Applications of MODIS-visible bands index, greenery ratio to estimate CO₂ budget of a rice paddy in Japan

Yoshinobu HARAZONO* **, †, Kazuhiro CHIKAMOTO***, Shunsaku KIKKAWA***, Toru IWATA***, Nana NISHIDA**, Masahito UYEYAMA**, Yoshiaki KITAYA**, Masayoshi MANO****, and Akira MIYATA****

*International Arctic Research Center, University of Alaska Fairbanks, Fairbanks, AK, 99775 USA

**Graduate School of Life and Environmental Sciences, Osaka Prefecture University, Sakai, 599–8531, Japan

***Graduate School of Environmental Science, Okayama University, Okayama, 700–8530, Japan

****Agro-Meteorology Division, National Institute for Agro-Environmental Science, Tsukuba, 305–8604, Japan

Abstract

NDVI (Normalized Difference of Vegetation Index) was employed to estimate the carbon budget remotely with satellite data. However, NDVI has some difficulties in application to agricultural crops, boreal forest, and tundra ecosystems. We proposed a new vegetation index *GR* (greenery ratio) to detect the vegetation change remotely, and we applied it to estimate CO₂ budget of Japanese rice paddy with MODIS satellite data. *GR* was ratio of green (G) to the trichromatic visible bands (R+G+B) of MODIS, and an empirical GR-CO₂ budget model was developed as functions of MODIS-data and observed micrometeorology and fluxes at the rice paddy of Mase-site. The daily PAR (photosynthetically active radiation) was also estimated by MODIS. The parameterized model provided good performance to estimate daily magnitudes and seasonal trends of GPP (gross primary productivity), however, RE (ecosystem respiration) showed a little under-estimation, especially differed in late growing season. In contradiction to the observed CO₂ budget, the estimated budgets were 2% greater of GPP and 5% less of RE and 9% greater of NEE (net ecosystem exchange). The large discrepancy in NEE was owing to the poor estimation of RE after drainage. Further study to improve RE estimation was needed.

Key words: CO₂ budget, Greenery ratio, MODIS, Remote sensing, Rice paddy.

1. Introduction

Tower-based flux observations, such as FLUXNET (*e.g.* Baldocchi *et al.*, 2001) have been conducted widely to determine the carbon dioxide exchange (CO₂) between the atmosphere and each terrestrial ecosystem. However, the applicability of results is constrained spatially (<10⁴ to 10⁶ m²) by the limited locality of the tower flux footprint.

In order to measure the ecosystem carbon exchange spatially, remote-sensing techniques have been introduced. These techniques have the great advantage of detecting spatially the characteristics of surface

conditions at a glance (Gamon *et al.*, 1993). Satellite images covering a large area were widely applied to remote sensing studies, and the synthesis of field observation, remote sensing and modeling has become a good tool for detecting the carbon budget over terrestrial ecosystems (Stow *et al.*, 2004; Kimball *et al.*, 2006; Turner *et al.*, 2006).

Satellite remote sensing is useful for scaling up the point observations to estimate spatial patterns. NDVI (Normalized Difference of Vegetation Index) has been employed to estimate the carbon budget remotely (Goetz *et al.*, 1999). This provided many successful results on the terrestrial carbon budget study by synthesizing with tower based flux observations (Heinsch *et al.*, 2006; Kimball *et al.*, 2009). However, the application of NDVI derived from MODIS (moderate

Received; March 25, 2009.

Accepted; August 10, 2009.

†Corresponding Author: Y. harazono@uaf.edu

resolution imaging spectro-radiometer) to agricultural crops, boreal forest, and tundra ecosystems provided insufficient results (Xiao *et al.*, 2004; Gitelson *et al.*, 2006; Harazono *et al.*, 2007). Instead of NDVI, only visible bands have been applied as ground-based remote sensing and have succeeded in detecting vegetation phenology (Richardson *et al.*, 2007). However, the visible bands of satellites have seldom been applied to estimate the terrestrial carbon budget. We introduced a new index, the simple greenery ratio $GR = G/(R+G+B)$ of visible bands, to estimate gross primary productivity (GPP) remotely. The definition of GR and the detail of the components are shown in the latter section. In this paper, we examine the applicability of GR to estimate GPP for a rice paddy in central Japan by developing an empirical remote sensing model using the relationship between the MODIS derived GR and the observed tower-based CO_2 fluxes. This study is the first application of MODIS derived GR to estimate GPP of croplands. We also incorporated the unique scheme to estimate photosynthetically active radiation (PAR) at ground surface into the developed empirical remote-sensing model. This was the first application to calculate daily GPP of a cropland by using two parameters of GR and PAR derived from satellite data.

