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Simulation of daily field management and crop performance in Southwest Germany under climate and technological change

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1. Introduction

The research undertaken for this dissertation served an interdisciplinary research project titled: “Structure and Functions of Agricultural Landscapes under Global Climate Change - Processes and Projections on a Regional Scale”. Part of a microeconomic contribution to the project was the author’s task to construe the decision-making process of field crop management and calibrate and validate a mechanism to incorporate it into agroecosystem modelling. This is to broaden the scope of regional simulation to include economic actors whose actions, as ecological interventions, reverberate throughout agricultural landscapes. A robust human behavior element is a significant contribution to an interdisciplinary approach to furthering the discussion of how agroecosystems change with the climate.

1.1. Climatic Context

Germany is getting warmer. Trend analysis of troposphere temperatures throughout Germany between 1950 and 2013, by Pattantyús-Ábrahám & Steinbrecht (2015), shows an increase of ≈ 0.2 ± 0.1 K decade^{-1}. As temperature is the primary driver of the plant maturation process, the trend inevitably exerts a notable effect on crop production in the country. Besides temperature, precipitation is among the most important meteorological factors determining local agricultural productivity. The German Weather Service (DWD, 2016) uses an ensemble of weather generation models to provide a multifaceted approach to projections of future climate in Germany. Precipitation in Germany has, during the last decade, exceeded the norm during the meteorological reference period 1961-1990 and is projected to further increase in the future. In contrast, in the Southwest of the country, the recent trend has been negative, and projections of precipitation levels by the ensemble of weather models do not diverge much from the average during the reference period. These predicted trends could bode well for Germany as a whole, but are a bit worrisome for the Southwest, where warmer temperatures in conjunction with relatively constant precipitation could lead to increased water stress. To accompany these trends is a noticeable recent increase in weather extremes in the country (Kropp, 2015), which further threatens the productivity in the agricultural sector. Even in the unlikely event of relatively constant climate, agricultural production should be adapted to better take advantage of local conditions. Climate change makes adaptation imperative. The following uses historic and simulated future weather to plot the likely adaptation pathways that will help German farmers cope, and even benefit from, the changing environmental conditions in the country.

1.2. Simulation modelling

Integrated crop modelling has emerged as an effective means of evaluating possible adaptation pathways. The goal of this dissertation is to elucidate some of the most important mechanisms by which agricultural production will likely be adjusted to future environmental conditions. A farmer can be expected, in the future as today, to weigh the risks and benefits relevant to strategic management decisions. A main focus of the work is therefore planting dates, one of the more flexible and influential decisions facing German farmers. For example, planting maize earlier in the spring is a way to increase expected yield, but this is tempered by the possibility of late frost that can irreparably damage or destroy the crop and thus entail additional costs for replanting. Or in late summer, when deciding when to harvest a mature or nearly mature crop, there is a deliberation of alternatives involving grain moisture and drying costs, damage to the soil incurred by driving on it when wet, and the uncertainty with regard to the suitability of the same conditions in the near future.

An agent-based model is used to simulate the important strategic agronomic decision of when to plant crops, both in the fall and spring, at specific research field locations, as part of a collaborative project. A statistical model is also developed to represent the decision-making process throughout Germany, regarding the spring planting of silage maize. Another pliable farming action is the timing of harvest. There are complementary criteria to consider, such as soil trafficability and grain moisture content, both of which become less favorable with increased precipitation. There are also conflicting gauges of the suitability of a day for action. For instance, up to a certain point, crops continue to accrue economically important biomass (especially seeds) as harvest is prolonged. However, there are also advantages to harvesting before peak biomass is reached, such as freeing a field for planting of consequent crops and reducing the risk of worsening environmental conditions. The agent-based model is used to account for these risks and incorporate them into the decision-making of a simulated farmer. Simulating strategic farmer actions in this way systematically represents an economic agent responding to the specific local environmental conditions with which it is faced. The repetition of these actions through time and space results in patterns of significant events occurring on agricultural landscapes that are linked to ultimate crop productivity, therefore grounded in rational agronomy, and thus provide a plausible outlook on the dynamic appearance, function and productivity of future agricultural landscapes. The effects of preferences, e.g. risk aversion, by acting agro-economic agents, or system-manipulative interventions such as goal-oriented subsidy changes can then be traced through the simulated agricultural system from input to eventual output, that is, the effect on the system as a whole and selected components can be observed, at broader temporal and spatial scale.

Crop growth simulation modelling has been improving for decades. Modern models, improved over many generations, were used to simulate growth processes of winter wheat, summer and winter barley, maize and winter rapeseed, five crops that cover 80%, 75% and 50% of cropland in Baden-Württemberg, Germany and Europe, respectively. Realistic simulation of the management and growth of these crops can provide definitive scenario analysis with regard to questions of food security, land-use and policy planning.

The primary objective of this work is presenting a methodology for projecting future farmer behavior, which is, like crop modelling, valuable for scenario analysis as long as it can realistically capture natural processes. The timing of cropping actions, especially planting, has a distinct impact on crop performance and is therefore an important part of reliable simulation. This can be easily overlooked when using crop modelling without dynamic management.

1.2.1. FarmActor/Expert-N

The principle method to achieve the given objective focuses on using the recently developed agent-based, field-level model named FarmActor, as integrated with the crop-growth simulation model Expert-N. The integrated model package is applied to two arable regions of Southwest Germany, the *Kraichgau* and its sharply contrasting counterpart, the *Schwäbische Alb*, as part of a collaborative research project on dynamic land-use under climate change. A third region, the *Wetterau*, has been simulated in a parallel study.

FarmActor summarizes the multitude of factors involved in the on-farm decision-making process into several rules that determine the timing of field-level actions, including planting and harvesting, based on farmer reactions to simulated field conditions.

The model replicates this decision-making process with virtual farmers responding to current weather and soil conditions on a daily basis, as well as learning from historic patterns to generate expectations and steer behavior. The model is built to test different expectation-building algorithms where the temporal weighting of historic data as well as the number of years in it, are adjusted as agent profile scenarios[1]. Expectations for each simulated season include crop yields which determine gross margins and nutrient losses that determine fertilizer inputs, and the beginning of the period suitable for performing an action such as planting crops. Within its period, performance of an action is triggered by thresholds including soil and air temperature and moisture, plant development and field workflow.

After definition of a learning algorithm to establish the windows for action, calibration focused on daily action triggers. During calibration, in reducing the error between observed and simulated planting dates, short-term (less than one week) temperature

[1] Without a significant difference resulting from opposing learning scenarios or other criteria, a running average over ten years was used in most consequent work. Later survey results however, revealed that an exponential decrease in weighting, inverse with time, with a history horizon of eight years was the most reasonable to respondent farmers.

sums were the most influential, followed by simulated soil moisture as a measure of workability/trafficability. Simulated planting dates were less sensitive to single-day precipitation and air and soil temperatures, such that the latter could be omitted without much loss of accuracy. The initial FarmActor trigger implementation and calibration were the author's contribution to a paper introducing the model (Aurbacher *et al*. 2013).

Model development continued, and this author led a paper included in this cumulative dissertation, "Simulating regional climate-adaptive field cropping with fuzzy logic management rules and genetic advance" (Parker *et al*. 2016a), in part to introduce alternative methods for reconciling the daily values of all the triggers used as threshold criteria for management action. Fuzzy logic and trending criteria or "shifting triggers" were implemented. In validation the new trigger paradigms showed improved accuracy in simulated planting dates by incorporating flexibility in the trade-offs between action triggers. Fuzzy logic proved especially advantages and is thus part of the base settings in the current model. Further research can quantify the link between risk aversion and field actions by modifying the fuzzy logic parameters that resolve conflicting messages from simultaneous observations in the simulated agricultural system. It is a rudimentary field management artificial intelligence available for experiment.

Results from these simulations, incorporating the heterogeneity of soil, weather and responsive management are also being used as input for ongoing farm-level economic modelling as part of the regional project. Further work should also work on regional calibrations of the agent-based and crop models. This would dampen the overall environmental influences on management and yield at the regional level, as is the case in reality, to make regional projections more robust.

1.3. Climatic and agricultural data

Calibration of crop and farm-agent models is dependent on data from experiments and observations containing the information that goes into simulation. For this reason, a significant portion of the work in this dissertation involved the preparation of relevant data from various sources.

Through the interdisciplinary collaboration, detailed soil profile information, precise weather records at sub-hourly measurements and exceptionally detailed plant phenotype measurements were all available at multiple points in project-specific experimental fields from the two starkly contrasting locations in Southwest Germany.

Courser, publically available data was also assembled where longer time series and broader geographic scale were needed. Daily climate station data was selected for proximity in/to one of the two study areas and duration/completeness of time series. Calculation of global radiation and some gap-filling was necessary. Parallel data were likewise refined from a patchwork of phenological stations in the study areas that have records of the development phases of crop development, including the day of management actions or “false-phases”. The assembled data was then used to calibrate and validate both a mechanistic and a statistical model, to generate an outlook on field management and how it interacts with crop performance, including plant development and potential yield. The goal being to accurately replicate historic, site-specific observations that can instill confidence in hypothetical scenarios, including cropping on previously unexploited areas, or in the future using generated weather scenarios.

Historic yield data has been recorded at the district level for several decades, in complete time series, for hundreds of districts in Germany. There is a difference however between these and yields from experimental farms, including in state trials, which can be interpreted as nearing potential yield, district averages include less productive land and scientific management practices. So that when comparing a simulation calibrated to yield potential with a district average there is also an indication of the yield gap, or how much local agricultural productivity could improve under optimal management. Moving from point simulation to spatial coverage should then lower this yield gap indicator, depending on how well the models can capture the heterogeneity of weather, soil, plant and human interactions at the given scale.

The yield gap makes district averages less than ideal candidates for model validation. Correlation between simulated and observed yields is thus emphasized as a measure of validity. Ongoing work is to spatially aggregate simulated results to incorporate regional heterogeneity into simulated regional averages, to better match historic district yields. There is further potential to use yield data at the field level from throughout regions. If within the model framework, crop yields can be well enough assigned to the concomitant set of managed environments on which they were achieved, this field level data could be valuable for extended model calibration and validation. Ongoing research is pursuing this possibility.

To exploit the abundance of high-quality environmental and productivity records spanning the whole of Germany, in line with the dissertation theme of climate-management-yield, at broader geographic scale, a statistical model was proposed, partly as something against which to compare the coupled FarmActor/Expert-N models. In the third paper included in this cumulative dissertation Parker *et al.* (2016b), a spatial-panel regression model is used to predict maize planting dates at network observatories throughout the country, to a degree of accuracy comparable to that of the agent-based, mechanistic model[2]. This is achieved through summing weekly temperature and precipitation, controlling for large geographic regions and assigning individual intercepts to each station in the panel regression. Planting dates and the weekly weather after them were further spatially assigned to districts to continue the statistical analysis

[2] Both the statistical and agent-based models achieved a root-mean-squared-error between simulated and observed maize planting dates of less than one week, over the thirty years 1981-2010 in both study areas.

through to yields attained. German farmers were shown to be mitigating climatic risk by planting later than they could for maximum yield, in order to avoid the increasing danger of late frosts that are easily hidden behind the obvious general warming trend. Through the timing of their plantings and the selection of maize cultivars of varying maturity classes, farmers can further mitigate, here the risk of early frost or other yield interference in the fall. Combining planting dates and crop maturity are simple and effective means by which farmers can adapt their production to perceived climatic risk. How much later than a statistical optimum German farmers actually plant their maize is a quantifiable link to foregone opportunity, or the price of being more certain that a recently planted crop will not be destroyed by an anomalous weather event. If the method proves robust, it could for instance create a range of planting date recommendations based on the intended level of climatic risk. It can also be applied to several other German field crops for which sufficient data is available. The statistical model has another advantage in terms of run-time, so that its offers an efficient way to create comparative results or even provide management inputs for more complex models. Comparative results can be quickly produced with the same scenario-generated weather data that drives the mechanistic models. It cannot however, provide daily simulation of dozens of agroecosystem variables in the way that physiological process-based models can represent the interactive system, especially when the human element is incorporated into the system to increase its functional complexity.

The simulated future weather used in the main body of this work is statistical in nature in that randomized, resampled historic data was modified through assumptions of a popular future emissions scenario. This weather data is oriented to existing weather stations, therefore useful for point analysis. Due to its random nature it must be utilized in aggregate, so that multiple weather model generations are used to force simulation scenarios from which the results are then aggregated. This increases model runtime and results in dampening of weather extremes. Meteorologists argue for the use of an alternate weather-generation method. Dynamics-based modeling circumvents the limitations of resampling. There is weather data of this nature from a weather model intercomparison project for which simulated weather is compiled on a raster basis, downscaled to twelve square kilometers, available for all of Germany. In one collaborative experiment, a version of this dynamic weather simulation data that was produced within the regional climate change project were combined with soil profile mapping data to force simulations of the entire *Schwäbisch*e *Alb*. This work was presented as a poster titled: “Generated Weather Raster and Soil Profiles in Simulating Adaptive Crop Management and Consequent Yields for Five Major Crops throughout a Region in Southern Germany” at an international crop modeling conference. It emphasizes the method to spatially refine weather and soil data as model inputs, and then aggregate the results based on the prevalence of each soil/weather combination in the region. This should convey more realistic regional yields and management projections. Further analysis of the same model runs compared the effect of weather-generation models on predicted management and crop yields and was presented at the German national climate conference. “Generated Weather Raster and Soil Profiles in Simulating Adaptive Crop Management and Consequent Yields for Five Major Crops throughout a Region in Southern Germany”

1.4. Technology

The Green Revolution, as referred to by Gould (1969), revolved around advances in genetics being complemented by improved fertilizer and irrigation practices and political mandates, to facilitate rapid growth in agricultural productivity. Hayami and Ruttan (1971) introduced their “induced development model” to explain how synergy between agriculture, industry, politics and consumers, especially in the developed world, has driven technical innovation to enable increasing productivity. Adoption of new technology is still vital to increasing productivity in the developing world, while other concerns such as environmental protection are gaining importance in countries such as Germany, where food security is not a pressing concern (Loevinsohn, *et al*., 2013). The continuing motivation to produce more food and fiber associated with decreased negative externalities will further drive innovation that changes the face of contemporary agriculture. Precision agriculture is the modern catchphrase for optimized management to increase yields and simultaneously reduce costs. This work addresses some of the limitations of modern agriculture that may eventually be overcome, but for now characterize the management of agricultural landscapes. An example of this is mechanized traffic, which plays a major role in farm management, and is addressed below. Perhaps the most deterministic technological component of agriculture is crop genetics, which is therefore given special attention in this work.

Crop model calibration is a process to account for crop genetic factors as they interact with the atmosphere and soil. Existing calibrations based on regional and experimental were redone and expanded by the author to include the five major crops in the study area, winter wheat, winter barley and winter rapeseed, spring barley and silage maize. Further calibrations for grain maize are starting to be used, and rye calibrated to data from the *Wetterau* in the state of Hesse has been presented in a conference paper. Experimental data from cultivar trials of rye, barley and maize were received from institutional sources and used to calibrate crops for which no project experimental data were available.

In the search for experimental data with enough detail it became clear to the author that simulating a crop species becomes a broad undertaking when considering the genetic diversity within a species. Genetic heterogeneity is a source of model uncertainty, much like that of geographic and economic elements. Using finer scale in weather data interpolation improves model accuracy, especially where there is diverse topology. Simulated management, as shown above, reduces uncertainty by distributing the causes for action over several criteria. Extending this reasoning to the highly influential genetic component of the modelling system, it became pertinent to augment the model to account for genetic diversity or flexibility in some way.

Reviewing the contemporary literature on yield simulations showed that technological progress, especially through breeding, was an oft-cited source of uncertainty in simulation studies and that it would therefore be an important step in model improvement to break away from simulating at the species level. Literature also showed a clear trend in yield-driving plant physiological characteristics that could be easily incorporated into the crop model being used. Comprehensive historic to modern cultivar trials demonstrated a linear annual trend in the number of grains per ear. Maize genetic advance is not so clearly explained, but one pliable trait within cultivars is the amount of photo-thermal accumulation needed to induce flowering. Rapeseed plants have been being bred to reduce plant height and redirect this growth to fruit. Genetic advance is thus simply portrayed as an annually changing seed size in oil crops, length of season in maize and number of grains per head in cereals. This was then built into the model by the author to be genetic coefficients that are dependent on the year of the simulation, so that older cereal varieties with fewer grains, maize that ripens faster and rapeseed with smaller seeds are used to simulate historic scenarios. A linear extrapolation of grain number into the future, capped at fifty grains per head has a noticeable impact on projected yields, in some cases reversing a prognosis from declining to increasing productivity in the near future. Further work should delve deeper into the sources of breeding success, and how to simulate this to better capture some of the technological progress wanted by current work in agroecosystem simulation.

In Parker *et al*. (2016a), FARMACTOR was run to project management and crop performance as it would occur on the experimental fields in the *Kraichgau*. Fuzzy logic was used for future scenarios and dynamic genotype-specific parameters were compared to the static alternative. Simplifying genetic advance to a linear trend in one parameter is a start toward more detailed representation of how an agriculture system is adapted to changing or even relatively constant growing conditions. The method developed, in which simulated farmers can choose progressively more productive cultivars may be found in future research forecasting adaptive agricultural activity.

1.5. Risk & Learning

Two themes that were to be addressed in this work were risk aversion and learning on the part of agro-economic agents. While a thorough assessment of the role of risk in decision making was not pursued, several mechanisms were developed that enable the incorporation of risk management profiles that should be useful in ongoing research. Learning was also a theme in the microeconomic portion of the overarching climate change project that was principally managed by other project participants, but similarly to risk, a framework was validated for incorporating different functional forms representing how farmers build expectations relevant to agricultural production. Learning was solely used to determine the beginning of planting periods when there is potential to use it to further capture agricultural adaptation, or how agronomic and economic adjustments are planned by farmers, such as adjusting fertilizer applications to expected yields or planning crop shares with consideration of expected crop prices. A more thorough representation of how previous experience affects decision-making, together with a quantitative way to account for the influences of risk aversion, are important next steps in the development and application of the FARMACTOR model. Crop selection and patterns of crop rotations are key components of adaptation to changing climate. It is possible to simulate the shares of individual crops in a rotation, in individual fields in the model, depending on expected gross margin, which is driven by price and yield. As volatile as yields and commodity prices can be, in reality and in simulation, there is a need to dampen the variance of simulated gross margins over time, via learning; and an additional element, risk aversion, to decelerate the response by farmers to changing production circumstances, relative to exogenous factors such as market prices, climate and political mandates. Scrupulously accounting for both learning and risk, as FARMACTOR is designed to do, partly to enable dynamic annual crop selection, is arguably a missing element in this dissertation. The three components were, however, assigned to others in the interdisciplinary project and there were pressing needs that arose regarding crop model calibration that needed to be addressed to move the whole project forward. The extensive work with crop growth simulation can thus be seen as a distraction from the economic gist of this work, or alternatively, seen as an agronomic complement. One advantage of FARMACTOR is the ability to combine biophysical processes with those of microeconomics to reconcile what could be conflicting influences, or conversely, factors, such as the increasing productivity of a crop together with an increase in its demand, are additive in their influence on changes in agricultural landscape function. Moreover, mechanisms to account for risk and learning have been validated in this work but not yet used to create scenarios reflecting the diversity of economic agent attributes and how they will influence the course of adaptation through time.

1.6. Aims and structure of the thesis

This work is a test of improved methods in bio-economic simulation aimed at reducing uncertainty in agricultural landscape modeling. It was undertaken to integrate agent-based field management with crop growth simulation to account for human behavior in modeling of agricultural landscape systems. This mechanism for adaptive management was complemented by an outlook on trends in available crop genetics built into the model, to address a further source of uncertainty in crop performance projections.

A statistical model was also developed to predict local field management (planting dates of maize) in response to weather at the national scale.

Success in this endeavor is defined by the accuracy in simulating field management actions, especially planting, in a way that is robust outside the conditions used for calibration. The calibrated model must perform adequately across a range of environmental conditions, specifically soil and weather heterogeneity, and over a vector of time.

Projecting crop genetics must be based on observable phenotypic trends, rationally accounted for in crop model calibration, while effectively reducing the error between simulated and observed crop performance criteria, e.g. yield, over an adequate validation range, e.g. years.

The paper introducing the agent-based bio-economic simulation model FARMACTOR (Aurbacher *et al*., 2013), though not part of this cumulative dissertation, involved work to establish the agronomic context and demonstrate the functionality of the model's field management decision mechanism, as a foundation for consequent work. The author provided research on the availability of days for fieldwork which verified the existing model framework and led to completion of action trigger definitions. Further contribution was in the acquisition and preparation of weather data and verification of an existing database including soil parameters, farm mechanization and field inputs that interact during simulation. The FARMACTOR interface to EXPERT-N was managed by the author; performing and reporting on model runs to be published. This work was relevant to, or repeated in, the following papers.

Paper 1: Simulation-based projections of crop management and gross margin variance in contrasting regions of Southwest Germany

The first paper submitted under the auspices of this doctoral work, (Parker *et al*., 2015a), was a study to employ the updated model to both the Schwäbische Alb and the Kraichgau to merge both projected climatic and market risk into one measure, gross-margin variability. This utilized a randomized price forecast developed by the author, who was assisted with the background and analysis of agricultural risk.

The goal of the paper was to demonstrate the accuracy of the calibrated models in predicting planting and harvest dates, and yields of the major crops in two contrasting biomes in Baden-Württemberg. Management and yields were projected into the future and coupled with simulated future prices to provide an augmented simulation of risk factors in the future. Environmental and economic risk were coupled and made available to the model, which was developed to be able to respond to these and other risks in the form of adaptive management.

This paper also featured new calibration of EXPERT-N to project-collaborator field observations, and expansion of modelling capacity through calibration of additional crops to external data. Additional duties were development of the methodology to simulate genetic advance by programming annually changing crop model parameters and assistance in the conception and implementation of and reporting on the genetic algorithm used to calibrate agent parameters determining planting and harvest dates and the implementation of fuzzy logic as a means of considering complementary or conflicting criteria for field work.

The author's work for this paper constituted calibration of the crop model and the agent-based management procedure for all five crops at both locations; also the design and preparation of the future price generator, with consultative supervisorial contributions. All model runs, preparation of results and the majority of the paper text were completed by the author.

Paper 2: The resilience of different cultivars of winter cereals wheat, barley and rye to climate change in Central Europe – a localized regional simulation study

The second paper, a conference presentation, along with a pair of conference posters, applied the point simulation methods from the first two papers to gridded regional simulations in two regions of Germany. These contributions focused on the sensitivity of simulated yields and gross margins to soil and weather (dis)aggregation. The author's work for these presentations included, in addition to the groundwork established in previous work, preparing all simulation runs, combining gridded weather data with soil polygons; also, guidance in the calibration process, done, in part, as a portion of a coauthor's master's thesis. The preparation of text and figures, almost 100%, as well as the delivery of conference presentations was done by the author.

Paper 3: Simulating regional climate-adaptive field cropping with fuzzy logic management rules and genetic advance

The third paper examined the benefits of several alternatives in the simulation of how agronomic criteria are weighed by an economic agent (farmer). Fuzzy logic and a shifting tradeoff mechanism were tested against the simpler precursor with rigid criteria. Here was also introduced a method for dynamic crop genetics to account for breeding progress in historic and future simulations. The paper focused on a single field in the Kraichgau, partially in preparation for regional gridded simulations to follow. The Author conceived and constructed the shifting trigger mechanism and contributed to implementation (coding) of the fuzzy logic alternative. Construction of the genetic algorithm was the work of a coauthor. Half of the crop model calibrations (All crops, submodule CERES) and all management calibrations were performed by the author. Validation and projection runs were likewise the author's responsibility, together with approximately 80% of the text and all figures and tables.

Paper 4: Cause and consequence in maize planting dates in Germany

The fourth paper presents the statistical alternative to agent-based modeling that is not as detailed, but still viable for integration in agroecosystem modeling. A panel regression isolated the observatories of maize planting dates throughout Germany to assign each a base (intercept) planting day, and for all observatory locations, one set of coefficients responding to observed local weekly weather totals for precipitation and temperature. Consultation on choice of data resources and statistical methods was provided by coauthors; otherwise the author was responsible for the entirety of the work, and approximately 90% of the text in the paper.

In all four papers of the work presented here, literature review was almost completely done by the author, with the exception of agricultural risk in the first paper.

2. Simulation-based projections of crop management and gross margin variance in contrasting regions of Southwest Germany

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Simulation-based Projections of Crop Management and Gross Margin Variance in Contrasting Regions of Southwest Germany

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Abstract

Crop simulation is a modern tool used to mimic ordinary and extraordinary agriculture systems. Under the premise of continuing foreseeable climatic shift we combine adaptive field-level management decisions with their effects on crop performance. Price projections are used to examine yield and price effects on gross margins of the predominant crops in two specific regions of Southwest Germany into the coming decades. After calibration and validation to historic records, simulated future weather is used to explore how farmer behavior and performance of wheat, barley, rapeseed and maize could develop under anticipated global change. This development is examined based on a comparison of historic and projected gross margin variance. Simulations indicate that when yield levels increase, the relative variability of gross margins may decline in spite of some increasing variability of yields. The coefficient of variance of gross margins decreases even more due to the independence of price and yield fluctuations. This shows how the effects of global change on yields could be offset by economic conditions.

Keywords: Integrated modelling, Yield forecasts, Simulated gross margins, Global change,

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Agricultural adaptation, Risk.

