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Performance and sensitivity of the DSSAT crop growth model in simulating maize yield under conservation agriculture

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ABSTRACT

With the practice of conservation agriculture (CA) soil water and nutrient dynamics are modified by the presence of a mulch of crop residues and by reduced or no-tillage. These alterations may have impacts on crop yields. The crop growth model DSSAT (Decision Support Systems for Agrotechnology Transfer) has recently been modified and used to simulate these impacts on crop growth and yield. In this study, we applied DSSAT to a long-term experiment with maize (*Zea mays* L.) grown under contrasting tillage and residue management practices in Monze, Southern Province of Zambia. The aim was (1) to assess the capability of DSSAT in simulating crop responses to mulching and no-tillage, and (2) to understand the sensitivity of DSSAT model output to input parameters, with special attention to the determinants of the model response to the practice of CA. The model was first parameterized and calibrated for the tillage treatment (CP) of the experiment, and then run for the CA treatment by removing tillage and applying a mulch of crop residues in the model. In order to reproduce observed maize yields under the CP versus CA treatment, optimal root development in the model was restricted to the upper 22 cm soil layer in the CP treatment, while roots could optimally develop to 100 cm depth under CA. The normalized RMSE values between observed and simulated maize phenology and total above ground biomass and grain yield indicated that the CA treatment was equally well simulated as the CP treatment, for which the model was calibrated. A global sensitivity analysis using co-inertia analysis was performed to describe the DSSAT model response to 32 model input parameters and crop management factors. Phenological cultivar parameters were the most influential model parameters. This analysis also demonstrated that in DSSAT mulching primarily affects the surface soil organic carbon content and secondly the total soil moisture content, since it is negatively correlated with simulated soil water evaporation and run-off. The correlations between the input parameters or crop management factors and the output variables were stable over a wide range of seasonal rainfall conditions. A local sensitivity analysis of simulated maize yield to three key parameters for the simulation of the CA practice revealed that DSSAT responds to mulching particularly when rooting depth is restricted, i.e., when water is a critical limiting crop growth factor. The results of this study demonstrate that DSSAT can be used to simulate crop responses to CA, in particular through simulated mulching effects on the soil water balance, but other, often site-specific, factors that are not modeled by DSSAT, such as plough pan formation under CP or improved soil structure under CA, may need to be considered in the model parameterization to reproduce the observed crop yield effects of CA versus CP.

1. Introduction

Conservation agriculture (CA) is nowadays perceived as a set of best-management practices based on no-tillage, crop residue mulching and the use of crop rotations and/or associations, through which African agriculture can combat soil degradation, secure crop yields and mitigate to some extent negative effects of climate change (Gowing and Palmer, 2008; Thierfelder et al., 2014), even

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if its potential is site-specific and depends on the socio-economic environment of the farming communities (Uri, 2000; Giller et al., 2009; Corbeels et al., 2014). Under CA management, soil water and nutrient dynamics are modified by reduced or no-tillage and the presence of a mulch of crop residues on the soil surface. Mulching with crop residues reduces soil water evaporation and run-off (Scopel et al., 2004), increases topsoil organic matter and improves near-surface soil aggregate properties (Blanco-Canqui and Lal, 2007), with potentially positive effects on crop productivity (Rusinamhodzi et al., 2011).

Cropping system models, such as DSSAT (Decision Support Systems for Agrotechnology Transfer, Jones et al., 2003) or APSIM (Agricultural Production Systems Simulator, Keating et al., 2003), are based on ecological principles for simulating crop development and growth as a function of weather conditions, soil properties and management practices (through simulated water and nutrient limitations to plant growth). This type of models has been used in recent years to assess and analyze the agronomic performance of CA systems. In particular, users have compared simulated yields of a given crop grown under conventional tillage-based practices with those under CA management at specific sites in diverse edaphic and climatic conditions (e.g., Sommer et al., 2007; MacCarthy et al., 2010; Gerardeaux et al., 2011; Ngwira et al., 2014).

DSSAT (Jones et al., 2003) is a process-based cropping system simulation model that has been regularly revised to improve the biophysical representation of soil water, organic matter and nutrient (nitrogen and phosphorous) dynamics and their effects on crop growth and yield. For instance, the CENTURY soil organic matter model (Parton et al., 1987) was incorporated into DSSAT by Gijsman et al. (2002) to improve simulations of long-term soil carbon and nitrogen dynamics. More recently, further modifications of DSSAT were made in order to simulate the effects of tillage and surface crop residues on soil water and organic matter dynamics (Porter et al., 2010). DSSAT has increasingly been used as a tool to compare the performance of different cropping systems and crop production technologies (e.g., Jagtap and Abamu, 2003; Fofana et al., 2005; Saseendran et al., 2007; Caviglia et al., 2013). Its overall aim is to gain better understanding of how cropping systems and their components function and to guide decisions about transferring production technologies from one location to others where soils and climate are different. However, the capability of DSSAT to simulate crop responses to CA practices has not yet been assessed thoroughly.

In this study, we applied DSSAT to a long-term experiment comparing crop performance of maize (*Zea mays* L.) under conventional tillage-based and CA practices in Monze, Southern Province, Zambia. The objectives of the study were (1) to assess the capability of DSSAT in simulating the effect of the practice of CA (viz. no-tillage and mulching) on crop yield, and (2) to understand the sensitivity of DSSAT model output to input parameters, with special attention to the determinants of the model response to the practice of CA.

2. Materials and methods

2.1. Overview of DSSAT

In this study we used DSSAT version 4.5, with CERES-Maize as the crop model (Jones and Kiniry, 1986), CENTURY to simulate soil carbon and nitrogen dynamics (Gijsman et al., 2002), and the Ritchie soil water balance model which uses the one dimensional 'tipping bucket' approach (Ritchie et al., 2009). DSSAT is a complex non-linear dynamic model that simulates outputs such as crop development and yield as a function of a large number of input parameters, including plant and soil parameters, for which values are commonly estimated based on field experiments or from available literature, or determined through model calibration. The large number of model input parameters and their uncertainty lead to questions on how large the resulting prediction uncertainty is for different model outputs and for different plant growth situations.

To begin a DSSAT simulation, the model is informed about the specific weather, crop and soil characteristics. The corresponding input files are linked to the main structure of the model (Fig. 1), comprising the modules for the field characterization, the initial soil conditions and the management operations. The main structure of DSSAT is designed as a matrix of simulation treatments that implements the selected crop and soil models to describe on a daily basis the changes in plant and soil variables that occur on a specific land unit (field) in response to weather and management. A detailed description of the DSSAT model with its modules is given in Jones et al. (2003).

To simulate tillage effects it is assumed in DSSAT that the following four soil properties change (Andales et al., 2000): (1) soil bulk density; (2) saturated soil hydraulic conductivity; (3) the soil runoff curve number, and (4) soil water content at saturation. These soil properties are input after a tillage event and they change back to a settled (user-specified) value, following an exponential curve that is a function of cumulative rainfall kinetic energy since the last tillage operation. Tillage events also result in a mixing of soil components including soil water, inorganic soil nutrients and soil organic matter pools within the specified tillage depth. The mixing efficiency, or percentage of soil that is mixed, is also a user-specified input for each type of tillage operation. Finally, tillage increases the decomposition rate of the soil organic matter pools for a period of 30 days after the tillage event (Porter et al., 2010). Without tillage, all crop residues remain on the soil surface. The surface residues decompose over time with the occurrence of immobilization/mineralization of nitrogen as simulated by CENTURY, and part of the organic matter transforms in more stable organic matter pools in the soil (Gijsman et al., 2002). Mineralized nitrogen from decomposing surface organic matter is assumed to leach into the (top) soil and is available for plant uptake. Mulching effects on the soil water balance are simulated by DSSAT through three soil water-related processes: (1) rainfall interception by the mulch; (2) reduction of soil evaporation rates, and (3) reduction of surface water runoff (Porter et al., 2010). DSSAT version 4.5 does not specifically simulate effects of surface residues on soil temperature dynamics.

Root growth in DSSAT is simulated as a function of above ground biomass production, i.e., above ground biomass has priority for assimilated carbohydrates and at the end of each day carbohydrates not used for above ground biomass are allocated for root growth. The root distribution weighing factor is used to simulate the relative root growth in all soil layers in which roots actually occur (Ritchie, 1998). It is multiplied by a soil water factor to obtain the actual root distribution. The root distribution weighing factor is an input for each soil layer and reflects physical or chemical constraints on root growth in certain soil layers. Its value ranges from 1 (indicating that the soil layer is most hospitable to root growth to near 0 indicating that the soil is inhospitable for root growth).

