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Article

Integrating Mathematical Optimization to Enhance Sustainability in a Crop and Dairy Production Agent-Based Model for Luxembourg

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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 (EF) 3.0 life cycle impact assessment (LCIA) method and the study is conducted “from cradle to farm gate”. The model is applied to all the farms in Luxembourg, whose network is constructed utilizing neighborhood interactions, through which a parameter known as farmer's green consciousness (GC) 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' GC is de-activated), the results show a 9% reduction in the aggregated environmental impacts (obtained as EF “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 using the EF single score impact in the objective function, though this results in an 8% reduction in profitability over ten years.

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

1. Introduction

The agriculture sector accounts for approximately 54% of total methane emissions in the EU and nearly 79% of total N₂O emissions [1], and at the global (world) level, it is responsible for 16.5% of total greenhouse gas (GHG) emissions [2], besides affecting several other environmental impact categories besides climate change. Therefore, it is a non-negligible sector to apply sustainability-oriented policies.

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 (ABM) 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) [3]. The

agents are autonomous entities that may be physical or virtual [4]. They follow a broad set of rules within an environment where learning and adaptation can also generate changes in other agents or the environment [5]. However, in the literature the applications of ABMs go beyond agrifood systems and cover most coupled human-natural systems (CHANS) [6], including socio-economic, techno-social and environmental systems [7–15].

Because of their fitness to deal with complex systems, ABM 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 [16]. 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 so-called areas of protection (AoP) resources, ecosystems and human health [17].

In this work, we enhance the model presented in [18] by using mathematical programming (MP) to optimize the farm business, considering not only the economic dimension but also the environmental one, tackled from a LCA-based perspective, i.e. by encompassing the entire production and supply chain and not just the farm-based phase. The advantage of a lifecycle-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 [19].

2. State of the Art

Farming is a highly strategic endeavor that requires careful consideration of many factors, including careful utilization of water resources, management of workforce, besides all the activities related to seeding, field operations, and strategic decisions thereafter [20,21]. MP is often used to solve complex decision-making problems using statistical, optimization, and other analytical approaches [22]. Techniques from this discipline, when coupled with LCA, may assist realize 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 [23], and storage planning are all part of this. Some studies address strategic and tactical concerns from a modelling standpoint, such as [24], which evaluates the efficacy of various agricultural systems. A plethora of ABMs have been developed to model farming activities. The extensive review by [25] compares 20 different models that are applied to European case studies. [26] perused the ABM literature on agricultural policy evaluation from 2000 to 2016 and 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 [27], although the overall level of transparency could be further improved.

[28] 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 [28] is quite recent, we did not repeat this endeavour, but nevertheless applied the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) method [29,30] 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 [28], linear programming (LP) appeared as the most prevalent technique used for optimization of environmental goals in crop-livestock production systems (13 of 27 studies analysed). 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 [31].

Most environmental impact objective functions addressed in the literature were emission-based, focusing on GHGs mitigation [32]. 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, 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 [33]. 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 multi objective optimization (MOO) [34]. 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) [35]. Non-elitist methods, on the other hand, allow for the potential dominance of solutions over one another [36]. 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 [37,38]. On the other hand, most GA-based research only considers economic constraints, although some research has also considered environmental ones [20,39]. The benefits of GAs include their conceptual clarity, adaptability, suitability for MOO, and use of stochastic optimization.

The NSGA-III evolutionary algorithm [40], 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

2. 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.

The environmental impact assessment of farmers' decisions is carried out using the Environmental Footprint (EF) 3.0 method [41].

In our model, 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 1 of the S4 file, to calculate a single score value.

The time step used in our simulations is one month, and the simulation covers the span of ten years. This time step was chosen because crop rotation changes occur at different moments of the year, and 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 farm-produced animal manure. 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 on 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. As a result, we proceeded in two stages. First, we used the body weight mid infrared based calculation provided by for dairy cows developed by [42] 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 (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.

$$BW(kg) = y_{intercept} + w_1n_{parity} + w_2WOL + w_3WOL^2 + w_4WOL^3 + w_5WOL^4 + w_6WOL^5 \quad (1)$$

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 (1) that is used to calculate the body weight of dairy animals.

	Y _{intercept}	W ₁	W ₂	W ₃	W ₄	W ₅	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

2.1. Multi-Objective Optimization Problem (MOOP) Formulation

In the S3 file, 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 MOOP.

