

Agroforestry can reduce trade-offs between economic and ecological benefits, but only when uncertainties are considered

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48

49 **Abstract** Persistent uncertainty about the economic implications of agroforestry presents a
50 major barrier to adoption. Despite this, most research to date ignores the impact of uncertainty
51 on land allocation decisions, with studies commonly relying on simplistic scenarios involving
52 a dichotomous choice between switching entirely to agroforestry or retaining the *status quo*
53 system. For a more realistic decision problem, we explore partial adoption choices by analysing
54 how the performance of landscape portfolios under combined ecological and economic
55 uncertainty changes when managers can incorporate two agroforestry alternatives (silvopasture
56 and alley cropping) alongside existing land-use options. Drawing on published data from
57 smallholders in Panama, we use robust optimisation to allocate fractions of land area across six
58 agroforestry and non-agroforestry land uses under a range of possible futures. We visualise
59 trade-offs between uncertain ecological and economic benefits using robust Pareto frontiers.
60 We find that neglecting uncertainty reduces the attractiveness of agroforestry. Instead,
61 agroforestry becomes increasingly competitive as uncertainty grows, and incorporating it into
62 landscape portfolios can mitigate trade-offs between ecological and economic objectives when
63 the future is uncertain. We conclude by outlining a research agenda for a more holistic approach
64 to agroforestry economics under global change.

65 **Keywords:** Land-use allocation; Robust optimisation; Multicriteria decision analysis; Pareto
66 frontiers; Portfolio approach; Sustainable land use

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76 **1 Introduction**

77 Agroforestry is a land-use practice that involves cultivating trees alongside crops or animals on
78 the same parcel of land. Today, it is particularly prevalent among smallholder farms in the
79 Global South (Nair et al. 2021; Sousa-Silva et al. 2024) but is also garnering growing attention
80 as an alternative to agricultural practices in the Global North (Rigueiro-Rodríguez et al. 2008)
81 due to its ecological benefits (Fagerholm et al. 2016; Torralba et al. 2016; Sollen-Norrlin et al.
82 2020). However, the actual rate of agroforestry adoption remains low, partly because of the
83 unclear economic consequences of agroforestry adoption (Abdul-Salam et al. 2022), and
84 systematic economic assessments are scarce (Thiesmeier and Zander 2023).

85 We present an innovative environmental-economic approach that captures partial adoption
86 decisions under uncertainty about future benefits. The key to our approach is explicitly
87 accounting for such uncertainty by considering a range of possible benefits from different land-
88 use types representing multiple possible futures. We demonstrate this technique through a case
89 study of smallholder farms in Panama but contend that the research approach is generalisable
90 to agroforestry adoption decisions in other settings. The discussion highlights critical
91 considerations for transferring this approach to other contexts.

92 Panama is an example of large-scale afforestation projects with exotic and native tree species
93 (Hall et al. 2011; Sinacore et al. 2023) often financed by private investors (Griess and Knoke
94 2011; Paul et al. 2015). Agroforestry has a strong research history in Panama (Dibala et al.
95 2023). Over the last 15 years, some regions in Panama have been the focus of new developments
96 in economic and multiple-criteria assessment of agroforestry (Paul and Weber 2012, 2013; Paul
97 2014; Paul et al. 2015; Paul and Weber 2016; Paul et al. 2017; Gosling et al. 2020b; Gosling et
98 al. 2020a; Gosling and Reith 2020; Reith et al. 2020; Gosling 2021; Reith et al. 2022; Reith
99 2024). Building on such previous research is an excellent opportunity to demonstrate our
100 ecological-economic research approach.

101 The main contribution of our study is an exploratory non-spatial portfolio optimisation method
102 to analyse the impact of different levels of uncertainty on the simulated desirable landscape
103 compositions and the trade-offs between economic and ecological benefits associated with
104 agroforestry adoption decisions.

105 **2 State of knowledge**

106 Existing stochastic land-use allocation approaches build on random variables and associated
107 probabilities (Knoke et al. 2011; Castro et al. 2013; Neuner et al. 2013; Castro et al. 2015; Hauk
108 et al. 2017; Friedrich et al. 2019; Matthies et al. 2019; Fuchs et al. 2022; Fuchs et al. 2024).
109 However, the available historical information on the distribution of possible benefits from
110 different land-use types is often too unreliable for assigning future probabilities to each outcome
111 and land-use type. Instead of referring to *risk* (which implies sufficient information to estimate
112 probabilities), we suggest that referring to *uncertainty* (Knight 1921; Bewley 2002) can be more
113 realistic, which implies that the set of potential outcomes is known but not their probabilities of
114 occurring (see, e.g. Walker et al. 2010; Knoke et al. 2022a; Knoke et al. 2023).

115 Land management under global change increasingly involves making decisions under
116 uncertainty. Considerable inherent uncertainty is related to climate change, its mitigation
117 pathways and the impacts of extreme events, which are increasing in frequency and intensity
118 (Reyer et al. 2013). Thus, many so far unassessed adaptation options in agriculture and forestry
119 to droughts and extreme precipitation events exist, and the higher risk of compound extremes
120 and their less-studied legacy effects add additional uncertainties (Seidel et al. 2019). For
121 example, the increasing uncertainties about the impact of climate change on agriculture (Asseng
122 et al. 2013), the resulting market fluctuations and policy changes (Long et al. 2016) are still
123 unresolved (Molina Bacca et al. 2023). Uncertainty prevails in any economic assessment of
124 ecosystem services, particularly for more complex or unconventional land-use practices like
125 agroforestry. In this context, the policy influence of subsidies, e.g. for photovoltaic parks to be

126 established on croplands, must be considered. Such policies reduce the uncertainty exposure of
127 the subsidized non-ecosystem-based land-use alternatives. Policies insuring landowners against
128 financial losses likely boost the expansion of the subsidized alternatives, which may become a
129 barrier to enhancing the share of sustainable land-use alternatives.

130 From a practical standpoint, allocating agricultural land to perennial woody species is a long-
131 term investment that requires patience to receive future economic benefits from trees.
132 Establishing trees is expensive; once planted, they must be maintained for years or decades to
133 recover the initial investment; during this transition period, they may yield far lower cash flows
134 than alternative land uses, and the revenue anticipated at the end of the planning horizon may
135 not materialise at all due to adverse environmental or market conditions. Thus, uncertainty
136 about the economics of transitioning to agroforestry can pose a significant barrier to its wider
137 adoption (Rössert et al. 2022). Clarifying the interaction between agroforestry and uncertainty
138 could facilitate greater uptake (Hosier 1989).

139 Although agroforestry economics has yet to mature into a specialised subfield, scholars have
140 been laying the foundations. A recent special issue by Cialdella et al. (2023) offers a helpful
141 window into the current state of the art. For instance, it is standard practice to use discounted
142 cash flow methods like net present value (NPV) to evaluate agroforestry against current
143 alternatives. However, this approach has a significant limitation: it assumes that investors can
144 obtain money elsewhere in periods with zero or negative cash flows while waiting for deferred
145 income from trees (Knoke et al. 2020). Cash flow discontinuities are typical of production
146 systems involving trees, which tend to entail long waiting periods between establishing and
147 harvesting marketable products. These discontinuities can often be smoothed through land-use
148 diversification, which presumably applies to agroforestry adoption as well: rather than allocate
149 one's entire holding to a single land use that produces a discontinuous income stream, managers
150 may be more likely to integrate agroforestry on a portion of their land while retaining existing

151 land-use types with more regular income on the remainder (Reidsma et al. 2023). Crucially,
152 most previous work in agroforestry economics largely neglects uncertainty (e.g. Žalac et al.
153 2023; Smith et al. 2023; Thevs and Aliev 2023; Martinelli et al. 2019; Giannitsopoulos et al.
154 2020; Etherington and Matthews 1983).

