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A landscape lens to evaluate agroforestry using robust multi-objective optimization in eastern Panama

Esther Reith

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Vorsitz:

Prof. Dr. Annette Menzel

Prüfende der Dissertation:

1. Prof. Dr. Thomas Knoke
2. Prof. Dr. Anja Rammig

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“A good word is like a good tree, having its root firm and its branches in the sky”

[Quran 14:24]

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Summary

Introduction

Agricultural expansion in the tropics has transformed landscapes with adverse effects on primary forests and, consequently, on carbon sequestration and biodiversity. Climate change exacerbates these problems and makes agricultural harvests increasingly uncertain. However, future demand for food and renewable resources will likely continue to propel land-use change. Therefore, the challenge of our time is to reconcile agricultural production with conservation objectives in the face of land scarcity. One popular and widely promoted strategy is to include land-use systems that reconcile both needs. Agroforestry, which combines the production of crops and/or livestock products with tree products on the same land, is discussed as one of such systems. While agroforestry has been promoted as a system using trees to restore agricultural land, research is needed to explore its regional desirability. This is particularly challenging given the lack of data on innovative land-cover.

So far, it remains unclear whether agroforestry is a desirable contribution to the socio-ecological systems of the forest frontier of eastern Panama, and if it is, which shares would be required to achieve the best ecological and socio-economic outcomes. Socio-ecological production systems are developed areas managed for human well-being and can be characterized by a mosaic of different land-cover systems (e.g., forests, forest plantations, farmlands, etc.). Against the backdrop of Forest Landscape Restoration (FLR) processes, this study is dedicated to exploring the potential of agroforestry in socio-ecological systems and the appropriate level of landscape diversification to reconcile potentially conflicting objectives of a multifunctional landscape faced with uncertainty. This is approached from four different angles, which are captured in four research questions that guide this thesis:

1. Which and how much Forest Landscape Restoration (FLR) options in a landscape composition are desirable for society to meet multiple objectives under uncertainty?
2. How to reconcile the conflicting perspectives of farmers and the public?
3. How do the current and optimized landscape compositions impact ecological and socio-economic functions?
4. How robust are the optimization model results across model input databases and tropical landscapes?

Methods

To help fill the above-mentioned research gaps, this monograph demonstrates an innovative multi-objective land allocation modeling approach. It is parsimonious in data needs and links social science with land-use planning to better understand socio-ecological systems. The modeling approach accounts for uncertainty regarding variability in land-cover performance, future preferences, and risk-reducing land-use diversification strategies. At the same time, all aspects of sustainability (ecological, economic, and social) can be addressed and their trade-offs explored. Therefore, it allows the integration of interdisciplinary data sets that bring together scientific and local knowledge to assess prevailing and innovative land-cover options. Predefined objectives, for example, income, are quantified and can be integrated with indicators, such as the net present value of a land-cover option or a landscape. In addition, the impact of agroforestry adoption on ecological, social, and economic functions and forest cover can be analyzed using optimized future landscape compositions.

The combination of four different angles provides an original and comprehensive analysis of agroforestry as an FLR option, which has not been achieved in the existing literature. The first angle is an overall multifunctional perspective to identify the most promising FLR options under uncertainty. The second angle looks more closely at the issues raised from opposing perspectives (farmer and the public). This includes comparing optimized landscapes with and without agroforestry to show whether agroforestry can reconcile conflicting perspectives. Both the first and second angles consider the attractiveness of agroforestry relative to other FLR and conventional land-cover options in a hypothetical, optimal landscape composition based on perceptions and preferences. Systematic surveys of farmers and other experts were conducted in Panama (online and face-to-face) to obtain preference and perception data. The third angle encompasses quantified ecological and socio-economic impacts of agroforestry adoption in eastern Panama based on literature data. Therefore, the literature was reviewed and complemented with computed data to obtain ecological and socio-economic model input coefficients. The analysis compares the optimized and the current landscape composition of the study region and their achieved indicator levels for the different uncertainty scenarios. This allows us to evaluate the efficiency of the current landscape and to assess (un)intended impacts of land-use change. The fourth angle tests the robustness of the optimization outcomes to different data sets and the transferability of the results to similar tropical landscapes (Ecuador, Indonesia, Panama).

Results

The survey reveals that experts from different backgrounds perceive agroforestry as superior to the other FLR options (i.e., forest plantation, natural succession of abandoned land) but inferior to conventional land-cover options for specific ecological or socio-economic objectives. Hence, optimized multifunctional landscape compositions based on these perception data include significant agroforestry land shares (with and without accounting for uncertainty). This means that survey respondents perceived agroforestry as a desirable contribution to a landscape mosaic that reduces trade-offs between multiple objectives and low-performance levels of individual objectives. The results also highlight that heterogeneous landscapes may best mitigate uncertainty and balance multiple objectives.

However, the surveys also showed that farmers' perceptions and preferences (private perspective) differ from those of public interest groups (governmental, non-governmental, academia, companies). These differences are reflected in the optimized landscape compositions from both perspectives. The optimization results show that heterogeneous landscapes, including agroforestry, are particularly interesting as a compromise solution to reduce trade-offs and for land-use decision-makers wishing to buffer uncertainty regarding the socio-economic underperformance of the landscape (i.e., farmers). However, regardless of the perspective, the model always includes agroforestry for optimal land-use strategies, highlighting its multifunctional benefits and potential to reconcile competing perspectives.

Yet, the current landscape of the study area in eastern Panama does not include agroforestry. Identifying (dis)similarities between the current and an optimized multifunctional landscape helps to understand the advantages and drawbacks of FLR adoption at the landscape scale. Compared to the current land-cover composition, the optimized, heterogeneous, and multifunctional landscape composition could improve most of the studied ecological and socio-economic indicators in the worst-case scenarios. However, transitioning towards a multifunctional landscape composition could be associated with opportunity costs for farmers (in terms of liquidity, labor demand, experience, and farmer land-cover preference) and for society (carbon premium). Furthermore, increasing landscape heterogeneity (including agroforestry) to meet multiple objectives may negatively affect forest cover, as shown by comparing the optimization results across three tropical agriculture-forest frontier regions. While agriculture-dominated tropical landscapes (such as the study site of this thesis and a study in Indonesia) may benefit from increasing landscape heterogeneity through increased tree and forest cover, forest-dominated landscapes (e.g., a study in Ecuador) may see a reduction in forest cover to balance food and income with ecological objectives and associated uncertainty.

Since the land-cover input data is based on survey and literature data from field studies and modeling, the data and optimization results are tested for plausibility. The comparison of the optimized landscape compositions derived with different input data sets confirms that the interviewees' perception is plausible and that the model outcomes are relatively robust to input data changes.

Discussion

This monograph (including two published studies) advances agroforestry research by further developing the presented robust multi-objective optimization model to study the potential of agroforestry and trade-offs with alternative land-cover options at landscape scale. In this way, multifunctionality, uncertainty, and landscape diversification can be considered in various contexts, thus expanding the limits of cost-benefit analysis or risk and return optimization. Furthermore, by integrating different interest groups a priori, this thesis answers calls for stakeholder involvement and integrating both scientific and empiric knowledge.

It enhances understanding of the perceptions and impacts of introducing agroforestry on the tropical agriculture-forest frontier from a landscape perspective under the common circumstances of data scarcity. This work builds on former empirical research on agroforestry carried out in the same study region in Panama. This study represents the next step in improving the development of attractive agroforestry systems and finding the appropriate mix of FLR options for multifunctional landscapes by using a robust multi-objective optimization model and evaluating agroforestry from the public perspective. The optimization outcomes are compared across three tropical countries to test the transferability of model results.

The results highlight that for finding compromise solutions, heterogeneous landscapes may be better suited than homogeneous landscapes to reduce trade-offs. The optimization results are robust to model input changes and comparable tropical landscapes. They suggest that risk aversion leads to landscape diversification to buffer against uncertainty. The results also highlight that uncertainty, together with the goal of multifunctional landscapes, can promote the integration of agroforestry in the FLR mix to increase landscape heterogeneity depending on the landscape context. In the agricultural-dominated study area in eastern Panama, the model selected agroforestry to minimize trade-offs between the ecological and socio-economic objectives of farmers and the public. This suggests a consensus between the different perspectives of local farmers and the public on the perceived capability of the studied agroforestry systems. However, the results demonstrate potential trade-offs between agroforestry and other land-cover options. These are especially apparent in the optimization results of the forest-dominated landscape in Ecuador, where the model suggests a more diversified landscape consisting of agricultural and forest area shares (without agroforestry), in contrast to the current silvopasture-dominated landscape allocation. This means that natural forest cover may be essential to mitigate trade-offs and that agroforestry can represent a socio-economically viable tree-planting option rather than a win-win solution.

Conclusions and outlook

In the face of competing land-cover objectives and uncertainty, this research underscores the value of land-cover mosaics that integrate conventional agriculture, natural forest, and FLR options to create multifunctional land allocation solutions. In socio-ecological systems, where forest conservation alone is not feasible, multifunctional landscapes can benefit from including agroforestry systems to harmonize multiple objectives under uncertainty and mitigate the loss of ecological functions.

Panama's private-public partnership, *Alianza por el millón*, which aims to reforest 1 million hectares of degraded land, can serve as a powerful overarching example for reforestation efforts. This 1-million-hectare goal can streamline intervention strategies to help overcome barriers to FLR adoption.

Science can play a vital role in shifting land-use paradigms by presenting both the advantages and limitations of agroforestry and diversified landscapes compared to traditional agricultural systems and existing land allocation. The approach presented here provides an essential tool for restoring degraded landscapes. Future developments in hybrid land-use allocation models that integrate the (dynamic) robust multi-objective optimization model can deepen our understanding of socio-ecological systems and trade-offs between several objectives. Collaboration with stakeholders can help discuss the feasibility of model results for land managers, derive policy recommendations, and inform the establishment of field trials.

Zusammenfassung

Einleitung

Die Ausweitung der Landwirtschaft in den Tropen hat die Landschaften verändert, was sich nachteilig auf die Primärwälder und damit auf die Kohlenstoffbindung und die biologische Vielfalt auswirkt. Der Klimawandel verschärft diese Probleme und macht die landwirtschaftlichen Ernten zunehmend unsicherer. Die künftige Nachfrage nach Nahrungsmitteln und nachwachsenden Rohstoffen wird die Landnutzungsänderung jedoch wahrscheinlich weiter vorantreiben. Die Herausforderung unserer Zeit besteht daher darin, angesichts der Landknappheit die landwirtschaftliche Produktion mit den Zielen des Naturschutzes in Einklang zu bringen. Eine beliebte und weithin befürwortete Strategie ist die Einbeziehung von Landnutzungssystemen, die beide Bedürfnisse miteinander in Einklang bringen. Als eines dieser Systeme wird die Agroforstwirtschaft diskutiert, bei der die Produktion von Feldfrüchten und/oder tierischen Erzeugnissen mit der Produktion von Bäumen auf demselben Land kombiniert wird. Obwohl die Agroforstwirtschaft als ein System gefördert wird, bei dem Bäume zur Wiederherstellung landwirtschaftlicher Flächen verwendet werden, sind weitere Untersuchungen erforderlich, um ihre regionale Eignung zu bewerten. Dies ist eine besondere Herausforderung angesichts des Mangels an Daten über innovative Landnutzungsformen.

Bislang ist unklar, ob die Agroforstwirtschaft einen wünschenswerten Beitrag zu den sozio-ökologischen Systemen an der Waldgrenze im Osten Panamas leisten kann, und wenn ja, welche Anteile erforderlich wären, um die besten ökologischen und sozio-ökonomischen Ergebnisse zu erzielen. Sozio-ökologische Produktionssysteme sind bewirtschaftete Gebiete, die dem menschlichen Wohlergehen dienen und durch ein Mosaik verschiedener Landflächen (z.B. Wälder, Forstplantagen, Ackerland usw.) charakterisiert werden können. Vor dem Hintergrund von Prozessen zur Wiederherstellung von Wäldern und waldreichen Landschaften (Forest Landscape Restoration, FLR) widmet sich diese Studie der Erforschung des Potenzials der Agroforstwirtschaft in sozio-ökologischen Systemen und des angemessenen Grades der Landschaftsdiversifizierung, um potenziell widersprüchliche Ziele einer multifunktionalen Landschaft unter Unsicherheit in Einklang zu bringen. Dies wird aus vier verschiedenen Blickwinkeln betrachtet, die in vier Forschungsfragen zusammengefasst werden und die vorliegende Arbeit prägen:

1. Welche Optionen zur Wiederherstellung von Waldlandschaften (FLR) sind gesellschaftlich wünschenswert, um mehrere Ziele unter Unsicherheit in einer Landschaft zu erreichen, und in welchem Verhältnis?
2. Wie können die widersprüchlichen Perspektiven der Landwirte und der Öffentlichkeit in Einklang gebracht werden?
3. Wie wirken sich die aktuellen und optimierten Landschaftszusammensetzungen auf die ökologischen und sozioökonomischen Funktionen aus?
4. Wie robust sind die Ergebnisse des Optimierungsmodells gegenüber unterschiedlichen Eingangsdaten und tropischen Landschaften?

Methoden

Um die oben genannten Forschungslücken zu schließen, wird in dieser Monographie ein innovativer, multifunktionale Modellierungsansatz für die Landnutzungsverteilung vorgestellt. Dieser zeichnet sich durch einen geringen Datenbedarf aus und verbindet die Sozialwissenschaften mit der Landnutzungsplanung, um ein besseres Verständnis sozio-ökologischer Systeme zu ermöglichen. Der Modellierungsansatz berücksichtigt Unsicherheiten in Bezug auf die Variabilität der landschaftlichen Leistungsfähigkeit, zukünftige Präferenzen und risikomindernde Strategien zur Diversifizierung der Landnutzung. Gleichzeitig können alle Aspekte der Nachhaltigkeit (ökologisch, ökonomisch und sozial) berücksichtigt und deren Wechselwirkungen erforscht werden. Dies ermöglicht die Integration von interdisziplinären Datensätzen, die wissenschaftliches und lokales Wissen zusammenführen, um bestehende und innovative Landnutzungsoptionen zu bewerten. Vordefinierte Ziele, z.B. Einkommen, können mit Indikatoren, wie dem Kapitalwert einer Landnutzungsoption oder einer Landschaft, quantifiziert werden. Darüber hinaus können die Auswirkungen der Einführung der Agroforstwirtschaft auf die ökologischen, sozialen und wirtschaftlichen Funktionen und den Waldbestand anhand optimierter zukünftiger Landschaftszusammensetzungen analysiert werden.

Die Kombination von vier verschiedenen Blickwinkeln bietet eine originelle und umfassende Analyse der Agroforstwirtschaft als FLR-Option, die bisher in der bestehenden Literatur nicht erreicht wurde. Der erste Blickwinkel umfasst eine multifunktionale Perspektive, um die vielversprechendsten FLR-Optionen unter Unsicherheit zu identifizieren. Der zweite Blickwinkel befasst sich eingehender mit Zielkonflikten, die aus entgegengesetzten

Perspektiven aufgeworfen wurden (Landwirte und Öffentlichkeit). Dazu gehört der Vergleich von optimierten Landschaften mit und ohne Agroforstwirtschaft, um zu zeigen, ob die Agroforstwirtschaft widersprüchliche Perspektiven in Einklang bringen kann. Sowohl der erste als auch der zweite Blickwinkel betrachten die Attraktivität der Agroforstwirtschaft im Vergleich zu anderen FLR- und konventionellen Landflächen in einer hypothetischen, optimalen Landschaftszusammensetzung auf der Grundlage von Wahrnehmungen und Präferenzen. Um Daten über Wahrnehmungen und Präferenzen zu erhalten, wurden in Panama systematische Umfragen unter Landwirten und anderen Experten durchgeführt (online und persönlich). Der dritte Aspekt umfasst die quantifizierten ökologischen und sozioökonomischen Auswirkungen der Einführung der Agroforstwirtschaft im Osten Panamas auf der Grundlage von Literaturdaten. Dazu wurde die Literatur gesichtet und mit berechneten Daten ergänzt, um ökologische und sozioökonomische Modell-Inputkoeffizienten zu erhalten. Die Analyse vergleicht die optimierte und die aktuelle Landschaftszusammensetzung der Untersuchungsregion sowie die erreichten Indikatorwerte für die verschiedenen Unsicherheitsszenarien. Dies ermöglicht die Effizienz der aktuellen Landschaft zu bewerten und die (un-)beabsichtigten Auswirkungen der Landnutzungsänderung zu beurteilen. Der vierte Blickwinkel testet die Robustheit der Optimierungsergebnisse gegenüber verschiedenen Datensätzen und die Übertragbarkeit der Ergebnisse auf ähnliche tropische Landschaften (Ecuador, Indonesien, Panama).

Ergebnisse

Die Umfrage zeigt, dass Experten mit unterschiedlichem Hintergrund die Agroforstwirtschaft den anderen FLR-Optionen (d.h. Forstplantagen, natürliche Sukzession von offen gelassenen Flächen) überlegen sehen, sie aber für bestimmte ökologische oder sozioökonomische Ziele den konventionellen Landnutzungsoptionen unterlegen sehen. Optimierte multifunktionale Landschaftskompositionen, die auf diesen Wahrnehmungsdaten basieren, enthalten daher signifikante Agroforstflächenanteile (mit und ohne Berücksichtigung der Unsicherheit). Dies bedeutet, dass die Befragten die Agroforstwirtschaft als einen wünschenswerten Beitrag zu einem Landschaftsmosaik wahrnehmen, das Zielkonflikte und Leistungsdefizite einzelner Zielsetzungen reduziert. Die Ergebnisse verdeutlichen auch, dass heterogene Landschaften am besten geeignet sind, Unsicherheiten zu mindern und mehrere Ziele miteinander in Einklang zu bringen.

Die Erhebungen haben jedoch auch gezeigt, dass die Wahrnehmungen und Präferenzen der Landwirte (private Perspektive) von denen der öffentlichen Interessengruppen (Regierung, Nichtregierungsorganisationen, Wissenschaft, Unternehmen) abweichen. Diese Unterschiede spiegeln sich in den optimierten Landschaftskompositionen aus beiden Perspektiven wider. Die Optimierungsergebnisse zeigen, dass heterogene Landschaften, die auch Agroforstwirtschaft integrieren, besonders interessant sind als Kompromisslösung zur Verringerung von Zielkonflikten und für Landnutzungsentscheider, die die Ungewissheit über die sozioökonomische Leistungsfähigkeit der Landschaft abfedern wollen (d.h. Landwirte). Unabhängig von der Perspektive schließt das Modell jedoch immer die Agroforstwirtschaft für optimale Landnutzungsstrategien ein, was ihre multifunktionalen Vorteile und ihr Potenzial, konkurrierende Perspektiven in Einklang zu bringen, unterstreicht.

Die aktuelle Landschaft des Untersuchungsgebiets im Osten Panamas enthält jedoch keine Agroforstwirtschaft. Die Identifizierung von (Un-)Gleichheiten zwischen der aktuellen und einer optimierten multifunktionalen Landschaft hilft, die Vor- und Nachteile der Einführung von FLR auf der Landschaftsebene zu verstehen. Im Vergleich zur derzeitigen Landschaftszusammensetzung könnte die optimierte, heterogene und multifunktionale Landschaft die meisten der untersuchten ökologischen und sozioökonomischen Indikatoren in den Worst-Case-Szenarien verbessern. Allerdings könnte der Übergang zu einer multifunktionalen Landschaft mit Opportunitätskosten für die Landwirte (in Bezug auf Liquidität, Arbeitsbedarf, Erfahrung und Landnutzungspräferenz) und für die Gesellschaft (Kohlenstoffprämie) verbunden sein. Darüber hinaus kann sich eine zunehmende Landschaftsheterogenität (einschließlich Agroforstwirtschaft) zur Erreichung mehrerer Ziele negativ auf den Waldbestand auswirken, wie ein Vergleich der Optimierungsergebnisse in drei tropischen Waldgrenzregionen zeigt. Während landwirtschaftlich geprägte tropische Landschaften (wie das Untersuchungsgebiet dieser Arbeit und eine Studie in Indonesien) von einer zunehmenden Landschaftsheterogenität durch eine Erhöhung des Baum- und Waldbestandes profitieren können, kann es in walddominierten Landschaften (z.B. in einer Untersuchungsregion in Ecuador) zu einer Verringerung des Waldbestandes kommen, um ein Gleichgewicht zwischen Nahrungsmittelproduktion und Einkommensgenerierung mit ökologischen Zielen und den damit verbundenen Unsicherheiten herzustellen.

Da die Daten für die Landflächen auf Befragungen und Literaturdaten aus Feldstudien und Modellierungen beruhen, werden die Daten und Optimierungsergebnisse auf Plausibilität geprüft. Der Vergleich der optimierten Landschaftskompositionen, die mit verschiedenen Eingangsdaten abgeleitet wurden, bestätigt, dass die Wahrnehmung der Befragten plausibel ist und dass die Modellergebnisse relativ robust gegenüber Änderungen der Eingangsdaten sind.

Diskussion

Diese Monographie (einschließlich zweier veröffentlichter Studien) bringt die Agroforstforschung voran, indem sie das vorgestellte robuste multifunktionale Optimierungsmodell weiterentwickelt, um das Potenzial der Agroforstwirtschaft und die Wechselwirkungen mit alternativen Landnutzungsoptionen auf Landschaftsebene zu untersuchen. Auf diese Weise können Multifunktionalität, Unsicherheit und Landschaftsdiversifizierung in verschiedenen Kontexten berücksichtigt werden, wodurch die Grenzen der Kosten-Nutzen-Analyse oder der Risiko- und Ertragsoptimierung erweitert werden. Diese Arbeit entspricht außerdem der Forderung nach der Einbeziehung von Interessengruppen und der Integration von wissenschaftlichen und empirischen Erkenntnissen durch die Einbeziehung verschiedener Interessengruppen.

Sie verbessert das Verständnis für die Wahrnehmungen und Auswirkungen der Einführung von Agroforstwirtschaft an der tropischen Waldgrenze aus einer Landschaftsperspektive unter den üblichen Umständen der Datenknappheit. Diese Arbeit baut auf früheren empirischen Untersuchungen zur Agroforstwirtschaft auf, die in der gleichen Studienregion in Panama durchgeführt wurden. In dieser Arbeit wird ein robustes multifunktionale Optimierungsmodell verwendet, um die Agroforstwirtschaft aus der Sicht der Öffentlichkeit zu bewerten. Dies ist der nächste Schritt zur Verbesserung der Entwicklung attraktiver Agroforstsysteme und der sinnvollen Mischung von FLR-Optionen für multifunktionale Landschaften. Die Optimierungsergebnisse werden in drei tropischen Ländern verglichen, um die Übertragbarkeit der Modellergebnisse zu testen.

Die Ergebnisse zeigen, dass heterogene Landschaften für die Suche nach Kompromisslösungen besser geeignet sein können als homogene Landschaften. Die Optimierungsergebnisse sind robust gegenüber Änderungen der Eingangsdaten und vergleichbaren tropischen Landschaften. Sie deuten darauf hin, dass Risikoaversion zu einer Diversifizierung der

Landschaft führt, um Unsicherheiten abzufedern. Die Ergebnisse zeigen auch, dass Unsicherheit in Verbindung mit dem Ziel multifunktionaler Landschaften die Integration von Agroforstwirtschaft in den FLR-Mix fördern kann, um die Heterogenität der Landschaft je nach Landschaftskontext zu erhöhen. In dem landwirtschaftlich geprägten Untersuchungsgebiet im Osten Panamas entschied sich das Modell für die Agroforstwirtschaft, um Kompromisse zwischen den ökologischen und sozioökonomischen Zielen der Landwirte und der Öffentlichkeit zu minimieren. Dies deutet auf einen Konsens zwischen den verschiedenen Perspektiven der lokalen Landwirte und der Öffentlichkeit hinsichtlich der wahrgenommenen Leistungsfähigkeit der untersuchten Agroforstsysteme hin. Die Ergebnisse zeigen jedoch auch potenzielle Zielkonflikte zwischen der Agroforstwirtschaft und anderen Landnutzungsoptionen. Besonders deutlich wird dies in den Optimierungsergebnissen für die walddominierte Landschaft Ecuadors, wo das Modell eine stärker diversifizierte Landschaft mit land- und forstwirtschaftlichen Flächenanteilen (ohne Agroforstwirtschaft) vorschlägt, im Gegensatz zur derzeitigen silvopastoral dominierten Landschaftsaufteilung. Dies bedeutet, dass der natürliche Wald für die Abschwächung von Zielkonflikten wesentlich sein kann und dass die Agroforstwirtschaft eher eine sozioökonomisch tragfähige Aufforstungsoption als eine Win-Win-Lösung darstellen kann.

Schlussfolgerungen und Ausblick

Angesichts von Zielkonflikte und Unsicherheiten unterstreicht diese Forschung den Wert von Landschaftsmosaiken, die konventionelle Landwirtschaft, Naturwald und FLR-Optionen integrieren, um multifunktionale Lösungen zu schaffen. In sozio-ökologischen Systemen, in denen die Erhaltung von Wäldern allein nicht machbar ist, können multifunktionale Landschaften von der Einbeziehung agroforstwirtschaftlicher Systeme profitieren, um mehrere Ziele unter Unsicherheit zu harmonisieren und den Verlust ökologischer Funktionen zu mindern.

Panamas öffentlich-private Partnerschaft „Alianza por el Millón", die darauf abzielt, 1 Million Hektar degradierten Landes aufzuforsten, kann als ein starkes Beispiel für Aufforstungsbemühungen dienen. Dieses 1-Million-Hektar-Ziel kann die Interventionsstrategien bündeln und dazu beitragen, Hindernisse für die Einführung von FLR zu überwinden.

Die Wissenschaft kann eine wichtige Rolle bei der Änderung von Landnutzungsparadigmen spielen, indem sie sowohl die Vorteile als auch die Grenzen der Agroforstwirtschaft und diversifizierter Landschaften im Vergleich zu traditionellen landwirtschaftlichen Systemen und der bestehenden Landverteilung aufzeigt. Der hier vorgestellte Ansatz ist ein wichtiges Instrument zur Wiederherstellung degradierter Landschaften. Zukünftige Entwicklungen von hybriden Landnutzungsmodellen, die robuste (dynamische) multifunktionale Optimierungsmodelle integrieren, können unser Verständnis von sozio-ökologischen Systeme und Zielkonflikten vertiefen. Die Zusammenarbeit mit Interessensvertretern kann dazu beitragen, die Umsetzbarkeit der Modellergebnisse für Landbewirtschafter zu diskutieren, Politikempfehlungen abzuleiten und Feldversuche zu planen.

Resumen

Introducción

La expansión agrícola en los trópicos ha alterado los paisajes, generando impactos negativos en los bosques primarios y, por tanto, en la captura de carbono y la biodiversidad. El cambio climático está agravando estos problemas y haciendo que las cosechas agrícolas sean cada vez más inciertas. De igual manera, es probable que la futura demanda por alimentos y recursos renovables impulse aún más el cambio en el uso de la tierra. Es así que nuestro reto es conciliar la producción agrícola con los objetivos de conservación ante la escasez de tierras. Una estrategia popular y ampliamente promovida consiste en incorporar sistemas de uso de la tierra que concilien ambas necesidades. Entre los sistemas que se encuentran en discusión se destaca la agroforestería, la cual combina la producción de cultivos y/o productos ganaderos con productos forestales en la misma área. Aunque el sistema agroforestal se ha promovido como un sistema para restaurar las tierras agrícolas, aún es necesario investigar su viabilidad en la región. Sin embargo, esta tarea es particularmente difícil dada la falta de datos sobre usos innovadores del suelo.

Hasta la fecha, no queda claro si la agroforestería supone una alternativa deseable para los sistemas socioecológicos de la frontera forestal al este de Panamá. Y en caso de que lo sea, se desconoce qué proporciones serían necesarias para lograr los mejores resultados ecológicos y socioeconómicos. Los sistemas socioecológicos de producción son áreas manejadas que sirven al bienestar humano y pueden caracterizarse por un mosaico de diferentes sistemas de cobertura de la tierra (por ejemplo, bosques, plantaciones forestales, tierras de cultivo, entre otros). En el contexto de los procesos de restauración del paisaje forestal (Forest Landscape Restoration, FLR), este estudio se dedica a explorar el potencial de la agroforestería en los sistemas socioecológicos; así como el grado apropiado de diversificación del paisaje para conciliar objetivos potencialmente conflictivos de un paisaje multifuncional bajo incertidumbre. Esto se considera desde cuatro perspectivas diferentes, que se resumen en las siguientes preguntas de investigación:

1. ¿Cuáles y cuántas opciones de restauración del paisaje forestal (FLR) son deseables en la composición de un paisaje para que la sociedad alcance múltiples objetivos en condiciones de incertidumbre?

2. ¿Cómo pueden conciliarse las perspectivas contradictorias de agricultores y ciudadanos?
3. ¿ Cómo afectan la composición del paisaje actual y la composición optimizada a las funciones ecológicas y socioeconómicas?
4. ¿Cuán fiables son los resultados del modelo de optimización en función a los datos de entrada y los paisajes tropicales?

Métodos

Para contribuir a colmar las brechas de investigación mencionadas, esta monografía presenta un enfoque innovador de modelización multiobjetivo para la distribución del uso de la tierra. Este enfoque es parsimonioso en cuanto a las necesidades de datos, combinando las ciencias sociales con la ordenación territorial para comprender mejor los sistemas socioecológicos. El modelo tiene en cuenta las incertidumbres relacionadas con la variabilidad del rendimiento del paisaje, las preferencias futuras y las estrategias de mitigación de riesgos para la diversificación del uso de la tierra. Al mismo tiempo, puede incluir aspectos de la sostenibilidad (ecológicos, económicos y sociales) y analizar sus interacciones. Esto permite la integración de conjuntos de datos interdisciplinarios que reúnen conocimientos científicos y locales para evaluar las opciones de uso del suelo existentes, así como usos innovadores. Los objetivos predefinidos, por ejemplo, los ingresos económicos, se cuantifican y pueden vincularse a indicadores como el valor actual neto de una opción de cobertura del suelo o de un paisaje. Además, el impacto de la introducción de la agrosilvicultura en las funciones ecológicas, sociales y económicas, asi como en la cubierta forestal puede analizarse utilizando composiciones optimizadas del paisaje futuro.

La combinación de cuatro perspectivas diferentes proporciona un análisis original y exhaustivo de la agrosilvicultura como opción de FLR que no se ha logrado en la bibliografía existente. El primer ángulo incluye una perspectiva multifuncional para identificar las opciones de FLR más prometedoras en condiciones de incertidumbre. El segundo ángulo examina más de cerca las cuestiones planteadas desde perspectivas opuestas (agricultores y público). Esto incluye una comparación de paisajes optimizados con y sin agrosilvicultura para demostrar si la agrosilvicultura puede conciliar perspectivas opuestas. Tanto la primera como la segunda perspectiva consideran el atractivo de la agrosilvicultura en comparación con otras opciones de FLR y de cobertura de suelo convencional en una composición óptima hipotética del paisaje basada en percepciones y preferencias. Para obtener datos sobre percepciones y preferencias, se realizaron encuestas sistemáticas en Panamá entre agricultores y otros expertos (online y en persona). El tercer ángulo abarca los impactos ecológicos y socioeconómicos cuantificados de la adopción de sistemas agroforestales al este de Panamá basados en datos bibliográficos. Para ello, se revisó la literatura y se complementó con datos calculados para obtener los coeficientes de entrada del modelo ecológico y socioeconómico. El análisis compara la composición optimizada y actual del paisaje de la región de estudio y los niveles de indicadores alcanzados para los diferentes escenarios de incertidumbre. Esto permite evaluar la eficiencia del paisaje actual y valorar los efectos (no) previstos del cambio de uso de la tierra. La cuarta perspectiva pone a prueba la fiabilidad de los resultados de la optimización frente a diferentes conjuntos de datos y la transferibilidad de estos resultados a paisajes tropicales similares (Ecuador, Indonesia, Panamá).

Resultados

La encuesta revela que expertos de diferentes disciplinas perciben la agrosilvicultura como superior a las otras opciones de FLR (es decir, plantación forestal, sucesión natural de tierras abandonadas), pero inferior a las opciones convencionales del uso del suelo para objetivos ecológicos o socioeconómicos específicos. Por lo tanto, las composiciones optimizadas de paisajes multifuncionales que se basan en estos datos de percepción incluyen porcentajes significativos de tierras agroforestales (con y sin tener en cuenta la incertidumbre). Esto significa que los encuestados perciben la agrosilvicultura como una alternativa deseable a un mosaico paisajístico que reduciría las compensaciones y los bajos niveles de rendimiento de los objetivos individuales. Los resultados también ilustran que los paisajes heterogéneos podrían ser los más adecuados para minimizar las incertidumbres y conciliar múltiples objetivos.

Sin embargo, las encuestas también han demostrado que las percepciones y preferencias de los agricultores (perspectiva privada) difieren de las de los interesados públicos (gobierno, organizaciones no gubernamentales, mundo académico, empresas). Estas diferencias se reflejan en las composiciones optimizadas del paisaje desde ambas perspectivas. Los resultados de la optimización muestran que los paisajes heterogéneos que también integran la agrosilvicultura son especialmente interesantes como una solución conciliadora para reducir las compensaciones; así como para los responsables de la toma de decisiones sobre el uso del suelo que quieren mitigar la incertidumbre sobre el rendimiento socioeconómico del paisaje (es decir, los agricultores). Sin embargo, independientemente de la perspectiva, el modelo siempre incluye la agrosilvicultura entre las estrategias óptimas de uso de la tierra, lo que resalta sus beneficios multifuncionales y su potencial para conciliar perspectivas contrapuestas.