The NSGA III method was used to implement the MOO in this work. We employed the multi objective evolutionary algorithm (MOEA) framework [43], 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 [44]. The probabilities of crossover [45] and mutation [46] 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 period of 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.

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 .	€
$f_{a,t}$	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 .	€
$VC_{vet,t}$	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 farm profit.	€
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 .	€
M_t	transition matrix for fields at time t .	—

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

$$f_{c,t} = \sum_{c,t} p_{c,t} A_{c,t} - \sum_{c,t} v_{c,t} A_{c,t} \quad (2)$$

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

$$P_{milk,t} = \sum_a P_{milk,a,t} \quad (3)$$

$$P_{meat,t} = \sum_a P_{meat,a,t} \quad (4)$$

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

$$f_{a,t} = \sum_t p_{milk,t} P_{milk,t} + \sum_t p_{meat,t} P_{meat,t} - \sum_{a,t} v_{c_{vet},a,t} - \sum_{a,t} v_{c_{feed},a,t} \quad (5)$$

The subsidy schemes explained in [18] are still in place. Therefore, they are part of a farm revenue stream. However, the amount of subsidy for compensatory allowance has been recently changed. Farmers get 165 €/ha up to 90 ha and 90 €/ha above 90 ha.

$$f_{s,t} = \sum_t sub_t \quad (6)$$

Then we define the first objective function as:

$$f_{p,t} = f_{a,t} + f_{c,t} + f_{s,t} \quad (7)$$

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:

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

The EF single score impact of a farm (f_{EF}) were calculated using the weights in Table 1 of the S4 file:

$$f_{EF,t} = \sum_{t,i} \frac{f_{i,t}}{n_i} w_i \quad (9)$$

Each farm is assigned a certain number of fields, or unitary agricultural areas (UAAs¹). 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:

$$\sum_c A_{c,t} \leq A_f \forall t \quad (10)$$

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

$$A_{pasture,t} = A_{pasture,t-1} \quad \forall t \quad (11)$$

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

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

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 (see **Table 6**) 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:

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

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. (12) is also subject to the constraints:

$$h_x - 1 \leq m \leq h_x + 1 \quad (13)$$

$$s_y - 1 \leq m \leq s_y + 1 \quad (14)$$

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).

Table 3. The constraints on culling decisions.

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)	$NL_{newborn} + 2$

As stated in Section **Error! Reference source not found.**, while selecting crop 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 [47], which may be represented as :

$$NE_{roll} = \sum_t^{t-11} NE_t \leq \sum_t^{t-11} 170 \frac{kg - N_{org} / ha}{year} A_{pasture,t} \quad (21)$$

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

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. 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 [48], 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 [48]. 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
$0 \leq A_f \leq 10\text{ ha}$	—	—
$10\text{ ha} \leq A_f \leq 30\text{ ha}$	$0 \leq A_c = c_{1,t} \leq 0.75A_f$ (22)	$NC \geq 2$ (23)
	$A_c = c_{1,t} \geq A_c = c_{x,t}$ (24)	
$A_f \geq 30\text{ ha}$	$0 \leq A_{c_1,t} \leq 0.75A_f$ (25)	$NC \geq 3$ (26)
	$0 \leq A_{c_1,t} + A_{c_2,t} \leq 0.95A_f$ (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 get extensification of permanent grassland subsidy scheme.

Corresponding stocking rate (LSU/ha)	NE _{roll} (kg – N _{org})	Subsidy (€ / ha)
1.2	$0 \leq NE_{roll} \leq \sum_{t=11}^t 130 \frac{kgN_{org} / ha}{year} A_{pasture,t}$ (30)	150
0.8	$0 \leq NE_{roll} \leq \sum_{t=11}^t 85 \frac{kgN_{org} / ha}{year} A_{pasture,t}$ (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 Eq. 32:

$$f_{p,roll} = \sum_t^{t-m_p} f_{p,t}$$

(30)

If it is smaller than zero, the farmer optimizes the farm using just the first objective function (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 taken into account. 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 Eqs. 10 to 32.

Case 2 (Maximize profit, minimize EF Climate Change): In this case the EF method uses the GWP₁₀₀ (Global Warming Potential over 100 years) indicator to calculate the impact of GHG emissions on global warming. The problem can be formulated as follows:

$$\max f_p, \min f_{EF_{climate\ change}} \quad s.t. \quad (10) - (30)$$

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 lifecycle 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 1 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 formalised as follows:

$$\max f_p, \min f_{EF_{single\ score}} \quad s.t. \quad (10) - (30)$$

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

3. 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 ten years, with fifty 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 [16].

