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by

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HYBRID LCA–ABM OF DAIRY FARMING SYSTEMS INCLUDING NONLINEAR OPTIMIZATION UNDER ENVIRONMENTAL, TECHNICAL AND ECONOMIC CONSTRAINTS

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In the final year of my Master's, I was still unsure of how my future career would develop. Working as an engineer was more appealing to me at the time than going into research. I later left my job, which I have many fond memories of, and concentrated on finishing my Master's. Then, I applied for PhD positions where I might combine my work and research experience. I can clearly recall my interviews with Antonino, Tomás, and Enrico, to whom I am grateful for giving me the chance to work with outstanding people at LCSA. I felt honored when I received the email confirming my acceptance.

The coffee house where I read that acceptance email is no longer there. Shops always close down; new ones pop up every day in Istanbul. A lot more has changed since the summer of 2019. My former university, my home, was taken over. A virus shut down the world. A war started in Europe. An earthquake struck in the middle of one night. People lost their lives, and the ones who remained are "moving on". I am always fascinated by how people can keep their sanity and adapt after such tragedies. After all, the same things can happen again. The reason is simply, we have to. This is not a drill. We have to make the most out of this life.

The question then becomes how to cherish the one life we get. Our lives become more meaningful if we build on the knowledge of previous lives and if the future lives take what we created even further. Because life is transient. Ideas and knowledge are eternal. That's why I chose to pursue a PhD. Every time I learn from others and build for future generations, others' lives and mine become more meaningful.

The least we can do for those who dedicated their lives to research is to honor their contributions. Unfortunately, our world has become polarized, and the objective truth is no longer highly valued. We have suffered enough death and poverty through environmental catastrophes, wars and pandemics. It is only because we have failed to listen to the scientists and experts before those tragedies happen.

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Lastly, I would like to thank my love, Selen, for holding my hand and never giving up on me.

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ABSTRACT

Agriculture is essential to meeting billions of people's food needs. As the human population grows, agricultural activities will inevitably continue to expand. Unfortunately, these activities contribute to climate change by emitting greenhouse gases (GHGs) either directly (via methane, field operations, land-use change etc.) or indirectly (across the entire supply chain). Aside from air pollutants, agricultural processes that utilize pesticides, fertilizers, and other farm chemicals can contaminate fresh water, marine ecosystems and the soil. They can also remain in the environment for generations. All these environmental impacts point to one conclusion: agricultural policies must prioritize sustainability.

Policymakers have demonstrated efforts to mitigate the adverse effects of agriculture on the environment. Since the 1980s, environmental goals have become an increasingly important component of the EU's Common Agricultural Policy (CAP). The European Commission's Green Deal proposes policies to make production decisions more environmentally responsible. However, given the complex nature of agriculture, assessing the potential outcomes of these policies is difficult. Agriculture is regarded as a complex system because it includes a high level of human–environment symbiosis. Furthermore, the economic and political consequences of such policies must be carefully evaluated before they are implemented.

In the SIMBA project, we aimed to address the sustainable farm management problem. We propose a hybrid model combining agent-based modeling (ABM) and life cycle assessment (LCA) where farmer agents maximize their profits and minimize environmental impacts via mathematical optimization. ABMs are particularly appealing for modeling complex systems, investigating and simulating possible scenarios to address today's environmental problems. The agents follow a set of rules within a context in which learning and adaptation can cause changes in other agents or the environment. These changes may be attributed to agents' behavioral properties which influence the production decisions.

Sustainability assessment from an environmental point-of-view must be applied to understand and reflect on the emissions caused by agricultural production activities. The LCA methodology can assist strategic actors in quantifying the impacts of those activities. LCA can be used to assess the impacts of farm-level activities and those that occur throughout the entire production chain.

A coupled ABM-LCA model is already a useful stepping stone in understanding and quantifying the environmental impacts of pro-

duction decisions in a complex system. However, policymakers need to incentivize (most often with targeted subsidies) agricultural businesses to pursue sustainable practices. This is important because, although prioritizing profit-making over emission reduction is not a sustainable model for the planet, agricultural businesses need nonetheless to be financially sustainable. It is necessary to have models that consider both sides of the coin, i.e., trade-offs between profit maximization and emission mitigation. Therefore, we integrated mathematical optimization into our model, which enables agents to optimize their farms from economic or environmental standpoints. Our case study focuses on agricultural activities in Luxembourg; consequently, the recommendations were established after in-depth consultation with the various project partners in the region. Nonetheless, our model can be adapted to be used in various other countries and regions.

To summarize, the first novel contribution made by this thesis is the hybrid ABM-LCA model. This model simulates the possible farm management scenarios for more sustainable dairy farming activities. In our model, the primary production units are an animal and a field, and the status of each production unit is updated at each time step in accordance with the livestock management, crop production and rotation requirements. The resolution of the simulations is one month, at which point the farmer agents can make decisions according to the rules that have been pre-set. The farmer agents interact with one another and, as a result of these exchanges, modify their behavior to reflect their awareness of environmental impacts. The multi-objective optimization of farming activities within the constraints of economic and environmental factors constitutes the second novel contribution of this thesis. Land-use change and animal population density are two of the decision variables that are considered. The optimization model can be used to see the trade-off between various scenarios involving maximizing profits and reducing possible environmental impacts.

This study incorporates a number of case studies gleaned from a hybrid ABM-LCA model's progression through its phases. The two novel contributions outlined above made it possible to conduct a number of case studies and based on the findings of those case studies, the following conclusions can be drawn: (1) The connection between the farmers and the sharing of information helps to lessen the overall negative impacts on the environment. (2) It is possible to lower stocking rates without jeopardizing the economy's long-term viability. (3) Altering animals' diets or increasing soybean output on a local level are both viable options for lowering soybean production. (4) An increase in biogas production in Luxembourg is conceivable with the addition of additional amounts of animal manure and food waste to the existing biogas feedstock. (5) An obvious trade-off between environmental and economic goals arises from optimizing farming activities. This trade-off can be evaluated by policymakers to decide on future regulations and subsidies for the sector of agriculture.

PUBLICATIONS

Bayram, Alper and Antonino Marvuglia (2022). "A Web-Based Dashboard for Estimating the Economic and Ecological Impacts of Land Use Class Changes for Key Land Patches." In: *International Conference on Computational Science and Its Applications*. Springer, Cham, pp. 281–293.

Bayram, Alper, Antonino Marvuglia, Tomás Navarrete Gutierrez, Hélène Soyeurt, and Anthony Tedde (2023a). "Mathematical programming to optimize crop and dairy production in Luxembourgish farms." In: *Journal of Cleaner Production (Submitted)*.

Bayram, Alper, Antonino Marvuglia, Maria Myridinas, and Marta Porcel (2022). "Increasing Biowaste and Manure in Biogas Feedstock Composition in Luxembourg: Insights from an Agent-Based Model." In: *Sustainability* 15.1, p. 264.

Bayram, Alper, Antonino Marvuglia, Tomás Navarrete Gutierrez, Jean-Paul Weis, Gérard Conter, and Stéphanie Zimmer (2023b). "Sustainable farming strategies for mixed crop-livestock farms in Luxembourg simulated with a hybrid agent-based and life-cycle assessment model." In: *Journal of Cleaner Production* 386, p. 135759.

Marvuglia, Antonino, Alper Bayram, Paul Baustert, Tomás Navarrete Gutiérrez, and Elorri Igos (2022). "Agent-based modelling to simulate farmers' sustainable decisions: Farmers' interaction and resulting green consciousness evolution." In: *Journal of Cleaner Production* 332, p. 129847.

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ACRONYMS

ABM Agent-Based Modelling

APIs Application Programming Interfaces

ALCA Attributional Life-Cycle Assessment

ASTA Administration des Services Techniques de l'Agriculture

BC Betweenness Centrality

BIM Building Information Modelling

BW body weight

CV Coefficient of variation

CAP Common Agricultural Policy

CC Climate Change

CHANS Complex Coupled Human-Natural Systems

CLCA Consequential Life-Cycle Assessment

CoP Community of Practice

CV Coefficient of Variation

DALY Disability Adjusted Life Years

DM Dry Matter

DMI Dry Matter Intake

EAs Evolutionary Algorithms

EF Environmental Footprint

EQ Ecosystem Quality

ESR Effort Sharing Regulation

ETS Emissions Trading System

EU European Union

EVs Electric Vehicles

FADN Farm Accountancy Data Network

FNR	National Research Fund of Luxembourg
FU	Functional Unit
GC	Green Consciousness
GAs	Genetic Algorithms
GEI	Gross Energy Intake
GHG	Greenhouse Gas
GIS	Geographic Information System
GLEAM	Global Livestock Environmental Assessment Model
GWP	Global Warming Potential
HH	Human Health
IAM	Integrated Assessment Model
IBLA	Institut fir Biologësch Landwirtschaft an Agrarkultur Luxemburg
IIC	Integral Index of Connectivity
IPCC	Intergovernmental Panel on Climate Change
IRR	Internal Rate of Return
LCIA	Life-Cycle Impact Assessment
LCI	Life-Cycle Inventory
LCA	Life-Cycle Assessment
LP	Linear Programming
LSU	Livestock Unit
MAP	Mathematical Programming
MF	Multifunctional Process
MIP	Mixed-Integer Programming
MOEA	Multi-Objective Evolutionary Algorithms
MOO	Multi-Objective Optimization
MP	Milk production
MUSA	MUlti agent Simulation for consequential Life Cycle Assessment of Agrosystems
NLP	Non-Linear Programming
NSGA	Non-dominant Sorting Genetic Algorithms
ODD	Overview, Design concepts and Details
ODM	Organic Dry Matter
ORM	Object Relational Mapping

PC Probability of Connectivity

PSO Particle swarm optimization

RA Risk Aversion

RED The Renewable Energy Directive

SBS Soluble Bio-based Substances

SER Service d'Economie Rurale

SIMBA SIMulating economic and environmental impacts of dairy cattle management using Agent BAsed Models

SME Small and medium-sized enterprise

SNA Social Network Analysis

STATEC Institut national de la statistique et des études économiques du Grand-Duché de Luxembourg

TEA Techno-Economic Analysis

UAA Utilized Agricultural Area

VAT Value-Added Tax

WCCS Whole Crop Cereal Silage

1

INTRODUCTION

This chapter provides an introduction to the thesis's contents and the larger context in which it is situated. The objective is to illustrate the need for new and reliable modeling tools to quantify the environmental impacts of farming systems by tying agricultural production demand to some of the most challenging environmental concerns of our time. The thesis is being conducted under the SIMulating economic and environmental impacts of dairy cattle management using Agent BAsed Models (SIMBA) project funded by the National Research Fund of Luxembourg (FNR) under the grant INTER-FNRS/18/12987586. The SIMBA project seeks to optimize agricultural production by combining Agent-Based Modelling (ABM) with Life-Cycle Assessment (LCA), and the goal of this thesis is to present a model of the farming system in Luxembourg and simulate several scenarios that aim to reduce the environmental impact of farming activities under economic and environmental constraints. In the sections that follow, section 1.1 will describe the broader context, section 1.2 will discuss the background of the SIMBA project, and section 1.2.1 will elaborate on the objectives and structure of the thesis.

1.1 AGRICULTURE, SUSTAINABILITY AND HUMAN BEHAVIOUR

1.1.1 *Agriculture and environmental impacts*

Agriculture has a crucial role in meeting basic human requirements. It provides the means for millions of individuals worldwide. In turn, the cultivation and consumption of food are associated with a wide variety of human needs, including sustenance, socialization, and cultural expression. Producing crops, raising cattle and harvesting trees are all included in the agricultural industry. Resources including land, water, energy, and human labor are necessary for these actions. Using these inputs effectively and adopting best practices and technologies is crucial to the efficiency and sustainability of agricultural production.

On the other hand, agriculture has significant environmental implications. Soil and water contamination can come from agrochemicals like fertilizers and pesticides, and biodiversity loss and carbon emissions can result from land use change and deforestation. Droughts, floods, and other extreme weather occurrences are ways climate change threatens the agriculture industry. Sustainable agriculture practices are being promoted and used on a global scale as a solution to these problems. The long-term health of the agricultural sector is prioritized, and these methods are used to lessen its environmental footprint. Crop rotation, conservation tillage, agroforestry, and the utilization of renewable energy sources are all examples of sustainable agricultural techniques.

According to (Nabuurs et al., 2022), agriculture accounts for around 21% of Greenhouse Gas (GHG) emissions, including emissions from livestock, deforestation, and using fertilizers and other agrochemicals. (Pendrill et al., 2022) reports that agriculture drives more than 90% of tropical deforestation. Using synthetic fertilizers and other agrochemicals can lead to soil and water pollution, harming human health and wildlife. (Alexandratos and Bruinsma, 2012) has estimated that global food production will need to increase by around 60% by 2050 to meet the needs of a growing global population. This will place further pressure on natural resources and the environment. According to (Cederberg and Sonesson, 2011) one-third of global food production is lost or wasted each year, representing a significant waste of resources and contributing to GHG emissions. Livestock use for food production is essential to environmental impacts, including GHGs, land use change, and water pollution. (Gerber et al., 2013) estimates that livestock production accounts for around 14.5% of global GHG emissions.

1.1.2 *LCA and human behavior*

A product or process's environmental and health impacts can be estimated using LCA, which involves measuring the inputs and outputs of the product or process in question. However, in systems involving personal decisions and human interactions, like agriculture and farming systems, complicated and unpredictable aspects of human behavior come into play. These aspects are generally disregarded by mere LCA models. The accuracy of LCA predictions can be compromised by ignoring human behavior, as acknowledged by other authors (Gutowski, 2018).

To circumvent this shortcoming, LCA studies sometimes make assumptions about the intended usage behavior of humans or rely on stylized scenarios. Unfortunately, the understanding of human behavior that may be gained by using these techniques is oversimplified. Hence, it has been suggested that ABM be used to incorporate a more nuanced description of human behavior into LCA investigations.

ABM, started as Individual Based Modeling in Ecology and then was developed in Computer Science, with many applications to solve problems of the Social Sciences domain. A more accurate depiction of human behavior in complex systems can be attained through the use of ABM, which simulates individual agents and their interactions. ABM has been applied to agriculture for the purpose of modeling farmer decision-making and the spread of innovative farming techniques.

One of the phenomena in which environmental factors and social factors are strongly intertwined is the rebound effect, in which greener lifestyle choices lead to more consumption and cancel out any early positive impact on the environment is essential. Individuals' reactions to shifts in environmental policy or market conditions are determined mainly by human behavior, which is vital to the rebound effect (Font Vivanco et al., 2022; Murray, 2013). Because of this strong tie with social phenomena, environmental policy and the rebound effect have been modeled using ABM.

In terms of Life-Cycle Impact Assessment (LCIA), agricultural emissions contribute to climate change, which can have significant impacts on ecosystems, human health, and the economy. Moreover, agriculture can change land use, affect habitat destruction, and enhance soil erosion. This can result in biodiversity loss, reduced soil fertility, and increased vulnerability to natural disasters. Agriculture is a major user of freshwater resources, particularly for irrigation. Excessive water use can lead to water scarcity, impacting ecosystems and human populations. Using fertilizers and other agrochemicals in agriculture can lead to eutrophication, which is the excessive growth of algae and other aquatic plants due to increased nutrients (nitrogen and phosphorus concentration). This can result in oxygen depletion and harm aquatic ecosystems.

1.1.3 *Agricultural emission reduction policies in EU and Luxembourg*

The European Union (EU) has set a number of policies and targets aimed at reducing agricultural emissions and promoting sustainable agriculture practices. The Common Agricultural Policy (CAP) is the EU's main policy for supporting agriculture and rural development. The latest CAP reform, which came into effect in 2021, includes a new "green architecture" that aims to incentivize farmers to adopt more sustainable practices, such as agroforestry, organic farming, and the use of precision farming techniques. The new CAP also includes an "eco-scheme" that provides additional funding for farmers who undertake specific actions to reduce emissions and improve the environment.

The Effort Sharing Regulation (ESR) is an EU-wide policy that sets binding emissions reduction targets for sectors not covered by the EU Emissions Trading System (ETS), including agriculture (Yougova, 2021). Under the latest ESR targets for 2021-2030, the agriculture sector is expected to reduce emissions by 10% compared to 2005 levels. There is also The Renewable Energy Directive (RED) which sets targets for using renewable energy in the EU, including biofuels and other forms of renewable energy produced from agricultural crops and waste (Dusser, 2019). The latest RED target for 2021-2030 includes a 14% share of renewable energy in the transport sector, which is expected to drive demand for biofuels and other sustainable transport fuels.

The EU Farm to Fork Strategy is a new strategy launched in 2020 that sets targets for reducing GHGs, improving the sustainability of food production, and promoting healthier diets (European Commission, 2020). The Farm to Fork Strategy includes a number of actions aimed at reducing emissions from agriculture, including promoting organic farming, reducing the use of fertilizers and pesticides, and improving soil health. Overall, the EU has set ambitious targets for reducing emissions from agriculture and promoting sustainable agriculture practices. It remains to be seen how effective these policies will be in practice, but they represent an important step towards a more sustainable and low-carbon food system.

Since all the case studies discussed in this thesis are set in Luxembourg, it is very much relevant to learn and adapt the model to the policies of the Luxembourgish government (MECDD, 2021a,b). A national plan for sustainable agriculture launched in 2020 outlines the government's vision for a more sustainable and resilient agriculture sector in Luxembourg. The plan includes numerous actions to reduce emissions from agriculture, such as promoting organic farming, improving nutrient management practices, and supporting agroforestry. The water management plan also sets out measures to protect and improve water quality in Luxembourg, including measures aimed at reducing pollution from agriculture. For example, the plan includes measures to promote sustainable agriculture practices that reduce nutrient runoff and improve soil health.

1.2 THE PROJECT SIMBA

The SIMBA project tries to bridge agronomy, computational modeling, sustainability science and complex systems. Phenotypical aspects of animals are used to model emissions and production. The simulations can be run on the model to assess the agricultural policies of the Luxembourgish government. The innovative aspects of the SIMBA project include the development of an ABM to simulate the population's agricultural practices and the hard–coupling (Marvuglia et al., 2017) of that ABM to LCA[1]. To assess the environmental impacts of individual farming practices, the ABM's outputs are transformed into a demand for farm products and services.

1 The three different types of coupling between ABM and LCA as described in (Micolier et al., 2019):

- Soft–coupling: At the end of the simulation, the ABM outputs are compiled and used as inputs for the LCA.
- Tight–coupling: At each time step, ABM outputs are used as the LCA's inputs.
- Hard–coupling: At each time step, LCA results are used as inputs to the ABM.

The LCA part of the model allows assessing the environmental impacts from a life cycle perspective of this demand for farm products and services, where the system-specific processes are modeled using regional data and projections. There is a general agreement in the LCA community that two main types of LCA (attributional and consequential) modeling exist (Finnveden et al., 2022) for what concerns the system studied and research questions that one wants to answer.

"The attributional approach attempts to provide information on what portion of global burdens can be associated with a product (and its life cycle)" (Schaubroeck et al., 2021; UNEP, 2011). The recent advancements in this area have concentrated on enhancing the modeling of emissions and resource consumption, Life-Cycle Inventory (LCI) data accuracy and comprehensiveness. The second most common LCA modeling is the consequential approach, which *"attempts to provide information on the environmental burdens that occur, directly or indirectly, as a consequence of a decision (usually represented by changes in demand for a product)"* (Schaubroeck et al., 2021; UNEP, 2011). It considers the ramifications of indirect effects and potential changes in supply and demand. Recent advancements have aimed to incorporate consequential approaches into policy frameworks and decision–making processes, allowing for the evaluation of various scenarios and policy interventions.

Temporal aspects in LCA can be addressed in different levels (Beloin-Saint-Pierre et al., 2020). Intersecting temporal aspects with the maturity of the studied technology, different denominations have been coined for the resulting LCA type (Arvidsson et al., 2023). One of them, which is recently gaining considerable momentum, is Prospective LCA, which focuses on assessing the potential effects of novel technologies, improved efficiency and incorporation of predictive models and scenario analysis (Arvidsson et al., 2018). (Sacchi et al., 2022) addresses the need of an inventory database in prospective LCA to track expected changes in technologies and the environment over time, following specific socio-techno-economic pathways as energy systems and industries rapidly shift toward cleaner production. The study introduces the tool *premise*, a Python library that allows propsective LCA in the LCA calculation framework Brightway2 (Mutel, 2017) and the Activity Browser (Steubing et al., 2020). *premise* simplifies prospective inventory database generation by integrating Integrated Assessment Model (IAM) scenarios. In a socio-economic narrative, the climate change mitigation target affects nearly all activities in the database. The sector-based transformation and climate change mitigation target affect direct air capture of CO_2, lithium-ion batteries, electricity, clinker, and road freight transport. From the temporal perspective, we can distinguish between fully–fledged dynamic LCA (Levasseur et al., 2010) and temporally differentiated LCA (sometimes also referred to as time–resolved LCA). In the former, the life-cycle impact of each emission is a function of time instead of a static number. This happens because of dynamic background[2] and foreground[3] inventories in addition to dynamic characterization factors (e.g., for Global Warming Potential (GWP)) (Pigné et al., 2020). In the latter, normally only the foreground activities are differentiated (Beloin-Saint-Pierre et al., 2020).

Among these approaches, SIMBA follows the attributional approach where the policy interventions are incorporated through scenarios in ABM and through hard-coupling (Baustert et al., 2019) the resulting environmental impacts are quantified using LCA.

To describe the functional unit used in this study, we first need to explain the territorial LCA approach territorial LCA approach (Loiseau et al., 2018). The first issue is brought up by the requirement to define territory within the context of LCA. Geographers define a territory as the collection of interactions between society and the environment (Loiseau et al., 2018). It is a geographical area where human societies can expand their operations through territorial functions (like waste management), which offer goods and services based on the characteristics of the land and how its resources are used (from tangible ones like the provision of food or housing to intangible ones, like landscape quality or cultural heritage). Therefore, the territory is not an administrative region but rather the collection of connections between various spatial territorial units (settlements, districts, and regions) that interact and exchange flows of various kinds (goods, people, and services, for example), supporting various territorial functions.

The definition and quantification of territorial functions pertinent for the territory at issue after the concept of territory has been established allows for the subsequent description of the supporting activities and, as a result, the evaluation of the associated environmental burdens. To accomplish two goals: 1) to distribute the costs of various activities to the territorial units that directly or indirectly support them (partially or entirely), and 2) to enable the calculation of an eco-efficiency index (Seppäläa et al., 2005) of the studied territory, it is crucial to characterize the territory through its territorial functions. According to (Seppäläa et al., 2005), eco-efficiency is the proportion between the services a territory offers and the resulting environmental impacts. As stated in (Seppäläa et al., 2005), the challenge of obtaining data of sufficient accuracy prevents the inclusion in its calculation of upstream inventory flows that go beyond the industry sectors (namely the activities related to the households). As a

2 *"The background system consists of processes on which no or, at best, indirect influence may be exercised by the decision–maker for which an LCA is earned out. Such processes are called background processes"* (Frischknecht, 1998).

3 *"The foreground system consists of processes which are under the control of the decision–maker for which an LCA is earned out. They are called foreground processes"* (Frischknecht, 1998).

result, this strategy still needs to be researched and enhanced in order to expand its application (Loiseau et al., 2018). Also, (Loiseau et al., 2018) differentiate between two territorial LCA applications. The first one, type A, "contextualizes the LCA of an activity (i.e., production or consumption activities) that is anchored in a specific territory and dependent on the geographical context". The second one, type B, "assesses the environmental impacts of all production and consumption activities located in a given territory". In SIMBA we follow type A but only consider agriculture and farming production activities (additionally biogas production in several scenarios, which is a production activity that is tightly linked to agricultural production). Therefore, we can define the functional unit in this study as *the land within the geographical boundaries of Luxembourg*, which is studied only concerning the agriculture and farming production activities (additionally biogas where applied), excluding pastures, vineyards and orchards. The scope is cradle-to-farmgate, i.e., the LCA does not consider activities occurring after farmgate such as transportation to the market.

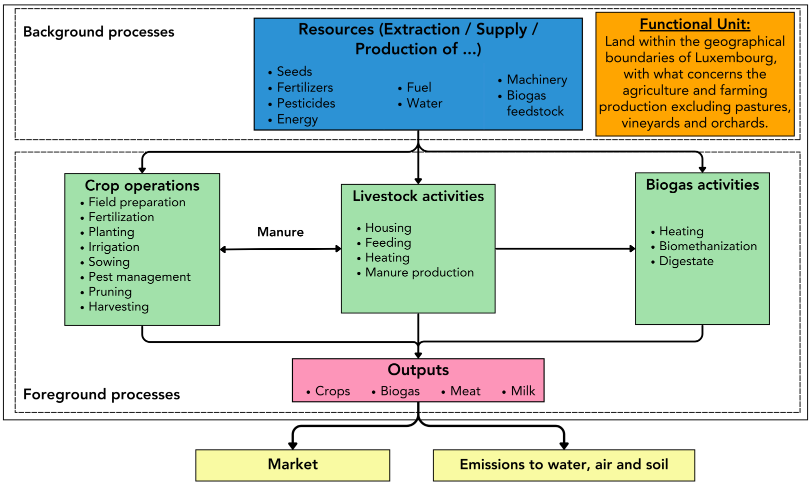

Figure 1: Foreground, background and system boundaries of LCA in SIMBA.

1.2.1 *Objectives of the PhD Project*

As mentioned above, agriculture is a complex system with numerous actors and activities. Although policymakers set goals to reduce emissions through agricultural activities, there is a lack of understanding of achieving these goals. To model and run possible scenarios on Luxembourgish agriculture, this work focuses on a hybrid ABM-LCA model that optimizes farm outputs based on environmental and/or economic objectives. The goal is to provide policy support for the stakeholders in Luxembourgish agriculture and evaluate possible scenarios for emission reduction.

Figure 2 shows how the thesis and publications are structured from the start. The structure of this thesis follows the order in which the publications appeared, showing the gradual improvement brought by each publication.

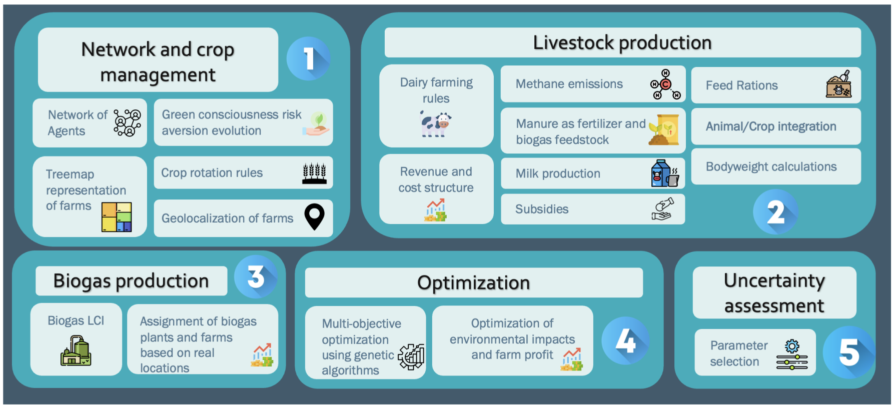

Figure 2: Organization of the thesis in building blocks.

Following Figure 2, the research questions that were addressed in this thesis and corresponding chapters are as follows:

- What are the consequences of farmer behaviors concerning environmental consciousness and their interactions by utilizing a modeling methodology that integrates ABM and LCA? (Chapter 2)
- What are the financial and environmental outcomes of livestock farming using the coupled ABM-LCA model? (Chapter 3)
- How can the biogas production system be modeled and how can biogas production be increased from different feedstock compositions? (Chapter 4)
- Would mathematical optimization be useful to find a balance between economic and environmental sustainability? (Chapter 5)

Afterward, a dashboard was built in order to visualize the findings of corresponding research outcomes (described in chapter 6). Using the dashboard, the results can be presented to the project partners and the agriculture stakeholders. Finally, chapter 7 concludes the PhD thesis and provides a discussion of the findings.

REFERENCES

Alexandratos, Nikos and Jelle Bruinsma, eds. (2012). *World agriculture towards 2030/2050: the 2012 revision*. eng. ESA Working Papers 12-03. ISSN: 2521-1838. DOI: 10.22004/ag.econ.288998.

Arvidsson, Rickard, Björn Sandén, and Magdalena Svanström (2023). "Prospective, Anticipatory and Ex-Ante – What's the Difference? Sorting Out Concepts for Time-Related LCA." en. In: URL: https://research.chalmers.se/en/publication/535660 (visited on 05/22/2023).

Arvidsson, Rickard, Anne-Marie Tillman, Björn A. Sandén, Matty Janssen, Anders Nordelöf, Duncan Kushnir, and Sverker Molander (2018). "Environmental Assessment of Emerging Technologies: Recommendations for Prospective LCA." en. In: *Journal of Industrial Ecology* 22.6, pp. 1286–1294. ISSN: 1530-9290. DOI: 10.1111/jiec.12690. (Visited on 05/17/2023).

Baustert, Paul, Tomás Navarrete Gutiérrez, Thomas Gibon, Laurent Chion, Tai-Yu Ma, Gabriel Leite Mariante, Sylvain Klein, Philippe Gerber, and Enrico Benetto (Jan. 2019). "Coupling Activity-Based Modeling and Life Cycle Assessment—A Proof-of-Concept Study on Cross-Border Commuting in Luxembourg." en. In: *Sustainability* 11.15. Number: 15 Publisher: Multidisciplinary Digital Publishing Institute, p. 4067. ISSN: 2071-1050. DOI: 10.3390/su11154067. (Visited on 01/03/2023).

Beloin-Saint-Pierre, Didier, Ariane Albers, Arnaud Hélias, Ligia Tiruta-Barna, Peter Fantke, Annie Levasseur, Enrico Benetto, Anthony Benoist, and Pierre Collet (2020). "Addressing temporal considerations in life cycle assessment." In: *Science of the Total Environment* 743. Publisher: Elsevier, p. 140700.

Cederberg, Christel and Ulf Sonesson (2011). *Global food losses and food waste: extent, causes and prevention; study conducted for the International Congress Save Food! at Interpack 2011, [16 - 17 May], Düsseldorf, Germany*. en. Ed. by Jenny Gustavsson. Meeting Name: International Congress Save Food! Rome: Food and Agriculture Organization of the United Nations. ISBN: 978-92-5-107205-9.

Dusser, Philippe (2019). "The European Energy Policy for 2020–2030 RED II: what future for vegetable oil as a source of bioenergy?" In: *Ocl* 26, p. 51.

European Commission (2020). *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions on an EU Strategy to Reduce Methane Emissions*. COM(2020) 663 Final.

Finnveden, Göran, Rickard Arvidsson, Anna Björklund, Jeroen Guinée, Reinout Heijungs, and Michael Martin (2022). "Six areas of methodological debate on attributional life cycle assessment." en. In: *E3S Web of Conferences* 349. Ed. by S. Albrecht, M. Fischer, C. Scagnetti, M. Barkmeyer, and A. Braune, p. 03007. ISSN: 2267-1242. DOI: 10.1051/e3sconf/202234903007. URL: https://www.e3s-conferences.org/10.1051/e3sconf/202234903007 (visited on 05/17/2023).

Font Vivanco, David, Jaume Freire-González, Ray Galvin, Tilman Santarius, Hans Jakob Walnum, Tamar Makov, and Serenella Sala (2022). "Rebound effect and sustainability science: A review." In: *Journal of Industrial Ecology* 26.4. Publisher: Wiley Online Library, pp. 1543–1563.

Frischknecht, Rolf (Jan. 1998). "Life cycle inventory analysis for decision-making." In: *The International Journal of Life Cycle Assessment* 3, pp. 67–67. DOI: 10.1007/BF02978487.

Gerber, P. J., H. Steinfeld, B. Henderson, A. Mottet, C. Opio, J. Dijkman, A. Falcucci, and G. Tempio (2013). "Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities." English. In: *Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities.* (Visited on 02/07/2022).

Gutowski, Timothy G (2018). "A critique of life cycle assessment; where are the people?" In: *Procedia CIRP* 69, pp. 11–15.

Levasseur, Annie, Pascal Lesage, Manuele Margni, Louise Deschênes, and Réjean Samson (Apr. 2010). "Considering Time in LCA: Dynamic LCA and Its Application to Global Warming Impact Assessments." In: *Environmental Science & Technology* 44.8. Publisher: American Chemical Society, pp. 3169–3174. ISSN: 0013-936X. DOI: 10.1021/es9030003. (Visited on 05/17/2023).

Loiseau, Eléonore, Lynda Aissani, Samuel Le Féon, Faustine Laurent, Juliette Cerceau, Serenella Sala, and Philippe Roux (Mar. 2018). "Territorial Life Cycle Assessment (LCA): What exactly is it about? A proposal towards using a common terminology and a research agenda." en. In: *Journal of Cleaner Production* 176, pp. 474–485. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2017.12.169. (Visited on 05/03/2023).

MECDD (2021a). *Observatoire Politique Climatique: Rapport Annuel*. https://environnement.public.lu/content/dam/environnement/documents/klima_an_energie/observatoire-politique-climatique/opc-ra-executive-summary-ok.pdf. Accessed on March 15, 2023.

MECDD (2021b). *Stratégie nationale à long terme en matière d'action climat*. https://gouvernement.lu/dam-assets/documents/actualites/2021/10-octobre/29-strategie-nationale-action-climat/Strategie-nationale-a-long-terme-en-matiere-d-action-climat-octobre-2021.pdf. Accessed on March 15, 2023.

Marvuglia, Antonino, Sameer Rege, Tomás Navarrete Gutiérrez, Laureen Vanni, Didier Stilmant, and Enrico Benetto (Jan. 2017). "A return on experience from the application of agent-based simulations coupled with life cycle assessment to model agricultural processes." en. In: *Journal of Cleaner Production* 142, pp. 1539–1551. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2016.11.150. (Visited on 02/07/2022).

Micolier, Alice, Philippe Loubet, Franck Taillandier, and Guido Sonnemann (2019). "To what extent can agent-based modelling enhance a life cycle assessment? Answers based on a literature review." In: *Journal of Cleaner Production* 239, p. 118123.

Murray, Cameron K. (2013). "What if consumers decided to all 'go green'? Environmental rebound effects from consumption decisions." In: *Energy policy* 54. Publisher: Elsevier, pp. 240–256.

Mutel, Chris (2017). "Brightway: An open source framework for Life Cycle Assessment." In: *Journal of Open Source Software* 2.12, p. 236. DOI: 10.21105/joss.00236.

Nabuurs, G.-J. et al. (2022). "Agriculture, Forestry and Other Land Uses (AFOLU)." eng. In: Cambridge University Press, pp. 747–860. URL: https://urn.kb.se/resolve?urn=urn:nbn:se:nai:diva-2752 (visited on 05/22/2023).

Pendrill, Florence et al. (Sept. 2022). "Disentangling the numbers behind agriculture-driven tropical deforestation." In: *Science* 377.6611. Publisher: American Association for the Advancement of Science, eabm9267. DOI: 10.1126/science.abm9267. URL: https://www.science.org/doi/abs/10.1126/science.abm9267 (visited on 05/03/2023).

Pigné, Yoann, Tomás Navarrete Gutiérrez, Thomas Gibon, Thomas Schaubroeck, Emil Popovici, Allan Hayato Shimako, Enrico Benetto, and Ligia Tiruta-Barna (Feb. 2020). "A tool to operationalize dynamic LCA, including time differentiation on the complete background database." en. In: *The International Journal of Life Cycle Assessment* 25.2, pp. 267–279. ISSN: 1614-7502. DOI: 10.1007/s11367-019-01696-6. (Visited on 05/17/2023).

Sacchi, R., T. Terlouw, K. Siala, A. Dirnaichner, C. Bauer, B. Cox, C. Mutel, V. Daioglou, and G. Luderer (May 2022). "PRospective EnvironMental Impact asSEment (premise): A streamlined approach to producing databases for prospective life cycle assessment using integrated assessment models." en. In: *Renewable and Sustainable Energy Reviews* 160, p. 112311. ISSN: 1364-0321. DOI: 10.1016/j.rser.2022.112311. (Visited on 05/17/2023).

Schaubroeck, Thomas, Sophie Schaubroeck, Reinout Heijungs, Alessandra Zamagni, Miguel Brandão, and Enrico Benetto (2021). "Attributional & Consequential Life Cycle Assessment: Definitions, Conceptual Characteristics and Modelling Restrictions." In: *Sustainability* 13.13, p. 7386. DOI: 10.3390/su13137386.

Seppäläa, Jyri, Matti Melanen, Ilmo Mäenpää, Sirkka Koskela, Jyrki Tenhunen, and Marja-Riitta Hiltunen (2005). "How Can the Eco-efficiency of a Region be Measured and Monitored?" en. In: *Journal of Industrial Ecology* 9.4, pp. 117–130. ISSN: 1530-9290. DOI: 10.1162/108819805775247972. (Visited on 05/17/2023).

Steubing, Bernhard, Daniel de Koning, Adrian Haas, and Christopher Lucien Mutel (Feb. 2020). "The Activity Browser — An open source LCA software building on top of the brightway framework." en. In: *Software Impacts* 3, p. 100012. ISSN: 2665-9638. DOI: 10.1016/j.simpa.2019.100012. (Visited on 06/01/2022).

UNEP (2011). *Global guidance principles for life cycle assessment databases :: a basis for greener processes and products : 'Shonan guidance principles' /: produced by the UNEP/SETAC Life Cycle Initiative*. en. UNEP, ISBN: 978-92-807-3174-3. URL: https://digitallibrary.un.org/record/785158 (visited on 05/17/2023).

Yougova, Dessislava (2021). "Revising the Effort-Sharing Regulation for 2021-2030:'Fit for 55'package." In: *EPRS: European Parliamentary Research Service*.

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

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2

AGENT-BASED MODELLING TO SIMULATE FARMERS' SUSTAINABLE DECISIONS: FARMERS' INTERACTION AND RESULTING GREEN CONSCIOUSNESS EVOLUTION

2.1 ABSTRACT

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 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.

2.2 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 (Guinee et al., 2011; Heijungs, 2010; 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, ABM is a well-suited technique to study 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, 2019; 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 (Gaud et al., 2008; Gilbert, 2019; Grimm and Railsback, 2005; Heath et al., 2009; Heckbert et al., 2010; Micolier et al., 2019a; Teglio et al., 2011; Wu et al., 2017).

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 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 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 2.4), 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 2.3 provides a brief background on ABM-LCA coupling and how social network analysis is combined with ABM. Section 2.4 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 2.5, 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 2.6. Section 2.7 discusses the limitations, conceptual barriers and future development of our study and Section 2.8 draws some relevant conclusions.

2.3 LITERATURE REVIEW

2.3.1 *Coupling ABM with LCA*

In its classical implementation, in the so-called Attributional Life-Cycle Assessment (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 Life-Cycle Assessment (CLCA) model has been conceived to deal with specific contexts where the underlying hypotheses of ALCA cannot be applied (Marvuglia et al., 2013; Rege et al., 2015a; Weidema et al., 2018). 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 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.

2.3.2 *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; Bohlmann et al., 2010; Goldenberg et al., 2007). 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 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.

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 ABM 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.

Table 1: Summary of the approaches found in literature coupling ABM and LCA. (continued)

AUTHORS	TOPIC, SCOPE, OR CASE STUDY	APPROACH USED	MAIN ASSETS AND LIMITATIONS
(Querini and Benetto, 2014)	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.

Table 1: Summary of the approaches found in literature coupling ABM and LCA. (continued)

AUTHORS	TOPIC, SCOPE, OR CASE STUDY	APPROACH USED	MAIN ASSETS AND LIMITATIONS
(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.

Table 1: Summary of the approaches found in literature coupling ABM and LCA. (continued)

AUTHORS	TOPIC, SCOPE, OR CASE STUDY	APPROACH USED	MAIN ASSETS AND LIMITATIONS
(Micolier et al., 2019a)	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., 2019b)	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).

Table 1: Summary of the approaches found in literature coupling ABM and LCA. (continued)

AUTHORS	TOPIC, SCOPE, OR CASE STUDY	APPROACH USED	MAIN ASSETS AND LIMITATIONS
(Lan et al., 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.

Table 1: Summary of the approaches found in literature coupling ABM and LCA. (continued)

AUTHORS	TOPIC, SCOPE, OR CASE STUDY	APPROACH USED	MAIN ASSETS AND LIMITATIONS
(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 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.

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 (Liu et al., 2020; Zakrajšek and Vodeb, 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).

2.4 MATERIALS 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 2.4.3; (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.

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, 2017), 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.

2.4.1 *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 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 Institut national de la statistique et des études économiques du Grand-Duché de 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 represent-

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

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

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

ing 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, 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 UAA (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.

(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. 3 shows the resulting distributions of UAA samples that belong to different classes of farm size. For the sake of providing an exam-

Algorithm 1 : Constrained polygon allocation

M_{ij} is the binary neighbor matrix;
η is neighborhood distance threshold;
L_{UAA} is list of UAAs;
F_{class} is list of farm classes and attributes;
Function `Neighbor`(L_{UAA}, η):
  for $i = 0;\ i < L_{UAA}.size();\ i = i + 1$ **do**
    if $\mathrm{Distance}(L^i_{UAA}, L^j_{UAA}) \leqslant \eta$ **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**
    $nFarms \leftarrow f^c.numberOfFarms()$;
    for $i = 0;\ i < nFarms;\ i = i + 1$ **do**
      $area_{bound} \leftarrow$ **PERT**$(f^c_{min}, f^c_{max}, f^c_{mean})$;
      $UAA_m \leftarrow L_{UAA}.random()$;
      $farm^{area}_i \leftarrow UAA^{area}_m$;
      while $farm^{area}_i < area_{bound}$ **do**
        $N_{UAA} \leftarrow L_{UAA}.all(x_n : M_{mn} = 1)$;
        for UAA_n ***in*** N_{UAA} **do**
          if $farm^{area}_i < area_{bound}$ **then**
            $farm^{area}_i \mathrel{+}= UAA^{area}_n$;
          else
            break;

ple, Fig. 4 shows an excerpt of the map obtained after running the Algorithm 1.

2.4.2 *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 et al., 2008; Krichene, 2017). In (Ng et al., 2011)

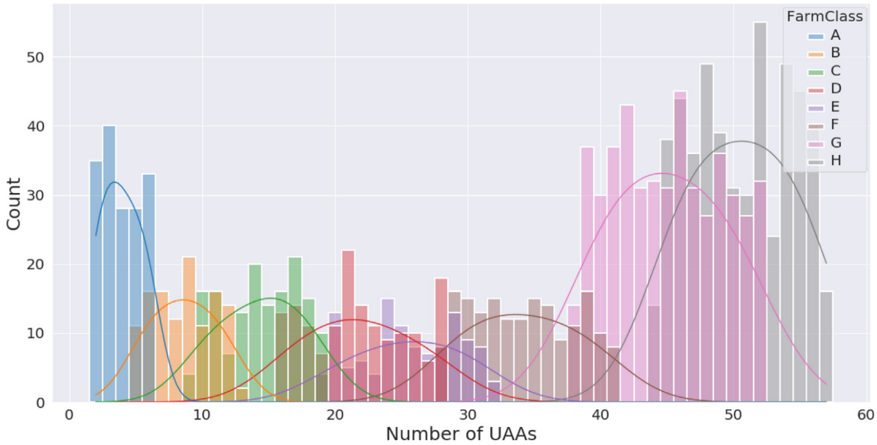


Figure 3: Histograms of UAAs for each farm class.

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 (Marvuglia et al., 2017) in the framework of the past project MUlti agent Simulation for consequential Life Cycle Assessment of Agrosystems (MUSA) funded by National Research Fund of Luxembourg (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

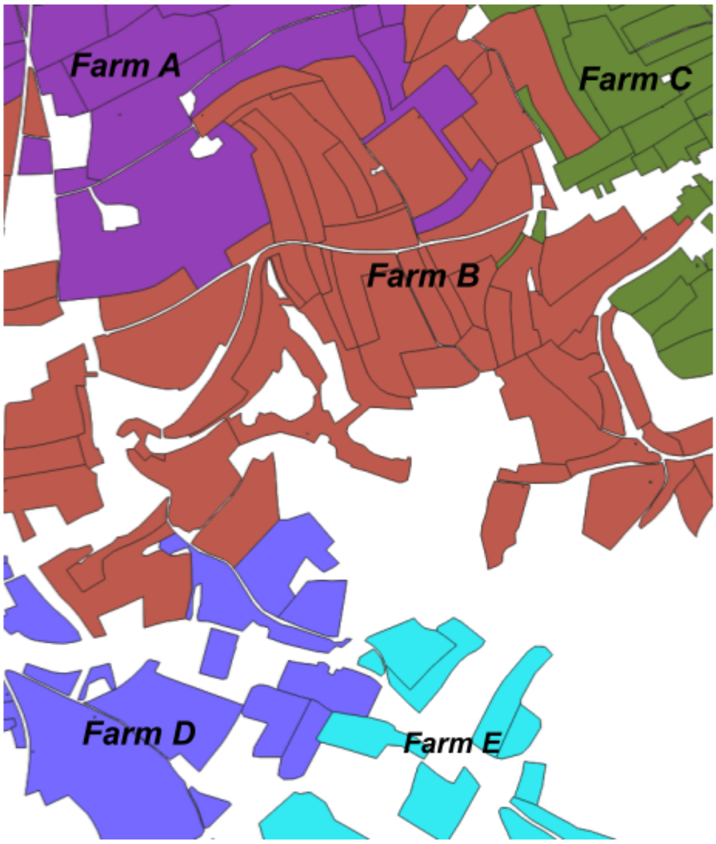


Figure 4: Detail on a part of the map obtained after running Algorithm 1. Different colours refer to different farms. The contours of the UAAs are visible on the map.

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

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

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 $p(\mathtt{pred}_i|C_k)$. 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 3). Using the frequencies one can estimate the likelihoods in Table 4 and finally posterior probabilities (Table 5).

2.4.3 *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 5.

Then, the farmers are grouped into two risk aversion levels that are represented in Fig. 6. 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

Table 3: Frequency table of age and farm size

Risk aversion level	Age				Farm size (ha)				
	<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

Table 4: Likelihood table. The values in italics express the $p(pred|C_k)$

Risk aversion level	Age					Farm size (ha)					
	<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	

Table 5: 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

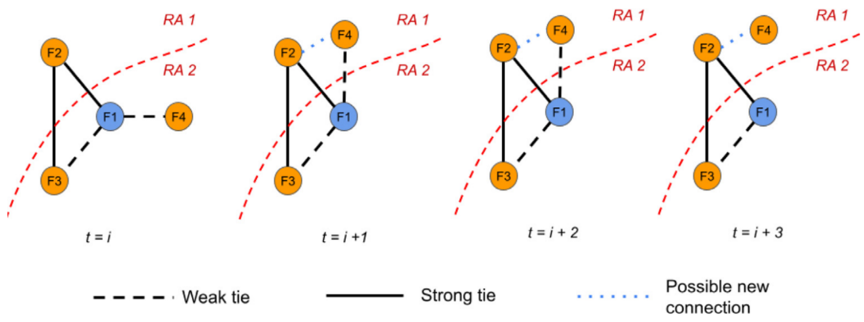


Figure 5: Schematic representation of the edge addition and removal mechanism during the simulation. The ties between nodes F1 and F2, and between nodes F1 and F3, are strong ties and cannot be removed. Since node F4 changes Risk Aversion (RA) cluster (from RA2 to RA1), the tie F1–F4 is removed after 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.

more than three years before the current timestep. An example of tie removal can be seen in Fig. 5.

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:

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

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 *i*-th and the *j*-th agent.

2.4.4 *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 6. The crop plantation times have been suggested by the experts on farming in Luxembourg. The crop rotation

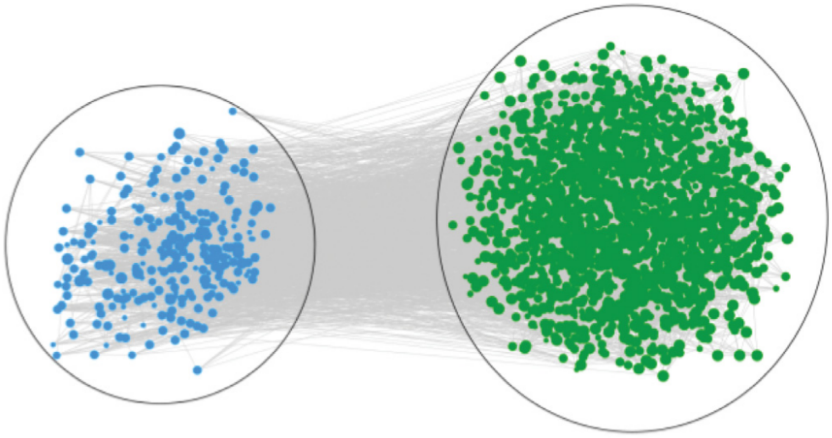


Figure 6: Network of farmers clustered at the beginning of the simulation according to the risk aversion levels. The edges between the nodes from different risk aversion level clusters are based on neighbourhood relations. The size of each node is proportional to the GC of the farmer. As can be inferred 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.

schemes were determined by extraction of common recurring n-gram substrings for a given list of UAA plantation history. In Table 7, 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 7. 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 multicropping (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 7, 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.

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	O	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 6: 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.

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).

2.5 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 (Marvuglia et al., 2017; Navarrete Gutiérrez et al., 2017). More details on the struc-

Crop history extraction (Step 1)		
UAA_1 (CCFFCCFFCC)		
UAA_2 (FFMOCFFMOC)		
UAA_3 (FFGFMOCMOC)		
$\vdots$		
UAA_n (FLCFMMFLCF)		
Identifying common rotation schemes (Step 2)		
3-gram	4-gram	5-gram
MGF		
FCC	**LLCC**	
MOC	FFMM	**FFMOC**
LFF	**FFCC**	
LLC		

Table 7: The crop rotations used in the simulations. The bold ones are assigned to organic farms whereas the italic one can be used in both conventional and organic farming. The rest is generally used in conventional farming.

ture of the model, not concerning the agents' interaction mechanism, are given in (Navarrete Gutiérrez et al., 2017) and (Marvuglia et al., 2017). Fig. 7 shows the initial GC distribution functions used in this study.

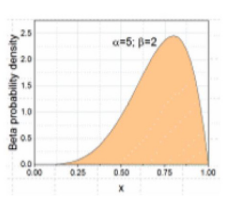
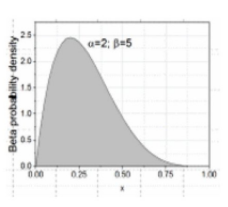
Distribution	Parameters
	GC_{high}: GC is distributed to the agents with a Beta probability function with shape parameters $\alpha = 5$ and $\beta = 2$. This means that the probability of an agent to be initialized with $GC > 0.5$ is higher than of being initialized with $GC < 0.5$.
	GC_{low}: GC is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

Figure 7: GC initialization scenarios.

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) 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 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. 8.

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.

2.6 RESULTS AND DISCUSSION

Fig. 9a and 9b 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

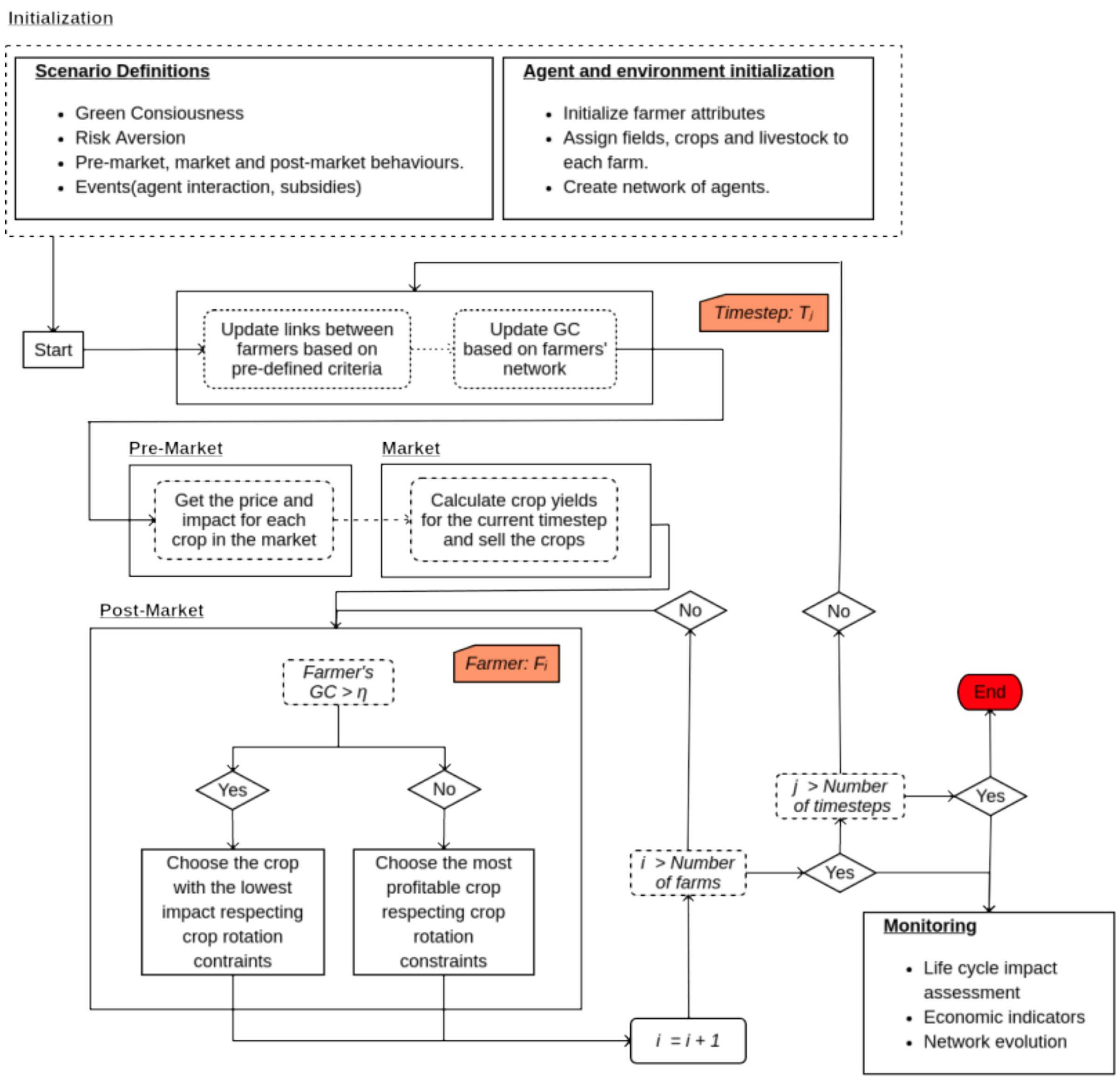


Figure 8: Simulation flowchart

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 8), 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. 10).

