Recovery Of Vegetation Characteristics Using Neural Networks

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ABSTRACT A number of sensor systems will collect large data sets of the Earth's surface in the coming years. These data sets will enhance the temporal, spatial and spectral coverage of the Earth. 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. The success of efforts to extract vegetation variables from these data will determine the degree and scope of vegetation-related science performed.

Neural networks have attributes which facilitate the extraction of vegetation variables from remote sensing data and ancillary data. In many areas of research, physically-based radiative scattering models of particular vegetation canopies that treat all the vegetation variables of interest do not exist or are not accurate. Using neural network methods, input and output variables can be related without any knowledge or assumptions about the underlying mathematical representation. Neural networks employ a more powerful and adaptive nonlinear equation form as compared to traditional index transformations and simple nonlinear analyses.

In many regional and global scale studies, a physical modeling approach is necessary for realistic applications that span the entire range of vegetation conditions of interest. However, to actually use physically-based models for extracting vegetation variables, the models must be inverted. Many difficulties occur when using traditional numerical optimization techniques to invert these complex nonlinear models. Neural networks can provide an accurate, efficient, and stable inversion method for radiative transfer models using directional/spectral data.

KEY WORDS Vegetation, Directional Reflectance, Neural networks, Radiative Transfer, Modeling, Inversion.

1. Introduction

A number of sensor systems will collect large data sets of the Earth's surface in the coming years. These data sets will enhance the temporal, spatial and spectral coverage of the Earth (King and Greenstone, 1999). 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. Numerous vegetation variables, e.g. biomass, leaf area, height, fraction of cover, 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 (Hall *et al*., 1995). The success of efforts to extract vegetation variables from remotely sensed data and available ancillary data will determine the degree and scope of vegetation-related science performed.

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 and estimates may be made using remotely sensed data (e.g. nadir and directional optical wavelength, multifrequency radar backscatter, etc.) 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 the 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. Neural networks can provide solutions to some of these problems. The advantages and power of neural networks for extracting continuous vegetation variables using remote sensing data and ancillary data are discussed and compared to traditional techniques.

Literature studies and the authors' research are used as examples.

2. Traditional 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*. (1998). A brief summary of these models are discussed along with the respective advantages and problems of each.

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 is nonlinear (e.g., Jakubauskas, 1996).

More complicated linear models involve transformations on the independent and/or dependent variables. Many transformations are some kind of vegetation index. For example, in the optical region Myneni et al. (1995) reported that there are more than12 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. Kimes et al. (1998) reviews other indices. Although these models can be related to crude physical principles, it does not give the scientist any useful insight into the physical system. It is often difficult to decide what transformation to make. Generally, the choice is made based on results of the previous studies and on trial and error.

In some studies, one has knowledge that a nonlinear form (nonlinear in coefficients) is the more realistic and potentially more accurate model. When using a nonlinear model, 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. (1998).

Ideally, one would like to develop accurate, physically-based models for vegetation canopies. Physically-based models for vegetation serve as a basis for extracting vegetation variables using directional and spectral data from modern-borne sensors The use of physically-based models is potentially more effective (e.g., more generalizable and accurate) than the application of more empirical models, including spectral indices. Although many models have been inverted, only recently have significant efforts been made to provide operational algorithms. These efforts have exposed a need to significantly improve the efficiency and accuracy of methods for inverting these physically-based models. The characteristics of the traditional inversion, table look-up, neural network, and other methods were discussed by Kimes *et al.* (1999b) as well as the major achievements, advantages/disadvantages, and research issues for each method.

Physically-based models range in complexity from simple nonlinear models to complex numerical radiative transfer models in realistic three-dimensional vegetation canopies. The optical models are reviewed by Goel and Thompson (1999), Qin and Lang. (1999), Kuusk (1994), Myneni and Ross (1991), Myneni *et al.* (1989), and Goel (1987). These physically-based models are forced to address the entire radiative transfer problem, which includes a large number of variables. This physically-based modeling approach has been used to characterize the full range of possible vegetation conditions when only a limited number of field measurements of vegetation canopies and remote sensing data have been collected.