2. Methods

To examine the performance of the GR application to the rice paddy, we used the observed data obtained at Mase-site and the MODIS dataset covering the site area and the cultivation period in 2003. The empirical relationship among observed CO_2 flux, micrometeorology and spectrum characteristics of the MODIS are analyzed.

2.1 Observation site

A tower-based flux observation was carried out at a rice paddy of Mase-site beginning in 1999. The site is located at Tsukuba, Japan ($36^\circ 03' 14.3''$ N, $140^\circ 01' 36.9''$ E, elevation 11 m). The mean annual precipitation of the area is 1235.6 mm and the annual mean air temperature is 13.5°C (1971–2000; Tateno Observatory of the Japanese Meteorological Agency; 5 km east of the site). Around the site, artificially irrigated flat fields of single rice-crop extended to an area of 1.5 km from north to south by 1 km from east to west. The fields were managed following customary practices in central Japan. The rice (*Oriza sativa* L.; cultivar Koshihikari) was transplanted in early May

and harvested in early September. The field condition was standing water (ca. 3 cm in depth) from late April through mid-August, except for two temporary drainage periods in the middle of the growing season. Details of the field management and condition are shown in previous papers (Miyata *et al.*, 2005; Saito *et al.*, 2005).

2.2 Flux and micrometeorology measurements

Micrometeorology—such as wind speed, temperature, humidity, and radiation (long, short, and PAR)—was measured in a selected plot (50 m $\times$ 100 m) at the center of the area. Fluxes were measured by the eddy correlation method; the fluctuations of wind velocity, temperature, and densities of CO_2 and H_2O were measured at a 10 Hz sampling rate at a height of 3.2 m above the ground, using a sonic anemometer (DA-600; Kaijo, Japan) and an open-path infrared gas analyzer, IRGA (LI-7500; Li-Cor, USA). Data were compiled at half-hourly averages after quality control.

Before calculating the eddy correlations, wind velocity components were rotated so that the time-averaged lateral and vertical components were zero (Tanner and Thurtell, 1969). The influence of humidity and crosswinds on the sonic temperature measurement was corrected (Kaimal and Gaynor, 1991; Hignett, 1992), and high-frequency losses in the co-spectrum due to path-length averaging and the sensor separation between the anemometer and the IRGA were corrected following Massman (2000, 2001) and Rannik (2001). The effect of air density fluctuations on the measurement of CO_2 and H_2O fluxes was corrected following Webb *et al.* (1980). Quality control of the fluxes at the Mase-site was presented by Mano *et al.* (2007).

Each covariance of CO_2 , H_2O , sensible heat and momentum was calculated at half-hour intervals, providing half-hourly eddy fluxes. The CO_2 storage below the eddy flux measurement point was also calculated every half-hour using a CO_2 concentration profile. Then the sum of the eddy CO_2 flux and the CO_2 storage term provided the half-hourly net ecosystem exchange (NEE). In this paper, negative and positive NEE means a net sink and source of atmospheric CO_2 , respectively. Observed NEE was divided into gross primary productivity (GPP) and ecosystem respiration (RE) by using measured micrometeorology in which relationships between PAR and GPP, and between air temperature and RE were analyzed. Details of data analysis and some results of the Mase-site were

shown in previous papers (Saito *et al.*, 2005; Miyata *et al.*, 2005).

2.3 Satellite data

The products of the MODIS are widely distributed and available to develop the estimation method of ecosystem productivity remotely (Justice *et al.*, 1998; Running *et al.*, 2004). As shown in Table 1, we used 8-day composite surface reflectance of MOD09A1 to determine the vegetation index *GR*, daily band-1 of MOD09GQ for daily PAR, and daily surface temperature (LST) of MOD11A1 for air temperature (Justice *et al.*, 1998; Wan *et al.*, 2002). Composite data in MODIS are the highest values during each period.

Several pixels covering the Mase area were selected to examine the relationships among observed factors and selected bands. The numbers of analyzed pixels were different depending on each spatial resolution and error flag specifying the availability of MODIS data. We excluded error specified data from analysis, and some data contaminated by clouds were also excluded. This resulted in different pixel numbers (1-9) for each analysis.

