Climate change will most likely confront agricultural producers with natural, economic, and political conditions that have not previously been observed and are largely uncertain. As a consequence, extrapolation from past data reaches its limits, and a process-based analysis of farmer adaptation is required. Simulation of changes in crop yields using crop growth models is a first step in that direction. However, changes in crop yields are only one pathway through which climate change affects agricultural production. A meaningful process-based analysis of farmer adaptation requires a whole-farm analysis at the farm level. We use a highly disaggregated mathematical programming model to analyze farm-level climate change adaptation for a mountainous area in southwest Germany. Regional-level results are obtained by simulating each full-time farm holding in the study area. We address parameter uncertainty and model underdetermination using a cautious calibration approach and a comprehensive uncertainty analysis. We deal with the resulting computational burden using efficient experimental designs and high-performance computing. We show that in our study area, shifted crop management time slots can have potentially significant effects on agricultural supply, incomes, and various policy objectives promoted under German and European environmental policy schemes. The simulated effects are robust against model uncertainty and underline the importance of a comprehensive assessment of climate change impacts beyond merely looking at crop yield changes. Our simulations demonstrate how farm-level models can contribute to a process-based analysis of climate change adaptation if they are embedded into a systematic framework for treating inherent model uncertainty.

**JEL codes:** C61, C63, Q12, Q54.

Climate change has the potential to profoundly affect agriculture in many regions of the world and confront farmers with conditions that have not been observed in their area before. Given the potential for structural shifts in agricultural production systems, scientists cannot simply rely on statistical analysis of past observations to analyze climate change adaptation but need to build on their understanding of the fundamental processes shaping farmer adaptation behavior (Antle and Capalbo 2001). Partly, this is achieved by relying on the representation of biophysical processes in process-based crop growth models to predict changes in crop yield potentials (Robertson et al. 2013). Still, climate change will affect agricultural production through more pathways than just yield changes (Olesen and Bindi 2002). Changes in input prices, shifted growing periods, changed time slots for crop and herd management, increased dependence on irrigation water supply, new policy restrictions, the need to dry and store cereals or ventilate stables, and changes in yield quality (Högy and Fangmeier 2008) are some examples. As case in point for nonyield pathways, we analyze in this article the importance of shifted
crop management time slots for understanding adaptation in a study area in southwest Germany.

Shifted time slots affect field work capacity and possible crop rotations, which in turn also depend on size, resource endowment, and production mix of a farm holding. As a consequence, effects on agricultural production, income, and policy outcomes need to be analyzed at the level of individual farms (Reidsma et al. 2010). Farm-level mathematical programming (MP) models are suitable tools for this type of analysis because they are able to reflect the complex interlinkages between different production options, farm resources, and household objectives. For example, farmers might simultaneously produce various crops for subsistence consumption, crops that serve as inputs for other production processes on the farm, or crops that complement or compete with each other in crop rotations (Janssen and van Ittersum 2007). Arguably, farm-level MP models are the closest equivalent to a process-based model available to agricultural economists and have been used for the analysis of climate change adaptation (e.g., Leclère, Jayet, and de Noblet-Ducoudré 2013; Peck and Adams 2012; Gibbons and Ramsden 2008). Their use is, however, associated with two major challenges or pitfalls of a disaggregated process-based analysis at the farm-level.

The first major challenge is obtaining aggregate regional results (Gibbons et al. 2010). Even if the nature of the analyzed effect demands a farm-level analysis, researchers are often also (and sometimes primarily) interested in consequences for regional agricultural production and policy outcomes. Classical approaches that multiplied the results for a few representative farms or directly used farm-level models as regional models suffered from aggregation bias, overspecialization on just a few crops, “jumpy” behavior between corner solutions, and only weak goodness-of-fit at a regional level (Buyssse, Huylenbroeck, and Lauwers 2007; Gibbons and Ramsden 2008). Their use is, however, associated with two major challenges or pitfalls of a disaggregated process-based analysis at the farm-level.

The second challenge is dealing with often considerable model uncertainty. Disaggregating phenomena into smaller, well-observed, time-invariant processes to derive conclusions about unobserved situations and, at the same time, allow for heterogeneous behavior requires information that is often not available in the required depth and breadth for a full region. In these cases, standard technical coefficients have to be used, parameters have to be chosen ad hoc, and parameter variability is often neglected. Overparameterization, however, limits the extent of possible calibration of these parameters without compromising the process-based nature of the model through overfitting (Reichert and Omlin 1997; Zucchini 2000). This model uncertainty needs to be clearly communicated to readers and analyzed to assess the robustness of results and, in the long run, improve process understanding (Jakeman, Letcher, and Norton 2006). One suggestion is to present simulation outcomes not as point estimates but as global distributions over the uncertain parameter space. Then, however, repeatedly solving a detailed MP decision model for all farms in a region and a sufficient number of potential parameter
combinations to adequately represent model uncertainty creates a computational burden that presents an additional challenge to the modeler.

Herein we report on how we coped with these challenges in our analysis of the importance of shifted time slots on climate change adaptation in southwest Germany. We first describe how the design and parameterization of our decision model captures climate change effects on farmer production decisions and ensures a sufficient degree of heterogeneous behavior. We then discuss the framework we used to deal with parameter uncertainty, which consists of a cautious approach to calibration and the application of suitable experimental designs that allow global representation of the parameter space with a feasible number of model runs. We next present simulation results that demonstrate the importance of shifted time slots for crop management on regional agricultural supply behavior, farm incomes, and the outcomes of two major regional policy programs. We conclude by discussing the lessons learned about process-based analysis of climate change adaptation using regionalized farm-level MP models.

Heterogeneous Behavior in a Regionalized Farm-Level Model

The Central Swabian Jura is a low mountainous area in southwest Germany with shallow soils and a comparatively harsh climate (mean annual temperatures around 7°C; mean annual precipitation of 800–1,000 mm). Agriculture in this area is characterized by a relatively balanced mix of crop production, dairy farming, bull fattening, pig production, and biogas production. Most farm holdings simultaneously produce three to five different crops, with summer barley, winter wheat, winter barley, and winter rapeseed being the dominant crops, while dairy and cattle farmers tend to also grow silage maize, clover, and field grass. Farmer production decisions have to respect a complex set of crop rotation constraints, feed and manure balances, machinery and labor capacity constraints, and policy restrictions.

Climate has been a predominant constraining factor for agricultural production when compared with neighboring regions; as a consequence, even slight changes in climate may have significant impacts. In this analysis, we are especially interested in two consequences of potential shifts in time slots for crop management that are not directly reflected in changes in crop yields. The first affects possible crop rotations. Currently, late wheat harvest dates that overlap with rapeseed sowing dates make wheat–rapeseed sequences infeasible for most farms in the study area. If wheat could be harvested slightly earlier or rapeseed sown slightly later, this might become an important crop rotation option. The second consequence is related to field work capacity. Field work requires suitable weather conditions, and farmers need to plan production such that they can muster the necessary amount of labor and machinery power with sufficient certainty within a critical time slot. A change in climate may widen, shrink, or shift these windows of opportunity.

