sCASE: A primary productivity monitoring system for the forests of North Pindus National Park (Epirus, Greece)

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Abstract
sCASE is an automated continuous monitoring system that produces near real-time daily gross primary productivity (GPP) estimates of North Pindus National Park forests. The algorithm is based on the light use efficiency (ε) approach, incorporating species-specific maximum ε values (εₒ) and εₒ downscaling according to temperature, water scarcity and leaf developmental stage. sCASE was calibrated using a series of 2-year field ecophysiological measurements on the 4 dominant forest species of the Park and validated against a canopy photosynthesis model (R² = 0.9, RMSE = 1.29 g C m⁻² day⁻¹). sCASE offers a comprehensive view of the spatial distribution and the temporal progress of GPP and other products (e.g. LAI, FAPAR, ETₒ) through a freely accessible online GIS platform (http://pindosgpp.bat.uoi.gr).

Keywords: Gross primary productivity, light use efficiency, remote sensing, GIS, MODIS.

Introduction
It is estimated that terrestrial ecosystems absorb about 60 Gt of C annually through the photosynthetic process [Janzen, 2004], forming the largest flux component of the global carbon cycle. This process is considered to be affected by increasing atmospheric CO₂ concentration and climate change [Nemani et al., 2002, 2003]. Terrestrial gross primary productivity (GPP) monitoring is required in order to understand the dynamics of the global carbon cycle, forecast future climate and design management practices of natural resources [Schimel, 2007]. Numerous ecosystem models have been developed for quantifying GPP spatial and temporal variations. Among them, models that use the light use efficiency approach [Monteith, 1977] may have the largest potential to adequately address GPP
dynamics because they take advantage of the unique spatiotemporal coverage of satellite observations [Yuan et al., 2014]. Light use efficiency (LUE) models are based on the simplified approach Monteith originally used to estimate net primary productivity of well-watered annual crops [Monteith, 1977]. Using this approach, GPP is estimated as the product of absorbed photosynthetically active radiation (APAR) by the canopy and the efficiency ($\varepsilon$) that the absorbed radiation is converted to biomass. APAR and $\varepsilon$ determine the potential ecosystem photosynthetic rate that environmental or physiological factors may reduce through various mechanisms that affect APAR, $\varepsilon$, or both. Environmental stresses are usually incorporated in LUE models as scalars that reduce the maximum $\varepsilon$ ($\varepsilon_0$), while physiological factors are expected to be incorporated in APAR estimation. A typical form of a LUE model is:

$$GPP = FAPAR \times PAR \times \varepsilon_0 \times scalars \quad [1]$$

where $FAPAR$ is the fraction of PAR absorbed by the vegetation canopy, $PAR$ is the incident photosynthetically active radiation (mol m$^{-2}$) per time period (e.g. day, 10-day, month), $\varepsilon_0$ is the potential LUE (g C mol$^{-1}$ APAR) without environmental stresses and $scalars$ represent the reduction of $\varepsilon_0$ under limiting environmental conditions (e.g. Temperature, Water), varying from 0 to 1. Various LUE models have been developed [e.g. Potter et al., 1993; Running et al., 2004; Turner et al., 2006b; Yuan et al., 2007] and each one is based on particular assumptions regarding the processes controlling vegetation production, formulated in different ways and diverse complexity. One of the most simplified and widely used LUE model is C-Fix [Veroustraete et al., 2002] that is driven only by field based estimates of temperature and radiation and satellite derived FAPAR. It assumes a standard $\varepsilon_0$ value for all kind of ecosystems and, unlike most of the LUE models published, its original configuration does not include a scalar for possible water stress effects on photosynthesis. C-Fix model modifications in order to account for drought effects when applied in arid or semi-arid environments have been proposed by Verstraeten et al. [2006] and Maselli et al. [2009]. Another typical LUE algorithm is used by MODIS-GPP [Running et al., 2000] with inputs of MODIS LAI/FAPAR (MOD15A2), field based temperature, PAR and VPD (Vapour Pressure Deficit), land cover, biome-specific $\varepsilon_0$ and scalar configuration. This algorithm reduces $\varepsilon_0$ when cold temperatures limit plant function and when VPD is high enough to inhibit photosynthesis. It is assumed that VPD co-varies with soil water deficit and thus vegetation water stress. Even though MODIS-GPP algorithm has been extensively evaluated and its inputs have been much improved during the last decade, its products have not yet reached the required accuracy [Heinsch et al., 2006; Wu et al., 2010]. The main sources of error are recognized to be the limited accuracy and the low resolution (1 km$^2$) of the land cover classification, problems in the estimation of the meteorological and FAPAR inputs and the assumption of VPD as a water stress proxy [Zhao et al., 2005, 2006; Heinsch et al., 2006]. The latter is a flaw of the core MODIS-GPP algorithm that remains unsolved. FAPAR is predominantly estimated by satellite data in LUE models due to the connection between absorbed solar radiation and satellite-derived spectral information [Myneni and Williams, 1994]. Vegetation indices such as NDVI (Normalized Difference Vegetation
Index) and RDVI (Renormalized Difference Vegetation Index) are widely used for the estimation of FAPAR and LAI (Leaf Area Index) using simple linear [Myneni and Williams, 1994; Moreno et al., 2012] or non-linear [Myneni et al., 1995; Carlson and Ripley, 1997] relationships. Alternatively, FAPAR or LAI can be estimated by radiative transfer inversion modeling [Myneni et al., 2002] such as MODIS LAI/FAPAR product. Both strategies retain some uncertainty in FAPAR estimation that is mostly induced by weather conditions, illumination-acquisition geometry, or other acquisition problems [Myneni et al., 2002]. Defining a function used by remote sensing to capture water stress effects on photosynthesis has been a major challenge for many years [Yuan et al., 2014]. The effects of water availability on GPP have been modeled in existing LUE models as a function of meteorological data (soil moisture, evaporative fraction, VPD) or satellite water indices [Yuan et al., 2014]. All approaches have several advantages or disadvantages in terms of efficiency, input availability and practicality. It remains difficult to characterize water available for plants and its effect on photosynthesis over large areas. However, the key-issue is recognized to be the integration of more detailed ecophysiological knowledge of plant responses to water availability in order to develop reliable water limitation equations [Yuan et al., 2014]. This study presents a monitoring system that is developed based on the LUE approach and produces near real-time daily GPP products of the forests of North Pindus National Park in Northwestern Greece. It is a regional scale system that is based on high spatial resolution land cover classification and elevation maps, a compact network of installed meteorological stations across the Park, local scale ecophysiological measurements on the dominant forest species and satellite monitoring of vegetation dynamics. The scope is to take advantage of field ecophysiological and meteorological measurements to develop a LUE algorithm that best describes the forest production across the Park, build an automated system that incorporates this algorithm and produce high quality GPP and other ecophysiological and meteorological products of the Park area. The evaluation of GPP product accuracy is performed using a process-based canopy photosynthesis model that is parameterized for the dominant forest species of the Park based on systematic field ecophysiological measurements during a two-year period.

