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Importance of crop varieties and management practices: evaluation of a process-based model for simulating CO_2 and H_2O fluxes at five European maize (*Zea mays* L.) sites

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Abstract. This paper is a modelling study of crop management impacts on carbon and water fluxes at a range of European sites. The model is a crop growth model (STICS) coupled with a process-based land surface model (ORCHIDEE). The data are online eddy-covariance observations of CO_2 and H_2O fluxes at five European maize cultivation sites. The results show that the ORCHIDEE-STICS model explains up to 75 % of the observed daily net CO_2 ecosystem exchange (NEE) variance, and up to 79 % of the latent heat flux (LE) variance at five sites. The model is better able to reproduce gross primary production (GPP) variations than terrestrial ecosystem respiration (TER) variations. We conclude that structural deficiencies in the model parameterizations of leaf area index (LAI) and TER are the main sources of error in simulating CO_2 and H_2O fluxes. A number of sensitivity tests, with variable crop variety, nitrogen fertilization, irrigation, and planting date, indicate that any of these management factors is able to change NEE by more than 15 %, but that the response of NEE to management parameters is highly site-dependent. Changes in management parameters are found to impact not only the daily values of NEE and LE, but also the cumulative yearly values. In addition, LE is shown to be less sensitive to management parameters than NEE. Multi-site model evaluations, coupled with sensitivity analysis to management parameters, thus provide important information about model errors, which helps to improve the simulation of CO_2 and H_2O fluxes across European croplands.

1 Introduction

The global carbon budget has significantly changed due to various human activities. Agriculture, as a main way to produce food and feed, is one of these activities. In Europe, where they cover 1.10 to 1.24 M km^2 (FAOSTAT, 2003; Gervois et al., 2008) croplands are estimated to be a net source of CO_2 to the atmosphere (Vleeshouwers and Verhagen, 2002; Janssens et al., 2003; Ciais et al., 2009). In addition, cropland CO_2 fluxes impact the phase and amplitude of atmospheric CO_2 concentration over the European continent (Smith et al., 2002; Freibauer et al., 2004). Similarly, H_2O fluxes are strongly modified by the presence of cropland vegetation (Baldocchi, 2003; Valentini, 2003), which in turn feeds back

on regional temperature and on soil moisture (Pongratz et al., 2009). In turn, climate change is likely to have wide-ranging influences on crop productivity and water resources (IPCC, 2007) in many regions of the world. Compared to forest and grasslands, croplands are more intensively managed, resulting in a complex and dynamic interrelation of physical, biological processes with human management parameters (Antle et al., 2001). This suggests that cropland management have considerable impacts on the fluxes of CO_2 and H_2O. Interactions between climate and crops must deserve more attention in assessing greenhouse gas mitigation and adaptation options in the agricultural sector (Falloon and Betts, 2010). Continuous micrometeorological measurements of the net exchange of CO_2, H_2O and heat between various terrestrial ecosystems and the atmosphere have been developed worldwide using the eddy-covariance technique since the 1990's (Baldocchi et al., 2001; Baldocchi, 2003; Valentini, 2003). However, these point-scale flux measurement time-series may prove difficult to scale up for quantifying regional carbon and water budgets due to spatial and temporal variations in climate, soil properties and management practices (Kucharik and Twine, 2007), although promising up-scaling studies were recently published (Jung et al., 2009; Beer et al., 2010).

Land surface models are powerful tools for quantifying and understanding the energy, H_2O and CO_2 exchanges between the terrestrial biosphere and the atmosphere. During the past few decades, numerous models have been developed worldwide. ORCHIDEE (ORganising Carbon and Hydrology In Dynamic EcosystEms) is a model developed for conducting continental carbon and water cycle research (Ciais et al., 2005; Piao et al., 2007). ORCHIDEE, initially designed based upon leaf and plant-scale physiological theories, has been tested in simulating energy transfer, water vapor and carbon exchanges between vegetation and atmosphere at forest flux sites (Viovy, 1997; Ciais et al., 2005). At crop sites, ORCHIDEE, which considers grid cells with croplands to be covered by productive natural grasses, is shown to be unable to capture the seasonal cycles of CO_2 and H_2O fluxes (Krinner et al., 2005).

We hypothesize that this shortcoming of the model reflects the absence of crop-specific phenology and management parameterization. Therefore, a specifically-designed crop growth model named STICS (Simulateur mulTIdisciplinaire pour les Cultures Standard; Brisson et al., 1998; Brisson et al., 2002) has been coupled with ORCHIDEE. The ORCHIDEE-STICS coupled model was tested against flux measurements at two eddy covariance sites in the US, over winter wheat and maize, respectively (Gervois et al., 2004; De Noblet-Ducoudre et al., 2004). At these two US sites, the model showed a satisfactory fit to observed NEE and energy budget, but its performance regarding different components of carbon fluxes has not been evaluated.

The CO_2, H_2O and energy exchanges between the atmosphere and cultivated lands depend not only on climate variables and soil properties, but also on management practices (Kucharik and Twine, 2007). Parameters such as crop variety, planting date, N-fertilization, and irrigation differ across regions and change with time as well. Although remote sensing may provide some information about crop N content (Bausch and Duke, 1996), crop water status (Jackson et al., 1981; Moran et al., 1994) and phenology (Viña et al., 2004), these observations do not meet the requirement of direct regional GPP estimation over croplands (Reeves et al., 2005). On the other hand, cropland models, driven by meteorological variables and site-specific parameters, can be used to conduct regional estimation of carbon and water vapor budgets (Andrew et al., 2005; Verma et al., 2005; Yan et al., 2007), but crop variety and management information are often lacking. An accurate estimation and analysis of the model uncertainties at site scale, where the fluxes can be directly compared against observations, are necessary prior to regional or continental applications.

The objectives of this paper are: (1) to evaluate the performance of the ORCHIDEE-STICS land surface model in modelling CO_2, H_2O fluxes and biometric variables over croplands at five maize sites in Europe; and (2) to quantify the uncertainties caused by different management parameters, in order to estimate their impacts on large scale integration studies.

2 Material and method

2.1 European maize cultivation sites description

Among the crop sites studied during the CarboEurope project (Dolman et al., 2006) we select the site-years for which maize was cultivated at least one year. This leads to select five sites each with one year of maize rotation (two sites in France, two sites in Netherlands and one in Germany). The geographic information (longitude and latitude), cropping year, soil type (FAO classification) and mean growing season meteorological variables (temperature and rain) for five European maize sites are listed in Table 1. Soil properties (e.g. texture, field water capacity and wilting point), which are essential parameters of ORCHIDEE-STICS model, are measured or estimated at each site. At all sites, maize is grown for animal feed production in the study year. Variety, planting and harvest dates, fertilization and irrigation events are listed in Table 2. These data are used to develop the control simulation of the model.

The Grignon (GRI) site is located about 40 km west of Paris, France. The crop rotation of the Grignon experiment includes maize, winter wheat, winter barley and mustard which is planted to serve as a catch crop to reduce nitrate leaching during winter. Dairy cow slurry is applied between the harvest of barley and the planting of mustard on 31 August 2004, and before maize sowing on 16 April 2008. Lamasquère (LAM) is located in south west of France.

Table 1. Geographic information (longitude, Lon. and Latitude, Lat.), cropping year, soil type (FAO classification) and main growing season (GS) meteorological variables (temperature, Ta and Rain, unit in °C and mm, respectively) for five European maize sites. The 3-letters code name is the abbreviation used in the paper.

Site	Full name	Country	Lon.	Lat.	Year	Soil type	GS Ta	GS Rain
DIJ	Dijkgraaf	Netherlands	5°38′ E	51°59′ N	2007	Haplic Gleysol	15.8	453
GRI	Grignon	France	1°58′ E	48°51′ N	2005	Luvisol	17.2	169
KLI	Klingenberg	Germany	13°31′ E	50°53′ N	2007	Gleysol	14.4	593
LAM	Lamasquère	France	1°24′ E	43°50′ N	2006	Luvisol on Alluvium	19.6	153
LAN	Langerak	Netherlands	6°21′ E	53°24′ N	2005	Eutric thaptohistic Fuvisol	17.0	403

Table 2. Crop variety, planting/harvest date, fertilization and irrigation.

