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Influence of climate change on short term management of field crops – A modelling approach

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ABSTRACT

Climatic change is likely to have an influence on arable farms in Central Europe. We use a modelling approach to assess the effects of weather and its long term development due to climate change on short-term decisions like planting and harvesting, as well as yields. Two models are coupled, a farm management model FarmActor and the crop growth model system Expert-N to investigate the interplay between management and crop growth on a daily basis. We examine different methods of adapting expectations concerning the timing of cropping actions and annual yields to actual observed weather and yield data. Our study focuses on the two major crops winter wheat and silage maize in the Swabian Alb in southwestern Germany. Results show that the model can satisfactorily reproduce the development of planting and harvesting as well as yields that have occurred in the past. Different methods of expectation formation only show minor differences in their effect on action dates and yields. Future climatic change is likely to shift the timing of field actions. Assuming no change in technology (e.g. cultivars), summer crops may be seeded earlier while winter crops could tend to be sown later; harvest may occur earlier and yields might slightly decrease while showing more volatility. This modelling approach has the potential to increase the knowledge about risk profiles of short time agricultural management actions and to improve the land use modelling part of coupled earth system models.

1. Introduction

Agriculture is not only one of the significant drivers of climate change but is also directly affected by shifting climatic conditions as it relies upon natural processes in the field. Thus, research on the effects of climate change on agriculture has to take these effects into account. Agriculture in Europe is subject to continuous structural development and has for decades faced the challenge of poor profitability (Deutsche Bundesregierung (Ed.), 2011). Climate change is considered to have an ambivalent influence on farming in Central Europe. While the increase in average temperatures and atmospheric CO_2 content are assumed to increase yields, reduced precipitation during summer as well as increasing variability of precipitation is likely to reduce yields (Schaller and Weigel, 2007).

To estimate the effects of future climate scenarios on agriculture, several approaches are reasonable. There are a number of econometric approaches that relate certain land uses to climate parameters. Cabas et al. (2010) use an econometric model to explain yield as a function of climatic and economic variables. They infer that yields will rise with increasing temperatures and longer growing seasons despite greater variability in rainfall, which in principle negatively influences yields.

The so-called Ricardian approach which uses land values as a dependent variable was pioneered by Mendelsohn et al. (1994) and has meanwhile been applied mainly in North America (Mendelsohn and Reinsborough, 2007; Schlenker et al., 2006) but also in Germany (Lippert et al., 2009). The latter found that increasing temperatures should result in higher rates of return and land rental prices in Germany.

Apart from econometric approaches, programming models are widely used to focus on regional scale as this allows a depiction of the economic situation of agriculture and elements of technical–biological processes of land use. Typically, these models are coupled with crop growth models and refer to climate scenarios published by the Intergovernmental Panel on Climate Change (IPCC).

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This research field has been covered by the following projects. Both the EURuralis project and the ATEAM study apply top-down methodology to explore changes in land use, scaling continent-level data. (Busch, 2006; Verburg et al., 2008). EURuralis disaggregates results of a general equilibrium model to local scale according to biophysical, socio-economic and policy considerations (Van Meijl et al., 2006). A bottom-up method is utilized in ACCELERATES (Audsley et al., 2006), GLOWA-Elbe (Gömann et al., 2005) and SEAMLESS (Flichman et al., 2006; Van Ittersum et al., 2008; Van Ittersum, 2009) to examine regional decision-making processes. While ACCELERATES uses linear programming (LP) in an individual farm model to judge optimal land use, GLOWA-Elbe and SEAMLESS-IF base regional agricultural sector models on Positive Mathematical Programming in order to simulate dynamic land-use (Flichman et al., 2006; Van Ittersum et al., 2008). Farm System Simulator (FSSIM), a component of SEAMLESS-IF, is a component-based, bio-economic model widely applicable to modelling generic processes (Janssen et al., 2010; Kanellopoulos et al., 2010; Louhichi et al., 2010). FSSIM uses regional supply and response functions (NUTS2) to analyse the implications for farm management stemming from political and technological developments. Hermans et al. (2010) compare different arable crops considering climate change, predicting an increase in yields and a shift of production into the most competitive regions for each crop. Henseler et al. (2009) model both impacts of policy scenarios as well as climate change on agricultural land use as well as farm income using a regional PMP approach. Their main finding is that policy change towards liberalisation is likely to exert major influence on agriculture. Freier et al. (2011) use a Markov chain meta-model of EPIC (Environmental Policy Impact Calculator) to explore the economic and ecological effects of drought on rangeland management in southern Morocco.

All these studies work at rather coarse spatial levels such as region or district. However, as shown by Reidsma et al. (2009), the individual farm is an important level of analysis concerning yield variability and adaptation to climate change, as farm characteristics and management greatly influence adaptation processes.

Farm based bio-economic models are used to study the interaction of farms with their environment (Janssen and Van Ittersum, 2007). Many of these exist already. As Balbi and Giupponi (2009) show in their review article, this type of model is felicitous for coupling economic and environmental models. Matthews et al. (2007) confirm this by reviewing different applications of agent-based models. Matthews (2006) sets up an agent-based model (PALM) that closely links farmer behaviour to plant growth and nutrient cycles. He makes use of object-oriented programming techniques and explicit formalisation of knowledge. The modelling system MODAM (Zander and Kächele, 1999) also explores farm-level management decisions and their reciprocity with ecological aspects. MODAM has recently been used for policy and multifunctionality analysis (Uthes et al., 2010). Finger (2012) modelled climate change impacts on maize production in the eastern Swiss Plateau region combining a crop growth model with a bio-economic model representing the behaviour of a risk-averse farm manager. Moss et al. (2001) highlight the suitability of agent-based models for the study of implications of climate change. They advocate a better behavioural foundation for decision-making in contrast to pure economic reasoning. Balbi and Giupponi (2009) mention a persistent lack of application of agent-based models to the field of climate change. They emphasise the potential for using these types of models to evaluate adaptation to a changing environment. Gandorfer and Kersebaum (2008) modelled the effects of climate change at three sites in Bavaria, Germany concerning the profitability of farms and its variability by linking a crop growth model driven by climate scenario data with an economic evaluation model. They concluded that yields and profits should tend to decrease while risk is likely to increase. However, they did not account for adaptation other than modifying nitrogen fertilisation intensity. Rowan et al. (2011) developed a dynamic modelling framework designed to map farm behaviour related to irrigation issues. They applied this model to a fictitious Australian farm and found that increasing weather variability decreases farm profits and increases the uncertainty related to prediction of farm viability.

The literature shows that intra-annual variability of weather, interaction between crop growth and management decisions and the management actions influenced by these weather conditions have not yet been sufficiently analysed. This interaction, however, is important for explaining short-term land-use decisions. Based on the concepts of Aubry et al. (1998), in the framework of the GLOWA-Danube project an extension (the "DeepFarming" module) to the scope of agricultural farm modelling was developed, taking short-term actions into account (Apfelbeck et al., 2009). Similar to the approach of DeepFarming, Flichman et al. (2006) combined Agricultural Production and Externalities Simulator (APES) and FSSIM to evaluate short-term management by farmers. DeepFarming builds on their work by dynamically modelling interactions between weather, crop growth and agricultural management.

While in the GLOWA-Danube project the economic reasoning is evaluated at district level, we present here a newly developed bottom-up model with the working name FarmActor that links both economic optimisation and management at the individual farm level and interacts closely with the crop growth modelling system Expert-N. This is intended to improve the land-use side of coupled land-atmosphere models and derive sophisticated adaptation strategies for agricultural stakeholders.

The remainder of the paper is organized as follows: Section 2 presents the models FarmActor and Expert-N and their calibration and coupling. Section 3 presents the results of their application to the study region in southern Germany. Section 4 provides discussion on these results and Section 5 draws conclusions.

