

<sup>1</sup> Agroforestry SmartAgroforst: Poplar biomass modelling

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<sup>3</sup> **Abstract**

Short-rotation agroforestry systems are increasingly promoted as a low-carbon feedstock option for bio-based value chains, but their economic viability depends on coordinated decisions on stand establishment, multi-cycle harvesting, and product cascading in spatially distributed supply chains. This paper develops a mixed-integer linear programming (MILP) model for the integrated design and operation of an agroforestry biomass supply chain with explicit age-lag constraints that link consecutive harvests at each site. The formulation couples allometric yield functions for different biomass types with a multi-product, multi-period network design model including storage, processing, and product quality cascades. The model is applied to a stylised case study of Central European poplar-based alley-cropping systems to explore trade-offs between harvest rotation length, product portfolios, and infrastructure configuration. We outline a computational experimentation plan to test the impact of allometric parameter uncertainty, price scenarios, and policy incentives on the optimal deployment of agroforestry systems in cleaner bioeconomy pathways.

<sup>4</sup> *Keywords:* Agroforestry, Short-rotation coppice, Biomass supply chain, Product  
<sup>5</sup> cascading

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<sup>6</sup> **1. Introduction**

<sup>7</sup> Agroforestry systems that integrate trees with agricultural crops are increasingly  
<sup>8</sup> recognised as a promising land-use option to reconcile climate mitigation, biodiversity  
<sup>9</sup> conservation, and rural income generation on the same hectare of land [8, 14]. Temper-  
<sup>10</sup> ate short-rotation agroforestry systems (SRAFS) based on fast-growing species such as

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11 poplar, willow, alder, and black locust can deliver competitive biomass yields while im-  
12 proving soil quality and providing multiple ecosystem services compared to conventional  
13 monocultures [5, 15]. At the same time, the deployment of wood-based bioenergy and  
14 bioproduct value chains raises concerns regarding land competition, lifecycle emissions,  
15 and economic risks, which calls for integrative planning tools that capture both landscape  
16 dynamics and supply chain performance [16, 3].

17 In the last two decades, a large body of research has analysed biomass supply chains  
18 for bioenergy and biorefineries using mathematical programming models, often in the  
19 form of mixed-integer linear programming (MILP) [16, 10]. These models typically opti-  
20 mise network configuration, feedstock sourcing, and logistics under cost or profit objec-  
21 tives, but they often treat biomass availability as an exogenous input or rely on simplified  
22 yield functions that neglect stand growth dynamics and age-related constraints. Recent  
23 work has started to integrate biomass growth and regeneration processes in multi-period  
24 supply chain models, yet most applications focus on grassland or forest residues rather  
25 than agroforestry systems with repeated coppice cycles and strong interactions between  
26 stand structure and harvesting decisions [2].

27 Short-rotation agroforestry systems exhibit pronounced temporal variability in biomass  
28 production due to species-specific growth trajectories, competition, and management  
29 practices, which has been documented in long-term trials in Central Europe [5, 15]. For  
30 poplar, willow, alder, and black locust, allometric tree biomass models based on stem  
31 base diameter (SBD) or similar biometric variables provide a compact and empirically  
32 grounded link between stand structure and aboveground woody biomass at the tree and  
33 stand level [4]. These models allow the derivation of age-dependent yield coefficients for  
34 different product types, but they are rarely coupled with tactical and strategic supply  
35 chain optimisation. From a cleaner production perspective, it is particularly relevant to  
36 capture the cascading use of biomass along quality gradients (e.g., chemical feedstocks,  
37 pulp, and energy), as this can significantly affect both economic returns and environmen-  
38 tal outcomes [1, 6].

39 The present paper contributes to this literature in four ways. First, we propose a  
40 novel MILP formulation for agroforestry biomass supply chain design that explicitly links  
41 consecutive harvest cycles through age-lag constraints and binary path variables, ensuring

42 that harvesting decisions at each site are consistent with minimum and maximum rotation  
43 ages over multiple cycles. Second, we embed allometric yield functions for different  
44 biomass types into the model by translating age-specific biomass increments into site- and  
45 product-specific yield parameters, thereby capturing species- and management-dependent  
46 growth dynamics in an optimisation-compatible way [4, 15]. Third, we model a product  
47 cascading hierarchy in which higher-quality products can satisfy lower-quality demands,  
48 which is relevant for cleaner production strategies that prioritise material uses before  
49 energy recovery [1, 6]. Finally, we outline a computational experimentation framework  
50 for a regional case study in Central Europe that will test the sensitivity of optimal system  
51 design to rotation length, allometric parameter uncertainty, price and policy scenarios,  
52 and infrastructure options.