**Methods**

**Study area**

North Pindus National Park (area 1969.74 km²) is located in the northwestern Greece (Lat 39° 56.45’ N, Lon 20° 57.04’ E) and includes a major part of the northern Pindus mountains. There are 15 different forest habitats in North Pindus National Park, but most of the forest area (1041.15 km²) is covered by black pine (*Pinus nigra*), deciduous oaks (*Quercus frainetto, Quercus cerris*), beech (*Fagus sylvatica*), fir (*Abies borisii-regis*) and bosnian pine (*Pinus heldreichii*) (Fig. 1). There is increased complexity in the topography of the Park with elevation range from 400 to 2637 m. The climate across the Park is variable according to altitude and topography and ranges from mesomediterranean to submediterranean [Tselepidakis and Theoharatos, 1989].

**Field measurements**

A series of Leaf Area Index (LAI), leaf photosynthesis (A<sub>leaf</sub>) and leaf water potential (Ψ) measurements were conducted during a 2-year period (2013 – 2014) on the 4 dominant forest species of the Park (*Fagus sylvatica, Quercus frainetto, Quercus cerris, Pinus nigra*)
at three study sites (Tab. 1, Fig. 1). Field measurements were conducted once a month for each species. During May, the field measurements for the deciduous species were more frequent in order to capture the rapid developmental processes. The study sites were selected to meet the following criteria: I) the canopy must be dense without large gaps; II) the area must not have mixed species (except *Quercus* sp. site that two species are equally mixed); III) the extent of this area must be at least 1 km$^2$.

![Figure 1 - Land cover map of North Pindus National Park showing the main five forest types (Pinus nigra, Quercus sp., Fagus sylvatica, Abies borisii-regis and Pinus heldreichii). The non-forest cover types along with small areas of other forest types are classified as “other land cover types”. The red dots denote the available meteorological stations. Only the ones with white outline possess PAR sensors. The white spots denote the places that the field measurements were performed for each species.](image)

LAI (m$^2$/m$^2$) was measured using an AccuPAR LP-80 PAR/LAI Ceptometer (Decagon Devices, Inc., Pullman, Washington, USA) following Norman and Jarvis model [Norman and Jarvis, 1974] of radiation transmission and scattering. LAI measurements covered two parallel to the slope 100 m transects of East-West orientation at each study site. $A_{\text{leaf}}$ (μmol CO$_2$ m$^{-2}$ s$^{-1}$) measurements were performed with a portable photosynthesis system (LCpro+, ADC BioScientific Ltd, Hoddesdon, UK). Instantaneous photosynthesis of about 25 randomly selected leaves of the outer canopy was measured at ambient conditions. Additionally, using the instrument’s capability for climatic control (blue-red LED light source and temperature control), photosynthesis responses to PAR (A-PAR curves) and
temperature (A-T curves) were measured. Ψ (MPa) was measured using a Scholander-type pressure chamber (SKPM 1400, Skye Instruments Ltd., UK). About 8 to 10 samples from the outer part of the canopy and randomly distributed along the site were wrapped in aluminum foil and sealed in plastic bags for 10 minutes and then cut and measured immediately with the pressure chamber.

### Table 1 - Characteristics of the selected study sites for field measurements and sCASE time-series evaluation.

The annual meteorological data are extracted from the station nearest to each site that had complete data recordings for the last six years (2009 - 2014).

| Study site | Coordinates | Dominant forest species | Altitude (m) | Annual precipitation (mm) | Annual mean temperature (°C) |
|------------|-------------|-------------------------|--------------|----------------------------|-----------------------------|
| 1          | 39° 49.31’N 21° 3.73’E | Fagus sylvatica | 1430 | 1751 | 9.2 |
| 2          | 39° 50.73’N 20° 49.22’E | Quercus frainetto, Quercus cerris | 825 | 1622 | 11.8 |
| 3          | 39° 49.87’N 20° 59.81’E | Pinus nigra | 1055 | 1658 | 11.9 |

### Canopy photosynthesis modeling

$A_{\text{leaf}}$ measurements were used to parameterize a leaf level photosynthesis model for the 4 dominant forest species of the Park (*Fagus sylvatica*, *Quercus frainetto*, *Quercus cerris*, *Pinus nigra*) [Markos and Kyparissis, 2011; Markos et al., 2014; Stagakis et al., 2014]. The leaf photosynthesis model is combined with a multi-layer canopy integration model [Spitters, 1986; Leuning et al., 1995; dePury and Farquhar, 1997; Markos, 2013]. In the whole modeling process, species-specific A-PAR and A-T curves, LAI (measured in the field), PAR and T (recorded by the meteorological stations) are used as inputs in order to estimate daily total canopy GPP (g C m$^{-2}$ day$^{-1}$) for each species. This process has been evaluated in two levels: I) leaf level photosynthesis model was validated against the independent dataset of random photosynthesis measurements that were performed seasonally at ambient conditions in the field; II) canopy integration model was validated comparing the canopy total APAR (μmol photons m$^{-2}$ s$^{-1}$) estimations against APAR values that were measured seasonally in the field (measurements for LAI estimation). The model APAR estimations for the exact measurement time of each date were used in the validation. The accuracy assessment results showed that both leaf photosynthesis and canopy APAR modeled values show very good agreement with the values measured in the field ($R^2 = 0.91$, RMSE = 1.28 μmol CO$_2$ m$^{-2}$ s$^{-1}$ and $R^2 = 0.99$, RMSE = 28.53 μmol photons m$^{-2}$ s$^{-1}$ respectively) [Markos et al., 2014]. Similar models have already been tested successfully against eddy flux measurements [Falge et al., 2005; Mercado et al., 2007, 2009; Verbeeck et al., 2008].

