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A return on experience from the application of agent-based simulations coupled with life cycle assessment to model agricultural processes

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ABSTRACT

Agent-Based Models (ABMs) are becoming a widespread approach to model human-environment interactions. They belong to the class of individual-based modelling approaches, which allow a bottom-up representation of the system being modelled, eliciting its macro-level evolution while modelling the micro-level behavior of its individuals.

This paper deals with the application of an ABM to simulate future crop patterns in the Grand-Duchy of Luxembourg under a pre-defined scenario. The simulated scenario deals with the introduction of a "green consciousness" component in farmers' decisions, substituting a purely rational approach based only on profit maximization. The results of the ABM are used to perform a life cycle assessment of Luxembourg's agricultural system. The paper first describes the difficulties and the challenges connected with building an ABM for agriculture and then shows the results of the selected case study. The results show that, from a lifecycle perspective, a "greenness" criterion aimed only at reducing greenhouse gases emissions reveals patently a sub-optimal choice and causes burden shifts to other impact categories. Finally the ABM-based (bottom-up) approach is compared with a top-down approach applied in a previous study by the same authors to model the same system. Assets and drawbacks of the two approaches are highlighted.

1. Introduction

Under business-as-usual conditions, the expected cropland expansion would overshoot the "safe operating space" by 2050, both for the case of net and gross expansion of cropland ((UNEP, 2014), page 13). Sustainability assessment of agricultural systems, is therefore a key issue for policy makers, from local to global scales (McIntyre et al., 2009).

Farmers' choices depend not only on the ecological, economic, and social environments of their farms, but also on the perceptions they have about these environments (Edwards-Jones, 2006). The general choices at farm scale are translated into strategies and then into practices through decision-making processes which are not easily taken into account by classical bio-economic farm modelling tools (Edwards-Jones, 2006), essentially due to their human dimension. In fact, human behavior is often the result of bounded rationality, due to limited information about exogenous factors or because of personal preferences and beliefs. Moreover, cultural reasons may play an important role in land use decisions, and information biases may limit knowledge about market developments and technology trends. For this reason, purely rational approaches fall short in capturing the complexity of human behavior (Navarrete Gutiérrez et al., 2015, 2017).

A better understanding of the knowledge and behavior of the main actors of farms management, i.e. the farmers, is crucial and this is why approaches based on Agent-Based Models (ABMs) have gained increasing attention in modelling human-environment interactions (Rounsevell et al., 2012, 2011), such as land management (Matthews et al., 2007; Wise and Crooks, 2012) and agricultural modelling (Freeman et al., 2009; Mialhe et al., 2012; Murray-Rust

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et al., 2014; Valbuena et al., 2010). Given the elements briefly outlined above, agricultural systems exhibit the features of *complex systems*, as they have multiple scales of interactions, are strongly influenced by human decision-making and include feedbacks with natural ecosystems (Bert et al., 2014). Complex systems simulations are increasingly being used to shed light upon issues of social and policy importance (Squazzoni et al., 2014). Such work is starting to be influential in policymaking, being used to explore some of the complex consequences of policy action (Smajgl and Bohensky, 2013). However, as pointed out by Waldherr and Wijermans (2013), still some criticisms persist towards ABMs and social simulation methods, mainly due to: 1) lack of understanding (the model is very often seen as a "black box"); and 2) academic territorialism, i.e. academics defending their areas of competence. Nonetheless there are signs of some maturation in the acceptance and use of such models (Hegselmann, 2012), including conceptual frameworks and successful practical applications to policy steering (Smajgl, 2010; Smajgl et al., 2015a; Smajgl and Ward, 2013).

Several ABMs have been built to simulate agricultural and land use change systems. A comprehensive review would however be out of the scope of this paper. Some of them rely on heuristic rules or single-objective optimization to determine agents' actions. Consequently, agents are often programmed to act in an economically rational way (Berger et al., 2006; Filatova et al., 2009; Happe et al., 2008; Parker et al., 2008; Schreinemachers and Berger, 2011). Such models, like the agricultural model AgriPoliS (Happe et al., 2006), have substantial explanatory power, in describing for instance the evolution of farms in competitive markets. However, humans employ a number of strategies in land use decision making that go beyond maximization of profit, and opportunity cost and risk minimization (Bonabeau, 2002; Parker et al., 2008). Therefore the optimization approaches exclusively based on microeconomic theory need to be complemented by other approaches implementing a more behavioral-based set of rules of action. These approaches have indeed gained increasing attention in land use change (Matthews et al., 2007; Parker et al., 2003) and agricultural modelling (Berger et al., 2006; Freeman et al., 2009; Happe et al., 2008; Mialhe et al., 2012; Schreinemachers and Berger, 2011).

Kaye-Blake et al. (2010) provides a review of multi agent (MA) simulation models in agriculture, also including optimization. They suggest that a two-part model including both a MA sub-model and a cellular automata (CA) sub-model is the most suitable to describe agricultural systems.

However, in this solution, the two parts still remain separated, therefore one cannot really think about "spatial agents". Marohn et al. (2013) assess low-cost soil conservation strategies for highland agriculture, using an AB modelling approach to couple two software packages: i) a process-based model of natural resource dynamics and crop yields to simulate soil, water and plant dynamics, and ii) a mathematical programming-based MA system to simulate farm decision-making. Zellner et al. (2008) present a generic ABM to model land use decisions and consequent energy consumption and pollution dynamics. The model described in Wise and Crooks (2012) is empirically grounded, reaching a very realistic representation of a complex socio-physical system. The model is a spatially explicit ABM programmed in Java, and based on the use of GIS maps; it consists of a number of modules that capture the physical, economic, and social processes that impact land-use patterns. It is endowed with a graphical user interface (GUI), and includes a number of parameters which can be adjusted to suit the underlying assumptions of the researcher. The same empirically grounded character and GUI functionalities are shared by Smajgl et al. (2015b). Astier et al. (2012) in their critical analysis of sustainability assessment of natural resource management by small farmers, use AB modelling together with role play games to support participatory processes. Murray-Rust et al. (2014) presents a new ABM framework that allows exploring the influence of different factors (such as social, economic and environmental factors, and subsidy adoption) in farmers' decision making process. The approach described combines several advances in ABM of land use, a detailed multilevel handling of temporality, a varied socio-economic context, and ecosystem service modelling.

Manson et al. (2016) is an example of application of ABMs to simulate the effect of bottom-up social interaction components in the adoption of a systemic change (namely rotational grazing) in the United States dairy system. The social network model is implemented starting from interviews conducted with 53 selected farmers in three different US states. The interviews support the definition and estimation of parameters to formalize the process of ties formation with peers, institutions, organizations, and people groups.

The examples of coupling of ABMs with life cycle assessment (LCA) are not numerous in the literature because, on one side the AB paradigm probably still lacks shared acceptance in the LCA community, and on the other side, it suffers from the difficulties linked to its implementation.

In the field of agricultural modelling (Miller et al., 2013) applied ABM, from an LCA perspective, to the assessment of planting switchgrass by farmers responding to policies. All agents are landowners who have the potential to adopt the use of switchgrass and Bayesian probabilities are used to evaluate farmers' orientation towards switchgrass adoption as opposed to resistance to change. The same problem is addressed by Bichraoui-Draper et al. (2015), who use a decision tree based on variables such as familiarity with the new crop, risk aversion, economic profit and neighbours' imitation to implement agents decisions to plant switchgrass.

The present paper deals with the application of a bottom-up approach (an ABM) to simulate future crop patterns in the Grand-Duchy of Luxembourg under a pre-defined scenario. The results of the ABM are used to perform a LCA of Luxembourg's agricultural system. The paper first describes the difficulties connected with building an ABM for agriculture, then shows the results of the selected case study and finally compares the ABM-based approach with a top-down approach applied by the same authors to the same system in a previous study (Rege et al., 2015). Assets and drawbacks of the two approaches are highlighted here. This paper is not meant to provide an exhaustive discussion and a possible solution to all the existing challenges in the empirical characterization and parameterisation of an ABM, but to approach and analyse some of these challenges from the point of view of LCA and not only AB modellers. For a broader discussion the interested reader can refer to Smajgl et al. (2011) and Smajgl and Barreteau (2014).

2. Methods

In the framework of the project MUSA we have built an ABM to simulate the agricultural system in the Grand-duchy of Luxembourg. In a previous study a similar problem had been tackled exclusively from a rational perspective, considering only revenue maximization and opportunity cost minimization as the farmers' decision criteria (Rege et al., 2015; Vázquez-Rowe et al., 2014). The implementation of an ABM allowed reversing the modelling perspective, passing from a top-down (economic model) to a bottom-up (ABM) approach, thus allowing, among other things, the addition of the farmers' behavioral aspects to the modelling exercise.

In this section we outline our experience with the model building and highlight the difficulties encountered, including the way they have been addressed. We begin with the goals that one wishes to achieve in the "ideal" situation and the model structure in such a case. We then identify the data available and the limitations that are imposed on the modelling structure and how they force the modeller to modify the original conceptual structure of the ABM. We finally highlight the implications for LCA in the light of these modifications.

