Recent Applications of Artificial Neural Networks in Forest Resource Management: An Overview

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Abstract

Making good decisions for adaptive forest management has become increasingly difficult. New artificial intelligence (AI) technology allows knowledge processing to be included in decision–support tool. The application of Artificial Neural Networks (ANN), known as Parallel Distributed Processing (PDP), to predict the behaviours of nonlinear systems has become an attractive alternative to traditional statistical methods. This paper aims to provide an up–to–date synthesis of the use of ANN in forest resource management. Current ANN applications include: (1) forest land mapping and classification, (2) forest growth and dynamics modeling (3) spatial data analysis and modeling (4) plant disease dynamics modeling, and (5) climate change research. The advantages and disadvantages of using ANNs are discussed. Although the ANN applications are at an early stage, they have demonstrated potential as a useful tool for forest resource management.

Introduction

For many years, forest resources researchers and managers have used empirical statistical models or complicated mathematical models predict the consequences of management regimes or actions, and to assist in decision making. These models are expressed as a mathematical equations. However, some decision-making processes contain qualitative components that do not lend themselves to being integrated into mathematical equations. As Gimblett and Ball (1995) point out, decision making in natural resources often leads to complexities beyond the reach of empirical statistical techniques, and requires approaches that are sometimes more heuristic than algorithmic. In many cases, statistical models cannot be used to solve the more unstructured problems in forest resource management.

The application of artificial intelligence (AI) in forest and natural resources management started with the development of expert systems for problem-solving and decision-making (Coulson et al. 1987). Recently, interest in the use of artificial neural networks (ANN), known as Parallel Distributed Processing (PDP), has grown in various fields (Maren et al. 1990; Swingler 1996). ANN has also begun to emerge as an alternative approach for modeling nonlinear and complex phenomena in forest science (McRoberts et al. 1991; Gimblett and Ball 1995; Lek et al. 1996; Atkinson and Tatnall 1997). The potential predictive capability of ANN, based on some supervised learning and training, can provide optimal solutions to forest resource management problems. The objectives of this paper are: 1) to introduce the key features of ANN; 2) to review recent applications of ANN in forest resource management; and 3) to discuss the strengths, limitations, and prospects of ANN in future applications.

Major Features of ANN

About 30 different neural network models have been developed since the first prototype neural network was proposed in 1943 (McCulloch and Pitts 1943). The characteristics of 10 most well-known neural network paradigms are briefly reviewed by Sui (1994). One of the most commonly used neural networks in natural resources management is the back-propagation feed-forward network (also referred as the Multi-Layer Perceptrons (MLP) network) (Rumelhart et al. 1986a,b). As one of many possible examples, this section provides a brief introduction to the major features of the MLP.

Structure. ANN is a type of parallel computer that consists of a number of smaller processing elements (PEs), or nodes, joined together. PEs are usually organized into neuron layers: an input layer where data are presented to the network, an output layer where that holds the response of the network to a given input, and one or more layers in between called hidden layers (Figure 1a). The PEs in the these different layers are either partially or fully interconnected. These connections are associated with a corresponding weight which is adjusted based on the strength of the connection.

Operations. In the MLP algorithm, the propagation of data through the network begins with an input pattern stimulus at the input layer. The data then flow through and are operated by the network until an output stimulus is yielded at the output layer (Figure 1b). Each PE or node receives the weighted outputs ($W_{ji}X_i$) from the PEs in the previous layer, which are summed to produce the node input (Net_j) (Figure 1b). The node input (net_j) is then passed through a non-linear sigmoid function ($f\ (Net_j)$) to generate the node output (Y_j), which is passed to the weighted input paths of many other nodes. For example,

$$net_j = \sum W_{ji}X_i \qquad (1)$$

where W_{ji} represents the weights between node i and node j, and X_i is the output from node i. The output from a given node j is then calculated from:

$$Y_j = f\ (net_j) = 1/\ (1+\exp(-(net_j+b))) \qquad (2)$$

The coefficients b (called bias) and W (weights) are estimated to minimize the deviations between the targets and the estimates.

