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Energy and Carbon Flux Coupling: Multi-ecosystem Comparisons Using Artificial Neural Network

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Abstract: A multi-ecosystems carbon flux simulation from energy fluxes is presented. A new statistical learning technique based on Artificial Neural Network (ANN) back propagation algorithm and multi-layer perceptron architecture was used in the CO_2 simulation. Four input layers (net radiation, soil heat flux, sensible and latent heat flux) were used for training (calibration) and testing (verification) of model outputs. The 15-days half-hourly (grassland) and hourly (forest and cropland) micrometeorological data from eddy covariance observations of AmeriFlux towers were divided into training (5-days) and testing (10-days) sets. Results show that the ANN-based technique predicts CO_2 flux with testing R^2 values of 0.86, 0.75 and 0.94 for forest, grassland and cropland ecosystems, respectively. The technique is reliable and efficient to estimate regional or global CO_2 fluxes from point measurements and understand the spatiotemporal budget of the CO_2 fluxes.

Key words: CO_2, AmeriFlux, Energy Flux, Artificial Neural Network, Ecosystem

INTRODUCTION

Global climate change studies identify the increase of atmospheric carbon dioxide (CO_2) level as one of the precursors for the shift in climate. Understanding the complexity of the carbon cycle, the linkages to physical, biogeochemical, ecological processes and human influences and quantifying carbon cycle effects on climate and climate change is a central goal of current carbon research [1]. Understanding processes responsible for CO_2 level rise, knowledge of the amount of CO_2 in the atmosphere and identifying carbon sinks and sources are then crucial for reducing climate change impacts. Conjoined observations and modeling of terrestrial CO_2 are important in understanding the contribution of the different ecosystems in the global carbon budget. This information will be useful in carbon related climate change mitigation planning and carbon reduction policies to avert climate change impacts. Current strategies involve networks of flux towers (AmeriFlux, CarboEurope and AsiaFlux) to monitor water, energy and carbon fluxes using eddy covariance technique. These flux towers collect micrometeorological data with only few square kilometers foot-print. The need for larger area spatial carbon flux information, limitation of the existing carbon flux simulation models and the close coupling of energy and carbon fluxes necessitates the use of new statistical learning techniques such as Artificial Neural Network (ANN) to model carbon flux using non-conceptual approach.

The non-linear energy-CO_2 flux relationship can be easily modeled using ANN, a non-conceptual but effective machine learning technique. A multi-ecosystem (forest, grassland and cropland) ANN-based CO_2 flux simulation is presented with the objective of presenting ANN as an effective alternative technique to model CO_2 flux using energy flux (net radiation, R_n, latent heat, LE, sensible heat, H and soil heat flux, G) and evaluate the model performance using statistical indices for the three ecosystems.

MATERIALS AND METHODS

A multilayer perceptron (MLP) ANN technique with an error back propagation (BP) algorithm was applied to a CO_2 flux simulation comparison of three different ecosystems (forest, grassland and wheat (cropland)). The ecosystems studied are represented at three localities in the U.S.; 1) mixed forest-Morgan-Monroe State Forest, Indiana (39°19'N, 86°25'W); 2) grassland-Fort Peck Indian Reservation, Montana (48°18.473'N, 105°6.032'W); and 3) winter wheat field-16 km north of Ponca City, Oklahoma (36°45'N, 97°5'W). These sites are all part of the AmeriFlux network of eddy covariance flux towers that quantify variation in CO_2 and water vapor exchange between terrestrial ecosystems and the atmosphere [2]. This network, in addition to the similar regional networks CarboEurope, AsiaFlux, OzFlux and Fluxnet Canada, participates in synthesis activities across large geographical areas in order to study the underlying mechanisms responsible for observed fluxes and carbon pools.

