



Comparison of multiple models for estimating gross primary production using MODIS and eddy covariance data in Harvard Forest

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ABSTRACT

Gross primary production (GPP) defined as the overall rate of fixation of carbon through the process of vegetation photosynthesis is important for carbon cycle and climate change research. Three models, the Vegetation Photosynthesis Model (VPM), the Temperature and Greenness (TG) model and the Vegetation Index (VI) model have been compared for the estimation of GPP in Harvard Forest from 2003 to 2006 using climate variables acquired by eddy covariance (EC) measurements and Moderate Resolution Imaging Spectroradiometer (MODIS) satellite images. All these models provide more reliable estimates of GPP than that of MODIS GPP product. High Pearson's correlation coefficients r equal to 0.94, 0.92 and 0.90 are observed for the VPM, the TG and the VI model, respectively. Relationships between GPP and land surface temperature (LST, $R^2 = 0.72$), and vapor pressure deficit (VPD, $R^2 = 0.45$) indicate that climate variables are important for GPP estimation. Due to proper characterization of temperature, water stress and leaf age by three scalars, VPM best follows the seasonal variations of GPP. By incorporation of the MODIS surface reflectance and LST product, the TG model is the most suitable choice for areas without prior knowledge as it is based entirely on remote sensing observations. Results from the VI model demonstrate the possibility of using a single vegetation index for light use efficiency (LUE) estimation in deciduous forest that is of high spatial heterogeneity. The validation and comparison of models will be helpful in development of future GPP models using combinations of climate variables and/or remote sensing observations.

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1. Introduction

Quantification of the magnitude of net terrestrial carbon (C) uptake, and how it varies inter-annually, is an important question with future potential sequestration influenced by both increased atmospheric CO₂ and changing climate (Nemani et al., 2003). Therefore, estimation of the net ecosystem exchange (NEE) and the gross primary production (GPP) of terrestrial ecosystems for regions, continents, or the globe can improve our understanding of the feedbacks between the terrestrial biosphere and the atmosphere in the context of global change and facilitate climate policy-making (Canadell et al., 2000; Xiao et al., 2008).

The eddy covariance (EC) technique provides the best approach to measure net CO₂ exchange at ecosystem scales that can be used for GPP calculation by modeling the ecosystem respiration component

and subtracting. It is still a challenge, however, to partition respiration of ecosystems into autotrophic respiration and heterotrophic respiration (Li et al., 2007). Furthermore, the EC technique only provides integrated CO₂ flux measurements over footprints with sizes and shapes that vary with the tower height, canopy physical characteristics and wind velocity (Osmond et al., 2004). Satellite remote sensing can provide consistent and systematic observations of vegetation and ecosystems, and has played an increasing role in the characterization of vegetation structure and estimation of GPP or net primary production (NPP) that can overcome the lack of extensive flux tower observations over large areas (Behrenfeld et al., 2001; Running et al., 2000).

Among all the predictive methods, the light use efficiency (LUE) model may have the highest potential to adequately address the spatial and temporal GPP dynamics. It proposes a direct proportional relation between biological production and the amount of photosynthetically active radiation absorbed by the vegetation canopy (APAR) (Monteith, 1972, 1977; Running et al., 2000). The fundamental methodology of GPP estimation is based on the Monteith (1972) equation as:

$$GPP = LUE \times f_{APAR} \times PAR \quad (1)$$

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where LUE is the light use efficiency and f_{APAR} represents the fraction of absorbed PAR (photosynthetically active radiation).

Many current models of ecosystem carbon exchange based on remote sensing, such as the Moderate Resolution Imaging Spectroradiometer (MODIS) product termed MOD17, still require considerable input from ground-based meteorological measurements and lookup tables based on vegetation type. Since these data are often not available at the same spatial scale as the remote sensing imagery, they can introduce substantial errors into the carbon exchange estimates, either in the original estimate of LUE for a particular vegetation type or in the assignment of vegetation type to a pixel (Sims et al., 2008; Yang et al., 2007). Although these LUE models have been used to estimate global or regional patterns of GPP, the LUE values on which they are based need to be calibrated rigorously because they have a large impact on the model accuracy (Yuan et al., 2007). Furthermore, recent studies suggest that this approach may lead to considerable errors in modeled GPP and that uncertainty in LUE spatiotemporal variation is a crucial limiting factor for models (Turner et al., 2003; Zhao et al., 2005).

Vegetation indices (VIs) derived from more than one band of reflectance offer important and convenient measures for the estimation of ecosystem biochemical components (e.g., chlorophyll content) and leaf area index (LAI) which is defined as half the all-sided green leaf area per unit ground area (Chen & Black, 1992). These results provided the basis for estimating production by combination of such indices and climate variables (Gitelson et al., 2006; Sims & Gamon, 2002; Wu et al., 2009; Xiao et al., 2004a,b). Therefore, VIs are frequently used in GPP estimation models because these models either use climate variables to acquire LUE (e.g., the Vegetation Photosynthesis Model, VPM) or are entirely based on remote sensing observations (e.g., the Temperature and Greenness model, TG) (Gitelson et al., 2008; Sims et al., 2008; Xiao et al., 2003). Based on the previous research of Inoue et al. (2008), a new model

incorporating vegetation index (VI) was proposed to estimate of GPP in wheat using MODIS images and PAR (Wu et al., 2010).

Despite intensive use of GPP models, research is needed to further evaluate these models, especially the operational application in forest ecosystems with a high temporal and spatial inhomogeneity (Coops et al., 2007; Gitelson et al., 2006; Sims et al., 2008; Xiao et al., 2004a). In this paper, three GPP models, i.e. the VPM, the TG model and a newly proposed VI model, are tested in the estimation of GPP for the Harvard Forest in 2003–2006 using the MODIS images (8-day surface reflectance and 8-day LST products) and climate variables acquired by EC measurements. The objectives of the study are: 1) to make full evaluation of the three models for the estimation of GPP in a forest ecosystem, 2) to compare between these models and 3) to improve the understanding for quantifying the temporal changes in GPP of forest ecosystem uses either meteorological variables or remote sensing observations.

2. Methods

2.1. Study area

The Harvard Forest eddy flux tower site (42°32'16" N and 72°10'17" W, 340 m elevation) is located in western Massachusetts, USA (Fig. 1). The vegetation is primarily deciduous forest, dominated by red oak (*Quercus rubra*), red maple (*Acer rubrum*), black birch (*Betula lenta*) and white pine (*Pinus strobus*) (Urbanski et al., 2007). The canopy height is approximately 20–24 m. Soils are mainly sandy loam glacial till with some alluvial and colluvial deposits. The climate is cool, moist temperate with July mean temperature 20 °C. Annual mean precipitation is about 1100 mm, and the precipitation is distributed approximately evenly throughout the year.

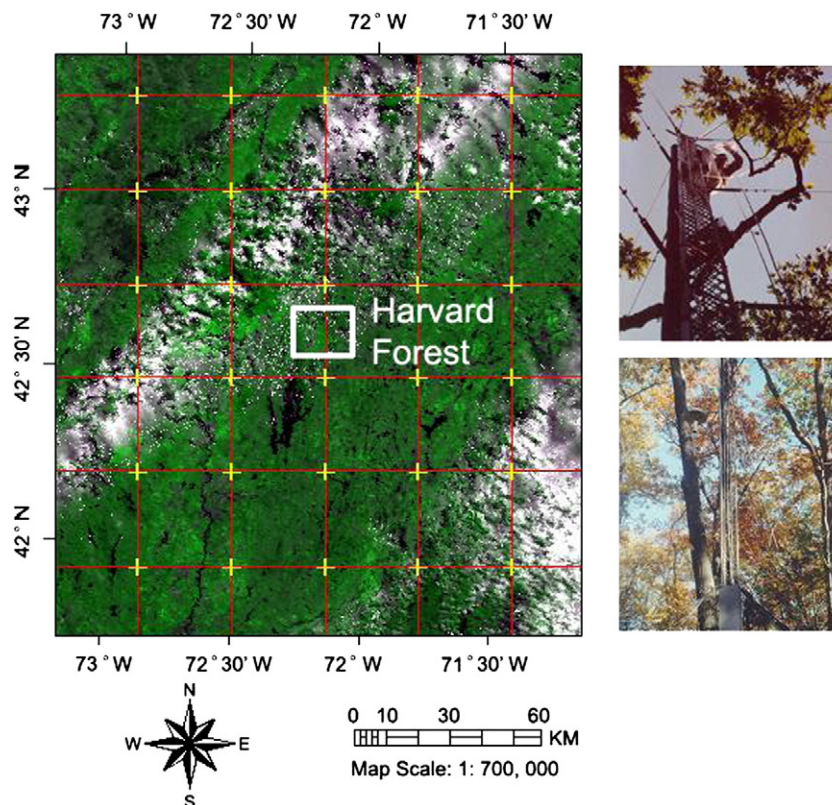


Fig. 1. Study area in view using MODIS image of 2009 (DOY of 121), and photos were downloaded from <http://atmos.seas.harvard.edu/lab/hf/hfsite.html>.

2.2. Eddy covariance data

Eddy flux measurements of CO₂, H₂O and energy at Harvard Forest have been collected since 1991 (Barford et al., 2001; Goulden et al., 1996; Urbanski et al., 2007; Wofsy et al., 1993). Daily data of air temperature (°C), soil temperature, precipitation (mm), PAR (mol/m²/day), NEE, derived GPP and ecosystem respiration (Re) from 2003 to 2006 are provided by researchers at Harvard Forest (<http://public.ornl.gov/ameriflux/dataproducts.shtml>).

