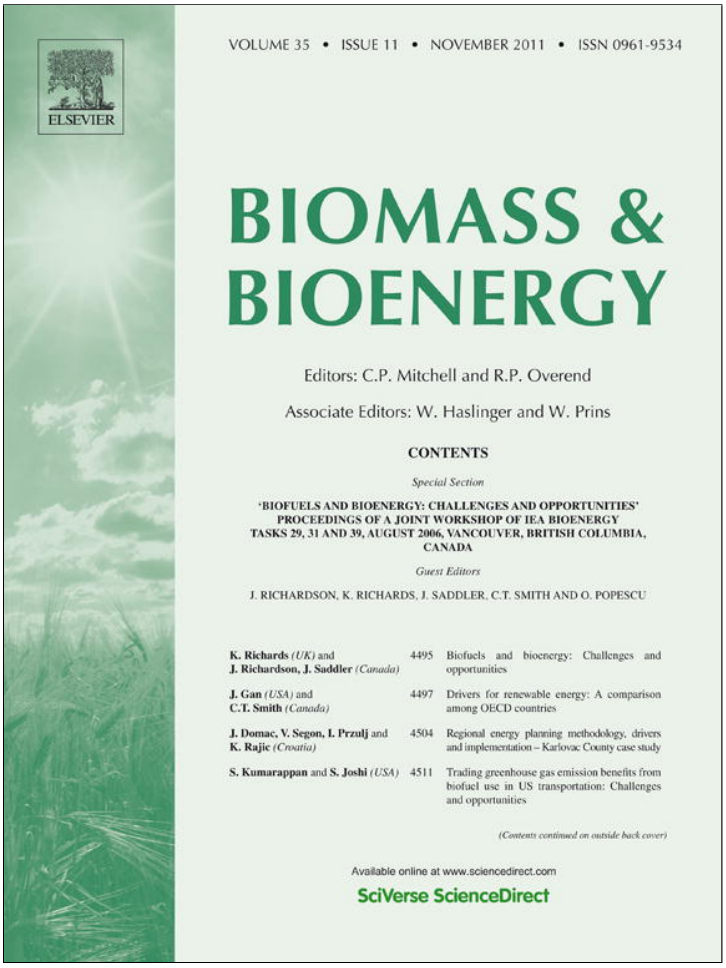

VOLUME 35 • ISSUE 11 • NOVEMBER 2011 • ISSN 0961-9534

ELSEVIER

BIOMASS & BIOENERGY

Editors: C.P. Mitchell and R.P. Overend

Associate Editors: W. Haslinger and W. Prins

CONTENTS

Special Section

'BIOFUELS AND BIOENERGY: CHALLENGES AND OPPORTUNITIES'
PROCEEDINGS OF A JOINT WORKSHOP OF IEA BIOENERGY
TASKS 29, 31 AND 39, AUGUST 2006, VANCOUVER, BRITISH COLUMBIA, CANADA

Guest Editors

J. RICHARDSON, K. RICHARDS, J. SADDLER, C.T. SMITH AND O. POPESCU

(Contents continued on outside back cover)

BIOMASS AND BIOENERGY 35 (2011) 4665–4674

Available online at www.sciencedirect.com

SciVerse ScienceDirect

http://www.elsevier.com/locate/biombioe

Validating modelled NPP using statistical yield data

Markus Tum*, **Kurt P. Günther**

German Aerospace Center (DLR), German Remote Sensing Data Center (DFD), Münchener Straße 20, D-82234 Oberpfaffenhofen, Germany

ARTICLE INFO

Article history:
Received 11 June 2010
Received in revised form
6 September 2011
Accepted 21 September 2011
Available online 17 October 2011

Keywords:
Validation
Modelling
Remote sensing
National statistics
NPP

ABSTRACT

The German Remote Sensing Data Center operates the Biosphere Energy Transfer Hydrology Model, a process model that estimates the net primary productivity of agricultural areas. The model is driven by remote sensing data and meteorological data. Remotely sensed datasets including a time series of the leaf area index, which describes vegetation condition, and a land cover classification, which provides information about land use, are needed. Currently leaf area indices and land cover data derived from the sensor vegetation are used. Both datasets have spatial resolutions of about 1 km × 1 km and are freely available for the area of investigation (Germany and Austria). The meteorological input parameters are air temperature (at 2 m height), precipitation, cloud cover, wind speed (at 10 m height) and soil water content (in the four uppermost soil layers); these are obtained from the European Centre for Medium-Range Weather Forecasts, with a spatial resolution of about 0.25° × 0.25° and a temporal resolution up to four times daily. The output of the model, the gross primary productivity, is calculated at daily resolution. By subtracting the cumulative plant maintenance and growth respiration, the net primary productivity is then determined. In order to validate the modelled net primary productivity, crop yield estimates derived from the national statistics of Germany and Austria are used. After estimating above-ground biomass using plant-specific above- to below-ground ratios, conversion factors (corn-to-straw and leaf-to-beet relations) are applied to estimate total biomass. Finally the carbon content of dry matter is estimated. To correlate model results with these statistical data, the modelled data are aggregated to net primary productivity per administrative district. The results show that a process model using remote sensing data as input can deliver reliable estimates of agricultural biomass potential which are highly correlated with statistically derived estimates of actual biomass produced.

1. Introduction

In one of the earliest forays into computational prediction of agricultural yield [1] developed the Crop Environmental Resource Synthesis (CERES) model for simulating the daily growth and development processes of wheat and maize. Later this model was expanded to sorghum, millet, rice and barley. Many factors including environment, nitrogen availability, water stress, pests, genetics and management are considered in CERES to model growth and development. The development processes are differentiated in two stages: the vegetative stage with germination, emergence, end of juvenile and leaf numbers, and the reproductive stage with floral induction, flowering, begin of grain filling and maturity. Stress components, such as water stress, act in different ways depending on the development stage.

The daily growth of plants is modelled in CERES according to the Radiation Use Efficiency (RUE) approach, which is based on

---

* *Corresponding author*. Tel.: +49 8153 28 1292; fax: +49 8153 28 1363.
E-mail address: markus.tum@dlr.de (M. Tum).

0961-9534/$ – see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.biombioe.2011.09.015

the concepts of [2] and [3]. In this approach, the potential maximum dry matter production is linearly correlated with the absorbed light. As in most mechanistic models, RUE also varies with temperature, nitrogen and water availability, CO_2 level and fertilization. The allocation of assimilated carbon to particular plant components is modelled, with daily time steps.

Phenology, the timing of biological processes, is driven by temperature, expressed as either thermal temperature or growing-degree-days. In order to calibrate the CERES model, field data are needed, especially the number of plants planted per unit area and the timing of phenological events such as tilling, stem elongation, and maturation. Grain yield metrics are also mandatory.

The CERES model is now integrated in the Crop Simulation Model (CSM) of the Decision Support System for Agrotechnology Transfer (DSSAT) distributed by the International Consortium for Agricultural Systems Applications in Honolulu [4]. In its earliest form the DSSAT model was developed to simulate maize growth and development, but in the DSSAT-CSM, 27 different cropping system models are combined. At a minimum, it needs input data regarding incoming solar radiation, minimum and maximum temperatures, and rainfall. It can additionally utilize several soil-related metrics, such as bulk density, carbon content, and pH, as well as management-related metrics such as planting density, fertilization rates and irrigation data.

