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Quantifying biosphere–atmosphere exchange of CO_2 using eddy covariance, wavelet denoising, neural networks, and multiple regression models

Fatih Evrendilek*

Department of Environmental Engineering, Abant Izzet Baysal University, Bolu, Turkey

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ABSTRACT

Net ecosystem exchange of CO_2 (NEE) over a temperate peatland in northwestern Turkey was directly measured using the eddy covariance (EC) method for 590 days. Both the response variables of diurnal and nocturnal NEE (NEE_d and $R_{eco\text{-}n}$) and the explanatory variables of latent heat (LE), relative humidity (RH), and atmospheric CO_2 and H_2O concentrations ($AtmCO_2$ and $AtmH_2O$) were denoised with discrete wavelet transform (DWT) using coiflet (coif10-6). Denoised NEE fluxes and their temporal components were modeled using multiple linear regression (MLR), polynomial regression (PR) and artificial neural network (ANN) models as a function of LE, RH, $AtmCO_2$, $AtmH_2O$, air temperature (T_{air}), day of year (DOY), and local time. Peak NEE_d flux, and peak $R_{eco\text{-}n}$ efflux were $-0.37\,mg\,CO_2\,m^{-2}\,s^{-1}$ in late July and $0.27\,mg\,CO_2\,m^{-2}\,s^{-1}$ in mid-August. Mean annual NEE was estimated at $-1157\,g\,CO_2\,m^{-2}$ which is in agreement with previous results of peatland studies. The use of DWT-augmented ANN, MLR and PR models significantly increased predictive power and reduced uncertainties in predicting the temporal dynamics of the biosphere–atmosphere CO_2 exchange, relative to the models without DWT denoising. Out of 28 DWT-augmented ANNs, multilayer perceptron (MLP) and recurrent network (RN) models were the best diurnal and nocturnal ones, respectively, based on accuracy metrics derived from training, cross-validation and independent validation. Among the DWT-based ANN, MLR and PR models, diurnal MLP and nocturnal MLR outperformed the others. Wavelet-augmented ANN and MLR models appear to be a promising tool to quantify diurnal and nocturnal NEE dynamics, respectively.

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1. Introduction

A better understanding of spatio-temporal dynamics of carbon (C) sources and sinks under human-induced disturbances necessitates a better quantification and partitioning of long-term net ecosystem exchange of CO_2 (NEE) into flux and temporal components. Such quantitative estimates may assist in a better tailoring of preventive and mitigative measures in a changing global environment (Wali et al., 1999; Baldocchi, 2008; Evrendilek et al., 2011). Continuous eddy covariance (EC) measurements across different ecosystems of the world play a vital role in elucidating magnitude, trajectory, and diel-to-interannual variability of NEE fluxes, particularly, when used with process-based (mechanistic) and/or data-driven models to interpolate NEE dynamics over a given spatio-temporal resolution.

However, analyzing EC time-series data is challenging as these signals include meteorological and instrumental noises that need to be decomposed from ecologically meaningful signals, and thus, there are always gaps of a differing time length in filtered EC datasets (Falge et al., 2001; Papale et al., 2006; Richardson and Hollinger, 2007). In response to these challenges, numerous approaches such as process-based models, look-up tables, multiple regression models, stochastic gap-filling algorithms, and artificial neural networks (ANNs) have been developed to estimate NEE (Papale and Valentini, 2003; Grinsted et al., 2004; Reichstein et al., 2005; He et al., 2006). An analysis of comparative performances of 15 gap-filling techniques by Moffat et al. (2007) showed that ANNs outperformed the other techniques.

