PREDICTING ECOLOGICALLY IMPORTANT VEGETATION VARIABLES FROM REMOTELY SENSED OPTICAL/RADAR DATA USING NEURAL NETWORKS

Daniel S. Kimes and Ross F. Nelson
Biospheric Sciences Branch, Code 923,
Laboratory for Terrestrial Physics
NASA Goddard Space Flight Center,
Greenbelt, MD 20771
dan@pika.gsfc.nasa.gov, ross@ltpmail.gsfc.nasa.gov

Abstract

A number of satellite sensor systems will collect large data sets of the Earth's surface during NASA's Earth Observing System (EOS) era. Efforts are being made to develop efficient algorithms that can incorporate a wide variety of spectral data and ancillary data in order to extract vegetation variables required for global and regional studies of ecosystem processes, biosphere-atmosphere interactions, and carbon dynamics. These variables are, for the most part, continuous (e.g. biomass, leaf area index, fraction of vegetation cover, vegetation height, vegetation age, spectral albedo, absorbed photosynthetic active radiation, photosynthetic efficiency, etc.) and estimates may be made using remotely sensed data (e.g. nadir and directional optical wavelengths, multifrequency radar backscatter) and any other readily available ancillary data (e.g., topography, sun angle, ground data, etc.). Using these types of data, neural networks can: 1) provide accurate initial models for extracting vegetation variables when an adequate amount of data is available; 2) provide a performance standard for evaluating existing physically-based models; 3) invert multivariate, physically based models; 4) in a variable selection process, identify those independent variables which best infer the vegetation variable(s) of interest; and 5) incorporate new data sources that would be difficult or impossible to use with conventional techniques. In addition, neural networks employ a more powerful and adaptive nonlinear equation form as compared to traditional linear, index transformations, and simple nonlinear analyses. These neural networks attributes are discussed in the context the authors' investigations of extracting vegetation variables of ecological interest.

Introduction

The large data sets engendered during the EOS era will enhance the temporal, spatial, and spectral coverage of the Earth (Asrar and Greenstone, 1995; Wharton and Myers, 1997). The satellite digital data sets and ancillary data products will require the development of efficient algorithms that can incorporate and functionally utilize disparate data types. Numerous vegetation variables e.g., leaf area, height, canopy roughness, land cover, stomatal resistance, latent and sensible heat flux, radiative properties, and many others, are required for global and regional studies of ecosystem processes, biosphere-atmosphere interactions, and carbon dynamics (Asrar and Dozier 1994, Hall et al. 1995). The success of efforts to extract vegetation variables such as these from remotely sensed data and available ancillary data will determine the degree and scope of vegetation-related science performed using EOS data.

In remote sensing missions of vegetation canopies, the problem is to accurately extract vegetation variables from remotely sensed data. These variables are, for the most part, continuous (e.g. biomass, leaf area index, fraction of vegetation cover, vegetation height, vegetation age, spectral albedo, absorbed photosynthetic active radiation, photosynthetic efficiency, etc.) and estimates may be made using remotely sensed data (e.g. nadir and directional optical wavelengths, multifrequency radar backscatter) and any other readily available ancillary data (e.g., topography, sun angle, ground data, etc.). Inferring continuous variables implies that a functional relationship must be made between the predicted variable(s), the remotely sensed data, and ancillary data. This is opposed to classification studies where the goal is to produce discrete categories of vegetation types as reviewed by Atkinson and Tatnall (1997).

A significant portion of the remote sensing community is active in developing techniques to accurately extract continuous vegetation properties. It is clear from the literature that significant problems exist with the "traditional techniques" being used. These are very topical and truly difficult problems that are being encountered in the remote sensing community. Neural networks can provide solutions to many of these problems. The intent of this paper is to raise the awareness of the ecological community to the advantages of using neural networks techniques in this area of research. The advantages and power of neural networks for extracting continuous vegetation variables using optical/radar data and ancillary data are discussed and compared to traditional techniques. The authors' research are used as examples.

Traditional Extraction Techniques

Several common approaches exist to extract continuous vegetation variables. These are classified as linear, nonlinear and physically-based models and are discussed in detail by Kimes et al. (1998a). A brief summary of these models are discussed along with the respective advantages and problems of each. Classification studies where the goal is to produce discrete categories of vegetation types are reviewed by Atkinson and Tatnall (1997).

Ideally, there exists a functional relationship between the independent variables (e.g., remotely sensed signals) and the estimated variables (e.g., biomass, leaf area index, etc). However even if a physical relationship exists, often it is not known. Consequently, one is often forced to make simplifying assumptions that allow one to develop a predictive equation in the form of a general linear model. Many physical biological processes are nonlinear. Therefore a general linear model often performs poorly in predicting vegetation variables because the relations between scattered radiation above vegetation canopies and vegetation variables may be nonlinear (e.g., Jakubauskas, 1996).

More complicated linear models involve transformations on the independent and/or dependent variables. Transformations allow one to reduce a more complex model to a linear form. Many transformations used in the literature are some kind of vegetation index. For example, in the optical region Myneni et al. (1995) reported that there are more than 12 vegetation indices and they have been correlated with vegetation amount, fraction of absorbed photosynthetically active radiation, unstressed vegetation conductance and photosynthetic capacity, and seasonal atmospheric carbon dioxide variations. Indices have been developed to enhance the spectral contribution from green vegetation while minimizing those from soil background, sun angle, sensor view angle, senesced vegetation, and the atmosphere as reviewed by Kimes et al. (1998a). Although these models can be related to a crude physical principle, it does not give the scientist any deep insight into the physical system. It is often difficult to decide what transformations to make, if any. Generally, the choice is made based on the results of previous studies in similar study areas and on trial and error.