No obstante, el paisaje actual del área de estudio en el este de Panamá no incluye a la agroforestería. La identificación de (dis)similitudes entre el paisaje actual y un paisaje multifuncional optimizado ayuda a comprender las ventajas y desventajas de introducir la FLR a nivel de paisaje. En comparación con la composición actual del paisaje, el paisaje optimizado, heterogéneo y multifuncional podría mejorar la mayoría de los indicadores ecológicos y socioeconómicos investigados en los peores escenarios. Sin embargo, la transición a un paisaje multifuncional podría estar asociada a costes de oportunidad para los agricultores (en términos de liquidez, requerimientos de mano de obra, experiencia y preferencia de los agricultores por el uso de la tierra) y para la sociedad (prima de carbono). Además, el aumento de la heterogeneidad del paisaje (incluida la agrosilvicultura) para alcanzar objetivos múltiples puede tener repercusiones negativas en la cubierta forestal, como demuestra una comparación de los resultados de la optimización en tres regiones tropicales de fronteras forestales. Los paisajes tropicales dominados por la agricultura (como el área de estudio de este trabajo y un estudio en Indonesia) pueden beneficiarse del aumento de la heterogeneidad del paisaje mediante el incremento de la cubierta arbórea y forestal. Por su parte, los paisajes dominados por bosques (por ejemplo, una región de estudio en Ecuador) pueden experimentar una reducción de la cubierta forestal para equilibrar la producción de alimentos y la generación de ingresos con los objetivos ecológicos y las incertidumbres asociadas.

Dado que los coeficientes relativos a las superficies se basan en encuestas y en datos bibliográficos procedentes de estudios de campo y de modelizaciones, se comprueba la plausibilidad de los datos y de los resultados de la optimización. La comparación de las composiciones optimizadas del paisaje obtenidas con diferentes datos de entrada confirma que la percepción de los encuestados es plausible y que los resultados del modelo son relativamente fiables a los cambios en los datos de entrada.

Discusión

Esta monografía (que incluye dos estudios publicados) avanza en la investigación agroforestal mediante el desarrollo del modelo robusto de optimización multiobjetivo, para investigar el potencial de la agroforestería y las compensaciones con opciones alternativas de uso de la tierra a escala de paisaje. De este modo, la multifuncionalidad, la incertidumbre y la diversificación del paisaje pueden considerarse en diferentes contextos, ampliando los límites del análisis coste-beneficio o de la optimización del riesgo y la rentabilidad. Al integrar a priori diferentes grupos de interés, este trabajo también responde a las necesidades de involucrar a las partes interesadas e integrar tanto el conocimiento científico como el empírico.

Así mismo, mejora la comprensión de las percepciones e impactos de adoptar la agroforestería en la frontera agrícola-forestal desde una perspectiva paisajística bajo las circunstancias habituales de escasez de datos. Este trabajo se basa en investigaciones empíricas previas sobre agroforestería realizadas en la misma región de estudio en Panamá. Se utiliza un modelo robusto de optimización multiobjetivo para evaluar la agroforestería desde la perspectiva del público. Este estudio representa el siguiente paso para mejorar el desarrollo de sistemas agroforestales atractivos y encontrar la combinación adecuada de opciones de FLR para paisajes multifuncionales. Los resultados de la optimización se comparan en tres países tropicales para comprobar la transferibilidad de los resultados del modelo.

Los resultados muestran que los paisajes heterogéneos pueden ser más adecuados para encontrar soluciones conciliadoras que los paisajes homogéneos. La optimización demuestra ser robusta a los cambios en los datos de entrada y los paisajes tropicales comparables. Estos resultados indican que la aversión al riesgo conduce a una diversificación del paisaje para mitigar la incertidumbre. También revelan que la incertidumbre, combinada con el objetivo de paisajes multifuncionales, puede promover la integración de la agrosilvicultura en la combinación de FLR para aumentar la heterogeneidad del paisaje, dependiendo del contexto paisajístico. En el área de estudio dominada por la agricultura en el este de Panamá, el modelo optó por la agroforestería para minimizar las compensaciones entre los objetivos ambientales y socioeconómicos tanto de los agricultores como el público. Esto indica un consenso entre las diferentes perspectivas de los agricultores locales y el público en cuanto al rendimiento percibido de los sistemas agroforestales estudiados. Sin embargo, los resultados también muestran posibles compensaciones entre la agrosilvicultura y otras opciones de uso de la tierra. Esto es evidente en los resultados de optimización para el paisaje dominado por los bosques de Ecuador, donde el modelo sugiere un paisaje más diversificado con cuotas de tierras agrícolas y forestales (sin agroforestería), en contraste con la actual distribución del paisaje dominado por el silvopastoreo. Esto significa que el bosque natural puede ser esencial para mitigar las compensaciones y que la agrosilvicultura puede ser una opción de reforestación socioeconómicamente viable más que una solución beneficiosa para todos.

Conclusiones y perspectivas

Frente a la competencia entre objetivos e incertidumbres sobre la cobertura del suelo, esta investigación subraya el valor de los mosaicos paisajísticos que integran agricultura convencional, bosques naturales y opciones de FLR para crear soluciones multifuncionales para los paisajes. En sistemas socioecológicos donde la conservación forestal por sí sola no es viable, los paisajes multifuncionales pueden beneficiarse de la incorporación de sistemas agroforestales para armonizar múltiples objetivos en condiciones de incertidumbre y mitigar la pérdida de funciones ecológicas.

La alianza público-privada panameña "Alianza por el Millón", cuyo objetivo es reforestar un millón de hectáreas de tierras degradadas, puede servir de ejemplo para los esfuerzos de reforestación. Este objetivo de un millón de hectáreas puede centrar las estrategias de intervención y ayudar a superar los obstáculos a la adopción de la FLR.

La ciencia puede desempeñar un papel importante en el cambio de los paradigmas de uso de la tierra; presentando tanto los beneficios como las limitaciones de la agrosilvicultura y los paisajes diversificados en comparación con los sistemas agrícolas tradicionales y la distribución actual de la tierra. El enfoque presentado aquí ofrece una herramienta importante para restaurar los paisajes degradados. El desarrollo futuro de modelos híbridos de asignación de uso de la tierra que integren el modelo robusto (dinámicos) de optimización multiobjetivo pueden profundizar nuestra comprensión de los sistemas socioecológicos y de las compensaciones entre varios objetivos. La colaboración con las partes interesadas puede ayudar a debatir la viabilidad de los resultados de la modelización para los gestores del territorio, derivar recomendaciones políticas e informar sobre el establecimiento de pruebas encampo.

Table of content

1 Introduction

1.1 Research motivation

Tropical forests are vital for our planet, providing multiple ecological benefits (Giam 2017). However, approximately 1 billion people live near tropical forests globally, depending on provisioning services (Newton et al. 2020). The increasing need for food and fiber, which results in the expansion of agricultural land, has replaced vast native tropical forests (Albrecht et al. 2017; Fischer and Vasseur 2000; Pendrill et al. 2022). In Panama, like in many other tropical countries, the need for effective Forest Landscape Restoration (FLR) strategies has become increasingly urgent. Recognizing this, Panama has committed to restoring one million hectares of its degraded landscapes (equivalent to 13 percent of Panama’s land area) under the *Bonn Challenge* international agreement (García et al. 2016) and has partnered with private institutions in the *Alianza por el Millón de Hectareas Reforestadas* (Alliance for One Million Hectares Reforested). However, with increasing land scarcity (Lambin and Meyfroidt 2011) the urgent question arises of how to allocate our resource land to balance different purposes, such as increasing food production and sustaining livelihoods, while preventing further depletion of natural resources.

One promising restoration approach to meet these multiple objectives is agroforestry, a diversified land-use system that includes intercropping and/or integrating livestock with trees (Santos et al. 2023). Agroforestry has been recognized as an ecologically sound and socio-economically beneficial system for restoring forest landscapes while simultaneously supporting sustainable agriculture (Nair et al. 2021b; Somarriba et al. 2012; van Noordwijk 2021). As such, agroforestry aligns with the Sustainable Development Goals (SDGs) and is being promoted globally across science and policy (Liu et al. 2019; Nair and Garrity 2012; van Noordwijk et al. 2019). The success of agroforestry as an FLR option in Panama depends on several interrelated factors, including managing trade-offs between multiple, often conflicting objectives (Kaim et al. 2018; Zheng et al. 2019). These objectives typically encompass ecological demands such as enhancing carbon sequestration, biodiversity, soil fertility, and socio-economic well-being (Grass et al. 2020; Groot et al. 2010; Hodbod et al. 2016). As such, agroforestry offers a unique opportunity to reconcile the socio-economic needs of local communities and the objectives of other interest groups (e.g., biodiversity conservation and climate change mitigation). However, competition for light, water, and nutrients can also decrease the productivity of individual species in agroforestry systems (Rao et al. 1997). Furthermore, local biophysical or socio-economic factors may render agroforestry less competitive than simple farm mosaics (Paul et al. 2017b). These drawbacks include higher investment costs and uncertainty concerning markets compared to conventional land use (Calle et al. 2009; Connelly and Shapiro 2006; Sinacore et al. 2023a).

In addition to the considerations about these trade-offs, land-use planning must consider the inherent uncertainties associated with the variable ability of land-cover to meet given objectives (Alavalapati and Mercer 2004). To address these complex challenges, a robust multi-objective optimization approach has emerged as a valuable tool (Knoke et al. 2015; 2016; 2023). Robust multi-objective optimization integrates multi-criteria optimization to identify optimal land-cover allocation solutions that fulfill a predefined set of objectives and are robust to uncertainties (Paul et al. 2019). Another advantage of the model is that it allows to integrate the generally separate disciplines of social science and land-use planning and brings together scientific and local knowledge on the potential of agroforestry. This research of agroforestry integration at the tropical agriculture-forest frontier in eastern Panama illustrate the approach under the common circumstances of data scarcity. Eastern Panama was selected for data collection and analysis because it typifies a common tropical landscape marked by systematic deforestation (Sloan 2008) and ongoing debate about proper policy interventions to regain tree cover (e.g., Duke et al. 2014; Peterson St-Laurent et al. 2013). As part of a sensitivity analysis, the model results were tested for their transferability to comparable tropical landscapes (in Ecuador and Indonesia).

This research approach holds promise not only for Panama but also for other regions facing similar challenges in restoring forest landscapes amid a changing climate and growing societal demands. The results of this thesis are expected to contribute to further research into the development of science-based policies and strategies that promote the ecological resistance and socio-economic viability of Panama's forested landscapes, ultimately advancing global efforts to restore forest landscapes sustainably.

1.2 Objectives and research questions

The primary aim is to systematically analyze opportunities, trade-offs, and ecological and socio-economic impacts of agroforestry as an FLR option. This research bridges critical aspects of landscape planning, including stakeholder engagement, uncertainty incorporation, risk reduction strategies, analysis of sustainability trade-offs, and unintended consequences of agroforestry promotion. It identifies optimal land-cover compositions to develop land-use strategies that minimize potential trade-offs and address uncertainties, offering valuable insights for researchers and decision-makers.

This study extends previous research focused on forestry contexts (e.g. Knoke et al. 2020a; Uhde et al. 2017) or the role of agroforestry at the farm scale (Gosling 2021). The notable contribution to the scientific community lies in developing this innovative approach for eastern Panama's agriculture-forest frontier landscape and transferring it to Ecuadorian and Indonesian landscapes (as part of the sensitivity analysis).

The overarching hypothesis of this thesis is:

> Agroforestry will be included in the Forest Landscape Restoration mix because it reduces trade-offs between multiple objectives of different interest groups when uncertainty is considered.

Derived from the hypothesis, the following RQs are specified to guide this thesis:

1. Which and how much Forest Landscape Restoration (FLR) options in a landscape composition are desirable for society to meet multiple objectives under uncertainty?
2. How to reconcile conflicting perspectives of farmers and the public?
3. How do the current and optimized landscape compositions impact ecological and socio-economic functions?
4. How robust are the optimization model results across model input databases and tropical landscapes?

1.3 The case study area in Panama

The study area of Tortí, located 250 km east of Panama City on the Pan-American Highway, represents a transition zone between Panama's degraded western landscapes and the pristine eastern tropical forests, where conversion to agricultural land continues (from here on "forest frontier"). It is characterized by predominantly flat terrain, with rolling hills to the south, and experiences a humid tropical climate.

Population and economic growth led to the expansion of the Pan-American Highway eastward in the 1950s, attracting settlers from Panama's western provinces (Wali 1993). This led to forest clearance in eastern Panama for pasture expansion and shifting cultivation (Fischer and Vasseur 2000).

To address deforestation and land degradation, the Panamanian government introduced federal subsidies through Law 24 of 1992, promoting reforestation and sustainable forest resource utilization (Simmons et al. 2002). This led to increased tree cover, primarily driven by large international timber companies planting monocultures of teak (*Tectona grandis*), an exotic species to Panama (Garen et al. 2009; Sloan 2008). However, these forest plantations, especially with exotic species, are debated for their social, ecological, and biodiversity value (Bremer and Farley 2010; MiAmbiente 2010; Sloan 2008). In the study region, Tortí, teak plantations account for 1% of the total area, with no record of native tree plantations during recent surveys (Gosling 2021).

Water scarcity concerns have heightened locals' appreciation for the remaining forests (Sloan 2016), comprising 13% of the study landscape. Pastures, managed by settlers, dominate the area at 60% area share, while cropland occupies 26% of the region (Gosling et al. 2021). Despite the greater profitability of crops compared to livestock, pastures persist because of the high value of cattle to farmers and the limitations imposed on crop production by soil properties and degradation (Coomes et al. 2008; Paul 2014; Wright and Samaniego 2008). Agroforestry practices are commonly employed in the form of scattered trees in pastures, living fences, and home gardens (Kirby and Potvin 2007; Paul 2014).

Scaling up agroforestry could offer a sustainable solution to combat the adverse ecological impacts of deforestation and land degradation (Fischer and Vasseur 2000; Tscharntke et al. 2012) while contributing to the increased food demand (Collado et al. 2019). The new Law 69 (2017) promotes agroforestry and other reforestation options, which suggests a potential shift towards reforestation with a more diversified mix of options.

1.4 Conceptual background

1.4.1 Forest Landscape Restoration and multifunctionality

FLR is a strategic landscape management process that balances ecological and socio-economic objectives in deforested and degraded landscapes (Dudley et al. 2005; Lamb et al. 2012). This includes the recognition of the ecological and socio-economic heterogeneity of landscapes. It provides guiding principles, including tree-based and treeless systems to restore biodiversity, productivity, and other structural or functional attributes at the landscape scale (Lamb et al. 2012; Mansourian 2005). The FLR options encompass assisted and unassisted reforestation, afforestation, and agroforestry (Erdmann 2005; Vásquez et al. 2022).

Agroforestry systems offer numerous advantages but also pose challenges, which have been intensively studied over the past 50 years (Nair et al. 2021a). The multifunctional benefits of agroforestry can be particularly emphasized when integrated into a landscape to increase heterogeneity (Meli et al. 2019; Willmott et al. 2023). Multifunctionality is defined here as the ability of a landscape or land-cover to provide multiple ecological, economic, and social functions and benefits (Hodbod et al. 2016). By establishing a permanent vegetative cover in agricultural landscapes, agroforestry systems can increase landscape connectivity (Willmott et al. 2023) and support biodiversity conservation (Bhagwat et al. 2008; Lin 2010; Somarriba et al. 2012). In the tropics, their advantage is that trees provide shade beneficial to crops or animals (Ivezić et al. 2021). At the farm scale, agroforestry systems exhibit a greater structural and functional complexity than their monoculture counterparts (pasture, cropland, or forest plantation) (Jose 2009). This can allow for more efficient use of nutrients, light, and water (Plieninger et al. 2020) and can enhance a wide range of ecological ecosystem functions (Plieninger and Huntsinger 2018), including soil improvement (Kessler et al. 2012), carbon sequestration (Kirby and Potvin 2007; López-Santiago et al. 2023), microclimate regulation (Jose and Udawatta 2021), prevention of water erosion (Aguiar et al. 2010), improvement of air quality (Jose 2009), and potentially increased yields and restoration of degraded land (Gibbons 2010; Nair and Garrity 2012; Silva-Galicia et al. 2023; Vieira et al. 2009). In addition, agroforestry systems provide farmers with a greater variety of products, which can increase diversity for home consumption or marketable goods. This makes farmers less vulnerable to changing market and environmental conditions (Willmott et al. 2023).

However, the complexity of the different components of an agroforestry system also poses challenges for farmers. For example, farmers need to know the positive and negative biophysical interactions between tree and crop components and potential competition for resources (Cubbage et al. 2012; Dagang and Nair 2003; Silva-Galicia et al. 2023; Somarriba et al. 2012). In eastern Panama, several obstacles exist to agroforestry adoption, particularly for smallholder farmers who dominate the region (Gosling 2021). These farmers, typically operating family-run farms with limited incomes and weak market connections (Baker et al.

2017), face challenges such as higher labor demands and investment costs associated with transitioning to agroforestry (Andreotti et al. 2020; Fischer and Vasseur 2000). Furthermore, farmers may face problems with reduced flexibility when planting trees on agricultural land compared to conventional land use (Langenberg et al. 2018). Besides, product commercialization can be a hurdle, as farmers need traders to pay fair prices for the comparatively small quantities of individual products from their diverse systems (Willmott et al. 2023). Additionally, insecure land tenure and the cumbersome process of obtaining permits for tree harvest and transport further add to the challenges (Somarriba et al. 2012).

Ecologically, agroforestry has been argued to be a poor alternative to forests because they often resemble small forest fragments surrounded by open land, potentially limiting the richness of endemic forest species (Bhagwat et al. 2008; Caparrós and Jacquemont 2003).

Hence, the desirability and extent of agroforestry systems in eastern Panama's study area remains unclear. Importantly, research on sustainable landscape management across various land-cover options, including agroforestry, remains limited (Grass et al. 2020; Plieninger et al. 2020).

1.4.2 Analyzing trade-offs in landscapes

Landscapes typically serve multiple purposes, such as food production and biodiversity conservation. A major challenge for decision-makers is managing trade-offs between conflicting objectives (Zheng et al. 2019). Trade-offs arise when an individual or group prioritizes and exchanges one ecological, economic, or social benefit of an ecosystem for another. These can be driven by land-use change (Steffan-Dewenter et al. 2007; TEEB 2010). A typical example is the increase in agricultural productivity at the expense of biodiversity loss (Mehrabi et al. 2018). Therefore, a deep understanding of trade-offs between competing objectives is a prerequisite for sustainable landscape planning (Bolliger et al. 2011; Kaim et al. 2018; Zheng et al. 2019).

Various studies have explored, quantified, and visualized trade-offs between ecosystem services to improve management (Grass et al. 2020; Kremen and Miles 2012; Palm et al. 2010). Four main approaches have been identified to manage trade-offs (Zheng et al. 2019): (1) empirical studies of ecosystem services to identify ecosystem values and trade-offs (e.g. (Campagne et al. 2018), (2) investigations of land-use strategies (e.g., Steffan-Dewenter et al. 2007; Tscharntke et al. 2012), (3) scenario analysis of policy intervention to create effective financial incentives (e.g., Nelson et al. 2009), and (4) multi-criteria decision analysis considering multiple stakeholder objectives of different interest groups (e.g., Andreotti et al. 2018).

Multi-criteria decision support tools, particularly multi-objective optimization, can simultaneously consider ecological, economic, and social objectives, which can provide essential insights for effective landscape planning strategies (Goldstein et al. 2012; Liu et al. 2019). These optimization models can be categorized as discrete multi-attribute decision-making models and scalarization-based continuous optimization models (Kaim et al. 2018). Discrete multi-attribute decision-making models can evaluate a finite number of land-cover patterns and predefined scenarios regarding ecological and socio-economic objectives (Palma et al. 2007b). However, such an approach risks that the optimal solution lies in between two or outside the scenarios (Kaim et al. 2018). Alternatively, scalarization-based, continuous multi-objective optimization (as presented in this thesis) can evaluate multiple objectives simultaneously without relying on predefined scenarios (García-de Ceca and Gebremedhin 1991; Grass et al. 2020). The results are potentially desirable land-cover compositions at the farm or landscape scale, representing compromise solutions. This is helpful because it may be unlikely to find a win-win solution, as not all objectives can yield maximum values concurrently. Therefore, compromise solutions may be more promising when mitigating trade-offs (Bennett et al. 2009; Mendoza et al. 1987), contrary to the views of some other researchers (e.g., Zheng et al. 2019).

In FLR research, studies simultaneously analyzing agroforestry as one of several land-cover options and the trade-offs between ecological, economic, and social objectives of different interest groups are still rare. Existing studies often focus on single ecosystem services and restoration options, neglecting the full range of essential land-cover types (Adamowicz et al. 2019; Simonit and Perrings 2013). Furthermore, calls have been raised to bring together scientific knowledge and empirical experience in the search for sustainable land management solutions (Turnhout et al. 2012). Integrating diverse interest groups, such as local farmers and government agencies, into research can help link social science to land-use planning (traditionally two separate disciplines). Such links are essential to derive desirable landscape compositions and understand trade-offs and potential conflicts for future planning.

Researchers, policy makers, and practitioners continue to explore innovative ways to navigate the challenges of sustainable landscape planning. Hence, there is a need for normative models that can analyze trade-offs between multiple ecological and socio-economic objectives and involve different interest groups at different stages of the research to derive recommendations.

1.4.3 Exploring desirable landscape compositions under uncertainty

Effective landscape planning considers both composition and configuration to achieve desired outcomes (Gámez-Virués et al. 2015). Landscape composition refers to the types and quantities of land-cover elements, such as forests and agricultural land, while configuration pertains to their spatial arrangement (Verhagen et al. 2016). However, as a first step, this study focuses specifically on questions related to landscape composition.

Exploring desirable landscape compositions becomes increasingly complex when considering the inherent uncertainty surrounding current and future land-cover capabilities. The agricultural production sector is inherently subject to risks and uncertainties, which significantly challenges decision-making (Do et al. 2020; Gundimeda 2019; Mercer 2004). The risks and uncertainties can be attributed to variations in production conditions, market dynamics (e.g., price fluctuations), and political changes (Anderson 2003; Komarek et al. 2020). Risk refers to the limited knowledge of decision-makers regarding the likelihood of future events, which can be quantified by probabilities (Paul et al. 2020). In contrast, uncertainty (as considered in this thesis) arises from the lack of knowledge concerning the variability in land-cover performance, such as crop production, due to natural phenomena (e.g., weather) that cannot be quantified through probabilities (Kangas and Kangas 2005; Walker et al. 2013). Incorporating risk and uncertainty into decision-making is essential to consider resource allocation strategies, such as land-use diversification, to mitigate these challenges (Grêt-Regamey et al. 2013). Such land allocation strategies may differ based on the decision-maker’s attitude towards risk, i.e., risk-neutral, risk-averse, and risk-seeking. For example, risk-averse farmers may employ diversification strategies to buffer uncertainty (e.g., Baumgärtner and Quaas 2010).

Researchers use various techniques to explore desirable landscape compositions under uncertainty. Simulation approaches, such as agent-based models, can analyze trade-offs between multiple objectives and theoretically account for uncertainty in the decision-making of the agents (Dislich et al. 2018; Kelley and Evans 2011; Lusiana et al. 2012; Paul et al. 2019). The benefits of this model approach include its suitability for configurational land-use allocation problems and its ability to simulate the agent's interaction (Gonzalez-Redin et al. 2019; Lenfers et al. 2018). However, it is relatively data-intensive, which poses challenges given the common situation of data scarcity in landscape research (Paul et al. 2019). Another drawback is that it is challenging to reproduce results (Kremmydas et al. 2018).

Alternatively, scalarization-based and Pareto-based multi-objective optimization models offer land allocation solutions that strike a balance between improving one objective without degrading another. Scalarization-based optimization aims to balance conflicting objectives by aggregating them into a single scalar value or objective function, which finds a single optimal solution (Kaim et al. 2018). Scalarization methods include weighted sum and goal programming (Reith et al. 2022; Schmidt et al. 2019). Such an optimization method allows the exploration of different trade-offs between multiple objectives, for example, by adjusting the weights assigned to each objective (Reith et al. 2022). Pareto-based optimization approaches generate a set of efficient land-cover allocations, wherein each solution cannot be improved without worsening one or more objectives, thus facilitating trade-off analysis. The advantage of this approach lies in enabling discussions with interest groups based on optimal land-cover compositions and associated trade-offs (Andreotti et al. 2018). However, conventional scalarization and Pareto-optimization approaches typically do not account for uncertainty (Kaim et al. 2018; Paul et al. 2019). However, Gang et al. (2023) present an approach that integrates uncertainty into the optimization framework to assess the value of different tree species under competing objectives using Pareto frontiers.

Like Markowitz's (1952) Modern Portfolio Theory, portfolio-based optimization approaches account for uncertainty by advocating diversification to reduce the risks associated with individual assets/land-cover. For example, Blandon (2004) assessed the expected net present value and associated risk (measured as the standard deviation) of monocultures and crop mixes (agroforestry systems) to evaluate crop combinations with the highest return for a given level of risk. When combined with scalarization-based optimization, this approach can account for uncertainty and land-use diversification effects to balance multiple predefined objectives with a given land-cover set. Such an approach can identify one optimal solution within a continuous land-use allocation set, facilitating discussions with decision-makers. One example of such a model is the robust multi-objective optimization model developed by Knoke et al. (2015; 2016) and tested at a landscape scale in Latin America (e.g., Knoke et al. 2020b; Uhde et al. 2017). While the model has been tested for different agroforestry options at the farm level (Gosling et al. 2020a; 2020b; 2021), it has not yet been used to assess agroforestry as part of a range of FLR options at the landscape scale.

1.5 Research framework

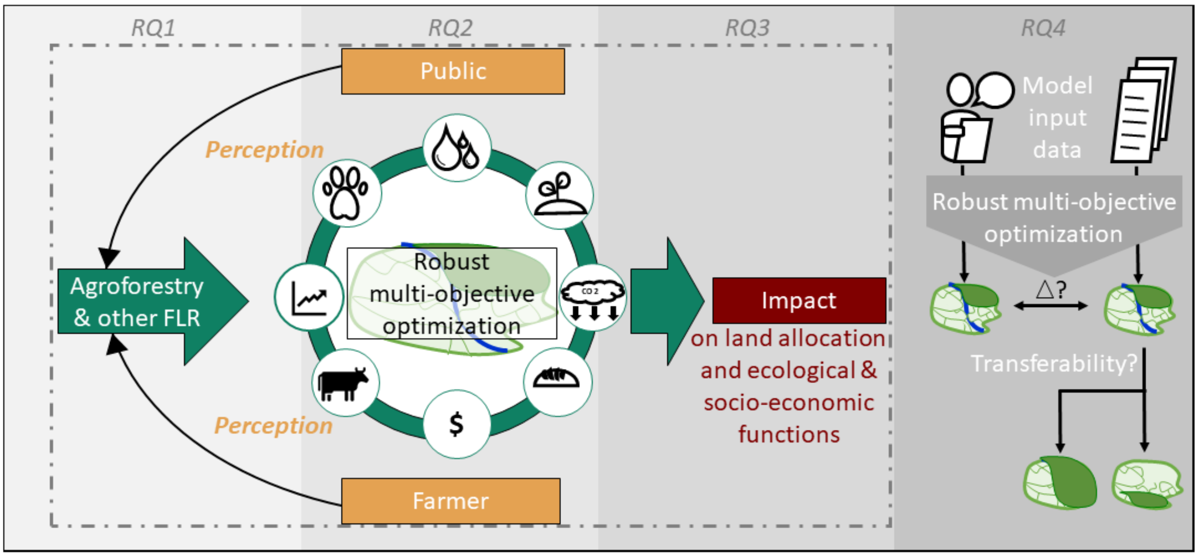

Figure 1 Schematic framework of the thesis. The shades of gray in the background represent the scope of the four RQs (RQ). The corner stone of this research is the robust multi-objective optimization model. The fourth RQ assesses the robustness of the model against variations of the input information and examines the transferability of results to similar tropical regions.

This thesis is structured into five chapters. Chapter one introduces the contextual background and study area. It delves into the existing knowledge regarding FLR and multifunctional landscapes, the analysis of trade-offs, and tools employed to investigate desirable landscape compositions under uncertainty. This chapter ends with an overview of the thesis’s structure.

Chapter two provides a comprehensive outline of the methodologies applied in this research. This encompasses acquiring data through surveys and literature review, as well as using a robust multi-objective optimization model.

Chapter three presents the main findings, which are organized into four sub-chapters aligning with the four RQs (Figure 1). This thesis comprises contributions from two published studies (Appendix: Table 1). Chapter 3.1 is based on the publication of Reith et al. (2020). This initial study employed surveys to assess land-cover perception and preferences, and robust multi-objective optimization to evaluate the desirability of agroforestry in a multifunctional landscape at the forest frontier in eastern Panama. Derived from this publication, the first RQ of this thesis examines the perceived effectiveness of various FLR options (agroforestry, forest plantation, and natural succession of abandoned land) in fulfilling multiple objectives at the landscape scale under uncertainty.

The second published study (Reith et al. 2022) contributes to the second RQ, which examines potential land-use conflicts arising from ecological, social, and economic trade-offs between the public and local farmers (Chapter 3.2). Therefore, the dataset augmented the model input data from the first study by incorporating additional survey responses and objectives from farmers obtained by Gosling et al. (2020b).

To address the third RQ, another dataset was compiled based on literature data and calculations to assess the impact of agroforestry adoption at the landscape scale (Chapter 3.3). This data set allows for quantifying land-use change and their impacts on ecological and socio-economic functions.

For the fourth RQ, the literature dataset was extended to encompass data from study sites in two additional tropical countries (Chapter 3.4). This final RQ evaluates the robustness and transferability of the model and its outcomes.

Chapter four interprets the main findings and undertakes a cross-thematic discussion in light of the relevant literature. This includes a critical reflection on the methodology and an outline of the conceptual contribution of this study to the fields of FLR research and land-use planning. It also highlights directions for future research.

Finally, chapter five concludes with implications relevant to the interest groups involved.

2. Materials and Methods

2.1 Model input data sets

Seven land-cover options were selected to explore theoretically optimal landscape compositions for the study area (Table 1). This selection includes common and purely agricultural land uses, forest and FLR options (including afforestation and regeneration of deforested and degraded land), and the reintroduction of trees through agroforestry. The agroforestry systems (silvopasture and alley cropping) in this study represent innovative land-cover options because they are not currently practiced in the study area. Previous studies have shown that these agroforestry systems, with substantial tree densities suitable for timber use, are economically competitive in the study region (Gosling et al. 2021; Paul et al. 2017b).

The thesis assesses the land-covers against various ecological and socio-economic indicators. The indicators commonly found in the existing literature serve to specify or quantify the potential objectives of different interest groups and encapsulate the diverse demands on a landscape. These encompass the direct and indirect contributions of an ecosystem to human well-being. The objectives are categorized as ecological and socio-economic objectives that cover the four ecosystem service categories outlined in the Millennium Ecosystem Assessment (Millennium Ecosystem Assessment 2005), as well as considerations for biodiversity conservation, social requirements, and economic benefits (Table 2). In this study, the demands are termed *objectives* in the surveys, while the quantifiable elements used for measurement and calculation purposes are referred to as *indicators*.

A dataset based on primary and secondary data sources was compiled to address each RQ (Table 2). Surveys with experts from various backgrounds provided essential data on perceptions and preferences for the selected land-cover options to meet multiple ecological and socio-economic objectives. The survey data set was particularly relevant to the first RQ. To facilitate comparison between farmers and other experts in the second RQ, this dataset was expanded to include additional responses and objectives from farmers.

For the third and fourth RQs, secondary data provided estimates for ecological and socio-economic indicators for impact assessment. Due to data scarcity, estimates for each indicator were unavailable for all the land-cover options in the study area. As a result, the research primarily concentrated on two of five ecological indicators associated with carbon sequestration and soil fertility, which play a crucial role in mitigating climate change and supporting agricultural productivity (Kraenzel et al. 2003; Moore et al. 2018; Neumann-Cosel et al. 2011; Shi et al. 2018; Tschakert et al. 2007). A subset of the dataset from the third RQ was used to assess and compare three tropical landscapes to address the fourth RQ.

Table 1 Description of the land-cover options included in this thesis. Superscript denotes the Forest Landscape Restoration (FLR) options. *Natural succession was part of the optimization regarding the RQ1 but was omitted in optimizations later on for technical reasons (see discussion on perception data in Chapter 4.4.2). Adapted from Table 2 in Reith et al. (2020).

Land-cover	Description
Conventional agricultural options	
Cropland	Land can include various species of annual crops, such as maize, cultivated as monocultures or crop-mix on one plot of land at the same time or rotated over time. Land receives fertilizer and pesticides, is not irrigated, and is planted and harvested using manual/traditional methods (Schuchmann 2011).
Pasture	Improved pasture with a stocking rate of around two cows per hectare may include scattered trees (INEC 2011; Paul 2014).
Agroforestry options	
Alley cropping^{FLR}	Rows of annual crops (such as maize) are grown in between alleys of trees such as teak, *Tectona grandis* (with a distance of around six meters in between). Initially, 550 trees are grown for timber (with a rotation of 20 years). After five years, shading prevents crop cultivation (Paul et al. 2017b).
Silvopasture^{FLR}	Cattle grazing (conservative count of around one cow per ha) is combined with timber production (initial tree density of 200 Spanish cedar (*Cedrela odorata*) per ha) on the same land. Planted or naturally generated trees are harvested for timber after 20 years (Cerrud et al. 2004; Montagnini et al. 2013; Reyes Cáceres 2018).
Forest cover options	
Forest plantation^{FLR}	Teak plantations are grown as even-aged monocultures regularly spaced with an initial density of 1100 trees and undergo thinning and harvesting after 20 years (Paul et al. 2017b).
Natural succession^{FLR,*}	Abandoned crop- or pasture land, which has not been managed or cultivated for more than five years and undergoes natural succession of vegetation(INEC 2011).
Forest	Mature and humid tropical forest that is unmanaged and not used for commercial timber production but can be used to collect firewood or fruits (INEC 2011; Paul 2014).

