APPLICATION OF NEURAL NETWORKS TO ESTIMATE THE LATENT HEAT FLUX USING EDDY-COVARIANCE DATA FROM DATA FROM THE AMAZON FOREST

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ABSTRACT

Artificial Neural Networks (ANN) are applied to estimate turbulent fluxes such as latent heat (*LE*) and sensible heat (*H*) from slow response and fast response sampled micrometeorological data obtained in ARME (Amazon Forest Micrometeorology Experiment) Project. This was performed because turbulent fluxes are difficult to measure directly under adverse conditions, in contrast to some other micrometeorological variables such as slow response vertical profile data. This paper briefly describes the basic concept of ANN, shows the network modeling and training procedure and presents some preliminary estimated results which are validated against measured data. To estimate *LE*, 72 continuously sampled one hour mean data are used to train the ANN and 41 similarly obtained data to test the validity of the proposed method. The mean relative error of the estimated *LE* value is 0.27 with a standard deviation of 0.21. Bowen ratios from the measured and estimated *LE* and *H* values are calculated too, and match well among them even during time intervals in which Bowen ratio changes of sign.

INTRODUCTION

Turbulent flows above and inside forest environments are fundamental processes to exchange momentum, heat, water vapour and trace-gases between the atmosphere and the biologically active canopy (Shuttleworth, 1989). The better understanding of such a micrometeorological processes was one of the main goals of the Anglo-Brazilian Experiment ARME (Shuttleworth et al., 1984) carried out in the Ducke Reserve Forest (2^{o} 57'S: 59^{o} 57'W), a site situated 26 km far from Manaus, Amazonas (Sá et al., 1988). In spite of the lengthy data bases provided by four intensive ARME's field campaigns, there are some intervals of missing flux data. This is because the fast response turbulent fluctuations measuring system used in ARME, the HYDRA device (Shuttleworth et al., 1988),

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was very sensitive to some adverse experimental conditions, such as rainy ones. One way to overcome this problem is to estimate turbulent fluxes by some kind of flux-gradient or flux-profile parameterizations provided by the Monin-Obukhov Similarity Theory for the atmospheric surface boundary layer (Arya, 1988). But authors such as Raupach and Thom (1981) argued that such relationships probably do not hold next very complex surfaces as forests. As recently shown by Abareshi and Schuepp (1998), Artificial Neural Networks (ANN) could represent a useful tool to solve this interesting kind of problem. ANN is an artificial method to simulate the human's information memorizing and processing activities. Numerous studies have shown that ANN can be successfully applied to meteorological data. It has been applied to forecasting various time series, and comparing with forecasts by autoregressive models (Elsner and Tsonis, 1992); El Niño seasonal climate forecasting (Derr and Slutz, 1994); nonlinear prediction of turbulent signals from data measured above Amazon Forest and Pasture (Weigang et al., 1995); Arctic sea ice and sea-level pressure (Hsieh and Tang, 1998); ambient air temperature time series and prediction (Mihalakakou et al., 1998); and data analysis in meteorology and oceanography (Hsieh and Tang, 1998).

The objective of this study is 1) to design a suitable ANN model to estimate *LE* and *H*; 2) to replace missing *LE* and *H* using well trained ANN, thus creating a continuous data set; 3) to study the sensitivity of the ANN model to different input variable sets. This paper describes the basic concept of ANN, shows the network modeling and training procedure and reports preliminary results.

MATERIAL AND METHODS

The Amazon Region Micrometeorological Experiment (ARME) data were collected using a 45 m scaffolding tower located in the Ducke Reserve Forest site (2^o 57' S, 59^o 57' W) 26 km northeast of Manaus, Amazon, Brazil from 1983 to 1985 (Sá et al., 1988; Viswanadham et al, 1990). The latent and sensible heat fluxes (*LE* and *H*) were measured hourly in a way which is explained in Shuttleworth et al. (1984). Temperature, humidity, wind and radiation data were originally measured over 20-min intervals, and after were smoothed into hourly mean values to match with the *LE* and *H* hourly measured data. There are 963 available micrometeorological data runs to estimate *LE*, and 1124 ones to estimate *H*. However, there are only a few days with a continuous 24-hour recorded data set to use in learning process, which converts training Neural Networks a difficult task. The longest sequence of data was collected from 20, 21, 22, 23, 24, 25 and 26 August of 1984. Figure 1 shows humidity data from these days where *LE* is latent heat flux (W/m^2), *Rn* net radiation (W/m^2);

Dq_1 is the specific humidity vertical gradient (between the 44.66 and 41.04m levels); U is the mean wind velocity (at the 44m level).

