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Agent-based modelling to simulate farmers' sustainable decisions: Farmers' interaction and resulting green consciousness evolution

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ABSTRACT

Agent-based models (ABMs) have been adopted to simulate different kinds of complex systems, from biological systems to complex coupled human-natural systems (CHANS). In particular, when used to simulate man-managed systems, they allow considering human behavioural aspects within the modelling framework. On the other hand, environmental Life Cycle Assessment (LCA) has become an acknowledged tool in research, industry and policy to assess systems' environmental sustainability. More recently, LCA is being applied to assess the potential environmental impacts of large scale policy actions (e.g., actions to combat climate change). This paper describes the application of a coupled ABM-LCA model to simulate cropping activities in the Grand Duchy of Luxembourg. The ABM considers farmers' proneness to risk, which was assessed via a naïve Bayesian model trained with the results of a survey distributed to the farmers of the study region. The goal of the study is to assess the effects of the agents' interactions, that can take place in a farmers' social network, on the agricultural activities. Geographic Information System (GIS) information, national statistics and naïve Bayesian model are used to parameterize agents' behaviour and interaction rules. We believe such assessment is necessary for the successful design of public adaptation strategies and subsidy schemes since governmental adaptation actions are needed to reduce emissions due to agricultural activities. Two scenarios (with different levels of farmers' environmental awareness) were simulated. The results show that the mean and variance of the distribution of farmers' environmental awareness change due to the effect of the interactions and, as a consequence, farmers' long-term decisions concerning agricultural activities are affected. This is reflected in the environmental impacts generated by such activities.

1. Introduction

Beyond the different possible definitions of sustainability science, the application of advanced analytical–descriptive quantitative tools are recognized as an essential element to guide decision-making towards the goal of meeting human needs, while remaining within a "safe operating space" (planetary boundaries) (Wiek et al., 2012). Hence the concept of quantitative sustainability assessment (Marvuglia et al., 2015), whose final aim is supporting decision-making in a broad context encompassing three dimensions: economic, environmental and social (Heijungs, 2010; Guinee et al., 2011; Sala et al., 2015). One of the most peculiar elements of this extensive assessment is the consideration of the effects of human behaviour as cause, and at the same time effect, of collective actions that are the result of the interaction of social actors. These collective actions are the drivers of the so-called "emerging features" of a system, which rise with no central planning and would not be possible to observe by limiting the analysis to the consideration of single actors or representative actors (Mitchell, 2009).

The above-mentioned components call for important implications of computational social sciences and for a trans-disciplinary approach as essential elements of modern sustainability research (Popa et al., 2015) and inevitably connect to the concept of complex systems when dealing with the human–environment interaction.

In the domain of complex simulations, Agent-Based (AB) Modelling is a well-suited technique to study coupled human-natural systems (CHANS) (Hare and Deadman, 2004; Rounsevell et al., 2012). ABMs are used to assess system-level patterns that emerge from the actions and interactions of autonomous entities (Gilbert, 2008; North and Macal, 2007). They have been applied in recent years, spanning a very wide landscape of application domains, including economics, techno-social systems, and environment (Heath et al., 2009; Heckbert et al., 2010;

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Teglio et al., 2011; Gaud et al., 2008; Gilbert, 2008; Grimm and Railsback, 2005; Wu et al., 2017; Micolier et al., 2019b; Baustert et al., 2019).

Agents can be defined as social autonomous entities that interact with other agents and/or with their environment to achieve their goals when necessary. They can represent a physical or a virtual entity (Ferber and Weiss, 1999). Agents are embedded in a dynamic environment, and are capable of learning and adapting in response to changes in other agents and the environment (An, 2012).

While the agricultural sector has been increasingly threatened by climate change (CC), it is also one of the major sources of greenhouse gas (GHG) emissions. In Europe, the agricultural sector accounted for almost 10% of the total greenhouse gas emissions in 2015 (Hart et al., 2017) and as we explained above, it fits the description of complex systems due to high level of human–environment symbiosis. As a complex system, the use of solely Life Cycle Assessment (LCA) to quantify the environmental impacts risks to underestimate many of the complex characteristics of the domain. In this paper, we will especially focus on a particular field of quantitative sustainability assessment. By using a modelling approach that integrates ABM and LCA (as will be described later in Section 3), this paper evaluates the implications of different farmers' behaviours concerning environmental awareness and their mutual interactions. The modelling framework developed in this work has the potential to simulate the interactions among different actors in the agriculture sector and can be used to incorporate temporal dynamics into sustainability assessment.

The remainder of the paper is organized as follows: Section 2 provides a brief background on ABM-LCA coupling and how social network analysis is combined with ABM. Section 3 explains the conceptual background behind our simulation model and introduces the naïve Bayesian classifier that has been used to estimate farmers' risk aversion attribute. Finally, we discuss the crop rotation strategies that can be attributed to a farmer. A case study that concerns the agricultural land of Luxembourg is introduced in Section 4, where the simulation rules are explained and the flowchart of the adopted simulation methodology is presented. The results for two different scenarios for ten years of simulation are presented and discussed in Section 5. Section 6 discusses the limitations, conceptual barriers and future development of our study and Section 7 draws some relevant conclusions.

2. Literature review

2.1. Coupling ABM with LCA

In its classical implementation, more specifically in the so-called attributional LCA (ALCA) setting, LCA represents the world via static connections between technologies and with linear relationships between production and supply (constant efficiency of production processes and unconstrained market). However, its limitations are being addressed by many researchers since a number of years and the consequential LCA (CLCA) model has been conceived to deal with specific contexts where the underlying hypotheses of ALCA cannot be applied (Weidema et al., 2018; Marvuglia et al., 2013; Rege et al., 2015a). In particular, ALCA reaches its limitations when evaluating complex systems (Davis et al., 2009). In this context ABMs have been advanced to circumvent some of these limitations (Davis et al., 2009). Using ABMs in a consequential LCA (CLCA) (Marvuglia et al., 2013) context can be a valuable option whenever the impacts that one wants to model are ultimately the effect of the interaction of a multitude of actors whose behaviour in the system is difficult to schematize in a rational manner using deterministic equations. In these cases, ABM appears to be a very valuable tool to derive consistent foreground data for the life cycle inventory (LCI) (Davis et al., 2009). According to Davis et al. (2009) ABM complements LCA because it provides a means to create nonlinear dynamic systems, which allow the consideration of social and economic aspects, while ALCA is a tool for linear modelling of static systems. The promises of ABM-LCA coupled models include the consideration of human behaviour and local variability in the studied system, as well as scenario modelling for emerging systems (Baustert and Benetto, 2017).

However, the examples of ABM-LCA coupling are not numerous in the literature because, on one side the ABM paradigm probably still lacks full acceptance in the LCA community, and on the other side, it suffers from the difficulties linked to its implementation. Table 1 resumes the main characteristics of the papers screened in our analysis of the state of the art concerning the coupling between ABM and LCA.

2.2. Agent based modelling on social network dynamics

Social network analysis (SNA) and ABM are both valuable tools to analyse human interactions in a given environmental and societal context. Manson et al. (2016) combined SNA and ABM to model farmer transition to rotational grazing production in the United States (US). In their approach each tie between agents represents a certain type of relationship according to a predefined definition. There are also primary and secondary types of ties, where the former is a strong one (that links the agent with family and friends) and the latter can be a tie with an extension agency or other farmers in the grazing network.

In market research, the integration between these two modelling components was also addressed in multiple studies. Several studies have showed how the choice of a new product may be influenced by the agents' peers (Amini et al., 2012; Goldenberg et al., 2007; Bohlmann et al., 2010). Also an activity such as transition to sustainable mobility was analysed in the same way by Huétink et al. (2010) and Noori and Tatari (2016). The social influence over attitude dissemination has been studied by Moglia et al. (2018) regarding sustainable energy use, and by Kaufmann et al. (2009) to analyse the dissemination of organic farming practices in the European Union (EU).

Using ABM, one can model each agent (in our case a farmer) with its own peculiar characteristics. Each agent can be modelled such that there is no central governance in the model. They can process and exchange information with other agents while making autonomous decisions. This autonomy creates heterogeneity in the model and thus more aggregate phenomena can be developed. Agents can still take decisions based on a pre-specified objective (i.e. they are proactive) or they can learn during the simulations by the experiences or observations and take decisions accordingly. This heterogeneity allows capturing the diverse personality traits, such as emotion or risk aversion and complex psychology.

One of the mechanisms that is most likely to influence the creation of a network, and therefore the occurrence of interactions between agents, is their geographical proximity. Farmers whose farms are close in space are likely to know each other, interact, exchange materials (such as manure) and take advice from each other. Using GIS information in the definition of the agents in ABMs through coupling and embedding is a growing trend in the literature on ABM (Zakrajšek and Vodeb, 2020; Liu et al., 2020).

Farmers' interaction has been often studied using network science tools (Barbuto et al., 2019; Wood et al., 2014). However, our analysis of farmers' networks of practice differs markedly from previous research because the social network layer is interlinked with the environmental layer, expressed in terms of the impacts created by farmers' activities, studied from an LCA perspective.

These are important ingredients for those human-behavioural mechanisms (such as conformity to peers) that influence especially the diffusion of green products and green practices (Byrka et al., 2016; Young, 2011).

Table 1
Summary of the approaches found in literature coupling ABM and LCA.

