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

Cui Jin, Xiaming Xiao, Pradeep Wagle, Timothy Griffis, Jinwei Dong, Chaoyang Wu, Yuanwei Qin, David R. Cook

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A B S T R A C T

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 \( T_{\text{NARR}} \) and downward shortwave radiation \( R_{\text{NARR}} \) 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 \( \text{GPP}_{\text{VPM}} \) at seven AmeriFlux crop sites, and investigated the uncertainties in GPP\text{VPNM} from climate inputs as compared with eddy covariance-based GPP \( \text{GPP}_{\text{EC}} \). Results showed that \( T_{\text{NARR}} \) agreed well with in-situ measurements; \( R_{\text{NARR}} \), however, was positively biased. An empirical linear correction was applied to \( R_{\text{NARR}} \), and significantly reduced the relative error of \( R_{\text{NARR}} \) by ~25% for crop site-years. Overall, \( \text{GPP}_{\text{VPNM}} \) calculated from the in-situ \( \text{GPP}_{\text{EC}} \), original \( \text{GPP}_{\text{VPNM}} \) and adjusted NARR \( \text{GPP}_{\text{VPNMadjNARR}} \) climate data tracked the seasonality of \( \text{GPP}_{\text{EC}} \) well, albeit with different degrees of biases. \( \text{GPP}_{\text{VPNMadjNARR}} \) showed a good match with \( \text{GPP}_{\text{EC}} \) for maize \( \text(Zea mays} \) L.), but was slightly underestimated for soybean \( \text(Glycine max} \) L.). Replacing the in-situ climate data with the NARR resulted in a significant overestimation of \( \text{GPP}_{\text{VPNMadjNARR}} \) (18.4/29.6% for irrigated/rainfed maize and 12.7/12.5% for irrigated/rainfed soybean). \( \text{GPP}_{\text{VPNMadjNARR}} \) showed a good agreement with \( \text{GPP}_{\text{EC}} \) for both crops due to the reduction in the biases of \( \text{R}_{\text{NARR}} \). The results imply that the bias of \( \text{R}_{\text{NARR}} \) 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 (Gunter 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...
(fPAR), and the conversion efficiency of absorbed PAR for carbon fixation (\(\varepsilon\), g CM\(^{-1}\)) (\(GPP = \varepsilon \times fPAR \times PAR\)). The PEMs for croplands can be classified into two categories based on fPAR and \(\varepsilon\) estimation methods. The first category calculates fPAR and \(\varepsilon\) separately. This approach has been applied in the Global Production Efficiency Model (GLO-PEM) (Prince and Howard, 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 to the Greenness and Radiation (GR) model, uses the chlorophyll-related vegetation indices (\(V_{\text{chl}}\)) as a proxy of \(\varepsilon \times fPAR\) (\(GPP \propto V_{\text{chl}} \times PAR\)) (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 (Bastb 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 (\(T_{\text{NARR}}\)) and downward shortwave radiation (\(R_{\text{NARR}}\)) from http://www.esrl.noaa.gov/psd/ (http://www.esrl.noaa.gov/psd/). The daily \(T_{\text{NARR}}\) and \(R_{\text{NARR}}\) 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).

\[
\text{EVI} = 2.5 \times \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + 6 \times \rho_{\text{red}} - 7.5 \times \rho_{\text{blue}} + 1}\tag{1}
\]

\[
\text{LSWI} = \frac{\rho_{\text{NIR}} - \rho_{\text{SWIR2}}}{\rho_{\text{NIR}} + \rho_{\text{SWIR2}}}\tag{2}
\]

where \(\rho_{\text{NIR}}, \rho_{\text{red}}, \rho_{\text{blue}}, \) and \(\rho_{\text{SWIR2}}\) are the MOD09A1 surface reflectance for \(\text{NIR}\) (841-876 nm), red (620–670 nm), blue (459–479 nm), and SWIR1 (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 \(\text{CO}_2\) 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 (\(T_{\text{EC}}\)), downward shortwave radiation (\(R_{\text{EC}}\)), and \(\text{CO}_2\) flux data. This study used the standardized GPP (\(\text{GPP}_{\text{EC}}\)) which was partitioned from net ecosystem \(\text{CO}_2\) exchange (NEE). By screening quality flags, only the most reliable observations were chosen for analysis. \(T_{\text{EC}}\) and \(R_{\text{EC}}\) 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 \(T_{\text{EC}}\) and \(R_{\text{EC}}\) and 40 site-years of \(\text{GPP}_{\text{EC}}\) 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
NARR might be too coarse to delineate local environment variations. However, the AmeriFlux is currently the best available dataset providing high-quality and synthesized observation of radiation, temperature, water and carbon fluxes under standard protocols.