Another important crop growth model is the DeNitrification and DeComposition (DNDC) model, originally developed by [5]. In DNDC, crop growth is parameterized by generalized crop growth curves together with a crop-specific potential maximum grain yield. The actual grain yield is determined by the availability of nitrogen in the soil. Nitrogen uptake by the plants is controlled by the soil temperature profile and soil moisture. With this approach, the effects of differences in tilling, fertilizer use and irrigation can be taken into account by DNDC, because all of these management practices modify the soil regime and thus affect plant growth. DNDC also integrates crop growth processes with biogeochemical processes by including important nitrogen- and carbon-related processes like mineralization, ammonia volatilization, denitrification and nitrification, nitrogen uptake and leaching. The DNDC model, presently implemented with a daily time step, has been validated and used for many subnational and national case studies (e.g.: [6–8]).

The Environment Policy Integrated Climate (EPIC) model is a further Monteith type parametric model which is driven by the International Institute for Applied System Analysis. EPIC was originally designed to quantify the effects of erosion on soil productivity [9], but has since been expanded into a complex agro-ecosystem model that simulates the growth of crops under complex rotation management operations, such as irrigation, fertilization and tillage [10]. EPIC's main inputs are meteorological data, provided by the European Center for Medium-Range Weather Forecasts (ECMWF), soil type information from the Food and Agriculture Organisation (FAO) of the United Nations, and field management data.

A further example is the DAYCENT (Daily Century) model, developed by [11] and by [12,13].

These examples show a broad scientific and practical acceptance of the mechanistic modelling approach, particularly when coupled with analysis of management practices, in order to forecast agricultural outputs. However, in contrast to these mechanistic growth and development models, other approaches are typically used to account for the interaction between plants, atmosphere and soil. These so-called dynamic models calculate the uptake of atmospheric CO_2 by plants and the release of CO_2 by plants and soil in a physically consistent way that respects the conservation of energy and momentum. In the literature one can find descriptions of established dynamic vegetation models for use at scales from global to local. Examples are (LPJ), developed by [14] and modified by [15], ORCHIDEE, developed by [16], and BIOME3, developed by [17]. These models are driven by meteorological input data and parameterized for all land cover/land use classes, such as forest, grassland, shrubland and agricultural areas. The spatial resolution for most dynamic models ranges from a few degrees (global usage, e.g. [15] and [17]), to kilometres (regional usage, e.g. [18]). Their main outputs are Gross Primary Productivity (GPP), Net Primary Productivity (NPP), Net Ecosystem Exchange (NEE), Total Ecosystem Respiration (TER), and evapotranspiration. Plant development using plant-specific allocation rules is modelled mainly for global climate change analysis or historic plant development. Yield information of agricultural crops is not an output of these dynamic vegetation models.

We here discuss the Biosphere Energy Transfer Hydrology (BETHY/DLR) model, operated by the German Remote Sensing Data Center (DFD). BETHY/DLR is based on the formulation of [19] and modified by [18]; a description of the model can also be found in [20]. Besides meteorological input data, BETHY/DLR also requires land cover/land use maps and Leaf Area Index (LAI) time series as input. These observational data are obtained from satellite images. Thus the LAI time series of a pixel (typically 1 km^2) represents the mean phenology of the vegetation of that pixel. It is assumed that management practices as well as plant development are reflected and observed by the LAI time series.

The primary objective of this study is to investigate a new approach to the validation of modelled NPP from BETHY/DLR, at 1 km^2 spatial resolution, using statistical yield data for major crops. The crops used in validation are the major crops at level 3 of the "Nomenclature des Unités Territoriales Statistiques" (NUTS), a system of hierarchically organised territorial units intended for statistical purposes. For this validation approach, plant-specific yield data and modelled NPP are both downscaled to NPP per NUTS unit, providing a common basis for comparison. The presented validation results were cross-checked with the results of a validated EPIC run for a selected area (Marchfeld) in Austria [21]. Germany and Austria were selected as test areas due to the availability of detailed statistical data for validation and availability of the EPIC results. Computing time and hard disk storage issues restricted our modelling to the years 2000 and 2001.

2. Model and input data

2.1. *Model*

BETHY/DLR models photosynthesis using the combined approach of [22] and [23], which parameterizes the enzyme kinetics of photosynthesis at the leaf level. In this context, so-called C3 and C4 plants are distinguished because significant differences exist between the carbon fixation strategies of the two classes of plants (C3 and C4). In particular, C4 plants (including corn and sugar cane) can fix more atmospheric carbon dioxide at high temperatures than C3 plants (such as wheat and barley). In either case, in the next step the rate of photosynthesis is extrapolated from leaf to canopy level, taking into account the construction of the canopy as well as interactions between soil, atmosphere and vegetation. Radiation absorption in the canopy is approximated using the two-flux scheme of [24] with three canopy layers.

Stomatal conductance, evapotranspiration and soil water balance are also included for calculating NPP on an annual basis. The water supply available to plants is considered by calculating the demand for evapotranspiration using the approach of [3] against the criteria of [25], which assumes that evapotranspiration cannot be greater than the possible soil water supply to the roots. Water deficit (or water stress) is thus considered to occur at a soil water content at or below the permanent wilting point (PWP).

Autotrophic respiration is modelled in BETHY/DLR as the sum of the maintenance and growth respiration. Maintenance respiration is mainly determined by the plant-specific dark respiration, while growth respiration is assumed to be proportional to the difference between GPP and maintenance respiration.

The output of BETHY/DLR is a time series, in daily steps, of NPP at the spatial resolution and projection of the land cover classification (1 km^2, latitude – longitude projection with WGS84 (World Geodetic System 1984) datum). A schematic overview of the currently used input data and the internal model processes is presented in Fig. 1.

2.2. Input data – meteorology

BETHY/DLR uses remote sensing data and meteorological data to model the photosynthesis of plants, depending on weather and phenological conditions. The meteorological data (see Table 1) are derived from the operational processing chain of the ECMWF with temporal resolution up to four times daily and a spatial resolution of 0.25° × 0.25°. The meteorological data used are model analysis of the temperature (at 2 m height), wind speed (at 10 m height), soil water content (in the four uppermost soil layers), and cloud cover. Daily precipitation values are also derived from the ECMWF re-analysis project (ERA-Interim). From this dataset, the daily mean, minimum and maximum temperatures are calculated, as well as the daily mean cloud cover in three strata (high, medium and low) and the water vapour pressure. Daily temperatures are scaled by the difference of ECMWF reference height and global ETOP05 5-minute gridded elevation data and the temperature gradient of the U.S. Standard Atmosphere, which is −0.65 K/100 m:

$$T' = T_{\mathrm{ECMWF}} \times 0.0065\frac{\mathrm{K}}{\mathrm{m}} \times (h_{\mathrm{ECMWF}} - h_{\mathrm{ETOP}}) \tag{1}$$

T_{ECMWF} represents the reference temperature given by the ECMWF, h_{ECMWF} for the ECMWF reference height (geopotential) and h_{ETOP} for the height given by ETOP05 (which has a spatial resolution of about 9 km^2).

