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Coupling optimization with territorial LCA to support agricultural land-use planning

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ABSTRACT

The life cycle assessment framework was adapted to the territorial level (the "territorial LCA") to assess the environmental impacts and services of land-use planning scenarios. Given the various geographical conditions of the territory, the potential alternatives of land-use scenarios could be enormous. To prevent the iterative process of proposing and comparing alternative scenarios, this work aims to move one step further to automatically generate optimal planning scenarios by linking the novel territorial LCA with multi-objective optimization (MOO). A fuzzy optimization approach is adopted to deal with the trade-offs among objectives and to generate optimized scenarios, minimizing the environmental damages and maximizing the satisfaction level of the desired land-use functions subjected to constraints such as area availability and demand. Geographical Information System (GIS) is employed to manipulate geographic datasets for spatial assessment. An illustrative case study tests the novel integrated method (the territorial LCA, MOO, and GIS) on its ability to propose optimal land-use planning for bioenergy production in a region in Belgium. The study results reveal the competition of land uses for different energy products, the trade-offs among impact categories, and potential impacts on other territories if implementing optimal land planning for the territory under study. The optimization outcomes can help decision-making on the optimal locations for different crop types (i.e., miscanthus, willow, and maize in the case study) and utilizations (i.e., electricity, heat, biogas, and bioethanol in this study) complying with the objectives and constraints. This integrated tool holds the potential to assist policymakers when deciding on how to use the territory facing the global context of increasing demands for multiple uses of bio-based products, such as for food, feed, fuel, fiber, and chemicals. Limitations of the current method and its potential for real-world applications are discussed, such as expanding the scope to include life cycle sustainability assessment and taking farmers' behavior and crop rotation into account.

1. Introduction

In the global spirit toward bioeconomy, many countries and regions have committed to promoting bio-based products as an essential strategy to reduce greenhouse gas emissions (GHG) while safeguarding the regulating, supporting, provisioning, and cultural ecosystem services (Bryan et al., 2015). Meanwhile, researchers have observed increasing land-use competition in the food production (Tilman et al., 2009) and undesirable environmental issues due to direct and indirect land-use changes (dLUC, iLUC) (Sala et al., 2000). In this context, optimal land-use planning with a holistic perspective is needed in organizing agricultural activities to reach multiple objectives for sustainable development (Barral and Maceira, 2012).

To prevent significant adverse effects on the environment while reaching specific development objectives (e.g., to reduce energy-related GHG), the corresponding development plans (e.g., the provisioning of a significant part of the territorial energy mix with biomass) need to be carefully evaluated at the early stage in the decision-making process, as required by European directive on the strategic environmental assessment (SEA) (EU, 2001). Such plans can be defined at different scales and recent studies have put a particular emphasis on the territorial level (Sohn et al., 2018; Beaussier et al., 2019, 2022; Borghino et al., 2021). The territory is defined as a geographical area in which stakeholders are under the same local government, signifying the role of local

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stakeholders who can make strategic decisions tailored to that region's environmental constraints and potentials (Koponen and Le Net, 2021; Mazzi et al., 2017). This work focuses on agricultural territory, in which most land uses, or economic activities are based on agriculture, and the decision-makers need to balance multiple agricultural products and services and the environmental impacts (Nitschelm et al., 2016).

Among different assessment tools, Life Cycle Assessment (LCA) has been advocated to support land planning due to its ability to identify trade-offs across impact categories, life cycle stages, and different territories (Loiseau et al., 2012). Several studies aim to support land-use planning by combining with LCA to assess emissions from agricultural inputs (Li et al., 2021; Carauta et al., 2021), comparing impacts from alternative land-use choices (Solinas et al., 2019), and analyzing regional variances for producing energy (Nilsson et al., 2020). These studies first select one major function (e.g., biogas production) and compare different scenarios from a life-cycle environmental perspective. A territory (including agricultural territory) is a multifunctional system providing multiple environmental, social, and economic services (Borghino et al., 2021). In this direction, the "Territorial LCA" was proposed, which adapts LCA at the territorial scale to compare alternative land planning scenarios that provide multiple functions (Loiseau et al., 2013, 2014, 2018). The territorial LCA could be used to assess all production and consumption activities within the territory (Loiseau et al., 2013), or focus on one sector, e.g., agricultural territory that provides multiple products and services. For example, Nitschelm et al. (2016) developed the conceptual framework of the "spatialized territorial LCA" to assess the environmental impacts of an agricultural territory with a higher level of spatial accuracy. Borghino et al. (2021) and Rogy et al. (2022) compared alternative agricultural land planning scenarios with the territorial LCA framework. Beaussier et al. (2022) couple the territorial LCA with the economic model of the forest sector and compare the eco-efficiency of scenarios with or without a subsidy for wood energy consumption.

While comparing a baseline with proposed alternative scenarios is necessary to achieve final land planning proposals, this does not ensure that optimal scenarios are identified (Saner et al., 2014). The optimal plan could be hard to reach because the number of potential land-use configurations could be high, resulting from the spatial heterogeneity in the territory (e.g., soil type, climate zone) (Nitschelm et al., 2016), increasingly diversified land-use purposes (e.g., biofuel and fine chemicals), and constraints (e.g., land availability) (Budzinski et al., 2019). Furthermore, these land-use scenarios would present the trade-offs between different objectives, which poses a challenge to making decisions (Nilsson et al., 2020). Multi-objective optimization (MOO) could be used to overcome these challenges, which allows incorporating all planning variables and constraints into a mathematical model and offering the planners the land-use scenarios that are already optimized over multiple objectives.

