Artificial neural network approach for modelling and prediction of algal blooms

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Abstract

Following a comparison of current alternative approaches for modelling and prediction of algal blooms, artificial neural networks are introduced and applied as a new, promising model type. The neural network applications were developed and validated by limnological time-series from four different freshwater systems. The water-specific time-series comprised cell numbers or biomass of the ten dominating algae species as observed over up to twelve years and the measured environmental driving variables. The resulting predictions on succession, timing and magnitudes of algal species indicate that artificial neural networks can fit the complexity and nonlinearity of ecological phenomena apparently to a high degree. © 1997 Elsevier Science B.V.

Keywords: Blue–green algae; Algal blooms; Modelling; Prediction; Artificial neural networks; Case studies

1. Introduction

Aquatic ecosystems are very complex due the diversity and connections of the components governing the system's dynamics. Nonlinear dynamics underlie the ecosystem behavior and pass it through successional stages aiming at a steady state. This process is more complicated when a single species or substance rapidly increases in number or concentration, whereby they become a pollutant for the ecosystem and can subsequently affect their surroundings drastically.

Explosion-like formations of algal blooms increasingly pollute both: salt and fresh water ecosystems throughout the world. They lead to enormous costs by affecting seafood, drinking water supply, aquaculture systems and tourism. In addition to the characteristics described by Hallegraeff (1993), the following harmful algal blooms can be distinguished:

(1) *Species which cause water discolorations.* Algae can grow in abundance to the extent that they change the color of water to red, brown or green. Resulting water discoloration can significantly impair recreational uses of aquatic systems. In shallow waters, blooms can grow occasionally so dense that they cause, not only water discoloration but also fish and invertebrate mortality due to oxygen depletion.

(2) *Species which affect human health by toxins.*

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Blue–green algal toxins are contained within the living cells and will be released by cell cracking or decay. The toxins can find their way to humans through either drinking water or the food chain. As reported by Falconer (1993) algal toxins in solution pass through the normal water treatment and are resistent to boiling. They can cause gastroenteritis, hepatoenteritis and toxic injury to the liver. Additionally, the occurrence of fish and shellfish poisonings as reported by Todd (1993) can considerably reduce consumption and export of seafood. (3) *Species which cause high mortality of fish and invertebrates.* Barica (1978) reported massive seasonal mortalities of rainbow trout during summer in Canadian prairie lakes caused by blue–green filamentous algae *Aphanizomenon flos-aqua* and related degradation products. Some algae species can cause serious damage in aquaculture systems by damming or clogging fish gills. Okaichi (1989) reported on a bloom of *Chattonella antiqua* in the Japanese Seto Island Sea which killed 500 million dollars worth of caged yellow-tail fish. (4) *Species which impair water treatment by their biomass, taste and odor.* Al-

gogenic organic matter can seriously impede the supply of drinking water by clogging of filters, inhibition of flocculation processes and encrustation of pipes in water works. Some species such as *Synura uvella* can cause taste and odor problems in drinking water and give rise to customer complaints (Burlingame et al., 1992).

Most of these deleterious effects might be prevented or minimized if algal blooms could be predicted in a early stage. This is a permanent challenge for modelers worldwide.

In the context of this paper a comparison of current alternative approaches for modelling and prediction of algal blooms is made. Artificial neural networks are then introduced and applied as a new, promising model type. The neural network applications were developed and validated by limnological time series from freshwater lakes in Japan and Finland and an Australian river. The resulting predictions on succession, timing and magnitudes of algal species indicated that artificial neural networks fit the complexity and nonlinearity of ecological phenomena apparently to a high degree.
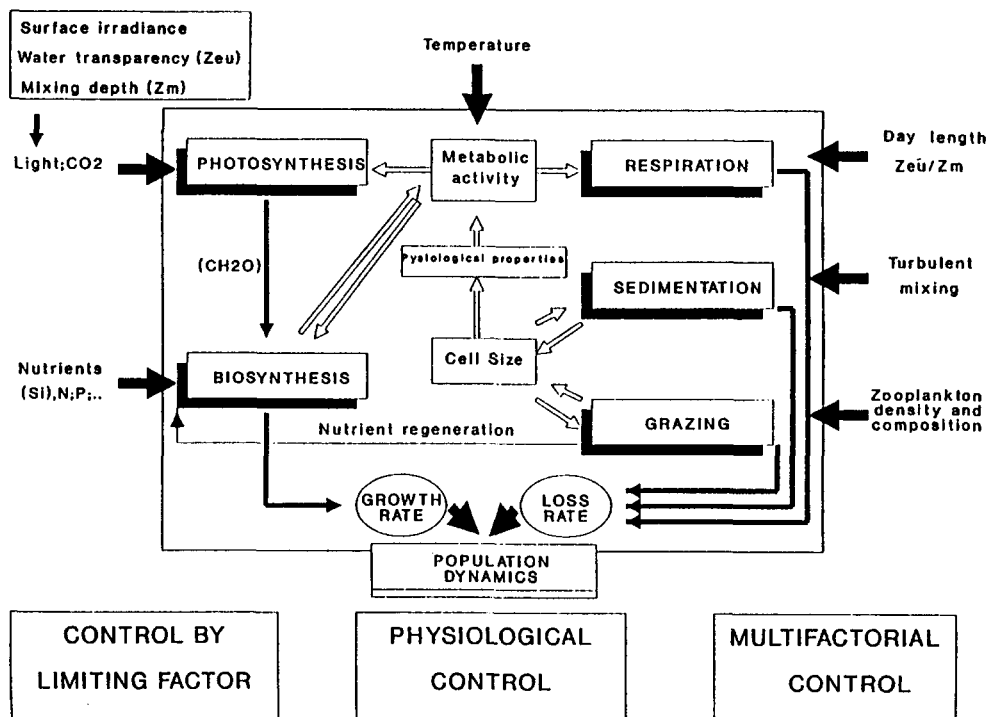

Fig. 1. Factors and processes controlling phytoplankton dynamics (from Capblancq and Catalan, 1994).

Table I
Characteristics of phytoplankton models

	Empirical steady-state models	Deterministic models	Time-series analysis models	Heuristic models	Fuzzy models	Neural network models
Data type	cross-section	cross-section/time-series	time-series	cross-section/time-series	cross-section/time-series	time-series
Time step for simulation		minute/hour/day	day		month	day
Time resolution of predictions	season/year	day/week/month	month	month/season	month/season	day/week
Considered control factors for phytoplankton growth	limiting factors	limiting, physiological and multiple factors	limiting factors	limiting, physiological and multiple factors	limiting and multiple factors	limiting and multiple factors
Bases for predictions	relationships	trend/seasonality/serial dependency	multivariate relationships	seasonality/serial dependency serial dependency	seasonality/	connections
Predicted phytoplankton composition	chlorophyll-a	species/functional groups	chlorophyll-a	species assemblages	species assemblages	species

2. Modelling and prediction of phytoplankton in freshwater systems

To model the dynamics of phytoplankton populations, the limiting, physiological and multiple factors controlling their growth and composition have to be considered as represented in Fig. 1.

The validity of the model depends upon the availability of either cross-sectional or time-series data and the choice of the modelling technique. Limnological cross-sectional data are obtained from measurements of different lakes (e.g. of equatorial lakes) where each data point represents a seasonally or annually averaged set of measurements for a different lake. Limnological time-series data is composed of a deterministic and a random component. The deterministic component changes over time in a regular and predictable way caused by underlying processes. It can be characterized by a trend, periodicity and serial dependency. The trend is characterized by the long-term tendency of observations to increase or to decrease, e.g. the increased phosphorus concentrations in lakes due to cultural eutrophication. The periodicity occurs when observations follow a pattern that changes regularly with time, e.g. diurnal changes of oxygen concentration or the seasonal succession of phytoplankton in lakes. The periodicity can be caused by other periodic phenomena such as limit cycles of prey–predator relationships between phytoplankton and zooplankton. The serial dependency occurs when observations in the time series are dependent on past observations, e.g. the phosphorus concentration of lakes in spring depends on the phosphorus level in the previous winter. The random component is superimposed on the deterministic component and can be characterized by short-term fluctuations due to transitory or unexplained factors. Their nature can be truly random or chaotic. Truly random components such as the level of water in a river can be characterized by a statistical distribution function or by the statistical moments of the data. Chaotic components of a time series are characterized by values that appear to be randomly distributed and non-periodic but are the result of a deterministic process due to underlying nonlinear dynamics.

