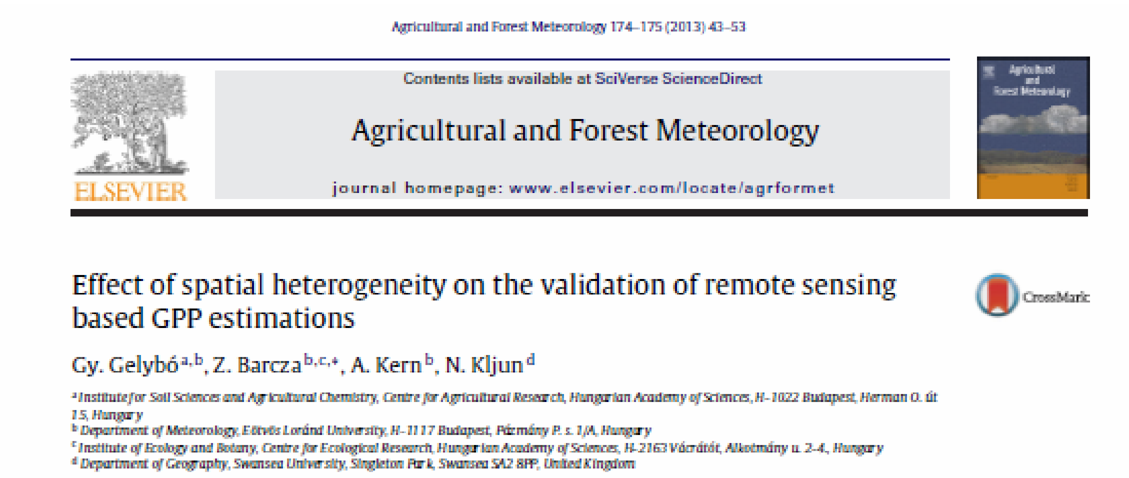
Manuscript of the article:
Gelybó, Gy., Barcza, Z., Kern, A., Kljun, N., 2013. Effect of spatial heterogeneity on the validation of remote sensing based GPP estimations. Agricultural and Forest Meteorology, 174-175, 43-53. doi: 10.1016/j.agrformet.2013.02.003


Agricultural and Forest Meteorology 174–175 (2013) 43–53

Contents lists available at SciVerse ScienceDirect

Agricultural and Forest Meteorology

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

# Effect of spatial heterogeneity on the validation of remote sensing based GPP estimations

Gy. Gelybó[a,b], Z. Barcza[b,c,*], A. Kern[b], N. Kljun[d]

[a] Institute for Soil Sciences and Agricultural Chemistry, Centre for Agricultural Research, Hungarian Academy of Sciences, H-1022 Budapest, Herman O. út 15, Hungary
[b] Department of Meteorology, Eötvös Loránd University, H-1117 Budapest, Pázmány P. s. 1/A, Hungary
[c] Institute of Ecology and Botany, Centre for Ecological Research, Hungarian Academy of Sciences, H-2163 Vácrátót, Alkotmány u. 2-4., Hungary
[d] Department of Geography, Swansea University, Singleton Park, Swansea SA2 8PP, United Kingdom

EFFECT OF SPATIAL HETEROGENEITY ON THE VALIDATION OF REMOTE SENSING BASED GPP ESTIMATIONS

Gelybó, Gy.[1,2], Barcza, Z.[2,3*], Kern, A.[2], Kljun, N.[4]

[1] Institute for Soil Sciences and Agricultural Chemistry, Centre for Agricultural Research, Hungarian Academy of Sciences, H-1022 Budapest, Herman O. út 15, Hungary
[2] Department of Meteorology, Eötvös Loránd University, H-1117 Budapest, Pázmány P. s. 1/A, Hungary
[3] Institute of Ecology and Botany, Centre for Ecological Research, Hungarian Academy of Sciences, H-2163 Vácrátót, Alkotmány 2-4, Hungary
[4] Department of Geography, Swansea University, Singleton Park, Swansea SA2 8PP, United Kingdom

Correspondence:
*dr. Zoltán BARCZA*
*Department of Meteorology*
*Eötvös Loránd University*
*H-1117 Budapest, Pázmány P. s. 1/A, Hungary*
*Phone: +36 1 372 2500 ext. 6603*
*Fax: +36 1 372 2904*
*E-mail: bzoli@elte.hu*

**Abstract**

Satellite based remote sensing provides an efficient way to estimate carbon balance components over large spatial domains with acceptable temporal and spatial resolution. In the present study remote sensing based gross primary production (GPP) estimations were evaluated using data from a tall eddy-covariance flux tower, located over a heterogeneous agricultural landscape in Hungary. Four different methods were used to simulate 8-day mean GPP for the tower site based on the MOD17 light use efficiency model. Additionally, we present a novel approach for model validation to exploit the advantage of footprint size similarity between remote sensing and the hourly eddy covariance signal measured at the tall tower. Besides using footprint information for the model validation we performed downscaling of MOD17 using 250 m resolution MODerate resolution Imaging Spectroradiometer (MODIS) Normalized Difference Vegetation Index (NDVI) dataset in order to address land use heterogeneity. The results showed that GPP was underestimated by MOD17 especially in years with average precipitation during the growing season, while model performance was better during dry years. Our downscaling technique significantly improved agreement between the MOD17 model results and the eddy covariance measurements (modeling efficiency (ME) increased from 0.783 to 0.884, root mean square error (RMSE) decreased from 1.095 g C $m^{-2}$ $day^{-1}$ to 0.815 g C $m^{-2}$ $day^{-1}$), although GPP remained underestimated (bias decreased from -0.680 g C $m^{-2}$ $day^{-1}$ to -0.426 g C $m^{-2}$ $day^{-1}$). Model evaluation results suggest that model performance should be optimally evaluated using RMSE, index of agreement (IA), ME and bias. The presented method is applicable to any eddy-covariance tower with limitations depending of the complexity of landscape around the flux tower. As incorporation of footprint information clearly impacts validation results, future model validation and/or calibration should also involve source area estimation which can be easily implemented following the presented approach.

Keywords: cropland, eddy covariance, footprint, light use efficiency model, MODIS

## 1 Introduction

Croplands occupy significant areas of the ice-free land surface (Foley et al., 2005) including Europe (Wattenbach et al., 2010), and they are the dominant land-cover type of many industrial countries, newly industrializing countries, as well as developing countries (Ramankutty and Foley, 1999; Goldewijk, 2001; Ramankutty et al., 2002, 2008; Monfreda et al., 2008; Pittman et al., 2010). This means that croplands play a significant role in the greenhouse gas (GHG) balance of the global land surface (Bondeau et al., 2007).

Croplands are also among the most heterogeneous land cover types in many regions of the world. Cropland heterogeneity is the consequence of rotations of crops with different photosynthetic pathway (C3 or C4), farmland size and extent, occasional abandonment of cultivated land, irrigation practices, application of manure or synthetic fertilizers, harvest timing, and other management practices (Lobell and Asner, 2004; Barcza et al., 2009a; Kutsch et al., 2010). Spatially representative, cropland specific carbon balance estimations are crucial to constrain the greenhouse gas (GHG) balance of regions with agriculture as the dominant land cover type (Bondeau et al., 2007; Barcza et al., 2009b; Ciais et al., 2010). This represents a major challenge primarily caused by cropland heterogeneity.

Direct field measurements based on the eddy covariance (EC) technique (Baldocchi, 2003) are widely used to assess the carbon balance of croplands (Suyker et al., 2005; Kutsch et al., 2010; Gebremedhin et al., 2012; Wu et al., 2012). However, EC measurements alone are unable to provide regional or country scale estimations because of their limited spatial representativeness, which means that the results cannot be simply upscaled (Wang et al., 2006; Barcza et al., 2009a). The available plot level measurements can help to constrain the large scale estimations, e.g., through calibration of ecosystem models (Braswell et al., 2005; Van Oijen et al., 2005; Hidy et al., 2011; Ma et al., 2011). In spite of significant advances in biogeochemical modeling, carbon balance estimations relying purely on process based models are usually highly uncertain (Vetter et al., 2008; Schwalm et al., 2010; Wang et al., 2011).

One possible way to reduce uncertainty is to use state-of-the-art data-oriented models (Ciais et al., 2010). Satellite based radiance measurements provide invaluable, high accuracy information on the properties of land and ocean surfaces, and the atmosphere. The radiances information can be used to construct sophisticated data-oriented models that provide insight into several processes related to the environment (Turner et al., 2004). Thanks to their global spatial coverage, remotely sensed data can provide estimates for the carbon balance components on regional and continental scale, thus they can be used as additional input for synthesis studies (Schulze et al., 2009; Ciais et al., 2010). However, it is essential to evaluate and – if necessary – to improve the performance of the remote sensing based models before applying them to larger spatial scale (Turner et al., 2006; Heinsch et al., 2006).

In the present paper we focus on remote sensing based gross primary production (GPP) estimates. The basic requirements for remote sensing based GPP simulation are the following: 1) due to the dynamic nature of ecosystem functioning, satellite based observations with relatively high temporal frequency are needed to detect changes in productivity and phenological state (especially in case of agroecosystems); 2) the spatial resolution of the remote sensing based observations should be comparable with the footprint extent of the available, ground based measurements; 3) the spatial resolution

should also allow the upscaling to estimate regional, country, continental or global scale studies (Running et al. 1999a).
As a compromise between spatial and temporal resolution of remotely sensed data, information from the MODerate resolution Imaging Spectroradiometer (MODIS) sensors (onboard the National Aeronautic and Space Administration Earth Observing System (NASA EOS) Aqua and Terra satellites) are frequently used to construct data-oriented GPP models. The MOD17 product (which is one of the official MODIS products disseminated by NASA Earth Observing System Data and Information System (EOSDIS)) is widely used in biogeochemical research which provides GPP data in 1 km resolution with global coverage (Running et al., 1999b).
Results of the EC measurements are widely applied for the evaluation of MOD17 based estimations of ecosystem scale carbon balance components (Leuning et al., 2005; Gebremichael and Barros, 2006; Heinsch et al., 2006; Turner et al., 2006; Zhang et al., 2008; Kanniah et al., 2009; Chasmer et al., 2011; Chen et al., 2012). Measurement-model differences are frequently recognized by the validation studies. If the EC instruments are mounted at ~5-30 m height above the canopy top (we refer to those flux towers as “small” towers), the flux footprint is usually smaller than the 1 km spatial resolution of the MOD17 model (at least for daytime, unstable stratification when the satellite measurements take place; Göckede et al., 2008). This means that discrepancies between measurements and model results can partly be caused by the mismatch in spatial representativeness of the remote sensing and flux tower measurements (Schmid and Lloyd, 1999; Turner et al., 2005; Kim et al., 2006; Chasmer et al., 2011). Following this logic it can be hypothesized that tall tower based EC measurement results should be in better agreement with estimations from remote sensing data, because the scale of their spatial representativeness is similar (Barcza et al., 2009a), although land cover heterogeneity is expected to have more influence on EC measurements in this case.
The agreement of model results and observations is usually also affected by land use/land cover heterogeneity (Turner et al., 2005). For example, Göckede et al. (2008) showed that in the CARBOEUROPE-IP network only one third of the flux sites are located in homogeneous terrain, which means that a relatively large number of EC sites are not ideal for remote sensing based model validation.
Measurement-model deviation can also be caused by the special location of the flux tower relative to the 1 km resolution MOD17 grid cells, which means that information from more than one pixel should be considered for the proper interpretation of the results. This problem is generally addressed by simply averaging e.g. 3×3 or 5×5 MOD17 pixels for the validation (e.g. Turner et al., 2005; Chasmer et al., 2011). As an example, limitations imposed by the different spatial representativeness of small EC tower and satellite based measurements were addressed in a similar fashion within the Bigfoot project (Reich et al., 1999; Turner et al., 2005). Within Bigfoot, EC measurements over different land cover types (cropland, hardwood forest, coniferous forest, boreal forest, tundra and grassland) have been scaled up to 5×5 km using a process based ecosystem model in order to compare with MOD17 GPP/NPP estimations. The study was based on small tower measurements, and footprint impacts have not been incorporated.
Recent studies linking MOD17 data with EC measurements using footprint information have been limited to small flux towers over forests (Chen et al., 2008, 2009; Chasmer et al., 2011). No similar study exists for tall tower measurements over croplands to the

knowledge of the authors in spite of the large footprint area of tall towers (Wang et al., 2006; Barcza et al., 2009a).

