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# Multisectoral optimization of residual resource valorization for bioeconomy

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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 proposes a scalable, multisectoral constrained optimization approach for assessing the large-scale allocation of residual biomass under technical and demand constraints, here applied to metropolitan France. Environmental performances of optimal residual biomass valorization strategies were evaluated for 13 streams and 31 valorization pathways targeting nutrient, food, feed, power and heat recovery, across five prospective scenarios. 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. By highlighting the enabling conditions under which specific pathways contribute to optimal solutions, the proposed approach offers actionable insights for process eco-design and bioeconomy policy modeling.

## Keywords

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

## Synopsis

Identifying optimal valorization of residual streams lacks scalable and flexible methods. This study shows that substantial environmental gains are achievable, though contingent on the future performances of emerging recovery technologies.

## 34 Introduction

35 Residual biomass -including wastes and residues from agricultural, forestry, agrifood and  
36 waste management- is recognized as a key renewable supply for the bioeconomy<sup>1</sup>. In France,  
37 residual biomasses represent the energy equivalent of 20% of primary consumption, yet only  
38 3% is currently recovered for energy, with most returning to soils<sup>2</sup>. Looking towards 2050,  
39 emerging residual biomass-to-X pathways are expected to generate value-added products, such  
40 as novel feed, jet fuel, construction materials and chemicals<sup>3-5</sup>. Yet, as valorization options  
41 expand, critical questions arise to ensure the deployment of a sustainable bioeconomy: which  
42 pathways should be prioritized, for which services, at what scale, and under which constraints?

43 These questions define the *residual biomass allocation problem*: how to distribute predefined  
44 residual biomass streams across competing valorization pathways to optimize one or more  
45 system-level objectives (e.g., minimizing environmental impacts) within a specified geographical  
46 and temporal scope. This formulation abstracts from site-specific details -such as the spatial  
47 distribution of facilities and resources or temporal dynamics- and instead focuses on identifying  
48 promising feedstock-pathway combinations under general constraints.

49 This problem has been examined through various case studies in land use<sup>6</sup>, biomass utilization<sup>7</sup>,  
50 and waste management<sup>8</sup>, with a benchmark of previous works provided in the **Supporting**  
51 **Information (SI)**. However, comparing and generalizing findings across studies remains  
52 challenging due to the variations in geographic coverages, time horizons, feedstocks,  
53 valorization pathways, and sectoral focus<sup>9,10</sup>. Most studies have centered on energy recovery -  
54 disaggregated into heat, power, and transport fuels- with occasional inclusion of non-energy  
55 sectors (e.g., chemicals, materials). Feedstocks -ranging from manure to lignocellulosic wastes-  
56 and their valorization pathways have been modeled at varying levels of granularity, with  
57 associated environmental performances estimated either through fixed coefficients or life cycle  
58 assessment (LCA) with differing methodological assumptions. For example, Calvo-Serrano et al.,  
59 (2019)<sup>7</sup> used a biomass network model to convert feedstocks into fuels, ethylene, and power in  
60 Europe, minimizing both environmental and economic impacts through fixed conversion and  
61 impact factors. Vadenbo et al., (2017, 2018)<sup>11,12</sup> combined process-based modeling with  
62 consequential LCA to explore optimal biomass-to-energy strategies under future scenarios. Yu  
63 et al., (2022)<sup>13</sup> integrated material flow analysis and LCA to optimize the reuse of agriculture  
64 waste for energy and fertilizer, focusing on climate mitigation.

65 Overall, suggested optimal residual biomass allocation strategies are almost as numerous as the  
66 specific cases assessed by the studies themselves, limiting their applicability to broader  
67 bioeconomy planning<sup>14</sup>. It is well acknowledged in benchmarked studies that optimal strategies  
68 depend on many factors -including biomass availability, technology options, and stakeholder-  
69 defined objectives, but none, to our knowledge, systematically identified which and how  
70 problem features influence outcomes. Furthermore, the lack of reusable optimization models  
71 and code hampers efforts to extend the exploration of the residual biomass allocation problem  
72 to new pathways, feedstocks, regions, scenarios, or sectors. To address this gap, we propose a

73 modular and reusable approach for the systematic identification of optimal valorization  
74 strategies for residual biomass, accounting for varying contextual, technological and decision-  
75 making conditions at the regional or broader scale.

76 Specifically, our approach (i) enables consistent and expandable cross-sectoral comparison of  
77 biomass conversion strategies into various services (such as fertilizers, energy, food, etc.),  
78 highlighting potential sectoral competition under resource constraints, (ii) supports scenario-  
79 based planning by assessing valorization strategies across prospective futures, multiple  
80 objectives and forecasted technological performances, (iii) integrates process-based modeling  
81 to compute pathway-specific efficiencies, avoiding fixed performance ratios, and (iv) prescreens  
82 promising feedstock-pathway combinations for policy prioritization. By identifying system-level  
83 value-maximizing uses of residual biomass, proposed approach facilitates the exploration of  
84 multisectoral trade-offs, and supports robust decision-making in contexts of technological and  
85 policy uncertainty. The approach is illustrated by using metropolitan France as a case study,  
86 offering not only a methodological contribution but also the first residual biomass allocation  
87 analysis conducted for this national context. The analysis focuses on the food, feed, fertilizer,  
88 heat, and power sectors, evaluated under five contrasting prospective scenarios projected to  
89 2050 (see **Figure 1**).

## 90 Materials and Methods

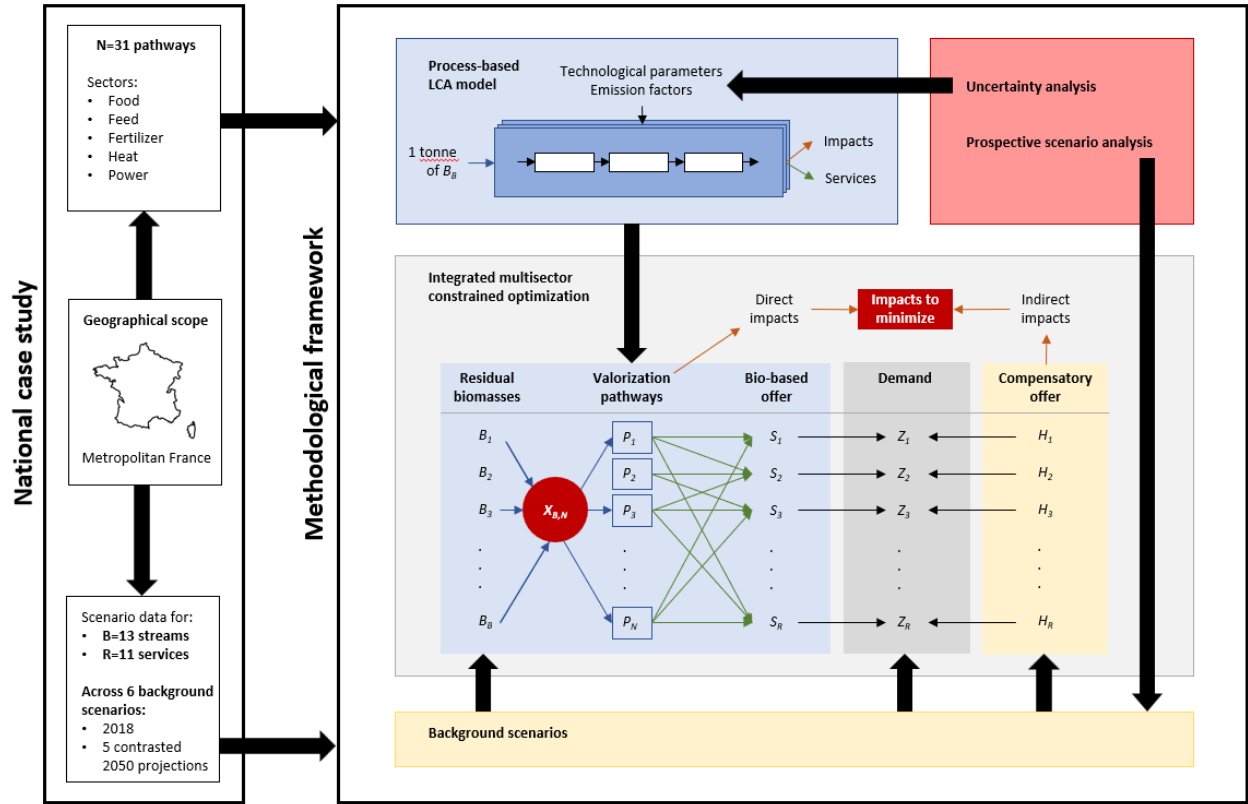
### 91 Goal and scope definition

92 *Residual biomass* encompasses biowastes and bioresidues from forestry, agricultural,  
93 agrifood, and waste management sectors<sup>1</sup>. *Valorization pathways* refer to end-of-life  
94 management strategies for residual biomass, ranging from conventional practices (e.g., crop  
95 residue incorporation into soil) to emerging technologies (e.g., conversion into bioenergy or  
96 edible insects). Valorizing -or managing- residual biomass streams generate environmental  
97 impacts while providing societal services. The residual biomass allocation problem consists in  
98 identifying optimal valorization strategies that minimize total impacts -including the end-of-life  
99 of residual streams- while fulfilling system-level service demands.

100 LCA quantifies potential environmental impacts of products or activities across their life cycle,  
101 relative to a *functional unit*<sup>15</sup>. For the residual biomass allocation problem, we propose the  
102 functional unit: “Managing all available residual biomass streams while meeting the demand for  
103 selected services in the study area”. The geographical scope determines the residual streams,  
104 valorization pathways, and background scenarios under evaluation. Although not explicitly  
105 spatial or temporal (stream quantities are aggregated for the scenario’s reference year), the  
106 approach targets long-term consequences of investing in one valorization pathway over  
107 another.

