Korean J. Ecol. 28(6): 405~415, 2005

〈 **Review** 〉

Machine Learning Application to the Korean Freshwater Ecosystems

Jeong, Kwang-Seuk, Dong-Kyun Kim, Tae-Soo Chon and Gea-Jae Joo*
Department of Biology, Pusan National University, Busan 609-735, Korea

ABSTRACT: This paper considers the advantage of Machine Learning (ML) implemented to freshwater ecosystem research. Currently, many studies have been carried out to find the patterns of environmental impact on dynamics of communities in aquatic ecosystems. Ecological models popularly adapted by many researchers have been a means of information processing in dealing with dynamics in various ecosystems. The up-to-date trend in ecological modelling partially turns to the application of ML to explain specific ecological events in complex ecosystems and to overcome the necessity of complicated data manipulation. This paper briefly introduces ML techniques applied to freshwater ecosystems in Korea. The manuscript provides promising information for the ecologists who utilize ML for elucidating complex ecological patterns and undertaking modelling of spatial and temporal dynamics of communities.

Key words: Artificial neural networks, Ecological models, Evolutionary computation, Fuzzy logic, Interdisciplinary research, Korean freshwater ecosystems, Machine learning

INTRODUCTION

The goal of building a computational model is to produce a system that could quantitatively reveal underlying properties (characteristics and relationships) of interest in the target systems. The ability to simulate characteristics of a system is particularly important when it is difficult or dangerous to collect sufficient data from the target, or when the system is so complex that it may not be feasible to measure every important feature at an appropriate scale.

There are two significant points that should be considered while ecological models are being constructed: (1) quality of data sets providing comprehensive information on the target system, and (2) selection of the model architecture that is suitable for application to the target system. The first point is easily overcome because, at present, it is possible to use high resolution detection devices or other innovative technological methods to obtain high quality datasets. Many types of ecological datasets are available throughout the world, for example, abundance of biological entities, quantified characteristics (e.g. movement, LC_{50} data), genetic sequences, and satellite images. These would be useful for finding important relationships existing among variables in ecosystem dynamics. The second point is a kind of "limiting factor" for developing reliable simulation tools (Blanco *et al.* 2000). When the simulation technique includes good capacity of explanatory and predicting ability, it can support a sequence of useful information about the target system.

Quantifying ecosystem dynamics can be accomplished via experiments (e.g., Schindler 1974, Schindler 1977, Lund and Reynolds 1982), long-term descriptive studies (e.g., Edmonson 1969, McQueen *et al.* 1989), or modeling of descriptive data sets (e.g., Willing and Lyons 1998). An ecosystem is one of the most complicated systems in the world (see Odum 1983, Fielding 1999) because the system consists of a variety of forcing functions, state variables, and their complicated interactions among them. To cope with the complexity residing in ecosystem data in quantification point of view, it is strongly requested to adopt adequate technologies to handle the complexity of ecological data set (Recknagel 1997, Jeong *et al.* 2003b).

A variety of linear, deductive-deterministic or statistical approaches have been used to identify important dynamics in ecosystems, although various authors have criticized these approaches because ecological relationships are rarely linear (Lek *et al.* 1996).

South Korean freshwater ecosystems are known as one of the most modified systems, mainly because of heterogeneous rainfall distribution along with seasons (Park *et al.* 2002). The importance of water resources in the country has increased the request of alteration of freshwater systems in morphology, resulting in regulated river systems or large reservoirs (Joo *et al.* 1997). It may be difficult for researchers to apply well-established ecological models to the Korean freshwater systems, because those systems have been highly disturbed by industrial development in Korea. The increase of uncertainty due to disturbances could be possibly solved by an alternative paradigm of non-linear modelling such as Machine Learning (ML). This technique has been extensively used for prediction and patterning of input-output relationships in engineering

* Corresponding author; Phone: +82-51-510-2258, e-mail: gjjoo@pusan.ac.kr

(Zurada 1992, Haykin 1994).

In this paper we briefly review contribution of ecological models for the interpretation of complexity in ecosystems, and focus on the recent development of ML techniques implemented to freshwater ecosystems in South Korea. There are numerous papers regarding advantages and disadvantages of ML when it is applied to freshwater ecosystems (e.g., Recknagel 2001, Recknagel 2003a, 2003b). The main purpose of this paper is as the following: (1) to reveal the possible consequence of ML application in Korean freshwater ecosystems which are unique in the sense that the system were exceptionally disturbed due to rapid development in industry, and (2) to provide perspectives on the future utilization of ML techniques.

SIGNIFICANT ADVANTAGES OF MACHINE LEARNING IN ECOLOGICAL MODELLING

Machine Learning enables computers to gather information from a given data set empirically, as a subset of Artificial Intelligence (AI) (Fielding 1999). The major purpose of ecological models is usually oriented to explain the system dynamics as well as predict or discover patterns, so that the information discovery from the data set would be much helpful in this point of view. Machine Learning could be differentiated from the conventional techniques used for analyzing ecological data sets, such as statistical methods, and deterministic and stochastic methods in two criteria: (1) capacity of dealing with non-linearity, and (2) way of reasoning. The former can be mainly thought as ML against statistics, and the latter is for the conventional models and ML.

Statistical methods that have been popularly adapted in ecological researches usually assume the data sets are normal distribution. Park *et al.* (2005) presented intensive review on the algorithms in ecological modelling, and summarized three general steps for statistical approaches: (1) clustering samples into some groups based on the biological data set, (2) relating groups with environmental data, and (3) using reverse process whereby regression techniques use environmental variables to predict the biological communities. Although the statistical models were successful to analyze the dynamics in ecosystems, the models were mainly applied to linear data. However, biological properties as well as environmental factors in ecosystems are not expressed in the linear manner in fields. For instance, Gevrey *et al.* (2003) emphasized two fatal flaws of regression models in analyzing field data: i.e., incapacity to take into account non-linear relationships between dependent and independent variables, and inability to explain the characteristics of ecosystem dynamics from the model. Olden *et al.* (2004) supported the significance of ML technique in quantifying variables' importance. Perhaps statistical methods might be adequate to find overall patterns of ecological systems, but the non-linear behavior of ecosystems could not be efficiently reviewed by conventional linear methods. Most algorithms in ML contain the models to deal with non-linear data based on adaptive or heuristic methods.

Machine Learning could be differently characterized with conventional deterministic models. For instance, population dynamics in food chain could be addressed by non-linear dynamics (Hastings and Powell 1991). Population dynamics are usually expressed deterministically based on pre-determined models (e.g., Lotka-Voltera equation). Although the system behavior could be exactly expressed according to the proposed parameters and variables provided in the equations, the capacity of deterministic models are restricted in the sense that dynamics of populations are somewhat limited to the original framework of the proposed equations. The techniques in ML, however, are more flexible in accommodating the variations in population dynamics. Instead of pre-determination in the equations in the deterministic models, ML usually receives the input-output data to determine quantitative relationship gradually by adjusting weights existing in the computation nodes (Lek and Guégan 1999, Recknagel 2001). ML is somewhat similar to the stochastic models where noise is used for probabilistic determination of systems. The techniques in ML are usually operated with noise as well. In this case, however, the calculation procedure is carried out in an adaptive manner, while the noise term in the stochastic models is not necessarily used for adaptive operation. Additionally, the stochastic models are limited in the sense that the proposed equations are usually difficult to find exact solutions due to complexity in ecological data sets. Machine Learning, however, is more flexible in dealing with problems, since the solutions (or approximations) could be revealed through adaptive processes.

