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Abstract

Efficient use of constrained biomass and waste resources is a central challenge in circular bioeconomy planning. As bio-based technologies increasingly enable the recovery of diverse products and services, identifying optimal valorization strategies becomes a high-dimensional problem. This study presents a scalable, multisectoral constrained optimization tool for assessing the optimal allocation of residual biomass at regional to national scale. The tool relies on continuous modeling across scales –from unit operation-level process descriptions to system-level performance– allowing quantification of trade-offs among competing valorization pathways under technological and contextual constraints. The tool was applied to metropolitan France, to evaluate the environmental impacts of baseline and optimized residual biomass valorization strategies across five prospective scenarios. Thirteen streams and 31 valorization pathways targeting nutrient, food, feed, power and heat recovery were considered. Results indicate that optimized strategies reduce environmental impacts by 25-60% compared to conventional management. However, optimized valorization strategies are highly sensitive to the performances of individual technologies. Coupling optimization with uncertainty analysis highlights the enabling conditions under which specific pathways contribute to optimal solutions, offering actionable insights for both technology developers and policy modelers. While the tool is adaptable for assessing other indicators such as economic performances, its static nature and data intensity position it best as a prescreening and exploratory decision-support tool.

Keywords

Biomass, Multi-objective Optimization, Life Cycle Assessment, Linear programming, Waste management, Circular economy

Introduction

Residual biomass -including wastes and residues from agricultural, forestry, agrifood and waste management- is increasingly recognized as a key renewable supply for the bioeconomy (Hamelin et al., 2019). In France, residual biomass streams represent the energy equivalent of 20% of primary consumption, yet only 3% is currently recovered for energy, with most returning to soils (Javourez et al., 2024). Looking towards 2050, emerging residual biomass-to-X pathways are expected to generate value-added products, such as novel feed, jet fuel, construction materials and chemicals (Mori, 2023; Su-ungkavatin et al., 2023; Zuiderveen et al., 2023). Yet, as valorization options expand, critical questions arise to ensure the deployment of a sustainable bioeconomy: which pathways should be prioritized, for which services, at what scale, and under which constraints?

These questions frame what we define as the *residual biomass allocation problem*: how to allocate predefined residual biomass streams across competing valorization pathways to optimize one or more system-level objectives (e.g., minimizing environmental impacts), within a given geographical and temporal scope. This formulation abstracts from site-specific factors such as spatial distribution of valorization units or temporal dynamics (e.g., localized biomass availability, technological deployment, etc.), focusing instead on identifying promising feedstock-pathway combinations under general constraints.

Previous studies have addressed aspects of this challenge in land use (Ding et al., 2023), biomass utilization (Calvo-Serrano et al., 2019), and waste management planning (Abdallah et al., 2024). Most have focused on specific streams (such as lignocellulose; Lubjuhn and Venghaus, 2023) or target services (often, energy; Steubing et al., 2012). While such studies offer valuable insights, they tend to be sector-specific, and their results are difficult to generalize for broader bioeconomy planning (Colla et al., 2022). Yet, several studies proposed more comprehensive frameworks (Calvo-Serrano et al., 2019; Gerssen-Gondelach et al., 2014; Vadenbo et al., 2017). Calvo-Serrano et al., (2019) used a biomass network model to optimize biomass conversion into transportation fuels, ethylene and power in Europe minimizing both environmental and economic impacts. However, their approach used fixed conversion efficiencies and environmental impacts proportional to energy consumption. Vadenbo et al., (2017, 2018) introduced a process-based modeling integrated with consequential life cycle assessment (LCA) enabling a more robust evaluation of biomass reuse strategies under multiple prospective scenarios. Yet, even these advanced models remain limited in flexibility, requiring full recalibration for new case studies, or when introducing new pathways or feedstocks.

Here, we propose a modular and adaptable framework to formulate and solve the residual biomass allocation problem. Our approach allows for systematic identification of optimal valorization strategies for residual biomass under varying contextual, technological and decision-making conditions at territorial scale. Specifically, we aim to:

(i) Enable cross-sectoral comparison of biomass conversion strategies into various services such as fertilizers, fuels, chemicals, food and feed, highlighting potential sectoral competition under resource constraints.
(ii) Support scenario-based planning by evaluating the performance of valorization strategies across prospective futures, incorporating multiple objectives and forecasted technological performances.
(iii) Integrate process-based modeling to compute pathway-specific efficiencies, avoiding fixed ratios to guide R&D and process eco-design.
(iv) Pre-screen promising feedstock-pathway combinations for investment or policy prioritization, offering a system-level overview of residual biomass valorization potential.

This framework is designed as a flexible screening tool for bioeconomy planning. It facilitates the exploration of multisectoral trade-offs, identifies value-maximizing uses of residual biomass, and supports robust decision-making in contexts of technological and policy uncertainty.

Material & Method

System and scope definition

Residual biomass encompasses biowastes and bioresidues from forestry, agricultural, agrifood, and waste management sectors (Hamelin et al., 2019), while "valorization pathways" refer to end-of-life management strategies for residual biomass, ranging from conventional practices (e.g., incorporation of crop residues on land) to emerging valorization technologies (e.g., conversion to bioenergy or edible insects). The process of valorizing residual biomass streams generates environmental impacts but delivers societal services. The problem can thus be formulated as "searching for the optimal valorization strategies that minimize total impacts while providing the requested services at the system level". In terms of LCA methodology, this problem corresponds to the functional unit: "managing all identified residual biomass streams while meeting the demand for all selected services, for the area under study". The approach requires to unambiguously define a geographical scope, in turn setting the scope of residual streams, valorization pathways, and background scenarios to consider in the analysis. Beyond the predefined geographical (studied area) and temporal (scenario) scope, the procedure is neither spatially nor temporally explicit (quantities are aggregated for the reference year of the scenario under study). Yet it targets the long-term consequences of investing in one over the other valorization pathways.

The proposed optimization procedure is displayed in **Figure 1** comprising four steps that will be detailed in the following sections. The methodology is illustrated using France as an illustrative geographical scope due to the availability of a comprehensive dataset and suitable models for the study. The case study focuses on environmental impacts indicators via LCA for 11 services delivered by 31 biomass valorization pathways, including 17 conventional residual biomass management options and 14 emerging waste-to-nutrition pathways, assessed across six scenarios.

<Figure 1 here>

Process-based LCA model

The French residual biomass streams ($B_b, b \in [1, B]$) reported by Javourez et al., (2024) and containing explicit biochemical compositions, where here classified into B=13 categories (**Table 1**). Vegetable tops were separated from the crop residues category, management grass cuttings were distinguished from green/garden wastes, and agro-industrial waste was subdivided into food waste and wood-processing wastes. Each B_b category was designed to group individual residual streams with sufficiently similar characteristics, allowing the assumption of identical valorization performances.

A number N of valorization pathways ($P_n, n \in [1, N]$) was proposed for the B residual biomass streams. These were taken from the study of Javourez et al., (2025a), who elaborated consolidated process-based LCA models for 14 emerging valorization pathways covering insect farming, microbial and mycoprotein production, leaf protein extraction, and direct livestock feeding, referred to as "waste-to-nutrition" pathways. Their work also detailed 17 pathways targeting energy and nutrients recovery, such as anaerobic digestion, gasification, composting, decay on land, and various combustions variants (e.g., incineration,

industrial furnace valorization), herein referred to as "conventional" pathways. Landfilling was excluded, as it is being phasing out in France for organic streams. Variants of the same pathway (e.g., insects for food vs. feed) were treated as distinct pathways, leading to a total number of coherently designed valorization pathways of *N*=31.

