A two-stage light-use efficiency model for improving gross primary production estimation in agroecosystems

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Abstract

Accurate quantification of gross primary production (GPP) in agroecosystems not only improves our ability to understand the global carbon budget but also plays a critical role in human welfare and development. Light-use efficiency (LUE) models have been widely applied in estimating regional and global GPP due to their simple structure and clear physical basis. However, maximum LUE (ε_{max}), a key photosynthetic parameter in LUE models, has generally been treated as a constant, leading to common overestimation and underestimation of low and high magnitudes of GPP, respectively. Here, we propose a parsimonious and practical two-stage LUE (TS-LUE) model to improve GPP estimates by (a) considering seasonal variations of ε_{max}, and (b) separately re-parameterizing ε_{max} in the green-up and senescence stages. The TS-LUE model is inter-compared with state-of-the-art ε_{max}-static moderate resolution imaging spectroradiometer-GPP, eddy-covariance-LUE, and vegetation production models. Validation results at 14 FLUXNET sites for five crop species showed that: (a) the TS-LUE model significantly reduced the large bias at high- and low-level GPP as produced by the three ε_{max}-static LUE models for all crop types; and (b) the TS-LUE model generated daily GPP estimates in good agreement with in-situ measurements and was found to outperform the three ε_{max}-static LUE models. Especially compared to the well-known moderate resolution imaging spectroradiometer-GPP, the TS-LUE model could remarkably decrease the root mean square error (in gC m^{-2} d^{-1}) by 24.2% and 35.4% (from 3.84 to 2.91 and 2.48) and could increase the coefficient of determination by 14.7% and 20% (from 0.75 to 0.86 and 0.9) when the leaf area index (LAI) and infrared reflectance of vegetation (NIR_v) were used to re-parameterize the ε_{max}, respectively. The TS-LUE model provides a brand-new perspective on the re-parameterization of ε_{max} and indicates great potential for improving daily agroecosystem GPP estimates at a global scale.

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1. Introduction

Terrestrial gross primary production (GPP) represents the total amount of carbon sequestration by vegetation through photosynthesis and is the most considerable component of the terrestrial carbon cycle (Anav et al. 2015, Ryu et al. 2019). Approximately 15% of global CO$_2$ fixation, which provides food, fiber, and other social supplements for human beings, is contributed by cultivated cropland that accounts for ~12% of the Earth’s non-ice-covered land surface (Yuan et al. 2015, Jiang et al. 2021, Bai et al. 2022). Accurate quantification of agroecosystem production is therefore an essential keystone to better understanding the global carbon budget and guaranteeing food security worldwide.

Due to the superiorities of a simple structure, few inputs, and ease of use, light-use efficiency (LUE) models [e.g. the moderate resolution imaging spectroradiometer (MODIS)-GPP algorithm (Running et al. 2004), the vegetation production model (VPM) (Xiao et al. 2004), and the eddy-covariance (EC)-LUE model (Yuan et al. 2007)], which regard GPP as the product of LUE (derived from downscaling the maximum LUE by using the scalars of environmental constraints) and absorbed photosynthetically active radiation (APAR), have been extensively applied for simulating terrestrial GPP (including agroecosystems) at local, regional, and global scales (Zhang et al. 2017, Yan et al. 2020, Zheng et al. 2020, Huang et al. 2021). These LUE-based models widely consider the maximum LUE ($\varepsilon_{\text{max}}$) as a constant during the entire growing period across specific species (i.e. C3 and C4) and/or biomes (e.g. crops to forests), with seasonal variations of actual LUE only produced by the constraints of environmental factors (e.g. water, thermal, leaf age, etc). However, Zheng et al. (2017) and Xie et al. (2018) both demonstrated that the $\varepsilon_{\text{max}}$, obtained by fitting the light response curve with in-situ data, obviously fluctuates during the entire growing season. Lin et al. (2017) elucidated that the $\varepsilon_{\text{max}}$ inferred by the Bayesian method, had a significant positive linear correlation with leaf area index (LAI), especially for deciduous plant functional types, and considering seasonal dynamics of $\varepsilon_{\text{max}}$ could improve GPP estimations at a monthly scale within the LUE-based schemes.

In reality, $\varepsilon_{\text{max}}$ could be significantly influenced by internal physiological traits (e.g. chlorophyll content, carotenoid content, or the relative levels of xanthophyll cycle pigments), as implicitly indicated by Dawson et al. (2003), who attributed seasonal variations in actual LUE to variations in foliar chlorophyll content. One underlying explanation for the close relationship between the $\varepsilon_{\text{max}}$ and chlorophyll content is that increasing chlorophyll content could enhance the electron transport activity closely linked with the photosynthesis rate. Moreover, Peng et al. (2011) illustrated that the total canopy chlorophyll in the green-up stage might be more than two times higher than that in the senescence stage even under identical green LAI observations, indicating that the $\varepsilon_{\text{max}}$ may substantially differentiate between the green-up and senescence stages characterized by the same total LAI (since the total LAI can be regarded as the green LAI in the green-up stage but higher than the green LAI in the senescence stage).