In our MP model, we disaggregate the production decision problem with enough detail to directly capture the impact of these climatic effects on the relevant decision parameters of the individual farmer to track potential impacts on farm production, income, and participation in agri-environmental policy schemes currently implemented in the area. The model uses the multiagent software package MPMAS\(^1\) (Schreinemachers and Berger 2011). MPMAS provides a framework for recursive-dynamic modeling of farm holdings using mixed integer programming (MIP) for the representation of agent investment, production, and consumption decisions. MPMAS builds on the pioneering work of Balmann (1997) and has been applied, for example, in Chile (Berger 2001), Uganda (Schreinemachers, Berger, and Aune 2007), Thailand (Schreinemachers et al. 2009; Schreinemachers et al. 2010), and Vietnam (Quang, Schreinemachers, and Berger 2014). In this study, we abstract from any interactions or individual or collective learning processes of agents available in the MPMAS framework.

Farm Production Decisions

In our model, we assume that farm agents maximize expected income by choosing the optimal combination of land use, animal husbandry, and biogas production subject to resource availabilities. The MIP matrix

\(^{1}\) https://mp-mas.uni-hohenheim.de.
representing the production decision problem comprised approximately 6,900 variables in approximately 3,800 equations. Here we can only provide an overview of the model relationships; a full model description can be found in the model documentation in the supplementary appendix online.

The objective function representing expected income is calculated as the sum of expected revenue from crop production, \( R_c \), animal husbandry, \( R_h \), biogas production, \( R_b \), and received premiums from policy schemes, \( R_p \), minus variable costs, \( V \), and fixed costs, \( F \), as shown in equation (1), where \( p_e \) denotes expected prices, \( y_e \) denotes expected yields, \( a \) denotes crop and grassland activities, \( f \) denotes the part of the crop that is used as animal feed, \( h \) denotes animal husbandry activities, \( k \) denotes biogas production, \( z \) denotes the first year of biogas production, \( M \) denotes the machinery owned and employed, \( B \) denotes buildings and infrastructure owned, \( A_r \) denotes the amount of land rented in, \( l \) denotes hired labor, and \( I \) denotes the balance of interest paid and received.

\[
\pi_e = R_c(p_e, y_e, a, f) + R_h(p_e, h) + R_b(k, z) + R_p(a, h) - V(p_e, a, h, f, M, l) - F(p_e, B, M, A_r) + I.
\]

Crop production of agents includes winter wheat, winter rapeseed, winter fodder barley, summer malting barley, summer fodder barley, silage maize, wheat silage, and fallow. Crop management plans were derived from typical input use observed in the area. Crop yields depend on soil types, and agents can choose between plow and low tillage and mineral and organic fertilization. For grassland production, agents can select among four levels of intensity: three uses per season, two uses per season, extensive use, or abandonment. Potential uses of grassland are grazing, cutting fresh grass for direct feeding, production of grass silage, or production of hay. Combinations of one type of fresh and one type of conserved fodder production on a single grassland plot are possible. For extensive grassland production, we consider three use options: year-round pasture, late cut (beginning of July, every two years), and very late cut (beginning of October, every two years). On arable land, field grass can be produced, allowing up to four uses a year. Agents can produce biogas from manure, maize silage, grass silage, and wheat silage. Electricity production from biogas is rewarded according to the German Renewable Energy Act (REA). Agents receive decoupled EU direct payments and can participate in four agri-environmental measures from the current MEKA III portfolio (the implementation of pillar II of the EU Common Agricultural Policy in the state of Baden-Württemberg) that reward crop rotation diversification and grassland extensification.

The constraints of the MIP decision problem that each agent has to solve reflect the major interrelationships of farming activities and resources. To begin, financial balances ensure that agents have the necessary cash to pay the down payment and ongoing debt service on investments. Consumable balances connect production, use, purchase, and sales of farm products, inputs, intermediate products, and farmyard manure. Animal feeding requirements have been formulated in terms of energy, nutrient, and fiber demands, allowing the farm agent a great deal of flexibility in the combination of bought and self-produced fodder. Policy-related restrictions follow from EU CAP regulations, as well as from the national MEKA and REA schemes that impose additional constraints on livestock intensity, diversity of crop production, and set-aside requirements. Complying with a specific set of these later restrictions is required only if the agent decides to receive payments from the related policy scheme.

The share of arable land and grassland is considered fixed in the model because conversion of grassland to arable land is currently forbidden in the area. Crop production and grassland production are restricted by the available land and its allocation to different crop rotations. Cropping activities are constrained by agronomic upper limits for the overall share of cereals (80%), maize (uncertain parameter, 40%-60%), and rapeseed (25%) in the rotation. Further, a realistic crop rotation is ensured by requiring a corresponding amount of a suitable preceding crop planted on the same soil type for each crop used in a rotation. Table 1 shows the current compatibility of preceding and following crops in MPMAS, as obtained from expert interviews in the area.

All crop, animal, and biogas production activities are associated with a specific schedule of tasks, which must be performed at
### Table 1. Compatibility of Crops in Rotation

<table>
<thead>
<tr>
<th>Preceding Crop</th>
<th>FA</th>
<th>FG</th>
<th>SM</th>
<th>SB</th>
<th>WW</th>
<th>WB</th>
<th>WR</th>
</tr>
</thead>
<tbody>
<tr>
<td>FA</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>FG</td>
<td>1/2</td>
<td>2/3</td>
<td>1/2</td>
<td>1/2</td>
<td>1/2</td>
<td>1/2</td>
<td>0</td>
</tr>
<tr>
<td>SM</td>
<td>1</td>
<td>1</td>
<td>X</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>SB</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1/2</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>WB</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>WR</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>WW</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1/2</td>
<td>0</td>
<td>CC</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: FA, fallow; FG, field grass; SB, summer barley; SM, silage maize; WB, winter barley; WR, winter rapeseed; WW, winter wheat. 0: Incompatible. 1: Compatible, full area can be considered for following crop. 1/2: Maximum half of the area can be considered (e.g., wheat can directly follow wheat only once, then another crop has to be grown before wheat can be grown again). 2/3: Field grass is a semipermanent culture that is usually kept two to three years on the same field. So at maximum half the area can be considered preceding crop for other crops and at maximum 2/3 can be considered preceding crop for next year’s fields grass. X: Uncertain, subject to calibration. CC: 0 in the baseline, 1 if climate change shifts crop management dates.

Specific points of time in the season. Model agents can only perform a task if they own or hire the necessary equipment and provide or hire the necessary amount of labor. The required amount of labor depends on the task and the equipment used (e.g., plowing with a larger plow requires less time but a more powerful tractor). Available labor that is not bound in daily recurring tasks (e.g., milking or feeding the biogas plant) can be used for seasonal tasks. We divided the production year into nine work seasons, with a coarse resolution in winter (3.5 months) and a fine resolution in summer (2 weeks). The amount of a certain type of work that can be performed in each work season depends on the agent’s labor and equipment available, but also on the amount of days with suitable weather.