The process-based LCA models represent industrial-scale production for all pathways, calculate midpoint environmental impacts using Environmental Footprint (EF) v3.1. and rely on Ecoinvent consequential product system v3.8 (ecoinvent, 2022). Biogenic CO_2 was assigned a GWP_{100} characterization factor of 0, and residual streams, as constrained resources, are considered to have no embedded emissions prior to processing (Pizzol et al., 2024). These models thus resemble to input-based unitary LCA models commonly used in waste management (Bisinella et al., 2024). However, instead of estimating total cradle-to-grave impacts, only cradle-to-services impacts are evaluated. The *N*=31 valorization pathways here supply demands ($Z_r, r \in [1, R]$) for *R*=11 primary services as identified in Javourez et al., (2025a), including power, heat, fertilization, food, and feed production. The identification and classification of primary services provided by each of the *N* pathways included in the analysis can be performed, for example, by listing the set of services explicitly stated by pathways promoters (e.g., incineration for heat and power recovery, land decay for fertilization services, etc.). The suitable aggregation level for services (i.e., demand categories Z_r) is case-specific and mostly driven by data availability documenting total system-level demand and compensatory supplies. Importantly, the residual biomass allocation problem assumes that service demands are exogenously driven and independent, while in practice demands are often interrelated.

Let us define $ipo_{c,b,n}$ as the direct impacts on category *c* generated by the utilization of 1 tonne of residual biomass stream *b* through a valorization pathway *n*. For LCA-based environmental impacts, this represents the life cycle impact assessment (LCIA) result for the selected impact category, meaning $ipo_{c,b,n}$ could be expressed in $kgCO_2$-eq per tonne of *b* for the climate change GWP_{100} indicator. These are cradle-to-services impacts, meaning that it excludes the downstream impacts related to the *R* selected services (such as power, heat, or feed ingredients self-consumption and production for the present case study). As the process-based LCA models are applied to a given geographical area of relevance for decision-making (here, France), the total amount of available biomass stream *b* is split to be valorized in different pathways. An allocation factor $x_{b,n}$, lying within [0, 1], is thus introduced to consider the share of biomass stream b that will be diverted towards valorization pathway *n*. The direct impacts on category *c* of a given system-level residual biomass valorization strategy (that is, set of $x_{b,n}$) is denoted as IO_c and calculated with **Equation 1**.

Equation 1

$$IO_c = \sum_{b=1}^{B} \sum_{n=1}^{N} ipo_{c,b,n}\, x_{b,n} B_b$$

Valorizing residual biomass streams not only aims at providing an end-of-life management solution, but also contributes to meet the system-level demand for services. Therefore, the substitutability of services provided by valorization pathways (bio-based offer) against those

provided by compensatory technologies must be accounted for in the modeling (e.g., through adoption rates or additional refining operations to equalize quality of bio-products with conventional products). Therefore, the total impacts on category *c* of managing the residual biomasses to meet total demands (system-level functional unit) will be the sum of impacts generated by the use of biomass in valorization pathways (analogy to direct impacts) and impacts generated by the rest of technologies (analogy to indirect impacts) required to meet total demands Z_r. Indirect impacts, denoted as II_c, are calculated with **Equation 2**.

Equation 2

$$II_c = \sum_{r=1}^{R} ipi_{c,r} H_r$$

Where $ipi_{c,r}$ is the impacts on category *c* generated when producing one unit of service *r* through compensatory technologies and H_r is the net total amount of service *r* supplied by compensatory technologies over the studied area. Compensatory technologies for a given service *r* corresponds to the technologies which would be mobilized to supply *r* in the absence of residual biomass streams, but these might encompass technologies processing primary biomass streams (e.g., anaerobic digestion of maize silage). Only unconstrained suppliers, able to respond to changes in demand, are included (Weidema et al., 1999). H_r is calculated with **Equation 3**.

Equation 3

$$H_r = Z_r + S_r$$

Where S_r is the cumulative amount of service *r* consumed by the residual biomass valorization strategy (set of $x_{b,n}$), accounting for self-consumption. On top of the exogenously-fixed total demands Z_r (e.g., 205 TWh industrial heat for France in 2018), residual biomass valorization strategy may add an additional demand of *r* (for example, industrial heat is required during biomass conversion), leading to an apparent demand higher than Z_r as previously defined. Positive S_r reflects this situation, meaning that selected valorization strategy is a net consumer of service r at the system-level. Conversely, $S_r < 0$ reflects what is expected when designing alternative residual biomass strategies at the first place, namely situations where valorization leads to overall net production of service *r*. S_r is calculated with **Equation 4**.

Equation 4

$$S_r = \sum_{b=1}^{B} \sum_{n=1}^{N} a_{r,b,n}\, x_{b,n} B_b$$

Where $a_{r,b,n}$ is the net amount of service *r* consumed by the utilization of 1 tonne of residual biomass stream *b* through a valorization pathway *n*. To quantify the share of demand categories Z_r met by residual biomass valorization, an indicator $\%BIO_r$ is calculated as with **Equation 5**. If negative, compensatory technologies not only need to supply all demand Z_r, but also the additional demand of *r* induced by valorizing residual streams.

Equation 5

$$\%BIO_r = \frac{-S_r}{Z_r} \times 100$$

In summary, the total system-level cradle-to-grave impacts on category c (LCA_c) corresponding to the functional unit "managing all identified residual biomass streams while meeting the demand for all selected services for the area under study, for the valorization strategy x" is the sum of direct and indirect impacts, as in **Equation 6**.

Equation 6

$$LCA_c = IO_c + II_c = \sum_{b=1}^{B}\sum_{n=1}^{N} x_{b,n} B_b \left(ipo_{c,b,n} + \sum_{r=1}^{R} ipi_{c,r} a_{r,b,n} \right) + \sum_{r=1}^{R} ipi_{c,r} Z_r$$

Where $x_{b,n} \in x$, the vector of variables referring to the allocation fractions of a given valorization strategy. A case study thus consists in a unique combination of values (B_B, Z_R, $ipi_{R,C}$, $a_{R,B,N}$ and $ipo_{B,N,C}$). Here, we opt to evaluate parameters representing the technological performances of valorization pathways – a coherent set of ($a_{R,B,N}$ and $ipo_{B,N,C}$) – independently from the background scenario – a coherent set of (B_B, Z_R, $ipi_{R,C}$) – which reflects the geographical and temporal scope in which these pathways are implemented, as in Javourez et al., (2025a).

Background scenarios

Six scenarios were analyzed for France: one reference scenario representing year 2018, here named as "Current", and five contrasting prospective scenarios for year 2050. Data for the reference scenario is based on Javourez et al., (2024) where French residual biomass resources and their uses for the year 2018 are characterized. The other scenarios were retrieved from the French Agency for the Ecological Transition (ADEME), who detailed and quantified five prospective scenarios for national production and consumption systems towards 2050 (ADEME, 2021), with most supporting data publicly available (ADEME, 2022). In summary, the "*Tend*" scenario represents a business-as-usual projection, "*S1*" corresponds to a frugal society, "*S2*" to a sharing society, "*S3*" to green growth, and "*S4*" maintains current consumption trends while relying on adaptative solutions. For example, *S1* forecasts a threefold decrease in meat demand compared to 2018, whereas *S4* anticipates an increase in intensive meat production systems (see **Table 1**).