Authors	Topic, scope, or case study	Approach used	Main assets and limitations
Davis et al. (2009)	Simulation of the evolution of a bioelectricity infrastructure system in The Netherlands.	Energy conversion facilities modelled as a set of agents.	**Assets**: Use of a dynamic set of agents, which can enter or exit the simulation. **Limitations**: LCA not fully dynamic since the agents do not use dynamic production or delivery functions in the background system (Tiruta-Barna et al., 2016). High uncertainty in the economic data.
Davis et al. (2010)	Support stakeholders involved in the development of bio-electricity infrastructure.	Agents taking a certain feedstock and generating electricity. The ABM is underpinned by an Ontology built ad hoc. The exchanges among agents take place in the form of contracts arrangement, bidding and negotiation.	**Assets**: Flows between the agents visualized graphically. Good transparency achieved through visualization. **Limitations**: Integration between LCA and AB simulator achieved via the use of pre-calculated LCA results for several goods. No hard coupling.
Miller et al. (2013)	Lifecycle impact assessment of planting switchgrass by farmers responding to policies.	Stochastic model integrated with LCA module to analyse the effect of decision-making patterns over time. Farmer agents update their degree of switching propensity from cotton to switchgrass and their actions influence the LCA impacts generated.	**Assets**: Farmers switching propensity estimated using Bayesian probabilities and the results used to inform the LCI. Spatial information is included in the model. **Limitations**: Sensitivity analysis and validation not performed. Data availability and uncertainty limit the framework. The model can be used only to understand general trends, but not as a predictive tool.
Querini and Benetto (2014, 2015)	Assess mobility policies, in particular the deployment of electric vehicles in Luxembourg and the neighbouring French region Lorraine under different scenarios.	Coupling an ABM model built in NetLogo, with an LCA model underpinned by ecoinvent 2.2 data modified to take into account the evolution of technology in the car market as well as in the energy mixes.	**Assets**: The model allows to consider several aspects related to customers' behaviour. Consistent example of an effective model for the assessment of new technologies and their penetration into the market. **Limitations**: Model not generalizable to other geographical regions without significant adaptations. Only cars used for private purpose included in the model. LCA model affected by high uncertainties regarding the battery technologies and electricity consumption of electric vehicles (EVs) in 2020. The model cannot be used to assess the impacts of EVs deployment when this reaches a mass dimension at national scale.
Bichraoui-Draper et al. (2015)	Identify the main social and economic factors that contribute to the life cycle environmental performance of switchgrass-based bioenergy, by modelling the adoption of switchgrass as a new crop.	ABM underpinned by 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.	**Assets**: Structure of farmers' decision process well explained, and plausibility the model's results suggested by the similarity with the evolution of genetically engineered soybean adoption. **Limitations**: Model not calibrated for a specific location. Validation missing. GIS extension with real-world spatial information missing.
Wu et al. (2017)	LCA of planting switchgrass by farmers responding to policies	Comparison of two scenarios: a static (predefined) policy scenario model and an ABM. Model developed using C programming language with post-processing and analysis of the outputs in R. Three types of agents: the government, the public, and the developers.	**Assets**: Good level of originality in proposing and applying a general concept to integrate ABM in building LCA standards via the example of a hypothetical city. The model includes a spatial visualization of the results (even though on a fictitious space, using virtual cells). **Limitations**: The results apply only to a hypothetical example using virtual land cells. The model does not specify the types of buildings or stakeholders. Zoning restrictions (about building permits) not considered in the simulations. Validation and sensitivity analysis missing.
Walzberg et al. (2019)	Account for the role of human behaviour on the environmental impacts of technologies. Case study on the use of electricity use in smart homes.	An ABM underpinned by a detailed tree of decision rules for household agents following energy feedback. Each household agent generates a stochastic electricity load profile based on a previously existing method (Paatero and Lund, 2006). The model is run for 100 cities.	**Assets**: Inclusion of dynamic aspects in LCA, allowing to assess the environmental benefit of demand-side management strategies. Modelling of the behavioural aspects, especially the so-called nudge effects. **Limitations**: Use of data from various contexts which may not always represent closely the reality. LCA limited to the use phase and accounting only for electricity use (other sources of energy were neglected). Potential rebound effects not considered.

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3. Material and methods

In this paper we simulated cropping activities in the Grand Duchy of Luxembourg using a modelling framework based on ABM-LCA coupling. In comparison to the model described in Marvuglia et al. (2017), three main improvements have been introduced: (1) a social network of farmers was implemented, in order to model the dynamic interactions between the agents and interpret the changes in their environmental awareness (expressed using the green consciousness attribute already presented in Marvuglia et al., 2017) that may arise from these interactions. The social network is based on the membership of the agents to clusters of different types, that will be explained in Section 3.3; (2) a Naïve Bayesian classifier (used to attribute a level of risk aversion to each farmer), that determines one of the types of clusters mentioned in the previous point; (3) a mechanism for the attribution of elementary agricultural areas to each farm from the available GIS data for Luxembourg. This allowed the construction of realistic farms both in terms of size and location on the territory of the Grand Duchy of Luxembourg.

Table 1 (*continued*).

Authors	Topic, scope, or case study	Approach used	Main assets and limitations
Micolier et al. (2019b)	Investigate the contribution of ABM to behaviour-driven modelling in LCA.	A review of 18 case studies of application of hybrid ABM-LCA models.	**Assets**: A detailed guidance diagram for possible options of ABM and LCA coupling at different LCA phases is presented. **Limitations**: The paper deals only with articles using ABM to enhance LCA, but not with studies where LCA is used to enhance ABM.
Micolier et al. (2019a)	Simulate the occupant-building interaction in one residential building	An ABM block implemented in GAMA used to simulate, via a high-resolution cognitive model, the occupants' interaction with a mono-family building. Physical model block used to simulate thermal balances, energy demand and indoor comfort levels in the building. Every building component, described by using building information modelling (BIM), is agentified and all the components are linked to each other via spatial relationships.	**Assets**: The model makes it possible to detect the effect of any design parameter modification on the occupants' comfort and quantify the impact of the occupant's behaviour on building performances. **Limitations**: The model was not validated for different types of buildings. Difficulty to catch reality and produce precise forecasting. High dependency from data about the occupants (behaviour profiling).
Lan and Yao (2019)	Simulate dynamic farming activities and investigate the impacts of farmers' environmental awareness on large-scale agricultural system. Case study based on a large-scale agriculture system consisting of 1000 farms in North Carolina, U.S.A.	A dynamic system modelling framework that integrates LCA, ABM, and Techno-Economic Analysis (TEA). ABM-LCA model coded in MATLAB 2017a. LCA and TEA coupled with dynamic simulation models of crop yields, costs, and prices. A probabilistic approach used to determine the crop choices, considering crop profitability, familiarity of the farmers with the crop and their environmental awareness.	**Assets**: Model well documented with a clear workflow diagram. The hard coupling allows dynamic modelling in the foreground system. **Limitations**: Uncertainty in the coupled ABM-LCA based on the stochastic approach used to consider the probability in decision making, not discussed in detail. Validation not discussed.
Walzberg et al. (2020)	Evaluating the potential indirect rebound effects arising from smart homes.	The same model presented in Walzberg et al. (2019).	**Assets**: The paper advances the concept of a wide functional unit which evolves dynamically through time. **Limitations**: Impacts other than climate change not considered. Direct environmental pressures from households' consumption were assumed constant in all the simulated scenarios. Study is limited to the use phase and accounted only for electricity use. Further work needed to validate the results.
Kerdlap et al. (2020)	Evaluating different scenarios of plastic sorting and recycling systems.	An ABM programmed in the AnyLogic software to simulate waste generation, collection, sorting, and recycling processes, as well as the interaction between entities (the collection points, sorting and recycling facilities, trucks and incinerators). The coupling with LCA not clear (likely a soft coupling scheme of coupling).	**Assets**: The study takes the standpoint of LCA and clearly defines a real (not hypothetical) functional unit. **Limitations**: Interaction rules among the agents are succinctly described. Data limitations and hypotheses affect the results.
Zupko (2021)	Evaluating biorefinery placement also assessing the impact that a new technology (in this case hydropyrolysis and hydroconversion) can have on a region. The case study is an integrated biorefinery in Ontonagon, Michigan, USA.	An ABM with two primary types of agents: forest owners and loggers. Soft coupling realized between the ABM and the LCA model. Data from the ABM and inventory items manually entered into the LCA software SimaPro 8.5. The functional unit is 1 MJ of gasoline or diesel produced through the IH2 process.	**Assets**: The model includes geographic data loaded in a geographic information system (GIS), thus considering spatial heterogeneity. It is well documented, including a complete Overview, Design concepts and Details (ODD) protocol. Aesthetic impacts of forests are considered. The economic implications on labour market are calculated. The functional unit is clearly defined. **Limitations**: Simulation based still on a virtual forested landscape. Validation neither carried out, nor discussed.

As elicited from the literature review, one of the main priorities one has to bear in mind when embarking on the implementation of an ABM of an agricultural system is the collection of farm-specific data. This issue holds at two levels: at the level of the property and technical activities and at the level of farmers' personal thinking and behaviour tendencies, since a simulation of the evolution in both physical and social dimensions is required to shape large scale socio-technical systems (λ-systems) and steer them towards sustainability (Nikolic et al., 2009).

At the first level the modeller needs data on the crops (yields, agricultural processes and market prices), meat and milk production, land rental costs, time elapsed since the beginning of the rental lease contract, etc. At the level of farmers' behaviour, the modeller needs data on social interaction level, risk aversion, familiarity with a certain technology or trend.

In the model presented in this paper, farmers' social network is built based on farmers' geographical locations, the belonging to previously determined risk aversion classes, and a set of farm-specific attributes. The risk aversion classes are determined via a naïve Bayesian model. The ABM is tightly coupled with the LCA calculator, which is based on the fast LCA calculation framework Brightway2 (Mutel, 2016), thus allowing an automatic calculation at each run of the ABM simulator (*tight-coupling*). From a computational point of view, the ABM outputs become inputs to the LCA final demand vector, as described in Baustert and Benetto (2017). The following sections will describe the model in more detail.

