Presented at:
The Agricultural Economics Society's 81st Annual Conference, University of Reading, UK
2nd to 4th April 2007

The importance of spatial, temporal and social scales in Integrated modeling; simulating the effects of climatic change on district- and farm-level decision making in the Danube catchment area.

Josef Apfelbeck, Marco Huigen and Tatjana Krimly

University of Hohenheim
Institute for Farm Management
Section: Production Theory and Resource Economics
Schloss-Osthof-Sued
70593 Stuttgart
Germany

Contact: apfelb@uni-hohenheim.de

Abstract

Many scientific publications discussing the effects of climate change on the agricultural system express these in terms of changing crop production at coarse spatial and temporal scales. But in agro-economy, where crop production is the result of the interaction between bio-physical and management components, the temporal drivers operate at much smaller resolutions. Climate change affects the agricultural system via the interrelated, bio-physical layers of air, water, soil and crops. Furthermore, it influences the farm-system manager in their choice of their crops. In our paper the main question is how to deal systematically with the different time extents and time resolutions when studying agricultural management impacts due to climatic change. Agent based modeling offers an elegant way to tackle such challenges, where agents represent simplified farm managers. The agricultural management model is dynamically connected to a regional agro-economic model, a ground water model, a crop growth model and a soil model. Hence, we endogonize climatic change and make its effects a (risk)-factor in the agents considerations along different temporal scales. This paper reports on the fundamental issues regarding use of different temporal modeling scales with several clear practical examples.

Introduction

During recent decades, there have been notable changes in the global and European climate. Temperatures are rising, precipitation patterns in many parts of Europe are changing and weather extremes show an increasing frequency in some regions (IPCC, 2001a, Kane et al., 1992). The agricultural sector has a direct link with climate change; crop growth is driven for a large part by climatic conditions. In other words, climate change is a large potential driver for change in agriculture.This is nothing new; many scientific groups study the link between climate change and agricultural change. They do that with the help of advanced computer models.

Climate models are based on global circulation circumstances. These models are known as General Circulation Models (GCM´s). Such computer models numerically solve fundamental

equations describing the conservation of mass, energy, momentum for each atmospheric subsystem, while taking into account the transfer of those quantities between subsystems. They also consider, often in parameterized form, the physical processes within the subsystems, including sources and sinks of these quantities (McGuffie, et al, 1997).
In the recent past several scientific model-couplings were drafted to illustrate the future development of agricultural production under different climate scenarios. One general characteristic of most coupling efforts is that they feed highly sophisticated climate model outputs into a 'one-crop' growth model, where the main variables affecting crop growth are annual temperature change and CO_2-concentration. Furthermore, the modeling results are often based on a large spatial area with a coarse spatial and temporal resolution.

However, from an agricultural point of view this is an over-simplified representation. Crop growth certainly is affected by these two variables, but other climatic aspects such as precipitation frequency and amplitude, length and moment of frost periods and daily sun hours play a much bigger role for crop development (Rosenzweig, Iglesias, Yang, Epstein, Chivian, 2000). In our view, using temperature change and CO2 concentrations as drivers for crop change do not have much predictive value on how an agricultural landscape might develop. At the most it says something about the individual crop potential. In order to study climatic change effects on crop development the regional consequences, such as frequent weather extremes like droughts and increases in climate variability on a regional resolution and a highly detailed temporal resolution have to be taken into account (Rosenzweig et al., 2000; Seneviratne et al., 2006).

Furthermore, a crop is always part of a sophisticated crop rotation system that optimizes the economic and time-management of overlapping crop development periods in a farm system. And, equally important, crops play different roles in the farm systems' production directions. In order to understand possible agricultural change due to climatic change the role of the crop in the rotation system and in the production system is potentially highly susceptible to climatic effects. Amplitude changes in climate patterns, temporal shifts of crop development times, temporal shifts of frost periods and changes in the length of the crop development time may cause crops to become unsuitable or overlapping with other crops in the crop rotation cycle of an agricultural manager. Another pattern is the spreading of precipitation and droughts these factors have big effects on the development of the crop and hence on the potential yield and the associated pests. For instance, warmer daily temperatures allow planting to proceed earlier in spring, thus avoiding risk of damaging mid-summer heat during the critical reproductive period. Such a longer vegetation period allows farmers to grow varieties that take longer to reach maturity which enables longer grain filling periods and thus higher yields. But the following crop can be affected by later planting possibilities and this crop may loose in expectations of yield.

In this paper we present an approach that combines high detail climate change with sophisticated crop growth management practices. Central question in our current study is what possible agricultural changes we may expect in our research area under three different IPCC climate-scenarios. In our approach which is embedded in the interdisciplinary project GLOWA-Danubemany scientific disciplines are involved. An important part is a tight connectivity between the bio-physical and management components.

Climate affects the agricultural system via the interrelated, bio-physical layers of air, water, soil and crops. Essential in integrating such detailed computer models is that the correct drivers are linked on the correct spatial, temporal and unit-of-analysis scales. Climate change (or better: the interpretation of) influences the farm system manager in their choice of their crops. These different systems operate on different time extents and resolutions (e.g. crop growth is modeled

in hourly time steps while a crop-rotation cycle in a farm system is four to eight development periods) and different time chronologies (e.g. a bio-physical year is different from an economic accounting year). The choices of simulated temporal resolutions are pivotal. Effects on a micro-time scale affect a higher time scale. E.g. farmers' daily choices regarding planting and harvesting affect the yield and potentially the choice of a less optimal crop the next year.
Our research area (the Upper Danube catchment) has a fixed the spatial extent, while the spatial resolution varies according to the models used. The highest resolution is a grid cell of 1 by 1 km (proxel). The temporal resolutions used are hourly, daily, seasonal and yearly depending on the models. Usually a simulation run of the integrated modeling system has a fixed temporal extent. The units of analysis that we use in our models are crops, the farm-system and the district ('landkreis').

As said, in integrated modeling the fine-tuning of data exchanges on the correct scales is of major importance. In this paper we illustrate how we deal with this intricate issue. In the methodology we present the architecture of our integrated approach, where emphasis lies on our dealing with the correct representation of scales in our simulation model. In the results section we present the outcomes of one of the major tasks in empirical integrated modeling: the model initialization. In the discussion and conclusion section we come back on the issue of scales.

Methodology

Project GLOWA Danube & Research Area

The GLOWA-Danube research project, in the framework of GLOWA (Global Change in the Hydrological Cycle) and funded by the Federal Ministry of Education and Research (BMBF) began in 2001. The project aims to develop strategies and integrative techniques for dealing with regional effects of global change on water cycles and their utilization by man in the Upper Danube catchment (Mauser and Ludwig, 2002).

The project involves various disciplines such as hydrology, ecology, glaciology, geography, water resource management, agricultural economy, tourism, environmental economy, environmental psychology and computer science.

The Upper Danube basin covers an area of 77,000 km², enclosing 8 million residents in two German States and three major countries. Approximately 55 % of the catchment area is agriculturally used. The project area is represented by a rectangular mesh of 1 x 1 km proxel-(process-pixel)-objects.

