Remote Sensing of Environment 113 (2009) 1808–1822

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Evaluation of Collections 4 and 5 of the MODIS Gross Primary Productivity product and algorithm improvement at a tropical savanna site in northern Australia

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ARTICLE INFO

Article history:
Received 22 June 2008
Received in revised form 29 March 2009
Accepted 11 April 2009

Keywords:
MODIS
Collection 4
Collection 5
Gross primary productivity
Leaf Area Index
Fraction of photosynthetically active radiation
Light use efficiency
Evaporative Fraction
Vapor pressure deficit

ABSTRACT

In this study, we assessed the accuracy of the MODIS (Moderate Resolution Imaging Spectroradiometer) GPP (gross primary productivity) Collections 4.5, 4.8 and 5 along with Leaf Area Index (LAI), fraction of absorbed Photosynthetically Active Radiation (fPAR), light use efficiency (LUE) and meteorological variables that are used to estimate GPP for a northern Australian savanna site. Results of this study indicated that the MODIS products captured the seasonal variation in GPP, LAI and fPAR well. Using the index of agreement (IOA), it was found that Collections 4.5 and 4.8 (IOA 0.89 respectively) agreed reasonably well with flux tower measurements between 2001 and 2006. It was also found that MODIS Collection 4.5 predicted the dry season GPP well (Relative Predictive Error (RPE) 4.17%, IOA 0.72 and Root Mean Square Error (RMSE) of 1.05 g C m^{-2} day^{-1}), whilst Collection 4.8 performed better in capturing wet season dynamics (RPE 1.11%, IOA 0.80 and RMSE of 0.91 g C m^{-2} day^{-1}). Although the wet season magnitude of GPP was predicted well by Collection 4.8, an examination of the inputs to the GPP algorithm revealed that MODIS fPAR was too high, but this was compensated by PAR and LUE that was too low. Although LAI and fPAR estimated by Collection 5 were more accurate, GPP for this Collection resulted in a much lower value (RPE 25%) due to errors in other factors. Recalculation of MODIS GPP using site specific input parameters indicated that MODIS fPAR was the main reason for the differences between MODIS and tower derived GPP followed by LUE and meteorological inputs. GPP calculated using all site specific values agreed very well with tower data on an annual basis (IOA 0.94, RPE 6.06% and RMSE 0.83 g C m^{-2} day^{-1}) but the early initiation of the growing season calculated by the MODIS algorithm was improved when the vapor pressure deficit (VPD) function was replaced with a soil water deficit function. The results of this study however, reinforce previous findings in water limited regions, like Australia, and incorporation of soil moisture in a LUE model is needed to accurately estimate the productivity.

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1. Introduction

Savannas cover one sixth of the world's land surface, and are important in terms of carbon sequestration and storage (Grace et al., 2006). Globally, they sequester as much as 0.5 Petagram (Pg) Carbon per year (Scurlock and Hall, 1998), and account for 30% of the primary production of all terrestrial vegetation (Grace et al., 2006). In Australia, savannas cover a quarter of the land surface, which contributes 12% to the total global savanna woodlands and accounts for 33% of the terrestrial carbon stores in Australia (Williams et al., 2004). Fire is an important factor in most of northern Australia, shaping the landscape and consequently affecting the vegetation productivity (Beringer et al., 1995, 2003, 2007). During 2001–2005, a total of 1.6 million km^2 of land burned in northern Australia (Department of Land Information, Satellite Remote Sensing Services, Western Australia). Fire has been shown to reduce productivity of these mesic north Australian savannas by approximately 50% (Williams et al., 2004) with post-fire canopy reconstruction costs being of the order of 1 t C ha^{-1} $year^{-1}$ for moderate intensity fires of 3000 kW m^{-1} (Beringer et al., 2007). The dynamic nature of carbon stocks in this extensive ecosystem due to the highly seasonal climate, frequent fire and disturbance from storms and cyclones implies a significant exchange of CO_2 and other greenhouse gases between the savanna and the atmosphere (Henry et al., 2005). Remote sensing has the potential to capture the highly heterogeneous savanna landscape and seasonal dynamics over vast areas.

Gross Primary Productivity (GPP) is one of the fundamental parameters of the carbon cycle as it is related to the transfer of carbon from the atmosphere to terrestrial ecosystems. In the context of northern Australia, quantifying and mapping the spatial and seasonal variations in GPP is necessary not only to understand the role of savannas in sequestering atmospheric CO_2, but also to reduce the uncertainty in Australia's national carbon inventory, greenhouse gas abatement and projections of future emissions (Hutley et al., 2005).

The quantification of GPP has received a great deal of attention in recent years with the availability of flux towers that use the eddy

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doi:10.1016/j.rse.2009.04.013

covariance technique (Baldocchi, 2008). Although flux towers provide high temporal resolution of carbon, water and energy fluxes, they are limited spatially by the number of flux stations (~400 flux stations operating around the world as part of FLUXNET http://www.fluxnet.ornl.gov/fluxnet/index.cfm). Alternatively, the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite sensors routinely measures radiances across the entire globe at moderate spatial (250 to 1000 m) and temporal resolutions (twice daily). Radiances from these channels are used to produce a range of products, including: GPP and net photosynthesis (MOD17); fraction of absorbed Photosynthetically Active Radiation (fPAR) and Leaf Area Index or LAI (MOD15); land cover and land cover dynamics (MOD12Q) as well as vegetation indices (MOD13).

Since MODIS products are generated based on inference from surface reflectance, their accuracies need to be validated against ground measurements before the products can be of value. There is a need for validation against ground measurements to determine the accuracy of these products. A number of validation activities are being carried out at a range of sites and different ecosystems to assess the accuracy of MODIS land products. MODIS LAI (one-sided green leaf area per unit ground area, Chen and Black, 1992) is perhaps the most extensively validated product (Cohen et al., 2006; Hill et al., 2006; Yang et al., 2006a,b; Rizzi et al., 2006; Pandya et al., 2006 etc.). Although the GPP product has been validated for a range of ecosystems such as natural forests in northern America (Turner et al., 2006a,b; Nightingale et al., 2007; Coops et al., 2007), humid tropical ecosystems (Gebremichael and Barros, 2006) and crops (Zhang et al., 2008; Reeves et al., 2005), product accuracy requires further attention within tropical savanna ecosystems. Only a few studies have reported MODIS product validation for savannas: Leuning et al. (2005) and Heinsch et al. (2006) for GPP; Fensholt et al. (2006) for net primary productivity; Privette et al. (2002), Fensholt et al. (2004), and Huemmrich et al. (2005) for LAI; and Privetter et al. (2003), Fensholt et al. (2004), and Huemmrich et al. (2005) for fPAR.

Savannas are tropical ecosystems with a mixture of continuous herbaceous cover and a discontinuous cover of trees or shrubs (Frost et al., 1986). The productivity of tropical savannas, woodlands, and grasslands are controlled by water rather than temperature with several months of prolonged dry season that cause plants to dry out and become susceptible to fire (Huntley and Walker, 1982). Tropical savannas in Australia occur at the drier end of the savanna spectrum with woody plants characterized by evergreen *Eucalyptus* tress compared to drought deciduous savannas in Africa and humid savannas in central and South America. Although MODIS can capture the seasonality of site GPP quite well across different climate regimes (wet and dry savanna, alpine forests, temperate deciduous and evergreen forests (Justice et al., 2002; Running et al., 2004; Leuning et al., 2005; Heinsch et al., 2006), it generally fails to accurately estimate the magnitude of productivity under water deficit conditions such as in savannas (Leuning et al., 2005; Heinsch et al., 2006; Zhang et al., 2007). Some studies have found that the use of a vapor pressure deficit (VPD) function can lead to an overestimation of GPP as VPD does not explicitly incorporate soil water deficit in canopy gas exchange (Fensholt et al., 2006; Leuning et al., 2005; Yuan et al., 2007; Coops et al., 2007). Validation and improvement of MODIS derived GPP from tropical savannas will aid application in arid and semi-arid areas.

In this study, we validated MODIS GPP Collections 4.5, 4.8 and 5 with GPP estimated from flux tower measurements. Our aim was to examine if improvements in upstream products (climate and fPAR) used in MOD17 GPP algorithm enhance the performance of the product in determining the seasonal variation and absolute magnitude of GPP for a woody savanna site in northern Australia. We also assessed the error associated with using the standard MODIS input values for the parameters used to estimate GPP, namely fPAR, light use efficiency (LUE), Photosynthetically Active Radiation (PAR) and thresholds for the down-regulating factors of minimum air temperature (T_{MIN}) and VPD. We further investigated the performance of the MODIS algorithm by substituting VPD with a soil water deficit function to compare dry season GPP. Evaluation and validation of the performance of these products is a necessary process for product refinement if we are to correctly quantify carbon exchange over large spatial areas.

2. Data and methodology

2.1. Site description

We selected the Howard Springs flux tower site, located in a tropical savanna in the Northern Territory of Australia for this study. This site is located approximately 35 km to the south east of Darwin (Fig. 1a) at 12° 29.712′S and 131° 09.003′E. Howard Springs is classified as an open woodland savanna forest, 14–16 m tall with 50–60% canopy cover (classified as grassy woodland by the University of Maryland land cover classification scheme, http://www-modis.bu.edu/landcover/userguidelc/index.html). The over storey is co-dominated by evergreen tree species, *Eucalyptus miniata* and *Eucalyptus tetrodonta* with other species in fewer numbers such as *Erythrophloem chlorostachys* and *Terminalia ferdinandiana* (Hutley et al., 2000). The under storey is covered by C_4 grasses *Sarga* spp. during the wet season (Fig. 1b). Woody stems have a density of 500–700/ha, with mature individuals rooting to ~5 m depth (Kelley et al., 2002). The deep rooting system enables the trees to access sub-soil moisture reserves from 2 to 5 m over the dry season, thus enabling reasonably constant transpiration (Hutley et al., 2000) and carbon sequestration rates throughout the dry season except during fire occurrences (Beringer et al., 2007). Fire occurs frequently in this vegetation biome and at the flux tower site, a range of experimental fires of low to moderate intensity occurred during the study period as documented in Beringer et al. (2007). The over storey LAI fluctuates between 0.9 in the wet season (December–April) and 0.6 in the dry season (May–November), while the under storey LAI is far more dynamic, being dominated by annual C_4 grass growth varying from a green LAI of 1.5 in the wet season that drops to 0.2 in the dry season (O'Grady et al., 2000). Evaluating the performance of MODIS GPP and LAI at this site is useful given the large seasonal range driven by an annually senescing grassy under storey, a deciduous mid-storey and an evergreen dominant over storey, along with periods of very low LAI in the proceeding month following fire events in the dry season.

2.2. Flux tower data

Carbon, water and energy fluxes have been measured at Howard Springs continuously since August 2001 using eddy covariance flux instrumentation and an open-path CO_2/H_2O analyzer (Beringer et al., 2003, 2007). GPP was calculated as the difference between net ecosystem exchange and ecosystem respiration following Beringer et al. (2007). Incoming solar radiation was measured above the canopy using Kipp and Zonen (m7b, Delft, The Netherlands) and PAR was determined as 47% of incoming solar radiation using a site specific relationship (data not shown). Thirty-minute rainfall, air temperature, relative humidity and soil moisture at 10 cm depth were also measured at the tower site. Missing meteorological data were derived from the Australian Bureau of Meteorology (BoM) and the Atmospheric Radiation Measurement (ARM) site at Darwin airport.