The modeling process scales up from leaf to canopy, providing GPP estimates that are descriptive of a dense uniform forest canopy with LAI equal to the value measured in the field. These canopy characteristics are met in the selected study sites and field measured LAI covered a large extent (two 100 m parallel transects) that can be assumed to be representative of the surrounding area. Therefore, these GPP estimates are further used as reference to sCASE estimates at the selected study sites despite the spatial scale differences of field and satellite data. Model simulations are also used in order to derive the species-
specific constants [Markos et al., 2014] that are used in sCASE modeling process (Tab. 2). \( \varepsilon_0 \) was estimated through canopy photosynthesis model simulations for each species, by dividing daily GPP with daily APAR estimations and accounting for the average \( \varepsilon \) for clear days with favourable conditions. Favourable conditions prevail during end of spring – early summer, when deciduous species have fully expanded leaves and there is no environmental or physiological stress for all species.

|                  | Fagus sylvatica | Quercus sp. | Pinus nigra |
|------------------|-----------------|-------------|-------------|
| \( \varepsilon_0 \) (g C mol\(^{-1}\) APAR) | 0.29            | 0.29        | 0.25        |
| \( T_{\text{min}} \) (°C)  | 0               | 0           | -10         |
| \( T_{\text{opt}} \) (°C)  | 20              | 25          | 20          |
| \( T_{\text{max}} \) (°C)  | 40              | 45          | 45          |

**sCASE function**

sCASE uses two dynamic data sources in order to produce near real-time GPP estimates for the forest area of the North Pindus National Park. Satellite data provide forest spatial and temporal dynamics and meteorological recordings are used to model forest responses to abiotic parameters. Satellite data are provided at 8-day time step and 500 m resolution, while meteorological data are continuously recorded and daily 50 m resolution products are calculated. Therefore, daily GPP estimates are driven mainly by daily variations of the meteorological parameters and vegetation dynamic variations are refreshed every 8 days. Additionally, the land cover map (Fig. 1) and an elevation map [Ryan et al., 2009] of the area with 50 m spatial resolution provide auxiliary information used in the modeling process (Fig. 2). The final products are generated in 50 m spatial resolution in order to preserve the intense spatial variability of the meteorological parameters according to the landscape.

**Satellite data**

The MOD09A1 MODIS surface reflectance product (500 m, 8-day) is used to calculate NDVI [Tucker, 1979] and RDVI [Roujean and Breon, 1995] according to the equations:

\[
\text{NDVI} = \frac{R_{\text{nir}} - R_{\text{red}}}{R_{\text{nir}} + R_{\text{red}}} \quad [2]
\]

\[
\text{RDVI} = \frac{R_{\text{nir}} - R_{\text{red}}}{\sqrt{R_{\text{nir}} + R_{\text{red}}}} \quad [3]
\]

where \( R_{\text{nir}} \) and \( R_{\text{red}} \) are the reflectance of the second (841 - 876 nm) and the first (620 - 670 nm) MODIS band accordingly. MOD09A1 pixel quality assessment is used to recognize problematic pixels and correct them according to previous clear acquisitions. NDVI is used to calculate LAI through an empirical relationship (Fig. 3a) and then FAPAR is derived...
from LAI using the relationship [Ruimy et al., 1999]:

\[ FAPAR = \left( 1 - e^{-kd*LAI} \right) * 0.95 \]  \[ 4 \]

where \( k_d \) is the canopy light extinction coefficient, set to 0.65 for all forest types according to the field radiation transmission and scattering measurements conducted for LAI estimation.

Figure 2 - Flow diagram of sCASE function. The inputs used at each step are marked with different colors according to the data types presented on top.

RDVI is used to calculate a developmental scalar for \( \varepsilon_o (D_{scalar}) \) that scales for canopy photosynthetic performance mostly during the stages of leaf development and senescence. The following empirical relationship is applied on deciduous forests:

\[ D_{scalar} = \frac{1}{1 + 100 * e^{-120 * \frac{RDVI - 0.15}{0.55}}} \]  \[ 5 \]

that sets a lower boundary for RDVI values of about 0.2 and a maximum over RDVI 0.5 (Fig. 3b). Such scalar would not be proper for evergreen forest types since there are no clear stages of leaf development and senescence. However, it is observed that this scalar acts auxiliary to NDVI, compensating cases of FAPAR overestimation. Therefore, applying a similar scalar with increased tolerance in the RDVI boundaries for evergreen forests (Fig. 3b) can improve sCASE accuracy:

\[ D_{scalar} = \frac{1}{1 + 150 * e^{-150 * \frac{RDVI}{0.6}}} \]  \[ 6 \]
Both FAPAR and $D_{\text{scalar}}$ products are clipped in the borders of the forest areas and then resampled to 50 m resolution in order to be comparable with the meteorological data.

**Figure 3** - (a) Empirical relationship between MODIS NDVI and ground measured Leaf Area Index (LAI) in three forest areas of the Park dominated by different species (indicated in the figure). Past LAI measurements at the same *Quercus* sp. and *Fagus sylvatica* sites are additionally used in the relationship [Kyparissis et al., 2007; Stagakis et al., 2007] (b) The scaling pattern of the developmental scalar ($D_{\text{scalar}}$) according to RDVI values for the deciduous and the evergreen forest types.

**Meteorological data**

Temperature (T) and precipitation are continuously recorded by a network of 13 online automated ground meteorological stations distributed across the Park (Fig. 1). Four of them are equipped with PAR sensors for continuous measurements of solar radiation. In case of problematic function or data transmission of a station, it is omitted from the daily routine of data processing and interpolation. Daily ground measured PAR (mol m$^{-2}$ day$^{-1}$) is used to compute real-sky beam and diffused radiation coefficients that are incorporated in a solar irradiation model ($r_{\text{sun}}$, Hofierka and Suri [2002]) to calculate daily PAR for the whole Park area (resolution 50 m). The shadowing effect of topography is also incorporated by $r_{\text{sun}}$ using an elevation map [Ryan et al., 2009] of the area.

T ($^\circ$C) recordings are used to derive daily (24h) minimum ($T_{\text{min}}$), average ($T_{\text{av}}$) and maximum ($T_{\text{max}}$) values. These values are spatially interpolated for the Park area (resolution 50 m) using the Linear Lapse Rate Adjustment (LLRA) method [Dodson and Marks, 1997] that uses specified lapse rates for elevation adjustment (-0.01 and -0.005 $^\circ$C m$^{-1}$ for $T_{\text{max}}$ and $T_{\text{av}}$ accordingly). $T_{\text{min}}$ values do not present any specific elevation gradient pattern. LLRA method is selected because it is a simple, fast and easily implemented methodology that provides accurate results that are comparable to more complicated algorithms [Dodson and Marks, 1997]. The temperature scalar for $\varepsilon_o$ ($T_{\text{scalar}}$) uses a bell-shaped equation [Raich et al., 1991]:

$$T_{\text{scalar}} = \frac{(T_{\text{day}} - T_{\text{min}}) \times (T_{\text{day}} - T_{\text{max}})}{\left[(T_{\text{day}} - T_{\text{min}}) \times (T_{\text{day}} - T_{\text{max}})\right] - (T_{\text{day}} - T_{\text{opt}})^2}$$  [7]
where $T_{\text{min}}$, $T_{\text{max}}$ and $T_{\text{opt}}$ are species-specific constants for minimum, maximum and optimal temperature for photosynthesis respectively (Tab. 2) and $T_{\text{day}}$ stands for the mean daytime temperature, estimated as the average of $DT_{\text{max}}$ and $DT_{\text{av}}$ [Aber and Federer, 1992] (Fig. 4a). All meteorological recordings are used to produce a water scarcity indicator for $\varepsilon_o$ downscaling during water stress periods. Temperature and solar radiation are used to estimate reference evapotranspiration ($ET_o$, mm) according to the FAO Penman-Monteith method [Allen et al., 1998]. Daily precipitation (mm) records from station data are spatially interpolated for the Park area (resolution 50 m) using an inverse-squared-distance weighting function [Isaaks and Srivastava, 1989] that generates each interpolated value based on the observed data of the nearby stations and the distance from each station. The difference between precipitation and $ET_o$ is calculated in a short (10-day) and a long (4-month) term time scale to produce water balance indicators according to the different usable water resources for vegetation [McKee et al., 1993]. The 4-month water balance indicator corresponds to the deep groundwater resources that principally depend on winter precipitation and the 10-day water balance indicator corresponds to the upper soil moisture that depends on temperature, solar radiation and recent precipitation events [Allen et al., 1998]. The choice of the specific time periods to describe the two water balance phenomena is empirical and is based on comparisons between the resulting indicators with $\Psi$ field measurements. The two water balance indicators are transformed to a short ($stW_{\text{scalar}}$) and a long term ($ltW_{\text{scalar}}$) water scalar (Fig. 4b) through two empirical equations:

\begin{align}
stW_{\text{scalar}} &= 1 - e^{-(WB+80)/36} \tag{8} \\
lW_{\text{scalar}} &= 1 - e^{-(WB+600)/210} \tag{9}
\end{align}

where $WB$ is the difference between precipitation and $ET_o$ at the corresponding time periods. The final $W_{\text{scalar}}$ is the maximum value between $stW_{\text{scalar}}$ and $ltW_{\text{scalar}}$.

\[Figure 4 - \text{The scaling pattern of (a) the temperature scalar (T}_{\text{scalar}}) \text{ according to daytime temperature (T}_{\text{day}}) \text{ for the Fagus sylvatica, Quercus sp. and Pinus nigra forests, (b) the short (stW}_{\text{scalar}}) \text{ and the long term (ltW}_{\text{scalar}}) \text{ water scalar according to the water balance of the respective time periods.}\]
Results and Discussion

*sCASE imagery*

*sCASE* offers a comprehensive view of the spatial distribution and the temporal progress of GPP and other intermediate products of the modeling process (e.g. LAI, FAPAR, PAR, $DT_{av}$ scalars) through a freely accessible and user-friendly online GIS platform (http://pindosgpp.bat.uoi.gr). The daily projected images reveal the spatial patterns of each calculated parameter and their effects on GPP. FAPAR reflects the vegetation capacity of absorbing incoming radiation. Therefore, FAPAR is the primal determinant of GPP dynamics [Monteith, 1977; Ruimy et al., 1994]. In Figure 5a FAPAR spatial distribution of the North Pindus National Park generated by *sCASE* algorithm for a day of June 2013 is presented. It can be observed that *sCASE* FAPAR product of the specific day shows near-maximum values at almost all Park forest area. There is an agreement of *sCASE* FAPAR product and species physiology since the canopy of the deciduous forests has already reached full expansion in June. There are some areas of *Pinus nigra* and *Pinus heldreichii* forests in the northern part of the Park that present low FAPAR values (Fig. 5a) due to the reduced canopy closure. Comparing *sCASE* FAPAR (Fig. 5a) with the GPP product of the same day (Fig. 5b), it can be observed that the spatial distribution of GPP is clearly affected by FAPAR. That happens because June is a period with nearly no environmental constraints on vegetation function. Temperature rarely reaches extreme high values in the Park and water reserves are still abundant. Therefore, neither $T_{scalar}$ nor $W_{scalar}$ have important effects on GPP during this period. The effects of species-specific $\varepsilon_o$ on June GPP spatial distribution can also be discerned in Figure 5b. The areas of deciduous forests (*Quercus* sp., *Fagus sylvatica*) present slightly higher GPP than conifer forests (*Pinus nigra*, *Abies borisii-regis*, *Pinus heldreichii*) due to the higher $\varepsilon_o$ (Tab. 2).

August and early September is the period with possible water stress events in the Park area. Such phenomena might be severe or mild, depending mostly on the precipitation of the summer months. 2013 was a year with mild regional water stress events. In Figure 6a the $W_{scalar}$ image that is produced by *sCASE* algorithm at a day of August 2013 is presented. It can be observed that *sCASE* algorithm can detect spatial variations of water stress effects. As shown in Figure 6a, the most severe water stress effects are detected at south-western *Quercus* sp. areas, while *F. sylvatica* and conifer forests that are located at higher altitudes

![Figure 5 - sCASE (a) FAPAR and (b) gross primary productivity (GPP) products at a clear day of June 2013.](image-url)
are less affected. Field measured Ψ values in August 2013 are at relatively high levels in the *F. sylvatica* and *P. nigra* study sites (-1.24 and -1.45 MPa respectively), while the *Quercus* species presented lower Ψ values (-2.92 MPa), indicative of water stress conditions [Iovi et al., 2009]. Moreover, Α\textsubscript{leaf} field measurements in the same day gave an average of 5.51 μmol CO\textsubscript{2} m\textsuperscript{-2} s\textsuperscript{-1} for the *Quercus* species, that normally reach a photosynthetic rate of 15 – 20 μmol CO\textsubscript{2} m\textsuperscript{-2} s\textsuperscript{-1} [Markos and Kyparissis, 2011]. Therefore, sCASE W\textsubscript{scalar} estimates for August 2013 are in accordance with Ψ and Α\textsubscript{leaf} field measurements that were conducted during this period. Similar results were presented by Maselli et al. [2009] who applied a short term evaporative fraction W\textsubscript{scalar} on the entire Italian territory and found that during dry summers the upper mountain zones on the Apennine chain and around Etna volcano remained unaffected by water stress. In water stress periods GPP is affected by both biophysical (i.e. FAPAR, D\textsubscript{scalar}) and environmental parameters (i.e. T\textsubscript{scalar}, W\textsubscript{scalar}), thus the sCASE GPP product of an August day (Fig. 6b) preserves FAPAR spatial distribution pattern (Fig. 5a) combined with water stress effects (Fig. 6a).