Daily measurements are calculated from the half-hourly readings of covariance of the fluctuations in vertical wind speed and CO₂ concentration measured at 5 Hz (Urbanski et al., 2007). Half-hourly flux values are excluded from the analysis if the wind speed is below 0.5 m s⁻¹, if half-hour sample periods are incomplete, or in the case of instrument malfunction. Nighttime flux values are excluded from analysis if the friction velocity (u*) is below a threshold that varied among years (Xiao et al., 2004a). Both NEE and GPP are filled using the Artificial Neural Network (ANN) method (Papale & Valentini, 2003) and the Marginal Distribution Sampling (MDS) method (Reichstein et al., 2005).

Despite the use of GPP calculations by modeling the ecosystem respiration component and subtracting, uncertainties still exist in this technique, such as ignoring the reduction in leaf respiration in light relative to darkness (Coops et al., 2007). Also, the direction of the bias in estimated GPP is still unclear, as the uncertainty in the respiration coefficients will contribute to uncertainty in the estimated GPP. Moreover, Richardson et al. (2006) demonstrates that random errors of flux measurements follow consistent and robust patterns in relation to environmental variables, indicating the increased mismatch between EC measured GPP and model predictions. In this paper, the flux derived GPP will be considered as the “ground truth” in the subsequent analysis.

To run models with 8-day MODIS data, both NEE and GPP have been generated from the sums of daily flux data in 8-day intervals (consistent with the days used in MODIS 8-day composite data). Means of daily daytime mean temperature, VPD (Vapor Pressure Deficit) and the sums of PAR are also calculated over 8-day periods.

2.3. MODIS data

The MODIS is a key instrument aboard the Terra and Aqua satellites, acquiring data in 36 spectral bands from 450 nm to 2100 nm. These data provide important insights for global dynamics research both on the land and in the oceans.

In order to form a suite of data, three collection 5 MODIS products (8-day surface reflectance, 8-day GPP product and 8-day LST product) from 2003 to 2006 are downloaded (https://lpdaac.usgs.gov/lpdaac/get_data/wist) aiming to test and validate GPP models in the Harvard Forest flux site.

2.3.1. MODIS 8-day surface reflectance product

The Terra MODIS Surface Reflectance atmospheric correction algorithm Product (MOD09A1, 500 m) is computed from the MODIS Level 1B land bands 1, 2, 3, 4, 5, 6, and 7 (centered at 648 nm, 858 nm, 470 nm, 555 nm, 1240 nm, 1640 nm, and 2130 nm, respectively) (Vermote et al., 1997). Based on the geo-location information (latitude and longitude) of the Harvard forest flux tower site, vegetation index data from the MOD09A1 product are extracted from 3 × 3 MODIS pixels (~1.5 km × 1.5 km) that are centered on the flux tower.

2.3.2. MODIS 8-day GPP product

The Gross Primary Production product (MOD17A2) is designed to provide an accurate regular measure of the growth of the terrestrial vegetation using daily MODIS landcover, f_{APAR}/LAI and surface meteorology at 1 km for the global vegetated land surface (Field et

al., 1998). This product is calculated using a LUE type model with the following equation:

$$GPP = \varepsilon_{\max} \times m(T_{\min}) \times m(VPD) \times FPAR \times SWrad \times 0.45 \quad (2)$$

where ε_{\max} is the maximum LUE obtained from lookup tables on the basis of vegetation type. The scalars $m(T_{\min})$ and $m(VPD)$ reduce ε_{\max} under unfavorable conditions of low temperature and high VPD. FPAR is the Fraction of Photosynthetically Active Radiation absorbed by the vegetation and SWrad is shortwave solar radiation. T_{min}, VPD and SWrad are obtained from large spatial-scale meteorological data sets that are available from the NASA Global Modeling and Assimilation Office (GMAO) (<http://gmao.gsfc.nasa.gov/>).

Owing to difficulty in determination of which pixel the footprint falls in, we have tried both the central and mean values of 3 × 3 pixels and results indicate that the latter provided better correlation with GPP from flux measurements. Subsequently, we use the mean values of the 3 × 3 pixels for MODIS GPP product.

2.3.3. MODIS 8-day LST product

The MODIS 8-day Land Surface Temperature (LST) and Emissivity products (MOD11A2) are retrieved at 1 km pixels by the generalized split-window algorithm and at 6 km grids by the day/night algorithm. In the split-window algorithm, emissivity in bands 31 and 32 are estimated from land cover types, atmospheric column water vapor and lower boundary air surface temperature are separated into tractable sub-ranges for optimal retrieval (Wan et al., 2002). Pixel extraction is similar to that of MODIS GPP product method which is using the 3 × 3 pixels around the flux site.

2.4. Vegetation index

Two vegetation indices are used in the estimation of GPP using the MODIS data. The first is the Land Surface Water Index (LSWI), which is proposed by Xiao et al. (2002). As the short infrared (SWIR) spectral band is sensitive to vegetation water content and soil moisture, a combination of NIR and SWIR bands have been used to derive LSWI which is calculated by the following equation:

$$LSWI = \frac{R_{Nir} - R_{Swir}}{R_{Nir} + R_{Swir}} \quad (3)$$

where R_{Nir} and R_{Swir} represent the reflectance of the near infrared bands and short infrared bands, respectively. As leaf liquid water content increases or soil moisture increases, SWIR absorption increases and SWIR reflectance decreases, resulting in an increase of LSWI value. Recent validation also indicated the usefulness of LSWI for water content estimation in evergreen needleleaf forests (Maki et al., 2004).

The second index is the Enhanced Vegetation Index (EVI) using the blue band to primarily account for variable soil and canopy background reflectance (Huete et al., 1997). EVI directly normalizes the reflectance in the red band as a function of the reflectance in the blue band:

$$EVI = 2.5 \times \frac{R_{Nir} - R_{Red}}{1 + R_{Nir} + 6 \times R_{Red} - 7.5 \times R_{Blue}} \quad (4)$$

EVI has been successfully used for the study of temperate forests (Zhang et al., 2003), and is much less sensitive to aerosols than NDVI (Xiao et al., 2003). Recent studies by Sims et al. (2008) and Wu et al. (2010) also validated such EVI use for GPP estimation in both forest and crop ecosystems.

2.5. LUE calculation

Calculation of light use efficiency (LUE) from the flux tower data commonly requires an estimate of the absorbed photosynthetically active radiation (APAR). APAR can be calculated from the incident PAR recorded at the eddy covariance tower and from an estimate of the fraction of incident PAR absorbed by green vegetation (f_{APAR}). The vegetation indices (VIs), for example NDVI, or LAI are used in literatures for f_{APAR} calculation (Sims et al., 2006; Viña & Gitelson, 2005; Wu et al., 2010). After calculation of APAR as a product of f_{APAR} and PAR, LUE can be acquired using GPP and APAR. Therefore, based on results of Sims et al. (2006), a linear relationship ($f_{APAR} = 1.24 \times NDVI - 0.168$, $R^2 = 0.95$) between NDVI and f_{APAR} was used to determine f_{APAR} and the LUE could be further calculated from tower GPP and APAR.

2.6. Models overview

2.6.1. The VPM model

The Vegetation Photosynthesis Model (VPM) proposed by Xiao et al. (2004a,b) assumes that the leaf and forest canopies are composed of photosynthetically active vegetation (PAV, mostly chloroplast) and non-photosynthetic vegetation (NPV, mostly senescent foliage, branches and stems). The VPM has been successfully validated for GPP estimation in different ecosystems, including tropical evergreen forest (Xiao et al., 2005), temperate deciduous forest (Xiao et al., 2004a) and evergreen needle leaf forest (Xiao et al., 2004b). The VPM was built upon the conceptual partitioning of chlorophyll (F_{PAR}_{PAV}) and non-photosynthetically active vegetation (NPV) within the canopy. It estimates GPP over the photosynthetically active period of vegetation (Xiao et al., 2004a).

$$GPP = \varepsilon_g \times FPAR_{PAV} \times PAR \quad (5)$$

where $FPAR_{PAV}$ is the fraction of photosynthetically active radiation (PAR) absorbed by leaf chlorophyll in the canopy, PAR is the photosynthetically active radiation (mmol photosynthetic photon flux density, PPFD), and ε_g is the light use efficiency (g C/mol PPFD).

To run VPM, input parameters must be determined, in particular, LUE. LUE is a challenging variable to be determined at a global scale because it is often expressed as a biome-specific constant, adjusted through globally measurable meteorological variables representing canopy stresses, such as temperature and water content (Running et al., 2004). In the VPM, ε_g is determined as:

$$\varepsilon_g = \varepsilon_0 \times T_{scalar} \times W_{scalar} \times P_{scalar} \quad (6)$$

where ε_0 is the apparent quantum yield or maximum light use efficiency ($\mu\text{mol CO}_2/\mu\text{mol PPFD}$), and T_{scalar} , W_{scalar} and P_{scalar} are the down-regulation scalars for the effects of temperature, water and leaf phenology on the light use efficiency of vegetation, respectively.

T_{scalar} is estimated at each time step, using the equation developed for the Terrestrial Ecosystem Model:

$$T_{scalar} = \frac{(T - T_{min})(T - T_{max})}{[(T - T_{min})(T - T_{max})] - (T - T_{opt})^2} \quad (7)$$

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} , 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 water vapor pressure deficit (VPD) (Running et al., 2000). In the VPM, an alternative and

simple approach that uses a satellite-derived water index (LSWI) to estimate the seasonal dynamics of W_{scalar} ,

$$W_{scalar} = \frac{I + LSWI}{I + LSWI_{max}} \quad (8)$$

where $LSWI_{max}$ is the maximum LSWI within the plant growing season for individual pixels. When multi-year LSWI data are available, we calculate the mean LSWI values of individual pixels over multiple years at individual temporal points (8-day), and then select the maximum LSWI value within the photosynthetically active period as an estimate of $LSWI_{max}$ (Xiao et al., 2004a).