2. Methods and data

To account for the interactions between weather, management and crop growth at daily time scale, we couple a farm management model with a plant growth model. Both models are driven by daily weather data. The two models and their relationship are presented in this chapter.

2.1. Farm management model FarmActor

The farm management model FarmActor follows the assertion that agent-based models are especially suitable for modelling impacts of climate change (Moss et al., 2001). In contrast to existing agent-based models, we refine the scope of the model from annual planning decisions to daily management decisions and hence incorporate dynamic determination of action dates. This capacity was inherited from the DeepFarming component of the Danubia model which, however, does not take farm-level economic considerations into account (Apfelbeck et al., 2008).

The schematic sequence of the several modules within FarmActor is shown in Fig. 1 and proceeds as follows. A model run starts with an initialisation procedure. All farm-specific data, such as the number and size of fields, fixed assets, crops that can be planted on each field and all other production and marketing activities are exogenous input, as is weather data (temperature, precipitation, solar radiation, relative humidity and wind speed) at daily resolution. The model proceeds in daily time steps, commencing in August with the annual planning of crops to be cultivated. August was chosen because in southwest Germany, at this point in the year, decisions as to the subsequent crop on a field has the greatest

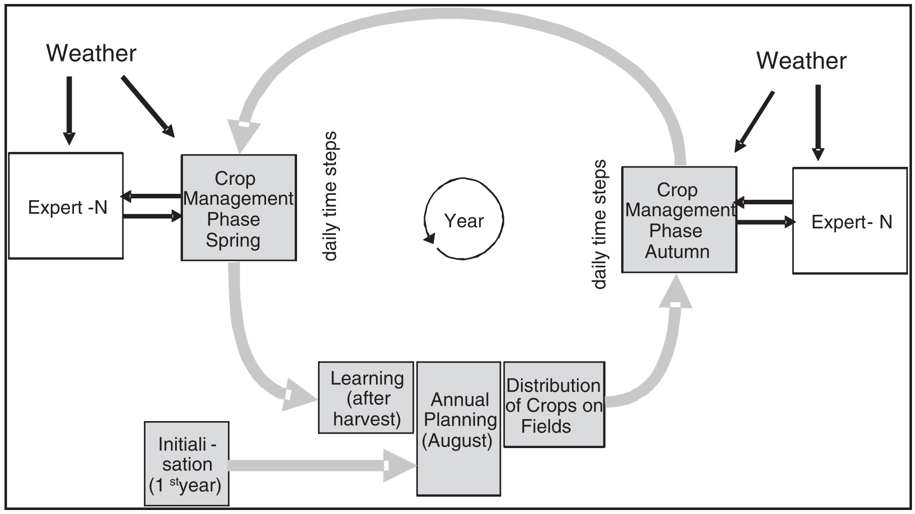

Fig. 1. Schematic sequence of FarmActor modules.

degree of flexibility, as no crop that will be harvested in the following year has yet been seeded. The first crop to be sown in late summer is usually winter rape, towards the end of August. Late-maturing crops such as maize or sugar beets that are still in the field preclude the planting of a winter crop until after harvest. The main annual planning procedure is based on an LP model arranged at the field level. This allows for costs or yields to differ between fields, as a result of different soil qualities, field sizes, or other factors. With the planning procedure particular crops are allocated to each field. This step is necessary because LP-type models usually deliver not just one crop as a solution but a share of different crops that can be seen as shares in a crop rotation. The allocation of a single crop to each field is modelled by a Markov chain stochastic simulation, which takes usual crop rotations of the region, results of the planning procedure, and the previous crop into account. Where reasonable, a catch crop is added before summer crops. The planning and distribution algorithms are published in detail in Aurbacher and Dabbert (2011). The main focus of this paper is the crop management module of FarmActor and its connection to crop growth. For this reason, in this study, we created farm models where only one crop (winter wheat or maize) was included to focus on the management and performance of these two crops. If several crops were included in the crop rotation, their selection would also depend on economic considerations and farm characteristics that would require inclusion of additional detailed assumptions.

2.1.1. Crop management

Depending on weather, soil conditions and plant development, management is conducted on a daily basis. Thus, the execution date of management actions like planting, fertilising or harvesting is endogenous to the model and dependent on weather and crop development. Each crop requires certain actions to be carried out in sequence. In FarmActor this is soil preparation, seeding, fertilising, and harvesting. The execution of actions is controlled by a set of conditions, or "triggers", associated with each action. Triggers are defined by a range of tolerable values for each applicable variable. Only when all conditions are simultaneously fulfilled will an action be carried out. Fig. 2 shows the triggers for the sowing of winter wheat. The following variables act as triggers and are derived as follows. Air temperature and amount of precipitation are read directly from a database of weather records while soil temperature and water content are output from the coupled crop growth model Expert-N. Information on the present state of the crop being grown (BBCH crop stage and current biomass) is also taken from the crop growth model each simulated day. The proper sequence of actions (e.g. soil preparation before planting), is controlled by a defined crop status that changes as actions are performed. Another type of triggers refers to the day of the year and contains the "usually suitable" periods for certain actions ("time windows"). This is necessary because not all action dates can be determined by actual weather and plant information but must consider expectations of weather throughout the growing season. Depending on the nature of an action, variables and triggers are assigned. This flexibility should ensure a realistic execution of actions depending on relevant conditions.

2.1.2. Adaptation of management to changing climate and learning from observations

As climate changes, the time windows designated for particular actions, as well as yield expectations are subject to modification over the years. Capturing this aspect in a farm management model is crucial to long-term accuracy (O'neill, 2008). The chosen approach of an agent-based model is especially suitable therefore (Nolan et al., 2009). We implement a so-called "learning algorithm" which modifies activities before planning of the next season. Yield expectations are updated based on the observed yields of previous years. The amount of nitrogen fertiliser is adapted to the expected yield. Time windows for seeding are also shifted according to observed weather during previous years. To adjust the time window for seeding of winter crops, the remaining cumulative heat in a year is used, defined as the sum of daily average temperatures exceeding 0 °C for the rest of the year. To account for the fact that actions are normally carried out a few days after the beginning of the time window, the beginning of the window is set to 4 days before the remaining temperature sum is expected to reach a given threshold. For spring crops, a temperature threshold is used that refers to the average temperature of the upper 5 cm of topsoil during a sequence of 7 days. The planting period is set to begin on the first day at which this (crop-specific) threshold is expected to be exceeded, based on a calculation of past years' soil temperatures. The end of a planting period is set to a crop-specific later date, (eight weeks for maize, six for winter wheat). Temperature thresholds, as well as the other triggers for both winter wheat and maize are given in Tables 1 and 2.

