Adjustment of A Simplified Satellite-Based Algorithm for Gross Primary Production Estimation Over Korea

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Abstract : Monitoring the global Gross Primary Production (GPP) is relevant to understanding the global carbon cycle and evaluating the effects of interannual climate variation on food and fiber production. GPP, the flux of carbon into ecosystems via photosynthetic assimilation, is an important variable in the global carbon cycle and a key process in land surface-atmosphere interactions. The Moderate-resolution Imaging Spectroradiometer (MODIS) is one of the primary global monitoring sensors. MODIS GPP has some of the problems that have been proven in several studies. Therefore this study was to solve the regional mismatch that occurs when using the MODIS GPP global product over Korea. To solve this problem, we estimated each of the GPP component variables separately to improve the GPP estimates. We compared our GPP estimates with validation GPP data to assess their accuracy. For all sites, the correlation was close with high significance ($R^2 = 0.8164$, $RMSE = 0.6126 \text{ g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$, $\text{bias} = -0.0271 \text{ g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$). We also compared our results to those of other models. The component variables tended to be either over- or under-estimated when compared to those in other studies over the Korean peninsula, although the estimated GPP was better. The results of this study will likely improve carbon cycle modeling by capturing finer patterns with an integrated method of remote sensing.

Key Words : GPP, MODIS, Korea peninsula, Vegetation Index

1. Introduction

Vegetation primary production is vital to human society because it provides essential materials and environments suitable for human habitation (Zhao *et al.*, 2006). Primary production has received increasing attention in recent years and is directly related to the global carbon cycle. The atmospheric concentration of

CO₂ has increased by 31% since 1750 (IPCC, 2001) due to human activities. This increase can alter the energy balance of the land surface and change the climate (Knutson *et al.*, 1999; Scott *et al.*, 2000). The terrestrial biosphere can sequester significant amounts of atmospheric CO₂ (Wofsy *et al.*, 1993), a process that is largely influenced by the increased atmospheric CO₂ and the changing climate (Nemani *et al.*, 2002, 2003;

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Schimel *et al.*, 2000). The magnitude and cause of carbon uptake are still uncertain (Barford *et al.*, 2001) and knowledge of the carbon cycle on regional and global scales is required to understand spatial and temporal monitoring of earth surface processes (Running *et al.*, 1999). Monitoring the global Gross Primary Production (GPP) is relevant to understanding the global carbon cycle and evaluating the effects of interannual climate variation on food and fiber production (Running *et al.*, 1999). GPP, the flux of carbon into ecosystems via photosynthetic assimilation, is an important variable in the global carbon cycle and a key process in land surface-atmosphere interactions (Coops *et al.*, 2009; Jung *et al.*, 2008). The continuous monitoring of GPP in general, and the highly accurate spatial and temporal variations on a regional scale in particular, can provide reliable data for carbon-related climate change studies and useful information for ecosystem management (Wang *et al.*, 2010). One of the most widely used concepts for modeling GPP is the Light-Use Efficiency (LUE) approach of Monteith (1972, 1977). This expresses GPP ($\text{g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$) as the product of the absorbed Photosynthetically Active Radiation (PAR) ($\text{MJ} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$), which is defined as absorbed solar radiation with a wavelength of 400-700 nm, and the efficiency with which the absorbed PAR can be converted into biomass:

$$GPP = FPAR \times PAR \times \varepsilon_g \quad (1)$$

where FPAR (photosynthetically active radiation absorbed by vegetation) represents the fraction of PAR absorbed by the canopy and ε_g ($\text{g} \cdot \text{C} \cdot \text{MJ}^{-1}$) is the photosynthetic efficiency term. The LUE concept is based on the functional convergence theory (Field, 1991) hypothesizing that plants scale the canopy leaf area and light harvesting by the availability of resources as a result of evolutionary processes to optimize their carbon fixation (Goetz *et al.*, 1999).

The Moderate-resolution Imaging Spectroradiometer (MODIS) is one of the primary global monitoring

sensors. The MODIS GPP algorithm's key components are the Data Assimilation Office (DAO) climate data, the MODIS FPAR, and the parameterization of the LUE lookup table (Running *et al.*, 2000). This study revealed a variety of differences between those components implemented in 2001 and ground-based measurements. Because of the comprehensive archiving of MODIS data, reprocessing of data for specific algorithms will be possible at any time during the expected five-year lifetime of the sensor. It is thus worth considering possible improvements.