The daily average photosynthetic active radiation (PAR) is a function of global irradiation, calculated following [26] from the geographical coordinates, the day and year, and the atmospheric transmission, which depends on the degree of cloudiness. The daily average degree of cloudiness is calculated as a weighted sum of the cloud strata. The advantage of this approach, in contrast to the direct use of ECMWF radiation data, is the use of analysis data of cloud coverage which leads to more exact results than the direct use of radiation forecast data, as shown by [18]. The global irradiation is calculated for each location for each 1-h time step. The volumetric soil water content was needed to calculate the soil water budged of the model.

2.3. Input data – remote sensing

In addition to the meteorological data, the BETHY/DLR model is driven by two satellite remote sensing datasets, time series of the LAI, and detailed and homogeneous land cover/land use information. Phenology of the vegetation is indicated by the LAI time series, which is based on CYCLOPES 10-day compositae datasets downloaded from the POSTEL (Pole d'Observation des Surfaces continentales par Teledetection) databank (http://postel.mediasfrance.org).

For each pixel, analysis of the LAI time series is conducted to fill data gaps and eliminate outliers, using harmonic analysis (HA). HA decomposes a time series into a linear combination of suitable trigonometric functions, i.e. sine and cosine oscillations of particular periodicities. The HA technique corresponds to an approximate deconvolution of the power spectrum by iteratively finding and subtracting the highest peak of the time series power spectrum. This method was adapted for the correction of LAI time series data.

CYCLOPES provides land cover and land use information in their GLC2000 dataset. For the derivation of the GLC2000 land cover classes the "Land Cover Classification System (LCCS)" of the FAO was used [27,28]. In the GLC2000 dataset a classification with 22 different land cover classes is available representative for the year 2000. The global LAI and GLC2000 data are available in tiles of 10° by 10° as maps in rectangular projection annotated with latitude, longitude, and WGS84 date, with complete coverage of the study area (Germany and Austria). The CYCLOPES dataset was chosen because it is thought to be the most accurate dataset for agricultural areas [29].

In order to use the GLC2000 land use/land cover classification for NPP modelling with BETHY/DLR, the GLC2000 vegetation classes were translated to one of the 33 inherent BETHY/DLR vegetation classes (Table 2) which can be regarded as vegetation types. The translation will be discussed in the following section.

2.4. Plant parameters

In BETHY/DLR each vegetation type is linked with biochemical parameters such as the maximum carboxylation rate, the maximum electron transport rate, and other plant-specific photosynthesis related parameters. As can be seen in Table 3,

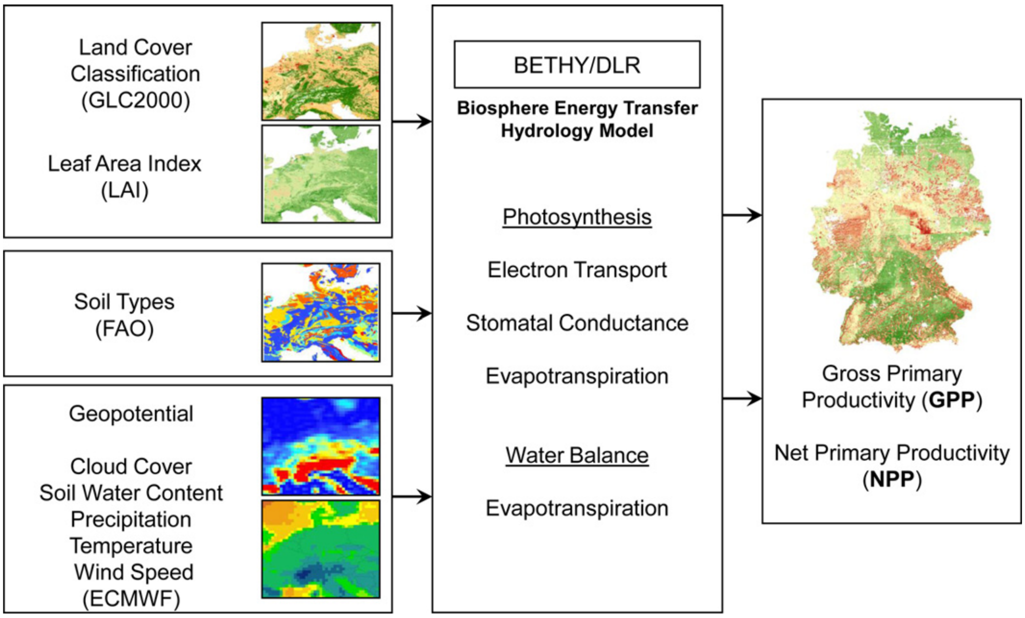

Fig. 1 – Model schematic for BETHY/DLR, left: input data, middle: internal model processes, right: output data.

it is possible to describe one GLC2000 class using a weighted average of two BETHY/DLR vegetation types. For this study only the two GLC2000 classes which are directly linked with crops are used. The weighting factors are set to 1.0 for the GLC2000 class “cultivated and managed area” (GLC-16). This is done under the assumption that this class describes a homogenously crop-covered area. The class “Mosaic: cropland/shrub cover or grass cover” (GLC-18) of GLC2000 was split between arable crops and grass cover using a weighting factor of 0.5 for each. This is done under the assumption that the area is completely vegetated, but only half with crops.

2.5. *Validation data*

To validate the modelled NPP of agricultural crops, empirical estimates of corn yields from the Federal Statistical Office of Germany and from Statistics Austria were used. In both countries farm structure surveys are conducted yearly. The agricultural surveys contain information about arable land, vineyards, horticultural farms, field vegetable farms and commercial fruit plantations, with associated yields. The “NUTS” hierarchical spatial classification starts with the member states of the European Community (EU) (NUTS-0), followed by regions of the EU (NUTS-1), separated to basic administrative units (NUTS-2) and ends with subdivisions of those basic administrative units (NUTS-3). As an example, Austria has been divided into three units, Eastern, Southern and Western Austria (NUTS-1). Each NUTS-1 level comprises the federal provinces (NUTS-2) such as the “Burgenland”. The NUTS-2 level is split into several NUTS-3 levels; in this case, the “Nordburgenland”, “Mittelburgenland” and “Südburgenland”. Besides these NUTS levels, a further subdivision is established in the empirical data indicating towns with charters, political districts and judicial districts.

For Germany and Austria the empirical data are given in NUTS-3 resolution. For Austria yields for summer rapeseed and grain maize are included, which are not present in the Germany statistics; otherwise the datasets provide the same information. As the German dataset contains gaps, necessitating a criterion to fill such gaps; we assumed that gaps for a given crop may be filled using the mean yield of the given crop from the German NUTS-3 units.

Before validating the modelled results, the 1 km^2 resolution NPP model output must be transferred to a Geographical Information System, taking into account the equi-rectangular map projection (latitude-longitude projection with WGS84 datum). Finally, the model results are aggregated to higher NUTS levels for comparison with the statistical data.

Table 1 – Summary of meteorological input data (including short names and code numbers) derived from ECMWF.