In the VPM, calculation of P_{scalar} depends upon life expectancy of leaves (deciduous versus evergreen). For a canopy dominated by leaves with a life expectancy of 1 year P_{scalar} is calculated at two different phases:

$$P_{scalar} = \frac{I + LSWI}{2}, \text{ during bud burst to leaf full expansion} \quad (9)$$

$$P_{scalar} = 1, \text{ after full leaf expansion}$$

For the Harvard Forest (deciduous broadleaf forest), the P_{scalar} is a linear scalar ranging between 0 and 1 because LSWI values range from -1 to 1 (Xiao et al., 2004a).

It is challenging to accurately estimate $FAPAR_{PAV}$. In this first version of the VPM, $FAPAR_{PAV}$ within the photosynthetically active period of vegetation is estimated as a linear function (the coefficient a is simply set to be 1.0) of EVI (Xiao et al., 2004a):

$$FAPAR_{PAV} = a \times EVI \quad (10)$$

In practical use of the VPM, some input variables are determined according to literature survey and former research carried out in Harvard Forest (see Table 1) (Ruimy et al., 1995; Xiao et al., 2004a).

2.6.2. The TG model

The Temperature and Greenness (TG) model was recently developed by Sims et al. (2008) that based on the Enhanced Vegetation Index (EVI) and the Land Surface Temperature (LST) products from MODIS. An important finding is the correlation between LST and both vapor pressure deficit (VPD) and photosynthetically active radiation (PAR). Combination of EVI and LST in the model substantially improves the correlation between the predicted and measured GPP at 11 eddy correlation flux towers in a wide range of vegetation types across North America and provided substantially better predictions of GPP than the MODIS GPP product (Sims et al., 2008).

The results described in Sims et al. (2008) indicate that the relationship between GPP and LST for the non-drought sites shows no sign of reaching an optimum, but for the drought sites there appears to be an optimum around 30 °C, with GPP declining to zero as LST declines to 0 °C or increases to 50 °C. Although it is unclear to what extent this results from direct temperature effects on photosynthetic

Table 1
Determination of input variables of VPM.

Variables	Values	References
ε_0	0.528 g C/mol PPFD	Ruimy et al., (1995); Wofsy et al., (1993)
T_{min}	-1 °C	Xiao et al. (2004a,b)
T_{max}	40 °C	Aber and Federer (1992); Xiao et al., (2004a,b)
T_{opt}	20 °C	Aber and Federer (1992); Xiao et al. (2004a,b)

rates as opposed to relationships between LST and drought stress, the relationship was consistent and a scaled LST was defined as:

$$\text{ScaledLST} = \min \left[\left(\frac{\text{LST}}{30} \right); (2.5 - (0.05 \times \text{LST})) \right] \quad (11)$$

where *scaledLST* is defined as the minimum of two linear equations. This results in a maximum value of *scaledLST*=1.0 for LST=30 °C and minimum values of *scaledLST*=0 when LST<=0 °C and >=50 °C (Sims et al., 2008).

Earlier studies (Sims et al., 2006) reported that GPP drops to zero around an EVI value of 0.1. We accordingly defined a scaled EVI as:

$$\text{ScaledEVI} = \text{EVI} - 0.1 \quad (12)$$

The TG model hence equals

$$\text{GPP} \propto \text{ScaledEVI} \times \text{ScaledLST} \quad (13)$$

2.6.3. The VI model

A new Vegetation Index (VI) model for GPP estimation has been proposed by Wu et al. (2010). It incorporates vegetation indices for both LUE and f_{APAR} estimation. This VI model was based on findings of current literatures that demonstrated the usefulness of VIs as proxies of both LUE and f_{APAR} (Gitelson et al., 2006; Inoue et al., 2008; Sims et al., 2006; Wu et al., 2009).

As EVI derived from MODIS images were reliable proxies of both light use efficiency (LUE) and the fraction of absorbed PAR (f_{APAR}) in maize, the VI model can be defined according to Monteith logic as:

$$\text{GPP} \propto \text{EVI} \times \text{EVI} \times \text{PAR} \quad (14)$$

3. Results and discussion

3.1. Flux climate variations

Seasonal and yearly fluctuations of NEE and GPP in 8-day interval of Harvard Forest showed the similar patterns from 2003 to 2006 (Fig. 2). Seasonal variations of GPP ranged from 20 gC/m²/(8-day) after April (DOY ≈ 140) to 120 gC/m²/8-day during the summer period (DOY ≈ 200). With seasonal growth and senescence of vegetation, GPP decreased to approximately zero after DOY ≈ 300. When comparing data of different years, we found that both NEE and GPP show different ranges, with an increasing NEE (−20 gC/m²/8-day at DOY ≈ 200) and a decreasing GPP (80 gC/m²/8-day at DOY ≈ 200).

As demonstrated by Wu et al. (2010), GPP may depend on both vegetation and meteorological variables. Therefore, in situ climate data (Ta, PAR and VPD) are also measured for better understanding the GPP variations (Fig. 3). The three variables show similar seasonal patterns during a year which is consistent with variation in GPP. Less difference is observed for Ta variation across the years as compared to that of VPD and PAR. This indicates that VPD and PAR are highly variable in time. Interestingly, a time lag exists in reaching the

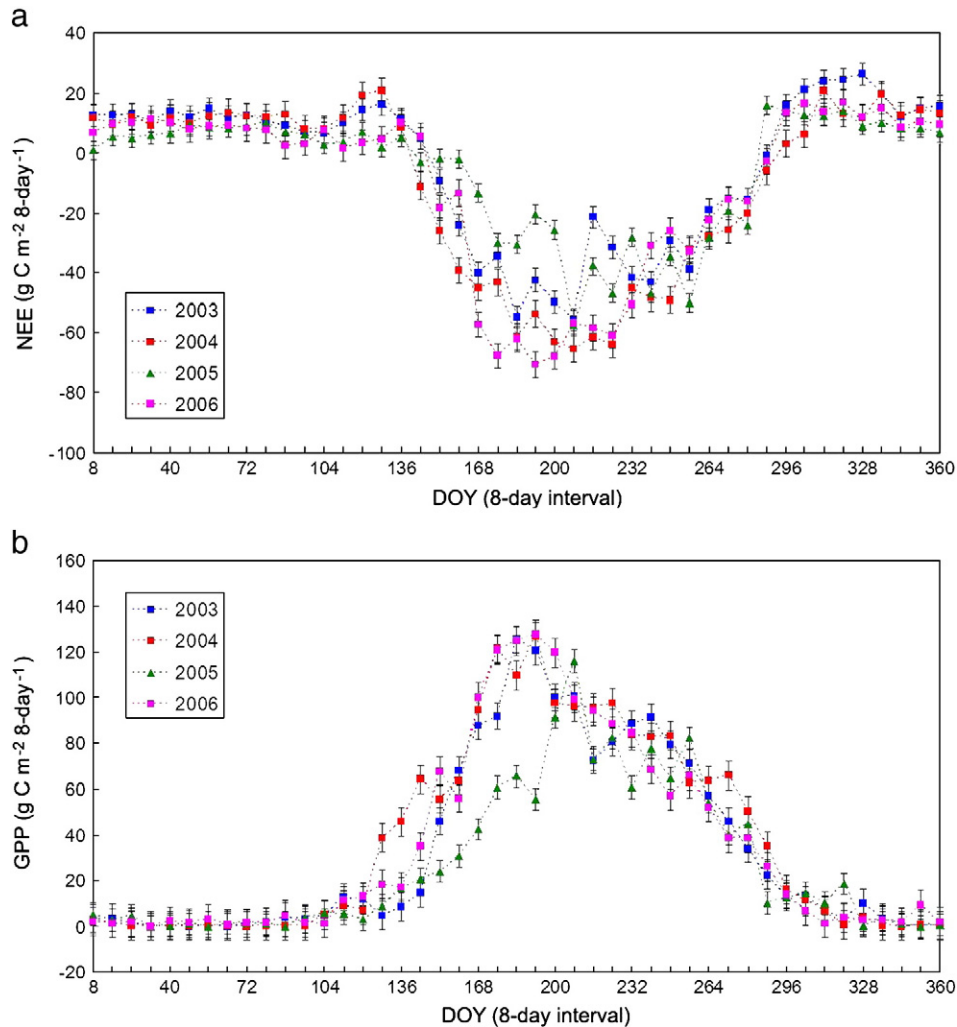


Fig. 2. The 8-day composites of NEE and GPP from covariance flux measurements in Harvard Forest from 2003 to 2006 (points represent data ± standard error).