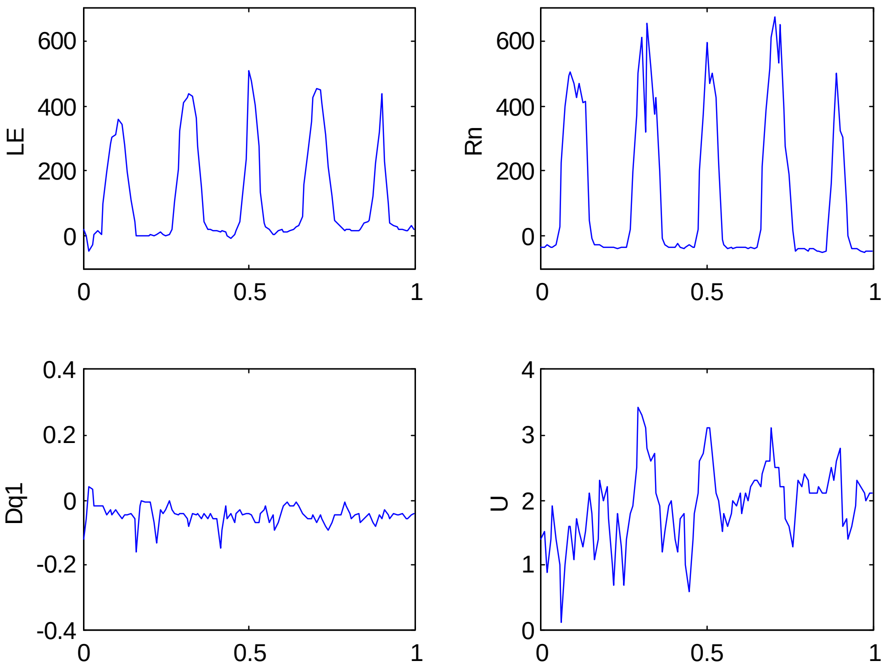

Figure 1 Observed *LE* and other data from 20 to 26 of August of 1984

From research of Abareshi and Schuepp (1998), the sensible heat flux *H* could be expressed as:

$$H = f(DT_1, U, Rn, t) \quad (1)$$

where $DT_1 = Ts - Ta$; Ts is the observed radiometric surface temperature; Ta, is the air temperature; t is time, and f is a nonlinear function which can be used to estimate H.

Following this idea, we used ANN procedure to estimate scalars fluxes from the only information provided by low frequency micrometeorological data. For the sensible heat flux H, we use the same equation as (1). The latent heat flux LE can be estimated by :

$$LE = f_{le}(Rn, Dq1, U) \quad (2)$$

where, Dq_1 is the specific humidity vertical gradient (between the 44.66 and 41.04m levels), f_{le} is a nonlinear function which can be used to estimate LE.

To test the ability of ANN to identify relevant variables, we used the observed and estimated Bowen ratios as an index when analyzing the results. The Bowen ratio is defined as

$$b = H / LE \quad (3)$$

In part of application of ANN, Backpropagation Networks (BPN) are used in this study as a basic estimating method. Backpropagation was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer function (Demuth and

Beale,1997) as a way of improving neural networks procedure. The structure of BPN for estimation of the sensible heat flux is shown in the figure 2. BPN is composed by four layers: an input layer, two hidden layers and an output layer. There are three neurons in input layer which are used for input *DT*, *U*, and *Rn* information. The first hidden layer of sigmoid neurons receives the input data and then propagate their output to another hidden layer. This hidden layer of linear neurons computes the network output, i.e. *H*.