2.2. Site and field experiment

DSSAT was run using data from a field experiment with maize under contrasting tillage and residue management practices in order to test its responses to CA practices (tillage and mulching) and to obtain a realistic framework for model sensitivity analysis. The field experiment was conducted by CIMMYT (International Maize and Wheat Improvement Centre) at the Farmer Training Centre in Monze (16°14′24″s, 27°26′24″E, 1103 m.a.s.l.), during six cropping seasons from 2005 to 2011 (Thierfelder and Wall, 2009; Thierfelder et al., 2013). The climate at the site is tropical wet and

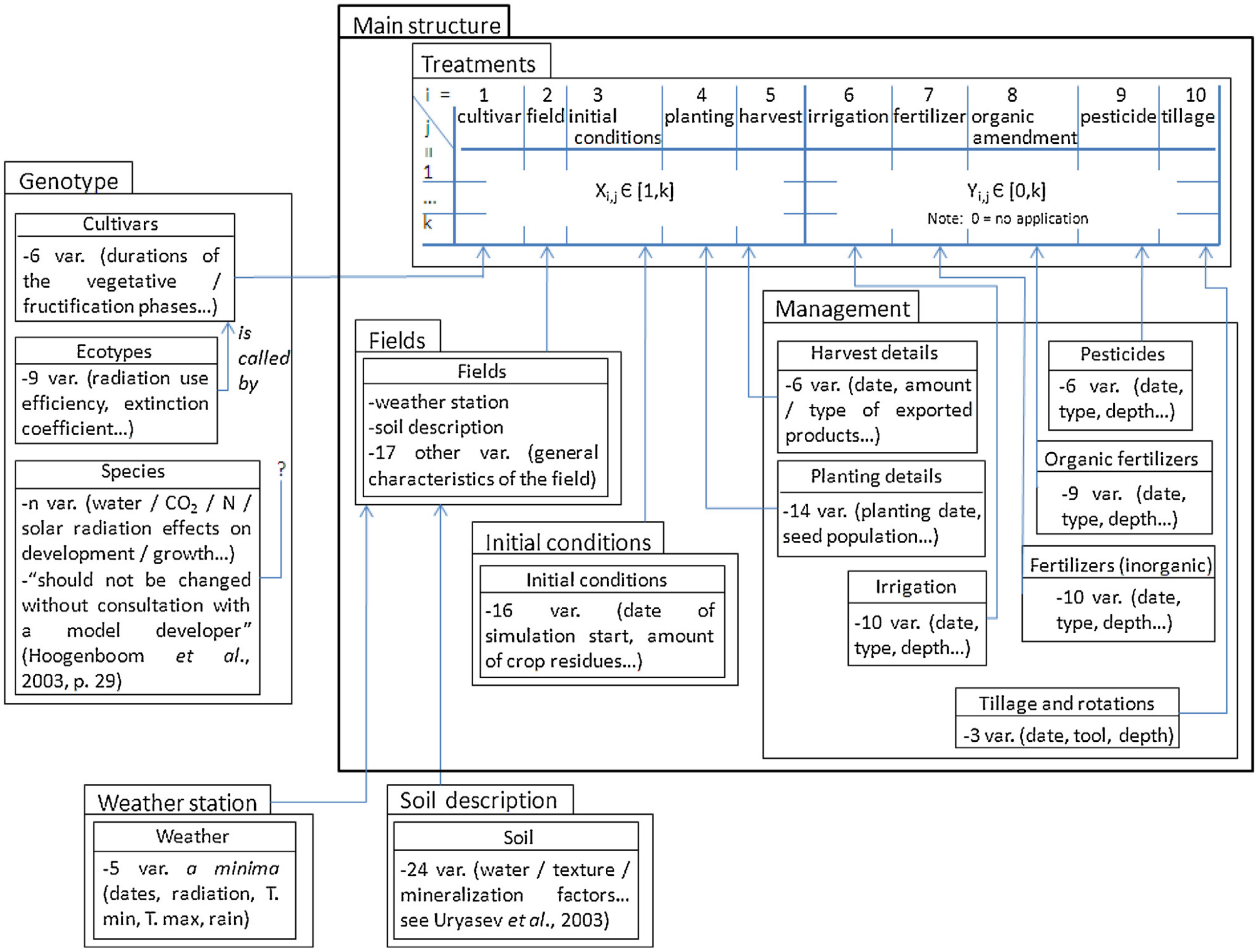

Fig. 1. Overview of the components and modular structure of the DSSAT model.

Table 1
Values of soil parameters of the soil module of DSSAT for the maize experiment in Monze, Zambia.

Soil layer (cm)	Albedo	Soil evaporation limit (mm)	Drainage rate (day^{-1})	Runoff curve number						
surface	0.14	3	0.75	84						
	Clay (%)	Silt (%)	Organic C (%)	pH in water	CEC ($cmol\,kg^{-1}$)	Bulk density ($g\,cm^{-3}$)	Crop-determined lower limit ($cm^3\,cm^{-3}$)	Drained upper limit ($cm^3\,cm^{-3}$)	Saturated upper limit ($cm^3\,cm^{-3}$)	Hydraulic conductivity ($cm\,h^{-1}$)
0–22	16	5	0.6	4.4	3.1	1.67	0.122	0.187	0.38	2.6
23–56	37	8	0.3	5.1	4.0	1.48	0.228	0.314	0.40	0.4
57–80	38	8	0.05	5.3	5.3	1.48	0.264	0.309	0.39	0.1
81–107	44	7	0.05	5.6	5.4	1.33	0.296	0.331	0.39	0.1
>–107	43	7	0.05	5.7	6.7	1.48	0.304	0.324	0.39	0.1

dry (Aw, Köppen Climate Classification) with a unimodal rainfall pattern (Fig. 2). Rains start in November and end in April. The average annual rainfall at the site is 750 mm. During the duration of the experiment, four seasons had normal rainfall, whilst the 2006/2007 season was drier (510 mm) and that of 2007/2008 was wetter (1000 mm) than normal. The soil at the experimental site is a ferric Lixisol (Thierfelder and Wall, 2009). Five soil profiles were characterized on the experimental site as a variation of the same soil type. For the model simulations we considered the most typical soil profile for the site, as described in Table 1.

From ten experimental treatments that were set up in 2005, two contrasting treatments were selected for the model simulations: the conventional tillage (using a moldboard plough) treatment (CP) with removal of the crop harvest residues, and the CA treatment (CA) with the use of an animal traction direct seeder and crop residue mulching. Maize was sown between late November and early December with a target population of 44 000 plants ha^{-1}. The commercial hybrid maize variety SC513 was used in 2005/2006 and 2006/2007, thereafter it was replaced with the variety MRI624. Both are early to medium maturing varieties. Basal fertilization was carried out with 165 kg ha^{-1} of Compound D (10:20:10, $N{:}P_2O_5{:}K_2O$) at planting and 200 kg ha^{-1} urea (46% N) was applied as top-dressing in a split application, five to seven weeks after planting. Weed control was done by a pre-emergence application of

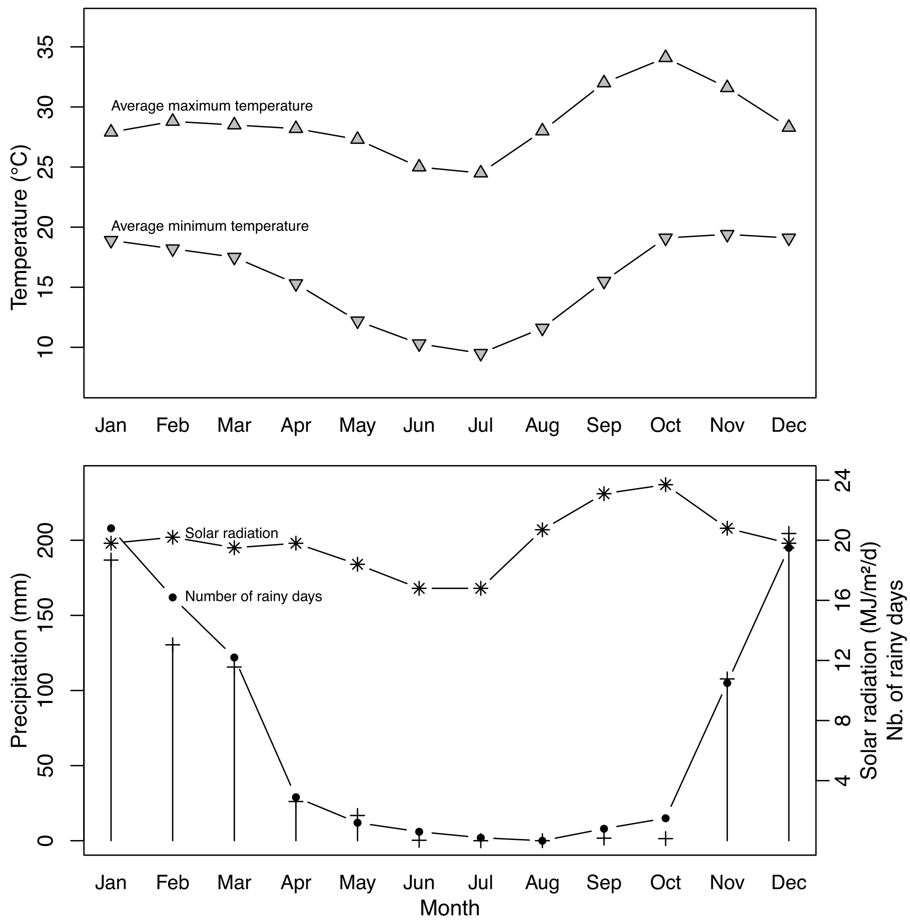

Fig. 2. Average weather conditions for Monze, Zambia.