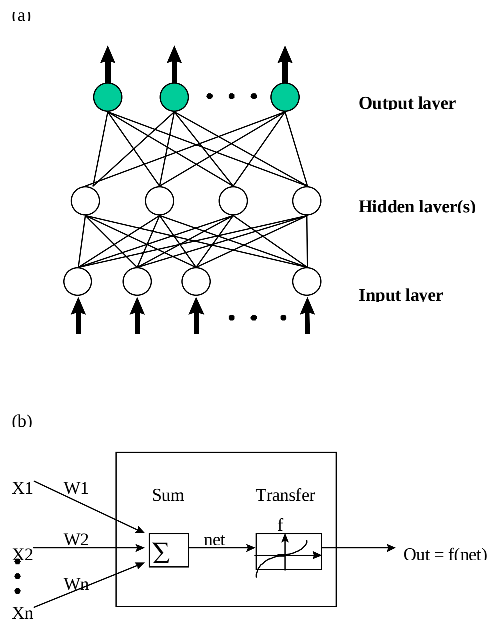

Fig. 1: (a) Typical architecture of an artificial neural network; (b) a single artificial neuron contains input, weight, sum, and transfer functions to produce an output.

Learning and Training. Learning and training are fundamental to nearly all neural networks. Training is the procedure by which the network learns; learning is the end result of that procedure. Learning consists of making systematic changes to the weights to improve the network's response performance to acceptable levels. The networks learn by adjusting the weights connecting the layers. The network starts by finding linear relationships between the inputs and the output. Weight values are assigned to the links between the input and output neurons. Once those relationships are found, neurons are added to the hidden layer so that nonlinear relationships can be found. The aim of training is to find a set of weights that will minimize error. During training, the output predicted by the network (Y(t)) is compared with the actual (desired) output (A(t)), and the mean squared error (MSE) between the two is calculated. The error function at time t, E(t), is given by:

$$E(t) = ½ \sum(Y(t)-A(t))^2 \qquad (3)$$

The learning algorithm modified the weights associated with each PE such that the system minimizes the error between the target output and the network's actual output. The back-propagation algorithm (Rumelhart et al. 1986b) is the most computationally straightforward algorithm for training the MLP. More detailed explanation is available in most neural network text books (e.g., Bishop 1995).

Applications in Forest Resource Management

Land Classification and Mapping

One of the common applications of neural networks in remote sensing is classification. Ecological land mapping and classification play an important role in natural resources management. ANN technology is an alternative to constructing a computer-based simulation system for land classification (Huang and Lippmann 1987; Hepner and Ritter 1989; Hepner et al. 1990; Civco 1993; Gong and Chen 1996). Decatur (1989) applied neural networks to classify terrain from synthetic aperture radar (SAR) imagery. Campbell et al. (1989), McClelland et al. (1989), Hepner et al. (1990), and Downey et al. (1992), all used neural networks to classify land cover from Landsat Thematic Mapper data and all found to varying degrees that the neural network approach was more accurate than traditional statistical classification.

Atkinson and Tatnall (1997) point out that a significant advantage of neural networks is the ability to combine data from different sources into the same classification. Several studies have tested the ability of neural networks to classify multi-source spatial data. For example, Bennediktsson et al. (1990) used Landsat multispectral scanner network (MSS) imagery and three topographic data sets (elevation, slope and aspect) to classify land cover. Peddle et al. (1994) applied the neural network approach to classify land cover in Alpine regions from multi-source remotely sensed data. Gong and Chen (1996) have tested the feasibility of applying a back-propagation, feed-forward neural network algorithm to land-systems mapping using digital elevation and forest-cover data.