Table 1 lists some characteristics of different types of phytoplankton models. Empirical models are

based on cross-section data and predict mean sea-sonal or annual chlorophyll-a concentrations (e.g. Vollenweider, 1976). They utilize correlative rela-tionships with limiting factors such as water trans-parency and nutrients. Deterministic models are based on cross-section and time-series data and simulate trends, seasonality and serial dependencies controlled by limiting, physiological and multiple factors. De-terministic ecosystem models calculate the daily biomass of functional algal groups within the pelagic food-web (e.g. Park et al., 1979) while deterministic process models calculate the hourly biomass of sepa-rate algae species (e.g. Okada and Aiba, 1983).

Time-series analysis models predict time-depen-dent chlorophyll-a based on multivariate relation-ships with limiting and multiple factors (e.g. White-head and Hornberger, 1984). Heuristic word models predict qualitatively the seasonal dynamics of phyto-plankton composition by combining species assem-blages with causal knowledge on limiting, physio-logical and multiple factors (e.g. Sommer et al., 1986). Fuzzy models quantify periodically (e.g. monthly) the possible dominance of algal species (e.g. Recknagel et al., 1994). The possibility of the occurrence of algal species is calculated by member-ship functions depending on seasons, limiting, physiological and multiple factors. Artificial neural network models are driven by time-series data of algal species and control factors (French and Reck-nagel, 1994). They allow to predict timing and mag-nitudes of algal species based upon the strength of associations with limiting and multiple control fac-tors.

3. Time series modelling of algal blooms by artificial neural networks

3.1. General approach

Artificial neural networks typically consist of an input layer, hidden layers and an output layer. In the input layer the external inputs such as surface irradi-ance and nutrient concentrations, and the density and composition of zooplankton are represented by nodes. In the output layer interesting outputs such as cell numbers of dominating algal species are represented by nodes. Neural networks determine the weighted connections between input and output nodes by in-terconnected computing elements, the neurons, where feed-forward or feedback algorithms are utilized. The neurons are located in the hidden layers and feed a nonlinear function, such as a sigmoid func-tion, by the sum of its inputs either coming from input nodes by feed-forward or from output nodes by feedback. The resulting value of a neuron is multi-plied by a weighting factor after passing the nonlin-ear function. Therefore each neuron has a separate weight parameter for each connection with the input and output nodes, the so-called firing rate. A learn-ing process, the training, forms the interconnections between the neurons and the nodes. It is accom-plished using measured inputs, represented in the

Table 2
Characteristics of four freshwater systems and corresponding neural network models

	Lake Kasumigaura (Japan)	Lake Biwa (Japan)	Lake Tuusulanjaervi (Finland)	River Darling (Australia)
Trophic State	hypertrophic	meso-/eutrophic	eu-/hypertropic	hypertrophic
Morphometry:				
– Maximum depth (m)	7	103	10	
– Mean depth (m)	4	41	3.2	
– Surface area (km^2)	220	670	5.95	
– Volume (million m^3)	900	27800	19.15	
Range of water temperature (°C)	2.1–32.0	3.3–31.1	0.0–22.4	7.5–29.5
Mean water retention time (year)	0.55	5.5	0.68	0.002
Structure of neural network	see Fig. 2	see Fig. 3	see Fig. 4	see Fig. 5
Time series for training (years)	8 ('84, '85, '87, '88, '89, '90, '91, '92)	6 ('84, '85, '88, '89, '90, '91)	10 ('72, '74, '75, '76, '81, '82, '83, '84, '85, '86)	10 ('80–'86, '87–'90, '91–'92)
Time series for validation (years)	2 ('86, '93)	2 ('86, '87)	2 ('73, '87)	2 ('86–'87, '90–'91)

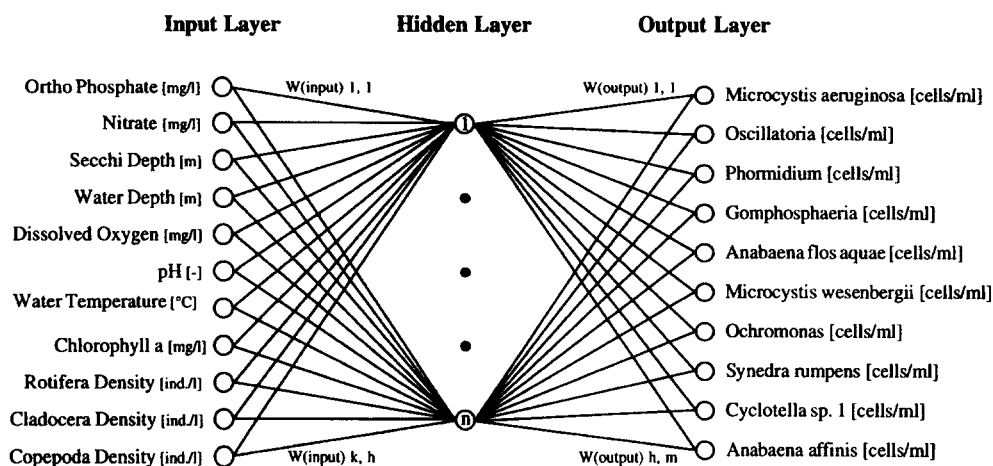**Input Layer**   **Hidden Layer**   **Output Layer**

Fig. 2. Neural network structure for Lake Kasumigaura (Japan).

input layer, and measured outputs, represented in the output layer. The strength of the interconnections is adjusted using an error convergence technique such as the back-propagation algorithm. The aim of the training of a neural network is to minimize the output error with respect to the known desired output. The output error is defined to be the sum of the differences between the network outputs and the measured outputs they are supposed to predict. To meet the aim of minimizing the output error can be supported additionally by optimization techniques such as the method of steepest descent. Once formed by training, the interconnections may remain fixed in

the hidden layer and the neural network can be used for predictions.

The neural network shell EXPLORER from Neural Ware. Inc. (1993) was used for modelling of algal blooms in four different freshwater systems. EX-PLORER is a feed-forward network with backpropagation for training. For each of the four applications the hyperbolic function was chosen to calculate the firing rates. The numbers of hidden layers, nodes and neurons as well as learning rates and momenta have been used as control parameters to find optimum training and prediction results. The training of any network involved 500,000 iterations.
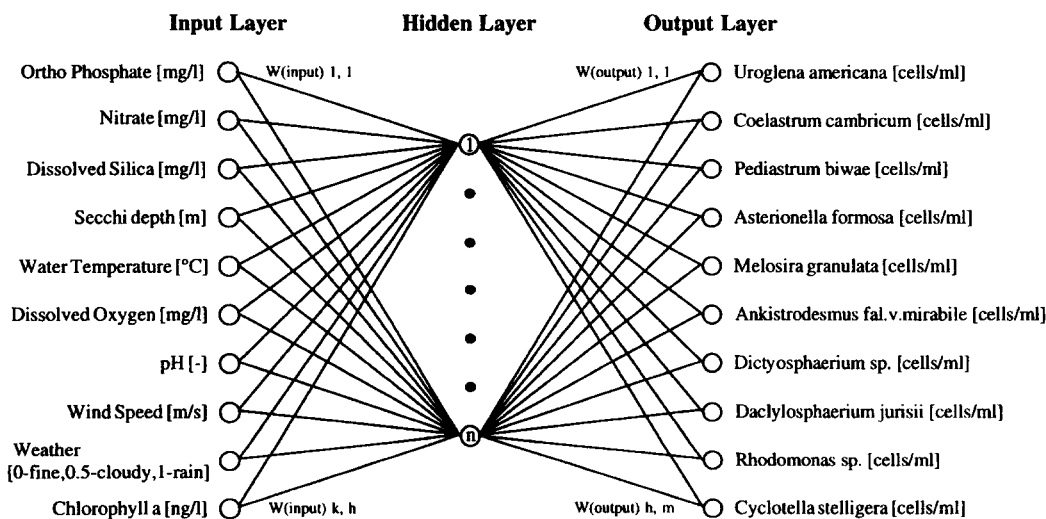
Input Layer   **Hidden Layer**   **Output Layer**