Available residual stream volumes B_B for each prospective scenario were estimated by adapting the estimation methods of Javourez et al., (2024) to the granularity of the data provided by ADEME. Forecasted uses of residual streams were also estimated to derive the baseline valorization strategy x for each scenario, characterizing the system before optimization. Similarly, demands Z_R and compensatory technologies mixes for the R=11 services were directly retrieved or calculated using ADEME data. Dependencies in-between demands for energy services were quantified, as these depend on future technological choices. For example, a scenario adopting electrolysis-based hydrogen for industrial heat increases system-level power demand. Here, deriving exogeneous and independent demand

levels for energy services was achieved by defining Z_r as the difference between the total apparent (system-wide) demand for service *r* in a given scenario and the consumption of r required by the compensatory technologies supplying the other *R* services. This was not possible to achieve for agrifood services as data granularity did not allow to unravel interlinkage between food, feed, and fertilizer services for prospective scenarios. Finally, unitary impacts of compensatory technologies ($ipi_{c,r}$) for all scenarios and services were averaging multiple Ecoinvent background processes and linking the compensatory technologies mixes in-between them where required (e.g., impacts of industrial heat production using electric arc furnaces integrates the scenario-specific compensatory power mix). All data sources, calculations and resulting sets of (B_B, Z_R, $ipi_{R,C}$) for each scenario are available in the **supporting data** (Javourez et al., 2025b), with a summary of key values in **Table 1**.

Integrated multisector constrained optimization

The residual biomass allocation problem considers *B* available biomass streams and *N* valorization pathways, and therefore involves a vector of allocation variables x of length $B \times N$ (also referred to as the valorization strategy). By integrating novel emerging valorization pathways, the problem can potentially involve hundreds to thousands of allocation variables, illustrating the high-dimensional nature and the scalability problem of such a multisector optimization framework for bioeconomy. Yet, the total impacts LCA_c to minimize is linear to x (**Equation 6**), hence the optimization problem can be arranged to a linear system as formulated in **Equation 7**, by introducing two constant vectors α_c and β_c. In terms of LCA methodology, the term $\alpha_c x$ represents the cradle-to-grave environmental impacts on category *c* associated with the functional unit "managing all identified residual biomass streams for the area under study, under the valorization strategy x" when considering system expansion with substitution to account for the environmental credits of the services supplied through valorization (Brandão et al., 2017). On the other hand, the term β_c corresponds to the cradle-to-grave environmental impacts on category *c* associated with the functional unit "meeting the total demand for all selected services for the area under study, using compensatory technologies only". Thus, this component is independent of the valorization strategy x.

The optimization problem is subject to both equality and inequality constraints. Since all residual biomass streams have an end-of-life even if not supplying a demanded service (e.g., natural decay on land), the total amount of each residual stream *b* must be allocated. That is, the sum of $x_{b,n}$ over all pathways *N* for a given stream *b* is equal to 1, resulting in *B* linear equality constraints (**Equation 7**). On the other hand, *R* linear inequality constraints are required to ensure consistency between supply and demand at the territorial scale while enabling the generalization of residual biomass valorization strategies (**Equation 7**). These are referred to as *no-exports* constraints; this prevent surplus service production from being absorbed by external markets beyond the geographical scope. Without these *no-exports* constraints, the single-objective optimization problem (**Equation 7**) becomes separable, allowing each residual biomass stream to be assessed independently. In this case, the trivial solution is to allocate 100% of each residual stream *b* to the valorization pathway *n* with the lowest impacts ($\alpha_{b,n,c} \in \alpha_v$). Imposing *no-export* constraints is thus essential to maintain

the relevance of the optimization framework. However, this approach necessitates selecting a sufficiently large geographical scope to validate the self-sufficiency assumption where supply and demand are balanced within the system boundaries. If the total residual biomass potential B_B is insufficient to fully meet any of the R demand categories Z_r under any valorization strategy x, the linear inequality loss significance, leading again to the trivial solution. There is a unique allocation x satisfying **Equation 7**.

Equation 7

$$\text{Minimize } f_1(x) = LCA_c = \alpha_c x + \beta_c$$

Subject to:

$$\text{linear equality constraints: } \sum_{n=1}^{N} x_{b,n} = 1 \quad \forall b = 1, \dots, B \text{ and } x_{b,n} \in x$$

$$\text{linear inequality constraints: } -S_r \leq Z_r \quad \forall r = 1, \dots, R$$

$$0 \leq x_{b,n} \leq 1 \quad \forall x_{b,n} \in x$$

The optimization problem can be considered as single-objective if only one impact category is selected as the objective, which is the case in **Equation 7**, or multi-objective if other conflicting impact categories are also involved. Nevertheless, regardless of the number of objective functions chosen, the problem is intrinsically constrained, under several soft demand constraints (Z_r), and hard resource closure constraints oriented towards valorization pathways ($\sum_{n=1}^{N} x_{b,n} = 1$) for each biomass category $b \in B$.

Multi-objective optimization concerns problems involving multiple objective functions to be optimized simultaneously, where there is no single solution but a set of optimal solutions (Pareto front) on which, at any feasible point, none of the objective functions can be improved without degrading other objective functions (Miettinen, 1998). Methods for handling multi-objective optimization include *a posteriori* and *a priori* methods. The former includes stochastic methods such as multi-objective evolutionary algorithms (Ahmadi et al., 2016; Deb and Jain, 2014) that offer no-preference Pareto results for decision-making, but suffer from constraint handling, especially for high-dimensional problems with many soft and hard constraints. The latter include methods that involve information for aggregation or scalarization of the problem beforehand, where the task is to construct a Pareto front by solving a series of single-objective optimization problems. In this work, the ϵ-constraint method (Mavrotas, 2009) was selected to address the constrained multi-objective optimization problem of resource allocation because this *a-priori* method is practical in the case of high-dimensional constrained optimization and compatible with well-established linear programming approaches.

In the case of a tri-objective optimization problem, instead of using a single-objective function representing one impact category or the total aggregated impacts (**Equation 7**), three categories of conflicting environmental impact categories LCA_1, LCA_2 and LCA_3 have to be considered and minimized. The ϵ-constraint method in this case consists of transforming the two last objective functions into additional inequality constraints, as formulated in **Equation 8**, where both upper bounds of these new constraints (ϵ_2, ϵ_3) vary

between their respective lower and upper bounds ($\epsilon_{i,L}, \epsilon_{i,U}$) in order to shape the multi-objective Pareto front.

Equation 8

$$\text{Minimize } LCA_1(x)$$

$$\text{Subject to:}$$

$$LCA_2(x) \leq \epsilon_2$$

$$LCA_3(x) \leq \epsilon_3$$

$$\epsilon_{i,L} \leq \epsilon_i \leq \epsilon_{i,U} \quad \forall i = 2,3$$

$$\text{linear equality constraints: } \sum_{n=1}^{N} x_{b,n} = 1 \quad \forall b = 1, \dots, B \text{ and } x_{b,n} \in x$$

$$\text{linear inequality constraints: } -S_r \leq Z_r \quad \forall r = 1, \dots, R$$

$$0 \leq x_{b,n} \leq 1 \quad \forall x_{b,n} \in x$$

Case study implementation

A generic Python-based routine was developed to initialize and solve the residual biomass allocation problem for any case study (sets of B_B, Z_R, $ipi_{R,C}$, $a_{R,B,N}$ and $ipo_{B,N,C}$). Next, single-objective optimization, formulated in **Equation 7**, was performed for each of the 16 LCA midpoint environmental impact categories of E.F. v3.1. method, as well as for the single LCA score. This single score is calculated by weighting and aggregating 13 midpoint impact categories (excluding toxicity-related categories), normalized to the estimated average environmental impact of a person globally in 2010 (Andrea Bassi et al., 2023; Sala et al., 2018). The single score represents environmental impacts relative to an average individual.

The present case study involved a total of 154 allocation variables ($x_{b,n}$), considered as decision variables for optimization (not all *N*=31 pathways are compatible with all streams *B*), and 25 linear constraints. Yet, the problem fits the context of high-dimensional constrained optimization as any novel pathway duplicates the number of decision variables. Since all the objective functions and constraints are linear, constrained linear programming strategies using simplex and interior point solvers are used for being fast and stable, especially for large problems. Here, *SciPy* linear programming (Virtanen et al., 2020) has been implemented in Python to minimize a linear objective function subject to equality and inequality constraints using “highs” solver that automatically chooses between the dual revised simplex implementation (HSOL) and the interior-point method (Huangfu and Hall, 2018). In addition, an Excel-based single-objective implementation using the Simplex PL solver has also been adapted to the case study for cross-validation. The procedure for the single-objective optimization is described in the **supporting information** (**SI**).