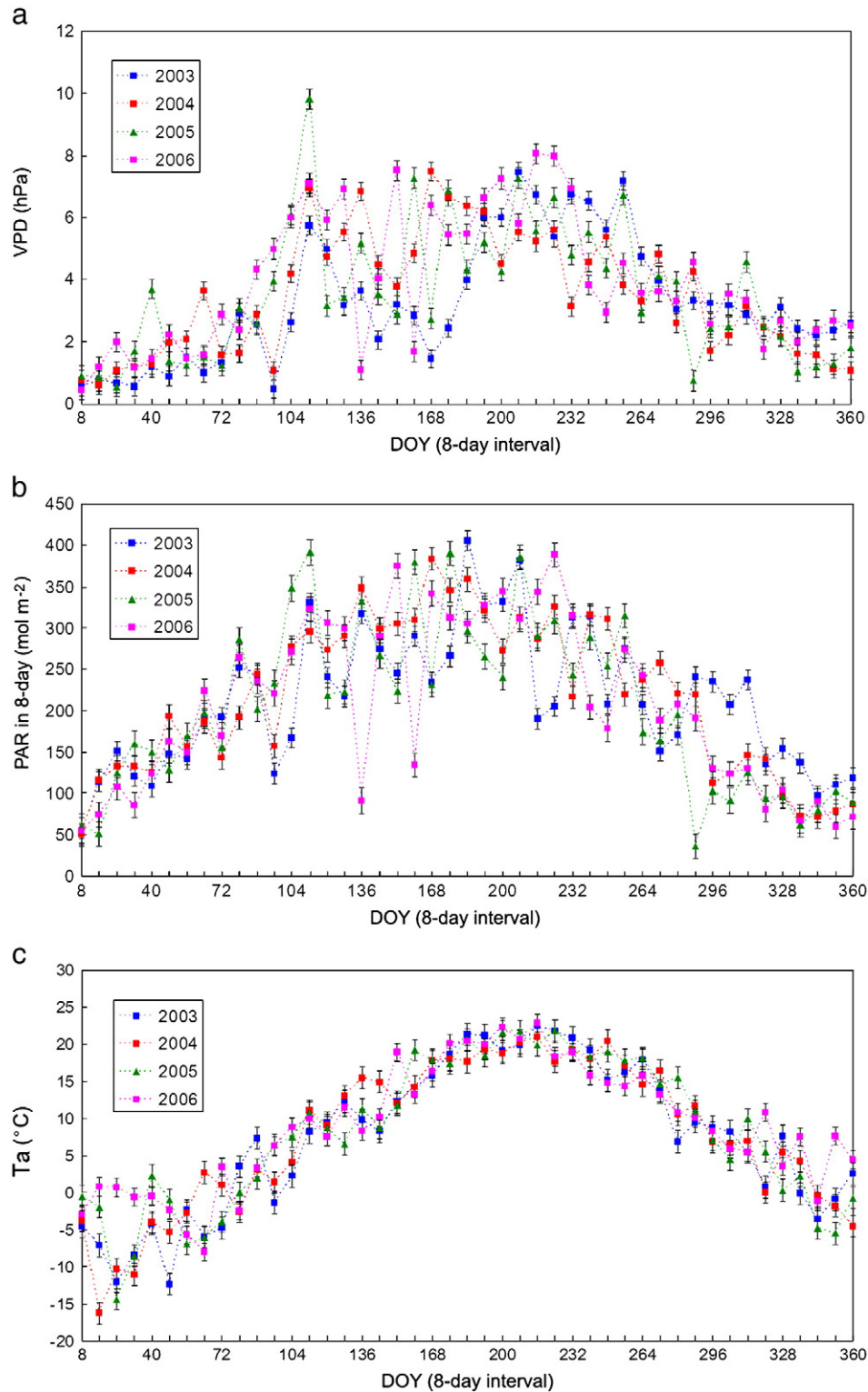


Fig. 3. In situ climate variables of Harvard Forest from 2003 to 2006 for (a) VPD, (b) PAR and (c) Ta in 8-day interval (points represent data \pm standard error).

maximum values for these climate variables, as the highest values of PAR occur between DOY 130 and DOY 210 whereas those for VPD and Ta are between DOY 200 and DOY 230.

3.2. MOD_GPP validation

Estimates of daytime R_e from the nighttime R_e -T relation are usually associated with considerable uncertainty because of overes-

timination of daytime respiration due to the extrapolation of nighttime respiration fluxes (Schultz, 2003). Thus, the GPP will be also affected by such disturbances. Here we compare the MODIS GPP (GPP_MOD) with results from EC technique (GPP_EC).

A Pearson's correlation coefficient (r) value equal to 0.88, and a root mean square error (RMSE) equals to $18.464 \text{ gC m}^{-2} (\text{8 day})^{-1}$ for the overall data were observed between the GPP_EC and GPP_MOD (r of 0.82–0.91 for each individual years, Fig. 4a). However,

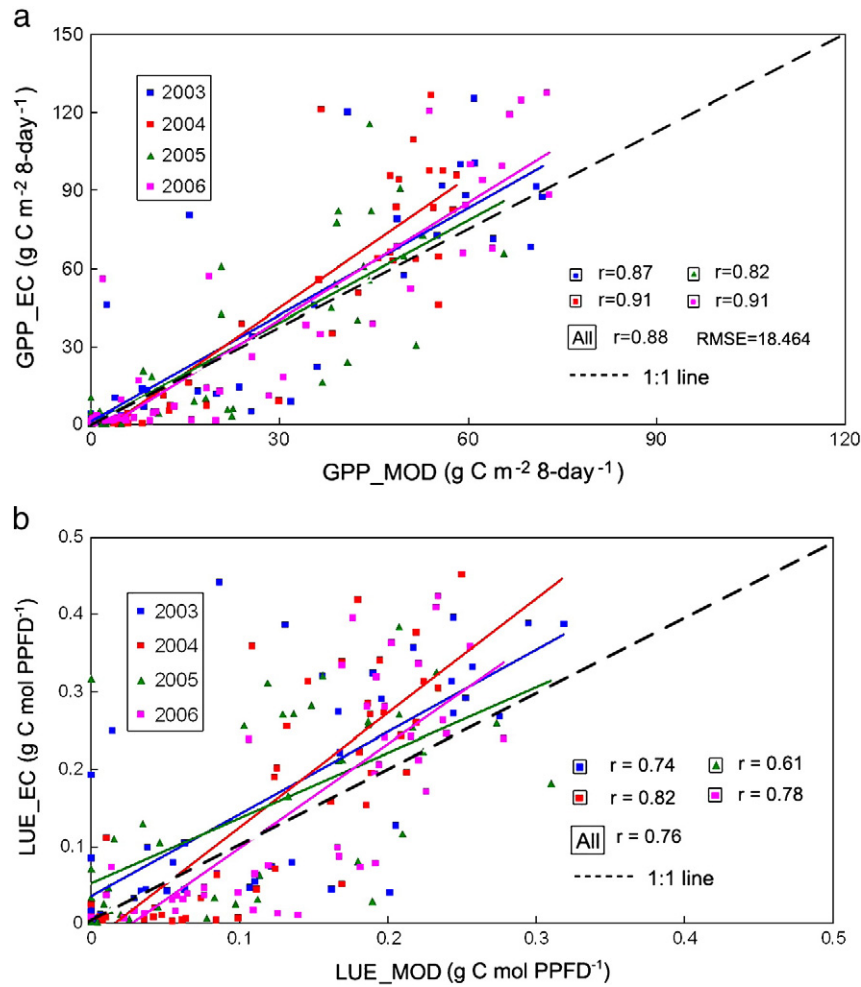


Fig. 4. Relationship of GPP_EC/GPP_MOD (a, correlation determined in r , RMSE in GPP unit) and LUE_EC/LUE_MOD (b, correlation determined in r) in Harvard Forest. All correlations are significant at the 0.01 level.

it seems that the GPP_EC values tend to be higher than that of the GPP_MOD. Similar results were also observed in Sims et al. (2006), in which the MODIS GPP was found significantly underestimated peak GPP values of flux measurements.

The most significant limitation of MODIS GPP algorithm is the improper of characterizing of LUE as it uses lookup tables of maximum LUE determination for a given vegetation type and then adjust those values downward on the basis of environmental stress factors (Running et al., 2004; Sims et al., 2006). However, the environmental stress factors may only be available in coarse resolution (e.g., $1^\circ \times 1.25^\circ$) and thus leading to errors in estimates of LUE (Heinsch et al., 2006; Sims et al., 2006). In this section, we compared the LUE derived from both tower GPP and MODIS GPP (Fig. 4b). Generally, moderate correlation ($r=0.76$ for all data) was found between LUE_EC and LUE_MOD, and it can be seen that MODIS algorithm underestimated high LUE values ($\sim 30\%$ for LUE higher than $0.2 \text{ g C mol PPF}^{-1}$) which may be the largest uncertainty of MODIS GPP product.

3.3. Results for the VPM

3.3.1. Seasonal variations of LSWI and EVI

The time series of LSWI from MODIS has a different seasonal cycle as compared to other climate variables (e.g., LST and VPD). A spring trough and a fall trough were observed in one year (Fig. 5a). The high LSWI values in early spring and winter are attributed to snow cover, either above or below the canopy (Xiao et al., 2004a). According to

VPM theory, the green-up period for the calculation of W_{scalar} is defined as the period from the date that had the minimum LSWI in spring to the date that had the maximum LSWI values in early summer. Thus, LSWI values were generated in 8-day intervals over the 4-year period (2003–2006), and the maximum LSWI ($LSWI_{\text{max}} = 0.43$, $DOY = 168$, 2004) was selected as an estimate of $LSWI_{\text{max}}$ and used in subsequent calculations of W_{scalar} .

Seasonal variation of EVI showed the same patterns in terms of phase and magnitude with a clear peak in summer for the four years of data (Fig. 5b). As EVI is a measure of canopy greenness, EVI may increase with the increase of biomass (green period, from $DOY = 140$) and then suffers decline when vegetation senesces in fall and winter (after $DOY = 300$).

3.3.2. GPP estimation from VPM

High Pearson's correlation coefficients between GPP from flux measurements (GPP_EC) and GPP from VPM model (GPP_VPM) were observed with $r=0.94$ ($RMSE = 5.791 \text{ g C m}^{-2} (8 \text{ day})^{-1}$) for the overall data and $r=0.89$ – 0.96 for individual years (Fig. 6a).