The farmer network is created utilizing the neighborhood and risk aversion classes specified in [16], 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 [41].

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.

3.1. 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).

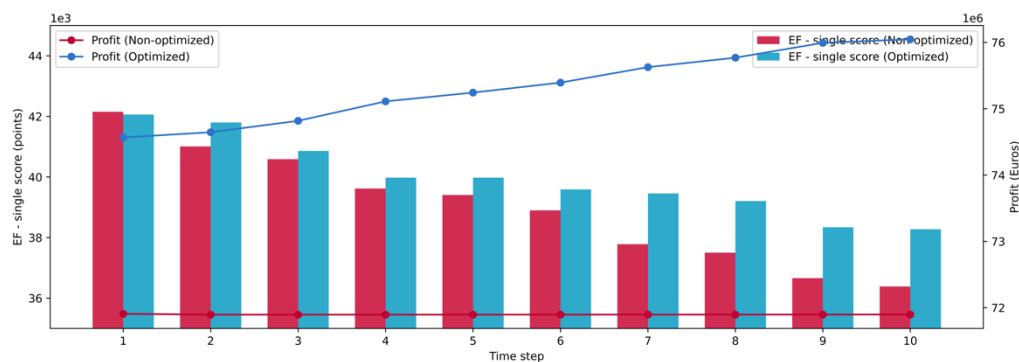


Figure 1. Comparison of the model with and without farm mathematical optimization.

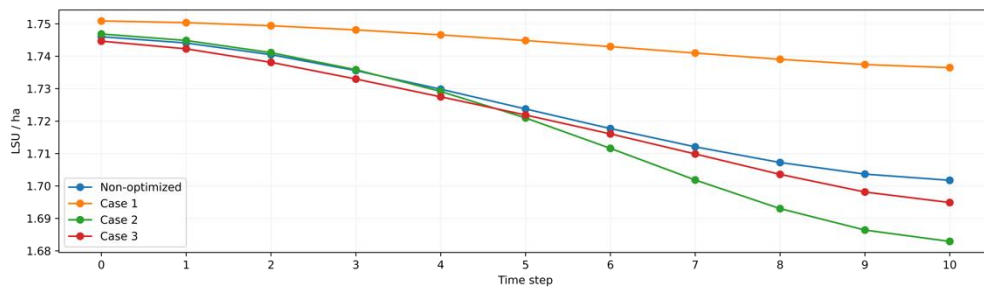


Figure 2. LSU / ha change for different cases.

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 and economic sustainability. 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 ten years. As shown in Figure 2, the average stocking density 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. Nevertheless, as shown, if a mathematical optimization is put in place, around 9% of EF single score reduction can still be achieved while making 5.5% more profit. Nonetheless, as seen in Figure 1, if mathematical optimization is used, a 9% decrease in EF single score may still be achieved while increasing profit by 5.5%.

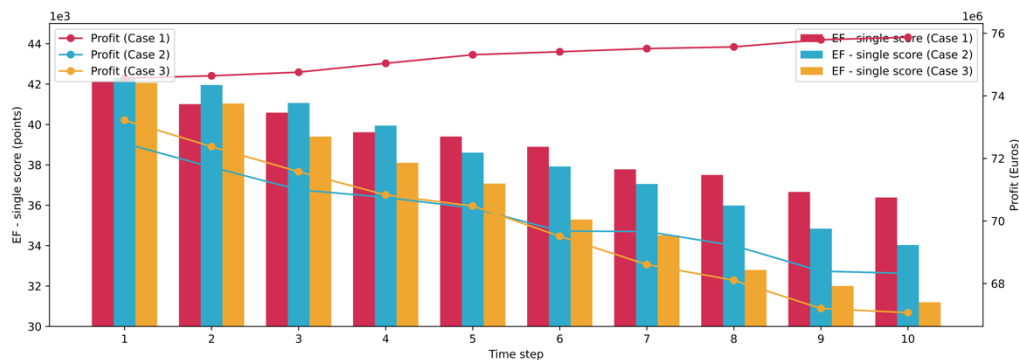


Figure 3. Comparison of EF single scores based on each optimization case.

3.2. 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 choose 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 other farms' behavior is fairly similar. **Table 6** lists the farm's properties. Some characteristics, like as 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 are explained in [18].