To date, in order to model agroecosystem GPP from LUE-based models, numerous studies have concentrated on structure modification (e.g. reformulating the environmental scalars (Yuan et al. 2007, Guan et al. 2022)) and parameter adjustment (e.g. through the Bayesian inference and random forest regression (Lin et al. 2017, Huang et al. 2021, Wellington et al. 2022)). However, physiological traits-induced variations of daily $\varepsilon_{\text{max}}$ during different phenological stages are rarely taken into consideration in existing LUE-based schemes (Pei et al. 2022) and this may lead to large biases at high- and low-level GPP observations (Jiang et al. 2021). Albeit with a relatively satisfactory performance, Lin’s statistics-based model without a clear mechanistic explanation for the monthly varying $\varepsilon_{\text{max}}$ introduced excessive model parameters and required sufficient input data to calibrate the model for each month (Lin et al. 2017). Thus, a parsimonious, applicable, and robust LUE-based model is urgently needed to improve GPP estimations in cropland.

The objectives of this study are twofold: (a) to develop a simple and practical two-stage LUE (TS-LUE) model to improve the estimation of daily GPP in agroecosystems by separately parameterizing the dynamic $\varepsilon_{\text{max}}$ in the green-up and senescence stages; and (b) to validate the daily GPP estimates via the TS-LUE model through a comparison to both in-situ GPP observations and GPP estimates from three state-of-the-art LUE-based models (MODIS-GPP, EC-LUE, and VPM). To this end, we reconstructed the $\varepsilon_{\text{max}}$ by: (a) taking seasonal fluctuations of photosynthetic parameters into account with the application of LAI and recently proposed near-infrared reflectance of vegetation (NIR$_r$) representing internal physiological traits, respectively, and (b) considering the discrepancy of photosynthesis capacities between the green-up and senescence stages. Observations of 14 sites from the FLUXNET2015 dataset were collected to evaluate the performances of the TS-LUE and three $\varepsilon_{\text{max}}$–static LUE-based models over five major crop types.

2. Material and methods

2.1. FLUXNET data and remote sensing data

In this study, 14 out of a total of 20 cropland sites from the FLUXNET2015 dataset (http://fluxnet.fluxdata.org/data/fluxnet2015-dataset/), distributed in Europe and America and planted with five major crop species (namely summer maize, summer...
soybean, winter wheat, winter rapeseed, and winter barley) were selected for analysis, as listed in table S1. The selected cropland sites needed to meet the following criteria: (a) one crop type was planted on at least two sites to ensure that the calibrated parameters were not site-specific for each crop type; (b) sites that were interplanted were excluded to guarantee surface homogeneity; and (c) growing seasons and crop species information could be accessed (from the supplementary material of Bai et al. (2018) and Jiang et al. (2021)). In terms of GPP, we used the variable termed ‘GPP_DT_VUT_REF’ for analysis, which is derived based on the daytime partitioning method, since the nighttime partitioning method may be biased due to the frequent nighttime suppression of turbulence and dominance of advective fluxes not measured by conventional EC systems (Lasslop et al. 2010). In order to reduce the impact of inaccurate input data on the calibration processes and, consequently, the robustness of our proposed model, the following criteria were implemented to further screen the available data for daily GPP estimation: (a) only daytime observations with SW > 5 W m$^{-2}$ were used; and (b) only measured and good quality gap-filling data (quality flag = 0 and 1) were used. After rigorous quality-control steps, half-hourly/hourly input data were upscaled to a daily-scale for calibration and validation of the model estimates.

Remote sensing data involved in this study included the Global Land Surface Satellite (GLASS) LAI product (www.glass.umd.edu/LAI/MODIS/500m/) and the MODIS MCD43A4 Version 6 Nadir Bidirectional Reflectance Distribution Function-Adjusted Reflectance (NBAR) product (https://lpdaac.usgs.gov/products/mcd43a4v006/). Based on general regression neural networks, the 8 d 500 m GLASS LAI product (with a time span of 2000–2020) was generated for overcoming the weaknesses of the MODIS LAI product (e.g. tempo-spatial discontinuity and unrealistic short-term fluctuation) caused by residual cloud contamination. It has been recognized that the GLASS LAI product outperforms other prevailing LAI products (including but not limited to the MODIS LAI) in tempo-spatial continuity and accuracy (Xiao et al. 2014, 2017, Li and Xiao 2020), and was therefore employed in this study in order to reduce GPP simulation errors induced by the remote sensing LAI as much as possible. The original 8 d LAI time series were interpolated to a daily scale by cubic spline interpolation. The daily 500 m MCD43A4 NBAR product, with a time span of 2000 to present, was used to calculate the daily NIR$_r$, (and normalized difference vegetation index, enhanced vegetation index, and land surface water index (LSWI) for input data of the EC-LUE and VPM models). In order to reduce the impact of uncertainties/errors of the remote sensing data on the model calibration and validation, growing seasons with low correlation (coefficient of determination $R^2 < 0.6$) between daily LAI (and NIR$_r$) and in-situ GPP observations were excluded. Finally, input datasets of a total of 78 growing seasons were acquired for five crop species: 27 for maize, 12 for soybean, 27 for wheat, seven for rapeseed, and five for barley.