Linking LCA with multi-objective optimization (MOO), first proposed by Azapagic and Clift (1999), has been applied in the environmental management of bio-based production systems, such as supply chain management (Miret et al., 2016), process optimization (Arora et al., 2017), and farm activity management (Capitanescu et al., 2017). We reviewed articles that use optimization for the agriculture sector based on LCA (Supplementary Information, SI-1, section 1), and presented the studies that determine which lands are the most suitable for which crops or uses (i.e., the optimal spatial distribution of land uses). In total, eight research articles were found, indicating that this field has been underexploited, which confirms the statement made by Almeida et al. (2016). In these works that focus on the optimal spatial distribution of land uses, Geographic Information System (GIS) is used to calculate spatially explicit LCA (Almeida et al., 2016; Kreidenweis et al., 2016; Galán-Martín et al., 2017; Nguyen et al., 2019), assess land suitability (Yuan et al., 2018), record water sources allocation (Marzban et al., 2022; Ren et al., 2022) and propose optimal facility locations (Almeida et al., 2016). However, these works mainly focus on the spatial allocation of single-use (e.g., bioethanol production), which should be extended to optimize land uses for multiple purposes as the land use competition intensifies (Miret et al., 2016; Yao et al., 2017).

This work aims to make a methodological advancement in linking territorial LCA with MOO and GIS, generating optimal agricultural land use scenarios at a territorial scale considering their spatial performances, multiple and potentially conflicting objectives, and territorial constraints. The paper proceeds by first describing the methods in general, followed by a proof-of-concept case study focusing on the functions of producing meat and various bioenergy products in the Walloon agricultural territory to illustrate the framework's capabilities. Limitations and potential utilizations are discussed.

2. Material and methods

2.1. The territorial life cycle optimization framework proposal

The proposed framework (Fig. 1) proceeds by first defining the goal and scope, followed by inventory and indicator assessment (i.e., environmental impacts and products and services), multi-objective optimization, and interpretation.

Defining the goal and scope sets the main features of an LCA study, including the research objectives and the system boundaries (e.g., from "cradle-to-gate") (ISO, 2006). In the proposed territorial life cycle optimization (TLCO) framework, the objectives (e.g., increasing biogas production by 10%) and planning variables (e.g., the potential locations for the new services or productions and the associated alternative crop types) are first defined in this step. Since the study is carried out to support informed decision-making processes in land planning, the functional unit (FU) is defined as the management of the territory for providing, usually, various agricultural products and services. Note that the provided products and services by the land uses within the territory are defined as the land use function (LUF) in correspondence with the territorial LCA approach (Loiseau et al., 2013). The geographically limited area of the agricultural territory under management acts as a constraint in the optimization model.

The inventory assessment stage calculates the spatially explicit inventory on a pre-defined spatial resolution for the unit processes of all the land use options specified in the goal and scope stage. The output of this step indicates the potential emissions and resources used if allocating different land uses at different locations. The unit processes describing land use for different purposes are spatialized based on spatially explicit simulation models and corresponding spatial data. For the process that does not change as a function of their location (e.g., emissions from producing 1 kg of fertilizers), the life cycle inventory (LCI) database could be used to extract their emission factors.

The indicator evaluation step assesses two categories of indicators, i.e., spatially explicit environmental impacts and products and services (i.e., LUFs), for the unit processes of all the land use options. The spatially explicit inventory would be translated to environmental impacts through the life cycle impact assessment (LCIA) method using characterization factors (CFs), representing the damage caused in that location. For the categories that are sensitive to local conditions, such as freshwater eutrophication and terrestrial acidification, using CFs with fine native spatial resolution could better represent the spatial variability of the impacts (Mutel et al., 2019; Pfister et al., 2020). Spatial variances could also be accounted for in LUFs evaluation.

At the step of MOO, the outputs of the spatialized environmental impacts and the LUFs for each alternative land use serve as input variables feeding into the optimization model, including objectives and constraints. The output of the TLCO framework is the optimal land-use scenarios, including biomass utilization strategies (which crop for which purpose?) and spatial allocations (which location for which crop?) under territorial objectives and constraints. In the final interpretation step, the optimal scenarios and their associated environmental impacts and LUFs are discussed, and suggestions are made.

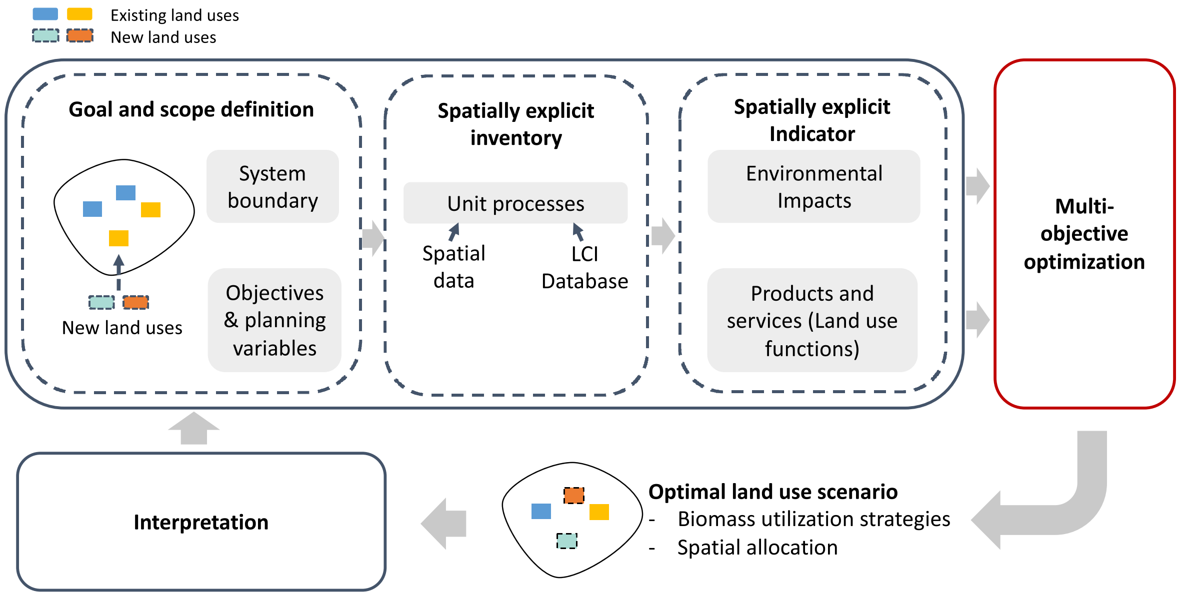

Fig. 1. The proposed territorial life cycle optimization framework (TLCO). LCI: life cycle inventory.