glyphosate (*N*-(phosphonomethyl) glycine, 41% active ingredient) at a rate of 3 L ha^{-1} followed by regular hand-weeding as necessary to keep the plots free of weeds. In each cropping season, dates of emergence, tasseling (when 50% of the plants had mature tassels) and silking (when silks were visible outside the husks on 50% of the plants) were recorded. Dates of physiological maturity were available only for two seasons and were estimated for the other seasons from data provided by the seed producers. The final harvest was conducted manually by harvesting eight sub-plots of each 9 m^2 from each main plot. Plants were separated into cobs and vegetative biomass and then dried for estimation of grain and straw dry matter yields. There were four repetitions per treatment per year. More details on the experiment and observations can be found in Thierfelder and Wall (2009), Thierfelder and Wall (2010) and Thierfelder et al. (2013).

2.3. Model settings

2.3.1. Model parameterisation and calibration under CP

The model was first parameterised and calibrated for the CP treatment of the experiment. It was run for the six consecutive seasons of the experiment starting at the planting date of the 2005/2006 season. Daily rainfall was recorded at the experimental site, whilst daily values for minimum and maximum temperature and radiation were obtained from the nearby weather station of the Monze Farm Training Centre (Fig. 2). Input parameters for the soil were derived from measurements on a typical soil profile (Table 1) of the experimental site. The fraction of stable carbon was initialized based on silt and clay contents (see Porter et al., 2010). It represents the physically protected soil carbon, but may underestimate stable soil carbon for some soil types which also contain significant portions of biochemically protected carbon (Six et al., 2002). The drained upper limit of plant water availability was determined through laboratory measurements; it depends solely on soil properties. In contrast, we used a crop determined lower limit of plant water availability defined as the lowest field-measured soil water content after plants have stopped extracting water (Ogindo and Walker, 2005). Maize crop parameters are divided in three subsets in the model: species-, ecotype- and cultivar-specific (or genetic coefficients) parameters (Fig. 1). Values used for species-specific parameters were the default values for maize in the CERES-Maize model. The values for ecotype and cultivar-specific phenological parameters (Table 2) required in CERES-Maize were obtained by fitting the model to the observed dates of emergence, flowering, and maturity of the experimental treatment with maize under conventional tillage in rotation with sun hemp (*Crotalaria juncea* L.) and cotton (*Gossypium hirsutum* L.), as this treatment was the best yielding treatment with the highest average maize grain yields over the six seasons (6380 kg ha^{-1}). The radiation use efficiency (RUE) was estimated by calibrating the model to fit the aboveground biomass production to observations from the CP treatment. The final value obtained for RUE was 3.0 g dry matter MJ^{-1} PAR. Model parameters related to grain filling were obtained by fitting the model to observed grain yields in the CP treatment.

For the calibration we used the generalized likelihood uncertainty analysis (GLUE) tool that is available in DSSAT. GLUE is a Bayesian method, allowing information from different types of observations to be combined to estimate probability distributions of parameter values and model predictions (He et al., 2010). GLUE software was run 3 times, executing 18000 tests per run. The

Table 2
Values of maize cultivar parameters as calibrated in the CERES-Maize crop model of DSSAT for the maize experiment in Monze, Zambia.

Cultivar	P1 (°C day)	P2 (days)	P5 (°C days)	G2 (number)	G3 (mg day^{-1})	PHINT (°C day)
SC513	240	0.0	770	550	9	55
MRI624	260	0.0	500	950	9	65

P1: Thermal time from seedlings emergence to the end of the juvenile phase (expressed in °C day, above a base temperature of 8 °C) during which the plant is not responsive to changes in photoperiod. P2: Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 h). P5: Thermal time from silking to physiological maturity (expressed in °C day above a base temperature of 8 °C). G2: Maximum possible number of kernels per plant. G3: Kernel filling rate during the linear grain filling stage and under optimum conditions (mg day^{-1}). PHINT: Phyllochron interval, i.e., the interval in thermal time (°C day) between successive leaf tip appearances.

following variables were fitted: dates of emergence, flowering and maturity, grain yield and total above ground biomass at maturity. Model performance was evaluated by calculating the normalized root mean square error (RMSE), expressed in percentage, and the percentage prediction deviation. Calibration was considered as achieved when the RMSE for all fitted maize phenology and yield output variables was minimal.

An important feature under the CP treatment was the existence of a plough pan, as suggested by the higher bulk density values in the 22–25 cm soil layer (unpublished data) compared to the 0–22 cm soil layer. This plough plan restricts the penetration of roots of maize plants into deeper layers, which was visually observed in the experiment. In contrast, in the CA treatment the plough plan had disappeared rapidly over time and the soil developed a better soil structure with cracks and voids, which is attributed to greater soil biological activity (e.g., more earthworms) (Thierfelder et al., 2013). The importance of this phenomenon for crop growth on similar soils in the region has already been highlighted in other studies (e.g., Materechera and Mloza-Banda, 1997). In order to reproduce this effect of soil tillage in the model simulations, optimal root development rate was restricted in the model to the upper 22 cm soil layer in the CP treatment, i.e., we reduced the root distribution weighing factor by 80% (from 1 to 0.2) for the soil layers deeper than 22 cm resulting in restricted root growth over depth.

2.3.2. Model testing for CA

We then ran the model for the CA treatment by turning off the tillage module in DSSAT, restoring the normal root development over soil depth, i.e., resetting the root distribution weighing factor equal to 1 over the whole soil depth, and initializing DSSAT with a mulch of crop residues with resulting modeled effects on soil properties and processes. Simulated biomass and grain yield values were then compared with observed values and model performance was calculated as described for the CP treatment. The amounts of maize surface residues set in the CA simulations were 3000, 2300, 1300, 4000, 2700, 850 kg dry matter ha^{-1} at planting from 2005 to 2010. Values were estimated from the percentage of observed soil cover in the experiment. The C:N ratio of maize residues is a user-specified input value in DSSAT and was set at 60. Depending on the initial amounts of residues it represents between 6 and 30 kg N ha^{-1}. Part of this organic nitrogen is mineralized during the growing season (simulated by the CENTURY module) and becomes available as inorganic nitrogen for the crop. Values for all other model parameters were kept the same for CP and CA.

2.4. Sensitivity analyses

First, a global sensitivity analysis was performed to describe the DSSAT model response to 32 model input parameters and crop management factors (see Table 3). In this analysis simulations were conducted under 'normal' rainfall conditions of Monze (i.e., the 2009/2010 season) with the experimental field characteristics of that season: planting date was 19th November; plant density was set at 44 000 plants ha^{-1}. Second, we analyzed the effects of rainfall on the stability of the correlations between the input parameters or crop management factors and the output variables through model simulations for a drier (2006/2007) and wetter (2007/2008) season. Third, we determined the local sensitivity of simulated maize yield to three key parameters/variables (i.e., stable soil carbon fraction, depth of optimal root growth and amount of surface crop residues) for the simulation of the CA practice (viz. no-tillage and mulching). In the sections below we describe the details of the performed sensitivity analyses.

2.4.1. Global sensitivity analysis

For the global sensitivity analysis, we used the Latin Hypercube Sampling method as described by McKay et al. (1979). This method ensures that the whole range of possible parameter values is randomly sampled and that effects of interactions between input parameters, between input parameters and crop management factors, and between crop management factors on model output variables are taken into account (Pathak et al., 2007).