3.1. Farm creation

To achieve better simulation results, defining the components of the farming business and initializing the model accordingly are of utmost importance. As it is the case in most of the applications, data availability and data protection issues represent some important constraint

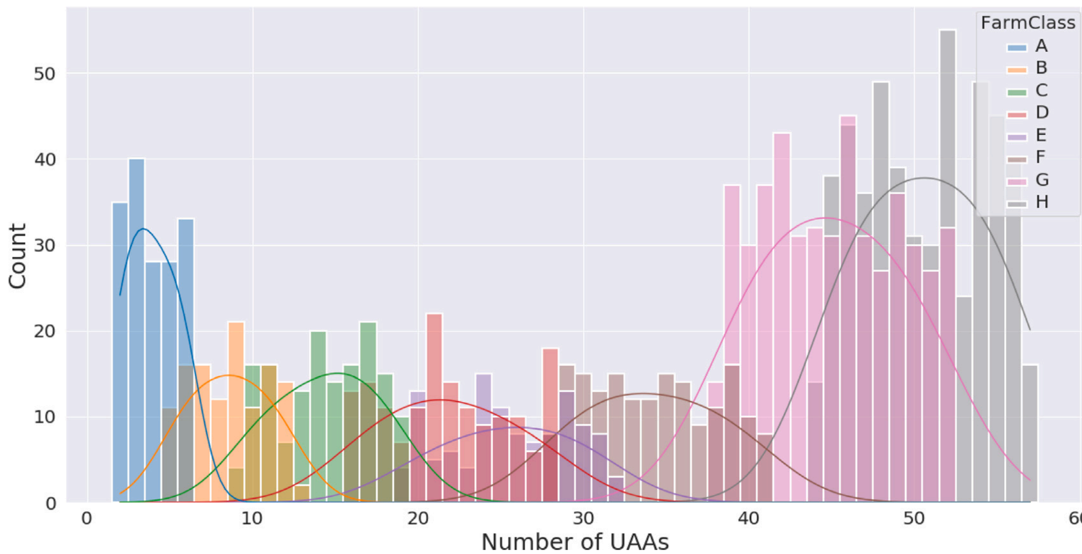


Fig. 1. Histograms of UAAs for each farm class.

Table 2
Number of farms in Luxembourg categorized by the size of their utilized agricultural areas (UAA) (2019).

f_{class}	f_{area} (min.)	f_{area} (max.)	Number of farms
A	–	2 ha	164
B	2 ha	5 ha	119
C	5 ha	10 ha	152
D	10 ha	20 ha	156
E	20 ha	30 ha	114
F	30 ha	50 ha	174
G	50 ha	100 ha	483
H	100 ha	–	510

for the modellers. In our case GIS data are available for the entire country. They contain information about the crop planted each year (from 2010 to 2019) in each elementary agricultural area registered in the national cadastre. For the sake of simplicity, we call these latter "utilized agricultural areas" (UAA). They could be as small as 50 m^2 or as large as 58 ha, are represented in the GIS files as individual polygons and are the smallest land parcels in which information about the planted crops is known. In the GIS file for a given year, the attribute table contains for each UAA the sequence of crops planted in that area in that given year. However, the information regarding the exact farm to which that UAA (i.e. that polygon) belongs is unknown. A known piece of information is instead the distribution in the size-classes (showed in Table 2) of the 1872 farms registered in Luxembourg in 2019. This piece of information is available in the statistics portal of the Grand-Duchy of Luxembourg (STATEC)[1] and on Eurostat.[2]

From the model implementation standpoint, our goal was first to assign geographical information (i.e. a position on a map representing the territory) as an attribute to each agent. This geographical information was then used to build a network among farmers based on geographical proximity. Moreover, in future phases of the model development, geographical information may allow to use weather forecast or soil properties concurrently with the other farm attributes, like farm type (organic vs. conventional or dairy).

To this aim, in order to circumvent the limitation given by the lack of information about the actual locations of the farms on the territory,

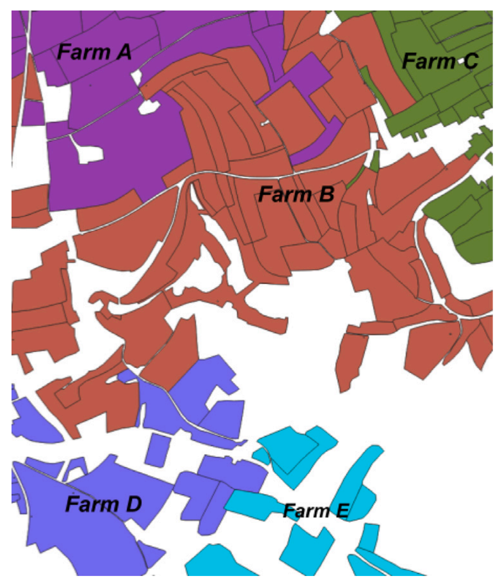


Fig. 2. Detail on a part of the map obtained after running Algorithm 1. Different colours refer to different farms. The contours of the UAAs are visible on the map.

we applied a constrained polygon allocation based on a particular image segmentation technique, called "seeded region growing" (Adams and Bischof, 1994). Using the GIS data and the farms' distribution according to farm sizes showed in Table 2, we created realistic farms, i.e. farms with designated boundaries and reasonable crop patterns in terms of farm types. The pseudo code of the algorithm is given in Algorithm 1. In summary the algorithm consists of the following steps:

(1) Designate the neighbourhood relations amongst polygons based on a given distance threshold.
(2) Start from the largest farm class to allocate polygons to farms. Choose a random UUA (a polygon), then build the farm around it by adding other polygons until the area constraint is satisfied (i.e. until the area of the farm reaches the value randomly assigned to it, within its size-class). Iterate through the farm classes until the total number of farms in the Grand Duchy of Luxembourg is reached.

[1] STATEC — https://statistiques.public.lu/.
[2] Eurostat — https://ec.europa.eu/eurostat/data/database.

Algorithm 1: Constrained polygon allocation

```
M_ij is the binary neighbour matrix;
η is neighbourhood distance threshold;
L_UAA is list of UAAs;
F_class is list of farm classes and attributes;
Function Neighbour(L_UAA, η):
    for i = 0; i < L_UAA.size(); i = i + 1 do
        if Distance(L^i_UAA, L^j_UAA) ≤ η then
            M_ij ← 1;
        else
            M_ij ← 0;
Function Allocate(L_UAA, M_ij, Farm_class):
    sort Farm_class by descending farm size;
    for f^c in Farm_class do
        nFarms ← f^c.numberOfFarms();
        for i = 0; i < nFarms; i = i + 1 do
            area_bound ← PERT(f^c_min, f^c_max, f^c_mean);
            UAA_m ← L_UAA.random();
            farm^area_i ← UAA^area_m;
            while farm^area_i < area_bound do
                N_UAA ← L_UAA.all(x_n : M_mn = 1);
                for UAA_n in N_UAA do
                    if farm^area_i < area_bound then
                        farm^area_i += UAA^area_n;
                    else
                        break;
```

(3) Merge the polygons belonging to each farm and create farm boundaries. If there are non-allocated polygons, then assign them to the closest farm.

Fig. 1 shows the resulting distributions of UAA samples that belong to different classes of farm size. For the sake of providing an example, Fig. 2 shows an excerpt of the map obtained after running the Algorithm 1.

3.2. Naïve Bayesian model for risk aversion attribution

Modelling farmers' risk attitude in farm decision-making is a quite complex task. In farm business optimization models, farmers' risk aversion has been modelled using mathematical programming based on observed farmers' actions or surveys (Norton and Hazell, 1986). The topic of embedding risk orientation in behavioural models of farming systems is briefly discussed by Jones et al. (2017). Van Winsen (2014) uses a qualitative and information-intensive methodology from the social sciences (the *grounded theory*) together with cognitive mapping to elicit a quantitative estimation of farmers' risk perception. Van Winsen et al. (2016) uses structural equation modelling to understand farmers' intention to implement different risk management strategies at their farms.

Few applications of Bayesian models exist, for the assessment of financial risks (Ardia and others, 2008; Krichene, 2017). In Ng et al. (2011) a Bayesian model has been used to update the farmers' expectations of prices, costs, yields, and weather conditions.

As mentioned above, in this paper we implement the risk aversion component of the agents using a naïve Bayesian model, which uses Bayes rule with an assumption that attributes are conditionally independent. This model has been trained with the results of a survey distributed to a sample of farmers in 2015 (see Marvuglia et al., 2017) in the framework of the past project MUSA (MUlti agent Simulation for consequential Life Cycle Assessment of Agrosystems) funded by Luxembourg National Research Fund (FNR). The entire text of the questionnaire is provided as a supporting information file to the paper. We used the level of risk aversion to cluster the agents which are then used to build the network of agents.

In particular, to infer the risk aversion scores we used the answers to the following question (question 66 of the survey):

Among the situations described below, which one seems closer to the level of financial risk that you are willing to take when you usually make investments?

(a) *Taking substantial financial risks hoping to gain a lot.*
(b) *Taking above average financial risks hoping to obtain earnings above the average.*
(c) *Taking average financial risks hoping to have average earnings.*
(d) *Not taking any financial risk*

In our modelling approach, we used the survey data to assign a risk aversion attribute to each farmer. Although there are other questions in the survey that may be related to family values and environmental awareness, we had a low response rate for those questions. If a higher rate of responses had been available for those specific questions, other personal characteristics of the agents could have been integrated into our Bayesian model. However, the current answers to the survey suggest that farm size and farmer's age are the best indicators for a farmer's risk aversion level.

