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Exploring trade-offs in agro-ecological landscapes: Using a multi-objective land-use allocation model to support agroforestry research

Esther Reith[a], Elizabeth Gosling[a], Thomas Knoke[a], Carola Paul[b,c,*]

[a]*Institute of Forest Management, TUM School of Life Sciences Weihenstephan, Technische Universität München, Hans-Carl-von-Carlowitz-Platz 2, Freising 85354, Germany*
[b]*Department of Forest Economics and Sustainable Land Use Planning, University of Göttingen and Department of Forest Economics and Sustainable Land Use Planning, Büsgenweg 1, Göttingen 37077, Germany*
[c]*Centre of Biodiversity and Sustainable Land Use, Büsgenweg 1, Göttingen 37077, Germany*

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Abstract

Finding the optimal land allocation for providing ecosystem services, conserving biodiversity and maintaining rural livelihoods is a key challenge of agricultural management and land-use planning. Agroforestry has been widely discussed as a sustainable land-use solution and as one strategy to improve the provision of multiple ecological and economic functions in agricultural landscapes. In this study, we use the backdrop of agroforestry research to evaluate a method from the multi-criteria decision analysis toolbox: robust multi-objective optimization. The key feature of this modelling approach is its capacity to integrate uncertain ecological and socio-economic data. We illustrate the optimization model with a case study from eastern Panama, showing how the model can bring together scientific and practical knowledge to provide potentially desirable landscape compositions from the perspective of farmers, a public perspective, and a compromise solution. Example results of our case study show how to assess whether agroforestry is a desirable component in a landscape composition to satisfy multiple objectives of different interest groups. Furthermore, we use the model to demonstrate how different objectives influence the optimal area share and type of agroforestry. Due to its parsimonious nature, the model could be used as a starting point of an interactive co-learning process with decision-makers, researchers and other stakeholders. The model, however, is not yet suitable for an exact prediction of future land-use dynamics, for questions of spatially explicit land-use configuration, studies going beyond the regional scale or for socio-economic interactions of agents. Therefore, we outline future research needs and recommendations for other types of models or hybrid approaches.

Keywords: Agroforestry; Decision-support tools; Ecosystem services; Integrated landscape management; Multi-objective optimization; Simulation models

Introduction

Agroforestry - the integration of crops and/or livestock with trees on the same plot - has gained popularity in science

*Corresponding author at: Institute of Forest Management, TUM School of Life Sciences Weihenstephan, Technische Universität München, Hans-Carl-von-Carlowitz-Platz 2, Freising 85354, Germany.
E-mail address: carola.paul@uni-goettingen.de (C. Paul).

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and policy (Liu et al., 2019). Due to its hypothesized potential to reconcile ecological objectives (e.g., biodiversity conservation) with socio-economic objectives (e.g., long-term profit), agroforestry has become an integral part of national strategies to supplement landscape mosaics and bring back trees into agricultural landscapes (García et al., 2016; MiAmbiente, 2010; van Noordwijk et al., 2021). The pressing question of whether embedding agroforestry into agricultural landscapes can enhance the provision of multiple ecological and socio-economic functions and services is an interdisciplinary research endeavor. In the last five decades, agroforestry research has matured to become more interdisciplinary to address complex trade-offs between social, economic and ecological objectives related to tree-based farming systems. The focus has shifted from investigating agroforestry as a stand-alone system to considering it as a part of a mix of land-use options in an agro-ecological landscape (Grass et al., 2019; Paul & Knoke, 2015).

However, research that assesses multiple ecological and economic ecosystem functions and services (which we refer to as "multifunctionality") across multiple land uses is still scarce, which limits successful planning of agro-ecological landscapes (Grass et al., 2020). Land-use allocation models have emerged as useful tools to investigate the composition of a desirable land-use matrix at a farm or landscape scale and to analyze trade-offs between potentially competing objectives. One example of such a land-use allocation model is the robust multi-objective optimization model developed by Knoke et al. (2015, 2016). The model is especially relevant for interdisciplinary teams, as ecological, economic and social indicator data from different sources can be integrated (Knoke et al., 2016). Furthermore, the approach is a rare example of a multi-criteria decision analysis model that actively integrates uncertainty of land-use preferences and performance into modelling and accounts for attitudes towards risk in decision-making. Recent research further developed the robust optimization model to evaluate the potential of agroforestry for land-use allocations in eastern Panama from a local farmer's perspective (Gosling et al., 2021, 2020) and from a public perspective (Reith et al., 2020).

In this article, we critically discuss the potential and limitations of this robust multi-objective optimization model to support fellow agroforestry researchers in their selection of suitable land-use allocation models in agroforestry and landscape research. We show the approach using a consolidated dataset from previous research in Panama (Gosling et al., 2020; Reith et al., 2020), which brings together scientific and local knowledge about the ecological and socio-economic potential of land uses. The example outlines the general model philosophy of contrasting socio-economic (i.e. farmer's perspective), socio-ecological oriented (which we here refer to as public perspective) and compromise-oriented decision-making for the purpose of understanding the potential of agroforestry in sustainable land-use compositions to meet differing objectives. To put our modelling approach into context, we start with a brief review of existing modelling approaches in agroforestry research (summarized in Table 1).

Summary of agroforestry model development

Starting with the establishment of the International Council for Research in Agroforestry (ICRAF) in 1977 in response to tropical deforestation, ecological degradation and food insecurity, agroforestry has gained increasing scientific attention and has developed into its own research discipline (Liu et al., 2019; Mercer & Miller, 1998). Early studies mostly focused on identifying and classifying existing agroforestry systems (Nair, 1998). Empirical research gained momentum in the 1980s (Nair, 1998), with statistical or correlative modelling at the plot and farm scale being applied to better understand biophysical effects such as plant growth (Stromgaard, 1985) or predict impacts of land uses such as soil carbon, nutrients and erosion (Young et al., 1998). Later, statistical models were also used to analyze the drivers for farmers to adopt agroforestry (Jara-Rojas et al., 2020).

In the 1990s, agroforestry research shifted towards process-based (or mechanistic) tree and crop simulation models, which could quantitatively explain how agroforestry systems work and study the biophysical consequences of adopting agroforestry. Two popular plot-level process-based models are the Water, Nutrient and Light Capture in Agroforestry Systems (WaNuLCAS) model (van Noordwijk & Lusiana, 1999) and FracRoot (Ozier-Lafontaine et al., 1999).