Site	Variety	Planting	Harvest	Nitrogen fertilization	Irrigation
DIJ	La Fortuna	4 May	27 Sep	212 kg N ha^{-1}	0 mm
GRI	Anjou 288	9 May	28 Sep	140 kg ha^{-1}	0 mm
KLI	Rosalie*	23 Apr	2 Oct	84 kg ha^{-1}	0 mm
LAM	Goldaste	1 May	31 Aug	91 kg ha^{-1}	147.8 mm
LAN	La Fortuna	18 May	19 Oct	65 kg ha^{-1}	0 mm

The symbol "*" indicates unknown crop variety, and recommended variety is used.

Previous cultivated crops are maize (2004) – triticale (2005) – maize (2006) – winter wheat (2007) – maize (2008) – winter wheat (2009). More detailed information on site characteristics and general information on soil and meteorology can be found in Béziat et al. (2009).

The sites Dijkgraaf (DIJ) and Langerak (LAN) are located in east and west of the Netherlands, respectively. Flux measurements started in 2007 at DIJ and in 2005 at LAN. The main cultivated crop is maize at both sites.

The site Klingenberg (KLI) is located in East of Germany. This site has been established in 2004. Cultivated crops include winter barley (2004), rapeseed (2005), and winter wheat (2006), maize (2007) and spring barley (2008).

Grown variety is different at each of these five sites. Planting dates differ by up to 25 days, ranging from 23 April (KLI) to 18 May (LAN) and the growing season length extends from 123 to 163 days. Amount of N fertilizer also varies from 65 kg N ha^{-1} (LAN) to 212 kg N ha^{-1} (DIJ). Irrigation (147.8 mm) is applied at LAM site only (Table 2).

2.2 Eddy covariance system and meteorological measurements

At each site an eddy covariance (EC) system is installed to measure the fluxes of CO_2, water vapor and sensible heat. The EC system consists of a fast response infrared gas analyzer (LI7500, LiCor, Lincoln, NE, USA) and a three-

dimensional sonic anemometer (CSAT3, Compbell Scientific Inc, Logan, UT, USA). The system is a standard monitoring system used in the *Carboeurope* and *Fluxnet* networks (Dolman et al., 2006). Data are recorded with personal computer at a sampling frequency of 25 Hz for each channel. Average values are calculated and recorded at 30 min interval and used for analysis.

Meteorological measurements are made at each site on an hourly time step. Measured meteorological variables consiste of long- and short-wave radiation, air temperature, relative humidity, wind speed, precipitation, and mean near surface atmospheric pressure.

The flux time series are handled for checking for anomalous values arising from sensors malfunctioning caused in particular by interference of water condensation and rain drops with the optical path of the IRGA. NEE data associated with weak turbulence conditions are also rejected. Good quality data are then gap-filled using the CarboEurope-IP methodology (Reichstein et al., 2005; Papale et al., 2006a, b; Moffat et al., 2007; Béziat et al., 2009). The gap-filling procedure consists in replacing missing values of NEE by average values under similar meteorological conditions within a time window of 67 d. Similar meteorological conditions are defined with global radiation, air temperature and vapor pressure deficit that must not deviate from the period to gap-fill by more than 50 W m^{-2}, 2.5 °C, and 5.0 hPa, respectively. If no similar conditions were present within the time window, the length of the averaging window was increased.

Net radiation, air temperature, and precipitation during the growing period at the five sites are shown in Fig. 1. The meteorological conditions are largely different among sites. DIJ and LAN sites have median precipitation (400–450 mm), and KLI is wetter site (593.0 mm) during the growing season. The growing season precipitation at GRI and LAM is quite low, with 152.7 mm and 169.4 mm, respectively. These two dryer sites in France have high solar net radiation (278.6 and 234.7 W m^{-2}) and warmer air temperature (19.6 and 17.2 °C) during the growing season, mirroring low precipitation. In contrast, the wettest KLI site in Germany is characterized by a cooler growing season air temperature of 14.4 °C.
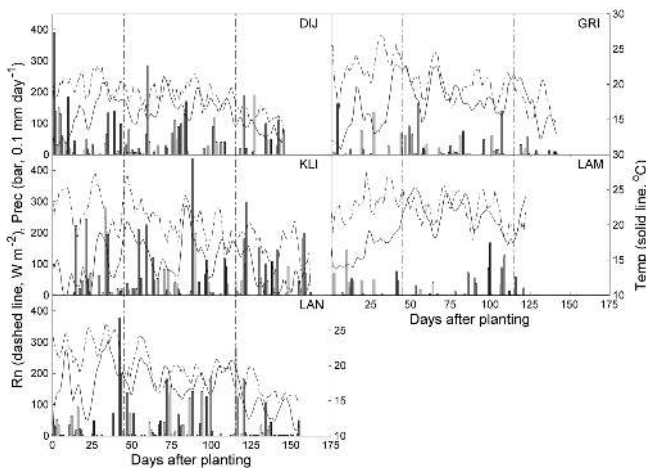
Fig. 1. Net radiation (Rn, dashed line), temperature (Temp, solid line), and precipitation (Prec, gray bar) during the growing season at 5 maize sites. Rn and Temp are smoothed for 5 days and Prec is shown on daily basis. The first vertical dashed line x = 45 is defined as the end of the early crop growth period, and x = 115 is defined as the start of the late crop growth period. Between the two lines, it is defined as the middle crop growth period.

2.3 Biometric measurements

At KLI site, leaf area index (LAI) and above ground biomass (AGB) are measured in a destructive manner. At other sites, LAI is measured on the basis of 30 randomly spatially distributed plants by means of a LiCor planimeter (LI3100, LiCor, Lincoln, NE, USA). LAI measurements are made on 15 to 20-day interval. At harvest, 30 randomly spatially distributed plants are destructively collected and crop aboveground biomass including stem, leaf and ear (for grain maize) are measured using a balance (SPU 4001, OHAUS, Pine Brook, NJ, USA).

2.4 ORCHIDEE-STICS model

ORCHIDEE-STICS is a coupled model (Gervois et al., 2004; De Noblet-Ducoudre et al., 2004) between the generic process-oriented ecosystem model ORCHIDEE (Krinner et al., 2005) and the crop growth model STICS (Brisson et al., 1998, 2002, 2003). ORCHIDEE has robust physiological parameterizations to simulate energy-, hydrology- and carbon-related processes for diverse natural vegetation grouped into Plant Functional Type (PFT). On the one hand, the version of ORCHIDEE used in this study has no supply of nitrogen, and thus misses a critically important process to sustain growth and to achieve higher crop yield. In addition, crops have a very specific phenology, that is discarded in ORCHIDEE. On the other hand, STICS model developed for agronomical research is able to simulate crop growth processes for different crops and varieties (Brisson et al., 1998; Brisson et al., 2002), but it is rather simple for handling ecosystem pro-

cesses. In the coupled ORCHIDEE-STICS model, STICS is responsible for calculating LAI and crop height that are given on a daily time step to ORCHIDEE. STICS also accounts for management action not available for ORCHIDEE, and consequently allows for nitrogen and water stress can be alleviated by fertilization and irrigation. STICS automatically calculates fertilization and irrigation requirements and timing, based upon calculated "optimal" plant requirements (Brisson et al., 1998, 2002). When nitrogen or water become limiting, a certain amount is applied daily until requirements are fulfilled. This "automatic management" option is used for investigating the model sensitivity to management practices (see Sect. 2.5). ORCHIDEE-STICS was previously found to have underestimated 30 % of maize yields at country scale in Europe (Gervois et al., 2008). Smith et al. (2010) adjusted parameters related to photosynthetic capacity (V_{cmax}) and environmental stress factors to apply the coupled ORCHIDEE-STICS model across the European continent. However, even after these improvements, the model still underestimated the assimilation capacity and maize yields. The most likely reason may be a too-low value of V_{cmax} (i.e. without any stress). In the first version of ORCHIDEE (Krinner et al., 2005), V_{cmax} for maize is set as 39 μmol m^{-2} s^{-1} which is directly derived from a universal model of C$_4$ photosynthesis (Collatz 1992). In the CLASS crop model, the V_{cmax} value is 54 μmol m^{-2} s^{-1} (Kothavala et al., 2005) and a V_{cmax} value of 63 ± 4 μmol m^{-2} s^{-1} is found by Kim et al. (2007). The V_{cmax} value of maize determined from field measurements at the DIJ site is in the range 62–72 μmol m^{-2} s^{-1} (Cor Jacobs, personal communication, 18 February 2009). In this study, we prescribed $V_{cmax} = 100$ μmol m^{-2} s^{-1}, in absence of any stress.