The linear models above are linear in the coefficients and can be solved using least squares. In some studies, one has knowledge that a nonlinear form (nonlinear in the coefficients) is the more realistic and potentially more accurate model. Specifically, these models are intrinsically nonlinear in that it is impossible to convert them into a linear form. Numerous numerical iterative techniques exist to solve these nonlinear models. When using a nonlinear analysis, it is implied that the researcher knows the proper nonlinear form to implement. Generally, only simple nonlinear forms can be envisioned by the researcher. A few examples are described by Kimes et al. (1998a).

Ideally, in the scientific community, one would like to develop accurate, physically-based models for the physical system being studied. This model serves as a hypothesis for our current understanding of the physical system and as a basis for extracting desired vegetation variables from other readily known/measured variables. These physically-based models are forced to address the entire radiative transfer problem which includes a large number of variables. In remote sensing applications many of these variables are not of interest. Physically-based models range in complexity from simple nonlinear models to complex radiative transfer models in realistic three-dimensional vegetation canopies. The optical and radar models are reviewed by Kimes et al. (1998a).

To actually use physically-based models for extracting vegetation variables, the models must be inverted. In most cases these models are complex nonlinear systems which must be solved using numerical methods. The traditional approach employs numerical optimization techniques that, once initialized searches for the optimum parameter set that minimizes the error. There are difficulties in using these techniques. A stable and optimum inversion is not guaranteed and the technique can be computationally intensive when using complex radiative transfer models of vegetation. In addition, physical vegetation models have many parameters other than the variable(s) that is (are) being estimated. If one is to invert the model using numerical optimization techniques, many parameters have to be known and/or estimated using other methods. Initial conditions must be set to deduce the desired variable(s). Many studies have all or some of these problems.

Efforts to invert optical vegetation models are summarized by Privette et al. (1994, 1996), Pinty et al. (1990), Ross and Marshak (1989), and Goel (1987). An example of an effort to invert a Radar model is described by Polatin et al. (1994). Several approaches have been adopted to overcome the difficulties in inverting a model with many parameters. Goel (1987) noted that for a model to be successfully inverted, the number of measurements must be greater than or equal to the number of canopy parameters that need to be determined. Furthermore, to invert nonlinear relationships, there should be many more measurements than unknown parameters to facilitate a numerical solution.

Several approaches have been taken to achieve these parameters/measurements criteria. Often physical constraints are imposed. For example, the number of physical parameters to describe the geometric and scattering properties of vegetation components are limited (e.g. Kuusk 1994, Pinty et al. 1990, Jacquemoud 1993, Moghaddam 1994, Saatchi and Moghaddam 1994). In addition, the radiative transfer functions are often simplified (e.g. Pinty and Verstraete 1991, Prevot and Schmugge 1994, Govaerts and Verstraete 1994). Most inversion strategies must consider some combination of multi-angle data and multispectral data. In addition, some optical studies have used multiple sun angles. For inversions to be accurate, near optimal numbers of reflectance samples, spectral regions, signal anisotropy, and model sensitivity are required (Myneni et al. 1995). The amount of directional/multispectral data required to obtain accurate inversions is often appreciable and can not always be collected. Often, assumptions must be made about unknown variables (e.g. leaf-angle distribution, leaf size, plant spacing, reflectance and transmittance distributions of vegetation components, etc.). Generally, only one-dimensional models have been successfully inverted against measured data (Govaerts and Verstraete, 1994).

There is a trade off between model accuracy and the number of model parameters considered. The most accurate and robust models generally have the most canopy parameters and are least appropriate for direct inversion. The models with few parameters are easier to invert but are also the most inaccurate models.

Because direct inversion of models is computationally intensive, it generally is not applied on a pixel by pixel basis over large regions. Generally, inversions in the literature are carried out on only a few selected canopies rather than the entire range of vegetation variations that would exist in real applications.

Neural Networks

In many areas of research an appropriate and accurate, physically-based model for the purpose of extracting continuous vegetation variables does not exist. Consequently, one is forced to adopt a linear or simple nonlinear form that must be explicitly designed by a researcher. Coefficients are then fitted by traditional regression or simple numerical routines. If the researcher has not correctly envisioned all of the complex functional relationships between the input and output data, this approach will not work well. What is needed is a structure which adaptively develops its own basis functions, and their corresponding coefficients, from data.

Neural networks have the ability to learn patterns or relationships given training data, and to generalize or extract results from the data (Anderson and Rosenfeld 1988, Wasserman 1989, and Zornetzer et al. 1990). The approximation capability of neural networks is based on connectionism (Fu 1994). After training, the network is a machine that approximately maps inputs to the desired output(s). Kimes et al. (1998a) discusses the structure of neural networks, important approximation properties, training algorithms and properties, and pruning strategies of network structures.

Uses of Neural Networks and Remote Sensing Data

Neural networks have several attributes which facilitate extraction of vegetation variables from remotely sensed data. The advantages of neural networks as compared to traditional techniques are discussed and example studies are presented. Neural network approaches have been shown to be equal or superior to conventional techniques, especially when strong nonlinear components exist in the system being studied.