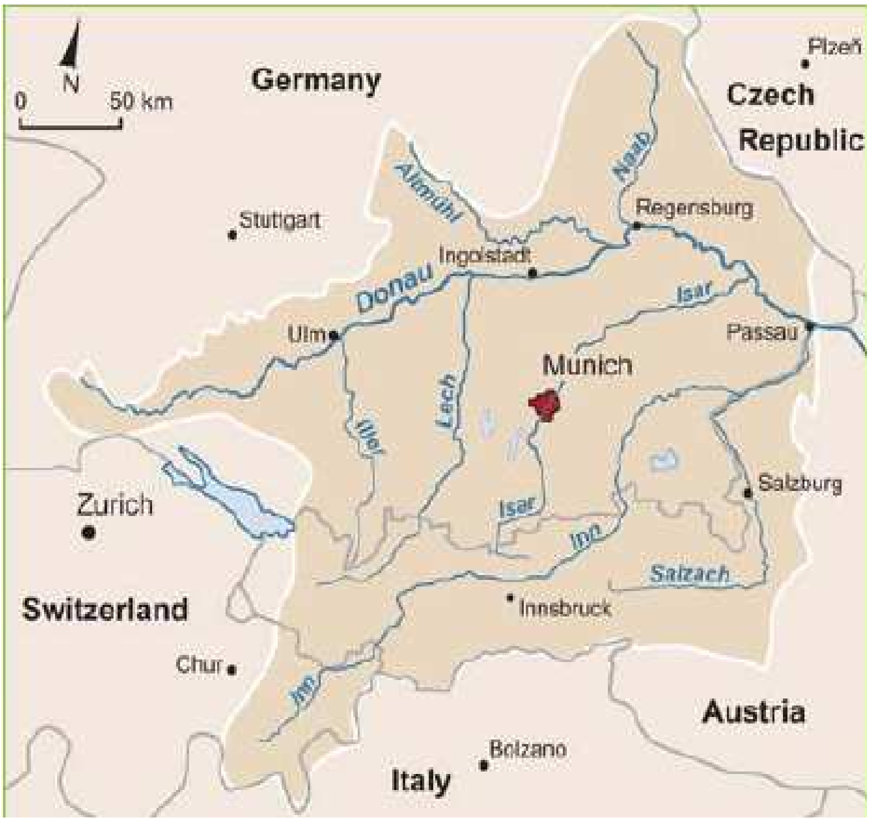


Figure 1: Research Area

Integrated Modelling Approach

Figure 2 shows schematically the architecture of our modeling components.

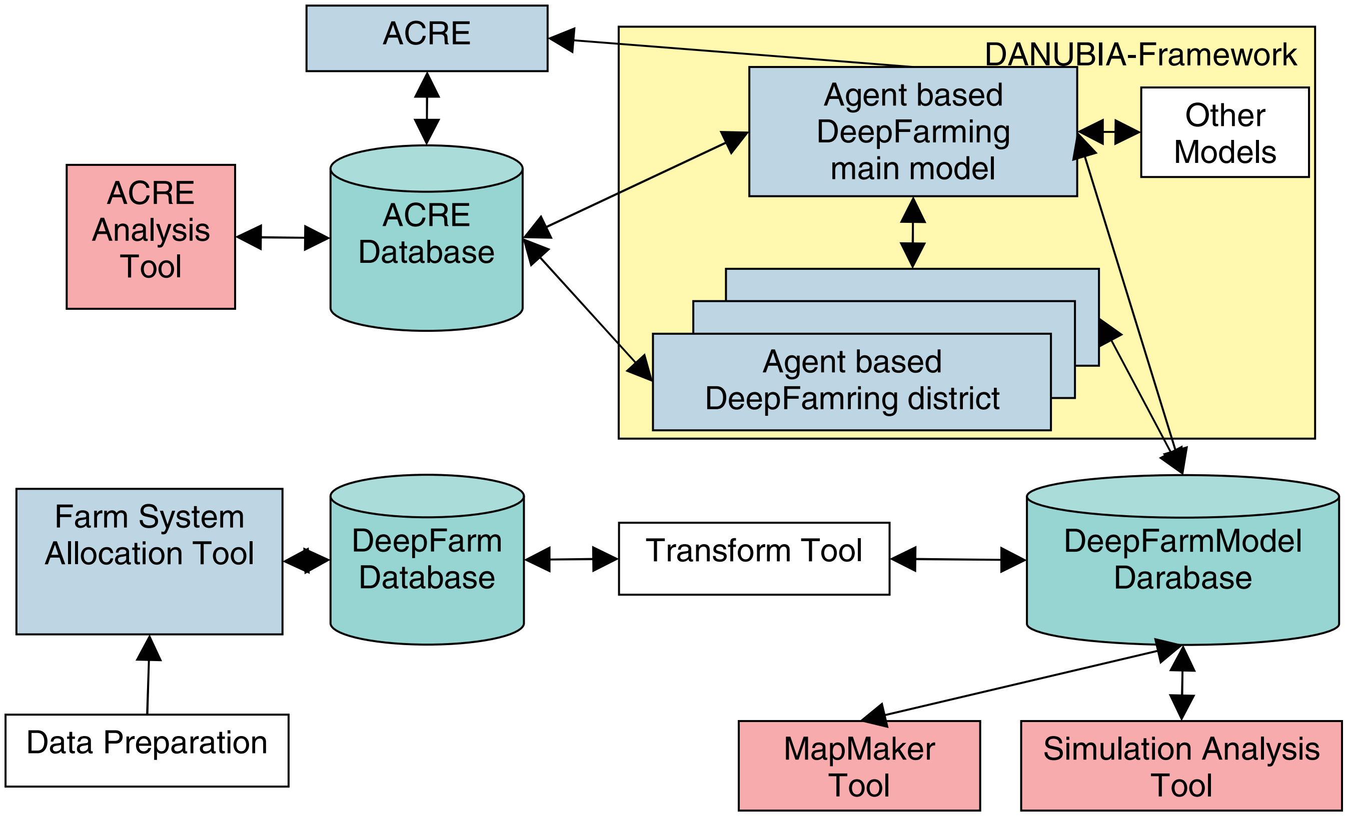


Figure 2: Integrated Modelling Architecture

The DANUBIA-system is a java simulation framework that dynamically couples the single simulation models (in figure represented by 'other models') while safeguarding and guaranteeing the correct exchange of information runtime during an integrative simulation. The DANUBIA managing component controls the different timing and spatial needs of every single model (Barth et al, 2004).

The DANUBIA framework contains again the so-called deepactors framework. This deepactors' framework is a generalized architecture for agent based models in the DANUBIA framework (Barth et al., 2004).

Our agent based model components (DeepFarming main model and DeepFarming district models) function fully according to the principles of the DANUBIA framework and the deepactors framework. The multiple DeepFarming models are all based on the same model-template. Multiple district models are generated so that we can simulate on a distributed system allowing for higher performance. The DeepFarming main model is the connection between our components and the 'outside' world, hence all dynamic coupling activities are guided by the main model.

ACRE is an Agro-eConomic model for agricultural pRoduction on rEgional level. The model is used to simulate and forecast different policy measures in agriculture. ACRE is a comparative static partial-equilibrium model with a simulation period of one year. The process-analytical optimization model combines linear and non-linear functions to optimise agricultural production by maximising agricultural total gross margin (CGM) on district level (NUTS3). The model considers 17 land use activities and 12 livestock production activities for a total of 74 districts. Livestock feed is produced model-endogenously based on the output of fodder, ma-

nure is produced by livestock. Mineral fertilizers and feed concentrates are purchased. Trade between districts is not possible (Henseler, etal., 2006).
During a simulation run our agent based DeepFarming components store and use data from the DeepFarmingModel database. The two other databases depicted are used for storing and retrieving ACRE data and model initialisation data. The analysis tools (MapMaker, ACRE Analysis and Simulation Analysis) also retrieve simulation results from these databases.
In order to simulate reliable futures with an integrative modelling system the first and perhaps most important step is the model initialisation. This has been conducted with the FarmSystem Allocation Tool. Below a description and the results of this model initialisation process is given.