Above ground biomass is diagnosed from the ORCHIDEE-STICS output as the sum of leaf, above ground sap and heart wood tissues, and fruit carbon output variables weighted by a conversion coefficient of carbon to biomass (Goudriaan et al., 2001).

2.5 Simulation set-up for model's sensitivities to crop varieties and management practices

In this section, we describe the ORCHIDEE-STICS model control and sensitivity runs.

2.5.1 Control simulation

The model is run on hourly time step. Soil properties including texture (sand, silt and clay fractions) and meteorological forcing are derived from site measurements. In the control simulation experiment, on-site observed information on fertilization, irrigation, and planting dates is prescribed to ORCHIDEE-STICS. For crop variety, the version of STICS that we use includes 8 different maize varieties, each described by a set of parameter values, but none of these matches the exact variety planted on the studied sites. Thus,

Table 3. A summary of the simulation set-up for the model sensitivity tests.

Simulation	Variety	Fertilization	Irrigation	Planting date
Control simulation	FURIO	Observed	Observed	Observed
Variety sensitivity 1	DK250	Observed	Observed	Observed
Variety sensitivity 2	DK604	Observed	Observed	Observed
Fertilization sensitivity	FURIO	Model calculated	Observed	Observed
Irrigation sensitivity	FURIO	Observed	Model calculated	Observed
Early planting sensitivity	FURIO	Observed	Observed	Observed−25
Late planting sensitivity	FURIO	Observed	Observed	Observed+25

we select a moderate thermal requirement variety, FURIO, as the control variety by default (Lemaire et al., 1996).

2.5.2 Sensitivity tests with perturbed management parameters

A summary of the simulation set-up for model sensitivities is listed in Table 3. For testing the model sensitivity to different crop varieties, two other sets of simulation with two varieties with shorter (DK250) and longer (DK604) thermal requirements than FURIO are performed. For the sensitivity to planting date, two scenarios are created, with planting prescribed 25 days earlier and later than the observed planting date, respectively. In order to guarantee the crop being matured for the late planting sensitivity test, the harvest date is set as 1 December. For early planting simulation, the harvest date is kept as observed. For these sensitivity tests far from real world conditions, we use the automatic management option of STICS, instead of the true values prescribed in the control simulation.

2.6 Taylor plot analysis

A Taylor diagram (Taylor, 2001) is used to present the agreement between model and data and the model sensitivities to management parameters. Three statistical indicators, correlation coefficient (R), standard deviation (STD) normalized by observed STD (NSTD) and root mean square error (RMSE), are displayed on a Taylor diagram. The performance of model simulation is specified by a single point, the R value being the polar angle, and NSTD the polar axis. The higher the R and the closer to 1 the NSTD, the better the agreement between model and data is. When comparing two simulations with different parameter values, the longer the distance between the two simulation points, the greater the sensitivity to that parameter.
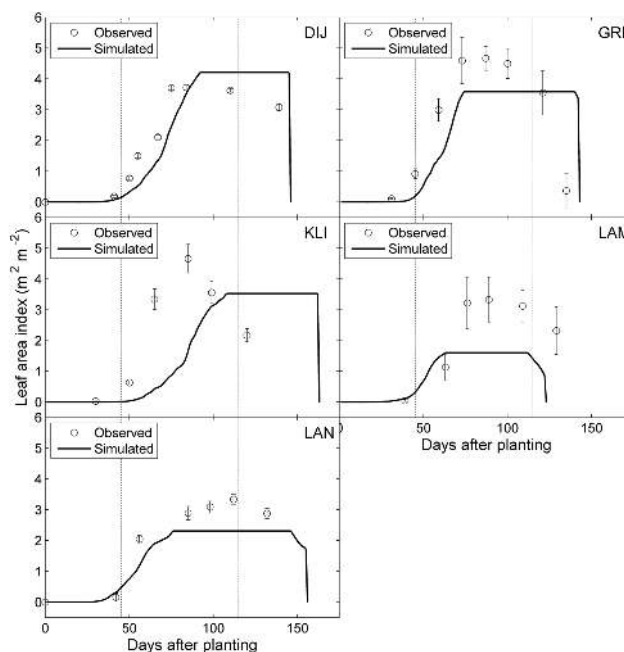

Fig. 2. Simulated vs. measured LAI at site DIJ, GRI, KLI, LAM, and LAN. The first vertical dashed line x = 45 is defined as the end of the early crop growth period, and x = 115 is defined as the start of the late crop growth period. Between the two lines, it is defined as the middle crop growth period. Error bars are the stand error of the mean at DIJ, GRI, LAM and LAN, and are the 10 % of the observations at KLI where only mean values of observations are available.

3 Results and discussion

3.1 Comparison between simulated and measured biometric variables

Figure 2 compares the simulated LAI for control simulation and the observations at DIJ, GRI, KLI, LAM, and LAN sites. ORCHIDEE-STICS is able to produce a good agreement with observed LAI at DIJ, GRI, and LAN sites. At KLI site, the simulated LAI lags the measurements by 7 to 10 days during the stage of quick increase of LAI (45–80
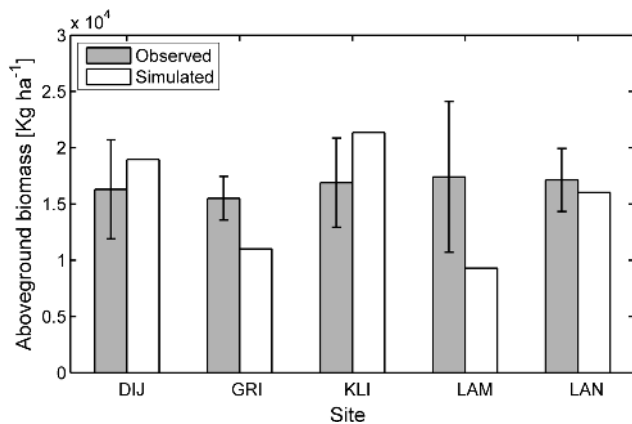
Fig. 3. Simulated (white bar) vs. measured (gray bar) above ground biomass (AGB) at harvest date. Error bars are the standard error of the mean at DIJ, GRI, LAM and LAN, and is the mean standard error of the other four sites at KLI where only mean value of observation is available.
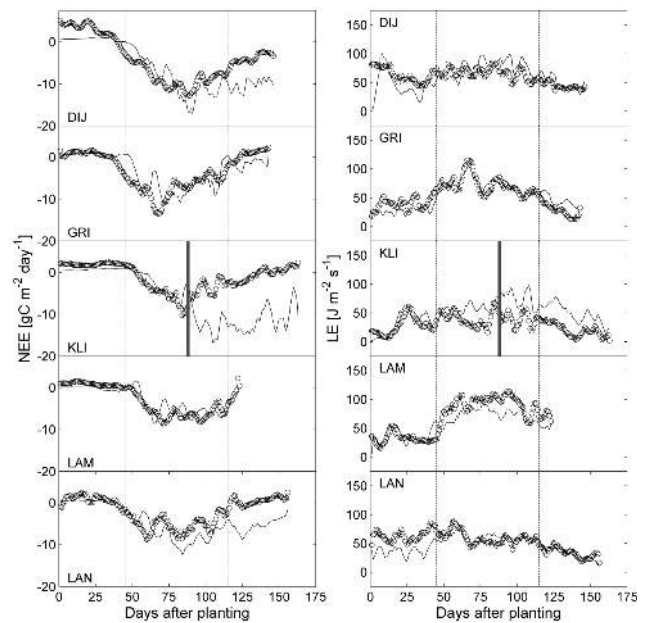

Fig. 4. Evolution of 5-days smoothed NEE (left) and LE (right) during the growing period at the five maize sites. Circle symbols indicate eddy covariance observed values and blue line indicates values simulated by ORHICDEE-STICS. The fluxes are smoothed over consecutive 5 days. The first vertical dashed line x = 45 is defined as the end of the early crop growth period, and x = 115 is defined as the start of the late crop growth period. Between the two lines, it is defined as the middle crop growth period. The solid bold line at KLI subplot indicates the hail storm event on x = 88.