Table 2 Summary of objectives defined by indicators and corresponding datasets for the study site in eastern Panama. For RQs 1 and 2, datasets were assembled from primary data sources, while RQs 3 and 4 used secondary data for the indicators. Adapted from Table 1 in Reith et al. (2020).

Objective	**Indicator (unit)**	**Description**	**RQ1**	**RQ2**	**RQ3**	**RQ4**
Ecological group						
Water regulation	Saturated hydraulic conductivity (Ks; mm h^{-1})	The ability of a land-cover to mitigate surface runoff and store water in the soil and avoid soil erosion. High values indicate better soil infiltration (e.g., dense vegetation cover), whereas lower values suggest reduced soil permeability (e.g., due to livestock-induced compaction) (Alegre and Cassel 1996; Hassler et al. 2011; Kumar et al. 2012; Zimmermann et al. 2006)	●	●	o	o
Global climate regulation	Total estimated carbon (Mg ha^{-1})	The capacity of land-cover to retain atmospheric carbon within above-ground and below-ground vegetation and soil to mitigate global climate change (excluding substitution effects) (Kirby and Potvin 2007; Kraenzel et al. 2003; Tschakert et al. 2007)	●	●	●	●
Microclimate regulation	Evapotranspiration (mm)	The influence of a land-cover on local and regional climates (Ogden et al. 2013; Siles et al. 2010)	●	●	o	o
Long-term soil fertility	Soil organic carbon (Mg ha^{-1})	The ability of a land-cover to maintain soil fertility, quality and health over an extended period crucial for biomass production (Moore et al. 2018; Neumann-Cosel et al. 2011; Shi et al. 2018; Siles et al. 2010)	●	●	●	o
Biodiversity	Species richness of animals and plants	The degree to which the land-cover promotes biodiversity by offering diverse habitats (Cerda et al. 2014; Petit et al. 1999; Simonit and Perrings 2013; van Bael et al. 2013)	●	●	o	o

Table continued

Objective	**Indicator (unit)**	**Description**	**RQ1**	**RQ2**	**RQ3**	**RQ4**
Socio-economic group						
Food security	Dietary caloric supply (Mcal ha^{-1} yr^{-1})	The contribution of a land-cover in ensuring consistent food production regarding dietary caloric supply (Gosling et al. 2021; Paul et al. 2017a).	●	●	●	●
Long-term profit	Net present value ($ ha^{-1})	The revenue generated from a land-cover over an extended period, such as 20 years (Coomes et al. 2008; Current et al. 1995).	●	●	●	●
Liquidity	Payback period (years)	Consistent income generation and the ease with which land-cover can be converted into cash (Coomes et al. 2008; Jarisch et al. 2022)	●	●	●	o
Investment costs	The sum of all costs incurred in year 0 ($ ha^{-1})	The initial expenses associated with setting up a land-cover (Do et al. 2020; Gosling et al. 2021; Rahman et al. 2017)	o	o	●	o
Stability of economic return	Financial loss ($ ha^{-1})	Stable income is generated by land-cover despite potential risks like pests and diseases, extreme weather events, and price fluctuations (Ramírez et al. 2001; UN 2017)	●	●	o	o
Labor demand	Labor days (Days ha^{-1} yr^{-1})	The average number of workdays needed to establish and maintain a specific land-cover (Dagang and Nair 2003; Gosling et al. 2021; Kingwell 2011)	o	●	●	o
Experience	Farmers' reported experience	An expression of the degree of acquaintance with a given land-cover, as a lack of such knowledge, can hinder its practical implementation (Andreotti et al. 2020)	o	●	●	o

Table continued

Objective	Indicator (unit)	Description	RQ1	RQ2	RQ3	RQ4
Management complexity	Perceived complexity	An expression of the heterogeneity of tasks and special equipment and technical knowledge needed to manage the land-cover (Calle et al. 2009; Kingwell 2011; Gosling et al. 2020b)	o	●	●	o
Scenic beauty	Cultural preference	Personal preference for the land-cover to reflect cultural values (Knoke et al. 2014)	●	●	●	o

2.2 Data collection

2.2.1 Analytic hierarchy process survey

Quantitative survey data can serve as a valuable complement or even alternative to empirical data when assessing the ecological and socio-economic performance of different land-cover options (Burkhard et al. 2014; Fontana et al. 2013; Kangas and Kangas 2005; Knoke et al. 2014; Qureshi and Harrison 2003; Uhde et al. 2017). This is particularly beneficial in the realm of landscape planning, where comprehensive datasets for a diverse range of land-cover options may be limited or unavailable, especially in cases where innovative land-use systems are not yet practiced.

This study employed a stratified and purposive sampling approach to elicit informed opinions from individuals with relevant land-cover expertise (Bryman 2016). The survey targeted five groups assumed to have a vested interest in land use: government agencies, non-governmental organizations, corporations, universities, and research institutes (from hereon called *experts*), and farmers and other locals in the study region, Tortí (for detailed information on sampling and survey design refer to Reith et al. 2020). We conducted face-to-face surveys in both Spanish and English over six weeks in Panama (April – May 2018), with additional online surveys conducted between April and September 2018. Before commencing the survey, we explained the purpose of the research to participants, emphasized the voluntary and confidential nature of their participation, and provided information about the region, including definitions of each objective and land-cover option (see Tables 1 and 2). In total, 54 experts representing 36 organizations and 26 farmers and locals participated in the survey.

We used the Analytic Hierarchy Process (AHP) developed by Saaty (1987), which is a widely used multi-criteria decision analysis technique known for its versatility and applicability across various domains, including ecological economics (Parra-López et al. 2008) and natural resource management (Schmoldt 2011; Uhde et al. 2017). AHP accommodates diverse survey techniques (both online and face-to-face), caters to multiple interest groups with varying backgrounds, and can consider a wide array of objectives, including intangible factors like personal land-use preferences. It is especially valuable when comparing several options and ranking them when there is no clear best choice (Parra-López et al. 2008).

Respondents were tasked with deciding which of the two land-covers performs better against a given objective and to what degree. In total, they completed 21 such pairwise comparisons for each objective. Following Saaty (1987), survey participants provided responses on a nine-point scale, where one indicated that two land-covers (e.g., pasture and cropland) were equally suitable for a given objective (e.g., food security), and nine denoted an extreme preference for one land-cover over the other. These scores were subsequently transformed to a scale ranging from 1 to 17, with one indicating extreme unsuitability and 17 representing Saatys' value of 9 (extremely better). Finally, following Uhde et al. (2017), individual responses were aggregated using the arithmetic mean to derive a group judgment for each objective and land-cover option. To account for response variability, the standard deviation was calculated.

To prevent survey fatigue, the number of objectives assessed per session was limited by bundling ecological and socio-economic objectives into two separate surveys. If participants were willing, they were invited to complete the other objective bundle later, either online or in a face-to-face setting. Ultimately, we obtained 36 to 40 evaluations or completed sets of comparisons for each indicator.

2.2.2 Literature review

An extensive literature review was conducted to assess and quantify the ecological functions and socio-economic benefits of different land-cover options. The focus was on studies with regional relevance, preferably those conducted in Tortí and its surroundings, which provided scores for the studied land-cover options and indicators (Tables 1 and 2).

The socio-economic indicators can reflect factors that have the potential to influence land-use decisions made by local farmers (Fischer and Vasseur 2000; Tschakert et al. 2007). For this study, socio-economic indicator scores were based on the work of Gosling et al. (2020b; 2021). Their farmer surveys and extended cost-benefit analysis focused explicitly on the Tortí study region. They included nearly identical land-cover options to those examined in this study (except for the *natural succession of abandoned land*). To elicit expected mean scores and the associated variability of land-cover options against multiple socio-economic indicators, Gosling et al. (2020b; 2021) applied a rank and scoring method with farmers and a discrete land-use model. In this study, the indicator *experience* extends the socio-economic indicator set (Table 2). A lack of experience has been reported as a barrier to adopting agroforestry practices (Holmes et al. 2017; Somarriba et al. 2012). The experience with land-cover options was quantified based on experience scores (1 = no experience, 2 = some experience, 3 = extensive experience) obtained in farmer surveys conducted by Gosling et al. (2020b) (unpublished data). Similar to the quantification of land-cover preference (Knoke et al. 2014), the experience measure does not reflect the expected mean score (like the other indicator scores), but represents the number of times that farmers expressed having experience with a given land-cover (with a preference for higher scores). The uncertainty measure of this count data was derived by computing the standard error of the mean following Knoke et al. (2014). In this case, and for the indicator of land-cover preference of farmers, the uncertainty measure was computed as the standard error of the mean (Gosling et al. 2020b), which can be interpreted as the standard deviation (like the other indicators) for count data.

The ecological indicators were selected based on their capacity to reflect the ecosystem services of carbon sequestration and long-term soil fertility. Carbon sequestration is a pivotal component in endeavors to mitigate climate change (Albrecht and Kandji 2003; IPCC 2008). Numerous national and international policies and funding mechanisms have been established to bolster carbon sequestration initiatives (Chazdon 2019; García et al. 2016; MiAmbiente 2018; Nair et al. 2009). By giving precedence to carbon sequestration in land-use planning, communities may access financial incentives and resources to promote sustainable land management practices (Jose 2009). Beyond directly addressing climate change, carbon sequestration also yields supplementary ecological benefits. Forests and land-covers that sequester carbon often support biodiversity, improve water quality and soil health, and offer recreational value (Alamgir et al. 2016; Arroyo-Rodríguez et al. 2020). The ability of each land-cover to store carbon was estimated by deriving an expected mean score and associated variation (as described below in Chapter 2.2.3).

Related to carbon sequestration is the indicator soil organic carbon (SOC). Increasing SOC levels can assist in the sequestration of carbon dioxide from the atmosphere, thus contributing to efforts to reduce greenhouse gas emissions and mitigate climate change (Nair et al. 2009). SOC is primarily comprised of organic materials, such as decomposed plant residues, that have become integrated into the soil over time (FAO 2017). Elevated SOC levels correlate with enhanced soil structure, nutrient retention, and water-holding capacity, which are paramount for agriculture and food production (Lal 2020; Tamene et al. 2019). Consequently, SOC is pivotal in ecosystem services associated with soil fertility and productivity. SOC is a widely employed indicator, facilitating data collection across various land-cover options. The relevant studies derived SOC stocks from carbon concentrations and bulk densities of soil samples (Kraenzel et al. 2003; Neumann-Cosel et al. 2011; Tschakert et al. 2007). When data were absent for the study region, these gaps were addressed by extrapolating scores from analogous research sites in Panama. In the case of the alley cropping system, the SOC score had to be approximated. This was achieved by using the specified carbon concentration and bulk density values from field measurements by Paul (2014) and applying the equation delineated by Kirby and Potvin (2007). Silvopasture data had to be taken from a study that reported values for the tropics worldwide (Shi et al. 2018). In this study, reference is made to the soil carbon content in the surface soil layer, specifically within a depth of 0 to 10 centimeters, expressed in mega grams per hectare (Mg ha^{-1}), with higher scores indicating a more favorable outcome.

2.2.3 Estimating total carbon stock by land-cover

Despite the increasing research interest in nature-based climate solutions (Chausson et al. 2020; Cohen-Shacham et al. 2019; Matthews et al. 2022; Seddon et al. 2021; van Noordwijk et al. 2020), few studies have explored the carbon storage and sequestration potential across the full spectrum of forest and agriculture-based land-cover options in a single location. A major challenge involves addressing data gaps and variability associated with allometric models and sample sizes to establish a consistent dataset for six specific land-cover options, focusing on carbon sequestration. The Intergovernmental Panel on Climate Change (IPCC) offers datasets for major land-use categories worldwide and provides clear guidelines for estimating carbon stocks in soils to determine a consistent dataset of expected mean scores and associated uncertainties.

The three IPCC land categories can be subdivided based on whether the land remains in the same category or is converted from one category to another (IPCC 2006). This study adopts the first static approach. However, a drawback is that the FLR options are not listed as distinct categories. Consequently, forest plantations are categorized under *forest land*, alley cropping under *cropland*, and silvopasture under *grassland* (IPCC 2006).

According to the IPCC, carbon is stored in living-standing vegetation, including stems, branches, and bark, and below-ground biomass in roots and the soil (IPCC 2008). Dead organic matter pools, such as dead wood and litter, also store carbon (IPCC 2006), although they are not explicitly included in this study. Pastures can store substantial carbon in their roots and soil (Fujisaki et al. 2015). Therefore, accounting for total carbon stored in pasture is necessary to adequately represent this land-cover option, rather than only considering above-ground biomass. Moreover, soils have the potential to store approximately three times more carbon than plant biomass (Batjes and Sombroek 1997).

Therefore, the total carbon stored by land-cover at the end of the rotation period was estimated and expressed in megagrams per hectare (Mg C ha^{-1}), where higher values are more desirable. IPCC's Tier 1 approach provides highly aggregated estimates, and it is advisable to consider employing a Tier 2 or Tier 3 approach whenever feasible (IPCC 2006). Additionally, it is recommended to calculate error estimates, such as the standard deviation (IPCC 2006). For this study, the estimation methodologies employed for agricultural land and tropical rainforests were consistent with the IPCC Tier 1 approach (Table 3). Specifically, IPCC Tier 1 estimates encompassed both above- and below-ground pasture biomass, relying on multi-year averages within tropical moist and wet climate zones (IPCC 2006). An above-ground biomass estimate was omitted for annual crops, as it is assumed that any biomass increment is offset by losses incurred from harvesting and mortality within a given year (IPCC 2006).

For forests, above-ground biomass estimates were provided for primary natural tropical forests in North and South America (IPCC 2019). These estimates are primarily derived from allometric equations rooted in direct measurements and database values of tree attributes such as diameter at breast height (DBH) and height (e.g., Álvarez-Dávila et al. 2017; Sullivan et al. 2017). To estimate below-ground biomass in roots, the default root-to-shoot ratio of 0.24 was used as recommended by Cardinael et al. (2018), IPCC (2006), Kirby and Potvin (2007) for perennial woody vegetation in the tropics. Subsequently, the carbon fraction of dry matter was applied to convert biomass into a carbon stock (Table 3).

To determine SOC content in the 0-30 cm depth range, this research adhered to IPCC guidelines and used regional-specific data for estimations. This decision was motivated by the IPCC default values being based on relatively undisturbed native ecosystems, which may not accurately represent the conditions in the study area. Following the approach delineated by Ogle et al. (2003), the SOC stocks were estimated rather than relying on the IPCC default values. A reference SOC score and its corresponding range of variability were established, employing Monte Carlo Simulation (MCS; Ogle et al. 2003). These modifications were guided by field measurements conducted near the study area for various land-cover types, including cropland, pasture, and managed forest land (Kirby and Potvin 2007; Paul 2014; Tschakert et al. 2007).

A frequency distribution was generated using an MCS of 50,000 repetitions and the random selection of reported SOC stores (ranging from 40 to 60 Mg C ha^{-1}). This distribution derived a mean score of 50 Mg C ha^{-1} and the standard deviation to represent a SOC reference for forests (Table 3). Notably, this reference score is lower than the IPCC default score of 60 Mg C ha^{-1} but is assumed to offer a more accurate reflection of local conditions across most of the landscape. Moreover, the calculation of the standard deviation allows for the consideration of variability in local conditions.

The estimated SOC reference score was multiplied by factors that broadly define land-use and management aspects to obtain land-cover-specific estimates for SOC. These specific factors were obtained from the relevant IPCC tables. They included scores for permanent cropland and grassland, no-till or moderately degraded pasture, and medium input levels of organic matter (IPCC 2006). To determine the associated standard deviation for each land-cover, the coefficient of variation of the SOC reference value derived from the MCS was used, amounting to 12%.

Table 3 Biomass and carbon stock estimates for the three IPCC land categories within the Tropical Moist and Wet Climate Zones of North and South America, defaulted to IPCC (2006, 2019) unless otherwise specified.

	Forest	Cropland	Grassland
Above-ground biomass (t ha^{-1})	307.10 (±104.90)	0	
Total above and below ground biomass (t ha^{-1}) [a]	380.80	0	16.10
Proportion biomass to carbon [b]	0.5	-	0.43
Total above- and below-ground carbon (Mg C ha^{-1})	190.40	0	6.85
Estimated SOC (Mg ha^{-1}) [c,d,e]	50 (±6.06)	35.67 (±4.32)	48.50 (±5.88)
Total estimated carbon by land-cover (Mg C ha^{-1}) [e]	240.40 (± 82.12)	35.67 (± 4.32)	55.35 (± 5.88)

[a] The forest's below-ground biomass is approximated at 24% of its above-ground biomass (Cardinael et al. 2018; Kirby and Potvin 2007)

[b] Carbon stocks were determined by multiplying biomass with the respective carbon content values for forests (according to IPCC guidelines) or herbaceous plants (as per Ma et al. 2018)

[c] IPCC method for SOC stock estimates, IPCC (2006), Chapter 3, Equation 3.3.3

[d] Standard deviation for forest land (SOC reference) was estimated using Monte Carlo simulation (MCS)

[e] The coefficient of variation (12%) of the SOC reference was used to compute standard deviations for SOC cropland and grassland

It was necessary to estimate the biomass to calculate the potential carbon sequestration in the FLR systems. This was accomplished by simulating the growth of trees within forest plantations, silvopastore, and alley cropping systems using the land-use model by Gosling et al. (2021). This model incorporates various factors, such as tree growth with fluctuations in yield over a 20-year timeframe and reduced grass production area due to shading.

Subsequently, the estimation of above-ground biomass was conducted through the application of allometric equations (1) and (2) below (Pretzsch 2019). For teak and cedar, the modeling of tree diameter at breast height (DBH) and height was carried out using the land-use model (Gosling et al. 2021). An expansion factor was applied to ensure a comprehensive assessment of total tree biomass. This age-dependent factor assumes a value of 1 below a DBH of 10 cm and 3.4 above that threshold until the trees reach 20 years of age (IPCC 2006).

$$\mathrm{AGV} = \sum_{k=1}^{N} BA * H * FF * EF \tag{1}$$

where

AGV: above-ground volume [m^3]

BA: basal area as $(DBH/200)^2$ x pi [m^2]

H: tree height [m]

FF: form factor of 0.5 (Wishnie et al. 2007)

EF: age-dependent expansion factor of broadleaves to account for all of the tree and not just marketable timber IPCC (2006), Table 3A.1.10

N: number of trees

Following Pretzsch (2019), the biomass estimation encompassed the mean wood density per tree. This value is divided by 1000 to convert kg into tons to calculate the above-ground biomass per hectare. Additionally, within the silvopasture system, the biomass of pasture grass was diminished over a 20-year timeframe as a consequence of shading, following the methodology described by Gosling et al. (2021).

$$\mathrm{AGB} = AGV * WD * 0.001 \tag{2}$$

where

ABG: above-ground biomass (t ha^{-1})

WD: species-specific wood density (kg m^{-3}) for cedar 475.4 (ICRAF 2011) and teak 500 (IPCC 2006)

It is necessary to convert the biomass into carbon to compute the carbon stock present in above-ground biomass (3).

$$\mathrm{AGC} = AGB * CD \tag{3}$$

where

AGC: above-ground carbon (Mg C ha^{-1})

CD: carbon density in the dry wood biomass of teak 0.49 and cedar 0.46 (Elias and Potvin 2003) or herbaceous plants 0.43 (Ma et al. 2018)

Ultimately, the estimated above-ground and below-ground values can be added to the estimated SOC scores to calculate the total carbon stock potential for each FLR option, as indicated in equation (4). The SOC scores assigned to each FLR option correspond to their respective IPCC category SOC scores. Consequently, it was assumed that alley cropping and cropland share the same SOC score, just as silvopasture and pasture and forest plantation and forest were assigned identical SOC scores.

$$TC = AGC + BGC + SOC \tag{4}$$

where

TC: total carbon stock per ha (Mg C ha^{-1})

BGC: below-ground carbon stocks (in roots) as the proportion of below-ground carbon to above-ground carbon (woody vegetation = 0.24, Cardinael et al. 2018; Kirby and Potvin 2007; tropical grassland = 1.6 IPCC 2006)

SOC: estimated carbon stock in 0-30 cm soil depth based on IPCC (2006), Chapter 3, Equation 3.3.3

Finally, uncertainties related to the carbon storage capacity of the land-cover options were addressed. Standard deviations approximated with coefficient of variation expressed uncertainty for cropland, pasture, and forests (Table 3). For the FLR options, uncertainty, considering yield variations and SOC variability, was addressed using an MCS. The simulation model generated multiple outputs by randomly selecting input values for yields and SOC. Multiple runs of the MCS were performed, totaling 50,000 repetitions, from which a mean total carbon stock value was obtained. As a representation of uncertainty, the standard deviations were derived.

2.3 Robust multi-objective optimization

This study adopts the scalarization-based continuous multi-objective optimization methodology. Figure 2 illustrates the model's conceptual framework, while Table 4 offers a comprehensive summary of its elements. This model was originally developed by Knoke et al. (2015; 2016), drawing on the optimization solution algorithms introduced by Ben-Tal et al.

(2009). This approach represents a novel method for exploring multifunctional landscape compositions in Panama’s forest frontier and expands the boundaries of cost-benefit analysis or optimization of risk and return.

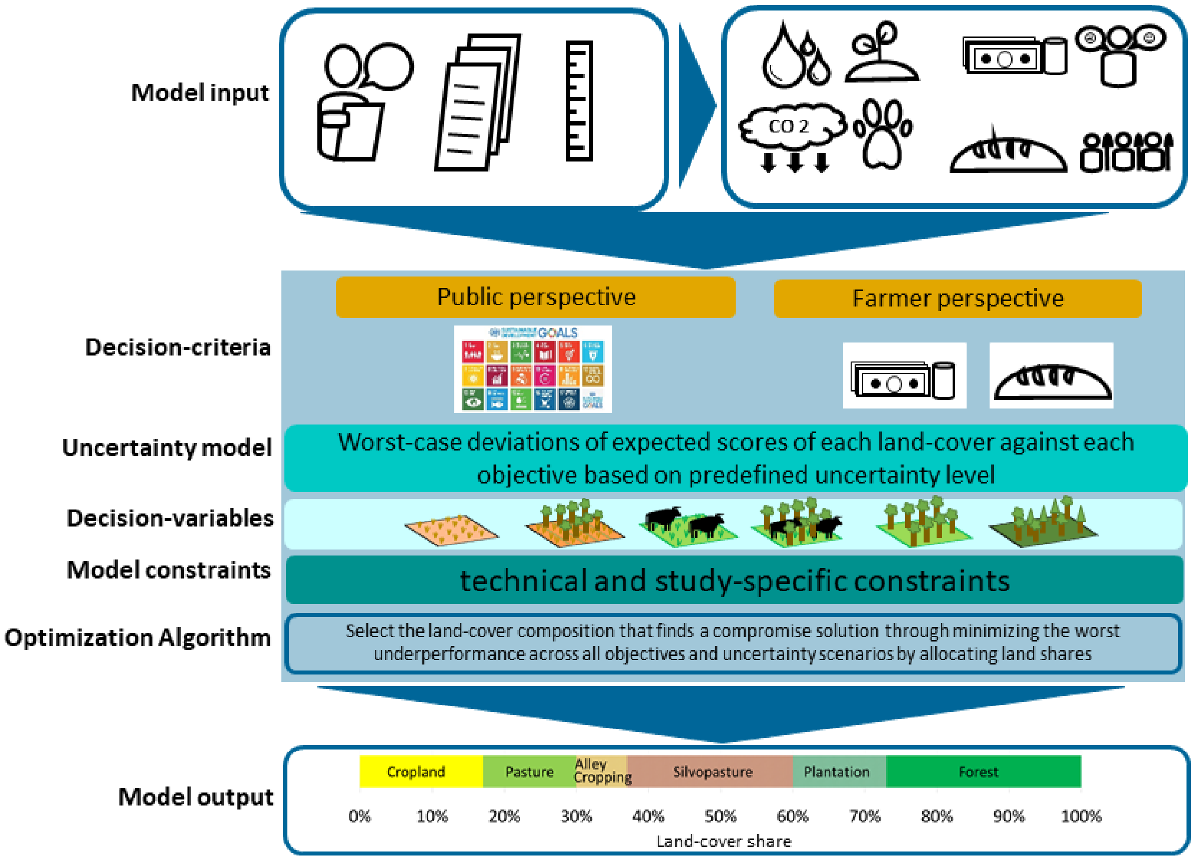

Figure 2 Schematic overview of the robust multi-objective land allocation model. The model developed by Knoke et al. (2015; 2016) draws upon optimization solution algorithms introduced by Ben-Tal et al. (2009). Figure adapted from Reith et al. (2022).

This optimization model is distinguished by its robust approach, enabling the active consideration of uncertainty regarding land-cover performance and the risk tolerance of decision-makers. This is in contrast to many other multi-criteria decision analysis tools that often overlook uncertainty (Castro et al. 2018; Kaim et al. 2018).

Uncertainty is incorporated through numerous constraints which each encapsulate one deterministic uncertainty scenario *u*, and represent all combinations of expected ecological or socio-economic land-cover performance and pessimistic or worst-case deviations (Knoke et al. 2020a). The level of uncertainty can then be adjusted with the uncertainty factor *fu* (Table 4) to create a range of potential worst cases (Knoke et al. 2022). Therefore, the parameter uncertainty is non-stochastic in contrast to stochastic programming frameworks that deal with probabilistic uncertainty (Castro et al. 2018). Compared to stochastic optimization this non-stochastic framework relies on just two input parameters per land-cover and indicator: an expected performance score that quantifies the ability of a given land-cover to achieve a given indicator R_{li}, and an associated uncertainty measure such as standard deviation SD_{li} or standard error of the mean (Castro et al. 2018). Unlike alternative approaches like mean-variance optimization, the robust multi-objective optimization model does not require data on correlations.

In this study, the focus is on uncertainty related to undesirable deviations from expected landscape performance R_{iu} for predefined indicators *i,* which depends on the land-cover shares a_l and their respective performance contributions R_{liu}. This reflects a risk-averse perspective when unfavorable outcomes occur (Bonilla and Vergara 2021). The performance level of landscape composition for each uncertainty scenario is normalized between 0 and 100 to allow for the integration of indicators with different units. The model selects the landscape composition that minimizes the greatest underperformance β across all indicators and uncertainty scenarios, where $100 - \beta$ represents the guaranteed performance for that landscape composition under uncertainty scenarios (Table 4). The optimization model is robust against uncertainty because it ensures compliance with the constraint, where the greatest underperformance β is indeed greater than or equal to the relative underperformances of hypothetical landscapes across all indicators and uncertainty scenarios D_{iu} (Knoke et al. 2022).

To attain this exact optimal land allocation, the optimization solution algorithm relies on a version of goal-programming, which facilitates the resolution of multiple indicators concurrently rather than addressing single-objective problems exclusively. Each indicator is assigned a theoretical target level of 100% (best achievable indicator value for a given landscape composition in each uncertainty scenario, R_{iu}^{*}). The optimization model seeks to minimize the most substantial deviations D_{iu} between achievement indicator levels for a given landscape R_{iu} and its target level R_{iu}^{*} across all indicators and uncertainty scenarios, following a MINMAX decision model (Härtl and Knoke 2019; Romero 2001; Romhadhoni et al. 2020; Shavazipour and Stewart 2021). The application of the MINMAX decision rule, which focuses on improving the underperformance of the worst-performing indicator, precludes compensation for poor-performing indicators with high-performing ones. This aspect is particularly crucial in the context of land-use planning, where the fulfillment of all defined indicators is necessary to achieve a satisfactory land allocation. This approach allows for the simulation of risk-reducing strategies, aimed at mitigating adverse outcomes in worst-case scenarios with the highest potential loss. This implies that decision-makers anticipate various possible outcomes.

Furthermore, by avoiding low performances of individual indicators, the model reduces the trade-offs between potentially conflicting indicators of different interest groups. This results in a compromise solution, meaning that enhancing one indicator is not possible without diminishing another (Knoke et al. 2016). In this regard, our model aligns with the principles of Pareto optimization. It is noteworthy that the form of goal programming employed in this research does not permit outcomes to surpass the assumed target level, thereby ensuring the avoidance of non-efficient or inferior solutions. However, it is important to distinguish between our optimization approach and Pareto optimization. While Pareto optimization offers a range of alternatives, all of which represent Pareto optimal solutions for a decision maker to select from, the optimization method in this study yields a single global optimum that is part of the Pareto frontier (i.e., the model works with scalarization). Both approaches have their merits, but having a single optimal solution simplifies the determination of a desirable land-cover composition (Reith et al. 2022).

The land allocation problem can be solved using open-source software, such as Excel Open Solver (Reith et al. 2022) or R (Husmann et al. 2021). The theoretically optimal land-cover compositions in the presence of uncertainty can be interpreted as desirable future landscape compositions that fulfill a predefined set of objectives while adhering to given constraints, even in worst-case scenarios. This normative research approach may help improve understanding of trade-offs, unintended consequences (such as deforestation), and compromise solutions for different interest groups. It is important to note that this approach does not aim to dictate or predict the specific appearance of a landscape. Nonetheless, the model can find application in a positive research context to represent existing land management decisions, as demonstrated by Gosling et al. (2020b) or to make predictions considering heterogeneous future expectations, how multiple farmers would likely decide about their land-use allocation, including deforestation decisions (Knoke et al. 2020b; 2023).

Table 4 Description of variables in the robust multi-objective optimization model. Adjusted from Table 4 in Reith et al. (2020) and Table A1 in Reith et al. (2022).

Model elements		**Description**
Objective function	$\min \beta$	The objective function, with $\beta = \max\{D_{iu}\}$, subject to the constraints $\beta \geq D_{iu}$ (see below).
	β	The worst underperformance (highest D_{iu} across all indicators *i,* and all uncertainty scenarios *u*). The optimization model aims to minimize this greatest distance D_{iu} between the highest achieved indicator level and the highest achievable level (100%) by allocating land to the given land-cover options.
	100-β	The guaranteed or minimum performance of the optimal land allocation solution for all indicators *i* and in all uncertainty scenarios *u*.
Decision criteria	D_{iu}	The MINMAX normalized distance between the hypothetical maximum R^*_{iu} ($\max\{R_{liu}\}$ or $\min\{R_{liu}\}$ for indicators where $more$ or $less\ is\ better$, respectively) and the achieved level R_{iu}. It represents the underperformance across all uncertainty scenarios, where a high value reflects a low performance (ranging between 0 and 100%) formulated as follows: $\frac{\lvert R^*_{iu} - R_{iu} \rvert}{R^*_{liu} - R_{liu*}} \cdot 100$
	R_{iu}	The performance score of a hypothetical landscape composition for each uncertainty scenario *u*, calculated as the sum of the indicator scores for each land-cover option multiplied by the area share in the landscape composition: $\sum_{l=1}^{L} R_{liu}\, a_l$.
	R_{liu}	The uncertainty adjusted score of indicators *i,* for land-cover *l*, in uncertainty scenario *u.* The mean expected score R_{li}, represents the best case in an optimistic scenario, while $R_{li} - f_u\, SD_{li}$ forms the unfavorable deviation from the expected score or worst-case in a pessimistic uncertainty scenario, when the indicator direction is *more is better* ($R_{li} + f_u\, SD_{li}$ if *less is better*).
Model input data	R_{li}	The nominal score of an indicator *i,* for a given objective (see Table 2) provided by land-cover *l* (Table 1), quantified via survey (Reith et al. 2020), measurements (Knoke et al. 2014), calculations (Gosling et al. 2021), or secondary data. It represents the expected mean performance score of a given land-cover to achieve a given objective.
	SD_{li}	The standard deviation of R_{li}. It represents a measure of uncertainty associated with the expected mean score. A high SD can indicate a high disagreement among survey participants (Reith et al. 2020).

Table continued

Model elements		**Description**
Uncertainty model	f_u	The uncertainty factor determines the undesirable deviation from R_{li}. The model is designed to optimize land allocations considering different levels of uncertainty ranging from 0 (ignoring uncertainty) to 3 (high level of uncertainty). A high level of uncertainty reflects a low predictability of the given land-cover achieving an objective. The level of uncertainty can also simulate the risk aversion of a decision-maker, where a risk-averse decision-maker would select a high level of uncertainty to include more pessimistic worst cases.
	u	The uncertainty scenario. The model actively integrates uncertainty into the modeling process using a set of deterministic scenarios (a combination of $2^{\text{number of land-cover considered}}$ on expected and worst-case scores for each indicator).
Decision variable	a_l	The allocated area shares of given land-cover *l*, in a landscape composition. This represents the decision-variable allocated in the optimization model to maximize the normalized worst-case performance of the optimized landscape. The shares (expressed as fractions) of a theoretical optimal land allocation under uncertainty represent the model output. The solution to the allocation problem provides the best landscape performance for the worst-case uncertainty scenario.
Model constraints	$a_l \geq 0$, $\sum_{l=1}^{L} a_l=1$	The non-negativity constraint and the area budget constraint in the model ensure that the hypothetical landscape’s coverage remains consistent, neither exceeding nor falling short of the designated area. Further study-specific constraints may be integrated, for example, to constrain the area share of a given land-cover (see Reith et al. 2020).
	$\beta \geq D_{iu}$	Feasibility constraint ensures that the greatest underperformance of a hypothetical landscape is reduced across all relative deviations from the highest achievable indicator level for each indicator and uncertainty scenario, which linearizes the allocation problem: $\beta \geq \frac{\lvert R_{iu}^{*} - \sum_{l=1}^{L} R_{liu} a_l \rvert}{R_{liu}^{*} - R_{liu*}} \quad \forall i \; \forall u \;\; 0 \leq \beta \leq 100$

When interpreting the optimization results, one needs to keep in mind that the decision criteria (i.e., objectives or indicators) and model constraints drive the optimization results. This means that optimization results need to be checked for plausibility and include extensive sensitivity analysis to avoid bias from researchers when selecting indicators and input data (Do et al. 2020). Therefore, transparency is essential regarding decision criteria and study-specific model restrictions.