2.2. Case study

The case study is shaped along with the 2050 low-carbon scenario for Belgium (Cornet et al., 2013), which projects the transitioning scenarios for each sector to reach the promised GHG reduction target of 80–95% by 2050 relative to 1990. In the agriculture sector, the number of animals can be reduced by 43% in 2050 compared to 2010 as a result of reducing meat consumption to a healthy diet, which can lead to up to a 46% reduction in GHG emissions (Cornet et al., 2013). As animal production heavily relies on land use, including cropland and pasture (temporary and permanent) (Phelps and Kaplan, 2017), reducing the animal number (in head) would release part of the land occupied for animal and animal feed production. This released area could be utilized for energy crops to facilitate another low-carbon society goal, i.e., increase biomass for energy from indigenous production, reaching 30% more in 2050 in the most ambitious scenario (Cornet et al., 2013). Note that bioenergy could be generated from various biomass resources, including agriculture and forestry residues, organic wastes, surplus

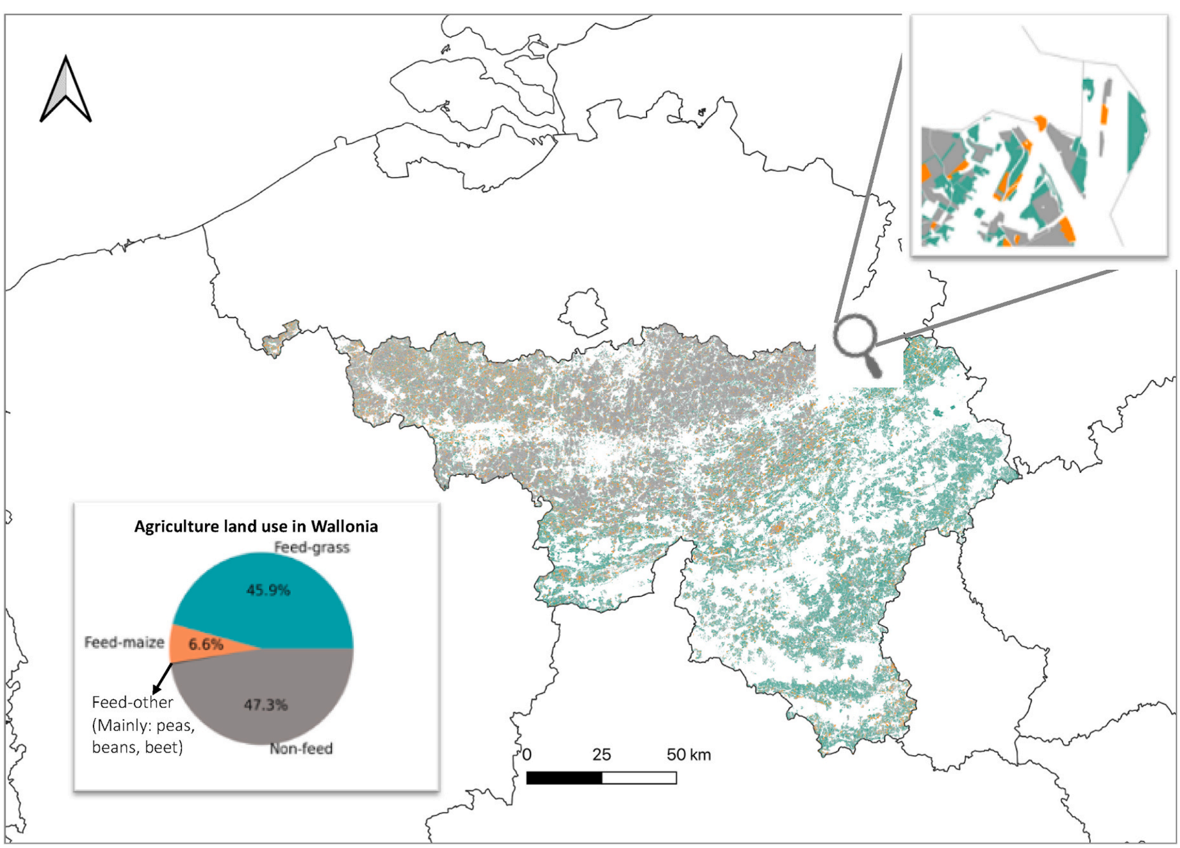

Fig. 2. Agricultural land use and proportion for animal feed in the Walloon region (South of Belgium).

forestry, and energy crops (Cornet et al., 2013). Resources such as organic waste are considered to be more sustainable as it entails fewer direct impacts on land compared to energy crops that are land-demanding (Beringer et al., 2011). However, energy crops such as miscanthus that are land-demanding constitute most of this bioenergy increase potential in Belgium, as identified by (Gauthier and Somer, 2013). Since the large-scale cultivation of bioenergy crops would reflect changes in environmental impacts and products and services, it is meaningful to develop a model that generates optimal scenarios to have the maximum satisfaction on the bioenergy demand and minimum environmental impacts, taking full account of objectives, constraints, and spatial variances.

In this context, the framework is implemented in the Wallonia administrative region (1690 Kha), where more than half of agricultural land is for animal production (Fig. 2). Walloon authority is responsible for setting the regional strategic plans to define territorial development objectives (such as agriculture, environment, and land uses) (Hanocq, 2011).