2.3. MODIS data

MODIS GPP is calculated based on a LUE model (Eq. (1)) proposed by Monteith (1972). This algorithm estimates GPP by including T_{MIN} (daily minimum temperature) and VPD (daytime average vapor pressure deficit) scalars that can reduce the productivity for

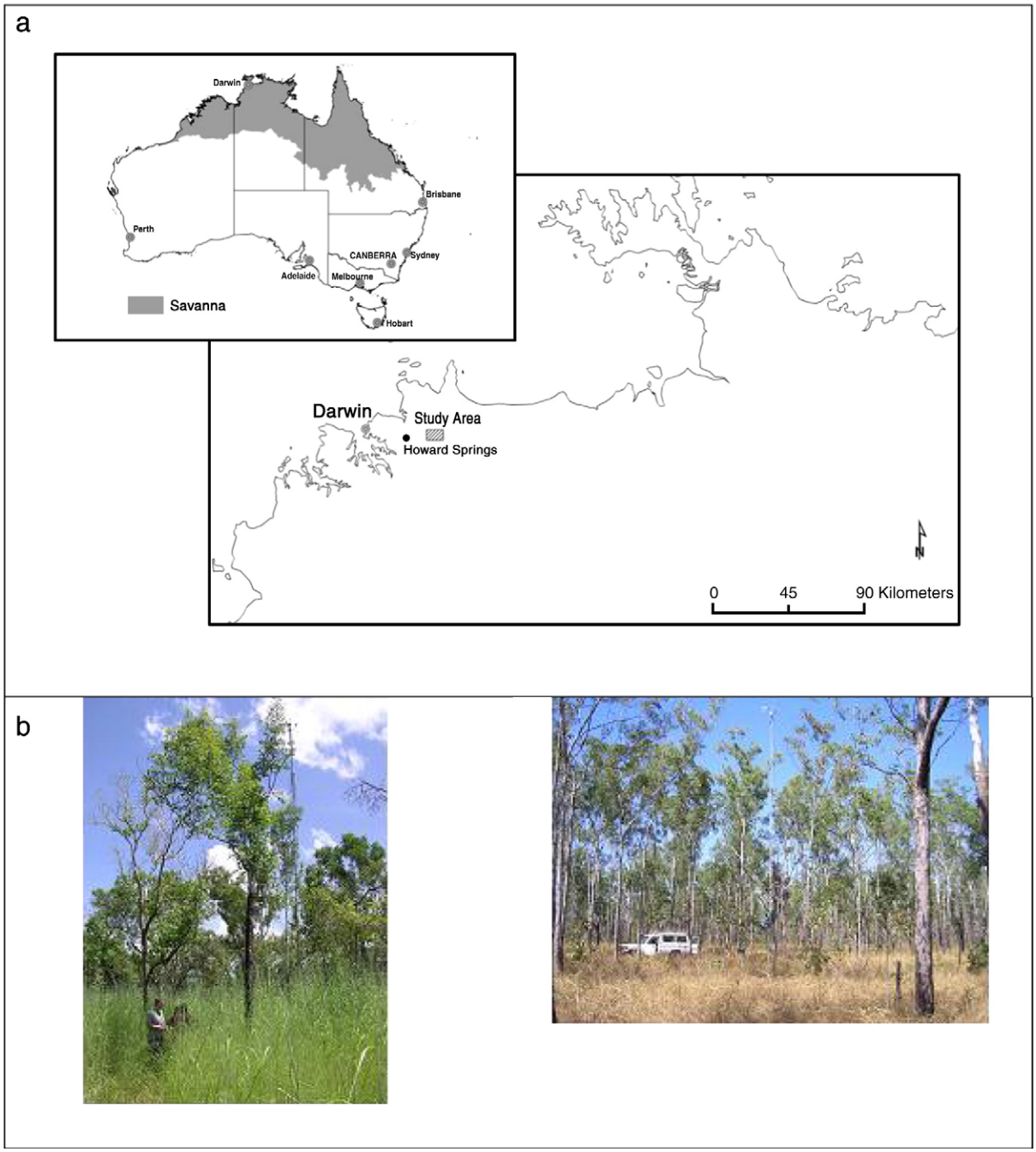

Fig. 1. (a) Location of the study area: Howard Springs (12.425°S and 130.891°E) and boundary of savanna in northern Australia. Savanna boundaries were provided by Tropical Savanna, CRC. (b) Typical vegetation at Howard Springs during wet (left) and dry (right) seasons. Over storey is dominated by *Eucalyptus* open savanna woodland trees with 50–60% canopy cover and under storey is dominated by annual grasses.

unfavorable climate conditions (Heinsch et al., 2003). For each 1 km MODIS pixel, GPP is calculated as a function of LUE that is modeled using a biogeochemical model (Running et al., 2000) and APAR is provided as 8 day composite values based on maximum fPAR during the 8 day period to eliminate cloud contamination (Eq. (1)).

$$\mathrm{GPP}\left(\mathrm{kg\ C\ m^{-2}\ day^{-1}}\right) = \mathrm{APAR(MJ)} \times \mathrm{LUE}\left(\mathrm{kg\ C\ MJ^{-1}}\right) \times T_{\mathrm{MIN}}\ \mathrm{scalar} \times \mathrm{VPD\ scalar} \quad (1)$$

APAR is the total absorbed PAR by a canopy and it is estimated by multiplying fPAR with PAR (APAR = fPAR × PAR). fPAR is the fraction of absorbed PAR and it can be calculated directly in the field as the balance of the incoming and outgoing PAR of the canopy (Huemmrich et al., 2005). In the MODIS GPP algorithm fPAR is used to directly calculate the GPP of a pixel (Heinsch et al., 2003), therefore errors in the estimation of fPAR will lead to an inaccurate estimate of GPP. MODIS estimates LAI and fPAR values for green leaves using atmospherically corrected daily bidirectional reflectance and land cover classification. MODIS uses a constraint view maximum value composite technique where a given scene represents the maximum LAI for a consecutive 8 day period based on the maximum clear sky fPAR value (Knyazikhin et al., 1999).

Daily maximum potential GPP is then reduced by daily T_{MIN} and VPD. T_{MIN} and VPD scalars are multipliers that reduce the conversion efficiency when cold temperature and/or high VPD inhibit

photosynthesis (Heinsch et al., 2003). The multipliers range from 0 to 1, where 0 represents total inhibition and a value of 1, indicates no inhibition. The scalars are calculated as follows:

$$T_{MIN}\ \text{scalar} = (T_{MIN} - T_{MINmin}) / (T_{MINmax} - T_{MINmin}) \quad (2)$$

where, T_{MINmin} = daily minimum temperature at which LUE = 0; T_{MINmax} = daily minimum temperature at which LUE is maximum

$$\text{VPD scalar} = (\text{VPD}_{max} - \text{daytime average VPD}) / (\text{VPD}_{max} - \text{VPD}_{min}) \quad (3)$$

where, VPD_{min} = daily minimum VPD at which LUE is maximum VPD_{max} = daily maximum VPD at which LUE = 0.

MODIS GPP products have undergone continued improvement since the initial launch of Terra in November 1999 and Aqua in May 2002 and the various product versions are called Collections. GPP Collections 4.5 and 4.8 used fPAR Collection 4 (Heinsch, personal communication) which utilized a turbid medium radiative transfer (RT) model to estimate LAI and fPAR and land cover product Collection 3 (Shabanov et al., 2007). GPP Collection 4.5 differs from Collection 4.8 in terms of the use of meteorological data and maximum LUE values gained from a global lookup table according to vegetation type (Table 1). Collection 4.5 covered a period from February 2000 to December 2003 and used meteorological data from NASA's Data Assimilation Office (DAO) using Goddard Earth Observing System (GEOS) satellite version 4.02 which provided gridded surface downward shortwave radiation, surface air pressure, 10 m air temperature and specific humidity.

In early 2004, however, DAO, now known as Global Modeling and Assimilation Office (GMAO) changed its meteorological data version to GEOS 4.03. This version used a new land surface model, modified skin temperature analysis and near ground moisture modification, and an improved quality control algorithm to flag outliers/bad quality values (Bloom et al., 2005) and therefore provided more consistent meteorological variables. In order to compensate for the inherent biases in different meteorological reanalysis, the MODIS GPP team readjusted the input variables used to estimate GPP, specifically maximum LUE, and VPD scalars (Table 1) (Zhao et al., 2006). GPP estimated with these new meteorological data and adjusted Biome Parameter Look up Tables (LUT) is called Collection 4.8 and it covered a period from February 2000 to December 2006.

Meteorological variables such as PAR, T_{MIN} and VPD are provided by NASA's DAO or GMAO as a 3-hour global product at 1°×1.25° spatial resolutions. In earlier versions of the MODIS GPP algorithm (i.e. Collection 4), each 1 km pixel falling into the same 1°×1.25° DAO grid cell will inherit the same meteorological data (Zhao et al., 2005). This created a noticeable DAO footprint, which may be acceptable on a regional or global scale estimation of GPP (Zhao et al., 2005). However, at local scale and for the terrain with topographical variation or located at relatively abruptly climatic gradient zones, it may cause large inaccuracies (Zhao et al., 2005). Therefore, in Collections 4.5 and 4.8, a non linear scheme was used to interpolate the four meteorological cells surrounding a given 1 km MODIS pixel to a 1 km grid.

Table 1
Values for maximum light use efficiency, T_{MINmin}, T_{MINmax}, VPDmin, and VPDmax as calculated using data collected in the field and default values used in MODIS GPP algorithm for savanna (Maosheng Zhao, personal communication).

Input parameters values	Collection 4.5	Collection 4.8 and 5	Site specific values for Howard Springs
Maximum light use efficiency (g C MJ^{-1})	0.80	1.03	1.26
T_{MINmin} (°C)	−8	−8	−8
T_{MINmax} (°C)	11.39	11.39	11.39
VPDmin (Pa)	930	650	900
VPDmax (Pa)	3100	3500	3500

This DAO spatial interpolation technique was found to improve the accuracy of meteorological data for each 1 km pixel when compared to observational data around the world (Zhao et al., 2005). However, the degree of the accuracy is also largely dependent on the accuracy of DAO data and local environmental conditions, elevation and weather patterns (Zhao et al., 2005). fPAR values (Collection 4) were temporarily interpolated to replace pixels that were missing and/or had poor quality labels (Zhao et al., 2005).

The latest GPP product is Collection 5 and it covers the period from February 2000 to present with some gaps in the data as they are being reprocessed currently. This Collection has been available for users to be downloaded freely from the EOS (Earth Observing System) Data Gateway (http://edcimswww.cr.usgs.gov/pub/imswelcome/) since end of 2006. GPP Collection 5 uses an improved LAI and fPAR (Collection 5) product simulated by a new stochastic RT model which allows a better representation of canopy structure and spatial heterogeneity and using a new land cover product (Collection 4). Other input parameters such as meteorological data and LUE values used in Collection 5 are similar to Collection 4.8 (Table 1, Zhao, personal communication). Collection 5, LAI/fPAR products released by NASA at the time of analysis were not gap-filled to provide values for missing data due to sensor malfunction or cloud cover. The LAI/fPAR Collection 4 used to estimate GPP in Collections 4.5 and 4.8 are gap-filled from the Numerical Terradynamic Simulation Group (NTSG) (Zhao et al., 2005).