There will always be limitations for DAO data in the degree to which the general circulation model-based estimates agree with ground measurements at particular sites because of the coarse scale of the DAO model outputs (Turner *et al.*, 2003). The differences observed in this analysis are related to this mismatch in scale as well as possible limitations of the DAO product. While the MODIS FPAR product captures the high mid-growing season values, problems appear to exist outside the growing season. Their effect on the MODIS GPP product is limited because the PAR and minimum temperature scalar are usually low in any case. The MODIS FPAR has a strong spring green-up signal and appears to achieve its summer maximum somewhat earlier than indicated by ground measurements. This causes a corresponding overestimation of GPP early in the growing season. The MODIS Leaf Area Index (LAI) product does show the autumn leaf drop (Cohen *et al.*, 2003), so the FPAR algorithm could be modified to capture this effect. The MODIS ε_g parameterization is perhaps the most amenable to modification of all the algorithm's components because it relies on a simple lookup table. The threshold and maximum for the Vapor Pressure Deficit (VPD) scalar have already been modified once. The original biome-specific ε_g maxima and scalar parameterizations were based on model outputs rather than on observations of ε_g , and there is significant potential for improvement now that an extensive global network of eddy covariance flux

towers is in place (Running *et al.*, 1999).

Turner *et al.* (2003) evaluated MODIS GPP products with GPP values derived from the measured net ecosystem exchange in flux towers, which were part of FLUXNET, a network of micrometeorological tower sites that used eddy covariance methods to measure the exchanges of CO₂, water vapor, and energy between terrestrial ecosystems and the atmosphere. They analyzed the 2001 MODIS data set at two sites and showed that, relative to tower-based estimates, MODIS overestimated GPP by 35% in boreal forest areas, whereas estimates were within the accuracy of the tower results for temperate zone hardwood forest areas. Gebremichael and Barros (2006) studied the quantitative estimation of the uncertainty associated with MODIS GPP end-products that depend on several MODIS-derived vegetation indices. The MODIS GPP products were compared against simulations made with a process-based biochemical-hydrology model driven by flux tower meteorological observations. They examined the error contribution from the DAO meteorological data used in standard MODIS GPP products. Their results showed that the bias between the GPP estimates using DAO and tower meteorology was 77% of the mean of the tower-based GPP.

The object of this study was to solve the regional mismatch that occurs when using the GPP global product over Korea. We also estimated the GPP production from remotely sensed inputs and developed remote-sensing-based models of the terrestrial carbon cycle. To achieve this, we used a different approach to determine each component variable in the GPP estimate. First, we first used atmospheric corrections, reflectance normalizations, and Normalized Difference Vegetation Index (NDVI) corrections to calculate the FPAR. Second, we estimated the PAR using the physical model of Yeom (2010). Without relying on ground observations, we estimated ε_g based on important environmental parameters such as soil moisture.

2. DATA

1) Data set

The study area was a section of Northeast Asia bounded by 32.50–40.0° N and 124.48–130.0° E. The GPP was estimated over the study period of January 1 to December 31, 2006. This study used MODIS products (FPAR/LAI and GPP), VEGETATION sensor data, MTSAT-1R data, and meteorological data to estimate the GPP. We used the 8-day LAI and FPAR data sets from the Land Processes Distributed Active Archive Center web site at <https://lpdaac.usgs.gov/>. The MOD15 LAI and FPAR are 1 km (at launch) products provided on a daily and eight-day basis (Myneni *et al.*, 2003). The MODIS LAI/FPAR algorithm consists of a main procedure that exploits the spectral information content of MODIS surface reflectance in up to seven spectral bands based on a three-dimensional formulation of the LAI/FPAR inverse problem. Should the main algorithm fail, a backup algorithm is triggered to estimate the LAI and FPAR using vegetation indices (Myneni *et al.*, 2003). The MOD17A2 algorithm provides the first operational, near-real-time calculation of global GPP products from the EOS MODIS sensor. It also produces the eight-day composite GPP, net photosynthesis (PsnNet), and corresponding Quality Control (QC). While GPP is calculated on a daily basis, eight-day GPP summaries are made publicly available.