Agroforestry research in the 1990s also saw the rise of management decision models at the farm and landscape scales. These models helped to assess if agroforestry is economically desirable compared to conventional land uses (e.g., Adesina & Coulibaly, 1998), and to investigate the drivers and biophysical or economic consequences of adopting agroforestry (e.g., Current et al., 1995; Kwesiga et al., 1999). Driven by the UN Conference of Environment and Development and the Brundtland report, a paradigm shift occurred from emphasizing protected areas and reserves towards a holistic approach to environmental management accounting for social demands (Reed et al., 2017). Similarly, the idea of using agroforestry for increased landscape multifunctionality emerged, putting landscapes and livelihoods into the foreground (Plieninger et al., 2020). These developments supported the integration of non-market ecosystem goods and services (such as carbon sequestration) in economic models for agroforestry valuation (Price, 1995; Smith et al., 1998).

Another development in agroforestry research during the 1990s was the shift from cause-and-effect thinking to systems thinking by using feedback loops (Reed et al., 2017; van Noordwijk & Lusiana, 1999). Coupling economic simulations with biophysical growth models led to decision

Table 1. Brief history of the development of major agroforestry models, associated research questions, and key events.

Timeline	1970	1980	1990	2000	2010	2020
Important events	**1977** International Council for Research in Agroforestry (ICRAF) established	**1982** inception of the journal “Agroforestry systems”	**1992** UN Conference on Environment and Development	**2000** UN’s Millennium Development Goals (MDGs)	**2010s** rise of integrated landscape approaches (e.g., Forest Landscape Restoration)	**2020** agroforestry increasingly included in national climate change adaptation strategies
	1970s/80s advancement in computer processing allow for computer-based modelling	**1987** Brundtland Commission report coined the term “sustainable development”	**1990s** agroforestry recognized for increasing landscape multifunctionality	**2004** first World Agroforestry Congress in Orlando, Florida	**2016** UN’s Sustainable Development Goals (SDGs)	**2021** 15th Conference of the Convention on Biological Diversity to confirm a global biodiversity conservation framework for 2020-2050
Major research questions	what types of agroforestry exist?	how and where does agroforestry work?	what are the biophysical/economic consequences of adopting agroforestry? what are the economic drivers of adopting it? is agroforestry desirable from the farmer’s perspective (compared to traditional land uses)? is agroforestry desirable by stakeholders to increase landscape multifunctionality?	what are the social and economic drivers/barriers of adopting agroforestry? what are the ecological and economic trade-offs at the landscape scale? how much agroforestry is desirable?	where to put what? how do national and global external factors such as market developments, policies, and climatic variability affect local land-use decisions? how can agroforestry mitigate global issues such as greenhouse gas emissions and biodiversity loss?	what are the ecological and economic trade-offs of land-use adoption? what does a desirable mix of land uses look like? how can effective and efficient incentives for agricultural sustainability be designed?
Modelling developments	Development of databases and concepts	Development of empirical statistical models with biophysical focus for cause-effect analysis	Formulation of computer-based models to describe biophysical aspects; management decision and bio-economic models	Rise of normative optimization models and agent-based models	Rise of spatially explicit models for land-use allocation problems and trending participatory research	Potential focus on synthesis and a rise of interdisciplinary research and hybrid models, with continued interest in multi-objective models

models that allowed for economic analysis to be linked to biophysical growth models and vice versa. For example, Thomas (1991) developed a process-based bio-economic simulation model to assess profitability of agroforestry systems under changing technical and economic conditions.

The 2000s were marked by a rise of optimization models in agroforestry research. Portfolio-based optimization methods can suggest compositions for efficient agroforestry systems (plot-level) or they can suggest land-use portfolios (landscape-level) that maximize return for any given level of risk (e.g., Blandon, 2004; Paut et al., 2019). Portfolio approaches actively account for the effects of risk aversion and economic diversification in economic decision-making. The more recent development of multi-criteria optimization models permitted the evaluation of multiple, potentially conflicting, environmental and socio-economic objectives simultaneously, and accounted for trade-offs between them. Discrete multi-attribute decision-making models can evaluate a finite number of land-use alternatives (Kaim et al., 2018), assessing the environmental and economic performance of land uses based on predefined scenarios (Palma et al., 2007). Alternatively, scalarization-based (methods combining multiple objective functions into one final objective function, as presented in this study) and Pareto-based multi-objective optimization models can also evaluate multiple criteria simultaneously, without needing to rely on a very limited set of scenarios (García-de Ceca & Gebremedhin, 1991; Grass et al., 2020). Depending on the computational power needed, these types of continuous optimization models can investigate a theoretically unlimited number of alternatives without the risk that the optimal land-use allocation solution lies in between two or outside considered scenarios (Kaim et al., 2018). Dynamic optimization models can consider changes of decision-relevant information over time to estimate, for example, the optimal timber rotation age (Alavalapati & Mercer, 2004). Combined with portfolio analysis, such multi-criteria optimization models can account for land-use diversification effects, i.e. maintaining different land-use options to reduce financial and ecological risks (Blandon, 2004; Knoke et al., 2015).

Another set of models for analyzing trade-offs are agent-based models (Lusiana et al., 2012; Paul et al., 2019). Agents are autonomous entities that have certain simple operational properties and/or are able to make decisions and learn. Simulations of their behavior will consist of a sequence of decisions. Agents interact with other agents and their environments, while their behavior follows a set of rules (Lenfers et al., 2018). Agent-based models came into the focus of agroforestry research in the 2000s because they are capable of incorporating social interactions between farmers that shape land-use decisions (van Noordwijk et al., 2019). For example, Lusiana et al. (2012) investigated land-sharing and land-sparing in Indonesia using the agent-based model FALLOW.

From around 2010 onwards, agroforestry models began to increasingly account for site heterogeneity (van Noordwijk et al., 2019). Research sought to generate promising land-use and landscape designs to solve global land-management problems embodied by the UN's Millennium Development and Sustainable Development Goals (Nair & Garrity, 2012; van Noordwijk et al., 2019). Coupling biophysical, financial and economic models with geographic information systems (GIS) allows for spatially explicit empirical statistical models that describe management decisions at a landscape scale, answering questions of "where to put what" (e.g., Palma et al., 2007).

In the last decade, the idea of "integrated landscape management" (Estrada-Carmona et al., 2014; Plieninger et al., 2020) has also gained interest among researchers, policy-makers and other stakeholders in the tropics. This includes frameworks such as the "Ecosystem approach" (e.g., "Forest Landscape Restoration", Reed et al., 2016) and "climate-smart landscapes" (Scherr et al., 2012) to investigate and implement land management decisions that meet the public's various demands on the landscape while reducing trade-offs between ecological and socio-economic objectives. To better reconcile conservation and development objectives, the integrated landscape approach explicitly aims to involve stakeholders from multiple sectors, for example through participatory research (Reed et al., 2017; van Noordwijk et al., 2021). This may involve working with farmers and other stakeholders, before, during or after the modelling process (Andreotti et al., 2020; Kaim et al., 2018; Voinov et al., 2018).