Then, to identify relevant midpoint impact categories for multi-objective analysis -beyond climate change or the single score- the following criteria were applied. Freshwater ecotoxicity and human toxicity (cancer and non-cancer) were discarded for being considered as interim method and insufficiently robust (Sala et al., 2018). Impact categories with

normalized LCIA results below 10% of the 2018 French population (expressed in person-equivalents) or with a variation range below this threshold across single-objective optimizations were excluded. These criteria indicate the relevance of a given impact category regarding residual biomass valorization strategies. A principal component analysis (PCA) was performed on α_c data using R v.4.4.1. with *factoextra* and *corrplot* libraries to identify sets of non-redundant impact categories for tri-objective study following the problem formulation in **Equation 8**. Here, the lower and upper bounds ($\epsilon_{i,L}, \epsilon_{i,U}$) corresponding to the two impact categories dealt as constraints were respectively set to their single-objective LCA_c minimal values (lower bound) and to the LCA_c value corresponding to the baseline distribution x (upper bound).

Finally, to assess the influence of modeling framework components on the outcomes of optimization studies, we combined scenario analysis with stochastic simulations. Scenario analysis evaluates how optimal solutions vary based on modeling choices (e.g., the selection of valorization pathways) and contrasting prospective scenarios. Stochastic simulations assess the impact of uncertain future technological performances on the outcomes, providing insight into investor confidence for emerging pathways (Vadenbo et al., 2017). Since the *N* process models share a common set of technological parameters, each documented with uncertainty ranges (Javourez et al., 2025a), a paired sampling using Monte Carlo was applied to systematically propagate uncertainties between simulations. This methodology generates sets of ($a_{R,B,N}$ and $ipo_{B,N,V}$) that consistently cover the forecasted range of technological performances, which are then integrated in the optimization process.

<Table 1 here>

Results and discussion

Single-score optimization of environmental impacts under multiple scenarios

Applied to the six proposed scenarios, key results of the single-objective solutions are analyzed regarding total E.F. v3.1 single-score impacts and the contribution of residual biomass valorization pathways. Numerical values comparing results before (baseline) and after optimization, for all scenarios, are available in the **SI**.

Optimizing residual biomass valorization reduces impacts by 25% (*Current*, *Tend*) to 60% (*S1*, *S2*) compared to foreseen baseline valorization strategy. The difference between these scenario groups is primarily driven by the higher demand (**Table 1**) and the greater environmental impacts of compensatory technologies in the former, resulting in a β_c summing 40 million person-equivalents, compared to approximately 20 million in the latter. In absolute terms, optimizing residual biomass valorization yields a consistent impact reduction potential across scenarios, ranging from around 7 million person-equivalents for *S1* and *S2* to around 10 million in *S4*, *Current* and *Temp*. This consistency arises from similar foreseen baseline valorization strategies, prioritizing agronomic valorization (e.g., composting), followed by anaerobic digestion for energy recovery. Wood processing residues are allocated to industrial heat, while forestry and pruning residues decompose on land. Consequently, in such baseline valorization strategies, residual biomass contributes 20-40% of nitrogen, 40-60% of phosphorus, and 80-100% of potassium fertilizer demand, while

covering 30-80% of industrial heat requirements (*%BIO* indicator in **Figure 2**). However, the baseline valorization strategies induce net environmental impacts (positive α_v values) rather than mitigating them, in contrast to optimized strategies. Optimization of single score favors heat and meat-equivalent services over fertilizers and feed ingredients across all scenarios. Only for *S1*, lipid feed demand is met at 80% through insect larvae production, likely due to lower overall demand, enabling a more diverse service portfolio from the same residual biomass pool. Across all cases, *%BIO* for power is negative, indicating that optimal strategies induce an additional power demand by 5-15% (equivalent to an additional 20-40 TWh at the national scale). This implies that power is not a major environmental concern for this system, reflecting the low impact of projected mix -either predominantly nuclear (ca. 70% in *Current* and *Tend*) or renewable (four other scenarios).

Notably, the mono-objective solution to the residual biomass allocation problem is predictable by comparing $\alpha_{b,n,c}$ values for all compatible valorizations *n* of each biomasses *b*. These values, fixed here, can be ranked in ascending order, with the optimal solution allocating available biomass *b* to valorization *n* sequentially until the biomass is exhausted or the demand is met. As a result, the allocation is highly sensitive to the relative values of $\alpha_{b,n,c}$ and lacks diversification at the national scale, as volumes are concentrated in the most favorable pathway. This is a consequence of limiting constraints to the minimum. Diversification occurs only when supply-demand mismatches exist, allowing abundant feedstocks to serve broader range of demands. The sensitivity of the solution to $\alpha_{b,n,c}$ also implies that modifying the set of available valorization pathways substantially alters outcomes (**Figure 2A**). For instance, removing waste-to-nutrition pathways eliminates options for producing meat-equivalent services from residual streams, such as insect farming on food waste or mycoprotein production from lignocellulosic sugars. These pathways consistently exhibit the lowest $\alpha_{b,n,c}$ values (**Figure 2C**), ranging from -50 to -130 milliperson-equivalent impacts per tonne valorized across all scenarios. In their absence, allocation still targets heat-producing pathways (e.g., wood and straw combustion, biomethane production from manure, with benefits of -30 to -50 milliperson-equivalent per tonne), while remaining streams are diverted towards direct livestock feeding when possible (e.g., vegetable tops and food waste).

<Figure 2 here>

Optimizing residual biomass valorization thus requires robust $\alpha_{b,n,c}$ estimations, yet these values remain uncertain and contingent on future technological developments (Javourez et al., 2025a). Process-based LCA models facilitate the generation of consistent $\alpha_{b,n,c}$ sets, enabling solution averaging across multiple independent yet coherent optimizations (see **Methods**). Here, 300 such sets were generated (**Figure 2C**), yielding more distributed solutions as technological advancements shift $\alpha_{b,n,c}$ relative ranking (**Figure 2B**). We estimate that uncertainties in future technological performances of valorization pathways affect the minimal achievable system-wide single-score impacts by ± 10%, or 2-3 million person-equivalents across scenarios (**Figure 2A**). Despite this uncertainty, single-score optimized $\%BIO_r$ distributions (**Figure 2A**) indicate that certain services, such as industrial heat, are consistently supplied by residual biomass (100% across all scenarios and

performance levels), whereas others, such as domestic heat in *S1-S4*, are highly dependent on specific enabling technological developments. Integrating the proposed optimization procedure with process-based models effectively identifies conditions favoring specific pathways, supporting process eco-design by highlighting critical enabling factors, including targeted technological performances. Notably, while optimal residual biomass valorization strategies no longer include direct return to land, these still provides nearly equivalent nitrogen and phosphorus supplies compared to current situation. This is mostly due to nutrient cycling via anaerobic digestion of livestock excreta, which returns these elements to arable land indirectly through digestates. Conversely, large potassium supplies formerly sourced from plowed crop residues, now requires mineral-based supplementation, as crop residues are predominantly combusted for energy recovery in optimal solutions, for all scenarios.