The SPOT/VEGETATION (VGT) sensor developed by the Centre National d'Etudes Spatiales provides daily monitoring of terrestrial characteristics such as surface albedo, reflectance, and vegetation indices, which are obtained on a global scale from remotely sensed data. The VGT sensor provides daily global images with a 1-km spatial resolution. We acquired the VGT S10 product for the period January–December 2006. Vegetation indices such as NDVI, Fraction of Vegetation Cover (FVC), and Normalized Difference Water Index (NDWI) were calculated for

Table 1. Locations of the 76 meteorological stations

Station No.	Station name	Latitude (N)	Longitude (E)	Station No.	Station name	Latitude (N)	Longitude(E)
90	Sokcho	38.2481	128.5670	185	Gosan	33.2833	126.1667
95	Cheorwon	38.1451	127.3063	189	Seogwipo	33.2428	126.5674
98	Dongducheon	37.8991	127.0628	192	Jinju	35.2054	128.1213
99	Munsan	37.8844	126.7625	201	Ganghwa	37.7046	126.4486
100	Deagwallyeong	37.6841	128.7610	202	Yangpyeong	37.4858	127.4966
101	Chuncheon	37.8999	127.7379	203	Icheon	37.2611	127.4863
102	Baengnyeong	37.9661	124.6305	211	Inje	38.0573	128.1692
105	Gangneung	37.7486	128.8933	212	Hongcheon	37.6808	127.8826
106	Donghae	37.5043	129.1266	216	Taebaek	37.1675	128.9915
108	Seoul	37.5714	126.9658	221	Jecheon	37.1564	128.1965
112	Incheon	37.4747	126.6266	226	Boeun	36.4847	127.7363
114	Wonju	37.3340	127.9504	232	Cheonan	36.7767	127.1213
115	Ulleung	37.4800	130.9000	235	Boryeong	36.3243	126.5594
119	Suwon	37.2695	126.9875	236	Buyeo	36.2694	126.9229
121	Yeongwol	37.1784	128.4597	238	Geumsan	36.1027	127.4839
127	Chungju	36.9672	127.9522	243	Buan	35.7265	126.7186
129	Seosan	36.7737	126.4959	244	Imsil	35.6092	127.2877
130	Ulsan	36.9889	129.4153	245	Jeongeup	35.5601	126.8682
131	Cheongju	36.6363	127.4428	247	Namwon	35.4023	127.3351
133	Daejeon	36.3690	127.3742	248	Jangsu	35.6539	127.5224
135	Chupungyeong	36.2170	127.9967	256	Suncheon	35.0719	127.2412
136	Andong	36.5701	128.7095	260	Jangheung	34.6856	126.9216
137	Sangju	36.4000	128.1500	261	Haenam	34.5504	126.5711
138	Pohang	36.0297	129.3820	262	Goheung	34.6151	127.2778
140	Gunsan	36.0022	126.7633	265	Seongsanpo	33.3836	126.8824
143	Deagu	35.8822	128.6212	271	Bonghwa	36.9407	128.9168
146	Jeongu	35.8185	127.1571	272	Yeongju	36.8689	128.5191
152	Ulsan	35.5571	129.3225	273	Mungyeong	36.6243	128.1510
155	Masan	35.1671	128.5751	277	Yeongdeok	36.5304	129.4117
156	Gwangju	35.1698	126.8936	278	Uiseong	36.3531	128.6908
159	Busan	35.1016	129.0343	279	Gumi	36.1276	128.3228
162	Tongyeong	34.8423	128.4378	281	Yeongcheon	35.9744	128.9537
165	Mokpo	34.8138	126.3832	284	Geochang	35.6682	127.9132
168	Yeosu	34.7362	127.7428	285	Hapcheon	35.5620	128.1720
169	Heuksando	34.6833	125.4500	288	Miryang	35.4885	128.7464
170	Wando	34.3927	126.7039	289	Sancheong	35.4099	127.8813
175	Jindo	34.4720	126.3236	294	Geoje	34.8851	128.6067
184	Jeju	33.5109	126.5317	295	Namhae	34.8135	127.9286

all the 10-day composite images.

MTSAT-1R, operated by the Japanese Meteorological Agency and controlled by the Civil Aviation Bureau of the Ministry of Land, Infrastructure, and Transport, was successfully launched on February 26, 2005. This study

used hourly data and considered all the bands as potential input data. All of the MTSAT-1R data were obtained from the National Institute of Meteorological Research and were sufficient to produce values for normalized reflectance, surface albedo, and solar

Fig. 1. Flowchart of reference data filtering process using MODIS QC and VGT SM.

surface insolation.

Ground observation takes place using automated equipment at 76 manned stations located as shown in Table 1. The ground-based measurement data were acquired from the Korea Meteorological Administration in 2006. The 16 elements including pressure, temperature, humidity, precipitation, cloud coverage, wind, and solar radiation are measured every three hours. The dense surface observation data collected from automatic weather stations also play an important role in the preparation of the initial conditions for the numerical prediction models. We used two kinds of meteorological data: temperature and solar radiation. Temperature data were used to estimate T_a with MODIS Land-Surface Temperature (LST) data, and

solar radiation data was used to estimate PAR.