2.4. The Vegetation Photosynthesis Model (VPM)

The VPM is one PEM based on the conceptual partition of the light absorption by chlorophyll pigments and nonphotosynthetic vegetation (NPV such as branches, trunks, or senescent leaves) (Xiao et al., 2004a,b). The VPM defines the fPAR as the fraction of PAR absorbed by plant chlorophyll (fPAR\textsubscript{chl}):

\[
\text{GPP} = \varepsilon \times \text{fPAR}_{\text{chl}} \times \text{PAR}
\]

\[
f\text{PAR}_{\text{chl}} = \text{EVI}
\]

\[
\varepsilon = \varepsilon_0 \times T_{\text{scalar}} \times W_{\text{scalar}}
\]

where PAR is calculated as 0.45 \times R (R, downward shortwave solar radiation); \text{fPAR}_{\text{chl}} is equivalent to EVI; Light use efficiency, \varepsilon, is estimated as a function of the maximum light use efficiency (\varepsilon_0), temperature (T_{\text{scalar}}) and water condition (W_{\text{scalar}}). The \varepsilon_0 values of 3.12 g C MJ\textsuperscript{-1} for maize (Kalfas et al., 2011) and 1.75 g C MJ\textsuperscript{-1} for soybean (Wagle et al., 2015) were used in this study.

The effect of temperature scalar (T_{\text{scalar}}) on GPP is calculated using the equation from the Terrestrial Ecosystem Model (Raich et al., 1991):

\[
T_{\text{scalar}} = \left\{ \begin{array}{ll}
\frac{(T - T_{\text{min}})(T - T_{\text{max}})}{(T - T_{\text{max}})(T - T_{\text{min}})} & , T_{\text{min}} \leq T \leq T_{\text{max}} \\
0 & , T \leq T_{\text{max}} \quad T \geq T_{\text{max}}
\end{array} \right. \tag{6}
\]

where T is 8-day mean air temperature; T_{\text{min}}, T_{\text{opt}}, and T_{\text{max}} are minimum, optimum, and maximum temperatures for vegetation photosynthesis, respectively, and were set to 10 °C, 28 °C, 48 °C for maize (Kalfas et al., 2011), and −1 °C, 28 °C, 50 °C for soybean (Wagle et al., 2015).

The effect of water scalar (W_{\text{scalar}}) on GPP is calculated with LSWI:

\[
W_{\text{scalar}} = \left\{ \begin{array}{ll}
1 + \text{LSWI} & , \text{LSWI} > 0 \\
\frac{1}{1 + \text{LSWI}_{\text{max}}} & , \text{LSWI} \leq 0
\end{array} \right. \tag{7}
\]

where LSWI_{\text{max}} is the maximum LSWI during growing season.

This study used the VPM to simulate three sets of GPP{\textsubscript{VPM}}: GPP{\textsubscript{VPM/EC}}, GPP{\textsubscript{VPM/NARR}}, and GPP{\textsubscript{VPM/adj-NARR}}, using T and R from eddy flux sites (T_{\text{EC}}, R_{\text{EC}}), the NARR (T_{\text{NARR}}, R_{\text{NARR}}), and the adjusted NARR (T_{\text{NARR}, \text{adj}}, R_{\text{NARR, adj}}), respectively.

2.5. Statistical analysis

To quantify the differences between T_{\text{NARR}} and T_{\text{EC}}, R_{\text{NARR}} and R_{\text{EC}}, correlation coefficient (\rho), ratio of standard deviation (\sigma_{R_{\text{ratio}}}), bias, and root-mean-square-error (RMSE) were calculated for each non-crop site-year. The histogram of each statistics was summarized for all non-crop site-years to characterize the overall accuracy of T_{\text{NARR}} and R_{\text{NARR}}.

Mean squared error (MSE) was calculated for T_{\text{NARR}} and R_{\text{NARR}} of each site-year, and decomposed into three terms (Decker et al., 2012; Gupta et al., 2009), such that

\[
\text{MSE} = 2\sigma_{\text{NARR}}\sigma_{\text{EC}}(1 - \rho) + (\sigma_{\text{NARR}} - \sigma_{\text{EC}})^2 + (\mu_{\text{NARR}} - \mu_{\text{EC}})^2 \tag{8}
\]

where \mu_{\text{EC}} and \sigma_{\text{EC}} are the mean and standard deviation for the in-situ observations, respectively, \mu_{\text{NARR}} and \sigma_{\text{NARR}} are the mean and standard deviation for the NARR, respectively. The first, second, and third terms in Eq. (8) were represented in ternary diagrams to concisely visualized the contribution of correlation (\rho), consistency of variation (\sigma_{\text{ratio}}), and bias (bias and RMSE) to the overall disagreements between T_{\text{NARR}} and T_{\text{EC}} and between R_{\text{NARR}} and R_{\text{EC}}.

The simple linear regression between R_{\text{EC}} and R_{\text{NARR}} was also calculated for all non-crop site-years (R_{\text{EC}} = \alpha \times R_{\text{NARR}}). On the basis of the spatial pattern of regression coefficients (\alpha), an empirical ratio-based adjustment was applied to R_{\text{NARR}} at the crop sites (R_{\text{adj-NARR}}).