155 Even with these simplifications, economic assessments of agroforestry often produce
156 conflicting results. For instance, a recent review by Thiesmeier and Zander (2023) concludes
157 that agroforestry generally shows lower economic performance than agricultural alternatives
158 (but higher than forestry). In contrast, Kay et al. (2019) find that agroforestry outperforms
159 conventional agriculture when one accounts for machinery, labour costs, and the economic
160 value of ecosystem services. Against this backdrop of potentially irregular cash flows and
161 conflicting scientific results, we think it is crucial to examine agroforestry adoption as a process
162 that can unfold alongside (rather than strictly in opposition to) alternative land uses within larger
163 farm or landscape portfolios (Castro et al. 2013; Castro et al. 2015).

164 To that end, we outline an approach that embeds agroforestry into landscapes from which
165 multiple ecosystem services (“benefits”) are expected to be generated by land uses ranging from
166 intensive maize agriculture and livestock grazing to unmanaged natural forests. In doing so, we
167 hope to lay the groundwork for more rigorous and realistic economic assessments of
168 agroforestry transitions.

169 If we consider agroforestry essential for sustainable landscape management because of
170 ecological arguments favouring such land-use practices (Plieninger et al. 2020), we need
171 methods to derive desirable proportions of agroforestry in multifunctional landscapes under
172 uncertainty, which must not ignore economic benefits.

173 The method we describe below builds on a handful of pioneering studies (e.g. Paul et al. 2017;
174 Reith et al. 2020). To demonstrate our approach, we also adopt example data from Gosling et
175 al. (2021) and Gosling et al. (2020a), who use robust optimisation to design landscape portfolios

176 providing multiple ecosystem benefits. These studies report economic cost-benefit information
177 and quantify estimates for two ecological benefits (water supply and soil protection) for each
178 land-use type. This allows us to analyse ecological-economic trade-offs. However, they also
179 assume equal weights for all decision criteria, and as a result, their solutions consist of a single
180 optimal landscape portfolio.

181 Existing studies using robust multiple-criteria optimisation commonly assume that all
182 objectives have equal weight (Knoke et al. 2016; Uhde et al. 2017; Friedrich et al. 2021; Jarisch
183 et al. 2022; Kindu et al. 2022; Reith et al. 2022). We relax this equal-weight assumption using
184 Pareto optimisation, named after the Italian economist Vilfredo Pareto (1848–1923). This
185 technique yields a set of portfolios representing all possible weighting schemes (or preferences)
186 for a set of decision criteria. It has emerged as an increasingly popular tool for trade-off analysis
187 in multicriteria environmental decision support (e.g. Vasilakou et al. 2024) and is also widely
188 used in life-cycle assessment (e.g. Azapagic and Clift 1999), agriculture (e.g. Andreotti et al.
189 2018; Milne et al. 2020; Kaim et al. 2020; Wesemeyer et al. 2023), and forestry (e.g. Borges et
190 al. 2014). Applying Pareto methods to land-use allocation problems allows the analyst to
191 generate an 'efficient' set of landscape portfolios, meaning that it is impossible to modify one
192 criterion without worsening the performance of another. Land managers can select the portfolio
193 that aligns with their criteria weights or multi-attribute utility functions.

194

195 **3 Material and methods**

196 To demonstrate our approach, we used data from farm surveys in the district of Chepo, in the
197 East of the Republic of Panama. The study area represents a typical pasture-dominated
198 landscape in the lowland humid tropics (average rainfall is 1910 mm per annum). The mean
199 relative humidity is 87.4%, with a dry season from January to March and an average annual
200 temperature of 26.4 C. The elevation of the mostly flat area is around 100 m above sea level,
201 with some hills to the southeast reaching 400 m in elevation. Vertisol is the classified soil type
202 where a high clay content limits agricultural productivity in the area. Pasture, crops and exotic
203 tree plantations with small areas of secondary forest remnants dominate land use. Currently,
204 agroforestry has yet to be widely implemented. However, retaining trees in pastures to provide
205 shade and living fences is a common agricultural practice. This study considers two agroforestry
206 systems - alley cropping and silvopasture - as land-use alternatives known to farmers but with
207 limited adoption (information obtained from Gosling et al. 2020a).

208 The farm size of the farmers interviewed in 2018 was, on average, 77 ha (ranging from 5 to 271
209 ha), with a land-use distribution of 60% pasture, 26% crops, 13% natural forest and 1% forest
210 plantation. The total area managed by the surveyed farmers sums to 2681 ha. At the time of the
211 survey, >50% of these farms had allocated the largest share of their land area to pasture, while
212 most crop-based farms also comprised some pasture area (Gosling et al. 2020b).

213 **3.1 Land-use types and decision criteria**

214 We adopted subjective ecological indicators (from Gosling et al. 2020a) and benefit-cost
215 derived economic indicators (from Gosling et al. 2021) for six Panamanian land-use types
216 (Table 1) to conduct a series of exploratory analyses on the economic impacts of integrating
217 agroforestry into landscape portfolios. We consider two agroforestry land uses: silvopasture
218 and a polycyclic alley cropping system locally known as *taungya*, which involves planting
219 maize (*Zea mays*) between rows of teak (*Tectona grandis*) (Table 3) (Paul et al. 2015).

220 *Table 1 Description of the land-use types considered for agroforestry land-use optimisation for smallholder farms*
 221 *in Eastern Panama (adopted from Gosling et al. 2020a). Names for the land-use types were not changed from the*
 222 *original publication, although ‘alley cropping’ could have also been named ‘Taungya system’*

Land-use	Description
Cropland	Corn croplands were assumed as land-use types for conducting cost-benefit analyses. The interviews to quantify the ecological indicators described various annual or (non-woody) perennial crops, either grown as a monoculture, a mix of crops in the same area, or rotated over time. Traditional planting methods were assumed, with some use of herbicides and fertilisers.
Pasture	Traditional pastures were assumed for cost-benefit analyses and interviews, with a stocking rate of 1.5–2.0 cattle per ha, which can include scattered trees.
Alley cropping	Trees and crops grown on the same parcel of land were assumed for cost-benefit analyses and interviews: teak lines are grown every 6 m, with corn (<i>Zea mays</i>) grown in between. Initial tree spacing is 3 m × 6 m, representing 550 trees per ha. Trees are grown for timber with a rotation length of 20 years; crops are no longer planted after year five due to shading.
Silvopasture	Trees and cattle on the same parcel of land were assumed for cost-benefit analyses and interviews: tree densities of around 200 trees per ha on traditional pastures, with a stocking rate of one cow per ha. Trees may be exotic or native and are planted or regenerated naturally (in which case they are guarded); trees may be harvested for timber after 20 years.
Plantation	Teak plantations were assumed for cost-benefit analyses and interviews: trees planted with 3 m × 3 m spacing (initial tree density of 1110 trees per ha) and harvested after 20 years.
Forest	Natural forests of native species were assumed for cost-benefit analyses and for interviews, which we used to collect firewood, fruits, etc., but not for commercial timber production.