In light of increasing calls for transdisciplinary and cross-sectoral approaches (Carter et al., 2018; Neely et al., 2017), hybrid land-use allocation models that reduce the drawbacks of individual models and can analyze multiple conflicting objectives might become increasingly important in landscape and agroforestry research (Paul et al., 2019). Furthermore, modern agro-ecological research calls for early and continuous involvement of multiple stakeholders to identify opportunities and mitigate obstacles of biodiversity-friendly farming (van Noordwijk et al., 2020; Wanger et al., 2020).

In the following section, we present a robust multi-objective optimization model that may support a participatory analysis of land-allocation problems.

A robust multi-objective land-use allocation model

The modelling approach presented here is inspired by the concept of portfolio optimization (Markowitz, 1952). This concept stems from finance and describes the selection of the best allocation of money investments to single assets according to a single (e.g., profit maximization) or multiple objectives (e.g., conservation-oriented and economic objectives). This concept can be transferred to land allocation problems (Macmillan, 1992), where different land-use systems represent single assets of a land-use portfolio and the optimization process allocates land to land-use types, seeking the composition that best meets given objective/s (Matthies et al., 2019; Paut et al., 2019). The novelty of the approach described in this study lies in the robust non-stochastic optimization technique that selects the land-use portfolio which best balances multiple ecological and socio-economic objectives concurrently across numerous discrete uncertainty scenarios (Knoke et al., 2015). For solving this allocation problem, the solution algorithm builds on the basic logic of the MINMAX (Chebyshev) version of goal-programming (see, e.g., Tamiz et al., 1998; Uhde et al., 2017).

Model concept

The model input comprises two parameters per land-use and objective: an expected performance score (to quantify the ability of a given land-use to achieve the objective) and a measure of uncertainty associated with this estimate (e.g., standard deviation of performance score; Fig. 1). The model is flexible regarding sources of input data. As such, the expected score can be derived through expert interviews (e.g., via the analytic hierarchy process by Saaty, 1987), calculated and/or simulated data (e.g., net present value), or measurements (e.g., soil pH) (Knoke et al., 2016). Because normalization of data is inherent in the model, different units and score ranges of the indicators can be used. Indicators may represent marketable and non-marketable ecosystem functions and services (e.g., yield and soil fertility) and disservices (e.g., soil erosion), biodiversity related indicators (e.g., habitat quality), financial factors (e.g., payback period) and difficult-to-quantify social factors (e.g., cultural preferences). These indicators represent the objectives in the multi-objective optimization model (e.g., net present value of a given land-use to represent long-term profit). They can be given equal or different weights to prioritize individual indicators or indicator groups.

The novel aspect in our modelling is the quantification of land-use benefits in the form of guaranteed performance levels, which are sensitive to the degree of uncertainty in the land uses' provision (see below). Guaranteed performance means that under variable indicator input information we will always achieve at least the guaranteed performance (or even a higher performance) of a land-use composition, as long as the input information is included in the uncertainty spaces used for the optimization.

The optimization model allocates land-use shares (the decision variables) in a way that maximises the normalised worst-case performance of the portfolio of land uses across all considered objectives under a set of uncertainty scenarios. The result is a compromise land-use allocation that reduces trade-offs between potentially conflicting objectives by balancing the achievement of all objectives and does not allow for compensation between them (Knoke et al., 2020). For example, poor performance in carbon sequestration cannot be compensated for by high performance in economic return.

A series of model constraints ensure the following: the objective function minimizes the normalised greatest distance of the achieved indicator level to the most desirable indicator value, i.e. the reference point of 100% (greatest

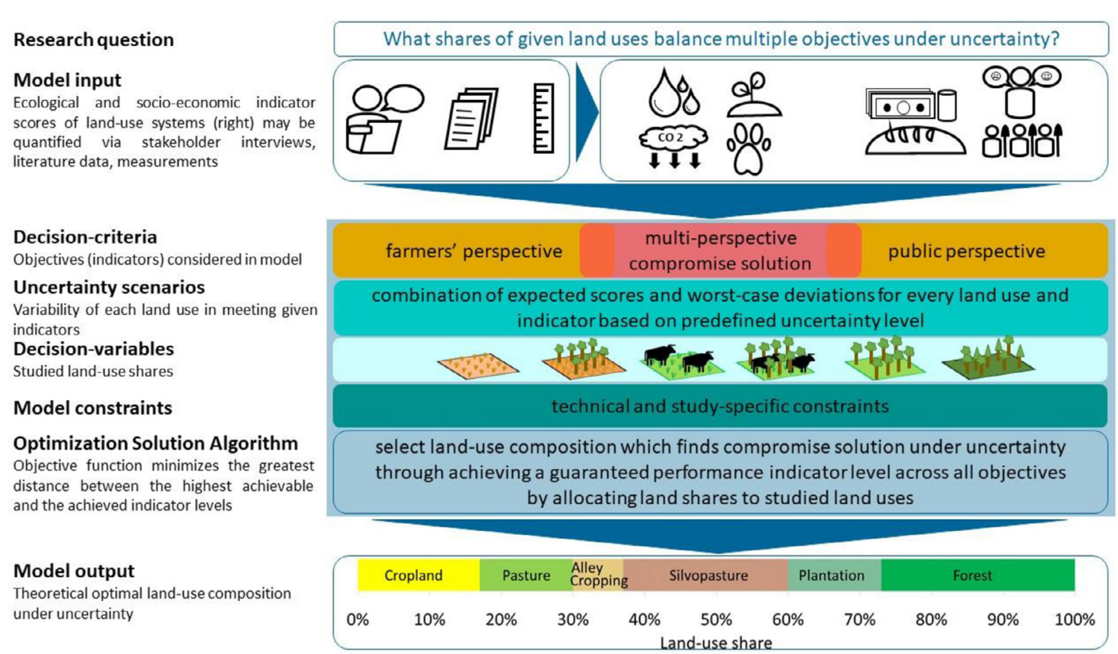

Fig. 1. Model concept of the robust multi-objective land-use allocation model. Model developed by Knoke et al. (2015, 2016) based on optimization solution algorithms presented by Ben-Tal et al. (2009).

distance constraints). Achieving the minimal greatest distance implies guaranteeing a minimum performance level across all indicators and uncertainty scenarios. Land-use shares are greater than or equal to 0 (non-negativity constraint), and the sum of all land-use shares is equal to 1 (area budget constraint). Study-specific constraints can also be added, for example, that agroforestry should not exceed a certain area share of the land-use portfolio (Reith et al., 2020). An example of a potential model construct as used in this study for optimizing land-use allocation at the forest frontier in eastern Panama is given in Appendix A: Table 1.