2) Reference data set

Before starting this study, reference data were established to improve the accuracy of the results. Fig. 1 shows a flowchart of the reference data filtering process. First, geometric correction was used to match the three types (SPOT/VGT, Terra/MODIS, and ECOCLIMAP) of data over the study area with a spatial resolution of 1 km. The nearest-neighbor method was used to correct geometric distortion. The temporal resolution was also corrected to the MODIS 8-day baseline because the VGT S10 and ECOCLIMAP data were in 10-day composite images. The SPOT/VGT dataset included one status map for radiometric

quality, cloud masks, and snow masks. The MODIS data set included the QC, the definition of which was optimized during data reprocessing. The QC field in MOD17A2 was inherited from MOD15A2, and each pixel's QC value was based on the sensor and cloud conditions. As previously stated, we used quality data, i.e., Status Map (SM) and QC, to improve the accuracy of the results. Eleven conditions were used to select the reference collocation pixels. The conditions for the reference pixels were as follows:

CONDITIONS

- MODIS FPAR/LAI_QC: MODLAND {0,1} = 0 0
- MODIS FPAR/LAI_QC: SCF_QC {5,6,7} = 0 0 0
- MODIS GPP_QC: MODLAND {0,1} = 0 0
- MODIS GPP_QC: SCF_QC {5,6,7} = 0 0 0
- MODIS GPP ≠ 32761, 32762, 32763, 32764, 32765, 32766, 32767
- MODIS LAI: lai < 6.0
- VGT NDVI: ndvi > 0.01
- VGT band: b0, b2, b3 ≠ 0
- ECOCLIMAP: fpar, lai, veg ≠ 999.0

Fig. 2. Filtering results. Black point are pixels selected on Julian day 49, 2006.

Table 2. Number of samples quality control of best flagged pixel of MODIS QC map

Data (8-day)	Cropland (No. of pixels)	Forest (No. of pixels)	Total (No. of pixels)
2006001	12,726 (49.5%)	12,976 (50.5%)	25,702
2006009	12,276 (48.8%)	12,860 (51.2%)	25,136
2006017	11,430 (46.2%)	13,308 (53.8%)	24,738
2006025	12,541 (48.6%)	13,273 (51.4%)	25,814
2006033	12,873 (49.6%)	13,059 (50.4%)	25,932
2006041	13,909 (51.2%)	13,250 (48.8%)	27,159
2006049	13,964 (50.8%)	13,534 (49.2%)	27,498
2006057	13,959 (51.1%)	13,369 (48.9%)	27,328
2006065	13,952 (51.1%)	13,336 (48.9%)	27,288
2006073	13,959 (50.8%)	13,533 (49.2%)	27,492
2006081	13,966 (50.8%)	13,542 (49.2%)	27,508
2006089	13,964 (50.8%)	13,544 (49.2%)	27,508
2006097	13,964 (50.8%)	13,527 (49.2%)	27,491
2006105	13,960 (50.9%)	13,493 (49.1%)	27,453
2006113	13,965 (50.8%)	13,534 (49.2%)	27,499
2006121	13,963 (51.4%)	13,186 (48.6%)	27,149
2006129	13,932 (70.1%)	5,947 (29.9%)	19,879
2006137	13,927 (78.8%)	3,752 (21.2%)	17,679
2006145	13,963 (80.9%)	3,286 (19.1%)	17,249
2006153	13,912 (86.9%)	2,091 (13.1%)	16,003
2006161	13,918 (87.2%)	2,052 (12.8%)	15,970
2006169	13,942 (77.6%)	4,030 (22.4%)	17,972
2006177	13,313 (92.5%)	1,084 (7.5%)	14,397
2006185	10,696 (98.4%)	175 (1.6%)	10,871
2006193	6,830 (94.5%)	399 (5.5%)	7,229
2006201	10,699 (89.4%)	1,268 (10.6%)	11,967
2006209	11,884 (82.2%)	258 (17.8%)	14,465
2006217	12,874 (77.7%)	3,703 (22.3%)	16,577
2006225	12,976 (78.0%)	3,454 (21.0%)	16,430
2006233	12,163 (89.3%)	1,455 (10.7%)	13,618
2006241	13,503 (79.7%)	3,444 (20.3%)	16,947
2006249	13,785 (82.4%)	2,937 (17.6%)	16,722
2006257	13,897 (66.1%)	7,114 (33.9%)	21,011
2006265	13,909 (81.6%)	3,142 (18.4%)	17,051
2006273	13,943 (68.0%)	6,567 (32.0%)	20,510
2006281	13,940 (58.1%)	10,062 (41.9%)	24,002
2006289	13,768 (54.0%)	11,718 (45.0%)	25,486
2006297	13,961 (52.2%)	12,791 (47.8%)	26,752
2006305	13,959 (50.8%)	13,501 (49.2%)	27,460
2006313	13,963 (50.8%)	13,533 (49.2%)	27,496
2006321	13,961 (50.8%)	13,534 (49.2%)	27,495
2006329	13,951 (51.5%)	13,136 (48.5%)	27,087
2006337	13,948 (50.8%)	13,499 (49.2%)	27,447
2006345	13,493 (52.5%)	12,215 (47.5%)	25,708
2006353	13,478 (50.2%)	13,356 (49.8%)	26,834
2006361	13,451 (50.1%)	13,444 (49.9%)	26,895

