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Balancing Environmental Sustainability and Economic Viability in Luxembourgish Farms: An Agent-Based Model with Multi-Objective Optimization

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Abstract: To curb the impacts arising from the agricultural sector, the actions undertaken by policymakers, and ultimately by the farmers, are of paramount importance. However, finding the best strategy to reduce impacts, and especially assessing the effects of the interactions and mutual influence among farmers, is very difficult. To this aim, this paper shows an application of an agent-based model (ABM) coupled with life cycle assessment (LCA), which also includes multi-objective optimization of farming activities (including both crop cultivation and livestock breeding) from an economic and environmental perspective. The environmental impacts are assessed using the impact assessment scores calculated with the Environmental Footprint 3.0 life cycle impact assessment method and the study is conducted "from cradle to farm gate". The model is applied to all the farms in Luxembourg, whose network is built utilizing neighborhood interactions, through which a parameter known as farmer's *green consciousness* is updated at each time step. The optimization module is instantiated at the end of each time step, and decision variables (the number of livestock units and land allocation) are assigned based on profitability and specified environmental impact categories. If only profit optimization is considered (i.e., when farmers' green consciousness is de-activated), the results show a 9% reduction in the aggregated environmental impacts (obtained as the Environmental Footprint *single score*) and a 5.5% increase in overall profitability. At the farm level, simulations display a clear trade-off between environmental sustainability and financial stability, with a 25% reduction in overall emissions possible if farming activities are carried out using the *single score* impact in the objective function, though this results in an 8% reduction in profitability over 10 years.

Keywords: dairy farm management; agricultural modeling; multi-objective optimization; mathematical programming; life cycle assessment; common agricultural policy

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1. Introduction

The agriculture sector accounts for approximately 54% of total methane emissions and nearly 79% of total N_2O emissions in the EU [1], and at the global level, it is responsible for 16.5% of total greenhouse gas (GHG) emissions [2]. Moreover, agri-food systems are also responsible for the possible alteration of soil organic carbon, ecosystems functioning, biodiversity decline, and other relevant important regional impact categories, such as water and land use, acidification, eutrophication, and toxicity [3,4]. Therefore, it is a non-negligible sector to apply sustainability-oriented policies. However, it is important to underline that the implementation of sustainable practices by the farm holders may have impacts on the farm's economic viability. These impacts depend on several factors, such as farm size, typology (organic vs. traditional), techno-economic orientation, and geographical location (because of access to labor and materials, and their costs) and cannot be generalized [5–7].

Nevertheless, modeling efforts are required to capture new features arising from the interactions among the many actors engaged in agricultural production systems due to their complexity. In this respect, agent-based models (ABMs) allow the consideration of different actors and the exploration of their reciprocal interactions at the micro- (farmer's level) or macro-level (regional or national) [8]. The agents are autonomous entities that may be physical or virtual [9]. They follow a broad set of rules within an environment where learning and adaptation can also generate changes in other agents or the environment [10]. The applications of ABMs that can be fond in literature go beyond agri-food systems and cover most coupled human–natural systems (CHANS) [11], including socio-economic, techno-social, and environmental systems [12–20].

Because of their fitness to deal with complex systems, ABMs have been proposed in combination with environmental life cycle assessment (simply called LCA hereafter) to model the evolution of agricultural systems and at the same time assess their sustainability holistically, i.e., across all their phases [21]. This is motivated by the fact that LCA is a standardized methodology able to quantify impacts of a product or a service in its entire life cycle, in the three so-called areas of protection (AoPs)—resources, ecosystems, and human health [22].

A plethora of ABMs have been developed to model farming activities. The extensive review presented in [23] compares 20 different models that are applied to European case studies. The interesting perusal conducted in [24] of the ABM literature on agricultural policy evaluation from 2000 to 2016 detected a significant increase in the number of publications after 2008. Interestingly, they noticed that ABMs deal with farm interaction and the integration of spatial dimension reasonably well; however, there is a large margin for improvement to model interactions in a direct way and ground them on empirical data. In terms of model transparency, they found that most of the papers follow the ODD protocol [25], although the overall level of transparency could be further improved.

The literature, however, is clearly lacking the applications of models (and the presentation of related case studies) that integrate farm environmental sustainability assessment using the LCA methodology in conjunction with ABMs and multi-objective optimization (MOO), and where a farm's economic viability is also considered. We believe that the complexity and level of interaction of the many factors influencing farm business are such that the use of MOO is a necessary step to thoroughly explore farmers' operation space.

Therefore, in this work, we move in the direction of filling this gap enhancing the model presented in [26] by using mathematical programming (MP) to optimize the farm business, considering not only the economic dimension but also the environmental one, tackled from an LCA-based perspective, i.e., by encompassing the entire production and supply chain and not just the farm-based phase. The advantage of a life cycle–based approach is that it allows to identify possible hotspots, preventing the shifting of environmental burdens (i.e., the generation of environmental impacts and the consumption of natural resources) from the farm operation phase to other phases outside of the control of the farm manager [27].

2. State of the Art

Farming is a highly strategic endeavor that requires careful consideration of many factors, including careful utilization of water resources and management of the workforce, in addition to all the activities related to seeding, field operations, and strategic decisions thereafter [28,29]. MP is often used to solve complex decision-making problems using statistical, optimization, and other analytical approaches [30]. Techniques from this discipline, when coupled with LCA, may assist with realizing efficiency increases and impact reductions in agricultural and livestock production systems. The target functions of tactical models are often linked to an economic goal, such as lowering input costs or boosting farm profitability. Short-term (daily) questions and farm-scale planning are classified as operational decisions, which have attracted less attention than tactical ones. Crop management timing, farm input mix and amount, harvest timetable [31], and storage planning are all part of this. Some studies address strategic and tactical concerns from a modeling standpoint, such as [32], which evaluates the efficacy of various agricultural systems.

Ref. [33] is the most recently updated and comprehensive review about the application of operational research (OR) for environmental impacts minimization in agricultural crop and livestock production systems, which identifies current trends and limitations, and provides recommendations for different applications and contexts in this sector.

Since ref. [33] is quite recent, we did not repeat this endeavor, but nevertheless applied the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) method [34,35] in order to identify even the most recent papers in this field, and quantify the frequency of application of each approach in the scanned literature. The results of this exercise are presented in the Supporting Information (SI) Files S1 and S2.

Because of its simplicity of use and flexibility in dealing with multiple choice factors, in the survey carried out by [33], linear programming (LP) appeared as the prevalent technique used for optimization of environmental goals in crop–livestock production systems (13 of 27 studies analyzed). LP models have been applied to a broad spectrum of agricultural problems to maximize crop production while minimizing environmental impacts, including crop rotation, farm system design, financial choices, optimization of cropping strategies and resource use management between crop and livestock farms, resource allocation, and more [36].

Most environmental impact objective functions addressed in the literature were emission-based, focusing on GHGs mitigation [37]. Economic objective functions frequently aim to maximize the economic surplus that farms generate. The objective functions can be defined by several choice variables, varying from product to product. Land allocation, sowing time, crop protection agents and fertilizers, irrigation, and management and resource factors (such as seed, water, fertilizer, crop protection, energy input levels, yield, and so on) are some examples.

However, the use of MP models has been criticized for being too limited in scope when constructing objective functions such as land use, irrigation, or agricultural technology, as well as for including just a few selected stakeholders in the modeling process [38]. Therefore, because of their ability to optimize a wide variety of factors simultaneously, evolutionary algorithms, like genetic algorithms (GAs), have been successfully applied in the context of MOO [39]. The approaches that GAs take to solving problems can be categorized as either *elitist* or *non-elitist*. To solve MOO problems without favoring any solution over the others, one can use elitist solution-finding approaches like the Non-dominated Sorting Genetic Algorithm (NSGA) [40]. Non-elitist methods, on the other hand, allow for the potential dominance of solutions over one another [41].