The following model input parameters and management factors were chosen for the sensitivity analysis (Table 3): (1) a set of input parameters associated with the crop cultivars, since these parameters are usually determined under sub-optimal plant growth conditions, whilst in the model their values refer to non-limiting growth conditions; (2) a second set of model input parameters that relate to soil moisture properties, that are often not measured in the field, but are inferred from laboratory measurements, which may cause a laboratory-scale related systematic bias; (3) third, factors related to nitrogen management and parameters of the soil organic matter module (CENTURY) were selected, because nitrogen is considered as the main limiting nutrient for the site (and other nutrients are not considered in the model) and, moreover the absence of tillage under CA is assumed to affect the rate of nitrogen mineralization; and (4) finally, we selected the amount and quality (lignin content) of crop residues as key input factors for simulating the potential effect of CA on crop yield as a result of mulching. Boundary values of the ecotype- and cultivar-specific input parameters were fixed to represent African maize cultivars (Table 3). Boundary values for the soil parameter values were set to characterise ferric Lixisols as described by CIMMYT (5 profiles, see Section 2.2). The model's sensitivity to soil available water capacity and soil organic carbon content was assessed for values for two soil layers: the first layer of the top 22 cm and the second layer from 22 to 56 cm (see Table 1). Finally, the boundary values for the nitrogen and residue management factors were set according to the practices adopted by the local farmers (recorded from household surveys) and those applied at the CIMMYT experiment in Monze. In total, we ran 1388 combinations of input parameters and management factors with R software (R Development Core Team, 2009).

The model's sensitivity to the selected input parameters and crop management factors was assessed by looking at a set of model output variables that are listed in Table 4. Crop grain yield and total above ground biomass are the integrative outputs of the model simulations, the other model outputs can be regarded as key variables that help in explaining simulated crop growth and yields.

Table 3
Selected input parameters and crop management factors for the global sensitivity analysis of DSSA for the maize experiment in Monze, Zambia.

Module/Class	Variable	Acronym	Unit	Min	Max	Source
Genotype/ecotypes	Radiation use efficiency (dry matter conversion)	RUE	g MJ^{-1} PAR	2	5	Lindquist et al. (2005)
	Light extinction coefficient	KCAN	–	0.45	0.90	APSIM + DSSAT
	Thermal time from silking to effective grain filling period	DSGFT	°C day	85	255	DSSAT (default value ± 50%)
	Thermal time per cm seed depth required for emergence	GDDE	°C day cm^{-1}	4	9	DSSAT + CIMMYT
Genotype/cultivars	Thermal time from emergence to end of juvenile phase	P1	°C day	130	380	DSSAT (range of values
	Thermal time from silking to physiological maturity	P5	°C day	600	1100	for African cultivars)+
	Potential kernel number/plant	G2	$plant^{-1}$	400	1100	Jagtap and Abamu
	Potential grain filling rate	G3	mg day^{-1}	4.0	11.5	(2003)
	Phyllocron interval	PHINT	°C day	30	90	
Soil description/surface layer	Soil evaporation limit	SLU1	mm	3	12	DSSAT + CIMMYT +
	Drainage rate	SLDR	day^{-1}	0.01	0.95	Gijsman et al. (2002)
	Runoff curve number	SLRO	–	61	94	
Soil description/first soil layer (0–22 cm)	Lower limit	SLLL.22	cm^3 cm^{-3}	0.02	0.25	
	Drained upper limit	SDUL.22	cm^3 cm^{-3}	0.08	0.45	
	Saturated upper limit	SSAT.22	cm^3 cm^{-3}	0.3	0.6	
	Bulk density	SADM.22	g cm^{-3}	0.8	1.8	
	Total organic C	SAOC.22	%	0.2	3.0	
	Stable organic C	SASC.22	%	60	90	
Soil description/second soil layer (22–56 cm)	Lower limit	SLLL.56	cm^3 cm^{-3}	0.02	0.25	
	Drained upper limit	SDUL.56	cm^3 cm^{-3}	0.08	0.45	
	Saturated upper limit	SSAT.56	cm^3 cm^{-3}	0.3	0.6	
	Bulk density	SADM.56	g cm^{-3}	0.8	1.8	
	Total organic C	SAOC.56	%	0.1	1.0	
	Stable organic C	SASC.56	%	60	90	
Main structure/initial conditions	Initial soil volumetric water content	SH2O	cm^3 cm^{-3}	0.0	0.3	CIMMYT
	Initial soil nitrate content	SNO3	g N Mg^{-1} soil	0	10	
Main structure/inorganic fertilizers	N at seeding (0 DAP*)	FAMN.0	kg N ha^{-1}	0	20	CIMMYT
	N at 30 DAP	FAMN.30	kg N ha^{-1}	0	50	
	N at 50 DAP	FAMN.50	kg N ha^{-1}	0	50	
Main structure/organic fertilizers	Amount of crop residues (dry matter) at planting	RAMT	kg ha^{-1}	0	6000	CIMMYT + Waddington and Karigwindi (2004)
	Lignin content crop residues	PSLIG	(fraction)	0.05	0.20	
	N content crop residues	SCN	%	0.5	2.0	

* DAP: days after planting.

Table 4
Selected output parameters for the global sensitivity analysis of DSSAT for the maize experiment in Monze, Zambia.

Category	Variable	Unit	Acronym
Crop growth and development	Grain yield	kg ha^{-1}	Yield
	Vegetative above ground biomass (straw yield)	kg ha^{-1}	Biom
	LAI max	–	LaiM
	Cumulative plant N uptake	kg N ha^{-1}	Nup
	Emergence	Days after planting	Emer
	Silking	Days after planting	Silk
	Maturity	Days after planting	Mat
	Cumulative plant transpiration	mm	Transpi
Soil water	Cumulative soil evaporation	mm	sEvap
	Cumulative runoff	mm	Run
	Total soil moisture at maturity	mm	sMoist
Soil fertility	Cumulative net N mineralization	kg N ha^{-1}	netNminer
	Total soil N	kg N ha^{-1}	sN
	Surface organic C	kg C ha^{-1}	surfC

To summarize, the sensitivity analysis design comprises two tables: (1) an input table with 1388 lines that correspond to the number of simulations (one simulation for one combination of values for input parameters or management factors), and 32 columns corresponding to the selected parameters and management factors (see Table 3) and (2) an output table, with the 1388 lines (number of simulations) and 14 columns that are the 14 variables of the model response (see Table 4).

The method used for coupling the two tables was co-inertia analysis, which can be considered as an alternative to the classical multivariate methods based on variance decomposition. It provides an overview of the linear relationships between the input and the output tables and produces scores that are the result of the maximization of both the covariance of parameters or variables belonging to the same table and the covariance of parameters or variables from one table to another. In other words, co-inertia analysis helps to synthesize at the same time the redundancy between output variables and relationships between input parameters or factors and output variables. It can deal with a large number of input parameters or factors and with co-linearity between output variables, and can take account of an imbalance between the number of simulations and the number of inputs, in contrast to other data coupling methods known as principal component analysis and canonical correlation analysis (Thioulouse and Lobry, 1995). Theory and details of the algorithms of co-inertia analysis are described in Chessel and Mercier (1993) and Dolédec and Chessel (1994).

2.4.2. Weather effects on the model input/output relationships

The effect of weather conditions (in particular rainfall) on the stability of the relationships between input parameters or factors and output variables was analyzed by repeating the 1388 simulations performed under the climatic conditions of 2009/2010 for a drier (2006/2007) and a wetter (2007/2008) cropping season. The stability of the model response was assessed using the

RV-correlation coefficient, a multivariate generalization of the squared Pearson's correlation coefficient (Robert and Escoufier, 1976). Thus, the RV-coefficient (0 = not correlated, 1 = correlated) measures the reproducibility of the correlation between the model input and the output tables from one season to another.

2.4.3. Model sensitivity to CA-related parameters

A local sensitivity analysis was performed in order to better understand the potential effects of the CA practice (no-tillage and mulching) on crop yield. The model's sensitivity to the following three model parameters and variables was analyzed: the stable (or passive—see CENTURY, Parton et al., 1987) soil carbon fraction (fixed at 60%, 70%, 80% and 90% of the total organic carbon in the soil), the depth of optimal root growth (limited at 22, 30, 56 and 100 cm) and the amount of crop residues left on the soil surface at planting (0, 1270, 2700 and 3940 kg dry matter ha^{-1}). The combination of parameter values that represents best the conventional ploughing treatment is the stable soil carbon set at the lowest value, i.e., 60% (because of the tillage effects on soil aggregation and protected soil carbon), a depth of optimal root development restricted to 22 cm (because of the plough pan between 20 and 25 cm) and no mulch of maize residues. The combination of values representing the CA treatment is the stable soil carbon set at 90%, an optimal root growth over 100 cm soil depth and a mulch amount set at 1270 kg dry matter ha^{-1} or more.

