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Research article

Response of carbon uptake to abiotic and biotic drivers in an intensively managed Lei bamboo forest

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A R T I C L E I N F O

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A B S T R A C T

Lei bamboo (*Phyllostachys praecox*) is widely distributed in southeastern China. We used eddy covariance to analyze carbon sequestration capacity of a Lei bamboo forest (2011–2013) and to identify the seasonal biotic and abiotic determinants of carbon fluxes. A machine learning algorithm called random forest (RF) was used to identify factors that affected carbon fluxes. The RF model predicted well the gross ecosystem productivity (GEP), ecosystem respiration (RE) and net ecosystem exchange (NEE), and displayed variations in the drivers between different seasons. Mean annual NEE, RE, and GEP were -105.2 ± 23.1, 1264.5 ± 45.2, and $1369.6 \pm 52.5\,g\,C\,m^{-2}$, respectively. Climate warming increased RE more than GEP when water inputs were not limiting. Summer drought played little role in suppressing GEP, but low soil moisture contents suppressed RE and increased the carbon sink during drought in the summer. The most important drivers of NEE were soil temperature in spring, summer, and winter, and photosynthetically active radiation in autumn. Air and soil temperature were important drivers of GEP in all seasons.

1. Introduction

Bamboo forests are widely distributed in warm temperate, subtropical, and tropical zones between 46° N and 47° S (Mcdowell et al., 2015). Bamboo forests cover 32 million ha globally, accounting for 0.8% of the global total forest area in 2015 (FAO, 2015). China is called "Kingdom of Bamboo" since it has the highest richness of bamboo species (more than 500 varieties of 39 species) in the world (Li et al., 2015; Mao et al., 2016). According to the Eighth National Forest Inventory (2009–2013), bamboo forests cover 6.01 million ha in China, and the area had increased by 12% from the previous inventory (SFAPRC, 2015).

The management of bamboo forests differs from that of other forest plantations, i.e., bamboo forests are managed by annual thinning (Li et al., 2013; Mao et al., 2016). Rather than leading to long- or medium-term reduction of carbon stocks (Zhou and Jiang, 2004; Zhou et al., 2006), as in other forest types, harvesting leads to long term stable carbon stocks. Moso bamboo (*Phyllostachys edulis* (Carrière) J. Houz.) forest, could sequester 4.91–5.45 t C $ha^{-1}\,yr^{-1}$, i.e., 1.41–1.57 times that of fast-growing Chinese fir (*Cunninghamia lanceolata* (Lamb.) Hook) plantations (Zhou and Jiang, 2004). The management requirements of different bamboo species differ widely. Intensively managed Lei bamboo (*Phyllostachys praecox* Chu et Chao cv. Prevernalis S. Y. Chen et C. Y. Yao) with a high rate of production and edible shoots (Zhou et al., 1999) is cultivated widely in four provinces of subtropical China (Zhuang et al., 2011).

While productivity of northern forests is limited by temperature (Suni et al., 2003), and that of southern tropical forests (Wang et al., 2016) and Mediterranean forests (Keenan et al., 2009) often by drought, the limiting factors of carbon exchange in subtropical forests are not clearly known. In subtropical forests the growing season coincides with the period of ample precipitation, and drought is not assumed to be frequent, making it difficult to form meaningful hypothesis on which factors limit the carbon assimilation within these forests. Albert et al. (2017) proposed that approaches based on machine learning could help to get a "more complete picture" of interactions between carbon exchange and environment. For example, neural networks have been used to establish carbon exchange relationships

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(Moffat et al., 2010; Albert et al., 2017). Another popular algorithm, random forest model has received less attention (Pham and Brabyn, 2017). It has been used previously for scaling up (from ecosystem level) eddy covariance measurements to large geographical scales (Jung et al., 2009), but it has not been used for inferences on carbon exchange-environment interactions in forests. We propose that the use of inductive data analysis could be particularly promising for ecosystems that have received little attention and where limitation by environmental drivers and their interactions are complex. Subtropical ecosystems are good candidates for this study approach due to their high humidity but low temperatures that may limit production in the winter.

This study analyzed the carbon fluxes and balance in a Lei bamboo plantation in Lin'an, Hangzhou, China, from 2011 to 2013 using the eddy covariance technique. The objectives of this study were to estimate the carbon uptake ability and seasonal and annual changes of Lei bamboo stands, and to investigate the factors driving the carbon flux in such changes. We used random forest to establish these relationships and interpreted these in terms of limiting factors.

2. Materials and methods

2.1. Study site

The study was conducted in a Lei bamboo plantation (30°18′17.27″N, 119°34′10.42″E; Fig. S1) in the suburbs of the town of Taihuyuan in Lin'an, Hangzhou, Zhejiang Province, China. The 854 ha plantation was established in 2007. The average height and mean diameter at breast height was about 4.5 m and 4 cm, respectively. The approximately 17,000 bamboo stems ha^{-1} were mainly two- and three-year-old bamboo. Understory vegetation comprised only a few shrubs and herbs due to regular manual weeding.