The model can be operated with readily accessible, open-source software (e.g., Libre Office or OpenSolver) (see spreadsheet in supplementary of Gosling et al., 2020) and has also been transferred to the R environment (Husmann et al., 2021). The linear programming problem is solved by the Simplex algorithm, which guarantees an exact solution.

Disclosure of uncertainty

The model is robust in that it considers uncertainty around the ability of each land use to achieve a given objective. Hence, uncertainty refers to the variability of land-use performances across all indicators. However, we limit the definition of possible performance scores to the expected value (as the optimistic scenario) and the worst-case value (as the pessimistic scenario), thus focusing on undesirable deviation, also termed “downside risk aversion” (Bonilla & Vergara, 2021). We follow the approach of “deep uncertainty” for the performance of studied land uses where we cannot assign individual probabilities to our indicator data (Walker et al., 2013). We address this lack of knowledge with our model by systematically forming a set of discrete uncertainty scenarios based on a combination of expected mean and worst-case scores of given land uses in terms of given indicators. For example, in a given uncertainty scenario one land use may meet its expected score for a given indicator, while all other land-use options may meet worst-case scores. In another uncertainty scenario two land-use options may meet their expected score for the same given indicator, while all others meet worst-case scores, and so on. All possible combinations of expected and worst-case scores form what we refer to as uncertainty sets for each indicator ($2^{\text{number of land uses}}$). In this way the optimization simultaneously considers a range of input scores (including worst-case scores) for each land use and indicator when determining the optimal land allocation of one model run (Knoke et al., 2020).

Furthermore, the risk attitude of the decision-maker is incorporated into our robust optimization approach by defining the size of the uncertainty space by the multiple of the considered standard deviation (or standard error) (Ben-Tal et al., 2009; Knoke et al., 2015; Palma & Nelson, 2009). Depending on their risk attitudes, decision-makers can decide how pessimistic or optimistic the included worst cases for the indicators shall be, where a more risk-averse decision-maker would include more pessimistic worst cases. In the following example we assumed a moderately risk-averse decision-maker (moderate level of uncertainty). This means that the worst-case scenario is set as the expected value minus two times the standard deviation of the expected scores. The model then allocates land shares in a way that the land-use performance across all objectives and uncertainty scenarios is enhanced in worst cases.

Identifying trade-offs

In the framework of our approach, trade-offs between different objectives are analyzed in multiple ways: First, trade-offs can be simply visualised, e.g. by rose diagrams, where model input data of objectives is synthesized. Second, the optimization approach reduces trade-offs by avoiding a very low performance of individual indicators under uncertainty. This is achieved by minimizing the greatest distance between achieved performance levels and reference points across all indicators and uncertainty scenarios. Third, trade-offs can be explored more deeply by analyzing the consequences of considering different (bundles of) indicators or different indicator weights (see example below). This includes the effects on the resulting land-use composition, on the value of the guaranteed performance level across all indicators (Reith et al., 2020), and/or individual indicators (Friedrich et al., 2021).

Application example of the robust optimization model

The model described above can synthesize empirical and modelled data from field trials. The collected functions would then represent the different indicators in the model (see applications by Knoke et al., 2016, 2020). While field trials are essential for the establishment of innovative land-use systems, they are costly and extend over long time periods. As a comparatively quick and low-cost ex-ante study of potential agroforestry systems, the robust multi-objective optimization model can also help to identify promising agroforestry systems for subsequent field trials, and allows for rapid assessment of trade-offs between ecological and socio-economic functions and services in a given socio-ecological system. This approach would then need to rely on available expert knowledge, which can provide quite reliable results (Uhde et al., 2017). Thus, the model can be used to integrate decision-makers and stakeholders prior to modelling to obtain input data for the presented optimization model. However, we outline below how the approach could be extended towards a collaborative modelling exercise. In this study, land-owners, -managers, scientists and stakeholders (of governmental and non-governmental organizations and private companies) working and/or located in Panama have been asked to evaluate various land uses in terms of their potential to meet predefined indicators (see Appendix: Table 2). Land uses include natural forest, exotic forest plantations (teak, *Tectona grandis*), silvopasture (>200 trees per ha pasture), alley cropping (annual crop planted in between rows of teak), conventional pasture and cropland (Appendix: Table 3). The dataset represents the perceived performance of different land uses in terms of our studied indicators (Appendix: Table 4). Data was collected in 6 weeks (additional online surveys were accessible for another 17 weeks) in 2018. Our example landscape represents aggregated surveyed farms covering an area of around 9100 ha, near the agricultural forest frontier in eastern Panama (Gosling et al., 2020).

How to assess whether agroforestry is desirable to satisfy multiple needs of stakeholders?

To illustrate the model's potential, we ran separate optimizations that balance multiple indicators for objectives from three perspectives: the farmers' perspective, the public's perspective and a desirable compromise solution between the two. For this example, we assume that the perspective of farmers is represented by 7 socio-economic indicators: long-term income, labor demand, meeting household needs, financial stability, liquidity, investment costs and management complexity. Even though the interviewed farmers actively stated that climate and water regulation was important to them, Gosling et al. (2020) found that there was a mismatch of this statement with the short-term socio-economic objectives which best explained current land use. The public's perspective is assumed to be represented by 6 indicators: global climate regulation, water regulation, biodiversity, long-term soil fertility, micro climate regulation and food security (Appendix A: Table 2). The land-use composition that represents a compromise solution for farmers and the public was obtained by optimizing the land-use allocation across all 13 indicators simultanously.

As a reference for our results we use the current land-use allocation (left column Fig. 2A, Gosling et al., 2020), which shows that farmers currently do not practice agroforestry, but have allocated 60% land-use share to pasture. In contrast, optimising the land allocation given only the potential socio-economic objectives of farmers results in a theoretically optimal land-use allocation including agroforestry through a large silvopasture share (23%) and a small alley cropping share (7%, second column Fig. 2A). This would mean a large reduction of pasture land, compared to the current land-use allocation in favor of forest and agroforestry.

From the public's perspective the model suggests allocating a smaller share to silvopasture (5% share) and a larger share to alley cropping (56% share, furthest right column in Fig. 2A).

The desirable compromise solution for farmers and the public which balances all ecological and socio-economic indicators comprises a large share of both agroforestry systems, forest plantation and natural forest, while almost a third of the land area would be under conventional agricultural production (third column from left in Fig. 2A).

