Determination of rice paddy parameters in the global gross primary production capacity estimation algorithm using 6 years of JP-MSE flux observation data

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Abstract

Gross primary production (GPP) capacity is defined as GPP under low stress, and the algorithm for its estimation was developed by Thanyapraneedkul et al. (2012) using a light-response curve. The idea behind this algorithm is that the light response curve under low stress is related to chlorophyll content. The parameter is estimated from a vegetation index derived from satellite observations of the green chlorophyll index (CI_{green}) for seven vegetation types, including rice paddy. These previous studies included 1 year of data for the flux site and MODIS reflectance data. Recently, long-term data have become publicly available for flux data covering a period of 6 years, and MODIS reflectance data covering a period of more than 16 years.

This study determined the parameters in the GPP capacity estimation algorithm for rice paddies using 6 years of Mase paddy flux site data and clear daytime reflectance data observed using MODIS. The fitted parameter-related initial slopes of the light-photosynthesis curves for each year were identical within the fitting error. Using the averaged parameter-related initial slope over 6 years, we were able to determine a linear relationship between CI_{green} and the maximum photosynthesis rate at 2000 PAR (μmol m^{-2} s^{-1}), the slope of which was slightly higher than has been reported previously. Using the parameters for the period 2001-2006, we investigated how GPP capacity varied for irrigated rice paddy. The ratio of the average GPP capacity to the GPP after transplanting until harvesting was 0.91 for the period 2001 to 2006. This result shows that GPP capacity provides a useful first approximation of GPP for irrigated rice paddies as a framework of the global GPP estimation algorithm.

Key words: AsiaFlux, Chlorophyll, Light-response curve, Photosynthesis, Vegetation index

1. Introduction

Accurate observations of CO2 exchange in plant canopies and the atmosphere for different types of vegetation are key for understanding the influence of plants on climate change. The FLUXNET project has observed the CO2 flux of various types of vegetation globally (Baldocchi et al., 2001). Rice paddies occupied approximately 161 million ha (FAS, 2016) worldwide in 2016, representing 0.8% of the land area (NAOJ, 2016). The area used to produce rice is predicted to increase by 4.5% from 1999 until the end of 2030 (Bruinsma, 2003). Rice is the major staple food in Asia, where rice paddies comprise about 87% of the total area of rice cultivation in the world (Bhattacharyya et al., 2013; FAS, 2016). Therefore, rice paddy is an important study target (Miyata et al., 2000, 2005) especially in Asia both for the carbon cycle and food security. Gross primary production (GPP) is one of the most important processes involved in carbon exchange (Huntzinger et al., 2012) and up-scaling methods are required to understand the carbon cycle regionally and globally. For this up-scaling, satellite remote sensing offers an efficient approach.

When studying GPP using satellite sensor data, the additional information is often required such as the rice paddy’s map and the phenology. There are many forms of rice paddies including scale, irrigated or non-irrigated, the number of times of the crop in a year. The times for transplanting differ depending on the number of crops per year, and the farmers’ situation. This causes the spatial variety of the phenology. The many forms cause that rice paddy mapping data are not sufficiently accurate (Xiao et al., 2005, Salmon et al., 2015). Although rice paddy category is often included cropland category, the categories between cropland and grassland are often misclassified (Poulter, et al., 2011). This misclassification could result in an error in the global GPP estimation when the algorithm is applied to each vegetation type. From these facts, it is needed at global scales to develop GPP estimation algorithm with less sensitive to vegetation types and the phenology.

When calculating GPP using satellite sensor data, the LUE-based model (Monteith et al., 1972) is widely used (Running et al., 2000; Heinsch et al., 2006). The quantity of incident light
absorbed by plants and their light-use efficiency (LUE) are key parameters. In this model, GPP is determined from the product of LUE and the absorbed photosynthetically active radiation (APAR), where APAR is given by the product of the fraction of absorbed PAR (fAPAR) and PAR. The model assumes a linear relationship between GPP and PAR.

The chlorophyll-based GPP estimation model was suggested for crops (Gitelson et al., 2006, 2012; Peng et al., 2013). In this model, GPP relates to the product of chlorophyll content (Chl) and PAR as follows:

\[ GPP \propto Chl \times PAR. \]  

(1)

To estimate GPP remotely, the total chlorophyll content can be estimated using vegetation indexes (VIs). The VI CIgreen (Gitelson et al., 2003), which is sensitive to leaf chlorophyll content, is defined using the near infrared (NIR) and green reflectance (Green) bands as follows:

\[ CI_{green} = \frac{NIR}{Green} - 1. \]  

(2)

When CIgreen is used for estimating the total chlorophyll content, the midday GPP shows a linear relationship with the product of CIgreen and PAR (Gitelson et al., 2006). However, when using other VIs, GPP occasionally does not show a clear linear relationship with the products of VIs and PAR.

The rate of photosynthesis and the light intensity is often nonlinear for canopies (Gu et al., 2002; Saito et al., 2005). Several studies have used GPP calculation methods with a light–response curve (Furumi et al., 2005; Harazono et al., 2009; Ide et al., 2010) using satellite sensor data. However, most of them did not include the concept of the “photosynthesis capacity”. Ide et al. (2010) studied the parameters of a light-response curve with two parts of seasonal variations and day-to-day short-term variations affected by meteorological conditions. The photosynthetic process starts by light absorption, and requires open stomata for carbon dioxide absorption. The amount of light absorbed depends on the amount of chlorophyll, which is reflected by its color (green); this can be detected by optical sensors. The rate of photosynthesis changes with the degree of stomata closure due to temporarily changing environmental conditions, such as changes in air temperature, humidity, and water supply. Strictly, the photosynthetic capacity depends on the amount of both chlorophyll and Rubisco enzyme (Sellers et al., 1992) in a leaf; chlorophyll content is a key parameter in the estimation of photosynthesis capacity.