2.1. Setting the context

All farming system are composed of farmers who may be involved in growing only crops, rearing animals in a traditional open pasture or an industrial intensive operation, or a combination of both, i.e. growing crops and rearing animals. Additionally, farmers own fields that may aggregate to farms. Each field may well have a soil type that is different and may be suitable to a specific crop. In order to preserve soil quality, crop rotation is practiced. Crop rotation is considered essential for integrated farming (Brankatschk and Finkbeiner, 2015; Dury et al., 2011) as monocropping has major consequences in terms of environmental sustainability, such as a reduction in the biodiversity of arable ecosystems and a decline in landscape diversity (Stoate et al., 2001).

As a consequence, when one wants to model the agricultural system, all fields have a rotation scheme wherein the farmer plants different crops on the same field. We modelled the rotation scheme as per the information taken from agronomists and from KTBL (2005). The choice of a rotation scheme depends on the farmer and is assumed to be stable for a farmer over time. Pastures and meadows are not a part of the rotation scheme because preservation of permanent pasture is one of the main principles for the Basic Payment Scheme under the Common Agricultural Policy (CAP). The other principles are crop diversification and preservation of Ecological Focus Areas on arable land (SER, 2014). Vineyards are also exempt from changes, because of the very favourable microclimate conditions in the areas where grapes are grown (basically the region along the river Moselle). Finally, orchards and fruits are also not subject to changes (therefore they do not enter in the crop rotation schemes) because they are specialized cultures, that cannot be changed on a short term horizon.

In the case of Luxembourg, the majority of the farmers are involved in growing crops as well as rearing animals. In such a case, feed for animals is an important aspect of the agricultural system. Table 1 shows the distribution of farms by size in Luxembourg in 2009 (the base year used to calibrate our ABM model).

As shown in Table 1, in 2009 there existed 2242 farms in Luxembourg covering an area of 130,762 hectares (ha). The farms were split into nine farm size classes (A to I) based on their area. Each farm would have a certain number of fields with crops being planted by season (summer or winter) along with number and type of animals.

In order to program a consistent ABM model, able to reproduce reality in a likely way, the modeller should have access to the number and size of each and every field belonging to each farmer. In addition one should also have information on the crop planted on each field and the prevalent rotation scheme on that field. Information on the number and type (bovines, swine, horses and poultry) of animals by age, sex and purpose (meat, milk or suckler cows) should also be available for each farm. In the case of the application introduced in this paper, only a small part of the abovementioned information was available in the public domain. The data available for 2009 are reported in Table 2 (KTBL, 2005; STATEC, 2015).

Each labelling has different explanations: "mixed grain" includes all the possible mixtures of the different cereal species; "other forage crops" all the crops not included in the categories listed in the table are included; "maize (dry matter)" is the maize used as forage or to produce biogas; "dried pulses" means peas, lupine, etc.; "clover grass mix" represents temporary grasslands with clover; "crops NES" stands for "crops not elsewhere specified" and refers to orchards, vegetables and other marginal crops that are observed as statistics but are marginal in area under plantation.

For additional data manipulations to produce a data set consistent with the 2009 information, the reader is forwarded to (Rege et al., 2015).

In the given context, we face three different problems: a need for fine grained spatial information (fields associated to farms, farms associated to farmers); the exogenous nature of crop prices that must be included in the model and the need for additional data to what current public statistics offer. We discuss each problem in the remaining of the paper.

2.2. The different components of the ABM model

The modelling strategy used for the ABM described in this paper follows the KISS (Keep it simple, stupid!) principle (Edmonds and Moss, 2005). In the following paragraphs we describe how specific problems related not only to the model building, but also on the retrieval of the necessary data, were dealt with.

2.2.1. Dealing with lack of fine grained spatial information

In the absence of information on the number of fields belonging to each farm, we generated this information randomly such that the initial allocation matches the base data of 2009. For each farm type (A to I) we generated a random number extracted from a uniform distribution and allocate the area to each farmer between the minimum and maximum for that farm type. We then randomly allotted a rotation scheme to each farmer from the original list of six schemes mentioned earlier. As indicated in Table 2, crops are classified as leaf (L), cereals (C) or others (O). The crops falling in group O (meadows, pastures, vineyards and crops NES) do not take part in the crop rotation process, because their allocation never changes.

Rotation schemes rotate leaf (L) and cereal (C) crops in different sequences; LCC, LCCC, LCCLC, LC, LLCC, LLLLC are some of the rotation schemes, where crops are planted in the sequence they appear. We take the share of each crop in the total for that type (share of a cereal crop in total cereals) and use that share to compute the number of farms that would be planting the specific crop. In case we find the number too low, we scale it up such that the crop is being planted by a reasonable number of farms. Having selected the number of farms planting a specific crop, we randomly

Table 1
Distribution of Farms by Size (ha) in Luxembourg in 2009 (letters from A to I indicate the farm size class).

	Total	A	B	C	D	E	F	G	H	I
		<2	2–4.9	5–9.9	10–19.9	20–29.9	30–49.9	50–60.9	70–99.9	100+
Number	2242	230	165	217	186	116	246	263	398	421
Area (ha)	130,762	131	598	1533	2667	2890	9956	15,743	33,583	63,661
Average size (ha)	58.32	0.57	3.62	7.06	14.34	24.91	40.47	59.86	84.38	151.21

Table 2
Public information available for the crops planted in Luxembourg in 2009 (T = Type, S = Start Month, E = End Month, Output = quantity yielded; NES = not elsewhere specified).

Crop name	T	S	E	Season	Yield (t/ha)	Price (€/t)	Output (t)
Wheat (winter)	C	10	8	Winter	6.66	145.74	43,761
Wheat (summer)	C	2	8	Summer	6.62	105.76	45,451
Spelt	C	10	8	Winter	4.64	208.94	1866
Rye (winter)	C	10	8	Winter	6.29	80.30	6937
Barley (winter)	C	10	7	Winter	6.15	87.02	36,050
Barley (spring)	C	3	8	Summer	5.23	90.76	18,354
Oats	C	3	8	Summer	5.20	87.68	7197
Mixed grain (winter)	C	10	8	Winter	5.26	87.68	652
Mixed grain (spring)	C	3	8	Summer	5.26	87.68	615
Maize grain	L	4	11	Summer	6.00	134.12	2453
Triticale (winter)	C	10	8	Winter	6.27	86.16	25,415
Other forage crops	L	4	10	Summer	13.67	98.57	155,108
Maize (dry matter)	L	4	10	Summer	13.67	98.57	173,691
Dried pulses	L	3	8	Summer	3.95	25.29	1206
Beans	L	1	1	All	3.52	125.00	271
Potatoes	L	4	10	Summer	33.19	179.14	20,044
Rapeseed	L	9	7	Winter	3.92	259.84	17,572
Clover grass mix	L	9	7	Winter	53.13	29.26	98,297
Meadows	O	1	1	All	8.22	163.53	74,229
Pastures	O	1	1	All	8.23	222.87	479,877
Vineyards	O	1	1	All	10,851.37[a]	1.97[a]	14106786[a]
Crops NES	O	1	1	All	6.2023	330.04	1985

[a] Yield expressed in litres of wine per ha; price expressed in €/l; output expressed in litres of wine.

choose which farms will plant the crop. The total area for the crop under each farm type is then distributed to each farm in proportion to the farm's area amongst the total area of the farms chosen to plant the crop. Repeating the procedure for each crop, we have the initial allocation of crops to farms. The summation of the area under each crop planted by each farm then equals the total area of the farm.

The problem with this approach is that there are no specific numbers of fields assigned to each farm in the beginning and there is no information about the distribution of the crops on those fields. From a simulation perspective, the change in cropping pattern due to environmental, policy or financial shock is restricted to the field level and built up from the field level. In absence of field information, the same transmission mechanisms hold but to different scales of cropping areas.

A LCA modeller is interested in knowing the variations of cropping areas (and their environmental implications) (Marvuglia et al., 2013). The strategy to deal with field related information (described above) has implications for the quantification of these variations in the system because the scale is much larger and hence prone to more extreme values in response to shocks.

Farmers plant crops based on the expected future price of the harvest. The expectation could be naïve or based on past price data, with constraints of crop rotation playing a role. The expectation of price would implicitly filter the subsidy component, if any, which is normally crop-based. However, if the subsidy component is based on the amount of land held, then it is not a driving force behind the decision to select a crop for sowing.

ABMs are bottom-up models with no closed feedback loop architecture. In closed feedback loop architectures, agents think about a decision and the implications of their decisions on others and the response of others and repeat this process until it results in equilibrium, where no agent has any incentive to deviate from the proposed behavior. Agents respond to external stimuli based on pre-programmed behavior eliciting a response when the threshold is triggered, thus moving in a unidirectional forward looking time path.

For a very detailed analysis at the level of an individual agent, and in order to enable a greater degree of confidence in the variance of the results, one would require information on field ownership by each farmer besides the soil type and rotation scheme on each field over time to arrive at reasonable estimates of crop output and variations.

