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Modelling and Validating Biomass Potentials over Agricultural and Forest Areas

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Modelling and Validating Biomass Potentials Over Agricultural and Forest Areas

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Abstract

Using vegetation models to describe the carbon uptake by vegetation, Net Primary Production (NPP) has become an important tool to study the mechanisms of carbon exchange and to quantify the magnitude of terrestrial carbon sinks and sources. Various vegetation models are driven to simulate the carbon cycle in vegetated areas to estimate the NPP for different regions on regional to national scales. In this study the three models BETHY/DLR, G4M and EPIC are used to compute NPP for agricultural and forest test areas using high resolution datasets for the Wienerwald, Harz and Marchfeld regions in Austria and Germany. For the forest test areas, a validation for the G4M model is performed. Underestimations of up to 57% are shown, which are linked with high coefficients of determination (R^2 up to 0.75). For the agricultural test area a sensitivity analysis for the EPIC and BETHY/DLR is performed. Here it was demonstrated that variabilities of up to 62% could occur with changing climate conditions.

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Modelling and Validating Biomass Potentials Over Agricultural and Forest Areas

Markus Tum

1. Introduction

Modelling the net carbon uptake by vegetation (Net Primary Productivity, NPP) has become an important tool to study the mechanisms of carbon exchange between atmosphere and vegetation and to quantify the magnitude of terrestrial carbon sinks and sources. Simple, deterministic models describing the physical, chemical and plant physiological processes of plant development and the interaction of plants with the atmosphere can be applied to calculate the rate of carbon dioxide uptake of the plant through photosynthesis (called Gross Primary Productivity (GPP)). These models calculate photosynthesis according to a concept of Monsi Saeki, 1953 and Monteith, 1965. The general concept used to calculate carbon uptake by plants is that carbon uptake of well-watered and fertilized annual crop plants is linearly related to the amount of absorbed Photosynthetically Active Radiation (PAR). GPP may thus be calculated for each land cover type as the product of plant specific light use efficiency (LUE) and absorbed solar radiation. Modifying LUE functions to account for plant stress due to temperature or water and nutrient availability is required. Absorption of light by plants can be derived from satellite data (i.e. the fraction of PAR which is absorbed by the canopy (McCallum et al., 2010) or is calculated on the accumulation of dry matter).

Following the determination of GPP, autotrophic respiration of plants can be estimated. Autotrophic respiration is the oxidation of organic compounds found in roots, stems and leaves, to CO_2 and water. Different approaches to estimate autotrophic respiration can be found, taking into account the actual biomass or GPP Knorr, 1997. Goetz et al., 1999 proposed to scale the autotrophic respiration with the above-ground biomass and to include an exponential response of respiration to air temperature. The MODIS NPP algorithm requires the computation of autotrophic respiration based on inputs of Leaf Area Index (LAI) and temperature, along with look-up table values for allometric constants and the base rate of respiration Running et al., 2000. NPP is defined as the difference between GPP and autotrophic respiration. Taking into account heterotrophic (soil) respiration, one can estimate the Net Ecosystem Productivity (NEP). The C-Fix model is another Monteith type parametric model and was used by Veroustraete et al., 2002 to estimate the net ecosystem fluxes for the European continent. It is driven by NOAA/AVHRR data of the Normalized Difference Vegetation Index and meteorological data (temperature and daily incoming global radiation) which were obtained from about 800 weather stations administered by the World Meteorological Organisation. To derive meteorological data for the surrounding pixel of a station, a distance-weighted spatial interpolation technique was used. Veroustraete et al., 2002 validated their results with eddy correlation measurements and found coefficients of determination (r^2) of 0.64 for pine wood forests and 0.83 for deciduous mixed forests in Europe.

The Carnegie-Ames-Stanford Approach (CASA – model) introduced by Potter et al., 1993 and expanded by Field et al., 1995 is another example of a Monteith type parametric model. When the LUE approach is integrated in a coupled soil – plant - atmosphere model, e.g. the ALEX (Atmosphere–Land Exchange) model, daily estimates of evapotranspiration and carbon assimilation fluxes can be obtained Anderson et al., 2000.

In contrast to deterministic models, more sophisticated approaches are in use and under development taking into account the interaction between plants, atmosphere and soil. These dynamic models calculate the uptake of carbon by plants and the release of carbon by plants and soil in a physically consistent way regarding conservation of energy and momentum. In the literature one can find descriptions of established dynamic biomass models for use on different scales (global to local). Examples are the Lund-Potsdam-Jena Dynamic Global Vegetation Model (LPJ) which was developed by Prentice et al., 1992 and modified by Bondeau et al., 2007, ORCHIDEE, developed by Krinner et al., 2003 or BIOME3 by Haxaltine and Prentice, 1996. Each of these models is driven with meteorological input data and is parameterized for global use. Spatial resolution for most dynamic models ranges from some degrees (global usage e.g. Bondeau et al., 2007 and Haxaltine and Prentice, 1996), to kilometres (regional usage e.g. Wisskirchen, 2005). The main outputs are GPP, NPP and Net Ecosystem Exchange (NEE), Total Ecosystem Respiration (TER), and evapotranspiration.

Validation approaches typically employ data from eddy covariance flux towers. The inter-comparison of carbon and energy fluxes across ecosystems is a scientific goal in the FLUXNET and AmeriFlux network as well as in e.g. the CarboEurope project. With eddy covariance flux tower measurements only NEE can be determined quantifying the carbon fluxes at the scale of the footprint of the tower. Therefore, robust methods are developed to estimate heterotrophic respiration in order to partition NEE into NPP or GPP. As an example, the MODIS GPP product (MOD17, C4.5) for the time span from 2000 to 2003 was validated with tower eddy CO_2 flux-based estimates across diverse land cover types and climates Heinsch et al., 2007. Most selected sites are forest ecosystems in North America, but also arctic tundra, northern grassland, oak savannah and chaparral are included in the investigation. The authors found that MODIS GPP overestimates tower-based calculations by 20% - 30% dependent on the season and the ecosystem. The comparison of the annual MODIS GPP, modelled with global meteorological data from NASA’s Data Assimilation Office’s, with tower-based GPP revealed a coefficient of determination (r^2) of about 0.72.

The primary objective of this study is to validate NPP outputs of the BETHY/DLR model against the EPIC and G4M models on a high resolution (up to stand level (hectare)) for agricultural as well as forest areas in Austria and Germany. A further aim is to perform a sensitivity analysis of the BETHY/DLR and the EPIC model concerning their main input data e.g. land cover classification and meteorology. A part of the Harz Mountains, Germany and a part of the Wienerwald were chosen as test areas for forests and the Marchfeld region, Austria for agriculture.

2. Models and Input data

2.1 BETHY/DLR model description

BETHY/DLR integrates photosynthesis using the combined approach of Farquhar et al. 1980 and Collatz et al. 1992 which parameterizes the enzyme kinetics on the leaf level. Within this context, the enzyme kinetics of photosynthesis of C3 and C4 plants are distinguished. This is done, due to the reason that C3 and C4 plants have significant differences in the carbon-fixation. C4 plants (e.g. corn and sugar cane) can fix more atmospheric carbon dioxide at higher temperatures than C3-plants (e.g. wheat and barley). The photosynthesis of C3 plants is saturated within such environmental conditions. In a second step the rate of photosynthesis is extrapolated from leaf to canopy level taking into account the construction of canopy as well as the interaction between soil, atmosphere and vegetation. Radiation absorption in the canopy is approximated using the two-flux scheme of Sellers, 1985 with three canopy layers. Evapotranspiration, Stomatal conductance and soil water balance is included also regarding snow for calculating NPP on an annual basis. Water stress is considered by calculating the demand for evapotranspiration using the approach of Monteith, 1965 against the criteria of Federer, 1979. Here it is assumed that evapotranspiration can not be greater than a certain soil water supply via roots. 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 given by time series of NPP in daily steps. The resolution is given by the land cover classification. A schematic overview of the currently used input data and the internal model processes is presented in Figure 1. A more detailed model description can be found in Wisskirchen, 2005.

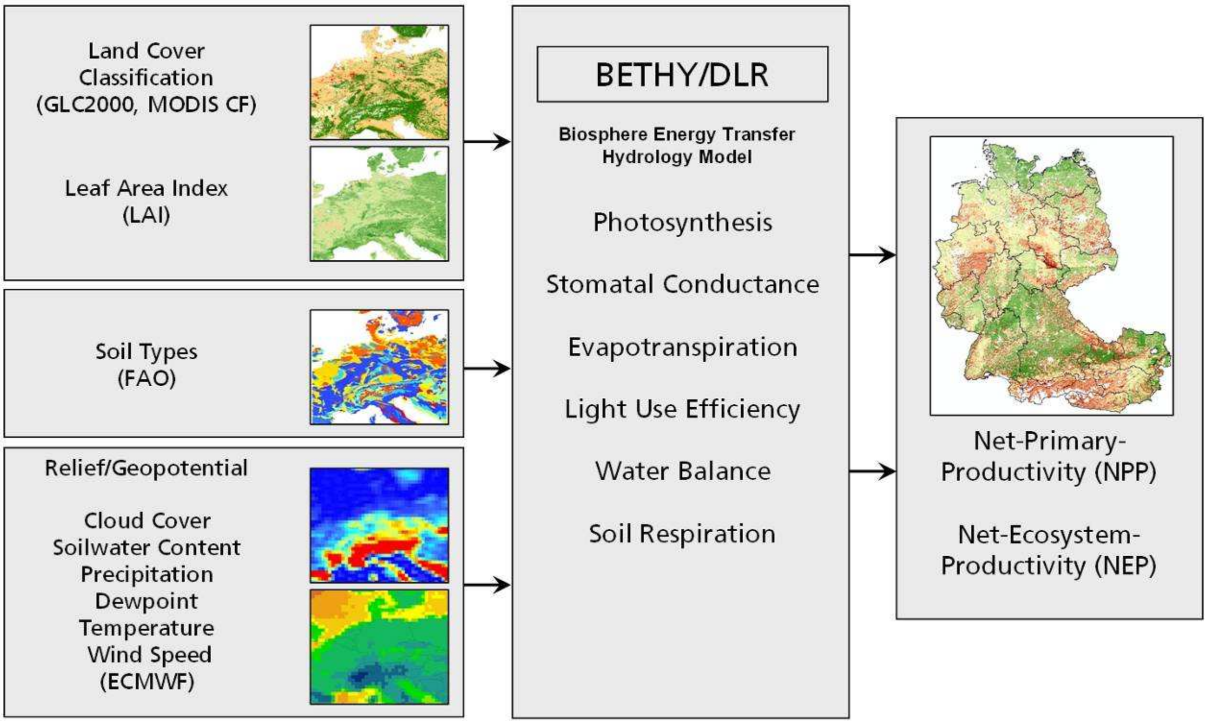

Figure 1 Model setup for BETHY/DLR, left: input data, middle: internal model processes, right: output data

2.1.1 BETHY/DLR input data

The BETHY/DLR model is driven by remote sensing data and meteorological input data to model the growth of plants, depending on climate conditions. In frame of this study meteorological input parameters from two different sources were used. . In its general model setup BETHY/DLR is run with data (see Table 1) derived from operational data by the ECMWF with temporal resolution of up to four times a day and a spatial resolution of 0.25° x 0.25°. These are model analysis of 2m air temperature, wind speed at 10m above ground, the soil water content of the four upper layers and cloud cover. Daily values of precipitation are derived from the ECMWF re-analysis project (ERA-40). From this dataset, the daily mean, minimum and maximum of temperature are calculated, as well as the daily mean of cloud cover in all three strata (high, medium and low) and the water vapour pressure. The daily temperature values are scaled with 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 -0.65K per 100m.