The different agroforestry shares of each perspective reflect their given rankings. Farmers ranked silvopasture higher than alley cropping for five out of seven indicators, while experts (a proxy for the public in our study) scored alley cropping higher than silvopasture for all six evaluated ecological and social indicators. Surprisingly, the farmer's optimized land-use portfolio was more similar to the compromise solution than the land allocation optimized according to the public's rating. This may reflect that a very heterogenous landscape may not automatically provide high levels of ecological services such as biodiversity protection (Knoke et al., 2020), but may be particularly interesting to meet socio-economic demands in the face of uncertainty for risk-averse farmers.

In this example, we have applied equal weight to all objectives resulting in optimized land-use compositions of all farms in a landscape that best balances given indicators equally. Giving equal weight to each indicator is recommended when the researcher is uncertain about the current and future preferences and needs of stakeholders (Walker et al., 2013). However, giving more importance to some indicators over others can simulate different preferences or perspectives of stakeholder groups (Palma et al., 2007). This may influence the agroforestry share, providing valuable insights in the role of agroforestry (see the following chapter and Fig. 2B).

How to explore the conditions favoring an inclusion of agroforestry in land-use portfolios?

In this example, we want to show how the model can help to improve our understanding of which conditions agroforestry may be suited to use for reducing land-use conflicts between farmers and the public given different priorities. To illustrate this type of sensitivity analysis, we reran the optimization for all 13 indicators combined but assigned twice the weight to the implicit drivers of farmers' current land-use decision in eastern Panama ("household needs" and "liquidity" as identified by Gosling et al., 2020) or to one of the widely discussed benefits of agroforestry (i.e., supporting biodiversity, increasing carbon sequestration potential, improving farmers' long-term income, and food security, respectively, Fig. 2B).

Compared to the baseline compromise solution between farmers and the public (third column Fig. 2A), the total share of agroforestry systems was drastically reduced for a land-use composition that weights household needs and liquidity higher than other indicators (to 6% alley cropping and 1% silvopasture, first column Fig. 2B).

Rerunning the optimization to give more importance to biodiversity or carbon regulation resulted in decreased agroforestry shares and significantly increased natural forest shares compared to the baseline compromise solution (27 to 29 percentage points more, second and third column Fig. 2B). This result indicates trade-offs between both ecological and socio-economic indicators. Focusing on biodiversity or carbon sequestration, the optimized land-use allocations suggest a land-sparing approach with agro-ecological and conventional land uses as productive systems. This result underscores another interesting feature of our optimization-based approach: we can infer optimal land-use strategies by representing specific preferences of decision-makers, rather than predefining certain land-use strategies and assessing them post-hoc.

Our model may also highlight an unintended effect. Emphasizing long-term profitability resulted in agroforestry dominating the land-use composition. The silvopasture share increased to 46% and alley cropping was reduced to 8% compared to the baseline compromise solution (Fig. 2B fourth column). This composition excluded natural forest, demonstrating the rebound effect, meaning that highly profitable land-use systems meant to spare land may foster accelerated deforestation (Angelsen & Kaimowitz, 2004; DeFries & Rosenzweig, 2010; Perfecto & Vandermeer, 2010).

Furthermore, the presented model approach can convincingly highlight the virtues of agroforestry. When food security was prioritized over other indicators, alley cropping dominated the composition (61%) and silvopasture comprised 7% (fifth column Fig. 2B). This result also highlights the multifunctional benefits of agroforestry, in particular, its potential to produce high yields (Tscharntke et al., 2012).

To adequately account for hard economic constraints (such as available labor and capital) on farmers' land-use decisions or changes in land-use performance under different market and environmental conditions, modelled or measured coefficients are needed as input data for our model. For example, Gosling et al. (2021) used data derived from an extended cost-benefit analysis in the same modelling framework and same study region to investigate how a range of biophysical and economic constraints for farmers may influence the attractiveness of agroforestry. Their results revealed that the silvopasture share could be increased on farms with less productive soils and supported by tax incentives, but labor constraints posed a serious barrier to adopting agroforestry (Gosling et al., 2021).

Critical appraisal of the modelling approach and recommendations for model selection

In this section we discuss six main model characteristics which may determine the suitability of our and other models to answer agroforestry research questions: (i) aspects of landscape diversity considered (composition vs. configuration), (ii) programming solution, (iii) trade-off analyses, (iv) required input data, (v) aspects of spatial scale and (vi) opportunities for stakeholder participation (Table 2).

Aspects of landscape diversity

An important requirement for model selection is to clearly define which aspects of landscape diversity or patterns shall be investigated. The design of agroforestry, such as the layout of trees and crops, is implicitly a question of configuration at plot scale, while the amount and type of pre-defined agroforestry systems within a farm or landscape is mainly a question of compositional diversity. Using the robust optimization approach presented here, land-use allocation problems can be answered while land-use configuration effects are disregarded. Aspects of agroforestry design or arrangement are only accounted for by pre-defining specific agroforestry systems. However, site heterogeneity could be accounted for in the optimization model by integrating indicator scores for different site conditions. Interdisciplinary research teams of ecologists and economists may apply hybrid process-based bio-economic simulations and optimization approaches to better account for aspects of spatial arrangement (Kaim et al., 2018; Paul et al., 2019). Standard methods would include evolutionary methods, such as the genetic algorithm (Roberts et al., 2011). Alternatively, empirical approaches and agent-based models can deal with configurational land-use allocation problems (e.g., land sharing/sparing analysis, Gonzalez-Redin et al., 2019; Palma et al., 2007) and compositional allocation questions (Santana et al., 2016). Such models are particularly suitable to account for diffusion of innovations in a given network and to analyze trade-offs between ecological and economic indicators (Berger, 2001; Dislich et al., 2018). Agent-based models are particularly suited if the interactions between decision makers is the key research question. However, their demand for data and computational power is relatively high, they rely on predefined scenarios (O'Sullivan et al., 2016) or often use very simple decision rules, and it can be challenging to reproduce obtained results (Lusiana et al., 2012). Another benefit of the presented optimization approach is that it actively integrates uncertainty and can provide valuable information on the risk-reducing effect of land-use diversification (Paul et al., 2017).

With our model, further crucial factors that influence the type and share of agroforestry systems selected in a desirable land-use composition may be investigated. This includes the effect of varying landscape contexts (Reith et al., 2020) and income strategies on agroforestry adoption (Gosling et al., 2020). Future studies could investigate political (dis)incentives on land-use decisions such as payments for ecosystem services (Calle, 2020) and penalties for disservices (Kay et al., 2019), and land degradation effects (Kuiper, 1997).

Table 2. Strengths and weaknesses of the robust optimization approach, research questions that can currently be answered with the model, research needs and recommendations for alternative land-use allocation approaches.

