Integrating mathematical optimization to enhance sustainability in a crop and dairy production agent-based model for Luxembourg

Supporting Information 4: Impact assessment indicators, Uncertainty and Survey

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1. Environmental impact assessment (EIA)

The method used for the calculation of the impact assessment scores is Environmental Footprint (EF) 3.0, which was proposed by the European Commission[[1]](#footnote-1).

In this section, we focus on the normalisation and weighting steps, which are optional steps of Life Cycle Impact Assessment (LCIA). These steps, however, allow expressing results calculated in the different impact categories, using a common reference impact (e.g. the impact generated by the entire European population in a certain year, in the impact category at stake) and then aggregating the results into a single score, giving different weight to impacts. This supports the comparison between alternatives using reference numerical scores [1].

The methodological details and the inventory behind the global normalization factors for the EF 3.0 method are given in [2]. The list of normalization and weighting factors can be found at the URL: https://eplca.jrc.ec.europa.eu/permalink/Normalisation \_ Weighting \_Factors\_EF\_3.0.xlsx. For the sake of convenience, we report them also in Table S4.1.

**Table S4.1.** EF normalization factors and weights for each impact category that were used to calculate single score impact.

|  |  |  |  |
| --- | --- | --- | --- |
| **Category** | **Unit for the Normalization Factor** | **Normalization Factor** | **Weighting factor (%)** |
| Climate change | kg CO2 eq./person | 8.10E+03 | 21.06 |
| Ozone depletion | kg CFC-11 eq./person | 5.36E-02 | 6.31 |
| Ionising radiation | kBq U-235 eq./person | 4.22E+03 | 5.01 |
| Photochemical ozone formation | kg NMVOC\* eq./person | 4.06E+01 | 4.78 |
| Particulate matter | disease incidences/person | 5.95E-04 | 8.96 |
| Human toxicity, non‑cancer | CTUh/person | 2.30E-04 | 1.84 |
| Human toxicity, cancer | CTUh/person | 1.69E-05 | 2.13 |
| Acidification | mol H+ eq./person | 5.56E+01 | 6.20 |
| Eutrophication, freshwater | kg P eq./person | 1.61E+00 | 2.80 |
| Eutrophication, marine | kg N eq./person | 1.95E+01 | 2.96 |
| Eutrophication, terrestrial | mol N eq./person | 1.77E+02 | 3.71 |
| Ecotoxicity, freshwater | CTUe/person | 4.27E+04 | 1.92 |
| Land use | pt/person | 8.19E+05 | 7.94 |
| Water use | m3 water eq. of deprived water/person | 1.15E+04 | 8.51 |
| Resource use, fossils | MJ/person | 6.50E+04 | 8.32 |
| Resource use, minerals, and metals | kg Sb eq./person | 6.36E-02 | 7.55 |
| \*NMVOC= Non-Methane Volatile Organic Compounds | | | |

Some of the terms appearing in Table S4.1 are specific to the LCIA terminology, therefore we explain them in below:

* CTUh= Comparative Toxic Unit for human. It expresses the estimated increase in morbidity in the total human population per unit mass of a chemical emitted (cases per kg);
* CTUe= Comparative Toxic Unit for freshwater ecosystems. It provides an estimate of the potentially affected fraction of species (PAF) integrated over time and volume per unit mass of a chemical emitted;
* pt is a dimensionless, aggregated index, used by the EF method to quantify the impacts on land use. The symbol pt stands for "points" and it expresses the "soil quality index" developed in [3], which is based on the LANCA method [4, 5], which accounts for four soil biophysical properties: biotic production, erosion resistance, mechanical filtration, and groundwater replenishment.

The single score impact is then calculated as the weighted sum of the normalised impacts across all the impact categories:

Where is the single score indicator for the EF impact method; is the emission in the *i*-th impact category; and and are respectively the normalization and the weighting factor of the same category.