2.2.1. Goal and scope

The purpose of the study is to decide where to cultivate which crop and to which energy form to convert so that the environmental impacts are minimized while the satisfaction of the bioenergy target is maximized, respecting the meat demand in the study region. The case study aims to demonstrate the integrated model of TLCO to support land planning, which relies on several assumptions and simplicities as below.

We defined the available area from meat production for conversion as 191 Kha, which was calculated based on meat demand (i.e., animal head number) to maintain a healthy and balanced diet (Cornet et al., 2013) and average land area demand per animal head (Ding et al., 2021). This behavior change in meat consumption reduction could lead to an increase in consumption of, e.g., vegetables, which is not considered in this study. Similarly, any indirect effect from increased bioenergy through market mechanisms is not considered. Besides, it should be noted that plowing permanent grassland to cultivate annual crops is not allowed in Europe (Commission Delegated Regulation (EU), 2014). However, the assumed available area for conversion (191 Kha) includes cropland and both temporary and permanent grassland, given that the specific locations of the permanent grassland are not available. Crop rotation is not considered in this study.

The FU is defined as utilizing the potentially available area, i.e., 191 Kha, from animal land use for one year to satisfy the demand for animal and bioenergy. We evaluated climate change (CC) and freshwater eutrophication (FE) as two environmental indicators and bioenergy production, including electricity (E), heat (H), biogas (BG), and bioethanol (BE) as the functional indicators along with environmental impacts and associated with the FU. The selected potential bioenergy crops are miscanthus, willow, and maize according to their attractive environmental profile and cultivation experience in the Walloon region. The three conversion approaches (i.e., combustion, anaerobic digestion, and bioethanol refinery) and the bioenergy crop types (i.e., miscanthus, willow, and maize) exist in Wallonia. However, not all links could be observed, e.g., bioethanol production also exists in the region, but the feedstock is mainly from wheat.

Fig. 3 shows all the possible land use options with the three feedstocks and conversion techniques without considering the limitations on their industrial potential. The conversion pathways are used in the optimization model to analyze all the possibilities of feedstock selection and utilization. The study's system boundary for environmental impact assessment is "cradle to factory gate", including the farm cultivation, transportation, and conversion in the facilities to energy products. This case study does not include other steps, e.g., storage.

2.2.2. Inventory and indicator evaluation

The cultivation stage includes the processes associated with 1 ha of land being cultivated by a particular crop for one year (without

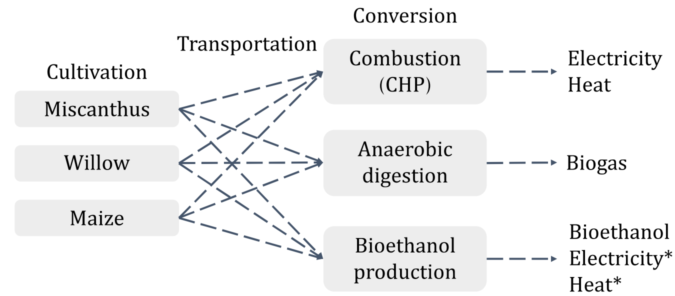

Fig. 3. Conversion pathways of producing bioenergy. *Co-products from residue.

considering crop rotation). Depending on the crop type, the specific operations are different, but all the operations ranging from field preparation to the harvested crops are included. They were extracted from crop cultivation inventory in the ecoinvent database (ecoinvent v3.5 cut-off, SI-1) with Brightway2, an open-source framework for advanced LCA calculations (Mutel, 2015), and Activity-browser (Steubing et al., 2019) which provide a graphical interface to Brightway2. The in- and off-territory processes for each pathway were differentiated manually, according to (Ding et al., 2020).

This study accounts for four location-dependent parameters: dLUC emissions, regionalized characterization factors (rCF) for FE, potential dry matter yield, and distance to the closest conversion facilities, which were aggregated at the municipal level (SI-1, section 2 equation 1). dLUC emission was calculated as the CO_2 released due to soil disturbance and removing current land cover for energy crop cultivation amortized for a rotation period of 20 years following IPCC guidelines (SI-1 section 2). The average transportation distance between the municipality to the conversion facility was calculated from the municipal center to the closest facility that can perform the corresponding conversion for each crop. The facilities are the real authorized plants, and their locations were extracted directly from (SPW., 2020) and converted to the coordinates through a python package of Geopy (2020). These plants' locations are displayed in the SI-1. The transportation distances were determined on a layer of the existing Belgium road network, retrieved and manipulated with a python package of OSMnx (Boeing, 2017). Converting 1 ha of feedstock into alternative energy forms was calculated based on the inventory of energy production data from the ecoinvent database (v3.5) and literature, combined with spatially-explicit biomass yield (SI-1).

The two environmental indicators, CC and FE, were calculated through the LCIA method of IMPACT World + at the midpoint (Bulle et al., 2019). The rCF for FE were imported with Brightway2 and clipped to the Walloon region to quantify different crops' spatial explicit FE impacts within the region. The impact on CC is not a regionalized impact indicator. Thus, we calculated its value with global default CFs provided by IMPACT World+. Site-generic CFs were used to quantify off-territory impacts on CC and FE. The main gases involved are CO_2, CH_4, and N_2O for CC, phosphate, and phosphorus for FE.

2.2.3. Multi-objective optimization

The MOO was designed to search for the optimal land-use allocation scenarios, including land-use (i.e., meat-related or bioenergy production from miscanthus, willow, or maize) and bioenergy products selection (i.e., heat, electricity, biogas, or bioethanol) so that the impacts on CC and FE are minimized while the satisfaction of the 2050 transition target is maximized.