- $|LAI(modis) - LAI(ecoclimap)| / LAI(MODIS) < 0.1$
- $|LAI(modis) - LAI(ecoclimap)| < 0.1$

Fig. 2 shows the result obtained when reference pixels were selected to meet *all* the conditions. In this figure, black points represent the selected pixel by filtering on Julian day 49, 2006. The study area consisted of areas classified mainly as forest and cropland. Table 2 shows detailed information about the number of samples and QC of the pixel best flagged by the land cover classification. Because the QC information for each file was different, the number of selected pixels was also different. The final reference data were acquired such that the average was calculated for each type of land cover based on the result of the filtering process. Finally, the process above was used to select more reliable reference data. Reference data were used as the key data in estimating GPP, and selected from those with the best QC values.

3. METHODOLOGY

Fig. 3 explains the methodology used in this study. SPOT/VGT NDVI data were used to estimate the FPAR. To improve FPAR accuracy, we were applied to the model of Pi (2010). Pi presented that the FPAR is usually estimated by the LAI, but we estimated it directly using the FVC. We used an empirical method that is usually based on a linear or nonlinear function of vegetation indices. These results were compared with the validation reference FPAR data.

We estimated the PAR using the physical model of Yeom (2010). The first step included a calculation for the solar zenith angle and the varying distance between the earth and the sun. The next step was to parameterize atmospheric transmittance due to ozone, water vapor, aerosols, and Rayleigh scattering. Cloud mask information was used to classify pixels as clear or cloudy. In the case of cloudy sky, attenuation coefficients were used to estimate cloudy PAR. These

Fig. 3. Flowchart of gross primary production (GPP) modeling method.

results were also compared with ground-based measured measurements.

We used the modified VPM model to estimate the GPP. The first step was to estimate satellite-based T_a by regression analysis between the meteorological measurement data and MODIS LST. Next, the NDWI was estimated from SPOT/VGT spectral bands. We improved the input data to the VPM model and also improved the quality of ε_g . The data obtained this way were then applied to the VPM model. These results were compared with validation ε_g reference data and also with ε_g values calculated using other methods.

The final step was to estimate the GPP by applying the improved parameters. The three input variables (FPAR, PAR, and ε_g) were analyzed on correlation analysis scatter plots before they were used in the GPP. Finally, the estimated GPP was validated with the reference GPP data and compared with the MODIS GPP time series about a pixel that was selected at random. These results and those from other models were then compared to ascertain the suitability of the global product. Finally, we analyzed the spatial patterns of the GPP over the study area.

4. RESULTS AND ANALYSIS

1) Estimation of FPAR and PAR

The FPAR was estimated using an expression derived from Pi (2010). The following expressions were also derived:

$$\text{PAR} = \text{FVC}_{\text{adi}} + \text{FVC}_{\text{md}}^3 \cdot \text{FVC}_i, \quad (1a)$$

where FVC_{adj} is the adjusted minimum FVC and FVC_{md} is the minimum FVC difference;

$$\text{FVC}_{\text{adi}} = \text{FVC}_{\text{min}} \cdot w \text{ and} \quad (1b)$$

$$\text{FVC}_{\text{md}} = \text{FVC}_{\text{max}} - \text{FVC}_{\text{min}} \quad (1c)$$

where w is the weight per land cover type. The weights were determined from the regression analysis

between the FVC and the training FPAR data, and set to a constant value of 0.1 in cropland and 1.0 in forest. The minimum and maximum FVC (FVC_{min} and FVC_{max}) were set to 0.02 and 0.93, respectively.

