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Abstract

Carbon fluxes between croplands and atmosphere are highly conditioned by farmer practices that involved intense atmospheric CO_2 uptake during crop growing season compared to other terrestrial ecosystems. Modelling and measuring land-atmosphere carbon exchanges from arable lands are important tasks to predict the influence of vegetation dynamics on climate change and its retroactive effects on crop productivity. We tested the agro-ecosystem model CERES-EGC against gap-filled daily net CO_2 exchanges over crop rotations monitored in three arable sites in Europe. The model parameters were estimated using Bayesian calibration and the model prediction accuracy was assessed with two supplementary independent data sets. As a result, the calibrated model allows us to compute the net ecosystem production (NEP) and net biome production (NBP) for entire crop rotations. The Bayesian calibration method results in an improvement of goodness of fit compared to initial parameter-based simulations. The calibrated model was accurate to estimate the NEP from daily time scale to aggregated NEP for entire crop rotation. The carbon returns from application of organic manure and the carbon uptake from catch crops and crop volunteers generated an important C sink effect on the NBP. Adding the nitrous oxide and methane fluxes from soils to the CO_2balance will allow us to compute the global warming potential of agro-ecosystems.

Keywords

Carbon dioxide; Agro-ecosystem model; CERES-EGC; Bayesian calibration; Independent validation; Greenhouse gases; Carbon balance; Net Biome Production

1 Introduction

Agriculture contributes about 10-12% of the global anthropogenic emissions of greenhouse gases (GHGs), a share expected to rise due to an increase in land use and management intensity of agriculture worldwide (Smith et al., 2007). The direct GHG emissions of agro-ecosystems comprise nitrous oxide (2.8 Gt CO2-eq yr^{-1}), methane (3.3 Gt CO2-eq yr^{-1}), their exchanges of CO_2 being considered approximately balanced with a net emission of 0.04 Gt CO2-eq yr^{-1} to the atmosphere (Smith et al., 2007). The net fixation of $CO_2$by crops and soil respiration are the two main processes by which adapted management practices may increase the potential of C sequestration in soils (Johnson et al., 2007). The balance of these two terms corresponds to the net ecosystem production (NEP) of carbon, which is a measure of the C source or sink strength of ecosystems respective to the atmospheric compartment.

Experimental monitoring of net ecosystem exchanges (NEE) have been increasingly carried out using eddy-covariance (EC) techniques, and for all types of managed ecosystems: grasslands (Ammann et al., 2007; Veenendaal et al., 2007), forests (Pilegaard et al., 2001; Kurbatova et al., 2008), and croplands (Moureaux et al., 2006; Anthoni et al., 2004). Their values varied across ecosystem types but also within each class due to pedoclimatic differences and management practices. In Russia, Kurbatova et al. (2008) reported annual net ecosystem production (NEP=-NEE) of -2000 kg C ha^{-1} yr^{-1} (denoting a C source) and 1440 kg C ha^{-1} yr^{-1} (C sink) for a wet and dry spruce forest, respectively, during the same time period. In the Netherlands, the NEP of two grasslands on peat soils were measured at 57 kg C ha^{-1} yr^{-1} when they were managed extensively, and at -1339 kg C ha^{-1} yr^{-1} for an intensive management (Veenendaal et al., 2007). Soussana et al. (2007) reported an averaged NEP for nine grassland sites in Europe of 2400 ± 700 kg C ha^{-1} yr^{-1}, correspond to strong C sinks. In Nebraska, Verma et al. (2005) measured NEP for irrigated and rainfed maize crops which were 3800 and 5200 kg C ha^{-1} yr^{-1},

respectively. Croplands are usually characterized by episodes of high C uptake during the crops growing season, directly related to farmers' management practices. A large part of the fixed C is removed from the field after harvest, and the residues are returned to the soil and processed by soil microbial biomass. Accounting the absolute carbon balance of croplands requires to take into consideration the export and import of organic C within the agricultural field. This balance, called the net biome production (NBP), presents large range of variations between crop species, management intensity and temporal variations at interannual scale. For example, Grant et al. (2007) reported that a maize-soybean rotation in Nebraska (USA) was a net C source because of the failure of positive maize NBP to offset negative soybean NBP in the next year. Anthoni et al. (2004) estimated the effect of manure application on NBP, and pointed out that manure largely offsets the C loss in the year of application. They also noticed that C input in the previous years significantly contributed to the next year C exchanges. Turner et al. (2007) mentioned the strong influence of climate on the interannual variations of the C budget over a large domain (Oregon state, USA). Accordingly, it appears that croplands may be sources or sinks of C and that entire crop rotations should be considered to compute the C balance.

Because the C balance of croplands is heavily manipulated by farmers, and regulated by environmental conditions, biophysical models that simulate the turnover of C in agro-ecosystems appear a promising approach to estimate them (Huang et al., 2009). Grant et al. (2007) considered that process-based ecosystem models are the best method to predict net ecosystem production for known or hypothesized management practices or climate and where NEP measurements are incomplete or non available. Complexity, provenance and applications explained the main differences between the modelling approaches of C exchanges from crops. Carbon models were developed either from agronomic sciences (*Agro-C*, Huang et al. (2009)), biogeochemical sciences (*Ecosys*, Grant et al. (2007); *DNDC*, Zhang et al. (2002)), or for land surface models for use in larger-scale atmospheric models (*ORCHIDEE-STICS*, Gervois et al. (2008); *ChinaA-*

grosys, Wang et al. (2007)). Eddy-covariance measurements have widely been used for development and testing of the latter category of models, generally known as soil-vegetation-atmosphere transfer (SVAT) models, which couple C to energy and water balances on an hourly (or less) time step. There is a wide body of work on forests (Klemedtsson et al., 2007; Svensson et al., 2008; Kurbatova et al., 2008; Dufrêne et al., 2005) or cropland (Wang et al., 2007; de Noblet-Ducoudré et al., 2004), but limited to maximum one year time span.

Crop models integrate longer timeframes (growing season or crop rotation), and may include more regulators (eg, N cycling) and drivers (crop management). They have been widely used to simulate the growth and development of arable crops, and tested against field data such as crop dry matter or leaf area index (Zhang et al., 2002), but have rarely been compared to data of daily net C exchanges. Adiku et al. (2006) were surprised that such measurements had not been amply used before their study for the development and validation of crop gas exchange and growth models. They developed a model for simulating the net carbon exchanges of spring barley and compared its predictions with observations of gross primary production over one cropping season. Since their pioneering study, EC measurements are actively used for SVAT model development and validation but their use is still limited for crop model development.

In a large number of crop models, crop mass accumulation is estimated with the relationship between plant dry matter and interception of solar radiation. Daily biomass production is usually calculated as the product of the daily cumulative radiation intercepted with the radiation use efficiency (RUE, g DM MJ^{-1}). Radiation use efficiency is determined by measuring crop growth commonly based on measurements of above-ground biomass without estimating root compartment (Sinclair and Muchow, 1999). Gabrielle et al. (2002) noticed that low C mineralization fluxes in soil simulated by soil-crop models may be attributed to a strong under-estimation of the turnover of below-ground plant biomass. The authors advised that much more dry matter should be partitioned to the roots and that RUE should be accordingly increased. Here we assume that

calibration of RUE parameters of crop growth sub-models against net C exchanges would allow us to take into account the whole plant C fixation integrating the root growth and rhizodeposition.

Our general objective was to test the capacity of the soil-crop model CERES-EGC to predict daily NEP over crop rotations, using experimental data from arable sites in Europe (part of the CarboEurope measurement network). We first calibrated the model parameters against field data using Bayesian techniques, and subsequently assessed the model prediction error using two supplementary independent data sets. Finally, we calculated the carbon balances of the crop rotations involved in the various field sites.

2 Material and Methods

We used four different data sets from intensively monitored cropping systems to test the ability of the biophysical CERES-EGC model to simulate CO_2 exchanges at the field scale. The experimental sites are located in Grignon (Fr.), Auradé (Fr.) and Gebesee (Germ.), and involved different pedoclimatic conditions, crop types and management. At the three sites, net carbon fluxes were measured using the eddy covariance technique following the methodology of the CarboEurope integrated project. The model was parameterized using a Bayesian calibration method based on the Metropolis-Hastings algorithm against two data sets of daily NEP measurements collected over crop rotations. We also tested the prediction accuracy of calibrated model with two other independent data sets and finally, we applied the model to compute carbon balances for crop rotations.

2.1 The CERES-EGC model

2.1.1 A process-based agro-ecosystem model

CERES-EGC was adapted from the CERES suite of soil-crop models (Jones and Kiniry, 1986), with a focus on the simulation of environmental outputs such as nitrate leaching, emissions of N_2O and nitrogen oxides (Gabrielle et al., 2006). CERES-EGC runs on a daily time step, and requires daily rain, mean air temperature and Penman potential evapo-transpiration as forcing variables. The CERES models are available for a large number of crop species, which share the same soil components (Jones and Kiniry, 1986).