This work uses a fuzzy programming approach, which was first proposed by Zimmermann (1978), to deal with trade-offs among different objectives. Compared to other widely-used MOO techniques, e.g., ε-constraint optimization searching a set of Pareto solutions (Mavrotas, 2009) and weighted sum approach (Marler and Arora, 2010), the fuzzy approach offers a computationally efficient and simple alternative to program optimization under uncertainty (Tan, 2005). Instead of crisp objectives and constraints, fuzzy optimization allows a certain level of tolerance deviating from aspirant value and converts the problem to maximize the satisfaction level of all objectives and constraints (Tan et al., 2008).

The fuzzy formulation of the case study is presented in SI-1 (section 3). The tolerance and aspirant values of each objective are defined in SI-1, which were calculated based on the upper bounds and lower bounds. The upper limits of CC and FE were set not to exceed the current impacts caused by feed production, which were based on our previous work (Ding et al., 2021). The energy production bounds were defined as 40% lower or higher than the energy production targets (the target for each energy form is defined as providing 30% of current bioenergy production according to Cornet et al. (2013). Note that these values can be defined by experts or stakeholders, in the same manner that LCA defines the weighting factors (ISO, 2006). Besides, this study defines the constraint of the maximum area that could be released from animal land use (i.e., 191 Kha) so that the rest of the animal land use could satisfy the meat demand in a healthy and balanced diet. The available area in each municipality is also limited to not exceed the land use area for livestock production in each municipality (data provided in SI-2).

3. Results

3.1. Indicator performance

The impacts (Fig. 4) and functional indicator (Fig. 5) score of each conversion pathway (Fig. 3) are presented first in this section, which were calculated as the average values over different municipals in the Walloon region. The results indicate that for biogas production, miscanthus is feasible since it has the lowest impacts on CC and FE (Fig. 4) and the highest biogas yield (Fig. 5). Using maize for bioethanol production shows advantages from both environmental and energy yield perspectives. Note that though CC impacts from maize cultivation are significantly higher than the others, the total value accounting for transportation and conversion (Fig. 4) is lower mainly due to its lower impacts from conversion. Detailed process contributions at the cultivation stage are presented in SI-1 (section 2). The feasible crop for electricity and heat production is miscanthus from the perspectives of lower CC impact and higher bioenergy yield, whereas willow is a better choice from the FE perspective. Such results indicate the conflicts in the choices of feedstocks.

The indicator scores of converting through CHP from alternative crops at the municipal level are presented in Fig. 6 (Performances of other conversion pathways are presented in SI-1 (section 2). The results indicate the conflicts in the choices of locations. Allocating crops in the northwestern part of the region shows better performance on CC than on the southeastern side. This spatial variation is mainly because the northwestern side has a higher occupation of the annual crops (Fig. 2). Substituting annual crops will generate less GHG emissions, thereby less CC impacts than substituting grassland, which has a higher occupation on the southeastern side. The miscanthus and willow have similar soil organic carbon as grassland (Holder et al., 2019), leading to even negative CC substituting annual crops at the municipal level (SI-1 section 2). In contrast, the northwestern side tends to cause a higher impact on FE due to the higher rCF provided by IMPACT World+. Regarding energy yield, strong spatial contrast can be observed among crop types. For example, the municipalities located on the northwestern side tend to have higher yields for miscanthus production but lower for willow production.

3.2. Multi-objective optimization

The objective values when optimizing single objectives and multiple objectives are presented in Table 1. We also present the optimal municipalities assigned to crop implementation and their conversion pathways in Fig. 7. The municipalities marked as “not assigned” will keep the current land use for feed to satisfy the meat demand. The detailed assigned area for each municipality is presented in SI-2.

In single-objective optimization, this illustrative example shows an extreme case when no energy production target is set. The results show that there are trade-offs among bioenergy production and environmental impacts. Minimizing FE impacts (both in- and off-territory impacts) would allocate no bioenergy production while maximizing energy production would allocate miscanthus, willow, or maize for different conversions (Table 1, Fig. 7). Besides, minimizing CC (both in- and off-territory impacts) would cause a 2 ton PO_4 P-limeq impact on FE, which is higher than the optimal status (0 kton PO_4 P-limeq) if the objective is to minimize FE.

The values in the brackets are the outcomes of the single objective model when the objective is set to only minimize in-territory impacts on CC without taking the off-territory performance into account. These values in brackets are higher than the outcomes when both in- and off-territory performance are considered. This is because the model tends to assign all the municipalities with a negative score on in-territory CC impacts with energy crops, which causes total impacts higher when adding off-territory impacts. The distinction of whether taking off-territory performance into optimization highlights the pollution transfers between territories.

Fuzzy linear programming results provide a compromised solution for the six objectives, with objective function values lying between the optimum and the worst status, satisfying more than 71% of the objectives. The optimal allocation map from the fuzzy optimization model

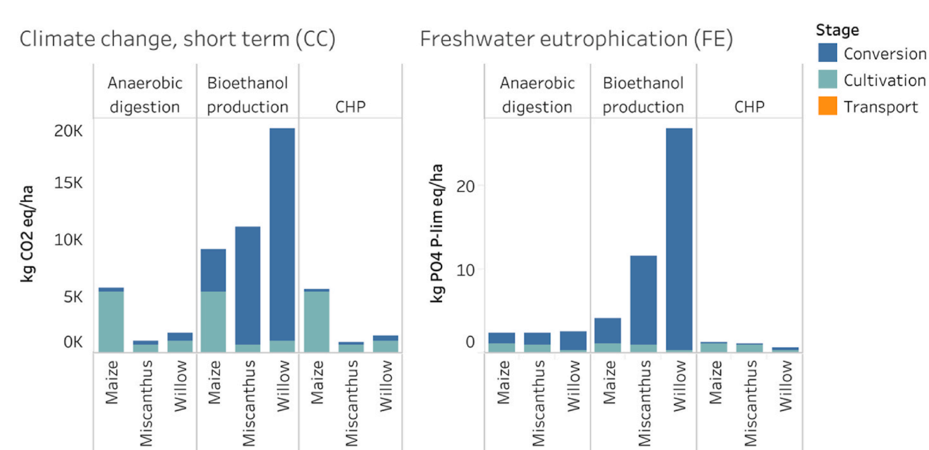

Fig. 4. Contribution of different life cycle stages to the impacts on climate change and freshwater eutrophication (CHP: combined heat and power).