GAs are search algorithms based on the ideas of natural selection and evolutionary processes. They 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 various goals in crop–livestock research, from increasing farm revenues to enhancing livestock and crop productivity to lessening the adverse environmental effects [42,43].

On the other hand, most GA-based research only considers economic constraints, although some research has also considered environmental ones [28,44]. The benefits of GAs include their conceptual clarity, adaptability, suitability for MOO, and use of stochastic optimization.

The NSGA-III evolutionary algorithm [45], which is the approach followed in this paper, is one of the most popular approaches to resolving MOO problems, and it has found use in fields as diverse as engineering, finance, and bioinformatics.

3. Materials and Methods

The model simulates the activities of 1872 farms in Luxembourg, including livestock (dairy and meat production) and crop farming activities and integrating a mathematical optimization of each farm at every time step based on economic and environmental objectives and constraints. As explained in [21,46], data about the farms were collected using national statistics and questionnaires and were complemented with first-hand data supplied by a small sample of nine pilot farms (see File S4) for a consistency check, as well as with qualitative and quantitative information supplied by local experts.

The environmental impact assessment of farmers' decisions is carried out using the Environmental Footprint (EF) 3.0 method [47].

The model is based on the same ABM and LCA coupling methodology used in [21], where it is described in a detailed way, also including a description provided using the Overview, Design concepts, Details (ODD) protocol.

The objective function that each agent uses to optimize its operations includes EF impact scores on one or multiple impact categories, which are normalized and weighted, using the normalization and weighting factors listed in Table S1 of the S4 File, to calculate a *single score* value.

The time step used in our simulations is 1 month, and the simulation covers the span of 10 years. This time step was chosen because crop rotation changes occur at different moments of the year, and a 1-month time step allows to follow more precisely harvesting and planting decisions for each crop. Furthermore, decisions that impact the structure of the herd (for example, culling decisions) are made by the farmer monthly rather than on an annual basis. Finally, crop, milk, and meat prices all have seasonal patterns that may impact farmer decisions. Crop fertilizer requirements can be met in a variety of ways. The first alternative is to use either solid or liquid animal manure produced in the farm. The second option is to purchase inorganic fertilizers at a set price during the experiment. Dairy farms, which account for most farms in Luxembourg, use animal manure first and then purchase inorganic fertilizer if the crop requires further fertilization. Farmers who are members of a biogas cooperative may use the digestate from the biogas facility as a third alternative. However, due to a lack of precise farm-specific data, the model provided in this research does not incorporate biogas-producing operations. The costs included in the model are divided into two categories: fixed and variable. Fixed costs are those primarily determined by the size of the farm, such as material costs, fixed capital consumption, cost of labor, and energy costs, which are not taken into consideration in the optimization owing to a lack of accurate data. Variable expenses, on the other hand, are those that vary according to the number of animals and the cultivated area, such as fertilizers, animal feed, plant seeds, and veterinary charges.

The animals in our model are represented individually, which means that their phenotypical traits (body weight, gender, age, etc.) are allocated to each cattle head separately. Body weight estimate is needed to calculate an animal's energy requirements. We proceeded in two stages. First, we used the body weight (BW) mid-infrared–based calculation developed for dairy cows by [48] on the Walloon milk spectral database managed by the Walloon Breeding Association. This database contained 713,428 records (45,488 cows and 222 herds) collected from 2006 to 2020. The predicted body weight was then modeled using Equation (1), where the independent variables (weeks of breastfeeding and parity) were classified into five classes (first to fifth+ parity; i.e., we set to 5 every parity larger than 5). Based on parity and week of breastfeeding, this equation reflects the theoretical averaged calculation of expected BW. Table 1 shows the coefficients of the equation utilized to perform the BW simulation.

$$BW(\text{kg}) = \text{y}_{\text{intercept}} + w_1 n_{parity} + w_2 WOL + w_3 WOL^2 + w_4 WOL^3 + w_5 WOL^4 + w_6 WOL^5 \quad (1)$$

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

Table 1. The coefficients for Equation (1) that is used to calculate the body weight of dairy animals.

	$\mathbf{Y_{intercept}}$	$\mathbf{w_1}$	$\mathbf{w_2}$	$\mathbf{w_3}$	$\mathbf{w_4}$	$\mathbf{w_5}$	$\mathbf{w_6}$
Mean	539.344995	37.1976496	−8.204927	0.98199403	−0.0470851	0.00102944	−0.00000831
St. Dev.	0.32182335	0.0275649	0.130811	0.01723356	0.00095285	0.00002321	0.000000205

Multi-Objective Optimization Problem (MOOP) Formulation

In the S3 File, the definition of mathematical optimization, a generic explanation of linear programming, the weighted sum method, and details of how the NSGA-III algorithm works can be found. In this section, we will introduce the problem formulation, i.e., the objectives and constraints of the MOOP.

The NSGA III method was used to implement the MOO in this work. We employed the multi-objective evolutionary algorithm (MOEA) framework [49], an open-source Java library that supports multiple evolutionary algorithms, including NSGA III. This choice was considered suitable for our case, because our agent-based simulator is written in Java [50]. The probabilities of crossover [51] and mutation [52] were set to 0.9 and 0.1, respectively. The algorithm's convergence is dependent on the population size (N). This latter can affect the efficiency of evolution, preventing iteration from stopping at local optima. A population of 100 individuals can be attained in a reasonable processing time, and increasing the size has little effect on the answers.

The ideal values for various decisions, such as the number of animals to keep in the farm at each iteration, or cropland allocation to different crops, are established by solving the objective functions. The optimization module is run in the post-market phase, i.e., when the revenues for the sales of the farm produce have been already calculated. Table 2 lists the variables used in the optimization problem.

The goal of the model is to reduce the environmental impact while maximizing profit from crops, milk, and dairy products at the farm level. Crop production profit is computed as the difference between revenue and variable costs of cropping operations

$$f_{c,t} = \sum_{c,t} p_{c,t} A_{c,t} - \sum_{c,t} vc_{c,t} A_{c,t} \tag{2}$$

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

$$P_{milk,t} = \sum_{a} P_{milk,a,t} \tag{3}$$

$$P_{meat,t} = \sum_{a} P_{meat,a,t} \tag{4}$$

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

$$f_{a,t} = \sum_{t} p_{milk,t} P_{milk,t} + \sum_{t} p_{meat,t} P_{meat,t} - \sum_{a,t} vc_{vet,\ a,t} - \sum_{a,t} vc_{feed,\ a,t} \tag{5}$$

The subsidy schemes explained in [26] are still in place. Therefore, they are part of a farm revenue stream. However, the amount of subsidy for compensatory allowance has recently been changed. Farmers receive 165 EUR/ha up to 90 ha and 90 EUR/ha above 90 ha:

$$f_{s,t} = \sum_{t} sub_t \tag{6}$$

Then we define the first objective function as

$$f_{p,t} = f_{a,t} + f_{c,t} + f_{s,t} \tag{7}$$

Table 2. Variables used in the optimization problem.