1. Introduction

In a market economy, profitability is a crucial condition of farm management efficacy and at least short-term sustainability. How climate change might affect the comparative profitability of different crops in a given region is thus an important question in agricultural research and to farmers directly. To have more comprehensive projections of economic and ecological conditions under which future agriculture will be practiced is to be better able to plan for and react to likely circumstances. To this end, integrated crop and farm-agent modeling have become important tools for exploring how the environment, technology and human behavior interact and drive development in agricultural systems. The aim of this paper is to compare past and future gross margin fluctuations using integrated simulation models.

1.1 Field-Level Simulation

This paper is based on simulated cropping of winter wheat (*Triticum aestivum* L.), spring and winter barley (*Hordeum vulgare* L.) and silage maize (*Zea mays* L.) using CERES (Jones and Kiniry, 1986) and winter rapeseed (*Brassica napus* L.) with GECROS (Xinyou and van Laar, 2005) as embedded in the soil-plant-atmosphere model EXPERT-N (Priesack, 2006). These crops are of major economic importance, covering almost half of Europe's arable land, and three-fourths of that in Germany (Eurostat, 2013).

Governing crop simulations is the agent-based model FARMACTOR (Aurbacher et al., 2013). Performance of cropping actions, including planting and harvesting, is based on the simulated farmer reacting at a daily time interval to conditions in the field. Annual management decisions are also dependent on learning from historic patterns that generate expectations and steer behavior. For this paper a genetic algorithm is used to iteratively calibrate the timing of management actions to observed records, as well as fuzzy logic imitating a farmer's decision-making process. Management and crop performance measures are validated to historic records which then lead to projections into the future using simulated weather based on anticipated climate change.

1.2 Risk in Agricultural Production

Weather is largely responsible for the annual variability of agricultural production. It represents the uncertainty associated with production and makes outcomes difficult to predict compared to industrial production. Risk, the undesirable part of uncertainty (Knight, 1921) is intrinsic to agricultural production and therefore unavoidable (Hardaker et al., 2004). Climate change can be expected to alter farm income in both ways and at different magnitudes than previously experienced. It is the farmer´s challenge to balance risk and return, given personal willingness to withstand a certain range of outcomes (Harwood et al., 1999, Hardaker et al., 2004). Risk has been found together with learning to be the major driver of adaptation (Baerenklau, 2005). As knowledge is gathered over time, information about the known part of uncertainty changes, meaning that adaptation is a continuous process of change over time.

Herein is a proposition of what might happen with the variability, and hence level of risk, of

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several field crops under a changing climate. Simulations at the field level and with an artificial single-crop choice leave us with the interpretation of the gross margin variability under "optimal choice" conditions where management, especially planting, is only constrained by weather, both daily and long-term patterns. This provides a foundation upon which adaptive cropping decisions may be based in the future.

2. Methods and Materials

2.1 Study Areas

The Kraichgau and Schwäbische Alb are two distinct regions in Baden-Württemberg, Southwest Germany. The former is a fertile, intensely cropped region along the Rhine River while the latter, 100 km to the Southeast, is a relatively harsh plateau of predominant extensive agricultural use (Gayler et al., 2014). The study location in the Kraichgau lies in Karlsruhe Rural District (Landkreis) while the Central Schwäbische Alb location is in Alb-Donau-Kreis. Average yields of the five simulated crops in these two districts are the basis for comparison of the respective study areas. Simulated field cropping on a hypothetical farm in each region, as contrasting agricultural environments, presents a broad perspective on climate-driven farm management and crop performance in the foreseeable future. A map below portrays the study areas and key locations (Appendix 1).

2.2 Calibration/Validation Data

Calibration data for EXPERT-N, including soil parameters, daily weather and plant performance was derived from winter wheat, silage maize and winter rapeseed grown on experimental fields near Pforzheim in the Kraichgau and Nellingen in the Schwäbische Alb during the 2009-2011 growing seasons (Ingwersen et al., 2011, Wizemann et al., 2014). Spring and winter barley data were provided by Baden-Württemberg state variety trial stations (LTZ Augustenberg, 2013), augmented with data from the German Weather Service (DWD, 2012a) and the soil map of the Federal State of Baden-Württemberg (LGRB, 1997). To account for breeding progress in field crops, the calibrated value of one growth parameter per crop is shifted each simulation year (Parker et al., submitted).

The DWD maintains a network of weather and phenological observatories (DWD, 2012b) in close enough proximity to allow derivation of causal relationships between them (Menzel, 2013). DWD weather at Eppingen was used for planting date calibration in the Kraichgau, together with the nearest phenology station with complete data - Oberderdingen (for all crops except winter barley, for which the paucity of data led to choosing Helmstadt). In the Schwäbische Alb, Merklingen weather and Nellingen phenology were chosen for calibration. Time periods outside of the calibration period are available for validation of simulated planting dates, while harvest date and yield, calibrated to other data, are validated to phenological records and district yields for the whole period 1981-2010. For barley, when DWD phenological records are not existent, planting and harvest dates from various LTZ trials sites are used for validation.

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2.3 Price Assumptions

To generate comparable product price series, we use a 20-year price index from the German Statistical Office (DESTATIS, 2013) from 1994 to 2013, converted to absolute (nominal) prices p_t with base year (2005) prices from the Federal Ministry of Food and Agriculture (BMELV, 2013) for the wheat, fodder (winter) barley, malting (spring) barley and oilseeds (winter rapeseed). To account for a geometric price trend, we estimate the model $\ln(p_t) = \mu + \beta \cdot t + \varepsilon$, results of which for each crop are given in Table 1. The trend parameters are only in part significantly different from zero, but still they are a better estimation for the trend than assuming no trend. This allows an annual calculation of $p_t/\hat{p}_t$, where $\hat{p}_t$ is the model-estimated price at time t. These ratios can be interpreted as the annual divergence from the estimated trend, in which we are especially interested. For the past, these divergence values are multiplied by the mean of the observed prices to obtain a fluctuating, but de-trended price series. For the future scenarios, we use the five-year average of prices 2009-2013 as a base, multiplied by a randomly resampled series of the annual divergences. Silage maize is the exception as there is no long-term market price series available, only very local markets started to evolve with the advent of biogas plants. Thus we do not apply the above approach given to silage maize, but instead use a constant price of 28 € per ton of fresh matter, as given by KTBL (2012). This accounts for the tendency to make multi-year contracts at constant prices even when local silage maize markets do exist.

The advantage of the above approach is to abstract from price trends and focus on the variability of prices, which, together with yield variation comprise the majority of profitability fluctuations. However, we implicitly assume that the magnitude of the price fluctuations stay constant, which may or may not be the case.

Table 1. Estimated model parameters from 1993-2012 prices, with intercept M and trend b, of a geometric price trend for each crop

	Wheat	Winter barley	Spring barley	Rapeseed
M	-27.89	-25.39	-11.07	-61.94
b	0.01635	0.01505	0.007989	0.03362
p-value(b)	0.107	0.125	0.409	0.000

Source: Own calculations based on DESTATIS (2013)

Total variable input costs per hectare are maintained constant at their crop-specific 1993-2012 averages (KTBL, 2012) for calculation of both historic and future gross margins.

2.4 Model Calibration

EXPERT-N was calibrated according to methods in Aurbacher et al. (2013). Dynamic genetic parameters were developed to replicate how wheat and barley breeding has produced an

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increasing number of grains per plant (Ahlemeyer and Friedt, 2012, Parker et al., submitted), while changing initial leaf nitrogen concentration in rapeseed is used to reproduce the observed yield trend. Silage maize yields have been relatively steady in the two study areas and the complexity of genetic factors involved led to an assumption of static genetic parameters for this study[1].

2.4.1 Calibration of Field Management

FarmActor conducts daily integration of Expert-N with database soil and weather records and internal management decision-making, subject to "learning", herein represented by the simulated farmer building expectations based on a 10-year moving average of environmental factors. These are 1-week average soil temperatures for spring crops ("learning soil-temp") and remaining cumulative air temperatures for fall-planted crops ("learning GDD") (Aurbacher et al., 2013). Field-specific soil properties determine the moisture level corresponding to a favorable response to action, and at which traffic and tillage can be withstood without the long-term damage of compaction (Rotz and Harrigan, 2005). The model's crop rotation algorithm (Aurbacher and Dabbert, 2011) was omitted to simplify the extraction of annual performance measures of each crop and to determine planting and harvest dates based solely on daily crop, soil and weather conditions. To accommodate the lack of crop rotation, soil nutrient values are reset each year.

2.4.2 Planting

Learning from several years of weather designates planting periods each year, during which daily soil moisture and temperature, air temperature(s) and precipitation are action triggers. The fall planting window begins when the year's (learning-based) expected remaining growing degree days (GDD) reaches a certain minimum threshold, or "trigger". Spring planting of barley and maize begins when the next week's expected mean soil temperature is above a crop-specific value. Within their respective allotted time periods, planting of each crop is associated with a set of additional triggers, all of which include soil moisture (volumetric water content of the upper 30 cm) as an indicator of trafficability. Additionally, the weather over several days is evaluated by the simulated farmer to build short-term expectations that guide behavior (Aurbacher et al., 2013). This is a pre-period minimum temperature where spring planting is only possible when the air is consistently warm enough that it is unlikely that temperatures will subsequently fall to crop-damaging levels. Following Oleson et al. (2012) maximum daily temperature values were added as criteria for autumn sowing. In addition, maximum temperatures over a 3-day pre-period were included. Our justification of this mechanism is that excessive temperatures after planting are likely to result in overdevelopment before winter dormancy, while also being conducive to insect, pathogen and weed growth. Farmers are generally reluctant to work a field during rain, justifying a maximum for daily precipitation. However, the daily resolution of weather data does not account for partial days without precipitation that would allow work.

[1] Crop simulation model calibration details are omitted from this paper, but available from the authors upon request.

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FarmActor can be run iteratively using a genetic algorithm to minimize the error (RMSE) between observed and simulated planting dates by altering action triggers according to an evolutionary strategy. Further, multiple behavioral paradigms can govern the timing of action: fixed triggers throughout the planting period, combinations of trigger values subject to fuzzy logic, and "shifting" triggers[2] that are relaxed linearly throughout the time window. The genetic algorithm was run for thirty years, the first ten to establish learned temperature expectations and the last twenty comparing simulated to observed planting dates. To limit the necessary computational capacity, calibration was limited to ten iterations with a population of sixteen trigger combinations each, for a total of 160 model runs for each crop and location. This establishes optimal base values plus "fuzziness" ranges and amounts of daily trigger shift. Fuzzy logic proved to be the most appropriate paradigm in hind-casting planting dates in the Kraichgau. The Schwäbische Alb, however, presents a different situation where, as revealed below, shifting triggers proved more suitable.

2.4.3 Harvest

Harvest is subject to a set of simultaneously evaluated feasibility criteria including crop development stage, soil trafficability and daily precipitation. In seed crops a proxy for moisture content (affecting drying costs) is a combination of minimum pre-period temperature and maximum precipitation (8°C and 10 mm over three days).

2.5 Implications of Risk

This paper works with the assumption that farmers "wish to increase their wealth over time" (Pannell et al., 2000, p. 76), implying a preference for greater yields. A further assumption is that farmers in general are risk-averse and favor a less volatile yield distribution. The important point for relative profitability and risk is the artificiality of observed yields over time under a changing climate under "optimal choice conditions". Annual yields and their variance are used as "agronomic utility" parameters defining the trend distribution of each crop and serve as a reference for farmer behavior in terms of perceived gains and losses. Simulating adaptive management heuristically incorporates the consideration of risk and reward.

3. Results and Discussion

3.1 Management Calibration Results

Table 2 shows results of calibration with the genetic algorithm using fuzzy triggers in the Kraichgau and both fuzzy and shifting triggers for the Schwäbische Alb. The best target value is given along with its corresponding set of trigger values.

Table 2. Optimized planting trigger values and target (RMSE)

	Winter wheat	Winter barley	Winter rapeseed	Spring barley	Silage maize

[2] Planting is subject to each trigger so that, with shifting: (min) $v \geq base - shift \cdot day$, and (max) $v \leq base + shift \cdot day$; and with fuzzy logic: the composite t^* of *n* triggers must exceed a given threshold of 0.5 where: $t^* = [\prod_{k=0}^{n} t_k]^{1/n}$ where (min) $t = [v - (b - \frac{f}{2})]/f$ and (max) $t = [b + \frac{f}{2} - v]/f$ with *n* triggers at base value *b* and fuzzy range *f*, while *v* is the currently simulated value. All *t*s are truncated to be between 0 and 1.

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Kraichgau - with fuzzy planting triggers					
Learning GDD (°C)	439.47	873.33	1093.49	-	-
Learning Soil Temp. (°C)	-	-	-	9.06	12.53
Max. Soil Moisture (% Vol.)	39.69	31.50	45.78	35.76	50
Range* (% Vol.)	10.02	19.82	0	32.59	17.22
Max. Precip. (mm day^{-1})	3.49	0	0	20	0
Range* (mm day^{-1})	0.61	28.01	1.71	10.71	41.64
Max. Air Temp (°C)	19.69	11.78	18.30	-	-
Range* (°C)	5.57	0	2.13	-	-
Max. 3-Day Air Temp (°C)	11.73	25.79	24.13	-	-
Range* (°C)	38.84	0	0.66	-	-
Min. GDD	105.20	3000	1395.92	-	-
Range* (°C)	0	288.91	17.63	-	-
Min. Air Temp (°C)	-	-	-	6.14	10.17
Range* (°C)	-	-	-	47.34	36.10
Min. 3-Day Air Temp (°C)	-	-	-	0.53	1.69
Range* (°C)	-	-	-	0.46	14.11
RMSE (days)	9.93	3.42	9.75	9.69	5.15
Schwäbische Alb - with fuzzy planting triggers					
Learning GDD (°C)	1000	734.36	794.29	-	-
Learning Soil Temp. (°C)	-	-	-	4.97	2.73
Max. Soil Moisture (% Vol.)	48.05	46.29	42.05	59.79	43.46
Range* (% Vol.)	3.96	4.72	5.00	0.00	21.89
Max. Precip. (mm day^{-1})	0.49	3.01	0.29	4.24	5.75
Range* (mm day^{-1})	3.32	2.87	4.03	17.62	43.46
Max. Air Temp (°C)	7.00	8.31	15.00	-	-
Range* (°C)	0.23	0.39	1.54	-	-
Max. 3-Day Air Temp (°C)	7.77	26.55	13.69	-	-
Range* (°C)	5.00	1.64	0.00	-	-
Min. Air Temp (°C)	-	-	-	8.96	14.95
Range* (°C)	-	-	-	42.83	13.12
Min. 3-Day Air Temp (°C)	-	-	-	0.00	14.91
Range* (°C)	-	-	-	50.00	21.89
RMSE (days)	8.84	4.11	12.65	7.90	7.25
Schwäbische Alb - with shifting planting triggers					
Learning GDD (°C)	699.61	710.61	1000	-	-
Learning Soil Temp. (°C)	-	-	-	0.00	11.03
Max. Soil Moisture (% Vol.)	44.90	35.68	42.01	24.55	14.24
Shift** (% Vol. day^{-1})	0.13	0.34	0.10	0.74	0.88
Max. Precip. (mm day^{-1})	2.97	1.59	0.33	0.82	15.79
Shift** (mm day^{-1} day^{-1})	0.48	0.00	0.28	0.16	0.39
Max. Air Temp. (°C)	24.58	10.00	0.00	-	-
Shift** (°C day^{-1})	0.28	0.29	30.00	-	-
Max. 3-Day Air Temp. (°C)	15.53	29.21	16.57	-	-
Shift** (°C day^{-1})	0.36	0.14	0.50	-	-

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Min. Air Temp. (°C)	-	-	-	17.89	8.22
Shift** (°C day^{-1})	-	-	-	0.78	0.97
Min. 3-Day Air Temp (°C)	-	-	-	3.88	2.12
Shift** (°C day^{-1})	-	-	-	0.28	0.54
RMSE (days)	7.29	4.81	5.43	8.53	4.56

* Range signifies the width of the transition from possible to impossible surrounding each trigger's base value which, in conjunction with all other triggers, restricts action (planting). ** Shift is likewise the amount each trigger is relaxed each day after the beginning of the planting period. Source: Own calculations

It is apparent that the two trigger paradigms alternate in their superiority matching simulated to observed planting dates among the different crops. The decision of which ultimately to use for projections is thus a matter of validation metrics.

3.2 Model Validation

Validation compares the timing of simulated planting and harvest dates to DWD network and LTZ observations and simulated yields to district averages. The model was run for the five crops 1970-2010 (the first ten years a warm-up for expectation building/learning) so that outside of the calibration period planting dates can be validated for the harvest years 1981-1990 for wheat, rapeseed and maize planting dates, likewise 1991-2010 for the two barley crops (because of the different data availability). Table 3 shows validation results for planting dates at both locations.

Table 3. Validation measures of fit for simulated planting dates by crop and location

	Kraichgau fuzzy triggers	Schwäbische Alb fuzzy triggers	Schwäbische Alb shifting triggers
Winter wheat (1981-1990)			
Correlation coefficient	0.52	0.09	0.54
RMSE (days)	9.43	8.54	8.41
Bias (days)	-7.23	-2.1	-6.1
Winter barley (1991-2010)			
Correlation coefficient	0.48	-0.50	0.48
RMSE (days)	12.74	11.52	7.29
Bias (days)	-1.03	-3.4	-5.1
Spring barley (1991-2010)			
Correlation coefficient	0.12	0.15	0.64
RMSE (days)	14.45	26.02	15.20
Bias (days)	1.65	-15.8	-0.7
Winter rapeseed (1981-1990)			
Correlation coefficient	0.33	0.12	-0.08
RMSE (days)	13.28	13.86	5.53
Bias (days)	-10.40	10.9	0.6
Silage maize (1981-1990)			
Correlation coefficient	0.37	0.12	-0.25

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RMSE (days)	8.03	46.35	13.87
Bias (days)	-2.20	45.90	12.40

Source: Own calculations

Functioning at fine tempo-spatial resolution FARMACTOR produces accurate predictions of planting date, especially compared to coarser models (Waha et al., 2012). Correlation coefficient, RMSE and bias are chosen measures of the accuracy of simulated management, how well the model captures the underlying agronomic and behavioral principals. Considering the three measures together it was decided to proceed with shifting triggers in the Schwäbische Alb while fuzzy triggers were utilized in the Kraichgau.

Next, simulated crop performance for harvests years 1981-2010 is validated to Karlsruhe and Alb-Donau District yields for the Kraichgau and Schwäbische Alb, repectively, and the most nearby phenological records of harvest dates (see section 2.2.). Table 4 provides metrics on the accuracy of simulated harvest date and yield.

Table 4. Validation period measures of fit for simulated harvest dates and yield by crop and location (harvest years 1981-2010)

	Kraichgau		Schwäbische Alb	
	Harvest (day of year)	Yield (dt ha^{-1})	Harvest (day of year)	Yield (dt ha^{-1})
Winter wheat				
Correlation coefficient	0.78	0.52	0.83	0.86
RMSE	12.73	12.37	9.79	6.18
Bias	-8.10	-1.79	-10.28	0.28
Winter barley				
Correlation coefficient	0.57	0.52	0.69	0.72
RMSE	10.18	7.88	8.67	6.17
Bias	-1.40	-3.43	0.03	2.33
Spring barley				
Correlation coefficient	0.65	0.55	0.26	0.64
RMSE	16.09	11.22	11.17	11.55
Bias	-13.50	0.16	2.84	9.19
Winter rapeseed				
Correlation coefficient	0.51	0.52	0.78	0.50
RMSE	11.40	14.87	8.19	8.14
Bias	9.01	0.14	-5.63	1.17
Silage maize				
Correlation coefficient	-0.24	0.26	-0.26	0.17
RMSE	21.96	75.48	23.65	59.32
Bias	-6.60	49.61	17.13	-33.14

Source: Own calculations

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Compared to similar multiple-year simulation endeavors such as Palosuo et al. (2011), validation accuracy is satisfactory and supports the following projections of how agricultural production at the two locations will develop in the coming decades. The following projections of field management and crop performance utilize WETTREG 2010 simulated future weather scenarios (Kreienkamp et al., 2010) at Eppingen and Merklingen based on historic records and assuming IPCC scenario A1B (IPCC, 2007).

3.3 Projections

Projections until the year 2031 were completed for the simulated farms at both locations. Three runs for each were performed using separate realizations of the same WETTREG scenarios (Kraichgau: Eppingen 25002-11, 25002-77 and 25002-99; Schwäbische Alb: Merklingen 2814-33, 2814-55 and 2814-99). Linear regression function intercept and slope for planting, harvest and yield averages from the three future runs are presented in Table 5.

Table 5. Projected management and crop performance statistics 2012-2031 (harvest years)

		Winter wheat	Winter barley	Spring barley	Winter rapeseed	Silage maize
Kraichgau (with fuzzy planting triggers)						
Planting -intercept	(day)	286.21	254.90	81.72	255.55	119.13
-trend	(days yr^{-1})	+0.52	+0.43	-0.36	+0.36	-0.11
Harvest -intercept	(day)	200.96	212.92	200.47	209.62	290.81
-trend	(days yr^{-1})	-0.63	-0.28	-0.35	-0.37	-0.79
Yield -intercept	(t ha^{-1})	5.523	5.855	5.939	5.866	70.032
-trend	(t ha^{-1} yr^{-1})	+0.075	+0.026	+0.052	-0.066	-0.181
Schwäbische Alb (with shifting planting triggers)						
Planting -intercept	(day)	269.52	260.25	89.11	231.46	123.20
-trend	(days yr^{-1})	+0.10	+0.08	-0.05	+0.14	-0.09
Harvest -intercept	(day)	226.12	216.67	231.75	219.73	288.78
-trend	(days yr^{-1})	-1.02	-0.72	-0.16	-0.60	-1.05
Yield -intercept	(t ha^{-1})	8.056	7.167	6.354	4.378	47.840
-trend	(t ha^{-1} yr^{-1})	+0.009	+0.086	+0.036	+0.029	+0.039

Source: Own calculations

3.3.1 Planting

According to model projections for the Kraichgau, winter crops will be sown about one day later for every two to three years into the future. Sowing of spring barley should occur earlier at a similar rate, while sowing of maize in spring should advance slower, about one day every nine years. Projections for the Schwäbische Alb also show gradually later sowing in autumn and earlier planting in spring.

3.3.2 Harvest

The warmer temperatures in simulated future weather drives harvest dates earlier in all crops, at both locations, between roughly one to two days every three years in the Kraichgau. Harvests in the Schwäbische Alb, notwithstanding spring barley, occur earlier at an even faster rate,

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wheat and maize maturing more than one day sooner per year. While the simulated future growing season, e.g. time between spring and fall frosts, is expanding, warmer temperatures result in crops ripening faster so that no advantage can be gained from the extended season. This would, however, likely be counteracted with the use of later-ripening, more biomass-generating cultivars.

Overall, projected phenological trends appear plausible. However, at some point the climate-induced changes, e.g. toward earlier harvests, should lead to structural change in cropping methods such as greater appearance of previously uncommon crop rotations. Further research will focus on this possibility.

3.3.3 Yields

Kraichgau simulations project a slight increase in yields for all crops except rapeseed and silage maize. In contrast are the increasing yields of all crops in the Schwäbische Alb. Aurbacher et al. (2013), modeling the nearby Schwäbische Alb, projected negative trends in wheat and maize yields. The process-based inclusion breeding progress, not included in the latter, demonstrates one way in which the detrimental effects of climate change may be mitigated (Parker et al. submitted). Angulo et al. (2013) project decreasing yields for five major European crops, based solely on climate change. However, when technological change and CO_2 fertilization are included their projections were more optimistic.

3.4 Gross margins

Gross margins serve as a basic measure of profitability and their variance can give an impression of associated risk. Simulated yields from 1992-2011 are multiplied by the de-trended historic producer price in each year before the average variable input cost over the same period is subtracted to derive a gross margin for each year. The coefficient of variation of gross margins over this period serves as the measure of the historic level of risk in each crop and study location.

For the future, yield results from the three simulated weather realizations are multiplied by year-specific modeled prices, minus per-hectare input costs (section 2.3) to derive projected gross margins. These are shown in Figure 1 together with simulated historic gross margins for each crop in the Schwäbische Alb, (Kraichgau in Appendix 2). However, their trends are not the focus of this paper as they depend largely on price trends which were purposefully removed. Input prices are kept constant, if they were not it could reduce the effects of price variability as factor prices (e.g. fertilizer) may correlate to product prices.