The agent based DeepFarming Model components

As said, at the heart of our integrative system is an agent based system (DeepFarming main model and districts model) that interacts with several other models along different timelines and on different spatial scales.

An agent-based model can be easily implemented in an interdisciplinary project like the GLOWA-Danube project and it is an ideal method to integrate various scientific disciplines with different ontologies. Agent-based modeling is a tool where heterogeneous and scalable representations of space, time and social entities are allowed. It offers a very flexible way of programming, there is the possibility of using different mathematical or functional terms for calculation like linear programming or heuristic decision making. Agent-based models can be fully or only partly process-based or they are a combination of both (Parker et al. 2003, Ferber 1999, Franklin/Graesser, 1996Epstein/Axtell, 1999) Balmann, 2000).

The DeepFarming models combine two key components. The first component is a cellular model that represents the landscape over which actors make decisions. The second component is an agent-based model that describes the decision-making architecture of the key actors in the system under study (Parker et al., 2003). We make use of so-called heuristic agents. These are agents that have relative simple rules that guide them in their decision-making.

The agents; 28 Farm systems with their own crop rotation and production direction

The DeepFarming components differentiate between 28 different types of farm systems (agents) managing their land and constantly interpreting and deciding on the climatic factors. In Table 1 three examples of farm system types are given. The farm system type categorization is based on statistical data on production directions in combination with agricultural expert knowledge on the area (refs.).

Each type of farm system agent has its own production direction. A production direction is a combination of a crop rotation, animals and grassland. A crop rotation consists of one to eight different crops.

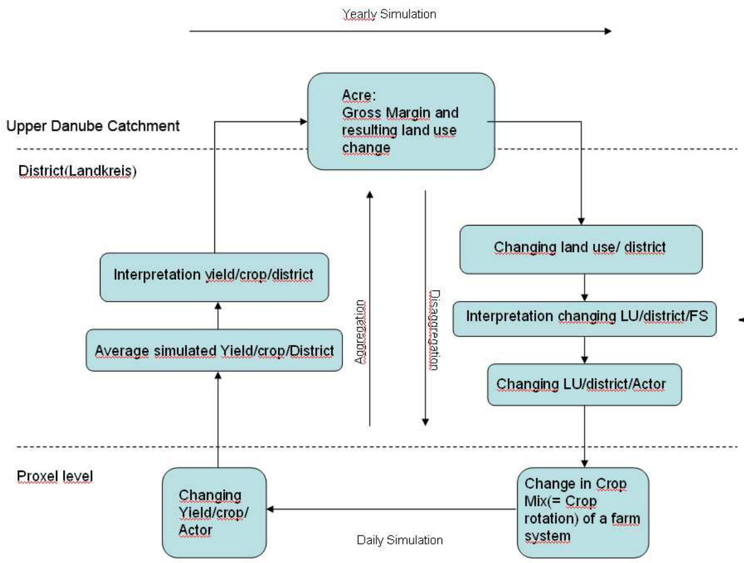
Agent Deep-farmType	Production direction	Husbandry	Crops in rotation	Type of Grassland
CashSugMaize	Cash cropping		Sugar beet, Winter wheat, Winter barley, Maize, Set aside	
MeatBreedSum	Meat,egg and poultry production	Breeding sow	Winter barley, Rye, Summer wheat, Maize, Set aside	

ForagDairGra	Forage growing farms	Dairy farm		Extensive grassland Intensive grassland

Table 1: Examples of Farm System types used in the DeepFarming components

Agents making a plan; the link between Acre and the DeepFarming components

Our Farm System agents do not have economic knowledge but retrieve a personal plan based on the ACRE district-level land use optimization. Every year, after the execution of the annual crop rotation plan our agents retrieve the new plan from ACRE via a disaggregation step. Before ACRE starts calculating the new plan on the district level, an aggregation algorithm delivers per crop per district the weighted average yield from previous simulated years. This is shown on the left side of Figure 3 depicting the connection between Acre and the agents.



Land use	Action	Reaction
Sugar beet	+	winter barley
Sugar beet	-	winter wheat
Winter wheat	+	winter barley
Winter wheat	-	winter barley
Winter barley	+	Maize
Winter barley	-	winter wheat
Maize	+	winter barley
Maize	-	winter wheat
Set aside	+	Maize
Set aside	-	sugar beet

Example: FarmSystem CashSugMaize

Figure 3: Information exchange between the DeepFarming Agents and ACRE

After a yearly run of ACRE the district level output is disaggregated to the farm system level. This disaggregation is conducted with a heuristic algorithm. The basis of this algorithm is the table at the right of Figure 3. Every farm system has a similar table, while in the figure only the one for the farm system *CashSugMaize* is given. This table has a simple build up, in the first column it shows the changing crop and in the second column the action is given. A positive action sign (+) says that if the crop (column one) hectarage increases in a certain district compared to the previous year, then the Farm system will increase if also the crop in the third column goes down. So, if for example ACRE gives that winter barley increases and maize goes down than the farm systems in the example will participate in the crop change. The quantity of change depends on the relative importance of the crop in the district and the relative importance of the crop in the production direction of the farm system. This table contains a lot of expert knowledge about different farm system and their strategies taking into account the crop distribution channels, production direction requirements and long term assets.

Agents decision making; 'When do I plant, fertilize or harvest what crop?'

So, the farm system agents have derived their personalized yearly economic plan and here the climate change is expressed as annual yield in the ACRE model. But as stressed above, climatic effects also take place on a higher temporal detail. In essence, the key question that occupies our agents is: "When do I plant, fertilize and harvest the crops I have in my plan (crop-rotation)". These decisions are simulated in daily time steps and have a different algorithm for each type of crop in the simulation.

Planting

The most complex decision for an agent is when to plant a crop. Theoretically, an agent has to optimally fit the crop development frame with its requirements over the expected climate parameter frames. For example, if an agent wants to plant winter wheat it has to take into account that winter wheat requires vernalization at a given growth stage, while also considering the need for precipitation during the 'heading' stage of winter wheat. In the decision algorithm for planting winter wheat the agent therefore tries to find a possible crop growing period where the expected climate variables meet the requirements of the crop development. The farm system agents get runtime information about their crop growth and development stage from the crop growth model. The crop growth model is directly connected to a soil/groundwater model and both respectively simulate the growth of agricultural plants and the flow of water and nitrogen in the soil. (Lenz et al, 2006).

Every crop in our system has requirements per action. Hence, for winter wheat the required temperature (+0.5 to +8°C for a period of minimum one week) between the BBCH[1]-stages (Meier et al, 2001) 10 and 30 is stored while, for example, for potatoes the BBCH-stage 47 (70% crop mass) is given as the possible starting day for harvesting and BBCH-stage 49 (haulm is dead) for the optimal moment of harvesting. In this exemplary potato case the agent decides on the moment of harvesting while considering the expected precipitation; if he expects a long period of rain while the possible harvesting stage is already reached it will harvest its potatoes to prevent them from rotting. In Table 2 a compiled example for these requirements for winter wheat and potatoes is given.

