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published in
Landscape Ecology
2010

DOI (link to publisher)
10.1007/s10980-009-9380-6

document version
Publisher's PDF, also known as Version of record

citation for published version (APA)
Valbuena, D., Verburg, P. H., Bregt, A., & Ligtenberg, A. (2010). An agent-based approach to model land-use change at a regional scale. *Landscape Ecology*, *25*(2), 185-199. https://doi.org/10.1007/s10980-009-9380-6

Landscape Ecol (2010) 25:185–199
DOI 10.1007/s10980-009-9380-6

RESEARCH ARTICLE

An agent-based approach to model land-use change at a regional scale

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Received: 11 February 2009 / Accepted: 11 June 2009 / Published online: 27 June 2009

Abstract Land-use/cover change (LUCC) is a complex process that includes actors and factors at different social and spatial levels. A common approach to analyse and simulate LUCC as the result of individual decisions is agent-based modelling (ABM). However, ABM is often applied to simulate processes at local scales, while its application in regional studies is limited. This paper describes first a conceptual framework for ABM to analyse and explore regional LUCC processes. Second, the conceptual framework is represented by combining different concepts including agent typologies, farm trajectories and probabilistic decision-making processes. Finally, the framework is illustrated through a case study in the Netherlands, where processes of farm cessation, farm expansion and farm diversification are shaping the structure of the landscape. The framework is a generic, straightforward approach to analyse and explore regional LUCC with an explicit link to empirical approaches for parameterization of ABM.

Keywords Land-use/cover change · Decision-making · Agent-based modelling · Rural regions

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Introduction

Land-use/cover change (LUCC) is the result of the interaction between humans and their environment. At the same time, LUCC influences both human and natural systems at different temporal and spatial scales (Foley et al. 2005; Turner et al. 2007; Vitousek et al. 1997). To understand these interactions, research should include not only the patterns and processes that link human-natural systems and the feedbacks between them, but also the feedbacks between different organisational levels that influence the human-environment interactions (Liu et al. 2007; O'Sullivan et al. 2006). In the case of LUCC in rural regions, these processes consist of actions and interactions of different actors operating at different levels who are continuously changing the structure and composition of the landscape. These actors include farmers, nature conservation organisations, urban developers and policy makers among others.

LUCC in a farm is determined by the use that people make of land, in particular of their own fields (Rindfuss et al. 2004). Farmers' decisions on how to use their land are complex as they are influenced by internal and external factors (Beratan 2007; Siebert et al. 2006). Internal factors include those personal, socio-economic and biophysical factors inherent to the farmer and to the farming system. In particular, existence of a successor, type of farm, amount of land and environmental constraints and possibilities are likely to influence land-use decisions (Gasson 1973;

Gorton et al. 2008; Ilbery 1978; Willock et al. 1999). External factors relate to the biophysical and socio-economic context. They include climate, the market, access to technology and policies. While internal factors determine whether the agent is willing and able to take certain decisions (Siebert et al. 2006), external factors regulate or influence the range of farmers' options by modifying these willingness and ability (Lambin and Geist 2003; Lambin et al. 2001).

Regional LUCC processes are often determined by the cumulative effect of changes occurring in farms, as well as processes of urbanisation, nature protection and infrastructure development. Often in rural regions, changes in the agricultural sector strongly affect the LUCC given the large areas used for agricultural activities. The diversity of decision-making of individual farms in a region reflects a range of possible combinations of different internal and external factors (Busck 2002; Köbrich et al. 2003). While internal factors are related to the farmer and their farm, external socio-economic factors are linked to institutions and social networks, which have a role outside the farm. Institutions include local and regional governments, agricultural associations and the market. These institutions can react to market changes and to changes at landscape and regional level by setting legislation or providing incentives (e.g. policies to protect cultural landscapes).

A common approach to simulate LUCC as a result of variations in individual decisions and actions is the use of agent-based modelling (ABM) (Matthews et al. 2007; Parker et al. 2003, 2008; Robinson et al. 2007). ABM makes the modelling of interactions between both human and natural systems possible by defining different decision-making units or agents. Agents can have different internal characteristics and strategies, and can interact with other agents and their environment (Bonabeau 2002; Sawyer 2003). Although, the use of ABM offers the potential for understanding and exploring LUCC processes (Matthews et al. 2007; Parker et al. 2003), their relevance to predict LUCC has been limited by the inherent complexity of the processes that they try to address and by high data requirements (Couclelis 2002; Verburg 2006). Because of this complexity, the data requirements and the diversity of farming systems within agricultural regions, ABM has mainly been implemented in simulating local scale LUCC processes (e.g. Acosta-Michlik and Espaldon 2008; Le et al. 2008). When modelling regional LUCC processes, models are normally parameterised with artificial data (e.g. Ligtenberg et al. 2004). In fact, this parameterisation allow the use of ABM as a computational laboratory to investigate system responses (Berger and Schreinemachers 2006). The level of abstraction in these applications has restricted their use in planning and policy-making processes.

The objective of this paper is to describe a conceptual framework for ABM to analyse and simulate regional land-use change, making best use of empirical data that may be collected at this extent. In the following section of the paper, we describe the conceptual framework, including a probabilistic approach that aims to represent part of the diversity of decision-making strategies at the farm level within agricultural regions. In the next section, we explain how this framework can be represented. Next, the representation of the framework is illustrated through a case study in the Netherlands, where farm cessation, farm expansion and landscape conservation are shaping the structure and composition of the rural landscape. In the final section, we discuss the advantages, challenges and limitations of this approach.

Conceptual framework

In this section, the conceptual framework that describes the decision-making process of farmers and its interaction with internal and external factors is described, followed by its representation in ABM.

