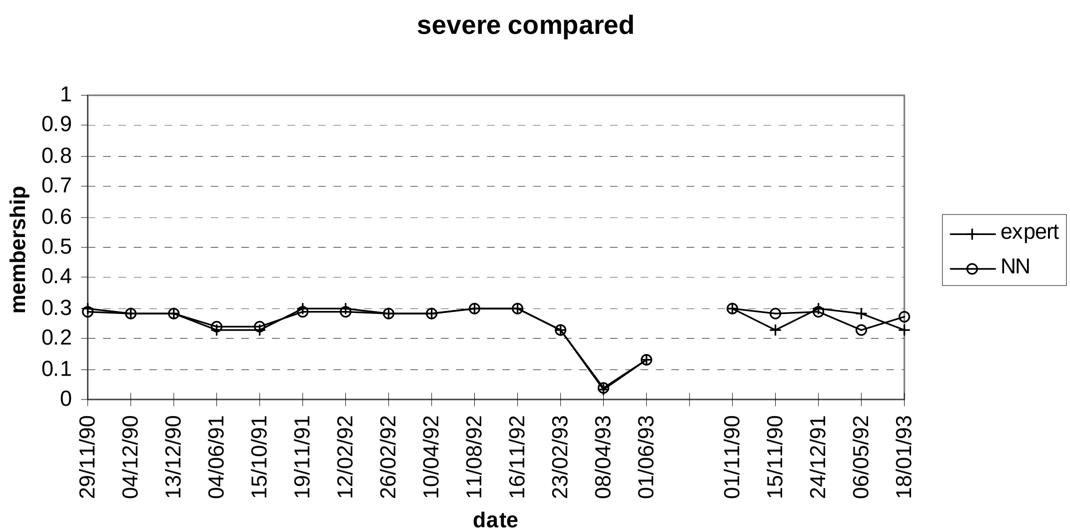

Figure 4 ***Comparison of expert SEVERE assignments with NN assignments***

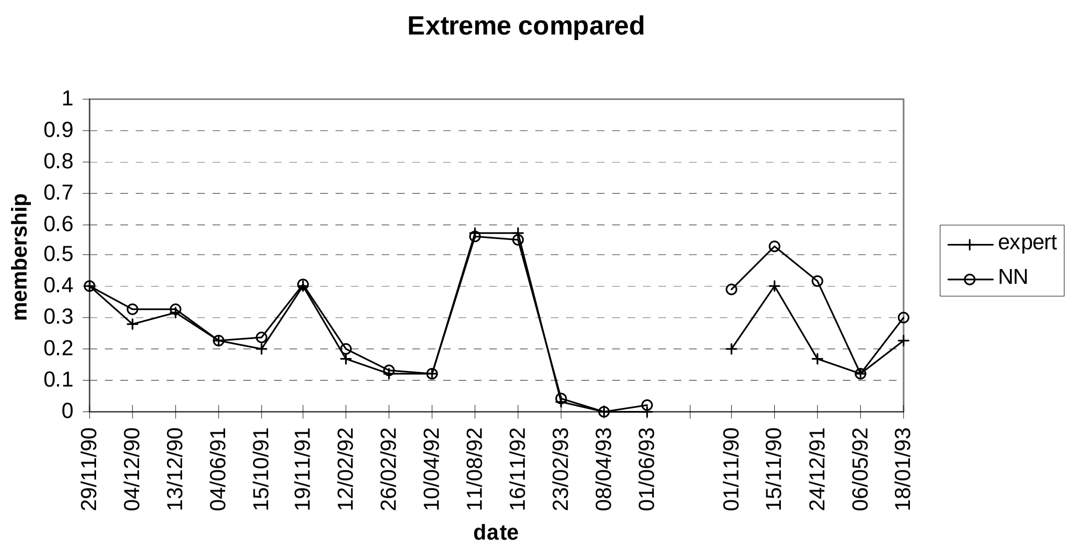

Figure 5 ***Comparison of expert EXTREME assignments with NN assignments***

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