Indices and Sets		Units
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		
$UAA_{c,t}$	Utilized agricultural area (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
w_i	weight of the EF impact category i	—
n_i	normalization factor of the EF impact category i	—
$imp_{c,i}$	environmental impact of crop c in impact category i	—
$imp_{milk,i}$	environmental impact of milk in impact category i	—
$imp_{meat,i}$	environmental impact of meat in impact category i	—
Continuous variables		
$f_{c,t}$	profit from crop production at time t	EUR
$f_{a,t}$	profit from animal production at time t	EUR
$f_{s,t}$	revenue from subsidies at time t	EUR
$f_{p,t}$	total profit of a farm at time t	EUR
$f_{i,t}$	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	EUR/ha
$vc_{c,t}$	variable cost of production of crop c sold at time t	EUR/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	EUR/kg
$y_{milk,t}$	total yield of milk at time t	kg
$p_{meat,t}$	price of meat sold at time t	EUR/kg
$y_{meat,t}$	total yield of meat at time t	kg
$vc_{feed,t}$	variable cost of feeding at time t	EUR
$vc_{vet,t}$	variable cost of veterinary at time t	EUR
$P_{milk,t}$	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	current month of the simulation	—
m_p	number of months to be considered for rolling sum profit	—
$f_{p,roll}$	m_p-month rolling sum of farm profit.	EUR
NE_{roll}	12-month rolling sum of nitrogen excretion	kg
NE_t	nitrogen excretion at the current time t	kg
sub_t	total subsidies received by the farmer at time t	EUR
M_t	transition matrix for fields at time t	—

The environmental impacts are calculated using the impact scores of crops and animal production activities. As mentioned above, the EF 3.0 LCIA method was used to formulate the optimization problem. The objective function may include more than one impact category. Its expression for one category can be written as follows:

$$f_{i,t} = \sum_{t,i} y_{milk,t} imp_{milk,i} + \sum_{t,i} y_{meat,t} imp_{meat,i} + \sum_{t,i} A_{c,t} imp_{c,i} \tag{8}$$

The EF *single score* impact of a farm (f_{EF}) was calculated using the weights in Table S1 of the S4 File as

$$f_{EF,t} = \sum_{t,i} \frac{f_{i,t}}{n_i} w_i \tag{9}$$

Each farm is assigned a certain number of fields, or unitary agricultural areas (UAAs; where a UAA is defined as the smallest georeferenced land object registered in the agriculture cadaster). During the simulations, the extension and boundaries of a farm or the geometry of fields are not modified (because fields cannot be sold or split). As a result, the size of a farm is always equal to or larger than the cultivated area

$$\sum_{c} A_{c,t} \leq A_f \forall t \tag{10}$$

By regulation, the pastureland total area cannot change and pastures cannot be turned into cropland

$$A_{pasture,t} = A_{pasture,\ t-1} \qquad \forall\ t \tag{11}$$

Crop harvesting and sowing are subjected to several constraints. Transitioning from one agricultural plantation to another is only possible during the harvesting and sowing seasons of the related crops. Furthermore, a farm's crop rotation scheme must be respected. Farmers can pick crops with lesser environmental impacts if the value of their green consciousness (GC) parameter is greater than the threshold that was set (0.5 in all tests in this study). If not, they select the most lucrative option while keeping the plantation calendar and crop rotation scheme limits in mind.

If M is the transition matrix (the matrix containing the probability of changing crops), then the transition from crop x to crop y can take place as

$$UAA_{C_y,t+1} = M_t^{x,y} UAA_{C_x,t} \tag{12}$$

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. Equation (12) is also subject to the constraints

$$h_x - 1\ \leq \mathrm{m} \leq h_x + 1 \tag{13}$$

$$s_y - 1\ \leq \mathrm{m} \leq s_y + 1 \tag{14}$$

Therefore, the harvesting and sowing seasons for current and following crop plantations are considered respectively in transitioning.

Dairy producers must choose which animals to cull and how many. If the culling decisions in our model are not controlled, two major issues may arise. First, while animals must always be culled owing to age constraints, farmers may desire to cull more animals to receive more subsidies or reduce adverse environmental effects. The other issue is the exact opposite of excessive culling. Farmers may wish to raise herd size to boost milk output and therefore optimize profit. As a result, the number of culled animals is limited by the number of births and farm class (Table 3).

As stated in Section 4.2, while selecting crops to plant, farmers assess the whole set of environmental impacts of each crop (estimated using the EF method). Furthermore, there is an annual hard limit for nitrogen emissions to soil [53], which may be represented as

$$NE_{roll} = \sum_{t}^{t-11} NE_t \leq \sum_{t}^{t-11} 170 \frac{\left(\mathrm{kg} - N_{org}\right)\ /\ \mathrm{ha}}{year} A_{pasture,t} \tag{21}$$

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

Table 3. The constraints on culling decisions (NL_{cull} = number of culled animals; $NL_{newborn}$ = number of newborn animals).

Farm Class	Culling Condition		Culling Decision
A,B,C,D	$NL_{newborn} - 1 \leq NL_{cull} \leq NL_{newborn} + 1$	(15)	NL_{cull}
	$NL_{cull} \leq NL_{newborn} - 1$	(16)	$NL_{newborn} - 1$
	$NL_{cull} \geq NL_{newborn} + 1$	(17)	$NL_{newborn} + 1$
E,F,G,H	$NL_{newborn} - 2 \leq NL_{cull} \leq NL_{newborn} + 2$	(18)	NL_{cull}
	$NL_{cull} \leq NL_{newborn} - 2$	(19)	$NL_{newborn} - 2$
	$NL_{cull} \geq NL_{newborn} + 2$	(20)	$NL_{newborn} + 2$

Since the 1980s, environmental targets have been an increasingly important component of the EU's Common Agricultural Policy (CAP). The EU's climate change strategy requires a shift in agricultural techniques to help reduce GHG emissions, increase energy efficiency, and preserve soil quality. In our simplified simulations, these policy objectives were addressed by direct subsidies to encourage environmental measures (Pillar 1 of CAP) and multi-year rural development regulations with climate change as one of the guiding considerations (Pillar 2 of CAP). It is important to note, however, that in order to obtain these subsidies, all farms must first meet the cross-compliance norms [54], as has been the case for all farms in Luxembourg in recent years.

To qualify for the subsidies, farmers must fulfill certain criteria, such as land allocation or nitrogen emissions from animals. Farms with more than three hectares of land ($A_f \geq 3$ ha) are eligible for the compensating allowance if they fulfill the cross-compliance conditions [54]. The greening subsidy, on the other hand, may be obtained only if the farm fits the standards outlined in Table 4.

Table 4. Criteria for greening subsidy.

Farm Area	Crop Diversity		Number of Crops on the Plantation	
$0 \leq A_f \leq 10$ ha	—		—	
$10 \text{ ha} \leq A_f \leq 30$ ha	$0 \leq A_{c=C_1,t} \leq 0.75 A_f$	(22)	$NC \geq 2$	(23)
	$A_{c=C_1,t} \geq A_{c=C_x,t}$	(24)		
$A_f \geq 30$ ha	$0 \leq A_{c_1,t} \leq 0.75 A_f$	(25)	$NC \geq 3$	(26)
	$0 \leq A_{c_1,t} + A_{c_2,t} \leq 0.95 A_f$	(27)		
	$A_{c=C_1,t} \geq A_{c=C_2,t} \geq A_{c=C_x,t}$	(28)		
	$C_1 \neq C_2$	(29)		

The specifications that were established for the subsidy program "Extensification of permanent grassland" may assist regulators and farmers in avoiding excessive nitrogen leakage into the soil. Using NE_{roll} in (21), we may define constraints in this scheme as shown in Table 5.

Table 5. Specifications to obtain extensification of the permanent grassland subsidy scheme.

