Estimation of Net Primary Production for Paddy Fields of Nara Basin in Japan Using LANDSAT/ETM＋ Data

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ABSTRACT

An new algorithm was developed for the estimation of net primary production. The algorithm needs a vegetation index VIPD obtained from multi-spectral reflectance data and some climate data. The validation of this algorithm should be carried out for vegetation of various types and climate area. In previous study, it is concluded that NPP estimated from Landsat/TM or ETM＋ data agrees with the ground truth data for grass fields in Mongolia and cedar forest in Japan. This study concentrates paddy fields of Kansai Area in Japan and compared the estimated NPP with the ground truth data. As a result, it was clear that the estimated value is about a half of ground truth data.

1 INTRODUCTION

Release of carbon dioxide into the atmosphere causes global warming and understanding of carbon cycle in the terrestrial, ocean, atmosphere is very important. Vegetation is carbon stock by absorbing carbon dioxide via photosynthetic activity.

Remotely-sensed data can thus be used to estimate net primary production (NPP) by vegetation. Many estimation methods have been developed and global NPP distribution map was produced using NOAA/AVHRR and Terra/MODIS data. Most of research using these satellite data is based on LUE (Light Use Efficiency) model. In LUE model, the light energy absorbed by vegetation is used for photosynthesis with an efficiency ε. Thus, photosynthesis P (assimilated carbon dioxide) is described as following equation.

$$P = \varepsilon \times fAPAR \times PAR \tag{1}$$

Here, PAR is photosynthetic active radiation incident to vegetation and fAPAR is fraction of absorbed PAR.

Satellite data is mainly used for obtaining fAPAR according to the study that normalized difference vegetation index (NDVI) is linear to fAPAR. Also, multi-spectral data observed by MODIS are used for the estimation of the other vegetation parameters such as Leaf Area Index (LAI). In addition to these vegetation parameters, numerous environmental parameters such as air temperature and humidity are also used as input parameters for the physiologically based models(e.g., BIOME-BGC (Running 1988, 1993)).

We have developed a NPP estimation algorithm for the purpose of simple calculation using satellite multi-spectral data. The estimation algorithm needs a vegetation index VIPD (vegetation index based on pattern decomposition method) obtained from satellite data and climate data such as solar radiation and air temperature. At present, the estimated NPP is productivity without considering vegetation stress constraint the photosynthesis. For the modification and validation of the algorithm, it is necessary to apply the method to satellite data and examine the applicability for vegetation of various types and climate area. By now, we studied about NPP of grass fields in Mongolia and cedar forest in Japan and confirmed that the NPP estimated from Landsat/ETM＋ data agrees with the ground truth data. In this study, we estimate the NPP of paddy fields in Nara basin of Japan using Landsat/TM and ETM＋ data and compare the result with NPP obtained from the rice yield data.

2　Algorithm For Estimation of Net Primary Production Using Multi-Spectral Data

2. 1　Vegetation Index Used for NPP Estimation

The NPP estimation algorithm is based on a vegetation index (VIPD). VIPD is calculated from the pattern decomposition coefficient obtained by pattern decomposition method (PDM) (Muramatsu, 2000). PDM was developed for land-feature extraction and data reduction of multi-spectral reflectance data observed by satellite sensors. The method is based on spectral linear mixture analysis(Adams, 1986) and fixes three standard patterns ： water, vegetation, and soil. Using the PDM, we can obtain the three decomposition coefficients from multi-spectral reflectance data as follows :

$$A(1)=C_w\times P_w(1)+C_v\times P_v(1)+C_s\times P_s(1)+\varepsilon(1) \tag{2}$$
$$\vdots$$
$$A(n)=C_w\times P_w(n)+C_v\times P_v(n)+C_s\times P_s(n)+\varepsilon(n)$$

Reflectance of band i is given as $A(i)$, and $P_w(i)$, $P_v(i)$, and $P_s(i)$ are the standard patterns of water, vegetation, and soil, respectively. The remainder of each band is given as $\varepsilon(i)$, and n represents the number of bands. The patterns $P_{w,v,s}(i)$ are normalized so that the summation over the used bands is one. Coefficients of water (C_w), vegetation (C_v), and soil (C_s) are determined by the least squares method so that $\Sigma\varepsilon(i)^2$ is as small as possible.

