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Parameterizing ecosystem light use efficiency and water use efficiency to estimate maize gross primary production and evapotranspiration using MODIS EVI

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ABSTRACT

Quantifying global carbon and water balances requires accurate estimation of gross primary production (GPP) and evapotranspiration (ET), respectively, across space and time. Models that are based on the theory of light use efficiency (LUE) and water use efficiency (WUE) have emerged as efficient methods for predicting GPP and ET, respectively. Currently, LUE and WUE estimates are obtained from biome-specific look-up tables and coarse resolution remote sensing data with large uncertainties. The major objective of this study was to parameterize eddy covariance tower-based ecosystem LUE ($ELUE_{EC}$), defined as the ratio of tower-based GPP (GPP_{EC}) to photosynthetically active radiation (PAR), and ecosystem WUE ($EWUE_{EC}$), defined as the ratio of GPP_{EC} to tower-based ET (ET_{EC}), using the Moderate Resolution Imaging Spectroradiometer (MODIS)-derived enhanced vegetation index (EVI) for predicting maize (*Zea mays* L.) GPP and ET, respectively. Three adjacent AmeriFlux maize sites with different rotations (continuous maize vs. annual rotation of maize and soybean, *Glycine max* L.) and water management practices (rainfed vs. irrigated) located near Mead, NE, USA were selected. The EVI tracked the seasonal variations of $ELUE_{EC}$ ($R^2 = 0.83$) and $EWUE_{EC}$ ($R^2 = 0.74$) across sites, indicating that EVI can be explicitly used as a measure of $ELUE_{EC}$ and $EWUE_{EC}$. The predicted GPP (GPP_{ELUE}) using the parameterized ELUE model correlated well with GPP_{EC} (slope = 1.0, $R^2 = 0.83$, and RMSE = 2.85 $g\,C\,m^{-2}\,d^{-1}$) and was significantly improved when compared to widely used models that estimate GPP by integrating EVI and climate variables (Greenness and Radiation, Temperature and Greenness, and Vegetation Index) and the standard MOD17 GPP product. Similarly, the predicted ET (ET_{EWUE}) using the parameterized EWUE correlated well with ET_{EC} (slope = 1.02, $R^2 = 0.62$, and RMSE = 0.83 $mm\,ET^{-1}$) and was significantly improved when compared to the standard MOD16 ET product. Preliminary data demonstrate that ELUE and EWUE can be parameterized using EVI, offering new methods for predicting GPP and ET.

1. Introduction

Accurate estimation of gross primary production (GPP) and evapotranspiration (ET) across space and time is crucial to quantify global carbon and water balances, respectively. Eddy covariance (EC) systems can measure carbon uptake and water losses by ecosystems at the landscape level (Baldocchi et al., 2001). However, these EC measurements are representative of fluxes only from within the EC tower footprint. Satellite remote sensing approach can complement the limited coverage of GPP and ET estimates by EC systems. Consequently, a variety of methods that leverage remotely-sensed products to predict GPP and ET have been developed and validated using EC data.

Current remote sensing estimations of GPP fall into two broad approaches. The first approach is to estimate GPP based on the theory of light use efficiency (LUE) proposed by Monteith (1972). Several existing broad-scale carbon flux models such as Moderate Resolution Imaging Spectroradiometer Photosynthesis, MODIS-PSN (Running et al., 2004), Carnegie–Ames–Stanford Approach, CASA (Potter et al., 1993), Global Production Efficiency Model, GLO-

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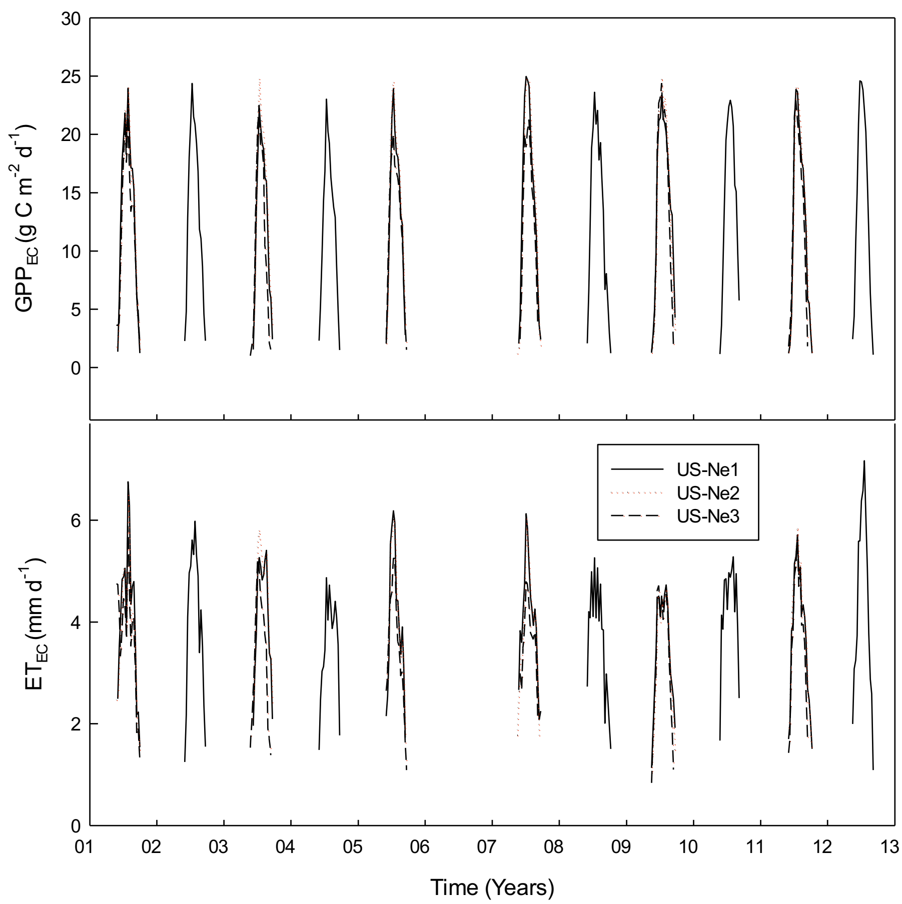