Corresponding Stocking Rate (LSU/ha)	$NE_{roll}(\text{kg}-N_{org})$		Subsidy (EUR/ha)
1.2	$0 \leq NE_{roll} \leq \sum_{t}^{t-11} 130 \frac{\text{kg}N_{org} \ / \ \text{ha}}{year} A_{pasture,t}$	(30)	150
0.8	$0 \leq NE_{roll} \leq \sum_{t}^{t-11} 85 \frac{\text{kg}N_{org} \ / \ \text{ha}}{year} A_{pasture,t}$	(31)	200

Notwithstanding the objective of emissions reduction, the farmer's business must obviously remain always financially sustainable. Therefore, it makes sense to include a constraint that prevents non-profitable enterprises from operating throughout the simulation.

As a result, for each farm, the rolling sum of revenues over m_p months is computed with Equation (32):

$$f_{p,roll} = \sum_{t}^{t-m_p} f_{p,t} \tag{32}$$

If $f_{p,roll}$ is smaller than zero, the farmer optimizes the farm using just the first objective function (Equation (7)).

Three different cases were simulated as follows, which differed in the formulation of the objective function and constraints.

Case 1 (Maximize Profit): In this case, none of the environmental objectives or constraints are considered. In Section 3, the impact scores and farm earnings obtained in the other cases are compared to this case, which is used as a baseline scenario. The problem can be represented as a MOOP in which the goal is to maximize f_p subject while respecting the constraints described by Equations (10)–(32).

Case 2 (Maximize profit, minimize EF Climate Change): In this case, the EF method uses the GWP_{100} (Global Warming Potential over 100 years) indicator to calculate the impact of GHG emissions on global warming. The problem can be formulated as follows:

$$max\ f_p,\ min\ f_{EF_{climate\ change}}\ \ s.t.\ \ (10)–(32)$$

where $f_{EF_{climate\ change}}$ is the climate change impact score calculated with the EF method.

Case 3 (Maximize profit, minimize EF *single score*): In this case, the EF method relies on a set of weighting and normalization factors to express as a single impact score the life cycle environmental impacts calculated on different impact categories. To define the weighting criteria for each impact category, a stakeholder engagement approach is employed, in which experts and interested parties express their opinions on the relative importance of various environmental concerns. The weighting factors are expressed as percentages that total 100%. Normalization factors for each impact category are used to compare the environmental impacts to a reference value, which is the equivalent impact produced in the same impact category by a reference population (such as Europe's population in a certain year). The values in Table S1 of the S4 File are used to find the *single score* result, which is then applied in the optimization problem. In this case, the problem can be formalized as follows:

$$max\ f_p,\ min\ f_{EF_{single\ score}}\ \ s.t.\ \ (10)–(32)$$

where $min f_{EF_{singlescore}}$ is the *single score* impact calculated with the EF method.

4. Results and Discussion

Our research focuses on Luxembourg's total agricultural and pastureland area (i.e., the sum of all UAAs), as well as total milk and meat output. The simulations were run for 10 years, with 50 repeats every year. After applying the farm generation algorithm to the spatial data, each run assigns the same set of fields to the farms already recorded in the database [21].

The farmer network is created utilizing the neighborhood and risk aversion classes specified in [21], which affect the updated GC value of each farmer at each time step. The optimization module is instantiated at the end of each time step, and the decision variables (the number of animals and land allocation) are determined as described above.

We simulated numerous situations to examine the effects of improving farming activities based on various environmental indicators. While each instance includes the first objective (economic profitability), the second objective is either missing (baseline scenario) or takes into consideration the effects of one (Case 2) or many (Case 3) environmental impact categories. As already mentioned, the effects are quantified using the EF 3.0 LCIA method [47].

Figure 1 depicts the outcomes of the optimization-based model and the non-optimized scenario (in which the farm agents do not use mathematical optimization at every decision step) for Case 1.

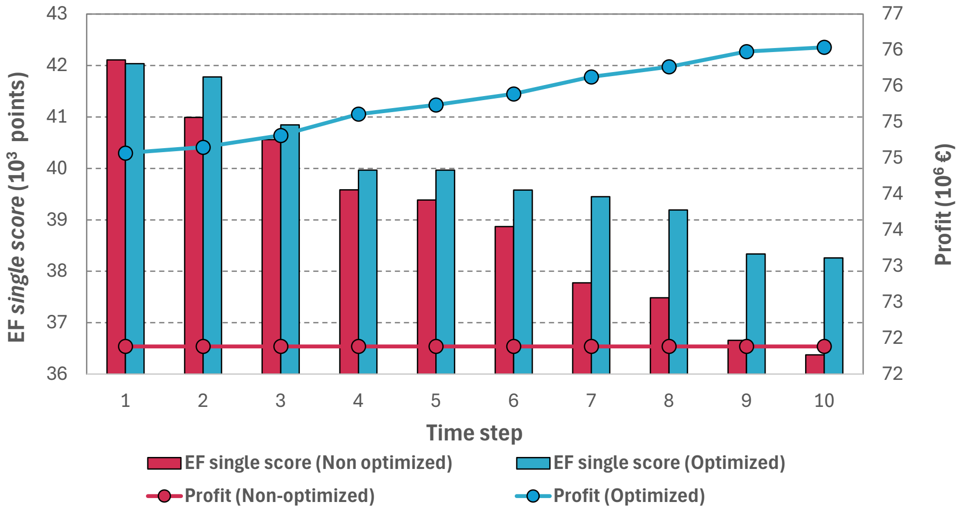


Figure 1. Comparison of the model with and without the farm mathematical optimization.

4.1. Country-Level Results

As shown in Figure 1, the *single score* impacts are already decreasing as a result of the subsidies in place and the livestock management rules that control the simulations. Although the EF *single score* impacts decreased in both optimized and non-optimized cases (approximately 9% and 13%, respectively, as shown in Figure 1), the stocking rate in the model with optimization does not decrease as much as in the case without optimization, owing to the fact that the number of livestock is a decision variable that has a significant impact on farm profitability (Figure 2). The crop selection is solely centered on profitability, and this results in a 5.5% improvement in total profitability in the optimized decisions compared to essentially no change in the non-optimized case (Figure 1).

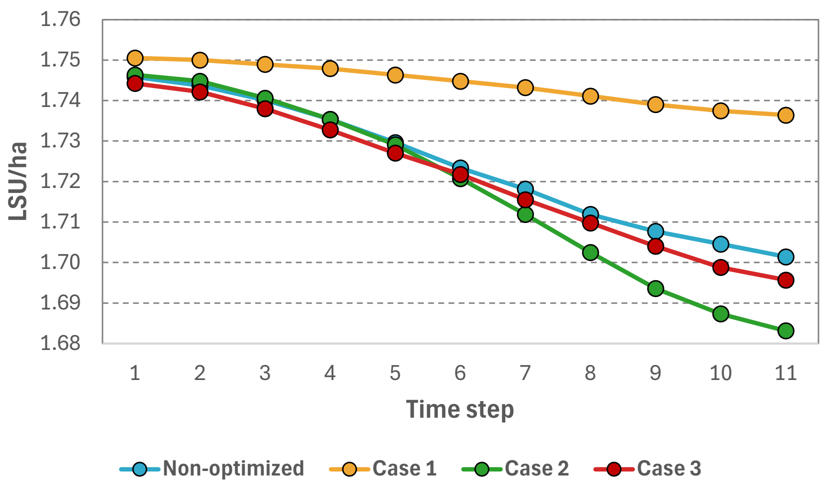


Figure 2. LSU/ha change for different cases.

