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Can We Have a Universal Light Use Efficiency of Vegetations?

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Abstract

Models based on light use efficiency (LUE) are often used to estimate gross primary production (GPP), a key indicator of ecosystem performance. Information on spatiotemporal distribution of GPP helps in many ecological decision making processes. We evaluated the eddy covariance–light use efficiency (EC–LUE) model for estimating GPP in the Great Plains, United States. Photosynthetically active radiation (PAR) and fraction of absorbed PAR were computed using net radiation (R_n) and the normalized difference vegetation index (NDVI), respectively. A strong correlation was found between daily PAR and Landsat-based midday instantaneous R_n (R^2 =0.94, N=24) as well as Moderate Resolution Imaging Spectroradiometer (MODIS) based instantaneous R_n (R^2 =0.98, N=24). The EC–LUE model validation has shown that the potential light use efficiency varies with vegetation species (e.g., C_3 and C_4 plants). Interannual comparison of model outputs has also indicated temporal changes in potential light use efficiency. Our results suggest that the universal potential light use efficiency in the EC–LUE model should be replaced with species-dependent potential light use efficiency.

I. Introduction

GPP, the fixation of carbon dioxide (CO_2) principally through photosynthesis, is the largest global C flux, drives the C budget of ecosystems, and is partly responsible for offsetting the anthropogenic CO_2 emission. Information on GPP can help to quantify ecosystem performance and assist in planning adaption and mitigation strategies for climate change. Thus, spatiotemporal distribution of GPP has significant importance for the scientific community, policy makers, and resource managers. Modeling approaches combining remotely sensed images with flux measurements (for example, FLUXNET data) have emerged as a powerful method for accurate, consistent, and reliable estimation of primary production.

The principle of LUE is routinely used in deriving satellite-based estimates of primary production. The EC–LUE model is one of the approaches to estimate primary production at different spatial and temporal scales. The objectives of this study are to develop a new approach for estimating PAR and to examine the performance of the EC-LUE model in the Great Plains, United States.

II. Data and Methods

We used eight Landsat images (path 28, row 31) and corresponding MODIS images from the 2001 crop growing season (Fig. 1). The eddy covariance measurements were obtained from three AmeriFlux sites located near Mead, Nebraska. A schematic flowchart of the EC-LUE model is shown in Fig.2.

In this study a novel approach was developed and used for computing PAR using the linear relationship between midday R_n as estimated from Landsat and daily PAR based on field observations.

Potential light use efficiency (ε_{max}) determines plant productivity under different land use and management. Previous studies have shown that LUE varies across vegetation types. It was hypothesized that a universal invariant ε_{max} exists which can be used across biomes and sites. The calibrated value of ε_{max} was found to be 2.14 g C MJ^{-1} (Yuan et al., 2007) and 2.25 g C MJ^{-1} (Yuan et al., 2010). The limiting factor, f, is controlled either by the non-optimal air temperature or soil moisture availability based on Liebig's law. The soil moisture limiting factor is computed based on evaporative fraction, the ratio of latent heat flux to total available energy. The latent heat flux was computed using an energy balance approach.