2.4 Greenery Ratio, *GR* and CO₂ budget calculation model

NDVI is a popular vegetation index of the remote sensing study and is widely applied (Tucker and Sellers, 1986; Kitamoto *et al.*, 2007). However, time series of NDVI at cropland and arctic tundra did not follow the observed seasonality of leaf area index (LAI) or NEE of the targeted vegetations (Harazono *et al.*, 2007). We introduced the new vegetation index, greenery ratio (*GR*) derived from satellite remote-sensing data as the following formula. *GR* is a simple ratio of green (*G*, band-4, 545-565 nm) to total visible-bands (*R*, red, band-1, 630-670 nm; *G*; *B*, blue, band-3, 459-479 nm) of MODIS data.

$$GR = G / (R + G + B) \quad (1)$$

The coefficients of determination (*R*²) between GPP

and *GR* and other vegetation indexes for the 2003 season were examined for comparison. They were 0.925 (*n*=11) for *GR*, 0.827 (*n*=12) for NDVI, 0.352 (*n*=14) for EVI (enhanced vegetation index) and 0.172 (*n*=17) for MSI (moisture stress index), respectively (definitions are shown in Xiao *et al.*, 2004).

We found unsuitable *GR* caused by cloud contamination, in which the reflectance of band-3 (*B*) of the contaminated pixel was apparently large, thus, the unsuitable *GR* was eliminated. The threshold was set as the *B*-reflectance-ratio (band-3 to total visible-bands) of 28%. Since *GR* was determined at an 8-day interval, the eliminated *GR* was complemented for consecutive analysis by a fitted fourth-polynomial curve of the remaining *GR*.

In order to estimate the observed CO₂ flux (g CO₂ m⁻² h⁻¹) by applying *GR*, we developed a satellite-based empirical model, GR-CO₂ budget model (Fig. 1), which was constructed by calculations of GPP (equation 2, hereafter cited as Eq.2) and ecosystem respiration (RE, Eq.5). GPP (g CO₂ m⁻² h⁻¹) is a rectangular hyperbola function of PAR (mol m⁻² h⁻¹) and *GR* (the implicit function of *P*_{max} (g CO₂ m⁻² h⁻¹)) and RE is an exponential function of air temperature (*T*_a, function of LST). Where, *P*_{max} is the maximum level of the GPP-PAR curve and *α* (g CO₂ mol⁻¹), the initial slope of the curve of the Eq.2.

$$GPP = \frac{P_{\max} \times \alpha \times PAR}{P_{\max} + \alpha \times PAR} \quad (2)$$

The parameter set of GPP (*P*_{max} and *α*) was determined by curve-fit (GPP-PAR curve) of Eq.2 applying the measured GPP and PAR, in which measured data were divided to 18-terms of the *GR* determination period (every 8-days). As a result, 18 sets of the parameters were obtained during day of year (DOY) 122 and 262, 2003. Applied parameters, *P*_{max} and *α* in this study were determined from Mase-site data during the 2003 cultivation season. *P*_{max} changed with

Table 1. MODIS products that applied in this study.

Data type	Products	Frequency	Name	Resolution (m)
Surface Reflectance	MOD09A1	8-day Composite	Band-1	500
			Band-3	500
	MOD09GQ	Daily	Band-1	250
Land Surface Temp.	MOD11A1	Daily	LST	1000

Fig. 1. Model scheme and relationship among satellite data (inputs) and observed data for parameterization of GR-CO₂ budget model.

a single peak of rice developing stage and α was set as a constant of 2 g CO₂ mol⁻¹. GR was defined as a linear function of P_{max} to execute the GR-CO₂ budget model. The regression coefficient and the interception were determined as $P_{max}=11.90 \times GR - 4.6464$ ($R^2=0.843$, $n=18$).

PAR was calculated by Eq.3 using the radiation at the top of atmosphere (Q) and the transmittance factor within the atmosphere (fT) (Nasahara, 2009). Hourly Q was determined following the calculation scheme of an URL by Nakagawa (http://es.ris.ac.jp/~nakagawa/met_cal/solar.html) and fT was defined as Eq.4.

$$PAR = Q \times fT \quad (3)$$

$$fT = \frac{1 - Ra - (a + b \times Ra)}{1 - Rg} \quad (4)$$

where, Ra is reflectance of band-1 at the top of the atmosphere and Rg is that at the ground surface. Parameters of a and b in Eq.4 are indexes of absorption and scattering of PAR in the atmosphere, which were determined as daily basis by linear regression of absorbed PAR in the atmosphere ($a+b \times Ra$ in Eq.4) applying Ra and measured PAR at Mase-site in 2003. These were $a=-0.787$ and $b=0.758$ ($R^2=0.971$, $n=365$), respectively. Daily MOD09GQ was applied to Ra and the minimum within two terms of 8-day composite MOD09A1 was applied to Rg , which provided the calculation of fT as a constant within a day. Thus, hourly Q and fT provide hourly PAR for

GPP calculation.