Figure 3 shows a comparison of the EF *single scores* for each case. The aggregated impacts and profits at the country level reveal that there is an obvious trade-off between environmental sustainability and economic viability. Although a 25% reduction in total emissions is attainable if farming operations are affected by environmental concerns, this results in an 8% decrease in profitability over 10 years. As shown in Figure 2, the average stocking rate drops to 1.6 LSU/ha, but the subsidy "Extensification of permanent grassland" necessitates a far lower stocking rate. Most farms fall short of this target because the quantity of subsidies supplied is insufficient to allow farmers to make more culling decisions. Nonetheless, as seen in Figure 1, if mathematical optimization is used, a 9% decrease in the EF *single score* may still be achieved while increasing profit by 5.5%.

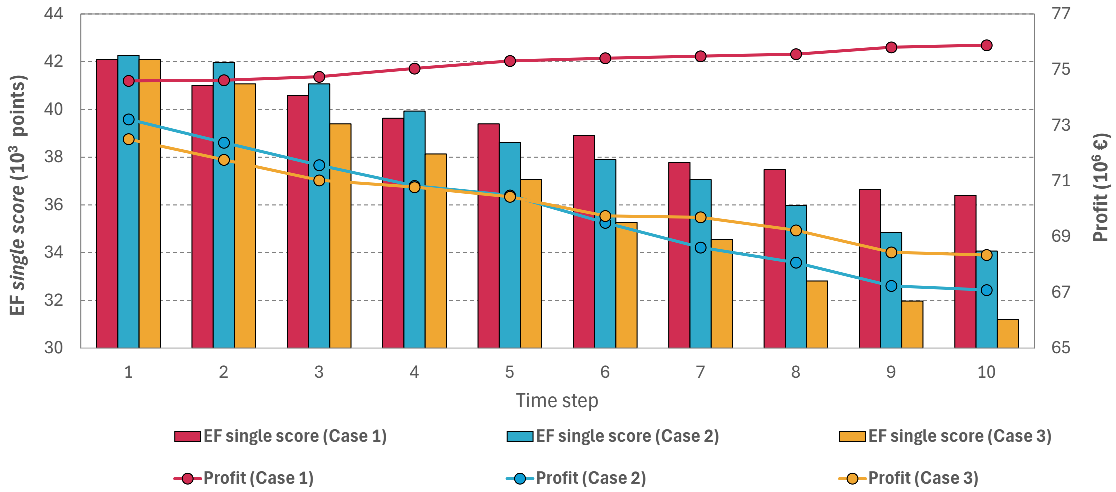


Figure 3. Comparison of EF *single scores* on a country level, based on each optimization case.

4.2. Farm-Level Results

Because agricultural activities, agent choices, and optimization occur at the farm level, it is natural to focus on farm-level results for the simulated scenarios. As a result, we used ground-truth data to initialize several farms. For example, we chose one of those farms whose parameters, such as location, size, and animal count, are known, and in this section, we will illustrate the outcomes of the simulations for this specific farm. The behavior of the other farms is fairly similar. Table 6 lists the farm's properties. Some characteristics, like GC and livestock count, adjust throughout the simulation. For those attributes, the initial, minimum, mean, and maximum values are reported. The GC, degree centrality of the farm in the network, and crop rotation scheme are allocated using a random distribution.

Table 6. Properties of the farm selected as an example. It is a dairy farm located around the center of the Grand Duchy of Luxembourg. Farm class and rotation scheme codes (which are successions of crop types) are explained in [21]. MLC = Maize-Leaf-Cereal rotation.

Attribute		Value
Farm class		G
Degree centrality		2
Green consciousness (GC)	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

To preserve the privacy of each farm's outer geographical boundaries while also preserving the inner boundaries (i.e., field boundaries) and relative sizes, a treemap representation of the UAAs was applied [21]. Figure 4 depicts the treemap representation of the chosen farm.

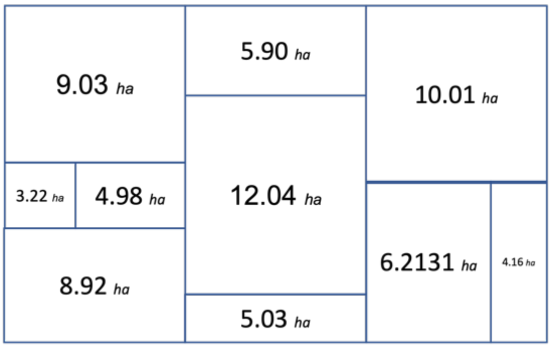


Figure 4. Treemap visualization of the chosen farm's UAAs. The sizes of the fields used in the simulator are shown in the map.

This representation is also used in Figures 5, 8 and 11, where, the treemaps depict the progress of agricultural plantations during 10 years of simulation from the top left (step 1) to the bottom right (step 10) corner, for Case 1, Case 2, and Case 3, respectively. To retain the geolocation of fields on the specified farm, the treemap representation shows the positions of the fields and crops. Observing these figures, one can identify which crops were prevalent on the fields, knowing that transitions from one crop to another in a specific UUA can occur at any time step, as long as crop rotation, seeding and harvesting months, and optimization objectives and constraints permit. Crop rotation constraints compel farmers to select only a few crops. As a result, the environmental impact and economic profitability of crop selections are the same in each case. However, in Case 1 (Figure 5), potatoes are chosen more frequently than other leaf (L) crops, owing to the greater market value of potatoes in comparison to other crops. Because of its significance as animal feed, maize is a crop that practically every farm cultivates and includes into its crop rotation strategy.

Figures 6, 9 and 12 depict the progression of the EF impact scores during the simulation steps for Case 1, Case 2, and Case 3, respectively. The other choice variable in the optimization problem, i.e., the quantity of cattle to be retained on the farm (*NL*), has the greatest influence on the environmental impact generated.

Figures 7, 10 and 13 (respectively for Case 1, Case 2, and Case 3) indicate the change in cattle heads at each time step when associated optimization targets are taken into account. They also show the associated earnings (in thousands of euros on the *x*-axis) and environmental impacts. The arrows reflect the advancement of the simulation steps and each point on the graph represents one year. Since Case 1 solely optimizes profit, farmers prefer to slaughter fewer animals, resulting in a 7% reduction in the EF *single score* (Figure 7). However, profits remain almost unchanged over the last 10 years. In Case 2, the optimization problem takes the EF Climate Change score into account, and a 19% decrease in climate change impact may be obtained (Figure 9), but this comes at a cost, because more culling choices are taken than in the baseline scenario. In this scenario, the *NL* has lowered by 15% after the environmental component was introduced to the objective function. Finally, when compared to Case 2, Case 3 shows a 12% fall in *NL* (Figure 12), which may be explained by the fact that livestock agricultural operations contribute significantly more to the EF Climate Change score than to the EF *single score*. Therefore, the culling decisions can be taken more easily in Case 2 than in Case 3.

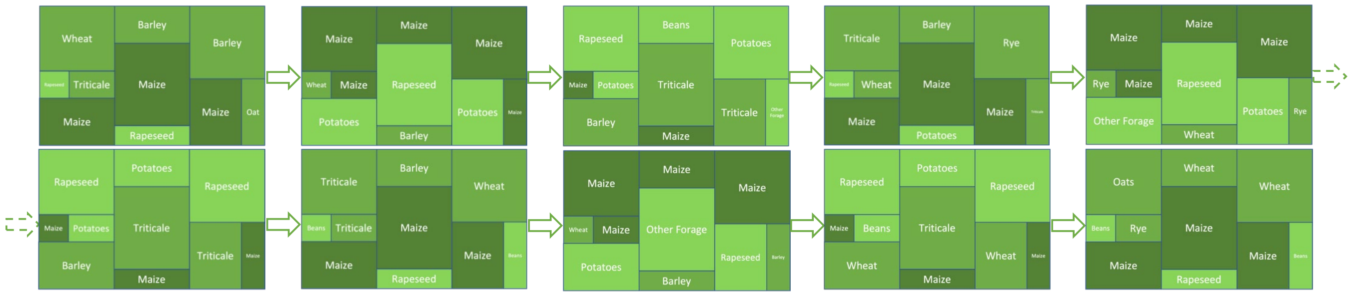


Figure 5. Crop rotations for a pilot farm with the scheme MLC (Case 1).

