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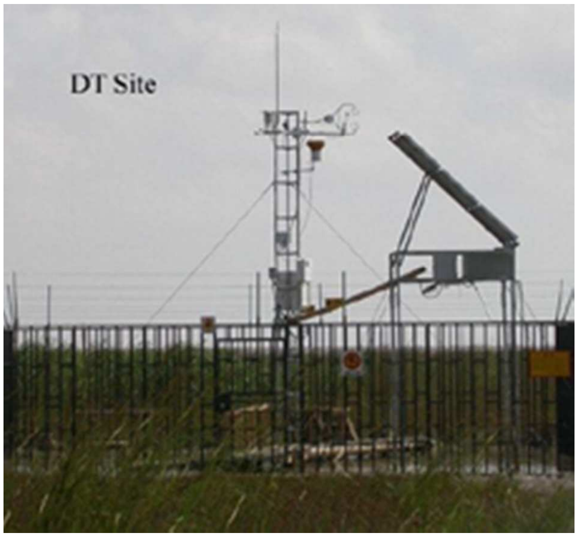
A new model performance better than MODIS GPP product for wetland ecosystems was proposed and validated.



Gross primary productivity (GPP) is a measure of photosynthesis and represents the primary conduit of carbon flux from the atmosphere to the land. The accurate estimation of GPP is essential for the quantification of net ecosystem carbon exchange (NEE), which is the main factor that determines whether the ecosystem is a carbon source or a carbon sink. This paper proposed and validated a new model to for the estimation of GPP for wetland ecosystems using Moderate Resolution Imaging Spectroradiometer (MODIS) products, including these vegetation indices, LST and the fraction of photosynthetically active radiation absorbed by the active vegetation (FAPAR). This model was validated for a study site on Chongming Island, Shanghai, China. Our results show that this new model can provide reliable estimates of GPP (R2 of 0.87 and RMSE of 0.009 kg C m-2 8d-1 (P<0.0001)) which is better than the MODIS product. Since GPP is an important parameter in carbon cycle, high accuracy estimation of GPP will help us understand the ecosystem carbon cycle.

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**ARTICLE TYPE**

# Combining remote sensing and eddy covariance data to monitor Gross Primary Production of an estuarine wetland ecosystem in East China

**Mingquan Wu,*[a] Shakir Muhammad[a], Fang Chen[b], Zheng Niu[a], Zheng Niu[a] and Changyao Wang[a]**

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**Abstract:** Wetland ecosystems are very important for ecological diversity and have a strong ability to sequester carbon. Through comparisons with field measured eddy covariance data, we evaluated the relationships between the light use efficiency index (LUE) and the enhanced vegetation index (EVI), normalized difference vegetation Index (NDVI), and land surface temperature (LST). Consequently, we have proposed a new model for the estimation of gross primary production (GPP) for wetland ecosystems using Moderate Resolution Imaging Spectroradiometer (MODIS) products, including these vegetation indices, LST and the fraction of photosynthetically active radiation absorbed by the active vegetation (FAPAR). This model was developed and validated for a study site on Chongming Island, Shanghai, China. Our results show that photosynthetically active radiation (PAR) was highly correlated with LST, with a coefficient of determination ($R^2$) of 0.59 ($p<0.001$). Vegetation indices, such as EVI, NDVI and LST, were highly correlated with LUE. We found that the product of vegetation indices (VIs) and a modified form of LST ($T_e$) can be used to estimate LUE, with an $R^2$ of 0.82 ($P<0.0001$) and an RMSE of 0.054 kg C per mol PAR. This new model can provide reliable estimates of GPP ($R^2$ of 0.87 and RMSE of 0.009 kg C $m^{-2}$ $8d^{-1}$ ($P<0.0001$)).

**Keywords:** Wetland ecosystem; MODIS; GPP; Remote sensing

## 1. Introduction

Gross Primary Production (GPP) is an important parameter in carbon cycle research [1-3]. GPP is a measure of photosynthesis and represents the primary conduit of carbon flux from the atmosphere to the land [4]. The accurate estimation of GPP is essential for the quantification of net ecosystem carbon exchange (NEE), which is the main factor that determines whether the ecosystem is a carbon source or a carbon sink [5].

The eddy covariance technique measures the ecosystem-level exchange of $CO_2$ (NEE) directly [6]. However, regional-scale applications of field-based measurement techniques are economically expensive and time-consuming. A flux tower-based GPP measurement technique is difficult to extend to large regions because of several factors, including its footprint and size, surface roughness, atmospheric stability and surface heterogeneity [7].

Due to the ease with which global data can be obtained, remote sensing is very useful for scaling up eddy covariance-estimated GPP to larger scales and remote sensing-based estimates of GPP can provide a sustained source of global GPP observations and play a vital role in global change studies [8-10]. Several approaches have been developed to estimate GPP using remote sensing technology [11-13]. These models generally can be divided into empirical and biogeochemical models. Empirical models use regression analysis to link field-measured GPP to biogeophysical parameters extracted from remote sensing data [14-17]. These parameters are usually environmentally related factors, such as temperature and rainfall, or parameters that are sensitive to ecosystem conditions, such as vegetation indices (VIs) [18]. Biogeochemical models are based on the physiological and ecological processes of plant growth and estimate GPP from its physical relationship with environmental factors [19-23]. For example, Running et al. have produced the global GPP product (MOD17A2) with the MODIS FPAR product (MOD15A2) as one of the inputs [24]. However, remote sensing-estimated GPP models and their parameters depend on the type of ecosystem and study location. Different types of ecosystems and different study locations consistently have different optimal model parameters [25]. Therefore, the satellite-based estimation of GPP requires calibration and validation with ground-based measurements [26-28].