RE is commonly parameterized as an exponential function of soil or surface temperature with temperature sensitivity coefficient Q_{10} , while we parameterized RE as the exponential function of air temperature (Ta) (Eq.5). R_0 is basic ecosystem respiration at air temperature of 0°C, which was determined as $R_0=0.8072$ g CO₂ m⁻² d⁻¹ and $Q_{10}=0.1339$ by fitting to Eq.5 using the measured daily RE and daily average Ta at Mase-site during the 2003 cultivation period ($n=141$).

In order to estimate Ta from MODIS, we parameterized Ta as a linear function of surface temperature (LST) of MOD11A1-daily (Eq. 6). LST was provided daily basis; however, there were many data gaps caused by unsuitable weather (gap-rate 79%), so that we used the 8-day average of both daytime LST and nighttime LST (MOD11A1-day and MOD11A1-night) to determine the parameter. The regression coefficient and the offset between 8-day averaged measured Ta and LST were 1.251 and -9.856 ($R^2=0.720$, $n=18$).

$$RE = R_0 \times \exp(\ln(Q_{10})/10 \times Ta) \quad (5)$$

$$Ta = 1.251 \times LST - 9.856 \quad (6)$$

The model empirically calculates GPP and RE using satellite variables of GR , PAR , and LST. Again, GR was determined at 8-day intervals of MOD09A1, and PAR was calculated hourly. Thus, GPP was calculated hourly and compiled as daily summations for analysis. Ta was determined for 8-day intervals by 8-day averages of both LST-day and LST-night of MOD11A1-daily. Thus, RE was calculated at 8-day intervals. NEE was calculated by the difference between GPP and RE finally.

3. Results and Discussions

3.1 PAR calculation

The unique point of this study is that the GPP was calculated as hourly basis by applying the calculated PAR and then summarized as a daily GPP. Fig. 2 shows the comparison of estimated and measured PAR (daily summation) at Mase-area over the rice-growing period in 2003. The weather during the growing period was unusual. The air temperature was cool and the rainy season (Baiu) continued until early August, resulting in many rainy days and fluctuating daily radiation (Miyata *et al.*, 2005).

The daily variation of estimated PAR showed quite

Fig. 2. Daily variations of observed PAR at the Mase-site and that calculated by applying daily MOD09GQ following Nasahara (2009).

close daily variations to the observed PAR. The observed PAR fluctuated evidently day-by-day in 2003. The introduction of the PAR calculation scheme improved the PAR estimation at the same accuracy as the measured PAR at the ground surface. The regression coefficient between the observed daily PAR and estimated daily PAR was 1.037, and the offset was $0.60 \text{ mol m}^{-2} \text{ d}^{-1}$ ($R^2=0.78$, $n=365$).

Most products of satellite remote sensing were provided as 8-10 day composite. The mostly higher numbers during the measured period provided an overestimation of applied results. The high number of the composite PAR should provide an overestimate compared to the actual GPP. Thus, the introduction of the PAR estimation scheme in this study, the accurate input of the GR-CO₂ budget model, might provide great advantage to the GPP calculation.

3.2 GPP calculation

Daily variations of calculated GPP and observed GPP were shown in Fig. 3. Since the weather was unstable in summer 2003, the GPP was not high compared to normal years during the peak period between DOY 190 and 210. In early August 2003, daily GPP levels were lower than those before DOY 190 and after DOY 210. The daily variation and the seasonal trend of calculated GPP were almost the same as those observed, and the GPP levels each day agreed well with those observed. The regression coefficient between the observed GPP and calculated GPP was 0.98, and the offset was only $0.068 \text{ g CO}_2 \text{ m}^{-2} \text{ d}^{-1}$ ($R^2=0.79$, $n=141$). The GPP of the rice paddy was reproduced well by the current GR-CO₂ budget model.

Remote sensing estimation of terrestrial carbon budget tended to fail when the weather was unstable.

Fig. 3. Daily variations showing the seasonal trend of observed GPP and calculated by GR- CO₂ budget model for the Mase-site.

However, the MODIS derived *GR* application to a rice paddy in Japan provided good agreements in GPP, even though the weather was rainy and the temperature was low during the mid-summer. The performed results approved the performance of *GR* as a vegetation index and the applicability of *GR* to croplands. Also, the PAR estimation scheme introduced in this study performed well in reproducing the daily GPP in unstable weather conditions.

3.3 RE calculation

We defined the ecosystem respiration (RE) of the rice paddy at Mase-site as an exponential function of air temperature (T_a) shown in Eq.5, which required T_a to be calculated from the satellite variable LST (Eq.6).