1. Uncertainty analysis

The results are impacted by the uncertainty associated with the multiple assumptions made in the study. These assumptions include model parameters, price forecasts, agent interaction rules, and LCI data uncertainty. The parameters associated with the livestock production system (such as the culling rate and the duration of each phase of a lactation period) were thoughtfully selected following consultation with stakeholders. However, in general, they vary from farmer to farmer. This justifies using an agent-‑based simulation to model the agricultural sector; however, it introduces uncertainty in areas lacking information. In [6], 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 [7].

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 S4.1a and Figure S4.1b use violin plots to show the density distribution of the values obtained over 50 simulations for the two impact categories. Table S4.2 shows the values of the main descriptive statistics for the LCIA results of the average of ten years of the 50 simulation runs, for each of the three simulated cases. From Figure S4.1a and Figure S4.1b one can also observe that the objective being optimized results in the least coefficient of variation in terms of uncertainty. Furthermore, it can also be seen that optimizing by EF single score indicator always brings the system to the lowest levels of emissions. In fact, as also shown in Table S4.2, even the maximum values reached in Case 3 (36.22 kg CO2-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 CO2-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 (CV) 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.

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(a) EF Climate Change

(b) EF Single Score

**Figure S4.1.** Violin plots of the results of two impact categories obtained over 50 simulations for the three simulated cases.

**Table S4.2.** Main descriptive statistics for the average of ten years over 50 simulation runs for each of the three simulated cases.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **EF Climate Change (107)** | | | **EF Single Score (103)** | | |
| ***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% |

1. Short survey highlights

Within the project SIMBA (Simulating economic and environmental impacts of dairy cattle management using Agent-Based Models), of which this paper is an output, a short survey was conducted among the nine pilot farms that were part of the projects. The sample size is not statistically significant to generalise to the entire set of Luxembourgish farms, therefore we present here only some highlights regarding a few strategic questions that can give at least an idea about the perception that farmers could have with respect to the role of their activities towards environmental issues or to the role of other actors in their decision-making progress. Five out of the nine farms (55.6%) were conventional and the rest (44.4%) organic. All the farms were dairy farms, of which 11.1% declared being extensive and 22.2% being intensive (the rest did not enter any classification).

The questions that we extracted from the survey are reported below, and the results are represented in the charts after each question:

1. **Which one of the following(s) do you think offers reliable information about farming?**
   * Commercial firms (selling feed, fertilizer, etc.)
   * Public institutions (administrations, ministries etc.)
   * Professional organizations (syndicates etc.)
   * Media (agriculture press)
   * Universities and research institutions
   * Extension services (cooperatives, research institutions, etc.)
   * Other farmers
   * Other (please specify)



1. **How would you score the role of following entities on your land use decision?**
   * Family members
   * Other farmers
   * Other friends
   * Counselling agency or cooperative
   * Association or Union



Interestingly enough, in this case one can notice the important role played by family members in the decision-making process of the interviewed farmers.

1. **Which of the following(s) do you have considered or would consider to install/adopt in your farm?**
   * Biogas plant
   * Solar panel
   * Geothermal system
   * Wind turbine
   * Animal feed that lowers methane emissions



1. **What is the obstacle(s) for taking the initiatives beneficial for the environment?**
   * Lack of time
   * Large investment
   * The production will be lower
   * Not have enough knowledge or information on the subject
   * Already made efforts for sustainable farming
   * Other (please specify)



In the case of Question 4, two of the farmers specified other obstacles, being them “each farmer” and “bureaucracy”.

Finally, to the further question “Do you think agriculture has a significant environmental impact on the environment?”, 70% of the interviewed farmers answered yes, and 30% answered no, testifying that the awareness about the role and importance of the agriculture and farming sector on the impacts generated on the environment is not fully diffused among the farmers.

**References**

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1. https://eplca.jrc.ec.europa.eu/EnvironmentalFootprint.html [↑](#footnote-ref-1)