On the other hand, discrete wavelet transform (DWT) decomposes a signal concurrently into time and frequency domains with high and low resolutions (Torrence and Compo, 1998; Grinsted et al., 2004). Separation of a signal into high and low resolutions enables fine and coarse scale features to be captured in the signal, respectively. To the author's best knowledge, wavelet denoising has not been applied to long-term EC measurements to augment both multiple (non-)linear regression models and ANNs in quantifying diurnal and nocturnal dynamics of NEE. The objective of this study was therefore to model diurnal and nocturnal NEE fluxes over a temperate peatland based on wavelet-augmented ANNs and multiple (non-)linear regression models of long-term EC measurements between day of year (DOY) 193 in 2010 and DOY 51 in 2012.

* Tel.: +90 374 2541000; fax: +90 374 2534558.
E-mail addresses: fevrendilek@ibu.edu.tr, fevrendilek@yahoo.com

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2. Materials and methods

2.1. Study area

Yenicaga peatland is located at an altitude of 988 m above sea level in the northwestern Black Sea region of Turkey. The prevailing climate in the study area is cool temperate with mean annual precipitation, evapotranspiration (ET) and air temperature (T_{air}) of 538 mm, 1200 mm and 13.6 °C, respectively. About 40% and 30% of the mean annual rainfall are received in the summer and spring seasons, respectively. Plant functional type of the study area is mostly grassland used as a pasture with vegetation height of about 0.6 m.

2.2. Data acquisition

The net ecosystem exchange of CO_2 flux densities (NEE, mg CO_2 m^{-2} s^{-1}) between the biosphere and atmosphere in Yenicaga peatlands was measured using a 3-m EC flux tower between DOY 193 (12 July 2010 17:00) and DOY 51 (20 February 2012 16:00). An open-path CO_2/H_2O gas analyzer (LI-7500, Licor Inc., Lincoln, NB, USA), a 3-D sonic anemometer/thermometer (CSAT3, Campbell Scientific Inc., Logan, UT, USA), and a data logger (CR3000, Campbell Scientific Inc.) were used to continuously measure the three wind components and the scalar components at a sampling rate of 10 Hz. Then, latent (LE, W m^{-2}) fluxes, and atmospheric CO_2 and H_2O concentrations (AtmCO_2, mg m^{-3}; and AtmH_2O, g m^{-3}, respectively) were estimated. EC-measured flux densities were adjusted for influences of variations in air density on NEE and LE fluxes using the standard Webb–Leuning (WPL) correction (Webb et al., 1980) and block-averaged over one hour (h) via the online flux computation. Air temperature (T_{air}, °C) and relative humidity (RH, %) were measured using a HMP45C probe (Vaisala, Finland). Positive or negative NEE values measured indicate fluxes to the atmosphere (carbon source) or to the biosphere (carbon sink), respectively.

Rates of NEE between the biosphere and the atmosphere are governed by net biome productivity (NBP), total ecosystem respiration (R_{eco}), and human-induced disturbances (Chapin et al., 2002; Reichstein et al., 2005).

$$\underbrace{(R_a + R_h)}_{R_{eco}} = \text{EC-measured nocturnal NEE} = R_{eco\text{-}n}$$

where R_{eco} refers to the rate of total CO_2 efflux to the atmosphere by both autotrophic (R_a) and heterotrophic respiration (R_h). NEE is the net C balance between photosynthetic CO_2 gain and respiratory CO_2 losses from plants and animals. Eddy covariance-measured nocturnal NEE was assumed to be equal to R_{eco} at night ($R_{eco\text{-}n}$) as GPP ceases at night. Effluxes of $R_{eco\text{-}n}$ can also be extrapolated to daytime to estimate diurnal R_{eco} ($R_{eco\text{-}d}$) as a function of closely associated predictors which can in turn be used to derive GPP values.