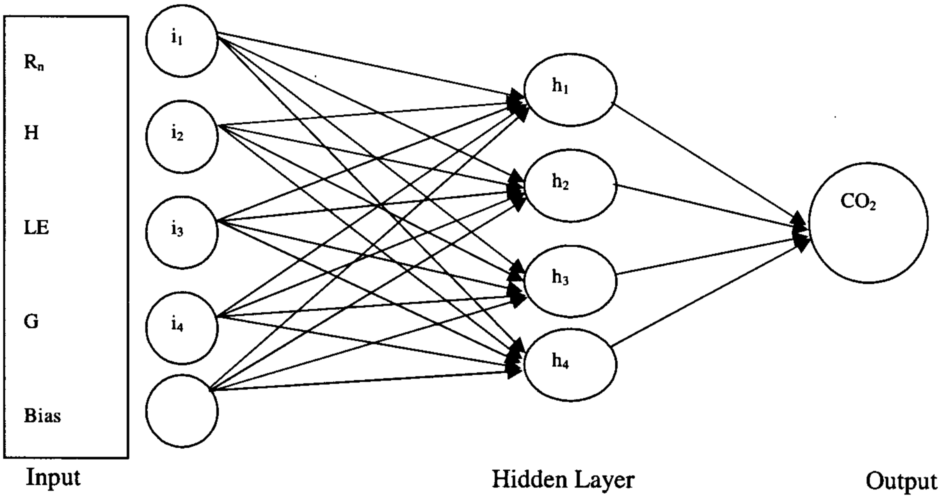

Fig 1: ANN Input-output Data Architecture

Artificial neural networks represent new technology that have proven to be highly effective in modeling CO_2 and water fluxes [3, 4]. ANN's are machine learning (i.e. self adjustment of internal control parameters), non-parametric, mathematical structures that identify complex non-linear relationships between input and output data sets [5]. A neural network with MLP architecture is designed to function within non-linear phenomena and consist of input/output layers with input/output neurons and one or more hidden layers with some number of neurons on each. An artificial neuron in ANN architecture receives a set of inputs or signals (x), calculates a weighted average of them (z) using the summation function and then uses some activation function to produce an output (Equation 1).

$$z = \sum_{i=1}^{n} x_i w_i \qquad (1)$$

Connections between the input layer and the middle or hidden layer contain weights, which are determined through training the system [5, 6]. The hidden layer sums the weighted inputs (w_i) and uses the following transfer function (Equation 2) to create an output value:

$$f(x) = \frac{1}{(1+e^{-x})} \qquad (2)$$

In time series predictions, supervised training is used where the ANN is trained to minimize the difference between the network output and the target (observed). The BP algorithm is widely implemented in all ANN paradigms and is based on multi-layered feed forward topology with supervised learning methodology [7].

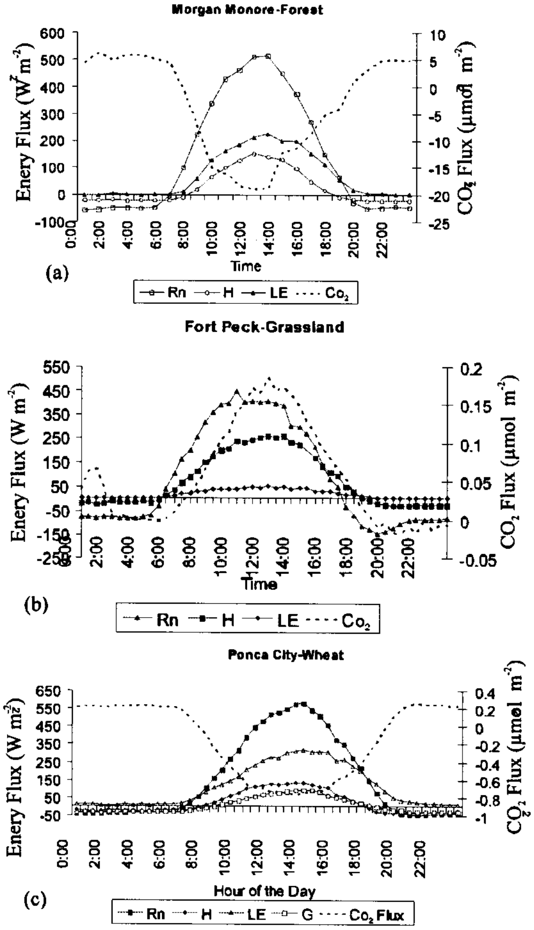

Fig. 2: Average Hourly Variation of Micrometeorological Variables (a) Forest (b) Grassland and (c) Cropland

In our ANN-MLP architecture, four input parameters that represent measurements of energy fluxes (R_n, G, LE and H) were used to train the ANN and predict the flux of CO_2 (Fig. 1). Diurnal hourly flux data from 15 days of observations at each site were divided into training (5 days) and testing (10 days) categories. Energy and carbon flux data are available at Carbon Dioxide Information Analysis Center [2]. The data used were from June-July of 1999, 2000 and 2002 for cropland, forest and grassland ecosystems, respectively.

The performance of the ANN model was evaluated using statistical comparisons of the predicted and observed outputs. This comparison used two measures of error: root mean of squares of errors (RMSE) and mean absolute percent error (MAPE). RMSE is sensitive to outliers, but is not scale free, while MAPE calculates the forecast error as a percentage of the actual value in order to avoid problems associated with scaling.