Table 1 - Summary of meteorological input data (including short names and code numbers), which are 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 meter U-velocity	10U	165
10 meter V-velocity	10V	166
2 meter temperature	2T	167
Low cloud cover	LCC	186
Medium cloud cover	MCC	187
High cloud cover	HCC	188

The daily average PAR is calculated from global irradiation. This is done following the approach taken by Burride and Gadd, 1974 from Stull, 1988 from the geographical coordinates of the day and year, and a transmission, which depends on the degree of cloudiness. The daily average degree of cloudiness is calculated as weighted sum of each 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 Wisskirchen, 2005. For each location the global radiation is calculated in the time step of one hour.

The soil water content is only needed for the transient phase of the model. Afterwards the model calculates the soil water content independently, according to the hydrological boundary conditions. Investigations of Wisskirchen, 2005 have shown that in most cases sufficient condition are reached after a transient phase of about one year. In the current version of BETHY/DLR the stable conditions are determined dynamically.

In the frame of this study an additional dataset was used. Daily data of maximum and minimum temperature, precipitation and wind-speed are taken from high resulted data provided by BOKU, Vienna. The data was computed to create climate change scenarios for the Austrian territory, with a spatial resolution of 1km x 1km and daily temporal resolution (Strauss et al., 2010). In order to compute various scenarios, measured data from 1975 to 2007 from various sources were taken to trim the data. For this Austria was divided in sixty climate clusters. These climate clusters have been derived from the ÖKLIM dataset (Österreich Klima; Auer et al., 2000) using mean annual precipitation sums and mean annual temperatures from the period 1961-1990 and are shown in Figure 2. This dataset has been tested for its quality. The mean annual temperatures and precipitation sums from the period 1961-1990 are used to find the respective weather stations for the climate clusters. The climate clusters and cluster classification criteria based on the ÖKLIM dataset can be found in (Auer *et al.*, 2000).

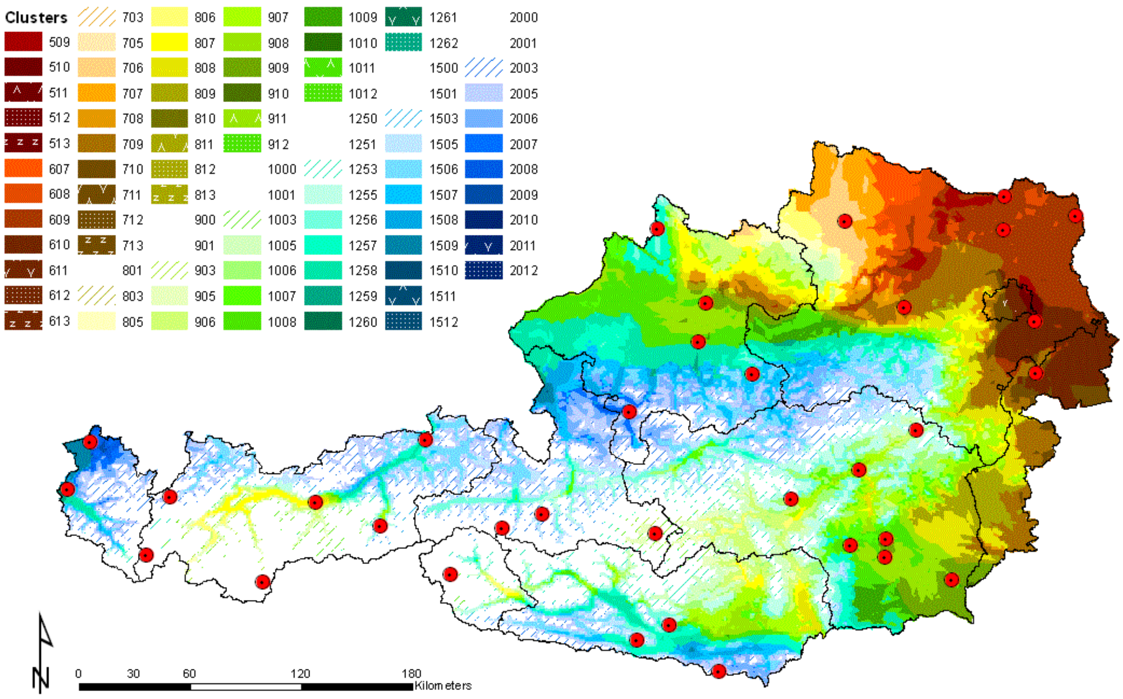

Figure 2. Climate clusters based on precipitation and temperature classes for Austria averaged over the period 1961-1990. Red dots represent weather stations. (Strauss et al., 2010)

33 inherent weather stations were used to compute the climate scenarios. A weather station can be representative for more than one climate cluster. The primal criteria to find a respective weather station for a climate cluster are the mean annual precipitation sums. Mean annual temperatures are adjusted with a correction factor. The temperature correction factor is calculated using the mean annual temperature, which is increasing from 1961 (starting year of classification) to 1975 (starting year of the historical 33 year long daily weather time series) by 0.75 °C. Consequently, the average annual temperature trend is approximately 0.05 °C per year. The temperatures are corrected for each climate cluster using the differences between the class mean together with the fifteen-year temperature trend of 0.75 °C and the mean annual temperature from the period 1975-2007. Consequently, 33 year long daily weather time series of historical meteorological data (1975-2007) for the 60 climate clusters including the temperature corrections were built and used as input data for BETHY/DLR.

In addition to the meteorological data, the BETHY/DLR model is driven by two remote sensing data sets. A time series of the LAI and a detailed and homogeneous land cover / land use information. Phenology of the vegetation is initiated by time series of LAI, which is based on CYCLOPES 10 day composites datasets from POSTEL (Pole d'Observation des Surfaces continentales par TELedetection). For each pixel, time series analysis is applied in order to eliminate data gaps and outliers. In this study the method of the harmonic analysis (HA) is used. The HA belongs to the method of "least squares”, whose most famous member is the Fourier transformation. The German Remote Sensing Data Center uses this method for operational processing of data from the Global Ozone Monitoring Experiment Dech, 1998 where it has been adapted for the use of LAI data. CYCLOPES also provides information of land cover and land use and is available as GLC2000. For the derivation of the GLC2000 land cover classes the “Land Cover Classification System (LCCS)” of the FAO was used (Bartholome et al, 2002; DiGregorio, 2001). With GLC2000 a classification with 22 different land cover classes is available representative for the year 2000.

In order to use the GLC2000 land use / land cover classification for NPP modelling with BETHY/DLR, the GLC2000 vegetation classes have to be translated to one of the actual 33 inherent BETHY/DLR vegetation classes which can be regarded as vegetation types. In BETHY/DLR each vegetation type is linked with biochemical parameters as i.e. the maximum carboxylation rate or the maximum electron transport rate and other plant specific parameters i.e. maximum rooting depth and maximum height. These parameters describe the photosynthesis of plants.

In addition to the GLC2000 the Corine Land Cover 2000 (CLC2000) was used to quality control the GLC2000 dataset. The CLC2000 (Bossard et al., 2000) data was derived from LANDSAT and SPOT satellite images and is valid for the year 2000. It was forced by the European Commission, aimed at gathering information relating to the environment on certain priority topics for the European Union (air, water, soil, land cover, coastal erosion, biotopes, etc.). The CLC2000 is available in different spatial resolutions (100m x 100m, 1km x 1km). For this study the high resolution version (100m x 100m) was used.

2.2 G4M

The Global Forest Model (G4M) is a geographically explicit model to assess land use change decision making. The model evolved from a model to assess afforestation in Latin America (Benitez et al., 2004) to a global forestry scenario analysis tool covering avoided deforestation, afforestation and forest management decision making (Kindermann et al., 2006) and Kindermann et al., 2008). The model is driven by the global mean NPP map from Steve Running (Citation?), forest cover information, taken from GLC2000 and monthly average temperature and precipitation from worldclim (Hijmans et al., 2005). Increment functions are used to calculate land use change decisions within a 0.5x0.5° grid taking sub-grid information into account as described in (Kindermann et al., 2006). Deforestation is modelled assuming that if the net present value of agriculture together with benefits from selling wood after clear-ut of the forest is greater than net present value of forestry. The net present value of agriculture is modelled with an agricultural land price in form of a Cobb-Douglas production function, which assumes that agricultural sustainability and population density are independent variables (Benitez et al., 2004). Afforestation takes places in areas were the environmental conditions are suitable for forestry and the net present value of forestry is greater than for agriculture. To assess afforestation and deforestation, yield tables and yield estimations are used to parameterize increment functions. This is done with the use of maps describing NPP, forest cover, soil, temperature and precipitation.

2.3 Epic

The Environment Policy Integrated Climate (EPIC) model was originally designed to quantify the effects of erosion on soil productivity Williams et al., 1984. Since its inception, EPIC was modified into a complex agro-ecosystem model suitable to simulate the growth of crops taking into account complex rotation management operations, such as irrigation, fertilization and tillage Williams, 1995. It is capable to simulate many processes that occur on the land as a result of climate forcing, landscape characteristics, soil conditions and management schemes (Williams et al., 1984; Williams, 1995; Izaurralde 2006). Biophysical processes, which can be simulated with the EPIC model include among others plant and crop growth, heat and water balance, wind and water erosion, and nutrient cycling.

