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Effects of in-situ and reanalysis climate data on estimation of cropland gross primary production using the Vegetation Photosynthesis Model

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ABSTRACT

Satellite-based Production Efficiency Models (PEMs) often require meteorological reanalysis data such as the North America Regional Reanalysis (NARR) by the National Centers for Environmental Prediction (NCEP) as model inputs to simulate Gross Primary Production (GPP) at regional and global scales. This study first evaluated the accuracies of air temperature (T_{NARR}) and downward shortwave radiation (R_{NARR}) of the NARR by comparing with in-situ meteorological measurements at 37 AmeriFlux non-crop eddy flux sites, then used one PEM – the Vegetation Photosynthesis Model (VPM) to simulate 8-day mean GPP (GPP_{VPM}) at seven AmeriFlux crop sites, and investigated the uncertainties in GPP_{VPM} from climate inputs as compared with eddy covariance-based GPP (GPP_{EC}). Results showed that T_{NARR} agreed well with in-situ measurements; R_{NARR}, however, was positively biased. An empirical linear correction was applied to R_{NARR}, and significantly reduced the relative error of R_{NARR} by ~25% for crop site-years. Overall, GPP_{VPM} calculated from the in-situ ($GPP_{VPM(EC)}$), original ($GPP_{VPM(NARR)}$) and adjusted NARR ($GPP_{VPM(adjNARR)}$) climate data tracked the seasonality of GPP_{EC} well, albeit with different degrees of biases. $GPP_{VPM(EC)}$ showed a good match with GPP_{EC} for maize (*Zea mays* L.), but was slightly underestimated for soybean (*Glycine max* L.). Replacing the in-situ climate data with the NARR resulted in a significant overestimation of $GPP_{VPM(NARR)}$ (18.4/29.6% for irrigated/rainfed maize and 12.7/12.5% for irrigated/rainfed soybean). $GPP_{VPM(adjNARR)}$ showed a good agreement with $GPP_{VPM(EC)}$ for both crops due to the reduction in the bias of R_{NARR}. The results imply that the bias of R_{NARR} introduced significant uncertainties into the PEM-based GPP estimates, suggesting that more accurate surface radiation datasets are needed to estimate primary production of terrestrial ecosystems at regional and global scales.

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1. Introduction

Croplands cover 12% of the global ice-free terrestrial surface (Ramankutty et al., 2008) and provide food for more than seven billion people in the world. Increasing demand for food under the changing climate is one of the great challenges in the coming decades (Guanter et al., 2014; Lobell and Asner, 2003). Gross Primary Production (GPP) of croplands is the total carbon uptake through photosynthesis. A recent modeling study estimated that croplands have an annual sum of 11 Pg C yr^{-1} GPP, accounting for ~10% of the global terrestrial GPP (Chen et al., 2014). Crop cultivation and production vary substantially over space and time. Thus, an accurate quantification of cropland GPP is critical for global food security (Wheeler and von Braun, 2013), biofuel production (Landis et al., 2008), and understanding variations in the terrestrial carbon cycle (Haberl et al., 2007).

Production Efficiency Models (PEMs) have been widely used to quantify the spatial-temporal GPP variations of terrestrial ecosystems using the satellite and climate data as inputs. The PEMs, originating from Monteith's theoretical concept about light use efficiency (LUE) (Monteith, 1972; Monteith and Moss, 1977), estimate GPP as the product of the photosynthetically active radiation (PAR, MJ m^{-2}), the fraction of PAR absorbed by the vegetation

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(fPAR), and the conversion efficiency of absorbed PAR for carbon fixation (ε, $\mathrm{g\,C\,MJ^{-1}}$) ($\mathrm{GPP} = \varepsilon \times \mathrm{fPAR} \times \mathrm{PAR}$). The PEMs for croplands can be classified into two categories based on fPAR and ε estimation methods. The first category calculates fPAR and ε separately. This approach has been applied in the Global Production Efficiency Model (GLO-PEM) (Prince and Goward, 1995), the MODIS Daily Photosynthesis model (MODIS-PSN) (Running et al., 2000), the C-Fix model (Veroustraete et al., 2002), and the Vegetation Photosynthesis Model (VPM) (Xiao et al., 2004a,b). The second type of PEMs, referred as the Greenness and Radiation (GR) model, uses the chlorophyll-related vegetation indices ($\mathrm{VI_{chl}}$) as a proxy of $\varepsilon \times \mathrm{fPAR}$ ($\mathrm{GPP} \propto \mathrm{VI}_{chl} \times \mathrm{PAR}$) (Gitelson et al., 2006; Peng and Gitelson, 2011, 2012; Peng et al., 2011; Wu et al., 2009; Zhang et al., 2014, 2015).

Challenges remain, however, in applying PEMs due to model structure and model inputs. Several attempts have been made to address the uncertainties from the PEM algorithm itself, including the assumption of linear response of photosynthesis to light intensity (Chen et al., 1999), constant maximum LUE for one ecosystem (Heinsch et al., 2006), the impacts of diffuse radiation (He et al., 2013; Zhang et al., 2012), and the incomplete integration of environmental regulations (temperature, water, phenology, etc.) to photosynthetic processes (Dong et al., 2015; Yuan et al., 2014). Most uncertainty analyses overlooked the potential impacts of model inputs on the application of PEMs to regional or global primary production monitoring.