2.4 Post-processing and analysis

2.4.1 Trade-off analysis

The optimization approach aims to mitigate trade-offs by selecting a land allocation solution that balances all indicators under uncertainty without allowing for compensation between those indicators. Altering the weights assigned to these indicators or incorporating different sets of indicators could provide more information on trade-offs (Reith et al. 2022).

Furthermore, selecting different indicator bundles allows for portraying different perspectives (RQ 2, Chapter 3.2). Such an analysis facilitates the comprehension of conflicts and commonalities in shaping the envisioned future landscape compositions. For instance, to simulate farmers' perspective, one can consider various socio-economic objectives (Gosling et al. 2021). Conversely, to encapsulate a public viewpoint encompassing a range of interest groups, one can incorporate objectives aligned with the SDGs, considered relevant to Panamanian society. For example, this could be SDG 2 (zero hunger) and 15 (life on land) (UN 2017). Achieving food security through agricultural practices that enhance the resistance of production systems (e.g., agroforestry) is one aspect of SDG 2 (UN 2017). SDG 15 pertains to the restoration and sustainable management of terrestrial land. These concepts are quantified using ecological indicators in this study.

2.4.2 Adopting agroforestry

Sensitivity and scenario analysis can be carried out by manipulating input data or the optimization model. For example, it is possible to completely exclude specific land-cover options from the set available for selection by the model, as shown in Chapter 3.2 (RQ 2). This approach ensures that the coefficients of the excluded land-cover options do not impact the optimization results, assuming that a decision-maker is either unaware of or unable to choose those excluded options (e.g., agroforestry). Such a sensitivity analysis helps understand the potential and limitations of land-cover options.

Furthermore, the model enables the assessment and comparison of landscape performance between optimized and existing landscape compositions, as shown in Chapter 3.3 (RQ 3). The indicator with the lowest level of achievement in some uncertainty scenarios determines the landscape composition, where a score of zero indicates the least desirable outcome and 100% is the most desirable (as described above). This means that the specific indicator is pivotal in shaping the solution and can suggest significant or constraining factors for decision-makers. The optimization model can compute the realized performance levels. Alternatively, the landscape performance can be effectively simulated by aligning the decision variables (land area allocations) with the current landscape composition.

In addition, both the positive and negative impacts of agroforestry integration on the environment and human well-being can be studied (RQ 3, Chapter 3.3). Quantifying the impacts of the modeled landscape compositions can offer insights into the factors that either encourage or hinder the adoption of agroforestry and other FLR options on a landscape-wide scale. This analysis can also pinpoint unintended consequences and opportunity costs. For instance, comparing the (dis)similarities between the current landscape and an optimized multifunctional landscape can provide decision-makers with valuable insights into the effectiveness of the current land-use practices. This transparency can help garner broader support for implementing sustainable land-use concepts. This research focuses on assessing the effects of landscape compositions on natural capital (e.g., forest land), agricultural production, required resources, and the impacts on ecosystem services within the broader socio-ecological system (Eigenraam et al. 2020).

Subsequently, the landscape's performance concerning a specific indicator can be calculated and compared (Chapter 3.3). For example, by summing the land area allocations for agroforestry and/or forest plantations and natural forests, the overall tree cover of a landscape can be determined. Additionally, calculating the Shannon Index for an optimized landscape composition can assess landscape diversity, providing insight into the extent of diverse habitats needed to support biodiversity (for details, see Reith et al. 2020). Furthermore, multiplying the land area allocations within a landscape composition by the corresponding coefficients for a particular indicator can determine the potential worst-case performance of that composition in terms of the indicator. For example, the carbon sequestration potential of an optimized landscape solution can be calculated as the product of the expected carbon sequestration potential per land-cover and the optimized land-cover fractions.

Consequently, a carbon premium can be calculated following Friedrich et al. (2021). They calculated a *multifunctionality premium* to quantify the cost of shifting from an optimal solution for a single objective to a compromise solution for multiple objectives (Friedrich et al. 2021). Similarly, comparing the carbon sequestration potential of an optimized multifunctional landscape with the composition optimized for carbon sequestration alone can indicate the opportunity cost of not prioritizing a carbon-optimal landscape composition in favor of multifunctionality (Chapter 3.3).

3. Results

3.1 Which and how much Forest Landscape Restoration (FLR) options in a landscape composition are desirable for society to meet multiple objectives under uncertainty?

3.1.1 The perception of land-covers

The surveys with individuals from government agencies, non-governmental organizations, corporations, universities and other research institutes, and farmers and locals provided valuable land-cover perception and preference data, which are essential to consider for sustainable land-use strategies and policy interventions. The survey data on land-cover performance revealed perceived trade-offs between ecological and socio-economic objectives (Figure 3). This implies that expanding one land-cover option may increase benefits but sacrifice others. For example, respondents considered forests to be vital ecologically but less important economically. In contrast, respondents perceived traditional agricultural options as superior to meeting the need for regular and frequent cash flows (liquidity) and food security (Figure 3).

The comparison of the perceptions of the FLR options revealed that agroforestry was perceived as superior to forest plantation and natural succession of abandoned land in terms of socio-economic objectives but not for all ecological objectives (Figure 3). The average score of agroforestry systems ranged from 9 to 13 on a scale of 1 to 17, where the higher the score, the better (Table 5). The respondents perceived forest plantations to have similar ecological scores on average compared to alley cropping, with a slight advantage over agroforestry systems regarding global climate regulation. Natural succession of abandoned land had the lowest ecological and socio-economic importance for respondents among all land-covers.

Analyzing disagreements between survey respondents helps to understand mismatched expectations, biases, or associated uncertainty. Here, disagreement in the perceived performance of land-cover was quantified using standard deviation, where the higher the standard deviation, the greater the disagreement among respondents. The disagreement among survey participants was lower for the socio-economic objectives than the ecological ones (quantified by the high standard deviation, Table 5). The highest disagreement in land-cover rankings occurred for the objective economic stability (average standard deviation 3.13). The highest consensus (lowest standard deviation) was found when ranking the land-covers regarding biodiversity and climate regulation (standard deviation from 1.83 to 1.91). Among the land-cover options, the least consensus was found for natural succession of abandoned land (average standard deviation of 3.00), perhaps because respondents had different land-cover stages in mind, ranging from former agricultural land to future secondary forest (see further discussion on perception data in Chapter 4.4.2).

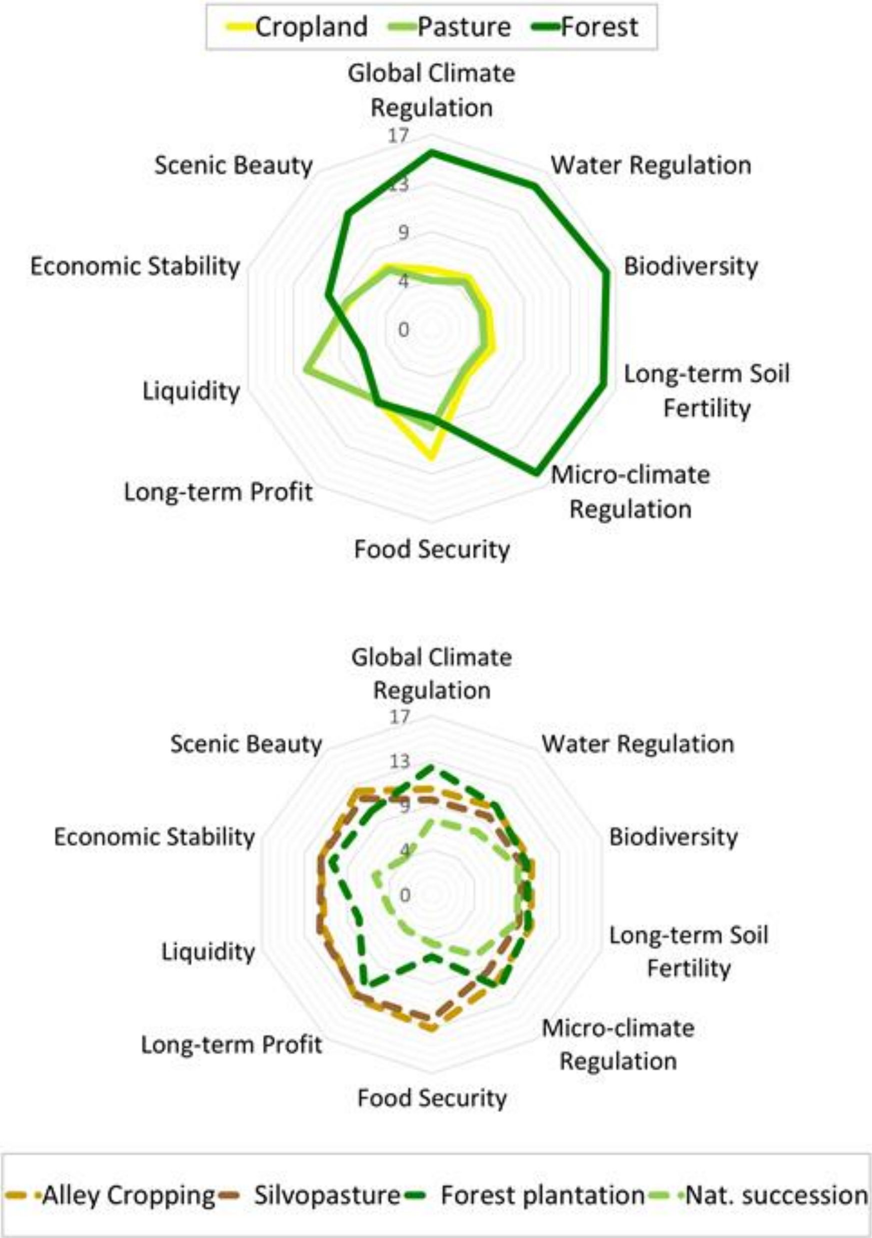

Figure 3 Rose diagrams of the relative perceived performance of the land-cover options against the ten ecological and socio-economic objectives. The scores refer to aggregated responses of individual survey participants to derive a group judgment (36 to 40 responses per objective), where the higher the score, the better the perceived land-cover performance**.** The figure above compares mature forests with traditional agricultural systems. The graph below compares studied FLR options (dashed lines). Data were taken from Table 3 in Reith et al. (2020).

Table 5 The mean perception and preference scores and their standard deviation of ten objectives and seven land-cover options. The objectives are categorized into ecological and socio-economic. The scores were derived from the Analytic Hierarchy Process (Saaty 1987) survey (1 = low and 17 = high). The higher the standard deviation (± Sd), the higher the disagreement of perceived land-cover performance among survey participants. N is the number of survey participants per objective. Adapted from Table 3 in Reith et al. (2020).

Objectives	Cropland	Pasture	Alley cropping	Silvopasture	Forest plantation	Natural succession	Forest	N
Ecological Group								
Global climate regulation	5.2	4.2	10.1	9.0	12.1	7.0	15.4	40
	±1.4	±1.5	±1.7	±2.1	±2.3	±2.9	±1.5	
Water regulation	5.5	5.0	10.2	9.2	10.4	7.3	15.4	39
	±1.4	±2.1	±2.2	±1.8	±2.1	±3.3	±2.3	
Biodiversity	5.2	4.6	10.0	9.0	9.5	8.6	16.1	38
	±1.4	±1.5	±1.8	±1.6	±2.5	±3.6	±1.0	
Long-term soil fertility	5.6	4.8	9.9	8.7	9.6	8.5	15.8	38
	±1.2	±1.8	±1.8	±1.7	±2.6	±3.3	±1.9	
Micro-climate regulation	5.1	4.7	10.4	9.0	10.9	7.1	15.7	38
	±1.2	±1.4	±2.0	±1.7	±2.0	±3.3	±1.3	
Socio-economic Group								
Food security	11.3	8.7	12.8	11.9	5.9	4.7	7.9	36
	±4.0	±2.8	±2.1	±2.4	±2.2	±2.4	±2.9	
Long-term profit	7.9	7.9	12.2	11.9	10.9	4.2	8.0	37
	±3.2	±2.8	±2.4	±2.1	±3.1	±2.3	±3.9	
Liquidity	11.5	11.6	10.8	11.2	7.3	4.2	6.4	37
	±3.0	±2.4	±2.6	±2.5	±2.7	±2.8	±3.6	
Stability of economic return	7.6	7.8	11.1	11.1	10.0	5.7	9.6	36
	±3.2	±3.0	±3.1	±2.0	±3.2	±3.9	±3.4	
Scenic beauty	6.7	6.4	12.1	11.3	9.8	4.3	12.5	37
	±2.2	±2.5	±2.5	±2.2	±2.6	±2.3	±3.2	

3.1.2 The FLR options in an uncertain future

The perceived trade-offs between studied land-covers mean that not all objectives can be maximized at the same time. Therefore, a compromise solution is necessary for the ten selected objectives, which is the subject of this chapter. For a landscape that reduces perceived trade-offs between and low-performance levels of individual objectives, agroforestry seemed superior to other FLR options considered (Figure 4). The optimization model selected large shares of agroforestry (between 27% and 62% area share of alley cropping and silvopasture) for the simulated landscape both when ignoring uncertainties about land-cover performance ($f_U = 0$, left bar in Figure 4) and when considering uncertainty (Figure 4). While forest plantations were not present in hypothetically optimal landscapes when ignoring uncertainty or considering only a low level of uncertainty, they seem desirable as part of a land-cover mix to buffer moderate or high levels of uncertainty. Although an important FLR option, natural succession of abandoned land was not selected by the model to meet the given objectives, which indicates that it may be inferior to other land-cover options for reducing trade-offs between given objectives.

The results also show that landscape heterogeneity may best support landscapes in mitigating uncertainty. In other words, risk aversion leads to landscape diversification as a strategy to buffer against uncertainty. With increasing uncertainty, i.e., with higher deviations of individual scores from the mean expected scores, lower-performing land-cover options became more critical, and their shares increased. For example, when uncertainty in the ecological and socio-economic performance of land-covers was ignored ($f_U = 0$), the simulated landscape consisted of alley cropping and forest (62% and 38%, respectively, Figure 4). In comparison, for a moderate level of uncertainty ($f_U = 2$), a mix of agroforestry, forest plantation, forest, and traditional agricultural land may be best suited to foster a multifunctional landscape. Furthermore, to stabilize the performance level and mitigate potential under achievements of individual objectives, the model not only selected a greater diversity of land-cover options but also allocated land more evenly across the available land-covers. This effect becomes quite pronounced from $f_U = 2$ onward.

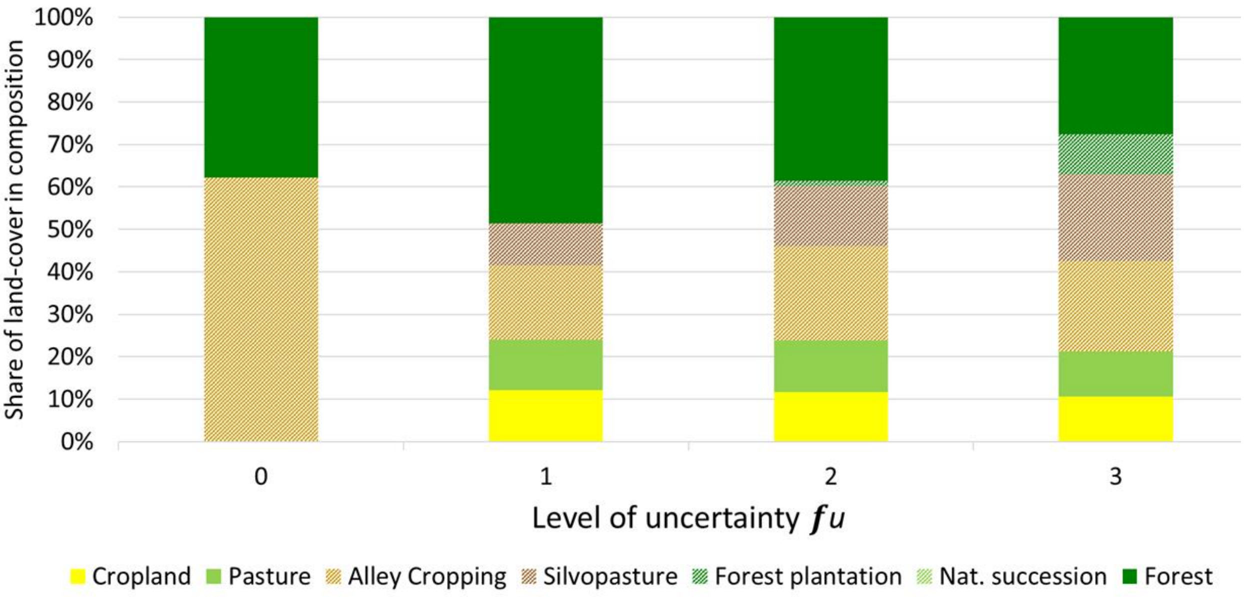

Figure 4 Optimized landscape compositions to provide multiple ecological and socio-economic objectives under different levels of uncertainty. The y-axis shows the percentage of land allocated to each of the seven land-cover options based on perception data (from Reith et al. 2020). The optimization model considered the expected performance scores regarding the ten objectives (left bar, ignoring uncertainty or low risk-aversion) and their deviations from the expected mean score under increasing levels of uncertainty (f_U = 1 to 3). Figure adapted from Figure S4 in Reith et al. (2020).

While this section addressed multifunctionality for society as a whole, the following section acknowledges that hypothetical, optimal landscapes may differ for different decision-makers.

3.2 How to reconcile conflicting perspectives of farmers and the public?

This chapter contrasts the perceptions of farmers and the public and analyzes optimized landscape compositions from their respective perspectives. This analysis is intended to provide insights into the influence of different preferences and perspectives of both groups on the proportion of FLR options to highlight and later address commonalities and potential conflicts of interest between the two groups.

3.2.1 Perception comparison of farmers and other experts (the public)

To bring together and contrast scientific and local empirical knowledge about the potential of current land-cover and agroforestry, the survey dataset of Chapter 3.1 (adjusted from Reith et al. 2020) was expanded to integrate a larger number of surveyed farmers (Figure 5); the data from the farmers surveyed by Gosling et al. (2020b) replaced those from the farmers surveyed by Reith et al. (2020).

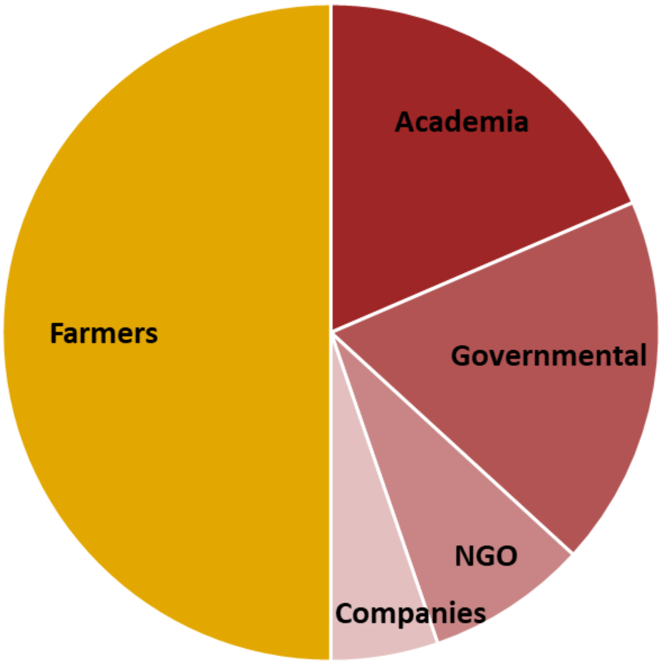

Figure 5 Sampling groups for surveys to assess perceptions and preferences of land-cover against ecological and socio-economic objectives.

The comparison of the survey results revealed that the farmers and experts represented two different perspectives with different perceptions and preferences, which may lead to conflicts when planning a multifunctional landscape (compare objectives marked with an asterisk in Table 6)**.** These differences were most pronounced in the preference for different land-cover options. Experts preferred forests first, followed by alley cropping, then silvopasture, forest plantation, and lastly, agricultural options (as indicated by the decreasing scores in Table 6). From the opposite perspective, farmers preferred silvopasture, and then pasture and cropland over the other land-cover options, with forest and forest plantation coming last.

Differences in land-cover ranking also occurred for perceived land-cover performance for the socio-economic objectives of long-term income, financial stability, and household needs. Experts ranked alley cropping first and silvopasture second for playing a key role in achieving the socio-economic objectives. In contrast, farmers perceived silvopasture as performing better than alley cropping, and ranked pasture and forest plantation higher than experts (Table 6). The different perceptions of the ability of each land-cover to achieve each objective point to potential conflicts between farmers and the wider public. The general cultural preference for the land-covers might have influenced these differences in perception. However, the perception of land-cover performance regarding liquidity and ecological objectives was similar (Table 6).

Table 6 The mean perception and preference scores and their standard deviation of 15 ecological and socio-economic objectives and six land-cover options. The surveys involving experts from diverse disciplines were derived from the Analytic Hierarchy Process (adjusted by Reith et al. (2020)) (public perspective). Farmers' mean scores and standard deviation were obtained from the rank and score survey method by Gosling et al. (2020b) (farmer perspective). The survey scores represent input data for the optimization model for the public perspective (expert data as proxy), farmer perspective, and the *compromise* perspective (all combined). Scoring range for the public is 1 to 17 (more is better), and for farmers is 0 to 10 (more/less is better). Adapted from Table A4 in Reith et al. (2022). The asterisk indicates similar objectives that were included in the farmer and expert surveys and are subject to comparison.

Perspective	**Objectives**	**Direction**	**Cropland**	**Pasture**	**Alley cropping**	**Silvopasture**	**Forest**	**Forest plantation**
Public	Global climate regulation	more is better	5.0 ±1.5	4.0 ±2.0	10.0 ±1.8	9.0 ±2.0	15.0 ±2.8	12.0 ±2.5
	Water regulation*	more is better	5.0 ±1.4	5.0 ±2.0	10.0 ±2.2	9.0 ±1.9	15.0 ±2.9	11.0 ±2.0
	Biodiversity	more is better	5.0 ±1.2	5.0 ±1.3	10.0 ±1.8	9.0 ±1.4	16.0 ±1.1	9.0 ±2.4
	Long-term soil fertility*	more is better	6.0 ±1.3	5.0 ±1.2	10.0 ±1.9	9.0 ±1.8	16.0 ±1.2	10.0 ±2.4
	Micro-climate regulation	more is better	5.0 ±1.2	5.0 ±1.3	11.0 ±2.0	9.0 ±1.7	16.0 ±1.2	11.0 ±1.7
	Food security*	more is better	11.0 ±4.2	8.0 ±2.8	13.0 ±2.1	12.0 ±2.5	8.0 ±3.0	6.0 ±2.3
	Land-cover preference*	more is better	0.0 ±0.0	1.0 ±1.0	21.0 ±3.8	14.0 ±3.3	23.0 ±3.9	8.0 ±2.7
Farmer	Long-term income	more is better	6.0 ±2.2	8.0 ±2.2	7.0 ±1.8	8.0 ±1.8	3.0 ±2.6	8.0 ±2.4
	Labor demand	less is better	8.0 ±2.1	7.0 ±2.0	8.0 ±1.9	7.0 ±1.7	2.0 ±2.2	7.0 ±2.6
	Meeting household needs*	more is better	10.0 ±1.3	8.0 ±1.3	7.0 ±2.0	8.0 ±1.2	4.0 ±2.9	4.0 ±2.3
	Financial stability*	more is better	6.0 ±2.5	7.0 ±3.0	6.0 ±2.0	8.0 ±2.4	6.0 ±3.8	8.0 ±2.4
	Liquidity*	more is better	7.0 ±1.9	10.0 ±0.4	6.0 ±2.1	9.0 ±1.5	3.0 ±2.6	5.0 ±2.3
	Investment costs	less is better	7.0 ±2.1	8.0 ±2.1	7.0 ±2.4	8.0 ±2.0	1.0 ±1.9	7.0 ±2.7
	Management complexity	less is better	8.0 ±2.3	7.0 ±2.0	9.0 ±1.7	8.0 ±1.8	2.0 ±2.2	7.0 ±2.6
	Land-cover preference*	more is better	15.0 ±3.4	21.0 ±3.9	11.0 ±3.1	23.0 ±3.9	1.0 ±1.0	0.0 ±0.0

3.2.2 Optimal landscape compositions from competing perspectives

A hypothetical compromise solution for farmers and the public was optimized to concurrently include 15 ecological, economic, and social objectives (Table 6). The public perspective was represented by socio-ecological objectives that can be linked to SDGs 2 and 15. To cover the heterogeneity of different farm types, the farmer perspective was assumed to be represented by a range of socio-economic objectives. The model was either presented with the option to select agroforestry for the optimal allocation of land-covers, or agroforestry was omitted entirely (Figure 6).

Without the option to select agroforestry, the model chose a more or less equal distribution of the four land-cover options cropland, pasture, forest plantation, and forest to reduce trade-offs while buffering uncertainty (first, third, and second last column in Figure 6). This means that in the absence of multifunctional land-cover options (such as agroforestry), the highest possible level of land diversification may be best to balance multiple objectives under a moderate level of uncertainty (f_U = 2). However, from the public's perspective, the best balance of socio-ecological objectives under a moderate level of uncertainty was achieved by setting aside 43% of the forest area, as opposed to approximately 30% of the area from the farmers or compromise perspective, and keeping only 42% for agricultural use (first, third, and fifth columns in Figure 6).

A striking finding is that the model selected agroforestry (when offered to the model) for the optimal landscape compositions from both perspectives to reduce perceived trade-offs between socio-ecological (public) and socio-economic (farmer) objectives in worst-case scenarios (second and fourth column in Figure 6). This suggests consensus between the different perspectives about the perceived ability of the studied agroforestry systems to reduce trade-offs between their respective set of objectives. Furthermore, the proposed compromise solution, including agroforestry, is more in line with the optimized landscape from the standpoint of farmers than from the public. This suggests that a diverse landscape may be beneficial to fulfilling both the socio-economic objectives of farmers and the ecological ones as well.

However, the differences between farmers and the public in the type and proportion of FLR options within desirable landscapes may lead to conflicts. The optimized landscape compositions of the public demonstrated greater forest and tree cover than the optimized compositions of the farmers. While both compositions included agroforestry and excluded other FLR options, their proportions deviate. For example, experts perceived alley cropping as superior to silvopasture for all seven ecological and social objectives, while farmers perceived silvopasture as superior for five out of the seven socio-economic objectives (Table 6). This resulted in optimized landscapes with high proportions of the preferred agroforestry system (alley cropping for experts, silvopasture for farmers, Figure 6).

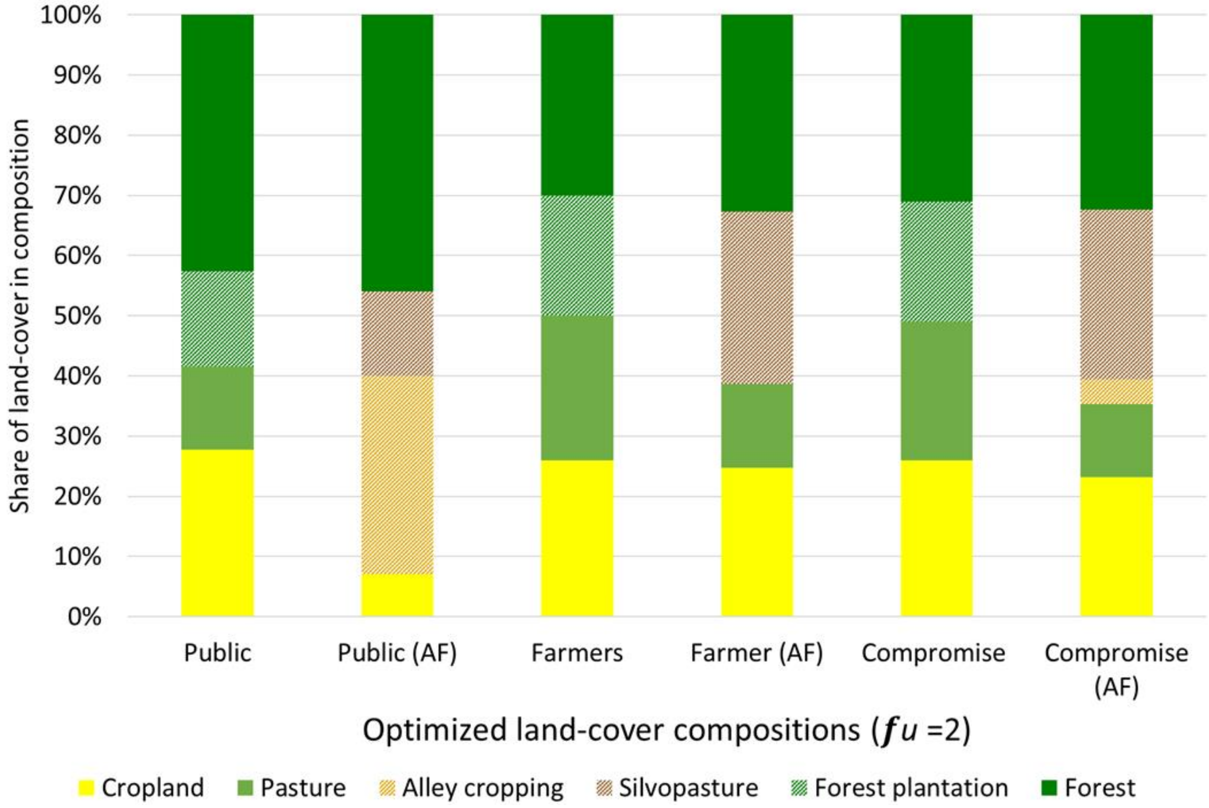

Figure 6 Optimized landscape compositions with and without agroforestry derived for a moderate level of uncertainty. The model was provided with two alternative sets of land-cover options to select from, either including agroforestry systems (indicated with "AF") or not including them. The public perspective is represented by socio-ecological objectives (adjusted dataset from Reith et al. (2020), two left columns). The farmers' perspective is represented by socio-economic objectives assessed by local farmers (based on Gosling et al. (2020b), two middle columns). A compromise perspective for the two groups balanced all objectives (two right columns).

3.3 How do the current and optimized landscape compositions impact ecological and socio-economic functions?

While the first two sections deal with understanding the current socio-ecological system of Panama's forest frontier and assessing the opportunities and potential conflicts of investing in agroforestry, this section evaluates the impacts of agroforestry adoption. However, the survey-derived data set based on perceptions does not allow us to quantify the ecological and socio-economic impacts of adopting agroforestry. Therefore, literature data on socio-economic indicators and the much-discussed ecological function of carbon sequestration were collected for the studied land-cover options (Table 7) and used as input for the robust optimization approach. This allows quantifying the impacts (including potential undesirable consequences) of adopting agroforestry in eastern Panama ex-post optimization. Such an analysis provides insights for decision-makers and creates transparency to gain wider acceptance for implementing sustainable land-use concepts and decrease opportunity costs for different interest groups.

3.3.1 The current landscape vs. an optimized future landscape

Table 7 The mean scores and their standard deviation of 11 ecological and socio-economic indicators and seven land-cover options derived from literature and own calculations. Generally, the direction of indicators is *more is better*, except when marked with an asterisk to signify *less is better*.

Indicator	Rice	Maize	Pasture	Alley cropping	Silvo-pasture	Forest	Forest plantation	Source
Total estimated carbon ($Mg\ C\ ha^{-1}$)	35.7 ±4.3	35.7 ±4.3	55.4 ±5.9	161.3 ±18.3	113.2 ±5.9	240.4 ±82.1	215.4 ±30.7	Own calculation based on IPCC (2006)
Soil organic carbon ($Mg\ C\ ha^{-1}$)	29.7 ±2.8	34.3 ±6.8	24.8 ±8.2	32.0 ±9.2	27.1 ±18.4	34.0 ±22.3	34.4 ±11.3	Kraenzel et al. (2003), Neumann-Cosel et al. (2011), Paul (2014), Shi et al. (2018), Tschakert et al. (2007)

Table continued

Indicator	Rice	Maize	Pasture	Alley cropping	Silvo-pasture	Forest	Forest plantation	Source
Dietary energy produced (Mcal $ha^{-1}yr^{-1}$)	6295.0 ±143.0	9866.0 ±417.0	976.0 ±2.8	1551.0 ±141.0	814.0 ±2.4	0.0 ±0.0	0.0 ±0.0	Gosling et al. (2021)
Net Present Value (\$ ha^{-1})	8310.0 ±1756.0	8066.0 ±2643.0	3496.0 ±522.0	5690.0 ±1792.0	4914.0 ±696.0	0.0 ±0.0	5267.0 ±2019.0	Gosling et al. (2021)
Payback period (years)*	0.0 ±0.4	1.1 ±1.6	4.6 ±1.1	7.7 ±8.6	10.7 ±2.8	0.0 ±0.0	20.0 ±0.0	Gosling et al. (2021)
Investment costs (\$ ha^{-1})*	949.0 ±95.0	1072.8 ±109.0	1433.0 ±142.0	1835.4 ±185.0	1970.0 ±196.0	0.0 ±0.0	2184.0 ±218.0	Gosling et al. (2021)
Labor demand (days $ha^{-1}yr^{-1}$)*	32.0 ±0.7	22.2 ±0.5	8.4 ±0.2	12.1 ±0.4	13.8 ±0.4	0.0 ±0.0	15.7 ±0.6	Gosling et al. (2021)
Experience	34.0 ±1.0	34.0 ±1.0	35.0 ±0.0	15.0 ±2.4	26.0 ±2.6	32.0 ±1.4	22.0 ±2.8	Own calculation based on Gosling et al. (2020b) (unpublished data)
Management difficulty*	8.1 ±2.3	8.1 ±2.3	6.8 ±2.0	8.6 ±1.7	7.6 ±1.8	1.9 ±2.2	7.0 ±0.5	Gosling et al. (2020b)
Land-use preference farmer	15.0 ±3.4	15.0 ±3.4	21.0 ±3.8	11.0 ±3.0	23.0 ±3.9	1.0 ±1.0	0.0 ±0.0	Gosling et al. (2020b)
Land-use preference public	0.0 ±0.0	0.0 ±0.0	1.0 ±1.0	21.0 ±3.8	14.0 ±3.3	23.0 ±3.9	8.0 ±2.7	Reith et al. (2020)

The current landscape of Tortí is dominated by pasture, which gives farmers the flexibility to sell cows when they need money while keeping labor demands and management complexity manageable. In contrast, the optimized multifunctional landscape is much more heterogeneous due to finding a compromise solution that reduces the trade-offs between the equally weighted indicators for worst-case scenarios in the face of uncertainty (Figure 7).