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. 9c and 9d show the LCIA results for three different endpoint values obtained with the ReCiPe 2016 method, for 10 consecutive years, respectively for the scenarios GC_{low} and GC_{high}. In Table 8, 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 8 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. 9c and 9d.

In Table 6 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

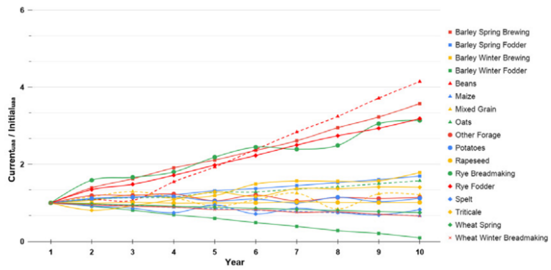


Figure 9(a): UAA change per crop GC_{low} ($\alpha = 2$ and $\beta = 5$)

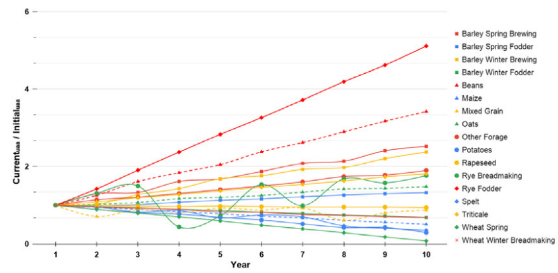


Figure 9(b): UAA change per crop GC_{low} ($\alpha = 5$ and $\beta = 2$)

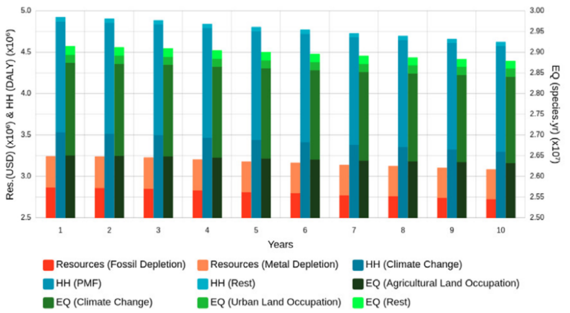


Figure 9(c): LCIA for three different endpoints (GC_{low})

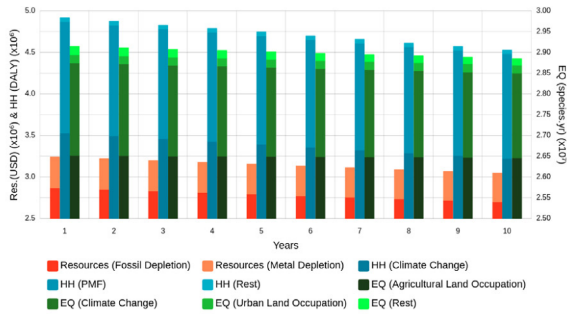


Figure 9(d): LCIA for three different endpoints (GC_{high})

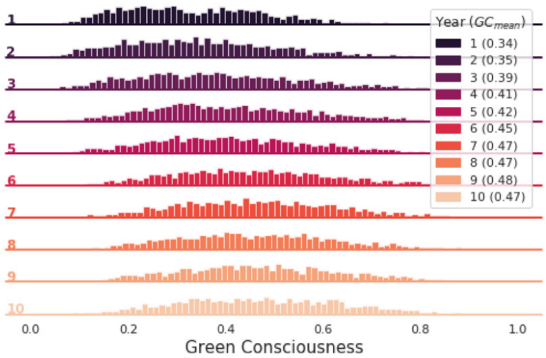


Figure 9(e): Evolution of GC distribution (GC_{low})

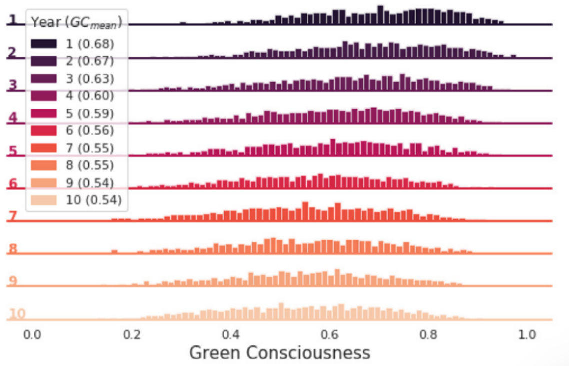


Figure 9(f): Evolution of GC distribution (GC_{high})

Figure 9: UAA change per crop, expressed as the ratio between crop areas at every timestep and area under the same crop at year 1 9a and 9b. LCIA results over the years 9c and 9d 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 9e and 9f for scenario (GC_{low}) and scenario (GC_{high}), respectively. In Figs. 9e and 9f, the mean value of each GC distribution is indicated in the legends next to the corresponding year of the simulation.

Table 8: 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 (4600/0)	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

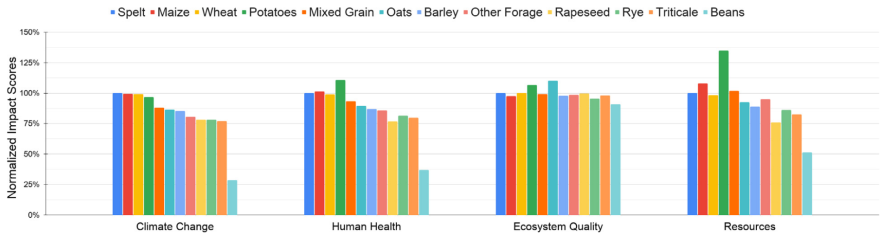


Figure 10: Comparison of CC and endpoint impact of crops per hectare. The impact score are normalized to the one of spelt, which has the highest impact on CC.

other types of animals (and therefore relying on other types of organic manure) is not very common in Luxembourg.

Tables 9 and 10, 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. 9c and 9d 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 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. 9e), 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 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.

	Resources (10^6)	Human Health (10^6)	Ecosystem Quality (10^6)
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 (CV)	1.79%	2.09%	0.43%

Table 9: Main descriptive statistics of the LCIA results in 50 simulation runs for the last simulated year (GC_{low}).

	Resources (10^6)	Human Health (10^6)	Ecosystem Quality (10^6)
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
CV	2.07%	2.59%	0.33%

Table 10: Main descriptive statistics of the LCIA results in 50 simulation runs for the last simulated year (GC_{high}).

Each individual agent updates the GC value at every timestep. Therefore the initial distributions showed in Fig. 7 change at every timestep. The evolution of GC distributions can be seen in Figs. 9e and 9f. 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 CVs of the corresponding LCIA endpoint categories. Tables 11-12, 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 CVs 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 Ecosystem Quality (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. 11 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 CO2-eq emissions, due to the fact that it is the most densely built area, therefore with the lowest extension of agricultural 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.

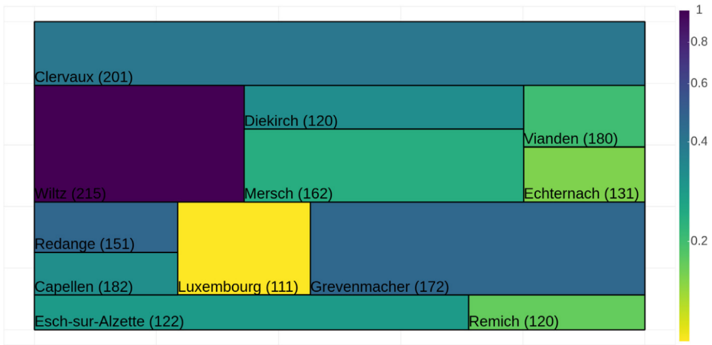


Figure 11: Treemap representation of the CC impacts normalized to the total agricultural area (kg CO_2-eq/ha) of each canton in the Grand Duchy of Luxembourg averaged over simulation duration and number of simulations. The numbers in brackets represent the number of farms falling within the territory of each canton.

2.7 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 (l'Agriculture, 2019). 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

Case	Description	Resources	Human Health	Ecosystem Quality
U_1	CV (Base)	1.79%	2.09%	0.43%
U_2	CV (Farm Locations)	1.72%	2.04%	0.32%
U_3	CV (GC)	1.77%	1.92%	0.30%
U_4	CV (RA)	1.85%	1.88%	0.33%

Table 11: The CV for a chosen parameter (GC_{low}).

Case	Description	Resources	Human Health	Ecosystem Quality
U_1	CV (Base)	2.07%	2.59%	0.33%
U_2	CV (Farm Locations)	1.82%	2.03%	0.30%
U_3	CV (GC)	2.00%	2.15%	0.35%
U_4	CV (RA)	2.01%	2.45%	0.31%

Table 12: The CV for a chosen parameter (GC_{high}).

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 2.4.1 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 (organ-

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

ic/conventional) or its livestock density. We will address these points in future research.

2.8 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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Appendix A. Supplementary data

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

Adams, R. and L. Bischof (1994). "Seeded region growing." In: *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 16.6, pp. 641–647.

Amini, Mehdi, Tina Wakolbinger, Michael Racer, and Mohammad G. Nejad (2012). "Modeling the effect of social networks on adoption of multifunctional agriculture." In: *European Journal of Operational Research* 216 (2), pp. 301–311.

An, Li (2012). "Modeling human decisions in coupled human and natural systems: Review of agent-based models." In: *Ecological Modelling* 229, pp. 25–36.

Appel, Franziska, Arlette Ostermeyer-Wiethaup, and Alfons Balmann (2016). "Effects of the German Renewable Energy Act on structural change in agriculture–The case of biogas." In: *Utilities Policy* 41, pp. 172–182.

Ardia, David et al. (2008). *Financial risk management with Bayesian estimation of GARCH models*. Vol. 18. Springer.

Barbuto, Angela, Antonio Lopolito, and Fabio Gaetano Santeramo (2019). "Improving diffusion in agriculture: an agent-based model to find the predictors for efficient early adopters." In: *Agricultural and food economics* 7.1, p. 1.

Baustert, Paul (Apr. 2021). "Development of an uncertainty analysis framework for model-based consequential life cycle assessment: Application to activity-based modelling and life cycle assessment of multimodal mobility." PhD thesis.

Baustert, Paul and Enrico Benetto (2017). "Uncertainty analysis in agent-based modelling and consequential life cycle assessment coupled models: a critical review." In: *Journal of Cleaner Production* 156, pp. 378–394. DOI: 10.1016/j.jclepro.2017.03.193.

Bichraoui-Draper, Najet, Ming Xu, Shelie A Miller, and Bertrand Guillaume (2015). "Agent-based life cycle assessment for switchgrass-based bioenergy systems." In: *Resources, Conservation and Recycling* 103, pp. 171–178.

Bohlmann, Jonathan D., Roger J. Calantone, and Meng Zhao (2010). "The Effects of Market Network Heterogeneity on Innovation Diffusion: An Agent-Based Modeling Approach." In: *Journal of Product Innovation Management* 27 (5), pp. 741–760.

Byrka, Katarzyna, Arkadiusz Jedrzejewski, Katarzyna Sznajd-Weron, and Rafał Weron (2016). "Difficulty is critical: The importance of social factors in modeling diffusion of green products and practices." In: *Renewable and Sustainable Energy Reviews* 62, pp. 723–

735. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2016.04.063.

Davis, Chris, Igor Nikolić, and Gerard PJ Dijkema (2009). "Integration of life cycle assessment into agent-based modeling: Toward informed decisions on evolving infrastructure systems." In: *Journal of Industrial Ecology* 13.2, pp. 306–325.

Davis, Chris, Igor Nikolic, and Gerard PJ Dijkema (2010). "Infrastructure modelling 2.0." In: *International Journal of Critical Infrastructures* 6.2, pp. 168–186.

FAO (2018). *Nitrogen Inputs to Agricultural Soils from Livestock Manure: New Statistics*. Food and Agriculture Organization of the United Nations.

Faller, Fabian and Christian Schulz (2017). "Sustainable practices of the energy transition—Evidence from the biogas and building industries in Luxembourg." In: *Applied Geography* 30, pp. 1–8.

Ferber, Jacques and Gerhard Weiss (1999). *Multi-agent systems: an introduction to distributed artificial intelligence*. Vol. 1. Addison-Wesley Reading.

Gaud, Nicolas, Stéphane Galland, Franck Gechter, Vincent Hilaire, and Abderrafiaa Koukam (2008). "Holonic multilevel simulation of complex systems: Application to real-time pedestrians simulation in virtual urban environment." In: *Simulation Modelling Practice and Theory* 16.10, pp. 1659–1676.

Ghoniem, Mohammad, Maël Cornil, Bertjan Broeksema, Mickaël Stefas, and Benoît Otjacques (2015). "Weighted maps: treemap visualization of geolocated quantitative data." In: *Visualization and Data Analysis 2015*. Vol. 9397. International Society for Optics and Photonics, 93970G.

Gilbert, Nigel (2019). *Agent-based models*. Sage Publications.

Goldenberg, Jacob, Barak Libai, Sarit Moldovan, and Eitan Muller (2007). "The NPV of bad news." In: *International Journal of Research in Marketing* 24 (3), pp. 186–200.

Grimm, V and SF Railsback (2005). *Individual-based modeling and ecology.- Princeton Univ.*

Guinee, Jeroen B, Reinout Heijungs, Gjalt Huppes, Alessandra Zamagni, Paolo Masoni, Roberto Buonamici, Tomas Ekvall, and Tomas Rydberg (2011). *Life cycle assessment: past, present, and future.*

Hare, M and Peter Deadman (2004). "Further towards a taxonomy of agent-based simulation models in environmental management." In: *Mathematics and computers in simulation* 64.1, pp. 25–40.

Hart, Kaley, Ben Allen, Clunie Keenleyside, Silvia Nanni, Anne Maréchal, Kamila Paquel, Martin Nesbit, and Julia Ziemann (Feb. 2017). "The consequences of climate change for EU agriculture: follow-up to the COP21 UN Paris Climate Change Conference." en. In: Publisher: EUAA: European Union Agency for Asylum.

URL: https://policycommons.net/artifacts/2199607/the-consequences-of-climate-change-for-eu-agriculture/2955969/ (visited on 01/03/2023).

Hauschild, Michael Z and Mark AJ Huijbregts (2015). "Introducing life cycle impact assessment." In: Springer, pp. 1–16.

Heath, Brian, Raymond Hill, and Frank Ciarallo (2009). "A survey of agent-based modeling practices (January 1998 to July 2008)." In: *Journal of Artificial Societies and Social Simulation* 12.4, p. 9.

Heckbert, Scott, Tim Baynes, and Andrew Reeson (2010). "Agent-based modeling in ecological economics." In: *Annals of the New York Academy of Sciences* 1185.1, pp. 39–53.

Heijungs, Reinout (2010). "Ecodesign—carbon footprint—life cycle assessment—life cycle sustainability analysis. A flexible framework for a continuum of tools." In: *Environmental and Climate Technologies* 4.1, pp. 42–46.

Huang, Shiyang, Guiping Hu, Carrie Chennault, Liu Su, Elke Brandes, Emily Heaton, Lisa Schulte, Lizhi Wang, and John Tyndall (2016). "Agent-based modeling of bioenergy crop adoption and farmer decision-making." In: *Energy* 115, pp. 1188–1201.

Huijbregts, M.A.J., Z.J.N. Steinmann, P.M.F. Elshout, G. Stam, F. Verones, M. Vieira, M. Zijp, A. Hollander, and R. van Zelm (2017). "ReCiPe2016: A Harmonised Life Cycle Impact Assessment Method at Midpoint and Endpoint Level." In: *Int J Life Cycle Assess* 22, pp. 138–147. DOI: 10.1007/s11367-016-1246-y.

Huétink, Floris J., Alexander van der Vooren, and Floortje Alkemade (2010). "Initial infrastructure development strategies for the transition to sustainable mobility." In: *Technological Forecasting and Social Change* 77 (8), pp. 1270–1281.

Igos, Elorri, Enrico Benetto, Rodolphe Meyer, Paul Baustert, and Benoit Othoniel (2019). "How to treat uncertainties in life cycle assessment studies?" In: *The International Journal of Life Cycle Assessment* 24, pp. 794–807.

Jones, James W, John M Antle, Bruno Basso, Kenneth J Boote, Richard T Conant, Ian Foster, H Charles J Godfray, Mario Herrero, Richard E Howitt, Sander Janssen, et al. (2017). "Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science." In: *Agricultural systems* 155, pp. 269–288.

Kalbar, Pradip P., Morten Birkved, Simon Elsborg Nygaard, and Michael Hauschild (2017). "Weighting and Aggregation in Life Cycle Assessment: Do Present Aggregated Single Scores Provide Correct Decision Support?" en. In: *Journal of Industrial Ecology* 21.6, pp. 1591–1600. ISSN: 1530-9290. DOI: 10.1111/jiec.12520. (Visited on 03/02/2022).

Kaufmann, Peter, Sigrid Stagl, and Daniel W. Franks (2009). "Simulating the diffusion of organic farming practices in two New EU Member States." In: *Ecological Economics* 68 (10), pp. 2580–2593.

Kerdlap, Piya, Aloisius Rabata Purnama, Jonathan Sze Choong Low, Daren Zong Loong Tan, Claire Y. Barlow, and Seeram Ramakrishna (2020). "Environmental evaluation of distributed versus centralized plastic waste recycling: Integrating life cycle assessment and agent-based modeling." In: *Procedia CIRP* 90, pp. 689–694.

Krichene, Aida (2017). "Using a naive Bayesian classifier methodology for loan risk assessment." In: *Journal of Economics, Finance and Administrative Science*.

Lan, Kai, Yuan Yao, and Giovanni Baiocchi (2019). "Integrating Life Cycle Assessment and Agent-Based Modeling: A Dynamic Modeling Framework for Sustainable Agricultural Systems." In: DOI: 10.1016/j.jclepro.2019.117853. URL: https://doi.org/10.1016/j.jclepro.2019.117853.

Liu, Dongya, Xinqi Zheng, and Hongbin Wang (2020). "Land-use Simulation and Decision-Support system (LandSDS): Seamlessly integrating system dynamics, agent-based model, and cellular automata." In: *Ecological Modelling* 417, p. 108924.

Malawska, Anna and Christopher John Topping (2016). "Evaluating the role of behavioral factors and practical constraints in the performance of an agent-based model of farmer decision making." In: *Agricultural Systems* 143, pp. 136–146.

Manson, Steven M., Nicholas R. Jordan, Kristen C. Nelson, and Rachel F. Brummel (2016). "Modeling the effect of social networks on adoption of multifunctional agriculture." In: *Environmental Modelling & Software* 75, pp. 388–401.

Marvuglia, A, E Benetto, and B Murgante (2015). "Calling for an integrated computational systems modelling framework for life cycle sustainability analysis." In: *J. Environ. Account. Manag* 3, pp. 213–216.

Marvuglia, Antonino, Enrico Benetto, Sameer Rege, and Colin Jury (2013). "Modelling approaches for consequential life-cycle assessment (C-LCA) of bioenergy: critical review and proposed framework for biogas production." In: *Renewable and Sustainable Energy Reviews* 25, pp. 768–781.

Marvuglia, Antonino, Sameer Rege, Tomás Navarrete Gutiérrez, Laureen Vanni, Didier Stilmant, and Enrico Benetto (2017). "A return on experience from the application of agent-based simulations coupled with life cycle assessment to model agricultural processes." In: *Journal of cleaner production* 142, pp. 1539–1551.

Micolier, A, F Taillandier, P Taillandier, and F Bos (2019a). "Li-BIM, an agent-based approach to simulate occupant-building interaction from the Building-Information Modelling." In: *Engineering Applications of Artificial Intelligence* 82, pp. 44–59.

Micolier, Alice, Philippe Loubet, Franck Taillandier, and Guido Sonnemann (2019b). "To what extent can agent-based modelling enhance a life cycle assessment? Answers based on a literature review." In: *Journal of Cleaner Production* 239, p. 118123.

Miller, Shelie A, Stephen Moysey, Benjamin Sharp, and Jose Alfaro (2013). "A stochastic approach to model dynamic systems in life cycle assessment." In: *Journal of Industrial Ecology* 17.3, pp. 352–362.

Mitchell, Melanie (2009). *Complexity: A Guided Tour*. New York: Oxford University Press.

Moglia, Magnus, Aneta Podkalicka, and James McGregor (2018). "An Agent-Based Model of Residential Energy Efficiency Adoption." In: *Journal of Artificial Societies and Social Simulation* 21 (3), p. 3. DOI: 10.18564/jasss.3729.

Mutel, Chris (2017). "Brightway: An open source framework for Life Cycle Assessment." In: *Journal of Open Source Software* 2.12, p. 236. DOI: 10.21105/joss.00236.

Navarrete Gutiérrez, Tomás, Sameer Rege, Antonino Marvuglia, and Enrico Benetto (2017). "Sustainable farming behaviours: an agent based modelling and LCA perspective." In: *Agent-Based Modeling of Sustainable Behaviors*. Springer, pp. 187–206.

Ng, Tze Ling, J Wayland Eheart, Ximing Cai, and John B Braden (2011). "An agent-based model of farmer decision-making and water quality impacts at the watershed scale under markets for carbon allowances and a second-generation biofuel crop." In: *Water Resources Research* 47.9.

Nikolic, Igor, Gerard PJ Dijkema, and Koen H van Dam (2009). "Understanding and shaping the evolution of sustainable large-scale socio-technical systems." In: *The dynamics of regions and networks in industrial ecosystems* 156.

Noori, Mehdi and Omer Tatari (Feb. 2016). "Development of an agent-based model for regional market penetration projections of electric vehicles in the United States." en. In: *Energy* 96, pp. 215–230. ISSN: 0360-5442. DOI: 10.1016/j.energy.2015.12.018. (Visited on 02/26/2023).

North, Michael J and Charles M Macal (2007). *Managing business complexity: discovering strategic solutions with agent-based modeling and simulation*. Oxford University Press.

Norton, Roger D and Peter BR Hazell (1986). *Mathematical programming for economic analysis in agriculture*. Macmillan.

Paatero, Jukka V and Peter D Lund (2006). "A model for generating household electricity load profiles." In: *International journal of energy research* 30.5, pp. 273–290.

Pigné, Yoann, Antoine Dutot, Frédéric Guinand, and Damien Olivier (2008). *GraphStream: A Tool for bridging the gap between Complex Systems and Dynamic Graphs*. arXiv: 0803.2093 [cs.MS].

Popa, Florin, Mathieu Guillermin, and Tom Dedeurwaerdere (2015). "A pragmatist approach to transdisciplinarity in sustainability research: From complex systems theory to reflexive science." In: *Futures* 65, pp. 45–56.

Querini, Florent and Enrico Benetto (2014). "Agent-based modelling for assessing hybrid and electric cars deployment policies in Luxembourg and Lorraine." In: *Transportation Research Part A: Policy and Practice* 70, pp. 149–161.

Rege, S, M Arenz, A Marvuglia, I Vázquez-Rowe, E Benetto, E Igos, and D Koster (2015a). "Quantification of Agricultural Land Use Changes in Consequential Life Cycle Assessment Using Mathematical Programming Models Following a Partial Equilibrium Approach." In: *Journal of Environmental Informatics* 26.2.

Rege, Sameer, Tomás Navarrete Gutiérrez, Antonino Marvuglia, Enrico Benetto, and Didier Stilmant (2015b). "Modelling Price Discovery in an Agent Based Model for Agriculture in Luxembourg." In: *Computing in Economics and Finance*. Springer, pp. 91–112.

Rounsevell, Mark DA, Derek T Robinson, and Dave Murray-Rust (2012). "From actors to agents in socio-ecological systems models." In: *Philosophical Transactions of the Royal Society B: Biological Sciences* 367.1586, pp. 259–269.

Sala, Serenella, Biagio Ciuffo, and Peter Nijkamp (2015). "A systemic framework for sustainability assessment." In: *Ecological Economics* 119, pp. 314–325.

Smajgl, Alex, Daniel G Brown, Diego Valbuena, and Marco GA Huigen (2011). "Empirical characterisation of agent behaviours in socio-ecological systems." In: *Environmental Modelling & Software* 26.7, pp. 837–844.

Teglio, Andrea et al. (2011). "From agent-based models to artificial economies." PhD thesis. Universitat Jaume I.

Tiruta-Barna, Ligia, Yoann Pigné, Tomás Navarrete Gutiérrez, and Enrico Benetto (2016). "Framework and computational tool for the consideration of time dependency in Life Cycle Inventory: proof of concept." In: *Journal of Cleaner Production* 116, pp. 198–206.

Van Winsen, F., Y. de Mey, L. Lauwers, S. Van Passel, M. Vancauteren, and E. Wauters (2016). "Determinants of risk behaviour: effects of perceived risks and risk attitude on farmer's adoption of risk management strategies." In: *Journal of Risk Research* 19.1, pp. 56–78.

Van Winsen, Frankwin (2014). "Rethinking farmers' intended risk behaviour: the role of risk perception, risk attitude and decision context." PhD thesis. Ghent University.

Vázquez-Rowe, Ian, Antonino Marvuglia, Sameer Rege, and Enrico Benetto (2014). "Applying consequential LCA to support energy policy: land use change effects of bioenergy production." In: *Science of the Total Environment* 472, pp. 78–89.

Walzberg, Julien, Thomas Dandres, Nicolas Merveille, Mohamed Cheriet, and R Ejean Samson (2020). "Should we fear the rebound effect in smart homes?" In: *Renewable and Sustainable Energy Reviews* 125, p. 109798. DOI: 10.1016/j.rser.2020.109798. URL: https://doi.org/10.1016/j.rser.2020.109798.

Walzberg, Julien, Thomas Dandres, Nicolas Merveille, Mohamed Cheriet, and Réjean Samson (2019). "Assessing behavioural change with agent-based life cycle assessment: Application to smart homes." In: DOI: 10.1016/j.rser.2019.05.038. URL: https://doi.org/10.1016/j.rser.2019.05.038.

Wei, Wei, Pyrene Larrey-Lassalle, Thierry Faure, Nicolas Dumoulin, Philippe Roux, and Jean-Denis Mathias (2015). "How to conduct a proper sensitivity analysis in life cycle assessment: taking into account correlations within LCI data and interactions within the LCA calculation model." In: *Environmental science & technology* 49.1, pp. 377–385.

Weidema, Bo P., Massimo Pizzol, Jannick Schmidt, and Greg Thoma (2018). "Attributional or consequential Life Cycle Assessment: A matter of social responsibility." In: *Journal of Cleaner Production* 174, pp. 305–314. ISSN: 0959-6526. DOI: https://doi.org/10.1016/j.jclepro.2017.10.340.

Wiek, Arnim, Barry Ness, Petra Schweizer-Ries, Fridolin S Brand, and Francesca Farioli (2012). "From complex systems analysis to transformational change: a comparative appraisal of sustainability science projects." In: *Sustainability science* 7.1, pp. 5–24.

Wood, Brennon A, Hugh T Blair, David I Gray, Peter D Kemp, Paul R Kenyon, Steve T Morris, and Alison M Sewell (2014). "Agricultural science in the wild: A social network analysis of farmer knowledge exchange." In: *PloS one* 9.8, e105203.

Wu, Susie Ruqun, Xiaomeng Li, Defne Apul, Victoria Breeze, Ying Tang, Yi Fan, and Jiquan Chen (2017). "Agent-based modeling of temporal and spatial dynamics in life cycle sustainability assessment." In: *Journal of Industrial Ecology* 21.6, pp. 1507–1521.

Young, H. Peyton (2011). "The dynamics of social innovation." In: *Proceedings of the National Academy of Sciences* 108.Supplement 4, pp. 21285–21291. ISSN: 0027-8424.

Zakrajšek, Franc J. and Vlasta Vodeb (2020). "Agent-based geographical modeling of public library locations." In: *Library & Information Science Research* 42.2, p. 101013.

Zupko, Robert (2021). "Application of agent-based modeling and life cycle sustainability assessment to evaluate biorefinery placement." In: *Biomass and Bioenergy* 144, p. 105916.

l'Agriculture, de la Viticulture et du Développement Rural Ministère de (2019). *Pachtrecht und faire Vertragsbedingungen - Leitfaden für die Praxis*. https://agriculture.public.lu/dam-assets/publications/ma/pdr2014-2020/pachtrecht.pdf. Accessed on 25 February 2023.

"Sustainable farming strategies for mixed crop-livestock farms in Luxembourg simulated with a hybrid agent-based and life-cycle assessment model "

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3

SUSTAINABLE FARMING STRATEGIES FOR MIXED CROP-LIVESTOCK FARMS IN LUXEMBOURG SIMULATED WITH A HYBRID AGENT-BASED AND LIFE-CYCLE ASSESSMENT MODEL

3.1 ABSTRACT

ABMs are particularly suitable to simulate human–natural systems since they allow modelers to consider the behavioral aspects of individuals. Life-Cycle Assessment (LCA) has also been widely used in research, industry, and policy to assess systems' environmental sustainability. In this paper, we introduce a coupled ABM-LCA model to simulate mixed crop-livestock farming activities in the Grand Duchy of Luxembourg. The simulator considers a wide range of aspects related to typical farming business activities and allows the calculation of the environmental and economic impacts of the decisions taken by agents as well. The paper simulates different scenarios. Scenario A is the baseline scenario. Scenario B considers reducing the stocking rate from 1.6 to 1.3 livestock units per ha (Livestock Unit (LSU)/ha). Scenario C aims to reduce the soybean ratio in animals' feed rations to the minimum possible level that is feasible for each farm. Scenario D simulates an increase in soybean autonomy: the farmer chooses to adopt local soybean (instead of imported one) into the crop rotation if its green consciousness exceeds a pre-fixed threshold. As expected, in scenario B, all impact categories show improvement with respect to the baseline scenario, the highest ones being an almost 25% reduction in freshwater eutrophication, 21% in climate change–human health, and 19% in freshwater ecotoxicity. For natural land transformation, the most significant improvements are obtained in scenarios C (11% reduction) and D (13% reduction). On the other hand, in scenario C, the change in feed composition, combined with an expected decrease in stocking rates, also has a positive effect (about 16% reduction compared to the baseline) on agricultural land occupation, due to the utilization of pasture and locally produced crops. An analysis of the systemic uncertainty calculated at the endpoint indicators level showed low Coefficient of Variation (CV) for all the scenarios, with scenario A always having the lowest values of CV in every impact category, scenario C having the highest CV in the ecosystem quality and the human health categories and scenario B having the highest CV in the resources category. The consideration of subsidy schemes in the Grand Duchy of Luxembourg allows the modelers to better interpret the resulting revenue and cost structures of different scenarios. The

results show that the farm profitability stays on the same level when the stocking rate is reduced, and the subsidy granted for reducing nitrogen emissions is in place at the same time. Moreover, the soybean autarky in Luxembourg can be increased to 17% if the farmers are willing to incorporate soybean into their rotation scheme, thus reducing the impacts due to the transportation and production of soybean in South American countries.

3.2 INTRODUCTION AND STATE OF THE ART

Acknowledging that anthropic activities have caused rapid and widespread changes in the earth's climate, the Intergovernmental Panel on Climate Change (IPCC) recognizes that combating Climate Change (CC) requires reaching "at least net–zero CO_2 emissions, along with strong reductions in other Greenhouse Gas (GHG) emissions" (Masson-Delmotte et al., 2021). Agriculture is one of the sectors that has been and will be, severely affected by the rising temperatures, with loss of productivity caused by thermal stress, extreme weather events and droughts. To cite just one example, wheat yields are expected to reduce significantly (4–6%) for each degree Celsius of an increase in global temperature (Liu et al., 2016). On the other hand, some crops could become cultivable at latitudes different from those traditionally grown. Moreover, it has been observed that since the 1960s, plant pathogens and pests have shifted latitudinally as the global temperature increases (Bebber et al., 2013). Temperature change also influences the spatial-temporal distribution of disease vectors. Animals may be exposed to diseases that have never been seen before in their regions. Additionally, the disease transmission rate is generally higher among the hosts in warmer temperatures (Thornton et al., 2009).

According to (Hempel et al., 2019), dairy farms in Europe are projected to experience a 2.8% of milk yield decrease and a 5.4% monthly financial loss in the summer months due to heat stress towards the end of the century. As suggested by (Rust, 2019) heat stress may be less relevant in intensive systems since intensive farming is usually practiced in more controlled spaces. However, it still affects the feed production for animal consumption. The total area of extensive systems, on the other hand, may see a slight decrease. Still, they will shift towards more conservative stocking rates (i.e., the number of livestock units – LSU per hectare) and pasture conservation (Rust, 2019). Furthermore, due to changing temperatures, the length of the growing season and the periods of available forage also change, which could reduce the quality of the forage, thus resulting in an increase in methane emissions due to ruminants' enteric fermentation per unit of gross energy (Benchaar et al., 2011).

While the agriculture sector is affected by the impacts of CC, it is also responsible for 16.5% of GHG emissions worldwide (Twine, 2021). The contribution has been both direct (i.e., through methane emissions and land-use changes) and indirect (i.e., across the entire supply chain) (Shukla et al., 2019). The world population is increasing at an unprecedented pace and this causes growth in demand for food, but also for the affluent food consumption patterns (Hadjikakou and Wiedmann, 2017). Unless this demand is fulfilled sustainably (Muller et al., 2017), the impact of agricultural production systems and their subsystems on the environment, combined with those of transport and industrial systems, may cause irreversible outcomes (Crippa et al., 2021; Gregory et al., 2005). All these facts call for an increase of attention to designing more suitable agriculture policies and thus adopting more sustainable agricultural practices.

In addition to agriculture, livestock production systems are responsible for relevant impacts on CV (Steinfeld et al., 2006). According to (Gerber et al., 2013), livestock systems account for 44% of all anthropogenic CH_4 emissions and 53% of N_2O emissions. Using the Global Livestock Environmental Assessment Model (GLEAM) (Gerber et al., 2013), which considers global supply chains, estimated the 14.5% of the total contribution of the livestock sector to the global anthropogenic GHG emissions. The direct contribution of the livestock sector to GHG emissions includes enteric fermentation, excretions, and respiration. Primarily enteric fermentation has significantly contributed to methane emissions and accounts for 39% of total GHG emissions (Beauchemin et al., 2009). After enteric fermentation, the second source of GHG emissions is manure management and its field application, which account for 26% of the sectoral emissions (IPCC, 2014). Livestock manure releases CH_4 and N_2O, which both have high GWP. The amount of methane released depends on the air and storage facility conditions, as well as the animal diet. Liquid manure tends to emit more methane than solid manure (Steinfeld et al., 2006). The emission of N_2O in agricultural land after manure application is the largest source of global N_2O emissions (Steinfeld et al., 2006). Like CH_4, N_2O emissions depend on the storage systems and the storage duration.

Sustainably managing agricultural and farming systems and tracking the impacts caused by them is a complex task, and even more so in a changing climate. As already highlighted by several studies on sustainable agriculture and farming (Jones et al., 2017; Marvuglia et al., 2022), agricultural systems are complex systems as they are the result of the interaction of many interconnected parts, where not only technical and engineering components play a role, but also human behavioral aspects. For this reason, agent-based modeling (ABM) has been gaining interest in socio-economic systems modeling since it allows the modelers to consider heterogeneous agents and their interactions (Kremmydas et al., 2018). This is particularly relevant in agricultural systems since the farms are run by actors (often family businesses) which may have different strategies that can be affected by bounded rationality and not necessarily driven only by profit maximization (Howley, 2015). The need to represent farmers' individual cognitive processes and social interactions has brought agricultural systems modelers to the conclusion that ABM could help capture these since the ABM community has gained maturity over the last decade (Reidsma et al., 2018).

(Kremmydas et al., 2018) makes a systematic literature review of ABM applied to agricultural policy evaluation and examines the status of the literature regarding model transparency, the modeling of the agents' decision processes, and the creation of the initial population. (Burg et al., 2021) focuses on manure-based biogas and applies ABM to elicit the necessary additional incentives that would be able to boost its production in Switzerland. (Yang et al., 2019) tackles the problem of cattle production and specifically its transportation from an ABM perspective. They use a model built into the AnyLogic software to generate cattle and truck movement data among premises based on regular business operating principles and assumed conditions. (Freeman et al., 2013) focuses only on a particular aspect of farming, which is dairy and manure land use. They use agent-based simulation to compare the performance of alternative policies. (Fernandez-Mena et al., 2020) developed an ABM to simulate material flows among actors in agro-food networks. They include in their model farming activities and emissions into the environment at the farm scale, interactions between farms and their partners through material exchanges, as well as waste and by-product recycling.

To the best of our knowledge, Agroscope's SWISSland is the only national-scale hybrid ABM-LCA simulator for the agriculture sector (Huber et al., 2018; Zimmermann et al., 2015). (Mack and Huber, 2017) uses SWISSland for projecting supply and demand while considering the external trade on global markets (Möhring et al., 2016). The model has three main objectives: policy evaluation, consideration of behavioral attributes of each farm, and modeling the structural changes in farms. The agents interact with one another to exchange of resources, but their behavioral attributes do not change because of this interaction. (Manson et al., 2016) tries to model the interactions between neighbors or among communities that may result in information exchange and, thus, behavior change in individual agents. Another modeling choice of SWISSland is that the calculations for animal intakes and production are not based on individual requirements but rather on the aggregation of all livestock. Animals of different types and age groups have different requirements to achieve growth and production goals.

The objective of this paper is the implementation of a hybrid ABM–LCA model and its application to the case of the Grand Duchy of Luxembourg via the simulation of multiple scenarios that go in the direction of reducing the emissions of the agriculture and farming sector, in line with the ambitious decarbonization objectives of the country (MECDD, 2021). The paper aims at providing a comprehensive coupled ABM-LCA model where all the aspects related to the detailed description of the farm business model, as well as the detailed modelling of individual animals' methane emissions, are integrated in a single model, which is also able to consider the effects of exogenous variables, like subsidies. This covers a gap in the literature, where several models covering different aspects exist, but an integrated model is missing. The organization of the paper is as follows. Section 3.3 gives the model description, objectives, data sources, and sub-models. Then a complete description of the coupling between ABM and LCA is given. Section 3.4 presents the case study and simulated scenarios. The results of the simulations and their uncertainty analysis are shown and discussed in Section 3.5. The limitations and possible future enhancements to the model are presented in Section 3.6. Finally, the conclusions and future goals are given in Section 3.7 and Section 3.8, respectively.

3.3 MATERIALS AND METHODS

The main objective of our model is to elicit possible scenarios (and the parameters characterizing them) under which the national agrosystem evolves towards a more sustainable state. In (Marvuglia et al., 2022) we simulated the information diffusion (GC attitude) in the network of farmer agents. However, only the cropping activities were considered, without full inclusion of animal farming into the model, even though most Luxembourgish farms are of a mixed type (producing crops, meat and milk in the same holding). The model developed by Marvuglia et al., 2022 has now been enhanced to include a full integration of dairy farming activities which are especially important for Luxembourgish agriculture.

3.3.1 *A short description of the model*

The model has different components which have been conceptualized based on stakeholders' consultation. The agents perform actions based on the economic value of the resulting outcome, as well as their impact on the environment. These actions can be reactions to the surrounding environment (i.e., the agricultural area each farmer manages) or they can be due to the preset behavioral attributes of an agent. The model is built on top of the simulator which was described in (Marvuglia et al., 2017) and (Marvuglia et al., 2022).

The main entities in the model are the following:

Farmer: The agent entity in our simulation model is a farmer, who takes decisions based on predefined constraints and behavioral attributes. A farmer owns a farm, which is the environment (s)he manages. The basic attributes of a farmer agent are age, GC, and risk aversion (Marvuglia et al., 2022). These attributes, combined with farm properties, impact farmers' decisions.

Farm: Each farm is governed by a farmer and has attributes that affect cropland and livestock management. For instance, the size of a farm may influence how many animals must be kept or how many neighbors there are. Crop rotation is another attribute that can be determined according to the farm's needs. A farmer may choose to arrange feed rations considering the cropland available and change the rotation accordingly. Based on the attributes mentioned above, the farm's total cropland is initialized using the Geographic Information System (GIS) data. The surface of each farm in the Grand Duchy of Luxembourg is divided in several field parcels, which are the smallest parcels of land registered at the land cadaster. We call them Utilized Agricultural Area (UAA). The GIS data that has information on UAAs in Luxembourg was provided by Service d'Economie Rurale (SER). [1] Each of these UAAs is represented as a polygon with the associated information on which a crop is being cultivated for a given year, the commune it belongs to, the surface area and its perimeter. The data is available from 2010 until 2020. Since the farm to which each UAA belongs is not known, we create farms using the algorithm recalled in (Marvuglia et al., 2022) and assign each one of them to an agent in the initialization phase.

Table 13 shows the distribution of farms in Luxembourg by size classes in 2020, which is the year used to initialize the model. After the farm boundaries are created, a certain number of cattle heads are also assigned to the farms according to the repartition shown in Table 14. The initial assignment considers the nitrogen excretion allowed per hectare in Luxembourg. Different limits of nitrogen that can be applied and excretion rates from manure per cattle class were taken from (FAO, 2018).

Crop: The cropland of each farm is initialized according to GIS data with details on crops planted in each UAA in 2020. The possible crops for each UAA are given in Table 15. In our simulations, the available crop types are cereal (C), legume (L), maize (M) and other (O). The crop rotations were specified after discussion with different actors in the sector and assigned to a farm according to its specifications (Marvuglia et al., 2022). A crop can be planted in a time interval of ±1 month from its usual seeding month and can be harvested ±1 month from its usual harvest month (the seeding can be anticipated if the previous crop has already been harvested).

1 SER: `https://ma.gouvernement.lu/fr/administrations/ser.html`

FARM CLASS	MIN AREA (HA)	MAX AREA (HA)	NUMBER FARMS	TOTAL UAA (HA)
A	0	2	164	95
B	2	5	119	442
C	5	10	152	1090
D	10	20	156	2126
E	20	30	114	2844
F	30	50	174	6906
G	50	100	483	36,515
H	100	200	510	81,573

Table 13: Farm classes and size-related data (STATEC, 2022)

Livestock: The farms in Luxembourg are mostly specialized in grazing livestock farming. For this reason, it is important to model the livestock production system along with cropland management to grasp the full business model of a farmer. This system mostly consists of dairy and suckler farms, therefore our focus is especially on those. According to the data from (Eurostat, 2022), the farms are initialized with livestock from different classes. Each livestock class differs from the other ones with attributes such as age, gender, and production purpose (i.e., suckler or dairy). According to its class, certain biological events and production mechanisms are applied to each animal in every step of the simulation (Figs 12 and 13). These events and mechanisms include key variables and parameters such as Dry Matter Intake (DMI), weight gain, Gross Energy Intake (GEI), lactation, and insemination, which are explained in more detail in Section 3.3.2.

Lactation: Each dairy animal is assigned a lactation period of a duration comprised between 305 and 320 days after the first insemination trial. Each insemination has a probability of success of 0.4 and it happens once in every time step. Once the cow is pregnant, until the dry-off phase, Milk production (MP) from each cow is calculated according to the Dijkstra equation given in (Nasri et al., 2008). After the calving, the newborn is added to the herd. The farmer waits for a certain period before the next insemination trial. The stages of each lactation are depicted in Fig. 12.

Price: The prices for all products are calculated by taking a moving average of previous n years, where n is the window size for the moving average and can be different for each farmer. The yearly prices for crops are taken from (STATEC, 2022) and monthly meat and milk prices are taken from (Eurostat, 2022). The prices are then updated according to their input time resolutions, i.e., monthly or yearly. The Value-Added Tax (VAT) is excluded from the prices that are being used in the model, therefore the crop prices in Table 15 do not include VAT.

LIVESTOCK CLASS ID	LIVESTOCK CLASS	AGE	A	B	C	D	E	F	G	H	SUM
1	Male	(L_{age}<12)	120	20	90	200	0	2140	17,180	34,470	54,220
2	Female	(L_{age} <12)	70	0	10	40	110	460	4200	7590	12,480
3	Male	(12 <L_{age} <24)	100	10	80	130	390	1360	10,020	19,400	31,490
4	Heifer	(12 <L_{age} <24)	50	10	30	30	80	240	1110	1540	3090
5	Heifer	(L_{age} >24)	70	20	20	90	350	960	6620	12,020	20,150
6	Dairy	(L_{age} >24)	0	0	0	0	130	1170	16420	33,300	51,020
7	Suckler	(L_{age} >24)	140	20	80	300	630	2000	8990	16,350	28,510

Table 14: Number of livestock in each farm class and livestock class in 2016. (Eurostat, 2022). L_{age}: The age of livestock in months.

CROP	TYPE	YIELD (t_{DM}/ HA)	PRICE (€/100KG)	TOTAL PRODUCTION (t_{DM})	STANDARD SEEDING MONTH	STANDARD HARVEST MONTH
Barley (spring)	C	5,96	14,21	10,951	3	8
Barley (winter)	C	5,51	14,21	21,500	10	8
Dried pulses (peas, beans, others)	L	3,41	18,00	1292	3	8
Grain maize	M	6,75	15,00	810	4	10
Green maize	M	13,74	–	222,219	4	10
Oats	C	4,99	13,5	7939	4	8
Potatoes	O	26,25	23,33	16,368	4	9
Rapeseed	O	3,30	35,65	8791	3	8
Rye	C	4,53	13,54	4670	10	8
Spelt	C	4,74	20,34	4217	10	8
Triticale	C	5,60	14,59	25,270	10	8
Wheat (spring)	C	6,13	17,05	2271	3	7
Wheat (winter)	C	6,06	17,05	63,910	10	8

Table 15: Some statistics for major crop types that are cultivated in Luxembourg in 2020. Yields are expressed in tons of dry matter (t_{DM}). Sources: (Marvuglia et al., 2022; STATEC, 2022).

Time: The time step of one month is chosen for the simulations. There are two main reasons behind this choice. The first one is the seasonal cultivation times for crops. As explained above, the seeding and harvesting months are respected throughout the simulation. If the current crop is harvested, the farmer chooses the next crop based on his or her farm's attributes. The second reason is the fact that decisions in livestock production are usually taken monthly. To implement lactation stages, a finer resolution than one year is needed. In fact, decisions like selling the animals or choosing grazing times are taken within the year, rather than at the end of the year. Each time step consists of three sequential phases. In the pre-market phase, the prices for the current timestep are updated, as well as seasonal decisions like feed rations or grazing times are chosen. Subsequently, in the market phase, the crop and animal outputs of the current year are collected. The farm revenue and costs are also calculated based on these outputs in the same phase. The updates to the farmer's behavioral attributes or farm structure (e.g., selection of animals to be culled) are all part of the post-market phase.

Environment: Each farm has been assigned cropland that comes from the real GIS data. The network of farmers is created based on geospatial neighborhoods, with a procedure that is explained in detail in (Marvuglia et al., 2022).

ABM-LCA coupling: The LCA model and the ABM are "tightly" coupled, in the acceptation discussed in (Baustert and Benetto, 2017).

Software implementation: The simulator has multiple software components communicating with each other. The initialization is achieved using the PostgreSQL (PostGIS) database, which includes the GIS data, country-specific statistics from STATEC and Eurostat and financial data such as cost items and product prices (Fig. 13). The ABM is built in Java (Arnold et al., 2005) to allow model builders enough flexibility and it is the main component that runs the simulation phase (Fig. 13). Finally, the environmental impacts of the crops and animal patterns obtained in each simulation are calculated using the classical LCIA indicators using the ReCiPe (Huijbregts et al., 2017) LCIA method. In the results monitoring phase (Fig. 13), the LCIA calculations are done automatically in Python using the Brightway2 life cycle assessment (LCA) framework (Mutel, 2017) and relying on Ecoinvent 3.7.1 as Life-Cycle Inventory (LCI) database for the background system (Wernet et al., 2016).

3.3.2 *The modeling of livestock production system*

The animal management part of the simulator is modeled such that one animal is the main physical component of a livestock production system. It has some phenotypical properties like gender, weight, and production type (female animals can be dairy or suckler), which are combined with its farm properties, like available grassland for animal consumption. The prevalent breed in Luxembourg is Holstein–Friesian, therefore every cattle in our simulations is assumed to be from this breed. Together with these properties, the choices made by the farmer determine the resulting production as well as the animal's lifetime. In Fig. 13 the life stages of one animal are depicted. After each calving, the calf is assigned to the farm with a certain gender, body weight, and birthdate. Until the heifers have the first calving, there is no milk or meat production, however, their DMI, gross energy intake, nitrogen excretion and methane emission are calculated. The heifers are kept until they reach 15 months of age when they are distinguished between suckler and dairy cows according to their genetic traits. After that, they start experiencing the lactation cycle depicted in Fig. 12 and go through it until they are sold, once they become 60 months old. Fig. 14 shows how the current stage of animal development affects the decision-making of a farmer in each time step. After the relevant updates are applied and the decision of keeping or selling is made, the production and resulting revenue are calculated at every time step (see Fig. 15).

3.3.2.1 *Milk production*

One of the two main purposes of livestock systems is to produce milk. There are different approaches in the literature to estimate daily MP and one of them is fitting standard growth functions to milk recordings. We chose to use the following one, which is known as the Dijkstra equation (Dijkstra et al., 1997):

$$MP\left(\frac{kg}{day}\right) = ae^{\frac{b(1-e^{ct})}{c}-dt} \tag{3}$$

where the parameters that define the lactation curve's shape and scale *(a = 23, b = 0.069, c = 0.066 and d = 0.0035)* are taken from (Nasri et al., 2008).

3.3.2.2 *Meat production*

After the dairy sector, the suckler production system is also important for Luxembourgish farmers. Although the feeding regimes in the current version of the simulator are adapted to dairy farms, in our simulations we calculate the meat produced via suckler cows and male cattle. The culling decision of a farmer agent is based on multiple factors such as age, gender, and efficiency of a cow (defined in Eq. 4). In Fig. 13, the cases where age and gender are decision factors are depicted.

However, the efficiency of a cow is another factor to consider, especially when the farmer wants to reduce the stocking rate. The efficiency of a cow is defined by Eq. 4 as the ratio between last month's MP and DMI:

$$\mathrm{Eff} = \sum_{t-1}^{t} \frac{\mathrm{MP}}{\mathrm{DMI}} \tag{4}$$

The farmer chooses to get rid of (sell or slaughter) the animal with the lowest efficiency to reach the objective stocking rate set by other constraints and mechanisms of the simulations. After the selection, the carcass weight of the animal is calculated. The assumption made by Ecoinvent is that the live weight of an animal should be halved to find the carcass weight. Therefore, we determine the meat produced by halving the live weight of the animal when the decision to cull is taken.

3.3.2.3 *Nitrogen excretion*

The manure and resulting nitrogen excretions to the soil due to livestock activities are calculated using the estimations in (Netherlands, 2012). The fixed parameters for one year of excretions are given in Table 16. The calculation of nitrogen input to the soil is particularly important to calculate subsidies and the animal capacity of the farm. The national limit of 170 kg-N_{org}/year/ha (where N_{org} is the organic nitrogen) is very strict and corresponds to 1.6 LSU in Luxembourg.

LIVESTOCK CLASS ID	1	2	3	4	5	6	7
Manure (kg/year)	5000	5000	11,500	11,500	11,500	13,000	15,000
Nitrogen (kg/year)	39,5	74,8	74,8	74,8	74,8	134,5	84,9

Table 16: Manure and Nitrogen excretions according to livestock type (Netherlands, 2012)

3.3.2.4 *Body weight and weight gain*

Normally, genetic traits and feed intake are major determinants in estimating the body weight of an animal. In the simulator, at the beginning of the simulation, the newborns are assigned an initial weight from a continuous uniform distribution in the range of 35–45 kgs. Then the body weight until 24 months of age is updated at every time step using the daily weight gain in (Handcock et al., 2019).