System description

When looking at a specific decision-making process (e.g. expansion of the farm), internal factors can be seen as those aspects related to the ability and the willingness of farmers to carry out certain actions related to that process (e.g. buy or sell land). Ability refers to conditioning factors of the farmer and farm such as age, family structure, labour, farm size, spatial location, soil characteristics and slope (Siebert et al. 2006). This ability defines the options farmers have at a certain period for a specific decision-making process, what Wilson (2007) refers as decision-making corridors (Fig. 1). According to this

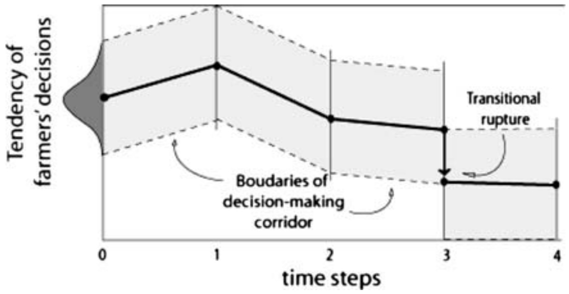


Fig. 1 Representation of a decision-making corridor (after Wilson 2007)

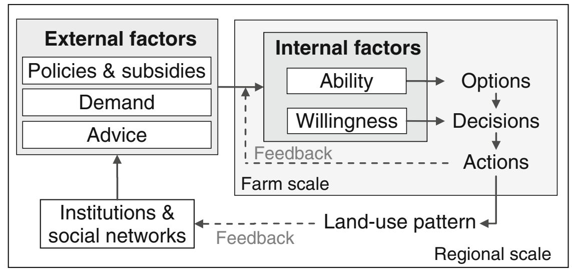


Fig. 2 Interactions between individual farming systems and external factors

author, decision-making corridors define the possibilities and constraints of farmers' decisions. Willingness relates to farmer's values and intentions (Siebert et al. 2006) and defines the preference of the farmer for choosing certain options. For instance, whether a farmer will participate in nature conservation programmes is largely dependent on whether the farmer thinks that nature is important. Because values do not change very often (Grube et al. 1994; Rokeach 1968), willingness is assumed to be relatively stable in time. However, large modifications in the system (e.g. bankruptcy or changes in farm ownership) can drastically change the trajectory of a farming system, what Wilson (2007) calls transitional ruptures (Fig. 1, time step 3). For example, a farmer with a large farm has been growing for the last years, but after major problems (e.g. lack of successor or illness) s/he decides to sell gradually her/his land. Ability and willingness are interrelated. If farmers have the willingness to grow but they lack the ability to do so, such a growth is almost impossible. Still, farmers can modify their ability in order to fulfil their willingness (e.g. take out loans to intensify the production of the farm; see external factors below).

Farmers' decisions lead to certain actions, which can also affect their future options and decisions by changing their internal factors (Fig. 2). This is an internal feedback mechanism that makes farmers' future options and decisions be dependent on previous actions (Fig. 1, time step 0–2), to what Wilson (2007) calls system memory (i.e. path dependency). For example, a farmer decides to expand his holding by buying a new field; the size of his farm increases, modifying her/his ability and future options. The structure of a decision-making process linking options, decisions and actions is equivalent to the conceptualization of decision-making processes described by Wooldridge and Jennings (1995) and the action-in-context framework (see de Groot 1992; Huigen 2004).

Factors that are external to the farm can also influence farmers' options and decisions. These factors include both compulsory and voluntary mechanisms such as policies, loans, advice and demand for goods and services (Aarts and van Woerkum 2000). These external factors reflect the interaction between farmers, social networks and institutions such as governmental organisations and the market (Fig. 2). Although these institutions and external factors occur at different organisational levels (e.g. from municipal governments to global market), this study only considers those that occur within the region as endogenous to the framework.

Interaction between farmers, institutions and social networks can be described by a number of different processes. First, institutions related to the development of rural areas can provide farmers with incentives that may influence farmers' ability, influencing their range of options and future decisions. Similarly, social networks (e.g. family and friends) can give advice to farmers, influencing their willingness for future decisions. For example, if a friend recommends a farmer to adopt a new technology, farmer's future decisions are likely to change (i.e. farmer's willingness). Second, to intervene or avoid certain actions of farmers, governments implement policies. Although these policies can influence directly the land-use/cover patterns of a region (e.g. the establishment of ecological networks to protect biodiversity through zoning legislation), they normally have an effect on farmers' ability by establishing certain policies such as subsidies for landscape conservation and manure policy. Finally, the demand for goods and services determines whether certain economic activity is a profitable option given the farm characteristics and its location. For instance, the demand for horse keeping is higher in rural areas located nearby urban areas than in other areas distant to cities.

The interactions between farmers, institutions and social networks affect the environment (Fig. 2). In a region, the cumulative result of farmers' actions can change the land-use pattern of rural areas. For example, to keep in business, many farmers in Europe have had to intensify their production activities affecting the connectivity and aesthetics of the landscape (Stoate et al. 2001). Changes in the composition and the structure of the land-use/cover patterns can affect in turn the functioning of the landscape and its capacity to provide goods and services, such as water storage, recreation and species habitat (de Groot 2006; Willemen et al. 2008). Often, changes in the functioning of the landscape are the reasons why institutions try to influence farmers' options and decisions. For example, the high concentrations of nitrogen in water systems due to agricultural practices induced the adoption of a European Nitrates Directive in the early 1990s, affecting many livestock farming systems (Petersen et al. 2007).

Model representation

For the representation of the agent's decision-making of Fig. 2, a parameterisation of the ABM should be possible based on empirical data. To achieve such a representation, four steps are proposed:

- Simplify the diversity of farmers' decision-making by defining an agent typology;
- Represent agents' decision-making, including the influence of internal factors;
- Define the interaction between external and internal factors; and
- Make a landscape representation in order to characterize the environment and to link it with agents' decisions and actions.