Aspects	Strengths	Weaknesses	Research focus	Research needs	Alternative approaches
Landscape diversity	• accounting for risk-reducing effects of land-use diversification	• focus on compositional diversity and weak representation of configuration • no site heterogeneity and related effects • not spatially explicit	• effect of increasing/decreasing share of the considered land uses on the optimized share of agroforestry and vice versa • amount and type of pre-defined agroforestry systems within an optimized farm or landscape balancing pre-defined objectives	• improved representation of site heterogeneity • link optimization with GIS	• select Pareto-based optimization for non-linear relationships and to generate Pareto frontier when number of land-use alternatives and indicators is low (for participatory Pareto-based presentation of multiple optimal land-use compositions and trade-offs) • agent-based models to account for interactions of decision-makers, trade-offs and land-use configuration • hybrid process-based bio-economic simulations/ optimization if spatial arrangement is of interest (evolutionary methods)
Programming solution	• low demand for computational power (linear programming), despite consideration of uncertainty • guaranteed land-use portfolio performance in worst case • optimization of continuous land-use portfolios (i.e. all possible combinations of land uses are considered)	• linear relationships between objectives and area proportion required	• amount and type of pre-defined agroforestry systems in optimized land-use portfolios that reduce trade-offs between multiple pre-defined objectives with linear relationships	• transform non-linear relationships into a linear form • incorporate constraints to integrate non-linear relationships • identify robust ecological indicators towards changes in the land-use area share	
Trade-off analyses	• compromise land-use allocation reducing trade-offs between all objectives, while avoiding compensation among indicators • facilitate communication of trade-offs with stakeholders	• trade-offs are not directly visualized as in Pareto Optimization	• examination of changes in guaranteed performance level under different land-use compositions/agroforestry systems		
Input data requirements	• low data demand (expected/mean score and standard error/deviation) • data does not need to be normally distributed • synthesize data from different sources and with different scales		• explore how desirable novel (pre-defined) agroforestry systems in a land-use portfolio are to meet pre-defined objectives		
Spatial scale	• farm scale to regional level	• spatial scale of analysis needs to fit to input coefficients	• investigate if promotion of agroforestry is desirable under high heterogeneity among decision-makers • investigate amount and type of pre-defined agroforestry systems in an optimized farm portfolio under high indicator uncertainty or in all portfolios of the different farm types	• beyond regional level requires price elasticities and non-linear solution algorithm	
Stakeholder participation	• interactive programming • show effect of including/excluding objective(s) • co-learning on trade-offs	• no social-psychological variables (e.g. social networks)	• test objectives that drive current land use and the conditions under which different land-use patterns offer a desirable option • include stakeholder perception and preference	• stakeholder participation during and after modelling • systematic documentation and analyses of co-learning processes • integration of effect of land-use history	

Type of programming solution

Our model approach uses a scalarization method by reformulating the multiple-objective problem as a problem with only one variable, which has to be maximized over all indicators and uncertainty scenarios. This variable is the guaranteed performance level associated with a given landscape composition. This means that we obtain a single optimal land-use composition among continuous land-use portfolios with our model that reduces trade-offs between given indicators. In contrast, Pareto optimization is a very popular alternative in multi-objective optimization of ecosystem services (Andreotti et al., 2018; Bugalho et al., 2016; Seppelt et al., 2013) which allows for a set of efficient solutions (each considered equally desirable). Efficient solutions imply that decision-makers cannot improve one specific objective without worsening one or more other objectives. Such efficient solutions are commonly represented by "efficient" or "Pareto" frontiers. However, for many applications we need to have one and not an unlimited set of possible solutions (for example for comparing land-use scenarios), so using a scalarization method is often helpful. Our model is consistent with Pareto optimization in that both provide land-use allocation solutions which cannot be improved for one objective without compromising one or more others (Appendix A: Fig. 1). However, our model assumes that decision makers want to maximize the guaranteed performance (under uncertainty) obtained from a landscape, which is the case only for one globally optimal landscape composition of the Pareto frontier.

Besides the use of a single objective function, one key advantage of the robust approach suggested here lies in the low computational power needed, which is achieved by formulating the problem mathematically in a way that can be solved with a computationally efficient linear programming method. However, this advantage comes at the cost of two main assumptions of linear programming, which may be challenging for some research questions: proportionality and additivity. The assumption of proportionality entails that the marginal contribution of a given indicator remains constant with increasing/decreasing area of a given land-use. The assumption of additivity implies that the total landscape performance is the sum of the individual land-use performance products. This implies a linear relationship between the provision of each indicator (objective) with area proportions. For some indicators, the assumptions of proportionality may be met, as for instance for profit or carbon storage potential, and can be represented by compositional diversity (Duarte et al., 2018). For other indicators, such as pollination or species diversity, non-linear relationships and importance of spatial configuration can be assumed (Herrero-Jáuregui et al., 2018). For example, species area relationships may be assumed to show positive-concave relationships between the number of species and increasing patch size (Nowack et al., 2019) or increasing quality of an agro-ecological land-use matrix of small patches (Perfecto & Vandermeer, 2010). The modelling approach discussed here is currently not designed to answer such questions but could be extended to do so by incorporating additional constraints. For example, Knoke et al. (2020) applied a recursive iteration process to integrate the dependence of tree survival on species mixture or the dependence of tree growth on stand density into the optimization process. Alternatively, the allocation problem could be solved as a non-linear optimization problem. For example, Grass et al. (2020) used a spatially explicit Pareto-based optimization model using an evolutionary solution algorithm to obtain optimal landscape compositions for maximizing biodiversity for given profitability. Such non-linear approaches are highly valuable for representing e.g. effects of landscape composition on different taxonomic groups and detailed ecosystem functions. However, they are computationally very demanding and theoretically cannot guarantee the "global optimum". To better integrate biodiversity-related and other indicators with non-linear relationships with area proportions into our robust modelling approach, we call for support in the ecological research community. This could include ideas to simplify and transform non-linear relationships into a linear form, incorporate reasonable constraints or identify (biodiversity-)related indicators, which might be more robust towards changes in the land-use area share (e.g. structural diversity measures as a proxy).

Exploring trade-offs

While the results of the optimized land-use composition are straightforward to interpret for the user, the trade-offs between indicators remain more implicit (e.g. in the guaranteed performance level) of the resulting land-use composition when adjusting the selection of indicators or indicator weights. Trade-offs can be made more explicit, for example, by calculating an economic multifunctional premium. Accordingly, Friedrich et al. (2021) used a variant of goal programming to compare and calculate the difference between the achieved performance of the indicator economic return and an optimization of multiple indicators (here ecosystem services).