There are many ways to include and weight the observations from past years when calculating expectations for upcoming periods. A simple method is to base expectations entirely on the obser-

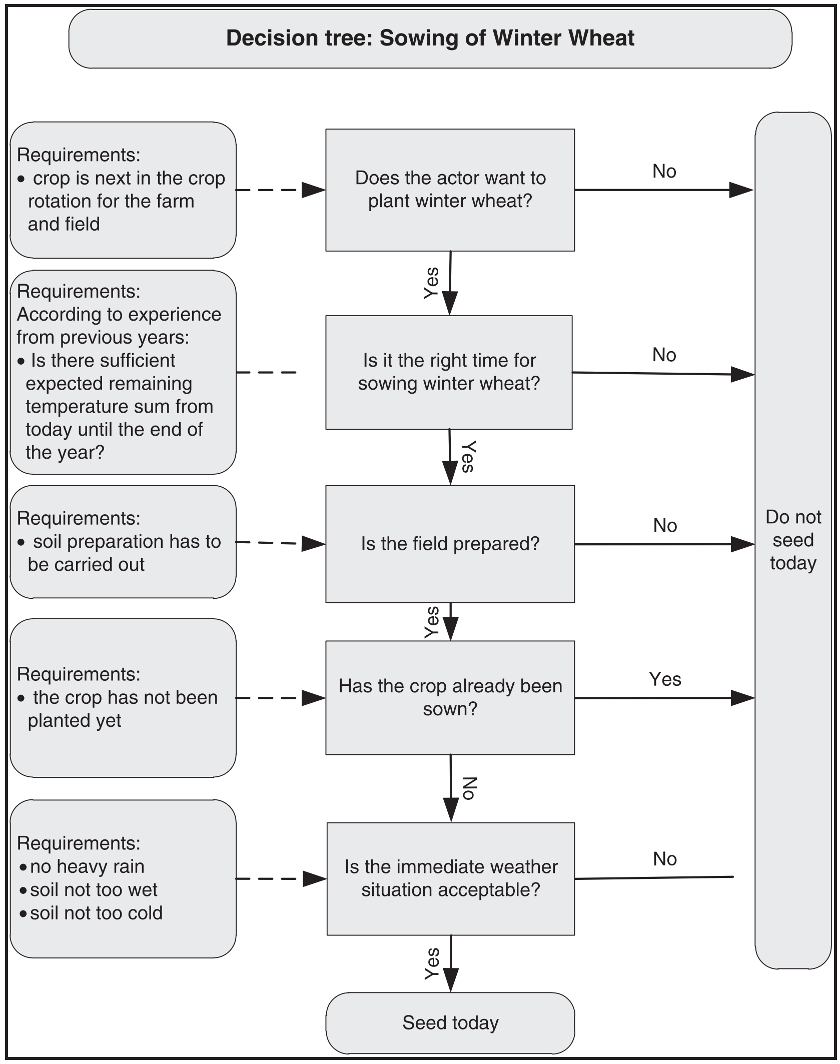

Fig. 2. Decision tree for the triggers using the example of sowing winter wheat. *Source*: Own depiction based on Apfelbeck et al. (2008)

Table 1
Action triggers for planting and harvest of winter wheat.

Action	Trigger	Observed[a] Mean	Range	Assigned
Sowing	Crop status	–	–	"Prepared"
	Day (Julian)	270	255–294	continuously adapted
	Soil moisture (%)	32.5	22–42	⩽38
	Precipitation (mm)	2.53	0–40.7	0
	Soil temperature (°C)	13.8	8.5–23.1	⩾3
	Remaining GDD[b]	–	–	⩾475
Harvest	Crop status	–	–	"planted"
	Crop stage (BBCH)	–	–	⩾92
	Day (Julian)	227	213–247	180–250
	Soil moisture (%)	31.4	22.9–46.5	⩽41
	Precipitation (mm)	1.3	0–16.3	0
	Air temperature (°C)	17.9	8.4–24.6	⩾8

[a] Comparing observed action dates with observed weather data; 1980–2010 (DWD, 2011, 2012).
[b] The trigger 'remaining GDD' is not applied directly. It is used retrospectively to adapt the 'day' trigger for the next year.

Table 2
Action triggers for planting and harvest of silage maize.

Action	Trigger	Observed[a] Mean	Range	Assigned
Sowing	Crop status	–	–	"prepared"
	Day (Julian)	122	101–137	continuously adapted
	Soil moisture (%)	30.5	23–46.5	⩽38
	Precipitation (mm)	1.3	0–12	0
	Soil temperature (°C)	11.8	3.5–19	⩾10 °C
	Air temperature (°C)	10.8	4.9–16.8	⩾10 °C
	3-day air temp. (°C)	8	0.6–13.4	⩾10 °C
	7-day soil temp.[b]	–	–	⩾10 °C
Harvest	Crop status	–	–	"planted"
	Crop stage (BBCH)	–	–	⩾85
	Day (Julian)	267	233–291	225–300
	Soil moisture (%)	33.5	22.7–43.7	⩽38
	Precipitation (mm)	1.2	0–9.9	⩽3

[a] Comparison of observed action dates with observed weather data; 1980–2010 (DWD, 2011, 2012).
[b] The trigger '7-day soil temp.' is not applied directly, but used retrospectively to adapt the 'day' trigger for the next year.

vations from 1 year prior. More realistic are methods that aggregate values from past years. We examined the following methods we refer to as "learn modes" further on. The first option is to use a 10-year moving average (MA) to represent how agents form their own expectations. However, people tend to forget events further in the past (Birbaumer and Schmidt, 2010, p. 206), so exponential smoothing (ES) (Ragsdale, 2011, p. 482) is used to 'discount' each previous year's observations by an assigned factor. In contrast to Waha et al. (2012), we use 0.9 as the "discounting factor" for each previous year because 0.95 assigns too much weight to distant years. A third option is to compute a regression trend (RT) from past observations. We use a linear regression over 20 rolling observations to extrapolate expectations for the coming year. The mathematical representations of the learning algorithms are given in Table 3.

As the learning algorithm with its adaptation of yield expectations is carried out at the end of July each model year, only yield observations of crops that have been harvested by then can be taken into account. As maize and wheat are usually harvested later, inclusion of their yield observations in the learning algorithm is lagged 1 year.

2.1.3. Data and calibration of FarmActor

The model has been set up using numerous data sources. The general cropping method has been designed according to standard data from the Association for Technology and Structures in Agriculture (KTBL, 2010).

Trigger values were derived using agronomic literature and expert knowledge as a base and adjusting values to fit modelling results to crop phenology observations in the period 1980–2010. As phenological observations refer to the beginning each year of planting and other actions, correlation between observed and simulated dates was the emphasis of calibration, with the aim of capturing inter-year variability. The limits used for this paper are given in Tables 1 and 2 as well as in Tables 10 and 11 in the appendix.

Actions are only possible when crops are of the correct status (prepared, planted, etc.) and within their allotted time windows. For most actions these windows are fixed and long enough to perform actions when immediate conditions are acceptable.

The suitability of a given day for planned field actions depends largely on soil moisture and immediate precipitation (Rounsevell, 1993; Mueller et al., 2003; Van Oort et al., 2012).

First, an estimate of volumetric moisture content based on soil suction (pF) at the lower plasticity limit (LPL) of the silty clay soil in the study area provided a maximum for field trafficability (Jumikis, 1984; Mapfumo and Chanasyk, 1998; Ad-Hoc-Ag Boden, 2005). This proved to be too restrictive, so as in Rotz and Harrigan (2005) the ability of soil to withstand traffic and respond well to tillage was defined according to percentage of field capacity (FC), with soil-engaging actions (ploughing, planting, etc.) optimal at approximately 95% of FC, surface actions at 100% and harvesting possible at 105%. Despite the possibility of partial days without rain being sufficient to accomplish fieldwork but concealed in daily weather resolution (Rotz and Harrigan, 2005), in our model, any amount of rainfall precludes action on a prospective day due to the daily resolution of weather data.

The sowing date of winter wheat is planned according to expected remaining growing degree days (GDDs) to winter dormancy (Mcmaster and Smika, 1988) and assigned a 6-week period beginning 4 days before the latest expected day at which a given total GDD will be reached before winter dormancy (see above). Wheat is flexible in terms of sowing date, able to enter winter dormancy at various stages of development. Earlier planting, however, has been shown to increase kernel weight and the number of seeds per unit area, but increase the risk of damage from certain pests (Tapley et al., 2013). Early establishment of the crop leads to greater root and above ground biomass, which makes for resilience to drought and cold stress throughout the growing season.