Neural Networks as Initial Models

In many areas of research physically-based radiative scattering models do not exist or are not accurate. In cases where models are lacking, neural networks can be used as the initial model. If accuracy is the only concern, then a neural network may be entirely adequate and desirable. A neural network can model the system on the basis of a set of encoded input/output examples of the system. The network maps inputs to the desired output by learning the mathematical function underlying the system. With this method, input and output variables can be related without any knowledge or assumptions about the underlying mathematical representation. Several examples follow.

Kimes et al. (1996) used a MLP (multilayer perceptron) network as an initial model to extract forest age in a Pacific Northwest forest using Thematic Mapper and topographic data. Understanding the changes of forest fragmentation through time are important for assessing alterations in ecosystem processes (forest productivity, species diversity, nutrient cycling, carbon flux, hydrology, spread of pests, etc.) and wildlife habitat and populations. The development of physically-based radiative scattering models that incorporate forest growth and topography, and that can be used to extract forest variables, is in its infancy. Consequently, accurate models that are invertible in this context are lacking.

The study area was the H.J. Andrews Experimental Forest on the Blue River Ranger District of the Willamette National Forest in western Oregon. Timber has been harvested from this forest for the past 45 years and the cutting and replanting history has been recorded. The study area was extracted from a georeferenced TM scene acquired on July 7, 1991. A coincident digital terrain model (DTM) derived from digital topographic elevation data was also acquired. Using this DTM and an image processing software package, slope and aspect images were generated over the study area. Sites were chosen to cover the entire range of forest stand age and slope and aspect. The oldest recorded clearcut stands were logged in 1950. A number of sites were chosen as primary forest which had no recorded history of cutting. Various feed-forward neural networks trained with back propagation were tested to predict forest age from TM data and topographic data.

The results demonstrated that neural networks can be used as an initial model for inferring forest age. The best network was a 6 -> 5 -> 1 structure with inputs of TM bands 3, 4, 5, elevation, slope and aspect. The RMSE (root mean squared errors) values of the predicted forest age were on the order of 5 years (Fig. 1). TM bands 1, 2, 6, and 7 did not significantly add information to the network for learning forest age. Furthermore, the results suggest that topographic information (elevation, slope and aspect) can be effectively utilized by a neural network approach. The results of the network approach were significantly better than corresponding linear systems. As discussed in the Traditional Extraction Techniques Section, many transformations (ratios, indices etc.) of optical and radar wavelengths are used to infer vegetation variables of interest. The goal of these studies is to find the transformation that produces the maximum degree of accuracy when applied to a particular class of remote sensing problems. Researcher often use simple transformations (ratios, indices etc.) because they are fast and easy to apply and they are well known in the literature. However, they provide little if any physical insights that can be used effectively to increase the accuracy of inference. Consequently, we propose that an adaptive learning technique such as neural networks would be superior to these simple transformations in many applications. For example, Sader et al. (1989) found that the NDVI (TM4-TM3)/(TM4+TM3) was not significantly correlated with forest regeneration age classes. Neural networks have the potential to learn more accurate relationships because they are not confined to the fixed relationships represented by the above simple transformations. The neural network approach is free to learn complex relationships that could not be envisioned by researchers.

Kimes et al (1998b) employed neural nets in conjunction with SPOT multispectral data to discriminate secondary from primary forest in Rondonia, Brazil. Their work demonstrated that neural networks consistently outperformed linear discriminant functions with respect to forest classification. Neural nets differentiated primary forest, nonforest, and secondary forest at an overall accuracy of 91.0% using 2 SPOT bands, and at 95.2% using one SPOT band and two texture channels. The corresponding linear discriminant overall accuracies were

88.9% (3 SPOT bands) and 92.6% (3 SPOT bands and 5 texture channels). Neural nets also estimated secondary forest age more accurately than linear, parametric functions. Using 2 spectral and 2 texture channels, a 4 -> 17 -> 1 neural network predicted secondary forest age over a 9 year range with an RMSE of 2.0 years and and $R^2_{(actual\ vs\ predicted)}$ of 0.38. The corresponding mulitple linear regression employing 3 SPOT bands and 4 texture channels had an RMSE of 2.1 years and an R^2 of 0.31. Though neither technique could be said to accurately estimate secondary forest age, neural networks consistently outperform parametric, linear discriminant and regression procedures using fewer spectral and textural bands.

Additional work by Nelson, Kimes, Rothier, and Salas near the same area in Rondonia using Thematic Mapper multispectral data verifies these findings. For instance, a linear discriminant function using four spectral/textural measures differentiated primary forest, nonforest, and secondary forest with an overall accuracy of 96.6%. Using 3 channels (3 -> 3 -> 3), the comparable neural net yielded an overall accuracy of 97.2%. The TM spectral and textural data were also used to estimate secondary forest age. The multiple linear predictive regression utilized 6 spectral-texture channels and yielded an RMSE of 1.62 years and an $R^2_{(actual\ vs\ predicted)}$ of 0.35. The comparable neural net, using 4 channels, had an RMSE of 1.59 years and an R^2 value of 0.37. The differences between the linear and neural net results are small, but in this and the Kimes et al. (1998b) studies, they are consistent. In general, using fewer bands, utilizing automatic variable selection procedures, and utilizing automatic weighting procedures, neural net results are, in general, comparable to or better than linear discriminant and linear regression results.