Based on Eq. (1a), we estimated the FPAR as follows:

$$\text{FVC}_{\text{cropland}} = 0.003 + 0.73 \cdot \text{FVC} \text{ and} \quad (2a)$$

$$\text{FVC}_{\text{forest}} = 0.1 + 0.68 \cdot \text{FVC} \quad (2b)$$

using the FVC-FPAR relationship and compared the results with the FPAR validation data from MODIS; the validation data were selected at random from the reference data. The results of a correlation analysis

Fig. 4. Surface solar insolation from MTSAT-1R on 0433 UTC, August 1, 2006.

Fig. 5. Scatter plot of measured PAR and PAR estimated using new cloud lookup table.

between the validation FPAR data and the estimated FPAR, indicate that the correlation was good ($R^2 = 0.8390$). The Root Mean Square Error (RMSE) was 0.0739 and the bias was low (-0.000438).

We estimated the incident PAR using the Solar Surface Insolation (SSI), which was obtained using the method of Yeom (2010). Fig. 4 shows the output SSI product for an MTSAT-1R scene captured on August 1, 2006 at 0433 UTC. The trends shown in this image were a function of the solar position, specifically, the cosine of the solar zenith angle. The satellite-based insolation to 11×11 for comparison with ground-station measurements was spatially averaged (Yeom, 2010). Yeom presented a cloud factor optimized for the modified Kawamura physical model to calculate the attenuated cloud transmittance from MTSAT-1R channel data. When simulating cloudy attenuation with the cloud factor, this model does not use the brightness temperature from a lookup table. Values from a newly developed cloud lookup table, which are a function of solar zenith angle, were used to reflect those characteristics instead of relying on the corresponding brightness temperature. The new cloud lookup table for the presented SSI retrieval model was described in detail by Yeom (2010). Fig. 5 contains a scatter plot showing the relationship between the remotely sensed PAR and the pyranometer data using the new cloud lookup table. The RMSE was $7.668 \text{ MJ} \cdot \text{m}^{-2} \cdot \text{day}^{-1}$ and the bias was $0.842 \text{ MJ} \cdot \text{m}^{-2} \cdot \text{day}^{-1}$. The latter indicates significantly increased accuracy, and the results were better than in previous studies.

3) Estimation of ε_g using the modified VPM model

We estimated FPAR on the basis of the VPM, which is a LUE-based, remote-sensing-oriented model developed by Xiao *et al.* (2004a, 2004b). The VPM is based on the concept of partitioning vegetation canopies into Photosynthetically Active Vegetation (PAV) such as chloroplasts, and Non-Photosynthetically

active Vegetation (NPV) such as the stem, branches, and cell walls. The VPM model may be described briefly by

$$\text{GPP} = \varepsilon_g \cdot \text{FPAR}_{\text{PAV}} \cdot \text{PAR} \quad (3)$$

$$\varepsilon_g = \varepsilon_0 \cdot T_{\text{scalar}} \cdot W_{\text{scalar}} \cdot P_{\text{scalar}}, \quad (4)$$

where FPAR_{PAV} is the fraction of PAR absorbed by PAV and ε_g is the LUE under environmental stress. Parameter ε_0 is the apparent quantum yield or maximum LUE, and T_{scalar} , W_{scalar} , and P_{scalar} are the environmental stress indices of temperature, water, and leaf phenology on LUE, respectively. In the current version of the VPM model, FPAR_{PAV} is assumed to be a linear function of the enhanced vegetation index (EVI) (Xiao *et al.*, 2004a, b). However, we estimated FPAR using a corrected NDVI instead of the EVI. At each time step, T_{scalar} is estimated using the equation developed for the Terrestrial Ecosystem Model (Raich *et al.*, 1991),

$$T_{\text{scalar}} = \frac{(T - T_{\min})(T - T_{\max})}{[(T - T_{\min})(T - T_{\max})] - (T - T_{\text{opt}})^2} \quad (5)$$

where $T_{\min}$, $T_{\max}$, and T_{opt} are the minimum, maximum, and optimal temperature for photosynthetic activities, respectively. If air temperature falls below $T_{\min}$, then T_{scalar} is set to zero. The effect of water on plant photosynthesis, W_{scalar} , has been estimated as a function of soil moisture and/or VPD in a number of production efficiency models (Field *et al.*, 1995; Prince and Goward, 1995; Running *et al.*, 2000). As a first-order approximation, we propose a simple alternative approach that uses a satellite-derived water index to estimate the seasonal dynamics of W_{scalar} (Xiao *et al.*, 2004a, 2004b),