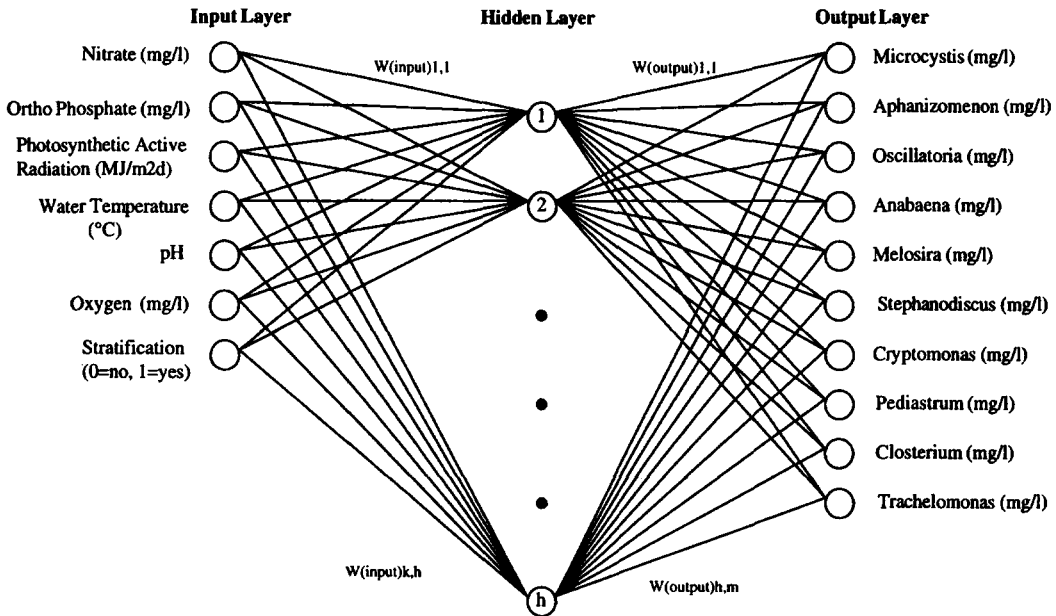Fig. 3. Neural network structure for Lake Biwa (Japan).

Fig. 4. Neural network structure for Lake Tuusulanjaervi (Finland).

3.2. Case studies

Table 2 summarizes information about the four freshwater systems under investigation and the corresponding neural network models. Figs. 2–5 illustrate the specific structures of the water specific neural network models.

As can be seen in Table 2 the neural network approach has been applied to very different freshwater systems in the framework of this paper. The Lake
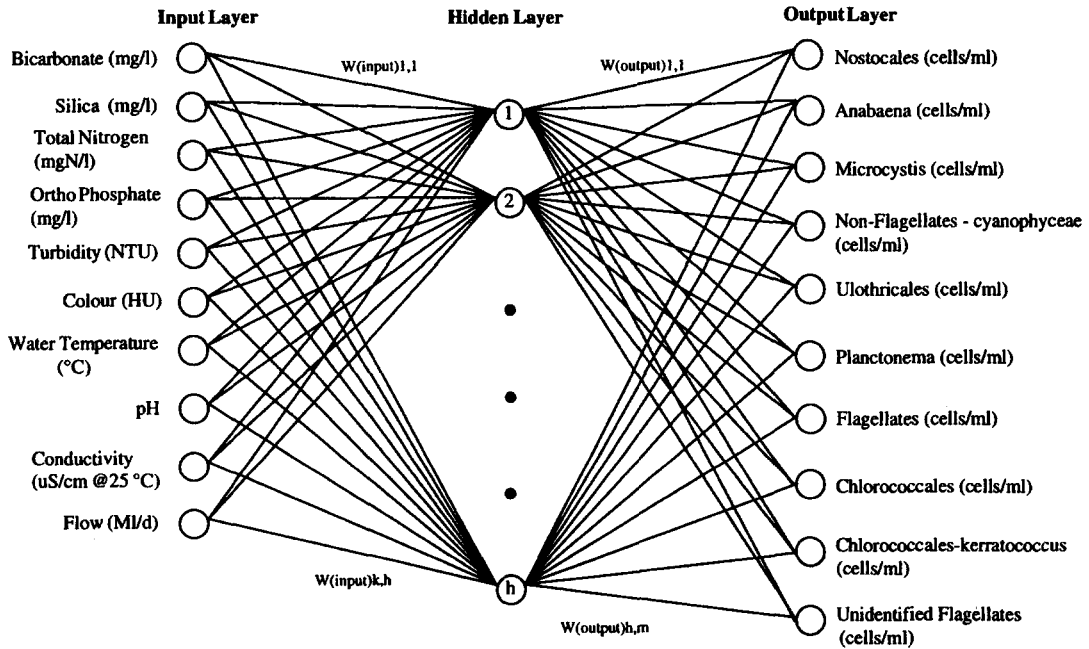
Fig. 5. Neural network structure for River Darling (Australia).

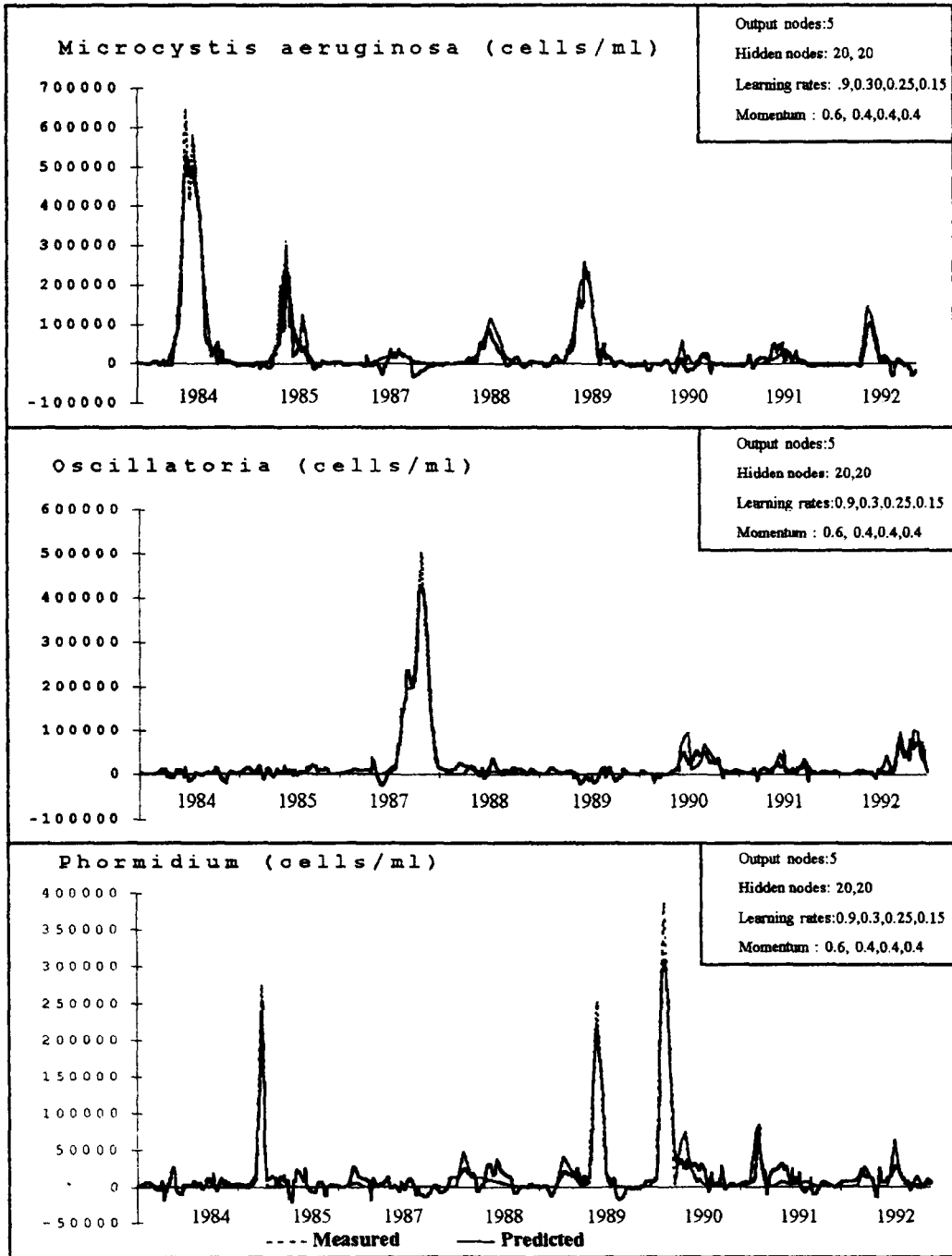## Lake Kasumigaura : Neural Network Training

Microcystis aeruginosa (cells/ml)

Output nodes:5
Hidden nodes: 20, 20
Learning rates: .9,0.30,0.25,0.15
Momentum : 0.6, 0.4,0.4,0.4

700000
600000
500000
400000
300000
200000
100000
0
-100000

1984 1985 1987 1988 1989 1990 1991 1992

Oscillatoria (cells/ml)

Output nodes:5
Hidden nodes: 20,20
Learning rates:0.9,0.3,0.25,0.15
Momentum : 0.6, 0.4,0.4,0.4

600000
500000
400000
300000
200000
100000
0
-100000

1984 1985 1987 1988 1989 1990 1991 1992

Phormidium (cells/ml)

Output nodes:5
Hidden nodes: 20,20
Learning rates:0.9,0.3,0.25,0.15
Momentum : 0.6, 0.4,0.4,0.4

400000
350000
300000
250000
200000
150000
100000
50000
0
-50000

1984 1985 1987 1988 1989 1990 1991 1992

- - - - Measured   —— Predicted

Fig. 6. Validation of training results for *Microcystis*, *Oscillatoria* and *Phormidium* in Lake Kasumigaura (Japan).