![Figure 6 - sCASE (a) water scalar (W\textsubscript{scalar}) and (b) gross primary productivity (GPP) products at a clear day of August 2013.](image)

The use of sCASE reveals that T\textsubscript{scalar} rarely has serious constraining effects on GPP during spring and summer. Similar conclusions were drawn by Yuan et al. [2007] who applied a LUE model (EC-LUE) that uses the same T\textsubscript{scalar} equation with sCASE on 28 eddy covariance flux towers. During autumn, when deciduous species have not yet shed their leaves, some periods of severe cold can occur forcing GPP in even zero levels at high altitudes. In late October 2014 there were some days with such conditions that sCASE T\textsubscript{scalar} products showed near-zero values in *Fagus sylvatica* areas (Fig. 7a). T\textsubscript{scalar} image revealed that *Quercus* sp. areas were also affected by the low temperature (Fig. 7a) but not so intensively due to the lower altitude. T\textsubscript{scalar} of conifer species remained in high levels since these species are more resistant to low temperature (Tab. 2). Field measurements of leaf photosynthesis on *Pinus nigra* showed that this species preserves high photosynthetic rates even during winter that daytime temperature falls to near zero degrees [Vanikiotis et al., 2013]. Therefore, even though T\textsubscript{scalar} effects on GPP are not intense in areas that freezing temperatures are not frequent events [Yuan et al., 2007, 2014], in cases of coexistence of species with different responses to temperature, T\textsubscript{scalar} contribution is significant on daily high spatial resolution GPP estimates (Figs. 7a, c).
Figure 7 - sCASE (a) temperature scalar ($T_{\text{scalar}}$), (b) PAR and (c) gross primary productivity (GPP) products at a clear day of October 2014.

sCASE is incorporating the shadowing effect of topography in order to estimate realistic high resolution PAR spatial distribution. The effect of topography on PAR is more pronounced during autumn and winter that sun zenith angle is low. In Figure 7b PAR spatial distribution estimated by sCASE algorithm for a sunny day in late October is presented.
Significant spatial variability of PAR can be observed for this day. Northern aspects with steep slopes receive very low incoming radiation while southern aspects receive maximum PAR. It appears that PAR spatial distribution is a major determinant of GPP during autumn and winter period (Fig. 7b, c) and must not be neglected by spatial LUE modeling. It can be observed that the spatial distribution of sCASE GPP at the specific autumn day (Fig. 7c) is mostly determined by both $T_{\text{scalar}}$ (Fig. 7a) and PAR (Fig. 7b) spatial distribution.

**sCASE time-series evaluation**

![Graphs of GPP time series](image)

**Figure 8 - Gross primary productivity (GPP) time series estimated from sCASE compared to reference GPP estimates from the canopy photosynthesis model for the (a) *Fagus sylvatica* (b) *Quercus* sp. and (d) *Pinus nigra* study sites.**

sCASE GPP estimates were evaluated at the three study sites where field ecophysiological and meteorological measurements were used in canopy photosynthesis modeling to compute daily reference GPP values. sCASE GPP time series were extracted for the three study sites for the period 2013–2014 and were compared with reference GPP of the same period (Fig. 8).
It can be observed that sCASE GPP follows very well the seasonal GPP variations for both deciduous (Figs. 8a, b) and evergreen (Fig. 8c) species. In the deciduous species, GPP rises steeply at the end of April with leaf emergence and falls gradually from August due to the reduction of daily PAR until November when leaf fall is completed. Other effects such as water stress can also depress GPP during late summer. Such an event took place during August 2013 and affected mostly Quercus sp. areas as described earlier (Fig. 6a). This event is also obvious in both sCASE and reference Quercus sp. GPP time series (Fig. 8b). In contrast, the summer of 2014 was sufficiently moist and water stress effects were not detected by neither sCASE algorithm nor field measurements. Seasonal GPP variations of the evergreen Pinus nigra clearly follow seasonal PAR variability presenting maximum values in June, decreasing gradually until December and rising again gradually from January (Fig. 8c).

sCASE daily GPP estimates present high accuracy compared to the reference values ($R^2 = 0.90$, RMSE = 1.29 g C m$^{-2}$ day$^{-1}$), indicating that sCASE algorithm is well calibrated for the ecosystems of North Pindus National Park (Tab. 3, Fig. 9). sCASE performed best in F. sylvatica site ($R^2 = 0.94$, RMSE = 1.15 g C m$^{-2}$ day$^{-1}$) and its performance was a little lower in Quercus sp. ($R^2 = 0.89$, RMSE = 1.50 g C m$^{-2}$ day$^{-1}$) and P. nigra ($R^2 = 0.83$, RMSE = 1.22 g C m$^{-2}$ day$^{-1}$) sites (Tab. 3). MODIS vegetation indices are efficient estimators of vegetation spatial and temporal dynamics [Huete et al., 1999; Broge and Leblanc, 2001; Boschetti et al., 2011]. More importantly, sCASE automated recognition and correction of problematic pixels based on the MODIS quality flags is working efficiently, preventing occasional unjustifiable GPP drops due to cloudiness or other acquisition problems that are frequent for this area.

The contribution of each sCASE scalar to the final GPP estimates at each study site during 2013 – 2014 was quantified comparing the full sCASE algorithm with three modified sCASE versions (removing one scalar at each version). The contribution of the $D_{scalar}$ is important for the accurate recognition of seasonal GPP variations, especially in deciduous forests, preventing early GPP increase in spring and enhancing on-time GPP fall in autumn. As shown in Table 3, the contribution of $D_{scalar}$ on the estimated GPP is high for the deciduous forests and low for the evergreen conifer site. Early GPP increase in deciduous forests is a common problem of the MODIS-GPP product [Heinsch et al., 2006; Turner et al., 2006a] and developmental scalars are recognized that could be very useful in eliminating that effect [Wu et al., 2010].

Table 3 - Coefficients of determination ($R^2$) and root mean square errors (RMSE, in g C m$^{-2}$ day$^{-1}$) between sCASE and reference canopy photosynthesis model daily gross primary productivity (GPP) estimates at each species separately and all species together. All relationships are statistically significant ($p < 0.01$). The contributions of the 3 sCASE scalars to the final GPP products for each species during 2013 - 2014 are also provided.

| Study site | Dominant forest species | Accuracy statistics | Scalar contribution % |
|------------|--------------------------|----------------------|-----------------------|
|            | $R^2$ | RMSE | $D_{scalar}$ | $T_{scalar}$ | $W_{scalar}$ |
| 1 | Fagus sylvatica | 0.94 | 1.15 | 15.82 | 4.93 | 7.00 |
| 2 | Quercus sp. | 0.89 | 1.50 | 21.42 | 3.94 | 17.89 |
| 3 | Pinus nigra | 0.83 | 1.22 | 3.67 | 7.16 | 9.43 |
| ALL | | 0.90 | 1.29 | 13.62 | 5.34 | 11.40 |
T\textsubscript{scalar} contribution to sCASE performance is not very important (Tab. 3). T\textsubscript{scalar} effects on the final GPP estimates is around 4\% for the deciduous species and a little higher for the evergreen species (7.14\%). It seems that during the growing period of the deciduous forest species, temperature variations at the selected study sites are within the favourable limits for plant growth. The most significant effects of temperature occur during winter and are affecting only the evergreen conifer species. These results confirm previous studies that presented non-significant temperature effects on GPP during spring and summer [Yuan et al., 2007, 2014].