The current remote sensing-based GPP models have mainly focused on forest [5, 29], crop [30-32] and grassland ecosystems [12, 33]. Limited studies have been conducted on wetland ecosystems, which are considered to be the "kidney" of the Earth [34]. Despite the small area of the Earth's surface occupied by wetlands, wetland ecosystems are very important for ecological diversity [35] and have a strong ability to sequester carbon [36]. Therefore, it is important to model the GPP of wetland ecosystems.

In this paper, we estimated the GPP of an estuarine wetland ecosystem using the light use efficiency (LUE) equation [37] at the Dongtan (DT) site on Chongming Island, Shanghai, China. The MODIS-derived VIs, land surface temperature (LST) and the absorbed fraction of photosynthetically active radiation (FAPAR) were examined for their potential usefulness for estimating GPP of estuarine wetland ecosystems. The eddy covariance-estimated GPP (GPPtower) was used to validate and calibrate the remote sensing-estimated GPP. The objectives of this study were: (1) to analyze the potential usefulness of parameters extracted from the MODIS satellite, such as VIs, LST and FAPAR, for estimating the 8-day GPP of the estuarine wetland ecosystem, (2) to derive a new model to estimate GPP of the estuarine wetland ecosystem entirely based on MODIS observations, such as the MODIS VIs, LST and FAPAR products, (3) to validate and calibrate the remote sensing-estimated GPP using the eddy covariance-estimated GPP, and (4) to compare the estimation precision of GPP with inputting different spatial resolution MODIS reflectance data.

## 2. Study area and data preparations

### 2.1. Study area

The DongTan (DT) site, which is located on Chongming Island, Shanghai, China (31°31.013'N, 121°58.297'E) (Fig. 1), was selected for this study. Chongming is an alluvial island of the Yangtze River and located in the Yangtze River estuary. The elevation ranges from 3.5 m to 4.5 m above sea level with a mean monthly temperature from 2.8 to 27.5 °C. The annual precipitation ranges from 606.1 to 1480.5 mm, and the main vegetation types include *Spartina alterniflora* and *Scirpus mariqueter* [38].

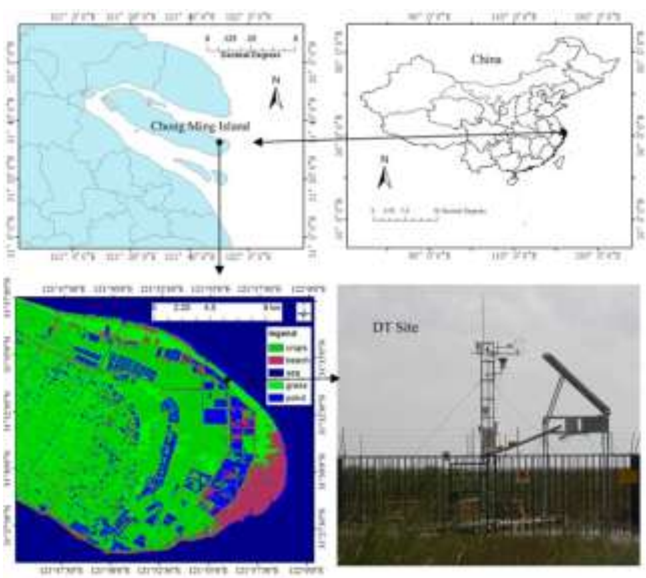


**Fig. 1** Location of the DT study site (A picture of the DT site was provided by the Institute of Biodiversity Science, Fudan University, Shanghai, China.)

### 2.2. Data preparation

#### 2.2.1. Eddy covariance data

The eddy covariance flux tower data for the DT site was provided by the Institute of Biodiversity Science, Fudan University, Shanghai, China. These data were acquired from January 1, 2005 to December 31, 2005 and included the air humidity, air pressure, wind speed, wind direction, PAR, NEE and GPP recorded every 30 minutes. These eddy covariance data were processed using the EC_Processor software developed by the University of Toledo. To ensure the quality of the data, the data acquired during bad weather conditions, such as rain, fog and weak turbulence conditions, were excluded [38]. Those data gaps were gap-filled using a dynamic parameters model [40-41]. The 30-minute PAR and GPP data were summed to 8-day values for later analysis. Detailed observation instruments and data processing please see references 38. Those data had a good quality. Several paper had been published using those data [38-40].

There were 45 of these 8-day eddy covariance estimated data points in 2005. Ten (10) of them were acquired during cloudy conditions, which have no matching MODIS data and thus were not used. Eighteen (18) observations were randomly selected from the left thirty-five ones to derive the model, and 17 observations were used to validate the precision of the model.

#### 2.2.2. MODIS products

Four MODIS land surface products were used in this study, including the 8-day MODIS reflectance product (MOD09A1, 500 m, collection5), the 8-day MODIS land surface temperature (LST) and emissivity product (MOD11A2, 1000 m, collection5), the 8-day MODIS FAPAR product (MOD15A2, 1000 m, collection5) and the 8-day MODIS GPP product (MOD17A2, 1000 m, collection5.1). To ensure the quality of the data, water, clouds, heavy aerosols, and cloud shadows were masked. The MOD09A1 products were used to calculate the 8-day vegetation indices of NDVI and EVI. The EVI, NDVI, FAPAR, LST and GPP data for the DT site were extracted from the 3×3 MODIS pixels (3km×3km) centered on the eddy covariance flux tower and the mean values were then calculated. Preliminary results [9] indicated that the mean values of 3×3 pixels provided better correlation with GPP from flux measurement.

