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Original Articles

A growing season climatic index to simulate gross primary productivity and carbon budget in a Tibetan alpine meadow

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ABSTRACT

Accurate estimation of gross primary production (GPP) of ecosystem is needed to evaluate terrestrial carbon cycle at various spatial and temporal scales. Eddy covariance (EC) technique provides continuous measurements of net ecosystem CO_2 exchange (NEE) and can be used to separate GPP from NEE in real time series. However, seasonal and inter-annual variation and consequently ecosystem carbon budget is still very difficult to simulate from climatic and environment. To address this limitation, we develop a growing season indicator (GSI) based on low temperature and soil water stress to model and predict intra and inter-annual dynamic of gross primary productivity (GPP). Validation of this new index was conducted using continuous six-year consective EC measurement from 2004 to 2009 at a Tibetan alpine meadow. Simulated GPP agreed well with the observed GPP in terms of seasonal and inter-annual variation. The six-year correlation coefficients on seasonal scale between GSI and scalar GPP derived from EC reached more than 0.85 no matter in dry years or wet years. In addition, the temporal GPP estimation derived from GSI model was quite similar to those from observed values by EC measurement. Moreover, accumulated GSI values can predict annual variability of net ecosystem production (NEP). Higher yearly accumulated GSI corresponded to more annual NEP. When cumulative GSI arrived up to 92, the target ecosystem was a carbon sink. This is probably a threshold which Tibetan alpine meadow changes from carbon source to carbon sink. It is indicated that the GSI model is a simple, alternative approach to estimating GPP and has the potential to simulate spatial GPP in a larger scale. However, the performance of GSI model in other vegetation types or regions still needs a further verification.

1. Introduction

Gross primary production (GPP), is defined as the sum of the photosynthesis carbon uptake by primary producers (Chapin et al., 2002). It is the first step of carbon input from atmospheric CO_2 to terrestrial ecosystem and a key component of carbon cycle in ecosystems (Hall and Scurlock, 1991; Scurlock and Hall, 1998; Yuan et al., 2010). Quantifying GPP at regional and global scale is necessary to understand the capacity of ecosystems in sequestering carbon (Beer et al., 2010; Gao et al., 2014; Gitelson et al., 2006; Kanniah et al., 2009). Quantifying and predicting the GPP of ecosystems have so far received more concerns in global change studies (Canadell et al., 2000; Li et al., 2013). However, it is far more difficult to do so because a variety of environmental and internal drivers interact to influence GPP at different growth stages (Ito et al., 2005).

At local scales, the most prominent method of measuring GPP is the use of data of eddy covariance (EC) instrument observations (Baldocchi and Dennis, 2003; Baldocchi et al., 2001). Although EC technique has been proven to be important in estimating carbon flux at site scale, its measurement only provides very limited CO_2 fluxes over footprints with

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restricted-size and varied shape. So it is difficult to extrapolate the GPP to a larger scale with scarce sites and limited observational data, especially in the remote high-altitude areas, like the Tibetan Plateau. Moreover, scaling up those CO_2 flux measurements from site level to regional or global scales is challenging because of large spatial heterogeneity (Asner et al., 2012; Belshe et al., 2012) and interactions among ecosystems (Chen, 2006).

To address these limitations, models have been developed for estimating GPP at different spatial and temporal scales (Ito et al., 2005; Kalfas et al., 2011; Luo et al., 2001; Xiao et al., 2004). These models are mainly divided into two categories. One is based on light use efficiency (LUE) approach to simulate GPP such as CASA (Potter et al., 1993), GLO-PEM (Goetz et al., 1999; Prince and Goward, 1995), vegetation production efficiency model, and MODIS-GPP algorithm as well. The other one is process-based biogeochemical models, driven by a multi-layer database of climate, soil and vegetation types (Churkina and Sprinz, 2003; Law et al., 2000; Xiao et al., 2004). The most widely used regional model of GPP based on LUE concept (Monteith, 1972) indicates that GPP is linearly correlated to the amount of absorbed photosynthetically active radiation (APAR) and the efficiency of vegetation production (ε) (Ogutu et al., 2013). Although this method has been popularly used at different spatial and temporal scales owing to its easily accessible variables from Earth Observation data, uncertainties still remain in the GPP output from the model (Keenan et al., 2012; Kevin et al., 2012). For instance, the estimation of the LUE terms is often difficult as it varies over a range of vegetation types and changes with seasonal development and environmental conditions (Gower et al., 1999; Sims et al., 2006). In addition, the relationship between the LUE and climatic factors in different ecosystems are still not clarified, with these relationships deriving from models rather than actual measurement (Garbulsky et al., 2010). Finally, the uncertainties in land cover classification maps may result in further errors when it is propagated into the LUE based models (Ogutu et al., 2013; Zhao et al., 2005).