A significant innovation of sCASE is that it incorporates the network of the meteorological stations across the Park to produce high resolution water stress estimations. The design of a universal method for vegetation water stress estimation is still a challenging research task and a critical component of LUE modeling [Maselli et al., 2009; Yuan et al., 2014]. sCASE algorithm for water stress detection is not species-specific and is proved sufficient for the extent of the Park. W\textsubscript{scalar} effects on sCASE performance are more pronounced at Quercus sp. study site and less at F. sylvatica and P. nigra sites (Tab. 3). Overall, W\textsubscript{scalar} seems as important as D\textsubscript{scalar} on sCASE performance (Tab. 3). It is possible that W\textsubscript{scalar} effects on sCASE performance would be stronger if more years with more intense drought conditions were available in the validation scheme. The good performance of the designed W\textsubscript{scalar} is firstly attributed to the high accuracy of the meteorological parameters and secondly to the development of the equations based on field measured responses of each species to water stress. As noted by Yuan et al. [2014], knowledge of plant physiological adaptive mechanisms is critical in order to accurately simulate the impacts of water stress on GPP. The examination of this algorithm in other regions / ecosystems is required in order to demonstrate its potential of generalized application.

![Figure 9 - Gross primary productivity (GPP) comparison between sCASE and reference canopy photosynthesis model daily estimates.](image-url)
The comparison plot between sCASE and reference GPP shows that sCASE tends to slightly underestimate GPP (Fig. 9). Significant part of this effect may be attributed to the lack of $\varepsilon_0$ adjustment for atmospheric conditions. During cloudy days the daily fraction of diffuse radiation is high, causing an increase of the efficiency that radiation is incorporated by the canopy [Alton et al., 2007]. This means that $\varepsilon_0$ should be higher for cloudy days and that keeping a constant $\varepsilon_0$, which is a typical principle of LUE models, causes GPP underestimation. Such innovation in LUE model principles and function has been attempted by CFlux model [Turner et al., 2006b] and is currently recognised as an important requirement for LUE model development [Yuan et al., 2014]. A further improvement of sCASE accuracy is expected when a $\varepsilon_0$ scalar based on the daily fraction of diffuse radiation is incorporated based on the work by Markos et al. [2014].

Conclusions
sCASE is an automated high resolution monitoring system of the forest dynamics for a significant protected forest area in Greece. It is an innovative tool for various practices, such as natural resource management, carbon cycle analysis, ecosystem status assessment and environmental change monitoring. This system receives inputs from satellite and field meteorological data and applies an algorithm in order to create various ecophysiological and meteorological outputs. The algorithm incorporates various innovative elements in order to produce high quality products, such as the automated correction of satellite data, the high resolution solar irradiation maps and the methodology for vegetation water stress detection. The evaluation of sCASE products was performed on specified sites of the Park using canopy photosynthesis modeling estimates that were based on systematic field measurements on the four main forest species of the Park. It is proved that the accuracy of the system is sufficient ($R^2 = 0.9$, RMSE = 1.29 g C m$^{-2}$ day$^{-1}$) with potentiality of further improvements. sCASE demonstrates that online vegetation monitoring systems are viable solutions for various practices, posing the challenge of building such systems in more extended spatial scale.

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References
Aber J.D., Federer C.A. (1992) - *A Generalized, Lumped-Parameter Model of Photosynthesis, Evapotranspiration and Net Primary Production in Temperate and Boreal Forest Ecosystems*. Oecologia, 92: 463-474. doi: http://dx.doi.org/10.1007/BF00317837.

Allen R.G., Pereira L.S., Raes D., Smith M. (1998) - *Crop evapotranspiration: guidelines for computing crop requirements*. Irrigation and Drainage Paper N. 56, FAO, Rome, Italy.

Alton P.B., North P.R., Los S.O. (2007) - *The impact of diffuse sunlight on canopy light-use efficiency, gross photosynthetic product and net ecosystem exchange in three forest biomes*. Global Change Biology, 13: 776-787. doi: http://dx.doi.org/10.1111/j.1365-2486.2007.01316.x.

Boscetti M., Stroppiana D., Confalonieri R., Brivio P.A., Crema A., Bocchi S. (2011) - *Estimation of rice production at regional scale with a Light Use Efficiency model and MODIS time series*. Italian Journal of Remote Sensing, 43: 63-81. doi: http://dx.doi.org/10.5721/Itjrs20114335.

Broge N. H., Leblanc E. (2001) - *Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density*. Remote Sensing of Environment, 76: 156-172. doi: http://dx.doi.org/10.1016/S0034-4257(00)00197-8.

Carlson T.N., Ripley D.A. (1997) - *On the relation between NDVI, fractional vegetation cover, and leaf area index*. Remote Sensing of Environment, 62: 241-252. doi: http://dx.doi.org/10.1016/S0034-4257(97)00104-1.

dePury D.G.G., Farquhar G.D. (1997) - *Simple scaling of photosynthesis from leaves to canopies without the errors of big-leaf models*. Plant Cell and Environment, 20: 537-557. doi: http://dx.doi.org/10.1111/j.1365-3040.1997.00094.x.

Dodson R., Marks D. (1997) - *Daily air temperature interpolated at high spatial resolution over a large mountainous region*. Climate Research, 8: 1-20. doi: http://dx.doi.org/10.3354/Cr008001.

Falge E., Ret S., Bruggemann N., Butterbach-Bahl K., Goldberg V., Olteche A., Schaaf S., Spindler G., Stiller B., Queck R., Kostner B., Bernhofer C. (2005) - *Comparison of surface energy exchange models with eddy flux data in forest and grassland ecosystems of Germany*. Ecological Modelling, 188: 174-216. doi: http://dx.doi.org/10.1016/j.ecolmodel.2005.01.057.

Heinsch F.A., Zhao M.S., Running S.W., Kimball J.S., Nemani R.R., Davis K.J., Bolstad P.V., Cook B.D., Desai A.R., Ricciuto D.M., Law B.E., Oechel W.C., Kwon H., Luo H.Y., Wofsy S.C., Dunn A.L., Munger J.W., Baldocchi D.D., Xu L.K., Hollinger D.Y., Richardson A.D., Stoy P.C., Siqueira M.B.S., Monson R.K., Burns S.P., Flanagan L.B. (2006) - *Evaluation of remote sensing based terrestrial productivity from MODIS using regional tower eddy flux network observations*. IEEE Transactions on Geoscience and Remote Sensing, 44: 1908-1925. doi: http://dx.doi.org/10.1109/Tgrs.2005.853936.

Hoffierka J., Suri M. (2002) - *The solar radiation model for Open source GIS: implementation and applications*. International GRASS users conference, Trento, Italy.

Huete A.R., Justice C., Leeuwen, W.V. (1999) - *MODIS Vegetation Index, Algorithm Theoretical Basis Document (ATBD), Version 3*. University of Arizona, Tuscon.

