



Modeling net primary productivity of terrestrial ecosystems in the semi-arid climate of the Mongolian Plateau using LSWI-based CASA ecosystem model

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ABSTRACT

Since the estimate of moisture stress coefficients (MSC) in the current Carnegie-Ames-Stanford-Approach (CASA) model still requires considerable inputs from ground meteorological data and many soil parameters, here we present a modified CASA model by introducing the land-surface water index (LSWI) and scaled precipitation to model the vegetation net primary productivity (NPP) in the arid and semiarid climate of the Mongolian Plateau. The field-observed NPP data and a previously proposed model (the Yu-CASA model) were used to evaluate the performance of our LSWI-based CASA model. The results show that the NPP predicted by both the LSWI-based CASA model and the Yu-CASA model showed good agreement with the observed NPP in the grassland ecosystems in the study area, with coefficients of determination of 0.717 and 0.714, respectively. The LSWI-based CASA model also performed comparably with the Yu-CASA model at both biome and per-pixel scales when keeping other inputs unchanged, with a difference of approximately 16 g C in the growing-season total NPP and an average value of 2.3 g C bias for each month. This indicates that, unlike an earlier method that estimated MSC based entirely on climatic variables or a soil moisture model, the method proposed here simplifies the model structure, reduces the need for ground measurements, and can provide results comparable with those from earlier models. The LSWI-based CASA model is potentially an alternative method for modelling NPP for a wide range of vegetation types in the Mongolian Plateau.

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1. Introduction

Vegetation net primary productivity (NPP) is defined as the net accumulation of organic matter through photosynthesis by green plants per unit of time and space and represents the net primary source of food energy for Earth's living entities, including human beings (Yu et al., 2009a). It is a key component of the terrestrial carbon cycle (Piao et al., 2005) and serves as a sensitive indicator of ecosystem performance at both local and global scales (Lobell et al., 2002). Quantitative estimates of NPP at regional to global scales are therefore significant for understanding changes in ecosystem

structure and function, predicting terrestrial carbon cycle trends (Field et al., 1995; Nemani et al., 2003; Yu et al., 2009a), determining sustainable use of natural resources, and making policy decisions (Mu et al., 2013a,b).

Remote sensing is currently regarded as a powerful and unique tool for characterizing vegetation structure both globally and reproducibly and has also played an increasing role in estimating ecosystem NPP (Hicke et al., 2002; Running et al., 2000; Zhao and Running, 2010). Numerous RS-based models for estimating NPP, such as the Carnegie-Ames-Stanford-Approach (CASA) model (Potter et al., 1993), the MOD-Sim-Cycle model (Hazarika et al., 2005), the GLO-PEM model (Prince, 1991), and the Biome-BGC model (Running et al., 2000), have been developed in recent decades to study the dynamics of vegetation productivity and its responses to climate change and anthropogenic activities at

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scales ranging from local to global. However, several recent studies have highlighted that all these models for estimating NPP globally have a number of uncertainties and systematic errors when implemented in certain specific ecoregions (Fensholt et al., 2006; Yu et al., 2009b; Zhao et al., 2005, 2006), although their results are excellent at the global scale (Nemani et al., 2003; Potter et al., 1993). For example, the MODIS NPP products (MOD17A3), which are the first regular and near-real-time vegetation primary productivity data sets modeled by the Biome-BGC model at 1 km resolution, contain considerable errors in certain small regions (Zhao et al., 2005), particularly in some regions with arid and semi-arid climate (Fensholt et al., 2006) and tropical regions (Zhao et al., 2006). These errors arise because of the coarse and inconsistent spatial resolution of the meteorological reanalysis data (not the observed data) ($1.00^\circ \times 1.25^\circ$) compared with the MODIS pixels ($1 \text{ km} \times 1 \text{ km}$) (Sims et al., 2008). These reanalysis data were used as a key input for MODIS NPP modeling (Sims et al., 2008; Zhao et al., 2005). Another reason for the uncertainties of the MODIS NPP products in certain small regions may be that global-scale studies may neglect small-scale heterogeneity to some extent if local heterogeneity did not have a decisive effect on the whole (Bao et al., 2015). Furthermore, the MODIS NPP products provide only annual NPP (annual summations) (Running et al., 2000; Zhao et al., 2005), making it impossible to perform analysis at finer temporal scales (such as seasonal, monthly, or shorter timescales).

Therefore, it is imperative to improve or adjust these models, which were developed at a global scale, to adapt to different ecosystems in specific ecoregions as well as finer temporal scales by introducing available local information (Yu et al., 2009b) or other remote-sensing information (Sims et al., 2006b). In particular, models that are based entirely on remote-sensing data and can therefore produce truly continuous output at the same spatial resolution as satellite imagery are increasingly becoming a major focus of ecological modelers (Sims et al., 2006b; Wu et al., 2010a,b). Among the models that estimate NPP globally, the CASA ecosystem model, also called the light-use efficiency (LUE) model, is one of the most widely used models which adequately addresses NPP spatial and temporal dynamics at regional to global scales (Field et al., 1995; Mu et al., 2013b; Piao et al., 2005; Potter et al., 1993). Its success at the global scale is primarily due to its incorporation of per-pixel remote-sensing observations into the model and the relative simplicity of its algorithm (Mu et al., 2013b; Yu et al., 2009b). The fundamental concept of NPP for a given location x and time t in the CASA model is a variant of the LUE model originally proposed by Monteith (1972), in which NPP is the product of the photosynthetically active radiation (PAR) absorbed by green vegetation (APAR) and LUE:

$$\text{NPP}(x, t) = \text{PAR}(x, t) \times \text{FPAR}(x, t) \times \varepsilon(x, t) \quad (1)$$

$$\varepsilon(x, t) = \varepsilon_{\max} \times T_{\varepsilon 1}(x, t) \times T_{\varepsilon 2}(x, t) \times W_{\varepsilon}(x, t), \quad (2)$$

where ε is the LUE and FPAR represents the fraction of absorbed PAR. It has been demonstrated in previous studies that APAR ($\text{PAR} \times \text{FPAR}$) is relatively easy to estimate from remotely sensed data because FPAR is a strong function of the normalized difference vegetation index (NDVI) (Goward and Huemmrich, 1992; Los, 1998; Sims et al., 2006b; Yu et al., 2009b). By comparison, ε has proved more difficult to estimate because it varies over seasons, biomes, or even species (Ahl et al., 2004; Sims et al., 2006b). Typical methods for estimating ε in the CASA model require prior specification of a maximum LUE (ε_{\max}) for a given biome. This maximum LUE has been downscaled by the temperature stress coefficient (TSC) and the moisture stress coefficient (MSC) (Eq. (2)) (Field et al., 1995; Potter et al., 1993). Early studies set ε_{\max} to 0.405 gC/MJ (Potter et al., 1993) worldwide, but more recent studies have set ε_{\max} to various values ranging from 0.389 to 0.978 gC/MJ for 13 types of

biomes in East Asia (Yu et al., 2009b). Therefore, when ε_{\max} is specified as a constant value for different biomes, the estimates of TSC and MSC are of key importance for using the CASA model. Generally, the two TSCs are relatively easily computed using the monthly mean temperature and the optimal temperature for plant growth, which is the temperature during the month of maximum NDVI (Piao et al., 2005; Potter et al., 1993). In comparison, an estimate of MSC can usually be obtained from a one-layer budget soil moisture model (SMM) (Malmström et al., 1997; Potter et al., 1993). However, an SMM always has a very complex model structure and needs many input soil parameters, including wilting coefficient, percentages of soil, sand, and clay particles, and soil depth (Saxton et al., 1986; Yu et al., 2009b) as well as monthly temperature and precipitation. Such data are often unavailable at sufficiently detailed spatial scales and are usually extracted from a soil class map with lower resolution in both space and time (Piao et al., 2005). Consequently, such data can introduce considerable errors into the output values of both MSC and final NPP and have been highlighted as one of the major limitations in the CASA model (Piao et al., 2005; Yu et al., 2009a,b), particularly when the model is implemented in specific ecoregions with a limited number of ground observations. Furthermore, no remote-sensing information was used in the MSC estimates in CASA, unlike the estimates of both APAR and TSC, which all include satellite NDVI data. Although it may be possible to improve the accuracy of MSC and final NPP outputs by improving the accuracy of soil parameters and climatic variables, it might be simpler and more direct to base the MSC estimates, at least partly, on remote-sensing data and thus undertake to provide continuous output with the same temporal and spatial resolution as the NDVI-used APAR and TSC. The land-surface water index (LSWI), a combination of the near-infrared and shortwave infrared bands, is a representative parameter of leaf and canopy water content as well as of soil moisture (Fensholt and Sandholt, 2003; Mao et al., 2014; Xiao et al., 2004a). The LSWI is based on the contrast between reflection in the infrared band caused by vegetation leaf cellular structure and absorption in the shortwave infrared band due to vegetation water content and soil moisture and can be calculated as $\text{LSWI} = (\text{NIR} - \text{SWIR}) / (\text{NIR} + \text{SWIR})$, where NIR and SWIR represent the reflectance in the near-infrared and shortwave infrared bands, respectively. A high index value indicates larger quantities of water in the canopy, whereas a low value indicates canopy water stress. In the vegetation photosynthesis model (VPM), developed to estimate gross primary productivity (GPP) proposed by Xiao et al. (2004a), the LSWI was successfully used to estimate the coefficient of water stress restriction on ε_{\max} using the near-infrared (841–876 nm) and shortwave infrared bands (1628–1652 nm) of the Moderate Resolution Imaging Spectroradiometer (MODIS). This approach has been validated in various ecosystems, including evergreen needleleaf forest (Xiao et al., 2004a, 2005a), temperate deciduous forest (Wu et al., 2010b; Xiao et al., 2004b), tropical evergreen forest (Xiao et al., 2005b), and (semi-) arid grassland ecosystems (John et al., 2013). However, to date there is a dearth of information in the literature describing the use of LSWI to estimate MSC in the CASA model as well as in other remote-sensing-based NPP models. Furthermore, the VPM model that estimates GPP based on LSWI has been used only at the very small scale of a flux tower footprint, which is generally $<1 \text{ km}$ and cannot provide truly per-pixel GPP output (Rahman et al., 2005). Therefore, large-scale LSWI applications (per pixel) need to be further tested for both NPP and GPP modeling, particularly with the aim of providing a MSC with the same spatial and temporal resolution as NDVI data, which is used to estimate APAR and TSC.

Due to the limitation of estimating MSC in the CASA model (Yu et al., 2009b), an effort has been made in this research to improve and evaluate the CASA model by introducing LSWI (an LSWI-based CASA model) derived from the MODIS near-infrared and short-

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