[1] The development stages of plants are often quoted as BBCH-Code. It is an abbreviation of the involved German institutes: **B**iologische Bundesanstalt, **B**undessortenamt and the **ch**emical industry represented by Industrieverband Agrar. For more information: www.bba.bund.de

Crop	Action	BBCH-stage	Additional info	Minimum germination temperature	Avg. soiltemperature of the next 6 days	Farmers' knowledge
Potato	**Planting**	00		8-10°C	10°C	
	First Fertilization of Nitrogen	00				0 - 5 days after planting
	Start Harvesting	47	70% crop mass			Depends on the weather of the next two weeks
	Optimal harvesting	49	The haulm is dead			
	Fertilization of phosphate					Before Ploughing
Winter wheat	**Planting**	Before 21	Winter cereals should reach the stage before tillering. Before winter dormant starts	2-5°C	6.5°C	0-30 days before the first frost is recorded
		10-30	Requires vernalisation :Temperature: +0.5 - +8°C; minimum period one week during given BBCH stages			
	First Fertilization of Nitrogen					With the day of the last frost
	Second Fertilization of Nitrogen	30-32	Stem elongation			
	Third Fertilization of Nitrogen	39-49	heading			
	Start Harvesting	87	Yellow ripeness			Depends on the next 2 weeks weather forecast
	Optimal Harvesting	92	After over ripe dry matter contents in the corn of 84%			
	Fertilization of phosphate					Before Ploughing

Table 2: Example of crop requirements linked to the BBCH-stage per agent action for potato and winter-wheat

Notice that the agent has to have a notion of 'expected' climate conditions, just like real farmers in real life. Our agents derive these 'expected' climate conditions (soil temperature, sun hours, precipitation per day) from three-year rolling forward tables stored in the database on district level. Furthermore, also the average number of days that a crop took to transform from one stage into another stage, given the day it was planted is stored on district level in the database. The agents use these highly dynamic datasets to calculate their optimal planting strategy. Besides dealing with the expected climate conditions, the agents also have to deal with the 'real' simulated climate conditions. On a specific day that an agent has calculated to plant, the actual conditions (too much rain, field to wet to use machinery) might prevent it to go out on the field to plant. In Figure 4 this decision making structure is given schematically.

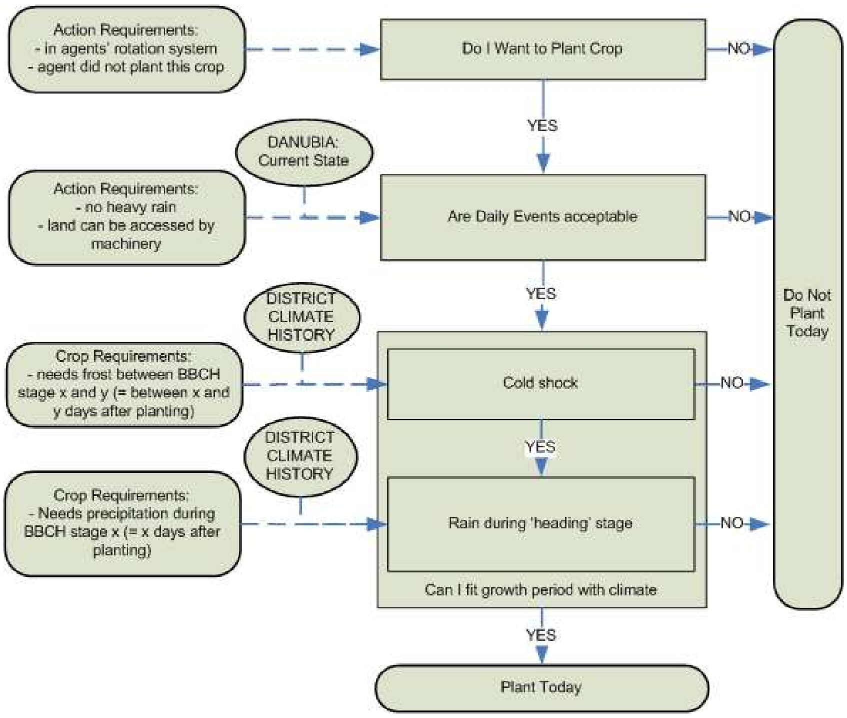


Figure 4: Decision-tree for planting winter wheat

Fertilizing

In a similar but simpler way the agent decides to fertilize the different crops. From the crop growth model the agents receives information about the stage of the plant. This information in combination with the specific crop needs and the daily climate conditions allows the agent to come to a decision when it should fertilize the crop.

Harvesting

In general harvesting depends on the crop stage ripeness but there are crops like sugar beet, where agents do not wait until the crop is ripe. The farmers start with harvesting after a specific time period when they know the harvestable part has reached a specific weight or degree of ripeness.At the moment farmers wait with harvesting until the crops are ripe for most plants in the Upper Danube it is possible to wait for the optimal harvesting stage and the stage will be conveyed by the crop growth model.

FarmSystem Allocation Tool

Most modelers know the principle of: "Garbage In, Garbage Out", hence any good simulation run starts with a well initiated model. In the text above we mention the 28 farm system types being used in our models, but to find these was a difficult task. First and foremost we had to deal with the difficulty that we model on the farm system level, but only had available data on the district. Furthermore, this available data is not spatially referenced, so we had to develop a tool (FarmSystem Allocation Tool) that spatially allocates our farm system agents on the model grid.

Each farm system has a production direction consisting of a combination of one or more of the following components: a crop rotation, animals and grassland. A crop rotation scheme consists of one to eight crops elected from a total of 17. Depending on the production direction a farm system may have animals chosen from 11 types. Lastly a farm system may have an area with either intensive or extensive grassland or a combination of both.

German statistics (StaLa, 2005; StMLF, 2004) provides data about farm system types with production directions like cash cropping farms, fodder growing farms, meat-egg-poultry production, permanent crops and mixed farms. The definition depends on the total gross margin, a farm system belongs to a certain production direction if 50% or more of the total gross margin is derived from one production component. For mixed farms the production direction is derived for less than 50% of the total gross margin from one component.

In the allocation process the crop rotation is taken as the corner stone for finding a suitable location (proxel) for a given farm system. For every proxel the suitability for each crop is determined based on: Landwirtschaftliche Bodengüte indicators (including for instance EMZ[2] in Baden-Württemberg, and the LVZ[3] in Bayern), and ground elevation. The suitability of a proxel for a crop is classified as follows:

a. Suitability level 1: very good conditions for this type of land use.
b. Suitability level 2: moderate conditions for this type of land use.
c. Suitability level 0: poor conditions for this type of land use.

For a more detailed overview of deriving these suitability classes, see Krimly et al, 2003.

Based on the statistics we derived per district the total number of a given farm system where the total land size per farm system per district differs depending on the total initial crop produces per district. We started out with 11 different farm systems covering the core production directions, but during this process step it became clear that at least 28 farm systems are required to match the large heterogeneity of farms in our research area. This step is represented in Figure 2 by the box 'Data Preparation' and resulted in the initialisation data for the Farm System Allocation Tool.

The FarmSystem Allocation Tool allocates per proxel best suitable farm system, where the suitability score is a function of the weighted sum of the suitability per crop in the complete crop rotation corrected with a factor representing the percental number of farm systems still necessary to be allocated.

[2] Ertragsmesszahlen EMZ (Statistisches Landesamt Baden-Württemberg)
[3] Landwirtschaftliche Vergleichszahlen LVZ (Bayerisches Staatsministerium für Landwirtschaft und Forsten)

The data with the allocated farm systems is stored in a database. Because the proxel order is randomized in the allocation process, different allocation runs result in different outcomes allowing us to test for the robustness of the allocation tool. In the result section we report on the robustness based on ten allocation runs. The allocation of farm systems is calibrated for the situation of land use in the year 1995, because this is the starting year for all our simulation runs. Also we will report on the success of this calibration. The final part of the result section will report on a model to model validation. Validation of the allocation with empirical data is impossible due to unavailability of such data on this resolution.