53 The remainder of the paper is structured as follows. Section @ref(sec:litreview) re-  
54 views the relevant literature on agroforestry biomass systems, allometric biomass mod-  
55 ellng, and biomass supply chain optimisation. Section @ref(sec:allometrics) introduces  
56 the allometric models adopted to represent biomass growth of different tree species and  
57 biomass types. Section @ref(sec:milp) summarises the MILP formulation for the agro-  
58 forestry supply chain with age-lag constraints. Section @ref(sec:experiments) outlines the  
59 planned computational experiments for the case study and discusses expected insights  
60 for cleaner production strategies.

## 61 **2. Literature review**

### 62 *2.1. Agroforestry and short-rotation systems*

63 Agroforestry encompasses a wide range of land-use systems in which woody perennials  
64 are deliberately integrated with crops and/or livestock on the same land management unit  
65 [8]. In temperate regions, short-rotation agroforestry systems (SRAFS) often take the  
66 form of alley-cropping, where double or multiple rows of fast-growing trees alternate with  
67 crop strips, enabling simultaneous production of agricultural commodities and woody  
68 biomass [5]. Empirical studies in Southern Germany and Central Europe have shown that  
69 SRAFS based on poplar, willow, black alder, and black locust can achieve mean annual  
70 increments (MAI) of about  $7\text{--}10 \text{ t ha}^{-1} \text{ a}^{-1}$  in aboveground woody biomass during the

71 first rotation, with species-specific differences in growth dynamics, size hierarchies, and  
72 mortality [5, 15].

73 Huber et al. [5] analyse the growth dynamics and stand structure development of four  
74 tree species in organic and conventional SRAFS over a four-year rotation in Southern  
75 Germany. They report that poplar and black locust exhibit the highest mean annual  
76 biomass increments (around  $10 \text{ t ha}^{-1} \text{ a}^{-1}$  over four years), while willow shows lower  
77 biomass due to lower diameter growth and wood density, despite high shoot numbers.  
78 Trnka et al. [15] report similar MAI ranges ( $10\text{--}15 \text{ t ha}^{-1} \text{ a}^{-1}$ ) for short-rotation poplar  
79 clones under high-density plantations in the Czech-Moravian highlands, highlighting the  
80 importance of clone selection and site conditions. These findings underline that species  
81 choice, rotation length, planting density, and management practices (e.g., coppicing, weed  
82 control) crucially influence biomass yields and thus the design of downstream supply  
83 chains.

84 Economic assessments of short-rotation coppice (SRC) and very short rotation cop-  
85 pice (vSRC) poplar plantations in Italy and Central Europe show that SRC systems  
86 with 5–7 year rotations and moderate planting densities can be financially competitive  
87 with conventional arable crops, particularly when biomass prices and policy support are  
88 favourable [13]. However, profitability is sensitive to yield assumptions, establish-  
89 ment costs, and logistics, motivating integrated analyses that couple stand-level growth mod-  
90 els with supply chain optimisation. Beyond yield and economics, agroforestry and SRC  
91 systems are widely studied for their environmental performance, including carbon se-  
92 questration, nutrient cycling, biodiversity, and soil and water protection [14, 5]. Cleaner  
93 production strategies that leverage agroforestry biomass in biorefinery and bioenergy  
94 systems therefore require tools that can simultaneously account for temporal biomass  
95 availability, quality differentiation, and value chain design.

96 *2.2. Allometric models for tree biomass*

97 Allometric tree biomass models relate easily measurable biometric variables such as  
98 diameter and height to aboveground biomass, typically using power-law relationships of  
99 the form

$$M = b_0 \cdot \text{SBD}^{b_1},$$

100 where  $M$  is the oven-dry biomass of an individual tree, SBD is stem base diameter, and  
101  $b_0$  and  $b_1$  are species-specific coefficients [4]. Such models are attractive because they  
102 allow the estimation of tree and stand biomass from non-destructive measurements and  
103 can be embedded in growth and yield models for management and planning purposes [5].

104 For SRAFS in Southern Germany, Huber et al. [4] and Huber et al. [5] develop  
105 species-specific allometric models based on SBD measured 10 cm above ground to predict  
106 aboveground leafless dry biomass of black alder, black locust, poplar (Max 3), and willow  
107 (Inger). They report common exponents  $b_1 = 2.603$  across species, with species-specific  
108 factors  $b_0$  of 0.025, 0.041, 0.036, and 0.037, respectively, reflecting differences in wood  
109 density and branching patterns [4]. These models, calibrated on destructive sampling  
110 at the same site, are used to estimate annual biomass increments and derive MAI and  
111 current annual increment (CAI) for each species and management system [5]. The study  
112 emphasises that diameter distributions, stand inequality, and mortality strongly affect  
113 aggregate yields, particularly for black locust, which shows large size asymmetry and  
114 high mortality, and for willow, where late sprouting leads to bimodal size distributions  
115 [5].