Valorization strategies introduce trade-offs across impact categories, with compensatory effects hidden by single-score calculations. Prioritizing a single impact category alters optimal distributions compared to minimizing the single-score, which is driven by climate change (weighting 22%). Certain impact categories remain unaffected by residual biomass reuse, either because they are unrelated to the studied system (e.g., ozone depletion linked to halogen source gases) or linked to specific technologies of high-demand services not targeted in the optimization (e.g., photochemical ozone formation and water use; **Figure 3A**). For instance, the system-wide water uses impacts of optimal scenarios (regardless of the impact category being minimized) are primarily driven by power generation (photovoltaic and nuclear) and irrigated crops required to meet feed demand. As power and feed services are rarely prioritized for impact minimization, corresponding LCA results for these impact categories remain largely independent of valorization strategies. However, this dependence shifts with compensatory technologies. The system-wide relevance of ionizing radiations and fossil resource depletion, for example, is dictated by nuclear share in the future power mix: LCA results for these impact categories are sensitive to residual biomass valorization under nuclear-dependent scenarios (*Current*, *Trend*) but negligible in a nuclear-free future (*S1*). Similarly, mineral and metal resource use escalates with increased share of renewables in compensatory power supplies, rendering it more sensitive to residual biomass valorization (*S1-S4*).

<Figure 3 here>

System-wide terrestrial and marine eutrophication, acidification, and to a lower extent, particulate matter formation impacts, remain significant relative to total national impacts and are strongly influenced by residual biomass valorization across all scenarios. These categories are directly linked to conventional livestock excreta management (Javourez et al., 2024); thus alternative valorization strategies for these streams directly reduce associated impacts (**Figure 3A**). Here, extensive diversion towards anaerobic digestion, exceeding scenario projections (about 20-35%), enhances impact mitigation. However, particulate matter formation exhibits a weaker reduction due to partial compensation by increased direct biomass combustion. Comparisons with baseline valorization strategies suggest that optimizing residual stream reuse for a single impact category also consistently yields net

reduction for the rest of impact categories, except for resource use and ionizing radiation (**Figure 3A**). The magnitude of these benefits diminishes in more sustainable background scenarios -those characterized by lower overall demand and cleaner technologies. For instance, current (2018) system-wide climate change impacts are estimated at ca. 300 $MtCO_2$-eq (40 million person-equivalents, **Figure 3A**). Optimal residual streams valorization can halve these impacts, yet climate benefits from such optimization are limited in already climate-efficient scenarios such as *S1*, where baseline climate impacts are estimated at 10 million person-equivalents.

Multi-objective optimization and analysis for decision-making

Net impact reduction is achievable across most impact categories compared to baseline residue valorizations. However, further minimizing one impact category may exacerbate others. Illustrated for the *Tend* scenario in **Figure 3B**, the Principal Component Analysis (PCA) performed on all scenarios allowed to cluster the cradle-to-grave midpoint impact categories in three groups for this case study: (i) water use, land use and marine eutrophication, which are negatively correlated with (ii) resource use (fossil, and minerals & metals); (iii) climate change, particulate matter formation and acidification, all correlated, and relatively independent to the two other groups.

For bioeconomy decision-making based on multi-criteria considerations, multi-objective optimization is here illustrated by selecting one category per group (see **Methods**): marine eutrophication (also proxy for nitrogen impacts), climate change, and mineral and metal resource use that shape the three axes of 3D Pareto front in **Figure 4**. Pareto-optimal solutions exhibit distinct trade-offs in pathway selection from the baseline valorization strategy, called “current use” in **Figure 4**. Marine eutrophication and mineral resource use are conflicting objectives; but in the worst case, marine eutrophication impacts increase by 10% from its theoretical minimum but remains at least 20% below current residual biomass reuse (*Current* scenario). Two trade-offs’ regions emerge: (i) zone A-B, where climate change mitigation opposes mineral resource savings; and (ii) zone B-C where these go along. Regardless of the optimization target, a 22% reduction in climate impacts is achieved compared to current residual biomass reuse, with an additional 22% attainable at the expense of at least one other objective. Zone A-B is further divided into two parts. In the linear section close to A, shifting 100% of crop residues from anaerobic digestion with gas injection to direct combustion, while redirecting surplus livestock manure to anaerobic digestion to meet industrial heat demand, together contributes to achieve up to 20% of the additional 22% attainable climate impacts reduction. Further 2% reduction towards theoretical minimum (close to B) requires alternative protein production (including diverting 20% of crop residues to mycoprotein, and full transition from sewage sludge digestion to incineration). Notably, such marginal impact reductions demand substantial changes in biomass management. On top of identifying pathways consistently selected across the Pareto front (e.g., food waste reuse to produce insect biomass for food applications), one can also highlight the ca. 70% of all (feedstock; pathways) combinations never selected (e.g., combined heat and power production from crop residues) when conjointly considering these three objectives, underscoring the diverse insights enabled by this approach.

<Figure 4 here>

Limits and perspectives

This work provides a generic and flexible tool to explore the residual biomass allocation problem, which is adaptable to new case studies and applicable to a broader set of indicators, such as economic. Application to the France case focusing on LCA-based environmental impacts indicators demonstrated that the national-scale optimal residual biomass valorization strategy is less sensitive to the technological background and demand levels (i.e., the underlying scenario) compared to (i) the set of available valorization pathways, (ii) their actual technological performances, and (iii) the indicators of interests.

Data collection represents a major challenge in expanding the analysis. Integrating additional valorization pathways requires process-based models of similar granularity. Moreover, when introducing novel services through these novel pathways, such as conversion of waste to materials, chemicals, fuels for transportation, the procedure must characterize them in terms of demand and compensatory supplies across multiple scenarios. Achieving exogeneous and independent demand categories formulation is also difficult to uphold due to supply chain interconnections. Additionally, the linear simplification of scenarios, treated as static snapshots, present limitations. For instance, the crop residues and livestock excreta considered here as input streams for valorization are actually byproducts of the compensatory supply of food and livestock production. Large-scale direct valorization of residual streams into novel food and feed commodities could thus significantly affect the levels of these compensatory supplies and subsequent residual biomass availability. Assuming that all residual biomass is exogenously fixed and theoretically available for the bioeconomy without constraints aims at simplifying the problem, but overlook the multiple factors -such as carbon stock maintenance (e.g., leaving a portion of crop residues to soils; Andrade Díaz et al., 2023), socioeconomic factors, local conditions, which are all affecting the actual residual biomass valorization deployment decisions (Sun et al., 2023). For instance, the *no-export* constraint was set to allow for large scaling of optimal solutions, while this constraint is not adequate below a certain size as not able to represent the intrinsic specialization of territories. The use of the 2010 E.F. normalization factors to assess 2050 environmental impacts is another limitation to be noted.

Future developments could define a demand-to-biomass ratio, aiding in the assessment of residual biomass potential for bioeconomy applications in a given area. Not assessed here, this ratio likely varies across scenarios: for example, *S1* has lower demand levels than *Current* and *Trend* across all services, while others (e.g., *S4*) show increased power demand (**Table 1**). Lower demand also results in less residual feedstock availability, as seen in *S1* and *S2*, where halved meat consumption leads to halved manure availability for energy recovery. These variations highlight additional insights that could be derived from such an indicator.

Regardless of the background scenario, optimal residual biomass reuse consistently prioritized heat and meat-equivalent service supply. Currently, meat production has approximately ten times the environmental impacts of crop production per dry weight (Javourez et al., 2025a), a relationship maintained across all scenarios. For instance, in *S1*, meat-equivalent production climate impacts decrease by 25% compared to *Current* while

protein feed production declines by 56%. Similarly, industrial heat production remains about three time more impactful for climate than power generation per energy unit, while domestic heat production is approximately twice as impactful across scenarios. The *Current* scenario stands out due to its high heat demand (both for industrial and domestic applications), which is twice the equivalent (in TWh) of power demand. In prospective scenarios, demand for power and heat are better balanced, allowing feedstock to be freed for other services. However, increased processing leads to a consistent 5-15% additional power demand nationwide, which may not be feasible given forecasted constraints on power supply technologies. Adding constraints on the maximal allowable additional power from valorization strategies could help refine the analysis.