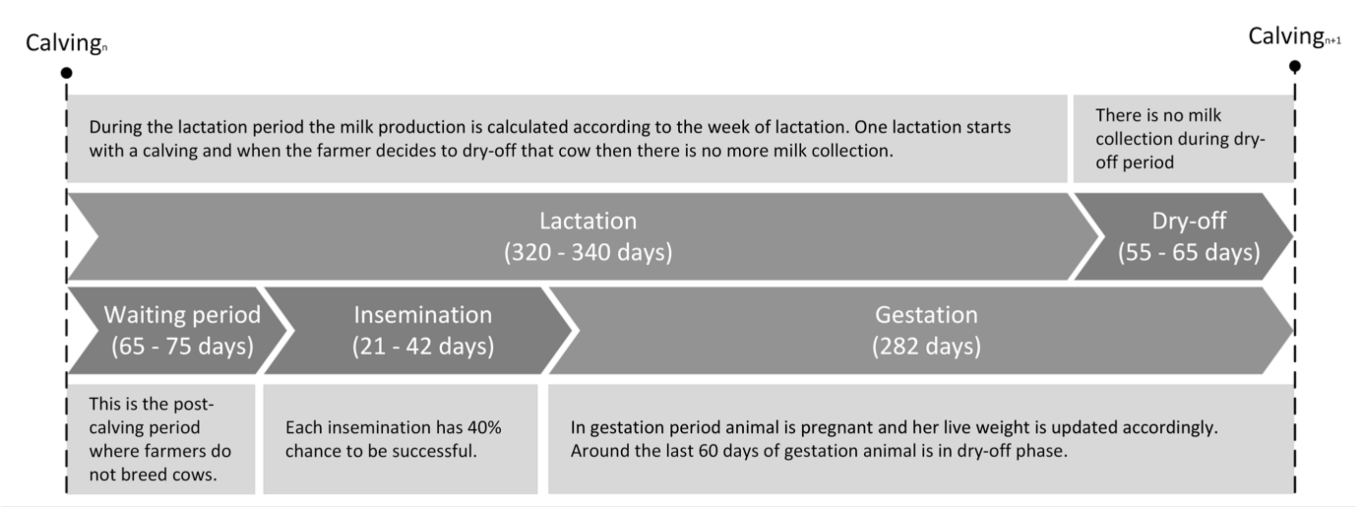

Figure 12: One lactation cycle as implemented in the ABM simulator.The parameters are chosen after consultation with project partners. If ranges are specified, it means that a random number is chosen from a uniform distribution within that range.

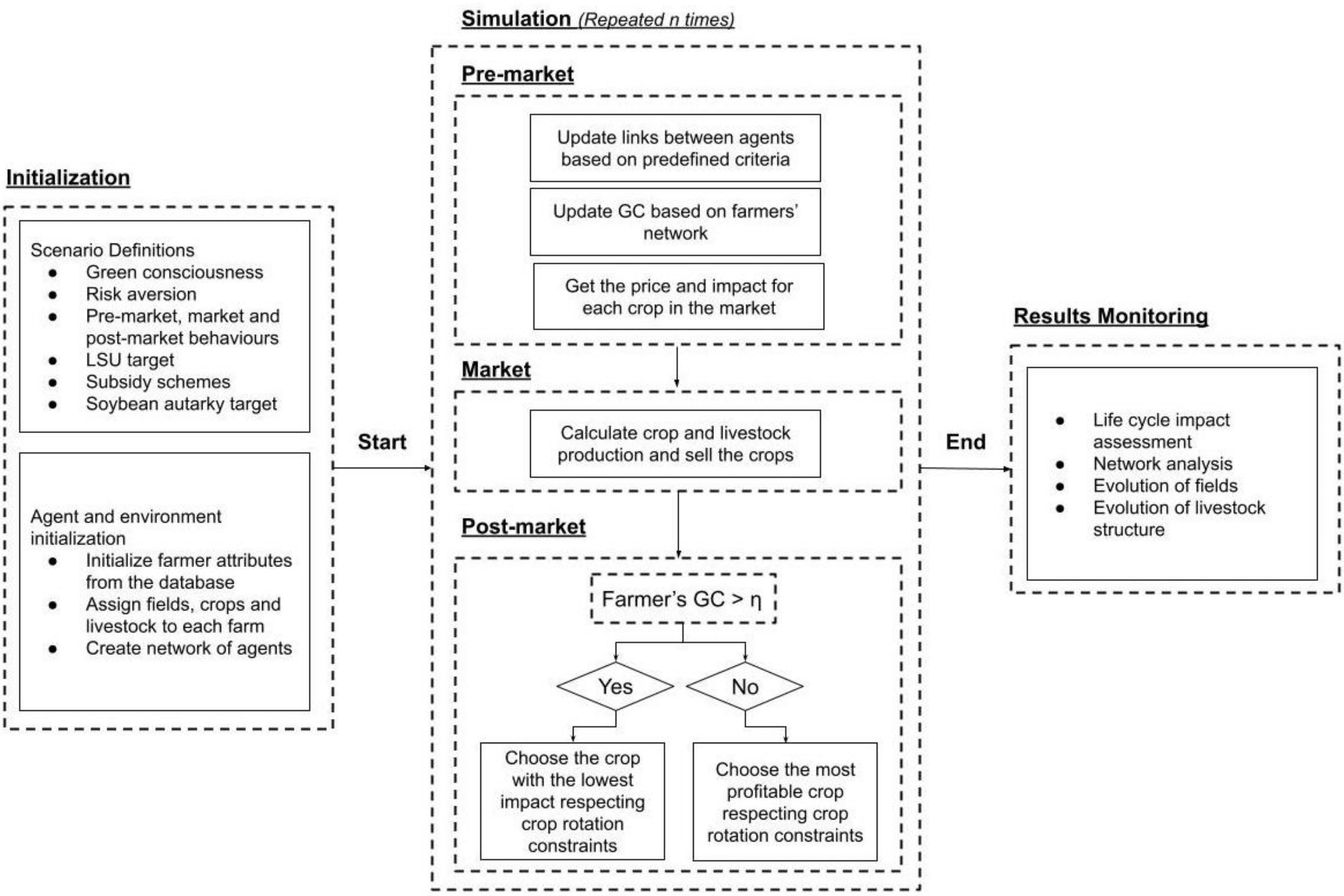

Figure 13: Overview of the modeling scheme. The main stages are initialization, simulation and monitoring.

3.3.2.5 *Gross Energy Intake (GEI)*

The GEI is calculated using Eq. 5 according to (Dong et al., 2006), where the calculations of different energy requirements can also be found.

$$\mathrm{GEI}\left(\frac{\mathrm{MJ}}{\mathrm{day}}\right) = \left[\frac{\left(\frac{NE_m+NE_a+NE_l+NE_{work}+NE_p}{REM}\right)+\left(\frac{NE_g}{REG}\right)}{\frac{DE\%}{100}}\right] \quad (5)$$

where NE_m is the net energy for maintenance, which is the amount of energy required to keep the animal's body energy in balance; NE_a is the net energy for activity, i.e., the energy required to get feed, water and shelter; NE_l is the lactation energy, which is a function of milk produced and its fat content; NE_{work} is the energy required for draft power, which is assumed to be zero in our simulations; NE_p is the energy required for pregnancy and NE_g is the energy required for weight gain. The ratio of net energy available in the diet for maintenance to digestible energy consumed (REM), the ratio of net energy available in the diet for growth to digestible energy consumed (REG) and digestible energy expressed as a percentage of gross energy (DE%) are fixed parameters that can be found in (Dong et al., 2006).

3.3.2.6 *Dry Matter Intake (DMI)*

The DMI for each animal is calculated according to its energy requirements for the given period. The energy content of each type of ration is precalculated and given in. The GEI of each animal is calculated according to (Eq. 5). Then the DMI is calculated proportionally to the average GEI of grown Holstein cows in the herd because the feed rations in are adjusted according to those ones.

3.3.2.7 *Methane (CH_4) emissions*

CH_4 emissions per cow is then calculated using the equation developed by IPCC (Dong et al., 2006):

$$\mathrm{EF}\left(\frac{\mathrm{kg}-\mathrm{CH}_4}{\mathrm{head}\times\mathrm{year}}\right) = \frac{\mathrm{GEI}\left(\frac{\mathrm{MJ}}{\mathrm{head}\times\mathrm{day}}\right)\times\frac{Y_m}{100}\times 365}{55.65} \quad (6)$$

where GEI is calculated according to (Dong et al., 2006), EF is the emission factor and Y_m is the methane conversion for different types of animals. This is a considerably more detailed approach than the lumped approach usually used in LCA, where animal–driven emissions often lack precision (e.g., averaged values for cow live weight, dry matter intake, diet composition, herd MP, average methane production and animal density).

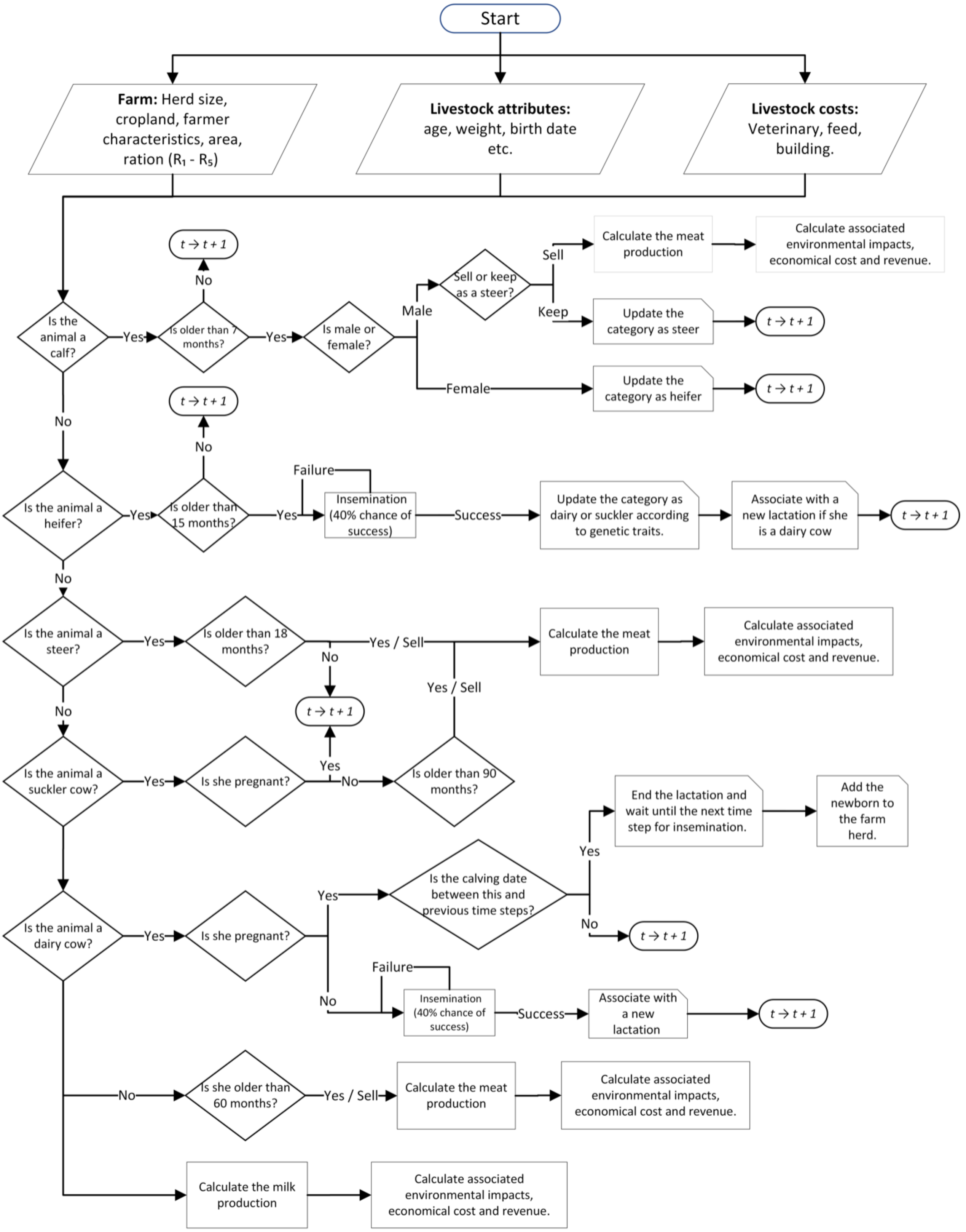

Figure 14: The simulation flowchart of dairy farming system.

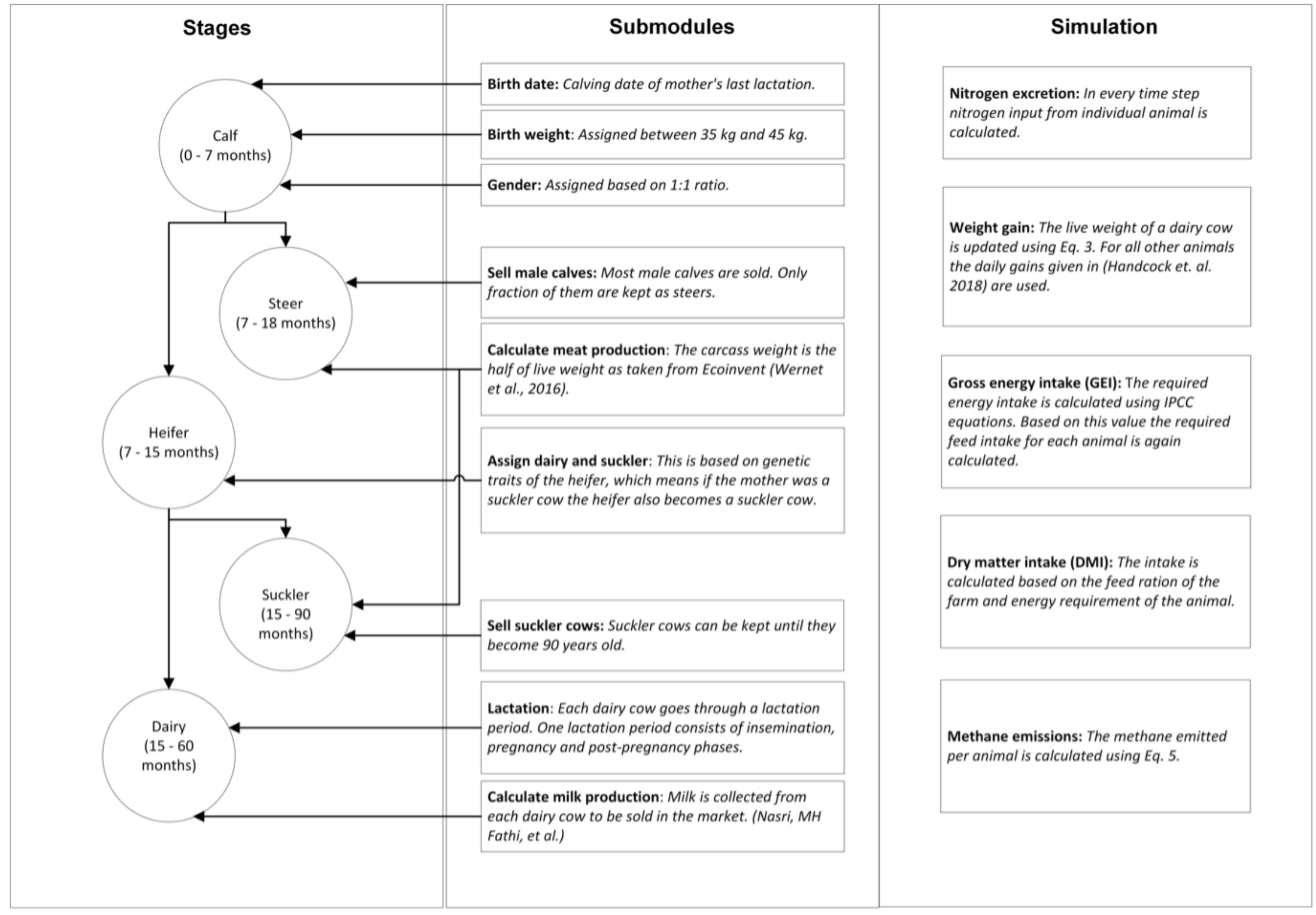

Figure 15: The lifecycle of an animal in the simulator.

3.3.3 *The subsidy schemes*

Since the 1980s, environmental objectives have gradually become a part of the EU's CAP. EU's CC policy requires a change in agricultural practices to contribute to reducing GHG emissions, improving energy efficiency and protection of soil. In our simulations, these policy objectives were addressed through direct payments that support environmental measures (Pillar 1) and multi-year rural development regulations that have CV as one of the guiding considerations (Pillar 2).

In the simulator, these subsidies are implemented in a simplified form, i.e., they have been considered only when the other components in our ABM allowed their integration. More specifically, for example, since the ecologically valuable areas are not part of the simulator, the subsidies that must consider those areas have been neglected in our simulations. Only the ones shown in Table 17 have been implemented. They account for most of the payments received by the farmers in Luxembourg. It is important to note that all farms must first meet the cross-compliance requirements in order to get these subsidies (SER, 2015), which is the case for almost all the farms in Luxembourg in recent years.

3.3.4 *The feed rations*

Most farms in Luxembourg operate as dairy or suckler farming, which influences the farmers' decisions on how to increase the efficiency of their animals. The animal diet is a major determinant when it comes to maximizing its production. In Table 18 the rations calculated by (Zimmer et al., 2021) are given for an adult Holstein cow. Farms are initialized with mixtures of these rations initially in our simulations. Each animal's energy intake for the given month of the simulation is calculated using the IPCC equation for GEI (Dong et al., 2006), and then the total daily DMI of an animal is calculated with respect to an adult Holstein cow. According to their strategy (organic, conventional, GMO, non-GMO, etc.), farmers choose different mixtures of feed rations to achieve their animals' capacity, keep the animals healthy and optimize their profits (Table 19).

3.4 CASE STUDY

The strategies implemented in our simulations are described as scenarios after careful consultations with the local stakeholders. In these scenarios, we mainly focus on livestock production systems and their generated impact on the environment. The crop selection is done in a similar fashion as in (Marvuglia et al., 2022), where the farmer takes

NAME	DESCRIPTION AND IMPLEMENTATION	PAYMENT
Greening	It is based on area. Greening is about environmentally friendly management methods, which go beyond cross-compliance, and applies to crop diversification, preservation of existing grassland and designation of ecologically valuable areas. Greening is not a voluntary regulation, but mandatory for everyone who wants to benefit from the basic premium. Organic farms are exempt from the greening requirements. Permanent crops (vineyards, orchards, ...) are also not affected by greening. Almost all the farmers in Luxembourg get this subsidy, like a basic premium, if they comply with the cross compliance standards. The subsidy requirements differ based on the total UAA. The following farms are entitled to get the subsidy in the simulator: – Farms with less than 10 ha of UAA; – Farms with a total UAA between 10 ha and 30 ha must have at least two crops and the main crop must not cover more than 75% of UAA; – Farms with more than 30 ha of UAA must have at least three crops and the main crop must not cover more than 75% of the area; moreover, the main two crops must not cover more than 95% of the area.	90 €/ha
Basic-Premium	It is based on area. Almost all the farmers in Luxembourg get this subsidy as long as they comply with the cross compliance standards.	185 €/ha
Compensatory allowance	In the simulator, there is no distinction between professional farmers and part-time farmers. Therefore, the subsidy is implemented considering all farmers are professionals. Farms with more than 3 ha of land are entitled to get the subsidy. A farmer can get the subsidy for at most 120 ha of land.	For the first 60 ha, 150 €/ha. For every additional area up to 120 ha it is 75 €/ha.
Extensification of permanent grassland	The amount is calculated based on the amount of nitrogen input to the soil. It has to be less than 170 kg-N_{org}/year/ha for all the farms throughout the simulations to comply with current regulations. This corresponds to nearly 1.6 LSU/ha.	When input is below: • 130 kg-N_{org}/year/ha: 150 €/ha. • 85 kg-N_{org}/year/ha: 200 €/ha.

Table 17: The subsidy schemes implemented in the ABM simulator.

the decision based on crop rotation constraints, crop price and the crop's CV impact.

RATION	R_1	R_2	R_3	R_4	R_5	P
Grass Silage (%)	70	40	70	40	100	0
Maize Silage (%)	30	60	30	60	0	0
Soya (kg/day)	0,7	1,1	1	1,5	0	0
Maize Silage (kg/day)	16	28	16	28,8	0	0
Grass Silage (kg/day)	29,7	17	29,7	17,1	34	0
Barley (kg/day)	1	0,8	0	0,5	1	0
Triticale (kg/day)	1	0,8	0	0,5	0,6	0
Maize (kg/day)	1,2	1	2,5	0,5	0,15	0
Rapeseed (kg/day)	0,7	1,1	1	1,5	0,3	0
SoyaMax (kg/day)	1	1,5	0,33	0,5	0	0
SoyaMin (kg/day)	0,7	1,1	0,23	0,36	0	0

Table 18: The mixture of feed rations in different seasons for each type of farm (Zimmer et al., 2021). SoyaMax corresponds to the current level of soybean extraction in feed rations of Luxembourgish dairy, whereas SoyaMin is the reduced extraction level that is feasible for farms and is the target of our scenarios.

FARM TYPE	WINTER	SUMMER
Conventional	50% R_1, 50% R_2	33% R_1, 33% R_2, 33% P
Conventional-GMO	50% R_3, 50% R_4	33% R_3, 33% R_4, 33% P
Organic	33% R_1, 67% R_5	100% P

Table 19: The feed rations of different types of farms as they are implemented in the simulator (Zimmer et al., 2021).

3.4.1 *Scenario A: Baseline scenario*

The current average stocking rate in Luxembourg is 1.6 LSU/ha.This is used as a baseline in our model and farms must stay under this threshold in every scenario. The objective in the baseline scenario is to preserve the herd structure, which implies that the number of livestock heads only changes according to established rules. Farmer agents do not adjust livestock production, and they make decisions based on pre-defined constraints and not on their behavioral attributes. On crop production, however, the choice is based on the farmer's GC, crop prices and crop rotation constraints as described in (Marvuglia et al., 2022).

3.4.2 *Scenario B: Reducing stocking rates*

One way to reduce the carbon footprint of farming systems is by changing the herd structure. This can be achieved by improved reproduction systems as well as by gradually changing the stocking rates on the farm. Keeping fewer animals means not only generating fewer emissions to the air but also less nitrogen input to the soil. Within this context, certain subsidies are set for different levels of nitrogen input reduction in Luxembourg (Table 17).

As in every scenario of our simulations, the culling decision based on gender and age is made first. Then, at year *n*, the farmer agent checks the nitrogen input of the herd left at year *n-1*. If it exceeds the objective set previously based on the livestock unit per hectare, then there is a secondary culling decision that is based on the efficiency of an animal defined in Eq. (3). The selection of the target stocking rate in terms of LSU/ha is done according to the subsidy criteria and the simulations were run according to those selections. The selected target for this scenario is 1.3 LSU/ha. This scenario is applied in conjunction with the subsidy scheme "extensification of grassland". The decision process for this scenario B is described by the flowchart presented in Fig. 16. The farmers choose the animals to be sent away from the herd (i.e. slaughtered or sold alive) in the post-market phase, and subsequently, the collection of all products and corresponding revenue generation are calculated.

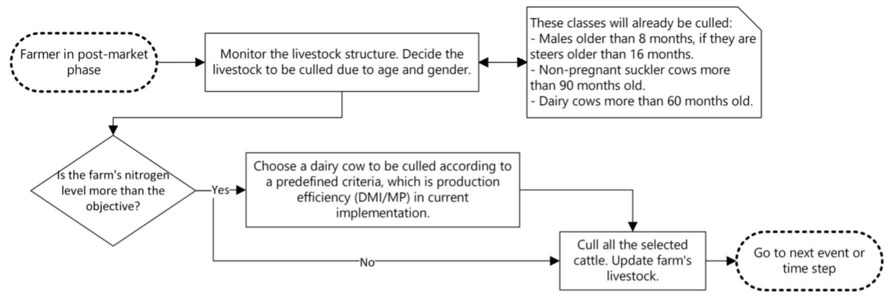

Figure 16: Flowchart of the decision process for scenario B.

3.4.3 *Scenario C: Reducing soybean ratio in feed rations*

This scenario aims to reduce the soybean ratio in animals' feed rations to the minimum possible level. Soybean imports in Europe currently hold more than 95% of the total consumption (AGRI, 2022). Soymeal accounts for most of this consumption and it causes ecological and socio-economic impacts in North and South American countries, like deforestation, soil erosion and rural displacement (Song et al., 2021; Zalles et al., 2021). (Zimmer et al., 2021) assessed the potential of reduction in soybean rate in feed rations in Luxembourg. They discussed the possibility of using less soybean in different rations which would lead up to a 42% reduction of soybean imports in Luxembourg according to their analysis. We built a scenario considering this as a realistic objective to achieve in ten years and at every time step the soybean consumption in every farm gradually decreased. The current level of soybean extraction (SoyaMax) is reduced to the minimum possible level that is feasible for farms (SoyaMin). We, therefore, consider a SoyaMin quantity in each ration, and we monitor the consequent change in soybean import (which is currently the only source of soybean in Luxembourg) and the corresponding change in environmental impacts. The decision process for this scenario is described in the flowchart presented in Fig. 17.

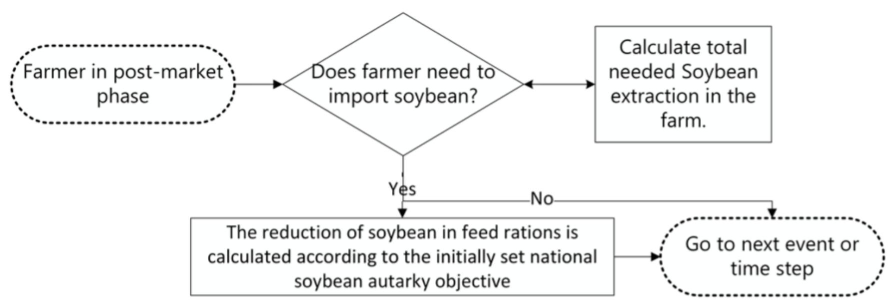

Figure 17: Flowchart of the decision process for scenario C.

3.4.4 *Scenario D: Producing soybean locally*

Another possibility for reducing the impact of soybean import is to produce soybeans locally as suggested by (Zimmer et al., 2021). According to a survey conducted by Institut fir Biologësch Landwirtschaft an Agrarkultur Luxemburg (IBLA), the institute for organic agriculture in Luxembourg, most farmers are willing to adopt soybean into the crop rotation in Luxembourg (Zimmer et al., 2015). Considering that the production of soybeans is feasible only in the south of the country, this may account for 3200 ha of land every year. In our simulations this decision is taken based on the farmer's GC, i.e., the farmer chooses to adopt local soybean into the crop rotation if GC $>$ 0.5 and in this case a soybean import is not needed to feed the herd. This means that we avoid the impacts due to overseas transportation. The decision process for this scenario is described by the flowchart shown in Fig. 18.

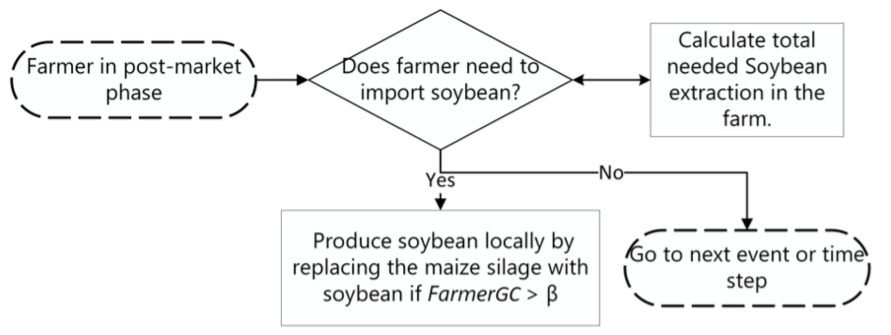

Figure 18: Flowchart of the decision process for scenario D.

3.5 RESULTS AND DISCUSSION

3.5.1 *Simulations*

From the LCA point of view, the Functional Unit (FU) is represented by the total agricultural and pastureland of the country (i.e., the sum of all the UAAs) and by its entire production of milk and meat. The simulations are run for 10 years and an average of 50 repeats are reported in this paper. The random seed assignment for each run is explained in (Marvuglia et al., 2022). The same set of fields is assigned to the farms in every run, which were previously saved in the database after the farm creation algorithm is applied to the GIS data (Marvuglia et al., 2022). The network of farmers is created based on the neighborhood and risk aversion classes which affect the GC update at the beginning of every time step. As explained in Section 3.3.2, the livestock production system holds the largest part of the required computational time of the simulations. Since every livestock-related decision is taken by the farmer at the animal (and not the herd) level, the calculations for production and emissions are done based on single animals. The objective of a scenario can be changing the stocking rate of a farm, adapting a different feed ration, or encouraging local feed production.

Fig. 19a-19d show the LCIA results for three different endpoint values obtained with the (Reidsma et al., 2018) method, for 10 consecutive years, respectively for scenarios A-D. As Fig. 19a shows, the Human Health (HH) and Ecosystem Quality (EQ) impacts are already decreasing in the baseline scenario. This is due to already decreasing stocking rates, which is the case in Luxembourg in recent years. Another reason is that in every scenario the agents are choosing crops based on climate-change impacts if their GC is higher than 0.5. The decrease in HH and EQ become more apparent in scenario B, where we progressively reduce the stocking rate until reaching the value of 1.3 LSU/ha at the end of ten years. The resources endpoint scores do not vary between the scenarios.

Fig. 20 gives some important midpoint scores, that are affected significantly as a result of scenario B. As expected, when we reduce the stocking rates all impact categories show improvement (with respect to the baseline scenario, almost 25% reduction in freshwater eutrophication, 21% in climate change-human health, 19% in freshwater ecotoxicity). In fact, as there are fewer and fewer animals in the system, freshwater ecotoxicity and eutrophication categories show significant improvements since less manure is produced and thus there is less nitrogen leakage to the soil. As the total feed consumption by animals also decreases, the feed imports have lower impacts on the agricultural land occupation category (4% less than in the baseline scenario). The same happens also for natural land transformation, with about 6% reduction. This category shows more significant improvements in scenario C (11% reduction) and D (13% reduction), because the land usage for soybean production is reduced due to feeding changes in scenario C, or because other crops were replaced with soybean in scenario D. Apart from LCIA results, the methane emissions from each individual animal in the system is calculated as explained in Section 3.3.2.7. The result is a significant reduction (19% compared to the baseline) throughout the simulation for scenario B (Fig. 21a). This was expected, due to decreasing number of LSU/ha (from 1.6 to 1.3), which is given in Fig. 21b. On the other hand, in scenario C, the change in feed composition, combined with an expected decrease in stocking rates (like the baseline scenario), also has a positive effect on agricultural land occupation (up to 16% compared to the baseline, based on Fig. 20) due to the utilization of pasture and locally produced crops.

The mitigation of certain emissions comes with an economical cost for the farmers, especially in the short term. The animal and crop productions, and thus the related revenues, are affected by each aspect of our scenarios. In reality, these can be compensated via incentives, such as subsidies. As explained in Section 3.3.3, the subsidy schemes that are already in place for Luxembourgish farmland help farmers to compensate for their losses while diversifying their crop structure or protecting the soil from nitrogen stress. Fig. 21 shows the resulting cost and revenue structure of Luxembourgish farms under scenario A (baseline scenario). In the baseline scenario, the animal and crop output does not change significantly, as well as the subsidies earned by the farmers. For scenario B, the subsidy contribution is 16% higher than the baseline scenario (Fig. 22). In this case, the animal production decreases, but the subsidies compensate to a large extent the consequent economic loss for the farmer. The cropland is also used more for human consumption since the need for animal consumption is reduced significantly.

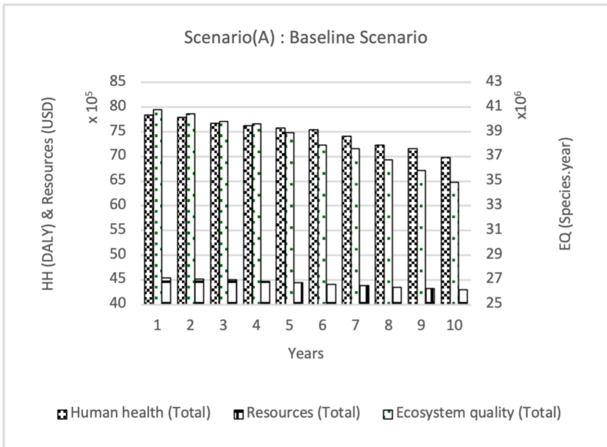

Figure 19(a): Baseline scenario

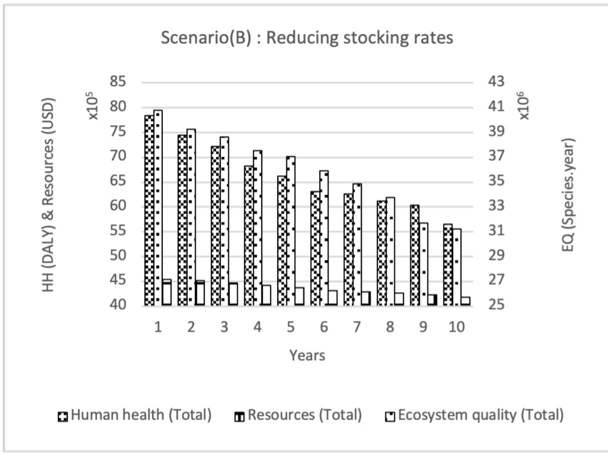

Figure 19(b): Stocking rate reduction scenario

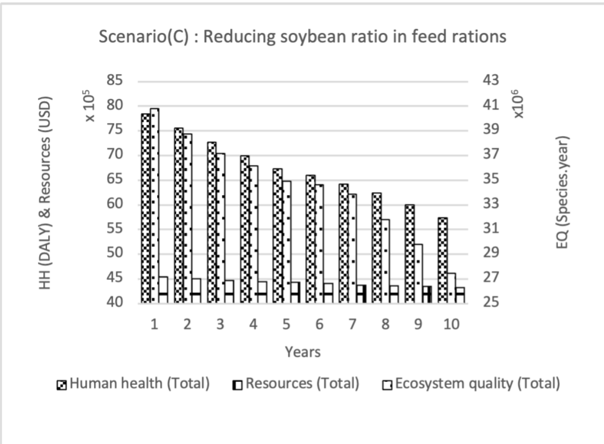

Figure 19(c): Reducing soybean ratio in feed rations

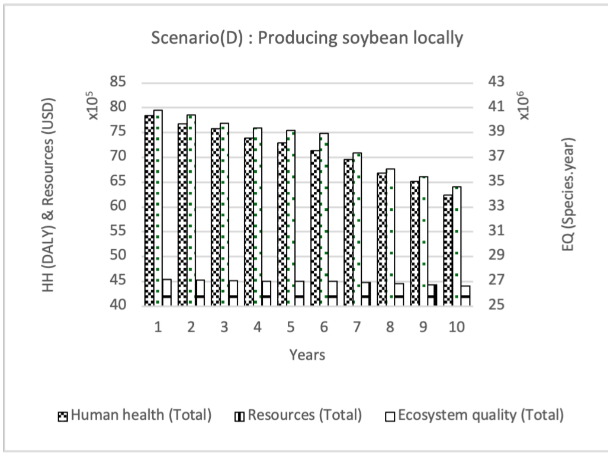

Figure 19(d): Producing soybean locally

Figure 19: Endpoint LCIA scores over the 10 years of the simulation for the four different scenarios.

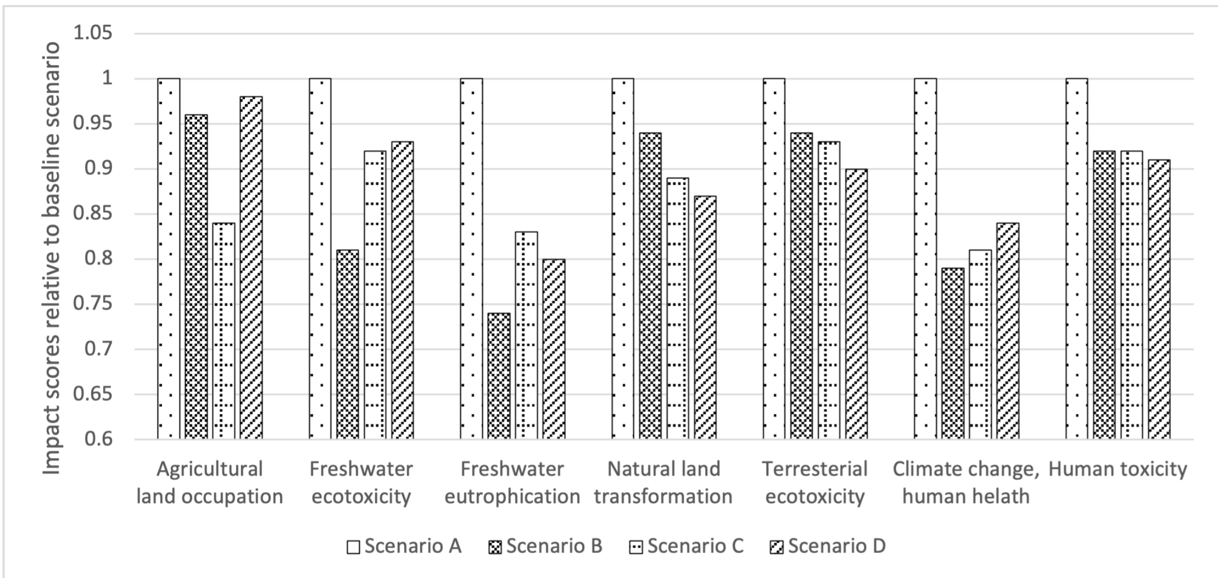

Figure 20: Comparison of different midpoint impact scores in each scenario.

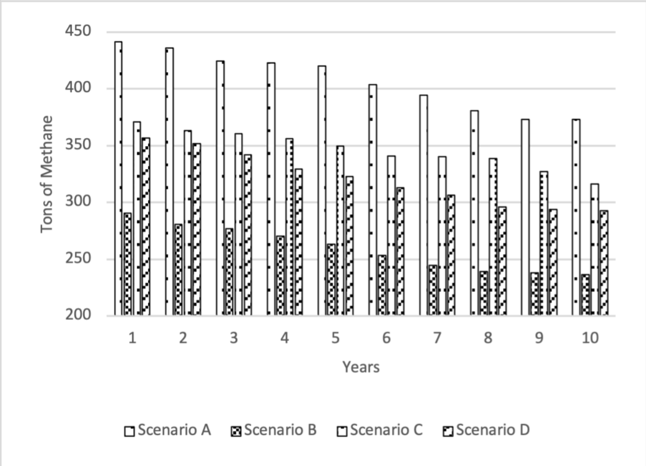

Figure 21(a): Methane emissions due to agricultural activities.

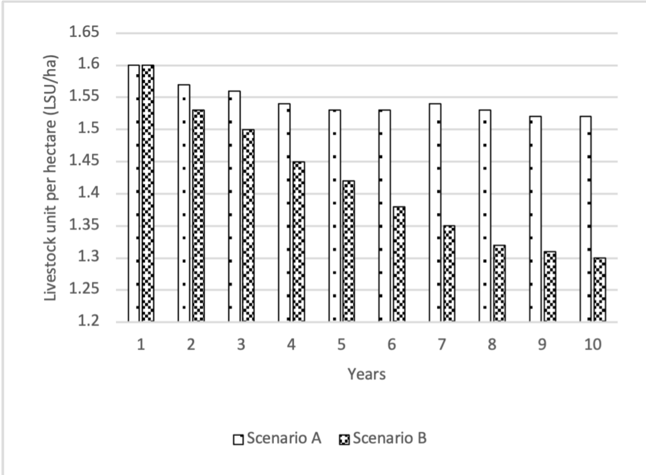

Figure 21(b): The reduction of LSU/ha until the specified 1.3 threshold.

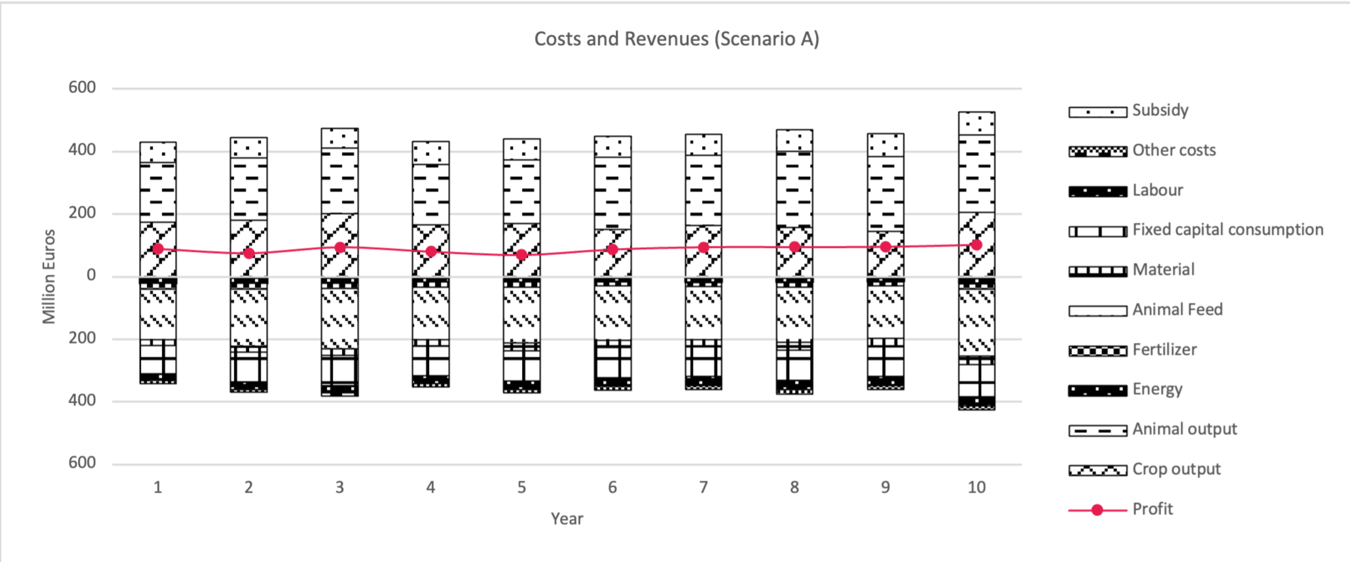

Figure 21: Total costs and revenues for the baseline scenario.

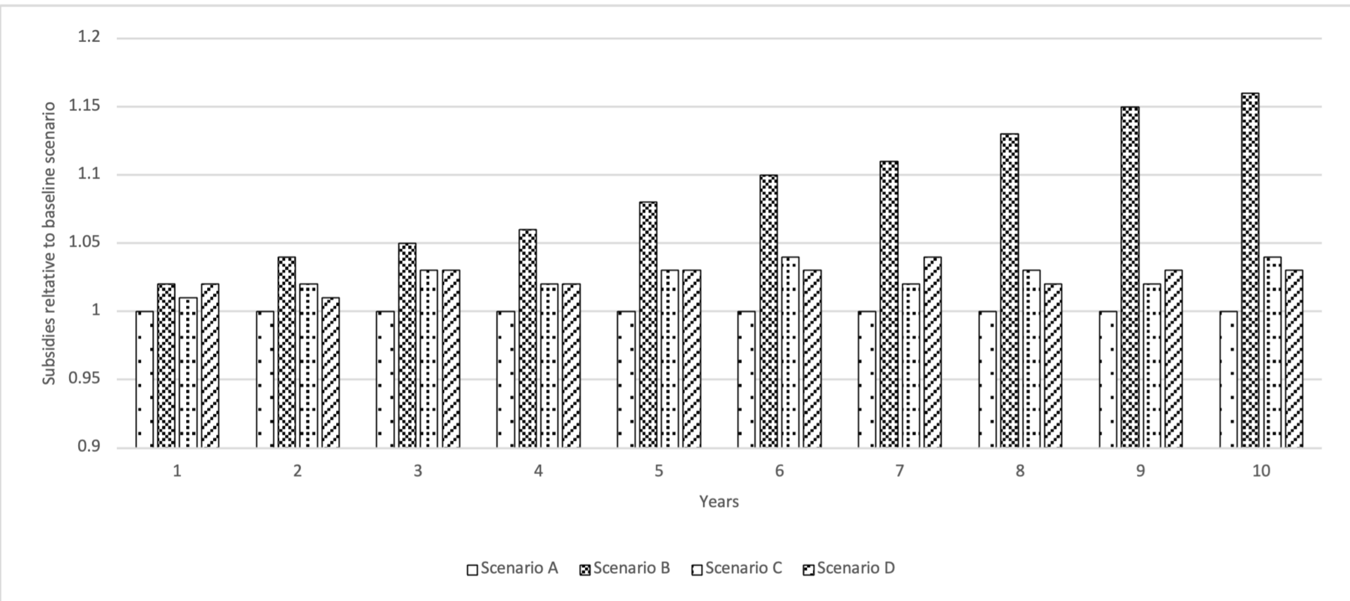

Figure 22: The progression of premiums throughout the simulation steps and across scenarios.

In scenario C, the change in animal diet brings a 13% reduction in animal feed costs. In scenario D, the local soybean production brings additional costs, such as seeds and fertilizer, but the animal feed purchases decrease as the simulation progresses. There is a slight decrease in crop output because the farmer agents dedicate some of the lands to soybean production, which ends up as animal consumption2 rather than being sold on the market.

3.5.2 *Uncertainty*

The results shown in this paper are affected by the uncertainty related to its multiple assumptions, such as model parameters, price forecasts, agent interaction rules, as well as LCI data uncertainty. The parameters that are related to the livestock production system (e.g., culling rate, duration of each phase of a lactation period) have been chosen carefully after stakeholder consultation, but they normally change from one farmer to another. This justifies the choice of an individual-based simulation to model the sector but brings uncertainty where there is lack of information.The different locations of uncertainty in coupled ABM-LCA models are addressed in detail by (Baustert and Benetto, 2017) where a distinction is made between uncertainty due to measurement errors or data quality (parameter uncertainty), and uncertainty due to inherent variance of the underlying system (systemic uncertainty). Model parameters can take true values, or they can be assigned values using *random variables*. The random variables are described by given probability density functions, which are also described by equations containing parameters, thus contributing to an increase of the parameter uncertainty. Systemic uncertainty is the result of stochastic events (e.g., farmer agents' choices and interactions in the case of the model described in this paper) and is responsible for variations from one model run to another. Since parameters were carefully chosen after discussing them with stakeholders, or they are exogenous to our model (such as prices, subsidies, etc.), in this paper we will focus only on the systemic uncertainty. The parameter (or structural) uncertainty due to product prices, LCI, and livestock life-stage attributes is not discussed in this paper but will be the object of future investigation.

Uncertainty Nomenclature. For the uncertainty analysis we follow the structure proposed in (Baustert, 2021). Let us consider a LCA source-system (i.e. a network of interconnected processes that define the studied LCA model). The generic *i*-th agent-based sub-system M^i of a source-system with n calibrated parameters P_M and m random variables V_M is executed over a time period T using a simulator S. For a concrete instance M^i the set Ω_{M^i} contains the defined parameter values. The instance M^i can be used to simulate a set of results r_{M^i} using an instance S^i of the simulator, containing different output variables of interest. The value of each of these output variables can vary for different concrete instances of the sub-model ($M_1, M_2, \dots$) and for different simulations of the same concrete instance M^i, due to the systemic variability of M caused by the random variables V_M within the sub-model.

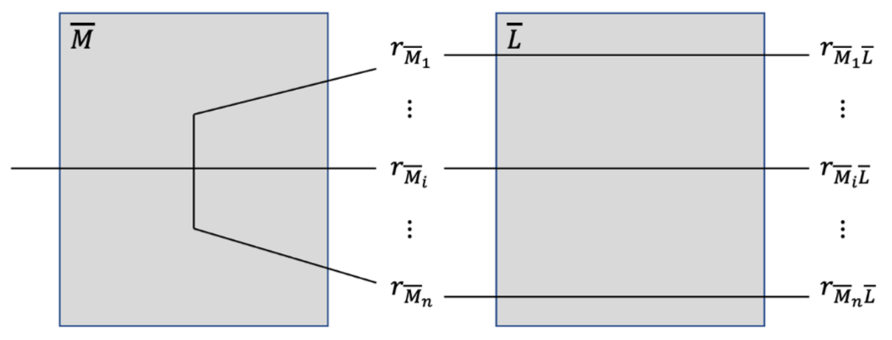

Figure 23: Uncertainty propagation scheme for systemic variability (adapted from ((Baustert, 2021), p. 88)).

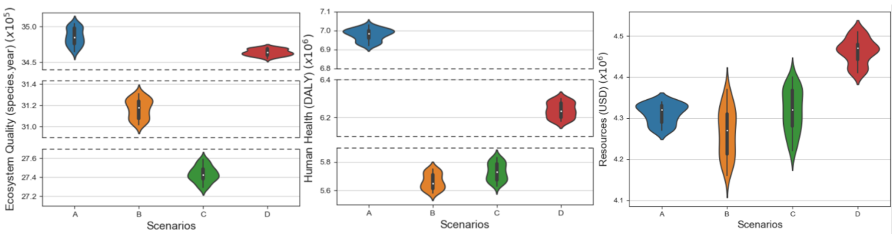

Figure 24: Violin plots of the results of three endpoint categories obtained over 50 simulations for four scenarios.

The nomenclature of an LCA can be defined analogously: the LCA sub-model L has a set of parameters P_L which contains the elements of the technosphere, biosphere and characterization matrices. For a concrete instance L_j the set Ω_{L^j} contains the defined parameter values. L^j is a concrete instance of the LCA model L producing a set of results $r_{M^iL^j}$. As L is not a computational model, the results of one concrete instance do not fluctuate for different simulations, or in other words, L will always give the same results for one Ω_{L^j}. Note that parameters of L can be part of the different phases of an LCA (inventory or impact assessment). To address the systemic variability in an ABM-LCA coupled model, the following scheme is proposed. Firstly, Ω_M and Ω_L are defined such that each parameter takes its nominal value. Then, n simulations are performed, where m random variables are sampled in M. This results in n vectors of the r_{M^i} type, namely the outputs of ABM and inputs to the LCA model. Then, for each vector, final LCA results r_{ML} can be computed.The uncertainty in the model output can be characterized, e.g., by assessing the coefficient of variation of the n model outputs for each midpoint or endpoint indicator. Fig. 23 illustrates the uncertainty propagation scheme, where M and L represent the concrete instances respectively of the ABM and the LCA models, in which the parameters take their nominal values. The subscripts of $M(i = 1, \ldots, n)$ correspond to the simulation identifiers.

To propagate the uncertainty according to the scheme described in Fig. 23, we ran a set of simulations (n = 50) and calculated the coefficient of variations of the corresponding LCIA endpoint categories. As explained above, the parameters are set to their nominal values, and the systemic variability due to the underlying model (i.e., random variables) are calculated. Fig. 24 uses violin plots to show the density distribution of the values obtained over 50 simulations for the three endpoint impact categories. The white dot in the middle of each plot represents the median value, the tick gray bar in the center represents the interquartile range and the thin gray line represents the rest of the distribution (excluding eventual outliers).

Table 20 shows the values of the main descriptive statistics for the LCIA results of the last year of the 50 simulation runs, for each of the four scenarios (see Table 21).

One can see that ecosystem quality has the lowest CV in all the endpoints with less than 0.5% in all scenarios, followed by human health and resources.From the ABM point of view, a larger variability is produced by the parts of the model where more random variables are present. Therefore, the fact that there are fewer random variables in the part of the model that describes the crop production, generates less variability in the impact assessment results for the ecosystem quality category, which is mostly affected by the flows coming from field operations (especially fertilizers and pesticides). Table 20 shows the list of random variables and the nominal values set in the systemic uncertainty analysis.

3.6 LIMITATIONS OF THE MODEL

Although a relatively comprehensive modeling of the farm business is achieved in this work, there are a few aspects that could still be improved (or further complexified) in the model.

Firstly, the farmers' behaviors and interactions could be modeled in a way that the land rentals or acquisitions are considered. The rental durations also affect the way subsidies are being paid, since long-term commitments are required for some of the premiums offered by the Government. By no means the subsidy schemes we implemented are complete and describe the whole structure, which can be improved with the addition of other components to the model, such as the designation of ecologically valuable areas. Another way to make the scenarios more appealing to stakeholders is to show the total cost of environmentally friendly actions considering environmental externalities. This can bring the possibility of optimizing the farmer's decisions using a single objective function that accounts for the monetary value of environmental impacts and economic value they can generate with a certain crop and animal pattern.

The addition of livestock production systems opens other possibilities to complexify the model. Biogas production in Luxembourg (and in the Greater Region) is being promoted by the stakeholders as another source of renewable energy (PNEC, 2020). The estimation of manure excretion can be done for biogas production, combined with the already available data sources for energy crop cultivation in Luxembourg, the farmers who decide to produce biogas are organized in cooperatives, just as they do for selling the produced milk. These cooperatives allow the modelers to include additional connections and information exchange between the farmers that belong to the same cooperative. The cooperative can also be modeled as an agent that disseminates information through the network; therefore, biogas cooperatives are in the end an important stakeholder in the sector.

Concerning crop prices, the forecasts are based on the Holt-Winters time series prediction model, as described in (Navarrete Gutiérrez et al., 2015). In this respect, the choice of window size for seasonal time series can have a drastic impact on predictions, especially on the milk prices since the input data is monthly.