Despite the theoretical concept is very simple, the realistic allocation of a rotation scheme for every farmer, for every field on the farm, and for the type of crop planted is far more difficult. Firstly, on account of the unavailability of the data for privacy reasons or the sheer size of collection making, it is impossible to cover the whole population. Just having sample estimates for larger countries like the Russia, Canada, China, Australia, Brazil, and India, to name a few, makes this approach all but feasible. Even for a country like Luxembourg where this data is available for each field for each farmer, privacy concerns makes it impossible to access the data and build an ABM based on the fields. In such a scenario, the modeller is left to use the top-down approach of calibrating the farm sizes to the data available with field sizes that may not reflect the reality. The variance in field sizes could be substantially different from what is observed and has a direct impact on the variance of land under crops and therefore leads to a chain reaction to analysis down the line. Using cellular automata (Kaye-Blake et al., 2010) to circumvent the problem is not a solution, as it leads to crucial loss of information regarding the cells that undergo change. This puts an added onus on the modeller to introduce biases on the cells that undergo or do not undergo cropping change. To complicate the problem further, in mixed farming systems wherein animals are an integral part of the system (despite the natural limitation on the maximum number of animals per hectare that are normally affordable), the sheer variability of the animals (cows, bulls, suckler cows, heifers, oxen for slaughter, pigs, sows, piglets, sheep, poultry) and the target of the farmer (meat, milk, rearing and selling calves) makes it impossible to allocate animals to farms. The amount and type of animals on each farm determine the feed needs and hence impose a constraint on the types of cash crops that can be sowed.

2.2.2. Solving the crops price discovery problem

The model under consideration does not include means to use global information to generate a set of prices for each crop in the future based on some formal mechanisms whose foundations are rooted in optimization or economic phenomena. This creates a particular dilemma for modelling farmer behavior. The variation in price of crops over time exhibits periods of high volatility followed by low volatility, as it has been the case with prices in Luxembourg. The year 2009 was particularly interesting due to the fact that prices had reached the lowest in years. In the absence of some exogenous data generation process for price generation that mimics the observed price fluctuations, ABM structures incorporating own and cross-price elasticity of supply would be irrelevant, because the price signals on which these responses are based would be incorrect.

We aim to study the changes in cropping patterns in Luxembourg, with the ideal aim of exploring under which conditions the system would evolve toward an increased production of a given crop (which in our case is represented by maize to be used for biogas production; with a minimum amount of fresh matter of 80,000 additional tons by 2020, as explained in Vázquez-Rowe et al. (2014) and Vázquez-Rowe et al. (2013)). This problem is not location-specific, nor is crop-specific. Therefore, upon information availability, the model could be replicated in a different geographical context while focusing the analysis on a different crop. The results from simulations though will be specific to the location and crop as the crop and location are interdependent due to constraints imposed by nature and climate.

Normal fluctuations in cropping patterns occur on account of crop rotations to maintain soil quality and fertility, to limit disease and pest pressure, to prevent erosion, to answer to market demands. Indeed, farmers' expectations on future prices, that exert financial pressures, lead to a bias for or against specific crops. Expectations of future prices, and responses to those expectations, are individual-specific and depend on the risk profile of a farmer. The remaining factors are instead determined by nature. Any generic farm across the globe would have fields on which a crop is planted for a specific season. Multiple crops on the same field during the same calendar year are a distinct possibility and one needs to be careful to account for it. This leads to statistical data showing greater area under crop cultivation than the arable land of a region. The rotation schemes and size of fields will lead to a natural fluctuation in the output of crops due to fluctuations in yield, in the absence of any market or behavioral response. The aim of the ABM is to account for changes over and above the normal ones.

In the mixed type of farms, the profit is a function of both the final animal product and also the crops production, wherein there is an opportunity cost associated with a crop used for feed. To complicate the situation further, national trade policies have an impact on the amount of feed that can be imported in case of a shortfall adding to the vagaries of an already risky situation in agriculture. This input uncertainty is a systemic uncertainty that cannot be mitigated except by accurate data at the field level for each farm. It is a herculean task that may well be outside the scope of many countries data monitoring systems.

2.2.3. Collecting information to define agent's profiles

When the level of knowledge of the entities that one intends to model using agents is not sufficient to achieve a realistic definition of the agents themselves, data surveys can be carried out in order to better define the characteristics (*attributes*) of the agents, as well as their rules of action and interaction.

This was the case for the model described in this paper. The survey we distributed to the farmers is available at the following website: http://musa.tudor.lu/surveyresults. The computer-assisted web interviewing (CAWI) surveying technique was employed to conduct the survey, which was completed at the end of January 2015. It was distributed to 1191 farmers, with a response rate of 14% (168 respondents) and respondents located in 97 different areas.[1] This is already a very good response rate generally speaking, and even more so given the length of the survey (Galesic and Bosnjak, 2009).

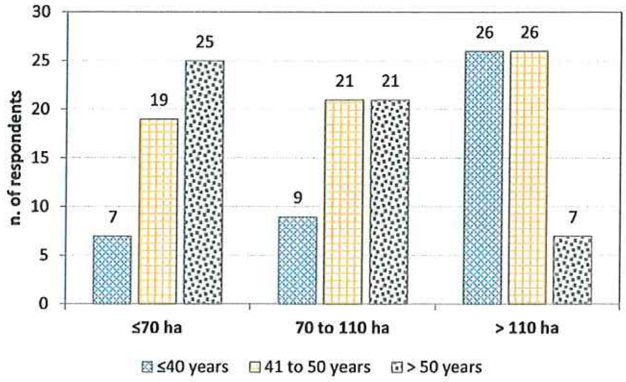

Fig. 1. Characteristics of the respondents (distribution by age of the farmer and size of the farm).

The survey took several months to be designed (requiring continuous refinement and interaction among the project partners) and three months to be completed. A reminder by email and another by phone call were necessary respectively after 1.5 months and 2 months from the first launch of the survey.

The questionnaire (translated and distributed to the farmers in German) included 79 questions (some of which were optional) and was divided in four parts: Part I about the farm; Part II about the farmer's land use choice (with section II.1 about a previous change; II.2 about a planned change; II.3 about a previous attempt to change which failed; II.4 about no change); Part III about farmer's inclination/aversion to risk and Part IV about the composition of farmer's household.

Fig. 1 presents the distribution of the answers by age of the farmer and size of the farm (7 respondents are missing because they did not specify their age and/or the size of their farm).

From the Part III of the questionnaire we could infer what share of farmers had a certain willingness to make changes in the traditional way of running their business.

In particular, when we asked how likely (on a scale from 1 to 10) would be that they could consider investing in biogas production in a time horizon of 10 years (supposing they had the financial means to do that), the distribution of the answers took the shape shown in Fig. 2.

It is therefore apparent that without a proper incentive, it would be very difficult getting to the objectives set for 2020 in terms of biomass production for biogas.

2.3. A short presentation of the proposed model

As to the agents' definition, our model is based on a *reactive approach* (Bandini et al., 2009), in which the agents have simple behaviors based on reaction to stimuli coming from the surrounding environment[2] and the observation of the results of their actions (which may trigger correcting behaviors). The behaviors are the actions the agents will take as a reaction to the interaction with

[1] The actual locations of the single farms was masked because of confidentiality reasons; only aggregated responses were disclosed, coming from 97 communes out of the 116 communes of the country.

[2] As the *environment* we mean here the setting in which agents operate.

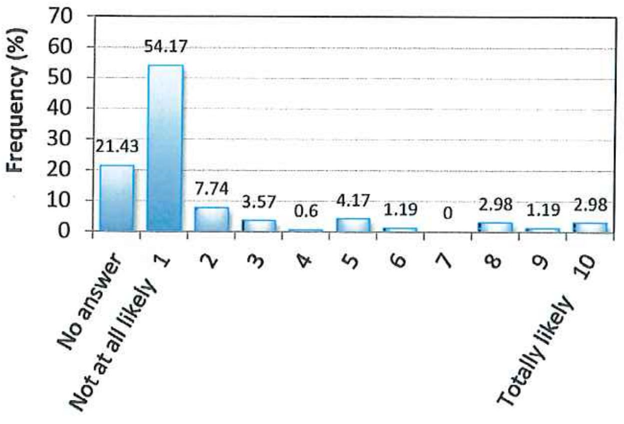

Fig. 2. Frequency distribution of the answers to the question about willingness to invest on biogas (question 59).

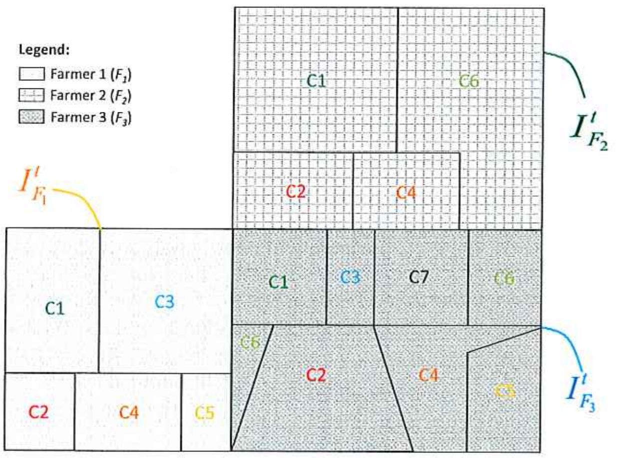

Fig. 3. Example of possible distribution of 6 different crops (C1 to C6) in 3 different farms. Each farm has its own value of the "index of relative environmental performance" I^t_F at time t.

the environment. These behaviors are governed by a set of rules that must be defined beforehand.

The model includes the following entities:

Farmers. These are the independent agents of the simulated system.