116 Similar allometric approaches have been applied to SRC and SRF poplar plantations.  
117 Trnka et al. [15] use diameter and height measurements to estimate aboveground biomass  
118 and assess clone-specific biomass production and survival over a six-year rotation in the  
119 Czech Republic. Laureysens and co-authors provide allometric equations for poplar and  
120 willow clones on waste disposal sites and agricultural land, often highlighting the role of  
121 wood density, site conditions, and stand structure for biomass estimates. In agroforestry  
122 contexts, allometric models have also been developed for mixed-species systems and  
123 silvopastoral systems, which can be used to derive carbon stock estimates and evaluate  
124 management options [14].

125 From a modelling perspective, allometric functions can be used in two main ways  
126 when coupling stand growth with supply chain optimisation. First, they can generate  
127 age-specific yield tables (e.g.,  $t \text{ ha}^{-1}$  at each stand age) that serve as exogenous param-  
128 eters in linear or integer programming models. Second, they can be integrated more  
129 dynamically into optimisation models through piecewise linear approximations or age-  
130 class state variables. For large-scale MILP models, the first approach is often preferred

131 due to computational tractability and the linearity requirement, but it needs to capture  
132 key nonlinearities such as the timing of MAI peaks and constraints on minimum and  
133 maximum harvest ages.

134 *2.3. Age-dependent biomass yield functions*

135 Existing allometric models link tree biomass to diameter or height but do not yet  
136 provide **stand-level** biomass as an explicit function of stand age. Age-dependent biomass  
137 functions are useful for yield projections in short-rotation forestry and agroforestry, where  
138 management is organized in discrete rotations (e.g. 5–15 years). [9, 12]

139 A common approach is to derive age functions from rotation trials that report mean  
140 annual increment (MAI) over time and identify the age at which MAI plateaus. For  
141 poplar SRWC in northern Poland, Niemczyk et al. (2021) showed that MAI in above-  
142 ground dry biomass increases up to about age 10; beyond this, the MAI curve flattens,  
143 suggesting a biologically optimal rotation age around 10 years because the slope of MAI  
144 is near zero. [9] Reported MAI values for single-stem poplar plantations in a 10-year  
145 rotation ranged approximately from 1–15 Mg DM ha<sup>-1</sup> yr<sup>-1</sup> depending on cultivar. [9]  
146 Similar magnitudes and rotation lengths (about 5–7 years for SRC, up to 10–15 years for  
147 SRC/SRF) are reported for poplar SRC systems in Italy, where whole-rotation averages  
148 of roughly 15 Mg DM ha<sup>-1</sup> yr<sup>-1</sup> are considered economically viable. [12]

149 A simple and widely used parametric form for age-dependent stand biomass  $B(t)$  is  
150 the Chapman–Richards (or Mitscherlich/monomolecular) function:

$$B(t) = B_{\max} (1 - e^{-k t})^m$$

151 with stand age  $t$  in years, asymptotic biomass  $B_{\max}$  (Mg DM ha<sup>-1</sup>), rate parameter  $k$   
152 (year<sup>-1</sup>), and shape parameter  $m$ . This formulation captures the rapid juvenile growth,  
153 a phase of approximately linear biomass accumulation, and a saturating phase where  
154 growth slows. [9] The corresponding current annual increment (CAI) and mean annual  
155 increment (MAI) are

$$\text{CAI}(t) = \frac{dB}{dt}, \quad \text{MAI}(t) = \frac{B(t)}{t}.$$

156 The age maximizing MAI (optimal rotation under a volume/biomass criterion) can be  
157 derived analytically or determined numerically. Fitting such functions to observed age–  
158 biomass or age–volume series from rotation trials (e.g. Niemczyk et al. 2021 for poplar,

159 Testa et al. 2014 for Italian SRC) allows cultivar-specific yield curves that are directly  
160 usable in agroforestry simulation models. [9, 12]

161 For illustration, we parameterize three stylized poplar curves representing low, medium,  
162 and high productivity on temperate mineral soils. Parameter values are loosely informed  
163 by the ranges reported by Niemczyk et al. (2021) and Testa et al. (2014) and should be  
164 recalibrated when site-specific data are available. [9, 12]