These processes are simulated with daily time steps. EPIC contains algorithms that allow for a complete description of the hydrological balance at the small watershed scale (up to 100 ha) including snowmelt, surface runoff, infiltration, soil water content, percolation, lateral flow, water table dynamics, and evapotranspiration. An included weather generator can be used to estimate precipitation, temperature, solar radiation, wind, and relative humidity or it can be input exogenously. EPIC uses the concept of radiation-use efficiency by which a fraction of daily photosynthetically active radiation is intercepted by the plant canopy and converted into plant biomass. The leaf area index is simulated as a function of heat units, crop stress and development stages. Daily gains in plant biomass are affected by vapor pressure deficits and atmospheric CO_2 concentration (Stockle et al., 1992). By estimating the harvest index which is affected by the heat unit factor and which includes the amount of the crop removed from the field as well as the above-ground biomass, crop yields are estimated. Stress indices for water, temperature, nitrogen, phosphorus and aeration are calculated daily using the value of the most severe of these stresses to reduce potential plant growth and crop yield. Similarly, stress factors for soil strength, temperature, and aluminum toxicity are used to adjust potential root growth (Jones et al., 1991). The potential water use is reduced when the soil water storage is less than 25% of plant-available soil water by using dependencies on the soil water contents at field capacity and wilting point.

3. Results and Discussion

The following provides the results and discussion of the comparison studies over the two forest regions (Part I) followed by the results and discussion of the comparison study over the agricultural region (Part II).

3.1 Part I: Forest

In order to perform quality control and sensitivity analysis of the models, test areas for agriculture and forested areas were chosen. The selection was performed for areas for which the most complete and high resolution input and validation data were available. Two test areas for forest sides (Harz and Wienerwald) were chosen.

3.1.1 Test area Harz

The Harz is the highest mountain range in northern Germany. The terrain extends over three German states (Lower Saxony, Saxony-Anhalt and Thuringia) and occupies an area of around 2200 km². The tree class distribution might be described as needle leafed in the centre but with a surrounding of deciduous forest (see Figure 3). Green colour represents deciduous trees whereas orange colour represents needle leaved forest. White spaces are either non forested areas or private forest areas and were not taken into account for this study

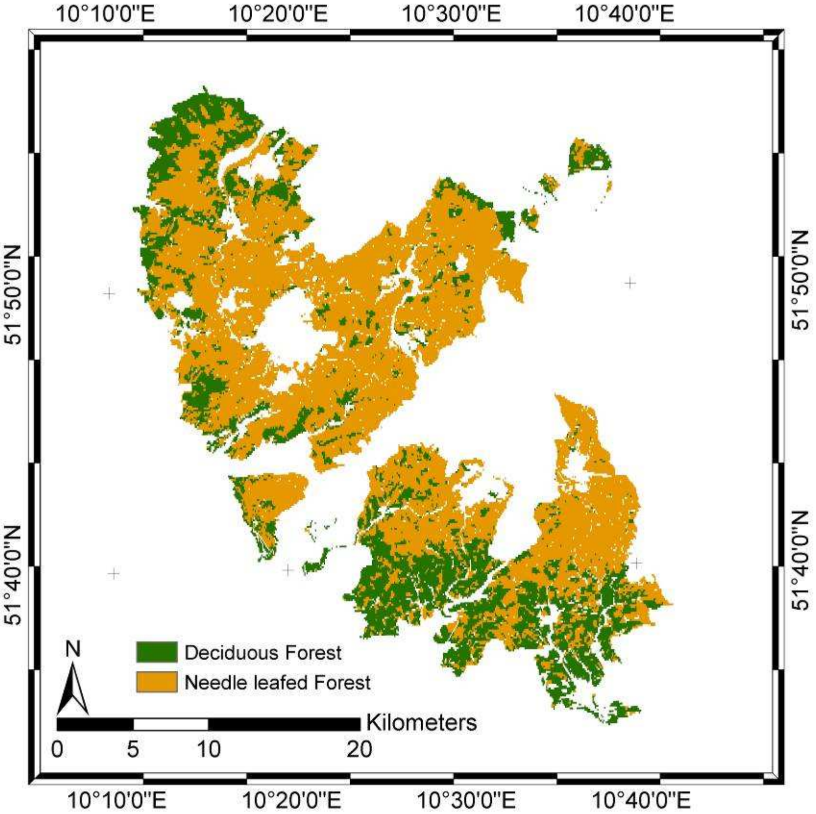

Figure 3. Tree cover distribution of the test area "Harz".

For the frame of this study a dataset for the state forest area of Lower Saxony was provided by the Northwest German Forest Research Station (NW-FVA). The dataset is vector based and contains data about the tree species, age, height and percentage of coverage distribution of the two mayor tree species for each vector cell. Furthermore the total percentage of coverage as well as increment and stock of merchantable wood is given for validation. Hence BETHY/DLR is run with grid based data the given dataset had to be rearranged. It was chosen that grid cells of 100m x 100m are capable to represent the original data properly without mayor information loss. In order to compare the results of BETHY/DLR with the G4M model, the G4M model was run with the same dataset. LAI time series for the BETHY/DLR model were taken from the CYCLOPES dataset, but had to be adapted. It is assumed that the mean total coverage (COV_m) of all pixels of NW-FVA data occupying one CYCLOPES pixel is representative as percentage coverage for the original LAI (LAI_o) value. Furthermore it is assumed, that the difference of mean total coverage and actual coverage of a single NW-FVA pixel (COV_p) is capable to linearly adapt the LAI value following the formula:

$$LAI_n = LAI_o + LAI_o \times \left(COV_m - COV_p\right) \qquad (1)$$

where LAI_n represents the adapted LAI.

3.1.2 Test area Wienerwald

A part of the Wienerwald is chosen as a second test area for forests. The dataset was provided by the Research and Training Centre for Forests, Natural Hazards and Landscape (BFW) Austria and represents a part of the Austrian forest inventory. For around 330 geo referenced locations up to 20 individual trees were measured and given for two time steps (1992/96 and 2000/02) (see Figure 4).

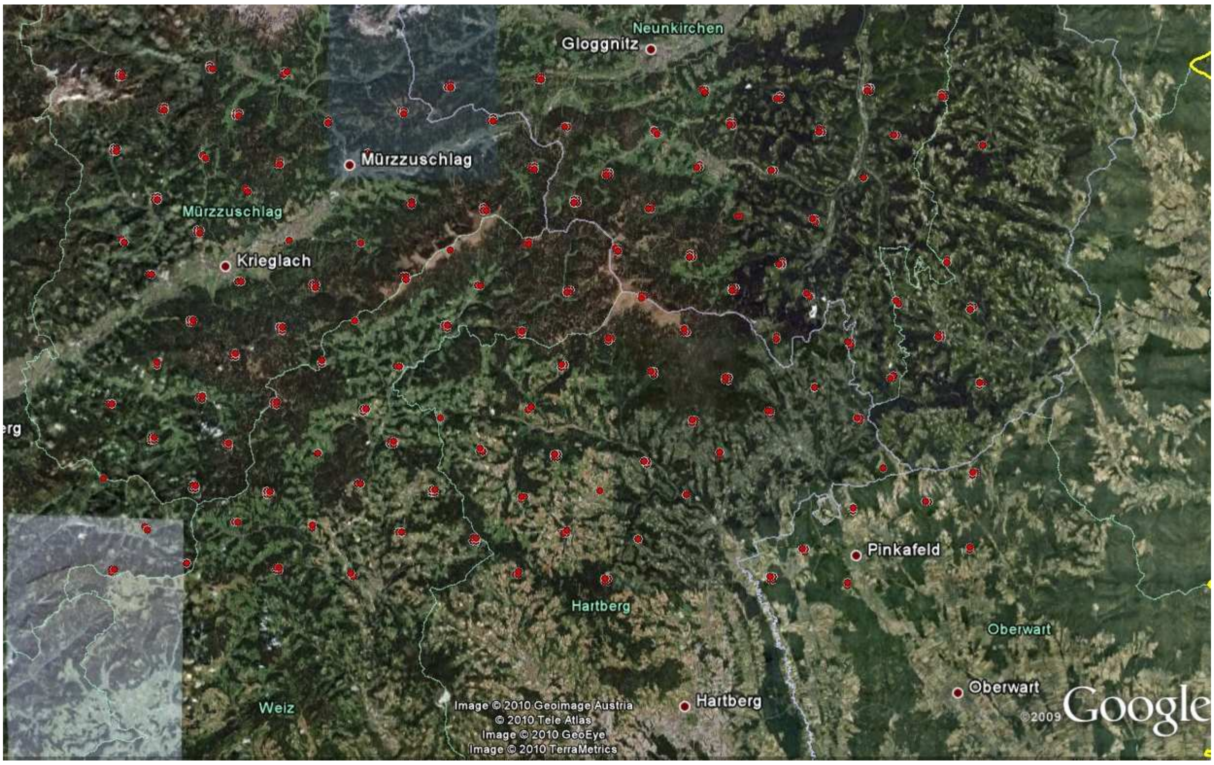

Figure 4.Overview over the test area Wienerwald. Red dots symbolise measurement points.

Information about tree age and tree species distribution, diameter in breast height and height are given.

In addition information is available of about how many single tree individuals of each of the measured and described trees are representative for one hectare. Also the standing merchantable wood is given. To estimate the percentage of coverage for each tree individual the diameter in breast height is taken to estimate total coverage (cov) of all representatives (n) following formula 2:

$$\text{cov} = \pi \times \frac{d^2}{4} \times n \qquad (2)$$

The so estimated total coverage for each tree type is used for the G4M. Hence the BETHY/DLR model is not taking into account the age distribution of forests only the percentage of coverage for each tree species for each data point is estimated in the same way as described above. To get information about the increment of standing merchantable wood (inc) given by the statistical data, the difference of standing merchantable wood (mw) of both time steps is calculated and multiplied with the number of representative tree units for the first observation following formula 3:

$$inc = \frac{mw_{(t_{(i)})} - mw_{(t_{(i-1)})}}{t_{(i)} - t_{(i-1)}} \times n \qquad (3)$$

Where t(i-1) represents the first measurement and t(i) for the second.

