Environment and Ecology 37 (1A) : 221—228, January—March 2019
Website: environmentandecology.com ISSN 0970-0420

Modelling the Gross Primary Productivity (GPP) of an Indian Mangrove Vegetation

**Kripa M. K., Ankit Gohel, Nikhil Lele,
Archana U. Mankad, T. V. R.Murthy**

Received 17 August 2018; Accepted 22 September 2018; Published on 13 October 2018

Abstract Spatio-temporal variability of Gross Primary Productivity (GPP) remains a challenge despite its importance in the global carbon budget. In this paper, we have attempted to model the Gross Primary Productivity of Indian mangroves with the aid of *in situ* measurements of biophysical and biochemical parameters using SCOPE model and the results are compared with the GPP outputs derived Vegetation Photosynthesis Model (VPM). Soil Canopy Observation, Photochemistry and Energy fluxes (SCOPE) model is used for simulation of GPP, using *in-situ* biochemical measurements of chlorophyll content (C_{ab}) and maximum carboxylation rate (V_{cmax}). The simulated values of GPP from the model ranged between 0.0 to 2.6 µmol $m^{-2}s^{-1}$ for summer season, 0.0 to 10 µmol $m^{-2}s^{-1}$ for post-monsoon and 0.0 to 6.6 µmol m^{-2} s^{-1} during winter season. Estimated GPP using *in-situ* measurements and satellite- based Vegetation Photosynthesis Model (VPM) during summer ranges from 0.0 to 6.7 µmol m^{-2} s^{-1},0.0 to 9.4 µmol m^{-2} s^{-1} in post-monsoon and during winter 0.0 to 6.8 µmol m^{-2} s^{-1} from Pichavaram mangrove forest, Tamilnadu. Correlation coefficient between SCOPE GPP and VPM GPP for summer, post-monsoon and winter were 0.88, 0.84 and 0.79 respectively.

Keywords GPP, Mangrove, SCOPE, Vegetation photosynthesis model, Pichavaram.

Kripa M. K.* , Nikhil Lele, T.V.R. Murthy
Agriculture and Land Ecosystem Division (AED), Biological and Planetary Sciences and Applications Group (BPSG), Earth, Ocean, Atmosphere, Planetary Sciences and Applications Area (EPSA), Space Applications Center (SAC), Indian Space Research Organization (ISRO), Ahmedabad, Gujarat, India

Archana U. Mankad, Kripa M. K.
School of Sciences, Department of Botany, Bioinformatics and Climate Change Impacts Management, Gujarat University, Ahmedabad, Gujarat, India

Ankit Gohel
Department of Physics, Government Arts and Science College, Patdi, Saurasthra University, Gujarat, India
e-mail : mrajeev77@gmail.com; ankitphysics007@yahoo.com; nikhillele@sac.isro.gov.in; aumankad@gujaratuniversity.ac.in; murthytvr@sac.isro.gov.in
*Corresponding author

Introduction

The study on the Gross Primary Productivity (GPP) of terrestrial ecosystems around the globe has emerged as an important necessity as it gives insight to the process of carbon sequestration, carbon cycle and even research on climate change. GPP can be described as the net rate of carbon fixation by vegetation, through the process of photosynthesis. With the changing climatic scenario and the increasing CO_2 concentration in the atmosphere, the carbon sequestration potential during the upcoming years will be seriously affected, which in turn affects the quantification of the amount of carbon uptake and its inter-annual variability (Ramakrishna et al. 2003). Terrestrial vegetation plays an important role in the fixation of global carbon dioxide (CO_2) into organic compounds through the process of photosynthesis. Understanding and quantifying spatiotemporal variation in GPP is thus important for monitoring food security, global carbon cycle and the climate system (Schimel et al. 2015). GPP drives the inter-annual variability of the CO_2 mixing ratio and may substantially affect the future climate trajectory (Le Quéré et al. 2015). Estimation of GPP from eddy covariance measurements at flux tower site (Dennis et al. 2001, 2003) are carried out to globally distribute mechanistic land surface model simulations (Friedlingstein et al. 2006, Sitch et al. 2008).

