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Land use management under climate change: a microeconomic analysis with emphasis on risk

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3 List of abbreviations, acronyms, and initialisms

DFG	German Research Foundation
IPCC	Intergovernmental Panel on Climate Change
DWD	German Meteorological Service
APSIM	Agricultural Production Systems sIMulator
wta	willingness-to-accept
ARS	Annual Risk Score
Expert-N	Crop Estimation through Resource and Environment Synthesis - crop model
py	peak yield
avy	average yield
sgy	still-good-yield

4 Introduction

This dissertation was conducted under a grant from the German Research Foundation (DFG) in the research group FOR 1695 - “Agricultural Landscapes under Global Climate Change – Processes and Feedbacks on a Regional Scale”. For a better understanding of the specific questions raised in this dissertation, the general goals and approach of the research group are explained first.

The Intergovernmental Panel on Climate Change (IPCC) defines climate change as “[…] *a change in the state of the climate that can be identified […] by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer*” (IPCC, 2013). In its Fifth Assessment Report, the IPCC states that climate change is expected to amplify existing climatic risks (IPCC, 2014). Changes in the biophysical processes affecting crop production have been found to be largely caused by a changing climate (Högy et al., 2013 (a); Högy et al., 2013 (b)), which represents a challenge for farmers’ crop management and decisions regarding the optimal allocation of land (Crane et al., 2011).

Agricultural landscapes are not only affected by but also contribute to the processes that drive changes in climatic conditions (Foley et al., 2005). The objective of FOR 1695 is to provide a better understanding of how agricultural landscapes evolve over time due to the influence of climatic change. The research group hypothesizes that this objective can only be reached by a combination of integrated modeling and advanced process understanding. To achieve this goal, the research group is developing a complex simulation model at high spatial and temporal resolutions that is capable of capturing complex interactions between the land, atmosphere and human environment (www.klimawandel.uni-hohenheim.de).

Climate change can be investigated at different spatial resolutions. The empirical work conducted by different parts of the research group focuses on two study regions in southwest Germany in the state of Baden-Wuerttemberg, the Swabian Alb and the Kraichgau region. These are regions with distinct climatic conditions and different intensities of agricultural land use (Aurbacher et al., 2013). Evidence for ongoing climate change on a regional scale can be found in the time series data from the German Meteorological Service (DWD) (Jänecke et al., 2016), which supports the research group’s use of a very high spatial resolution for their analyses.

One unique characteristic of the research group is that its research interest is not only to investigate the impacts of climate change on land use but is also to incorporate the manner in which potential feedback processes that are caused by agricultural land use may act on a global scale (www.klimawandel.uni-hohenheim.de). As a consequence, this means that any methodology developed within the scope of the research group must have the potential to incorporate feedback processes.

To achieve the group’s goal, the project was subdivided into nine sub-projects, each with a specific research focus that was intended to contribute to the overall modeling effort. In this sense, the research group is interdisciplinary. This dissertation stems from the “Microeconomic analysis of land use management under climate change with emphasis on risk and learning” sub-project. The goal of this sub-project was to explore, extend and strengthen the scientific basis for assessing farmers’ strategies and decision-making behavior under the influence of climate change. This dissertation examines risk in the context of land use management.

4.1 Climatic influence in agricultural planning decisions

Climatic influence is ubiquitous in crop production and can provide opportunities and challenges for farmers’ management. In this project, the goal is to identify how much influence perceived climatic changes have on farmers’ strategic reactions, particularly land use planning decisions in crop production.

In economic models, the planning of crop schedules is based on gross margin analysis (Hardaker et al., 2004). This methodology operates under the assumption that only the information about the variability of production outcomes in the gross margin equation is sufficient for adaptation analysis.

It has been found that available models either under- or overestimate farmers’ actual adaptation behavior, as has been criticized by many authors (Ortiz-Bobea, 2013; White et al., 2011; Just and Peterson, 2003; Just and Pope, 2003; McCown et al., 1991). The climatic effect has even been found to be overpowered by market or policy influences in strategic planning decisions (Lehmann et al., 2013; Henseler et al., 2009). This may be due to market and policy influences having unambiguous impacts and consequences for production in the form of prices, rules, and regulations imposed on the farmers as opposed to the climatic influence. Climatic influence is relatively difficult to separate from other influences, such as policy or market effects, when using the available methodological approaches.

Both Menapace et al. (2015) and Wheeler et al. (2013) found that a belief in an increase of climate-induced (production) risks in the future is not sufficient to trigger a change in farmer behavior on its own.

Whether farmers react to an expected increase in climatic risks depends on whether they consider those risks to be relevant to the production at their specific location (Hirschauer and Mußhoff, 2012; Hardaker et al., 2004). The most obvious sources for information about the influence of climate are farmers’ own perceptions made when rating and monitoring crop development throughout the season.

Li et al. (2017) found that connecting the drivers of planning decisions to their consequences, which is the actual behavior following the planning, is key to better understanding farmer’s decision-making process. This supports our approach.

We hypothesize that one reason for the bad model fit lies in not considering what occurred during production at the point of planning, as this may paint a different picture of the relevance of a certain yield levels. Crop yield is only a single point at the end of a long series of observations by the farmer regarding the climate's influence on a crop (Reinmuth et al., 2017).

4.2 Research objectives

Integrated bioeconomic simulation models, such as the FarmActor model (Aurbacher et al., 2013), provide an opportunity to assess how the evaluation of the production process could be integrated in economic risk analyses by using a method that is representative of real-world scenarios (Berger and Troost, 2014; Schreinemachers and Berger, 2011), as the decision-making component of the model is highly resolved to daily time-steps. FarmActor's dynamic nature would even allow for the inclusion of feedback processes from the production process in the economic decision component (Antle et al., 2016) and vice versa. This trait, however, is left for future research.

The overall hypothesis of this dissertation is as follows:

Incorporating risk perceptions from monitoring growth processes, from an economic point of view, into planning decisions will increase the understanding of how climatic changes drive farmers' adaptation of their land use decisions and thus increase the validity of the FarmActor model.

The specific objectives of this dissertation are as follows:

1. To investigate whether farmers are aware of changes in the climatic conditions at their location and to confirm the statistical evidence of changes in average values of climatic variables.
2. To determine farmers' subjective attitudes towards climate-induced variability in crop production. Perceptions about the riskiness of the climatic influence on the production process are subjective and process specific. Each perception during the process is also an economic evaluation of the eventual monetary value of the yield. Individual farmers' attitudes towards the climate's influence on the process should be gathered in order to identify different risk types, and these attitudes should be crop specific, as land allocation is by crop in the FarmActor model.
3. To develop a methodological approach that allows the integration of intertemporal perception processes in the planning decision.
4. To test the methodological approach to be developed using the bioeconomic simulation model FarmActor (Aurbacher et al., 2013). In other words, a mechanism must be developed that can be incorporated into the simulation model in order to represent the theoretical approach.

4.3 The empirical model/measuring subjective risk

The determination of risk profiles, which assesses how much risk a farmer is willing to accept, is an important factor when evaluating different risk strategies (Hirschauer and Mußhoff, 2012). A risk strategy in this context is a possible crop allocation scenario based on the riskiness of crops and given certain constraints, such as crop rotation to name one (Hardaker et al., 2004).

The results of the empirical work are to be implemented in the FarmActor model. As FarmActor is dynamic and highly resolved to the field level, risk analysis in this context must answer the question of how the allocation of a crop to a single field is influenced over time (Aurbacher et al., 2013). This is a resolution that is not covered by most of the available simulation models when investigating decision-making under risk. FarmActor is one of only a small number of models that operates on this resolution. The APSIM model (Keating et al., 2003) can also operate at this resolution, but it lacks a risk component that can be customized for our purposes.

Willingness-to-accept.

In pre-tests, farmers stated that their work needs to be worth the effort, which was an important criterion when evaluating the suitability of crops for their management plan.

The economic valuation of the production process and its ability to trigger adaptation processes both depend on farmers' "willingness-to-accept" (wta) outcome fluctuations (Hardaker et al., 2004). However, during the growth process, various biophysical states at the same development stage can finalize at the same yield level. Furthermore, many levels of the observed biophysical state can still finalize at a yield level associated with economic profitability. Additionally, many yield levels can lead to the same gross-margin outcome.

Following Antle (2010) and Just and Peterson (2003), this dissertation uses thresholds that approximate farmers' lower boundaries of acceptable yield variability while still generating a profitable production outcome from an economic point of view. This value is represented by the "still-good-yield" (sgy) and was derived empirically throughout both study regions (Reinmuth et al., 2017).

4.4 Coupling intertemporal perceptions with planning decisions

In the simulation model, the yield threshold "still-good-yield" was then embedded in a mechanism that scales the states of development during production by assigning utility values to observational parameters at sequential observation points for a given crop. This mechanism aggregates into a utility score that represents a downside risk measure based on evaluations of embedded risks. It is denoted as the Annual Risk Score (ARS) (Reinmuth et al., 2017).

Downside risk focuses on the point where decision makers perceive a loss (Sortino and van der Meer, 1991). The ARS score indicates how often a potentially risky development was perceived that might indicate a loss or non-profitability. Continuously high ARS scores over time indicate a negative climatic influence, meaning that over many points during the production process, the crop responded in a way that might indicate a loss in yield based on farmer's willingness-to-accept fluctuations. Because the sgy threshold triggers the ARS, farmers risk attitude is already included in this measure, which assesses the climatic impact.

An evaluation of the growth process at different points during crop production corresponds to what farmers do in the real world (Antle, 2010). This is the most obvious source for perceptions about how crops respond to climatic influences.

In the FarmActor model, observations occur either when an activity is taking place or at a defined temporal distance to an activity, which ensures that observations always occur at the same point during the process to make observation results comparable (Reinmuth et al., 2017). This is possible because one trigger condition for each production activity tests for the achievement of a predefined phenological development stage of the crop (BBCH stage (JKI, 2001)) (Aurbacher et al., 2013). Comparability is important when calculating the risk scores over time.

The utility score $\alpha_{t,c}$ is used to represent perceived risk in the simulation model; t stands for an observation point, and c is a crop. The utility score for an observation point can have several (crop-specific) observation parameters i with $i \in (1,\ldots,n)$.

The utility score $\alpha_{t,\mathrm{i},\mathrm{c}} = 0$ if the perceived value ($pv_{c,i}$) for an observation parameter i at an OP (t) lies within the predefined acceptable range (AC): $AC_{l,i,t,c} \leq pv_{i,t,c} \leq AC_{u,\mathrm{i},\mathrm{t},\mathrm{c}}$, with $AC_{l,c,i,t}$ and $AC_{u,c,i,t}$ being the lower (l) and upper boundaries (u), respectively, of the acceptable range for a certain parameter (i) and crop (c) at an OP (t).

A score of 1 represents perceived risk for a certain parameter and crop at an OP. The perceived value thus falls outside the predefined acceptable ranges $pv_{i,t,c} < AC_{l,\mathrm{i},\mathrm{t},\mathrm{c}}$ or $pv_{i,t,c} > AC_{u,\mathrm{i},\mathrm{t},\mathrm{c}}$. This means that the parameter is either smaller than the lower boundary of the acceptable range or higher than the upper boundary of the acceptable range (Reinmuth et al., 2017).

The intertemporal utility score at an OP is given by:

$\alpha_{t,c} = \sum_{i=1}^{n} \alpha_{i,c}$ for all t and c.

All the assessed utility values after the harvest add up to $\alpha_{T,c}$, which is the total utility score of a production year's conditions for crop c "*as the result of the intermediate rankings*" (Reinmuth et al., 2017, p. 6) of the ARS score. This can be written as:

$ARS = \alpha_{T,\mathrm{c}} = \sum_{t=1}^{m} \alpha_{t,c}$ with $T \in (1,\ldots,m)$ for all observation points during the growing season (Reinmuth et al., 2017).

With this utility score, the climatic influence can be separated from the economic or market influences in planning crop portfolios. It should be noted that market and political influences can also evidently influence the ARS score by changing the yield threshold representing profitability; however, the threshold “still-good-yield” is the lower boundary of the acceptable yield fluctuations and thus already includes various economic influences over the past. How fast the threshold changes is left for future research.

4.5 Technical challenges in bioeconomic modeling

The basic idea behind FarmActor is the dynamic representation of a linear planning model (Aurbacher et al., 2013). Linearity is broken up by explicitly modeling many processes that otherwise would be parameterized. The economic decision model component is coupled to the crop growth model Expert-N (Priesack et al., 2006). Growth processes are modeled with many parameters describing plant components using an endogenous mechanism (Aurbacher et al., 2013). The results of this process are documented in daily time-steps as development proceeds. Climatic influence is represented by daily weather data, which are stored in a relational database. The database also contains all parameters that are used to either trigger the decision-making process or calculate the outcomes of the management routine. However, there are also input parameters that come from within the programming code, which are so-called hard coded settings. The advantage provided by the FarmActor model’s highly resolved decision-making context that allows a high resolution of decision-making process data is at the same time technically challenging.

The methodology to be developed could not be fully tested. Ongoing technical problems and troubleshooting led to a strong theoretical focus of this work.

White et al. (2011) reviewed over 300 articles that described the application or development of a simulation model to be used for the analysis of a research problem. They concluded that almost none of these articles had sufficient documentation for the methodological aspects or input parameters of simulation models that contributed to the research outcome. Such missing information is most likely the result of very complex model mechanisms that are not sufficiently documented for users of a given model. Model developers and model users are usually not the same people (Dillon et al., 1991). In addition, those who develop such models are often non-IT trained persons who do not have the time to provide a good user experience in scientific simulation models (Reinmuth and Dabbert, 2017). It is apparent that what hindered the progress in this dissertation is the rule/reality for many such projects rather than the exception. On the downside, and as a consequence, many modeling efforts vanish after being used to answer a specific research question (van Ittersum et al., 2008; Janssen and van Ittersum, 2007).

Supported by the findings of White et al. (2011) and the papers of Nicolson et al. (2002), Keating and McCown (2001), and Dillon et al. (1991), we decided to use our experience and difficulties with the simulation model to provide lessons learned for all future modelers in an integrative review (Reinmuth and Dabbert, 2017). The last part of this dissertation is thus an effort to elaborate on the software engineering process when developing an integrated bioeconomic simulation model for research purposes. We suspect that many aspects that we cover in the last article of this dissertation (Reinmuth and Dabbert, 2017) are reasons for the infrequent re-use of research modeling.

Though we pursued this issue with a strong technical focus, our recommendations are for scientists in the field who are non-IT trained, which applies to the majority of developers, and who intend to contribute to developing, redesigning, innovating and applying simulation models. As such models are working versions of a future modeling software package, we provide the reader with critical issues to consider and resolve for their situation to help make such an endeavor more efficient for everyone involved. Furthermore, we encourage all future modelers to contribute to this list and test our recommendations. The goal is to promote an easier re-use of model designs (Reinmuth and Dabbert, 2017).

4.6 Organization of the thesis

The thesis is written as a cumulative dissertation and is composed of five articles. Articles one, three, four and five have been published by peer-reviewed journals. The second has been published as a peer-reviewed conference proceeding. The fourth manuscript was resubmitted after major revisions at the point of submission of the thesis. It was accepted shortly after submission without conditions and was published in PLOS ONE journal in August, 2017. Chapters 5-9 represent one publication each.

How farmers' risk perceptions due to climatic influence affect their land use decisions is the main research interest that we attempt to answer with the newly developed approach presented in the fourth article (Reinmuth et al., 2017). Articles two and three are preliminary analyses (Parker et al., 2015, Jänecke et al., 2016). The first and the last articles address the integrated bioeconomic simulation model, which is the technical framework that is used to investigate farmers' land use decisions (Aurbacher et al., 2013, Reinmuth and Dabbert, 2017).

The first article, by **Joachim Aurbacher, Phillip S. Parker, German A. Calberto Sánchez, Jennifer Steinbach, Evelyn Reinmuth, Joachim Ingwersen, and Stephan Dabbert,** is called **"Influence of climate change on short term management of field crops – A modeling approach"** and introduces the integrated bioeconomic simulation model and a first application of its functionality. The methodological contribution of this dissertation was the introduction of flexible time windows that trigger decision processes. This is the foundation for incorporating feedback processes into the modeling of production processes. The article is published in *Agricultural Systems* 119, pp.44-57 (2013). "FarmActor is intended to improve the land-use side of coupled land-atmosphere models and derive sophisticated adaptation strategies" (Aurbacher et al., 2013, p. 45).

The second article, by **Phillip S. Parker, Evelyn Reinmuth, Joachim Ingwersen, Petra Högy, Eckhart Priesack, Hans-Dieter Wizemann, and Joachim Aurbacher,** is called **“Simulation-based Projections of Crop Management and Gross Margin Variance in Contrasting Regions of Southwest Germany”**. It was published in the *Journal of Agricultural Studies*, Vol. 3 No. 1, pp. 79-98 (2015). “Past and future gross margin fluctuations” (Parker et al., 2015, p. 81) are compared using the integrated simulation model FarmActor. This article is a general investigation into how gross margins in crop production, which are the basis for strategic planning in standard planning models and thus land use, can be affected by climate change. This dissertation contributed the underlying methodological concept, specifically regarding the subject of risk. The article is based on preliminary works within the part of this dissertation that stems from using simulated production outcomes from the FarmActor model. It was found that price and yield fluctuations are independent, and as a consequence, the climatic impact on yields could be offset due to favorable price developments. Price projections are modeled as extrapolations of historical prices (Parker et al., 2015). The article pursues an established methodological approach that does not, however, exploit FarmActor’s full potential.