223

224 The six land-use types constitute the decision alternatives for the Pareto optimisation, which
 225 allocates fractions of the total land area ranging from 0-100% to each land-use type (see 2.3).
 226 The result is a Pareto efficient portfolio where the area fractions indicate the composition of the
 227 future landscape.

228 We used four indicators to describe the decision criteria: economic indicators (NPV and
 229 payback period) and ecological indicators (perceived protection of freshwater supply and soils
 230 obtained with interviews; Table 2). The payback period is the years until the cumulated
 231 discounted cash flows have recovered the initial investment.

232 **3.2 Data**

233 Values for the ecological indicators were adopted from Gosling et al. (2020a), who asked the
 234 interviewed farmers to rank each land-use type according to their experience and local
 235 knowledge (Table 2). Values for the economic indicators were taken from Gosling et al. (2021),

236 who conducted cost-benefit analyses and obtained standard deviations via Monte Carlo
 237 simulations using historical time series for yields and prices. The payback period and NPV were
 238 calculated from the cash flows shown in Table 3.

239 *Table 2 Description of economic and ecological indicators used as decision criteria for agroforestry land-use*
 240 *optimisation adopted from Gosling et al. (2021) (indicators 1 and 2) and from Gosling et al. (2020a) (indicators 3*
 241 *and 4)*

Indicator	Unit	Direction	Description	Calculation
(1) Net present value	US\$ ha ⁻¹ yr ⁻¹	More is better	Quantifies the economic return for the objective of increasing long-term income.	Sum of all discounted net cash flows (NCF) over 20 years, using a 5% discount rate: $NPV_l = \sum_t^T NCF_{l,t} \cdot (1.05)^{-t}$ [l refers to the land-use type, t to time and T is the considered period length]
(2) Payback period	Years	Less is better	We used the payback period, i.e. the time taken to earn back the initial investment, to account for cash flow and access to money. This indicator relates to the objective of liquidity.	We computed a discounted payback period, defined as the first year (within the 20-year rotation), with a positive discounted cumulative cash flow based on a 5% discount rate.
(3) Water supply	Score (0–10)	More is better	The degree to which land use can improve freshwater availability and quality.	Farmers ranked the six land-use types (Table 1) against these indicators. Their average and standard deviation were computed from the scores. Standard deviations were calculated from standard errors by multiplying with \sqrt{n} and using $n = 32$.
(4) Soil protection			The degree to which the land use maintains soil fertility long-term.	

242 The standard deviations of these ecological indicators represent the uncertainty in the rankings
 243 due to variations in farmer responses. They were calculated from the standard errors reported
 244 in the original publication, multiplied by the square root of the number of farmers interviewed.
 245 For the economic indicators, the standard deviation was obtained by Monte-Carlo simulations
 246 in the original publication considering the variation in historical time series for yield and
 247 product prices of each land-use type; for details, see Gosling et al. (2021). Other sources of
 248 uncertainty that are interesting for future research are included in our discussion. The resulting
 249 indicator values we expect on average for the different land-use types and their standard
 250 deviations are reported in Table 4 (in the Results chapter). We conservatively treated

251 *Table 3 Cash flows used to compute NPVs and payback periods (from Gosling et al. 2021, provided in their*
 252 *Supplementary Table S8); values do not include subsidies. Negative cash flows show that the investment*
 253 *(financial outflow) was higher than the financial inflow. We assumed no commercial products for the natural forest*
 254 *(called Forest in the Table) and thus zero cash flows.*

	Cash flows (US\$ ha ⁻¹)										
	Period (year)										
	0	1	2	3	4	5	6	7	8	9	
Cropland	444	531	531	531	531	531	531	531	531	531	
Pasture	-1435	456	393	393	393	393	393	393	393	393	
Alley cropping	-817	130	178	-242	-95	-209	-31	-95	-95	-95	
Silvopasture	-1970	177	114	183	248	244	240	236	278	272	
Plantation	-2185	-581	-485	-199	-423	-129	-129	-129	-129	-129	
Forest	0	0	0	0	0	0	0	0	0	0	
	Period, continued (year)										
	10	11	12	13	14	15	16	17	18	19	20
Cropland	531	531	531	531	531	531	531	531	531	531	531
Pasture	393	393	393	393	393	393	393	393	393	393	1168
Alley cropping	1393	-31	-95	-95	-95	-95	-95	-95	-95	-95	14132
Silvopasture	267	261	256	249	243	236	229	222	214	206	10234
Plantation	2336	-129	-129	-129	-129	-129	-129	-129	-129	-129	22710
Forest	0	0	0	0	0	0	0	0	0	0	0

255 expected indicator values as the best-case scenario and derived worst cases using multiples
 256 ($m = 2,3,4$) of the standard deviation. The best cases form an upper bound, and the worst cases
 257 form a lower bound of intervals, which we later integrate into the optimisations as the possible
 258 range of future indicator values.

259 3.3 Pareto optimisation

260 Constructing a Pareto-efficient set of landscape portfolios involves first solving for the portfolio
 261 that maximises economic performance without any regard to ecological effects, then
 262 introducing a constraint requiring a minimum provision of ecological benefits and solving again
 263 to obtain the following portfolio. By iteratively increasing the ecological requirement and
 264 calculating new solutions, we generate Pareto frontiers representing the maximum economic
 265 benefit that can be reliably obtained for all feasible levels of ecological benefits.

266 Our method also extends classical deterministic Pareto optimisation by integrating uncertainty.
 267 This is achieved by defining an interval of possible benefit levels for each land use and

268 indicator, the magnitude of which is scaled by multiples of the standard deviation (Table 4).
 269 Wider intervals reflect a more uncertain future (or more uncertainty-averse decision-makers).
 270 We combinatorically aggregate the best and worst cases (i.e. the bounds of the intervals) across
 271 all land uses to create the surface of a multi-dimensional uncertainty space containing all
 272 possible combinations of future benefit levels for all land-use types. Each unique interval-bound
 273 combination constitutes a future uncertainty scenario, corresponding to a corner point of the
 274 uncertainty space, with $2^6 = 64$ corner points per indicator. By considering only the bounds of
 275 the benefit intervals—a representation known as ‘box uncertainty’ (Gorissen et al. 2015)—the
 276 resulting portfolios guarantee a performance floor for all benefits and land uses included in the
 277 uncertainty space (e.g. Bertsimas et al. 2011). For each uncertainty scenario, we compute the
 278 distances between portfolio performance and the best-case value for each indicator, where
 279 portfolio performance is an area-weighted mean of the benefits associated with its constituent
 280 land uses.