- 165 • Low productivity:  $B_{\max} = 80 \text{ Mg DM ha}^{-1}$ ,  $k = 0.18$ ,  $m = 1.1$
- 166 • Medium productivity:  $B_{\max} = 120 \text{ Mg DM ha}^{-1}$ ,  $k = 0.20$ ,  $m = 1.2$
- 167 • High productivity:  $B_{\max} = 160 \text{ Mg DM ha}^{-1}$ ,  $k = 0.22$ ,  $m = 1.3$

168 These values yield MAI maxima between about 8 and 12 years with peak MAI values  
169 of roughly  $8\text{--}16 \text{ Mg DM ha}^{-1} \text{ yr}^{-1}$ , consistent with the empirical range where 10-year  
170 rotations produced MAI of about  $10\text{--}15 \text{ Mg DM ha}^{-1} \text{ yr}^{-1}$  for the best poplar cultivars  
171 in northern Poland and Italy. [9, 12]

172 In the agroforestry context, such age functions can be combined with tree density and  
173 allometric partitioning to above- and below-ground biomass to obtain tree-row biomass  
174 over time for different designs. Calibration against local inventory data or growth mea-  
175 surements (e.g. basal area increment and height growth) is recommended before using  
176 the curves for scenario analysis.

#### 177 2.4. Biomass supply chain modelling and MILP approaches

178 Biomass supply chain design and planning has been widely studied using MILP mod-  
179 els at strategic, tactical, and operational levels [16, 10]. Comprehensive reviews classify  
180 models according to decision scope (location, capacity, routing, inventory), time hori-  
181 zon, uncertainty treatment, and sustainability metrics [16, 3]. Many models focus on  
182 bioenergy supply chains for electricity, heat, or biofuels, considering feedstocks such as  
183 agricultural residues, forestry residues, dedicated energy crops, and municipal wastes [10].  
184 Environmental aspects, including greenhouse gas emissions and land use, are increasingly  
185 integrated, often using life-cycle assessment (LCA) data or emission factors [3].

186 Among generic models, OPTIMASS is a notable example of a multi-product MILP  
187 that optimises biomass supply chains with changing biomass characteristics and by-  
188 product re-injection [1]. It models the flow of multiple biomass types and products

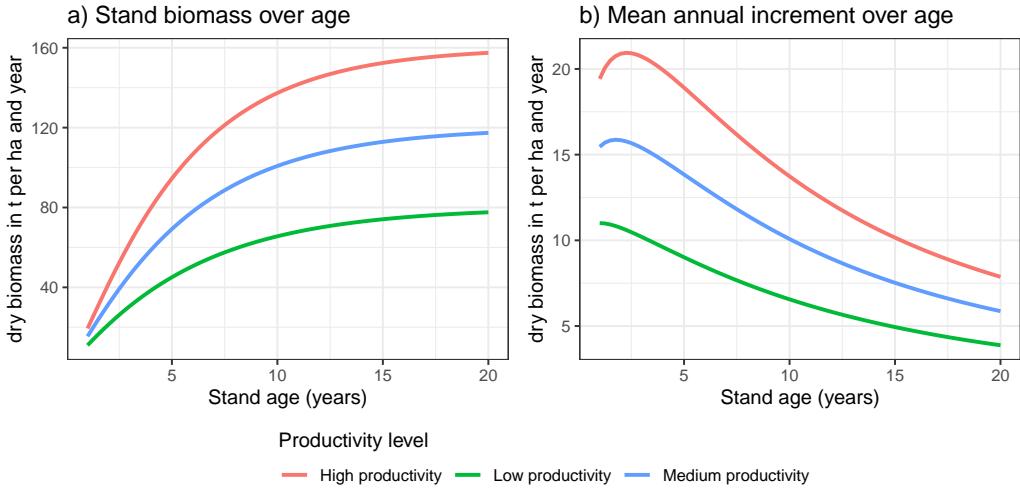


Figure 1: Age-dependent stand biomass (a) and mean annual increment (b) for three stylized poplar productivity levels.

189 through supply chain stages, capturing conversion yields, storage, and cascading uses.  
 190 The t-OPTIMASS extension further incorporates biomass growth and regeneration over  
 191 multiple periods, enabling the representation of time-dependent availability for biomass  
 192 supply chains [2]. However, these formulations generally assume exogenous biomass  
 193 availability profiles per period, and do not explicitly model stand-level age dynamics or  
 194 rotation constraints.