Iovi K., Kolovou C., Kyparissis A. (2009) - *An ecophysiological approach of hydraulic
performance for nine Mediterranean species. Tree Physiology, 29: 889-900. doi: http://dx.doi.org/10.1093/treephys/tpp032.

Isaaks E.H., Srivastava R.M. (1989) - An introduction to applied geostatistics. Oxford University Press. New York.

Janzen H.H. (2004) - Carbon cycling in earth systems - A soil science perspective. Agriculture, Ecosystems and Environment, 104: 399-417. doi: http://dx.doi.org/10.1016/j.agee.2004.01.040.

Kyparissis A., Markos N., Stagakis S., Levizou E., Sykioti O. (2007) - Ecosystem productivity and dynamics issued from multispectral and hyperspectral satellite imagery. Proceedings of SPIE - The International Society for Optical Engineering. Florence, 6742. doi: http://dx.doi.org/10.1117/12.737688.

Leuning R., Kelliher F.M., Depury D.G.G., Schulze E.D. (1995) - Leaf Nitrogen, Photosynthesis, Conductance and Transpiration - Scaling from Leaves to Canopies. Plant Cell and Environment, 18: 1183-1200. doi: http://dx.doi.org/10.1111/j.1365-3040.1995.tb00628.x.

Markos N. (2013) - Development of a photosynthesis model for the estimation of Mediterranean ecosystems productivity. PhD Thesis. University of Ioannina, Ioannina, Greece.

Markos N., Kyparissis A. (2011) - Ecophysiological modelling of leaf level photosynthetic performance for three Mediterranean species with different growth forms. Functional Plant Biology, 38: 314-326. doi: http://dx.doi.org/10.1071/Fp10155.

Markos N., Stagakis S., Vanikiotis T., Levizou E., Kyparissis A. (2014) - The use of a process based canopy photosynthesis model for the evaluation of a satellite-based primary productivity model. ForestSAT conference, November 2014, Riva del Garda, Italy.

Maselli F., Papale D., Puletti N., Chirici G., Corona P. (2009) - Combining remote sensing and ancillary data to monitor the gross productivity of water-limited forest ecosystems. Remote Sensing of Environment, 113: 657-667. doi: http://dx.doi.org/10.1016/j.rse.2008.11.008.

McKee T.B., Doesken N.J., Kleist, J. (1993) - The relationship of drought frequency and duration to time scales. American Meteorological Society, Eighth Conference on Applied Climatology, Preprints, Anaheim, pp. 179-184.

Mercado L.M., Bellouin N., Sitch S., Boucher O., Huntingford C., Wild M., Cox P.M. (2009) - Impact of changes in diffuse radiation on the global land carbon sink. Nature, 458: 1014-1017. doi: http://dx.doi.org/10.1038/Nature07949.

Mercado L.M., Huntingford C., Gash J.H.C., Cox P.M., Jogireddy V. (2007) - Improving the representation of radiation interception and photosynthesis for climate model applications. Tellus Series B-Chemical and Physical Meteorology, 59: 553-565. doi: http://dx.doi.org/10.1111/j.1600-0889.2007.00256.x.

Monteith J.L. (1977) - Climate and Efficiency of Crop Production in Britain. Philosophical Transactions of the Royal Society of London Series B-Biological Sciences, 281: 277-294. doi: http://dx.doi.org/10.1098/rstb.1977.0140.

Moreno A., Maselli F., Gilabert M.A., Chiesi M., Martinez B., Seufert G. (2012) - Assessment of MODIS imagery to track light-use efficiency in a water-limited Mediterranean pine forest. Remote Sensing of Environment, 123: 359-367. doi: http://dx.doi.org/10.1016/
Myneni R.B., Hall F.G., Sellers P.J., Marshak A.L. (1995) - The Interpretation of Spectral Vegetation Indexes. IEEE Transactions on Geoscience and Remote Sensing, 33: 481-486. doi: http://dx.doi.org/10.1109/36.377948.

Myneni R.B., Hoffman S., Knyazikhin Y., Privette J.L., Glassy J., Tian Y., Wang Y., Song X., Zhang Y., Smith G.R., Lotsch A., Friedl M., Morisette J.T., Votava P., Nemani R.R., Running S.W. (2002) - Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data. Remote Sensing of Environment, 83: 214-231. doi: http://dx.doi.org/10.1016/S0034-4257(02)00074-3.

Myneni R.B., Williams D.L. (1994) - On the Relationship between FAPAR and NDVI. Remote Sensing of Environment, 49: 200-211. doi: http://dx.doi.org/10.1016/0034-4257(94)90016-7.

Nemani R.R., White M., Thornton P., Nishida K., Reddy S., Jenkins J., Running S. (2002) - Recent trends in hydrologic balance have enhanced the terrestrial carbon sink in the United States. Geophysical Research Letters, 29. doi: http://dx.doi.org/10.1029/2002gl014867.

Nemani R.B., Keeling C.D., Hashimoto H., Jolly W.M., Piper S.C., Tucker C.J., Myneni R.B., Running S.W. (2003) - Climate-driven increases in global terrestrial net primary production from 1982 to 1999. Science, 300: 1560-1563. doi: http://dx.doi.org/10.1126/science.1082750.

Norman J.M., Jarvis P.G. (1974) - Photosynthesis in Sitka Spruce (Picea-Sitchensis (Bong) Carr). III. Measurements of Canopy Structure and Interception of Radiation. Journal of Applied Ecology, 11: 375-398. doi: http://dx.doi.org/10.2307/2402028.

Potter C.S., Randerson J.T., Field C.B., Matson P.A., Vitousek P.M., Mooney H.A., Klooster S.A. (1993) - Terrestrial Ecosystem Production - a Process Model-Based on Global Satellite and Surface Data. Global Biogeochemical Cycles, 7: 811-841. doi: http://dx.doi.org/10.1029/93GB02725.

Raich J.W., Rastetter E.B., Melillo J.M., Kicklighter D.W., Steudler P.A., Peterson B.J., Grace A.L., Moore B., Vorosmarty C.J. (1991) - Potential Net Primary Productivity in South-America - Application of a Global-Model. Ecological Applications, 1: 399-429. doi: http://dx.doi.org/10.2307/1941899.

Roujean J.L., Breon F.M. (1995) - Estimating PAR absorbed by vegetation from bidirectional reflectance measurements. Remote Sensing of Environment, 51: 375-384. doi: http://dx.doi.org/10.1016/0034-4257(94)00114-3.

Ruimy A., Kergoat L., Bonneau A. (1999) - Comparing global models of terrestrial net primary productivity (NPP): analysis of differences in light absorption and light-use efficiency. Global Change Biology, 5: 56-64. doi: http://dx.doi.org/10.1046/j.1365-2486.1999.00007.x.

Ruimy A., Saugier B., Dedieu G. (1994) - Methodology for the estimation of terrestrial net primary production from remotely sensed data. Journal of Geophysical Research-Atmospheres, 99: 5263-5283. doi: http://dx.doi.org/10.1029/93JD03221.