Furthermore, prices have a higher impact on gross margins (Henseler et al., 2009), as each change in prices is a change in the final outcome, while for crop production, the majority of changes, especially those due to climatic influences, are intertemporal in nature: they occur during the plant development process. The final result, the yield, is achieved only once a year for a crop. Thus, the climatic influence is easily overpowered in an equation that only uses final outcomes.

Climate as an uncertainty factor is something to which farmers constantly react. Thus, so-called risk profiles are actually the result of cumulative perceptions acquired during and after the production processes. This fact supports the need to develop a new methodological approach that uses the full potential of the FarmActor model. Such a model may improve economic risk analysis by incorporating intertemporal perceptions to qualify the statements about the actual climatic impact on crop production and, as a consequence, land use.

As a complement, the article by **Aileen Jänecke, Marius Eisele, Evelyn Reinmuth, Jennifer Steinbach, and Joachim Aurbacher,** with the title **“German Farmers’ Perceptions of Climate Change Effects and Determinants Influencing Their Climate Awareness,”** is published as a conference proceeding in Kühl, R., Aurbacher, J., Herrmann, R., Nuppenau, E.-A., Schmitz, M. (Edit.). Schriften der Gesellschaft für Wirtschafts- und Sozialwissenschaften des Landbaus e.v., Bd. 51, 2016, pp. 407-418. This article investigates whether farmers in the study regions of Kraichgau and Swabian Alb “perceive a change in weather conditions for their location and expect consequences for their farming activities due to these developments” (Jänecke et al., 2016, abstract). Farm owners, who make decisions about land use, were found to perceive an increased weather variability at their locations. The regression analysis yielded the result that, among other variables, the farm location is a significant predictor of how farmers evaluate changes in climatic conditions. The work of this dissertation contributed methodologically to the analysis and the preliminary empirical work when creating the questionnaire. The article builds a further argumentative basis for the newly developed approach employed in this dissertation, which focuses on perceptions in the specific context of crop production.

In the fourth article, the interdisciplinary methodology that was developed as the main part of this dissertation is presented as original research. The methodology is a utility concept that allows for the inclusion of Annual Risk Scores based on mid-season risk perceptions in strategic crop planning decisions. The methodology isolates the climatic influence in farmers' planning decisions based on their personal attitudes towards yield variability. This approach is employed for winter wheat production in the Kraichgau, a region in Southwest Germany, using the integrated bioeconomic simulation model FarmActor and empirical data from that region. The article by **Evelyn Reinmuth, Phillip S. Parker, Joachim Aurbacher, Petra Högy, Stephan Dabbert** is titled **"Modeling perceptions of climatic risk in crop production",** it is published in **PLOS ONE 12(8): e0181954. August, 2017.**

A full implementation of the new methodology in the simulation model could not be achieved due to technical problems. Thus, the hypotheses could not be fully tested. Throughout the existing literature, we found indications that many modeling efforts are not pursued by other modelers, but rather, new modeling approaches are developed. Given our experience, we hypothesize that many of the aspects that we had trouble with prevent modelers from reusing existing modeling efforts. The last article is thus a reflection on the issues of bioeconomic modeling from a technical standpoint. It can be seen as a synthesis in that regard. Thus, these aspects are briefly discussed in the synthesis of the thesis. The integrative review article by **Evelyn Reinmuth and Stephan Dabbert** is published in *Computers and Electronics in Agriculture*, Vol. 138, pp. 29-38, June, 2017 and has the title **"Toward more efficient model development for Farming Systems Research – an integrative review".**

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

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

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ABSTRACT

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

1. Introduction

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

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

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

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

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

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

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

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

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

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

2. Methods and data

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

2.1. Farm management model FarmActor

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

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

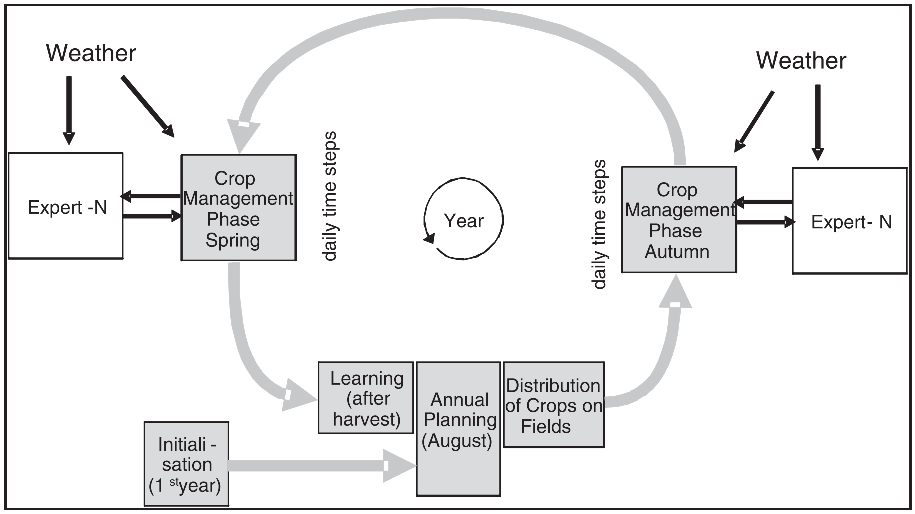

Fig. 1. Schematic sequence of FarmActor modules.

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

2.1.1. Crop management

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

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

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

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

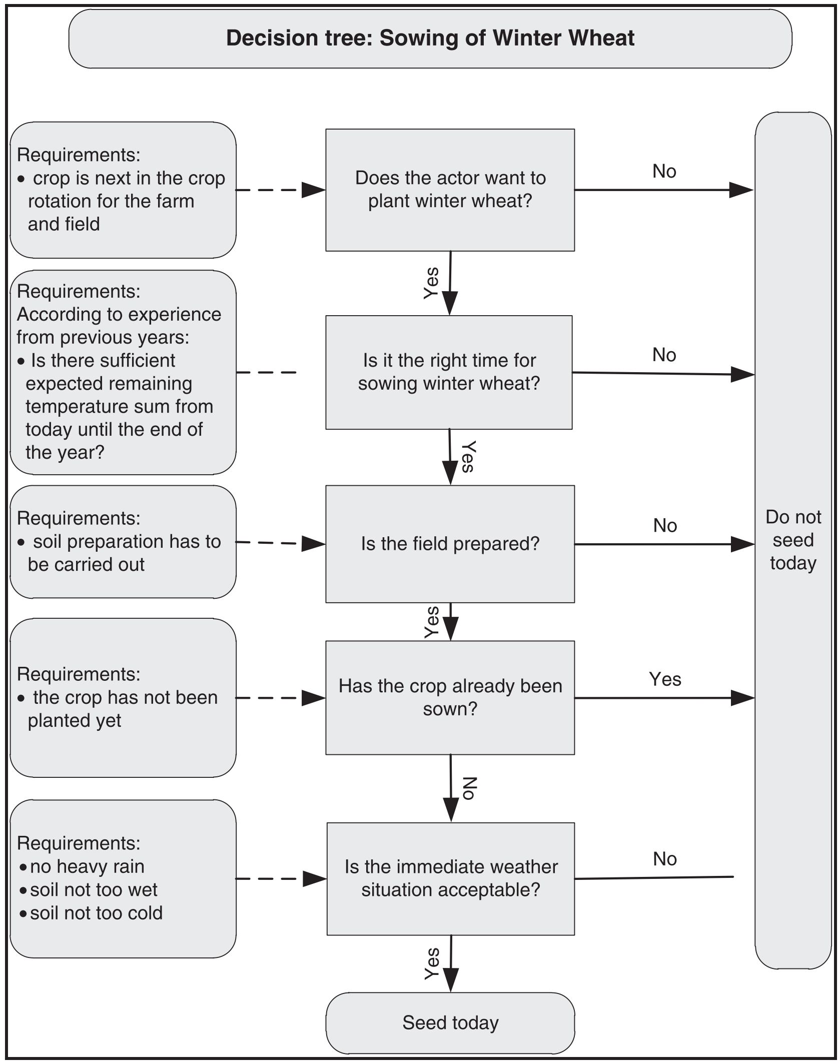

Fig. 2. Decision tree for the triggers using the example of sowing winter wheat. *Source*: Own depiction based on Apfelbeck et al. (2008)

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

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

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

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

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

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

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

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

2.1.3. Data and calibration of FarmActor

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

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

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

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

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

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

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

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

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

2.2. The crop growth model system Expert-N

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

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

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

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

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

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

2.2.1. Expert-N calibration

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

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

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

2.2.2. Soil parameter values

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

Table 4
Performance of calibrated Crop growth model.

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

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

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

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

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

2.3. Technical aspects and model coupling

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

Table 6
Soil properties and hydraulic parameters.

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

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

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

2.4. Study region and weather data

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

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

2.5. Simulation

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

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

3. Results

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

3.1. Winter wheat

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

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

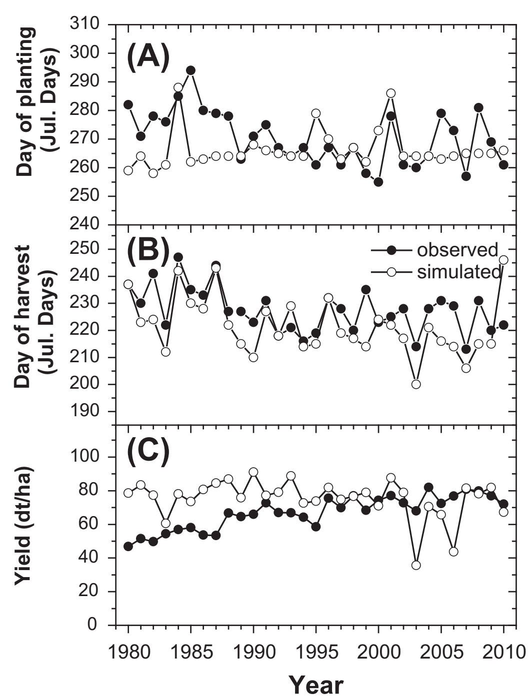

Fig. 3. Simulated and observed planting dates (A), harvesting dates (B) and yields (C) of winter wheat; learn mode moving averages (MA).

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

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

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

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

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

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

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

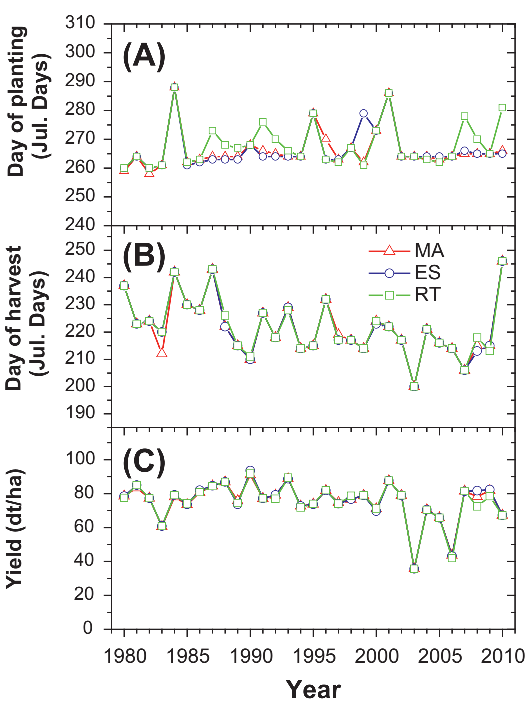

Fig. 4. Comparison of planting dates (A) and harvesting dates (B) as well as yields (C) for different adaptation methods (learn modes: MA: moving averages, ES: exponential smoothing, RT: regression trend) for winter wheat.

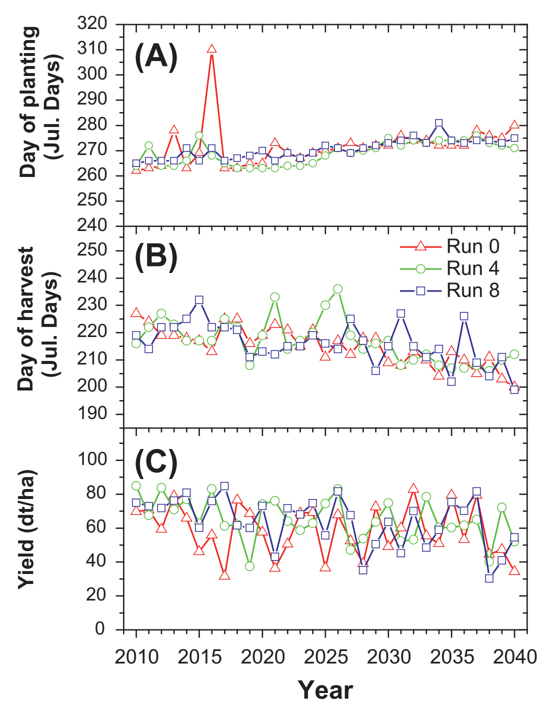

Fig. 5. Sowing dates (A), harvest dates (B) and yield (C) of three simulations using projected weather data (Model WETTREG) for winter wheat.

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

3.2. Silage maize

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

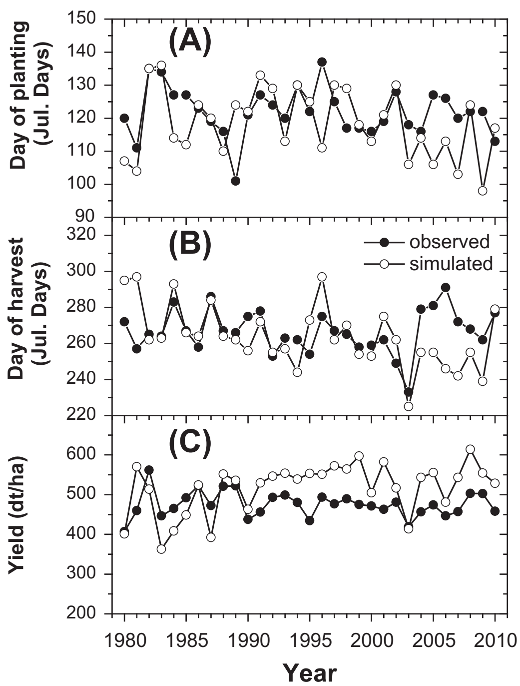

Fig. 6. Simulated and observed planting dates (A), harvest dates (B) as well as yields (C) of silage maize, learn mode moving averages (MA).

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

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

4. Discussion

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

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

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

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

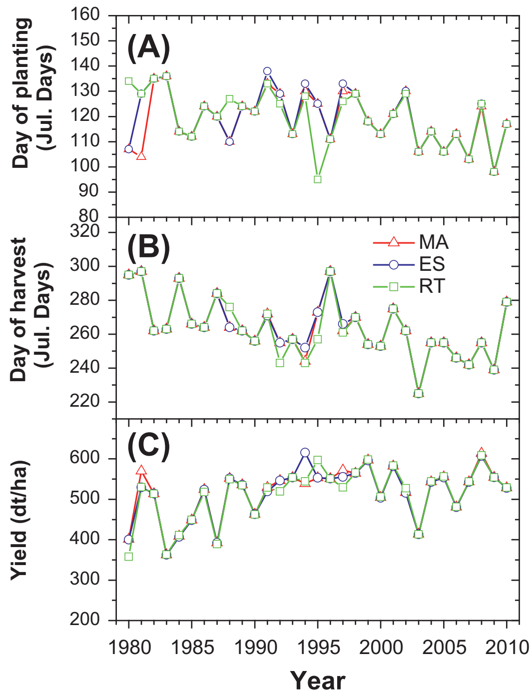

Fig. 7. Comparison of planting dates (A) and harvest dates (B) as well as yields (C) for different adaptation methods (learning modes: MA: moving averages, ES: exponential smoothing, RT: regression trend) for silage maize.

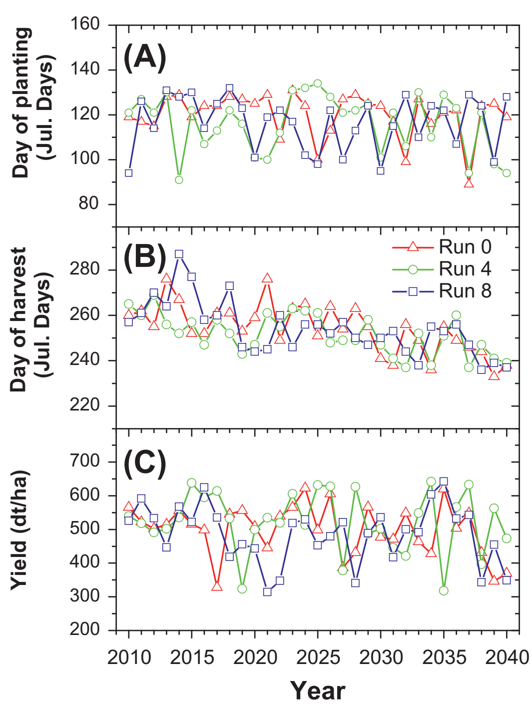

Fig. 8. Planting dates (A) and harvest dates (B) and yield (C) of three simulations using projected weather data (Model WETTREG) for silage maize.

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

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

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

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

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

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

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

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

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

5. Conclusions

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

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

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

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

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

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

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

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

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

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Appendix A.