We relied on the dataset by Kuratorium für Technik und Bauwesen in der Landwirtschaft e.V (KTBL 2010), which provides the expected number of days for field work, distinguished by weather sensitivity of the task, by the half-month of the growing season in which the field work occurs and by twelve climatic subdivisions of Germany. Following this approach, we classified tasks into five weather-sensitivity groups. The labor capacity $L_{T,K}$ of an agent to perform work of a specific weather sensitivity $k \in K$ in season $T$ is then calculated as $L_{T,k} = L_{a} \times h \times d_{T,K} - uL_{T,K<k}$—that is, the product of the person days reserved for seasonal work ($L_{a}$), the number of hours worked per day ($h$), and the number of days suitable for field work of this weather sensitivity level ($d_{T,K}$), minus the amount of time the labor is already used for field work with higher weather sensitivity ($uL_{T,K<k}$). A similar balance applies to each type of field work equipment.

As an alternative to performing field work with their own machinery, the agents can hire a service provider. Although in reality service providers also depend on suitable weather conditions, it is difficult to assess their capacity and to assess the chance that a specific farmer is able to hire teams for every day with suitable conditions. We therefore chose a simplified implementation and restricted hiring of services to an amount that is proportional to the amount of suitable days for field work, assuming a proportionality factor for the chance to hire ranging between 0.5 and 2.0.2

The data necessary to parameterize the agent decision were provided by regional and national statistical offices and extension services. Additionally, we used data from an in-depth farm survey ($n = 32$) in the study area and expert interviews. Technical coefficients for crop, animal, and biogas production, as well as machinery costs and capacities, were taken from KTBL (2010), cross-checked, and, if necessary, adapted to local conditions with information from our farm survey and expert interviews. We used long-term averages of prices, yields, and environmental conditions that are assumed to be known by the agents. Price information was obtained from Landesanstalt für Entwicklung der Landwirtschaft und der ländlichen Räume (2010; 2011a; 2011b), destatis (2012d), and KTBL (2010) and

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2 A proportionality factor of 2.0 would assume the agent can hire two service provider teams for each day with suitable weather.
compared with price expectations recorded in the farm survey. Crop yields for each soil type were taken from simulations using the Expert-N model (Stenger et al. 1999; Biernath et al. 2011) calibrated for the area by Aurbacher et al. (2013). Baseline yields were based on a meteorological time series of the weather station in Stötten for the years 1981–2010. Crop yields for future climate scenarios were based on the statistically downscaled projections provided by WET-TREG 2010 (Kreienkamp, Spekat, and Enke 2013) for the same weather station covering the years 2000–2030. (Details and extensions compared with Aurbacher et al. 2013 are documented in the supplementary appendix online.)

**Regionalization and Heterogeneity**

Results for the regional level are obtained by including an individual model agent for each of the 533 full-time farm holdings of the study area, characterized by individual household composition, asset ownership, and soil endowment. Aggregate land use and crop production in the study area emerge as the sum of these individual agent decisions. As discussed, such a model requires a sufficient degree of heterogeneity in agent behavior to generate realistic aggregate regional outcomes. The structure of the agent objective function and constraints in the MIP, however, is identical for all agents: it is a comprehensive representation of technology packages and local conditions for agricultural production. Heterogeneity is introduced into the decision module by different household compositions and resource availabilities of individual agents (e.g., the amount and type of available farm labor and land, as well as the machinery and buildings owned at the start of the simulation). These differences in starting conditions affect the profitability of production options and, in this way, produce heterogeneous agent behavior.

Household composition, for example, determines the amount of household labor available and affects the planning horizon for agent investment decisions. The head-of-household’s age and, additionally, his/her potential successor’s age determines the expected remaining operating time of the farm (i.e., the maximum lifetime considered in agent investment calculations). Farm succession is an important topic in family business and requires some additional rules for implementation in dynamic simulation models (Freeman, Nolan, and Schoney 2009; Happe et al. 2009). Here, we assumed agents are glad to employ their potential heirs on the farm and even willing to forgo own income if a major investment or expansion of the farm is necessary to employ their successors. In the MIP decision problem, agent household heads must remunerate their adult children’s work on the farm, but they do not consider this a cost as long as their own minimum income expectation has been met.

In the model, soil types determine attainable crop yields and the tractor power required for field work. Existing machinery and buildings are associated with sunk costs that may lead to hysteresis and path dependency (Balmann et al. 1996). Profitability of crops can differ given the possibility of selling or use for feeding. Further, the model structure exhibits certain economies of size at farm level. In southwest Germany, with rather small farm sizes and indivisible tractors and other field work implements, the cost-per-capacity ratio usually declines with increasing capacity, which we considered accordingly. Building costs and most livestock-related labor requirements are implemented using fixed and size-dependent costs, leading to decreasing average cost functions. Certain policy schemes, however, include special regulations for smaller farms, leading to dis-economies of size. Under REA regulations, for example, guaranteed biogas electricity prices decrease with volume. Again, we considered these farm-level effects accordingly.

To obtain a realistic distribution of farm characteristics in our agent population, we used FDZ (2010), a panel dataset formed from German farm census and farm structure survey data. Although the dataset contains data on every farm holding in our study area, a one-to-one use of the dataset is prevented by privacy restrictions. Instead, we used the dataset to estimate the distribution of farm size, arable and grassland shares, and livestock numbers for the full-time farms of the study area and then created a set of synthetic agent populations following the random sampling approach of Berger and Schreinemachers (2006). To capture the joint distribution of farm characteristics in the area, estimation was done in two steps: (a) we estimated empirical marginal distributions for each variable, calculating each percentile from the 1st to the 99th (estimating finer
percentiles or minima and maxima was prevented by restrictions); (b) we estimated the joint distribution as an empirical copula (Nelsen 2006). Privacy restrictions allowed creating the copula only from a sample of 80% of the population and only at the resolution of quintiles. We created a vector for each farm holding in the database, with a column for each variable containing the quintile of this variable to which the farm holding belongs. A table containing the frequency of the different vectors observed in the population then serves as the copula.

Machinery was allocated to agents following the rules developed from the machinery endowments observed in the farm survey. Household composition was randomly generated using statistical data on farm manager age in combination with marriage, birth, and death rates for the German population (destatis 2011; destatis 2012a; destatis 2012b; destatis 2012c). The location of farmsteads, arable land, and grassland was determined with a random allocation algorithm, as follows. Alternating between agents, we allocated groups of pixels in realistic, random plot sizes as close as possible to the farmstead, ensuring a mixed pattern of properties. Using CLC2006 (2009) land cover maps ensured realistic locations of arable and grassland areas. Overlaying the LUBW (2007) soil map over the resulting property map produced the distribution of soil types for each agent. A detailed account of the procedure for creating synthetic agent populations is provided in our model documentation in the supplementary appendix online.