Agent typology

To simplify the diversity of farmers' decision-making an agent typology is proposed. A typology is an approach to represent and analyse general farming strategies or trajectories based on specific objectives and techniques (Jollivet 1965; McKinney 1950). In particular, agents can be categorised based on their willingness and/or ability. For example, if we need to analyse the effect of voluntary programmes for nature conservation, the agent typology can be based on farmers who would like to participate in such programmes, those who are not sure and those who do not want to participate. The required data can be gathered by carrying out a detailed survey of a sample of the population including questions on the farmers' values and intentions (i.e. willingness), and the type, size and location of the farm (i.e. ability). Next, classification trees and/or cluster analyses can be used to identify the main agent types of a region and to characterise them (Le 2005; Valbuena et al. 2008).

The definition of a typology based on agents' willingness and/or ability partly determines the direction and the boundaries of the decision-making corridor of the agent types for a specific decision-making process. This decision-making corridor represents both the options and decisions of each agent type for that specific decision-making process (Fig. 1). Although agents of the same agent type share a similar willingness, differences in their ability (e.g. socio-economic conditions and different agent characteristics) may result in a large variability in decision-making. For example, two agents who have the willingness to diversify their farm practices into rural tourism can own farms with different sizes. This difference in farm size—or in labour, economic resources, family structure, age or location—affects whether they can increase their production scale in the coming years. The many different combinations between agents' willingness and ability explain why agents who belong to different agent types may take similar decisions or the other way around; agents who belong to the same agent type may take different decisions.

Decision-making and internal factors

Decision-making is specified for each decision-making process accounted for in the model. These processes can include either discrete decisions (e.g. stop or continue farming) or choices on a continuous scale (e.g. buy certain amount of hectares of land).

Each of these processes consists of a set of options, which depends on the studied process and the level of detail of the analysis. To illustrate this representation of decision making, we use a discrete process of farm expansion, which can be divided into three different and mutually exclusive options: buy, keep and sell land (Fig. 3a). To represent the diversity in decision making of agents within an agent type, a probability is assigned to each option. When the probabilities of the different options are represented on a cumulative scale (Fig. 3a) the thresholds between the different options represent the cumulative probability of the different decisions. The values of these thresholds can be determined based on either expert knowledge, or be based on frequencies of decisions within the agent type population derived from observations of previous decisions or questionnaires. In Fig. 3a, the cumulative probability is represented for the options of the process of farm expansion. The thresholds between the options are: 0.1 for sell-keep and 0.7 for keep-buy. This means that only 10% the population of this agent type sold land, 60% kept the same amount and 30% bought land in the dataset that was used to parameterize this function.

For each time-step and each agent a decision is determined by drawing a random number (d0, Fig. 3a). Different probability distributions (e.g. uniform and log-normal) can be used to draw these random numbers. The probability distribution is determined based on the characteristics of the decision-making process and the information in the empirical data available to represent this process. Depending on the values of the thresholds between options, different random numbers may lead to different decisions. For example in Fig. 3b, if the random number is r1, the agent would buy land, whereas if the random number is r2, s/he would keep the same amount of land. In other words, agents' decision-making is based on a probabilistic approach. This representation of agents' decision-making is similar to those formalizations mentioned by Benenson and Torrens (2004). These authors describe different implementations to represent agents with bounded rationality, which means that agents have limited knowledge and ability (Simon 1955). These implementations are seen as probabilistic choices between a range of options such as buy or sell land (Benenson and Torrens 2004). Agents' decisions can lead to actions that take place either at the same time step (e.g. cut a tree) or in the near future (e.g. start saving money to buy a field). Since future options, decisions and actions are dependent on previous ones (i.e. path dependence), the likelihood that an agent would decide for a specific option is influenced by her/his previous decisions and actions. To represent this path dependency of decision-making, the values of the thresholds between different options are affected by the previous decision. In Fig. 3c, her/his decision and action to buy land (t) partly limit the likelihood that the agent will buy (0.1) or sell (0.01) land in the next iteration ($t + 1$), being more likely to keep the same amount of land (0.89). This dependency of previous and subsequent probabilities can be considered as a Markov process, in which the next step of a stochastic process is determined by the previous one (Benenson and Torrens 2004).

Besides path-dependence in decision making, other internal factors and processes also influence agent's decision-making. First, to include the diversity of decision-making between agent types, agents of two different types have different likelihood to decide for a specific option. For example, if an agent belongs to an expansionist type (type X, Fig. 4a), the likelihood that this agent buys land is higher than that of an agent who belongs to a non-expansionist type (type Y). Second, to represent transitional ruptures of

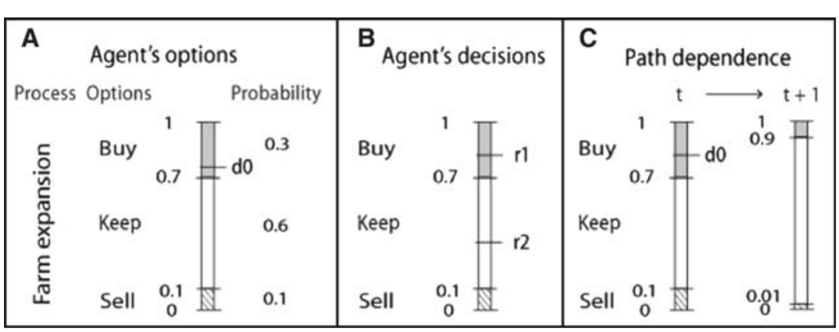
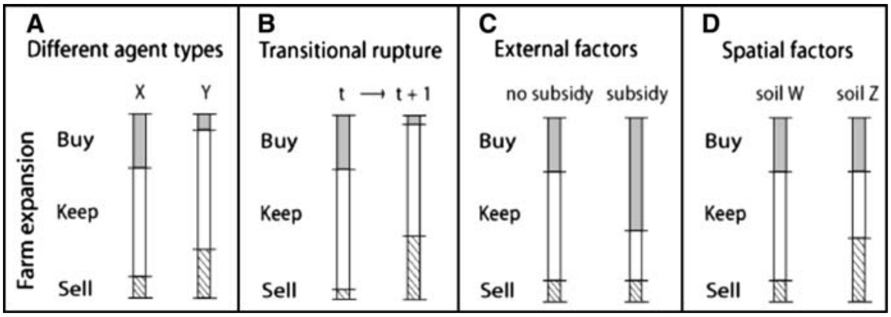