## 3. Approach

According to the LUE equation, a satellite-based estimation of GPP can be calculated as [37]:

$$GPP = LUE \times FAPAR \times PAR \qquad (1)$$

Where LUE is the light use efficiency, defined as the amount of carbon fixed in photosynthesis per unit of absorbed solar radiation; PAR is the incident photosynthetically active radiation; FAPAR is the fraction of photosynthetically active radiation absorbed by the active vegetation canopy. In this study, PAR was substituted with MODIS LST, and LUE was estimated from a new algorithm proposed by Wu et al. [44]. In addition, the MODIS FAPAR product was also included in our approach, making our model entirely based on MODIS observations.

The model proposed by Wu et al. [44] to estimate LUE is as follows:

$$LUE_m = a\ln(VI_m \times T_{m,i}) + b \quad (2)$$

$$T_{m,i} = \exp(LST / LST_{\max}) \quad (3)$$

Where *a* and *b* are coefficients that need to be calibrated; $LST_i$ is the mean ith month temperature and $LST_{max}$ is the maximum monthly temperature of the site for the experimental years.

However, this model was developed for boreal forests. Due to the differences between wetland ecosystems and boreal forests ecosystems, the relationship between LUE and VI×$T_m$ may also differ. Thus, we proposed a new method to estimate wetland ecosystem GPP that is based on the work of Wu et al. [44]. The steps of this method were described in detail in section 3.1-3.4.

### 3.1 Regression and related analyses

Using 18 randomly selected test samples, linear regression analysis was used to analyze the efficacy of LST for evaluating PAR, and nonlinear regression analysis was used to analyze the efficacy of LST, EVI and NDVI for estimating LUE. Nonlinear regression analysis was also used to evaluate the relationships between field LUE and the values of $T_m$, EVI×$T_m$ and NDVI×$T_m$. Field LUE was estimated as:

$$LUE = GPP/(FAPAR \times PAR) \quad (4)$$

Where PAR is field PAR; FAPAR is the MODIS Leaf Area Index - FPAR production (MOD15A2); GPP is the field GPP.

### 3.2 PAR, LUE and GPP estimations

Using linear regression analysis, a linear model for PAR estimation from the MODIS LST product was built. Through nonlinear regression analysis, exponential relationships were found between LUE and the VI, $T_m$ and VI×$T_m$ terms. Thus, a new model to estimate LUE was built as follows:

$$LUE_e = a \times \exp\left[b \times (VI_i \times T_{e,i})\right] \quad (5)$$

$$T_{e,i} = \exp(LST_i / LST_{\max}) \quad (6)$$

Where $VI_i$ is the 8-day vegetation index data; *a* and *b* are coefficients that need to be calibrated; $T_e$ is the 8-day $T_m$; $LST_i$ is the mean ith 8-day temperature and $LST_{max}$ is the maximum 8-day temperature of the site for the experimental years. Subsequently, GPP was estimated using the estimated LUE and PAR and the MODIS FAPAR product according to equation (1).

### 3.3 Validation and Comparison with MODIS GPP

Seventeen independent field-measured GPP data points were used to validate the precision of the model using linear regression analysis. A comparison with the standard MODIS GPP was also conducted.

### 3.4 Test of scaling effect

Four MODIS products were used in this study. The spatial resolution of MOD09A1 is 500 m, while the spatial resolutions of the other data are 1 km. To evaluate the influence of this difference on the estimation of GPP, the 500 m MOD09A1 product was upscaled to 1 km using the pixel aggregate resampling method. Then, the 1 km vegetation index was calculated and used to estimate LUE and GPP. Linear regression analysis was also used to evaluate the relationship between the estimated GPP and the field-measured GPP, and the GPP estimated using the 500 m MOD09A1 data was also compared with field-measured GPP. The influence of the spatial difference was then evaluated by comparing the difference in the coefficients of determination ($R^2$).

## 4. Results

### 4.1. Estimation of PAR

The results of the linear regression analysis demonstrate that LST has a strong and significant relationship with PAR, with an $R^2$ equal to 0.588 and an RMSE equal to 3.32 MJ $m^{-2}$ $8d^{-1}$ (P<0.001) (Fig. 2).