### Table 1: A summary description of the AmeriFlux eddy flux crop sites.

<table>
<thead>
<tr>
<th>Site ID</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Years of T\text{EC}, R\text{EC}</th>
<th>Crop type</th>
<th>Years of GPP\text{VPM}</th>
</tr>
</thead>
<tbody>
<tr>
<td>US-BI1</td>
<td>−88.2904</td>
<td>40.0625</td>
<td>2006</td>
<td>Rainfed maize</td>
<td>2005</td>
</tr>
<tr>
<td>US-Bo1</td>
<td>−88.2227</td>
<td>41.8593</td>
<td>2001</td>
<td>Rainfed maize</td>
<td>2005</td>
</tr>
</tbody>
</table>

*\(^a\) and *\(^b\)Air temperature and downward shortwave radiation observed from the AmeriFlux eddy flux sites.*

*\(^c\)8-day Level-4 GPP estimates from the AmeriFlux eddy flux sites.*

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**Fig. 1.** Location of the AmeriFlux eddy flux sites. Circles denote the non-crop sites for accuracy assessment of the NARR and stars denote the crop sites used to evaluate the VPM-based GPP estimates. The base map is the 2013 Cropland Data Layer (CDL) from the National Agricultural Statistics Service (NASS).**
Relative error (RE), RMSE, regression coefficient ($\alpha$), and coefficient of determination ($R^2$) of the simple linear regression between $R_{NARR}$ and $R_{EC}$, and $R_{adjNARR}$ and $R_{EC}$ were obtained to quantify the adjustment performance.

This study implemented a top-down strategy to evaluate the impact of different climate inputs on GPP$_{VPM}$. First, the statistics factors described above were used to quantify how GPP$_{VPM(EC)}$, GPP$_{VPM(NARR)}$, and GPP$_{VPM(adjNARR)}$ matched GPP$_{EC}$ for individual crops. Second, the similarities between GPP$_{VPM}$ and GPP$_{EC}$ across individual crop sites were evaluated using Taylor diagrams. Taylor diagrams provide a statistical summary of the similarity of variability pattern ($\rho$), the agreement of the variability amplitudes (represented by the ratio of normalized standard deviation, $\sigma_{ratio}$), and the centered RMSE between the modeled results and the observations (Gleckler et al., 2008; Taylor, 2001). In addition, annual mean RMSE of GPP$_{VPM}$ was calculated for each crop site-year.

3. Results

3.1. Comparison of air temperature

$T_{NARR}$ agreed well with $T_{EC}$ for almost all non-crop site-years. $T_{NARR}$ was significantly correlated with $T_{EC}$ ($\rho > 0.95$ for 139 site-years, Fig. 2). In addition, $T_{NARR}$ showed a similar amplitude of variation as in $T_{EC}$, as ~82% of site-years had $\sigma_{ratio} \leq 10\%$. $T_{NARR}$ was mostly overestimated with a positive bias of 0.5–2.5 °C and a mean RMSE of 1.67 °C. The simple linear regression confirmed the good agreement between $T_{NARR}$ and $T_{EC}$. $T_{NARR}$ showed a strong linear regression with $T_{EC}$ ($\rho$ across 129 site-years was in a range of 1 ± 0.1, $R^2 > 0.95$, $p < 0.001$). MSE was determined by both the bias and correlation, as the contribution of bias and correlation was over 0.8 at 86% of the site-years (Fig. 3).

$T_{NARR}$ was also relatively accurate at the crop sites. The simple linear regression indicated that $T_{NARR}$ agreed well with $T_{EC}$ for all crop site-years ($\rho = 1.04$, RE = 11.6%, RMSE = 1.4 °C, $R^2 = 0.99$, Fig. 4). $T_{NARR}$ accounted for over 98% of the seasonal dynamics of $T_{EC}$ for individual crop sites on annual scale (Table 2). $\alpha$ varied from 1.0 to 1.1 among the crop sites. RE and RMSE were −1.4% to 7.3% and 1.2–1.7 °C, respectively. Considering the relatively high accuracy at non-crop and crop site-years, the 8-day $T_{NARR}$ was used as the VPM input without any correction.

3.2. Comparison of downward shortwave radiation

$R_{NARR}$ was well correlated with $R_{EC}$ ($\rho > 0.9$ at 94% of the non-crop site-years, Fig. 5). However, it was overestimated with $\sigma_{ratio} > 1.1$ at 67% of the site-years. The bias was positive across all site-years on an average of 3.55 MJ m$^{-2}$ day$^{-1}$. 60% of the site-years had a RMSE of 3–5 MJ m$^{-2}$ day$^{-1}$. The bias was the dominant contributor to MSE (Fig. 6). The contribution of bias was >0.5 at 133 of 139 site-years, indicating the disagreement between $R_{NARR}$ and $R_{EC}$ was systematic.