Results

Validation - modelled allocation outcomes versus statistics

The defined farm systems are generated for the whole catchment area. The calibration of the farm system allocation results are also done on the level of the whole catchment.
In the calibration process several options were available to match the modelled outcomes to statistical data on the catchment level:

- adding new Farm system
- change of weight of a land use in a crop rotation for a farm system
- change total size of arable land use for a farm system
- change total number of a type of animal
- change of weight of a type of grassland in a farm system

Fine-tuning the land use, the number of animals, and the amount of grassland per district by altering the weights for a farm system on district level is not possible, because it would change the production direction of a farm system. Technically, this implies the creation of unrealistic new production directions; hence, the only way to calibrate the initial data on district level would have been by adding new realistic farm systems per district. However, such detailed statistics and knowledge are not available.
The calibration on the catchment level with only 28 defined farm systems was very successful (Table 3). Criteria used for acceptance was 10% deviation from statistics (except for farms system with hop). Table 3 shows per land use the initial number of hectares for the whole catchment as derived from statistics, the modelled number of hectares and the percental difference. Table 3 shows the results of allocation run 1 (id =9). Below it is shown that giving an illustration for only one allocation run is justified, because the allocation tool outcomes are very robust.

Land use	**Total hectares in catchment area (statistics)**	**Modelled hectares**	**Percental difference**
Hop	28636	33572	17.2
Sugar_beet	50452	49279	-2.3
Potato	51838	51549	-0.6
Maize	97103	99825	2.8
Crop_silage	282446	268745	-4.9
Summer_Barley	135619	121221	-10.6
Oleaginous	107877	100154	-7.2
Winter_Barley	197825	208245	5.3
Oat	95173	90231	-5.2
Summer_Wheat	11605	11243	-3.1
Rye	30095	30039	-0.2
Legumes	10528	10080	-4.3
Forage	114836	110591	-3.7
Set_Aside	88617	89404	0.9
Winter wheat	421773	436279	3.4

Table 3: Difference in the statistical amount of hectares and the modelled hectares per land use

The number of animals allocated is directly dependent on the arable land use allocation and therefore much harder to allocate within in the predefined range of acceptance (10%). In Table 4 the allocated animals per type are given and compared with the initial statistical data on catchment level. Most of the animal types are well within the range of acceptance; however the percental difference for fattening bulls, breeding sows, sheep and horses lies outside this range. We do feel however that we cannot improve much better without disturbing the arable land use allocation. The large percental differences indicate that in future calibration efforts there is a need for even more generalized farm systems on the catchment level.

	Statistics	**simulationrun**	
Animal name	**number**	**number**	**Percental difference**
dairy_cow	1812855	1668483	-7.9
suckling_cow	64238	59514	-7.3
fattening_bulls	717746	827297	15.3
breeding_heifers	1019747	940351	-7.8
male_calves	202661	195995	-3.3
female_calves	260984	243029	-6.9
breeding_sows	488834	647923	32.5
fattening_pigs	1455072	1543326	6.1
sheep	197881	152346	-23.0
horses	200999	237815	18.3

Table 4: Difference in the statistical number of animals and the modelled numbers per animal type

As said, calibration on the catchment area level does not guarantee that on the district level the statistical data and the modelled data match. This is illustrated in the following table (Table 5). Table 5 shows the amounts wanted based on statistics and the percental difference modelled of the different types of arable land for a relatively small and relatively large district. Note that the modelled percental difference ((statistical amount – modelled amount / statistical amount) * 100) depends largely on the statistical amount of a land use required. The smaller the amount, the quicker a larger percental difference occurs. For example, district B has only a small amount of legumes, yet there are modelled absolutely a bit more but still it shows a large percental difference.

Simulation run 9	District A: small size (sum arable lu = 17852 ha)		District B: large area (sum arable land=85474 ha)	
Land use	**No. HA stat**	**Percent difference Modelled (%)**	**No. HA wanted**	**Percent difference Modelled (%)**
Hop	78.2	-15.1	1485	-13.3
Sugar beet	140.6	5.7	1783.4	4.1
Potato	138.6	12.0	647.5	4.6
Maize	124.8	14.1	7671.1	-0.5
Crop silage	1877.3	-43.0	14935.2	21.1
Summer Barley	3115.7	33.5	607.3	6.9
Oleaginous	1487.1	24.4	7623.2	9.6
Winter Barley	1877.9	-6.6	12180.5	3.8
Oat	1150.2	13.3	2122.8	17.7
Summer Wheat	130.6	14.1	176	0.8
Rye	421	11.0	58.8	8.9
Legumes	411.3	35.6	309.2	62.7
Forage	1357.4	-35.7	3221.1	25.9
Set Aside	324.5	2.5	4794.5	9.6
Winter Wheat	5216.8	5.1	27858.5	-2.9

Table 5: Comparison of a small and large district on on percental differences per land use

Table 6 shows for two exemplary districts the difference between the statistical and modelled number of animals per animal type. Also here the percental differences are smaller for the larger district and again, smaller amounts of animals cause larger percental differences. Additionally, an animal type with a low allocation demand is often part of a farm system with a low allocation demand, which consequently has a lower priority in the allocation. In an allocation run it often occurs that total number of demanded farm systems cannot be allocated and hence the lower priority farm systems are left out.

Simulation run 9	District A: small size (sum arable land = 17852 ha)		District B: large area (sum arable land=85474 ha)	
Animals	**No. animals statistically required**	**Percent difference modelled (%)**	**No. animals statistically required**	**Percent difference modelled (%)**
Dairy cows	12328	-50.1	34113	4.8
Suckling cows	285	100	780	100
Fattening bulls	5852	-62.0	41689	-7.8
Breeding heifers	7518	-50.5	18634	3.8
Male calve	1512	-48.3	11364	5.6
Female calves	1680	-53.6	5519	5.6
Breeding sows	5596	11.6	30376	-7.4
Fattening pigs	14456	5.8	142680	1.8
Sheep	4674	65.5	2405	100
horses	2627	100	3510	100

Table 6: Comparison of a small and large district on on percental differences per land use

In general, the larger the amount of hectares in the district is the better the match between statistical and the modelled quantities per land use. Especially the Austrian districts proof to be relatively unfit for our defined farm systems and related land uses. Mainly because the amounts of land use are so small and the farm system characterisation that we used did not take these (special) cases into account.

As said, in our approach calibration is only allowed on the catchment level. The numbers nicely add up on catchment level. On district level there are sometimes large differences between statistics and modelled, especially in the smaller districts.

Perhaps more interesting is whether we were able to capture the allocation patterns for the different land uses and animals. This we can check by correlating the statistical land use data per district with the modelled data. The Pearson coefficient represents a measurement for the correctness of the modelled pattern (amounts allocated) of land use compared to the statistical amounts. A high positive correlation indicates we have an almost identical land use distribution pattern in that district.

	Arable land	**Animals**
Correlation (land use per district)	**Between Initial data and Simulation runs (districts)**	**Between Initial data and Simulation runs (districts)**
r>0.9	52 (72%)	53 (72%)
r<0.9	8 (11%)	9 (12%)
r<0.8	3 (4%)	3 (4%)
r<0.7	9 (12%)	9 (12%)
no value	2 (3%)	0 (0%)

Table 7: The number of districts categorized by the correlation coefficients per district per land use/animal type

Table 7 shows an overview of the correlations for the different land uses and animal allocations per district between one simulation run (run 1) and the initialization data. For the land use pattern 52 districts demonstrate a correlation higher than 0.9, while 60 districts have a correlation that is acceptable. Column three shows the correlation of animals in a district between the simulation run and the statistical data. 53 districts show a higher correlation than 0.9.
The districts with low amounts of arable land available for the farm system allocation witness the lower correlations. Main reason is the high path dependency of the proxel order in the allocation for such small districts.