Numerous predictive models exists for the quantification of GPP, among which, the widely used ones are the Light Use Efficiency Model, which was proposed by Monteith (1972, 1977). As the model proposes a direct relationship between the Absorbed photosynthetically Active Radiation (APAR) and the productivity in plants, it can addresss the temporal and spatial variability in GPP. GPP is proportional to incoming photosynthesis Active Radiation (PAR), the fraction of absorbed PAR by vegetation (fAPAR) and light use efficiency (LUE), which was proposed by Monteith (1972, 1977). Another main approach to estimate GPP at different temporal and spatial scales is to use process-based terrestrial biosphere models (TBMs) (Sellers et al. 1997). TBMs generally represent physiological, biophysical and biogeochemical processes in a mechanistic way of photosynthesis, respiration and canopy energy balance and they require more inputs, most importantly meteorological, soil and land cover information. Most of these models rely on C_3 and C_4 photosynthesis models (Farquhar et al. 1980, Collatz et al. 1992) to estimate GPP. SCOPE model belongs to this group and can be used to simulate carbon, water vapor, and heat fluxes.

Even though eddy covariance method is widely used to measure the CO_2 exchange, the number of eddy covariance towers are limited. Thus, the GPP data derived from these towers can be used for the validation of GPP derived or estimated using various models. Hence, model simulations have become an important method to estimate GPP at both global and regional scale. Depending upon their ability to estimate the fraction of adsorbed PAR (FPAR) these models can be divided into two. One group uses the fraction of PAR absorbed at the canopy level. For example, PSN (Photosynthesis model) (Zhao et al. 2005), CASA (Carnegie-Ames-Stanford Approach) model (Potter 1993, 1999) and GloPEM (Global Production Efficiency Model) (Stephen and Samuel 1995). These models mostly make use the vegetation index NDVI to estimate the fraction of absorbed PAR by the canopy.

The second group uses the fraction of absorbed PAR at the green leaf level, or at chlorophyll level. Vegetation photosynthesis Model (VPM) (Xiao et al. 2004, Zhang et al. 2014) is an example for this category. The advantage of using VPM model is that the model uses an additional phenology scalar (Pscalar), which is primarily dependent on the life expectancy of leaves, whether it be evergreen or deciduous. The model also emphasises on monitoring the Light Use Efficiency (LUE) which improves the estimation accuracy of LUE. This is very much important because LUE is highly variable from species to species and from time to time. In addition, the incorporation of physiological parameters of vegetation will greatly aid the functioning of the model as it generates accurate results on the Gross Primary productivity. It is challenging to determine the Light use efficiency across various vegetation types throughout the varying seasons. In this context, VPM model plays a significant role. When the climatic conditions are unfavorable, the model takes into account various climatic parameters, which are measured in -situ like water and temperature. In addition, the model demarcates photosynthetically active vegetation from the non-photosynthetically active ones.

The quantification of seasonal variation in GPP remains a difficult task (Grace et al. 1995, 1996, Loescher et al. 2003, Saleska et al. 2003). The major objectives of the study are (1) Modelling GPP through SCOPE using biochemical *in-situ* parameters, (2) Estimation of GPP using VPM method, (3) comparison between SCOPE GPPP and VPM GPP at seasonal scale.