Finally, the crop choices are made under crop rotation constraints and based on the comparison of CV impact or forecasted price of individual crops for agents with high GC and low GC, respectively. Rather than using CV impact, a combination of multiple indicators could be used (Kalbar et al., 2017), although this can bring further subjectivity and uncertainty in the model.

3.7 CONCLUSION

A hybrid ABM-LCA model that simulates mixed crop-livestock activities is presented in this paper. The focus is on the addition of dairy and suckler farming activities and on the exploration of possible scenarios that would reduce the environmental impact of those activities. The ABM allows the modeler to simulate the farmer agents' activities based on economic and behavioral constraints and apply the LCA methodology to the resulting crop and herd structure to calculate the environmental impacts of the simulated activities.

The paper shows the results of multiple scenarios. The first one (scenario B) simulates the decisions of the farmers to reduce their stocking rates by changing the herd structure (from 1.6 to 1.3 livestock units per hectare). This causes an improvement in terms of life-cycle impacts with respect to the baseline scenario, the highest ones being an almost 25% reduction in freshwater eutrophication, 21% in climate change–human health, and 19% in freshwater ecotoxicity. The farmers are not necessarily eager to apply such a change (because this would imply a reduction of their revenue) but considering the pos-

VARIABLE DESCRIPTION	PROBABILITY DENSITY FUNCTION (NOMINAL PARAMETERS)	RANGE OF VALUES
Farmer's environmental awareness	Beta distribution ($\alpha = 1; \beta = 1$)	$0 \leqslant F_{GC} \leqslant 1$
Farmer's risk aversion	Naïve Bayesian Classifier (Marvuglia et al., 2022)	$0 \leqslant F_{RA} \leqslant 1$
Farmer's age	Discrete Uniform Distribution *(a = 25; b = 65)*	$25 \leqslant F_a \leqslant 65$
Insemination success	Discrete Uniform Distribution *(a = 0; b = 1)*	0: Unsuccessful 1: Successful
Livestock gender	Discrete Uniform Distribution *(a = 0; b = 1)*	0: Male 1: Female
Days between waiting period and next pregnancy	Discrete Uniform Distribution *(a = 7; b = 21)*	$7 \leqslant D \leqslant 21$
Farm size	Pert Distribution (Marvuglia et al., 2022)	$0 < F_{Area} \leqslant 200$ *(ha)*

Table 20: List of random variables and nominal values set in the systemic uncertainty analysis.

	Ecosystem Quality (x10^5)				Human Health (x10^6)				Resources (x10^6)			
	A	B	C	D	A	B	C	D	A	B	C	D
Minimum	34,63	31,02	27,29	34,55	6,92	5,58	5,63	6,18	4,27	4,15	4,22	4,41
Mean	34,90	31,23	27,46	34,61	6,98	5,65	5,74	6,24	4,30	4,28	4,33	4,44
Maximum	35,04	31,31	27,60	34,71	7,03	5,75	5,83	6,30	4,35	4,37	4,41	4,52
Standard deviation	0,13	0,12	0,13	0,08	0,04	0,06	0,06	0,05	0,03	0,08	0,06	0,04
CV	0,37%	0,38%	0,47%	0,23%	0,57%	1,06%	1,04%	0,80%	0,70%	1,86%	1,38%	0,90%

Table 21: Values of the main descriptive statistics for the last year's LCIA results of the 50 simulation runs, for each of the four scenarios.

sible advantages of this practice (e.g., soil quality, animal health, reduced veterinary and labor costs) shown by the simulations, one can evaluate the possibility to compensate the farmers with additional subsidies to compensate their loss of revenue. The other two simulated scenarios (scenario C and scenario D) deal with establishing a soybean autarky in Luxembourg. The plantation of soybean in some regions of Luxembourg is possible, especially in the south. Otherwise, the current amount of soybean in feed rations is more than enough to ensure the required protein intake for animal growth, therefore, having less soybean in the animal diet is also possible, which would lead to a higher national soybean autarky. These two scenarios are the ones showing the most significant improvements for natural land transformation impacts are (11% reduction in scenario C and 13% reduction in scenario D). On the other hand, in scenario C, the change in feed composition, combined with an expected decrease in stocking rates, also has a positive effect (about 16% reduction compared to the baseline) on agricultural land occupation, due to the utilization of pasture and locally produced crops.

In conclusion, the results of different scenarios show that a certain mitigation of life-cycle impacts is possible, and the simulations also show the financial implications of their implementation for the farmers.

3.8 FUTURE WORK

Although the model has been significantly improved compared to the last version described in (Marvuglia et al., 2022), there are still parts that can be developed further. Our next goal is to add the fully-fledged biogas module that explains the financials and environmental impacts of producing biogas. The agents can choose to contribute to biogas production depending on their risk awareness and green consciousness levels in the future versions of our model. The user can simulate the outcomes of changing biogas feedstock in terms of impact on the environment and total biogas production.

We believe that the optimization of farming should be modeled by taking both the environmental and economic concerns of the farmers into account. In the next phases, we would like to use mixed-integer linear programming methods to optimize individual farms. This can be done in a multi-objective way, a model that optimizes different emission categories and farm profit at the same time. However, it is also possible to use the monetization of life-cycle impacts (Pizzol et al., 2015), which then allows modelers to model optimization based on a single-objective.

credit authorship contribution statement

Alper Bayram: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Antonino Marvuglia:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Project administration, Investigation, Methodology, Supervision, Validation, Writing – review & editing. **Tomás Navarrete Gutiérrez:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – review & editing. **Jean-Paul Weis:** Conceptualization, Data curation, Investigation, Methodology, Validation, Writing – review & editing. **Gérard Conter:** Conceptualization, Data curation, Investigation, Methodology, Validation, Writing – review & editing. **Stéphanie Zimmer:** Conceptualization, Data curation, Investigation, 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.

data availability

The authors do not have permission to share data.

acknowledgments

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AGRI, EC – DG (2022). *EC – DG AGRI - Oilseeds and Protein crops Trade Data*. URL: https://agridata.ec.europa.eu/extensions/DashboardCereals/OilseedTrade.html (visited on 02/18/2022).

Arnold, K., J. Gosling, and D. Holmes (2005). *The Java Programming Language*. Addison Wesley Professional.

Baustert, Paul (Apr. 2021). "Development of an uncertainty analysis framework for model-based consequential life cycle assessment: Application to activity-based modelling and life cycle assessment of multimodal mobility." PhD thesis.

Baustert, Paul and Enrico Benetto (2017). "Uncertainty analysis in agent-based modelling and consequential life cycle assessment coupled models: a critical review." In: *Journal of Cleaner Production* 156, pp. 378–394. DOI: 10.1016/j.jclepro.2017.03.193.

Beauchemin, K. A., T. A. McAllister, and S. M. McGinn (2009). "Dietary mitigation of enteric methane from cattle." English. In: *CAB Reviews*. Publisher: CABI. URL: https://doi.org/10.1079/PAVSNNR20094035 (visited on 02/07/2022).

Bebber, Daniel P., Mark A. T. Ramotowski, and Sarah J. Gurr (Nov. 2013). "Crop pests and pathogens move polewards in a warming world." en. In: *Nature Climate Change* 3.11. Number: 11 Publisher: Nature Publishing Group, pp. 985–988. ISSN: 1758-6798. DOI: 10.1038/nclimate1990. (Visited on 02/07/2022).

Benchaar, C., C. Pomar, and J. Chiquette (Mar. 2011). "Evaluation of dietary strategies to reduce methane production in ruminants: A modelling approach." en. In: *Canadian Journal of Animal Science*. Publisher: NRC Research Press Ottawa, Canada. DOI: 10.4141/A00-119. (Visited on 02/07/2022).

Burg, Verena, Klaus G Troitzsch, Damla Akyol, Uta Baier, Stefanie Hellweg, and Oliver Thees (2021). "Farmer's willingness to adopt private and collective biogas facilities: An agent-based modeling approach." In: *Resources, Conservation and Recycling* 167, p. 105400. DOI: 10.1016/j.resconrec.2021.105400.

Crippa, M., E. Solazzo, D. Guizzardi, F. Monforti-Ferrario, F. N. Tubiello, and A. Leip (Mar. 2021). "Food systems are responsible for a third of global anthropogenic GHG emissions." en. In: *Nature Food* 2.3. Number: 3 Publisher: Nature Publishing Group, pp. 198–209. ISSN: 2662-1355. DOI: 10.1038/s43016-021-00225-9. (Visited on 02/18/2022).

Dijkstra, J., J. France, M. S. Dhanoa, J. A. Maas, M. D. Hanigan, A. J. Rook, and D. E. Beever (Oct. 1997). "A Model to Describe Growth Patterns of the Mammary Gland During Pregnancy and Lactation." en. In: *Journal of Dairy Science* 80.10, pp. 2340–2354. ISSN: 0022-0302. DOI: 10.3168/jds.S0022-0302(97)76185-X. (Visited on 02/15/2022).

Dong, H., J. Mangino, T.A. McAllister, J.L. Hatfield, D.E. Johnson, K.R. Lassey, M.A. de Lima, and A. Romanovskaya (2006). "Chapter 10: Emissions from Livestock and Manure Management." In: *2006 IPCC Guidelines for National Greenhouse Gas Inventories; Agriculture, Forestry and Other Land Use*. Vol. 4, pp. 10.1–10.87.

Eurostat (2022). URL: https://ec.europa.eu/eurostat/data/database (visited on 02/07/2022).

FAO (2018). *Nitrogen Inputs to Agricultural Soils from Livestock Manure: New Statistics*. Food and Agriculture Organization of the United Nations.

Fernandez-Mena, Hugo, Benoit Gaudou, Sylvain Pellerin, Graham K MacDonald, and Thomas Nesme (2020). "Flows in Agro-food Networks (FAN): An agent-based model to simulate local agricultural material flows." In: *Agricultural Systems* 180, p. 102718.

Freeman, Tyler, Richard Schoney, and James Nolan (2013). "Man vs. manure: Examining the effects of residential demand on dairy farming in rural America." In: *Agricultural Systems* 115, pp. 129–136.

Gerber, P. J., H. Steinfeld, B. Henderson, A. Mottet, C. Opio, J. Dijkman, A. Falcucci, and G. Tempio (2013). "Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities." English. In: *Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities.* (Visited on 02/07/2022).

Gregory, P.j, J.s.i Ingram, and M Brklacich (Nov. 2005). "Climate change and food security." In: *Philosophical Transactions of the Royal Society B: Biological Sciences* 360.1463. Publisher: Royal Society, pp. 2139–2148. DOI: 10.1098/rstb.2005.1745. (Visited on 02/18/2022).

Hadjikakou, Michalis and Thomas Wiedmann (2017). "Shortcomings of a growth-driven food system." In: *Handbook on Growth and Sustainability*. Edward Elgar Publishing, pp. 256–276.

Handcock, Rhiannon C., Nicolas Lopez-Villalobos, Lorna R. McNaughton, Penny J. Back, Grant R. Edwards, and Rebecca E. Hickson (Apr. 2019). "Live weight and growth of Holstein-Friesian, Jersey and crossbred dairy heifers in New Zealand." In: *New Zealand Journal of Agricultural Research* 62.2. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/00288233.2018.1465984, pp. 173–183. ISSN: 0028-8233. DOI: 10.1080/00288233.2018.1465984. URL: https://doi.org/10.1080/00288233.2018.1465984 (visited on 02/16/2022).

Hempel, Sabrina et al. (Dec. 2019). "Heat stress risk in European dairy cattle husbandry under different climate change scenarios – uncertainties and potential impacts." English. In: *Earth System Dynamics* 10.4. Publisher: Copernicus GmbH, pp. 859–884. ISSN: 2190-4979. DOI: 10.5194/esd-10-859-2019. (Visited on 02/07/2022).

Howley, Peter (2015). "The Happy Farmer: The Effect of Nonpecuniary Benefits on Behavior." en. In: *American Journal of Agricultural Economics* 97.4, pp. 1072–1086. ISSN: 1467-8276. DOI: 10.1093/ajae/aav020. (Visited on 02/07/2022).

Huber, Robert et al. (2018). "Representation of decision-making in European agricultural agent-based models." In: *Agricultural Systems* 167, pp. 143–160. ISSN: 0308521X. DOI: 10.1016/j.agsy.2018.09.007.

Huijbregts, M.A.J., Z.J.N. Steinmann, P.M.F. Elshout, G. Stam, F. Verones, M. Vieira, M. Zijp, A. Hollander, and R. van Zelm (2017). "ReCiPe2016: A Harmonised Life Cycle Impact Assessment Method at Midpoint and Endpoint Level." In: *Int J Life Cycle Assess* 22, pp. 138–147. DOI: 10.1007/s11367-016-1246-y.

Jones, James W. et al. (July 2017). "Brief history of agricultural systems modeling." en. In: *Agricultural Systems* 155, pp. 240–254. ISSN: 0308-521X. DOI: 10.1016/j.agsy.2016.05.014. (Visited on 02/07/2022).

Kalbar, Pradip P., Morten Birkved, Simon Elsborg Nygaard, and Michael Hauschild (2017). "Weighting and Aggregation in Life Cycle Assessment: Do Present Aggregated Single Scores Provide Correct Decision Support?" en. In: *Journal of Industrial Ecology* 21.6, pp. 1591–1600. ISSN: 1530-9290. DOI: 10.1111/jiec.12520. (Visited on 03/02/2022).

Kremmydas, Dimitrios, Ioannis N Athanasiadis, and Stelios Rozakis (2018). "A review of agent based modeling for agricultural policy evaluation." In: *Agricultural Systems* 165, pp. 95–106. DOI: 10.1016/j.agsy.2018.03.010.

Liu, Bing et al. (Dec. 2016). "Similar estimates of temperature impacts on global wheat yield by three independent methods." en. In: *Nature Climate Change* 6.12. Number: 12 Publisher: Nature Publishing Group, pp. 1130–1136. ISSN: 1758-6798. DOI: 10.1038/nclimate3115. (Visited on 02/07/2022).

MECDD (2021). *Stratégie nationale à long terme en matière d'action climat: Vers la neutralité climatique en 2050*. Tech. rep. Accessed on: February 23, 2023. URL: https://environnement.public.lu/content/dam/environnement/actualites/2021/08/Projet-de-la-strategie-nationale-a-long-terme-en-matiere-d-action-climat.pdf.

Mack, Gabriele and Robert Huber (2017). "On-farm compliance costs and N surplus reduction of mixed dairy farms under grassland-based feeding systems." In: *Agricultural Systems* 154, pp. 34–44.

Manson, Steven M., Nicholas R. Jordan, Kristen C. Nelson, and Rachel F. Brummel (2016). "Modeling the effect of social networks on adoption of multifunctional agriculture." In: *Environmental Modelling & Software* 75, pp. 388–401.

Marvuglia, A., A. Bayram, P. Baustert, T.N. Gutierrez, and E. Igos (2022). "Agent-Based Modelling to Simulate Farmers' Sustainable Decisions: Farmers' Interaction and Resulting Green Consciousness Evolution." In: *Journal of Cleaner Production* 332, p. 129847. DOI: 10.1016/j.jclepro.2021.129847.

Marvuglia, Antonino, Sameer Rege, Tomás Navarrete Gutiérrez, Laureen Vanni, Didier Stilmant, and Enrico Benetto (2017). "A return on experience from the application of agent-based simulations coupled with life cycle assessment to model agricultural processes." In: *Journal of cleaner production* 142, pp. 1539–1551.

Masson-Delmotte, Valérie et al., eds. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Möhring, Axel, Gabriele Mack, Andrea Zimmermann, Ali Ferjani, Axel Schmidt, and Stefan Mann (2016). "Agent-based modeling on a national scale–experiences from SWISSland." In: *Agroscope Science* 30, pp. 1–46.

Muller, Adrian et al. (Nov. 2017). "Strategies for feeding the world more sustainably with organic agriculture." en. In: *Nature Communications* 8.1. Number: 1 Publisher: Nature Publishing Group, p. 1290. ISSN: 2041-1723. DOI: 10.1038/s41467-017-01410-w. (Visited on 03/20/2022).

Mutel, Chris (2017). "Brightway: An open source framework for Life Cycle Assessment." In: *Journal of Open Source Software* 2.12, p. 236. DOI: 10.21105/joss.00236.

Nasri, MH Fathi, J. France, N. E. Odongo, Secundino López, A. Bannink, and E. Kebreab (2008). "Modelling the lactation curve of dairy cows using the differentials of growth functions." In: *The Journal of Agricultural Science* 146.6. Publisher: Cambridge University Press, pp. 633–641.

Navarrete Gutiérrez, Tomás, Sameer Rege, Antonino Marvuglia, and Enrico Benetto (2015). "Introducing LCA Results to ABM for Assessing the Influence of Sustainable Behaviours." en. In: *Trends in Practical Applications of Agents, Multi-Agent Systems and Sustainability*. Ed. by Javier Bajo, Josefa Z. Hernández, Philippe Mathieu, Andrew Campbell, Antonio Fernández-Caballero, María N. Moreno, Vicente Julián, Amparo Alonso-Betanzos, María Dolores Jiménez-López, and Vicente Botti. Advances in Intelligent Systems and Computing. Cham: Springer International Publishing, pp. 185–196. ISBN: 978-3-319-19629-9. DOI: 10.1007/978-3-319-19629-9_21.

Netherlands, Statistics (2012). "Standardised calculation methods for animal manure and nutrients. Standard data 1990-2008." In: *Statistics Netherlands: Hague/Heerlen*.

PNEC (2020). *Le Plan national intégré en matière d'énergie et de climat (PNEC)*. fr. URL: http://environnement.public.lu/fr/actualites/2020/05/pnec.html (visited on 04/13/2022).

Pizzol, Massimo, Bo Weidema, Miguel Brandão, and Philippe Osset (2015). "Monetary valuation in Life Cycle Assessment: a review." In: *Journal of Cleaner Production* 86, pp. 170–179. ISSN: 0959-6526. DOI: 10.1016/J.JCLEPRO.2014.08.007.

Reidsma, Pytrik, Sander Janssen, Jacques Jansen, and Martin K van Ittersum (2018). "On the development and use of farm models for policy impact assessment in the European Union – A review." In: *Agricultural Systems* 159, pp. 111–125. ISSN: 0308-521X. DOI: 10.1016/J.AGSY.2017.10.012.

Rust, Jean M (Jan. 2019). "The impact of climate change on extensive and intensive livestock production systems." In: *Animal Frontiers* 9.1, pp. 20–25. ISSN: 2160-6056. DOI: 10.1093/af/vfy028. (Visited on 02/07/2022).

SER (2015). *Durchführung in Luxemburg der Cross Compliance im Rahmen der gemeinsamen Agrarpolitik*. de. URL: http://agriculture.public.lu/de/publications/weinbau/prime/crosscompliance.html (visited on 02/15/2022).

STATEC (2022). fr. URL: https://statistiques.public.lu/fr/acteurs/statec/index.html (visited on 02/07/2022).

Shukla, P. R. et al. (2019). *Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems*.

Song, Xiao-Peng, Matthew C. Hansen, Peter Potapov, Bernard Adusei, Jeffrey Pickering, Marcos Adami, Andre Lima, Viviana Zalles, Stephen V. Stehman, and Carlos M. Di Bella (2021). "Massive soybean expansion in South America since 2000 and implications for conservation." In: *Nature sustainability* 4.9. Publisher: Nature Publishing Group, pp. 784–792.

Steinfeld, Henning, Pierre Gerber, T. Wassenaar, V. Castel, Mauricio Rosales, and C. de Haan (2006). "Livestock's long shadow." In: Publisher: FAO of the UN. URL: https://www.fao.org/3/a0701e/a0701e00.htm (visited on 02/07/2022).

Thornton, P. K., J. van de Steeg, A. Notenbaert, and M. Herrero (July 2009). "The impacts of climate change on livestock and livestock systems in developing countries: A review of what we know and what we need to know." en. In: *Agricultural Systems* 101.3, pp. 113–127. ISSN: 0308-521X. DOI: 10.1016/j.agsy.2009.05.002. (Visited on 02/07/2022).

Twine, Richard (Jan. 2021). "Emissions from Animal Agriculture-16.5% Is the New Minimum Figure." en. In: *Sustainability* 13.11. Number: 11 Publisher: Multidisciplinary Digital Publishing Institute, p. 6276. ISSN: 2071-1050. DOI: 10.3390/su13116276. (Visited on 02/07/2022).

Wernet, G., C. Bauer, B. Steubing, J. Reinhard, E. Moreno-Ruiz, and B. Weidema (2016). "The Ecoinvent Database Version 3 (Part I): Overview and Methodology." In: *Int J Life Cycle Assess* 21, pp. 1218–1230. DOI: 10.1007/s11367-016-1087-8.

Yang, Qihui, Don Gruenbacher, Jessica L. Heier Stamm, Gary L. Brase, Scott A. DeLoach, David E. Amrine, and Caterina Scoglio (2019). "Developing an agent-based model to simulate the beef cattle production and transportation in southwest Kansas." In: *Physica A: Statistical Mechanics and its Applications* 526, p. 120856. ISSN: 0378-4371. DOI: https://doi.org/10.1016/j.physa.2019.04.092.

Zalles, Viviana, Matthew C. Hansen, Peter V. Potapov, Diana Parker, Stephen V. Stehman, Amy H. Pickens, Leandro Leal Parente, Laerte G. Ferreira, Xiao-Peng Song, and Andres Hernandez-Serna (2021). "Rapid expansion of human impact on natural land in South America since 1985." In: *Science Advances* 7.14. Publisher: American Association for the Advancement of Science, eabg1620.

Zimmer, Stéphanie, Laura Leimbrock-Rosch, Marita Hoffmann, and Sabine Keßler (Mar. 2021). "Current soybean feed consumption in Luxembourg and reduction capability as a basis for a future protein strategy." en. In: *Organic Agriculture* 11.1, pp. 163–176. ISSN: 1879-4246. DOI: 10.1007/s13165-020-00339-7. (Visited on 02/15/2022).

Zimmer, Stéphanie, Ulf Liebe, Jean-Paul Didier, and Jürgen Heß (Dec. 2015). "Luxembourgish farmers' lack of information about grain legume cultivation." en. In: *Agronomy for Sustainable Development* 36.1, p. 2. ISSN: 1773-0155. DOI: 10.1007/s13593-015-0339-5. (Visited on 03/07/2022).

Zimmermann, Albert, Anke Möhring, Gabriele Mack, Ali Ferjani, and Stefan Mann (2015). "Pathways to truth: Comparing different upscaling options for an agent-based sector model." In: *JASSS* 18.4. ISSN: 14607425. DOI: 10.18564/JASSS.2862.

"Increasing Biowaste and Manure in Biogas Feedstock Composition in Luxembourg: Insights from an Agent-Based Model"

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4

INCREASING BIOWASTE AND MANURE IN BIOGAS FEEDSTOCK COMPOSITION IN LUXEMBOURG: INSIGHTS FROM AN AGENT-BASED MODEL

4.1 ABSTRACT

Biowaste and manure are resources readily available as feedstock for biogas production. Possible scenarios with increased use of biowaste and manure for biogas production in the Grand Duchy of Luxembourg are investigated in this study using an Agent-Based Modelling (ABM) coupled with Life-Cycle Assessment (LCA). ABMs are particularly suitable to simulate human-natural systems, since they allow modelers to consider behavioral aspects of individuals. On the other hand, when it comes to the assessment of a system's environmental sustainability, LCA is largely recognized as a sound methodology and widely used in research, industry, and policy making. The paper simulates three different scenarios that reproduce 10 years and can help policymakers building emission mitigation strategies. The aim is to increase the number of biogas plants or change the feedstock composition for anaerobic digestion in Luxembourg whilst observing the expected environmental impacts generated by these changes. The first scenario (Scenario A) is the baseline scenario, which simulates the current situation, with 24 operating biogas plants. The results of Scenario A show that, on average, 63.02 GWh of electricity production per year is possible from biogas. The second scenario (Scenario B) foresees an increase in the manure share (which is initially 63%) in the biogas feedstock composition along with an increase in the number of biogas production plants. The third scenario (Scenario C) only concerns increasing the amount of manure in the feedstock composition without the introduction of new plants. The results of Scenario C show that an 11% increase in electricity production is possible if more farms contribute to the production by bringing their excess manure to the biogas plant. This value is even higher (14%) in Scenario D where more biowaste is made available. The aggregated Life-Cycle Impact Assessment (LCIA) single scores, calculated with the ReCiPe method, show that Scenario C has the lowest impacts (although by only around 7% compared to the worst performing scenario, i.e., Scenario D), while Scenario D allows the highest electricity production (71.87 GWh in the last year of the simulation). As a result, the inclusion of more livestock farms into already established biogas cooperatives (as in Scenario C) can pave the way for an increase in electricity production from renewables and can bring a reduction in environ-

mental impacts (more than 35% for the Terrestrial Ecotoxicity impact category and more than 27% in categories such as Agricultural Land Occupation, Marine Eutrophication and Water Depletion), thanks to the exploitation of manure for biogas production.

4.2 INTRODUCTION

With the launch of the European Green Deal, a European Climate Law was adopted in June 2021 by the European Union (EU) aiming to achieve net-zero GHG emissions by 2050, with an intermediate objective of reducing GHG emissions by at least 55% by 2030 compared to 1990 levels (European Commission, 2019). This ambitious goal requires fundamental changes in many strategic sectors, especially in energy, transportation, and agriculture. In particular, along with the European Green Deal, there are several strategies adopted by the EU that aim to promote biogas production across Europe. As one of them, the EU methane strategy (European Commission, 2020) aims to reduce the methane emissions mainly in energy, agriculture, and wastewater sectors. So far, the strategy has focused on routine venting and flaring and its success in mitigating methane in the energy sector provides an indirect incentive to achieve the same in agriculture. Furthermore, the renewable energy directive sets a target of producing 40% of the energy consumption from renewables by 2030 (European Commission, 2021). The directive specifies targets for renewable energy usage in transport, heating, buildings, and industry. It also reinforces the sustainability criteria to produce bioenergy by limiting the production of feedstock with a high risk of indirect land use change, which can arise when agricultural land is occupied by energy crops or animal feed crops, thus displacing certain cultures in different areas of the planet. This expansion can even reach to the areas with high-carbon stock, such as forests and wetlands, which is the outcome the renewable energy directive tries to avoid (European Commission, 2021).

In 2018, Luxembourg announced a new integrated energy and climate action plan (Government, 2019), which contains measures to promote biogas production and reduce GHG emissions. The ban on biogas slurry containers and promoting organic manure usage primarily for biogas production demonstrate efforts to reduce methane emissions. According to the plan, only 10% of available slurry was being used for biogas production in 2018. The plan suggests that tackling environmental issues like water protection and not just climate change requires attention to manure storage and its spreading practices.

The objective of this paper is to simulate possible scenarios for the promotion of manure- and biowaste-based anaerobic digestion in Luxembourg. Including the baseline, four scenarios are simulated in this paper. The first scenario (Scenario A hereafter) is the baseline scenario, which simulates the current situation in terms of biogas production in Luxembourg. The second scenario (Scenario B hereafter) is based on increasing the contribution of each farmer to the biogas production by encouraging them to provide excess manure to the nearest biogas production plant, as well as focusing on increasing the number of biogas plants to meet the manure capacity. The farmers that contribute to biogas production can subsequently use the digestate, which is a by-product of the biogas production process, as a soil fertilizer. The third scenario (Scenario C hereafter) concerns increasing the amount of manure in the feedstock composition. According to the information collected on the field, the simulations are run under the plausible assumption that 63% of the feedstock used for biogas in Luxembourg is currently made using manure, 21% using energy crops, and 16% using other organic matter (wastewater biosolids, food waste, etc.). The objective of Scenario C is to increase the share of manure in biogas feedstock to 90%, as targeted in a recent plan set out by the Luxembourgish government, resulting from the joint efforts of the Ministries for Energy, Environment, and Agriculture (Today, 2022). The fourth scenario (Scenario D hereafter) simulates an increase in the amount of biowaste used in the biogas feedstock until it reaches the full amount of biowaste that is produced today in Luxembourg from the five main supermarket chains operating in the country.

4.3 STATE OF THE ART

Considering the complex nature of human decision processes, as well as the complexity of human–environment interactions they entail, agricultural systems can be considered as complex systems (Marvuglia et al., 2017; Vannier et al., 2022). This is one of the reasons why approaches based on ABMs have been gaining increasing attention in this field. From a high-level perspective, the main components that can be identified and modelled with various levels of precision using the ABM applied to agricultural systems are: (1) the agent's component, which includes the way agents are identified, described and made to interact with each other; particularly relevant in the interaction is the way information exchange and mutual influence between various (types of) agents is described and coded in the model; (2) the geographical component, which includes the description of the land use, or more importantly the crop patterns, their evolution in the geographical area under investigation, and their representation using Geographic Information System (GIS); this component may or may not also include an accurate modelling of the weather (or even of the future climate projection) and its influence on crop yields; (3) the economic component, which includes the description and mathematical formalization of the farmer's business and their finances, which may also incorporate a mathematical optimization model; this may include crop management for farms which only have this type of tecno-economic orientation, or only animal farming activities for meat and dairy farms, or both, for mixed-type farms; (4) other components that describe additional activities that may be part of the farms business (in which case they must also be described in the economic component of the model), such as biogas production or large-scale electricity production using solar photovoltaic panels with injection of electricity into the national grid; (5) the environment component, meant as the natural environment and the interaction that the agents have with it in terms of the environmental impacts generated by their activities.

Addressing in a comprehensive way all these components in a single model would be a gigantic task, and therefore the several studies that have applied an ABM approach to the simulation of agricultural systems normally address only some of the above listed components, and with various levels of detail. Moreover, not all the studies include a complete description of the model using the Overview, Design concepts and Details (ODD) protocol (Grimm et al., 2020), a detailed presentation of the equations used at every step of the model, a complete characterization of the uncertainty, and results validation.

(Marvuglia et al., 2018) provides a review of the ABM applied to agriculture and land use, focusing on the main "modelling bricks" that this kind of model owns, including aspects related to the validation of ABMs. (Kremmydas et al., 2018) presents the various aspects of an agent's decision making process, providing a comprehensive review focused on ABM models for agricultural policy evaluation, distinguishing between individual-farm ABMs and not-individual or non-farm ABMs, and between data-driven and theory-driven approaches.

Probably one of the most advanced ABM models for agriculture is SWISSland (Möhring et al., 2016). It serves as a tool that improves the forecasting accuracy of policy change modelling in Swiss agriculture. It considers the terrain attributes and climate by utilizing GIS maps. The model deals mainly with animal sector activities and decisions are represented using a mixed-integer linear programming problem which maximizes the farm's income. The labor market and land exchanges are also parts of the model. SWISSland is linked to a life cycle assessment (LCA) tool, so that an environmental impact assessment can be achieved for each simulation.

Another powerful agent-based agricultural model is AgriPoliS (Happe et al., 2004). The model enables ex-post and ex-ante analyses of structural changes in agriculture, in particular with regards to the impact of alternative policies and assumptions, allowing the simulation of counterfactual scenarios. It has a high explanatory power in the modelling of a farm's evolution in competitive markets.

Various applications of ABM to agriculture and land use modelling have been presented in the literature, but since the focus of this paper is the estimation of biogas production potential, they will not be dealt with in detail in this section.

(Sorda et al., 2013) investigate electricity production from biogas plants in Germany using an ABM and relying on detailed GIS data that reach the district and community/municipality level of spatial granularity. The model optimizes a system-wide problem instead of looking for a solution that is based on a single farmer's profitability. The decision making agents choose to invest in a biogas facility whenever resources are available, and the investment yields a positive net present value. The paper does not tackle environmental sustainability assessment. (Troost et al., 2015) employed a farm-level ABM to analyze the reaction of a heterogeneous farming population in Southwest Germany to the incentives set by two subsidy schemes: the German Renewable Energy Act, and the agri-environmental policy measures of the second pillar of the EU Common Agricultural Policy (CAP). The economic component of the model is very well developed. The model optimizes, at the farm-level, the expected farm income as a function of revenues from crop production, animal husbandry, biogas production and received subsidies, subtracting variable and fixed costs, and the balance of interest paid and received. The optimization is implemented as a Mixed-Integer Programming (MIP) problem. (Appel et al., 2016) apply the spatially explicit and dynamic model AgriPoliS (Happe et al., 2004) to analyze the effects of the German Renewable Energy Act on the biogas investments in Germany. A detailed description of the applied model (including an ODD) is provided. A MIP model is used to maximize profits or the household income of the biogas producing farms. The economic business of the farms is modelled in detail, including any production and investment alternatives that farmers could pursue to maximize their profit. (Mertens et al., 2016) conducted semi-structured interviews with stakeholders (experts, dairy farmers and biogas plant managers) to develop an ABM that simulates the trade behavior of dairy farmers and biogas plant managers. The farmer's interaction is based on silage maize trading. Each farmer attaches a score to the farmers that have a maize surplus, based on a Cobb-Douglas function which makes a trade-off between buying silage maize at the best price and staying loyal to previous trading partners. The model is well documented with an ODD. No consideration of environmental impacts is present in the study. (Verhoog et al., 2016) apply an ABM framework to describe the biogas infrastructure in the Netherlands. Their model encompasses social interaction (contract negotiations), institutions, external markets, biogas production assets, networks, and resulting CO_2 emissions. What is particularly relevant is the way in which the social entities are described, using different forms of social interaction, including contracts and negotiations. In (Imran et al., 2017), the ABM approach is used to identify the suitable and economical distribution of biogas power plants over time in a certain area. The article makes use of the commercial software ArcGIS to produce detailed maps of the area, displaying some of the results of the simulation and showing optimal areas to locate biogas plants, but the description of the ABM and the economic component of it is not detailed. The ABM is implemented using the Agent Analyst toolkit developed by the Argonne National Laboratory in collaboration with ESRI (Wu et al., 2011). (Yazan et al., 2018) adopt an approach based on the ABM approach to investigate the interactions between manure suppliers, i.e., animal farmers, and biogas producers in an industrial symbiosis case example consisting of 19 municipalities. The interaction part of the model is well described in the paper, and so is the economic part (including investment costs, operational costs, etc.). The business profitability for animal farmers and biogas producers based on manure processing is explored with the model, but the environmental impacts generated by these activities are disregarded. (Rouleau and Zupko, 2019) carry out a bioenergy-potential assessment (from woody biomass) in regions with large numbers of private family forest owners or smallholders who own a significant share of available biomass. The ABM is well documented, and the full ODD is presented. The geographical component relies on a complete description of the territory using a GIS. The agents are the smallholders, and they have been defined according to two types: Economic Optimizers, whose harvest decisions are driven by the goal of maximizing financial gain, and (2) Multi-Objective Owners, who manage forests with different goals, not always including harvesting and not necessarily achieving financial optimization (e.g., to obtain habitat preservation, privacy, conservation, firewood provisioning, etc.). To conduct the sustainability assessment, several key indicators are tracked, based on criteria from all three sustainability pillars (economic, environmental, and social) identified by local bioenergy stakeholders in a series of interviews and focus-group workshops. (Abdel-Aal et al., 2020) quantify the impacts of the spatial and temporal diffusion of anaerobic digestion on the water-energy-food nexus and the associated environmental, social, and economic benefits. Three scenarios, following different technology and society narratives (arising from ad-hoc workshop discussions) are implemented. They apply an ABM built in the Anylogic (`https://www.anylogic.com/`, accessed on 1 October 2022) simulation software. The organization of the various interactive agents is more articulated than in the other papers that apply an ABM to agriculture. Ten different types of agents are set in the model (see Table 22). The model is well documented, with a proper ODD. In (Burg et al., 2021), the behaviour of Swiss farmers towards anaerobic digestion and the potential impact of changing incentives are investigated.

An ABM approach is followed to simulate the development of biogas facilities under different conditions, considering the agent's utility. The agents are the farmers, and their attributes are assigned based on the data collected on field interviews. The biogas facility objects are modelled as pure bookkeeping entities characterized by technical attributes (ownership type, capacity, information about founders, co-owners, and deliverers). The economic side of the model is well developed, but the environmental component is missing. (Nugroho et al., 2022) developed an ABM using Anylogic to assess the environmental and economic viability of the methanol supply chain. This is the only paper in which the LCA is explicitly mentioned and used as part of the analysis. The LCA is coupled with a techno-economic assessment, and the ABM paradigm is used to simulate and optimize the Internal Rate of Return (IRR) and lower the carbon emissions. Table 22 summarizes the characteristics of the above-mentioned studies.

Some other studies apply approaches that are rooted in mathematical optimization and do not have the traditional structure of an ABM, at least from the point of view of a proper implementation of the interaction component that is a distinctive feature of the ABM. (Shu et al., 2020) developed a dynamic model of the agricultural land use and applied it to the Lubelski voivodeship, in Eastern Poland, to simulate the effects on land use change with the introduction of sweet sorghum usage for biogas plants. They mimic farmers' decisions by means of mathematical programming; the model generates supply response curves using parametric optimization. (Chen and Li, 2016) apply a mathematical programming model to estimate the supply of cellulosic biomass in Illinois (USA). The study is used firstly to derive the economically viable supply of agricultural biomass under various biomass prices and to forecast what mix of cellulosic feedstocks is expected to be produced in a short-term time horizon. Secondly, to assess the impacts of biomass production on farmers' re-enrollment/exit decisions on a governmental conservation program. (Bartoli et al., 2016) apply a partial-equilibrium framework simulating the agricultural sector and the biogas industry in Lombardy (Italy) to evaluate the influence of biogas rapid spread on maize prices and land demand for energy crops at a regional level.

The aim of this paper is to provide an estimation of the biomethane (and the electricity thereof) that could be produced under some hypothetical scenarios in Luxembourg. The novelty of the paper, compared to the existing models shown in the literature, lies in the consideration and seamless integration in a single model of all the five components mentioned above, except for the economic component, which is only partly developed. In fact, this latter component is considered only as what concerns the farmer's operations that relate to the selling of crops, meat, and milk; no economic modelling is performed for the part that relates to the biogas infrastructure's construction and operation (including feasibility study and cash flows), as well as for the selling of electricity to the grid. This would have required a deeper analysis that would require more data on the biogas plant's business models as well as on government subsidies attribution for biogas production, among other things. The subsidies schemes for biogas production in Luxembourg are currently being revised by the government in and therefore we have decided not to take this aspect into account.

On the other hand, this study is to be considered only exploratory and not as a feasibility study for the actual implementation of a biogas policy. For this reason, in this instantiation of the model, only farmers have been coded as agents, whereas biogas plants have not; therefore, their economic accounting (the cash flows) and their economic viability have not been considered as part of the model.

The environmental component of the model is instead very advanced, not only because the LCA is coupled with the ABM, but also because, within the LCA module, the assessment of GHG emissions generated by the animal farming is achieved at a very high level of detail (as described in (Bayram et al., 2023)). In particular, the methane emitted by each cow due to enteric fermentation is calculated using the equations described in (Eggleston et al., 2006). This approach is much more detailed than the lumped approach usually used in LCA studies, where animal-driven emissions are based only on average values for cow live weight, Dry Matter Intake (DMI), diet composition, herd milk production, average methane production, and animal density. This is the most distinguishing feature of the model, compared to the above cited studies, of which only one (Nugroho et al., 2022) has tackled the environmental component using a LCA perspective, let alone using such a level of detail in the modelling of carbon emissions generated by animal breeding.

4.4 MATERIALS AND METHODS

4.4.1 *ABM Methodology*

The main objective of the model is to elicit possible scenarios (and the parameters characterizing them) under which the national biogas strategy of Luxembourg can help the agro-system to evolve towards a more sustainable state. In (Marvuglia et al., 2022), the information diffusion in a network of farmers is simulated (through a parameter called green consciousness—GC—) via an ABM. However, only the cropping activities were considered in that model, without a full inclusion of animal farming, even though most Luxembourgish farms are of a mixed type (producing crops, meat, and milk in the same holding). The model developed in (Marvuglia et al., 2022) has now

Table 22: Summary of the approaches found in the literature using ABM approaches to study biogas and bioenergy potential.

REFERENCE	TITLE	COUNTRY/REGION	METHODOLOGY AND AIM	AGENTS
(Sorda et al., 2013)	An agent-based spatial simulation to evaluate the promotion of electricity from agricultural biogas plants in Germany	North Rhine-Westphalia and Bavaria, Germany	Agent-based simulation model for investment decision-making is coupled with GIS data to assess the advantages of promoting electricity production from biogas.	– Information agents (Plant manufacturer, Bank, Electricity Utility and Federal Government). – Decision agents (Heat Consumer, Decision-Maker, District and Substrate Supplier).
(Troost et al., 2015)	Climate, energy and environmental policies in agriculture: Simulating likely farmer responses in Southwest Germany	Central Swabian Jura region (Southwest Germany)	Farm-level ABM to simulate the investment and production decisions of every full-time farm of the area. The optimization is implemented as a MIP problem.	– Farms
(Appel et al., 2016)	Effects of the German Renewable Energy Act on structural change in Agriculture—The case of biogas	Two German regions: (1) Altmark, Saxony-Anhalt; (2) Ostallgäu (East Allgäu), Bavaria	AgriPoliS model applied to biogas producing farms to model the effects of a German agricultural policy. Farm's profit maximization is implemented using a mixed-integer programming model.	– Biogas producing farms

Table 22: Summary of the approaches found in the literature using ABM approaches to study biogas and bioenergy potential. (continued)

REFERENCE	TITLE	COUNTRY/REGION	METHODOLOGY AND AIM	AGENTS
(Mertens et al., 2016)	Context Matters—Using an Agent-Based Model to Investigate the Influence of Market Context on the Supply of Local Biomass for Anaerobic Digestion	Flanders region, Belgium	ABM simulating the trades between agents for silage maize market and their interactions with a biogas plant manager	– Dairy farmers. – A biogas plant manager
(Verhoog et al., 2016)	Modelling socio-ecological systems with MAIA: A biogas infrastructure simulation	The Netherlands	Integrated sustainability assessment is used. Institutional analysis and multi-agent paradigm simulate the stakeholder behavior.	– Wastewater treatment facility agents. – Agricultural firm agents (which may also take up the role of biogas producers). – Household agents. – Small and medium-sized enterprise (SME) agents. – Large consumer agents.
(Imran et al., 2017)	Agent-based simulation for biogas power plant potential in Schwarzwald-Baar-Kreis, Germany: a step towards better economy	Schwarzwald-Baar-Kreis, Baden-Württemberg, Germany	The ABM approach is used to identify the suitable and economical distribution of biogas power plants over time in the area of interest.	– Biogas power plants

Table 22: Summary of the approaches found in the literature using ABM approaches to study biogas and bioenergy potential. (continued)

REFERENCE	TITLE	COUNTRY/REGION	METHODOLOGY AND AIM	AGENTS
(Yazan et al., 2018)	Cooperation in manure-based biogas production networks: An agent-based modeling approach	The Netherlands	The ABM approach is used to investigate the interactions between animal farmers and biogas producers in an industrial symbiosis in eastern Netherlands.	– Animal farmers (manure producers). – Biogas producers (manure users).
(Rouleau and Zupko, 2019)	Agent-Based Modeling for bioenergy sustainability assessment	Western Upper Peninsula of Michigan, United States	An ABM is used to conduct a bioenergy sustainability assessment to identify possible gains and trade-offs necessary to develop bioenergy in regions with large numbers of private family forest owners or smallholders who own a significant share of available biomass.	– Individual local smallholders with two ownership types: (1) Economic Optimizers; (2) Multi-Objective Owners. – Global harvester agent.

Table 22: Summary of the approaches found in the literature using ABM approaches to study biogas and bioenergy potential. (continued)

REFERENCE	TITLE	COUNTRY/REGION	METHODOLOGY AND AIM	AGENTS
(Abdel-Aal et al., 2020)	Modelling the diffusion and operation of anaerobic digestions in Great Britain under future scenarios within the scope of water-energy-food nexus	Great Britain	An ABM programmed in Anylogic is used to quantify the impacts the diffusion of future possible anaerobic digestion technology on the environment, society, and economy.	– Main: Manages the input parameters and triggers events. – DummyCollector: Evaluates feasibility for new food waste collectors and assigns relevant sources. – DummyPlant: Determines the location of a new Plant. – Collector: Food waste collector. – GridCell: Study area (50 km resolution) – Plant: Anaerobic digestion plants. – Scenario: Holds model input parameters for each scenario. – Source: Households, restaurants, and supermarkets. – SourceArea: Food waste collection areas. – SubGridCell: Sub-mapping grid of the study area (5 km resolution).

Table 22: Summary of the approaches found in the literature using ABM approaches to study biogas and bioenergy potential. (continued)

REFERENCE	TITLE	COUNTRY/REGION	METHODOLOGY AND AIM	AGENTS
(Burg et al., 2021)	Farmer's willingness to adopt private and collective biogas facilities: An agent-based modeling approach	Switzerland	An ABM is designed and used to simulate the development of biogas plants under different conditions. The agent's properties are derived from the farmer's survey.	– Farmers
(Nugroho et al., 2022)	Building an agent-based techno-economic assessment coupled with life cycle assessment of biomass to methanol supply chains	Indonesia	Agent-based simulation–optimization model programmed in Anylogic, coupled with techno-economic assessment and LCA to evaluate methanol synthesis pathways.	– Biomass suppliers. – Biogas producers. – Syngas producer. – Methanol producers. – Methanol distributors/retailers. – Farmers. – Transportation agents.

been enhanced to include a full integration of dairy farming activities, which are especially important for Luxembourgish agriculture (Bayram et al., 2023). In particular, livestock manure constitutes the majority of the feedstock for biogas production. The manure generated in dairy farms, along with the energy crops produced in Luxembourg for biogas production, are considered in this model.

In the model, the agents perform their activities based on the economic value of their actions, as well as on the environmental burden those actions generate. The actions taken by the agents are constrained by the limits defined in each of the implemented scenarios. The scenarios were defined by the authors via an iterative process with some local stakeholders, partners of the project SIMBA and experts on the Luxembourgish agricultural system.

4.4.2 *Description of the ABM Simulator*

The simulator has multiple software components. To store the data, PostgreSQL database is preferred (PostgreSQL, 2022) , since the GIS extension (PostGIS) can be used easily to store farm locations (PostGIS, 2022). Stand-alone PostgreSQL is also used to store country-specific statistics from STATEC (the Luxembourgish national statistics office) and Eurostat (the European statistics office) and financial data such as cost items and product prices. The ABM simulator is built in Java (Arnold et al., 2005) to allow model builders enough flexibility. Finally, the LCIA calculations to quantify the environmental impacts generated by the crops and animal patterns in each simulation are expressed using the LCIA indicators from the ReCiPe (Huijbregts et al., 2017) LCIA method. The LCIA calculations are performed in Activity Browser (Steubing et al., 2020), the graphical interface of the Brightway2 LCA calculation framework, relying on ecoinvent 3.8 cut-off version as a database for the background system (Wernet et al., 2016).

Like in every ABM, there are several entities that can help modelers to explain the model objective. The following ones are the main entities of the simulator.

Farmer: The agents in our simulator are farmers. Based on predefined attributes and constraints, they react to the external stimuli coming from their surrounding environment, which is their operation space. They may also have behavioral attributes which could change over time based on interactions with other agents or entities. Every farmer owns only one farm and the decisions the farmer takes only concern that single farm. Each farmer has attributes like age, green consciousness (a continuous random variable between 0 and 1), risk aversion (a binary value). These attributes, along with farm properties, impact farmers' decisions. The way they are calculated and assigned is described in (Marvuglia et al., 2017) and (Marvuglia et al., 2022).

Farm: Each farm is managed by a farmer and has attributes that affect cropland and livestock management. For instance, the size of a farm may influence how many animals must be kept or how many neighboring farms that farm has. Each farm's location is initialized using GIS data. According to that data, the surface of each farm is divided into parcels named Utilized Agricultural Area (UAA), which are the smallest land parcels registered at the land cadaster. The GIS data along with the information on the land parcels was provided by Service d'Economie Rurale (SER) (SER: `https://ma.gouvernement.lu/fr/administrations/ser.html`, accessed on 15 May 2022). Each of these parcels is represented as a polygon with the associated information on which crop was cultivated for a given year, the commune it belongs to, the surface area, and the perimeter. The farms are created by merging the fields that are assigned according to the algorithm described in (Marvuglia et al., 2022). The information regarding the ownership status of each field is confidential, thus this algorithm helps to assign each agent to a realistic farm and assign a geographical location and cropland information to it, without disclosing information on real farms. In addition to the cropland information, each farm is assigned a certain number of cattle heads of the different types (see Table 23). The initialization of the farms with the number of animals of each type is conducted based on the allowed organic manure levels per hectare in Luxembourg. The national limit of nitrogen that can be applied in Luxembourg is set to 170 kg-N_{org}/year/ha (where N_{org} is the organic nitrogen) (Gouvernement du Luxembourg, 2000, 2001). The excretion rates from manure per cattle class were taken from (FAO, 2018; Netherlands, 2012).

Plant: A biogas plant is an entity that collects the feedstock from nearby farms and produces biogas. The location of each plant is provided by SER. Figure 25 shows the location of the plants within the territory of the concerned communes in 2020. According to the information provided by SER, there are in total 113 farms that contribute to biogas production. During the initialization phase of the simulation, farms that contribute to biogas production are specified according to their distance from the closest biogas production plant. The distance between farm and biogas plant is highly influential on the transport cost and therefore it affects the economics of both the farm and the biogas plant. In our model, only the farms that are within a radius of 30 km (This value comes from a personal communication with Mrs. Porcel and Mr. Maka from Naturgas Kielen) from a plant can be marked as biogas producers until that plant reaches its capacity. In Scenario B, new plants are introduced into the system. Each com

Livestock class ID	Livestock class	Age	A	B	C	D	E	F	G	H	Sum
1	Male	(L_{age}<12)	120	20	90	200	0	2140	17,180	34,470	54,220
2	Female	(L_{age} <12)	70	0	10	40	110	460	4200	7590	12,480
3	Male	(12 <L_{age} <24)	100	10	80	130	390	1360	10,020	19,400	31,490
4	Heifer	(12 <L_{age} <24)	50	10	30	30	80	240	1110	1540	3090
5	Heifer	(L_{age} >24)	70	20	20	90	350	960	6620	12,020	20,150
6	Dairy	(L_{age} >24)	0	0	0	0	130	1170	16420	33,300	51,020
7	Suckler	(L_{age} >24)	140	20	80	300	630	2000	8990	16,350	28,510

Table 23: Number of livestock in each farm class and livestock class in 2016 (Eurostat, 2022). The letters from A to H describes the farm classes as explained in (Marvuglia et al., 2022).

Crop	Type	Yield (t_{DM}/ ha)	Price (€/100kg)	Total production (t_{DM})	Standard seeding month	Standard harvest month
Barley (spring)	C	5,96	14,21	10,951	3	8
Barley (winter)	C	5,51	14,21	21,500	10	8
Dried pulses (peas, beans, others)	L	3,41	18,00	1292	3	8
Grain maize	M	6,75	15,00	810	4	10
Green maize	M	13,74	-	222,219	4	10
Oats	C	4,99	13,5	7939	4	8
Potatoes	O	26,25	23,33	16,368	4	9
Rapeseed	O	3,30	35,65	8791	3	8
Rye	C	4,53	13,54	4670	10	8
Spelt	C	4,74	20,34	4217	10	8
Triticale	C	5,60	14,59	25,270	10	8
Wheat (spring)	C	6,13	17,05	2271	3	7
Wheat (winter)	C	6,06	17,05	63,910	10	8

Table 24: Some statistics for major crop types that are cultivated in Luxembourg in 2020. Yields are expressed in tons of dry matter ($t_{\text{Dry Matter (DM)}}$). Sources: (Marvuglia et al., 2022; STATEC, 2022). (C = cereal; L = leaf; M = maize; O = other.)

Commune that does not have a biogas plant in its territory is a candidate site in this scenario. According to the available biogas feedstock, site selection is made for the new plant.

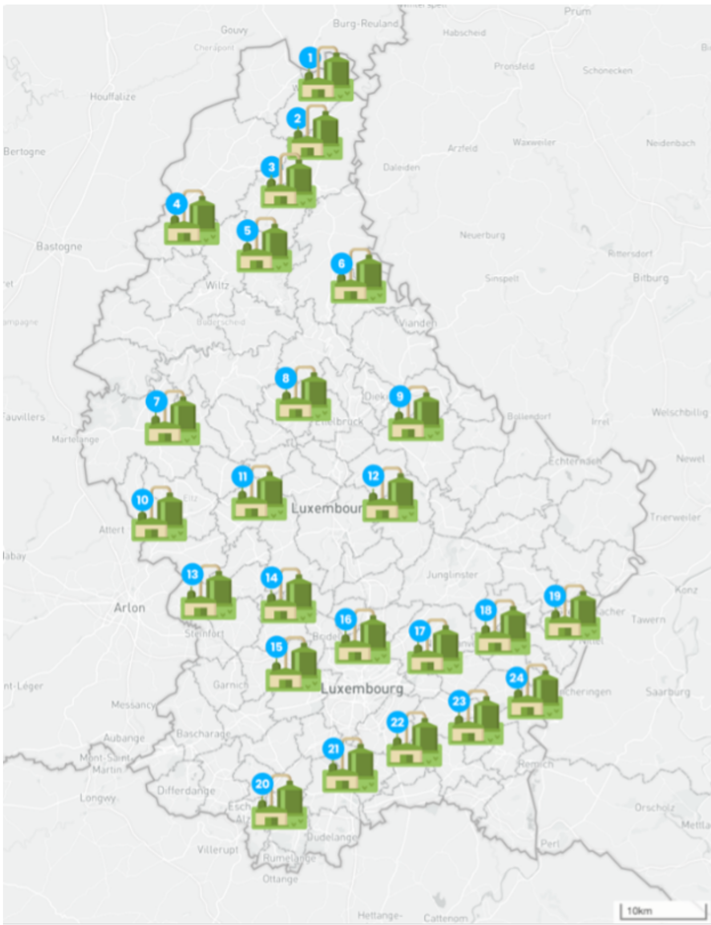

Figure 25: The locations of biogas plants in Luxembourg.