Farms. These are container objects underpinning the organization of the model. A given rotation scheme is associated to each farm. Besides the initial rotation scheme, an initial set of crops planted in given proportions is associated to each farm. When a farmer agent has to decide upon a crop to plant in his farm in a given rotation cycle, he will check the list of available crops that meet the existing rotation scheme constraints and maximise his revenue. In the web-based application interfacing the AB simulator (see Fig. 3) one can also select an option which activates a *green consciousness mechanisms* in agents' behavior. The green conscience (*gc*) of an agent is a value between 0 and 1. If an agent has $gc \geq 0.5$ he will look at the global warming potential (GWP) of each crop (in addition to its selling price on the market) before deciding which crop to plant (Navarrete Gutiérrez et al., 2015). This doesn't exempt the farmer from respecting the rules on crop rotation schemes in terms of rotation of crops of leaf (L) or cereal (C) type. Different scenarios are implemented using different probability distributions for the *gc* values (uniform between 0 and 1; Gamma with $\alpha = 2$ and $\beta = 5$; Gamma with $\alpha = 5$ and $\beta = 1$). A further scenario is also implemented, in which the green behavior is based on the environmental performance of the agent in comparison to the other agents. In order to do so, we rank the farms according to the value of the following "index of relative environmental performance":

$$I^t_{F_i} = \frac{GWP^t_{F_i}}{A_i} \tag{1}$$

where t is the time step of the simulation; F_i is the i-th generic farm (belonging to farmer i); A_i is the area of the farm F_i; $GWP^t_{F_i} = \sum_{j=1}^{n^t_i} GWP_{C_j}(t)$ is the GWP of the crops planted in the farm F_i at time t; n^t_i is the number of crops planted in farm F_i at time t; $GWP_{C_j}(t)$ is the GWP of the crop C_j planted in the farm F_i at time t (i.e. the GWP per hectare of crop C_j, multiplied by the area $A_{C_j}(t)$ of farm F_i planted under crop C_j at time t.

At each simulation step t, and for each farmer i, if $I^t_{F_i}$ is below the median of all the indices $I^t_{F_i}$, then the farmer will activate his green consciousness.

An example for only three farms and six different crops is given in Fig. 3.

Product Buyers. Buyers are actors offering to buy the produce of the farmers. In the model there is only one buyer offering to buy the entire produce of all the farms in the country. The prices offered by the buyer are set up beforehand in a given pre-set scenario. One option is applying a time series forecast model for crop prices (Rege and Navarrete Gutiérrez, 2015).

Crop. As mentioned above, crops can be either cereals (C) or leafs (L). Each crop has an associated yield in tons per hectare.

The following different elements represent the overall model:

Description levels. Concerning farms and farming resources, the model is run at the individual level. The prices, which are set identical for all farmers, are obtained using the Holt Winters time series forecast model (Navarrete Gutiérrez et al., 2015). A constant price set can also be chosen by the users.

Time. The simulations are currently run in time steps of one year. At the beginning of each time step the agent sows, then in the spam of one year he harvests, sells the produce, and finally decides which specific crop to plant (if he decides to replace some of the crops) for this rotation scheme (substitute a C or a L).

Space. Each farm has an assigned (and invariable) size of arable land. The spatial granularity of the available information (crops and fields in a given commune's territory) is not detailed enough to identify specific farms and geographically locate them in the country.

Design concepts. The model is implemented following the reactive architecture. The agents observe the prices and change their main behavior accordingly.

Implementation. The simulator is implemented in the Java programming language. The choice of building the model from scratch and not using an existing agent-based platform allows a maximum of flexibility and facilitates the coupling of the agent-based simulator with the LCA calculator.

A schematic representation of the model is provided in Fig. 4. Inventory data coming from the survey concluded in January 2015, as well as from agricultural technical support books (KTBL, 2005), the website of the Luxembourgish national statistics institute (STATEC), the project partners and national institutional sources (like the rural economic services bureau - SER), were used to describe the foreground system, while the Ecoinvent database version 2.2 (Frischknecht et al., 2007) was used for the background system. All these pieces of information, as well as other information about the external environment (e.g. time series of crop prices;

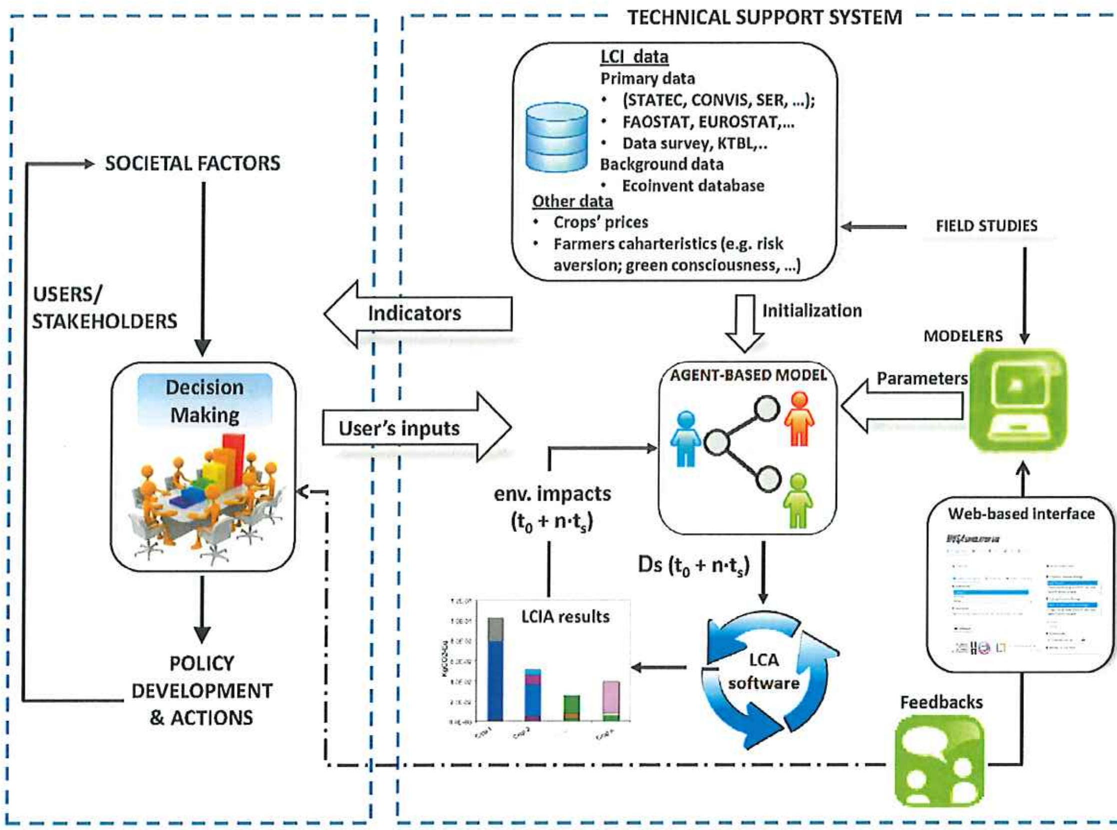

Fig. 4. Schematic representation of the model, made of an agent-based simulator coupled with a LCA software.

agents-related information, such as the estimated level of risk aversion) are used to initialize the model.

2.3.1. *ABM and LCA model coupling*

The modeller initializes the model (using an initial parameters setting procedure) and lets it run for a certain number of time steps. Time steps (t_s) of 1 year are used in our model. The simulation is run for the time period from 2009 to 2020. The result of each simulation step is the set of changes (that we call *deltas*, Δs) in land use patterns resulting from the chosen parameters and the interaction among the agents. These Δs are then fed to a LCA software to calculate the potential lifecycle environmental impact using a chosen life cycle impact assessment (LCIA) method. The LCIA method used in this paper is ReCiPe (Goedkoop et al., 2013). No other LCIA methods were used, based on the findings of Vázquez-Rowe et al. (2014), which proved no major differences existed in the results for the Luxembourgish agricultural sector between different LCIA methods. The functional unit used in our LCA model is the entire agricultural surface of the country, which remains constant over the simulation steps, given the fact that conversion of forest, pastures and meadows to cropland is not allowed (SER, 2014).

Ideally, a hard-coupling of the AB simulator with the LCA software should be achieved, so that the LCIA results produced by the LCA software (at time step $t_0+n \cdot t_s$) could be automatically fed back to the simulator. In this way the agents could possibly adjust their behavior using the behavioral rules set up by the modellers, until the end of the simulation. In our case $t_0+n \cdot t_s = 11$, which is the time between the calibration year (2009) and the end year (2020). A suitable solution to achieve the hard-coupling would be the utilization of the software Brightway2 (Brightway2, 2016), which has the advantage of having an open interface that can be accessed in different ways. For example, one could just write a script, and call it from an external program (the agent-based simulator in this case) or create a distributed remote service that can be accessed from a web browser. Although other LCA software include similar functionalities, they either require the use of a GUI, or are limited to a specific operating system platform, or cannot work as a standalone service provider for third applications.

The final aim of a model like the one we describe in this paper should be informing (e.g. via synthetic impact indicators) policy makers and allowing them the evaluation of the possible (expected) environmental consequences of certain choices. This in order to take better informed policy and development decisions and possibly activate correction actions, if necessary. The model is also accompanied by a web-based interface, through which users (with some limited expertise) can run simulations, changing a limited set of model's parameters. It is also foreseen to allow the communications of users' feedback to the modellers. Ideally, external users of the web-based interface could also communicate directly with decision makers (e.g. via farmers' associations), although this communication channel (represented with the dash dot line in Fig. 3) is probably more difficult to activate.