We previously developed a GPP estimation method using the light-response curve, and introduced the concept of “capacity” (Thanypadraeekul et al., 2012). GPP under low-stress conditions is defined as \( GPP_{\text{capacity}} \) and the light-response curve under low-stress conditions uses a rectangular hyperbolic function; i.e.

\[ GPP_{\text{capacity}}(\text{PAR}(t)) = \frac{a_{\text{slope}}P_{\text{max, capacity}} \times \text{PAR}(t)}{1 + a_{\text{slope}} \times \text{PAR}(t)}, \]  

(3)

where \( a_{\text{slope}} \) relates the initial slope of the curve and the photosynthetic quantum efficiency, \( P_{\text{max, capacity}} \) is the photosynthesis rate at light saturation, and \( \text{PAR}(t) \) (\( \mu \text{mol m}^{-2} \text{s}^{-1} \)) is the photosynthetically active radiation at time \( t \) (Fig. 1). \( P_{\text{max, capacity}}2000 \) is defined as \( GPP_{\text{capacity}} \) at \( \text{PAR}(t) = 2,000 \) (\( \mu \text{mol m}^{-2} \text{s}^{-1} \)) as shown in Fig. 1; \( P_{\text{max, capacity}2000} \) can be calculated using the VI CIgreen based on satellite reflectance data as follows (Thanypadraeekul et al., 2012):

\[ P_{\text{max, capacity}2000} = a \times CI_{green} + b. \]  

(4)

To calculate \( GPP_{\text{capacity}} \) globally (Muramatsu et al., 2012), the parameters \( a \) and \( b \) in Eq. (4) must be determined, as well as \( a_{\text{slope}} \) in Eq. (3), for each vegetation type using satellite and flux data. The parameters for the following seven vegetation types have been studied using data for 1 year (Thanypadraeekul et al., 2012; Mineshita et al., 2016): grass, needleleaf deciduous trees, needleleaf evergreen trees, broadleaf deciduous trees, cropland (i.e., rice paddies), open shrubland and closed shrubland. Grass and open shrubland were combined into a single group, and another group was formed from woody plants from closed shrubland, needleleaf deciduous trees, needleleaf evergreen trees and broadleaf deciduous trees. For rice paddy, the slope \( a \) in Eq. (4) is very similar to that for grass and open shrubland. Based on the data for the closed and open shrubland, we found that \( GPP_{\text{capacity}} \) and AmeriFlux GPP were almost identical if the vegetation had not experienced high stress levels, and that \( GPP_{\text{capacity}} \) reflects drought conditions. In our previous study, the parameters \( a \) and \( b \) in Eq. (4) were determined at the Mase paddy flux site in Japan (JP-MSE); we found \( a = 0.37 \) and \( b = -0.36 \) using data for the year 2003 (Thanypadraeekul et al., 2012), which was a relatively cool year with many cloudy days. To apply the method of calculating \( GPP_{\text{capacity}} \), the parameters for rice paddy need to be determined accurately.

Typically, reflectance data are observed using satellite imaging, and hence are influenced by cloud cover, atmospheric conditions, or observation angle conditions. In the presence of thick cloud, the pixels corresponding to cloud should be identified. However, it may be difficult to correct for these effects when contamination due to thin cloud, aerosols, or noise is not obvious using only a year data. Pixels with such contamination may lead to erroneous VI values and result in errors in \( GPP_{\text{capacity}} \). Recently, long-term eddy covariance measurement data were made public by FLUXNET, covering a period of more than 6 years, as well as MODIS reflectance data for more than 16 years. These long-term datasets make it possible to study these effects for a specific site.

The objective of this study was to improve the parameters used to estimate the \( GPP_{\text{capacity}} \), such as \( a_{\text{slope}} \) in Eq. (3) and \( a \) and \( b \) in Eq. (4), for rice paddy using the data for the JP-MSE rice paddy site, covering 6 years from 2001 to 2006, and MODIS reflectance data after selecting a clear pixel and appropriate observation angles. In our previous study, we used only data for 2003, which was a relatively cool year with many cloudy days. The parameters for rice paddy derived in this study were compared with those of other vegetation types in a previous study to consider the slope differences of Eq. (4) according to vegetation types. Then, we examined how the \( GPP_{\text{capacity}} \) differed from the GPP for rice paddy. In irrigated rice paddy, if the rice had not been subject to water stress, \( GPP_{\text{capacity}} \) and GPP should be close. Finally, the applicability of the \( GPP_{\text{capacity}} \) estimation method for rice paddy was considered.
2. Data and Methods

2.1 Data used in this study

2.1.1 Flux data of JP-MSE

We used flux data from the Mase paddy flux site in Japan (JP-MSE) in AsiaFlux site for the period 2001–2006. The study site was a rice paddy in Tsukuba, Ibaraki, Japan, located at 36°03′14.3″N, 140°01′36.9″E, and 11 m above sea level. The almost flat terrain measured 2 km by 1 km, and was located along the Kokai River. The net ecosystem exchange (NEE) data and meteorological data were downloaded from the AsiaFlux database, and Table 1 lists the version number of the data and the transplanting and harvesting dates. GPP was calculated using the MPK method (Falge et al., 2001; Reichestein et al., 2005; MPK web site) and NEE data, as well as weather data, including air temperature and friction velocity.

2.1.2 Satellite data

MODIS reflectance data (MOD09A1) were used in this study, which provide a spatial resolution of 500 m. Atmospheric scattering and absorption were minimized by selecting an 8-day period with a low viewing angle and no clouds, cloud shadow, or aerosol (Vermote et al., 2002). The MODIS data were downloaded from the MODIS Land Subsets website (ORNL DAAC, 2014). Data were provided for each 8-day period. The MODIS single-pixel reflectance data corresponding to the JP-MSE site for the period 2001 to 2006 were used to determine the parameters in Eq. (4). MODIS data for the period 2000–2015 were used to determine selection criteria for noise-free clear sky days.