Our main aim is to validate MOD17 GPP over croplands and to improve the methodology of remote sensing based GPP validation for eddy covariance towers. The method is demonstrated and evaluated at Hegyhátsál tall tower site (Hungary). The study site is ideal to test our hypothesis that remote sensing and EC measurements can be synchronized since (i) the tall flux tower's footprint is comparable to MODIS spatial resolution (EC sensors are mounted at 82 m height above the surface; see Barcza et al. 2009a), (ii) the tower is located within a heterogeneous agricultural landscape providing realistic spatial and temporal variability of ecosystem carbon exchange. Rapid changes of tower footprint locations due to varying meteorological conditions are considered in our approach, which means that the MOD17 GPP model results are combined with estimated footprint locations calculated from the available hourly flux data (Barcza et al., 2009a). Due to the heterogeneity of land cover around the tall EC tower, the 1 km resolution of the GPP model might smooth out small scale effects that influence the EC measurements. In order to find a better match between the spatial representativeness of the hourly EC measurements and remote sensing we introduce a new approach, where the MOD17 model is downscaled to a 250 m grid (corresponding to the MODIS Normalized Difference Vegetation Index (NDVI) product). This downscaling is also necessary because of the size of the individual agricultural fields surrounding the tower where the parcels represent homogeneous land cover type with similar spatial extent to the 250 m NDVI product. The downscaled model is also evaluated using footprint information derived from the EC measurements.

We would like to stress that the aim of the present study is to use exclusively MODIS data as remote sensing information. The reason for this approach being the fact that researchers have easy and straightforward access to this kind of data e.g. through the FLUXNET website (ftp://daac.ornl.gov/data/modis_ascii_subsets/) or through EOSDIS (NASA's Earth Observing System and Data and Information System http://earthdata.nasa.gov/).

## 2 Materials and methods

### 2.1 Site description

A tall tower based eddy covariance system was established in Western Hungary near village Hegyhátsál (46°57'21"N, 16°39'08"E 248 m asl) in 1997 with continuous measurements of atmosphere/ecosystem $CO_2$ exchange (Haszpra et al., 2001, 2005). The tower is surrounded by agricultural fields and forest patches (Barcza et al., 2009a). The surrounding mosaic type land use is typical for Hungary as changes in property and structure of farming systems in the last 20 years shifted the typical Hungarian farmlands toward smaller fields and more complex cultivation patterns. The soil type in the region is 'Lessivated brown forest soil' (Haplic Cambisol according to the WRB classification). The soil texture is loam/silt loam.

The EC system is mounted at 82 m height which has a significant impact on the spatial representativeness of the tower (Barcza et al., 2009a). Due to the height of the tower, hourly averaging is applied on raw EC data (Haszpra et al., 2001, 2005). For the present study, six years data of net ecosystem exchange (NEE) measurements at the Hegyhátsál tall tower from 2001 to 2006 have been selected in accordance with the availability of remote sensing data (availability of MOD17 results was constrained by availability of the meteorological reanalysis input dataset; M. Zhao, personal communication).

Climate data for the study period and the 1981-2010 reference period are presented in Table 1. Annual precipitation varied considerably during the study years. The 2001-2006 period can be separated to two subperiods: a dry and warm period in the beginning (2001-2003), and a cool period with higher precipitation (2004-2006) with meteorological characteristics closer to the longterm average. This feature provides a good opportunity to test the model in contrasting environmental conditions.

## 2.2 Eddy covariance data processing and flux partitioning

In recent years, several gap filling methods have been suggested to gain defensible annual sums of NEE (Falge et al., 2001; Moffat et al., 2007). Methods used for gap filling are also frequently used for the partitioning of NEE into gross primary production and total ecosystem respiration ($R_{eco}$). In flux partitioning at daily time step, first $R_{eco}$ is determined and GPP is calculated as the signed difference between NEE and the total daily $R_{eco}$.

As direct validation of daytime ecosystem respiration and GPP is not possible, the uncertainty of flux partitioning results can be quite large (Lasslop et al., 2009). One way to reduce this uncertainty and to provide a robust estimate of GPP is to apply several gap filling and flux partitioning (GF/FP) methods. As an example, Lasslop et al. (2009) recommended the combined use of two GPP/$R_{eco}$ separation methods to assess uncertainty in the GPP estimations, and the authors also suggested the application of additional methods for GPP/$R_{eco}$ separation. Following the logic of Lasslop et al. (2009) here we applied three GF/FP methods discussed in Stoy et al. (2006), namely the Short Term Exponential (STE, Reichstein et al., 2005), the Rectangular Hyperbolic (RH) and the Non-Rectangular Hyperbolic (NRH, Gilmanov et al., 2003) methods.

In the STE method, hourly $R_{eco}$ is determined using a temperature dependent respiration function (estimated exclusively from nighttime NEE, which is assumed to be equal to total ecosystem respiration) of the soil/vegetation system (Lloyd and Taylor, 1994). The Lloyd and Taylor function is used to estimate daytime ecosystem respiration (Reichstein et al., 2005). However, the STE method can lead to misinterpretations when applying it to tall tower data. The determined relationships using nighttime fluxes might not be applicable to daytime data since the nighttime source area can be much larger than the daytime one, thus different regions can be 'seen' through the course of the day (Horst and Weil, 1992; Wang et al., 2006). Moreover, prevailing wind can be different during night and day (Barcza et al., 2003), thus land cover heterogeneity and anthropogenic emission could also have different effects on the nighttime and daytime fluxes. The footprint mismatch problem may cause bias in the estimated GPP results based on STE.

In the RH and NRH methods $R_{eco}$ estimates are retrieved from daytime NEE data (Gilmanov et al., 2003), therefore they are appropriate methods to be used for flux partitioning of tall tower data. Applicability of the RH and NRH method is also supported by Stoy et al. (2006) where the authors found that GPP estimated using the NRH method matched best with independent estimates across different biomes.

Rectangular hyperbolic and non-rectangular hyperbolic functions (so-called light response curves) are used to describe the relationship between hourly daytime NEE and photosynthetic photon flux density (PPFD) and to determine daytime average rate of respiration ($R_d$). The RH and NRH methods only differ in the mathematical representation of the fitted function. RH method uses the following formulae:

$$\mathrm{NEE} = -\frac{a\,b\,\mathrm{PPFD}}{(b+\mathrm{PPFD})} + \mathrm{R_d}\ , \tag{1}$$

while NRH uses another equation:

$$\mathrm{NEE} = -\frac{a\,\mathrm{PPFD} + b - \sqrt{(a\,\mathrm{PPFD}+b)^2 - 4abc\,\mathrm{PPFD}}}{2c} + \mathrm{R_d}\ . \tag{2}$$

*a*, *b* and *c* are parameters determined by nonlinear (Levenberg-Marquardt least-squares minimization) regression process.
Because of the relatively small number of available daytime NEE measurements (due to hourly averaging and data gaps) and the scatter of tall tower data, NEE data from a period of maximum 10 days was used in curve fitting instead of daily time step that is typically applied for short flux tower data (Gilmanov et al., 2003). Part of the information about day-to-day variations of relationships between NEE and environmental parameters can be lost due to the relatively long time window, but as model validation is performed with 8-day averaging of GPP, accurate representation of the day-to-day variability has less importance.
In the two light response curve methods (RH and NRH) hourly ecosystem respiration is calculated in a second step, based on daytime average rate of respiration. $R_d$ data of a given period (minimum 10 data points covering minimum 15°C temperature range) were used to construct temperature dependent functions. Hourly $R_{eco}$ was calculated based on the temperature-$R_d$ function and hourly temperature measurements.
Best estimate for daily GPP was obtained as the mean of the results from the three GF/FP methods (Lasslop et al., 2009; Beer et al., 2010). Mean GPP obtained from tall tower measurements is referred as “GPP-tower”. Uncertainty arising from GF/FP procedure is estimated as half of the difference between the daily maximum and minimum GPP estimate (Beer et al., 2010).

## 2.3 Modeling approach

### 2.3.1 The MODIS GPP (MOD17) remote sensing based model

The MOD17 product provides global GPP estimates of 8-day temporal and 1 km spatial resolution (Running et al., 1999b; Heinsch et al., 2003). The underlying GPP model of the MOD17 product (the ‘MOD17 model’) is based on the light use efficiency approach (Monteith 1972, 1977). The model can distinguish 11 biome categories (Plant Functional Types, PFTs), including one agricultural category (‘croplands’). PFT specific model parameters, i.e. values of light use efficiency ($\varepsilon_{max}$, kg C MJ$^{-1}$), and parameters describing environmental (meteorological) stress factors are stored in the biome properties look-up table (BPLUT) for each PFT. These parameters do not vary with geographical location for a given PFT; they characterize biomes on a global scale. Input data requirements of the MOD17 model include land cover information (MOD12 land cover product; Strahler et al., 1999), fraction of absorbed photosynthetically active

radiation (MOD15 LAI/FPAR product; Knyazikhin et al., 1999), meteorological data (NASA Global Modeling and Assimilation Office (GMAO) reanalysis dataset): global radiation (GR, MJ $m^{-2}$ $day^{-1}$), minimum temperature ($T_{min}$, °C), vapor pressure deficit (VPD, Pa).
Different GPP model setups were used in this study, all of them based on MOD17 version 5.1 official data product, kindly provided by Numerical Terradynamic Simulation Group, University of Montana (UMT NTSG).