3.1.3 Validation of the G4M model (and BETHY)

To perform the validation analysis for the two models (BETHY/DLR and G4M) were run for the around 57.800 pixels in the Harz region, For each of the pixels the two main tree species as well as age, height, percentage of coverage and standing biomass was available. Around 40.000 pixels are covered with needle leaved tree species, mainly spruce. The rest (17.800) pixels are covered with broad leaved deciduous tree species. Hence for all of the pixel information about the two major tree species are available a new land cover classification is created. The statistical data distributes the major tree species in explicit species as well as mixed cover. In order to make the data available for BETHY/DLR the ne created land cover has to be translated to one of the currently 33 available vegetation types of BETHY/DLR, which can be found in Table 2. The weighting factor, giving information about the percentage of coverage was calculated following formula 4:

$$Weight_i = \mathrm{cov}_{tot} \times \mathrm{cov}_i \qquad (4)$$

Table 2 - Translation of Harz forest land cover vegetation classes to BETHY/DLR vegetation types with weighting factors

Forest landcover	BETHY/DLR vegetation type	Weighting factor
Oak	Oak (Type 31)	Formula 2
Beech	Beech (Type 30)	Formula 2
Mixed trees	Temperate broadleaf deciduous trees (Type 4)	Formula 2
Spruce and Fir	Spruce / Fir (Type 32)	Formula 2
Pine	Pine (Type 33)	Formula 2
Larch	Deciduous coniferous trees (Type 6)	Formula 2

Before a validation of the modelled results is possible, the modelled NPP needs to be transformed to merchantable wood content. Following the approach of *Pistorius and Zell (2005)* the accumulated yearly accrescence of carbon may be calculated, if the density of wood (divided in trunk and branches fraction), the ratio of below ground biomass to above ground biomass, the accrescence of merchantable wood, conversion factors for carbon content to dry matter content and a biomass expansion factor (BEF) are available. The BEF describes the ratio between crown and trunk development and depends on tree species and age (*Burschel et al. (1993); Wirth et al. (2004)*). Hence these numerous data are in general only valid for selected small scale areas *Pistorius and Zell (2005)* improved the BEF to the tree species depending volume expansion function (VEF). The advancement of the VEF is that the ratio between canopy and branch is calculated by using regression parameters (a and b). Further information about the stem wood volume (V_B) are not need, hence it can be estimated if the parameters a and b and the volume content of merchantable wood (Vmw) is available. The VEF of a tree species can be expressed as:

$$VEF = \frac{Vb}{Vmw} = \frac{a + b * Vmw}{Vmw} \tag{5}$$

The regression parameters were calculated by extensive field measurements by *Pistorius and Zell (2005)* and are available for the main tree species (birch, beech, oak, alder, spruce, chops, fir and larch) taking into account tree age and species specific variabilities in carbon allocation. For the frame of this study it is assumed that the mean ages of each tree specie is representative for an administrative region (NUTS-1 unit).

In order to estimate the carbon stock (C) of a tree, the living biomass is first divided to merchantable wood and branch volume and root mass. The wood stock of a single tree may be calculated using the diameter at breast height, tree height and steam diameter at seven meter height (*Kublin and Scharnagl (1998)*). This volume has to be expanded to above ground tree volume to take into account branches and twigs. Afterwards the masses are calculated with multiplication of the volumes of aboveground biomass with tree species specific densities:

$$C = \left[Vmv * D_{mw} + Vmv * D_b * (VEF - 1)\right] * (1 + R) * CF \tag{6}$$

where D_{mw} and D_b represent the bulk densities of merchantable wood and branches, R the shoot to root ratio and CF a conversion factor of the carbon content, which is estimated as 0.5. Typical values for D_{mv}, D_b and R can be found in *Pistorius and Zell (2005)*. By applying formula 5 to formula 6 V_{mw} can thus be expressed as:

$$Vmw = \frac{\frac{C}{(1 + R) * CF} - D_b * a}{D_{mw} + D_b * (b - 1)} \tag{7}$$

To gain information about total V_{mw} which has accrescenced in a NUTS unit the now available V_{mw} per tree species has to be summed to V_{mv} per NUTS area:

$$V_{mw_{NUTS}} = \sum_i \left(V_{mw_i} * area_i\right) \tag{8}$$

The so describable V_{mw} per administrative area can directly be linked with the prepared data.

In figure 5 the increment of merchantable wood derived from the statistical data for the Harz region is presented. These values are valid for the whole validation period (2000-2003). The spatial resolution of the map is 100m x 100m. The colour scheme is chosen to symbolize high NPP values with green, moderate with sandy and low values with red colours.

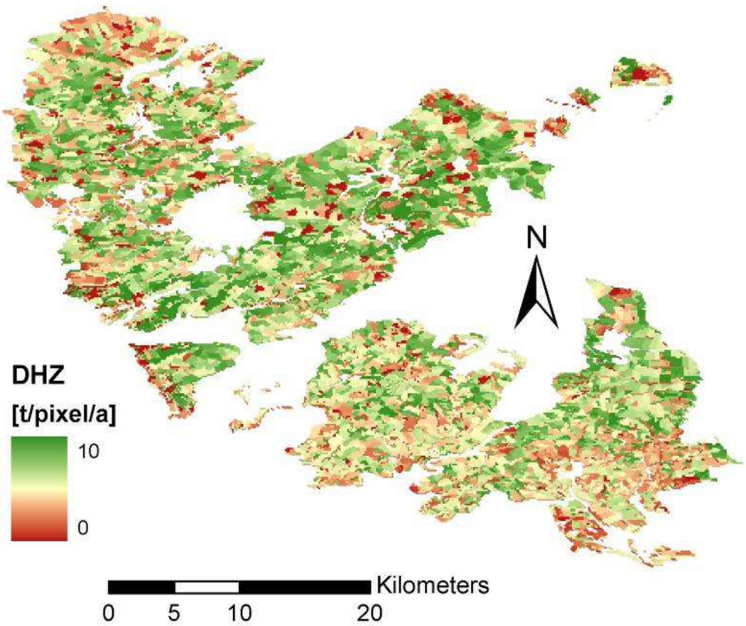

Figure 5: Statistical increment for the state forest of the Lower Saxony part of the Harz Mountains. Valid for 2000-2003.

It is obvious that the higher values can be found in the central part of the area of investigation, whereas lower values can be found at the borders. When comparing the results with the tree cover distribution (figure 3), it can be said that the systematic of higher and lower NPP values follow the distribution of deciduous and needle-leaved trees. For the whole area of investigation a mean annual increment of merchantable wood of around 332.571 tons distributed over an area of about 376 km².

In figure 6 the model result of BETHY/DLR for the years 2000 to 2003 is presented as annual sums of increment of merchantable wood in tons per pixel.

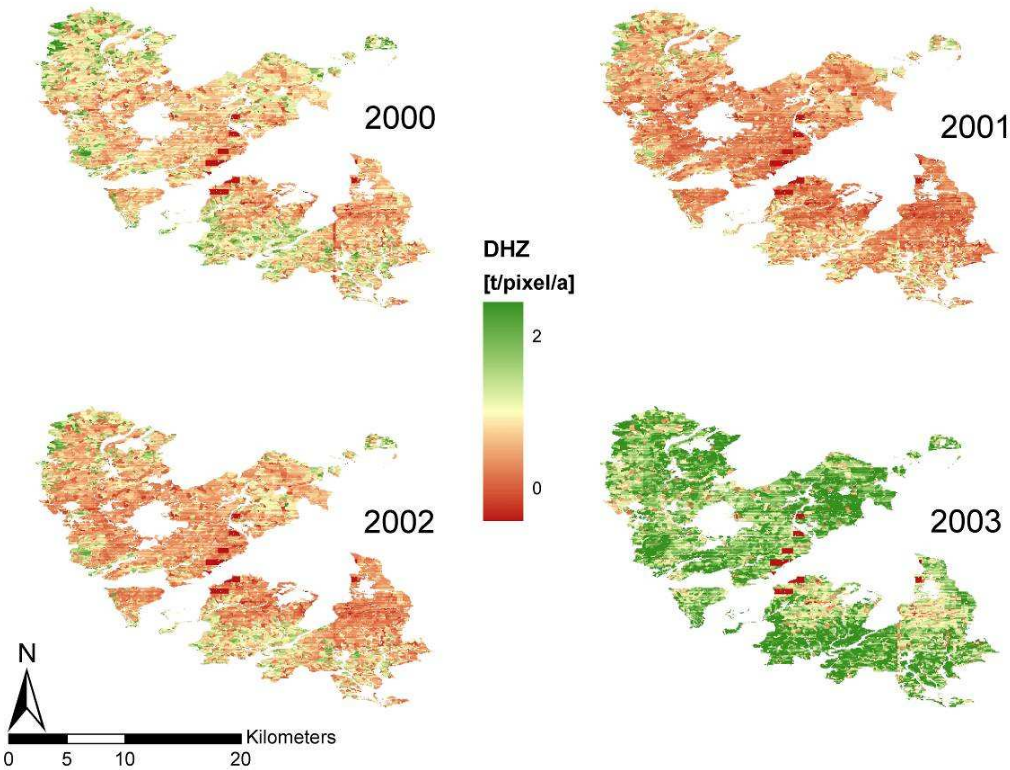

Figure 6: Merchantable wood content of modelled annual NPP increment for the Harz test area for the years 2000-2003.

One can see that the amount of increment highly differs during the year. The highest amounts are found for the year 2003. Furthermore it can seen, that the results show the opposite to the statistical data. The inner parts of the test area are the parts with lower merchantable wood increment and the outer parts have higher values.

Hence for the forest areas not only a validation of BETHY/DLR is performed, but also a validation for the G4M model, the G4M was driven with data from the same dataset. In a first step the vigour is estimated, regarding geographical position. Vigour is estimated by temperature, precipitation and soil data. In a second step tree species, age and stand density and its standing biomass are estimated to drive the G4M model.

In figure 7 the mean annual increment of stem wood for the years 2000 to 2003 is presented as annual sum.

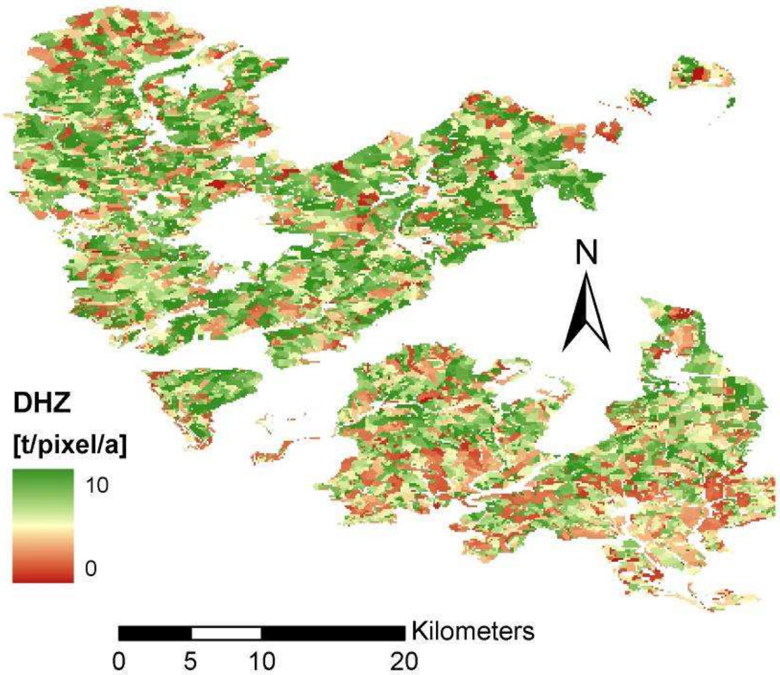

Figure 7: Mean annual increment of merchantable wood, modelled with the G4M. valid for the period 2000 to 2003.