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

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6 Simulation-based projections of crop management and gross margin variance in contrasting regions of southwest Germany

Authors: Phillip S. Parker, Evelyn Reinmuth, Joachim Ingwersen, Petra Högy, Eckhart Priesack, Hans-Dieter Wizemann, Joachim Aurbacher.

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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, Agricultural adaptation, Risk.

7 German farmers´ perceptions of climate change effects and determinants influencing their climate awareness

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Abstract

This paper focuses on the attitude of German farmers towards climate change effects and aims to identify determinants affecting their perception of weather conditions. For this purpose, descriptive statistics and multiple linear regression approaches were applied. Data was collected using a questionnaire survey, which was conducted in spring 2013 among 173 German farmers in the two regions Swabian Alb and Kraichgau. The analyses revealed that four main factors influence the perception of weather variability. In particular, respondents' age, the region where the farm is located, the share of agricultural income and the farm profit are statistically significantly related with the degree of support for the respective weather statements. The findings further indicated age of farmer, location of the farm, method of production and farm size as significant predictors concerning the farm leader's perception of climate change consequences. As descriptive statistics revealed, the majority of farmers perceive for their location a change in weather conditions, an increase in weather variability as well as decreasing predictability of weather and expect consequences for their farming activities due to these developments.

Keywords: Perception of climate change effects, weather variability, demographic characteristics, attributes of farm and household, regional scale, German farmers

8 Modeling perceptions of climatic risk in crop production.

Authors: Evelyn Reinmuth, Phillip S. Parker, Joachim Aurbacher, Petra Högy, Stephan Dabbert.

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RESEARCH ARTICLE

Modeling perceptions of climatic risk in crop production

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Abstract

In agricultural production, land-use decisions are components of economic planning that result in the strategic allocation of fields. Climate variability represents an uncertainty factor in crop production. Considering yield impact, climatic influence is perceived during and evaluated at the end of crop production cycles. In practice, this information is then incorporated into planning for the upcoming season. This process contributes to attitudes toward climate-induced risk in crop production. In the literature, however, the subjective valuation of risk is modeled as a risk attitude toward variations in (monetary) outcomes. Consequently, climatic influence may be obscured by political and market influences so that risk perceptions during the production process are neglected. We present a utility concept that allows the inclusion of annual risk scores based on mid-season risk perceptions that are incorporated into field-planning decisions. This approach is exemplified and implemented for winter wheat production in the Kraichgau, a region in Southwest Germany, using the integrated bio-economic simulation model FarmActor and empirical data from the region. Survey results indicate that a profitability threshold for this crop, the level of "still-good yield" (*sgy*), is 69 dt ha-1 (regional mean Kraichgau sample) for a given season. This threshold governs the monitoring process and risk estimators. We tested the modeled estimators against simulation results using ten projected future weather time series for winter wheat production. The mid-season estimators generally proved to be effective. This approach can be used to improve the modeling of planning decisions by providing a more comprehensive evaluation of field-crop response to climatic changes from an economic risk point of view. The methodology further provides economic insight in an agrometeorological context where prices for crops or inputs are lacking, but farmer attitudes toward risk should still be included in the analysis.

Introduction

Climate change contributes to the evolution of agricultural landscapes and is also subject to a feedback loop as changes in land use, especially conversion to cropland, drives processes such as the global carbon cycle that have been linked to changes in climatic conditions [1].

Variabilities in the biophysical processes in agricultural production have been found to be closely associated with climate [2–6]. The Intergovernmental Panel on Climate Change (IPCC) [7] stated in its Fifth Assessment Report that climate change is expected to amplify existing climatic risks. For crop farmers, this can represent a challenge in terms of the optimal allocation of land under their management [8]. The manager's job is to choose crops suited to the environment in their location [9], subject to stipulations including risk aversion [10]. Strategic crop selection and rotation are a cornerstone of successful agricultural enterprises [11]. Studies of agricultural production systems must account for managerial strategies that are based on dynamic environmental and economic conditions. Climate change impact assessment usually treats land use as a planning decision. The climatic influence is regarded as a source of gross-margin variation, which makes planning more difficult, and it is therefore considered to be a source of risk and uncertainty [12]. Available methodological approaches have been found to either over- or underestimate the rate of adaptation by farmers to climatic impacts [13–16].

Furthermore, economic drivers, such as commodity prices or agricultural policy, have been found to dominate climatic influences at the gross-margin level, particularly in terms of the speed of farmer response to stimuli [17, 18], through planning decisions. The challenge lies in the isolation of the climatic influence in such risk analysis [14, 19]. The aim of the present work is to exemplify a more comprehensive methodology for incorporating risk, in particular climate-induced risk, into agricultural simulation. This approach should contribute to the ongoing pursuit of more robust system representation to enable more reliable predictive capacity.

Materials and methods

Currently used models show how climate change can be expected to induce transition processes in agricultural land use, for example the Integrated Land-use Model (ILM) [20] and MPMAS [21]. Although they are coupled with complex biophysical models (EPIC [22] and Expert-N [23], respectively), these models consider only the final outcome of the production process, such as yield. Valuable information produced throughout the simulated growing cycle is ignored for lack of a realistic methodology to incorporate it into the representation of agricultural strategy.

Furthermore, in reality, farmers continuously evaluate crop development on their fields, even when no activities are pending. At certain intervals throughout the growing season, farmers base their estimates regarding eventual production outcomes on an evaluation of the current crop development stage [24]. This process is accompanied by an automatic perception of the crop's response to the season's climate at a certain location. This evaluative monitoring goes beyond a pure input efficiency analysis that accounts for (seasonal) variability in agricultural production, as has been investigated [24–28]. Over time, the aggregation of these evaluations shape a farm manager's cumulative perception of the climate-induced variability of a crop in the form of a perceived response pattern. This knowledge is, in practice, incorporated into planning decisions, and can be used to set crop yield within the context of the respective production processes while including how climate affects production efficiency.

Thus, the primary hypothesis here is that incorporating inter-temporal evaluations of agro-economic processes in planning decisions will cultivate a more thorough understanding of the impact of climatic changes on land-use (planning) decisions and, thus, of how agricultural landscapes evolve over time.

Bio-economic simulation models with dynamic module integration (e.g., crop-soil-management-weather-prices), operating at adequate spatio-temporal resolution [29], offer the possibility of investigating different processes and dynamics of decision-making over time while being representative of the real world [30]. Mid-season risk perceptions can only be modeled at fine (e.g., daily, at least sub-annual) resolution [14]. Few bio-economic models operate at an appropriate temporal resolution to allow the study of farmers' perception processes during the growing season (APSIM [31] and FarmActor [32]).

The APSIM model [31], is able to mimic production process decisions at daily resolution and at the field level. Crop management decisions can be made according to weather, plant and soil conditions. In the APSIM model, a trigger mechanism is used to adjust tactical decision-making in the context of response farming [33]. The FarmActor model, as coupled to the Expert-N crop model [23, 34–37], incorporates all the functionality of the APSIM model in terms of daily management in response to soil-crop-weather dynamics [32]. FarmActor is further able to adapt simulated crop management in response to long-term climatic influences through model-endogenous mechanisms. It therefore resonates with actual agricultural activity at multiple scales (daily, yearly, decadal, etc.) of the managerial perspective and, thus, at scales where strategy can be implemented. Both models are designed to explore the optimization of production routines and the planning process in an agro-meteorological context.

The FarmActor model's environmental condition triggers that govern field management decision-making are designed to mimic agronomic reasoning such that it can accurately reproduce empirically observed farmer behavior, particularly the timing of sowing and harvest [38]. Observed behavior, in a soil-weather context, is assumed to be in pursuit of profit maximization in response to embedded production risks. The timing of field management actions provides a traceable link between farm strategy and eventual yields. The extraction of economic reasoning that drives observed statistics is tenuous [39], whereas in bio-economic simulation, trigger settings provide a transparent mechanism to quantify the system components that steer productivity.

By definition, bio-economic simulation models go beyond agronomic aspects and are designed to use the coupling of model components to integrate agronomic aspects into economic analysis. This functionality is the key to integrated process evaluations in economic planning decisions but has yet to be well developed for APSIM and FarmActor.

Data and study region

Data were obtained empirically as part of a structured survey on risk and decision-making in agriculture that was conducted in the Kraichgau study region in Southwest Germany (~1,400 km^2) [32]. The Kraichgau is, from an agricultural point of view, a fertile region with intensive agricultural activity on mostly loess-rich soils and a relatively homogenous agricultural landscape [40, 41]. Elevations are between 100 and 400 m asl with a landscape defined by moderate slopes. The mean annual precipitation ranges from 730 to 830 mm and has a mean annual temperature of 9 to 10˚C.

The farmers were informed through an introductory cover letter about the content and purpose of the questionnaire and the planned use of their data. They were further assured that all procured data would be evaluated with the safeguard of anonymity and for scientific purposes only within the framework of the research group and that their personal information would be treated confidentially. As an incentive to increase the response rate, there was also the possibility of participating in a lottery drawing to win one of 20 vouchers for a farm supply company; each voucher had a value of 30 EUR. The response rate was 23.4%, or 91 completed questionnaires.

No ethics committee or institutional review board was contacted because it was not compulsory at the time. The questionnaires were read by all members of the research group and were approved by all responsible project leaders before they were sent out. The empirical work was subsequently approved by the Ethics Committee of the University of Hohenheim, 70599 Stuttgart.

Empirical approach

Mid-season evaluation is conducted to assess variations in the crop development process [42] and, when significant, can provide expectations regarding eventual yield levels. Preferential outcomes during the season or at harvest are constructed after consideration of an immense number of possible options that a decision-maker faces, many of which are similar in nature [43]. Therefore, the agroeconomic focus should be on thresholds as a component of wealth dynamics, as suggested by Just et al. [44] and Antle [25], to scale preferences properly. Risk bearing, which is also a scalar, is related to a decision-maker's willingness to accept (*wta*) outcome fluctuations [45]. Willingness to accept is a downside-risk measure because it focuses on incurred losses and individual assessment of such losses [46]. Because aspects of preferences and perceived risks are constructed according to local conditions, there is a need to establish a context within which an economic subject acts.

This need led to the execution of the farmer survey in the Kraichgau region. Farmers were asked to give a subjective evaluation of crop observations according to their experience with all crops in their production branch (question 1.11 of S1 Questionnaire). Downside-risk attitude was elicited in a crop-wise manner because of the highly resolved decision-making component in the FarmActor model that plans the allocation of crops for each field of a farm individually and, thus, mid-season observations are modeled crop-specific.

The willingness to accept is defined in physical units as follows: $py–sgy = wta$, where py = peak yield and sgy = (farmer-defined) "still-good yield". The *sgy* level was set as the lower boundary of a farmer's acceptable level of fluctuation. All values above the *sgy* provide utility to a farmer in an economic sense. Below the *sgy*, the values represent the production outcome levels that might imply agronomic non-profitability according to farmer experience; more specifically, they imply economic losses and thus represent risk.

To compare different *sgy* statements, a definition for a sensitivity type in this context is provided that uses the third elicited point of a farmers' crop yield distribution, i.e., the average yield ($\mathrm{avy}_{\mathrm{farm}}$). Sensitivity types are similar to risk aversion types, as suggested by Arrow [47] and Pratt [48] to account for farmers having a different subjective acceptance of risk [49] and are part of the methodological concept to be presented.

Sensitivity types. The average yield (avy_{farm}) determines the location of *sgy* in the yield distribution and allows for the identification of comparative performance between farms for a given crop. We can argue that when $avy_{farm} > avy_{region}$ for a given crop, the farmer's yield distribution and the processes underlying the result are likely to be favorably skewed. This reasoning is based on the assumption that climatic influences are comparable throughout the relatively uniform Kraichgau study region and production conditions, such as the availability of inputs are assumed to be relatively homogenous throughout this region.

If a farmer declares *sgy* to exceed avy_{farm}, despite avy_{farm} being higher than avy_{region}, the farmer can be considered to be more sensitive to yield for a particular crop as opposed to a farmer that declares his *sgy* below avy_{farm}.

A sensitivity type in this context is thus identified by two conditions with regard to a given crop: first, determine if *sgy* is above or below avy_{farm}; second, compare the individual average performance of a crop at the farm level avy_{farm} to the individual avy_{farm}.

Empirical results

Despite $avy_{\mathrm{farm}} > avy_{\mathrm{region}}$, only 13, or 17.81% (n = 73), of the farmers in the Kraichgau sample declared their *sgy* above avy_{farm} and could thus be identified as being highly sensitive with regard to fluctuations of one or more crops produced on their farm. Due to the low sample size and strong sample heterogeneity, neither regression nor cluster analysis yielded significant

Table 1. Empirical results for winter wheat from the Kraichgau sample.

	Mean	Min	Max	Std. Dev.	Skewness	Variance	Var. Coef.	n
Peak yield (dt/ha)	87.78	65	116	10.36	-0.17	107.43	0.12	81
Still-good yield (dt/ha)	69.17	40	90	10.05	-0.70	100.92	0.15	78
Average yield (dt/ha)	74.44	50	90	8.43	-1.00	70.98	0.11	80

Note: Min = Minimum, Max = Maximum, Std. Dev. = Standard Deviation; Var. Coef. = Variation Coefficient. Different sample sizes are related to various levels of questionnaire completion. Source: Own survey (2013), question 1.11 of S1 Questionnaire.

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results when attempting to categorize the sampled Kraichgau farmers into typical groups according to age, experience and stated farm characteristics. However, this particular information is not necessary to introduce the methodological approach.

Descriptive statistics for the three subjective values (peak, still-good and average yield) as reported by questionnaire respondents regarding winter wheat in the Kraichgau are displayed in Table 1. Winter wheat results are presented because of their economic importance and their use to exemplify the methodological approach. Of 91 returned questionnaires, 82 incorporated information related to this study.

For the Kraichgau sample, the average reported *sgy* is below the mean reported *avy*, which is near the five-year (2008–2012) mean yield of 71.4 dt/ha for winter wheat across the four districts (Landkreise) that comprise the study region [50].

The empirically elicited *sgy* threshold was then translated for mid-seasonal process observations using the FarmActor model based on the following utility concept. The *sgy* threshold is used to scale perceived variance during production from an economic perspective [14].

Utility concept

The introduction of utility is necessary and a useful measure for economic evaluations during the season and to ensure compatibility with economic reasoning at the level of planning [51] in the simulation model.

Thus, at sequential observation points (OPs), which represent specific crop management or monitoring actions, the modeled farmer evaluates crop development, soil water content and soil temperature, as driven by soil-plant-climate interactions, using simulation model output parameters, namely, the set that describes the current status, with $i \in (1,\ldots,n)$ as the total number of possible (crop-specific) observation parameters. The evaluation of each observed parameter value is assessed with a utility score $\alpha_{i,c}$ at each OP (c stands for crop).

Each parameter has an assigned acceptance range that triggers the monitoring procedure in the model. Anticipated economic profitability and thus an absence of risk ($\alpha_{i,c} = 0$) are implied when the observation parameter lies inside a predefined acceptance range; yield levels above the *sgy* threshold are expected based on the inter-temporal observation. A utility score of 1 results during a "risky" season when an observed parameter value lies ***outside*** a predefined acceptance range that is associated with crop profitability. The observational procedure is independent of simulated management. It is only used to accumulate perceptions of the climatic influence dependent on the *sgy* threshold.

The utility risk score at an individual OP for a crop is represented as the sum of the utilities of all observation point parameters:

$$\alpha_{t,c} = \sum_{i=1}^{n} \alpha_{i,c} \quad \text{for all } t \text{ and } c \tag{1}$$

where t is an OP at a certain point in time with $t \in (1,\ldots m)$ within the growing process of crop c. The season's accumulated utility values of all OP's are summed after harvest to obtain $\alpha_{T,c}$, the total utility score, or ARS, of a production year for a given crop as the result of the intermediate rankings. This relation can be written as

$$ARS = \alpha_{T,c} = \sum_{t=1}^{m} \alpha_{t,c} \quad \text{for all} \quad c. \tag{2}$$

Fig 1 exemplifies the ARS concept for winter wheat production in the Kraichgau. The timing for the OPs is inferred from the FarmActor model's list of field management actions for winter wheat production. The management procedure in the simulation model has been previously calibrated for Kraichgau (see, [32]). The chosen OPs represent one possible option and can be adjusted for other crops.

Most importantly and to understand the evaluative monitoring, an ARS score and its components are not used to govern the inter-temporal optimization process but, rather, as an instrument for risk assessment and selecting relevant information regarding the climatic influence. Therefore, each $\alpha_{t,c}$ identifies the composite risk (across observed conditions) for a given observation point that becomes part of an overall assessment at the end of the year.