195 Several scenario-based approaches have been developed for forest biorefinery supply  
 196 chains, linking product portfolios, process choices, and supply chain design under mar-  
 197 ket volatility [7]. Lamers et al. [6] discuss strategic feedstock supply system design for  
 198 biorefineries, emphasising the importance of economies of scale, conversion yields, and  
 199 logistics in achieving cost-efficient and robust systems. Reviews highlight that only a  
 200 limited subset of models explicitly consider biomass growth, spatially explicit land-use  
 201 change, or agroforestry systems [16, 10]. There is therefore a clear opportunity to de-  
 202 velop models that couple agroforestry stand dynamics with network design and cleaner  
 203 production objectives.

204    2.5. Cleaner production and cascading use of biomass

205    From a cleaner production perspective, the cascading use of biomass—prioritising  
206    high-value material uses before energy recovery—is widely advocated to maximise re-  
207    source efficiency and mitigate environmental impacts [6]. In wood-based value chains,  
208    this implies that high-quality timber or chemical feedstock fractions should first be al-  
209    located to material products such as engineered wood products, pulp and paper, or  
210    biochemicals, while lower-quality fractions and residues are used for energy [1, 6]. MILP  
211    models can represent such cascades by defining product quality classes and allowing  
212    substitution of higher-quality products for lower-quality demands, subject to hierarchy  
213    constraints.

214    The OPTIMASS framework explicitly models such product cascades by defining a  
215    product quality order and allowing flows from higher-quality products to lower-quality  
216    demand nodes [1]. Similar ideas have been applied in forest-based biorefinery supply  
217    chains, where product portfolios include platform chemicals, fuels, and electricity [7]. For  
218    agroforestry biomass, poplar and willow can supply different product streams, including  
219    sawlogs, peeled veneers, pulpwood, and energy chips, with quality primarily defined by  
220    diameter, straightness, and defect rates [13, 11]. Economic analyses in Italy and Central  
221    Europe suggest that the economic viability of SRC systems depends on access to higher-  
222    value markets such as panel products and pulp, in addition to energy markets [13].

223    Cleaner production strategies that integrate agroforestry biomass into regional bioe-  
224    conomies therefore require models that can allocate biomass flows along such cascades  
225    while respecting stand growth dynamics, rotation constraints, and logistical capacities.  
226    Explicit representation of age-dependent yield quality (e.g., diameter distributions, wood  
227    density) remains challenging in large-scale MILP models, but can be approximated  
228    through age- and species-specific product yield fractions.

229    3. Allometric models for biomass growth

230    3.1. Tree-level allometry in short-rotation agroforestry

231    In the SRAFS trial in Southern Germany, Huber et al. [4] estimate aboveground  
232    leafless dry biomass of individual trees using allometric functions with SBD as predictor,

233 derived from destructive sampling at the same site. The general functional form is

$$M_{ij} = b_{0,j} \cdot \text{SBD}_i^{b_{1,j}},$$

234 where  $M_{ij}$  is the aboveground dry biomass (kg) of tree  $i$  of species  $j$ ,  $\text{SBD}_i$  is stem base di-

235 ameter (cm) at 10 cm above ground, and  $b_{0,j}$ ,  $b_{1,j}$  are species-specific parameters [4]. The

236 coefficients reported for the four species are summarised in Table @ref(tab:allometrics).

237 All biomass values are expressed as oven-dry mass [4].

Table 1: Allometric coefficients for aboveground biomass of tree  
species in SRAFS [4]. {#tab:allometrics}

Species	$b_0$	$b_1$
Black alder ( <i>Alnus glutinosa</i> )	0.025	2.603
Black locust ( <i>Robinia pseudoacacia</i> )	0.041	2.603
Poplar Max 3 ( <i>Populus</i> hybrid)	0.036	2.603
Willow Inger ( <i>Salix</i> hybrid)	0.037	2.603

238 These functions are applied to all shoots per tree to compute total tree biomass, which  
239 is then aggregated at plot and stand level ( $t \text{ ha}^{-1}$ ) using observed tree densities [5]. By  
240 repeating measurements annually over four years, the authors derive CAI and MAI for  
241 each species and management system, and analyse the evolution of size distributions, Gini  
242 coefficients, and skewness as indicators of stand structure [5]. Their results show that  
243 black locust exhibits high wood density (around  $0.60 \text{ g cm}^{-3}$ ) and some large-diameter  
244 trees, leading to biomass comparable to poplar despite lower mean diameter and height  
245 [5]. Willow, in contrast, shows low wood density and lower diameter growth, resulting  
246 in lower biomass despite vigorous sprouting and high shoot densities [5].