2.2 Methods

2.2.1 Preprocessing MODIS reflectance data to select clear, appropriate observation angle pixels

Satellite reflectance is contaminated with cloud, cloud shadow, or aerosol and is affected by a large observation angle. These factors can lead to errors in the calculated VI. To determine the parameters in Eq. (4) accurately, the reflectance data collected under these undesirable conditions should not be used.

For contamination, we used data without MODIS flags for cloud, cloud shadow, and aerosol; however, some contamination remained in the form of thin cloud. MODIS data for the period 2000–2015 were used to determine the selection criteria for noise-free clear sky days. In this case, the nine MODIS pixels for one pixel corresponded to the flux position and the eight pixels surrounding the central pixel were used to detect the range of the seasonal changes in the reflectance of each band. When the corresponding pixels were rice paddy from 2000 to 2015, the reflectance values varied between their seasonal minima and maxima. Reflectance values with noise could lie outside this range. This should be clearer in visible bands than in near infrared bands, especially in blue. The reflectance of the blue band by plants and soil is often the lowest among the visible bands, and a noise signal is easily to identify in the blue band. With aerosols, the spectral scattering cross section can be described using Mie scattering theory (Mic, 1908), and a band that is contaminated depends on the aerosol composition, that is, particle size and the type and quantity of aerosol. From these reasons, the seasonal changes in the reflectance of the MODIS band were examined. Then, various ratios of the two bands were examined when noise from a signal was emphasized to determine the criteria of selecting clear pixels.

For the observing angle, Ishihara et al. (2015) reported that the MODIS NDVI value differs from the NDVI data observed in the field at the JP-MSE site, and that the conditions affecting these differences had been studied using the PROSAIL model (Jacquemoud et al., 2009). Differences occurred when the observing angle was > 40° with NDVI < 0.7. The NDVI values observed using MODIS were larger than those from field observations, especially when the observation angle was 60°. Based on this study, we decided that the data were excluded with an observation angle > 40° when NDVI < 0.7.

2.2.2 Preprocessing of the flux data to select GPP with low-stress conditions

GPP data with low-stress conditions were selected. The photosynthesis rate is reduced when the vapor pressure deficit (VPD) is high (Pathre et al., 1998; Pessarakli, 2005; Thanyapraneedkul et al., 2012); this often occurs around noon and is referred to as the “midday depression” (Pathre et al., 1998). To select data that were unaffected by the midday depression, daily changes in GPP, VPD, and PAR averaged over 8-day periods were examined. The VPD value when the midday depression of GPP occurred was used as the threshold; values higher than the VPD threshold were considered high-stress data and were not used in this study. In our previous study (Thanyapraneedkul et al., 2012), the VPD threshold for a rice paddy was determined to be

![Fig. 1. Light response curve of gross primary production capacity (GPP_capacity), αslope, P_max_capacity, and P_max_capacity2000 parameters.](image)

Table 1. JP-MSE flux data version and DOY for transplanting and harvest.

| Year | version | transplanting (DOY) | harvest (DOY) |
|------|---------|--------------------|---------------|
| 2001 | 01      | 124                | 245           |
| 2002 | 01      | 122                | 262           |
| 2003 | 01      | 122                | 262           |
| 2004 | 02      | 123                | 253           |
| 2005 | 02      | 122                | 256           |
| 2006 | 01      | 122                | 263           |
2.0 kPa; the averaging of data was carried out over 16 days. To detect plant growth precisely, we used a period of 8 days to calculate the daily variation (Mineshita et al., 2016). Although the MODIS data include the exact observing date, we did not use the flux data for the MODIS observation date only, but used an average of 8 days to extract the seasonal average characteristics because there is no guarantee that the exact day of satellite observation is a typical day for the season. As a result, the reflectance of the vegetation should not change as drastically when the weather conditions change on a daily variation.

2.2.3 Parameter determinations of the GPP capacity estimation algorithm for paddy using JP-MSE and satellite data

GPP with less stress of flux and satellite reflectance data without noise were used to determine the parameters in Eqs. (3) and (4) for the analysis in the following steps.

(i) The light-response curve was then fitted to PAR and GPP data with less stress to determine the parameters $\alpha_{\text{slope}}$ and $P_{\text{max_capacity}}$ in Eq. (3) for an 8-day period.

(ii) The average $\alpha_{\text{slope}}$ was calculated using the entire growing season to reduce the number of parameters.

(iii) Using the average growing season $\alpha_{\text{slope}}$ for each year, we calculated the average $\alpha_{\text{slope}}$ ($\alpha_{\text{slope_ave}}$) during the period 2001–2006. Using $\alpha_{\text{slope_ave}}$ the light response curve was re-fitted to determine the $P_{\text{max_capacity}}$ for each 8-day period.

(iv) $CI_{\text{green}}$ was calculated using MODIS reflectance data during the same period to calculate the light-response curve. The relationships between $CI_{\text{green}}$ and $P_{\text{max_capacity,2000}}$ were determined to fit the data using Eq. (4).

2.2.4 Calculating the ratio of GPP to GPP capacity using flux data

To study the difference between GPP capacity and GPP, the ratio of GPP to GPP capacity was calculated. The average daily GPP for an 8-day period was calculated by summing the average daily change in GPP for the 8-day period. The average daily GPP capacity for the 8-day period was calculated using Eq. (3) with $\alpha_{\text{slope_ave}}$, $P_{\text{max_capacity}}$ fitted for each 8-day period as described in Sec. 2.2.3 iii), and the half hourly PAR averaged over 8-day as described in Sec. 2.2.2.