### 2.2. Methodology

Similar to other LUE-based models, the TS-LUE model simulates GPP as follows:

$$GPP = PAR \times FPAR \times \varepsilon_{\text{max}} \times f.$$  \hspace{1cm} (1)

where PAR is the photosynthetically active radiation that, in this study, is calculated by multiplying the downward shortwave radiation with a conversion constant of 0.45; FPAR is the fraction of absorbed photosynthetically active radiation, which in this study is calculated based on the Beer–Lambert law as $FPAR = 1 - \exp(-0.5 \times \text{LAI})$; $f$ is the scalar of environmental constraint on photosynthesis and it is estimated for simplicity in this study as follows:

$$f = f(VPD) \times f(TMIN)$$  \hspace{1cm} (2)








\begin{align}
   f(VPD) &= \begin{cases} 0 & \text{VPD} < \text{VPD}_{\text{min}} \\ \text{VPD} \text{VPD}_{\text{max}} \\ \text{VPD}_{\text{min}} \leq \text{VPD} < \text{VPD}_{\text{max}} \\ \text{VPD} \leq \text{VPD}_{\text{min}} \end{cases} \\
   f(TMIN) &= \begin{cases} 0 & \text{TMIN} < \text{TMIN}_{\text{min}} \\ \text{TMIN}_{\text{min}} \leq \text{TMIN} < \text{TMIN}_{\text{max}} \\ \text{TMIN} \geq \text{TMIN}_{\text{max}} \text{VPD} \text{max} \\ \text{VPD} \text{min} \times \text{VPD} \text{max} \\ \text{TMIN}_{\text{min}} \leq \text{TMIN} < \text{TMIN}_{\text{max}} \\ \text{TMIN} \geq \text{TMIN}_{\text{max}} \end{cases}
\end{align}

(2a)

(2b)

where \(f(VPD)\) and \(f(TMIN)\) are the scalars of VPD and minimum air temperature (TMIN) representing the water and thermal stresses on photosynthesis, respectively. \(\text{VPD}_{\text{max}}\) and \(\text{VPD}_{\text{min}}\) are the daylight average VPD at which $\varepsilon = 0$ and $\varepsilon = \varepsilon_{\text{max}}$, respectively. \(\text{TMIN}_{\text{max}}\) and \(\text{TMIN}_{\text{min}}\) are the daily maximum and minimum air temperatures at which $\varepsilon = \varepsilon_{\text{max}}$ and $\varepsilon = 0$, respectively. Note that, except for $\varepsilon_{\text{max}}$, all the parameterization schemes of the TS-LUE model (i.e. FPAR, temperature, and water stress scalars) were aligned with the MODIS GPP algorithm (Heinsch et al. 2003) in order to explore how much improvement could be achieved by merely incorporating the TS $\varepsilon_{\text{max}}$ into the MODIS GPP algorithm.

In the TS-LUE model, given the fact that the vegetation photosynthesis capacities may be drastically discrepant even under the same LAI during different growing stages, $\varepsilon_{\text{max}}$ in the green-up stage and the senescence stage was separately linearly formulated with LAI for each crop type as follows:


\[
\varepsilon_{\text{max}} = \begin{cases} 
  a \times \min \left( 1, \max \left( \frac{\text{LAI}_{\text{max}} - \text{LAI}_{\text{min}}}{\text{LAI}_{\text{max}} - \text{LAI}_{\text{min}}} \times 0.1 \right) \right) & \text{in green-up stage} \\
  b \times \min \left( 1, \max \left( \frac{\text{LAI}_{\text{max}} - \text{LAI}_{\text{min}}}{\text{LAI}_{\text{max}} - \text{LAI}_{\text{min}}} \times 0.1 \right) \right) + c & \text{in senescence stage}
\end{cases}
\]