### 2.3.2 Processing of remote sensing data

The MOD15 FPAR/LAI MODIS product (UMT NTSG version 5) served as remote sensing input data for the MOD17 model. For quality assurance of FPAR data (quality flag based data selection and interpolation) we followed description provided by Zhao et al. (2006). These FPAR data are used as remote sensing input for most model runs in this study (see below).
Preprocessed, 250 m resolution NDVI data were also used in this study for GPP calculations. NDVI preprocessing steps have been previously documented in Barcza et al. (2009a). Here we provide a short description of the methodology used to construct daily temporal resolution NDVI courses. For detailed information on NDVI quality assurance, processing and analysis see Barcza et al. (2009a).
The NDVI analysis uses the 250 m resolution MOD13 vegetation index product (Huete et al., 1999) constructed from the multispectral information provided by the MODIS sensor. First, an area comprising 41×41 pixels surrounding the tower has been selected. In order to minimize the errors in NDVI time series, quality control of NDVI time series of all 250 m NDVI pixels were filtered and smoothed using wavelet transformation. Two basic crop types have been separated based on their typical annual NDVI courses. It has been concluded from the analysis that winter crops (typically winter wheat) and summer crops (typically maize) are both present in the vicinity of Hegyhátsál tower. The resulting daily resolution NDVI courses were used in this study to retrieve FPAR. The actual input for the modified MOD17 model was calculated following Sims et al. (2005):

$$FPAR = 1.24NDVI - 0.168\,. \qquad (3)$$

For simplicity, we use this simple linear approach rather than the more sophisticated retrieval of the official 1 km resolution FPAR product, or the nonlinear backup algorithm for MODIS FPAR (Knyazikhin et al., 1999). Note that the Sims et al. (2005) formula provides somewhat lower FPAR estimates than the MOD15 backup algorithm.

### 2.3.3 Footprint modeling

Synchronizing the spatial representativeness of remote sensing and EC based GPP estimations requires combined information on crop type and phenological state (obtained from NDVI above) and the dynamic variation of the source area.
The actual source area of the vertical $CO_2$ flux measured by the EC system can be estimated using a footprint model. In the present study the simple, parameterized footprint model of Kljun et al. (2004) was used (their Eqs. 17 and 11). Based on remote sensing information, objective crop classification, footprint modeling and separation of NEE signal according to crop types, Barcza et al. (2009) showed that the Kljun et al. (2004) footprint parameterisation (based on the Lagrangian footprint model of Kljun et

al., 2002) provides accurate estimates for maximum source weight locations. In order to propose a simple yet powerful method for footprint analysis only the maximum source weight location (zero dimension information) are used exclusively to assign surface elements to the measured signal (using the approach of Barcza et al., 2009). The surface elements are defined by the 250m resolution NDVI grid provided by MOD13. Fig. 1 shows the footprint climatology of the site for year 2007. It is clear from the plot that several 250m resolution pixels contribute to the measured signal, and it is also clear that such coarse resolution grid can be used to differentiate between the contributing surface elements.

## 2.4 Model formulation

Discrepancies between GPP derived from EC tower measurements and MOD17 estimates can be either caused by errors in the input data or originate from the structure of the model (including uncertainty in model parameters) (Running et al., 2004; Nightingale et al., 2007; McCallum et al., 2009), or by mismatch of EC validation data and remote sensing information. We performed calculations with different model setups (i) to examine and eliminate the effect of possible errors in the input data and (ii) to resolve spatial representativeness issues. Our primary aim is not to improve model performance by the modification of model structure or parameters, but to explore the main causes of model-measurement discrepancy that can affect the result of validation studies. An overview of main properties of these model setups is given in Table 2. Detailed description of each modeling experiment is given in the following. All calculations are performed on a daily temporal resolution and then summed for 8-day average values.

### 1) GPP-GMAO (reference run)

We adapted the MOD17 model algorithm (MOD17 User’s guide; Zhao et al., 2005) and performed simulations with original settings and input data (GMAO meteorology, MOD15 LAI/FPAR product Collection 5.1, MOD12 land cover information, BPLUT version 5.1; M. Zhao, personal communication). Our implementation was found to be in a good agreement with the official version 5.1 MOD17 product ($R^2$ = 0.99 and bias = $-0.018$ g C $m^{-2}$ $year^{-1}$ for the examined six years). The slight deviance between our implementation and the official product is most likely caused by the quality assurance of FPAR. In the following, we refer to this run as “GPP-GMAO”, and consider it to be equivalent with the official MOD17 product. Note that only the 1 km MODIS pixel containing the measurements site is considered in this setup and is compared with tower based GPP.

### 2) GPP-met (modification of meteorological input)

The MOD17 model has been shown to be sensitive to the meteorological input dataset (Running et al., 2004; Zhao et al., 2006). To address this issue we replaced the global meteorological reanalysis data with local (on-site) meteorological measurements (vapor pressure deficit and global radiation, daily minimum temperature). The MT-CLIM model was used to fill the gaps in the local meteorological measurements (Thornton et al., 2000). We refer to these estimations as "GPP-met". Similarly to GPP-GMAO, the 1 km MODIS pixel containing the flux tower is used for validation.

3) GPP-FP (simple representation of tower footprint)

To address heterogeneity in the vegetation cover, FPAR data at 1 km resolution was extracted according to the actual flux footprint (we refer to this method as "GPP-FP"). According to the footprint climatology presented in Fig. 1, the 1 km resolution already enables differentiation in the source region. This is a rough consideration of the dynamic variations of the source area in time especially in a region where typical size of agricultural parcels is still in the subpixel range (around 200 m), but a first step to synchronize representativeness of remote sensing and eddy covariance measurements. At flux towers where the land cover heterogeneity is not realized as random patches of different PFTs or crop types, but as different land cover types in well-defined directions from the tower, this method can provide sufficient background for the interpretation of eddy covariance measurements.

4) GPP-NDVI (downscaling MOD17 using 250 m resolution NDVI data)

It has been shown in Barcza et al. (2009a) that different locations (agricultural fields) over the heterogeneous landscape surrounding the tower do not have identical contributions to the measured signal (Fig. 1), therefore a mismatch between representativeness of the remotely sensed data and EC measurements inevitably occurs. In order to (i) account for land cover heterogeneity, and (ii) synchronize the representativeness of the GPP model and the tower, we developed a new methodology. Firstly, instead of using the 1 km resolution MOD15 FPAR, we applied a downscaling procedure using the 250 m MODIS NDVI time series and known relationship between FPAR and NDVI. Downscaling of model calculations is supposed to answer the question whether the coarse spatial resolution of the FPAR product is responsible for model inaccuracies to a certain degree.
Secondly, the use of the 250 m spatial resolution NDVI dataset offers the possibility of taking into account both the hourly footprint of the tower measurements (following Kljun et al., 2004) and the phenology of the individual fields with finer resolution. This is expected to result in improved differentiation of winter and summer crop phenology instead of modeling them as a fictional "average crop".
These modeling efforts are substantially based on the estimated spatial representativeness of the tall tower described in Barcza et al., (2009a). The discretized hourly footprint locations (for selection of the NDVI pixel location as primary sink/source location of $CO_2$ flux), together with the according daily NDVI data from the smoothed NDVI curve of the selected pixel are combined in GPP calculations (see Section 2.3.2 NDVI data preprocessing).
Suppose that according to the footprint model on the $i^{\mathrm{th}}$ day of the year the number of pixels that contributed to the measured flux was $P$ (out of the 41×41 pixels; see Section 2.3.2). $\mathrm{FPAR}_i^p$ denotes the FPAR value of the $p^{\mathrm{th}}$ individual pixel on the $i^{\mathrm{th}}$ day and is calculated from the according daily NDVI value ($\mathrm{NDVI}_i^p$).
Following the scheme of the MOD17 model (Running et al., 1999b), GPP of this pixel can be derived as:

$$\mathrm{GPP}_i^p = W_i^p \ \mathrm{FPAR}_i^p \ \mathrm{IPAR}\ \varepsilon_i \,. \tag{4}$$

Here $W_i^p$ is the weight of each contributing pixel (here calculated as the number of hours in the $i^{\text{th}}$ day when the source area was located at the $p^{\text{th}}$ pixel), $\varepsilon_i = \varepsilon_{\max} f(T_{\min i}) f(\mathrm{VPD}_i)$ is the actual light use efficiency, and IPAR = 0.45 GR$_i$. Daily GPP on the $i^{\text{th}}$ day is calculated from the weighted average of GPP of the contributing pixels:

$$\mathrm{GPP}_i = \frac{\sum_{p=1}^{P} \mathrm{GPP}_i^p}{\sum_{p=1}^{P} W_i^p} \,. \tag{5}$$

The footprint information is not always available for each hour of the day (when the footprint model does not provide result). Therefore the GPP calculation might be biased because it can only rely on available footprint location information. The CORINE2000 land cover database (Büttner et al., 2002) re-gridded to the 250×250 m NDVI grid provides the land cover information to assist the selection of the appropriate BPLUT category (Barcza et al. 2009a). Note that introduction of CORINE based land cover data was necessary for the downscaling to 250 m. In our approach the land cover categories retrieved in Barcza et al. (2009a) were comparable to MOD12 classification scheme. Therefore, discrepancies between model runs using MOD12 and MODIS-NDVI due to misclassification of land cover are unlikely to occur. Moreover, as the source area of $CO_2$ flux is attributed to croplands in ~80% of the cases for the selected years, land cover classification can not have significant effect on the results. The resulting dataset is referred to as “GPP-NDVI”.

## 2.5 Evaluation of model performance

For statistical evaluation of different model simulations several indices were used. The root mean square error (RMSE), bias, index of agreement (IA), modeling efficiency (ME), Kendall correlation coefficient (KR) and Pearson linear correlation coefficient ($R^2$) (Janssen and Heuberger, 1995; Ma et al., 2011) were calculated for each year separately and for the whole study period as well. These indices can be considered as measures of model 'goodness' from different aspects, thus behavior of the different indices will allow characterizing model efficiency from different aspects. RMSE measures the average absolute error in a quadratic sense; therefore it is sensitive to outliers. In unbiased estimations, RMSE is the standard deviation. RMSE has the same unit as the estimated parameter. Bias (or mean bias) describes the average deviation between the model results and measurements, and is zero for unbiased estimations. IA varies between 0 and 1 and describes a standardized measure of mean square error. The closer IA is to 1 (ideal agreement) the better our estimation is. IA is 0.4 for two random series therefore IA should be over 0.4 for two correlated variables. ME ranges between -∞ to 1, and gives the improvement in estimations compared to the mean of the observation. Any positive ME suggests improvement, but closer to 1 is better. KR and $R^2$ describe the association between observation and model predictions. Both indices vary between -1 and 1 (perfect agreement), and are zero when there is no agreement between the datasets. $R^2$ assumes linear dependence between the variables, while KR does not require linear relationship (KR does not have any assumption about the distributions of the variables).

Because GPP-NDVI was only available from 2003 (year after the launch of Aqua satellite), model performance was characterized for the whole 2001-2006 period where possible, and for 2003-2006 as well in case of GPP-GMAO, GPP-met and GPP-FP.