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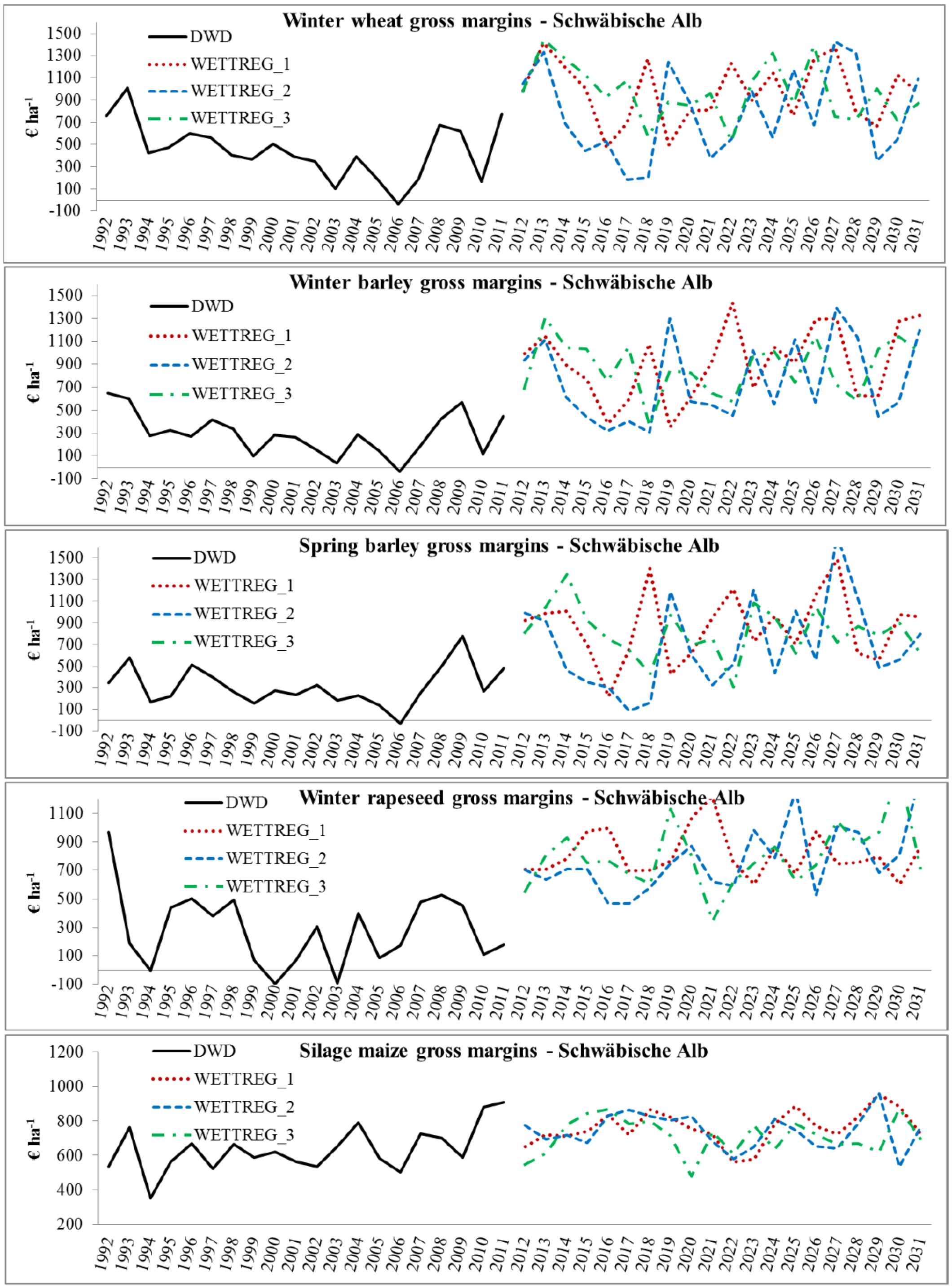

Figure 1. Simulated historic and future gross margins in the Schwäbische Alb

Source: Own calculations

For comparative metrics the individual coefficients of variation of gross margins in the three simulated future time series 2012-2031 are averaged for comparison to the twenty-year period 1992-2011 used to generate price forecasts. Table 6 offers a comparison of past and future yield

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and gross margin variation coefficients for each crop and location.

Table 6. Coefficients of variation of simulated historic and future yields and gross margins

		Winter wheat	Winter barley	Spring barley	Winter rapeseed	Silage maize
Mean historic producer price (€ t^{-1})		134.50	120.95	141.81	239.36	27.58
Mean forecasted producer price (€ t^{-1})		180.55	163.88	184.14	305.68	28.00
Schwäbische Alb						
Historic yield (t ha^{-1}) -mean		7.586	6.399	5.536	3.822	44.624
-std dev		0.683	0.763	0.945	0.635	4.643
-var. coeff.		0.090	0.119	0.171	0.166	0.104
Historic gross margin (€ ha^{-1}) - mean		445.77	292.73	313.53	280.49	635.81
-std dev		247.45	180.80	178.57	255.35	130.01
-var. coeff.		0.555	0.618	0.570	0.910	0.204
Projected yield (t ha^{-1}) -mean		8.148	8.065	6.734	4.684	48.249
-std dev		0.469	0.622	0.628	0.532	3.683
-var. coeff.		0.058	0.077	0.093	0.114	0.076
Projected gross margin (€ ha^{-1}) -mean		905.43	846.61	789.25	796.31	737.30
-std dev		302.68	298.47	315.70	205.51	100.68
-var. coeff.		0.345	0.358	0.410	0.259	0.137
Ratio of projected/historic variance coefficient	yield	0.639	0.647	0.547	0.684	0.734
	gross margin	0.621	0.579	0.720	0.284	0.669
Kraichgau						
Historic yield (t ha^{-1}) -mean		6.310	5.293	5.065	3.600	48.861
-std dev		0.865	0.653	1.059	1.342	6.221
-var. coeff.		0.137	0.123	0.209	0.373	0.127
Historic gross margin (€ ha^{-1}) - mean		278.07	162.56	248.48	246.08	754.46
-std dev		239.28	164.70	195.47	475.36	174.18
-var. coeff.		0.860	1.013	0.787	1.932	0.231
Projected yield (t ha^{-1}) -mean		6.315	6.128	6.490	5.169	68.128
-std dev		2.016	0.551	0.716	1.112	9.563
-var. coeff.		0.319	0.090	0.110	0.215	0.140
Projected gross margin (€ ha^{-1}) -mean		568.47	534.23	738.30	947.96	1293.91
-std dev		424.05	241.02	291.01	380.01	261.40
-var. coeff.		0.756	0.469	0.402	0.403	0.202
Ratio of projected/historic variance coefficient	yield	2.328	0.729	0.528	0.578	1.102
	gross margin	0.879	0.462	0.511	0.209	0.877

Source: Own calculations

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Only winter wheat and silage maize in the Kraichgau show increasing yield variability as a result of future climatic conditions. All other crops in Kraichgau and all crops in the Schwäbische Alb experience increased yield and decreased yield variance, so that their coefficients of variation decline in the future. In the case of wheat and Kraichgau, this is in line with other work. Fuss et al. (2011) also found increasing wheat yield and yield variability in Central Europe. Kersebaum & Nendel (2014) simulated slight increases in both absolute yield and its variability for wheat in regions throughout Germany. Here, in contrast, decreasing crop yield variances were projected. This is presumably due to the combination of the general trend towards a more favorable climate in Germany and the modelling of adaptive execution dates that mitigate some of the negative effects of climate change.

Results show that the variability (variation coefficient) of gross margins will decline even more than that of yields. Gross margin variability will decline even when yield variability has increased. This shows that price fluctuations have an additional effect on the stabilization of gross margins, even when price fluctuations are assumed to be statistically independent of yields. This is a conservative assumption, as prices and yields tend to be negatively correlated (El Benni & Finger, 2012), and this "natural hedge" in effect further reduces gross margin variability. A part of the effect is due to the increase of future prices. On the whole, in these sample model runs, gross margin variability does not increase for any crops at either location, suggesting a comprehensive reduction in producer risk.

4. Conclusion

Gross margin volatility, as a measure of economic risk in agricultural production, is influenced by both price and yield variability. In the above projections, the interaction of price and yield leads to a general stabilization of gross margin fluctuation. Even in cases where yield volatility increases (here, Kraichgau wheat and maize), this is offset by the superimposition of price fluctuations. Increases in absolute price and yield levels will further amplify this effect.

Some care has to be taken as the model does not incorporate all anticipated consequences of climate change, including CO_2-fertilization, extreme weather events and pest proliferation. As weather simulations continue to improve, use of new weather projections could likewise improve the robustness of the model.

Still, these results provide some insight into possible developments in the regional economic viability of field crops. This allows better estimation of future land use changes which should be reintegrated into land-atmosphere models to close the feedback loops. Further, designated decisions support systems could benefit from more detailed modelling.

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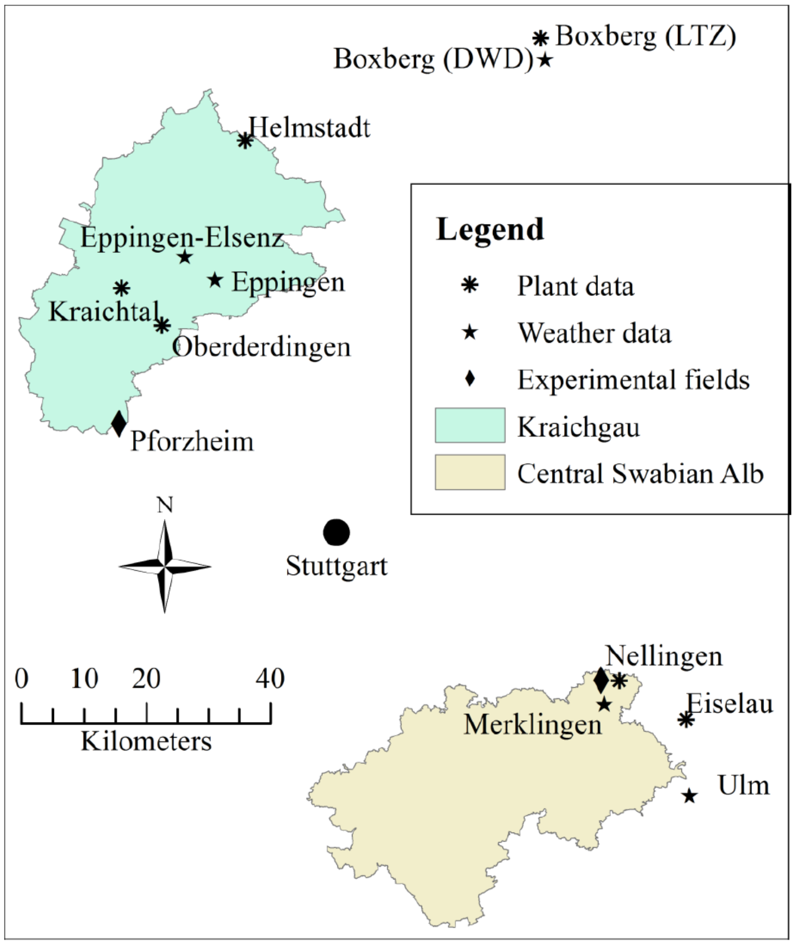
Appendix

Appendix 1. Map of study area with key locations



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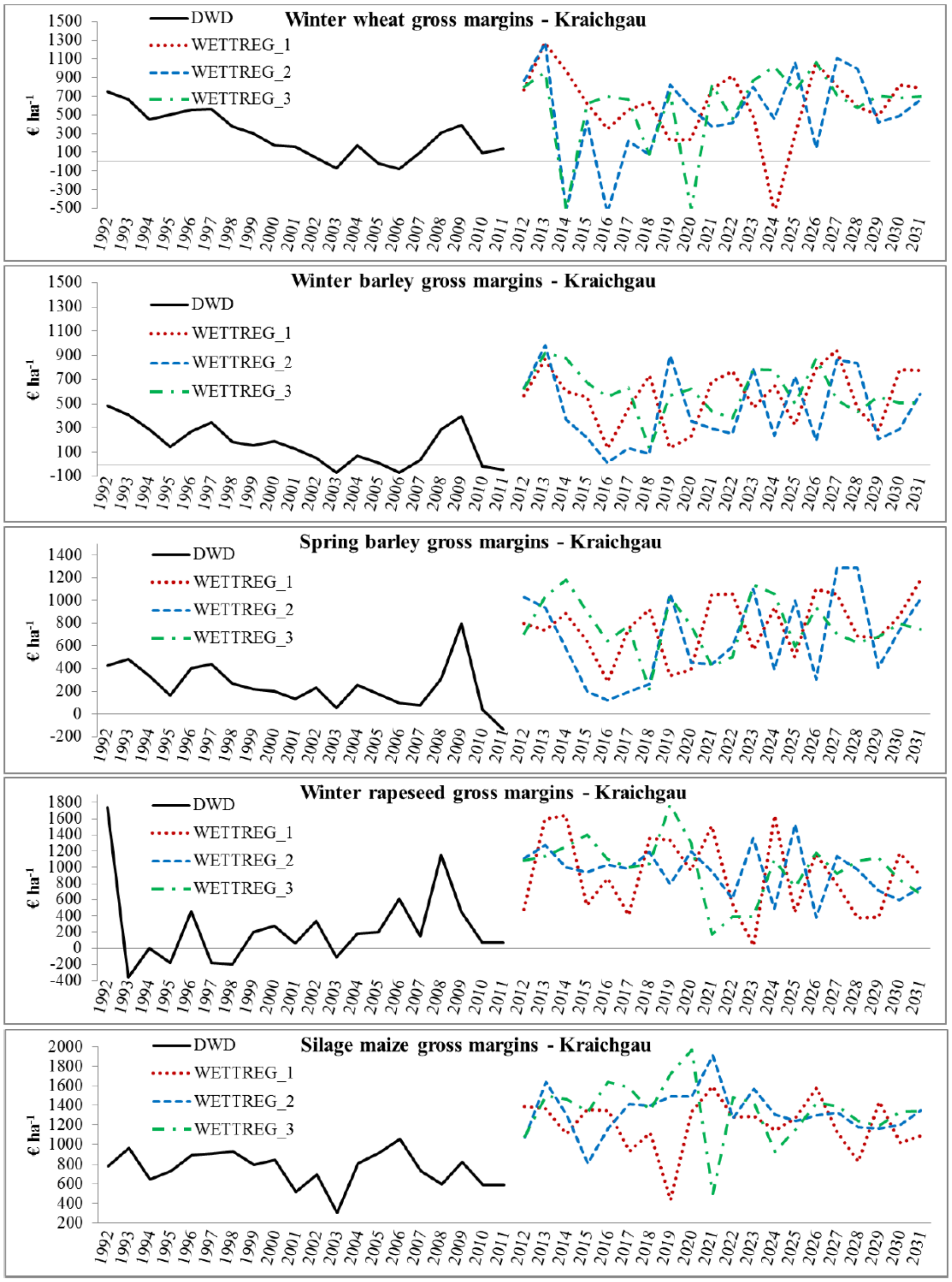
Appendix 2. Simulated historic and future gross margins in the Kraichgau



Source: Own calculations

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3. The resilience of different cultivars of winter cereals wheat, barley and rye to climate change in Central Europe - a localized regional simulation study

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The resilience of different cultivars of winter cereals wheat, barley and rye to climate change in Central Europe - a localized regional simulation study

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Introduction:

Cereal crops are the predominant food source produced in Central Europe and the level of their production is of utmost importance to future global food security. Despite extensive work modelling crop responses to changing climate, there are numerous factors responsible for uncertainty in yield projections that have yet to be sufficiently addressed. One of these is the varied response of different crop cultivars to identical environmental conditions. Methods to estimate the range of response within a crop species are therefore a step in the direction of more robust projections of future yields under anticipated climate change. It was therefore undertaken to calibrate a crop growth model to three cultivars each of winter wheat, winter barley, and winter rye in an effort to capture the possible divergence of yield levels among the different genotypes. A significant difference in cultivar productivity could indicate which should be given preference as local climate changes.

Methods:

This "cultivar choice" was combined with the adaptation of sowing dates to annual and long- term weather trends within an agent-based model governing field management in simulations, also calibrated to local conditions. The region of study encompasses all cropland in a highly productive administrative district (Wetterau Landkreis) in the state of Hesse, near the geographic center of Europe. Historic weather and local soil data were used to calibrate a dynamic sowing date algorithm to historic observations from a phenological observation network and the crop model to records from state experimental stations. After validation to parallel datasets, ten soil types present in the district (mapped at 1/1,000,000 scale) were combined with a generated weather raster at 10 km^2 resolution (see Fig. 1) to extend simulations up to the year 2050. Results quantify the trend in autumn sowing dates, subsequent harvest and projected yields by comparing 2011-2020 simulation averages with those from 2041-2050. Associated gross margins based on a simple price forecast model replicating the trend and fluctuations in prices over the last sixty years are included as potential drivers of farmer decision-making. Production costs were held constant into the future as they should not differ much between crops.

Results:

Validation shows high correlation between simulated and observed district yields, albeit with an overestimation bias common when comparing to regional averages. Simulations indicate that ubiquitous later planting and earlier temperature-driven crop maturity will significantly shorten the growing seasons of all crops and cultivars examined. Without adaptation to mitigate this shortened seasoned (e.g. later-ripening cultivars, irrigation) district average yields of all cultivars of winter wheat and barley will suffer from projected climate change (see Table 1), though in some weather/soil combinations yields will increase (see Fig. 2a-b). For winter rye, a more positive outlook is generated, where yields in general increase, though not for all three cultivars (Table 1), nor on all simulated fields (see Fig. 2c).

Discussion:

Winter wheat, the most important crop in Central Europe in terms of food security, appears to be the most vulnerable to climate change, followed by winter barley, while winter rye could benefit from the climatic shift. Despite these yield trends, gross margins increase the most for winter wheat, due to the assumption of persistent historic drivers of prices (e.g. population growth, decreasing marginal productivity) which may be exaggerated by static production costs. Profitability being a determining factor in agricultural resource use, the integrated model could provide useful insight into how agricultural landscapes are likely to change in the future, from which implications of local and global food supply can be derived. Based on the model output, cultivation of rye could gain importance in the region studied, at the expense of wheat and barley, crops more popular for human consumption. However, if a similar trend is seen at greater scale in Central European landscapes, prices of the former crops would likely adjust (increase) to compensate for the relatively poorer yields. The model's extended capacity to determine crop selection based on dynamic gross margin expectations could quantify changing crop rotations, or inversely, produce price-change projections based on simulated yields in static crop rotations. The integrated model may in this way be useful with its dynamic response to environmental and economic drivers.

Table 1.

winter barley			
change in sowing (days)	11.87		
cultivar	Lomerit	Souleyka	Nerz
change in harvest (days)	-5.33	-5.02	-5.05
change yield (dt/ha)	-0.16	-0.26	-0.44
change in gross margin (€/ha)	499.15	455.99	508.72
winter rye			
change in sowing (days)	20.06		
cultivar	Dukato	Mephisto	Helltop
change in harvest (days)	-1.66	-1.59	-2.12
change yield (dt/ha)	-3.37	1.73	5.50
change in gross margin (€/ha)	462.72	559.29	635.58
winter wheat			
change in sowing (days)	14.24		
cultivar	JB Asano	Julius	Kerubino
change in harvest (days)	-7.11	-6.19	-7.56
change yield (dt/ha)	-5.13	-5.34	-4.37
change in gross margin (€/ha)	704.92	671.35	676.08

Fig. 1 Study region Wetterau District (*Landkreis*) partitioning of soil and weather

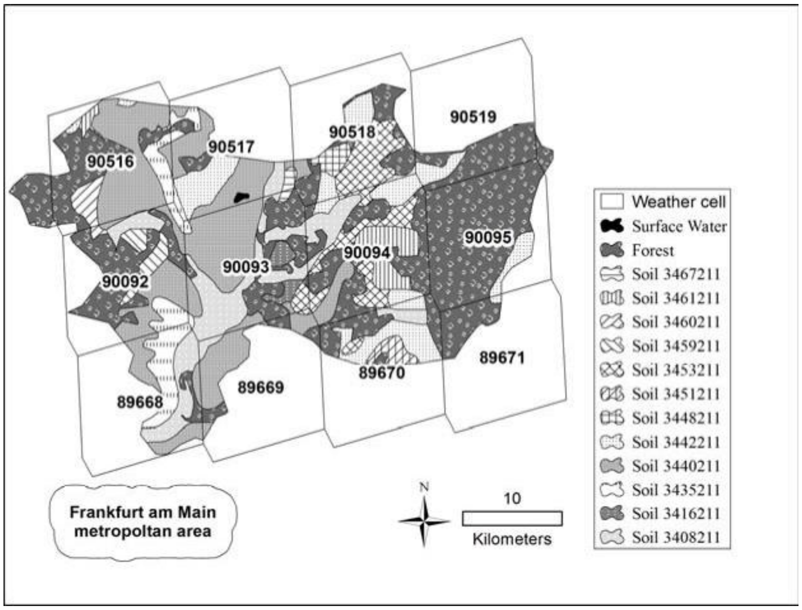
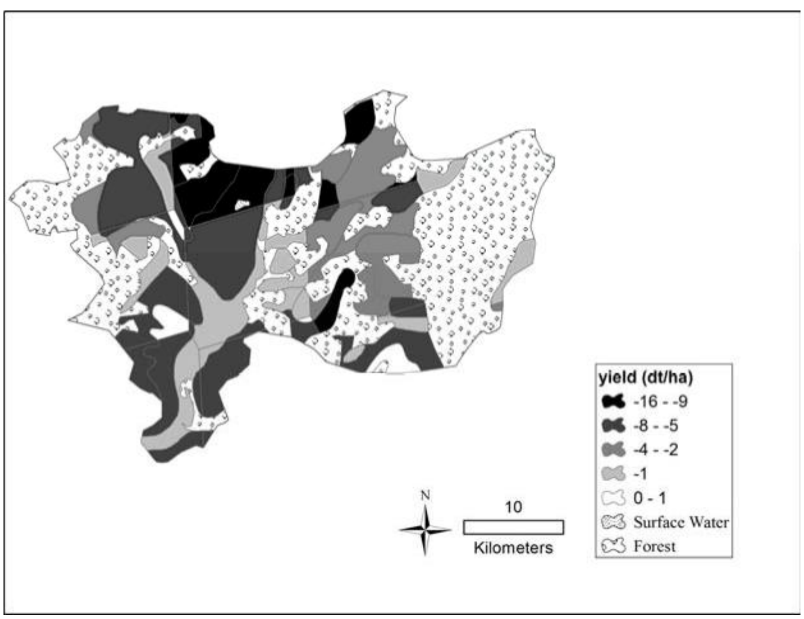
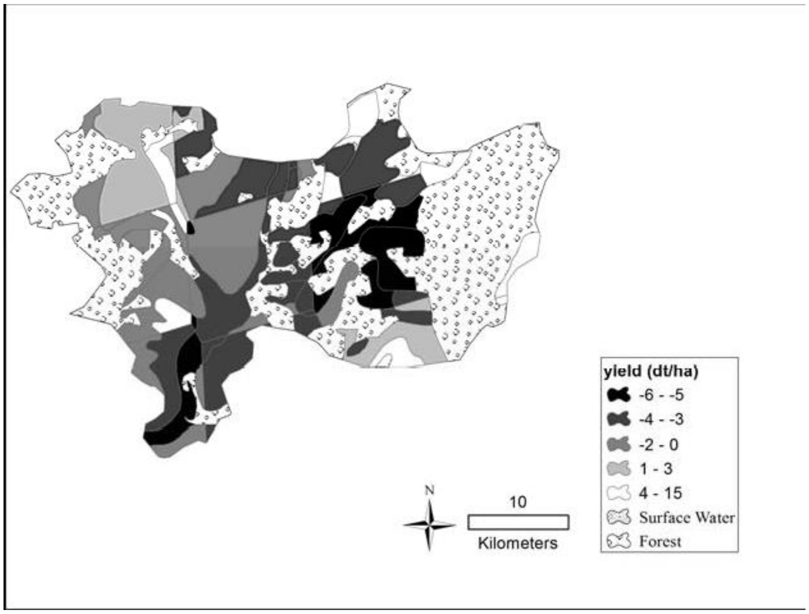


Fig. 2 Changes in average yields between 2011-2010 and 2031-2050 for: a) winter wheat cv.
Kerubino; b) winter barley cv. *Souleyka*; c) winter rye cv. *Dukato*

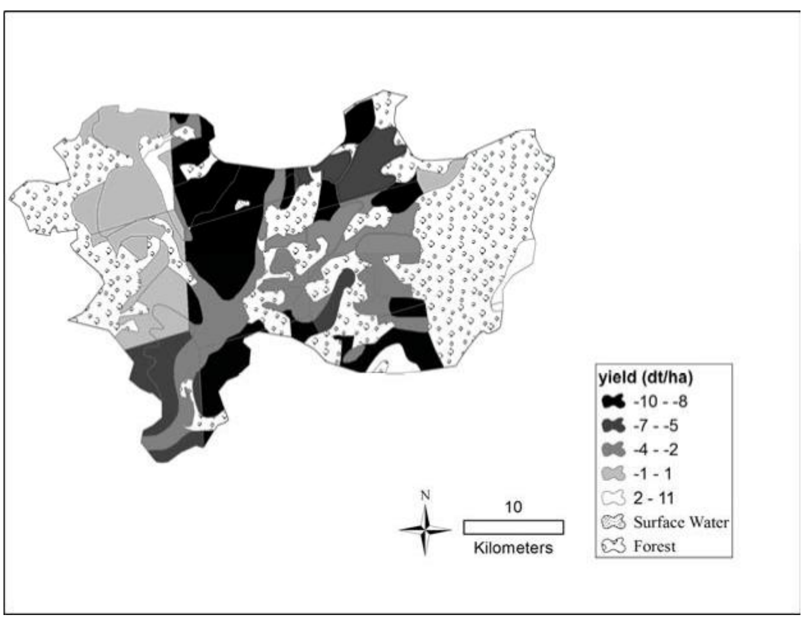
a)



b)



c)



Keywords: simulation, cultivars, cereals, adaptation

4. Simulating regional climate-adaptive field cropping with fuzzy logic management rules and genetic advance

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CLIMATE CHANGE AND AGRICULTURE RESEARCH PAPER

Simulating regional climate-adaptive field cropping with fuzzy logic management rules and genetic advance

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SUMMARY

Agriculture is a largely technical endeavour involving complicated managerial decision-making that affects crop performance. Farm-level modelling integrates crop models with agent behaviour to account for farmer decision-making and complete the representation of agricultural systems. To replicate an important part of agriculture in Central Europe a crop model was calibrated for a unique region's predominant crops: winter wheat, winter and spring barley, silage maize and winter rapeseed. Their cultivation was then simulated over multiple decades at daily resolution to test validity and stability, while adding the dimension of agent behaviour in relation to environmental and economic conditions. After validation against regional statistics, simulated future weather scenarios were used to forecast crop management and performance under anticipated global change. Farm management and crop genetics were treated as adaptive variables in the milieu of shifting climatic conditions to allow projections of agriculture in the study region into the coming decades.