The second significance of "way of reasoning" is based on the construction of model architecture. Fielding (1999) suggested two categories such as "deductive" and "inductive" reasoning. The first is that an ecological model would be built on knowledge-based assumption. When error terms are considered in this type of models, much flexible explanation of ecosystem dynamics would be available. Rather, inductive reasoning results in a model whose structure is constructed empirically from the given data sets. Most of mathematical models or expert systems are involved in the deductive reasoning, because they use "well-known" information to construct model architecture. Despite the fact that deductive-deterministic models conveyed a series of useful information to ecosystem researchers (see Pielou 1977, Renshaw 1991), newly discovered ecosystems or those with lack of knowledge would not provide sufficient information to construct adequate models. Because ML uses data itself to build ecological models, it is not much requested to find inter- or intra-relationships among environments and biological entities.

Nowadays, ML is recognized as an innovative and promising methodology for ecological modelling because of above major differences. It is possible to overcome non-linear characteristics of ecosystems, and could be utilized in knowledge-poor disciplines. Algorithms consisting of ML enable researchers to mine, forecast and analyze environmental impacts and community dynamics, covering causality of the changes and community-environment relationships (e.g., Maier *et al.* 2001b, Olden *et al.* 2004). For more detailed methods on ML, readers are recommended to consult Fielding (1999) and Park *et al.* (2005).

SOME MAJOR ALGORITHMS OF MACHINE LEARNING

Artificial Neural Networks (ANNs)

The ANN was inspired by an animal's nerve system, and was usually mentioned as "connectionism." The basic architecture of an ANN is via the linkage of McCulloch and Pitts (M-P, McCulloch and Pitts 1943) neurons. The M-P neurons can be combined to build a Multi-Layer Perceptron (MLP), generally called Feed-Forward Networks. The Backpropagation (BP) algorithm could be utilized on MLP to increase the network efficiency for training (Rumelhart *et al.* 1986).

There are diverse types of ANN models which were mainly derived from the MLP networks. The MLP model described above is called "supervised networks" because the network training is implemented through the supervision of desired values. In the other case, there are "unsupervised networks" which do not require the desired values. Self-Organizing Map (SOM) based on Kohonen network (Kohonen 1982, 2001) has been implemented to community patterning (Chon *et al.* 1996, Chon *et al.* 2000a, 2000b, 2000c, Chon *et al.* 2001). Relevant architecture can be selected according to the condition of ecological data and the purpose of modelling.

Evolutionary Computation (EC)

Evolutionary Computation is a discipline that makes use of principles from natural evolution to evolve solutions to complex computational problems (Whigham and Fogel 2003). Evolutionary algorithm comprises heritable variation and selection. The basic evolutionary algorithm consists of generational adaptation of initial population, provision of fitness function and selection, reproduction, and maintenance of population size. These techniques have been applied to such diverse areas as optimization, inductive modelling, constructing characteristic features of biological systems and as theoretical models of social and population-based interactions.

Evolutionary Computation is collectively used to describe computation system based on natural process of evolution, and a variety of algorithm has been proposed under the topic of evolutionary algorithm: Genetic Algorithm (GA), Evolutionary Programming, Evolution Strategies, Genetic Programming (GP), etc.

Genetic Algorithm translates data into a set of chromosomes (e.g. strings consists of 0 and 1 or bits), and the computationally embodied "natural selection" changes the structure of each chromosome. The operators adopted in the process are crossover, mutation and so on, which are seen in the evolution of biological properties. According to the fitness of the chromosomes, those that are superior can enter the next generation and they will again experience other changes of chromosome structure through the operators. Hopefully, some of the surviving offspring will produce even better offspring, and if the computation is continued long enough, it is possible to search a larger space to find an optimal solution (Fielding 1999).

Fuzzy Logics (FL)

Fuzzy Logic is one of the computation processes developed in the 1960's by Zadeh (1965). It is based on the idea of association in the human mind. FL has the possibility to handle uncertainty. It is particularly useful for the representation of vague expert knowledge as well as imprecise information (Salski 2003). Usually FL algorithms were adopted to find significant patterns in ecological dynamics (see Krysanova and Haberlandt 2002).

THE FRESHWATER ECOSYSTEMS AND MACHINE LEARNING

In addition to the major Machine Learning techniques discussed in previous section, there are various techniques such as Case-Based Reasoning (CBR), Cellular Automata etc. in the field of ML (see Fielding 1999). Each technique has numerous subdivided methods. It is important to know which method is suitable for the particular ecosystem being investigated. The followings can be regarded as classification concepts for selecting suitable techniques.

1. What will be done by the model?: classification, patterning, prediction, etc.;
2. What types of data will be utilized?: abundance, quantified characters, etc.;
3. Which process is important for?: finding the best solution, parameters or constants, getting simulation entities, rule-sets, etc.;
4. How will the ecosystems be elucidated?: sensitivity analysis, additional statistical approaches, etc.;

In general, Artificial Neural Networks are popular for forecasting, because this type of method has been suitable for short-term prediction for the variables whose data are complex to analyze (e.g., Yao and Liu 2001, Park *et al.* 2003a, Almasri and Kaluarachchi 2005, Ortín *et al.* 2005). They are also useful for knowledge discovery (e.g., Recknagel 1997, Jeong *et al.* 2003b). Recently, Evolutionary Computation methods are also proving satisfactory for prediction even though they have been generally utilized to tune constants or for finding the optimal solutions (e.g., D'heygere *et al.* 2003, Cao *et al.* 2005). Fuzzy Logic has been powerful for pattern recognition or classification (e.g., Clark and Richards 2002, Lekka *et al.* 2004). The combination of those techniques has been developed to deal with the increase in complexity in ecological data.

For pattern recognition and prediction, diverse architecture of ML has been utilized in the past two decades (Table 1). Its applicability was validated by spatial heterogeneity as well as time-series dynamics. Multi-species or multi-variables have been successfully manipulated through modelling. Target biological characteristics were environmental variations (e.g., Karul *et al.* 1998; Jeong *et al.* 2001, Walter *et al.* 2001), fishes (e.g., Brosse *et al.* 1999, Laë *et al.* 1999, Brosse *et al.* 2001), macroinvertebrates (e.g., Céréghino *et al.* 2001, Hoang *et al.* 2001), suspended phytoplankton and zooplankton species (e.g., Recknagel *et al.* 1997, Maier *et al.* 1998, Recknagel *et al.* 1998, Wilson and Recknagel 2001). Among ML choices, ANNs have been the most popular in studying freshwater ecosystems. Evolutionary Computation was frequently utilized to develop approximation models for plankton assemblage. Compared with ANN models, FL models were rarely applied even though classification capacity is well known. Hybrid architectures such as neuro-fuzzy network (Maier *et al.* 2001b) or evolving neural networks (Yao and Liu, 2001) have presented good applicability to ecological data sets as well. Some papers convey useful information with respect to comparison between conventional modelling techniques and ML, and authors are referred to consult the