MODIS products are also routinely sub-setted for a 7×7 km cut out around registered FLUXNET and core validation sites and provided in ASCII format. Subset data for the Howard Springs flux site were downloaded from the Oak Ridge National Laboratory website (http://daac.ornl.gov/MODIS/modis.html). MODIS GPP 8 day composites for Collections 4.5 and 4.8 that were available from 2001 to 2003 (Collection 4.5) and from 2001 to 2006 (Collections 4.8 and 5) were used in this study. GPP Collections 4.5 and 4.8 were gap-filled whereas, Collection 5 was not gap-filled at the time of the writing. In addition, annual GPP and monthly average LAI and fPAR (averaged from 8 day composites) data were also used in this study. Gap-filled LAI and fPAR Collection 4 were provided by NTSG (Heinsch, personal communication). Meanwhile, meteorological data (PAR, daily minimum temperature, daytime VPD and LUE) used to estimate GPP in Collections 4.5 and 4.8 were also validated against flux tower measured variables. These data (daily) were also obtained from NTSG (Zhao, personal communication) and averaged to 8 day bins. To be comparable with MODIS GPP, tower GPP were aggregated to 8 day bins. In addition, we also used annual GPP and monthly average LAI and fPAR data.

The MODIS land cover classification product, Collection 3 (MOD 12Q1) mostly correctly classified Howard Springs as woody savanna, where the majority of the total pixels (49) surrounding the flux tower were classified as woody savanna (38), savanna (9) and 2 pixels were incorrectly classed as evergreen broadleaf forest and grassland. According to our experience at the site, these 2 pixels should be grouped as savanna and swamp respectively. We excluded these two pixels from our further analysis. For GPP, LAI and fPAR Collection 5, only pixels that were derived using the main RT algorithm were selected in this study because main RT algorithm is employed mostly under clear sky and fewer atmospheric effects (Myneni et al., 2002). If more than 75% of the 47 pixels surrounding the flux tower were derived by MRT algorithm, that particular 8 day composite was included in the analysis.

2.4. Statistical analysis

Several statistical techniques were employed to adequately compare the performance of MODIS GPP with tower derived GPP because no single model evaluation statistic is sufficient to evaluate model performance (Willmott, 1984). We used student t-test to see if the variation between tower and MODIS GPP was significant or not, Root

mean square error (RMSE) to measure the actual average differences between MODIS and tower data, Willmott's index of agreement (IOA) (Willmott, 1984) to measure the degree to which the observed data were approached by the predicted data, and Relative Predictive Error (RPE) to quantify the percentage mean difference between MODIS and tower data. RPE provides the direction of change (underestimation or overestimation) in predicted values compared to measured values. Refer to Appendix A for the formulation of these techniques.

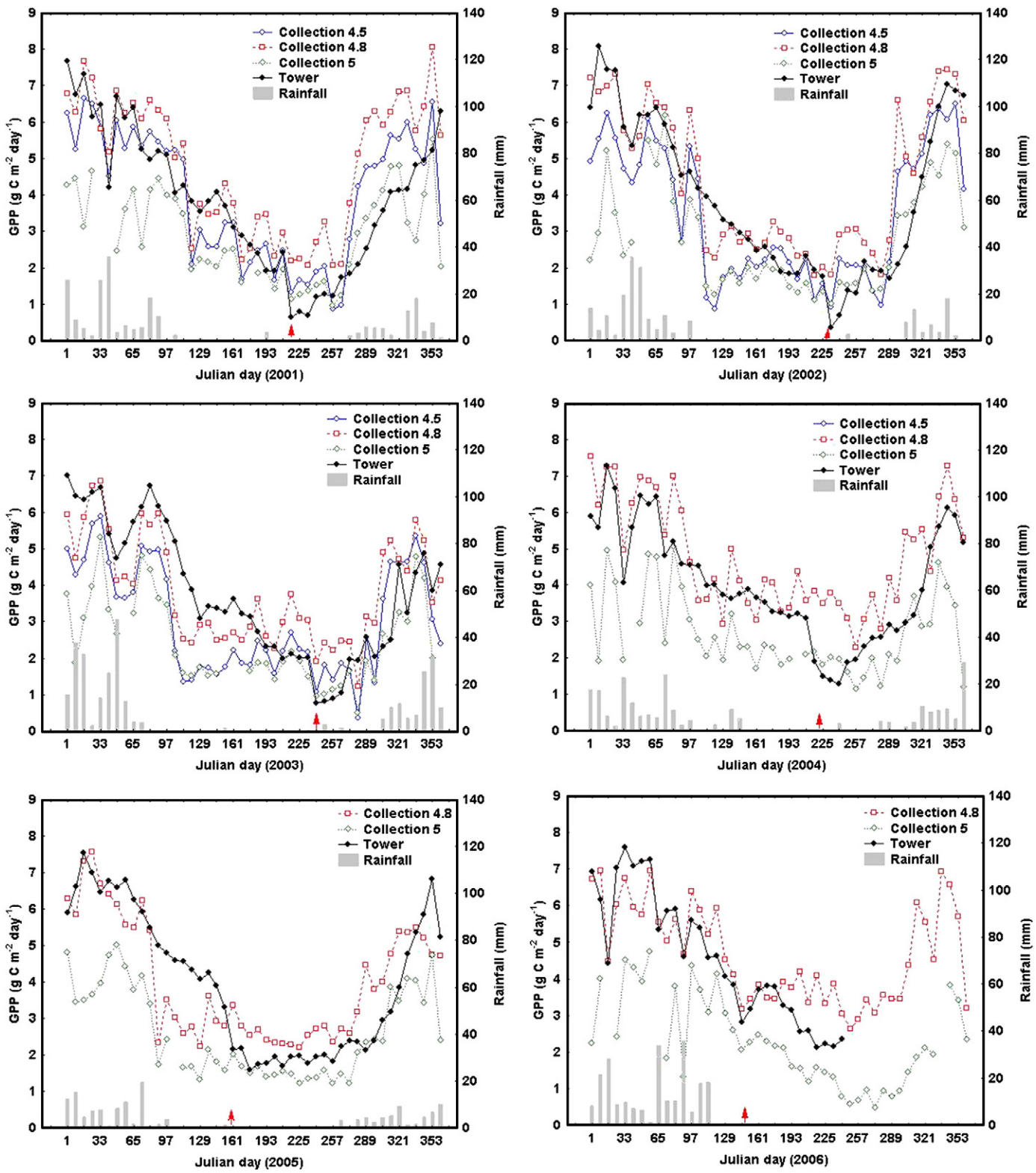

Fig. 2. Comparison between daily average tower and MODIS (Collections 4.5, 4.8 and 5) GPP from 2001 to 2006. The fire events in each year are shown by the triangles and rainfall is given as an 8 day average. Note the strong seasonal variation in GPP according to seasonal rainfall. High rainfall in 8 day composites in the wet season correspond to relatively lower GPP which may be related to reduction in solar radiation due to cloud cover (Beringer et al., 2007).

2.5. Leaf Area Index and fraction of PAR

LAI and fPAR are fundamental parameters for modeling both canopy photosynthesis and evapotranspiration (Myneni et al., 1997, 2002). Since LAI was not measured regularly at Howard Springs during the measurement period 2001–2006, we used previous over storey and under storey LAI measured in the field over a 12 month period in 2000 (Hutley and Williams, unpublished data) and over storey LAI (O'Grady et al., 1999) to provide a surrogate LAI time series for periods from 2001 to 2006. The inter-annual variation in total LAI is not large at this site and we used a multiple linear regression model between observed LAI and MODIS LAI ($R^2 = 0.94$) with varying intercept but constant slope for different seasons (wet, dry and transition between wet and dry) to then predict LAI using MODIS LAI Collection 4 (2000 to 2006).

With the estimated LAI, we computed monthly fPAR from 2000 to 2006 using a simple Beer's law (Jarvis and Leverenz, 1983) formulation as follows:

$$\mathrm{fPAR} = [1 - \exp(-k{*}\mathrm{LAI})] \tag{4}$$

A value of 0.5 was used for k (light extinction coefficient). This value is similar to previous studies for Australian savanna (Leuning et al., 2005) and other Australian vegetation (Roderick et al., 2001).

2.6. Light use efficiency

LUE refers to the amount of carbon a particular vegetation type can produce per unit of energy absorbed (Gower et al., 1999). Canopy LUE was calculated in this study as follows:

$$\mathrm{LUE} = \mathrm{GPP} / \mathrm{APAR} \tag{5}$$

Monthly values of GPP were obtained from flux tower and APAR was calculated by multiplying PAR with fPAR.

3. Results

Collections 4 and 5 of MODIS GPP along with their input values were assessed to determine the robustness of the MODIS GPP algorithm to estimate GPP for a woody savanna site during different seasons and environmental conditions (fire and non fire).

3.1. Comparison between tower and MODIS GPP

We compared mean tower and MODIS derived GPP at daily, seasonal and yearly intervals. We validated MODIS GPP accuracy with respect to seasonal trajectories, maximum and minimum values, initiation and cessation of the growing season plus annual and inter-annual variations after Turner et al. (2006b).

3.1.1. Daily and seasonal dynamics

Daily averages of tower GPP showed a strong seasonal pattern that corresponded to the amount of rainfall in the wet and dry seasons (Fig. 2). Tower GPP had a maximum value in the wet season (January) of 7–8 g C m^{-2} day^{-1} in all years, with a steady decline in GPP observed from May onward as the dry season progressed. Annual minimum GPP was measured in the late dry season (August or early September), which is often associated with fire events. For years in which fire occurrences were recorded, there was a loss of productivity associated with canopy scorch (loss of functional leaf area) and canopy re-building. The higher intensity fires (e.g. August 2001) resulted in ~80% canopy leaf scorch, after which the canopy regenerated from epicormic shoots. The flux tower estimated minimum annual GPP of between 0.3 and 1.6 g C m^{-2} day^{-1} for years 2001–2005 depending on the variability in fire intensity (Beringer et al., 2007).

Although MODIS predicted the seasonal patterns well (Fig. 2), there was an offset in GPP estimated by MODIS compared to GPP derived from flux tower at the beginning of the wet and dry seasons. MODIS Collections 4.5, 4.8 and 5 (to a larger degree) indicated an abrupt increase in GPP from September every year and reached a maximum GPP in December in the wet seasons of 2001/2002 and 2002/2003 (Fig. 2). This sharp increase was not reflected in the tower derived GPP (Fig. 2). For the subsequent wet seasons, MODIS Collection 4.8 predicted the highest GPP in January (7 to 7.5 g C m^{-2} day^{-1}), similar to tower data. Collection 5 indicated a maximum value of 5.8 g C m^{-2} day^{-1} in December 2001, which is lower than tower data. For other years, the wet season GPP was underestimated by Collection 5 compared to tower GPP.