INTRODUCTION

Individual crop and whole farm modelling has become an important tool for exploring how the environment and human behaviour affect agricultural systems. This simulation of on-farm circumstances makes it possible to incorporate hypothetical scenarios including plant genetics, climate and farm management profiles. Simulation is a worthwhile alternative to creating the intended conditions in controlled environments, e.g. experiments in climate chambers and under real conditions. Hypothetical plant genetics, for one, are impossible to demonstrate in this regard.

With the global population reaching 7 billion and a global atmospheric carbon dioxide (CO_2) concentration of 400 ppm (Ewald 2013), concerns about world food security being threatened by anthropogenic climate change have not waned (Högy & Fangmeier 2013). On the contrary, as stated by van Ittersum *et al.* (2013), the prognosis has deteriorated, putting more pressure on the scientific community to provide sound projections of agricultural production in the coming decades. To this end van Ittersum *et al.* (2013) have also emphasized the importance of crop simulation models at daily resolution with flexible simulation of management actions. The adaption of agriculture to global change is of interest to a range of stakeholders including researchers, policy makers and farmers (Bizikova *et al.* 2014), and crop modelling is an effective means of evaluating possibilities (Matthews *et al.* 2013). The goal is to elucidate some of the mechanisms by which agricultural production will be adjusted to future environmental conditions.

Calibration of crop models benefits from as much detail as can be provided by experiments and observations containing the information that goes into simulation. The current study demonstrates some of the advantages of precise, relevant data collection by using it to generate an outlook on crop performance, including plant development and potential yield.

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The premise is that the better past observations are replicated, the more reliable are projections into the future. The current study builds upon decades of work modelling winter wheat, summer and winter barley and maize with CERES (Jones & Kiniry 1986) and all four plus winter rapeseed with GECROS (Yin & Van Laar 2005). These crops cover almost half of Europe's arable land, three-quarters of Germany's and four-fifths of that in Baden-Württemberg (Eurostat 2013) making their economic and nutritional importance extreme. By calibrating and validating simulations of these crops with data from various sources, subsequent simulations of their cultivation 30 years into the future can be viewed with confidence.

The current study includes projected future farmer behaviour, which, as with crop modelling, is valuable for scenario analysis and bound to realistic simulations of reality. Performance of cropping actions, especially planting, has a noticeable impact on crop performance and hence is crucial to reliable simulation (Leenhardt & Lemaire 2002; Sacks & Kucharik 2011; Waha *et al.* 2012). The current study mimics the decision-making process that drives the timing of field-level actions including planting and harvesting, based on farmer reactions to environmental conditions. This includes farmers responding to current weather and soil conditions on a daily basis, as well as learning from historic patterns to generate expectations and steer behaviour. Again, accurate replication of historic, site-specific observations instils confidence in hypothetical scenarios. The current study presents the latest improvements to FarmActor as integrated with the agro-ecosystem model Expert-N (Priesack 2006). The improved model is applied to an arable region of south-west Germany (Kraichgau), contrasting sharply to the Swabian Alb of the previous application (Aurbacher *et al.* 2013). Projections of adaptive management and consequent crop phenology and likely yields are made using simulated future weather scenarios.

MATERIALS AND METHODS

Study area

The Kraichgau (*c.* 1400 km^2) is a region of rolling hills with thick loess soils located between the Rhine and Neckar Rivers. The region is characterized by a mild climate with an annual mean temperature of 9·1 °C, making it one of the warmest regions in Germany.

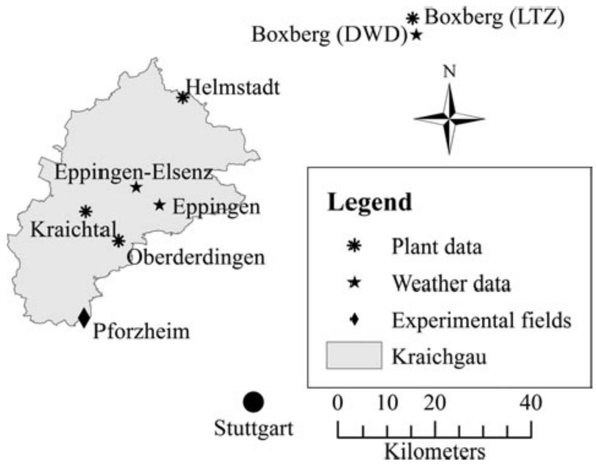

Fig. 1. Map of study area with key locations.

Mean annual precipitation ranges from 720 mm (in the west) to 830 mm (east and south). The Kraichgau is in Karlsruhe County (*Regierungsbezirk*) and composed of Karlsruhe Rural (0·38), Heilbronn (0·23), Rhein-Neckar (0·10) and Enzkreis (0·10) districts (*Kreise*). It represents prime Central European cropland. Figure 1 shows the study area and key locations within the state of Baden-Württemberg.

Experimental fields

The farm 'Katharinentaler Hof' (48°55′N, 8°42′E, 319 m a.s.l.) is located north of Pforzheim at the southern edge of the Kraichgau. Three research units or 'eddy-covariance stations' (RU EC1-3) were outfitted on separate fields (16–24 ha) to record weather and soil conditions at half-hourly resolution, subsequently aggregated to daily values; a detailed description is given in Ingwersen *et al.* (2011) and Gayler *et al.* (2013). The weather data recorded at experimental fields was used for calibration of the crops grown on them. Winter wheat, silage maize and winter rapeseed were grown on four fields in 2009 and three fields in 2010/2011 as part of normal crop rotations, grown over five, three and two seasons, respectively, to provide bi-weekly or monthly plant development (BBCH 1997) and leaf area index (LAI, 0+) measurements plus intermittent measurements on whole plant and generative biomass partitioned dry weight (DW, kg/ha) and nitrogen (N) concentration (% DW) (Högy *et al.* 2009; Ingwersen *et al.* 2011). Table 1 shows the number of plant measurements provided by field surveys for crop model calibration.

Table 1. *Weather source and number of data sets per observation and crop used for crop model calibration*

Weather	Winter wheat* RU EC	Winter barley† DWD	Spring barley† DWD	Silage maize* RU EC	Winter rapeseed* RU EC
Planting dates	5	3	3	3	2
Development stage (BBCH)	46	24	24	18	19
Generative biomass (kg/ha)	7	3	3	9	2
Above-ground biomass (kg/ha)	13	–	–	15	5
Leaf area index (m^2/m^2)	40	–	–	21	1
Nitrogen concentration vegetative (% DW)	13	–	–	12	4
Nitrogen concentration, generative (% DW)	5	–	–	12	2
Total	129	30	30	90	35

DW, dry weight.
* Own field observations at research unit (RU) eddy covariance (EC) stations.
† Source: LTZ (2013).

The differences between plot-measured and farmer-reported yields were averaged by crop and taken as a measurement bias to be applied to crop model results. Modelled yields were thus corrected by −19% for wheat, −18% for rapeseed and +4% for maize.

Supplemental data

The German Weather Service maintains a network of both weather (DWD 2012*a*) and phenological (DWD 2012*b*) observatories, often in close enough proximity to allow derivation of causal relationships between them (Menzel 2013). The DWD weather station at Eppingen was moved to a nearby location in 2002 and renamed Eppingen-Elsenz. Records from the two stations were merged and deemed to be from one location. Phenological observations indicate the local onset of crop phases, including the artificial ones used below, planting and harvest. The DWD Phenology station at Oberderdingen was chosen because of its location between the experimental fields and Eppingen.

Experimental fields were not sown with summer or winter barley during the period used for calibration so less detailed data, limited to development stage and final crop yield, were taken from Baden-Württemberg state field trial stations as close as possible to the experimental fields (LTZ Augustenberg 2013). One advantage provided by the LTZ data is multiple years of trials using specific cultivars, so that barley cvar *Braemar* and cvar *Lomerit* were chosen as representative of spring and winter cultivars, respectively, in the region. Experimental data covering several years were available for spring barley at the Kraichtal site, close enough that soil parameters from a Katharinentaler Hof field and DWD weather from Eppingen were used for calibration. For winter barley, the nearest source of LTZ experimental data was in Boxberg (Fig. 1). For this site, soil data were derived from the Soil Map of the Federal State of Baden-Württemberg (LGRB 1997) and weather data were taken from the nearest station (Bad Mergentheim) with records of each weather variable needed for simulation. The DWD phenological records for spring barley end in 1990, so they were amalgamated with planting and harvest data from various LTZ trials sites for validation 1991–2010. Table 2 gives a statistical summary of locations with sources of data.

Simulated field management and behavioural paradigms

Learning from several years of weather designates the onset of planting periods each year, during which daily soil moisture, air temperature and precipitation, plus temperatures over the last 3 days, serve as action triggers (Aurbacher *et al.* 2013). Following Olesen *et al.* (2012) maximum temperature values, daily and over 3 days prior were added as criteria for autumn sowing. The justification for this mechanism is the perceived risk on the part of a farmer that excessive temperatures are likely to result in over-development before winter dormancy, while also being conducive to insect, pathogen and weed growth.

Harvest is subject to a set of simultaneously evaluated feasibility criteria including crop growth stage (GS 92 for

Table 2. *Summary statistics (2010/2011) on data source locations*

	RU EC-1*	RU EC-2*	RU EC-3*	DWD Eppingen†	DWD Bad Mergentheim†	LTZ Kraichtal‡	LTZ Boxberg‡
Latitude (North)	48°55′	48°56′	48°56′	49°8′	49°28′	49°7′	49°29′
Longitude (East)	8°42′	8°43′	8°43′	8°55′	9°46′	8°42′	9°38′
Altitude (m a.s.l.)	319	319	319	210	250	210	360
Average temperature (°C)	9·25	9·39	9·71	9·87	9·52	9·3	8·4
Precipitation (mm/year)	825	837	831	730	708	650	720
Incident radiation ($MJ/m^2/d$)	12·18	12·00	12·50	11·48	11·84	–	–

* Sources: own field observations from research unit (RU) eddy covariance (EC) stations.
† DWD (2012*a*).
‡ LTZ Augustenberg (2013).

seed crops and GS 88·8 for silage maize; BBCH 1997), soil trafficability (water content below field capacity) and daily precipitation (0 mm on the day of harvest). In seed crops a proxy for grain moisture content is a combination of minimum pre-period temperature and maximum precipitation (8 °C and 10 mm over 3 days), to capture the importance of drying costs.

Reproducing farmer behaviour previously relied on fixed trigger values throughout allotted time windows with derestriction occurring at the end of these periods in order to prevent failed actions (Aurbacher *et al.* 2013). Two alternative decision-making paradigms were created to improve the accuracy of simulated management.

'Shifting' triggers

A mechanism for shifting triggers was developed so that each day after the start of the planting period, triggers were constantly relaxed to a calibrated degree. It was a daily check whether t: $t \geq base - shift \times day$ for a minimum trigger, or: $t \leq base + shift \times day$ for a maximum trigger, each day during the time window. This can be very restrictive early in the period when only exceptionally favourable combinations of environmental conditions will permit action, and also allow progressively sub-optimal combinations late in the period, facing the risk of late or failed action.

'Fuzzy' triggers

Fuzzy logic has already been applied to crop modelling (Wieland *et al.* 2013). Here, it was implemented as an option for simulating how a farmer determines the suitability of a day for action. The hard logic behind the fuzzy is the existence of a trade-off dynamic among reasons not to work a field, effectively measures of temperature and moisture.

Each trigger is given a base value and a degree of 'fuzziness' stipulating the range where the fulfilment of the trigger gradually moves from 0 (impossible) to 1 (perfectly suitable) for an action (Fig. 2). A composite of all triggers is calculated each day and must exceed a given threshold (for the current work: 0·50 or 'half-perfect') for action. This composite t^* is the geometric mean of the normalized fulfilment t of each fuzzy trigger k and is calculated as:

$$t^* = [\Pi_{k=0}^{n} t_k]^{1/n}$$

Where $t = [\upsilon - (b - f/2)]/f$ for minimum triggers and $t = [b + (f/2) - \upsilon]/f$ for maximum triggers, n is the number of triggers, b is the minimum or maximum base value for each, f is its band of fuzziness (halved between greater and less than the base) and v is the currently simulated value. All ts are truncated to be between 0 and 1.

This was implemented in FarmActor at daily resolution using the programming language Java. It provides a clear interface to simulated behaviour, an entry point for experiments in actor profiles.

Model calibration

Calibration was conducted in three stages, starting with the base calibration of Expert-N to experimental field observations, followed by calibration of planting dates to phenological records and finally, building on accurate simulation of recent years, annual changes in crop model parameters were added.

Crop model calibration

Two crop growth models, Genotype-by-Environment interaction on CROp growth Simulator (GECROS) and Crop Environment REsource Synthesis (CERES),

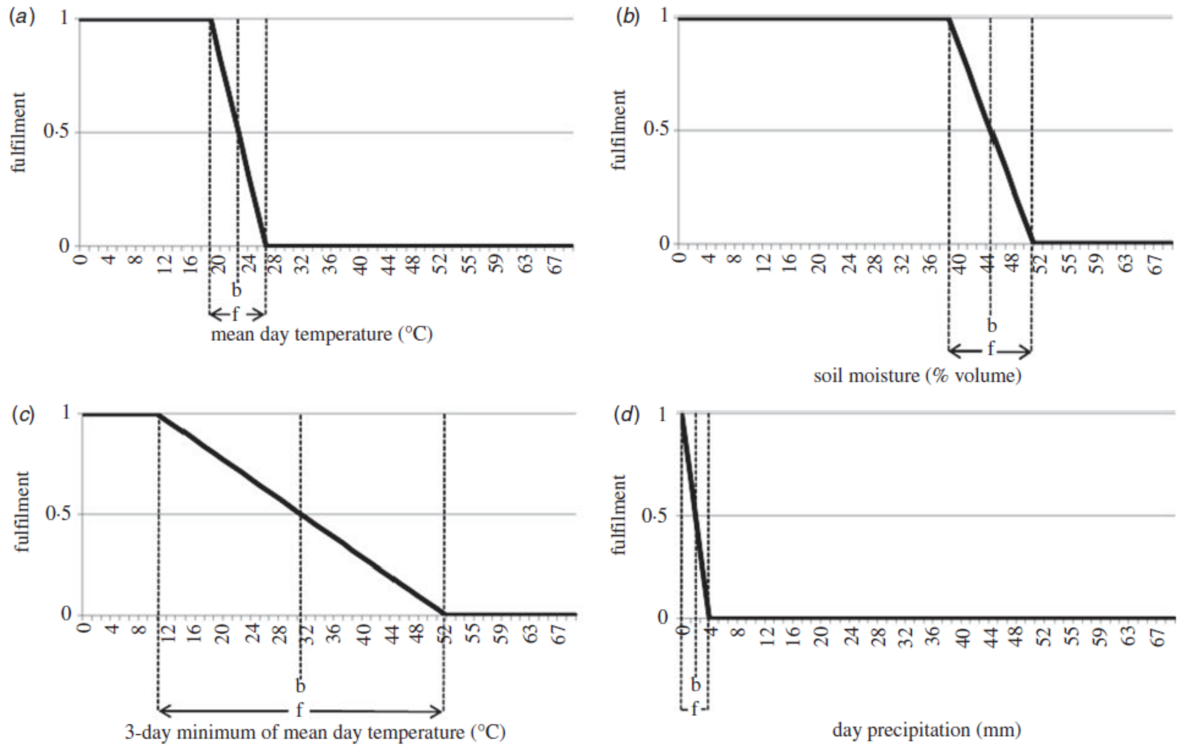

Fig. 2. Membership functions of fuzzy triggers for the planting of winter wheat. (*a*) Maximum mean daily air temperature, (*b*) maximum soil moisture (*c*) maximum 3-day minimum of mean daily air temperature and (*d*) maximum total daily precipitation. *b*: Trigger base value, *f*: fuzziness of trigger (source: own depiction)

were applied separately within Expert-N to provide a broader perspective on the effects of climate on crop performance. Both were calibrated using identical weather data, soil parameters and crop performance observations. See Table 3 for details of soil properties and hydraulic parameters.

Both models were iteratively calibrated using UCODE (Poeter *et al.* 2005). Phenological parameters were optimized first and then, with these fixed, drivers of crop growth and yield formation were calibrated. Default parameters that were not adjusted are available for CERES in Priesack (2006) and GECROS in Yin & Van Laar (2005).

Dynamic genetics

One of the latest capacities of crop modelling is accounting for the diversity of cultivars (Jeuffroy *et al.* 2014). While technological progress including the breeding of new crop cultivars has been credited with much of the yield increases in recent decades, allowing for this element has been elusive to crop modellers, leading to statistical correction of yields (Ewert *et al.* 2005). Further, simulating crop performance over a range of decades with static crop model parameters calibrated to specific years has resulted in failure to capture trends in crop yields and phenology (Aurbacher *et al.* 2013). Thus, one of the areas for improvement in crop modelling is a process-based way to account for the evolution of genotypes. To demonstrate how this can improve model accuracy, trends in some genetic parameters interpreted by the crop models were incorporated.

The genetic contribution to increased wheat and barley yields over recent decades has, through extensive cultivar trials, been largely attributed to grain number per ear (Ahlemeyer & Friedt 2012) so that breeding has resulted in an increase of around 0·15 grains/ear/year between 1966 and 2007. However, Ahlemeyer & Friedt (2012) also showed complementary improvements in disease resistance as a result of breeding. Further, technological and climatic factors, including atmospheric CO_2 fertilization, have contributed to yield trends (Lobell *et al.* 2011). This precludes an exaggerated use of dynamic grain number to match observed historic yields.

Table 3. *Soil properties and hydraulic parameters*

Horizon	Depth (cm)	Density P_b	Sand (l/l)	Silt (l/l)	Clay (l/l)	Porosity (l/l)	Total C (g/g)	C : N Ratio	Θ_r (1)	Θ_s (1)	α (1/cm)	n (-)	m (-)	K_S (cm/day)	Field capacity (l/l)	Water content, pF 4·2 (l/l)
Katharinentaler Hof field EC-1:																
Ap	0–32	1·31	2·5	79·4	18·2	48·3	1·02	11·8	0·075	0·460	0·0058	1·633	0·388	17·99	36·9	16·2
Sw-M	32–48	1·34	2·0	79·2	18·8	43·0	0·35	17·9	0·072	0·429	0·0063	1·602	0·376	9·38	36·5	22·3
M-Sw	90–200	1·32	0·9	80·4	18·7	40·2	0·24	23·8	0·073	0·439	0·0063	1·605	0·377	10·00	40·4	24·3
Katharinentaler Hof field EC-2:																
Ap	0–33	1·33	2·6	79·5	17·9	49·8	0·89	11·8	0·076	0·470	0·0057	1·638	0·390	21·62	34·3	15·3
Sw-M	33–72	1·46	2·9	77·0	20·1	44·9	0·30	17·9	0·075	0·439	0·0061	1·611	0·379	11·14	37·1	22·3
M-Sw	72–200	1·53	1·6	79·7	18·7	42·3	0·20	23·8	0·071	0·425	0·0064	1·595	0·373	8·50	41·7	23·9
Katharinentaler Hof field EC-3:																
Ap	0–32	1·37	1·8	81·1	17·1	48·3	0·95	11·8	0·074	0·462	0·0058	1·634	0·388	18·47	33·8	15·9
Sw-M	32–48	1·50	1·0	80·4	18·7	43·4	0·48	17·9	0·073	0·434	0·0063	1·601	0·375	9·30	35·5	16·3
M-Sw	90–200	1·51	0·8	83·0	16·1	43·0	0·37	23·8	0·069	0·432	0·0064	1·605	0·377	10·43	35·8	13·7
LTZ Boxberg*:																
Ap	0–35	1·63	37·5	37·6	24·9	41·5	1·21	15·0	0·070	0·415	0·0107	1·469	0·319	8·03	36·9	7·0
M1	35–100	1·45	28·1	48·2	23·7	42·7	0·52	15·0	0·072	0·427	0·0068	1·552	0·356	13·60	40·4	5·6
M2	100–200	1·51	33·2	44·9	21·9	39·6	0·01	15·0	0·056	0·396	0·0140	1·448	0·309	13·95	37·6	5·6

* LGRB reference profile DE6517-5 (LGRB 1997).

Based on yield sensitivity, the initial leaf N content in GECROS was used to create a trend in simulated winter rapeseed yields. Another option would be to adjust thousand kernel weight, since its genetic advance has been well documented (Ali *et al.* 2003; Marjanović-Jeromela *et al.* 2011).

Silage maize yields in Karlsruhe District show only a slight upward trend (+0·067 t/year) between 1981 and 2010. Phenological records at Oberderdingen however, show the start of local maize harvest trending later by 1·35 days/year. Bassu *et al.* (2014) propose that adaptation to greater cumulative temperatures in future growing seasons are likely to include the selection of later-ripening maize cultivars. This can be realistically achieved in simulations with an annual increase in the temperature requirement for the crop's juvenile stage, evidence for which has been established in German maize (Estrella *et al.* 2007).

Calibration of field management

Adaptive crop management in the face of global change could mean the difference between increasing and decreasing future yields, varying by crop (Leclère *et al.* 2013). To track historic climatic adaptation by local farmers and consequently project the same into the future, FarmActor conducts daily integration of Expert-N with database soil and weather records and internal management decision-making. Sensitivity analysis of simulated wheat yields produced by the coupled models during simulation years 2001–2010 showed a 370 kg/ha increase when planting a week earlier compared with a 121 kg/ha decrease when planting a week later than the average simulated planting date. Respective equivalents were: for winter barley, 47·8 and 1·0 kg/ha; spring barley, 114 and 142 kg/ha; oilseed rape, 342 and 449 kg/ha and silage maize, 131 and 323 kg/ha. FarmActor's dynamic crop rotation (Aurbacher & Dabbert 2011) was omitted to simplify the extraction of annual performance measures of each crop and to determine planting and harvest dates based on daily crop, soil and weather conditions, in addition to learning. Ten-year moving averages of soil temperature for spring crops and cumulative air temperature for winter crops were used to represent farmer learning from historic weather (Aurbacher *et al.* 2013). To accommodate the lack of crop rotation, soil nutrient values were reset each year.

The simulated farmer, in seeking to maximize crop yield and minimize risk, has an inevitably simplified set of criteria for each action, crop and field. Field-specific soil properties determine the moisture level corresponding to a favourable response to action, and that at which traffic and tillage can be withstood without the long-term damage of compaction (Rotz & Harrigan 2005). Recent and immediate weather determine soil moisture and are themselves direct criteria for action, varying with crop-specific temperature requirements.

Use of a genetic algorithm to calibrate management

The proper specification of action triggers is crucial for the functioning of the model. Although they are based in principle on expert knowledge, there remains a certain range of reasonable settings. The goal was to set the triggers such that the model optimally reproduced observed actions of farmers. To systematically apply the information from observations to trigger settings a genetic algorithm was used with a $(\mu + \lambda)$ evolutionary strategy, according to Schöneburg *et al.* (1994), where all former generations are retained.

Functioning of the genetic algorithm proceeded as follows (see also Fig. 3): The first step was to define the possible range for each action-specific trigger based on agronomic principles. A population of potential values was created by assigning a number of intervals within the possible range to each trigger. The resultant population size was the product of the number of intervals of the different triggers. In the first iteration, the population was generated by choosing the centre of each interval within each trigger range (with one interval the value was at midpoint of the range, two intervals gave values at one and three quarters, three intervals at one-sixth, half and five-sixths, etc.). The model was then run for all population members and a fitness function evaluated upon completion. Root Mean Squared Error (RMSE) in days between observed and modelled action dates was used as the measure of fitness. Additionally, for every simulated year in which a combination of triggers resulted in a failed planting (by being too restrictive) a 'penalty' of 10 days was added to the RMSE to lead the algorithm away from that solution. The members of the population (trigger set) were then ranked according to fitness and if identical fitness values arose the rank was assigned randomly. The penalty ensured that population members with failed runs always ranked behind completely successful runs.