There is no further weighting of inter-temporal utility coefficients because the utility of a value is only revealed *ex post* [12, 52] despite the fact that the utility regarding sequential observations has been referred to as the "utility of the moment" [53], indicating that it is only valid for a short period of time until the situation reveals new information to be processed [54]. The

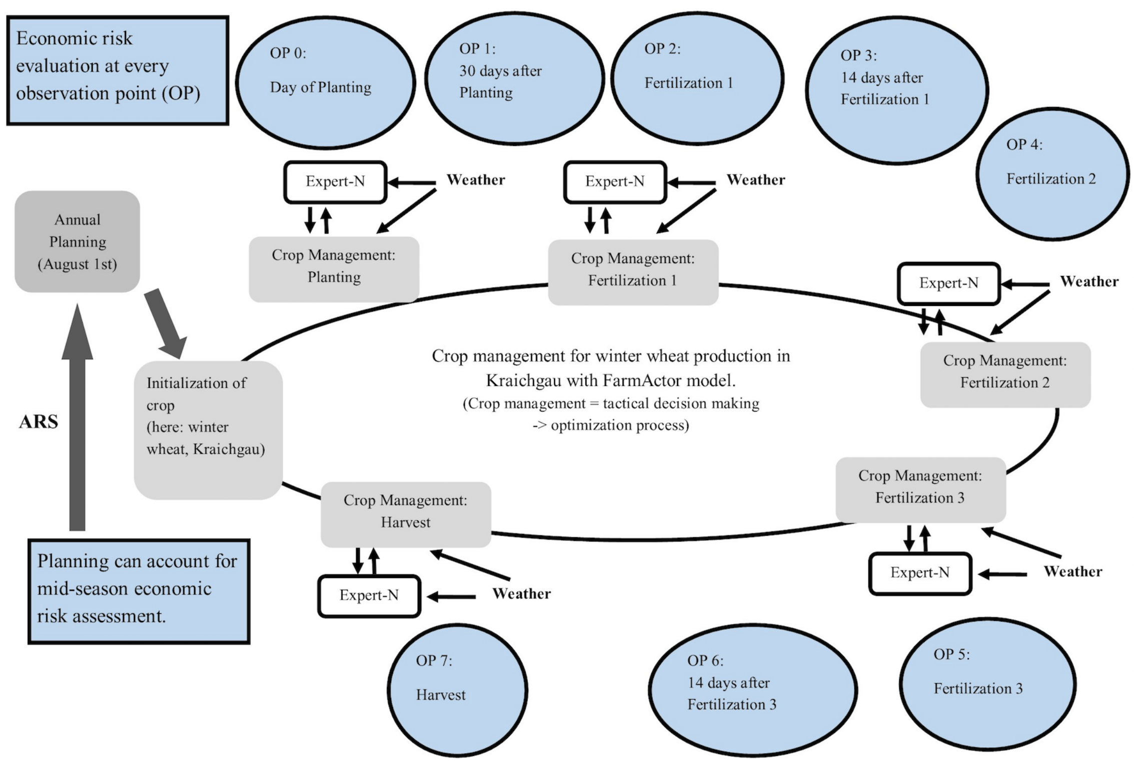

Fig 1. Economic risk evaluation via mid-season assessment. Risk perceptions are documented at eight OPs, 0 to 7, in the FarmActor model. The example of winter wheat production in the Kraichgau is shown. Each observation is conducted parallel to wheat production. Source: Adapted from [32].

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state of available information is the factor that changes with subsequent crop development and observation, while the uncertainty regarding further development remains the same [24].

Simulations. Before the simulation model is able to assess climatic impacts, based on the ARS methodology, the model must be provided with information about what level of mid-season variability is acceptable. The ARS methodology is exemplified using the empirically elicited average *sgy* from the Kraichgau sample, 69.17 dt/ha (Table 1), to scale the boundaries of the acceptance ranges in the simulation model.

Acceptance ranges for inter-temporal crop conditions embody the experience of a farmer in crop production. This experience pertains to a certain range of tolerable fluctuations in growth patterns from a downside risk perspective at a given point in time during the growing season. To initialize these ranges, it was necessary to simulate a reasonable number of "historical" growing seasons to accumulate an experience pool for the simulated farmer.

To create a knowledge pool, FarmActor's crop management routine was overridden in order to compile a comprehensive set of simulated agro-ecological states (crop biomass, soil moisture, etc.) arrived at through what-if scenarios using an array of day-of-year (DOY) starting points (sowing dates). A standard production procedure was used for these model runs, and input levels for fertilization were kept constant. All wheat-specific actions, apart from planting (three fertilization applications, harvesting, and preparation of fields; Fig 1) were governed by their existing weather and plant-growth-dependent trigger arrays [32] and [38]. A range of plausible starting points for winter wheat growth processes for the Kraichgau region extends from DOY 283 to 324 (early-mid October to mid-late November) [38]. The later the simulated DOY for sowing, through the associated growth-process simulation, the less likely the yields will be acceptable or greater than *sgy*, thus justifying the maximum in the sowing DOY chosen for simulation. For each of the 46 DOY, a time series of 30 years (1983–2013) was modeled. This produced "historical" growth processes for each weather year and resulted in 1,380 permutations of the annual growth processes for winter wheat.

Data from the modeled growth processes were then used to initialize the acceptance ranges of all observation points used to monitor the growth processes. A season's first observation point is the sowing date, OP 0 (see Fig 1). The acceptance range for OP 0 (sowing) is described by the relative frequency in which a DOY led to a yield $\geq$ *sgy (*average *sgy* for the Kraichgau region 69.17 dt/ha (Table 1)) throughout the historical time frame. This value is the ratio of desired to total yield outcomes compiled over all simulation years (n = 30) and stems from that particular sowing DOY. The higher the relative success frequency of a DOY, the more often a yield $\geq$ *sgy* is observable in the 30-year times series with this DOY as a starting point, and consequently, the more suitable a DOY is for sowing.

For crop surveillance after sowing, at OP 1 through 7, ten observable field parameters are used for monitoring to give a complete picture of crop response to external influences: *above-ground biomass* and *generative biomass* (kg/ha); *leaf area index* (LAI); *crop development stage* (BBCH) (BBCH-scale [55]); *soil water content* at 20, 50 and 120 cm depths (% volume); and *soil temperature* at 5, 20 and 50 cm depths (˚C). The crop development stage is used indirectly; it is incorporated into the decision triggers of the simulation management routine to ensure that observations each year are made at a comparable stage of crop development (compare [32]).

Mid-season indicators of forthcoming yields, or OP 1 to 7, are based on simulated growth processes, however, not all modeled values for a given parameter could serve as a reference for an economically interpretable observation. The base of 1,380 data points for each OP parameter was reduced to those in which the corresponding final yield did not fall below the downside-risk threshold, i.e., the average *sgy* for the Kraichgau region, 69.17 dt/ha (Table 1). The results represent the farm actor's "knowledge" that has accrued over a 30-year time-span.

These data provide a simulated knowledge base to generate expectations about crop response to seasonal variability, with reference to a yield benchmark, which implies agronomic utility.

Because the states of physical growth processes are compiled as observational data, it is important to determine acceptance ranges that cover a wide range of outcomes to prevent the model from being too sensitive to fluctuations. When plotting the data with boxplots, the limits for each observation point parameter were set at the whiskers of selected point-specific outcomes for a given parameter. The outliers represent a result of rare combinations of plant response and environmental conditions that still resulted in a yield ≥ *sgy* and were thus excluded. The outliers are data points that lie below the first quartile minus 1.5 times the inter quartile range ($x_{0.25}$−1.5 IQR) or above the third quartile plus 1.5 times the inter quartile range ($x_{0.75}$ + 1.5 IQR). Whiskers are assigned to the next inner data points, which are not considered outliers. Boxplots were calculated with STATA [56]. We examined the result of the data extraction further to test whether it made any difference in our acceptance ranges when all 1,380 data points were plotted. The acceptance ranges were consequently much greater in both directions.

Acceptance ranges. Table 2 gives an overview of all acceptance ranges we obtained from extracting simulation data for all OPs in winter wheat production in the Kraichgau using the FarmActor model.

Acceptance ranges represent tolerable fluctuation during the growth process from a downside-risk point of view. The values between the boundaries are not ranges that indicate the

Table 2. Observation trigger ranges for winter wheat production in the Kraichgau region for the production years 1983–2013 and 10 observation parameters throughout 7 observation points; average regional *sgy* level: 69.17 dt/ha (Table 1); weather data from Eppingen station (see details [32]).

OP 0: Planting (day-of-year)	Min	280									
	Max	313									
		Leaf Area Index	Soil Water at				Soil Temperature at			Above Ground Biomass	BBCH
			30 cm	60 cm	90 cm	120 cm	5 cm	10 cm	50 cm		
OP1: 30 days after planting	Min	0.07	28.5	26.62	25.64	26.7	-6.01	-4.58	-0.18	39.27	8.06
	Max	0.77	34	35.58	35.02	32.63	12.64	11.86	10.33	302.52	13.58
OP2: Fertilization 1	Min	1.32	19.25	21.88	23.53	25.78	4.34	5.26	5.72	913.18	25
	Max	4.17	34.78	33.21	32.03	32.14	19.58	17.88	13.06	2744.6	25.81
OP3: 14 days after fertilization 1	Min	2.54	21.67	20.97	22.34	24.62	6.65	6.47	7.04	1709.2	27.05
	Max	6.05	36.09	33.39	31.57	31.15	20.46	19.69	14.75	4126.6	33.74
OP4: Fertilization 2	Min	2.57	21.67	21.98	22.23	24.57	7.53	7.72	8.72	1695.8	30
	Max	6.84	35.81	32.63	31.37	30.03	20.43	19.33	14.48	4690	32.88
OP5: Fertilization 3	Min	3.62	18.31	17.43	19.8	23.4	8.66	8.96	9.16	3404.4	39
	Max	7.25	37.28	35.63	32.05	29.12	21.23	20.31	15.5	6505	42.83
OP6: 14 days after fertilization 3	Min	3.84	16.12	15.2	17	21.06	10.09	10.05	10.41	6380.1	52.14
	Max	6.88	40.12	32.4	30.26	30.22	22.42	21.74	17.51	9631.9	61.26
OP7: Harvest	Min	1.17	10.87	11.13	11.72	16.27	13.64	13.54	13.1	7343.6[1]	90.7
	Max	2.12	32.99	31.01	27.16	27.63	21.67	20.56	18.91	8803[1]	92.7

Note

[1] At **harvest,** the parameter observed is **generative (grain) biomass (kg/ha)**. The minimum and maximum values are respective of the lower and upper boundaries of an acceptance range for an observation parameter. Mid-season observations are based on aboveground biomass (dt FM/ha)—for example, at OP 2 (Fertilization 1). This measurement for winter wheat was usually between 913.18 and 2,744.6 in weather/production years that resulted in a yield ≥ *sgy* of 69.17 dt/ha. Thus, the observable biomass during a given year between these two values can still be considered as risk-neutral fluctuation or as not affecting downside risk in terms of economic loss expressed in yield levels.

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optimal state. The upper boundaries of the acceptance ranges, therefore, can be more than twice the value of the lower boundary, especially in the earlier observation point ranges. The later the observation point is, the closer the boundary values are. After initialization, the attained acceptance ranges with farmers' revealed preferences for yield fluctuations are used to test and exemplify the approach. Thus, in the next section, the knowledge pool based on past climatic impacts is used to test how changes in future climatic conditions can be perceived by the model farmer using the ARS methodology.

Application to future climate. Future simulations for winter wheat production in the Kraichgau were performed using the coupled FarmActor-Expert-N models forced with simulated future climate in the form of daily weather parameters in ten realizations (25002–00 and 25002–99) of WETTREG 2010 future scenarios [57], corresponding to the German Weather Service [58] weather station at Eppingen (Kraichgau study site) and based on the IPCC scenario A1B [59]. For each WETTREG future realization, the model simulated a 20-year (2014–2034) time series for winter wheat with only one standard production procedure each year on a representative field [32]. FarmActor's management routine was not manipulated in this case. These ten time series, each with 20 years of future growth processes, were then used to comprehensively test the methodological approach. All growth processes were evaluated with the ARS mechanism by comparing them to their acceptance range at each observation point (OP 0–7) to conduct a comparative analysis and investigate the performance of the proposed approach under diverse climatic conditions.

As described above, observations outside the acceptance ranges are assigned a binary utility value of 1 (0 otherwise). At the end of each year, from evaluating all observations made during the production season, the ARS is compiled. With 10 observation parameters and 7 observation points (OP 1 to OP 7) plus OP 0 for planting, a maximum score of 71 is possible for a year. OP 0 is related to the desirability of a given DOY for planting. If its relative frequency of yields $\geq$ *sgy* is less than 0.5, that is to say, if more than half of the time the harvest is disappointing, this observation is assigned a value of 1. Thus, if planting is forced to a day (through weather-dependent trigger conditions) that has a relative frequency value less than 0.5, then OP 0 is assigned a value of 1 for that production year.

Results of future climate simulations. The results of this investigation are displayed in a comparative static context in Table 3, in which the results are further refined into a mean-standard deviation approach.

The mean-standard deviation analysis provides an overview of how each of the ten future WETTREG weather realizations affects winter wheat production based on a standard production procedure. All ten realizations were used to avoid any bias in a single realization based on their statistical nature and to examine a range of possible outcomes using the *sgy* approach.

Table 3. Simulated yield statistics for over 20 years, 2014–2033, using 10 WETTREG future realizations for Eppingen weather station.

WETTREG future weather realization	00	11	22	33	44	55	66	77	88	99
Mean yield (dt/ha)	74.54	68.61	70.31	68.64	72.39	72.39	65.18	65.15	71.41	61.77
Standard deviation (dt/ha)	3.50	16.26	16.97	16.44	4.72	4.72	21.97	21.97	5.57	26.25
Skewness	0.31	-4.07	-3.88	-3.90	-1.94	-1.94	-2.76	-2.76	0.40	-2.04
Variation coefficient	0.05	0.24	0.24	0.24	0.07	0.07	0.34	0.34	0.08	0.43
Rel. Frequency y $\geq$ sgy	0.95	0.7	0.75	0.7	0.85	0.85	0.7	0.65	0.7	0.7
Mean ARS score	4	4.05	5	5.2	3.9	4.9	3.95	5.15	2.45	5.95
Std. dev. ARS score	3.70	3.76	4.22	4.10	3.16	4.52	4.61	4.11	2.01	7.90

Note: All results have been obtained from the FarmActor standard production procedure for winter wheat in Kraichgau (see [32, 38]). Source: Own calculations.

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At a *sgy* level of 69.17 dt/ha, the results for the WETTREG-forced winter wheat production in the Kraichgau can be interpreted from a risk point of view as follows. Realizations 44 and 55 show the second lowest yield standard deviation (4.72 dt/ha, Table 3) for all future weather years. The standard deviation of ARS scores for the same realizations is noticeably higher than its counterparts. For realization 55, the standard deviation of all ARS scores is the third highest, although the yield standard deviation is the second lowest in the mean variance comparison. The relative frequency is also relatively favorable, at 0.85 (Table 3) for realizations 44 and 55. Thus, for 85% of the 20-year yield time series, a yield $\geq$ *sgy* of 69.17 dt/ha could be achieved. This finding represents favorable skewness for a decision-maker who sets his economic profitability yield threshold at this level. However, when taking a farmer´s mid-season assessment into account, those future production years are characterized by relatively large deviations from the modeled acceptance ranges. This result gives an indication that farmers often experience anomalous winter wheat performance sometime during the season, even in favorable years with a yield $\geq$ *sgy*.

The additional information provided here for the analysis is that a farmer's mid-season observations are often ambiguous regarding what yield can be expected at a harvest [25, 45].

A different picture is drawn with realization 99. For such a projection of future climatic conditions, a mean-variance analysis at yield level illustrates the same issue as the ARS methodology, in which the highest mean of ARS scores corresponds to the highest standard deviation of ARS scores. The mean yield is among the lowest, and the standard deviation is the highest. Low yields that are traceable to a problematic climate at the 69.17 dt/ha *sgy* level show how mean-variance analysis at a yield level leads to the same conclusions as the ARS methodology. Farmers' knowledge of crop-response patterns to climatic influences holds true and leads to accurate expectations regarding their yields.

The picture drawn with realization 11 in Table 3 is most interesting. The mean-variance analysis shows a completely different picture than the ARS methodology. This realization led to one of the highest standard deviations (16.26 dt/ha) in yields and a relatively low mean yield (68.61 dt/ha) (Table 3), close to the average *sgy* level for the Kraichgau region (69.17 dt/ha, Table 1). However, the mean ARS score is at 4.05 (Table 3), which is not among the highest scores achieved over all future climate realizations. This finding indicates that conditions were not unfavorable throughout the studied growing season but rather single events were responsible for the production outcomes in this time series of winter wheat yields.

Discussion

A modeling approach that can account for climatic stress that is normally hidden from economic analysis can more thoroughly examine climatic impacts and provide more information.

The results of a first application of the ARS methodology with mid-season estimators show generally effective outcomes. Inter-temporal observations can provide better information as to where and how the production process is affected so that a modeled farmer can identify and apply the appropriate risk measures. Such information is more useful in annual planning decisions. ARS scores could be derived from 71 points, with an average score of less than 10 throughout the future time series for winter wheat in Kraichgau region (Table 3). This conclusion suggests that using near-term climate projections of a rather statistical nature, such as WETTREG 2010 [57], has a relatively low impact for winter wheat for a given average *sgy* threshold based on the Kraichgau regional sample. Considering that the average regional *sgy* threshold for this region is less than the region's average yield (Table 1), the picture could be drawn completely differently for any of the 13 highly sensitive farmer types found in the empirical sample who declared their *sgy* threshold above 69.17 dt/ha. However, a more in-depth analysis is left for future research applying the ARS methodology.