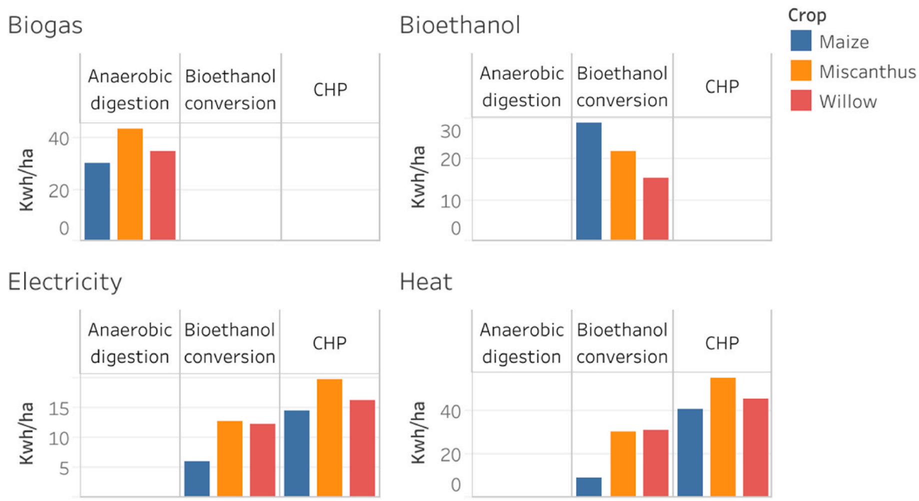

Fig. 5. Bioenergy yield of each conversion pathway (CHP: combined heat and power).

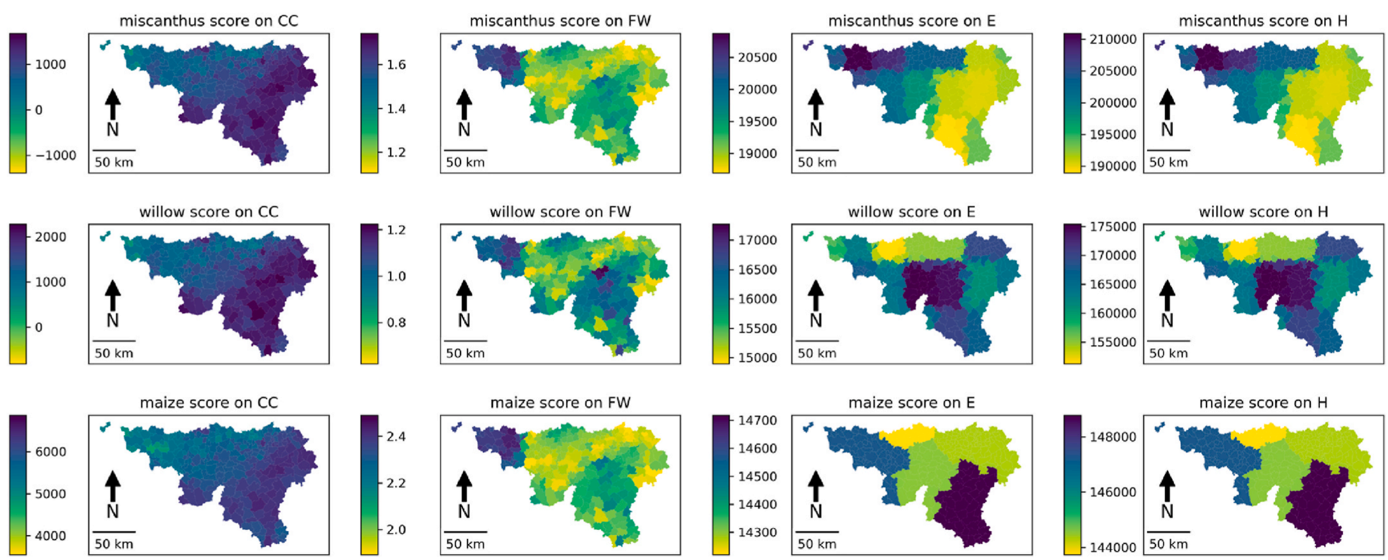

Fig. 6. Indicator score of CHP from alternative energy crops of miscanthus, willow, and maize (CC: climate change (kg CO_2eq/ha); FE: freshwater eutrophication (kg PO_4 P-lim eq/ha); E: electricity (kWh); H: heat (MJ/ha)).

Table 1
The trade-offs among six objectives and fuzzy optimization solutions (values in bracket represent in-and off-territory impacts when the objective is limited to only minimize in-territory performance. CC: climate change, FE: freshwater eutrophication, E: electricity, H: heat, BG: biogas, BE: bioethanol).

	Min. CC	Min. FE	Max. E or H	Max. BG	Max. BE	MOO (overall λ = **0.71**)	Membership value
CC (Mton CO_2eq)	−0.0001 (0.09)	0.00	0.17	0.20	1.89	0.19	0.71
FE (kton PO_4 P-limeq)	0.002 (0.19)	0.00	0.25	0.52	1.03	0.15	0.74
E (TWh)	0.02 (2.77)	0.00	3.82	0.00	1.15	0.85	1.00
H (TWh)	0.07 (7.77)	0.00	10.72	0.00	1.71	2.24	0.71
BG (TWh)	0.00	0.00	0.00	8.48	0.00	0.08	0.71
BE (TWh)	0.00	0.00	0.00	0.00	5.59	0.53	0.71

reveals that mainly the northwest municipalities would be assigned for bioenergy production. This compromised solution is achieved under the specific tolerance setting on the satisfaction level for each objective. By adjusting these pre-defined feasibility threshold parameters, one can prioritize the objectives (sensitivity to the tolerance setting on the optimal results are presented in SI-1 section 4).