CERES-EGC comprises sub-models for the major processes governing the cycles of water, carbon and nitrogen in soil-crop systems. A physical sub-model simulates the transfer of heat, water and nitrate down the soil profile, as well as soil evaporation, plant water uptake and transpiration in relation to climatic demand. Water infiltrates down the soil profile following a tipping-bucket approach, and may be redistributed upwards after evapo-transpiration has dried some soil layers. In both of these equations, the generalised Darcy's law has subsequently been introduced in order to better simulate water dynamics in fine-textured soils (Gabrielle et al., 1995).

A biological sub-model simulates the growth and phenology of the crops. Crop net photosynthesis is a linear function of intercepted radiation according to the Monteith approach, with interception depending on leaf area index based on Beer's law of diffusion in turbid media. Radiation use efficiency (RUE) is defined for each crop as the dry biomass produced per unit of radiation intercepted by the crop. Photosynthates are partitioned on a daily basis to currently growing organs (roots, leaves, stems, fruits) according to crop development stage. The latter is driven by the accumulation of growing degree days, as well as cold temperature and day-length for crops sensitive to vernalisation and photoperiod. Lastly, crop N uptake is computed through a supply/demand scheme, with soil supply depending on soil nitrate and ammonium concentrations and root length density.

A micro-biological sub-model simulates the turnover of organic matter in the plough layer. Decomposition, mineralisation and N-immobilisation are modelled with three pools of organic matter (OM): the labil OM, the microbial biomass and the humads. Kinetic rate constants define the C and N flows between the different pools. Direct field emissions of CO_2, N_2O, NO and NH_3 into the atmosphere are simulated with different trace gas modules.

2.1.2 Modelling of net carbon exchange

Carbon dioxide exchanges between soil-plant system and the atmosphere are modelled via the net photosynthesis and soil organic carbon (SOC) mineralization processes. Net primary production (NPP) is simulated by the crop growth modules of the different crop species (wheat, maize, barley, rapeseed and sunflower), while soil heterotrophic respiration (Rs) is deduced from the SOC mineralization rates calculated by the microbiological sub-model such as represented in Fig. 1. The net ecosystem production (NEP), which is calculated as NPP minus Rs, may be computed on a daily basis and directly tested against the net ecosystem exchanges measured by eddy covariance. The confrontation between the daily rates of simulated and measured NEP provides a good opportunity to calibrate the parameters related to CO_2 flux modelling and to test the simulation of C dynamics by the ecosystem model. In all sites, a complete rotation was ran before the measurement period to stabilize the soil C and N pools and dampen the effects of initial conditions.

The net biome production was calculated by aggregating daily NEP estimated by simulation or observation over cropping cycles, plus organic manure imports, minus C exported by harvested biomass.

2.2 Field sites

Net ecosystem exchange measurements were carried out with eddy covariance technique at three experimental sites located in Europe: Grignon (northern France, 48.9 N, 1.95 E), Auradé (south-

ern France, 43.5 N, 1.1 E) and Gebesee (Germany, 51.1 N, 10.9 E). The site characteristics and crop rotations are detailed in Table 2.

The Grignon site is located about 40 km W of Paris, France. The soil was a silt loam with 18.9% clay and 71.3% silt in the topsoil and in the top 15 cm, organic carbon content was 20 g kg^{-1}, the pH (water) was 7.6 and the bulk density 1.3 g cm^{-3}. In Grignon, two field-sites experiments (*NitroEurope*, NEU-Grignon and *BioPollAtm*, BPA-Grignon) were conducted on adjacent plots with the same soil characteristics. The crop rotation of the NEU-Grignon experiment included maize, winter wheat, winter barley and mustard which was planted to serve as a catch crop to reduce nitrate leaching during winter. Dairy cow slurry was applied between the harvest of barley and the planting of mustard on 31 August 2004, and before the maize sowing on 16 April 2008. For the BPA-Grignon experiment, NEE measurements were carried during the maize growing season in 2002.

Auradé is located about 30 km W of Toulouse, France. The soil was a clay loam with 30.2% clay and 48.4% silt in the top 15 cm, organic carbon was 10 g kg^{-1}, the pH (water) was 6.9 and the bulk density 1.4 g cm^{-3}. The Auradé site involved a winter wheat-sunflower-winter wheat-rapeseed rotation since at least 2000.

The Gebesee experimental site is located about 20 km NW of Erfurt in Germany. The soil was a Chernozerm (silty clay loam) with 35.8% clay and 60.3% silt in the top 20 cm, organic carbon was 23 g kg^{-1}, the pH (water) was 6.7 and the bulk density 1.3 g cm^{-3}. The crop sequence from 2003 to 2007 was rapeseed-winter barley-sugar beet-winter wheat. Two applications of organic fertilizers were carried out in 2007, one application of cattle slurry (18 m^3 ha^{-1}) on the wheat crop in 11 Apr. and 35 t ha^{-1} of farmyard manure in 4 Sept.

2.3 CO_2 fluxes and biomass measurements

In all sites, the measurements of CO_2 fluxes at the field scale were carried out following the methodology the CarboEurope integrated project (IP; Aubinet et al. (2000)). Water vapour and CO_2 fluxes were measured at a 2 to 3 m height above the crop canopy using the eddy covariance technique. Wind speed was monitored with three-dimensional sonic anemometers, and CO_2 concentration with infrared gas analysers (model Li7500 in Grignon and Auradé and model Li-7000 in Gebesee; LiCor Inc., Lincoln, NE, USA). Daily NEP of carbon dioxide (g C m^{-2} d^{-1}) and evapotranspiration rate (mm m^{-2} d^{-1}) were calculated by integrating the 30-minute fluxes obtained with the micrometeorological measurements over 24 h periods. The data sets were processed following the standardised methodology described in Papale et al. (2006). Carbon dioxide fluxes were corrected for CO_2 storage below EC measurement height, low turbulence conditions were filtered using a friction velocity threshold criterion. The eddy covariance technique and subsequent data processing produce gaps in the half-hourly C flux data, making it necessary to fill the missing values before integration at the daily time scale. The gap-filling methodology of CarboEurope-IP was applied to the experimental data sets (Falge et al., 2001).

Above-ground plant dry matter (DM) was measured every two weeks during crop growth, over the full crop sequences of the Auradé, NEU-Grignon and BPA-Grignon experiments. Daily weather data were recorded with automatic meteorological station, including maximum and minimum daily air temperatures (°C), rainfall (mm d^{-1}), solar radiation (MJ m^{-2} d^{-1}) and wind speed (m s^{-1}) at each site.

2.4 Parameter calibration

The parameters were estimated using the Bayesian calibration method described in Lehuger et al. (2009). Table 1 lists the parameters involved in the calibration as well as their prior probability density functions (pdf). Briefly, Bayesian methods are used to estimate model parameters by

combining two sources of information: prior information about parameter values and observations of model output variables. In our case, the observations consisted of the NEP measurements. Bayes' theorem makes it possible to combine the two sources of information in order to calibrate the model parameters. The first step is to assign a probability distribution to the parameters, representing our prior uncertainty about their values. We specified lower and upper bounds of the parameters' uncertainty, and defined the prior pdfs as uniform (Table 1). The aim of Bayesian calibration is to reduce this uncertainty by using measured data, thereby producing the posterior distribution for the parameters. This is achieved by multiplying the prior with the likelihood function, which is the probability of the data given the parameters. Because probability densities may be very small numbers, rounding errors needed to be avoided and all calculations were carried out using logarithms. The logarithm of the data likelihood was thus calculated for each data set D_i as follows:

$$logL_i = \sum_{j=1}^{K} \left(-0.5 \left(\frac{y_j - f(\omega_k; \theta_l)}{\sigma_j} \right)^2 - 0.5log(2\pi) - log(\sigma_j) \right) \quad (1)$$

where y_j is the NEP measured on sampling date j in the data set D_i, and σ_j the standard deviation, ω_k is the vector of model input data for the same date, $f(\omega_k; \theta_l)$ is the model simulation of y_j with the parameter vector θ_l, and K is the total number of observation dates in the data sets. Two additional parameters were involved in the calibration, corresponding to a site-specific experimental error of NEE measurements. Parameters *psys1* for systematic error of measurement in NEU-Grignon and *psys2* for Auradé were introduced in the log-likelihood function as multiplicative factors of D_i. We defined their prior pdfs as uniform over the [0.5-2] range. To generate a representative sample of parameter vectors from the posterior distribution, we used a Markov Chain Monte Carlo (MCMC) method: the Metropolis-Hastings algorithm (Metropolis et al., 1953). We formed Markov chains of length 10^4-10^5 using a multivariate Gaussian pdf to generate candidate parameter vectors. The variance matrix of this Gaussian was adjusted to

ensure an efficient exploration of the parameter space by the Markov chains. We first set the marginal variances to the square of 1% of the prior parameter ranges, and the covariances to zero (Van Oijen et al., 2005). In addition, the acceptance rate was artificially adjusted by increasing the measurement uncertainty in order to smooth the likelihood surface and make the calibration easier. Due to the large amount of observed data involved, the likelihood surface presented sharp peaks and the probability for the model to hit a 'target area' for a successful calibration was too small otherwise. Ten percent of the total number of iterations at the beginning of the chain were discarded as unrepresentative 'burn-in' segments of the chains (Van Oijen et al., 2005). The rest of the chains were considered as a representative sample from the posterior pdf, and were used to calculate the mean vector, the variance matrix and the 90% confidence interval for each parameter. Bayesian calibration was successively applied to the Auradé experiment and the NEU-Grignon treatment.