### 247 3.2. Stand-level yield functions and age classes

248 To integrate allometric growth into a MILP formulation, we abstract from individual  
249 trees and construct age-class yield functions for each biomass type  $p$  and age  $a$ . Following  
250 common practice in forest and SRC modelling, we define discrete annual age classes  
251 and compute the stand biomass yield  $Y_{pa}$  ( $t \text{ ha}^{-1}$ ) associated with harvesting at age  $a$

252 by combining allometric functions with empirically observed diameter distributions and  
 253 stand densities [5, 15]. Where detailed stand structure data are available, this can be done  
 254 by simulating SBD distributions over time (e.g., via mixed-effects models) and applying  
 255 tree-level allometrics to each diameter class [5]. In the absence of such detailed data, age-  
 256 dependent MAI and CAI curves reported in the literature can be used to approximate  
 257  $Y_{pa}$  [15, 5].

258 In the context of the agroforestry supply chain design (SCD) model, we assume  
 259 that each agroforestry site  $i$  is characterised by a species or species mix, a planting  
 260 density, and management regime, which jointly determine a site-specific yield profile  $\eta_{pa}$   
 261 ( $t \text{ ha}^{-1}$ ) for each product type  $p$  at age  $a$ . These yield profiles can be interpreted as the  
 262 maximum harvestable biomass per hectare for product  $p$  if the stand is harvested at age  
 263  $a$ , conditional on the stand having been established at an earlier time. In the current  
 264 MILP formulation, these profiles are captured through the parameter  $\eta_{pa}$ , termed base  
 265 yield, and are linked to decision variables via the constraint

$$Y_{ipt} = \sum_{s=1}^{t-1} \eta_{p(t-s)} \cdot \text{AREA}_i \cdot z_{ist} \quad \forall i, p, t \in \mathcal{T}^{\text{harv}}.$$

266 Here,  $Y_{ipt}$  is the maximum harvest quantity of product  $p$  at site  $i$  in period  $t$ ,  $\text{AREA}_i$  is  
 267 the site area (ha), and  $z_{ist}$  is a binary variable indicating that harvests at site  $i$  in periods  
 268  $s$  and  $t$  form consecutive harvests with an age lag  $t - s$  within allowed bounds. The term  
 269  $\eta_{p(t-s)}$  thus plays the role of an allometrically derived yield coefficient that depends only  
 270 on stand age  $a = t - s$ , not on calendar time.

### 271 3.3. Biomass types and product quality classes

272 In the model, three product types are distinguished:  $p = 1$  (chemical-grade biomass),  
 273  $p = 2$  (pulp-grade biomass), and  $p = 3$  (energy-grade biomass). This tripartite classi-  
 274 fication reflects a product quality hierarchy, with product 1 having the highest quality  
 275 and price, and product 3 being the lowest-quality fraction typically used for energy [1, 6].  
 276 From an allometric perspective, the differentiation among these products can be linked  
 277 to diameter classes, stem straightness, and defect rates, as these determine the suitability  
 278 of biomass fractions for different processing routes [13, 11].

279 In practice, allometric models provide estimates of total aboveground woody biomass,  
 280 which can be split into product classes using empirical conversion factors or allocation

281 rules derived from product recovery studies (e.g., share of biomass suitable for veneer  
 282 vs. pulp vs. chips as a function of diameter and log length) [11]. For the purposes of the  
 283 SCD model, we can represent this by specifying product-specific yield coefficients  $\eta_{pa}$   
 284 that sum to the total biomass yield at age  $a$  and reflect the expected proportion of each  
 285 product class under a given management regime.

286 The cascading hierarchy in the MILP formulation is implemented through demand  
 287 satisfaction constraints that allow higher-quality products to satisfy lower-quality de-  
 288 mands. Specifically, demand  $D_{kpt}^{\max}$  at consumer  $k$  for product class  $p$  in period  $t$  can  
 289 be met by flows of product  $p$  and all higher-quality classes  $p' \leq p$  from storage hubs, as  
 290 captured by

$$\sum_{j \in \mathcal{J}, p' \in \mathcal{P}: p' \leq p} X_{jkp'pt} \leq D_{kpt}^{\max} \quad \forall k, p, t.$$

291 This structure supports cleaner production by favouring material uses when possible and  
 292 relegating residual fractions to energy uses, depending on revenue parameters  $R_{k,p}$  and  
 293 system constraints [1, 6].