where \( \text{LAI}_{\text{max}} \) and \( \text{LAI}_{\text{min}} \) are the 95th quantile and 5th quantile during each growing season; \( a, b, \) and \( c \) are empirical fitting parameters. The slopes \( a \) and \( b \) physically represent the rate of \( \varepsilon_{\text{max}} \) increases and decreases with the alteration of LAI in the green-up stage and senescence stage, respectively. The intercept \( c \) is set mainly because of the fact that the \( \varepsilon_{\text{max}} \) could decrease to zero when the LAI remains at a certain value (e.g. dead leaf). The LAI was normalized to ensure that the maximum LAI during each growing season for each crop type corresponds to the same \( \varepsilon_{\text{max}} \). In this study, the green-up and senescence stages were defined as the periods before and after the peak of the growing season (POS), respectively, where the POS was determined through a double logistic function proposed by Gonsamo et al. (2018) (see text S1 in the supplementary material).

Since the NIR, \( = \text{NIR}_{\text{ref}} \times \left( \frac{\text{NIR}_{\text{ref}} - \text{Red}_{\text{ref}}}{\text{NIR}_{\text{ref}} + \text{Red}_{\text{ref}}} - 0.08 \right) \), where \( \text{NIR}_{\text{ref}} \) and \( \text{Red}_{\text{ref}} \) are the reflectance of red and NIR bands, respectively, was recently reported to be advantageous in explaining the variations of monthly GPP observation (Badgley et al. 2017, 2019) and to be moderately correlated to LUE (Dechant et al. 2020), it was also used to replace LAI in equation (3) for comparison in this study. Furthermore, to evaluate the relative performance of the TS-LUE model, this study also introduced three well-known LUE-based models, i.e. the MODIS-GPP algorithm (henceforth referred to as the MOD17 algorithm), the EC-LUE model, and the VPM model, for inter-comparison, where a constant \( \varepsilon_{\text{max}} \) was set in the latter three models during the entire growing season for each crop type. Please refer to the work of Heinisch et al. (2003), Xiao et al. (2004), and Yuan et al. (2007) for detailed descriptions of the three \( \varepsilon_{\text{max}} \)-static LUE-based models.

\[
\text{NSE}_{\text{GPP}} = 1 - \frac{\sum_{i=1}^{N} |\text{GPP}_{\text{sim},i} - \text{GPP}_{\text{obs},i}|^2}{\sum_{i=1}^{N} |\text{GPP}_{\text{obs},i} - \text{GPP}_{\text{obs}}|^2},
\]

where obs and sim represent the daily flux tower GPP observations and model-estimated GPP, respectively; \( i \) means the \( i \)-th daily sample, and \( N \) is the total number of daily observations.

### 3. Results

#### 3.1. Seasonal variations of daily maximum LUE, LAI and NIR<sub>e</sub>

Due to difficulties in quantifying various and complex down-scalars (Zhang et al. 2018), \( \varepsilon_{\text{max}} \) cannot be directly obtained by inverting the LUE-based models [\( \varepsilon_{\text{max}} = \text{GPP}/(\text{APAR} \times f) \)]. In light of this, we acquired the \( \varepsilon_{\text{max}} \) by fitting the light response curve with half-hour in-situ data (for a detailed method, see text S3 in the supplementary material), which is believed to be an alternative method to obtain \( \varepsilon_{\text{max}} \) (Gan et al. 2021). Taking the US-Tw2 site, for example, we could see that the \( \varepsilon_{\text{max}} \) firstly started to increase rapidly during the green-up stage and subsequently reached a peak on the 229th day of 2012 (see figure 1). After the peak, the \( \varepsilon_{\text{max}} \) gently decreased and ultimately shifted to zero during the complete senescence stage. Both the LAI and NIR<sub>e</sub> had similar patterns to the \( \varepsilon_{\text{max}} \) in seasonal variations, but they changed asynchronously. With identical LAI or NIR<sub>e</sub>, the \( \varepsilon_{\text{max}} \) during the green-up stage was higher than that during the senescence stage, indicating that the \( \varepsilon_{\text{max}} \) should be separately parameterized during the different phenological stages. The underlying explanation may be concluded that the chlorophyll content, which is directly connected with the \( \varepsilon_{\text{max}} \) declined rapidly at the initial period of the senescence stage while the LAI and NIR<sub>e</sub> failed to capture this swift alteration (Peng et al. 2011, Gitelson et al. 2018).