In this study, we used Landsat/TM and ETM＋ wavelength bands as an example and analyzed the reflectance data of six bands (bands 1–5 and 7), with the exception of the thermal bands.

The following equation calculates the vegetation index based on pattern decomposition (VIPD) (Hayashi, 1998) :

$$VIPD=\frac{C_v-C_s-\dfrac{S_s}{\sum A(i)}\cdot C_w+S_s}{S_v+S_s} \tag{3}$$

Here, S_v and S_s are the sum of reflectance over all bands for the standard vegetation and soil samples, respectively. These parameters are constant. The VIPD value is approximately one for a standard vegetation sample and approximately zero for non-vegetative objects and inactive vegetation such as dead leaves. The PDM is based on spectral linear mixture analysis ; the three coefficients are linear to the ratio of vegetation cover in an observed area. Therefore, the VIPD is linear to the vegetation cover ratio (Hayashi, 1998).The VIPD is also linear to quantum efficiency *(QE)* (Furumi, 2002). *QE* is a initial slope of light-photosynthetic curve and controls the photosynthesis under weak light source.

2. 2 Estimation Algorithm using Satellite Data

NPP is obtained by subtracting respiratory loss R_d from gross primary production (GPP) as follows :

$$NPP=GPP-R_d \tag{4}$$

It was reported that the respiratory loss of leaves depends on the air temperature. In this study, respiratory loss R_d is estimated using the following empirical relationship.

$$R_d=\frac{7.825+1.145\,T\,[℃]}{100}\times GPP \tag{5}$$

GPP is an accumulated photosynthesis over a term such as a year and a month. We estimate a photosynthesis using VIPD and photosynthetically active radiation (PAR).

$$GPP = \int P(PAR(t),VIPD(t))dt \tag{6}$$

The detail description of the photosynthesis $P(PAR(t), VIPD(t))$ is as follows :

$$P(PAR(t),VIPD(t)) \simeq \frac{VIPD(t)}{VIPD_{std}} P_{std}(PAR(t)) \tag{7}$$

$$P_{std}(PAR(t)) = \frac{0.515 \times 0.028 \times PAR(t)}{1 + 0.028 \times PAR(t)} \tag{8}$$
$$VIPD_{std} = 0.561$$

Here, $P(PAR(t),VIPD(t))$ and $P_{std}(PAR(t))$ are in units of $[mgCO_2/m^2/s]$ and $PAR(t)$ is in $[W/m^2]$. Thus, the photosynthesis of the vegetation can be estimated by its VIPD value using Equations 7 and 9 (Furumi, 2005).

In order to estimate GPP, we accumulate Eq. 7 over a term. It is expected that $VIPD(t)$ changes gradually with a time except for the sudden change such as a forest burning and crop cultivation. In contrast to that, $PAR(t)$ changes with shorter time range than $VIPD(t)$. In addition to that, it is necessary to accumulate photosynthesis with a change of PAR because photosynthesis expressed by Eq. 7 is not linear to PAR. However, it is difficult to acquire the detail change of PAR over wide area observed by satellite data.

Thus, we developed the method to calculate an accumulated photosynthesis by using daily or monthly mean PAR. In particular, it is important to study how to calculate the mean of PAR. In particular, simple daily mean of PAR for 24 hours is calculated including the night time in which vegetation does not photosynthesize. It suggests the daily mean of PAR for 24 hours is not suitable for estimating the accumulated photosynthesis for the day.