2.5 Goodness of fit

The goodness of fit between simulations and observations was assessed by calculating the root mean square error (RMSE). The RMSE was used to judge the performance of the parameter calibration as well as the model prediction error for the two independent data sets. It was calculated for each data set D_i as follows (Wallach, 2006):

$$RMSE = \sqrt{\frac{1}{K}\sum_{j=1}^{K}(y_j - f(\omega_k;\theta_l))^2} \tag{2}$$

where y_j is the observed NEP on day j of data set D_i, and $f(\omega_k;\theta_l)$ is the corresponding model predictions with input variables ω_k and parameters θ_l. Simulations were carried out using either the posterior expectancy of parameters ($\overline{\theta_l}$) or the maximum a posteriori (MAP) estimate of θ ($\theta_{MAP,l}$). θ_{MAP} is the single best value of the parameter vector in MCMC chain, which maximizes the posterior probability density (Van Oijen et al., 2005). The posterior expectancy of

Parameter vector $\theta = [\theta_1 ... \theta_{16}]$					Prior probability distribution			Posterior probability distribution			
θ_i	Symbol	Description	Unit	Default value	θ_{min}(i)	θ_{max}(i)	References	Mean NEU-Grignon	SD NEU-Grignon	Mean Auradé	SD Auradé
θ_1	ruemaize	Radiation use efficiency of maize	g DM MJ^{-1}	4.5	1.0	5.5	Sinclair and Muchow (1999); Choudhury (2001) Andrade et al. (1993); Lindquist et al. (2005)	3.0	0.1	NA	NA
θ_2	ruewheat	Radiation use efficiency of winter wheat[a]	g DM MJ^{-1}	7.5	2.5	8.0	Choudhury (2000); Hui et al. (2001); Sinclair and Muchow (1999)	6.3	0.2	5.4	0.6
θ_3	ruerap1	Radiation use efficiency of rapeseed for vegetative phase	g DM MJ^{-1}	2.7	0.8	4.0	Gabrielle et al. (1998); Justes et al. (2000)	1.83	0.04	4.75	1.48
θ_4	ruerap2	Radiation use efficiency of rapeseed for reproductive phase	g DM MJ^{-1}	2.7	0.8	3.2	Gabrielle et al. (1998)	2.81	0.17	1.85	0.17
θ_5	sflo1	Radiation use efficiency of sunflower for vegetative phase	g DM MJ^{-1}	1.4	0.7	3.0	Villalobos et al. (1996); Sinclair and Muchow (1999) Albrizio and Steduto (2005)	NA	NA	0.72	0.03
θ_6	sflo2	Radiation use efficiency of sunflower for reproductive phase	g DM MJ^{-1}	1.3	0.9	1.5	Villalobos et al. (1996); Sinclair and Muchow (1999)	NA	NA	1.62	0.61
θ_7	prop1	Partitioning coefficient of total C into microbial biomass pool	%	0.015	0.010	0.030	Molina et al. (1983); Gabrielle et al. (2004) Molina et al. (1997); Corbeels et al. (1999); Nicolardot and Molina (1994) Nicolardot et al. (1994)	0.024	0.006	0.014	0.003
θ_8	prop2	Partitioning coefficient of total C into humads pool	%	0.12	0.10	0.35	Corbeels et al. (1999); Molina et al. (1997) Nicolardot and Molina (1994); Gabrielle et al. (2002)	0.142	0.040	0.209	0.060
θ_9	coef1	Partitioning coefficient of residue C into residue carbohydrate pool	%	0.20	0.15	0.23	Henriksen and Breland (1999)	0.204	0.015	0.210	0.014
θ_{10}	coef2	Partitioning coefficient of residue C into residue cellulose pool	%	0.70	0.65	0.73	Henriksen and Breland (1999)	0.69	0.03	0.70	0.01
θ_{11}	cf1	Decomposition rate of labile microbial biomass pool	d^{-1}	0.332	0.25	0.50	Henriksen and Breland (1999); Godwin and Jone (1991) Nicolardot and Molina (1994); Lengnick and Fox (1994)	0.29	0.03	0.35	0.06
θ_{12}	cf2	Decomposition rate of resistant microbial biomass pool	d^{-1}	0.0404	0.0250	0.0600	Henriksen and Breland (1999); Nicolardot and Molina (1994) Dou and Fox (1995); Lengnick and Fox (1994)	0.0362	0.0062	0.0416	0.0083
θ_{13}	cf3	Decomposition rate of humads pool	d^{-1}	0.003	0.002	0.007	Molina et al. (1997); Nicolardot and Molina (1994) Dou and Fox (1995); Gabrielle et al. (2002)	0.004	0.002	0.003	0.001
θ_{14}	cfres1	Decomposition rate of residue carbohydrate pool	d^{-1}	0.20	0.15	0.80	Corbeels et al. (1999); Henriksen and Breland (1999) Godwin and Jone (1991)	0.29	0.11	0.61	0.13
θ_{15}	cfres2	Decomposition rate of residue cellulose pool	d^{-1}	0.050	0.013	0.055	Corbeels et al. (1999); Henriksen and Breland (1999) Godwin and Jone (1991); Hadas et al. (1993)	0.045	0.006	0.022	0.010
θ_{16}	cfres3	Decomposition rate of residue lignin pool	d^{-1}	0.0090	0.0095	0.015	Corbeels et al. (1999); Dou and Fox (1995)	0.0099	0.0008	0.0120	0.0017

[a]For wheat, net photosynthesis rate is fonction of ruewheat$\times$PAR$^{0.6}$

Table 1: Description of the 16 model parameters involved in the Bayesian calibration. The prior probability distribution is a multivariate uniform distribution between bounds θ_{min} and θ_{max}, as extracted from the above-cited literature references. The posterior parameter distributions are characterised by the mean value of the posteriors and their standard deviation (SD).

predictions were obtained from the posterior parameters pdfs. The root mean square errors were computed for the experiments used in the parameter calibration (NEU-Grignon and Auradé) and in the subsequent model testing against independent data sets (BPA-Grignon and Gebesee). In the latter case, the RMSE corresponded to the root mean squared error of prediction (RMSEP(θ)), since the data were involved neither in parameter estimation nor model development (Wallach, 2006). RMSEP is a measure of the model's accuracy in the prediction of NEP.

3 Results

3.1 Model calibration

Table 1 recapitulates the mean and standard deviations of the posterior parameter distributions obtained after calibration against the NEU-Grignon and Auradé data sets. The posterior radiation use efficiencies (RUEs) of maize and wheat were lower than their default values for both sites, by 30% for maize, and 15% to 30% for wheat. Thus, the uncalibrated wheat and maize crop components of CERES-EGC tended to over-estimate crop biomass. Conversely, the calibrated RUEs of rapeseed and sunflower were lower or higher than their initial values, depending on development phase and experimental site.

The posterior parameter values of SOC mineralization parameters were generally close to their default values excepted for the parameters *prop1*, *prop2*, *cfres1* and *cfres2*. The decomposition rate of residue carbohydrate pool (*cfres1*) was substantially increased for calibration against Auradé data set (0.61 vs. 0.20 d^{-1}) and slightly for calibration against NEU-Grignon data set (0.29 vs. 0.20 d^{-1}). The coefficients partitioning endogenous soil organic C into the microbial biomass (*prop1*) and humads (*prop2*) pools were also higher than their default values, respectively 60% for *prop1* in NEU-Grignon and 75% for *prop2* in Auradé. The parameters *psys1* and *psys2* were calibrated within the BC at the same time as the model parameters and their mean posterior values were 1.38 (± 0.26) and 0.87 (± 0.20) for NEU-Grignon and Auradé respectively. This result

means that the measurements in NEU-Grignon would be under-estimated whereas they would be over-estimated in Auradé.

