Agricultural and Forest Meteorology 263 (2018) 242–257

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Sources of uncertainty in gross primary productivity simulated by light use efficiency models: Model structure, parameters, input data, and spatial resolution

Yi Zheng[a,b], Li Zhang[a,b,*], Jingfeng Xiao[c], Wenping Yuan[d,e], Min Yan[a,b], Tong Li[a,b], Zhiqiang Zhang[f]

[a] Key Laboratory of Digital Earth Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing 100094, China
[b] Hainan Key Laboratory of Earth Observation, Hainan 572029, China
[c] Earth Systems Research Center, Institute for the Study of Earth, Oceans, and Space, University of New Hampshire, Durham, NH 03824, USA
[d] School of Atmospheric Sciences, Sun Yat-Sen University, Guangzhou 519082, China
[e] Zhuhai Joint Innovative Center for Climate-Environment-Ecosystem, Zhuhai Key Laboratory of Dynamics Urban Climate and Ecology, Beijing Normal University, Beijing 100875, China
[f] College of Soil and Water Conservation, Beijing Forestry University, Beijing 100083, China

ARTICLE INFO

Keywords:
Gross primary productivity
Light use efficiency
Uncertainty
Carbon cycle
Eddy covariance
Ecosystem model

ABSTRACT

Accurate estimation of gross primary productivity (GPP) is essential for understanding ecosystem function and global carbon cycling. However, there is still substantial uncertainty in the magnitude, spatial distribution, and temporal dynamics of GPP. Using light use efficiency (LUE) models, we conducted a comprehensive analysis of the uncertainty in GPP estimation resulting from various sources: model structure, model parameters, input data, and spatial resolution. We first evaluated the influences of model structures, namely the fraction of absorbed photosynthetically active radiation (FPAR), water scalar (W_S), and temperature scalar (T_S), on site-level GPP estimates. We then used the Sobol' sensitivity analysis to quantify the relative contributions of model input variables to the uncertainty in GPP. In addition, we used different land cover and meteorological datasets to examine the effects of input data and spatial resolution on the magnitude and spatiotemporal patterns of GPP. We found that the model structures affected not only model performance but also model parameters in a manner that differed with vegetation type and region. Thus, proper model structures and rigorous model parameterization and calibration should be adopted in GPP modeling. The Sobol' sensitivity analysis showed that the meteorological drivers including photosynthetically active radiation (PAR) and daily minimum temperature (TMIN) had larger contribution to the uncertainty in simulated GPP than did the surface reflectance-based indices including enhanced vegetation index (EVI) and normalized difference water index (NDWI). At the regional scale, different land cover datasets had the largest impacts on GPP simulations, especially in heterogeneous areas, followed by the scale effects from different spatial resolutions; changing meteorological datasets had the smallest effects. Therefore, more accurate and finer-resolution land cover maps and meteorological datasets are essential for more accurate GPP estimates. Our findings have implications for improving our understanding of the full uncertainty in carbon flux estimates and reducing the uncertainty in carbon cycle simulations.

1. Introduction

Gross primary productivity (GPP) is the amount of carbon absorbed by plants through photosynthesis. As an important component of the carbon cycle, GPP is the largest carbon flux between the terrestrial biosphere and the atmosphere. GPP also drives ecosystem services such as food, fiber, and wood production (Beer et al., 2010). Therefore, accurately quantifying GPP at various spatial and temporal scales is essential for better understanding ecosystem function and global carbon cycling. However, there is substantial uncertainty associated with the estimation of GPP, particularly at regional to global scales.

Light use efficiency (LUE) models have been widely used to estimate

* Corresponding author at: Key Laboratory of Digital Earth Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing 100094, China.
E-mail address: zhangli@radi.ac.cn (L. Zhang).

https://doi.org/10.1016/j.agrformet.2018.08.003
Received 27 December 2017; Received in revised form 9 August 2018; Accepted 11 August 2018

GPP (Potter et al., 1993; Running et al., 2004; Xiao et al., 2004; Yuan et al., 2007). These models are based on the classical LUE logic (Monteith, 1972; Monteith and Moss, 1977):

$$GPP = PAR \times FPAR \times \varepsilon_{max} \times f_S \tag{1}$$

where PAR is the incident photosynthetically active radiation (MJ m^{-2}) per time period, FPAR is the fraction of PAR absorbed by vegetation canopies, ε_{max} is the maximum LUE (g C MJ^{-1}) under the condition without environmental stresses, and f_S represents the environmental stresses (e.g., water scalar (W_S) and temperature scalar (T_S)) ranging from 0 to 1. LUE models have simple model structures and require only a small number of input variables. Despite their simplicity, the LUE models can generally capture the spatial and temporal dynamics of GPP fairly well (Yuan et al., 2007; Zhao and Running, 2010). However, similar to process-based ecosystem models (Cramer et al., 1999; Xiao et al., 2009; Thorn et al., 2015; Ma et al., 2017), LUE models can also lead to significant uncertainty in regional or global carbon flux estimates (Gebremichael and Barros, 2006; Verma et al., 2014; Yuan et al., 2014).

