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Research article

Transformation scenarios towards multifunctional landscapes: A multi-criteria land-use allocation model applied to Jambi Province, Indonesia

Volker von Groß [a,*], Kibrom T. Sibhatu [b], Alexander Knohl [c,d], Matin Qaim [e], Edzo Veldkamp [f], Dirk Hölscher [c,g], Delphine Clara Zemp [h], Marife D. Corre [f], Ingo Grass [i], Sebastian Fiedler [j], Christian Stiegler [d], Bambang Irawan [k,l], Leti Sundawati [m], Kai Husmann [a], Carola Paul [a,c]

[a] *Forest Economics and Sustainable Land-use Planning, University of Göttingen, Göttingen, 37077, Germany*
[b] *International Center of Insect Physiology and Ecology (icipe), Nairobi, Kenya*
[c] *Centre of Biodiversity and Sustainable land-use, University of Göttingen, Göttingen, 37077, Germany*
[d] *Bioclimatology, University of Göttingen, Göttingen, 37077, Germany*
[e] *Center for Development Research (ZEF), University of Bonn, Bonn, 53113, Germany*
[f] *Soil Science of Tropical and Subtropical Ecosystems, University of Göttingen, Göttingen, 37077, Germany*
[g] *Tropical Silviculture and Forest Ecology, University of Göttingen, Göttingen, 37077, Germany*
[h] *Conservation Biology Lab, University of Neuchâtel, Neuchâtel, 2000, Switzerland*
[i] *Department of Ecology of Tropical Agricultural Systems, University of Hohenheim, Stuttgart, 70599, Germany*
[j] *Ecosystem Modelling, University of Göttingen, Göttingen, 37077, Germany*
[k] *Forestry Department, Faculty of Agriculture, University of Jambi, Jambi, 36122, Indonesia*
[l] *Center of Excellence for Land-Use Transformation Systems, University of Jambi, Jambi, 36122, Indonesia*
[m] *Department of Forest Management, IPB University, Bogor, 16680, Indonesia*

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ABSTRACT

In tropical regions, shifting from forests and traditional agroforestry to intensive plantations generates conflicts between human welfare (farmers' demands and societal needs) and environmental protection. Achieving sustainability in this transformation will inevitably involve trade-offs between multiple ecological and socioeconomic functions. To address these trade-offs, our study used a new methodological approach allowing the identification of transformation scenarios, including theoretical landscape compositions that satisfy multiple ecological functions (i.e., structural complexity, microclimatic conditions, organic carbon in plant biomass, soil organic carbon and nutrient leaching losses), and farmers needs (i.e., labor and input requirements, total income to land, and return to land and labor) while accounting for the uncertain provision of these functions and having an actual potential for adoption by farmers. We combined a robust, multi-objective optimization approach with an iterative search algorithm allowing the identification of ecological and socioeconomic functions that best explain current land-use decisions. The model then optimized the theoretical land-use composition that satisfied multiple ecological and socioeconomic functions. Between these ends, we simulated transformation scenarios reflecting the transition from current land-use composition towards a normative multifunctional optimum. These transformation scenarios involve increasing the number of optimized socioeconomic or ecological functions, leading to higher functional richness (i.e., number of functions). We applied this method to smallholder farms in the Jambi Province, Indonesia, where traditional rubber agroforestry, rubber plantations, and oil palm plantations are the main land-use systems. Given the currently practiced land-use systems, our study revealed short-term returns to land as the principal factor in explaining current land-use decisions. Fostering an alternative composition that satisfies additional socioeconomic functions would require minor changes ("low-hanging fruits"). However, satisfying even a single ecological indicator (e.g., reduction of nutrient leaching losses) would demand substantial changes in the current land-use composition ("moonshot"). This would inevitably lead to a profit decline, underscoring the need for incentives if the societal goal is to establish multifunctional agricultural landscapes. With many oil palm plantations nearing the end of their production cycles in the Jambi province, there is a unique window of opportunity to transform agricultural landscapes.

* Corresponding author.
E-mail address: volker.vongross@uni-goettingen.de (V. von Groß).

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1. Introduction

Improving human well-being without further exceeding planetary boundaries is one of the most pressing problems of this time. This challenge and the often resulting land-use conflicts are particularly evident in tropical regions, where highly vulnerable ecosystems with high biodiversity and utmost importance for the climate system clash with the needs of (smallscale-)landholders to sustain livelihoods and compete in globalized markets (Sayer et al., 2013; Feintrenie et al., 2010a; Grass et al., 2020). One such example is the Jambi Province of Sumatra, Indonesia, where the share of land covered with rainforest decreased by 15 percentage points between 1990 and 2013. This decrease is primarily due to conversion to agricultural purposes (Grass et al., 2020), predominately managed by smallholders that rely on globally demanded oil palm (*Elaeis guineensis* Jacq.) and rubber (*Hevea brasiliensis* Müll. Arg.) products as their primary sources of income (Chrisendo et al., 2022). It is unclear how such monoculture-agrosystems could undergo a sustainable transformation towards "multifunctional landscapes" (Sayer et al., 2013) that fulfill farmers' needs (e.g., increasing income or reducing labor and input requirements) and meet rising global demands for agricultural and forestry products, while also supporting multiple ecological functions (e.g., increasing organic carbon in plant biomass or reducing nutrient leaching losses) (Clough et al., 2016; Grass et al., 2020; Martin et al., 2022).

Past research has shown that changing land-use composition can significantly enhance the multifunctionality (i.e., the ability to integrate multiple sustainability goals) of agricultural landscapes (Neyret et al., 2023). Suggested transformation pathways include, for example, increasing land-use diversification of farms and landscapes (Lavorel et al., 2022; Neyret et al., 2023) and increasing the shares of biodiversity-based land-use management, such as agroforestry (Gosling et al., 2020b) and reduced-input agriculture (Kremen and Merenlender, 2018; Iddris et al., 2023).

Achieving such multifunctional landscapes (Sayer et al., 2013) will inherently involve trade-offs among the multiple goals that are often quantified as ecosystem functions or services (Raudsepp-Hearne et al., 2010; Allan et al., 2015). Even if, in theory, compromise land-use compositions that sufficiently satisfy all competing needs can be identified, they may not be acceptable for farmers if the suggested land-use composition and land management require substantial changes, affecting the financial farm capacities but also cultural identity or social networks too much (Martin et al., 2022). The challenge in land-use science remains as follows: how can such theoretically ideal multifunctional landscapes be identified and how can transformation pathways, including compromise solutions, best be linked with current land-use composition and preferences.

To identify such compromise land-use compositions, land-use allocation models have been used to simulate land-use trajectories and explore trade-offs among socioeconomic and ecological goals under different scenarios or objectives (Bateman et al., 2016; Zhang et al., 2016; Kaim et al., 2021; Wesemeyer et al., 2023). Agent-based models (ABMs), for example, have been used to investigate the effects of crop prices on area exchange between rubber and oil palm (Dislich et al., 2018), or to explore the effectiveness of payments for ecosystem services (Villamor et al., 2014) on different land-use types in Jambi Province, Sumatra, Indonesia. These types of models simulate the decision-making of individual agents (e.g., farmers) based on a set of predetermined rules or scenarios (Bonabeau, 2002; Dislich et al., 2018). As an alternative to pure simulation approaches, multi-criteria optimization has emerged to explore trade-offs between ecological and economic functions or goals (see extensive review by Kaim et al. (2018)). Two such examples are Pareto optimization and scalarization-based methods. Pareto optimization identifies potentially "efficient" land-use compositions that provide specific services or functions without worsening one or more alternative goals (Verstegen et al., 2017; Andreotti et al., 2018; Kaim et al., 2020). Scalarization-based methods, conversely, work to achieve "multifunctionality" in one objective function, as the selection among the entire set of solutions can be demanding (Knoke et al., 2016; Kaim et al., 2018).

To quantify "multifunctionality" in one objective function, most research builds on the concept of ecosystem functions and services (Byrnes et al., 2014; Hölting et al., 2019a). For example, based on the concept of ecosystem services, Hölting et al. (2019a) and Hölting et al. (2019b) differentiate between ecosystem service richness, abundance, and diversity. Richness is quantified by the number of services provided, abundance by the number of services, and diversity by various indices, e.g., the Shannon Index, evenness, or weight of the dominant ecosystem service. However, Hölting et al. (2019b) also point out that those definitions and measurements of multifunctionality assessments only weakly capture the balance of supply among different ecosystem functions or services. Threshold approaches, which define a required minimum, could offer potential solutions for this problem. For example, Grass et al. (2020) used a multifunctional threshold approach and an Evolutionary Optimization Algorithm (EA) to explore trade-offs and synergies between multidiversity, multifunctionality, and profitability in Jambi. Land-use allocation models using EA and other non-linear optimization have so far often disregarded uncertainty associated with the actual provision of the functions under limited information, measurement and prediction errors, climate change, and heterogeneous behavior. Additionally, threshold approaches that do not calculate the full range of possible levels of set thresholds often require normative, and thus sometimes arbitrary, decisions.