Table 1. Important scientific papers with respect to the application of Machine Learning to freshwater ecological data sets

Topics		Applied algorithms			
		Artificial neural network	Evolutionary computation	Fuzzy logic	Hybrid algorithms
Environmental researches		Karul *et al.* (1998), Moatar *et al.* (1999), Schleiter *et al.* (1999), Walter *et al.* (2001), Huanga and Foo (2002), Lu and Lo (2002), Aitkenhead *et al.* (2003), Almasri and Kaluarachchi (2005)	Bonesi *et al.* (2002), Yilmaz (2005)	Haberlandt *et al.* (2002), Han *et al.* (2002), Lekka *et al.* (2004)	
Ecological researches	Fish	Aurelle *et al.* (1999), Brosse *et al.* (1999), Laë *et al.* (1999), Brosse and Lek (2000), Giraudel *et al.* (2000), Brosse *et al.* (2001), Reyjol *et al.* (2001), Ibarra *et al.* (2003)			
	Macroinvertebrates	Chon *et al.* (1996), Chon *et al* (2000b), Chon *et al.* (2000c), Céréghino *et al.* (2001), Chon *et al.* (2001), Hoang *et al.* (2001), Obach *et al.* (2001), Park *et al.* (2003a), Park *et al.* (2003b), Park *et al.* (2004)	D'heygere *et al.* (2003)		
	Plankton	Recknagel (1997), Recknagel *et al.* (1997), Recknagel *et al.* (1998), Maier *et al.* (1998), Scardi and Harding Jr. (1999), Jeong *et al.* (2001), Maier *et al.* (2001a), Scardi (2001), Wei *et al.* (2001), Jeong *et al.* (2003b), Jeong *et al.* (2003c), Millie *et al.* (2005)	Bobbin and Recknagel (2001), Wilson and Recknagel (2001), Whigham and Recknagel (2001b), Recknagel (2003a), Cao *et al.* (2005), Cao *et al.* (2006)	Marsili-Libelli (2004)	Maier *et al.* (2001b), Yao and Liu (2001)
	Others	Giraudel and Lek (2001), Werner and Obach (2001), Gevrey *et al.* (2003), Olden *et al.* (2004), Underwood *et al.* (2004), Ortín *et al.* (2005), Santiago (2005)	Džeroski (2001), Whigham and Recknagel (2001a), Morrall (2003), Whigham and Fogel (2003)	Salski (2003)	Recknagel (2001)

followings: Brosse and Lek (2000), Giraudel and Lek (2001), Walter *et al.* (2001), Gevrey *et al.* (2003), and Olden *et al.* (2004).

There are many types of neural network models. MLP with the BP algorithm has been frequently used for time-series prediction as well as pattern analysis as stated before. However, other ANNs networks are also gaining in popularity nowadays. Rapid improvement in computer performance enables sophisticated approaches to pattering ecological community data through complex networks (see Chon *et al.* 1996). Recently the Self-Organizing Map (SOM) has been increasingly utilized for pattern recognition (Giraudel and Lek 2001, Park *et al.* 2003b, Park *et al.* 2004). In this case, rather than using environmental parameters as input, the biological features (i.e. population abundance of each species) were placed at the input layer, and the clusters on the map were evaluated according to the environmental conditions.

Not only the ANNs, but other models such as Evolutionary Computation and Fuzzy Logics have been implemented to ecosystem study. Evolutionary Computation place the major focus on searching for the best solution for the target system as an equation or a set of rules. Especially, it was utilized as the parameter optimizer for developing models (Whigham and Recknagel 2001a, D'heygere *et al.* 2003) or as rule or equation discovery mechanism (Bobbin and Recknagel 2001), regarding ecosystem characterization. Evolutionary Computation took advantages of simple equation development (e.g. Jeong *et al.* 2003c). However, the number of application examples was relatively small in freshwater systems, compared with other ecosystems. The combination of FL and ANN would be promising, because the FL reduces the data dimension non-linearly while the efficiency of ANN training will be increased with reduction of dimension (e.g. Giraudel *et al.* 2000). Evolutionary Computation is newer concepts compared with ANN, and is still under improvement.

At present, model algorithms are experimentally approached through the combination of two or more algorithms (e.g. Evolving Neural Network whose neural network architecture is evolved by the Genetic Algorithm) (e.g., Blanco *et al.* 2000). Ecosystems are nonlinear phenomena, and the conventional methods applicable to linear data are limited in dealing with complexity residing in ecological data. Efficient use of ML technology may enable to succinctly elucidate complex systems behavior presented in ecological data.

APPLICATION OF MACHINE LEARNING TO KOREAN FRESHWATER SYSTEMS

A literature survey was conducted to evaluate the awareness and applicability of Machine Learning in freshwater ecosystem studies in S. Korea. Searching for the manuscripts was limited at the journals that have been qualified by the Korean Research Foundation. On-line

Table 2. The list of scientific researches reported in the Korean journals regarding the application of Machine Learning to freshwater systems

Research area	Papers		
Hydrology and hydraulics	Kang *et al.* (1992)	Lee and Lee (1996)	Oh and Sonu (1996)
	Park *et al.* (1997)	Kim *et al.* (1998)	Shim *et al.* (1998)
	Kim *et al.* (1999)	Shim and Kim (1999)	Shin and Park (1999a)
	Shin and Park (1999b)	Ahn *et al.* (2000a)	Ahn *et al.* (2000b)
	Ha *et al.* (2000)	Kim (2000a)	Kim (2000b)
	Kim and Salas (2000)	Lee *et al.* (2000a)	Lee *et al.* (2000b)
	Ahn and Chun (2001)	Jung *et al.* (2001)	Lee *et al.* (2001)
	Lee and Lee (2001)	Ahn *et al.* (2002)	Kim *et al.* (2002)
	La *et al.* (2002)	Rhee *et al.* (2002)	Cho and Lee (2003)
	Jeong *et al.* (2003a)	Kim (2003)	Lee and Park (2003)
	Lim (2003)	Park and Hwang (2003)	Son and Lee (2003)
	Lee *et al.* (2004)	Lee and Jeong (2004)	Lee and Kim (2004)
	Yoon and Seo (2004)	Kim *et al.* (2005)	
Water quality	Han and Kim (1999)	Cho (2000)	An *et al.* (2001)
	Shim *et al.* (2001)	Jang *et al.* (2002)	Jeong and Lee (2002)
	Oh *et al.* (2002)	Kim and Park (2003)	Park and Ha (2003)
	Cho *et al.* (2004)	Park (2004)	
Ecology	Chon *et al.* (2000a)	Kwak *et al.* (2000)	Kwak *et al.* (2003)

accessible journals from Korean studies Information Service System (KISS) were explored as well. Among enormous papers with Machine Learning algorithms in various scientific fields, fifty-two papers have been related to ML used for analyzing river or reservoir systems in Korea (Table 2).