ARS scores in a dynamic context

Given a series of weather years where mid-season observations appear to be poor determinants of yield outcomes greater than the *sgy*, farmers gain new experience. When apparently risky inter-temporal states lead to learning processes that change the perception of crop response to climatic influence, the *sgy* approach can be used to provide the foundation of learning processes, thus creating a useful feature for bio-economic models.

The decision-making mechanism in FarmActor is designed to modify annual decisions to account for long-term trends in climate, with implied relationships between production risk and annual weather [32].As a consequence, the observation parameter value ranges can change over time.

How acceptance ranges can adapt. As a consequence of evaluating inter-temporal production outcomes, the following implications are possible for the perception mechanism in the simulation model: (1) no consequence and (2) a shift in the acceptance range. These implications can be the consequence of three possible scenarios. First, an observation value is within the acceptance range and a yield higher than or equal to the *sgy* is achieved; then, the entire process can be assessed as having gone as expected for a given parameter value. The observed value from the now past production year is included in the distribution of observation points that constitute the observation parameters' acceptance ranges for the upcoming year without causing a shift of the range. Second, if an observed value is outside the acceptance range and a yield lower than the *sgy* is achieved, the observation parameter range for the upcoming year is not affected since this was an expected yield loss considering the set loss threshold (*sgy*). The third consequence is that observational fluctuations lie outside the acceptance range but do not result in negative consequences for the acceptance ranges because a yield above the *sgy* threshold is achieved. In that case, the observation is collated as a non-downside-risk value for the distribution of observations for a given parameter. However, depending on the amplitude of the fluctuation, a shift in the acceptance range may occur. When such outliers accumulate, they will add to a shift in the acceptance range that changes the expected performance of a given crop in its response to climatic (and management) influences. The larger the amplitude of the deviating value is, the longer it will most likely remain among the outliers that are excluded during the initialization process for the acceptance ranges in the model. Many outliers over several years in a row—again, depending on the learning mechanism—may indicate that a crop is quite difficult to cultivate at a given location. This can occur even though the simulated farmer annually adapts production procedures while also responding to daily environmental conditions.

Use of ARS scores for comparative analyses

Additionally, different learning patterns that assign weights to ARS scores allow the study of the arrangement of a farmer's crop portfolio and, thus, of land use over time. It is thus possible to give information about the climatic influence on crop portfolio and crop sequence choices as opposed to influences from prices and policies.

For crops that are not yet established in a region, simulation models could provide information regarding when cultivation of a certain crop in a region may become more likely and economically attractive. This analysis can be done by applying acceptance ranges governed by an averaged *sgy* level of a comparative region to growth processes of a potential future crop in the region of interest and under future climatic conditions.

Conclusion

This work introduces a new approach for bio-economic simulation models to integrate farmer perceptions of climatic changes through an economic downside-risk evaluation of plant performance at various stages of production. The approach operates alongside the modeling of the production process, which underlies an optimization mechanism that governs the immediate decision-making process.

Developed at the field level for a small-scale study region, this methodology was designed to be customized for any site to study the perception processes of farmers. It can be applied with relatively little and cost-efficient empirical effort once a bio-economic simulation model has been calibrated for a study site. The methodology may find its way into other regions, for which bio-economic simulation models are used for analysis of strategic decision-making processes in crop production. The above approach may be particularly interesting for farming regions where major components of the crop yield are not brought to market or where market prices are not available; an economic risk analysis regarding climate change should still be conducted. The *sgy* approach does not require price modeling for an economic risk analysis because the economic valuation of profitability is embedded and expressed in yield or other biophysical terms.

Recommendations

In the current version of the FarmActor model, the field allocation process is performed according to a predefined crop rotation that is based on a Markov sequence, relying on empirical observations of the past [60]. What occurs during the production cycle is no longer relevant at the time of the simulated field-use planning. Economic considerations are not incorporated in the field allocation process. The ARS score is the missing link to be used at the time of planning [61] for climate change impact analysis.

ARS scores in that context should be used as a constraint. The constraint should be modeled as follows:

$$\sum_{f}\sum_{c} ARS_c \geq ARS_{0,c} = \widehat{ARS}_c \qquad (3)$$

were f = field and c = crop;

$ARS_{0,c}$ = the reference ARS score for the current year (the latest year for which observations are available) of all fields that have been allocated with a crop c [60].

$\widehat{ARS}_c$ = the expected ARS score for an activity (i.e., crop) as explained in the following. The ARS score for an activity should not be lower than the expected ARS score for an activity. Otherwise, certain fields should no longer be planted with a certain crop, or management options need to be evaluated in the model, which would provide an improvement in the production process.

The expected ARS score ($\widehat{ARS}_{c,t}$) of crop c in year t is the average ARS score of past production processes for a certain crop in a farmer's fields. How the average ARS score is calculated is subject to how learning is modeled and thus past observations are weighted, a topic left for future research. Learning depends on the weighting of past observations and if-then rules [24], which lead to consequences for the farm agent´s decision-making in bio-economic models.

Overall, the *sgy* approach is designed to provide a more comprehensive understanding of the drivers of farm planning decisions by explicitly modeling how farmers monitor production. Only when such underlying processes are better represented in more up-scaled bio-economic simulation models [62, 63] can deterministic statements about the climatic impact on agricultural production and land-use decisions be improved, as stated by White et al. [16].

Future research should aim to attach different valuations and learning patterns to this suggested mechanism and thus gain a more realistic and less assumption-driven understanding of farmers' climate change perceptions and adaptation responses in their land-use decisions [62]. This approach may even assist in diminishing over- and underestimations of the rate of adaptation, which many models show through strong behavioral assumptions despite the high degree of complexity and level of detail of the approach [13–16, 33].

Supporting information

S1 Questionnaire.
(PDF)

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9 Toward more efficient model development for Farming Systems Research – An integrative review

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Review

Toward more efficient model development for farming systems research – An integrative review

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A B S T R A C T

Bio-economic simulation models are widely established in Farming Systems Research; they are used to investigate complex real-world phenomena in agricultural production. Such simulation models are largely designed and created by scientists from different disciplines who are not modeling experts. Thus, IT knowledge is required, but this area of expertise falls outside of most agricultural researchers' background. IT knowledge is essential for the maintenance, development, and applicability of simulation models. Often, bio-economic simulation models require a fair amount of time to ensure basic functionality before specific research questions can be answered. Researchers who contribute to the creation of a bio-economic simulation model often spend the majority of their time ensuring basic model functionality. This integrative literature review provides a few basic rules that are intended to ensure more efficient model development. There is an increased need for support from IT personnel who are not researchers in their own field but who can increase the quality of such models and their reusability in different contexts.

Contents

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1. Introduction

Farming Systems Research places the farm at the center, and everything in the analysis emanates from it. Farming Systems Research was revolutionized as a result of technical progress, and complex integrated bio-economic simulation models (Janssen and van Ittersum, 2007; Feola et al., 2012) were established as analysis tools. Definitions of integrated bio-economic simulation models are not precise, as this type of model is for the most part unique and resists labelling. Following Janssen and van Ittersum (2007) and Oriade and Dillon (1997), we define an integrated bio-economic simulation model as a model that has components, either parametrical or sub-model types, that are able to describe farmers' management processes according to the chosen context and scale or level of model resolution through computer simulation. An integrated model subsumes interdisciplinary modeling approaches (Dabbert et al., 1999; Oriade and Dillon, 1997; Rotmans and van Asselt, 1996), which can be of a bio-physical, (socio-) economic or institutional nature. Bio-economic simulation models are used in studies of system analysis or impact assessment (Thornton and Herrero, 2001). They are either used by scientists only or serve as a decision support system where scientists in cooperation with stakeholders (farmers for example) try to achieve decision support by modeling the consequences of decisions (Schreinemachers and Berger, 2011; Troost and Berger, 2014; Keating and McCown, 2001). This is a way to gain an understanding of complex real-world phenomena and systems (van Ittersum et al., 2008; Rotmans and van Asselt, 1996), which for the most part cannot be investigated in a laboratory (Schreinemachers and Berger, 2011) or can otherwise be achieved solely through long and costly experiments (Keating and McCown, 2001). "The necessity of a bio-economic model and integrated approaches comes from the fact that both systems (biology and economy) are interrelated (Prellezo et al., 2012, p. 423)."

Farming Systems Research with (integrated) bio-economic simulation models incorporates multiple research fields (Rotmans and van Asselt, 1996), from plant modeling to meteorology and the economic and social sciences. Covering so many disciplines is challenging when recruiting personnel (Dabbert et al., 1999). It is nearly impossible to find people who are experts in all of the required research fields. A specialist in a field of research is necessary to be able to produce results that are publishable in a scientific journal. The fact that results should be obtained via bio-economic modeling requires a commitment to interdisciplinary thinking and a willingness to gain skills that are specific or elementary to a discipline outside one's scientific expertise (Nicolson et al., 2002). As simulation models are computer based, basic knowledge of computational rules is essential. A successful simulation model depends on the application of rules that were established in the field of Information Technology. These rules relate to the establishment, documentation, maintenance, and application of simulation models.

The concept of using simulation models as a research tool dates back to the mid-sixties (Dillon et al., 1991). Tremendous technological progress has occurred since that time. However, the establishment of such a model is still a considerable undertaking that must not be underestimated (Fall and Fall, 2001). It is astonishing how many new models were developed rather than using established models and expanding or customizing them as Dillon et al. (1991) projected. Many of these modeling efforts are forgotten once there is no more funding or a specific research question is answered (van Ittersum et al., 2008; Janssen and van Ittersum, 2007). "A common problem with many models is that they are large, complicated, and poorly documented "black boxes", and consequently few if any researcher beyond the developers are able to use them (Antle and Stoorvogel, 2006, p. 41)." This is also a critical point with regard to replicability of results (Fall and Fall, 2001). Replicability of results, a fundamental aspect of the scientific method, depends heavily on compliance with software design principles in this context (Keating and McCown, 2001).

Models will only be of use for other scientists if their infrastructure offers a good basis for an efficient customization process. Most features that support user-friendliness and model flexibility require a great deal of work, which is seldom part of the research proposal (Holzworth et al., 2014) and does not necessarily lead to scientific or publishable results. Greater user-friendliness and flexibility are the result of high-quality software configuration management and an efficient documentation process. Knowledge about promoting these features in scientific software is gained from the development process. Preventing access to such knowledge can lead "to premature releases of science with users applying incomplete models to real world scenarios, something that risks incorrect analysis (Holzworth et al., 2014, p. 344)".

The crop growth modeler community (both bio-economic simulation models and stand-alone model frameworks) has already addressed this issue. Authors such as Porter et al. (1999) suggested that there is an increased need for research on approaches that support more effective model development as well as a documentation process.

We draw on their propositions when formulating the objective of this paper, for example, providing recommendations that are intended to support a more efficient development of bio-economic simulation models at all levels of complexity, thus making them attractive for re-use. There is certainly no standard or established methodology for formulating such recommendations. We use our own experience from active participation in such interdisciplinary modeling projects as the basis for an integrative literature review (Pautasso, 2013) to create this piece of inductive research. We found further support for our objectives in papers by Janssen and van Ittersum (2007), Nicolson et al. (2002), Keating and McCown (2001), and Dillon et al. (1991), which are in parts literature reviews themselves. Unlike these authors, we place greater emphasis on the practical, technical aspects of the software engineering process. By doing so, we aim to call attention to this issue among non IT-trained scientists who intend to build models for Farming Systems Research as well as to reviewers of these works. Given our limited experience, our recommendations are to be tested in terms of their usefulness to others.

The remainder of this paper is organized as follows. After classification of bio-economic simulation models according to their level of integration, we start by answering how such models should be designed. Then, we show how model improvements or developments at different stages should be managed. We further focus on the importance of testing. We provide a best evidence review of successful models that survived their initial stage and note why they are relevant for re-use. Finally, we explain why IT specialists should be hired to assist with model development and give a short list of mandatory recommendations for future modelers.

1.1. A classification

Simulation models come in all degrees of complexity, depending on the model focus. The implementation of one of the large model frameworks is determined based on research context (scope), expertise, time and financial constraints (Dillon et al., 1991). Often, data availability retards/hinders the generation of a solution by means of a complex bio-economic simulation model. In such cases, sub-models of large modeling frameworks are loosely coupled (Antle et al., 2001) with the parametrical function, where simulation output is used in the parametrical function. This is even more likely when the construct is only a means to investi-

Table 1
Concepts of model integration and their levels.

Levels of Integration (Crissman et al., 1998)	Level of Integration (Antle et al., 2001)	General Categorization (Brown, 2000)	Concepts of Model Integration (Brown, 2000; Crissman et al., 1998)
Depth of integration increases			
Level 1	Loosely coupled	One result as input for other model	• Independent simulation of economic and bio-physical models and subsequent combination of outputs
Level 2	Close coupled	One result influences the other result	• Output of economic model is used as input for bio-physical component and vice versa • No feedback between bio-physical and economic components
Level 3	Fully coupled	Includes feedback processes, dynamic models	• Joint simulation of economic and bio-physical component • Dynamic feedback (over subsequent periods) from bio-physical to economic component

gate a detail or is only one part of a research question rather than being another part of the overall result of the research study.

Model systems that are able to incorporate system dynamics are the most complex (Antle et al., in press; Antle and Stoorvogel, 2006). Such models are able to explicitly incorporate time and investigate results as well as all aspects that are necessary to achieve the result. In addition, they often pursue a positivistic approach that describes how a decision maker achieves his or her decision rules while also investigating the underlying mechanisms of a decision-making process (Feola et al., 2012). Due diligence with regard to rules of software integration management increases with the level of integration largely because interdependencies between model components and model complexity increases.

Table 1 gives an overview of how bio-economic simulation models can be categorized according to level of integration.

2. Recommendations for model system design

Solving research questions by means of an (integrated) bio-economic simulation model requires a deep understanding of the system components and how they are linked (Herrero et al., 1999). It is left to the modeler to determine how the components are linked and how the decision-making process is set up. With regard to how problems can be investigated, many (integrated) bio-economic simulation models are highly flexible; nevertheless, it is most likely that a model that fits every purpose is not available (van Ittersum et al., 2008). Either a custom design has to be developed from scratch, or if a prototype/framework exists, it has to be adjusted to generate results that answer a specific research question. Once the decision has been made to create an integrated bio-economic simulation model, there are several important points that must be taken into account to achieve easier re-use of model designs and to avoid a failed modeling effort.

2.1. Modeling objective

At the beginning of each modeling project, the scientific scope has to be communicated to each party (Dabbert et al., 1999). What is the goal of the modeling exercise? What is the modeling objective (Meynard et al., 2012)? What is the purpose of the research? Further, it should be certain that there is a common understanding of concepts and that everyone involved has the same understanding of key information and functionality of the simulation model at each stage of development (Nicolson et al., 2002).

One option to achieve a coherent model design is noted by Antle et al. (2015) in the AgMIP approach. Key system components are identified and characterized by the development of a representative system diagram or "cartoons". Meynard et al. (2012) refer to Le Masson et al. (2006) to describe additional ways to design a farming system. First, a rule-based design is described, and then an innovative design is presented. While the rule-based design builds on existing products, the innovative design makes it possible to explore new dimensions in modeling.

2.2. Model system design and documentation during development

Each model (framework) has a basic or core design that evolves with model development. It is created by the simulation model creator and updated by subsequent developers. Design relates to the technical structure of a model as well as the content structure. A structured design facilitates an overall understanding of the model (framework). Even if the model is at the conceptual stage, a documented model design in the form of a preliminary draft is useful for current users (Balzert, 2001).

A model consists of the overall model structure and has an inner core that consists of several sub-models. This is the basis of the modular approach, which is supported and promoted by many experienced modelers (Holzworth et al., 2014; Janssen and van Ittersum, 2007; Porter et al., 1999). It has the advantage that each part can be improved, developed and worked on separately (Porter et al., 1999).

"Developers and users of simulation models are typically different (especially in the case of agricultural economic applications) because of the expertise needed to develop such models (Dillon et al., 1991, p. 214)." However, there are cases where this separation is not given.

Ideally, a modeler is responsible for the overall model, which represents, for example, a farming system. That person does not have to be an expert in one of the sub-model types but must understand the interaction of sub-models and take control of the overall structure based on the model (framework). Sub-models, like plant growth models, are designed by specialists for a specific part of a simulation model. Before a sub-model can be designed, modelers gather ideas about how the overall farming system design should look and determine the functionality and resolution of the model. Gathering ideas and structuring them according to the overall model design leads to groups of ideas that have the closest connection (Balzert, 2001). These groups are the basis for a sub-model.

Once a model is built, it can be transformed into actual code, as the scheme in Fig. 1 attempts to display.

A good model structure is the best foundation for a sound programming code structure, as shown by State II in Fig. 1.