## 3 Results

GPP-GMAO estimations and the GPP calculated from tall tower measurements (GPP-tower) are shown in Fig. 2a. Overall, model results underestimate GPP obtained from tall eddy covariance tower measurements. It can be seen that for the first three years (2001-2003) the model results are in good agreement with tower GPP. However, for the last three years (2004-2006), the measured GPP increased significantly. GPP-GMAO, however, remained at similar levels throughout the study period (2001 – 2006). The highest GPP-GMAO values barely exceed 6 g C $m^{-2}$ $day^{-1}$ while measured GPP is above 8 g C $m^{-2}$ $day^{-1}$ in some periods. Higher measured GPP in 2004-2006 is caused by the higher precipitation during the vegetation season (Table 1; see also Haszpra et al., 2005), which provided favorable conditions for plant growth.

Results of statistical evaluation of the model performance for the whole study period are presented in Table 3. The evaluation of the model performance shows reasonable agreement with measured data both during the whole measurement period and the 2003-2006 subperiod. However, GPP-GMAO annual sums underestimate GPP-tower in each year (Fig. 3), and the underestimation increases toward the end of the investigated period, exceeding 500 g C $m^{-2}$ $year^{-1}$ in 2006 (i.e. underestimation by nearly 40 %). Note that in the second half of 2006 a large measurement gap occurred where the gap filled GPP (not shown in Fig. 2) was higher than simulated GPP, therefore tower based annual total may be biased.

For GPP calculations based on local meteorological measurements instead of GMAO reanalysis, model performance slightly improved (GPP-met in Table 3). Although RMSE increased compared to GPP-GMAO, correlation increased as KR and $R^2$ values suggest. Interannual variability of the statistical parameters is presented in Fig. 4. The improvement in model performance was not consistent for all years and for all parameters. When changing meteorological input data, correlation coefficient values (KR and $R^2$) increased, but RMSE, IA and ME do not show such a systematic pattern (Table 3). Annual totals are underestimated again, even more than for GPP-GMAO results (Fig. 3). According to Fig. 2b, in spite of the bias in magnitude of annual sums, daily GPP totals reach higher peak values than GPP-GMAO though still remaining well below measured peak daily sums.

Tracking footprint location on 1 km resolution in GPP-FP runs only slightly improved model agreement (Table 3). Annual totals got closer to flux tower based estimations than GPP-met results, although compared to GPP-GMAO estimations the improvement is not consistent in all years (Fig. 3). The statistical evaluation shows a similar pattern, as most of the indices show improvement except for KR and $R^2$ which decreased compared to both GPP-GMAO and GPP-met (Table 3).

Model performance further improved when NDVI based downscaling integrated with footprint information was applied (GPP-NDVI). RMSE and model agreement parameters (especially ME and bias) show the best results among all model runs in most years of the test period (Fig. 4, Table 3). Annual totals are closer to GPP-tower sums but again, model simulations underestimate measured GPP and were barely able to describe interannual variability (Fig. 3).

Modifications in model setup gradually improved model performance compared to measurements. However, different indicators suggest different degree of improvement. Certain indicators such as RMSE, IA, ME and bias showed significant and systematic improvement especially in case of GPP-NDVI, while KR and $R^2$ coefficients do not differ significantly among model runs (Fig. 4).

## 4 Discussion

Overestimation and underestimation of flux tower GPP by MOD17 have been extensively reported in the literature. Among possible causes, several factors have been discussed, such as effect of meteorological input data (Heinsch et al., 2006), or differences in spatiotemporal coverage (Heinsch et al., 2006; Yang et al., 2007). According to literature, in the case of croplands, MOD17 has a systematic negative bias, and the underestimation is especially pronounced at high productivity sites. Yang et al. (2007) found an average error of 50.3% for non-forested ecosystems, with the largest underestimation (61%) for cropland (irrigated maize, USA). The identification of the sources of these errors is critical to understand the limitations of the model and also to improve its performance especially over heterogeneous croplands.

### 4.1 The effect of GPP model parameterization and meteorological input data

As a possible source of model error, accuracy of input meteorological data was examined and compared to measurements at Hegyhátsál tall tower site. Global radiation and minimum temperature estimations of GMAO are in a good agreement with measurements (with RMSE of 3.23 MJ $m^{-2}$ $day^{-1}$ and 2.8°C and $R^2$ of 0.92 and 0.93, respectively). This agreement does not vary among years to an extent which could explain the underestimation of GPP in 2004-2006 (Fig. 2). However, VPD is overestimated by GMAO and it was found that the error is pronounced in the last three years (Table 1). This finding contradicts previous results in the literature, where GMAO provided lower estimates for VPD when compared with data measured at flux towers, and it has been proposed that spatial averaging of meteorological data causes the discrepancy (Running et al., 2004; Turner et al., 2005). However, Hegyhátsál area is a relatively wet part of the region, therefore spatial averaging might have increased VPD as influenced by dryer areas in the same pixel. Overestimation of VPD has been shown by Gebremichael and Barros (2006) for a humid tropical site, while Kanniah et al. (2009) found overestimation in dry season and underestimation in wet season in case of a tropical savanna.

If VPD is responsible for the discrepancies between GPP-tower and GPP-GMAO in 2004-2006, the results are supposed to match better if we use local meteorological measurements. However, in spite of using local meteorological measurements, GPP remained underestimated (Fig. 2b).

It is clear from Figs. 2a and 2b that differences in meteorological data affect the short term variation of the model results, but are not responsible for the substantial difference between model results and measurements.

The impact of meteorological data on the MOD17 model has been shown to be site-specific, and sometimes, like in our case, the use of local measurements tends to decrease the estimations of annual GPP sums (Heinsch et al., 2006; Running et al., 2004) (Fig. 3). GPP-met runs provide very similar or slightly lower estimates compared to GPP-GMAO, hence it can be concluded that errors in meteorological input data are not the primary sources of underestimation of GPP. Underestimated maximum light use efficiency ($\varepsilon_{max}$) parameter together with the lack of soil water availability stress parameterization (Hwang et al., 2008) could explain this behavior of the model. While the first condition results in an underestimation of flux measurements in wet years, the insufficient consideration of moisture stress cannot constrain GPP in dry years. Consequently, the model provides more or less the same estimations both in wet and dry years (Fig. 3). It suggests that the underestimation of light use efficiency is the key factor resulting in a systematic negative bias. (However, this is not necessarily the case with other biomes; see Turner et al. 2006; Heinsch et al. 2006).)

These findings are also supported by earlier studies presented in the literature. Zhang et al. (2008) evaluated the MOD17 model using both GMAO reanalysis and local meteorological measurements over cropland (winter wheat – maize crop rotation) and an alpine meadow. They found significant underestimation by MOD17 results particularly in case of the cropland site regardless of the meteorological data they used as model input, and they suggested that the underestimation of $\varepsilon_{max}$ is mostly responsible for the poor performance of MOD17.

The hypothesis about the trade-off between the effects of underestimated $\varepsilon_{max}$ and insufficient moisture constraint is also supported by Coops et al. (2007). Evaluation of the standard and modified MOD17 model runs have been carried out in this case using site specific $\varepsilon_{max}$ in the first step combined with a soil water modifier (initially proposed by Leuning et al., 2005) in the second step. They found underestimation by the standard MOD17 algorithm, and an overestimation using site specific $\varepsilon_{max}$. The overestimation decreased when the soil moisture modifier was included in the MOD17 model resulting in the highest agreement with measurements. Their findings hence suggest a combined effect of errors in $\varepsilon_{max}$ and the water stress parameterization.

### 4.2 The impact of the footprint analysis on low spatial resolution input

Tracking footprint locations at 1 km resolution improved model performance. However, GPP-FP still underestimates tower-based GPP estimations (Fig. 2c, Fig. 3). In the comparison of remote sensing based GPP estimations and eddy covariance measurements over a heterogeneous landscape the consideration of source area location should improve model-measurement agreement to draw a more realistic picture of model performance. In the present study, individual agricultural plots are typically subpixel sized, therefore differences between remote sensing and EC measurements can still occur as a result of spatial averaging. The different maximum light use efficiency parameters attributed to different crop types together with the typical field size raises the need for a downscaling of the model to benefit from footprint information.

### 4.3 Evaluation of the downscaling procedure combined with footprint analysis

Fig. 2d shows that GPP increased for GPP-NDVI and the magnitude of simulated GPP is very well captured also in the 2004-2006 time period when precipitation was higher. The increase in annual sums can also be seen in Fig. 3, however, the large difference between GPP-NDVI and GPP-tower annual totals may be biased (see Section 3). Though the tower is mainly surrounded by winter wheat (C3) and maize (C4), differences in the properties of C3 and C4 crops are not reflected in GPP courses although, as it can be seen from GPP-tower, C4 plants have higher light use efficiency and thus higher maximum $CO_2$ uptake. Note that our novel downscaling method can only eliminate errors in FPAR arising from spatial resolution and representativeness of the remote sensing measurements. Structural problems of the model, i.e. poor characterization of crop types cannot be resolved by this algorithm.
The analysis of statistical indices (Table 3) revealed that short term variability of simulated GPP is mainly caused by variability of the meteorological parameters ($T_{\mathrm{min}}$, VPD). As our modifications mainly address the shortcomings of the coarse resolution FPAR dataset, the explained variance is expected to remain basically unchanged. This means that model performance of GPP should be optimally evaluated using RMSE, IA, ME and BIAS, but not $R^2$ and KR. Future developments that might try to include e.g. soil moisture and other stress factors are supposed to involve improvements in $R^2$ and KR.

## 5 Concluding remarks

We presented a method for the adaptation and validation of the MOD17 light use efficiency model for a tall tower based eddy covariance site located within heterogeneous cropland in Hungary. The research is based on the previous footprint analysis and crop phenology characterization by means of NDVI analysis (Barcza et al., 2009a).
Four different methods were used to simulate 8-day mean GPP for Hegyhátsál based on MODIS data. GPP-GMAO and GPP-met (GPP calculated using the MOD17 algorithm using GMAO meteorology and local meteorological measurements) are widely used in MOD17 related validation studies (e.g., Leuning et al., 2005; Heinsch et al., 2006; Turner et al., 2006). In order to exploit the advantage of footprint size similarity between remote sensing and hourly tall tower eddy covariance signal we further used two refined methods. For the GPP-FP model setup the 1 km resolution MOD17 data was coupled with the footprint analysis which allowed selection of MOD17 pixels according to the prevailing meteorological conditions and turbulence conditions. For GPP-NDVI we used the 250 m resolution MODIS NDVI dataset to downscale GPP estimations to 250 m resolution. The downscaled model was also coupled with the footprint analysis to provide hourly varying source region for the measured GPP. Note that for the selection of the contributing surface elements we used the maximum source weight location of the footprint model. This approach was shown to provide good results for the Hegyhátsál tall tower (Barcza et al., 2009b).
The results showed that GPP-met and GPP-FP cause only modest improvements in model performance compared to the reference GPP-GMAO. However, we demonstrated that our new downscaling technique used in GPP-NDVI at 250 m resolution is

significantly more successful in modeling GPP at the typically heterogeneous landscape of sub-pixel sized croplands in Western Hungary than the conventional GPP-GMAO.