Ultimately, the scientific community needs to develop physically-based radiative scattering models for the above areas of research. These models need to be accurate and invertible for the desired variables. In research areas where these activities are immature, the neural network approach can provide an accurate initial model for predicting vegetation variables.

Neural Networks as Baseline Control

A network can be used as a baseline control while developing adequate physically-based models (Fu, 1994). Where adequate field and ground truth data sets exist, a neural network can be trained and tested on these data sets. These networks attempt to find the optimum functional relationships that exist between the input variables and the output variables of interest. The networks can be trained in the forward direction on the field data (e.g. vegetation canopy variables are the inputs and radiative scattering is the output).

Improvements to the physically-based model are indicated if it cannot surpass the accuracy of a neural network. Specifically, model accuracies less than neural network accuracies indicate that the physical processes embedded in the model must be improved (i.e. made more realistic). In this manner, neural networks provides a performance standard for evaluating current and future physically-based models (Fu, 1994).

Neural Networks For Inverting Physically-Based Models

In the Traditional Extraction Techniques Section, the difficulties in inverting physically-based models were discussed. In summary, the following difficulties can occur when using numerical optimization techniques to invert models. These techniques can be time consuming and generally can not be applied on a pixel by pixel basis for large regions. From a practical standpoint, often it is difficult to collect the measurements (multiple view angles and wavelengths) needed for an accurate inversion. Often models must be simplified before a stable and accurate inversion can be developed. The models are simplified by decreasing the number of parameters and/or simplifying the radiative transfer function. Simplified models tend to be more inaccurate than the full models. Neural network approaches provide potential solutions to all or some of these problems.

Significant simplification of physical models are made so that direct inversion using numerical techniques can be successfully applied. The disadvantage of this approach is that underlying relationships may be deleted that may be useful in extracting the variables of interest. In contrast, the neural network approach can be applied to the most sophisticated model without reducing the number of parameters or simplifying the physical processes. The models that have many parameters and include all physical processes tend to be the most accurate and robust models. Thus, the neural network approach applied to these models may, potentially, find more optimal relationships between the desired input and output variables. This approach provides a sound bench mark in terms of accuracy for extracting various variables. If direct inversion techniques of simplified models do not equal the accuracy obtained using the neural network approach on the full model then important underlying relationships are being ignored in the direct inversion approach.

A neural network approach can be used to accurately and efficiently invert physically-based models. The approach is as follows. The physically-based model describes the mathematical relationships between all the vegetation and radiative parameters. The model is used to simulate a wide array of vegetation canopies (the range of all canopies that would be encountered in the application space) in the forward direction--that is the vegetation canopy variables are the input and the radiative scattering above the canopy is calculated. Using the model a wide range of canopies and their associated directional reflectances or backscatter values can be calculated. Using these model-based data, training and testing data sets can be constructed and presented to various neural networks. These data sets consists of pairs of data containing the desired network inputs (e.g. optical and/or radar) and the true outputs (e.g., vegetation variables of interest). Embedded in these data are mathematical relationships between the inputs and the outputs. In theory the neural network approximates the optimal underlying mathematical relationships to map the inputs to the output. If only weak mathematical relationships exist between the input and output values then the network results will be poor. Thus, using this approach a neural network can be used to invert a model. This inversion scheme can be applied using input data that can be practically obtained in remote sensing missions. Many studies have successfully used this approach.

Kimes et al. (1997) used a neural network approach to invert a combined forest growth model and a radar backscatter model. The forest growth model captures the natural variations of forest stands (e.g. growth, regeneration, death, multiple species, and competition for light). This model was used to produce vegetation structure data typical of northern temperate forests in Maine.

Forest parameters such as woody biomass, tree density, tree height and tree age are important for describing the function and productivity of forest ecosystems. These data supplied inputs to the radar backscatter model which simulated the polarimetric radar backscatter (C, L, P, X bands) above the mixed conifer/hardwood forests. Using these simulated data, various neural networks were trained with inputs of different backscatter bands and output variables of total biomass, total number of trees, mean tree height, and mean tree age. Techniques utilized included transformation of input variables, variable selection with a genetic algorithm, and a cascade network and are described in detail by Kimes et al. (1997).

The accuracies (RMSE and R^2 values) for inferring various variables from radar backscatter were total biomass (1.6 kg m^{-2}, 0.94), number of trees (48 ha^{-1}, 0.94), tree height (0.47 m, 0.88), and tree age (24.0 yrs., 0.83). For example, Fig. 2 shows the true above ground biomass (kg m^{-2}) versus the predicted above ground biomass for a neural network with a structure of 5 -> 15 ->1 using frequencies C_{HH}, C_{VV}, L_{HH}, and P_{HH} (2 transformations were used for P_{HH}). The RMSE and R^2 values were 1.6 kg m m^{-2} and 0.94, respectively. These accuracies are considered good considering the complexity of the combined model and the fact that only simulated radar backscatter data were used without any other knowledge of the forest. Several networks were shown to be relatively insensitive to the addition of random noise to radar backscatter. The accuracy of these networks were superior to traditional index techniques developed by Ranson et al. (1997).