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 maintain the privacy of a farm's outer geographical boundaries while preserving the inner boundaries (i.e., field boundaries) and relative sizes, a treemap representation of the UAAs was applied (Marvuglia et al., 2022). **Figure 4** depicts the treemap representation of the chosen farm.

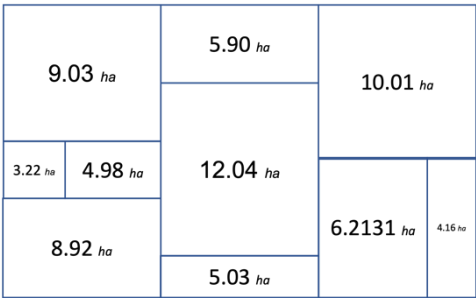


Figure 4. Treemap visualization of the chosen farm’s UAAs. The sizes of the fields used in the simulator are shown in the map.

This representation is also used in **Error! Reference source not found., Figure 8** and **Figure 11**, where, the treemaps depict the progress of agricultural plantations during ten years of simulation from the top left (step 1) to the bottom right (step 10) corner. 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 (**Error! Reference source not found.**), potatoes are chosen more frequently than other 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.

Figure 6, Figure 9, and Figure 12 depict the progression of the EF impact scores during the simulation steps for Cases 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.

Figure 7, Figure 10, and **Figure 13** (respectively for Cases 1, Case 2 and Case 3) indicate the change in cattle at each time step when associated optimization targets are taken into account. They also show the associated earnings (in k€ 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 merely optimizes profit, farmers prefer to slaughter fewer animals, resulting in a 7% reduction in EF single score (**Figure 7**). However, profits remain almost unchanged over the last ten 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, as 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.

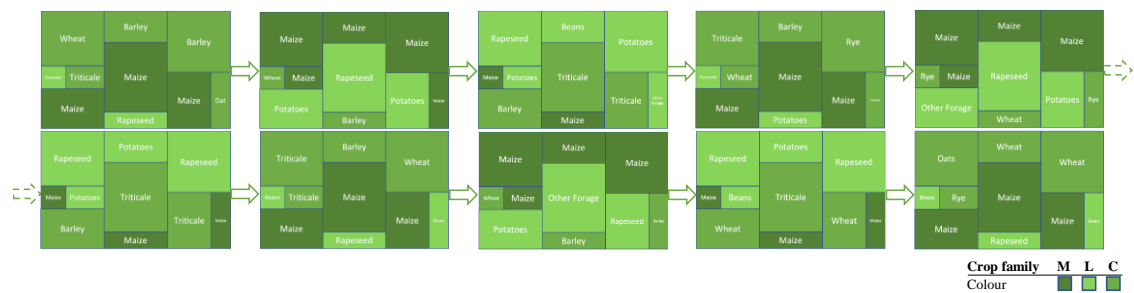


Figure 5. Crop rotations for a pilot farm with the scheme MLC (Case 1).

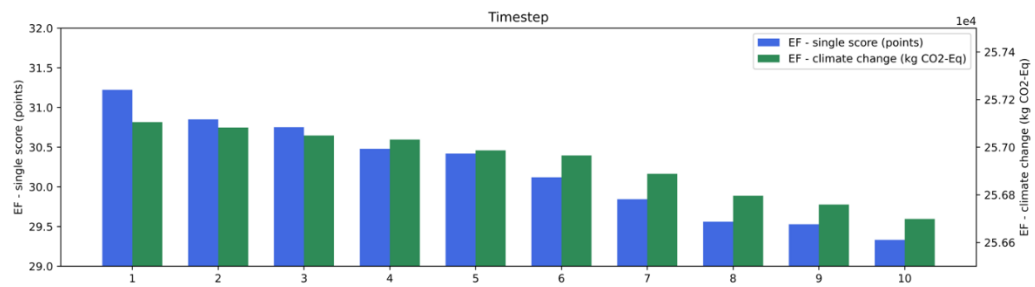


Figure 6. Evolution of single score and climate change impacts for Case 1 along the simulation steps.

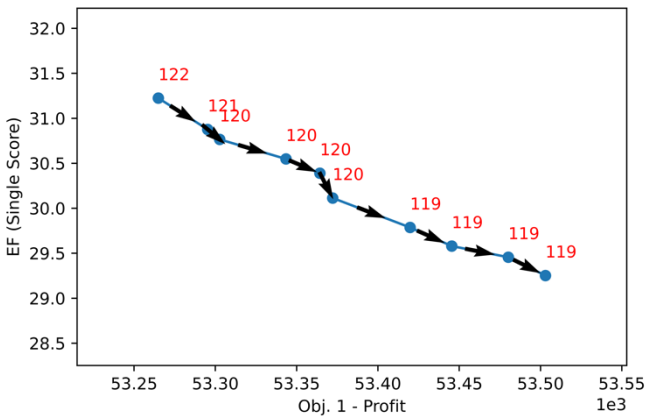


Figure 7. Change of number of livestock (in red), profit and environmental impact expressed as EF single score, in Case 1, for the selected farm.