The inversion of physically-based models introduces a higher level of complexity (e.g., large number of variables and physical processes, and complex mathematical formulations), a significant increase in required computer resources, a higher potential of ill-posed problems, and many method-specific problems such as sensitivity to noise and initial guesses at the solution. Kimes *et al*. (1999b) discussed the traditional inversion methods (standard optimization algorithms) and the associated problems with such methods. Computational inefficiencies prohibit using these techniques operationally on a per pixel basis. Methods designed to overcome these limitations are discussed by Kimes *et al*. (1999b) and include neural network methods.

3. Neural Networks

Neural networks employ a more powerful and adaptive nonlinear equation form as compared to traditional linear and simple nonlinear analyses. This power and flexibility is gained by repeating nonlinear activation functions in a network structure.

This unique structure allows the neural network to learn complex functional relationships between input and output data that cannot be envisioned by a researcher. 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.

Multilayer feedforward neural networks have been an influential development in the field of neural networks during the past decade. The problem addressed by such networks is the approximate implementation of an input-output relation, by means of supervised training. Hornik *et al*., (1989) and Cybenko (1989) have shown that such networks can approximate any continuous input-output relation of interest to any degree of accuracy, provided sufficiently many hidden units are used. Kimes *et al*. (1998, 1999b) discuss the details of network structure, training, and generalization. A wide variety of neural network structures have been designed and applied to various applications as reviewed by Lippman (1987) and Haykin (1994).

Neural networks have several attributes which facilitate the extraction of vegetation variables from remote sensing data and ancillary data as discussed in detail by Kimes *et al*. (1998). In this paper, two areas are discussed: (1) the use of neural networks as the initial model, and (2) the use of neural networks for inverting physically-based models.

3.1. Use of Neural Networks as the Initial Model

In many areas of research, physically-based radiative scattering models of particular vegetation canopies that treat all the vegetation variables of interest 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. Using neural network methods, input and output variables can be related without any knowledge or assumptions about the underlying mathematical representation. Neural networks employ a more powerful and adaptive nonlinear equation form as compared to linear, traditional index transformations and simple nonlinear analyses. Several examples are cited here and others are cited by Kimes *et al*. (1998).

Simpson (1994) used a neural network to predict crop yield. In many cases physically-based crop yield models do not exist. For many years the traditional method used to calculate crop yield was to develop a correlation between the cumulative normalized difference vegetation index (NDVI) and crop yield. The technique resulted in large errors in estimation (Simpson, 1994). The simple traditional techniques can be greatly improved by including relevant ancillary information. Neural networks can provide accurate initial models in these cases. Simpson (1994) developed a network based on the following inputs: NDVI (derived from TM data), rainfall (monthly), hours of sunshine (monthly), temperature (monthly mean, minimum and maximum), and maximum soil moisture deficit. The standard error divided by the average yield was 5%. This represents a significant decrease in error compared to traditional techniques (Simpson, 1994).

As discussed previously and by Kimes *et al*. (1998), 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. 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

As an other example of the advantages of neural networks over vegetation index techniques, Baret *et al.* (1995) compared vegetation index techniques to a neural network approach for estimating the canopy gap fraction (nadir view) of sugar beet canopies using red and near-infrared reflectances. Both field data and simulated data from the SAIL model with hot spots (Verhoef 1984, Kuusk 1991) and the PROSPECT model (Jacquemoud and Baret, 1990) were applied to each technique. The vegetation index technique used a simple nonlinear equation (Baret *et al*., 1995). This index technique is more sophisticated and more accurate than most vegetation index techniques. Several vegetation indices were tested (SAVI, TSAVI, MSAVI, PVI, GEMI, and NDVI) as well as a simple neural network. The neural network approach performed significantly better than the vegetation index techniques. Again, the neural network approach generally performed significantly better because the neural network is free to learn functional relationships that could not be envisioned by the researchers.