Forest Growth and Dynamics Modeling

Forest growth models that describe forest dynamics (i.e., regeneration, growth, succession, mortality, and survival) have been widely used in forest management to update inventory, predict future forest yield, and assess species composition and ecosystem structure and function under changing environmental conditions. Despite advancements in developing stand, and individual tree growth models, tree mortality components have been simplified (using random probability), yielding growth and yield models with large variability and major projection bias in their predictions (Gertner 1989). Much progress has been made in this area since the initial use of ANN to model individual–tree mortality in 1991 (Guan and Gertner 1991a). In the same year, Guan and Gertner (1991b) successfully developed a model, based on an ANN, that predicts red pine (*Pinus resinosa Ait*.) tree survival. They found that the ANN-based red pine survival model not only fit the data better than a statistical model, but also performed better on future data. The model was also flexible enough to model both small and large, and slow growing red pine trees. Their approach was further enhanced by integrating a proper training algorithm and computational platform to model individual tree survival probability by Guan and Gertner (1995). On other hand, Hasenauer and Merkl (1997) demonstrated an application of unsupervised neural networks for predicting individual tree mortality within growth and yield models in Austria. They found that the neural networks performed slightly better than a conventional statistical mortality model based on the LOGIT approach. Recently, Guan et al. (1997) proposed a framework for assessing the prediction quality of process-based mechanistic forest growth models. The method consists four steps: (1) assuming distributions for parameter values, (2) screening parameters, (3) outlining model behavior through sampling, and (4) approximating model behavior based on the sampled points. This proposed method was then applied to a carbon-balance-based forest growth model developed by Valentine (1988), and has been demonstrated to effectively analyzing large and complex models.

Spatial Data Analysis and GIS Modeling

The most widespread application of ANN is spatial data analysis from multiple sources. It has been 10 years since Ritter et al. (1988) first proposed the idea of integrating artificial neural network techniques with GIS. Since then, a wide variety of research has been conducted to explore the potential applicability of neural networks for spatial data analysis (Gong 1994; Sui 1994). Sui (1994) provided a comprehensive overview of the use of ANN in spatial data handling, and grouped the recent applications into two major categories: (1) applications of neural networks for remote sensing, and (2) integrating neural networks into GIS for spatial modeling.

• **Satellite Image Processing:** Over the past decade there have been considerable increases in both the availability of large remotely sensed data and the use of neural networks. This provides the opportunity to test the ability of neural networks, in particular the feed-forward back-propagation multi-layer perceptron, and compare the performance of particular neural networks with other traditional methods of satellite image processing (Atkinson and Tatnall 1997). Ryan et al. (1991) developed a back-propagation network for delineating shorelines from Landsat-TM (Thematic Mapper) data. They demonstrated that the neural network could be trained to distinguish land from water using Power Spectral Ring (PSR) data. Previous work by Hermann and Khazenie (1992), Pierce et al. (1992), Wilkinson et al. (1992), and Jan (1997) has shown that ANN has been successfully applied to classifying multispectral remote sensing data. The ANN approach has also been used to retrieve the correlation lengths and variance from rough surface (Yoshitomi et al. 1993); to reconstruct the snow parameters (Tsang et al. 1992); to estimate leaf area index (LAI); and to retrieve biomass including canopy height, canopy water content and dry matter fraction from high-dimensional active/passive remote sensing data (Jin and Liu 1997). Zhang et al. (1997) have reported the use of a supervised back-propagation neural network (BPNN) to identify vegetation types from TM satellite images in the northern part of the White Mountain area of Arizona. They found that the neural network produced an average correctness of about 94% in the most complex ground areas, and the cost and time associated with the neural network approach is much less than the cost of traditional techniques.

• **Spatial Modeling with GIS:** Recent research has shown that coupling ANN with GIS has significantly improved the modeling capabilities of GIS for spatial decision-making (Peuquet 1991; Sui 1993). In the pioneering work by Wang (1992), he successfully strengthened the spatial data modeling capabilities of GIS for agricultural land suitability analysis by integrating a neural network into a GIS environment. In a study similar to Wang's, Sui (1993) integrated a standard back-propagation artificial neural network with GIS to develop a suitability analysis. He demonstrated that the neural network-based GIS modeling approach can approximate an expert's decisions without the explicit elicitation of expert knowledge into if-then production rules. Further work of coupling genetic learning neural networks with GIS for suitability analysis was reported by Zhou and Civco (1996). More recently, Deadman and Gimblett (1997) provided an example of using neural networks and GIS for developing vegetation management plans. As concluded by Sui (1994): "Although the full integration of neural networks with GIS is still a long way off, these initial investigations have demonstrated the profound impact neural networks may have on GIS. Obviously, the integration of neural networks with GIS for spatial analysis and modeling is a very important area of research that will contribute significantly for the design of the next generation of GIS".