It was shown that the 250 m resolution NDVI dataset is suitable for the characterization of the Hegyhátsál cropland region where agricultural fields are typically small. This means that the presented method can theoretically also be used for shorter towers, keeping in mind that the applicability may be restricted depending on the complexity of landscape surrounding the flux tower.

Depending on the structure of farmlands in the area of interest, we propose to use the NDVI based GPP modeling methodology for regional scale studies at 250 m or 1 km resolution using the following input data and procedure: (i) Quality assurance and wavelet transformation of MODIS NDVI time series that can be reproduced following Barcza et al. (2009a), or quality controlled and interpolated NDVI time series calculated using an alternative method (e.g., linear or spline interpolation). (ii) FPAR data retrieved from NDVI (Eq. 3, cf. Sims et al., 2005); and (iii) meteorological data from the GMAO database (until 2006) or a suitable meteorological database (e.g. from national meteorological services) known to provide accurate results for the given region. (iv) Derive GPP following the scheme of the MODIS GPP-model.

Applying the proposed method to our study site, annual GPP sums are still underestimated (by ~18% in average in the vicinity of the Hegyhátsál tower), but the underestimation is less than with the original MOD17 model. This means that validation results are strongly affected by the joint interpretation of EC tower and remote sensing data.

The presented methods allow for a more flexible utilization of remote sensing data for simulation of crop phenology and productivity on local or regional scale over heterogeneous landscape. As we pointed out, the choice of input datasets is important for improving model accuracy. However, errors caused by poor characterization of the ecosystem cannot be eliminated without calibration and/or structural improvement of the LUE model. At least the physiological differences of winter crop (at our site typically winter wheat, C3) and summer crop (typically maize, C4) should be included in model parameterizations via calibration (cf. Chen et al., 2011). For Western Hungary, the NDVI based crop type information (see Section 2.1.3) provides this possibility of crop specific model runs and calibration of the MOD17 model.

Our results highlight that spatial representativeness issues can not be neglected when validating remotely sensed GPP data with tall tower GPP data.

**Acknowledgements**

We are very grateful to Maosheng Zhao (NTSG) for providing us the official MOD17 product, the version 5.1 model parameters and the GMAO meteorological database. The research is supported by the Hungarian Government and the European Union and cofinanced by the European Social Fund (Jedlik Ányos PhD Candidate Fellowship, project no. TÁMOP 4.2.4.A-1; and grant agreement no. TÁMOP 4.2.1/B-09/1/KMR-2010-0003). The research was also supported by Hungarian Scientific Research Fund (OTKA K101065, K104816), CarpathCC project (ENV.D.1/FRA/2011/0006), BioVel (Biodiversity Virtual e-Laboratory Project, FP7-INFRASTRUCTURES-2011-2, project number 283359), by GHG-Europe (Greenhouse gas management in European land use systems, FP7-ENVIRONMENT, EU contract number 244122), and by the Natural Environment Research Council (NERC) UK (NE/G000360/1). The eddy covariance measurements were supported by the Hungarian Scientific Research Fund K75638 and CK77550. Use of the TV-tower and transmitter building at Hegyhátsál is kindly provided by Antenna Hungária Corporation. We thank Markus Reichstein for the discussion about the possibility of joint use of eddy flux tower, footprint modeling and MOD17 data.

## References


Baldocchi, D.D., 2003. Assessing the eddy covariance technique for evaluating carbon dioxide exchange rates of ecosystems: past, present and future. Global Change Biol. 9, 479–492. doi:10.1046/j.1365-2486.2003.00629.x

Barcza, Z., Haszpra, L., Kondo, H., Saigusa, N., Yamamoto, S., Bartholy, J., 2003. Carbon exchange of grass in Hungary. Tellus B 55, 187–196. doi:10.1034/j.1600-0889.2003.00014.x

Barcza, Z., Kern, A., Haszpra, L., Kljun, N., 2009a. Spatial representativeness of tall tower eddy covariance measurements using remote sensing and footprint analysis. Agric. For. Meteorol. 149, 795–807. doi:10.1016/j.agrformet.2008.10.021

Barcza, Z., Haszpra, L., Somogyi, Z., Hidy, D., Lovas, K., Churkina, G., Horváth, L., 2009b. Estimation of the biospheric carbon dioxide balance of Hungary using the BIOME-BGC model. Időjárás – Quarterly Journal of the Hungarian Meteorological Service 113, 203-219.

Beer, C., Reichstein, M., Tomelleri, E., Ciais, P., Jung, M., Carvalhais, N., Rödenbeck, C., Arain, M.A., Baldocchi, D., Bonan, G.B., Bondeau, A., Cescatti, A., Lasslop, G., Lindroth, A., Lomas, M., Luyssaert, S., Margolis, H., Oleson, K.W., Roupsard, O., Veenendaal, E., Viovy, N., Williams, C., Woodward, F.I., Papale, D., 2010. Terrestrial gross carbon dioxide uptake: global distribution and covariation with climate. Science 329, 834–838. doi:10.1126/science.1184984

Bondeau, A., Smith, P.C., Zaehle, S., Schaphoff, S., Lucht, W., Cramer, W., Gerten, D., Lotze-Campen, H., Müller, C., Reichstein, M., Smith, B., 2007. Modelling the role of agriculture for the 20th century global terrestrial carbon balance. Global Change Biol. 13, 679–706. doi:10.1111/j.1365-2486.2006.01305.x

Braswell, B.H., Sacks, W.J., Linder, E., Schimel, D.S., 2005. Estimating diurnal to annual ecosystem parameters by synthesis of a carbon flux model with eddy covariance net ecosystem exchange observations. Global Change Biol. 11, 335–355. doi:10.1111/j.1365-2486.2005.00897.x

Büttner, G., Feranec, J., Jaffrain, G., 2002. Corine Land Cover Update 2000. Technical Report 89 (European Environment Agency, 2002) available at http://reports.eea.eu.int/technical_report_2002_89/en

Chasmer, L., Kljun, N., Hopkinson, C., Brown, S., Milne, T., Giroux, K., Barr, A., Devito, K., Creed, I., Petrone, R., 2011. Characterizing vegetation structural and topographic characteristics sampled by eddy covariance within two mature aspen stands using lidar and a flux footprint model: Scaling to MODIS. J. Geophys. Res. 116, G02026. doi:10.1029/2010JG001567

Chen, B., Black, T.A., Coops, N.C., Hilker, T., Trofymow, J.A., Morgenstern, K., 2008. Assessing Tower Flux Footprint Climatology and Scaling Between Remotely Sensed and Eddy Covariance Measurements. Boundary-Layer Meteorol. 130, 137–167. doi:10.1007/s10546-008-9339-1

Chen, B., Ge, Q., Fu, D., Liu, G., Yu, G., Sun, X., Wang, S., Wang, H., 2009. Upscaling of gross ecosystem production to the landscape scale using multi-temporal Landsat images, eddy covariance measurements and a footprint model. Biogeosci. Discuss. 6, 11317–11345. doi:10.5194/bgd-6-11317-2009

Chen, B., Coops, N.C., Fu, D., Margolis, H.A., Amiro, B.D., Black, T.A., Arain, M.A., Barr, A.G., Bourque, C.P.-A., Flanagan, L.B., Lafleur, P.M., McCaughey, J.H., Wofsy, S.C., 2012. Characterizing spatial representativeness of flux tower eddy-covariance measurements across the Canadian Carbon Program Network using remote sensing and footprint analysis. Remote Sens. Environ., 124, 742–755. doi:10.1016/j.rse.2012.06.007

Chen, T., van der Werf, G.R., Dolman, A.J., Groenendijk, M., 2011. Evaluation of cropland maximum light use efficiency using eddy flux measurements in North America and Europe. Geophys. Res. Lett. 38, L14707. doi:10.1029/2011GL047533W

Ciais, P., Wattenbach, M., Vuichard, N., Smith, P., Piao, S.L., Don, A., Luyssaert, S., Janssens, I., Bondeau, A., Dechow, R., Leip, A., Smith, P., Beer, C., van der Werf, G.R., Gervois, S., Van Oost, K., Tomelleri, E., Freibauer, A., Schulze, E.D., CARBOEUROPE Synthesis Team, 2010. The European carbon balance. Part 2: croplands. Global Change Biol. 16, 1409–1428. doi:10.1111/j.1365-2486.2009.02055.x

Coops, N.C., Jassal, R.S., Leuning, R., Black, A.T., Morgenstern, K., 2007. Incorporation of a soil water modifier into MODIS predictions of temperate Douglas-fir gross primary productivity: Initial model development. Agric. For. Meteorol. 147, 99–109. doi:10.1016/j.agrformet.2007.07.001

Falge, E., Baldocchi, D., Olson, R., Anthoni, P., Aubinet, M., Bernhofer, C., Burba, G., Ceulemans, R., Clement, R., Dolman, H., Granier, A., Gross, P., Grünwald, T., Hollinger, D., Jensen, N-O., Katul, G., Keronen, P., Kowalski, A., Lai, C.T., Law, B.E., Meyers, T., Moncrieff, J., Moors, E., Munger, J.W., Pilegaard, K., Rannik, Ü., Rebmann, C., Suyker, A., Tenhunen, J., Tu, K., Verma, S., Vesala, T., Wilson, K., Wofsy, S., 2001. Gap filling strategies for defensible annual sums of net ecosystem exchange. Agric. For. Meteorol. 107, 43–69. doi:10.1016/S0168-1923(00)00225-2

Foley, J.A., Defries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global consequences of land use. Science 309, 570–574. doi:10.1126/science.1111772

Gebremedhin, M.T., Loescher, H.W., Tsegaye, T.D., 2012. Carbon Balance of No-Till Soybean with Winter Wheat Cover Crop in the Southeastern United States. Agron. J. 104, 1321–1335. doi:10.2134/agronj2012.0072

Gebremichael, M., Barros, A., 2006. Evaluation of MODIS Gross Primary Productivity (GPP) in tropical monsoon regions. Remote Sens. Environ. 100(2), 150–166. doi:10.1029/2002GB002023

Gilmanov, T.G., Verma, S.B., Sims, P.L., Meyers, T.P., Bradford, J.A., Burba, G.G., Suyker, A.E., (2003). Gross primary production and light response parameters of four Southern Plains ecosystems estimated using long-term $CO_2$-flux tower measurements. Global Biogeochem. Cycles 17, 1071. doi:10.1029/2002GB002023