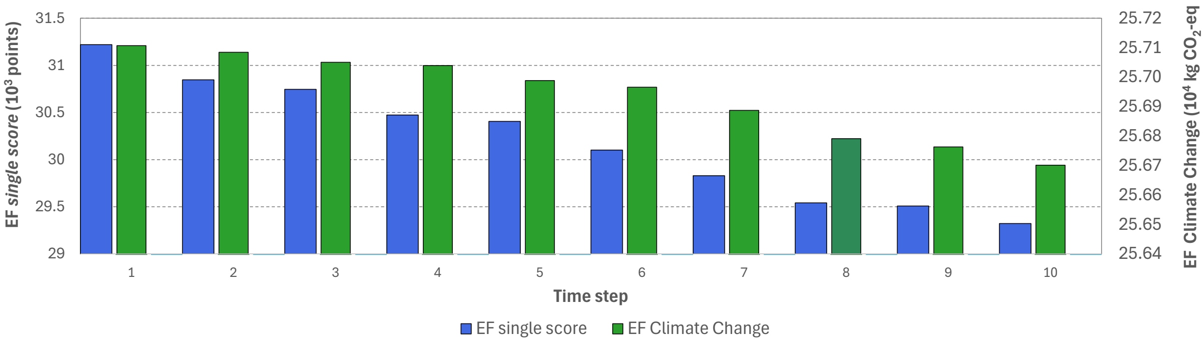


Figure 6. Evolution of the EF *single score* and EF Climate Change impacts for Case 1 along the simulation steps.

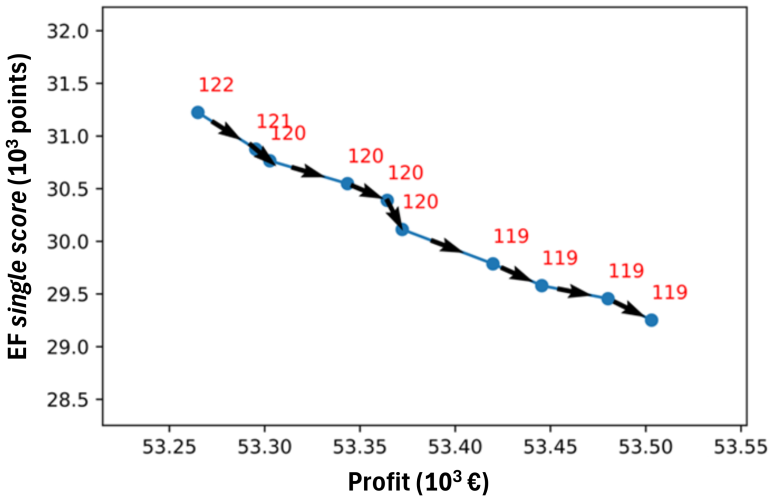


Figure 7. Change of number of livestock (in red), profit, and environmental impact expressed as the EF *single score*, in Case 1, for the selected farm.

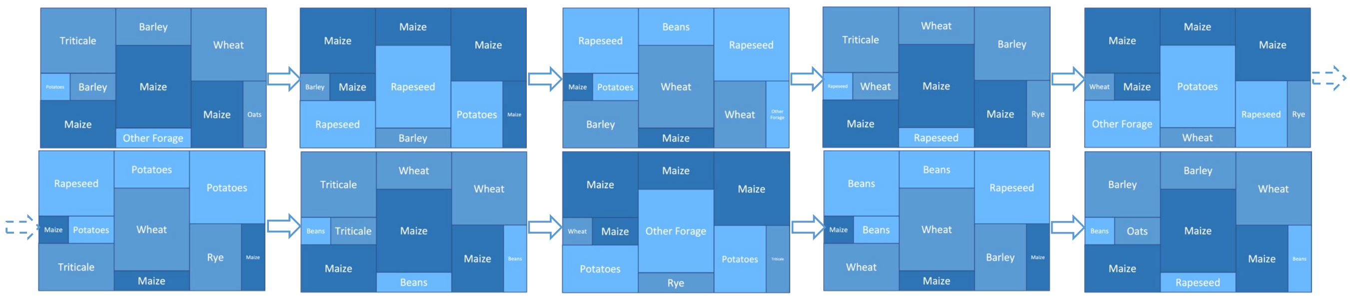


Figure 8. Crop rotations for a pilot farm with the scheme MLC (Case 2).

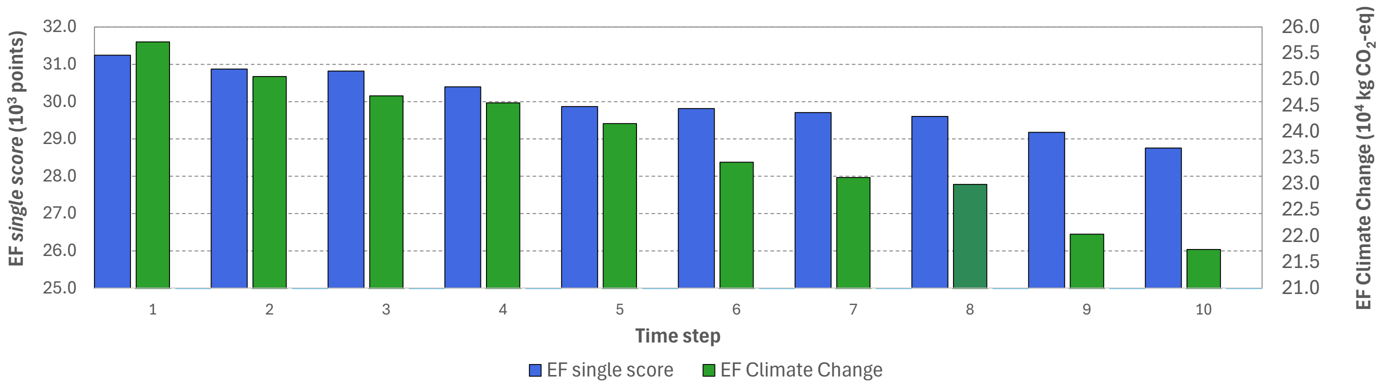


Figure 9. Evolution of the EF *single score* and EF Climate Change impacts for Case 2 along the simulation steps.