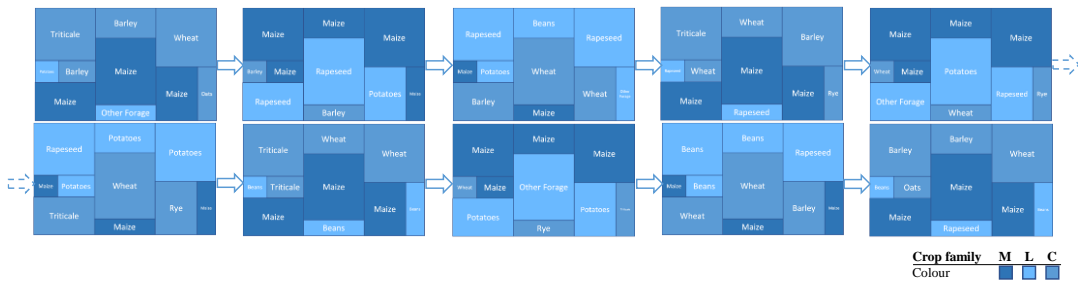


Figure 8. Crop rotations for a pilot farm with the scheme MLC (Case 2).

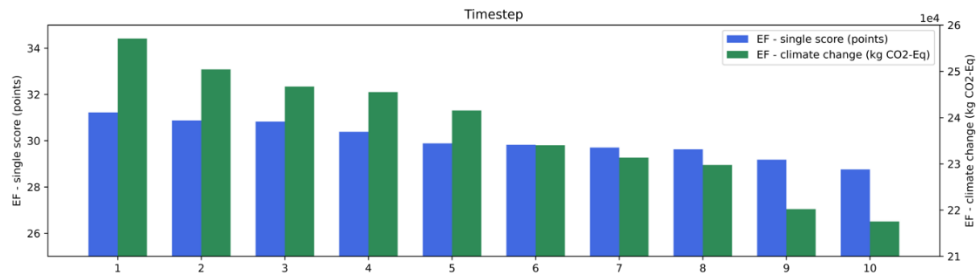


Figure 9. Evolution of single score and climate change impacts for Case 2 along the simulation steps.

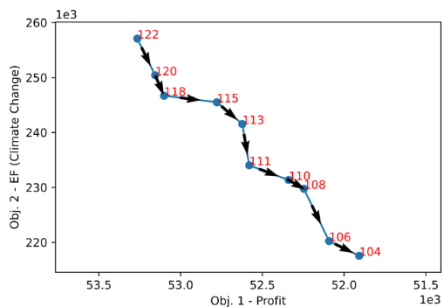


Figure 10. Change of number of livestock (in red), environmental impact expressed as EF Climate Change score, in Case 1, for the selected farm. Note: the x-axis is reversed.

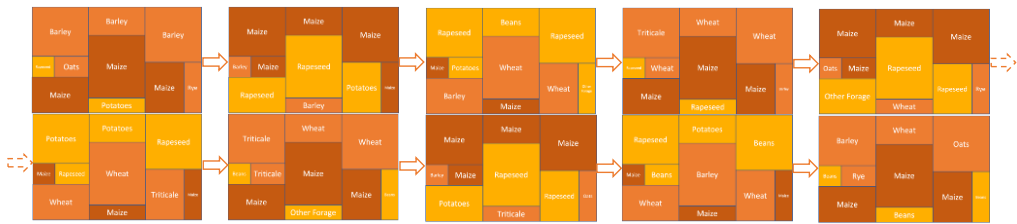


Figure 11. Crop rotations for a pilot farm with the scheme MLC (Case 3).