Fig. 4 shows the seasonal trends of observed daily T_a (line), the 8-day average with standard deviation (dot and vertical bar), and estimated 8-day T_a (open circle) calculated by Eq.6. The differences between observed and estimated were remarkable after DOY 210. Since LST was determined using daily data of MOD11A1 as an average for the term of the 8-day (MOD11A1 composite), however, the limited numbers (21%) of available LST for parameterization did not provide the reasonable T_a trend as parallel as the trend of observed (8-day average) T_a . Although, two-thirds of estimated T_a were within the standard deviation of the observed T_a , the estimated T_a included still some uncertainty. Thus, T_a was set as a stepwise variable for RE calculation, namely, a constant of the Eq.5 within each 8-day term.

Calculated RE (broken line), observed RE (line) and the 8-day average with standard deviation (dot with vertical bar) are shown in Fig. 5. Calculated RE was an 8-day average that reasonably agreed with observed

Fig. 4. Daily variations of observed T_a (line), its 8-day average with standard deviation (dot with vertical bar) at the Mase-site and estimated T_a (open circle) as 8-day average.

Fig. 5. Daily variations of observed RE (line), its 8-day average with standard deviation (dot with vertical bar) at the Mase-site and calculated RE (dashed line) for 8-day intervals.

RE before DOY 210, but was an underestimation after DOY 210. A little underestimation of T_a after DOY 210 under high temperature conditions resulted in a remarkable underestimation in RE. Underestimated RE might be partially caused by the miss-determination of parameters in Eq.5 by fitted for low summer temperature. Also, the rice paddy at Mase-site was drained for rice harvest after DOY 230, causing high CO_2 emission compared to the flooded conditions, when standing water prevents CO_2 emission from the soil layer (Miyata *et al.*, 2000). Considering that the air temperature was over 20°C and the observed RE was high after DOY 210, the water level of the rice paddy and the seasonal change in rice biomass have to be incorporated as parameters in the GR- CO_2 budget model to improve the RE estimation.

3.4 NEE and CO_2 budget during the growing period in 2003.

Since the GPP was well reproduced by the current GR- CO_2 budget model with satellite variables of GR and PAR , the new vegetation index GR was approved as a good vegetation index to simulate GPP remotely. NEE is the balance of GPP and RE, and NEE has been widely observed in various vegetations in the world as flux-network (Baldocchi *et al.*, 2001). If the GR application is also approved to calculate NEE remotely, it may provide great advantages to up-scale the tower base flux observations.

Fig. 6 shows the daily variations of observed NEE at Mase-site and the calculated NEE by the GR- CO_2 budget model for Mase-site. Observed NEE changed from positive (CO_2 source) to negative (CO_2 sink) around DOY 145, 2003. Daily levels of calculated NEE and the seasonal trends were almost the same as those observed until DOY 230, even though the weather in summer 2003 was unusual. On the other hand,

Fig. 6. Daily variations of observed NEE (line) and calculated NEE (dashed line with open circle) for rice paddy at Mase-site.

Fig. 7. Comparisons of cumulative CO_2 budget among observed NEE (box), GPP (open circle), RE (dot) and each estimations by the current GR- CO_2 budget model for rice paddy at Mase-site.

there was a remarkable difference between observed NEE and calculated NEE after DOY 230; calculated NEE was more negative than observed NEE, and the calculated negative NEE continued until end of rice cultivation (harvest day). Since there was little discrepancy between observed GPP and calculated GPP as shown in Fig. 3, the difference in NEE after DOY 230 was caused by the uncertainty of RE estimation. In order to improve the accuracy in NEE calculation, we have to improve the surface temperature estimation as a remote sensing study. Also, the sub-model for the drained periods of the rice field has to be incorporated into the RE calculation.

The trends of cumulative CO₂ budgets of GPP, RE, and NEE are shown in Fig. 7 for comparisons between observed and estimated. GPP was continuously reproduced well from the beginning of the rice cultivation period to the harvest. On the other hand, RE was underestimated after DOY 230, and NEE was also overestimated. The final CO₂ budgets at Mase-site during the 2003 growing season were observed as 3364 g CO₂ m⁻² of GPP and 1890 g CO₂ m⁻² of RE, resulting in 1474 g CO₂ m⁻² of sink NEE. Contrary to the observation, the estimated budgets were 2% greater GPP, and 5% less RE, resulting in 9% greater NEE. The determination coefficients of the regressions between observed and calculated were $R^2=0.918$ for GPP ($n=18$), 0.671 for RE ($n=18$), and 0.838 for NEE ($n=18$), respectively.