Lake Kasumigaura : Neural Network Prediction
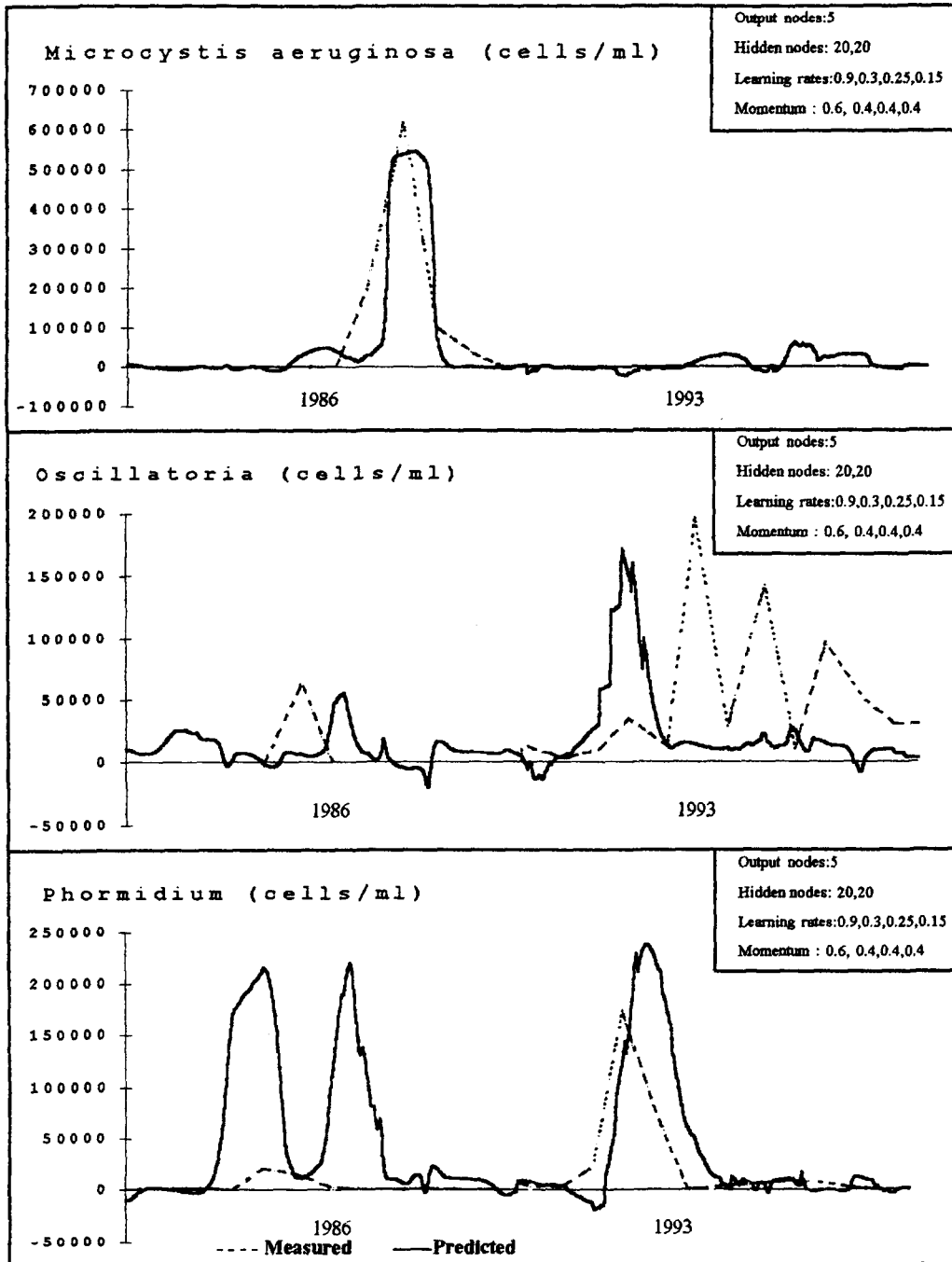
Fig. 7. Validation of prediction results for *Microcystis*, *Oscillatoria* and *Phormidium* in Lake Kasumigaura (Japan).

Biwa is a deep, stratified lake with a water retention time of 5.5 years. This lake has meso- to eutrophic conditions where diatoms, green and yellow–green algae are most common. The Lake Kasumigaura is a large and very shallow lake with a retention time of only 0.55 years. Because of hypertrophic conditions, blue-green algae dominate in the Lake Kasumigaura. Both Japanese lakes are located between the 35th and 36th Northern latitude with similar ranges of annual solar radiation and water temperature. Com-

prehensive limnological time-series have been collected for both lakes over more than 10 years (Hanazato and Aizaki, 1991; Takamura et al., 1992; Wakabayashi et al., 1985; Wakabayashi et al., 1986; Wakabayashi et al., 1991; Wakabayashi et al., 1994).