When comparing the figures 13 and 11 one can see, that the G4M model describes reality very close. Regions with high values represented by the statistics are also coloured with high values in the G4M output. The total amount of merchantable wood, modelled by G4M for the Harz test area is about 354.120 tons, which is slightly higher than the amount from statistics.

In table 3 the values of annual increment for all available data points of the Harz region are presented. It is obvious that BETHY/DLR underestimates the annual increment by a factor of up to 3.5, whereas the G4M model is very close to the statistical data, with only a slight overestimation.

Table 3 – Results of G4M and BETHY/DLR outputs

Year	Statistics [tons]	G4M [tons]	BETHY/DLR [tons]
2000	332.571	354.366	134.124
2001	332.571	354.349	94.991
2002	332.571	354.110	110.607
2003	332.571	353.657	255.213

From this one can see, that the BETHY/DLR model has a higher amount of uncertainty in its results than the G4 Model. This might be explained with the fact, that BETHY/DLR does not take into account the tree age within its NPP estimation. Hence it is known that the carbon fixation rate from younger to older trees differs, a reason for the underestimation could be explained with the fact, that BETHY/DLR only simulates mean trees with a mean age. Hence the mean tree age in the Harz can be seen as young

(40-80 years), BETHY/DLR might underestimate the carbon fixation rate of this young forest.

In a further step a pixel wise comparison for the G4M is performed. For this, a correlation of statistical and modelled stem wood distributed in needle-leaved and broad-leaved tree cover is done. In Figure 8 the pixel wise comparison for the mean increment for 2000 to 2003 is presented.

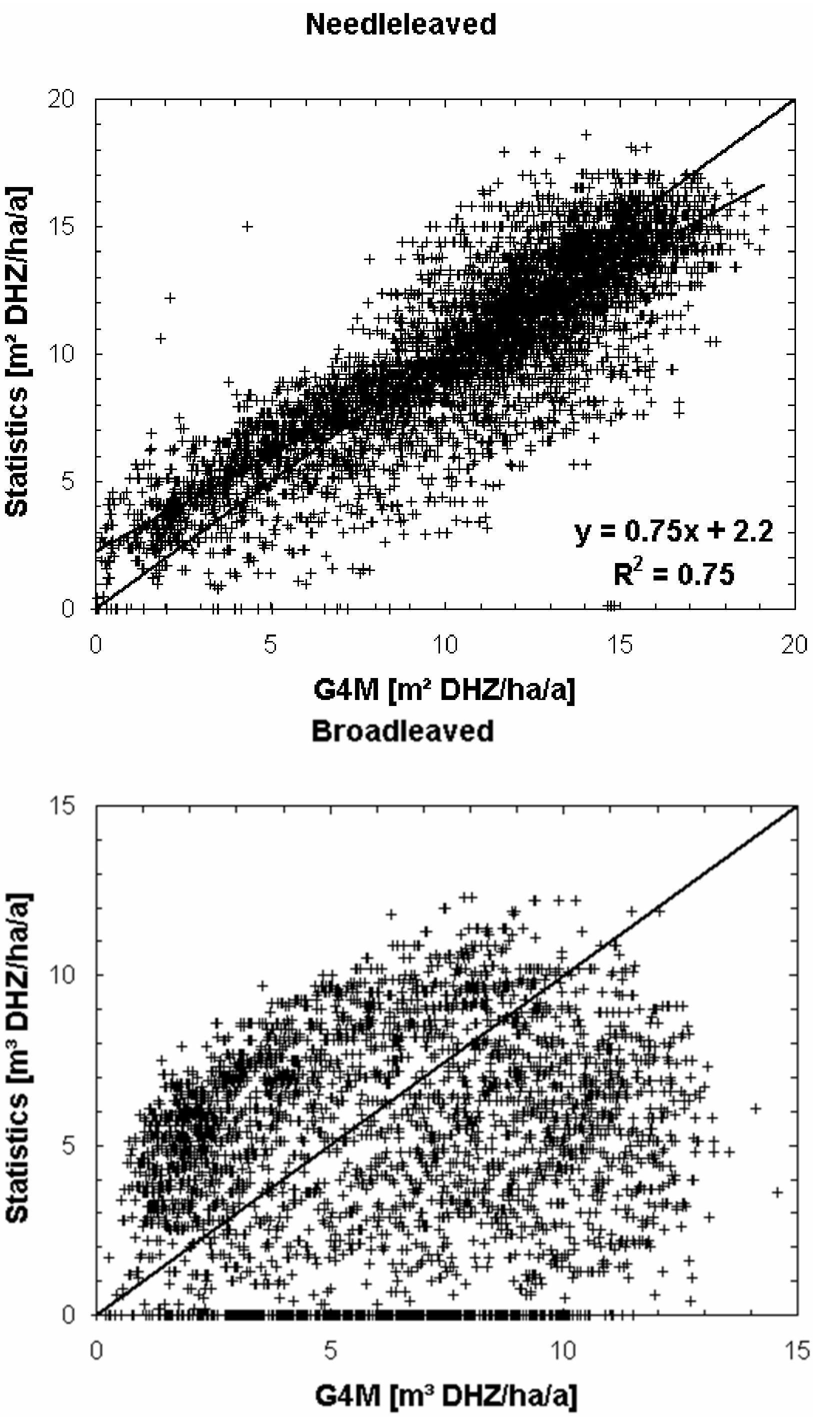

Figure 8: Pixel wise comparison of annual increment of merchantable wood. Top: Needle-leaved trees; Bottom: broadleaved trees.

From figure 8 it can be seen, that the G4M model slightly underestimates the annual increment of merchantable wood for needle leaved forests by 25%. This underestimation is linked with a high coefficient of determination of about 0.75. On the other hand, the correlation for broadleaved trees is not very strong. Hence the class of broad leaved is described as highly heterogeneous concerning their tree species distribution, it can be assumed, that the G4M model would perform better, if either a higher number of validation points per tree species or a better distinguishing of mixed classes, would be available.

In order to validate the results of both models not only for one region, the two models were also run for a second area, which is situated in the Wienerwald and contains information about 313 validation points. For this dataset the BETHY/DLR model overestimates the statistical increment of merchantable wood by 43%. This is linked with a standard deviation of about 37%. The overestimation stands in direct opposition to the results for the Harz region. As mentioned above a reason for this could again be seen in the fact, that BETHY/DLR does not include the tree age information. A second reason could be seen in the fact, that the statistical data also include measurement errors in the way, that for some validation points very low or negative increments were given. To get an assumption of how the increment of merchantable wood and the tree age is linked, a correlation of both is shown in figure 9.

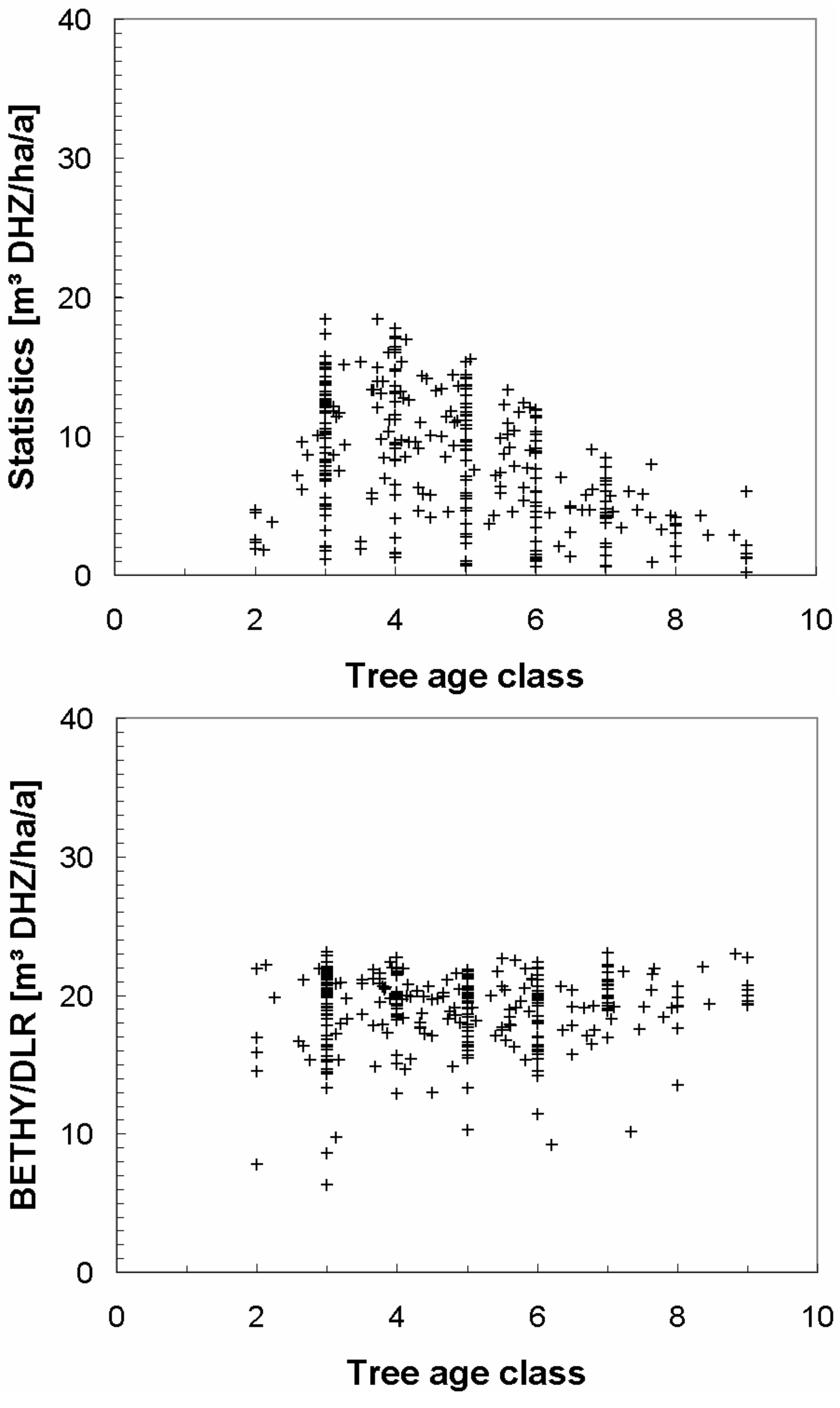

Figure 9: Tree age and merchantable wood content of the statistical data and BETHY/DLR for the Wienerwald region.