RESULTS AND DISCUSSION

Average diurnal variation of energy fluxes and CO_2 flux for the three ecosystems is shown in Fig. 2. In all the three ecosystems, it is shown that a close correlation was found between CO_2 flux and R_n, G, LE and H. For the forest and cropland sites (Fig. 2a and 2c), we found lower CO_2 concentrations during the day, probably due to the dominance of green vegetation in these ecosystems. On the other hand, the CO_2 concentration in the grassland site (Fig. 2b) is higher in the day peaking around noon. The absence or limited green vegetative cover (limited photosynthesis) and the CO_2 release due to soil respiration are likely responsible for this increase. The energy fluxes (R_n, H, LE and G) peaked around noon for all sites. Transpiration from the vegetative cover increases LE losses than the H losses for the forest and cropland sites. Attributed to the limited vegetative cover, the grassland site has higher average H losses than LE losses.

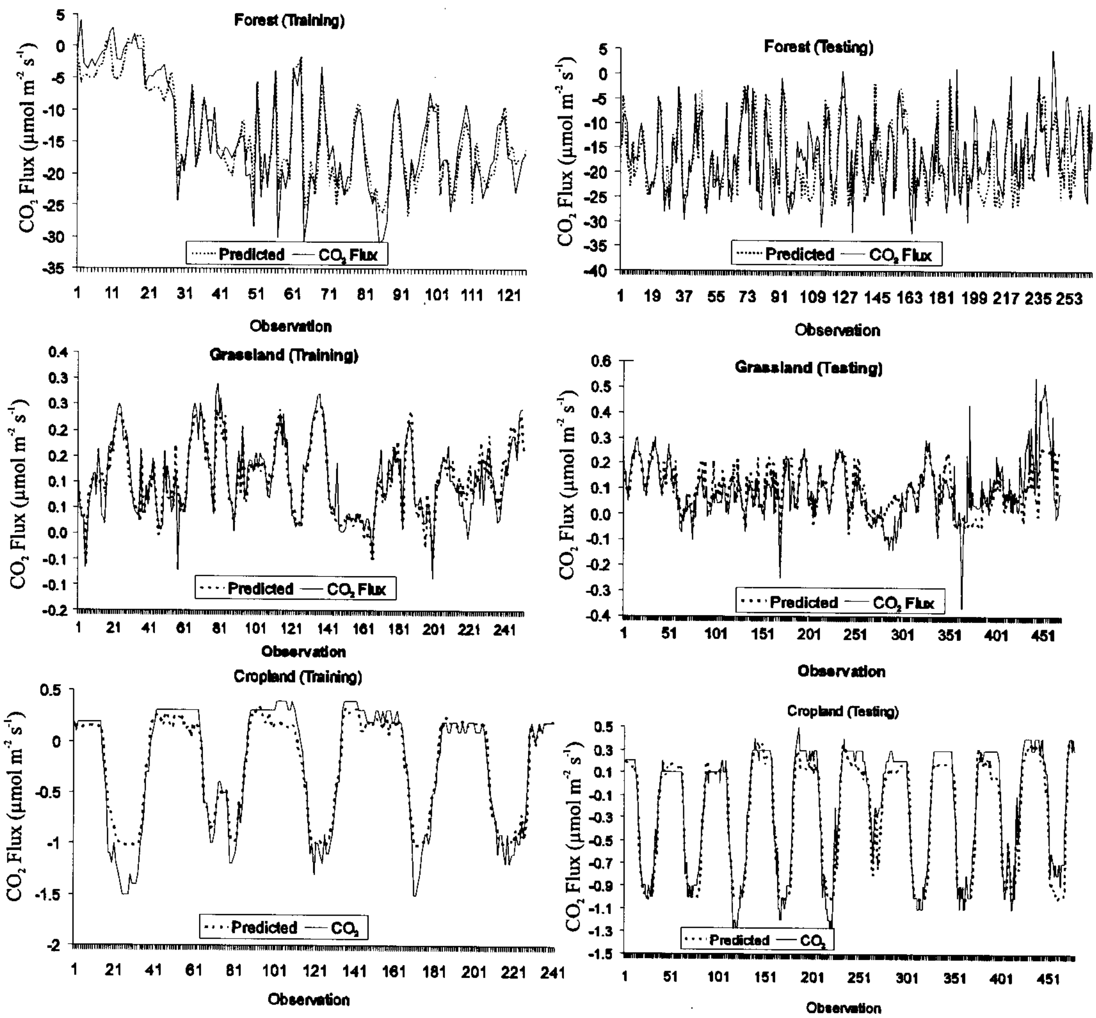

Fig. 3: ANN Predicted CO_2 Flux for the Three Ecosystems (a) Training (b)Testing

Table 1: Statistical Indices Showing the ANN Model Performance

Index	Training			Testing		
	Forest	Grassland	Wheat	Forest	Grassland	Wheat
RMSE	0.32	0.002	0.004	0.45	0.003	0.019
MAPE	0.43	0.62	0.017	0.57	1.81	0.56
R^2	0.89	0.83	0.98	0.86	0.75	0.94