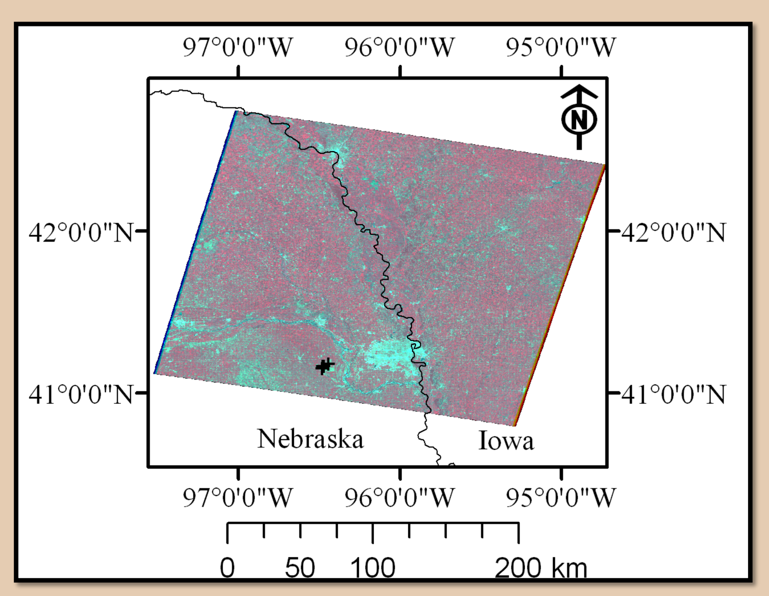

Figure 1. Location of the study area with AmeriFlux sites shown using cross symbols

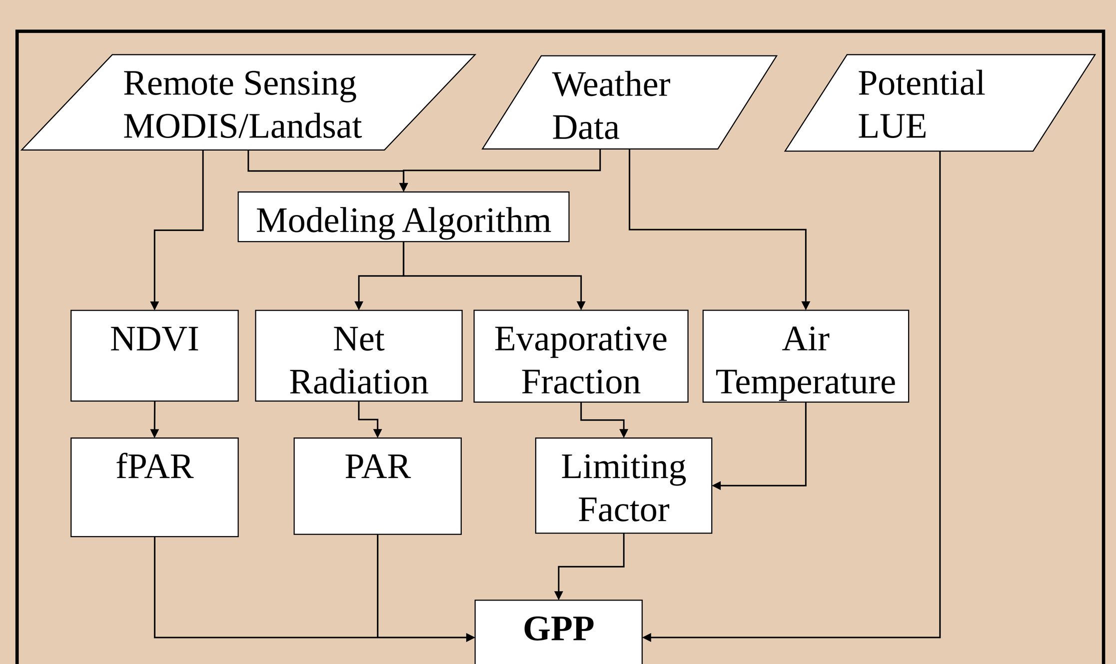

Figure 2. EC–LUE model flowchart

III Results and Discussions

The computed instantaneous R_n using Landsat images explained about 94 % variability in PAR (Fig. 3). High R^2 value can be attributed to the effects of sun angle and water vapor on absorption of shortwave radiation with separate components for direct and diffuse radiation. Model estimated PAR closely followed the measured PAR (Fig. 4) with a small root mean square error (RMSE) (about 8 % of the measured mean PAR). Computation of PAR using MODIS images resulted in lower RMSE (Fig. 5) compared to that of Landsat. This is most likely due to the larger pixel size of MODIS (1 km) relative to Landsat (60 m) in the thermal band, where temporal fluctuations are damped through spatial averaging. Our results indicate that using R_n as a surrogate for modeling PAR is a promising approach.