108

109 **Figure 1: Residual biomass allocation problem and application to France**



110

111 Pathways and scenario details are available in the SI. Notations are detailed in **Table 1**.

112

113 **Table 1: Nomenclature for residual biomass allocation problem**

Symbol	Definition	Comment
$B$	Number of residual biomass stream categories	Index: positive scalar
$R$	Number of service categories	Index: positive scalar
$N$	Number of valorization pathways	Index: positive scalar
$C$	Number of environmental impact categories	Index: positive scalar
$B_B$	Available quantities for each residual stream category	Parameter: vector of length $B$ , in wet tonnes, positive
$Z_R$	Total demand for each service category	Parameter: vector of length $R$ , service-dependent units (e.g., MJ), positive
$P_N$	Process-based LCA models (deterministic functions), one per pathway	Inputs: biochemical composition of residual stream, technological parameters. Outputs: direct impacts and net consumption of services
$\alpha_{R,B,N}$	Net amounts of services consumed by valorizing one unit of residual biomass streams	Parameter: vector of length $R \times B \times N$ , service-dependent units (e.g., MJ/wet tonne), estimated with $P_N$ . Can be negative, indicating that valorizing this stream through this pathway results in a net supply of the given service.
$ipo_{C,B,N}$	Impacts of valorizing one unit of residual biomass streams, excluding those related to the $R$ services	Parameter: vector of length $C \times B \times N$ , impact-dependent units (e.g., kgCO <sub>2</sub> -eq/wet tonne), estimated with $P_N$ . Can be negative.
$ipi_{C,R}$	Impacts of producing one unit of services through compensatory technologies	Parameter: vector of length $C \times R$ , impact- and service-dependent units (e.g., kgCO <sub>2</sub> -eq/MJ). Can be negative.
$x_{B,N}$ (or $\mathcal{X}$ )	Fractions of each residual stream category diverted towards each valorization pathway	<b>Optimization variables:</b> vector of length $B \times N$ in [0:1], also called <i>allocation vector</i> or <i>valorization strategy</i> . Incompatible feedstock-pathway combinations are set to 0.
$IO_C$	Direct impacts associated with a valorization strategy	Variable: vector of length $C$ , impact-dependent units (e.g., kgCO <sub>2</sub> -eq), calculated with <b>Equation 1</b> .
$II_C$	Indirect impacts associated with a valorization strategy	Variable: vector of length $C$ , impact-dependent units (e.g., kgCO <sub>2</sub> -eq), calculated with <b>Equation 2</b> .
$S_R$	Total net amounts of services consumed by a valorization strategy	Variable: vector of length $R$ , service-dependent units (e.g., MJ). Can be negative, indicating that the valorization strategy results in a net supply of the given service, calculated with <b>Equation 4</b> .
$H_R$	Total net amounts of services supplied by compensatory technologies under a valorization strategy	Variable: vector of length $R$ , service-dependent units (e.g., MJ), positive, calculated with <b>Equation 3</b> .
$\%BIO_R$	Share of total demand met by a residual biomass valorization strategy	Variable: vector of length $R$ , calculated with <b>Equation 5</b> . Can be negative, indicating that compensatory technologies not only need to supply total system-level demand for the given service, but also the additional demand induced by the valorization strategy.
$LCA_C$	Total impacts associated with a valorization strategy	Variable ( <b>optimization objectives</b> ): vector of length $C$ , impact-dependent units (e.g., kgCO <sub>2</sub> -eq), calculated with <b>Equation 6</b> .
$\alpha_{C,B,N}$ (or $\alpha_C$ )	Total impacts of valorizing one unit of residual streams, using <i>system expansion with substitution</i>	Parameter: vector of length $C \times B \times N$ , impact-dependent units (e.g., kgCO <sub>2</sub> -eq/wet tonne). See <b>Equation 6</b> .
$\beta_C$	Total impacts of fulfilling all service demands with compensatory technologies only	Parameter: vector of length $C$ , impact-dependent units (e.g., kgCO <sub>2</sub> -eq). See <b>Equation 6</b> .

114

## 115 General residual biomass allocation framework

### 116 System model formulation

117 Let there be  $B$  residual biomass categories, each grouping streams with similar  
118 characteristics, such that identical valorization performances can be assumed for a given  
119 pathway. These streams can be processed via  $N$  valorization pathways, each capable of  
120 supplying one or more services (e.g., power, feed). The services supplied by each pathway -  
121 based on stakeholders claims (e.g., heat and power from incineration, fertilizing benefits from  
122 composting)- are aggregated into  $R$  primary services for which system-level demand exists,  
123 denoted  $Z_R$ . The appropriate level of service aggregation depends on data availability regarding  
124 total demand and conventional supplies. These service demands ( $Z_R$ ) are considered exogenous  
125 and independent, although interdependencies often exist in practice. Residual streams are  
126 allocated to pathways to form a valorization strategy  $x_{B,N}$ , denoted  $x$ . The vector  $x$  contains all  
127 allocation variables, each ranging from 0 to 1 and set to zero for incompatible feedstock-  
128 pathway combinations (e.g., anaerobic digestion of wood).

129 Valorizing one unit of residual biomass through a pathway (e.g., insect farming) can generate  
130 several services (e.g., food, feed, fertilizers), consume others (e.g., heat, power), and result in  
131 environmental impacts (direct emissions, utilities and facilities use, etc.). Process-based LCA  
132 models quantify these outcomes based on feedstock composition and technological  
133 parameters<sup>16</sup>, corresponding to input-based unitary LCA models in waste management<sup>17</sup>. These  
134 models typically use *system expansion with substitution* to account for environmental credits<sup>18</sup>,  
135 assuming that recovered products (bio-based offer in **Figure 1**) displace conventional  
136 alternatives. Substitution effects require modeling adoption rates and additional refining to  
137 equalize product quality.

138 Residual biomass valorization not only manages waste but also contributes to fulfilling service  
139 demands ( $Z_R$ ). For a given strategy  $x$ , total environmental impacts ( $LCA_C$ ) are divided into *direct*  
140 impacts ( $IO_C$ ) from processing biomass and *indirect* impacts ( $II_C$ ) from conventional  
141 technologies to meet unmet demand. Impacts are calculated across  $C$  categories using LCA  
142 software. Individual process-based LCA models estimate the net consumption/supply of services  
143 per compatible feedstock-pathway combination ( $a_{R,B,N}$ ) and direct impacts ( $ipo_{C,B,N}$ ). The latter  
144 corresponds to the LCA values obtained when excluding flows related to the  $R$  selected services  
145 from the life cycle inventory. System-level direct ( $IO_C$ ) and indirect impacts ( $II_C$ ) are computed  
146 with **Equations 1 and 2**, respectively.

147

#### Equation 1

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

148

#### Equation 2

$$II_C = \sum_{r=1}^R ipi_{C,r} H_r$$

149  $ipi_{C,R}$  are unit impacts from compensatory offer, and  $H_R$ , the total net amounts of  
 150 compensatory offer required (see **Equation 3**). Compensatory offer represents the scenario-  
 151 specific mix of conventional technologies used to meet service demands in the absence of  
 152 residual biomass. These technologies include those using primary biomass (e.g., anaerobic  
 153 digestion of maize silage) but must not include those using residual biomass and should, in  
 154 principle, include only unconstrained suppliers<sup>19</sup>.

155 **Equation 3**

$$H_R = Z_R + S_R$$

156  $S_R$  is the net service consumption by the valorization strategy, calculated with **Equation 4**. For a  
 157 service  $r$ , if  $S_r > 0$ , the strategy is a net consumer of this service at system-level, meaning that  
 158 compensatory offer needs to fulfill an *apparent* demand above  $Z_r$  (**Equation 3**). In other words,  
 159 beyond meeting the exogeneous demand for this service, the compensatory offer must also  
 160 address additional demand generated by the valorization strategy. If  $S_r < 0$ , it indicates net  
 161 service production (accounting for self-consumption). The share of demand met by residual  
 162 biomass ( $\%BIO_R$ ) is quantified with **Equation 5**, as “ $-S_R$ ” corresponds to the net service  
 163 production by valorization strategies.

164 **Equation 4**

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

165 **Equation 5**

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

166 Total system impacts for the functional unit ( $LCA_C$ ) are linear in the allocation variables  $x_{B,N}$  as  
 167 shown in **Equation 6**.

168 **Equation 6**

$$\begin{aligned} LCA_C = IO_C + II_C &= \sum_{b=1}^B \sum_{n=1}^N x_{b,n} B_b \left( ipo_{C,b,n} + \sum_{r=1}^R ipi_{C,r} a_{r,b,n} \right) + \sum_{r=1}^R ipi_{C,r} Z_r \\ &= \alpha_C B_B x + \beta_C \end{aligned}$$

169 A case study for the residual biomass allocation problem thus corresponds to a specific  
 170 combination of ( $B_B$ ,  $Z_R$ ,  $ipi_{C,R}$ ,  $a_{R,B,N}$  and  $ipo_{C,B,N}$ ) parameters. In this work, we evaluate  
 171 valorization pathways performances ( $a_{R,B,N}$  and  $ipo_{C,B,N}$ ) independently from the background

172 scenario ( $B_B, Z_R, ipi_{C,R}$ ). This distinction allows assessing the technologies' performance  
 173 separately from the geographical and temporal context in which they are applied.

174 **Integrated multisector constrained optimization**

175 Minimizing the total impacts  $LCA_c$  defines a linear optimization problem, structured by  
 176 parameters  $\alpha_c$  and  $\beta_c$  (see **Table 1**). The term  $\alpha_c B_B x$  represents impacts associated with the  
 177 functional unit "Managing all identified residual biomass streams under strategy  $x$ " applying  
 178 *system expansion with substitution*<sup>18</sup>. The term  $\beta_c$  represents impacts for the functional unit  
 179 "Meeting total service demand using compensatory technologies only", and is therefore  
 180 independent of strategy  $x$ .

