Abstract No: A-102

ESTIMATING CO_2 FLUX FROM BARE LAND IN A PEAT ISLAND USING ARTIFICIAL NEURAL NETWORK MODEL

Yudi Chadirin[1*], Satyanto K. Saptomo[1], Rudiyanto[1], Budi I. Setiawan[1], Kazutoshi Osawa[2], Dian Novarina[3] and Muhajir Utomo

[1]Department of Civil and Environmental Engineering, IPB, Indonesia
[2]Department of Environmental Engineering, Utsunomiya University, Japan,
[3]PT April Management, Indonesia
[4]Faculty of Agriculture, University of Lampung, Indonesia

**Corresponding author: gooday926@yahoo.com*

SUMMARY

Temperature and soil moisture are cofounded factors that has influence on CO_2 soil emission while rainfall increase in soil moisture. These parameters were varied and easy to change by time and affected on CO_2 soil emission. A continuous measurement of CO_2 emission provides the accumulated emission more accurately but needs expensive instrument. Meanwhile, the measurement of soil moisture and temperature could be conducted with simpler and cheaper instruments. Thus it's a need to figure out the CO_2 emission from peat with low cost based on environmental biophysics to predict CO_2 emission based. The objective of this study was to develop an artificial neural network model to predict CO_2 emission from peat in tropical region based on environmental biophysics data. Environmental biophysics data such as soil temperature, soil moisture, its gradients and rainfall were used as covariates for the model. The model was trained based on continuous field measurement on bare peatland. CO_2 emission had positive correlation with soil temperature but had negative correlation with soil moisture and rainfall. Result showed that ANN model could predict CO_2 emission from bare peatland with R^2 and RMSE are = 0.71 and 0.49 for training and 0.5 and 0.76 for testing respectively. We proposed that this model can be used to figure out the CO_2 emission from peatland in low cost and conducted in simple measurement.

***Keywords**: artificial neural network, bare peatland, CO_2 emission, temperature gradient, soil moisture gradient*

INTRODUCTION

CO_2 flux as result of soil respiration is an important component of carbon budget in consideration for sustainability management for peat land. Soil respiration is affected by variety of biotic and abiotic factors, such as soil temperature, soil moisture, amount and quality of carbon stored, precipitation, soil properties and soil management activities (Rustad *et al*., 2000; Raich and Tufekcioglu, 2000; Hui and Luo, 2004; Carrasco *et al*., 2006; Davidson and Janssens, 2006; Borken *et al*., 2002; Shen *et al.,* 2008). Soil respiration is changing by temporal and spatial variation (Shen *et al*., 2008; Epron *et al*., 2004) and small changes in soil respiration may strongly affect soil carbon sequestration (Raich and Schlesinger, 1992). Thus, it is important to conduct long term and continues measurement. A long term and continues measurement produced accumulative CO_2 flux that more accurate than extrapolation (Chadirin *et al.,* 2015). However a long term and continues measurement of CO_2 flux need complex measurement system and expensive instrument. Therefore it is important to obtain good estimates of soil respiration from simple, cheap, long-term measurement. Artificial neural network (ANN) is one of promising method for estimating CO_2 flux from micrometeorological data (Melesse and Hanley, 2009) and soil carbon budget from soil C content, temperature, and moisture level (Alvarez *et al*., 2009). In this study, we developed an artificial neural network model top CO_2 flux from bare land in peat island in tropical region based on soil temperature, moisture and precipitation