Materials and Methods

Study area and field data collection

Pichavaram mangrove forest (Latitude : 11.46° N,

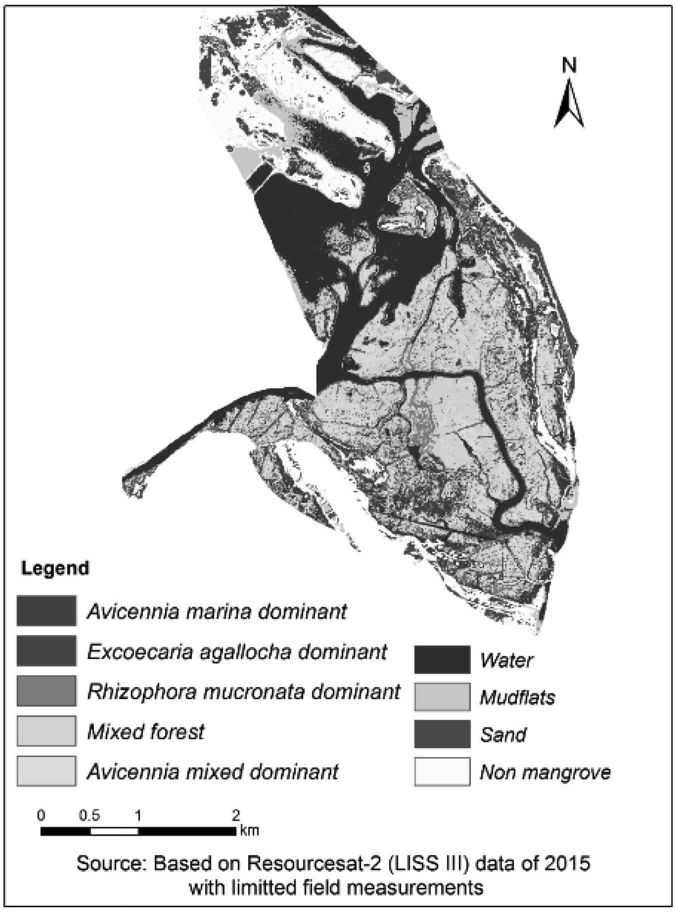

Fig. 1. Dominant Vegetation map of Pichavaram Mangrove using Resources at -2 LISS III and RISAT-1 (MRS) data.

Longitude : 79.79°E) which was declared as a reserve forest in 1987, covers an area about 1471 ha including mangrove forests, mudflats, back waters and sand dunes. The climate is sub-humid with very warm summer and with an annual average rainfall (70 years) of 1310 mm and annual average rainy days up to 56. Existing information on the species composition was gathered from available sources on the study area. This was followed by detailed field investigations to record the vegetation composition to derive phytosociological parameters. Analysis of phytosociological parameters from a total of 18 quadrats revealed five dominant categories of mangroves in the study area, viz. *Avicennia marina* dominant, *Excoecaria agallocha* dominant, *Rhizophora mucronata* dominant, mix of species of *Avicennia* (*A. marina* and *A. officinalis*) besides another class of mixed mangroves without the conspicuous dominance of a single species. *In-situ* measurements of photosynthetic rate and fluorescence measurements were crried out with the instrument LI-COR LI-6400XT-Portable Photosynthesis System (LI-COR 2004). Integrated Pulse Amplitude Modulation system (PAM) and integrated Leaf Chamber Fluorometer (LCF), has the capability to simultaneously measure the chlorophyll fluorescence and photosynthesis at leaf level with the aid of its Light Emitting Diode (LED) based fluorescence source accessory. Non-destructive diurnal measurements of the major mangrove species at leaf level was recorded from morning 5 : 30 to evening 5 : 30 repeatedly at an interval of every 45 minites. Two leaf samples (Sun and Shade leaves) of each species were studied

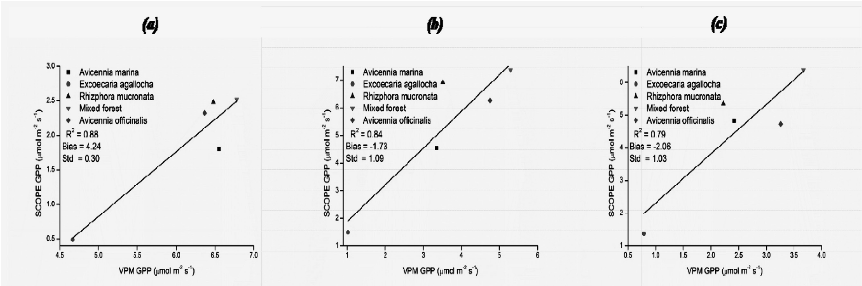

Fig. 2. Correlation between SCOPE GPP and VPM GPP for different seasons (a) Summer, (b) Post-Monsoon, and (c) Winter.

to account the variability within the species. Both photosynthesis and fluorescence measurements were carried out for the same leaf throughout the day. LAI measurements were carried out with the aid of Digital Plant Canopy Imager CID Bio-science CI 110. *In situ* measurements of chlorophyll-a and b were carried out on the basis of Arnon's estimation method (Arnon 1949). Both the optical and SAR data were used along with limited field observations to derive a spatial map of Dominant species of the study area based on decision rules (Figs. 1, 2).

Estimation of GPP using VPM model

VPM model proposed by Xiao (2004), was considered for the study with slight modifications. Mangroves being ubiquitous in the saline region, salinity was included as a limiting factor. Also, with the conjunctive use of *in-situ* measurements and satellite data, a spatial map of GPP was generated. From the diurnal photosynthetic rate measurements of summer (May 2015), post-monsoon (November 2015) and winter (February 2016) season, the corresponding Maximum Light Use Efficiency (ε_0) of the mangroves under study was derived as a ratio of the net photosynthesis and PAR (photosynthetically active radiation). KALPANA insolation images were downloaded and used for the derivation of PAR.