Days After Planting (DAP)). The discrepancy between the simulated and the measured LAI during the late period can be partly explained by a hail storm (38 mm in 30 min) that caused damage to plants on 88 DAP (20 July 2007). Overall, a shortcoming of STICS is the underestimated peak LAI value at four of the five sites (excluding DIJ site). STICS assumes that the crop is able to complete a specific phase of its development only once a cumulative temperature threshold is reached (Brisson et al., 1998, 2002). This oversimplified requirement of LAI development is a source of discrepancy with observed LAI. LAI calculated by STICS is closely dependent on the water and nitrogen stress. At the GRI and LAM sites, where growing seasonal temperature is high (17.2 and 19.6 °C, respectively) and growth period available water (precipitation plus irrigation) is low (169.4 mm and 300.5 mm, respectively), the model predicts lower LAI values compared to observations. High temperature definitely accelerates LAI development and shortens the period of leaf biomass accumulation, while low precipitation induces water stress on the development of LAI. In addition, our simulations do not consider organic fertilization delivered in the previous winter at LAM site, which may explain why simulated LAI is too low at this site. Finally, it is seen in Fig. 2 that the modeled senescence phase, when LAI is decreasing before harvest, occurs too sharply compared to the measurements (Fig. 2).

Comparisons between simulated and observed above ground biomass (AGB) at harvest are shown in Fig. 3. ORCHIDEE-STICS produces acceptable estimations of AGB at DIJ and LAN sites, with error percentage (EP = ratio of the difference between the observed and modeled to the observed value) of 16 % and −7 %, respectively. However, large discrepancies are seen at LAM site, with EP = −47 %. At the LAM site where LAI is highly underestimated, AGB

is consistently underestimated. Due to mismatch of LAI in early stage and hail storm damage in the middle of growth period, the model overestimates AGB at KLI site. The linear correlation coefficient between the average LAI bias (simulated minus observed LAI) and AGB bias is 0.81 at five sites, indicating that the AGB model error is mainly resulted from the error in LAI.

3.2 CO_2 and H_2O flux simulations

3.2.1 Seasonal variations of CO_2 fluxes

The dynamics of daily NEE and LE at the five maize sites are shown in Fig. 4. All model and data values are smoothed using a 5-days running means to eliminate high frequencies. The ORCHIDEE-STICS model has a fair ability to reproduce seasonal variations of NEE over all sites. The coefficient of determination (R^2) between simulated and measured NEE are 0.73, 0.57, 0.23, 0.74, and 0.48 at DIJ, GRI, KLI, LAM, and LAN sites, respectively. Root mean square error (RMSE) for NEE at the five sites are 0.55, 0.67, 1.63, 0.51, and 0.84 $gC\,m^{-2}\,day^{-1}$, which is lower than for the standard version of ORCHIDEE compared at selected FLUXNET sites (2 $gC\,m^{-2}\,d^{-1}$ in Chevallier et al.,

Table 4. Statistical model benchmarking criteria (R^2 and RMSE) for four major output flux variables (NEE, LE, GPP, and TER) at five European maize sites. The unit of RMSE for NEE, GPP, and TER is $\text{gC m}^{-2} \text{day}^{-1}$ and that for LE is W m^{-2}.

Site	R^2				RMSE			
	NEE	LE	GPP	TER	NEE	LE	GPP	TER
DIJ	0.73	0.33	0.68	0.09	0.55	1.28	0.79	2.53
GRI	0.57	0.65	0.72	0.74	0.67	0.61	0.56	0.69
KLI	0.23	0.43	0.34	0.41	1.63	1.07	1.65	1.50
LAM	0.74	0.79	0.83	0.81	0.51	0.50	0.45	0.59
LAN	0.48	0.29	0.32	0.03	0.84	0.96	1.06	1.19

Table 5. Variety-specific threshold values of growing degree day (GDD, °C) and the values described in STICS.

Site	Variety	GDD threshold	GDD threshold in STICS
DIJ	La Fortuna	1653	1730–1955
GRI	Anjou 288	1670	1730–1955
KLI	Rosalie	1700	1730–1955
LAM	Goldaste	1920	1730–1955
LAN	La Fortuna	1653	1730–1955

2006). Therefore, accounting for crop specific parameters given by STICS seems to reduce the error of ORCHIDEE. For GPP, the model is able to explain 68, 72, 34, 83 and 32 % of the variance, with RMSE values of 0.79, 0.56, 1.65, 0.45, 1.06 $\text{gC m}^{-2} \text{d}^{-1}$; against only 9, 74, 41, 81, and 3 % for TER, with RMSE values of 2.53, 0.69, 1.50, 0.59, and 1.19 $\text{gC m}^{-2} \text{d}^{-1}$ (Table 4). Among the five sites, the maximum of observed NEE reaches $-15 \text{gC m}^{-2} \text{d}^{-1}$. Controlled by different climatic conditions and crop development, the timing of peak uptake of NEE differs between sites. ORCHIDEE-STICS captures the amplitude and the timing of NEE peak uptake correctly at the GRI and LAM sites, and fairly DIJ and LAN. A visible mismatch is seen at KLI in the mid-late growth period, probably reflecting non-modeled hail storm (see above) damage. By splitting the growing season to pre- and post-hail storm periods, R^2 values are 0.75 before vs. 0.03 after; RMSE are 1.8 before vs. 5.3 $\text{gC m}^{-2} \text{d}^{-1}$ after, for NEE. For LE, R^2 is slightly improved from 0.45 to 0.62, but RMSE is increased from 16 to 27 W m^{-2} between pre- and post-hail storm periods.

During the early crop growth period (from planting date to 45 DAP), TER is larger than or comparable with GPP. Therefore, all sites show a small source of CO_2 or neutral, while air temperature remains relatively low. At three out of the five sites (GRI, KLI and LAM), the observed sign and trend of early-growth NEE is well captured by the model. At the two other sites (DIJ and LAN) the observed NEE values during the early crop growth fluctuate between 0 and 5 $\text{gC m}^{-2} \text{d}^{-1}$ (source) while the average differences between the simulated and observed NEE are -2 and $-0.5 \text{gC m}^{-2} \text{d}^{-1}$ (sink) respectively. This suggests that other factors such as rotation history and soil tillage that are not described in ORCHIDEE-STICS affect TER and consequently push NEE towards a CO_2 source (Aubinet et al., 2009).

During the middle crop growth period (from 46 DAP to 115 DAP), all maize fields act as CO_2 sinks, with GPP exceeding TER. The magnitude of the sink depends not only on meteorological variables but also on soil moisture. At the LAM site, the combination of high solar radiation and warm temperature, and the low precipitation (153 mm) com-

pensated by irrigation (150 mm) lead to high GPP, but the observed TER is high as well. As a consequence, NEE tends to be as small CO_2 sink. At the GRI site, crop growth period precipitation is also low (170 mm), but solar radiation and air temperature remain moderate. Therefore, the interactive effects of radiation, temperature and precipitation do not significantly suppress NEE uptake, unlike observed at LAM site. The ORCHIDEE-STICS model reproduces these variations of NEE in the middle crop growth period well, excepted for the colder KLI site, examined below.