Plant Disease Dynamics and Insect Pest Management

Plant diseases and insect pests are important issues for resource managers. To reduce losses caused by plant diseases, forest resource managers need information about disease dynamics. Traditionally, botanical epidemiologists have developed simulation models to predict diseases using statistical methods (e.g., logistic growth models) and mathematical simulation models. These models are based on relationships describing key processes of biological systems. The major challenge for traditional simulation models is that the mathematical relationships describing each process of the simulated system have to be known. This limitation affects the progress of disease prediction and may cause errors in the model simulations if incorrect. New AI techniques such as ANN may help to overcome this problem. For example, Yang and Batchelor (1997) have successfully used tree-layer feed forward neural networks to predict plant disease dynamics. They concluded that neural networks can be a powerful tool for forecasting plant disease and detecting disease patterns at different spatial and temporal scales. Other similar studies using ANN techniques to predict disease development (Yang et al. 1995; Batchelor et al. 1997), leaf wetness (Francl et al. 1995; Francl and Panigrahi 1997), and insect pest management (McClendon and Batchelor 1995) have recently appeared in the scientific literature.

Climate Change Research

Although climate change is a very active research area in the content of global change and sustainability, it is only the last few years that researchers have started to use neural networks to predict climate events, evaluate impacts of climate change on tree growth, and reconstruct past climate patterns. For example, Cook and Wolfe (1991) first developed a back-propagation neural network that predicts average air temperatures three months in advance, successfully using small data sets at specific locations. They also demonstrated the potential of neural networks to provide the stochastic weather inputs required by many modeling applications. At the global scale, Derr and Slutz (1994) have applied a back-propagation neural network to forecast sea surface temperatures as a indicator of El Niño events using the large ocean atmosphere data set from 1884 to present. The results showed that for lead times of one to six months the temperature is forecast to better than 1°C accuracy. Similar reports can be found in Tangang et al. (1997, 1998). The neural network also provided better forecasts for all but the shortest of lead times in comparison to powerful method of persistence. Yi and Prybutok (1996) have tested a neural network model for predicting daily maximum ozone concentrations in an industrialzed urban area, and found out that the neural network model is superior to two regression models they used for forecasting. Keller (1994) has proposed to use a neural network to enhance the capability of traditional statistical methods for modeling non-linear tree-ring/climate relationships. In a study similar to Keller's, Guiot et al. (1996) have recently developed a three-layers back-propagation neural network to calibrate the non-linear relationships between biome scores and climate variables, which can improve the accuracy of mapping terrestrial biomes from pollen data. This flexible non-linear method was further used to interpolate climatic variables at modern pollen data sites using longitude, latitude, and elevation as inputs (Peyron et al. 1998).

Other Applications

There are, however, a number of other potential applications of ANN in natural resources management, including the use of neural networks to predict water quality (Maier and Dandy 1996), soil hydraulic conductivity (Tamari et al. 1996), soil carbon in Mollisols (Levine and Kimes 1997), and pH changes in acidified eastern Canadian lakes (Ehrman et al. 1996). Vega-Garcia et al. (1996), for example, used a back-propagation feed-forward networks to predict human-caused wildfire occurrence in the Whitecourt Provincial Forest of Alberta, Canada. They found that the ANN was able to predict 85% of no-fire observations and 87% of fire observations. ANN techniques have also been applied in aquatic ecosystems (Recknagel et al. 1997; Maier et al. 1998) as well as in agriculture (Verdenius et al. 1997; Francl and Panigrahi 1997).