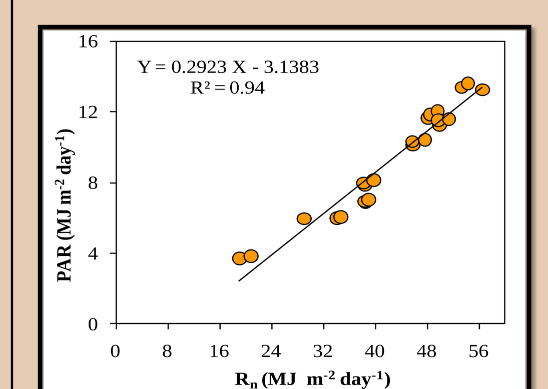

Figure 3. Relationship of measured PAR with the Landsat-estimated instantaneous R_n

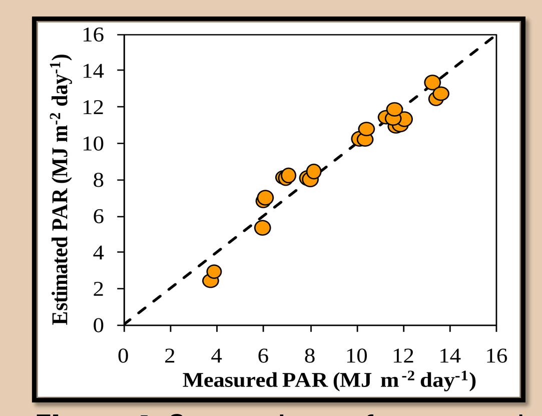

Figure 4. Comparison of measured and the Landsat-estimated PAR

Table 1. Statistical results of measured and estimated PAR showing coefficient of determination (R^2), predictive error (PE), standard error (SE), and root mean square error (RMSE)

	R^2	PE (%)	SE (MJ m^{-2} d^{-1})	RMSE (MJ m^{-2} d^{-1})
Landsat	0.94	0.01	0.75	0.75
MODIS	0.98	0.02	0.46	0.45

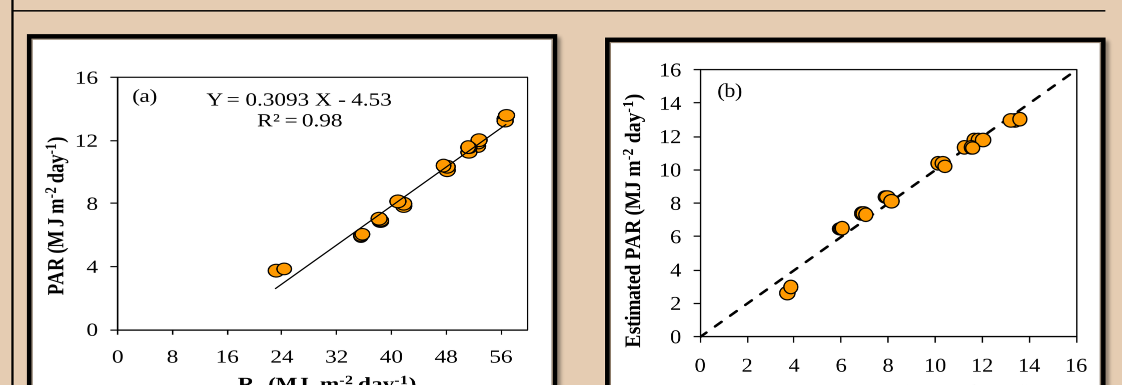

Figure 5. Relationship of (a) measured PAR with the MODIS–estimated instantaneous R_n and (b) measured and MODIS–estimated PAR

Temporal GPP data have shown that GPP increases with the progress of the crop growing season, decreases with crop maturity, and reaches a minimum or is absent during winter (Fig. 6). During the crop growing season, GPP is mainly limited by the evaporative fraction, while temperature is the limiting factor during the non-growing season.

III Results and Discussions (cont.)