The Finish Lake Tuusulanjaervi is located at the 62nd Northern latitude and has therefore different light and temperature conditions compared with the temperate Japanese lakes. Lake Tuusulanjaervi has hypertrophic conditions with a high abundance of
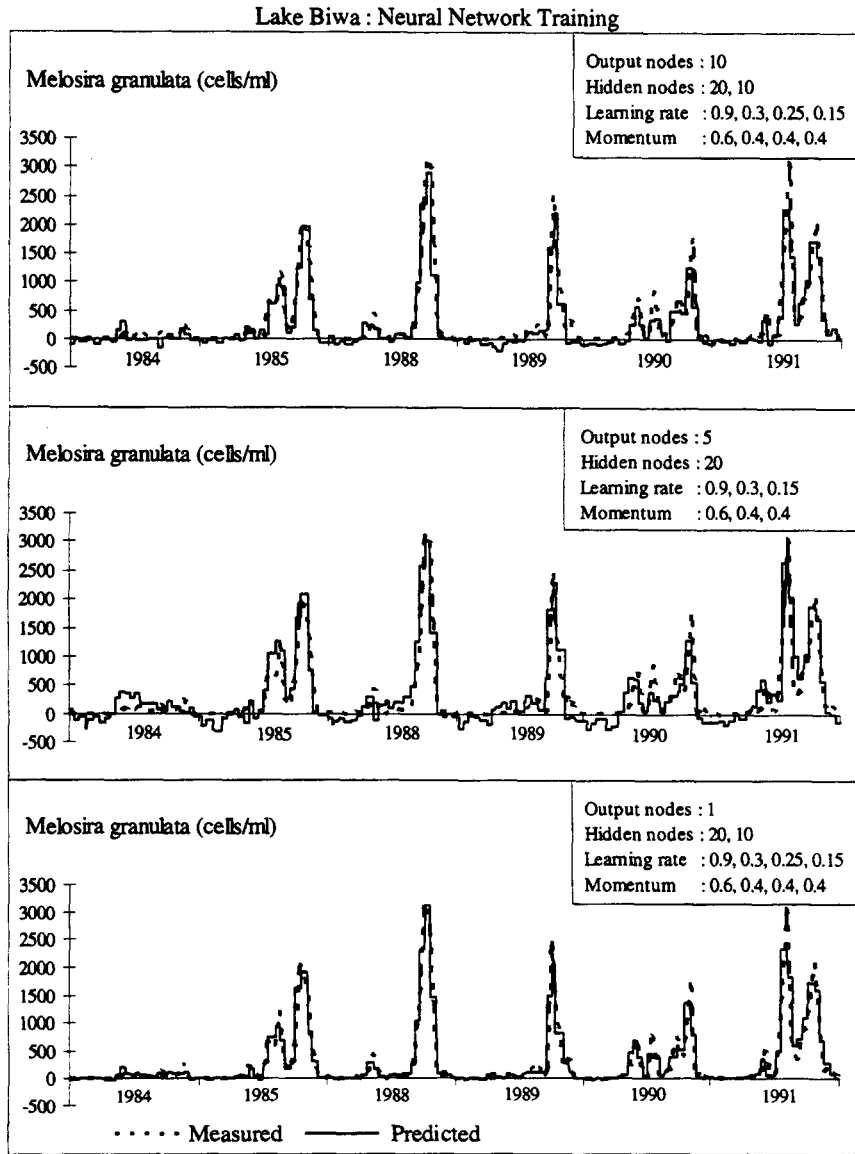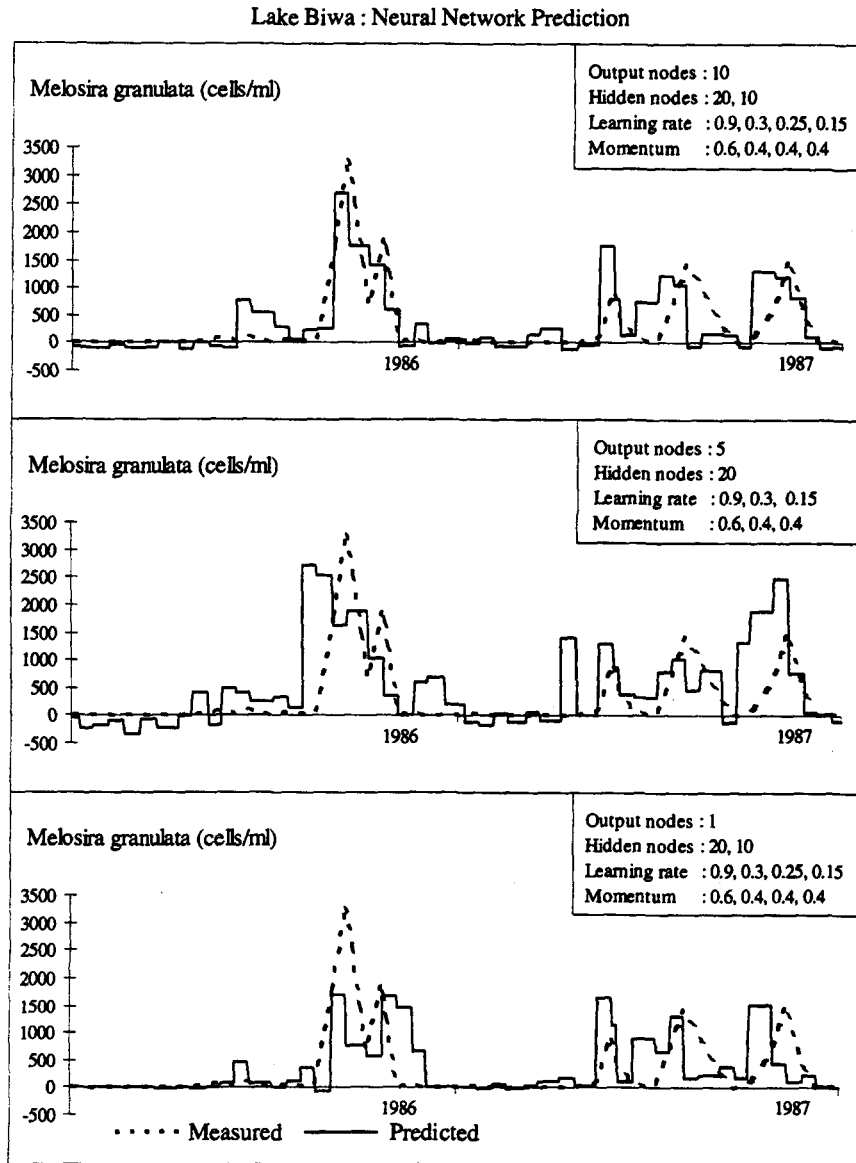

Fig. 8. Validation of training results for *Melosira granulata* in Lake Biwa (Japan) by different structures of the neural network model.

blue–green algae. Limnological time-series of Lake Tuusulanjaervi have been documented by Mutanen and Varis (1989) and Mutanen et al. (1989).

The River Darling stretches from subtropical to temperate regions in Australia and flows into the River Murray. Limnological time-series data was available from the site Burtundy (Sallivan et al., 1988; Hoetzel and Croome, 1994), where the River Darling has extremely variable flows during the sea-

sons and tends to have blooms of blue–green algae in summer.

The neural network structures applied to the four freshwaters have been defined in accordance with the data available from water quality and plankton measurements. The input layers consider measured data of control factors for algal growth, while the output layers represent cell numbers or biomass data for the ten dominant algae species during the time of
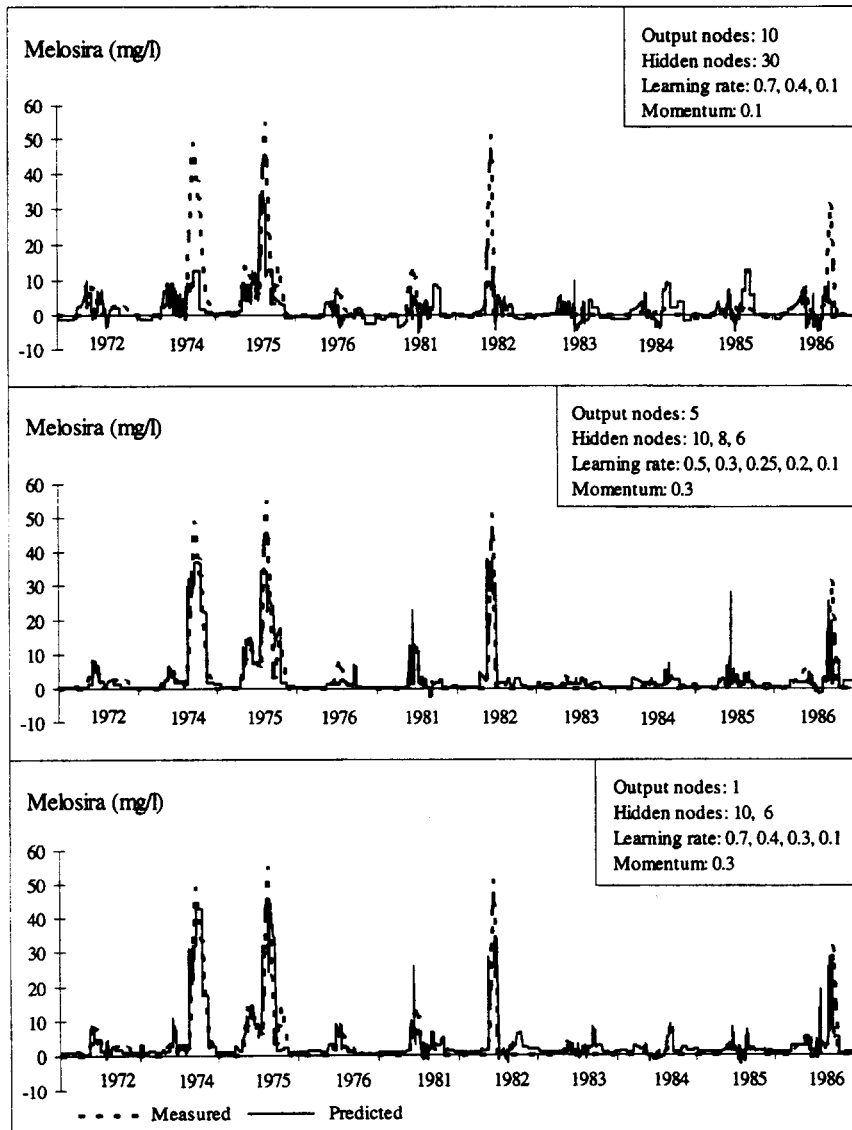
Lake Biwa : Neural Network Prediction

Fig. 9. Validation of prediction results for *Melosira granulata* in Lake Biwa (Japan) by different structures of the neural network model.

investigation. The algal composition of the output layers differs between the four freshwater systems. The more complete and accurate the input layers reflect the control factors accordingly to Fig. 1, the better the network is expected to fit observed output data during training and validation. While all input layers of the four neural network models use data on

limiting nutrients, water temperature and light conditions, density data of the zooplankton groups *Rotifera*, *Cladocera* and *Copepoda* were available only for Lake Kasumigaura (see Fig. 2). In the input layer of the neural network model for River Darling (see Fig. 5) water flow is considered additionally as a very import characteristic of conditions in rivers.