The level of GPP relates to the photosynthetic activity of plants, which depends on the absorption of PAR as a photochemical reaction of chloroplast. The absorbed spectrum by chlorophyll (A and B) and carotene (α , β and γ) of the photosynthesis are detected as low reflectance of band-1 (R) and band-3 (B) of MODIS, and the reflectance of band-4 (G) is an indicator of live becomes. When the vegetation is vigorous with high number of LAI, the G -reflectance becomes high and both R -reflectance and B -reflectance become low, resulting in high GR is calculated. Thus, GR tended to increase with increase of photosynthetic activity of vegetations and increase of LAI, indicating the development of vegetations. While, less activity of vegetation caused by senescence, stresses of temperature, long-term insufficient PAR during rainy seasons, and damages by insect and disease might be reflected as lower GR .

GR was examined for applicability to other vegetation. It was approved for wet tundra in arctic Alaska

with good estimation of CO₂ budget (Harazono *et al.*, 2008). However, we failed for the black spruce forest in interior Alaska, where sparse trees are main stands and bushes with tussock tundra are distributed as understory plants. From the limited examples of GR application and the preliminary discussion above, we suggest that GR is a good vegetation index to apply to vegetation with almost homogeneous canopy structure, and that seasonal changes of vegetation activity may be detected effectively. Further studies on the applicability and limitations of GR for many vegetation types have to be examined. Then the characteristics of the GR - P_{max} relationship and other parameter relationships with GR (implicit functions of GPP) might be analyzed to improve the estimation and to synthesize the flux observation network and the satellite remote sensing.

The great advantage of remote sensing is the ability to provide regional estimates of CO₂ budget. Kikkawa *et al.* (2008) estimated the regional CO₂ budget of a rice paddy by the current GR application scheme for the Chugoku-region in Japan (ca. 500 km×300 km), and obtained reasonable results. Although, the CO₂ budget was calculated well as pixel level (locally), the different development stages within the area caused by different field managements and the differences in cultivars made it difficult to obtain accurate estimates regionally.

4. Conclusions

A new vegetation index GR developed to detect the vegetation change remotely was applied to estimate the CO₂ budget of a rice paddy. GR was derived from visible bands of MODIS, and a GR -CO₂ budget model was parameterized as functions of satellite data of MODIS. The model applied to a rice paddy at Mase-site in Japan performed well in estimating daily magnitudes and seasonal trends of GPP, but it underestimated RE, especially late in the growing season during drained soil conditions. Contrary to the observed CO₂ budget, the estimated budgets were 2% greater GPP and 5% less RE and 9% greater NEE. The large discrepancy in NEE was owing to the poor estimation of RE after drainage.

Acknowledgements

The study was partly supported by the Terrestrial Carbon Management of Asia in the 21st Century Based on Scientific Advancement by the Global Environment

Research Fund (S-1) of the Ministry of the Environment, and also supported by IARC-JAXA-Information System Study, funded by both JAXA-Japan and NSF-IARC-USA. Useful comments and suggestions by reviewers of the journal, and the edition by Mr. Tom Alton of IARC contributed to improve the manuscript. We thank these supporters and contributors.