What is missing so far, is a modeling approach that (1) systematically searches for land-use allocations that satisfy different degrees of "multifunctionality" while also (2) accounting for the current land-use composition in transformation pathways and which is (3) still computationally feasible and efficient to allow for participatory approaches in land-use planning (Schlüter et al., 2019). Computationally intensive simulation models may risk excluding a "truly multifunctional" landscape composition by focusing on a pre-selected set of scenarios. In contrast, optimization approaches are usually quite abstract in that they plan theoretical optimal land-use compositions irrespective of current land-use compositions. In this study, we strive to overcome these weaknesses by developing a land-cover/-use optimization approach that applies a normative approach in a positive way. We aim to identify transformation scenarios of land-use allocation, including potential compromise solutions requiring the least change from current to theoretical optimal multifunctional landscape.

To accomplish this, we further develop and extend the scalarization-based optimization approach by Knoke et al. (2016) and Husmann et al. (2022) for multiple objectives, which is a type of reference point method (Knoke et al., 2020). The approach directly integrates uncertainty into the objective function and thus considers risk-reducing effects of land-use diversification (Knoke et al., 2016). The optimization problem is solvable through Linear Programming, ensuring low computational time and required resources (Husmann et al., 2022). However, the approach has mainly been used as a static approach to explore the effect of different ecological and economic functions on desirable landscape composition, but not for identifying transformation pathways (Gosling et al., 2020b; Reith et al., 2020). We use an earlier idea by Gosling et al. (2020b), who introduced a positive application of the robust multi-criteria optimization by Knoke et al. (2016) to identify the socioeconomic and ecological functions best explaining current land-use composition. We extend this approach conceptually by looking at a gradient of increasing ecological and socioeconomic function richness (i.e., multifunctionality), which we interpret as transformation scenarios. Methodologically, we extended it by developing an efficient *R* function for deriving this automatized succession of a large number of optimizations. This function (called *autoSearch*) was than added to the *R* package *optimLanduse* (Husmann et al., 2022).

We test the newly developed land-use allocation model on the case of smallholder farms in Jambi Province, Sumatra, Indonesia, a region crucial to global oil palm and natural rubber production. The smallholder farms are dominated by three land-use systems: a traditional rubber agroforestry system (here: 'jungle rubber'), rubber plantations, and oil palm plantations. The province has undergone notable agricultural expansion, causing conversion of rainforests and jungle rubber into intensive plantations (Grass et al., 2020; Huang et al., 2022). Due to strong economic and policy incentives for oil palm in Jambi in the last two decades and the crop's productive life of about 25 years, large areas of current oil palm plantations need to soon be replanted (Woittiez et al., 2017; Petri et al., 2022). Hence, our model and its findings can be very useful in this unique window of opportunity for transforming agricultural landscapes.

We aim to contribute to the following research questions:

1. What does a multifunctional (aggregated) agricultural landscape composition for the Jambi Province look like and how much does it deviate from the currently observed land-use composition? (RQ1)
2. Which ecological and/or socioeconomic function(s) likely drive(s) current land-use decisions? (RQ2)
3. How would an increase in function richness change the composition and performance of optimized land-use compositions that provide selected ecological and socioeconomic functions? (RQ3)

We use our model to investigate the ecological and socioeconomic functions driving current land-use decisions and explore the functions that can be achieved with minor ("low-hanging fruit") versus major ("moonshot") changes in land-use composition, considering their uncertain provision. Our results can assist policy-makers and serve as a basis for co-designing future land-use systems and contributing to more sustainable agricultural landscape development.

2. Materials and methods

2.1. Concept and definitions

Our approach consists of three main steps: (1) a normative step to identify the theoretical optimal land-use composition of a multifunctional landscape based on the land-use optimization model by Knoke et al. (2016) and Husmann et al. (2022) covering all considered ecological and socioeconomic functions, (2) a quasi-positive application of the optimization approach to better understand the ecological and socioeconomic functions driving current land-use decisions, and (3) a simulation–optimization study to calculate potential transformation scenarios from (2) to (1), reflecting the transition from current land-use compositions towards the normative "multifunctional" optimum.

In line with Hölting et al. (2019b), we refer to multifunctionality as the capacity of a given land-use composition to supply multiple ecosystem functions or services. However, the ecological and socioeconomic functions used here do not solely consist of distinct ecosystem functions or directly represent ecosystem services. Instead, the set of functions combines ecological and socioeconomic functions, where the ecological functions represent ecosystem functions in part directly and in part nutrient pools and ecosystem properties, which are important drivers of ecosystem functioning (Garland et al., 2021), and the socioeconomic functions (Gosling et al., 2020b) describe various needs from a farmer's perspective. Thus, we aim to integrate the ecological and socioeconomic spheres of social-ecological systems (Schlüter et al., 2019). In our approach, functions are reflected by indicators (see Section 2.3), which serve as proxies for the different ecological and socioeconomic functions. These indicators are used as the input data for optimizing land-use combinations.

We sought to combine different perspectives towards multifunctionality by (a) accounting for "function richness" (i.e., the number of functions considered in the optimization) and (b) considering the aspect of a balanced provision by searching for compromise solutions that, for each level of function richness, maximize the minimum achievement level across all ecological and socioeconomic functions. The minimum achievement level of all functions can be interpreted as the robust multifunctionality of the respective landscape composition. Compared to a threshold approach, robust multifunctionality does not show how many functions reach a certain threshold, but which minimum performance level is guaranteed across all considered functions. (c) We incorporated robustness, as one component of resilience (Meuwissen et al., 2019), by searching for this minimum achievement under a range of uncertainty scenarios. These may reflect different stakeholder expectations or uncertainty in future ecosystem function provisioning.

This understanding of multifunctionality is used as a normative goal of a public decision-maker in Step 1 (RQ1) of our approach (Fig. 1). Building on the robust multi-criteria land-use optimization model (further details in Section 2.2), we derived the average farm composition (with farms being aggregated to a virtual agricultural landscape composition) best fulfilling the above-mentioned criteria of a robust level of function provisioning across all considered ecological and socioeconomic functions. The objective function assumes that decision-makers prefer solutions that satisfy the provision across multiple functions rather than maximizing single ones ("satisficing behavior" (Simon, 1955)) and that the decision-maker accounts for uncertainty in the provision of these functions (Findlater et al., 2019; Knoke et al., 2023). The resulting average farm composition thus achieves a "good enough" performance for all ecological and socioeconomic functions (Findlater et al., 2019) by maximizing the minimum achievement level of all possible scenarios instead of, e.g., maximizing the average of all scenarios. This theoretical optimum was then compared to the current land-use composition. In line with Knoke et al. (2016) we quantified differences between land-use compositions by the Bray–Curtis measure of dissimilarity (BC) (Eq. (11)).

We explored differences in the land-use composition optimized for provisioning of all functions considered versus the current land-use composition, which we assumed to be driven by a smaller set of functions. Therefore, in Step 2 (RQ 2, Fig. 1), we used the optimization as a quasi-positive approach to identify the bundle of functions resulting in the land-use composition most similar (i.e., lowest BC) to the current land-use composition, while assuming typically risk-averse private smallholder decision-makers (Bowman and Zilberman, 2013; Nielsen et al., 2013). This required developing an efficient way to calculate a large number of optimizations using all potential combinations of indicators and filtering them by the lowest BC (further details in Section 2.2.2).

We analyzed potential transformation scenarios towards multifunctional landscape compositions in Step 3 (Fig. 1). Starting from the number and identity of indicators best explaining the current land-use composition, we cumulatively added indicators, i.e., increasing multifunctionality in terms of function richness (Fig. 1). The identity of this added function (i.e., its respective indicator) was selected according to the lowest BC when comparing resulting and current land-use compositions. This allowed us to identify "low-hanging fruits" of providing additional functions that would, in our model, only require minor changes in land-use composition. While our non-spatially explicit approach is not designed to identify exact land-use compositions and configurations for landscape planning, it could help to understand mismatches between the identified objectives driving the current land-use composition and the composition that simultaneously optimizes all indicators (highest function richness). Furthermore, it can help to identify trade-offs and synergies between compositions with different function richness.