Parameter	Short name	Code number
Volumetric soil water layer 1	SWVL1/(SWL1)	039
Volumetric soil water layer 2	SWVL2/(SWL2)	040
Volumetric soil water layer 3	SWVL3/(SWL3)	041
Volumetric soil water layer 4	SWVL4/(SWL4)	042
Geopotential	Z	129
Large scale precipitation	LSP	142
Convective precipitation	CP	143
10 m U-velocity	10U	165
10 m V-velocity	10V	166
2 m temperature	2T	167
Low cloud cover	LCC	186
Medium cloud cover	MCC	187
High cloud cover	HCC	188

2.6. *Validation strategy*

The yield given by the empirical data does not represent the available biomass or the biomass potential and thus cannot be compared directly with the modelled yearly NPP sum, which

Table 2 – Vegetation types of the BETHY/DLR model with type number and vegetation parameters after [19]. V_M: maximum carboxylation rate at 25°; J_M: maximum electron transport rate at 25°; height; rooting depth.

No.	Vegetation types of BETHY/DLR	V_M [μmol m^{-2} s^{-1}] CO_2	J_M [μmol m^{-2} s^{-1}] CO_2	Height [m]	Rooting depth [m]
1	Trop. BL evergreen trees	62	118	30.0	6.9
2	Trop. BL deciduous trees	90	179	15.0	3.7
3	Temp. BL evergreen trees	41	82	15.0	3.0
4	Temp. BL deciduous trees	35	70	15.0	3.0
5	Evergreen coniferous trees	29	52	15.0	3.9
6	Deciduous coniferous trees	53	95	15.0	1.5
7	Evergreen shrubs	52	102	1.0	3.5
8	Deciduous shrubs	160	266	1.0	3.5
9	C3 short grasses	42	80	0.3	1.8
10	C3 long grasses	42	80	2.0	1.8
11	C4 short grasses	8	140	0.3	1.8
12	C4 long grasses	8	140	2.0	1.8
13	Tundra vegetation	20	37	0.3	0.5
14	Swamp vegetation	20	37	0.6	0.5
15	Arable crops	117	220	0.6	1.8
16	Irrigated crops	123	227	2.0	1.8
17	Trop. tree crops	60	106	2.0	6.9
18	Citrus crops	60	106	2.0	3.7
19	Temp. deciduous tree crops	123	227	2.0	3.0
20	Sugar cane	39	700	2.0	1.8
21	Corn	39	700	2.0	1.8
22	Rice	98	190	0.3	0.3
23	Cotton	123	227	2.0	2.1
24	Sugar beet	129	226	0.5	1.8
25	Soy	94	168	0.8	1.8
26	Sunflower	80	213	2.0	2.7
27	Barley	68	169	1.2	1.8
28	Wheat	83	193	1.5	1.8
29	Rapeseed	61	187	1.0	1.8
30	Beech	46	109	15.0	4.0
31	Oak	40	72	15.0	4.0
32	Spruce/Fir	10	24	15.0	2.8
33	Pine	17	30	15.0	4.0

represents the accumulated carbon of pixel over one year. In order to make a comparison possible, the yield data were used to estimate the above- and below-ground biomass, using simple growth allocation schemes. As a first step, it is necessary to calculate the total above-ground biomass, its dry matter and its carbon content. The literature gives a wide selection of so-called conversion factors, which give estimated corn-to-straw or leaf-to-beet ratios (Table 4) [31–34].

For this study we used values from [31], since they represent the latest available values, and also describe the greatest diversity of plant species. These relations suggest that, for example, a grain yield of 10 t of winter wheat will correspond to 11 t of straw. To calculate the dry matter for both the straw and yield fractions, standard estimates of water and carbon content were used, also from [31]. In this way, the carbon content of the dry matter of straw and yield can be estimated using formulae 2 and 3:

$$NPP_{yi} = yi \times \left(1 - H_2O_{yi}\right) \times C_{yi} \quad (2)$$

$$NPP_{stw} = (yi \times \sigma_{stw}) \times (1 - H_2O_{stw}) \times C_{stw} \quad (3)$$

where yi represents the yield of a particular plant species. H_2O_{yi} and H_2O_{stw} represents the water content, and C_{yi} and C_{stw} the carbon content, of the yield and straw fractions, respectively, for that plant species. σ_{stw} represents the plant-specific conversion factor of yield-to-straw or leaf-to-beet (Table 4).

To calculate the total amount of above-ground NPP, NPP_{agb}, one has to aggregate the NPP for the straw and yield fractions for each crop according to formula 4:

$$NPP_{agb} = NPP_{yi} + NPP_{stw} \quad (4)$$

This above-ground NPP is still not comparable with the modelled NPP, however. Because BETHY/DLR gives no information about where the accumulated carbon is stored, it is also necessary to calculate the below-ground NPP, NPP_{bgb}, from the empirical yield data. Simple so-called "shoot-to-root" ratios can be found in, for example, [30] or [33]. We used those of [30] (Table 4), assuming that these estimates, found for crops in Canada, are also representative of Germany and Austria. With these ratios one can estimate NPP_{bgb}:

$$NPP_{bgb} = NPP_{abg} \times \sigma_{agb} \quad (5)$$

σ_{agb} represents the shoot-to-root conversion factor for a specific crop (Table 4). The total NPP can now be expressed as:

$$NPP = NPP_{agb} + NPP_{bgb} \quad (6)$$

To calculate the total carbon stored in a NUTS area, this total NPP is integrated over the total cultivation area for each NUTS area and summed over all crops:

Table 3 – Translation of GLC2000 vegetation classes to BETHY/DLR vegetation types with weighting factors.

GLC2000 class	BETHY/DLR vegetation type	Weighting factor
Cultivated and managed areas (GLC-16)	Arable crops (Type 15)	1.0
Mosaic: cropland/shrub or grass cover (GLC-18)	Arable crops (Type 15) C3 short grasses (Type 9)	0.5 0.5

$$NPP_{NUTS} = \sum_i (NPP_i \times area_i) \quad (7)$$

The NPP_{NUTS} per administrative district can now be directly compared with the modelled NPP, also aggregated per NUTS area as previously described.

A comparison with data from eddy covariance towers could not be performed because our area of investigation, Germany and Austria, contains only three agricultural FLUXNET towers. Only one gathered data in 2001, but it had too small a footprint (<300 m for wind speeds up to 4 m s^{-1}) to quantify CO_2 fluxes on a km^2 scale.

3. Results

Before validating the annual sum of accumulated carbon modelled by BETHY/DLR for large regions (Germany and Austria), we compared the BETHY/DLR NPP results with the output of the EPIC model over a smaller region.

3.1. *BETHY/DLR comparison with EPIC*

The study site for this comparison was the Marchfeld region of Lower Austria, which is part of the Vienna Basin. With an area of about 100,000 ha, it is one of the largest plains in Austria, and about 75% of its area is used for agricultural production. The Marchfeld's natural boundaries are the river March to the east (the Austrian border to Slovakia), the hills of Weinviertel to the north, the Bisamberg mountains and the city of Vienna to the west, and the river Danube to the south. The EPIC model has been validated for the Marchfeld [21], making it worthwhile to compare BETHY/DLR to EPIC for this region. Since land use practices are not homogenously distributed in this area, five sectors were identified using cluster analysis methods [35]. Each sector has an area between 85 km^2 and 250 km^2. For our analysis one sector was not used, since its land cover is predominantly designated as urban. The NPP of both models for 2000 and 2001 across the four sectors is presented in Fig. 2.