3. Results

3.1 Selecting MODIS reflectance data for clear and appropriate observation angle pixels

The seasonal changes in MODIS reflectance in blue, red, and 1.2-μm with no flags for cloud, cloud shadow, or aerosol from period 2000–2015 are shown in Fig. 2a, b and c, respectively. It was clear that the seasonal changes of reflectance, and the points outside the seasonal variation were clear in these three bands. (The seasonal changes of reflectance of other two bands, such as green and near infrared, of MODIS are shown in Appendix Fig. A.1a, and b.) To determine clear pixel selection thresholds, the blue reflectance divided by the red reflectance ($B/R$) was examined as shown in Fig. 2d. Most of these data had a value close to 0.5, although some were significantly outside the seasonal variation. The blue reflectance and red reflectance were strongly correlated in the study area, since the clear B/R values were almost all close to 0.5 when the pixel was unclear, the value of B/R differed from 0.5. To determine the

Fig. 2. MODIS reflectance data without cloud, cloud shadow, and aerosol flags. (a) The blue band, (b) the red band, (c) the 1.2-μm band, and (d) B/R.
criteria for selecting clear pixels, the average and standard deviation of these data were calculated for the 16 years for the blue and 1.2-µm bands, and B/R (see Table 2). We selected the data with the blue and 1.2-µm reflectance and the B/R that lay within three standard deviations of the mean.

Then, we checked the observation angle and finally selected the data for using further analysis. The DOY of the data was finally used and was not used which was selected as a clear pixel but large observation angles is shown in Table 3. The number of finally selected data was different in each year. Although there were 16–17 observations during the period from transplanting to harvest in each year, half data at the maximum were available as for clear pixels.

3.2 The selection criteria for GPP under a low-stress condition

Thanyapraneedkul et al. (2012) selected low-stress data using the condition that the VPD was > 2 kPa for JP-MSE sites and the friction velocity was > 0.1 m/s. To determine whether this condition could be used in this study, the daily variation in GPP, PAR, and VPD were averaged over the 8-day MODIS observation cycle. For an example, data for different growing stages were selected in 2001 from all of the processed data, as shown in Fig. 3. The daily variations of other years from 2002 to 2006 are shown in Appendix Fig. A.2–Fig. A.4.

For paddy, no clear midday suppression of photosynthesis was observed; however, slight suppression was observed on Jun. 26 2001 (Fig. 3(a)). In these cases, the PAR value exhibited a maximum around noon and GPP was higher before noon than in the afternoon (Fig. 3(b)). In the absence of a midday depression, GPP would be highest at noon, although the rate of increase of photosynthesis versus PAR would be low close to noon due to the non-linear relationship between light intensity and the rate of photosynthesis. It was clear that photosynthesis was slightly suppressed in the afternoon. The VPD values for these days (Fig. 3(c)) were higher than for other days. The maximum VPD was greater than 2 kPa in the afternoon. Based on these results, we used a threshold of 2.0 kPa for VPD in the remainder of this study.

3.3 The GPP capacity estimation parameters for paddy using JP-MSE and satellite data

3.3.1 The light-response curve parameters

To determine the \( P_{\text{max, capacity}} \) and \( \alpha_{\text{slope}} \) values of the light-response curve (Eq. (3)), the relationship between PAR and \( \text{GPP}_{\text{capacity}} \) during daytime was examined using the data selected with the VPD threshold and friction velocity. The parameter \( \alpha_{\text{slope}} \) was averaged using data for the growing season. The average values of \( \alpha_{\text{slope}} \) for each year were: 0.0012 ± 0.0002 (2001), 0.0011 ± 0.0002 (2002), 0.0014 ± 0.0003 (2003), 0.0010 ± 0.0002 (2004), 0.0012 ± 0.0002 (2005), and 0.0014 ± 0.0003 (2006). The average of \( \alpha_{\text{slope}} \) for the period 2001–2006 was:

\[
\alpha_{\text{slope, ave}} = 0.0012 \pm 0.0002. \tag{5}
\]

Using these data, we calculated the light–response curve \( \text{GPP}_{\text{capacity}} \) for the year 2001, as shown in Fig. 4. The results in the years for 2002 to 2006 are shown in Appendix Fig. A.5. The dots indicate the data during each 8-day period. The line represents the curves re-fitted as one free parameter of \( P_{\text{max, capacity}} \) using the average \( \alpha_{\text{slope, ave}} \) for each 8-day period. Using the averaged \( \alpha_{\text{slope, ave}} \) and \( P_{\text{max, capacity}} \), values for each of the eight days, \( P_{\text{max, capacity, 2000}} \) for each of the eight days was calculated.

3.3.2 The \( P_{\text{max, capacity, 2000}} \) estimation parameter

The relationship between \( CI_{\text{green}} \) from the MODIS reflectance data and \( P_{\text{max, capacity, 2000}} \) was studied for the period 2001–2006. Data were selected using the conditions described in Section (3.2). The results are shown in Fig. 5(a). For 2003, only one data point remained following the MODIS reflectance data selection procedure. The weather was poor during that year, and the values of PAR were lower than those for other years (see Fig. A.3.); for example, PAR on Aug. 13 in 2003 was the lowest of all of data shown here. Overall, the data were well fitted using linear regression, which gave the following relationship:

\[
P_{\text{max, capacity, 2000}} = 0.39 \times CI_{\text{green}} - 0.26, \tag{6}
\]

where the coefficient of determination was \( R^2 = 0.91 \). This relationship similar to that reported previously (Thanyapraneedkul et al., 2012), although the slope calculated in the present study was slightly higher.

The four points with a MODIS observation angle > 40° when NDVI < 0.7 were excluded in this study, and are shown with black circles in Fig. 5(a). The big black circle (Not used 2) represents the data for an observation angle > 50°. When the observation angle was larger than 50°, the value of \( CI_{\text{green}} \) tended to be higher. Had these points been included in the regression,
the resulting relationship would not have changed significantly, however, with these data included, we found $P_{\text{max\_capacity2000}} = 0.41 \times CI_{\text{green}} - 0.3$, and the coefficient of determination was $R^2 = 0.89$. This is because only a few data points were excluded, and the determination coefficient was slightly lower than in the case of Eq. (6).