3. Results

3.1. Zambian case study: model calibration and testing

Table 1 and 2 show the combination of values for selected model parameters that ensured the best fit to the observed data of the CP treatment, while Table 5 gives an overview of the capability of DSSAT to reproduce observed maize development and yield data from 2005 to 2011 under the CP and CA treatment, respectively.

3.1.1. Model calibration—CP treatment

Results of the model calibration for the CP treatment during the six seasons of the experiment are shown in Fig. 3. We chose not to consider the seasons 2005/2006 and 2008/2009 for calibration of the varieties SC513 and MRI624, respectively, since we were not able to fit the model well enough to the observed yield data of these seasons (Fig. 3, Table 5), probably because other factors than those simulated by DSSAT may have had a substantial effect on crop growth during these seasons. In 2005/2006, the model largely over-predicted (+51% prediction deviation) total above ground biomass, resulting also in an overestimation (+40% prediction deviation) of grain yield. In 2008/2009, grain yield was overestimated (+42% prediction deviation), while above ground biomass production was reasonable well predicted (+10% prediction deviation). The percentage prediction deviation for the harvest index during that season was +28%, which suggests that the partitioning of dry matter to grains was not correctly reproduced. For the other seasons, the model predicted total above ground biomass with prediction deviations between 0% and 4% (Fig. 3B). Normalized RMSE values for the grain yield simulations with model calibration were 10% for SC513 and 26% for MRI624 (Table 5).

3.1.2. Model testing—CA treatment

The above CP simulations were performed with optimal root development limited to the first 22 cm, reproducing the effects of a plough pan. For the model simulations of the CA treatment, optimal root development was no longer restricted to the top 22 cm soil depth but extended to 100 cm, tillage was removed and a mulch of maize residues was added at planting. The resulting simulated model outputs of maize phenology, total above ground biomass and grain yield compared to observed values are shown in Fig. 4.

For the variety SC513, the normalized RMSEs for grain yield and phenology predictions were 12% and less than 6%, respectively (Table 5). For the variety MRI624, the normalized RMSEs indicate that the CA treatment was simulated equally well as the CP treatment: a normalized RMSE of about 10% for the phenology and of about 25% for grain yield (Table 5). Percentage prediction deviations for total above ground biomass ranged between −14% and +8% (Fig. 4B). The box plots (Figs. 3 B and 4 B) also illustrate the large variability in observed maize above ground biomass and grain yield for a given season, a feature which was not captured by the deterministic DSSAT model.

3.2. Global sensitivity analysis of model output

Relationships between the model input parameters/management factors and the model output variables were first explored for a season with normal rainfall (2009/2010). Fig. 5 shows the results of the co-inertia analysis, linking the tables of model input and output variables. Four principal components were a priori pertinent (see the Eigenvalues, Fig. 5) for describing the relationships. However, since the fourth axis did not increase the global covariance, we limit our discussion to the first three principal axes. Each principal axis is associated with an eigenvalue and represents a portion of the explained covariance. Parameters that have the highest scores are represented by the longest arrows. Large arrows that point in the same direction have a strong positive correlation, whilst large arrows that point in opposite directions have a strong negative correlation, and perpendicular arrows are not correlated. Input parameters contributing less to the model response (the gray zones) are zoomed for better visualization. Acronyms used for input parameters/factors are those from DSSAT, explained in Table 3. Output variables and their abbreviations are described in Table 4.

On the two first principal components (Fig. 5, top, right), four model input parameters/factors were particularly well represented: thermal time from emergence to end of juvenile phase (P1), thermal time from silking to physiological maturity (P5) and the phyllocron or interval time between appearances of successive leaves (PHINT), and the amount of mulch (RAMT), meaning that they contributed highly to the model response. The large arrow size of the amount of mulch (RAMT) in the factorial—axis 1, axis 2—plane was partly related to the large variation in values of RAMT (from 0 to 6 Mg ha^{-1}). The first axis was mainly defined by P1 that was positively and highly correlated to two groups of output variables, including respectively above ground biomass (Biom) and maturity date (Mat). This means that P1 contributed largely to the variability of these crop production variables. P5 was positively and highly correlated to P1. From the arrow size, we can see that the model response was less sensitive to P5 than to P1. The factorial—axis 1, axis 3—plane (Fig. 5, bottom, left) shows that P5 affected principally the maturity date (Mat), while the silking date (Silk) was more specifically affected by P1. The co-inertia analysis also shows that PHINT was negatively correlated with total above ground biomass (Biom), leaf area index (LAIm) and cumulative crop transpiration (Transpi), while a positive correlation existed between PHINT and cumulative soil evaporation (sEvap) in the factorial—axis 1, axis 2—plane, and between PHINT and total soil moisture content (sMoist) in the factorial—axis 1, axis 3—plane. Indeed, the DSSAT model mechanisms cause that a delay in leaf development results in less transpiration by the crop, more soil moisture and eventually more soil evaporation. From the arrow sizes and locations of the amount of mulch (RAMT), the soil drainage rate (SLDR) and of the variables sEvap and surfC, we can infer that the second axis was mainly defined by the soil surface properties, while the third axis

Table 5
Normalized root mean square errors (RMSE) between observed and simulated values for the DSSAT runs for the maize experiment in Monze, Zambia. Season 1 corresponds to the 2005–2006 growing season, season 6 to 2010–2011. The seasons 1 (2005/2006) and 4 (2008/2009) were not considered for calibration of the varieties SC513 and MRI624, respectively, in the CP treatment.

Treatment	Variable	Variety SC513		Variety MRI624	
		Seasons 1 and 2	Season 2 (calibration)	Seasons 3 to 6	Seasons 3, 5 and 6 (calibration)
CP	Silking date	3.0%	4.0%	7.2%	7.1%
	Maturity date	2.4%	3.4%	9.3%	8.6%
	Grain yield	25%	10%	31%	26%
	Vegetative above ground biomass	38%	10%	23%	24%
CA	Silking date	5.3%		10%	
	Maturity date	2.4%		11%	
	Grain yield	12%		23%	
	Vegetative above ground biomass	13%		26%	

CP: conventional tillage treatment. CA: conservation agriculture treatment.

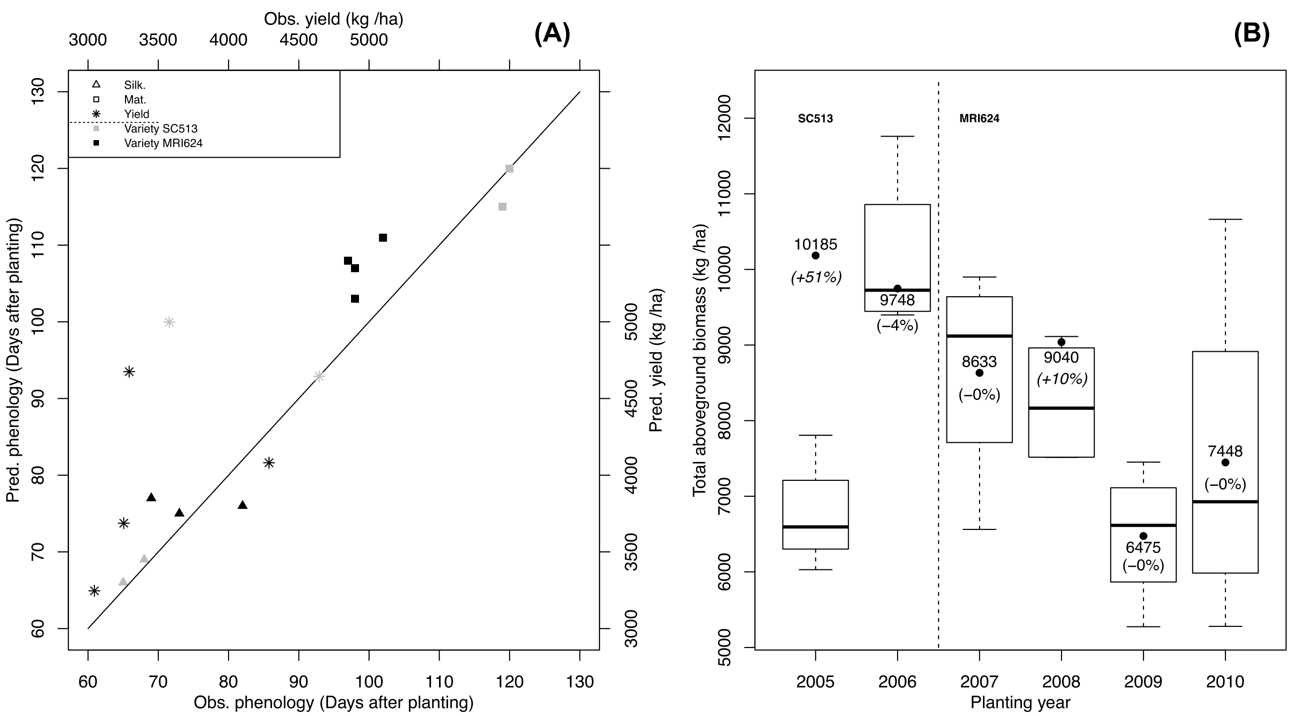

Fig. 3. (A) Comparison of observed and simulated (DSSAT model) maize phenology and grain yield, and (B) observed (box-and-whisker plots) and simulated (points, DSSAT model) above ground biomass for the CP treatment of the experiment at Monze, Zambia (2005/2006–2010/11 growing season). Model predictions were compared to the mean values of observations and expressed as percentage prediction deviation.