Crop: GIS data that has the details of each UAA includes the information on what type of crop is planted in every UAA for a given year. The initial crop of every UAA is assigned from the data for year 2020 (see Table 24). These are used to assign the crop rotations, which were specified after discussions with different actors in the sector. Maize cultivation is more significant than other types of cultures in this study because it constitutes 20% of the feedstock used for biogas production in Luxembourg. In the simulations, each crop can be planted in a time interval of ± 1 month from its usual seeding month (to consider the randomness introduced by weather conditions) and can be harvested ±1 month from its usual harvest month (the seeding can be anticipated if the previous crop has already been harvested).

Livestock: Most farms in Luxembourg are specialized in mixed crop–livestock farming. The biogas generation in Luxembourg also depends heavily on animal manure. The simulator has the capability to run scenarios of the dairy farming activities in Luxembourg, therefore making it possible to assess the amount of organic manure that is produced by the animals in each farm, which can be used as an input to the biogas production process. Each animal in a farm goes through biological events and production mechanisms which may differ depending on their livestock class (Figure 26).

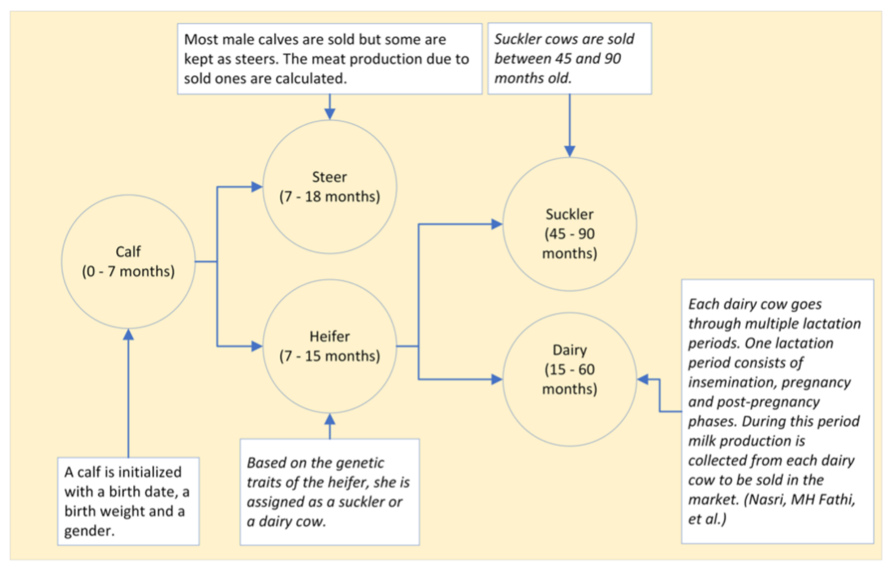

Figure 26: The lifecycle of an animal in the simulator.

Lactation: Every cow is assigned a lactation period that has a duration comprised between 305 and 320 days after the first insemination. An insemination trial has a success probability of 40% and it happens once in every simulation time step. Once the insemination trial is successful, the cow's status changes to "pregnant" and until the dry-off phase Milk production (MP) from each cow is calculated according to Dijkstra equation given in (Nasri et al., 2008). The newborn is added to the herd after calving.

Time: The simulation time step is chosen as one month due to two main reasons. The first one is the seasonal cultivation times for crops. If the farmer chooses to harvest the current crop on a given field, the next crop on that field is assigned based on the farmer's and the farm's attributes. The second reason is the fact that decisions are usually taken for shorter durations than a year, or phases such as lactation stages require resolution of less than one year. In fact, decisions such as selling the animals or choosing grazing times are taken within the year.

ABM-LCA coupling: The LCA model and the ABM are "tightly" coupled in the acceptation discussed in (Baustert and Benetto, 2017).

ABM validation: As discussed in (Marvuglia et al., 2018), ABM validation is not an easy task. Because of the limitations mentioned in Section 4.8 (especially lack of data and necessity to rely on many assumptions) an external validation (replication of real-world data), a.k.a. empirical validation, was not possible in our case. The agricultural policies and farmers' behaviors towards certain environmental and financial conditions change over time. The former factor requires a different model, which would be obsolete in today's circumstances (for example some biogas plants may have ceased to operate, and some new ones may have been built). The latter factor cannot be modelled without available survey data of the past. Borrowing the terminology used in (Marvuglia et al., 2018), we can state that only the internal validation (or ex ante validation) of the model described in this paper has been performed, thanks to the participation of local stakeholders that were partners of the project which validated most of the assumptions and agreed on the general conceptual validity of the model.

4.4.3 *LCA Methodology*

4.4.3.1 *Goal and Scope*

Goal definition: This study analyses the environmental impacts of biomethane production in Luxembourg from the co-digestion of animal slurry (pig and cattle, in a ratio between the two equal to 12:88), mixed silage and food waste in 24 biogas cooperatives in Luxembourg (Figure 25).

Scope definition: The geographical scope includes Luxembourg and stops at the point where the biogas is generated and ready to be injected into the national grid. From the LCA perspective, the study is of the attributional type (Schaubroeck et al., 2021).

The system boundaries include Manure management (P1), Silage production (P2–P4), Biogas production (P5), Biomethane production (P6), On-site heat production (P7), and Unpackaging food waste (P8).

Functional Unit (FU): The studied FU is the production of $1 m^3$ of biomethane that originates from the co-digestion of animal slurry, mixed silage, and food waste. As per the information obtained from the Naturgas Kielen plant, the mixed silage has the following composition: 39% grass silage, 17% WCSS, 44% maize silage. The WCSS is composed using a mix of wheat, triticale, and rye silage that is assumed in the same proportions. The simulator allows the calculation of the total amount of biomass produced by all the farms under the different scenarios described above. The results of the impact assessment are then scaled down to $1 m^3$ of biogas.

Alternative and larger systems could have been analyzed, such as injection into the national grid of biomethane that originates from the co-digestion of food waste with additional types of energy crops or types of manure currently being used in biogas production plants in Luxembourgish cooperatives. However, collecting data from all the biogas production plants in Luxembourg would have required a significant amount of time and resources and the establishment of contacts with several actors, which was out of reach for our study. Therefore, the analysis was limited to the data collected only from one site (the biogas plant Naturgas Kielen; plant n. 14 in Figure 25), assuming that each site can be treated similarly and uses the same type of feedstock. This strong assumption will clearly limit the results and conclusions obtained from the study, but the results can be used to show a trend and a plausible estimation of the biogas production potential in the country.

4.4.3.2 *Inventory Analysis*

The system boundaries exclude the animal husbandry activities that generate slurry. The slurry is assumed as a burden-free by-product. The packaging waste outflow in P8 is not part of the system as it does not undergo treatment. Digestate application is part of the system boundaries.

Waste packaging outflow from P8 has been omitted from the system because information on upgrading waste packaging to green fuels in Luxembourg was missing. Therefore, the environmental flows connected to this process are omitted from the Life-Cycle Inventory (LCI).

The data for the foreground processes were provided by the Naturgas Kielen biomethane production plant, located in the South of Luxembourg. The data on the remaining processes are secondary data collected from LCA studies, ecoinvent database 3.8, and partially calculated from literature-based assumptions.

The studied system is depicted in Figure 27. For the sake of readability, the input activities to the silage production processes are not shown in the figure.

The main foreground processes are described in the following.

Manure management (P1): As mentioned in Section 4.4.2, the slurry is transported from the farms to the biogas plant over a maximum distance of 30 km to be stored in an open facility. The CH_4 and N_2O emissions from the open storage of cattle slurry are calculated following IPCC guidelines for National Greenhouse Gas Inventories from Livestock and Manure Management (Eggleston et al., 2006). NO_x emissions are calculated following the ecoinvent guidelines on Life Cycle Inventories of Agricultural Production Systems (Nemecek and Kägi, 2007). The CH_4 emissions from pig slurry storage were calculated based on the values provided by (De Vries et al., 2012), considering the values referring to storage in winter since the yearly average temperature in Luxembourg is around 10°C (Weather, 2022). This process also accounts for the indirect emissions caused by liquid manure storage and processing facility construction. Table 25 reports data values and sources for manure.

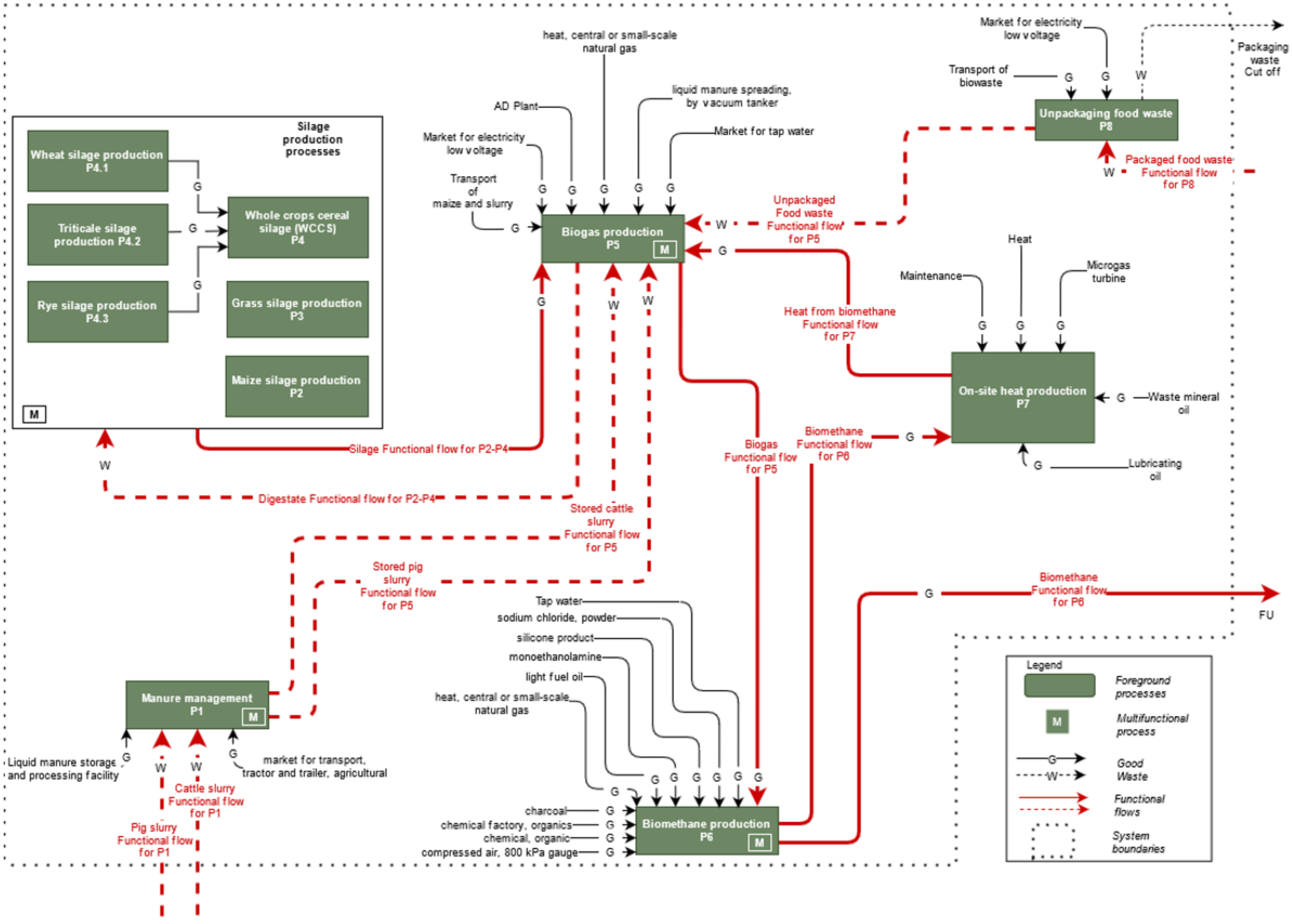

Figure 27: The biogas production system from LCA perspective.

VARIABLE	VALUE AND SOURCE	NOTES
Distance travelled (km)	30 [biogas plant]	–
Number of cattle heads on the slurry-based system in 2021	54,570 (Eurostat, 2022)	CH_4 emissions from cattle slurry were calculated using the IPCC guidelines for National Greenhouse Gas Inventories from Livestock and Manure Management ((Eggleston et al., 2006), Eqs. 10-22.)
Volume of cattle excreta per livestock type per week (m^3)	0.45 (Grains Research and Development Corporation (GRDC), 2005)	
Calculation of the N_2O emissions (kg); N volatilization ratio (%)	40 (Eggleston et al., 2006)	Indirect N_2O emissions were calculated using the IPCC guidelines for National Greenhouse Gas Inventories from Livestock and Manure Management ((Eggleston et al., 2006), Eq. 10.27.)
Emission factor for N_2O emissions from atmospheric deposition of nitrogen on soils and water surfaces (kg N_2O-N (kg NH_3-N + NO_x-N volatilized)$^{-1}$)	0.01 (Eggleston et al., 2006)	
NO_x emissions	0.21 × N_2O emissions (Burg et al., 2021)	–
CH_4 emissions from storing slurry (45 days in winter) (g CH_4/m^3)	28.7 (Petersen et al., 2013)	The amount of CH_4 emissions was calculated assuming only one day of storage.

Table 25: Data values and sources for manure.

Silage production (P2–P4): The ecoinvent 3.8 cut-off process "maize silage production, Swiss integrated production, intensive [CH]" was used as a proxy for maize silage (P2). Based on the lab tests provided by the biogas plant, the inorganic and organic flows of fertilizers in this process were replaced by the digestate produced from the anaerobic digestion. The inventory for grass silage (P3) was taken from ecoinvent 3.8 using the process "grass silage, Swiss integrated production, intensive [CH]" as a proxy. The Whole Crop Cereal Silage (WCCS) (P4) was assumed to be composed in equal proportions using wheat silage (P4.1), triticale silage (P4.2), and rye silage (P4.3). The inventory for wheat silage was adapted respectively from the ecoinvent 3.8 processes "wheat production, Swiss integrated production, intensive [CH]", considering the reduced time on field with respect to the main crop (wheat) and adding relevant processes such as chopping and fodder loading. The inventory for triticale silage was adapted in the same way, but from the triticale process that was built in (Vázquez-Rowe et al., 2014). The inventory for rye silage was adapted from (Huysveld, 2016).

The land occupation for each silage crop was calculated considering the respective yield and the number of days they stay on the field before being harvested. For maize silage 134 days were considered, for rye silage 264 days, and for the other crops used in WCCS it was assumed that the harvesting takes place between the stages 75 and 85 of Zadok's scale (Grains Research and Development Corporation (GRDC), 2005; Tottman, 1987).

Biogas production (P5): According to the data provided by the biogas plant, it produced on average 4.5 million m3 biogas/year, with a theoretical yield of 485 m3 biogas per ton of organic dry matter (t_{ODM}) and a Dry Matter (DM) ratio in the feedstock of 23%, as indicated in Table 26. According to the information collected at the biogas plant, 88% of the manure biomass can be considered as cattle slurry and 12% pig slurry.

The values of water and electricity used were calculated by deducting the amounts that go into biomethane production from the overall yearly values provided by the biogas plant. Heat requirements were calculated based on the amount of biomethane (produced on-site) and natural gas that is burned on-site. The produced biogas has a 55:45 content ratio of CH_4 and CO_2 that was used to calculate the respective amounts by considering a CH_4 and CO_2 density of 0.72 kg/m^3 and 1.96 kg/m^3 (Tampio et al., 2016). The NO_x emissions were calculated as 0.42 g/m^3 of biogas produced (Rouleau and Zupko, 2019). According to the information gathered at the biogas plant, CH_4 losses (leaking) are less than 1% of the produced CH_4. Transportation was calculated based on the distance provided by the plant for slurry and maize silage, while for food waste coming from supermarkets, an average distance of 20 km (This value comes from a personal communication with Mrs. Porcel and Mr. Maka from Naturgas Kielen) was assumed. The mass of produced digestate was calculated by subtracting the biogas mass from the total feedstock, as explained in (Tampio et al., 2016). The rest of the environmental flows were taken from the "anaerobic digestion of manure, CH" ecoinvent 3.8 process as a proxy. Table 26 reports the data and sources used for biogas production.

Biomethane production (P6): The data for this process were collected from the "biogas purification to biomethane by amino washing, [CH]" ecoinvent process. The only change was using the available Luxembourgish electricity mix in ecoinvent 3.8, instead of the one in Switzerland.

On-site heat production (P7): In this case, a part of the heat needed for biogas production is provided on-site by burning biomethane,

VARIABLE	DATA	SOURCE
Composition of substrate*	Silage 21% Biowaste 16% Manure 63%	Naturgas Kielen
Manure composition	Pig slurry 12% Cattle slurry 88%	
Yearly production of biogas (m^3)	4,500,000	
Biogas content in NK	55% CH_4 and 40% CO_2	
Biogas yield* (m^3/t_{ODM})	Silage: 625 Biowaste: 450 Manure: 450 Actual feedstock: 485	
DM ratio in feedstock*	0.23	
Moisture content in feedstock*	0.77	
CH_4 losses (%)	< 1	
CH_4 and CO_2 density (kg/m^3)	0.72	(Tampio et al., 2016)
CO_2 density (kg/m^3)	1.96	(Tampio et al., 2016)
Distance travelled	30 km (slurry and silage) 20 km (food waste)	Naturgas Kielen
NO_x emissions (g/m^3 of biogas produced)	0.42	(Rouleau and Zupko, 2019)

Table 26: Data values and sources for biogas production. *(*At the first year of simulation; the values change in every step as a result of the different composition of the feedstock.)*

which is also produced on-site. The data for this process were collected from the "biomethane, low pressure burned in micro gas turbine 100 kWe, [CH]" ecoinvent 3.8 process. The biomethane input entering this process is the biomethane produced by the producer itself.

Unpackaging food waste (P8): Before anaerobic digestion occurs, the food waste that is received goes through an unpackaging process where food waste is separated from its packaging. The unpackaging of 1 kg of food waste requires 0.005 kWh electricity, calculated based on the data provided by the biogas plant. According to the biogas producer Naturgas Kielen, up to 25% of the incoming food waste is packaged. It was assumed that 5% of food waste mass is constituted by packaging, which is later sent for green fuel upgrade in another Luxembourgish plant. Since there is no data available regarding the packaging treatment, nor a similar process in ecoinvent 3.8, this specific outflow has been cut off.

4.4.3.3 *Multifunctionality*

The definition of good (G) and waste (W) flows in both alternatives was made based on the price criteria. All the flows with an economic value higher than zero were considered goods, while those with an economic value lower than zero were considered waste flows. The functional flows were identified by keeping in mind that a functional flow can either be an outflow of a process in the case of goods, or an inflow of a process that treats waste, in the case of a waste flow (Guinée et al., 2002).

A process is considered a Multifunctional Process (MF) when it has one of the following characteristics (Guinée et al., 2002, 2004):

- Two or more good outflows (co-production)
- Two or more waste inflows (combined waste processing)
- One or more waste inflows and one or more good outflows (recycling).

The multifunctionality issue was solved by applying partitioning because it allows for the creation of "virtual mono-functional" processes, enabling the division of the nonfunctional flows over these virtual mono-functional processes (Guinée et al., 2004). The economic allocation principles were used for P5. Digestate was considered devoid of economic value; all the burdens where thus allocated to the biogas flow. The physical allocation principles were used for P1 and P6, while for P4 no allocation was deemed necessary since it represents a closed-loop recycling process.

4.5 CASE STUDY

Different scenarios were simulated using the ABM approach that was described in Section 4.4. The focus of these scenarios is to use as much organic manure as possible for biogas production, by introducing new plants into the system or changing the composition of feedstock for biogas production. The crop selection is achieved as explained in (Marvuglia et al., 2022) and livestock management as implemented in the simulator explained in Section 4.4. Therefore, the farmers respect crop rotation constraints and nitrogen requirements as required by regulations.

4.5.1 *Scenario A: Baseline Scenario*

This is the scenario that simulates the current situation in terms of biogas production in Luxembourg. Our aim is to assess the life cycle impacts of the current situation, which would then be used to compare with other scenarios.

4.5.2 *Scenario B: Addition of New Plants to the System*

As shown in Figure 25, there are 24 biogas cooperatives in Luxembourg. In the simulations, this number can be increased with additional small-scale plants that can be installed in communes that do not have any plants. The communes suitable for the theoretical installation of new plants were chosen based on the amount of manure that farms can provide. This is an analysis that only considers the supply of feedstock (i.e., the biomass supply potential for the new plants) and does not consider any other aspect (economic, social). However, in the current practice, the decision of building a biogas plant is a more complex process that requires the attention of local and country-level actors and imposes participatory planning.

In each one-year interval of simulation, a new plant is assigned to the commune with the most excess manure production in the previous year. The capacity of the plant is decided according to the possible contributors of manure around the plant and the contributors are assigned as the plant is initialized. If a farm is identified as a biogas contributor, then it remains as such throughout the simulation. The objective of this scenario is to show how Luxembourg could hypothetically increase its biogas potential using the available manure in regions that do not have biogas plants nearby.

4.5.3 *Scenario C: Biogas Feedstock Composition Change*

In the current composition of biogas feedstock shown in Table 26 and used in the simulations as a hypothetical composition for the biogas plants in Luxembourg in the absence of more detailed data, there is an average content of 63% of manure. The government's policy is to increase the rate of manure use to 90% (Today, 2022). To achieve this objective, in Scenario C more farms contribute to biogas production by collecting and sending excess manure to the closest biogas production plant instead of storing it for future use as organic fertilizer. In every time step, more and more farmers are expected to join the biogas production. The plants that have not reached their full capacity accept new contributors in every time step. Firstly, possible contributors for a given plant are selected among the farms that have excess manure. Then the farm with the largest amount of excess manure is assigned to that plant. This process is repeated in every time step.

4.5.4 *Scenario D: Increasing Biowaste in Biogas Feedstock*

The current percentage of food and organic waste (biowaste) in biogas feedstock is around 16% (see Table 26). The quantity of biowaste that can be collected only from the five major supermarket chains in Luxembourg (Delhaize, Cactus, CORA, Auchan, Match) can be estimated at around 12,000 tons/year (This value comes from a personal communication with Mrs. M. Porcel and Mr. X. Maka from Naturgas Kielen). Scenario D simulates a progressive increase in the quantity of food waste in the feedstock, until a full utilization of these 12,000 tons is reached in the last year of the simulation. Therefore, this scenario aims at exploring the possibility of valorizing biowaste for gas and electricity production, a potential that is nowadays still untapped in Luxembourg.

4.6 RESULTS AND DISCUSSION

The simulations are run for 10 years with monthly timesteps. The results reported in this paper are the average values of 50 repeats. The initial cropland of each farm is assigned using the GIS data from 2020, which contain information about the UAA of Luxembourg. A detailed description of the farm assignment algorithm applied can be found in (Marvuglia et al., 2022). The decisions related to the livestock production system are taken by each farmer at the animal level. For this reason, a high computational time is necessary to complete a set of simulations. Figure 28 shows the change in composition of feedstock for biogas production in every scenario.

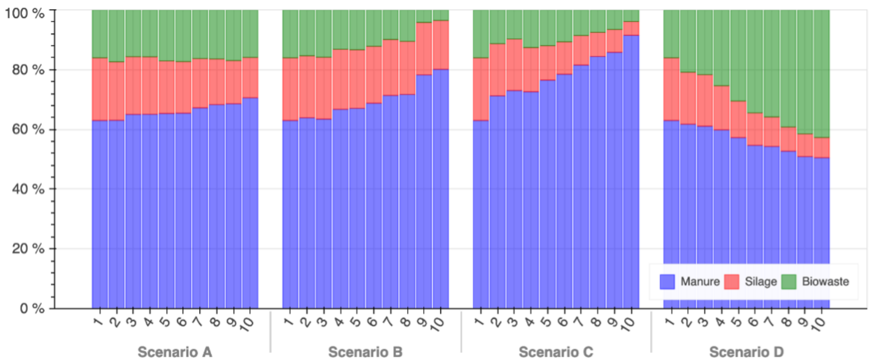

Figure 28: The feedstock composition of biogas production using each scenario.

The figure clearly shows that the manure percentage in each scenario increases with time. In the baseline scenario (Scenario A), the farmers choose to cultivate crops for human consumption rather than silage crops for bioenergy production, therefore the percentage of silage in the overall feedstock decreases and the percentage of manure increases. One reason for this is to slightly decrease livestock numbers, which fits to the current trajectory of the cattle production system in Luxembourg. In Scenario B, the introduction of new plants increases the use of excess manure as biogas feedstock, which ultimately increases the percentage of manure in the composition of the feedstock in every consecutive year. Every farm located at around a 30 km radius from the new plant is a candidate to become a contributor to biogas production. In Scenario C, more and more farms send excess manure to the established plants. There is no boundary in terms of the number of farms that can contribute to the production of biogas, and this leads to an increase in the manure percentage in the feedstock (up to 92%) at the end of the 10-year horizon of the simulation. Scenario D only aims at increasing the biowaste usage, although the total amount of crop silage and manure in biogas feedstock drops over the years due to a smaller number of animals and the reduced cultivation of energy crops for biogas production. At the end of the simulation, the biowaste percentage in feedstock composition is very close to the manure percentage.

Figure 29 shows the normalized LCIA results of each midpoint category obtained with the ReCiPe 2016 method and aggregated over 10 years of simulation.

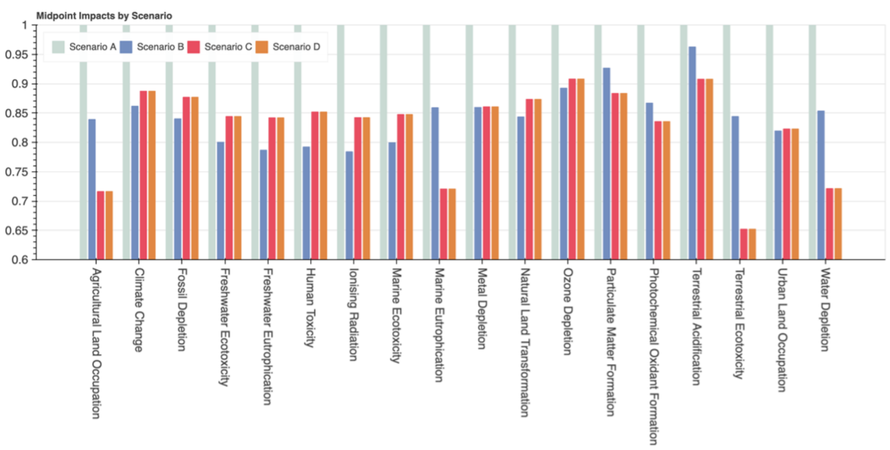

Figure 29: The 10-year aggregated LCIA scores using midpoint categories. Each impact category is normalized on the baseline scenario (Scenario A).

The midpoint scores are affected by the change in composition of feedstock, for example the impact on terrestrial ecotoxicity is 35% lower in Scenarios C and D compared to the baseline scenario. The creation of new plants does not only change the composition of the feedstock, but obviously also increases the overall biogas generation. Looking at the same midpoint impact scores from a biogas production efficiency perspective also, all the scenarios show improvements compared to the baseline (Figure 30). The midpoint category of Terrestrial Ecotoxicity this time shows more than a 35% improvement if Scenario C is enforced, and other categories such as Agricultural Land Occupation, Marine Eutrophication and Water Depletion show improvements higher than 27%. As Figure 6 shows, the Climate Change impact score (normalized by the amount of biogas produced) can be reduced by 14%, 17%, and 10% in Scenarios B, C, and D respectively, compared to the baseline scenario (Scenario A). Assuming the biogas production is promoted as described in Luxembourg's energy strategy for the current decade (Government, 2019), the electricity generation from biogas can reach almost 75% of its theoretical potential of 94 GWh (estimated in (Scarlat et al., 2018)) in the 10-year time horizon of the simulations, while at the same time the emissions can be reduced. In Figure 31, the projected electricity generated from biogas is shown, under the assumption that the methane content in biogas generated from silage is 52%, from food waste 60%, and from manure 55% (*KTBL-Taschenbuch Landwirtschaft* 2016). This assumption results in an energy production of about 2 kWh_{el} per m^3 of biogas (considering a value of 23 Mj/m^3 as the lower calorific value of the biogas and assuming an efficiency of the conversion of thermal energy in electricity of 32%). As Figure 31 shows, under Scenario B the potential production of electricity can increase by more than 7% at year 10, compared to the baseline scenario (Scenario A). Under Scenario D, the increase is about 15%. This brings additional emissions that affect some midpoint categories, for example Climate Change and Human Toxicity. Nonetheless, the cropland has a high contribution to some midpoint categories, such as agricultural land occupation or terrestrial ecotoxicity. As one can observe from Figure 29, as the farmers cultivate less and less maize for biogas production, the impacts related to these categories reduce up to 30% for Terrestrial Ecotoxicity and up to 25% for Agricultural Land Occupation.

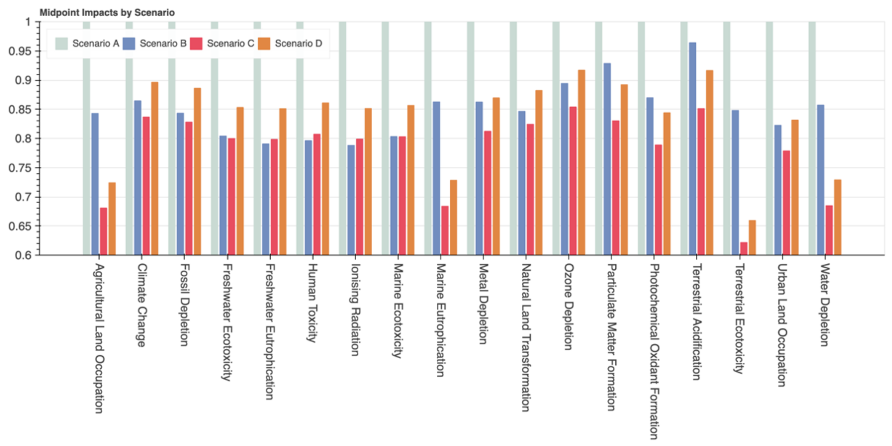

Figure 30: Midpoint impacts in Figure 29 with additional normalization using total biogas production in each scenario.

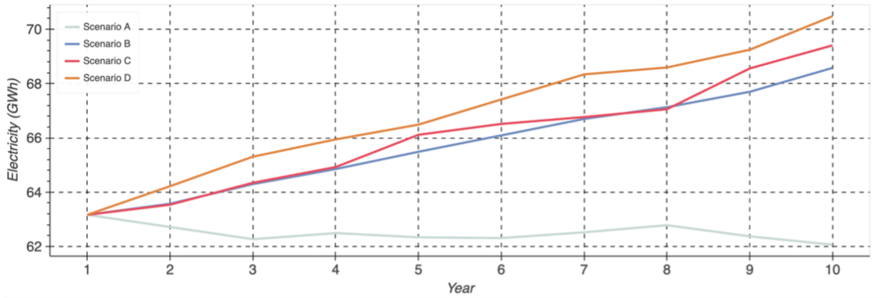

Figure 31: Projected electricity generation of each scenario over 10 years of simulation.

The normalized ReCiPe endpoint impact values for the four scenarios. Although Scenario D allows for the highest production of electricity (Figures 31 and 33), it scores the worst in all three endpoint categories (Human Health, Ecosystem Quality, and Resources), compared to the baseline scenario. This can be explained by looking at Table 27, which shows for each of the different feedstocks (silage, manure, and biowaste) the endpoint impacts referred both to the cubic meter of biogas produced and to the ton of Organic Dry Matter (ODM). The impacts are calculated after normalization and weighting, and expressed in Points (Pt), where 1 Point is equivalent to the impacts of 1 person (globally) over one year. According to this table, silage has a significantly larger impacts per t_{ODM} compared to the other two types of feedstocks. Therefore, one can say that Scenario A has the worst performance due to the high share of silage in the feedstock (ranging from 15% to 20% in Figure 28). Although the agricultural area is utilized more and more for human consumption, there is no additional manure foreseen in Scenario A. Therefore, the impacts per m3 of biogas produced remain higher in that scenario. Since manure has a lower impact per t_{ODM} than the other two feedstocks, the scenarios aimed at increasing manure usage in biogas feedstock show improvements in all the impact categories.

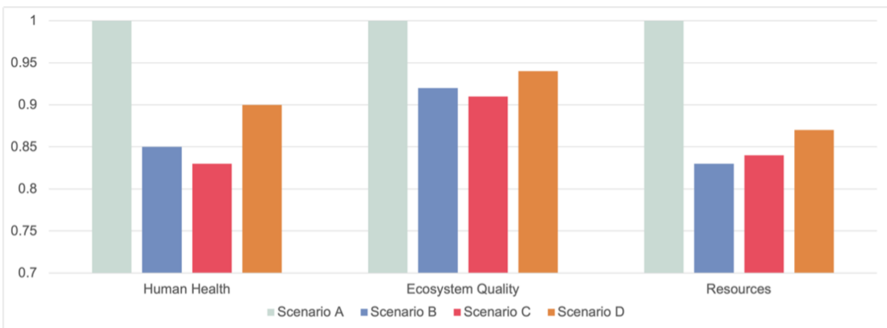

Figure 32: Normalized endpoint results over 10 years of simulation.

Although the biogas yield of biowaste is considered the same as the manure's one, the impact of biowaste per m^3 of biogas produced is

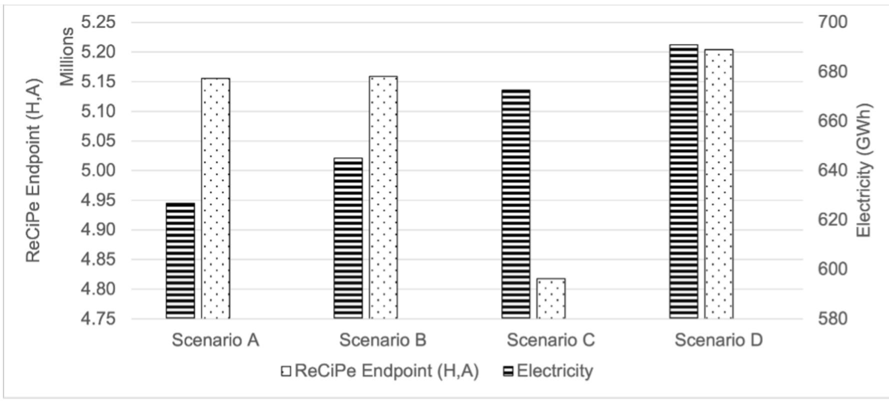

Figure 33: Total ReCiPe Endpoint (H, A) single scores (in MPts) and electricity productions (in GWh) for every scenario throughout 10 years of simulation.

Endpoint Impacts per m³ of Biogas Produced (Pt/m³)			
Endpoint category	Silage	Manure	Biowaste
Ecosystem Quality	0.0344	0.0011	0.0026
Human Health	0.0118	0.0018	0.0064
Resources	0.0069	0.0014	0.0037
Endpoint impacts per ton of ODM (Pt/t_{ODM})			
Endpoint category	Silage	Manure	Biowaste
Ecosystem Quality	21.48	0.5	1.17
Human Health	7.35	0.82	2.9
Resources	4.3	0.62	1.68

Table 27: Endpoint impacts of different feedstocks per m³ of biogas produced (using the biogas yields reported in Table 26) and per t_{ODM}.

higher than manure in every category. This explains higher endpoint impacts in Scenario D compared to Scenario B and C. The impact of silage does not affect the comparison, because the ratio of silage decreases in every scenario. Scenarios B and C have very similar impacts on Resources depletion and Ecosystem Quality, with Scenario B being slightly worse than Scenario C in the Human Health endpoint impact category. In Figure 33, the results of the LCIA are shown as single score values. The single scores calculation implies a step of normalization, followed by the weighting of the different impact categories, to provide a single impact value for each scenario, expressed in Points (Pt). This renders the comparison of the scenarios easier for the final users of the results, although it introduces a certain level of additional uncertainty (Itsubo, 2015). The hierarchist (H) version of

ReCiPe with average weighting (A) has been chosen to calculate the single scores (Huijbregts et al., 2017).

Along with the single scores, in Figure 33 the total electricity production for each scenario is also shown for the same simulation horizon. From the figure, it is possible to see that, although the foreseeable Scenario D allows for the highest electricity production in the 10 years, it has the highest aggregated impacts (more than 5.2 million Pt). Interestingly, based on the single score values, one can now see that Scenario C would be the preferred scenario (4.82 million Pt).

Concerning the validation of our results, as explained in Section 4.4, only an internal validation was possible in our case. Nonetheless, at least for what concerns the ranking of the different biogas feedstocks, our results are in line with those found by other recent studies (Fusi et al., 2016; Møller et al., 2022). (Møller et al., 2022) compare five different scenarios of biogas feedstock. Each scenario includes slurry ranging from 50% to 80%, but the amount of biowaste, energy crops, and crop residues differ. The total carbon emissions per ton are lower for biowaste than for crop residues and energy crops. In (Fusi et al., 2016) five plants with cow and pig slurry as wells as silage and crop residues are compared. The scenario where only cow slurry was used achieves better results in almost every impact category. The Climate Change impact score of that scenario shows a negative value, due to the avoidance of emissions of the traditional slurry management.

Moreover, according to (EurObserv'er, 2021), in the year of 2020 Luxembourg produced 62.7 GWh of electricity from biogas, which is comparable to the average value of 10 years of simulation (63.02 GWh/year) obtained in our business-as-usual case (scenario A). This validates our average results in this scenario.

4.7 CONCLUSIONS

The paper simulates four scenarios to assess the environmental impacts arising from a gradual change in the composition of the biomass feedstock used for biogas production in Luxembourg. Two main possibilities are explored: (1) exploiting more consistently the manure produced by farms and increasing its percentage in the composition of the biomass used in the digestors, and (2) including biowaste into the biogas feedstock, which is assumed to be always readily available. The following conclusions can be reached according to the scenarios' results.

According to Scenario C, the objective to increase the percentage of manure delivered to biogas production plants up to 90% of the excess manure available at farms (i.e., not useable for fields fertilization) is achievable. This can be obtained by adding new plants to the system, as well as integrating more farms to the production. The goal in both cases is to promote the usage of excess manure as biomass substrate for biogas production, which would in turn help achieve the objective of reducing GHG emissions set by the EU Green Deal.

The outcome one can derive from Figure 30 is that manure usage should be encouraged if one wants to reduce the environmental impacts per unit of biogas produced. If biowaste can be incorporated into the feedstock, this also generates less impact per unit of biogas produced than the business-as-usual case. The endpoint scores shown in Figure 32 and the single scores shown in Figure 33 also confirm that scenarios aiming to incorporate more manure into the feedstock (Scenarios B and C) have lower impacts than Scenario A (baseline scenario) and Scenario D, however the amount of biogas production and the electricity produced therein are higher with the addition of more biowaste to the feedstock (Scenario D).

In conclusion, one can see from Figure 33 that Scenario C is the best option to reduce the overall impacts and that Scenario D is the best option for producing more electricity. This shows a clear trade-off. However, if further efforts are put in place to increase the amount of manure usage in biogas feedstock, the total electricity production could become higher in Scenario C than Scenario D. For instance, instead of accepting only one more farm as a contributor per each time step of the simulation (as is the case in this paper), plants could welcome more farms in every step. Therefore, the total amount of manure in biogas feedstock can be increased.

4.8 LIMITATIONS AND FUTURE DIRECTIONS

Although the model factors in many of the decision variables that intervene in the real farm's business management, it certainly suffers from several limitations. Firstly, assuming that the biowaste would always be available, this does not fully reproduce reality, because there might be periods when, for various reasons, its delivery to the biomass plant is scarcer or potentially discontinued. On the other end, biowaste not used for biogas production is incinerated. This causes additional GHG emissions, which are not accounted for in the model.

Concerning the impact of organic manure, or silage cultivation for biogas production, it is calculated as the result of the agent's activities; however, the biowaste is not an output of farmer agents' activities, therefore we consider it as a burden-free input to the system (except for the impacts of biowaste un-packaging for the packaged biowaste that comes for example from supermarkets, which represents between 25% and 30% of all the biowaste received from supermarkets). Moreover, the model only deals with dairy and suckler farms, while pig slurry production is not modelled and is assumed to be available for biogas production. Finally, from the LCI point of view, certain processes have been adapted from existing ecoinvent processes available for other geographical contexts (namely Switzerland) and based on assumptions.

The results shown in the paper must be read with the important caveat that they do not come from a global optimization of the biogas production system in the entire country, including its integration into the national grid. This would require a much bigger effort (including the consideration of the feed-in tariffs granted to producers of electricity from biogas) and much larger data collection processes from all the biogas plants in the country, which would go beyond the scope of the paper. The model applied in this paper is only an attempt to provide an estimate of the potential of biogas production and the impacts related to field and plant operations, under the possible scenarios and the many assumptions that were considered and that are documented in this paper. The analysis of financial aspects related to biogas plants, as well as the cost of feedstock transportation from farms or supermarkets to the cooperatives were not considered in this paper. Therefore, this paper does not represent a feasibility study to assess the economic viability of building a new biogas plant or converting already built plants to adapt them to the digestion of a feedstock with a different composition, because this would require a more accurate, case-by-case, analysis. This paper merely intends to provide an estimation, with a life cycle perspective, of the potential environmental impacts that one could expect under the hypothetical scenarios that we have described and that could potentially be applied in Luxembourg.

It is once again worthy to point out that the biogas production segment is modeled using some of the information available at the Naturgas Kielen plant, and it does not mirror the full picture of Luxembourgish biogas production infrastructure (size, technology, etc.). Some variables such as the feedstock composition or the production technology are just assumed as constant from one plant to another. A larger data collection effort that encompasses more plants would be required for better estimation of the full biogas potential in Luxembourg.

Apart from the improvement in the limitations mentioned above, modelers will make new additions that can help better explain the current status of the biogas sector in Luxembourg. For instance, the government subsidies for the biogas sector are currently being studied and are subjected to future changes. In this respect, the consideration of the feed-in tariffs granted to producers of electricity from biogas will be an important addition to the current model. A government financial support exists in Luxembourg to improve storage facilities (Government, 2019); however, it has not been factored in the model because clear information about its amount was missing. There can be other types of subsidies which would entice the farmers into participating biogas cooperatives and, ideally, they should be considered in future versions of the model.

In the current study, the impact results are considered at the higher end because avoided emissions are not considered. Avoided emissions would include for example the avoided methane release in the atmosphere from open-air manure storage, since manure used for biogas is stored for a shorter time. Other avoided emissions that are not considered in this study are those eventually deriving from maize (as bioenergy crop, not as animal feed) substitution with other crops (since bioenergy maize is replaced by manure) and those deriving from a reduced consumption of natural gas from the grid, which is substituted using biomethane. This may very well change the total impact, however, assumptions on storage facilities and manure spreading times are not modelled within the current scope of the paper.

In our model, the farmers are connected to each other via a network and their green consciousness evolves according to the interaction with their neighbors. However, the farmers that belong to the same biogas cooperative may exchange information more frequently than the rest, therefore this requires more attention in terms of changes in behavior due to cooperative interactions. The cooperative itself can be modelled as an agent that disseminates information among its members. However, this element of interaction is not currently implemented in the model, and it may be introduced in future versions of it.

Although the scenarios introduced here were implemented separately, they can very well be applied concurrently. The objective of this study is to assess the feasibility of changing biogas feedstocks and their corresponding environmental impacts. Our model and simulator allow users to implement scenarios that can possibly be applied by policymakers. The advantage is that the ABM is combined with the LCA module, thus allowing the assessment of the environmental impacts arising from each simulated scenario.

4.9 MANAGERIAL INSIGHTS

There are some messages that might be conveyed to decision-makers in the agricultural sector in the light of the discussion and analysis made in this paper. First, the feedstock for biogas production affects the level of environmental impact. Therefore, it is possible to change from a silage-intense feedstock to a manure- or biowaste- intense one, while increasing the biogas production, but a close look always must be taken in regard to the full set of environmental impacts that each choice produces in all the impact categories and the trade-offs thereof. Second, the public stakeholders in the sector can look for ways to achieve an easier biowaste collection or promotion of manure usage in biogas feedstock. More farmers could be invited (or even incentivized) to contribute to biogas production in their proximities.

Another suggestion could be addressed to farmers who also benefit from digestate, a by-product from biogas production that can be used as soil amendment. The ones who contribute to the biogas production would have less inorganic fertilizer need, as they can get the digestate from biogas plants. However, digestate has a high-water content (80–90%), which makes the cost of transport higher than the fertilizer value they contain. Therefore, to be used in an economically viable way, it could be transported only to locations nearby the biogas plant, or some digestate liquid treatment systems should be considered as nitrogen and potassium concentration methods to concentrate a high share of the feedstock nitrogen into transportable fertilizer products with low mass (Tampio et al., 2016). In addition, the proportion between the different nutrients contained in the digestate does not exactly coincide in general with the nutritional needs of the crops. To ameliorate this problem and further decarbonise the agricultural sector, other possibilities exist, such as isolating Soluble Bio-based Substances (SBS) from the anaerobic digestate. These SBS can be used as environmental-friendly plant biostimulants and biofertilizers as alternatives to the (more expensive) commercial products based on fossil sources (Montoneri et al., 2022).

The second benefit for the farmers in the future could be the subsidies. Although the definition of a new subsidy scheme for biogas production is an ongoing work in Luxembourg, the farmers in the end would get a premium once the scheme is put in place. Most farms comply with the manure storage regulations in Luxembourg; however, the farmers would also avoid storing the manure (both liquid and solid) if they transport it to biogas production facilities more frequently, which would avoid emissions in the soil that come from open-air storage.

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Abdel-Aal, M., I. Haltas, and L. Varga (2020). "Modelling the diffusion and operation of anaerobic digestions in Great Britain under future scenarios within the scope of water-energy-food nexus." In: *Journal of Cleaner Production* 253, p. 119897. DOI: 10.1016/j.jclepro.2019.119897.

Appel, Franziska, Arlette Ostermeyer-Wiethaup, and Alfons Balmann (2016). "Effects of the German Renewable Energy Act on structural change in agriculture–The case of biogas." In: *Utilities Policy* 41, pp. 172–182.

Arnold, K., J. Gosling, and D. Holmes (2005). *The Java Programming Language*. Addison Wesley Professional.

Bartoli, A., D. Cavicchioli, D. Kremmydas, S. Rozakis, and A. Olper (2016). "The Impact of Different Energy Policy Options on Feedstock Price and Land Demand for Maize Silage: The Case of Biogas in Lombardy." In: *Energy Policy* 96, pp. 351–363. DOI: 10.1016/j.enpol.2016.06.018.

Baustert, Paul and Enrico Benetto (2017). "Uncertainty analysis in agent-based modelling and consequential life cycle assessment coupled models: a critical review." In: *Journal of Cleaner Production* 156, pp. 378–394. DOI: 10.1016/j.jclepro.2017.03.193.

Bayram, Alper, Antonino Marvuglia, Tomás Navarrete Gutierrez, Jean-Paul Weis, Gérard Conter, and Stéphanie Zimmer (2023). "Sustainable farming strategies for mixed crop-livestock farms in Luxembourg simulated with a hybrid agent-based and life-cycle assessment model." In: *Journal of Cleaner Production* 386, p. 135759.

Burg, Verena, Klaus G Troitzsch, Damla Akyol, Uta Baier, Stefanie Hellweg, and Oliver Thees (2021). "Farmer's willingness to adopt private and collective biogas facilities: An agent-based modeling approach." In: *Resources, Conservation and Recycling* 167, p. 105400. DOI: 10.1016/j.resconrec.2021.105400.

Chen, X. and L. Li (2016). "Supply of Cellulosic Biomass in Illinois and Implications for the Conservation Reserve Program." In: *GCB Bioenergy* 8, pp. 25–34. DOI: 10.1111/gcbb.12233.

De Vries, JW, TMWJ Vinken, L Hamelin, and IJM De Boer (2012). "Comparing Environmental Consequences of Anaerobic Mono- and Co-Digestion of Pig Manure to Produce Bio-Energy – A Life Cycle Perspective." In: *Bioresource technology* 125, pp. 239–248. DOI: 10.1016/j.biortech.2012.08.124.

Eggleston, H. S., L. Buendia, K. Miwa, T. Ngara, and K. Tanabe (July 2006). "2006 IPCC Guidelines for National Greenhouse Gas Inventories." English. In: URL: https://www.osti.gov/etdeweb/biblio/20880391 (visited on 01/13/2022).

EurObserv'er (2021). *The State of Renewable Energies in Europe*. URL: https://www.eurobserv-er.org/state-of-renewable-energies-in-europe/.

European Commission (2019). *A European Green Deal*. https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en. Accessed on 30 April 2022.

European Commission (2020). *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions on an EU Strategy to Reduce Methane Emissions*. COM(2020) 663 Final.

European Commission (2021). *Proposal for a Directive of the European Parliament and of the Council Amending Directive (EU) 2018/2001 of the European Parliament and of the Council, Regulation (EU) 2018/1999 of the European Parliament and of the Council and Directive 98/70/EC of the European Parliament and of the Council as Regards the Promotion of Energy from Renewable Sources, and Repealing Council Directive (EU) 2015/652*. COM(2021)557.

Eurostat (2022). URL: https://ec.europa.eu/eurostat/data/database (visited on 02/07/2022).

FAO (2018). *Nitrogen Inputs to Agricultural Soils from Livestock Manure: New Statistics*. Food and Agriculture Organization of the United Nations.

Fusi, Alessandra, Jacopo Bacenetti, Marco Fiala, and Adisa Azapagic (2016). "Life cycle environmental impacts of electricity from biogas produced by anaerobic digestion." In: *Frontiers in Bioengineering and Biotechnology* 4, p. 87. DOI: 10.3389/fbioe.2016.00087.

Gouvernement du Luxembourg (2000). *Règlement Grand-Ducal Du 24 Novembre 2000 Concernant l'utilisation de Fertilisants Azotés Dans l'agriculture*. Journal Officiel du Grand-Duché de Luxembourg. Memorial A n.124.

Gouvernement du Luxembourg (2001). *Règlement Grand-Ducal Du 9 Novembre 2001 Instituant Un Règime d'aides Favorisant Les Méthodes de Production Agricole Compatibles Avec Les Exigences de La Protection de l'environnement et de l'entretien de l'espace Naturel*. Journal Officiel du Grand-Duché de Luxembourg. Memorial A n.135.

Government, Luxembourg (2019). *Luxembourg's Integrated National Energy and Climate Plan for the Period 2021-2030*. Tech. rep.

Grains Research and Development Corporation (GRDC) (2005). *Cereal Growth Stages*.

Grimm, Volker, Steven F Railsback, Christian E Vincenot, Uta Berger, Colin Gallagher, Donald L DeAngelis, Bruce Edmonds, Jianping Ge, Jarl Giske, Jürgen Groeneveld, et al. (2020). "The ODD protocol for describing agent-based and other simulation models: A second update to improve clarity, replication, and structural realism." In: *Journal of Artificial Societies and Social Simulation* 23.2. DOI: 10.18564/jasss.4259.

Guinée, J.B., H. Bruijn, R. Duin, M.A.J. Huijbregts, M. Gorree, R. Heijungs, G. Huppes, R. Kleijn, A. de Koning, and L. Oers (2002). *Handbook on Life Cycle Assessment. Operational Guide to the ISO Standards*. Vol. 7. Eco-Efficiency in Industry and Science. Kluwer Academic Publishers.

Guinée, J.B., R. Heijungs, and G. Huppes (2004). "Economic Allocation: Examples and Derived Decision Tree." In: *Int J LCA* 9 (1), p. 23. DOI: 10.1007/BF02978533.

Happe, Kathrin, Alfons Balmann, and Konrad Kellermann (2004). *The Agricultural Policy Simulator (AgriPoliS): an agent-based model to study structural change in agriculture (version 1.0)*. Tech. rep. 71. Discussion Paper, Institute of Agricultural Development in Central and Eastern Europe (IAMO).

Huijbregts, M.A.J., Z.J.N. Steinmann, P.M.F. Elshout, G. Stam, F. Verones, M. Vieira, M. Zijp, A. Hollander, and R. van Zelm (2017). "ReCiPe2016: A Harmonised Life Cycle Impact Assessment Method at Midpoint and Endpoint Level." In: *Int J Life Cycle Assess* 22, pp. 138–147. DOI: 10.1007/s11367-016-1246-y.

Huysveld, Sophie (2016). "Exergy-Based Natural Resource Accounting in Sustainability Assessment of Agricultural Production Systems." PhD thesis. Ghent, Belgium: Ghent University.