Consistent with previous perception data-based results, the findings indicate that including substantial amounts of agroforestry in the optimized landscape composition can yield socio-economic benefits, maintain culturally preferred livestock production, and restore ecological benefits. According to the optimization model, a multifunctional landscape under uncertainty (f_U = 3) would consist of 30% traditional cropland, 11% pasture, 30% agroforestry, 8% teak plantation, and 21% forest (Figure 7). In comparison, the multifunctional landscape based on survey data for a high level of uncertainty (f_U = 3) showed 11% traditional cropland, 11% pasture, 41% agroforestry share, 9% forest plantation, and 28% forest area share (Figure 4).

In this analysis, an uncertainty level of f_U = 3 was assumed to maintain consistency with the results presented in Chapter 3.2. Owing to the availability of more reliable data in this chapter, the uncertainty was, on average, lower, so a higher uncertainty level (f_U = 3 instead of f_U = 2) was employed to uphold comparability.

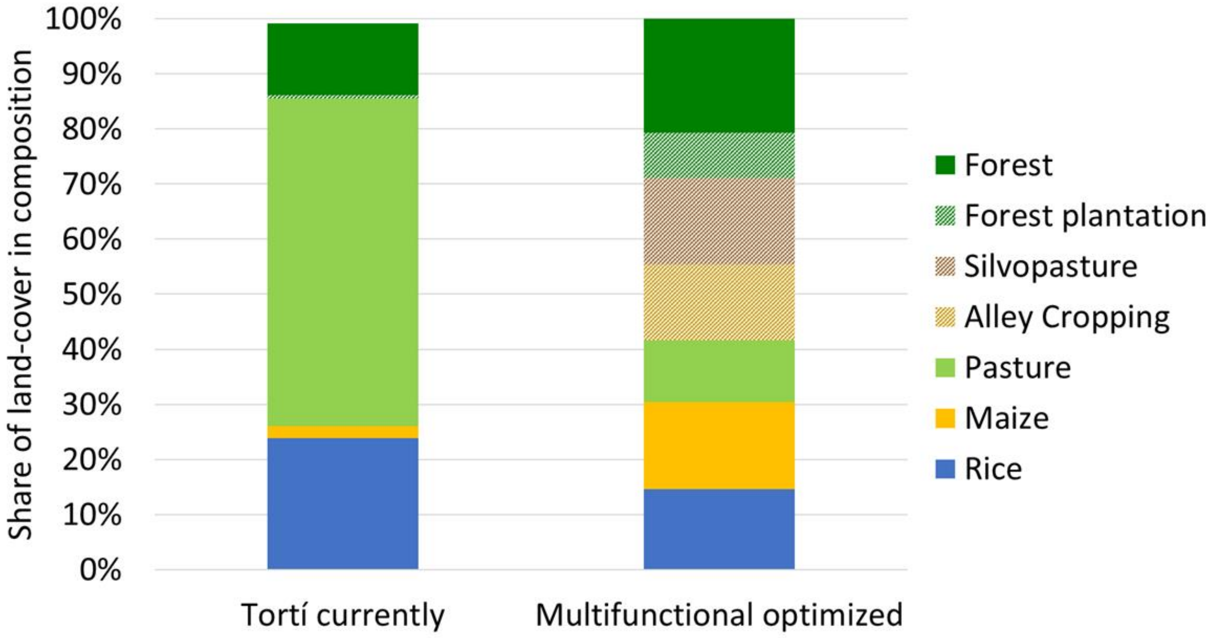

Figure 7 Composition of the current landscape in the study region Tortí and the optimized multifunctional landscape based on literature data. The multifunctional landscape considers ecological and socio-economic indicators (Table 7).

The ecological and socio-economic impacts of the current and an optimized multifunctional land-cover allocation were quantified by comparing the worst-case performance across all indicators. Considering numerous indicators only support a relatively low worst-case performance (Figure 8). For the optimized landscape composition, the lowest normalized worst-case performance (29% of the target level) occurred across six indicators: total estimated carbon, dietary energy produced, net present value, management difficulty, and land-use preferences of farmers and the public (Figure 8). The current landscape composition of Tortí performs worst in terms of public land-use preference, followed by total carbon stored. For these indicators, the landscape secures only 10% of the target level in worst-case scenarios. This means increasing the indicated poorest performing functions with the respective landscape compositions (current and optimized) is the most challenging.

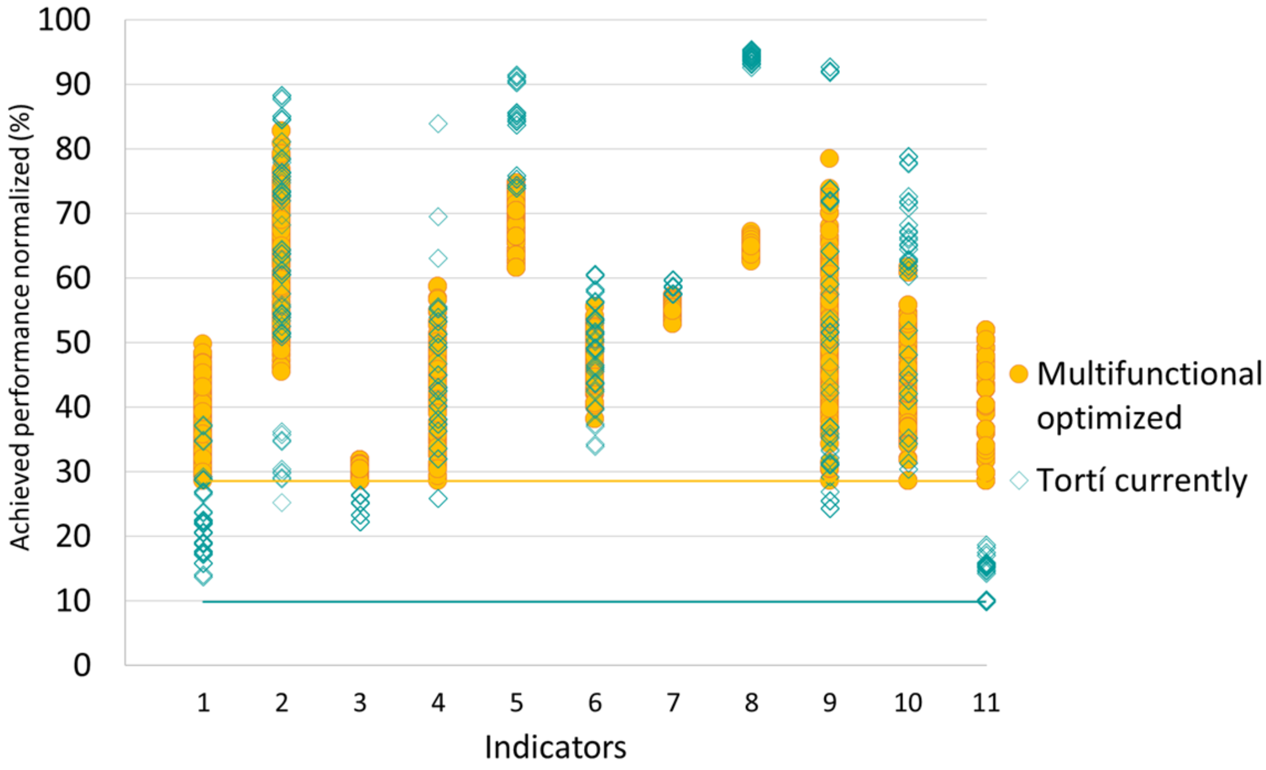

Figure 8 Visualization of the achieved composition performances of an optimized multifunctional landscape and the current land allocation of Tortí. The y-axis shows the MINMAX normalized performance levels of the 11 ecological and socio-economic indicators listed on the x-axis. The indicators (derived from literature data) are 1) total estimated carbon, 2) soil organic carbon concentration, 3) dietary energy produced, 4) net present value (5% discount rate), 5) payback period (5% discount rate), 6) investment costs 7) labor demand, 8) experience, 9) management difficulty, and land-use preference 10) of farmer and 11) of the public (Table 7). Each shape represents the level of achievement of each given indicator across the uncertainty scenarios. Petrol diamonds represent the indicator achievement levels for the current landscape allocation of Tortí (without optimization, see left column of Figure 7). Yellow circles represent the performance of an optimized multifunctional landscape composition (see right column of Figure 7, f_U = 3). The trend lines indicate the respective minimum achievement levels (here more is better for all indicators).

The other aspect that this analysis reveals is that there may be benefits and opportunity costs to transforming the agricultural system and creating a multifunctional landscape (Figure 8). The liquidity of farmers (indicator 5 *payback period*) was reduced in the optimized multifunctional landscape compared to the worst-case scenario of the current landscape due to the decrease in pasture area and increase in tree-based systems. Similarly, farmers' land-use preferences are better met with the current landscape composition (indicator 10).

Another disadvantage of the multifunctional landscape, including agroforestry, could be the increased labor demand (indicator 7). Furthermore, farmers face limited experience with FLR systems (indicator 8), dominating productive land areas in the optimized composition. However, the general trend is that the heterogeneous and multifunctional landscape composition could improve the landscape performance in the worst-case scenarios compared to the current land cover composition (indicated by the elevated trend line).

3.3.2 Impacts of multifunctionality and integrating agroforestry

The inclusion of trees on farms could increase the provision of quantifiable ecological and socio-economic benefits. The optimized landscape embedding agroforestry increased total tree cover (by 45 percentage points) and even forest cover (8 percentage points, Table 8) compared to the current landscape composition. It also increased landscape diversity in the simulation (Shannon index of 1.91 compared to 1.03), which can increase habitat diversity and potentially benefit biodiversity. Similarly, humans could benefit from improved regulating and supporting ecosystem services in a heterogeneous and multifunctional landscape. The total carbon stock above- and below-ground (to a depth of 30 cm) of the current landscape composition can potentially be increased in an optimized landscape solution (by an average of 50 Mg C ha^{-1}). This would be the carbon equivalent of the greenhouse gas emissions from about 38 steers (calculation based on Oliveira et al. (2020)) or about 40 cars running on gasoline for one year (calculation based EPA). The notable rise in carbon sequestration potential can be attributed to a substantial increase in tree-based systems, which can sequester substantially greater amounts of carbon both above and below the ground per hectare compared to traditional agricultural land uses. According to the results, such a multifunctional landscape may allow more SOC to be retained, benefiting soil fertility. At the same time, agroforestry combined with traditional agricultural systems could increase food production (on average 641 more Mcal ha^{-1} year^{-1} than current production potential) and could sustain higher incomes (average difference of \$604 ha^{-1}) in a worst-case scenario (Table 8).

Table 8 Impact of agricultural production based on the current land-cover composition of the study area and optimized land-cover allocation ($f_U = 3$). Evaluation inspired by TEEBAgriFood Evaluation Framework (Eigenraam et al. 2020).

Agricultural production			Tortí current landscape	Optimized multifunctional landscape
Stock / Outcome (change in capital)				
Natural capital	Forest land	Tree and forest area share (%)	14% tree cover, 13% forest cover	58% tree cover, 21% forest cover
	Arable land	Area share under agricultural use (%)	86 %	71%
	Biodiversity	Landscape diversity (Shannon index)	1.03	1.91
Flows				
Outputs				
Agricultural outputs	Food products	Nutrition (Mcal ha^{-1} year^{-1})	2296	2937
	Income	NPV (5% discount rate) ($ ha^{-1})	4269	4873
Inputs				
Labor	Labor demand	Days ha^{-1} year^{-1}	13	14
Investment	Investment costs	$ ha^{-1}	1116	1210
Ecosystem services				
Regulating	Carbon sequestration	Total estimated carbon (Mg C ha^{-1})	75	124
Supporting	Soil fertility	Soil organic carbon (Mg C ha^{-1})	27	31
Cultural	Aesthetics	Cultural preferences (farmers)	17	12

Note: although conversion of forest to agricultural land was not accounted for, it contributes to increased greenhouse gas emissions; other emission factors include leaching and run-off.

However, there are opportunity costs associated with changing the land-cover composition. Reducing cattle ranching, which is culturally preferred in Tortí, would mean foregoing benefits (the area of cattle ranching systems reduced by about 80% at landscape scale, Figure 7). Liquidity could be negatively affected as the landscape would be dominated by tree-based systems, which increases the payback period because of the long waiting time before trees provide an income from timber harvest. Labor demand may be slightly higher for the multifunctional landscape because the agricultural area at the landscape scale is slightly reduced in favor of the forest area (which does not require any labor). However, investment costs may increase on average by \$94 ha^{-1}.

It is also crucial to note that the optimized landscape is compared to the current landscape, which is already dominated by agriculture. Compared to a carbon-optimal landscape covered only by forest and tree-based systems, a diversified multifunctional landscape offers lower levels of carbon sequestration. The cost of diversifying landscapes to meet multiple objectives, or the *carbon premium*, accounts for 87 Mg C ha^{-1} of the potential carbon sequestered. However, maintaining current land-cover and allocation implies an even larger carbon premium of 136 Mg C ha^{-1}.

3.4 How robust are the optimization model results across model input databases and tropical landscapes?

This section examines the robustness of the model approach. First, optimal landscape compositions are derived with input data from the surveys and with literature data for a subset of ecological and socio-economic indicators. This comparison helps to assess the robustness of the model output to input data from different sources and the consistency of the interviewees' perceptions. Second, optimization results for three similar tropical landscapes are compared based on three ecological and socio-economic indicators. This exercise tests the transferability of the model to other regions and the generalizability of the model results.

3.4.1 Robustness against variations of input data

Optimization results based on two different data sets confirm that the model outcomes are relatively robust to input data uncertainty. The use of different data sets resulted in optimized agriculture-dominated landscapes with similar allocated forest cover of 20% to 23% (Figure 9). Given that the objectives and land-cover options evaluated by the survey participants were not identical to the indicators and land-cover definitions used in the existing reviewed literature, the landscape compositions show the expected dissimilarities in allocating productive land-use options (Figure 9). Rice and maize, which were not present as such in the surveys (only as cropland), outperformed and thus replaced pasture in the optimized landscape based on literature data in terms of dietary energy produced, net present value, and payback period. The differences in agroforestry shares were a result of the different rankings. In the surveys, agroforestry systems were ranked as the best or second-best option for the objectives of global climate regulation, long-term soil fertility, food security, long-term profit, and liquidity. In contrast, based on literature data, agroforestry was not ranked as the best option for any of these indicators (compare Table 5 and Table 7). Thus, the two conventional agricultural land uses were superior to agroforestry in terms of socio-economic indicators, resulting in a lower proportion of agroforestry in the optimization outcomes based on literature data (9% instead of 40% area share) and a higher proportion of conventional cropland (43% instead of 22% area share).

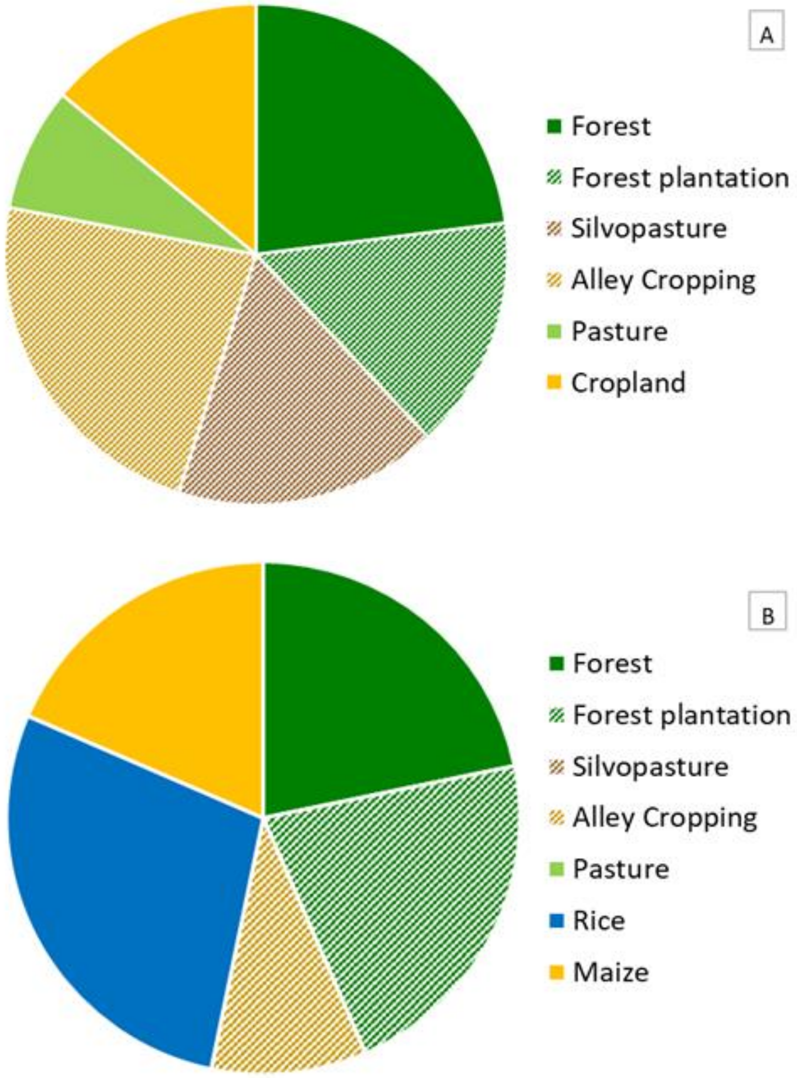

Figure 9 Optimized landscape compositions resulting from different model input data. (A) is based on survey data derived from Reith et al. (2020) (objectives: global climate regulation, long-term soil fertility, food security, long-term profit and liquidity, Table 5), (B) is based on literature and calculated data (indicators: total estimated carbon, soil organic carbon, dietary energy produced, net present value, payback period, Table 7). Optimized using the R package optimLanduse by Husmann et al. (2021) (uValue = 3; fixDistance = 3).

3.4.2 Optimal compositions across three tropical landscapes

The three selected landscapes have comparable characteristics as they are located in the tropics at the forest frontier and are managed mainly by smallholders (Table 9). To derive optimal landscape compositions for each landscape the same general land-cover options were considered in the optimization model: dominating agricultural land uses, agroforestry, and forests (forest plantations were also considered for the regions in Panama and Indonesia). Reflecting local differences, the land-covers that constituted the category *main agricultural activity* differed between the three regions (see Table 9).

Table 9 Brief description of the three tropical forest frontier landscapes and land-covers considered in the robust multi-objective optimization.

	Ecuador	**Indonesia**	**Panama**
Location	Forest-dominated region; tropical dry forests in the southwestern province of Loja in Ecuador (study area ca. 9502 ha)	Agriculture-dominated region; tropical rainforest in the lowlands of central Sumatra	Agriculture-dominated region; tropical rainforest in eastern Panama (ca. 9100 ha)
Main agricultural activity	Crop cultivation (maize, peanut, and beans)	Cash crop (rubber and oil palm)	Cattle ranching
Considered agroforestry systems	Silvopasture	Jungle rubber	Alley cropping and silvopasture
Other considered land-covers	Natural mature forest	Natural mature forest, rubber plantation, acacia plantation	Natural mature forest, teak plantation, crop land (rice and maize)
Agricultural methods and practices	Subsistence farming of mostly crops and use of forest as grazing ground for livestock	Smallholder farmers practice primarily plantation agriculture and use home gardens for subsistence farming	Smallholder farmers engaged in crop production but primarily cattle ranching
Source	Ochoa et al. (2016)	Clough et al. (2016)	Gosling et al. (2020b)

The optimizations were based on three ecological, economic, and social indicators for each landscape (Table 10). However, it should be noted that the considered land-cover systems in the Indonesian study region do not produce food. Therefore, for optimizing a multifunctional landscape, two economic indicators were chosen instead of one economic and one social indicator for food production (with one ecological indicator).

Table 10 Overview of the indicators considered in the robust multi-objective optimization of the three tropical forest-frontier regions in three countries. The indicator direction is *more is better*.

Indicator	Description	Ecuador	Indonesia	Panama
Ecological				
Carbon storage and sequestration	The capacity of a land-cover to store carbon in plant biomass (and soil) above ground (and below) (Mg C ha^{-1}; Clough et al. 2016; Paul et al. 2017a)	●	●	●
Economic				
Annuity	The profitability of a land-cover expressed as the mean annuity ($ ha^{-1} yr^{-1}; Ochoa et al. 2016)	●	o	o
Gross margin per labor hour	A representation of labor productivity by each land-cover (local currency ha^{-1} yr^{-1}; Clough et al. 2016)	o	●	o
Gross margin per ha	An expression of a land-covers' productivity (local currency ha^{-1} yr^{-1}; Clough et al. 2016)	o	●	o
Net present value	The revenue generated from a land-cover at a 5 % discount rate (Gosling et al. 2021)	o	o	●
Social				
Food production	The caloric value of agricultural yields provided by each land-cover (Mcal ha^{-1} yr^{-1}; Gosling et al. 2021; Paul et al. 2017a)	●	o	●
Total number of indicators		3	3	3

Interestingly, even though the landscapes represent three individual study sites that are quite different, the optimization results yielded similar results. The study landscape in Ecuador is dominated by forest used for goat grazing (66% area shares silvopasture, Ochoa et al. 2016), representing a comparatively extensive agroforestry system compared to the agroforestry systems in the other two countries. The remaining landscape consists of maize, peanuts, and beans (in order of decreasing area share). The study area in Indonesia consists mainly of rubber plantations, oil palm plantations, and small forest remnants (Drescher et al. 2016). The study area in Panama is dominated by pasture, with about a quarter under conventional crop production, small teak plantations, and forest remnants (Gosling et al. 2020b).

The optimization model consistently selected a greater diversity of land-cover options than current landscapes across all three forest-frontier landscapes (Figure 10). To achieve multifunctionality, the optimization resulted in a forest cover of about one-third in all three landscapes (29% and 36% area share). This ensured that the ecological objective was met. However, this had unexpected effects on tree cover. In Ecuador, the current share of forest used for extensive goat grazing (agroforestry share) was replaced by (non-use) forest and cropland shares to balance the multiple indicators under uncertainty. This reduced the total tree cover from 66% (under extensive goat grazing) to 29% (under forest protection). The displacement of this extensive silvopasture system in the optimized landscape can be attributed to its lower ecological performance compared to forest and inferior socio-economic performance in terms of food production and income generation compared to the other agricultural land uses. Thus, a (non-used) forest may better balance the low ecological performance of agricultural options, while agricultural land can better mitigate the (use) forests' low socio-economic performance. Therefore, to ensure multifunctionality of equally weighted ecological and socio-economic indicators under high levels of uncertainty, the model suggests a more or less equal distribution of those land-cover options.

As a diversification strategy for the largely deforested agriculture-dominated landscapes in Indonesia and Panama, the model allocated land more evenly across the available land-cover options, including agroforestry. This increased forest cover compared to the current landscape by 6 to 22 percentage points (Figure 10). This indicates that landscape diversification to achieve multifunctionality and buffer uncertainty could increase tree and forest cover in agriculture-dominated areas. However, in highly forested landscapes, this strategy could lead to deforestation.

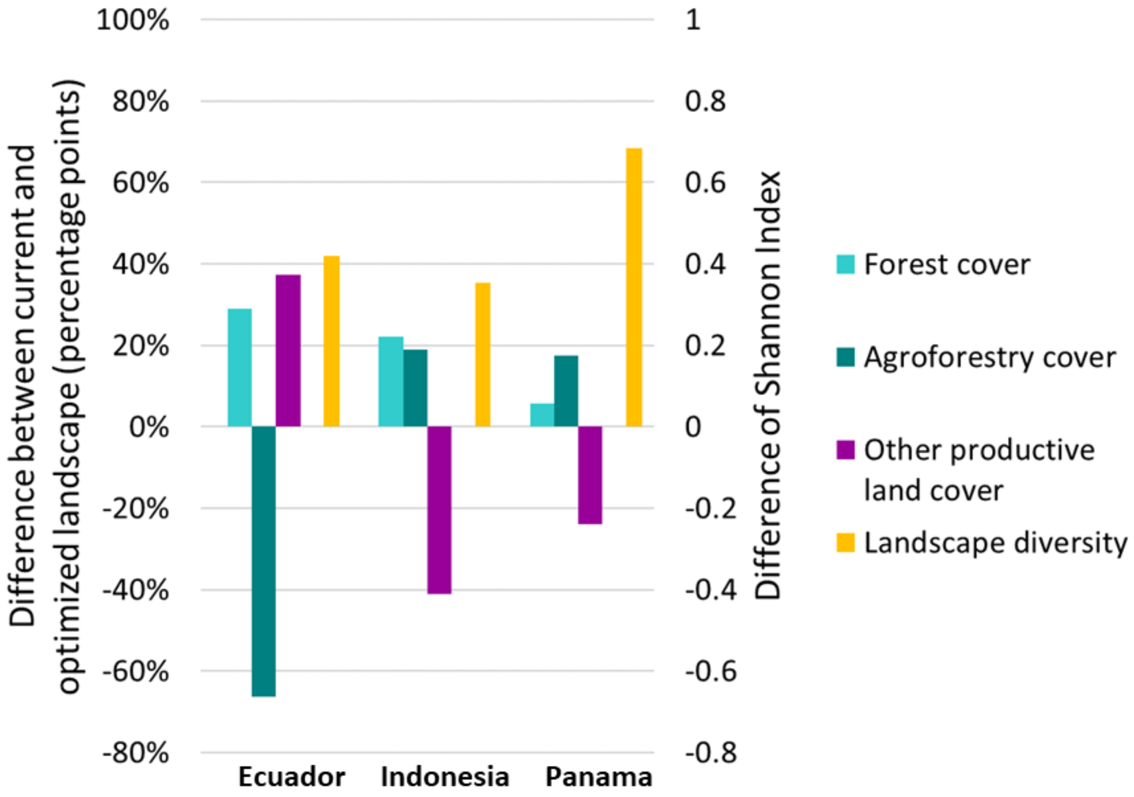

Figure 10 Difference between the current landscape composition and a hypothetical multifunctional optimized landscape for three tropical forest frontier landscapes. Left y-axis presents the comparison of changes in forest cover (turquoise color), agroforestry cover (petrol), and other productive land-cover options (purple) between landscapes in Ecuador (forest-dominated), Indonesia (agriculture-dominated), and Panama (agriculture-dominated). Right y-axis shows landscape diversity (yellow) expressed as the absolute change.

4. Discussion

4.1 Agroforestry as FLR complement

This thesis hypothesized that combining agroforestry with other options for restoring forest landscapes reduces the disparities between multiple objectives of different interest groups while cushioning uncertainty associated with variations in land performance. The optimization results of this thesis indicate that agroforestry may play an essential role in restoring tree cover in agricultural-dominated landscapes; results suggest that the tree-crop or tree-livestock systems may benefit nature while being socio-economically viable. However, agroforestry should be viewed as a complementary approach to other FLR practices and conventional agricultural systems rather than a panacea. The results of this study confirm that a landscape mosaic of multiple land-cover options seems most promising to satisfy human needs while preventing further depletion of natural resources under uncertainty (Cook-Patton et al. 2021; Raveloaritiana et al. 2023; Willmott et al. 2023). The results therefore generally support global targets for diversification of agricultural landscapes, such as those agreed in the proposal for a European-wide nature restoration law (European Commission 2022). However, evaluating impacts when adopting agroforestry and a multifunctional landscape also showed that such a transformation means farmers must shoulder opportunity costs.

Presently, agroforestry, with a marketable tree component, is not practiced in the study area in eastern Panama. The optimization results demonstrate that higher uncertainty in land-use performance (for example, due to environmental and market conditions) may favor land-use diversification. Hence, with climate change destabilizing the current production systems, increasing tree coverage and diversifying production may become more desirable. The interviewees' positive perceptions of agroforestry provide promising evidence for the willingness of interest groups to see agroforestry embedded in the current landscape.

Although an important nature-based restoration solution, survey respondents perceived the natural succession of abandoned land as inferior to all other studied land-cover options for considered ecological and socio-economic objectives. However, reforestation of abandoned land might still be a valuable option if local biophysical conditions are unsuitable for other land-cover options. Assisted or unassisted growth of secondary forests can be a low-cost, nature-based solution for ecosystem restoration, climate change mitigation, and biodiversity conservation (Bardino et al. 2023; Chazdon and Uriarte 2016; Poorter et al. 2021). Alternatively, intensified cultivation of formerly abandoned land has shown to be beneficial in socio-economic terms and for releasing pressure on forests (Green et al. 2005; Knoke et al. 2014). Knoke et al. (2014) stated that medium and large farmers with good accessibility to abandoned land close to farms may be inclined to cultivate abandoned land for intensive pasture, while farmers with smaller land areas that are further away from farms have a greater advantage in afforestation of abandoned lands (Knoke et al. 2014).

Although optimization results may be desirable, they may not always be feasible. For example, the area to successfully grow crops is limited by the soil conditions in eastern Panama (Paul 2014). Furthermore, trees' productivity and financial viability depend on careful site and timber species selection (Sinacore et al. 2023b). The model in this study considered homogenous site and household conditions and ignored land-use history.

Nevertheless, this study underscores that, when feasible, agroforestry emerges as a valuable asset in a landscape mosaic, inherently minimizing trade-offs between ecological and socio-economic objectives. Although it may not be a universally perfect win-win solution, agroforestry does stand out as a socio-economically viable tree-planting option.

4.2 Diversification strategies in socio-ecological systems

The findings of this research shed new light on the importance of heterogeneous landscapes for multifunctionality to successfully balance competing objectives between farmers and other interest groups, as exemplified using the tropical forest frontier in Panama.

Three aspects driving landscape diversity stood out: multifunctionality, consideration of uncertainty, and landscape context. To meet multiple objectives and coordinate trade-offs, heterogeneous landscapes appear better suited than homogenous landscapes, as the results of this and other studies indicate (Knoke et al. 2020b; van der Plas et al. 2018). For example, landscape compositions optimized solely for long-term profit were less diverse than landscapes equally providing a range of socio-economic (and ecologic) objectives (compare supplementary Figure 6 in Reith et al. 2020 with Figure 6 in this study). However, this implies that single objectives cannot be maximized with heterogeneous landscapes. Hence, the higher the number of objectives and targeted interest groups, the lower the capacity of a landscape to maximize single objectives (Cohen-Shacham et al. 2019). For example, liquidity, among other objectives, is reduced when changing the current landscape composition dominated by pasture to a more heterogeneous, multifunctional landscape (Figure 7). Similarly, Friedrich et al. (2021) showed that income may be reduced when multiple rather than single objectives are considered in forest management.

Another aspect impacting landscape diversity is uncertainty regarding the ability of given land-covers to achieve each objective, as optimization results indicate. Uncertainty is actively integrated into the presented optimization process (by standard deviation and uncertainty scenarios). Ignoring uncertainty would mean that the land-cover performance regarding each objective would precisely meet its expectations. In reality, the unpredictable performance of land-covers due to climate change, market, and political conditions can cause variation in current or future model input variables (Paul et al. 2017b; Rădulescu et al. 2014). In particular, new agroforestry systems may be associated with greater risk and uncertainty than conventional land uses (Mercer 2004). Using the goal programming approach, the model can reduce the risk of loss associated with single land-cover options by landscape diversification. This is an important feature of the model because it allows for greater income diversification to buffer uncertainty as a decision-maker becomes more risk-averse (Paul et al. 2019; Reith et al. 2020). The results in Chapter 3.1.2 demonstrate this phenomenon, where landscape diversification increased with uncertainty. This effect was also shown with the optimization model for other tropical regions in Ecuador and Chile (Knoke et al. 2016; Uhde et al. 2017).

Furthermore, landscape context seems to influence landscape diversity. The sensitivity analyses of optimization results based on perception data showed that landscapes with high shares of highly effective agroforestry systems tended to homogenize the remaining landscape (Reith et al. 2020). While this may have beneficial effects on forest cover as this (Reith et al. 2020) and other studies have shown (e.g., Angelsen and Kaimowitz 2004), landscape homogenization may have adverse effects on multifunctionality (van der Plas et al. 2016).