The VPM has been validated for GPP estimation in tropical evergreen forest (Xiao et al., 2005) and needleleaf forest (Xiao et al., 2004b). Results of our analysis also indicate the reliability of VPM for GPP estimation with multi-year observations. However, the magnitude of predict GPP still differs with the GPP of flux measurements. Previous study of Xiao et al. (2004a, 2005) acquired good GPP estimates of VPM in both phase and magnitude, this kind of agreement is not observed in our results. Fig. 6a indicates that VPM

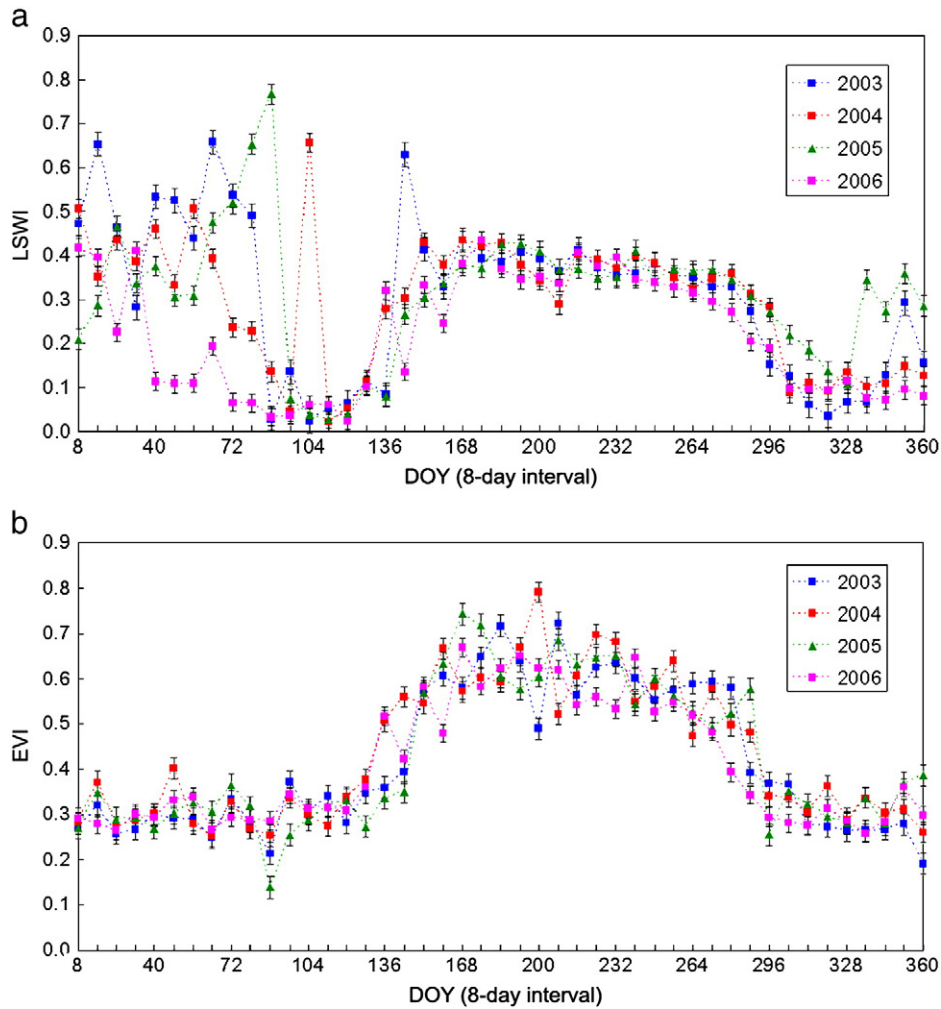


Fig. 5. Seasonal dynamics of LSWI (a) and EVI (b) calculated from MODIS product in Harvard forest in 2003–2006 (points represent data \pm standard error).

simulations may systemically underestimate in situ GPP. The same phenomenon was observed in Yan et al. (2009), who used the VPM to predict GPP of a wheat-maize double cropping system.

As VPM has its own basis for calculating LUE (Eq. 6), we explored the relationship between LUE calculated from tower GPP (LUE_EC) and the VPM (LUE_VPM). It can be seen from Fig. 6b that good correlation exists between these two types of LUE with r of 0.89 for all data and 0.84–0.92 for each individual years. This correlation is much improved compared to that of MODIS derived LUE, and this is the reason for better performance of VPM for GPP estimation than that of the MODIS GPP product. There seems to be an overestimation of LUE using VPM compared to LUE_EC. However, this problem points to the importance of ε_g determination. In this study, we used a ε_g of 0.528 gC/mol PPFD (Ruimy et al., 1995; Wofsy et al., 1993) and this assignment leads to the overestimation compared to LUE_EC. In fact, if we use an ε_g of 0.452 gC/mol PPFD (DOY 200, 2004), this overestimation can be successfully avoided. Therefore, the determination of ε_g remains an important task for the application of VPM model in GPP estimation.

3.4. Results for the TG model

3.4.1. GPP estimation from Scaled LST \times EVI

The mechanism of TG model lies in the dependence of GPP on both greenness and temperature. By incorporating temperature, it will closer follow the physiological aspects. This is consistent with the MOD17 model, where temperature and VPD were chosen as the two scalars directly modifying the LUE (Running et al., 2004).

Similar to the original form of the TG model, we used the MODIS LST and EVI derived from 8-day surface reflectance product to estimate GPP. From a biochemical and environmental perspective, GPP is largely affected by the leaf and canopy biochemical components (for photosynthesis and intercept of energy), the radiation conditions (PAR) and climate variables. Fig. 7 shows that GPP is related to both LST ($R^2 = 0.72$) and VPD ($R^2 = 0.45$). The LST was also found to be a measure of both VPD and PAR with determination of coefficients R^2 of 0.69 and 0.51 (Fig. 8). Therefore, LST is of importance for GPP estimation.

The results of the TG model indicate that multi-year GPP in Harvard Forest can be predicted with Pearson's correlation coefficients r values ranging from 0.92 in 2005 to 0.94 in 2004 ($RMSE = 5.831 \text{ g C m}^{-2} (\text{8 day})^{-1}$ for the overall data) (Fig. 9). For Harvard Forest, the TG model provides better GPP estimates than the MODIS GPP product. Poor correlation between MODIS GPP product and the flux measured GPP may result from errors in LUE determination (Sims et al., 2006), improper parameterization of soil water deficit (Turner et al., 2005) and problems with large-scale weather data inputs (Heinsch et al., 2006). As in the TG model, temperature is incorporated to better describe the actual environmental stress. For example, LST is correlated with VPD as plants experiencing extended drought will tend to either senesce or to conserve water, especially in deciduous forest (Sims et al., 2008). Moreover, correlation was also observed between LST and PAR ($R^2 = 0.51$), indicating that TG model may have potential use in daily GPP estimation as variation in PAR is an important determinant of GPP during shorter timescales.

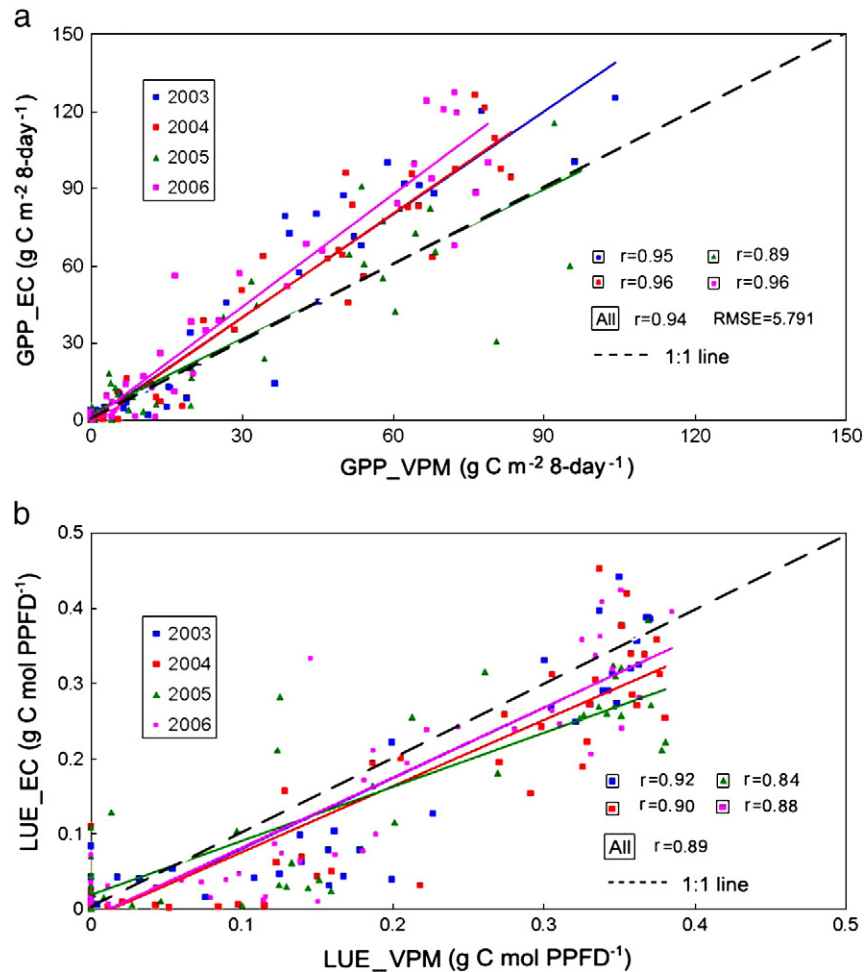


Fig. 6. Relationship of GPP_EC/GPP_VPM (a, correlation determined in r , RMSE in GPP unit) and LUE_EC/LUE_VPM (b, correlation determined in r) in Harvard Forest. All correlations are significant at the 0.01 level.