Benefits, Problems and Prospects

In general, ANN technology mimics the brain's own problem solving process. The use of ANN for forest management has been motivated by the realization that the human brain is very efficient at processing large quantities of data from a variety of different sources, and making decisions in a complex environment. As humans apply knowledge gained from past experience to new problems or situations, a neural network takes previously solved examples to build a system of "neurons" that makes new decision, classifications, and predictions accurately and rapidly. In particular, the ANN approach shows advantages over statistical modeling approaches traditionally used to study natural systems (Cuykendall et al. 1992; Gimblett and Ball 1995; Atkinson and Tatnall 1997). ANNs

- are more accurate than other statistical techniques, particularly when the problem or task addressed is either poorly defined or misunderstood, and observations of the process may be difficult or impossible to perform using incomplete data;

• are faster than other techniques when the problem is extremely complex and the neural network can develop its own weighting scheme based on relationships between the variables, thus reducing the requirement that user provide all known information about a problem;

• do not require *a priori* knowledge of the underlying process or assumptions of the structure of the target function. Once trained, the nets can be used to analyze new conditions and provide suggested solutions. The ability of the net to learn complex relationships and the capability of including both qualitative as well as quantitative data makes the neural net approach a very flexible and powerful tool.

However, it is equally important to understand the basic problems of ANN. Generally speaking, there are three issues to be aware of, particular for those who are new to the use of ANNs:

• **Black-Box:** ANN is usually treated as a "black-box", with which the weights are uninterpretable due to presence of hidden layers and the nonlinearity of the activation function. Neural nets are not self-explanatory; there are no standard tests can measure the degree of variability in the outputs explained by certain inputs or the significance level of the predictions. This is one of reasons that forest managers are less likely to use ANN when a more familiar and better understood procedure such as a regression analysis is available (Vega-Garcia et al. 1996).

• **Training Time:** Time is required to adequately train and test neural networks. The learning curve is steep, and only developer with experiences will become more efficient using this technique. The major challenge is to reduce the time required to choose a suitable number of nodes and layers and train the networks, while maintaining accuracy and generalization (Gimblett and Ball 1995; Atkinson and Tatnall 1997).

• **Overfit Data:** ANN with highly complex architecture and optimum network geometry (e.g., the number of hidden layers and the number of nodes in hidden layers) may performance well with on one data set and very poorly with another. This occurs when nonlinearities inherent in an ANN cause it to overfit data. The optimum number of hidden layers and nodes per layer are problem dependent and usually determined by trial-and-error. If the number of hidden nodes is too small, the back-propagation algorithm would fail to converge to a minimum during training. In contrast, too may hidden nodes will cause the network to overfit the training data. Fortunately, a few studies provide some useful guidance for choosing the initial network geometry (Baum and Haussler 1989; Maren et al. 1990; Weigend et al. 1990). Further discussion of these issues can be found in Sui (1994) and the neural networks newsgroup frequently asked questions (FAQ) site available on the Internet (Sarle 1997).

Although ANN has been showing potential for solving some difficult problems in forest resources management, it is still developing. On one hand, current applications of ANN are hampered by the development of ANN at theoretical, software, and hardware levels (Sui 1994). Future studies at these three levels will facilitate the further use of ANN as powerful tool for forest management decision-making. On other hand, the research on ANN applications has been limited compared to other AI techniques (e.g., expert systems) in natural resource management (Coulson et al. 1987). There is an urgent need to widely recognize the potential uses of ANN as an alternative tool in the forest science community.

Conclusions

ANN techniques have been proven as a useful tool for predicting, classifying, and approximating functions in various fields, and are finding a wide range of applications in forest resource management. The practical benefits of the ANN approach are apparent in applications (1) where the problem addressed may be either poorly understood, or observations of the process may be difficult to carry out using noisy or incomplete data; and (2) when the problem is extremely complex, particularly when dealing with non-linear systems, where traditional statistical techniques or mathematical models cannot to be formulated. However, ANN also has drawback including uninterpretable black-box components, numerous training time and possible data overfitting. We should balance its strengths against limitations when compared to traditional statistical techniques. The discipline of ANN is still immature, not a panacea, and will not replace traditional quantitative techniques completely. Instead, only diversified approaches and integration of these different techniques into a decision-support system will be useful for forest resource management in 21st century.

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