Kang *et al.* (1992) used neural network model for predicting river discharge. The technique in ML has been increasingly utilized since the late 1990's after their approach. In many cases, Artificial Neural Networks were used for short-term prediction. Genetic Algorithm was utilized to achieve parameter estimations (e.g., Park *et al.* 1997, Jung *et al.* 2001, Lee and Lee 2001, Shim *et al.* 2001), while Fuzzy Logic was not adapted as frequent as former two algorithms (e.g., Lee and Lee 1996, Kim *et al.* 2002). Hybrid architecture such as Evolving Neural Networks (e.g., Lee *et al.* 2001) or Neuro-Fuzzy set with Markov chain (e.g., La *et al.* 2002) was applied to forecast hydrological variations. Most of the models, however, were adapted to hydrology, especially runoff prediction. The techniques in ML have been not much frequently used as shown in hydrological studies. Eleven papers were published to present the applicability of ML to water quality. Only 3 papers have dealt with community data set in ML modelling (Chon *et al.* 2000a, Kwak *et al.* 2000, Kwak *et al.* 2003). In their studies, Multi-Layer Perceptron with Back-Propagation algorithms has been used. In other similar international practices (e.g., Smith and Eli 1995, Konda and Deo 1998, Jain *et al.* 1999), the applicability of ANN to hydrodynamics was satisfactory. Some researches on hydrology and hydraulics published their results for graduate works, however the authors of MS thesis and Ph. D. dissertation were not involved in the literature survey in the present review.

In the international journals, compared with the domestics, relatively small number of research papers have been published for the application of ML to freshwater systems in S. Korea. When the search engines provided by major publication companies (e.g., Elsevier, Springer-Verlag, Wiley Interscience, Blackwell Science, etc.) were explored, results from Korean freshwater systems could be found such as Hydrological responses (e.g., Jeong and Kim 2005, Paik *et al.* 2005), river water quality prediction and management (e.g., Lee *et al.* 1997, Cho *et al.* 2004a, Cao *et al.* 2005), macroinvertebrates residing in mountainous streams (e.g. Chon *et al.* 1996, Chon *et al.* 2000b), and phytoplankton proliferation in rivers (e.g., Jeong *et al.* 2001, Jeong *et al.* 2003b, 2003c). It is notable that research efforts on the application of ML to ecosystem dynamics in Korea was still not sufficient, even though ML is well recognized as the alternative modelling paradigm internationally (see Table 1 and Table 2).

Two possibilities can be considered to explain the unbalanced development in ML between hydrology and community study in the Korean freshwater ecosystems: (1) insufficient awareness of ML applicability, and (2) unsuitable database of ecological studies for the implementation of machine learning techniques. Lack of awareness was also the case in other countries, while some scientific communities are actively working to encourage the use of ML for ecosystem studies (e.g. The International Society of Ecological Informatics). International communities of ecological informatics have been continuously reporting the applicability of ML on diverse fields in ecology including various habitat conditions, different biological components and ecological scales. Further, the marriage between ecological and computational science should be achieved. This must trigger interdisciplinary research on freshwater system dynamics. Powerful and effective analyzing capacity can be guaranteed.

The second problem, regarding availability of suitable data, is more crucial. The effort of constructing a long-term ecological database can be a solution. From the review of Joo *et al.* (1997), in the example of the Nakdong River system, most freshwater ecological studies were limited to duration of less than two years. Sampling frequency is also sparse. Few researches have been carried out with sampling frequency less than a week. The interval of sampling was monthly in most cases, and even seasonal sampling was undertaken. Additionally, long-time survey would be desired for implementation of machine learning. At the present time, there are some efforts at collecting ecological data on a long time scale (e.g. Lake Soyang, Daechung Reservoir and Nakdong River). Recently, the Korean government has realized the importance of Long-Term Ecological Researches (LTER), and allocated various research grants. Information on spatial heterogeneity of habitat and biological entities has been gradually being revealed on nation-wide (e.g. Jang *et al.* 2001). From such databases collected in an organized way, fruitful ecological properties can be discovered by the ML studies.

When a new technique in ML is applied to ecological systems, the researchers need to assess many situations. Even though ML has powerful applicability to diverse ecosystem datasets, it is necessary to evaluate for which data the machine learning techniques are suitable. The users should consider maturity of tool development, awareness of modelling method, accessibility of software, appropriate match between model and problem, expertise in using the model, data suitability, etc. The appropriate use of techniques in ecological informatics would broaden the scope of ML in predicting and interpreting complex ecological data, thus draw more attention from model users in discovering feasibility of the biologically-inspired algorithms for extracting useful information from complex ecological data sets. We could conjecture that the ML techniques would be one of the key computation methods for assisting prediction, patterning and interpretation of freshwater systems in Korea that have been highly disturbed by extensive industrialization.

CONCLUSION

Machine Learning is a powerful tool for ecological modelling. For prediction and pattern analysis, many researchers in ecological sciences intend to utilize these techniques for analyzing complex data sets. Being accompanied with improvement of computers and algorithms, their application to ecosystems study has been satisfactory. Finding new information or getting results in high resolution could be expected on the global basis. In Korea, however, research on implementation to community data is relatively not sufficient, while the techniques have been extensively used in the field of hydrology and hydraulics. Two possible reasons for this are (1) less scientific awareness of ML and (2) unsuitable preparation of ecological data. The problems of insufficiency in awareness of machine learning and ecological datasets can be solved by interdisciplinary collaborations and long-term ecological research projects.

ACKNOWLEDGEMENT

Authors deeply appreciate Professor Gary D. Grossman in the Warnell School of Forest Resources, University of Georgia, for his encouragement. We also are indebted to Mr. Rich Zamor in the University of Georgia, for his effort to undergo English proofreading when this manuscript was being composed. This study was supported by the Research Fund of Overseas Post-Doc Support from the Korea Research Foundation (Project No. C00264).

LITERATURE CITED

Ahn, S.J. and G.W. Chun. 2001. Forecasting of the flood discharge using radial basis function. J. Korean Soc. Civil Eng. 21: 599-607.

Ahn, S.J., I.S. Yeon and K.I. Kim. 2000a. Rainfall forecasting using neural network. J. Korean Soc. Civil Eng. 20: 711-722.

Ahn, S.J., J.K. Lee, Y.S. Han and G.W. Chun. 2002. Flood runoff analysis using runoff forecasting model. J. Korean Soc. Civil Eng. 22: 311-319.

Ahn, S.J., K.W. Jung and K.I. Kim. 2000b. Forecasting of runoff hydrograph using neural network algorithm. J. Korean Water Res. Assoc. 33: 505-515.

Aitkenhead, M.J., A.J.S. McDonald, J.J. Dawson, G. Couper, R.P. Smart, M. Billett, D. Hope and S. Palmer. 2003. A novel method for training neural networks for time-series prediction in environmental systems. Ecol. Modelling 162: 87-95.

Almasri, M.N. and J.J. Kaluarachchi. 2005. Modular neural networks to predict the nitrate distribution in ground water using the on-ground nitrogen loading and recharge data. Environ. Modelling Software 20: 851-871.

An, S.J., I.S. Yeon, Y.S. Han and J.K. Lee. 2001. Water quality forecasting an Gongju station in Geum River using neural network model. J. Korean Water Res. Assoc. 34: 701-711.