Table 3 summarizes the RMSEs for daily and cumulative NEP, and above-ground plant biomass obtained with the various parameter sets (prior and posterior). The calibration led to a 15% to 30% reduction of the RMSE relative to the uncalibrated parameter set. There were small differences between the RMSEs computed with posterior expectancy of parameters and posterior expectancy of predictions. The simulations computed with the parameter set with maximum posterior probability, i.e. when likelihood is maximal, involved RMSE values for daily NEP lower than RMSEs computed with posterior expectancy of parameters. But this parameter set may involve higher RMSE values for cumulative sum of NEP and ABG biomass, compared to RMSEs computed with posterior expectancy of prediction and posterior expectancy of parameters.

3.2 Dynamics of net carbon exchanges

Figure 2 (a and d) compares the simulations of daily NEP after calibration and the observations for the crop rotations of the NEU-Grignon and Auradé experiments. There was good agreement between the two series at the time scale of a growing season (from sowing to harvest), and also for the time intervals in between two crops. The growing seasons of spring crops (maize and sunflower) were shorter than those of winter crops (rapeseed, wheat, barley), but simulations of daily C uptake reached higher values for maize and sunflower. The net carbon exchanges reached a peak value of 15 g C m^{-2} d^{-1} for the maize crop in Grignon, while they did not exceed 10 g C m^{-2} d^{-1} with winter crops. The net fixation of C was directly related to global solar radiation, which led to irregular patterns of net photosynthesis. Crop residues, senescent roots and the application of organic manure fed the fresh organic matter pool of soil and were slowly decomposed after incorporation in soil. Soil respiration mainly occurred in autumn and winter following the incorporation of crop residues in soil, with daily rates ranging between -5

and 0 g C m^{-2} d^{-1}.

In Grignon, after the harvest of barley crops in years 2004 and 2007, mustard was planted as a catch crop. Its growth was well simulated in 2008, whereas in 2004, the simulated time span of crop growth and net C fixation was shorter than observed. As a result, the total C fixation by the mustard was under-estimated in 2004 by the model, as was that of the maize crop in 2008 (Fig. 2.c). In Auradé, no catch crop was sown after the harvests of rapeseed in 2005 and wheat in 2006, but volunteers of previous crops grew up and entailed a net C uptake. This effect was modelled by resowing the same crop after harvest and stopping its growth upon tillage. Net ecosystem production was remarkably well predicted during the rapeseed and wheat growing seasons, but it was over-estimated over the sunflower crop. This was due to the model under-estimation of soil respiration rates in the months preceding the sowing of sunflower.

Figures 2.b and 2.e show the regressions between observed and modelled daily NEP at NEU-Grignon and Auradé. The coefficients of determination were fairly good, with an R^2 of 0.76 and 0.59 in Grignon and Auradé, respectively. There was also little systematic error in the predictions: the slope of the regressions was equal to unity (Grignon) or close to this value (0.82) in Auradé, and the intercepts were negligible (0.25 and 0.00 g C m^{-2} d^{-1} in Grignon and Auradé, respectively). When cumulated over the measurement period, net C fluxes were correctly predicted by the model for the NEU-Grignon and Auradé experiments (Fig. 2.c and 2.e), which proves its capacity to integrate the various C fluxes and turnover rates within the agro-ecosystem. The simulations of above-ground biomass of crops were also well within the experimental measurement errors (Fig. 3.a and 3.c), for the various crop species, with the exception of the 2008 maize upon harvest in Grignon, whose dry matter was under-predicted. The regression analysis evidenced a good match between observed and simulated data (after calibration). For the NEU-Grignon experiment, we obtained an R^2 of 0.95, an intercept of -0.75 t DM ha^{-1} and a slope of 1.2, and for Auradé, an R^2 of 0.94, an intercept of 0.35 t DM ha^{-1} and a slope of 1.12. Six

different crop species, involving 6 crop-specific sub-models, were involved in the rotations but did not hamper a good match to the field-measurements.

3.3 Model prediction assessment

The experiments of Gebesee and BPA-Grignon were used to assess the model prediction accuracy by computing the RMSEP, after calibration against the data from the NEU-Grignon trial (Table 4). The field experiments used in model testing represented different climate and soil conditions compared to the calibration sites, with similar crop management. The RMSEP for daily NEP was lower for the wheat in Gebesee than for the maize in BPA-Grignon, amounting to 1.55 and 3.78 g C m^{-2} d^{-1}, respectively. Conversely, the RMSEP for cumulative NEP was 3 times lower for BPA-Grignon than for Gebesee, being respectively of 31.61 and 90.95 g C m^{-2}. The RMSEP of above-ground (ABG) biomass was computed only for BPA-Grignon due to a lack of biomass measurements in Gebesee. Figures 4.a and 4.d depicts the dynamics of daily NEP for Gebesee and BPA-Grignon. At Gebesee, the model accurately captured the dynamics of net C fixation by the crop and the post-harvest soil respiration. In the BPA-Grignon trial, the measurement period was focused on the maize growing season, and the spike of net C fixation measured in July was not captured by the model. The radiation use efficiency of maize calibrated with the NEU-Grignon dataset appeared suboptimal for the BPA-Grignon experiment. The regressions between observed and simulated daily NEP were overall satisfactory, with an R^2 of 0.49 and 0.79 in Grignon and Gebesee, respectively, while the slopes ranged from 0.77 to 0.88, and the intercepts ranged from -0.37 to 0.79 g C m^{-2} d^{-1} (Figs 4.b and 4.e). The relatively low R^2 for the Grignon-BPA experiment stems from the model failing to mimic the peak C fixation fluxes in July, probably because it over-estimated the effect of water stress on photosynthesis. The model overestimated the cumulative sum of NEP in Gebesee whereas it slightly underestimated this variable in BPA-Grignon (Figs 4.c and 4.f).

Figure 5 depicts the time course of ABG dry matter for the maize crop of the BPA-Grignon experiment. Simulations were computed either with the posterior expectancy of parameters derived from the calibration of NEU-Grignon or with the initial (uncalibrated) parameter values. Surprisingly, the latter resulted in a more accurate simulation of crop biomass accumulation than the calibrated parameters. On the basis of these results, it appears that the calibration improved the simulation of NEP but without improving the prediction of biomass accumulation. As a result, the RMSEP for ABG biomass with calibrated model was quite high (Table 4).

3.4 Carbon balance of crop rotations

Figure6 shows the time course of carbon balance in all sites, as broken down across crops during the time period extending from their sowing to the sowing of the following crop. In the NEU-Grignon experiment, NPP was higher for the 2006 winter wheat and 2007 barley than for the 2005 and 2008 maize crops. On the other hand, soil respiration after winter wheat and barley were higher than for maize crops due to a longer period of net soil respiration from harvest to sowing. As a result, NEP was higher for maize than for winter cereals, averaging 4770 and 4090 kg C ha^{-1}, respectively. The mustard sown in 2004 was a net source of CO_2, i.e its net photosynthesis was lower than the net soil respiration. This pattern was reversed with the mustard sown in 2008, which was overall a net sink of CO_2. In both cases, the introduction of a catch crop between winter cereals and the following spring crop increases ecosystem uptake of C at the rotation scale.

In Auradé, seasonal net photosynthesis, soil respiration and net ecosystem production were similar for the 2005 winter rapeseed crop and the 2006 winter wheat (Fig. 6.b), resulting in a NEP (equivalent to a net C-uptake by the ecosystem) of 2800 kg C ha^{-1}. The net photosynthesis of sunflower was underestimated by the model, resulting in a NEP lower than for winter crops (1600 kg C ha^{-1}). In Gebesee, the net photosynthesis of winter wheat reached 6230 kg C ha^{-1},

soil respiration totalled -4000 kg C ha^{-1} and net ecosystem production 2230 kg C ha^{-1} (Fig. 6.c). In this site, soil organic carbon was higher than in the other sites, generating higher soil respiration rates. In the BPA-Grignon experiment, the net ecosystem production of maize totalled 6490 kg C ha^{-1} over the growing season, corresponding to the balance between net photosynthesis (7740 kg C ha^{-1}) and soil respiration (-1250 kg C ha^{-1} - Fig. 6.c).