### 3.4 The relationship between \(CI_{\text{green}}\) and \(P_{\text{max\_capacity2000}}\) among vegetation types

We compared the relationship between \(P_{\text{max\_capacity2000}}\) and \(CI_{\text{green}}\) calculated in this study with data from previous studies (Thanyapraneedkul et al., 2012; Mineshita et al., 2016), as shown in Fig. 5(b). Using the data from the current study, grass (Alberta - Mixed Grass Prairie site in Canada (CA-Le)) and open shrubland (Sevilleta shrubland site in USA (US-Ses)), Willard Juniper Savannah site in USA (US-Wjs)) were clustered together, while closed shrubland (Lost Creek site in USA (US-Los)) and deciduous broad-leaf forest (Takayama deciduous broadleaf forest site in Japan (JP-TKY)) were also clustered. The slopes for the two clusters differed, and the data were also divided into two groups in this study; the former cluster was named “grass-like”, and included open shrubland, and the latter cluster was named “deciduous woody plants”. In the grass-like cluster, the relationship between grass and rice paddy was similar. Although the range of \(CI_{\text{green}}\) and \(P_{\text{max\_capacity2000}}\) was small, the slope for open shrubland was slightly larger than that for grass and paddy.

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Fig. 3. Diurnal variation of data averaged over 8 days in 2001. (a) Gross primary production (GPP), (b) photosynthetically active radiation (PAR), and (c) Vapor pressure deficit (VPD).

Fig. 4. Relationship between \(PAR\) and the \(GPP_{\text{capacity}}\), and light response curve for each 8-day period in 2001.
Before DOY 150 and after DOY 250, stable.

2001 before harvesting, respectively

range 0.8-1 from 2001 to 2006. We investigated how Pmax_capacity2000 than 0.95 following transplanting and gradually decreased until 2006 and 2005.

dies. The seasonal changes in the ratio of GPP/GPP_capacity for the central date. The reference. The data were averaged over 8 days, and are shown for the period 2001 to 2006 was 0.91.

The yearly averages of GPP capacity were: 0.94 (2001), 0.90 (2002), 0.90 (2003), 0.92 (2004), 0.90 (2005), 0.90 (2006); the average for the period 2001 to 2006 was 0.91.

Fig. 5. Relationship between the parameters green chlorophyll index (CIgreen) and Pmax_capacity2000. (a) this work, and (b) this work and the data reported by Thanyapraneedkul et al. (2012) and Mineshita et al. (2016).

3.5 GPP and GPP_capacity

We investigated how GPP_capacity and GPP differ in rice paddies. The seasonal changes in the ratio of GPP to GPP_capacity from 2001 to 2006 are shown in Fig. 6, where Pmax_capacity2000 for 2001 (shown by the solid line with black circles) is shown for reference. The data were averaged over 8 days, and are shown for the central date. The GPP/GPP_capacity ratio was mostly in the range 0.8-1 from 2001 to 2006.

With data for 2001, the GPP/GPP_capacity ratio was higher than 0.95 following transplanting and gradually decreased until Pmax_capacity2000 reached the seasonal maximum. Days when GPP/ GPP_capacity ≈ 1 correspond to days when GPP_capacity ≈ GPP. Before DOY 150 and after DOY 250, Pmax_capacity2000 was low (these days correspond to shortly after transplanting and shortly before harvesting, respectively), and GPP/GPP_capacity was not stable.

The yearly averages of GPP/GPP_capacity were: 0.94 (2001), 0.90 (2002), 0.90 (2003), 0.92 (2004), 0.90 (2005), 0.90 (2006); the average for the period 2001 to 2006 was 0.91.

Fig. 6. Seasonal changes in the GPP/GPP_capacity ratio from 2001 to 2006 and Pmax_capacity2000 for 2001.

4. Discussion

4.1 The CIgreen and Pmax_capacity2000 relationship using long-term observation data

In this study, we used 6 years of flux data and 17 years of MODIS reflectance data to determine the selection criteria for clear pixels. From the 17 years of reflectance data, it was easy to identify the variation due to seasonal changes and noise. After selecting clear, appropriate observation angle pixels, CIgreen was not contaminated with noise and could observe the seasonal changes in paddy fields.

We assumed that the relationship between CIgreen and Pmax_capacity2000 was constant across the growing stages of rice plant although rice plant has several growing stages. The data after the heading, which are indicated with circles in Fig. 5(a), tends to distribute on or under the fitting line. After heading, non-photosynthetic organs emerge and the rice canopy gradually opens or even falls down, which could shift the observed CIgreen to higher values. Therefore, when estimating Pmax_capacity2000 from CIgreen using Eq. (6) after heading, the values of Pmax_capacity2000 value could be slightly overestimated.

4.2 The slope difference of the CIgreen and Pmax_capacity2000 relationship between the grass-like and deciduous woody plant groups

The slopes differed between the grass-like and deciduous woody plant groups as shown in Fig. 5(b). It is difficult to determine the reason for this difference. One possibility is how the leaves were exposed to light. As shown in Fig. 5(b) Pmax_capacity2000 for one unit of CIgreen in the grass-like group was larger than that for the deciduous woody plant group. CIgreen corresponds to the amount of chlorophyll in a leaf (Gitelson et al., 2003; Thanyapraneedkul et al., 2012). Hence, Pmax_capacity2000 for one unit of chlorophyll in the canopy in the grass-like group was larger than that in the deciduous woody plant group. On average, each leaf in the grass-like group should be exposed to more sunlight than each leaf in the deciduous woody plant group because of the sparseness of the canopy for open shrubs (their maximum LAs were less than 1 [around 0.6–0.75 using the MODIS LAI
4.3 Applicability of the GPP\textsubscript{capacity} estimation method to rice paddies

From this study, the slopes of \( P_{\text{max capacity}2000} \) Calculated based on \( C_{\text{Igreen}} \) for rice paddies (Eq. (6)) were similar to those of the grass-like group, and differed from those for the deciduous woody plants group. This suggests that our GPP\textsubscript{capacity} estimation method was less sensitive to the vegetation types within the grass-like group. Poulter, et al. (2011) reported that the categories between cropland including rice paddy, and grassland, were often misclassified. When the slopes of \( P_{\text{max capacity}2000} \) calculated based on \( C_{\text{Igreen}} \) differ for rice paddy and grassland, the misclassification of grassland and rice paddy could increase the estimation error of GPP\textsubscript{capacity}. Using one group for rice paddy and grassland would result in small errors in GPP\textsubscript{capacity}.