Resources at 2A, LISS-III and LISS-IV data near synchronous to our field data was archived. After pre-processing the images, various indices like simple ratio, Land Surface Water Index (LSWI), Normalized Difference Vegetation Index (NDVI) were computed. From NDVI, the Fractional Vegetation Cover image was derived. Using simple ratio, fraction of PAR absorbed by the chlorophyll (fPARcl) were

Table 1. SCOPE parameters.

Parameters	Values	Units
Incoming short wave radiation	Depending on months	W m^{-2}
Maximum carboxylation rate	Field data	μmol m^{-2} s^{-1}
Chlorophyll a + b content	Field data	μg cm^{-2}
Leaf area index LAI	0.5 – 4.0	/
Dry matter content	0.012	g cm
Leaf equivalent water thickness	0.009	cm
Senescent material	0.0	/
Leaf structure	1.4	/
Leaf angle distribution parameter *a*	-0.35	/
Leaf angle distribution parameter *b*	-0.15	/
Leaf width	0.1	m
Ball-Berry stomatal conductance	0.8	/
Dark respiration rate 25° as fraction of V_{cmax}	0.015	/
Cowan's water use efficiency	700	/
Leaf thermal reflectance	0.01	/
Leaf thermal transmittance	0.01	/

estimated. Water scalar was derived from the LSWI image. The phenology scalar (P_s) was considered as 1, considering that the leaf is in the fully expanded condition (Xiao et al. 2004). MODIS Land Surface Temperature (LST) data at 1 km resolution was down loaded and the area of interest was separated. Fractional Vegetation Cover after being resampled to 1 km, was correlated with the MODIS data to derive a model equation to generate temperature image, from which the temperature scalar images were developed. From the *in-situ* measured soil salinity, the respective salinity images were generated by the interpolation method through kriging. The respective salinity scalar (S_s) image was developed from this image. Finally, Maximum light use efficiency (equation 1) and GPP (equation 2) was computed.

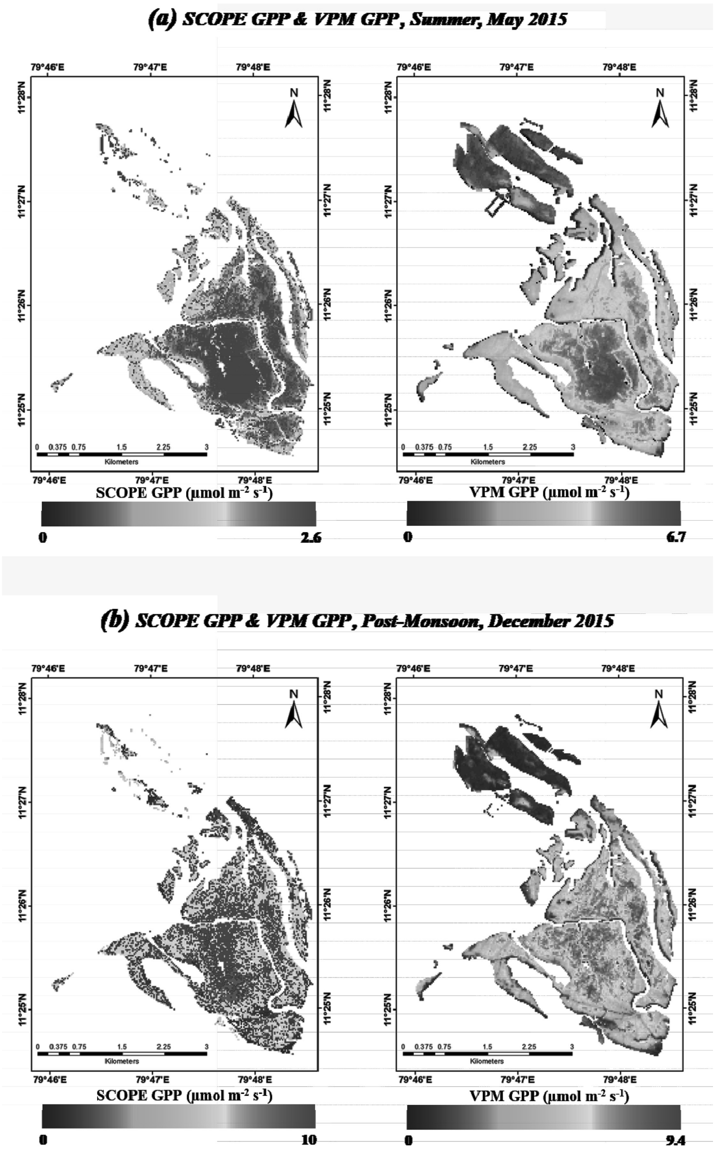

Fig. 3. (a) SCOPE GPP & VPM GPP, Summer, May 2015. (b) SCOPE GPP & VPM GPP, Post-Monsoon, December 2015.