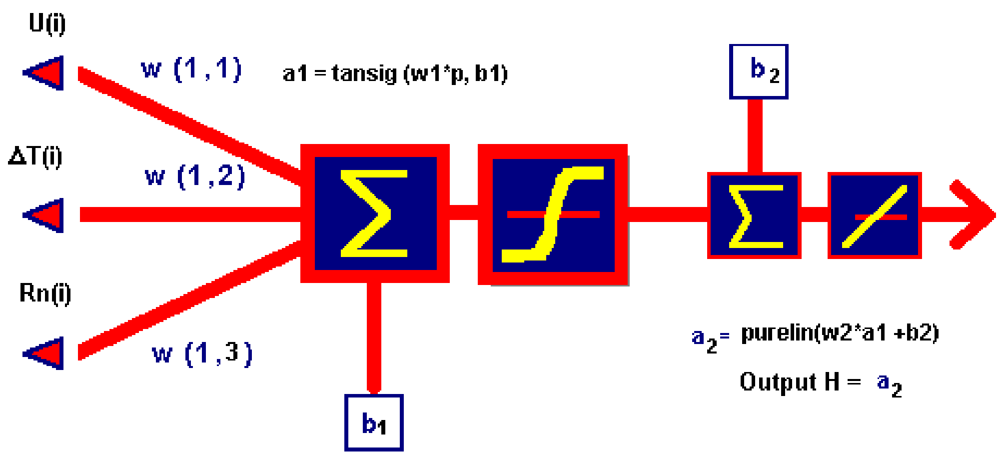

Figure 2 The structure of Backpropagation Networks to estimate H

RESULTS AND DISCUSSION

To estimate *LE* and *H*, a suitable network needs to be configured. The number of neurons within the hidden layer describes the nonlinearity of the network. To avoid over-fitting numerical problems, this number is defined after error analysis estimation. The objective is to choose the smallest neuron number yielding accurate estimation of the searched meteorological values. The number of the neurons within the input layer is designed according the physical models. In this paper, two cases of networks are considered:

Table 1 Networks to estimate *LE* and *H*

Cases	Inputs	Output	Available Data
LE_Net 1	*Rn, Dq1, U*	*LE*	963
H_Net 1	*Rn, DT1, U*	*H*	1124

In LE_Net 1 case, the network is constructed with three inputs: *Rn, Dq1, U* and one output *LE*. Using 72 data from days 20 to 23 of August of 1984, the network is trained with 1000 epochs and the SSE is 0.0417. The network successfully estimated the *LE* for 41 test data from day 23, with a mean relative error of 0.27 and a standard deviation of 0.21 (Figure 3).