We introduced the effective daylength for photosynthesis and determined the effective daylength based on the daylength between sunset and sunrise so that photosynthesis calculated by the mean of PAR for the effective daylength agrees with the accumulated photosynthesis. As a result, it was clear to be suitable to use the effective daylength defined as follows :

$$h = H - h' \tag{9}$$

Here, h is effective daylength [hour] for vegetation photosynthesis and H is the daylength [hour] between sunrise and sunset. Sunrise and sunset are calculated from the latitude, longitude, and date. We determined h' as 2 hours (Xiong, 2005).

Finally, we obtained the following equation to calculate the accumulated photosynthesis, namely GPP. It is assumed that VIPD value does not change for the day and the value is expressed by $VIPD_{day}$. $\overline{PAR_h}$ is mean of PAR during effective daylength(h) and its unit is [W/m^2].

$$daily\ GPP = \int_{day} \frac{VIPD_{day}}{VIPD_{std}} P_{std}(PAR(t))dt \tag{10}$$

$$\simeq \frac{VIPD_{day}}{VIPD_{std}} P_{std}(\overline{PAR_h}) \times (\Delta t \times h)$$

$$\Delta t = 3600[s] \tag{11}$$

3　Study Area and Satellite Data Used in This Analysis

The NPP estimation model described in previous section should be validated for vegetation in various types and climate area. In this study, validation site of the model is around Kansai area in Japan. In particular, we concentrate paddy fields in Nara basin. Fig. 1 shows the study area. Seven areas surrounded by lines are study area of paddy fields.

The rice is planted in the beginning of June and is cultivated in the middle of October. To study change of the rice growth, we selected seven seasonal images acquired by Landsat-5/TM and Landsat-7/ETM＋. The images are observed on May 6(TM), June 15(ETM＋), July 9(TM), August 10(TM), September 19(ETM＋), October 4(TM), and December 8(ETM＋), 2000. Image registration was carried out by selecting ground control point (about 15 points) and applying the affine transfer. As a result, the error of the position is within 2 pixels.

4　Estimation of Net Primary Production For Paddy Fields

4. 1　Ground Truth Data ： Rice Yield

The rice yield is examined for each city in Japan. The rice yield data means the almost dry weight of brown rice (unpolished rice) per a unit ground area. We estimate the dry weight of all rice matter using the two relationships between rice yield and the dry weight of above ground (Eq.(13)) and between the dry weight of above ground and below ground (Eq.(14)). These relationships are obtained from paddy fields in Akita Prefecture of Japan.

$$D_{all} = D_A + D_B \tag{12}$$

$$D_A = 2.69 \times D_{yield} \tag{13}$$

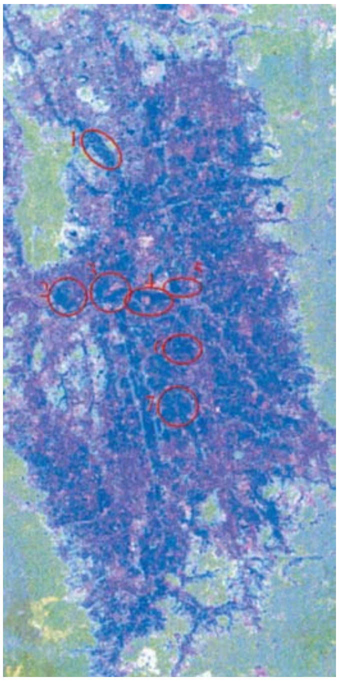

Figure 1　Paddy fields around Nara basin in Japan

Table 1　Rice yield and dry weight of all rice matter for five cities. The final line shows average value

city name	rice yield D_{yield}[kg/10 a]	dry weight of all rice matter D_{all}[g/m^2]
Nara	520	1496.7
Ikaruga	533	1534.1
Ando	535	1539.9
Kawanishi	530	1525.5
Tawaramoto	529	1522.6
Average	529.4	1523.8

$$D_B = 0.07 \times D_A \tag{14}$$

Here, D_{all} is dry weight of all rice matter. D_A is dry weight [kg] of above ground and D_B is dry weight [kg] of below ground. D_{yield} is almost dry weight [kg] of brown rice. Table 1 shows the rice yield for five cities including seven validation sites. Second column is rice yield data [kg/10 a] and third column is dry weight of all rice matter calculated from the above empirical equations.