Fig. 3 Representation of the decision-making process of farm expansion and agents' options (**a**), agents' decisions based on two different random numbers: r1 and r2 (**b**) and path dependence taking into account two iterations: t and $t + 1$ (**c**)

Fig. 4 Representation of effect on the probability distributions of: **a** different agent types; **b** transitional rupture; **c** external factors; and **d** spatial factors



agents' decision-making corridors, values of the thresholds between different options can be modified, changing the farming strategy of the agent. In Fig. 4b, an agent who had expanded her/his holding (t) decided to stop farming in the coming years drastically affecting her/his future options and decisions of buying or selling land (t+1). Finally, the influence of internal feedbacks can be represented in a similar way to that of the external factors.

External factors

The effect of external factors on agent's internal factors, and thereby on her/his options and decisions can be also represented by changing the likelihood for certain options. For example, the government adopts a policy that encourages farmers to expand their holdings by purchasing more land, which influences agent's options and decisions (Fig. 4c). To link agents' actions and external factors, indicators are used. Indicators help to measure changes in the agent population and in the land-use patterns of the region. When these indicators reach certain thresholds, institutions will respond by modifying the external factors, and therefore, agents' options and decisions. For example, if connectivity of nature areas decreases drastically, policy-makers can implement restrictions on the removal of landscape elements, limiting agents' options.

Landscape representation

Landscapes can be represented by different indicators, such as land-use patterns, farm size and agent density. This representation depends on both the objective of the study, which include the type of processes to be taken into account, and the availability of spatial data. The representation of the landscape by a number of variables is also used as a spatial factor that can describe agents' ability. For agricultural practices, these variables may include the suitability of the land for specific purposes, which may affect the probability distribution of a decision based on soil quality (Fig. 4d). To calculate these effects, spatial analyses on landscape characteristics and cadastral data can be carried out. Based on these data it is possible to analyse on which soils it is more common to cultivate a certain crop. Thus, based on the specific field conditions the same agent can take different decisions in different fields.

Model application

To illustrate the functioning of some key characteristics of the model a case study in the Eastern part of the Netherlands is used. It is a rural region that covers $\sim$600 Km^2, where small-scale agriculture, cultural and nature values are closely interrelated (Fig. 5). By 2005, there were around 2700 agricultural holdings; about 66% of them livestock farms (Farm Accountancy Data Network, FADN). As most of the rural areas in the Netherlands, three main spatial processes are taking place in this region: farm cessation, farm expansion and diversification of farm practices (e.g. nature conservation, tourism and recreation practices). In this illustrative application of the model, processes of urbanisation, nature protection and infrastructure development are not taken into account. Also the influence of social networks on agents' decisions is not implemented.

Data parameterisation

To built an agent typology and define the ability and willingness of the farmers, this study makes use of a

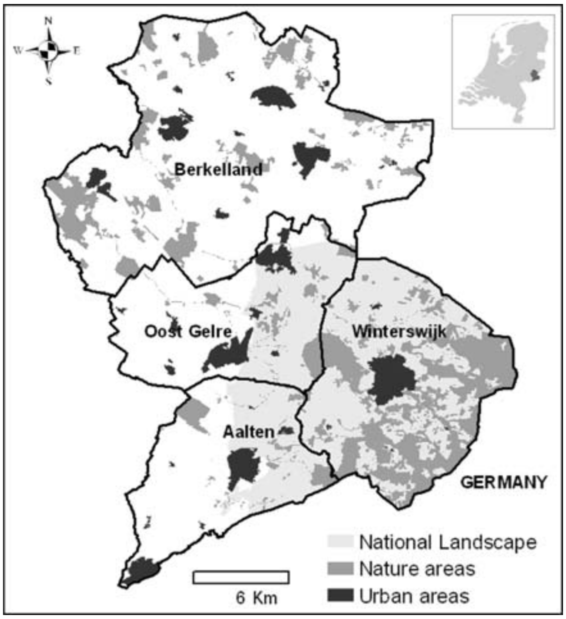


Fig. 5 Study region

detailed survey of 333 farmers carried out in winter 2004. The survey was originally conducted to explore the factors that determine the diversification of farm practices including farmers' views (positive, neutral and negative) and structural variables, such as the existence of a successor, production scale, degree specialization of the farm and past land-use changes (Jongeneel et al. 2005, 2008). As there is no database available that contains information on the willingness and ability of the whole population, census data for two different periods (FADN, 2001 and 2005) were used to describe part of the ability of the whole population and to determine previous land-use decisions in farm expansion. Additional socio-economic and spatial data of the region (e.g. soil characteristics, cadastral data and landscape structure, including the presence of linear landscape elements) were used to establish the ownership of the fields and other spatial characteristics of the fields. The model was built in NetLogo 4.0 (http://ccl.northwestern.edu/netlogo/).