The growing stages of a rice paddy often differ from those in neighboring rice paddies, and the number of rice crops cultivated per year often differs from those in a lower river basin. Methods for estimating rice plant phenology, such as planting, heading, and harvesting dates, using vegetation indices have been studied (Sakamoto, et al., 2005). The methods have been used to estimate the number of rice crops cultivated per year and the heading date in the Mekong Delta (Sakamoto, et al., 2006). To study a local area in detail, it would be better to detect phenology and assume the formula for the corresponding stage. However, it is impossible to observe the detailed phenology of each rice paddy globally.

The light-response curve parameter \( \alpha_{\text{slope}} \) in Eq. (5) was fixed to be one value, \( \alpha_{\text{slope ave}} \), during the 6 years targeted, and the relationship between \( P_{\text{max capacity}2000} \) and \( C_{\text{Igreen}} \) was represented by one equation (Eq. (6)). Furthermore, these parameters and the relationship could vary with crop growth, especially before and after heading, as described in Section 4.1. Nevertheless, this algorithm reproduced the daily GPP\textsubscript{capacity} with a practical accuracy throughout the growing season in every year. This also implies that the algorithm is not sensitive to the spatial heterogeneity of crop growth within the target area, which is often observed in farmland areas with small plots. We conclude that this algorithm is applicable to rice paddies at different stages of the growing cycle, even when rice paddies at different stage are neighbors.

When the target area includes rice at different stages of the growing cycle and small rice paddies, higher spatial resolution data than MODIS data may be used to calculate GPP\textsubscript{capacity} for an entire prefecture, city, or other target area. It is usual that the observation zenith angle is lower in higher spatial resolution data than that in low spatial resolution data. Here, the parameters were determined using observation data with a low zenith angle to avoid the influences of the observing angle that arise in global satellite data with a large observation angle. We expect that the same parameters could be used if the reflectance from satellite data with higher spatial resolution than the MODIS data were corrected for atmospheric effects. Further investigation is required to determine the applicability of the parameters determined here to other types of rice paddy with/without irrigation, observing angle effects, as well as the suitability of satellite data with a higher resolution.

In this study, we investigated how GPP\textsubscript{capacity} differed from GPP for irrigated rice paddy. On average, we found GPP/\( GPP_{\text{capacity}} = 0.91 \) for the period 2001 to 2006 for irrigated rice paddy in Japan. We believe that irrigation causes the high value of GPP/GPP\textsubscript{capacity}, i.e., 0.91 in the 6-year average, and GPP\textsubscript{capacity} is the first approximation of GPP for irrigated rice paddies as a framework of the global GPP estimation algorithm.

5. Conclusions

We estimated the parameter GPP\textsubscript{capacity} using JP-MSE data for the period 2001–2006 and MODIS reflectance data after selecting only clear-sky days and appropriate observing angles.

Using MODIS reflectance data for a 16-year period, the range of seasonal variation in the reflectance of the JP-MSE site was observed and the blue and 1.2-\( \mu \)m reflectance data, as well as B/\( R \), were useful for selecting clear-sky days. The selection criteria for GPP data with low-stress conditions were the same as in a previous study (Thanyapraneedkul et al., 2012).

The fitted values of \( \delta_{\text{slope}} \) in the light-response curve for each year were identical within the standard deviation. The average \( \alpha_{\text{slope}} \) for the period 2001–2006 was determined to use this algorithm and to obtain \( P_{\text{max capacity}2000} \). The relationship between \( C_{\text{Igreen}} \) and \( P_{\text{max capacity}2000} \) was investigated using data for the years 2001–2006. These data revealed a linear relationship similar to that reported previously (Thanyapraneedkul et al., 2012), although the slope calculated in the present study was slightly higher. The relationship between \( C_{\text{Igreen}} \) and \( P_{\text{max capacity}2000} \) was compared with those of other vegetation types in previous studies (Thanyapraneedkul et al., 2012, Mineshita et al., 2016). Consequently, the slope of the relationship in the current study was divided into two groups: the grass-like and deciduous woody plant groups. We believe that the difference in exposure to sunlight is the main reason for the difference. In global land-cover mapping, grass-like grouping enables accurate classification results and it must cause only small errors propagating into GPP\textsubscript{capacity} and GPP.

To study GPP\textsubscript{capacity} in detail for only the JP-MSE site, it would be better to use the parameters for each year; however, when studying the globe or a relatively large area such as an...
entire prefecture, parameters averaged over a relatively long period of time, as done in this study, are suitable. For irrigated JP-MSE rice paddy, on average we found $GPP/GPP_{capacity} = 0.91$ for the period 2001 to 2006, and we conclude that $GPP_{capacity}$ is the first approximation of $GPP$ for irrigated rice paddies as a framework of the global GPP estimation algorithm.

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References

AsiaFlux, JP-MSE site, 2011: http://asiaflux.net/index.php?page_id=83

Baldocchi D, Falge E, Gu L, Olson R, Hollinger D, Running S, Anthoni P, Bernhofer Ch, Davis K, Evans R, Fuentes J, Goldstein A, Katul G, Law B, Lee X, Malhi Y, Meyers T, Munger W, Oechel W, Paw UKT, Pilegaard K, Schmid HP, Valentini R, Verma S, Vesala T, Wilson K, Wofsy S, 2001: FLUXNET: A new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide, water vapor, and energy flux densities. *Bulletin of the American Meteorological Society* **82**, 2415–2434.