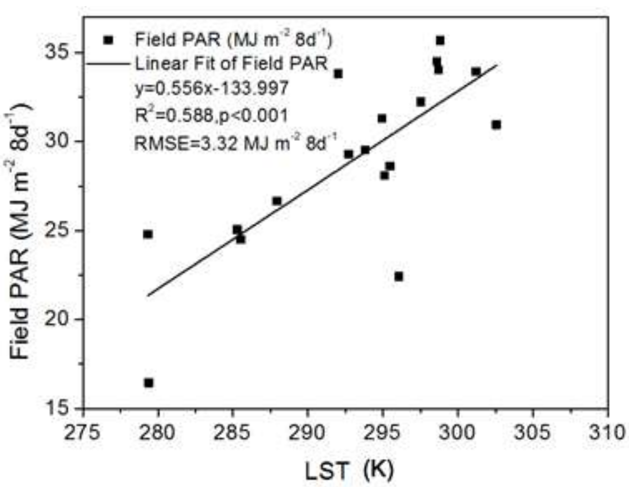


**Fig. 2** The relationship between the eddy covariance estimated PAR and LST for the DT site

### 4.2. Estimation of LUE using VI×Tm

#### 4.2.1. The relationship between LUE and VI

Previous studies by Wu et al. [44] and Gelybó et al. [45] have shown that EVI and NDVI have significant correlations with LUE in North American forest ecosystems. In this study, we found that both EVI and NDVI have strong and significant exponential relationships with the LUE of the estuarine wetland ecosystem. An $R^2$ equal to 0.76 and 0.73 with RMSE equal to 0.002 and 0.003 kg C $mol^{-1}$ PAR (P<0.0001) were found (Fig. 3).

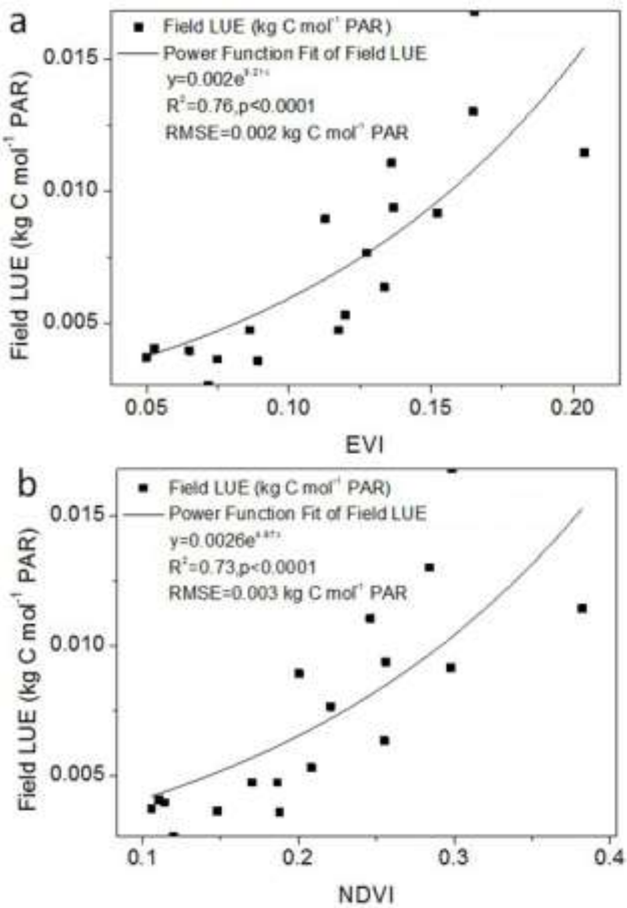


Fig. 3 The relationship between the eddy covariance-estimated LUE and VIs for the DT site: (a) EVI and (b) NDVI

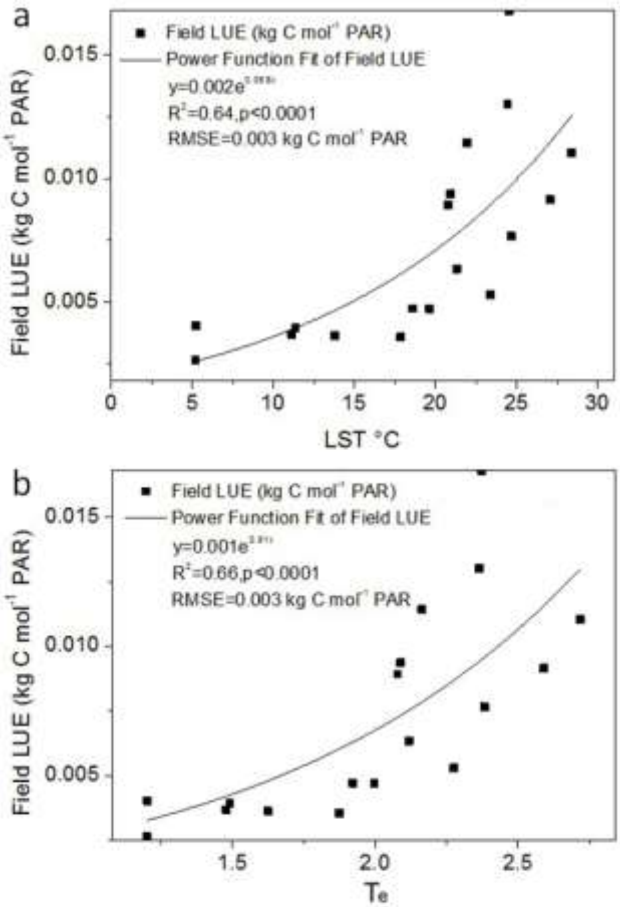


**Fig. 4** The relationship between the eddy covariance-estimated LUE and temperature for the DT site: (**a**) LST and (**b**) $T_e$

#### 4.2.2. The relationship between LUE and temperature

Air temperature is an important environmental variable that can affect vegetation growth [43-44]. Vegetation can grow within a suitable temperature range. Temperatures that are too high or too low will lead to a decline in the growth rate of vegetation [9]. Therefore, temperature also has an important influence on LUE and GPP.