Agent typology

The definition of the agent typology was based on both the willingness and ability of farmers in terms of farm expansion and diversification of farm practices. Specific attention was paid to differences in willingness to protect landscape elements such as hedgerows and tree lines. Willingness was defined by: whether diversification of farm practices is seen as an economic alternative; whether farmers would expand their holdings; and, whether they would participate in programmes for nature and landscape conservation practices. Ability was based on whether farming represents a core business or not (farmers vs. hobby farmers). Based on this combination of farmers' willingness and ability, five different agent types were defined for the region: hobby, conventional, diversifier, expansionist-conventional and expansionist-diversifier (see Valbuena et al. 2008). 'Hobby' includes agents whose income does not depend on farming activities and who do not own enough land or have no willingness to participate in programmes for nature and landscape conservation. 'Conventional' includes agents who prefer to keep farming, but who do not want to expand their farm. Although these agents prefer not to participate in conservation programmes, some of them may still participate because farming does not produce enough income. 'Diversifier' includes agents who instead of expanding their farm prefer to diversify their income by, for example, participating in programmes to manage nature and the landscape. 'Expansionist-conventional' includes agents who prefer to keep farming by increasing the size of their farm. Finally, 'expansionist-diversifier' represents agents who would like to do both: to expand and to diversify their farm practices (Table 1).

Decision-making and internal factors

Each decision-making process was represented as a range of probabilities between 0 and 1. The probability of selecting a certain option for each process was estimated by using the proportion of farmers of the detailed sample survey who belonged to the same agent type and who took/would take similar decisions. For instance, around 34% of the hobby agents would stop farming under the existing circumstances, whereas only 4% of the expansionist-diversifier agents would stop farming. Therefore, the probability to stop farming was much higher for the hobby (0.34) than for the expansionist-diversifier type (0.04). The initial conditions for each of the selected process were calculated based on a random number (uniform distribution) and historical data.

Table 1 Willingness and ability of the defined agent types by the likelihood to participate in certain processes (after Valbuena et al. 2008)

Agent type	Stop farming	Increase production	Decrease production	Diversification (including nature protection)	Participation in management programmes	Development of tourism and recreation
Hobby	+	−	+	−	−	+
Conventional	+	−	+	±	±	+
Diversifier	+	−	+	+	+	+
Expansionist-conventional	−	+	−	−	−	−
Expansionist-diversifier	−	+	−	+	+	+

+: high; ±: medium; and −: low

The set of options and variables affecting agents' decisions vary for each selected process (Table 2). For farm cessation, agents can decide whether they continue or stop farming. If an agent wants to continue, her/his strategy and the one of the successor will not drastically change. In this process, the decision to stop farming is possible when agent is 50-year-old. However, if an agent decides to stop farming, changes in the agent type (i.e. transitional ruptures) and in decision making are expected (i.e. the likelihood to sell land is larger than for an agent that has decided to keep farming).

For farm expansion, agents can buy or sell land, or keep the current position. The internal factors influencing the probability to decide for any of these options were agent type and previous decisions (i.e. agent memory). Specifically, the influence of previous decisions was calculated by comparing the farm size of the census data of the whole population of the region between 2001 and 2005. In this way, the more land an agent bought in the last 5 years, the less likely s/he will buy land. Related to this, if an agent buys a field, s/he would not be able to sell land after 5 years. The action of buying land is restricted by land availability in the neighbourhood. Thus, if there is a field or a farm available, the closest buyer can buy it. The selection of which field an agent will sell depends on the distance of the field to the owner. This relation was estimated based on a spatial analysis of the cadastral data. If an agent decides to stop farming the whole probability distribution is modified by calculating again the initial condition and by establishing the boundaries of her/his new agent type. Also, the agent can only sell or keep her/his land.

For the protection of linear landscape elements, agents can plant new elements, and then, remove or keep existing elements. The internal factors influencing the probability to decide for any of the options were agent type, previous decisions and availability of land. If an agent plants a new element, the whole probability distribution changes and the agent will have the option of cutting the landscape element only after some period of time. Agents with larger farms have more possibilities to plant new landscape

Table 2 Overview of simulated processes and variables used to define agents' options and decisions and select the fields

Process	Options	Periodicity	Variables: agent-level	Variables: field-level
Farm cessation	Stop	Once in the agent's life	Agent type	None
	Heritage		Age	
Farm expansion	Sell	Each time step	Agent type	Distance to the agent
	Stable		Previous actions[a]	
	Buy		Farm size and policies	
Protection of landscape elements	Cut	Each time step	Agent type	Soil type
	Keep		Previous actions	Surrounding linear landscape elements
	Plant		Farm size and policies	

[a] Including their decisions related to farm cessation

elements. To decide in which field a landscape element will be planted depends on the type of soil of each field (e.g. peat soils were more likely to have landscape elements than sandy soils) and the existence of landscape elements around that field. These relations were also quantified based on additional spatial analyses of the current landscape structure in the region.

External factors

The interaction between internal and external factors was defined by two indicators: the percentage of the area managed by agents with small-scale production (AREA) and the density of linear landscape elements (ELEMENT). Each indicator is related to a specific process. AREA was defined as indicator of farm expansion. Small-scale production was defined as those farms with less than 50 Dutch Standard Units (dsu; in 2005 a dsu was equal to 1400 Euros). When AREA drops below the 25% of the total agricultural area, a policy is adopted. This policy creates incentives that promote agents to keep their land by changing the probability of selling fields. It was assumed that this policy did not influence the process of farm cessation.

ELEMENT was defined as indicator of the protection of linear landscape elements. When a policy to protect these elements is adopted, agents can participate by planting new linear landscape elements, affecting the density of these elements in the landscape. The rate of adoption of this policy is influenced by the probability of an agent to belong to an agricultural association for nature and landscape management. For example, diversifiers are more likely to be part of one of these associations, and more likely to adopt this policy. To adopt again the policy, agents have to wait for 2 years. They also have to adopt the policy for at least 6 years.