During the late growth period (DAP > 115), the observed NEE uptake of CO_2 weakens due to plant senescence. The simulated NEE uptake is overestimated at DIJ, KLI, and LAN. The cause of this overestimation can be attributed to overestimation of LAI by STICS (Fig. 2). The observed LAI keeps its peak value for only about 2 weeks, and then slowly decreases towards zero. Oppositely, the simulated LAI remains at its maximum during four weeks after reaching its maximum value, and then drops to 0 at harvest. Such a mismatch of LAI during the late growth period affects the model performance for NEE, especially at sites like KLI or DIJ where growing season temperatures are relatively low (Table 1). The observed decline of LAI in the late growing period reflects plant senescence, but too cool temperatures at the KLI and DIJ sites do not allow to meet the STICS model requirement of growing degree day (GDD) to complete physiological maturity, and the modeled crops are just mature by the prescribed harvest date.

3.2.2 Seasonal variations of latent heat flux

At the GRI and LAM sites, both simulated and observed LE present seasonal variations. At the three other sites, however, LE does not show apparent seasonal variations, but fluctuates between 0 and 120 W m^{-2}. The lack of a trend in seasonal LE measured at these sites may come from frequent precipitation (total precipitation during growing season with 452, 593, and 403 mm, respectively), low net radiation (190, 228, and 215 W m^{-2}, respectively) and associated high relative humidity (75, 76, and 80 %, respectively). ORCHIDEE-STICS is generally able to capture the LE differences between sites. Overall, ORCHIDEE-STICS is able to explain 33, 65, 43, 79 and 29 % of the observed cross-sites variance,
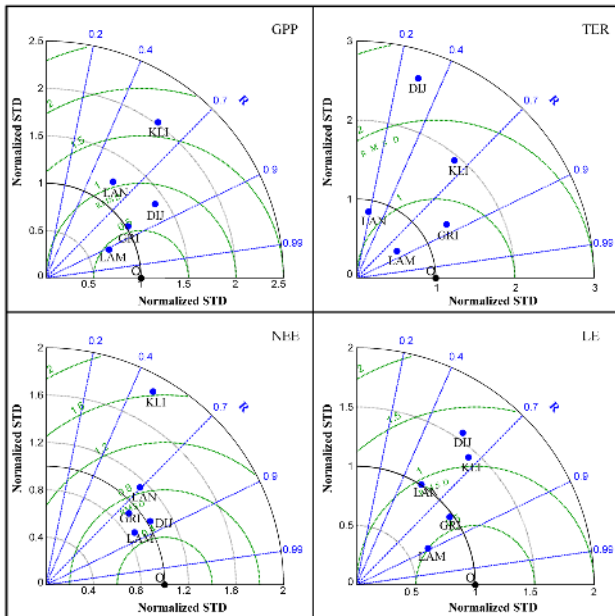
Fig. 5. Taylor diagram plot of the simulated daily GPP, TER, NEE, and LE against EC observations at five maize sites. Normalized standard deviation (STD) is defined as the simulated variables divided by the observed one. Point O is defined as the "observation". Root mean square error (RMSE) is also normalized by the observed mean value. R is the correlation coefficient.

respectively. The RMSE values at five sites are 1.3, 0.6, 1.1, 0.5, and $1\,\mathrm{W\,m^{-2}}$, respectively. The discrepancy between simulated and measured LE can also be partly explained by imbalance in the energy budget with the eddy covariance technique (Wilson et al., 2002; Li and Yu, 2007), whereas the model always ensures energy balance closure.

3.2.3 Overall evaluation of ORCHIDEE-STICS

The overall model performance in simulating the seasonal variations of NEE, LE, TER, and GPP is summarized with a normalized Taylor plot (Taylor, 2001) in Fig. 5. Among all plots in Fig. 5, normalized standard deviation (STD), root mean square error difference (RMSD), and correlation coefficient (R) for observations are always 1, 0, and 1, respectively. Correlation coefficients for modeled GPP are high around 0.9 except at the KLI and LAN sites with R values being slightly lower than 0.7. For TER simulations, R values are low at sites DIJ and LAN in the Netherlands (0.29 and 0.18). For NEE, high correlation coefficients are obtained between simulated and observed values at four out of five sites. Similar to the model good performances for GPP and NEE, the simulation results of LE also give R values in the range of 0.5 to 0.9.
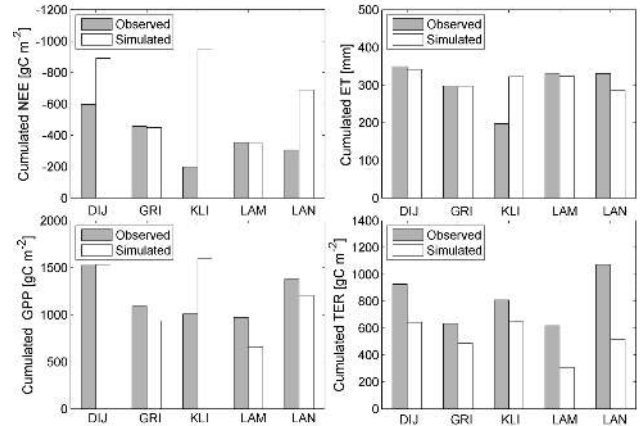

Fig. 6. Accumulated NEE, ET, GPP, and TER during the growing period. Gray bars indicate the observed values and white bars indicate the simulated ones.

3.2.4 Seasonal budgets

Figure 6 shows the comparisons between simulated and observed seasonally cumulative NEE, LE, GPP, and TER since planting date. The cumulative NEE is in good agreement with the observed values at GRI and LAM sites, with EP values of 2 % and 1 %. However, a large discrepancy exists between the simulation and the observation at the three other sites, cumulative NEE being over-estimated by the model (i.e. too much uptake). The EP values of NEE are 49 %, 125 %, and even 377 % at the DIJ, LAN and KLI sites. The cumulative NEE bias may result from overestimated GPP and LAI during the late crop growth, as shown above. At GRI and LAM sites, the seasonal change in NEE is maybe well reproduced because of error compensation between underestimated GPP and TER (Fig. 6). At DIJ, KLI, and LAN where the simulated seasonal change in NEE is overestimated, the bias results from the simulation of GPP or TER or both.

For cumulative LE seasonal changes, the model presents good (EP range between 2 % and −13 %) results compared to observation at four out of five sites. High-bias in LE simulation at the KLI site (EP = 64 %) may be due to non-modeled damage caused by hail.

The model reproduces an acceptable cumulative GPP at DIJ, GRI, and LAN sites, with EP values less than 15 %, but overestimates GPP at KLI and LAN sites (EP = 58 %) and underestimates it at LAM (EP = −32 %) (Fig. 5). The bias of GPP is related to the bias of LAI (Suyker et al., 2004; Xu and Baldocchi, 2004), and the bias of GPP also explains the bias of AGB (comparing Fig. 5 and Fig. 3).