Göckede, M., Foken, T., Aubinet, M., Aurela, M., Banza, J., Bernhofer, C., Bonnefond, J.M., Brunet, Y., Carrara, A., Clement, R., Dellwik, E., Elbers, J., Eugster, W., Fuhrer, J., Granier, A., Grünwald, T., Heinesch, B., Janssens, I.A., Knohl, A., Koeble, R., Laurila, T., Longdoz, B., Manca, G., Marek, M., Markkanen, T., Mateus, J., Matteucci, G., Mauder, M., Migliavacca, M., Minerbi, S., Moncrieff, J., Montagnani, L., Moors, E., Ourcival, J.-M., Papale, D., Pereira, J., Pilegaard, K., Pita, G., Rambal, S., Rebmann, C., Rodrigues, A., Rotenberg, E., Sanz, M.J., Sedlak, P., Seufert, G., Siebicke, L., Soussana, J.F., Valentini, R., Vesala, T., Verbeeck, H., Yakir, D., (2008). Quality control of CarboEurope flux data – Part 1: Coupling footprint analyses with flux data quality assessment to evaluate sites in forest ecosystems, Biogeosciences 5, 433–450. doi:10.5194/bg-5-433-2008

Goldewijk, K.K., 2001. Estimating global land use change over the past 300 years: The HYDE Database. Global Biogeochem. Cycles 15, 417–433. doi:10.1029/1999GB001232

Haszpra, L., Barcza, Z., Bakwin, P.S., Berger, B.W., Davis, K.J., Weidinger, T., 2001. Measuring system for the long-term monitoring of biosphere/atmosphere exchange of carbon dioxide. J. Geophys. Res. 106D, 3057–3070. doi:10.1029/2000JD900600

Haszpra, L., Barcza, Z., Davis, K.J., Tarczay, K., 2005. Long-term tall tower carbon dioxide flux monitoring over an area of mixed vegetation. Agric. For. Meteorol. 132, 58–77. doi:10.1016/j.agrformet.2005.07.002

Heinsch, F.A., Reeves, M., Votava, P., Kang, S., Milesi, C., Zhao, M., Glassy, J., Jolly, W.M., Loehman, R., Bowker, C.F., Kimball, J.S., Nemani, R.R., Running, S.W., 2003. User's Guide GPP and NPP (MOD17A2/A3) Products NASA MODIS Land Algorithm. http://datamirror.csdb.cn/modis/resource/doc/MOD17_UsersGuide.pdf

Heinsch, F.A., Zhao, M., Running, S.W., Kimball, J.S., Neman, 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., Wofsy, S.C., Dunn, A.L., Munger, J.W., Baldocchi, D.D., Xu, L., 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 Trans. Geosci. Remote Sens. 44, 1908–1924. doi:10.1109/TGRS.2005.853936

Hidy, D., Barcza, Z., Haszpra, L., Churkina, G., Pintér, K., Nagy, Z., 2011. Development of the Biome-BGC model for simulation of managed herbaceous ecosystems. Ecol. Modell. 226, 99–119. doi:10.1016/j.ecolmodel.2011.11.008

Horst, T.W., Weil, J.C., 1992. Footprint estimation for scalar flux measurements in the atmospheric surface layer. Boundary-Layer Meteorol. 59, 279–296.

Huete, A., Justice, C., Leeuwen, W.V., 1999. MODIS vegetation index – MOD13. Algorithm Theoretical Basis Document. http://modis.gsfc.nasa.gov/data/atbd/atbd_mod13.pdf

Hwang, T., Kang, S., Kim, J., Kim, Y., Lee, D., Band, L., 2008. Evaluating drought effect on MODIS Gross Primary Production (GPP) with an eco-hydrological model in the mountainous forest, East Asia. Global Change Biol. 14, 1–20. doi:10.1111/j.1365-2486.2008.01556.x

Janssen, P.H.M., Heuberger, P.S.C., 1995. Calibration of process-oriented models. Ecol. Modell. 83, 55–66. doi:10.1016/0304-3800(95)00084-9

Kanniah, K.D., Beringer, J., Hutley, L.B., Tapper, N.J., Zhu, X., 2009. Evaluation of Collections 4 and 5 of the MODIS Gross Primary Productivity product and algorithm improvement at a tropical savanna site in northern Australia. Remote Sens. Environ. 113, 1808–1822. doi:10.1016/j.rse.2009.04.013

Kim, J., Guo, Q., Baldocchi, D.D., Leclerc, M.Y., Xu, L., Schmid, H.P., 2006. Upscaling fluxes from tower to landscape: Overlaying flux footprints on high-resolution (IKONOS) images of vegetation cover. Agric. For. Meteorol. 136, 132-146, http://dx.doi.org/10.1016/j.agrformet.2004.11.015

Kljun, N., Rotach, M.W., Schmid, H.P., 2002. A 3D Backward Lagrangian Footprint Model for a Wide Range of Boundary Layer Stratifications. Boundary-Layer Meteorol. 103, 205-226.

Kljun, N., Calanca, P., Rotach, M.W., Schmid, H.P., 2004. A simple parameterisation for flux footprint predictions. Boundary-Layer Meteorol. 112, 503–523. doi:10.1023/B:BOUN.0000030653.71031.96

Knyazikhin, Y., Glassy, J., Privette, J.L., Tian, Y., Lotsch, A., Zhang, Y., Wang, Y., Morisette, J.T., Votava, P., Myneni, R.B., Nemani, R.R., Running, S.W., 1999. MODIS Leaf Area Index (LAI) and Fraction of Photosynthetically Active Radiation Absorbed by Vegetation (FPAR) Product (MOD15) Algorithm Theoretical Basis Document, http://eospso.gsfc.nasa.gov/atbd/modistables.html

Kutsch, W.L., Aubinet, M., Buchmann, N., Smith, P., Osborne, B., Eugster, W., Wattenbach, M., Schrumpf, M., Schulze, E.D., Tomelleri, E., Ceschia, E., Bernhofer, C., Béziat, P., Carrara, A., Di Tommasi, P., Grünwald, T., Jones, M., Magliulo, V., Marloie, O., Moureaux, C., Olioso, A., Sanz, M.J., Saunders, M., Søgaard, H., Ziegler, W., 2010. The net biome production of full crop rotations in Europe. Agric. Ecosyst. Environ. 139, 336–345. doi:10.1016/j.agee.2010.07.016

Lasslop, G., Reichstein, M., Papale, D., Richardson, A.D., Arneth, A., Barr, A., Stoy, P., Wohlfahrt, G., 2010. Separation of net ecosystem exchange into assimilation and respiration using a light response curve approach: critical issues and global evaluation. Global Change Biol. 16, 187–208, http://dx.doi.org/10.1111/j.1365-2486.2009.02041.x.

Leuning, R., Cleugh, H.A., Zegelin, S.J., Hughes, D., 2005. Carbon and water fluxes over a temperate Eucalyptus forest and a tropical wet/dry savanna in Australia: measurements and comparison with MODIS remote sensing estimates. Agric. For. Meteorol. 129, 151–173. doi:10.1016/j.agrformet.2004.12.004

Lloyd, J., Taylor, J.A., 1994. On the temperature dependence of soil respiration. Funct. Ecol. 8, 315-323.

Lobell, D.B., Asner, G.P., 2004. Cropland distributions from temporal unmixing of MODIS data. Remote Sens. Environ. 93, 412–422. doi:10.1016/j.rse.2004.08.002

Ma, S., Churkina, G., Wieland, R., Gessler, A., 2011. Optimization and evaluation of the ANTHRO-BGC model for winter crops in Europe. Ecol. Modell. 222, 3662–3679. doi:10.1016/j.ecolmodel.2011.08.025

McCallum, I., Wagner, W., Schmullius, C., Shvidenko, A., Obersteiner, M., Fritz, S., Nilsson, S., 2009. Satellite-based terrestrial production efficiency modeling. Carbon Balance Manage. 4:8. doi:10.1186/1750-0680-4-8

Moffat, A.M., Papale, D., Reichstein, M., Hollinger, D.Y., Richardson, A.D., Barr, A.G., Beckstein, C., Braswell, B.H., Churkina, G., Desai, A.R., Falge, E., Gove, J.H., Heimann, M., Hui, D., Jarvis, A.J., Kattge, J., Noormets, A. Stauch, V.J., 2007. Comprehensive comparison of gap-filling techniques for eddy covariance net carbon fluxes. Agric. For. Meteorol. 147, 209–232. doi:10.1016/j.agrformet.2007.08.011

Monteith, J., 1972. Solar radiation and productivity in tropical ecosystems. J. Appl. Ecol. 9, 747–766.

Monteith, J., 1977. Climate and efficiency of crop production in Britain. Philos. Trans. R. Soc. London, Ser. B 281, 277–294.

Monfreda, C., Ramankutty, N., Foley, J.A., 2008. Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. Global Biogeochem. Cycles 22, GB1022 doi:10.1029/2007GB002947.

Nightingale, J., Coops, N., Waring, R., Hargrove, W., 2007. Comparison of MODIS gross primary production estimates for forests across the U.S.A. with those generated by a simple process model, 3-PGS. Remote Sens. Environ. 109, 500–509. doi:10.1016/j.rse.2007.02.004

Pittman, K., Hansen, M.C., Becker-Reshef, I., Potapov, P.V., Justice, C.O., 2010. Estimating Global Cropland Extent with Multi-year MODIS Data. Remote Sensing 2, 1844–1863. doi:10.3390/rs2071844

Ramankutty, N., Foley, J.A., 1999. Estimating historical changes in global land cover: Croplands from 1700 to 1992, Global Biogeochem. Cycles 13, 997–1027. doi:10.1029/1999GB900046

Ramankutty, N., Foley, J.A., Norman, J., McSweeney, K., 2002. The global distribution of cultivable lands: Current patterns and sensitivity to possible climate change. Global Ecol. Biogeogr. 11, 377–392. 10.1046/j.1466-822x.2002.00294.x

Ramankutty, N., Evan, A.T., Monfreda, C., Foley, J.A., 2008. Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. Global Biogeochem. Cycles 22, GB1003 doi:10.1029/2007GB002952

Reich, P.B., Turner, D.P., Bolstad, P., 1999. An approach to spatially distributed modeling of net primary production (NPP) at the landscape scale and its application in validation of EOS NPP products. Remote Sens. Environ. 70, 69–81. doi:10.1016/S0034-4257(99)00058-9

Reichstein, M., Falge, E., Baldocchi, D., Papale, D., Aubinet, M., Berbigier, P., Bernhofer, C., Buchmann, N., Gilmanov, T., Granier, A., Grunwald, T., Havrankova, K., Ilvesniemi, H., Janous, D., Knohl, A., Laurila, T., Lohila, A., Loustau, D., Matteucci, G., Meyers, T., Miglietta, F., Ourcival, J., Pumpan, M., 2005. On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm. Global Change Biol. 11, 1424–1439. doi:10.1111/j.1365-2486.2005.001002.x

Running, S.W., Baldocchi, D.D., Turner, D.P., Gower, S.T., Bakwin, P.S., Hibbard, K.A., 1999a. A Global Terrestrial Monitoring Network Integrating Tower Fluxes, Flask Sampling, Ecosystem Modeling and EOS Satellite Data. Remote Sens. Environ. 70, 108–127. doi:10.1016/S0034-4257(99)00061-9