was mainly defined by the properties of the topsoil layer (SAOC.22, SASC.22 and SDUL.22, see Table 3). In both factorial planes (Fig. 5), RAMT affected primarily and positively the surface organic carbon content (surfC) and to a lesser extent the total soil moisture content (sMoist), as the latter was negatively correlated with cumulative soil evaporation (sEvap) and cumulative water run-off (Run).

Three main groups of crop production output variables (Table 4) could be distinguished on the first two principal components (Fig. 5, top, left). A first group was associated with the first axis and includes total above ground biomass (Biom), maximum LAI (LaiM), cumulative crop transpiration (Transpi) and cumulative crop nitrogen uptake (Nup). A second group that was projected on the axes 1 and 2, included the silking (Silk) and the maturity (Mat) dates. A third group was composed of grain yield (Yield) and was positively correlated with the first axis and thus the first group of output variables, but the size of the arrow indicated that its variance was more diffusely represented than those of the other groups. This means that grain yield was not strongly determined by a single model input parameter or factor. The sizes of the arrows of the input parameters/factors were altogether relatively small (Fig. 5, right).

The genetic coefficients, the mineral nitrogen fertilization and the organic carbon of the first soil layer were the most determining factors for the simulated crop production variables. The amount of mulch was explaining variability in grain yield to a relatively small extent. This is consistent with the fact that in DSSAT crop residue mulching has no direct effect on simulated crop yield. The application of mulch had mainly an effect on simulated organic carbon content, (in the first place in the surface soil layer, but also in the soil layer below), and on simulated soil evaporation.

3.3. *Effect of seasonal conditions on the stability of the model response*

To compare the possible impact of a drier (2006/2007, 510 mm rainfall) or wetter cropping season (2007/2008, 1000 mm rainfall) on the relationships between the model input parameters/management factors and the output variables, RV values were calculated. These RV values indicated that the relationships were very stable: RV = 0.98 between 2009/2010 and 2006/2007, RV = 0.98 between 2009/2010 and 2007/2008, and RV = 0.97

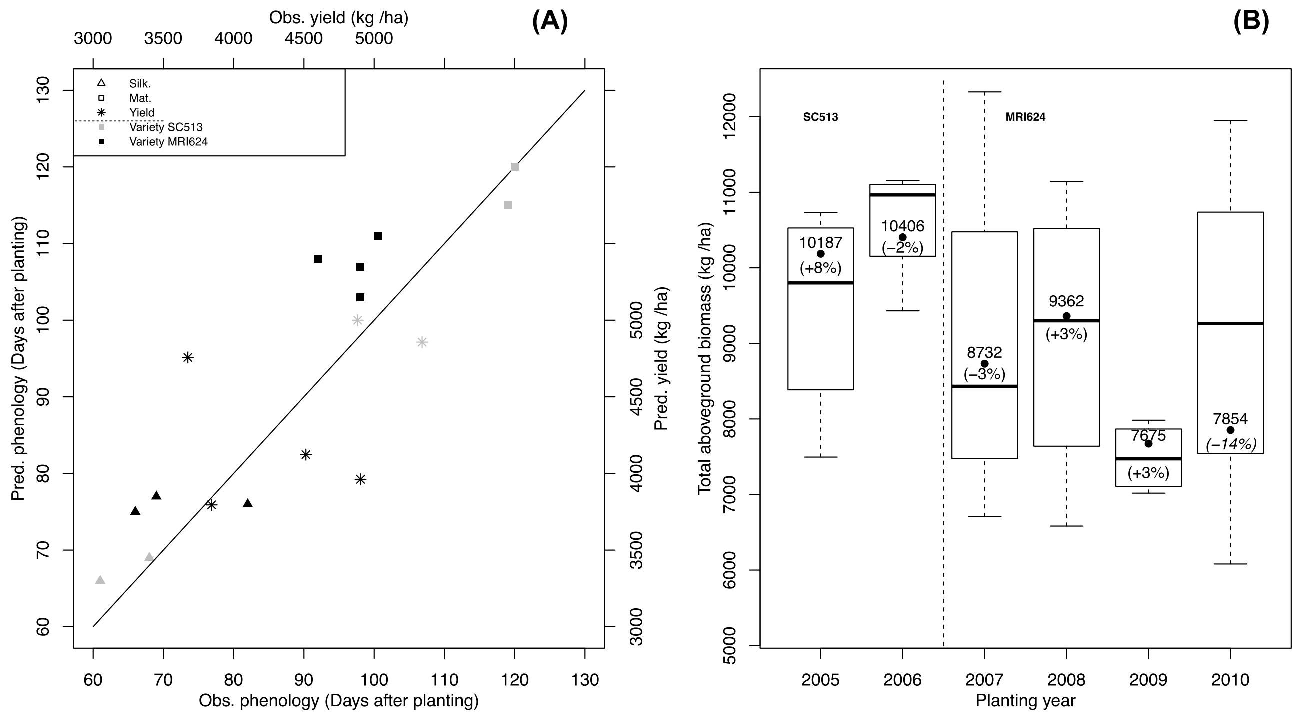

Fig. 4. (A) Comparison of observed and simulated (DSSAT model) maize phenology and grain yield, and (B) observed (box-and-whisker plots) and simulated (points, DSSAT model) aboveground biomass for the CA treatment of the experiment at Monze, Zambia (2005/2006–2010/11 growing season). Model predictions were compared to the mean values of observations and expressed as percentage prediction deviation.

between 2006/2007 and 2007/2008. Therefore, the findings on model behavior described in the previous section were valid for a relatively wide range of crop growing conditions.

3.4. Local model sensitivity to three key model parameters for CA model simulations

We analyzed the sensitivity of the model response to three model parameters/factors that are key for simulating the CA practice, i.e., the soil depth for optimal root development, the amount of mulch and the stable soil carbon fraction. As expected, highest simulated maize grain yield occurred with the maximal depth for optimal root development (100 cm depth), the highest amount of mulch (3940 kg ha^{-1}), and the lowest stable carbon fraction (60% of the total soil carbon), which results in the relatively highest mineralization of soil organic matter. Similarly, lowest grain yield was simulated with the minimal depth for optimal root development (22 cm depth), the highest fraction of stable soil carbon (90% of the total soil carbon), and without mulching. However, within these boundaries, the simulated effects of the stable soil carbon fraction (Fig. 6A), the depth for optimal root growth (Fig. 6B) and the mulch amount (Fig. 6C) were not linear. For instance, in the case of a 22 cm rooting depth without mulching (Fig. 6A), a 10% reduction of the stable soil carbon led to a grain yield increase of 0.1, 1.4 and 0.4% for initial stable carbon contents of, respectively, 90%, 80% and 70% of the total soil carbon. In the case of a 100 cm rooting depth and of 3940 kg mulch ha^{-1}, the yield increase became 0.5, 0.2 and 0.1%. These results show that simulated grain yield was weakly affected by changes in the stable soil carbon fraction in the context of this study (Lixisol, weather conditions of 2009/2010, >100 kg N ha^{-1} of chemical fertilizer application). On the other hand, an increase of the depth for optimal root growth from 22 to 30 cm led to a yield gain of between 3.3 and 8.7%. A deeper optimal root development permits a better soil water use. Interestingly, the yield increase remained weak when rooting depth increased from 30 to 56 cm. Herewith, we should note that in DSSAT, the root growth rate is simulated through an empirical non-linear function that determines that the deeper a soil layer, the lesser the absolute root growth in that layer is. Furthermore, the simulations showed that the presence of a mulch of crop residues had a strong effect on grain yield, when root growth was constrained, but the effect was small with deep optimal rooting and, thus, water uptake from deeper soil layers.