$$W_{\text{scalar}} = \frac{1 + \text{LSWI}}{1 + \text{LSWI}_{\max}} \quad (6)$$

where $\text{LSWI}_{\max}$ is the maximum Land Surface Water Index (LSWI) during the plant-growing season for individual pixels. We used a parallel water index, which is similar in mathematical formulation to the NDWI, that uses reflectance values in the 0.86 and 1.24 μm

spectral bands of hyperspectral data (Gao, 1996). Parameter P_{scalar} is included in Eq. (4) to account for the effect of leaf phenology (leaf age) on photosynthesis at the canopy level. In this version of the VPM model, the calculation of P_{scalar} is dependent on the leaf longevity. For a canopy that is dominated by leaves with a life expectancy of one year, P_{scalar} is calculated at two different phases as a linear function (Xiao *et al.*, 2004b) using

$$P_{scalar} = \frac{1 + LSWIa}{2} \quad (7)$$

Likewise, in this study, calculation of P_{scalar} used the NDWI instead of the LSWI.

We ran the VPM model (Xiao *et al.*, 2004a, 2004b) to estimate ϵ_g , using LST, meteorological data (air temperature, T_a), and NDWI. First, LST provided in the MODIS product was used to measure the T_a retrieval accuracy. The following was the equation of best fit:

$$T_a = -2.3937 + 0.6235LST + 0.0092(LST)^2 \quad (8)$$

We calculated T_a values using Eq. (8), plotted T_a recorded by meteorological stations, and estimated T_a from MODIS LST (Fig. 6). The RMSE was 2.6758°C and the bias was very low (2.9×10^{-9} °C). Fig. 7 presents a comparison of estimated T_a (black dots) and T_a based on meteorological data (gray dots). We used NDWI time series data to assess the level of leaf and canopy water content of the seasonally moist tropical forest over the seasons (Fig. 8). The parameter set was used to calculate T_{scalar} (see Eq. (5)). We used a minimum temperature T_{min} of -12°C, optimum temperature T_{opt} of 24°C, and maximum temperature T_{max} of 31°C, as implemented in the process-based Terrestrial Ecosystem Model. The next parameter set was calculated for W_{scalar} and P_{scalar} (see Eqs. (6 and 7)). Estimation of the maximum NDWI value during the plant-growing season was selected as an estimate of $NDWI_{max}$.

We determined each scalar using the above equations. Fig. 9 illustrates the seasonal dynamics of

Fig. 6. Scatter plot of air temperature observed by meteorological stations and estimated T_a from MODIS LST.

Fig. 7. Comparison of estimated T_a and air temperature based on meteorological data.

Fig. 8. Seasonal dynamics of NDWI from the study area.

the temperature scalar T_{scalar} , water scalar W_{scalar} , and leaf phenology scalar P_{scalar} for the simulation of the VPM model. A field-based light addition/augmentation experiment for rainforest trees in Panama has suggested that light, rather than water, temperature,

Fig. 9. Seasonal dynamics of (a) temperature scalar (T_{scalar}), (b) water scalar (W_{scalar}), and (c) leaf phenology scalar (P_{scalar}) for the VPM model simulation.

Fig. 10. Values of ϵ_0 derived from reference GPP: 0.25 for cropland and 0.29 for forest.

or leaf nitrogen, is the primary factor that limits CO_2 uptake during the rainy season (Graham *et al.*, 2003).

The maximum LUE ϵ_0 is an important parameter for calculating GPP. We estimated ϵ_0 using the existing GPP equation:

$$\epsilon_0 = \frac{\text{GPP}}{(T_{\text{scalar}} \cdot W_{\text{scalar}} \cdot P_{\text{scalar}}) \cdot \text{FPAR} \cdot \text{PAR}} \quad (9)$$

The final product from this study was used as input

Fig. 11. Comparison between the validation and estimated ϵ_g data.

Table 3. Results (R^2 , RMSE, bias) of comparison between validation ε_g data and estimated ε_g

	Cropland	Forest	Total
R^2	0.6901	0.6461	0.6681
RMSE	0.0319	0.0403	0.0355
Bias	-0.0015	-0.0035	-0.0023

data. In Eq. (9), GPP reference data was used to input data. Fig. 10 shows how the values of ε_0 derived from the reference GPP were set to 0.25 for cropland and 0.29 for forest.