Fig. 10. Validation of training results for *Melosira granulata* in Lake Tuusulanjaervi (Finland) by different structures of the neural network model.

4. Validation of the neural network models

The neural network model for the Lake Kasumi-gaura (see Fig. 2) was trained with measured input and output data from 8 years. For the validation of model predictions, data of the two independent years 1986 and 1993 have been used. In Figs. 6 and 7 the training and prediction results are represented for the

blue green algae *Microcystis*, *Oscilatoria* and *Phormidium* in Lake Kasumigaura. Whilst the training data closely matched, this did not apply to the predictions. The timing and magnitude of an observed bloom of *Microcystis* in 1986 has been predicted well (see Fig. 7). In 1993 *Microcystis* hasn't been observed and only negligible dynamics have been predicted. The observed peak of *Oscillatoria* in
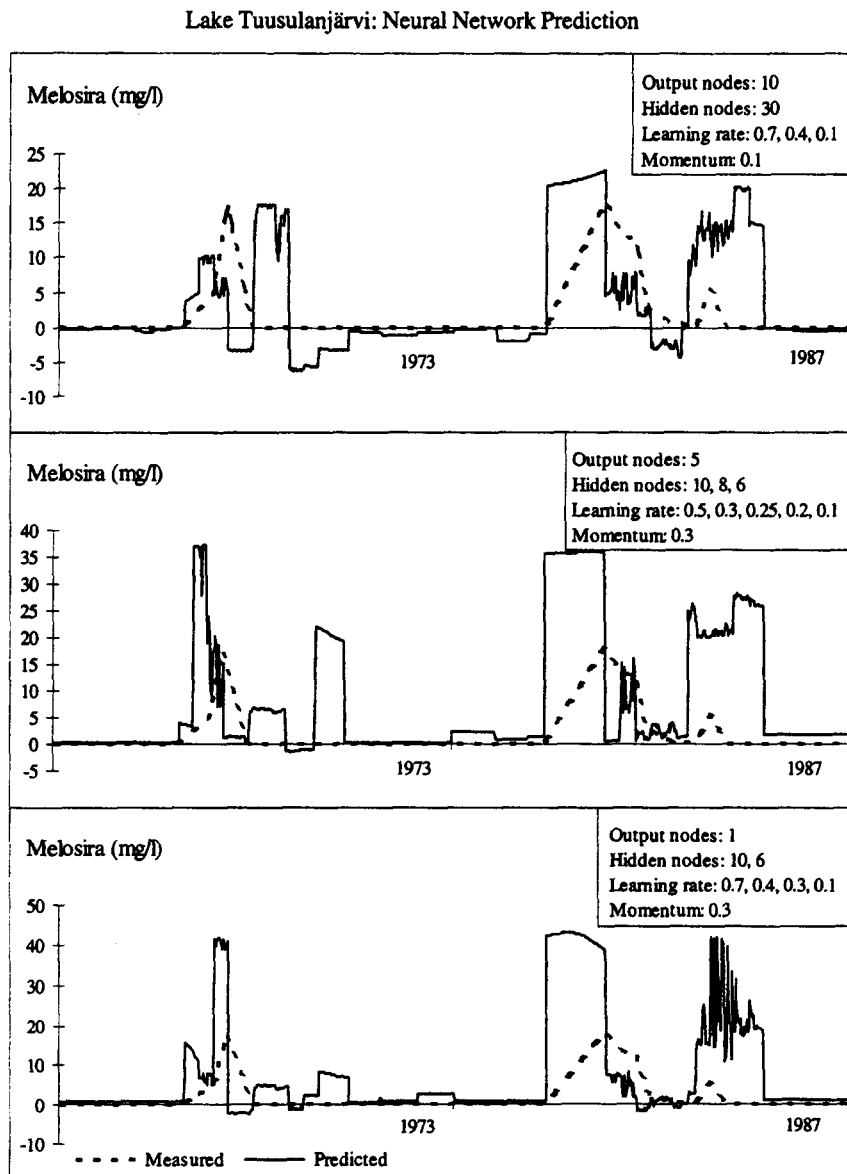
Lake Tuusulanjärvi: Neural Network Prediction

Fig. 11. Validation of prediction results for *Melosira granulata* in Lake Tuusulanjaervi (Finland) by different structures of the neural network model.

the late spring of 1986 is predicted by the model with some time delay but well corresponding magnitude. But in 1993 the three large peaks of *Oscillatoria* observed in summer and autumn haven't been predicted whilst the small spring peak is overestimated, corresponding with the observed summer peaks. The years 1986 and 1993 have been chosen for validation because a succession from *Microcystis* to *Oscillatoria* in the late eighties had been observed

in Lake Kasumigaura (Takamura et al., 1992). Regardless of timing of the spring peak of *Oscillatoria* in 1993, the model predicts the species succession qualitatively well. The predictions of dynamics of *Phormidium* are reasonable in timing and magnitudes for 1993 but nonrealistic for 1986.

The neural network model for the Lake Biwa (see Fig. 3) was trained by time-series data of six years and validated by data of the independent years 1986

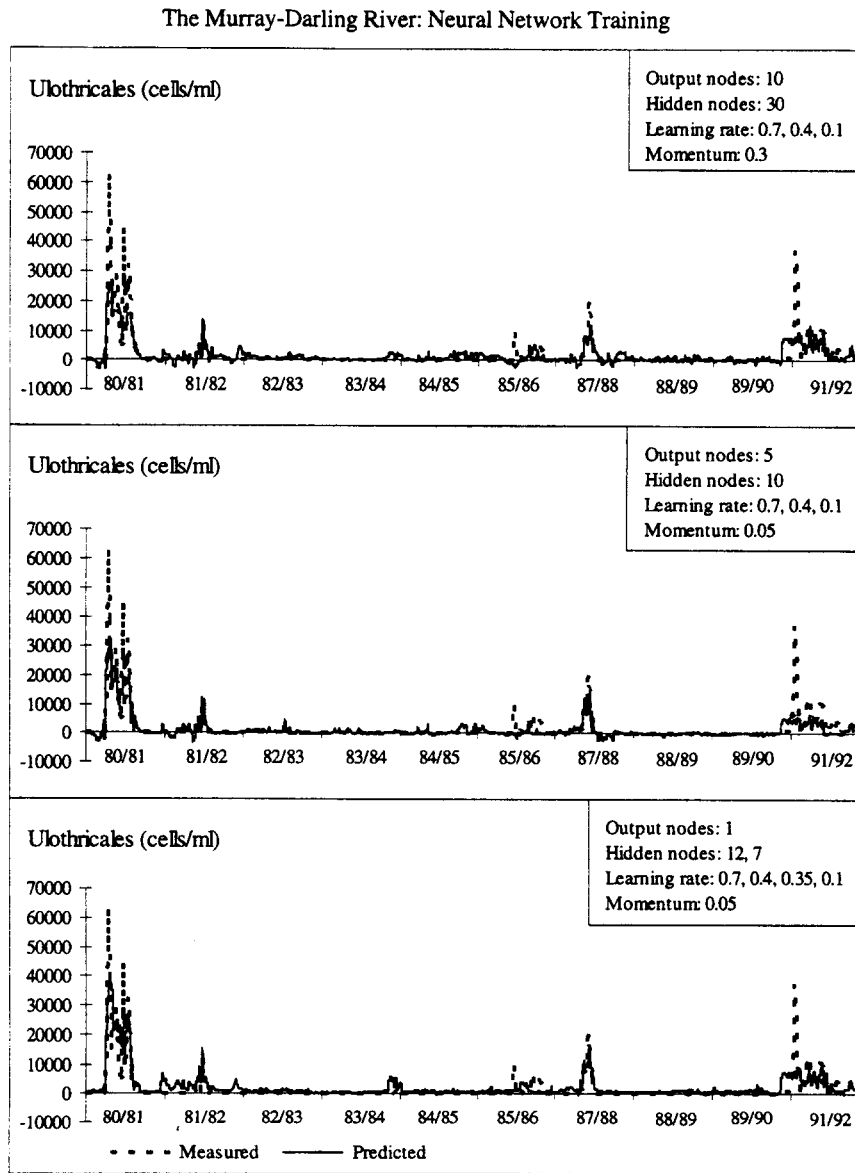The Murray-Darling River: Neural Network Training

Fig. 12. Validation of training results for *Ulothricales* in the River Darling (Australia) by different structures of the neural network model.

and 1987. The results show that predictions for the diatom *Melosira granulata* have been improved by changed numbers of output nodes (see Fig. 9). After training with one output node the model predicted the observed peaks of *Melosira granulata* in 1986 and 1987 the best (see Fig. 8). Similar findings appeared with predictions of *Melosira granulata* by the neural network model for the Lake Tuusulan-jaervi (Fig. 4).