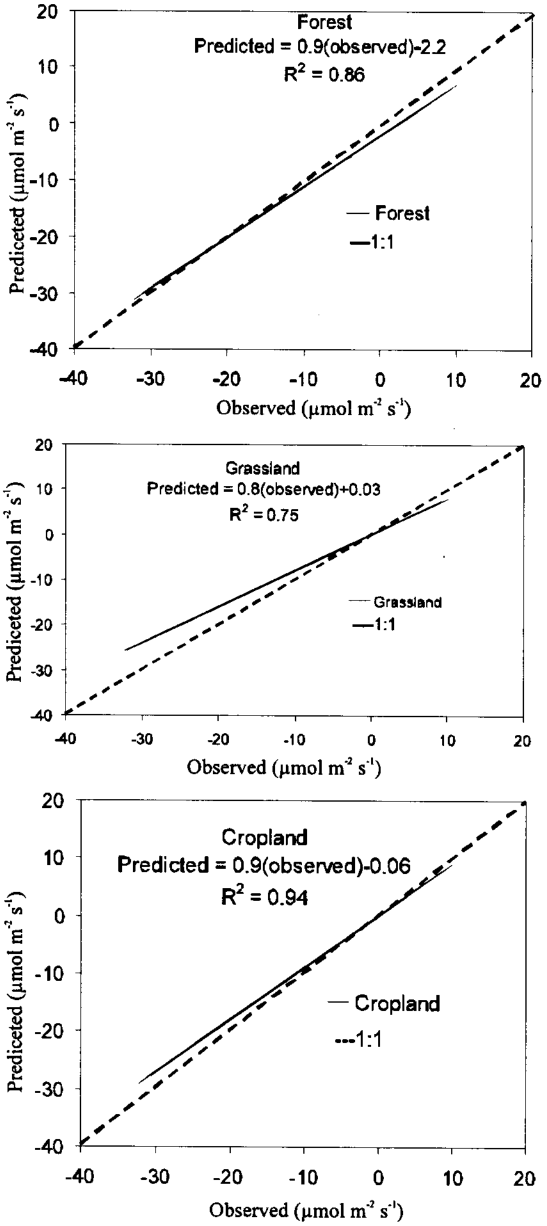

Fig. 4: Predicted vs. Observed CO_2 Flux (μmol m^{-2} s^{-1}) for the (a) Forest, (b) Grassland and (c) Cropland

The CO_2 simulation using an ANN-MLP technique for the three studied ecosystems (forest, grassland and cropland) corresponded well with the observed flux values (Fig. 3). It is shown that higher R^2 was observed for the three ecosystems during data training than the testing phase of the modeling (Table 1). The ANN simulations for each ecosystem type successfully predicted the observed values with R^2 values between 0.75 and 0.94 (Table 1). In the forest ecosystem, the 10-day hourly predicted carbon flux showed an average R^2 of 0.85 for the testing phase of modeling. In the grassland ecosystem, the average R^2 value for the testing phase of the prediction was 0.75. In the cropland ecosystem, the predicted carbon flux closely matched the observed values with an average R^2 of 0.94. Figure 4 shows predicted vs. observed CO_2 fluxes in relation to 1:1 trend line. The predicted CO_2 flux at the forest site under-predicts the observed values as the values of observed data increases, on the other hand predicted values seem to be lower than observed for grassland and cropland ecosystems at lower observed values (Fig. 4).

The grassland ecosystem, with less vegetative cover than either the forest or cropland ecosystems, likely has less contribution of vegetation to the net carbon exchange. However, the inclusion of soil moisture could improve the overall predictions since both soil moisture and soil temperature likely play an important role in the amount of soil respiration [8]. We have shown that our ANN-MLP method is a reliable, efficient and highly significant to estimate regional or global CO_2 fluxes from point measurements and to the examination of spatiotemporal budget of the CO_2 fluxes.

Surface energy fluxes modeled from remotely-sensed data can be used to model spatial carbon flux using ANN covering larger areas. The fact that energy fluxes and other microclimate variables can be easily mapped from remote sensing makes this technique easily applicable to provide carbon information at the spatial and timescale of interest. We believe future carbon mitigation strategies and climate change policies will benefit greatly from similar studies.

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