Aurelle, D., S. Lek, J.-L. Giraudel and P. Berrebi. 1999. Microsatellites and artificial neural networks: Tools for the discrimination between natural and hatchery brown trout (*Salmo trutta* L.) in Atlantic populations. Ecol. Modelling 120: 313-324.

Blanco, A., M. Delgado and M.C. Pegalajar. 2000. A genetic algorithm to obtain the optimal recurrent neural network. Int. J. Approx. Reason. 23: 67-83.

Bobbin, J. and F. Reckngael. 2001. Knowledge discovery for prediction and explanation of blue-green algal dynamics in lakes by evolutionary algorithms. Ecol. Modelling 146: 253-262.

Bonesi, L., S. Rushton and D. Macdonald. 2002. The combined effect of environmental factors and neighbouring populations on the distribution and abundance of Aricola terrestris. An approach using rule-based models. Oikos 99: 220-230.

Brosse, S. and S. Lek. 2000. Modelling roach (*Rutilus rutilus*) microhabitat using linear and nonlinear techniques. Freshwater Biol. 44: 441-452.

Brosse, S., J.-F. Guegan, J.-N. Tourenq and S. Lek. 1999. The use of artificial neural networks to assess fish abundance and spatial occupancy in the littoral zone of a mesotrophic lake. Ecol. Modelling 120: 299-311.

Brosse, S., J.L. Giraudel and S. Lek. 2001. Utilisation of non-supervised neural networks and principal component analysis to study fish assemblages. Ecol. Modelling 146: 159-166.

Cao, H., F. Recknagel, B. Kim and N. Takamura. 2005. Hybrid Evolutionary Algorithm for rule set discovery in time-series data to forecast and explain algal population dynamics in two lakes different in morphometry and eutrophication. *In* F. Recknagel (ed.), Ecological Informatics. 2nd Edition. Springer-Verlag, NY. (in press).

Cao, H.Q., F. Recknagel, G.J. Joo and D.K. Kim. 2006. Discovery of predictive rule sets for chlorophyll-a dynamics in the Nakdong River (Korea) by means of the hybrid evolutionary algorithm HEA. Ecol. Inform. (in press).

Céréghino, R., J.L. Giraudel and A. Compin. 2001. Spatial analysis of stream invertebrates distribution in the Adour-Garonne drainage basin (France), using Kohonen self organizing maps. Ecol. Modelling 146: 167-180.

Cho, H.K. 2000. Predictive modeling of river water quality factors using Artificial Neural Network Technique-focusing on BOD and DO. J. Korean Env. Sci. Soc. 9: 456-462.

Cho, J.H., K.S. Sung and S.R. Ha. 2004a. A river water quality management model for optimizing regional wastewater treatment using a genetic algorithm. J. Env. Mgmt. 73: 229-242.

Cho, Y.J., I.S. Yeon and J.K. Lee. 2004b. Application of neural network model to the real-time forecasting of water quality. J. Korean Soc. Water Qual. 20: 321-326.

Cho, H.K. and Y.H. Lee. 2003. Parameter estimation of runoff model using the Genetic Algorithm. J. Env. Sci. 12: 1109-1116.

Chon, T.-S., I.S. Kwak, Y.S. Park, T.H. Kim and Y.S. Kim. 2001. Patterning and short-term predictions of benthic macroinvertebrate community dynamics by using a recurrent artificial neural network.

Ecol. Modelling 146: 181-193.

Chon, T.-S., Y.S. Park and J.H. Park. 2000c. Determining temporal pattern of community dynamics by using unsupervised learning algorithms. Ecol. Modelling 132: 151-166.

Chon, T.S., I.S. Kwak and Y.S. Park. 2000a. Pattern recognition of long-term ecological data in community changes by using artificial neural networks: Benthic macroinvertebrates and chironomids in a polluted stream. Korean J. Ecol. 23: 89-100.

Chon, T.S., Y.S. Park and E.Y. Cha. 2000b. Patterning of community changes in benthic macroinvertebrates collected from urbanized streams for the short time prediction by temporal artificial neuronal networks. *In* S. Lek and J.-F. Guégan (eds.), Artificial Neuronal Networks. Springer, Berlin. pp. 99-114.

Chon, T.S., Y.S. Park, K.H. Moon and E.Y. Cha. 1996. Patternizing communities by using an artificial neural network. Ecol. Modelling 90: 69-78.

Clark, M.J. and K.J. Richards. 2002. Supporting complex decisions for sustainable river management in England and Wales. Aquatic Conserv. Mar. Freshw. Ecosyst. 12: 471-483.

D'heygere, T., P.L.M. Goethals and N. De Pauw. 2003. Use of genetic algorithms to select input variables in decision tree models for the prediction of benthic macroinvertebrates. Ecol. Modelling 160: 291-300.

D eroski, S. 2001. Applications of symbolic machine learning to ecological modelling. Ecol. Modelling 146: 263-273.

Edmondson, W.T. 1969. Cultural eutrophication with special reference to Lake Washington. Mit. Internat. Verein. Limnol. 17: 19-32.

Fielding, A.H. 1999. An introduction to machine learning methods. *In* A.H. Fielding (ed.), Machine Learning Methods for Ecological Applications. Kluwer Academic Publishers, Massachusetts. pp. 1-35.

Gevrey, M., I. Dimopoulos and S. Lek. 2003. Review and comparison of methods to study the contribution of variables in artificial neural network models. Ecol. Modelling 160: 249-264.

Giraudel, J.L. and S. Lek. 2001. A comparison of self-organizing map algorithm and some conventional statistical methods for ecological community ordination. Ecol. Modelling 146: 329-339.

Giraudel, J.L., D. Aurelle, P. Berrebi and S. Lek. 2000. Application of the self-organizing mapping and fuzzy clustering to microsatellite data: How to detect genetic structure in brown trout (*Salmo trutta*) population, in artificial neuronal networks. *In* S. Lek and J.-F. Guégan (eds.), Artificial Neuronal Networks. Springer, Berlin. pp. 187-202.

Ha, S.R., N.S. Seong and B.H. Lee. 2000. Optimization of pipeline route for multi-regional water supply system by applying genetic algorithm. J. Korean Soc. Civil Eng. 20: 429-438.

Haberlandt, U., V. Krysanova and A. Bárdossy. 2002. Assessment of nitrogen leaching from arable land in large river basins. Part II: regionalisation using fuzzy rule based modelling. Ecol. Modelling 150: 277-294.

Han, D., I.D. Cluckie, D. Karbassioun, J. Lawry and B. Krauskopf. 2002. River Flow Modelling Using Fuzzy Decision Trees. Water Resource. Mgmt. 16: 431-445.

Han, J.S. and M.S. Kim. 1999. Neural networks model for long term water quality prediction into river watershed. J. Korean Soc. Env. Admin. 5: 145-152.

Hastings, A. and T. Powell. 1991. Chaos in a three-species food chain. Ecology 72: 896-903.

Haykin, S. 1994. Neural Networks: A Comprehensive Foundation. MacMillian, NJ, 696 pp.

Hoang, H., F. Recknagel, J. Marshall and S. Choy. 2001. Predictive modelling of macroinvertebrate assemblages for stream habitat assessments in Queensland (Australia). Ecol. Modelling 146: 195-206.