$R_{NARR}$ showed a significant linear regression with $R_{EC}$ at each non-crop site-year (Fig. 5). However, $\alpha$ was quite variable (0.63–0.95). $\alpha$ slightly decreased with the latitude increasing or the longitude decreasing (Fig. 7). $\alpha$ was more stable within the longitude range of 85–100° W than it was across 40–47.5° N for the region covering the crop sites (Fig. 7 highlighted in gray). Thus, the median of $\alpha$ values (0.81) within the longitude of 85–100° W was used as a ratio to adjust the bias of $R_{NARR}$ at the crop sites.
Table 2

<table>
<thead>
<tr>
<th>Site ID</th>
<th>( T_{\text{EC}}^{a} ) vs. ( T_{\text{NARR}}^{b} )</th>
<th>( R_{\text{EC}}^{c} ) vs. ( R_{\text{NARR}}^{d} )</th>
<th>( R_{\text{EC}} ) vs. ( R_{\text{adjNARR}}^{e} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \text{RE} )</td>
<td>( \text{RMSE} )</td>
<td>( \alpha )</td>
</tr>
<tr>
<td>US-NE1/2/3</td>
<td>7.3 ± 5.9</td>
<td>1.7 ± 0.55</td>
<td>1.1 ± 0.04</td>
</tr>
<tr>
<td>US-RO1/3</td>
<td>-1.4 ± 5.2</td>
<td>1.6 ± 0.33</td>
<td>1.0 ± 0.01</td>
</tr>
<tr>
<td>US-IB1</td>
<td>4.6 ± 0.1</td>
<td>1.3 ± 0.12</td>
<td>1.1 ± 0.02</td>
</tr>
<tr>
<td>US-Ro1</td>
<td>7.1 ± 2.0</td>
<td>1.2 ± 0.17</td>
<td>1.0 ± 0.01</td>
</tr>
</tbody>
</table>

\(^{a}\) and \(^{b}\) Air temperature of the AmeriFlux and NARR data (°C).

\(^{c}\) Downward shortwave radiation of the AmeriFlux, the NARR before and after adjustment (MJ m\(^{-2}\) day\(^{-1}\)).

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Fig. 5. Distribution histograms of correlation coefficient (\( \rho \)), ratio of standard deviation (\( \sigma_{\text{ratio}} \)), bias, root-mean-square-error (RMSE), and regression coefficient (\( \alpha \)) for 8-day downward shortwave radiation between AmeriFlux (\( R_{\text{EC}} \)) and NARR (\( R_{\text{NARR}} \)) across the non-crop site-years.

The adjustment substantially reduced the bias of \( R_{\text{NARR}} \) at the crop sites (Fig. 8). \( R_{\text{NARR}} \) was overestimated by 28.2% on average. \( R_{\text{adjNARR}} \) evenly distributed along 1:1 line and RMSE was reduced to 1.7 MJ m\(^{-2}\) day\(^{-1}\).

\( R_{\text{NARR}} \) explained \( \sim 90\% \) of the variations of \( R_{\text{EC}} \) across each crop site (Table 2). Similar to the non-crop sites, \( R_{\text{NARR}} \) was strongly overestimated (RE > 22%) at the crop sites. The annual RMSE varied from 3.8 MJ m\(^{-2}\) day\(^{-1}\) to 4.9 MJ m\(^{-2}\) day\(^{-1}\). After the adjustment, \( \alpha \) was close to 1, and RE and RMSE of \( R_{\text{adjNARR}} \) decreased to \(-2.5\% \) to \(3\% \) and \(1.6-2\) MJ m\(^{-2}\) day\(^{-1}\), respectively.

3.3. Comparison of VPM-based (GPP\(_{\text{VPM}}\)) and the flux tower-based (GPP\(_{\text{EC}}\)) estimates

The seasonal dynamics of GPP\(_{\text{VPM(EC)}}\), GPP\(_{\text{VPM(adjNARR)}}\), and GPP\(_{\text{VPM(adjNARR)}}\) corresponded well with GPP\(_{\text{EC}}\) for both maize and soybean (Fig. 9). At the leaf-on stage during late-May to June, GPP\(_{\text{EC}}\) started to exceed 1 g m\(^{-2}\) day\(^{-1}\) and GPP\(_{\text{VPM}}\) also rose rapidly.

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Fig. 6. Contributions of correlation (\( \rho \)), consistency of variation (\( \sigma_{\text{ratio}} \)), and bias to the Mean Squared Error (MSE) for the 8-day NARR downward shortwave radiation (\( R_{\text{NARR}} \)) across the non-crop site-years.

Fig. 7. Spatial patterns of regression coefficient (\( \alpha \)) between 8-day downward shortwave radiation from AmeriFlux (\( R_{\text{EC}} \)) and NARR (\( R_{\text{NARR}} \)), with geographical distribution of crop sites highlighted: (a) \( \alpha \) averaged along the 2.5° latitude gradient and (b) \( \alpha \) averaged along the 5° longitude gradient.
and both reached a maximum at the peak growing season during late-July to early-August. After the crops matured and approached the harvest date in September, both GPP_EC and GPP_VPM began to decrease and were lower than 1 g C m\(^{-2}\) day\(^{-1}\).