However, because air temperature cannot be directly observed by remote sensing, LST products, such as the MOD11A2 product of the MODIS sensor, are usually used in place of air temperature. The preliminary work of Wu et al. [44] revealed that air temperature has a highly non-linear relationship with MODIS LST. In the previous studies, LST has been used to estimate GPP and LUE [24, 46]. The results of the nonlinear regression analysis show that LST has a strong and significant relationship with LUE for the estuarine wetland ecosystem, with an $R^2$ equal to 0.64 and an RMSE of 0.003 kg C $mol^{-1}$ PAR (P<0.0001) (Fig. 4a).

However, the MODIS LST tends to overestimate air temperatures below 25 °C [44]. Therefore, Wu et al. [44] defined a parameter named $T_{m,i}$ (Eq. 3) to improve sensitivity at high temperatures. For this purpose, we used the 8-day $T_m$ data calculated by equation (5). To prove that the 8-day $T_m$ can also be used to estimate LUE, nonlinear regression analysis was used to evaluate the relationship between the 8-day $T_m$ and LUE. The results of this nonlinear regression analysis indicate that the 8-day $T_m$ has a better correlation with LUE than LST (Fig. 4 b).

#### 4.2.3 Estimation of LUE using VI×$T_e$

Based on the determined relationships between LUE and both the VIs and the temperature, a new model was developed that incorporates both VI and $T_e$ to estimate the 8-day LUE (Fig. 5). Strong correlations between LUE and both EVI×$T_e$ and NDVI×$T_e$ were found, with an $R^2$ of 0.82 and 0.80 and RMSE equal to 0.002 kg C $mol^{-1}$ PAR (P<0.0001),respectively.

 

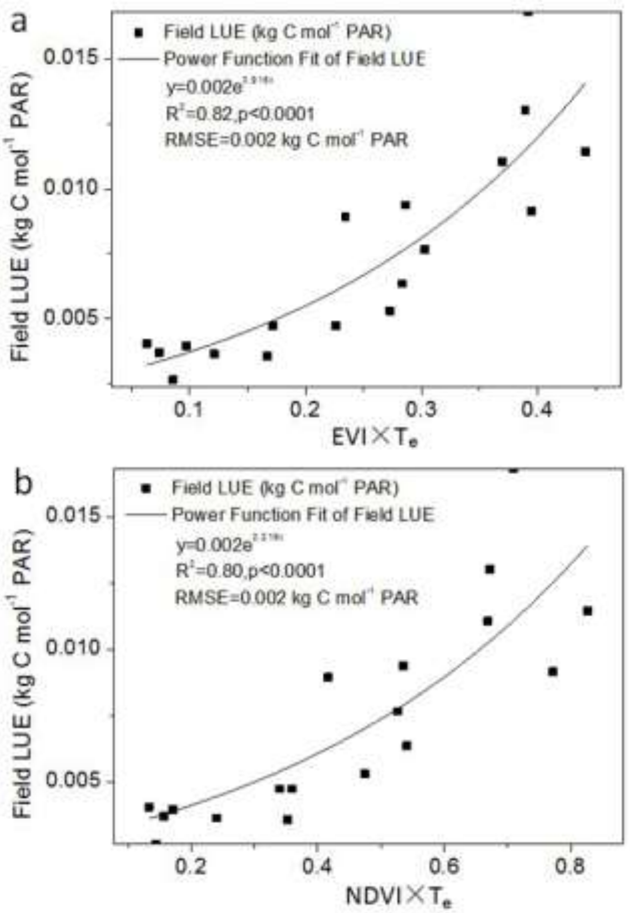


**Fig. 5** The estimation of LUE using (a) EVI$\times T_e$ and (b) NDVI$\times T_e$

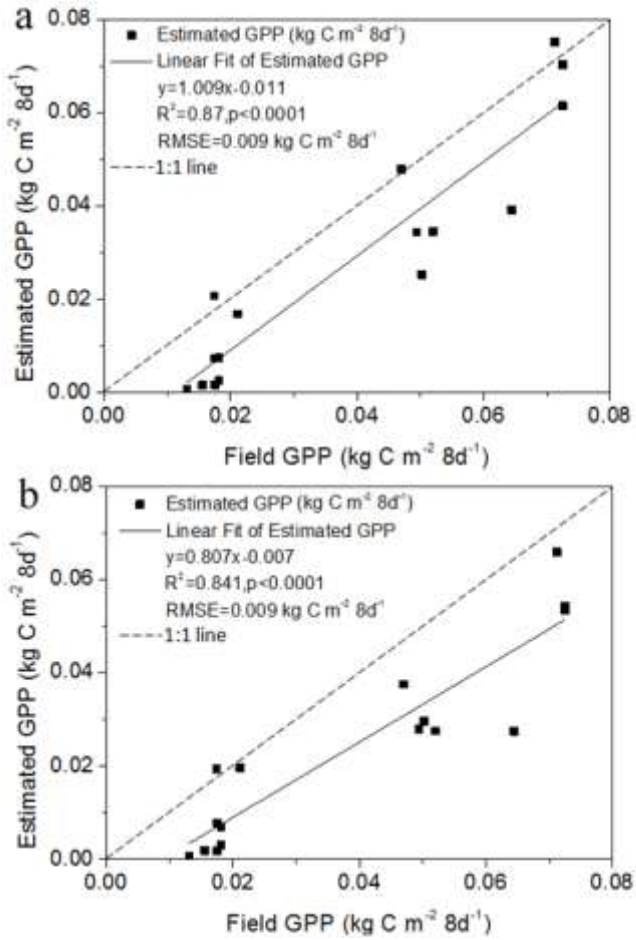


**Fig. 6** The estimation of GPP using FAPAR and (a) estimated LUE by EVI$\times T_e$ or (b) estimated LUE by NDVI$\times T_e$