Kucharik (2006) pointed out many advantages to earlier planting of maize, including a longer potential growing season, reduced risk of late-season frost and pest damage as well as greater flexibility in spring operations. Kucharik (2008) also estimated the contribution of earlier planting dates to yield increases in the US over recent decades to be between 19% and 53%. Maize planting is thus driven earlier by the potential for greater yields. This, however, is tempered by persistent weather risks. Spring planting dates vary with trafficability and crop-specific temperature requirements (Sacks et al., 2010; Waha et al., 2012). The first day of the earliest consecutive 7 days each year, during which average daily temperature is not less than a given threshold, is used as the beginning of the maize planting period. As silage maize will germinate at 8 °C soil temperature and grow with at least 14 °C air temperature, (Diepenbrock et al., 2005) these can be seen as minimum desirable thermal conditions for planting. Immediate soil and air temperature as well as a minimum air temperature during a given number of days prior, as an indication of consistent weather, (Honermeier, 2012, personal communication) are thus criteria for planting during the allotted window.

Harvest is commensurate with crop maturity, trafficability, and post-harvest activities such as grain-drying. For this reason, a minimum temperature for wheat harvest is given, along with the stipulation of no precipitation. The precipitation criterion is relaxed with silage maize as maturity is of primary importance.

The rigidity of triggers can lead to failed actions in years with persistent bad weather or a coincidence of prohibitive daily conditions. To overcome this, following Leenhardt and Lemaire (2002) near the end of a year's prescribed action period, triggers are relaxed in order to make the action possible (see Table 12 in the appendix). For maize, activation of these late-period 'catch' triggers was necessary four times each, in different years, for planting and harvesting maize in the simulated years 1980–2010.

2.2. The crop growth model system Expert-N

Expert-N is an integrated, modular-structured model that simulates the water, nitrogen, carbon and heat dynamics in a soil–plant–atmosphere system and details process dynamics on a daily basis. The model consists of different sub-modules, each composed of algorithms based on published concepts or developed by the Expert-N team (Stenger et al., 1999; Priesack, 2006; Priesack et al., 2001, 2006; Biernath et al., 2011). The simulation modules compute plant growth, soil water movement, heat transfer, and nitrogen/carbon dynamics.

In the simulations performed for this study the following sub-modules were employed. For soil water movement the module HY-

Table 3
The three expectation building procedures ("learn modes").

	Moving averages (MA)	Exponential smoothing (ES)	Regression trend (RT)
Calculation of expectation $\hat{Y}$	$\hat{Y}_{t_0+1} = \frac{1}{N}\sum_{t=t_0-N+1}^{t_0} Y_t$	$\hat{Y}_{t_0+1} = (1-\alpha)Y_t + \alpha\hat{Y}_t$	$\hat{Y}_{t_0+1} = b_0 + b_1(t_0+1)$ where b_0 and b_1 are derived from the linear model $Y_t = \beta_0 + \beta_1 t + \varepsilon_t$ for t in $[t_0 - N + 1, \ldots, t_0]$
Used parameters	$N = 10$	$\alpha = 0.9$	$N = 20$

t_0: current year (the latest year for which observations are available); Y_t: observed value of the concerned variable in year t.

DRUS 1D (Šimůnek and Van Genuchten, 2008; Šimůnek et al., 1998) was used. Soil heat transfer was taken from the DAISY model (Abrahamsen and Hansen, 2000) and nitrogen dynamics were simulated using the following configuration: mineralization and nitrification as well as soil carbon and nitrogen turnover with SOILN (Johnsson et al., 1987). Denitrification, urea hydrolysis, nitrogen transport, deposition and volatilization with LEACHN (Hutson and Wagenet, 1991). Management used EPIC (Williams et al., 1989), and plant growth was simulated based on the Crop Estimation through Resource and Environment Synthesis (CERES) model (Godwin et al., 1990; Jones and Kiniry, 1986; Ritchie, 1991). Some factors influencing crop growth are not included in these models; examples are damage from frost or pests and fertilisation by elevated ambient CO_2 content.

2.2.1. Expert-N calibration

Expert-N was parameterized starting with values from literature and optimized to on-farm measurements taken from the study area between 2009 and 2011, together with phenological observations from the German Weather Service (Deutscher Wetterdienst, DWD, 2012) and district-level yield data from the Statistical Office of Baden-Wuerttemberg (Statistisches Landesamt Baden-Württemburg, 2012). Sensitivity analysis and parameter optimization were conducted with the universal inverse code, UCODE_2005, from the United States Geological Survey (USGS). UCODE_2005 has a high degree of flexibility and adaptability to every kind of model or set of models (Poeter et al., 2005).

In Table 4 the model performance statistics used in the calibration are shown. The root mean squared (RMSE) was used to explain the average difference between simulated and observed data (Lenz, 2007; Lenz-Wiedemann et al., 2010). Modelling Efficiency (ME) was used to quantify the agreement between model predicted and observed values (Willmott, 1981, 1982; Wallach, 2006).

The parameter values that have been modified are presented in Table 5, other genotype-specific settings of the CERES model were not changed and are readily available in CERES model documentation (Jones and Kiniry, 1986; Godwin et al., 1990; Ritchie, 1991).

2.2.2. Soil parameter values

Pedo-transfer functions were applied to calculate soil physical properties (carbon pools, wilting point, field capacity, total pore volume, and saturated hydraulic conductivity). Further, soil hydraulic curve parameters were determined for the Van Genuchten equation (Table 6). Finally, we used the C/N ratio measured by project partners to calculate nitrogen pools from the carbon content for every soil horizon. As proposed in the DAISY model (Müller et al., 2003) soil organic matter is divided into three main pools: dead native soil organic matter (SOM) added organic matter (AOM) and microbial biomass (SMB). Moreover, with the purpose of describing all turnover processes, the main pools are divided into two sub-pools: slow turnover (SOM1, AOM1, and SMB1) and fast turnover (SOM2, AOM2, and SMB2). The turnover rates and related partition coefficients were obtained from literature review (Hansen et al., 1990; Müller et al., 1997, 2003).

Table 4
Performance of calibrated Crop growth model.

	Wheat			Maize		
	Biomass	Phenological Stages	LAI	Biomass	Phenological Stages	LAI
Bias	0.55	2.63	0.10	1.10	−6.63	−0.06
RMSE	0.95	4.75	0.19	1.32	7.71	0.17
ME	0.98	0.94	0.95	0.93	0.88	0.93

LAI: Leaf Area Index; RMSE: root mean square error; ME: model efficiency.

Table 5
Optimized model parameters for the crop growth model CERES.

Wheat			Maize		
Parameter	Unit	Value	Parameter	Unit	Value
P1V	–	3.6	P1	GDD	138
P1D	–	2.5	P2	h^{-1}	0
P5	–	2.6	P5	GDD	586
G1	–	4.2	G2	Kernel/g (stem)	996
G2	–	4.3	G3	(mg $seed^{-1}$ d^{-1})	8.5
G3	–	2.3			
fPhint	–	84			

P1V: vernalisation coefficient; P1D: photoperiodism coefficient; P1: time from seedling emergence to end of juvenile stage (degree days > 6 °C); P2: sensitivity to photoperiod set to zero; P5: grain fill duration coefficient; G1: kernel number coefficient; G2: kernel weight coefficient; G3: spike number coefficient; fPhint: Phyllochron interval, in Expert-N set to 84 (Priesack, 2006).

2.3. Technical aspects and model coupling

FarmActor is set up in a modularised way, using the programming language Java. It is separated into several parts (controller, farm model, crop growth model) that can be run on different computers that interact via network connections (Java remote method invocation (RMI)). Thus, the model is flexible to use different hardware as needed. All input and output data is stored in a relational database (MySQL) where it can easily be evaluated. The model has been coupled to the crop growth model system (Expert-N), so crop management actions are passed to the crop model and the effects on plant growth can be observed on a daily basis. In order for Expert-N, (which is normally used with static parameters for one season at a time) to account for dynamic management decisions that evolve during a simulation, FarmActor was programmed so that as soon as an action is executed, the Expert-N simulation reverts to the beginning of the current crop's season and runs until 3 months after the action date to take its effects into account. These results

Table 6
Soil properties and hydraulic parameters.