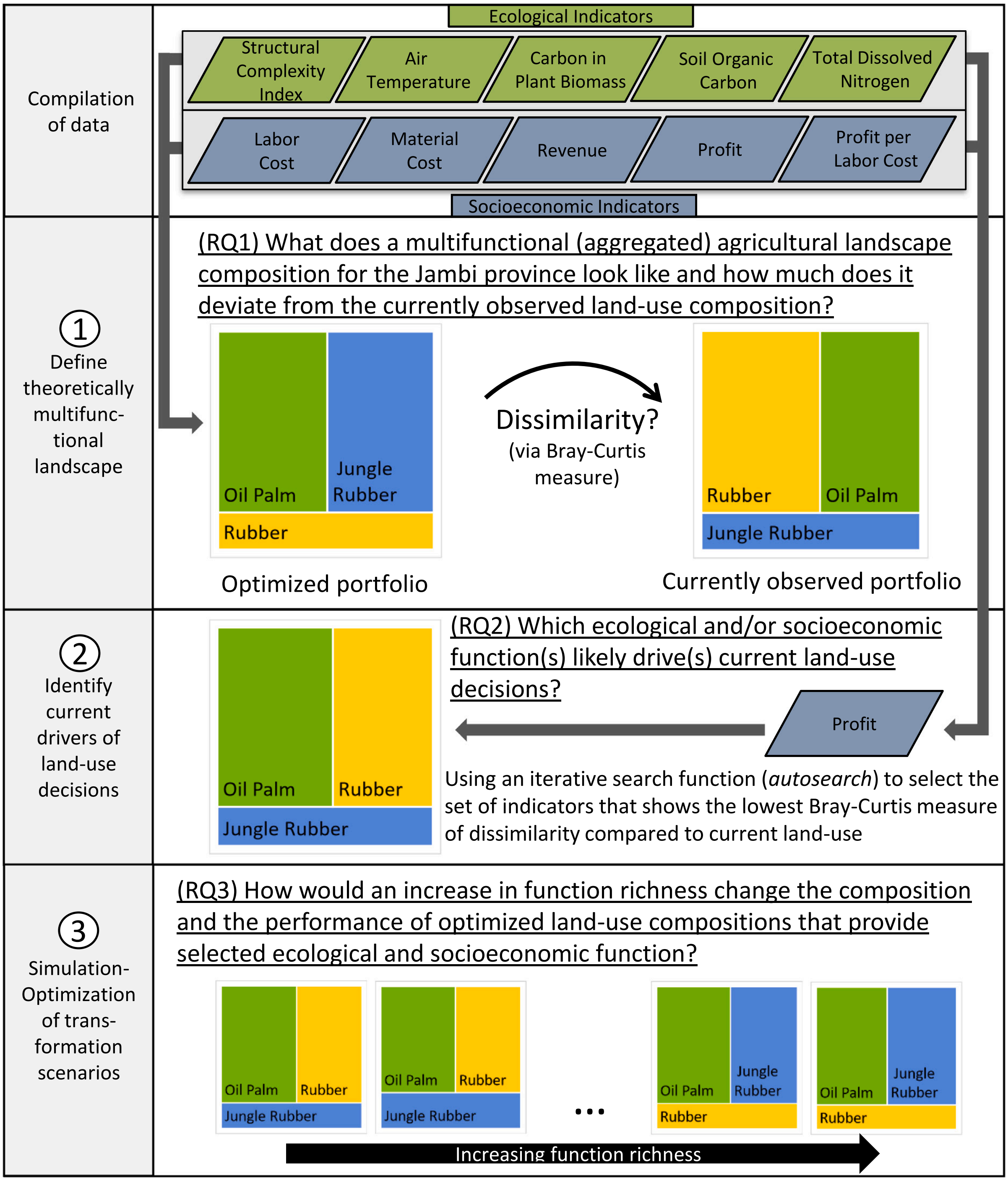

Fig. 1. Conceptual overview of the research approach. Step 1 uses a set of indicators reflecting multiple ecological and socioeconomic functions to create an optimized multifunctional landscape composition. The resulting multifunctional composition is compared to the currently observed composition using the Bray–Curtis measure of dissimilarity. In Step 2, the iterative search function *optimLanduse::autoSearch* from the *R* package *optimLanduse* is used to identify which indicator(s) in the objective function lead(s) to a land-use composition that approximates the currently observed land-use allocation, assuming a risk-averse decision-maker. This is done by *autoSearch* generating all possible indicator combinations and sequentially computing the respective optimization. In Step 3, the list covering all possible combinations is used to create a series of compositions (transformation scenarios) with increasing function richness, starting with the composition best explaining the current land-use composition (Step 2) and ending with the multifunctional landscape composition (Step 1).

2.2. Model description

2.2.1. Defining a multifunctional landscape portfolio using reference point optimization

In order to define a theoretical optimal multifunctional landscape (i.e., to elaborate RQ1), we used the robust optimization approach according to Knoke et al. (2016) by applying the *R* package *optimLanduse* of Husmann et al. (2022). The output of the model is a portfolio, which we defined as a land-use composition that includes both the number of land-use options and their proportions. The concept of this optimization approach is to minimize underperformance of the worst-performing indicator in the optimum. Underperformance is defined here as the difference (distance) between actual fulfillment of that indicator in the optimum and its hypothetical best fulfillment. This distance β

can thus be interpreted as the minimum fulfillment a landscape can provide given the functions considered in the objective. Indicators serve as proxies for respective ecological and socioeconomic functions. Each indicator has a mean value and an individual uncertainty. These measures are taken to calculate individual indicator best- and worst-case estimates (Eq. (4)), which are then used to create uncertainty scenarios by combining all estimates of all indicators. The total number of uncertainty scenarios (N_S) is thus calculated by multiplying the possible combinations per indicator ($N_U = 2^{N_L}$; N_L = number of land-use options) by the number of indicators considered ($N_S = N_U \cdot N_I$; N_I = number of indicators). The optimal landscape portfolio is the portfolio that minimizes maximum distances (d_{iu}) across all uncertainty scenarios. The method's philosophy is that the worst-performing indicator in the worst-possible scenario solely determines the solution. Better-performing indicators do not compensate for lower-performing indicators (Knoke et al., 2020).

Consequently, the objective is to minimize maximum distance β, which, according to Husmann et al. (2022), can be expressed as

$$\min \beta, \tag{1}$$

with

$$\begin{aligned} &\beta = max(d_{iu}), \text{ with} \\ &\quad i \in I, \text{ being the set of indicators, and} \\ &\quad u \in U_i \text{ being the set of individual} \\ &\quad \text{uncertainty scenarios for } i. \end{aligned} \tag{2}$$

β represents the worst-performing indicator in the worst-performing scenario by means of the distance between the actual level of this indicator in the optimum and its best-achievable level. All other indicators perform better (or equally) than β, ensuring the model's robustness. Since this minimum distance to the best-possible achievable indicator level must be held by all indicators in the optimum, β also determines the limit of the right-hand sides of all constraints. The distances d_{iu}, representing this gap between actual and best-achievable level under uncertainty, are calculated as

$$d_{iu} = \begin{cases} \frac{\max(R_{liu}) - R_{iu}}{\delta_{\min,\max_{iu}}} & \text{if more is better,} \\ \frac{R_{iu} - \min(R_{liu})}{\delta_{\min,\max_{iu}}} & \text{if less is better.} \end{cases} \tag{3}$$

The number of distances corresponds to the number of all uncertainty scenarios N_S. The best achievable level $max(R_{liu})$ is defined by the maximum among all uncertainty-adjusted indicators in scenario u. The distances d_{iu} are normalized by dividing them by the range between the maximum and minimum values of the uncertainty-adjusted indicators for each uncertainty scenario $\delta_{min,max_{iu}}$.

Pessimistic estimate:

$$R_{liu} = \begin{cases} R_{li} + f_u \cdot SD_{li} & \text{if more is better,} \\ R_{li} - f_u \cdot SD_{li} & \text{if less is better.} \end{cases} \tag{4}$$

Optimistic estimate:

$$R_{liu} = R_{li}.$$

R_{liu} are the uncertainty-adjusted indicators, which are composed of the indicators' mean values R_{li}, their respective uncertainties SD_{li}, and a factor f_u able to consider differing preferences towards risk in the optimization. f_u enables modification of the input uncertainties and thereby changes the risk setting of a stakeholder without changing the input data. Within the reasonable range of $f_u = 0$ (no aversion against uncertainty) and $f_u = 3$ (highly risk-averse), we assumed a moderate risk aversion ($f_u = 2$). For the pessimistic estimate, we added or subtracted it from R_{li} (Eq. (4)). For the optimistic outcome, the mean indicator value is directly taken. The scenarios cover each combination of pessimistic and optimistic outcomes for all indicators.

$$R_{iu} = \sum_{l \in L} R_{liu} \cdot a_l, \tag{5}$$

Multiplying the uncertainty-adjusted indicator values of each uncertainty scenario R_{liu} by the shares of the respective options of the landscape portfolio a_l gives the actual achieved level for a given landscape portfolio R_{iu}. The individual land-use options l add up to the set of all land-use options L. It follows that interactions between the land-use options are not integrated, as the options are additively connected. For this reason, neither spatial correlations nor other types of correlations between the alternatives can be accounted for in the optimization.

We widened the uncertainty space to not overly constrain the state space of the distances and to guarantee robust results (Gosling et al., 2021; Husmann et al., 2022). Thus, the maximum and minimum uncertainty-adjusted indicator R_{liu}, used in Eq. (3), is calculated with a higher uncertainty factor than R^*_{liu}

$$R^*_{liu} = \begin{cases} R_{li} + f^*_u \cdot SD_{li} & \text{if more is better,} \\ R_{li} - f^*_u \cdot SD_{li} & \text{if less is better.} \end{cases} \tag{6}$$

We opted for a widened uncertainty space of $f^*_u = 3$. This affected $\delta_{min,max_{iu}}$ in Eq. (3) which was then calculated based on these new $max(R^*_{liu})$ and $min(R^*_{liu})$. The calculation of R_{iu} (Eq. (5)) still remained on the uncertainty-adjusted indicator R_{liu} with $f_u = 2$.