We adopted the simplified abstraction that the risk aversion of farmer agents is described using a discrete variable with two levels (1: low risk aversion, 2: high risk aversion). The four possible answers to question 66 were therefore aggregated in two risk classes. We then estimated the conditional a-posteriori probabilities of a categorical variable (the risk aversion) using the Bayesian theorem under the assumption of independence between predictors. The a-posteriori probabilities can be computed by applying Eq. (1):

$$p(C_k|pred_1, \ldots, pred_n) = \frac{p(C_k)\prod_{i=1}^{n} p(pred_i|C_k)}{p(pred)} \tag{1}$$

where $pred_i$ are the independent predictors, $pred$ is the evidence, $p(pred)$ is the product of the probabilities of the predictors and C_k is the dependent variable.

In our simple model, the dependent variable corresponds to the categorical risk aversion with the two levels described above and farmers' age and farm size are chosen as predictors. The level of risk aversion thus calculated for each agent determines the cluster to which that agent belongs in the social network.

Out of the approximately 2500 farms existing at the time when the survey was deployed, we obtained 168 responses, which were used to derive the a-priori probabilities $p(C_k)$ and conditional probabilities $p(pred_i|C_k)$. When an agent is substituting the crops currently planted, its attributes (age and farm size) are used to estimate the posterior probabilities of its risk aversion, from which the risk aversion is sampled. The two predictors (farmer's age and farm size) are categorized: four age classes ($<35, 35–45, 45–55, >55$) and five farm size classes ($<50, 50–100, 100–150, 150–200, >200$) are used. For each predictor, the categorized data is then converted into a frequency table (Table 3a). Using the frequencies one can estimate the likelihoods in Table 3b and finally posterior probabilities (Table 3c).

3.3. Network of agents

The network is created using mainly two types of relationship between any two farmers: (1) geospatial information with respect to the adjoining farms, and (2) risk aversion group to which a given farmer belongs. Although the first tie is immutable (because we do not consider processes of farms selling or acquisitions), the latter is assigned from a normal distribution among the ones from the same risk aversion cluster. In the network, farmers are the nodes, and ties represent relationships between them.

At the beginning of the simulation, each farmer is assigned with a risk aversion level using the posterior probabilities given in Table 3c.

Table 3
Frequency table used for Bayesian analysis and resulting likelihood and posterior probabilities.

(a) Frequency table of age and farm size

	Age				Farm size (ha)				
Risk aversion level	<35	35–45	45–55	>55	<50	50–100	100–150	150–200	>200
1	3	3	6	2	1	7	2	0	4
2	27	37	34	16	16	49	32	10	7

(b) Likelihood table. The values in italics express the $p(pred|C_k)$.

	Age					Farm size (ha)					
Risk aversion level	<35	35–45	45–55	>55	$p(C_k)$	<50	50–100	100–150	150–200	>200	$p(C_k)$
1	*0.214*	*0.214*	*0.429*	*0.143*	0.109	*0.071*	*0.500*	*0.143*	*0.000*	*0.286*	0.109
2	*0.237*	*0.325*	*0.298*	*0.140*	0.891	*0.140*	*0.430*	*0.281*	*0.088*	*0.061*	0.891
$p(pred)$	0.234	0.313	0.313	0.141		0.133	0.438	0.266	0.078	0.086	

(c) Posterior probabilities for 20 combinations of predictors for each risk aversion level

Farm size (ha)	Risk aversion level (1)				Risk aversion level (2)			
	Age							
	<35	35–45	45–55	>55	<35	35–45	45–55	>55
<50	0.054	0.040	0.082	0.060	0.946	0.960	0.918	0.940
50–100	0.114	0.086	0.170	0.127	0.886	0.914	0.830	0.873
100–150	0.054	0.040	0.082	0.060	0.946	0.960	0.918	0.940
150–200	0.001	0.001	0.002	0.001	0.999	0.999	0.998	0.999
>200	0.341	0.274	0.451	0.368	0.659	0.726	0.549	0.632

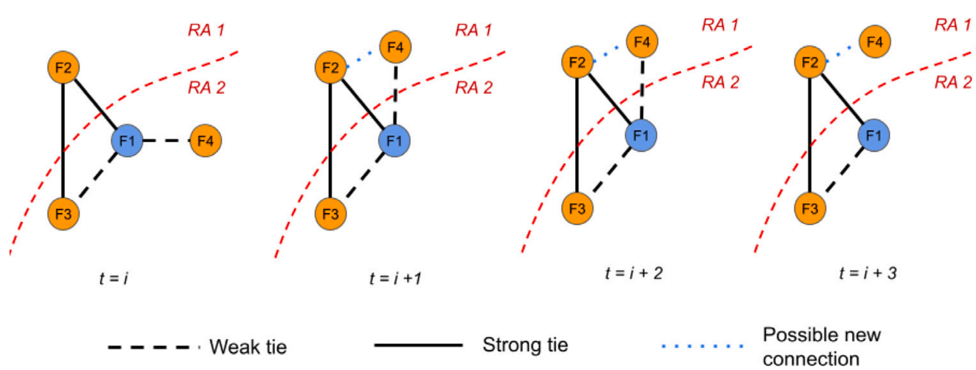


Fig. 3. Schematic representation of the edge addition and removal mechanism during the simulation. The ties between nodes F1 and F2, and between nodes F1 and F3, are strong ties and cannot be removed. Since node F4 changes RA cluster (from RA2 to RA1), the tie F1–F4 is removed after three years. Had node F1 moved to cluster RA1 as well, then the tie F1–F4 would have been kept. As a result of the RA cluster switch, F4 may now form a tie with F2 since they now belong to the same cluster.

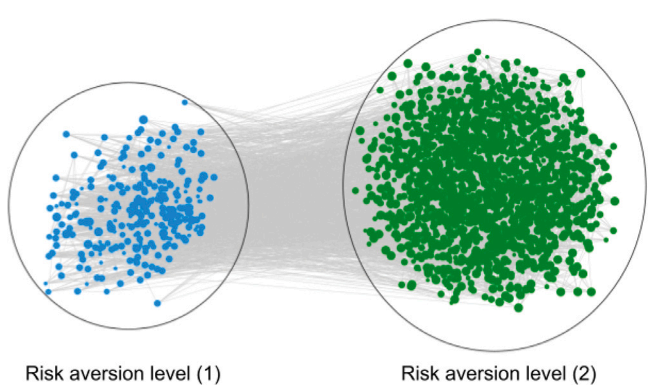


Fig. 4. Network of farmers clustered at the beginning of the simulation according to the risk aversion levels. The edges between the nodes from different risk aversion level clusters are based on neighbourhood relations. The size of each node is proportional to the GC of the farmer. As can be inferred from Table 3c there is a large difference between the number of agents in the clusters. Initially there are 352 farmers in group 1, whereas in group 2 there are 1520 farmers.

Then, the farmers are grouped into two risk aversion levels that are represented in Fig. 4. As the farmers get older during the course of the simulation, their risk aversion levels can also change, therefore at some point they may switch to a different risk aversion cluster. We update the risk aversion level if age class is changed. Each tie has also a weight according to its type. If it is based on the geospatial relationship, then it is a strong tie and we assign a weight $w_{ij} = 0.2$ to it; if it is only based on risk aversion clusters, then we consider it a weak tie and we assign a weight $w_{ij} = 0.1$ to it. The timestep of our simulations is one month, which means the decisions are taken monthly. However, ties are updated yearly only because the risk aversion clusters change as farmers become older. At every timestep (t_i), the decision is taken whether to keep or remove the tie based on its duration and strength. Only the weak ties (the ones based on risk aversion classes) are removed if farmers have switched to a different risk aversion cluster more than three years before the current timestep. An example of tie removal can be seen in Fig. 3.

During the simulation, also the farmer's green consciousness (GC) is updated (Marvuglia et al., 2017). The GC is an attribute assigned to farmers to include heterogeneity in their behaviour in terms of the importance that each farmer decides to assign to the environmental sustainability of the farming strategy undertaken. This attribute influences the decisions taken by each farmer. It is assigned to each farmer from a pre-defined statistical distribution at the beginning of the simulation. The update rule of the GC is described in Eq. (2):

$$GC_j^{t+1} = \frac{GC_i^t}{2} + \frac{\sum_{j=1}^{n} w_{ij} GC_j^t}{2\sum_{j=1}^{n} w_{ij}} \quad (2)$$

Table 4
Crop definitions, families and calendar. The family can be one of cereal (C), leaf (L), fodder (F), maize (M), grain (G), oil (O), permanent (X). Crops are harvested at their respective end months and they can only be planted if there are at least four months between current month and end month.

Crop name	Crop family	Start month	End month	Fertilizer requirement (kg N/ha)
Barley spring	C	3	8	134.5
Barley winter	C	9	7	134.5
Beans	G	1	12	22.4
Maize	M	4	11	134.5
Meadows	X	1	12	88.2
Mixed grain	C	1	12	103.1
Oats	C	3	8	103.1
Other forage	F	4	10	88.2
Others	X	1	12	–
Pastures	X	1	12	88.2
Potatoes	L	4	10	12.5
Rapeseed	O	8	7	67.2
Rye	C	1	12	103.1
Spelt	C	10	8	147.9
Triticale	C	1	12	103.1
Vineyards	X	1	12	22.4
Wheat spring	C	2	8	147.9
Wheat winter	C	10	8	147.9

Table 5
Crop rotation schemes used in the simulations. First the crop history for all the UAAs are extracted then using these common rotation schemes are identified. The ones in bold are assigned to organic farms, whereas the ones in italics can be used in both conventional and organic farming. The rest is generally used in conventional farming.