Fig. 2 shows that BETHY/DLR estimates slightly more NPP (about 15% higher) than the calibrated EPIC model. Indeed, only in one case, sector 2 in the year 2000, was BETHY/DLR's estimate lower than EPIC's. According to [20], the calibration of the EPIC model for sugar beets in the Marchfeld has a standard deviation of less than 10%. Similarly, BETHY/DLR's NPP estimate for 2001 for the NUTS-3 Gänserndorf region (dominated by the Marchfeld) was about 10% higher than the estimated true NPP (not shown). Looking at all results for the Marchfeld region, it can be concluded that the modelled NPP from BETHY/DLR is in good agreement with both empirical data and the calibrated EPIC results, although with a tendency for minor overestimation.

3.2. *Validation of BETHY/DLR with statistical data*

Modelled NPP, at 1 km^2 resolution, for Austria and Germany was calculated as the annual sum of accumulated carbon for 2000 and 2001 (Fig. 3).

Yearly NPP is clearly higher in the southern states of Germany than in Germany's northern and eastern regions, in both years. Statistical analysis revealed that the mean annual NPP in carbon (over the whole area of investigation) is 253 [t km^{-2} y^{-1}] with a maximum of 662 [t km^{-2} y^{-1}] for 2000, and 239 [t km^{-2} y^{-1}] with a maximum of 577 [t km^{-2} y^{-1}] for 2001. The annual NPP in carbon for Germany is 76.4 Mt for the year 2000 and 73.3 Mt for 2001; for Austria, annual NPP is 7.9 Mt for 2000 and 6.2 Mt for 2001. The conversion of statistical yield data to NPP, as described above, delivers annual sums for Germany of about 67.2 Mt for 2000 and 71.5 Mt for 2001. For Austria these values are about 6.9 Mt for 2000 and 6.3 Mt for 2001. From this it may be seen that the modelled NPP for Germany for both years is overestimated (~13% for 2000 and

Table 4 – Corn-to-straw (leaf-to-beet) ratios and above- to below-ground ratios for selected crops. Carbon and water content for yield and straw fraction.

Field fruit	Yield/straw (*)	Root/shoot (+)	C_{yi}	C_{stw}	H_2O_{yi} (*)	H_2O_{stw} (*)
Grain	1.13	0.14	0.45 ($)	0.45 ($)	0.14	0.14
Wheat	1.1	0.21	0.455 (#)	0.446 (#)	0.14	0.14
Maize	0.8	0.18	0.456 (#)	0.5 (#)	0.14	0.14
Barley	1.05	0.32	0.45 ($)	0.459 (#)	0.14	0.14
Rye	1.3	0.19	0.475 (#)	0.457 (#)	0.14	0.14
Oat	1.1	0.4	0.45 ($)	0.45 ($)	0.14	0.14
Triticale	1.2	0.19	0.436 (#)	0.436 (#)	0.14	0.14
Beet	0.33	0	0.45 ($)	0.45 ($)	0.88	0.88
Potato	0.2	0	0.45 ($)	0.45 ($)	0.78	0.75
Sugar beet	0.7	0	0.45 ($)	0.45 ($)	0.77	0.84
Oil fruits	1.75	0.14	0.45 ($)	0.605 (#)	0.09	0.14
Rape	2	0.14	0.45 ($)	0.605 (#)	0.09	0.14

+: after Ref. [30], *: Ref. [31], #: Ref. [32], $: own estimations.

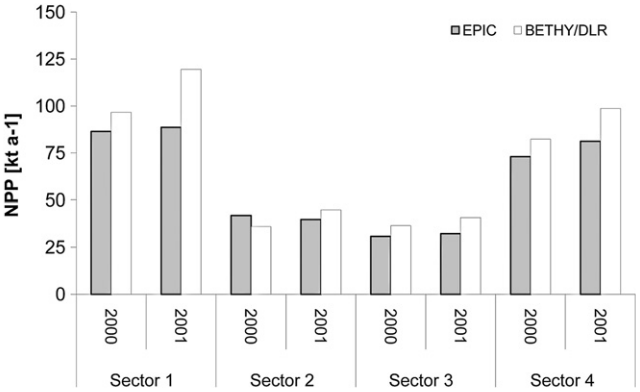

Fig. 2 – **Comparison of modelled NPP derived from BETHY/DLR and EPIC for all four sub-regions of the Marchfeld.**

~2% for 2001). For Austria the modelled NPP for 2000 is overestimated (~13%) for 2000, but underestimated (~1%) for 2001. Also notable is the very low annual NPP predicted for parts of eastern Germany (red pixels), particularly for 2001, but also, less strongly, for 2000. On the other hand, in 2001 modelled NPP in the southern parts of the study area are markedly higher than in 2000.

The sharp boundaries in the NPP maps (clearly visible for the year 2001 in the Saxo-Thuringia region) reflect the coarse pixel size of the ECMWF meteorological input data. This indicates that meteorology has a strong influence on the simulation. Examination of the meteorological input data for both years shows that large differences and leaps are not visible for most parameters; annual precipitation for the Thuringia region, however, is 480 mm y^{-1} for 2000, and about 760 mm y^{-1} for 2001.

Fig. 3 shows that the alpine regions of Germany and Austria have almost no modelled NPP. In contrast, the statistics of Germany and Austria report yield data for those areas. This is a consequence of the land cover data's spatial resolution of about 1 km^2, which is insufficient to describe the heterogeneous, small-scale structure of mid-European land use practices. Land cover classifications with higher-resolution exist for Europe, such as the CORINE land cover map. But when using high-resolution land cover maps, LAI time series data of the same spatial resolution are mandatory as input for BETHY/DLR. Since no high-resolution LAI time series are available for Austria and Germany, we selected the CYCLOPES LAI product together with the GLC2000, both available at 1 km^2, as best practice. Furthermore, the GLC2000 was derived with the same satellite sensor (VEGETATION on SPOT 4) as the LAI time series, providing data homogeneity.

To correlate empirical yields with BETHY/DLR's modelled data, the estimated biomass per pixel was aggregated to biomass per administrative district (NUTS-3 level) as previously described. Linear regression was used to assess the correlation between modelled and empirical yield, separately for 2000 and 2001, and separately for Germany and Austria (Fig. 4).

As shown in Fig. 4 BETHY/DLR underestimates the NPP for Germany in both years and for Austria in 2001. With a coefficient of determination of about 0.74 for 2000 and 0.78 for 2001, each bound with a slope of 1.21 and 0.86, respectively and an offset of 0.8 and 2.4, respectively, one can speak of a high degree of correlation. For Germany, the coefficient of determination for 2000 is 0.79 and for 2001 0.58. The slopes and offsets are 0.96 and 28.97 for 2000 and 0.73 and 51.56 for 2001.

