Agricultural and Forest Meteorology 213 (2015) 160–172

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

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

Modeling gross primary production of maize and soybean croplands using light quality, temperature, water stress, and phenology

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ARTICLE INFO

Article history:
Received 15 August 2014
Received in revised form 20 January 2015
Accepted 13 April 2015
Available online 14 July 2015

Keywords:
Gross primary production
Light use efficiency
Maize
Soybean
Modeling

ABSTRACT

Vegetation productivity metrics, such as gross primary production (GPP) may be determined from the efficiency with which light is converted into photosynthates, or light use efficiency (ϵ). Therefore, accurate measurements and modeling of ϵ is important for estimating GPP in each ecosystem. Previous studies have quantified the impacts of biophysical parameters on light use efficiency based GPP models. Here we enhance previous models utilizing four scalars for light quality (i.e., cloudiness), temperature, water stress, and phenology for data collected from both maize and soybean crops at three Nebraska AmeriFlux sites between 2001 and 2012 (maize: 26 field-years; soybean: 10 field-years). The cloudiness scalar was based on the ratio of incident photosynthetically active radiation (PAR_{in}) to potential (i.e., clear sky) PAR_{pot}. The water stress and phenology scalars were based on vapor pressure deficit and green leaf area index, respectively. Our analysis determined that each parameter significantly improved the estimation of GPP (AIC range: 2503–2740; likelihood ratio test: p-value < 0.0003, df = 5–8). Daily GPP data from 2001 to 2008 calibrated the coefficients for the model with reasonable amount of error and bias (RMSE = 2.2 g C m^{-2} d^{-1}; MNB = 4.7%). Daily GPP data from 2009 to 2012 tested the model with similar accuracy (RMSE = 2.6 g C m^{-2} d^{-1}; MNB = 1.7%). Modeled GPP was generally within 10% of measured growing season totals in each year from 2009 to 2012. Cumulatively, over the same four years, the sum of error and the sum of absolute error between the measured and modeled GPP, which provide measures of long-term bias, was ±5% and 2–9%, respectively, among the three sites.

1. Introduction

The efficiency of light converted into photosynthates, or light use efficiency (ϵ), is a useful measure of crop productivity (Monteith, 1972). Light use efficiency can be measured at the leaf (Garbulsky et al., 2013), plant (Onoda et al., 2014), or ecosystem/landscape level (Binkley et al., 2013). It is at the landscape level where light use efficiency is used as an important component of many ecosystem production models (e.g., Gilmanov et al., 2013; John et al., 2013) determining net and gross primary production (NPP and GPP, respectively). Therefore, accurate measurements and modeling of ϵ is important for estimating vegetation productivity in a variety of ecosystems. Many factors impact ϵ such as water content (e.g., Inoue and Peñuelas, 2006), nitrogen content (e.g., Peltoniemi et al., 2012), temperature (e.g., Hall et al., 2012), and CO_2 concentration (e.g., Haxeltine and Prentice, 1996). Because of the impacts of these factors, a maximum light use efficiency (ϵ_o) is typically used in ecosystem productivity models (e.g., Li et al., 2012) and downregulated as environmental conditions change. However, there are known assumptions and errors associated with using ϵ_o (Xiao, 2006) and improvements in estimating light use efficiency is necessary to improve these ecosystem production models.

Incorporating light quality, a major factor impacting ϵ (Gu et al., 2003), has been shown to improve ecosystem productivity models (Knohl and Baldocchi, 2008; Suyker and Verma, 2012). This is due to the sensitivity of ϵ to the light climate in the canopy (He et al., 2013; Zhang et al., 2011). The light quality impact suggests ϵ should not be defined as a down-regulated maximum value, but as a clear sky value that decreases due to environmental stress and increases due to cloud cover. The light use efficiency has been shown to increase under diffuse light conditions (Gu et al., 2002) in relation to the ratio of diffuse (PAR_d) to incident photosynthetically active radiation (PAR_{in}) (Schwalm et al., 2006). As diffuse light

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http://dx.doi.org/10.1016/j.agrformet.2015.04.008
0168-1923/

is not frequently measured, it would be advantageous to have an alternative to PAR_d/PAR_{in}. Turner et al. (2003) defined a cloudiness coefficient (CC) based on PAR_{in} and the clear-sky potential of photosynthetically active radiation (PAR_{pot}). The CC was used as a proxy for the quality of light affecting ϵ but not incorporated into their light use efficiency model.

The Vegetation Photosynthesis Model (VPM) is a light use efficiency model that utilizes remote sensing imagery to estimate GPP based on the impacts of temperature, water stress, and phenology (Xiao et al., 2004). These particular factors impact ϵ because (1) plants are affected but can recover quickly (i.e., short-term) from unfavorable temperatures (Crafts-Brandner and Law, 2000), (2) plants take longer to recover (i.e., long-term) from prolonged water stress (Miyashita et al., 2005; Souza et al., 2004), and (3) leaf age impacts photosynthesis rates (Reich et al., 1991). Richardson et al. (2012) indicated that accurate estimates of phenology were necessary for modeling productivity because errors can lead to large biases in cumulative estimates of GPP. In using satellite imagery, the VPM in most situations cannot be applied daily due to limited frequency of clear sky imagery and thus, would not include the impact of light quality on GPP estimates.