The animals are bounded to the farm system and they are depending on the number of farm systems which are allocated to a specific proxel. Here it is possible that a proxel is filled up with a farm system which has a smaller number than they were allocated on a whole proxel, in this case the number of animals will increase by the number of farm systems. But as you can see in Table 7 in most of the districts the results are very satisfying and they are perfectly fit to the requirements of the model.

Validation – Model to Model

Unfortunately no empirical spatial datasets are available to validate our allocation model. The only validation we can do is a mathematical validation or a model-with-model validation. This type of validation is based on the idea that two independent models with different modelling techniques and having the same objective share a large set of outcomes then they partly validate each other. Besides validation a comparison of outcomes may help us understand and analyse our own outcomes better.

In a previous phase of this project Schuster et al. had the same technical objective as the Farm-System Allocation Tool. Also Schuster et al. allocated different crops on the proxels in the same research area. The differences in their approach are threefold: Firstly, their unit of allocation was the proxel, while in our tool it is the farm system. Secondly, they calibrated the model on the municipality-level (‘gemeinde’), a spatial scale on a higher resolution. Our approach could not use these datasets because data on production directions is not available. And thirdly, Schuster et al. had to allocate the different crop quantities on so-called up-scaled proxels (proxels that were either classified as arable land, grassland, or non-agriculture), while our proxel dataset contains percental fractions for each of these classifications per proxel.
The allocation method of Schuster et al. searches for the proxel with the highest suitability for a crop and allocates as much as possible on that proxel. The maximum amount per crop is given by another GIS-layer. This layer represents the relative demand on the municipality for a crop combined with rudimentary crop rotation constraints.

Strict theoretically we are not allowed to validate our outcomes with the Schuster et al. outcomes because we share parts of the input data (suitability maps per crop per proxel), but because the approach is so different, a comparison is still valuable.

In Figure 5 a comparison between these different approaches illustrated for the land use sugar beet is given. Clearly visible is that in our approach the spreading of the land use sugar beet is higher. The main obvious reason is the difference in unit of allocation. While Schuster et al. had a complete proxel to their disposal our tool can allocate sugar beet as part of a crop rotation system on just a fraction of the proxel. As a result, the right figure displays sugar beet mainly on the proxels with the best suitability in the municipalities demarcated in the additional GIS layer, while our tool had to allocate much smaller amounts on less physically suitable land. Visible is that the main production area in the left figure (darker proxels) matches the results of Schuster et al. This is mainly explained by the high number of farm systems with sugar beet in their production system in the corresponding area. Along these lines, it can be deducted that, although the sum on the catchment level equals for both approaches, the district sums differ largely. Another reason for these differences is that Schuster et al. had to deal with large differences between the district level and municipality level statistics due to data security issues (protection of identity of respondents) and therefore excluded in certain cases districts for allocation, while on the district level they are included.

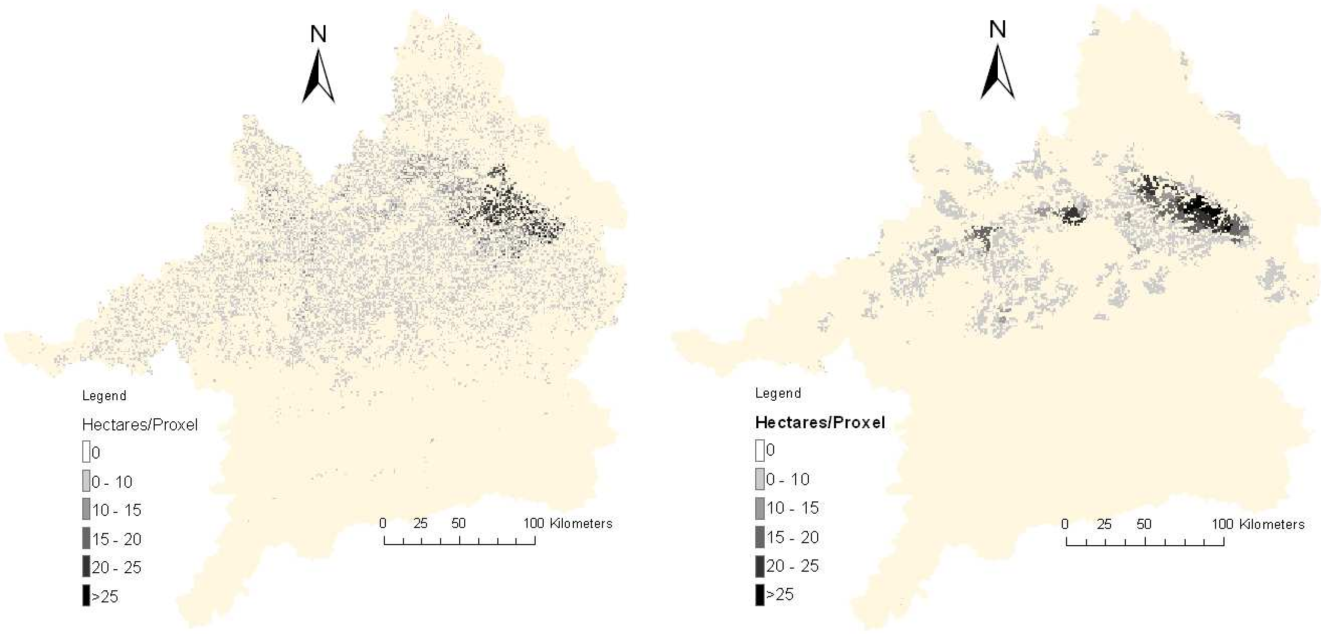


Figure 5: Comparison of Sugar beet allocation conducted by the FarmSystem Allocation Tool (left) and Schuster et al. (right).

Generally, based on expert knowledge and district level statistics our results match better with reality. This is further illustrated in Figure 6 which shows the histogram with the number of proxels (y-axis) and the amount of hectares (x-axis). Our approach on the left shows a huge number of proxels with only a small amount of hectares on sugar beets that matches statistical data on production direction more realistically than the (for southern germany) large number of large farms given by Schuster et al. (assuming a farm is located on one proxel).

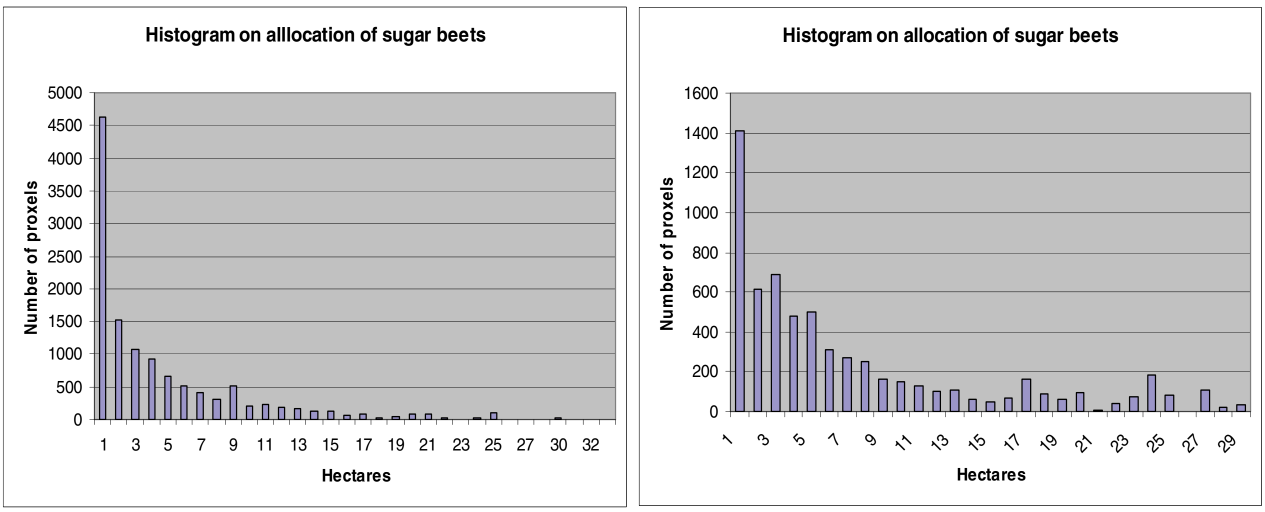


Figure 6: Histogram of the different model runs

The higher degree of dispersion compared to Schuster et al. occur for all land uses. Furthermore, the total sums per land use are quite similar between the two approaches except for the land use winter wheat. Schuster et al. modelled approximately 22% more winter wheat than our approach and 26% more than the statistical data indicated. Main reason for the large difference is that Schuster et al. had (too) much more arable land available for allocation (due to the up-scaled proxels) and winter wheat was the last crop to be allocated.