Next a propagation probability function was used to assign to each member of the population the likelihood

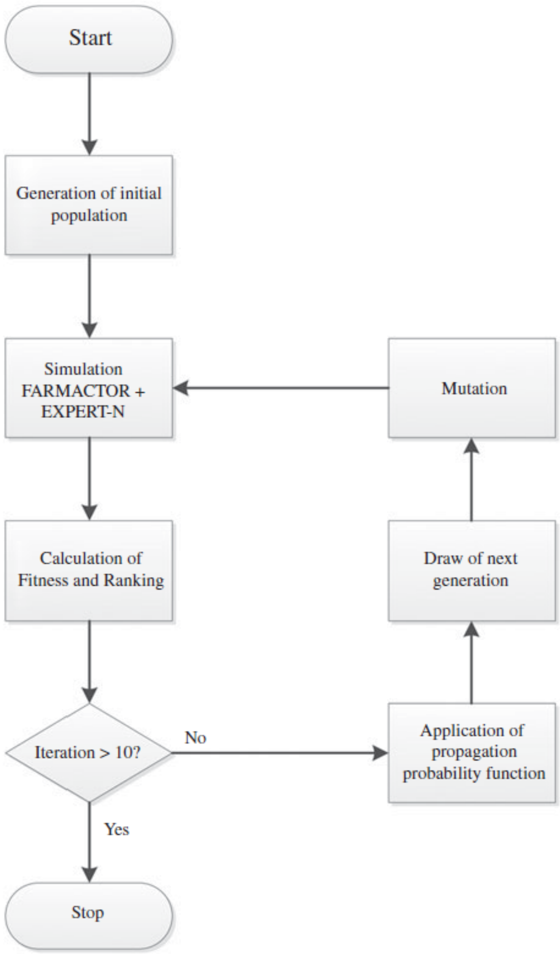

Fig. 3. Schematic representation of genetic algorithm for calibration of management action triggers (source: own depiction).

that it would be one of the starting points of the following iteration. The function used was:

$$p(r) = \frac{3(n+1-r)^2}{n^3}$$

where p is the assigned probability, n is the size of the population and r is the rank of each population member (1 being the best, n the worst). This quadratic function assigned the probability $3/n$ to the first-ranked member (equal to a multiplication of the 'fair chance' $1/n$ by the factor 3) and the probability $3/n^3$ (slightly larger than zero) to the one deemed of worst fitness. About 0·60 of the population members were assigned a value lower than fair chance while those remaining were privileged.

A new population of the same size was drawn from the preceding population using the assigned probabilities. Members of the new population were not exact copies of their 'ancestors', as 'mutation' occurred. Each trigger parameter was modified by adding a normally distributed random number with a pre-defined standard deviation. The standard deviation employed was reduced by the factor 0·9 in each successive iteration.

The model was re-run with the new generation of parameters, evaluated and successively propagated with respect to fitness rank. Members of previous iterations were not discarded but also included in the ranking and selection process of further iterations.

The parameter bounds, interval number and standard deviation used to find optimum values for each trigger were the same for winter wheat, barley and rapeseed, likewise for spring barley and maize. These values are given in Supplementary Table 1 (available from: http://journals.cambridge.org/AGS).

A drawback of this approach was the need to run the model repeatedly, resulting in a potentially long calibration time. To calibrate planting criteria, a population of 12 trigger sets was run for ten iterations from 1981–2010 for winter wheat, winter rapeseed and maize, establishing learning (expectations) for the first 10 years and comparing simulated planting dates during 1991–2010 to phenological observations at Oberderdingen. This left the years 1981–1990 at Oberderdingen available for validation of simulated planting of these crops. Summer and winter barley were likewise run from 1971–1990, calibrating to the latest available phenological observations at Oberderdingen and Helmstadt, respectively, while validation for spring barley depended on state field trial records.

RESULTS AND DISCUSSION

Crop model calibration results

Within Expert-N, GECROS was, for all crops, calibrated to a greater degree of Nash & Sutcliffe (1970) model efficiency than CERES, though yield accuracy (by RMSE) was better with CERES for winter wheat and winter barley, but better with GECROS for spring barley and silage maize. Both models attained the poorest fit with silage maize, the best with summer barley and wheat in between, keeping in mind the less comprehensive data for barley. Final sets of parameters and model fit after calibration of GECROS and CERES are given in the Supplementary Material (Supplementary Tables 2 and 3, respectively, available from: http://journals.cambridge.org/AGS).

Table 4. *Observed Karlsruhe Rural District yield trends, simulated genetic advance and yield trends with and without dynamic genetics, 1981–2010*

	Observed yield trend (t/year)	Genetic parameter	Annual rate of change	Simulated trend w/ dynamic genetics	Simulated trend w/ static genetics
Winter wheat	0·065	G1	0·30	0·035	−0·043
Winter barley	0·035	G1	0·30	0·037	−0·026
Spring barley	0·049	G1	0·30	0·063	−0·033
Winter rapeseed	0·056	LNCI	0·00005	0·039	0·013
Silage maize	0·067*	P1	7·0	0·792	−0·085

G1, grains/g stem; LNCI, initial leaf nitrogen [g N/g]; P1, cumulative temperature (base 8 °C) from emergence to end of juvenile stage

* In comparison, the yield trend from state trials, across all cultivars being tested in the Kraichgau, 1990–2010, was 1·072 t/year (LTZ Augustenberg 2013).

Calibrated dynamic genetics

Based on measurements for wheat by Ahlemeyer & Friedt (2012) and resolved to field measurements of combined stem and ear weight of 4·4 g DW/plant and 2·2 ears/plant (0·5 ears/g) (Högy & Fangmeier 2013), the CERES parameter for the number of grains/g of stem (G2) was adjusted by 0·3 each year relative to the calibrated values, decreasing before and increasing after 2010. This effect was also applied to winter and spring barley. The initial leaf N content of rapeseed (LNCI) was likewise set to change by 0·14% each year to better approximate the observed yield trend. The thermal requirement for the juvenile stage of maize (P1) was adjusted to improve model fit of simulated to observed harvest dates. This increased the 1981–2010 maize yield trend from less than to more than that of district averages. However, the new trend is still less than that observed at state cultivar trial stations during 1990–2010 (LTZ Augustenberg 2013). In winter wheat and rapeseed, simulated yield trends were a portion of that observed, while in both barley crops the chosen settings over-compensated for genetic advance. Table 4 shows the observed yield trends in the district, values for genetic advance used in simulation and the resultant simulated trends (sensitivity analysis results at the chosen rates of genetic change are not presented here but are available from the authors upon request).

While integrating genetic advance shows promise, extensive calibration to match historic yields was not undertaken, considering that other technological factors surrounding pest control, fertilization and farm management have played a significant role in recently increasing yields (Friedt & Ordon 2013). Further work should use additional experimental data and more extensive calibration to isolate those genotype parameters in both CERES and GECROS that are best used to account for breeding progress.

Management calibration results

In calibrating spring planting dates, shifting trigger values consistently produced the most accurate predictions, followed by fuzzy and then fixed/override triggers. Autumn planting was not as decisive, with each of the three paradigms resulting in the best predictions for one crop. Table 5 has results of calibration with the genetic algorithm for the different behavioural paradigms. The best target value is given along with its corresponding set of trigger values.

Model validation

Validation of simulated planting dates compares model output with DWD network observations outside of the calibration period. Outcomes determine which trigger paradigm and how changing genetics were used in later projections.

The model was run for the five crops from 1970–2010 (the first 10 years of temperatures needed as a warm-up phase for learning) with 'fixed', 'shifting' and 'fuzzy' action triggers to compare them by RMSE, correlation coefficient and bias.

Spring planting dates during the validation period were consistently predicted more accurately using fuzzy triggers, followed by shifting and then fixed/override. Simulation of autumn planting did not benefit so clearly from the more complicated paradigms, but a trade-off between accuracy measures

Table 5. *Optimized planting trigger values and fit (RMSE) for planting of different crops*

	Winter wheat*	Winter barley*	Spring barley*	Silage maize*	Winter rapeseed†
Fixed					
Learning GDD (°C, base 0)	386·79	567·23	–	–	1124·13
Learning week. Soil temp. (°C)	–	–	3·39	4·41	–
Max. soil moisture (% Vol.)	43·49	40·96	32·08	25·60	37·72
Max. precipitation (mm/day)	3·17	11·86	12·69	9·99	0·00
Max. current air temp (°C)	18·79	26·52	–	–	17·06
Max. 3–day air temp (°C)	19·56	15·71	–	–	21·11
Min. current air temp (°C)	–	–	9·57	0·00	–
Min. 3–day air temp (°C)	–	–	8·19	1·77	–
RMSE (days)	9·84	3·87	11·09	5·45	9·73
Shifting					
Learning GDD (°C)	423·06	250·0	–	–	763·92
Learning week. Soil temp. (°C)	–	–	5·72	9·56	–
Max. soil moisture (% Vol.)	25·91	42·25	30·86	36·72	50·00
Daily shift	0·52	0·00	0·89	0·55	0·00
Max. precipitation (mm/day)	11·81	18·07	13·30	0·99	11·11
Daily shift	0·36	0·90	0·31	1·00	0·31
Max. current air temp (°C)	21·18	10·00	–	–	15·10
Daily shift	1·00	1·00	–	–	0·34
Max. 3–day air temp (°C)	28·98	24·70	–	–	13·73
Daily shift	0·31	0·00	–	–	0·37
Min. current air temp (°C)	–	–	11·85	8·82	
Daily shift	–	–	0·18	0·58	–
Min. 3–day air temp (°C)	–	–	11·53	15·87	–
Daily shift	–	–	0·44	0·48	–
RMSE (days)	9·99	4·58	7·73	4·74	9·36
Fuzzy					
Learning GDD (°C)	439·47	873·33	–	–	1093·49
Learning week. Soil temp. (°C)	–	–	9·06	12·53	–
Max. soil moisture (% Vol.)	39·69	31·50	35·76	50	45·78
Range	10·02	19·82	32·59	17·22	0·00
Max. precipitation (mm/day)	3·49	0·00	20·00	0·00	0·00
Range	0·61	28·01	10·71	41·64	1·71
Max. current air temp (°C)	19·69	11·78	–	–	18·30
Range	5·57	0·00	–	–	2·13
Max. 3–day air temp (°C)	11·73	25·79	–	–	24·13
Range	38·84	0·00	–	–	0·66
Min. current air temp (°C)	–	–	6·14	10·17	–
Range	–	–	47·34	36·10	–
Min. 3–day air temp (°C)	–	–	0·53	1·69	–
Range	–	–	0·46	14·11	–
RMSE (days)	9·93	3·42	9·69	5·15	9·75

* Modelled with CERES for planting calibration.
† Modelled with GECROS for planting calibration.

leaves evaluation open to judgment (Table 6). It was decided to proceed with fuzzy triggers with all five crops in validation of harvest results and forthcoming projections.

Harvest date and yield validation is possible during the entire 1981–2010 simulation period using DWD records of harvest date and district average yields. Evident in the results is that simulated crop yields from

Table 6. *Validation period measures of fit for simulated planting dates by crop and action trigger paradigms*

	Trigger paradigm		
	Fixed	Shifting	Fuzzy
Winter wheat (1981–1990)			
Correlation coefficient	−0·16	0·30	0·52
RMSE (days)	7·78	9·25	9·43
Bias (days)	−4·26	−5·63	−7·23
Winter barley (1991–2010)			
Correlation coefficient	−0·14	0·02	0·48
RMSE (days)	19·26	15·63	12·74
Bias (days)	−16·40	−9·23	−1·03
Winter rapeseed (1981–1990)			
Correlation coefficient	0·42	−0·38	0·33
RMSE (days)	13·79	14·93	13·28
Bias (days)	−11·10	12·40	−10·40
Spring barley (1991–2010)			
Correlation coefficient	0·05	−0·21	0·12
RMSE (days)	25·40	14·26	14·45
Bias (days)	−1·60	3·50	1·65
Silage maize (1981–1990)			
Correlation coefficient	−0·63	0·12	0·37
RMSE (days)	8·65	9·34	8·03
Bias (days)	−0·90	−6·40	−2·20

both CERES and GECROS consistently exceeded those observed in the area as Karlsruhe rural district averages (see Table 7 yield biases). This, however, should be expected when comparing regional averages, irrespective of farm type, to simulations based on data from more optimally managed, highly productive fields, as is the case both at Katherinentaler Hof and state field trial stations. Incorporating dynamic genetics into the model reduces yield bias, as well as the other measures of model fit (Table 7) which also shows that simulated maize phenological development was slightly more accurate with CERES, while yields were more accurately reproduced with GECROS. Validation measures are comparable with that from other studies that generally involve shorter periods. Rötter *et al.* (2012) showed nine different crop models simulating spring barley at seven sites in Europe over a maximum of 14 years with yield RMSE between 1 and 2 t/ha. In a similar study Palosuo *et al.* (2011) modelled winter wheat with eight crop models at eight sites over a maximum of 14 years and reported the lowest yield RMSE to be 1·43 t/ha. Mast *et al.* (2014) simulated maize dry matter production, also in Southwest Germany, with a RMSE over 5 years of 9 t/ha; Angulo *et al.* (2013) with the most complex of three calibration strategies in their study simulating winter wheat and winter barley over 24 years achieved yield RMSE between 0·6 and 0·7 t/ha. In contrast to the above studies, simultaneous simulation of planting and harvest dates, rather than using observations, added to the scope of cropping simulations but detracted from the accuracy of replicating historic yields.

Satisfactory validation supports the following projections of Kraichgau agriculture in the coming decades. Climate forcing of field management and crop performance utilized WETTREG 2010 simulated future weather scenarios (Kreienkamp *et al.* 2010) for the Eppingen station, based on its historic records and assuming IPCC scenario A1B (IPCC Core Writing Team *et al.* 2007).

Projections

Projections were made for the 30 years after the base year 2010. Three runs were performed using separate realizations (ID# 2500200, 2500244 and 2500288) of the same WETTREG scenario at Eppingen. Regression function intercept and slope for planting, harvest and yield, averaged from the three runs are presented in Table 8.

Table 7. *Validation period measures of fit for simulated harvest dates and yield by crop and model*

	Harvest CERES	Harvest GECROS	Yield CERES	Yield GECROS	Yield w/genetic advance*
Winter wheat (1981–2010)	(days)	(days)	(t/ha)	(t/ha)	(t/ha)
Correlation coefficient	0·58	0·66	−0·14	0·06	0·73
RMSE	14·84	10·28	1·324	1·992	1·010
Bias	−14·07	−2·73	0·975	1·937	0·104
Winter barley (1981–2010)					
Correlation coefficient	0·65	0·45	0·06	0·17	0·49
RMSE	10·20	17·41	2·069	2·695	1·533
Bias	−1·30	−17·43	2·709	3·51	1·365
Spring barley (1981–2010)					
Correlation coefficient	0·65	0·41	0·02	0·50	0·53
RMSE	15·78	22·27	2·316	1·004	2·409
Bias	−13·07	−24·53	2·932	.108	2·914
Silage maize (1981–2010)					
Correlation coefficient	−0·23	−0·28	0·14	0·15	0·34
RMSE	22·97	23·44	13·940	13·490	10·599
Bias	−6·53	13·10	13·774	17·341	7·796
Winter rapeseed (1981–2010)					
Correlation coefficient	–	0·41	–	0·24	0·39
RMSE	–	12·51	–	1·219	1·112
Bias	–	−6·28	–	0·442	0·030

* Wheat, barley and maize with CERES, rapeseed with GECROS.

Table 8. *Projected management and crop performance statistics 2011–2040*

	Winter wheat	Winter barley	Spring barley	Silage maize	Winter rapeseed
Planting date – 2011 intercept (day of year)	282	277	78	120	238
– trend (days/year)	+0·29	+0·36	−0·78	−0·12	+0·34
CERES					
Harvest date – 2011 intercept (day of year)	199	213	201	263†	–
– trend (days/year)	−0·34	−0·34	−0·44	−0·55‡	–
Yield – 2011 intercept (t/ha)	7·13	9·03	8·37	59·04	–
– trend (t/ha/year)	−0·007	−0·004	−0·005	+0·058	–
GECROS					
Harvest date – 2011 intercept (day of year)	212	197	192	273	206
– trend (days/year)	−0·37	−0·50	−0·56	−0·88	−0·53
Yield – 2011 intercept (t/ha)	8·32	9·38	5·10	56·23	5·15
– trend (t/ha/year)	−0·001	+0·014	+0·046	−0·307	−0·075
With genetic advance*					
Yield – 2011 intercept (t/ha)	7·18	8·38	8·53	58·99	5·18
– trend (t/ha/year)	+0·029	−0·001	+0·020	+0·712	−0·064

* Wheat, barley and maize with CERES, rapeseed with GECROS.
† w/changing genetics = 260·04.
‡ w/changing genetics = +0·96.

Based on integration of simulated weather, soil conditions and farmer behaviour, the model indicated that winter crops will be sown about 1 day later for every 3 years into the future, in a warming climate, while still receiving the appropriate cumulative temperature for pre-vernalization development and satisfying other agronomic restrictions. Sowing of malting barley in the spring would change faster, 1 day earlier every 2 years based on CERES crop growth and concomitant soil conditions, and even faster according to GECROS-based simulations. Planting of maize would not be adapted as quickly, but would still shift to earlier dates.

The warmer temperatures in simulated future weather drove harvest dates earlier in all crops, 1 day per 3 years in winter wheat. Barley and rapeseed harvest dates were projected to be earlier by around 1 day every 2 years. Harvest of silage maize occurred >1 day earlier every 2 years according to CERES, nearer to 1 day per year using GECROS. Using dynamic genetics reversed this trend so that maize was harvested 1 day later each year.

Both crop models with static genetics projected yields of winter wheat to trend very slightly downward over the next 30 years. However, the increasing harvest index programmed as CERES input made for an increase in wheat productivity. CERES barley showed slightly declining yields with static genetics but an improved outlook with dynamic crop model parameters. GECROS projects slight and moderate increase in winter and spring barley, respectively. Maize yields using CERES were projected to increase slightly in the future, while with GECROS the trend is negative, with numerous poor crop yields, resulting from simulated soil moisture being near the permanent wilting point over extended periods during the summer. Continuing the shift in one rapeseed physiological parameter with GECROS reduced the simulated negative impact of global change on seed yield. In either case, winter rapeseed appeared to become the most negatively affected of the region's five major crops.

CONCLUSIONS

The current study presents an outlook on farm management and crop performance specific to the Kraichgau into the coming decades. Results show that cereal productivity may remain steady even under global climate change. The situation for maize and rapeseed is not, however, so evident. The two crop growth models produce contrasting results; with CERES maize yields appear to increase, while, due to greater sensitivity to drought, GECROS produces a declining yield trend. Rapeseed simulation with GECROS indicates that declining seed yields through 2040 could dampen or even reverse the current increase in rapeseed cultivation in the area (DESTATIS 2014). Yield declining due to climate change could be partially offset by breeding progress and increasing atmospheric carbon dioxide, but exacerbated by pest and disease prevalence; however these factors beg confirmation with more extensive modelling.

Aurbacher *et al.* (2013), modelling the nearby mountainous Swabian Alb, projected more drastic negative trends in wheat and maize yields, albeit with less extensive crop model calibration and no genetic dynamics. Angulo *et al.* (2013) projected decreasing yields for five major European crops, based solely on climate change. However, when technological change and CO_2 fertilization are included projections become more optimistic.

While the simulated future growing season, e.g. time between spring and autumn frosts, is expanding, warmer temperatures ripen crops faster so that farmers should choose later-ripening cultivars to profit from the extended season. Alternatively, the simultaneous trends toward earlier harvest and later (autumn) planting may affect future crop rotations. For example, by 2040, at base temperatures 0 °C (e.g. wheat) and 8 °C (maize) according to the average of the three future weather realizations there will be around 2200 and 1200 GDD, respectively, available for plant development between 1 July and 1 November (Kreienkamp *et al.* 2010), sufficient for a complete life cycle of a second crop (Deryng *et al.* 2011). As proposed in Waha *et al.* (2013), mitigation of climatic risks may well include such double cropping.

The use of simulated future weather in conjunction with flexible management accounts for some of the adaptation that should be expected from farmers under changing climate. Fuzzy logic is a promising way of depicting the decision-making process behind field management, adding credence to the timing of actions in bio-economic models which have a clear influence on results. This should improve both the accuracy of measures such as yields and offers further statements on alternative cropping practices, like double cropping. The adaptability of cultivar selection is another factor that contributes to model plausibility, as the attributes of available varieties change over time and through their use, alter the context of field cropping.

The latest extensions to FarmActor further extricate its subject, the simulated farmer and field, from the limitations of an agro-economic constellation in favour of an adaptive system evolving through time. Future work may include implementation of climate projections produced with coupled atmosphere-land surface models to allow inclusion of feedback between land-use changes and regional climate. Planting trigger calibration would benefit from more extensive calibration, and application of fuzzy logic into other actions (harvest, tillage, fertilization, etc.) may follow. Also, incorporation of CO_2 fertilization, crop pests, frost damage, plus further specification of changing crop genetics should add to overall robustness.

The supplementary material for this article can be found at http://www.journals.cambridge.org/AGS

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5. Cause and Consequence in Maize Planting Dates in Germany

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CHILLING/FREEZING STRESS

Cause and Consequence in Maize Planting Dates in Germany

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Abstract

An important part of agricultural adaptation is the timing of crop sowing dates, affecting yields and the level of risk incurred during a particular season. Cold stress is especially relevant in maize, *Zea mays* L., so that the timing of planting in the spring is a tactical response to short-term weather, but is also subject to strategic planning with regard to longer-term climate. Both factors compare the potential implications of cold stress to the additional yield obtainable through earlier planting. New cultivars suited to growing conditions in Europe and generally increasing spring temperatures have enabled earlier planting, but it is still dependent on short-term weather during the planting period. In the context of field-level decision-making, a panel regression is used to estimate the relationship between weekly local temperature and precipitation and planting dates at specific sites throughout Germany. Next, localised weather data and planting behaviour are linked to yields at the district (*Landkreis*) level to show the effects of planting date on yield. Based on these relationships optimal planting dates are explored with some associated costs and benefits. Results show a trend towards earlier planting that follows observed increasing spring temperatures and the availability of more cold-tolerant cultivars but this advance is buffered by the increasing severity of minimum temperatures during a critical period. Earlier planting potentially increases yield but this is offset by additional management costs and risk. A robust and simple depiction of farmer behaviour in climatic, technological and economic context can help to understand trends in crop management and productivity that effect agricultural landscapes.

Introduction

Strategic crop management entails the direct engagement of farmers with their environment. One of the most pliable decisions in this regard is when to plant a field, which especially with regard to the increasingly economically important German crop *Zea mays* L., is a weighed compromise between expected yield and risk. Earlier planting, in favourable conditions, leads to earlier development and better synchronisation of maximum leaf area, hence radiation interception, with the seasonal maximum of incident radiation (Stone et al. 1999). It also affords a longer growing season in which biomass can accumulate and the crop can mature (Darby & Lauer 2002). Concurrent with these benefits is an increased risk of damaging cold weather that is mitigated by both delayed planting, use of cold-hardy cultivars and other tactics (Farooq et al. 2008a,b,c). Earlier ripening cultivars, in the context of variable annual temperatures, mitigate late-season risk by increasing the odds of there being sufficient cumulative temperature for crop maturity before unfavourable fall weather. Planting later and using later-ripening cultivars increase the likelihood that the optimal growth period and, consequently, yield are not realised. An approach to reduce the risk of cold-weather stress is to delay planting and use fast-ripening cultivars, while the pursuit of maximum yield would mean planting late varieties as early as possible. Kucharik (2006) attributed the trend towards earlier maize planting more towards breeding and technological changes than to increasing spring temperatures. Kucharik (2008) also determined April temperatures and precipitation to be primary drivers of maize planting dates in the Central U.S. Further, planting date and August temperature were both significantly and inversely related to yield. Earlier planting increasing yield was also found by Fairey (1983), Staggenborg et al. (1998), Oluwaranti et al. (2008) and Kolo et al. (2012).

Modelling spring planting dates, especially in the context of climate change, have been well examined (e.g. Leenhardt and Lemaire 2002, Kaukoranta and Hakala 2008, Sacks and Kucharik 2011, White et al. 2011, Olesen et al. 2012, Van Oort et al. 2012, Waha et al. 2012, Aurbacher et al. 2013, Eitzinger et al. 2013). Studies to simulate regional or time series crop yields, as with crop growth models, have often held planting dates static over space and/or time to focus on model sensitivity to other inputs (Leclère et al. 2013, Bassu et al. 2014, Mast et al. 2014, Nendel et al. 2014). To reduce the uncertainty that is accentuated by omitting planting date dynamics in biophysical modelling, results from a planting date model (Sacks et al. 2010) can be used as input in yield simulation studies (Deryng et al. 2011). A model that can accurately estimate specific location-year planting dates can help account for climate-responsive farm management, the lack of which is a source of uncertainty in agroecosystem models. The benefit of calibrated planting dates must outweigh the cost, so that a simple method such as that presented here, which is based only on weather input, is advantageous. For this case study of Germany, the economic impact of planting date variability was examined by relating the spatiotemporal dynamics of maize planting to respective district yields with a simple statistical model of how management and weather influence regional yields.

The phenology of German agricultural species has been thoroughly examined in relation to climatic records (Chmielewski et al. 2004, Menzel et al. 2006a, Estrella et al. 2007, Ma et al. 2012, Siebert and Ewert 2012, Bock et al. 2013). And while these studies have done much to explain the relationships between weather and phenology, they are not designed as predictive models and have not been related to crop yields. Menzel et al. (2006b) raised the question of why farmers in Germany appear slow to respond to a clear shift in climate towards warmer conditions throughout the year. To answer this question it may be necessary to more thoroughly examine the relationship between site-specific annual planting dates and the respective local daily weather, together with some consideration of farmer strategy, as in Maton et al. (2007).

This study uses panel analysis of twenty recent years of planting dates as determined by local weather to suggest what is affecting farmers in their annual management decision-making and how this combines with seasonal weather to affect yields. Analysis is based on three datasets, daily weather conditions and annual crop phenology both from the German Weather Service (*Deutscher Wetterdienst*, DWD) and annual records of District (*Landkreis*) crop yields. Supplemental information including some background on breeding trends, further explains the existing agronomic context.