As a final example, Kimes *et al.* (1996) used a neural network as an initial model to extract forest age in a Pacific Northwest forest (USA) 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. Various networks were trained and 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 used inputs of TM bands 3, 4, 5, elevation, slope and aspect. The RMS values (root mean error square of the predicted forest age versus true forest age) of the network were on the order of 5 years. Such studies serve as bench marks for current and future modeling studies.

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.

3.2. Use of Neural Networks for Inverting Physically-based Models

In many regional and global scale studies, a physical modeling approach is necessary for realistic applications that span the entire range of vegetation conditions of interest. The use of physically-based models is potentially more effective (e.g., more generalizable and accurate) than the application of more empirical models, including spectral indices. However, to actually use physically-based models for extracting vegetation variables, the models must be inverted, Although many models have been inverted, only recently have significant efforts been made to provide operational algorithms. These efforts have exposed a need to significantly improve the efficiency and accuracy of methods for inverting these physically-based models. The characteristics of the traditional inversion, table look-up, neural network, and other methods were discussed by Kimes *et al.* (1999b) as well as the major achievements, advantages, disadvantages, and research issues for each method.

The inversion of physically-based models introduces a higher level of complexity (e.g., large number of variables and physical processes, and complex mathematical formulations), a significant increase in required computer resources, a higher potential of ill-posed problems, and many method-specific problems such as sensitivity to noise and initial guesses at the solution. Kimes *et al*. (1999b) discussed the traditional inversion methods (standard optimization algorithms) and the associated problems with such methods. Computational inefficiencies prohibit using these techniques operationally on a per pixel basis. Methods designed to overcome these limitations are discussed and include neural network methods.

Only a few studies have actually used directional/spectral data and neural networks to invert a physically-based-model as reviewed by Kimes *et al*. (1999b). The neural network approach to inversion is described in detail by Kimes *et al*. (1998, 1999b) and is summarized here. The problem of inversion of physically-based models can be treated as learning the underlying mathematical relationship and/or mapping between a set of input variables and a set of output variables; that is the directional/spectral reflectance and its corresponding vegetation variables. The physically-based model describes the mathematical relationships between all the vegetation and radiative variables. 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 the output. Using these model-based data, training and testing data sets can be constructed and presented to various neural networks. These data sets consist of pairs of data containing the desired network inputs (e.g. directional/spectral reflectance values) and the desired true outputs (e.g., vegetation variables). 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.

Kimes *et al*. (1998) reviewed several studies that successfully used neural networks to invert complex physically-based model. In a recent study by Kimes *et al*. (1999a), a complex 3D model (DART, Gastellu-Etchegorry, *et al.*, 1996) was inverted for a wide range of forest canopies using

POLDER like data. A summary of this effort is presented as an example of the advantages of a neural network approach.

The DART model was inverted to recover three forest canopy variables: forest cover (T), leaf area index (L), and a soil reflectance parameter (S). Two inversion methods were used – a traditional inversion technique using a modified simplex method (Nelder and Mead, 1965) that operates on pre-computed DART canopy reflectances and a neural network method in combination with an exhaustive variable selection technique (Kimes *et al,* 1998*).* A comparison of the techniques' efficiency, accuracy, and stability was made. Finally the advantages and disadvantages of the two general methods were discussed.

The Discrete Anisotropic Radiative Transfer (DART) model was designed to simulate radiative transfer in heterogeneous 3D landscape scenes containing trees, shrubs, grass, soil, etc. (Gastellu-Etchegorry *et al*., 1996). The scene is divided into rectangular cells of variable dimension containing materials (e.g. leaf, wood, soil, water, etc.). Radiative scattering and propagation are simulated with the exact kernel and discrete ordinate approaches. Topography, hotspot, leaf specular and polarization mechanisms are also modeled. The model output predicts any specified directional sensor response. The volume and scattering properties of the materials in the cells are specified.