H	Layer (cm)	ρb	Sand (%)	Silt (%)	Clay (%)	Θ_r (1)	Θ_s (1)	α (1/cm)	n (–)	m (–)
Ap1	0–21	1.31	6.2	56	37.8	0.095	0.492	0.0099	1.46	0.314
Ap2	21–29	1.34	8.9	52.5	38.6	0.094	0.482	0.0102	1.45	0.310
Tv	29–41	1.32	8.4	43.3	48.4	0.100	0.500	0.0142	1.36	0.262
H	K_S (cm/day)	Total N	C:N Ratio		Porosity (%)		Field capacity (%)		Water content, pF 4.2 (%)	
Ap1	13.59	0.28	0.095		50.2		39.5		21.7	
Ap2	11.93	0.13	0.098		49.4		37.0		33.1	
Tv	13.11	0.11	0.091		50.6		40.8		30.4	

H: horizon; Δz: depth interval; ρb: soil bulk density; Θ_r: residual vol. water content; Θ_s: saturated vol. water content; α, n, m: van Genuchten parameters; K_S: saturated hydraulic conductivity.

are kept on record to drive the management module until the next action is executed.

2.4. Study region and weather data

The study region Central Swabian Alb is a karst region located in southwest Germany in the federal State of Baden-Wuerttemberg. As part of the greater Swabian Alb, a hilly plateau having mostly clayey, weathered lime soils of the upper Jura, it is characterized by plateaus of different altitude between 700 m and 1000 m above sea level (Hauffe, 2010; Grees, 1993). Annual mean temperature is around 7 °C and annual mean precipitation fluctuates around 900 mm (Grees, 1993; Renner, 1991).

Agriculture occupies on average around 50% of the available land area and there is a nearly equal proportion of usage between permanent grassland and crop production (LEL, 2012). Slightly more than 20% of all farmers cultivate 50 ha or more (representing around 60% of the agricultural area) (Statistisches Landesamt Baden-Württemberg (Ed.), 2011b). Typical for this region is part-time farming (over 70%) (LEL, 2012). The main crops cultivated over the winter are wheat and barley and the latter also dominates the summer crops together with silage maize (Statistisches Landesamt Baden-Württemberg (Ed.), 2011a).

2.5. Simulation

The weather station "Stötten" (48.67°N, 9.87°E), of the German Weather Service (Deutscher Wetterdienst, DWD), lies within the study area. For this station historical weather data, phenological observations as well as projected climate simulations were available for this study. Historical weather data contain daily time series from 1947 onward (DWD, 2011). Phenological data are available for the same station starting in 1951 (DWD, 2012).

Prospective weather data were taken from the statistics-based WETTREG climate model (Kreienkamp et al., 2010). Values were used that correspond to the station "Stötten". Statistics-based models do not produce reliable results with a single run, so three (0, 4, and 8) of the 10 runs available from the "WETTREG 2010" experiment, corresponding to the IPCC climate scenario A1B were used. This scenario assumes an economic rather than environmental orientation of global development in connection with a balanced use of fossil and renewable energies. It presumes a moderate reduction of climate gas emissions from 2050 onward (Ipcc, 2007, p. 44). This scenario was chosen because it contrasts significantly with the current situation and climate scenario runs are available. Table 7 presents an overview of the weather data used in simulations. To ensure valid simulation by providing the learning modes with precursory observations, the model was started 20 years before the displayed results.

3. Results

We modelled two major crops of the region (winter wheat and silage maize). Model results show how planting and harvest dates react to changing weather conditions, adapt to changing climate and how yields vary over time. We compared modelled results to observed planting and harvest dates (from phenological observations) as well as observed yields (from statistical records of the district) in the region. Further, we present a comparison of different learning modes, and provide an outlook on possible developments in the future.

3.1. Winter wheat

Fig. 3 shows *simulated and observed planting and harvest dates* as well as yields for a 31-year period from 1980 to 2010 for the learn mode moving averages (MA). The average simulated planting day is 2.26–4.13 days earlier than that observed (Table 8). Although in some years the deviation from the average is well captured (e.g. 2001) in general the changes in seeding dates are not. This leads to a correlation of modelled and observed dates near zero. For harvest dates, the bias between modelled and observed day is between 5.55 and 5.90 days, however the correlation coefficient is between 0.62 and 0.63. Due to the greater bias, the RMSE ("root mean square error", which is a measure that captures both bias and fluctuation) of harvest dates is only slightly less than for sowing. Yields are generally overestimated (bias 8.1–8.4 dt/ha). However, yields of the last 20 years are better reproduced than for the decade from 1980 to 1990.

When looking at the last decade modelled, some differences in model accordance are noticeable. Correlation coefficients and

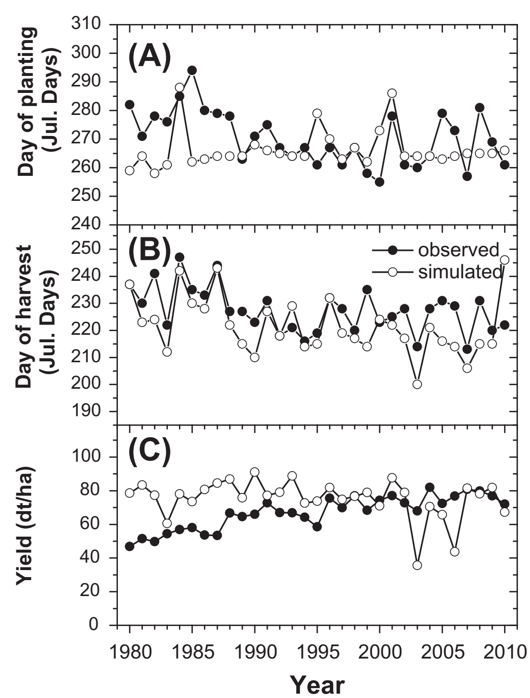

Fig. 3. Simulated and observed planting dates (A), harvesting dates (B) and yields (C) of winter wheat; learn mode moving averages (MA).

Table 7
Summary statistics on weather data used for simulation (Station "Stötten" 48.67°N, 9.87°E). *Source*: DWD (2011), Kreienkamp et al. (2010) and (WETTREG).

	DWD 1980–2010	WETTREG Run 0 2010–2040	WETTREG Run 4 2010–2040	WETTREG Run 8 2010–2040
Average temperature (°C)	7.48	8.37	8.37	8.40
Standard deviation (°C)	0.76	0.65	0.55	0.56
Precipitation (mm/yr)	1089	991	966	953
Standard deviation (mm/yr)	172	130	119	162
Global radiation (MJ/m^2 d)	11.01	11.30	11.36	11.28
Standard deviation (MJ/m^2 d)	0.55	0.33	0.37	0.33

Table 8
Summary of observed and modelled results for winter wheat.

	Parameter	Observed data	Modelled data		
			MA[a]	ES[b]	RT[c]
Winter Wheat 1980–2010	Average sowing day (Jul. days)	270.39	266.26	266.45	268.13
	Correlation coefficient of sowing days		0.02	−0.08	−0.02
	RMSE of sowing days (Jul. days)		12.1	12.7	12.3
	Average harvest day (Jul. days)	227.42	221.52	221.61	221.87
	Correlation coefficient of harvest days		0.63	0.62	0.63
	RMSE of harvest days (Jul. days)		10.2	10.2	9.9
	Average yield (dt/ha)	66.95	75.35	75.57	75.09
	Correlation coefficient of yields		−0.11	−0.11	−0.14
	RMSE of yields (dt/ha)		18.0	18.3	18.2
Winter Wheat 2000–2010	Average sowing day (Jul. days)	267.09	267.18	267.27	270.00
	Correlation coefficient of sowing days		0.18	0.19	−0.06
	RMSE of sowing days (Jul. days)		10.1	10.0	12.7
	Average harvest day (Jul. days)	224.00	217.82	217.55	217.91
	Correlation coefficient of harvest days		0.30	0.28	0.34
	RMSE of harvest days (Jul. days)		12.6	12.8	12.3
	Average yield (dt/ha)	75.73	69.26	69.46	68.27
	Correlation coefficient of yields		0.53	0.55	0.49
	RMSE of yields (dt/ha)		15.2	15.3	15.6

[a] Expectation building based on Moving Averages (10 years included).
[b] Expectation building based on exponential smoothing (factor 0,9).
[c] Expectation building based on regression trends (20 years included).