Geography

Germany ranges from about 47° to 55° N latitude and 6° to 11° E longitude, encompassing maritime lowlands in the North, Central uplands, the Rhein River basin in the Southwest and foothills and mountains in the South. Although a trend towards higher annual temperatures has been generally observed, a clear distinction is observable over the last decades wherein the southern part of the country has seen faster warming during the cold season while increasing mean temperatures in summer months have been more pronounced in northern areas, and further, rainfall during the same period has been generally increasing in the West and decreasing in the East (Hattermann et al. 2013). The country has been partitioned into 52 soil-climate zones (*Boden-Klima-Räume*, Roßberg et al. 2007) based on generalised homogeneity of soil properties and weather patterns. The zones in which observational data satisfying the selection criteria are available are included in the model as binary variables to capture geographic factors including soil, latitude, longitude and elevation.

Genetics

Although there is no consensus on the minimum temperature required for maize growth, Birch et al. (2003) concluded 8 °C, while Knappenberger and Knoller (2012) and Bonhomme (2000) maintain 10 °C. The latter explains that intraspecies variation appearing to contradict this can be attributed to photoperiod sensitivity, so that long-day genotypes are slowed in development during coincidentally lower temperatures. Subject to cultivar variation, generally, temperatures under 20 °C limit the ability of maize to reach its genotype-determined yield potential, temperatures under 5 °C result in injury that reduce yield potential and negative (Celsius) temperatures are lethal (Greaves 1996).

For several decades, European maize breeding has been crossing North American dent with European flint lines to produce new hybrids (Reif et al. 2005), so that German farmers have at their disposal a large variety of maize cultivars, among other traits differing in early vigour, (cold-resistance) and time to maturity, with which farmers can adjust cropping strategies according to local conditions. Increased early vigour facilitates earlier planting and thus an extended growing season at a given level of risk of cold-weather stress. The standard FAO maturity rating of maize relates moisture content in the harvested crop to accrued temperature over time and is therefore an estimate of the time required between planting and maturity, a critical factor for farmer's planning a season (Amler 2006). Relatively faster-ripening cultivars permit later sowing while maintaining the expected date of maturity in the fall (Strigens et al. 2012). This is another way to mitigate the risk of early season cold stress. To meet the needs of Germany's maize farmers the Federal Plant Variety Office (*Bundessortenamt*, BSA) had 96 maize cultivars registered in 1992, increasing to 200 by 2011. Figure 1 shows the trends within registered cultivars over the last thirty years first towards earlier, then later ripening (lower FAO maturity rating) and greater early vigour, (less cold-sensitive) as evaluated by the BSA (2010). Maton et al. (2007) show how planting date and maize earliness selection are both strategic decisions made by farmers. Farmer demand has to some degree driven these trends in commercial cultivars. Their availability has enabled adaptive field practices that reverberate throughout German agricultural landscapes. Cultivar selection and its link to planting date decisions have ecological and economic implications that can be traced through integrated farm modelling (Troost and Berger 2014). Demonstrated in the following is a method to model an important management decision and link it to yields in a simple model accounting for geographic heterogeneity throughout Germany.

Methods and Materials

The German Weather Service network of weather stations throughout the country includes climate stations that have daily records of temperature and rainfall dating as far back as 1781 (DWD 2013a). Parallel to weather observations, phenological records have been collected since 1951, including the annual onset of sowing/planting for several field crops (DWD 2013b). The local nature of both weather and phenology data results in incomplete time series when observational stations are decommissioned or moved, so that of the 1965 phenological observatories with some record of maize planting dates in the years 1993–2012, the number of stations with all 20 years was 435. Schaber et al. (2010) showed how to reconcile the 'messy' phenological records, but also, because of the considerable amount of data, time series can be filtered by strict standards to remove incomplete or erroneous series, while still maintaining sufficient spatial and temporal variability in the

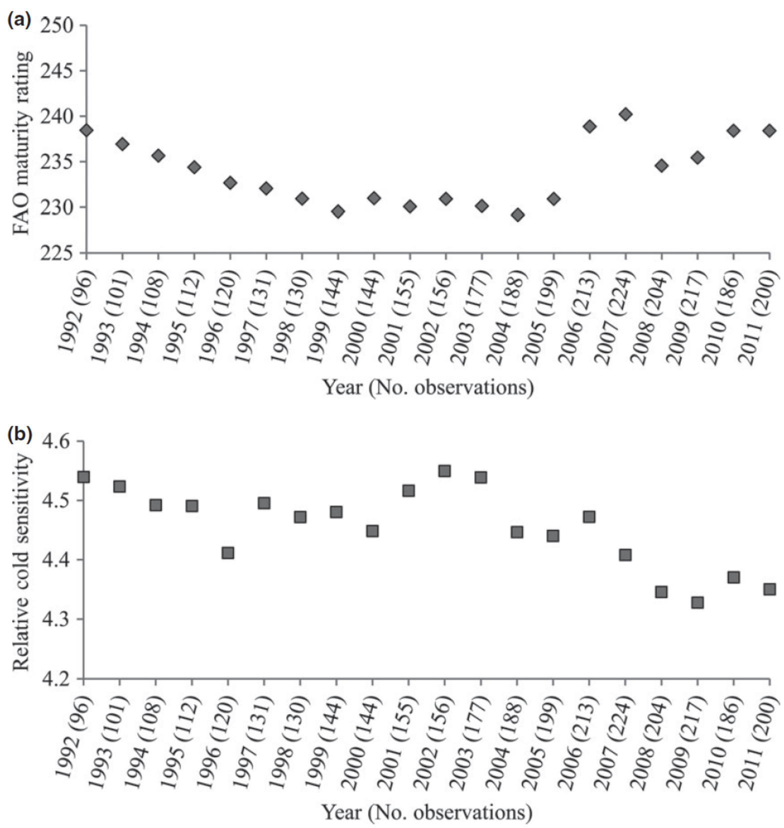

Fig. 1 Recent trends in maize breeding: (a) FAO maturity rating (relating moisture content to photothermal accumulation, roughly equivalent to days between planting and maturity) and (b) Index values for cold sensitivity (opposite of early vigour), year and number of observations along the *x*-axis.

Table 1 Maize planting day summary statistics by selected criteria

	All	1993–2002	2003–2012	≥250 m a.s.l.	<250 m a.s.l.	≥51°N	<51°N	≥8.5°E	<8.5°E
Mean	116.5	118.4	114.7	117.4	115.6	116.2	116.7	116.2	117.2
sta. dev.	7.80	7.18	7.97	8.29	7.12	7.08	8.23	7.3	9.13
Trend	−0.31	0.06	−0.29	−0.26	−0.34	−0.37	−0.26	−0.30	−0.32
P-value of trend	0.000	0.102	0.000	0.000	0.000	0.000	0.000	0.000	0.000

remaining dataset (see below). After looking for a causal relationship between weather and phenology, the two were used together to elucidate their influence on a third dataset, a time series of yields at district (*Kreis*) scale, (an administrative scale between municipality and county).

Maize phenology

To have a thorough geographic distribution of data, including records from the north-eastern states of the country, 1993 was selected as the start of time series data, including only stations with 20 years of uninterrupted observations of maize planting dates recorded as occurring before day 180, that is, before July. The time period 1993–2012 also coincides with the onset of a distinct climatic reference period (1991–2020) as defined by the World Meteorological Association (WMO 2013). With the above filters imposed, 432 stations containing 8640 data points for planting dates became the basis for analysis. Table 1 uses these data to show how planting occurred earlier in the more recent decade (2013–2012), at lower elevations and to the North and East. Variance increases recently, at higher elevations and to the South and West.

Figure 2 compares the distribution of planting dates between the two decades 1993–2012 and 2003–2012, including the broadening distribution and shift earlier during the recent decade, with a noticeable gap at day 121, the first of May holiday.

Weather

For the initial model, to explain maize planting dates with spring weather, explanatory records were chosen to be limited to weather stations without gaps in daily mean temperature, minimum temperature or precipitation measurements. Although winter weather directly affects planting via spring soil conditions (Van Oort et al. 2012), it was assumed that weather during March, April and May are primarily responsible for the date of maize planting in a respective year. Based on this, weather records for the relevant growing season were compiled, so that weather data were used only from stations without missing average or minimum temperature or precipitation between days 57 (Feb. 26th) and 294 (≈ Oct. 21st) throughout the years 1993–2012. This provided 160 stations throughout the country. These data series were partitioned into 42 one-week periods, for which the minimum and mean temperatures and precipitation were established as explanatory variables. The first model, explaining planting dates with weekly weather, uses the first 20 weeks and the second model, relating district yields to planting dates and weather, uses weeks 21–42.

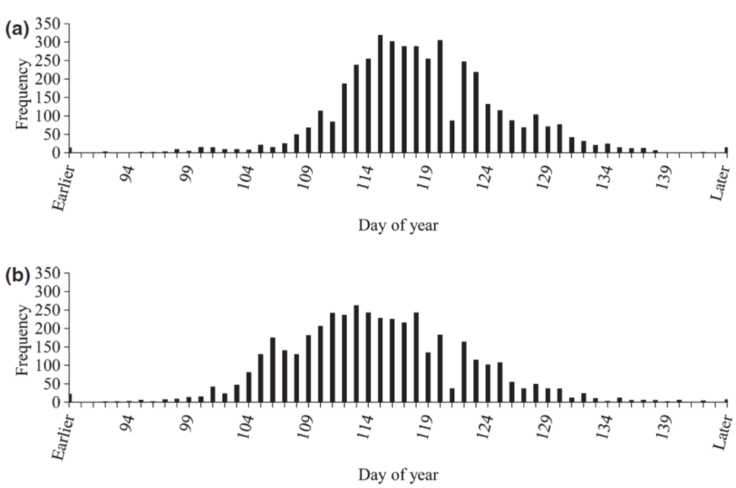

Fig. 2 Distribution of observed maize planting dates, by day of year, of a total of 4319 observations: (a) 1993–2002 and (b) 2003–2012. The significance of mean planting dates being earlier in the latter period is P = 0.15.

If the minimum ambient temperature for growth of maize is 10 °C, this threshold is reached on average, throughout the country in week 17, in the centre of the distribution of planting dates in Figure 2.

Phenology and weather stations were collated with ArcGIS based on Euclidian surface distance and difference in elevation. To account for the influence of elevation on temperature/phenology (Jochner et al. 2012), metres of elevation were weighted ten-to-one vs. kilometres of distance and in this way each phenology station was assigned a weather station to provide explanatory weekly precipitation and temperature data, with multiple phenology stations able to share one weather station. This and a consequent filter limiting distance and difference in elevation between phenology and weather stations (below) reduced the number of weather stations to 115. The final phenology and weather stations are shown in Figure 3.

Weather trends

Recent climate change in Europe has entailed a general warming as well as increased temperature variability, both of which are expected to continue in the future (Zebisch et al. 2005, Fischer and Schär 2009). The general warming trend masks one component of local weather that is relevant to maize cultivation, minimum spring temperatures. Kim et al. (2014) found fewer but more extreme frost days occurring in recent decades in the conterminous US. Similarly, observations from the final 115 weather stations confirm the warming trend but also indicate decreasing minimum temperatures during four consecutive weeks

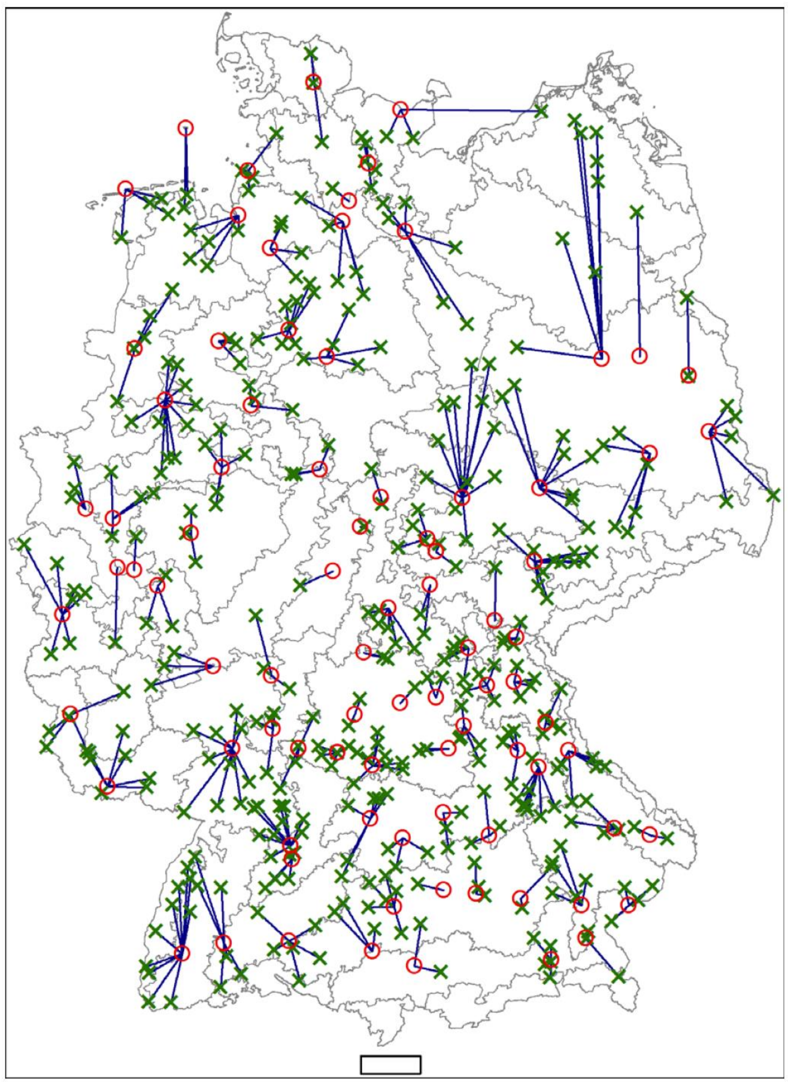

Fig. 3 Soil-climate zones (outlines), phenology (X) and weather (O) stations, with lines adjoining explanatory pairs. Bar at bottom represents 50 km. Source: Own Compilation based on Josberg et al. (2007), DWD (2013a,b).

(17–20) at the latter half of the planting period. In most of the 16 federal states, over the two recent decades, weekly minimum temperatures during weeks 17 and 20 decreased by around 1 °C every 10 years, at a minimum of 0.05 degrees of significance. In weeks 18 and 19, the decrease was observable but not as dramatic, and the combination of a large number of observations, small magnitudes of change and low levels of significance make any conclusive statement difficult. Table A1 has coefficients, by federal state, for minimum temperature changes during the period.

While the trend towards more extreme low temperatures during these weeks is only significant for some of the federal states, it shows a consistent decrease in minimum temperatures around the typical time for planting, a clear increase in one major source of abiotic stress for maize farmers throughout the country. This poses an increased risk of fatal or permanent damage to young maize stands. This abiotic risk alone would encourage a farmer to plant maize later in the year. In conjunction with risk-mitigating actions such as cultivar choice, the more extreme cold snaps may have only limited the progression of planting dates towards earlier in the year, as the general warming trend would provoke.

District yields

The German Federal Statistics Office compiles regional (*Länder*) records of crop yields at district (*Kreise*) scale. There are a combined 475 rural and urban districts covering between 36 and 5470 km^2 with a mean of 888 km^2 (DESTATIS 2014a). Records on silage maize fresh-matter yields are available for less than half of the districts in the country throughout the examined time period. Time series with yields greater than zero and no gaps are available from 1993 to 2012 for 164 districts (DESTATIS 2014b). This increases to 253 for the period 1994–2012 so the latter period was chosen to increase both geographic range and number of observations. Two separate districts contain questionable minima of 4.74 Mg ha^{-1} in 1996 and 8.64 Mg ha^{-1} in 2008, so the two districts were dropped, leaving a minimum of 17 Mg h^{-1}, recorded in both 2003 and 2006, 2 years of extreme weather. The lowest mean yield for the whole country was 40.6 Mg ha^{-1} in 2003, and the highest was 50 Mg ha^{-1} in 2011, which also had the highest yearly maximum at 72.4 Mg ha^{-1}. Some of this positive trend in yields can be attributed to farmer adaptation to the dynamic production risk posed by abiotic stresses. The general increase in temperatures together with successful breeding for improved early vigour has permitted earlier planting of maize, facilitating a longer growing season, and also the coordination of specific crop development phases to observed weather patterns, such as to achieve flowering before early summer drought (Hund et al. 2004).

Panel regression of planting dates

It was undertaken to model maize planting dates with weekly weather and binary indicators of soil-climate zone in which phenology stations are located. First, simple regressions were run to test which restrictions of distance and elevation difference produced the most accurate results with Akaike's (1974) information criterion, divided by the number of observations: $AIC/n = -2\ln L + 2k/n$ where lnL is the maximised log-likelihood of the model, k is the number of parameters estimated and n is the number of observations. This method determined that limiting the distance between weather and phenology stations to 77.5 surface km and 80 vertical m produced the best model version. This reduced the number of phenology stations to 374 and weather stations to 86, with a total of 7480 observations, which were then partitioned into panels by phenology station and, because of the recurring binary variables, run as a random effects panel regression, defined by STATA (2011) as: $y_{it} - \theta\bar{y}_i = (1-\theta)\alpha + (x_{it} - \theta\bar{x}_i)\beta + \{(1-\theta)\nu_i + (\epsilon_{it} - \theta\bar{\epsilon}_i)\}$ where y_{it} denotes the day of planting at the ith phenology station in year t, the x_{it} are conditioning variables for the ith station in year t, ν_i is a random error unique to the ith station with variance σ_y^2, and ε_{it} is a random error that varies over phenology stations and time with variance σ_ϵ^2. Temporal dependence within a phenology station is represented by the correlation coefficient $\rho = \sigma_\nu^2/(\sigma_\epsilon^2 + \sigma_\nu^2)$ such that the larger the parameter θ, the greater this correlation. This may be seen by considering the relationship $\theta = 1 - \sigma_\epsilon/(\sigma_\epsilon^2 + T_\rho(\sigma_\epsilon^2 + \sigma_y^2))^{1/2}$, where T is the number of temporal observations. Alternatively, as it is also the case that $\theta = 1 - \sigma_\epsilon/(\sigma_\epsilon^2 + T\sigma_\nu^2)^{1/2}$, where T is the number of temporal observations, a value of zero for θ implies that the variance of the phenology-specific random errors is zero and hence there is no temporal dependence within the cross-section. (For further explanation see for example Greene 2011).

The day of planting was thus regressed against year (after 1992), mean temperatures and precipitation during weeks 9 through 20 (as twk9-20 and pwk9-20, respectively) and all but one of the indicator variables for soil-climate zone (SCZ).

Panel regression of yields

A subset of the above phenology and associated weather records were related to district-level yields. Included districts with 19 years each produced a total of 2831, which were regressed against the mean planting date at stations within each district, along with the weekly mean and minimum temperatures and mean precipitation at stations allocated to these phenology stations, and the soil-climate zone (SCZ) encompassing each district. In a subsequent

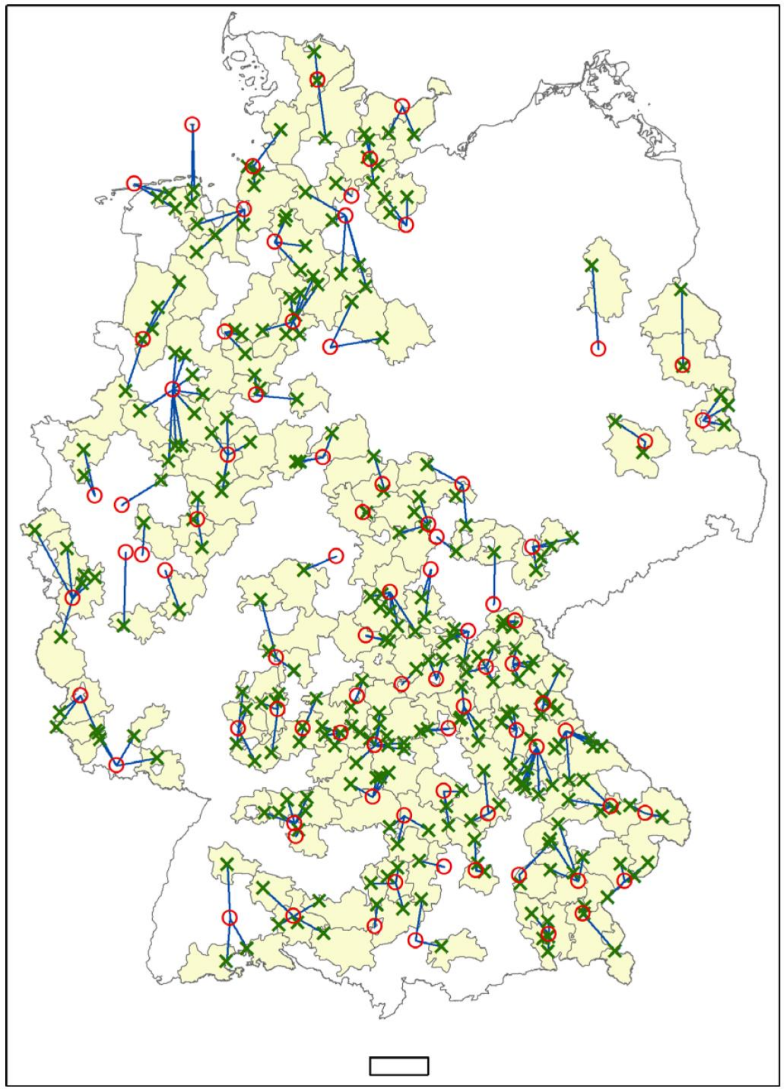

Fig. 4 Districts (outlined) and Phenology(X) and weather (O) stations used in yield model. Bar at bottom represents 50 km. Source: Own compilation based on Josberg et al. (2007), DWD (2013a,b).

regression, deviations of planting date from district means, and its square root, were used to derive a non-linear relationship between planting date and yield. While this model is not as robust, it allows theoretical optimisation. The districts, phenology and weather stations used are in Figure 4.

The indicator for SCZ199 was again omitted from the regression, while all others were retained.

Results

Planting dates

Using the 7480 observations, the planting date regression model achieved an overall R^2 of 0.28 and a RMSE of 5.36 days. Table A2 has the complete results from this regression, showing that weekly temperatures are mostly highly significant and have negative coefficients, indicating that higher temperatures encourage farmers to plant earlier. This could be a combination of more rapid drying of the soil to allow traffic and an indicator to farmers that maize can be planted with relatively low risk of cold damage. Precipitation during weeks 14 through 17, the middle of the normal planting period is significantly explanatory of the same year's planting date. Positive coefficients show how rain delays planting, partly due to the diminished ability of a wet soil to withstand field traffic.

District yields

Regression of the 2831 maize yield data against mean district planting date and weekly weather variables produced an R^2 of 0.62 and RMSE of 3.41 Mg ha^{-1}. An annual trend was indicated at 0.34 Mg ha^{-1} year^{-1}, but was not significant. Number of years after 1994 and its square (both highly significant) were substituted for it. Overall model accuracy was comparable before and after the substitution. This quadratic function of yield with respect to year produced modelled yields that slightly decrease from 1994 to 2002 and increasing yields thereafter. This may be tied to the increasing prevalence of earlier ripening cultivars in the first decade that reversed in the second (see Fig. 1a). The highly significant mean planting date indicated an increase of 46 kg ha^{-1} for every day earlier that the crop is planted. Table A3 has the complete results of the yield regression model. Where mean weekly temperatures are significant, coefficients alternate between being positive and negative. Mean weekly precipitation, where significant, is predominantly positive, as is the case with minimum weekly minimum temperatures, not surprisingly, as more rainfall and less extreme cold temperatures should be expected to boost yields.

Optimal planting dates

Crop growth simulation can be used to determine the optimal planting dates for maize (e.g. Saseendran et al. 2005) or a weather-based algorithm can be used (Elnesr et al. 2013). The above linear coefficient relating yield to planting date is valuable in its simplicity and should be accurate to within a few days of divergence from the norm. However, it is unreasonable to assume that the relationship continues more than a few days in either direction. In order to obtain theoretically optimal planting dates, the planting date variable was expanded into d and $d^{1/2}$, the first indicating how many days each year's district mean planting day preceded the 19-year mean, and another as its square root. Their significance was first tested individually by substituting each for mean planting date in the above regression while omitting the year variables. The coefficient and significance were, respectively, 0.051 Mg ha^{-1} and P = 0.051 for days prior and 0.21 Mg ha^{-1} and P = 0.007 for the root. Both variables were then included together in the same regression producing equivalent overall model accuracy and a function for Mg of yield, for all included districts, $y = -0.0827d + 0.4318d^{1/2} + c$ where d is days prior to the station mean and c is a constant encompassing all other variables. Yield maximised with respect to days prior is thus $D^* = (0.5 \times 0.4318/0.0827)^2$ or 6.82 days. The latter regression performed by federal state produced results ranging from 0.92 days earlier in Bavaria, to 16.91 days earlier in Baden-Württemberg. However, coefficients for d and $d^{1/2}$ were only significant for some states. This could indicate some of the technical inefficiency in the yield gap, or demonstrate how the model captures farmer behaviour better in a certain region.

Discussion

Estimating the nature of adaptive field crop management is an important theme in climate change impact studies. And while the expansive phenological dataset of the German weather service has proven to be a valuable tool in exploring the relationships between climate and vegetation (e.g. Schaber and Badeck 2005, Englert et al. 2008), less work has focused on the human influence on landscapes, as driven by weather. Crop management, especially planting dates, ultimately has a profound effect on landscape function by way of farmers seeking to increase yields and/or decrease yield uncertainty. Difficulty arises in the application of principles derived from site-specific interactions between weather, soil and management to the regional scale where geographic heterogeneity strains the plausibility of behavioural assumptions. To confidently estimate planting dates throughout a country the size of Germany, a balance must be found between geographic detail which is of limited availability, and aggregation to impose homogeneity.