The different validation results for Germany and Austria might be explained by differences in the distribution of cultivated plants between Germany and Austria, and by the method used to convert yield to NPP. The residual of miscellaneous crops for both statistics are 9% (Austria) and 13% (Germany). This is because additional crops (grain maize and summer rapeseed) are reported for Austria. Since the difference in the residuals can be regarded as low, the validation result for 2000 must be argued in a different way. For 2000, NPP in Austria is overestimated by BETHY/DLR for large NUTS-3

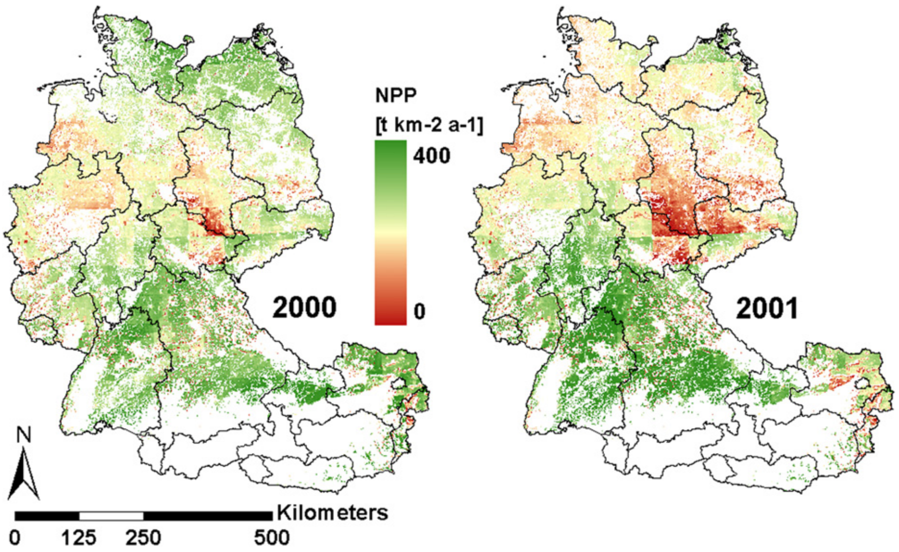

Fig. 3 – **Yearly NPP from BETHY/DLR for agricultural areas in Germany and Austria for 2000 (left) and 2001 (right). High NPP values are green, medium values are beige, and low values are red. White represents areas that do not belong to the GLC2000 classes GLC-16 or GLC-18 (Table 3). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)**

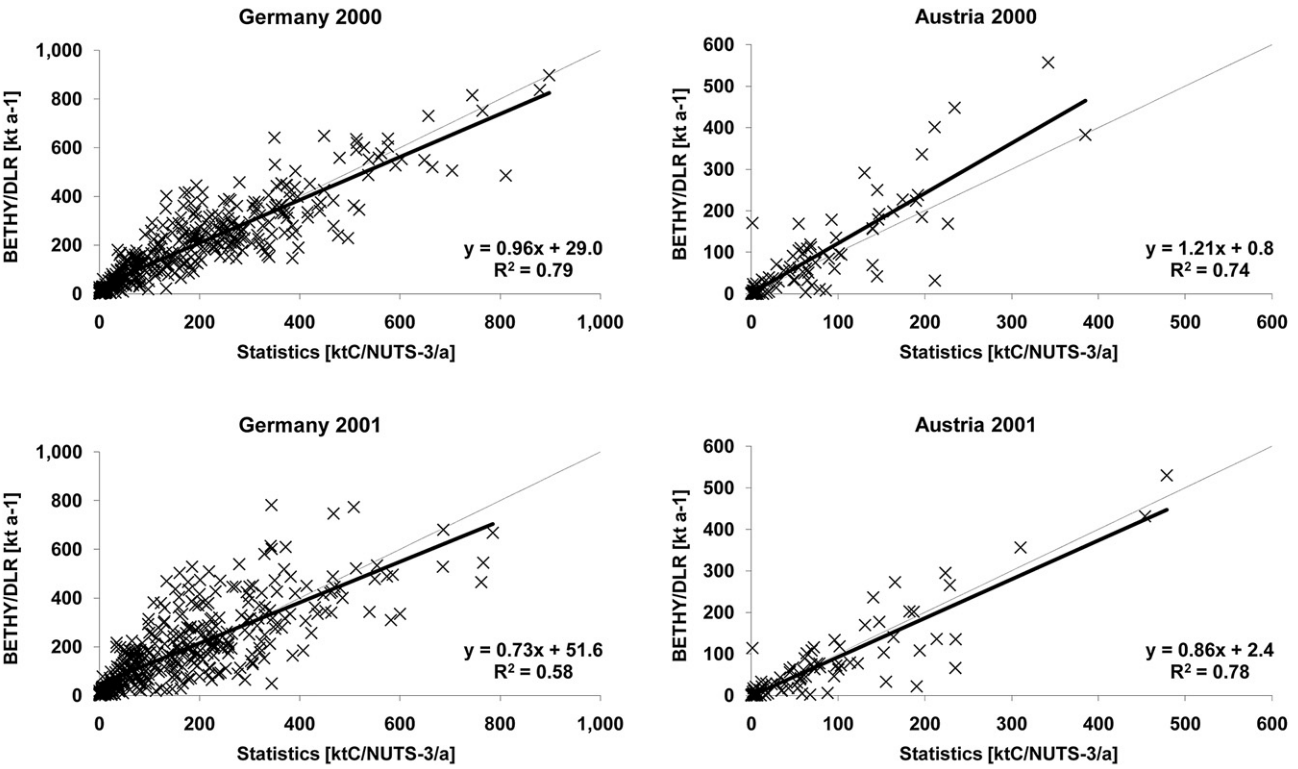

Fig. 4 – Correlation of modelled NPP with empirical NPP data for Germany (left) and Austria (right) for the years 2000 (top) and 2001 (bottom). Crosses indicate individual NUTS-3 administrative districts. Dotted lines indicate perfect correlation; solid lines indicate the correlation found by linear regression.

units as Hollabrunn, Horn, Mistelbach, and Neusiedel am See by a factor of about 2. A closer look at the empirical data reveals that up to 30% lower yields are reported for 2000 (in comparison to 2001) for the main crops of these NUTS-3 units. This yield reduction might be explained by a drought starting in April and ending in mid-May when the transition to the reproductive stages begins. Since the input data for BETHY/DLR (meteorological data and LAI time series) do not show large differences between the two years in this region, it is obvious that BETHY/DLR will estimate the NPP for these regions within the same order of magnitude. The ECMWF meteorological data show precipitation of 19.3 mm from April 3rd to May 18th, while the weather station Laa Thaya (Mistelbach, Austria) only reported 4.6 mm precipitation from that period. This water deficit resulted in a reduction in yield which could not be modelled by BETHY/DLR due to the unrealistic precipitation data from ECMWF.

It can be seen in Fig. 4 that the scatter for the German data is markedly greater than for the Austrian data, due to the difference in the number of available validation data points (Germany: 412, Austria: 99).

A closer look at the validation results for Germany in 2001 shows two distinct clouds within the scatter plot (Fig. 4). Detailed investigation reveals that most differences between the modelled and empirical biomass data in 2001 occur in regions which experienced low annual precipitation in 2000, especially in the Saxo-Thuringia region. We therefore hypothesize that the parameterization of the water cycle in BETHY/DLR might account for the underestimation of annual NPP.