2.3.2. *Model validation*

Our experience in ABMs suggests the use of the "Simulation and modelling" framework of Zeigler et al. (2000) to evaluate the validity of our model. This would be related to the specific ABM, but as our work is inscribed in the sustainability domain, and LCA in particular, we would also need to look at the validity of the LCA results. However, in this section we will deal only with the validation of the ABM model and not of the LCA background inventory data and of the LCIA results.

Following Zeigler et al. (2000) we could identify elements that would allow defining the validity of the model at replicative, predictive and structural levels. As the model is currently still being refined, we can only consider this first validation as preliminary. Given the nature of our model (a cropping pattern change model with a few interlinked economic and environmental variables) a suitable validation procedure would be what (Topping et al., 2012) refer to as Post-hoc Pattern Oriented Modelling (POM) (Grimm et al., 2005), where the variable to be considered as an indicator for validity will be the overall distribution of crops being planted per year.

Over the simulations run during the construction of the model, the different proportions of crops planted (which altogether make the existing cropping pattern) we observed are in line with the information available for the base year 2009. Although we could quantify the difference between the proportions output by the simulator and the statistics available (from 2009 to 2014) we would not be able to do equally until the end of the simulation (2020) for obvious reasons. Now, if we consider that our model can actually include unforeseen elements in the timeline, such as a change in crop prices, this accounts for at least a first example of predictive validity. Finally, for what concerns the structural validity, we are incapable to asses it at this stage of the development of the model. So far, we have not identified the different transitions that the system would be able to undergo. This is not an inherent characteristic of the ABM in general, but rather an issue in direct relationship to a European agricultural system. With the recent changes in the CAP, the future evolution will certainly modify practices in the agricultural sector (Galán-Martín et al., 2015).

A word of warning must be issued considering LCA results validity. The results of an LCA are expressed in terms of "potential" environmental consequences, but are by nature not suitable to be measured and compared against theoretical values. There is little room to question the scientific groundings of the LCA methodology, but it is impossible to measure exactly which specific actor of an ABM for example produced a given proportion of greenhouse gases. At least from this point of view, validation of the LCA results must be considered with caution.

2.3.3. Stakeholders' interaction

Stakeholders' interaction is part of the so-called *participatory approach* philosophy. Following the classification by Jan Rotmans (2006) our interaction with stakeholders in building the model has conferred them the role of "advisors". In our approach we did not apply neither an *ex ante*, nor an *ex post* evaluation with stakeholders (Smajgl and Ward, 2015), but rather an evaluation *in itinere*. As we built parts of the model we tried to interact with local stakeholders (namely public servants from the Ministry of Agriculture, Vine growing and Consumers' protection, and, in a later phase, the Chamber of Agriculture), showing the functionalities of our model and asking for their advice in terms of missing elements and possibilities to improve the model's capabilities, given the quality (especially the high level of aggregation) of the available data.

Moreover, a preliminary version of the model and the related web-based application was presented in the framework of a workshop organized in early 2015. During the workshop, we tried to highlight the importance and potential added value of using ABMs to steer policy. The audience was composed of about 35 people coming mostly from research environment and a few stakeholders (members of farmers associations, partners of the project, public servants, etc.).

At the end of each presentation, a discussion session was held, during which interaction was promoted. During the various discussion sessions, the following questions were asked to the audience, which was invited to answer on post-it papers to stick on a whiteboard:

1) Do you believe ABMs are potentially a good tool to obtain useful results to base strategic decisions on, or they are too far from a practical application?
2) Let us suppose you had the possibility to design an ABM of the farming system of your country.
   - Who would you ask what?
   - What are the elements you think you would never forget to add to your agents' profiles?

In Table 3 we grouped the main answers to each question.

The attendees were also asked to comment on important elements that an ABM of agriculture should in their opinion have and the addition of the weather component emerged as a fairly shared point. However, it is noteworthy underlining that issues like the difficulty to model structural changes to the system (e.g. when a completely unforeseen event occurs that cannot be modelled given the existing and past data) is a shortcoming plaguing all tools of research from econometrics, to partial and general equilibrium modelling, and time series forecast.

3. Results and discussion

The areas under each crop for each simulation step (i.e. each year), for the scenario with farmers' green consciousness activated by the "index of relative environmental performance" based on the GWP scores of the crops are plotted in Fig. 5. For the same scenario, Fig. 6 shows the areas differences with respect to 2009 and Fig. 7 the related impacts for the climate change (CC) category and the other ReCiPe midpoint categories affected by the most relevant changes. The results for the remaining categories are shown in Fig. S24 of the supplementary material. As one can see, implementing this scenario allows the reduction of the CC effects over the entire simulated period, but it worsens the performances (as compared to 2009) in all the other environmental impact indicators, except the agricultural land occupation (ALO) category.

This fact shows that a plan to reduce environmental impacts based only on one indicator (which in this case is the CC, that is directly linked to GWP and is the most known by the general public) risks to cause burden shifts to other impact categories, thus orienting the decision-making process towards sub-optimal choices. A more comprehensive and holistic approach should be based on an index which encompasses several impact categories.

The main reason for the reduction of the CC impacts is the drastic and rapid decrease of maize cultivation, being maize's impacts on CC higher that the other crops. The reason for that is linked to the nitrogen oxides emissions during the production of nitric acid, which is used for the neutralization of ammonia in the production of ammonium nitrate, used as mineral fertilizer (in the quantity of 150 kg/ha) in maize cultivation. Maize elimination from the crops pattern is also the reasons for the reduction of the impacts on the ALO category. As one can see from Fig. 6, maize is in fact the crop that undergoes by far to the highest loss of area.

ALO shows an increase around years 2013 and 2018 due to rises in the area under other forage crops and triticale (see Fig. 5).

The categories showing the most significant increases are marine eutrophication (ME), terrestrial ecotoxicity (TET), freshwater eco-toxicity (FET), marine ecotoxicity (MET), ionising radiation (IR), and metal depletion (MD). Most of these effects are due to the

Table 3
Answers to the questions asked to the workshop's participants, grouped by background of the respondents.

Answers	Respondents main background
Question 1	
ABMs could be the appropriate approach, but unforeseeable developments and changes of the context of farmers might "overlay" the model development	Computer scientists with limited ABM background; people with some energy background
Can be useful for decision, but should be used for "supporting", not "making" the decision.	Agronomy/agriculture management background
There are limitation because of the irrational behavior of humans and more particularly the independent spirit of farmers. There is potential to study animal population behavior	
ABM could be interesting to model environmental processes for strategic decisions (elements)	Scientists/Engineers from the biomass field
Good tool to feed multi-actor discussions and interactions that can lead at the end to decision making	Agriculture and farming experts
It is a quite fragile tool to rely your decisions on. But, if fed with relevant data, it would be a non-negligible additional piece of information	Energy optimization experts
There is potential in ABMs for practical applications but only if the outcomes are spatially explicit (i.e. maps at the highest possible resolution). However, only if the model abides by the KISS (Keep It Simple, Stupid) principle. Excessive complication keeps the model far from reality	Academic, not better specified
Question 2	
It depends on the purpose. Ask data to the national statistics office. The elements to consider and quantify in the definition of farmers' profiles are: the preference (when making choices) for profit (economic net-benefits), environment and family traditions; the suitability of the soils available in the specific farms; the experience of the farmer with specific crops and also availability of technical equipment and know how; crop rotation issues/schemes; legal aspects (Common Agricultural Policy, subsidies, fertilizers, pesticides)	Computer scientists with limited ABM background; people with some energy background
Behaviors linked to the acceptance and practice of agricultural management practices play a major role in defining sustainable agricultural development	Agronomy/agriculture management background
Ask data to the national statistics institute (STATEC); Ministry of Agriculture; Administration of technical agricultural services (ASTA) for legal regulations, statistics, farmer reactions and behavior; the Service of Rural Economy (SER); CONVIS and other farmers associations (if they exist).	Not specified
Farmers are income-driven, but also strongly legislation-driven. Farmers do not like changing their habits without legal requirements or financial (preferably both) support it might be difficult to influence a change of the current profits	Scientist/Engineers from the biomass field
Administration; Food chain actors; Focus groups. Strongly encourage to work through open questioning.	Agriculture and farming experts
Elements of the EU Common Agricultural Policy (CAP); Input prices, Workload; Land availability.	
Farmers drivers for achieving their financial good or their well-being; EU CAP; Ministry of Agriculture; Farmers associations; Industries producing for agriculture (subsidies, fertilizers).	Agronomy/agriculture management background
How long has the farm been in the "family"? Who will take over, or are they planning to sell when retired? What is the (rough) location (post code)?	Academic, not better specified

increased area of potatoes (see Figs. 5 and 6). The cultivation of this crop requires a high amount (in terms of kg per unit area) of seeds (2520 kg/ha based on (Nemecek and Kägi, 2007) and 2500 kg/ha, considered as optimal value in (KTBL, 2005), i.e. at least 14 times more compared to the other crops). The seeds production generates nitrates leaching from fertilization processes, which causes high impacts on ME (since this category generically accounts for impacts arising from aquatic emissions of N-compounds), on TET and FET (due to heavy metals emissions from fertilization process and from agricultural machines production), on IR (due to electricity use with significant share of imported nuclear energy), and on metal depletion (due to the construction of storage infrastructure). MD impacts are also caused by the production of agricultural machinery used for the field operations. Finally, the increase of MET impacts is caused by potatoes, rye fodder and other forage crops, all of which undergo an increase with respect to 2009, in the simulated scenario. In particular, the process contributing the most to this impact category is the disposal of sulfidic tailings in the production of copper used for the infrastructures of ammonium nitrate (used as fertilizer) manufacturing.