METHODS

This research was conducted in Pulau Padang, a peat island located on eastern of Sumatera Island. The location of observation is a bare field that was dedicated for monitoring station, at a site of pulpwood plantation. CO_2 flux and environmental biophysics parameters were measured and monitored automatically in monitoring station. Electrical conductivity, moisture and temperature of soil were measured by using sensor Decagon 5TE. Depth of water level in peat was measured by CTD-10. Those sensors were connected to data logger (Decagon, EM50) for recording the measurements data. Data were recorded in 15 minutes interval. Weather condition was measured and monitored by using Automatic Weather Station (Davis, Vantage Pro 2). This instrument measured solar radiation, wind speed and direction, precipitation, air temperature and humidity and recorded in 15 minutes interval, too. A Licor Li-8100 Automatic Soil CO_2 Emission Measurement System (Licor, USA) was set up on bare peat in the monitoring station to measured and monitored CO_2 flux from bare peat. The system includes mechanical chamber and gas analyzer unit. This measurement system was powered by solar panel. Soil emission was measured from area that covered by mechanical chamber and the gas analyser unit controlled the movement of chamber. Measurement of CO_2 was set to be conducted hourly with 3 times replication. The hourly average CO_2 emission was obtained as average from those replications.

We proposed ANN model to predict CO_2 flux based on measurement of soil moisture and temperature and also precipitation. The ANN consists of three layers: input, hidden and output layers. Input layer has 5 nodes for inputs (covariates), hidden layer has 6 hidden nodes and CO_2 flux as a single output layer. The Sigmoid function was used as activation function in each node. Before the data were used in the calculation, the data were linearly normalized into 0 to 1 for input and 0.2 to 0.8 for output. The optimization of weights that connected between nodes in different layers was performed using the feed-forward back propagation learning method (Hecht-Nielsen, 1989). Learning rate and momentum were set equal to 0.9 and 0.8, respectively. Training process was terminated when iteration reached 10000.

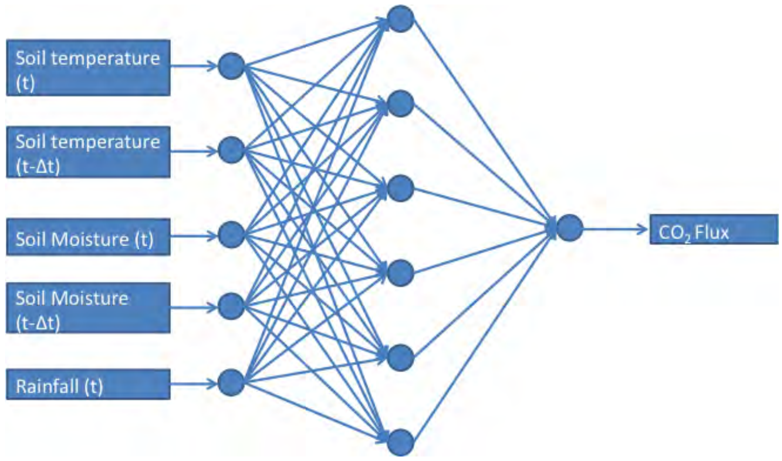

Figure 1: Structure of ANN model

RESULTS AND DISCUSSION

The ANN model shows that the CO_2 flux modeled from soil temperature, moisture and rainfall showed a good agreement with the observed values (Figure 2). The CO_2 flux model has same pattern with observed value. The shape of the curve of CO_2 emission flux following the change in soil temperature in form a sinusoidal curve which is generally highest during the day and lowest at night. CO_2 flux decreased dramatically when soil moisture increased from 0:23 became 0:28 cm^3/cm^3 volumetric water content (VWC). It caused by rain, where the soil pores filled with water so that the aeration is reduced and lowering microorganism activity. The influence of soil moisture and temperature had variability to soil respiration. Temperature affected soil respiration either as independent factor or as cofounded factors (Saiz *et al.*, 2007; Davidson *et al.*, 1998). As independent factor, soil temperature has positive correlation (R^2=0.24) and had negative correlation with soil moisture (R^2=0.09) and precipitation (R^2=0.001). Thus we applied soil moisture, temperature and precipitation as ANN model to estimate CO_2 flux. In this study, soil respiration had different rate at same temperature, thus the gradient soil moisture and temperature was applied as input parameters together with soil moisture and temperature itself.

The ANN model was trained using hourly inputs and output diurnal data. The ANN model performance between training and testing were evaluated by RMSE and R^2. Figure 3 shows that the performance of ANN model was better at training (R^2=0.71 and RMSE=0.49) compared to testing (R^2=0.5 and RMSE=0.76). The accuracy of the model at testing was lower than training because the baseline data for CO_2 flux decreased from 4.1 mmol/m^2/s to 0.38 mmol/m^2/s. Then it resulted the model overestimated at testing.