Table 5 recapitulates the modelled and observed carbon inputs and exports for the 4 experiments, by crop. As in the previous section, the C budget for each crop started upon sowing and ended upon sowing of the following crop, except for Auradé, Gebesee and BPA-Grignon where the starting date was the first day of measurement. In the NEU-Grignon experiment, the model predicted the 3-yr rotation to be a net sink of 215 kg C ha^{-1} whereas the observations indicated a net source of C (-1520 kg C ha^{-1} over the three years). This discrepancy was due to the underestimation of C fixation by the 2005 maize crop and of the amount of straw removed after winter wheat in 2006. In this site, the straw of winter wheat and barley was harvested, whereas in the other sites it was incorporated into the soil. The experimental determination of straw removal rate may also have led to an over-estimation of this term, since losses probably occurred upon harvest. The simulated year-round NEP for the year 2005 at NEU-Grignon (encompassing the maize cropping cycle) was 4350 kg C ha^{-1} yr^{-1} (vs. 3120 kg C ha^{-1} yr^{-1} observed) and was 5200 kg C ha^{-1} yr^{-1} for the year 2002 at BPA-Grignon.

In Gebesee, cattle slurry and farmyard manure were applied in 2007 during the winter wheat growing season, making this crop cycle a large C sink. The simulated year-round NEP for 2007 (encompassing a part of the wheat cropping cycle) was 2400 kg C ha^{-1} yr^{-1}, which is much lower than the total of 1133 kg C ha^{-1} measured from 1 Jan. 2007 to 5 Oct. 2007 (the end of measurement period). The modelled NEP was slightly higher than the value of 1930 kg C ha^{-1} yr^{-1} reported by Anthoni et al. (2004) and based on measurements for the same site in 2001 for winter wheat. In addition, Anthoni et al. (2004) reported that when they removed C exported by the

harvest to the NEP, the site became a net source of CO_2 (of -970 kg C ha^{-1} yr^{-1}), whereas we modelled for the year 2007 a NBP of -4765 kg C ha^{-1} yr^{-1} when we removed harvested biomass to the NEP. In Auradé, we overestimated the C sink of the rotation 2005-2007 as compared with the observations, 2270 vs. 500 kg C ha^{-1} over 2.5 years which is due to a 30% underestimation of rapeseed grain yield in 2005 and an overestimation of NEP for rapeseed and winter wheat by 10 and 35% respectively as compared with observations. In the BPA-Grignon experiment, the model underestimated harvested biomass by 40% which induced a large bias in NBP: 25 vs. 2575 kg C ha^{-1} over 117 days.

4 Discussion

4.1 Model calibration and prediction error

Our goal was to parameterise the agro-ecosystem model CERES-EGC in order to estimate the daily NEP over crop rotations, assuming that the calibration against daily NEP data would simultaneously improve the predictions of net ecosystem production, crop growth and carbon balance at rotation scale.

In order for the calibration algorithm to converge, we had to artificially increase the measurement uncertainty to smooth the likelihood surface. The large number of daily observations in our sample (several hundreds of data points) led to a sharply peaked likelihood which is difficult to reach and explore by traditional Metropolis-Hastings algorithm. Processing the data in weekly or monthly means would help in reducing the amount of information and thus it would improve the calibration process. Using an adaptive MCMC sampling algorithm, such as developed by Haario et al. (2001), could also help in adapting the proposal distribution and in optimising MCMC algorithm. Bayesian calibration was applied on daily NEP data, making the assumption that whether daily values were well simulated, thus the cumulative sum would also be well estimated. This assumption could be questioned and we should compare a calibration against NEP data cumu-

lated for cropping cycles with daily NEP. The processing of data and time length of summary statistics (daily, weekly..) would then depend on the goal to which the model is applied for.

The Bayesian calibration on the NEU-Grignon and Auradé experiments resulted in a slight reduction of RMSE compared to the initial parameterization. There was also a close correlation between observed and modelled NEP on daily or seasonal basis, evidencing a good capacity of the model to predict NEP at both scales. The coefficients of determination (R^2) we obtained ranged from 0.59 to 0.76, and compare well to literature. Huang et al. (2009) reported an R^2 of 0.43 when simulating two years of NEP data over an arable field in China with an agro-ecosystem model. Wang et al. (2005) parameterised an ecosystem model against NEP measurements over a wheat-maize sequence in China, and obtained R^2 between 0.74 and 0.76, in the range we obtained in the NEU-Grignon experiment.

After calibration, we estimated the model prediction error (RMSEP) using independent data sets from two experiments with similar crop management but different soil or climate conditions (BPA-Grignon and Gebesee). The RMSEP ranged between 1.5 and 3.8 g C m^{-2} d^{-1}, indicating a good capacity of CERES-EGC to capture NEP at daily and seasonal scales, and were 4 to 7 times lower than the value of 11.3 g C m^{-2} d^{-1} reported by Huang et al. (2009). However, the crop growth at BPA-Grignon was not well simulated because the RUE parameter for maize, calibrated against NEU-Grignon dataset, was not accurate for the maize crop of the BPA-Grignon field site experiment.

4.2 Using a crop model to simulate the net carbon exchanges

We originally assumed that calibration of RUE parameters of crop growth sub-models against net C exchanges would allow us to take into account the whole plant C fixation by integrating the root growth and the RUEs would have been increased. As a result, the RUEs of maize and wheat were substantially reduced after calibration, in comparison with their initial values. An

underlying explanation of such results could be that the calibration directly applied on C balance between net C fixation and heterotrophic respiration do not make possible to well calibrate simultaneously both processes. Calibrating each process separately with their specific measured data may help in better estimating the RUEs and soil respiration. The main limitation being that it is difficult to measure separately the C fluxes from soil and plants compartments, especially for roots.

While the modelled estimates of NEP were in agreement with observations, those for grain yield and straw removal were lower than observed, which had a large effect on the final C balances. However, the observations of straw removal in the NEU-Grignon experiment were relatively uncertain since they were based on destructive sampling of plants prior to harvest, and did not take harvest losses or cutting height into account. The differences in the modelled and measured C balances should therefore be mitigated, considering the potentially large experimental error on the removal terms.

Grant et al. (2007) showed that the *Ecosys* model well captured the ABG biomass dynamic for maize and soybean crops and that the model predicted with high accuracy the grain removal for the two crops of the rotation. The CERES-EGC predicted above-ground biomass and grain yield in the same range of accuracy but it remains an uncertainty with the estimation of straw removal. At the crop rotation scale, the simulated NEP of the year encompassing maize cropping season in Grignon are in accordance with literature data for temperate climates. Verma et al. (2005) measured NEP values for irrigated and rainfed maize crops ranging from 3800 to 5200 kg C ha^{-1} yr^{-1}. Wang et al. (2005) simulated with a biogeochemical model a NEP of 3340 kg C ha^{-1} yr^{-1} for wheat and 3850 kg C ha^{-1} yr^{-1} for maize, while Moureaux et al. (2006) measured a higher value of 6100 kg C ha^{-1} yr^{-1} for a spring crop, sugar beet in Belgium.

Lastly, Huang et al. (2009) measured a NEP over 608 days for a winter wheat-maize-winter wheat rotation in Yucheng (China; semi-humid and monsoon climate), and obtained a mean NEP

of 7200 kg C ha^{-1}, with no time interval between two successive crops. Their modelled estimate was very similar, at 7810 kg C ha^{-1}. We estimated for a similar crop sequence of maize-winter wheat-winter barley (893 days) in Grignon an observed NEP of 13137 kg C ha^{-1} and simulated NEP of 13510 kg C ha^{-1}. The difference between both studies is due to difference between the estimation of NPP. In fact, Wang et al. (2005) modelled the NPP for the same site in China equal to 3340 for wheat growing season and 3850 kg C ha^{-1} for maize growing season, whereas we estimated NPP of 6680 kg C ha^{-1} for maize in 2005 and 7435 kg C ha^{-1} for winter wheat in 2006.

Net biome production is very sensitive to the estimation of biomass removal from the field and organic manure inputs. Our model predicted the rotations of NEU-Grignon and Auradé to be net C sinks, whereas Grant et al. (2007) simulated rainfed or irrigated maize-soybean rotations as being net sources of C, emitting between 400 and 800 kg C ha^{-1} yr^{-1} into the atmosphere. They compared their estimation of NBP by simulating the variation of soil C stock over 100-year simulation periods. In this way, they estimated a soil organic C loss of 300 kg C ha^{-1} yr^{-1} for rainfed system and an increase of 600 kg C ha^{-1} yr^{-1} for irrigated system. The carbon returns from application of organic fertilizers generates also an important effect on NBP reducing it by 50 to 115% in case of the rotation of NEU-Grignon. Carbon uptake from catch crops and volunteers also appear as non negligible input of C in the crop system.

Our agro-ecosystem model simulates water, C and N cycling and GHG fluxes as well as the drivers controlling plant and microbial processes. Simulating net carbon exchanges and crop productivity for various crop species requires to combine a large number of processes. In particular special attention should be focused on simulating accurate crop phenology (date of harvest), water and N stress on crop growth, sharing between biomass exported out of the field and residue return to soil.