281 Mathematically, the objective function identifies the portfolio that minimises the maximum
 282 distance across the economic indicators β_r and their uncertainty scenarios without violating the
 283 maximum tolerable distance across the ecological indicators β_e :

$$284 \quad \beta_r = \max_{(r,u)} D_{ru}\% \quad (\text{Eq. 1})$$

$$285 \quad \beta_e = \max_{(e,u)} D_{eu}\% \quad (\text{Eq. 2})$$

286 $D_{ru}\%$ and $D_{eu}\%$ are relative distances between the desired and achieved indicator levels for the
 287 portfolio given uncertainty scenario u :

$$288 \quad D_{ru}\% = \frac{Y_{ru}^* - Y_{ru}(a_l)}{Y_{ru}^* - Y_{ru*}} \cdot 100 \quad (\text{Eq. 3})$$

$$289 \quad D_{eu}\% = \frac{Y_{eu}^* - Y_{eu}(a_l)}{Y_{eu}^* - Y_{eu*}} \cdot 100 \quad (\text{Eq. 4})$$

290 Distance $D_{ru\%}$ describes the degree of economic ‘underperformance’ and depends, *inter alia*,
 291 on the best (Y_{ru}^*) and worst (Y_{ru*}) economic indicator values for each land use and uncertainty
 292 scenario. y_{lr_u} represents the economic benefit of a single land-use type l in uncertainty scenario
 293 u .

$$294 \quad Y_{ru}(a_l) = \sum_l a_l \cdot y_{lr_u} \quad (\text{Eq. 5})$$

295 with

$$296 \quad y_{lr_u} = \begin{cases} E(y_{lr}) & \text{as the optimistic economic indicator level} \\ E(y_{lr}) \pm m \cdot sd_{lr} & \text{as the pessimistic economic indicator level} \end{cases} \quad (\text{Eq. 6})$$

297 $E(y_{lr})$ refers to the expected level of an indicator. Standard deviations sd_{lr} for each land use and
 298 indicator are reported in Table 4. The size of the uncertainty space is controlled by the factor
 299 m . The same description applies to the variables included in Eq. 4 for the ecological benefit
 300 indicators.

301 Note that the best-case indicator value Y_{ru}^* or Y_{eu}^* can be either the maximum or minimum values
 302 (Knoke et al. 2022b)--after all, managers prefer shorter payback periods but larger NPVs.
 303 Because the numerator and the denominator of $D_{ru\%}$ are both negative when the minimum
 304 represents the best case (zero is also possible in the case of the numerator), the distance to the
 305 reference point is always positive, and Eqs. 3,4 hold irrespective of whether the indicator should
 306 be minimized (payback period) or maximized (*NPV*).

307 To minimize the maximum distance $D_{ru\%}$, we allocate area proportions (a_l) across land-use
 308 types (l), thus controlling the area-weighted portfolio benefit $Y_{ru}(a_l)$, subject to stepwise
 309 reductions in the tolerated maximum distances Z_{et} for the ecological decision criteria e (Eq. 9)
 310 (see Knoke et al. 2024). We initialise the Pareto frontier by maximizing the economic benefit
 311 without any ecological requirement (tolerating $\beta_{et} = 100$), then iteratively reduce Z_{et} (i.e.
 312 increase the ecological requirement) in 5% steps until no feasible solution remains. Requiring
 313 Eq. 8 and 9 for all uncertainty scenarios ($\forall u$) entails a robust optimisation problem.

314 $\min_{a_l} \beta_r$ (Eq. 7)

315 *s.t.*

316 $\beta_r \geq D_{ru\%} \quad \forall u$ (Eq. 8)

317 $Z_{et} \geq \beta_e \quad \forall u$ (Eq. 9)

318 Requiring Eq. 8 and 9 for all uncertainty scenarios ($\forall u$), we have selected a robust
 319 mathematical representation of the optimisation problem. The resulting landscape portfolios
 320 thus provide solutions that are deterministically immune to realisations of the uncertain land-
 321 use type benefits from uncertainty spaces (Bertsimas et al. 2011). We started without any
 322 specific required ecological benefit, thus tolerating $\beta_{et} = 100$, which means we maximised the
 323 economic benefit only. Subsequently, we reduced Z_{et} in Eq. 9 in steps of 5% to enhance the
 324 required ecological benefits as long the problem optimisation remained feasible.

325 To visualize the Pareto frontier, we translated the maximum distances into robust benefits p_r
 326 and p_e :

327 $p_r = 100 - \beta_r$ (Eq. 10)

328 $p_e = 100 - \beta_e$ (Eq. 11)

329 Because p_r and p_e are guaranteed for all possible values within the uncertainty interval, the
 330 portfolio solutions for each scenario are also deterministically immune to future variations in
 331 benefit levels, provided they do not exceed bounds of the uncertainty space (Bertsimas et al.
 332 2011).

333

334 4 Results

335 4.1 Indicators

336 Best-case NPVs ranged from US \$0 ha⁻¹ (unmanaged natural forest) to \$7061 ha⁻¹ (croplands)
337 (Table 4). Although croplands and teak plantations can achieve the highest NPVs, they
338 comprise only a minor share of the actual study area. The real-world landscape predominates
339 in pastureland, whose NPV ranks only above unmanaged natural forests. However, this
340 apparent discrepancy is readily resolved by considering uncertainty aversion. The NPV for
341 croplands and teak plantations is high but also highly variable, whereas pasture is remarkably
342 consistent. As a result, pasture offers the highest reward-to-variability ratio (NPV/SD) of any
343 land-use type (\$7.31 vs. \$2.67 for cropland).

344 *Table 4 Expected indicator values used for the optimisations (mean ± SD). SD for NPV and payback period*
345 *obtained from Table 4 in Gosling et al. (2021), and scores and SD for freshwater supply and soil protection*
346 *adopted from Table 4 in Gosling et al. (2020b). These indicator levels are considered best cases, ranking in*
347 *brackets.*

Land-use	Net present value	Payback period	Water supply	Soil protection
	US\$ ha ⁻¹	Years	Score (0-10)	
Cropland	7061 (±2643) [1]	1 (±1.6) [2]	4.0 (±2.4) [6]	5.5 (±2.60) [5]
Pasture	3815 (±522) [5]	5 (±1.1) [3]	4.7 (±2.3) [5]	5.0 (±1.81) [6]
Alley cropping	4605 (±1792) [4]	8 (±8.6) [4]	6.8 (±1.5) [4]	6.5 (±2.26) [4]
Silvopasture	4622 (±696) [3]	11 (±2.8) [5]	7.6 (±1.2) [2]	6.9 (±1.81) [2]
Plantation	5273 (±2019) [2]	20 (±0) [6]	7.2 (±2.5) [3]	6.6 (±2.60) [3]
Forest	0 [6]	0 [1]	9.9 (±0.5) [1]	9.1 (±2.15) [1]

348

349 Despite exhibiting similar, moderate best-case NPVs (i.e. superior to pasture but worse than
350 teak plantations), the agroforestry systems can also be differentiated by benefit volatility:
351 silvopasture offers a reward-to-variability ratio of \$6.64, versus \$2.56 for alley cropping.

352 Cropland exhibited short but variable payback periods, while those for pasture were both short
353 and consistent. The agroforestry options were moderate performers; teak plantations feature the
354 longest payback period, with the initial investment recovered with the final harvest in year 20.

355 Cashflow continuity is primarily a function of the prevalence of trees in each land-use type
356 (Table 3). Cropland and pasture generate cash flows quickly and regularly. The agroforestry
357 options produce early revenue but exhibit more significant fluctuations associated with timber
358 harvests. In alley cropping, timber revenue dominates the cash flow distribution. Although the
359 maize cultivated in the alleys generates net-positive cashflows as early as the second year, it is
360 shaded out by year five. As a result, positive returns are expected in only four years of the 20-
361 year-long production period.