In BETHY/DLR the soil water budget is tracked using a simple "bucket model" that represents the soil as a single layer. Modelling outputs show that the modelled soil water content diminished to nearly dry conditions (below the PWP) in 2000 in areas with relatively moderate annual precipitation. In contrast, the empirical soil water content data of ECMWF is available as a four-layered unequally spaced soil core. Fig. 5

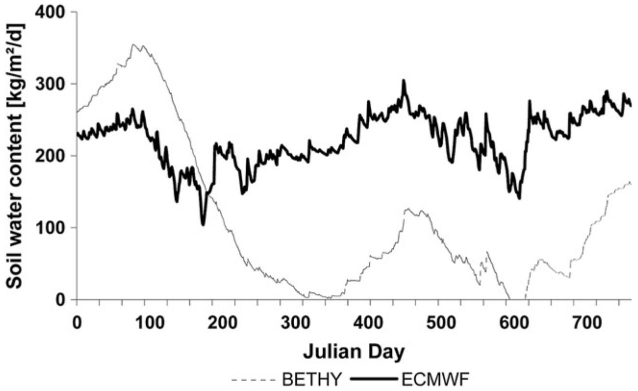

Fig. 5 – Comparison between the empirical mean plant-available soil water content derived from ECMWF data (solid line) and computed mean available soil water content of BETHY/DLR (dotted line) aggregated across the NUTS-3 regions Burgenland and Merseburg-Querfurt (Germany, Saxo-Thurinigia region) for the years 2000, 2001 and January 2002. January 1st, 2000, is represented by Julian day 0.

shows a comparison of measured (ECMWF) versus modelled (BETHY/DLR) soil water content for 2000, 2001, and January of 2002. This comparison is aggregated across the NUTS-3 regions “Burgenlandkreis” and “Merseburg-Querfurt,” because those regions are situated in one ECMWF tile. The four-layered ECMWF data was combined and adapted to a single layer with a soil water content having the same soil core depth as used for the BETHY/DLR simulation, to make comparison possible.

The ECMWF soil water content data are clearly different from the BETHY/DLR results. Differences of up to 100% can be found. The mean difference over the two years is about 51%. With the beginning of the vegetation cycle in 2000 (day 95), BETHY/DLR’s soil water content begins a continuous decrease that lasts to the end of the year. As a consequence, the soil water content remains unrealistically low in 2001, and is well below the PWP (zero) at the end of the vegetation cycle (day 600). At the end of 2001 the soil water content starts to recover, due to precipitation and the missing demand from vegetation. This trend is continued in 2002 (not shown in Fig. 5). In contrast to this pattern in the modelled soil water content, the ECMWF soil water content shows only a small increase at the beginning of 2000 and a small decrease from Julian Day 95 to Julian Day 180. From Julian Day 400 onward, both datasets show similar patterns.

This indicates that in principle the soil water model of BETHY/DLR exhibits the same patterns in soil water content as the ECMWF, but offset. This offset in soil water content affects the modelled NPP only when the modelled soil water content falls below the PWP, which reduces photosynthesis due to water deficiency. This offset might have been triggered by low annual precipitation rates for the region. As mentioned previously, ECMWF annual precipitation in this region was only 480 mm m^{-2} in 2000, but jumped to 760 mm m^{-2} in 2001. We hypothesize that the parameterization of the soil water budget in BETHY/DLR overestimates plant water use or evaporation from the soil, leading to the unrealistically low soil water content at the beginning of 2001 ($DOY = 365$). Annual precipitation in 2001 in Burgenland and Merseburg-Querfurt was insufficient to support soil water conditions adequate for plant growth. We conclude that the red marked regions in Fig. 3 for 2001 may be explained by an excessive loss of modelled soil water content during 2000, as a consequence of low precipitation in 2000. This underestimation of soil water content leads, as described above, to an underestimation of NPP in 2001. The lower correlation cloud found in Fig. 4 for Germany in 2001 is strongly linked with the overestimated decrease of soil water in these regions.

4. Conclusions

The Net Primary Productivity for the territories of Germany and Austria for 2000 and 2001 were modelled using the dynamic vegetation model BETHY/DLR. Inputs for the model were meteorological data from ECMWF, LAI time series from vegetation, and land cover/land use data from GLC2000. We here presented a new approach to validate modelled NPP using empirical data on acreage and averaged grain yields of main crops at the NUTS-3 level. Using conversion factors (corn-to-straw and shoot-to-root ratios), the statistical data were converted to NPP per NUTS unit for comparison. This method yielded high coefficients of determination (R^2 up to 0.74), allowing strong conclusions to be drawn about model validity. For German districts, BETHY/DLR substantially underestimated the NPP (17%), whereas for Austrian districts a slight overestimation (8%) was observed.

In areas where the land cover classification (GLC2000) provided insufficient information (particularly in the Alps), modelled NPP was significantly underestimated (even to zero), producing high discrepancies between modelled NPP and empirical data in those regions. This indicates that a spatial resolution of 1 km^2 is insufficient to describe the heterogeneous small-scale structure of mid-European land use practices. To improve modelling results, we recommend the use of a higher-resolution land cover product such as the MERIS GlobCover, with a resolution of 300 m × 300 m together with LAI time series also derived from MERIS.

In the Saxo-Thuringian Basin very low NPP values were modelled for 2001. Most of the large differences between modelled and observed NPP data for 2001 were found in regions with low annual precipitation in 2000. We demonstrated that the parameterization of the water cycle in BETHY/DLR (in particular, the use of a bucket model for estimating soil water content) was the underlying reason driving low NPP estimates in these regions that had experienced low precipitation the previous year.

Finally, we showed that natural drought were not reflected in the model results due to unrealistically precipitation rates reported in the input data.

This study illustrates a novel method of model validation that we believe will be useful in estimating biomass potentials from modelled NPP products on a medium resolution. This method could also be used as a downscaling approach for empirically derived NUTS-level data, since the model results could help to spatially represent the NUTS information.

Acknowledgements

This study was conducted under the “Regionale und globale räumliche Verteilung von Biomassepotenzialen” Project, promoted by BMVBS. Thanks are given to ECMWF and MediasFrance for providing their data. Thanks are extended to Prof. M. Kappas (Georg-August University, Göttingen) for mentoring and supervision, to Dr. M. Schroedter-Homscheidt (DLR) for detailed discussions on biomass-related topics, and to Benjamin C. Haller (McGill University, Montreal) for improving the readability and anonymous referees for reviewing and improving the manuscript.

REFERENCES

[1] Ritchie J, Otter S. Description of and performance of CERES-Wheat: a user-oriented wheat yield model. In: Willis WO, editor. ARS wheat yield project. Department of agriculture, agricultural research service. Washington, DC: ARS-38; 1985. p. 159–75.

[2] Monsi M, Saeki T. Über den Lichtfaktor in den Pflanzengesellschaften und seine Bedeutung für die Stoffproduktion. Jpn J Bot 1953;14:22–52.

[3] Monteith JL. Evaporation and environment in the state and movement of water in living organisms. In: Fogy GT, editor. Symposia of the society for experimental biology, vol. 19; 1965. p. 205–34.

[4] Jones CA, Kiniry JR. CERES-Maize: a simulation model of maize growth and development. Texas A & M University Press; 1986.