Imran, Hafiz Azeem, Dirk Schröder, and Bilal Ahmad Munir (2017). "Agent-Based Simulation for Biogas Power Plant Potential in Schwarzwald-Baar-Kreis, Germany: A Step Towards Better Economy." In: *Geocarto International* 32, pp. 59–70. DOI: 10.1080/10106049.2015.1128485.

Itsubo, N. (2015). "Weighting." In: *Life Cycle Impact Assessment*. Ed. by M.Z. Hauschild and M.A.J. Huijbregts. Springer Netherlands, pp. 301–330. ISBN: 978-94-017-9744-3.

KTBL-Taschenbuch Landwirtschaft (2016). KTBL. ISBN: 978-3-945088-12-8.

Kremmydas, Dimitrios, Ioannis N Athanasiadis, and Stelios Rozakis (2018). "A review of agent based modeling for agricultural policy evaluation." In: *Agricultural Systems* 165, pp. 95–106. DOI: 10.1016/j.agsy.2018.03.010.

Marvuglia, A., A. Bayram, P. Baustert, T.N. Gutierrez, and E. Igos (2022). "Agent-Based Modelling to Simulate Farmers' Sustainable Decisions: Farmers' Interaction and Resulting Green Consciousness Evolution." In: *Journal of Cleaner Production* 332, p. 129847. DOI: 10.1016/j.jclepro.2021.129847.

Marvuglia, Antonino, Tomàs Navarrete Gutiérrez, Paul Baustert, and Enrico Benetto (2018). "Implementation of agent-based models to support life cycle assessment: a review focusing on agriculture and land use." In: *AIMS Agriculture and Food* 3.4, pp. 535–560. doi: 10.3934/agrfood.2018.4.535.

Marvuglia, Antonino, Sameer Rege, Tomás Navarrete Gutiérrez, Laureen Vanni, Didier Stilmant, and Enrico Benetto (2017). "A return on experience from the application of agent-based simulations coupled with life cycle assessment to model agricultural processes." In: *Journal of cleaner production* 142, pp. 1539–1551.

Mertens, Amelie, Jef Van Meensel, Koen Mondelaers, Ludwig Lauwers, and Jeroen Buysse (2016). "Context Matters—Using an Agent-Based Model to Investigate the Influence of Market Context on the Supply of Local Biomass for Anaerobic Digestion." In: *BioEnergy Research* 9, pp. 132–145. doi: 10.1007/s12155-015-9668-0.

Möhring, Axel, Gabriele Mack, Andrea Zimmermann, Ali Ferjani, Axel Schmidt, and Stefan Mann (2016). "Agent-based modeling on a national scale–experiences from SWISSland." In: *Agroscope Science* 30, pp. 1–46.

Møller, Henrik Bjarne, Poul Sørensen, Jørgen Eivind Olesen, Søren O Petersen, Tavs Nyord, and Sven G Sommer (2022). "Agricultural biogas production—climate and environmental impacts." In: *Sustainability* 14.4, p. 1849. doi: 10.3390/su14031849.

Montoneri, Enzo, Andrea Baglieri, and Giancarlo Fascella (2022). "Biostimulant Effects of Waste Derived Biobased Products in the Cultivation of Ornamental and Food Plants." In: *Agriculture* 12.7. issn: 2077-0472. doi: 10.3390/agriculture12070994.

Nasri, M.F., J. France, N.E. Odongo, S. López, A. Bannink, and E. Kebreab (2008). "Modelling the Lactation Curve of Dairy Cows Using the Differentials of Growth Functions." In: *The Journal of Agricultural Science* 146, pp. 633–641.

Nemecek, Thomas and Tenzin Kägi (2007). *Life Cycle Inventories of Agricultural Production Systems*. Zurich and Dubendorf: Swiss Centre for Life Cycle Inventories.

Netherlands, Statistics (2012). "Standardised calculation methods for animal manure and nutrients. Standard data 1990-2008." In: *Statistics Netherlands: Hague/Heerlen*.

Nugroho, Yohanes K., Lianhua Zhu, and Cathal Heavey (2022). "Building an agent-based techno-economic assessment coupled with life cycle assessment of biomass to methanol supply chains." In: *Applied Energy* 309, p. 118449. doi: 10.1016/j.apenergy.2021.118449.

Petersen, Søren O, Noemi Dorno, Sabine Lindholst, Anders Feilberg, and Jørgen Eriksen (2013). "Emissions of CH4, N2O, NH3 and Odorants from Pig Slurry during Winter and Summer Storage." In: *Nutrient Cycling in Agroecosystems* 95, pp. 103–113. doi: 10.1007/s10705-013-9551-3.

PostGIS (2022). *PostGIS — Spatial and Geographic Objects for PostgreSQL*. url: http://postgis.net/ (visited on 02/15/2022).

PostgreSQL (Feb. 2022). *PostgreSQL*. en. URL: https://www.postgresql.org/ (visited on 02/15/2022).

Rouleau, Mathieu and Robert Zupko (2019). "Agent-based modeling for bioenergy sustainability assessment." In: *Landscape and Urban Planning* 188, pp. 54–63. DOI: 10.1016/j.landurbplan.2019.04.019.

STATEC (2022). fr. URL: https://statistiques.public.lu/fr/acteurs/statec/index.html (visited on 02/07/2022).

Scarlat, N., F. Fahl, J.-F. Dallemand, F. Monforti, and V. Motola (2018). "A Spatial Analysis of Biogas Potential from Manure in Europe." In: *Renewable and Sustainable Energy Reviews* 94, pp. 915–930. DOI: 10.1016/j.rser.2018.06.035.

Schaubroeck, Thomas, Sophie Schaubroeck, Reinout Heijungs, Alessandra Zamagni, Miguel Brandão, and Enrico Benetto (2021). "Attributional & Consequential Life Cycle Assessment: Definitions, Conceptual Characteristics and Modelling Restrictions." In: *Sustainability* 13.13, p. 7386. DOI: 10.3390/su13137386.

Shu, K., M. Kozak, N.B. Fradj, T. Zylowski, and S. Rozakis (2020). "Simulation of Sorghum Introduction and Its Impacts on Land Use Change—A Case Study on Lubelski Region of Eastern Poland." In: *GCB Bioenergy* 12, pp. 252–274. DOI: 10.1111/gcbb.12669.

Sorda, G, Y Sunak, and Reinhard Madlener (2013). "An agent-based spatial simulation to evaluate the promotion of electricity from agricultural biogas plants in Germany." In: *Ecological Economics* 89, pp. 43–60.

Steubing, B., D. de Koning, A. Haas, and C.L. Mutel (2020). "The Activity Browser – An Open Source LCA Software Building on Top of the Brightway Framework." In: *Software Impacts* 3, p. 100012. DOI: 10.1016/j.simpa.2019.100012.

Tampio, Elina, Sanna Marttinen, and Jukka Rintala (2016). "Liquid Fertilizer Products from Anaerobic Digestion of Food Waste: Mass, Nutrient and Energy Balance of Four Digestate Liquid Treatment Systems." In: *Journal of Cleaner Production* 125, pp. 22–32. DOI: 10.1016/j.jclepro.2016.03.127.

Today, RTL (2022). *Biogas: New National Strategy Envisions Higher Levels of Recycling*. Accessed on 10 June 2022. URL: https://today.rtl.lu/news/luxembourg/a/1734536.html.

Tottman, David R. (1987). "An Explanation of the Decimal Code for the Growth Stages of Cereals, with Illustrations." In: *Annals of Applied Biology* 110, pp. 441–454.

Troost, Christian, Teresa Walter, and Thomas Berger (2015). "Climate, Energy and Environmental Policies in Agriculture: Simulating Likely Farmer Responses in Southwest Germany." In: *Land Use Policy* 46, pp. 50–64. DOI: 10.1016/j.landusepol.2015.01.028.

Vannier, C., T.A. Cochrane, P. Zawar Reza, and L. Bellamy (2022). "An Analysis of Agricultural Systems Modelling Approaches and Examples to Support Future Policy Development under Disruptive Changes in New Zealand." In: *Applied Sciences* 12.5. DOI: doi.org/10.3390/app12052746.

Verhoog, Roel, Amir Ghorbani, and Gerard Pieter Jozef Dijkema (2016). "Modelling Socio-Ecological Systems with MAIA: A Biogas Infrastructure Simulation." In: *Environmental Modelling & Software* 81, pp. 72–85. DOI: 10.1016/j.envsoft.2016.03.011.

Vázquez-Rowe, Ian, Antonino Marvuglia, Sameer Rege, and Enrico Benetto (2014). "Applying Consequential LCA to Support Energy Policy: Land Use Change Effects of Bioenergy Production." In: *Science of The Total Environment* 472, pp. 78–89. DOI: 10.1016/j.scitotenv.2013.10.097.

Weather, Holiday (2022). *Luxembourg, Luxembourg - Average Annual Weather - Holiday Weather*. https://www.holiday-weather.com/luxembourg/averages. Accessed on 15 June 2022.

Wernet, G., C. Bauer, B. Steubing, J. Reinhard, E. Moreno-Ruiz, and B. Weidema (2016). "The Ecoinvent Database Version 3 (Part I): Overview and Methodology." In: *Int J Life Cycle Assess* 21, pp. 1218–1230. DOI: 10.1007/s11367-016-1087-8.

Wu, Jie, Jiquan Wa, and Michael P Strager (2011). "A Two-Stage GIS Based Suitability Model for Sitting Biomass-to Biofuel Plants and Its Application in West Virginia, Quebec, Canada." In: *Quebec, Canada*.

Yazan, Devrim Murat, Luca Fraccascia, Martijn Mes, and Henk Zijm (2018). "Cooperation in Manure-Based Biogas Production Networks: An Agent-Based Modeling Approach." In: *Applied Energy* 212, pp. 820–833. DOI: 10.1016/j.apenergy.2017.12.074.

"Mathematical programming to optimize crop and dairy production in Luxembourgish farms"

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5 MATHEMATICAL PROGRAMMING TO OPTIMIZE CROP AND DAIRY PRODUCTION IN LUXEMBOURGISH FARMS

5.1 ABSTRACT

As the human population grows rapidly, meeting people's food security while respecting the planet's boundaries requires strenuous efforts. It is known that agriculture's role in contributing to environmental impact categories such as climate change, land use, ecotoxicity, and water pollution is significant. In this paper, a hybrid model that couples an ABM and life cycle assessment LCA is proposed, which also includes multi–objective optimization to optimize farming activities from an economic and environmental perspective. The model uses indicators that hinge upon LCA methodology and encompass the entire production chain. Like any classical ABM, social interactions among agents are also considered. The proposed model is the only simulation model in the literature that uses a hard-coupled ABM LCA along with an optimization module at the individual farm operation level. The model also encompasses both livestock and crop farming activities. The farmer network is built using neighborhood relations, which influence the update of the farmers' GC parameter at every time step. At the end of every time step, the optimization module is instantiated and decision variables (the number of livestock and land allocation) are determined based on profitability and selected environmental impact categories. The impacts are quantified using the EF LCIA method. If only profit optimization is considered, model results show a 9% reduction in EF single score impacts and a 5.5% increase in overall profitability. At the farm level, simulations show a clear trade-off between environmental and economic sustainability, with a 25% reduction in overall emissions being possible if farming activities take place by considering the EF single impact score in the objective function, although this results in an 8% reduction in profitability over ten years.

5.2 INTRODUCTION

As the human population grows rapidly (Crist et al., 2017; Gerland et al., 2014), meeting people's food security while respecting the planet's boundaries becomes increasingly essential. To that end, the agricultural sector's role must be properly defined due to its significant contributions to various environmental impact categories, such as climate change, land use, ecotoxicity, and water pollution (Clark et al., 2020). In recent years, analytical descriptive tools have been widely used to address these issues in sustainability assessment (Gava et al., 2019). Quantitative sustainability assessment(Marvuglia et al., 2015) is meant to assist decision makers in the three pillars of sustainability: economic, environmental, and social (Guinée et al., 2004; Heijungs, 2010; Sala et al., 2015). In this work, we deal with the optimization of the farm business from the standpoint of profit maximization, considering not only the economic dimension but also the environmental one, tackled from a life cycle based perspective. To this end, we use indicators that hinge upon the Life Cycle Assessment (LCA) methodology, encompassing the entire production chain and not just the field operation or animal husbandry phase. The advantage of this approach is that it prevents the shifting of environmental burdens from the field operation phase to the upstream or downstream phases (Repar et al., 2017).

The decision-makers have been trying to foster international monitoring and cooperation by defining goals for the upcoming decades (Assembly, 2015). The Green Deal that was set out by the European Commission proposes the 'Farm to Fork Strategy' (European Commission, 2020) which aims to make production decisions more environmentally accountable. The assessment of possible outcomes of these proposals is not obvious and requires the consideration of human behavior as an important factor to reach a successful integration of green strategies and, concurrently, the effect of collective actions in consequence of social interactions among different actors.

In 2015, the agriculture sector accounted for 11.3% (514.1MtCO_2-eq) of total GHG emissions and 10% of total non-CO_2 emissions (nitrous oxide and methane) in Europe (Hart et al., 2017). This figure rises to 16.5% globally (Twine, 2021). Moreover, the sector accounts for approximately 54% of total methane emissions in the EU and nearly 79% of total N_2O emissions (Eurostat, 2022). Agriculture and its subsystems can have irreversible consequences on the environment (Crippa et al., 2021). Therefore, sustainability needs to be prioritized in agricultural policy. Beyond simple on-farm assessment, LCA methodology can help actors understand and reflect on the emissions caused by agricultural production activities. Using LCA, one can assess the impacts of activities not only at the farm level, but throughout the entire production chain. Nonetheless, the complexity of agricultural production systems necessitates modeling efforts capable of capturing emerging features resulting from the interactions among the different actors involved. As a result, LCA alone will inevitably fall short of quantifying and monitoring every aspect of the sector. In (Marvuglia et al., 2022), a hybrid model coupling Agent-Based Modelling (ABM) and LCA was therefore proposed with the goal of encompassing farm management on a larger scale. The main novelty of that work lays in the inclusion of several aspects of dairy farm management, as well as economic and environmental optimization on a farm level.

Among computer-aided modelling methods, ABM is particularly appealing for investigating and simulating relevant scenarios that aim to tackle the environmental problems we face today. ABM allows the consideration of different actors and the exploration of their reciprocal interactions at the micro-level (farmer's level) or macro-level (regional or national) (Schreinemachers and Berger, 2011). The agents are autonomous entities that may be physical or virtual (Ferber and Weiss, 1999). They follow a wide set of rules within an environment, where learning and adaptation are also possible to generate changes in other agents or the environment (An, 2012). The applications of ABMs go beyond agri-food systems and cover most Complex Coupled Human-Natural Systems (CHANS) (Hare and Deadman, 2004) including socio-economic, techno-social and environmental systems (Baustert et al., 2019; Gaud et al., 2008; Gilbert, 2019; Grimm and Railsback, 2013; Heath et al., 2009; Heckbert et al., 2010; Micolier et al., 2019; Teglio et al., 2011; Wu et al., 2017).

Mathematical programming models and solves complex decision-making problems using statistics, optimization techniques, and other analytical approaches (Carravilla and Oliveira, 2013). In the field of agriculture and farming, when combined with LCA, techniques from this field may help realize efficiency gains and impact reductions in crop-livestock production systems. Optimization using linear programming techniques and evolutionary algorithms are two possible avenues. In this work we further enhance the model presented in (Bayram et al., 2023) by adding a farm level optimization that aims at optimizing the farm's business from economic and environmental perspectives based on the constraints set from real life conditions. To the best of our knowledge, this model is the only simulation model in the literature that uses a LCA approach to optimize the individual farms' operation over a given time interval. It also encompasses both livestock and crop farming activities, with the option of adding biogas production activities, leveraging on the work presented in (Bayram et al., 2023).

5.3 Literature review

5.3.1 *Mathematical optimization methods*

Three essential approaches of Mathematical Programming (MAP) are known as linear programming, non-linear programming, and mixed-integer programming, respectively. Linear Programming (LP), Non-Linear Programming (NLP), and Mixed-Integer Programming (MIP). In certain circles, these methods are also referred to as mathematical optimization approaches. These three techniques, when applied along with LCA, may optimize objective function(s) with reference to a set of particular constraints, and as a result, present a set of optimal solutions for improving the environmental performance of a product system. During both the Life-Cycle Inventory (LCI) and Life-Cycle Impact Assessment (LCIA) stages of the LCA process, management practices can be utilized in combination with LCA. Depending on the goals of the investigation, objective functions may be evaluated using either an aggregated single environmental effect or multi-objective mathematical programming. The term "constraints" refers to any activities that take place between the extraction of raw materials and the end-of-life stage (Caldeira et al., 2019).

The integration of LP and LCA models introduces a significant amount of uncertainty (due to uncertain data points like farm revenue and crop yields), yet LP is still the most popular choice among MP models because of its ease of use and flexibility in dealing with a wide range of decision factors. In order to maximize crop productivity while minimizing environmental impacts, LP models have been applied to a wide range of agricultural issues, including crop rotation, farm system design, economic decisions, optimization of cropping patterns and resource use management between crop and livestock farms, resource allocation, and more (Galán-Martín et al., 2017).

One has the option of using deterministic, stochastic, or resilient modeling methodologies when it comes to the uncertainty of the parameter values (Jornada and Leon, 2016). Using traditional optimization techniques that are, for the most part, founded on linear algebra is what is meant by the phrase "deterministic modeling." LP and MIP models are frequently used in situations in which the parameters of the model can be determined with certainty (Kong et al., 2019). When the parameters are deemed to be stochastic, the use of stochastic programming techniques is recommended according (Huang et al., 2012).

Mathematical optimization methods have mostly been used to crop production in the agricultural sector. Cereal crops including corn, wheat, and rice may be to blame for this. Historically, mathematical optimization has been applied to problems on a regional scale, when the objectives are limited to a certain group of farms.

Most of the papers we looked at optimized for at least two goals, but we didn't find any instances when this was done simultaneously. The overarching goal was to improve the farm's financial situation while reducing its negative effects on the environment. Most environmental impact objective functions were emission-based, with a focus on GHG emission mitigation (Gebrezgabher et al., 2014). Economic objective functions frequently aim to maximize the surplus over expenses that farms generate. The objective functions can be defined by a number of different choice variables, which vary from product to product. Land allocation, sowing time, crop protection agents and fertilizers, irrigation, and other such management and resource variables (i.e. seed, water, fertilizer, crop protection, and energy input amounts, yield, etc.). Farming is a highly strategic endeavor that requires careful consideration of many moving parts, including when and how much water to use, how many people to hire, when to harvest, and what to do thereafter (Chandrasekaran and Ranganathan, 2017; He et al., 2018). Tactic models' objective functions are typically paired with an economic purpose, such as cutting down on input costs or increasing farm profitability. Short-term (daily) issues and farm-scale planning fall under operational decisions, which have received less attention than tactical decisions. This includes matters like crop management scheduling, farm input mix and amount, harvest schedule (Xie et al., 2018), and storage planning. From a modeling perspective, some studies address both strategic and tactical issues, such as a 2020 study that compares the effectiveness of various farming methods (Yuanyuan, 2020).

The use of mathematical programming models is sometimes criticized for being too narrow in scope when it comes to establishing objective functions like land use, irrigation, or farm technology, and for only allowing a select few stakeholders to participate in the modeling process (Udias et al., 2018). Multi-objective optimization models based on LP, MIP, and NLP models take into account a wide variety of farm management concerns; this is how they make up for the limitations of single-objective LP models.

5.3.2 *Genetic Algorithms (GAs)*

Evolutionary Algorithms (EAs) show promise as powerful resources for optimizing a wide variety of factors simultaneously. The approaches that GAs take to solving problems can be categorized as either elitist or non-elitist. To solve multi-objective issues without favoring any one solution over the others, one can use elitist solution finding approaches like NSGA-II. On the other hand, non-elitist approaches make it possible for competing alternatives to emerge victorious (Yusoff et al., 2011). GAs are attractive for use in various fields of study because they can be modeled specifically for the task at hand. GAs are a form of search algorithm based on the ideas of natural selection and evolutionary processes. These algorithms are classified as stochastic search algorithms because they use probabilistic methods to decide which parameters to use.

Multi-objective GAs have been used to maximize a wide range of goals in crop-livestock research, from increasing farm revenues to enhancing livestock and crop productivity to lessening the negative effects on the environment (Maiyar and Thakkar, 2019; Pishgar-Komleh et al., 2020). On the other hand, most of the sources relied on employed exclusive approaches. The majority of GA-based research only considers economic limitations, although some research has also considered environmental constraints (Chandrasekaran and Ranganathan, 2017; Pastori et al., 2017).

The first step in combining GAs and LCA is often obtaining the study's results. Environmental consequences are often assumed as outputs from joint GA-LCA models, while the farm inputs (such as crop and livestock traits) are inputted as choice factors. Together, GAs and LCA models aim to reduce environmental consequences at both the local and global scales. GAs are then used to generate the best possible options (López-Andrés et al., 2018; Maiyar and Thakkar, 2019). The benefits of GAs include their conceptual clarity, adaptability, multi-objective optimization, and use of stochastic optimization. The lack of a standardized integration mechanism is the primary drawback of joint GAs-LCA. The stopping point (i.e., the point at which the global optimum is reached) in GAs is not always obvious (Sarker and Ray, 2009). The NSGA-III evolutionary algorithm is one of the most popular approaches to resolving multi-objective optimization problems, and it has found use in fields as diverse as engineering, finance, and bioinformatics. In order to optimize for multiple goals at once, the NSGA-III uses EA principles (Deb and Jain, 2014).

Table 5.3.3 summarizes the information obtained from the literature on the use of mathematical programming and genetic algorithms in crop-livestock system environmental assessments.

5.3.3 *Paper contributions and organization*

The following are the key original contributions of the article:

- A novel multi-stage optimization model for optimal farm management that takes both crop and livestock farming activities into account.
- Incorporation of linear LCA-based environmental constraints based on ReCiPe midpoint impact categories into the model investigation of various environmental constraints
- A farming management system that optimizes the decisions based on subsidies with the goal of minimizing environmental impacts.

The rest of the paper is structured as follows. The proposed multi-objective farm optimization scheme is introduced in Section 5.4. Section 5.6 presents extensive results for the proposed approach while discussing the key outcomes. Section 5.7 concludes and gives insights for future work.

Table 28: An overview of approaches explored in the literature that use mathematical optimization methods to improve farm outputs from an economic, environmental, and technical standpoint.

REFERENCE	COUNTRY/REGION	METHODOLOGY AND AIM
(Behera et al., 2014)	Northern India	Profit maximization, capital and labor minimization under economic constraints using linear programming.
(Chandrasekaran and Ranganathan, 2017)	India	Supply maximization, cost reduction and CO_2 minimization under economic and environmental constraints using genetic algorithms
(Capitanescu et al., 2017)	Luxembourg	Only profit maximization under economic and environmental constraints using mixed-integer programming.
(Cobuloglu and Büyüktahtakın, 2015)	Kansas, USA	Maximization of the total economic value obtained from switchgrass production under production, environmental and economic constraints using mixed-integer linear programming.
(Cortignani and Severini, 2012)	Central Italy	The objective function considers land allocation, water price, and cost under economic constraints.
(Ding et al., 2021)	Wallonia, Belgium	Six objectives are specified, namely climate change, freshwater eutrophication, electricity, heat, biogas, bioethanol. Territorial constraints are defined and problem is solved using fuzzy linear programming.
(Dowson et al., 2019)	New Zealand	Maximize the profit of milk and minimize the cost of feed, harvesting and irrigation under economic and technical constraints.
(Gital Durmaz and Bilgen, 2020)	Izmir, Turkey	Maximize the profit and minimize the distance between biogas plants and poultry farms under economic and technical constraints using multi-objective mixed integer linear programming
(Fasakhodi et al., 2010)	Isfahan, Iran	Maximize net return per water consumption and labor per water consumption under economic constraints using nonlinear programming.
(Galán-Martín et al., 2017)	Spain	Three objectives are (1) maximizing production, minimizing damage to (2) ecosystem quality and (3) resources under demand satisfaction, capacity limitations and water demand constraints.

Table 28: An overview of approaches explored in the literature that use mathematical optimization methods to improve farm outputs from an economic, environmental, and technical standpoint. (continued)

REFERENCE	COUNTRY/REGION	METHODOLOGY AND AIM
(Gebrezgabher et al., 2014)	Salland, Overijssel, the Netherlands	Gross margin, GHG emissions, NH_3 emissions and land use change are optimized under manure availability, demand requirement and land availability. The chosen methodology is compromise programming (CP).
(Hassani et al., 2019)	Khorasan Razavi, Iran	Resilience is defined using multiple economic, technical and environmental indicators, which then being normalized and optimized under eight different sets of constraints which can be economical, nutritional, technical and environmental. Both GAs and Particle swarm optimization (PSO) are used in this study to solve the optimization problem.
(Huang et al., 2012)	Tarim River Basin, China	The objective is to develop a two-stage interval quadratic programming (TIQP) which is then used to obtain an optimal water-allocation scheme by maximizing the economic and environmental benefits.
(Jabarzadeh et al., 2020)	Iran	The objective function is formed by minimizing total costs and CO_2 emissions, along with maximizing responsiveness to customer demand. Constraints are defined considering the supply and demand for a particular product; within a region or for a time of the year.
(Liang et al., 2018)	New York, US	Maximization of farm profit, water productivity and soil organic matter accumulation are objectives under economic, nutritional, and soil-related constraints. The solution method is mixed-integer quadratic constrained programming (MIQCP) (Zhong and You, 2014).
(López-Andrés et al., 2018)	Mexico	The objectives are maximizing the profit and minimizing the four endpoint categories of IMPACT 2002+ under production and mass balance constraints. GAs are used to solve the optimization problem.
(Ma et al., 2018)	Northeast China	Minimizes cost of transportation and quality degradation of goods. Technical and environmental constraints are defined according to the capacity and regulations of containers. Mixed-integer programming is used as the solution method.
(Maiyar and Thakkar, 2019)	Andhra Pradesh and Tamil Nadu, India	Total supply network costs, along with transportation emissions and wastages are minimized. Environmental, economic and production constraints are considered; MOPSODE (Su and Chi, 2017) and NSGA-II (Deb et al., 2002) are solution methods.

Table 28: An overview of approaches explored in the literature that use mathematical optimization methods to improve farm outputs from an economic, environmental, and technical standpoint. (continued)

REFERENCE	COUNTRY/REGION	METHODOLOGY AND AIM
(Manos et al., 2013)	Larisa and Trikala, Greece	Gross margin maximization, labor and fertilizer minimization are the objectives. Agronomic and regulatory constraints, as well as environmental ones, are considered and Weighted Goal Programming (Sumpsi et al., 1997) is used to solve the optimization problem.
(Mansoori et al., 2009)	Mashhad, Iran	Various economic and environmental objectives are defined and optimized in different scenarios under economic constraints. Goal programming was used to solve the problem.
(Pishgar-Komleh et al., 2020)	Iran	Tomato production is optimized based on carbon footprint, benefit-cost ratio and energy use efficiency. The constraints are the lower and upper bounds of production parameters. First ANNs were applied to model relationships between the objectives, then GAs and PSO were used to optimize the objectives.
(Ow et al., 2020)	Switzerland	Minimization of aggregated environmental impacts is considered under environmental and nutritional constraints. Linear programming was used as the solution methodology.
(Rohmer et al., 2019)	Netherlands	Cost and environmental indicators are minimized (either together or separately). Constraints are defined according to nutritional requirements and consumer demands. Compromise programming and ϵ-constraint methods were used for multi-objective optimization.
(Xavier et al., 2018)	Nine agrarian regions of Portugal	Twelve agricultural sustainability indicators were optimized under technical constraints and Extended Goal Programming was used to solve the multi-objective optimization problem (Diaz-Balteiro and Romero, 2004).
(Yuan et al., 2018)	Taiwan	Impact reduction maximization is the only objective of this study. Technical, nutritional and environmental constraints were used and the problem was solved using linear programming.

5.4 MATERIALS AND METHODS

5.4.1 *Hybrid ABM LCA model and simulations*

ABM. Several scenarios were already simulated in our previous work, which concerns animal stocking rate reduction and animal dietary change (Bayram et al., 2023), farmers' GC evolution (Marvuglia et al., 2022) and change of biogas feedstock composition (Bayram et al., 2022). The model that was developed to include dairy farming activities and cropping activities in Luxembourg has now been extended to run optimizations of each farm at every time step based on economic and environmental objectives and constraints. Within the framework of the model, the agents carry out their activities while giving due consideration to both the monetary worth of their businesses and the possible environmental implications of their actions. The limits that are defined in each of the implemented scenarios act as a constraint on the actions that the agents can take.

LCA. The environmental impact assessment of farmers' decisions is carried out using the EF method (Saouter et al., 2019). In our model, the objective function that each agent looks at when optimizing its operations includes EF impact scores on one or multiple impact categories, which are normalized and weighted according to Table 29, taken from (European Commission, 2018).

Simulations. The time step used in our simulations is one month, and the simulation lasts ten years. For various reasons, a month was chosen as the unit of time for the simulation. Because crop rotation changes occur at different times of the year, harvesting and planting decisions can be made more precisely. Furthermore, choices that affect the structure of the herd (for example, culling decisions) are made monthly rather than annually. Crop, milk, and meat prices all have seasonal tendencies, which might influence specific decisions made by farmers. The fertilizer requirement for crops can be fulfilled in several ways. The first option is to employ farm–produced animal manure, which can be either solid or liquid. The second alternative is to buy inorganic fertilizers at a fixed price throughout the simulation. Dairy farms, which constitute most farms in Luxembourg, employ animal manure first and subsequently purchase inorganic fertilizer if the crop plantation requires it. As a third option, farmers may use the digestate from the biogas facility if they are part of a cooperative for biogas production, as described in (Bayram et al., 2022). However, the model described in this paper does not include biogas production activities because of a lack of detailed farm-specific data on biogas activities (composition of the feedstock, association with biogas cooperatives, etc.). The costs considered in the model fall into two different categories: fixed and variable costs. The fixed costs are the ones that depend mainly on the size of the farm, such as mate-

Category	Unit (μ_i)	Normalization Factor (η_i)	Weighting Factor (w_i)
Climate change	kg CO_2 eq.	8.10×10^{3}	2.11×10^{-1}
Ozone depletion	kg CFC-11 eq.	5.36×10^{-2}	6.35×10^{-2}
Ionising radiation	kBq U-235	4.22×10^{3}	5.01×10^{-2}
Photochemical ozone formation	kg NMVOC	4.06×10^{1}	4.78×10^{-2}
Particulate matter	disease incidences	5.95×10^{-4}	8.96×10^{-2}
Human toxicity, non-cancer	CTUh	2.30×10^{-4}	1.84×10^{-2}
Human toxicity, cancer	CTUh	1.69×10^{-5}	2.13×10^{-2}
Acidification	mol H^+ eq.	5.56×10^{1}	6.20×10^{-2}
Eutrophication, freshwater	kg P eq.	1.61	2.80×10^{-2}
Eutrophication, marine	kg N eq.	1.95×10^{1}	2.96×10^{-2}
Eutrophication, terrestrial	mol N eq.	1.77×10^{2}	3.71×10^{-2}
Ecotoxicity, freshwater	CTUe	4.27×10^{4}	1.92×10^{-2}
Land use	pt	8.19×10^{5}	7.94×10^{-2}
Water use	m^3 of deprived water	1.15×10^{4}	8.51×10^{-2}
Resource use, fossils	Mj	6.50×10^{4}	8.32×10^{-2}
Resource use, minerals and metals	kg Sb eq.	6.36×10^{-2}	7.55×10^{-2}

Table 29: EF normalization factors and weights for each impact category that were used to calculate single score impact (European Commission, 2018).

rial costs, fixed capital consumption, labor and energy costs, which are not considered in the optimization problem due to a lack of reliable information on those cost items. On the other hand, the variable costs are the ones that depend on the number of animals and the area that is cultivated, namely fertilizers, animal feed, plant seeds and veterinary costs. As explained in (Bayram et al., 2023), the livestock is modeled individually such that their phenotypical attributes (body weight, gender, age, etc.) are assigned individually. The estimation of body weight is necessary to calculate the energy requirements of an animal. Therefore, we operated in two steps. First, we applied the body weight mid-infrared-based equation for dairy cows developed by (Tedde et al., 2021) on the Walloon milk spectral database managed by the Walloon Breeding Association (Elévéo, Ciney, Belgium). This database contained 713,428 records (45,488 cows and 222 herds) collected from 2006 to 2020. Then, the predicted body weight was modeled using 7 in which the independent variables (weeks of lactation and parity) were divided into 5 classes (first to fifth+ parity, i.e., we set to 5 every parity greater than 5). This equation represents the theoretical averaged estimation of predicted body weight (BW) based on parity and week of lactation. The coefficients of the equation used to perform the BW simulation of this study are shown in Table 30.

$$BW(kg) = y_{intercept} + w_1 n_{parity} + w_2 WOL + w_3 WOL^2 + w_4 WOL^3 + w_5 WOL^4 + w_6 WOL^5 \tag{7}$$

where n_{parity} is the number of parities (the number of pregnancies a cow has completed) of the animal and WOL is the week of lactation.

	Mean	Standard Deviation
$y_{intercept}$	5.39×10^2	3.22×10^{-1}
w_1	3.72×10^1	2.76×10^{-2}
w_2	8.20	1.31×10^{-1}
w_3	9.82×10^{-1}	1.72×10^{-2}
w_4	4.71×10^{-2}	9.53×10^{-4}
w_5	1.03×10^{-3}	2.32×10^{-5}
w_6	8.31×10^{-6}	2.05×10^{-7}

Table 30: The coefficients for Eq. 7 that is used to calculate the body weight of dairy animals.

5.4.2 *MOO problem formulation*

In the Supplementary Information, the definition of mathematical optimization, a generic explanation of linear programming, weighted sum method and details of how NSGA-III works can be found. In this section we will introduce the problem formulation, i.e., the objectives and constraints of the Multi-Objective Optimization (MOO) problem.

In the present study, the MOO was implemented using the NSGA-III algorithm. As explained in (Bayram et al., 2023), the simulator is built in Java (Arnold et al., 2005). Therefore, we used the Multi-Objective Evolutionary Algorithms (MOEA) Framework (Hadka, 2012), an open-source Java library that supports several evolutionary algorithms, including NSGA-III. The crossover (Deb et al., 1995) and mutation (Kita et al., 1999) probabilities were set at 0.9 and 0.1, respectively. The population size (N) is critical for the algorithm's convergence. The size of the population can influence the efficiency of evolution, or the iteration may stop at the local optima. A population size of 100 can be reached in a feasible amount of computational time and increasing the size has not changed the solutions vastly.

Indices and Sets		*Unit*
t	index for the planning time step	—
c	index for crop products	—
a	index for animals	—
i	index for environmental impact categories	—
C	set of crops	—
NC	size of current crop plantation	—
$NL_{newborn}$	number of newborns	—
NL_{cull}	number of livestock to be culled	—
Decision Variables		
$\mathrm{UAA}_{c,t}$	UAA with crop plantation c for a given time t.	ha
NL	number of livestock	—
Parameters		
T	simulation time horizon.	years
h_c	harvesting month of crop c.	—
s_c	seeding month of crop c.	—
A_f	total acreage available in farm f.	ha
μ_i	unit of the EF impact category i	—
w_i	weight of the EF impact category i	—
η_i	normalization factor of the EF impact category i	μ_i / person
$imp_{c,i}$	environmental impact of crop c in impact category i	—
$imp_{milk,i}$	environmental impact of milk c in impact category i	—
$imp_{meat,i}$	environmental impact of meat c in impact category i	—
Continuous Variables		
$f_{c,t}$	profit from crop production at time t.	€
$f_{a,t}$	profit from animal production at time t.	€
$f_{s,t}$	revenue from subsidies at time t.	€
$f_{p,t}$	total profit of a farm at time t.	€
$f_{i,t}$	impact of farming activities for impact category i at time t.	—
$f_{EF,t}$	EF single score impact of farming activities at time t.	—
$p_{c,t}$	price of crop c sold at time t.	€ / ha
$vc_{c,t}$	variable cost of production of crop c sold at time t.	€ / ha
$A_{c,t}$	area of crop c at time t.	ha
$A_{pasture,t}$	area occupied by pastureland at time t.	ha
$p_{milk,t}$	price of milk sold at time t.	€ / kg
$y_{milk,t}$	total yield of milk at time t.	kg
$p_{meat,t}$	price of meat sold at time t.	€ / kg
$y_{meat,t}$	total yield of meat at time t.	kg
$vc_{feed,t}$	variable cost of feeding at time t.	€
$vc_{veterinary,t}$	variable cost of veterinary at time t.	€
$P_{milk,t}$	total milk production in the farm at time t.	kg
$P_{milk,a,t}$	total milk production of animal a at time t.	kg
$P_{meat,t}$	total meat production in the farm at time t.	kg
$P_{meat,a,t}$	total meat production from animal a at time t.	kg
m	the current month of the simulation	—
m_p	the number of months to be considered for rolling sum profit	—
$f_{p,roll}$	m_p month rolling sum of profit	€
NE_{roll}	12-month rolling sum of nitrogen excretion	$kg - N_{org}$
NE_t	nitrogen excretion at the current time t	$kg - N_{org}$
sub_t	total subsidies received by the farmer at time t	€
M_t	transition matrix for fields at time t	—

Table 31: The nomenclature of variables used in the optimization problem

A MOO problem is designed to maximize the economic values of crop and animal production while minimizing environmental impacts. The ideal values for various decisions, such as the number of animals to keep or cropland allocation, are established by solving the objective functions. The optimization module is run in the post-market phase (Bayram et al., 2023) of our simulations and the decision variables are selected as the average value over the population. The following sections fully explain the proposed model's objective functions and restrictions.

5.4.3 *Objective functions*

The model aims to minimize environmental impact while making the most profit out of animal and crop production at the level of each farm. The profit for crop production is calculated by subtracting the variable costs of cropping operations from the revenue:

$$f_{c,t} = \sum_{c,t} p_{c,t} A_{c,t} - \sum_{c,t} vc_{c,t} A_{c,t} \tag{8}$$

To calculate the total milk and meat production, individual productions of animals are first calculated and then aggregated over the farm.

$$P_{milk,t} = \sum_{a} P_{milk,a,t} \tag{9}$$

$$P_{meat,t} = \sum_{a} P_{meat,a,t} \tag{10}$$

The profit for animal production is calculated similarly to crops by subtracting the variable costs of veterinary and feeding spending from the revenue:

$$\begin{aligned} f_{a,t} = &\sum_{t} p_{milk,t} P_{milk,t} + \sum_{t} p_{meat,t} P_{meat,t} \\ &- \sum_{a,t} vc_{vet,\ a,t} - \sum_{a,t} vc_{feed,\ a,t} \end{aligned} \tag{11}$$

The subsidy schemes explained in (Bayram et al., 2023) are still in place. Therefore, they are parts of a farm revenue stream. However, the amount of subsidy for compensatory allowance has been changed. Farmers get 165 €/ha up to 90 ha and 90 €/ha above 90 ha.

$$f_{s,t} = \sum_{t} sub_t \tag{12}$$

Then we define the first objective function as:

$$f_{p,t} = f_{a,t} + f_{c,t} + f_{s,t} \tag{13}$$

The environmental impacts are calculated using the impact scores of crop and animal production activities. As explained in Section 5.4.1, the EF LCIA method was used to formulate the optimization problem. The objective function to minimize the environmental impact may include more than one impact category. The objective function for one category can be expressed as follows:

$$f_{i,t} = \sum_{t,i} y_{milk,t} imp_{milk,i} + \sum_{t,i} y_{meat,t} imp_{meat,i} + \sum_{t,i} A_{c,t} imp_{c,i} \tag{14}$$

The EF single score of a farm can be calculated using the weights in Table 29:

$$f_{EF,t} = \sum_{t,i} f_{i,t} w_i n_i \tag{15}$$

5.4.4 *Production constraints*

Each farm is assigned a certain number of fields, as explained in (Marvuglia et al., 2022). The external boundaries of a farm or the shape of fields are not changed (fields cannot be sold or split) during the simulations. Therefore, the size of a farm is always equal to or greater than the size of the cultivated area:

$$\sum_{c} A_{c,t} \leqslant A_f \forall t \tag{16}$$

It should be noted that the pastureland always remains constant and cannot be converted into cropland:

$$A_{pasture,t} = A_{pasture,\ t-1} \qquad \forall\ t \tag{17}$$

There are multiple constraints on the harvesting and seeding of crops. The transition from one crop plantation to another can only be done within the validity period of corresponding crops' harvesting and seeding seasons. Moreover, the crop rotation scheme of a farm should be respected, which is considered a field-wise practice. The farmers can choose crops with lower impacts if their GC value (Marvuglia et al., 2022) is above the pre-specified threshold (which is 0.5 in all experiments in this paper). If not, they choose the most profitable one, respecting the plantation calendar and crop rotation scheme constraints. If the transition matrix M has the probabilities of changing state, then the transition from crop x to crop y can take place as:

$$UAA_{C_y,t+1} = M_t^{x,y} UAA_{C_x,t} \tag{18}$$

Where each element of M_t (i.e., $M_t^{x,y}$) is determined according to crop rotation and the GC value of the farmer. 18 is also subject to:

$$h_x - 1 \leqslant m \leqslant h_x + 1 \tag{19}$$

$$s_y - 1 \leqslant m \leqslant s_y + 1 \tag{20}$$

Therefore, the harvesting and seeding seasons for current and following crop plantations are considered respectively in transitioning. Dairy farms must decide which and how many animals to cull. In our model, two main problems may occur if the culling decisions are not restricted. First, although there are always animals that need to be culled due to age limits (as explained in (Bayram et al., 2023)), farmers may want to cull more animals to get more subsidies or to minimize environmental impacts. The other problem is the opposite of excessive culling. The farmers may want to expand the herd size to increase milk production and therefore maximize the profit objective. Therefore, the number of culled animals is constrained by the number of newborns and the farm class (Table 32).

Farm Class	Culling condition	Culling decision
A, B, C, D	$NL_{newborn} - 1 \leqslant NL_{cull} \leqslant NL_{newborn} + 1$ (21)	NL_{cull}
	$NL_{cull} \leqslant NL_{newborn} - 1$ (22)	$NL_{newborn} - 1$
	$NL_{cull} \geqslant NL_{newborn} + 1$ (23)	$NL_{newborn} + 1$
E, F, G, H	$NL_{newborn} - 2 \leqslant NL_{cull} \leqslant NL_{newborn} + 2$ (24)	NL_{cull}
	$NL_{cull} \leqslant NL_{newborn} - 2$ (25)	$NL_{newborn} - 2$
	$NL_{cull} \geqslant NL_{newborn} + 2$ (26)	$NL_{newborn} + 2$

Table 32: The constraints on culling decisions.

5.4.5 *Environmental constraints*

As mentioned in Section 5.4.1, the farmers consider the entire set of environmental impacts of each crop (calculated using the EF method) while choosing the crop plantation for the fields. Moreover, there is a hard limit for nitrogen emissions to soil for the entire year (Gouvernement du Luxembourg, 2000), which can be expressed as:

$$NE_{roll} = \sum_{t}^{t-11} NE_t \leqslant \sum_{t}^{t-11} 170 \frac{kg - N_{org}/ha}{year} A_{pasture,t} \tag{27}$$

where $kg - N_{org}$ are the kilograms of organic nitrogen fertilizer spread on the field.

5.4.6 *Economic constraints*

Environmental goals have increasingly formed an element of the EU's CAP since the 1980s. To contribute to decreasing GHG emissions, boosting energy efficiency, and protecting soil, the EU's climate change policy mandates a change in farming methods. These policy objectives were met in our simulations in a simplified form (Bayram et al., 2023) by direct subsidies to support environmental measures (Pillar 1) and multi-year rural development laws with climate change as one of the guiding considerations (Pillar 2). However, it is crucial to emphasize that, to receive these subsidies, all farms must first achieve the cross-compliance standards (SER, 2015), which has been the case for all farms in Luxembourg in recent years. To get the subsidies, the farmers must meet some constraints concerning land allocation or nitrogen emissions due to livestock farming. The farms with more than three hectares of area ($A_f \geqslant 3$ ha) can get the compensatory allowance as long as they meet the cross-compliance standards (SER, 2015). On the other hand, the greening subsidy can be acquired only if the farm meets the criteria given in Table 33:

Farm Area	Crop Diversity		Number of Crops on the Plantation
$0 \leqslant A_f \leqslant 10$ ha	—		—
$10 \text{ ha} \leqslant A_f \leqslant 30$ ha	$0 \leqslant A_{c=C_1,t} \leqslant 0.75A_f$	(28)	$NC \geqslant 2$ (29)
	$A_{c=C_1,t} \geqslant A_{c=C_x,t}$	(30)	
$A_f \geqslant 30$ ha	$0 \leqslant A_{c_1,t} \leqslant 0.75A_f$	(31)	$NC \geqslant 3$ (32)
	$0 \leqslant A_{c_1,t} + A_{c_2,t} \leqslant 0.95A_f$	(33)	
	$A_{c=C_1,t} \geqslant A_{c=C_2,t} \geqslant A_{c=C_x,t}$	(34)	
	$C_1 \neq C_2$	(35)	

Table 33: Criteria for greening subsidy.

The rules set for the subsidy scheme "Extensification of permanent grassland" may help regulators and farmers avoid excessive nitrogen leakage into the soil. Using NE_{roll} that was set in 27, we may express the constraints in this scheme as in 34.

It is desirable to avoid as many emissions as possible, but the farming business should also be sustainable from a financial perspective. Therefore, adding a constraint that avoids non-profitable businesses throughout the simulation is reasonable. For this reason, the rolling

Stocking rate (LSU/ha)	NE_{roll} ($kg - N_{org}$)	Subsidy (€ / ha)
1.2	$0 \leqslant NE_{roll} \leqslant \sum_{t}^{t-11} 130 \frac{kg - N_{org}/ha}{year} A_{pasture,t}$ (36)	150
0.8	$0 \leqslant NE_{roll} \leqslant \sum_{t}^{t-11} 85 \frac{kg - N_{org}/ha}{year} A_{pasture,t}$ (37)	200

Table 34: The criteria to get extensification of permanent grassland subsidy scheme.

sum of profits over m_p months is calculated for each farm 38, and if that is lower than zero, the farmer optimizes the farm by using only the first objective function 13.

$$f_{p,roll} = \sum_{t}^{t-m_p} f_{p,t} \tag{38}$$

5.5 CASE STUDY DEFINITIONS

Three cases were simulated, as discussed in the rest of this section. The difference between the three cases lies in formulating the objective function and constraints.

5.5.1 *Case 1: Maximize Profit*

This case corresponds to purely greedy farm management. None of the environmental objectives or constraints are considered. This case is used as a baseline scenario and the impact scores and farm revenues from other cases are compared to this case in Section 5.6. The problem can be represented in compact form as a MOO problem, which is as follows:

$$\max f_p \quad s.t. \quad Eq.\ 16 - Eq.\ 38$$

5.5.2 *Case 2: Maximize Profit, minimize EF Climate Change*

EF method uses the GWP_{100} (Global Warming Potential over 100 years) indicator to calculate the impact of GHG emissions on global warming. In this case, the problem formulation can be expressed as the following:

$$\max f_p, \min f_{i\,=\,EF_{climate\ change}} \quad s.t. \quad Eq.\ 16 - Eq.\ 38$$

5.5.3 *Maximize profit, minimize EF Single Score*

EF has a set of weighting and normalization factors for quantifying the environmental impacts of a product or service over its entire life cycle. Weighting factors show the relative importance of each impact category in a product's or process's overall environmental impact. A stakeholder engagement process is used to determine the weighting criteria, in which experts and interested parties provide opinions on the relative relevance of various environmental issues. The weighting elements are often stated as percentages that add up to 100%. Normalization factors are used to compare the environmental impacts of a product or process to a reference value. The reference value is usually the environmental impact of producing one unit of a particular product or service. Data from a representative sample of items or processes in each impact category is used to compute the normalization factors. They are often expressed in terms of the product or service being evaluated. The values in Table 29 are used to find the single score result, which is then used in the optimization problem. The problem, in this case, can be written as follows:

$$\max f_p, \min f_i = \mathrm{EF}_{\text{single score}} \quad \textit{s.t.} \quad \textit{Eq. 16 - Eq. 38}$$

5.6 RESULTS AND DISCUSSION

The FU of our study is the country's total agricultural and pastureland area (i.e., the sum of all UAAs[1]), together with total milk and meat production. The simulations run for ten years, with fifty repetitions applied yearly. Each run's random seed assignment is explained in (Marvuglia et al., 2022). Every run assigns the same set of fields to the farms previously saved in the database after the farm creation algorithm is applied to the spatial data (Marvuglia et al., 2022). The farmer network is built using the neighborhood and risk aversion classes, which influence the updated GC value of each farmer at every time step. At the end of every time step, the optimization module is instantiated and decision variables (the number of livestock and land allocation) are determined as explained in the previous sections.

In this paper, we simulated several cases to observe the effects of optimizing farming activities based on different environmental indicators. Although each case takes the first objective function into account, the second objective is either absent (baseline scenario) or considers the impacts due to one (Case 2) or multiple (Case 3) environmental impact categories. As explained above, the impacts are quantified using the EF LCIA method (Saouter et al., 2019). To see how the optimization affected our results in terms of environmental impacts and

1 UAA is defined as the smallest georeferenced land object registered in the agriculture cadastre.

farm finances, we first needed to establish that optimization module performs as intended, i.e., model where agents optimize their farms based on a given objective achieve that goal consistently. In order to compare the optimization-based model with the (non-optimized) baseline scenario from (Bayram et al., 2023), where the LCIA was done using ReCiPe 2016 (Huijbregts et al., 2017), we ran the latter again using EF (which is the method used in the current paper) as LCIA method. The resulting impacts in terms of the aggregated single score for that scenario and Case 1 can be seen in Figure 34.

5.6.1 *Country-level results*

As Figure 34 shows, the single score impacts already reduce thanks to the subsidies in place and livestock management rules that govern the simulations. Although the EF single score impacts reduced in both optimized and non-optimized cases (9% and 13% respectively, as shown in Figure 34), the stocking rate in the model with optimization does not reduce as much as in the non-optimized decisions, mainly because the number of livestock is a decision variable that largely influences farm profitability (Figure 35). The choice of crops is based only on profitability and this reflects an increase in the overall profitability of 5.5% in the optimized decisions compared to almost no change in the non-optimized case (Figure 34).

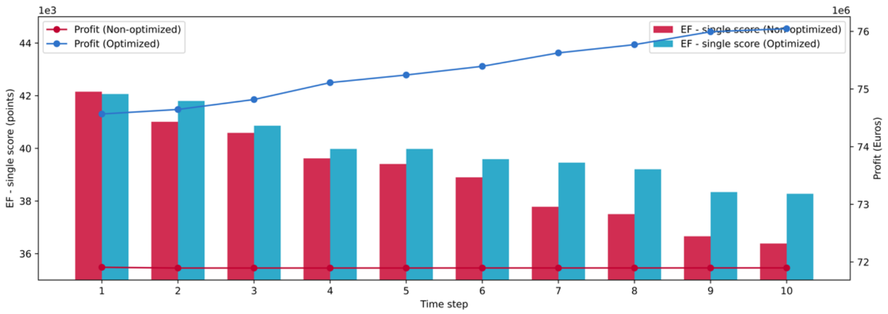

Figure 34: The comparison of the model with and without farm optimization.

Figure 36 compares the EF single scores based on each optimization case. The country-level aggregated impacts and profits show a clear tradeoff between environmental and economic sustainability. Although a 25% of reduction in overall emissions is possible if environmental considerations influence the farming activities, this brings an 8% decline in profitability over ten years. As seen from Figure 35, the average stocking density reduces only to a level of 1.6 LSU/ha. In contrast, the subsidy "Extensification of permanent grassland" requires a much lower stocking rate. Most farms fail to achieve this goal because the amount of subsidies received is insufficient to let farmers make

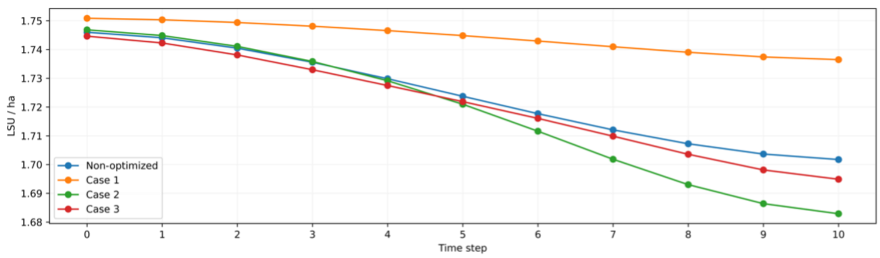

Figure 35: LSU / ha change for different cases.

more culling decisions. Nevertheless, as shown in Figure 34, around 9% of EF single score reduction can still be achieved while making 5.5% more profit.