Crop history extraction (Step 1)		
$LUAA_1$ (CCFFCCFFCC)		
UAA_2 (FFMOCFFMOC)		
UAA_3 (FFGFMOCMOC)		
⋮		
UAA_n (FLCFMMFLCF)		
Identifying common rotation schemes (Step 2)		
3-gram	4-gram	5-gram
MGF	*LLCC*	FFMOC
FCC	FFMM	
MOC	FFCC	
LFF		
LLC		

where GC_i^t is the green consciousness of ith agent at time step t; n is the number of neighbours an agent has in the network; w_{ij} is the weight of the link between the ith and the jth agent.

3.4. Crop rotation modelling

In the simulation we used different crop rotation schemes which were pre-assigned according to the initial crop pattern of a farm. These rotation schemes were extracted from the GIS files mentioned above. Firstly, the crops present in the GIS files were assigned to a family as shown in Table 4. The crop plantation times have been suggested by the experts on farming in Luxembourg. The crop rotation schemes were determined by extraction of common recurring n-gram substrings for a given list of UAA plantation history. In Table 5, one can see the common 3-4-5-grams which are used as crop rotation schemes in the model. The sequence of the letters in each n-gram corresponds to the time sequence of crop family on a given UAA. We first found the sequence of crops as shown in the step 1 of Table 5. Although most UAAs have not been changed throughout the years (according to the records of the local agricultural cadastre), few of them have been merged or split into different UAAs in the course of time. This happened only for a small amount of UAAs, and we discarded them when searching for the common rotation schemes. There are also multi-cropping (or intercropping) cases, i.e. cases in which there is more than one crops planted in the same UAA in one year. We also excluded those from our dataset since our model does not yet account for such cases. After we found the common n-grams, these were then discussed and validated by the project partners with farming expertise in the Luxembourgish context, who separated the ones used for organic and the ones used for conventional farming. In Table 5, the ones in bold show the organic rotation schemes, bold and italic is used for both conventional and organic and the rest is only for conventional farming.

Obviously, at the moment when the decision takes place, in order to be eligible for being planted, a crop has to fit in the list of suitable crops determined by the crop rotation constraints and the crop calendars (i.e. the typical planting seasons).

4. Case study: an agent-based agricultural model in Luxembourg

The focus of this paper is mainly on the enforcement of some agents' social interaction mechanisms and the observation of their influence on the life-cycle environmental impacts they generate, due to their influence on farmers actions. In order to do this, we observe the evolution of the network of agents under two scenarios that differ in terms of the initial values assigned to the GC parameter (Gutiérrez et al., 2017; Marvuglia et al., 2017). More details on the structure of the model, not concerning the agents' interaction mechanism, are given in Gutiérrez et al. (2017) and Marvuglia et al. (2017). Fig. 5 shows the initial GC distribution functions used in this study.

In our model, an agent looks at the midpoint climate change impacts of each crop per ha of cultivation (in addition to its selling price on the market) before deciding which crop to plant at the end of a rotation cycle. The climate change impacts are calculated using the ReCiPe 2016 (Huijbregts et al., 2017) life cycle impact assessment (LCIA) method based on life cycle inventories (LCI) that have been refined for Luxembourg via consultation with local experts, as explained in Rege et al. (2015a) and Vázquez-Rowe et al. (2014) and Marvuglia et al. (2017).

Simulation As in Marvuglia et al. (2017), from the LCA perspective, the functional unit is represented by the entire cropland area of the country, with the exclusion of pastures, vineyards and orchards, whose area remains constant over the years and is not affected by crop rotation choices. We simulate each scenario for a time span of ten years with a simulation timestep of one month. This procedure is repeated 50 times for each scenario and the results are averaged. In each scenario run, a different initial random seed is specified, while the same seeds are applied across scenarios to assure that differences between scenarios for a model run are not due to different seeds being used. This initial random seed is used to produce other random seeds used by the components of

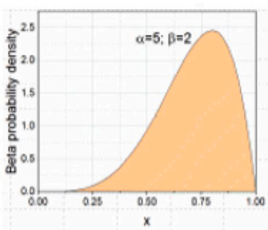
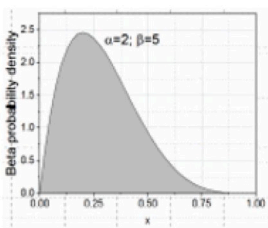
Distribution	Parameters
	GC_{high}: GC is distributed to the agents with a Beta probability function with shape parameters $\alpha = 5$ and $\beta = 2$. This means that the probability of an agent to be initialized with $GC > 0.5$ is higher than of being initialized with $GC < 0.5$.
	GC_{low}: GC is distributed to the agents with a Beta probability function with shape parameters $\alpha = 2$ and $\beta = 5$. This means that the probability of an agent to be initialized with $GC < 0.5$ is higher than of being initialized with $GC > 0.5$.

Fig. 5. GC initialization scenarios.

the simulator that require random number generation. Random number generation is involved in the following processes inside the simulator: the initialization of the crops assigned to each agent, as well as the rotation scheme; the initial assignment of risk aversion level and GC value. The results of each simulation are the areas cultivated under each crop and parameters that are affected by the evolution of the network, such as GC values, risk aversion clusters and tie strength. A flowchart showing the logical sequence of the simulation steps is showed in Fig. 6.

At the end of each timestep, each farmer has to take a decision for the next timestep. The farmer has to decide which crop to plant, if in the previous timestep the crop had been harvested. This decision is primarily based on crop rotation and crop calendar constraints, but the agent also chooses according to its current GC level. If it is below a pre-specified level η, then the most profitable crop is chosen for the next timestep. Otherwise the agent looks at the ReCiPe 2016 midpoint CC impacts of possible crops (i.e. crops which are eligible because they respect the crop rotation schemes constraints and the crop calendars) and chooses the one with the lowest impact. The crop's selling price on the market is decided based on the Holt-Winters time series prediction model, as described in Rege et al. (2015b). Although the value of η affects the LCI results, the objective of this study is to explore the interactions and their effects on agents' behaviour. Therefore, in this study η is fixed and it is equal to 0.5 in every simulation.

5. Results and discussion

Fig. 7(a) and 7(b) show the time evolution of the crop areas (i.e. the sum of all the UAA cultivated with the same crop in the entire territory of the Grand Duchy of Luxembourg) for each of the two GC initialization scenarios and each crop. For each scenario and crop, the plotted areas are the average calculated over the 50 model runs. It can be easily observed that in both cases the total UAA for triticale, rye fodder, other forage, beans and barley spring fodder and barley spring brewing increase significantly, because they replace other crops (like maize and wheat spring) from the start until the end of the simulation. Some of these crops, like beans and oats, represent only a small portion of the total UAAs (see Table 6), therefore they do not have a significant contribution on impacts' reduction. In fact, since the CC midpoint is the main contributor to HH impacts (51% for the first year), values of the GC variable higher than the fixed 0.5 threshold also contribute to the decrease of HH impacts. For example, the choice of barley, oats, beans and triticale crops reduces both CC and HH impacts compared to wheat, maize and spelt (Fig. 8).

It is worth noting also that the crop areas are subject to fluctuations, due to the implementation of the crop rotation, which causes an alternation of the crops and prevents the permanence of the same crop on the same UAA on two consecutive crop rotation periods. For this reason, one should not observe only a single year crop pattern, but needs to observe the evolution of the crop areas of each crop over time and consider their average trend. The same consideration holds also for the evaluation of the environmental impacts related to each scenario. Fig. 7(c) and 7(d) show the LCIA results for three different endpoint values obtained with the ReCiPe 2016 method, for 10 consecutive years, respectively for the scenarios GC_{high} and GC_{low}. In Table 6, average UAAs for 50 simulation runs are given for the baseline year and the last year of the simulation (as well as the percentage differences between the two) for the same two scenarios GC_{high} and GC_{low}.

As Table 6 shows, throughout the simulation, in the UAAs that hosted wheat and maize, these two crops are replaced especially with rye, triticale, beans and barley. These latter crops are therefore the main responsible for the decrease of HH impacts that one can observe in Figs. 7(c) and 7(d).

In Table 4 the nitrogen requirement of each crop is given. Although in this version of the model agents do not take livestock-related decisions, we initialize each farm with a certain number of cattle heads in order to be able to calculate the quantity of organic manure produced by the cattle that is used as soil fertilizer. According to FAO (2018), one cattle unit in Luxembourg produces 60.92 kg N per year on average, of which 48% stays on the ground, while the rest is stored for spreading. The nitrogen loss is estimated to be 42% when it is stored. For instance, in the first year of our simulation the organic manure stored and readily available for spreading (3516 tons of N content) corresponds to only half of the nitrogen amount (6952 tons of N content) required by crops. The remaining amount that is required by each farm is compensated with mineral fertilizers, since breeding other types of animals (and therefore relying on other types of organic manure) is not very common in Luxembourg.

Tables 7 and 8, report the main descriptive statistics for the LCIA results of the last year of the simulation, respectively for the cases of GC_{low} and GC_{high}. They are calculated over 50 simulation runs. The HH impact score is the one affected by the highest variability. As Figs. 7(c) and 7(d) show, in both scenarios the general trend is towards a global decrease of the HH impact. This decrease is more pronounced in the scenario GC_{high}. In both scenarios the impacts on resources do not change significantly over the years, however there is also a slight decrease in the ecosystem quality impact category in both cases. The fact that HH is consistently decreasing is not surprising, as in the current version of the model environmentally conscious agents (i.e. those with $GC > 0.5$) only look at crops' ReCiPe 2016 CC impacts (which are the main contributors to the HH endpoint category). This obviously creates a trade-off with the other impacts. In fact, the crops that have a worse impact than others both in terms of CC and the other impact categories, like maize and wheat, are those for which a decrease in the area results also in a decrease of the total impacts on impact categories different from CC. However, there could be cases when a crop being replaced because of its high CC impacts, has nonetheless lower impacts in other categories than the crops from which it is replaced. This is the case for maize, since it has lower impact on freshwater eutrophication compared to triticale or other forage. Thus, the simulations show a slight increase in total freshwater eutrophication in both scenarios (2% for GC_{high} and 0.3% for GC_{low}). In terrestrial ecotoxicity, the decrease is even more pronounced since the contribution of maize is much higher than for other crops.