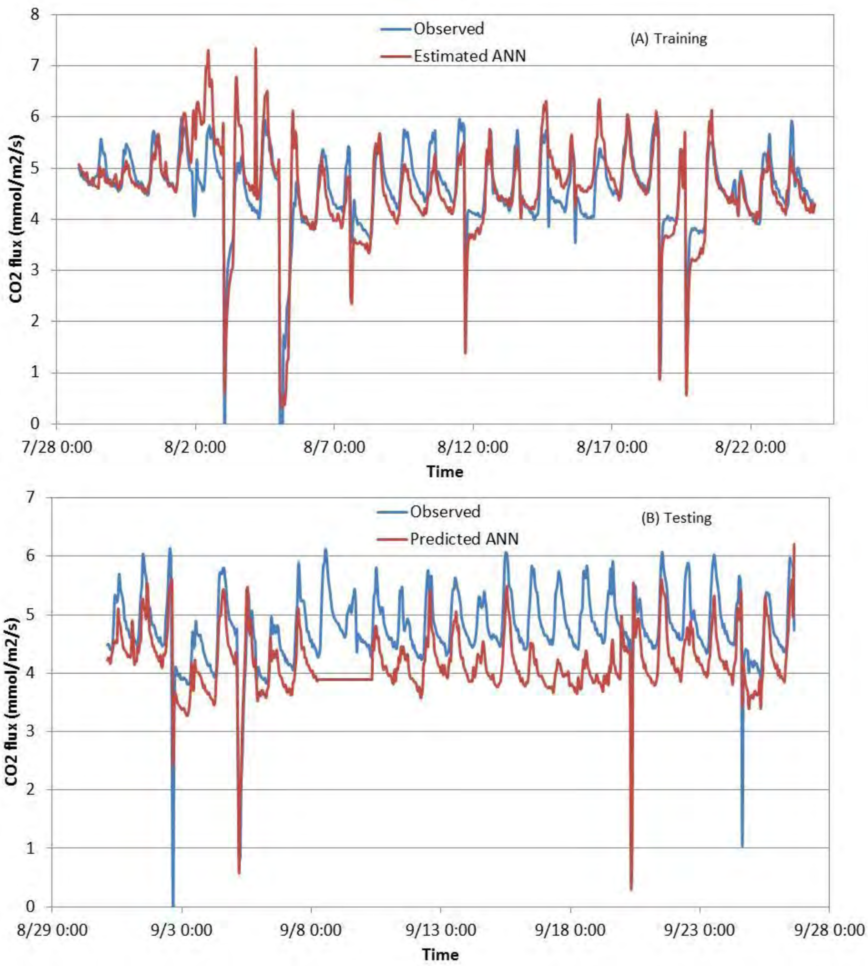

Figure 2: Predicted CO_2 flux based on ANN model for (A) training and (B) testing