Neural Networks For Defining Relevant Variables

Networks can be used as a variable selection tool to determine a set of variables that are relevant to the desired variable(s) to be inferred. If the mapping of a network is not accurate, then perhaps some input variable(s) is(are) missing. Also an input variable is relevant to the problem only if it significantly increases the network's performance. Alternately, if there is an unacceptably large number of input variables, several types of algorithms can be used to find desirable subsets of input variables. Genetic algorithms (Koza, 1993) may be used to select an optimal subset of input variables. In this type of application, the genetic algorithm searches for a subset of input variables that behave synergistically to produce the highest network accuracy. The algorithm starts with a small subset of inputs of limited size and adds input variables according to network performance. This evolutionary process is detailed by Koza (1993) and a specific application relevant to this paper is described by Kimes et al. (1997). In these ways, networks can be used to identify input variables which best predict the variable(s) of interest. Several examples follow.

The network analysis in the forest age study discussed previously (Kimes et al. , 1996), defined a set of variables that were relevant to modeling efforts designed to infer forest age. Specifically it was discovered that the best inputs were TM bands 3, 4, 5, elevation, slope and aspect. TM bands 1, 2, 6, and 7 did not significantly add information to the network for learning forest age. Furthermore, the study suggests that topographic information (elevation, slope and aspect) can be effectively utilized by a neural network approach. However, it was shown that this same topographic information was not useful when used in a traditional linear approach and had RMSE values on the order of 35-40% higher than the neural network approach.

Neural networks can also be applied to simulated data from physically-based models to define a set of variables which may be used to infer variable(s) of interest. As discussed previously, Kimes et al. (1997) used a neural network approach to develop accurate algorithms for inverting a complex forest backscatter model. Using these simulated data, various neural networks were trained with inputs of different backscatter bands and output variables of total biomass, total number of trees, mean tree height, and mean tree age. The authors found that the networks that used only AIRSAR bands (C, L, P) had a high degree of accuracy. The inclusion of the X band with the AIRSAR bands did not seem to significantly increase the accuracy of the networks. The networks that used only the C and L bands still had a relatively high degree of accuracy for all forest variables (R^2 values from 0.75 to 0.91). The significance of this fact is that there is no current instrument or planned instrument that is collecting or will collect P band data. However, there are planned instruments collecting C and L band data. Modest accuracies (R^2 values from 0.65 to 0.84) were obtained with networks that used only the L band and poor accuracies (R^2 values from 0.36 to 0.46) were obtained with networks that used only the C band.

Neural Networks as Adaptable Systems

Neural networks are readily adaptable. They can easily incorporate new ancillary information that would be difficult or impossible to use with conventional techniques. For example, Kimes et al. (1996) included topographic data (slope, aspect, elevation) as ancillary information to infer forest age from TM data. They found that by introducing this ancillary information the network accuracy improved significantly (from 8.0 yrs. to 5.1 yrs. RMSE). It was not known how to incorporate topographic information effectively using traditional techniques. However, neural networks are ideally suited to learning new relationships between ancillary information, other input variables and the desired output variable. New input variables can be introduced to the network and tested with ease. This is especially useful when a researcher expects a new variable to add information to the problem of interest but does not have any knowledge of the functional form to use in introducing the new variable using traditional techniques.

Traditional numerical methods have difficulty in inverting multiple disconnected models. For example, Ranson et al. (1997) used a forest growth model to simulate growth and development of northern mixed coniferous hardwood forests. Output from this model were used as input to the canopy backscatter model that calculated radar backscatter coefficients for simulated forest stands. Classic numerical inversion of such a disconnected system (multiple models) is difficult when the functional connection between the different models is not explicitly defined. In these situations, researchers often adopt simple linear or nonlinear forms. For example, Ranson et al. (1997) choose to develop a simple index relationship to infer forest biomass from the radar backscatter coefficients. Neural networks are ideally suited for such problems. Networks find the best nonlinear function based on the networks complexity without the constraint of linearity or pre-specified nonlinearity used in traditional techniques. No explicit functional relationships between the disconnected models is required. Kimes et al. (1997) found that networks were significantly more accurate than traditional techniques for inverting the disconnected models of Ranson et al. (1997). Specifically, using the above neural network approach, the above ground biomass (kg m^{-2}) was extracted with RMSE and R^2 accuracies of 1.6 kg m^{-2} and 0.94, respectively as opposed to 2.6 kg m^{-2}

and 0.85, respectively, using the traditional index method of Ranson et al. (1997).

Conclusions and Implications

Neural networks have attributes which facilitate extraction of vegetation variables. Neural networks have significant advantages as compared to traditional techniques when applied to both measurement and modeling studies.

In many areas of research physically-based radiative scattering models do not exist or are not accurate. In cases where accurate models are lacking, neural networks can be used as the initial model. A neural network can model the system on the basis of a set of encoded input/output examples of the systems.

Neural networks can provide a baseline against which the performance of physically-based models can be compared. The networks can be trained on field data. Improvements to the physically-based model are indicated if it cannot surpass the accuracy of a neural network.

A neural network approach can be used to accurately and efficiently invert physically-based models. The neural network approach can be applied to the most sophisticated model without reducing the number of parameters or simplifying the physical processes. The models that have many parameters and include all physical processes tend to be the most accurate and robust models. Thus, the application of neural networks to invert these models has the potential of finding more optimal relationships between the desired input and output variables.