However, these results suggest that starting from a left skewed GC distribution ($\alpha = 5$ and $\beta = 2$) produces slightly better results (at

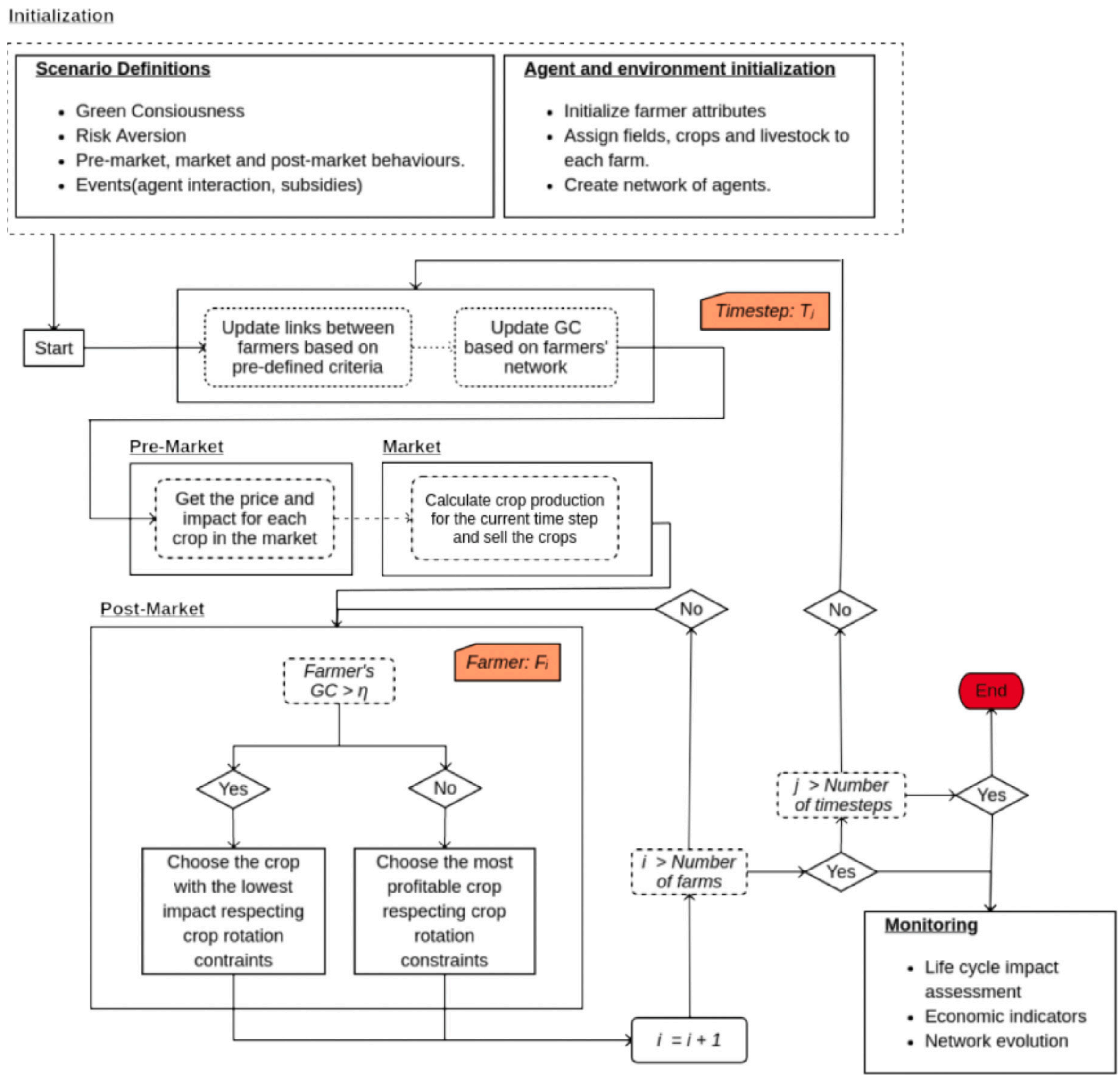
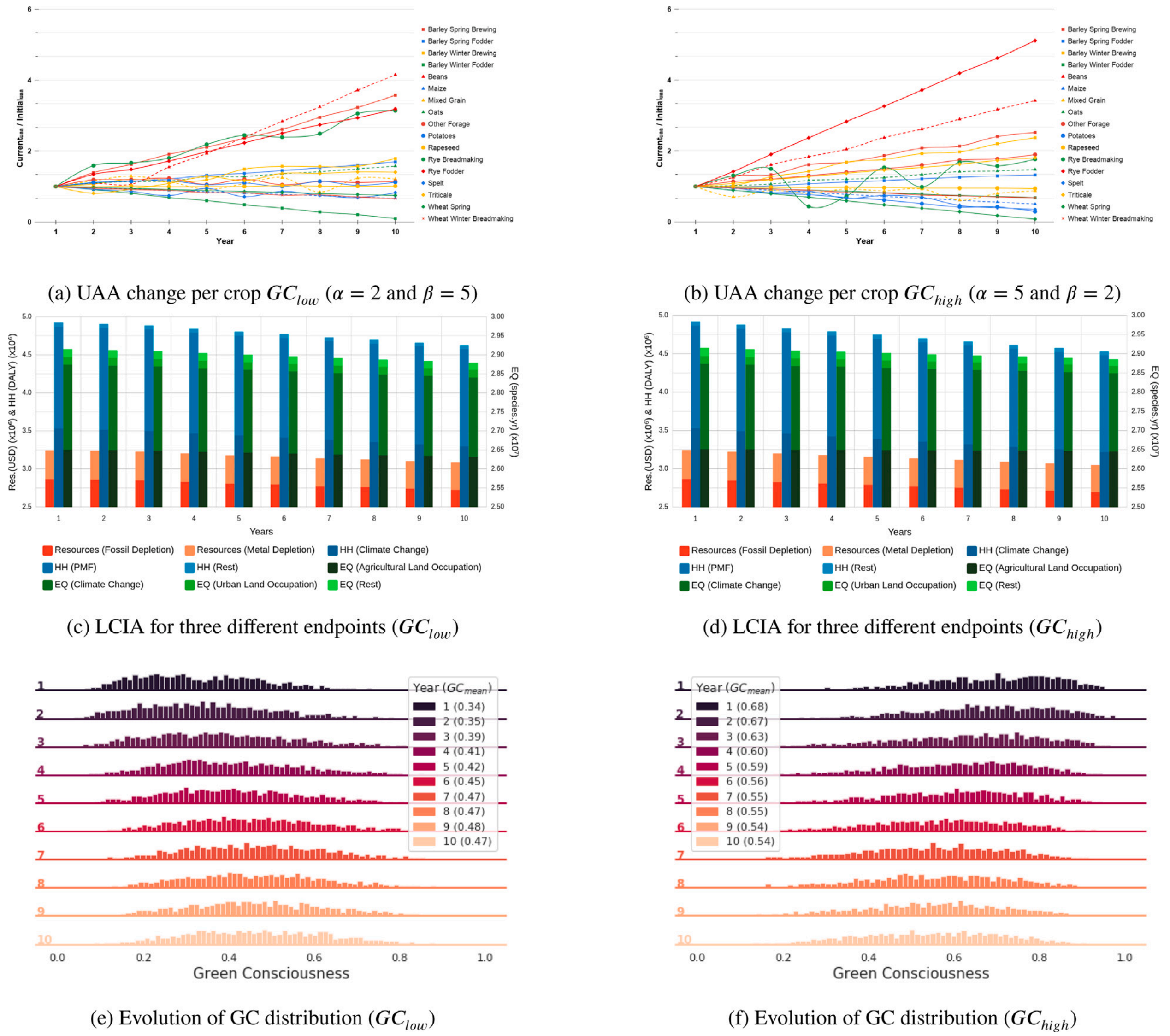


Fig. 6. Simulation flowchart.

Table 6
UAA of each crop in the baseline year and in the last year of simulation, and respective percentage area changes in both simulation scenarios.