Dealing with Model Uncertainty

Inevitably, our simulation model for the Swabian Jura is associated with considerable uncertainty due to the complexity in model structure, as well as gaps and fuzziness in input data. In total, we identified thirty-one parameters in the whole model setup that are associated with data uncertainty and ad hoc model assumptions. Five parameters are relevant only for simulations over more than one period (i.e., one year). Of the twenty-six parameters that are relevant in one-period simulations, four are related to the creation of the starting population. One parameter controls whether and to what extent investment decisions are affected by the expected remaining lifetime of the agent. Five parameters result from omitting local resource markets, in our case demand for silage maize, renewable energy products in general, surplus heat of biogas plants, supply of young female cattle, and supply of brewery by-products for feeding. These five parameters control whether all agents face either unlimited or zero demand or supply for these goods. Twelve parameters represent uncertainties in prices for hired field work services, labor requirements and yields for pasturing and fresh grass harvest, yields of wheat, wheat silage and silage maize, maximum manure application, and rotational constraints for maize. One parameter controls whether wheat silage is considered a production option at all because this was not captured explicitly in the observation data. Three parameters are related to available days for field work: the climatic region chosen (the study area lies in two regions), the probability (60% or 80%) with which the estimated days of field work are expected to occur (KTBL 2010), and the proportionality parameter for the chance of hiring field work service. The five parameters that are relevant only in longer-term simulations govern the share of income the household consumes on top of its minimum consumption, the maximum reduction in consumption if the income does not satisfy minimum consumption, the initial cash reserves of the farm agent, restrictions on the expansion of pig production, and the minimum income expectation for a successor to take over the farm business.

The uncertainty incorporated in these parameters was reduced by calibration in a first step and then incorporated into experimental designs to allow documenting and analyzing its influence on simulation results. This procedure is summarized in figure 1.

Reducing Uncertainty by Calibration

Calibration can be understood as a reduction of model uncertainty based on the likelihood of parameter combinations given observation data (Hansen and Heckman 1996). Classical calibration (i.e., identifying the best-fitting parameters) is equivalent to maximum likelihood estimation if the correct goodness-of-fit measure is used (e.g., minimizing loss functions based on squared deviations for normally distributed error terms centered around zero). Discarding all other parameter
combinations, however, artificially assigns the best-fitting parameter combination a probability of one. More often than not it is not warranted to make such a drastic judgment (Kennedy and O’Hagan 2001). Highly disaggregate MP models, especially agent-based models with large degrees of heterogeneity and interaction between agents, are typically overparameterized and underdetermined by available observation (Zimmermann, Heckelei, and Pérez Domínguez 2009; Berger and Troost 2014). Considering the fact that underdetermined models can be tuned to fit almost any observation, restricting simulations to the use of one best-fitting parameter combination hides the uncertainty in model
inputs and results, rather than truly reducing it (Ehret et al. 2012). Moreover, achieving a perfect fit to reality is not the primary concern for a process-based model and is not necessarily an indicator of model validity (McCarl and Apland 1986; Oreskes, Shrader-Frechette, and Belitz 1994; Barlas 1996; Beck et al. 1997).

Bayesian parameter estimation (Hoeting et al. 1999; Gibbons et al. 2008) improves the traditional approach to calibration by retaining all potential parameter combinations and assigning them posterior probability distributions calculated using a suitable likelihood function for the model and prior probability distributions for the parameters (e.g., Schoups and Vrugt 2010). These posteriors are then used to create probability distributions for model outcomes derived from different parameter combinations. By providing the full probability distribution of results instead of a point estimate, the parameter uncertainty can then be communicated to model users. For both Bayesian and maximum likelihood approaches, a suitable likelihood function has to be determined based on the expected error distribution for model predictions. Although we made an effort to reduce systematic errors by creating a detailed representation of the production decision problem, we have reason to believe that the prediction error cannot be considered white noise. For agricultural production models, McElroy (1987), Pope and Just (2002), and Kumbhakar and Tsionas (2011) analytically derived heteroskedastic error terms with nonzero means specifically for cost, cost-share, and input demand functions derived as duals. Mixed integer programming problems such as ours can only be solved numerically, which precludes the analytical derivation of an error distribution for the model from individual inputs’ error distributions. This means we have to consider the correct error distribution of our model unclear but most likely nonstandard. Alternative approaches such as GLUE (Beven and Freer 2001), which do not rely on a formal derivation of the likelihood but use standard goodness-of-fit measures to calculate informal likelihood functions, are somewhat subjective and do not necessarily increase transparency (He et al. 2010).

Instead, we opted for a robust, conservative approach, defining a criterion to exclude only those parameter settings that clearly performed inferior and treating all remaining parameter combinations as equally likely. For exclusion, we followed the basic principles of classical cross-validation (Browne 2000) that suggest to stop the process of calibration to an observation dataset when the goodness-of-fit to an unrelated test sample, which will usually increase at first, starts to decrease because this is usually a good indicator that the model starts fitting noise rather than systematic components of the observation (Whittaker et al. 2010).

We used three test samples. The FDZ (2010) panel provided us with data for the years 1999, 2003, and 2007. We created a set of agent populations for each of these years and recreated boundary conditions using corresponding price data and implementations of EU-CAP premiums, MEKA, and REA regulations for each of the years. Production decisions simulated for the three years were then compared with the production patterns recorded in the FDZ (2010) panel for that year. Specifically, we compared simulated and observed land use at an aggregate level and used the classification of farms by EU typology, which reflects the mix of crop production activities of individual farms, to assess the degree to which the model was able to capture farmer decisions at a more disaggregated level. Goodness-of-fit was measured using model efficiencies based on standardized absolute errors (ESAE), as suggested by Voas and Williamson (2001):

$$ESAE = 1 - \frac{\sum_i |Y_i^{obs} - Y_i^{sim}|}{\sum_i Y_i^{obs}}.$$  

$Y_i$ denotes the number of observations (area, farms) in category $i$. The simulated grand total over all categories must be equal to the observed grand total. The ESAE accommodates the categorical land use and farm type distributions, and by using absolute errors, it weighs each wrongly classified plot and farm equally in the calculation of goodness-of-fit. This seemed the most robust choice in the absence of more precise information on the error distribution.

Using this setup, we could observe how the 26 parameters relevant in the short run affect goodness-of-fit (figure 1, step 2). To account for the uncertainty of the crop growth model

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3 Calibrating in addition the parameters relevant only for multiperiod simulations would require the inclusion of land and labor markets to be able to reproduce the development of the farm population over several years.
calibration, we repeated the simulations with two alternative sets of crop yields taken from statistical data to avoid overfitting parameters to potential bias in the simulated crop yields (Asseng et al. 2013). We then fixed or reduced the range for a calibration parameter only if this consistently improved results of both aggregate land use and farm type distribution in all three observation years (except parameters related to the starting agent population) and for all three crop yield sets. Requiring improvements in two output dimensions against different yield sets and over several observation years makes best use of the available data to avoid overfitting and overconfident reductions of uncertainty, especially because the chosen years cover a time span with multiple changes in the policy environment (two EU CAP reforms, two MEKA reforms, introduction and first revision of the Renewable Energy Act).