Most often, budget constraints limit the number of participating modelers, or the modelers are scientists who focus on a particular research question that is not necessarily model related. To be able to participate in sub-model development, a significant amount of time is required to familiarize oneself with model design. Thus, the content driven scientist must study the basic principles of programming model design. As a consequence, this person can never be as experienced as an IT-trained expert, which may have a negative impact on the quality of the overall model (Dillon et al.,

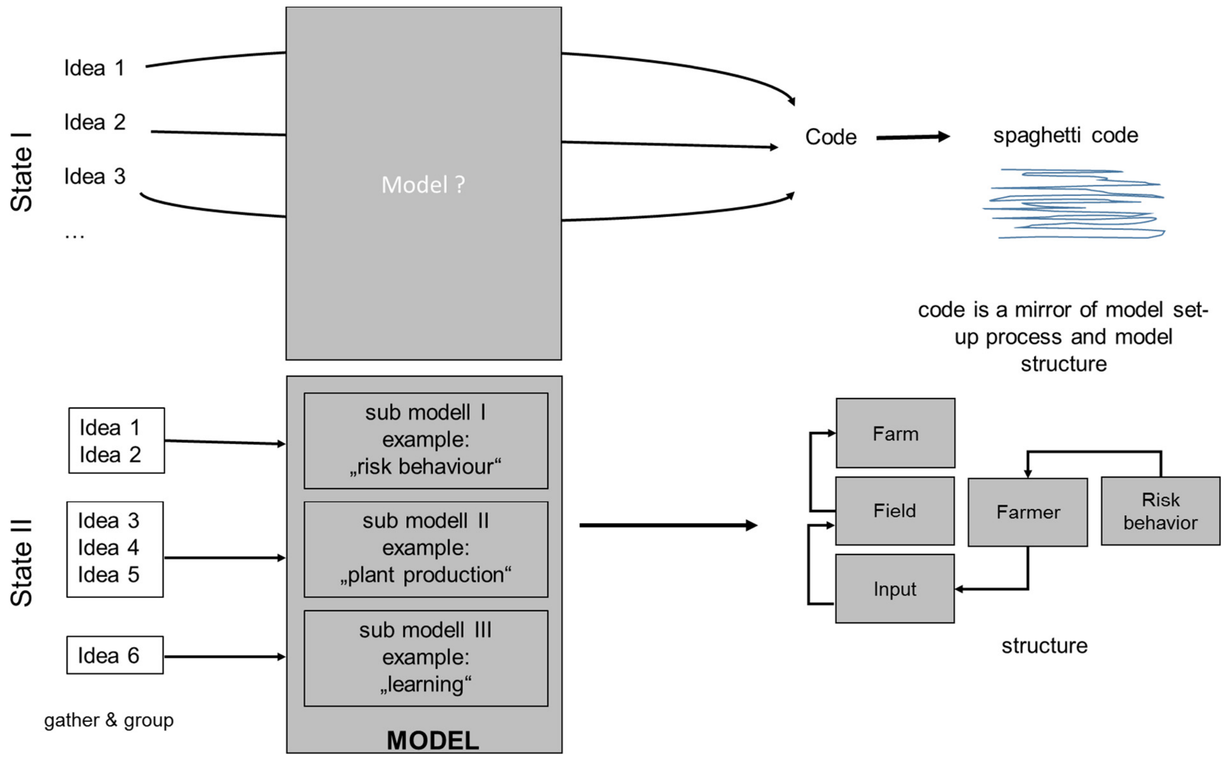

Fig. 1. Model design – target (State II) vs. non-ideal state (State I). Source: Own depiction based on Balzert (2001) and Arthur (1988).

1991). Consequently, a good model structure is nonexistent, and State I (Fig. 1) is the actual state, which is the result of a missing structuring process. All ideas are translated unfiltered into code. As a result, so-called anti-patterns or "spaghetti code" can be found in the programming code, or model conjunctions are not thought through.

Spaghetti code can have several negative consequences for model maintenance. Errors are more likely, and it may take a significant amount of time to find the source of an error. Further, the execution time of the code is slowed down as the code is less efficiently structured; this increases with the size or resolution of the simulation model.

2.2.1. Common terminology

A common terminology helps to avoid misunderstandings. Communication among modelers, who are specialists from different scientific fields, can be challenging (Farrell et al., 2013; Nicolson et al., 2002). Every modeler obtains his own understanding while working with the model and applies his discipline-specific terminology. When communicating with other modelers, it is essential to gain a common understanding and define certain terms. This is similar to creating a "corporate" language (Dabbert et al., 1999). An incorrect understanding of model terminology may lead to an incorrect use of the model. Such model-related terminology is equivalent to the provision of appropriate tools for all specialists.

However, in addition to a common understanding is an understanding of the model system design. A sound model design offers two advantages; first, it provides a benchmark against which everyone can test their contributions and expectations, whether technical or content related. Second, the overall goal is to achieve a sound software infrastructure, which results from the aforementioned. The better the software infrastructure, the better is the reusability of the model or model components in different contexts. Furthermore, it supports the ability to link other model components to the basic components of the model (framework) (van Ittersum et al., 2008).

2.2.2. Model integration

Once a model design is established, the actual work of programming and assembling model components begins. One should start with the base of the model (which, in a farming system, is most likely the farm), as everything else is linked to it. Other submodels should be added only when the farm, as the base submodel, is fully functioning. Initially, other sub-components should be kept as abstract as possible. In this context, abstraction is related to the level of detail with which the model entity is described (Prellezo et al., 2012).

The number and type of fields to be modeled may remain undecided. A field is an abstract entity with abstract characteristics, though it can later become a more specific entity, such as a field becoming a wheat field with certain seeds, fertilizer and activities.

Another critical design decision that must be made at this stage is how to best integrate the economic and bio-physical dimensions in such a model. To account for feedback processes in a Level 3 model (Table 1), the economic component must use measures consistent with those used in the bio-physical model. In particular, when representing technology, it is not possible to achieve a sound integration if a dual approach (through costs) is applied, as is the case in many economic models (Flichman and Allen, 2014). The influencing factors that determine the units of shared measures between the economic and bio-physical models include the temporal resolution, the theoretical approach behind the economic model and the resolution of available data.

There are two ways to couple the economic and bio-physical model components to achieve complete integration (see Fig. 2).

2.2.3. Examples for coupling via exchange of simulation output

The simulation results can be used in one of two ways: (a) They are linked via a call-up mechanism to trigger dynamic adaptation of daily crop management decisions. The overall results from the

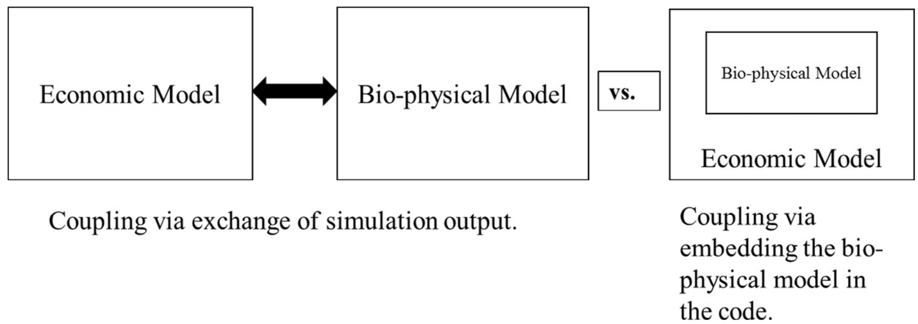

Fig. 2. Examples for the integration of economic and bio-physical models to simulate feedback.

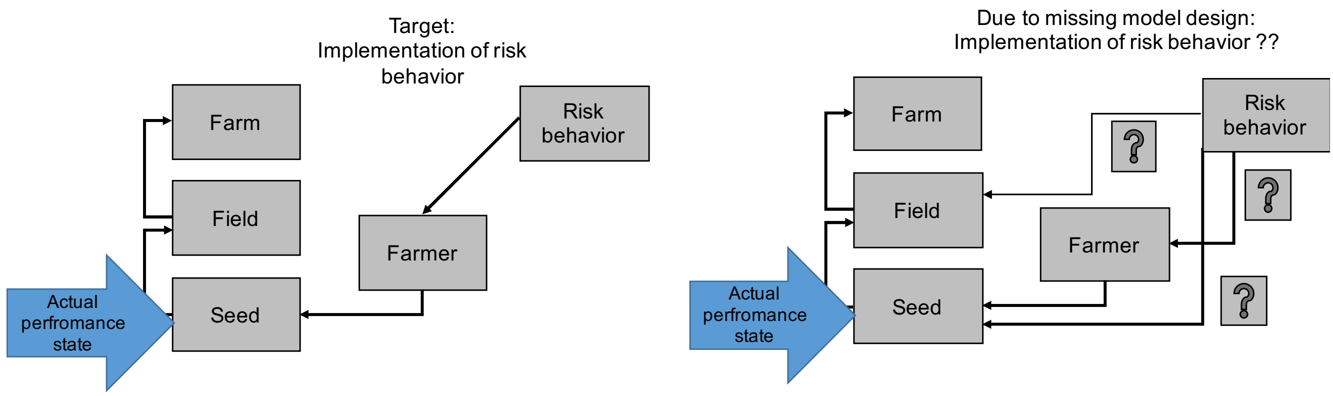

Fig. 3. Issues of sub-model development with missing structure at superordinate level. Source: Own depiction.

management routine are evaluated from an economic perspective at the point of planning and feedback to the crop management module (Aurbacher et al., 2013). Alternatively, (b) simulation results are used to define states of selected variables to be used as engineering coefficients in a production function, as in the meta-modeling approach of Belhouchette et al. (2012).

2.2.4. Coupling via embedding the bio-physical model in the code

In the case of Holden et al. (2005), the bio-physical dimension is represented by modeling the yield as a function of select variables, such as the soil type or soil depth.

The yield is used as the reference value to benchmark changes on both the economic consideration side and the production side to analyze the effects of conservation technology over time.

When the bio-economic model is included in the code, the compatibility of the economic model code with the code of the bio-physical model should be evaluated beforehand, and the way that model calibration influences the progress of development at each stage should also be considered. Each coupling approach has its own merits. Coupling via exchange of simulation output allows for an independent development of each sub model by specialized modelers. If such specialists are not part of the team or data for calibrating a stand-alone bio-physical model are not available and given it serves the overall modeling objectives, embedding the bio-physical model in the code can be an efficient way to achieve complete integration.

For the overall model framework, Schreinemachers and Berger (2011) recommend a case-by-case development whose steps follow a particular research question. Such a procedure may be most convenient for scientific models, but there are pitfalls in case-by-case development that should be avoided.

2.2.5. What happens when step 2 is forced to come before step 1?

Depending on the availability of experts, a model feature attached to a lower level of abstraction (scheduled for a later stage) may be implemented before the basic model is fully employed. The problems that can occur in such a situation are demonstrated in the example “Implementation of Risk Behavior”.

Risk behavior is most often modeled by a sub-model modeler who is an expert in risk analysis. Risk behavior is a feature that is not part of the basic functionality; it is an add-on analysis tool. An expert for such a specific part of a model may join the team later in the process. Possible consequences are displayed in Fig. 3 for a model where a) State II (see Fig. 1) is not achieved and b) the overall model is not yet fully employed and only sub-components are functioning; the functionality for risk behavior shall be implemented at this stage.

Risk behavior in principle can be implemented at different levels of a farming system. Typically, it is implemented at the highest level, which is the farm, as displayed in Fig. 3; this triggers components throughout the sub-levels with regard to risk. In this example, the implementation takes place at an intermediate model development stage. It is not possible to implement risk behavior where it was initially intended to occur. Thus, it may have to be implemented in a different part of the model so that the hired expert can be on time and achieve usable results. Nevertheless, developers creating the sub-model for risk cannot ignore the final state of the simulation model. Here, the importance of a sound structure is evident. The risk expert has to change his initial plans and create a new implementation. A poor structure complicates the understanding of how and where this behavioral aspect is appropriately implemented. In addition, comprehensive documentation is the foundation of a successful model.

2.3. Documentation

White et al. (2011) and Antle and Stoorvogel (2006) criticized the lack of transparency regarding how results are obtained by simulation models. They found that almost all research papers fail to provide full documentation on how outputs were actually

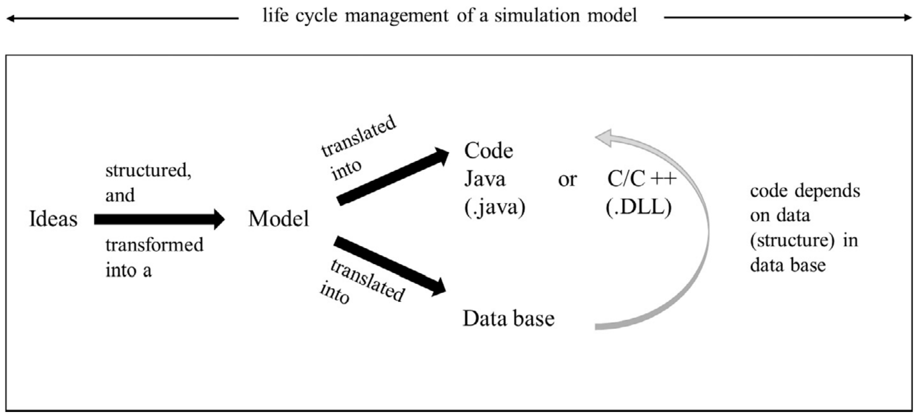

Fig. 4. Documentation life cycle management. Source: Own depiction based on Balzert (2001) and Arthur (1988).

achieved. Only a model with proper documentation meets scientific standards, in particular for the reproduction of results (Antle et al., 2015; Nicolson et al., 2002).

Furthermore, documentation supports the scientific practice of revision and change. It is an ongoing task that must be performed by all model developers. With proper documentation, changes can be reversed, thought processes are reproducible, and errors may be avoided.

Fig. 4 gives an overview of how documentation should evolve over the life cycle of a simulation model.

Once an idea has been transformed into a model and translated into code, a new chapter of the life cycle of a simulation model begins.

Certain key information must be part of each (intermediate) documentation procedure regarding changes to any part of the model.

– Who is affected by the changes?
– Is it a fundamental change in the model or only an additional feature of the model?
– What part of the model is affected and how? A functional graph may be very helpful for everyone involved.
– If settings are affected, how are they affected? Do configuration files have to be set up differently? If yes, how?
– Is the data base or its structure affected? If so, how and is it necessary to update the data base?
– Does it change model behavior? If so, where and how?
– Can errors occur and what are possible causes for them? How can they be solved?

Whatever the case, documentation must help all users – regardless of the level of familiarity with the model – become acquainted with innovations in a reasonable amount of time at any stage of model development.

Once everything is written down, there is a structured way of making information available to others. This can be done via version management. One of the most important aspects of this form of management is the ability to use a certain development stage as a functioning model version, while those who develop the model structure can operate with their "own versions".

2.4. Version management via SVN

Ideas, updates and model versions are usually stored at a single location that serves as a version control center. Here, access to all files and versions is coordinated. The location where all versions are saved is called a repository. It is recommended that the repository be placed on a server that is accessible by anyone who needs to work with a certain version of the model. A popular form of version control is SVN, which stands for Subversion (Collins-Sussman et al., 2005). SVN systematics makes it possible to manage versions and developments of single parts of the program. It structures the versions of a model that are usually stored on a server. SVN follows a tree systematic (Collins-Sussman et al., 2005). The main branch contains the latest version of the software. Side branches are usually used for bug fixing or specific developments that are scheduled to be tested. These ideas are typically tested separately in order not to compromise the main program, as it may remain an idea and only be incorporated into the main program after sufficient testing. Branches are there for side developments, like special features of a software that are not necessary to operate the main system but can be useful when exploring specific problems (Collins-Sussman et al., 2005). The SVN systematic can also be used to manage updating processes. Updating processes are intended to provide end-users or other modelers with new versions of the software. The secondary effect of the updating process is the documentation of all stages of development. Nevertheless, it must be noted that the updating process is a major source of error. Users who are not modelers take the new version from the repository without having the option to check for the correctness or completeness of the content. What may be forgotten is that not all changes can be easily recognized via the model output. Model misbehavior may occur despite the fact that a user was using the new version of the software correctly. Thus, a fundamental part of model development is testing by developers before a new model version can be provided to other users.

2.5. Testing

Accadia et al. (2013) defined three types of tests. A Unit Test is performed when code developers change a section of the code. This is a rather basic test that checks parts of the software code. The Integration Test accounts for changes in multiple code sections that have passed the Unit Test successfully and are now integrated into the software. This is the last test before the whole framework is tested in the System Test.

During model construction, there are certain stages when model testing is strongly recommended. With a State II design as displayed in Fig. 1, testing is usually conducted after a sub-model has been implemented or an implemented sub-model has been extended.

Testing is a plausibility check (Balzert, 2001). This procedure requires the current version of the overall model to be rebuilt from the beginning, as would be done by an "external" model user who installs this simulation model for the first time. If any part malfunctions, this part must be revised immediately before any other extension is implemented. Meanwhile, everyone else who participates in the development of a model or uses interim versions has to operate with the "old" but fully functioning version.

2.5.1. How should testing be conducted?

Preparation: The device used for testing must be free of any part of the program to be tested. Ideally, one uses a different computer than the one the program has been developed with. If this is not possible, the complete program has to be deleted from the computer with which it will be tested, including any supporting software or programs that are necessary to ensure software operability. Testing is a strong deterministic procedure (Balzert, 2001). Every outcome of a test has to be defined in detail before the procedure begins. Tests must be repeatable, always giving back the same predefined result at a given parameterization (Accadia et al., 2013).

If a modeling framework is designed to be operable in different hardware environments and thus transportable, testing must be extended to include issues other than the code. The whole testing procedure needs to be conducted with different compilers and computers (Dillon et al., 1991). If model improvements are tested successfully, they can be released to all participating parties in a new model version. Release documentation is recommended in order for all participating units to be able to update the old version and become familiar with the new version (Troost and Berger, 2014). It is strongly recommended that each modeler creates documentation according to his or her own view of the model as well as how version updates affect his or her model usage, in particular with regard to errors.