RMSE increase slightly, except for the learn mode "regression trend" where these measures worsened. For harvest dates, the quality measures also decrease slightly, whereas the accordance of simulated and observed values increases. The correlation coefficient rises from about −0.11 to 0.53 for the learn mode MA for instance.

Fig. 4 shows the *effect of different adaptation algorithms ("learn modes")* on the results. Overall, the results for the different modes are very similar. For sowing dates, the regression trend (RT) learn mode tends to result in greater volatility, especially in the late 1980s, early 1990s and late 2010s.

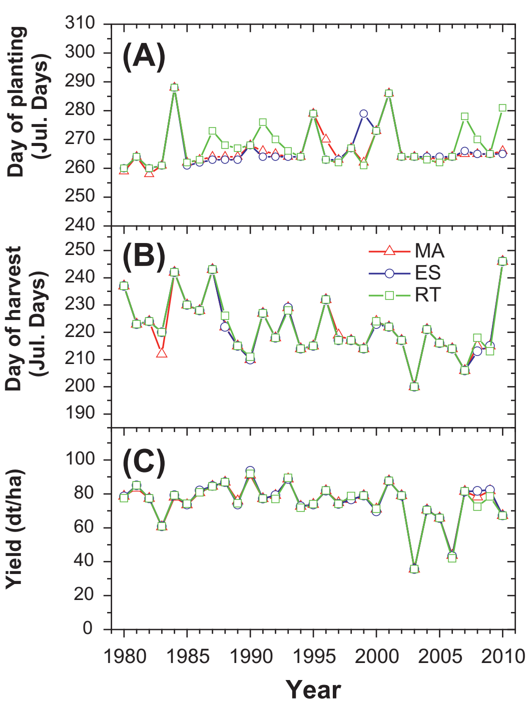

Fig. 4. Comparison of planting dates (A) and harvesting dates (B) as well as yields (C) for different adaptation methods (learn modes: MA: moving averages, ES: exponential smoothing, RT: regression trend) for winter wheat.

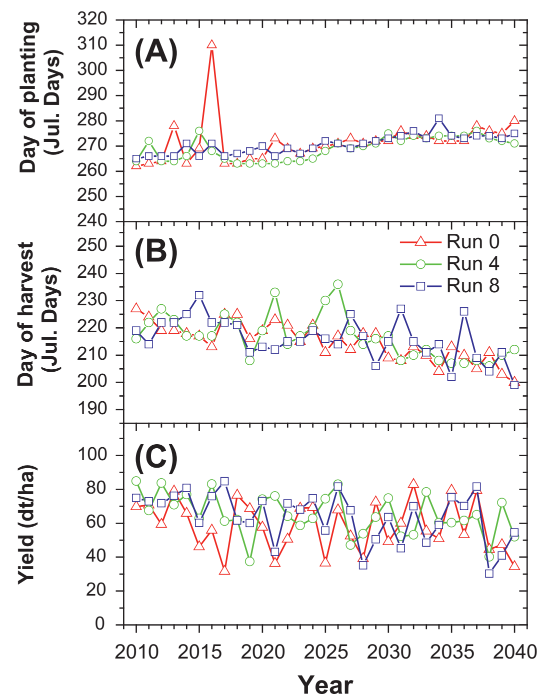

Fig. 5. Sowing dates (A), harvest dates (B) and yield (C) of three simulations using projected weather data (Model WETTREG) for winter wheat.

Fig. 5 shows the *results of the model for a simulation forced with future weather data* obtained from the WETTREG model. Based on that data, our model produces time series of sowing and harvest dates as well as yields. The overall trends are toward later sowing and earlier harvest of winter wheat. As in the model sowing of winter wheat is mainly dependant on the time window calculated by the learning algorithm, the curves are very smooth. Actual (simulated) weather exerts greater influence on harvest dates and yields which leads to deviating results when using different climate scenario runs. The trend throughout all three runs, however, is very similar. While sowing tends to be postponed with future climate (by about 0.31 days per year, significant at the 0.1% level) harvest tends to occur earlier by about 0.52 days per year (significant at the 0.1% level). Yields also show a slightly decreasing trend by about 0.51 dt/year (significant at the 1% level).

3.2. Silage maize

The model was able to reproduce past observations concerning planting and harvest dates as given in Fig. 6; Table 9 further summarises the results. Sowing dates are modelled on average 2.32–3.52 days earlier than observed. A positive correlation coefficient between modelled and observed dates (for MA: 0.3) indicates that the main drivers of the decision of when to plant are captured by the triggers. The RMSE is between 11.1 and 12.5 days, about the same level as for wheat. Harvest dates are modelled, on average, 2.61–3.55 days earlier than observed yielding a correlation coefficient of 0.34 (RMSE between 17.1 and 17.3 days). In spite of using calibration techniques, modelling yield development was much more difficult. The model overestimates yields, e.g. for the learn mode MA with 517 dt/ha vs. the observed 475 dt/ha. For the other learn modes the results are similar (bias between 38.0 and 41.2 dt/ha). While in the 1980s, the modelled yields tend to be lower than observed; in the remaining 20 years modelled yields exceed those observed in almost every year. The correlation coefficient between modelled and observed yields is still decent at 0.42 indicating that some relation between annual weather and yield has been captured. When regarding just the last decade of the simulation, accordance of seeding and harvesting dates declines slightly, whereas the correlation between observed and modelled yields improves (Table 9).

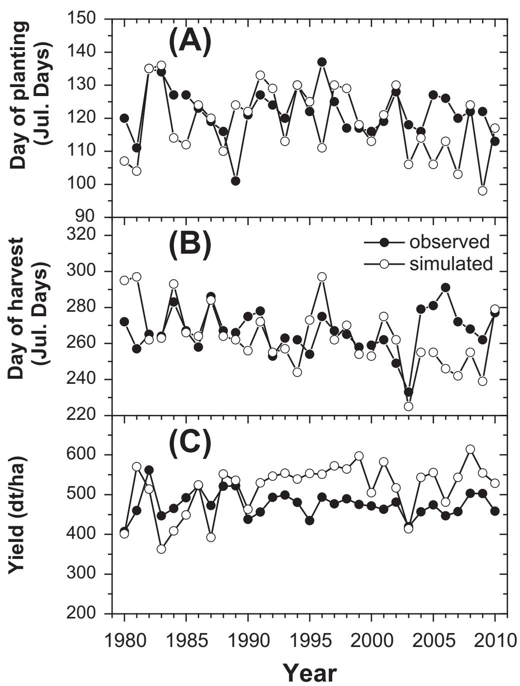

Fig. 6. Simulated and observed planting dates (A), harvest dates (B) as well as yields (C) of silage maize, learn mode moving averages (MA).

The *comparison of different learning modes* for silage maize leads to similar results as with wheat (see Fig. 7). The differences between the different learning modes are generally minor, except in the mid-1990s, where the regression trend algorithm leads to earlier planting and harvest. This leads to a slightly higher yield for this algorithm in the year 1995 whereas in 1997 the yield is less than with the other modes. In 1994 the exponential smoothing (ES) learning mode leads to positive deviation of the yield from the other modes.