4. Conclusions

Generally speaking, the use as ABM, as opposed to other approaches (in particular top-down approaches, like those based on economic equilibrium models), carries some opportunities, as well as some drawbacks.

Table 4 summarizes our lessons learned from the two approaches. The first column lists various aspects of the modelling exercise and the other columns mention how they are addressed in the two types of modelling approaches.

The biggest challenge in any model is to portray the behavior and the response to external stimuli as accurately as possible. In models with economic underpinnings, the profit motive is the driving force and is a function of the price. The price is either discovered endogenously within the model, or imposed from the outside to study the adjustment response of the system. In typical top-down models there exists a coherent profit maximization structure that accounts for "all" markets in the system and thus accounts for any feedbacks. Computational general equilibrium (CGE) models are a typical illustration of this approach. Using CGE models for every problem is neither feasible, nor appropriate, despite the need for some sort of consistent global price discovery

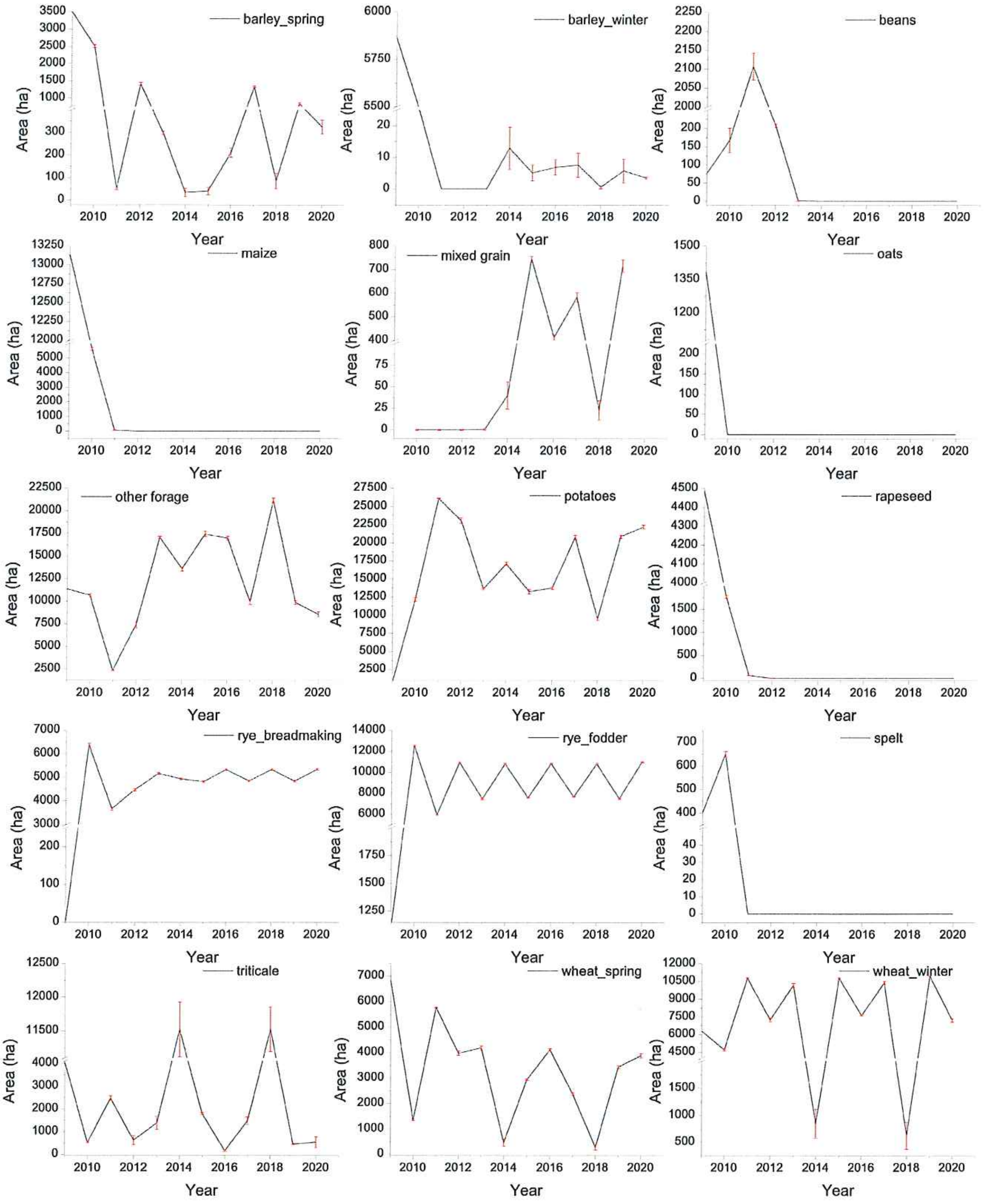

Fig. 5. Areas under each of the crops included in the model for each simulation step (i.e. each year), for the scenario with farmers' green consciousness activated by the "index of relative environmental performance" based only on the GWP scores of each crop. The areas are the means calculated over 90 simulations per each year and the red whiskers represent the standard errors. Note: Compared to the list reported in Table 2, some crops have been aggregated with no loss of information.

as the behavior aspect for a single market is superficial. To model electricity, natural gas, agriculture markets etc., one needs a detailed structural edifice before one can draw meaningful conclusions from shocks. The markets structure on the supply

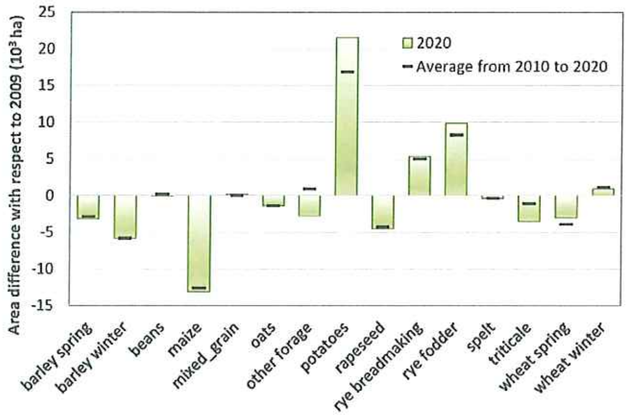

Fig. 6. Areas differences with respect to 2009.

(monopoly, duopoly, oligopoly, perfect competition) and demand side (monopsony, perfect competition etc.) drives the way the model will respond to changes.

In the top-down framework farmers respond to exogenously given prices and based on optimization criteria they modify their land allocation to crops. These exogenous prices are subject to sensitivity analysis and one then observes the variation in the land allocation across crops. One thus obtains a distribution of the Δs needed for conducting a LCA. On a conceptual level, the modeller can model as many farmers as there exist with an optimization problem for each farmer. The difficult arises when one is forced to implement this in practice.

In the bottom-up ABM framework, the prices are also given exogenously, except for the fact that response to shock is not based on optimization principles, but rooted in behavior responses. Thus, based on individual responses on expectations of future prices, attitude to risk, concern for environment, ability to store crops to smoothen inventory etc., the land allocation is decided. Running multiple simulations leads to a distribution of the land allocation across crops. One can build sophisticated mechanisms to endogenise the price discovery process, but this approach has the limitation that the existing information set is the driver for price determination. In such a case, it is difficult (if not impossible) to replicate the volatility in prices, as there is no external information on the price setting. To cite an example, a drought in China or India or war in Ukraine will destroy the output of wheat and impose an upward pressure on the prices. Conversely a bumper crop of maize in USA or Brazil would lead to lower prices for maize. These aspects are starkly missing from the endogenous price discovery and affect both models, although there have been attempts to combine ABM and CGE in a soft coupling fashion, where the price paths derived from the CGE are used to partly parameterize the ABM (Smajgl, 2010). Another approach to overcome this lacuna is using time series forecast methods to generate the prices over time, but this approach also suffers from the usual limitations of time series, in addition to the fact that this data is generated on an annual basis for agriculture.

The ABM models can best approximate the distribution of responses. Thus it becomes difficult to infer the actual adjustment mechanism from the ABM model itself, owing to the numerous parameters prevalent in the model. In principle, both models will tend asymptotically to each other if the top-down approach has the granularity of the bottom-up and the bottom-up has the optimization behavior of the top-down.