Robustness of FarmSystem Allocation Tool

In order to measure the robustness of our tool, we correlated the land use quantities per district for 10 different allocation runs. This method is comparable with the correlation coefficient used for Table 7. Figure 7 gives an additional illustration for this method with 8 allocation runs and statistical data for the district `Straubing` in Bavaria. The bars show eight different simulation runs (A-H) and the statistical data. The amount of arable land is the same in all simulation runs only statistics shows a higher value this can be caused by the borders of the district. The original district has more available arable land than in our framework.

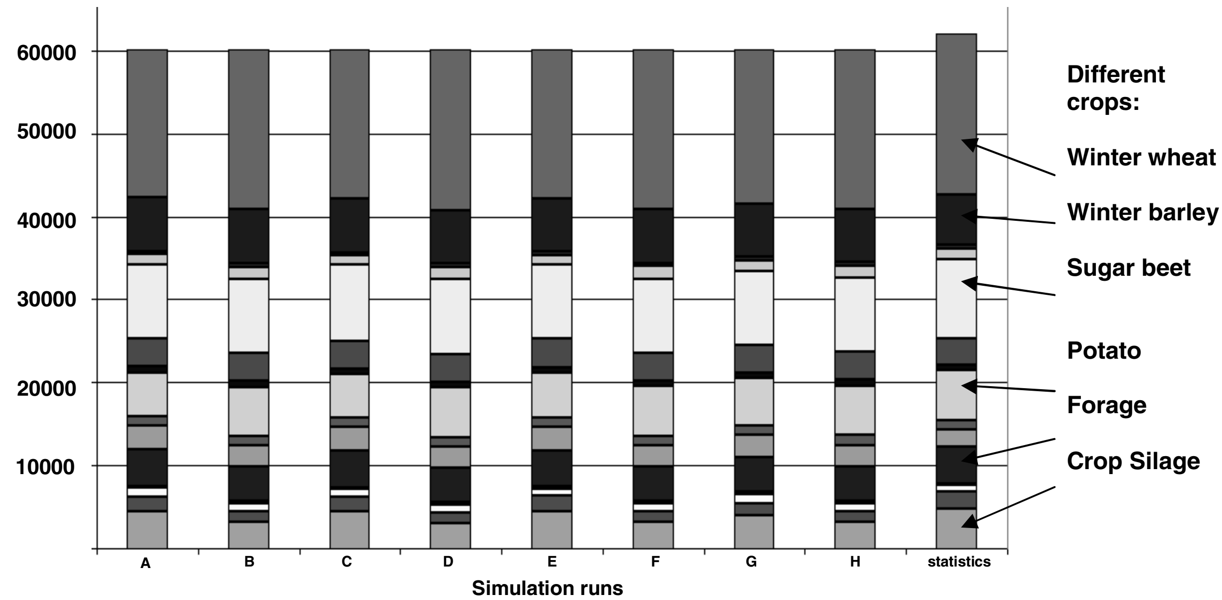


Figure 7: Variation of different land use types in a district inbetween different allocation runs and in comparison to the statistical data

On the x-axis there are different allocation runs with the same initialisation data. For the different land use types the amounts of hectares allocated vary (e.g. in Figure 7 different amounts of crop silage per allocation run).

This is caused by the allocation of the same farm system on different proxels during the different runs, because of several reasons. First reason is the relation arable land to grassland in the farm system; this can be different to the relation on the proxel. Explain!! Secondly, the district size also causes differences in the amount of arable land and grassland. In the example statistics provides more arable land than it is available, resulting in less farm systems allocated than needed. Thirdly, the randomized proxel order in the allocation algorithm results from allocating different farm systems first.

As result we have 66 districts with correlation higher than 0.95 and eight districts where the values of correlation are lower than 0.9. The correlation is depending on the different land use types. Two districts have no arable land available and by this no correlation values. Three districts have correlation values around 0.7 and two other districts have a correlation value around 0.89. These differences are mainly caused by the small amount of arable land in these districts. One district has a nice example of path dependency here nine runs have a correlation value higher than 0.95 but one run has a very bad value of 0.55. This is caused by the random proxel order, in this special case the allocation tool started with a proxel which has a very special land use type which allows the allocation of only one or two specific farms systems, which have for example only a small number of actors in this district. This reason can change the order of allocation of farm system and it can cause this result.

The correlation of the different animal types shows a "better" result, there we have 70 districts with a correlation value higher than 0.95 and only three districts where the values are between 0.65 and 0.85. There we have also one district where all the simulation runs have a higher value than 0.95 expect for one run where the correlation values are bad (around 0.6). This is also caused by path depends with the same explanation just like in the case of land use.
Then, the results show the robustness of the algorithm in between the runs.

Discussion & Conclusion

In this paper we present a novel approach for studying agricultural change due to climatic change. Within an advanced simulation framework we couple a climate model with a crop growth model. However, we do not only study the effects on the crop development, but we also integrate the crop managerial aspects, because crop growth is an element of a crop rotation cycle which is an integral part of a managed production system. In order to couple these different models we used an agent based approach, because it delivers the flexibility of integrating data and processes on different spatial, temporal and social scales.

In order to conduct meaningful simulations the initialisation of the models is essential and the farm system allocation tool has been created to allocate the non-spatial, statistical data on a spatial scale. This effort was necessary to get farm systems (agents) with special characteristics in size, crop rotation and production direction on the spatial scale of a proxel. In order to bridge the different time-scales, we have designed agent' decision trees based on the knowledge of crop production and expert knowledge. A central element is the use of crop development stages (BBCH).

The results of our allocation tool are highly satisfying. Our allocated farm systems represent the land use of the Upper Danube catchment quite accurately. The tool proves to be very robust.

In the near future simulation runs with three different IPCC climate change scenarios will be conducted. Results will give the climate change effects on agricultural production per crop on a seasonal scale and per farm system. These results are spatially explicit.

Some aspects should be rethought and changed. The allocation tool allocates only one farm system type on a proxel. In reality you can find different farm system types in an area of 100 hectares. So in a next step it should become possible to allocate different farm system types and have different planting dates for one crop on one proxel. This arrangement setting one farm system on one proxel was made between the crop growth model and our DeepFarming model because for crop growth it is impossible to calculate different planting dates of the same plant on one proxel.
An allocation run for one district with different farm systems on one proxel would show that the allocated farm systems would fit better to the statistical data especially in districts with a small amount on arable land.
Furthermore, the agents are not able to change the crop rotation or production directions. Later in the research process the agents' capacity should increase by the implementation of more economical knowledge, dynamic crop rotations or changing production directions.
Finally, at the moment the farmers` knowledge about weather depends on the historical weather of the last three years. To get better reactions on the actions planting and harvesting time a weather forecast capacity for the agents would reflect reality better.