Overall, the present simple residual biomass allocation problem formulation proved valuable for first screening of most favorable recovery technologies in a given context. It strongly suggests to move beyond fixed values to characterize the performances of these technologies ($\alpha_{R,B,N}$ and $ipo_{B,N,C}$), as usually performed. Indeed, an infinitesimal difference between two $\alpha_{b,n,c}$ for the same biomass *b* is enough for the optimization procedure to prioritize one, allocating 100% of the stream to the selected pathway until exhausted. Coupling process-based LCA models to the optimization procedure, as initiated here, is a promising approach to automate uncertainty and sensitivity analysis of optimal solutions regarding technological forecasts, hence achieving a more nuanced assessment of the potential of emerging valorization pathways. The interpretation of system-wide mitigation potential also largely depends on the scope of demand categories included, and their levels. To minimize distortions induced by high demands, one option is to only account for the maximum share of total demand that could theoretically be met by residual biomass instead of the total demand when determining Z_r. While this adjustment would not change the optimal allocation solution, it would influence system-level relative gains and inter-scenario comparisons. Potential enhancements to the interpretation of the results include integrating the frequency of occurrence of pathways among optimal solutions (Vadenbo et al., 2017), and incorporating other environmental impact assessment methods (Steubing et al., 2012).

Conclusions

We developed a multisector optimization tool with integrated LCA for bioeconomy to address the large-scale allocation of residual biomass under technical and demand constraints. Applied to metropolitan France as a case study, the tool assessed the environmental impacts of baseline and optimized valorization strategies across six contrasting scenarios, 13 residual streams and 31 valorization pathways targeting nutrient, food, feed, power and heat recovery. Optimization reduced environmental impacts by 25-60% compared to baseline biomass reuse, albeit with a 5-15% increase in power demand and a substantial shift of crop residues away from soil incorporation. Beyond the French context, findings show that optimal valorization strategies are more sensitive to the scope and performance of valorization technologies than to background scenario variations.

Overall, this work lays the foundation for the systematic identification of optimal multisector valorization strategies for residual biomass, supporting decision-making in bioeconomy planning across diverse technological and contextual settings.

Data and code availability statement

The raw data required to reproduce the above findings, as well as corresponding Python scripts, are available to download from 10.17632/gyzd25nfv4.1 (Javourez et al., 2025b).

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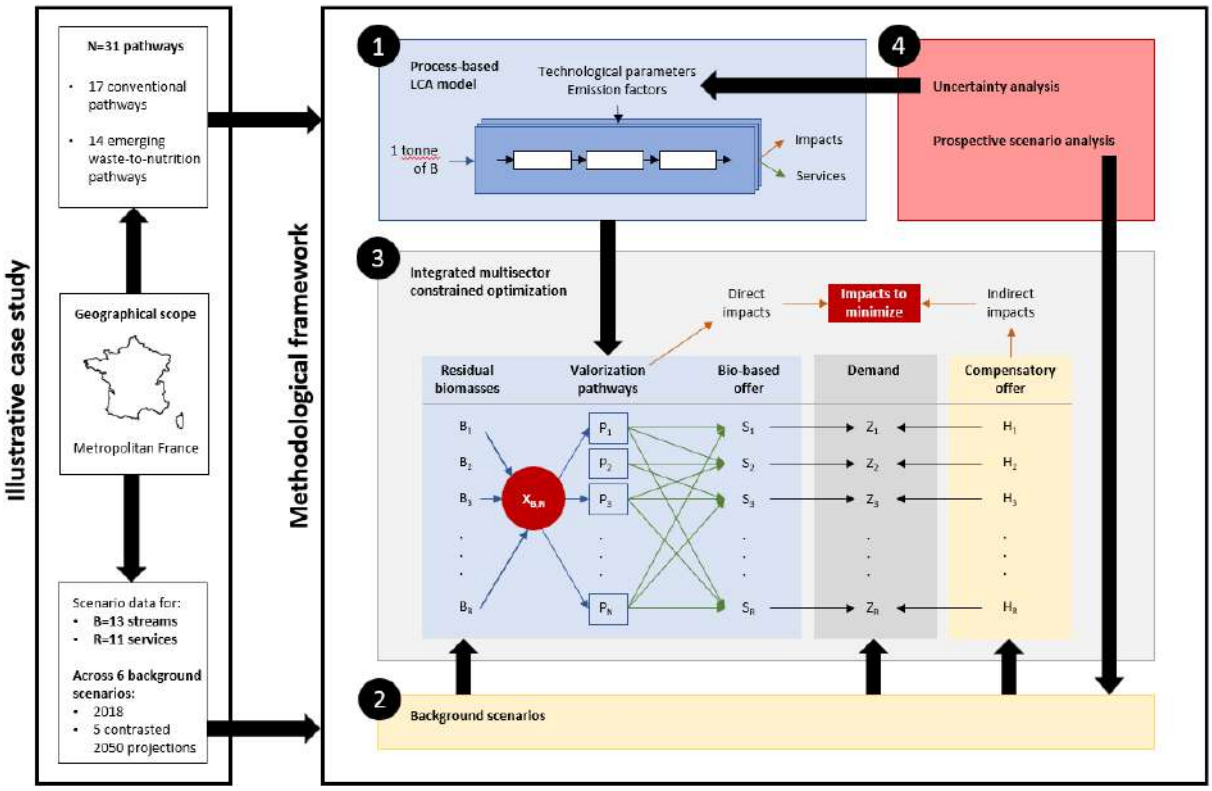
Figures and Tables

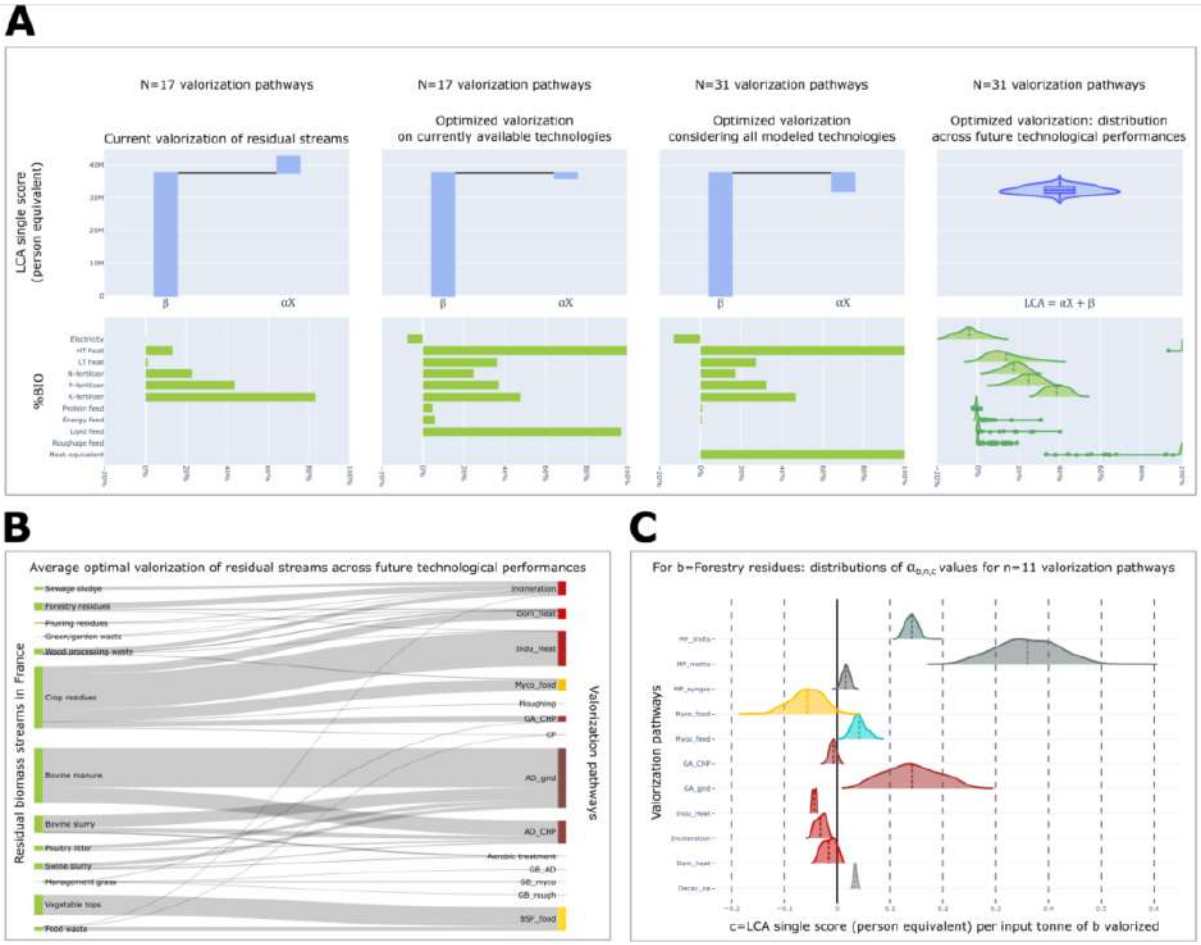
Figure 1: The residual biomass allocation problem.