4. Discussion

4.1. Support land-use planning with territorial LCA and optimization

This work aims to develop an integrated methodological framework that combines the territorial LCA, MOO, and GIS to generate optimized land-use scenarios, which could support agricultural land-use planning. The consideration of the life cycle impacts of multiple products and

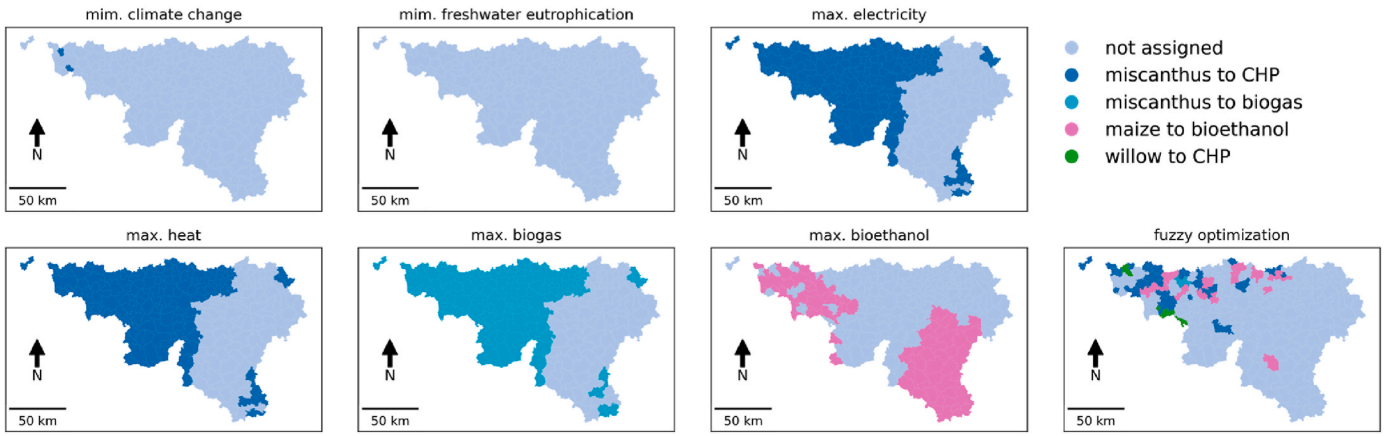

Fig. 7. Optimal allocations of the three alternative crops under six single objective optimization scenarios and fuzzy optimization (The first six figures were obtained by optimizing a single objective function subject to the constraints of the limited available area; the last figure on the lower right was obtained through fuzzy optimization with pre-defined tolerance values for each objective in SI-1; not assigned represent the land will remain the same as the present land use, i.e., animal land use).

services produced by the land uses facilitates comprehensive analysis, which is meaningful and novel in supporting land-use planning (Loiseau et al., 2018). Although many tools and models developed to evaluate environmental impacts and services and could support land-use planning (Polasky et al., 2008; Kennedy et al., 2016; Azuara-García et al., 2022), LCA stands out to perform multi-criteria assessment throughout the life cycle of the products and services provided by land uses (Loiseau et al., 2012). This work generating optimal land-use allocation for multiple products based on their spatial explicit life cycle impacts is needed, as mentioned by Miret et al. (2016) and Beaussier et al. (2019).

The case study shows that the framework can facilitate decision-making at the strategic level, providing optimal solutions that comply with the pre-defined objectives and restrictions (Fig. 7). The optimal allocation for multiple land uses could provide on-ground guidance on farmers' land-use decisions. For example, many academic articles have pointed out that although a high budget has been already allocated to support farmers' adopting sustainable practices, a limited steering effect is observed in Europe (Lupp et al., 2014; Reed et al., 2014; Hristov et al., 2020). They also pointed out that one of the potential solutions is to introduce a spatial dimension and align per-hectare payments for land use promotion with spatial parameters. Our work could contribute to this potential solution, by providing insights on optimal allocation for multiple land uses based on the territorial LCA approach that takes spatial variances and territorial objectives into account. In the case study, the optimal allocation for bioenergy land use is on the northwest side, which might indicate that strategic planners could focus on bioenergy crop promotion (e.g., through subsidies) on the northwest side rather than the southeast side.

4.2. Outlooks of TLCO framework to support land-use planning

The key limitation of the TLCO model is its application in guiding real-world land-use planning. The optimal solutions may provide on-ground guidance but may not be used as the "blueprint" to replicate the optimal land planning. A real-world agricultural territory is a complex and dynamic system, in which multiple stakeholders and associated socio-economic factors influence its future development. Especially the current work has not accounted for real land-use decision makers – farmers, who have their preferences and objectives (e.g., farm income) that may drive the landscape development in the real world away from the optimal land-use allocation that complies with territory objectives.

Further study could be conducted to account for farmers' decisions in the model by using agent-based modeling (ABM), which allows the simulation of a set of agents interacting and system dynamicity (Miller et al., 2013; Baustert and Benetto, 2017). Besides, the participatory approach is also feasible to enhance the applicability of the current work by capturing stakeholders' insights (including farmers) in land-use planning, improving stakeholders' understanding of the system, and clarifying the impacts of changes to help the decision-making (Shahpari, 2019; Shahpari et al., 2021; Chopin et al., 2019). By accounting for multiple stakeholders' preferences and simulating their decisions, researchers could explore alternative policy interventions and associated simulated results to propose the ones that align with the optimal solutions at the territorial level (Brunner et al., 2016; Bartkowski et al., 2020). Besides, researchers have explored generating directly feasible policy solutions that account for farm-level optimization objectives, e.g., bilevel optimization (Whittaker et al., 2017; Bostian et al., 2021), and multi-agent system coupling heuristic optimization (Huang and Song, 2019; Zhao et al., 2019).