The following restrictions are technical and limit the parameter space of possible options.

$$\sum_{l \in L} a_l = 1, \text{ and} \tag{7}$$

$$a_l \geq 0, \forall l \in L \tag{8}$$

The last restriction relates to distances shown in Eq. (2). Each distance d_{iu} may, in any case, only be as large as the distance of the worst-performing scenario of the worst-performing indicator (β).

$$d_{iu} \leq \beta, \forall i \in I, \text{ and } \forall u \in U_i, \tag{9}$$

2.2.2. Identifying current drivers of land-use decisions

To identify and understand indicators driving current land-use decisions (RQ2), we extended the *R* package *optimLanduse* by an iterative *R* search function, *optimLanduse::autoSearch*. The *autoSearch* function generates distinct and independent optimizations with differing indicator sets while all other settings remain unchanged. To do so, *autoSearch* generates all possible indicator combinations and calculates the respective optimization sequentially. A detailed overview of *autoSearch* was added to the README of the *R* package *optimLanduse* (Husmann et al., 2022). The total number of possible indicator combinations N_K results from

$$N_K = 2^{N_I} - 1, \tag{10}$$

with N_I as the total number of unique indicators provided in the coefficient table.

Out of this list, we used the Bray–Curtis measure of dissimilarity (BC) to identify the set of ecological and socioeconomic functions, resulting in an optimized land-use portfolio with the lowest dissimilarity $BC_{opt;obs/all}$ compared to the current land-use portfolio. The BC is calculated as

$$BC_{opt,obs/all} = \frac{\sum_l^{lmax} \left| a_{l,opt} - a_{l,obs/all} \right|}{2} * 100, \tag{11}$$

with a_l being the proportion of land-use option l for the optimized portfolio (index *opt*) and either the observed land-use portfolio (index *obs*) or the land-use portfolio including all ecological and socioeconomic indicators (index *all*). $BC_{opt;obs/all}$ is close to 100 with a high dissimilarity and close to 0 with a low dissimilarity.

2.2.3. Simulation–optimization of transformation scenarios

The derived list with all possible indicator combinations (generated by *R optimLanduse::autoSearch*) is used to create an interpretable and manageable result list by filtering and ordering all of the calculated list entries (RQ3). The starting point was always the portfolio best explaining the current land-use decision (Section 2.2.2). To this starting point, additional portfolios were added that met the following three criteria:

- The set of indicators from the previous land-use portfolio is considered.
- The previous indicator set is extended by one additional indicator.
- BC is as close as possible to the portfolio best explaining the currently observed land-use portfolio.

These three criteria ensured that one more indicator was added to the indicator set of the previous portfolio. The portfolio optimized for this new indicator set offers the slightest difference from the portfolio that best explains the current land-use decision (measured through the BC, Section 2.2.2). This allowed us to increase the function richness between the portfolios and analyze which indicators are achievable with minor land-use composition changes and which require substantial changes. The outcome is a series of portfolios with increasing function richness (hereafter: "transformation scenarios"), starting with the portfolio best explaining the current land use and ending with the multifunctional landscape, which includes all indicators in the optimization.

To analyze the robust performance of optimized land-use portfolios, the guaranteed minimum achievement indicator level (GMAL) was calculated. GMAL is calculated by subtracting β (Eq. (1)) from the maximum achievable level. This GMAL can be interpreted as the degree of minimum indicator fulfillment level across all indicator sets and uncertainty scenarios of each portfolio and is used hereafter as a measure of robust performance. We calculated GMAL from three perspectives:

- for each optimized portfolio of the transformation scenario towards the multifunctional landscape portfolio. Within each portfolio, each indicator of the optimized indicator set reaches at least this level (robust performance of considered functions).
- for solely indicator(s) best explaining the current land-use decision. Thus, only how this currently important indicator set performs in the different portfolios with increasing function richness (robust performance of currently important function(s)).
- for all ten indicators for each portfolio with increasing function richness, i.e., the performance that is guaranteed achievable across all 10 indicators when assuming the land-use shares of the portfolios from function richness 1 to 10 (robust multifunctionality).

In general, the model requires only a small set of input information (indicators' mean values and their respective uncertainties). This small data requirement, in combination with the openly available *R* package *optimLanduse* (see Data availability), including the new *autoSearch* function, and the explanation provided in this section, enables interested researchers to straightforwardly apply the model to their study regions with different land-cover types and indicators where the required input information can be provided. Here, we exemplify the model using a database of ecological and socioeconomic functions for Jambi Province, Indonesia.

2.3. Case study example

Our analyses built on an extensive database of the interdisciplinary project "Ecological and Socioeconomic Functions of Tropical Lowland Rainforest Transformation Systems" (EFForTS). EFForTS conducted research in the Jambi Province, Indonesia, including environmental processes, biota and ecosystems, and the human dimension (Drescher et al., 2016). We selected five ecological and five socioeconomic functions from available data to incorporate aboveground, belowground, climate, and socioeconomic aspects, each represented by one measured or surveyed indicator (Table 1). We selected the ten ecological and socioeconomic functions and the respective indicators from the entire extensive database based on three criteria: (1) they meet the technical requirements needed for the optimizer (see Sections 2.2 and 4.2), (2) they are only slightly correlated, and (3) they were found to be important for decision-making based on expert knowledge from several talks and discussions with scientists and stakeholders as well as previous studies (Table 1).

The ecological indicators are Stand Structural Complexity index, Air Temperature 95th percentile, Carbon Total Biomass, Soil Organic Carbon, and Total Dissolved Nitrogen. Socioeconomic indicators refer to the farmer's perspective. In order to get a comprehensive picture, it is important to consider not only the indicator Profit but also further aspects of farmers' everyday lives relevant to their decision-making, e.g., Labor and Material Cost, Revenue, and Profit per Labor Cost (Table 1), even if some of the corresponding indicators are slightly correlated. As data input for the optimizer, we calculated the indicators' mean values and their uncertainties for each land-use type of the study region (Table 2). We used an equal number of socioeconomic and ecological functions to weigh both perspectives equally.

Ecological data was collected from the core plots of the overall research design (Drescher et al., 2016) during the years 2012 and 2016: Eight 50 m x 50 m plots were established for four common land-use systems in the Jambi Province (rubber plantation, jungle rubber, oil palm plantation, and primary degraded forest (Margono et al., 2014)), resulting in a total of 32 plots. Jungle rubber is a traditional agroforestry system and describes a secondary forest enriched with rubber trees (Gouyon et al., 1993).

All oil palm and rubber plantation plots were established in smallholder farms. Smallholder farms contribute significantly to the plantation economy in Jambi: 71% of oil palm area and 99% of rubber area is managed by them (BPS-Statistics Indonesia, 2022b,a). We excluded primary degraded forest in our main analyses because land conversions of agricultural land to primary degraded forest are not feasible within a reasonable time frame (Martin et al., 2022).

We used an extensive household survey carried out in 2018 (Sibhatu, 2019) to calculate the socioeconomic indicators' mean values and uncertainties and derive the aggregated land-use portfolio. 701 households in the Jambi Province belonging to the tropical lowlands were surveyed. Details of how the survey was conducted and how the socioeconomic indicators were calculated are provided in the Supplementary materials (see Section S.1). Thus, our indicators reflect the variability of socioeconomic conditions and expectations within smallholder farms in the study region. The derived portfolios do not aim at representing daily-life decision-making within individual farms, but rather a generalized land-cover pattern from the perspective of a public decision-maker — a perspective that may be expected when farmers consider the respective indicators, and that also accounts for the uncertainty in the provision of these functions between farms. Thus, the farmer's decision-making is exclusively represented in an aggregated land-use composition and depends solely on the considered indicators and their uncertainties. The current land-use portfolio is a result of this average decision-making, including this variability between expected function provision between farms. We therefore used this plot-level and survey data to construct average farm portfolios, assuming that aggregating average farm portfolios sufficiently represents hypothetical agricultural landscape portfolios that have a potential for adoption by farmers in the shorter-term.

We conducted sensitivity analyses to assess robustness of our results to various assumptions. We investigated the influence of altering indicators for the ecological functions and including new ecological functions (Table S1). To do this, we altered (1) SSCi with the Effective

Table 1
Overview and description of the predefined ecological and socioeconomic functions and respective indicators used in the optimization process.