Fig. 1. Seasonality and interannual dynamics of tower-based gross primary production (GPP_{EC}) and evapotranspiration (ET_{EC}) at three maize sites.

PEM (Prince and Goward, 1995), Vegetation Photosynthesis Model, VPM (Xiao et al., 2004), and Eddy Covariance Light Use Efficiency Model, EC-LUE (Yuan et al., 2007) follow the fundamental GPP estimation method (Monteith, 1972) as:

$$GPP = \varepsilon \times fAPAR \times PAR \tag{1}$$

where ε is light use efficiency, PAR is photosynthetically active radiation, and fAPAR is the fraction of PAR absorbed by vegetation. In Eq. (1), separate estimations of fAPAR and ε are required to compute GPP for the current LUE-based models. A major limitation for this GPP estimation approach is that direct measurements of LUE are not available at the landscape scale. Conclusive results have not been achieved to directly compute LUE even by using narrow-band vegetation indices such as photochemical reflectance index, PRI (Gamon et al., 1992) and solar-induced chlorophyll fluorescence, SIF (Parazoo et al., 2014). Even though the PRI performance is good at leaf or plant levels, it is problematic at the ecosystem level when using MODIS data (Moreno et al., 2012; Tan et al., 2013). Further, parameterization of LUE is difficult as it is influenced by vegetation types (Turner et al., 2003), seasonality and plant phenology (Jenkins et al., 2007), and environmental stresses (Ruimy et al., 1995). Due to these reasons, maximum LUE values have been specified for a limited number of biome types and are available in vegetation-specific look-up table. In most LUE-based models, a constant potential or maximum LUE value is used and then down-regulated by environmental constraints (Running et al., 2004).

Differences in the GPP estimates from LUE-based models are generally due to differences in the determination or selection of LUE and the use of environmental stress scalars. The second remote sensing GPP estimation approach is the development of empirical/statistical models based on tower-based GPP (GPP_{EC}), climate variables, and remotely-sensed vegetation indices (Gitelson et al., 2006; Sims et al., 2008; Wu et al., 2010) and most recently based on GPP_{EC} and SIF (Guanter et al., 2014; Wagle et al., 2015c).

Remote sensing estimations of ET also fall broadly into two approaches. The first approach is to estimate ET using physical models based on the surface energy balance (SEB) concept (Gillies et al., 1997). Several SEB models have been developed in past two decades to estimate large-scale ET (Allen et al., 2007; Bastiaanssen et al., 1998; Roerink et al., 2000; Senay et al., 2013; Su, 2002). Those SEB models typically estimate sensible heat flux (H) from the difference between ground-based air temperature (T_a) and satellite-based land surface temperature (LST). The lack of 1:1 correspondence between LST and aerodynamic surface temperature poses a number of difficulties in estimating H (Kustas and Norman, 1996) and ultimately reliable ET estimates. Further, relatively complex computation of several land surface physical parameters and turbulent heat fluxes, and too many required parameters with detailed information in physically-based models can cause more inconveniences and uncertainties when data are not readily available (Liou and Kar, 2014). Several surface variables like land surface temperature, surface albedo, soil moisture, emissivity, fractional vegetation cover, leaf area index can significantly affect the precise partition of energy components and consequently the accuracy of SEB models. The second remote sensing ET estimation approach is the development of empirical/statistical models (Choudhury et al., 1994) based on tower-based ET (ET_{EC}), vegetation indices, and climate variables. Increasing number of flux towers and availability of remote sensing vegetation indices offer a tool for upscaling of ecosystem level measurements of ET over large areas (Glenn et al.,