After neural network training with measured input and output data for ten years (see Fig. 10), predictions have been made using independent input data of the years 1973 and 1987 (see Fig. 11). After training the model with different numbers of output nodes good results have been found for predicting of *Melosira granulata* using 10 output nodes (see Fig. 11).

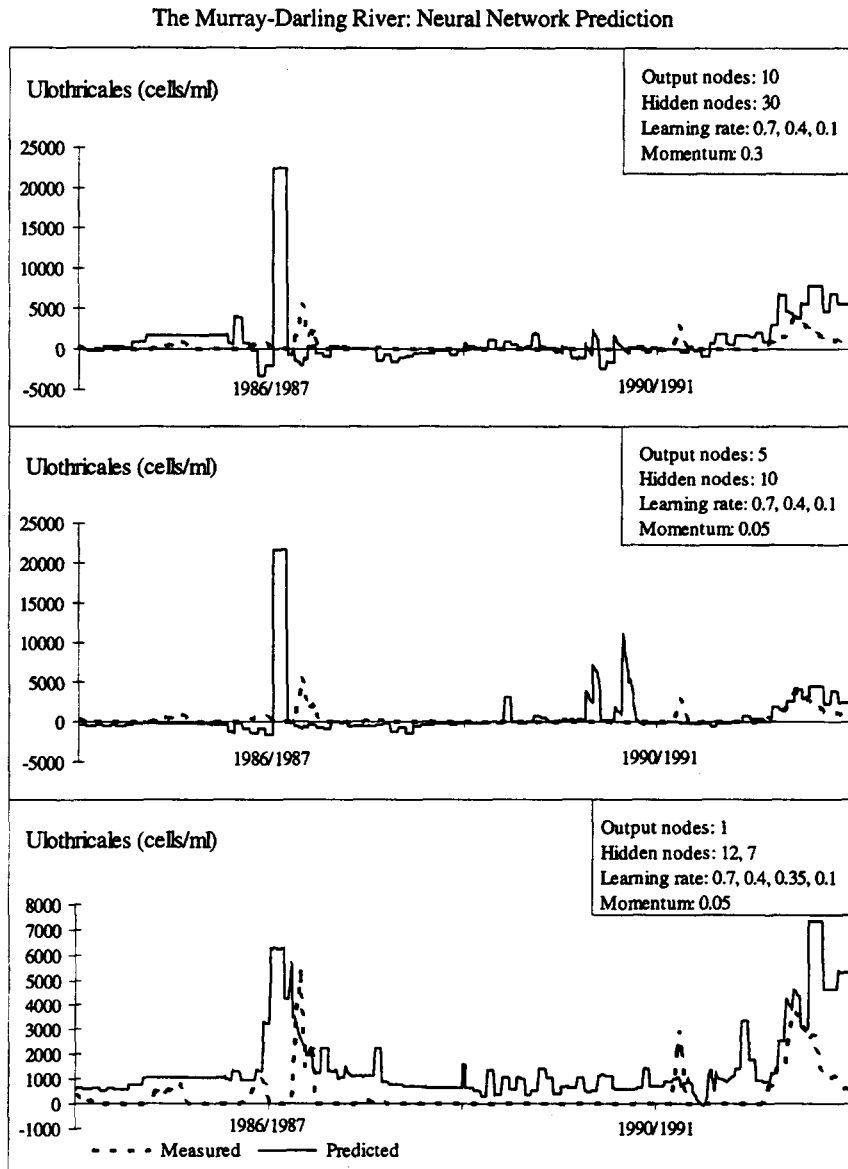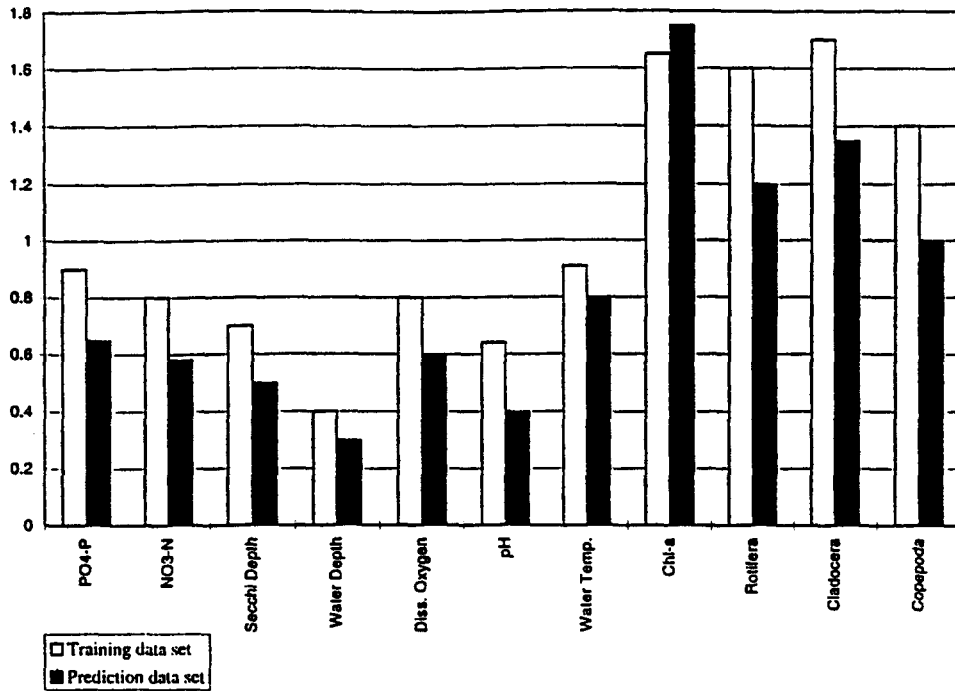The neural network model for the River Darling

Fig. 13. Validation of prediction results for *Ulothricales* in the River Darling (Australia) by different structures of the neural network model.

Lake Kasumigaura: Sensitivity (%) of *Microcystis aeruginosa* for input changes by 10%

☐ Training data set
■ Prediction data set

Lake Biwa: Sensitivity (%) of *Melosira granulata* for input changes by 10%
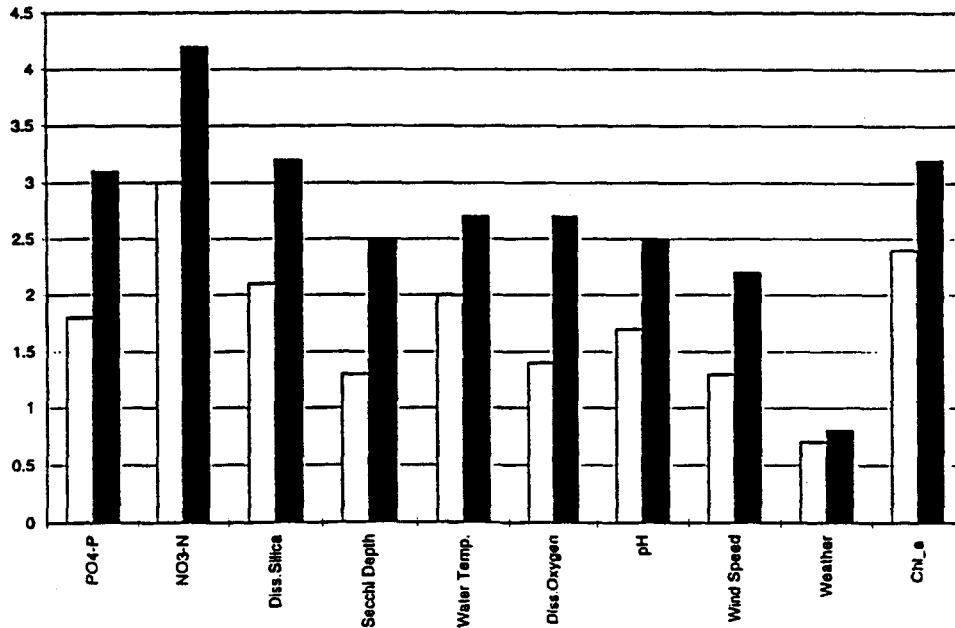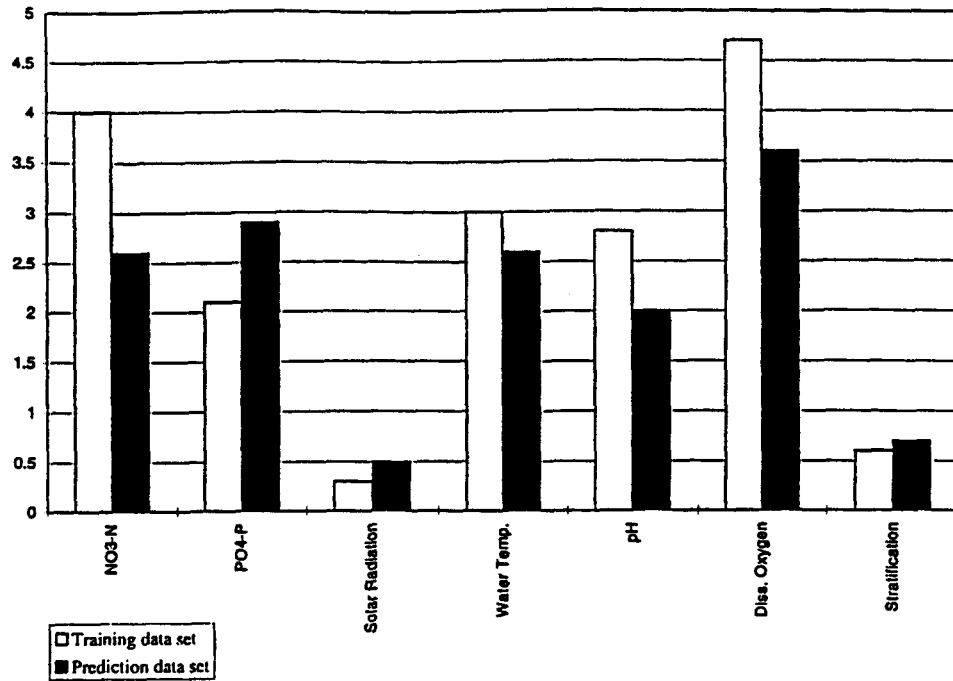