Many forest scenes were simulated in order to build up the table of pre-computed DART canopy reflectances using the DART model. Simulations were made using three spectral bands (green, red, and NIR) using POLDER band characteristics having center wavelengths at 443 nm, 670 nm, and 865 nm, respectively. Other variables were solar zenith angle (20 to 60 degrees), tree cover (0 to100%), foliar density m^{-1} (0.2 to 0.8), and Lambertian soil reflectance (0 to 30% for each band). Simulations were conducted with the characteristics of a typical beech stand of the Fontainebleau forest, near Paris (France). The structural characteristics (tree dimension, leaf angle distribution, etc.), foliage transmittance and reflectance values, and soil reflectance used were described by Demarez (1997) and Estève (1998). The foliar density was converted to LAI from knowledge of the three dimensional architecture of the trees as described by Estève (1998). Approximately 80 view angles were calculated for each simulation. Among these angles, 13 view directions were selected to test the inversion methods with zenith view angles of 0, 20, 30, 40, and 50 degrees and azimuth angles of 0, 90, and 180 degrees where an azimuth of 0 degrees represents the backscatter toward the sun. The soil parameter (S) is given by the expression R(green band)=S*0.2; R(red band)=S*0.25; and R(NIR)=S*0. 3, where R is the soil spectral reflectance.

Inversion of the DART model was done using the simplex routine (Press *et al*., 1992). The simplex method is a non-linear multi-dimensional optimization technique (Nelder and Mead, 1965). It is a robust technique that requires less a priori information, weaker assumptions, and finds the optimum solution more reliably than other traditional techniques (Renders *et al*., 1992). Five initial simplexes were used for each minimization and the best result was recorded . The first simplex was built in order to be as large as possible in the variables subspace. Then other simplexes are built around randomly chosen points.

Eight equal steps of T, L, S, and solar zenith angle were defined in the range of each variable as defined above creating 4096 points for training the neural networks and described in detail by Kimes et al. (1999a). The range of the T, L, and S variables, was 0.4-1.0, 0.8-9.3, and 0.0-1.0, respectively.

The specific kind of neural network used in this study to invert the DART model was a cascade method of network construction (Fahlmann and Lebiere, 1988) that adds a hidden node one at a time during its training phase. As each hidden node is added it is fully connected to all previous nodes. Once a hidden node is added and trained its weights are fixed. The advantages are that it learns quickly, determines its own network size, and does not require the relatively slow backpropagation learning algorithm. The network seems to be robust in learning complex mapping functions relevant to the radiative transfer problem (Kimes et al., 1998).

Several combinations of directional/spectral data that could be collected by POLDER were used in the inversion tests. In many scenarios, one does not have the luxury of building up a large number of directional reflectances over many overpasses due to cloud and changing ground conditions. As a demonstration, the directional/spectral combinations in Table 1 were selected. These three combinations were the "best" directional/spectral combinations for extracting each variable (L, T, S). These "best" combinations are a subset of the 13 possible view angles and 3 spectral bands as described above. The "best" combinations were selected using a search algorithm as discussed in detail by Kimes et al. (1998). The algorithm searches for a subset of directional/spectral data that behave synergistically to cause the best network performance (e.g., highest prediction accuracy of the variable of interest). The data can interact in a highly nonlinear fashion. A particular directional view and spectral band was added only if it significantly increased the accuracy of prediction. In addition to these "best" directional/spectral combinations, a nadir only view with the 3 spectral bands were tested. Finally, all 39 directional/spectral data (13 directions, 3 spectral bands) were tested.

Table. 1. The "best" combinations of directional/spectral data for inferring tree cover, leaf area index, and the soil reflectance parameter. The tables show view angles used for each variable and the spectral bands used for each view direction. The azimuth directions of 0 and 180 degrees represent the backscatter and forward scatter directions, respectively. The three spectral bands are green (G), red (R), and near IR (NIR).