Bhattacharyya P, Neogi S, Roy KS, Rao KS, 2013: Gross primary production, ecosystem, respiration and net ecosystem exchange in Asian rice paddy: an eddy covariance-based approach. *Current Science* **104**, 67–75.

Bruinsma J, 2003: World agriculture: towards 2015/2030. *Earthscan*, pp.143.

Falge E, Baldocchi D, Olson R, Anthoni P, Aubinet M, Bernhofer C, Burba G, Ceulemans R, Clement R, Dolman H, Granier A, Gross P, Grünwald T, Hollinger D, Janssen N-O, Katul G, Keronen P, Kowalski A, Lai CT, Law BE, Meyers T, Moncrieff J, Moors E, Munger JW, Pilegaard K, Rannik Ü, Rehmann C, Suyker A, Tenhunen J, Tu K, Verma S, Vesala T, Wilson K, Wofsy S, 2001: Gap filling strategies for defensible annual sums of net ecosystem exchange. *Agricultural and Forest Meteorology* **107**, 43–69.

Foreign Agricultural Service (FAS), United States Department of Agriculture, 2016: http://apps.fas.usda.gov/psdonline/psdDataPublications.aspx

Furumi S, Xiong Y, Fujiwara N, 2005: Establishment of an algorithm to estimate vegetation photosynthesis by pattern decomposition using multi-spectral data. *Journal of Remote Sensing Society of Japan* **25**, 47–59.

Gitelson AA, Gritz Y, Merzlyak MN, 2003: Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. *Journal of Plant Physiology* **160**, 271–282.

Gitelson AA, Vina A, Verma SB, Rundquist DC, Arkebauer TJ, Keydan G, Leavitt B, Ciganda V, Burba GG, Suyker AE, 2006: Relationship between gross primary production and chlorophyll content in crops: Implications for the synoptic monitoring of vegetation productivity. *Journal of Geophysical Research* **111**, D08S11.

Gitelson AA, Peng YJ, Masek G, Rundquist DC, Verma SB, Suyker A, Baker JM, Hatfield JL, Meyer T, 2012: Remote estimation of crop gross primary production with Landsat data. *Remote Sensing of Environment* **121**, 404–414.

Gitelson AA, Peng Y, Viña A, Arkebauer T, Schepers JS, 2016: Efficiency of chlorophyll in gross primary productivity: A proof of concept and application in crops. *Journal of Plant Physiology* **201**, 101–110.

Gu L, Baldocchi D, Verma BS, Black AT, Vesala T, Falge ME, Dowty RP, 2002: Advantages of diffuse radiation for terrestrial ecosystem productivity. *Journal of Geophysical Research* **107**-D6, 10.1029/2001JD001242.

Harazono Y, Chikamoto K, Kikkawa S, Iwata T, Nishida N, Ueyama M, Kitaya Y, Mano M, Miyata A, 2009: Application of MODIS-visible band index, greenery ratio to estimate CO$_2$ budget of a rice paddy in Japan. *Journal of Agriculture and Forest Meteorology* **146**, 357–364.

Heinisch FA, Zhao M, Running SW, Kimball JS, Nemani RR, Davis KJ, Bolstad PV, Cook BD, Desai AR, Ricciuto DM, Law BE, Oechel WC, Kwon H, Luo L, Wofsy SC, Dunn AL, Munger JW, Baldocchi DD, Xu L, Hollinger DY, Richardson AD, Stoy PC, Siqueira MBS, Monson RK, Burns SP, Flanagan LB, 2006: Evaluation of remote sensing based terrestri al productivity from MODIS using regional tower eddy flux network observations. *IEEE Transactions on Geoscience and Remote Sensing* **44**, 1908–1925.

Huntzinger DN, Post WM, Wei Y, Michalak AM, West TO, Jacobson AR, Baker IT, Chen JM, Davis KJ, Hayes DJ, Hoffman FM, Jain AK, Liu S, McGuire AD, Neilson RP, Potter C, Poulter B, Price D, Raczka BM, Tian HQ, Thornton P, Tomelleri E, Viovy N, Xiao J, Yuan W, Zeng N, Zhao M, Cook R, 2012: North American Carbon Program (NACP) regional interim synthesis: Terrestrial biospheric model inter-comparison. *Ecological Modeling* **232**, 144–157.

Ide R, Nakaji T, Oguma H, 2010: Assessment of canopy photosynthetic capacity and estimation of GPP by using spectral vegetation indices and the light-response function in a larch forest. *Agricultural and Forest Meteorology* **150**, 389–398.

Ishiihara M, Inoue Y, 2015: Evaluation of the effects of observer zenith angle on MODIS NDVI values by using radiative transfer model. *The Proceedings of 59th Meeting of the Remote Sensing Society of Japan*, 153–154.

Jacquemoud S, Verhoef W, Baret F, Bacour C, Zarco-Tejada PJ, Asner GP, Francois C, Ustin SL, 2009: PROSPECT+SAIL models: a review of use for vegetation characterization. *Remote Sensing of Environment* **113**, 556–566.

Mie G, 1908: Contributions to the optics of turbid media, particularly of colloidal metal solutions. *Library translation, Annalen der Physik* **25**, 377–445.

Mineshita Y, Muramatsu K, Soyama N, Thanyapraneedkul J, Daigo M, 2016: Determination of parameters for shrubs in the global gross primary production capacity estimation algorithm. *Journal of the Remote Sensing Society of Japan* **36**, 236–246.

Miyata A, Leuning R, Denmead TO, Kim J, Harazono Y, 2000: Carbon dioxide and methane fluxes from an intermittently flooded paddy field. *Agricultural and Forest Meteorology* **102**, 287–303.