Results of simulation of future scenarios using WETTREG weather data for maize are depicted in Fig. 8. Planting dates show a very small tendency towards earlier dates (−0.19 days per year) which is not significant however. Harvest dates, however, occur about 0.75 days earlier per year, significant at the 1% level. The yield development however is noticeable. Fluctuations seem to increase compared to the already high volatility in the past (see Figs. 6 and 8). The trend of yields shows a slope of about −1.8 dt/year, significant at the 10% level.

4. Discussion

Model performance and results are subject to some noteworthy annotations. The deviations of seeding dates from the average has been captured well for wheat in some years (e.g. 2001), in general

Table 9
Summary of observed and modelled results for silage maize.

	Parameter	Observed data	Modelled data		
			MA[a]	ES[b]	RT[c]
Silage Maize 1980–2010	Average planting day (Jul. days)	121.94	118.42	119.61	119.35
	Correlation coefficient of planting days		0.30	0.20	0.09
	RMSE of planting days (Jul. days)		11.1	11.7	12.5
	Average harvest day (Jul. days)	266.71	263.74	264.10	263.16
	Correlation coefficient of harvest days		0.34	0.33	0.39
	RMSE of harvest days (Jul. days)		17.3	17.1	17.2
	Average yield (dt/ha)	475.41	516.63	516.35	513.45
	Correlation coefficient of yields		0.42	0.43	0.41
	RMSE of yields (dt/ha)		70.9	71.1	71.1
Silage Maize 2000–2010	Average planting day (Jul. days)	120.64	113.18	113.27	113.18
	Correlation coefficient of planting days		0.11	0.11	0.1
	RMSE of planting days (Jul. days)		12.3	12.3	12.3
	Average harvest day (Jul. days)	266.64	253.27	253.27	253.27
	Correlation coefficient of harvest days		0.33	0.33	0.33
	RMSE of harvest days (Jul. days)		22.0	22.0	22.0
	Average yield (dt/ha)	466.57	530.58	529.45	531.71
	Correlation coefficient of yields		0.77	0.77	0.78
	RMSE of yields (dt/ha)		73.4	72.0	73.9

[a] Expectation building based on moving averages (10 years included).
[b] Expectation building based on exponential smoothing (factor 0,9).
[c] Expectation building based on regression trends (20 years included).

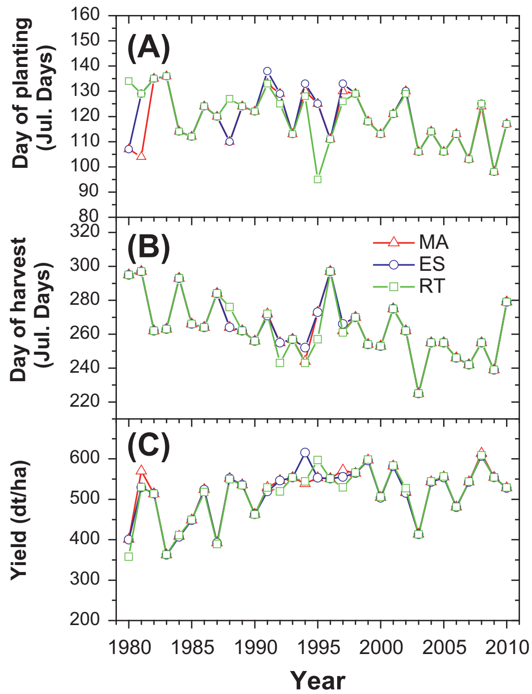

Fig. 7. Comparison of planting dates (A) and harvest dates (B) as well as yields (C) for different adaptation methods (learning modes: MA: moving averages, ES: exponential smoothing, RT: regression trend) for silage maize.

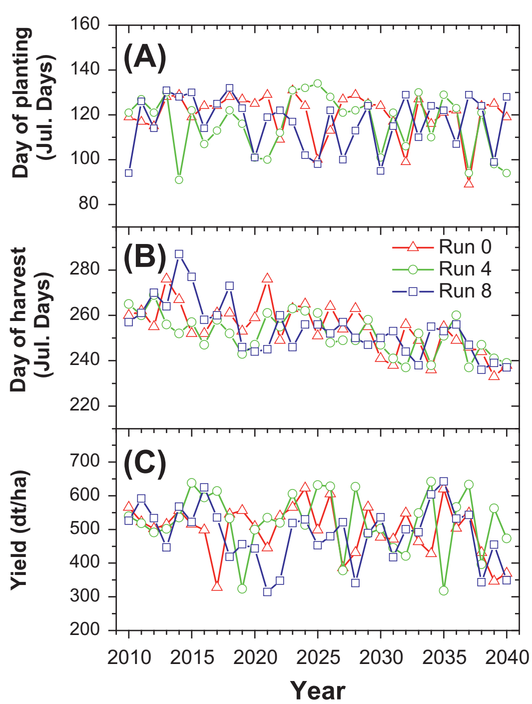

Fig. 8. Planting dates (A) and harvest dates (B) and yield (C) of three simulations using projected weather data (Model WETTREG) for silage maize.

though, the changes in seeding dates are not yet captured well. This explains the correlation between modelled and observed dates near zero. One reason might be that observed winter wheat sowing dates depend on the harvest dates of the previous crop in the crop rotation, e.g. maize, a dependence not covered in this study. For harvest dates, the correlation coefficient is much greater. This indicates that the actual harvest dates depend largely on effects that have been captured in the model. For maize the RMSE for planting is at about the same level as for wheat, however slightly lower. This shows that planting dates have been modelled slightly better for maize than for wheat. A reason could be that seeding of maize is more determined by actual weather conditions than that for winter wheat is. Sowing dates for maize show a positive correlation coefficient between modelled and observed dates (for MA: 0.3), which indicates that the main drivers of the decision of when to plant are captured by the triggers. For harvest of maize, the correlation coefficient is positive, while the RMSE is greater than for wheat, which implies that the direction of the deviations from the average date is accurately modelled whereas the magnitude of the deviation is on average greater than for wheat.

As mentioned, yields for wheat have been, on average, overestimated. However, yields of the latest decades are better reproduced than for the first one (1980s). This is likely to be a result of changing agricultural practices, including cultivars used, while the model simulates static cultivars and technology (Ahlemeyer and Friedt, 2012). Further, simulated yields and those from district-level statistics have to be compared carefully as the latter are averages over a multitude of fields, whereas the model produces results for just one site. Thus, modelled values tend to fluctuate more than the yields from statistical survey, particularly observable in the years 2003 and 2006, when average temperatures in June and July were more than three degrees greater than the 1980–2010 average, and less than half of the period's average total rainfall occurred. Regarding only the last decade, the model fitness improved compared to the overall period. This emphasises that the calibration of the model concerning yield is more suitable for recent years than for the past as a consequence of not modelling technical progress and calibrating the plant growth model to recent observations. For maize, in the 1980s, the modelled yields tend to be lower than observed, in the remaining 20 years modelled yields exceed those observed in almost every year. Again, one has to take into account that the observed yields are averages over many, not necessarily identical fields, where an extension of maize cropping into less suitable areas may be cause for the stagnation of observed yields.