Generally MODIS Collection 4.5 underestimated tower GPP in all years by 3 to 25% (negative RPE values) in the wet season (Table 2a). Collection 4.8 tended to slightly overestimate GPP (9%–11%) in 2001, 2001/2002, and 2003/2004 wet seasons, although this was reversed (underestimation of <10%) in other years. Similarly, Collection 5 largely underestimated GPP in the wet season between 35 and 44%. The IOA values were higher for Collection 4.8 and the RMSE was much lower compared to Collections 4.5 and 5 (Table 2a) indicating improvement in the latest available GPP of Collection 4.8. The dry season senescence also appeared earlier in MODIS (Collections 4.5, 4.8 and 5) compared to the tower GPP as indicated in Fig. 2. MODIS recorded its lowest productivity by the mid late dry season (0.4 to 0.9 in Collection 4.5, 2 to 2.5 in Collection 4.8 and <2 g C m^{-2} day^{-1} in Collection 5).

Fire is a major environmental disturbance that affects the carbon sequestration or GPP in the dry season in northern Australia (Beringer et al., 2007). Fire can destroy the senescent portion of the under storey grasses and reduce productivity of over storey *Eucalyptus* trees by scorching the leaves and thereby reducing photosynthesis and transpiration (Beringer et al., 2007). Carbon budget analysis would be much easier and efficient if satellites could routinely monitor and provide reliable estimates of carbon loss due to fire in this harsh environment. Thus, we evaluated MODIS GPP during fire-affected periods (~40 days from day of fire) separately to see if MODIS could detect the effect of fire on productivity. In 2001 for instance, a fire started at Howard Springs on Julian day 218 (6th August). As a consequence, the average GPP estimated from the flux tower was only 0.9 g C m^{-2} day^{-1} from days 217 to 257, but MODIS predicted higher GPP with 1.7 g C m^{-2} day^{-1} in Collection 4.5, 2.5 g C m^{-2} day^{-1} in Collection 4.8 and 1.4 g C m^{-2} day^{-1} in Collection 5 during this period (Table 2b). The relative mean GPP between MODIS and tower during fire period was more variable (Table 2b) than when fire periods were excluded from dry season analysis (Table 2c) especially for Collection 4.8. This suggests that currently none of the available Collection 4 MODIS GPP products could be used to estimate carbon loss in this ecosystem due to fire, but Collection 5 could estimate the reduction in GPP quite closely.

3.1.2. Inter annual variation

Quantifying the inter-annual variation in GPP is important to assess ecosystems response to climatic variation (Turner et al., 2006b) and disturbance via fire. Annual GPP estimated from the flux tower indicated small variation from 2001 to 2003 (<50 g C m^{-2} $years^{-1}$), with a small increase in 2004 and 2005 (~100 g C m^{-2} $year^{-1}$, Fig. 3). MODIS Collections 4.5 and 4.8 indicated a decrease in 2002 and 2003 compared to 2001 (12–24% in Collection 4.5 and 9–21% in Collection 4.8) (Fig. 3). For periods from 2001 to 2005, the highest tower GPP was in 2004 but MODIS Collection 4.8 showed its highest value in 2001 (only 25 g C or 1.4% higher than 2004 MODIS GPP). MODIS Collection 4.8 actually matched the highest tower GPP, but additionally had the highest GPP in 2001. The lowest GPP within the 5 year period occurred in 2003 for both Collections of MODIS GPP in

Table 2
Differences between MODIS and tower GPP in the (a) wet season, (b), dry season fire period, (c) dry season fire excluded period for 2001–2006.

	Collection 4.5			Collection 4.8						Collection 5					
(a) Wet season (Dec–Apr)	Jan–Apr01	Dec01–Apr02	Dec02–Apr03	Jan–Apr01	Dec01–Apr02	Dec02–Apr03	Dec03–Apr04	Dec04–Apr05	Dec05–Apr06	Jan–Apr01	Dec01–Apr02	Dec02–Apr03	Dec03–Apr04	Dec04–Apr05	Dec05–Apr06
Mean tower GPP	5.78 (0.30)	5.75 (0.26)	6.08 (0.18)	5.78 (0.30)	5.75 (0.26)	6.08 (0.18)	5.23 (0.23)	5.95 (0.20)	6.01 (0.23)	5.85 (0.31)	5.72 (0.27)	6.13 (0.18)	5.25 (0.26)	6.02 (0.19)	6.15 (0.23)
Mean MODIS GPP	5.61 (0.15)	4.79 (0.29)	4.58 (0.30)	6.27 (0.19)	6.03 (0.29)	5.50 (0.32)	5.73 (0.31)	5.57 (0.36)	5.69 (0.18)	3.78 (0.20)	3.61 (0.32)	3.63 (0.27)	3.50 (0.29)	3.49 (0.27)	3.46 (0.26)
RMSE	0.79	1.50	1.69	0.88	1.06	1.01	0.88	1.05	0.82	2.43	2.61	2.63	2.04	2.61	2.88
RPE (%)	−2.92	−16.71	−24.63	8.55	4.85	−9.55	9.50	−6.46	−5.35	−34.57	−36.94	−40.76	−33.42	−41.02	−43.73
IOA	0.75	0.56	0.53	0.76	0.75	0.78	0.85	0.79	0.74	0.002	0.16	0.25	0.39	0.25	0.18
No. of 8 day composites	15	19	19	15	19	19	19	19	19	13	18	18	17	18	17
(b) Dry season (May–Nov) fire period (40 days from fire)	2001	2002	2003	2001	2002	2003	2004	2005	2006	2001	2002	2003	2004	2005	2006
Mean tower GPP	0.92 (0.14)	1.18 (0.31)	1.09 (0.22)	0.92 (0.14)	1.18 (0.31)	1.09 (0.22)	1.65 (0.13)	2.78 (0.10)	3.46 (0.20)	0.92 (0.14)	1.18 (0.31)	1.09 (0.22)	1.65 (0.13)	2.78 (0.10)	3.46 (0.20)
Mean MODIS GPP	1.70 (0.13)	1.86 (0.24)	1.70 (0.15)	2.51 (0.22)	2.70 (0.23)	2.30 (0.10)	3.33 (0.23)	2.78 (0.17)	3.48 (0.08)	1.38 (0.09)	1.52 (0.15)	1.19 (0.12)	1.79 (0.15)	1.65 (0.10)	2.25 (0.07)
RMSE	0.78	0.87	0.65	1.61	1.62	1.26	1.82	0.97	0.30	0.48	0.52	0.22	0.54	0.28	1.23
RPE (%)	85.60	57.54	85.60	173.86	128.73	110.25	102.18	81.54	29.16	50.80	28.95	30.54	8.41	3.42	−65.34
IOA	0.29	0.46	0.59	0.14	0.18	0.11	0	0.15	0.73	0.41	0.71	0.92	0	0.49	0.09
No. of 8 day composites	5	5	5	5	5	5	6	5	5	5	5	5	6	5	5
(c) Dry season (May–Nov) fire excluded periods (40 days)	2001	2002	2003	2001	2002	2003	2004	2005	2006	2001	2002	2003	2004	2005	2006
Mean tower GPP	2.94 (0.20)	2.66 (0.21)	2.80 (0.15)	2.94 (0.20)	2.66 (0.21)	2.80 (0.15)	3.34 (0.13)	2.78 (0.21)	3.00 (0.86)	2.96 (0.20)	2.66 (0.21)	2.17 (0.17)	3.35 0.14	2.78 (0.21)	3.00 (0.86)
Mean MODIS GPP	3.20 (0.32)	2.57 (0.32)	2.34 (0.24)	4.07 (0.35)	3.27 (0.31)	3.15 (0.20)	3.98 (0.24)	3.19 (0.22)	4.01 (0.23)	2.53 (0.24)	2.15 (0.23)	1.89 (0.15)	2.29 0.13	1.96 0.18	1.94 (0.29)
RMSE	1.23	1.19	1.24	1.76	1.30	1.14	1.04	1.07	1.14	1.00	0.94	1.10	1.20	1.20	1.11
RPE (%)	8.7	−3.15	−16.60	38.30	23.13	12.42	18.83	14.61	33.78	−14.33	−18.97	−30.37	−31.80	−29.64	−35.27
IOA	0.67	0.70	0.31	0.50	0.65	0.20	0.31	0.63	0.58	0.70	0.75	0.36	0.32	0.55	0.77
No. of 8 day composites	22	22	22	22	22	22	22	22	11	21	22	19	21	22	11

Wet season is defined here from December to April and dry season covers periods from May to November. Values in brackets are standard error of the mean.

agreement with lowest tower GPP. This indicates the capability of MODIS to detect the interannual GPP changes reasonably well.

3.2. Comparisons of LAI and fPAR

We also validated all the input parameters used to estimate MODIS GPP in order to tease out the contribution of each of the factors in estimating GPP. Comparison between monthly average MODIS LAI Collection 4 and LAI estimated using field data indicated that MODIS generally over-predicted both dry and wet seasons LAI, although it captured the seasonality reasonably well (Fig. 4). The average MODIS LAI from 2000 to 2006 in the wet season was 3.74 ± 0.20 (mean ± Standard Error) whereas, in the dry season it was 1.30 ± 0.10, 41% and 32% higher than field based LAI in the wet and dry seasons respectively. The difference between Collection 5 and field based LAI was minimal with only 11–12% in the wet and dry seasons respectively, (Fig. 4a) indicating improvement in the LAI product.

The average MODIS fPAR Collection 4 ranged from a minimum of 0.64 ± 0.03 (September) to a maximum of 0.91 ± 0.01 (April). These values are far too high compared to the calculated minimum value of 0.36 ± 0.00 in September and maximum value of 0.67 ± 0.01 in March. These ranges of observed values for Howard Springs are comparable to other studies such as Berry and Roderick (2002) who estimated fPAR for the same location using Normalized Difference Vegetation Index from Advanced Very High Resolution Radiometer and obtained maximum fPAR of 0.61 in March and minimum value of 0.33 in September (average from 1981 to 1991). Similarly, Huemmrich et al. (2005) measured fPAR ranging from 0.47 to 0.62 in Mongu for African savanna. In comparison, MODIS Collection 5 captured the average maximum (0.57 ± 0.012) in March and minimum (0.37 ± 0.013) fPAR

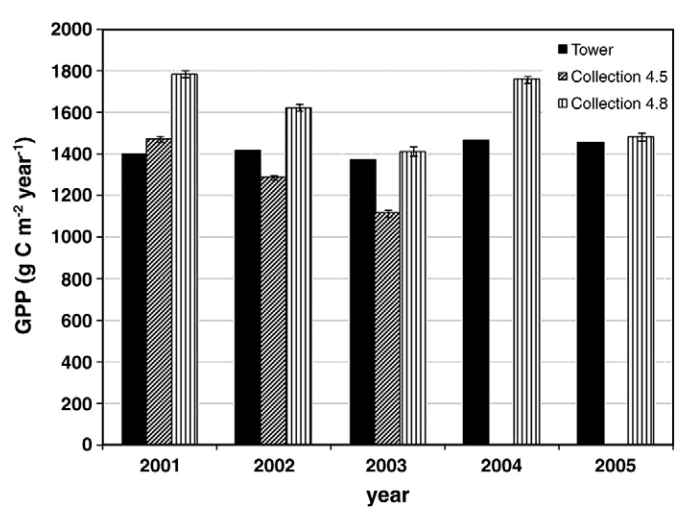

Fig. 3. Comparison of annual total GPP between tower and MODIS Collections 4.5 and 4.8 from 2001 to 2005. Error bars show ±Standard Deviation of 47 pixels surrounding the flux tower.