This analysis illustrated the interactive effects of these model parameters/factors on predicted grain yield. DSSAT responded to crop residue mulching particularly if rooting depth is restricted e.g., by a hard plough pan.

4. Discussion

4.1. Need for a global sensitivity analysis

The initial development of DSSAT began in the late eighties with the aim to integrate knowledge about crops, soils, climate and management for making better decisions about transferring crop production technologies from one location to others where soils and climate differ (Jones et al., 2003). Before, researchers in crop genetics, plant physiology and soil science worked from their own disciplines to advance on the development of specific components of crop and soil models. These efforts resulted in the development of e.g., the CERES-Maize model (Jones and Kiniry, 1986), and the CENTURY soil model (Parton et al., 1987). With the development of the cropping system model DSSAT, these earlier models were revised to make them compatible and additional crop and soil models were built (Jones et al., 2003). DSSAT kept evolving during more recent years, with e.g. the incorporation of the surface crop residue module (Porter et al., 2010). The increasing model complexity led to an increasing difficulty on how to handle a tool that suffers from 'over-parameterization' in the sense that given model outputs could be obtained from different combinations of (collinear) parameter values. In other words, the effect of one parameter on model output

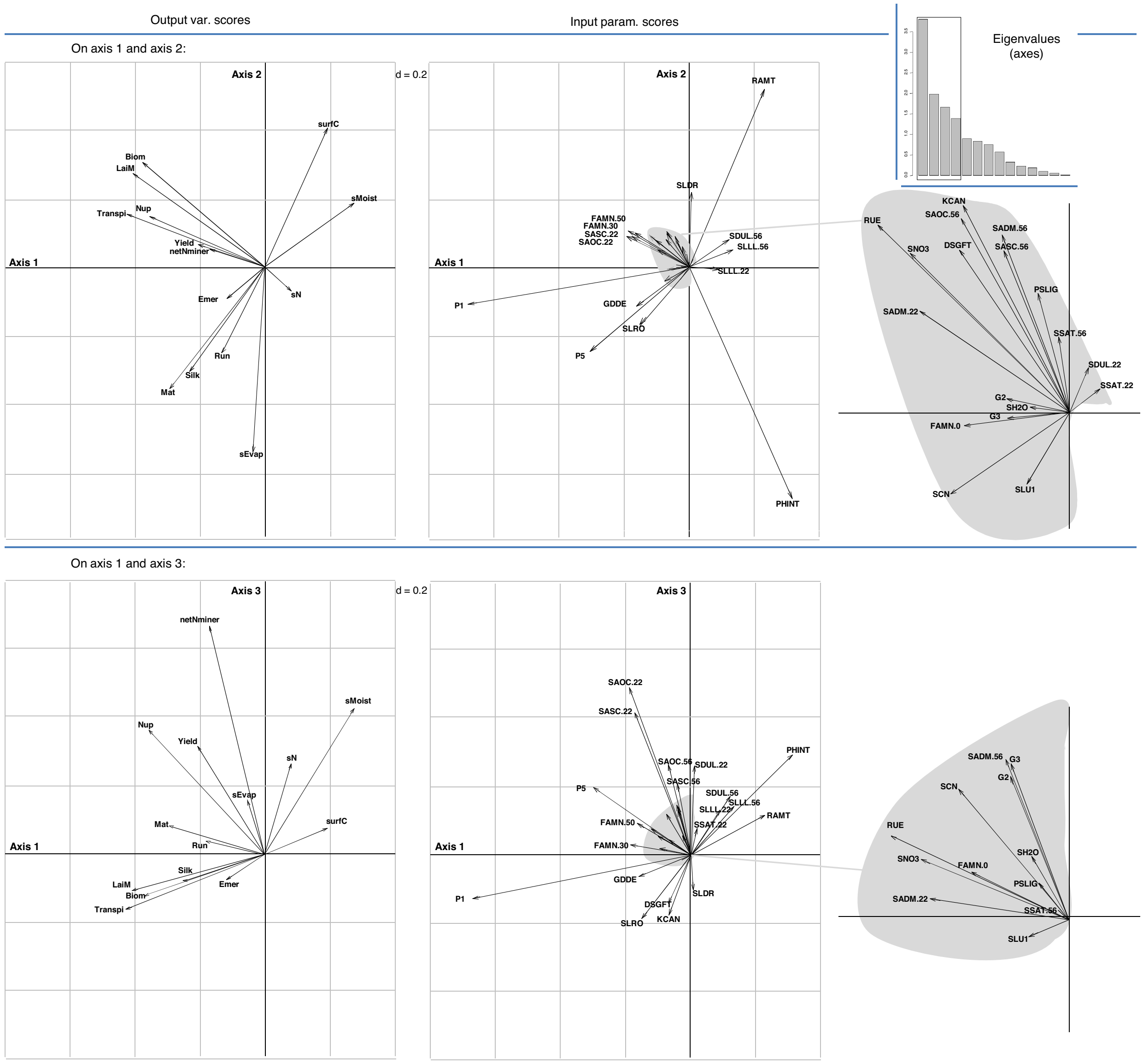

Fig. 5. Co-inertia analysis plots of the results of the global sensitivity analysis of the DSSAT model: top, factorial—axis 1, axis 2—plane for model output variables (left) and input parameters (right), and bottom, factorial—axis 1, axis 3—plane for model output variables (left) and input parameters (right). DSSAT was run for a maize experiment in Monze, Zambia. Eigenvalues (total covariance explained by each co-inertia axis) are shown in the inset (top right). Input parameters contributing less to the model response (the grey zones) are zoomed for better visualization. Acronyms used for input parameters are those from DSSAT, explained in Table 3. Acronyms for output variables are given in Table 4. See text for further explanation.

is not only correlated with the model structure, but also with the values of other parameters and input data (Reichert and Omlin, 1997; Wallach et al., 2002). This makes model parameterization and use difficult. Sensitivity analysis is a useful means for identifying the important parameters that govern model output and, in consequence, whose values need to be quantified carefully.

With the parametrization of DSSAT for a maize experiment in Zambia under contrasting tillage and residue management practices, we faced difficulties in accurately quantifying values of various crop parameters such as the genetic cultivar coefficients or the radiation use efficiency, and of soil parameters such as soil water evaporation limit, drainage rate or stable organic carbon. Even with available field data on soil properties, crop phenology, biomass and grain yield, major assumptions were necessary to set the values of several model parameters. On the other hand, some of these parameters may account only for a small part of the output variance and, thus, do not require an accurate determination. The sensitivity analysis evaluated the contribution of different model parameters to the model output.

4.2. The co-inertia method

There is no unique approach for sensitivity analysis of simulation models. Overall, two major categories are distinguished (Cariboni et al., 2007): local and global sensitivity analysis. The local sensitivity analysis examines the local response of model outputs by varying values of input parameters one at a time while holding the values of other parameters fixed. Local sensitivity analyses are relatively easily implemented and have a low computational cost, but the results depend to a great extent on the initial value of the input parameters. Instead, global sensitivity analysis explores the entire multi-dimensional parameter space simultaneously, i.e.,