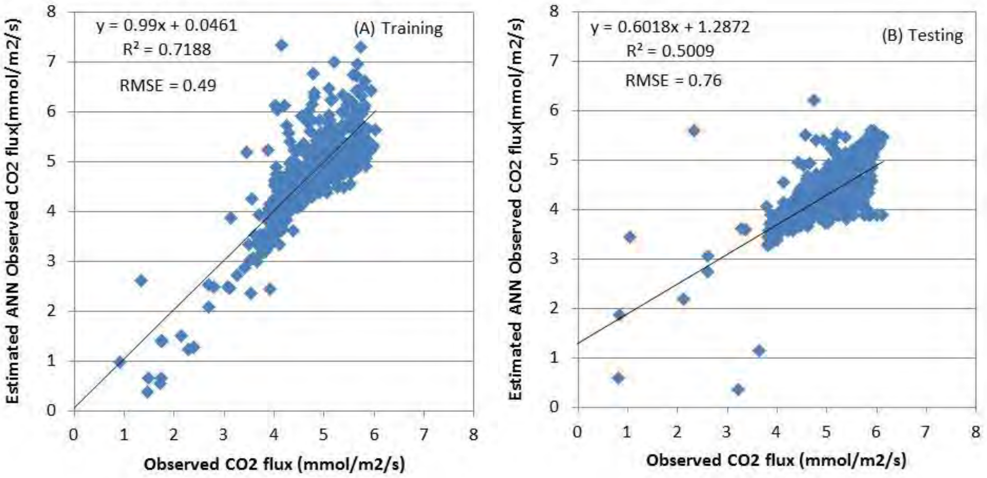

Figure 3: Agreement between observed and predicted CO_2 flux from ANN model for (A) training and (B) testing

CONCLUSION

The applicability of ANN to CO_2 flux model from environmental biophysics data was studied in range of dry condition for bare peat land. Soil moisture, temperature, precipitation and it`s gradient were used as cofounded factor for ANN model to obtain higher correlation compare to its as independent factor for CO_2 flux estimation. We proposed that this model can be used to figure out the CO_2 emission from bare land in peat island with low cost and conducted in simple measurement.

REFERENCES

1. Borken, W., Xu, Y.-J., Davidson, E.A., Beese, F., 2002. Site and Temporal Variation of Soil Respiration in European Beech, Norway Spruce, and Scots Pine Forests. Global Change Biology 8, 1205–1216.
2. Carrasco, J. J., N. C. Jason, and J. W. Harden (2006), *Modeling Physical and Biogeochemical Controls Over* Carbon *Accumulation in A Boreal Forest Soil*, Journal of Geophysical Research, 111.
3. Chadirin, Y., Saptomo, K.S., Setiawan, B.I., Osawa, K., and Novarina, D., 2015. CO_2 Emission from Bare Peat Land Using Continues Measurement. Advances in Environmental Biology, 9, 180-183
4. Daniel Epron, Yann Nouvellon, Olivier Roupsard, Welcome Mouvondy, André Mabiala, Laurent Saint-André, Richard Joffre, Christophe Jourdan, Jean-Marc Bonnefond, Paul Berbigier, Olivier Hamel, 2004. *Spatial and Temporal Variations of Soil Respiration in A Eucalyptus Plantation in Congo, Forest Ecology and Management*, 202: 1–3, 149-160.
5. Davidson, E. A., and I. A. Janssens (2006), T*emperature Sensitivity of Soil Carbon Decomposition and Feedbacks to Climate Change,* Nature, 440, 165 – 173
6. Hecht-Nielsen, R., 1989. *Theory of the Backpropagation Neural Network*. Proceedings of International Joint Conference on Neural Networks Vol 1, 593–605.
7. Hui, D., and Y. Luo (2004), *Evaluation of Soil CO_2 Production and Transport in Duke Forest Using A Process-Based* Modeling *Approach*, Global Biogeochemical Cycles, 18.
8. Lloyd, J., and J. A. Taylor. 1994. ―On the Temperature Dependence of Soil Respiration". Functional Ecology 8 (3). [British Ecological Society, Wiley]: 315–23.
9. Raich, J. W., and A. Tufekcioglu (2000), *Vegetation and Soil Respiration: Correlations and Controls,* Biogeochemistry, 48, 71–90.
10. Raich, J.W., Schlesinger, W.H., 1992. *The Global Carbon Dioxide Flux in Soil Respiration and Its Relationship to Vegetation* and *Climate*. Tellus, 44B, 81–99.
11. Rustad, L. E., R. G. Huntington, and R. D. Boone (2000), *Controls on Soil Respiration: Implications for Climate* Change, Biogeochemistry, 48, 1–6.
12. Shen, W., G. D. Jenerette, D. Hui, R. P. Phillips, and H. Ren (2008), *Effects of Changing Precipitation Regimes on Dryland Soil Respiration and C Pool Dynamics at Rainfall Event, Seasonal and Interannual Scales*, Journal of Geophysical Research, 113.