Mirschel et al. (2014) with the YIELDSTAT model showed how a statistical model can offer advantages over process-based simulation models when seeking yield predictions at the regional scale. The model developed here uses less specific data, but it is available throughout Germany. Not to be compared with YIELDSTAT as a yield prediction model, the intention here was to demonstrate how farmers planting maize respond to early season weather, and how this affects eventual yields. Spring weather was shown to reliably determine planting dates that influence yields, while one could skip the determination of planting dates and use spring weather as direct drivers of yield. This would, however, omit an important mechanism by which Germany farmers may adapt to climate using the facilities, that is cultivars, at their disposal. Also, implications of planting dates such as land cover dynamics and field work requirements/availability are influenced directly by crop management independently of yield.

Germany-wide, planting 7 days earlier, according to the implied production function, would increase the per-hectare yield by 563 kg, or about one per cent of typical yield. At a price of 30 Euros per ton, this provides approximately 17 Euros of additional revenue per hectare but implies potential variable cost increases in fertiliser, depending on the combination of organic and mineral fertilisers, (e.g. additional nitrogen at the rate of 0.1 % of marginal yield or 5.63 kg ha^{-1}) and transportation, depending on silage delivery terms (KTBL 2012). Additionally, earlier planting leads to increased risk of damaging cold weather early in the growing season. Within the 7480 weekly weather observations throughout the country (section Panel regression of planting dates), the probability of a frost (min $T \leq 0$ °C) increases from 0.09 % during week 17 to

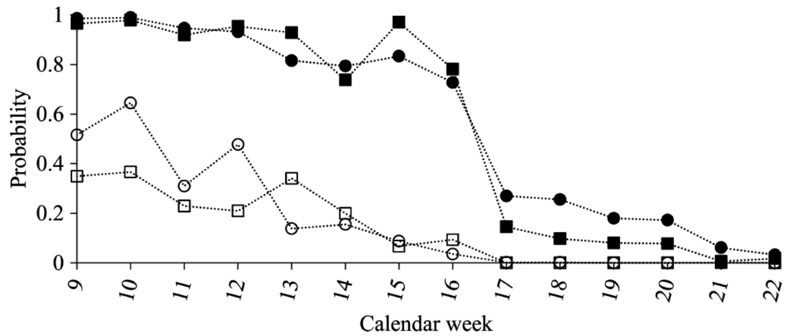

Fig. 5 Empirical probability of crop-stressful cold weather, during each week of the analysis, at two temperature thresholds and over two time periods. Solid symbols: P(minT) ≤ 5 °C; Hollow: P(minT) ≤ 0 °C; Circles: 1993–2002; Squares: 2003–2012.

6.47 % in week 16, respective probabilities that temperatures drop below 5 °C are 21 % and 75 %. Figure 5 shows the empirical probability of weekly minimum temperatures dropping below 5 °C (upper lines) and 0 °C (lower lines) by week and comparing decades.

The occurrence of lethal low temperatures may be damaging enough that replanting, at a cost of 200 Euros ha^{-1} (KTBL 2012), is worth the expense. This replanting cost can be combined with the increase probability of frost to partially quantify the risk inherent in a chosen planting date. For example, this additional cost, planting in week 16 instead of week 17, can be calculated as: 6.38 % × 200 = 12.76 Euro. Non-deadly but damaging low temperatures (<5 °C) can also be associated with a given level of yield loss and associated with a probability of occurrence to further assign a cost, via risk, in choosing a day to plant maize.

Observed and estimated planting dates are station-specific, but they could be used to represent the surrounding area. Yields at the district level, to some degree, are likewise applicable to neighbouring districts not included in the analysis. To obtain a statistical forecast of maize planting dates and yields in the future, simulated weather data could be used as model input, as in Schröder et al. (2014) for phenology and Ewert et al. (2005) for yields. This could provide a flexible alternative to more complicated and time-consuming methods of agent-based and crop simulation modelling such as in Aurbacher et al. (2013). Statistical models to forecast planting dates based on local weather could be the most efficient way to account for strategic management and adaptation in agroecosystem modelling, such as with process-based crop modelling where simulated yields are sensitive to planting dates (Parker et al. 2016). The same climatic data used for simulation can be quickly rendered into projections of planting dates and yields to respectively complement and accompany simulations of field crops throughout Germany, maize in this example. The use of region and location constants in the predictive model limit its applicability to Germany, an equivalent model outside the country would need a set of local observations and regional distinctions to capture geographic characteristics.

Conclusions

A simple statistical model has been developed to predict maize planting dates and yields throughout Germany. The models show that farmers planting maize earlier can expect greater yield, notwithstanding the increased probability of damaging cold weather. Crop management alters the effective environmental conditions determining plant growth, and genetic advance has enabled greater managerial flexibility. While it may appear that farmers are not adequately adapting to observable climate change, here is elucidated some of the sacrifice of expected yield/revenue in favour of reduced yield/cost uncertainty. Despite generally increasing spring temperatures in Germany, evidence suggests that the risk of cold stress is not abating from the climatic side, but breeding progress is alleviating some of this risk. Some of the upward trend in silage maize yields is traceable to the fact that farmers are planting the crop earlier, in response to the likelihood of cold stress and available management options.

The methods applied above could produce respective datasets and analysis on other major German field crops. Sufficient phenological (planting date) and district yield data are available to greater or lesser extent for winter wheat, rye, barley and rapeseed, and the summer crops sugar beets, oats and potatoes. Two different sets of weekly weather data, including late summer weather for planting and the rest of the year for yields, would be applicable to all fall-planted crops, while the other summer crops, planted earlier than maize, should include earlier spring weather records to estimate planting dates.

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Appendix A

Table A1 Trends in weekly minimum temperatures in degrees Celcius (°C) per year (yr) by Federal State 1993–2012, *t*-test P-values (P>|t|) of the regression coefficient of the linear trend, and number of observations (Obs.), a product of station-count in a state and the 20 years

		Week 17		Week 18		Week 19		Week 20	
State	Obs.	°C yr^{-1}	P>|t|	°C yr^{-1}	P>|t|	°C yr^{-1}	P>|t|	°C yr^{-1}	P>|t|
Brandenburg	140	−0.134	0.00	−0.027	0.45	−0.058	0.09	−0.141	0.00
Baden-Württemberg	360	−0.116	0.00	−0.104	0.00	−0.038	0.10	−0.130	0.00
Bavaria	700	−0.146	0.00	−0.073	0.00	−0.031	0.05	−0.216	0.00
Bremen	40	−0.081	0.13	0.012	0.82	−0.030	0.66	−0.058	0.36
Hessen	140	−0.118	0.00	−0.070	0.04	−0.051	0.15	−0.139	0.00
Hamburg	40	−0.136	0.01	−0.034	0.59	−0.075	0.21	−0.101	0.07
Mecklenburg-Vorpommern	40	−0.178	0.00	−0.075	0.27	−0.055	0.39	−0.139	0.02
Lower Saxony	160	−0.102	0.00	−0.017	0.58	−0.048	0.13	−0.079	0.01
North Rhine-Westphalia	200	−0.101	0.00	−0.039	0.14	−0.067	0.03	−0.117	0.00
Rhineland-Palatinate	60	−0.086	0.03	−0.057	0.17	−0.036	0.54	−0.128	0.01
Schleswig-Holstein	80	−0.071	0.02	−0.022	0.58	−0.049	0.23	−0.066	0.07
Saarland	20	−0.033	0.60	−0.082	0.25	0.000	1.00	−0.119	0.19
Saxony	100	−0.154	0.00	−0.027	0.46	−0.036	0.36	−0.142	0.00
Saxony-Anhalt	60	−0.150	0.00	−0.041	0.45	−0.029	0.55	−0.114	0.02
Thuringia	160	−0.130	0.00	−0.071	0.02	−0.018	0.54	−0.117	0.00

Source: DWD (2014a)

Table A2 Coefficients, standard errors and levels of significance for planting dates regressed against year, mean weekly temperatures (t) and precipitation (p) and soil-climate zone (SCZ)

Variable	Coef.	Std. err.	P>|z|	Variable	Coef.	Std. err.	P>|z|
Constant	118.163	3.260	0.000	SCZ113	7.349	3.142	0.019
year	−0.187	0.019	0.000	SCZ114	7.040	3.109	0.024
twk9	−0.146	0.029	0.000	SCZ115	4.456	3.190	0.162
twk10	−0.192	0.041	0.000	SCZ116	3.215	3.258	0.324
twk11	−0.178	0.048	0.000	SCZ117	6.577	3.371	0.051
twk12	−0.101	0.044	0.022	SCZ120	6.456	4.267	0.130
twk13	0.017	0.036	0.629	SCZ121	6.805	3.118	0.029
twk14	−0.174	0.038	0.000	SCZ122	7.794	3.376	0.021
twk15	−0.233	0.055	0.000	SCZ123	4.297	3.336	0.198
twk16	−0.513	0.048	0.000	SCZ127	12.681	3.306	0.000
twk17	−0.146	0.061	0.016	SCZ128	9.612	3.375	0.004
twk18	−0.013	0.046	0.785	SCZ129	7.394	3.900	0.058
twk19	0.140	0.038	0.000	SCZ130	8.000	3.895	0.040
twk20	−0.010	0.042	0.805	SCZ132	15.321	5.225	0.003
pwk9	0.087	0.045	0.054	SCZ133	10.918	4.267	0.011
pwk10	0.056	0.052	0.284	SCZ134	11.249	3.572	0.002
pwk11	0.071	0.043	0.095	SCZ141	3.894	3.696	0.292
pwk12	0.057	0.039	0.141	SCZ142	5.993	3.338	0.073
pwk13	0.063	0.050	0.208	SCZ143	10.877	3.423	0.001
pwk14	0.184	0.055	0.001	SCZ145	10.017	3.697	0.007
pwk15	0.309	0.044	0.000	SCZ146	8.567	3.183	0.007
pwk16	0.445	0.047	0.000	SCZ147	8.075	3.423	0.018
pwk17	0.362	0.053	0.000	SCZ148	6.854	3.375	0.042
pwk18	0.042	0.044	0.338	SCZ150	11.252	3.490	0.001
pwk19	0.018	0.032	0.578	SCZ151	7.729	3.574	0.031
pwk20	0.055	0.041	0.184	SCZ152	11.786	3.382	0.000
SCZ101	7.266	3.490	0.037	SCZ153	5.951	3.342	0.075
SCZ102	8.221	3.898	0.035	SCZ154	6.957	3.701	0.060
SCZ104	7.530	3.229	0.020	SCZ156	3.111	5.231	0.552
SCZ106	9.992	5.226	0.056	SCZ157	6.061	5.231	0.247
SCZ107	4.448	3.244	0.170	SCZ158	8.946	5.229	0.087
SCZ108	6.131	3.184	0.054	SCZ192	9.122	5.226	0.081
SCZ109	10.615	3.898	0.006	SCZ193	8.711	5.227	0.096
SCZ111	7.280	3.183	0.022	SCZ196	10.341	3.698	0.005
SCZ112	7.658	3.185	0.016	SCZ198	6.884	3.569	0.054

Table A3 Coefficients, standard errors and levels of significance for district yields, in Mg ha^{-1}, regressed against mean district planting date (day_year), year (after 1994), its square (ysq), weekly temperature (avgt) and weekly precipitation (avgp); the minimum weekly minimum temperature (minmin) of each district and the soil-climate zone (SCZ) in which it is located

Variable	Coef.	Std. err.	P>|z|	Variable	Coef.	Std. err.	P>|z|
Constant	52.173	4.801	0.000	minminwk27	0.339	0.129	0.009
day_year	−0.046	0.015	0.002	minminwk28	0.118	0.139	0.395
year	−0.367	0.143	0.010	minminwk29	0.095	0.117	0.417
ysq	0.022	0.007	0.003	minminwk30	0.068	0.127	0.591
avgtwk21	0.276	0.084	0.001	minminwk31	−0.006	0.118	0.960
avgtwk22	0.081	0.102	0.428	minminwk32	0.367	0.105	0.000
avgtwk23	0.124	0.109	0.253	minminwk33	−0.023	0.134	0.863
avgtwk24	0.227	0.122	0.064	minminwk34	−0.169	0.123	0.167
avgtwk25	−0.197	0.112	0.078	minminwk35	0.084	0.129	0.516
avgtwk26	−0.090	0.138	0.512	minminwk36	0.071	0.102	0.488
avgtwk27	−0.006	0.136	0.965	minminwk37	0.203	0.107	0.057
avgtwk28	−0.557	0.119	0.000	minminwk38	0.172	0.101	0.089
avgtwk29	0.221	0.140	0.115	minminwk39	0.120	0.119	0.313
avgtwk30	−0.433	0.132	0.001	minminwk40	0.032	0.118	0.787
avgtwk31	−0.124	0.129	0.338	minminwk41	−0.263	0.115	0.022
avgtwk32	−0.446	0.119	0.000	minminwk42	−0.048	0.123	0.696
avgtwk33	0.206	0.143	0.151	SCZ_102	−16.485	3.528	0.000
avgtwk34	0.117	0.130	0.367	SCZ_104	−16.306	2.887	0.000
avgtwk35	0.090	0.156	0.566	SCZ_106	−12.832	3.519	0.000
avgtwk36	0.465	0.122	0.000	SCZ_107	−3.044	2.802	0.277
avgtwk37	−0.296	0.127	0.020	SCZ_108	−1.473	3.065	0.631
avgtwk38	−0.589	0.142	0.000	SCZ_111	−3.954	2.671	0.139
avgtwk39	−0.165	0.135	0.222	SCZ_112	0.429	2.670	0.872
avgtwk40	0.209	0.147	0.154	SCZ_113	−0.078	2.603	0.976
avgtwk41	0.408	0.153	0.008	SCZ_114	1.326	2.579	0.607
avgtwk42	−0.039	0.161	0.809	SCZ_115	1.469	2.609	0.573
avgpwk21	−0.030	0.047	0.523	SCZ_116	1.896	2.761	0.492
avgpwk22	−0.065	0.043	0.126	SCZ_117	1.387	2.664	0.603
avgpwk23	−0.025	0.038	0.518	SCZ_120	−1.051	3.533	0.766
avgpwk24	0.063	0.045	0.160	SCZ_121	−0.232	2.692	0.931
avgpwk25	0.047	0.045	0.296	SCZ_122	−2.464	2.880	0.392
avgpwk26	−0.022	0.043	0.609	SCZ_123	−2.546	3.036	0.402
avgpwk27	0.201	0.036	0.000	SCZ_127	−2.708	2.749	0.324
avgpwk28	0.069	0.040	0.084	SCZ_128	−1.729	3.066	0.573
avgpwk29	0.078	0.035	0.025	SCZ_129	−2.299	3.580	0.521
avgpwk30	−0.065	0.043	0.132	SCZ_130	0.922	3.507	0.793
avgpwk31	0.126	0.044	0.004	SCZ_132	4.219	3.527	0.232
avgpwk32	0.016	0.032	0.620	SCZ_133	2.518	3.057	0.410
avgpwk33	0.095	0.047	0.041	SCZ_134	−6.177	2.807	0.028
avgpwk34	−0.053	0.035	0.128	SCZ_141	−1.202	2.877	0.676
avgpwk35	−0.045	0.040	0.263	SCZ_142	0.767	2.792	0.784
avgpwk36	0.043	0.046	0.347	SCZ_143	−1.658	2.891	0.566
avgpwk37	−0.026	0.041	0.527	SCZ_145	1.050	2.903	0.718
avgpwk38	−0.009	0.051	0.857	SCZ_146	−2.662	2.674	0.319
avgpwk39	0.066	0.049	0.179	SCZ_147	−1.416	3.064	0.644
avgpwk40	0.221	0.043	0.000	SCZ_148	−3.876	2.806	0.167
avgpwk41	0.091	0.062	0.143	SCZ_150	−6.127	2.884	0.034
avgpwk42	−0.153	0.073	0.036	SCZ_151	−4.314	3.571	0.227
minminwk21	0.006	0.015	0.688	SCZ_152	−4.269	3.073	0.165
minminwk22	−0.031	0.111	0.781	SCZ_153	−12.478	2.777	0.000
minminwk23	−0.094	0.116	0.417	SCZ_154	−12.200	2.922	0.000
minminwk24	−0.280	0.113	0.013	SCZ_156	−13.202	3.558	0.000
minminwk25	0.313	0.120	0.009	SCZ_192	−3.093	3.534	0.381
minminwk26	−0.131	0.113	0.246	SCZ_198	−0.523	3.043	0.864

6. Discussion

The FARMACTOR model framework to integrate an agent-based agricultural management model with a crop growth simulation model builds upon historic work examining how farm decision-making exists in concert with ecological processes. Previous work in this area includes that by Berger (2001), Gömann *et al*. (2005), Audsley *et al*. (2006), Busch (2006), Flichman *et al*., 2006, Van Ittersum *et al*., (2008), Verburg *et al*. (2009) and Van Ittersum (2009). Driven by a different research focus, or limited model complexity, these earlier studies are conducted at coarser spatial and/or temporal resolution. The focus is either at the regional scale, necessarily ignoring the heterogeneity within a region, or aggregated temporal scale, likewise omitting the effects of daily environmental conditions. None of these studies are able to address in sufficient detail the complex reaction of an individual farmer with the environment. They may, however, include more comprehensive consideration of socio-economic factors, such as multi-agent interactions (Berger, 2001) factors of competing demand regarding agricultural lands (Gömann *et al*., 2005; Busch, 2006), and input constraints such as labor (Flichman *et al.* 2006; Van Ittersum *et al*., 2008). What FARMACTOR, as coupled with EXPERT-N offers is a dynamic relationship between management and crop performance, a complete feedback loop at the field scale, where modifications to either model affect the combined performance of the coupled modeling system. Variation in the simulated timing of field management is a model-endogenous process based on integrated simulation of plant-atmosphere-soil interactions, rather than being solely dependent on model inputs such as weather time series and site characteristics. This dynamic feedback is an important component to the plausibility of adaptation scenarios, and also allows the creation of scenarios based on the preferences of the economic agents represented by FARMACTOR, and the parameters, such as genetics, underlying EXPERT-N biophysical simulation. Another clear advantage to the FARMACTOR integrated model framework is the ability to extract a range of agroecological outcomes, such as nitrogen leaching, on a daily basis, which can be directly linked to agent parameters and/or scenario-based field management.

With respect to the scale of the above studies, at this stage in its development/usage FarmActor can be seen as a precursory simulation tool, able to deliver detailed projections pertaining to field management and crop performance to such such studies, whose analysis is more land-use or policy-oriented, with macroeconomic implications. Either those models should be expanded to account for the detail in FarmActor, or the latter could be expanded to perform the broader-scale functions.

6.1. Methodology

Results from FARMACTOR and the panel statistics model are both encouraging in terms of their accuracy in replicating historic data and their plausibility in projecting future developments on agricultural landscapes. In general, prediction of planting dates is much easier for spring-sown crops, due to their greater dependence on environmental factors rather than other farm management activities, for instance, through crop rotations that effect phenological observations but are not revealed in the data, the harvest of a crop preceding overwintering crops is influential on the date of its planting. This effects winter wheat, winter barley and winter rapeseed planting dates, important input for the crop growth simulation model. Attesting to the accuracy of the EXPERT-N crop model is the fact that harvest dates are relatively well-simulated. Results corroborate findings by Bondeau *et al*. (2007), Waha *et al*. (2012) and Olesen *et al*. (2012), that predict a trend toward earlier maturity in the future. Maize harvest date is also dependent on cultivar choice, and the phenological data used for validation does not take into account the differences in maturity of different cultivars.

While the statistical model is based on observed district-level yields and therefore is able to accurately reproduce them, the FARMACTOR/EXPERT-N coupled models were calibrated to experimental fields. The average of district yields by definition leads to smoothing of spatial variation in the time series, so that simulated results fluctuate much more, and as the district average includes much less productive fields, overall values are depressed. This leads to an inherent discrepancy between observed district yield statistics used for validation and simulated yields. One solution is to validate the model to state field trials, where growing conditions and management are similar to the conditions used for model calibration.

Use of a genetic algorithm to optimize the chosen triggers was a methodological approach to exploring the domain of possible trigger combinations[3]. A major limitation was the computational time required, which increases with the number of years simulated, in which comparisons are made between predicted and observed planting dates, driving the iterative adjustment of triggers, and further by the number of triggers to be optimized and the number of permutations tested for each trigger. It was found that after 10 iterations, each with 16 trigger permutations, (more variations of the most influential triggers compounded with fewer variations of less influential ones), the most effective triggers (aggregate temperature and soil moisture), varied within a relatively narrow range, while the triggers to which model accuracy is less sensitive varied within a broader range. Considering conventional use of genetic algorithms, 10 iterations is a relatively low number, this can be justified however, by how quickly the parameters

[3] An alternative was explored to fill a database with simulated daily soil moisture levels and learning-defined planting window start dates, which were combined with daily weather measurements (available for aggregation). This reduced the time required to test trigger settings against observations from around 30 minutes to a few seconds, and produced comparable results, but was not an automated procedure, nor deemed scientifically robust enough for publication and thus abandoned.

being optimized converged, so that further iterations would bring very little benefit in terms of model accuracy.

One significant accomplishment in this work, included in Parker *et al.* (2016a) was dynamic simulation of breeding progress through time. The significance of this methodology is immense, as it transformed simulations of declining future yield trends into an outlook with increasing yields. An increase in the number of grains per head, as reported in Ahlemeyer & Friedt (2012), is a quantified and major cause of the trend in increasing grain yields over recent decades. This trend, at approximately 1.7 grains per head, per year, is arguably an essential component of simulation into the future. Simulating dynamic genetics in maize, however, did not refer to breeding progress, but rather to adaptation on the part of farmers, to choose already-existing, later-ripening cultivars (as a result of greater photothermal accumulation requirements) as ambient temperatures increase, historically and in projected future weather. Breeding progress in the remaining simulated crop, rapeseed, is not as clearly defined as for cereals and maize, so that a dynamic genetic parameter (initial leaf nitrogen content) was selected based on simulated yield sensitivity, in a pragmatic, if less realistic, way to mimic breeding progress. While in the course of this dissertation it has been possible to develop a mechanism to account for breeding progress, there are other components of technological change that can be expected to bolster yields in the future (Bindi *et al*., 2011). One still missing element in the coupled models as they have been applied for this work is that EXPERT-N is not yet capable of dynamically simulating atmospheric CO_2 concentration, which with grain and oil crops the “C3 pathway” increased CO_2 increase yields (Högy *et al*., 2010), (Ko *et al*., 2010). Models that do incorporate CO_2 fertilization effects in simulation demonstrate the significance of the ambient atmospheric level of the gas. Challinor & Wheeler (2009) summarized the results of an ensemble study of crop model response to variable CO_2 to show that within the ensemble, yield increases attributed to CO_2 were between 0 and 73%. This effect, as with dynamic genetic parameters to account for breeding progress, has major implications when simulating future scenarios. The results published in this dissertation could thus be interpreted as pessimistic, because rising atmospheric CO_2 should increase projected future yields. This increase would favor cereals and oil crops with respect to maize and other C4 crops not included in this work. While the scope of this work did not go so far as to include the dynamic crop rotation based on simulated yields that is part of FARMACTOR’s facilities, CO_2 fertilization could be expected to play a significant role in this mechanism.

6.2. Empirical findings

Using FARMACTOR has many advantages over the panel statistics model, the latter only advantageous in terms of the simplicity with which it can generate planting dates and yields. The statistical model is further dependent on the existence of comprehensive data throughout the country and has so far only been applied to silage maize. Figure 1 demonstrates how both FarmActor and the panel regression model are able to predict historic planting dates in response to historic weather records at nearby stations. This demonstration is an important component in validating both models before being used to predict future planting dates based on simulated future weather, as one way to represent adaptation to anticipated climate change. The graphics reflect the correlation between observed day of planting and simulated (statistic) day of planting in (a)) the Alb to be 0.25 (0.41), respectively and (b)) the Kraichgau to be 0.62 (0.74), respectively. The positive correlation affirms the benefit of using a dynamic planting day model to capture farmer response to annual weather and edaphic conditions, for more robust agricultural simulation. The linear form of the data in Figure 1 for observed planting day d, in year y is: $d = 0.1146 \cdot \mathrm{y} + 118.86$ for the Alb, compared to $d = -0.3635 \cdot \mathrm{y} + 124.37$ with dynamic simulation and $d = -0.2923 \cdot \mathrm{y} + 119.43$ with panel statistics. While the general error, or model bias, of within a week is reassuring, the annual change in both models being of opposite sign than observed trend raises the question of "over-adaptation" by both models, however, the fact that the Schwäbische Alb is geographically exceptional (and hence part of the study) is reiterated by the greater accuracy in reproducing trends in the Kraichgau. This is a more typical Central European landscape that is following the trend in Germany toward earlier planting, which is predicted to continue by Bondeau et al. (2007) and Olesen et al. (2012). In observed planting dates the trend was $d = -0.2766 \cdot \mathrm{y} + 114.29$ while with simulation it was $d = -0.3024 \cdot \mathrm{y} + 112.26$ and with panel statistics it was $d = -0.2168 \cdot \mathrm{y} + 114.13$, the two models straddling observations.