Huanga, W. and S. Foo. 2002. Neural network modeling of salinity variation in Apalachicola River. Water Res. 36: 356-362.

Ibarra, A.A., M. Gevrey, Y.-S. Park, P. Lim and S. Lek. 2003. Modelling the factors that influence fish guilds composition using a back-propagation network: Assessment of metrics for indices of biotic integrity. Ecol. Modelling 160: 281-290.

Jain, S.K., A. Das and D.K. Srivastava. 1999. Application of ANN for reservoir inflow prediction and operation. J. Wat. Res. Plng. Mgmt. 125: 263-271.

Jang, M.H., J.G. Kim, G.I. Cho, J.R. Bahk and G.J. Joo. 2001. Change of fish fauna and longitudinal distribution in the Nakdong River. J. Nakdong River Res. 3: 63-83.

Jang. H.J., S.J. Lee and H.K. Lee. 2002. Water quality forecasting of Chungju Lake using artificial neural network algorithm. J. Env. Sci. 11: 201-207.

Jeong, D.I. and Y.O. Kim. 2005. Rainfall-runoff models using artificial neural networks for ensemble streamflow prediction. Hydrol. Process. 19: 3819-3835.

Jeong, D.I., Y.O. Kim, S.Z. Cho and H.J. Shin. 2003a. A study on rainfall-runoff models for improving ensemble streamflow prediction-I. rainfall-runoff models using artificial neural networks. J. Korean Soc. Civil Eng. 23: 521-530.

Jeong, H.J. and H.K. Lee. 2002. Comparison of the BOD forecasting ability of the ARIMA model and the Artificial Neural Network model. Korean J. Env. Health Soc. 28: 19-25.

Jeong, K.S., D.K Kim, P. Whigham and G.J Joo. 2003c. Modelling *Microcystis aeruginosa* bloom dynamics in the Nakdong River by means of evolutionary computation and statistical approach. Ecol. Modelling 161: 63-75.

Jeong, K.S., F. Recknagel and G.J. Joo. 2003b. Prediction and elucidation of population dynamics of the blue-green algae *Microcystis aeruginosa* and *Stephanodiscus hantzschii* in the Nakdong River-Reservoir system (South Korea) by artificial neural networks. *In* F. Recknagel (ed.), Ecological Informatics: Understanding Ecology by Biologically Inspired Computation. Springer, Berlin. pp. 195-213.

Jeong, K.S., H.W. Kim, K. Ha, G.J. Joo and F. Recknagel. 2001. Prediction and elucidation of phytoplankton dynamics in the Nakdong River (Korea) by means of a recurrent artificial neural network. Ecol. Modelling 146: 115-129.

Joo, G.J., H.W. Kim and K. Ha. 1997. The development of stream ecology and current status in Korea. Korean J. Ecol. 20: 69-78.

Jung, K.S., C.S. Yoo and J.H. Kim. 2001. Estimation of the WGR multi-dimensional precipitation model parameters using the genetic algorithm. J. Korean Water Res. Assoc. 34: 473-486.

Kang, G.W., C.Y. Park and J.H. Kim. 1992. The non-linear prediction of river discharge by the pattern recognition method. J. Korean Hydrol. 25: 105-113.

Karul, C., S. Soyupak and E. Germen. 1998. A new approach to mathematical water quality modeling in reservoirs: Neural networks. Internat. Rev. Hydrobiol. 83: 689-696.

Kim, H.J., H.J. Paek and W.T. Kwon. 1999. A neural network for long-term forecast of regional precipitation. J. Korean Assoc. Geogr. Inf. Sci. 2: 69-78.

Kim, H.S., C.J. La, J.H. Kim and I.J. Kang. 2002. Precipitation forecasting by fuzzy theory: II. applicability of fuzzy time series. J. Korean Water Res. Assoc. 35: 631-638.

Kim, H.S., S.H. Hwang and J.H. Kim. 1998. Reconstruction of river flows using tree-ring series and neural network. J. Korean Soc. Civil Eng. 18: 583-589.

Kim, S.W. 2000a. A study on the forecasting of daily streamflow using the multilayer neural networks model. J. Korean Water Res. Assoc. 33: 537-550.

Kim, S.W. 2000b. The application of neural networks method for the flood discharge forecasting in the river basin. J. Korean Soc. Civil Eng. 20: 801-811.

Kim, S.W. 2003. Streamflow estimation using coupled stochastic and neural networks model in the parallel reservoir groups. J. Korean Water Res. Assoc. 36: 195-209.

Kim, S.W. and J.D. Salas. 2000. The flood water stage prediction based on neural networks method in stream gauge station. J. Korean Water Res. Assoc. 33: 247-262.

Kim, Y.G. and S.C. Park. 2003. Estimation of reaction coefficients of QUAL2E model using evolutionary algorithm and prediction of water quality in the Tamjin River. J. Korean Soc. Water. Wastewater. 17: 682-689.

Kim, Y.S., S.G. Jung, C.W. Son and S.M. Kwon. 2005. The prediction of shear behavior on silts in the middle part of Nak Dong River using Artificial Neural Network. J. Korean Soc. Civil Eng. 25: 285-292.

Kohonen, T. 2001. Self-Organizing Map. Springer, Berlin, 501 pp.

Kohonen, T., 1982. Self-organized formation of topologically correct feature maps. Biol. Cyber. 43: 59-69.

Konda, T. and M.C. Deo. 1998. River stage forecasting using artificial neural networks. J. Hydro. Engrg. 3: 26-32.

Krysanova, V. and U. Haberlandt. 2002. Assessment of nitrogen leaching from arable land in large river basins. Part I. Simulation experiments using a process-based model. Ecol. Modelling 150: 255-275.

Kwak, I.S., J.K. Kim and T.S. Chon. 2003. Community patterning of benthic macroinvertebrates in urbanized streams by utilizing an Artificial Neural Network. Korean J. Limnol. 36: 29-37.

Kwak, I.S., G. Liu, T.S. Chon and Y.S. Park. 2000. Community patterning of benthic macroinvertebrates in streams of South Korea by utilizing an Artificial Neural Network. Korean J. Limnol. 33: 230-243.

La, C.J., H.S. Kim, J.H. Kim and I.J. Kang. 2002. Precipitation forecasting by fuzzy theory: I. application of neuro-fuzzy system and Markov chain. J. Korean Water Res. Assoc. 35: 619-629.

Laë, R., S. Lek and J. Moreau. 1999. Predicting fish yield of African lakes using neural networks. Ecol. Modelling 120: 325-335.

Lee, C.Y., E.S. Kim, H.S. Shin and J.H. Kim. 2000a. A study of deterioration estimation model for drinking water pipe using Probabilistic Neural Network (PNN). J. Korean Soc. Civil Eng. 20: 197-210.

Lee, G.S. and E.S. Jeong. 2004. Optimal operation rules for multireservoir system using genetic algorithm. J. Korean Soc. Civil Eng. 24: 9-17.

Lee, H.K., K.D. Oh, D.H. Park, J.H. Jung and S.J. Yoon. 1997. Fuzzy expert system to determine stream water quality classification from ecological information. Water Sci. Tech. 36: 199-206.