In addition, the agricultural territory is a social-ecological system (Huber et al., 2018). Thus improving socioeconomic consideration is necessary for dealing with land-use planning issues in the real world (Santibañez-Aguilar et al., 2014). This work adopts the concept of LUFs, which could reflect the socioeconomic performances of different land uses. However, further work should be conducted to assess sustainability indicators on the same dashboard using the life cycle thinking (Loiseau et al., 2013). Social LCA (Macombe et al., 2013) or life cycle sustainability assessment (Notarnicola et al., 2017) is therefore promoted to be adopted at the territorial level (Loiseau et al., 2018). Besides, developing an integrated model has been promoted by several studies to assess the sustainability of the territory system, e.g., linking the bottom-up approach of ABM for socioeconomic consideration from individual stakeholders (Vance et al., 2022; Bichraoui-Draper et al., 2015) and top-down approach of system dynamics to account feedback relationship between socioeconomic and environmental impacts (Cavicchi, 2020; Onat et al., 2017).

Another issue for land planners is to have a comprehensive understanding of the indirect consequences of local bioenergy development. For example, the decision to introduce a large amount of new crops to the territory could cause iLUC due to the displacement of marginal crops in the global market (Vadenbo et al., 2017). Besides, changes in one sector might also bring indirect effects in another sector through competition and synergy (Beaussier et al., 2019). However, modeling these indirect effects is challenging to capture the causal relationship accurately (Van Stappen et al., 2011) and how to integrate these developments systematically and coherently in this framework needs further study.

4.3. Limitations of the case study

This case study is limited in data collection for simplicity and demonstration purpose. Researchers could enhance their case studies by collecting more comprehensive and accurate data. For example, more sophisticated models and spatial data could be used to estimate the spatially explicit inventory for in-territory activities (Beaujouan et al., 2002). In the calculation for off-territory impacts, we extracted inventory from the ecoinvent and used site-generic CF to quantify their impacts instead of regionalized CF provided at the country level as performed in the work of Mutel and Hellweg (2009). As the planners have little influence on the products outside the territory, and the locations of the off-territory activities are not certain, our results using site-generic CF for off-territory activities are relevant and informative for decision-makers at the territorial level. Further studies could be performed to improve the accuracy by collecting more accurate information on the locations of off-territory activities (e.g., using multi-regional-input-output data) and using regionalized CF to assess their impacts (Pfister et al., 2020).

Besides, we assumed that all the grassland could be potentially released from animal production reduction, regardless of whether it is permanent or temporary, due to a lack of data. However, this assumption can be arbitrary and cause results less accurate as the conversion of permanent grassland is restricted in Europe (Commission Delegated Regulation (EU), 2014) for its essential role in maintaining carbon stocks (Lessire et al., 2019). Crop rotation is also one of the major practical issues regarding integrating bioenergy crop production in the existing farming practice (e.g., maize silage followed by miscanthus) (Mangold et al., 2019).

In the case study, we only introduced different bioenergy products as the new LUFs and estimated two impact categories (CC and FE), which can be expanded by considering other biomass functions (e.g., bioplastics, fine chemicals) and more impact categories (or endpoint impact evaluation, e.g., ecosystem quality). Such expansion could improve the model by optimizing the full biomass uses over rather holistic impact categories. Also, the facilities' locations were assumed to be fixed, and their conversion capacities are not considered in the optimization. By parameterizing the potential new locations and facility capacity (e.g., modifying the linear optimization model in this study into mixed-integer linear programming), other elements in the whole supply chain of energy production can participate in the optimization.

4.4. Application in other territories

Though the general modeling approach proposed by this work is widely applicable, the data should be tailored for the specific region that is under study. Especially, the magnitude of the emissions from dLUC calculated depends largely on the previous land use (grassland or annual land) and other site-specific conditions. It should be noted that various data sources with different spatial resolutions are aggregated at the same level, which is necessary to facilitate the results' communication. However, since different resolutions to aggregate data could lead to significant differences in the optimization results (Sharara et al., 2020), selecting the appropriate one is critical to reducing the uncertainty of the results (O'Keeffe et al., 2016). Our resolution selection (i.e., municipals) is reasonable considering the spatial variability, data availability, and results' communication (SI-1, section 2). However, the appropriate resolution for the applications implemented in other territories might be different, which needs to be carefully selected.

5. Conclusion

As a policy instrument, land-use planning plays a critical role in balancing conflicting objectives, especially in increasingly intense competition for limited land resources. It is required to think about the land allocation for different purposes wisely to come to optimal land-use plans so that environmental disturbance can be minimized while societal needs and benefits can be maximally satisfied. The developed framework is meaningful as it provides a solid foundation linking the territorial LCA with optimization to support such plans. The territorial LCA is used to assess the impacts and services provided for different land planning scenarios. The optimization is used to build optimal scenarios automatically based on the assessed results from territorial LCA. By linking these two approaches coherently, facilitated with GIS to handle spatial data, the proposed method can propose optimal crop allocation and its energy conversion, contributing to supporting agricultural land-use planning decisions.

The illustrative case study explores the application of the model on land use for bioenergy purposes in the Walloon region. Though simplified with several limitations, the case study shows that the model holds the potential to search for the territory's optimal locations for multiple land-use functions complying with multiple territory objectives and constraints. Further research focusing on the extensions of the basic model is needed to improve the framework's utility and results' accuracy, such as including other functions than energy production, assessing the social impacts of land-use planning at the territorial level, and adding a dynamic dimension and indirect impacts.

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Author Contribution

Tianran Ding: Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, **Bernhard Steubing:** Conceptualization, Methodology, Supervision, Validation, Writing – review & editing, **Wouter Achten:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2022.116946.

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