From a practical perspective, both models require a complete diverse set of skills to put them into practice. The top-down approach requires competencies in optimization, while the bottom-up requires competencies in object oriented programming. Conceptually speaking, the ABMs are much simpler in their mathematical structure as compared to the top-down approach. After the simulation the ABMs will produce a number that may or

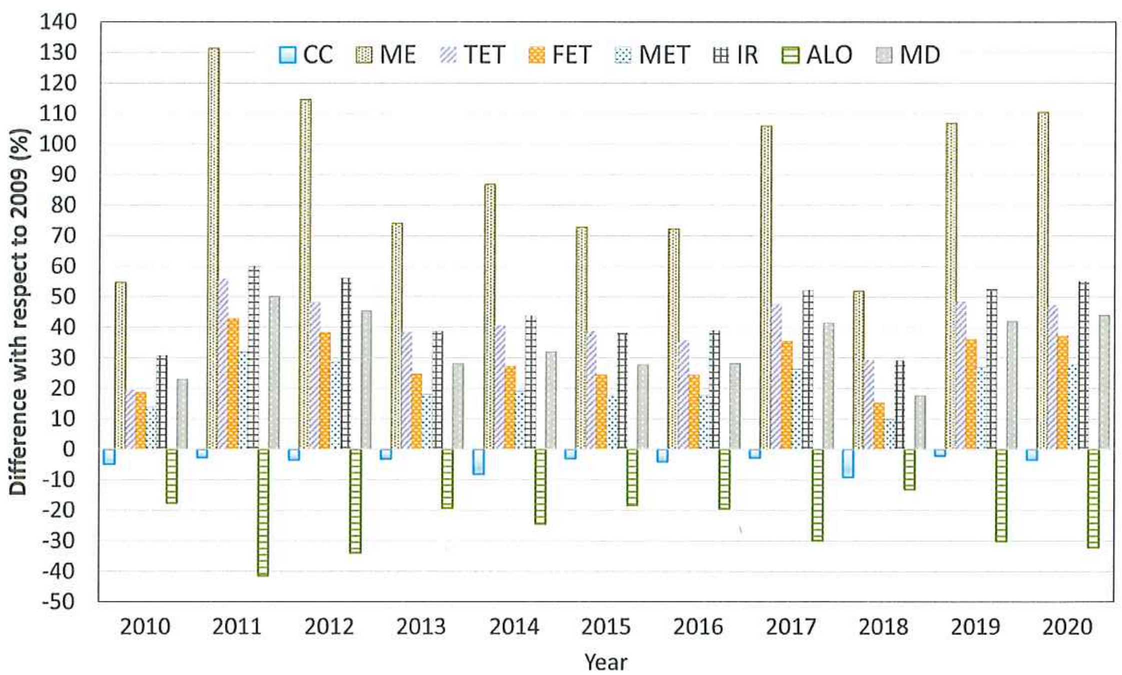

Fig. 7. Variation of the ReCiPe midpoint indicators for the scenario with farmers' green consciousness activated by the "index of relative environmental performance" based only on the GWP scores of each crop. CC – Climate change; ME Marine eutrophication; TET terrestrial ecotoxicity; FET freshwater eco-toxicity; MET Marine ecotoxicity; IR Ionising radiation; ALO Agricultural land occupation; MD Metal depletion.

Table 4
Synopsis of top-down vs bottom-up approaches in agricultural system's modelling.

Issue	Top-down approach	Bottom-up approach
Objectives	Maximise Profits; Environmental Protection	Maximise Profits; Environmental Protection
Number of players	Normally 1 or few but can be 2242 in principle	2242 agents or farms
Price discovery	Any time-series method	Any time-series method
Parameters	Fixed, but in case of 2242 farms, random if data unavailable, else fixed	Random if data unavailable, else fixed
Model Structure	Objective function and constraints (LP/NLP) or just objective function (PMP)	No objective function but behavioral rules and individual responses
Shock	Exogenously imposed as direct change or indirect change via policy tool like subsidy, quotas ...	Only possible via policy tool like subsidy, quotas ...
Social Interaction	Feasible but difficult	Easily incorporated
Behavior	Rooted in optimization, exhibit **"rational"** approach of maximising profits or minimising environmental damage	Some farmers (agents) may exhibit behavior that appears **"irrational"** to the outsider, such as specific crop rotation schemes out of sync with profits
Computing Δs	non-stochastic and depend only on exogenous parameter	Stochastic, even though they depend on exogenous parameters as behavioral response is random under a pre specified distribution
Total shock	Imposed exogenously and if a feasible solution exists one can find an optimal	Difficult to generate the level of aggregate shock due to stochastic response of agents

may not make sense to the researcher and, as seen above, there is limited space for a concrete validation. In the top-down approach, infeasibility of the solution is instead a real practical issue and incorrect parameters or prices may not have a feasible solution given the constraints.

Any other mathematical tool, such as artificial neural networks, time series analysis, logistic regressions etc., would be the same for both approaches and not a distinguishing factor while choosing a particular approach over the other. The main factor discerning the two approaches is the extent of bias that one can accept. In the top-down approach, one has to accept the bias towards optimization while in case of the bottom-up approach, it is one of the possibilities albeit difficult to implement in practice.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jclepro.2016.11.150.

References

Astier, M., García-Barrios, L., Galván-Miyoshi, Y., González-Esquivel, C.E., Masera, O.R., 2012. Assessing the sustainability of small farmer natural resource management systems. A critical analysis of the MESMIS program (1995-2010). Ecol. Soc. 17.
Bandini, S., Manzoni, S., Vizzari, G., 2009. Agent based modeling and simulation: an informatics perspective. J. Artif. Soc. Soc. Simul. 12, 4.
Berger, T., Schreinemachers, P., Woelcke, J., 2006. Multi-agent simulation for the targeting of development policies in less-favored areas. Heterog. Divers. Favour. Areas 88, 28–43.
Bert, F.E., Rovere, S.L., Macal, C.M., North, M.J., Podestá, G.P., 2014. Lessons from a comprehensive validation of an agent based-model: the experience of the Pampas Model of Argentinean agricultural systems. Ecol. Model 273, 284–298.
Bichraoui-Draper, N., Xu, M., Miller, S.A., Guillaume, B., 2015. Agent-based life cycle assessment for switchgrass-based bioenergy systems. Resour. Conserv. Recycl 103, 171–178.
Bonabeau, E., 2002. Agent-based modeling: methods and techniques for simulating human systems. Proc. Natl. Acad. Sci. 99, 7280–7287.
Brankatschk, G., Finkbeiner, M., 2015. Modeling crop rotation in agricultural LCAs — challenges and potential solutions. Agric. Syst. 138, 66–76.
Brightway2, 2016. Brightway2. Advanced Life Cycle Assessment Framework. https://brightwaylca.org/.
Dury, J., Schaller, N., Garcia, F., Reynaud, A., Bergez, J.E., 2011. Models to support cropping plan and crop rotation decisions. A review. Agron. Sustain. Dev. 32, 567–580.
Edmonds, B., Moss, S., 2005. From KISS to KIDS – an "Anti-simplistic" modelling approach. In: Multi-agent and Multi-agent-based Simulation, Lecture Notes in Computer Science, pp. 130–144.
Edwards-Jones, G., 2006. Modelling farmer decision-making: concepts, progress and challenges. Anim. Sci. 82, 783–790.
Filatova, T., Parker, D.C., van der Veen, A., 2009. Agent-based urban land markets: agent's pricing behavior, land prices and urban land use change. J. Artif. Soc. Soc. Simul. 12.
Freeman, T., Nolan, J., Schoney, R., 2009. An agent-based simulation model of structural change in canadian prairie agriculture, 1960–2000. Can. J. Agric. Econ. Can. Agroecon. 57, 537–554.
Frischknecht, R., Jungbluth, N., Althaus, H.J., Doka, G., Heck, T., Hellweg, S., Hischier, R., Nemecek, T., Rebitzer, G., Spielmann, M., Wernet, G., 2007. Overview and Methodology. Ecoinvent report No. 1. Swiss Centre for life cycle inventories, Duebendorf, Switzerland.
Galán-Martín, Á., Pozo, C., Guillén-Gosálbez, G., Antón Vallejo, A., Jiménez Esteller, L., 2015. Multi-stage linear programming model for optimizing cropping plan decisions under the new Common Agricultural Policy. Land Use Policy 48, 515–524.
Galesic, M., Bosnjak, M., 2009. Effects of questionnaire length on participation and indicators of response quality in a web survey. Public Opin. Q. 73, 349–360.
Goedkoop, M., Heijungs, R., Huijbregts, M.A.J., De Schryver, A., Struijs, J., van Zelm, R., 2013. A Life Cycle Impact Assessment Method Which Comprises Harmonised Category Indicators at the Midpoint and the Endpoint Level. ReCiPe 2008.
Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W.M., Railsback, S.F., Thulke, H.-H., Weiner, J., Wiegand, T., DeAngelis, D.L., 2005. Pattern-oriented modeling of agent-based complex systems: lessons from ecology. Science 310, 987–991.
Happe, K., Balmann, A., Kellermann, K., Sahrbacher, C., 2008. Does structure matter? The impact of switching the agricultural policy regime on farm structures. Agent-Based Models. Econ. Policy Des. Based Models 67, 431–444.
Happe, K., Kellermann, K., Balmann, A., 2006. Agent-based analysis of agricultural policies: an illustration of the agricultural policy simulator AgriPoliS, its adaptation and behavior. Ecol. Soc. 11.
Hegselmann, R., 2012. Thomas C. Schelling and the computer: some notes on Schelling's essay "on letting a computer help with the work". J. Artif. Soc. Soc. Simul. 15.
Rotmans, Jan, 2006. Tools for Integrated Sustainability Assessment: a Two-track Approach [WWW Document]. http://academic.research.microsoft.com/Paper/3999336.aspx (Accessed 18 February 2015).
Kaye-Blake, W., Li, F.Y., McLeish, M.A., McDermott, A., Rains, S., Sinclair, S., Kira, A., 2010. Multi-agent Simulation Models in Agriculture: a Review of Their Construction and Uses (No. 318). Lincoln University.
KTBL, 2005. Kuratorium für Technik und Bauwesen in der Landwirtschaft. Faustzahlen für die Landwirtschaft.
Manson, S.M., Jordan, N.R., Nelson, K.C., Brummel, R.F., 2016. Modeling the effect of social networks on adoption of multifunctional agriculture. Environ. Model. Softw. 75, 388–401.
Marohn, C., Schreinemachers, P., Quang, D.V., Berger, T., Siripalangkanont, P., Nguyen, T.T., Cadisch, G., 2013. A software coupling approach to assess low-cost soil conservation strategies for highland agriculture in Vietnam. Themat. Issue Spat. Agent Based Models Socio Ecol. Syst. 45, 116–128.
Marvuglia, A., Benetto, E., Rege, S., Jury, C., 2013. Modelling approaches for