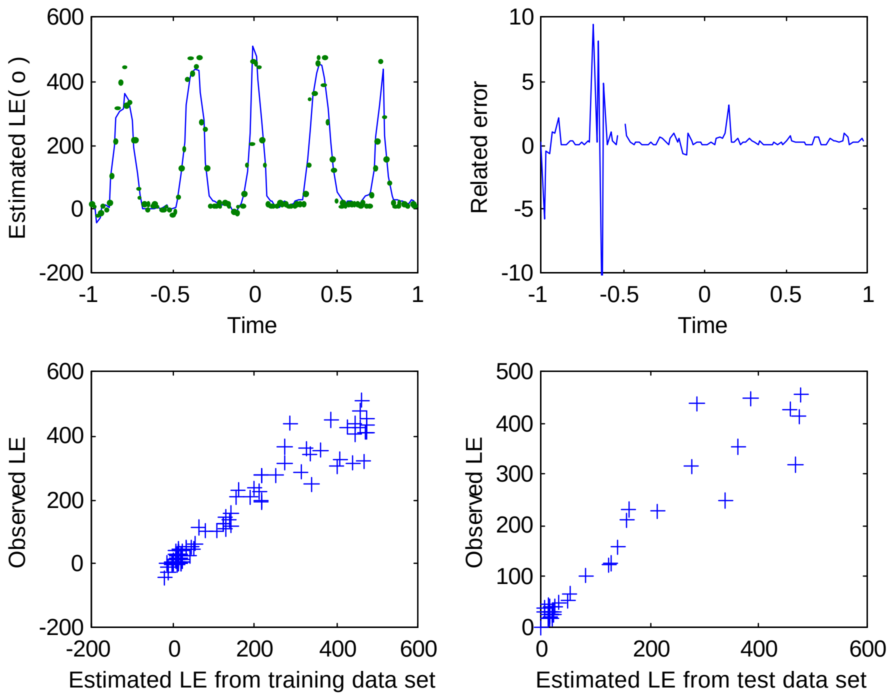

Figure 3 Estimation of *LE* using data from 20 to 26 of August of 1984, in case LE_Net 1
a) Estimated (**.**) and observed (-) *LE*; b) Related error; c) Correlation between estimated and observed *LE* from training and test data; d) Correlation between estimated and observed *LE* from test data.

In H_Net 1 case, the network is constructed with three inputs: *Rn*, *DT1*, *U* and one output *H* where *DT1* is the air temperature vertical gradient (between 44.66 and 41.04m levels). Using 72 data from days 20 to 23 of August of 1984, the network is trained with 2000 epochs and the SSE is 0.0302. The network can also estimate *H* for 41 test data from day 23, with a mean relative error of 0.8 and a standard deviation of 2.3. There are two points in which the relative error was higher than 9.9; if these are taken as outliers and are deleted, the mean relative error drops 0.27 with a standard deviation of 0.23.

Figure 4 gives the Bowen ratios from observed and estimated *LE* and *H* for 41 test data. It shows that generally, ANN estimated *LE* and *H* well both during the day and night. The estimated Bowen ratio follows the observed Bowen ratio even at times when the ratio switches sign, typical for the transitional period between daytime and nighttime (at 18:00 of 08/23 and 18:00 0f 08/24). Specially, for the data from 8:00 to 17:00, the network estimated very well. For the data from 19:00 to 23:00 and 0:00 to 5:00, the networks have little difficulty in describing the potentially complicated nocturnal nonlinear relationships, although there does appear to be a slightly greater error between estimated and observed values than during the day.

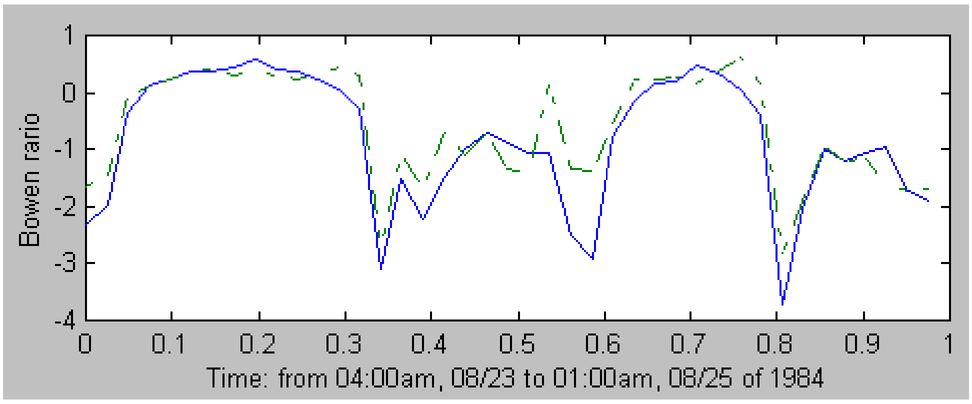

Figure 4 Bowen ratio from observed (-) and estimated (- -) *LE* and *H*

CONCLUSION

ANN can be used to estimate the latent and sensible heat fluxes with acceptable precision. The preliminary results show the potential application of this method. Latent energy estimates exhibited a mean relative error 0.27 and a standard deviation of 0.21 for a set of test data. Estimated Bowen ratio matched the time course of the observed Bowen ratio well, including during the transitional period between daytime and nighttime. However, to decrease errors, different ANNs should be designed to process daytime and nighttime data. Future research is using more ANN techniques to study the sensitivity of the model to different input variable sets. The data from different experiments from different regions should also be tested. In addition, greater number of data points should be employed when possible.

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