Fig. 14. Average sensitivity of *Microcystis aeruginosa* (Lake Kasumigaura) and *Melosira granulata* (Lake Biwa) related to changes of inputs by 10%.

Lake Tuusulanjaervi: Sensitivity (%) of *Melosira granulata* for input changes by 10%

☐ Training data set
■ Prediction data set

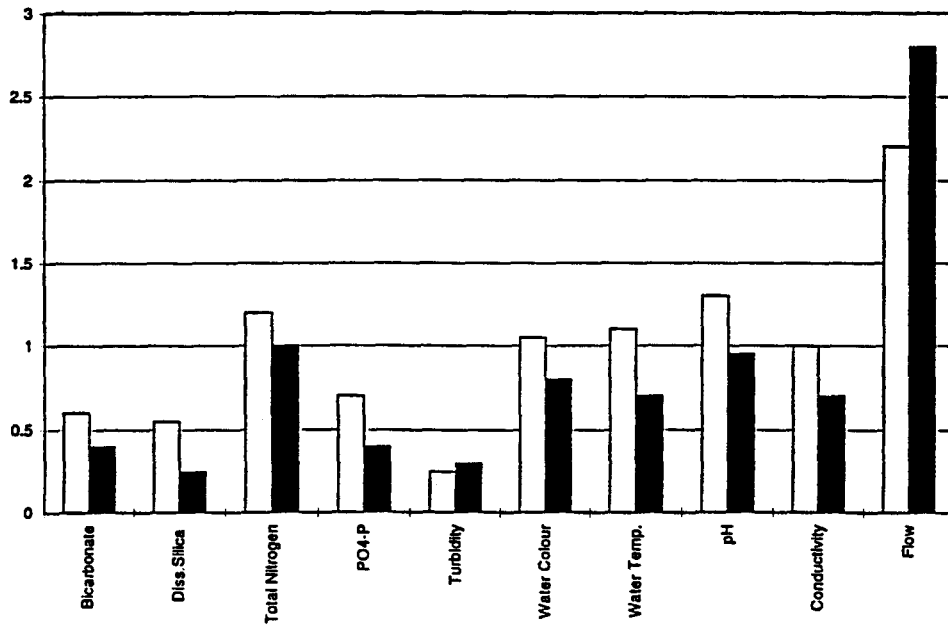**River Darling: Sensitivity (%) of *Ulothricales* for input changes by 10%**

Fig. 15. Average sensitivity of *Melosira granulata* (Lake Tuusulanjaervi) and *Ulothricales* (River Darling) related to changes of inputs by 10%.

(Fig. 5) was trained using limnological time series of ten years (see Fig. 12). Using independent data of the years 1986/87 and 1990/91, the best prediction result was found for the filamentous green algae *Ulothricales*. After experiments with different network structures, the observed summer peak in 1987 and the autumn peak in 1992 have been predicted well choosing one output node and two hidden layers (see Fig. 13).

Interesting insights into internal weightings of the inputs in a trained neural network can be obtained by sensitivity analyses. The input sensitivities of algae predicted for the four freshwater systems are represented in Figs. 14 and 15. The sensitivity analysis for the Lake Kasumigaura (Fig. 14, above) shows that chlorophyll-a (as a cumulative feedback factor for the whole algae biomass) determines most the dynamics of *Microcystis*. It is interesting to see that density data of the zooplankton groups *Rotifera*, *Cladocera* and *Copepodes* have a higher weighting as forcing functions for *Microcystis* than the nutrient components orthophosphate and nitrate. But the grazing of *Microcystis* by zooplankton is not expected to be intensive as they tend to form big cell colonies and produce toxins. Therefore, this result seems to reflect the indirect effect of competition advantages of *Microcystis* due to preferred grazing of non-toxic algae by zooplankton.

The sensitivity analysis for Lake Biwa (Fig. 14, below) indicates that the diatom *Melosira granulata* is mainly driven by nutrients including silica and — as expected — by the feed-back factor chlorophyll-a. The input sensitivity of the diatom *Melosira granulata* in Lake Tuusulanjaervi (Fig. 15, above) gives dissolved oxygen a high weighting although oxygen is not the real driving variable for algal growth. This result may be caused by the stronger annual dynamics of the oxygen data compared with nutrients data. There is no clear explanation for the low weighting of solar radiation at the water surface and the indicator of thermal stratification of the water body during summer. An interesting result provides the sensitivity analysis for *Ulothricales* in the River Darling (Fig. 15, below). It proves the importance of flow as control factor for the growth of algae in rivers.

5. Conclusions

This work presented a study on the application of artificial neural networks to the task of modeling and prediction of algal blooms. A set of four freshwater systems was evaluated, three lakes and a river. The lakes were of different characteristics including a variety of nutrient levels, light and temperature conditions, depth and water retention time. The river presented a unique application of the approach in a water system with extremely short retention time.

A neural network structure was developed for each system where the availability of time-series data dictated to some extent the neural network design. Results showed that the neural network approach is a successful method of modeling such complex and nonlinear phenomena as algal blooms in freshwater systems with different environmental conditions.

The validation of the neural network model using independent data not included in the training procedure showed good agreement for predictions of the occurrence of specific algae species in all four freshwater systems.

In the case of Lake Kasumigaura, the model validation has proven that artificial neural networks are able to predict timing, magnitudes and succession of several algal species realistically, such as *Microcystis, Oscillatoria* and *Phormidium*.

Using the interconnection weights as a guide, a sensitivity analysis of the model performance under variations in the input data magnitudes was conducted. The results provide a means of defining the primary components driving the dynamics of algae species. Additionally, the number of output variables included in each of the models was varied to identify the variables that play a major role in algae growth. This concept is complementary to traditional approaches that require a large number of system characteristics to be estimated when data is unavailable.

In conclusion the work supports the concept that the neural network approach can be successful for modeling and prediction of very complex and nonlinear ecological phenomena such as algal blooms. As a complement to traditional modelling techniques, the neural network approach was shown to be useful for identification of the primary driving mechanisms in the system dynamics.

To improve the predictive validity of the neural network model current work includes: (1) the optimization of neural network training using genetic algorithms and modified data structures, (2) the utilization of not only time-series data but also ecological knowledge represented by fuzzy rules for neural

network training, (3) the extension of the forecast time scale to enable decision makers to circumvent an expected algal bloom. Furthermore, it is tried to extract knowledge from validated neural network models about natural control mechanism of algal species in specific freshwater systems.

Acknowledgements

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