References

- Aubinet, M., Grelle, A., Ibrom, A., Rannik, U., Moncrieff, J., Foken, T., Kowalski, A. S., Martin, P. H., Berbigier, P., Bernhofer, Ch., Clement, R., Elbers, J., Granier, A., Grünwald, T., Morgenstern, K., Pilegaard, K., Rebmann, C., Snijders, W., Valentini, R., and Vesala, T., 2000: Estimates of the annual net carbon and water exchange of forests: The EUROFLUX Methodology. *Adv. Ecol. Res.* **30**, 113–175.
- 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 U, K. T., Pilegaard, K., Schmid, H. P., Valentini, R., Verma, S., Vesala, T., Wilson, K., and 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. *Bull. Amer. Meteorol. Soc.*, **82**, 2415–2434.
- Gamon, J. A., Field, C. B., Roberts, D. A., Ustin, S. L., and Valentini, R., 1993: Functional patterns in an annual grassland during an AVIRIS overflight. *Remote Sens. Environ.*, **44**, 293–253.
- Gitelson, A. A., Vina, A., Verma, S. B., Rundquist, D. C., Arkebauer, T. J., Burba, G. G., and Suyker A. E., 2006: Relationship between gross primary production and chlorophyll content in crops: Implications for the synoptic monitoring of vegetation productivity. *JGR*, **111**, D08S11, doi:10.1029/2005JD006017.
- Goetz, S. J., Prince, S. D., Goward, S. N., Thawley, M. M., and Small, J., 1999: Satellite remote sensing of primary production: an improved production efficiency modeling approach. *Ecol. Model.*, **122**, 239–255.
- Harazono, Y., Nishida, N., Kitaya, Y., Ueyama, M., and Oechel, W. C., 2007: Application of greenery ratio (visible trichromatic strengths) to estimate stand scale CO₂ budget. *Proc. 7th International Workshop, Global Change Connection to the Arctic (GCCA7)*, 312–315.
- Harazono, Y., Nishida, N., Ueyama, M., Kitaya, Y., and Oechel, W. C., 2008: Regional estimation of CO₂ budget over arctic wet tundra by applying MODIS-visible bands. *Proc. First International Symposium, Arctic Research (ISAR-I)*, 379–382.
- Heinsch, F. A., Zhao, M., Running, S. W., Kimball, J. S., Nemani, R. R., Davis, K. J., Bolstad, P. V., Cook, B. D., Desai, A. R., Ricciuto, D. M., Law, B. E., Oechel, W. C., Kwon, H., Luo, H., Wofsy, S. C., Dunn, A. L., Munger, J. W., Baldocchi, D. D., Xu, L., Hollinger, D. Y., Richardson, A. D., Stoy, P. C., Siqueira, M. B. S., Monson, R. K., Burns, S. P., and Flanagan, L. B., 2006: Evaluation of remote sensing based terrestrial productivity from MODIS using regional tower eddy flux network observations. *IEEE Geosci. Remote Sens.*, **44**, 1908–1925.
- Hignett, P., 1992: Corrections to temperature measurements with a sonic anemometer. *Bound.-Layer Meteorol.*, **61**, 175–187.
- Justice, C. O., Vermote, E., Townshend, J. R., Defries, R., Roy, D. P., Hall, D. K., Salomonson, V. V., Privette, J. L., Riggs, G., Strahler, A., Lucht, W., Myneni, R. B., Knyazikhin, Y., Running, S. W., Nemani, R. R., Wan, Z., Huete, A. R., van Leeuwen, W., Wolfe, R. E., Giglio, L., Muller, J., Lewis, P., and Barnsley, M. J. 1998: The moderate resolution imaging spectroradiometer (MODIS): Land remote sensing for global research. *IEEE Geosci. Remote Sens.*, **36**, 1228–1249.
- Kaimal, J. C., and Gaynor, J. E., 1991: Another look at sonic thermometry. *Bound.-Layer Meteorol.* **56**, 401–410.
- Kikkawa, S., Takimoto, T., Iwata, T., and Yamamoto, S., 2008: Estimation of regional CO₂ flux in rice paddy field using MODIS data, *Abst. 7th AsiaFlux Workshop*, 57, Seoul, Korea, Nov. 17–19, 2008.
- Kimball, K. S., Zhao, M., McDonald, K. C., and Running, S. W., 2006: Satellite remote sensing of terrestrial net primary production of the pan-arctic basin and Alaska. *Mitigation and Adaptation Strategies for Global Change*, doi: 10.1007/s11027-005-9014-5.
- Kimball, K. S., Jones, L. A., Zhang, K., Heinsch, F. A., McDonald, K. C., and Oechel, W. C., 2009: A satellite approach to estimate land-atmosphere CO₂ exchange for boreal and Arctic biomes using MODIS and AMSR-E. *IEEE Geosci. Remote Sens.*, **47**, 569–587.
- Kitamoto, T., Ueyama, M., Harazono, Y., Iwata, T., and Yamamoto, S., 2007: Applications of NOAA/