### 2.3. Model calibration

Growing-season data for each crop species were randomly partitioned into two equal parts: calibration dataset and validation dataset. A 1 000 000 Monte Carlo simulation was adopted to calibrate all the four free parameters (\( \varepsilon_{\text{max}} \) for the MOD17, EC-LUE, and VPM models, and \( a, b, \) and \( c \) for the TS-LUE model) within a reasonable range for each crop species, respectively (see text S2 in the supplementary material). For the three \( \varepsilon_{\text{max}} \)-static LUE models, \( \varepsilon_{\text{max}} \) varied from 0 to 6 g C MJ<sup>-1</sup>. For the TS-LUE model, both \( a \) and \( b \) ranged between 0 to 6 g C MJ<sup>-1</sup>; \( c \) was artificially set to vary with a wide range from −3 to 3 g C MJ<sup>-1</sup> to test whether it is interpreted reasonably (the fitted \( c \) should be negative if interpreted correctly). Additionally, slope \( a \) was expected to be lower than slope \( b \) because the decreasing rate of chlorophyll content directly linked with \( \varepsilon_{\text{max}} \) was higher in the senescence stage than its increasing rate in the green-up stage. The optimal parameters of the models can be obtained by maximizing the agreement index (Nash–Sutcliffe efficiency (NSE)):

\[
\text{NSE}_{\text{GPP}} = 1 - \frac{\sum_{i=1}^{N} |\text{GPP}_{\text{sim},i} - \text{GPP}_{\text{obs},i}|^2}{\sum_{i=1}^{N} |\text{GPP}_{\text{obs},i} - \text{GPP}_{\text{obs}}|^2},
\]

where obs and sim represent the daily flux tower GPP observations and model-estimated GPP, respectively; \( i \) means the \( i \)-th daily sample, and \( N \) is the total number of daily observations.
3.2. Performance of the TS-LUE and three \( \varepsilon_{\text{max}} \)-static LUE-based models

For the three \( \varepsilon_{\text{max}} \)-static LUE-based models, the \( \varepsilon_{\text{max}} \) for C4 species (Maize, 2.5–2.9 gC MJ\(^{-1}\)) was obviously higher than that for C3 species (the remaining crop types, 1.3–2.0 gC MJ\(^{-1}\)) (see table 1). For both of the TS-LUE\(_{\text{LAI}}\) and TS-LUE\(_{\text{NIRv}}\) models, slope \( b \) in the senescence stage was higher than slope \( a \) in the green-up stage across all five crop species, which could be explained by the higher decreasing rate of \( \varepsilon_{\text{max}} \) in the senescence stage than the increasing rate of \( \varepsilon_{\text{max}} \) in the green-up stage. As expected, the intercept \( c \) was negative for all crop species. In addition, no significant differences on the three free parameters (\( a, b, \) and \( c \)) were found between the two TS-LUE models for all species.

Overall, the performance of the five models was sequenced as follows: TS-LUE\(_{\text{NIRv}}\) > TS-LUE\(_{\text{LAI}}\) > VPM > EC-LUE > MOD17, with the root mean square error (RMSE) ranging between 2.48 gC m\(^{-2}\) d\(^{-1}\) and 3.84 gC m\(^{-2}\) d\(^{-1}\) and the \( R^2 \) varying from 0.90 to 0.75 (see figure 2 and table 2). Specifically, the TS-LUE\(_{\text{NIRv}}\) model and the MOD17 algorithm showed the best and worst performance over each crop type, respectively, while the TS-LUE\(_{\text{LAI}}\) model was also remarkably superior to the MOD17 algorithm. Besides, the TS-LUE\(_{\text{NIRv}}\) model significantly outperformed the EC-LUE and VPM models, especially over the two winter crops, with the RMSE decreasing from 3.98 gC m\(^{-2}\) d\(^{-1}\) and 3.03 gC m\(^{-2}\) d\(^{-1}\) to 2.44 gC m\(^{-2}\) d\(^{-1}\) and the \( R^2 \) increasing from 0.48 and 0.68 to 0.82 for wheat, and the RMSE decreasing from 3.06 gC m\(^{-2}\) d\(^{-1}\) and 3.13 gC m\(^{-2}\) d\(^{-1}\) to 2.46 gC m\(^{-2}\) d\(^{-1}\) and the \( R^2 \) increasing from 0.56 and 0.54 to 0.74 for rapeseed. It is worth mentioning that the overestimation at low in-situ GPP and the underestimation at high in-situ GPP in the MOD17 algorithm (a similar phenomenon could also be observed for the EC-LUE and VPM models, but not as pronounced as for the MOD17 algorithm) was remarkably reduced by both the TS-LUE\(_{\text{NIRv}}\) and TS-LUE\(_{\text{LAI}}\) models (see figure 3). In terms of comparative performances for the TS-LUE model, no significant discrepancies between the TS-LUE\(_{\text{NIRv}}\) and TS-LUE\(_{\text{LAI}}\) models were identified over soybean and rapeseed, while the former outperformed the latter over maize, wheat, and barley by reducing the RMSE by 17.4%, 13.8%, and 24.8% and increasing the \( R^2 \) by 4.6%, 9.3%, and 14.5%, respectively. Note that the TS-LUE models were also superior to the one-stage-LUE models (modeling GPP without considering the distinct dynamic patterns of \( \varepsilon_{\text{max}} \) in different phenological stages) when using NIRv and LAI as the proxies of \( \varepsilon_{\text{max}} \), respectively (see table S2).
Table 1. Calibrated parameters of the TS-LUE model and the three \( \varepsilon_{\text{max}} \)–static LUE-based models (i.e. MOD17, EC-LUE, and VPM) over five crop types.