## 294 4. MILP model for agroforestry supply chain design

### 295 4.1. Sets, indices, and time structure

296 The model considers a set of agroforestry sites  $\mathcal{I}$ , storage/processing facilities  $\mathcal{J}$ ,  
 297 consumer sites  $\mathcal{K}$ , and product types  $\mathcal{P} = \{1, 2, 3\}$ . Time is discretised into annual periods  
 298  $t \in \mathcal{T} = \{1, \dots, T_{\max}\}$ . To represent stand establishment and harvest timing, extended  
 299 time sets  $\mathcal{T}^+ = \{0, \dots, T_{\max} + 1\}$  and harvest periods  $\mathcal{T}^{\text{harv}} = \{A^{\min} + 1, \dots, T_{\max}\}$  are  
 300 defined, where  $A^{\min}$  and  $A^{\max}$  are minimum and maximum stand ages (years) at harvest.  
 301 The set  $\mathcal{S}$  comprises all ordered pairs  $(s, t)$  of consecutive harvest periods (including  
 302 establishment at  $s = 0$ ) satisfying the age-lag bounds:

$$\mathcal{S} = \{(s, t) \mid s, t \in \{0, \dots, T_{\max} + 1\}, t - s \in \{A^{\min}, \dots, A^{\max}\}\}.$$

### 303 4.2. Decision variables

304 Binary variables  $z_{ist}$  indicate whether, at site  $i$ , periods  $s$  and  $t$  form consecutive har-  
 305 vests (or establishment and first harvest if  $s = 0$ ), with  $(s, t) \in \mathcal{S}$ . These variables define  
 306 a path of consecutive harvest cycles at each site over the planning horizon. Continuous

307 variables  $Y_{ipt} \geq 0$  represent the maximum harvest quantity ( $t$ ) of product  $p$  at site  $i$   
 308 in harvest period  $t$ . Flow variables  $X_{ijpt}$  and  $X_{jkpp't}$  represent transport of products  
 309 from sites to storage and from storage to consumers, respectively, and  $S_{jpt}$  represent  
 310 inventories at storage locations.

#### 311 4.3. Objective function

312 The model maximises net present value over the planning horizon, expressed as total  
 313 revenues minus establishment, opportunity, harvest, transport, and storage costs:

$$\begin{aligned}
 \max Z = & \sum_{k,p,t} R_{k,p} \cdot \sum_{j \in \mathcal{J}, p' \in \mathcal{P}: p' \leq p} X_{jkp'pt} \\
 & - \sum_i C_i^{\text{est}} \cdot \text{AREA}_i \cdot \sum_{t \in \mathcal{T}} z_{i0t} \\
 & - \sum_i C_i^{\text{opp}} \cdot \text{AREA}_i \cdot \sum_{t \in \mathcal{T}} (T_{\max} - t) \cdot z_{i0t} \\
 & - \sum_{i,(s,t) \in \mathcal{S}: s>0} C_i^{\text{harv}} \cdot \text{AREA}_i \cdot z_{ist} \\
 & - c^{\text{tr-raw}} \sum_{i,j,p,t} d_{ij} \cdot X_{ijpt} - c^{\text{tr-pre}} \sum_{j,k,p,t} d_{jk} \cdot X_{jkpt} - \sum_{j,p,t} c_j^{\text{stor}} \cdot S_{jpt}.
 \end{aligned}$$

314 Here,  $R_{k,p}$  are product- and consumer-specific revenues ( $\text{€}/t$ ),  $C_i^{\text{est}}$  are establishment  
 315 costs per hectare,  $C_i^{\text{opp}}$  are annual opportunity costs per hectare, and  $C_i^{\text{harv}}$  are harvest  
 316 and refitting costs per hectare [13]. Transport costs are proportional to flow and distance  
 317 with rates  $c^{\text{tr-raw}}$  and  $c^{\text{tr-pre}}$  for raw and pre-treated biomass, respectively, and storage  
 318 incurs linear holding costs  $c_j^{\text{stor}}$  per tonne.

#### 319 4.4. Key constraints

320 The path connectivity constraint ensures that each harvest period at a site has exactly  
 321 one predecessor and one successor in the age-lag graph, effectively forming a path over  
 322  $\mathcal{T}^+$ :

$$\sum_{s=0: (s,t) \in \mathcal{S}}^t z_{ist} = \sum_{u=t+1: (t,u) \in \mathcal{S}}^{T_{\max}+1} z_{itu} \quad \forall i \in \mathcal{I}, t \in \mathcal{T}.$$

323 Establishment is restricted to at most one time per site:

$$\sum_{t \in \mathcal{T}^+} z_{i0t} \leq 1 \quad \forall i \in \mathcal{I}.$$

324 Biomass yield is linked to age-lag decisions through the allometric yield coefficients:

$$Y_{ipt} = \sum_{s=1}^{t-1} \eta_{p(t-s)} \cdot \text{AREA}_i \cdot z_{ist} \quad \forall i \in \mathcal{I}, p \in \mathcal{P}, t \in \mathcal{T}^{\text{harv}}.$$