Landscape representation

Based on the selected indicators, the landscape was represented by the area managed by agents with small production, and by the density of linear landscape elements per hectare. Urban areas, bodies of water and nature areas were represented as static land-use types. Based on cadastral data, agents owned a farm that was formed by one or several fields. These fields could be clustered or spread over the region. Each field could be formed by one or several pixels. This means, that each pixel belonged to a certain field, a certain farm and a certain agent. For each field, and therefore each pixel, the size, the soil type, the distance to the owner and the density of linear landscape elements were determined.

Simulation

To illustrate the functioning of the conceptual framework implemented in a simulation model, the model was run for three different sets of parameters for a period of 20 years. First, the model was run to illustrate the decision-making process and the influence of internal feedbacks on the trajectory of individual agents and on the regional population. Second, the model was run including external factors, specifically the effect of external factors on the agent population. Third, the model was run to illustrate the potential effect of external factors on the structure of the landscape. In addition, for this parameter setting the model was run 100 times, each time with a different random seed. These additional runs illustrate how to calculate and visualize the uncertainty in a decision-making process in which each decision was specified through probability distributions.

Decision-making and internal factors

Figure 6a shows the different simulated trajectories of a number of individual agents of the agent type conventional. Most agents have a clear tendency: to grow (agent b), to keep the same amount of land (agent a) or to decrease their farm size (agent d). Other agents, however, drastically changed the direction of their trajectory caused by a transitional rupture (agent e), which in this case was the result of the decision of the agent to stop farming in the following years. Related to this, before agents stopped farming, a decrease in their farm size was often seen (agent c). Although similar trajectories were present in all the agent types, the general tendencies for each agent type differed (Fig. 6b). While the average farm size of the agent type hobby decreased almost 1 ha, the average size of the other agent types increased. Yet, such an increase was higher for expansionist types ($\sim$6 ha) than for non-expansionist types ($\sim$3.5 ha).

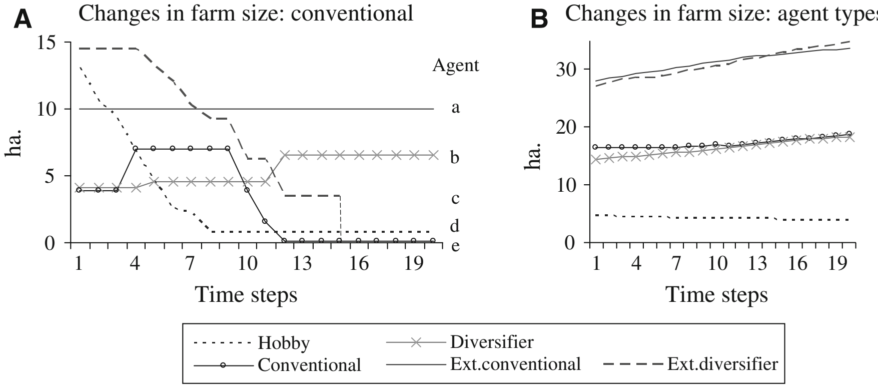


Fig. 6 Different trajectories of the simulated changes in farm size for the agent type conventional (**a**), and the average farm size of each agent type based on the entire agent population (**b**)

Changes in the average farm size between agent types are also related to other changes in the agent population of the simulated results (Table 3). Although there was a decrease in the agent population of almost 16% due to farm cessation, most of the agents who stopped farming belonged to the hobby, conventional and diversifier agent types. In a similar way, around 17% of the agents who belonged to these agent types decreased the size of their farms. Still, around 23% of those agents who belonged to agent type conventional and diversifier bought land. Finally, most of the expansionist bought land and few of them sold their land or stopped farming. These results show that the agent type defines the different options and trajectories that an agent can follow, but still keeping the diversity of agent decisions within each of these agent types.

External factors

The adoption of the policy that promoted agents to keep their land (indicator AREA) had a different impact on the options and decisions of the different agent types (Table 4). Specifically, the likelihood that many non-expansionist agents sold their land was lower. Thus, the adoption of this policy reduced the percentage of these agents selling their land. However, as this policy did not influence agents' decisions related to the process of farm cessation, the percentage of agents per agent type who stopped farming was similar with or without the adoption of the policy. As many agents with small-scale production stopped farming, the area they managed still dropped to 18% of the total area. The adoption of a policy to protect the linear landscape elements (indicator ELEMENT) also showed differences between agent types (Fig. 7). While around 35% of the diversifier and expansionist-diversifier agents participated in the policy, only around 20% of the other agents participated.

The spatial distribution of each agent type is not homogeneous throughout the region, and therefore, the adoption of the policy is also unevenly distributed (Fig. 8a). This spatial link between individual decisions and policy adoption facilitates the analysis and exploration of the potential influence of policies on

Table 3 Summary of the simulated results of changes in farm size per agent type, including the initial number of agent per agent type, the number of agents after the simulation, the proportion of farmers who stopped farming, who increased their farm size and who decreased it

Agent type	Initial number	Final number	Stop farming (%)	Increase land (%)	Decrease land (%)
Hobby	1036	816	21.2	19.7	12.9
Conventional	566	442	21.9	27.0	20.3
Diversifier	294	240	18.4	27.6	22.4
Exp. conventional	715	679	5.0	46.0	1.3
Exp. diversifier	130	125	3.8	52.3	0.0
Total	2741	2302	16.0	30.5	11.8

Exp expansionist

Table 4 Summary of the simulated results of changes in farm size per agent type for the small-scale policy scenario, including the initial number of agent per agent type, the number of agents after the simulation, the proportion of farmers who stopped farming, who increased their farm size and who decreased it

Agent type	Initial number	Final number	Stop farming (%)	Increase land (%)	Decrease land (%)
Hobby	1036	789	23.8	16.5	4.2
Conventional	566	448	20.8	24.9	6.4
Diversifier	294	227	22.8	29.6	4.8
Exp. conventional	715	701	2.0	44.5	0.1
Exp. diversifier	130	125	3.8	56.2	0.0
Total	2741	2290	16.5	28.8	3.5