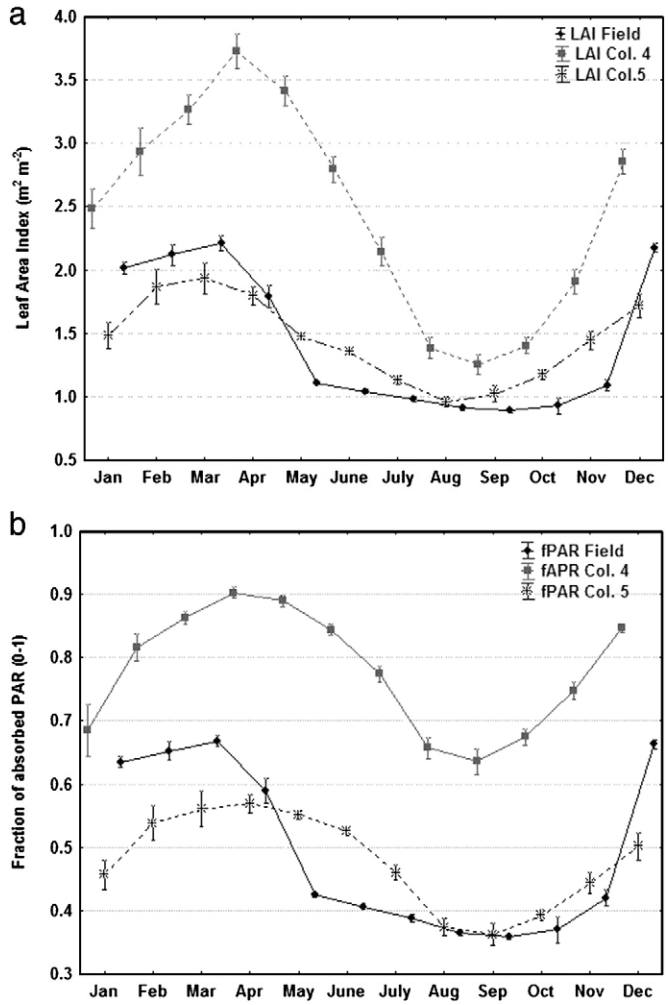

Fig. 4. Comparison between calculated and MODIS Collections 4 and 5 (a) Leaf Area Index and (b) fraction of photosynthetically absorbed radiation from January 2000 to August 2006. Collection 5 LAI and fPAR includes data from 2000 to August 2002. Error bars show ±Standard Error of monthly average values.

values (for 2000–2006) reasonably well. Both Collections of MODIS LAI/fPAR product indicate a sharp increase in LAI and fPAR from September, whereas field based LAI and fPAR showed a slower

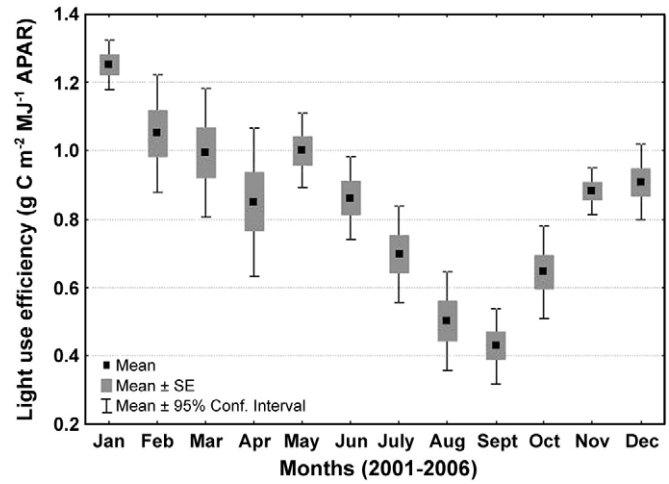

Fig. 6. Monthly average values of light use efficiency from January 2001 to August 2006. The mid point in each of the boxes is the means, the boxes are ±SE and the whiskers are the 95% confidence intervals.

increase that indicates the recovery of the over storey canopy from a long dry season and/or fire and flushing of the under storey grasses and deciduous and semi-deciduous trees with the onset of the wet season.

We further examined the effect of fire on MODIS LAI and fPAR at Howard Springs. We selected 40 days before, during and after the day of fire to see phenological changes in LAI as a function of fire. Results (Fig. 5) show that both Collections 4 and 5 of MODIS LAI and fPAR can detect the reduction in LAI and fPAR during fire, indicating the use of MODIS LAI/fPAR to detect reduction in green vegetation due to fire. Although the magnitude of the reduction in LAI and fPAR could not be verified against field data, MODIS was likely to overestimate LAI following fire.

3.3. Light use efficiency

The temporal variation in monthly canopy LUE from 2001 to 2006 shows a strong seasonality (Fig. 6). The savanna ecosystem utilizes radiation more efficiently in the wet season, notably in January (1.26 ± 0.03 g C MJ^{-1} APAR) (average ± SE) and least efficiently in September (0.43 ± 0.08 g C MJ^{-1}). This is primarily related to high biomass and LAI that is driven by rapid grass growth following the onset of the wet

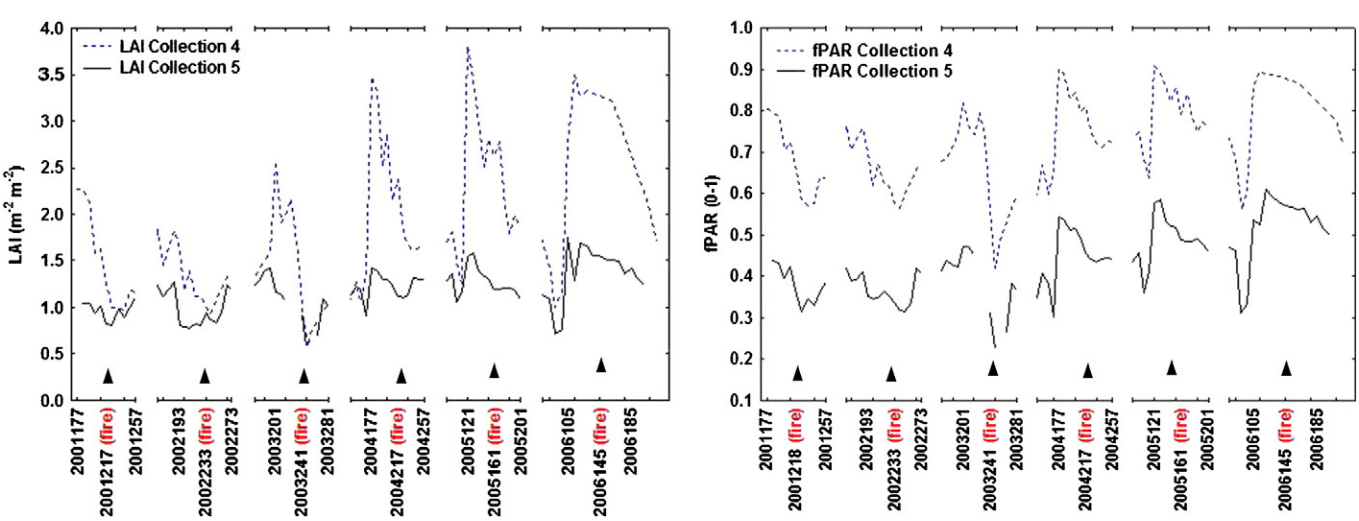

Fig. 5. The effect of fire on MODIS LAI and fPAR Collections 4 and 5. Solid triangles show the dates of fire at Howard Springs on 8 day composites of 2001217, 200223, 2003241, 2004217, 2005153 and 2006145. The intensity of fire was 3000 to 3600 kW m^{-2} from 2001 to 2004 and <1400 kW m^{-2} in 2005 and 2006 (Beringer et al., 2007).

season. LUE reached its minimum in September when fires were most prevalent and increased from October onwards, when the ecosystem recovered from canopy scorch due to fire and/or the wet season began. To develop a site specific maximum LUE, the 6 highest monthly values (from 2001 to 2006) were averaged to produce a maximum LUE of 1.26 ± 0.03 g C MJ^{-1} following Coops et al. (2007). This value is 18% higher than the standard MODIS algorithm value of 1.03 g C MJ in Collections 4.8 and 5.0 and 37% higher than the value of 0.8 g C MJ in Collection 4.5 for grassy woodland land cover class (Table 1) (Maosheng Zhao, personal communication).

We further analyzed the controlling factors of LUE at our study site in order to effectively parameterize the LUE and GPP models. Most LUE models use temperature, VPD and/or soil moisture as factors regulating LUE (Prince and Goward, 1995; Running et al., 2000; Xiao et al., 2004a). We tested these factors using a simple linear relationship and found that VPD explained 49% of the variation in observed LUE (yearly) and 36% in the wet season ($R^2 = 0.36$, $p < 0.05$, LUE = 1.57 − 0.66 * VPD) but < 1% ($R^2 = 0.0008$, $p = 0.89$, LUE = 0.58 + 0.06 * VPD) in the dry season. This is consistent with a previous canopy scale study that showed a weak influence of VPD on transpiration or stomatal conductance in the dry season (Eamus et al., 2001). Temperature on the other hand, explains only 0.05% variation in LUE, indicating temperature is not a critical factor in either the wet or dry seasons. Mean volumetric soil water content (SWC) at 10 cm is more strongly correlated with LUE than VPD ($R^2 = 0.59$, $p < 0.05$, LUE = 0.26 + 0.05 * SWC) especially in the dry season ($R^2 = 0.28$, $p < 0.05$, LUE = 0.12 + 0.07 * SWC). Therefore, soil moisture could be used as an additional (or replacement) factor to constrain savanna LUE rather than VPD. The use of soil water to estimate GPP is described in Section 3.6.

3.4. Meteorological data

A cross comparison between NASA DAO (used to estimate GPP in Collection 4.5) and GMAO (Collection 4.8) meteorological data vs. the tower data in this study revealed notably lower PAR (underestimated by approximately 0.8 MJ m^{-2} day^{-1} (RPE −9%) in DAO and 1 MJ m^{-2} day^{-1} (RPE −11%) in GMAO in the wet season. Similarly, in the dry season both DAO and GMAO underestimated PAR ~ 0.4 (RPE −5%) and 0.6 MJ m^{-2} day^{-1} (RPE −6%) respectively (Fig. 7a). High cloud cover in the wet season caused substantial day to day variation and relatively large discrepancies between tower and DAO/GMAO PAR. Similarly, VPD (Fig. 7b) also showed large discrepancies in the wet season where both versions of meteorological data underestimated values (up to 400 Pascal in DAO and around 350 Pa in GMAO) relative to tower VPD. In the dry season (May–October), both versions had a positive bias (50–450 Pa). Daily minimum temperature (data not shown) was overestimated (up to 1.8 °C) in the dry season but slightly underestimated in the wet season (~0.4 °C) in DAO and negligible overestimation of 0.1 °C in GMAO.