For cumulative TER, the model has rather poor performances with an obvious underestimation of this flux at all sites. The EP values range between 31 % and 52 % across the five sites. This indicates structural model deficiencies in describing the processes controlling cumulative TER, e.g. no vertical distribution of soil C pools, soil C initialization bias
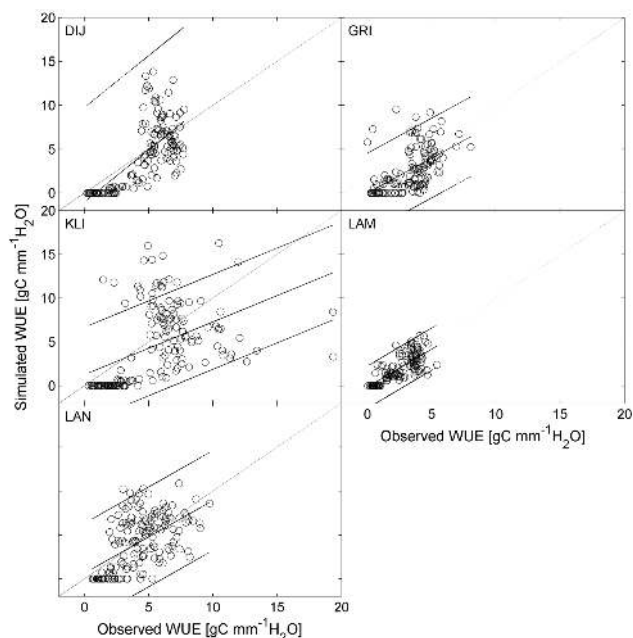
Fig. 7. Modeled vs. simulated daily average water use efficiency (WUE) at 5 maize sites. The dotted line indicates the 1:1 line. The solid line indicates the linear regression and the dashed lines represent the 3σ confidence limits.
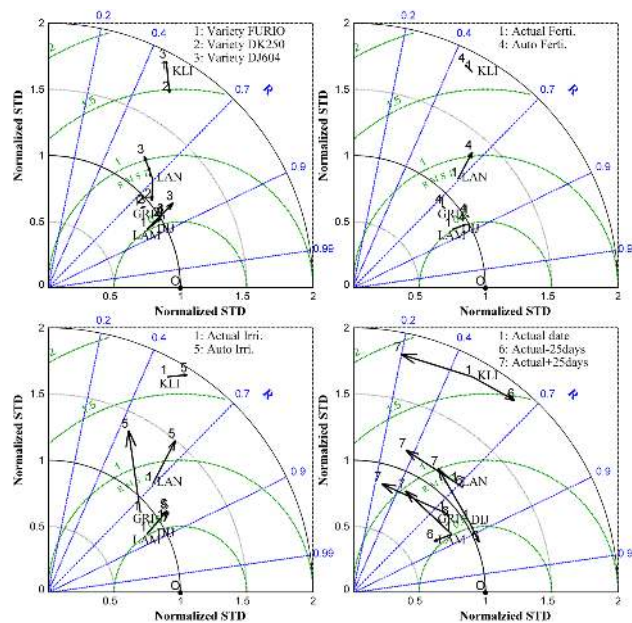

Fig. 8. Changes in model benchmarking statistics for the sensitivity of the simulated NEE to management parameters, varieties (upper left), fertilization (upper right), irrigation (lower left), and planting date (lower right). The statistics for the management practice simulation are plotted at the tail of the arrows (number 1), and the arrows (number from 2 to 7) point to the statistics for the control simulations. At each site, the longer the arrow, the more sensitive is ORCHIDEE-STICS to a change in management parameter. Normalized standard deviation (STD) is defined as the simulated variables divided by the observed one. Root mean square error (RMSE) is also normalized by the observed mean value. R is the correlation coefficient.

caused by unknown site cultivation history. Currently, TER is considered as the sum of heterotrophic and autotrophic respirations (Krinner et al., 2005). Part of the model-data mismatch for TER at LAM and LAN may be explained by a GPP bias (see Fig. 5). On the other hand, at DIJ and KLI where modeled NEE right after planting is underestimated (see Fig. 4), most of the model error should be related to TER simulation since no autotrophic respiration was involved in this period. The heterotrophic respiration in the model is computed by assuming the soil carbon balance in steady-state equilibrium, but this hypothesis may not be true in reality (Carvailhais et al. 2008), especially for agroecosystems where the soil is commonly disturbed by various human activities.

3.3 Water use efficiency

The crop water use efficiency (WUE, $gC\,mm^{-1}H_2O$) is defined as the ratio of daily GPP to daily ET. The comparison between simulated and observed daily WUE at the 5 maize sites is shown in Fig. 7. Generally, the WUE is low in the beginning of the growing season and immediately after harvest. The higher values of WUE occur during the peak of the growing season, when crop LAI approaches or stays at its maximum. During this peak crop growth period, the WUE of maize is observed to reach 8–15 $gC\,mm^{-1}\,H_2O$. Comparison between simulated and observed WUE shows a linear relationship at the 5 sites. The model is able to explain 51, 31,

23, 57, 31 % of the variance in observed WUE at DIJ, GRI, KLI, LAM, and LAN, respectively. Although the correlation coefficients between the simulated WUE and the measured WUE are low, the majority of the measured WUE values are within the 3σ confidence limits of the linear regression. Another possible source of errors in simulating WUE may originate from the energy imbalance problem of eddy covariance technique (Li and Yu, 2007).

3.4 Sensitivity of modeled fluxes to management practice

3.4.1 Effects of different management parameters on NEE and LE daily fluxes

We select NEE and LE as two representative fluxes impacted by varying management parameters. Figure 8 shows the Taylor plot (Taylor, 2001) of the response of NEE to parameter values for varieties, fertilization, irrigation, and planting date.

From Fig. 8, we find that NEE responds sensitively to crop varieties at three sites (KLI, LAM, and LAN). However, at
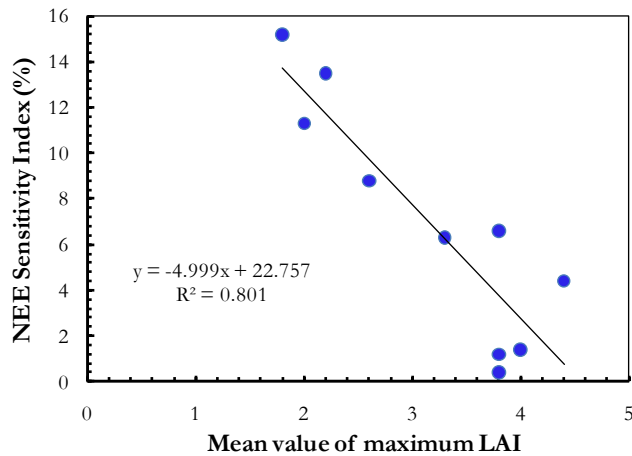
Fig. 9. NEE Sensitivity Index versus mean value of maximum LAI. Sensitivity Index is defined as the ratio of difference between "reference simulation" and "control simulation" to "control simulation". Control simulation is referred to: variety FURIO, observed fertilization, irrigation, and observed planting and harvest dates. Mean value of maximum LAI is referred to the mean LAI between control and alternative variety simulations.

the other two sites (DIJ and GRI), NEE is weakly sensitive to that parameter. It is the difference in climate which modulates the sensitivity to crop varieties among sites. In the STICS model, varieties are described by different GDD thresholds (listed in Table 5), especially for the crop development stage during which leaves grow the most. Compared to the control simulation variety parameters, the total GDD requirement of the 2 other varieties used in the sensitivity study differ by ± 100 degree-days. Thus, this GDD difference impacts on the length of the period of maximal leaf growth (up to the maximal LAI) and consequently on the maximal LAI value reached during the growing period. When changing of crop variety, the date at which LAI is maximal (dmax) is shifted by ± 6 days and the maximal LAI changes from 0.25 to 0.85 $m^2 m^{-2}$ depending of the site. This spread in the response on maximal LAI value is attributed to different leaf growth rate simulated on each site and to the shift of dmax, but it can't explain the simulated NEE sensitivity to crop varieties amongst sites. In fact, the NEE sensitivity is best correlated with the mean value between control variety and alternative variety of the maximal LAI. Figure 9 shows the mean LAI value (between control and alternative variety) on the 5 studied sites against the sensitivity index of NEE to crop variety (see Fig. 11). It is found that the absolute values of sensitivity index of NEE to crop variety is closely related to the mean value of maximum LAI between the control and alternative variety ($R^2 = 0.80$) (Fig. 9). Because the LAI value reached amongst site is mainly function of climate, we can confirm that the NEE sensitivity to crop varieties is driven by climate.
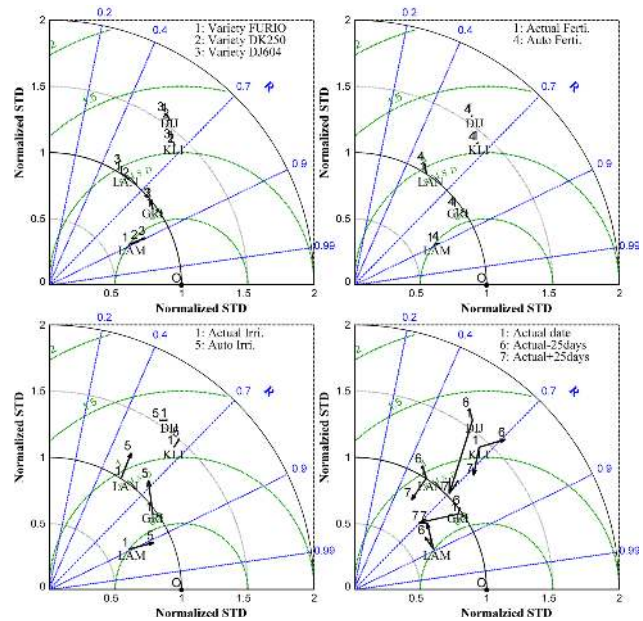