Miyata A, Iwata T, Nagai H, Yamada T, Yoshikoshi H, Mano M, Ono K, Han G, Harazono Y, Ohtaki E, Baten M, Inohara S, Takimoto T, Saito M, 2005: Seasonal variation of carbon dioxide and methane fluxes at single cropping paddy fields in central and western Japan. *Phyton* **45**, 89–97.
Monteith J, 1972: Solar radiation and production in tropical ecosystems. *Journal of Applied Ecology* 9, 747–766.

MPK web site, Eddy covariance gap-filling & flux-partitioning tool, http://www.bgc-jena.mpg.de/~MDIwork/eddyproc/index.php (accessed on 26 May 2016).

Muramatsu K, Thanyapraneedkul J, Furumi S, Soyma N, Daigo M, 2012: Estimation of gross primary production capacity from global satellite observations. *SPIE Asia-Pacific Remote Sensing* 8524–21, 1–8.

National Astronomical Observation of Japan (NAOJ), National Institutes of Natural Sciences (NINS), 2016: *Chronological Scientific Tables*, Maruzen Publishing, pp. 585. (in Japanese)

Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC), 2014: MODIS subsetted land products, Collection 5. Available on-line [http://daac.ornl.gov/MODIS/modis.html] from ORNL DAAC, Oak Ridge, Tennessee, U.S.A. Accessed on May 28, 2016, Subset obtained for MOD09A1 product around sites of JP-MSE site, time period: Jan 1, 2000 to Dec. 31, 2015.

Pathre U, Sinha AK, Shirke PA, Sane PV, 1998: Factors determining the midday depression of photosynthesis in trees under monsoon climate. *Tree* 12, 472–481.

Peng Yi, Gitelson AA, Sakamoto T, 2013: Remote estimation of gross primary productivity in crops using MODIS 250 m data. *Remote Sensing of Environment* 128, 186–196.

Pessarakli M, 2005: *Handbook of Photosynthesis*, 2nd edition, CRC press, pp. 288.

Poulter B, Ciais P, Hodson E, Maignan F, Plummer S, Zimmermann NE, 2011: Plant functional type mapping for earth system models. *Geoscientific Model Development* 4, 993–1010.

Reichstein M, Falge E, Baldocchi D, Papale D, Aubinet M, Bernhofer C, Buchmann N, Gilmanov T, Granier A, Grünwald T, Havránková K, Ilvesniemi H, Janous D, Knohl A, Laurila T, Lohila A, Loustau D, Matteucci G, Meyers T, Miglietta F, Ourcival J-M, Panmpanen J, Rambal S, Rotenberg E, Sanz M, Tenhunen J, Seufert G, Vaccari F, Versala T, Yakir D, Valentini R, 2005: On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm. *Global Change Biology* 11, 1424–1439.

Running SW, Thornton PE, Nemani R, Glassy J, 2000: Global terrestrial gross and net primary productivity from the earth observing system. In *Methods in Ecosystem Science* (ed. by Sala OE, Jackson RB, Moony HA, Howarth RW). Springer, New York, pp. 44–57.

Saito M, Miyata A, Nagai H, Yamada T, 2005: Seasonal variation of carbon dioxide exchange in rice paddy field in Japan. *Agricultural and Forest Meteorology* 135, 93–109.

Sakamoto T, Yokozawa M, Toritani H, Shibayama M, Ishitsuka N, Ohno H, 2005: A crop phenology detection method using time-series MODIS data. *Remote Sensing of Environment* 96, 366–374.

Sakamoto T, Nguyen VN, Ohno H, Ishitsuka N, Yokozawa M, 2006: Spatio-temporal distribution of rice phenology and cropping systems in the Mekong Delta with special reference to the seasonal water flow of the Mekong and Bassac rivers. *Remote Sensing of Environment* 100, 1–16.

Salmon JM, Fried MA, Frolking S, Wisser D, Douglas EM, 2015: Global rain-fed, irrigated, and paddy croplands: A new high resolution map derived from remote sensing, crop inventories and climate data. *International Journal of Applied Earth Observation and Geo information* 38, 321–334.

Sellers PJ, Berry JA, Collatz GF, Field CB, Hall FG, 1992: Canopy reflectance, photosynthesis, and transpiration. III. A reanalysis using improved leaf models and a new canopy integration scheme. *Remote Sensing of Environment* 42, 187–216.

Thanyapraneedkul J, Muramatsu K, Daigo M, Furumi S, Soyma N, Nasahara NK, Muraoka H, Noda MH, Nagai S, Maeda T, Mano M, Mizoguchi Y, 2012: A vegetation index to estimate terrestrial gross primary production capacity for the global change observation mission-climate (GCOM-C)/second generation global imager (SGLI) satellite sensor. *Remote Sensing* 4, 3689–3720.

Vermote EF, El Saleous NZ, Justice CO, 2002: Atmospheric correction of the MODIS data in the visible to middle infrared: First results. *Remote Sensing of Environment* 83, 97–111.

Xiao X, Boles ST, Liu J, Zhuang D, Frolking S, Li C, Salas W, Moore III B, 2005: Mapping paddy rice fields in southern China. *Remote Sensing of Environment* 95, 480–492.
Fig. A1. MODIS reflectance data without cloud, cloud shadow, and aerosol flags. (a) the green band, and (b) the near infrared (NIR) band.

Fig. A2. Diurnal variation of GPP averaged over 8 days. (a) 2002, (b) 2003, (c) 2004, (d) 2005 and (e) 2006.
Fig. A3. Diurnal variation in photosynthetically active radiation (PAR) averaged over 8 days. (a) 2002, (b) 2003, (c) 2004, (d) 2005 and (e) 2006.
Fig. A4. Diurnal variation in VPD averaged over 8 days. (a) 2002, (b) 2003, (c) 2004, (d) 2005 and (e) 2006.
Fig. A5. Relationship between \( \text{PAR} \) and the \( \text{GPP}_{\text{capacity}} \), and light response curve for each 8-day period. (a) 2002, (b) 2003, (c) 2004, (d) 2005 and (e) 2006.