3.5. T_{MIN} and VPD scalars

Discrepancies in meteorological data can introduce errors when calculating VPD and T_{MIN} scalars that are used to constrain the maximum LUE and subsequently estimate GPP. We calculated T_{MINmin}, T_{MINmax}, VPDmin and VPDmax (Eqs. (3) and (4)) values for Howard Springs by relating daily light use efficiency (GPP/PAR) with daily daytime average VPD and daily T_{MIN}. Analysis between T_{MIN} and LUE at daily time steps indicated that temperature does not constrain LUE at any minimum temperature level observed at the site. Therefore the T_{MINmin} and T_{MINmax} values of −8 °C and 11.39 °C (Table 1) provided by MODIS seem reasonable and we used these values to calculate the T_{MIN} scalar using daily T_{MIN} measured at the tower site (Eq. (3)). These values provided T_{MIN} scalar values of 1 at all times, thereby proving no temperature limitation on LUE in this tropical savanna ecosystem. For

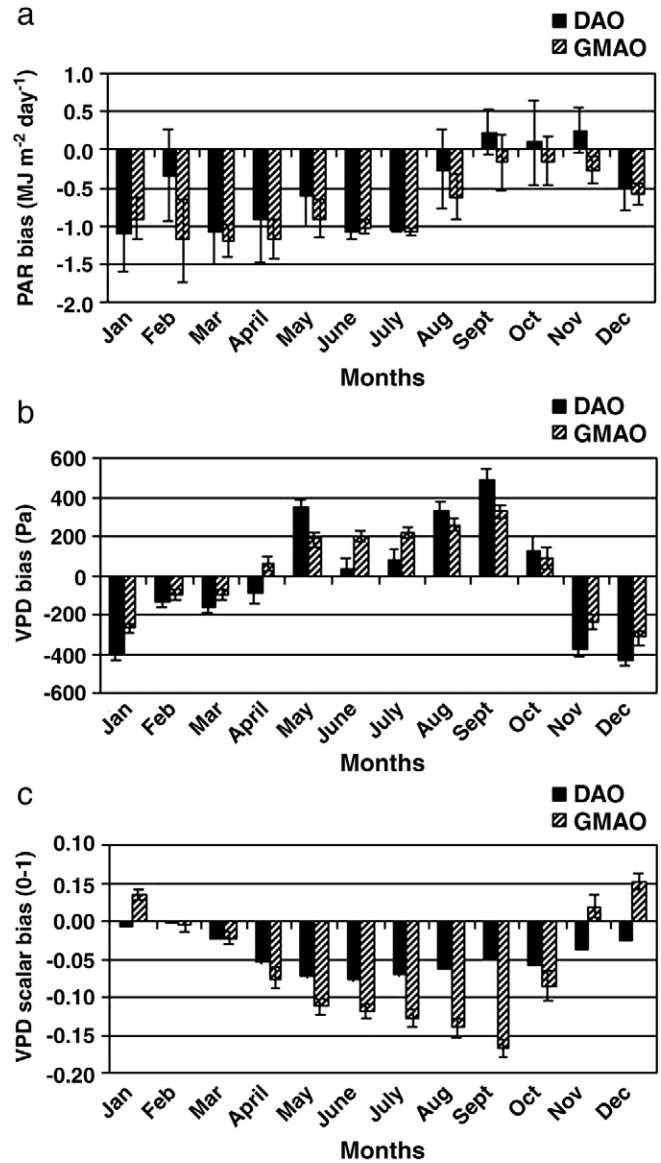

Fig. 7. Bias (MODIS minus tower) of (a) daily solar radiation (b) daytime vapor pressure deficit and (c) vapor pressure deficit scalar calculated using Eq. (3) for DAO and GMAO compared to the observations for Howard Springs from January 2001 to August 2006. Error bars show ±SE from monthly average values.

VPD, the VPDmin and VPDmax values derived from flux tower were 900 and 3500 Pa respectively (Table 1). The VPDmin is close to the value used in Collection 4.5 but higher than Collection 4.8, whilst VPDmax as derived from flux tower was similar to the value used in Collection 4.8 but, higher than the value in Collection 4.5 (Table 1). The VPD scalar calculated with Eq. (3) using these values were compared with VPD scalars that were calculated using default values for VPDmin and VPDmax in MODIS Collections 4.5 and 4.8 (Table 1). Results (Fig. 7c) indicated a good agreement (RPE of 0%) in the wet season for Collection 4.8 and (−4%) for Collection 4.5. In the dry season both Collections underestimated the VPD scalar with an RPE of −17% in Collection 4.8 and −11% in Collection 4.5.

3.6. Algorithm improvement

Since we found discrepancies in meteorological variables, down-regulating functions, LUE and fPAR values used to calculate GPP in MODIS we recalculated GPP using site specific meteorology, LUE and fPAR values. In order to find out which of these input parameters

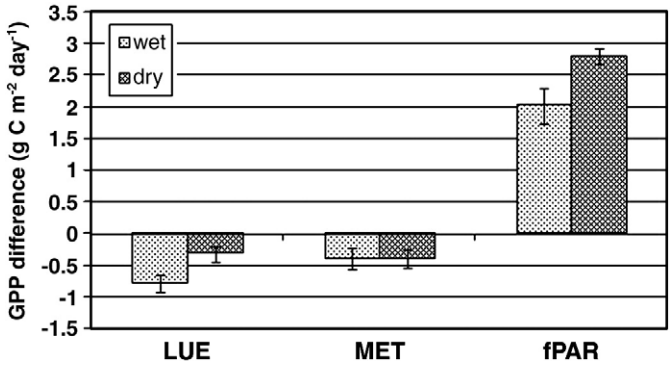

Fig. 8. Difference between tower derived GPP and GPP estimated using site specific input variables and light use efficiency from MODIS Collection 4.8 (Test 1), meteorological from GMAO (Test 2) and fPAR from MODIS Collection 4 (Test 3). Error bars show ±SE from seasonal average values.

caused the major differences between MODIS and tower derived GPP, we conducted three tests as follows:

(i) TEST 1 (LUE) – we used all input variables measured in the field except for LUE where we used MODIS Collections 4.5 and 4.8;
(ii) TEST 2 (MET) – all input variables measured in the field except for meteorology from DAO and GMAO (PAR, VPD scalar and T_{MIN} scalar);
(iii) TEST 3 (fPAR) – all input variables measured in the field except for fPAR from MODIS Collection 4.

Results (Fig. 8) show that GPP estimated using TEST 1 and TEST 2 for Collection 4.8 compared well with tower derived GPP on an annual basis with high IOA ranging between 0.92 and 0.93, low RPE (−10 to −13%) and RMSE (0.93 to 0.98 g C m^{-2} day^{-1}). A *t*-test for independent samples indicates that the two sets of observations were not significantly different from tower estimated GPP ($t_{129,\ 68}=-1.83$, $p=0.07$ for Test 1 and $t_{133,\ 68}=-1.25$, $p=0.21$ for Test 2). Similarly, Collection 4.5 (TEST 2) agreed well with the observations with very low RPE (−4%) and RMSE (0.94 g C m^{-2} day^{-1}) and high IOA (0.92). Results showed a non significant difference from tower GPP ($t_{68,\ 36}=0.35$, $p=0.73$) (data not shown). TEST 1 using MODIS Collection 4.5 LUE did not show a very good agreement and it underestimated tower GPP by 31% with high RMSE of 1.55 g C m^{-2} day^{-1} and a moderate IOA of 0.75 A *t*-test analysis also indicated a significant difference from tower GPP ($t_{99,\ 36}=-4.72$, $p<0.05$) (data not shown). TEST 3 which used MODIS fPAR indicated very high error (RPE 62% and RMSE 2.75 g C m^{-2} day^{-1}) and low agreement (IOA

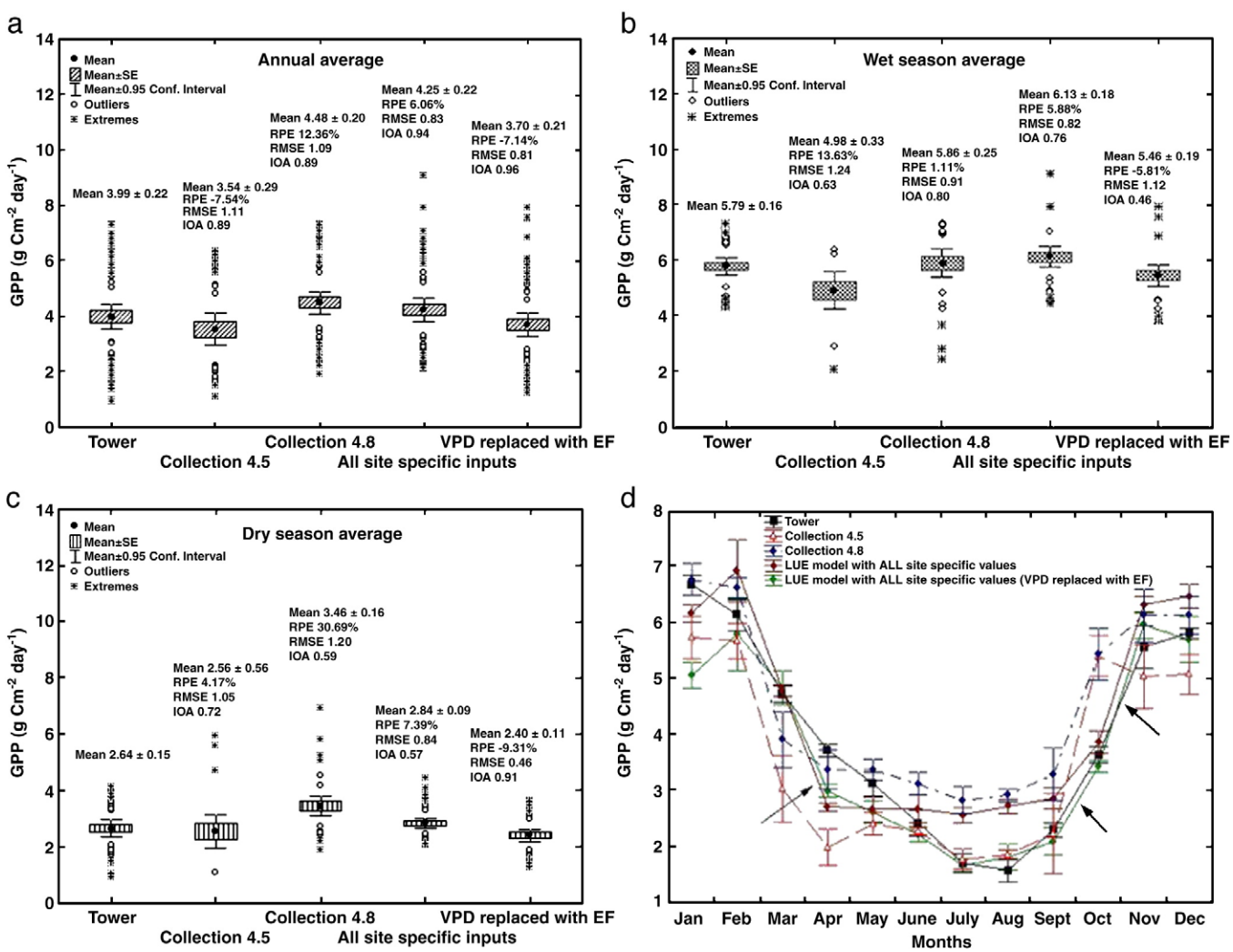

Fig. 9. Comparison between (a) annual (b) wet season and (c) dry season averages of GPP derived from flux tower, GPP from MODIS Collections 4.5 and 4.8, and GPP estimated by a modified LUE algorithm similar to MODIS with site specific values with vapor pressure deficit and modified algorithm with Evaporative Fraction (EF). The mid point in each of the boxes is the means, the boxes are ±SE and the whiskers are the 95% confidence intervals. Panel d compares the seasonal patterns in monthly average ±SE GPP as predicted by the 5 methods. Arrows in panel d indicate the capability of the improved algorithm with Evaporative Fraction in capturing the dynamic from dry to wet season (right) but poor performance to capture the dynamic from wet to dry season (left).