181 The optimization is subject to both equality and inequality constraints. Since all residual biomass  
 182 streams must be managed (even if not valorized for service provision, e.g., natural decay on  
 183 land), the entire quantity of each residual stream must be allocated. This requirement yields  $B$   
 184 linear hard *resource closure* constraints (**Equation 7**). In addition,  $R$  inequality constraints are  
 185 required to ensure consistency between the supply and demand of services within the study  
 186 area. These *no-exports* constraints prevent the production of surplus bio-based services (beyond  
 187 total demand), which would otherwise imply absorption by markets beyond the defined  
 188 geographical scope. Without these constraints, the problem becomes separable, allowing each  
 189 biomass stream to be optimized independently. This leads to a trivial solution: assigning 100% of  
 190 each stream  $b$  to its compatible pathway  $n$  that yields the lowest  $\alpha_{c,b,n} \in \alpha_c$  (i.e., the pathway  
 191 generating the least impacts when applying *system expansion with substitution*). Imposing *no-*  
 192 *export* constraints is therefore essential to preserve the relevance of the optimization  
 193 framework. However, this requires choosing a sufficiently large geographical scope to justify the  
 194 assumption that supply and demand are internally balanced (self-sufficiency). Similarly, if the  
 195 available biomass quantities  $B_B$  are insufficient to meet any of the service demands  $Z_R$  under  
 196 any strategy  $x$ , the inequality constraints become ineffective, again resulting in a trivial solution.

197 Let  $x \in \mathbb{R}^{B,N}$  be the allocation vector, composed of  $x_{b,n}$  for  $b = 1, \dots, B$  and  $n = 1, \dots, N$ . The  
 198 single-objective optimization problem, for each impact category  $c \in 1, \dots, C$  is then formulated  
 199 in **Equation 7**. This formulation suggests that there is a unique solution.

200 **Equation 7**

201 Minimize  $f_1(x) = LCA_c(x) = \alpha_c B_B x + \beta_c$

202 Subject to:

203 *resource closure* linear equality constraints:  $\sum_{n=1}^N x_{b,n} = 1 \quad \forall b = 1, \dots, B$

204 *no-export* linear inequality constraints:  $-S_r(x) \leq Z_r \quad \forall r = 1, \dots, R$

205  $0 \leq x_{b,n} \leq 1 \quad \forall x_{b,n} \in x$  and pathway  $n$  compatible with feedstock  $b$

206 The optimization problem becomes multi-objective when multiple, conflicting impact categories  
 207 must be optimized simultaneously, rather than relying on a single-objective function

208 representing one impact category or an aggregated total (as in **Equation 7**). In such cases, no  
 209 single optimal solution exists. Instead, a set of optimal trade-offs, known as the Pareto front, is  
 210 identified -where improving one objective necessarily worsens at least one other<sup>20</sup>. *A posteriori*  
 211 stochastic methods, such as multi-objective evolutionary algorithms<sup>21,22</sup>, are commonly used to  
 212 approximate the Pareto front. However, they often struggle with constraint handling in high-  
 213 dimensional problems. To address this challenge, the *a priori*  $\epsilon$ -constraint method<sup>23</sup> was  
 214 selected. This approach constructs the Pareto front by solving a series of single-objective  
 215 optimization problems, each with varying bounds on the remaining objectives. In a tri-objective  
 216 context, the method reformulates two of the three objective functions as inequality constraints,  
 217 which are varied within predefined limits (see **Equation 8**). Limiting the analysis to three  
 218 objectives ensures tractability, enables clear trade-off interpretation, and avoids the  
 219 computational and analytical challenges associated with many-objective optimization. While the  
 220  $\epsilon$ -constraint method effectively builds the Pareto front, flat regions in the solution space -  
 221 caused by objective redundancy or linear dependence- can reduce sensitivity to variations in  $\epsilon$ .  
 222 This may result in repeated or weakly dominated solutions, often due to linear programming  
 223 degeneracy. Post-processing is essential to mitigate these effects. This include removing weakly  
 224 dominated or duplicate points, and applying appropriate filtering to improve the quality and  
 225 interpretability of the Pareto front.

#### 226 **Equation 8**

227 Minimize  $LCA_1(x)$

228 Subject to:

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

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

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

229 *resource closure* linear equality constraints:  $\sum_{n=1}^N x_{b,n} = 1 \quad \forall b = 1, \dots, B$

230 *no-export* linear inequality constraints:  $-S_r \leq Z_r \quad \forall r = 1, \dots, R$

231  $0 \leq x_{b,n} \leq 1 \quad \forall x_{b,n} \in x$  and pathway n compatible with feedstock b

232

### 233 Case study set-up

#### 234 Process-based LCA models

235 The French residual biomass streams previously characterized with detailed biochemical  
 236 compositions<sup>2</sup>, were classified into  $B=13$  categories (see **Table 2**). Corresponding process-based  
 237 LCA models were compiled for  $N=31$  valorization pathways from previous works<sup>24</sup>. These  
 238 include 14 emerging *waste-to-nutrition* pathways, covering insect farming, microbial and  
 239 mycoprotein production, leaf protein extraction, and direct livestock feeding. These also include

240 17 *conventional* pathways -currently implemented- such as anaerobic digestion, gasification,  
 241 composting, decay on land, and multiple combustion variants (e.g., incineration, industrial  
 242 furnace valorization). Landfilling was excluded, as France is phasing out this option for organic  
 243 waste. Variants of a single pathway (e.g., insect farming for food vs. feed) were treated as  
 244 distinct. Selected pathways supply  $R=11$  services, including power, heat, fertilization, food, and  
 245 feed (see **Table 2**). A detailed description of each pathway is provided in the **SI**.

#### 246 Background scenarios

247 Six scenarios were evaluated for France: one reference scenario for year 2018, labeled  
 248 “Current”, and five prospective scenarios for 2050, retrieved from the French Agency for the  
 249 Ecological Transition (ADEME). Data for the 2018 reference is based on our previous work<sup>2</sup>,  
 250 characterizing national residual biomass resources and their uses. The five future scenarios are  
 251 based on ADEME’s quantified projections<sup>25</sup> with most data publicly available<sup>26</sup>. These are the  
 252 “*Tend*” scenario, representing a business-as-usual projection, “*S1*” for a frugal society, “*S2*” for a  
 253 sharing society, “*S3*” for green growth, and “*S4*” maintaining current consumption patterns with  
 254 adaptive solutions. For example, *S1* anticipates a threefold reduction in meat demand compared  
 255 to 2018, whereas *S4* projects an increase in intensive meat production systems (see **Table 2**).

256 Residual stream volumes  $B_B$  were estimated for each scenario by adapting the method of  
 257 Javourez et al., (2024)<sup>2</sup> to the data granularity provided by ADEME. The baseline valorization  
 258 strategy  $x$  for each scenario was derived from the projected uses of residual streams,  
 259 characterizing the system prior to optimization. Service demands  $Z_R$ , as well as compensatory  
 260 technologies mixes for each service, were retrieved or calculated using ADEME data.  
 261 Interdependencies between heat and power demands were explicitly modeled, as these vary  
 262 depending on scenario-specific technological choices. For instance, a scenario relying on  
 263 hydrogen production via electrolysis for industrial heat results in a higher *apparent* system-level  
 264 power demand. To derive exogenous and independent demands for heat and power,  $Z_R$  was  
 265 calculated as the system-wide *apparent* demand (as documented by data sources), minus the  
 266 consumption of these services by compensatory technologies. This approach ensured consistent  
 267 modeling across scenarios while avoiding double counting, and is detailed in the **SI** with  
 268 calculations in the **Supporting data**<sup>27</sup>. However, such disaggregation was not applied to agrifood  
 269 services, due to insufficient data granularity to untangle interlinkages between food, feed, and  
 270 fertilizers in the prospective scenarios. Finally, the unitary environmental impacts of  
 271 compensatory mixes ( $ipi_{C,R}$ ) were estimated by matching the scenario-specific share of each  
 272 technology within the compensatory mix to appropriate background inventory data<sup>24</sup>.  
 273 Coherency of each compensatory system model was ensured by linking dependent processes.  
 274 For example, the impacts of industrial heat via electric arc furnaces incorporates the scenario-  
 275 specific power mix. All data sources, calculations and scenario values are available in the  
 276 **Supporting data**, with key values summarized in **Table 2**.

277 **Table 2: Scenario rounded values for key variables.**

Scenario	Current	Trend	S1	S2	S3	S4
----------	---------	-------	----	----	----	----

Year	2018	2050	2050	2050	2050	2050
<b>Service demands for France (<math>Z_R</math>)</b>						
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 <sub>2</sub> O <sub>5</sub> )	797	667	668	735	679	733
K fertilizing (ktK <sub>2</sub> O)	2072	1734	1736	1911	1765	1905
Protein feed (Mt <sub>DM</sub> )	6.1	7.0	4.8	7.1	5.7	7.9
Energy feed (Mt <sub>DM</sub> )	15.3	18.0	8.6	9.0	15.3	17.1
Lipid feed (Mt <sub>DM</sub> )	0.20	0.23	0.11	0.11	0.19	0.17
Roughage feed (Mt <sub>DM</sub> )	54	77	38	40	56	61
Meat-equivalent (Mt <sub>DM</sub> )	1.34	1.28	0.48	0.72	0.99	1.28
<b>Available residual streams in France (<math>B_B</math>), in million tonnes (wet weight)</b>						
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
<b>Total</b>	<b>256.7</b>	<b>235.0</b>	<b>176.2</b>	<b>168.3</b>	<b>222.4</b>	<b>298.5</b>
<b>Compensatory industrial heat production supplies mix for France</b>						
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%
<b>Compensatory domestic heat production supplies mix for France</b>						
<b>District heat network</b>	5%	10%	13%	20%	21%	10%
<b>Wood</b>	9%	10%	27%	24%	15%	5%
<b>Power-based heat</b>	22%	38%	40%	32%	36%	35%
<b>Gas network</b>	46%	39%	15%	23%	23%	34%
<b>Oil</b>	16%	2%	0%	0%	0%	9%
<b>Liquid petroleum gas</b>	2%	1%	0%	0%	1%	3%
<b>Thermal solar</b>	0%	0%	5%	2%	4%	5%
<b>Compensatory meat-equivalent production supplies mix for France</b>						
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%

278 Supporting data sources, calculations, and values for the rest of compensatory supplies mixes are available in the  
279 **Supporting data**<sup>27</sup>. Compensatory supplies mixes impact for all scenarios are also summarized in the **SI**.