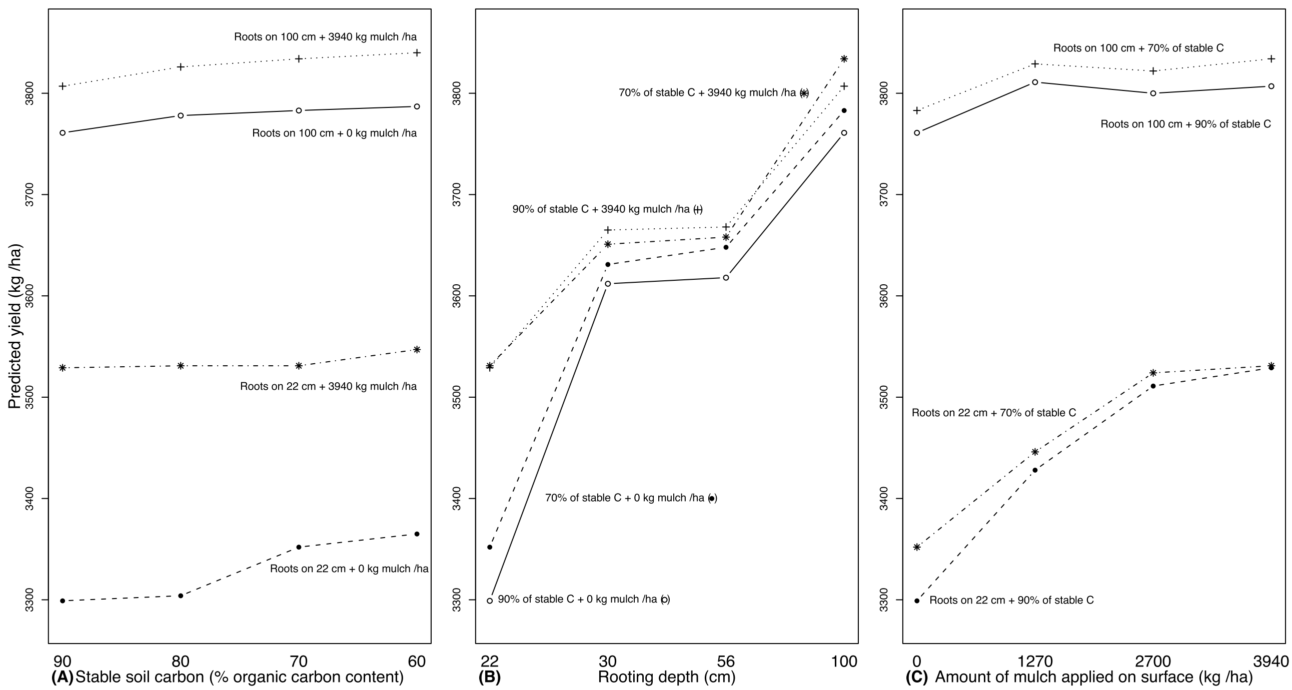

Fig. 6. Results of the local sensitivity analysis of DSSAT showing maize grain yield responses as function of the stable soil carbon fraction (A), the depth of optimal root development (B) and the amount of crop residue mulch at planting (C) for the maize experiment at Monze, Zambia.

for a specific output variable the influence of single parameters and the interactions between parameters are quantified. Several methods exist for global sensitivity analysis, based on variance decomposition (e.g., the method of Sobol'), on regressions or on screening (e.g., the Morris method). Confalonieri et al. (2010) compared different global sensitivity analysis approaches for a rice growth model (WARM, Water Accounting Rice Model) and concluded that all resulted in relative similar outcomes. The simplest among the methods used (i.e., the Morris method) produced results comparable to those obtained by methods more computationally expensive. We argue that besides the handling time, visualization of the results is an important criterion for the choice of a sensitivity analysis method, as it facilitates the interpretation of high dimensional data.

Co-inertia is a multivariate method that allows the analysis of a pair of numerical data tables in a robust way, i.e., regardless of the number of columns or lines, and with possible co-linearity between the variables. We used this method for our global sensitivity analysis. The co-inertia analysis searches for pairs of axes with maximum covariance (Dolédec and Chessel, 1994). It adapts a multi-dimensional cloud of data points in such a way that when it is projected onto a two dimensional space any intrinsic patterns the data may possess becomes apparent upon visual inspection. The ordination diagrams or factorial planes are thus an important aid in the interpretation of the data and helped us to understand the overall functioning of the DSSAT model by showing patterns of co-variability between the model parameters and between model parameters and output variables (Fig. 5). The genetic cultivar coefficients P1 (thermal time from emergence to end of juvenile phase), P5 (thermal time from silking to physiological maturity) and PHINT (phyllocron interval) were found to determine largely the crop production variables, including grain yield. Our results were in agreement with those of Jones et al. (2012) who explored the DSSAT model response in terms of grain yield to 17 crop and soil parameters using the Sobol's method. These authors concluded that in non-limiting plant growth environments simulated grain yields are principally determined by the genetic cultivar coefficients, while under semi-arid climates and on poor soils the contribution of genetic cultivar input parameters was largely reduced at the expense of model parameters describing soil water and nutrient dynamics.

4.3. Parameterisation of DSSAT

Our parameterization of the genetic cultivar coefficients (Table 2) and soil parameters (Table 1) in DSSAT led to a reasonably good reproduction of the observed maize development, biomass and grain yield values over the six cropping seasons both for the CP and CA treatments, as indicated by the RMSE values between observed and simulated data. Phenology was well predicted for all seasons (Figs. 3 A and 4 A). Above ground biomass and grain yields were, however, not well reproduced for all six cropping seasons (Figs. 3 and 4). In particular, biomass and grain yields of the CP treatment during the first season were strongly overestimated. The reasons for this were not clear. Surprisingly, biomass and grain yields of the CA treatment during this season were well fitted by the model. Similarly, grain yield of the CP treatment for the season 2008/2009 was not well reproduced and overestimated by the model. Here, it has to be noted that the observed harvest index was unusually low (0.38), while the simulated harvest index was rather high (0.52).

The cultivar parameters, 'P1′', thermal time from seedlings emergence to the end of the juvenile phase, 'P5′', the thermal time from silking to maturity and the end of the juvenile phase and 'PHINT', phyllochron interval, i.e., the interval in thermal time between successive leaf tip appearances are most influential model input parameters for which accurate values have to be determined. End of juvenile phase is defined as the time at which tassel initiation can be observed on 50% of the observed plants, and should be determined through destructive sampling by dissecting plants and observing the apical meristem using a microscope for any development of floral buds at the 2–3 days interval starting from the 10th day after emergence (Gungula et al., 2003). PHINT is estimated by the inverse of the slope of the linear regression of the number of accumulated or emerged leaves on the main stem against accumulated thermal time. Determining the number of fully expanded leaves and leaf tips needs accurate (and weekly) monitoring of a sufficient number of plants under field conditions. For P5, time of silking is recorded in the field when silks are noticed on 50% of the observed plants. In a similar way, time of physiological maturity is recorded in the field as the day when 50% of the grains in each observed ear have formed a black layer, indicating that no further accumulation of assimilates is possible.

4.4. DSSAT response to CA practice

The co-inertia analysis scores (Fig. 5) illustrated that the applied amount of mulch (RAMT) strongly and positively affects simulated soil surface carbon content (surfC) and soil moisture (sMoist), and negatively soil evaporation (sEvap) and runoff (Run). Consequently, under drought stress the practice of mulching affects simulated grain yield positively. Results from the local sensitivity analysis corroborated this. The application of a mulch of crop residues affected more positively simulated grain yield when water uptake was limited as a result of limited optimal root growth, as compared to a situation with deep optimal root development and greater access to more soil water.

To be able to reproduce with DSSAT the yield increase under CA compared to CP, it was necessary to include a rooting depth effect, in addition to the mulch and the no-tillage effects. Under CP optimal root development was restricted to the plough layer (22 cm), while under CA roots could optimally develop to 100 cm depth. The occurrence of a hard pan caused by repeated ploughing to the same depth is a common feature in loam and clay soils (Materechera and Mloza-Banda, 1997). A hard pan restricts root growth and water percolation, which can have severe effects on plant growth, especially if the topsoil dries out (Adeoye and Mohamed-Saleem, 1990).

Finally, in our study, simulated effects of crop residue mulching on soil carbon content and nitrogen immobilization/mineralization were relatively small and had no effect on grain yield given the mineral fertilizer application of 108 kg N ha^{-1} $year^{-1}$. (Simulated) effects of the CA versus CP treatment on soil carbon become pronounced in the long term (Corbeels et al., 2014).

5. Conclusions

The results of our study illustrate that in order to simulate yield effects of CA, an agronomic diagnosis is required on what the site-specific factors are that explain the yield differences between CA and CP. Some of these factors are not mechanistically simulated by DSSAT, but can be incorporated in the model through a proper parameterisation of relevant parameters. This is the case for e.g., soil structure differences as a result of the practice of CA versus CP, which may have an effect on crop yield. DSSAT does not simulate these soil structural effects. In our study we had to introduce a rooting depth effect in order to reproduce the observed maize yield differences between the CP (tillage and no residues) and CA (no-tillage and crop residue mulching). Under CP the optimal root growth was restricted to the upper 22 cm soil layer as a result of the formation of a hard pan just below ploughing depth, whilst under CA optimal root growth in the model was unrestricted. Simulated effects of mulching on yields were more pronounced when the depth for optimal root development, and thus crop water (and nutrient) uptake was restricted.

Co-inertia analysis was used in order to analyze and visualize how 16 DSSAT model output variables respond to 32 input parameters, considering parameter correlations and nonlinear relations. Co-inertia analysis can be used to visually inspect and identify influential model parameters that must be estimated from experiments and observations. On the other hand, those parameters with a small contribution to model output can be excluded from the calibration exercise and can be set equal to any value within their range. This contributes to a simplification of model use and is useful for calibration of this type of complex crop growth models for multiple sites or at a regional scale. Under the conditions of our study, genetic cultivar coefficients were the most influential model parameters.

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