0.54) and a significant difference ($t_{133,\ 68}=8.26$, $p<0.05$) relative to tower derived GPP. This analysis revealed that MODIS fPAR was the major source of discrepancy followed by LUE and meteorological parameters in estimating GPP using satellite data at Howard Springs. But this was countered by a negative bias in LUE and meteorology which meant that average MODIS GPP was close to observed GPP.

We further estimated GPP for the Howard Springs savanna site using a simple LUE approach (MODIS GPP algorithm) with all input values (PAR, fPAR, LUE, and VPD scalar) that were derived at the tower site. GPP estimated with this method agreed very well (annual) with tower derived GPP (Fig. 9a) with IOA 0.94 and was not significantly different ($t_{133,\ 68}=-0.83$, $p=0.41$). This method also produced lower RMSE (0.83 g C m^{-2} day^{-1}) and RPE (6%) values compared to MODIS Collections (Fig. 9a).

Further seasonal analysis indicated that in the wet season, this method performs well compared to Collection 4.5 and this is shown by the improved IOA, RPE and RMSE (Fig. 9b). However, when compared to Collection 4.8, this method does not indicate any noteworthy improvement in terms of the agreement, or errors. The dry season agreement between tower derived GPP and GPP estimated with this method produced much lower RMSE and RPE (RPE 7.39% and RMSE 0.84 g C m^{-2} day^{-1}) compared to Collection 4.8. Also it only moderately agreed (IOA 0.57) with tower data (Fig. 9c). This confirms that VPD may not be a very good measure of soil water and therefore it cannot accurately reflect the loss of productivity in the dry season for this environment.

Alternatively, we attempted to further improve the estimation of GPP especially in the dry season by replacing the VPD scalar with a moisture index. Here, we used a simple index called the Evaporative Fraction (EF) following Kurc and Small (2004), Gentinea et al. (2007) and Yuan et al. (2007) to test how effective is EF in capturing GPP both in the dry and wet seasons at Howard Springs. EF was calculated as follows:

$$EF = LE / (LE + H) \tag{6}$$

where LE is latent heat and H refers to sensible heat that was measured by the flux tower at the study site. EF is a useful measure of energy partitioning into evapotranspiration (latent heat) which is a function of soil moisture because soil or vegetation water limitation is indicated by decreasing amounts of energy partitioned into latent heat (Gentinea et al., 2007).

Incorporation of the Evaporative Fraction (replacing VPD) to constrain maximum LUE in the dry season in MODIS GPP algorithm improved the estimation of GPP compared to MODIS or GPP estimated using site specific VPD (Fig. 9c). This is indicated by the high IOA (0.91) and relatively lower RPE (−9.31%) and very low RMSE (0.46 g C m^{-2} day^{-1}). In addition, this method captured the beginning of the wet season well (Fig. 9d). Although its performance to capture the end of the wet season and quantify the magnitude of GPP in the wet season was not very satisfactory (Fig. 9b and 9d), the annual patterns of GPP estimated with this method agreed well with tower derived GPP with IOA 0.96, RMSE 0.81, and RPE −7% (Fig. 9a). Like tower derived GPP (Fig. 3), the annual total GPP estimated from the modified GPP algorithm that uses Evaporative Fraction as a moisture index indicates only minor variation (data not shown) from 2001 to 2003 (~90 g C m^{-2} $years^{-1}$), with a small increase from 2004 to 2005 (~40 g C m^{-2} $years^{-1}$). Conversely, this pattern is not shown by GPP estimated by modified GPP algorithm that uses VPD.

4. Discussion

4.1. GPP

In general, seasonal GPP trends were captured by MODIS for all 6 years at the Howard Springs flux site (Fig. 2). This is consistent with other studies that demonstrate the MODIS algorithm's strength in depicting seasonal dynamics of plant production (Coops et al., 2007; Heinsch et al., 2006; Leuning et al., 2005; Turner et al., 2006a,b). However, at several locations such as Tonzi Ranch oak savanna (Heinsch et al., 2006), Lethbridge grassland (Zhang et al., 2007) and Harvard forest (Turner et al., 2006a; Xiao et al., 2004a) MODIS failed to capture the seasonal dynamics. MODIS GPP did not precisely capture the seasonal dynamics at Howard Springs, particularly the transition phases from dry to wet seasons, a period of great phenological activity and rapid changes in LAI, driven by changes in soil moisture (Hutley et al., 2000). The overestimation of MODIS GPP in the late dry season transition period can be related to the phenological changes in the mid- and over storey canopy species. Over the weeks and months following fire events, or as part of the pre-monsoonal canopy flushing, new foliage emerges. At the Howard Springs site, Cernusak et al. (2006) found that this foliage is not immediately assimilating carbon and had high respiration rates (construction respiration) relative to mature foliage and flushing leaves did not fully mature physiologically for some months after a fire event. This foliage is green in color and would contribute to increasing LAI or fPAR (Fig. 4a and b) estimates as detected by MODIS, but would not contribute to GPP of the ecosystem during this phase, resulting in an overestimated MODIS GPP (Fig. 2).

In terms of the magnitude of GPP, although there was good agreement between the tower GPP and MODIS Collection 4.8 in the wet season, we suggest that estimates were of the correct magnitude for the wrong reasons. Specifically, we suggest that this was due to the counteracting effects of increased fPAR (37%) but decreased LUE (18%) and PAR (11%) as estimated by MODIS (Fig. 4b, Table 1 and Fig. 7a). Also the counteracting biases are clearly revealed in Fig. 8. The reduction of GPP by a factor of two in Collection 5 in the wet season is attributed to the decreased LAI and fPAR as estimated in Collection 5 (Fig. 4b). Although Collection 5 LAI and fPAR are much closer to the observed values, (Fig. 4) the LUE and other parameters are the same as in Collection 4.8 (Maosheng Zhao – personal communication). LUE is lower than the observed value and therefore GPP is also lower (Table 1 and Fig. 2) compared to observations. If fPAR values from Collection 5 are used with site specific meteorology and LUE values, it would provide more accurate GPP compared to tower GPP. GPP Collection 5 provided by NASA is however, not a real or improved product as Collections 4.5 and 4.8. Since LAI and fPAR Collection 4 was higher, NTSG (Numerical Terradynamic Simulation Group) had to retune the BPLUT (Biome Parameter Lookup Table) based on the LAI/fPAR and meteorological data from NASA to provide reliable GPP estimates (Collections 4.5 and 4.8). Similarly, an improved Collection 5 GPP will be released by NTSG by gap filling the poor quality LAI/fPAR Collection 5 and readjusting the BPLUT based on the new LAI/fPAR and latest version of GMAO data. This will be done when NASA releases its complete LAI/fPAR version 5 and GMAO data sets (Zhao, personal communication).

4.2. fPAR

High fPAR values as estimated in Collection 4 MODIS data was mainly due to the overestimated LAI values. Overestimated LAI was also reported in other ecosystems such as in a temperate mixed forest (Kang et al., 2003), open forests and woodlands in Australia (Hill et al., 2006), woodlands and open savanna (Privette et al., 2002), dry grasslands (Fensholt et al., 2004), woody savanna (Huemmrich et al., 2005), Sudano–Sahelian dry grasslands (Fensholt et al., 2004), Tonzi Ranch savanna (Heinsch et al., 2006), and semi-arid Senegal (Fensholt et al., 2006), although MODIS predicted plausible temporal and spatial patterns. High LAI values for Collection 4 as seen in this study could be associated with the RT model used in Collection 4 for LAI/fPAR estimation which can be a source of error in representing canopy structure and spatial heterogeneity of woody vegetation (Shabanov et al., 2007). The main RT algorithm that is used to simulate surface

reflectance does not account for multi layer context, but rather it considers all photosynthesizing vegetation as a single layer. At our savanna site there is a distinct dual layer canopy which complicates the relationship between LAI and the reflected signal from the canopy especially if the dominant canopy is open as in Howard Springs (50–60% over storey cover). This is consistent with Howard Springs where the retrieval of LAI was more accurate in the dry season where the grasses have senesced and there is only a single active over storey trees (Fig. 4a). Despite dry season LAI being correct, the fPAR was overestimated at our savanna site (Fig. 4b), in agreement with Huemmrich et al. (2005) who found that the underestimation of fractional canopy cover for savanna from the MODIS algorithm caused higher fPAR values in a woody savanna site in Mongu, Africa despite the LAI values being consistent with observations. In the dry season, MODIS fPAR Collection 4 was a factor of two higher than field observations, which was the main reason for the overestimation of GPP especially during periods of fire in MODIS Collections. Nevertheless, the MODIS LAI/fPAR product (Collection 4) detected the dynamics in LAI (Fig. 5) when fire destroyed the under storey grasses and deciduous and semi-deciduous trees and scorched leaves of the over storey *Eucalyptus* trees. This indicates that MODIS LAI/fPAR products are very useful in detecting changes in vegetation due to disturbances such as fire although it fails to provide accurate estimation of the magnitude of LAI and fPAR.

Shabanov et al. (2007) recognized that there was an inconsistency between LAI and fPAR retrieval which propagated into overestimation of fPAR for sparse vegetation. In Collection 5, however, both LAI and fPAR were estimated correctly by MODIS because Collection 5 uses a new stochastic RT model that captures 3D effects of foliage clumping and species mixtures of natural ecosystems (Shabanov et al., 2007). The parameters of the new Biome Parameter Lookup Table in Collection 5 avoid this problem by ensuring consistency between simulated and measured MODIS surface reflectance which can minimize LAI overestimation and algorithm failure over medium/dense vegetation and correct fPAR estimation over sparse vegetation (Shabanov et al., 2007). Furthermore, uncertainty levels for each spectral band were introduced in Collection 5 (Shabanov et al., 2007). As a result, the fPAR overestimation was resolved in Collection 5 for savanna (Fig. 4b) and a reasonable agreement was found in the dry season GPP between Collection 5 and tower data. If MODIS can provide correct estimates of the magnitude of fPAR such as in Collection 5, the loss of GPP due to fire can also be predicted more accurately.