In figure 9 the tree age class represents the age of the trees. Dots in between two age classes represent validation sides where more than one age class is described. From the upper part one can clearly see that young trees (age class 2) are not able to fix high amounts of carbon and so the increment of merchantable wood is low. Trees with a mean age in the opposite can fix have an increment of merchantable wood of up to 20m³ per year and hectare. Very old trees instead have the same amount of increment than very young trees. This is due to the fact, that old trees have a higher ratio of maintenance respiration than younger trees and cannot be seen as carbon sinks anymore.

In the lower part of figure 9 the same comparison for the BETHY/DLR is shown. In direct comparison with the upper part of figure 9 one can clearly see, that BETHY/DLR overestimates the amount of increment for young and old trees.

To compare the results of the G4M model with the statistical results, a correlation is built, which is presented in figure 10.

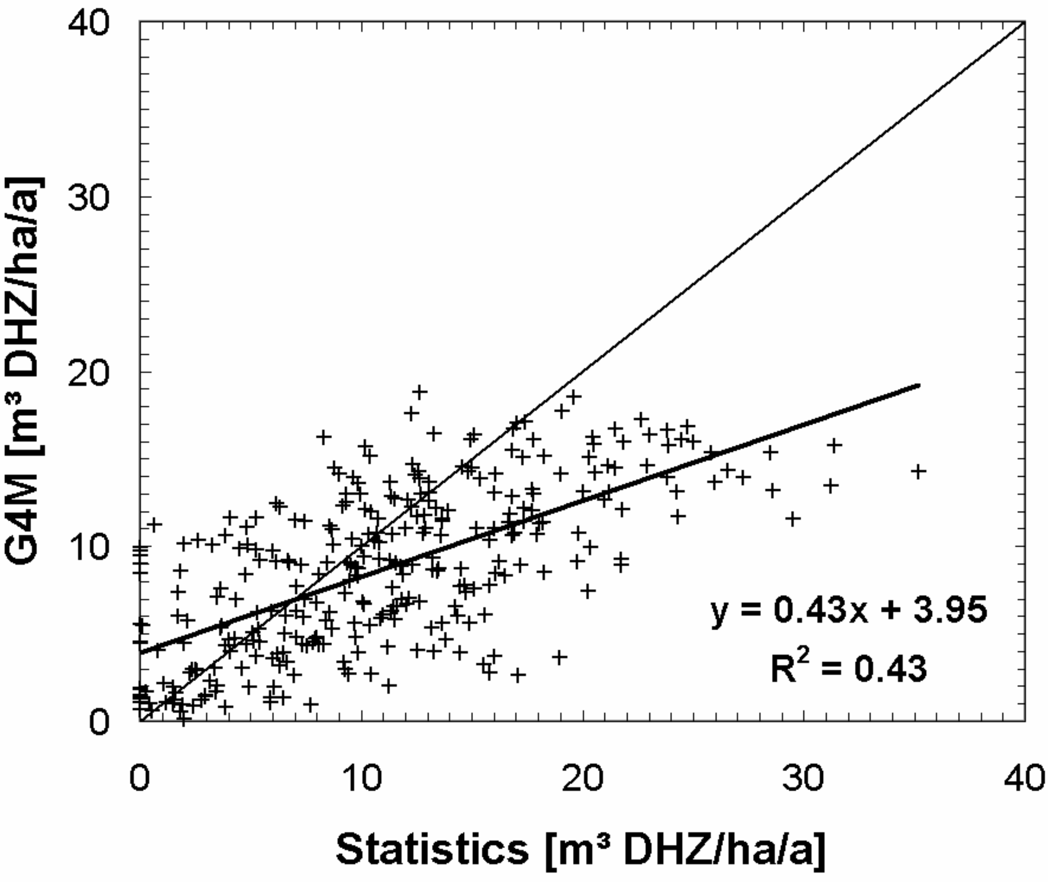

Figure 10: Comparison of merchantable wood – G4M and statistics for the Wienerwald test area.

From figure 10 one can see, that the G4M model underestimates the amount of merchantable wood of about 57%. This is linked with a coefficient of correlation of about 0.43. The reason why the G4M performs worse for this area than for the Harz region has to be seen in the input data. Hence no distribution in needle-leaved and broadleaved trees is possible, the validation results for the Wienerwald are far more heterogeneous than for the Harz region. As explained above, the G4M performs not very well for broadleaved trees, the higher amount of uncertainty could be seen in the fact, that for most of the validation sides both, needle leaved and broadleaved tree species are described.

Furthermore for the Harz region the statistical data directly provided information about the increment of merchantable wood, whereas for the Wienerwald region had to be calculated from the statistical data.

3.1.4 Conclusions Part I: Forest

The two models BETHY/DLR and G4M were run for two test sites: Harz and Wienerwald. Although the G4M model underestimates the increment of merchantable wood for both regions, it does a reasonable job of matching the statistics. However, if the input datasets allow for distinguishing between needleleaved and broadleaved tree species, the G4M model performs well for needleleaved trees, but has a higher amount of uncertainty for broadleaved trees. This could be shown for the Harz region in particular, where the G4M model results showed an underestimation of about 25% for needleleaved trees. This underestimation is linked with a coefficient of determination of about 0.75. For broadleaved trees no correlation could be found, which might be due to the fact that from the statistical data, broadleaved tree species were more heterogeneous than the needleleaved species. Hence for the Wienerwald region a distribution of needle-leaved and broadleaved species was not possible, the model correlation was slightly worse (57% underestimation), but still linked with a coefficient of determination of abut 0.43. This leads to the conclusion that theG4M model, which was developed for global modelling, could be used for local modelling as well.

In contrast, BETHY/DLR had difficulty predicting the statistical data in these two regions. Apparent causes seem to arise from the lack of tree age in the model. Based upon the results of this case study it would seem appropriate to add such a parameter to BETHY/DLR and perform further tests. The model has however proven effective in capturing forest productivity in Europe, but with a resolution of 0.25° x 0.25° (Wisskirchen, 2005).

3.2. Part II: Agriculture

3.2.1 Marchfeld Region

In the second part of this study a validation and sensitivity analysis of the BETHY/DLR model and the EPIC model was performed. As area of investigation the Marchfeld region was chosen. The Marchfeld region is an agricultural region east of Vienna, Austria (see Figure 11).

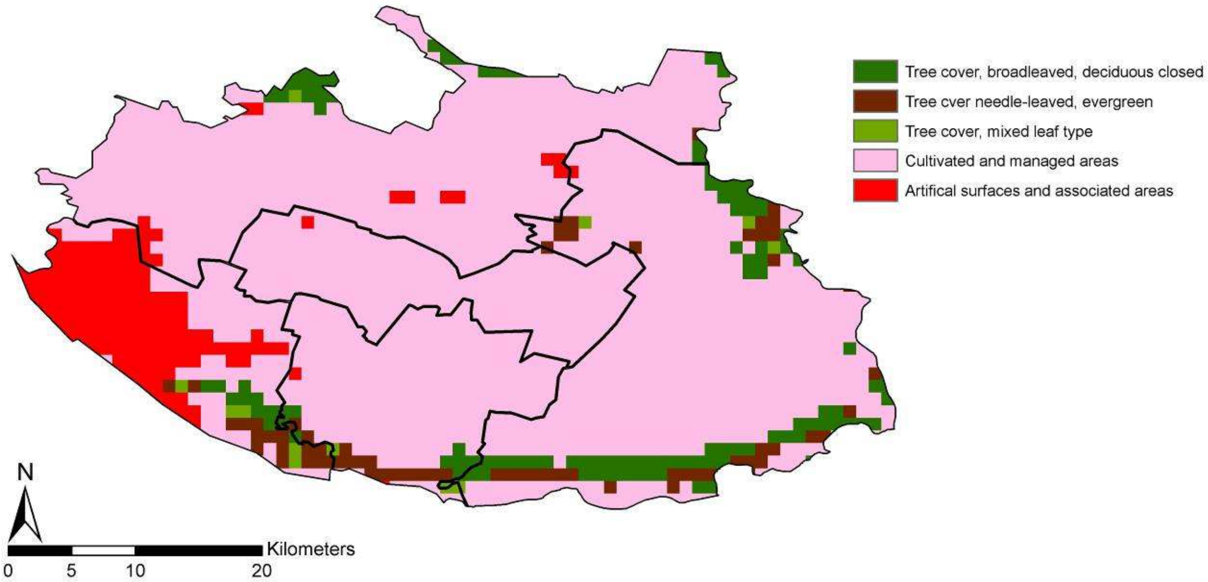

Figure 12.Overview over the test area Marchfeld.

In figure 11 the Marchfeld region is presented with the GLC2000 land cover classification as background. Pink areas represent agricultural areas, red areas urban areas and green and roan areas forests. For this study only the pink areas were taken into account. Black lines in the figure represent the borders to the five clusters to which the Marchfeld region was divided. Hence the left cluster only contains a few agricultural pixel, this cluster was ignored for further research. The Marchfeld region was chosen as test area, hence the EPIC model was already validated and calibrated for this area. The EPIC output data is so to be seen as reference data, hence of the low bias to the reality.

In addition to the validation exercise of the BETHY/DLR model for both models a sensitivity analysis was performed. This was done by using different input data sets of different sources for e.g. land cover classification and meteorology.

3.2.2 Validation and Sensitivity Analysis of BETHY/DLR and EPIC

In a first model run BETHY/DLR was driven with meteorological input data provided by ECMWF and the GLC2000 land cover. In order to validate modelled NPP computed with BETHY/DLR for the Marchfeld region, EPIC model runs with the general model setup as described above are chosen as reference data. The Marchfeld was divided in five sectors according to political district boarders. Hence one sector consists only of urban territory of Vienna it was not taking into account for further investigations. For each of the sectors the distribution of the five main soils were available, which were seen as representative for the whole region. In addition for each sector the percentage of coverage of planted crops was available. Biomass estimations for the main crops (see table 2) for each of the four sectors and five main soil types were computed with EPIC or the years 2000-2003.

Table 2: Distribution of main crops and soils in Marchfeld sectors.