	Function	Indicator	Description and source of data	Rationale
Ecological functions	Structural complexity	Stand Structural Complexity index (SSCi)	The SSCi is calculated via the mean fractal dimension index that depends on the density of vegetation elements and the effective number of layers describing the vertical stratification (Ehbrecht et al., 2017; Zemp et al., 2019). Data source: Zemp et al. (2019)	Structural complexity is an important driver for enabling biodiversity across trophic levels, habitat structure, and ecosystem functioning (Perles-Garcia et al., 2021; Zemp et al., 2023). It has shown positive impacts on abundance, species richness, litter input or micro-climate (Ehbrecht et al., 2017; Schuldt et al., 2019), although the impacts depend on the taxa and the ecosystem function (Zemp et al., 2023).
	Microclimatic conditions	Air Temperature 95th percentile	Upper 95% percentile for air temperature (°C). Data source: Meijide et al. (2018)	The maximum temperature is an important indicator of stability of microclimatic conditions (Clough et al., 2016). The dramatic and rapid changes in microclimatic conditions are presumed to contribute to biodiversity loss in tropical regions (Hardwick et al., 2015; Meijide et al., 2018). Furthermore, the increasing heat exposure can negatively impact cognitive performance of rural workers and human well-being (Masuda et al., 2020).
	Organic carbon in plant biomass	Carbon Total Biomass	Carbon total biomass including organic carbon (Mg C ha^{-1}) from fine roots, coarse roots and aboveground biomass. Data source: Kotowska et al. (2015)	Conversion of tropical rainforest to agricultural land strongly influences soil organic carbon stocks, biomass carbon storage and sequestration and, thus, greenhouse gas emissions (van Straaten et al., 2015; Kotowska et al., 2015; Fitzherbert et al., 2008).
	Soil organic carbon	Soil Organic Carbon	Soil organic carbon (Mg C ha^{-1}) at a depth of 0 – 0.5 meters. Data source: Allen et al. (2015)	
	Nutrient leaching losses	Total Dissolved Nitrogen (TDN)	Total dissolved nitrogen leaching flux (kg ha^{-1} yr^{-1}). Data source: Kurniawan et al. (2018)	TDN is one important indicator for evaluating nutrient leaching fluxes. High nutrient leaching can have a negative impact on groundwater quality and cause pollution of streams and rivers (Clough et al., 2016; Jacobs et al., 2017).
Socioeconomic functions	Labor requirements	Labor Cost	Total labor cost required (US dollars (USD) ha^{-1} yr^{-1}). Data sources: Sibhatu (2019), Kühling et al. (2022)	Both labor and input requirements can be important constraints of smallholder farmers that drive land-use decisions of smallholder farmers (Connelly and Shapiro, 2006; Santos Martin and van Noordwijk, 2011; Clough et al., 2016). The optimization considers labor and input requirements separately, as labor and input costs vary widely among respective land-use types considered.
	Input requirements	Material Cost	Total material cost required (USD ha^{-1} yr^{-1}). Data sources: Sibhatu (2019), Kühling et al. (2022)	
	Total income to land	Revenue	Revenue made (USD ha^{-1} yr^{-1}; production output multiplied by average market price). Data sources: Sibhatu (2019), Kühling et al. (2022)	Increasing income from land-use is expected to be an important driver for land-use decisions (Grass et al., 2020). For many households, labor is covered by family labor which is not explicitly paid. Therefore, Revenue and Profit are considered separately.
	Returns to land	Profit	Profit made (USD ha^{-1} yr^{-1}; subtracting labor and input requirements from Revenue). Data sources: Sibhatu (2019), Kühling et al. (2022)	Profitability is an important indicator in selection of land-use alternatives (Connelly and Shapiro, 2006; Santos Martin and van Noordwijk, 2011).
	Returns to labor	Profit per Labor Cost	Profits per invested USD for labor (dividing profit by labor requirements). Data sources: Sibhatu (2019), Kühling et al. (2022)	Labor is often a limiting variable (Santos Martin and van Noordwijk, 2011; Clough et al., 2016). At the same time, increasing profitability is an expected incentive for smallholder farmers when choosing land-use options. Thus, profit earned per USD invested is an important variable for decision-making.

Number of Layers, (2) considered depth for Soil Organic Carbon, (3) Air Temperature 95th percentile with Humidity, Soil Moisture Range, and Soil Temperature Range, and (4) TDN with Aluminium (Al), Calcium (Ca) and Magnesium (Mg). Additionally, we added Litter Mass Loss, *N* Mineralization, and Methane flux each as an eleventh indicator. Furthermore, we evaluated the robustness of the portfolios considering degraded primary forest as an additional land-cover type (Fig. S3), interpreting the effects as consequences of hypothetical reforestation, even though this land-cover transformation is currently not practiced. Lastly, we evaluated the effects of uncertainty by removing the uncertainty. For each analysis, we kept all other assumptions constant (*ceteris paribus*).

3. Results

3.1. Multifunctional landscape portfolio

Optimizing land-use allocation for all ten indicators simultaneously (i.e., deriving the multifunctional landscape portfolio for the highest function richness) resulted in a landscape composition consisting of approximately equal shares of jungle rubber (41%) and oil palm plantation (42%), with a smaller share allocated to rubber plantation (17%) (function richness 10 in Fig. 2b). The dominance of jungle rubber and oil palm plantations was driven by their superior mean values across most indicators compared to rubber plantation (Table 2). Jungle rubber showed the highest mean values for four out of five

Table 2
Mean values and standard deviations (uncertainty) for selected indicators of the three land-use types (jungle rubber, oil palm plantation, and rubber plantation). The superscript letters indicate whether having more or less of an indicator is better. N = number of measured plots (for ecological indicators) and number of plots from surveyed households (for socioeconomic indicators).

Indicator	Unit	N	Jungle rubber	Oil palm plantation	Rubber plantation
SSCi[a]	index	8	6.85 ± 0.81	3.50 ± 0.48	4.77 ± 1.14
Air Temp. 95th percentile[b]	°C	8	30.20 ± 0.50	31.10 ± 0.11	31.20 ± 0.18
Carbon Total Biomass[a]	Mg C ha^{-1}	8	76.12 ± 9.24	43.09 ± 8.21	38.35 ± 11.46
Soil Organic Carbon[a]	Mg C ha^{-1}	8	106.47 ± 36.54	80.57 ± 25.84	75.32 ± 29.09
Total Dissolved Nitrogen[b]	kg ha^{-1} yr^{-1}	8	5.35 ± 4.97	12.63 ± 12.78	4.63 ± 2.85
Labor Cost[b]	USD ha^{-1} yr^{-1}	824	500.43 ± 373.06	179.51 ± 151.27	665.40 ± 470.48
Material Cost[b]	USD ha^{-1} yr^{-1}	824	13.87 ± 15.27	118.29 ± 123.19	29.13 ± 28.07
Revenue[a]	USD ha^{-1} yr^{-1}	824	707.22 ± 447.09	949.68 ± 628.15	1107.39 ± 715.55
Profit[a]	USD ha^{-1} yr^{-1}	824	186.80 ± 425.03	634.22 ± 556.88	394.70 ± 728.25
Profit per Labor Cost[a]	USD	824	0.80 ± 1.11	9.28 ± 18.87	1.31 ± 2.32

[a] = more is better.
[b] = less is better.

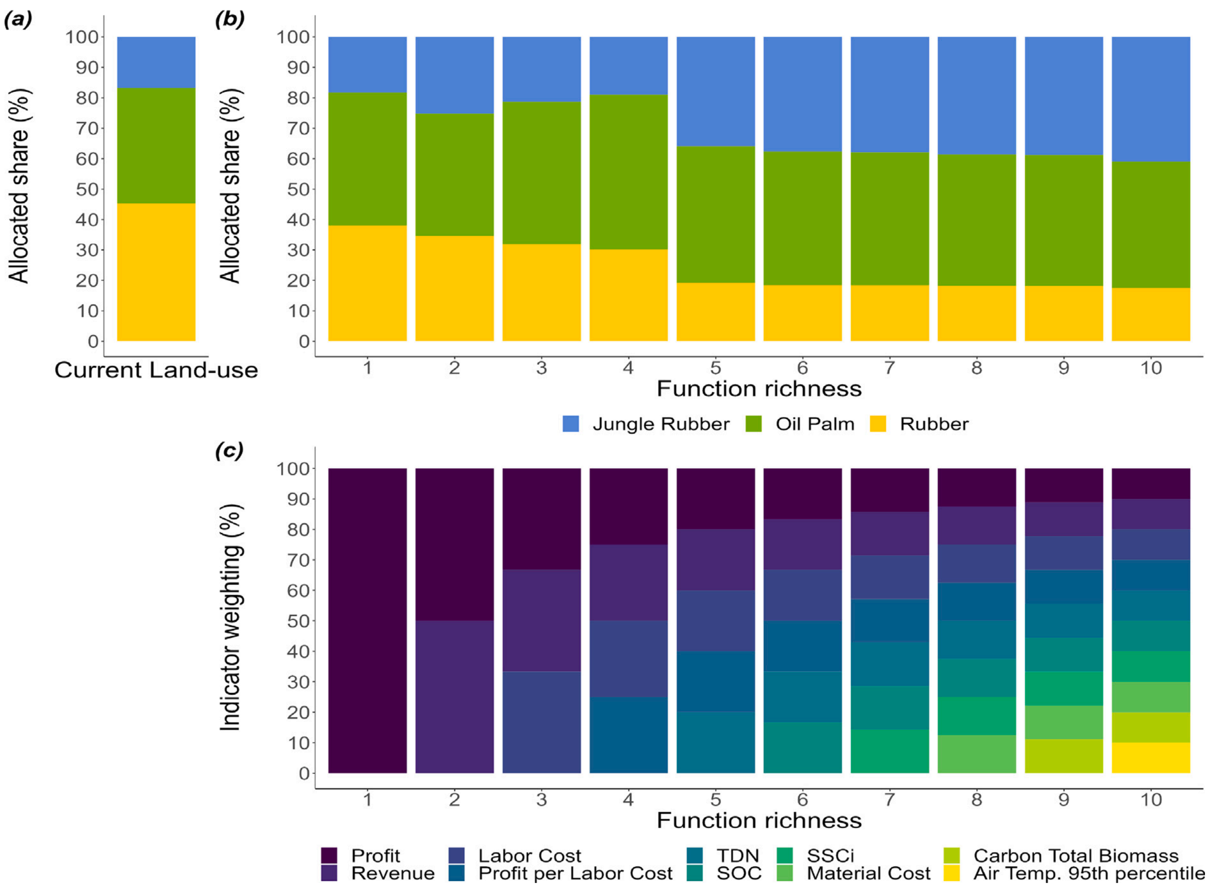

Fig. 2. (a) The current land-use portfolio of farmers, taken from household surveys of 587 farm households (824 plots) in Jambi Province, Indonesia, representing a total area size of 1520 hectares. (b) Transformation scenario showing the effect of increasing function richness on the optimized land-use portfolio. Optimized portfolios start with the portfolio most closely explaining the currently observed land-use decision (function richness (1) and end with the portfolio that optimizes all indicators simultaneously (function richness 10). For intermediate portfolios, one more indicator is added to the previous portfolio to increase function richness, where the identity of the added indicator is selected according to lowest BC when compared with the observed land-use portfolio. (c) The explicit indicator set selected by the model for each level of function richness leading to the respective portfolios shown in (a). Each of these indicators is equally weighted in the optimization. All portfolios were calculated for an uncertainty factor of two.

ecological indicators (SSCi, Air Temperature, Carbon Total Biomass, and Soil Organic Carbon), outperforming the alternative options, while also having the lowest material cost on average. Conversely, oil palm plantation performed best in three out of five socioeconomic indicators (Labor Cost, Profit, and Profit per Labor Cost) (Table 2). The only exceptions were Revenue and Total Dissolved Nitrogen, which showed the best values for rubber plantations among all land-use types. This also explained the relatively lower share of rubber plantations in the optimized land-use portfolio.