Fig. 10. Changes in normalized pattern statistics for the response of the simulated LE to crop varieties (upper left), fertilization (upper right), irrigation (lower left), and planting date (lower right). The statistics for the management practice simulation are plotted at the tail of the arrows (number 1), and the arrows (number from 2 to 7) point to the statistics for the control simulations. At each site, the longer the arrow, the more sensitive is ORCHIDEE-STICS to a change in management parameter. Normalized standard deviation (STD) is defined as the simulated variables divided by the observed one. Root mean square error (RMSE) is also normalized by the observed mean value. R is the correlation coefficient.

Regarding fertilization, at LAN site where fertilization is applied at a low rate (65 kg N ha^{-1}), a large sensitivity of NEE is found when automatic fertilization is given by STICS, instead of the prescribed observed values. At sites with moderate fertilization (LAM and KLI with 84 kg N ha^{-1} and 91 kg N ha^{-1}, respectively), the model shows smaller sensitivities than at sites with low fertilization rate. At sites with high fertilization rates (DIJ and GRI with 212 and 140 kg N ha^{-1}, respectively), the NEE sensitivity is very small (Fig. 8). Therefore, the sensitivity to N-fertilization depends on how close to optimal fertilization each site is, which indicates good performances of STICS to diagnose plant nitrogen requirements.

The response of the simulated NEE to irrigation has large difference among five sites. The change in the statistical criteria (STD, RMSD, and R) is very large at GRI, a dry site (Fig. 8). However, this response is weaker at the DIJ site. Such inter-site differences in the NEE sensitivity to irrigation can be explained by differences in the total amount of available water in soil profile during the crop growth period. The total growing season precipitation at KLI and DIJ are 593 mm and 453 mm, respectively. compared to only
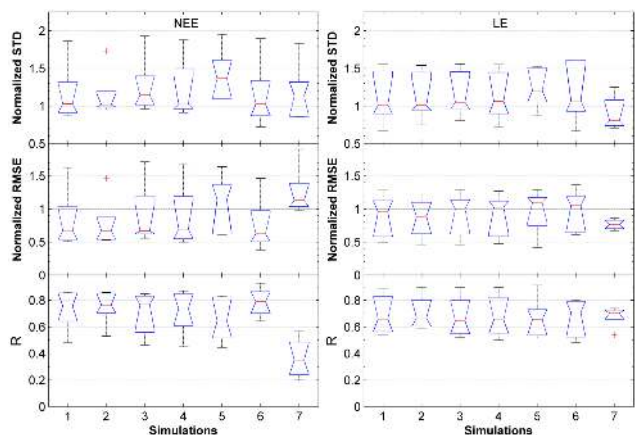
Fig. 11. Summary sensitivity of NEE (left) and LE (right) to crop varieties (simulations 1, 2, 3), fertilization (4), irrigation (5), and planting dates (6 for early planting and 7 for late planting). Normalized standard deviation (STD) is defined as the simulated variables divided by the observed one. Root mean square error (RMSE) is also normalized by the observed mean value. R is the correlation coefficient. All statistical indicators (STD, RMSE, and R) are computed with five maize sites. The lower and upper lines of the box indicate 25 and 75 percentiles, respectively. The thick black line in the box is the median value. The whiskers (horizontal bars beyond the box) represent 1.5 times of the interquartile range. Outliers are displayed with a red "+" sign.

169 mm at GRI, where no additional water is supplied by irrigation. At the other low-precipitation site, LAM, the growing season precipitation is only 153 mm, but 148 mm of irrigation is applied during the growing period. Therefore, the response of NEE to irrigation at LAM shows a weaker sensitivity than at GRI. Thus, like for fertilization, the differences between actual amounts and optimal crop water requirements determine the NEE sensitivity to the irrigation parameter.

Simulated seasonal variations of NEE are sensitive to changes in planting date (Fig. 8). A planting date shifted by 25 days causes a very significant change in simulated NEE over all the sites. The change is reflected by decreased R and increased STD in the Taylor diagram. The reason of this is that in the Control simulation, crop development has generally already benefited of several GDD during the 25 first days after planting. In the "late planting" sensitivity, crop development cannot benefit for these GDD which causes a large phase lag of NEE. By contrast, planting the seeds 25 days earlier than in the "control" experiment induces a shorter phase lag (asymmetric sensitivity) because generally few GDD are accumulated in this early 25-day period. Figure 10 shows the sensitivity of LE to crop management practice parameters. There is no large change (see length of the arrow) in statistical criteria for the responses of LE to varieties and fertilization at most sites, contrary to NEE. Only a weak sensitivity is found for the response of LE to varieties (LAM) and fertilization (LAN). At the dry
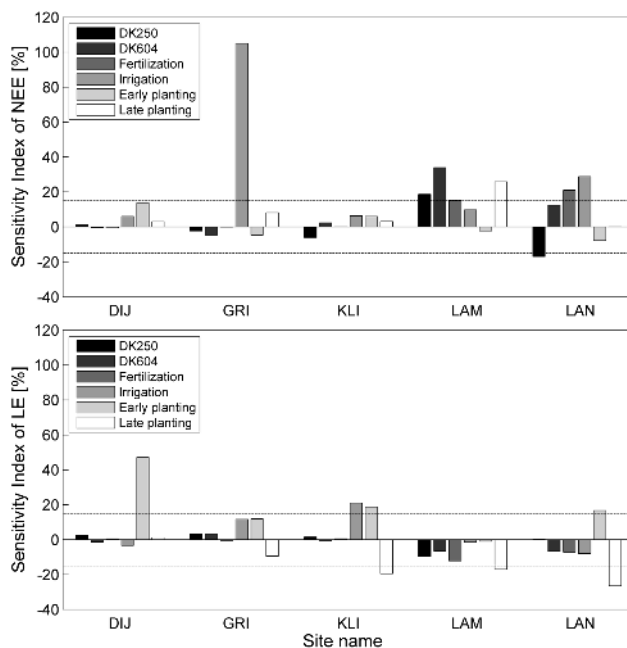

Fig. 12. Sensitivity index (SI) of cumulated NEE (upper) and LE (lower) during the growing season to different management practices. Sensitivity index is defined as the ratio of difference between "reference simulation" and "control simulation" to "control simulation". Control simulation is referred to: variety FURIO, observed fertilization, irrigation, and observed planting and harvest dates. The two horizontal dashed lines y = ±15 % indicate the threshold value for significant sensitive index.

sites GRI and LAM where the available water (precipitation plus irrigation) is low, a significant sensitivity of LE to irrigation is found. At other sites, the automatic model irrigation amounts given by STICS do not induce any significant change in LE because of the difference in available water between prescribed and model automatic irrigation amounts is very small. Compared to crop varieties, fertilization, and irrigation parameters, planting date is the most sensitive parameter in determining LE, and NEE as well. A later planting date causes a greater change in simulated LE.