Networks can be used as a variable selection tool to define a set of variables which accurately predict variable(s) of interest. If the mapping of a network is not accurate, then perhaps some input variable(s) is(are) missing. Also an input variable is relevant to the problem only if it significantly increases the network's performance. Thus, networks can be used to identify relevant variables in complex nonlinear system.

Neural networks are readily adaptable. They can easily incorporate new information that would be difficult or impossible to use with conventional techniques. Neural networks are ideally suited to learning new relationships between ancillary information, other input variables and the desired output variable. New input variables can be introduced to the network and tested easily. This is especially useful when a researcher expects a new variable to add information to the problem of interest but does not have any knowledge of the functional form to use in introducing the new variable using traditional techniques.

References

Anderson, J.A., and E. Rosenfeld (eds.), 1988, Neurocomputing: Foundations of Research. The MIT Press, Cambridge, Massachusetts, 729 p.

Asrar, .G, and J. Dozier, 1994, EOS-Science Strategy for the Earth Observing System. AIP Press, Woodbury, New York, 119 p.

Asrar, G., and R. Greenstone, ed., 1995, MTPE EOS Reference Handbook. EOS Project Science Office, NASA/GSFC, Greenbelt, Maryland, 277 p.

Atkinson, P.M., and A.R.L. Tatnall, 1997, Neural Networks in Remote Sensing. *Int. Jour. of Remote Sens.* 18: 699-709.

Fu, L. 1994, Neural Networks in Computer Intelligence, McGraw-Hill, New York, 460 p.

Goel, N., 1987, Models of Vegetation Canopy Reflectance and Their Use in Estimation of Biophysical Parameters from Reflectance Data. *Remote Sens. Reviews* 3: 1-212.

Govaerts, Y. and M.M. Verstraete, 1994, Evaluation of the Capability of BRDF Models to Retrieve Structural Information on the Observed Target as Described by a Three-Dimensional Ray Tracing Code. *Society of Photo-Optical Inst. Eng.(SPIE)*, 2314: 9-20.

Hall, F.G., J.R. Townshend, E.T. Engman, 1995, Status of Remote Sensing Algorithms for Estimation of Land Surface State Parameters. *Remote Sens. of Environ.* 51: 138-156.

Jacquemoud, S., 1993, Inversion of the PROSPECT + SAIL Canopy Reflectance Model from AVIRIS Equivalent Spectra- Theoretical Study. *Remote Sens. of Environ.* 44: 281-292.

Jakubauskas, M.E., 1996, Thematic Mapper Characterization of Lodgepole Pine Seral Stages in Yellowstone National Park. USA. *Remote Sens.of Environ.* 56: 118-132.

Kimes, D.S., B.N. Holben, J.E. Nickeson and A. McKee, 1996, Extracting Forest Age in a Pacific Northwest Forest from Thematic Mapper and Topographic Data. *Remote Sens. of Environ.* 56: 133-140.

Kimes, D.S., R.F. Nelson, M.T. Manry, and A.K. Fung, 1998a, Attributes of neural Networks for Extraction Continuous Vegetation Variables from Optical and Radar Measurements. *Int. Jour. Remote Sens.* Vol. 19 (In Press).

Kimes, D.S., R.F. Nelson, D.L Skole, and W.A. Salas, 1998b, Mapping Secondary Tropical Forest and Forest Age from SPOT HRV Data. *Int. Jour. Remote Sens.* (In Press).

Kimes, D.S., K.J. Ranson, and G. Sun, 1997, Inversion of a Forest Backscatter Model using Neural Networks. *Int. Jour. of Remote Sens.* 18: 2181-2199.

Koza, J., 1993, Genetic Programming. MIT Press, Cambridge, Massachusetts, 746 pp.

Kuusk, A., 1994, Multispectral Canopy Reflectance Model. *Remote Sens. of Environ.* 50:75-82.

Moghaddam, M., 1994, Retrieval of Forest Canopy Parameters for OTTER. Society of Photo-Optical Instrumentation Engineers (SPIE), Multispectral and Microwave Sensing of Forestry, Hydrology, and Natural Resources, 26-30 Sept., Rome, Italy,

Myneni, R.B., F.G. Hall, P.J. Sellars, and A.L. Marshak, 1995, The Interpretation of Spectral Vegetation Indices. *IEEE Trans. on Geoscience and Remote Sens.* 33: 481-486.

Pinty, B. and M.M. Verstraete, 1991, Extracting Information on Surface Properties from Bidirectional Reflectance Measurements. *Jour. of Geophy. Res.* 96, 2865-2874.

Pinty, B., M.M. Verstraete and R.E. Dickinson, 1990, A Physical Model of the Bidirectional Reflectance of Vegetation Canopies. 2. Inversion and Validation. *Jour. of Geophy. Res.* 95:11767-11775.

Polatin, P.F., K. Sarabandi, F.T. Ulaby, 1994, An Iterative Inversion Algorithm with Application to the Polarimetric Radar Response of Vegetation Canopies. *IEEE Trans. on Geoscience and Remote Sens.* 32: 62-71.

Prevot, L. and T. Schmugge, 1994, Combined Use of Theoretical and Semi-empirical Models of Radar Backscatter to Estimate Characteristics of Canopies. Physical Measurements and Signatures in Remote Sensing, Sixth Symposium of International Society of Photogrammetry and Remote Sensing, 17-21 January 1994, Val d'Isere, France, 415-430.