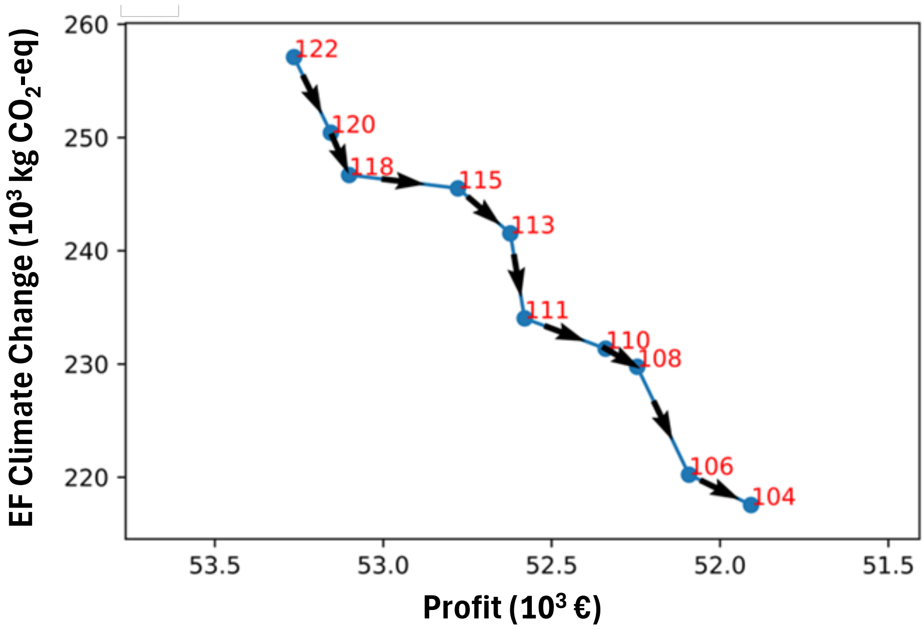


Figure 10. Change of the number of livestock (in red), and environmental impact expressed as the EF Climate Change score, in Case 2, for the selected farm. Note: the *x*-axis is reversed.

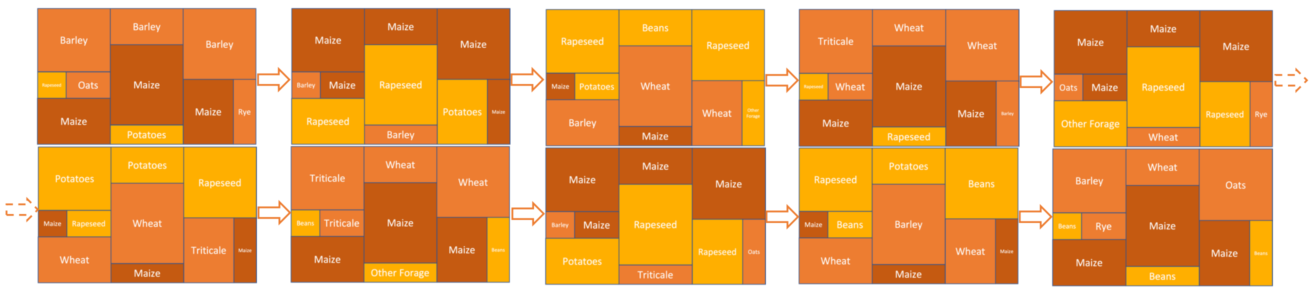


Figure 11. Crop rotations for a pilot farm with the scheme MLC (Case 3).

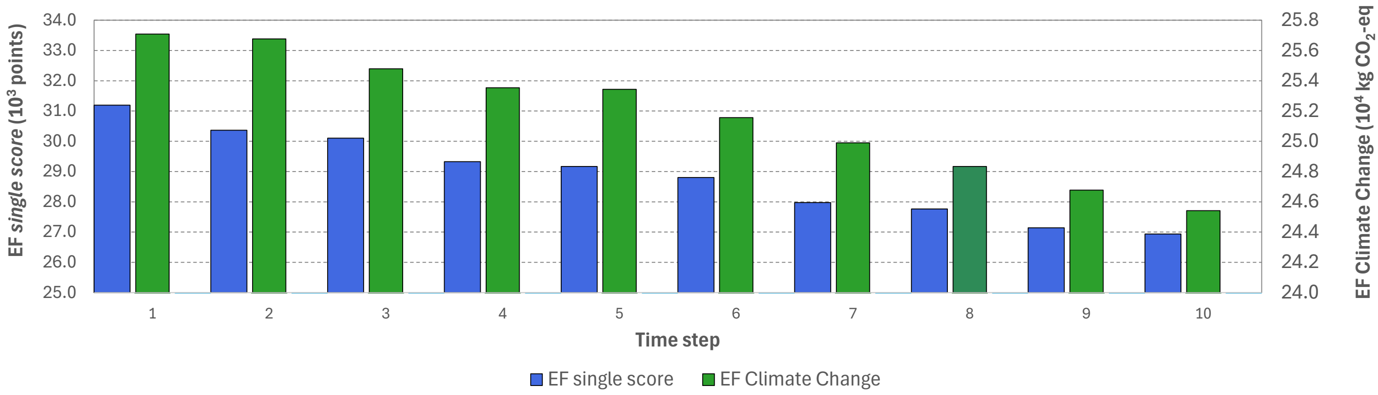


Figure 12. Evolution of the EF *single score* and EF Climate Change impacts for Case 3 along the simulation steps.

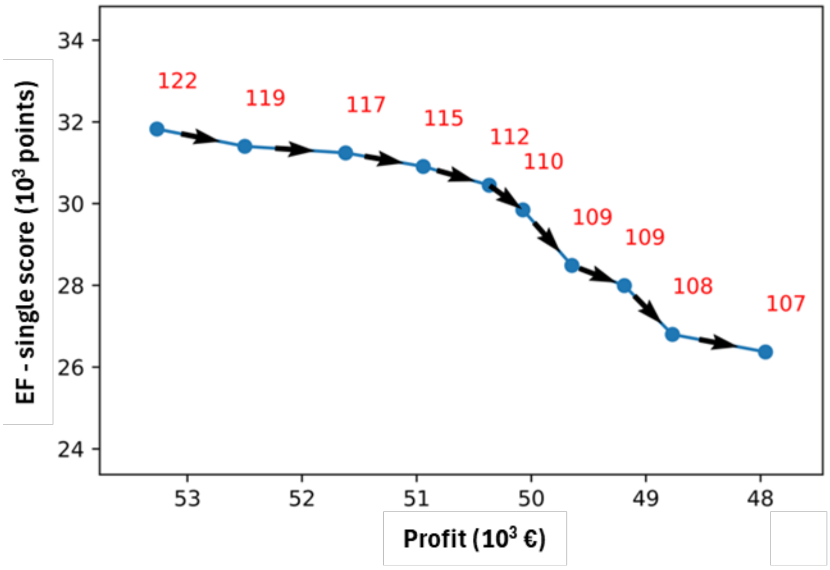


Figure 13. Change of number of livestock (in red), and environmental impact expressed as the EF *single score*, in Case 3, for the selected farm. Note: the *x*-axis is reversed.

4.3. Uncertainty Analysis

The results of the model are obviously impacted by the uncertainty associated with the multiple assumptions made in the study. These assumptions include model parameters, price forecasts, agent interaction rules, and life cycle inventory (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 [55], 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).

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 in [56].

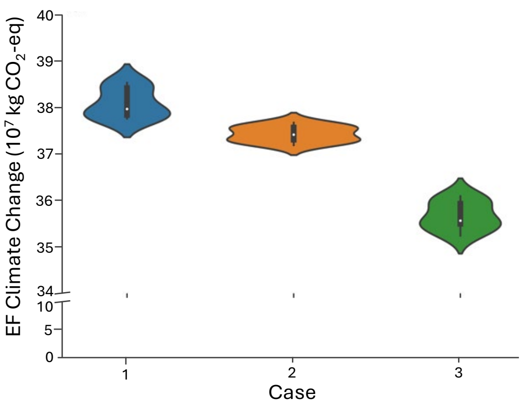
We executed a set of simulations (n = 50) and determined the coefficient of variations of the respective LCIA impact categories to propagate the uncertainty. The parameters are set to their nominal values, and the systemic variability caused by the underlying model (i.e., random variables) is determined. Figure 14a,b use violin plots to show the density distribution of the values obtained from over 50 simulations for the two impact categories. Table 7 shows the values of the main descriptive statistics for the LCIA results of the average of 10 years of the 50 simulation runs, for each of the three simulated cases.