## 280 Environmental impacts assessment

281 Environmental impacts were assessed using the Environmental Footprint (EF) method  
282 version 3.1, which includes 16 midpoint impact categories<sup>28</sup>. The EF method also provides a  
283 standardized procedure for normalizing, weighting, and aggregating 13 of the 16 midpoint  
284 impacts into a single score, expressed in points -or person-equivalents. This score estimates the  
285 total environmental impact of the studied system relative to that of an average global individual  
286 in 2010. Three midpoint categories -freshwater ecotoxicity and human toxicity (cancer and non-  
287 cancer)- are excluded, as they are considered interim and lack sufficient robustness<sup>29</sup>.  
288 Normalization and weighting coefficients were directly sourced from EF documentation<sup>28,29</sup>.

289 Process-based LCA models for both valorization pathways and compensatory technologies  
290 incorporate all relevant inventory flows in accordance with ISO 14040/44 standards<sup>15</sup>. These  
291 models rely on the Ecoinvent consequential product system<sup>30</sup>, version 3.8. The use of a  
292 consequential product system is more appropriate than attributional for the residual biomass  
293 allocation problem because it avoids background selection of processes that depend on  
294 constrained resources (including waste streams) and it inherently applies the *system expansion*  
295 *with substitution* principle (no cut-off). Consequential LCA aligns conceptually with the residual  
296 biomass allocation framework goal -to evaluate the long-term consequences of changing  
297 current biomass valorization strategies<sup>12</sup>. The characterization factor for biogenic CO<sub>2</sub> in GWP<sub>100</sub>  
298 was set to zero, and residual streams were assumed to carry no embedded emissions prior to  
299 processing<sup>31</sup>. All background activities used for compensatory mixes (across all scenarios) are  
300 detailed in the **Supporting data**<sup>27</sup>, while those related to valorization pathways are documented  
301 previous works<sup>2,24</sup>.

## 302 Case study implementation

### 303 Single-objective solutions exploration

304 A generic Python routine was developed to initialize and solve the residual biomass  
305 allocation problem for any case study. The procedure is outlined in the **SI**. The *SciPy* linear  
306 programming package<sup>32</sup> was used to automatically select between the dual revised simplex  
307 implementation (HSOL) and the interior-point method<sup>33</sup>, which are fast and stable solvers.

308 The French case study involved 154 optimization variables after excluding incompatible  
309 feedstock-pathway combinations, and 25 linear constraints. Scenario analysis and stochastic  
310 simulations were used to investigate how individual components of the residual biomass  
311 allocation problem influences single-objective optimization results, with the EF single score as  
312 the objective to minimize. Scenario analysis examined how optimal solutions shift under  
313 different modeling decisions (e.g., selected valorization pathways) and future scenarios.  
314 Stochastic simulations assessed solution robustness under uncertainty in future technological  
315 performances<sup>12</sup>. All process-based models mobilize a consistent set of technological  
316 parameters, with uncertainty ranges described by uniform distributions<sup>24</sup>. Coherent yet  
317 independent valorization performance samples ( $a_{R,B,N}$ ,  $ipo_{C,B,N}$ ), were generated via Monte  
318 Carlo paired sampling of these parameters. A sample size of 300 was deemed sufficient, yielding

319 comparable results to 200 samples, suggesting convergence. EF single score minimization was  
320 performed for each combination of background scenario and valorization performance sample.

### 321 Multi-objective application

322 Tri-objective optimization was performed using the baseline valorization performance  
323 sample, and required the selection of three conflicting EF midpoint categories. First,  
324 dimensionality reduction was performed using principal component analysis (PCA) on the  
325 resulting  $\alpha_C$  parameters (using impact categories as columns and compatible feedstock-  
326 pathways as rows), as these determines the optimization outcomes. A subsequent Pearson  
327 correlation analysis quantified synergies and trade-offs between impact categories<sup>34</sup>. Impact  
328 categories were then manually gathered into three groups based on their contribution to the  
329 first principal component, without applying a formal clustering method. One representative  
330 impact category from each contrasting group was selected by qualitatively analyzing how  
331 different  $LCA_C$  impacts varied across multiple valorization strategies, as estimated by  
332 individually optimizing each of the 16 categories across the 300 valorization performance  
333 samples. For instance, impact categories with narrow distributions suggests a low sensitivity to  
334 national-scale residual biomass valorization strategy, therefore less relevant for analysis (see  
335 **Results**). This procedure was repeated across all background scenarios using *R* software v.4.4.1.,  
336 with the *factoextra* and *corrplot* libraries.

337 Moderate variability across scenarios was observed in the grouping of impact categories, with a  
338 clear distinction emerging between the three groups: (i) water use, land use, and marine  
339 eutrophication; (ii) resource use -fossil, minerals & metals-; and (iii) climate change, particulate  
340 matter formation, and acidification. The correlation analysis revealed a negative correlation  
341 between groups (i) and (ii), while group (iii) appeared relatively independent. In the  $\epsilon$ -constraint  
342 method, the main objective is selected based on its central trade-off position -capable of  
343 improvements without substantially worsening other objectives- while constraints represent  
344 objectives associated with policy targets or conflicting priorities. Climate change was selected as  
345 the main objective due to its policy relevance and moderate to weak correlation with the other  
346 two groups (improving climate change is less likely to penalize the other two objectives).

347 For these two objectives, lower and upper bounds ( $\epsilon_{i,L}, \epsilon_{i,U}$  in **Equation 8**) were set to the  
348 minimal single-objective  $LCA_C$  values (baseline technological performances) and the values  
349 from the unoptimized -baseline- valorization strategy, respectively. To ensure dominance check  
350 and visualize trade-offs, a non-dominated sorting operator -based on ranking procedures used  
351 in multi-objective evolutionary algorithms- was applied to filter and rank the  $\epsilon$ -constraint-  
352 generated solution set.

## 353 Results and discussion

### 354 Minimizing the *single score* impacts under multiple scenarios

355 Optimizing residual biomass valorization for France reduced total environmental impacts  
356 by 25% (*Current, Tend*) to 60% (*S1, S2*) compared to the foreseen baseline valorization strategy.

357 The difference between these scenario groups is primarily driven by the higher demand (**Table**  
358 **1**) and the greater environmental impacts of compensatory technologies in the former. Indeed,  
359 supplying all service demands without using residual biomass would generate impacts summing  
360 40 million person-equivalents, compared to approximately 20 million in the latter ( $\beta_C$  in **Figure**  
361 **2**). Across scenarios, optimizing residual biomass valorization yielded a consistent impact  
362 reduction potential compared to their baseline reuse, ranging from around 7 million person-  
363 equivalents savings for *S1* and *S2* to around 10 million in *S4*, *Current* and *Temp* (net values  
364 available in the **SI**). This consistency arises from the similar baseline valorization strategies  
365 forecasted by future scenarios, prioritizing agronomic valorization (e.g., composting), followed  
366 by anaerobic digestion for energy recovery. These allocated wood processing residues to  
367 industrial heat production, while leaving forestry and pruning residues on ground.  
368 Consequently, before optimization, residual biomass contributes to 20-40% of nitrogen, 40-60%  
369 of phosphorus, and 80-100% of potassium fertilizer total demand, while covering 30-80% of  
370 industrial heat requirements in these scenarios ( $\%BIO_R$  in **Figure 2**). Yet, such baseline  
371 valorization strategies induce net environmental impacts (positive  $\alpha_C$  values) rather than  
372 mitigating them, in contrast to optimized strategies. When minimizing the EF single score, the  
373 production of heat and meat-equivalent services from residual biomass valorization was favored  
374 over fertilizers and feed ingredients, across all scenarios. Only for *S1*, the demand for lipid feed  
375 was supplied at 80% by insect farming, likely due to lower total service demands enabling the  
376 production of more services from the same residual biomass pool. Yet, optimal strategies  
377 induced an 5-15% additional power demand across all scenarios (equivalent to an extra 20-40  
378 TWh at national scale), suggesting that power was not a major environmental concern for this  
379 case study. Indeed, projected power mixes presented low EF single score impacts: either  
380 predominantly nuclear (ca. 70% in *Current* and *Tend*) or renewable (four other scenarios).

381 The single-objective solution to the residual biomass allocation problem is predictable by  
382 comparing the  $\alpha_C$  values across all compatible valorization pathways for each feedstock. These  
383 values are fixed for a given performance sample and can be ranked in ascending order, with the  
384 most environmentally efficient pathways ranked highest. The optimal solution sequentially  
385 allocates each feedstock to the top-ranked pathways until the biomass is exhausted or demand  
386 is met. Consequently, optimal solutions are highly sensitive to the relative  $\alpha_C$  values and tend to  
387 lack diversification at the national scale, with feedstocks concentrated in a few pathways. This  
388 outcome stems from minimal constraint imposition. Diversification only occurs under supply-  
389 demand mismatches, allowing surplus feedstocks to serve a broader range of demands.  
390 Sensitivity to  $\alpha_C$  also means that altering the scope of considered valorization pathways can  
391 substantially shift outcomes (**Figure 2A**). For example, excluding waste-to-nutrition pathways  
392 removed options producing meat-equivalent services such as insect farming on food waste or  
393 mycoprotein production from lignocellulosic sugars. These consistently had the lowest  $\alpha_C$   
394 values (**Figure 2C**), ranging from -0.05 to -0.13 person-equivalents impacts per tonne valorized  
395 across all scenarios. In their absence, optimal solutions prioritized heat-generating pathways  
396 (e.g., combustion of wood and straw, biomethane from manure, with benefits of -0.03 to -0.05

397 person-equivalent per tonne), and redirected remaining feedstock toward direct livestock  
 398 feeding (e.g., vegetable tops and food waste).