In the study area of subtropical monsoon climate, the mean annual air temperature is 15.8 °C, with extreme minimum and maximum temperatures of −13.3 and 41.9 °C, respectively (both occurring in 1967). The average annual frost-free period is 234 days, with 1939 h of sunshine annually. Average annual precipitation (P) is 1600 mm, with 70% falling from spring to summer. The Krasnozem soil type (Chen et al., 2014), equivalent to the Ferralsols in the FAO soil classification system (FAO, 2014), is sandy loam texture with pH of 4.17. In the study site, the content of available phosphorus, rapidly available potassium, and alkali-hydrolyzable nitrogen were 414, 120, and 271 mg kg^{-1}, respectively. Soil organic carbon and total nitrogen contents were 30.30 and 2.39 g kg^{-1}, respectively, in the uppermost 30 cm of the soil (Chen et al., 2014). The site has an elevation of 185 m above sea level, is relatively flat (2°–3° slope), and has a northeasterly (35°) aspect.

2.2. Meteorological and flux measurements

A 20-m-tall steel tower was built in the center of the study area in 2010. An open-path eddy covariance (EC) system was mounted on the tower 17 m above the ground. The EC system consisted of an LI-7500 infrared gas analyzer (Li-7500, Li-Cor Inc., USA) and a three-dimensional ultrasonic anemometer (CSAT-3, Campbell Scientific, Inc., Logan, UT, USA). Raw 10-Hz data were logged onto a CR1000 data logger (Campbell Scientific, Inc.). Flux data (30-min means) were calculated as the covariance of vertical wind speed, air temperature, and CO_2/H_2O densities using the Webb–Pearman–Leuning correction (Leuning, 2006; Webb et al., 1980). Axis rotation correction was performed as described previously (Chen et al., 2013b), and the flux data were processed using the EdiRe (University of Edinburgh http://www.geos.ed.ac.uk/abs/research/micromet/EdiRe/).

We adopted a double rotation method in this study. Footprint analysis using a model (Horst and Weil, 1992; Schuepp et al., 1990) showed that under 90% contribution level, the area contributing to the carbon flux was homogenous under different atmospheric conditions in four directions. Under stable and unstable atmospheric conditions, the footprint was in the range 96–941 and 29–313 m, respectively (Chen, 2015).

Micrometeorological instruments, i.e., wind speed anemometers (010C, Metone, USA) and air temperature and humidity instruments (HMP45C, Vaisala, Helsinki, Finland) were mounted at 1, 5, and 17 m above ground. A net radiation sensor (CNR4, Kipp & Zonen, Holland) was mounted at 17 m above the ground. SI-111 (Apogee Inc., USA) infrared temperature radiometers were installed at 1.5 and 5 m above the ground to record surface and canopy temperatures. Precipitation measurements were obtained from a meteorological station 150 m from the site.

Soil temperature (Ts, °C), and soil volumetric water content (VWC, $m^3\ m^{-3}$) were monitored at5, 50, and 100 cm depths using three CS-109 probes (Campbell Inc., USA) and three CS-616 probes (Campbell Inc., USA). Sensible heat fluxes were measured with HFP-01 flux plates (Hukseflux) buried 3 and 5 cm below the ground. Latent heat flux was calculated based on the difference between the measured water vapor flux and the storage change of water vapor flux in the canopy–air space using the EC system. All 30-min data were recorded with a CR1000 data logger (Campbell Inc., USA).

Leaf area index (LAI, $m^2\ m^{-2}$), i.e., the MODIS 8-day 1-km LAI product (MOD15A2), was acquired from NASA's website (https://ladsweb.nascom.nasa.gov/data/) with an online subset output of a 1 × 1 km pixel subset centered on the flux site. The LAI time series of the flux site was extracted using ENVI5.1 software.

2.3. Data quality and gap-filling method

We used the methods and criteria of ChinaFLUX for processing and quality control of CO_2 measurements (Li et al., 2008). To avoid influence from precipitation, water condensation, insects, and abnormalities of the random signal, the 30-min flux data were checked for quality (Chen et al., 2013a). Data were filtered out and treated as gaps when (1) when the CO_2 flux was beyond the range of −2.0 to 2.0 mg CO_2 $m^{-2}\ s^{-1}$, CO_2 concentration was < 500 or > 800 mg m^{-3}, and water vapor concentration was outside the range of 0–40 g m^{-3}; (2) the value was abnormal, i.e. when the absolute value of the difference between a numerical value and a continuous five points was > 2.5 times of its variance; (3) when the measurements occurred during precipitation events; (4) the number of valid samples was < 15,000; (5) the measurements had a low friction velocity ($u^* < 0.2\ m\ s^{-1}$). Data were classified as daytime or nighttime based on the criterion of net radiation (Rn), i.e., data were considered daytime data when net radiation (Rn) > 0. Gaps occurred more frequently at night than during the day. After data filtering, the mean valid daytime and nighttime data of the three years accounted for 80.87% and 48.18% of the totals, respectively.

Different gap-filling treatments were applied to the daytime and nighttime data series (The width of the window was 14 days for daytime and 7 days for nighttime). Missing ecosystem respiration values at night (RE_{night}, being equal to net ecosystem exchange at night, NEE_{night}) were filled using an empirical exponential relationship between ecosystem respiration and soil temperature (Chen et al., 2013a, Eq. (1)):

$$RE_{night} = a_0 \times \exp(a_1 \times T_s) \quad (1)$$

where a_0 and a_1 are empirical coefficients, and T_s (°C) is the soil temperature at the depth of 5 cm at the corresponding time (on a 30-min scale). Based on Eq. (1), the nighttime respiration was estimated and then extrapolated to daytime using parameters estimated for each month, supposing the nighttime relationship between RE and Ts remained unchanged during daytime.

Based on available daytime estimations of RE, the gaps in daytime NEE (NEE_{day}) were filled using the Michaelis–Menten equation (Falge et al., 2001):