Lee, J.K. and C.H. Lee. 1996. A study on the introduction of fuzzy theory to the adjustment of time-variant parameter of storage function method. J. Korean Water Res. Assoc. 29: 146-159.

Lee, J.K. and H.J. Kim. 2004. A study on peak flow prediction by Fuzzy-Neuro Network. J. Korean Soc. Civil Eng. 24: 209-219.

Lee, J.K. and S.J. Park. 2003. Comparative study on peak flow prediction using multilayer neural network. J. Korean Soc. Civil Eng. 23: 105-114.

Lee, K.S., S.C. Park and C.O. Hong. 2004. The river flood runoff forecasting using GA and T-S Fuzzy system. J. Korean Soc. Civil Eng. 24: 453-460.

Lee, K.S., S.C. Park, H.M. Lee and K.B. Rho. 2001. A daily river flow forecasting using GANN. J. Korean Soc. Civil Eng. 21: 609-617.

Lee, K.S., S.C. Park, H.M. Lee and Y.H. Jin. 2000b. The study on the forecasting of runoff applied the B.P. algorithm of the artificial neural network in the Young-San River. J. Korean Soc. Civil Eng. 20: 679-688.

Lee, S.C. and S.I. Lee. 2001. Genetic algorithms for optimal augmentation of water distribution networks. J. Korean Water Res. Assoc. 34: 567-575.

Lek, S. and J.F. Guégan. 1999. Artificial neural networks as a tool in ecological modelling, an introduction. Ecol. Modelling 120: 65-73.

Lek, S., M. Delacoste, P. Baran, I. Dimopoulos, J. Lauga and S. Aulagnier. 1996. Application of neural networks to modelling nonlinear relationships in ecology. Ecol. Modelling. 90: 39-52.

Lekka, E., I. Kagalou, M. Lazaridou-Dimitriadou, T. Albanis, V. Dakos, D. Lambropoulou and V. Sakkas. 2004. Assessment of the water and habitat quality of a Mediterranean river (Kalamas, Epirus, Hellas), in accordance with the EU Water Framework Directive. Acta Hydrochim. Hydrobiol. 32: 175-188.

Lim, J.S. 2003. Reservoir permeability determination using artificial neural network. Geosy. Eng. 40: 232-238.

Lu, R.S. and S.L. Lo. 2002. Diagnosing reservoir water quality using self-organizing maps and fuzzy theory. Water Res. 36: 2265-2274.

Lund, J.W.G. and C.S. Reynolds. 1982. The development and operation of large limnetic enclosures in Blelham Tarn, English Lake District, and their contribution to phytoplankton ecology. Prog. Phycol. Res. 1: 12-65.

Maier, H., M.D. Burch, M. Bormans. 2001a. Flow management strategies to control blooms of the cyanobacterium, *Anabaena circinalis*, in the River Murray at Morgan, South Australia. Regul. Rivers Res. Mgmt. 17: 637-650.

Maier, H.R., G.C. Dandy and M.D. Burch. 1998. Use of artificial neural networks for modelling cyanobacteria *Anabaena* spp. in the River Murray, South Australia. Ecol. Modelling 105: 257-272.

Maier, H.R., T. Sayed and B.J. Lence. 2001b. Forecasting cyanobacterium *Anabaena* spp. in the River Murray, South Australia, using

B-spline neurofuzzy models. Ecol. Modelling 146: 85-96.

Marsili-Libelli, S. 2004. Fuzzy prediction of the algal blooms in the Orbetello lagoon. Env. Modelling Software 19: 799-808.

McCulloch, W.S. and W. Pitts. 1943. A logical calculus of ideas immanent in nervous activity. Bull. Math. Biophys. 5: 115-133.

McQueen, D.J., M.R.S. Johannes, J.R. Post, T.J. Stewart and D.R.S. Lean. 1989. Bottom-up and top-down impacts on freshwater pelagic community structure. Ecol. Monogr. 59: 289-309.

Millie D.F., G.R. Weckman, H.W. Paerl, J.L. Pinckney, B.J. Bendis, R.J. Pigg and G.L. Fahnenstiel. 2005. Neural net modeling of estuarine indicators: Hindcasting phytoplankton biomass and net ecosystem production in the Neuse (North Carolina) and Trout (Florida) Rivers, USA. Ecol. Indicators (in press).

Moatar, F., F. Fessant and A. Poirel. 1999. pH modelling by neural networks. Application of control and validation data series in the Middle Loire River. Ecol. Modelling 120: 141-156.

Obach, M., R. Wagner, H. Werner and H.-H. Schmidt. 2001. Modelling population dynamics of aquatic insects with artificial neural networks. Ecol. Modelling 146: 207-217.

Odum, E.P. 1983. Basic Ecology. Saunders College Publishing, Florida. 613 pp.

Oh, C.R., S.C. Park, H.M. Lee and Y.P. Pyo. 2002. A forecasting of water quality in the Youngsan River using neural network. J. Korean Soc. Civil Eng. 22: 371-382.

Oh, N.S. and J.H. Sonu. 1996. A study on rainfall prediction by neural network. J. Korean Water Res. Assoc. 29: 109-118.

Olden, J.D., M.K. Joy and R.G. Death. 2004. An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. Ecol. Modelling 178: 389-397.

Ortín, S., J.M. Gutiérrez, L. Pesquera and H. Vasquez. 2005. Nonlinear dynamics extraction for time-delay systems using modular neural networks synchronization and prediction. Physica A. 351: 133-141.

Paik, K.R., J.H. Kim, H.S. Kim and D.R. Lee. 2005. A conceptual rainfall-runoff model considering seasonal variation. Hydrol. Process. 19: 3837-3850.

Park, B.J., H.S. Cha and J.H. Kim. 1997. A study on parameters estimation of storage function model using the genetic algorithms. J. Korean Water Res. Assoc. 30: 347-355.

Park, J.K. and M.Y. Hwang. 2003. Development of rainfall-runoff process forecasting model using Artificial Neural Network. J. Korean Soc. Env. Admin. 9: 127-135.

Park, S.B., S.K. Lee, K.H. Chang, K.S. Jeong and G.J. Joo. 2002. The impact of Jangma (monsoon rainfall) on the changes of water quality in the lower Nakdong River (Mulgeum). Korean J. Limnol. 35: 161-170.

Park, S.C. 2004. Forecasting the water quality of Youngsan River by combined of GA and Fuzzy system. J. Korean Soc. Civil Eng. 24: 595-602.

Park, S.C. and S.J. Ha. 2003. Forecasting the water quality of river using GANN. J. Korean Soc. Civil Eng. 23: 507-514.

Park, Y.S., P.F.M. Verdonschot, T.-S. Chon and S. Lek. 2003a. Patterning and predicting aquatic macroinvertebrate diversities using artificial neural network. Water Res. 37: 1749-1758.

Park, Y.S., R. Céréghino, A. Compin and S. Lek. 2003b. Applications of artificial neural networks for patterning and predicting aquatic insect species richness in running waters. Ecol. Modelling 160: 265-280.

Park, Y.S., T.S. Chon, I.S. Kwak and S. Lek. 2004. Hierarchical community classification and assessment of aquatic ecosystems using artificial neural networks. Ecol. Modelling 327: 105-122.