Tree Cover

Zenith	Azimuth	Spectral
20	90	NIR
40	90	G, NIR
40	180	R
50	180	G

Leaf Area Index

Zenith	Azimuth	Spectral
20	180	NIR
30	180	G
40	0	NIR
50	0	G
50	90	G, R, NIR

Soil Reflectance Parameter

Zenith	Azimuth	Spectral
20	180	R, NIR
50	180	R, NIR

Approximately 200 points for 11 noise levels were generated for testing the neural network approach and the simplex approach. White noise was used for the 11 noise levels. Inversions were performed for the 11 noise levels from 0 to 10% of the true signal. To generate these data, random error was added to each simulated directional reflectance, e.g., $R'_\lambda = R_\lambda + \Delta R_\lambda$ where $|\Delta R_\lambda| < E * R_\lambda$ and E is the random error level 0 to 10%. The inversions were then performed using the R'_λ values. These noisy data sets were presented to the simplex method and the neural network method (trained on error free data) and the root mean squared error (RMSE) were calculated between the true and predicted T, L, and S. In addition, the coefficient of determination (R^2) for the predicted versus the true value was calculated in all cases.

Table 2 shows the results of using only the nadir view angles and sun angle to predict forest cover (T), LAI (L), and the soil parameter (S) for both the neural network and simplex methods. The root mean squared error (RMSE) for the neural network method was significantly lower than the simplex method. These results support the findings (Kimes *et al*., 1999b) that neural networks can give relatively accurate solutions to inversion problems given a small subset of directional/spectral data.

Table 2. Results of neural network and simplex methods (in parentheses) using three nadir spectral bands and the solar zenith angle. The variable inferred, the resulting root mean squared error (RMSE), and the coefficient of determination (R^2) are shown.

Variable Inferred	RMSE	R^2
Tree Cover	0.025 (0.074)	0.98 (0.88)
LAI	0.24 (0.42)	0.98 (0.96)
Soil Parameter	0.15 (0.20)	0.80 (0.60)

Table 3 shows the results of using the "best" directional/spectral combinations (Table 1). The RMSE for the neural network method was lower than the simplex method. Specifically, the RMSE of the neural network method was 68, 91, and 55% that of the simplex method for the T, L, and S variables, respectively. A graph of the true tree cover versus the predicted tree cover is shown in Fig. 1 for the neural network and simplex methods. The neural network method had the lowest RMSE's for both the nadir and the "best" directional/spectral data. Again, this suggests that the neural network method is capable of extracting more information from a small number of directional/spectral data relative to the more traditional simplex inversion method. This is coherent with the fact that the best accuracy with the simplex inversion approach is achieved with all directional/spectral data and solar zenith angle as input (Table 4).

Table3. Results of neural network and simplex methods (in parentheses) using the "best" directional/spectral data (Table 1) and solar zenith angle. The variable inferred, the resulting root mean squared error (RMSE), and the coefficient of determination (R^2) are shown.

Variable Inferred	RMSE	R^2
Tree Cover	0.021 (0.031)	0.99 (0.97)
LAI	0.21 (0.23)	0.99 (0.99)
Soil Parameter	0.11 (0.20)	0.84 (0.60)

Table 3. Results of neural network and simplex methods (in parentheses) using the "best" directional/spectral data (Table 1) and solar zenith angle. The variable inferred, the resulting root mean squared error (RMSE), and the coefficient of determination (R^2) are shown.

Table 4. Results of simplex method using all directional/spectral data (n=39) and solar zenith angle as input. The variable inferred, the resulting root mean squared error (RMSE), and the coefficient of determination (R^2) are shown.

Variable Inferred	RMSE	R^2
Tree Cover	0.011	0.99
LAI	0.20	0.99
Soil Parameter	0.16	0.72

Variable Inferred	RMSE	R^2
Tree Cover	0.021 (0.031)	0.99 (0.97)
LAI	0.21 (0.23)	0.99 (0.99)
Soil Parameter	0.11 (0.20)	0.84 (0.60)

Table 4 shows the results of the simplex method using all directional/spectral data (n=39). This additional directional/spectral data significantly increased the accuracy of the simplex method for all three variables. However, the increased data did not improve the accuracy of the neural network method. The neural network method consistently found that the best accuracy was obtained using a relatively small number of view directions as shown in Table 1.