2.6. Documentation of errors

An often neglected aspect of documentation for scientific models is the importance of sources of error. It is also important to illustrate how errors have been fixed and can be avoided in the future.

Errors may be of diverse origin, which are not obvious to every user. Potential errors are typically documented in the code, so-called run-time errors; they are presented in the console with which the program is operated. However, there are errors that are not included in the code; such errors are difficult to find, even for experienced modelers.

Possible reasons for errors are the following:

– misapplication;
– misbehavior of model components due to incorrect parameterization;
– errors caused by incorrect model settings in general, for example, missing data in the data base.

2.7. Misapplication

Misapplication of a model can have many sources. One is the wrong combination of settings in the initialization file. Settings are commands with which a program can be operated.

Depending on the quality of a software, the initialization settings for a model run can be set in one file (van Ittersum et al., 2008) or may have to be set in different files. The worst case occurs if settings are hidden somewhere within thousands of lines of code. This is called hard-coded settings, which means that each time this part of the model has to function differently, it cannot be triggered by a different command in the initialization file; the setting has to be changed directly in that part of the source code (Dillon et al., 1991). In working versions, hard-coded parameter settings may not be the exception but the rule, as this can be an efficient way to test ideas for new features. However, once these features become part of the actual model, settings should be moved to a single initialization file. If a modeler decides to use a hard-coded setting, there are two important points to be considered. First, it has to be made explicit in the documentation where these settings are hidden in the code. Second, this part of the code should receive special attention when new versions are created and all code is compiled.

In commercial software packages, settings are often provided in the form of a drop down menu with instructions describing which settings are necessary for the type of model run scenario. This often is not the case for scientific software that is under development. It is thus necessary to provide target users with information about the settings and combinations of settings that are required for a certain output.

Settings can also be summarized and provided via files. This applies in particular for dynamic models where sub-components can be endogenously operated by the main model. A prominent example is settings for plant growth models, such as Crop Syst (Stöckle et al., 2003) or Expert-N (Priesack, 2006). Such models simulate the bio-physical processes of a plant in integrated bio-economic simulation models (Oriade and Dillon, 1997). In Crop Syst, simulation runs can be produced by using the simulation control file. Different types of input files that are necessary for a specific type of run are combined in this file. Users are also able to choose whether they want to switch additional effects on or off (Stöckle et al., 2003).

For more convenient handling of input file settings, small executable programs can be created – so-called shared libraries (e.g. DLL) files – that contain the correct settings to run a simulation and that only have to be saved by the user at a predefined location. This is highly recommended, in particular when the end-users are scientists who are not experts in plant growth models, for example, agricultural economists. First, finding the correct settings within a given time is most likely not their field of expertise, and second, this task can usually be completed during validation and calibration of the sub-model component "plant growth model" (see Fig. 1). It is recommended that users be provided with such files and a reference output so that they may test the file with their version of the program.

Apart from this option, a common place for settings is a data base.

2.8. Data base

Data bases usually store input data and simulation outputs. They are the foundation of many successful models. Instead of initialization files, data bases offer an easy way to store initialization settings for model run scenarios. A drawback of using them is that settings can very easily be changed by accident. Depending on the size of the data base, such unintended changes may not be revealed or found very easily. Furthermore, database maintenance can be very time consuming depending on the level of detail of the information that is covered by the data base (Feola et al., 2012).

Another important aspect of data base content is that it is usually processed data or a unit free "version" of raw data, i.e., plain figures. Therefore, it is mandatory at any preliminary stage that units be defined. When information regarding units is not listed in the column of a data base, it must either be provided in the information box of the data base tables or in a related part of the documentation repository. Further, the original source of the data stored in the database that has not been created by simulation needs to be documented. Sources should be easily accessible and made explicit in the documentary file; a corresponding version number should be provided that indicates the version in which the data are to be used.

The size and design of a database can affect the performance of a simulation model. The more data that are stored and taken from the data base during simulation, the more likely is the occurrence of technical problems. This case applies in particular to users who access data bases via a VPN (Virtual Private Network) connection. A VPN is a secure connection that makes it possible to exchange data. In such cases, data bases are managed from a headquarters and are not provided for local storage. At a certain amount of data volume exchanged during runtime, this can affect either the performance of the simulation model, or results may require more time due to connection problems, not to mention a loss of results.

A solution for such problems is to make the data base scheme available by providing a so-called dump for other model users so that the data base is set up at a different computer or location. Dumps can be made available for the whole structure or only parts of the data base that must be stored at different locations, and they are useful for performing updates. Programs that can be used to facilitate a data base dump can offer users support in creating database queries that provide access to (inter-temporal) results, for example, TOAD for SQL (www.toadworld.com), which is a freeware software.

2.9. Successful examples of bio-economic simulation models

Over time, several models have survived the initial stages and are available for re-use. The number of publications that emerged from the application of these models is the best evidence of their usefulness within the scientific community. Most of the recommendations mentioned earlier are realized in successful models. A small selection of these models are introduced below as part of a review that includes information about their creation and what makes them relevant to other scientists.

The Agricultural Production Systems sIMulator (APSIM) software was developed to study the influence of climatic risks on agricultural systems. Its structure is modular, with components that represent plant, soil, and farm management. Its simulation options make it possible to analyze long periods of time within the research framework, thus accounting for how resource issues can be best managed under a changing climate (Keating et al., 2003). The APSIM Initiative offers one of the most professional managed research frameworks available for Farming Systems Research, providing not only the software but full documentation, user tutorials and support for users (Holzworth et al., 2014). They also support their modelers by offering "science and software peer reviews, automated testing, continuous integration, training users to undertake "due diligence" (Holzworth et al., 2014, p. 344)" in order to promote models of high quality that ensure correct analysis.

Foundation Members of the APSIM Initiative are, among others, the State of Queensland (Department of Agriculture Fisheries and Forestry) and The University of Queensland.

The System for Environmental and Agricultural Modelling (SEAMLESS) is a platform that is used to study "land-bound agricultural activities and their interactions with the environment, economy and rural development" (van Ittersum et al., 2008, p. 152). The interdisciplinary and multinational modeling approach unites more than 100 scientists. The model design for SEAMLESS was distributed among modelers according to expertise. Two types of modelers are distinguished: integrative modelers and domain-specific modelers. Integrative modelers implement and run model chains. Domain-specific modelers manage the sub-components of the model and their source code or data (van Ittersum et al., 2008). For SEAMLESS, interaction with users has a strong influence on the design of the model.

OpenDanubia is an integrated simulation model that incorporates coupled sub-models under the term deep-actor to assess "future impacts of Global Change on agriculture, industrial production, water supply, households and tourism businesses (http://www.glowa-danube.de/eng/opendanubia/opendanubia.php, accessed by 2016/07/20)" (Hennicker et al., 2016; Ernst et al., 2016). The model framework was designed for answering a wide range of research questions. Feedback between system components can be modeled within the framework of the model, which offers documentation that addresses system installation as well as a reference simulation that shows an example application of the system. When models are coupled, it is sometimes necessary to install additional programs or scripts to convert model languages or make them compatible with a system. For this purpose, OpenDanubia offers suggestions on the homepage.

"MPMAS, Mathematical Programming-based Multi-Agent Systems, is a software package for simulating land use change in agriculture and forestry. It combines economic models of farm household decision-making with a range of biophysical models, simulating the crop yield response to changes in the crop water supply and changes in soil nutrients (https://mp-mas.uni-hohenheim.de/, accessed by 2016/20/07)". MPMAS is a multi-agent system model that couples physical landscape models with an agent-based component in order to study land use decisions (Parker et al., 2003). The outstanding feature is its ability to model interactions between decision makers that then have an effect on their environment. The modeling scale is highly flexible and can be adapted to the model context (Troost and Berger, 2014).

Input files for MPMAS are MS-Excel workbooks with additional add-ins needed for scenario set-ups. Further, a toolbox was created that supports the creation of model inputs. It relies on a database that stores important model inputs and outputs. In addition, as with other software packages, MPMAS offers a user manual with additional documentation of country-specific equations and model parameters. Their homepage offers tutorials for sample applications (https://mp-mas.uni-hohenheim.de).

IMAGE (Integration modeling of global environmental change) as an earth system model, is a framework that allows for "integrated assessment of global sustainability issues (MNP, 2006, p.6)". IMAGE has evolved over a history of 36 years of development and application with several model versions. It has an Advisory Board that makes strategic decisions regarding model improvement, enhancements and extensions. Model improvements built on prototypes and updates are regularly published (MNP, 2006).

3. Discussion and conclusion

Agricultural scientists are often the initiators of simulation models that aim to solve problems in Farming Systems Research by mimicking real-world processes in the virtual world. A priority for any scientist is therefore good representation of all relevant elements of the farming system to be investigated. This is what drives software establishment rather than the technical side. The principles of software development, presented in the methodological part of this article, are rules that should be mandatory for everyone involved in software design. However, we do not claim that these are complete, as farming systems are multifarious.

When researchers attempt to address a research question with a new simulation model, they should think about what makes established models so successful, and they should set themselves the objective of achieving the same reliability with their own design.

Some agricultural scientists may be well trained in computer languages or principles of software design; the majority of model designers are, however, specialists in their scientific field; they are therefore content driven (Dabbert et al., 1999). Therefore, it should be noted that the in-depth technical knowledge of an IT specialist cannot be easily duplicated with study, in particular in terms of objectivity, disciplined testing and adequate documentation (Antle et al., 2015).

A lack of testing discipline can result in model users acting as involuntary model testers. There may be models that are never completed and end up as working versions. Whatever the case, results must be replicable, and important elements should be reusable.

A scientific simulation model cannot be a secret tool. The process requires transparency. Ideas that have been translated into a model should nourish new ideas, both technical and content related. Otherwise, the simulation model approach as a scientific analysis tool may lose its relevance when no improvements can be added to the body of literature (Janssen and van Ittersum, 2007, p. 634) and many issues remain to be solved in that regard.

An IT specialist whose only task is to provide support for such projects may be a resource for future endeavors. Such specialists should be available at every research facility as they are able to control the development process and offer technical support. An additional point in that regard is that such a specialist may contribute to ensuring that each participating unit is able to clearly delineate their contribution from that of others (Dabbert et al., 1999).

Working in the context of decision support models, Antle et al. (in press) argue for greater emphasis on (target) user needs when creating a new generation of models "by starting with user needs and working back to the models (Antle et al., in press, p. 2)." This claim fits our purpose.

Finally, each researcher who is funded has a certain time limit within which his research is to be completed (Dillon et al., 1991) and most often has limited resources (Holzworth et al., 2014). Most critical is the aforementioned for projects where simulation models are built from scratch and the model is part of the overall research output. Simulation results can then only be a preliminary output for a significant amount of time and may be restricted for use in technical papers only. Furthermore, the nature of software engineering is such that a great deal of time goes into work that is necessary but of no use for a specific research objective (Holzworth et al., 2014; Dabbert et al., 1999). The development of a trouble-free model forces the commitment of all parties involved, and individual interests can easily be pushed into the background. However, pushing individual interest into the background and committing oneself 100% to a project instead of completing individual tasks is impossible, in particular in an academic environment (Dabbert et al., 1999). A simulation model should be planned carefully with regard to budget, time and scope.

The points presented in the recommendation part of this article are lessons that are provided for future modelers, as we found that many of these critical aspects are rarely discussed from a technical point of view. If they are discussed, it is for the most part in terms of interdisciplinary or less practical recommendations. In our experience, these are key factors that can be decisive in the success or failure of modeling projects. For IT specialists, they are mandatory but not for inexperienced modelers.

The following bullet points summarize our findings. Successful farming system model development, redesign, innovation and application are dependent on the following:

1. Definition of a common terminology to avoid misunderstandings.
2. A well-structured model design with agreed upon modeling objectives.
3. Proper testing of newly implemented model system parts.
4. Comprehensive and understandable documentation. Ideally, users should create their own documentation according to their understanding of the model.
5. Full documentation of errors, which can occur at all stages, from model set-up to complex cases of model usage.
6. Professionally managed version management.

Future model designers should contribute to this list to facilitate successful model developments.

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10 Synthesis and Outlook

Integrated bio-economic simulation models have become an established means to investigate agricultural land use systems which are affected by many exogenous factors such as climate change (Jones et al., 2017; Flichmann et al., 2014).

On the technical side, these simulation models mostly consist of different model components such as bio-physical and economic sub-models, which are integrated in a model framework (Jones et al., 2017; Reinmuth and Dabbert, 2017). Through an interplay of the model components, dynamics in decision-making and feedback processes can be mimicked (Aurbacher et al., 2013), which otherwise could not (or through costly endeavors only) possibly be investigated in the real world (Berger and Troost, 2014; Schreinemachers and Berger, 2011).

Crop production is one of the most important land use components worldwide (Foley et al., 2005). Climatic influence represents an uncertain input factor for agricultural production. Crop management and, specifically, the strategic planning of crop-related land use are most likely to become more challenging in a future with a projected increase in climatic variability (IPCC, 2014)

During production and at yield level, certain variability in a crop's response to climatic influence is perceived as "business-as-usual" to a farmer. However, depending on the level of acceptance of variability, certain fluctuations are perceived as risks by the farmers because this divergence may imply a financial loss (Hardaker et al., 2004).

Through technical developments, many aspects of the steps involved in a decision-making process under risk can be mimicked more realistically with state-of-the-art dynamic integrated bio-economics simulation models.

However, highly resolved integrated bio-economic simulation models still lack a proper method to operationalize risk (perception). Oftentimes, risk is not integrated but analyzed in a comparative static way using a simulation model output that does not feed back into the decision-making process of the upcoming production cycles. One very obvious reason lies in the nature of available statistical models for risk analyses, which could be implemented in simulation models.

Although decision makers' attitudes towards risks can be included in statistical models, these attitudes only refer to the result of the (agricultural) production process, although farmers' assessments of the riskiness of a crop are not based solely on yields. The yield is only one single point at the end of a long process. A proper assessment of risk that integrates the assessment from process to planning requires a solution tailored to the nature of state-of-the-art highly resolved integrated bio-economic simulation models.

The main body of work of this dissertation thus represents a newly developed methodology for dynamic risk assessment in agricultural planning decisions. It was developed using the highly resolved dynamic bio-economic farm-simulation model FarmActor (Aurbacher et al., 2013).

So-called ARS scores summarize farmers´ perceptions from the process to be used during planning (Reinmuth et al., 2017). This way, it is possible to operationalize dynamic risk assessment.

An important side-effect of this approach is that it enables modelers to better isolate the climatic influence in planning decisions from other influences. This is another important achievement because the isolation of single effects in the decision-making process was found to be a challenge in many contexts of previous decision-making analyses (Gbetibouo, 2009; Just and Pope, 2003) and is necessary to provide the best basis for decision makers.

In the following, the objectives of this dissertation are discussed critically in terms of achievement and further research needs. The critical analysis of the technical tool, the integrated bio-economic simulation model, is presented as an integrative review article in the last component of this cumulative dissertation. Thus, more emphasis is placed on the research needs that emerged during the development of the new methodological approach.

10.1 Empirical work

The empirical work that underlies this dissertation was part of a mail survey conducted by four PhD students. This method did require a limitation in the number of possible questions supporting the methodological task of each of the students involved.

As presented in the third article, farmers were found to perceive a change and increased variability in climatic conditions. Additionally, the predictability of weather decreased, and consequences from these changes are expected for farmers' businesses (Jänecke et al., 2016). Though methodologically correct, strong assumptions about the actual distribution of the variables underlie the analysis.

The number of respondents in both study regions was low overall, which is why the number of observations for the regression models in the third article, for example, ranged from 114 to 133 cases. The predictor variables in the empirical sample are also very heterogeneous, which affects the underlying distributions of the models.

This also affected the analysis of risk sensitivity types that resulted from the empirical work presented in the fourth article of this dissertation (Chapter 8) and discussed in the next chapter.

10.2 Farmers' subjective attitudes towards climate-induced variability

As part of the farmers' tolerance for yield variability, three points about the yield distribution of each of their crops were assessed. This three-point approach was used to investigate how farmers classify their crop distributions at their farms based on their personal experience. The three points assessed were the peak yield (py), the average yield (avy) and the sgy (Reinmuth et al., 2017).

This approach is based on the following assumptions: The most important is that, because the data were collected from a relatively small region, the overall climatic conditions lead to a certain achievable average output that can be used as a reference output for this region with which it is possible to be profitable. This output was achieved by calculating regional average yield for a given crop from the distribution of farmers' avy (farm) for that given crop (Reinmuth et al., 2017).

The py minus the sgy represents farmers' absolute wta. The location of the sgy, whether above or below the avy of the farm, gives a first indication of farmers' yield sensitivity. Benchmarking farmers' sgy and avy against the avy of the region further categorizes their performance level and leads to a second indication that describes their sensitivity. A farmer who has an avy for a given crop that is above the avy of the region can be seen as relatively more successful for that given crop. If that farmer still places his sgy above his or her avy, he or she can be considered to be highly sensitive to variability in yields. This can be seen as an indication that such farmers pay more attention to changes in the response of their crops to exogenous influences such as climate (Reinmuth et al., 2017).

Whether, how and how fast farmers adapt to climatic changes are subject to learning, which is not investigated in this dissertation. However, all the work done in this dissertation is preparatory and to be used to investigate learning and adaptation strategies in the future because it underlies learning processes (Baerenklau, 2005).