3.4.2. Temperature selection in the TG model

The objective of the TG model is to add temperature and drought stress information to the GPP model. Since the MODIS LST will provide a proxy of an averaged temperature across a pixel, the TG model will be based entirely on remotely sensed variables without any ground-based meteorological input. In the Harvard Forest site, both T_a and T_s are systematically measured and a discussion is necessary about the three measures of temperature.

According to the original TG model, LST should be a useful measure of physiological activity of the top canopy leaves, provided that leaf cover is large enough to avoid LST being significantly affected by soil surface temperature (Sims et al., 2008). From this perspective, T_s is not a proper indicator, because a measure of surface temperature is preferred. We compared the MODIS LST product with both T_a and T_s (Fig. 10). MODIS LST is more closely related to the air temperature directly above the canopy as shown by the higher R^2 value (0.88). On the other hand, a tendency exists for MODIS LST to be higher than T_a at the upper end of the temperature range and lower than T_a at the low end of the range, possibly resulting from summer droughts (Sims et al., 2008) and/or spatial averaging across the small scale.

Table 2 shows the correlation between T_a , T_s , LST and climate variables (PAR, VPD). An interesting aspect concerns the results of MODIS LST. It provides the best estimates of both PAR and VPD, but it gives the lowest precision for the TG model. If the temperature better indicates the environmental stress (e.g., VPD, PAR), then the TG model driven by this temperature will provide better results in GPP estimation. This is indeed the case when we compare results of T_a and T_s . For MODIS LST product, however, it did not follow this assumption. It is still difficult

to explain the performance using the MODIS LST product. Possible reasons are the scale difference between the MODIS LST retrievals and ground-based measurements, and the large heterogeneity of the LST during daytime (Wang and Liang, 2009).

There are two potential sources of errors about the TG model that need consideration that are uncertainties both in the MODIS reflectance and LST products. First is about the geo-location accuracy of MODIS data (Wolfe et al., 2002), although this uncertainty affects all the three models, it has more influence on the TG model as the radiation emitted and scattered multiple times by adjacent pixels would contribute to modify remotely sensed estimates (emissivity) for LST calculation. The largest uncertainty is the use of LST because satellite sensors measure a signal that is a combination of the radiant temperature of the land surface and the intervening atmosphere (Goetz et al., 2000). This happens especially during daytime as information (e.g. solar radiation, cloud-cover, wind speed, soil moisture and surface roughness) is not easily available (Prince et al., 1998; Vancutsem et al., 2010). Particular attention should be paid to the role of cloud contamination because of the inherent limitation of the thermal infrared remote sensing. These include the failure to remove slightly and modestly cloud-contaminated LST, as well as the different degrees of influence of cloud contaminations between estimation of LST and emissivity (Wan, 2008).

3.5. Results for the VI model

3.5.1. Relationship between EVI and LUE

The VI model provided a convenient use of GPP estimation, because the vegetation index was found to be a proxy of LUE and f_{APAR}

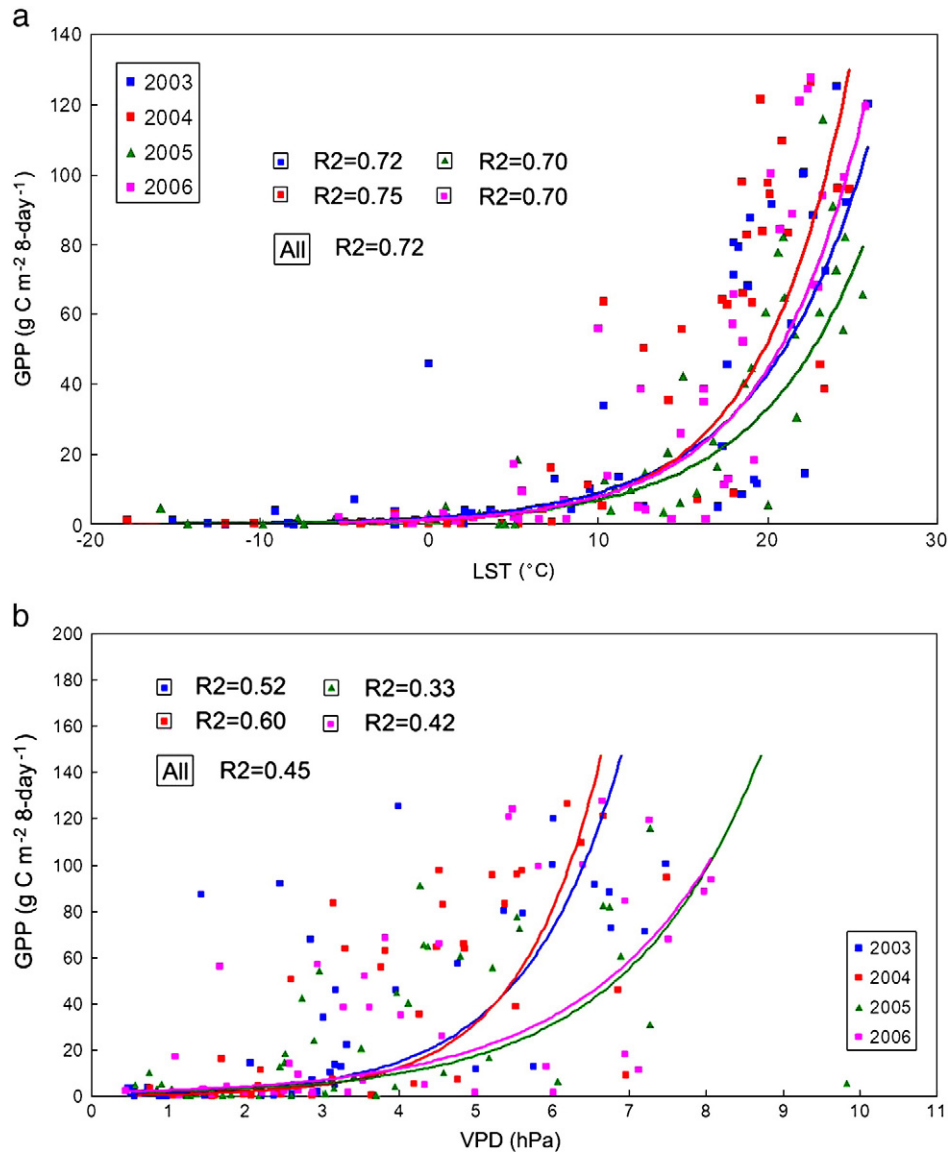


Fig. 7. Relationship between GPP and LST (a), VPD (b) in Harvard Forest in 2003–2006 (all correlations are significant at the 0.01 level).

(Wu et al., 2010). Thus, correlations between EVI and LUE, f_{APAR} are necessary before model development. In this paper, we only validated the use of EVI in LUE estimation because f_{APAR} was calculated from NDVI/ f_{APAR} relationship. Correlation between EVI and NDVI make the relationship possible for EVI/ f_{APAR} .

An R^2 of 0.78 was acquired between EVI and LUE for the overall dataset, varying from 0.64 to 0.84 for each individual year (Fig. 11). Although scatter plots show that EVI may provide underestimates of LUE for dense canopies, the linear model actually gives the highest correlation. LUE can change dramatically across seasons and between vegetation types (Gower et al., 1999; Green et al., 2003) and EVI is a measure of greenness of vegetation and will be insufficient for short time LUE estimation. In this study, the LUE is calculated in 8-day intervals and relatively better correlation between EVI and LUE was observed for deciduous forest. The reason is that EVI accounts for atmospheric correction and variable soil and canopy background reflectance by incorporation of a blue band and therefore is better for the interpretation of LUE variations (e.g., deciduous forest) (Huete et al., 2006). This agrees with research of Sims et al. (2006), indicating that GPP/EVI relationship was best for sites of large seasonal EVI variations. For evergreen plants, however, EVI may be inappropriate for addressing LUE variations, since low temperature will reduce LUE

dramatically but has little effect on canopy greenness at short time scale.

3.5.2. GPP estimation from $\text{EVI} \times \text{EVI} \times \text{PAR}$

The VI model provides moderate GPP estimates with Pearson's correlation coefficient r of 0.90 ($\text{RMSE} = 5.828 \text{ g C m}^{-2} (8 \text{ day})^{-1}$) for the overall dataset. This is the lowest value among the three models, but still slightly higher than MODIS GPP product (Fig. 12). The VI model was proposed first by Wu et al. (2010) in the relatively simple maize ecosystem, having only water and nutrient confounding factors. Our results indicate the usefulness of VI model in GPP estimation for deciduous forests stand and this may have potential implications for other ecosystems, such as for grassland and shrubs.