Running S.W., Nemani R.R., Heinsch F.A., Zhao M.S., Reeves M., Hashimoto H. (2004) - A continuous satellite-derived measure of global terrestrial primary production. Bioscience, 54: 547-560. doi: http://dx.doi.org/10.1641/0006-3568(2004)054[0547:ACSMOG]2.0.CO;2.
Running S.W., Thornton P.E., Nemani R.R., Glassy J.M. (2000) - *Global terrestrial gross and net primary productivity from the earth observing system*. In: Methods in ecosystem science, Sala O., Jackson R., Mooney H. (Eds.), Springer-Verlag, New York, pp. 44-57.

Ryan W.B.F., Carbotte S.M., Coplan J.O., O’Hara S., Melkonian A., Arko R., Weissel R.A., Ferrini V., Goodwillie A., Nitsche F., Bonczkowski J., Zemsky R. (2009) - *Global Multi-Resolution Topography synthesis*. Geochemistry Geophysics Geosystems, 10. doi: http://dx.doi.org/10.1029/2008gc002332.

Schimel D. (2007) - *Carbon cycle conundrums*. Proceedings of the National Academy of Sciences of the United States of America, 104: 18353-18354. doi: http://dx.doi.org/10.1073/pnas.0709331104.

Spitters C.J.T. (1986) - *Separating the Diffuse and Direct Component of Global Radiation and Its Implications for Modeling Canopy Photosynthesis Part II. Calculation of Canopy Photosynthesis*. Agricultural and Forest Meteorology, 38: 231-242. doi: http://dx.doi.org/10.1016/0168-1923(86)90061-4.

Stagakis S., Markos N., Levizou E., Kyparissis A. (2007) - *Forest ecosystem dynamics using SPOT and MODIS satellite images*. European Space Agency, (Special Publication) ESA SP, Issue SP-636.

Stagakis S., Markos N., Sykioti O., Kyparissis A. (2014) - *Tracking seasonal changes of leaf and canopy light use efficiency in a Phlomis fruticosa Mediterranean ecosystem using field measurements and multi-angular satellite hyperspectral imagery*. ISPRS Journal of Photogrammetry and Remote Sensing, 97: 138-151. doi: http://dx.doi.org/10.1016/j.isprsjprs.2014.08.012.

Tselepidakis I.G., Theoharatos G.A. (1989) - *A Bioclimatic Classification of the Greek Area*. Theoretical and Applied Climatology, 40: 147-153. doi: 10.1007/Bf00866177.

Tucker C.J. (1979) - *Red and photographic infrared linear combinations for monitoring vegetation*. Remote Sensing of Environment, 8: 127-150. doi: http://dx.doi.org/10.1016/0034-4257(79)90013-0.

Turner D.P., Ritts W.D., Cohen W.B., Gower S.T., Running S.W., Zhao M.S., Costa M.H., Kirschbaum A.A., Ham J.M., Saleska S.R., Ahl D.E. (2006a) - *Evaluation of MODIS NPP and GPP products across multiple biomes*. Remote Sensing of Environment, 102: 282-292. doi: http://dx.doi.org/10.1016/j.rse.2006.02.017.

Turner D.P., Ritts W.D., Styles J.M., Yang Z., Cohen W.B., Law B.E., Thornton P.E. (2006b) - *A diagnostic carbon flux model to monitor the effects of disturbance and interannual variation in climate on regional NEP*. Tellus Series B-Chemical and Physical Meteorology, 58: 476-490. doi: http://dx.doi.org/10.1111/j.1600-0889.2006.00221.x.

Vanikiotis T., Markos N., Stagakis S., Tzotsos A., Sykioti O., Kyparissis A. (2013) - *Estimating light use efficiency of a pine and a beech forest from leaf to ecosystem scale using the photochemical reflectance index*. European Space Agency, (Special Publication) ESA SP, Issue SP-722.

Verbeeck H., Samson R., Granier A., Montpied P., Lemuer R. (2008) - *Multi-year model analysis of GPP in a temperate beech forest in France*. Ecological Modelling, 210: 85-103. doi: http://dx.doi.org/10.1016/j.ecolmodel.2007.07.010.

Veroustraete F., Sabbe H., Eerens H. (2002) - *Estimation of carbon mass fluxes over Europe using the C-Fix model and Euroflux data*. Remote Sensing of Environment, 83: 376-
Verstraeten W.W., Veroustraete F., Feyen J. (2006) - On temperature and water limitation of net ecosystem productivity: Implementation in the C-Fix model. Ecological Modelling, 199: 4-22. doi: http://dx.doi.org/10.1016/j.ecolmodel.2006.06.008.

Wu C.Y., Munger J.W., Niu Z., Kuang D. (2010) - Comparison of multiple models for estimating gross primary production using MODIS and eddy covariance data in Harvard Forest. Remote Sensing of Environment, 114: 2925-2939. doi: http://dx.doi.org/10.1016/j.rse.2010.07.012.

Yuan W.P., Cai W.W., Xia J.Z., Chen J.Q., Liu S.G., Dong W.J., Merbold L., Law B., Arain A., Beringer J., Bernhofer C., Black A., Blanken P.D., Cescatti A., Chen Y., Francois L., Gianelle D., Janssens I.A., Jung M., Kato T., Kiely G., Liu D., Marcolla B., Montagnani L., Raschi A., Roupsard O., Varlagin A., Wohlfahrt G. (2014) - Global comparison of light use efficiency models for simulating terrestrial vegetation gross primary production based on the La Thuile database. Agricultural and Forest Meteorology, 192: 108-120. doi: http://dx.doi.org/10.1016/j.agrformet.2014.03.007.

Yuan W.P., Liu S., Zhou G.S., Zhou G.Y., Tieszen L.L., Baldocchi D., Bernhofer C., Gholz H., Goldstein A.H., Goulden M.L., Hollinger D.Y., Hu Y., Law B.E., Stoy P.C., Vesala T., Wofsy S.C. (2007) - Deriving a light use efficiency model from eddy covariance flux data for predicting daily gross primary production across biomes. Agricultural and Forest Meteorology, 143: 189-207. doi: http://dx.doi.org/10.1016/j.agrformet.2006.12.001.

Zhao M.S., Running S.W., Nemani R.R. (2006) - Sensitivity of Moderate Resolution Imaging Spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalyses. Journal of Geophysical Research-Biogeosciences, 111. doi: http://dx.doi.org/10.1029/2004jg000004.

Zhao M.S., Heinsch F.A., Nemani R.R., Running S.W. (2005) - Improvements of the MODIS terrestrial gross and net primary production global data set. Remote Sensing of Environment, 95: 164-176. doi: http://dx.doi.org/10.1016/j.rse.2004.12.011.

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