Exp expansionist

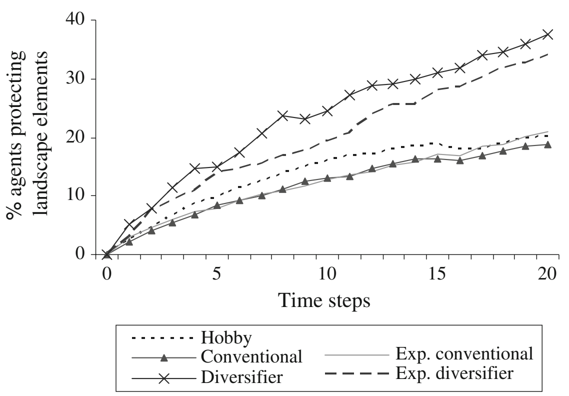
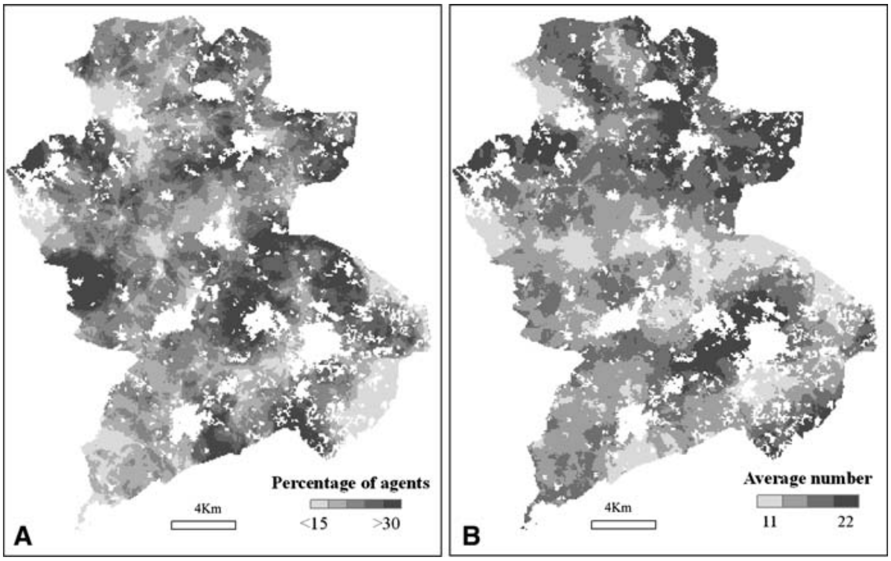


Fig. 7 Percentage of agents per agent type who participate in the policy to protect linear landscape elements

regional changes. For example, with these results it is possible to have an overview on the potential number of participants in a specific policy, as well as the potential changes in the structure of the landscape that this policy might cause (Fig. 9).

The results of running the model 100 times with different random seeds showed a high variability in the results (Fig. 8b). While the number of agents adopting the policy was relatively similar between runs (average 440, standard deviation 45), the group of agents adopting the policy changed, as well as the spatial distribution of the adoption of the policy. This illustrates the uncertainty attached to the probabilistic approach, the overlap of decision-making between

Fig. 8 Agents' participation in the policy to protect linear landscape elements. Percentage of agents who participate in the policy by running the model once (**a**). Average number of times that agents participated in the policy by running the model 100 times (**b**)



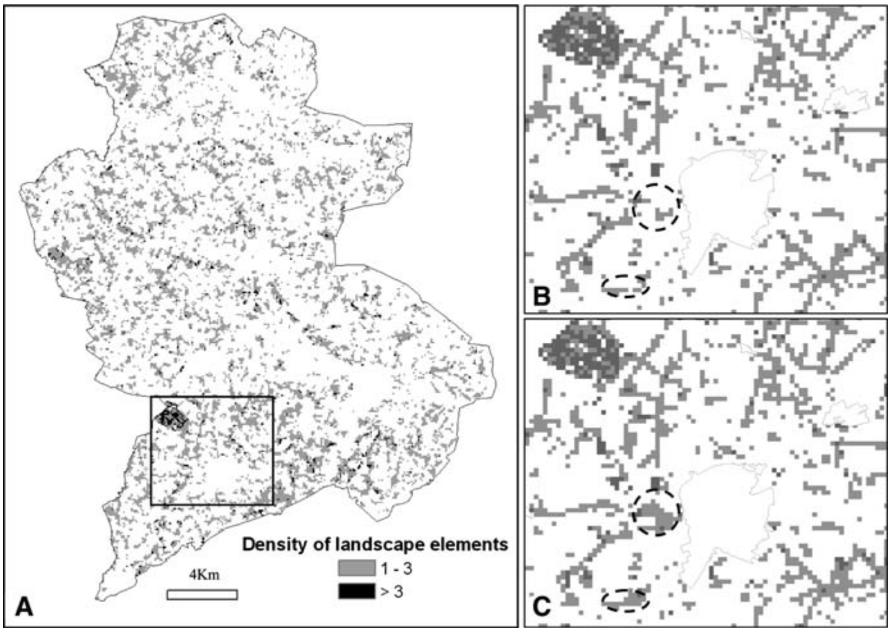


Fig. 9 Percentage of landscape elements per hectare: base map year 2005 (**a**, **b**); and simulated map after 20 years (**c**)

the different agent types and the complexity of human-environmental systems.