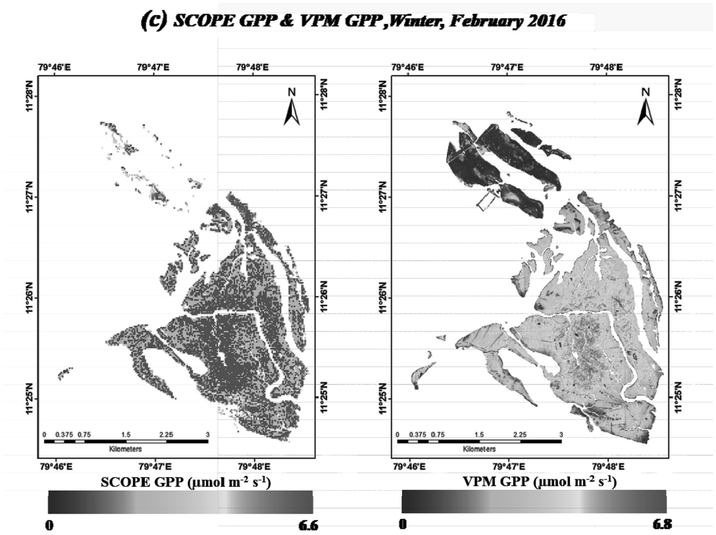

Fig. 4. Comparison between SCOPE GPP and VPM GPP Winter seasons at 24 m of Pichavaram.

$$\text{Light Use Efficiency } (\varepsilon) = \varepsilon_0 \times P_s \times W_s \times T_s \times S_s \qquad (1)$$

Where, ε_0 = Maximum light use efficiency, P_s = Phenology scalar, W_s =Water scalar, T_s =Temperature scalar, S_s = Salinity scalar.

$$\text{Gross Primary Productivity (GPP)} = \varepsilon \times f\,PAR_{chl} \times PAR \qquad (2)$$

SCOPE model and input parameter

SCOPE is a vertical (1-D) integrated radiative transfer and energy balance model. The model calculates radiation transport in a multilayer canopy as a function of the solar zenith angle and leaf orientation to simulate fluorescence in the direction of observation. The biochemical component has been updated based on (Collatz et al. 1991), (Collatz et al. 1992) for C_3 and C_4 plants, respectively. It determines the illumination and net radiation of leaves with respect to their position (distance from the top of canopy in units of leaf area) and orientation (leaf inclination and azimuth angle) and the spectra of reflected and emitted radiation as observed above the canopy in the specified satellite observation geometry. SCOPE requires inputs of meteorological forcing (incoming short wave and long wave radiation, air temperature, humidity, wind speed and CO_2 concentration) and four categories of factors : (1) vegetation structure parameters, such as canopy height, leaf size, leaf angle distribution, and LAI ; (2) leaf biophysical parameters : leaf chlorophyll content (C_{ab}), dry matter content (C_{dm}) leaf equivalent water thickness (C_w) senescent material (C_s) and leaf structure (N); (3) optical parameters : Reflectance of soil in the visible, near infrared and thermal bands, and vegetation (thermal) emissivity; (4) plant physiological parameters : stomatal conductance parameter (m) and maximum carboxylation capacity, V_{cmax} (Zhang et al. 2014). The required SCOPE parameters are described in Table 1. Output of the model is the spectrum of outgoing radiation in the viewing direction, turbulent heat fluxes, photosynthesis and chlorophyll fluorescence. Physical parameters were incoming short wave radiation (www.clearskycalculator.com), air temperature, air pressure, atmospheric vapor pressure, solar zenith angle and *in-situ* measurements of biochemical parameters like V_{cmax} and C_{ab}. After setting LAI, V_{cmax} and $C_{ab,}$ SCOPE simulations was run for 1 : 30 pm (IST) to observe the variability of GPP in high light condition for summer, post-monsoon and winter seasons over Pichavaram mangrove. We are using LAI map and Dominant mangrove species map for mapping of GPP.