713 **Table1: Scenario rounded values for key variables**. Supporting data sources, calculations, and values
714 for the rest of compensatory supplies mixes are available in the supporting data Javourez et al., (2025b).

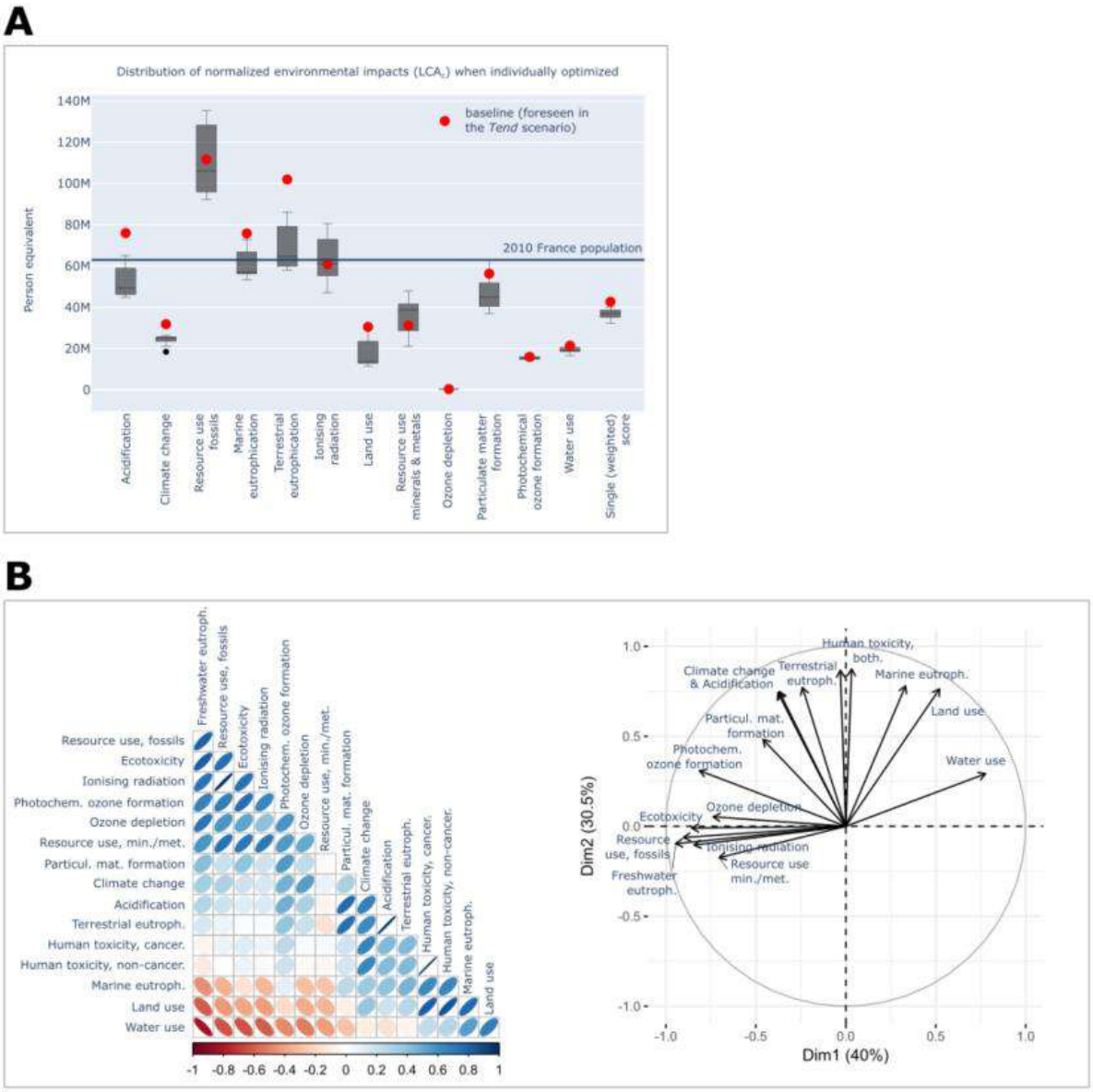
Scenario	Current	Trend	S1	S2	S3	S4
Year	**2018**	**2050**	**2050**	**2050**	**2050**	**2050**
Demand in services for France (Z_R)						
Power (TWh)	304	426	236	348	430	582
Industrial heat (TWh)	205	189	114	109	132	181
Domestic heat (TWh)	480	345	207	202	254	303
N fertilizing (ktN)	1991	1722	1371	1087	1929	2188
P fertilizing (ktP_2O_5)	797	667	668	735	679	733
K fertilizing (ktK_2O)	2072	1734	1736	1911	1765	1905
Protein feed (Mt_{DM})	6.1	7.0	4.8	7.1	5.7	7.9
Energy feed (Mt_{DM})	15.3	18.0	8.6	9.0	15.3	17.1
Lipid feed (Mt_{DM})	0.20	0.23	0.11	0.11	0.19	0.17
Roughage feed (Mt_{DM})	54	77	38	40	56	61
Meat-equivalent (Mt_{DM})	1.34	1.28	0.48	0.72	0.99	1.28
Available residual streams in France (B_B), in million tonnes (wet weight)						
Forestry residues	10.1	11.8	10.1	11.8	13.8	13.9
Crop residues	83.4	77.5	80.6	64.9	69.8	108.5
Wood processing waste	7.2	7.1	7.3	7.5	7.2	7.2
Pruning residues	1.8	1.3	1.3	1.4	1.3	1.7
Bovine manure	74.5	57.2	22.7	27.6	55.7	77.3
Bovine slurry	23.5	18.0	7.2	8.7	17.6	24.4
Swine slurry	8.0	4.5	2.7	3.7	4.7	4.8
Poultry litter	7.3	10.3	9.3	7.6	8.1	10.3
Management grass	0.9	0.9	0.9	0.9	0.9	0.9
Green/Garden waste	4.3	4.3	4.3	4.3	4.3	4.3
Vegetable tops	26.7	34.2	22.9	22.9	32.2	38.4
Sewage sludge	4.2	4.5	4.5	4.5	4.5	4.5
Food waste	4.8	3.4	2.4	2.4	2.4	2.4
Total (B)	**256.7**	**235.0**	**176.2**	**168.3**	**222.4**	**298.5**
Compensatory industrial heat production supplies mix for France						
Power-based heat	8%	10%	10%	14%	30%	19%
Natural gas	63%	67%	8%	14%	7%	50%
Biomethane	0%	7%	19%	23%	23%	14%
Reformed hydrogen	0%	0%	0%	0%	0%	0%
Oil	14%	5%	9%	6%	8%	6%
Steam	0%	4%	6%	5%	11%	5%
Wood	9%	7%	31%	21%	13%	7%
Coal	6%	0%	0%	0%	0%	0%
Compensatory meat-equivalent production supplies mix for France						
Ruminant, intensive	16%	18%	5%	6%	14%	26%
Ruminant, extensive	15%	12%	17%	21%	13%	4%
Swine	47%	46%	35%	41%	42%	46%
Poultry	19%	22%	28%	28%	27%	22%
Plant-based	2%	2%	15%	4%	3%	2%