Results show that using the calibrated value of ε_{max} under C_3 dominant ecosystems led to an underestimate of GPP by about 34% with high RMSE (4.31 g C m^{-2} day^{-1}).

Using the C_4 –specific calibrated values also led to overestimate of GPP.

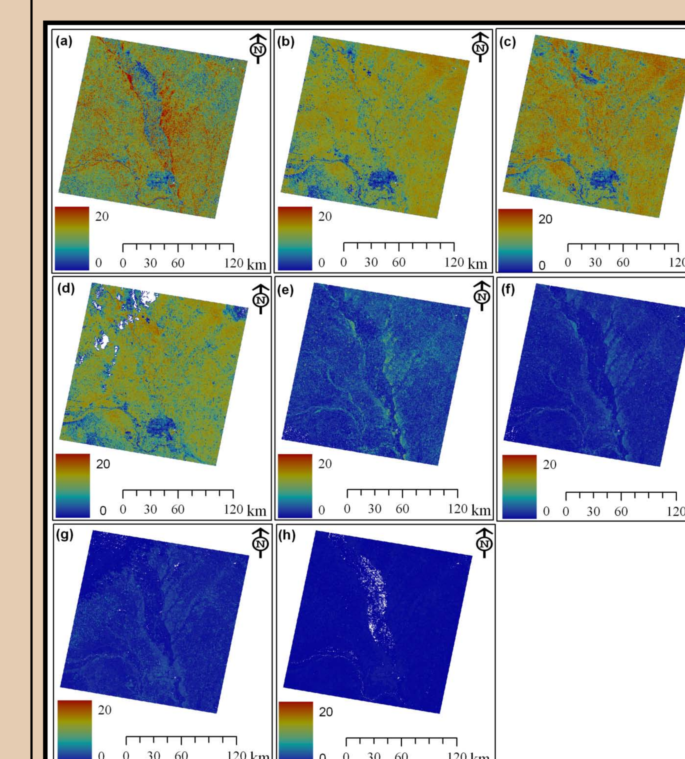

Figure 6. Spatial distribution of GPP (g C m^{-2} d^{-1}) in the study area for the day of satellite overpass on (a) July 4, (b)August 5, (c)August 13, (d)August 29, (e)September 30, (f)October 16, (g)October 24, and (h)December 11, 2001

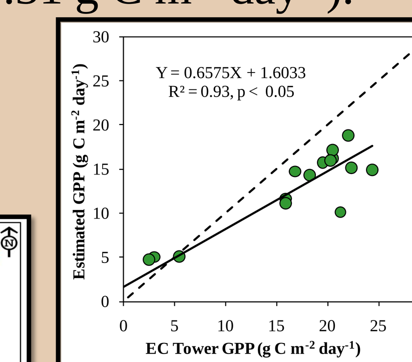

Figure 7. Comparison of estimated GPP and EC-measured GPP at Mead Nebraska sites (ε_{max}=2.25 g C MJ^{-1}, T_{opt}=21 °C)

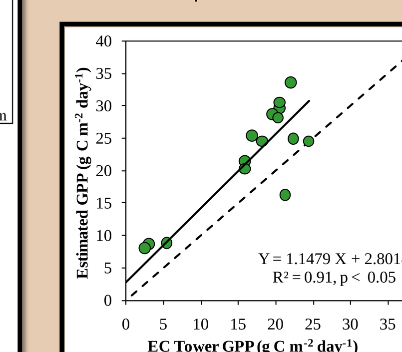

Figure 8. Comparison of estimated GPP and EC-measured GPP at Mead, Nebraska sites (ε_{max}=4.06 g C MJ^{-1}, T_{opt}=19°C)

IV. Conclusions

- ✓ A novel approach for estimating PAR based on R_n is very promising.
- ✓ Energy balance models used to estimate evapotranspiration can be extended to compute GPP.
- ✓ It is necessary to separate potential light use efficiencies for C_3 and C_4 plants to estimate GPP.

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