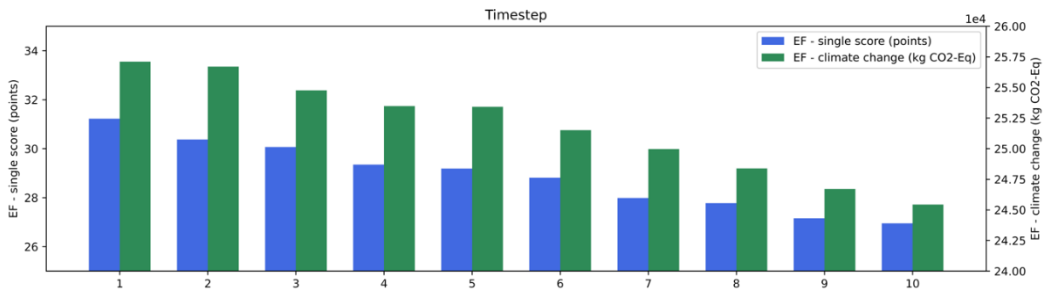


Figure 12. Evolution of single score and climate change impacts for Case 3 along the simulation steps.

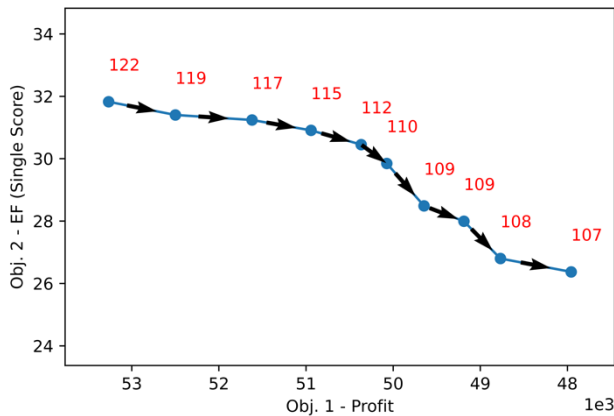


Figure 13. Change of number of livestock (in red), environmental impact expressed as EF single score, in Case 3, for the selected farm.

5. Conclusions

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

The article's main original contributions consist in:

- A unique multi-stage optimization model for efficient farm management that takes crop and livestock operations into account.
- An agricultural management system that optimizes decision-making based on subsidies to minimize environmental impacts.

To examine the impact of including optimization in our model, we first compared the baseline scenario's non-optimized instantiation (i.e. a version without mathematical optimization) to the optimized version. The baseline scenario only contains decisions dealing with financial actions in

optimized and non-optimized variants. We discovered that the version with optimization in place performs better in terms of profit generation, with a 5.5% rise in revenue whereas the prior version of our model showed no change in profit over 10 years.

After determining that the optimization model produces superior outcomes for the objectives under consideration, we concentrated on many scenarios that optimize decisions based on economic, environmental, or both objectives. 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 former minimizes EF climate change scores, whereas the latter targets EF single scores utilizing all 16 categories listed in the S4 file. Cases 2 and 3 suggest a greater fall in stocking rates (3.5% and 2.3%, respectively) than Case 1, which may be explained by the environmental effect of cattle production operations. These two scenarios take into account the environmental objective and farmers who are "green conscious" enough to make decisions to lessen the environmental impact of their activity.

Figure 7 and **Figure 10** demonstrate a pattern of decreasing stocking rate on the example farm mentioned in Section 0. In Cases 2 and 3, the number of livestock is reduced by 15% and 12%, respectively.

In conclusion, even though the cases we evaluated are by no means exhaustive, they highlight the general utility and efficacy of farm optimization as well as demonstrating the compromise between environmental and economic objectives. Maximizing profit mainly means keeping a higher stocking rate and relatively stable income (besides changes in market conditions, which are not considered in our simulations), but this does not allow to make emissions decrease. In fact, the results of our simulations show that, although reducing overall impacts by 25% is possible if an optimization model is put in place to steer farmers' decisions, this brings an inevitable reduction in economic profitability over ten years (about 8%) in Case 3. Obviously, this consideration holds true (besides the limits of the uncertainty that such a complex hybrid model bears, and which are discussed in the S4 file) without considering other complementary investments by the farmers or institutional economic incentives and income support for non-mandatory actions that may seem necessary to compensate for the economic losses.

However, on this last point we need to spend a word of caution, since, as it was observed by [49], 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 [50]. Therefore, from a policy perspective, a delicate equilibrium should be found between requesting compliance with mandatory environmental regulations and decreasing unconditional income support. In their accurate analysis, [49] point 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 [51]. 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 doing 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 the website of this paper posted on Preprints.org. S1.xlsx: Literature search results; S2.docx: PRISMA flowchart; S3.docx: Mathematical optimization; S4.docx: Impact assessment indicators, Uncertainty and Survey.

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