Results and Discussion

In the current study, comparison of seasonal dynamics of SCOPE GPP and VPM GPP in summer, post-monsoon and winter seasons at 24 m (Figs. 3, 4) was carried out. For summer, SCOPE and VPM GPP ranges from 0.0 to 2.6 µmol m^{-2} s^{-1} and 0.0 to 6.7 µmol m^{-2} s^{-1} . In post-monsoon, we estimated SCOPE and VPM GPP varies from 0.0 to 10 µmol m^{-2} s^{-1} and 0.0 to 9.4 µmol m^{-2} s^{-1} respectively. For winter, we observed SCOPE GPP and VPM GPP ranges from 0.0 to 6.6 µmol m^{-2} s^{-1} and 0.0 to 6.8 µmol m^{-2} s^{-1} . Fig. 1 shows comparison between SCOPE and VPM GPP against different seasons and different mangrove species. The largest difference of 2.06 µmol m^{-2} s^{-1} is observed in winter season. The lowest difference 4.24 µmol $m^{-2}s^{-1}$ is found in summer season. In summer, Standard deviation of 0.30 µmol m^{-2} s^{-1}, bias of 4.24 µmol m^{-2} s^{-1} and correlation of 0.88 was recorded . For post- monsoon, Std deviation of 1.09 µmol m^{-2} s^{-1} , bias of -1.73 µmol m^{-2} s^{-1} and correlation of 0.84 was estimated. In winter , Std deviation of 1.03 µmol m^{-2} s^{-1}, bias of -2.06 µmol m^{-2} s^{-1} and correlation of 0.79 was recorded.

Conclusion

We compared SCOPE GPP and VPM GPP for summer, post-monsoon and winter seasons at 24 m resolution. The coefficient of correlation was found to be 0.88 during summer, which was the highest. A good correlation was found between the two models during post-monsoon also (R^2 =0.84). Winter season witnessed the least correlation coefficient (R^2 =0.79). Thus, to conclude, results from both the models were in good agreement to each other. Either of both the models could be efficiently used to determine the Gross Primary Productivity depending on the nature of *in-situ* data available. The results indicate that both the models can be effectively used for the estimation of GPP. Thus, the model can be effectively applied to other ecosystems also, provided a thorough research is carried out on the climatic variables, which effects the temporal variation in GPP of that particular region. The results not only validates the models, but also identifies areas conductive for production and further plantation could be done on its basis. Thus, studies related to carbon estimates need to be given more importance in the present scenario of changing climatic conditions. Even though, these models have widely used the physiological, biochemical, optical and biophysical parameters, future research should emphasize more on anatomical aspects too.

References

Arnon DI (1949) Copper Enzymes in Isolated Chloroplasts Polyphenol Oxidase in Beta vulgaris. Pl Physiol 24 : 1-5. doi : 10.1104/pp 24.1.1.

Collatz GJJ, Ball T, Grivet C, Berry JA (1991) Physiological and environmental regulation of stomatal conductance, photosynthesis and transpiration : A model that includes a laminar boundary layer. Agric For Meteorol 54 : 107—136.doi : 10.1016/0168-1923 (91) 90002-8.

Collatz G, Ribas-Carbo M, Berry JA (1992) Coupled photosynthesis-stomatal conductance model for leaves of C_4 plants. Australian J Pl Physiol 19 : 519—538, doi : 10.1071/ PP9920519.

Dennis D Baldocchi et al. (2001) FLUXNET : A New Tool to Study the Temporal and Spatial Variability of Ecosys tem-Scale Carbon Dioxide, Water Vapor and Energy Flux Densities. https : //doi.org/10.1175/1520-0477 (2001) 082<2415 : FANTTS>2.3.CO;2.

Dennis DBaldocchi et al. (2003) Assessing the eddy covariance technique for evaluating carbon dioxide exchange rates of ecosystems : Past, present and future. https ://doi.org/10.1046/j.1365-2486.2003.00629.x.

Farquhar GD, Caemmerer S Von, Berry JA (1980) A biochemical Model of Photosynthetic CO_2 Assimilation in Leaves of C_3 Species. Planta 149 : 78—90.

Friedlingstein P et al. (2006) Climate-Carbon Cycle Feedback Analysis : Results from the C_4 MIP Model Inter-compari son. https : //doi.org/10.1175/JCL13800.1.