Discussion and conclusions

The conceptual framework presented in this paper addressed two main challenges in the study of regional LUCC. The first challenge relates to including the diversity of decision-making in regional modelling. In agent-based models developed for local case studies, all the different decision-making strategies can be described and quantified in detail by using individual questionnaires or participatory calibration (Bousquet and Le Page 2004; Janssen and Ostrom 2006; Robinson et al. 2007). To gather these data of the population of an entire region is less feasible. This relates to the common practice of ignoring the diversity of decision-making strategies in regional land use models (e.g. Clarke et al. 1997; Overmars et al. 2007; Pijanowski et al. 2002). In the conceptual framework proposed in this paper, the combination of individual agents, an agent typology and a probabilistic decision-making approach allow us to simplify and include the inherent variability of the population and decision-making in rural regions. Further, the proposed conceptualisation makes a relatively simple parameterisation of the model possible based on data that are available or can be collected in rural regions.

The second challenge relates to the empirical parameterization of ABM, specifically models with a regional extent. In the application of this framework, the parameterization with empirical data of both the agents' decision-making process and the influence of internal and external factors on agents' options and decisions was achieved by linking different concepts and different datasets. Spatial data, including cadastral data, were used to represent and understand general land-use patterns at field level. The analysis of survey data was used to develop an agent typology that accounted for differences in decision-making. Census data of the whole population were used to identify and quantify internal feedbacks. The use of different datasets relates to the statement of Robinson et al. (2007) that using different collection methods is the best way to parameterised empirically an ABM.

The definition and application of this conceptual framework have several advantages. One of the main advantages is that by merging general concepts and approaches such as farmers willingness and ability (Siebert et al. 2006), decision-making corridors (Wilson 2007), agent typologies (Valbuena et al. 2008) and probabilistic decision-making, this is a flexible and generic framework to implement regional ABM/LUCC. In fact, this flexibility allows us to implement this framework to different LUCC processes and different regions. In regional studies the framework allows, by defining and using different decision-making strategies, to include the diversity of farming systems. Such a diversity is an important factor explaining the interaction between farmers' decision-making and the landscape structure of rural regions (Thenail and Baudry 2004). Further, a generic framework facilitates the comparison not only between conceptual approaches, but also between ABM applications (e.g. Grimm et al. 2006; Parker et al. 2008). Both generalisation and comparison have been identified as key topics in ABM/LUCC research (Rindfuss et al. 2008). Another advantage is that the probabilistic approach used in this framework facilitates the quantification and visualisation of the uncertainty of the modelling process. This is in line with the statement of several authors that uncertainty needs to be quantified, represented and included in the outputs of ABM (Messina et al. 2008; Parker et al. 2003), and even in policy-making processes (Bradshaw and Borchers 2000). Finally, by including the diversity between and within agent types, this conceptual framework includes part of the diversity of decision-making processes, which is an essential characteristic of the human-environmental system (Köbrich et al. 2003; Matthews et al. 2007).

The application of the conceptual framework reveals some challenges and limitations. A challenge of this framework, but also of ABM in general, is the validation of the model (Crooks et al. 2008; Messina et al. 2008). Although sensitivity analyses, the visualisation of uncertainty, and multi-temporal surveys and census provide relevant datasets to verify the simulated processes (Bousquet and Le Page 2004; Crooks et al. 2008), the availability of detailed data on the willingness and ability of the whole population is often lacking or restricted. Still, statistical methods to control further the bias, noise and collinearity in such probabilistic models can be also carried out (Santner et al. 2003). These methods can be used to verify the internal properties of the simulation processes itself. Also, if consistent high-resolution data for 2 years are available, validation may be possible by comparing the simulated results to past or current land use patterns (Brown et al. 2005; Pontius et al. 2008). Another challenge is linked to the interactions between agents and their social networks. Although decision-making of other actors such as policy makers and nature conservationists can also be represented by using the conceptual framework described in this paper, to quantify and to represent spatially these socio-economic interactions is challenging. Yet, the use of external feedbacks in this conceptual framework is a first step to include empirically these interactions in regional ABM. Finally, agricultural practices in this paper were represented by the main agricultural activity, disregarding the diversity of these practices in the farm and in the region (e.g. different livestock systems and crop rotations). Agricultural practices are closely related to the structure and dynamics of landscapes in rural regions and the agent type itself (Thenail and Baudry 2004). To include this diversity of agricultural practices in the conceptual framework described in this paper would help us to analyse and explore better the interaction between farmers' decisions and the landscape patterns in rural regions.

The main limitation of this probabilistic approach is the randomness attached to it. As ABM/LUCC models are developed to deal with complex human-environmental systems, it is unlikely to gather all the required data to parameterise the model. Related to this, we need to understand the meaning of those probabilities and to link them to real processes (Batty and Torrens 2001). In this specific application, several assumptions were made including the initial conditions of each agent, the stability of the probabilities of the agent types in time and the quantification of the link between past and future decisions. This limitation relates to the statement of several authors that these tools have a limited predictive capacity and that their use relies on their capacity to analyse and to explore the dynamics of such complex systems (Batty and Torrens 2001; Couclelis 2002; Matthews et al. 2007; Zellner 2008). Still, as mentioned by Matthews et al. (2007), this level of uncertainty can be decreased by including the knowledge of different stakeholders in the construction of ABM.

The conceptual framework described in this paper represents a step towards the development of empirical regional models that take explicitly into account the diversity of decision-making strategies. To achieve this, we combined existent concepts and approaches to create a generic approach in regional ABM. By being flexible and generic, this framework can be implemented for different LUCC processes and different regions where the diversity of individual decision-making is an important factor in LUCC processes.

Acknowledgments We would like to thank Sytze de Bruin and Erez Hatna for their suggestions on an early draft of this paper. We also wish to thank two anonymous reviewers for their useful comments to improve this paper. Many thanks to Nico Polman, Roel Jongeneel, Tom Kuhlman, the LEI and the Province of Gelderland for allowing us the use of their data. This research is endorsed to the GLP project.

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