| Crop types | Parameters | TS-LUE\(_{\text{NIRv}}\) | TS-LUE\(_{\text{LAI}}\) | EC-LUE | VPM | MOD17 |
|------------|------------|----------------|----------------|--------|------|-------|
| Maize      | \( a \)    | 3.19           | 2.82           | —      | —    | —     |
|            | \( b \)    | 3.37           | 3.36           | —      | —    | —     |
|            | \( c \)    | -0.61          | -0.67          | —      | —    | —     |
|            | \( \varepsilon_{\text{max}} \) (gC MJ\(^{-1}\)) | — | — | 2.6 | 2.9 | 2.5 |
| Soybean    | \( a \)    | 1.80           | 1.88           | —      | —    | —     |
|            | \( b \)    | 2.68           | 2.56           | —      | —    | —     |
|            | \( c \)    | -1.08          | -0.89          | —      | —    | —     |
|            | \( \varepsilon_{\text{max}} \) (gC MJ\(^{-1}\)) | — | — | 1.7 | 2.0 | 1.6 |
| Wheat      | \( a \)    | 2.43           | 2.57           | —      | —    | —     |
|            | \( b \)    | 2.85           | 2.97           | —      | —    | —     |
|            | \( c \)    | -0.77          | -0.76          | —      | —    | —     |
|            | \( \varepsilon_{\text{max}} \) (gC MJ\(^{-1}\)) | — | — | 1.7 | 2.0 | 1.5 |
| Rapeseed   | \( a \)    | 2.12           | 2.18           | —      | —    | —     |
|            | \( b \)    | 3.31           | 3.56           | —      | —    | —     |
|            | \( c \)    | -1.98          | -1.81          | —      | —    | —     |
|            | \( \varepsilon_{\text{max}} \) (gC MJ\(^{-1}\)) | — | — | 1.7 | 1.9 | 1.3 |
| Barley     | \( a \)    | 2.05           | 1.99           | —      | —    | —     |
|            | \( b \)    | 2.67           | 2.10           | —      | —    | —     |
|            | \( c \)    | -1.00          | -0.50          | —      | —    | —     |
|            | \( \varepsilon_{\text{max}} \) (gC MJ\(^{-1}\)) | — | — | 1.6 | 1.8 | 1.3 |

Figure 2. Performance of the TS-LUE model and the three \( \varepsilon_{\text{max}} \)–static LUE-based models for daily agroecosystems GPP simulation.

Obviously, the TS-LUE\(_{\text{NIRv}}\) outperformed the other three models during most growing seasons (see figure 4), as indicated by a lower RMSE and a higher \( R^2 \). Compared with the traditional MOD17 algorithm, the TS-LUE\(_{\text{NIRv}}\) model showed a reduced RMSE and an increased \( R^2 \) by merely re-parameterizing \( \varepsilon_{\text{max}} \) over 73 and 75 out of the total 78 growing seasons, respectively, with the largest reduction in RMSE of 3.20 gC m\(^{-2}\) d\(^{-1}\) over maize and the largest improvement in \( R^2 \) of 0.47 over barley. Meanwhile, in comparison to the EC-LUE and VPM models, the TS-LUE\(_{\text{NIRv}}\) model could also reduce the retrieval errors (i.e. lower RMSE) in 65% and 77% of total growing seasons, and better explain the variations of daily in-situ GPP (i.e. higher \( R^2 \)) in 88% and 83% of total growing seasons, respectively.

3.3. Seasonal variations of estimated and in-situ GPP

Overall, all the four models could capture the seasonal variations of observed daily GPP well (see figure 5). For two summer crop species (i.e. maize and soybean), all three \( \varepsilon_{\text{max}} \)–static models tended to obviously overestimate in-situ GPP at the beginning and end of growing seasons and slightly overestimate or underestimate the in-situ GPP at the POSs. For three winter agroecosystems (i.e. wheat, barley, and rapeseed), all three \( \varepsilon_{\text{max}} \)–static models were inclined to
Table 2. Statistical metrics (including the root mean square error (RMSE, in gC m$^{-2}$ d$^{-1}$) and coefficient of determination ($R^2$)) of validation results from the TS-LUE model and the three $\varepsilon_{\text{max}}$–static LUE-based models for daily GPP simulations.