5 Conclusion and future work

We applied a Bayesian method to calibrate the CERES-EGC model against two data sets of NEP from contrasted pedoclimatic conditions and crop sequences (NEU-Grignon and Auradé). The calibrated model allows us to predict the net carbon exchanges between soil-crop and atmosphere from daily to rotation time-scale. We computed the error of model prediction by comparing simulations and observations of NEP from two other independent data sets (BPA-Grignon and Gebesee). The model correctly predicted NEP in both sites, but under-estimated crop biomass in one of them. The originality of our approach is that we can compute the different terms of the C balance for entire crop rotations and then assign equally the C source and sink between the crops of the rotation. The model estimates the crop productivity that is exported out of the field for being used in food, feed or bioenergy supply chains. The C balance at the field gate could then be introduced into life cycle assessment of agricultural products such as recommended by Rabl et al. (2007) who advised to count C-uptake and emissions at each stage of the life cycle instead of counting a zero C balance between C fixation and emission.

Anthoni et al. (2004) reported that up-scaling C fluxes from croplands from plot to regional scale was the most complicated task to establish C budget of a selected region due to wide variations in crop species, rotations, residue and fertilizer management and soil C stocks. The use of process-based models such as CERES-EGC would help in estimating the regional net carbon fluxes. The calibration developed in Lehuger et al. (2009) for N_2O makes it possible to apply plot-scale models at regional level by providing robust estimates for generic (ie non site-specific) parameters over this domain. Such a strategy could also be used for CO_2 using the calibration method we used here on a wider range of data sets to find parameter values that would be universally applicable. The calibrated model could then be used to simulate a wide range of environmental conditions, and coupled with GIS databases to generate high-resolution

regional maps of net CO_2 fluxes with daily time resolution. Estimating C fluxes from forests, grasslands and other ecosystems (shrublands, wetlands...) would also be integrated for budgeting biospheric C fluxes at regional or landscape scale (Turner et al., 2007). Regional validation of model simulations with landscape or regional measurements, such as carried out by Soegaard et al. (2003), would combine the different sources and sinks of carbon. Regional strategies of C-abatement would then be tested using the model at this spatial scale.

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Site	Experiment	Year	Soil texture class	Sequence of crops	Number of daily NEP measurements
Grignon	NEU	2004-2008	Silt Loam	M-WW-WB-m	1627
Grignon	BPA	2002	Silt Loam	M	115
Auradé		2005-2007	Clay Loam	R-WW-SF	926
Gebesee		2007	Silty Clay Loam	WW	310

Table 2: Selected characteristics of the various sites and experiments (M: Maize; WW: winter wheat; WB: winter barley; m: mustard; R: rapeseed; SF: sunflower).

Site	Output variables	Unit	RMSE computed with:			
			Initial parameter values	Posterior expectancy of parameters	Maximum a posteriori parameter vector	Posterior expectancy of predictions
NEU-Grignon	Daily NEP	g CO_2-C m^{-2} d^{-1}	2.22	1.90	1.90	1.89
	Cumulative sum of NEP	g CO_2-C m^{-2}	415.85	137.65	92.57	127.11
	Above-ground biomass	t DM ha^{-1}	1.87	1.82	1.99	1.83
Auradé	Daily NEP	g CO_2-C m^{-2} d^{-1}	2.68	1.88	1.80	1.88
	Cumulative sum of NEP	g CO_2-C m^{-2}	217.83	68.68	83.36	70.03
	Above-ground biomass	t DM ha^{-1}	1.84	1.24	2.93	1.24

Table 3: Root mean square errors (RMSEs) of daily NEP, cumulative sum of NEP and above-ground biomass based on the initial (prior) parameters values, the posterior expectancy of parameters, the maximum a posteriori parameter vector and the posterior expectancy of predictions.

Site	RMSEP of:		
	Daily NEP g CO_2-C m^{-2} d^{-1}	Cumulative sum of NEP g CO_2-C m^{-2}	Above-ground biomass t DM ha^{-1}
Gebesee	1.55	90.95	no data
BPA-Grignon	3.78	31.61	3.65

Table 4: Root mean square errors of prediction (RMSEP) based on the posterior expectancy of parameters for daily NEP, cumulative sum of NEP over crop rotation and above-ground biomass.

Site	Crop	Time period		Net ecosystem production (kg C ha^{-}1)		Harvested biomass (kg DM ha^{-}1)		Manure (kg C ha^{-}1)	Net biome production (kg C ha^{-}1)	
		Start	End	Modelled	Observed	Modelled	Observed		Modelled	Observed
NEU-Grignon	Mustard	2004-09-01	2005-05-08	-822	-456			988	166	532
	Maize	2005-05-09	2005-10-15	5515	5139	-13510	-15470		111	-1049
	Winter wheat	2005-10-16	2006-10-05	3510	2621	-7597 (-5859)	-7500 (-8430)		-1872	-3751
	Barley	2006-10-06	2007-10-21	4485	5377	-8630 (-3632)	-8200 (-3640)		-419	641
	Mustard	2007-10-22	2008-04-26	632	875			1763	2395	2638
	Maize	2008-04-27	2008-10-14	6627	8005	-13730	-20470		1135	-183
	Rotation	2005-05-09	2008-04-26	14143	14012				215	-1521
Auradé	Rapeseed	2005-03-18	2005-10-24	2745	2504	-3768	-5300		1237	384
	Winter wheat	2005-10-25	2007-04-09	2816	2088	-6378	-6000		265	-312
	Sunflower	2007-04-10	2007-09-29	1611	1311	-2116	-2200		765	431
	Rotation	2005-03-18	2007-09-29	7172	5903				2267	503
Gebesee	Winter wheat	2007-01-01	2007-10-05	2622	1134	-7165	-4700	4460	4216	3714
BPA-Grignon	Maize	2002-06-15	2002-10-07	6476	6643	-16130	-23040		24	-2573

Table 5: Carbon budgets of the crop sequences of NEU-Grignon, Auradé, Gebesee and BPA-Grignon. The C balance is broken down into net ecosystem production, harvested biomass, manure inputs.

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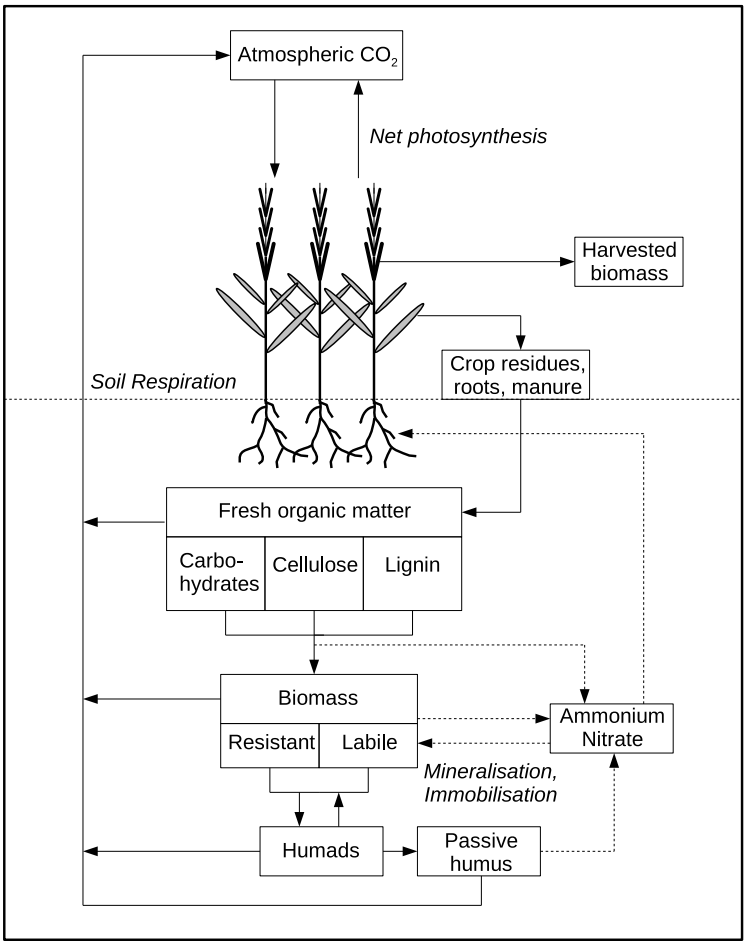

Figure 1: Schematic of C fluxes (solid arrows) and N flows (dashed arrows) within the CERES-EGC model.