The analysis comes with an important caveat: the use of different cultivars in the future, different cropping technologies as well as the influence of CO_2 fertilisation will alter the results. Ahlemeyer and Friedt (2012) carried out field trials of wheat cultivars released during the last 40 years and show a roughly 30 kg/ha annual increase in grain yield as a result of breeding alone. This, largely a result of increasing numbers of grains per spike, can be incorporated into hypothetical future wheat cultivars to be used in simulation. CO_2 increase will have a fertilising effect on plant growth. For wheat, a crop with a so-called C3 metabolism, an increase of ambient CO_2 content from 409 to 537 ppm is estimated to lead to a yield increase of between 11% (Högy et al., 2010) and 15% to 25% in dry years (Ko et al., 2010). On the other hand, crop protein content is likely to decline in this regard (Högy and Fangmeier, 2008). For crops like maize with a C4 metabolism, the CO_2 fertilisation effects are likely to be minor and influence yield mainly by the reduction of drought stress (Manderscheid et al., 2012; Sicher and Barnaby, 2012). Thus for maize the results are likely to be only slightly biased by the omission this effect in the model while for wheat the estimated yield decline may be overestimated. CO_2 fertilisation may reduce yield decline by about half of the given numbers. Later versions of the model should aim at including CO_2 fertilisation effects especially for wheat. Ziska et al. (2012) show that there is high potential to increase the yield responsiveness with respect to CO_2 of crops by breeding, thus CO_2 fertilisation effects may be higher for future cultivars.

The included triggers can explain a significant share of variation in the observed action dates. However, a large amount of this variation cannot so far be explained. There are a number of possible explanations. First, the observed values, especially district-level yields, do not measure exactly what is modelled. Second, calibration of the two models is imperfect, and the given calibration data fail to cover the whole picture. Third, the used model is naturally only a simplification of real farmer decision-making, where many other factors including experience, weather forecasts and even chance play a role.

Results show that different learn modes produce very similar results. Especially harvest and yields are much more determined by actual weather in the respective year than by the learn mode chosen to adapt planting periods and yield expectations. Although 20 annual observations were used in the regression trend (RT), opposed to the 10 used in the moving average (MA) learn mode, the increased volatility is a result of the extrapolation being less conservative than calculation of averages. By extrapolating trends, estimated values can lie outside the observed range, something impossible with averaging. All in all, the selection of learn modes does not seem to be critical (at least from those we chose and which are in about the same range as reported by Waha et al., 2012). However, not adapting planting and harvest periods at all may significantly increase error, because the gradual shift of dates would not be modelled whatsoever.

Given the caveats of the present model as discussed above, the future trends are plausible. For wheat the slight delay of seeding dates is also shown by Bondeau et al. (2007), which also ignore crop rotation timing effects. The rationale is that a winter crop should develop to within a certain range of maturity before winter dormancy, and that outside this range implies increased exposure to biotic and abiotic risks (i.e. pests and weather). Earlier harvesting dates are acknowledged also by Bondeau et al. (2007), Waha et al. (2012) and Olesen et al. (2012). When wheat, as a deterministic crop, passes through its development stages, it depends on certain temperature sums, which, with anticipated warmer climate, will be reached earlier. This characteristic also explains some of the decrease in yields of wheat, as the grain-filling period is shortened (Schaller and Weigel, 2007, p. 84). A similar result is obtained by Strauss et al. (2012) and Gandorfer and Kersebaum (2008) who also omit the effects of genetic and atmospheric CO_2 developments. In contrast, Ewert et al. (2005) and Bindi and Olesen (2011) project increasing future wheat yields. They, however, include continuing trends in technical and biological progress, which supersedes the effects of climate change.

For maize, literature suggests an advancement of planting dates for the future. Sacks and Kucharik (2011) analysed the advancement of maize seeding for the period from 1981 to 2005. Bondeau et al. (2007) and Olesen et al. (2012) estimate the advancement of maize seeding dates to continue in the future. A slight tendency to earlier dates is also shown in our results; however it cannot be confirmed with statistical significance. Further, the trend towards earlier harvest dates as given by the model is very plausible, given the assumption of unmodified cultivars. The prolongation of the growing season provides opportunity to adapt cultivar choice and thus the possibility to obtain higher yields (Sacks and Kucharik, 2011). Slightly decreasing yields when not taking cultivar adaptation into account conforms to the simulation by Strauss et al. (2012).

Both for wheat and maize an increase in yield volatility due to increased volatility in weather is in line with findings from Cabas et al. (2010).

Future research should try to increase the share of explained variation in action dates and yields. Starting points could be inclusion of the development of cultivars over time or the introduction of fuzzy logic into the triggers. Further, inclusion of risk aversion parameters, for example in the planting of summer crops might reduce the error of specific dates.

5. Conclusions

Modelling experience and results permit drawing several noteworthy conclusions. The approach to modelling crop planting and harvest dates seems to be promising, as it is capable of reproducing

Table 10
Actions and action triggers for soil preparation and fertilisation of winter wheat.

Action	Trigger	Calibration
Ploughing	Crop status	“Initiated”
	Day (Julian)	174–301
	Soil moisture (%)	⩽36.1
	Precipitation (mm)	0
Seedbed preparation	Crop status	“Prepared”
	Day (Julian)	210–306
	Soil moisture (%)	⩽38
	Precipitation (mm)	0
Fertilisation N1	Crop stage (BBCH)	⩾15
	Day (Julian)	20–151
	Soil moisture (%)	⩽38
	Precipitation (mm)	0
Fertilisation N2	Crop stage (BBCH)	⩾30
	Day (Julian)	85–180
	Soil moisture (%)	⩽38
	Precipitation (mm)	0
Fertilisation N3	Crop stage (BBCH)	⩾39
	Day (Julian)	95–212
	Soil moisture (%)	⩽38
	Precipitation (mm)	0
Fertilisation P	Crop status	“Initiated”, “prepared”, or “planted”
	Crop stage (BBCH)	⩽30
	Day (Julian)	173–300
	Soil moisture (%)	⩽38
	Precipitation (mm)	0

Table 11
Actions and action triggers for soil preparation and fertilisation of silage maize.

Action	Trigger	Calibration
Ploughing	Crop status	“Initiated”
	Day (Julian)	274–150
	Soil moisture (%)	⩽36.1
	Precipitation (mm)	=0
Seedbed preparation	Crop status	“Prepared”
	Day (Julian)	75–150
	Soil moisture (%)	⩽38
	Precipitation (mm)	=0
Fertilisation N1	Crop status	“Planted”
	Day (Julian)	100–160
	Soil moisture (%)	⩽38
	Precipitation (mm)	=0
Fertilisation N2	Crop status	“Planted”
	Crop stage (BBCH)	⩾19
	Day (Julian)	150–195
	Soil moisture (%)	⩽38
	Precipitation (mm)	=0
Fertilisation P	Crop status	“Planted”
	Day (Julian)	100–160
	Soil moisture (%)	⩽38
	Precipitation (mm)	=0

Table 12
Relaxed triggers at the end of the time windows.

		Value 7 days before end of period	Value 3 days before end of period
Winter wheat	Soil moisture (%)	40	42
Seeding	Precipitation (mm)	2	4
Winter wheat	Soil moisture (%)	42	44
Harvest	Precipitation (mm)	2	5
Silage maize	Soil moisture (%)	42	46
Seeding	Precipitation (mm)	4	6
Silage maize	Soil moisture (%)	43	45
Harvest	Precipitation (mm)	3	10

the main trends and reactions to weather events. Main findings are in line with expected results, given the mechanisms of climate change and the effects included in the model. Not all adaptations of farmers may be smooth and can directly be derived from observations. For example, the optimal seeding time for winter crops depends very much on expectations of the remaining weather of the year and is thus subject to nontrivial adaptation. Further the model allows deriving statements on the statistical characteristics of these short-term decisions, for example, on the likelihood of a certain strategy for planting maize being successful. It will also allow creating risk profiles for different cropping strategies, which are likely to depend on climatic change. The results may benefit stakeholders and policy makers not only in terms of short-term management, but may also have consequences for agricultural capacity adaptations, e.g. when optimal seeding and harvesting periods will narrow or broaden.

Finally there is great potential to improve climate change models, as the feedbacks between land-use and climatic development can be modelled more precisely.

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Appendix A.

(See Table 10).
(See Table 11).
(See Table 12).

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