However, models incorporating satellite data (e.g., VPM) are critical in developing regional/global estimates of GPP (Yuan et al., 2010). In this study, we adapt a remote sensing-based light use efficiency model to in-situ meteorological (e.g., temperature, VPD) and biophysical data (e.g., green LAI) to estimate the impacts of temperature, water stress, and phenology on ϵ in order to estimate daily GPP. We note that with the development of gridded meteorological data sets (e.g., Maurer et al., 2002) and remotely sensed biophysical parameters (e.g., Nguy-Robertson et al., 2014), this approach could potentially be applicable on a daily basis at regional/global scales. In this study, our objectives are to (1) enhance the light use efficiency model estimation of GPP on a daily and seasonal basis utilizing four scalars for light quality, temperature, water stress, and phenology for in-situ data collected from both maize and soybean at three Nebraskan sites between 2001 and 2008 and (2) evaluate these models from crop data collected at these sites between 2009 and 2012 on a daily, seasonal, and multi-year basis.

2. Materials and methods

2.1. Study site summary

The study area included three fields located at the University of Nebraska-Lincoln (UNL) Agricultural Research and Development Center (ARDC) near Mead, Nebraska, U.S.A. The three sites belong to the AmeriFlux Network, which is sponsored by the U.S. Department of Energy, monitoring carbon fluxes across the North and South American continents. US-Ne1 (41.165°N, 96.4766°W, 361 m; 49 ha) and US-Ne2 (41.1649°N, 96.4701°W, 362 m; 52 ha) were equipped with a center pivot irrigation system while US-Ne3 (41.1797°N, 96.4396°W, 363 m; 65 ha) was rainfed. In 2001, the sites were prepared by disking the top 0.1 m of the soil to achieve a uniformly tilled surface that incorporated fertilizers as well as accumulated crop residues. US-Ne1 was planted as continuous maize and US-Ne2 and US-Ne3 were under a maize/soybean rotation (Table 1). After the initial tillage operation in 2001, the three sites were no-till until 2005 when US-Ne1 was tilled due to declining yields associated with the effects of high residue cover. Thus for US-Ne1, a conservation plow method, that does not completely invert the topsoil, was initiated in the fall of each year starting in 2005. In 2010, a biomass removal study was initiated where the management of US-Ne2 was changed to match US-Ne1 (continuous maize with tillage operations in the fall) except for one factor. Stover was baled and removed from US-Ne2 prior to tillage in order to study the impact of residue removal on carbon and water fluxes. All fields have been fertilized and treated with herbicide and pesticides following best management practices for Eastern Nebraska. For maize, in the irrigated fields, approximately 180 kg N ha^{-1} was applied each year. This was conducted in three applications using the center pivot. Approximately two-thirds (120 kg N ha^{-1}) was applied pre-planting and the remaining (60 kg N ha^{-1}) was applied in two fertigations. Only a single pre-plant N fertilizer application of 120 kg N ha^{-1} was made on the rainfed site during maize years. Table 1 summarizes the three study sites from 2001 to 2012 (e.g., yield, planting, emergence, and harvest dates).

2.2. Flux measurements

The eddy covariance flux measurements of CO_2 (F_c), latent heat (LE), sensible heat (H), and momentum fluxes were collected using a Gill Sonic anemometer (Model R3; Gill Instruments Ltd., Lymington, UK), a closed- and open-path CO_2/H_2O water vapor sensor (LI-6262 and LI-7500, respectively; LI-Cor Lincoln, NE). Storage of CO_2 below the eddy covariance sensors was determined from profile measurements of CO_2 concentration (LI-6262) and combined with F_c to determine net ecosystem productivity (NEP). Processing methods for correcting flux data due to coordinate rotation (e.g., Baldocchi et al., 1988), inadequate sensor frequency response (e.g, Massman, 1991), and variation in air density (Webb et al., 1980) were applied to all data sets. Key supporting meteorological variables measured included soil heat flux, humidity, incident solar radiation, in situ air and soil temperature, windspeed, and incident photosynthetically active radiation (PAR_{in}). Missing data due to sensor malfunction, unfavorable weather, power outages, etc., were gap-filled using a method that combined measurements, interpolation, and empirical data (Baldocchi et al., 1997; Kim et al., 1992; Suyker et al., 2003; Wofsy et al., 1993). Problems associated with insufficient turbulent mixing during nighttime hours was also corrected (Barford et al., 2001; Suyker and Verma, 2012). When mean windspeed (U) was below the threshold value (U = 2.5 m s^{-1} corresponding to a friction velocity of approximately 0.25 m s^{-1}), data were filled in using night CO_2 exchange-temperature relationships from windier conditions. The daytime estimates of ecosystem respiration (Re) were determined from the temperature-adjusted nighttime CO_2 exchange (Xu and Baldocchi, 2004). The GPP was obtained from the difference between NEP and Re (sign convention: GPP and NEP are positive during C uptake by the vegetation and Re is negative).

Energy budget closure is a known issue with regards to eddy covariance measurements and is due, in part, to errors associated with the angle of attack (Frank et al., 2013; Nakai et al., 2006) and phase shifts when estimating energy storage terms (Leuning et al., 2012). For this study, the energy budget closure was determined by comparing the sum of latent and sensible heat fluxes (LE + H) measured by eddy covariance methods with the sum of net radiation and energy storage (R_n + G). The growing season energy budget closures for all three sites from 2001 to 2012 (0.78–0.97) were reasonable considering the errors inherent in the measurements of these terms.

2.3. Other supporting measurements

Destructive leaf area measurements were collected from six small (20 × 20 m) plots (i.e., intensive measurement zones or IMZs). The IMZs represent all major soil types of each site, including Tomek, Yutan, Filbert, and Filmore soil series (Suyker et al., 2004). The green LAI, or photosynthetically active leaf area index, was calculated from a 1 m sampling length from one or two rows (6 ± 2 plants) within each IMZ. Samples were collected from each field every 10–14 days starting at the initial growth stages (Abendroth et al., 2011), and ending at crop maturity. To minimize edge