References:

Balmann, A., (2000): Modeling Land Use with Multi-Agent Systems Perspectives for the Analysis of Agricultural Policies, Humboldt University Berlin.
Epstein J., Axtell R., (1996): Growing Artificial Societies: Social Science from the Bottom Up, MIT Press/Brookings, MA.

Balmann, A.; Happe, K.; Kellermann, K.; Kleingarten, A., (2001): Adjustment Costs of Agri-Environmental Policy Switchings A Multi-Agent-Approach, American Agricultural Economics Association, 2001 Annual Meeting, August 5-8, 2001, Chicago, Illinois.

Barth, M.; Hennicker, R.; Kraus,A.; Ludwig, M., (2004): DANUBIA: An Integrative Simulation System for Global Change Research in the Upper Danube Basin, Institute for Informatics, Ludwig-Maximilians-Universität München Oettingenstr. 67, D-80538 Munich, Germany.

BERGER, T., (2001): Agent-Based Models Applied to Agriculture: A Simulation Tool for Technology Diffusion, Resource Use Changes and Policy Analysis. Agricultural Economics, 25(2/3), pp.245-260.

Deadman, P.J.; Robinsson, D.T.; Moran, E.; Brondizio, E., (2004): Effects of Colonist Household Structure on Land Use Change in the Amazon Rainforest: An Agent Based Simulation Approach. Environment and Planting B: Planning and Design, 31(5), pp.693-709.

Ferber, J., (1999): Multi-Agent Systems: An Introduction to Distributed Artificial Intelligence, Addison-Wesley.

Franklin S.; Graesser A., (1996): Is it an Agent, or just a Program? A taxonomy for Autonomous Agents, in Proceedings of the Third Intrenational Workshop on Agent Theories, Architectures, and Languages, Berlin, Springer.

Giorgi, F.; Mearns, L. O., (1991): ‘Approaches to the Simulation of Regional Climate Change: A Review’, Rev. Geophys. 29, 191–216.

GLOWA-Danube Papers Technical Release No. 0001, (2006): DANUBIA-DeepFarm components.

Henseler, M.; Wirsig, A.; Krimly, T., (2006): Anwendung des Regionalmodells ACRE in zwei interdisziplinären Projekten. In: Wenkel, K.-O., Wagner, P., Morgenstern, Luzi, K. und P. Eisermann (Ed.): Land- und Ernährungswirtschaft im Wandel - Aufgaben und Herausforderungen für die Agrar- und Umweltinformatik, Proceedings of the 26th GIL-Jahrestagung, Potsdam (Germany), 06.-08.03.2006, pp.101-104. GIL, Potsdam.

Huigen, M.G., (2004): First principles of the MameLuke multi-actor modelling framework for land use change, illustrated with a Philippine case study. Modelling land use change and environmental impact, Journal of Environmental Management ,Volume 72, Issues 1-2 , Pages 5-21.

IPCC (2001a): Climate change 2001: The scientific basis, Cambridge University Press, Cambridge, UK.

Janisch, S., (2005): DeepActor Framework Reference Manual, Internal working document GLOWA DANUBE project.

Kane, S.; Reilly, J.; Tobey, J., (1992): An empirical study of the economic effects of climate change on world agriculture, Climatic Change 21: 17-35, Kluwer Academic Publishers, Printed in the Netherlands.

Krimly, T.; Herrmann, S.; Schuster, H.; Winter, T.; Dabbert, S., (2003):
Integrative techniques to connect economic, social and natural science aspects for sustainable water use.- Poster presentation at the 25th International Conference of Agricuktural Economists in Durabn/RSA, 16.-22. August 2003.

Lenz, V.; Klar, C.; Fiener, P.; Schneider, K.; Tenhunen, J.; Scharfenberg, H.-J., (2006): Pflanzenwachstum und Biomasseproduktion. In:
GLOWA-Danube-Projekt, Universität München (LMU) (Hrsg.), Global Change Atlas, Einzugsgebiet Obere Donau. Eigenverlag LMU München.

Mauser, W.; Ludwig, R., (2002): A research concept to develop integrative techniques, scenarios and strategies regarding global changes of the water cycle. In: Beniston, M. (ed.) (2002): Climatic Change: Implications for the hydrological cycle and for water management. - Advances in Global Change Research 10. Dordrecht, Netherlands: 171-188.

McGuffie, K.; Henderson-Sellers, A., (1997): A Climate Modelling Primer, John Wiley & Sons, pp253.

Meier, U. et al, (2001): Growth stages of mono-and dicotyledonous plants, BBCH Monograph2. Edition, 2001, Federal Biological Research Centre for Agriculture and Forestry; www.bba.bund.de.

Parker, D. C.; Manson, S. M.; Janssen, M.; Hoffmann, M. J.; Deadman, P. J.,(2003): Multi-agent systems for the simulation of land use and land cover change: a review. Annals of the Association of American Geographers 93 (2): (316-340).

Rahwan, I.; Sonenburg, L.; Jennings, N. R.; McBurney, P., (2007): Stratum: A methodology for designing heuristic agent negotiation strategies., International Journal of Applied Artificial Intelligence 21.

Rosenzweig, C.; Iglesias, A.; Yang, X. B.; Epstein, P. R.; Chivian, E., (2000): Climate Change and U. S. Agriculture: The Impacts of Warming and Extreme Weather Events on Productivity, Plant Diseases, and Pests, Center for Health and the global environment, Havard Medical School, Boston.

Schreinemachers, P.; Berger, Th., (2006): Land-use decisions in developing countries and their representation in multi-agent systems, Journal of Land Use sciences, Taylor & Francis, Volume 1, Number 1/ March 2006: (29-44).

Schuster, H.; Max, J.; Winter, Th.; Vogel, T.; Hermann, S.; (2002): Sozioökonomische Analyse und Modellierung von Wassernutzung und Landnutzung durch Landwirtschaft, GLOWA – Danube Jahresbericht 2002; Integrative Techniken, Szenarien und Strategien zur Zukunft des Wassers im Einzugsgebiet der Oberen Donau; www.glowa-danube.de/frameset.htm (20.03.2007) pp. 159-175.

Seneviratne, S. I.; Lüthi, D.; Litschi, M.; Schär, Ch., (2006): Land-atmosphere coupling and climate change in Europe, Letters, Nature Publishing Group.

Smith, J. B.; Tirpak, D. A. (eds.), (1989): The Potential Effects of Global Climate Change on the United States, U.S. EPA, Report to Congress No. 230-05-61-050, U.S. Environmental Protection Agency, Washington, D.C.

StaLa (2005): (Statistisches Landesamt Baden Württemberg).Struktur- und Regionaldatenbank. Statistisches Landesamt Baden-Württemberg, Stuttgart. URL: www.statistik-bw.de.

StMLF (2004): (Bayrisches Staatsministerium für Landwirtschaft und Forsten): GAP-Reform 2005. Europäische Agrarreform 2005 - Nationale Umsetzung. StMLF, München.

Lamb, P. J., (1987): 'On the Development of Regional Climatic Scenarios for Policy-Oriented Climatic-Impact Assessment', Bull. Amer. Meteorol. Soc. 68, 1116–1123.

Mearns, L. O., (2000): 'Climatic Change and Variability', in Reddy, K. R. and Hodges, H. (eds.), Climate Change and Global Crop Productivity, Chap. 2, CAB, Melbourne, pp. 7–29.