The relationships between GPP_VPM and GPP_EC for individual crop types were evaluated through simple linear regression models (Fig. 10). For irrigated and rainfed maize, both GPP_VPM(EC) and GPP_VPM(adjNARR) agreed well with GPP_EC; but GPP_VPM(NARR) was overestimated due to the positive bias of RNARR (Fig. 10a and b). GPP_VPM(EC) accounted for 89% of the variations of GPP_EC. GPP_VPM(NARR) was also correlated well with GPP_EC, but it was overestimated by 18.4% and 29.6% for irrigated and rainfed maize, respectively. After adjusting RNARR, α, RE, and RMSE for GPP_VPM(adjNARR) were close to those of GPP_VPM(EC). For irrigated and rainfed soybean, GPP_VPM(EC) and GPP_VPM(adjNARR) estimated GPP reasonably well with an underestimation less than −10% (Fig. 10c and d). GPP_VPM(NARR) over-predicted GPP_EC by ∼13% for irrigated and rainfed soybean.

The relationships between GPP_VPM and GPP_EC were further evaluated for maize through individual crop-sites and individual site-years (Fig. 11a, b, and Table 3). GPP_VPM(EC) and GPP_VPM(adjNARR) showed reliable GPP estimates for the irrigated and rainfed maize across the sites (Fig. 11a and b). Most sites had similar patterns and amplitudes of variability between GPP_VPM(EC) and GPP_EC (1 < σ_{ratio} < 1.05 and 0.95 < ρ < 0.98. Fig. 11a) with low annual mean RMSEs (ca. 1.5–2.4 g C m\(^{-2}\) day\(^{-1}\), Table 3). GPP_VPM(EC) at R01 and Bo1 didn’t appear to adequately capture the amplitudes of variability of GPP_EC (σ_{ratio} = 0.7 and 1.3) as indicated by relatively low ρ (0.92 and 0.82) and high RMSE (3.2 g C m\(^{-2}\) day\(^{-1}\) and 4.9 g C m\(^{-2}\) day\(^{-1}\)). The discrepancies were due to the under-estimation of GPP_VPM(EC) during the peak growing season at R01 and the significant overestimation of GPP_VPM(EC) after the peak growing season at Bo1 (Fig. 9). GPP_VPM(NARR) simulated the phasing and timing of GPP_EC well (ρ was ca. 0.93–0.98). The RMSE of GPP_VPM(NARR) (ca. 4.2–6.4 g C m\(^{-2}\) day\(^{-1}\)) was significantly higher than that of GPP_VPM(EC) at most sites, indicating an overestimation caused the NARR. The adjustment of RNARR resulted in similar patterns of GPP_VPM(adjNARR) and GPP_VPM(EC) at all sites, with a slight increase of RMSE (ca. 1.6–3.1 g C m\(^{-2}\) day\(^{-1}\), Fig 11b and Table 3).

The relationships between GPP_VPM and GPP_EC were also evaluated for soybean through individual crop-sites and individual site-years (Fig. 11c, 11d, and Table 3). GPP_VPM(EC) and GPP_VPM(adjNARR) matched GPP_EC reasonably well. The variability of GPP_VPM(EC) was similar to that of GPP_EC (0.83 < ρ < 0.93, Fig. 11c). NE2 and R01 had a good agreement between GPP_VPM(EC) and GPP_EC, as σ_{ratio} was close to 1 showing a low RMSE (1.4–2.0 g C m\(^{-2}\) day\(^{-1}\), Table 3). At other sites (NE3, IB1, and Bo1), GPP_VPM(EC) underestimated the variability of GPP_EC (0.85 < σ_{ratio} < 0.9, Fig. 11c) with a high RMSE (2.0–2.6 g C m\(^{-2}\) day\(^{-1}\)). GPP_VPM(NARR) correlated well with GPP_EC (0.9 < ρ < 0.94). However, the σ_{ratio} of GPP_VPM(NARR) was larger than that of GPP_VPM(EC) caused by the positive bias of RNARR. After adjusting the bias of RNARR, GPP_VPM(adjNARR) matched GPP_EC better than did GPP_VPM(NARR) (Fig. 11d).

![Fig. 8](image-url) Comparisons of 8-day downward shortwave radiation between AmeriFlux (R_EC) and the NARR before and after adjustment (R_{NARR}, R_{adjNARR}) for all crop-site years.

![Fig. 9](image-url) Seasonal dynamics and interannual variations of GPP_EC, GPP_VPM(EC), GPP_VPM(NARR), and GPP_VPM(adjNARR) for the crop site-years. The soybean site-years are highlighted.
Fig. 10. Comparisons of $GPP_{VPM(EC)}$, $GPP_{VPM(NARR)}$, and $GPP_{VPM(adjNARR)}$ with $GPP_{EC}$ for individual crop: (a) irrigated maize, (b) rainfed maize, (c) irrigated soybean, and (d) rainfed soybean.