| Crop types | Statistical metrics | TS-LUE$_{\text{ESIRy}}$ | TS-LUE$_{\text{LAI}}$ | EC-LUE | VPM | MOD17 |
|------------|---------------------|--------------------------|----------------------|--------|-----|-------|
| Maize      | RMSE                | 2.7                      | 3.27                 | 3.19   | 3.14| 4.52  |
|            | $R^2$               | 0.91                     | 0.87                 | 0.88   | 0.89| 0.8   |
| Soybean    | RMSE                | 2.06                     | 2.15                 | 2.42   | 2.58| 3.43  |
|            | $R^2$               | 0.89                     | 0.88                 | 0.82   | 0.81| 0.71  |
| Wheat      | RMSE                | 2.44                     | 2.83                 | 3.98   | 3.03| 3.2   |
|            | $R^2$               | 0.82                     | 0.75                 | 0.48   | 0.68| 0.65  |
| Rapeseed   | RMSE                | 2.46                     | 2.43                 | 3.06   | 3.13| 3.27  |
|            | $R^2$               | 0.74                     | 0.77                 | 0.56   | 0.54| 0.47  |
| Barley     | RMSE                | 2.31                     | 3.07                 | 2.32   | 2.68| 3.75  |
|            | $R^2$               | 0.87                     | 0.76                 | 0.85   | 0.8 | 0.61  |
| Overall    | RMSE                | 2.48                     | 2.91                 | 3.27   | 2.98| 3.84  |
|            | $R^2$               | 0.9                      | 0.86                 | 0.81   | 0.84| 0.75  |

Figure 3. Comparisons of daily GPP simulated by the TS-LUE model and the three $\varepsilon_{\text{max}}$–static LUE-based models from the validation dataset against in-situ observations at the 14 FLUXNET sites for five crop species. The solid lines are linear regression lines and the black dashed lines are 1:1 lines.

seriously overestimate the in-situ GPP at the end of senescence stage, especially for wheat (see figure 5). The abovementioned large retrieval errors, generated from the $\varepsilon_{\text{max}}$–static LUE-based models, were common and could also be found in a recent work of Jiang et al (2021) who revealed a similar phenomenon when comprehensively comparing the performance of seven LUE-based models for simulating daily GPP in agroecosystems. In contrast, the TS-LUE model reduced these large biases well and better reproduced the magnitude of seasonal fluctuations of GPP observations for all the five agroecosystems. For most of the species, no significant differences in the seasonal pattern of GPP estimates could be found between the LAI-based and NIR$_v$-based TS-LUE models.
4. Discussion

4.1. Strength of the TS-LUE model

The strength of the TS-LUE model can be summarized into three aspects: (a) simple structure; (b) practical operability; and (c) higher accuracy. Firstly, the TS-LUE model, formulated by a multiplication of only APAR, $\varepsilon_{\text{max}}$, and $f$ to estimate GPP, inherits other common LUE-based models in the model structure. It is therefore consistent with those LUE-based models in the superiority of a simple model structure compared to process-based models. Secondly, easy access to the model’s remotely sensed inputs (e.g. LAI and NIR$_v$) for re-parameterization of the $\varepsilon_{\text{max}}$ (and determination of the POS) makes the TS-LUE model practically operational. Finally, owing to a deeper and more reasonable interpretation of the $\varepsilon_{\text{max}}$, the TS-LUE model is capable of providing higher-accuracy daily GPP estimates.

In fact, LUE-based models can be mainly divided into two subcategories: APAR$_{\text{canopy}}$-based models (including but not limited to the MOD17 and EC-LUE models) and APAR$_{\text{chl/green}}$-based models (such as the VPM model), where the former (the majority of LUE-based schemes) use the radiation absorbed by both the non-photosynthetic vegetation (e.g. branch, stem, dead leaf) and photosynthetic vegetation (PV, e.g. green leaf) while the latter use radiation absorbed only by chlorophyll or green leaves (Zhang et al. 2016, Pei et al. 2022). For APAR$_{\text{canopy}}$-based models, using an invariable $\varepsilon_{\text{max}}$ has been somewhat questioned by Gitelson and Gamon (2015) and was found by many works to generate overestimation in low in-situ GPP and underestimation in high in-situ GPP (Yuan et al. 2015, Huang et al. 2021, Guan et al. 2022). In contrast, a temporally dynamic $\varepsilon_{\text{max}}$ constrained by the internal physiological traits (e.g. chlorophyll content) was supported by Peng et al. (2011) and should be differentiated even under the same LAI between different growing stages due to (a) the higher proportion of PV in the green-up stage and (b) the higher chlorophyll content under the same PV in this stage. On the other hand, although the APAR$_{\text{chl/green}}$ was shown to have stronger correlation with the in-situ GPP, thus theoretically characterized by a more temporally stable LUE (or $\varepsilon_{\text{max}}$) (Gitelson et al. 2018, Zhang et al. 2018), variations of LUE (or $\varepsilon_{\text{max}}$) could still not be easily dismissed (Gitelson and Gamon 2015).