Meteorological reanalysis data produces continuous and near real-time climate monitoring via data assimilation models, and has been the major climate input of PEMs for the large-scale primary production simulation (Feng et al., 2007; Running et al., 2004; Xiao et al., 2011; Yuan et al., 2010). Studies have reported that the meteorological reanalysis data can be spatially and temporally biased from the ground observations, in particular for downward shortwave radiation when estimating PAR (Babst et al., 2008; Cai et al., 2014; Decker et al., 2012; Troy and Wood, 2009; Zhang et al., 2007; Zhao et al., 2006, 2013a; Zib et al., 2012). PEMs have been found very sensitive to the accuracy of climate reanalysis variables (Cai et al., 2014; Heinsch et al., 2006; Zhang et al., 2007; Zhao et al., 2006). For example, Heinsch et al. (2006) reported that the errors associated with the standard MODIS GPP product were mainly attributed to the NASA's Data Assimilation Office (DAO) reanalysis data. Previous sensitivity analyses of PEMs to climate inputs focused on global reanalysis data, the spatial resolution of which is too coarse to delineate the local climatic variations.

The North America Regional Reanalysis (NARR) by the National Centers for Environmental Prediction (NCEP) is the only currently available long-term regional reanalysis data. Compared with the NCEP global reanalysis datasets, the NARR substantially improves the spatio-temporal resolutions along with the accuracy of climate variables (Mesinger et al., 2006) and could be an alternative climate driver of regional GPP estimates in particular for croplands, one of the most heterogeneous landscapes. There has been very limited research regarding the uncertainties of PEMs in relation to the NARR. Therefore, careful investigation of the accuracy of the NARR and its impacts on cropland GPP estimates at site level is an indispensable step prior to the large scale application of these tools.

The objectives of this study were to: (1) evaluate the accuracy of the NARR (air temperature and downward shortwave radiation) as compared to the in-situ observations from the AmeriFlux network at 8-day intervals; (2) adjust the NARR based on the statistical differences from in-situ meteorological measurements; and (3) quantify the impacts of different climate inputs (in-situ meteorological data and the original and adjusted NARR data) on the GPP simulation for maize and soybean using the VPM at seven AmeriFlux crop sites (40 site-years).

2. Data and methods

2.1. NARR

The NARR is produced at a spatial resolution of 32 km and a temporal resolution of 3-h. We obtained the NARR daily gridded air temperature (T_{NARR}) and downward shortwave radiation (R_{NARR}) from http://www.esrl.noaa.gov/psd/. The daily T_{NARR} and R_{NARR} for the pixels covering AmeriFlux sites were extracted for the available site-years at 44 AmeriFlux sites and were aggregated to 8-day intervals to match the temporal resolution of MODIS products.

2.2. MODIS land surface reflectance, vegetation indices products

This study used the 8-day 500 m MODIS Surface Reflectance product – MOD09A1 to derive vegetation indices. The time-series MOD09A1 data for the crop sites were extracted from the MODIS data portal at the Earth Observation and Modeling Facility (EOMF), University of Oklahoma (http://www.eomf.ou.edu/visualization/manual/). The Enhanced Vegetation Index (EVI) and Land Surface Water Index (LSWI) were calculated for every 8-day observation using Eqs. (1) and (2).

$$\mathrm{EVI} = 2.5 \times \frac{\rho_{NIR_1} - \rho_{red}}{\rho_{NIR_1} + 6 \times \rho_{red} - 7.5 \times \rho_{blue} + 1} \quad (1)$$

$$\mathrm{LSWI} = \frac{\rho_{NIR_1} - \rho_{SWIR_1}}{\rho_{NIR_1} + \rho_{SWIR_1}} \quad (2)$$

where ρ_{NIR_1}, ρ_{red}, ρ_{blue}, and ρ_{SWIR_1} are the MOD09A1 surface reflectance for NIR_1 (841-876 nm), red (620–670 nm), blue (459–479 nm), and $SWIR_1$ (1628–1652 nm), respectively. A two-step gap-filling procedure was applied to gap-fill bad-quality observations within the time series of vegetation indices (Xiao et al., 2004a,b).

2.3. In-situ meteorological observations and CO_2 flux data

The AmeriFlux network consists of eddy covariance flux sites for monitoring the long-term ecosystem-scale exchange of carbon, energy, and water in North America (Baldocchi et al., 2001). Meteorological observations such as temperature, precipitation, and radiation are also collected at these sites.

We obtained all available 8-day Level 4 data of the AmeriFlux sites covering the conterminous U.S. from http://ameriflux.lbl.gov/Pages/default.aspx (Fig. 1). The Level 4 data included air temperature (T_{EC}), downward shortwave radiation (R_{EC}), and CO_2 flux data. This study used the standardized GPP ($\mathrm{GPP_{EC}}$), which was partitioned from net ecosystem CO_2 exchange (NEE). By screening quality flags, only the most reliable observations were chosen for analysis. T_{EC} and R_{EC} from 37 non-crop sites (139 site-years) were used to evaluate and to adjust the NARR, if there were large biases. A total of 23 site-years of T_{EC} and R_{EC} and 40 site-years of $\mathrm{GPP_{EC}}$ from seven crop sites were used to validate the adjusted NARR and to evaluate the VPM-simulated GPP, respectively (Table 1). The crop sites were located in the Midwest U.S. corn and soybean belt, and were under different agricultural management practices. US-NE1 was a continuous irrigated maize site and US-NE2 was an irrigated maize/soybean rotation site. The other five sites were rainfed maize/soybean rotation sites. The detailed descriptions about these sites can be found in site specific publications (Griffis et al., 2005; Meyers and Hollinger, 2004; Verma et al., 2005).

It is important to mention that a direct comparison between the in-situ AmeriFlux observations and the NARR data without considering the differences of spatial scales might introduce some uncertainties. The in-situ observations can be affected by local environment conditions (terrain, hydrology, land cover etc.), while the

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