362 Unmanaged natural forests' payback period and NPV are null (no initial investment is required,
363 and no revenue is generated). Note that the opportunity costs of keeping the unmanaged natural
364 forest were considered implicitly, as any area allocated to the unmanaged natural forest reduced
365 the landscape-level NPV proportionally. However, natural forests offer the highest ecological
366 benefits from the six land uses. Depending on the indicator, teak plantations or agroforestry
367 offer the second-best ecological performance. Ecological benefits are lowest for pasture and
368 cropland.

369 **4.2 The economic contribution of agroforestry when ignoring uncertainty**

370 In scenarios that ignore uncertainty and ecological benefits, the optimal landscape portfolio
371 consists exclusively of intensive maize agriculture (Figure 1). Introducing ecological
372 requirements stimulates the inclusion of silvopasture and natural forests, with the maximum
373 ecological benefit being achieved by allocating roughly two-thirds of the total land area to
374 silvopasture. Interestingly, however, the economic performance of portfolios including
375 silvopasture was only marginally higher than those excluding agroforestry. Without
376 agroforestry, the ecological constraint is satisfied mainly by increasing the share of tree

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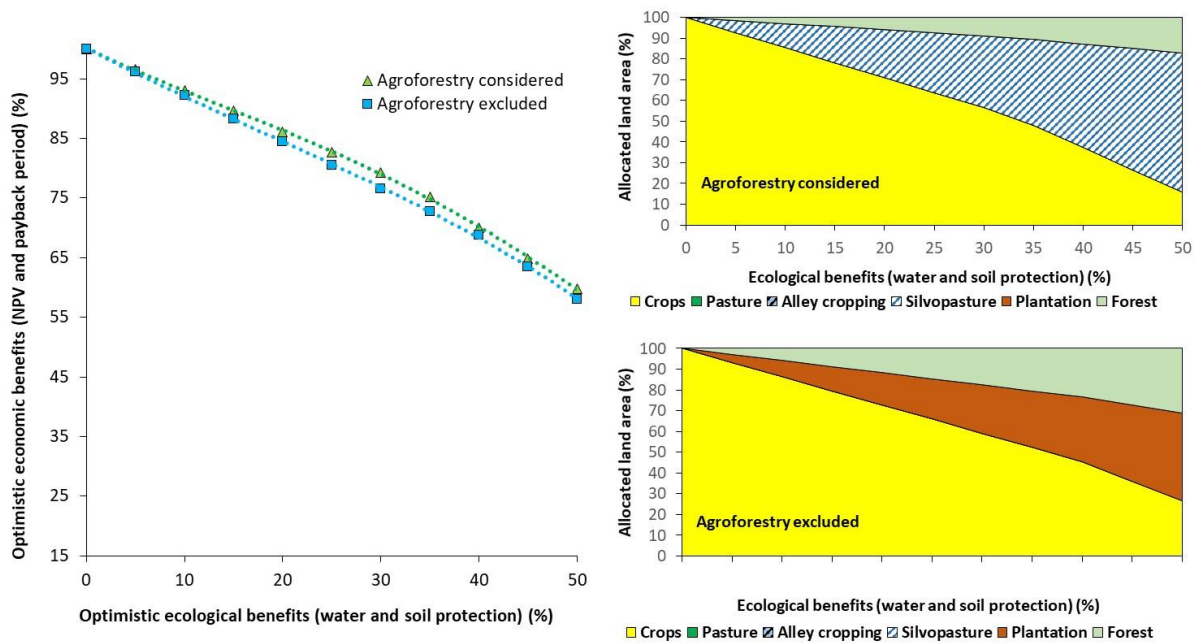


Figure 1 Left: Pareto frontiers (i.e. efficiency frontiers) and landscape portfolio compositions for maximum economic benefits under increasing levels of required ecological benefits when uncertainty was ignored. The frontiers show the maximum (optimistic) economic benefit achievable when requiring certain levels of ecological benefits, either allowing for agroforestry or not. Right: Changes in the landscape composition with increasing levels of required ecological benefits, the upper part allowing for agroforestry and the lower part excluding it

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379 plantations and natural forests (Figure 1). No land was allocated to pasture or alley cropping
 380 without uncertainty, regardless of the ecological requirement.

381 4.3 The economic contribution of agroforestry in an uncertain world

382 Under moderate uncertainty ($m = 2$), agroforestry options are only included in the solution if
 383 there is also a demand for ecological benefits (Figure 2A). However, accounting for higher
 384 uncertainties ($m \geq 3$) results in incorporating both agroforestry land-use types even without
 385 ecological requirements (Figure 2B).¹

386 As uncertainty grows, portfolios with agroforestry increasingly outperform those without it. At
 387 the highest uncertainty levels, 11.8% and 21.8% of the land area is allocated to alley cropping

¹ An uncertainty level of $m = 2$ means that the worst-case indicator value is two times the standard deviation worse than the best-case indicator value; $m = 3$ means three times the standard deviation; and so forth (Table 4).

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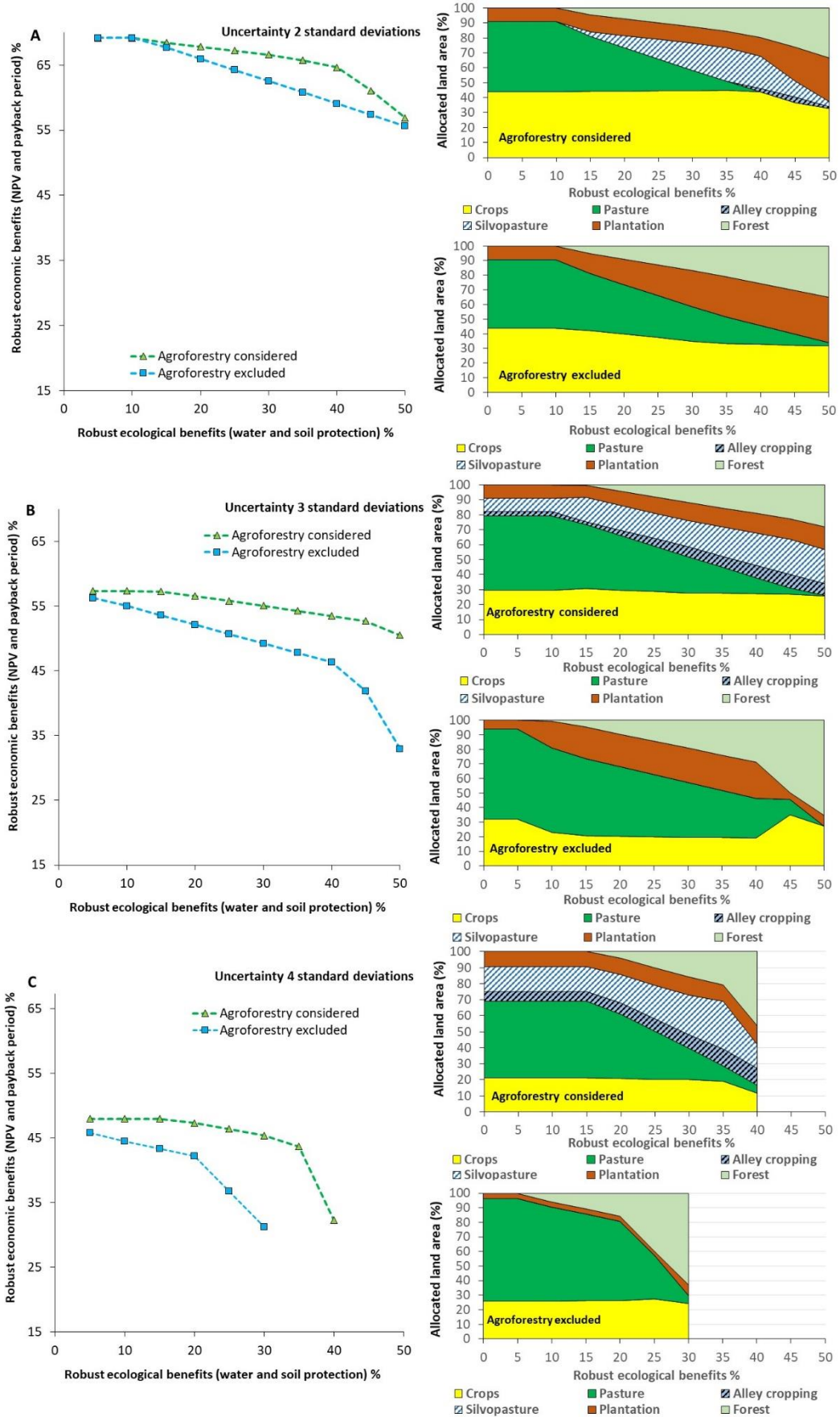