We calculated ε_g using these variables. The comparison of the validation ε_g and estimated ε_g in Fig. 11 shows that a correlation existed ($R^2 = 0.69$ for cropland and $R^2 = 0.65$ for forest). Table 3 presents detailed information on the estimated ε_g accuracies. The RMSE was $0.0355 \text{ g} \cdot \text{C} \cdot \text{MJ}^{-1}$ and the bias was -0.0023. Low values were slightly overestimated, but this is not a bad result according to the overall RMSE and bias. With further validation and development, the VPM model has the potential for use on large spatial scales to estimate forest GPP. This would improve our understanding of the carbon cycle of the terrestrial biosphere (Xiao, 2004b).

4) Accuracy assessment of estimated GPP

We assessed the accuracy of the simulated GPP data by performing a linear regression with validation GPP data (Fig. 12). The RMSE and bias between the validation and estimated GPP data for different land cover types indicated that the GPP was simulated with reasonable accuracy (Table 4). The linear regression model also produced good agreement among different land cover types. For all sites, the correlation was close and highly significant ($R^2 = 0.8164$, $\text{RMSE} = 0.6126 \text{ g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$, $\text{bias} = -0.0271 \text{ g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$). Cropland had the highest correlation of the different ground types with high significance ($R^2 = 0.83$, $\text{RMSE} = 0.56 \text{ g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$, $\text{bias} = -0.015 \text{ g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$) and forest had the lowest correlation with moderate significance ($R^2 = 0.80$, $\text{RMSE} = 0.69 \text{ g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$).

Fig. 12. Comparison between the validation and estimated GPP.

Table 4. Results (R^2 , RMSE, bias) of comparison between validation GPP data and estimated GPP

	Cropland	Forest	Total
R^2	0.8308	0.8029	0.8164
RMSE	0.5591	0.6856	0.6126
Bias	-0.0149	-0.0455	-0.0271

Table 5. Comparison with error statistics of GPP calculated using various models for the study period

Method	R^2	RMSE ($\text{g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$)	Bias ($\text{g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$)
GPP by TURC ε_g model	0.6461	2.3263	2.1289
GPP by Ruimy's FPAR model	0.8899	0.7689	-0.5652
Present study	0.8164	0.6126	-0.0271

¹, $\text{bias} = -0.046 \text{ g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$).

We also compared with GPP calculated to be using input variable presenting in other model (Fig. 13). Fig. 13 shows a comparison between validation GPP data

Fig. 13. Comparison between validation GPP data and GPP data from other models (Ruimy's FPAR model and TURC ϵ_0 model).

Fig. 14. Comparison of seasonal dynamics between reference and estimated GPP data.

Fig. 15. Comparison of seasonal dynamics between reference GPP data and GPP data from the TURC ϵ_0 model.

and other models (Ruimy's FPAR model and the TURC ϵ_0 model) and Table 5 provides detailed

information about the estimated GPP accuracies. As shown in Table 5 and Figs. 14-16, our method resulted

Fig. 16. Comparison of seasonal dynamics between reference GPP data and GPP data from Ruimy's FPAR model.

Fig. 17. Comparison of spatial patterns between MODIS GPP and estimated GPP (January, April, July, and October, 2006).

in overestimation or underestimation compared to other studies over the Korean peninsula. Even so, the final estimated GPP was better than that in other studies, as supported by statistical results (Table 5). The estimated GPP was closer for cropland than for forest (Fig. 14).

Fig. 17 compares spatial GPP patterns with MODIS and estimated GPP values for January, April, July, and October. A large portion of the July MODIS GPP data is missing. This illustrates clearly that even though MODIS global products are readily available, they

contain errors, and input variables may not be corrected properly. In this study, errors in the estimated GPP were observed in MODIS products. Therefore, it is unreasonable to use them in research without improved processing.

5. Conclusions

We tested the performance of the MODIS

operational algorithm on satellite data when calculating GPP. Typically, using GPP global product results in a regional mismatch over Korea and using MODIS GPP data and tends to produce poor GPP estimates. To solve this problem, we estimated each of the GPP component variables separately to improve the GPP estimates. We compared our GPP estimates with validation GPP data to assess their accuracy. For all sites, the correlation was close with high significance ($R^2 = 0.8164$, $RMSE = 0.6126 \text{ g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$, $\text{bias} = -0.0271 \text{ g} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$). We also compared our results to those of other models. The component variables tended to be either over- or under-estimated when compared to those in other studies over the Korean peninsula, although the estimated GPP was better.

This work underscores the importance of studying extreme environments where large interannual variations in photosynthetic activity and hydrologic regime occur. This importance extends to model and algorithm intercomparison studies. The results of this study will likely improve carbon cycle modeling by capturing finer patterns with an integrated method of remote sensing. We hope this method will improve regional GPP modeling to some extent by introducing pixel-level resolution.

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