399 **Figure 2: Single score-optimized residual biomass strategy results for the *Current* scenario.**



400  
 401 **Panel A:** Optimized EF single score impacts for different prescreened sets of valorization pathways, considering  
 402 fixed technological performances. Last right-hand subplot displays impacts distribution after optimizing across the  
 403 300 technological performance samples, representing future pathways' performance uncertainties (see **Methods**).  
 404 **Panel B:** Optimal valorization strategies averaged across the 300 EF single score optimization. Pathways never  
 405 selected in optimal solutions were not displayed. **Panel C:** Distributions of the 300  $\alpha_c$  values for the 11 selected  
 406 valorization pathways compatible with forestry residues (paired simulation, see **Methods**). Data and visualization  
 407 for the other scenarios are available in the **Supporting data**. Pathway acronyms are detailed in the **SI**: Dom\_heat,  
 408 Indu\_heat: biomass combustion for domestic and industrial heat production; Myco\_food, BSF\_food: respectively  
 409 mycoprotein and insect production processed as meat-analogues; Myco\_feed when mycoproteins is fed to  
 410 livestock; AD\_CHP, AD\_grid: anaerobic digestion with biogas valorized as combined heat and power (CHP) or used  
 411 for industrial heating (grid); GA\_CHP, GA\_grid: same gas valorization from gasification; CF: direct livestock feeding;  
 412 GB\_AD, GB\_myco, GB\_rough: leaf protein extraction through green biorefining with three variants for valorizing  
 413 the press-pulp, anaerobic digestion, livestock feeding, or feedstock for mycoprotein production; MP\_shift,  
 414 MP\_meths, MP\_syngas: three variants of microbial protein production from gasification outputs; Decay\_na:  
 415 natural non-arable land decay.

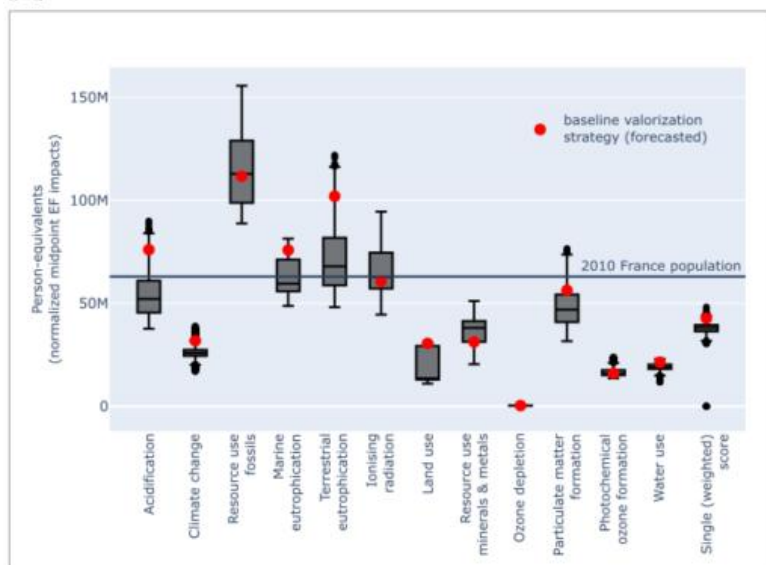
416 Robust estimation of  $\alpha_C$  is essential but inherently uncertain due to dependence on future  
417 technological developments<sup>24</sup>. Nevertheless, process-based LCA models enabled generation of  
418 consistent  $\alpha_C$  samples, facilitating the exploration of solution variability across multiple  
419 independent, yet coherent, optimizations (see **Methods**). Technological advancements may  
420 alter pathway rankings, potentially increasing solution diversification (**Figure 2B**). Uncertainties  
421 in future technological performance affected minimal achievable EF single score impacts by  $\pm$   
422 10% equivalent to 2-3 million person-equivalents across scenarios (**Figure 2A**). Some services,  
423 such as industrial heat, were consistently supplied by residual biomass (%*BIO* ~ 100% for all  
424 scenarios), while others, like domestic heat, were only met under specific performance levels  
425 (e.g., *S1-S4*). Land decay was consistently excluded from optimal strategies. However, these  
426 strategies still matched baseline levels of bio-based nitrogen and phosphorus supply, primarily  
427 through nutrient cycling via anaerobic digestion of livestock excreta, returning nutrients to  
428 cropland via digestates. Conversely, large potassium supplies previously sourced from plowed  
429 crop residues then required mineral-based inputs, as crop residues were predominantly  
430 combusted for energy in optimal solutions across all scenarios.

431 Valorization strategies introduced trade-offs between environmental impact categories, often  
432 masked by single score aggregation. Prioritizing one midpoint category over others led to  
433 different optimal strategies than when minimizing the aggregated score, which was primarily  
434 driven by climate change (weighting 22%). Some impact categories were relatively unaffected  
435 by residual biomass valorization strategies, either for being unrelated (e.g., ozone depletion  
436 linked to HCFCs use), or associated with specific technologies supplying high-demand services  
437 not targeted by the optimization (e.g., photochemical ozone formation and water use; **Figure**  
438 **3A**). For instance, water use impacts across optimal scenarios were mainly driven by power  
439 generation (photovoltaic and nuclear) and irrigated crops for feed demand. Since power and  
440 feed services were rarely prioritized for impacts reduction, their LCA results remained largely  
441 independent of valorization strategies for these impact categories. However, this independence  
442 changes with compensatory technologies. For example, ionizing radiation and fossil resource  
443 depletion impacts depended on the nuclear share in the future power mix: these impacts were  
444 substantial in nuclear-heavy scenarios (*Current, Trend*) but negligible in a nuclear-free future  
445 (*S1*). Likewise, mineral and metal resource use increased with a higher share of renewables in  
446 compensatory power supplies, making this impact more sensitive to valorization strategies in  
447 scenarios *S1-S4*.

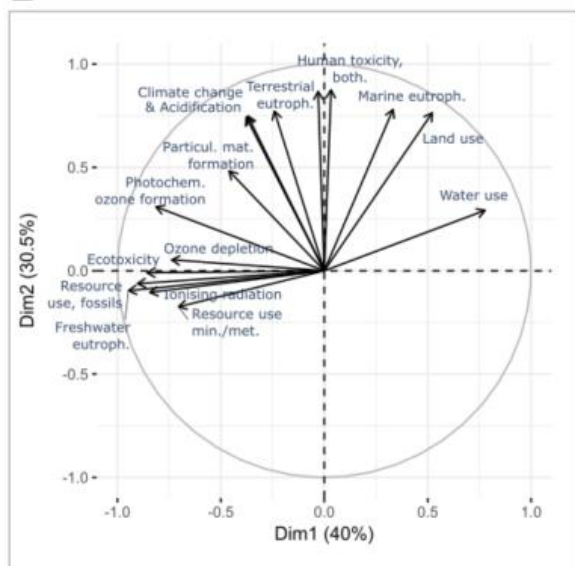
448

449 **Figure 3: Multisector integration breakdown per impact categories, for the *Tend* scenario.**

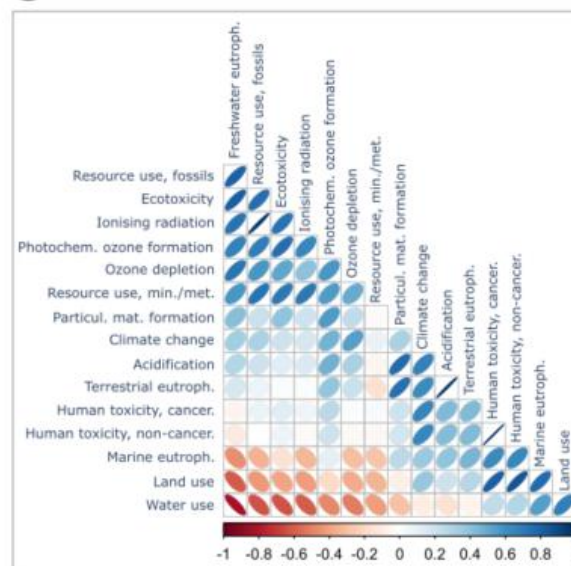
**A**



**B**



**C**



450  
 451 **Panel A:** Distribution of normalized EF midpoints across n=4800 optimizations (each 16 EF impact categories  
 452 individually optimized on each 300 valorization performance samples; see **Methods**) Boxplots display medians  
 453 (center line), IQR (box bounds from 25th to 75th percentiles), and whiskers extend within 1.5× IQR. **Panel B:** Results  
 454 of the PCA performed on the 16 EF midpoint impact categories (see **Methods**). Third, fourth, fifth, sixth  
 455 components (or dimensions) captured respectively 11.5%, 5.9%, 3.6% and 3.1% of the variance, others being below  
 456 2%. **Panel C:** Pairwise Pearson correlation matrix classified according to the first principal component. Blue ellipses  
 457 indicate a positive correlation between two categories, while negative correlations are in red tones. Unsignificant  
 458 correlation (with p-values < 0.05) are blank. Background data and visualization for the other scenarios are available  
 459 in the **Supporting data**.

460 Across all scenarios, terrestrial and marine eutrophication, acidification, and particulate matter  
461 formation impacts remained among the highest normalized impacts and were strongly  
462 influenced by the selected valorization strategies. These impact categories are primarily driven  
463 by conventional livestock excreta management<sup>2</sup>, which was rarely included in optimal  
464 valorization strategies. Instead, optimized strategies consistently redirected livestock excreta to  
465 anaerobic digestion, exceeding baseline scenario projections (about 20-35%), thereby reducing  
466 these impacts (**Figure 3A**). The benefits on particulate matter formation were partly offset by  
467 increased direct biomass combustion. Nonetheless, compared to baseline valorization,  
468 minimizing any EF midpoint impact category consistently reduced impacts across most other  
469 categories, with the exception for resource use and ionizing radiation (**Figure 3A**). The  
470 magnitude of these reductions decreased in more sustainable background scenarios -those with  
471 lower demand and cleaner technologies. For example, current (2018) system-wide climate  
472 change impacts are estimated at ~300 MtCO<sub>2</sub>-eq (40 million person-equivalents). Optimal  
473 valorization strategies can cut these impacts by half. However, in already climate-efficient  
474 scenarios such as S1, where baseline climate impacts are around 10 million person-equivalents,  
475 the additional climate benefits from optimization are limited.