In Pareto optimization, trade-offs are often visualized and interpreted more explicitly (Strauch et al., 2019). Land-use allocations with the best (guaranteed) performance of each objective can be presented to explore trade-offs between each single objective (Seppelt et al., 2013). This way the entire potential of the landscape and trade-offs can be explored without limiting the search space to certain goals. However, this method can be computationally expensive and the selection of preferred solutions a posteriori can be difficult to understand for stakeholders.

Our approach can be used in a similar manner to Pareto Optimization to visualize trade-offs between guaranteed performance levels of different indicators when assigned different weights. This explores the potential Pareto Optimal

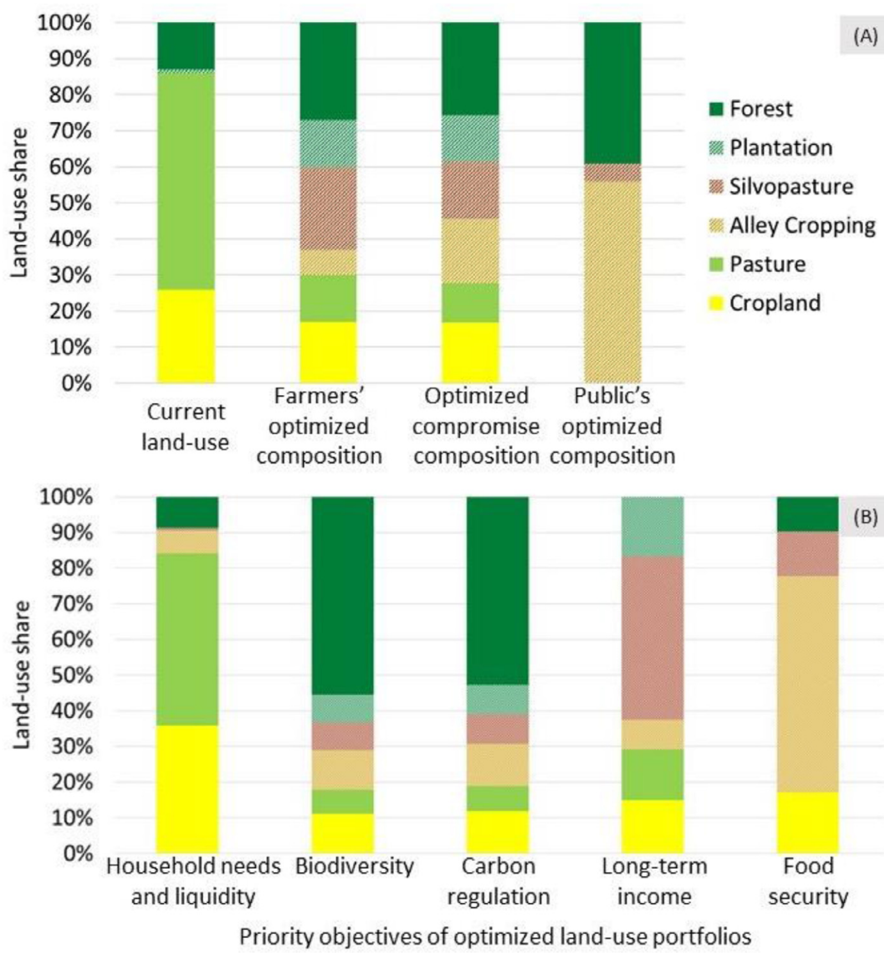

Fig. 2. Optimized land-use allocations derived for a moderate level of uncertainty. **(A)** Current land-use allocation of aggregated farms in the study region in eastern Panama and optimized land-use allocations from different perspectives (indicators weighed equally): farmers' perspective represented by socio-economic indicators and evaluated by local farmers (based on perception data from Gosling et al., 2020), a compromise solution between farmers and the public balancing all ecological and socio-economic indicators (based on perception data from Gosling et al., 2020, and adjusted dataset from Reith et al., 2020), and the perspective of the public represented by ecological and a social indicator and evaluated by experts (adjusted dataset from Reith et al., 2020). **(B)** Land-use allocations from the combined perspective of farmers and the public (compare center column in Fig. 2A), but the indicators named at the x-axis are weighted higher (twice as important) than the others.

frontier under variable preferences. The consistency between the Pareto Optimization efficiency frontier and goal programming in our approach is achieved by using a reference point method, which avoids the possibility of achievement levels exceeding the reference points (see Appendix A: Fig. 1 for further explanation).

Requirements of input data

Another important aspect for selecting an appropriate modelling approach is the input data requirements. One key advantage of our optimization approach is that the data demand is low compared to other approaches, particularly agent-based models, and requires only two input parameters for a given indicator provided by a given land use (expected score, standard deviation/error). Data scarcity is a very common situation in agroforestry and landscape research, particularly for novel agroforestry systems. We demonstrate the land-use allocation model using input data obtained from surveys with farmers and other stakeholder groups (Gosling et al., 2020; Reith et al., 2020). Both approaches result in an assessed relative performance level for each land use and indicator. Despite the fact that the min-max normalization (e.g. recommended by Diaz-Balteiro et al., 2018) allows for combining any type of data and source, care needs to be taken during data preparation and interpretation of results, for example when comparing metric data to interval-scaled data.

Using expert interviews in land-use science always comes with challenges of potential bias and the fact that results can only be interpreted as current perceptions, not as “hard facts”. This becomes apparent in our example application, where all interviewed groups assessed the economic and ecological potential of agroforestry very optimistically.

Nevertheless, expert opinion and perceptions may be helpful to inform a participatory pre-test of potential land-use conflicts for a specific and so far understudied region. At a later stage the model can then be fed with more advanced measured or simulated data. For example, Knoke et al. (2016) synthesized data for carbon, water and soil related indicators, as well as socio-economic indicators, which were derived through field measurements, farmer interviews, or through extended cost-benefit analyses. Another advantage of the robust multi-objective optimization method is compared to the classical portfolio approach (i.e., solving the farmers' decision problem via mean variance of profits), that it does not require data on correlations and covariances between land uses (Paul et al., 2019). Furthermore, the concept is inherently non-stochastic so the data does not need to follow a normal distribution, which can usually not be assumed for ecological and socio-economic values of ecosystem services (Campagne et al., 2018; Knoke et al., 2021).