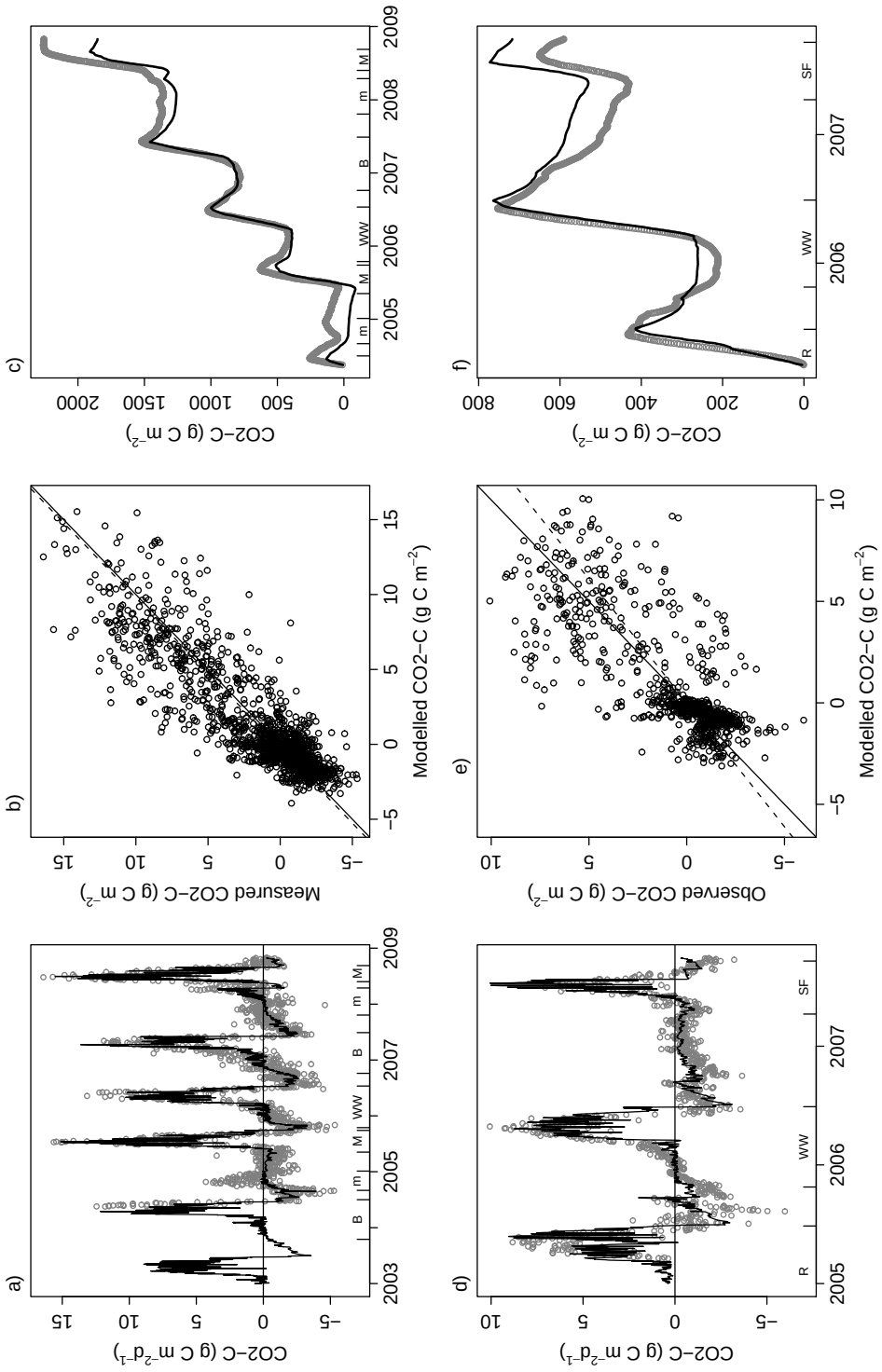

Figure 2: Time course of simulated (black line) and observed (grey symbols) of net ecosystem production (NEP), on a daily time scale (a,d) or cumulated for each growing season (c,f), and scatter plot of simulated versus measured NEP (b,e). The top graphs pertain to the Grignon-NEU experiment (a,b,c), the bottom one to the Auradé experiment (d,e,f). Simulation lines correspond to the posterior expectancies of simulations, and the crop cycles are represented with the following letters: B: barley, m: mustard, M: maize, WW: winter wheat, R: rapeseed and SF: sunflower.

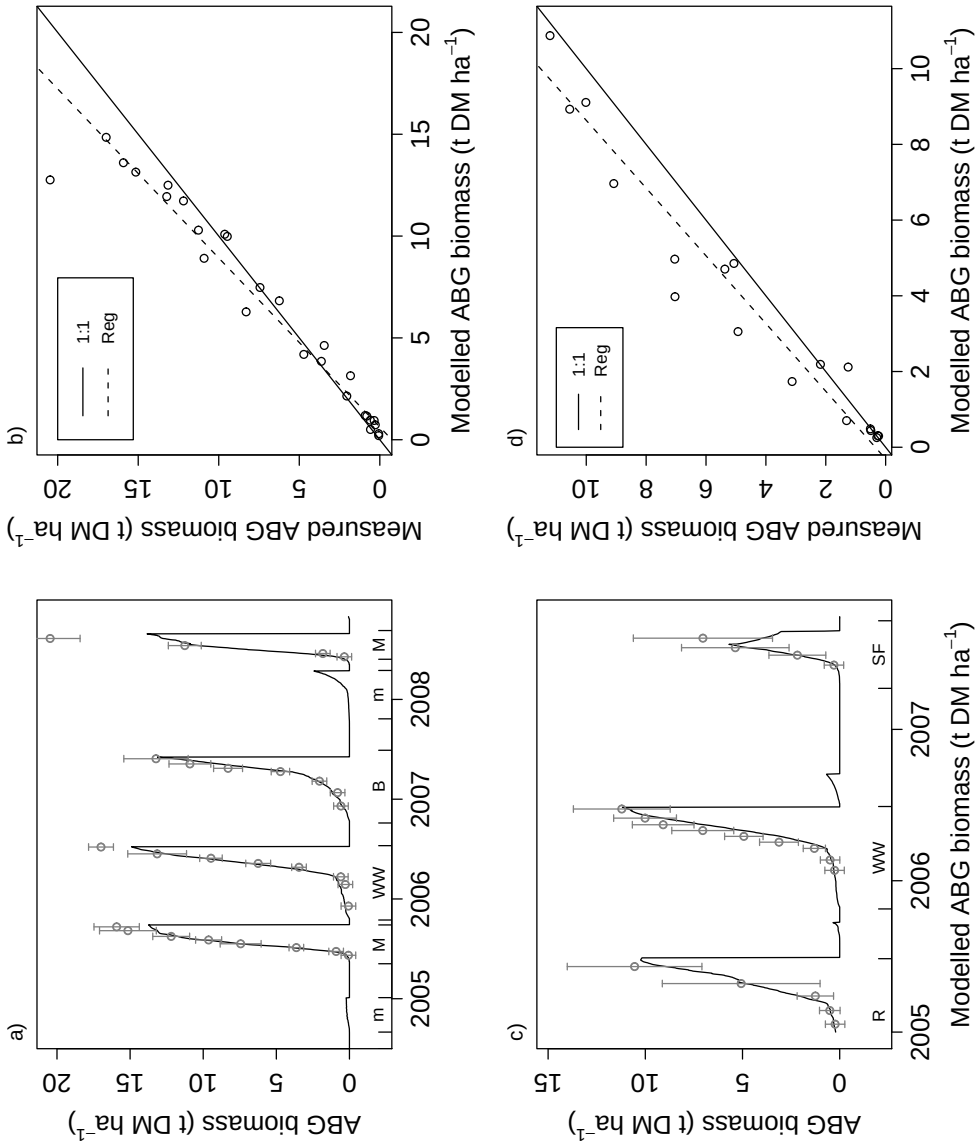

Figure 3: Simulations (black line) and observations (grey points) of above-ground (ABG) crop biomass (a,c) and simulated versus measured ABG biomass (b,d) for the crop sequence of Grignon site (a,b) and Auradé site (c,d). Simulation lines correspond to the posterior expectancies of simulations, and the crop cycles are represented with the following letters: B: barley, m: mustard, M: maize, WW: winter wheat, R: rapeseed and SF: sunflower.