### 4.3. Estimation of GPP using LUE×FAPAR×PAR

Using the estimated LUE and PAR and the MODIS FAPAR product, the GPP of the estuarine wetland ecosystem was estimated. Very strong and significant correlations between the eddy covariance-estimated GPP and the estimated GPPs using the MODIS FAPAR product, and the PAR and LUE values estimated using either EVI$\times T_e$ or NDVI$\times T_e$, were found, with an $R^2$ of 0.87 and 0.84 and RMSE equal to 0.009 kg C m$^{-2}$ 8d$^{-1}$ ($P<0.0001$, Fig. 6), respectively.

### 4.4. Comparison with MODIS GPP

A comparison with the standard MODIS GPP product was also conducted. The result showed that MOD17A2 GPP have a good relationship with eddy covariance flux tower measured GPP with $R^2$ equal to 0.818, and RMSE equal to 0.009 kg C m$^{-2}$ 8d$^{-1}$ ($P<0.0001$) (Fig.7). However, GPP estimated using FAPAR, PAR and LUE by EVI$\times T_m$ and NDVI$\times T_m$ had comparatively better results than MODIS GPP.

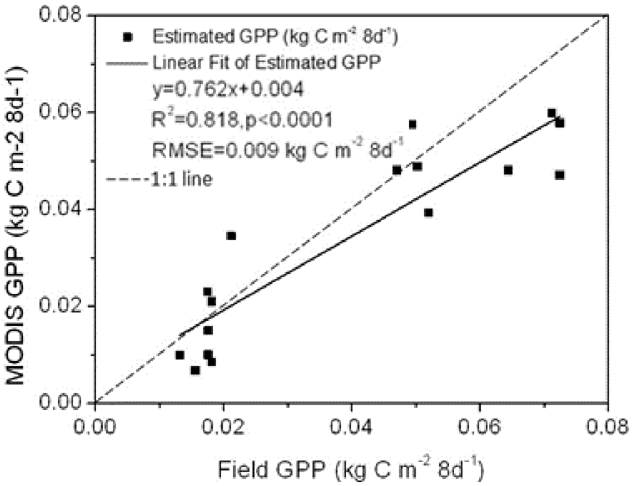


**Fig. 7** Relationship between the eddy covariance estimated GPP and MOD17A2 GPP for DT site

### 4.5 Test of scaling effect

Using linear regression analysis, the GPPs estimated using either 500 m or 1000 m MODIS reflectance data were compared to evaluate the effects of scaling. The results show that the 1000 m vegetation index had a lower capability for estimating GPP, with an $R^2$ equal to 0.667 and 0.663 and RMSE equal to 0.017 and 0.011 kg C $m^{-2}$ $8d^{-1}$ (P<0.0003, Fig. 8) when using either EVI$\times T_e$ or NDVI$\times T_e$, respectively.

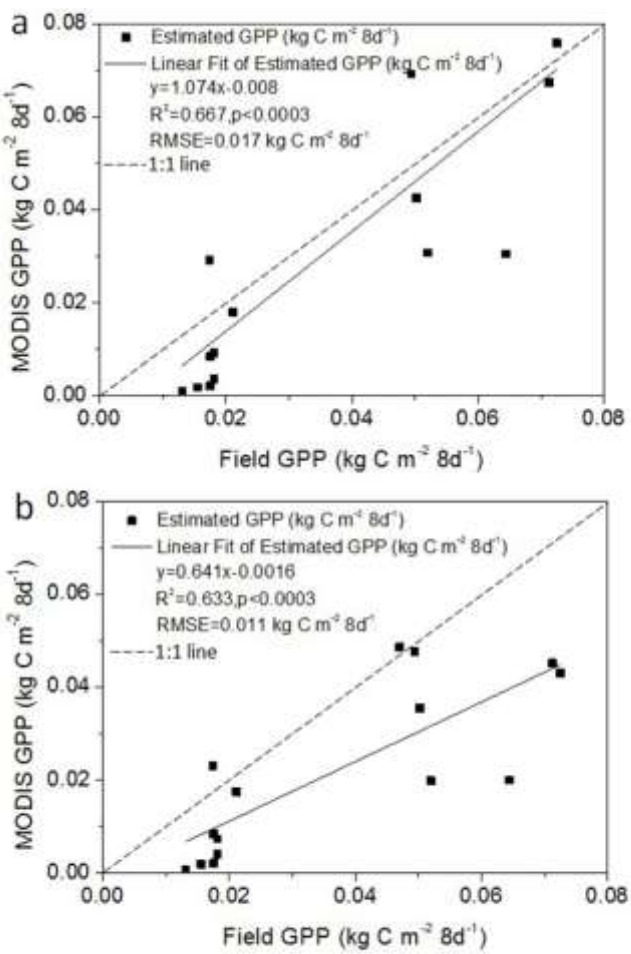


**Fig. 8** The estimation of GPP using 1 km MODIS reflectance and (a) LUE estimated by EVI$\times T_e$ or (b) LUE estimated by NDVI$\times T_e$

## 5. Discussion

### 5.1. Model improvement

The algorithm proposed by Wu et al. [44] for a forest ecosystem was improved upon in this paper to estimate the GPP of a wetland ecosystem. Due to the differences between wetlands and forest ecosystems, the model proposed by Wu et al. [44] was improved in the following aspects: (1) the GPP of the wetland ecosystem was estimated with an 8-day temporal resolution; (2) exponential relationships between VIs and the LUE of the wetland ecosystem were determined, while the relationship for the forest was linear; (3) an exponential relationship between LUE and VI, $T_e$ was discovered, while the relationship for the forest was logarithmic.