325 Harvest quantities bound outbound flows from each site:

$$\sum_{j \in \mathcal{J}} X_{ijpt} \leq Y_{ipt} \quad \forall i, p, t \in \mathcal{T}^{\text{harv}}.$$

326 At storage hubs, inventories obey standard balance equations with initial inventory

327 zero:

$$S_{jpt} = S_{jp,t-1} + \sum_i X_{ijpt} - \sum_{k,p' \geq p} X_{jkpp't} \quad \forall j, p, t \in \mathcal{T}^{\text{harv}}.$$

328 Storage and processing capacities are enforced via:

$$\sum_p S_{jpt} \leq \text{CAP}_j^{\text{stor}} \quad \forall j, t, \quad \sum_{i,p} X_{ijpt} \leq \text{CAP}_j^{\text{proc}} \quad \forall j, t.$$

329 Demand satisfaction with cascades is modelled as described above, where higher-

330 quality products can satisfy lower-quality demands up to maximum demand levels  $D_{kpt}^{\max}$ .

## 331 5. Case study and computational experiment plan

332 The proposed MILP model is intended to support the design of agroforestry biomass  
333 supply chains for cleaner production in specific regional contexts. In a forthcoming case  
334 study, we focus on poplar-based alley-cropping systems in a temperate European setting,  
335 informed by empirical data from SRAFS trials in Southern Germany and SRC plantations  
336 in Central Europe [5, 15, 13].

337 We envisage the following steps and experimental scenarios for computational analy-  
338 sis:

- 339 1. **Parameterisation of allometric yield profiles:** Use species- and site-specific  
340 allometric models and observed growth trajectories to construct age-dependent  
341 yield coefficients  $\eta_{pa}$  for chemical, pulp, and energy product classes at representative  
342 agroforestry sites. Where necessary, scenario ranges will be defined to capture  
343 uncertainty in MAI and CAI due to climate variability and management differences  
344 [4, 5, 15].

- 345     **2. Baseline optimisation:** Solve the MILP model for a baseline configuration with  
 346       fixed prices, capacities, and policy settings, obtaining optimal establishment timing,  
 347       harvest schedules, and supply chain structure (locations, flows, inventories).
- 348     **3. Rotation length scenarios:** Vary the age-lag bounds  $A^{\min}$  and  $A^{\max}$  to represent  
 349       alternative rotation strategies (e.g., 3–5 years vs. 8–10 years) and analyse their  
 350       impacts on profitability, product mix, and land use. This will shed light on trade-  
 351       offs between shorter rotations favouring energy chips and longer rotations enabling  
 352       higher shares of material products [15, 13].
- 353     **4. Product price and cascading scenarios:** Explore scenarios with different rel-  
 354       ative prices for chemical, pulp, and energy products, reflecting changes in market  
 355       demand and policy incentives (e.g., bioenergy subsidies, green chemicals markets).  
 356       Assess how the product cascade hierarchy and yield quality structure influence the  
 357       marginal value of species and rotation decisions [1, 6].
- 358     **5. Infrastructure and logistics scenarios:** Evaluate the effect of alternative stor-  
 359       age and processing network configurations (e.g., decentralised vs. centralised hubs,  
 360       different capacity levels, transport cost parameters) on the optimal spatial deploy-  
 361       ment of agroforestry sites and biomass flows [1, 2, 6].
- 362     **6. Sensitivity to allometric and growth uncertainty:** Conduct parametric sen-  
 363       sitivity and, where computationally feasible, stochastic analyses to quantify the  
 364       impact of uncertainty in allometric parameters and growth responses (e.g., under  
 365       drought or management differences) on optimal decisions and system robustness  
 366       [5, 15].
- 367     **7. Cleaner production indicators:** For selected solutions, compute derived indica-  
 368       tors such as biomass cascading index (share of biomass used for material products  
 369       before energy), utilisation rates of higher-quality fractions, and, where coupled with  
 370       LCA data, greenhouse gas emission savings relative to fossil benchmarks [3, 16].

371     **6. Conclusions**

372       This paper outlines a research framework that couples allometric biomass growth  
 373       models with a MILP-based agroforestry biomass supply chain design model featuring

374 age-lag constraints and product cascading. Building on empirical evidence from tem-  
375 perate SRAFS and SRC systems and established biomass supply chain models, the pro-  
376 posed approach aims to capture key interactions between stand-level growth dynamics  
377 and network-level design decisions that are central to the cleaner production potential  
378 of agroforestry [5, 1, 2]. Future work will implement and calibrate the model for a re-  
379 gional case study, conduct the computational experiments sketched above, and extend  
380 the framework towards multi-objective optimisation including environmental indicators  
381 such as greenhouse gas emissions and biodiversity proxies.

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