Grace J et al. (1995) Carbon dioxide uptake by an undisturbed tropical rain forest in southwest Amazonia, 1992 to 1993. Science 270 : 778—780.

Grace J, Malhi Y, Lloyd J, Mcintyre J, Miranda AC, Meir P, Miranda HS (1996) The use of eddy covariance to infer the net carbon dioxide uptake of Brazilian rain forest. Global Change Biology, pp 209—217.

Le Quéré et al. (2015) Global Carbon Budget 2015. Earth Syst Sci Data 7 : 349—396. www.earth-syst-sci-data. net/7/349/2015/doi: 10.5194/essd - 7-349-2015.

LI-COR (2004) Using the LI-6400 Portable Photosynthesis System Bioscience, Inc. Lincoln, NE, USA. http : //www. licor.com/env/products/photosynthesis/measurements. html.

Loescher H, Oberbauer SH, Gholz HL, Clark DA (2003) Environmental control on net ecosystem-level carbon exchange and productivity in a Central American tropical wet forest. Global Change Biol 9 : 396—412.

Monteith Jl (1972) Solar Radiation and Productivity in Tropical Ecosystems. J Appl Ecol 9 (3) : 747—766. DOI : 10.2307/ 2401901. https : //www.jstor.org/stable/2401901.

Monteith JL (1977) Climate and the efficiency of crop production in Britain. Philosophical Transactions Of The Royal Society B. DOI : 10.1098/rstb.1977.0140.

Potter CS (1993) Terrestrial Ecosystem Production : A Process

Model Based on Global Satellite and Surface Data, Global Biogeochemical Cycles 7 (4) : 811—841. DOI : 10.1029/93GB02725.

Potter CS (1999) Terrestrial biomass and the effects of deforestation on the global carbon cycle. Bio Sci 49 : 769—778.

Nemani Ramakrishna R, Charles D Keeling, Hirofumi Hashimoto,William M, Jolly, Stephen C, Piper Compton J Tucker, Ranga B Myneni, Steven W, Running (2003) Climate-Driven Increases in Global Terrestrial Net Primary Production from 1982 to 1999. Science pp 1560—1563.

Saleska SR et al. (2003) Carbon fluxes in old-growth Amazonian rainforest : Seasonality and disturbance-induced net carbon loss. Sci (302), pp 1554—1557.

Schimel David, Britton B, Stephens, Joshua B Fisher (2015) Effect of increasing CO on the terrestrial csarbon cycle 112 (2) : 436—441. https ://doi.org/10.1073/pnas.1407302112.

Sellers PJ, Dickinson RE, Randall DA et al. (1997) Modeling the exchange of energy, water, and carbon between conti nentss and the atmosphere.Science 275 : 502—509.

Sitch S et al. (2008) Evaluation of the terrestrial carbon cycle, future plant geography and climate-carbon cycle feedbacks using five,Dynamic Global Vegetation Models (DGVMs).
Global Change Bio 14, pp 1—25. doi : 10.1111/j.1365-2486.2008.01626.x.

Prince Stephen D, Goward Samuel N (1995) Global Primary Production : A remote sensing approach. J Biogeography, Vol. 22, No.4/5, Terrestrial Ecosystem Interactions with Global , Volume 2. pp.815—835, DOI : 10.2307/2845983. https : //www.jstor.org/stable/2845983.

Xiao X, Hollinger D, Aber JD, Goltz M, Davidso EA, Zhang QY (2004) satellitebased modeling of gross primary production in an evergreen needleleaf forest. remote sens Environ 89: 519—534.

Xiao X, Zhang Q, Braswell B, Urbaski S, Boles S, Wofsy SC et al. (2004) Modeling gross primary production of a deciduous broadleaf forest using satellite images and climate data. Remote Sens Environ 91 : 256—270.

Zhang Y, Guinter, Berry JA, Joiner J, Van Der Tol C, Huete A, Gitelson A, Voigt M, Kohler P (2014) Estimation of vege tation photosynthetic capacity from space-based measure ments of chlorophyll fluorescence for terrestrial biosphere models. Global Change Biol 20 (12) : 3727-3742.doi : 10.1111/gcb.12664.

Zhao MS, Heinsch FA, Nemani RR, Running SW (2005) Improvements of the MODIS terrestrial gross and net primary production global data set. Remote Sens Environ 95 (2) : 164-176. DOI : 10.1016/j.rse.2004.12.011.