4. 2　Estimation of NPP for Paddy Fields

Seasonal changes of vegetation indices NDVI and VIPD were examined using seven TM or ETM＋

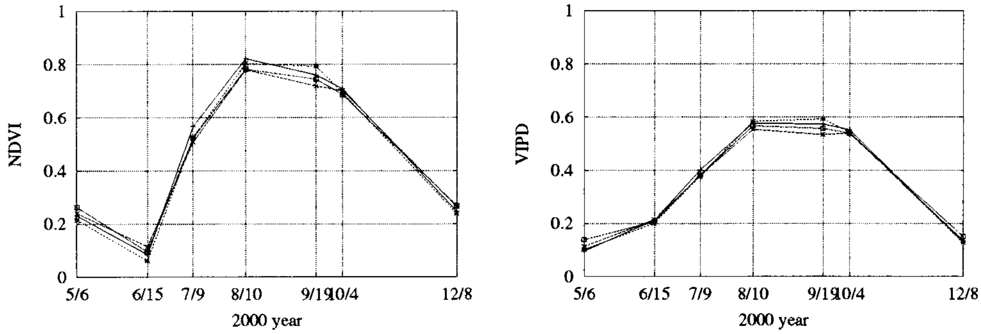

Figure 2　Seasonal change of NDVI and VIPD for paddy fields

data. Fig. 2 shows the change of NDVI and VIPD for paddy fields No. 3 indicated in Fig. 1. Both indices are large around August and September. In general, rice around Nara basin is cultivated around the middle of October. From seasonal change of indices, we can guess the cultivation was carried out between Oct. 4 and Dec. 8.

In this study, it was assumed that the growing term of rice was between the beginning of June and the middle of October and it was considered that VIPD values of the beginning of June and the middle of October was the average of the values of May, 6 and Dec. 8. VIPD value between the values acquired from satellite data was interpolated linearly. In addition to the change of VIPD, we used the monthly PAR and air temperature data for the NPP estimation. Table 2 shows solar radiation and air temperature data measured at Nara Women's Univ. in Nara and the daylength between sunrise and sunset. PAR [W/m^2] is calculated from solar radiation (SR) [W/m^2] using the empirical following relationship.

$$PAR = SR \times 0.48 \tag{15}$$

Data for October are averaged for the term (15 days) from the beginning to the middle of October.

From the above climate data and VIPD, monthly NPP for seven paddy fields are calculated by

Table 2　Climate data and daylength for each month from June to October

Month (2000)	Solar radiation [MJ/m^2]	Air Temperature [℃]	daylength H [hour]
June	14.74	23.10	14.5
July	18.17	27.97	14.0
August	18.64	29.00	13.5
September	13.96	24.64	12.5
October(1–15)	13.04	20.28	11.5

accumulating daily NPP obtained from Eq. (10) and average NPP for seven paddy fields is 804.0 [g/ m^2]. Average NPP obtained from rice yield data is 1523.8 [g/m^2] as described in Table 1. The NPP value estimated from Landsat/TM and ETM＋ data is about a half of ground truth data.

We describe two reasons why the NPP estimated for paddy fields is underestimated. First reason is that VIPD cannot reflect the leaf amount of rice because of almost vertical distribution of leaves. Second reason is that the productivity of rice is higher than expected. From now, we have to modify the estimation algorithm based on the above results.

5　Conclusions

The purpose of this study is to validate the applicabilty of an NPP estimation algorithm based on VIPD for paddy fields in Nara basin of Japan. Using seven seasonal images obtained from Landsat-5/ TM and Landsat-7/ETM＋ data, we estimated NPP for the paddy fields and compared with the dry weight of all rice matter obtained from rice yield data. As a result, the estimated NPP is about a half of ground truth data. Based on these results, we will modify the NPP estimation algorithm using VIPD.

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