consequential life-cycle assessment (C-LCA) of bioenergy: critical review and proposed framework for biogas production. Renew. Sustain. Energy Rev. 25, 768–781.
Matthews, R., Gilbert, N., Roach, A., Polhill, J.G., Gotts, N., 2007. Agent-based land-use models: a review of applications. Landsc. Ecol. 22, 1447–1459.
McIntyre, B.D., Herren, H.R., Wakhungu, J., Watson, R.T., 2009. International Assessment of Agricultural Knowledge, Science and Technology for Development. Synthesis Report. Island Pres, Washington, DC.
Mialhe, F., Becu, N., Gunnell, Y., 2012. An agent-based model for analyzing land use dynamics in response to farmer behaviour and environmental change in the Pampanga delta (Philippines). Agric. Ecosyst. Environ. 161, 55–69.
Miller, S.A., Moysey, S., Sharp, B., Alfaro, J., 2013. A stochastic approach to model dynamic systems in life cycle assessment. J. Ind. Ecol. 17, 352–362.
Murray-Rust, D., Robinson, D.T., Guillem, E., Karali, E., Rounsevell, M., 2014. An open framework for agent based modelling of agricultural land use change. Environ. Model. Softw. 61, 19–38.
Navarrete Gutiérrez, T., Rege, S., Marvuglia, A., Benetto, E., 2015. Introducing LCA results to ABM for assessing the influence of sustainable behaviours. In: Bajo, J., Hernández, J.Z., Mathieu, P., Campbell, A., Fernández-Caballero, A., Moreno, M.N., Julián, V., Alonso-Betanzos, A., Jiménez-López, M.D., Botti, V. (Eds.), Trends in Practical Applications of Agents, Multi-agent Systems and Sustainability, Advances in Intelligent Systems and Computing. Springer International Publishing, pp. 185–196.
Navarrete Gutiérrez, T., Rege, S., Marvuglia, A., Benetto, E., 2017. Sustainable farming behaviours: an agent based modelling and LCA perspective. In: Alonso-Betanzos, A. (Ed.), Agent-Based Modeling of Sustainable Behaviors, Understanding Complex Systems. Springer International Publishing, Switzerland. http://dx.doi.org/10.1007/978-3-319-46331-5_9.
Nemecek, T., Kägi, T., 2007. Life Cycle Inventories of Agricultural Production Systems (Ecoinvent Report No. 15). Swiss Centre for life cycle inventories, Zurich and Dubendorf.
Parker, D.C., Hessl, A., Davis, S.C., 2008. Complexity, land-use modeling, and the human dimension: fundamental challenges for mapping unknown outcome spaces. Conversat. Divid. Time Place Polit. Ecol. Life-Work Piers Blaikie Biocomplexity Coupled Hum.-Nat. Syst. Study. Popul. Environ. Interact. 39, 789–804.
Parker, D.C., Manson, S.M., Janssen, M.A., Hoffmann, M.J., Deadman, P., 2003. Multi-agent systems for the simulation of land-use and land-cover change: a review. Ann. Assoc. Am. Geogr. 93, 314–337.
Rege, S., Arenz, M., Marvuglia, A., Vázquez-Rowe, I., Benetto, E., Igos, E., Koster, D., 2015. Quantification of agricultural land use changes in consequential Life Cycle Assessment using mathematical programming models following a partial equilibrium approach. J. Environ. Inf. 26, 121–139.
Rege, S., Navarrete Gutiérrez, T., 2015. Modelling price discovery in an agent based model for agriculture in Luxembourg. In: Proceedings of CEF2015. 21st Computing in Economics and Finance (Taipei, Taiwan).
Rounsevell, M.D.A., Pedroli, B., Erb, K.-H., Gramberger, M., Busck, A.G., Haberl, H., Kristensen, S., Kuemmerle, T., Lavorel, S., Lindner, M., Lotze-Campen, H., Metzger, M.J., Murray-Rust, D., Popp, A., Pérez-Soba, M., Reenberg, A., Vadineanu, A., Verburg, P.H., Wolfslehner, B., 2012. Challenges for land system science. Land Use Policy 29, 899–910.
Rounsevell, M.D.A., Robinson, D.T., Murray-Rust, D., 2011. From actors to agents in socio-ecological systems models. Philos. Trans. R. Soc. Lond. B Biol. Sci. 367, 259–269.
Schreinemachers, P., Berger, T., 2011. An agent-based simulation model of human–environment interactions in agricultural systems. Environ. Model. Softw. 26, 845–859.
SER, 2014. Die GAP Reform 2015 im Bereich Direktzahlungen. Ministère de l'Agriculture, de la Viticulture et de la Protection des Consommateurs. Service d'économie rurale (SER).
Smajgl, A., 2010. Challenging beliefs through multi-level participatory modelling in Indonesia. Themat. Issue - Model. Stakehold. 25, 1470–1476.
Smajgl, A., Barreteau, O. (Eds.), 2014. Empirical Agent-based Modelling - Challenges and Solutions. Springer.
Smajgl, A., Bohensky, E., 2013. Behaviour and space in agent-based modelling: poverty patterns in east Kalimantan, Indonesia. Themat. Issue spat. Agent Based Models Socio Ecol. Syst. 45, 8–14.
Smajgl, A., Brown, D.G., Valbuena, D., Huigen, M.G.A., 2011. Empirical characterisation of agent behaviours in socio-ecological systems. Environ. Model. Softw. 26, 837–844.
Smajgl, A., Ward, J., 2015. Evaluating participatory research: framework, methods and implementation results. J. Environ. Manag. 157, 311–319.
Smajgl, A., Ward, J., 2013. A framework to bridge science and policy in complex decision making arenas. Futures 52, 52–58.
Smajgl, A., Ward, J.R., Foran, T., Dore, J., Larson, S., 2015a. Visions, beliefs, and transformation: exploring cross-sector and transboundary dynamics in the wider Mekong region. Ecol. Soc. 20.
Smajgl, A., Xu, J., Egan, S., Yi, Z.-F., Ward, J., Su, Y., 2015b. Assessing the effectiveness of payments for ecosystem services for diversifying rubber in Yunnan, China. Environ. Model. Softw. 69, 187–195.
Squazzoni, F., Jager, W., Edmonds, B., 2014. Social simulation in the social sciences: a brief overview. Soc. Sci. Comput. Rev. 32, 279–294.
STATEC, 2015. Statistics Portal. http://www.statistiques.public.lu/en.
Stoate, C., Boatman, N., Borralho, R., Carvalho, C.R., Snoo, G.R., de Eden, P., 2001. Ecological impacts of arable intensification in Europe. J. Environ. Manag. 63, 337–365.
Topping, C.J., Dalkvist, T., Grimm, V., 2012. Post-hoc pattern-oriented testing and tuning of an existing large model: lessons from the field vole. PLoS One 7, e45872.
UNEP, 2014. Assessing Global Land Use : Balancing Consumption with Sustainable Supply. United Nations Environment Programme (UNEP) - International Resource Panel.
Valbuena, D., Verburg, P.H., Veldkamp, A., Bregt, A.K., Ligtenberg, A., 2010. Effects of farmers' decisions on the landscape structure of a Dutch rural region: an agent-based approach. Landsc. Urban Plan. 97, 98–110.
Vázquez-Rowe, I., Marvuglia, A., Rege, S., Benetto, E., 2014. Applying consequential LCA to support energy policy: land use change effects of bioenergy production. Sci. Total Environ. 472, 78–89.
Vázquez-Rowe, I., Rege, S., Marvuglia, A., Thénie, J., Haurie, A., Benetto, E., 2013. Application of three independent consequential LCA approaches to the agricultural sector in Luxembourg. Int. J. Life Cycle Assess. 18, 1593–1604.
Waldherr, A., Wijermans, N., 2013. Communicating social simulation models to sceptical minds. J. Artif. Soc. Soc. Simul. 16.
Wise, S., Crooks, A.T., 2012. Agent-based modeling for community resource management: acequia-based agriculture. Spec. Issue Adv. Geocomputation 36, 562–572.
Zeigler, B.P., Praehofer, H., Kim, T.G., 2000. Theory of Modeling and Simulation: Integrating Discrete Event and Continuous Complex Dynamic Systems. Academic Press.
Zellner, M.L., Theis, T.L., Karunanithi, A.T., Garmestani, A.S., Cabezas, H., 2008. A new framework for urban sustainability assessments: linking complexity, information and policy. GeoComput. Model. Spat. Agents 32, 474–488.