An evaluation of the VI model lies in the correlation between EVI and LUE. As LUE is related to plant physiological activities, EVI/LUE correlation can more support the use of EVI model in GPP estimation. The most convenient use of the VI model lies in its only dependent on EVI, and it could be used with earlier satellites that did not have as many bands (e.g., AVHRR and Landsat). More specifically, with development of new EVI (a two band EVI, Jiang et al., 2008) that only uses red and NIR bands, the VI model (using EVI2) can be applied to the MODIS 250 m product. This would be helpful in improving the

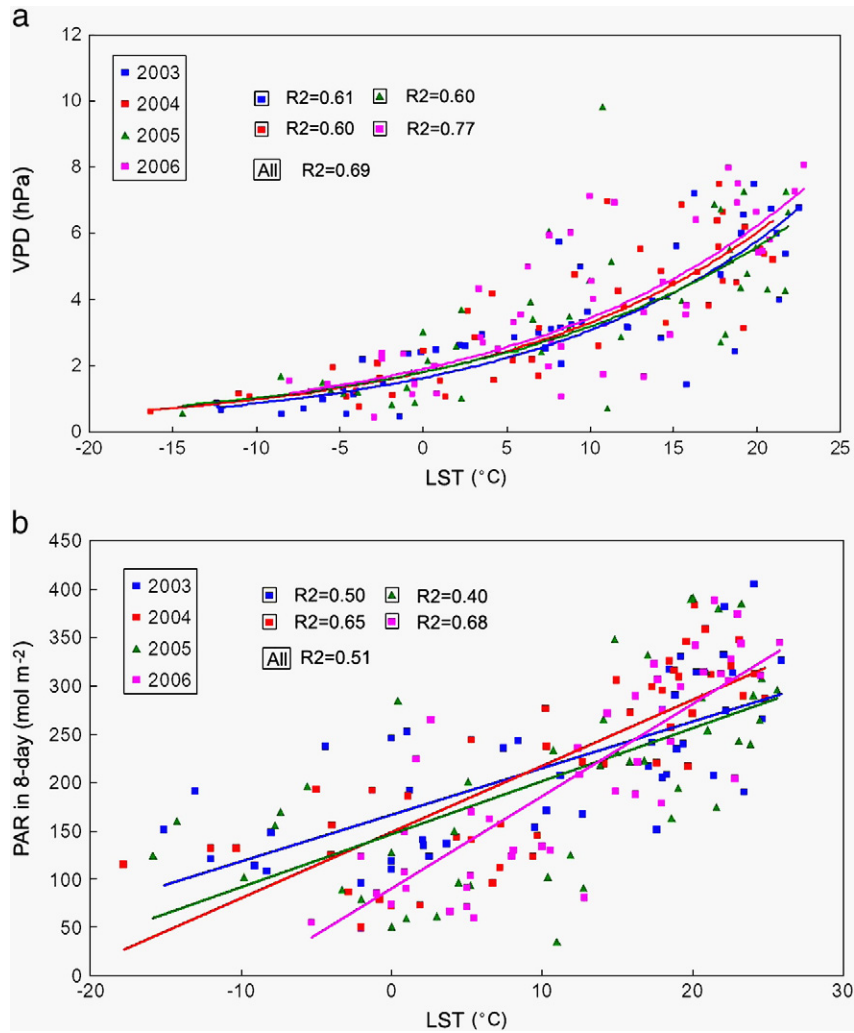


Fig. 8. Relationship between LST and VPD (a), PAR (b) in Harvard Forest in 2003–2006 (all correlations are significant at the 0.01 level).

resolution of MODIS GPP product provided the reliability of EVI2 in LUE and f_{APAR} estimation across a range of species.

Another important meaning of the VI model is its linear regression. The proposed VI model is based on Monteith (1972) logic, which

demonstrated that efficiency (ϵ) with which crops or natural communities product dry matter is defined as the net amount of solar energy stored by photosynthesis in any period, divided by the solar constant integrated over the same period. That means that GPP

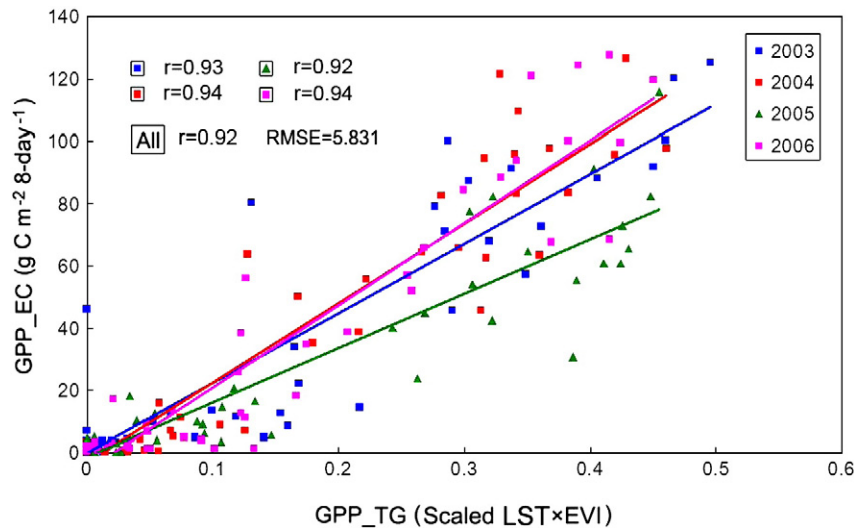


Fig. 9. Relationship of GPP_EC/GPP_TG determined in Pearson's correlation coefficient r (RMSE in GPP unit). All correlations are significant at the 0.01 level.

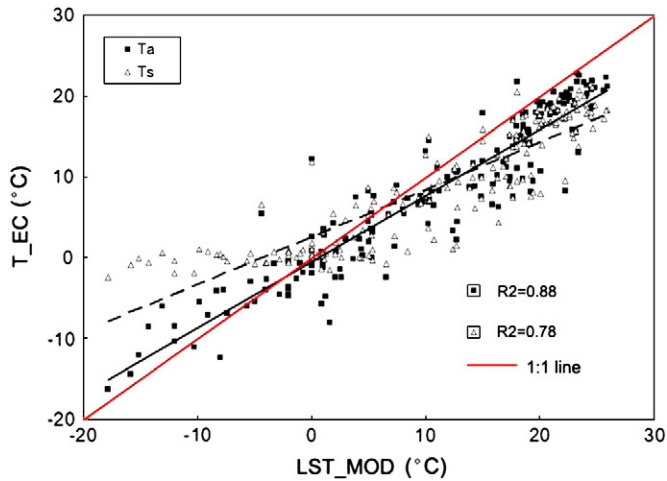


Fig. 10. Relationship between MODIS LST product and Ta, Ts from flux measurements (all correlations are significant at the 0.01 level).

Table 2

Relationship between Ta, Ts, MODIS LST and climate variables and predicted GPP (R^2 is the coefficient of determination and r is the Pearson's correlation coefficient, all correlations are significant at the 0.01 level).

Variables	PAR	VPD	GPP_TG
Ta	$R^2 = 0.47$	$R^2 = 0.66$	$r = 0.95$
Ts	$R^2 = 0.45$	$R^2 = 0.54$	$r = 0.93$
LST	$R^2 = 0.51$	$R^2 = 0.69$	$r = 0.88$

over a period can be calculated as the efficiency multiplied by the integrated solar radiation. This was validated in our results and the linear regression model confirmed the best fit for GPP estimation, implying that this method can keep the sensitivity and can overcome saturation in high vegetation coverage areas, and thus is more robust in global GPP estimation.

4. Discussions

4.1. Impacts of drought on models

Response of GPP models to temporal patterns of climate variables is important for the evaluation of the stability and reliability of models. To show the detailed usefulness of three models, results of GPP estimation (Table 3), as well as correlation between other variables, at one year interval were calculated (Table 4).

Table 3 shows that all correlations of the four year data provide relatively consistent results, differing within two folds. The best results for GPP estimation are acquired by the VPM, both for the overall dataset and data of individual years. Correlations of 2005 are the lowest compared to those for other years. For example, the lowest relationships of GPP_EC/Ta and GPP_EC/VPD are observed in 2005. This may lead to the lowest GPP estimates using VPM because climate variables are used in the LUE calculation. Low relationships of VPD/LST and PAR/LST for 2005 also contribute to low GPP estimation using the TG model. One can also ascribe the low GPP estimates using the VI model to relatively low correlation between LUE and EVI in that year.

We conduct an analysis of climate variables using the daily average values of Ta, VPD and sums of precipitation (PP) from DOY = 150 to DOY = 270, a typical growing season, to understand reasons of model performances in 2005 (Fig. 13). Ta and VPD are highest with values of 18.62 (°C) and 5.59 (hPa), respectively. High Ta will result in increasing VPD, which in turn will lead to an exponential decrease in canopy stomatal conductance and will reduce the net photosynthetic rate, as the plant needs to draw more water from its roots under high VPD or Ta (Addington et al., 2004; Day, 2000). Furthermore, the precipitation in 2005 is the low in that period (56.28 mm). Fang et al. (2005) demonstrated that a positive relationship exists between NDVI and precipitation of deciduous broadleaf forest. This suggests that the response of vegetation production to changes in precipitation patterns differs by varying precipitation amounts. Previous research already indicated that many GPP models inappropriately estimate GPP under drought conditions (Sims et al., 2006, 2008). This is also the case in our analysis. A possible reason is that initiate drought conditions later in summer reduce both vegetation productivity and greenness, but in different magnitudes. This inconsistency introduces error in the vegetation index, considered as a proxy of vegetation greenness when estimating LUE, and further reduces the correlation between flux measured GPP and model estimates. For example, 8-day GPP values are lower in 2005 than in other years, especially during DOY = 150 to DOY = 270 when a forest is in a vigorous period (Fig. 2). It is still unclear why all these models have low precisions in drought conditions. Further analysis is needed to better understand the climate factors in relation to GPP in forest ecosystems.

4.2. Comparison between models

Previous research indicated that MODIS GPP estimation was difficult to apply in a mixed forest biome or in open scrublands (Gebremichael & Barross, 2006). In this paper, three models (the VPM, TG and VI) are used for the estimation of GPP in Harvard Forest. All these models provide better results than the MODIS GPP product.