Sensitivity of the fluxes (NEE and LE) to crop variety and management practice at all maize sites is summarized in Fig. 11. Box plot with median and interquartile values show that all statistical criteria for model performances (STD, RMSE, and R) vary largely across the different sites. Normalized STD varies from 0.7 to 2.0, and normalized RMSE between 0.3 and 2.0 for NEE. The median values of normalized STD and RMSE for NEE also deviate from unity. However, normalized STD and RMSE for LE are located in relatively narrow range and the median values of normalized STD and RMSE are close to unity, showing clearly that the simulated LE is less sensitive than NEE.

3.4.2 Effect of management parameters on cumulative seasonal fluxes

In order to test the sensitivity of cumulative fluxes to management parameters, a sensitivity index (SI) is defined as the ratio of the difference between cumulative simulated and measured fluxes to the cumulative measured flux (Fig. 12). It is found that SI can vary with crop varieties and management practices, but the sensitivity to a specific management parameter is site-dependent. It is evident that the magnitude of SI is closely related to the difference between the observed and the model-automatically assigned values for fertilization and irrigation. If the difference is large, the value of SI is large as well. For example, at the driest and non-irrigated GRI site, NEE shows a largest SI for the irrigation parameter. At the least fertilized site of LAN (65 kg N ha^{-1}), the simulated cumulative NEE has a significant sensitivity to fertilization. For the sensitivity of the cumulative NEE to crop varieties, at the LAM and LAN sites, SI values are larger than 15 %. For planting date simulations, the SI shows a value larger than 15 % at LAM site for late planting and at LAN site for early planting, while all the SI values are lower than 15 % at the three other sites. In this respect, it is found that the cumulative annual NEE is less sensitive to planting date than the daily NEE variation. By contrast, the sensitivity of annual NEE to other management parameters is similar to the one of seasonal NEE. This finding suggests that a shift in planting date strongly impacts the phase of the NEE while the other drivers impact more the amplitude.

Compared to seasonally cumulative NEE, cumulative LE is found to be less sensitive to crop varieties and nitrogen applications (Fig. 12) at all five sites, where all SI values are less than 15 %. The model presents large response of LE to irrigation with a larger than 15 % of SI at KLI site only. Early planting with 25 days causes large LE responses at DIJ, KLI and LAN sites, while late planting with 25 days produces negative effects on cumulative LE at three out of five sites (KLI, LAM and LAN).

4 Discussion

Compared to other terrestrial systems, agricultural ecosystems are maybe more complicated to simulate, and highly affected by management. Some recent ecosystem models are capable of taking into account for the effects of management practices. Although these ecosystem models are far from perfect, they are widely used for applications related for instance to food security or soil C sequestration rates. However, ecosystem models should be benchmarked against in situ measurements and their sensitivities to those management factors with largely spatial variations should be investigated before running regional or global applications.

In this paper, by evaluating the ORCHIDEE-STICS model at five maize sites over Europe, it is found that the model performance differs across sites, and for the different output variables (e.g. GPP, TER, NEE or LE) even at one site. At the sites where LE and GPP are poorly modeled, the main reason of the model-data mismatch is the phase-lag in simulated LAI, given by STICS in our case. Therefore, improving the LAI seasonal dynamic in future studies should potentially improve the performance in simulating GPP and LE because both are highly dependent of LAI, as documented by Suyker et al. (2004) and Xu and Baldocchi (2004). TER in ORCHIDEE-STICS is simulated as the sum of autotrophic and heterotrophic respirations. Autotrophic respiration is strongly depended on plant biomass and temperature, while heterotrophic respiration is related to soil temperature, soil moisture and soil carbon pools. Quantifying heterotrophic respiration is subject to large uncertainties (Trumbore, 2006). In the current version of ORCHIDEE, two bucket layers (ground and below ground) are considered for soil moisture and 7 layers for soil temperature. The accuracy of soil moisture simulation is not good enough. The deficiency of modeled soil temperature and moisture may be part of the reason of the disagreements between the measured and the simulated TER. Further, the response of TER to soil moisture is also found to be very uncertainty in nature (Falloon et al., 2011). At the sites where GPP and LE are well simulated, but TER (and therefore NEE) are poorly captured, apart from the errors from soil temperature, moisture and carbon pools, the steady-state spin up of soil C pools is a likely reason of over-estimated TER. Each crop site soil C content is strongly affected by various human activities, for example ploughing, crop rotation, fertilization and irrigation, which all have the potential for moving soil C away from steady state (Aubinet et al., 2009). Therefore, taking into account previous land-use history will certainly improve the model performance in TER and hence NEE simulations, for instance by replacing steady-state carbon stocks with observed soil C stocks.

Maize, a thermophilous crop, is widely cultivated in Western Europe over a region bounded by 40° N–55° N in latitude and 9.5° W–19.5° E in longitude (Gervois et al., 2008). Over this maize grown area (defined as maize exceeding 5 % of the total land area), total annual precipitation ranges from 500 to 1400 mm, and annual mean temperature varies from 6 to 17 °C. At the five studied sites, total annual precipitation fluctuates between 460 and 970 mm and mean annual temperature varies from 8.5 to 13.5 °C during the simulated year. Thus, four out of the 5 sites are representative of the climate space of maize cultivation in Europe. However, precipitation may not suffice to satisfy with the water-demand during the crop growing period, with water stress causing lower yield. Irrigation, therefore, is applied to guarantee crop yield in areas such as LAM site. Across the 5 sites of the study, nitrogen application and precipitation ranges have large gradients. Planting date has 25-day difference across the sites and we also conducted additional simulations with actual planting date ±25 days. The sites representativeness of European-wide maize cultivation climatic conditions and of management practice makes our result suitable to infer

which parameters will impact European scale maize yield simulations. The lack of the information about crop varieties and management practices may not produce very significant change in LE but may cause large uncertainties for NEE when the model is applied on a grid. In order to enhance the model performance, further improvement in the calculation of LAI and TER are necessary. Another potential way to improve the performance of CO_2 and H_2O budgets would be to assimilate remotely sensed LAI, soil moisture and/or soil temperature into the model (Viovy et al., 2001; Peylin et al, 2005; Luo et al., 2009).

5 Conclusions

We evaluated the performance of the ORCHIDEE-STICS model against online CO_2 and H_2O fluxes at five maize eddy-covariance sites from the CarboEurope project. The results suggest that this generic land surface model driven by a crop-specific phenology, is able to capture the seasonal dynamics of NEE and LE. However, at sites with low air temperature during the growing period, the model presents a phase lag of 7 to 10 days in LAI compared to the observations. This model LAI bias explains most of the error of GPP and LE. Overall, ORCHIDEE-STICS explains more than 70 % of the variances (R^2) of any observed daily component of NEE and LE fluxes at DIJ and LAM, around 50 % of the variance at GRI and LAN, and less than 30 % at KLI site. Among four flux variables against which the model was benchmarked, cumulative GPP during the growing season is best reproduced. For LE, the agreement between the measurement and the simulated is acceptable as well. The cumulative TER is consistently underestimated at all sites, causing overestimation of the mean annual NEE.

Sensitivity analysis by varying management parameters indicates that crop variety, fertilization, irrigation and planting date, shows that any of considered factors is able to cause large changes in the simulated NEE and LE. Nevertheless, the sensitivity of LE to management parameters is lower than that of NEE. The variations of management practices affect not only daily NEE and LE changes, but also seasonal cumulative values, the latter being much more site-dependent. For irrigation and fertilization changes, the sensitivity to specific management practice on NEE and LE strongly depends on the difference between actual and potential (optimum) water or nitrogen status of each site.

Multi-site model benchmarking and sensitivity analysis is useful to identify the model weaknesses and to further improve the model structure. This study provides a hint on the accuracy and uncertainties that can be expected from of model gridded simulation of carbon and water vapor flux at European scale.

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