These calibration experiments involved a sequence of elementary effects screenings (Campolongo, Cariboni, and Saltelli 2007) and, finally, a full factorial design resulting in a total of 2,367 simulation runs for calibration. As a result of the calibration, some parameters could be fixed. External demand for silage maize and renewable energy products and external supply of young female cattle were set to zero. The probability of occurrence used to calculate field work days was set to 80%, and three parameters related to input uncertainty could be fixed or have their range reduced. Three best-performing initial agent populations could be identified for each base year. We could also confirm that there was no market for surplus heat of biogas plants in the past and wheat silage was not considered a production option (rendering also the yield coefficient for wheat silage meaningless). This leaves sixteen uncalibrated parameters. However, the last three parameters are not fixed in the climate adaptation simulations because they might change in the future, implying nineteen uncertain parameters.

Documenting Uncertainty

In the analysis of our climate impact simulations, we will take into account the full distribution of simulation results over the unfixed parameter space (at least by indicating the mean and standard deviation). In evaluating the outcomes, we may then be confronted with two situations: (a) either the simulated distribution for an outcome shows a clear, unambiguous result, and the conclusions can be considered robust with respect to the parameter uncertainty in the model, or (b) the effect may be ambiguous and vary strongly with the chosen parameter combination. In the second case, sensitivity analysis can be used to identify the parameters responsible for the extent and direction of the effect, and further research can be dedicated to improving knowledge and representation of the parameters.

Evaluating the model for every potential parameter combination that remained after calibration, however, was infeasible so we used experimental designs to efficiently cover the parameter space with reasonable computational effort. Latin hypercube samples (McKay, Beckman, and Conover 1979) allow the fullest coverage of a parameter space for a given number of model runs. To measure the predictive skill that can be achieved with the calibrated parameter space, we ran an LHS sample of one hundred runs over the sixteen uncalibrated parameters for the year 2007 (figure 1, step 3). In this sample, the $ESAE$ for total land use was between 0.73 and 0.84, and the model efficiency for total livestock numbers was between 0.9 and 0.95 (goodness-of-fit for livestock numbers was calculated using the standard squared deviations measure of model efficiency). We found a tendency of the model to overestimate total wheat, rapeseed, and fallow areas and underestimate silage maize and summer barley areas. The bias in the silage maize area is consistent with the omission of silage maize trade as a result of the calibration. The $ESAE$ for the farm type distribution was between 0.62 and 0.71. Deviations can partly be explained due to the omission of horticulture, fruticulture, and sheep production from the current model. (See the full documentation in the supplementary appendix online for details.)

Latin hypercube samples are not the ideal choice to track the effects of individual parameters on outcomes if the second situation arises. Morris, Moore, and McKay (2008) suggest replicating LHS by permuting columns according to an unbiased permuted column sample (UPCS) scheme. This retains the space-filling attributes of the LHS while allowing the calculation of first-order effects of parameters if necessary. It does, however, increase the necessary number of model runs, making them a nonlinear function of parameters. We therefore used the elementary
effects method (Campolongo, Cariboni, and Saltelli 2007) and identified the eleven parameters most important for determining the extent of climate change effects on land use, animal numbers, installed biogas capacity, MEKA participation, and farm income (figure 1, step 4). The UPCS for these eleven parameters was constructed using six subarrays (66 design points) of an OA (121, 12, 11, 2) orthogonal array and will be termed the SR-UPCS design because it will be used for short-run (one period) simulations (figure 1, step 5).

For long-run simulations, we need to take the additional five parameters relevant for recursive-dynamic simulations into account, and we further reconsider the parameter governing the expected remaining lifetime of the farm, which the elementary effects screening determined to be of minor importance for short-run simulations but which can be expected to have much higher relevance for multiyear runs. Combining these six parameters with the eleven parameters of the short-run design, we formed a seventeen-parameter UPCS based on four subarrays (68 design points) of an OA (289, 18, 17, 2) orthogonal array for long-run simulations (the LR-UPCS design) (figure 1, step 6).

**Simulating Climate Change Adaptation**

In this study, we are concerned with evaluating the importance of climate-induced changes to the crop calendar that lead to changes in available days for field work and allow rapeseed-after-wheat rotations. To this end, we compare simulated agricultural production, incomes, and policy outcomes in three scenarios.

In the baseline scenario B, we used the crop yields simulated for 1981–2010 weather observations, the current distribution of days suitable for field work, and no rapeseed-after-wheat rotations. In the adaptation scenario C1, we used our model for a standard assessment that considers only yield effects. We took the yield simulated for the 2000–2030 WETTREG projection (table 2), retaining current rotation options and field work days. In the extended scenario C2, we made use of the full potential of our model, additionally allowing rapeseed-after-wheat rotations and assuming a shift in available days of field work. Lacking a detailed projection for the latter, we used the current KTBL observations of field work days in the neighboring regions at lower elevations. (See supplementary appendix online for details.)

Our climate scenarios should not be interpreted as accurate local predictions of global warming in the study area. Obtaining suitable representations of future weather is one of the major challenges when using crop growth models for economic analysis (Robertson et al. 2013; Ehret et al. 2012). Our intention here is to provide useful scenarios to test the robustness of estimated climate change effects against different

**Table 2. Yields [t/ha] in Baseline (B) and Climate Change Scenarios (C) by Soils**

<table>
<thead>
<tr>
<th>Code</th>
<th>Soil Mapping Unit</th>
<th>SM B</th>
<th>C</th>
<th>SB B</th>
<th>C</th>
<th>WB B</th>
<th>C</th>
<th>WR B</th>
<th>C</th>
<th>WW B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>RT</td>
<td>Rendzic leptosols, Chromic cambisols, Chromic luvisols</td>
<td>48.7</td>
<td>47.5</td>
<td>4.5</td>
<td>4.2</td>
<td>6.0</td>
<td>5.9</td>
<td>3.6</td>
<td>3.5</td>
<td>8.1</td>
<td>8.8</td>
</tr>
<tr>
<td>Z</td>
<td>Calcaric regosols</td>
<td>43.5</td>
<td>45.6</td>
<td>4.6</td>
<td>4.2</td>
<td>6.1</td>
<td>6.0</td>
<td>3.3</td>
<td>3.5</td>
<td>8.1</td>
<td>8.7</td>
</tr>
<tr>
<td>VB</td>
<td>Vertic cambisols, vertisols</td>
<td>51.3</td>
<td>49.8</td>
<td>4.8</td>
<td>4.8</td>
<td>6.8</td>
<td>6.3</td>
<td>3.1</td>
<td>3.4</td>
<td>8.1</td>
<td>9.8</td>
</tr>
<tr>
<td>PT</td>
<td>(Chromic) luvisols, Chromic cambisols</td>
<td>45.8</td>
<td>46.0</td>
<td>4.7</td>
<td>4.4</td>
<td>6.4</td>
<td>6.2</td>
<td>3.6</td>
<td>3.5</td>
<td>8.1</td>
<td>9.0</td>
</tr>
<tr>
<td>PB</td>
<td>Luvisols, cambisols</td>
<td>53.4</td>
<td>51.1</td>
<td>5.1</td>
<td>5.7</td>
<td>7.6</td>
<td>6.5</td>
<td>3.6</td>
<td>3.8</td>
<td>8.1</td>
<td>10.1</td>
</tr>
<tr>
<td>P</td>
<td>Luvisols</td>
<td>49.8</td>
<td>49.6</td>
<td>4.7</td>
<td>4.5</td>
<td>6.3</td>
<td>6.2</td>
<td>3.5</td>
<td>3.5</td>
<td>8.1</td>
<td>9.3</td>
</tr>
<tr>
<td>BT</td>
<td>Cambisols, chromic cambisols</td>
<td>41.3</td>
<td>41.7</td>
<td>4.5</td>
<td>3.6</td>
<td>5.8</td>
<td>5.8</td>
<td>3.2</td>
<td>3.4</td>
<td>7.7</td>
<td>7.9</td>
</tr>
<tr>
<td>A</td>
<td>Fluvisols</td>
<td>51.4</td>
<td>50.4</td>
<td>4.9</td>
<td>5.3</td>
<td>7.2</td>
<td>6.4</td>
<td>3.4</td>
<td>3.7</td>
<td>8.1</td>
<td>9.6</td>
</tr>
<tr>
<td>K</td>
<td>Cumulic anthrosols</td>
<td>53.5</td>
<td>51.1</td>
<td>5.1</td>
<td>5.7</td>
<td>7.3</td>
<td>6.5</td>
<td>2.9</td>
<td>3.6</td>
<td>8.1</td>
<td>10.0</td>
</tr>
</tbody>
</table>