4.3. Light use efficiency

The site specific maximum LUE as calculated in this study was considerably higher (18%) than the values used in MODIS GPP algorithm for woody grassland (Table 1). This may be due to the readjustments required to counteract the high Collection 4 LAI/fPAR or different versions of meteorological data (Zhao, personnel communication) and the global nature of the algorithm, since all savannas (tropical or otherwise) are given the same LUE in the algorithm. Similarly, Turner et al. (2003) noticed an underestimation of LUE by a factor of 3 in the Harvard forest site which was compensated by high fPAR to result in a close agreement between MODIS and field GPP on an annual basis. Underestimation of LUE also has been found to be responsible for reduced GPP in other ecosystems such as in a tall grass Prairie and crop species corn and soybean (Turner et al., 2006b) and wheat (Reeves et al., 2005). The maximum LUE was comparatively smaller in Collection 4.5 (0.8 vs. 1.03 for Collection 4.8), compared with the observed value of 1.26 g C MJ^{-1} at Howard Springs. In addition, the VPD scalar in the wet season was also underestimated in Collection 4.5 (Fig. 7c) compared to Collection 4.8 and therefore GPP was underestimated in the wet season in Collection 4.5.

4.4. Meteorology

PAR and VPD are the two primary meteorological factors that down-regulate maximum LUE, since T_{MIN} is unlikely to constrain GPP in this savanna ecosystem. An accuracy assessment of DAO meteorological data at global scale by Zhao et al. (2005) indicated that incoming shortwave radiation and VPD from DAO are underestimated in many parts of the globe which can introduce relatively large errors in GPP estimation. Similarly, Heinsch et al. (2006) demonstrated that DAO underestimated local VPD and therefore overestimated GPP at humid and dry sites in North America. In combination with underestimated LUE by MODIS Collections 4.5 and 4.8, these both offset higher fPAR values from Collection 4 to match tower data on an annual basis (Fig. 9a). When we examined the bias in site specific LUE, meteorology and fPAR to estimate GPP for Howard Springs (Figs. 7 and 8), it suggested that some improvement could be gained by using site specific meteorology. Although meteorological variables (PAR, VPD and temperature) provided by GMAO are supposedly improved values, for this site it does not show much improvement compared to DAO.

4.5. Soil moisture

Previous studies have indicated that the MODIS algorithm did not capture the reduced productivity of savanna during dry periods but, inclusion of a soil water index improved GPP prediction at a tropical savanna site in Australia (Leuning et al., 2005), a semi-arid vegetation site in Senegal (Fensholt et al., 2006), and correctly captured the beginning and length of the growing season in Mediterranean savanna ecosystems (Yuan et al., 2007). Regional analysis also indicated that in areas where soil water is severely limiting, MODIS underestimates water stress, overestimates GPP, and fails to capture intra-annual variability of water stress (Mu et al., 2007).

In this study, when we replaced the VPD scalar with a moisture index (EF) we found that it reduced GPP in the dry (Fig. 9c) consistent with tower data and captured the beginning of the wet season better (Fig. 9d). However, the performance of EF modification was poor (IOA 0.46) in the wet season compared to the dry season (IOA 0.91) to estimate GPP (Fig. 9b). This is because in the dry season, latent heat represents much of the transpiration and therefore EF is tightly coupled with GPP. Thus adding this index not only improved the estimation of GPP, but it also correctly captured seasonal dynamics of GPP. Whereas, in the wet season, latent heat is a combination of transpiration and soil evaporation, thus EF is not tightly coupled with GPP. Consequently, EF performed poorly in the estimation of the magnitude and capturing the transition period from wet to dry (Fig. 9b and d).

EF is a relatively simple parameter to calculate if data on latent and sensible heats are available and it can be used to infer soil water availability (Gentinea et al., 2007; Yuan et al., 2007). In this study, EF accounted for 71% variation in soil water content ($EF = 0.27 + 0.03 * \text{soil water content}$, $R^2 = 0.71$ – data not shown). We used EF instead of soil water directly, because scaling up EF over large spatial areas becomes promising with remote sensing sensors such as MODIS and AVHRR (Advanced Very High Resolution Radiometer) that provide land surface temperature, albedo and NDVI that can be used in conjunction with tower meteorology to estimate EF (Wang et al., 2006; de Ridder and Mensink, 1998). Surface soil moisture is also provided by satellites such as Advanced Microwave Scanning Radiometer (AMSR-E, http://www.geo.vu.nl/~jeur/lprm/) on the Earth Observing System Aqua satellite (Njoku et al., 2003) daily at 25 km (resampled) or Soil Moisture and Ocean Salinity (SMOS) that can be used in GPP models. SMOS aims to provide surface soil moisture with a repeat cycle of 3 days and at a spatial resolution of 40 km and with a precision of 4% by volume in the future (http://www.esa.int/esaLP/LPsmos.html).

Lastly, it should be noted that although tower GPP is used as a ground truth for MODIS, the flux tower measurements themselves can

be a source of error as tower GPP is calculated as the difference between NEE and R_e. Estimates of day time ecosystem respiration at the flux tower site are made using a neural network model of nocturnal u^* corrected NEE, soil moisture and temperature (Beringer et al., 2007). This method actually ignores the reduction in leaf respiration in day time compared to night time (Reichstein et al., 2005) and therefore the eddy covariance method can consistently overestimate GPP (Coops et al., 2007). This effect may be limited at the Howard Springs site as the diurnal temperature range in the growing season (wet season) is relatively small and nocturnal temperatures of 25–27 °C regularly occur. Errors can also arise from filling the gaps for periods of unavailable tower measurements due to sensor malfunction or poor quality data. For Howard Springs neural network models were developed for gap filling carbon flux variable using Statistica software package (Beringer et al., 2007).

Also, scale mismatch between flux tower footprint size (usually within a few hundreds of meters to 1 km) and MODIS 7×7 km cut outs can be a reason for the discrepancy in GPP estimates between MODIS and flux tower. The average of 7×7 pixel block by MODIS may produce representation of a "pseudo pixel" that is often too large in spatial domain with the tower footprint (Xiao et al., 2004b). This problem could become worse if the landscape is heterogeneous or comprised of complex topography. Again, this may not be an issue at the Howard Springs site because 80% of the Howard River catchment in which Howard Springs is located is dominated by open forest savanna with adequate homogeneous fetch in all directions (41 km) and slopes of <1° (Beringer et al., 2007).

5. Conclusion

This study evaluated different collections of MODIS GPP products and their respective input parameters of LAI, fPAR, LUE, PAR and down-regulating scalars of VPD and T_{MIN} in a tropical savanna ecosystem. Despite the input values being generic for the entire savanna biome (and different from our site), it still provided a reasonable estimation of GPP (~±12% mean relative predictive error to tower) on an annual basis, a near perfect agreement in the wet season in Collection 4.8 (~1%) and in the dry season in Collection 4.5 (~4%). The observed discrepancy between MODIS and tower derived GPP at this site was mainly due to the large overestimation of fPAR values in Collection 4 compared to other input parameters such as meteorology and LUE. Overestimation in fPAR was however, compensated by the relatively low PAR, VPD scalar and LUE in MODIS relative to site specific values that brought MODIS GPP in closer agreement to tower derived GPP.

Collection 5 LAI/fPAR (not gap-filled) provides a more accurate estimation of LAI and fPAR compared to Collection 4 for this site. The accuracy of Collection 5 LAI/fPAR may be expected to further improve once this product is gap-filled. This indicates the success of an improved radiative transfer algorithm for savanna. Nevertheless, Collection 5 underestimates GPP mainly in the wet season as a consequence of the underestimation of PAR and LUE. Therefore, the Biome Parameter Lookup Table used to calculate GPP needs to be readjusted, especially by, increasing LUE and VPD scalar to achieve more accurate estimation of GPP in this Collection.

Our study also indicated that the improved GPP Collection 4.8 is superior to its previous version, in agreement with Zhao and Running (2006), although Collection 4.5 performed better in the dry season. In northern Australia, soil moisture rather than VPD was an important factor limiting savanna productivity in the dry season. This was suggested by the improved estimation of GPP and correct capture of the seasonal dynamics when we replaced VPD with a moisture index in the GPP algorithm. This means that the current MODIS GPP algorithm has a systematic limitation applicable to arid and semi-arid areas in capturing the productivity. Hence, the effect of soil moisture needs to be adequately represented in the MODIS algorithm in order to capture both the magnitude of GPP and the start and end of the growing seasons correctly. However, it is very difficult to use soil moisture or proxy to soil moisture such as Evaporative Fraction over the entire globe at sufficient spatial and temporal resolutions. This is because there are not many flux towers available in arid or semi-arid area that can provide data or verify soil moisture provided by satellite sensors such as AMSR-E. Nevertheless, there are promising research projects underway to incorporate soil moisture in MODIS GPP algorithm (Leuning et al., 2005; Mu et al., 2007; Coops et al., 2007). Minimum temperature seems not to constrain productivity in this tropical ecosystem. Given the extensive land area occupied by savanna in Australia, these results confirm the usefulness of MODIS GPP in studying the regional carbon dynamics of this ecosystem. Monitoring and mapping the changes of terrestrial GPP will contribute to the understanding of the carbon cycle and identifying its natural and modified patterns in this extensive tropical ecosystem, important for understanding global carbon dynamics and impacts on climate change.

Acknowledgments

This work is supported by Australian Research Council grants (DP0344744 and DP0772981) and PhD scholarships by the faculty of Arts, Monash University and University of Technology Malaysia. We are grateful to Dr. Maosheng Zhao and Dr. Faith Ann Heinsch for providing gap-filled Collection 4 LAI/fPAR data and DAO and GMAO climatological data. Many thanks are also extended to Dr. Maosheng Zhao for his valuable comments on the earlier version of this manuscript. We thank four anonymous reviewers for their comments and suggestions on the earlier version of the manuscript.

Appendix A. Statistical analysis

Several statistical techniques were employed to adequately compare the performance of MODIS GPP with tower derived GPP because no single model evaluation statistic is sufficient to evaluate model performance as each has its unique strengths (Willmott, 1984). The following indices were used in this study:

(i) Root mean square error (RMSE), provides an estimate of model error in units of the variable (g C m^{-2} day^{-1}) and is calculated as:

$$\sqrt{\frac{\sum_{n=1}^{n}(x_i-y_i)^2}{n}}$$

where; x_i = tower GPP, y_i = MODIS GPP and n = number of samples.

(ii) Willmott's index of agreement (IOA), (Willmott, 1984) ranges between 0 and 1, where 0 indicates no agreement between the predicted and observed data and 1 indicates perfect agreement. This index is dimensionless and therefore it is easier to interpret than other measures of relative difference. Willmott IOA is an improved model evaluation tool over R^2 because it takes into account differences in observed and modeled means (biases) and variances as well as correlations (Willmott, 1984).

$$\mathrm{IOA} = 1 - \frac{\sum_{i=1}^{n}(x_i-y_i)^2}{\sum_{i=1}^{n}[(x_i-\overline{x}) + (y_i-\overline{x})]^2}$$

where; x_i = tower GPP, y_i = MODIS GPP, $\overline{x}$ = mean of tower GPP.

(iii) Relative Predictive Error (RPE), to quantify the percentage mean difference between MODIS and tower data. This index provides the direction of changes (underestimation or overestimation) in predicted values compared to measured values

$$\mathrm{RPE} = \frac{(\overline{y} - \overline{x})}{\overline{x}} \times 100$$

where; $\overline{x}$ = mean tower GPP, $\overline{y}$ = mean MODIS GPP.

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