Furthermore, to our knowledge, the simple formulation of FPAR$_{\text{chl/green}}$ may not be able to accurately capture the seasonal variations of in-situ GPP.
in some scenarios. For example, the VPM model was shown to seriously overestimate the in-situ GPP at the end of the senescence stage for wheat, similar to the results of the MOD17 and EC-LUE models (see figure 5). In this study, re-parameterizing the $\varepsilon_{\text{max}}$ to consider its seasonal variations in the TS-LUE model has been proven to evidently reduce the positive bias at low in-situ GPP and the negative bias at high in-situ GPP as found in the MOD17 algorithm, with the overall RMSE decreased by 24.2% and 35.4% and $R^2$ increased by 14.7% and 20% in agroecosystems based on the LAI-based and NIR$_v$-based TS-LUE models, respectively. The higher-accuracy GPP simulations using NIR$_v$ rather than LAI as the proxy of $\varepsilon_{\text{max}}$ can be in large part attributed to the closer relationship between NIR$_v$ and LUE. Taking maize as an example, we found that the NIR$_v$ was more closely related with LUE than the LAI during both the green-up and senescence stages, indicated by the higher coefficient of correlation (see figure S1). The underlying explanation lies in the fact that the higher NIR$_v$ usually occurs in canopies with high carbon assimilation rates, which display leaves in a way that tends to fully leverage absorbed PAR (i.e. higher LUE) (Badgley et al 2017), whereas the LAI may less readily capture these nuanced variations in the canopy structure as well as LUE.

The better performance of the TS-LUE model for all five crop types in this study demonstrated that the newly developed model is robust and capable of providing higher-accuracy daily GPP estimates. Note that, though a three-stage strategy may be more efficient and appropriate than a TS strategy under some specific scenarios (e.g. see the seasonal dynamics of $\varepsilon_{\text{max}}$ at the US-CRT site in figure 1), it may introduce excessive calibrated parameters and complicate the model parameterization scheme.

4.2. Possible implications and limitations

The temporally dynamic $\varepsilon_{\text{max}}$, considering seasonal variations and discrepancy of photosynthesis capacities in different growing stages, could also improve other LUE-based models that apply different environmental scalars. For example, incorporating the TS $\varepsilon_{\text{max}}$ into the VPM model (using the daily average air temperature and LSWI as the temperature and water scalars, respectively) could achieve a decrease of RMSE by 0.35 gC m$^{-2}$ d$^{-1}$ and an increase of $R^2$ by 0.05 (see table S3). Meanwhile, in comparison to the use of an invariable $\varepsilon_{\text{max}}$ using the 'two stage' concept may be more beneficial and may better portray the sophisticated seasonal features of carbon fixation under the global warming-induced shifting phenology pattern (such as the advance of the start of

![Figure 5](https://example.com/f5.png)

**Figure 5.** Seasonal variations of daily in-situ GPP observations and GPP estimates based on the TS-LUE model and the three $\varepsilon_{\text{max}}$–static LUE-based models at five representative flux sites during one growing season.
5. Conclusions

This study proposed a simple and practical TS-LUE model to improve the GPP estimate in agroecosystems. The novelty of the TS-LUE model primarily lies in that (a) in our knowledge, the TS-LUE model is the first to take seasonal variations of physiological traits-related ε\text{max} into account at a daily scale in agroecosystems; (b) the TS-LUE model considers the distinct dynamic patterns of ε\text{max} between the green-up and senescence stages; and (c) the TS-LUE model is not only parsimonious and applicable, but also is capable of providing high-accuracy GPP estimates from a physics-based standpoint. The TS-LUE model was evaluated at 14 FLUXNET flux towers for five major crop species and the results showed that the improved model significantly reduced the large bias at high- and low-level GPP and outperformed three state-of-the-art ε\text{max}–static LUE models (i.e. MOD17, EC-LUE, and VPM) in simulating daily agroecosystems production. The proposed model promises to more accurately update the global agroecosystems production via remote sensing techniques, which is beneficial for a better understanding of the global carbon budget in a changing climate.

Data availability statement

The data that support the findings of this study are openly available at the following URL: DOI for the FLUXNET network, the GLASS data team, and the MODIS data team. This research was supported by the National Natural Science Foundation of China (41922009, 42071332) and the National Key R&D Program of China (2018YFA0605401). The authors thank the three anonymous referees for providing valuable and thoughtful suggestions to improve the quality of the manuscript.

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