Due to the low sample size, the number of highly sensitive famers was 13 for the Kraichgau sample (Reinmuth et al., 2017). Thus, descriptive statistics were not a suitable means of analysis because providing too much detail would have conflicted with the confidentiality agreement given to the farmers. However, there are some very interesting results that build the basis for further research that applies this approach in eliciting farmers' attitudes towards risk in the context of climate change research. Among these highly sensitive farmers, farmers were found to be classified simultaneously as both risk prone in the context of portfolio theory (which is how they constitute their crop portfolio) and highly risk sensitive at the yield level. These were comparatively successful farmers regarding their avy level, which was significantly above the region's average. Despite this result, they placed their sgy above the avy for a given crop at their farms. Their crop portfolios, on the other hand, consisted of very few crops as opposed to almost six crops on average over the whole Kraichgau sample. These interesting aspects require more analysis and are subjects for further research, especially with regard to learning behavior.

10.3 Modeling risk perceptions

The empirical results have been produced by a newly developed interdisciplinary methodology that was derived from a combination of established theoretical models, excessive studies of bio-economic simulation model approaches for assessing risk perception and farmers' actual production practices.

Even though it was not possible to fully implement the approach in the simulation model, a first impression was derived. It was shown that the methodology is sensitive to different climatic conditions. The acceptable ranges turned out to be not very sensitive but captured extreme amplitudes in physical growth processes that can be considered risky from a farmer's perspective. The ARS scores provide a different picture of the assessment of climatic influence on crops compared to a simple mean-variance analysis (Reinmuth et al., 2017).

10.4 Outlook

The overall goal of the sub-project to which this dissertation contributed was to advance the FarmActor model by implementing the methodology as described in this section. With FarmActor being constantly under construction, this endeavor turned out to be more challenging than expected throughout the thesis and could not be completed. Thus, the outstanding integration procedure is presented here theoretically.

Planning decisions in the FarmActor model are made once a year (July 31st), which is post-harvest for most crops (Aurbacher et al., 2013). The current model version of FarmActor uses a Markov Sequence that relies on empirical observations from the past (Aubacher and Dabbert, 2011). This means that the actual process of allocating crops in the field is independent to what occurred during production and is not coupled with economic considerations in the model. FarmActor operates on daily time steps (Aurbacher et al., 2013). This means that the majority of information produced as a result of extensive modeling efforts is not used (Reinmuth et al., 2017).

The methodology behind the field allocation process was published by the creator of FarmActor, Joachim Aurbacher, in 2011. It is based on a linear planning approach. The field allocation process is triggered by the maximum entropy criterion (Aurbacher and Dabbert, 2011).

> The LP is disaggregated at the field level by distinguishing both activities at the field and farm levels as well as constraints for the two levels. This yields land-use decisions for specific fields. The structure of the model is as follows:
>
> Objective:
>
> $$\max!\ TG = \sum_{f} \sum_{af} G_{f,af} * X_{f,af} + \sum_{ah} G_{ah} * X_{ah,} \quad (1)$$
>
> $$s.t. \sum_{f} \sum_{af} d_{f,af,rh} * X_{f,af} + \sum_{ah} d_{ah,rh} * X_{ah} \leq C_{rh}\ \forall\ \text{rh}, \quad (2)$$
>
> $$\sum_{af} d_{f,af,rf} * X_{f,af} \leq C_{f,rf}\ \ \forall\ f, rf, \quad (3)$$
>
> $$X_{f,af,} X_{ah} \geq 0\ \forall\ f, af, ah, \quad (4)$$
>
> With the following symbols:

f	field
af	activity at the field level
ah	activity at the farm level
d	factor demand (technical coefficient)
X	activity level
G	gross margin of activity
rf	constraint at the field level
rh	constraint at the farm level
C	capacity
TG	objective (total gross margin)

Aurbacher and Dabbert (2011, p. 472).

In the optimization process, the land allocation is triggered by the maximum entropy criterion, which is the second optimization step to achieve a unique solution. Entropy is a measurement of uncertainty in a probability distribution and goes back to the work on information theory of Shannon (1948). Shannon proposes a measure of $H = -\sum_{i=1}^{n} p_i \log p_i$ for the information content of a data source, where u denotes the number of possible outcomes i and p_i their respective probabilities.

The entropy H is maximal when p is evenly distributed.

Minimum cross entropy is a generalization of maximum entropy that uses prior information.

Mathematical formulation of cross entropy is:

$H = \sum_{i=1}^{n} p_i \log \frac{p_i}{q_i}$ where q_i = prior distribution (Golan et al., 1996, p. 11). This approach minimizes H and thus the difference between the unknown distribution p_i and the given prior distribution q_i .

$\text{min! } H(\mathrm{X}_{f,af}) = \sum_{f} \sum_{f,af} * X_{f,af} * \log \frac{\log X_{f,af}}{A_f}$ and another constraint is added

$\sum_{f} \sum_{f,af} * X_{f,af} + \sum_{h} G_h * X_h \geq \mathrm{TG}_0$ with TG_0 is the minimum gross-margin level (Aurbacher and Dabbert, 2011, p. 473).

As one result of the methodological work in this dissertation, and in order to emphasize the impact of climate on the crop distribution process over the fields and thus land allocation, it is recommended that the ARS level for each activity be added as a further constraint. This allows for an introduction of type-dependent risk considerations from an economic point of view to the field allocation process.

"*The constraint should be modeled as follows:*

$$\sum_{f}\sum_{af} ARS_{af} \geq ARS_{0,af} = ARS_{af}$$

with af = activity at field level = crop, $ARS_{0,af}$ *= the ARS score of the current year (the latest year for which observations are available). The* ARS_{af} *= the expected ARS score for an activity (= crop) as explained in the following. The ARS score for an activity should not be lower than the expected ARS score for an activity. Otherwise, certain fields should no longer be planted with a certain crop, or management options need to be evaluated in the model, which would provide an improvement in the production process. […] The expected ARS (* $ARS_{a,t}$ *) of an activity* α *in year* t *is the average ARS score of past production processes for a certain crop in the farmer's fields"* (Reinmuth et al., 2017, p 12). The average ARS is used in the formula that represents learning processes in the simulation model. Learning is represented by how farmers value past observations (Aurbacher et al., 2013). To provide an example, we display the ARS score as a moving average to represent a learning processes in the FarmActor model.

$$ARS_{a,t} = \frac{1}{N}\sum_{t=t_0-N+1}^{t_0} ARS_{a,t}$$

where ARS = the expected ARS score, and N = the number of parameters used, which is the number of past ARS scores.

A second option for an implementation and thus application of ARS scores is given below:

ARS scores could be implemented to trigger yield expectations, which would make the FarmActor model less sensitive to single extreme yields with regard to the adaptation of actions or inputs when using a limited number of past observations to trigger adaptation processes.

Future research should use the ARS score to weight past yield observations and thereby help improve the learning mechanism $\hat{Y}_{a,t_0+1} = \frac{1}{N}\sum_{t=t_0-N+1}^{t_0} Y_{a,t}(ARS_{a,t})$ (adapted from Aurbacher et al., 2013, p. 48) by attaching the corresponding ARS score to a year's yield. In this way, not only is the final outcome used as a basis for expectation building ($\hat{Y}$) but also is the assessment of the whole production process, which could be used to put yield variability into a different perspective.

Further research is necessary to evaluate the best mechanisms to be included in the FarmActor model for representing more realistic learning processes about the climatic influences on crops and the resulting consequences for agricultural landscapes.

10.5 Concluding remarks

The application of integrated bio-economic simulation models as a means and basis for original research is a challenge for everyone involved. On the one hand, the justification for the application of such models comes from the opportunity to investigate aspects of human behavior that cannot be represented easily in parametrical or statistical approaches due to the strong assumptions behind such methodologies (Schreinemachers and Berger, 2011). On the other hand, complex models require a deep understanding of their functionality (Reinmuth and Dabbert, 2017) and demand a high level of creativity with regard to the empirical work that is required to validate new modeling approaches to decision making.

There is an increased need for model developers to be very accurate regarding all aspects of Information Technology that affect the use, application and development of bio-economic simulation models (Reinmuth and Dabbert, 2017).

Methodologically, future research must face the challenge of identifying learning types with regard to climatic influences, which can then be used to fully employ the risk perception methodology that was developed in this dissertation to be used in the economic component of an integrated bio-economic simulation model.

Another question that could be answered by an implementation of this methodology is how risk profiles evolve over time. One influential aspect is how farmers update their information and form their expectations. The methodology developed within the scope of this dissertation provides a basis for the research on learning types, as risk attitude is one aspect of how people can learn and thus adapt their behavior over time (Baerkenklau, 2005).

As an overall goal, ARS Scores are to be used in the integrated modeling component of the Research Group FOR 1695 to couple processes in the field with larger-scale land use models and thus will offer the opportunity to move towards the overall goal, which is to assess the processes and feedbacks of climate change on a regional scale. The goal is to provide an understanding of how agricultural landscapes evolve over time due to climate change.

10.6 References

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11 Summary

This cumulative dissertation was conducted under a grant from the German Research Foundation (DFG) for the research group FOR 1695 - “Agricultural Landscapes under Global Climate Change – Processes and Feedbacks on a Regional Scale”. The goal of the sub-project from which this dissertation stems from was to explore, extend and strengthen the scientific basis for learning and risk strategies and the adaptation behavior of farmers’ economic planning decisions in crop production under the influence of climate change. The integrated bioeconomic simulation model FarmActor, was to be used as an experimental tool to develop an interdisciplinary methodological approach supported by empirical work in two study regions in Southwest Germany, the Kraichgau and the Swabian Alb. This dissertation examines risk in the context of land use management and specifically crop production. Risk in this context is related to how outcome distributions are affected by climatic influences. Risk strategies assess these contributions and account for them in the resulting decisions.

The thesis is written as a cumulative dissertation and is composed of five articles. Four articles have been published by peer-reviewed journals. A fifth article has been published as a peer-reviewed conference proceeding. The article at fifth place represents the results of the main focus of this dissertation as presented in the following.

Available economic models assume that farmers assess climatic risks only through yields or costs when building their land use management risk strategy for crop production. However, the available methodological approaches have been criticized for either under- or overestimating farmers’ actual behavior. In reality, and as a basis for field allocation planning, farmers have additional knowledge from monitoring crop development throughout the whole season. Yield is actually just the last point in a long sequence of (economic) evaluative observations about the production process. This influences how farmers define not only the riskiness of a yield distribution but also its costs. We hypothesize that, because it is not possible to methodologically integrate process evaluations in economic planning decisions, models lack performance, and as a consequence, it is very difficult to conduct proper research on the climate’s influences on land use management decisions.

In this original research, we present a newly developed downside risk measure based on evaluations throughout the production process that can be included in the planning process as an additional parameter—so-called Annual Risk Scores. A comparative static analysis was performed to demonstrate how ARS scores assess future climatic conditions in the example of winter wheat production in the Kraichgau region as supported by empirical data. It was shown that the mechanism is sensitive to different climatic conditions. Furthermore, the ARS scores provide a different picture of climatic influence compared to an analysis based only on yields.

The last article presented in this dissertation represents an integrative review that promotes more efficient model development and the reuse of newly developed

methodologies in the field of integrated bio-economic simulation models. The review is based on lessons learned from working with the simulation model. Thus, the intended and outstanding full implementation of the ARS mechanism is presented in the last part of the synthesis, where we advise including the ARS scores as another constraint in the field allocation mechanisms of the FarmActor model. This is expected to improve the integration of both bio-physical and economic dimensions for complex integrated bio-economic simulation models.

12 Zusammenfassung

Diese kumulative Dissertation wurde im Rahmen eines Teilprojekts der interdisziplinären DFG Forschergruppe FOR 1695 “Agricultural Landscapes under Global Climate Change – Processes and Feedbacks on a Regional Scale” durchgeführt. Das Ziel des Teilprojekts war, Grundlagenforschung in Bezug auf Risiko-, Lernstrategien und sich daraus ergebendes Anpassungsverhalten für strategische Landnutzungsentscheidungen unter Klimaeinfluss zu erforschen. Unterstützt wurde die Arbeit durch eine empirische Datenerhebung in zwei Untersuchungsgebieten im Südwesten Deutschlands, dem Kraichgau und der Schwäbischen Alb. Diese Dissertation beschäftigt sich schwerpunktmäßig mit dem Thema Risiko und Risikostrategien in Bezug auf Landnutzungsentscheidungen, speziell in der Getreideproduktion.

Die Dissertation wurde als kumulative Dissertation erstellt. Sie besteht aus fünf Artikeln. Vier dieser Artikel wurden in Peer-Review Zeitschriften veröffentlicht. Ein weiterer Artikel ist in einem Peer-Review Konferenzband erschienen. Die ersten drei gelisteten Artikel stellen vorbereitende Analysen dar und beschäftigen sich mit dem verwendeten Simulationsmodell. Der Schwerpunkt des an vierter Stelle gelisteten Artikels, ist gleichzeitig auch der Schwerpunkt dieser Dissertation, der nun im Folgenden kurz vorgestellt werden soll.

Bestehende ökonomische Modelle zur Risikoanalyse unterstellen, dass landwirtschaftliche Entscheidungsträger lediglich die Endergebnisse des Produktionsprozesses, also die Erträge heranziehen, um ihre Risikostrategien in Bezug auf die Klimaeinwirkung festzulegen. Diese Ansätze werden dafür kritisiert, dass sie das tatsächliche Verhalten der Landwirte entweder stark über- oder unterschätzen.

In der Realität und als Grundlage für die Planungsentscheidungen, steht Landwirten weiteres Wissen über den Klimaeinfluss auf die Getreideproduktion an einem bestimmten Standort zur Verfügung. Im Rahmen von sequentiell durchgeführten Bonituren bewerten Landwirte den Klimaeinfluss nicht nur pflanzenbaulich, sondern auch ökonomisch. Sie bilden Erwartungen darüber, wie die klimatischen Einflüsse das Erreichen eines profitablen Ertragsniveaus beeinflussen. Der Ertrag ist eigentlich nur der letzte Beobachtungspunkt der Boniturenabfolge. Das hierbei erworbene Wissen hat einen starken Einfluss darauf, wie Landwirte das tatsächliche Risiko einer Ertragsverteilung und die damit verbundenen Kosten bewerten. Dies führte zu folgender Hypothese: Ökonomische Modelle zur Bewertung des Klimaeinflusses bleiben hinter ihren Möglichkeiten zurück, weil es derzeit nicht möglich ist, ökonomische Boniturbewertungen in die strategischen Planungsentscheidungen einzubeziehen.

Eine methodische Grundlage für die Entwicklung eines interdisziplinären Modellansatzes, bot das gekoppelte, dynamische bioökonomische Simulationsmodell FarmActor. Als Ergebnis präsentieren wir einen neu entwickelten Ansatz, der den

Einbezug von sequentiellen ökonomischen Bewertungen von Produktionsrisiken, in Form einer zusätzlichen Variablen, für strategische Planungsentscheidungen ermöglicht. Diesen Parameter haben wir ARS Score, den sogenannten Jahresrisikoscore, genannt. In einem ersten Anwendungsfall, im Rahmen einer komparativ-statischen Analyse, haben wir dargestellt, wie ARS Scores den zukünftigen Klimaeinfluss bewerten. Dies wurde am Beispiel für Winterweizen im Kraichgau durchgeführt, unter Hinzunahme von empirischen Daten aus dieser Region, besonders in Bezug auf die Akzeptanzbereitschaft für Schwankungen im Produktionsprozess, die den ARS Mechanismus steuern. Es konnte gezeigt werden, dass der Risikomechanismus auf verschiedene Klimaeinflüsse reagiert. Darüber hinaus bieten die ARS Scores zusätzliche Informationen über die risikotypenabhängig Einschätzung des Klimaeinflusses, der die bestehenden Analysemethoden ergänzt.

Der an fünfter Stelle gelistete Artikel dieser Dissertation beinhaltet eine integrative Literaturanalyse, die sich mit der Frage beschäftigt, wie integrierte bioökonomische Simulationsmodelle effizienter (weiter-)entwickelt werden können und wie man darüber hinaus sicherstellt, dass neu entwickelte Modellierungsansätze von anderen Modellierern weiterverwendet werden können. Dieser Artikel baut auf unserer eigenen mehrjährigen Erfahrung in der Arbeit mit Simulationsmodellen in einem interdisziplinären Kontext auf und verbindet diese mit den relevanten Aussagen, die wir in der Literatur gefunden haben.

Eine noch ausstehende vollständige Integration des neu entwickelten ARS Ansatzes, wird am Ende dieser Dissertation als Empfehlung vorgestellt. Wir sehen den ARS Score als zusätzliche Variable, die den strategischen Feldplanungsprozess in Landnutzungsmodellen, wie FarmActor, steuert. Wir erhoffen uns durch die Implementation des ARS Mechanismus, die Modellqualität zu erhöhen, weil hierdurch der bio-physikalische Prozess mit dem ökonomischen Planungsprozess besser gekoppelt werden kann.

13 Eidesstattliche Versicherung

Gemäß § 8 Absatz 2 der Promotionsordnung der Universität Hohenheim zum Dr. sc. agr..

1. Bei der eingereichten Dissertation zum Thema:
   Land use management under climate change: a microeconomic analysis with emphasis on risk
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Evelyn Reinmuth

Stuttgart, im März 2018