Running, S.W., Nemani, R.R., Glassy, J.M., Thornton, P.E., 1999b. MODIS Daily Photosynthesis (PSN) and Annual Net Primary Production (NPP) product (MOD17) algorithm theoretical basis document. www.ntsg.umt.edu/modis/ATBD/ATBD_MOD17_v21.pdf

Running, S.W., Nemani, R.R., Heinsch, F.A., Zhao, M., Reeves, M., Hashimoto, H., 2004. A continuous satellite-derived measure of global terrestrial primary production. Bioscience 54, 547–560. doi:10.1043/0006-3568(2004)054(0547:ACSMOG)2.0.CO;2

Schmid, H.P., Lloyd, C.R., 1999. Spatial representativeness and the location bias of flux footprints over inhomogeneous areas. Agric. For. Meteorol. 93, 195-209, http://dx.doi.org/10.1016/S0168-1923(98)00119-1

Schulze, E.D., Luyssaert, S., Ciais, P., Freibauer, A., Janssens, I.A., Soussana, J.F., Smith, P., Grace, J., Levin, I., Thiruchittampalam, B., Heimann, M., Dolman, A.J., Valentini, R., Bousquet, P., Peylin, P., Peters, W., Rödenbeck, C., Etiope, G., Vuichard, N., Wattenbach, M., Nabuurs, G.J., Poussi, Z., Nieschulze, J., Gash, J.H. the CarboEurope Team, 2009. Importance of methane and nitrous oxide for Europe's terrestrial greenhouse-gas balance. Nature Geoscience 2, 842–850. doi:10.1038/ngeo686

Schwalm, C.R., Williams, C.A., Schaefer, K., Anderson, R., Arain, M.A., Baker, I., Barr, A., Black, T.A., Chen, G., Chen, J.M., Ciais, P., Davis, K.J., Desai, A., Dietze, M., Dragoni, D., Fischer, M.L., Flanagan, L.B., Grant, R., Gu, L., Hollinger, D., Izaurralde, R.C., Kucharik, C., Lafleur, P., Law, B.E., Li, L., Li, Z., Liu, S., Lokupitiya, E., Luo, Y., Ma, S., Margolis, H., Matamala, R., McCaughey, H., Monson, R.K., Oechel, W.C., Peng, C., Poulter, B., Price, D.T., Riciutto, D. M., Riley, W., Sahoo, A.K., Sprintsin, M., Sun, J., Tian, H., Tonitto, C., Verbeeck, H., Verma, S.B., 2010. A model-data intercomparison of $CO_2$ exchange across North America: Results from the North American Carbon Program site synthesis. J. Geophys. Res. 115, G00H05, doi:10.1029/2009JG001229.

Sims, D.A., Rahman, A.F., Cordova, V.D., Baldocchi, D.D., Dennis, Flanagan, L.B., Goldstein, A.H., Hollinger, D.Y., Misson, L., Monson, R.K., Schmid, H.P., Wofsy, S.C., Xu, L., 2005. Midday values of gross $CO_2$ flux and light use efficiency during satellite overpasses can be used to directly estimate eight-day mean flux. Agric. For. Meteorol. 131, 1–12. doi:10.1016/j.agrformet.2005.04.006

Stoy, P.C., Katul, G.G., Siqueira, M.B.S. Juang, J.-Y., Novick, K.A., Uebelherr, J.M., Oren, R., 2006. An evaluation of models for partitioning eddy covariance-measured net ecosystem exchange into photosynthesis and respiration. Agric. For. Meteorol. 141, 2–18. doi:10.1016/j.agrformet.2006.09.001

Strahler, A., Muchoney, D., Borak, J., Friedl, M., Gopal, S., Lambin, E., Moody, A., 1999. MODIS Land cover product Algorithm Theoretical Basis Document (ATBD). http://modis.gsfc.nasa.gov/data/atbd/atbd_mod12.pdf

Suyker, A.E., Verma, S.B., Burba, G.G., Arkebauer, T.J., 2005. Gross primary production and ecosystem respiration of irrigated maize and irrigated soybean during a growing season. Agric. For. Meteorol. 131, 180–190. doi:10.1016/j.agrformet.2005.05.007

Thornton, P.E., Hasenauer, H., White, M.A., 2000. Simultaneous estimation of daily solar radiation and humidity from observed temperature and precipitation: application over complex terrain in Austria. Agric. For. Meteorol. 104, 255–271. doi:10.1016/S0168-1923(00)00170-2

Turner, D.P., Ritts, W.D., Cohen, W.B., Maeirsperger, T.K., Gower, S.T., Kirschbaum, A.A., Running, S.W., Zhao, M., Wofsy, S.C., Dunn, A.L., Law, B.E., Campbell, J.L., Oechel, W.C., Kwon, H.J., Meyers, T.P., Small, E.E., Kurc, S.A., Gamon, J.A., 2005. Site-level evaluation of satellite-based global terrestrial gross primary production and net primary production monitoring. Global Change Biol. 11(4), 666–684. doi:10.1111/j.1365-2486.2005.00936.x

Turner, D.P., Ritts, W.D., Cohen, W.B., Gower, S.T., Running, S.W., Zhao, M., Costa, M.H., Kirschbaum, A.A., Ham, J.M., Saleska, S.R., Ahl, D.E., 2006. Evaluation of MODIS NPP and GPP products across multiple biomes. Remote Sens. Environ. 102, 282–292. doi:10.1016/j.rse.2006.02.017

Turner, D.P., Ollinger, S.V., Kimball J.S., 2004. Integrating remote sensing and ecosystem process models for landscape- to regional-scale analysis of the carbon cycle. BioScience 54, 573–584. doi:10.1641/0006-3568(2004)054[0573:IRSAEP]2.0.CO;2

Van Oijen, M., Rougier, J., Smith, R., 2005. Bayesian calibration of process-based forest models: bridging the gap between models and data. Tree Physiol. 25, 915–927. doi:10.1093/treephys/25.7.915

Vetter, M. Churkina, G., Jung, M., Reichstein, M., Zaehle, S., Bondeau, A., Chen, Y., Ciais, P., Feser, F., Freibauer, A., Geyer, R., Jones, C., Papale, D., Tenhunen, J., Tomelleri, E., Trusilova, K., Viovy, N., Heimann, M., 2008. Analyzing the causes and spatial pattern of the European 2003 carbon flux anomaly using seven models. Biogeosciences 5, 561–583. doi:10.5194/bg-5-561-2008

Wang, W., Davis, K.J., Cook, B.D., Butler, M.P., Ricciuto, D.M., 2006. Decomposing $CO_2$ fluxes measured over a mixed ecosystem at a tall tower and extending to a region: A case study. J. Geophys. Res. 111, G02005. doi:10.1029/2005JG000093

Wang, W., Dungan, J., Hashimoto, H., Michaelis, A.R., Milesi, C., Ichii, K., Nemani, R.R., 2011. Diagnosing and assessing uncertainties of terrestrial ecosystem models in a multimodel ensemble experiment: 1. Primary production. Global Change Biol. 17, 1350–1366. doi:10.1111/j.1365-2486.2010.02309.x

Wattenbach, M., Sus, O., Vuichard, N., Lehuger, S., Gottschalk, P., Li, L., Leip, A., Williams, M., Tomelleri, E., Kutsch, W.L., Buchmann, N., Eugster, W., Dietiker, D., Aubinet, M., Ceschia, E., Béziat, P., Grünwald, T., Hastings, A., Osborne, B., Ciais, P., Cellier, P., Smith, P., 2010. The carbon balance of European croplands: A cross-site comparison of simulation models. Agric. Ecosyst. Environ. 139, 419–453. doi:10.1016/j.agee.2010.08.004

Yang, F., Ichii, K., White, M.A, Hashimoto, H., Michaelis, A.R., Votava, P., Zhu, A.-X., Huete, A., Running S.W., Nemani, R.R., 2007. Developing a continental-scale measure of gross primary production by combining MODIS and AmeriFlux data through Support Vector Machine approach. Remote Sens. Environ. 110(1), 109–122. doi:10.1016/j.rse.2007.02.016

Zhang, Y., Yu, Q., Jiang, J., Tang, Y., 2008. Calibration of Terra/MODIS gross primary production over an irrigated cropland on the North China Plain and an alpine meadow on the Tibetan Plateau. Global Change Biol. 14, 757–767. doi:10.1111/j.1365-2486.2008.01538.x

Zhao, M., Heinsch, F.A., Nemani, R.R., Running, S.W., 2005. Improvements of the MODIS terrestrial gross and net primary production global data set. Remote Sens. Environ. 95, 164–176. doi:10.1016/j.rse.2004.12.011

Zhao, M., Running, S.W., Nemani, R.R., 2006. Sensitivity of Moderate Resolution Imaging Spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalyses. J. Geophys. Res. 111, G01002. doi:10.1029/2004JG000004

Table 1. Climate data for the Hegyhátsál region. Annual sums of photosynthetically active photon flux density (PPFD) and average daytime vapor pressure deficit (VPD) are measured locally at Hegyhátsál. 2001–2006 air temperature and precipitation data are from the nearby (~17 km) Rábagyarmat climate station, while the 1981-2010 means are from Farkasfa regional meteorological observatory (~26 km from tower). A comparison of measured and GMAO-based VPD is also shown. Vegetation period denotes the period from beginning of March to end of October.

| | | **1981-2010** | **2001** | **2002** | **2003** | **2004** | **2005** | **2006** |
|---|---|---|---|---|---|---|---|---|
| average temperature (°C) | vegetation period | 13.8 | 15.4 | 15.1 | 15.3 | 13.9 | 14.1 | 14.8 |
| | whole year | 9.5 | 10.7 | 11.3 | 10.6 | 9.8 | 9.6 | 10.3 |
| cumulative precipitation (mm) | vegetation period | 588 | 466 | 469 | 381 | 564 | 595 | 604 |
| | whole year | 762 | 550 | 598 | 487 | 705 | 801 | 738 |
| sum of PPFD (mol $m^{-2}$) | vegetation period | n.a. | 7611 | 7359 | 8020 | 7086 | 7540 | 7261 |
| | whole year | n.a. | 8530 | 8120 | 9047 | 7931 | 8494 | 8258 |
| average daytime VPD (kPa) | vegetation period | n.a. | 0.761 | 0.801 | 1.045 | 0.664 | 0.704 | 0.670 |
| | whole year | n.a. | 0.510 | 0.608 | 0.774 | 0.521 | 0.541 | 0.451 |
| GMAO VPD versus observation | RMSE (Pa) | - | 282 | 264 | 301 | 397 | 376 | 277 |
| | Bias (Pa) | - | 109 | 65 | 134 | 213 | 187 | 105 |
| | $R^2$ | - | 0.791 | 0.784 | 0.884 | 0.747 | 0.724 | 0.767 |

Table 2. Overview of the properties of different model setups used in this study.