Privette, J.L., R.B. Myneni, and W.J. Emery, 1996, Optimal Sampling Conditions for Estimating Grassland Parameters via Reflectance Model Inversions. *IEEE Trans. on Geoscience and Remote Sens.* 34: 272-284.

Privette, J.L., R.B. Myneni, C.J. Tucker, and W.J. Emery, 1994, Invertibility of a 1-D Discrete Ordinates Canopy Reflectance Model, *Remote Sens. of Environ.* 48: 89-105.

Ranson, K.J., G. Sun, J.F. Weishampel, and R.G. Knox, 1997, Forest Biomass from Combined Ecosystem and Radar backscatter Modeling. *Remote Sens. of Environ.* 59: 118-133.

Ross, J.K. and A.L. Marshak, 1989, Influence of Leaf Orientation and the Specular Component of Leaf Reflectance on the Canopy Bidirectional Reflectance. *Remote Sens. of Environ.* 24: 213-225.

Saatchi, S.S. and M Moghaddam, 1994, Biomass Distribution in Boreal Forest Using SAR Imagery. Society of Photo-Optical Instrumentation Engineers (SPIE), Multispectral and Microwave Sensing of Forestry, Hydrology, and Natural Resources, 26-30 Sept., Rome, Italy

Sader, S.A., R.B. Waide, W.T. Lawrence, A.T. Joyce, 1989, Tropical Forest Biomass and Successional Age Class Relationships to a Vegetation Index Derived from Landsat TM Data. *Remote Sens. of Environ.* 28: 143.

Wasserman, P.D. 1989. Neural Computing: Theory and Practice. Van Norstrand Reinhold, Pub., New York. p. 230.

Wharton, S.W., and M.F., Myers, ed., 1997, MTPE EOS Data Products Handbook. NASA/Goddard Space Flight Center, Code 902, Greenbelt, Maryland 20771, 266 pp.

Zornetzer, S.F., J.L. Davis, and C. Lau, 1990, An Introduction to Neural and Electronic Networks. Academic Press, New York, 493 p.

Figure Captions

Fig. 1. Predicted year logged versus the true year logged for the testing data. The network structure was the 6 -> 5 -> 1 (#inputs, #hidden nodes, #outputs). The inputs were TM bands 3, 4, 5, elevation, slope and aspect. The number of pixels/points shown are 3555 for the testing data. The RMSE and R^2 values for the testing data were 5.6 and 0.69, respectively.

Fig. 2. True above ground biomass (kg m^{-2}) versus the predicted above ground biomass. The network structure was 5 -> 15 -> 1 (#inputs, #hidden nodes, #outputs). The inputs were frequencies C_{HH}, C_{VV}, L_{HH}, and P_{HH}. The RMSE and R^2 values were 1.6 kg m^{-2} and 0.94, respectively.