	Sector 1	Sector 2	Sector 3	Sector 4
Arable land	24 131 ha	13 538 ha	9 421 ha	19 815 ha
Summer Wheat	10.3%	6.8%	3.8%	1.5%
Winter Wheat	28.0%	27.7%	29.6%	29.6%
Rye	2.4%	1.2%	3.8%	3.4%
Gain Maize	2.2%	3.7%	4.7%	2.7%
Winter Barley	4.3%	0.9%	4.5%	3.9%
Summer Barley	14.2%	5.0%	8.2%	23.2%
Grain Peas	3.7%	0.6%	3.9%	6.0%
Winter Rape	1.4%	1.5%	3.0%	5.9%
Sunflowers	2.0%	0.5%	1.0%	3.5%
Potatoes	2.2%	5.9%	5.2%	1.0%
Sugar Beet	12.0%	11.9%	10.0%	7.0%
Vegetables	4.8%	19.9%	9.2%	0.3%
Rest (incl. fallow)	12.6%	14.4%	13.2%	13.0%
Soil				
Cluster 1	53.8%	67.0%	41.7%	22.8%
Cluster 2	3.5%	8.8%	2.1%	21.6%
Cluster 3	15.5%	10.2%	10.4%	5.1%
Cluster 4	15.8%	12.5%	20.3%	23.4%
Cluster 5	11.4%	1.6%	25.5%	27.1%

In order to validate modelled NPP from BETHY/DLR with the EPIC output the model output of BETHY/DLR had to be aggregated to sector level. This was performed with GIS tools.

On the other hand, the yield estimated, computed by the EPIC model had to be recalculated to NPP per plant and soil. This was performed following the approach of Tum and Günther, 20xx. Afterwards the NPP for each of the sectors was calculated following formula 9:

$$NPP_{Sec} = \sum_{i=1}^{n} \left(NPP_{plant,soil} \times area_{plant} \times area_{soil} \right) \quad (9)$$

Where NPP_{sec} represents the NPP of a sector, $area_{plant}$ the area occupied by a plant in a sector and $area_{soil}$ the area that is occupied by a soil type in the sector.

The comparison of NPP calculated from yield data estimated by the EPIC model and the general BETHY/DLR model setup output is presented in Figure 12.

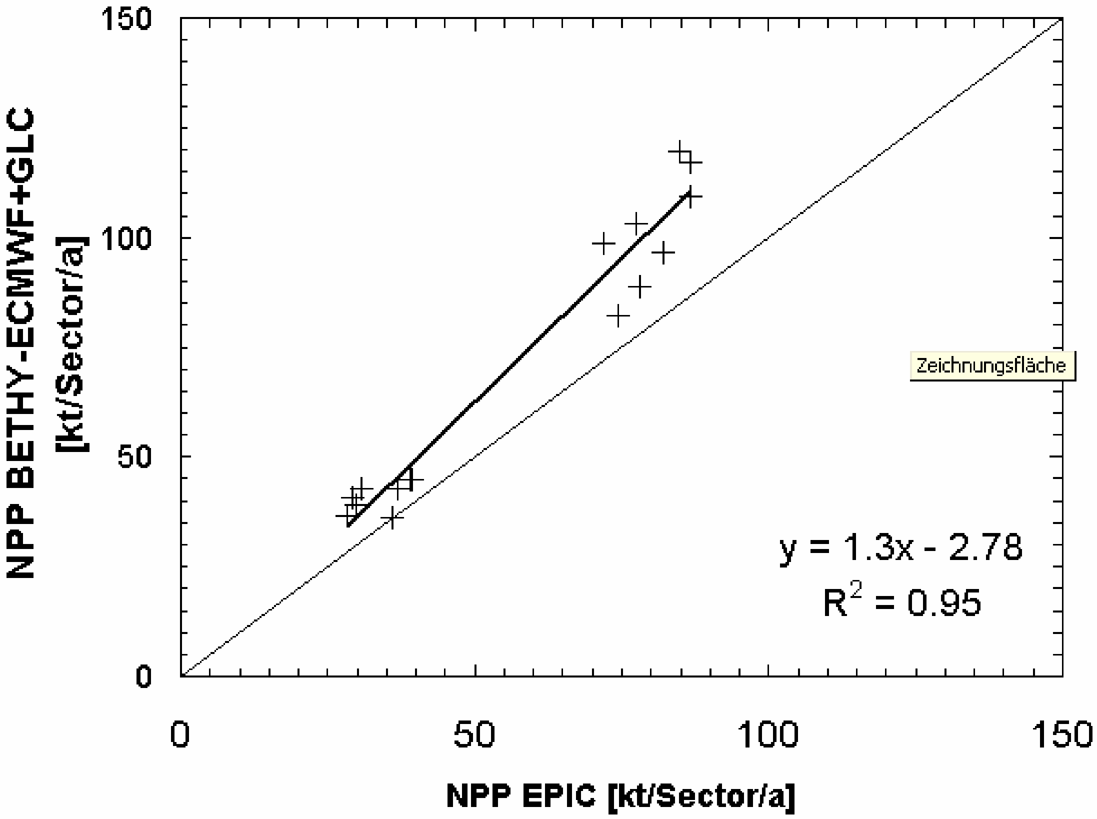

Figure 12: Correlation of modelled NPP with statistical data for the Marchfeld region for the years 2000 to 2003.

It is obvious that the strong correlation of 0.95 is linked with a mean overestimation of NPP by BETHY/DLR of about 30%. This might be explained with the use of the GLC2000 as land cover information, hence it overestimates the amount of arable land in Europe. This is due to the fact that a spatial resolution of about 1km x 1km does not describe the heterogeneous small-scale structure of the mid European land use practices. For an improved investigation the GLC2000 was changed versus the CLC2000 land cover classification, as described above.

It is assumed that only the CLC2000 vegetation class 2.1.1 (Non-irrigated arable land) describes arable land. This class was translated 100% to the BETHY/DLR vegetation type 15 (arable land). Figure 13 shows an overview over the Marchfeld area with the CLC2000 as background.

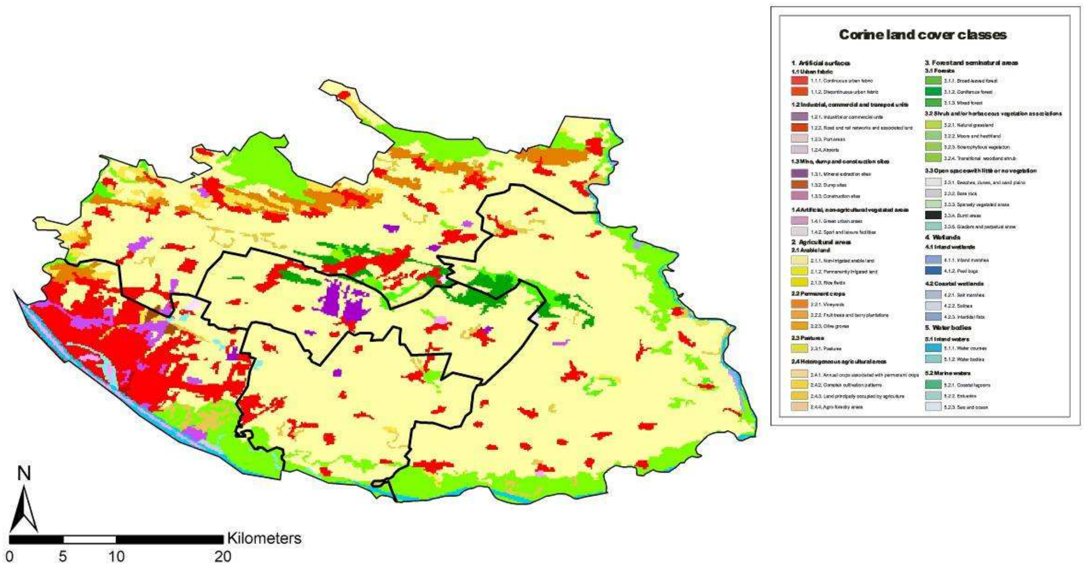

Figure 13: Marchfeld region with validation sectors and CLC200.

In Figure 13 yellow areas represent the agricultural areas. Green colours represent forest areas and red colours urban areas. In direct comparison to the GLC2000 (815km² arable land) the CLC2000 only reports 715 km² arable land. This is around 20% less than the GLC2000. According to official statistics this value is not exactly the reality, but very close. From figure 11 it is obvious that almost the whole area is described as arable land, whereas in figure 13 more areas are described as urban or forest areas. The comparison of EPIC and the BETHY/DLR model run with the corrected land cover classification is shown in Figure 14.

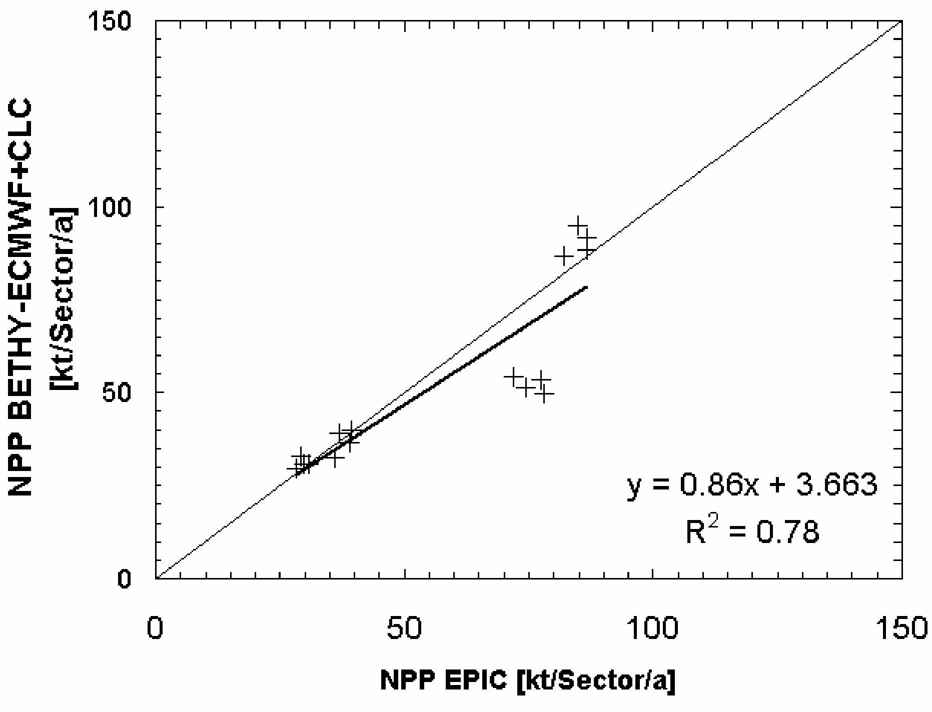

Figure 14: Correlation of modelled NPP with statistical data for the Marchfeld region for the years 2000 to 2003 with corrected land cover classification.