Compared to the currently observed land-use portfolio, the multi-functional portfolio exhibited higher shares of both low management-intensity jungle rubber and highly productive oil palm plantation (function richness 10 Fig. 2b). The increase in jungle rubber and oil palm plantation came at the expense of rubber plantation (compare function richness 10 Fig. 2b with Fig. 2a). The current land-use composition was predominantly composed of oil palm (45%) and rubber plantation (38%), with a relatively low share of 17% allocated to jungle rubber

(Fig. 2a). This suggests that the composition of the current portfolio was driven by a different set or number of functions.

The composition of the optimized multifunctional portfolio was robust when we considered different ecological indicators for the ecological functions, e.g., altering depth for Soil Organic Carbon or using Humidity for microclimatic conditions (Supplementary Fig. S1). Even when new ecological functions like Litter Mass Loss were introduced, the pattern remained largely unchanged (Supplementary Fig. S2). Including primary degraded forest as an additional land-cover system shifted the portfolio to 34% forest, 29% jungle rubber, 36% oil palm, and 1% rubber (Supplementary Fig. S3), reducing rubber plantation shares by 16 percentage points. This showed that forest in the landscape portfolio mainly occurred at the expense of rubber plantations, which were perceived as the least desirable option overall. The composition of the multifunctional portfolio remained robust when the uncertainty factor was set to zero (Supplementary Fig. S5).

3.2. Indicator(s) driving current land-use decisions

The analysis of the indicators best explaining current land-use decisions showed that optimizing solely for Profit (function richness 1 in Fig. 2b and Fig. 2c) yielded a portfolio closely resembling the current land-use portfolio. Optimizing for Profit with an uncertainty factor of two resulted in a portfolio comprising 18% jungle rubber, 44% oil palm plantation, and 38% rubber plantation. This portfolio was remarkably similar to the currently observed land-use portfolio (Fig. 2a), as measured by a BC of only 7.2 (lowest BC possible = 0, equation (11)).

Further sensitivity analysis demonstrated that our findings are robust, as different sets of indicators (first bars Supplementary Fig. S1) consistently highlighted Profit as the primary explanatory indicator of the current land-use decision (Supplementary Table S2). Variations arose only when we replaced some indicators of "Nutrient leaching losses" or "Microclimatic conditions", i.e., when (1) the TDN indicator was replaced with Al, which is toxic in dissolved form, or Ca, an important base cation, and (2) the Air Temperature 95th percentile indicator with Humidity. These new indicators became part of the indicator set best explaining the current land-use portfolio (Supplementary Table S2). However, Profit consistently remained part of the indicator set best explaining the current land-use portfolio. Adding various other ecological functions to the optimization did not alter the dominance of the Profit indicator in explaining the observed land-use decisions (Supplementary Table S3). When including primary degraded forest, the portfolio best explaining the current land-use composition still relied on a single socioeconomic indicator (Revenue)(Supplementary Fig. S3). With zero uncertainty, indicators TDN, Profit per Labor Cost, and Labor Cost best explained current land-use composition.

3.3. Simulating transformation scenarios

From the set of all nine remaining indicators, socioeconomic indicators were added first and had the lowest change in land-use composition compared to current land-use composition (Fig. 2c). This reflects that the mean values of many socioeconomic indicators showed their highest levels for the same land-use type. For example, the mean value of Profit performed best in oil palm plantations (Table 2). Similar results were observed for indicators Labor Cost and Profit per Labor Cost, which were added in function richness 3 and 4 (Fig. 2), leading to an increase of shares of oil palm in the portfolios. However, given the high proportion of rubber plantation in the current portfolio (Fig. 2a), the indicator Revenue, which performs best for rubber, was first added to the indicator set in function richness 2 (Fig. 2b). Overall, adding additional socioeconomic indicators (function richness 1 to 4) only slightly affected the share of jungle rubber but increased the percentage of oil palm plantation at the expense of rubber plantation (Fig. 2).

As the number of indicators increased, the first ecological indicator included in the optimization was Total Dissolved Nitrogen at function richness 5 (Fig. 2). This led to a considerable change in land-use composition along the transformation scenario. The proportion of jungle rubber strongly increased by 17 percentage points between function richness 4 and 5, while the proportion of oil palm and rubber plantation reduced by 6 and 11 percentage points, respectively. The BC increased from 15.2 at function richness 4 to 26.2 at function richness 5. Interestingly, adding just the first ecological indicator already resulted in a landscape portfolio closely resembling the multifunctional portfolio (function richness 5 and 10 in Fig. 2b and Fig. 2c). This outcome was driven by the dominant performance of jungle rubber across average mean values of various ecological indicators (Table 2). The last two indicators included in this cumulative analysis were Carbon Total Biomass and Air Temp. 95th percentile, requiring the largest change in currently observed portfolios (BC = 27.2 and 27.8, respectively).

The pattern of the transformation scenario (where (1) additional socioeconomic indicators resulted in minor changes in landscape portfolio followed by (2) considerable changes with the inclusion of ecological indicators) was robust against changing the ecological indicators for different ecological functions or adding additional ecological functions (Supplementary Fig. S1 and S2), except for "Nutrient leaching losses", where exchanging TDN with indicators Al or Ca resulted in their inclusion in the indicator set best explaining the current land-use portfolio. The general pattern persisted when primary degraded forest was included (Supplementary Fig. S3). Only the identity of indicators, i.e., at what level of function richness different indicators were optimized, changed slightly. The indicators Labor and Material Costs were included in later landscape portfolios (function richness 6 and 8 Supplementary Fig. S3) since forest performed best for these indicators (Supplementary Table S4). The last two added indicators were Air Temp. 95th percentile and Carbon Total Biomass (function richness 9 and 10 in Supplementary Fig. S3).

With zero uncertainty, the transformation scenario followed a similar pattern. Apart from TDN (part of the first portfolio), all socioeconomic indicators were optimized first (function richness 3–5 in Supplementary Fig. S5). However, the identities of indicators along this transformation scenario were different. Material Cost led to first major changes (function richness 6 in Supplementary Fig. S5), followed by four ecological indicators, with Carbon Total Biomass and Air Temp. 95th percentile in the concluding two portfolios.

Continuing with the simulation of transformation scenarios, we conducted a performance analysis to assess trade-offs between achieving high performance for single indicators and considering multiple indicators simultaneously. The results showed that as function richness increased, the minimum guaranteed achievement level (GMAL) of the indicator set selected by the model for each level of function richness decreased (Fig. 3a). Optimizing land-use allocation for a single indicator achieved a minimum performance of 0.61, while optimizing all indicators simultaneously achieved a lower performance of 0.43. This indicates that pursuing multifunctionality (high function richness) comes at the cost of lowering the GMAL compared to landscapes satisfying fewer functions, highlighting the trade-off between achieving high performance for single indicators and considering multiple indicators simultaneously. Analyzing the performance of the indicator Profit illustrated this effect (Fig. 3b). Specifically, the increase in function richness reduced the GMAL of Profit, i.e., the indicator best explaining current land-use decisions. The portfolio for a function richness level of 1, where only Profit is optimized, showed the highest performance value of 0.61. Increasing function richness by first adding socioeconomic indicators (up to function richness 4) reduced the minimum achievement level of Profit only slightly to 0.57. Optimizing for the first ecological indicator (function richness 5) resulted in a sharp decrease in performance from 0.57 to 0.48. This showed a trade-off between indicator performance, currently crucial to farmers, and consideration of additional indicators (higher multifunctionality), highlighting the