| abbreviation | input data | | | spatial resolution | utilization of footprint model |
|---|---|---|---|---|---|
| | meteorology input | FPAR | land cover | | |
| GPP-GMAO | GMAO | MOD15 | MOD12 | 1 km | no |
| GPP-met | local meteorology | MOD15 | MOD12 | 1 km | no |
| GPP-FP | local meteorology | MOD15 | MOD12 | 1 km | yes |
| GPP-NDVI | local meteorology | linear dependence on NDVI | CORINE-2000 | 250 m | yes |

Table 3. Indicators of model performance (cf. Sections 2.4 and 2.5). Note that GPP–NDVI is not available before 2003 (launch of Aqua satellite in May 2002). The best values of the indicators are highlighted in bold font

| | period | RMSE | IA | ME | KR | $R^2$ | BIAS |
|---|---|---|---|---|---|---|---|
| GPP-GMAO | 2001-2006 | 1.095 | 0.930 | 0.783 | 0.812 | 0.905 | -0.680 |
| | 2003-2006 | 1.128 | 0.927 | 0.778 | 0.817 | 0.902 | -0.672 |
| GPP-met | 2001-2006 | 1.134 | 0.928 | 0.767 | 0.805 | 0.911 | -0.801 |
| | 2003-2006 | 1.163 | 0.926 | 0.764 | 0.818 | 0.916 | -0.810 |
| GPP-FP | 2001-2006 | 0.999 | 0.949 | 0.819 | 0.795 | 0.895 | -0.634 |
| | 2003-2006 | 1.031 | 0.946 | 0.815 | 0.816 | 0.915 | -0.703 |
| GPP-NDVI | 2003-2006 | **0.815** | **0.969** | **0.884** | **0.823** | **0.917** | **-0.426** |


Figure 1. a) Satellite image of the Hegyhátsál region (source: Google Earth). b) Footprint climatology of the tall tower for 2007 (representative for all selected years). Footprint climatology is visualized by the relative frequency of the contribution of the different, discretized land cover elements using the 250 m x 250 m resolution of the MODIS NDVI grid. X symbol marks the location of the flux tower. Contour lines show the land cover elements defined by the CORINE2000 database.

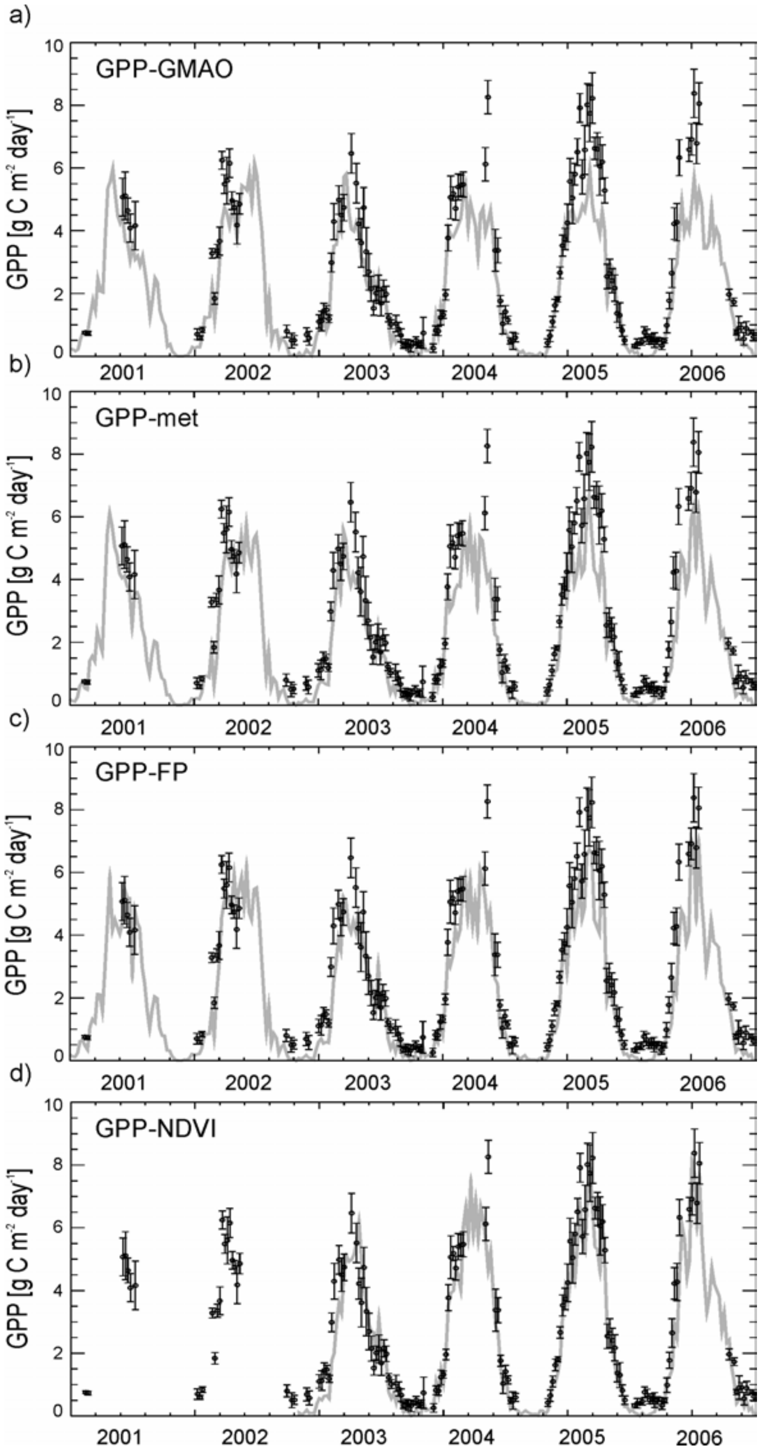



Figure 2. GPP based on EC measurements (GPP-tower; circles) and simulations (solid line): a) GPP-GMAO, b) GPP-met, c) GPP-FP and d) GPP-NDVI for the period of 2001-2006. See Section 2.4.for definitions. Uncertainty of GPP-tower is also shown (one uncertainty range is plotted as error bar).

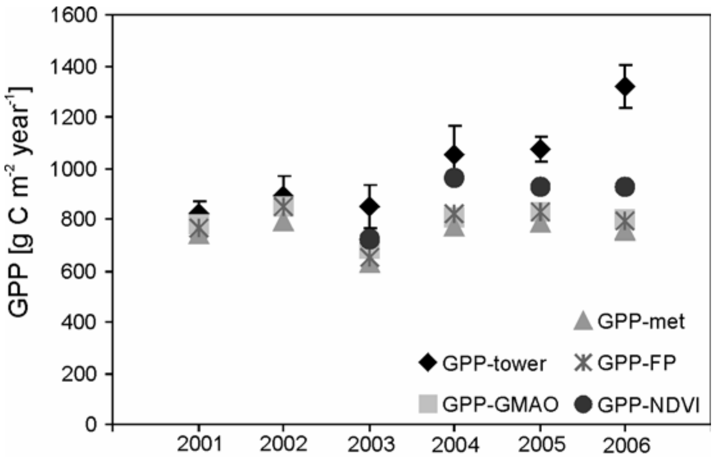



Figure 3. Annual sums of GPP based on EC tower measurements and model calculations. Uncertainties for tower based GPP are also shown (calculated as half of the difference between the daily maximum and minimum GPP estimate). See 2.4 for model description. Note that GPP-tower in 2006 may be biased due to a large data gap.

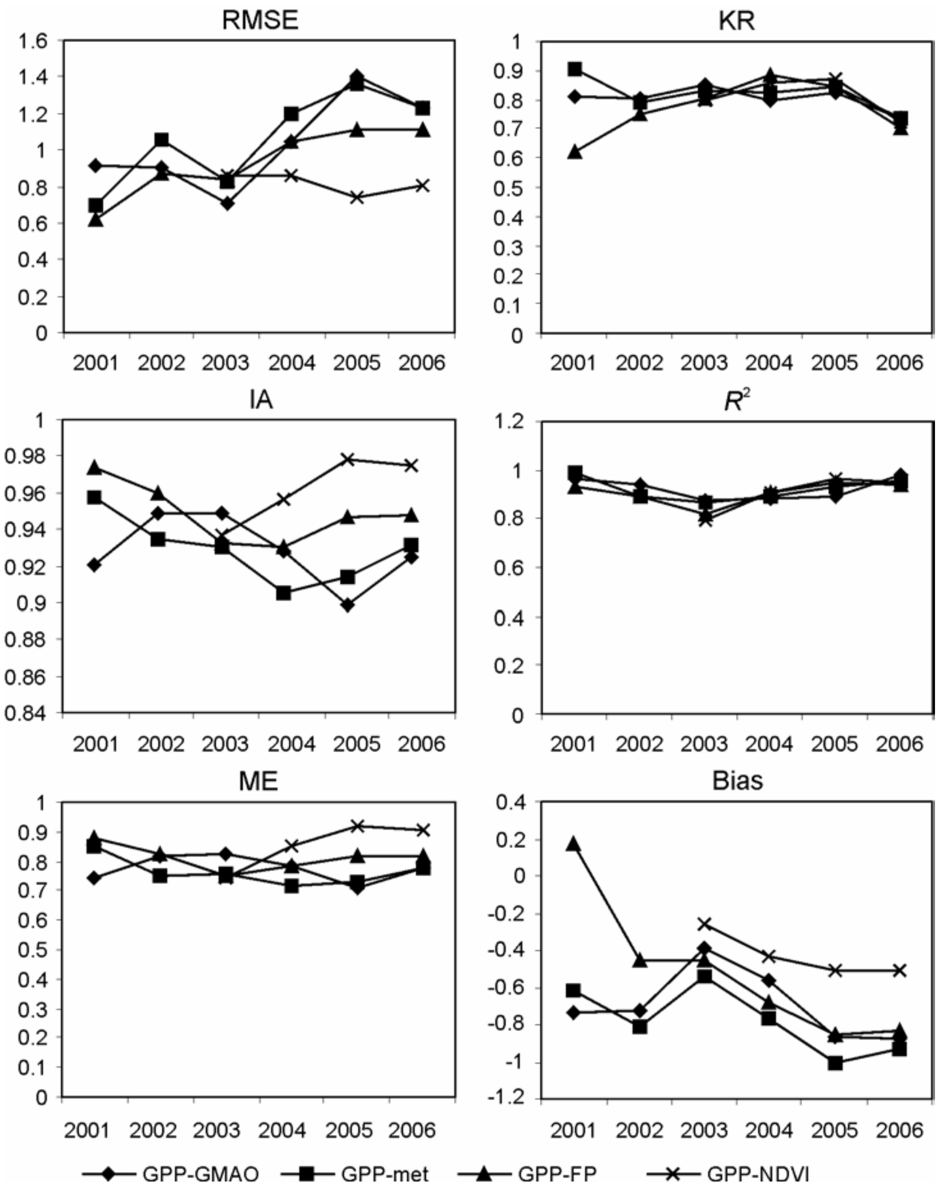



Figure 4. Yearly indicators of model performance for different model runs. Note that GPP-NDVI was not available on an annual basis before 2003 (launch of Aqua satellite in May 2002).