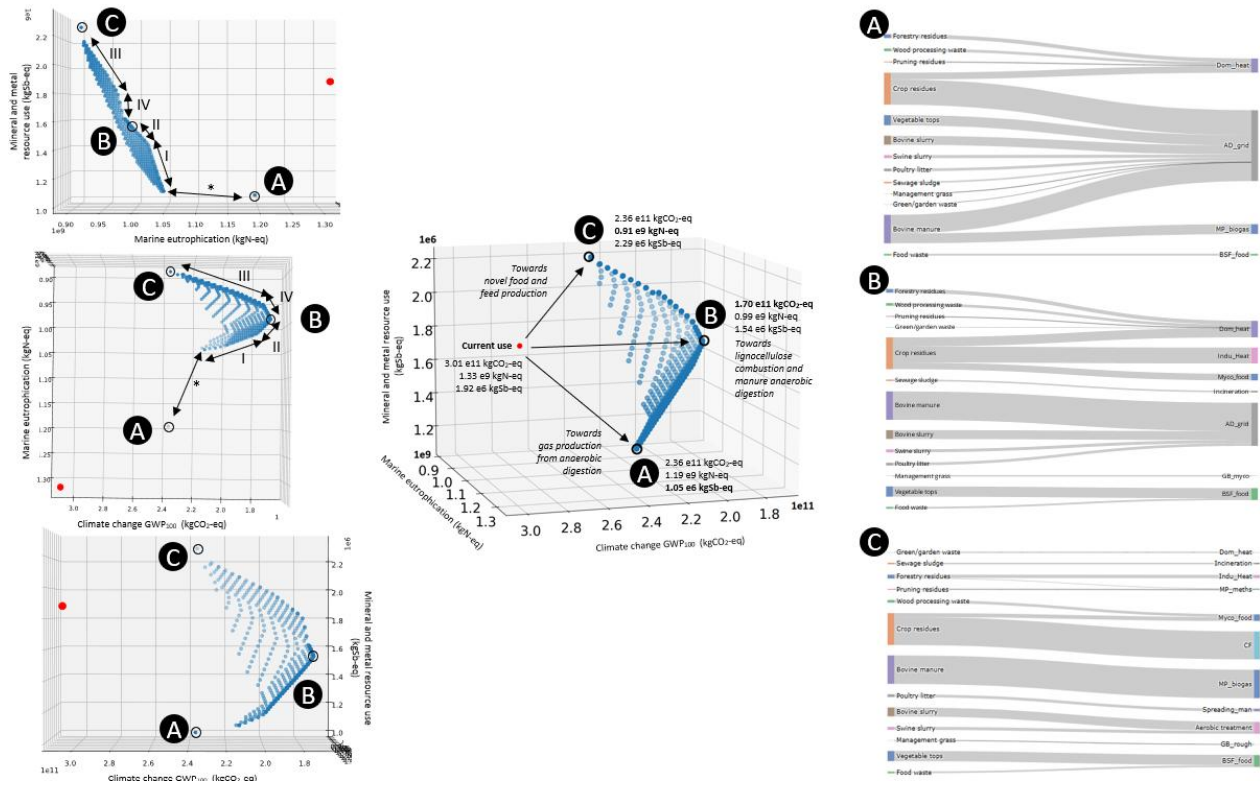
#### 476 Multi-impacts optimization and analysis for decision-making

477 While net impact reductions were achievable across most categories compared to  
478 baseline residue valorization, minimizing a single impact often exacerbated the others. Tri-  
479 objective optimization was used to explore trade-offs between climate change (a primary  
480 environmental policy target), marine eutrophication (a proxy for nitrogen emissions linked to  
481 biomass management), and mineral and metal resource use (associated with power demands of  
482 valorization pathways; described above). The Pearson correlation analysis revealed that climate  
483 change and marine eutrophication tended to increase together. Yet, climate change and  
484 resource use were only weakly correlated, while marine eutrophication and resource use  
485 showed a strong trade-off (**Figure 3C**). Consequently, minimizing climate impacts may also  
486 reduce marine eutrophication, though constraints are needed to avoid excessive nitrogen  
487 losses. Conversely, reducing mineral and metal resource use can increase marine  
488 eutrophication, trade-offs limited by constraining these impacts.

489 These three impact categories defined the axes of the 3D Pareto front (**Figure 4**). Pareto-optimal  
490 solutions all diverged substantially from baseline valorization strategy (“current use” for *Current*  
491 scenario), particularly in pathway selection. Marine eutrophication and mineral and metal  
492 resource use were clearly conflicting. Most solutions achieved at least a 20% reduction in  
493 marine eutrophication impacts compared to baseline (up to 30% for global minimum; point C in  
494 **Figure 4**). However, global minimum for resource use led to only a 10% reduction in marine  
495 eutrophication (point A), as the final reduction in resource use (from 1.07 to 1.05x10<sup>6</sup> kgSb-eq)  
496 required diverting all vegetable tops from insect farming to biomethane production -causing  
497 nitrogen losses through digestates (\* in **Figure 4**). All solutions reduced climate impacts by at  
498 least 15% compared to baseline valorization, but up to an additional 27% reduction was possible  
499 at the expense of other objective.

500 Two main trade-off zones emerged: (i) zone A-B, where climate change mitigation conflicted  
 501 with resource savings; and (ii) zone B-C where these were aligned. Zone A-B divided into two  
 502 subzones (denoted I and II in **Figure 4**). Subzone I involved shifting 100% of crop residues from  
 503 anaerobic digestion (with gas injection) to direct combustion, while redirecting surplus livestock  
 504 excreta to digestion to meet industrial heat demand. This yielded ~22% additional climate  
 505 impacts reduction but increased resource use by ~32%. Achieving the final 5% climate impacts  
 506 reduction (point B in **Figure 4**) required alternative protein production -diverting 20% of crop  
 507 residues and green wastes to mycoprotein production-, and rerouting all sewage sludge from  
 508 digestion to incineration -illustrating how marginal gains in one objective can demand  
 509 substantial valorization strategy shifts.

510 **Figure 4: Tri-objective optimization of the residual biomass allocation problem applied to**  
 511 **France under the *Current* scenario.**



512 Three EF midpoint impact categories as objectives: climate change (GWP<sub>100</sub>), marine eutrophication, mineral and  
 513 metal resource use. Black circles represent coordinates of each single-objective optimization result, with  
 514 corresponding optimized valorization strategy displayed in Sankey diagrams A, B, and C. Red dots represent impacts  
 515 of current residual biomass use. Blue dots represent Pareto-optimal solutions, see **Methods**. Subzones in the  
 516 solution space were denoted “\*”, “I”, “II”, “III”, and “IV” and described in the **Results** section. Background data is  
 517 available in **Supporting data**<sup>27</sup>. Pathway’s acronyms are explicated in **Figure 2** caption.

518 Similarly, zone B-C also divided into two subzones. Global marine eutrophication minimum  
 519 (point C) resulted in the highest resource use (~20% above baseline), despite similar climate  
 520 performance to resource use minimum (point A). These outcomes stemmed from completely  
 521

522 different valorization strategies. Marine eutrophication minimization involved feeding dried  
523 crop residues to livestock, increasing power demand and thus resource depletion. In subzone III,  
524 24% of the potential 27% additional climate benefits was achieved by shifting from livestock  
525 feeding to energy recovery and redirecting forestry residues from industrial to domestic heat.  
526 This also reduced resource use by ~20%. The remaining 3% climate gains required diverting 10%  
527 of crop residues to mycoprotein production and completely phasing out microbial protein  
528 production from biogas.

### 529 Implications for bioeconomy planning

530 The French case study revealed that optimal national-scale strategies for residual  
531 biomass valorization are more sensitive to the range of scalable valorization pathways, their  
532 technological performances, and selected indicators, than to background scenario variations.  
533 The multisectoral optimization framework developed here can serve as a pre-screening tool to  
534 prioritize sectors for bioeconomy planning.

535 In the French context, optimal strategies consistently favored heat and meat-equivalent service  
536 recovery due the high impacts of their conventional supply chains. For example, conventional  
537 meat production generates ten times the impacts of feed crop production<sup>24</sup> (on a dry weight  
538 basis), and even under the most sustainable scenario (*S1*), meat remained the most impactful  
539 service. Meat-equivalent-producing pathways were only disfavored under assumptions of low  
540 animal-based met substitution rates and conversion efficiencies (outliers in **Figure 2A**). Similarly,  
541 industrial heat supply is three time more climate-intensive than power production per unit of  
542 energy, while domestic heat is twice as impactful, regardless of forecasted technology mix  
543 (**Table 2**). These findings suggest that directing residual biomass toward services with high  
544 environmental impacts few sustainable alternatives -such as meat and heat- can deliver robust  
545 impact reductions, even under uncertain future conditions. The framework can also be  
546 extended to identify other high-impacts services (e.g., currently supplied by specific chemicals  
547 or materials) with potential for bio-sourced alternatives<sup>5</sup>.

548 Trade-offs emerged notably in the power demand of the valorization processes themselves.  
549 Optimal strategies led to a 5-15% increase in national power demand, compromising their  
550 feasibility. Deploying large-scale residual stream valorization hinges on sustainable,  
551 unconstrained power availability, raising concerns about critical material supply chains required  
552 by power-producing technologies<sup>35</sup>. Incorporating constraints on allowable additional power  
553 use in future analyses could improve realism.

554 Transitioning towards a circular bioeconomy also requires closing or inverting the residual  
555 supply-demand gap. Meeting the estimated current French heat demand (industrial and  
556 domestic) would alone absorb almost all French residual resource potential, limiting feedstock  
557 availability for other services. Yet, prospective scenarios with reduced demand levels not  
558 necessarily allowed more diversified valorization, as lower service demands may also reduce  
559 feedstock availability. For instance, halved meat-equivalent demand in *S1* and *S2* halved manure  
560 availability for energy recovery.