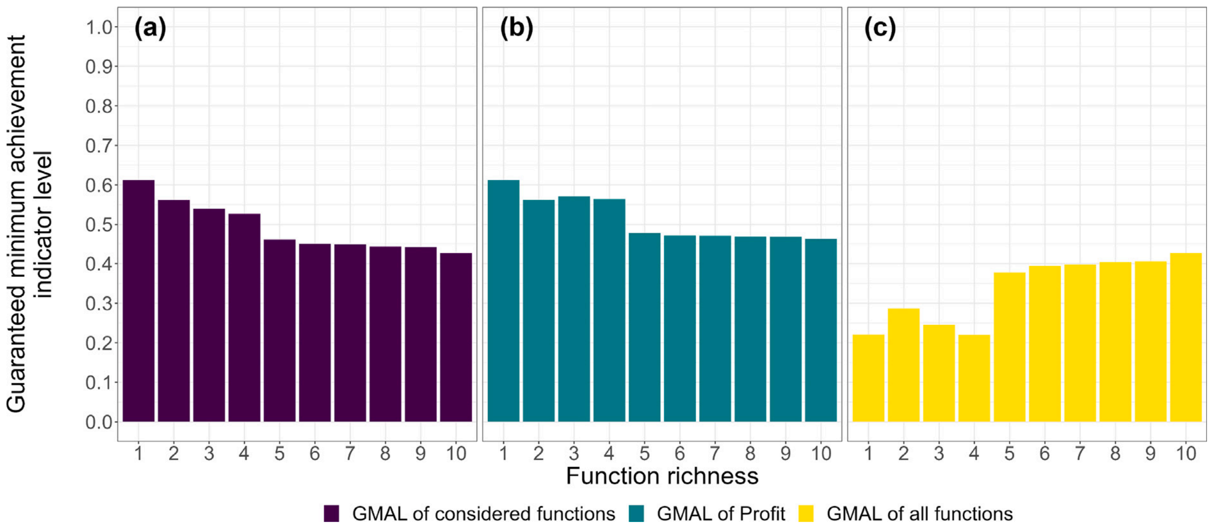

Fig. 3. The guaranteed minimum achievement indicator level (GMAL) from three perspectives. (a) shows the GMAL for each indicator set used to optimize portfolios with increasing function richness (robust performance of the considered functions) (Fig. 2). For example, all uncertainty scenarios of all five indicators, i.e., function richness of 5, achieve at least a performance of 0.46. (b) shows the GMAL of solely the indicator Profit (robust performance of currently important function). The minimum achievement level of a function richness of 1 is thus equal in (a) and (b). (c) shows the GMAL over all ten indicators for each portfolio with increasing function richness (robust multifunctionality). The GMAL of function richness 10 is thus equal in (a) and (c).

tension between prioritizing the performance of single indicators and considering additional – particularly, ecological – ones.

However, the opposite trend emerged when examining robust multifunctionality (representing the GMAL across all ten indicators while assuming the land-use shares of the portfolios from function richness 1 to 10) (Fig. 3c). The GMAL increased with increasing function richness. While there was only a slight increase when socioeconomic indicators were optimized (function richness 1 to 4), including the first ecological indicator (function richness 5) led to a sharp rise in robust multifunctionality from 0.22 to 0.38. This indicates that a decrease in Profit due to higher function richness went hand in hand with better performance across all ten indicators. Including primary degraded forest as an additional land-cover option showed a similar pattern (Supplementary Fig. S4a). However, the synergy effect among ecological functions was much less pronounced. The robust multifunctionality steadily increased when adding more ecological functions (Supplementary Fig. S4c). In comparison, the GMAL for purely agricultural portfolios remained relatively stable from function richness 5 onward (Fig. 3c). This difference arose from much higher and more variable levels of ecological functions associated with forests.

4. Discussion

We proposed a parsimonious land-use optimization approach to explore and visualize a transformation scenario with increasing function richness. Our approach introduces two novel aspects. It automates identifying the ecological or socioeconomic functions driving current land-use decisions and precisely identifies each added ecological or socioeconomic function during the increase of function richness. Furthermore, our approach enables the evaluation of robust multifunctionality as the minimum achievement level of all functions. While the approach presented here refers to a balanced mix of ecological and socioeconomic functions from EFForTS, the model is applicable to different regions and flexible to the conceptual approach of different landscape functions.

4.1. Potential transformation scenarios towards multifunctional landscape

For RQ1, which investigates how a multifunctional landscape portfolio would look like and how much it deviates from the current land-use decision, our case study in the Jambi Province reveals a clear mismatch between compositions of the current landscape portfolio and the landscape portfolio that simultaneously considers all indicators in the optimization, reflecting the highest multifunctionality (see Section 3.1). Answering research question two (RQ2), i.e., which indicators best explain the current land-use decisions, our findings demonstrate that optimizing for solely profit yields a land-use allocation most similar to the current one. These findings indicate that farmers' decisions are most likely driven by a limited set of socioeconomic functions rather than aiming for high function richness (multifunctionality). This aligns with previous research by Feintrenie et al. (2010a), showing that farmers shift from traditional farming systems to more profitable options when available to satisfy their livelihood needs. Similar results have been observed in, e.g., Gosling et al. (2020b), where target land-use compositions for multifunctional systems differed significantly from current practices. However, the target land-use composition was very sensitive to functions considered in the optimization (Knoke et al., 2016; Gosling et al., 2020b). For example, Gosling et al. (2020b) showed that "immediate" indicators (maintaining liquidity and meeting household consumption needs) best represented the observed land-use portfolio. The discrepancy between current land-use practices and the desired multifunctional composition highlights the challenge of normative approaches in constructive stakeholder discussions when the current land-use portfolio is not directly considered. For example, sustainable transformation scenarios might be unrealistic to obtain in the near future, or the identified land-use portfolio might not be achievable owing to an inability to convert between land-use types (Martin et al., 2022).

One limitation of the approach remains the missing retrospective path dependency of current land use. The land-use portfolios defined as "current" and the data collected are from 2018 and are thus snapshots in a dynamic system. The indicators may not fully capture historical and prospective aspects of farmers' decision-making. For example, aspects like past policies and incentives and changes in technological knowledge are not considered. Given that we included mostly perennial land-use alternatives, decisions on currently observed land use were made 20–30 years ago under potentially differing indicator values and functions considered. However, the observed large increase in oil palm area in recent decades (Chrisendo et al., 2021) suggests that reasons for 2018 land-use decisions might not have been very different from historical ones. Our robust approach explicitly integrated uncertainty in indicator values, while we also carried out extensive sensitivity analyses. Therefore, possible decision-relevant deviations from observed indicator values are considered in the model. To capture more than a snapshot, future research could incorporate dynamic information on the development of functions over time and the discounting of indicators, thereby better reflecting time preferences (Jarisch et al., 2022). Moreover, further indicators like farmer preferences or perceived management complexity from interviews (Gosling et al., 2020a; Reith et al., 2020) could complement so far disregarded decision-making criteria. However, given the results of robust optimization and sensitivity analyses, we would not expect that incorporating these aspects would change the overall patterns found in our study.

Concerning the last research question (RQ3), regarding the effect of increased function richness on composition and performance of the land-use portfolios, the transformation scenario reveals that the first three added functions, which require minor changes in the landscape portfolio (“low-hanging fruits”), are socioeconomic indicators (Revenue, Labor Cost, Profit per Labor Cost). Including these indicators results in a larger share of oil palm in the average portfolio, reflecting the current trend in Jambi, Indonesia. This trend towards larger shares of oil palm cultivation and a focus primarily on a few socioeconomic indicators, rather than a high ecological and socioeconomic function richness, might be reasonable from the perspective of smallholder farmers. With limited capital and labor, farmers maximize profit based on their scarcest resource (Feintrenie et al., 2010a), which is often labor (Santos Martin and van Noordwijk, 2011). Even if oil palm needs higher investment, increasing the share of land cultivated by oil palm, which requires less labor than other crops, may be an important strategy to help address this labor constraint, if financial resources are available. This is also evident in our study region, where rubber plantations initially replaced jungle rubber agroforestry, and now the area of both rubber systems is being reduced by the cultivation of palm oil plantations (Drescher et al., 2016; Grass et al., 2020). This trend is also apparent in our transformation scenario, as portfolios with the highest shares of oil palm are achieved when Labor Cost (function richness 3) and Profit per Labor Cost (function richness 4) are added for optimization. This adaption of oil palm cultivation is also likely to increase further socioeconomic functions not considered here, e.g., an increase in infrastructure, healthcare facilities, higher returns to education, and lower poverty rates in respective villages (Kubitza et al., 2018; Edwards, 2019; Qaim et al., 2020; Chrisendo et al., 2022). In contrast, it is likely that negative impacts on other ecological functions not considered here, e.g., water storage and supply (Merten et al., 2016), pest control (Denan et al., 2020), or pollination (Sodhi et al., 2010), will also occur.

Despite its simplicity, our approach thus seems to reflect current trends in land use adequately. However, our mechanistic approach does not provide exact behavioral predictions, but rather explores potential trade-offs and synergies between ecological or socioeconomic functions from a normative perspective. Finding a compromise that satisfies farmers’ needs while tackling performance loss of ecological functions is important. As functional richness increases, the transformation scenario suggests reestablishing the share of traditionally used jungle rubber agroforestry systems to improve ecological functions. Historically, in the Jambi Province, jungle rubber was the standard rubber production system and, therefore, is a well-known practice and could be easier to reestablish or promote. However, input variables for jungle rubber used in this study are based on measurements in rubber-enriched secondary forests. It is important to note that our suggestion is by no means to convert additional forests. Instead, existing rubber plantations could be converted to jungle rubber through succession to enhance the performance of ecological functions. As Zeng et al. (2021) showed, soil properties significantly improved after a decade of natural succession in rubber plantations. Furthermore, new land-use systems that could potentially enhance environmental functions and narrow trade-offs between these and socioeconomic functions could be introduced. Examples include ecological enhancement of oil palm plantations through enrichment planting with multi-purpose trees (Zemp et al., 2023) or environmentally friendly oil palm management (Iddris et al., 2023). In addition to the ecological advantages, agroforestry systems are considered a good diversification strategy to reduce farmers’ exposure to volatilities (Feintrenie and Levang, 2009; Baker et al., 2017; Waldron et al., 2017). Nevertheless, economic factors play a crucial role in decision-making (Feintrenie et al., 2010b), so incentives for systems that enhance ecological functions may require payments for environmental services or functions (Do et al., 2020; Rudolf et al., 2022). For example, involvement of smallholders in recently launched carbon emission credit trading in Indonesia could help enhance certain ecological functions.