Table 7. Main descriptive statistics for the average of 10 years over 50 simulation runs for each of the three simulated cases.

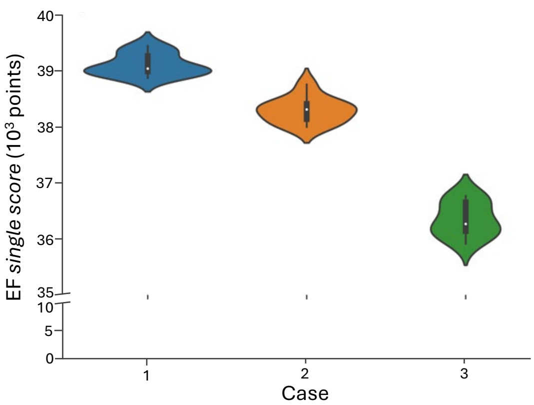
	EF Climate Change (10^7)			EF Single Score (10^3)		
Case	1	2	3	1	2	3
Minimum	37.76	37.18	35.53	38.71	37.97	36.25
Mean	37.95	37.53	35.78	39.01	38.39	36.43
Maximum	38.65	37.82	36.22	39.47	38.54	36.89
Standard Deviation	0.29	0.25	0.27	0.26	0.26	0.23
CV	0.76%	0.67%	0.75%	0.67%	0.68%	0.63%

From Figure 14a,b, one can also observe that the objective optimized has the lowest coefficient of variation in terms of uncertainty. Furthermore, it can also be seen that optimizing by the EF *single score* indicator always brings the system to the lowest levels of emissions. In fact, as also shown in Table 7, 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).

The coefficients of variations (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.



(**a**) *EF Climate Change*



(**b**) *EF Single Score*

Figure 14. Violin plots of the results of two impact categories obtained over 50 simulations for the three simulated cases.

In addition to the variation on the results induced by the elements mentioned above, another limitation can be identified in the use of the *single score* indicator. In fact, it has the advantage of considering multiple impact assessment indicators instead of just the Climate Change one, but it has been recognized as incapable of realistically represent stakeholders' perspectives, since it is based on a simple linear weighted sum, which cannot account for the effect of weighting schemes [57]. In [57], the distance-based multiple attribute decision-making method TOPSIS, which takes into account the weighting schemes and types of indicators, was proposed to calculate the *single scores*. The method is a substantial modification of the one readily available with the current LCIA methodologies and requires the consultation of a large number of respondents (experts) for alternatives ranking. Therefore, its implementation in the context of this study was impractical.

5. Conclusions and Recommendations

This paper describes a coupled ABM-LCA model for agricultural livestock operations that includes MOO under economic and environmental constraints. The potential of different modeling strategies to decrease the environmental impacts of farms' practices was assessed based on several environmental impact indicators.

The comparison between a baseline scenario (which is represented by a version of the model without mathematical optimization and containing only decisions aiming solely to maximize profit) with the scenario that is obtained using the version of the model that includes mathematical optimization, showed that the optimized scenario exhibits a 5.5% rise in revenue, while the non-optimized one has no change in profit over 10 years.

Afterwards, different cases were explored with respect to the formulation of the objective function. In Case 1, the optimization model just examines agricultural profitability, with no environmental goals in mind. Cases 2 and 3 additionally include an environmental goal in the decision function to minimize. The results of the simulations in the model configurations described in the paper show that the inclusion of environmental objectives in the decision function by those farmers who are "green conscious" enough to make decisions to lessen the environmental impact of their activity force them to a decrease in the stocking rates of their farm. One of the conclusions and recommendations of this study is that the reduction in the stocking rate is certainly one way to reduce the environmental pressures generated by farms, although there is a trade-off with economic viability for the farmer (about 8% loss over 10 years in our Case 3 in exchange for an overall 25% reduction in environmental impacts).

However, reducing the stocking rate is only one of the possibilities that the farmers have to reduce the environmental impacts of their farm. There is a plethora of strategies (and combinations of them) that can be adopted [58] to approach as much as possible a sustainability status that is able to ensure food security, nutritional sufficiency, safety, and the economic stability of these conditions [59]. In addition, in modern agriculture, the role of smart and precision farming to maximize profit and minimize environmental impacts cannot be disregarded [60], although it goes beyond the scope of this article [58].

Although a very large number of cases could be virtually explored, combining slightly different farm management strategies with different formulations of the decisions function (e.g., choosing still different indicators to express environmental impacts), the study already highlights the general utility and efficacy of farm optimization as well as demonstrating the compromise between environmental and economic objectives. Obviously, the picture about the economic implications of farmers' management strategies is complete only if one also looks at other sources of income that the farmers may use to back up their financial stability, such as institutional economic incentives and income support for non-mandatory actions that may compensate for their economic losses.

However, on this last point, we need to spend a word of caution, since, as it was observed by [61], if on one hand there is evidence that farmers prefer voluntary over mandatory measures (especially if mandatory instruments are overly complex or inflexible), on the other hand, crowding out (and only to a lesser extent also crowding in) has been observed when economic incentives are used to encourage the voluntary instruments [62]. Therefore, from a policy perspective, a sensible equilibrium should be found between requesting compliance with mandatory environmental regulations and decreasing unconditional income support. In their accurate analysis, ref. [61] pointed out that, from an economic standpoint, the unilateral adoption of mandatory compliance with more stringent environmental regulations without monetary compensation "can hamper the competitiveness of agriculture and may also lead to dissatisfaction and protest on the side of the farmers". Voluntary instruments, on the other hand, may strengthen farmers' motivation to safeguard the environment (i.e., their green awareness) through education more than obligatory instruments [63]. Concerning this last point though, the short survey presented in the S4 File, which was distributed to a small number of pilot farms (not statistically significant), shows that some farmers in Luxembourg have the perception that they are already carrying out enough efforts to protect the environment (and therefore implicitly considering that no further effort should be requested from them), while others are not fully aware of the important impacts that agriculture and farming generate on the planet. Obviously, the sample is too small (0.5% of the farmers' population) to generalize any conclusion, but at least we can use it to confirm some of the considerations that can be very useful in the design of an agricultural ABM, such as the important role played by family members in the decision-taking process of the farmers, or the popularity of solar panel installations as complementary investment that combines economic return with environmental protection.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su16198536/s1, S1.xlsx: Literature search results; S2.docx: PRISMA flowchart; S3.docx: Mathematical optimization; S4.docx: Impact assessment indicators, Uncertainty and Survey. References [64–69] are citied in the Supplementary Materials.

Author Contributions: Conceptualization, A.B., A.M. and T.N.G.; methodology, A.B., A.M. and H.S.; software, A.B. and T.N.G.; validation, A.M., T.N.G. and H.S.; formal analysis, A.B. and A.M.; investigation, A.B. and A.M.; resources, A.M. and H.S.; data curation, A.B., A.M. and T.N.G.; writing—original draft preparation, A.B. and A.M.; writing—review and editing, A.B. and A.M.; visualization, A.B. and A.M.; supervision, A.M.; project administration, A.M. and H.S.; funding acquisition, A.M. and H.S. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Not applicable, because the study did not involve experiments on humans (other than the administration of a survey) or animals.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in the study are included in the article and its Supplementary Materials. Access to the primary data used in this research has been restricted by the data providers only to the researchers involved in the SIMBA project and therefore they cannot be shared. Further inquiries can be directed to the corresponding author.

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