[5] Li C, Frolking S, Frolking TA. A model of nitrous oxide evolution from soil driven by rainfall events: 1. Model structure and sensitivity. J Geophys Res 1992;97(D9): 9769–76.

[6] Stange F, Butterbach-Bahl K, Papen H, Zechmeister-Boltenstern S, Li C, Aber J. A process-oriented model of N_2O and NO emissions from forest soils – 2. Sensitivity analysis and validation. J Geophys Res 2000;105(D4):4385–98.

[7] Cai Z, Sawamoto T, Li C, Kang G, Boonjawat J, Mosier A, et al. Field calidation of the DNDC model for greenhouse gas emissions in East Asian cropping systems. Glob Biogeochem Cycles 2003;17(4):1–10.

[8] Beheydt D, Boeckx P, Sleutel S, Li C, Van Cleemput O. Validation of DNDC for 22 long-term N_2O field emission measurements. Atmos Environ 2007;41(29):6196–211.

[9] Williams JR, Jones CA, Dyke PT. A modeling approach to determine the relationship between erosion and soil productivity. Trans ASAE 1984;27(1):129–44.

[10] Williams JR. The EPIC model. In: Singh VP, editor. Computer models of watershed hydrology. Highlands Ranch, CO: Water Resource Publications; 1995. p. 909–1000.

[11] Parton WJ, Ojima DS, Cole CV, Schimel DS. A general model for soil organic matter dynamics: sensitivity to litter chemistry, texture and management. In: Bryants RB, Arnoldm RW, editors. Quantitative modeling of soil forming processes. Madison, WI: Soil Sci Soc Am; 1994. p. 147–67.

[12] Del Grosso SJ, Parton WJ, Mosier AR, Hartman MD, Brenner J, Ojima DS, et al. Simulated interaction of carbon dynamics and nitrogen trace gas fluxes using the DAYCENT model. In: Schaffer M, Ma L, Hansen LS, editors. Modeling carbon and nitrogen dynamics for soil management. Boca Raton, Florida: CRC Press; 2001. p. 303–32.

[13] Parton WJ, Hartman MD, Ojima DS, Schimel DS. DAYCENT: its land surface submodel: description and testing. Glob Planet Change 1998;19:35–48.

[14] Prentice IC, Cramer W, Harrison SP, Leemans R, Monserud RA, Solomon AM. A global biome model based in plant physiology and dominance, soil properties and climate. J Biogeogr 1992;19(2):117–34.

[15] Bondeau A, Smith PC, Zaehle S, Schaphoff S, Lucht W, Cramer W, et al. Modelling the role of agriculture for the 20th century global terrestrial carbon balance. Glob Change Biol 2007;13:679–706.

[16] Krinner G, Viovy N, de Noblet-Decoudré N, Ogée J, Polcher J, Friedlingstein P, et al. A dynamic global vegetation model for studies of the coupled atmosphere-biosphere system. Glob Biogeochem Cycles 2005;19(GB1015). doi:10.1029/2003GB002199.

[17] Haxeltine A, Prentice AC. BIOME3: an equilibrium biosphere model based on ecophysiological constraits, resource availability and competition among plant functional types. Glob Biogeochem Cycles 1996;10(4):693–709.

[18] Wisskirchen K. Modellierung der regionalen CO_2-Aufnahme durch Vegetation. PhD Thesis. Bonn (Germany): Meteorologisches Institut der Rhein. Friedrich – Wilhelm –Universität; 2005.

[19] Knorr W. Satellite remote sensing and modelling of the global CO_2 exchange of land vegetation: a Synthesis Study. PhD Thesis. Hamburg (Germany): Max-Planck-Institut für Meteorologie; 1997.

[20] Knorr W, Heimann M. Uncertainties in global terrestrial biosphere modeling 1. A comprehensive sensitivity analysis with a new photosynthesis and energy balance scheme. Glob Biogeochem Cycles 2001;15(1):207–25.

[21] Schmid E, Sinabell F, Liebhard P. Effects of reduced tillage systems and cover crops on sugar beet yield and quality, ground water recharge and nitrogen leaching in the Pannonic region Marchfeld, Austria. Pflanzenbauwissenschaften 2004;8(1):1–9.

[22] Farquhar GD, von Caemmerer S, Berry JA. A biochemical model of photosynthesis in leaves of C3 species. Planta 1980; 149(1):58–90.

[23] Collatz GJ, Ribas-Carbo M, Berry JA. Coupled photosynthesis – stomatal conductance model for leaves of C4 plants. Aust J Plant Physiol 1992;19(5):519–38.

[24] Sellers PJ. Canopy reflectance, photosynthesis and transpiration. Int J Remote Sens 1985;6(8):1335–72.

[25] Federer CA. A soil-plant-atmosphere model for transpiration and availability of soil water. Water Resour Res 1979;15(3): 555–62.

[26] Burridge DM, Gadd AJ. The meteorological office operational 10-level numerical weather prediction model. London Road, Bracknell, Berkshire RG12 2SZ England; 1974. British Meteorological Office Tech. Notes Nos. 12 and 48. p. 57.

[27] Bartholome E, Belward. GLC2000: a new approach to global land cover mapping from earth observation data. Int J Remote Sens 2005;26(9):1959–77.

[28] DiGregorio A, Jansen LJM. Land cover classification system (LCCS): classification concepts and user manual for software version 1.0. Rome: United Nations Food and Agricultural Organization; 2001. 208 pp.

[29] Garrigues S, Lacaze R, Baret F, Morisette JT, Weiss M, Nickeson JE, et al. Validation and intercomparison of global leaf area index products derived from remote sensing data. J Geophys Res 2008;113(G02028). doi:10.1029/2007JG000635.

[30] Bolinder MA, Angers DA, Dubuc JP. Estimating shoot to root ratios and annual carbon inputs in soil for cereal crops. Agric Ecosyst Environ 1997;63(1):61–6.

[31] Köhler B, Kolbe H. Nährstoffgehalte der Fruchtarten im ökologischen Landbau. Leipzig: Sächsische Landesanstalt für Landwirtschaft, Fachbereich Pflanzliche Entwicklung; 2007. 21 pp.

[32] Kaltschmitt M, Hartmann H. Energie aus Biomasse – Grundlagen, Techniken und Verfahren. Berlin, Heidelberg: Springer-Verlag; 2001.

[33] Jackson RB, Canadell J, Ehleringer JR, Mooney HA, Sala OE, Schulze ED. A global analysis of root distributions for terrestrial biomes. Oecologia 1996;108(3):389–411.

[34] Kuratorium für Technik und Bauwesen in der Landwirtschaft e.V. (KTBL). Faustzahlen für die Landwirtschaft. Darmstadt: KTBL; 2005.

[35] Hofreither M, Eder M, Feichtinger F, Kniepert M, Liebhard P, Salhofer K, et al. Modellanalyse von ökonomischen Instrumenten zum Grundwasserschutz im Zusammenhang mit dem ÖPUL Programm. Endbericht Forschungsprojekt Nr. 1133 im Auftrag des BMLF und BMUJF. Vienna: Institute for Sustainable Economic Development, University of Natural Resources and Life Sciences; 2000. 135 pp.