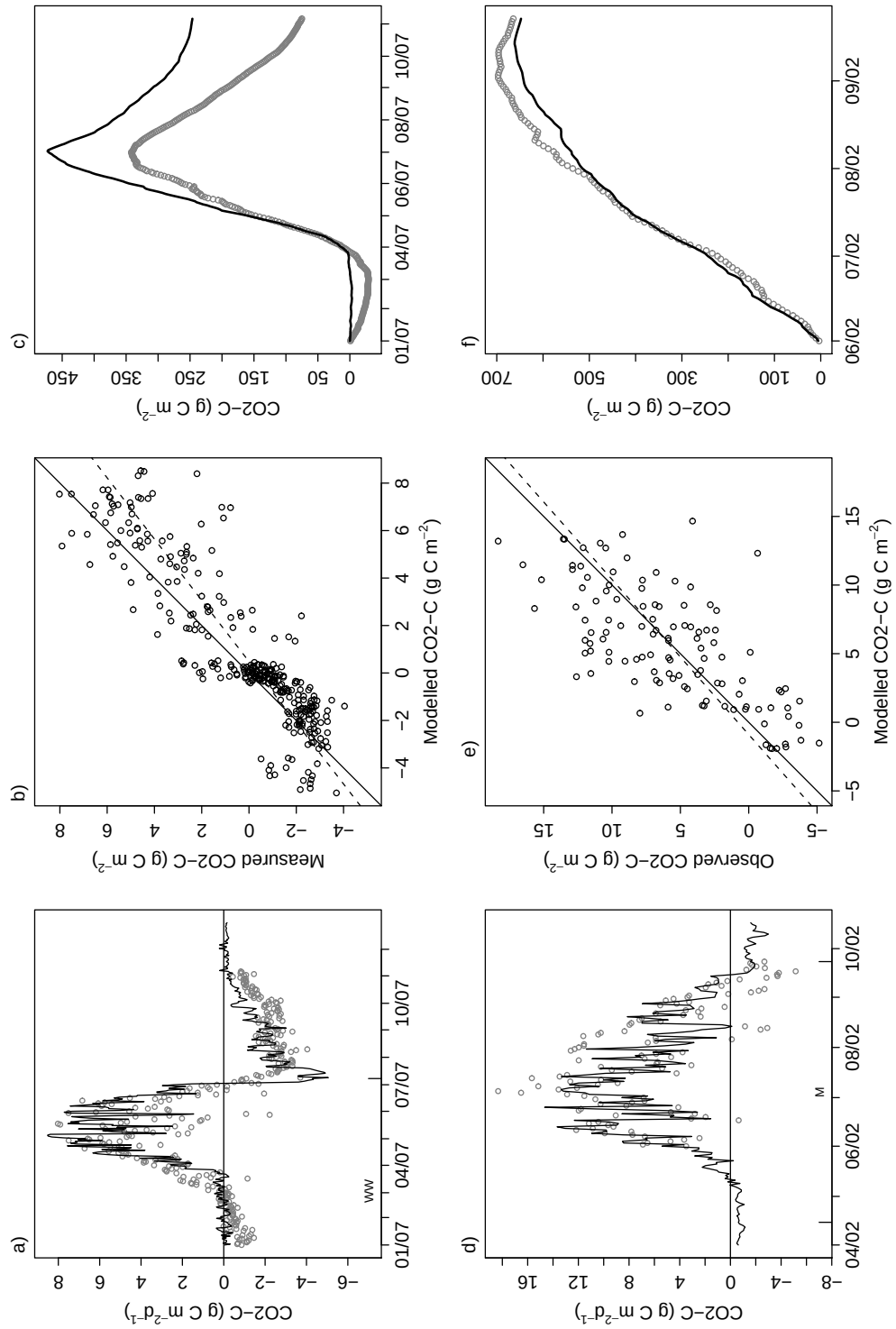

Figure 4: Simulations (black line) and observations (grey points) of daily net ecosystem production (NEP), simulated versus measured NEP and simulations (black line) and observations (grey points) of cumulative sum of NEP for the wheat crop cycle of Gebesee site (a,b,c) and the maize crop cycle of Grignon-BPA experiment (d,e,f).

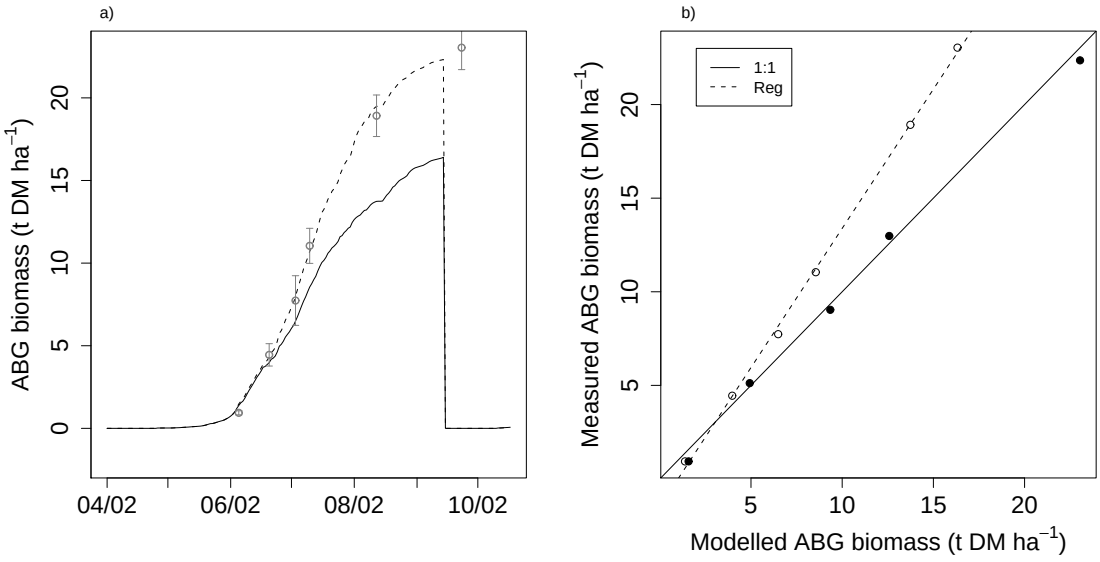

Figure 5: Simulations with calibrated parameter values (solid line) and initial parameter values (dashed line) and observations (grey points) of above-ground (ABG) crop biomass (a). Simulated versus measured ABG biomass for simulations with calibrated parameters (empty points) and initial parameter values (full points) for the maize crop cycle of BPA-Grignon site (b, the measurement of 7 Oct. 2002 was removed of the data set). Simulated lines with calibrated parameters are the posterior expectancies of simulations.

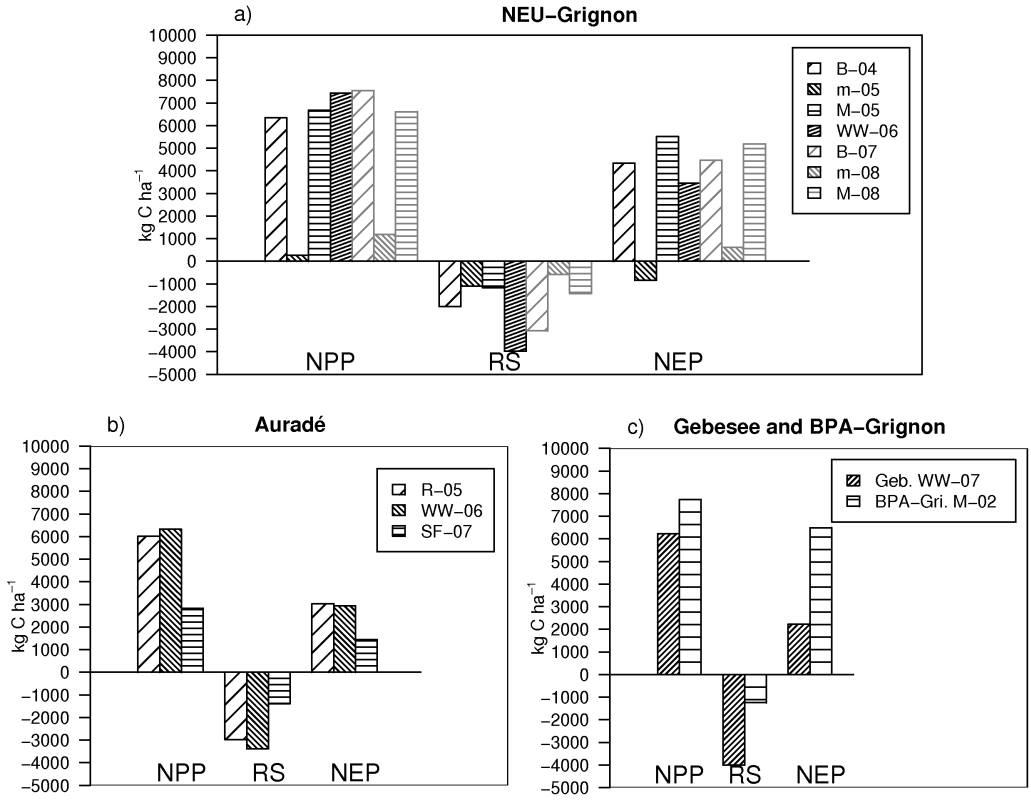

Figure 6: Carbon balances of the crop sequences at Grignon, Auradé and Gebesee based on simulations with the calibrated model. Net ecosystem production (NEP) is broken down into net primary production (NPP) and heterotrophic soil respiration (Rs).