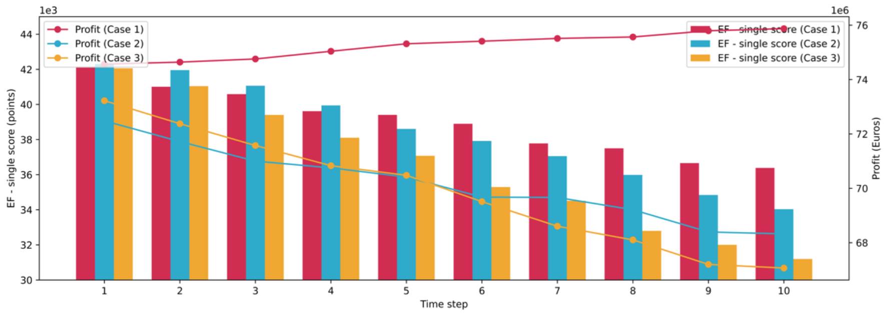

Figure 36: Comparison of EF single scores based on each optimization case.

5.6.2 *Farm-level results*

Since the farming operations, agent decisions and optimization happen on a farm-level, it is logical to focus on-farm level results for the simulated cases. We, therefore, initialized some farms using ground truth data. For example, we selected one of those farms whose properties such as location, size, and the number of animals are known, and in this section, we will show the results of simulated cases for this specific farm. The behavior of the other farms is very similar. The farm properties are given in Table 35. Some properties, such as GC and the number of livestock, change across the simulation. Initial, minimum, mean, and maximum values are reported for those attributes. GC, degree centrality and rotation scheme are assigned from a random distribution since they are not available in the data provided for this study.

In (Marvuglia et al., 2022), we introduced the treemap representation as a way of preserving the privacy of a farm's external geographical boundaries while respecting the interior boundaries (i.e.,

Attribute		**Value**
Farm class		G
Degree centrality		2
Green Consciousness	Initial:	0.44
	Min:	0.44
	Mean:	0.47
	Max:	0.51
Number of fields		36
Number of arable fields		10
Size of pastureland (ha)		22.00
Size of arable land (ha)		69.50
Total size of UAA (ha)		91.51
Number of Livestock	Initial:	122
	Min:	105
	Mean:	114
	Max:	125
Organic		No
Rotation Scheme		MLC

Table 35: The selected farm's properties. The farm is located around the center of Luxembourg and practices dairy farming activities. For the interpretation of the farm class and rotation scheme codes, see (Bayram et al., 2023)

field boundaries) and relative sizes. The treemap representation of the UAAs of the selected farm is given in Figure 37.

This representation is also used in Figures 38a, 39a and 40a. These figures show the crops that stayed over the field for most of the time each year. It must be noted that the transitions can happen at any time step, as long as the crop rotation, the seeding and harvesting months, and optimization objectives and constraints allow them.

The crop rotation constraints force farmers to choose only a handful of crops. Therefore, the impact and profitability due to crop selections do not differ from one case to the other. However, in the first case, potatoes are selected more often instead of other L crops, which stems from the high market value of potatoes compared to other crops. Maize, on the other hand, is a crop that almost every farm cultivates and incorporates in its crop rotation scheme due to its value as animal feed.

The real impact comes from the other decision variable in the optimization problem, which is the number of livestock to be kept on the farm (NL). Figures 38c, 39c and 40c show the change in the number

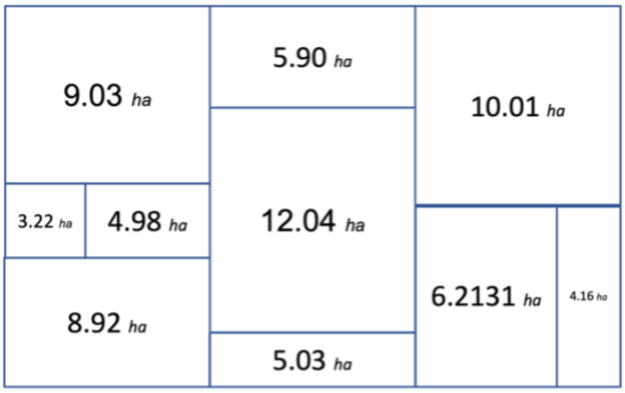

Figure 37: The treemap visualization of farm UAAs. The sizes of the fields used in the simulator are given.

of livestock in each time step when corresponding optimization objectives are considered. Since Case 1 only maximizes the profit, farmers tend to cull fewer animals, ending up with 7% mitigation in EF single score, as shown in Figure 38c. However, the profits almost do not change over the ten years. In Case 2, the reduction of EF climate change is considered in the optimization problem and 19% mitigation can be achieved, as shown in Figure 39c. Notice that the NL decreased by 15% since the environmental objective is added to the objective function in this case. Compared to Case 2, Case 3 shows a 12% reduction in NL (see Figure 40c), which can be explained by the fact that the contribution of livestock farming activities to the EF climate change score is relatively higher than the EF single score. Therefore, the culling decisions can be taken more easily in Case 2 than in Case 3.

5.6.3 *Uncertainty*

The results are impacted by the uncertainty associated with the multiple assumptions made in the study. These assumptions include model parameters, price forecasts, agent interaction rules, and LCI data uncertainty. The parameters associated with the livestock production system (such as the culling rate and the duration of each phase of a lactation period) were thoughtfully selected following consultation with stakeholders. However, in general, they vary from farmer to farmer. This justifies using an agent-based simulation to model the agricultural sector; however, it introduces uncertainty in areas lacking information. In (Baustert and Benetto, 2017), the various sources of uncertainty in coupled ABM LCA models are addressed, making a distinction between the uncertainty caused by measurement errors or poor data quality (known as parameter uncertainty) and the uncertainty caused by the inherent variance of the underlying system (systemic uncertainty).

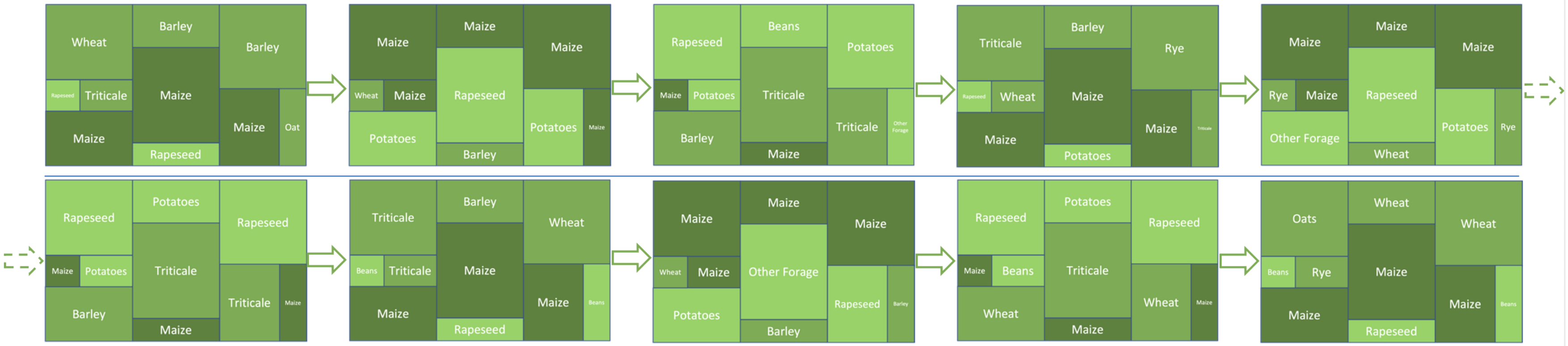

Figure 38(a): Crop rotations for a pilot farm with the scheme MLC. The treemap visualization shows the locations of the fields and crop plantations to preserve the geolocation of fields. From the top left (step 1) to the bottom right (step 10), the treemaps show the evolution of crop plantations for ten years of simulation. (Case 1) (**Crop Family:** M: ▇ L: ▇ C: ▇)

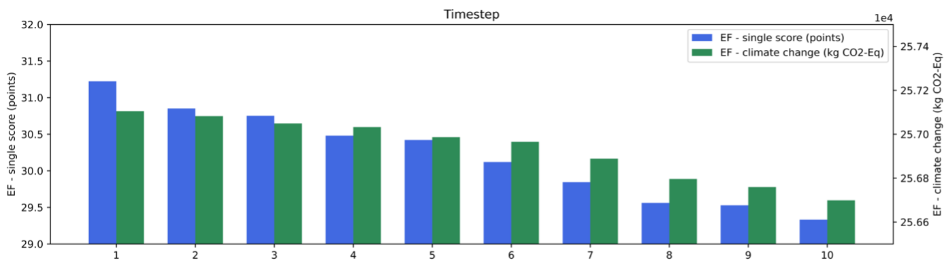

Figure 38(b): The change of impacts for Case 1.

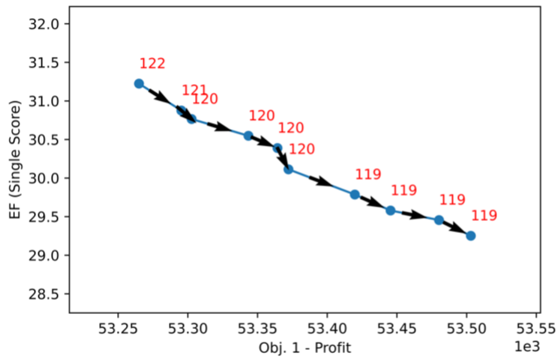

Figure 38(c): Change of number of livestock (in red), profit and environmental impact in Case 1 for the selected farm. As the impact reduces, the farm profit remains almost the same. The arrows show the direction of simulation and each point on the graph represents one year.

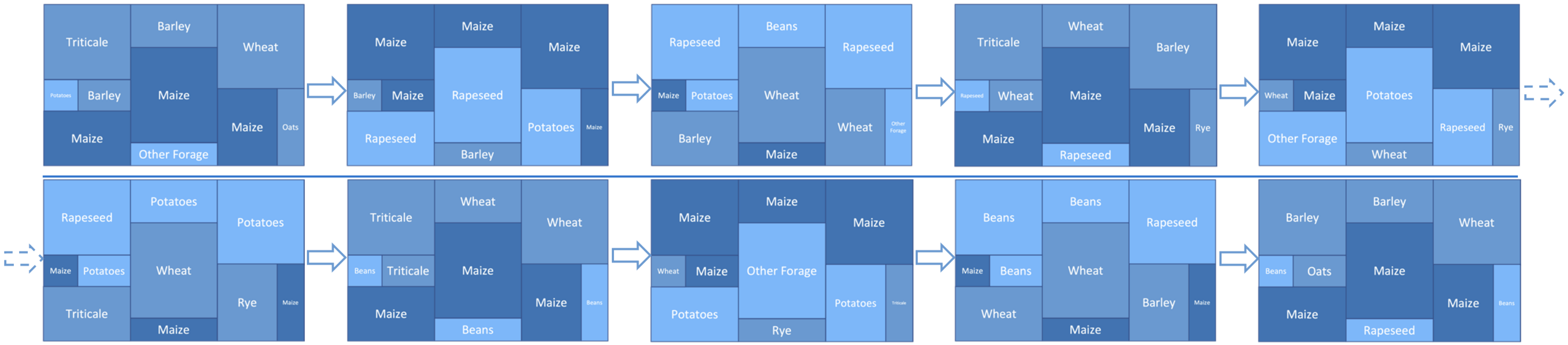

Figure 39(a): Crop rotations for a pilot farm with the scheme MLC. The treemap visualization shows the locations of the fields and crop plantations to preserve the geolocation of fields. From the top left (step 1) to the bottom right (step 10), the treemaps show the evolution of crop plantations for ten years of simulation. (Case 2) (**Crop Family:** M: ■ L: ■ C: ■)

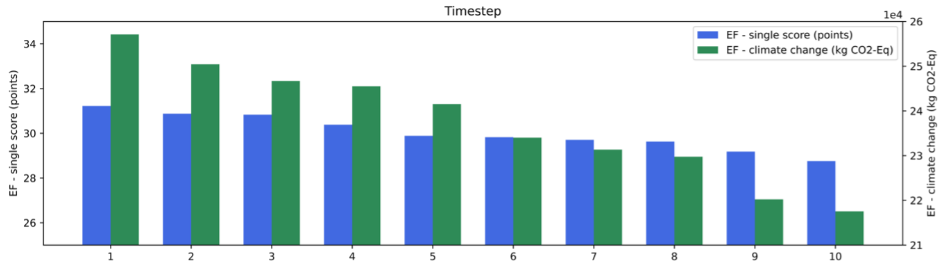

Figure 39(b): The change of impacts for case 2.

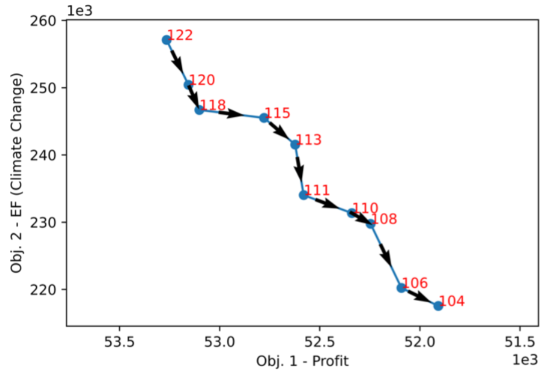

Figure 39(c): Change of number of livestock, EF Climate Change score, and environmental impact in greedy scenario for the pilot farm. The impact reduction comes with profit reduction as more culling decisions are made compared to baseline scenario. The arrows show the direction of simulation and each point on the graph represents one year. (Notice that the x axis is reversed.)

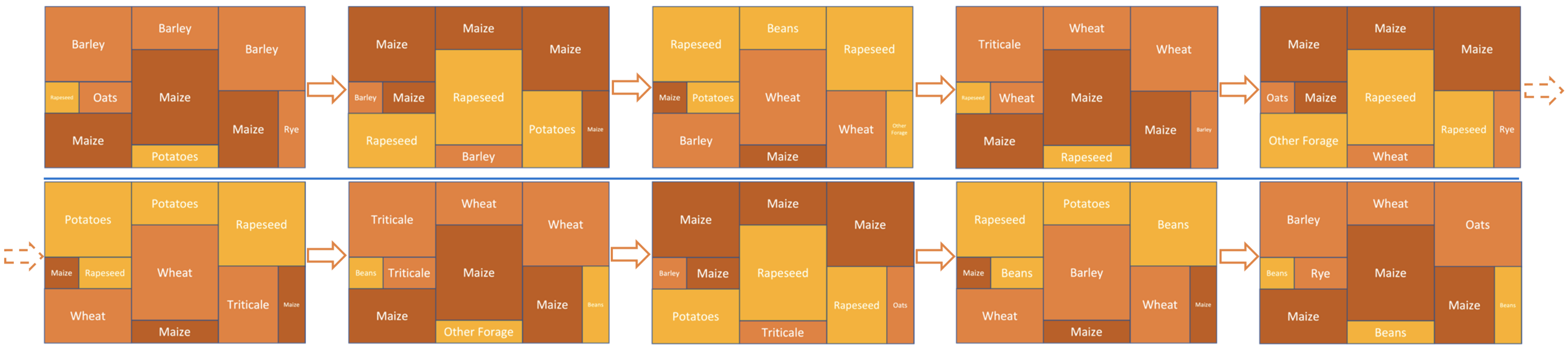

Figure 40(a): Crop rotations for a pilot farm with the scheme MLC. The treemap visualization shows the locations of the fields and crop plantations to preserve the geolocation of fields. From the top left (step 1) to the bottom right (step 10), the treemaps show the evolution of crop plantations for ten years of simulation. (Case 3) (**Crop Family:** M: ■ L: ■ C: ■)

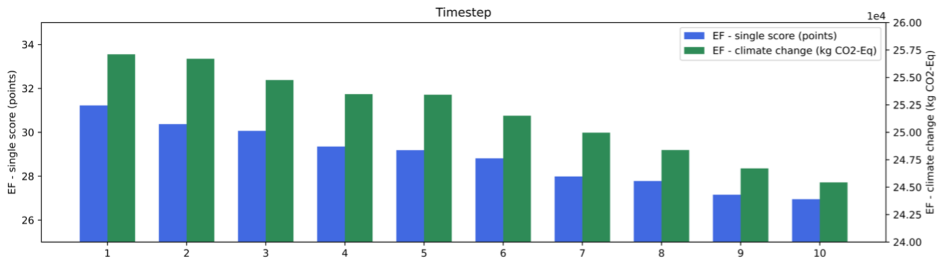

Figure 40(b): The change of impacts for Case 3.

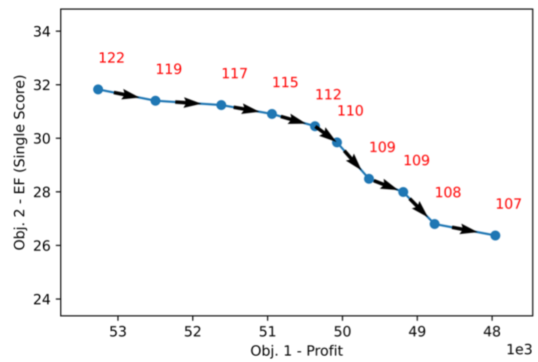

Figure 40(c): Change of number of livestock, EF single score, and profit in greedy scenario for the chosen pilot farm. The profit reduces even more compared to Case 2 in the case of EF single score minimization (Case 3). The arrows show the direction of simulation and each point represents one year. (Notice that the x axis is reversed.)

Model parameters can either take values representative of reality or be treated as random variables whose values are assigned via random distributions. In this paper, we employ uncertainty analysis to evaluate systemic uncertainty caused by stochastic events (such as the decisions and interactions of farmer agents). The parameter uncertainty is further compounded by the fact that the random variables are characterized by probability density functions, which are characterized by equations containing parameters. We follow the same structure proposed by (Baustert, 2021), which was also applied in (Bayram et al., 2023).

We executed a set of simulations ($n = 50$) and determined the coefficient of variations of the respective LCIA impact categories to propagate the uncertainty outlined in (Bayram et al., 2023). As previously explained, the parameters are set to their nominal values, and the systemic variability caused by the underlying model (i.e., random variables) is determined.

Figures 41a and 41b use violin plots to show the density distribution of the values obtained over 50 simulations for the two impact categories. From Figures 41a and 41b one can also observe that the objective being optimized results in the least coefficient of variation in terms of uncertainty. Furthermore, it can also be seen that optimizing by EF single score indicator always brings the system to the lowest levels of emissions. In fact, as also shown in Table 36, even the maximum values reached in Case 3 (36.22 kg CO_2-eq for EF climate change, and 36.89 for EF single score) are lower than the minimum values obtained by the other cases (37.76 and 37.18 kg CO_2-eq for EF climate change for Case 1 and Case 2, respectively and 38.71 and 37.97 for EF single score for Case 1 and Case 2, respectively).

Table 36 shows the values of the main descriptive statistics for the LCIA results of the average of ten years of the 50 simulation runs, for each of the three simulated cases. The CVs are mostly similar in all cases and impact categories. In general, the parts of the ABM that contain more random variables produce more variability. As a result of having fewer random variables in the component of the model that reflects crop production, there is less variability on average in the impact assessment results for the EF single score, which is mostly affected by flows from field operations (especially fertilizers and pesticides). On the other hand, the EF climate change score is affected more by the livestock activities which is the part of the model with more random variables.

5.7 CONCLUSION

This study presents a hybrid ABM–LCA model for crop–livestock activities that include multi–objective optimization under economic and environmental constraints. The model presented in (Bayram et al.,

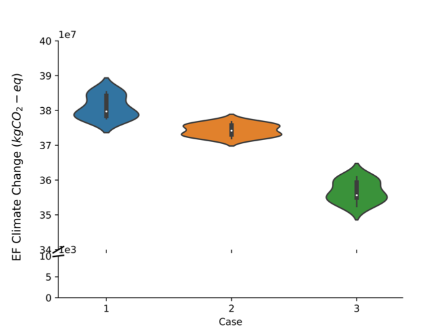

Figure 41(a): EF Climate Change

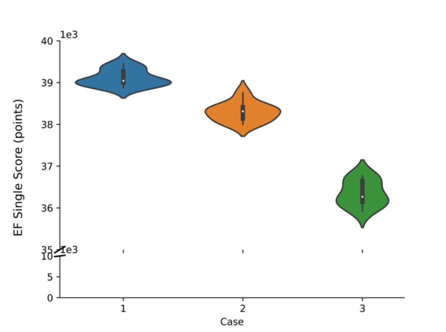

Figure 41(b): EF single score

Figure 41: Violin plots of the results of two impact categories obtained over 50 simulations for the three simulated cases.

	EF Climate Change (x10^7) *(kg CO_2 eq.)*			**EF Single Score** (x10^3) *(pt.)*		
Case	1	2	3	1	2	3
Minimum	37,76	37,18	35,53	38,71	37,97	36,25
Mean	37,95	37,53	35,78	39,01	38,39	36,43
Maximum	38,65	37,82	36,22	39,47	38,54	36,89
Standard Deviation	0,29	0,25	0,27	0,26	0,26	0,23
CV	0.76%	0.67%	0.75%	0.67%	0.68%	0.63%

Table 36: Main descriptive statistics for the average of ten years over 50 simulation runs for each of the three simulated cases.

2023) is now enhanced and includes farm optimization using economic and environmental objectives (according to the case simulated). In this paper, we investigated potential cases that evaluate the potential of optimizing farms based on different impact categories.

The followings are the key original contributions of the article:

- A novel multi-stage optimization model for optimal farm management that considers crop and livestock farming activities.
- A farming management system that optimizes the decisions based on subsidies with the goal of minimizing environmental impacts.

To assess the impact of the inclusion of optimization in our model, we first compared the non-optimized version of the baseline scenario to the optimized version. The baseline scenario only includes decisions dealing with monetary actions in optimized and non-optimized versions. We saw that the optimized version performs better in profit generation with a 5.5% increase in profit, whereas the previous version of our model virtually shows a change in profit over ten years.

After establishing that the optimization model achieves better results regarding considered objectives, we focused on several cases that optimize decisions based on economic or environmental objectives or both. In Case 1, the optimization model considers only farm profitability without any environmental objective being targeted. Case 2 and Case 3 differ in terms of the EF impact score that is minimized as an environmental objective. In the former, EF climate change scores are minimized, whereas in the latter EF single score is targeted using all 16 categories given in Table 29.

Case 2 and Case 3 show a more significant reduction in stocking rates (3.5% and 2.3%, respectively) than Case 1, which can be explained by the impact of livestock production activities on the environment. These two cases consider the environmental objective and farmers who are "green-conscious" enough to make decisions to reduce the impact of their activities. The example farm described in Section 5.6.2 shows a trend of reducing stocking rate, as seen in Figures 39c and 40c. The number of livestock reduced is reduced by 15% and 12% in Case 2 and Case 3, respectively.

The cases we evaluated are by no means exhaustive, but the overall usefulness and effectiveness of farm optimization are shown in this work. Furthermore, the trade-off between environmental and economic objectives is clear, which can be addressed by better regulations, subsidies, and farm management strategies.

credit authorship contribution statement

Alper Bayram: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Antonino Marvuglia:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Project administration, Investigation, Methodology, Supervision, Validation, Writing – review & editing. **Tomás Navarrete Gutiérrez:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – review & editing. **Hélène Soyeurt:** Conceptualization, Methodology, Validation, Writing – review & editing. **Anthony Tedde:** Conceptualization, 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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SUPPLEMENTARY INFORMATION

Linear programming is one of the main Operations Research techniques (Hillier and Lieberman, 2015). The model contains sets of linear equations and inequalities. There should be a linear objective function that is maximized or minimized. There are constraints that a linear equation is subject to and the formulation of a MOO problem (MOOP) is written like the following:

$$\max z_1 = p'x, \quad \min z_2 = i'x \quad \text{s.t} \quad Ax \leqslant b; x \leqslant 0 \tag{39}$$

where, in farming activities, z_1 can be the objective function for profit, p is the profit vector of different types of production and z_2 can be the objective function for environmental impacts due to production. x is the vector that represents the amount of each production, A is the coefficient matrix and b is the vector that includes the resources available in a farm.

The weighted sum method can be used in LP to achieve MOO. In this method, each objective is assigned a weight before being combined into a single scalar objective function. For example, in a farm optimization problem, the multi-objective function could be profit maximization while minimizing environmental impact. These goals usually conflict because maximizing profit may result in increased environmental impact. The weighted sum method has the following general form for a multi-objective linear programming problem:

$$\max w_1 z_1 + w_2 z_2 + \ldots + w_n z_n \quad \text{s.t} \quad Ax \leqslant b; x \leqslant 0 \tag{40}$$

where w_1, w_2, ..., w_n are the weights assigned to each objective. It is important to note that the weighting method does not always find the best compromise solution because it assumes that the objectives can be ranked and traded against one another. Furthermore, this method may be limited because the decision maker may not know which weight to assign to each objective a priori. Instead of assigning weights using EAs, we may have a set of solutions.

GAs move from one set of solutions to the other using crossover, selection and mutation operators. Through the crossover process, two chromosomes, referred to as parents, are chosen and combined to create a new population, which is referred to as offspring. The search process does not reach a local optimal solution thanks to mutation operators. Several changes are made at the gene level by the mutation operator, which also generates new chromosomes. The new chromosomes will be very similar to those already present. In this way, a new population is produced through a selection procedure in the following step. GAs searches the solution space for optimal values (based on objective functions and constraints) and will keep searching for the optimal solution until one of the termination conditions is met. The GAs is terminated when one of the following criteria is attained:

1. The value of the objective function has reached a certain satisfactory level.
2. The maximum number of generations has been exceeded.
3. The time limit has been exceeded.
4. The results have not improved after a fixed number of iterations.

In our case, we represent a farm as a set of individuals, each representing a possible farm configuration. The fitness function assesses each individual's performance based on financial profitability, crop selection, livestock density and environmental factors such as GHG emissions, land use, and water usage. Crossover and mutation are two genetic operators that can create new individuals from existing ones, allowing the GA to experiment with different farm configurations. Feed optimization, livestock density adjustment and manure management are examples of how GAs can optimize farms. Crop rotation optimization is one example of GA application in farm optimization. Crop rotation is the practice of planting various crops in a specific order on the same field in consecutive years. This practice can improve soil health, reduce pest and disease pressure, and boost crop yields. A GA can be used to determine the best crop rotation schedule for maximizing crop yield while minimizing costs and minimizing environmental impacts. Another variable that can be optimized in a farm is livestock density, which is represented by several variables, including the number of animals per unit area, the types of animals, and the feeding schedule. In the case studies discussed in this paper, we apply the NSGA–III algorithm (Deb and Jain, 2014).

The information readily available to manage farming operations is directly related to the degree to which those operations can be optimized. For example, we have data on farm properties, crop and livestock structures, cost and price information regarding those two categories, and lastly, information on subsidies. At the conclusion of each time step, the optimization module is activated to assist farmers in making decisions based on several criteria.

Crop production and animal husbandry are the two primary forms of farm production activities in our model. Multiple crop types can be cultivated on a farm. After the harvest, they are either sold in the market or used as animal feed on the farm. The production of milk and meat are examples of animal products sold on the market; however, manure can also be considered an essential product for crop production due to the value it possesses as a fertilizer. Farmers buy inorganic fertilizers if they need to fulfill the fertilizer requirements. Because farmers typically trade their excess manure for digestate, a byproduct of biogas production, manure is considered part of the biogas feedstock. This feedstock has an economic value for biogas producers, but this value is not passed on to the farmers. In addition, the nitrogen content of digestate is exceptionally high, and unlike manure, it is much simpler to store.

The characteristics that define a crop are its yield, requirements for fertilizer, price, production costs, and effect on the environment. On the other hand, animals are sorted into different groups based on their age, gender, and the kind of offspring they produce (dairy or suckler). Each livestock category is described in terms of its milk or meat production capability, prices for milk and meat, costs to maintain the livestock and the impact on the environment, meaning the level of nitrogen excretion into the soil. Crop production is constrained due to several different factors. The model considers the typical crop rotation schemes in the region and the seeding and harvesting seasons of each crop during the land allocation phase of the simulations. The model aims to determine the quantity of each production activity in vector x in Eq. 39 that will result in the most efficient operation of the farm system. In our model, each farm's performance is optimized individually, and farms do not collaborate by exchanging products or pooling resources. There are two optimization criteria in our model, where the first one is economic optimization, where we maximize the gross margin of animal and crop production. The second is environmental optimization, where we minimize the selected environmental indicator.

The way in which NSGA-III deals with multiple objectives is the primary factor that sets it apart from other GAs. NSGA-III makes use of a non-dominated sorting mechanism in order to sort the solutions in accordance with the values of the objective function. This enables the algorithm to find a set of non-dominated solutions, where the definition of a non-dominated solution is that it is the only solution that satisfies all the objectives better than any other solution. Environmental selection is a novel operator that has been added to NSGA-III. This operator is used to determine who will be a part of the generation after this one. This operator seeks to maintain the diversity of the solutions available and is based on the crowding distance metric.

NSGA-III for farm optimization can be utilized through the following steps. In addition, a summary of these steps can be found in Fig. 42.

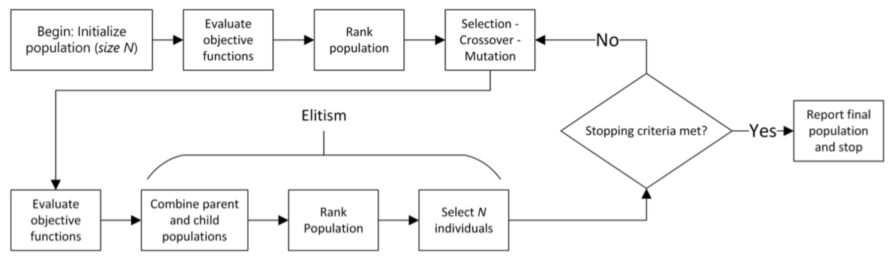

Figure 42: NSGA-III optimization scheme

1. **Problem representation:** Represent the farm as a collection of individuals, where each individual represents a distinct arrangement of the farm that could be used. This may involve considerations such as the schedule for crop rotation.

2. **Objective functions:** Define the objective functions that will be used to evaluate the performance of each individual. These objective functions will be used to evaluate their performance. These could include the production of crops and livestock, as well as the environmental and financial impacts of these activities.

3. **Non–dominated sorting:** Using the non–dominated sorting mechanism, sort the individuals into groups according to the values of the objective functions they possess. This will result in a set of solutions that are not dominated by any other solutions.

4. **Genetic operators:** It is possible to generate new individuals from existing ones by making use of genetic operators such as crossover and mutation. This will enable the algorithm to explore various configurations of the farm.

5. **Stopping criterion:** Determine when the algorithm should stop running by deciding on a stopping criterion, such as a fixed number of generations or a threshold value of the fitness function. Stopping criteria can be anything from a fixed number of generations to a threshold value.

6. **Initial population:** The first step is to produce an initial population of individuals, which is typically done in a random fashion. The effectiveness of the algorithm is directly related to the degree of diversity present in the initial population.

7. **Running the algorithm:** Start the algorithm and repeat steps 4 through 5 until the termination criteria are satisfied. The final group of non–dominated solutions will represent a set of trade-off solutions that can be utilized in the process of making decisions pertaining to the farm.

An, Li (2012). "Modeling human decisions in coupled human and natural systems: Review of agent-based models." In: *Ecological Modelling* 229, pp. 25–36.

Assembly, General (2015). *Resolution adopted by the General Assembly on 11 September 2015*. Tech. rep. A/RES/69/315 15 September 2015. New York: United Nations.

Baustert, Paul (Apr. 2021). "Development of an uncertainty analysis framework for model-based consequential life cycle assessment: Application to activity-based modelling and life cycle assessment of multimodal mobility." PhD thesis.

Baustert, Paul and Enrico Benetto (2017). "Uncertainty analysis in agent-based modelling and consequential life cycle assessment coupled models: a critical review." In: *Journal of Cleaner Production* 156, pp. 378–394. DOI: 10.1016/j.jclepro.2017.03.193.

Baustert, Paul, Tomás Navarrete Gutiérrez, Thomas Gibon, Laurent Chion, Tai-Yu Ma, Gabriel Leite Mariante, Sylvain Klein, Philippe Gerber, and Enrico Benetto (Jan. 2019). "Coupling Activity-Based Modeling and Life Cycle Assessment—A Proof-of-Concept Study on Cross-Border Commuting in Luxembourg." en. In: *Sustainability* 11.15. Number: 15 Publisher: Multidisciplinary Digital Publishing Institute, p. 4067. ISSN: 2071-1050. DOI: 10.3390/su11154067. (Visited on 01/03/2023).

Bayram, Alper, Antonino Marvuglia, Maria Myridinas, and Marta Porcel (2022). "Increasing Biowaste and Manure in Biogas Feedstock Composition in Luxembourg: Insights from an Agent-Based Model." In: *Sustainability* 15.1, p. 264.

Bayram, Alper, Antonino Marvuglia, Tomás Navarrete Gutierrez, Jean-Paul Weis, Gérard Conter, and Stéphanie Zimmer (2023). "Sustainable farming strategies for mixed crop-livestock farms in Luxembourg simulated with a hybrid agent-based and life-cycle assessment model." In: *Journal of Cleaner Production* 386, p. 135759.

Behera, U. K., H. Kaechele, J. France, U. K. Behera, H. Kaechele, and J. France (Dec. 2014). "Integrated animal and cropping systems in single and multi-objective frameworks for enhancing the livelihood security of farmers and agricultural sustainability in Northern India." en. In: *Animal Production Science* 55.10. Publisher: CSIRO PUBLISHING, pp. 1338–1346. ISSN: 1836-5787, 1836-5787. DOI: 10.1071/AN14526. (Visited on 01/04/2023).

Caldeira, Carla, Fausto Freire, Elsa A. Olivetti, Randolph Kirchain, and Luis C. Dias (Apr. 2019). "Analysis of cost-environmental trade-offs in biodiesel production incorporating waste feedstocks: A multi-objective programming approach." en. In: *Journal of Cleaner Production* 216, pp. 64–73. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2019.01.126. (Visited on 01/10/2023).

Capitanescu, F., A. Marvuglia, T. Navarrete Gutiérrez, and E. Benetto (Mar. 2017). "Multi-stage farm management optimization under environmental and crop rotation constraints." en. In: *Journal of Cleaner Production* 147, pp. 197–205. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2017.01.076. (Visited on 01/04/2023).

Carravilla, Maria Antónia and José Fernando Oliveira (2013). "Operations research in agriculture: Better decisions for a scarce and uncertain world." eng. In: URL: http://repositorio.inesctec.pt/handle/123456789/4677 (visited on 01/16/2023).

Chandrasekaran, Manivannan and Rajesh Ranganathan (Jan. 2017). "Modelling and optimisation of Indian traditional agriculture supply chain to reduce post-harvest loss and CO2 emission." In: *Industrial Management & Data Systems* 117.9. Publisher: Emerald Publishing Limited, pp. 1817–1841. ISSN: 0263-5577. DOI: 10.1108/IMDS-09-2016-0383. (Visited on 01/04/2023).

Clark, Michael A., Nina G. G. Domingo, Kimberly Colgan, Sumil K. Thakrar, David Tilman, John Lynch, Inês L. Azevedo, and Jason D. Hill (Nov. 2020). "Global food system emissions could preclude achieving the 1.5° and 2°C climate change targets." In: *Science* 370.6517. Publisher: American Association for the Advancement of Science, pp. 705–708. DOI: 10.1126/science.aba7357. (Visited on 01/03/2023).

Cobuloglu, Halil I. and İ. Esra Büyüktahtakın (Feb. 2015). "Food vs. biofuel: An optimization approach to the spatio-temporal analysis of land-use competition and environmental impacts." en. In: *Applied Energy* 140, pp. 418–434. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2014.11.080. (Visited on 01/04/2023).

Cortignani, Raffaele and Simone Severini (2012). "A constrained optimization model based on generalized maximum entropy to assess the impact of reforming agricultural policy on the sustainability of irrigated areas." en. In: *Agricultural Economics* 43.6, pp. 621–633. ISSN: 1574-0862. DOI: 10.1111/j.1574-0862.2012.00608.x. (Visited on 01/04/2023).

Crippa, M., E. Solazzo, D. Guizzardi, F. Monforti-Ferrario, F. N. Tubiello, and A. Leip (Mar. 2021). "Food systems are responsible for a third of global anthropogenic GHG emissions." en. In: *Nature Food* 2.3. Number: 3 Publisher: Nature Publishing Group, pp. 198–209. ISSN: 2662-1355. DOI: 10.1038/s43016-021-00225-9. (Visited on 02/18/2022).

Crist, Eileen, Camilo Mora, and Robert Engelman (Apr. 2017). "The interaction of human population, food production, and biodiversity protection." In: *Science* 356.6335. Publisher: American Association for the Advancement of Science, pp. 260–264. doi: 10.1126/science.aal2011. (Visited on 01/03/2023).

Deb, Kalyanmoy, Ram Bhushan Agrawal, and others (1995). "Simulated binary crossover for continuous search space." In: *Complex systems* 9.2. Publisher: Citeseer, pp. 115–148.

Deb, Kalyanmoy and Himanshu Jain (Aug. 2014). "An Evolutionary Many-Objective Optimization Algorithm Using Reference-Point-Based Nondominated Sorting Approach, Part I: Solving Problems With Box Constraints." In: *IEEE Transactions on Evolutionary Computation* 18.4. Conference Name: IEEE Transactions on Evolutionary Computation, pp. 577–601. issn: 1941-0026. doi: 10.1109/TEVC.2013.2281535.

Deb, Kalyanmoy, Amrit Pratap, Sameer Agarwal, and TAMT Meyarivan (2002). "A fast and elitist multiobjective genetic algorithm: NSGA-II." In: *IEEE transactions on evolutionary computation* 6.2, pp. 182–197.

Diaz-Balteiro, Luis and Carlos Romero (2004). "Sustainability of forest management plans: a discrete goal programming approach." In: *Journal of Environmental Management* 71.4, pp. 351–359.

Ding, Tianran, Stéphane Bourrelly, and Wouter MJ Achten (2021). "Application of territorial emission factors with open-access data—a territorial LCA case study of land use for livestock production in Wallonia." In: *The International Journal of Life Cycle Assessment* 26.8, pp. 1556–1569.

Dowson, Oscar, Andy Philpott, Andrew Mason, and Anthony Downward (May 2019). "A multi-stage stochastic optimization model of a pastoral dairy farm." en. In: *European Journal of Operational Research* 274.3, pp. 1077–1089. issn: 0377-2217. doi: 10.1016/j.ejor.2018.10.033. (Visited on 01/04/2023).

European Commission (2018). *PEFCR Guidance*. url: https://eplca.jrc.ec.europa.eu/permalink/Normalisation_Weighting_Factors_EF_3.0.xlsx.

European Commission (2020). *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions on an EU Strategy to Reduce Methane Emissions*. COM(2020) 663 Final.

Eurostat (2022). url: https://ec.europa.eu/eurostat/data/database (visited on 02/07/2022).

Fasakhodi, Abbas Amini, Seyed Nouri, and Manouchehr Amini (2010). "Water Resources Sustainability and Optimal Cropping Pattern in Farming Systems; A Multi-Objective Fractional Goal Programming Approach." en. In: *Water Resources Management: An International Journal, Published for the European Water Resources Association (EWRA)* 24.15. Publisher: Springer & European Water Resources Association (EWRA), pp. 4639–4657. url: https://

ideas.repec.org//a/spr/waterr/v24y2010i15p4639-4657.html (visited on 01/04/2023).

Ferber, Jacques and Gerhard Weiss (1999). *Multi-agent systems: an introduction to distributed artificial intelligence*. Vol. 1. Addison-Wesley Reading.

Galán-Martín, Ángel, Pavel Vaskan, Assumpció Antón, Laureano Jiménez Esteller, and Gonzalo Guillén-Gosálbez (Jan. 2017). "Multi-objective optimization of rainfed and irrigated agricultural areas considering production and environmental criteria: a case study of wheat production in Spain." en. In: *Journal of Cleaner Production*. Towards eco-efficient agriculture and food systems: selected papers addressing the global challenges for food systems, including those presented at the Conference "LCA for Feeding the planet and energy for life" (6-8 October 2015, Stresa & Milan Expo, Italy) 140, pp. 816–830. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2016.06.099. (Visited on 01/04/2023).

Gaud, Nicolas, Stéphane Galland, Franck Gechter, Vincent Hilaire, and Abderrafiâa Koukam (Nov. 2008). "Holonic multilevel simulation of complex systems: Application to real-time pedestrians simulation in virtual urban environment." en. In: *Simulation Modelling Practice and Theory*. The Analysis of Complex Systems 16.10, pp. 1659–1676. ISSN: 1569-190X. DOI: 10.1016/j.simpat.2008.08.015. (Visited on 01/03/2023).

Gava, Oriana, Fabio Bartolini, Francesca Venturi, Gianluca Brunori, Angela Zinnai, and Alberto Pardossi (Jan. 2019). "A Reflection of the Use of the Life Cycle Assessment Tool for Agri-Food Sustainability." en. In: *Sustainability* 11.1. Number: 1 Publisher: Multidisciplinary Digital Publishing Institute, p. 71. ISSN: 2071-1050. DOI: 10.3390/su11010071. (Visited on 01/03/2023).

Gebrezgabher, Solomie A., Miranda P. M. Meuwissen, and Alfons G. J. M. Oude Lansink (Feb. 2014). "A multiple criteria decision making approach to manure management systems in the Netherlands." en. In: *European Journal of Operational Research* 232.3, pp. 643–653. ISSN: 0377-2217. DOI: 10.1016/j.ejor.2013.08.006. (Visited on 01/04/2023).

Gerland, Patrick et al. (Oct. 2014). "World population stabilization unlikely this century." In: *Science* 346.6206. Publisher: American Association for the Advancement of Science, pp. 234–237. DOI: 10.1126/science.1257469. (Visited on 01/03/2023).

Gilbert, Nigel (2019). *Agent-based models*. Vol. 153. Sage Publications.

Gital Durmaz, Yeşim and Bilge Bilgen (Aug. 2020). "Multi-objective optimization of sustainable biomass supply chain network design." en. In: *Applied Energy* 272, p. 115259. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2020.115259. (Visited on 01/09/2023).

Gouvernement du Luxembourg (2000). "Règlement Grand-Ducal Du 24 Novembre 2000 Concernant l'utilisation de Fertilisants Azotés Dans l'agriculture." In: *J. Off. Grand-Duché Luxembourg* A n.124.

Grimm, Volker and Steven F. Railsback (Nov. 2013). *Individual-based Modeling and Ecology*. en. Publication Title: Individual-based Modeling and Ecology. Princeton University Press. ISBN: 978-1-4008-5062-4. DOI: 10.1515/9781400850624. (Visited on 01/03/2023).

Guinée, J.B., R. Heijungs, and G. Huppes (2004). "Economic Allocation: Examples and Derived Decision Tree." In: *Int J LCA* 9 (1), p. 23. DOI: 10.1007/BF02978533.

Hadka, David (2012). *MOEA framework-a free and open source Java framework for multiobjective optimization*. URL: https://github.com/MOEAFramework/MOEAFramework.

Hare, M and P Deadman (Jan. 2004). "Further towards a taxonomy of agent-based simulation models in environmental management." en. In: *Mathematics and Computers in Simulation*. MSSANZ/IMACS 14th Biennial Conference on Modelling and Simulation 64.1, pp. 25–40. ISSN: 0378-4754. DOI: 10.1016/S0378-4754(03)00118-6. (Visited on 01/03/2023).

Hart, Kaley, Ben Allen, Clunie Keenleyside, Silvia Nanni, Anne Maréchal, Kamila Paquel, Martin Nesbit, and Julia Ziemann (Feb. 2017). "The consequences of climate change for EU agriculture: follow-up to the COP21 UN Paris Climate Change Conference." en. In: Publisher: EUAA: European Union Agency for Asylum. URL: https://policycommons.net/artifacts/2199607/the-consequences-of-climate-change-for-eu-agriculture/2955969/ (visited on 01/03/2023).

Hassani, Leila, Mahmoud Daneshvar kakhki, Mahmoud Sabouhi sabouni, and Reza Ghanbari (Aug. 2019). "The optimization of resilience and sustainability using mathematical programming models and metaheuristic algorithms." en. In: *Journal of Cleaner Production* 228, pp. 1062–1072. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2019.04.324. (Visited on 01/04/2023).

He, Pengfei, Jing Li, and Xin Wang (Feb. 2018). "Wheat harvest schedule model for agricultural machinery cooperatives considering fragmental farmlands." en. In: *Computers and Electronics in Agriculture* 145, pp. 226–234. ISSN: 0168-1699. DOI: 10.1016/j.compag.2017.12.042. (Visited on 01/04/2023).

Heath, Brian, Raymond Hill, and Frank Ciarallo (2009). "A survey of agent-based modeling practices (January 1998 to July 2008)." In: *Journal of Artificial Societies and Social Simulation* 12.4, p. 9.

Heckbert, Scott, Tim Baynes, and Andrew Reeson (2010). "Agent-based modeling in ecological economics." In: *Annals of the New York Academy of Sciences* 1185.1, pp. 39–53.

Heijungs, Reinout (2010). "Ecodesign—carbon footprint—life cycle assessment—life cycle sustainability analysis. A flexible framework for a continuum of tools." In: *Environmental and Climate Technologies* 4.1, pp. 42–46.

Hillier, Frederick and Gerald Lieberman (Jan. 2015). *Introduction to operations research*. ISBN: 978-0-07-352345-3.

Huang, Y., Y. P. Li, X. Chen, and Y. G. Ma (May 2012). "Optimization of the irrigation water resources for agricultural sustainability in Tarim River Basin, China." en. In: *Agricultural Water Management* 107, pp. 74–85. ISSN: 0378-3774. DOI: 10.1016/j.agwat.2012.01.012. (Visited on 01/04/2023).

Huijbregts, M.A.J., Z.J.N. Steinmann, P.M.F. Elshout, G. Stam, F. Verones, M. Vieira, M. Zijp, A. Hollander, and R. van Zelm (2017). "ReCiPe2016: A Harmonised Life Cycle Impact Assessment Method at Midpoint and Endpoint Level." In: *Int J Life Cycle Assess* 22, pp. 138–147. DOI: 10.1007/s11367-016-1246-y.

Jabarzadeh, Younis, Hossein Reyhani Yamchi, Vikas Kumar, and Nader Ghaffarinasab (Jan. 2020). "A multi-objective mixed-integer linear model for sustainable fruit closed-loop supply chain network." In: *Management of Environmental Quality: An International Journal* 31.5. Publisher: Emerald Publishing Limited, pp. 1351–1373. ISSN: 1477-7835. DOI: 10.1108/MEQ-12-2019-0276. (Visited on 01/09/2023).

Jornada, Daniel and V. Jorge Leon (July 2016). "Biobjective robust optimization over the efficient set for Pareto set reduction." en. In: *European Journal of Operational Research* 252.2, pp. 573–586. ISSN: 0377-2217. DOI: 10.1016/j.ejor.2016.01.017. (Visited on 01/10/2023).

Kita, H., I. Ono, and S. Kobayashi (July 1999). "Multi-parental extension of the unimodal normal distribution crossover for real-coded genetic algorithms." In: *Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406)*. Vol. 2, 1581–1588 Vol. 2. DOI: 10.1109/CEC.1999.782672.

Kong, Qingyuan, Kamal Kuriyan, Nilay Shah, and Miao Guo (Dec. 2019). "Development of a responsive optimisation framework for decision-making in precision agriculture." en. In: *Computers & Chemical Engineering* 131, p. 106585. ISSN: 0098-1354. DOI: 10.1016/j.compchemeng.2019.106585. (Visited on 01/04/2023).

Liang, Yingzong, Chi Wai Hui, and Fengqi You (Sept. 2018). "Multi-objective economic-resource-production optimization of sustainable organic mixed farming systems with nutrient recycling." en. In: *Journal of Cleaner Production* 196, pp. 304–330. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2018.06.040. (Visited on 01/09/2023).

López-Andrés, Jhony Josué, Alberto Alfonso Aguilar-Lasserre, Luis Fernando Morales-Mendoza, Catherine Azzaro-Pantel, Jorge Raúl Pérez-Gallardo, and José Octavio Rico-Contreras (Feb. 2018). "Environmental impact assessment of chicken meat production via an integrated methodology based on LCA, simulation and genetic algorithms." en. In: *Journal of Cleaner Production* 174, pp. 477–491. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2017.10.307. (Visited on 01/16/2023).

Ma, Qianli, Wenyuan Wang, Yun Peng, and Xiangqun Song (Mar. 2018). "An Optimization Approach to the Intermodal Transportation Network in Fruit Cold Chain, Considering Cost, Quality Degradation and Carbon Dioxide Footprint." de. In: *Polish Maritime Research* 25.1, pp. 61–69. DOI: 10.2478/pomr-2018-0007. (Visited on 01/04/2023).

Maiyar, Lohithaksha M and Jitesh J Thakkar (July 2019). "Environmentally conscious logistics planning for food grain industry considering wastages employing multi objective hybrid particle swarm optimization." en. In: *Transportation Research Part E: Logistics and Transportation Review* 127, pp. 220–248. ISSN: 1366-5545. DOI: 10.1016/j.tre.2019.05.006. (Visited on 01/16/2023).

Manos, Basil, Parthena Chatzinikolaou, and Fedra Kiomourtzi (Jan. 2013). "Sustainable Optimization of Agricultural Production." en. In: *APCBEE Procedia*. 4th International Conference on Environmental Science and Development- ICESD 2013 5, pp. 410–415. ISSN: 2212-6708. DOI: 10.1016/j.apcbee.2013.05.071. (Visited on 01/08/2023).

Mansoori, Hooman, Mohammad Reza Kohansal, and Mohammd Farid Khadem Ghousi (Jan. 2009). "Introducing a lexicographic goal programming for environmental conservation program in farm activities: A case study in Iran." In: *China Agricultural Economic Review* 1.4. Publisher: Emerald Group Publishing Limited, pp. 478–484. ISSN: 1756-137X. DOI: 10.1108/17561370910989284. (Visited on 01/04/2023).

Marvuglia, A., A. Bayram, P. Baustert, T.N. Gutierrez, and E. Igos (2022). "Agent-Based Modelling to Simulate Farmers' Sustainable Decisions: Farmers' Interaction and Resulting Green Consciousness Evolution." In: *Journal of Cleaner Production* 332, p. 129847. DOI: 10.1016/j.jclepro.2021.129847.

Marvuglia, A, E Benetto, and B Murgante (2015). "Calling for an integrated computational systems modelling framework for life cycle sustainability analysis." In: *J. Environ. Account. Manag* 3, pp. 213–216.

Micolier, A, F Taillandier, P Taillandier, and F Bos (2019). "Li-BIM, an agent-based approach to simulate occupant-building interaction from the Building-Information Modelling." In: *Engineering Applications of Artificial Intelligence* 82, pp. 44–59.

Ow, Albert von, Tuija Waldvogel, and Thomas Nemecek (Mar. 2020). "Environmental optimization of the Swiss population's diet using domestic production resources." en. In: *Journal of Cleaner Production* 248, p. 119241. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2019.119241. (Visited on 01/04/2023).

Pastori, M., A. UdÃas, F. Bouraoui, and G. Bidoglio (Mar. 2017). "A Multi-Objective Approach to Evaluate the Economic and Environmental Impacts of Alternative Water and Nutrient Management Strategies in Africa." In: *JOURNAL OF ENVIRONMENTAL INFORMATICS* 29.1. Number: 1, pp. 16–28. ISSN: 1684-8799. URL: http://www.jeionline.org/index.php?journal=mys&page=article&op=view&path%5B%5D=201500313 (visited on 01/16/2023).

Pishgar-Komleh, S. H., A. Akram, A. Keyhani, Paria Sefeedpari, Philip Shine, and Miguel Brandao (2020). "Integration of life cycle assessment, artificial neural networks, and metaheuristic optimization algorithms for optimization of tomato-based cropping systems in Iran." eng. In: *The International Journal of Life Cycle Assessment*. URL: http://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-268298 (visited on 01/04/2023).

Repar, Nina, Pierrick Jan, Dunja Dux, Thomas Nemecek, and Reiner Doluschitz (Jan. 2017). "Implementing farm-level environmental sustainability in environmental performance indicators: A combined global-local approach." en. In: *Journal of Cleaner Production*. Towards eco-efficient agriculture and food systems: selected papers addressing the global challenges for food systems, including those presented at the Conference "LCA for Feeding the planet and energy for life" (6-8 October 2015, Stresa & Milan Expo, Italy) 140, pp. 692–704. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2016.07.022. (Visited on 01/16/2023).

Rohmer, S. U. K., J. C. Gerdessen, and G. D. H. Claassen (Mar. 2019). "Sustainable supply chain design in the food system with dietary considerations: A multi-objective analysis." en. In: *European Journal of Operational Research* 273.3, pp. 1149–1164. ISSN: 0377-2217. DOI: 10.1016/j.ejor.2018.09.006. (Visited on 01/04/2023).

SER (2015). *Durchführung in Luxemburg der Cross Compliance im Rahmen der gemeinsamen Agrarpolitik*. de. URL: http://agriculture.public.lu/de/publications/weinbau/prime/crosscompliance.html (visited on 02/15/2022).

Sala, Serenella, Biagio Ciuffo, and Peter Nijkamp (2015). "A systemic framework for sustainability assessment." In: *Ecological Economics* 119, pp. 314–325.

Saouter, Erwan, Fabrizio Biganzoli, Lidia Ceriani, Donald Versteeg, Eleonora Crenna, Luca Zampori, Serenella Sala, and Rana Pant (Jan. 2019). *Environmental Footprint: Update of Life Cycle Impact Assessment methods – Ecotoxicity freshwater, human toxicity cancer, and non-cancer*. en. ISBN: 9789276171430 9789276171423 ISSN: 1831-9424, 1018-5593. DOI: 10.2760/300987. (Visited on 03/07/2023).