Fig. 11. Performances of the VPM driven by three climate datasets for individual crop-site: (a) and (b) $GPP_{VPM(EC)}$ vs. $GPP_{VPM(NARR)}$ and $GPP_{VPM(EC)}$ vs. $GPP_{VPM(adjNARR)}$ for the irrigated and rainfed maize; (c) and (d) $GPP_{VPM(EC)}$ vs. $GPP_{VPM(NARR)}$ and $GPP_{VPM(EC)}$ vs. $GPP_{VPM(adjNARR)}$ for the irrigated and rainfed soybean. The locations of the heads and tails of arrows quantify how $GPP_{VPM}$ matches with $GPP_{EC}$, and the arrows show how the agreement of $GPP_{VPM}$ with $GPP_{EC}$ changes using different climate inputs. The distance to the origin is the ratio of the standard deviations of $GPP_{VPM}$ and $GPP_{EC}$ (Normalized standard deviation, $\bar{\sigma}/\sigma$). The azimuthal angle is the correlation ($\rho$) showing the similarity of variation patterns between $GPP_{VPM}$ and $GPP_{EC}$. The most ideal $GPP_{VPM}$ estimate is the point “observed” with $\bar{\sigma}/\sigma = 1$ and $\rho = 1$. 
### Table 3
A summary of the performances of the VPM driven by three sets of climate inputs at the crop sites.

<table>
<thead>
<tr>
<th>Site ID</th>
<th>Crop type</th>
<th>GPP_VPM_SEC *</th>
<th>GPP_VPM_NARR *</th>
<th>GPP_VPM_NARR *</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\rho$</td>
<td>$\sigma_{\text{ratio}}$</td>
<td>RMSE</td>
</tr>
<tr>
<td>US-NE1</td>
<td>Irrigated maize</td>
<td>0.95</td>
<td>1.03</td>
<td>2.4 $\pm$ 0.7</td>
</tr>
<tr>
<td>US-NE2</td>
<td>Irrigated maize</td>
<td>0.96</td>
<td>1.02</td>
<td>2.2 $\pm$ 0.8</td>
</tr>
<tr>
<td>US-NE3</td>
<td>Irrigated soybean</td>
<td>0.91</td>
<td>0.89</td>
<td>2.0 $\pm$ 0.6</td>
</tr>
<tr>
<td>US-RO1</td>
<td>Rainfed maize</td>
<td>0.96</td>
<td>1.08</td>
<td>2.1 $\pm$ 0.5</td>
</tr>
<tr>
<td>US-RO3</td>
<td>Rainfed maize</td>
<td>0.91</td>
<td>0.89</td>
<td>2.6 $\pm$ 0.4</td>
</tr>
<tr>
<td>US-B1</td>
<td>Rainfed maize</td>
<td>0.97</td>
<td>1.06</td>
<td>1.5</td>
</tr>
<tr>
<td>US-R1</td>
<td>Rainfed maize</td>
<td>0.83</td>
<td>0.88</td>
<td>2.3</td>
</tr>
<tr>
<td>US-D1</td>
<td>Rainfed maize</td>
<td>0.82</td>
<td>1.31</td>
<td>4.9</td>
</tr>
<tr>
<td>US-D2</td>
<td>Rainfed maize</td>
<td>0.93</td>
<td>0.86</td>
<td>2.0</td>
</tr>
</tbody>
</table>

\* The VPM-based GPP estimates from in-situ, original and adjusted NARR climate data.

### 4. Discussion

#### 4.1. Uncertainties of the NARR air temperature

$T_{\text{NARR}}$ has been assumed to be relatively accurate in the studies of drought monitoring and the response of vegetation to climate change (Karnaukas et al., 2008; Karniel et al., 2010; Wang et al., 2011). In this study, the 8-day $T_{\text{NARR}}$ was mostly overestimated with a mean bias of 0.62$^\circ$C. This was consistent with the previous finding that $T_{\text{NARR}}$ was biased warm at monthly intervals (Jiang and Yang, 2012). In general, the 8-day $T_{\text{NARR}}$ agreed well with the in-situ observations across non-crop and crop site-years with the mean RMSE of 1.67$^\circ$C and 1.4$^\circ$C, respectively, showing relatively higher accuracy than other global reanalysis datasets (DAO, ECMWF, NCEP, MERRA) investigated by Zhao et al. (2006) and Decker et al. (2012).

#### 4.2. Uncertainties of the NARR downward shortwave radiation

This study made an assumption that $R_{\text{EC}}$ were ground truth. However, the errors or uncertainties associated with in-situ radiation observations also contributed to the differences between $R_{\text{SEC}}$ and $R_{\text{EC}}$ at the Ameriflux. Measurements by different pyranometers. The errors from pyranometers include instrument deployment and maintenance (leveling and shading) and sensor response errors such as thermal offset (Buish et al., 2000; Reda et al., 2005) determined the errors of $R_{\text{EC}}$. The errors of $R_{\text{EC}}$ are subtle compared with the $R_{\text{NARR}}$ biases, but one should not neglect their impacts considering the significant role of long-term sensor stability (Stanhill and Cohen, 2001).