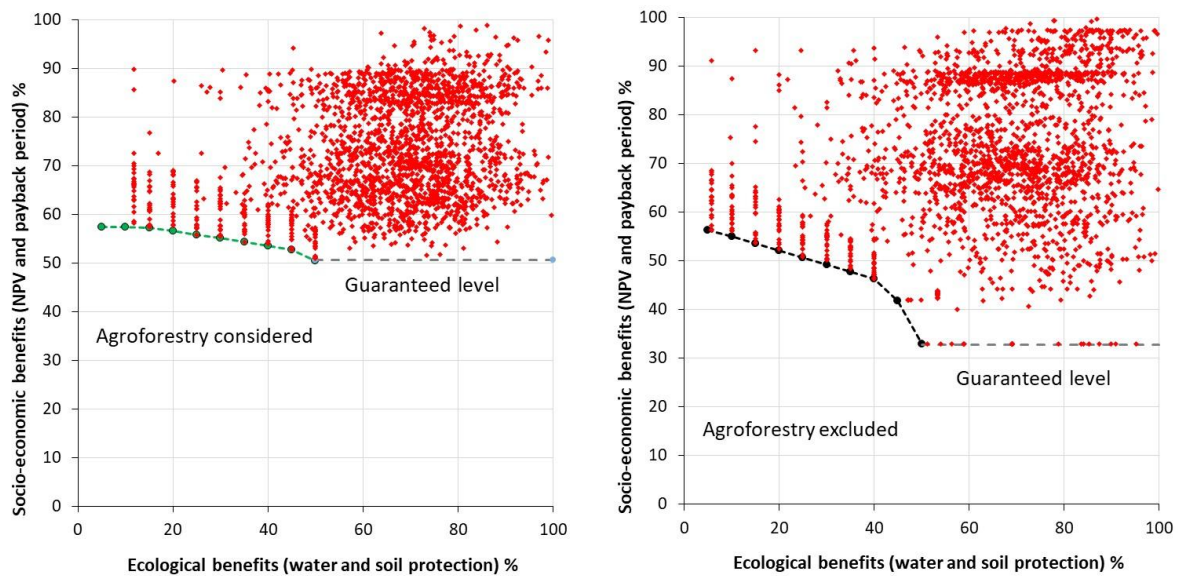
Figure 2 Pareto frontiers (i.e. efficiency frontiers) and landscape portfolio compositions for maximum economic benefits under increasing required ecological benefits for different levels of uncertainty. Panel A considers $m=2$ standard deviations to compute the worst-case benefits of the individual land-use types, while panels B and C account for 3 and 4 standard deviations, respectively, in finding the worst-case benefits.

417 and silvopasture, respectively (Figure 2, left corner). Agroforestry also mitigates trade-offs
418 between ecological and economic performance in scenarios featuring a high demand for
419 ecological benefits. Expanding the uncertainty space enhances the maximum proportion of
420 agroforestry (silvopasture plus alley cropping) from 23.9% for $m = 2$ to 40.1% for $m = 4$.
421 However, even these proportions are notably smaller than the 67.1% achieved in the no-
422 uncertainty scenario with maximum ecological requirements.

423 In addition to modulating the share of agroforestry in the landscape, the size of the uncertainty
424 space also alters the curvature of the Pareto frontiers. Large uncertainty spaces magnify the
425 sensitivity of economic benefits to ecological demands, notably when agroforestry options are
426 excluded. The no-agroforestry frontiers exhibit clear economic tipping points: beyond a certain
427 threshold, ecological requirements force sharp increases in the land area allocated to natural
428 forests (Figure 2). Including agroforestry options attenuates this effect when uncertainty is
429 elevated by displacing part of the natural forest area: for uncertainty $m = 4$, for example, robust
430 ecological benefits top out at 30% without agroforestry versus 40% with agroforestry. This ten-
431 point increase also comes with economic benefits that exceed the best-performing non-
432 agroforestry portfolio (Figure 2).

433 **4.4 Testing for the robustness of the desirable landscape portfolios**

434 Mathematically, the performance of our landscape portfolios should be robust as long as benefit
435 variability remains within the uncertainty intervals. To test this empirically, we confronted the
436 optimised portfolio sets with benefit levels randomly drawn from the uncertainty intervals
437 (Figure 3). We also forced pessimistic benefit combinations as an additional robustness check
438 but could not generate any empirical outcomes that underperformed the frontier (Figure 3).



439

440 *Figure 3 Simulated benefits of the efficient landscape portfolios when benefits of the single land-use types were*
 441 *drawn from the considered benefit intervals formed by worst and best cases. The Figure is built on $m = 3$, meaning*
 442 *the worst case is three times the standard deviation of the considered benefit smaller than the best case.*

443

444 Thus, the frontiers visualise a guaranteed floor below which portfolio performance will not fall
 445 for a given uncertainty scenario (dashed grey lines in Figure 3). Landscape portfolios containing
 446 agroforestry maintained robust economic benefits of at least 51% over the full range of
 447 ecological constraints (Figure 3, left). When agroforestry was excluded, economic performance
 448 fell to 33% under elevated ecological constraints (Figure 3, right side).

449 **5 Discussion**

450 This study builds on earlier efforts to consider risk and uncertainty in agroforestry economics.
 451 In particular, Paul et al. (2017) set the stage by providing a framework to economically assess
 452 land-use combinations using Markowitz portfolio optimisation. While it offers a helpful
 453 reference, their approach encounters several limitations. For instance, it is probabilistic and
 454 does not situate allocation decisions within the conventional agricultural landscapes where
 455 agroforestry transitions would presumably occur.

456 In contrast, our non-stochastic approach embeds agroforestry in portfolios encompassing
 457 *status-quo* agricultural alternatives. Unlike the Markowitz model, our approach does not require

458 outcome probabilities to be assigned *a priori*. Instead, it captures benefits guaranteed across
459 entire uncertainty spaces (see Figure 3) defined by land managers according to their degree of
460 caution (e.g. Knoke et al. 2022a). As far as we know, ours is the first study to adopt this broader
461 Pareto perspective, at least in the context of agroforestry research.