However, diversification strategies are still debated between proponents of land-sparing and land-sharing. While the optimization model would include agroforestry (when presented with this land-sharing option) in a socio-ecological system, other schools of thought promote the land-sparing approach. Land-sparing proponents argue for intensifying agricultural land use and setting aside forests for ecological purposes instead of combining agricultural and tree components on the same plot (Green et al. 2005; Phalan 2018). They argue that trade-offs between human food demand and biodiversity conservation are best reconciled this way (e.g. Grass et al. 2020; Feniuk et al. 2019; Phalan 2018). Discussions go so far as to recommend that 50% of the Earth should be left to nature (Dinerstein et al., 2017). However, the land-sparing approach is seen as a remedy and curse in reconciling landscape-level conservation and production goals. For example, Didham et al. (2015) showed the adverse effects of intensified agriculture on adjacent forests.

The results of this thesis confirm that diversification seems to be a desirable land-use strategy for a multifunctional compromise solution (Meli et al. 2019; Willmott et al. 2023). The optimization outcome for agricultural-dominated regions is consistent with the triad concept of sustainable forestry, which combines intensively and extensively managed lands with protected reserves along a land-sharing/-sparing continuum (Betts et al. 2021). This optimized landscape would still allow for culturally preferred cattle ranching on pastures with and without a tree component.

4.3 Multifunctionality and forest cover

The model outcomes highlight the importance of natural forest cover in multifunctional landscapes. To mitigate trade-offs between equally weighted ecological and socio-economic objectives, the model would always select the ecologically superior natural forest. For climate mitigation, other ecological functions, and forest-dependent species, natural forest cover is especially important (Arroyo-Rodríguez et al. 2020; Kremen and Merenlender 2018). Nevertheless, the carbon sequestration potential may be uncertain, because forests and reforestation projects can face fires or suffer from pests and droughts.

The integration of literature data on land-cover performance in measurable units quantifies the potentially intended and unintended impacts of a multifunctional landscape on ecological and socio-economic functions and land-cover shares. Seeking multifunctionality in agriculture-dominated landscapes (such as the landscapes in Panama and Indonesia) may increase tree cover through restorative land-cover systems such as agroforestry (Figure 10). However, as the comparison with the forest-dominated example landscape in Ecuador demonstrates, a strategy to increase multifunctionality can also drastically reduce tree cover. With forest conservation instead of forest-use, the agricultural area would need to be extended compared to the current landscape in Ecuador to balance equally weighted ecological and socio-economic objectives. Hence, the model did not select the ecologically and socio-economically inferior extensive silvopasture system for the optimized multifunctional landscape. Also, Knoke et al. (2020b) quantified that aiming for multifunctionality may conflict with the goal of reducing deforestation. They applied an innovative, dynamic optimization approach to model deforestation for tropical mountain forests in Ecuador and found that deforestation may be accelerated in landscapes with high forest shares (38% – 80% area share) when accounting for multiple ecosystem services and high uncertainty. Hence, caution is required with landscape diversification strategies to increase landscape multifunctionality.

Proponents of land-sharing argue that agroforestry practices may reduce deforestation by combating land degradation and increasing the long-term productivity of agricultural land in contrast to conventional more intensive land uses (Angelsen and Kaimowitz 2004). Furthermore, agroforestry may also be suitable for restoring abandoned lands, which represents a large opportunity to expand agricultural areas without the need for deforestation (Knoke et al. 2013). However, not all abandoned land may be suitable for agricultural production (DeFries and Rosenzweig 2010). Moreover, while the presence of agroforestry systems can break the downward spiral of forest clearing for agricultural purposes, in some cases it can also accelerate deforestation. While higher yields can increase food production and therefore reduce the need for deforestation, increased profitability (given no price declines) can incentivize the expansion of agricultural land at the expense of forest cover (*rebound effect*, DeFries and Rosenzweig 2010). Similarly, in the case of potentially lower yields in agroforestry systems compared to conventional ones, reduced food production may result in a spill-over effect. This means that the failure to produce enough food locally results in the need to buy food from somewhere else, where deforestation may take place and the same ecological problems then occur (Heilmayr et al. 2020; Leijten et al. 2021).

Hence, it is recommended to first preserve forest remnants to mitigate trade-offs between ecological and socio-economic objectives (Kremen and Merenlender 2018; Raveloaritiana et al. 2023). The second most important is to prioritize the management of existing forests, and only thirdly consider restoration efforts (Cook-Patton et al. 2021).

4.4 Research approach and outlook

Apart from the empirical findings on sustainable landscape planning and the role of agroforestry, this thesis contributes to the methodological and conceptual development of agroforestry and landscape research. This section outlines the methodological contributions and limitations and derives future research opportunities from those.

4.4.1 Conceptual contributions to research

This thesis has demonstrated an innovative approach to understanding the perception and impact of introducing agroforestry on the tropical forest frontier from a landscape perspective. What sets the methodology apart is its simultaneous consideration of prevailing and innovative land-cover options, multiple objectives, and uncertainty for investigating desirable landscapes from different perspectives under the common circumstances of data scarcity.

In pursuing a holistic understanding of agroforestry's potential within the tropical landscape against the backdrop of FLR, this study unfolded in three steps. The initial step included a comprehensive review of background information on the landscape, potentially important objectives of identified interest groups, and political conditions. The path in this feasibility study is marked by the selection of innovative land-cover options, which could then be implemented as part of specific agroforestry trials or policies. Specifically, alley cropping and silvopasture were chosen for their potential suitability to the study region, scalability potential, and promising timber production capabilities, unlike conventional choices such as home gardens (Gosling et al. 2021; Paul 2014). This is usually the first step in empirical studies in land-use planning research (e.g., Rahman et al. 2016).

The work involved obtaining baseline data on the performance of various land-cover options for meeting different objectives, using a strategic blend of expert surveys and literature review (in contrast to field measurements for ecological data, e.g., Kirby and Potvin 2007; Paul 2014). This included considering diverse societal perspectives by integrating perceptions and preferences through AHP (Saaty 1987). The convergence of expert and farmer surveys brought forth a comprehensive dataset, defying the conventional separation of scientific and practical knowledge (Turnhout et al. 2012). The data used in this thesis stand out due to their extensive coverage of all three dimensions of sustainability. This encompassed the novel interpretation of uncertainty spaces to reflect the agreement or disagreement among survey participants.

On a related note, pretesting the surveys with experts proved extremely helpful in determining the final set of objectives and later generating valid data.

The second step of the thesis was constructing a robust optimization model, breaking away from the norm of isolated investigations into agroforestry systems. Unlike previous studies that primarily examined single restoration options, this research ventured into optimizing the entire spectrum of prevalent land-covers, including the natural succession of abandoned land and forest plantations (Adamowicz et al. 2019; Adesina and Coulibaly 1998; Kirby and Potvin 2007; Simonit and Perrings 2013; van Noordwijk and Lusiana 1999). A systematic sensitivity analysis unveiled the impacts of varying land-cover systems, shedding light on trade-offs and landscape diversity effects (Reith et al. 2020). While this work follows a top-down land-use planning approach, research into a bottom-up approach to sustainable land-use planning is just as important. However, this has been done in other research for the study region in eastern Panama (Gosling 2021).

The investigation progressed to trade-off analysis, using the previously developed optimization model to navigate conflicts between diverse interest groups (Reith et al. 2022). Unlike traditional Pareto-based optimization, this approach sought efficiency and a singular optimal solution, facilitating potential meaningful discussions with stakeholders.

The final step magnified the study's impact by evaluating the landscape-scale effects of transitioning to agroforestry systems. This step is essential to report the benefits of agroforestry and the failures of the traditional agricultural systems to decision-makers to bring about a change in the agricultural production system.

4.4.2 Perception data

Conducting surveys can help to integrate intangible and difficult-to-measure perceptions, cultural preferences, as well as local knowledge into land-use planning, which could potentially lead to better success in agroforestry adoption (Díaz et al. 2018; Fischer and Vasseur 2000; Temesgen et al. 2018; Turnhout et al. 2012). As a survey method, AHP is both comprehensive and objective (Parra-López et al. 2008). It is comprehensive because it can consider all ecological and socio-economic dimensions and incorporate people's perceptions (Tiwari et al. 1999). It is sufficiently objective because the survey participants directly express their perceptions and preferences for a given land-cover, increasing the decision-making process's transparency (Parra-López et al. 2008). Another benefit is that obtaining the survey data was relatively quick and easy (compared to for example field measurements for biodiversity). For survey participants, the complex decision of ranking land-cover in terms of its performance against different objectives is simplified by its decomposition into pairwise comparisons. Furthermore, land-cover performance was evaluated relative to another, which is more realistic in land-use planning than evaluating performance individually.

However, capturing the knowledge of interest groups using AHP proved to be more complex than, for example, with a rank and scoring method (see Gosling and Reith 2019). Each pairwise comparison of land-cover systems in AHP includes a range of considerations. For example, comparing land-covers in terms of biodiversity and other ecological objectives is challenging because of the inherent complexity of environmental systems. However, a lower standard deviation associated with the ecological objectives (standard deviation between 1.83 and 2.17) compared to the socio-economic objectives displays a high consensus among survey participants (standard deviation between 2.50 and 3.13), which means that the objectives were simple enough to be evaluated and characterized the ecological functions well. The difference of opinion for socio-economic objectives was higher, perhaps because the considerations for costs and revenues over time differed among the survey participants from different backgrounds.

To reduce the potential fatigue of survey participants through monotonous pairwise comparison, the survey design should have a limited number of land-cover options and objectives. In this case, a maximum of seven different land-cover options was compared against no more than five objectives in one sitting. Especially with farmers not used to these assessments, the AHP survey was lengthy with an average of 19 min to complete the pairwise comparison of land-covers for each objective (Gosling and Reith 2019). This limited the number of objectives that were evaluated by farmers and resulted in an underrepresentation of farmers in the final dataset (Reith et al. 2020). Besides, it resulted in a higher-than-usual consistency ratio, which measures the reliability of responses. Consistency ratios are adequate, below 10% (Saaty 1987), and acceptable below 20% (Wedley 1993). However, due to the described complexity, participants' answers with a higher consistency ratio were considered because the aggregated judgments (mean score and standard deviation) for each of the seven land-cover options and per objective were similar (see supplementary in Reith et al. 2020). Only the aggregated judgments were used as input data for the optimization.

Although all participants were given equal weights in this study, it is possible to assign different weights based on their experience level. This can be achieved by including a question in the survey, such as for self-evaluation or years of experience in their field. However, giving different weights can potentially cause bias. Furthermore, the scope of this study was to find a multifunctional landscape that balances all equally weighted objectives of all participants of different interest groups. Nevertheless, judgment heterogeneity was accounted for by including standard deviation and by explicitly investigating how participants' (dis) agreement about the relative land-cover performance affects the theoretical optimal landscape composition.

Another aspect worth considering is that asking participants to evaluate land-cover options relative to each other can also be a drawback when eliminating one alternative. For this study, *natural succession of abandoned land* was eliminated for the second RQ. Pre-testing indicated that farmers perceived forest and abandoned land to be very similar, so Gosling et al. (2020b) did not include abandoned land in their rank and scoring surveys. Therefore, natural succession of abandoned land was eliminated from the land-cover options of the expert survey data to compare the perception data of farmers and other experts. However, there is an ongoing debate on removing or adding alternatives to the AHP (Maleki and Zahir 2013). The issue of rank reversal can occur when similar alternatives are part of the decision-making problem and criteria weights depend on alternatives. For example, Belton and Gear (1983) showed that after adding a copy of one alternative, the ranks of two alternatives were reversed. However, Saaty and Hu (1998; 2010) stated that rank reversals are allowed. In this study, rank reversals did not occur when eliminating one land-cover alternative.

Another critical aspect of the survey is that acquired land-cover performance data represents subjective perception and preference. Personal dislikes or wishful thinking, expertise, and experience level can influence judgment (Burkhard et al. 2012). This may be particularly challenging with land-covers that are not currently practiced (Gosling 2021). However, the pastures in the study region commonly include trees in the form of living fences or dispersed trees (Paul 2014). Therefore, survey participants are not entirely unfamiliar with silvopasture systems.

Moreover, surveys are susceptible to bias and inaccuracies (Döring and Bortz 2016). For example, on the interviewer's part, their expectations might hinder objectivity, thereby influencing the interviewee's responses positively or negatively (Bryman 2016). However, the surveys followed a systematic approach to mitigate bias, including the same introductory information on the study region, land-cover, and objective definitions (Baur and Blasius 2019). Surveys in the participants' language (English or Spanish) further safeguarded against language-based biases (Döring and Bortz 2016). On the interviewee side, inaccuracies in responses might occur. There are many reasons for this to occur, for example, because the interviewee wants to align their response with what is socially acceptable or what they believe the interviewer is expecting to hear (Bryman 2016; Döring and Bortz 2016). However, the rankings of the FLR options differed, and they did not score best across all objectives, indicating that survey participants were not subject to a strong response bias in this regard. In addition, a plausibility check was done with empirical findings at other tropical sites (in literature). Optimization results with both data sets confirm that the data derived through surveys represents a good proxy for expert data from peer-reviewed publications (Chapter 3.4).

4.4.3 Literature-based and computed data

While perception and preference data can capture subjective influences of decision-making, computed or measured data are suitable when considering and comparing tangible constraints, advantageous and disadvantageous (Gosling 2021). Consequently, literature data was compiled for impact evaluation of land-use change.

Obtaining a consistent dataset from the literature for the focus region in eastern Panama proved challenging. This drastically reduced the number of indicators considered in this study. In general, multiple indicators can reflect each ecosystem service. For example, secondary indicators (such as biomass production, plant carbon accumulation, and SOC) can be used to reflect primary indicators such as carbon sequestration, which in turn reflect important ecosystem services such as climate regulation, wood supply, and life support (Knoke et al. 2014). Clough et al. (2016) quantified nine ecological and five socio-economic functions to highlight drivers and trade-offs of land-use decisions in a smallholder landscape in Indonesia (whereas this study's dataset contained three ecological and eight socio-economic indicators for RQ 3). Knoke et al. (2014) used 23 ecological, economic, and social indicators to represent a landscape's potential to balance multiple different ecosystem services. However, their subsequent study tested the influence of the number of indicators on the level of landscape diversification (Knoke et al. 2016). Their results showed that with 8 to 12 different indicators, the level of landscape diversification becomes stable (*multifunction effect*, Knoke et al. 2016). Therefore, this study employed 11 indicators for the multifunctional landscape, covering critical ecological and socio-economic factors. Despite the limited ecological dataset, the 11 indicators might be sufficient for optimizing the multifunctional landscape (RQ 3).

A comparison of the calculated ecological indicator values with literature values showed that the estimates appear plausible. For example, the total carbon stored in pasture was estimated to be 55 Mg ha^{-1}, while Kirby and Potvin (2007) reported an estimate of 39 Mg C ha^{-1} (including soil carbon for 0 - 30 cm) for the farms of indigenous families in the vicinity of the study area. This slight difference is mainly due to the higher SOC score based on Ogle et al. (2003) and IPCC (2006) guidelines for calculation in this thesis. However, Torres et al. (2023) reported similar total carbon stocks of pastures in monocultures in the lowlands of the Ecuadorian Amazon with 52.53 Mg C ha^{-1}. The estimated value of carbon stored in tropical rainforest (above- and below-ground) in the Americas may have been underestimated, as it was lower (287 Mg C ha^{-1}) compared to estimates close to the study area (335.1 Mg C ha^{-1}) by Kirby and Potvin (2007). However, it still seems plausible as the average above-ground biomass of 154 Mg C ha^{-1} derived from several studies for tropical forests in North and South America (IPCC 2019) aligns with values reported for other tropical rainforests, for example, in Indonesia (between 106 and 204 Mg C ha^{-1}, Grass et al. 2020). The estimate for teak plantations is comparatively low due to the relatively low tree density. While this study considered about 224 trees at harvest age, the study cited by the IPCC (2019) reports an average of 624 trees per hectare (Kraenzel et al. 2003). Similarly, the results for the agroforestry systems are conservative estimates compared to the results for home and field gardens in eastern Panama (Kirby and Potvin 2007). Given that carbon typically increases with biomass, the ranking of land-cover in terms of estimated carbon storage seems reasonable (forest > FLR options > pasture > cropland), with agroforestry and teak plantations sequestering comparable amounts of carbon (Kirby and Potvin 2007).

However, the variability of SOC (in the 10 cm topsoil layer) associated with land use history, stand age, and biophysical conditions call for caution in interpreting optimal landscape compositions. For example, Neumann-Cosel et al. (2011) reported no significant increase in soil carbon storage for 15 years, underlining the slow recovery from previous land use (Tschakert et al. 2007). Therefore, the estimates for the alley cropping systems may more closely reflect the values of the previous pasture and underestimate the effect of trees measured at the age of 1.5 years (Paul 2014). In fact, little difference was found between monoculture and agroforestry systems (Paul 2014). Similarly, SOC concentrations in teak plantations may be similar to those in natural forests because these plantations were established on relatively fertile sites (Kraenzel et al. 2003).

Furthermore, land use and management activities can influence soil carbon stocks (Neumann-Cosel et al. 2011; Sanchez 2019). Hence, local biophysical factors may differ and affect the amount of soil carbon stored (Barré et al. 2017; Deng et al. 2016). While the data provide a good proxy and the associated uncertainty accounts for some variability in conditions, local heterogeneity should always be considered. Hence, the results of landscape-scale optimization models need to be discussed with local experts for feasibility.

4.4.4 Outlook

The scope and results of this research lead to five potential research topics for future research on the landscape level.

First, stakeholder participation is becoming increasingly important in agroforestry research (van Noordwijk et al. 2021) to investigate how agroforestry systems should be designed to be socio-economically attractive while contributing to ecological improvements. While this study included surveys with interest groups, greater involvement of interest groups a priori and posterior modeling can help find land-cover compositions with greater potential for success and validate results (Kaim et al. 2018; Turnhout et al. 2012). In the future, the model could help strengthen social concerns and cross-sector collaboration, which were identified as important aspects at the joint restoration event held in San Pedro, Belize, attended by actors of the Bonn Challenge, the 20x20 Initiative, the UN Decade 2030, and the World Resources Institute in 2023 (IKK 2023). In discussing desirable futures for multiple stakeholders of the post-2020 agenda for biodiversity, the model can support deriving nature-people scenarios using the Nature Futures Framework (Pereira et al. 2020). Applying participatory land-use planning, optimization results can be discussed with decision-makers to identify feasible sustainable land-use compositions (Le Gal et al. 2013), opportunities and obstacles to tree presence (Andreotti et al. 2020), and common ground between interest groups (Temesgen and Wu 2018). Results can then be adapted to ensure all relevant land-cover options and desirable new ones are integrated, and the most relevant objectives and biophysical and socio-economic restrictions are accounted for. Subsequently, decision-makers could identify necessary steps to change the current land-use allocation into the envisioned future in a back-casting workshop (Andreotti et al. 2020). Together with social scientists, a co-learning process could then be documented and analyzed. This could aid effective policies.

Second, future studies could better account for heterogenous environmental and socio-economic conditions. While the results of this study show that agroforestry is certainly a valuable contribution to a multifunctional land-use mosaic, future studies may test other diversification strategies that may be locally more suitable. For example, farm mosaics combine forest plantations with conventional land uses on separate plots. While still providing ecological benefits, such a system may be particularly suitable for heterogeneous site conditions with higher-quality land and larger farm sizes exceeding 10 hectares (Paul et al. 2017b). Compartmentally organized land-use strategies, included in the diversified land-use concept by Haber (1990) and building on Odum's strategy of ecosystem development (Corman et al. 2019), could be a valuable alternative (Knoke et al. 2012). Future studies can test the sustainable intensification of agriculture, enhancing efficiencies while preserving natural ecosystems without expanding at the expense of forests (Feniuk et al. 2019; Phalan 2018), but blended with less intensively managed land-cover types. Local experts could evaluate the feasibility of optimization results and specific land-use strategies (farm mosaic or agroforestry) by considering local biophysical and socio-economic constraints.

One socio-economic aspect not included in this study but potentially influencing land-use decisions is access to off-farm income. For example, Ochoa et al. (2019) showed that southern Ecuador's small-scale farmers with off-farm income tend to homogenize land use. In contrast, farmers highly dependent on household income from the farm tend to diversify their land use to reduce risks (Ochoa et al. 2019). Off-farm income may also reduce the need for deforestation to expand agricultural areas (Knoke et al. 2022; Zeb et al. 2019). Future studies could investigate the impacts of off-farm income on deforestation and reforestation projects in eastern Panama. For example, income from eco-tourism, such as bird watching and agro-ecotourism, could be investigated (Basnet et al. 2021; Kumar et al. 2021).

Furthermore, by applying different input coefficients for different farm types (as identified by Gosling et al. 2020a), the optimization results could provide insights into socio-economic heterogeneity among farmers. This could aid in the design of more effective policies to restore tree cover. Such data could also be used to model socio-economic constraints and explore policy (dis)incentives through scenario analysis such as payments for ecosystem services (Calle 2020) or penalties for disservices (Kay et al. 2019).

Another aspect not accounted for is the time preference for ecosystem service. In this study, time preference in economic indicators (NPV, payback period) is accounted for through discounting. However, time value for many biophysical indicators can also be assumed, such as the need to sequester carbon today before a tipping point is reached (van Kooten et al. 2004). Jarisch et al. (2022) suggest discounting ecosystem services and financial objectives in multi-objective optimization to reduce bias and for more comprehensive land-use planning.

The third direction for future research involves different representations of uncertainty. The robust optimization approach in this thesis used box-shaped uncertainty sets, following Knoke et al. (2015; 2016). Meaning that all possible combinations of land-cover performances were treated equally instead of giving different weights to uncertainty scenarios that are more or less likely (Castro et al. 2018). This approach is practical when decision-maker's current and future demands and priorities are uncertain (Walker et al. 2013). Alternatively, ellipsoidal or other shapes of uncertainty space could be used, which can increase precision, but also data demand (Messerer et al. 2017). One application of elliptical uncertainty sets in forest optimization is Knoke et al. (2020a).

Fourth, dynamic modeling could extend the research scope. When investigating optimal landscape compositions, this study did not account for temporal aspects of land-use decisions, such as seasonal fluctuations of land-cover performance (Burkhard et al. 2014), growth dynamics (e.g., succession of pasture to abandoned land to forest), and degradation effects (Kuiper 1997). However, a dynamic version of this optimization approach was used to model deforestation scenarios (Knoke et al. 2020b). This could be further developed to refine feasible strategies to attain the desired sustainable landscape. For example, staggered tree planting in agroforestry systems could be accounted for to provide farmers with more liquidity and spread investment risk over several years (Bertomeu and Giménez 2006; Gosling 2021). Such a dynamic approach could also be developed to investigate questions of resilience, for instance, the effect of climate change on how fast a given system can recover after disturbance. The presented approach can demonstrate the resistance of socio-ecological systems, meaning the ability of a system or a landscape to withstand fluctuations and maintain relatively stable conditions (Seipel et al. 2019). A robust land-use composition can be found that better withstands variability in land-use performance, reflected by the various uncertainty scenarios. However, resilience, i.e., the dynamic property of a given system to recover from a disturbance (Seidl et al. 2016), has not been investigated with the model.

Another advancement could be combining robust optimization with other modeling approaches to better understand social-ecological systems (Kaim et al. 2018; Paul et al. 2019). For instance, the integration of these models with Geographic Information Systems could enable the creation of spatially explicit hybrid models capable of addressing questions related to the optimal placement of various land-cover options and predicting the consequences of widespread agroforestry adoption (Palma et al. 2007a; Paul et al. 2019). Such approaches could answer RQs regarding landscape configuration (in contrast to the presented landscape composition questions) and account for heterogeneous site conditions across the landscape. This is an important consideration in land-use planning as land quality may influence land-use decisions. For example, agroforestry showed the most advantage in poor-quality soils (Gosling et al. 2021; Tsonkova et al. 2014). Furthermore, the process-based model WaNulCas, which simulates tree and crop yields, among other ecosystem services, could be used to systematically model various agroforestry layouts designed to facilitate regular harvests and cash flow (Paul et al. 2017b). Combined with the robust optimization approach, this modeling can help identify the most promising agroforestry systems for subsequent field trials.

5. Conclusions

5.1 Implications for sustainable development through land use

Policy-makers must navigate trade-offs between socio-ecological and socio-economic objectives in eastern Panama, a region heavily deforested for agriculture. The robust multi-objective optimization model presented in this thesis can help policy-makers identify unintended effects of particular land-use strategies or (dis)incentive programs. For instance, optimization outcomes revealed that promoting multifunctionality in agriculture-dominated regions, such as eastern Panama, can lead to increased forest cover. In contrast, aiming for multifunctionality in still-forested regions (e.g., the Ecuadorian landscape) could decrease tree cover. Furthermore, incentivizing the widespread adoption of agroforestry might result in its dominance within the landscape, potentially homogenizing the remaining area at the expense of multifunctionality (Reith et al. 2020). Therefore, legislators should use optimization models for comprehensive restoration plans to avoid unintended effects (including rebound and spill-over effects) and ensure that farmers needing financial support are the beneficiaries.

The presented optimization approach may support future studies that pursue scenario analysis of incentive- and restriction-based policy instruments to encourage agroforestry adoption and forest conservation. For instance, creating an economic benefit from forest conservation may encourage land managers to preserve or sustainably use their forests (Miller et al. 2012). For instance, Ochoa et al. (2016) identified compensation payments, coupled with sustainable forest use, as an effective strategy for preserving tree cover and preventing its conversion into agricultural land in southern Ecuador. Alternatively, restrictions can serve as legislative levers to discourage unsustainable practices like slash-and-burn and safeguard habitats and ecosystem services (Garmestani et al. 2019). For example, restrictions could ensure the subsidies are only available for agriculture production on land previously used for agriculture (including rested or abandoned agricultural land) and not on newly deforested land. Such an approach may balance the costs of forest conservation with food prices.

Furthermore, the FLR approach presents a challenge due to its cross-sectoral and multidisciplinary nature, particularly in integrating various stakeholders (Mansourian et al. 2021). Unlike previous methods that have narrower scopes, our optimization approach uniquely enables this integration and supports participatory processes urgently needed for the success of afforestation projects (Fischer and Vasseur 2000; Holl and Brancalion 2020; Höhl et al. 2020; Turnhout et al. 2012; Vermunt et al. 2020). In the future, the presented approach can serve as a valuable tool for collaborative projects with land-use-related companies, NGOs, and land managers, aiding in the definition of shared objectives, identification of potential conflicts, and facilitating constructive discussions among interest groups, all of which are essential for developing multifunctional landscapes.

5.2 Implications for land-use management

The optimization results of this thesis show that investments in a heterogeneous landscape with traditional agricultural practices, natural forests, and different FLR options in the face of uncertainty are consistent with the FLR goal of reconciling environmental and socio-economic objectives. However, integrating agroforestry into the current landscape would reduce the liquidity of farmers, which appears to be an important prerequisite for greater agroforestry adoption in the study area (Gosling 2021). Hence, future studies could test the feasibility of other silvopasture systems and crop-tree-layouts to ensure liquidity. Examples include the use of fodder trees (such as Leucaena, Reyes Cáceres 2018), wider-spaced alleys of trees (Paul et al. 2017b), or gradual establishment of agroforestry systems through staggered tree planting (Current et al. 1995; Bertomeu and Giménez 2006).

Another barrier to agroforestry adoption identified in this study is the lack of experience with such systems. Farmers in the study area have good knowledge of agricultural practices but not so much of silvicultural practices (Gosling et al. 2021). This aligns with other studies that have found that silvicultural training and technical assistance may be paramount for promoting agroforestry systems (Calle et al. 2009). Hence, farmers must receive adequate training to acquire the knowledge and skills to produce high-value timber (Souza-Alonso et al. 2023). Extension workers and community leaders can be crucial by providing training and presenting best practices.

5.3 Implications for research

This thesis extends the sustainable land-use planning toolbox. It advances our knowledge of the potential of agroforestry, among other FLR options, at the tropical forest frontier in eastern Panama and beyond. More research is required to gain an even deeper understanding of socio-ecological systems and facilitate the development of effective intervention strategies that promote sustainable land use alongside environmental conservation. Developing hybrid models incorporating multi-objective robust optimization could further facilitate sustainable landscape planning.

In conclusion, supporting decision-makers in realizing the ecologically detrimental consequences of conventional practices and fostering a positive attitude toward forest conservation and the new agroforestry systems may be one of the most essential conditions for land-use change (Calle et al. 2009). This research is another paving stone to sustainable land-use strategies that mitigate trade-offs and uncertainty by objectively presenting the advantages and drawbacks of existing land-covers compared to agroforestry and diversified multifunctional landscapes.

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Appendices

List of publications

Peer-reviewed publications during the time of the PhD (November 2017–December 2023)

Reith E, Gosling E, Knoke T, Paul C (2020) How much agroforestry is needed to achieve multifunctional landscapes at the forest frontier? —Coupling expert opinion with robust goal programming. Sustainability 12:6077. https://doi.org/10.3390/su12156077

Reith, E.; Gosling, E.; Knoke, T.; Paul, C. (2022): Exploring trade-offs in agro-ecological landscapes: Using a multi-objective land-use allocation model to support agroforestry research. Basic and Applied Ecology 64: 103-119. doi: 10.1016/j.baae.2022.08.002 .

Paul C, Reith E, Salecker J, Knoke T (2019) How integrated ecological-economic modelling can inform landscape pattern in forest agroecosystems. Current Landscape Ecology Reports 4:125–138. https://doi.org/10.1007/s40823-019-00046-4

Gosling E, Reith E (2019) Capturing farmers' knowledge: Testing the analytic hierarchy process and a ranking and scoring method. Society & Natural Resources 33:700-708. https://doi.org/10.1080/08941920.2019.1681569

Gosling E, Reith E, Knoke T, Paul C (2020) A goal programming approach to evaluate agroforestry systems in Eastern Panama. Journal of Environmental Management 261: 110248. https://doi.org/10.1016/j.jenvman.2020.110248

Gosling E, Reith E, Knoke T, Gerique A, Paul C (2020) Exploring farmer perceptions of agroforestry via multi-objective optimisation: a test application in Eastern Panama. Agroforestry Systems 94:2003-2020. https://doi.org/10.1007/s10457-020-00519-0

Gosling E, Knoke T, Reith E, Reyes Cáceres A, Paul C (2021) Which socio-economic conditions drive the selection of agroforestry at the forest frontier? Environmental Management 67:1119-1136. https://doi.org/10.1007/s00267-021-01439-0

Knoke, T.; Gosling, E.; Reith, E.; Gerique, A.; Pohle, P.; Valle Carrión, L.; Ochoa Moreno, W.S.; Castro, L.M.; Calvas, B.; Hildebrandt, P.; Döllerer, M.; Bastit, F.; Paul, C. (2022): Confronting sustainable intensification with uncertainty and extreme values on smallholder tropical farms. Sustainability Science: 1-18. doi: 10.1007/s11625-022-01133-y.

Knoke, T.; Gosling, E.; Reith, E. (2022): Understanding and modelling the ambiguous impact of off-farm income on tropical deforestation. Journal of land use science: 1-20. doi: 10.1080/1747423X.2022.2146220.

Non-peer-reviewed publications

Gosling, E.; Reith, E.; Paul, C. (2020): Agroforstwirtschaft – ein Gewinn für Landwirte und Umwelt? AFZ - Der Wald (17): 26-28. Download

Reith, E.; Gosling, E.; Knoke, T.; Uhde, B.; Paul, C. (2018): Ökosystemleistungen bewerten – Beispiele aus Chile und Panama. AFZ-Der Wald (14): 13-15. Download

Reith, E.; Gosling, E.; Knoke, T.; Paul, C. (2021): Das Potenzial der Agroforstwirtschaft zur Wiederbewaldung. AFZ - Der Wald (19): 22-25. Download

Selected Presentations

Reith, E.; Gosling, E.; Paul, C. (2018): Auswahl von Agroforstsystemen auf unsicherer Datenbasis am Beispiel Panama. 6.Forum Agroforstsysteme, Göttingen.

Reith, E.; Gosling, E.; Knoke, T. Paul, C. (2021): The role of agroforestry in a multifunctional and uncertain world: a landscapes perspective. 5th European Agroforestry Conference, online, 17 May 2021.

Reith, E. (2021): Agroforstwirtschaft in einer multifunktionalen und unsicheren Welt: wie robuste Optimierungsmodelle die Forschung bereichern können. Risikoworkshop 2021, Freising

Reith, E.; Gosling, E.; Knoke, T.; Paul, C. (2022): Potential of Agroforestry in Panama. AgScience on Tap, Feising.

Reith, E. (2023): Exploring the Role of Agroforestry as a Tool for Forest Landscape Restoration in Eastern Panama Using Robust Optimization. Symposium Research on Natural Resource Management.

Reith, E. (2023): Reshaping Land Use: Multifunctional Landscapes as Win-Win Strategies? Seminar Waldbau, Ökosystemdynamik und Forstplanung, Freising.