It is therefore imperative to establish a simpler model structure with fewer input variables without sacrificing the modelling accuracy of GPP (Goetz et al., 1999; Yang et al., 2013; Zhang et al., 2015). However, models above-mentioned require complicated calculations and introduce many indices, such as data from MODIS and environmental factors (Li et al., 2007; Yan et al., 2015). In this study, a growing season index (GSI) model using only a set of common hygrothermal conditions interacting to limit GPP is developed to simulate the seasonal and inter-annual variability of GPP, and to predict annual carbon budget of ecosystem. GSI is a simple, generalized index derived from temperature, water and photoperiod limitation to simulate phenological responses to climate change (Jolly et al., 2005). We follow this thought to develop the seasonal temperature and hydrological controls of GPP in order to predict inter-annual variation of net ecosystem CO_2 exchange (NEE) and carbon budget.

The Tibetan Plateau is mostly covered by alpine meadow and steppe, which are recognized as fragile and sensitive ecosystems in response to climate changes (Zheng et al., 2000). Due to low temperature and low precipitation, gross primary production is low in most of the alpine vegetation (Hui et al., 2004). However, PAR is not a constraint of primary production on the Plateau (Zhang et al., 2000). Considering thermo-hydrological imprint in driving primary production rather than light constraint, we simply develop a low temperature and soil water stress constrained GSI index to model GPP and predict NEE in the case of a typical alpine meadow on the Tibetan Plateau. The objectives of this study are to: 1) simulate seasonal dynamics and inter-annual variability of GPP over dry, normal and wet years, using GSI index; 2) predict annual carbon budget using accumulated GSI values.

2. Materials and methods

2.1. Site description

The study site is located at Damxung Alpine Meadow Research Station, one of the ChinaFlux sites (91°05′E, 30°51′N, 4333 m a.s.l), in the south-face slope of Nyainqentanglha Mountains, northern Tibetan Plateau. A detailed site description is available in literatures (Shi et al., 2006; Zong et al., 2015). The site is characterized by intense solar radiation, low air temperature and large daily temperature difference (Fan et al., 2011) and low soil moisture, belonging to a semi-arid alpine climate. The growing season starts in May and ends in September. The vegetation type is an alpine steppe meadow, comprising dominant species of *Kobresia pygeama*, *Stipa capillacea*, *Carex montis-everestii*, and accompanying species *K. capillofolis*, *Anaphalis xylorhiza*, *Potentilla bifurca Linn* (Shi et al., 2006)

2.2. EC measurements

CO_2 fluxes, sensible heat, latent heat and microclimate were measured continuously with the eddy covariance technique from 2003 on. The EC system was installed at two meter above the ground surface, consisting of open-path infrared gas analyzers (model LI-7500, LICOR, Lincoln, NE, USA) and three-dimensional sonic anemometers (Model CSAT3, Campbell Scientific, Logan, UT, USA). Signals were recorded at 10 HZ by a CR5000 datalogger (Model CR5000, Campbell Scientific) and then block-averaged over 30-min intervals for analysis and archiving. Profiles of environmental factors, such as air temperature (T_a, °C), relative humidity (RH, %), precipitation (PPT, mm), photosynthetically active radiation (PAR, μmol $m^{-2} s^{-1}$), soil temperature (T_s, °C) and soil moisture (SWC) at different depth and soil heat flux were also measured.

Gap-filling of lost data is important prerequisite to control data quality and ensure data reliability when extreme weather, power supply and equipment failure happen. The methods of data preprocessing and gap-filling include spike removal (± 3σ), coordinate rotation and Webb-Pearman-Leuning (WPL) correction etc. The data in rainy days and the data during nighttime with $\mu^* < 0.15\ m\ s^{-1}$ was discarded (Yu et al., 2008). The missing data could be filled by the nonlinear relationship established between carbon fluxes and the environment factors (Yu et al., 2008).

The carbon fluxes (F_c) can be filled by the exponential function with T_s in the non-growing season (from November to next April) and the nighttime NEE (PAR < 1 μmolCO_2 $m^{-2} s^{-1}$) in the growing season (from May to October). The missing NEE during nighttime and daytime respiration Re is filled by Eq. (1).

$$F_c = R_{10}\, Q_{10}\, ((T_s - T_{ref})/10) \tag{1}$$

$$Q_{10} = \exp\,(10b_1) \tag{2}$$

Where F_c is carbon fluxes of $\mu^* > 0.15\ m\ s^{-1}$ during nighttime; R_{10} (μmol CO_2 $m^{-2} s^{-1}$) is the ecosystem respiration rate at 10 °C; Q_{10} is the sensitivity coefficient of respiration, i.e. the increasing multiple of respiration rate while the soil temperature was increased by 10 °C; T_{ref} is the reference soil temperature at 10 °C; b_1 is a temperature coefficient.

The missing daytime NEE can be described via the rectangular hyperbolic function (Eq. (4)) between daytime NEE and PAR.

$$F_{cday} = F_{max}{*}\alpha{*}PAR/(\alpha PAR + F_{max}) + R \tag{3}$$

In which, F_{max} (μmolCO_2 $m^{-2} s^{-1}$) is the maximal ecosystem assimilation; α (μmol CO_2·μmol^{-1}·photon^{-1}) is apparent quantum yield; R (μmol CO_2 $m^{-2} s^{-1}$) is daytime ecosystem respiration.