- AVHRR and observed fluxes to estimate carbon budget at Alaska black spruce forests. *J. Agric. Meteorol.*, **63**, 171–183.
- Mano, M., Miyata, A., Yasuda, Y., Nagai, H., Yamada, T., Ono, K., Saito, M., and Kobayashi, Y., 2007: Quality control for the open-path eddy covariance data, *J. Agric. Meteorol.*, **63**, 125–138, 2007.
- Massman, W. J., 2000: A simple method for estimating frequency response corrections for eddy covariance systems. *Agric. For. Meteorol.*, **104**, 185–198.
- Massman, W. J., 2001: Reply to comment by Rannik on “A simple method for estimating frequency response corrections for eddy covariance systems”. *Agric. For. Meteorol.*, **107**, 247–251.
- Miyata, A., Leuning, R., Denmead, O. T., Kim, J., and Harazono, Y., 2000: Carbon dioxide and methane fluxes from an intermittently flooded paddy field. *Agric. For. Meteorol.*, **102**, 287–303.
- Miyata, A., Iwata, T., Nagai, H., Yamada, T., Yoshikoshi, H., Mano, M., Ono, K., Han, G. H., Harazono, Y., Ohtaki, E., Baten, M. A., Inohara, S., Takimoto, T., and Saito, S., 2005: Seasonal variation of carbon dioxide and methane fluxes at single cropping paddy fields in central and western Japan. *Phyton*, **45**(4), 89–97.
- Nasahara, N. K., 2009: Simple algorithm for estimation of photosynthetically active radiation (PAR) using satellite data. *SOLA*, **5**, 37–40.
- Rannik, U., 2001: A comment on paper by W. J. Massman ‘A simple method for estimating frequency response corrections for eddy covariance systems’. *Agric. For. Meteorol.*, **107**, 241–245.
- Richardson, A. D., Jenkins, J. P., Braswell, B. H., Hollinger, D. Y., Ollinger, S. V., and Smith, M-L., 2007: Use of digital webcam images to track spring green-up in a deciduous broadleaf forest. *Oecologia*, **152**, 323–334.
- Running, S. W., Namani, R. R., Heinsch, F. A., Zhao, M., Reeves, M., and Hashimoto, H., 2004: A continuous satellite-derived measure of global terrestrial primary production. *Bio Sci.*, **54**, 547–560.
- Saito, M., Miyata, A., Nagai, H., and Yamada, T., 2005: Seasonal variation of carbon dioxide exchange in rice paddy field in Japan. *Agric. For. Meteorol.*, **135**, 93–109.
- Stow, D. A., and other 23 authors, 2004: Remote sensing of vegetation and land-cover change in Arctic Tundra Ecosystems. *Remote Sens. Environ.*, **89**, 281–308.
- Tucker, C. J., and Sellers, P. J., 1986: Satellite remote sensing of primary production. *Int. J. Remote Sens.*, **7**, 1295–1416.
- Turner, D. P., Ritts, W. D., Cohen, W. B., Gower, S. T., Running, S. W., Zhao, M., Costa, M. H., Kirschbaum, A. A., Ham, J. M., Saleska, S. R., and Ahl, D. E., 2006: Evaluation of MODIS NPP and GPP products across multiple biome. *Remote Sens. Environ.*, **102**, 282–292.
- Wan, Z., Zhang, Y., Zhang, Q., and Li, Z. I., 2002: Validation of the land-surface temperature products retrieved from Terra Moderate Resolution Imaging Spectroradiometer data. *Remote Sens. Environ.*, **83**, 163–180.
- Webb, E. K., Pearman, G. I., and Leuning, R., 1980: Correction of flux measurements for density effects due to heat and water vapour transfer. *Q. J. R. Met. Soc.*, **106**, 85–100.
- Xiao, X., Hollinger, D., Aber, J., Goltz M., Davidson, E. A., Zhang, Q., and Moore, B., 2004: Satellite-based modeling of gross primary production in an evergreen needleleaf forest. *Remote Sens. Environ.*, **89**, 519–534.

MODIS 可視画像による指標，緑色度を用いた 日本の水田の CO₂ 収支評価

原藺芳信 *・***・近本一宏 **・吉川俊作 **・岩田 徹 **・西田奈菜 ***・
植山雅仁 ***・北宅善昭 ***・間野正義 ****・宮田 明 ****

* 国際北極圏研究センター
** 岡山大学大学院環境科学研究科
*** 大阪府大学大学院生命環境科学研究科
**** 農業環境技術研究所大気環境研究領域

要 約

陸域生態系の CO₂ 収支を明らかにするために，タワーを用いたフラックス観測が行われているが，その群落境界層の影響範囲の制限から，広域的に評価するには限界がある。これを広い地域レベルで評価するために，リモートセンシングが用いられ，従来 NDVI を植生指標として利用することが多かった。しかし，一部の植生や農耕地では NDVI が必ずしも良い指標となっていなかった。筆者らは MODIS 衛星データの中の可視波長を用いた新たな植生指標，GR (緑色比) を提案し，GR をリモートセンシングの指標として水田の CO₂ 収支を評価するモデルを構築し，妥当性を検証した。

茨城県真瀬のフラックス観測サイトの 2003 年度のデータを用い，MOD09 および MOD11 データをモデルに適用して，総一次生産量 (GPP) と生態系呼吸量 (RE) ならびに両者の差である生態系交換量 (NEE) を評価し

た。GR は MOD09 (8-day) から求め，これと MOD09 から日別に推定した光合成有効放射 PAR を変数として日別の GPP を計算した。RE の評価では，地上気温 T_a を MOD11 の 8 日平均 LST から推定して 8 日毎の値として求めた。

2003 年は冷夏で 8 月上旬まで天候不順であったが，GPP は高い精度で再現できた。RE も妥当な再現性であったが，生育後期に過小評価となった。生育期全体では，観測値に対して GPP は 102%，RE は 95% となり，結果，NEE は 109% と過大評価になった。以上の結果から，新指標 GR は農耕地の CO₂ 収支評価に有効であることが確かめられた。

キーワード：衛星データ，CO₂ 収支，水田，リモートセンシング，緑色比