Park, Y.S., P.F.M. Verdonschot and S. Lek. 2005. Review of modelling techniques. *In* S. Lek, M. Scardi, P.F.M. Verdonschot, J.-P. Descy and Y.S. Park (eds.), Modelling Community Structure in Freshwater Ecosystems. Springer, Berlin. pp. 21-40.

Pielou, E.C. 1977. Mathematical Ecology. John Wiley & Sons, NY, 384 pp.

Recknagel, F. 1997. ANNA-Artificial Neural Network model for predicting species abundance and succession of blue-green algae. Hydrobiologia 349: 47-57.

Recknagel, F. 2001. Applications of machine learning to ecological modelling. Ecol. Modelling 146: 303-310.

Recknagel, F. 2003a. Simulation of aquatic food web and species interactions by adaptive agents embodied with evolutionary computation: A conceptual framework. Ecol. Modelling 170: 291-302.

Recknagel, F. 2003b. Ecological Informatics: Understanding Ecology by Biologically Inspired Computation. Springer, Berlin.

Recknagel, F., M. French, P. Harkonen and K.I. Yabunanka. 1997. Artificial neural network approach for modelling and prediction of algal bloom. Ecol. Modelling 96: 11-28.

Recknagel, F., T. Fukushima, T. Hanazato, N. Takamura and H. Wilson. 1998. Modelling and prediction of phyto- and zooplankton dynamics in Lake Kasumigaura by artificial neural networks. Lakes Reserv. Res. Mgmt. 3: 123-133.

Renshaw, E. 1991. Modelling Biological Populations in Space and Time. Cambridge University Press, NY.

Reyjol, Y., P. Lim, A. Belaud and S. Lek. 2001. Modelling of microhabitat used by fish in natural and regulated flows in the river Garonne (France). Ecol. Modelling 146: 131-142.

Rhee, K.H., B.S. Moon, G.J. Nam and I.H. Kang. 2002. Forecasting of runoff hydrograph using Neural Network and Fuzzy Algorithms. J. Korean Soc. Water. Wastewater. 16: 161-168.

Rumelhart, D.E., G.E. Hinton and R.J. Williams. 1986. Learning representations by back-propagating errors. Nature 323: 533-536.

Salski, A. 2003. Ecological application of fuzzy logic. *In* F. Recknagel (ed.), Ecological Informatics: Understanding Ecology by Biologically Inspired Computation. Springer, Berlin. pp. 3-14.

Santiago, R.R. 2005. Predicting the distribution of the amphibian pathogen *Batrachochytrium dendrobatidis* in the new world. Bioltropica 37: 209-221.

Scardi, M. 2001. Advances in neural network modeling of phytoplankton primary production. Ecol. Modelling 146: 33-45.

Scardi, M. and L.W. Harding Jr. 1999. Developing an empirical model of phytoplankton primary production: A neural network case study. Ecol. Modelling 120: 213-223.

Schindler, D.W. 1974. Eutrophication and recovery in experimental lakes: Implications for lake management. Science 184: 897-898.

Schindler, D.W. 1977. The evolution of phosphorus limination in lakes. Science 195: 260-262.

Schleiter, I.M., D. Borchardt, R. Wagner, T. Dapper, K.-D. Schmidt, H.-H. Schmidt and H. Werner. 1999. Modelling water quality, bioindication and population dynamics in lotic ecosystems using neural networks. Ecol. Modelling 120: 271-286.

Shim, S.B. and M.S. Kim. 1999. A comparison study of neural networks model and storage function model for inflows forecasting. J. Korean Soc. Civil Eng. 19: 79-90.

Shim, S.B., M.S. Kim and K.C. Shim. 1998. Flood inflow forecasting on multipurpose reservoir by neural network. J. Korean Water Res. Assoc. 31: 45-57.

Shim, S.B., Y.K. Kim, M.S. Kim and K.C. Shim. 2001. Estimation of optimal parameter on WASP5/EUTRO5 model using genetic algorithm. J. Korean Soc. Civil Eng. 21: 315-326.

Shin, H.S. and M.J. Park. 1999a. Spatial analysis for mean annual precipitation based on neural networks. J. Korean Water Res. Assoc. 32: 3-13.

Shin, H.S. and M.J. Park. 1999b. Spatial-Temporal drought analysis of South Korea based on neural networks. J. Korean Water Res. Assoc. 32: 15-29.

Smith, J. and R.N. Eli. 1995. Neural-network models of rainfall-runoff process. J. Water Resour. Plng. Mgmt. 121: 499-508.

Son, M.W. and G.S. Lee. 2003. Forecasting of flood stage using neural networks and regression analysis. J. Korean Soc. Civil Eng. 23: 147-155.

Underwood, E.C., R. Klinger and P.E. Moore. 2004. Predicting patterns of non-native plant invasions in Yosemite National Park, California, USA. Diversity Distrib. 10: 447-459.

Walter, M., F. Recknagel, C. Carpenter and M. Bormans. 2001. Predicting eutrophication effects in the Burrinjuck Reservoir (Australia) by means of the deterministic model SALMO and the recurrent neural network model ANNA. Ecol. Modelling 146: 97-113.

Wei, B., N. Sugiura and T. Maekawa. 2001. Use of artificial neural network in the prediction of algal blooms. Water Res. 35: 2022-2028.

Werner, H. and M. Obach. 2001. New neural network types estimating the accuracy of response for ecological modelling. Ecol. Modelling 146: 289-298.

Whigham, P. and F. Recknagel. 2001a. An inductive approach to ecological time series modelling by evolutionary computation. Ecol. Modelling 146: 275-287.

Whigham, P. and F. Recknagel. 2001b. Predicting chlorophyll-a in freshwater lakes by hybridizing process-based models and genetic algorithms. Ecol. Modelling 146: 243-251.

Whigham, P. and G.B. Fogel. 2003. Ecological applications of evolutionary computation. In F. Recknagel (ed.), Ecological Informatics: Understanding Ecology by Biological-Inspired Computation. Springer, Berlin. pp. 49-71.

Willing, M.R. and S.K. Lyons. 1998. An analytical model of latitudinal gradients of species richness with an empirical test for marsupials and bats in the New World. Oikos 81: 93-98.

Wilson, H. and F. Recknagel. 2001. Towards a generic artificial neural network model for dynamic predictions of algal abu.ndance in freshwater lakes. Ecol. Modelling 146: 69-84.

Yao, X. and Y. Liu. 2001. Evolving neural networks for chlorophyll-a prediction. Proceedings of Fourth International Conference on Computational Intelligence and Multimedia Applications. pp. 185-189.

Yilmaz, I. 2005. Genetic algorithm usage in water quality monitoring networks optimization in Gediz (Turkey) River Basin. Env. Monitor. Assess. 108: 261-277.

Yoon, K.H. and B.C. Seo. 2004. The study on real-time neural network forecasting model of flood runoff using dam discharge in Han River. J. Kor. Soc. Civil Eng. 24: 47-53.

Zadeh, L.A. 1965. Fuzzy sets. Inf. Control. 8: 338-353.

Zurada, J.M. 1992. Introduction to Artificial Neural Systems. West Publishing Company, NY.

(Received October 12, 2005; Accepted December 21, 2005)