Figure 2



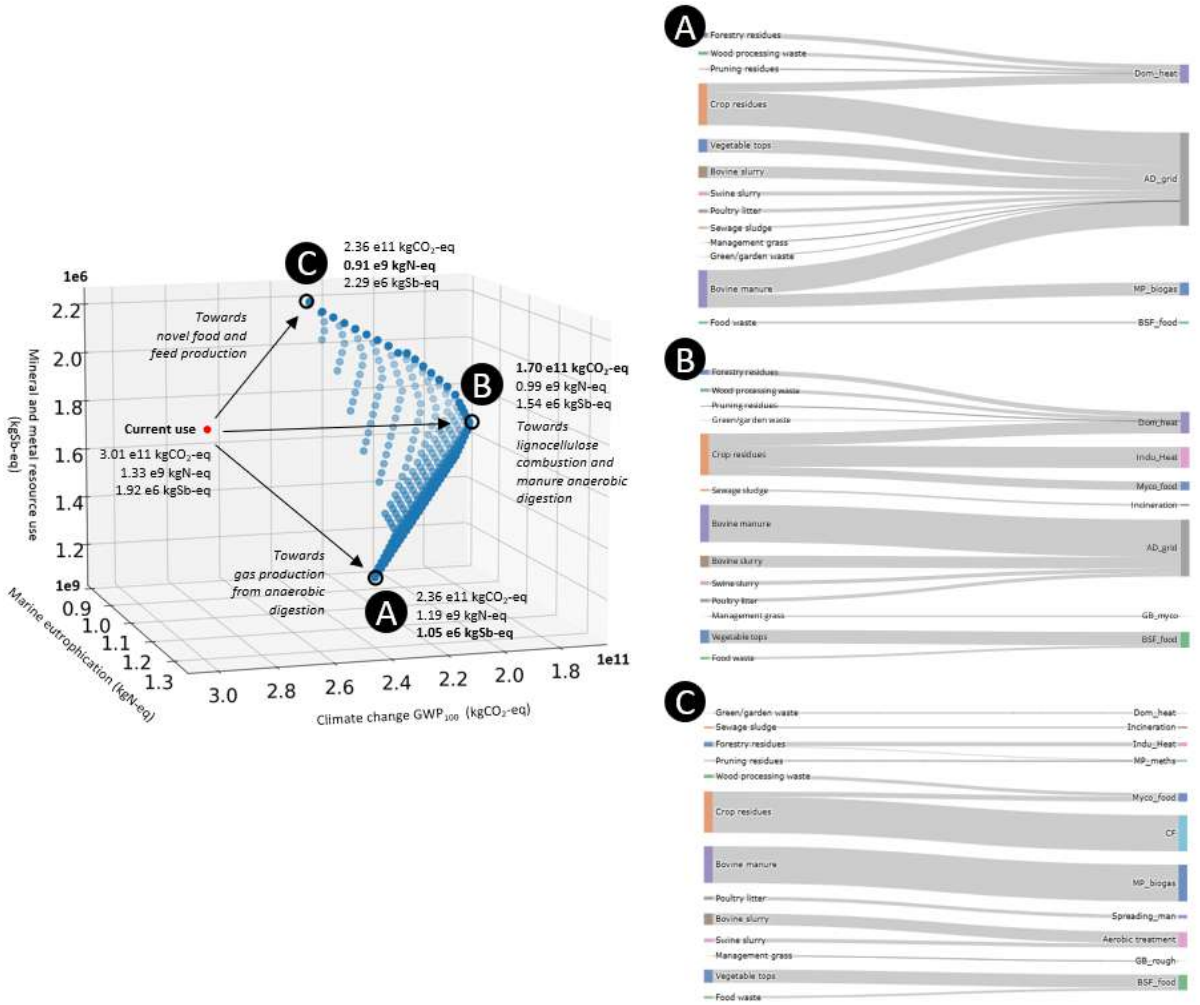
Single-score optimized residual biomass strategy results for the *Current* scenario. Panel A: Optimized single-score for different prescreened sets of valorization pathways, considering fixed technological performances. Last right-hand subplot displays single-score distribution by repeating the optimization procedure for 300 simulations, resulting from Monte Carlo sampling of technological parameters across their forecasted variation range (see **Methods**). **Panel B:** Average of resulting optimal valorization strategy across the 300 simulations, pathways never selected in optimal solutions are not displayed. **Panels C:** $\alpha_{b,n,c}$ value distribution across the 300 simulations (11 of the 31 selected pathways are compatible with forestry residues). Supporting data and visualization for the other scenarios are available in the supporting data Javourez et al., (2025b) Dom_heat and Indu_heat: biomass combustion to produce domestic and industrial heating respectively. Myco_food and BSF_food are respectively the production of mycoproteins and insect larvae to produce meat-analogues. Myco_feed: mycoproteins are used as livestock feed. AD_CHP and AD_grid: anaerobic digestion with biogas production either valorized as combined heat and power (CHP) or injected in gas grid for industrial use (grid). GA_CHP and GA_grid refers to both aforementioned gas valorization variants for gasification. CF: direct use as compound feed for livestock. GB_AD, GB_myco and GB_rough: extraction of proteins from leafy materials through green biorefining, with three valorization variants for the fibrous co-products (anaerobic digestion, use as roughage for livestock or feedstock for mycoprotein production). MP_shift, MP_meths and MP_syngas represents three variants of producing microbial proteins based on the gaseous outputs of gasification. Decay_na: direct decay on land (here, non-arable) of residues.

Figure 3



Multisector integration breakdown per impact categories, for the *Tend* scenario. **Panel A**: Distribution of normalized environmental impacts (expressed in 2010 person-equivalent, see **Methods**) when individually optimized (one-at-the-time). Boxplot with median (center line of box plot), IQR (25th to 75th percentiles, box bounds) and range (whiskers extending to the minimum and maximum within 1.5× IQR) based on 12 values. **Panel B**: Results of Principal Component Analysis (PCA) on the 16 impact categories of E.F. 3.1. Left: Blue ellipses indicate a positive correlation between two impact categories, while those in red tones indicate a negative correlation. Supporting data and visualization for the other scenarios are available in the supporting data (Javourez et al., 2025b).

Figure 4



Tri-objective optimization of the residual biomass allocation problem applied to France under the *Current* scenario. Three objectives: climate change (GWP_{100}), marine eutrophication, mineral and metal resource use. Black dots represent coordinates of each single-objective optimization result, with corresponding optimized valorization strategy displayed in Sankey diagrams A, B and C. Here, the baseline (fixed) values for technological performances were considered. Supporting data available in Javourez et al., (2025b). Pathway's acronyms are explicated in captions of **Figure 2**.