Crop	Initial UAA (ha)	Last UAA (ha) (%) (GC_{low})	Change (ha) (GC_{low})	Last UAA (ha) (%) (GC_{high})	Change (ha) (GC_{high})
Barley spring brewing	729	2664 (265%)	1935	1685 (131%)	956
Barley spring fodder	2671	4660 (74%)	1988	3526 (32%)	855
Barley winter brewing	627	1152 (83%)	524	1267 (101%)	639
Barley winter fodder	5881	565 (−90%)	−5315	4050 (−31%)	−1830
Beans	711	3172 (345%)	2460	2531 (255%)	1819
Maize	13929	8844 (−37%)	−5085	6677 (−52%)	−7252
Mixed grain	336	414 (23%)	78	343 (2%)	7
Oats	1553	2466 (58%)	912	2295 (47%)	742
Other forage	4882	5635 (15%)	752	10772 (120%)	5889
Potatoes	816	942 (15%)	126	231 (−71%)	−585
Rapeseed	4781	4927 (3%)	145	4560 (−4%)	−220
Rye breadmaking	121	431 (256%)	310	203 (68%)	82
Rye fodder	1297	4377 (237%)	3079	7276 (460%)	5978
Spelt	576	506 (−12%)	−69	170 (−70%)	−405
Triticale	4456	6284 (41%)	1827	7981 (79%)	3525
Wheat spring	7054	5333 (−24%)	−1720	568 (−91%)	−6485
Wheat winter breadmaking	3418	2289 (−33%)	−1129	2330 (−31%)	−1088
Wheat winter fodder	3611	2788 (−22%)	−822	982 (−72%)	−2629



(a) UAA change per crop GC_{low} ($\alpha = 2$ and $\beta = 5$)

(b) UAA change per crop GC_{high} ($\alpha = 5$ and $\beta = 2$)

(c) LCIA for three different endpoints (GC_{low})

(d) LCIA for three different endpoints (GC_{high})

(e) Evolution of GC distribution (GC_{low})

(f) Evolution of GC distribution (GC_{high})

Fig. 7. UUA change per crop, expressed as the ratio between crop areas at every timestep and area under the same crop at year 1 7(a) and 7(b). LCIA results over the years 7(c) and 7(d) where Res. denotes the Resources impacts, HH denotes human health related impacts and finally EQ denotes ecosystem quality. Evolution of GC distribution due to network and GC update rules 7(e) and 7(f) for scenarios GC_{low} and scenario GC_{high}, respectively. In Figs. 7(e) and 7(f), the mean value of each GC distribution is indicated in the legends next to the corresponding year of the simulation.

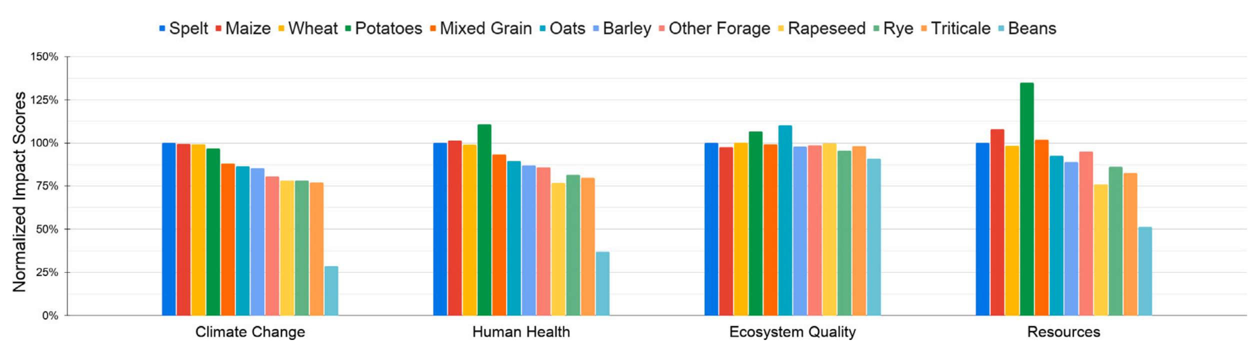


Fig. 8. Comparison of CC and endpoint impact of crops per hectare. The impact score are normalized to the one of spelt, which has the highest impact on CC.

least in terms of the variable that is directly targeted by the agents' actions, i.e., in this case the CC impact of the crops and its consequent effect on the HH impact category) than starting from a right skewed GC distribution ($\alpha = 2$ and $\beta = 5$) (with a mean value of 0.38; see Fig. 7(e)), even though in both cases we observe that, as an effect of agents' interaction, the Beta distributions representing the probability density function (pdf) of their GC values tend to become symmetric (converging towards a distribution centred in $GC = 0.5$) and undergo only a small variation of their skewness approximately after five years. The result does not suggest a very clear advantage of one starting GC initial

Table 7
Main descriptive statistics of the LCIA results in 50 simulation runs for the last simulated year (GC_{low}).

	Resources ($\times10^6$)	Human health ($\times10^6$)	Ecosystem quality ($\times10^6$)
Minimum	3.08	5.28	28.7
Mean	3.17	5.45	28.9
Standard deviation	0.05	0.11	0.1
Maximum	3.24	5.60	29.1
Coefficient of variation	1.79%	2.09%	0.43%

Table 8
Main descriptive statistics of the LCIA results in 50 simulation runs for the last simulated year (GC_{high}).

	Resources ($\times10^6$)	Human health ($\times10^6$)	Ecosystem quality ($\times10^6$)
Minimum	3.05	5.18	28.85
Mean	3.14	5.39	29.00
Standard deviation	0.06	0.13	0.09
Maximum	3.24	5.60	29.14
Coefficient of variation	2.07%	2.59%	0.33%

distribution over the other and suggests that there is probably still much to learn about the diffusion of ethical behaviours through social networks in general, and the diffusion of farming practices through the agricultural sector in particular. Survey practices from social sciences are needed to measure predictors for "green" or ethical behaviour, building the basis for behavioural models that take into account these predictors along other factors (such as risk aversion) to predict choices relating to farming practices. These predictors and practical constrains need to be considered in order to understand the behaviour of a system at a more aggregated scale.

Each individual agent updates the GC value at every timestep. Therefore the initial distributions showed in Fig. 5 change at every timestep. The evolution of GC distributions can be seen in Figs. 7(e) and 7(f). As one can observe, for both scenarios the network and update rule given in Eq. (2) help the agents to reach a quasi steady distribution of the GC values, which is approximately a symmetric Beta distribution ($\alpha = \beta$). It is worthy noting that this convergence effect that brings to a stable distribution after approximately the same number of timesteps in both scenarios is a consequence of the fact that in Eq. (2) one part of the updated GC value of each agent depends on a weighted average of the GC values of its neighbours, therefore a sort of equalization effects takes place. This would be different if some other update rule was put in place, whereby the agent could also have a certain probability to have a GC value higher (or even significantly higher) than its neighbours at the next timestep.

Model validation In this context, validating the ABM that is coupled with an LCA model, does not mean validating the LCA model the ABM is meant to feed. The ABM results are used only as inputs to the LCA module. As in any LCA study, the assumptions behind the LCA model, as well as the quality of the LCI data, will obviously influence the final results of the environmental assessment. In addition to that, one has to remember that, while the LCI data, at least the so-called *foreground data*, can be partially validated (with measurements, experts' opinions, etc.), validation of LCIA results is impractical. However, their consistency with previous literature can be checked. They are expressed in terms of "potential" environmental impacts (on humans and on ecosystems), but they cannot be directly measured and they cannot be compared against "actual" impacts, because of the life cycle scope and of the relative approach considered in LCA. Empirical validation of LCA results per se, is therefore not possible in practice. The validity of the LCA results rests upon the validity (based on scientific consensus) of characterization models applied in LCIA, which are very difficult to validate (Hauschild and Huijbregts, 2015).

Uncertainty A similar line of reasoning holds about the uncertainty by which the results of the coupled ABM-LCA model are affected. They obviously carry the uncertainty of the ABM data and assumptions (e.g., on risk aversion, crop prices, level of social interaction, network rules, etc.), but also the uncertainty of the LCI data. Like for the ABM model, also for the LCA model sensitivity analysis can be used to study the robustness of results and their sensitivity to uncertainty factors. Dealing with uncertainty and sensitivity analysis in our ABM-LCA model is outside the scope of this paper. A very informative description on sensitivity analysis in LCA can be found in Wei et al. (2015), while the topic of uncertainty analysis in LCA models is extensively described in Igos et al. (2019) and in the context of ABM-LCA coupled models is addressed in detail in Baustert and Benetto (2017).

In our model the locations of uncertainty could be in the inputs (data uncertainty) or in the model itself (structural uncertainty). For instance, each process in the LCI includes its own uncertainty, and the forecasted crop prices bear their uncertainty as well. Furthermore, the model includes random assignment of certain parameters like GC or RA, which are locations of structural uncertainty (Baustert, 2021). To address the uncertainty due to random variables and the way agricultural areas are assigned to farms, we ran a set of simulations and calculated the coefficient of variations of the corresponding LCIA endpoint categories. Tables 9–10, summarize the outcomes of the uncertainty analysis. The first set of results presented in this paper, referred to as the base case (U_1), use the same farm locations in all of our 50 simulations, but different random seeds are used for the sampling of the GC and RA. In the second case (U_2), we sample GC and RA values using the same random seeds in each of 50 simulations, but field allocations are different for each simulation. Therefore, the connections of each agent can be different since the geographical locations of farms were changed. For the third (U_3) and fourth cases (U_4) we assign the same elementary agricultural areas to a farm and keep the random seed for RA and GC the same. The coefficients of variation do not vary significantly compared to the base case in both scenarios. The endpoint category which is most affected by the variation in parameters is HH, and the least affected is EQ. Model inputs, such as the product prices,are another possible location of uncertainty. In our simulations we use the same set of prices for every year; they are reported in Table S5 of the supporting information file. The agricultural product prices in Luxembourg follow the world prices, and thus they are considered exogenous. Further investigation could be made in future versions of the model by assessing the effects of price changes due to external market conditions or climatic changes.