TESTING DATA

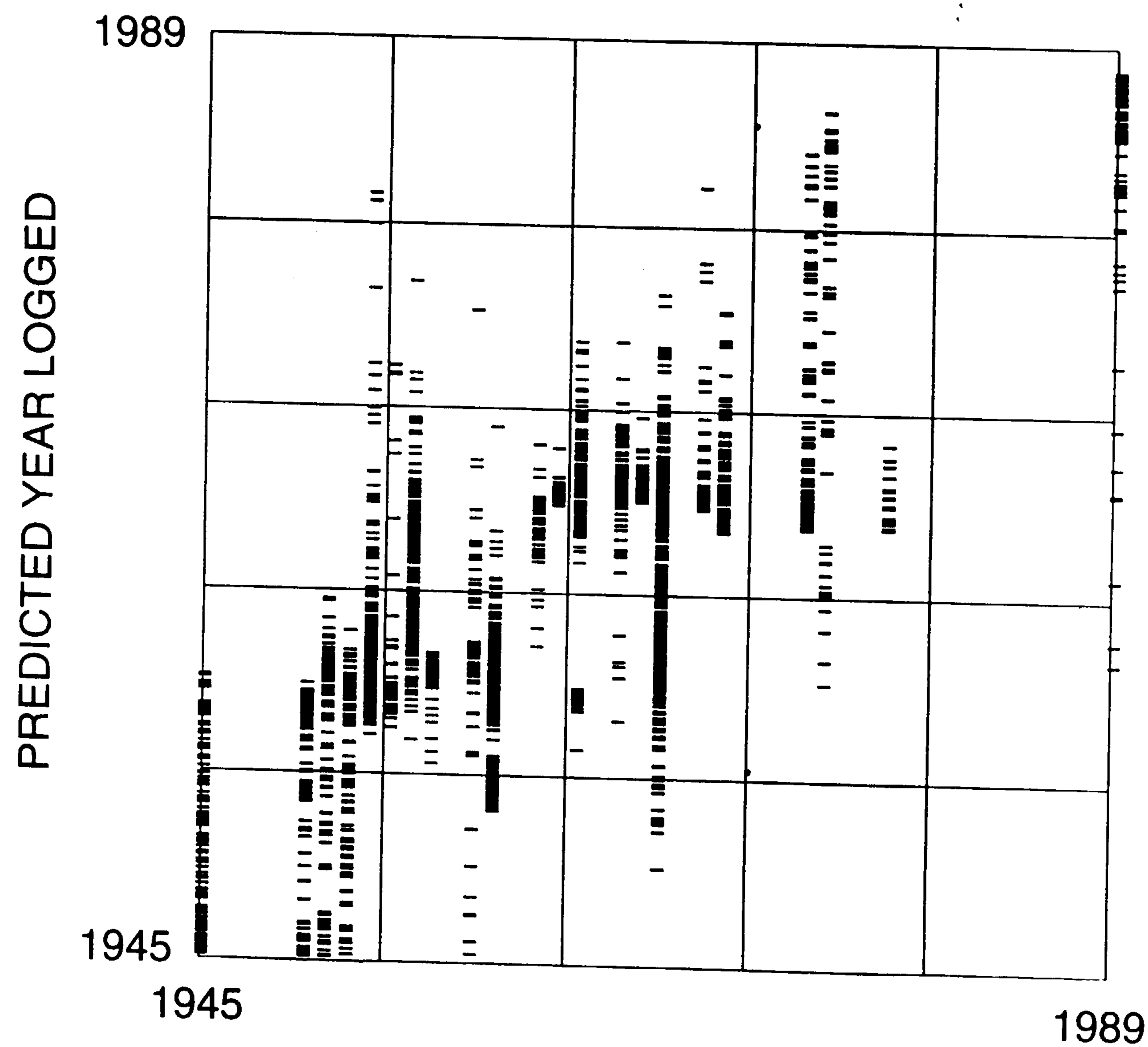

FIG. 2

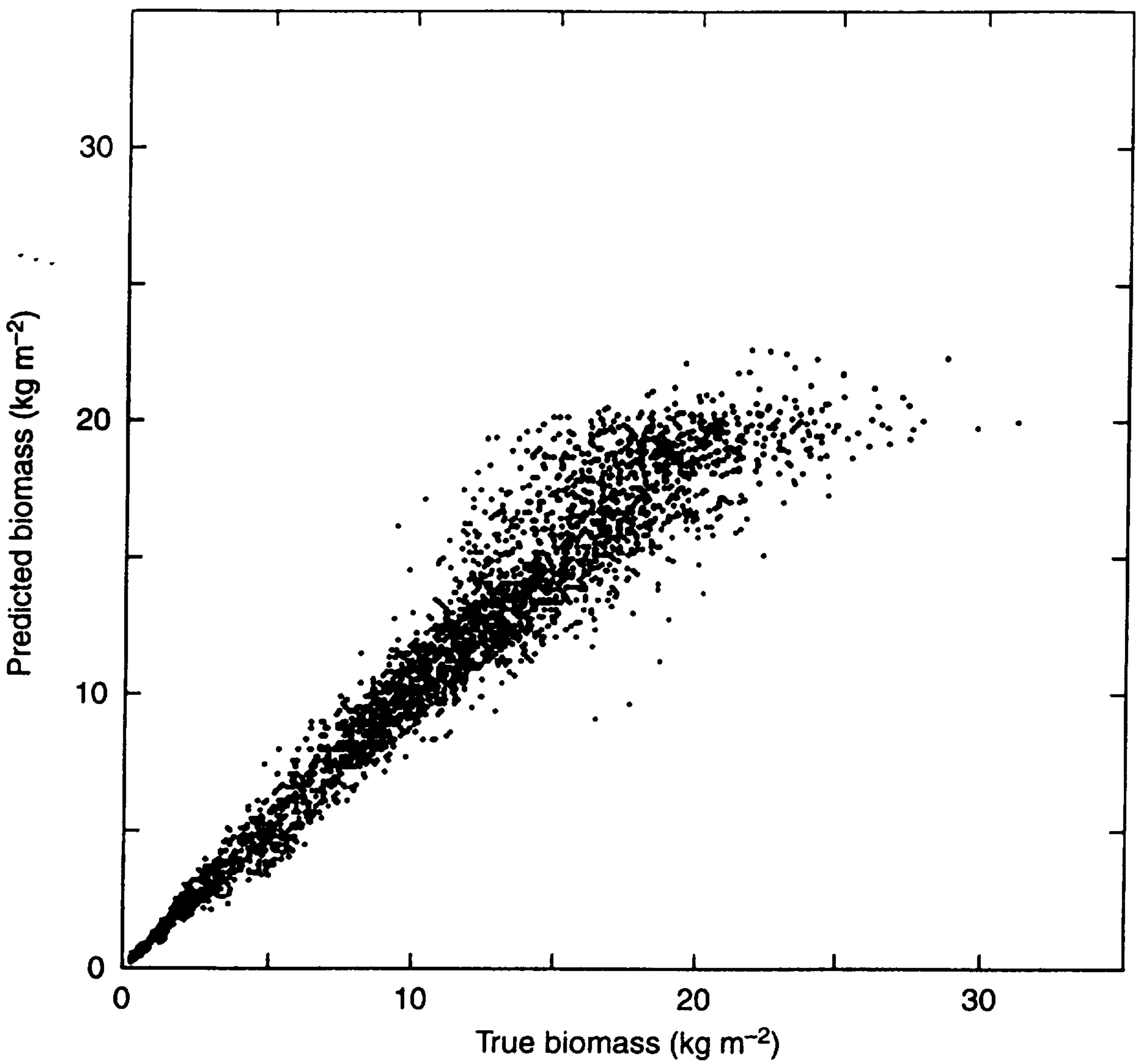

FIG. 2

<IMD961766/1