Table 1 The two studies contribute to the storyline of this thesis. CP = Carola Paul, EG = Elizabeth Gosling, ER = Esther Reith, TK = Thomas Knoke

Number (Chapter)	Study	Research objective	Data	Methods	Main findings	Author contributions
1 (Ch. 3.1)	Reith, E.; Gosling, E.; Knoke, T.; Paul, C. (2020): How Much Agroforestry is Needed to Achieve Multifunctional Landscapes at the Forest Frontier? — Coupling Expert Opinion with Robust Goal Programming. sustainability 12: 1-27.	Investigate the performance and composition of multifunctional landscapes, including agroforestry	Survey data was collected from a range of different experts	AHP and robust multi-objective optimization (Knoke et al. 2016, Uhde et al. 2017), analysis of Shannon Index, Sensitivity analysis of in/decreasing land-cover area	Results from the optimization indicate that agroforestry may have great potential to complement land-cover mosaics of multifunctional agriculture-dominated landscapes based on expert perceptions. The sensitivity analysis provides new insights into the impact of expanding agroforestry and other land-cover options on forest cover and landscape diversity.	idea & design – ER, CP data collection - ER, EG modeling - ER data analysis – ER, CP, EG manuscript drafting – ER manuscript revision- ER, CP, EG, TK
2 (Ch. 3.2)	Reith, E.; Gosling, E.; Knoke, T.; Paul, C. (2022): Exploring trade-offs in agro-ecological landscapes: Using a multi-objective land-use allocation model to support agroforestry research. Basic and Applied Ecology 64: 103-119.	Critical comparison of land allocation models in agroforestry research	Interview data based on Reith et al. (2020) for the public perspective, interview data from Gosling et al. (2020) for the farmer perspective	Literature review, robust multi-objective optimization, scenario analysis through weighing indicators	This paper highlights the strengths and limitations of robust multi-objective optimization compared to other land-use allocation models and suggests future directions for agroforestry research. An example application shows that agroforestry would be included in optimal landscape compositions from different perspectives based on scientific and practical knowledge for the study area.	idea & design – ER, CP data collection - ER, EG modeling - ER data analysis – ER, CP manuscript drafting – ER manuscript revision- ER, CP, EG, TK

Publication 1

Reith, E.; Gosling, E.; Knoke, T.; Paul, C. (2020): How Much Agroforestry is Needed to Achieve Multifunctional Landscapes at the Forest Frontier? — Coupling Expert Opinion with Robust Goal Programming. sustainability 12: 1-27.

sustainability MDPI

Article

How Much Agroforestry is Needed to Achieve Multifunctional Landscapes at the Forest Frontier? —Coupling Expert Opinion with Robust Goal Programming

Esther Reith [1,*], Elizabeth Gosling [1], Thomas Knoke [1] and Carola Paul [2,3]

[1] Institute of Forest Management, TUM School of Life Sciences Weihenstephan, Technische Universität München, Hans-Carl-von-Carlowitz-Platz 2, 85354 Freising, Germany; elizabeth.gosling@tum.de (E.G.), knoke@tum.de (T.K.)
[2] Department of Forest Economics and Sustainable Land Use Planning, University of Göttingen, Büsgenweg 1, 37077 Göttingen, Germany; carola.paul@uni-goettingen.de
[3] Centre of Biodiversity and Sustainable Land Use, Büsgenweg 1, 37077 Göttingen, Germany
* Correspondence: esther.reith@tum.de; Tel.: +49-08161-71-5397

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Abstract: Agroforestry has been promoted as a key forest landscape restoration (FLR) option to restore ecosystem services in degraded tropical landscapes. We investigated the share and type of agroforestry selected in an optimized landscape, accounting for a mosaic of alternative forest landscape restoration options (reforestation and natural succession) and forest and common agricultural land-uses. We extend previous studies on multi-objective robust optimization and the analytic hierarchy process by a systematic sensitivity analysis to assess the influence of incorporating agroforestry into a landscape. This approach accounts for multiple objectives concurrently, yet data and computational requirements are relatively low. Our results show that experts from different backgrounds perceive agroforestry (i.e., alley cropping and silvopasture) very positively. Inclusion of large shares of agroforestry (41% share of landscape) in the FLR mix enhanced simulated ecosystem service provision. Our results demonstrate that landscapes with high shares of agroforestry may also comprise of high shares of natural forest. However, landscapes dominated by single agroforestry systems showed lower landscape multifunctionality than heterogeneous landscapes. In the ongoing effort to create sustainable landscapes, our approach contributes to an understanding of interrelations between land-covers and uncertain provisions of ecosystem services in circumstances with scarce data.

Keywords: agroforestry; analytic hierarchy process; ecosystem services; forest landscape restoration; multifunctionality; optimization; uncertainty

1. Introduction

Agroforestry, the combination of trees and pasture or trees and crops on the same piece of land, is a promising system to reconcile ecological and socio-economic objectives in tropical regions [1–4]. For farmers and society as a whole, agroforestry may offer several advantages over conventional agriculture [4,5]. As a land-sharing strategy, agroforestry may be especially suited for re-integrating trees into degraded landscapes and has been discussed as a first step towards an agro-succession to increase forest cover [6,7]. Agroforestry systems, together with assisted natural reforestation and afforestation are among the forest landscape restoration (FLR) approaches [8]. FLR represents a landscape management strategy which aims to reconcile ecological and socio-economic objectives by restoring degraded agricultural and deforested lands [8–12]. By creating landscapes made up of diverse and complementary land-use types, the objective of FLR is to restore ecological integrity and benefit human well-being [6].

In Panama, like in other tropical countries, old growth forest cover has been decreasing due to agricultural expansion [13–15]. Land abandonment in some parts of Panama led to slight net increase of forest cover due to natural secondary forest succession between 1992 and 2000 [15]. In an effort to reforest degraded land across the country, the Panamanian government has committed to one of the largest global restoration initiatives, the "Bonn Challenge", and partnered with private institutions in the national initiative "Alianza por el Millón de Hectareas Reforestadas" (Alliance for One Million Hectares Reforested) [9]. Existing restoration efforts in Panama have predominately focused on afforestation. For example, financial incentives for afforestation, enacted in 1992, have promoted commercial monocultures of teak (*Tectona grandis*), a fast-growing exotic species often owned by international timber corporations [16]. However, the expansion of these plantations has been criticized to mainly serve the objectives of large, mostly foreign reforestation companies, while rural needs, such as the need for frequent and regular cash flows, may be in conflict with this restoration option [16,17]. Furthermore, forest-plantations are sometimes called "green deserts", which reflects the debate around the biodiversity value of forest-plantations [18]. Therefore, in conjunction with Panama's reforestation project "Alianza por el Millón", there may be a shift toward more diversified reforestation options. For example, a new law specifically promotes agroforestry through tax exemptions and subsidies [19].

However, agroforestry may drive further deforestation if these systems prove economically competitive with profitable cropping or pasture systems [20]. Hence, decision-makers, such as landowners and landscape planning authorities, face the question of how much and which type of forest restoration option(s) is needed in different pre-existing landscape compositions or contexts to benefit landowners and the broader community [11]. This is a challenging task, given that ideally all land-uses of a landscape mosaic should be considered simultaneously to create a multifunctional landscape that fulfills multiple ecological and economic objectives, and avoids adverse consequences, such as deforestation.

Most research into multifunctional landscapes is positive in nature, aiming to describe and predict interactions between landscapes and ecosystem services. To illustrate, the impact of landscape structure on ecosystem services has been investigated through empiric statistical models (e.g., [21–23]) and system dynamics modelling (e.g., [24]). Agent based modelling has also been used to model decision-making of agents (e.g., farmers) and analyze interrelations of ecosystem services and land-use at the landscape scale (e.g., [25,26]).

While these approaches provide valuable information for landscape planning, our focus was in examining what a future landscape composition should look like to fulfill the objectives of multiple stakeholders. This concerns the uncertain provision of multiple ecosystem services (normative approach).

As a normative decision-support tool, multi-criteria optimization can be used to explore optimal land-cover compositions for reconciling multiple, potentially conflicting objectives [27,28]. In the case of our approach, this concerns ecological and socio-economic ecosystem service indicators. A common normative decision-support method is mean-variance optimization, based on modern portfolio theory. Portfolio theory is borrowed from financial sciences and builds on the premise that investing into different (not perfectly correlated) assets will reduce the overall portfolio risk. Translated to problems of land allocation, the method has been used to demonstrate the importance of high compositional diversity to stabilize economic returns but also to provide multiple ecosystem services [29–31]. However, these methods can be very data intensive due to the need to consider covariances among the criteria considered [32]. Portfolio theory in the context of land allocation has furthermore mainly been applied to optimize a single, usually economic objective, but has rarely been coupled with multiple objective functions [30,33]. As an alternative to mean-variance optimization, robust portfolio optimization does not require specific knowledge on correlations. Furthermore, robust optimization is less data-demanding when accounting for perturbations or uncertainty, which stem from the underlying variation in the provision of ecosystem services in our context [20]. While stochastic mean-variance optimization assumes probabilistic uncertainty, robust optimization is deterministic. Considering numerous constraints to account for all input data included in so-called uncertainty sets, robust optimization finds a solution which guarantees that none of the constraints are violated [20,34]. Knoke et al. [35] developed a robust optimization model to optimize land-cover diversification that provides multiple ecosystem services, while reducing trade-offs between them. They investigated land allocation to provide socio-economic benefits and ecological functions in Ecuador [35].

To represent multiple objectives in land-use modelling, indicators can be used. Indicators help to assess changes in ecosystem services owing to changes in land-use practices [36]. For example, the status of biodiversity has been assessed using an indicator that uses land-use composition as proxy for potential habitats within a given landscape and relates this to the level of biodiversity within that area [37,38]. Datasets from field trials, remote sensing data and from approved databanks, such as those available for InVest [39,40], are valuable tools for quantifying many ecosystem services. Other important socio-economic objectives, such as expected profits, economic stability or cultural preferences, may be difficult to assess without involving stakeholder groups. In particular, perception of landscape value is not easily quantifiable, but may be important to include [41]. In addition, comprehensive datasets for ecological and socio-economic indicators for many land-cover types, including FLR, are seldom available.

As an alternative to measured field data, expert knowledge has been applied to estimate the performance of land-cover types in terms of ecological and socio-economic services [42–45]. For example, Lima et al. [46] combined remote sensing with expert knowledge to map ecosystem services in the Brazilian Savanna and to assess the impact of landscape properties on providing ecosystem services. While their approach has the advantage of not relying on complex modelling tools, it cannot inform about desirable future landscape compositions, including information on land-uses currently not practiced.

Fontana et al. [47] evaluated ecosystem service provisions across three land-use alternatives in the central European Alps, eliciting stakeholder opinion via the analytic hierarchy process (AHP; Saaty [48]). AHP is a popular multiple criteria decision support method that allows expert knowledge to be transferred to a ratio scale [43]. Through pairwise comparison, experts estimate the relative importance of items [48]. For example, Uhde et al. [49] asked experts to compare five forest management options in Chile in terms of ecosystem service provision using AHP. They used the quantified expert knowledge as input data for multi-objective robust optimization based on the model by Knoke et al. [35].

Our study deals with the important challenge of allocating land to different land-cover types while considering trade-offs between them. We intend to better understand the interrelations between different land-cover alternatives and landscape compositions for providing ecosystem services. The optimized landscape compositions might provide a useful starting point for landscape planning and stakeholder discussions, to agree on what an optimal landscape might look like, and to see how these optimal landscapes may change under different pre-existing land-use mosaics. This study advances on previous studies in determining how much of single restoration options is judicious to meet ecological objectives, while being socio-economically attractive and robust in the face of future uncertainties. We couple expert-interviews using AHP with multi-objective robust optimization, but extend the Uhde et al. [49] study, which is limited to forestry, to a landscape approach by considering natural forest, agricultural land-uses and different FLR options including agroforestry. The main contribution of our study is an extensive sensitivity analysis to investigate the potential of agroforestry and other FLR options to increase ecosystem services under various landscape compositions. Previous incentives led to an expansion of forest-plantations, making it the most widespread FLR option in eastern Panama [16]. Therefore, we were interested in analyzing the effect of increasing shares of single land-cover types on optimal land allocation of the remaining landscape and its multifunctionality. This includes exploring the impact of promoting agroforestry on the composition of the remaining landscape and on ecosystem service provision of the entire landscape.

Thus, this study is guided by three research questions:

1. How much agroforestry would be desirable in a mix of FLR options to balance ecological and socio-economic ecosystem services at the landscape scale under uncertainty?
2. How does the landscape context impact the share of agroforestry under uncertainty?
3. How does the promotion of agroforestry affect the remaining landscape composition under uncertainty?

2. Materials and Methods

2.1. Study Area

We exemplify our approach with a study area at the forest frontier of eastern Panama. Our study area covers around 9100 ha, centering of the rural township of Tortí, which belongs to the Chepo District and is located on the Pan-American Highway about 25 km from the border between the Panama and Darien provinces. Fifty years ago, this region was covered by rainforest [50]. Nowadays, the landscape consists of pasture (46%), exotic forest-plantation (22%), cropland (20%) and only a small remnant of natural forest (12%) (see supplementary Method S1).

2.2. Estimating Ecosystem Services Provided by Land-Cover Types

To capture the performance of a landscape for meeting multiple objectives, we used 10 ecosystem service indicators to evaluate ecological and socio-economic objectives (Table 1). To identify relevant ecosystem service indicators, we conducted a literature search and validated the final set of indicators with experts in the pre-test of our survey. The ecological indicators reflect the capacity of a given land-cover for hydrological and climatic regulation, supporting biodiversity and soil fertility. The socio-economic indicators address direct benefits to humans. Among them are the stable provision of food (food security), financial performance (long-term profit, liquidity and stability of economic return) and an aesthetic landscape for society. Our selected indicators cover the four classes of ecosystem services defined by the Millennium Ecosystem Assessment [51]: regulating, supporting, provisioning and cultural. Acknowledging that biodiversity is not an ecosystem service in a strict sense [52], we refer to biodiversity conservation as an additional objective associated with habitat provision. We recognize that there is uncertainty around which ecosystem services will be demanded in the future, and therefore examined a large set of indicators [28].

Table 1. Description of the ecosystem service indicators. They represent the objectives in robust multi-objective optimization.

Category	Ecosystem Service Indicators	Description
Ecological	Global climate regulation	Contribution of land-cover to regulate global climate, i.e., the capacity of vegetation to store atmospheric carbon (without taking into account substitution effects).
	Water regulation	Contribution of land-cover to regulate water flow and supply, e.g., reduced overland flow.
	Biodiversity	The extent to which the land-cover supports species richness, i.e., the number of plant and animal species.
	Long-term soil fertility	Capacity of land-cover to maintain soil fertility, protect soil quality and soil health over the long-term (e.g., 20 years). Potentially quantified through carbon-nitrogen-ratio.
	Micro climate regulation	Contribution of land-cover to local and regional climate regulation. For example, the effect of trees on air temperature and wind speed [53].

Socio-economic	Food security	The extent to which the land-cover type provides a stable food supply concerning dietary calories produced.
	Long-term profit	Contribution of land-cover to provide income in the long run (e.g., 20 years). Potentially quantified through the present value of cash flows generated by the land-cover over time.
	Liquidity	The extent to which the land-cover provides frequent and regular income flows, including how easily the land-cover can be converted to cash if needed.
	Stability of economic return	Contribution of land-cover to provide stable returns against risk (e.g., extreme weather events, price fluctuations). Potentially quantified through financial losses.
	Scenic beauty	The extent to which the land-cover provides an aesthetic landscape for society.

We analyze seven land-cover types in this study (Table 2). This includes the two purely agricultural land-cover types, cropland and pasture, as well as natural forest and four FLR options. In our study, FLR options entail afforestation and regeneration of deforested and degraded landscapes, as well as reintegrating trees in productive units through agroforestry [54]. Common FLR options in eastern Panama are commercial forest-plantation [31] and natural succession of abandoned land [55]. Potential new FLR options are alley cropping and silvopasture agroforestry systems, as defined in Table 2. We selected alley cropping because it can be expanded at different scales. Although not common in the study region, local trials coupled with bio-economic modelling found alley cropping to be an economically competitive land-cover type [31]. We focus on an alley cropping system with a tree and a crop component instead of considering that, with time, the tree canopy would close and annual crop production cease. This is because our analysis is static and does not consider time dynamics. Silvopastoral systems with living fences and scattered trees are common in the study region [56]; however, we were interested in a system with a higher tree density, which can be used for timber production. As stocking rates and tree densities per hectare vary in the literature [57–59], we opted for a conservative number of cattle and trees per hectare (Table 2).

Table 2. Description of the land-cover types. Superscript denotes the FLR options.

Land-Cover	Description	Source
Cropland	Cropland can include various species of annual crops. Different crops might be cultivated at the same time on one plot of land (crop-mix) or rotated over a time (crop rotation). For planting and harvesting, farmers mainly use manual/traditional methods.	[56]
Pasture	Traditional pasture with a stocking rate of one and a half to two cows per hectare, can include scattered trees.	[50,55]
Alley cropping$^{\text{FLR}}$	An agroforestry practice where alleys of trees (with a distance of around 6 meters between trees) are alternated with rows of annual crops. Trees are grown for timber.	[31]
Silvopasture$^{\text{FLR}}$	An agroforestry practice where cattle (conservative count of around one cow per ha) and trees (around 200 trees per ha) are combined on the same plot of land. Trees are planted or guarded against cows and harvested for timber.	[57,60]
Forest-Plantation$^{\text{FLR}}$	Forest-plantations comprising one introduced tree species (e.g., teak, *Tectona grandis*) forming even-aged stands and planted with regular spacing (3 x 3 m). Trees are pruned, thinned and harvested.	[31]
Abandoned land$^{\text{FLR}}$	Natural succession of abandoned land: Agricultural land (cropland or pasture) which has not been managed or cultivated for more than five years, mainly due to low productivity. There can be secondary succession of vegetation.	[55]
Forest	Humid tropical forest, specifically unmanaged secondary forest with natural regeneration. Forest is neither under conservation (i.e., can be used to collect firewood or fruits for human consumption), nor managed for commercial purposes (i.e., timber production).	[50,55]

To estimate the investigated ecosystem services provided by the selected land-cover types, we conducted expert surveys. To ensure that our sample represented an informed view, we used a stratified, purposive sampling approach [61] to target experts from five stakeholder groups: universities and research institutes, government agencies, non-government organizations (NGOs), corporations and farmers and local residents in the study region (who can also be considered shareholders). To identify relevant experts, we contacted organizations and institutes that contributed to a major environmental publication in Panama, the "Atlas Ambiental de la República de Panamá" (The Republic of Panama Environmental Atlas) [62]. We used these initial contacts to broaden our sampling frame through snowball sampling [61]. This allowed us to purposively select experts in pertinent organizations and institutions that hold a position relevant to our research, followed by the use of a primary sample to expand our research by including further relevant participants. We included experts who currently or have previously worked in Panama, and who had expertise in at least one of the following fields: agriculture, agroforestry, biodiversity, climate science, economics, forestry, hydrology and soil science. The field of expertise determined which ecosystem service indicator experts estimated (for further details see Method S2). International experts (with experience in Panama) were sourced by contacting authors of relevant literature. We targeted farmers and local residents by approaching randomly selected houses in the study area and asking the inhabitants if they manage a farm or have a background in farming. If they had that experience, they were asked if they would be willing to participate in the survey. A full breakdown of the number of respondents per indicator and stakeholder group is given in Table S2. We surveyed experts from April to September 2018.

During the survey, we used AHP to generate rankings of the land-cover performance against each of the ecosystem services as perceived by the experts. AHP decomposes complex decision-making processes into a series of pairwise comparisons. Survey participants were asked to complete 21 comparisons of seven land-cover types for each ecosystem service indicator. The output of the AHP survey were mean scores for each land-cover for each indicator. We aggregated the individual results across all respondents to obtain a group judgement reflected by the mean, and their standard deviation. Scores can range from 1 to 17, where high scores signify a land-cover which was better able to achieve a given ecosystem service indicator than the land-cover used for comparison (Table 3). The generated performance data of the land-cover types formed the input data for the optimization model (see below). An advantage of AHP is that it enabled us to consider a wide range of objectives, including those that are not easily quantifiable, such as scenic beauty. Details of the approach used can be found in the supplementary (Method S2).

A total of 54 representatives from 36 organizations and 26 farmers and local residents participated in the survey. We obtained 36 to 40 evaluations per ecosystem service indicator, where an evaluation represents a completed set of pairwise comparisons (Table S2).

Table 3. Ecosystem service indicator scores for land-cover types. Scores were derived from AHP survey and used as input data for multi-objective optimization to obtain a theoretically optimal landscape composition. Figures represent expected mean scores and standard deviation (in parentheses). N is the number of survey participants considered per ecosystem service indicator. The higher the mean score, the more important the land-cover for a given indicator (score range 1 to 17). Highest mean scores for each indicator are given in bold.

Category	Ecosystem Service Indicators	Cropland	Pasture	Alley cropping	Silvopasture	Forest	Forest-Plantation	Abandoned	N
Ecological	Global climate regulation	5.2 (±1.42)	4.2 (±1.48)	10.1 (±1.70)	9.0 (±2.10)	**15.4** (±1.46)	12.1 (±2.31)	7.0 (±2.92)	40
	Water regulation	5.5 (±1.44)	5.0 (±2.05)	10.2 (±2.20)	9.2 (±1.84)	**15.4** (±2.26)	10.4 (±2.10)	7.3 (±3.28)	39
	Biodiversity	5.2 (±1.37)	4.6 (±1.53)	10.0 (±1.78)	9.0 (±1.56)	**16.1** (±1.03)	9.5 (±2.49)	8.6 (±3.55)	38
	Long-term soil fertility	5.6 (±1.23)	4.8 (±1.81)	9.9 (±1.84)	8.7 (±1.74)	**15.8** (±1.89)	9.6 (±2.59)	8.5 (±3.31)	38
	Micro climate regulation	5.1 (±1.17)	4.7 (±1.41)	10.4 (±2.00)	9.0 (±1.74)	**15.7** (±1.25)	10.9 (±1.95)	7.1 (±3.29)	38
Socio-economic	Food security	11.3 (±3.98)	8.7 (±2.77)	**12.8** (±2.11)	11.9 (±2.37)	7.9 (±2.93)	5.9 (±2.20)	4.7 (±2.38)	36
	Long-term profit	7.9 (±3.23)	7.9 (±2.83)	**12.2** (±2.39)	11.9 (±2.06)	8.0 (±3.92)	10.9 (±3.05)	4.2 (±2.27)	37
	Liquidity	11.5 (±2.98)	**11.6** (±2.35)	10.8 (±2.64)	11.2 (±2.46)	6.4 (±3.55)	7.3 (±2.67)	4.2 (±2.79)	37
	Stability of economic return	7.6 (±3.16)	7.8 (±3.02)	11.1 (±3.08)	**11.1** (±2.03)	9.6 (±3.42)	10.0 (±3.23)	5.7 (±3.94)	36
	Scenic beauty	6.7 (±2.24)	6.4 (±2.49)	12.1 (±2.53)	11.3 (±2.16)	**12.5** (±3.23)	9.8 (±2.61)	4.3 (±2.25)	37

A strength of AHP is its ability to include various stakeholder groups and different techniques. We used two techniques to conduct the AHP survey: an online survey and face-to-face interviews. In both cases, we provided participants with information about the purpose of the research before starting the survey, and we informed them that their participation was voluntary and all answers confidential. The introduction of the survey also included information on the study region and the definitions of each indicator and land-cover (Tables 1 and 2).

A comparison of the mean indicator scores derived from the two survey methods showed no noteworthy differences between results (Figure S2). For instance, when comparing the aggregated mean scores of the online and face-to-face survey of the pairwise comparisons of two land-covers including 10 indicators, 69% of the comparisons had a difference of ±1 on a scale from 1–17 (Figure S2). Twenty-four percent of the aggregated mean scores of the online and face-to-face interviews had a difference greater than ±1, but lower than ±2.5. The remaining 7% of the mean scores differed by ±2.5 to ±5.5, which would not significantly impact the overall results.

Since we were analyzing a multifunctional landscape, we weighted all stakeholder groups and their rankings equally. We refrained from weighing experts to avoid bias, but to account for variability of expert answers, we included the standard deviation of indicator scores in our optimization. We explicitly investigate how the agreement and disagreement of experts about the relative provision of different ecological and socio-economic objectives affect the theoretical optimal landscape composition.

2.3. Optimization Approach

To find the optimal mix of land-cover types for securing a multifunctional landscape, we turn to robust multi-objective optimization. The input data for the optimization is the experts' evaluation of the ability of the seven land-cover types to provide the 10 ecosystem services (Table 3). The optimization model can simultaneously consider all studied land-cover types and potential fluctuations in their contribution to 10 ecosystem services, which cannot necessarily be predicted by experts during the survey.

Our optimization method is a variant of goal-programming implemented as a linear program to obtain an exact solution [63]. The goal-programming approach is coupled with a robust optimization to incorporate uncertainty in the decision process [64]. This normative approach suggests how land management can be improved to balance the achievement of multiple ecosystem services in eastern Panama. While optimization can be used positively to represent current land management or make predictions [65,66], our study is intended to illustrate how land-covers should be reallocated to better meet a pre-defined set of objectives (i.e., ecological and socio-economic ecosystem service indicators) and constraints, described below. Table 4 outlines the key variables of the optimization model.

As a first step, we used AHP to derive nominal values (R_{li}) of ecosystem service provision for each land-cover type, l, and indicator, i. Together with their standard deviation (SD_{li}), these scores represent the input values for our optimization model (Table 3). Through the standard deviation, we incorporate potential deviations from the expected nominal indicator value and account for uncertainty in the ability of the studied land-cover types to achieve a given ecosystem service indicator.

Uncertainty reflects two phenomena in our study: a lower consensus among experts (standard deviation, Table 3) and a lower predictability of the provision of the ecosystem services by the respective land-covers (multiplication of standard deviation with uncertainty factor fu, Equation (1)). With our treatment of uncertainty, we address "deep" uncertainty in our modelling, which Walker et al. [67] denote as level 4 uncertainty. Beyond this level of uncertainty is total ignorance. Deep uncertainty means that we are neither able to specify probabilities nor to provide exact rankings regarding the performance of each land-cover type for achieving each indicator. Consequently, we address uncertainty through uncertainty sets, defined by unique combinations of optimistic and pessimistic values for each indicator achieved by our land-cover types. In total, we incorporated 128 (2^7 for seven land-cover types) uncertainty scenarios (u) for each of the 10 ecosystem service indicators following Knoke et al. [28] (for an example see supplementary Figure S3). We include the nominal (mean) score R_{li} as our best case and compute an unfavorable deviation of this score as our worst case (Equation (1)).

$$\begin{aligned} R_{liu} &= R_{li} \text{ for best case} \\ R_{liu} &= R_{li} - fu \times SD_{li} \text{ for worst case} \end{aligned} \quad (1)$$

This way, we only consider unfavorable deviations from the expected (nominal) value and minimize underperformance in worst-case scenarios. Unfavorable deviations are computed by subtracting multiples of fu of the standard deviation from the mean score R_{li} (Equation (1)). A value of 0 for fu ignores uncertainty, whereas a value of $fu = 3$ represents a high level of uncertainty and risk aversion of a decision-maker in landscape planning. We ran the optimization for $fu = 0, 0.1, 0.2, \dots 3$. The ability of a given landscape composition to provide a given indicator under uncertainty is represented by the indicator level achieved for each uncertainty scenario (R_{iu}). We computed R_{iu} by weighing the indicator values adjusted for uncertainty (R_{liu}) with the shares of the total land area allocated to each land-cover type within that composition (a_l) (Equation (2)), with the constraints $\Sigma\, a_l = 1$ and $a_l \geq 0$.

$$R_{iu} = \Sigma\, R_{liu} \times a_l \quad (2)$$

We then normalize all indicator scores achieved per uncertainty scenario (p_{iu}) between the minimum (min $\{R_{liu}\}$) and the maximum (max $\{R_{liu}\}$) indicator scores within each uncertainty scenario. The derived value is given as a percentage (Equation (3)).

$$p_{iu} = (R_{iu} - \min\{R_{liu}\})/(\max\{R_{liu}\} - \min\{R_{liu}\}) \times 100 \quad (3)$$

Finally, we calculate the distance (D_{iu}) between the indicator value (achieved and normalized, p_{iu}) and the hypothetical maximum of 100% (Equation (4)) for each uncertainty scenario and indicator, where $0 \leq D_{iu} \leq 100$:

$$D_{iu} = 100 - p_{iu} \quad (4)$$

where p_{iu} is the normalized indicator performance value expressed as a percentage. The uncertainty scenario with the lowest performance value (highest D_{iu}) across all indicators then determines the maximum distance β to the hypothetical maximum (100%). The model seeks to minimize this maximum deviation β from the maximum achievement level among all indicators and uncertainty scenarios by allocating land to the different land-cover types. In other words, the optimization problem aims to minimize the worst underperformance:

Objective function:

$$\min \beta \quad (5)$$

with

$$\beta = \max\{D_{iu}\} \quad (6)$$

subject to:

$$\beta \geq D_{iu} \text{ (for all } i \text{ and } u) \quad (7)$$

The inequation (Equation (7)) summarizes individual constraints (here, 128 constraints: one for each uncertainty scenario, ×10 indicators), with β (the objective function) as the maximum tolerated distance on the left side of the inequation, and D_{iu} as the actual distance to the maximum achievement level on the right side. To solve the allocation problem, the land-cover weights a_l, the left side of the constraints (Equation (7)) and the objective function β are defined as changeable variables. The problem can then be solved by the Simplex algorithm offering an exact solution for a compromise land-cover composition that minimizes the worst underperformance across all ecosystem service indicators. Therefore, we used the Frontline Solver V2017-R2 (17.5.1.0) (Frontline Systems Inc., Incline Village, Nevada, USA) to run the optimization in a Microsoft Excel environment, but an open source software can also be used (e.g., OpenSolver (2.9.0) (Department of Engineering Science, University of Auckland, Auckland, New Zealand)).

When optimizing for a desirable landscape, we do not allow high performance in one objective (here indicator) to compensate for poor performance in another [28]. For example, high species richness of plants and animals (our biodiversity indicator) cannot compensate for low food security. Thus, the optimized landscape represents a compromise solution that meets all 10 objectives concurrently. This solution reflects the best performance for the worst-case uncertainty scenario across all ecosystem service indicators. Our optimized landscape portfolios represent a suggestion for a desirable future land allocation to best provide a compromise solution that meets the needs of a large group of stakeholders (normative perspective), rather than predicting what a future landscape composition would look like (positive perspective).

The optimization approach weighs all objectives equally. We abstained from weighing specific indicators to derive an objective compromise solution, which could then be used as a baseline for further participatory approaches.

Table 4. Overview and description of variables in multi-objective optimization model.

Variable	Description
i	ecosystem service indicator
l	land-cover type
R_{li}	nominal score of ecosystem service indicator, i, provided by land-cover, l, derived from the AHP survey
SD_{li}	standard deviation of nominal score for ecosystem service indicator, i, and land-cover, l
fu	uncertainty factor to determine the deviation from the expected nominal score, R_{li}, ranging from 0 (ignoring uncertainty) to 3 (high level of uncertainty)
u	uncertainty scenario
R_{liu}	score of ecosystem service indicator, i, for land-cover, l, adjusted for uncertainty, u
$\min \{R_{liu}\}$	minimum uncertainty-adjusted indicator score, R_{liu}, across all land-cover types in a given uncertainty scenario
$\max \{R_{liu}\}$	maximum uncertainty-adjusted indicator score, R_{liu}, across all land-cover types in a given uncertainty scenario
R_{iu}	represents the sum of the ecosystem service indicator scores for each land-cover type, weighted by their area share in the landscape composition for each uncertainty scenario
a_l	allocated share (area fraction) of a given land-cover type, l, in a landscape composition
p_{iu}	normalized indicator score, i, for a landscape composition per uncertainty scenario, u, expressed as a percentage (landscape performance value)—100% represents best possible performance
D_{iu}	distance between the normalized indicator score, p_{iu}, of a given ecosystem service indicator, i, and the hypothetical maximum of 100% (can be thought of as underperformance)
β	maximum underperformance, D_{iu}, across all indicators, i, and all uncertainty scenarios, u (worst underperformance)

2.4. Analysis of the Landscape Context

To better understand the interrelations between the landscape composition and agroforestry in terms of ecosystem services provision, we conducted a systematic sensitivity analysis. We aimed to provide insight on which mix of FLR options might be best-suited under different hypothetical land-cover contexts. To simulate different landscape contexts, we increased the shares of forest, forest-plantation, natural succession of abandoned land and agricultural land in steps 0, 0.1, 0.2, …1 imposed through a constraint, considering a moderate level of uncertainty ($fu = 2$). This allowed us to simulate landscapes covered with large shares of single land-cover types. We then examined the optimized composition of the remaining landscape portfolio (not occupied by the single land-cover type) and the ecological and socio-economic impact. Similarly, we increased the area share of the two agroforestry types (alley cropping and silvopasture) to understand the effect of promoting agroforestry as one FLR option.

We analyzed the overall landscape performance in terms of ecosystem service provision (min $\{p_{iu}\}$). We derived the guaranteed performance level achieved across all indicators and uncertainty scenarios by calculating the distance between the guaranteed level of the ecosystem service indicator to the hypothetical maximum indicator value:

$$\min \{p_{iu}\} = 100 - \beta \tag{8}$$

We also assessed the compositional landscape diversity of the optimized landscape portfolios. Using Shannon's index [68], we compared the diversity of the remaining land-covers in a portfolio, when one land-cover type dominated the landscape. We calculated the diversity index for each land-cover portfolio as follows:

$$H = -\Sigma\, a_l \ln a_l \tag{9}$$

where a_l: is share of land-cover, l, in a given landscape portfolio.

3. Results

3.1. Agroforestry and Other FLR Options to Balance Ecological and Socio-Economic Objectives

Based on expert opinion, under a moderate level of uncertainty, a large share of agroforestry (41%) was selected to complement other FLR options, natural forest and agricultural land-cover types to balance all studied ecosystem services simultaneously in a landscape mosaic.

Overall participants rated forest as the best land-cover type for achieving the ecological indicators, while agroforestry scored highly for the socio-economic indicators (Table 3). Pasture, which is currently the most common land-cover in the study area, was only selected as the best land-cover type for the socio-economic indicator liquidity (mean score 11.6 out of 17). The lower standard deviation of the ecological indicator scores suggest a higher level of consensus in expert opinion for this group of indicators (coefficient of variations ranged between 6% and 46% compared to 16% to 69% for socio-economic indicators (Table S3)).