Model simulations have several sources of uncertainty, including model structures, model parameters, and input datasets (Beck, 1987; Xiao et al., 2014). Although LUE models are all based on the LUE logic, they have been developed using different model structures. Different representations have been used for FPAR, W_S, and T_S. Model structure has been considered as the most important factor that affects parameter values (e.g., ε_{max}) and model performance (Yuan et al., 2014). Uncertainties in model parameters, particularly ε_{max}, significantly influence the accuracy of simulated GPP (Wagle et al., 2016). The spatial datasets that affect the uncertainty in GPP estimation mainly include land cover maps and meteorological data. Land cover maps adopted in carbon cycle modeling are usually derived from satellite data, and substantial uncertainties exist due to their data sources, classification schemes, and classifiers (Giri et al., 2005). For a given site or grid cell, the land cover type directly determines the value of parameters, particularly ε_{max} (Wang et al., 2010). Besides land cover maps, meteorological data are also critical drivers for the estimation of carbon fluxes. The uncertainty of the meteorological products may be propagated to modeling results (Gebremichael and Barros, 2006; Heinsch et al., 2006).

Many studies have examined the effects of individual source of uncertainty (e.g., model structures, parameters, or input data) on GPP modeling using LUE models. For example, Zhang et al. (2015a) evaluated the model performance of four LUE models using 51 eddy covariance flux towers and identified possible further improvements through structure optimization. Xiao et al. (2014) quantified the uncertainty of model parameters and assessed its effects on the estimation of regional carbon fluxes. A few studies also examined the influences of different meteorological data and land cover representation on GPP simulations (Zhao et al., 2006; Xiao et al., 2011; Cai et al., 2014). In addition, spatial heterogeneity and the resolution of input data (e.g., land cover map, meteorological data) may also lead to uncertainty in simulated carbon fluxes (Liu, 2014; Zhao and Liu, 2014). However, to our knowledge, no study has systematically evaluated the influences of model structure, model parameters, input data, and spatial resolution on the uncertainty in carbon fluxes.

In this paper, we assessed the uncertainty in simulated GPP resulting from the three main sources of uncertainty: model structures, model parameters, and model inputs. We first analyzed the influence of model structures on model parameters and model uncertainty at site level using different representations of FPAR, W_S, and T_S. We then quantified the relative contributions of model input variables to GPP uncertainty. Finally, we investigated the effects of different model input datasets (land cover maps and meteorological datasets) and spatial resolutions on the magnitude and spatiotemporal patterns of GPP at the regional scale. This study will improve our understanding of the uncertainty in GPP modeling and will potentially lead to more accurate carbon flux estimates.

2. Materials and methods

2.1. Study area

This study was carried out around the agro-pastoral ecotone of northern China (39.0 °N to 46.8 °N, 110.5 °E to 122.8 °E) (Fig. 1). From the northwest to the southeast, the annual mean temperature and precipitation range from –5°C to 10°C and 35 mm to 600 mm, respectively (calculated from the meteorological datasets in Section 2.2.3). The large temperature and precipitation gradients make the region a natural ecotone from arid and semi-arid to humid land, leading to grassland–cropland–forest mixed landscapes. The two dominant vegetation types of the ecotone are steppes and croplands, while forests (mainly deciduous broadleaf forest (DBF)) only account for a relatively small fraction of the region. The highly heterogeneous landscape accompanied with densely instrumented eddy covariance flux towers (Fig. 1) make the region a unique test bed for uncertainty analysis of ecosystem models (e.g., LUE models).

2.2. Data

2.2.1. Eddy covariance and meteorological data from flux towers

We used carbon flux and meteorological data from six eddy covariance flux sites across the study area (Fig. 1). Our study sites consist of four grassland sites – CN-Du2 (typical steppe), CN-Xi1 (typical fenced steppe), CN-Xi2 (degraded steppe), and Xfs (short grass steppe); one cropland site – CN-Du1; and one forest site – CN-Bed. The data for the forest site (CN-Bed) was obtained from the US-China Carbon Consortium (USCCC), and the data for all other five sites were obtained from the LaThuile Synthesis Dataset (http://fluxnet.fluxdata.org). More detailed information on these sites can be found in the references in Table 1.

For each site, we used daily or hourly GPP, photosynthetically active radiation (PAR), air temperature (T), and vapor pressure deficit (VPD). To match the intervals (8-day) of the data products derived from the moderate resolution imaging spectroradiometer (MODIS), we aggregated the daily or hourly values of each variable to 8-day time step. We ignored any 8-day interval with more than 5 days of missing daily values to minimize the errors and uncertainties of the flux and meteorological data.

The eddy covariance flux towers directly measure the net ecosystem exchange (NEE) of carbon dioxide between ecosystems and the atmosphere. GPP was calculated as the difference between daytime ecosystem respiration (RE_d) and daytime NEE (NEE_d). RE_d was estimated using daytime temperature and the equation between nighttime temperature and nighttime NEE. The partitioning of NEE and the gap-filling of missing or bad data were based on the methods described in Reichstein et al. (2005).

2.2.2. Remote sensing data

In this study, we used surface reflectance, FPAR, GPP, and leaf area index (LAI) products over the period 2001–2012. The surface reflectance (MOD09A1, collection 006), FPAR (MOD15A2, collection 005), and GPP (MOD17A2, collection 005) products were derived from MODIS and were obtained from NASA's Distribute Active Archive Center (DAAC) (https://ladsweb.nascom.nasa.gov/). The LAI product was the Global Land Surface Satellite Leaf Area Index (GLASS LAI) product provided by the Center for Global Change Data Processing and Analysis of the Beijing Normal University (http://glass-product.bnu.edu.cn/). Each product is available at 8-day interval. Because the footprint of eddy covariance flux towers is generally less than 1 km^2 (Schmid, 2002), we extracted the average values of all grid cells within the 1 km × 1 km area surrounding each tower for each variable and for each time step. The linear interpolation technique was used to fill the missing values or to replace the unreliable values determined by the quality assurance flags.