From figure 14 it is obvious that the overestimation of about 30%, which was described above could be explained with the use of the GLC2000 as land cover classification. The change from GLC2000 to CLC2000 effected a decrease of overestimation and resulted in an underestimation of about 16%. This underestimation is again linked with a high coefficient of correlation of about 0.78. It is also obvious from figure 14 that four of the 16 causes the underestimation. The other 12 represent the reference data of EPIC very close. The four outliers represent the years 2000 to 2003 for the Marchfeld sector four, which is situated in the north of the Marchfeld region.

Hence the BETHY/DLR model is also driven by meteorological input data a closer look to the model sensitivity was performed. Daily datasets of precipitation, minimum and maximum temperature and wind-speed were changed from ECMWF to BOKU climate data. Additional datasets like radiation were not changed, hence a comparison of both, the estimated radiation data derived from the three cloud strata of ECMWF data, and the radiation data of the BOKU dataset only had a mean difference of lower than 2%.

As the datasets were available in the needed form of daily values, no adaption was needed to be performed. It was chosen that hence the CLC2000 represents reality more closely than the GLC2000 data, a further run with the GLC2000 as background is expandable. Figure 15 presents the results of the comparison.

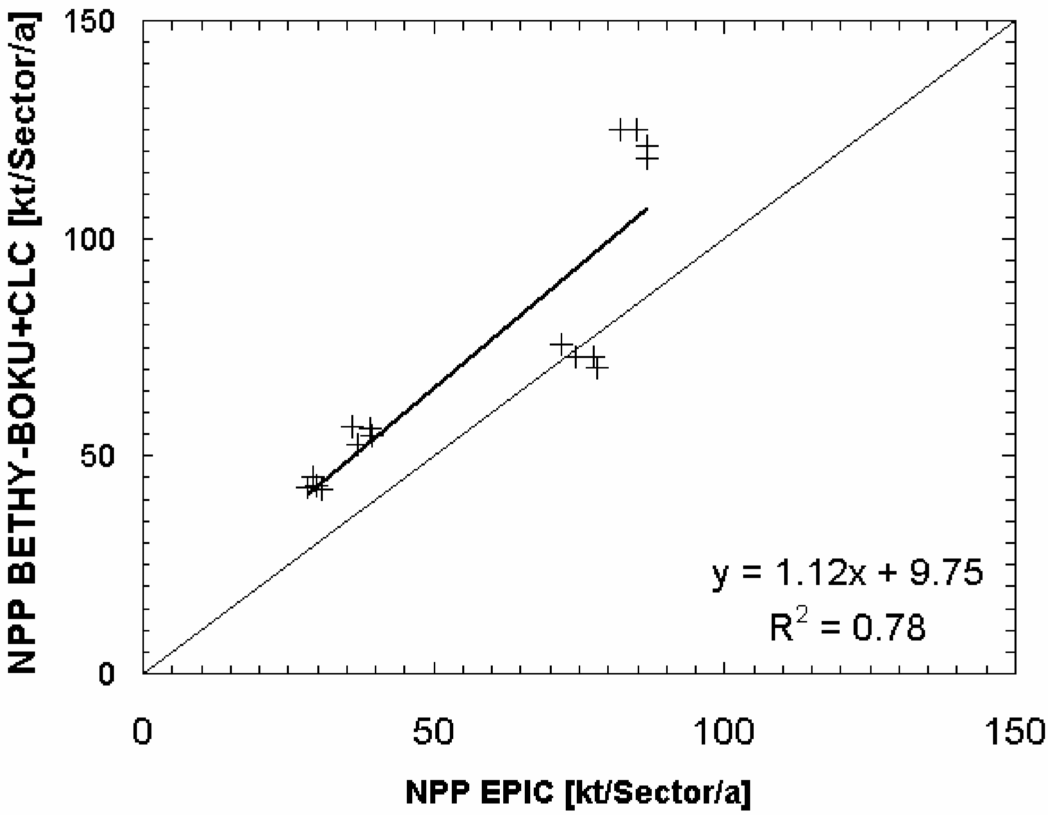

Figure 15: Correlation of modelled NPP with statistical data for the Marchfeld region for the years 2000 to 2003 with corrected land cover classification and meteorological data provided by BOKU.

From Figure 15 on can clearly see, that the change of the meteorology resulted again in an overestimation of NPP of about 12%, linked with a coefficient if determination of about 0.78. Furthermore it is obvious, that again 4 validation points, which represent again sector four, differ from the rest.

A closer look to the used land cover classification (GLC2000 and CLC2000) and the statistical data unbosomes that the GLC2000 overestimates the land cover by a factor of up to 50% for three of the Marchfeld sectors (Sectors 1,3 and 4) whereas it does well for sector 2 (0.4% overestimation). The CLC2000 on the other hand slightly overestimates the agricultural areas for sector 1 and 3 (17% and 14 %) and underestimates the areas for the sectors 2 (6%) and 4 (0.6%).

A comparison of the two different sets of meteorological data unbosomes that the mean annual minimum temperature of the BOKU data is averaged over the area of investigation of about 1.2 degree lower than the ECMWF data. Whereas the mean annual maximum is of about 0.3 degree warmer than the ECMWF data.

To get information of the sensitivity of the EPIC model, the meteorological input of precipitation, maximum and minimum temperature and wind speed were changed to daily ECMWF data. Hence the spatial resolution of the ECMWF data is 0.25° x 0.25°, five ECMWF data points are seen as valid for the area of investigation.

The comparison of the original EPIC run and the EPIC run performed with ECMWF data is shown in Figure 16.

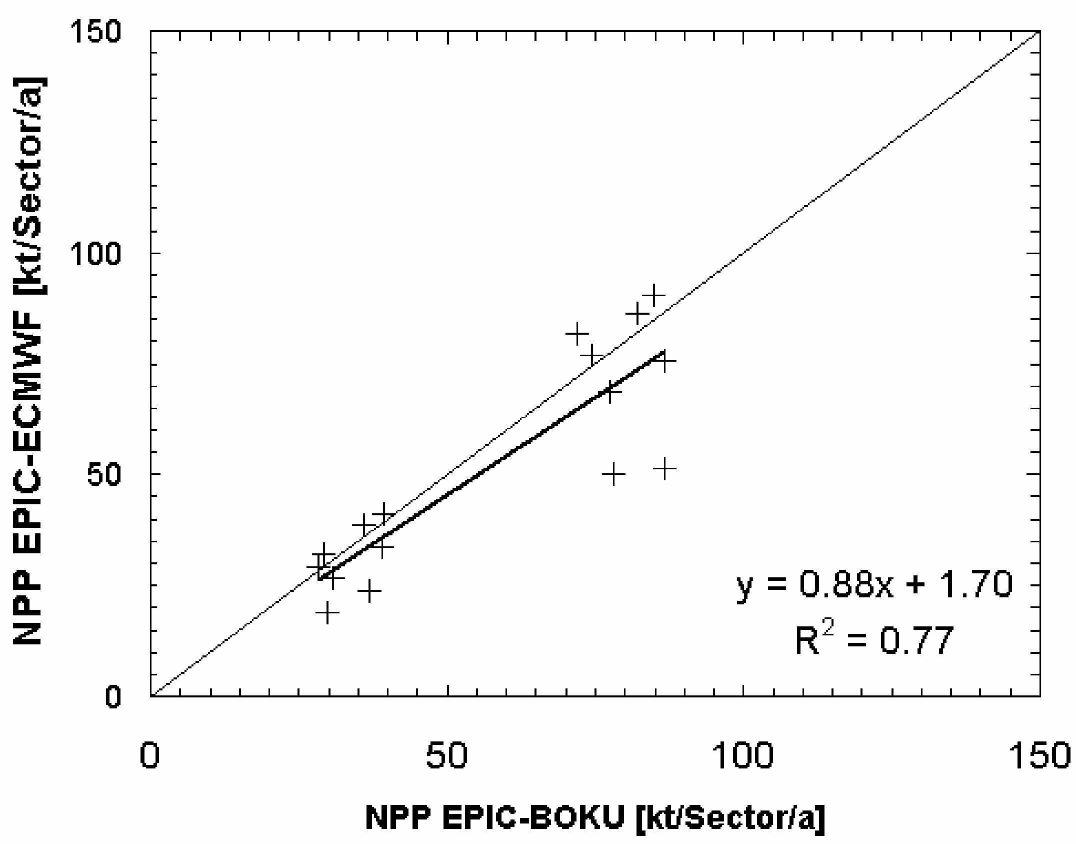

Figure 16: Correlation of modelled NPP with statistical data for the Marchfeld region for the years 2000 to 2003 with ECMWF data.

From Figure 16 one can see that EPIC underestimates the NPP for the Marchfeld region of about 12 percent, when it is driven with ECMWF data. This underestimation is linked with a high coefficient of determination of about 0.77. The result might be explained with the fact that four validation points, which represent the highest underestimations, affect the trend line. These four points represent the 2003 values for each of the four sectors.

3.2.3 Conclusions Part 2: Agriculture

The two models BETHY/DLR and EPIC were driven with different input datasets for the Marchfeld region for the years 2000 to 2003. It was assumed, that the general model setup of the EPIC model represents reality the closest and was seen as reference data. The BETHY/DLR model was first driven with ECMWF data and the GLC2000 as background land cover classification information. With this model setup an overestimation of about 30% could be proven. A stepwise change of input data (land cover classification and meteorology) for the BETHY/DLR model resulted in a final result, where BETHY/DLR overestimates the NPP by 12%. The final result might be explained with the fact that the climate data of BOKU describes a slightly longer growing season (mean maximum temperature around 1.2 degree higher) than the ECMWF data.

This could also be shown with the EPIC model, hence in direct comparison to its general model setup, the EPIC model underestimates NPP by 12% when driven with ECMWF data.

4. Conclusion

The aim of this study was to answer the question of how well global and regional vegetation models perform when they are driven with very high resolution datasets. For this purpose, three models were chosen (BETHY/DLR, G4M and EPIC) to compute increments of biomass for agricultural and forested areas on three test sites. The G4M model was chosen to compute the increment of stem wood for two forest test areas (Harz, Germany and Wienerwald, Austria). The EPIC model was chosen to estimate yields for the Marchfeld region (Austria) and the BETHY/DLR model to estimate NPP for all regions.

It could be shown, that the global forest biomass model G4M delivers reliable results for the local applications tested here. It generally underestimates the increment of stem wood, e.g. 25% for Harz region. This underestimation however is linked with a high coefficient of determination (0.75). It is interesting to note that a model designed for global applications (G4M) performed well at such a fine scale. The BETHY/DLR model struggled to accurately depict the in-situ data, perhaps owing to a lack of a forest age parameter in the model.

A sensitivity analysis of global and regional agricultural models revealed large differences in their output and response to input data. For both models (BETHY/DLR and EPIC) a variability of up to 62% could be demonstrated when altering climate conditions.

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