**Note:** SB, summer barley; SM, silage maize; WB, winter barley; WR, winter rapeseed; WW, winter wheat.
model parameterizations; we believe the magnitudes of change assumed are sufficiently realistic for this purpose. All scenarios use the EU, REA, and MEKA policies valid in the season 2012/2013, along with the 2007 agent population, the most recent one available in our dataset.

**Crop Areas**

We simulated the sixty-six SR-UPCS design points for each of the three climate scenarios assuming average prices observed between 2000 and 2009 (converted to 2009 real terms). An overview of results is given in table 3. In the standard scenario C1, we observe a strong decline in winter barley area (−11% to −64%) corresponding with a noticeable increase of winter wheat (+2% to +15%) and rapeseed area (+4% to +11%) compared with the baseline scenario B evaluated for the same UPCS design point. For the other crops, the effect is ambiguous. In the extended scenario C2, both the decline in winter barley area (−37% to −84%) and the increase in winter wheat (+24% to +64%) and rapeseed area (+13% to +23%) compared with scenario B are much stronger than in C1. Further, the summer barley area also experiences a strong decline (−18% to −56%) and silage maize area tends to increase (−3% to +43%). Overall, the model predicts that changes in available field working days and the possibility of growing rapeseed after barley may have a considerable influence on local land use and crop production. This observation is robust to the uncertainty represented in the sixty-six design points of the UPCS. Under current climate conditions, farmers in the study area are virtually forced to grow summer barley at some point in the cropping sequence between winter wheat and rapeseed. In the extended scenario C2, more wheat-intensive crop rotations (e.g. wheat–rapeseed–wheat–silage maize) become possible and are profitable for many farm agents.

It is likely that such drastic shifts in crop areas might trigger responses in regional output prices; accordingly, effects should not be evaluated at one price level only. We present, as an example, the simulated own

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**Table 3. Simulated Crop Areas in Baseline and Climate Scenarios: Mean, Minimum, and Maximum over the Sixty-Six SR-UPCS Design Points**

<table>
<thead>
<tr>
<th>Crop</th>
<th>Cultivated Area (ha)</th>
<th>Abs. Diff. to B (ha)</th>
<th>Rel. Diff. to B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Min</td>
<td>Max</td>
</tr>
<tr>
<td>Scenario B (Baseline)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fallow</td>
<td>142</td>
<td>0</td>
<td>838</td>
</tr>
<tr>
<td>Field grass</td>
<td>967</td>
<td>464</td>
<td>1,453</td>
</tr>
<tr>
<td>Silage maize</td>
<td>2,014</td>
<td>1,493</td>
<td>2,708</td>
</tr>
<tr>
<td>Summer barley</td>
<td>4,482</td>
<td>4,139</td>
<td>4,915</td>
</tr>
<tr>
<td>Winter barley</td>
<td>2,815</td>
<td>1,929</td>
<td>4,697</td>
</tr>
<tr>
<td>Winter rapeseed</td>
<td>4,144</td>
<td>3,907</td>
<td>4,438</td>
</tr>
<tr>
<td>Winter wheat</td>
<td>7,334</td>
<td>5,178</td>
<td>8,304</td>
</tr>
<tr>
<td>Scenario C1 (Direct climate effects on yields)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fallow</td>
<td>144</td>
<td>0</td>
<td>861</td>
</tr>
<tr>
<td>Field grass</td>
<td>898</td>
<td>461</td>
<td>1,331</td>
</tr>
<tr>
<td>Silage maize</td>
<td>2,067</td>
<td>1,634</td>
<td>2,753</td>
</tr>
<tr>
<td>Summer barley</td>
<td>4,468</td>
<td>4,076</td>
<td>4,866</td>
</tr>
<tr>
<td>Winter barley</td>
<td>4,170</td>
<td>668</td>
<td>4,159</td>
</tr>
<tr>
<td>Winter rapeseed</td>
<td>4,465</td>
<td>4,123</td>
<td>4,789</td>
</tr>
<tr>
<td>Winter wheat</td>
<td>7,866</td>
<td>5,278</td>
<td>9,588</td>
</tr>
<tr>
<td>Scenario C2 (Yield effects and shifts in time slots and rapeseed after wheat)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fallow</td>
<td>144</td>
<td>0</td>
<td>861</td>
</tr>
<tr>
<td>Field grass</td>
<td>1,012</td>
<td>700</td>
<td>1,424</td>
</tr>
<tr>
<td>Silage maize</td>
<td>2,317</td>
<td>1,875</td>
<td>2,869</td>
</tr>
<tr>
<td>Summer barley</td>
<td>2,465</td>
<td>1,859</td>
<td>3,463</td>
</tr>
<tr>
<td>Winter barley</td>
<td>1,252</td>
<td>336</td>
<td>2,027</td>
</tr>
<tr>
<td>Winter rapeseed</td>
<td>4,913</td>
<td>4,769</td>
<td>5,070</td>
</tr>
<tr>
<td>Winter wheat</td>
<td>9,932</td>
<td>8,242</td>
<td>11,061</td>
</tr>
</tbody>
</table>
price response of summer barley. Specifically, we ran thirteen repetitions of the $3 \times 66$ simulations varying the malting barley price from 70% to 130% of the decadal average in steps of 5%. Figure 2 shows the distribution of summer barley area over the sixty-six UPCS points at each malting barley price level in each scenario. As a first observation, the graph demonstrates that the model is indeed capable of producing a smooth regional area response to price changes. Regarding the effect of climate change, the decline in summer barley area in scenario C2 compared with scenario B virtually disappears for high levels of the malting barley price. For some UPCS points that show a comparatively lower positive area response to price increases, the climate-induced difference is even positive. As discussed, the UPCS design allows relating distinctive outcome patterns to first-order effects of parameters, and closer inspection reveals that these design points are characterized by low values of the proportionality parameter for hiring of field work services. This parameter becomes less important when weather constraints on field work are relaxed in scenario C2.