## 561 Reusable framework for exploring circular bioeconomy trade-offs

562 The proposed optimization framework is flexible, scalable, and applicable to other  
563 indicators, including economic ones. Applied to France, it effectively identified the most  
564 favorable recovery pathways, underlining the need to move beyond static performance  
565 assumptions and integrate projections of technological improvements. Coupling process-based  
566 LCA models with optimization enabled automated sensitivity analysis and refined the  
567 understanding on the conditional role of emerging pathways under future conditions.

568 The framework also highlighted which pathways are unlikely to be competitive. In the French  
569 case, about 70% of predefined feedstock-pathway combinations were never selected in optimal  
570 strategies -e.g., combined heat and power from crop residues. Integrating pathway selection  
571 frequency<sup>12</sup> and alternative impact assessment methods<sup>8,36</sup> could further improve decision-  
572 making. Importantly, selected EF impact categories were case-specific, derived from PCA and  
573 correlation analyses of predefined -non-exhaustive- scenarios. Using endpoint-oriented  
574 methods (e.g., Impact World +) can eliminate the need for selection, enabling a more  
575 comprehensive and consistent assessment of all impact pathways. Methodological challenges  
576 persist, particularly with scaling LCA from product to national levels and its applicability to long-  
577 term prospective analyses<sup>37,38</sup>. Addressing these requires integration with sector-specific  
578 integrated assessment models<sup>39</sup>, beyond the scope of this study's exploratory approach.

579 The framework remains applicable to other territorial contexts -such as the European Union-  
580 sharing similar market structures and policy environments. Applying the framework to European  
581 scale is a logical next step, but raises questions about the appropriate territorial scales for  
582 planning. For instance, the *no-export* constraints were used to enable scalability of optimal  
583 solutions, though this may not be adequate to assess regional specialization.

584 Data availability remains also key constraint to expand the analysis. Including additional  
585 valorization pathways (e.g., for materials, chemicals, fuels) requires detailed process models and  
586 coherent demand/supply characterization across scenarios. Ensuring all resulting demand  
587 categories are exogenous and independent demand is challenging due to supply chain  
588 interdependencies. Moreover, scenarios were here treated as static snapshots which limits  
589 representation of dynamic feedbacks -e.g., substitution of animal-based meat by novel foods  
590 which lower manure availability. The static assessment left apart many dynamic effects, such as  
591 long-term soil carbon consequences of diverting crop residues from fields<sup>40</sup>, the seasonality and  
592 geo-localization of residual resources, beyond contextualized socioeconomic factors which  
593 ultimately are those shaping residual biomass valorization decisions locally<sup>41</sup>.

594 Despite limitations, the framework explicitly helps quantifying the key variables shaping residual  
595 biomass valorization and provided a scalable optimization tool for early-stage trade-off analysis.  
596 The model included 154 allocation variables for the French case, but this could expand  
597 significantly with broader feedstock-pathways combinations due to refined modeling granularity  
598 and the inclusion of other sectors. While the circular bioeconomy cannot be exhaustively

599 modeled due to technological unpredictability, the framework can incorporate new  
600 technologies as conversion data become available.

## 601 Supporting information

602 Benchmark of previous residual biomass allocation studies, description of valorization pathways,  
603 scenario data collection, step-by-step optimization procedure, supporting data.

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612 Economies.

## 613 Data and code availability statement

614 The raw data required to reproduce the above findings, as well as corresponding Python scripts,  
615 are available to download from DOI: 10.17632/gyzd25nfv4.2 (ref<sup>27</sup>).

## 616 References

- 617 (1) Hamelin, L.; Borzęcka, M.; Kozak, M.; Pudełko, R. A Spatial Approach to Bioeconomy:  
618 Quantifying the Residual Biomass Potential in the EU-27. *Renew Sust Energ Rev* **2019**, *100*, 127–  
619 142. DOI: 10.1016/j.rser.2018.10.017.
- 620 (2) Javourez, U.; Karan, S. K.; Hamelin, L. Residual Biomasses at Scale: Ensuring Future  
621 Bioeconomy Uses Outperform Current Baseline. *Sci. Total Environ.* **2024**, *949*, 174481. DOI:  
622 10.1016/j.scitotenv.2024.174481.
- 623 (3) Mori, R. Replacing All Petroleum-Based Chemical Products with Natural Biomass-Based  
624 Chemical Products: A Tutorial Review. *RSC Sustain.* **2023**, *1* (2), 179–212. DOI:  
625 10.1039/D2SU00014H.
- 626 (4) Su-ungkavatin, P.; Tiruta-Barna, L.; Hamelin, L. Biofuels, Electrofuels, Electric or  
627 Hydrogen?: A Review of Current and Emerging Sustainable Aviation Systems. *Prog. Energy*  
628 *Combust. Sci.* **2023**, *96*, 101073. DOI: 10.1016/j.pecs.2023.101073.
- 629 (5) Zuiderveen, E. A. R.; Kuipers, K. J. J.; Caldeira, C.; Hanssen, S. V.; van der Hulst, M. K.; de  
630 Jonge, M. M. J.; Vlysidis, A.; van Zelm, R.; Sala, S.; Huijbregts, M. A. J. The Potential of Emerging  
631 Bio-Based Products to Reduce Environmental Impacts. *Nat. Commun.* **2023**, *14* (1), 8521. DOI:  
632 10.1038/s41467-023-43797-9.

- 633 (6) Ding, T.; Steubing, B.; Achten, W. M. J. Coupling Optimization with Territorial LCA to  
634 Support Agricultural Land-Use Planning. *J. Environ. Manage.* **2023**, *328*, 116946. DOI:  
635 10.1016/j.jenvman.2022.116946.
- 636 (7) Calvo-Serrano, R.; Guo, M.; Pozo, C.; Galán-Martín, Á.; Guillén-Gosálbez, G. Biomass  
637 Conversion into Fuels, Chemicals, or Electricity? A Network-Based Life Cycle Optimization  
638 Approach Applied to the European Union. *ACS Sustain. Chem. Eng.* **2019**, *7* (12), 10570–10582.  
639 DOI: 10.1021/acssuschemeng.9b01115.
- 640 (8) Abdallah, M.; Rahmat-Ullah, Z.; Hosny, M.; Alsmadi, S. Minimizing the Environmental  
641 Impacts of Waste Valorization Systems Using Multi-Criteria Life Cycle Optimization. *J. Clean.*  
642 *Prod.* **2024**, *449*, 141619. DOI: 10.1016/j.jclepro.2024.141619.
- 643 (9) Lubjuhn, S.; Venghaus, S. Unlocking the Potential of the Bioeconomy for Climate Change  
644 Reduction: The Optimal Use of Lignocellulosic Biomass in Germany. *J. Ind. Ecol.* **2023**, *28* (1),  
645 144–159. DOI: 10.1111/jiec.13455.
- 646 (10) Musonda, F.; Millinger, M.; Thrän, D. Optimal Biomass Allocation to the German  
647 Bioeconomy Based on Conflicting Economic and Environmental Objectives. *J. Clean. Prod.* **2021**,  
648 *309*, 127465. DOI: 10.1016/j.jclepro.2021.127465.
- 649 (11) Vadenbo, C.; Tonini, D.; Burg, V.; Astrup, T. F.; Thees, O.; Hellweg, S. Environmental  
650 Optimization of Biomass Use for Energy under Alternative Future Energy Scenarios for  
651 Switzerland. *Biomass Bioenergy* **2018**, *119*, 462–472. DOI: 10.1016/j.biombioe.2018.10.001.
- 652 (12) Vadenbo, C.; Tonini, D.; Astrup, T. F. Environmental Multiobjective Optimization of the  
653 Use of Biomass Resources for Energy. *Environ. Sci. Technol.* **2017**, *51* (6), 3575–3583. DOI:  
654 10.1021/acs.est.6b06480.
- 655 (13) Yu, B.; Liu, X.; Ji, C.; Sun, H. Greenhouse Gas Mitigation Strategies and Decision Support  
656 for the Utilization of Agricultural Waste Systems: A Case Study of Jiangxi Province, China. *Energy*  
657 **2022**, 126380. DOI: 10.1016/j.energy.2022.126380.
- 658 (14) Colla, M.; Blondeau, J.; Jeanmart, H. Optimal Use of Lignocellulosic Biomass for the  
659 Energy Transition, Including the Non-Energy Demand: The Case of the Belgian Energy System.  
660 *Front. Energy Res.* **2022**, *10*. DOI: 10.3389/fenrg.2022.802327.
- 661 (15) ISO. Environmental Management: Life Cycle Assessment; Principles and Framework.  
662 **2006**.
- 663 (16) Lodato, C.; Tonini, D.; Damgaard, A.; Fruergaard Astrup, T. A Process-Oriented Life-Cycle  
664 Assessment (LCA) Model for Environmental and Resource-Related Technologies (EASETECH). *Int.*  
665 *J. Life Cycle Assess.* **2020**, *25* (1), 73–88. DOI: 10.1007/s11367-019-01665-z.
- 666 (17) Bisinella, V.; Schmidt, S.; Varling, A. S.; Laner, D.; Christensen, T. H. Waste LCA and the  
667 Future. *Waste Manag.* **2024**, *174*, 53–75. DOI: 10.1016/j.wasman.2023.11.021.