Using 18 randomly selected test samples, we found that both VIs and VI $\times$ $T_e$ have exponential relationships with LUE by performing nonlinear regression analyses. Using 17 independent field-measured GPP data points, the ability of this method to estimate GPP with a high precision was verified.

The differences mentioned above are mainly attributed to the differences in ecosystem types. However, there is a need of further research for this differences. Our work demonstrates that LUE has a strong relationship with VI and $T_e$, but this relationship will change with the ecosystem type. Therefore, when applying this method to other ecosystems, this LUE estimation model should be rebuilt.

### 5.2. Limitations of the model

A new model was developed to estimate the GPP for an estuarine wetland ecosystem using the MODIS VIs, LST and FAPAR products. The linear correlation analysis demonstrated that this model produces GPP values that are very similar to eddy covariance-estimated GPP values. However, there are still some factors that may affect the precision of this method and should be considered in future applications.

First, the eddy covariance-estimated GPP represents the footprint of the tower, which is variable depending on the local environmental situation and land cover [47]. There is a need to translate between the size of the footprint and the pixel size of image data. The methods currently in use assume that the eddy covariance flux tower-measured GPP is equal to the central or mean values of 3×3 pixels. Relying on this assumption, an assessment of accuracy is possible because of the representativeness of both measured and estimated values for whole ecosystem productivities, comprising the contributions of all photosynthesizing plants (trees, shrubs, and grasses). The validity of this basic assumption is, however, questionable in heterogeneous forest areas, where the spatial scale of the variability in GPP is on the order of few hundred meters [45]. Considering the species diversity and land fragmentation of wetland ecosystems, the problem of heterogeneity for wetland ecosystems is also a serious factor for remote sensing models. However, on Chongming Island, the main vegetation types only include *Spartina alterniflora* and *Scirpus mariqueter*, which are zonally distributed along the beach [39-41]. Due to the single species and homogeneous land cover around the DT site, this issue was not discussed here. However, this is a topic on which future research should focus.

Second, cloudy weather can lead to the overestimation of PAR and GPP. More than eight cloudy days will lead to missing 8-day MODIS products. In this situation, optical remote sensing reveals its limitation. Less than eight cloudy days will result in an overestimation of PAR when using the MODIS LST product. The MODIS LST pixels contain the average LST values of clear-sky LSTs for an 8-day period. Thus, the PAR estimated using MODIS LST data is the total PAR for an 8-day period. If there are some cloudy days, the real PAR will be less than estimated PAR. Linear regression analysis was also used to evaluate the relationship between the estimated PAR and the field-measured PAR. The results revealed that the MODIS LST can be used to estimate PAR, with an $R^2$ equal to 0.68 and an RMSE equal to 2.0 MJ $m^{-2}$ $8d^{-1}$ (P<0.0001, Fig. 9a). However, the results also show that PAR will be overestimated when using the MODIS LST product if the PAR falls below 30 MJ $m^{-2}$ $8d^{-1}$. The GPP estimated using the estimated PAR was also compared with the GPP estimated using field-measured PAR by performing a linear regression analysis. The results showed that the GPP estimated using the estimated PAR was overestimated, with an $R^2$ equal to 0.973 and an RMSE equal to 0.004kg C $m^2$ $8d^{-1}$ (P<0.0001, Fig. 9b).

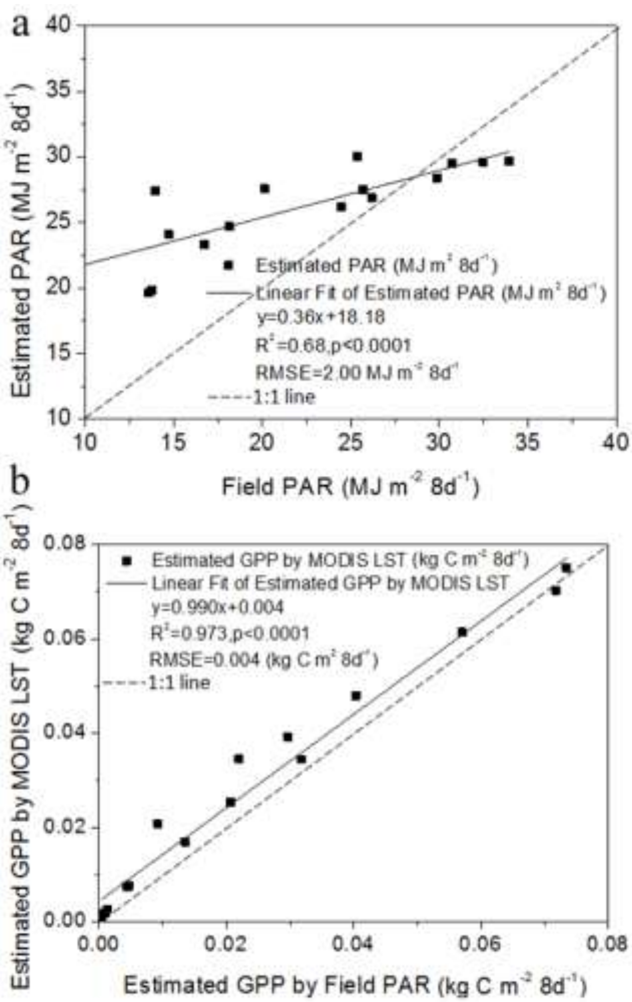


**Fig. 9** The relationships between (a) the eddy covariance-estimated PAR and estimated PAR, (b) the GPP estimated using the field-measured PAR and the estimated PAR, for the DT site