The climatic shift increases the competition between wheat and barley production: the correlation coefficient between wheat area and summer barley area changes from $-0.52$ in scenario B to $-0.96$ in scenario C2.

Strong negative area effects of climate change at lower price levels and insignificant or positive effects at higher price levels also imply a significant change in the price sensitivity of summer barley production. Our model allows translation of the expected structural shift in the agricultural system into changes in price elasticities, which can then be incorporated into national or global simulation models that balance the local effect with similar changes elsewhere to derive a new equilibrium supply level. The price elasticity of the summer barley area at prices calculated between 100% and 105% of the long-term price average is 1.2 in scenario B, 2.2 in scenario C1, and 8.9 in scenario C2 on average, implying a significant alteration to the malting barley supply function when more than just direct yield effects are included. Effects on the cross-price elasticities of winter barley (B: $-0.3$; C1: $-1.91$; C2: $-4.9$) and winter wheat (B: $-0.4$; C1: $-0.7$; C2: $-1.3$) can also be observed.4

4 These elasticities with respect to malting barley prices were assessed keeping other prices at observed averages, but experimental designs exploring changes in the levels of all prices and price relations can also be simulated.
Figure 3. Simulated climate change impacts on per-hectare farm income in scenarios C1 and C2. Distribution of the difference to scenario B in per-hectare income over the full agent population (box plots) and the sixty-six SR-UPCS runs (left to right).

Farm Incomes

Figure 3 shows the effect of the adaptation scenarios on farm agent incomes (at the long-term price average). For each of the sixty-six UPCS runs in each scenario, the graph includes one box plot. Each box plot depicts the distribution of changes in per-hectare incomes over the full agent population. We can see that income effects are quite heterogeneously distributed over the farm agent populations reaching up to +165 EUR/ha (median 32 EUR/ha) in scenario C1 and up to +266 EUR/ha (median 72 EUR/ha) in scenario C2. At the same time, the distribution of income effects does not differ much over the sixty-six different parameter combinations tested.

One of the strengths of a disaggregate setup is being able to differentiate which farm types are going to benefit more and which are going to benefit less from climate change impacts. To summarize the relationship between farm agent characteristics and simulated income effects predicted by our model, we regressed the differences in impacts between farm agents on differences in household labor capacity, soil types, livestock stalls, and biogas plants between farm agents. As the individual farm agent characteristics are differently scaled, we calculated standardized regression coefficients (SRCs) to allow a comparison of their importance. Given our representation of model uncertainty, we ran this regression for each of the sixty-six UPCS points and summarized the distribution of SRCs in table 4. As the table shows, income differences between scenario C1 and scenario B are predominantly explained by differences in soil types due to the dependence of yield effects on soil types. Because we did not model climate effects on grassland yields, it is not surprising that a higher grassland share is associated with lower climate effects on income. In the extended scenario C2, livestock production infrastructure, especially the number of dairy cow stalls, is much more important in determining income effects than in scenario C1. This is because increasing silage maize production best exploits the additional changes assumed in scenario C2, and this is most profitable for farm agents with dairy cows or biogas production.

Agricultural Policies

One of the objectives of the EU agri-environmental policies is to promote the diversification of crop production. To this end, the corresponding policy implementation in the state of Baden-Württemberg, the MEKA scheme, contains a support measure (N-A2) that rewards farmers with 20€/ha if they produce at least four crops, each with a minimum share of 15% of their total arable area, and use less than 40% of their land for maize production. If wheat yields increase relatively stronger and more wheat-intensive
Table 4. Association of Climate Change Impacts on Farm Income to Farm Attributes: Mean, Minimum, and Maximum of Standardized Regression Coefficients (SRC) over the Sixty-Six SR-UPCS Runs

<table>
<thead>
<tr>
<th>Agent Attribute</th>
<th>( \Delta \text{C1-B} )</th>
<th>( \Delta \text{C2-B} )</th>
<th>( \Delta \text{C2-C1} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Min</td>
<td>Max</td>
</tr>
<tr>
<td>Farm size (ha)</td>
<td>-0.10</td>
<td>-0.29</td>
<td>0.01</td>
</tr>
<tr>
<td>Hhld. labor (persons)</td>
<td>0.00</td>
<td>-0.04</td>
<td>0.05</td>
</tr>
<tr>
<td>Dairy cow stalls</td>
<td>-0.01</td>
<td>-0.11</td>
<td>0.05</td>
</tr>
<tr>
<td>Other cattle stalls</td>
<td>0.01</td>
<td>-0.06</td>
<td>0.11</td>
</tr>
<tr>
<td>Sow stalls</td>
<td>0.01</td>
<td>-0.06</td>
<td>0.05</td>
</tr>
<tr>
<td>Piglet stalls</td>
<td>-0.01</td>
<td>-0.04</td>
<td>0.00</td>
</tr>
<tr>
<td>Fattening pig stalls</td>
<td>0.01</td>
<td>-0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>Biogas plant (yes/no)</td>
<td>-0.01</td>
<td>-0.05</td>
<td>0.08</td>
</tr>
<tr>
<td>Share of grassland</td>
<td>-0.57</td>
<td>-0.60</td>
<td>-0.50</td>
</tr>
<tr>
<td>Share soil Z</td>
<td>0.02</td>
<td>0.00</td>
<td>0.05</td>
</tr>
<tr>
<td>Share soil VB</td>
<td>0.15</td>
<td>0.12</td>
<td>0.20</td>
</tr>
<tr>
<td>Share soil PT</td>
<td>0.07</td>
<td>0.05</td>
<td>0.10</td>
</tr>
<tr>
<td>Share soil PB</td>
<td>0.15</td>
<td>0.11</td>
<td>0.21</td>
</tr>
<tr>
<td>Share soil P</td>
<td>0.12</td>
<td>0.09</td>
<td>0.17</td>
</tr>
<tr>
<td>Share soil BT</td>
<td>-0.28</td>
<td>-0.30</td>
<td>-0.24</td>
</tr>
<tr>
<td>Share soil A</td>
<td>0.06</td>
<td>0.01</td>
<td>0.09</td>
</tr>
<tr>
<td>Share soil K</td>
<td>0.54</td>
<td>0.49</td>
<td>0.57</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.84</td>
<td>0.69</td>
<td>0.88</td>
</tr>
</tbody>
</table>

Note: Share of soil RT omitted to avoid perfect collinearity. All soil shares expressed as share of total arable land of the farm agent. Share of grassland expressed as share of total agent farm size. For the explanation of soil mapping units see Table 2.