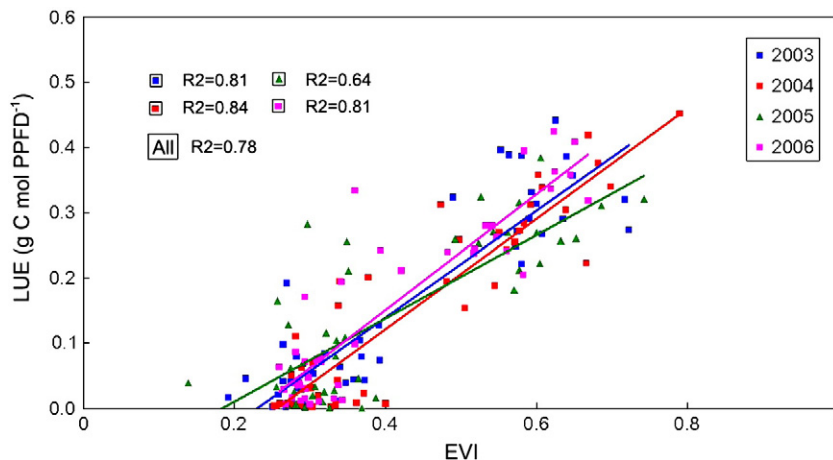


Fig. 11. Relationship between LUE and EVI calculated from MODIS surface reflectance. All correlations are significant at the 0.01 level.

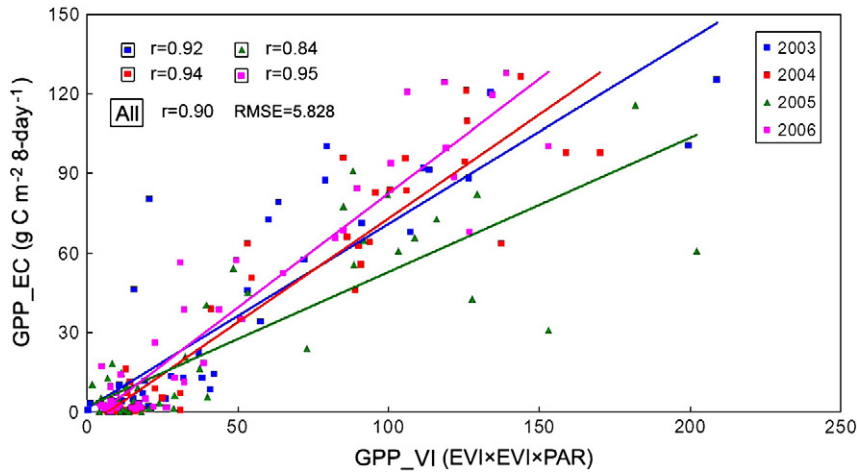


Fig. 12. Relationship of GPP_EC/GPP_VI determined in Pearsons correlation coefficient r (RMSE in GPP unit). All correlations are significant at the 0.01 level.

A typical difference between the VPM and the MODIS algorithm is the calculation of LUE, although both models use climate variables to reduce the maximum LUE under unfavorable conditions. VPM uses an additional P_{scalar} dependent upon life expectancy of leaves (deciduous vs. evergreen) to better monitor changes in LUE and this improves the LUE estimation accuracy (R^2 from 0.58 to 0.80, Figs. 4b and 6b). It indicates first that LUE is a variable of high heterogeneity between species and time. This is consistent with the existing knowledge (Huete et al., 2006; Sims et al., 2006). Secondly, incorporation of indicators that are related to the physiological basis of vegetation will benefit such models for GPP estimation.

Basically, both VPM and VI models are LUE models. The most challenging aspect of the LUE model is determination of LUE across seasons and between vegetation types. VPM uses *in situ* climate variables (e.g., temperature, water stress) to acquire the actual LUE under unfavorable conditions. VPM also differentiates vegetation by photosynthetically active vegetation (PAV) and non-photosynthetic vegetation (NPV), as NPV contributes little to photosynthesis (Zhang et al., 2009). Therefore, EVI, a measure of canopy greenness, is selected as a proxy of PAV. VPM gives the best estimation of GPP among all models. The VI model is based on the relationship between spectral indices (e.g., EVI) and LUE, f_{APAR} . In this study, EVI is validated for LUE estimation using the four year dataset (Fig. 11). Although the VI model provided no better GPP estimates than VPM, it does not depend on the acquisition of *in situ* climate variables for LUE estimation. However, using only EVI as a proxy of LUE cannot represent the actual environmental stress. Therefore, the VPM, which incorporates climate data for LUE evaluation, is expected to give better GPP estimates. One of the primary potential limitations of the VI model rests on the reliability of LUE estimation using only EVI both across species and time.

The VI model uses an $\text{EVI} \times \text{EVI}$ approach for GPP estimation, as EVI is a proxy of both LUE and f_{APAR} . Comparing the TG and VI model, we observe certain relationships. In the TG model, a combination of $\text{EVI} \times \text{LST}$ correlates well with GPP because EVI serves as a good

indicator of greenness and LST as a proxy of PAR. In the VI method, the *in situ* measured PAR is used and the $\text{EVI} \times \text{EVI}$ constitutes a non-linear stretch of a single EVI, thus increasing its sensitivity at high vegetation green biomass. The relationship indicates the potential of EVI as an indicator of water stress, because plants suffering drought may either senesce or partially lose their foliage to conserve water.

Apart from uncertainties in MODIS reflectance and LST products, the most promising merit of the TG model is its entirely remote sensing based observations for GPP estimation. No field data and no prior information are required for local sites. The VI model also possesses this virtue as PAR can be estimated from MODIS products that provide aerosol type and atmospheric conditions (Liang et al., 2006). This is not to say that *in situ* climate variables are not important for GPP estimation, but because meteorological inputs are often not available at sufficiently detailed temporal and spatial scales, leading to substantial errors in the output (Heinsch et al., 2006). If we use T_a in the TG model, correlations can be improved with a Pearsons correlation coefficient r value equals to 0.95 (Table 2), which is even better than for the VPM estimates.

5. Conclusions

GPP of Harvard Forest from 2003 to 2006 is estimated from three models, namely the VPM, the TG model and the VI model, using combination of flux measurements and MODIS observations. Pearsons correlation coefficients r values equal to 0.94, 0.92 and 0.90 are acquired for the VPM, the TG and the VI model, respectively, all of which are higher than those of the MODIS GPP product ($r = 0.88$). These results indicate both the potential of improvement on MODIS GPP algorithm, and the use of other remote sensing systems in longtime GPP evaluation (e.g., the extensive archive of Landsat imagery acquired since the early 1980s).

Table 3
Pearsons correlation coefficient (r) between flux GPP and model estimates (lowest correlation in bold). All correlations are significant at the 0.01 level.

Correlations	Year				
	2003	2004	2005	2006	ALL
GPP_EC/GPP_MOD	0.87	0.91	0.82	0.91	0.88
GPP_EC/GPP_VPM	0.95	0.96	0.89	0.96	0.94
GPP_EC/GPP_TG	0.93	0.94	0.92	0.94	0.92
GPP_EC/GPP_VI	0.92	0.94	0.84	0.95	0.90

Table 4
Coefficients of determination (R^2) between different variables for each individual years (lowest correlation in bold). All correlations are significant at the 0.01 level.

Correlations	Year				
	2003	2004	2005	2006	ALL
GPP_EC/LST	0.72	0.75	0.70	0.70	0.72
GPP_EC/VPD	0.52	0.60	0.33	0.42	0.45
GPP_EC/ T_a	0.82	0.80	0.72	0.81	0.78
VPD/LST	0.61	0.60	0.60	0.77	0.69
PAR/LST	0.50	0.65	0.40	0.68	0.51
LUE/EVI	0.81	0.84	0.64	0.81	0.78

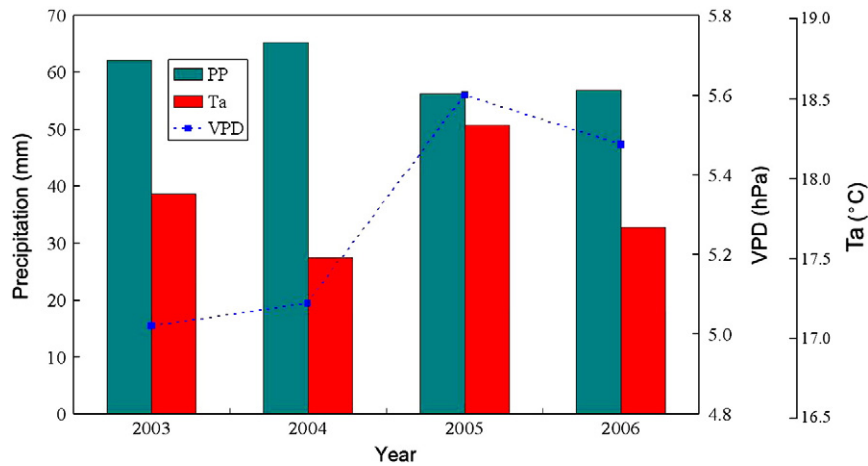


Fig. 13. Daily average values of Ta, VPD and sums of precipitation in Harvard Forest from DOY = 150 to DOY = 270 during 2003–2006.

Comparison analysis indicates that the VPM is the best model for GPP estimation because of its superiority in appropriately addressing the climate variables that are used for LUE calculation. Therefore, for cases which have substantial climate variables, the VPM is the most suitable for GPP estimation. The most important characteristic of the TG and VI models is their independence of prior climate variables at local sites. This will make the two models especially useful for GPP estimation at a global scale, provided they can as well as applied to other ecosystems (such as shrubs and grassland). Further research is needed to evaluate the GPP estimation models, either on the basis of remote sensing observations or on a combination of climate variables in other ecosystems. The underlying mechanism and the effects of climate variables on the temporal patterns of GPP should be better understood to allow incorporation into future models.

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