A number of studies have evaluated the monthly $R_{\text{NARR}}$ at individual sites. Walsh (2009) evaluated the monthly $R_{\text{NARR}}$ at the Alaska Barrow and found that it had a lower bias (2.6 MJ m$^{-2}$ day$^{-1}$) than did NCEP/NCAR (3.7 MJ m$^{-2}$ day$^{-1}$). Kennedy et al. (2011) concluded that the bias of monthly $R_{\text{NARR}}$ varied with sky conditions at the Atmospheric Radiation Measurement Program (ARM) Southern Great Plains (SGP) site. Markovic et al. (2009) reported that a systematic bias of monthly $R_{\text{NARR}}$ in summer (5.3 MJ m$^{-2}$ day$^{-1}$) was larger than that in winter (2.5 MJ m$^{-2}$ day$^{-1}$). These evaluations implied that $R_{\text{NARR}}$ had a large span of positive biases. However, their results cannot represent the overall accuracy of $R_{\text{NARR}}$ at continental scale using limited sites. A recent study did a large-scale assessment of monthly $R_{\text{NARR}}$ using 24 FLUXNET sites showing that $R_{\text{NARR}}$ exhibited a positive bias of 3.2 MJ m$^{-2}$ day$^{-1}$ (Zhao et al., 2013a). The ideal temporal interval of climatic drivers for ecological models should be finer, i.e. hourly, daily, or weekly intervals, to demonstrate the diurnal or seasonal dynamics of carbon and energy fluxes (Abatzoglou, 2013; Huntzinger et al., 2013; Wei et al., 2013). Thus, we evaluated the accuracy of $R_{\text{NARR}}$ at 8-day intervals and regional scale using all available Ameriflux sites. The 8-day $R_{\text{NARR}}$ well represented the seasonal dynamics of 8-day $R_{\text{SEC}}$. Similar to monthly $R_{\text{NARR}}$, the bias of the 8-day $R_{\text{NARR}}$ was positive and systematic with a large range across the U.S. The systematic overestimation of $R_{\text{NARR}}$ is mainly caused by the insufficient simulation of light extinction caused by clouds, aerosols, and water vapor in the radiative transferring models (Kennedy et al., 2011; Markovic et al., 2009; Zhao et al., 2013a), and other topographical factors (i.e. elevation, slope, and aspect) (Schroeder et al., 2009; Zhao et al., 2013a).

Empirical or semi-empirical approaches are applied to correct the bias of $R_{\text{NARR}}$. The empirical approach develops the linear statistical regression model between the reanalysis and in-situ observations, then applies the model to other locations (Feng et al., 2007; Qian et al., 2006; Xiao et al., 2014). The empirical approach ignores the spatio-temporal variations in the $R_{\text{NARR}}$ bias. Some studies developed the semi-empirical approach to account the impacts of clouds and topographical factors in the regression models (Schroeder et al., 2009; Zhao et al., 2013a). We followed the empirical approach to calibrate $R_{\text{NARR}}$ and meanwhile considered the spatial variation of regression models.

Simply estimating PAR as a constant ratio of $R_{\text{NARR}}$ can introduce uncertainties to PAR. Theoretically, the band range of downward shortwave radiation (0.3–2.8$\mu$m) does not match that of PAR (0.4–0.7$\mu$m) (Sakamoto et al., 2011). Moreover, the ratio of PAR to downward shortwave radiation is not constant, as it temporarily changes with the local weather condition (Gonzalez and Calbo, 2002; Jacobides et al., 2004; Papaioannou et al., 1993). Surface PAR datasets, such as the satellite-derived Global Land Surface Satellite (GLASS), might be an alternative PAR input for the regional and global ecological modeling (Cai et al., 2014; Eck and Dye, 1991; Frouin and Pinker, 1995; Jin et al., 2013; Pinker et al., 2010; Rubio et al., 2005; Zhao et al., 2013b).