Figure 4. Simulated area registered for MEKA A2 crop diversification in the three climate scenarios depending on the crop price level. Box plots indicate the distribution over the sixty-six SR-UPCS runs.
crop rotations become possible under climate change, the incentive to participate in this scheme could fall. We repeatedly simulated our $3 \times 66$ design varying the level of cereal, oilseed, and animal feed prices from 70% to 130% of the decadal average in steps of 10%. Figure 4 shows the simulated distribution of the area committed to measure N-A2 over the sixty-six design points at each relative price level in each scenario. Again we see a stronger decline in participation in the extended scenario C2 than in the standard scenario C1, which is strongest at higher crop price levels. The graph shows a relatively...
large range for potential participation at higher price levels. Again we exploited the UPCS setup to determine which parameters most strongly affected observable outcomes. Very low levels of participation can be observed in runs with a high chance to contract field work and a high yield parameter for wheat. We also used our model to determine how much the MEKA compensation would have to be raised to maintain the baseline participation level. We repeated the simulations increasing the per-hectare reward in steps of 5€. Our simulations suggest that in the median of repetitions the payment would have to be increased to 25€ if climate change only affected yields (scenario C1) and to 35€ if it also shifts time slots (scenario C2) in case the crop price level remained constant. If the crop price level increased to 110% of the past average, in the median an additional increase of 5€ would be necessary in both scenarios.

A second example for policy outcomes that might be affected by climate change is the promotion of biogas production through the Renewable Energy Act (REA). The law obliges electricity providers to buy electricity from biogas plants at a fixed price. The price an individual farmer receives is guaranteed for twenty years and depends on the size of the plant, the feedstock mix used, and the year the biogas plant first went into production. (The price guaranteed to new plants is lowered by 1% every year.) The simulations we presented so far show hardly any climate impact on biogas plant capacity. However, biogas investment depends on financing capacity, expected remaining lifetime of the farm, and guaranteed prices, all of which evolve over time. To assess climate effects on biogas assessments, we ran recursive-dynamic simulations over ten years with the LR-UPCS setup, updating farm assets and household composition at the end of each year. (For simplicity, we kept prices and yields constant over time as in the previous simulations.)

Figure 5 shows the development of the installed capacity for biogas electricity production in the study area over ten simulation years. Because the current version of the REA requires use or sale of excess heat, model assumptions about local demand for heating are crucial for simulated biogas investments. The graph therefore shows two boxplots for each simulation year and scenario, a dark one indicating the distribution over the thirty-two design points assuming unlimited heating demand on local markets and a light one indicating the distribution over the thirty-six design points assuming zero heating demand. Although the graph shows little difference in biogas capacity in the first simulation year, after ten years the standard scenario C1 shows on average 300 kW more capacity, and the extended scenario C2 shows on average approximately 900 kW more capacity than scenario B if unlimited demand for heating is assumed.

Conclusions

Using a highly disaggregate MP model of farm production decisions, we show that shifts in crop management time slots that allow new crop sequences and increase the number of suitable days for field work are important in shaping farmer response to climatic change. At least in the scenarios we tested for a typical low mountainous region in southwest Germany, this nonyield pathway of climate change effects had similar or even more important impacts than crop yield changes. Neglecting the nonyield pathway as in standard models would considerably underestimate climate impacts on agricultural supply elasticities, farm incomes, biogas investments, and participation in crop diversification policies. It would also alter assessments on which farm types would benefit or lose from climate change effects.

Overall, this conclusion and the direction and order of magnitude of simulated impacts proved robust to model uncertainty, which we comprehensively assessed using a framework for uncertainty analysis designed to address the specific challenges of our modeling context. The uncertainty in simulation outcomes is to a large extent a combined product of different uncertainties associated with input data, simulated yields, and omitted market interactions. We found that second- and higher-order effects (i.e., interactions between parameters) are generally responsible for more than half of the variance in simulation outcomes. Among the critical factors of model uncertainty, the auxiliary parameter representing the chance of hiring field work services stood out as having by far the strongest first-order effect on simulated climate change impacts. Analyzing to what extent climate change could affect the external supply of field work services is therefore
a crucial next step to improve the reliability of our climate adaptation simulations.

This finding is also an argument for extending our current model specification to a fully connected agent-based model with explicit agent–agent interactions. Besides relying on professional service providers, many family farms in southwest Germany cooperate in machinery-sharing rings or have sharing agreements with their neighbors. Both timeliness of machinery availability and potentially cooperating neighbors are major determinants for the formation and successful maintenance of such machinery-sharing agreements (de Toro and Hansson 2004; Artz, Colson, and Ginder 2010; Aubacher, Lippert, and Dabbert 2011).

In addition to machinery hiring and sharing, our uncertainty analysis also highlighted the importance of other types of agent–agent interactions to be addressed in a fully connected agent-based model. The existence of local heating markets is the single most important factor for the future expansion of biogas production. Further, our calibration procedure discouraged assuming unlimited demand for silage maize and renewable energy products, as well as unlimited supply of young female cattle. In our current model configuration without agent–agent interactions on local markets, we accordingly set the related model parameters to zero. Because these uncertain parameters showed a strong influence on goodness-of-fit and model outcomes, modeling these local markets explicitly in an agent-based model setup instead of setting them to zero should improve the quality of our simulations. The importance of these local and often fragmented markets is generally expected to increase in the future given the current expansion of biogas production and farm specialization (Delzeit, Britz, and Holm-Müller 2012). Our analysis provides the necessary foundation for such an extension: Similar to uncertainty in MP decision models, uncertainty in the implementation of agent interactions should be dealt with by including additional calibration parameters into the uncertainty assessment. The framework will then be capable of informing the modeler’s decision regarding the necessary level of complexity and, for example, show whether explicit agent–agent interactions in a fully connected agent-based setup significantly improve a disconnected farm-level model configuration.

Although the importance of climatic influence on possible crop sequences and time slots for field work may be specific to the diversified European family farms under temperate climate, it is an example of how agricultural production and livelihoods are strongly determined by region-specific conditions. Our results confirm that adaptation analysis is well-advised to go further than just feeding simulated crop yields into aggregate agricultural sector models (Reidsma et al. 2010). Understanding how a specific agricultural system will react to exogenous shocks such as climate change requires an in-depth analysis of the fundamental processes and relationships determining the decision logic of the important actors in the system, even though the resulting insights cannot always be generalized from one region to another.

In theory, disaggregate farm-level MP models and agent-based models are perfectly suited for this type of in-depth adaptation analysis, but they have often been criticized for prohibitive data requirements and arbitrariness of simulations results due to high model uncertainty, especially when used to derive regional level results (Nolan et al. 2009; Buyssse, Huylenbroeck, and Lauwers 2007; Zimmermann, Heckelei, and Pérez Domínguez 2009). Although these challenges cannot be denied, our results show that robust simulation outcomes can actually be achieved if the modeling approach is embedded into a systematic framework for treating the inherent model uncertainty.

Although our framework for calibration and uncertainty analysis is to a certain extent tailored to the modeling context of this study, we think that the general principles used can be transferred to other modeling applications, especially empirical agent-based models. We therefore hope that our results encourage farm-level and agent-based modelers to more actively analyze and document the uncertainty in their models and thereby spark a more in-depth discussion of suitable frameworks for uncertainty analysis in farm-level modeling. This pending discussion (see also Janssen and van Ittersum 2007) should ultimately improve our understanding of simulation error distributions in farm-level modeling and allow for a replacement of robust goodness-of-fit measures by formal Bayesian analysis and model selection criteria (e.g., Akaike information criterion or Bayesian information criterion).
Supplementary Material

Supplementary material is available at http://oxfordjournals.org/our_journals/ajae/online.

References