462 We are also indebted to a handful of previous studies that applied robust multi-criteria portfolio
463 optimisation to study the potential role of agroforestry in the study area where we obtained our
464 example data (Gosling et al. 2020b; Gosling et al. 2020a; Reith et al. 2020; Gosling 2021; Reith
465 et al. 2022). These studies have struggled to reproduce the real-world landscape composition
466 based on economic indicators alone, tending to overestimate cropland and underestimate
467 pasture, the predominant land use in the area, despite its seemingly uncompetitive NPV
468 (Gosling et al. 2021).

469 Our model successfully approximates this counterintuitive result, which occurs in scenarios that
470 account for uncertainty but ignore ecological performance. Thus, we also suggest a lens for
471 understanding existing landscape dynamics. If land managers favour pasture because it
472 generates modest but reliable returns, they are likely sensitive to future costs and benefits
473 volatility. Consequently, their land allocation decisions are unlikely to be captured by simple
474 NPV comparisons, arguably the default approach in agroforestry economics today (Do et al.
475 2020).

476 Methodologically, these earlier studies also assume equal weights for all decision criteria. In
477 contrast, we generate Pareto-efficient sets of portfolios representing all possible weighting
478 schemes (Figs. 2,3). This feature makes our method easier to generalise to other settings. For
479 instance, it could be deployed to support stakeholder consultations, participatory decision-
480 making (Marques et al. 2020), or co-creation heuristics like the Nature Futures Framework (e.g.
481 Pereira et al. 2020), which seeks to identify interventions that are responsive to diverse
482 perspectives and worldviews (Kim et al. 2023).

483 **6 A research agenda for agroforestry ecological economics**

484 This article presents an argument for broadening the ecological economics of agroforestry
485 beyond the narrow view offered by deterministic cost-benefit analysis to explore how adoption
486 decisions are shaped by the landscapes they are embedded in and how they shape, in turn, the
487 capacity of those landscapes to provide ecological and economic benefits in an increasingly
488 uncertain world.

489 To that end, this section sketches the contours of a new research agenda for agroforestry
490 ecological economics. We highlight eight points: (1) making uncertainty explicit; (2)
491 accounting for temporal discontinuities in cost-benefit flows; (3) focusing on the pivotal
492 establishment phase for agroforestry transitions; (4) quantifying the economic implications of
493 biophysical interactions and feedbacks; (5) using new monitoring technologies and simulating
494 models and accounting for their uncertainties; (6) taking a proactive approach to market-based
495 instruments; (7) exploring trade-offs in context; and (8) embedding agroforestry transitions in
496 landscapes.

497 *Making uncertainty explicit*

498 Our findings suggest a potential new economic argument for agroforestry adoption:
499 incorporating agroforestry into land-use portfolios could enhance their ability to provide
500 ecological and economic benefits robust to various possible futures. This advantage is not
501 captured by NPV alone but instead results from moderate reward-to-uncertainty ratios and
502 partially discontinuous cashflows. This hypothesis warrants further empirical testing in other
503 contexts, such as productive landscapes in the Global North.

504 Incorporating uncertainty into descriptive studies can complement the normative decision-
505 theoretical approach described here. For example, previous work has successfully applied
506 microeconomic stochastic frontier analysis to obtain efficiency information from uncertain
507 agricultural outputs (Stetter and Sauer 2022). This method can help to explore the production

508 frontier of uncertain agricultural output and input to obtain efficiency information related to the
509 joint provision of agroforestry solutions. Similarly, recent simulation experiments suggest
510 German farmers may consider agroforestry practices as a risk-hedging strategy in response to
511 increasing extreme weather events (Stetter and Sauer 2024), highlighting the importance of
512 uncertainty for future decision-making. Given the proliferating uncertainties associated with
513 land management planning (e.g. Molina Bacca et al. 2023; Verburg et al. 2013), we encourage
514 an explicit consideration of uncertainty in future work.

515 *Accounting for temporal discontinuities in cost-benefit flows*

516 Our study builds on dynamic economic data covering a timeline of 20 years for each benefit
517 and land use. Future work should take advantage of temporally disaggregated information,
518 particularly concerning the ‘early life’ of land-use practices that exhibit cashflow
519 discontinuities and significant discrepancies in the duration of production cycles. The economic
520 attractiveness of agroforestry could be plausibly enhanced by identifying strategies for
521 obtaining earlier and more continuous economic returns from the tree components. For
522 example, multi-purpose trees could enable land managers to earn income earlier from non-
523 timber products like fruits, nuts, or fodder. An alternative might involve incorporating
524 components with shorter production times into the tree lines themselves, as suggested by
525 syntropical (Andrade et al. 2020) and other successional agroforestry systems. This would
526 diversify the product portfolio and provide earlier and more frequent financial returns, although
527 potentially at the cost of additional labour input.

528 *Focusing on the pivotal establishment phase for agroforestry transitions*

529 Improving the design of agroforestry systems requires long-term information, beginning with
530 the pivotal “early life” phase. Establishing agroforestry involves navigating an array of
531 variables, many of which have yet to be researched systematically: ungulates browsing shoots
532 or damaging bark, spring drought, suboptimal planting conditions, and inadequate soil or fungal

533 symbionts can all contribute to tree mortality and increase material costs (Cossel et al. 2020).
534 Soil water, carbon, nutrient dynamics and the structure and function of biota living in soil and
535 acting as architects for soil health may gradually change when agroforestry systems are
536 established until a new stable equilibrium is reached; thus, managers might leverage supporting
537 factors (e.g., diverse vegetation) in early phases. While trees are growing, dynamic soil niche
538 spaces between crops and trees are created. Initially, resource competition in the same soil space
539 could be prevalent (Ludwig et al. 2004), while effective niche partitioning and more efficient
540 resource use between trees and crops may develop with tree growth (Bouttier et al. 2014;
541 Goisser et al. 2016). How these dynamics unfold presumably depends on interactions between
542 management decisions and environmental dynamics, but the nature of these relationships is still
543 poorly understood.

544 In short, there is considerable potential for statistically well-designed, long-term experimental
545 platforms to drive significant advances in our understanding of agroforestry transitions. Only a
546 handful of such platforms exist worldwide (Veldkamp et al. 2023; Fedrigo et al. 2024). While
547 expensive experimental approaches will always represent only a narrow ecological and socio-
548 economic context, they can serve as hubs for knowledge exchange through international and
549 interdisciplinary research initiatives.

550 *Quantifying the economic implications of biophysical interactions and feedbacks*

551 Generally, combining forestry and agriculture is believed to increase ecosystem services
552 provisioning (Torralba et al. 2016) and product diversification (Neupane and Thapa 2001) while
553 also supporting resistance, soil health, yield, and economic stability (Pumariño et al. 2015;
554 Isbell et al. 2017; Fahad et al. 2022). Ecosystem services associated with trees, such as water
555 or nutrient redistribution (Sun et al. 2014; Alagele et al. 2021), may reduce irrigation and
556 fertilization costs for neighbouring crops—a largely unquantified benefit. The diversification

557 of the agricultural ecosystems may also increase biodiversity, although current evidence is
558 mixed, see Mupepele et al. (2021), and more work is needed.