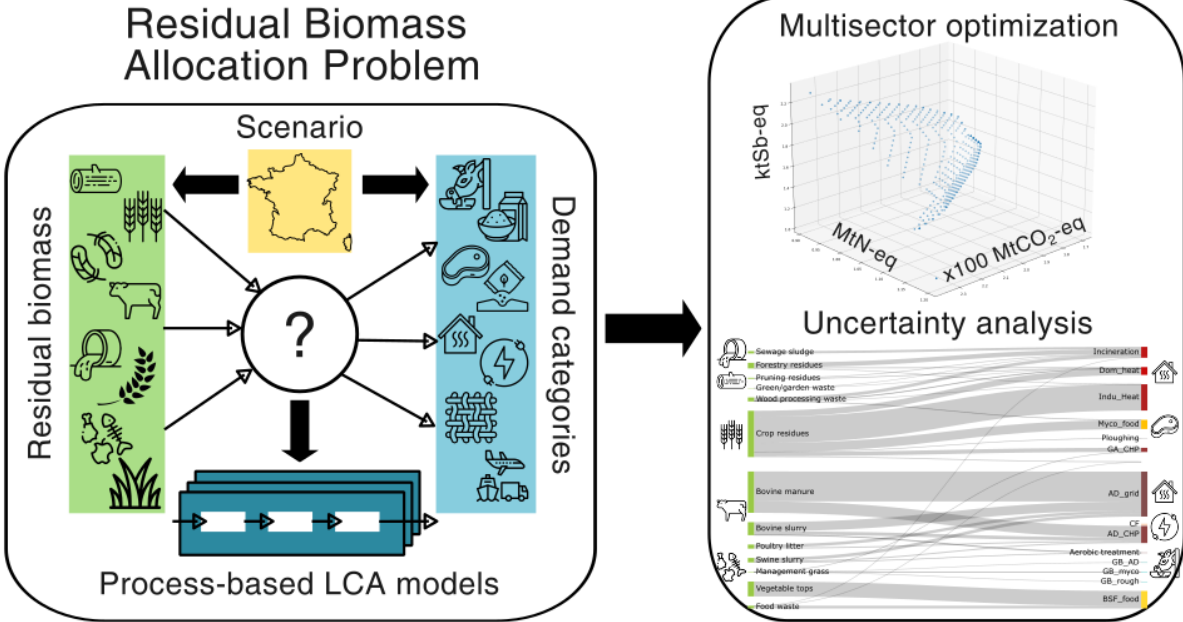
- 668 (18) Brandão, M.; Martin, M.; Cowie, A.; Hamelin, L.; Zamagni, A. Consequential Life Cycle  
669 Assessment: What, How, and Why? In *Encyclopedia of Sustainable Technologies*; Elsevier:  
670 Oxford, 2017; pp 277–284. DOI: 10.1016/B978-0-12-409548-9.10068-5.
- 671 (19) Weidema, B. P.; Frees, N.; Nielsen, A.-M. Marginal Production Technologies for Life Cycle  
672 Inventories. *Int. J. Life Cycle Assess.* **1999**, 4 (1), 48–56. DOI: 10.1007/BF02979395.
- 673 (20) Miettinen, K. *Nonlinear Multiobjective Optimization*; Hillier, F. S., Series Ed.; International  
674 Series in Operations Research & Management Science; Springer US: Boston, MA, 1998; Vol. 12.  
675 DOI: 10.1007/978-1-4615-5563-6.
- 676 (21) Ahmadi, A.; Tiruta-Barna, L.; Capitanescu, F.; Benetto, E.; Marvuglia, A. An Archive-Based  
677 Multi-Objective Evolutionary Algorithm with Adaptive Search Space Partitioning to Deal with  
678 Expensive Optimization Problems: Application to Process Eco-Design. *Comput. Chem. Eng.* **2016**,  
679 87, 95–110. DOI: 10.1016/j.compchemeng.2015.12.008.
- 680 (22) Deb, K.; Jain, H. An Evolutionary Many-Objective Optimization Algorithm Using  
681 Reference-Point-Based Nondominated Sorting Approach, Part I: Solving Problems With Box  
682 Constraints. *IEEE Trans. Evol. Comput.* **2014**, 18 (4), 577–601. DOI: 10.1109/TEVC.2013.2281535.
- 683 (23) Mavrotas, G. Effective Implementation of the  $\epsilon$ -Constraint Method in Multi-Objective  
684 Mathematical Programming Problems. *Appl. Math. Comput.* **2009**, 213 (2), 455–465. DOI:  
685 10.1016/j.amc.2009.03.037.
- 686 (24) Javourez, U.; Tiruta-Barna, L.; Pizzol, M.; Hamelin, L. Environmental Mitigation Potential  
687 of Waste-to-Nutrition Pathways. *Nat. Sustain.* **2025**, 1–11. DOI: 10.1038/s41893-025-01521-z.
- 688 (25) ADEME. *Transition(s) 2050 - Choisir Maintenant, Agir Pour Le Climat - Rapport*; ADEME  
689 Editions: Angers, 2021.
- 690 (26) ADEME. *Transitions 2050 - Portail de données*. [https://data-](https://data-transitions2050.ademe.fr/datasets)  
691 [transitions2050.ademe.fr/datasets](https://data-transitions2050.ademe.fr/datasets) (accessed 2024-02-06).
- 692 (27) Javourez, U.; Ahmadi, A.; Robles-Rodriguez, C.; Tiruta-Barna, L.; Hamelin, L. Cambioscop  
693 Residual Biomass Allocation Optimization Platform, **2025**. DOI: 10.17632/gyzd25nfv4.1.
- 694 (28) Andreasi Bassi, S.; Biganzoli, F.; Ferrara, N.; Amadei, A.; Valente, A.; Sala, S.; Ardente, F.  
695 *Updated Characterisation and Normalisation Factors for the Environmental Footprint 3.1*  
696 *Method*; JRC130796; Publications Office of the European Union: LU, **2023**. DOI:  
697 10.2760/798894.
- 698 (29) Sala, S.; Cerutti, A. K.; Pant, R. *Development of a Weighting Approach for the*  
699 *Environmental Footprint*; Publications Office of the European Union: Luxembourg, 2018.
- 700 (30) Ecoinvent. *ecoinvent databases*. <https://ecoinvent.org/> (accessed 2022-05-01).

- 701 (31) Pizzol, M.; Ghose, A.; Nørgaard Bollesen, K. ALIGNED D1.2 Description of Scientific  
702 Methods (Task 1.2 Framework for Foreground Life Cycle Inventory of Bio-Based Sectors -  
703 Constraints to Biomass Availability). **2024**. DOI: 10.5281/ZENODO.10843453.
- 704 (32) Virtanen, P.; Gommers, R.; Oliphant, T. E.; Haberland, M.; Reddy, T.; Cournapeau, D.;  
705 Burovski, E.; Peterson, P.; Weckesser, W.; Bright, J.; van der Walt, S. J.; Brett, M.; Wilson, J.;  
706 Millman, K. J.; Mayorov, N.; Nelson, A. R. J.; Jones, E.; Kern, R.; Larson, E.; Carey, C. J.; Polat, İ.;  
707 Feng, Y.; Moore, E. W.; VanderPlas, J.; Laxalde, D.; Perktold, J.; Cimrman, R.; Henriksen, I.;  
708 Quintero, E. A.; Harris, C. R.; Archibald, A. M.; Ribeiro, A. H.; Pedregosa, F.; van Mulbregt, P.  
709 SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nat. Methods* **2020**, *17*  
710 (3), 261–272. DOI: 10.1038/s41592-019-0686-2.
- 711 (33) Huangfu, Q.; Hall, J. A. J. Parallelizing the Dual Revised Simplex Method. *Math. Program.*  
712 *Comput.* **2018**, *10* (1), 119–142. DOI: 10.1007/s12532-017-0130-5.
- 713 (34) de Faria, A. B. B.; Ahmadi, A.; Tiruta-Barna, L.; Spérandio, M. Feasibility of Rigorous  
714 Multi-Objective Optimization of Wastewater Management and Treatment Plants. *Chem. Eng.*  
715 *Res. Des.* **2016**, *115*, 394–406. DOI: 10.1016/j.cherd.2016.09.005.
- 716 (35) Vidal, O.; Le Boulzec, H.; Andrieu, B.; Verzier, F. Modelling the Demand and Access of  
717 Mineral Resources in a Changing World. *Sustainability* **2021**, *14* (1), 11. DOI:  
718 10.3390/su14010011.
- 719 (36) Steubing, B.; Zah, R.; Ludwig, C. Heat, Electricity, or Transportation? The Optimal Use of  
720 Residual and Waste Biomass in Europe from an Environmental Perspective. *Environ. Sci.*  
721 *Technol.* **2012**, *46* (1), 164–171. DOI: 10.1021/es202154k.
- 722 (37) Charalambous, M. A.; Sacchi, R.; Tulus, V.; Guillén-Gosálbez, G. Integrating Emerging  
723 Technologies Deployed at Scale within Prospective Life Cycle Assessments. *Sustain. Prod.*  
724 *Consum.* **2024**, *50*, 499–510. DOI: 10.1016/j.spc.2024.08.016.
- 725 (38) Pizzol, M.; Sacchi, R.; Köhler, S.; Anderson Erjavec, A. Non-Linearity in the Life Cycle  
726 Assessment of Scalable and Emerging Technologies. *Front. Sustain.* **2021**, *1*. DOI:  
727 10.3389/frsus.2020.611593.
- 728 (39) Baustert, P.; Igos, E.; Schaubroeck, T.; Chion, L.; Mendoza Beltran, A.; Stehfest, E.; van  
729 Vuuren, D.; Biemans, H.; Benetto, E. Integration of Future Water Scarcity and Electricity Supply  
730 into Prospective LCA: Application to the Assessment of Water Desalination for the Steel  
731 Industry. *J. Ind. Ecol.* **2022**, *26* (4), 1182–1194. DOI: 10.1111/jiec.13272.
- 732 (40) Andrade Díaz, C.; Clivot, H.; Albers, A.; Zamora-Ledezma, E.; Hamelin, L. The Crop  
733 Residue Conundrum: Maintaining Long-Term Soil Organic Carbon Stocks While Reinforcing the  
734 Bioeconomy, Compatible Endeavors? *Appl. Energy* **2023**, *329*, 120192. DOI:  
735 10.1016/j.apenergy.2022.120192.

736 (41) Sun, X.; Durkin, A.; Guo, M. Life Cycle Optimisation Tool Development for Process  
737 Systems and Centralised Supply Chain Design. *RSC Sustain.* **2023**, *1* (9), 2224–2240. DOI:  
738 10.1039/D3SU00251A.

739

740



742

743