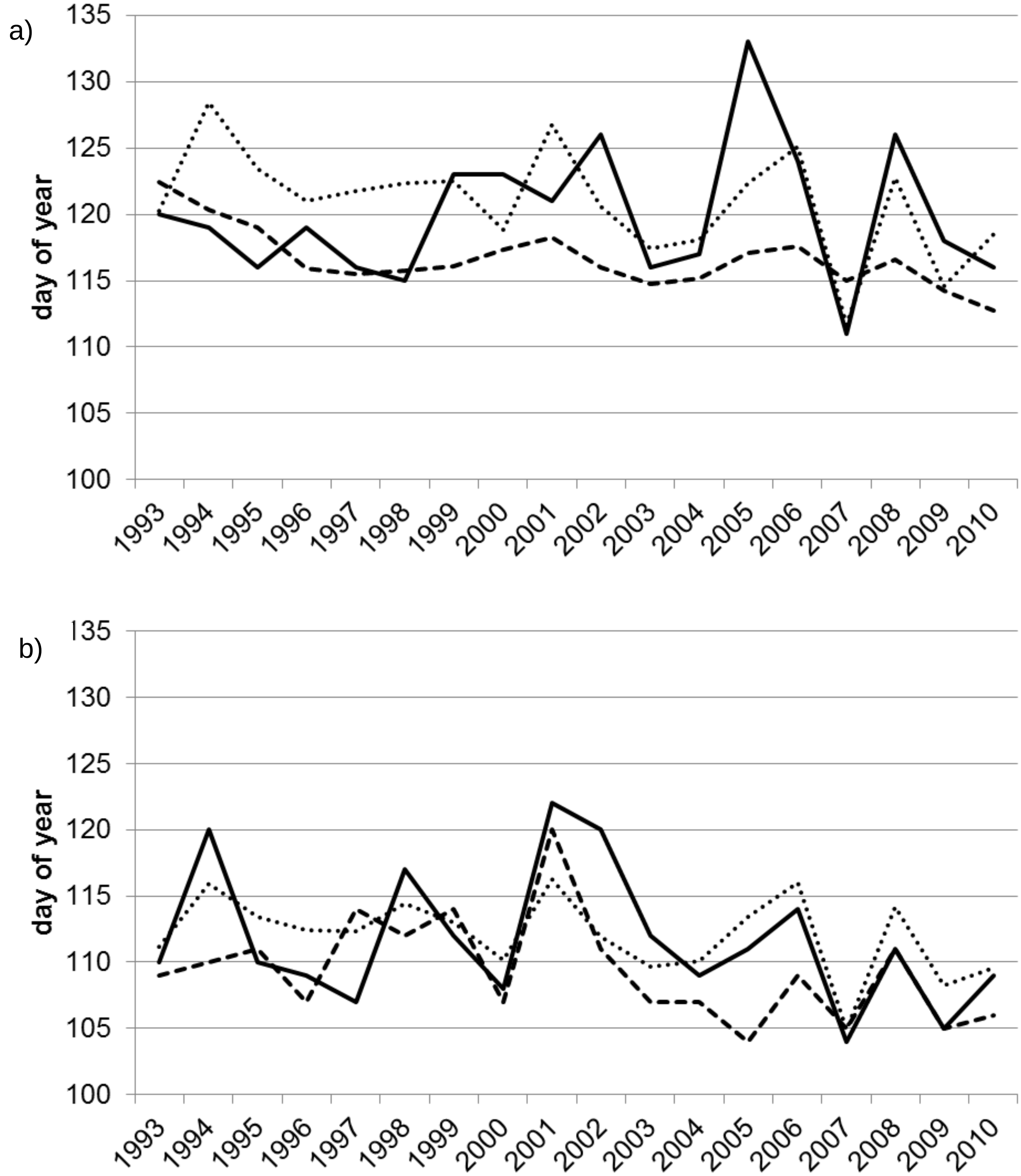
That learning paradigms (the way in which historic, e.g. over a ten-year period, temperatures determine the start of a planting period, and thus the entire planting window), only roughly influence the simulated planting date, their optimal values were considerably variable. As long as they enabled simulated planting to be as earlier as the earliest observations, the importance of their optimal values was subordinate to the triggers considering only the field conditions during individual years.

Among these, the most important, that is, the one to which the accuracy of simulated planting dates is the most sensitive, is an aggregated measurement of temperatures over several days. In the statistical model, weekly average temperatures were used, and in FarmActor, a 4-day period was found to be the most accurate predictor of observed planting dates. For spring planting this is a minimum temperature, meant to represent the consideration by farmers of recent temperatures, in determining if temperatures in the immediate future will be conducive to crop growth. In fall planting a maximum temperature is utilized, delaying planting to a point where temperature sums until the end of the year are appropriate for crop development. One question arising in calibration is if the triggers actually represent farmer decision making, or are only an artifact of the relationship between weather and the timing of field management actions.

Following aggregated temperatures, soil moisture was the most influential trigger in terms of predicting planting dates. This trigger concept, that farmers will wait for soil moisture levels to be a predictable amount less than field capacity, adheres to agronomic principles (avoiding soil compaction and smearing etc.), is less vulnerable to the question of weather/action correlation mentioned above. In the panel statistics model, weekly precipitation sums were conceived as a proxy for soil moisture, so that between weekly temperatures and precipitation, the statistical model was able to replicate the most influential triggers utilized in FARMACTOR.

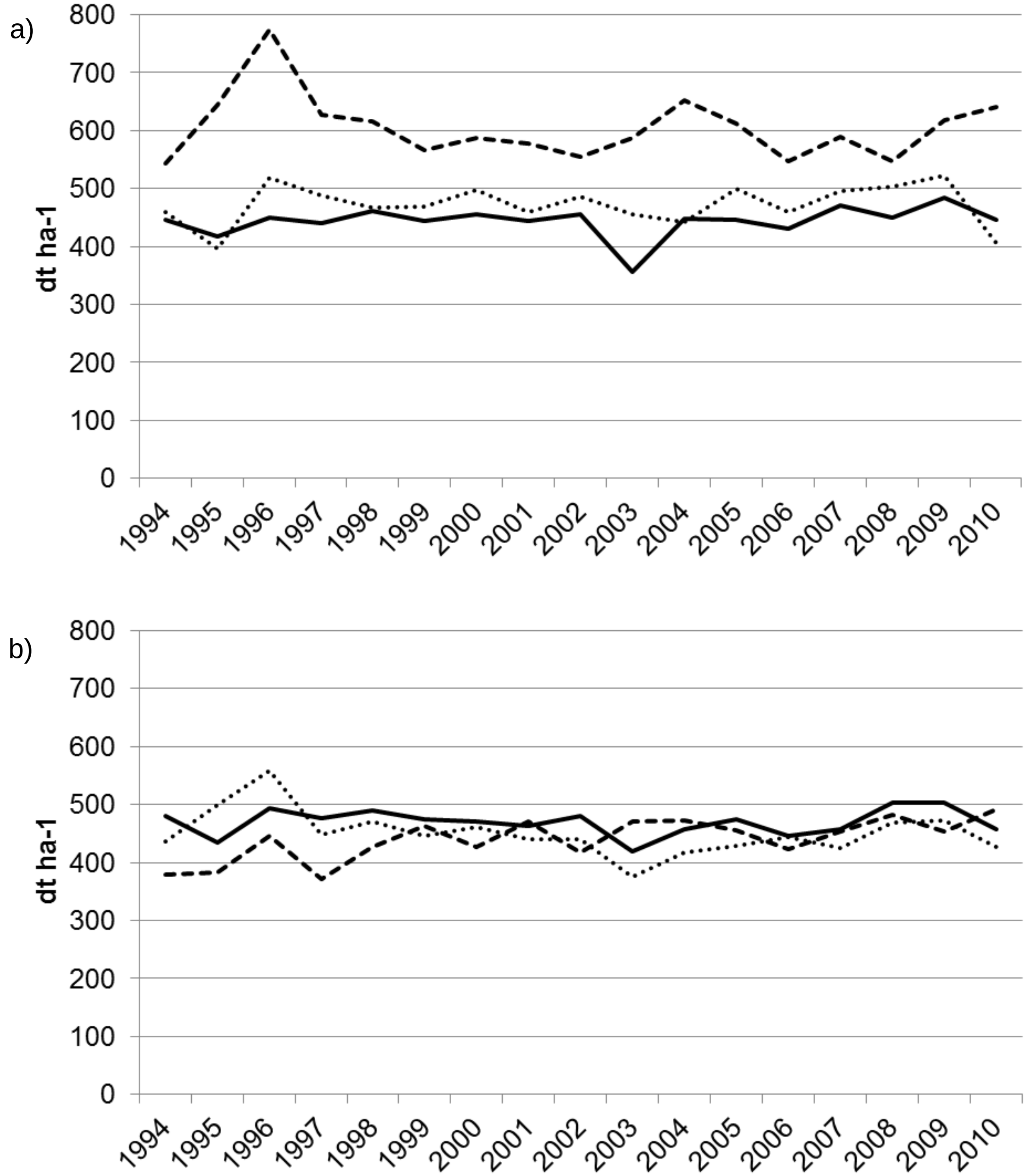
After short-term temperature aggregates and soil moisture constraints, the efficacy of triggers in predicting planting dates falls off sharply. The daily temperature trigger, again a minimum in spring and maximum in fall, together with daily precipitation alternated between third and fourth-most influential in improving the accuracy of site-specific planting dates. While their contribution to model accuracy was small, both were maintained in model applications. Daily soil temperature, originally included as a trigger, was dropped from the criteria after it showed to have negligible ability to improve the accuracy of simulated to observed planting dates.

Figure 1. FARMACTOR simulated maize planting dates (dashed lines), compared to observed planting dates (solid lines, [DWD 2016]) and panel-regression predictions (dotted lines), for a) Nellingen in the Schwäbische Alb and b) Oberderdingen in the Kraichgau.



Source: Own representation of data from Parker *et al*, (2016a) and Parker *et al*. (2016b)

Figure 2. Simulated maize yields (dashed lines), compared to observed district yields (solid lines [DESTATIS, 2014]) and panel-regression predictions (dotted lines), for a) Alb Donau Kreis (Biberach, adjoining district in statistical model) in the Schwäbische Alb and b) Karlsruhe Landkreis (Rhein Neckar Kreis, adjacent district in statistical model) in the Kraichgau.



Source: Own representation of data from Parker et *al.*, (2016a) and Parker *et al*. (2016b)

In a master's thesis supervised by the author and used for a conference paper titled: "The resilience of different cultivars of winter cereals wheat, barley and rye to climate change in Central Europe - a localized regional simulation study " (Parker *et al*., 2015b Conference Paper), dynamic weather and soil mapping was used as in the *Schwäbische Alb* study, and interacted with a cadre of winter wheat, barley and rye cultivars, to project the influence of climate change on gross margin variance throughout agricultural landscapes in the *Wetterau* district in the federal state of Hesse.

In Parker *et al*. (2015a), the current author calibrated and ran FARMACTOR/EXPERT-N to mimic the experimental fields in the *Schwäbische Alb* and the *Kraichgau* into the coming decades. The statistics-based weather generation was used and a roughly similar method was developed to forecast price scenarios. Agricultural commodity prices received in Germany served as the population, from which the actual price fluctuations in recent years were randomly resampled into future years, while also being driven by an underlying geometric trend calculated from the historic data, resulting in increasing prices with the same volatility as recently experienced. Multiple generations of price scenarios were each allocated a weather generation, assigned a scenario and then aggregated for a single projected measurable, a gross margin for each crop each year. With this, the study is able to provide a spatially explicit, albeit temporally vague prediction of crop performance based on adaptive management, at around a certain time in the future. Results of the study emphasize the multiplicity of risks to agricultural enterprise under anticipated climate change. Both volatile weather and markets can counteract the best farm management practices. Mitigating risk is a subject of planning and must be informed. This work seeks to improve on defining and simulating the interactions within agro-economic/ecological systems to ultimately explore paths toward resilience. The likely consequences of proposed adaptation scenarios can be traced from differentiation within the framework of the coupled models to the simulated field workflow and eventual outputs. If this linking of global economics to local ecology can produce reasonable forecasts, it will support private and public sector efforts to promote more climate-smart agriculture. The author's results indicate that if current demographic and climate trends continue, Germany should maintain or gain relevance in terms of world supply of staple nutrition, and this could become noticeable on agricultural landscapes throughout the country. Such modelling activity to trace and quantify productivity will add to the discussion of how conflicting land-use options will chase a fleeting equilibrium.

Ongoing effort to exploit the accomplishments of this work could take many directions. In the broader perspective of the regional climate change project the bioeconomic model FARMACTOR could be dynamically linked to a weather simulation model that would use model output such as land use or vegetative cover changes as input, closing the loop of field-atmosphere interaction. As a link between the environment and human activity FARMACTOR can provide recursive dynamic adaptation that forces changes in the environment. The model can be run to test hypothetical future combinations of political and economic scenarios, to see how a dynamic agricultural landscape model can predict future pathways of civil-natural interface. the potential shift away from customary crop rotations.

In the effort to reproduce the decision-making process that is at the foundation of farm management, there are some areas where FARMACTOR could see some improvement. Criteria for the harvest of crops were not as rigorously calibrated as those for planting. And while a proxy for grain moisture content was incorporated, in the form of recent temperature and precipitation, a more specific calculation could better account for this important economic decision that, through drying costs, is largely responsible for the timing of harvest. As such management actions are linked to the work flow of the entire farm enterprise, increased accuracy in predicting the timing of harvest would reverberate throughout the simulation process.

Further, this dissertation did not go so far as to define parameters for crop fertilization, another crucial aspect of field management alongside planting and harvest. Considering the increasing concerns with nitrogen runoff and ongoing developments in farm input efficiency (e.g. precision agriculture), accurately simulating fertilizer applications should be an important field of further research, one for which the FARMACTOR framework is well-suited.

Unlike planting and harvest, observational records for the timing of fertilizer applications are not comprehensive at the regional scale. State field trials do provide data that could be used for model calibration, but the lack of data available for validation would be a hurdle to model application.

From the perspective of model uncertainty, there are several areas in which the coupled FARMACTOR and EXPERT-N models could be made more complementary. Frost damage and pest prevalence are completely missing, when there are ways to incorporate them that would bring dividends in model accuracy. FARMACTOR is a field-action model that could be slightly modified to create events that change the trajectory of a growing season. Incorporating frost kill could be as simple as assuming a percentage of plants per hectare dead, and reducing yield by that portion. Additionally, in maize especially, a non-lethal occurrence of cold stress could trigger a modification in genotype, as a set of EXPERT-N parameters that determines plant growth for the rest of the simulated season. Pest infestation is more complicated at the plant physiological scale, so as to test the ability of the two models to exchange information. A reduction in leaf area, for example due to insect predation or disease infestation, may be best kept EXPERT-N internal. The dynamic crop rotation capacity of FARMACTOR was never fully utilized in the course of this dissertation, but it has potential to equate a well-calibrated crop model to major changes in field management, namely,

7. Summary

The work performed in the course of this dissertation has been to define a systematic agricultural management response to environmental and economic conditions that is functional under hypothetical scenarios, especially involving climatic forecasts into the future. This was done through the use of the FarmActor/Expert-N coupled modelling framework that links agent-based management parameters with crop growth simulation, as the two are strongly interconnected. Starting with the completed FarmActor framework that had yet to be thoroughly tested, this work involved the verification of the modelling procedure, population of appropriate data resources for calibration and application, and the presentation of simulation experiments in peer-reviewed publication. The innovative linkage of agent-based management with biophysical simulation has led to FarmActor becoming a reference for international research on integrated economic/ecological study, impacting the scientific community through its unique contribution to analysis of anthropogenic landscape systems.

FarmActor, as adapted in the course of this dissertation, has presented concepts that add to the robustness with which agroecosystem simulation is conducted on field and regional scale. Breaking away from the convention of static management input into crop models is an important step in this regard. Especially under scenarios of future climate change, dynamic field management lends to the plausibility of projected crop performance. If simulation modelling is to be an important tool in efforts to mitigate and/or adapt to climate change, elements such as dynamic management may be indispensable components of modelling frameworks. The impact of management has too great of an influence on agroecosystem functioning to be ignored.

The effort in the course of this dissertation to systematically account for the likewise crucial factor of subspecies genetic variation is also an early example of improving agroecosystem simulation. As of the commencement of this work, agricultural species were, for the most part, simulated as just that, a species, when the variance of growth process within a species is a fundamental component of agronomy. Cultivar choice is one of the most important tools available to agricultural practitioners in terms of regional/localized agriculture. At least the simulation of multiple cultivars, or agricultural subspecies, is necessary to capture the heterogeneous responses to identical environmental conditions. This work has presented a sound methodology to account for breeding progress, based on observed trends in crop phenotypes, while also demonstrating a methodology for comparing results of the regional simulation of multiple cultivars.

Spatial or temporal adaptation to climate is mandatory in terms of agricultural-sector profitability and food security, from local to global scales. Simulation modelling could eventually prove to be a useful tool in predicting the suitability of different crops or cultivars for unique biomes, whether in terms of agricultural intensification, producing

more on a fixed land area, or expanding production into new areas. Simulation will most likely prove be an effective alternative to resource-intensive field trials, at the very least the two are complementary. This dissertation has, in part, demonstrated the potential for utilizing field experiments, to varying degrees of specificity, through model parameter optimization procedures, to produce local and regional projections of crop performance and adaptive measures likely to be undertaken by farmers.

A statistical model developed alongside, and sharing the principals of environmental planting triggers incorporated in the agent-based model, was used to define a predictive model for maize planting dates throughout Germany. The two models achieved comparable accuracy, while differing in their advantages and drawbacks. The statistical model is not associated with a complete set of economic and biophysical attributes that can both be drivers of the bioeconomic model and informative outputs. Its advantage lies in its simplicity in regional applicability, able to predict (or project, if using future simulated weather), planting dates throughout the whole of Germany. The yield component of the statistical model demonstrates that the date of planting is a stronger driver of yields than the weather during the weeks that influence planting dates. Because maize is planted in spring, on bare fields, as opposed to wheat and other fall crops planted following the harvest of a previous crop, the statistical model is not as effective in predicting fall planting dates as FARMACTOR which can accurately simulate the harvest date of a crop preceding fall sowing. Furthermore, the bioeconomic model, by simulating all relevant processes on a given field, has the capacity to accurately predict the timing of all actions in a given season, as well as produce a myriad of output variables that can be equated with the ecological and economic performance of a farm system.

By utilizing both statistical and process-based models to predict and project management actions and crop performance on German cropland, this dissertation has added to the body of work on agricultural adaptation to climate. Its methods and results should provide helpful reference for further research, and also generate confidence in the use of modelling as part of the toolkit for technology transfer to agricultural practitioners. Thanks in part to this work FARMACTOR should be considered a useful computational tool to help with practical advice and policy development relevant to agricultural landscapes.

8. Zusammenfassung

Der Klimawandel stellt ein dauerhaftes Herausforderung für die Agrarwirtschaft dar. Das steigende wissenschaftliche Interesse an landwirtschaftlicher Produktivität unter veränderten Umweltbedingungen ist zielführend für diese Arbeit. Die Modellierung umwelt- und ökonomiebedingter Anpassungen landwirtschaftlicher Feldarbeiten ist eine Methode um dieser Fragestellung zu begegnen. Diese Modellierung kann unter hypothetischen Szenarien und insbesondere für Prognosen zukünftiger Klimaauswirkungen genutzt werden. Hierzu wurde das gekoppelte Modellsystem Farmactor/Expert-N verwendet, das die beiden interagierenden Bereiche des agentebasierten Managements und das Pflanzenwachstum miteinander verbindet. Beginnend mit dem FARMACTOR Modell, beinhaltet diese Dissertation eine Überprüfung der Modellfunktion, die Diskussion geeigneter Datenressourcen für die Kalibrierung und Anwendung, sowie die Präsentation der Ergebnisse von Simulationsexperimenten. Letztere wurden in peer-review Publikationen veröffentlicht. Durch die innovative Verbindung von agentenbasierten Management-Parametern und biophysikalischer Simulation ist FARMACTOR zu einer internationalen Referenz in der Forschung von integrierten ökonomischen / ökologischen Studien geworden und findet Berücksichtigung im wissenschaftlichen Diskurs zur Analyse anthropogener Landschaftssysteme.

Die Anwendung von FARMACTOR im Rahmen dieser Arbeit trägt wesentlich zur Erhöhung der Plausibilität von Agroökosystemsimulationen auf dem Feld und auf regionaler Ebene bei. Die Abwendung von der Annahme des statischen Managements in Modellierungssystemen ist dabei ein wichtiger Schritt. Gerade unter Szenarien zukünftiger Klimaänderungen steigt die Plausibilität der projizierten Erntemengen und anderer simulierter Leistungen durch die Annahme dynamischer Managementmethoden. Bei dem Einsatz der Simulationsmodellierung zur Anpassung an den Klimawandel sind Elemente wie das dynamische Feldmanagement daher unverzichtbare Komponenten von Modellierungssystemen.

Einen weiteren Beitrag zur Verbesserung der agrarökologischen Simulation leistet diese Arbeit durch die Berücksichtigung des Faktors der genetischen Variation. In bisherigen wissenschaftlichen Publikationen wurden landwirtschaftliche Pflanzenarten zum größten Teil nur als eine Spezies simuliert, obwohl die Varianz des Wachstumsprozesses innerhalb einer Spezies eine grundlegende Komponente der Agronomie darstellt. Die Sortenwahl ist eines der wichtigsten Instrumente der Landwirte zur regionalen/lokalen Anpassung an veränderte Umweltbedingungen. Diese Arbeit hat eine fundierte Methodik vorgestellt, um den Züchtungsfortschritt in das Modellsystem einzufügen. Dies erfolgte auf Grund der beobachteten Trends in Pflanzenphänotypen. Weiterhin wurde eine Vorgehensweise entwickelt, um die Ergebnisse der regionalen Simulation mehrerer Sorten zu vergleichen.

Räumliche und zeitliche Anpassung an das Klima sind notwendig in Bezug auf die Rentabilität des landwirtschaftlichen Sektors und für den Erhalt der Ernährungssicherheit auf lokaler sowie globaler Ebene. Simulationen können in der Vorhersage der Eignung verschiedener Managementverfahren, Kulturen und Sorten ein nützliches Werkzeug sein, ob im Hinblick auf die Intensivierung der Landwirtschaft - mehr auf bestehender Fläche zu produzieren - oder im Hinblick auf die Erschließung neuer Anbaugebiete. Der Einsatz von Simulationen kann eine wirksame Alternative zu ressourcenintensiven Feldversuchen darstellen oder zumindest komplementär zu diesen eingesetzt zu werden. Diese Dissertation hat das Potenzial der Verwendung von Feldversuchsdaten in Modellparameteroptimierungsverfahren aufgezeigt, um lokale und regionale Projektionen der Ernteleistung und Anpassungsmaßnahmen zu erstellen.

Zeitgleich wurde ein statistisches Modell entwickelt, um eine Vorhersage für Maisaussattermine in Deutschland zu erstellen. Die beiden in der Arbeit verwendeten Modelle erreichen eine vergleichbare Genauigkeit, während sie sich in ihren Vor- und Nachteilen unterscheiden. Das statistische Modell ist nicht mit einem kompletten Satz von wirtschaftlichen und biophysikalischen Eigenschaften ausgestattet, die sowohl Input als auch Output des bioökonomischen Modells sein können. Der Vorteil des statistischen Modells liegt in seiner Einfachheit und in der regionalen Anwendbarkeit, Aussaattermine vorherzusagen (oder zu projizieren). Die Ertragskomponente des statistischen Modells zeigt unter anderem, dass der Aussaattermin ein stärkerer Treiber für Erträge ist, als das Wetter während der Wochen, die die Aussaattermine beeinflussen. Mais und andere Sommerkulturen werden hauptsächlich auf kahlem Boden ausgesät, im Vergleich zu Winterkulturen wie Weizen, dessen Aussaat stark von der Vorkultur abhängig ist. Daher ist das statistische Modell hier nicht vergleichbar effektiv. Das bioökonomische Modell hingegen hat den Vorteil, mit Einbeziehung von Fruchtfolge und zuverlässiger Simulation von Ernteterminen, die Herbstaussaat zuverlässiger zu treffen. Weiterhin bietet FARMACTOR die Möglichkeit, alle Feldverfahren und deren zugehörigen ökologische und ökonomische Auswirkungen in den Modellausgaben zu berücksichtigen.

Diese Dissertation hat mit der Einführung beider Modelle einen Beitrag zur Erforschung der landwirtschaftlichen Klimaanpassung geleistet, indem Feldverfahren und damit einhergehende Leistungen zuverlässiger projiziert werden können. Methoden und Resultate sollten hilfreiche Referenzen für weitere Forschung liefern und ebenso das Vertrauen zur Nutzung von Systemmodellen als Teil des landwirtschaftlichen Wissenstransfers steigern. Mit Hilfe dieser Arbeit sollte FARMACTOR in der praktischen Beratung sowie der Politikentwicklung im landwirtschaftlichen Sektor Berücksichtigung finden.

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Eidesstattliche Erklärung

Ich erkläre: Ich habe die vorgelegte Dissertation selbständig und ohne unerlaubte fremde Hilfe und nur mit den Hilfen angefertigt, die ich in der Dissertation angegeben habe. Alle Textstellen, die wörtlich oder sinngemäß aus veröffentlichten Schriften entnommen sind und alle Angaben, die auf mündlichen Auskünften beruhen, sind als solche kenntlich gemacht.

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