Treemap representation of impacts Fig. 9 shows the treemap representation of the cantons (based on Ghoniem et al., 2015) of the Grand Duchy of Luxembourg. The colours represent the HH LCIA results normalized by area of each canton in the country and averaged over the simulation duration of 10 years and the number of simulations per year ($n = 50$). The emissions are normalized by the total UAA in each canton. This representation differs from regular treemap representations as it also respects the real geographical boundaries of locations, still remaining a privacy-preserving representation. As one can see from the figure, the canton that includes Luxembourg city has the lowest total agriculture-related CO_2-eq emissions, due to the fact that it is the most densely built area, therefore with the lowest extension of agricultural

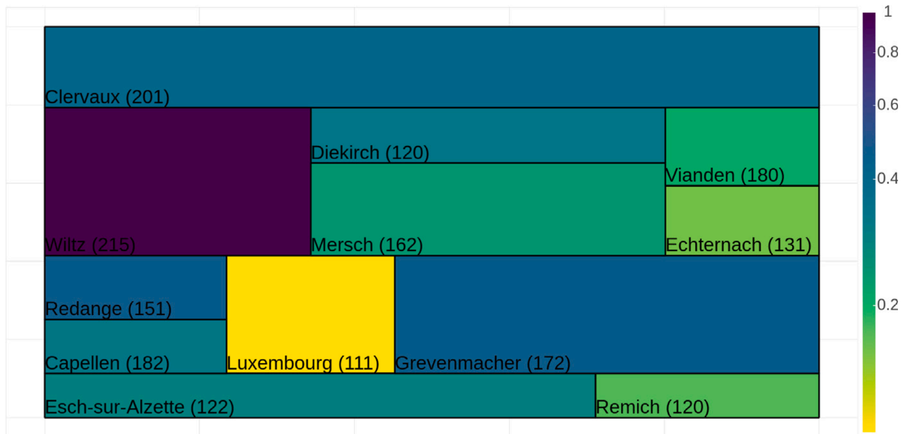


Fig. 9. Treemap representation of the CC impacts normalized to the total agricultural area (kg CO_2-eq/ha) of each canton in the Grand Duchy of Luxembourg averaged over simulation duration and number of simulations. The numbers in brackets represent the number of farms falling within the territory of each canton.

Table 9
The coefficient of variation for a chosen parameter (GC_{low}).

Case	Description	Resources	Human health	Ecosystem quality
U_1	Coefficient of variation (Base)	1.79%	2.09%	0.43%
U_2	Coefficient of variation (Farm Locations)	1.72%	2.04%	0.32%
U_3	Coefficient of variation (GC)	1.77%	1.92%	0.30%
U_4	Coefficient of variation (RA)	1.85%	1.88%	0.33%

Table 10
The coefficient of variation for a chosen parameter (GC_{high}).

Case	Description	Resources	Human health	Ecosystem quality
U_1	Coefficient of variation (Base)	2.07%	2.59%	0.33%
U_2	Coefficient of variation (Farm Locations)	1.82%	2.03%	0.30%
U_3	Coefficient of variation (GC)	2.00%	2.15%	0.35%
U_4	Coefficient of variation (RA)	2.01%	2.45%	0.31%

area of the entire country. The same information has been calculated at the level of granularity of the single farm; however, the representation in a figure would result in very low readability, therefore it is not showed here.

6. Limitations of the model

The analysis accomplished in this paper certainly does not provide the entire picture about the interaction between farmers in the Grand Duchy of Luxembourg and their behaviour towards certain agricultural activities, since a few elements are currently missing. The first element is the absence of meat and milk production, which is quite important in Luxembourg, given the fact that practically all the farms in the country are of a mixed type (they produce at the same time crops, meat and milk). Another potentially important missing element is the simulation of the land rental market. For example, as observed by Appel et al. (2016), the farms which tend to invest on biogas are in general very competitive on the land market and are willing to pay higher rents for land and the most efficient (biogas) farms are the drivers of rental prices. If one models a real market, then the duration of the lease contract has an influence on the model because it determines the moment in time when the market can experience variations on the distributions of land among the farmers. This is particularly relevant in the Grand Duchy of Luxembourg where the cost of the land is very high and there are a few land owners, while the majority of the farmers simply rent the land. The duration of the lease periods can vary depending on the land law. For example, in the Grand Duchy of Luxembourg the minimum duration of a lease contract for a piece of agricultural land is 15 years, and then it is automatically prolonged for 15 more years, unless the lease is resolved by one of the parties 5 years before the expiration date (ASTA, 2016). The rate of missing answers we got to the question of the survey that was related to the size of the rented area, the total duration of the lease contract and the number of years already elapsed since the beginning of the contract, and the price of the yearly rent paid, was close to 70% of the 168 respondents. This low rate prevents a reliable modelling of the land rental market in our ABM.

Finally, a thorough implementation of practical agronomic constraints (e.g., yield as a function of soil type) which act on farmers' activities was not achieved, besides the implementation of the crop rotation schemes. Although this is to be considered as a limitation in the large sense, as highlighted in Malawska and Topping (2016), very often in models which address behavioural elements in the farmer decision making, these latter are the pivotal point of the model, while the practical agronomic constraints in farming decisions are neglected. In order to overcome this limitation, the ABM developed in Malawska and Topping (2016) builds upon an existing economic farm optimization model. Based on a (linear programming) optimization model of farmers' decision-making is also the work by Huang et al. (2016). In Ng et al. (2011) interaction between only 50 agents is simulated, taking into account deterministic and stochastic elements of farmers' decision-making and using parallel programming so that multiple executions of the individual-farmer model can be run simultaneously.

It is legitimate to think that farmers' risk attitude could change for the effect not only of social interactions, but also farmers' history, regulations, subsidies, development of technical knowledge, etc. In fact, as observed in Faller and Schulz (2017) for the specific case of biogas production in Luxembourg (which can be considered as one of the possible farming-related investments), political frameworks and world market developments became the most influential factors in determining farmers decisions in the biogas context, overcoming even other traditionally important factors, like the belonging to a community of practice (CoP), which in the case of farmers can be identified in farmers' cooperatives. All these factors, which ultimately then influence farmers' risk orientation, are very hard to model and would require a knowledge of the sector and the availability of a quantity of information which goes beyond what was possible to achieve in the framework of the application presented in this paper. The estimation of farmers' risk orientation that we achieved in this paper is therefore probably the best possible compromise between model complexity and availability of information.

The crop prices are set at the beginning of the simulation based on the Holt-Winters forecasting model described in Rege et al. (2015b). More sophisticated price prediction models that also considers the market dynamics could be implemented. However, since they do not change over the course of a simulation and from one scenario to the other, we do not address the issues that may arise from different price predictions. Certainly, the feedstock exchanges between the farmers, as well as subsidies for certain crops and practices, could be included in the model. We are planning to incorporate subsidy and trade mechanisms in our model as soon as the related data will become available.

Concerning the threshold value of the GC used to trigger farmers' environmentally conscious behaviour (in this case the choice of the crops with the lowest CC related emissions among the list of available crops), we set this value to 0.5 in our simulations, since the goal of this study is to observe the effect of the network. We could have chosen a different threshold value, but running different experiments we noticed that this does not have as much influence on the final results as the fact to look only at the CC impact of crops,[3] rather than using some other criterion that looks at a wider spectrum of impacts, such as a composite indicator like the single score indicator (Kalbar et al., 2017). This would, however, bring in more uncertainty.

To complete the picture, we mention also the initial lack of real geospatial differentiation in our model. This is related to the lack of knowledge of the exact geospatial location of each farm. We addressed this issue in Section 3.1 and applied the above mentioned "seeded region growing" and treemap algorithms to create realistic farms with an assigned position in the treemap, which allowed the creation of geographical neighbourhood relationships among each the farmers. However, these relationships could also be enforced also based on other attributes of a farm, such as the type of a farm (organic/conventional) or its livestock density. We will address these points in future research.

7. Conclusions

The paper presented an ABM-LCA model of agricultural production in the Grand Duchy of Luxembourg, exploring in particular the effects (in terms of agricultural patterns and the consequent environmental impacts) of the interaction among farmers and the spreading of environmental awareness.

This paper was especially focused on placing the ABM approach in the context of its support to LCA. In this respect, processes of participatory modelling can certainly boost the acceptance of ABMs in the LCA community in the first place and among stakeholders and decision-makers in the second place, but practical user friendly tools allowing scenarios simulations also to non-expert users are clearly still lacking.

The implementation of certain features of the ABM, namely the distribution of the risk aversion attribute to the agents, was based on the results of a survey deployed to a sample of farmers. In this respect, we stress the importance of survey data as one of the effective strategies to parameterize behavioural responses of humans empirically (Smajgl et al., 2011). However, conducting surveys can be a very time and resources intensive process and the questions included in the surveys have to be carefully designed in order to prevent at least two risks: (1) the risk of asking redundant information or information which does not allow a proper estimation of the interviewee's "personal" feature one wishes to estimate; (2) the risk of obtaining a biased information due to the fact that the interviewee answers the questions in an inaccurate way, which does not reflect his/her real attitude.

Despite the limitations highlighted above, the model presented in this paper is an operational example of a hard-coupling between an ABM simulator and the LCA software Brightway2, which is quite unique in ABM-LCA models and is based on a very flexible software infrastructure relying on Java for the simulator code, .xml for scenarios definition and a series of python and bash scripts to work as the virtual laboratory. The virtual laboratory is in charge of running the different series of experiments, for each configuration and gather the results in form of .csv files. This framework is conceived to help field actors (e.g. farmers' cooperatives providing basic consultancy to farmers) to make some preliminary planning considerations.

The results of our simulations show that, at least in a simulation environment, social interaction influences the evolution of green consciousness among farmers and this causes an overall decrease of the cumulative environmental impacts targeted by the selected decision rules, over the simulated time span (10 years in our application). In particular, we noticed that farmers' green consciousness levels vary across the simulations, but when starting from high green consciousness values, the effect of interaction leads to a bigger reduction of the targeted cumulated impacts (HH effects of greenhouse gases emissions in this case) with respect to the scenario starting from lower average values of the green consciousness.

CRediT authorship contribution statement

Antonino Marvuglia: Conceptualization, Formal analysis, Funding acquisition, Project administration, Investigation, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. **Alper Bayram:** Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – review & editing. **Paul Baustert:** Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – review & editing. **Tomás Navarrete Gutiérrez:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – review & editing. **Elorri Igos:** Formal analysis, Methodology, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[3] Moreover, we compare the CC impacts of the crops per ha and not per kg.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jclepro.2021.129847.

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