Third, the estimated GPP using method proposed by this paper is underestimated which was showed in Fig. 6. This underestimate is mainly caused by the underestimation of the temperature by the MODIS LST product. The underestimation of temperature is also influenced by the underestimation of LUE. To evaluate the influence of the underestimates of temperature and LUE, we compared the MODIS LST and the estimated LUE with the field-measured temperature and LUE by performing linear regression analyses. The results show that the use of the MODIS LST product and the LUE estimated using EVI×$T_e$ will cause the model to underestimate LUE, with an $R^2$ equal to 0.8 and 0.754 and an RMSE equal to 3.523 °C and 0.002 kg C $mol^{-1}$ PAR, respectively (Fig. 10).

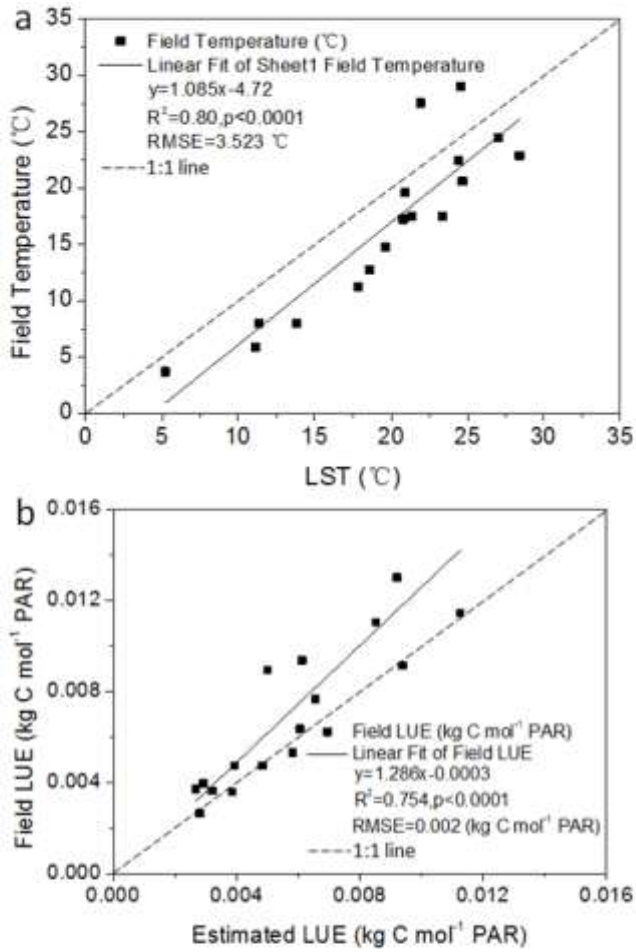


**Fig. 10** Comparisons between (a) MODIS LST and (b) LUE estimated by EVI×$T_e$ with field temperature and LUE, respectively.

Finally, the proposed method was validated for the estimation of the GPP of a homogeneous estuarine wetland ecosystem. However, only one eddy covariance tower data point was included in this validation study. More eddy covariance data should be tested to verify the suitability of this model, and its usefulness for heterogeneous wetland ecosystems and other ecosystem (e.g., crops, grasslands and forests) requires further validation as well. Moreover, impacts of the MODIS observation footprint and the vegetation bidirectional reflectance distribution function (BRDF) were no considered. Zhang et al. have found that footprint have an important influence on NDVI and EVI which were also used in this new model [48]. So this is a topic on which future research should focus.

## 6. Conclusions

A new method for the estimation of the GPP of an estuarine wetland ecosystem using the MODIS VIs, LST and FAPAR products was developed and validated for a study site located on Chongming Island, Shanghai, China. A linear regression analysis that was performed to compare the modeled data with field-measured eddy covariance data indicates that this new model provides accurate estimates of GPP, with an $R^2$ equal to 0.87 and an RMSE equal to 0.009 kg C $m^{-2}$ $8d^{-1}$ ($P<0.0001$). This performance is better than that of the standard MODIS GPP product. In addition, using nonlinear regression analysis, we also found that vegetation indices, such as EVI, NDVI and temperature, have strong and significant correlations with LUE. The proposed model can be applied to estimate the GPP for an estuarine wetland ecosystem. However, due to the limitation of field-measured GPP included in this study, more field-measured data should be compared to analyze the stability and applicability of this model, especially in other ecosystems.

## Acknowledgments

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## Notes and references

[a] *The State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing, China. Fax: +861064806258; Tel: +861064806258; E-mail: wumq@radi.ac.cn*

[b] *Laboratory of Digital Earth Sciences, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing,China. Fax: +861082178008; Tel: +861082178009; E-mail: Chenfang421@gmail.com*

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