#### 4.3. Sensitivity of PEVs to various climate inputs

All analyses about the sensitivity of PEVs to climate inputs were focused on the PEV of the standard MODIS GPP product – the MODIS-PSN (Heinsch et al., 2006; Zhang et al., 2007; Zhao et al., 2006). These studies found that radiation, air temperature, and vapor pressure deficit (VPD) of the global reanalysis data were largely biased, and introduced significant errors to the standard MODIS GPP product. For instance, Zhao et al. (2006) found that the MODIS GPP showed significant differences when driven by DAO, NCAR, and ECMWF (>20 Pg C yr$^{-1}$). Heinsch et al. (2006) collected 38 site-years of GPP$_{\text{EC}}$ from 15 Ameriflux sites to evaluate the accuracy of MODIS GPP driven by DAO and in-situ meteorology, and annual GPP derived from DAO was 23% higher than GPP$_{\text{EC}}$ and...
the RE of the GPP derived from DAO was much larger than that of the GPP derived from the in-situ meteorology. Note that these evaluations were conducted at monthly or longer intervals. Analyses on finer temporal scales such as weekly interval are needed in order to accurately evaluate the seasonal dynamics of the uncertainties of PEMs to climate data. Thus, we focused on quantifying the uncertainties of $\text{GPP}_{\text{VPM}}$ to in-situ and NARR climate data at 8-day interval. The 8-day $\text{GPP}_{\text{VPM}}$ driven by the in-situ meteorology, original and adjusted NARR data traced over 83–98% of $\text{GPP}_{\text{EC}}$ variations for individual site-years, confirming their capabilities to simulate the response of crop photosynthesis to the environment change (i.e. light, temperature, and water), and tracked the phenological phases well (i.e. leaf-on and leaf-off stages). Similar to the MODIS-PSN, climate inputs had a strong impact on the VPM for cropland GPP estimates. $\text{GPP}_{\text{VPM(EC)}}$ well estimated $\text{GPP}_{\text{EC}}$ for individual crops, sites, and site-years. $\text{GPP}_{\text{VPM/NARR}}$ significantly underestimated $\text{GPP}_{\text{EC}}$ as $R_{\text{NARR}}$ was positively biased. This study addressed two climate inputs of air temperature and downward shortwave radiation for the VPM. The accuracies of other climate variables (VPD, precipitation, etc.) in reanalysis products might be more variable (Decker et al., 2012). Therefore, more uncertainties might be introduced to the PEMs that are driven by multiple climate variables.

4.4. Challenges in comparing $\text{GPP}_{\text{VPM}}$ with $\text{GPP}_{\text{EC}}$

In one study like ours using $\text{GPP}_{\text{EC}}$ to validate or constrain the GPP estimates from PEMs, two assumptions are often made: (1) $\text{GPP}_{\text{EC}}$ is assumed to be accurate as the ground truth and (2) the eddy flux tower footprint is approximately equivalent to the image pixel. The uncertainties associated with these two assumptions, however, can contribute to the discrepancies between the PEM-based GPP estimates ($\text{GPP}_{\text{VPM}}$ in this study) and $\text{GPP}_{\text{EC}}$.

There are a number of errors or uncertainties (random and systematic) from eddy covariance measurements. Random errors are attributed to the stochastic nature of turbulence, sampling errors, instrument system, and variations in the flux footprint (Richardson et al., 2012). Systematic errors arise from the combination of the unmet underlying theoretical assumptions, instrument calibration, and data processing techniques (Falge et al., 2001; Papale et al., 2006; Richardson et al., 2012). Furthermore, the eddy covariance provides direct measurement of NEE and $\text{GPP}_{\text{EC}}$ is estimated as the difference between NEE and ecosystem respiration ($R_{\text{eco}}$) using flux-partitioning approaches, which may also introduce large uncertainties in $\text{GPP}_{\text{EC}}$ (Desai et al., 2008; Reichstein et al., 2005; Stoy et al., 2006). For example, Desai et al. (2008) found annual $\text{GPP}_{\text{EC}}$ varied ~100 g C m$^{-2}$ year$^{-1}$ among 23 partitioning methods. Thus, more efforts are needed to improve partitioning NEE into its component processes to help validate GPP in PEMs and other land surface models (Baldocchi et al., 2015).

The second assumption is questionable in heterogeneous landscapes. Limited by data availability, most PEMs are performed on 1 km spatial resolution of satellite images and might not represent the crop fields that towers are located in due to the mixed signals from other sub-pixel components. In this study, an in-situ landscape analysis showed that the heterogeneity of 500 m MODIS pixels was much improved over that of 1 km MODIS pixels at seven crop sites (Fig. S1). 500 m MODIS pixels were mainly covered by the crop fields that the towers measured except US-RO3 and US-Bo1. Even though the uncertainties of the GPP comparison caused by heterogeneous landscapes were diminished to some extent using the 500 m MODIS data in this study, further evaluations using high resolution images along with the downscaling techniques are required for implementing PEMs, especially at heterogeneous landscapes.

5. Conclusion

This study evaluated the uncertainties of the NARR surface meteorology and quantified the sensitivity of the VPM to the in-situ and NARR climate inputs at seven AmeriFlux crop eddy flux sites. Our results indicated that the bias of NARR resulted in considerable uncertainties in cropland GPP estimates. The 8-day NARR air temperature matched well with in-situ observations, but the NARR downward shortwave radiation showed large positive bias and led to the overestimation of $\text{GPP}_{\text{VPM}}$. An empirical correction of the NARR radiation improved the model performance.

The findings of this study confirm the good performance of the VPM on estimating maize and soybean GPP as long as meteorological inputs are accurate, and imply that the capability of the satellite-based PEMs for regional productivity monitoring at heterogeneous landscapes would be enhanced if the radiation of the regional reanalysis product can be improved to resolve the impacts of cloud cover and terrain. The proposed method to correct NARR radiation is limited to the crop sites in this study, and might not be applicable for other regions due to the large spatial variations of the NARR radiation bias. In addition to the meteorological data, further research is required to address the uncertainties of the PEM-based GPP estimates caused by other model inputs such as satellite data.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version, at http://dx.doi.org/10.1016/j.agrformet.2015.07.003

References