559 *Using new monitoring technologies and simulating models and assessing their uncertainties*

560 Remote sensing and artificial intelligence can play a crucial role in mitigating uncertainties in
561 agroforestry by providing real-time monitoring and predictive insights (Thapa et al. 2023).
562 Integrating the Internet of Things (a network that connects and controls sensors and devices,
563 exchanges data and communicates with users) and sensing technologies, such as strap-cameras,
564 multispectral drone imagery, and real-time monitoring devices (e.g. Valentini et al. 2019) can
565 enable early identification of stresses and diseases so that managers can react quickly to reduce
566 yield losses. Additionally, digital platforms can integrate weather forecasts and market trend
567 data to support a proactive approach to managing meteorological variability, market
568 fluctuations, and resource allocations. However, integrative research leveraging such
569 technologies in the context of agroforestry is still needed.

570 Frequent tree, crop and tree-crop-interaction measurements during the establishment phase will
571 be crucial for developing and testing dynamic agroforestry simulation models across their
572 lifespan. Some dynamic agroforestry models and modelling approaches exist (van Noordwijk
573 and Lusiana 1998; Riofrío et al. 2015; Morhart et al. 2016; Dupraz et al. 2019; Bohn Reckziegel
574 et al. 2021; Bohn Reckziegel et al. 2022; Rahman et al. 2023; Žalac et al. 2023), mainly focusing
575 on biomass and yield (Kraft et al. 2021), which can be translated to economic benefits using
576 price time series. However, these models still often ignore the impact of agroforestry on
577 ecological benefits related to water and nutrient dynamics, micro-climate, and soil biota, for
578 which detailed field data are a prerequisite for further model enhancements. In addition,
579 comprehensive assessments of the uncertainty associated with the model predictions are largely
580 missing. Dynamic agroforestry simulation models will be needed for evaluating agroforestry
581 practices for different soils, climatic conditions and future climate scenarios and for scaling up

582 agroforestry field experiments across regions, similarly as recently shown for simple crop-
583 disease system interactions (Pequeno et al. 2024). To quantify agroforestry model uncertainty
584 and understand uncertainty propagation in a system will eventually require a multi-model
585 approach combined with field experiments as proposed by the Agricultural Model
586 Intercomparison and Improvement Project, AgMIP (Wang et al. 2024).

587 *Taking a proactive approach to market-based instruments*

588 The idea of leveraging agroforestry as a buffer against uncertainty in sustainable landscape
589 portfolios raises the possibility of further mitigating ecological-economic trade-offs by seeking
590 to monetize their ecosystem services. To support this, market-based solutions, such as
591 Pigouvian subsidies or certification of agricultural products grown in ecologically favourable
592 agroforestry systems, warrant exploration. Certification schemes could differentiate products
593 in the marketplace, allowing farmers to charge premium prices based on consumer preferences
594 for sustainable goods, similar to organic, Fairtrade, or Forest Stewardship Council certifications
595 (Altmann and Berger Filho 2020; Ota et al. 2022). However, the costs of establishing and
596 acquiring such certifications are significant and may hinder farmers' entry.

597 An alternative approach could involve the creation of "ecological certificates," similar to the
598 trading forest certificates discussed by Soares-Filho et al. (2016). Under this system, farmers
599 who adopt land-use practices delivering measurable ecological benefits—such as improved soil
600 health or enhanced water retention—could sell their "ecological certificates" to companies
601 seeking to offset their environmental impacts. These certificates could be traded on markets
602 driven by consumer expectations or regulatory requirements for ecological sustainability, such
603 as non-financial reporting standards. Both approaches provide direct financial incentives for
604 farmers that could facilitate agroforestry transitions.

605 *Exploring trade-offs in context*

606 The inclusion of agroforestry into landscape portfolios may compromise alternative land-use

607 types with high conservation value. For example, under higher uncertainty levels, agroforestry
608 replaced part of the area that would have otherwise been allocated to natural forests with a high
609 conservation value (Fig. 3 and Reith et al. 2022, showing similar effects). While this is a
610 sensitive issue at the tropical forest frontier, it may not be a significant problem in other
611 contexts, such as Central Europe, where primary forests cover only 0.7% of the forest area
612 (Sabatini et al. 2018). However, agroforestry in Europe may compromise open-space
613 demanding species, such as skylarks or lapwings (Gayer et al. 2019). Also, while agroforestry
614 systems may harbour more animal (e.g. insect) species as mono-cropping systems, their insect
615 communities are still less diverse than those of natural forests (Perry et al. 2016; Mupepele et
616 al. 2021). Future land-use studies must address such trade-offs and possible legal implications.

617 While we have focused on small-scale uncertainties like fluctuations in productivity and prices
618 or expert uncertainty about ecological benefits, exploring risks and trade-offs associated with
619 agroforestry adoption in other settings will likely require incorporating assessments of the
620 policy landscape. For example, the EU's Common Agricultural Policy (CAP) focuses on
621 sustainable land use and incorporating environmental aspects into agricultural practices. Our
622 results confirm that agroforestry may align with these policy objectives while potentially
623 minimising trade-offs with economic objectives. Given the diverse agroecological zones across
624 Europe, from Mediterranean to temperate regions, it is crucial to adapt evidence-based
625 agroforestry practices to specific regional environmental and economic conditions.

626 *Embedding agroforestry transitions in landscapes*

627 Rather than examining the economics of an agroforestry system in isolation, this study sought
628 to capture partial adoption decisions by considering portfolios of land-use alternatives that
629 agroforestry systems may displace or be displaced by. This might include competition from
630 non-agricultural land uses. Solar farms, for example, represent an increasingly important land-
631 use alternative in many countries (Dias et al. 2019). Their deployment on potential agricultural

632 lands suggests the need for additional economic comparisons. Portfolio-based approaches like
633 the one we describe here (see also Paul et al. 2017) can be re-tooled to address how subsidising
634 financial risk in emerging land-use types could influence the competitiveness of agroforestry-
635 based land uses in different environmental settings.

636 **7 Outlook**

637 The extent to which agroforestry systems can compete economically with standard agricultural
638 practices *ceteris paribus* remains unclear. Indeed, substantial evidence suggests they might not
639 compete (e.g. Thiesmeier and Zander 2023). We argue that by failing to explicitly consider the
640 role of uncertainty and landscape context in agroforestry adoption decisions, the available
641 economic evidence—favourable or not—has overlooked a crucial consideration.

642 In our study area, allowing the partial adoption of agroforestry options into landscape portfolios
643 mitigated environmental-economic trade-offs and increased portfolio performance under
644 uncertainty. Beyond our study area, we hypothesise that uncertainty considerations can also
645 provide convincing arguments in support of agroforestry in the Global North, where adoption
646 remains slow despite growing scientific interest. Understanding how variations in uncertainty
647 and temporal discontinuities in benefit flows influence economic assessments of agroforestry
648 relative to conventional land uses is crucial for stimulating uptake. By offering a lens through
649 which the economics of agroforestry adoption can be assessed alongside *status quo* systems in
650 the face of growing uncertainty about future benefit flows, we aim to broaden the scope of such
651 assessments.

652 At the same time, we identify substantial knowledge gaps, beginning with the pivotal 'early life'
653 phase of agroforestry transitions. Developing rigorous, realistic, and helpful agroforestry
654 ecological economics will require ongoing cooperation between economists, natural scientists
655 and land managers.

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