Furthermore, our results show an overall decline in performance of the Profit indicator as function richness increases, causing opportunity costs. Since our model is intrinsically relative, we have not explicitly calculated these costs. If precise cost estimation is required, our approach allows for calculating additional payments and their associated uncertainties to achieve a desired share of a land-use type in the portfolio. This calculation can help determine the extent to which profit for a specific land-use type needs to increase when optimizing profit for it to appear in the portfolio at the required level. However, our method provides various compromise solutions, allowing decision-makers to choose between including all or fewer indicators with reduced performance loss in Profit. This flexibility assists decision-makers in determining an acceptable compromise and the desired level of multifunctionality to be achieved. For instance, pursuing one or more ecological indicators may result in higher farmer costs. Therefore, economic incentives might be necessary to achieve these goals. Our approach provides a framework that can support decision-makers in finding the right balance between ecological and socioeconomic objectives.

It is also noteworthy that the resulting land-use compositions still provide important ecological functions despite these functions not being directly considered in the optimization of lower function richness. For example, when optimizing solely for Profit, the land-use portfolio still provides a minimum achievement level across all functions of 0.22 in relation to 0.43 of the multifunctional portfolio. Yet, this minimum achievement level, as a measure of multifunctionality under uncertainty, can be considerably increased.

Our study demonstrated that a balanced mix of intensive crops and environmentally friendly options yields the highest robust multifunctionality. None of the options offered to the model showed a single best option to provide multiple ecological or socioeconomic functions simultaneously. This finding aligns with previous research by Grass et al. (2019, 2021), demonstrating the effectiveness of combining land-sharing and land-sparing approaches to design multifunctional landscapes successfully. Our study also showed the importance of oil palm plantations in achieving multifunctional portfolios, while rubber plantations emerged as the least selected land-use option. This result was robust against altering ecological functions, land-cover alternatives, and uncertainty scenarios. This shows how the approach can derive robust trends towards desirable land-use mixes without prescribing exact land-use allocations and provides valuable insights for decision-makers and researchers. The approach is also adaptable to other regions and other input data due to the parsimonious design (low data and computational requirements) and the availability of the method as an *R* package, *optimLanduse* (Husmann et al., 2022), which was further developed and also includes the latest *autoSearch* function.

4.2. Limitations and outlook

The robust reference point optimization in this study generates a single best land-use composition for each level of function richness. Improving one indicator’s performance would require a decrease in performance of another, reducing the GMAL of the entire portfolio. This single solution is based on the assumption that the decision-maker aims to minimize the distance to the worst-performing scenario of the worst-performing indicator, which is equivalent to a single global optimum of a Pareto frontier (Reith et al., 2022). Unlike Pareto optimization, the whole Pareto-efficient frontier is not directly visualized, which would be a disadvantage compared to Pareto optimization (Kaim et al., 2018, 2020) and may limit insightful participatory optimization results Wicki et al. (2021). However, depending on the research question, the model could be further developed to provide a robust counterpart of the Pareto-efficient frontier by solving the optimization problem multiple times using different indicator weights. Such weights could be captured through an analytical hierarchy process involving stakeholders (Gosling and Reith, 2020) and incorporated into the model. The computational efficiency of the optimization allows for direct implementation of the weights into a Shiny Dashboard (see Data availability), enabling real-time exploration of different ecological and socioeconomic functions and their resulting land-use compositions. This process could support a joint system understanding and co-creation of sustainability pathways as part of transdisciplinary research (Moallemi et al., 2021).

The low computational time and required resources open the approach for interactive modeling with stakeholder or batch analyses. However, it comes at the cost of assuming linearity, i.e., mainly proportionality and additivity (Reith et al., 2022). Additivity implies a constant marginal contribution from each indicator as land-use area changes, while proportionality assumes that total landscape performance is the sum of individual landscape performances, indicating a linear relationship (Reith et al., 2022). Consequently, the current model is not designed to handle non-linear relationships during optimization. However, additional constraints can be incorporated into the model to address such assumption limitations. For example, Knoke et al. (2020) incorporated dynamic deforestation into the modeling approach by periodically updating the initial landscape compositions during optimization.

Our approach provides plausible and consistent results concerning the overall trade-offs between ecological and socioeconomic functions of different land-use compositions. Here, we focus on compositional diversity of landscapes as an essential determinant for ecosystem functioning (Turkelboom et al., 2018; Arroyo-Rodríguez et al., 2020). However, future research could improve the representation of configurational diversity and connectivity, which are crucial factors for designing multifunctional landscapes (Lavorel et al., 2022). By construction of the method used, it is currently not possible to consider correlations between the land-use options, which means that, e.g., the spatial configuration or neighborhood effects of the land-use options cannot yet be included in the optimization. We, therefore, only included indicators that are directly proportional to land area and have only limited impact on neighborhood or connectivity of habitat. The *R* package *optimLanduse* can be further developed to implement hard constraints and consider different indicator values for sub-strata or regions, allowing for optimization results to be interpreted as groups of spaces or systems (Husmann et al., 2022). Additionally, the modeling approach could apply to decision-maker heterogeneity (i.e., variability in objective functions and expectations on future function provision, see Knoke et al. (2023)) or interaction between decision agents. Such processes have been developed for ABMs, e.g., learning processes (Dislich et al., 2018), and could also be integrated into this approach in the future, but only at the cost of non-linear relationships and endogenous effects, which usually increase computational needs. For this kind of question, ABMs have a high potential for representing issues related to agent or ecosystem connectivity (Paul et al., 2019; Reith et al., 2022). Furthermore, it would be possible to design hybrid approaches, e.g., the combination of parsimonious linear multi-criteria optimization and structurally complex ABMs (Paul et al., 2019), as well as using a rule-based approach combined with our optimization and a Geographic Information System (GIS) to generate spatially explicit results (Palma et al., 2007; Knoke et al., 2016).

5. Conclusion

Our model serves as a valuable tool to identify the ecological and socioeconomic functions best explaining current land-use decisions and to design theoretical transformation scenarios between the identified function(s) of the current land-use decision and a portfolio satisfying a wide range of socioeconomic and ecological functions, directly accounting for uncertainty. Although our case study focuses on smallholder farmers in the Jambi Province, Indonesia, the model is applicable to different regions and landscapes worldwide because of its flexibility in utilizing diverse data sources and its small data and computational requirements. The comparison between current landscape portfolio and multifunctional landscape portfolio derived from our dataset reveals an apparent mismatch. Optimizing the Profit indicator best explains the composition of the current portfolio, showing that farmers currently prioritize economic benefits. The optimization of further socioeconomic functions can be achieved with only minimal changes in landscape composition (“low-hanging fruit”). However, more extensive changes are required to satisfy even a single ecological indicator in the landscape portfolio (“moonshot”). These changes inevitably come at the expense of decreased performance in the Profit indicator. This highlights the need for economic incentives to offset this decrease, particularly considering that large areas of existing oil palm plantations are due for replanting in the near future.

CRediT authorship contribution statement

Volker von Groß: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Kibrom T. Sibhatu:** Data curation, Writing – original draft, Writing – review & editing. **Alexander Knohl:** Data curation, Writing – review & editing. **Matin Qaim:** Data curation, Writing – review & editing. **Edzo Veldkamp:** Data curation, Writing – review & editing. **Dirk Hölscher:** Data curation, Writing – review & editing. **Delphine Clara Zemp:** Data curation, Writing – review & editing. **Marife D. Corre:** Data curation, Writing – review & editing. **Ingo Grass:** Data curation, Writing – review & editing. **Sebastian Fiedler:** Writing – review & editing. **Christian Stiegler:** Data curation, Writing – review & editing. **Bambang Irawan:** Writing – review & editing. **Leti Sundawati:** Writing – review & editing. **Kai Husmann:** Methodology, Software, Supervision, Writing – original draft, Writing – review & editing. **Carola Paul:** Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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

Data availability

The raw data for the ecological indicators are published and openly available with the respective publication provided for each function in Table 1. The raw data for the socioeconomic indicators can be accessed upon reasonable request. The processed data used for this study are openly available from the Göttingen Research Online repository https://doi.org/10.25625/TUN248. *optimLanduse* (version 1.2.0), including the new *autoSearch* function, has been released on CRAN Husmann et al. (2022) and can be accessed via the project page: www.github.com/Forest-Economics-Goettingen/optimLanduse. The shiny dashboard can be accessed via https://rshiny.gwdg.de/apps/optimLanduse/, where the two processed data tables can be used directly to generate the different landscape portfolios.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.120710.

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