The effects of noise on the RMSE values of the three variables were explored. In general the neural network technique had significantly lower RMSE values at the low noise levels (0-3%). However, at moderate noise levels (>3, <7%) the simplex method was equal to the neural network method in RMSE values. At high noise levels (7-10%) the simplex method had significantly lower RMSE values than the neural network method. This general trend was expressed for all directional/spectral combinations for the three variables

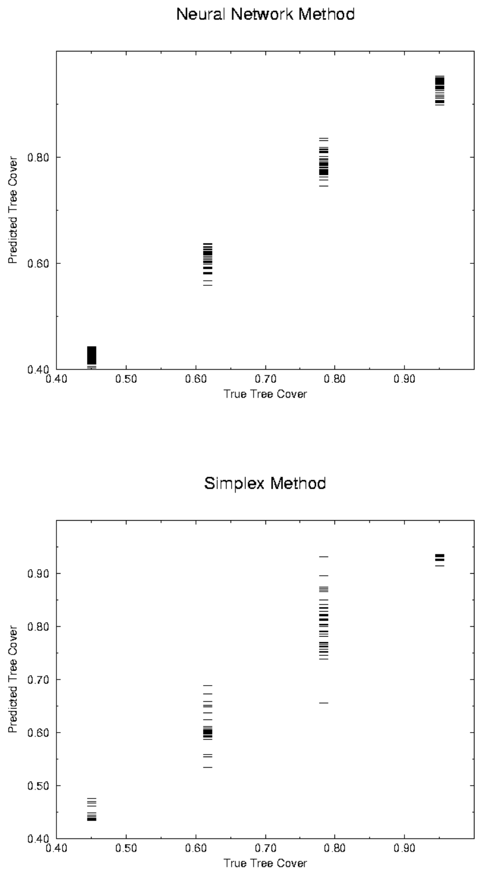

Figure 1. Comparison of neural network and simplex methods for inverting the DART model for tree cover. The “best” directional/spectral data were used as described in Tab.1. The results are statistically summarized in Table 3.

The simplex method of inverting the DART model took on the order of 15 seconds using a IBM RISK 6000 work station as compared to 6×10^{-4} seconds for the neural network method using a Sun Ultra 1 Model 170E.

4. Conclusions

Efforts are being made to develop efficient algorithms that incorporate a wide variety of spectral and directional data with other available ancillary data for extracting continuous vegetation variables. Neural networks have attributes that facilitate the extraction of vegetation variables and have significant advantages as compared to traditional techniques when applied to both measurements and modeling studies. They are readily adaptable and can easily incorporate new information that would be difficult or impossible to use with conventional techniques. Neural networks employ a more powerful and adaptive nonlinear equation form as compared to linear, traditional index transformations and simple nonlinear analyses.

In many areas of research, physically-based radiative scattering models of particular vegetation canopies that treat all the vegetation variables of interest 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. The unique structure allows neural networks to learn complex functional relationships between input and output data that can not be envisioned by a researcher.

In regard to model inversion, the neural network method gives relatively accurate solutions to inversion problems given a small subset of directional/spectral data. Specifically, the neural network method recovered the three forest variables from the DART model with a high level of accuracy using only 1 to 5 view angles. In general the neural network method was more accurate than the traditional simplex method. The results from both methods showed that the addition of directional view angles, as opposed to only a nadir view, can significantly improve the accuracy of recovering forest canopy characteristics.

The traditional inversion methods are computationally intensive and may not be appropriate for many operational applications on a per pixel basis for regional and global data. The neural network method is computationally efficient and can be applied on a per pixel basis. Neural networks, however, have not been generalized, as of yet, to handle any arbitrary subset of view angles In general the neural network technique had significantly lower RMSE values at the low noise levels. However, at moderate noise levels the simplex method was equal to the neural network method in RMSE values. At high noise levels the simplex method had significantly lower RMSE values than the neural network method.

Neural networks can provide an accurate, efficient, and stable inversion method for radiative transfer models using directional/spectral.

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