2.3. Data processing

Data processing consisted of (1) the removal of missing values, and spikes for NEE, LE, friction velocity (u^*), RH, AtmCO_2, AtmH_2O, and T_{air}; (2) temporal partitioning; and (3) DWT denoising. First, spikes in hourly mean values of the EC dataset were rejected when NEE, LE, and u^* fell outside the minimum and maximum limits recommended in the related literature as follows (Olson et al., 2004; He et al., 2006; Papale et al., 2006; Thomas et al., 2011):

NEE > 1.76 or <−1.76 mg CO_2 m^{-2} s^{-1} (where 1 μmol CO_2 m^{-2} s^{-1} ≈ 0.044 mg CO_2 m^{-2} s^{-1}); LE > 700 or <−100 W m^{-2}; and u^* > 6 or < 0 m s^{-1}.

Latent heat fluxes measured by EC were converted into equivalent ET rates (mm h^{-1}) when necessary as follows:

$$\mathrm{ET} = \left(\frac{3600 \times \mathrm{LE}}{\lambda_{LE}(T_{air}) \times \rho_w}\right)$$

$$\lambda_{LE}(T_{air}) = (2501 - 2.37 \times T_{air}) \times 10^3$$

where $\lambda_{LE}(T_{air})$ is the latent heat of vaporization of water (amount of energy to evaporate a unit weight of water) (J kg^{-1}) as a function of T_{air}. p_w is water density (~1 Mg m^{-3}), and 3600 is a time conversion coefficient for s h^{-1}.

Second, the non-gap-filled dataset after the removal of erroneous values was temporally partitioned into daytime (diurnal) and nighttime (nocturnal) datasets according to mean negative and positive NEE values obtained between 9:00 and 17:00, and between 18:00 and 8:00, respectively. Finally, diurnal and nocturnal datasets of NEE, LE, RH, AtmCO_2, and AtmH_2O were separately subjected to DWT denoising based on the orthogonal basis of Coiflet with order of 10 and decomposition level of six (coif10-6) using KyPlot 2.0 (Kyence Lab. Inc., Tokyo, Japan).

2.4. Wavelet denoising and neural networks

Unlike Fourier transform, DWT converts original time series from the time domain into the concurrent time/frequency domain as father wavelets (the low frequency components) and mother wavelets (the high frequency components) without loss of temporal information (Kang and Lin, 2007; Koirala et al., 2010). In the present study, Coiflet (order = 10) was used as the mother wavelet for denoising. Coiflets are a nearly symmetrical wavelet basis, unlike Daubechies wavelets, that has vanishing moments for wavelet function and scaling function and maintains the typical shape of the diurnal and seasonal cycles (Huang and Hsieh, 2002). Each of the datasets with and without DWT denoising for both nighttime and daytime was fed into a total of 28 ANNs. The ANNs run with and without denoising consisted of a combination of 10 different topologies (generalized feedforward – GFF; linear regression – LR; multilayer perceptron – MLP; MLP with principal component analysis – PCA; probabilistic neural network – PNN; radial basis function – RBF; classification support vector machine – SVM; time-delay network – TDNN; recurrent network – RN; and time-lag recurrent network – TLRN); three hidden layers (no hidden layer, 1 hidden layer, and 2 hidden layers); two learning algorithms (Momentum – M – versus Levenberg–Marquardt – L); and two learning modes (batch – B – versus online – O) (Table 1). The nine temporal (feedforward or feedback) ANNs used in this study (TDNN, TLRN, and RN) are based on the backpropagation through time (BPTT) algorithm that uses an adaptive memory structure of past time periods to predict the future. The 19 static (feedforward) ANNs are based on the backpropagation (BP) algorithm that does not use feedbacks or delays.

Levenberg–Marquardt algorithm composed of first order error BP and second order Newton algorithms runs the training to determine a set of weights that minimize the error for all samples in the training set (Wilamowski et al., 2008). Momentum algorithm utilizes a locally adaptive approach with a memory term to continue past local minima, and thus, to speed up training time (Haykin, 1999). Batch learning uses multiple passes repeatedly processing previously used training set and new examples and considers all the training instances at once, whereas online learning uses only one pass through the entire training set without processing previously learned data and considers one training instance individually at a time (Oza, 2005).

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