Spatial scale

The presented approach is flexible towards the spatial scale to be investigated. It has been applied to the farm level (Gosling et al., 2020; Knoke et al., 2015) and landscape level (Knoke et al., 2016; Reith et al., 2020) and could theoretically also be applied to the regional level. However, the linearity requirement and available input data can limit the spatial scale. Firstly, when considering the national scale or beyond, some socio-economic indicators will become endogenous. For example, income from cropland may not increase proportionally with extending the area share, but may decline per hectare, because large crop quantities may only be sold at decreased prices or only less suitable sites could be used for cultivation (Knoke et al., 2011). For national or higher scale level applications one would need price elasticities and non-linear solution algorithms to solve the land-use allocation problems. Secondly, the spatial scale of modelling needs to align with the collected input data. For example, if indicator input data by a given land use was collected at the farm level (e.g. in Gosling et al., 2020), then the optimization should also only refer to the land-use allocation at the farm level, not exceeding the sampled farm sizes. Upscaling can be problematic if indicator performance is non-proportional with area shares, which may not only be the case for ecological data, but also for economic data of very different farm sizes, due to economies of scale. However, these differences can also be captured by the deviations of the indicator if different-sized farms have been integrated in data collection. Another option is to differentiate between farm sizes or farm types as demonstrated by Gosling et al. (2020) who carried out separate optimization runs for farm types pre-defined by hierarchical clustering with different sets of indicator means and deviations. If data allows, optimized farms may be aggregated to represent an optimized land allocation at the landscape scale. For political decision-makers who need to think in landscape to regional spatial scales, the approach could generate an answer to the question of whether fostering a specific land-use option is desirable under high farm heterogeneity. Technically this means to investigate whether agroforestry is integrated in the optimized farm portfolio under high indicator uncertainty or in all portfolios of the different farm types.

Inclusion of stakeholders

Stakeholder participation is becoming an increasingly important part of agroforestry modelling (van Noordwijk et al., 2021). An advantage of our modelling approach is the low computational requirements, which potentially enable interactive research discussions and participatory research approaches as suggested by Kaim et al. (2018). When interpreting and communicating the results, it is important to keep in mind that the aim of our approach is to investigate trade-offs and synergies of land uses and indicators. Even though the optimization takes a normative perspective, it should not be used to prescribe exact land-use allocations that decision-makers should adhere to, because of the models' simplifications (i.e. site homogeneity, the missing impact of land-use history or effect of adjacent land uses on decisions). The intention is to explore the conditions under which different farm or landscape patterns offer a desirable option. This means that, in line with Pareto-based approaches, not only one single best solution can be presented, but rather the generic effect of changes in the objectives on the theoretical optimal land-use composition. For this purpose the model can be used to generate multiple optimal solutions, for example, to reflect different objectives, knowledge and perception or risk attitudes of stakeholder groups, by solving the optimization problem multiple times with different input coefficients as part of a sensitivity analysis or in-/excluding objectives (Kaim et al., 2018; Matthies et al., 2019). Alternatively, generating the whole efficiency frontier of Pareto optimal land-use compositions via Pareto-based multi-objective optimization (see e.g approach by Strauch et al., 2019) can be an advantage when discussing results with experts as demonstrated by Kaim et al. (2020). However, this way of displaying and interpreting multi-dimensional trade-offs may be challenging for stakeholders (Kaim et al., 2020). Displaying simple pie charts of land-use compositions may be more intuitive when discussing the effect of in- or excluding objective(s) or changing the accepted uncertainty level with farmers, researchers and other stakeholders. Due to the low computational power needed, re-running the model with different objectives or weights can be done interactively (i.e. in an R Shiny App) within seconds. Such an approach would follow the philosophy of collaborative modelling (Basco-Carrera et al., 2017), with the aim of allowing for a co-learning process, involving the knowledge of all stakeholder groups and aiming at achieving a common system understanding (Voinov et al., 2018).

Until now, studies featuring the presented robust optimization model have integrated stakeholders only a priori, either through input generation by the AHP process (Reith et al., 2020; Uhde et al., 2017) and ranking and scoring technique (Gosling et al., 2020) or by including land-use preferences as a separate indicator derived from rankings provided by household interviews (Knoke et al., 2016, 2020). Future research should also include stakeholder participation during or after modelling. For example, using the interactive approach outlined above could enable a discussion on feasibility, preferences and potential farm constraints. But, the approach can also be used in a positive way in order to reveal which objectives seem to drive current land use (Gosling et al., 2020). This can also be done by estimating which set of objectives generates the optimized land-use composition most similar to the current land use. From our experience with pre-tests of these approaches, we recommend one-to-one interviews rather than workshops for such modelling exercises, which is in line with findings from Pareto-based approaches (Kaim et al., 2020). The support of experts from the social sciences and psychology will be needed to scientifically assess reactions and learning processes among all participants, including the scientists involved.

Model results can also be used in a participatory forecasting gaming approach. In such gaming sessions, our model results may represent potential future landscape compositions that can be discussed among stakeholders (Andreotti et al., 2020). This may facilitate understanding of land-use decisions, and obstacles and opportunities for developing a multifunctional landscape. In a subsequent backcasting workshop, stakeholders could identify required steps to change land-use allocation from the current land-use situation into the envisioned future scenario (Andreotti et al., 2020).

Conclusions

The robust multi-objective optimization model presented here is one of a range of advanced mechanistic modelling approaches (e.g. Grass et al., 2020; Lusiana et al., 2012; Palma et al., 2007) to investigate the role of agroforestry in future landscape matrices. Here we focus on aspects of agroforestry, while the model may be applied to a range of land-use allocation questions and contexts, such as forest restoration (Knoke et al., 2016), forest management (Knoke et al., 2020) or purely agricultural landscapes (Knoke et al., 2015). Using an example application from eastern Panama, we showed that the model can be used to envision desirable land-use allocations and rapidly investigate trade-offs between ecological and socio-economic objectives from different perspectives, which could be discussed with the respective interest groups. Our example application found that agroforestry is integrated in theoretically optimal land-use compositions meeting multiple needs under uncertainty. However, the type and share of agroforestry included in the optimized landscapes was heavily influenced by stakeholders' perceptions. We highlight that we focused on a normative application of the model in this study to assist decision making and not to prescribe land-use allocation. However, the model can also be used as a positive approach to model land-use decision-making, for example, to reproduce past deforestation trends and obtaining hypotheses about future deforestation (Knoke et al., 2020). The model, however, is not suitable for an exact prediction of future land-use dynamics, and (at least in its current form) for representing detailed aspects of landscape configuration, as well as ecological and socio-economic interactions between land owners. From our experience, the model's greatest strengths are that it can synthesize empirical and modelled data from different sources, that uncertainty is integrated into the objective function directly influencing land-use allocation results, and that it is parsimonious in its data and computational requirements. We believe that the model has potential for future development of hybrid models. To reduce drawbacks of individual models and better account for complexities in indicators related to ecosystem functioning and biodiversity, the model could for example be coupled with process-based and agent-based models in the effort to support sustainable and multifunctional land-use planning in an uncertain world.

Declaration of Competing Interest

The authors declare no conflicts of interest

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.baae.2022.08.002.

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