Sarker, Ruhul and Tapabrata Ray (Oct. 2009). "An improved evolutionary algorithm for solving multi-objective crop planning models." en. In: *Computers and Electronics in Agriculture* 68.2, pp. 191–

199. ISSN: 0168-1699. DOI: 10.1016/j.compag.2009.06.002. (Visited on 01/16/2023).

Schreinemachers, Pepijn and Thomas Berger (July 2011). "An agent-based simulation model of human–environment interactions in agricultural systems." en. In: *Environmental Modelling & Software* 26.7, pp. 845–859. ISSN: 1364-8152. DOI: 10.1016/j.envsoft.2011.02.004. (Visited on 01/03/2023).

Su, Yi-xin and Rui Chi (2017). "Multi-objective particle swarm-differential evolution algorithm." In: *Neural Computing and Applications* 28, pp. 407–418.

Sumpsi, JoseMaria, Francisco Amador, and Carlos Romero (1997). "On farmers' objectives: A multi-criteria approach." In: *European Journal of Operational Research* 96.1, pp. 64–71.

Tedde, Anthony, Clément Grelet, Phuong N Ho, Jennie E Pryce, Dagnachew Hailemariam, Zhiquan Wang, Graham Plastow, Nicolas Gengler, Yves Brostaux, Eric Froidmont, et al. (2021). "Validation of dairy cow bodyweight prediction using traits easily recorded by dairy herd improvement organizations and its potential improvement using feature selection algorithms." In: *Animals* 11.5, p. 1288.

Teglio, Andrea et al. (2011). "From agent-based models to artificial economies." PhD thesis. Universitat Jaume I.

Twine, Richard (Jan. 2021). "Emissions from Animal Agriculture-16.5% Is the New Minimum Figure." en. In: *Sustainability* 13.11. Number: 11 Publisher: Multidisciplinary Digital Publishing Institute, p. 6276. ISSN: 2071-1050. DOI: 10.3390/su13116276. (Visited on 02/07/2022).

Udias, Angel, Marco Pastori, Céline Dondeynaz, Cesar Carmona Moreno, Abdou Ali, Luigi Cattaneo, and Javier Cano (Nov. 2018). "A decision support tool to enhance agricultural growth in the Mékrou river basin (West Africa)." en. In: *Computers and Electronics in Agriculture* 154, pp. 467–481. ISSN: 0168-1699. DOI: 10.1016/j.compag.2018.09.037. (Visited on 01/04/2023).

Wu, Susie Ruqun, Xiaomeng Li, Defne Apul, Victoria Breeze, Ying Tang, Yi Fan, and Jiquan Chen (2017). "Agent-based modeling of temporal and spatial dynamics in life cycle sustainability assessment." In: *Journal of Industrial Ecology* 21.6, pp. 1507–1521.

Xavier, António, Maria de Belém Costa Freitas, Rui Fragoso, and Maria do Socorro Rosário (June 2018). "A regional composite indicator for analysing agricultural sustainability in Portugal: A goal programming approach." en. In: *Ecological Indicators* 89, pp. 84–100. ISSN: 1470-160X. DOI: 10.1016/j.ecolind.2018.01.048. (Visited on 01/04/2023).

Xie, Y. L., D. X. Xia, L. Ji, and G. H. Huang (Sept. 2018). "An inexact stochastic-fuzzy optimization model for agricultural water allocation and land resources utilization management under considering effective rainfall.” en. In: *Ecological Indicators*. Multi-Scale Ecological Indicators for Supporting Sustainable Watershed Management 92, pp. 301–311. ISSN: 1470-160X. DOI: 10.1016/j.ecolind.2017.09.026. (Visited on 01/04/2023).

Yuan, Kuang-Yu, Ying-Chen Lin, Pei-Te Chiueh, and Shang-Lien Lo (Aug. 2018). “Spatial optimization of the food, energy, and water nexus: A life cycle assessment-based approach.” en. In: *Energy Policy* 119, pp. 502–514. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2018.05.009. (Visited on 01/04/2023).

Yuanyuan, Z. (2020). “Research on multi-objective planning model for agricultural pollution, environmental regulation and economic development.” undefined. In: *Arch. Latinoam. Nutr.* 70, pp. 423–433.

Yusoff, Yusliza, Mohd Salihin Ngadiman, and Azlan Mohd Zain (2011). “Overview of NSGA-II for optimizing machining process parameters.” In: *Procedia Engineering* 15, pp. 3978–3983.

Zhong, Zhixia and Fengqi You (2014). “Globally convergent exact and inexact parametric algorithms for solving large-scale mixed-integer fractional programs and applications in process systems engineering.” In: *Computers & Chemical Engineering* 61, pp. 90–101.

"A Web-Based Dashboard for Estimating the Economic and Ecological Impacts of Land Use Class Changes for Key Land Patches"

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6

A WEB-BASED DASHBOARD FOR ESTIMATING THE ECONOMIC AND ECOLOGICAL IMPACTS OF LAND USE CLASS CHANGES FOR KEY LAND PATCHES

6.1 ABSTRACT

The increasing pressure on land coming from the raising needs of a fast-growing population puts public and private landowners and decision makers in front of difficult choices concerning the best use of limited land resources. On one hand, agricultural land and grassland need to be used to support human food requirements. On the other hand, these land uses create trade-offs with other ecosystem functions, assets and services, such as ecological connectivity, biodiversity and natural habitat maintenance. In this paper a prototype web-based dashboard is presented, that aims at allowing a fully-fledged calculation of the economic and environmental trade-offs between different land uses of any land patch (excluding urban areas and infrastructures) and in the Grand Duchy of Luxembourg. An Agent-Based Modelling (ABM) coupled with Life-Cycle Assessment (LCA) runs on the background of the dashboard. The coupled model allows the simulation of the farm business and the calculation of the revenues made by farmers in every land patch under different farm management scenarios. Crossing the information coming from the model with other tools would also allow to integrate local environmental trade-offs, such as degradation of local habitats or ecological connectivity, and not only global ones defined in a non-spatialized way. The dashboard has a potentially high value to inform policy, strategies, or specific actions (e.g., environmental stewardship programs that integrate economic convenience as a condition) and has the necessary flexibility to integrate new aspects related to territorial analyses as they become available.

6.2 INTRODUCTION

Land is a limited resource and as such its use generates trade-off choices for landowners and public authorities who have the responsibility to incentivize and support certain land use choices over others. In this framework, simulation and visualization tools can help stakeholders to understand the possible outcomes of different strategies and select suitable alternatives.

Although intense research has been carried out and major developments have been achieved in the assessment of the impact of production systems on the environment, the complexity of the models calls for a growing need for software with user-friendly interfaces and visualization capabilities to present the results of the simulations (Cardinot et al., 2019). The final impact of a project relies heavily on the easiness of communication and the accessibility and usability of its results by the target audience and relevant stakeholders.

In the case of complex systems, evaluation of different scenarios is naturally a difficult task due to existence of large amount of simulation outputs. A pre-defined set of performance metrics and a dashboard that summarizes and visualizes them can help users to draw meaningful conclusions and comparisons between scenarios. However, as it is the case for most complex systems, the analysis and visualization of simulation outcomes require a combination of data analysis methods. From the experience of the authors, building a single tool to analyze large amounts of data that includes geospatial information, network analysis, sustainability assessment indicators and financial performance, is a non negligible effort, but can significantly help the recipients of a final research product, whether they are researchers or not. With such a tool can be possible to achieve the important task of clarifying the model goals and parameters for people who are not involved in the modeling process task. Furthermore, comparison of different scenarios and effect of changing parameters can aid users in the decision-making process.

As suggested in modern sustainability research, when dealing with human environment interaction a trans-disciplinary approach is required (Popa et al., 2015). To study coupled human-natural systems, agent-based modelling has been gradually accepted as a useful modelling technique (Rounsevell et al., 2012). Agents are defined as autonomous entities that react to the stimuli coming from the environment and interact with one another under certain rules that are imposed by the modeler and normally defined after consultation with domain experts and stakeholders. Each of them has an objective that can be defined as optimizing the societal or individual benefit. They are capable of learning, adapting, and changing their behaviors, which end up steering their actions.

In this paper we present the first prototype of a web-based dashboard that estimates the revenue and environmental impacts that a farmer can expect applying a certain management scenario on his/her farm. The environmental impacts are calculated making use of LCA and represent lifecycle-based (not just local) global impacts generated by the farm. Both can then be apportioned to each land patch using a given weighting procedure. Once the revenues and non-local environmental impacts are estimated and mapped, they can be overlaid onto other maps representing outputs of local analysis (e.g., habitat value, ecological connectivity, risk of soil erosion). These latter inform on the local environmental value of the land, complementing the lifecycle-based environmental assessment. The dashboard, together with local environmental analysis, would support a better-informed management of any land plot, based on the positive and negative environmental and economic outcomes of different land uses.

The calculation of the revenues and the environmental impacts is carried out using an ABM of the farming system (which includes mixed farms, dealing with crops, meat and milk at the same time) coupled with an LCA calculation run on the background of the dashboard which is then used to display pre-calculated results. Future developments incorporating local environmental analysis (e.g., ecological connectivity analysis) will inform about local environmental values of the land patches using indicators and tools such as landscape metrics, connectivity indices, circuit-theory models. The maps thus generated can be easily loaded into the dashboard as it can handle georeferenced files.

In the paper, visualization techniques and technologies behind the prototype are first discussed. The prototype that shows the results from our selected case study is then presented and planned future development are outlined.

6.3 THE DASHBOARD

The dashboard is created using Django web-framework and its structure is depicted in Fig. 43. It allows to run computations in the backend using other Python libraries that are already integrated into our simulation pipeline. Based on the feedback from project partners and reviewed literature, the dashboard was designed using the components depicted in Fig. 43. The data is stored using PostGIS which has the ability to manage Geographic Information System (GIS) and numerical data in one database. The PostGIS application is available in a docker container to make it compatible for different operating systems. Thanks to Django, we access the database and manipulate the tables with Python's powerful libraries. In the front-end, JavaScript allows to use interactive visualization tools to better investigate the simulation results, as well as the static properties of the farms. The dashboard can currently be used on the most common web browsers (Chrome, Firefox, Safari etc.). All the code is stored in Git and can be accessed by other contributors within the project team which allows further collaboration. The dashboard aims to provide user-friendly insights for farmers, advisors, agencies, and public administrations in terms of agricultural and financial sustainability. Although the development has been made mainly on a web-based portal, a mobile-based application would be necessary for farmers to make the interaction effortless. It may also be possible to allow other researchers to access the dashboard via Application Programming Interfaces (APIs) when they want to conduct their own research.

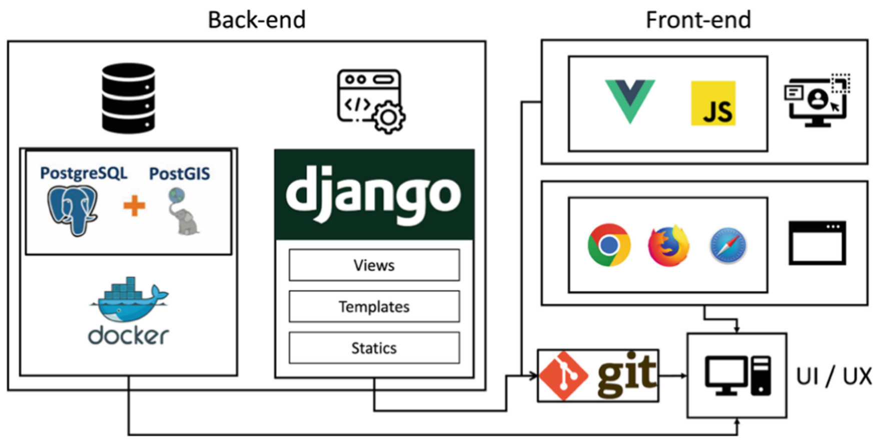

Figure 43: The back-end/front-end structure of the dashboard.

The Two-Way Communication Between Farmers and Organizations. In our platform the farmer is the main entity and the agencies will be able to access the farmer's data as long as it is allowed by the farmer. Depending on the nature of their relationship, the agency for example can give recommendations (in case of a consultant) or send reminders (in case of a public agency). The agency will have another version of the dashboard that is suitable for its purposes. Figure 44 shows the different levels of possible users of the dashboard and their motivations to use it.

The Input from Farmers. Although we mostly use static data, which is the data available in national inventories, one of the major steppingstones for future-work for our research can be the collection of data on a farm level. The classification of crop plantations from Sentinel imagery is possible thanks to computer vision algorithms (Immitzer et al., 2016), however the farmers still need to report the crop plantations to the agencies in Luxembourg. They are also required to fill out additional forms, such as grazing calendars, which would allow them to get subsidies. Our tool may allow seamless data-entry for the farmers. Apart from already required and usual data requests from agencies, farmers can choose to enter the real cost and production data to visualize and assess the business from the financial point-of-view. This can even be achieved utilizing the machinery or sensors around the farm, such as milking or feeding robots, wherever and whenever available. All these elements would result in a simplification of farmers' tasks and a fast reusability of up-to-date data.

The Fertilizer Usage and Nitrate Vulnerability. Most farmers are already aware of the nitrogen limits within and along the surroundings of their farms, however with the dashboard it is possible to show the nitrogen constraints on a map based on water body proximity.

Figure 44: The possible users of the dashboard and their possible motivations to use it.

This information can help them stay below the imposed limits, thus qualifying to get subsidies. There are several subsidy programs in Luxembourg that are based on nitrogen constraints and the imposed thresholds change according to the proximity to ecological protection zones. Based on the provided algorithm for nitrogen excretion from livestock and fertilizer usage for crops, the farmers can see the already released and projected fertilizer input to the soil for a given period. It will also be possible to recommend optimum organic and inorganic fertilizer levels for each type of crop once the soil properties map is incorporated into the model.

The Weather and Climate Forecasts. This information is important for extensive farms, where the farmers let their animals graze outside, depending on the weather conditions. These forecasts can be combined with several other pieces of information such as current levels of soil moisture, grass height, barn temperature and air-quality. Some of these can be made available on the dashboard for the farms where required sensors are available. Figure 45 (left) shows the visualization of the weather forecast in the dashboard for a random commune.

Since the calculation of the revenues and the environmental impacts is based on an ABM, the mutual interactions of the agents are taken into account, as explained in (Marvuglia et al., 2022). Figure 45

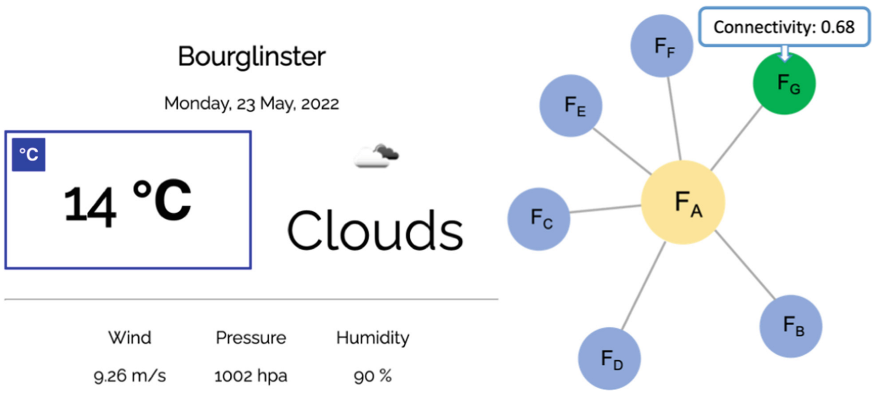

Figure 45: (Left) The weather information for the farm's location. (Right) The connections of Farmer A(F_A).

(right) shows the visualization of the connection of a given farmer to the other agents in the network.

The Overview of Simulation Environment. The farmer agents act on the same fields throughout the simulations. This means that the farm and field boundaries do not change. The geospatial data that includes those boundaries is stored in a PostGIS database. It is read by GeoAlchemy2, Python Object Relational Mapping (ORM) library for spatial databases, and then visualized with Folium, another Python library to create interactive maps. The users can interact with the map to see the crops planted and harvested in a given field throughout the simulation. Figure 46 shows a screenshot of the dashboard window where a selected farm and the Life-Cycle Impact Assessment (LCIA) scores related to it can be visualized. Currently we are using the ReCiPe LCIA method (Huijbregts et al., 2017) to calculate the impact scores, but any other existing method can be easily used in future updates of the tool. On the left-hand side of the figure one can see that each single field belonging to the farm (i.e., each polygon for which information is known at the cadaster level) is visualized.

Holdings' Financial Balances. The 2D charts that show the monthly and yearly finances of each farm holding allow users to see the seasonal trends in every cost and revenue category. Every time a scenario is simulated with the ABM, this has implications on different categories. Lower production does not necessarily mean less profit for the farmers, due to reduced costs and, in some scenarios, the increase of certain subsidies from the government. After each simulation run, the value of each cost and revenue item is stored in CSV files. Then they are curated using the Python data frame library Pandas and visualized using Charts.js. In a future version of the dashboard, we plan to visualize the results of sensitivity analysis on input variables, such as the amount of subsidy given for a particular activity.

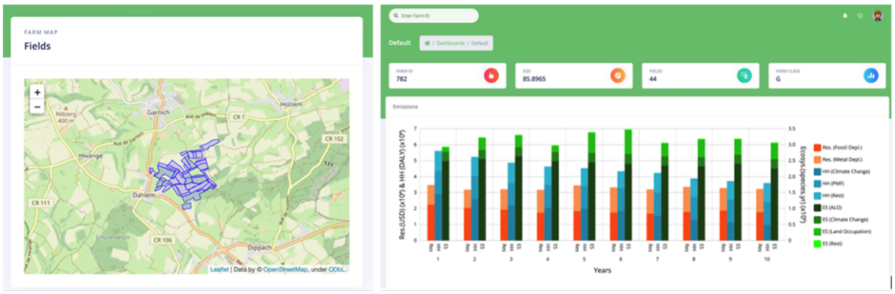

Figure 46: (Left) The fields that belong to one farm. The user can interact with the map to visualize the field attributes. (Right) Life-cycle impact scores for a given farm in the span of 10 years (chosen as time horizon of the simulation to obtain pre-calculated results).

LCIA of Each Holding. The agricultural activities generate impacts that have short- and long-term effects on the environment that must be monitored carefully by every stakeholder in the sector if an emission reduction strategy is put in place. LCIA allows to quantify these impacts and take necessary actions to mitigate the emissions that are the reasons behind them. In our model, the Brightway2[1] LCA library is used. It was created to enable modelling functionalities that can go beyond traditional LCA software. In particular, using Brightway2 it is possible to seamlessly connect LCA calculations with other simulation engines (in this case the ABM). With Brigthway2 the so-called Life-Cycle Inventory (LCI) background data that reside in a LCI database can be recalled automatically and used (together with the foreground data that contains the crop and animal outputs) to calculate the LCIA scores during the simulations. Brightway2 is integrated in the dashboard, in a way that the users can select the impact assessment method they want to adopt for impacts calculations and the impact categories they want to monitor.

The Network of Agents. One of the crucial mechanisms in agent-based modelling is the interaction and information exchange between the agents. In our model, classes of agents were first created according to their risk aversion orientation and their geographical position, as described in (Marvuglia et al., 2022). The farmer agents that belong to the same risk aversion class or the ones who are geographical neighbors of one another are considered as connected in a network analysis sense. Each farmer and its connections are shown in a way that their attributes evolve over time (for instance age) and due to information exchange (e.g., environmental awareness).

Assessment of Finances and LCIs at Country-Level. Since each farmer agent acts upon the land belonging to its single farmland, this latter is the reference spatial unit we can assess in terms of economic

1 https://brightway.dev/.

value and environmental impact generated. However, the policymakers have the interest to make assessments at regional level. Therefore, the dashboard allows to show the aggregated result scores as a drill-down weighted treemap with three levels, i.e., farm, commune and canton. The users can choose to visualize the farm outputs, revenues, costs or impact scores. Figure 47 shows a screenshot of the window used to visualize the net revenue of the farm over ten years as resulting from a pre-simulated scenario.

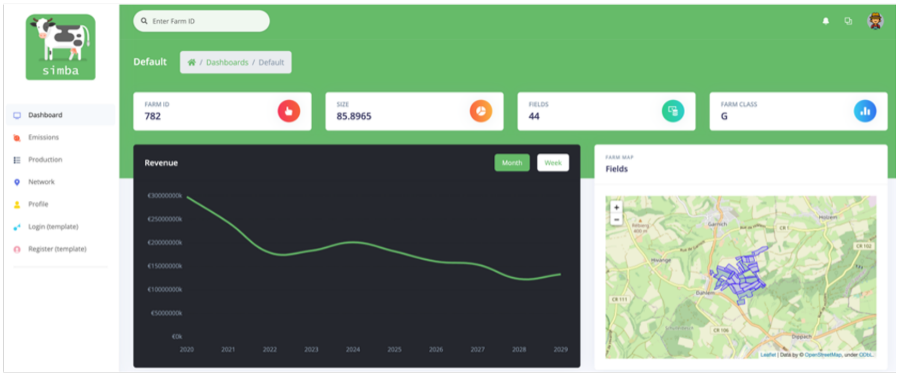

Figure 47: The graph showing the trend of the net revenue of the farm over ten simulated years.

6.4 CASE STUDY: FARMLAND REVENUE GENERATION AND IMPACT ASSESSMENT

The dashboard prototype was used to visualize the results of a scenario which has the objective of reducing stocking rates (i.e., the density of animals per ha) throughout Luxembourgish farms. The scenario was simulated for a time span of 10 years with time steps of one month. The simulations are repeated 50 times and the results are averaged to consider the intrinsic variability induced by the random choice of certain parameters (such as behavioral attributes of a farmer, the allocation of fields of a farm, seeding and harvesting months of crops, etc.). The objective in this case study was to observe the change in the herd structure of the farms over time, and its simultaneous impact not just on the farm finances, but also on the environment. Reducing the stocking rates can help the agricultural sector to mitigate its greenhouse gas emissions. A reduction on stocking rate would be certainly pushed by a reduction of meat and dairy products' consumption coming from consumers due to change of their dietary habits. Less animals would mean less direct costs (like feed imports), as well as an improved soil quality. Within this context, certain subsidies are set for different levels of nitrogen input reduction in Luxembourg. At every year *n* of a simulation, an agent checks the nitrogen emissions into the soil caused by the herd at year *n*-1.

If the objective level that was set based on the livestock unit area is exceed, then the agent chooses to get rid of the less efficient animals from the herd. Once this decision has been taken, the production of current year *n* is calculated and the corresponding revenue generation, as well as the emissions, are recorded. Afterwards, the selected animals are sent away from the herd (sold or slaughtered).

The emissions tab on the sidebar allows to see the evolution of the emissions throughout the simulation. If a farmer is logged in, the historical and simulated emissions are shown on the emissions tab; when the user is connected using administrative credentials, the country or regional level emissions are made available. In addition to monitoring the levels for whole country, we also use weighted treemaps (Ghoniem et al., 2015), along with real maps of subregions, to see the impacts in more detail. In Fig. 48 (Right), impacts on human health (expressed in the unit Disability Adjusted Life Years (DALY), which stands for disability adjusted life years (Kobayashi et al., 2015)) generated by emissions due to crop and cattle farming are given per each canton of the country. The same representation is provided also as a treemap (Fig. 48 (Left). The weighted treemap algorithm allows to represent the original polygons as rectangles, while respecting their boundary and topological relationships. As expected, the agricultural practices cause more emissions in northern Luxembourg than in the southern part of the country, since most farms are located in that region. The dashboard also includes the drill-down version of the weighted treemap, where the users can look at the treemap that is built based on a selected variable (i.e., size, production, number of livestock, impact score, revenue) in cantons' view at the highest level. By clicking on any canton, one can visualize the communes in that canton in a similar fashion. Finally, the farms in a selected commune can be visualized in the lowest level of the drill-down treemap. Figure 49 shows an example of drill-down treemap, that is built using the size of each region (canton, commune or farm). In this example, the user clicks on the canton of Esch-sur-Alzette canton and then on the commune of Pétange, to display the farms present in that area.

6.5 DISCUSSION AND CONCLUSION

The paper presents the first prototype of a web-based dashboard that can be used to assess the economic and ecological impacts of land transformation. The direct economic value of the land patches used as cropland or pasture (i.e., the net revenue for the farmer, without considering the cost of environmental externalities) is pre-calculated using a hybrid ABM-LCA model that mimics the evolution of the Luxembourgish farming system under management scenarios that can be designed upstream. The hybrid model is also used to calculate the environmental impacts of each management scenario (which are then

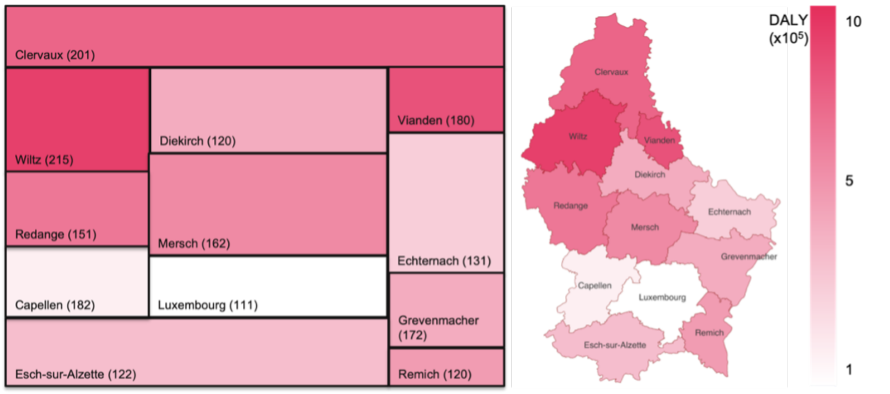

Figure 48: Left: the weighted treemap that shows the average human health impact over 10 years of simulation and 50 different iterations. Right: the same information visualized as a traditional geographical map.

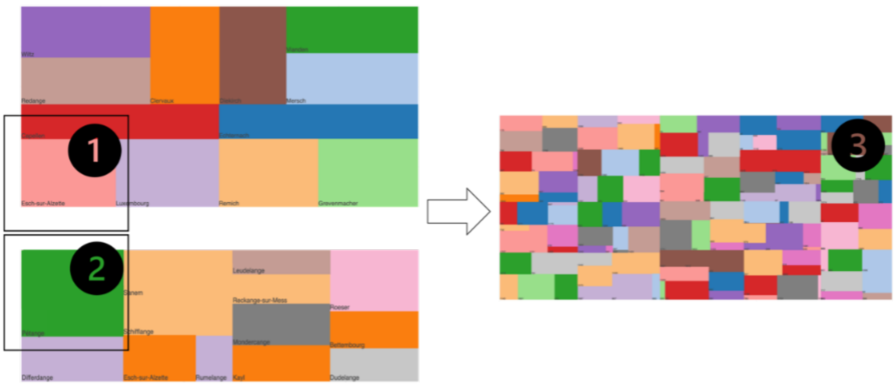

Figure 49: The drill-down treemap implementation of geographical boundaries of Luxembourg.

allocated to the single patches) using LCIA indicators (Huijbregts et al., 2017).

Looking also at future further developments of our dashboard, one important observation we can already make is that land is not only a source of food and material resources for humans (the so-called provisioning ecosystem services); it is also a source of regulating and cultural ecosystem services (CICES, 2018). Among the regulating services, natural, semi-natural and agricultural land support the maintenance of nursery populations and habitats on which plants and animal species depend. Anthropic land transformation (land use conversions) could harm ecosystem functions (e.g., ecological connectivity) that influence habitat maintenance. For example, the transformation of certain patches of land that are in strategic positions for species movement or the creation of human artifacts (e.g., agricultural fences, roads), beyond direct habitat loss, could result in a loss of ecological connectivity which also ends up influencing species survival negatively (Edelsparre et al., 2018). To assess the impacts in terms of habitat loss and ecological connectivity, indicators and tools such as landscape metrics, connectivity indices and ecological connectivity models have been developed. They are based on different approaches, spanning from least-cost path analysis (Douglas, 1994), to circuit theory (McRae et al., 2008), matrix theory (Caswell, 2000), agent-based or individual-based modelling (Allen et al., 2016), network analysis (Pereira et al., 2017) and other techniques. A wider overview on ecological connectivity approaches and models can be found in (Kool et al., 2013).

Given the importance of these ecological functions of land, the next step we plan for the dashboard is the addition of a further geospatial layer that represents the value of each land patch in terms of their contribution to habitat maintenance. For example, as proposed in (Almenar et al., 2019), using as input data species distribution models of Luxembourg developed in (Titeux et al., 2013), ecological connectivity analysis can be easily developed, informing on referred routes of movement of certain species (e.g., endangered or protected ones). In this way the relevance of specific land patches to enhance ecological connectivity of species populations can be evaluated. As another alternative, a combined use of connectivity indices such as the Integral Index of Connectivity (IIC), the Betweenness Centrality (BC) and the Probability of Connectivity (PC), could be considered to estimate the patches with the highest value for ecological connectivity (also applied in (Almenar et al., 2019)). If these key patches are close to protected areas and are currently used as cropland, the dashboard could be used to calculate the net revenue that the farmers can associate to those patches and therefore determine a value of a fair compensation that they should be granted if they are requested to hand over the ownership of those patches to the public administration that can then convert them into protected areas. We will therefore integrate the calculation of the value of each land patch from the habitat connectivity point of view, using landscape metrics and connectivity indices (for examples using tools such as Conefor (Saura and Torné, 2009) or Fragstats (McGarigal, 1995)). This will allow the identification of the most important patches that can then be selected as priority (key patches) to inform ecological planning or the definition of biodiversity action plans. When these key patches fall within existing farms (where they are used either as cropland or as pasture) the dashboard will then allow also to determine the expected monetary compensation that the farmers who own these patches should receive for the production capacity loss they would incur to reduce the pressure on the land (i.e., have a less intensive cultivation), if these patches become part of an environmental stewardship program to protect biodiversity and are therefore converted into protected areas.

Apart from technical perspectives and objectives of this tool, it is worth noting that the development procedure should be integrated with users' feedback along all the stages. That means working with agencies and farmers who understand the necessities of digitalization in agriculture and provide valuable feedback. Understanding the needs of farmers from different ages and whose farms differ in size helps building a helpful tool that reflects the characteristics of the farm system of the given territory. Moreover, the agencies that would be using this tool may decide on what to emphasize or communicate strongly to the farmers via this tool during the development phase which would possibly increase their motivation.

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Allen, Corrie H, Lael Parrott, and Catherine Kyle (2016). "An individual-based modelling approach to estimate landscape connectivity for bighorn sheep (Ovis canadensis)." In: *PeerJ* 4, e2001.

Almenar, Javier Babí, Alya Bolowich, Thomas Elliot, Davide Geneletti, Guido Sonnemann, and Benedetto Rugani (2019). "Assessing habitat loss, fragmentation and ecological connectivity in Luxembourg to support spatial planning." In: *Landscape and Urban Planning* 189, pp. 335–351.

CICES (2018). *Guidance Document: Common Metrics and Methods for LCA and Resource Efficiency Indicators in Buildings, Version 5.1*. https://cices.eu/content/uploads/sites/8/2018/01/Guidance-V51-01012018.pdf. Accessed on 25 February 2023.

Cardinot, Marcos, Colm O'Riordan, Josephine Griffith, and Matjaž Perc (2019). "Evoplex: A platform for agent-based modeling on networks." In: *SoftwareX* 9, pp. 199–204. ISSN: 23527110. DOI: 10.1016/j.softx.2019.02.009. arXiv: 1811.10116.

Caswell, Hal (2000). *Matrix population models*. Vol. 1. Sinauer Sunderland, MA.

Douglas, David H (1994). "Least-cost path in GIS using an accumulated cost surface and slopelines." In: *Cartographica: the international journal for Geographic Information and Geovisualization* 31.3, pp. 37–51.

Edelsparre, Allan H, Ashif Shahid, and Mark J Fitzpatrick (2018). "Habitat connectivity is determined by the scale of habitat loss and dispersal strategy." In: *Ecology and Evolution* 8.11, pp. 5508–5514.

Ghoniem, Mohammad, Maël Cornil, Bertjan Broeksema, Mickaël Stefas, and Benoît Otjacques (2015). "Weighted maps: treemap visualization of geolocated quantitative data." In: *Visualization and Data Analysis 2015*. Vol. 9397. International Society for Optics and Photonics, 93970G.

Huijbregts, M.A.J., Z.J.N. Steinmann, P.M.F. Elshout, G. Stam, F. Verones, M. Vieira, M. Zijp, A. Hollander, and R. van Zelm (2017). "ReCiPe2016: A Harmonised Life Cycle Impact Assessment Method at Midpoint and Endpoint Level." In: *Int J Life Cycle Assess* 22, pp. 138–147. DOI: 10.1007/s11367-016-1246-y.

Immitzer, Markus, Francesco Vuolo, and Clement Atzberger (Mar. 2016). "First Experience with Sentinel-2 Data for Crop and Tree Species Classifications in Central Europe." en. In: *Remote Sensing* 8.3. Number: 3 Publisher: Multidisciplinary Digital Publishing Institute, p. 166. ISSN: 2072-4292. DOI: 10.3390/rs8030166. (Visited on 04/12/2022).

Kobayashi, Yumi, Greg M Peters, Nicholas J Ashbolt, Sean Shiels, and Stuart J Khan (2015). "Assessing burden of disease as disability adjusted life years in life cycle assessment." In: *Science of the Total Environment* 530, pp. 120–128.

Kool, Johnathan T, Atte Moilanen, and Eric A Treml (2013). "Population connectivity: recent advances and new perspectives." In: *Landscape Ecology* 28, pp. 165–185.

Marvuglia, A., A. Bayram, P. Baustert, T.N. Gutierrez, and E. Igos (2022). "Agent-Based Modelling to Simulate Farmers' Sustainable Decisions: Farmers' Interaction and Resulting Green Consciousness Evolution." In: *Journal of Cleaner Production* 332, p. 129847. DOI: 10.1016/j.jclepro.2021.129847.

McGarigal, Kevin (1995). *FRAGSTATS: spatial pattern analysis program for quantifying landscape structure*. Vol. 351. US Department of Agriculture, Forest Service, Pacific Northwest Research Station.

McRae, Brad H, Brett G Dickson, Timothy H Keitt, and Viral B Shah (2008). "Using circuit theory to model connectivity in ecology, evolution, and conservation." In: *Ecology* 89.10, pp. 2712–2724.

Pereira, Juliana, Santiago Saura, and Ferenc Jordán (2017). "Single-node vs. multi-node centrality in landscape graph analysis: key habitat patches and their protection for 20 bird species in NE Spain." In: *Methods in Ecology and Evolution* 8.11, pp. 1458–1467.

Popa, Florin, Mathieu Guillermin, and Tom Dedeurwaerdere (2015). "A pragmatist approach to transdisciplinarity in sustainability research: From complex systems theory to reflexive science." In: *Futures* 65, pp. 45–56.

Rounsevell, Mark DA, Derek T Robinson, and Dave Murray-Rust (2012). "From actors to agents in socio-ecological systems models." In: *Philosophical Transactions of the Royal Society B: Biological Sciences* 367.1586, pp. 259–269.

Saura, Santiago and Josep Torné (2009). "Conefor Sensinode 2.2: a software package for quantifying the importance of habitat patches for landscape connectivity." In: *Environmental modelling & software* 24.1, pp. 135–139.

Titeux, N, X Mestdagh, and L Cantú-Salazar (2013). "Reporting under Article 17 of the Habitats Directive in Luxembourg (2007–2012): conservation status of species listed in Annexes II, IV and V of the European Council Directive on the Conservation of Habitats, Flora and Fauna (92/43/EEC)." In: *Centre de Recherche Public–Gabriel Lippman*.

7 CONCLUSION

7.1 INTRODUCTION

According to (Crippa et al., 2021), food systems are responsible for 34% of global anthropogenic GHG emissions. It is expected that this number will increase as the human population, and therefore, demand for agricultural products increases. In addition, the agriculture sector is a significant contributor to eutrophication through its emissions of nutrients (N and P). Emissions of pesticides are the root cause of the adverse effects on human health. Furthermore, land is a limited resource, especially in a small country like Luxembourg. The competition between food crops and energy crops (to produce biogas, bioenergy, and biofuels) is a delicate matter that is difficult to solve. Because agricultural systems involve human decision-making, which is not always fully rational but can be affected by bounded rationality (due to farmers' choices that can be dictated by family values and other human behavioral factors), the complexity of the issues that were outlined above is rendered even more challenging to manage, this is because agricultural systems involve humans.

We decided to use ABM to model the complex agricultural system because it allows us to simulate the seasonal activities of each farmer. This method has been shown to handle human behavioral components and show the results of human interaction and information diffusion in networks, both known to give rise to so-called "emerging behaviors". On the other hand, the sustainability assessment was made possible through LCA which allows the assessment of the environmental impacts of a wide range of agricultural processes from a life-cycle perspective. Using LCA, the demand can be translated into related impacts such as impacts on the environment, impacts on human health or impacts on resource depletion.

SIMBA is a hybrid ABM and LCA model where the agents of ABM are the farmers and production units of a farm are an UAA and an animal. The model integrates in detail several aspects of dairy farming in a detailed manner. Nonetheless, it suffers from some limitations. In particular, the model lacks price forecasting for crops and animal products and does not integrate the land-rental market, which covers a significant part of agricultural land in Luxembourg. These specifications were not in the scope of this thesis. Still, it would be helpful to integrate them into the subsequent versions of the model since they may influence the behavioral patterns of farmers.

7.2 METHODOLOGICAL CONTRIBUTIONS

Chapter 2 of the present thesis mainly explores the effects (in terms of agricultural activities and the consequent environmental impacts) of the interactions among farmers and the spreading of green consciousness. The network of farmers was established using the neighborhood connections between farmers. Those connections were used to spread green consciousness behavior amongst farmers. Farms are given real geographic locations, and the boundaries of those locations are determined by an algorithm called the field assignment algorithm. It groups a certain number of fields and assigns them to a farm such that the statistics on farm classes in national registration can be reached.

After the network of farmers was established, we focused on creating the most crucial part of the model and the thesis. In chapter 3, a hybrid ABM-LCA model that simulates mixed crop-livestock activities was presented. The focus was on the addition of dairy and suckler farming activities. The ABM allows the modeler to simulate the farmer agents' activities based on economic and behavioral constraints and apply the LCA methodology to the resulting crop and herd structure to calculate the environmental impacts of the simulated activities.

After establishing the network of farmers, we focused on developing the most crucial aspect of the model and the present thesis. A hybrid ABM-LCA model that simulates mixed crop and livestock activities was presented in chapter 3. The addition of dairy farming activities was the primary focus of this chapter. Dairy farming activities were modeled after careful discussions with the project stakeholders. Collaborative modeling allows ABMs to simulate the activities as realistically as possible. It allows us to see the incorporation of farm-level activities and national regulations in the same model. The ABM also gives the modeler the flexibility to simulate the activities of the farmer agents based on economic and behavioral constraints and then apply the LCA methodology to the resulting crop and herd structure to calculate the environmental impacts of the simulated activities. In this chapter, we also explored a scenario entailing the reduction of soybean importation from South America. In principle, this might result in indirect land use changes that ought to be investigated from the CLCA standpoint. However, the quantities required by the Luxembourgish farming system are too small to generate significant changes worldwide, as proven already by previous research (Vázquez-Rowe et al., 2013). Also, possible impacts of land use changes on soil carbon storage could be explored, but this was beyond the scope of the project. However, some approaches have been applied by other researchers (Deng et al., 2016; Yu and Song, 2023), that could be incorporated in future versions of our model.

Chapter 4 merely attempts to demonstrate biogas production activities in Luxembourg. Thanks to the data provided by a local biogas plant, we could incorporate the biogas production capabilities into our model, which holds an important place in the government's future energy policies. The farmers may also use these plans, by transferring the excess manure to the biogas cooperatives, where it is upscaled and injected into the natural gas grid.

The model was then enhanced by adding a multi-objective optimization model that uses environmental and economic objectives. In chapter 5 we introduce the model that uses genetic algorithms and optimizes farms based on profit and selected environmental impact categories. The consideration of subsidies is an essential part of the model because they enable farmer agents to quantify agricultural emissions in terms of monetary units. Adding optimization under various objectives and constraints makes the hybrid ABM-LCA model much more potent than other simulators that evaluate the sustainability of agricultural activities.

Finally, chapter 6 introduces the dashboard to show the results of our model. Although there are many commercially available mobile and desktop tools for agriculture, they usually focus on a single farm. In our dashboard, our focus is both the country- and farm- level outcomes. Although this tool is still under development, users can see the results of the simulation farm by farm or at the country level.

7.3 KEY RESULTS AND IMPLICATIONS

In chapter 2, we were able to simulate the interactions between agents and the outcomes of those interactions regarding changes in environmentally conscious behavior from one year to the next as a result of adding the network of farmers to our model. The findings indicate that green consciousness behavior can be diffused through the interactions among farmers. Over the course of the simulated period, this results in a reduction of cumulative environmental impacts targeted by the chosen decision rules. When starting from high green consciousness values, the effect of interaction leads to a more considerable reduction of the targeted cumulated impacts (in this case, the HH effects of greenhouse gas emissions) in comparison to the scenario starting from lower average values of the green consciousness which leads to a smaller reduction of the targeted cumulated impacts. In particular, we noticed that farmers' levels of green consciousness vary across the simulations. In this regard, we found that the simulations could accurately predict farmers' green consciousness levels.

In chapter 3, after incorporating the dairy farming aspects into our model, we run a few simulations to test various outcomes. One of the possible outcomes that we modeled was what would happen if the stocking rate was decreased from 1.6 LSU/ha to 1.3 LSU/ha. This results in an improvement in terms of lifecycle impacts compared to the scenario that served as the baseline, with the highest improvements being a reduction of almost 25% in freshwater eutrophication, 21% in climate change's effects on human health, and 19% in freshwater ecotoxicity. Even though farmers are unwilling to implement such practices on their farms, it is possible to evaluate the possibility of compensating farmers for their loss of revenue with additional subsidies by considering the potential benefits of this practice, which were demonstrated by the simulations. These benefits include improved soil quality, animal health, and reduced veterinary care and labor costs.

In addition to lowering stocking rates, we also considered two other courses of action that could lessen the adverse effects on the environment by altering the animals' diet. They anticipate Luxembourg will become self-sufficient in soy products (Zimmer et al., 2021). Cultivating soybeans in certain parts of Luxembourg, particularly in the southern part of the country, is possible. On the other hand, the current amount of soybean in feed rations is more than sufficient to ensure the required protein intake for animal growth. As a result, having less soybean in the animal diet is also possible, leading to a higher level of national soybean autarky. The scenarios where soybean autarky was targeted either by decreasing the amount of soymeal in animal diet (scenario C) or cultivating soybean locally in Luxembourg (scenario D) show the most significant improvements for natural land transformation impacts (11% reduction in scenario C and 13% reduction in scenario D, respectively). On the other hand, in scenario C, the modification of feed composition, in conjunction with the anticipated reduction in stocking rates, also has a positive effect (approximately a 16% reduction in comparison to the baseline) on the amount of agricultural land that is occupied, due to the utilization of pasture and crops that are grown locally.

The addition of dairy farming activities also allowed us to incorporate a biogas production system in Luxembourg introduced in chapter 4. In that chapter four scenarios were simulated to see the environmental impacts caused by changes in biogas feedstock. The objectives were mainly, to exploit the manure produced by farms more consistently and increase its percentage in the composition of the biomass used in the digestors, and include biowaste into the biogas feedstock, which is assumed to be always readily available. According to our results, the objective to increase the percentage of manure delivered to biogas production plants up to 90% of the excess manure available at farms is achievable. This can be obtained by adding new plants to the system and integrating more farms into production. In another scenario, we saw that if biowaste can be incorporated into the feedstock, this also generates less impact per unit of biogas produced than in the business-as-usual case. The overall reduction of impacts is possible via a change of manure in the biogas feedstock composition, whereas the electricity production from biogas can be maximized if biowaste is utilized more in the biogas feedstock.

In chapter 5, we see that agents can take decisions based on defined objectives, therefore, incorporating MOO into the ABM-LCA model can help influence the overall system towards more environmentally friendly decisions. When we compared the model without the optimization model with the model that considers profit generation as an objective, we clearly see an improvement toward profit generation in the latter one. After establishing the optimized model works as intended, we tested a couple of case studies that also consider environmental objectives. We simulated two case studies: in the first one EF climate change score is minimized and in the latter EF single score is targeted using all sixteen EF impact categories.

We see a clear reduction in stocking rates in both cases. This is due to the amount of impacts that livestock production activities cause on the environment taken into account by the optimization model. These two cases consider the environmental objective and farmers who are "green-conscious" enough to make decisions to reduce the impact of their activities.

It is important to emphasize that, from the LCA perspective, each scenario results in different products, and therefore, the functional unit follows the territorial LCA approach (Loiseau et al., 2018). Our functional unit is the land of Luxembourg, with what concerns agricultural and farming production excluding pastures, vineyards and orchards. The scenarios we simulated throughout these chapters are not exhaustive and can be simulated using different parameters and target values. We intended to build as many components as possible to encompass the agriculture sector of Luxembourg. In the end, our approach was to build a framework that includes dairy farming and the rest of the components were added according to the scenario requirements. These components can be extended as part of the further needs addressed in the next section as limitations and future recommendations.

7.4 LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORK

The current state of the model includes only the farmer agents. This can be enhanced by adding other types of agents including, but not limited to, cooperatives, government agencies and consultants within the sector, which would allow modelers to incorporate information exchange between actors more accurately. For instance, the farmers that belong to the same biogas or dairy cooperative may exchange information more frequently than the rest, therefore this requires more attention in terms of changes in behavior due to the interactions favored by the cooperative. The cooperative can be modeled as an agent disseminating information among its members. However, this interaction element is not currently implemented in the model.

Although the model covers various aspects of agricultural production, there are still missing pieces that would enhance the model. These limitations usually stem from unavailable or non-reliable data sources. For instance, land rentals are common in practice but we do not have the data on which fields are rented in a given year. When one models a real market, the length of the lease contract affects the model because it determines the moment in time when the market can experience variations on the distribution of land among the farmers. Because of this, the length of the lease contract influences the model. This is particularly important in the Grand Duchy of Luxembourg because there are only a small number of landowners in the country, the price of land is extremely high, and the vast majority of farmers rent their land. The land law may impose different limitations on the length of the available lease periods. In the questionnaire that was deployed in the project of which SIMBA is the follow-up (Marvuglia et al., 2022), 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 annual rent paid was close to 70% of the 168 respondents. Due to the low rate, accurate modeling of the land rental market is impossible in our ABM. In our work, the main data providers were Administration des Services Techniques de l'Agriculture (ASTA) for GIS data and Service d'Economie Rurale (SER) for farm accountancy data, both of which provided first–hand data. When obtaining farm detailed data is not possible, some researchers have proposed the use of aggregated data sources such as Farm Accountancy Data Network (FADN) (Ding and Achten, 2022).

The Holt-Winters forecasting model that is described in (Rege et al., 2018) is used to determine the crop prices at the beginning of the simulation so that the simulation can begin. More complex price prediction models that consider how the market moves could be used. However, we do not address the issues that may arise from different price predictions because they do not change over the course of a simulation or from one scenario to the next. This is because they are constants. Without a doubt, the feedstock exchanges that take place between the farmers as well as the subsidies that are offered for particular types of crops and management methods could be incorporated into the model.

In terms of biogas production, the model still suffers from several limitations. The module that concerns biogas production is built mainly using data and information from one plant. The assumptions should be elaborated by different resources, including other biogas plants, farms and national actors. For instance, assuming that biowaste would always be available may not fully reproduce reality, because there might be periods when, for various reasons, its delivery to the biomass plant is scarcer or potentially discontinued. On the other end, biowaste not used for biogas production is incinerated. This causes additional GHG emissions, which are not accounted for in the model. The subsidies for investments and maintenance of biogas plants also change frequently, which may make long-term simulations obsolete. The government subsidies for the biogas sector are subject to future changes. In this respect, considering the feed-in tariffs granted to producers of electricity from biogas will be an important addition to the current model. Government financial support exists in Luxembourg to improve storage facilities but it has not been factored in the model because clear information about its amount was missing. There can be other types of subsidies that would entice the farmers into participating in biogas cooperatives and, ideally, they should be considered in future versions of the model.

Apart from the simulator itself, the presentation of results is also essential for disseminating the outcomes of this research. Therefore, the dashboard introduced in chapter 6 should be developed further by working with agencies and farmers who understand the necessities of digitalization in agriculture and provide valuable feedback. By understanding the requirements of farmers of varying ages and whose farms are of varying sizes, it is possible to construct a useful tool that accurately reflects the features of the agricultural system in the given territory. In addition, the organizations that would be using this tool have the ability to decide what aspects to highlight or communicate strongly to the farmers through the use of this tool during the development phase, which could potentially increase the farmers' level of motivation. Besides providing insight into their businesses, farmers can also share real-time data through farming robots and sensors that have already become widespread thanks to developments in precision agriculture. If farmers can be made aware that sharing data could help improve their businesses and necessary precautions can be taken against data privacy, then their collaboration via such tools would be reached. Integration of digital platforms with real-time climate, water and soil data is also possible if public authorities share the related information on these tools.

Crippa, M., E. Solazzo, D. Guizzardi, F. Monforti-Ferrario, F. N. Tubiello, and A. Leip (Mar. 2021). "Food systems are responsible for a third of global anthropogenic GHG emissions." en. In: *Nature Food* 2.3. Number: 3 Publisher: Nature Publishing Group, pp. 198–209. ISSN: 2662-1355. DOI: 10.1038/s43016-021-00225-9. (Visited on 02/18/2022).

Deng, Lei, Guang-yu Zhu, Zhuang-sheng Tang, and Zhou-ping Shangguan (Jan. 2016). "Global patterns of the effects of land-use changes on soil carbon stocks." en. In: *Global Ecology and Conservation* 5, pp. 127–138. ISSN: 2351-9894. DOI: 10.1016/j.gecco.2015.12.004. (Visited on 05/24/2023).

Ding, Tianran and Wouter M. J. Achten (Dec. 2022). "Coupling agent-based modeling with territorial LCA to support agricultural land-use planning." en. In: *Journal of Cleaner Production* 380, p. 134914. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2022.134914. (Visited on 05/17/2023).

Loiseau, Eléonore, Lynda Aissani, Samuel Le Féon, Faustine Laurent, Juliette Cerceau, Serenella Sala, and Philippe Roux (Mar. 2018). "Territorial Life Cycle Assessment (LCA): What exactly is it about? A proposal towards using a common terminology and a research agenda." en. In: *Journal of Cleaner Production* 176, pp. 474–485. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2017.12.169. (Visited on 05/03/2023).

Marvuglia, A., A. Bayram, P. Baustert, T.N. Gutierrez, and E. Igos (2022). "Agent-Based Modelling to Simulate Farmers' Sustainable Decisions: Farmers' Interaction and Resulting Green Consciousness Evolution." In: *Journal of Cleaner Production* 332, p. 129847. DOI: 10.1016/j.jclepro.2021.129847.

Rege, Sameer, Tomás Navarrete Gutiérrez, Antonino Marvuglia, Enrico Benetto, and Didier Stilmant (2018). "Modelling Price Discovery in an Agent Based Model for Agriculture in Luxembourg." en. In: *Complex Systems Modeling and Simulation in Economics and Finance*. Ed. by Shu-Heng Chen, Ying-Fang Kao, Ragupathy Venkatachalam, and Ye-Rong Du. Springer Proceedings in Complexity. Cham: Springer International Publishing, pp. 91–112. ISBN: 978-3-319-99624-0. DOI: 10.1007/978-3-319-99624-0_5.

Vázquez-Rowe, Ian, Sameer Rege, Antonino Marvuglia, Julien Thénie, Alain Haurie, and Enrico Benetto (Sept. 2013). "Application of three independent consequential LCA approaches to the agricultural sector in Luxembourg." en. In: *The International Journal of Life Cycle Assessment* 18.8, pp. 1593–1604. ISSN: 1614-

7502. DOI: 10.1007/s11367-013-0604-2. URL: https://doi.org/10.1007/s11367-013-0604-2 (visited on 05/24/2023).

Yu, Hao and Wei Song (Jan. 2023). "Research Progress on the Impact of Land Use Change on Soil Carbon Sequestration." en. In: *Land* 12.1. Number: 1 Publisher: Multidisciplinary Digital Publishing Institute, p. 213. ISSN: 2073-445X. DOI: 10.3390/land12010213. (Visited on 05/24/2023).

Zimmer, Stéphanie, Laura Leimbrock-Rosch, Marita Hoffmann, and Sabine Keßler (Mar. 2021). "Current soybean feed consumption in Luxembourg and reduction capability as a basis for a future protein strategy." en. In: *Organic Agriculture* 11.1, pp. 163–176. ISSN: 1879-4246. DOI: 10.1007/s13165-020-00339-7. (Visited on 02/15/2022).

DECLARATION

I hereby confirm that the PhD thesis entitled "Hybrid LCA-ABM of dairy farming systems including nonlinear optimization under environmental, technical and economic constraints" has been written independently and without any other sources than cited.

Luxembourg, March 2023

Alper Bayram