Among the four FLR options, both agroforestry systems were perceived by experts as the best two land-cover types to provide food security, long-term profit and stable economic returns (Table 3). Generally, agroforestry was ranked best or second best for 6 out of 10 ecosystem service indicators investigated. Hence, agroforestry was consistently part of the optimized landscape for different levels of uncertainty in providing studied ecosystem services, from ignoring uncertainty ($fu = 0$, see Equation (1)) up to a high level of uncertainty ($fu = 3$) (supplementary, Figure S4). In contrast, natural succession of abandoned land was not part of the landscape portfolio, whereas forest-plantation was selected by the model only from a level of uncertainty of $fu \geq 1.5$. These two FLR options were not perceived as the best approaches for providing any ecosystem service indicator (Table 3).

Our results showed that the level of uncertainty affects landscape diversity. At lower levels of uncertainty, the landscape would comprise large shares of either alley cropping or silvopasture. For an uncertainty level of $fu \geq 1.5$, the landscape comprises increasingly equal shares of six land-cover types (supplementary Figure S4). In the following sections, we focus our analysis on a moderate uncertainty level ($fu = 2$). This means that the considered deviation from the expected score of the ecosystem service indicator is twice as large as the standard deviation of the indicator.

We found that the theoretically ideal landscape composition under a moderate level of uncertainty diverges strongly from the actual land-cover composition in the study area (compare left and right-most columns in Figure 1). In the current landscape, forest and agricultural land-covers were complemented by one FLR option only: forest-plantation. Pasture represented the greatest area share (46%). However, in the optimized landscape, pasture and cropland only comprised a 12% and 9% share, respectively. The remaining area was assigned to forest and FLR options with a large share of agroforestry (41%). When agroforestry systems were excluded from the optimization model, the optimized land-cover composition became more similar to the actual composition, but cropland was substituted by abandoned land (Figure 1). This is likely because natural succession of abandoned land (which can be thought of as recovering secondary forest) was perceived to perform better in terms of ecological indicators compared to cropland and pasture.

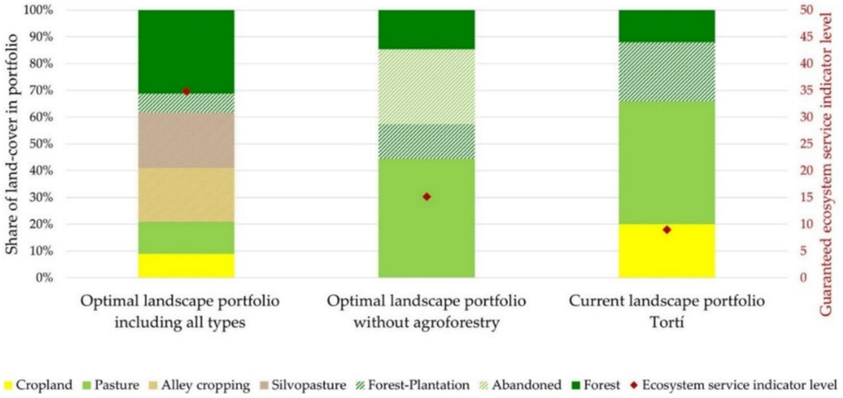


Figure 1. The composition and performance of optimized landscape portfolios (left and middle columns) and the current land-cover allocation in the study region (right column). Left axis shows the area shares of each of the seven land-covers. Right axis (red diamonds) shows the guaranteed level of ecosystem service indicators (min $\{p_{iu}\}$, see Equation (8)) for each portfolio. The optimized portfolios are derived for a moderate level of uncertainty ($f_u = 2$), when including (left column) and excluding (middle column) agroforestry from the multi-objective optimization.

Apart from studying the landscape performance in terms of balancing all 10 indicators for ecosystem services simultaneously, we examined the achieved performance level of the individual ecosystem services separately (Figure S5). For the optimal landscape portfolio including agroforestry (left column in Figure 1), the worst performing indicators were water regulation, food security, liquidity and economic stability (indicator values achieved $p_{iu} \geq 35\%$, Figure S5). This means that across all uncertainty scenarios, the 10 indicators achieved a performance level of at least 35% (where 100% is the hypothetical maximum). In comparison, excluding agroforestry resulted in a lower guaranteed ecosystem service indicator level (center column, Figure 1), with the poorest performance for food security, long-term profit and scenic beauty ($p_{iu} \geq 15\%$), closely followed by economic stability (Figure S5). This was due to the strong performance of agroforestry for those four ecosystem service indicators. For the current landscape portfolio, economic stability (closely followed by food security) was the worst performing indicator (with a guaranteed performance level of only 9% (Figure S5)).

In addition, we performed single-objective optimization, i.e., we determined the optimal land allocation for achieving each ecosystems service indicator individually instead of all indicators simultaneously (supplementary, Figure S6). As expected, landscape performance was higher when optimizing for single indicators. For example, a landscape entirely covered by forest may achieve the hypothetical maximum ecosystem service level (100%) for single ecological ecosystem service indicators. Optimized landscapes for single socio-economic indicators achieved guaranteed ecosystem service levels between 45% and 61% and were dominated by agroforestry systems (Figure S6).

3.2. Influence of Landscape Context on Agroforestry Selection

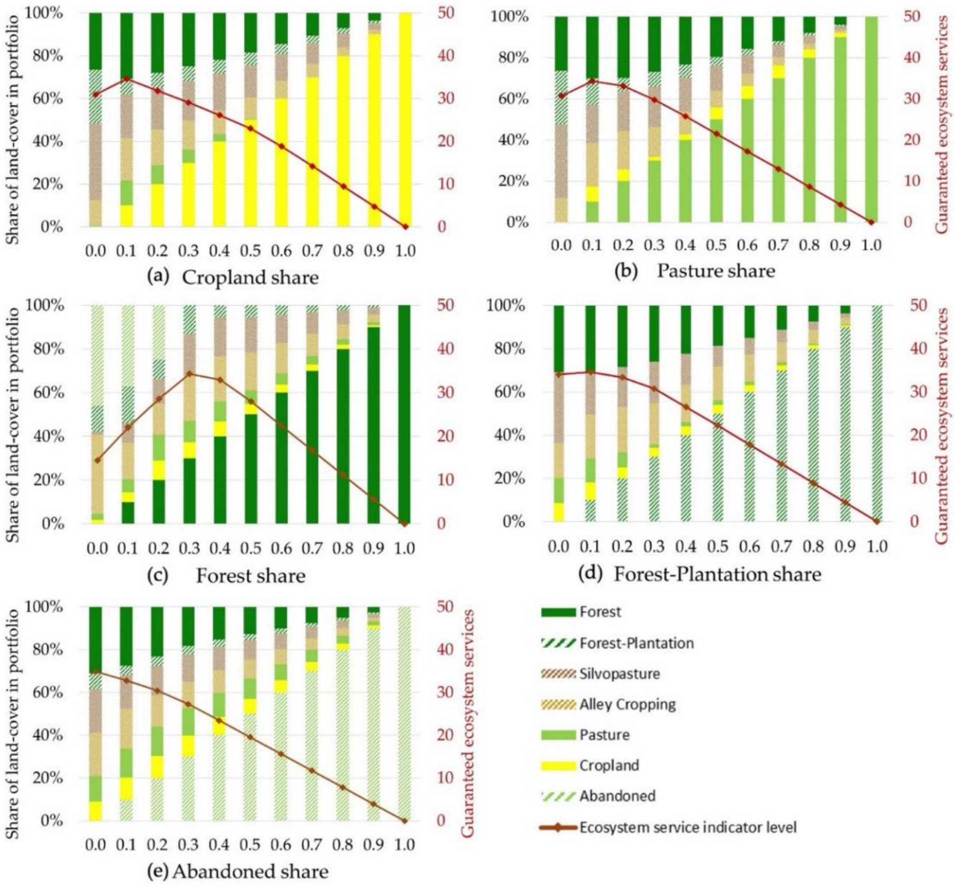
The sensitivity analysis showed how much agroforestry would be desirable in varying landscape contexts to balance multiple objectives under uncertainty (Figure 2). We analyzed the share of agroforestry, landscape diversification (Figure 2, stacked columns, left y-axis) and the performance of optimized landscape portfolios regarding ecosystem service provision (Figure 2, red line, right y-axis) for landscapes dominated by either a) cropland, b) pasture, c) natural forest or one of the FLR options, d) forest-plantation or e) natural succession of abandoned land (Figure 2, x-axis). The resulting landscape portfolios may be interpreted as the desirable land-cover allocation when following expert opinion, for situations in which single land-cover types are already widespread in the landscape.

To increase the level of ecosystem service indicators within the optimized portfolios, the model consistently selected a mix of FLR options including agroforestry when progressively increasing the share of a single (non-agroforestry) land-cover types. This suggests that a mix of FLR options, natural forest and agricultural land-uses are needed to balance the achievement of all 10 ecosystem services, irrespective of the dominant land-cover type (Figure 2). For example, to secure the highest guaranteed level of multiple ecosystem services an increase in forest-plantation share was not compensated for by an increase in cropland or pasture, but instead by allocating land to a mix of land-cover types including a large area of agroforestry (45% to 55% agroforestry share of the remaining landscape portfolio, Figure 2d).

Agroforestry comprised 50% to 66% of the remaining land-cover portfolios for landscapes dominated by cropland (Figure 2a) or with a forest share larger than 30% (Figure 2c), or forest-plantation share larger than 20% (Figure 2d). For increasing shares of pasture (Figure 2b) or abandoned land (Figure 2e), agroforestry shares comprised 34% to 49% of the remaining landscape.

When progressively increasing the share of single land-cover types, the share of agroforestry in the remaining portfolio was stable, except for the landscape with increasing forest shares (Figure 2c). For example, when increasing the FLR option of natural succession of abandoned land, the agroforestry share comprised 36% to 41% of the remaining landscape (Figure 2e). In contrast, when forest share was constrained to less than 30% of the landscape, agroforestry comprised only 29% to 38% of the remaining landscape (Figure 2c), whereas agroforestry dominated the remaining landscape when forest share was 30% or larger.

Hence, landscape composition influences the optimal share of agroforestry under a moderate level of uncertainty, but due to its high perceived performance agroforestry, shares of at least 34% were always selected to balance multiple ecosystem services at the landscape scale irrespective of the landscape context.



(**a**) Cropland share (**b**) Pasture share (**c**) Forest share (**d**) Forest-Plantation share (**e**) Abandoned share

Figure 2. Impact of progressively expanding shares of (**a**) cropland, (**b**) pasture, (**c**) natural forest, (**d**) forest-plantation or (**e**) natural succession of abandoned land on land-cover composition (bars, left y-axis) and guaranteed level of ecosystem service indicators (min $\{p_{iu}\}$, see Equation (8), red line, right y-axis). The gradual increase of land-covers in the model is reflected by the steps (x-axis). Depicted land shares represent optimal landscape compositions according to the multi-objective optimization approach for a moderate level of uncertainty (*fu* = 2).

3.3. Impact of Promoting Agroforestry

In this section, we test the effect of promoting agroforestry on the composition and diversification of the remaining landscape. We also explore how promoting agroforestry would influence ecosystem service provision of the entire landscape (Figure 3).

Interestingly, the forest share of the remaining landscape portfolio increased as agroforestry became more dominant in the landscape. When progressively increasing the share of alley cropping, the forest share increased until alley cropping comprised 70% of the landscape, at which point forest-plantation partially substituted forest (Figure 3a). Forest also dominated the remaining land-cover portfolio when the silvopasture share was above 40%, and replaced all other land-cover types when silvopasture comprised 80% of the landscape (Figure 3b). The development of the forest share was similar when the total area of agroforestry (alley cropping and silvopasture combined) progressively expanded (18% to 100% forest share of the remaining landscape (Figure 3c)).

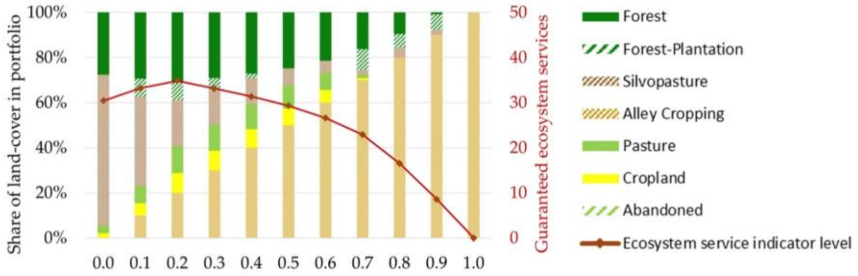
We observed that increasing shares of agroforestry tended to homogenize the remaining landscape portfolio. Our results show that landscape diversity of the remaining optimized landscape decreased with increasing shares of agroforestry. For example, when silvopasture was restricted to 10% and lower, the landscape diversity was high (Shannon index: 1.62 to 1.68 (Table S4)) and decreased faster than for other land-cover types with increasing share of silvopasture. Similarly, when alley cropping and silvopasture together made up more than 30% of the landscape, the diversity of the remaining landscape declined (Shannon index: 0 to 1.52 (Table S4)). In contrast, when increasing agricultural land-uses, forest or the two other FLR options, the diversification of the remaining portfolio remained relatively stable (Table S4).

We also found that the type of agroforestry affected the composition and level of diversification of the remaining portfolio: for very high shares of alley cropping (share > 80%), the model suggests diversifying the remaining landscape portfolio with forest-plantation, silvopasture and forest (Figure 3a). In contrast, in a silvopasture-dominated landscape, the model recommends a less diversified land-cover mix with forest making up the remaining land (Figure 3b).

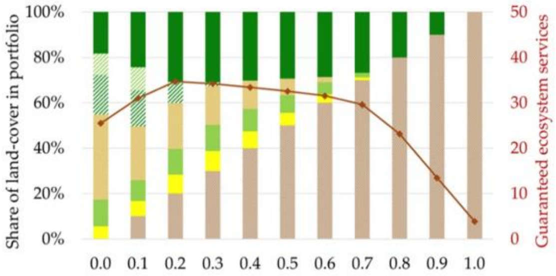
Furthermore, our results suggest that silvopasture may be more suitable than alley cropping as a compromise solution. Ecosystem service provision tended to be higher when increasing the share of silvopasture in the portfolio compared to alley cropping. This is reflected by the higher guaranteed level of ecosystem services provided from silvopasture shares of 30% and larger (Figure 3a, b, red line, right y-axis).

Generally, agroforestry-dominated landscapes provided better solutions to balance multiple ecosystem services compared to landscapes dominated by other land-cover types. For example, when the model landscape was dominated by large shares of single agroforestry systems, the performance of the optimized landscape portfolios decreased more slowly with increasing share of agroforestry (compare Figures 2 and 3, red line, right y-axis). A landscape with a share of 70% alley cropping still provided multiple ecosystem services at a guaranteed level of 23%, while a landscape with 70% cropland could only guarantee a level of 14% (Figures 2a and 3a). Furthermore, we find that excluding both agroforestry types (Figure 3c, first bar on the left) would reduce the level of guaranteed ecosystem services provided (right y-axis: 15% ecosystem service level) to the same level of complete deforestation (Figure 2c, first bar on left).

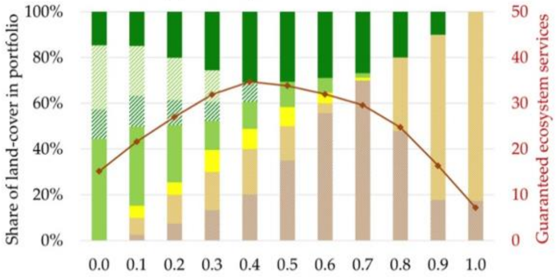
Hence, landscapes with larges shares of agroforestry showed a tendency to conserve larger shares of natural forest while maintaining a high landscape performance, but tended to homogenize the remaining landscape in favor of tree-based land-cover types.



(a) Alley cropping share



(b) Silvopasture share



(c) Agroforestry share

Figure 3. Impact of progressively expanding shares of (**a**) alley cropping, (**b**) silvopasture, and (**c**) both agroforestry systems combined on land-cover composition (bars, left y-axis) and guaranteed level of ecosystem service indicators (min $\{p_{iu}\}$, see Equation (8), red line, right y-axis). Landscape portfolios resulted from multi-objective optimization for a moderate level of uncertainty ($fu = 2$).

4. Discussion

4.1. The Role of Agroforestry in an Uncertain Multifunctional Landscape

In the face of global problems such as feeding a growing population while maintaining ecosystem functioning and biodiversity, allocating scarce land to various land-cover types has been a challenging task, which has led to controversial proposals such as giving half of our world's surface back to nature [69]. Our research approach allows decision-makers to explore the optimal mix of agroforestry and other FLR options in varying landscape contexts to meet a set of predefined objectives (10 ecosystem services in our case). We offer a decision support tool to explore the role of agroforestry and other FLR options for sustainable landscapes. It is particularly suitable in the common situation of scarce empiric data. Existing and hypothetical land-cover types can be considered while accounting for uncertainty of those land-covers in providing different ecosystem services.

Regarding our first research question, our results show that agroforestry was a particularly desirable FLR option to balance ecological and socio-economic ecosystem services at the landscape scale, based on current expert perception. In our survey, agroforestry was ranked higher than the alternative FLR options of forest-plantation and natural succession of abandoned land. Despite this clear expert judgement, agroforestry did not dominate the optimized land-cover portfolio under a moderate level of uncertainty; however, silvopasture and alley cropping did constitute a 41% share. Hence, the inclusion of both agroforestry systems in a FLR mix could lead to much higher guaranteed levels for all ecosystem service indicators compared to the optimized portfolio without agroforestry and the actual landscape portfolio (Figure 1). Despite half of the ecosystems service indicators reflecting socio-economic objectives, the optimized landscape only contained small shares of pasture and cropland. This reflects experts' positive judgment of the socio-economic potential of agroforestry, which replaced other agricultural land-uses in the optimized land-cover composition. Furthermore, to obtain high ecological performance at the landscape scale, our model suggests that including agroforestry in the land-use mosaic might avoid the need to leave large areas as unmanaged abandoned land. These findings are in line with other studies that demonstrate the advantage of agroforestry in enhancing landscape multifunctionality [5,70].

Furthermore, the share of agroforestry was affected by the degree of uncertainty assumed. To avoid underperformance of ecosystem service indicators, our model suggested an increase in compositional diversity with increasing level of uncertainty. Increasing uncertainty increases unfavorable deviations of ecosystem services provided in worst case scenarios. Therefore, the model selects more land-cover types to buffer against poor performance of individual objectives. This effect can be explained by the averaging or portfolio effect and is in line with findings from land allocation studies in Ecuador [20,35].

We found that the current landscape composition of the study region performed poorest in terms of securing economic stability and food security, suggesting that these two ecosystem services require most attention in landscape planning. Integrating agroforestry in a landscape mosaic may contribute to objectives of food security and stable economic returns as shown by our results and those of other studies [4,5,71].

Our sensitivity analysis provides insights into the land-sharing vs. land-sparing debate. Land-sharing and land-sparing may both contribute to a multifunctional landscape. However, regarding our second research question, we found that agroforestry was always included in the landscape irrespective of the landscape context to meet multiple objectives under uncertainty (Figure 2). Thus, the model suggested that mixing the strategies land-sharing and land-sparing would lead to optimal results, holding that the landscapes consists of a high degree of compositional diversification of different land-cover types with large shares of agroforestry. Combining both strategies is in line with Meli et al. [12], who recommend that FLR needs to be implemented in both land-sharing and sparing. Runting et al. [72] also found that neither strict land-sharing nor land-sparing are desirable, when aiming for a multifunctional landscape. However, Paul and Knoke [73] point out that landscape diversification on separate pieces of land can still increase provision of multiple ecosystems services, without the establishment barriers associated with agroforestry systems, such as increased management complexity. Paul et al. [31] have also shown that a mixture of trees and crops on separate plots might be economically favorable for very risk-averse farmers, for instance those who depend heavily on income from their farm.

However, agroforestry may be promoted to diversify reforestation options in Panama, due to the reforestation project "Alianza por el Millón". Regarding the third research question, alley cropping and silvopasture showed slightly different impacts on landscape allocation and performance. Our results showed a higher suitability of silvopasture as a compromise solution compared to alley cropping. This is in line with Gosling et al. [65], who found that farmers in eastern Panama rated silvopasture higher than alley cropping across a range of socio-economic and ecological criteria.

Providing high levels of multiple ecosystem service indicators under uncertainty requires a high degree of compositional diversification within the landscape and/or at the plot level (i.e., agroforestry). For example, in a pasture-dominated landscape, the land-cover compositions would include forest, agroforestry, cropland and forest-plantation to balance ecological and socio-economic objectives under uncertainty. In contrast, when silvopasture was the dominant land-cover type, the remaining landscape would consist of forest, alley cropping, and agricultural land-uses or consist of natural forest only for very large shares of silvopasture. Thus, increasing silvopasture tended to homogenize the remaining landscape composition in favor of forest. Similarly, landscapes with a share of 30% to 80% of alley cropping supported forest shares in the remaining portfolio of above 40% (Figure 3). Other studies also reported that land-sharing may support forest conservation. For example, Angelsen and Kaimowitz [74] state that in contrast to highly intensified agricultural systems, agroforestry may reduce pressure on forests by increasing ecological and socio-economic benefits. By increasing long-term productivity, agroforestry may counter land degradation, thereby reducing land abandonment and the need to convert forest into productive agricultural land [74].

Regardless which land-use strategy is followed, landscape scale heterogeneity is important to support the provision of multiple ecosystem services [75]. As illustrated in previous studies [28,76], we show that a multifunctional landscape is best supported by heterogeneity in our example of a diverse landscape mosaic. Homogenous landscapes dominated by one or two agroforestry systems may have detrimental effects for multifunctionality, as reflected by our sensitivity analysis and other studies [75]. Regulations and incentives should be in place to encourage a mix of FLR options (including different agroforestry types) to support the development of a diverse landscape [77]. Furthermore, promoted agroforestry types should align with the needs of local farmers to facilitate adoption [78].

While the goal of our study was to find optimal landscape compositions that enhance the achievement of multiple ecosystem services at a tropical forest frontier, it remains unclear how enhancing the landscape performance would impact deforestation in the long run. Although, our results showed a trend that forest cover could even be increased in a multifunctional landscape including agroforestry, market dynamics might result in further agricultural expansion, if those competing land-uses prove to be more profitable than natural forest [20]. Mitigating tropical deforestation is a major global challenge. Our approach can contribute to understanding the consequences of considering multiple ecosystem services and uncertainty for landscape planning and deforestation.

4.2. Combining Expert Opinion and Multi-Objective Optimization

We emphasize that our input data for the multi-objective optimization is based on surveys with experts in their respective fields. This means that the data will be affected by personal perception and should be carefully interpreted. Although certain types of agroforestry (e.g., living fences and scattered trees in pasture) are common in our study area and Panama, the alley cropping and silvopasture systems considered in this study are not widespread, which may limit experience-based expertise of some survey participants. However, when compared to empiric findings at other sites in the tropics, the judgments of experts concerning the provision of ecosystem services for land covers seem plausible. Forests and tree-based systems were ranked highest for ecological indicators, in line with findings by Potvin et al. [79] for Panama and databases used by the IPCC [80]. In terms of food security, the two agroforestry systems received the top rankings. Alley cropping ranked highest, followed closely by conventional cropland and pasture, which aligns with findings by Reed et al. [4]. In the literature, combining trees and agricultural systems on the same piece of land may enhance ecosystem services [70] and increase resilience against extreme weather compared to conventional agricultural systems [58,71,81].

As tree products provide additional farm revenue, it seems plausible that agroforestry systems and forest-plantations were ranked highest for long-term profit by survey participants. This is in line with bio-economic modelling in the study area [31]. For long-term profit, forest was ranked similarly to cropland and pasture, which may be due to the perception of forest as a land-cover having no ongoing management costs but having the potential to sell firewood. In terms of liquidity, pasture (followed by cropland) was ranked higher than the agroforestry types. This seems plausible because cattle can be sold at any point in time [82,83] and trees represent a long-term investment [84]. Experts ranked agroforestry types highest for economic stability (even before forest-plantation). This may reflect that the agroforestry types are polyculture systems, whereas forest-plantations in our study represented a monoculture. Furthermore, agricultural revenues can be generated during the year through an agroforestry system, whereas exotic timber is best harvested after ca. 25 years from an economic perspective [50]. Ratings for scenic beauty could reflect the experts' personal preferences towards forest and agroforestry systems.

However, experts may have overestimated the advantages of agroforestry (particularly alley cropping) and underestimated its disadvantages. For example, Clough et al. [85] found for Indonesia that rubber production was lower in the agroforestry system compared to the monoculture system and generated considerably less income. A review conducted by Reed et al. [4] on the contribution of trees in the tropics worldwide found that studies reported both positive and negative effects of the trees on food yield and overall livelihood. Despite both agroforestry types being ranked highly during our surveys, neither alley cropping nor silvopasture (according to our definition) are prevalent in our study region. The high ranks assigned to agroforestry systems might be due to the fact that agroforestry has become quite popular in science and politics and could reflect desirable thinking (e.g., [1–3]). However, it may also indicate that agroforestry systems are highly valued among the stakeholder groups in our study, but farm level constraints may prevent adoption, such as implementation costs [12], loss of agricultural production, investment costs in inputs and labor [70], and perceived investment risks [86]. Therefore, including calculated socio-economic indicators that reflect those potential farm level constraints may yield a different landscape composition with lower agroforestry share. However, the aim of this study was not to derive an optimal landscape composition from a farmer's perspective, but from the perspective of society.

While quantitative empiric data are valuable, they can be costly and time consuming to obtain. Using expert knowledge as input data for optimization has been shown to lead to similar results as measured or calculated data [49]. For example, in Uhde et al.'s [49] study, the share of a near-natural secondary forest was similar for the landscape portfolio based on expert opinion and the related variability (34% forest share) and the portfolio based on measured or calculated data and the corresponding uncertainties (29% forest share). Therefore, our model and results can provide a sound basis for further discussions with stakeholders regarding land-use planning for multifunctional landscapes.

However, our method to quantify expert knowledge using AHP also has its challenges. To illustrate, the number of land-cover and ecosystem service indicators which can be investigated is limited, because an increasing number of alternatives rapidly increases the number of pairwise comparisons which can make the survey time-consuming and tedious [43]. Including more land-covers in the study design may have resulted in a different landscape composition. However, we were prevented from including more alternatives because the length of the AHP survey would have become prohibitive.

As an alternative to using AHP, monetary values may be used to express ecosystem services provided across different land-covers [87–89]. By using monetary valuation, non-market goods may be excluded [90]. Alternatively, a combination of field measurements, model results, economic evaluation, survey data and calculations may be applied [91]. However, these approaches were not appropriate for our study because of data gaps, as we specifically wanted to test an approach under the common situation of data scarcity that allows land-use types that are not yet widespread or common in a given area to be included in the analysis.

We selected a robust multi-objective optimization approach to derive theoretical optimal landscape portfolios, because it supported our research aim and allowed to integrate uncertainty. Incorporating uncertainty in the modelling process is important when there is a lack of certainty about the demand and provision of ecosystem services [92]. We actively incorporated (dis)agreement in expert opinion about the provision of ecosystem services across different land-cover types into the optimization procedure. Such disagreements can be difficult to quantify in a group discussion, which are often used for ecosystem service valuation and prioritization studies (e.g., [93,94]). But it has a direct impact on the derived land-cover composition and may be an important piece of information for robust land-use planning. Disagreement in expert opinion is reflected by variation in land-cover scores. Higher disagreements are represented by higher standard deviations. This makes the respective land-cover less attractive for a risk-averse decision-maker. We focused on minimizing underperformance in worst-case scenarios by incorporating the negative (unfavorable) deviation from the expected mean, as opposed to accounting for both favorable and unfavorable deviations [35,49].

Another advantage of our optimization model is that it can be used for multiple and single objective optimization. In this study, single objective optimization allowed us to investigate the optimized landscape performance separately for each ecosystem service indicator. Furthermore, single objective optimization can be used to analyze which individual indicators are influencing the landscape portfolio.

In our optimization model, we assumed equal demand for all ecosystem services to avoid subjectivity [95] and therefore weighted the indicators equally. Weighing of indicators can reflect that some indicators may be valued higher than others. Although it was not the aim of our study, our approach allows for reflecting preferences of stakeholders through putting weights on specific indicators (see [28,65]). In the absence of determined weights for each ecosystem service, Gourevitch et al. [96] used an efficiency frontier for two objectives to display the range of preferences from valuing one objective over the other to 100%. However, since we considered more than two objectives and lack information of stakeholders' long-term preferences and constraints, we opted for equal weights [28]. Nevertheless, the current landscape composition of the study area diverged strongly from the optimized landscape, which indicates that current land-use decisions may not be driven by providing all 10 studied ecosystem services simultaneously at their best possible levels, but perhaps by a subset of our studied indicators. For example, Gosling et al. [65] showed that farmers' land-use decisions might be driven by more immediate objectives, such as meeting household needs and maintaining liquidity. However, predicting the current land-use allocation was not the intention of this study. We aimed to find a multifunctional landscape that meets the objectives of all stakeholder groups simultaneously.

Our results should not be interpreted as generally true for all of Panama. However, our findings regarding the positive perception of agroforestry and interrelations of agroforestry, other FLR options, agricultural land-uses and natural forest can be important for landscapes beyond our study area in eastern Panama. Even though quantitative empiric data are certainly favorable as a foundation for land-use planning, integrating expert knowledge into landscape planning can give important insights into general relationships to guide further research.

4.3. Opportunities for Future Research

Potential drawbacks of agroforestry (e.g., high investment costs and delayed financial returns) may lead to farmers rejecting sustainable land-use concepts based around agroforestry. Therefore, future studies may include greater consideration of farmers' objectives, perceptions and local knowledge. Bringing together scientific and experience-based knowledge can help find landscape compositions that reconcile competing demands of the public and private landowners [97].

It has been suggested that landscape planning for multifunctional landscapes today and in the future should account for landscape composition and configuration [12,98]. As a first step, our model investigated landscape composition. However, future landscape configuration should be considered for a holistic land-use plan and for investigating the impact of fragmentation on landscape multifunctionality. Fragmentation effects and impacts of adjacent land-covers on ecosystem services and biodiversity might be substantial [99]. To consider landscape configuration, spatially explicit models have been used [100] to map ecosystem services provided by different land-cover types based on expert knowledge [46] or monetary estimation [88]. Spatially explicit modelling may be crucial, when mapping potential costs and benefits of forest landscape restoration options that are spatially heterogeneous [96].

However, focusing on landscape composition instead of spatial configuration demands less computational power. This is preferable as long as spatial configuration is not expected to affect the results [101]. For instance, Duarte et al. [98] and Verhagen et al. [102] both emphasize the effects of compositional diversity on ecosystem service provision. In their reviews they found that only few services, such as nutrient retention, pollination or landscape aesthetics were found to be affected by configurational aspects. Hence, for most of the services investigated here, a linear relationship with area proportions may be assumed, given a relatively large landscape. Yet, this may be questioned for aspects such as biodiversity, water regulation and scenic beauty. Future studies could incorporate such aspects, for example through coupling the optimization approach with spatial simulation approaches or transferring the problem into more complex mixed-integer programming (see review [32]). While we used simplified indicators to reflect studied objectives, this approach would also allow for a better representation of biodiversity-related objectives. In a next step, biophysical characteristics may be considered to determine where exactly land-sharing or sparing is appropriate [12]. This could support site-specific land-use planning. Biophysical aspects such as soil condition and economic aspects, such as investments costs, could be incorporated in our model, e.g., through including additional constraints which the optimized landscape composition must not violate.

Another important aspect for future research is time dynamics. While our model approach was static to optimize land allocation for the highest and most stable level of ecosystem services, future research may involve dynamic modeling. This could involve integrating time dynamics into evaluation of land-cover types [42] and modelling deforestation scenarios for tropical forests [28]. Temporal aspects might include seasonal fluctuations of ecosystem service provision [42], development effects (e.g., abandoned land turns into forest, altering its contribution to climate regulation; crop growth alters water regulation), climatic change and degradation effects. By integrating uncertainty into our optimization, we account for some volatility in delivery of ecosystem services and anticipate worst case scenarios.

Furthermore, future studies may test different shapes of uncertainty space to enhance precision and reduce data demand. Our model considered uncertainty boxes. Alternative uncertainty space shapes include conic spaces [64,103].

5. Conclusions

Combining the analytic hierarchy process and robust optimization, we were able to investigate stylized landscape compositions that theoretically provide multiple ecosystem services under uncertainty at the forest frontier based on expert perception. Our approach may contribute to a better understanding of interrelations between land-covers (prevalent and potential) and uncertain provision of different ecosystem services encountered in the common situation of scarce data. Using underperformance of ecosystem service provision as a measure, the model suggests establishing a mix of different land-covers with large shares of agroforestry in this example tropical landscape. For our study region, agroforestry was perceived by experts from different backgrounds and stakeholder groups as a key strategy to provide multiple ecosystem services, though it is not currently present in the study area. However, to improve landscape management, agroforestry systems (i.e., alley cropping and silvopasture) may best enhance multifunctional landscapes as a complement within a land-cover mosaic irrespective of the landscape context, leaving room for both land-sharing and land-sparing strategies [104]. This includes FLR options in an agriculture-dominated landscape, which may increase socio-economic indicators in particular, such as economic stability, food security and long-term profit, according to our results. Promoting agroforestry, as might be the case with Panama’s reforestation initiative, may benefit forest and productive tree-based land-uses. However, measures against landscape homogenization may be considered to guarantee multiple ecosystem services.

We suggest that our approach, as a preliminary study, may help decision-makers to systematically analyze which mix of agroforestry and other FLR options may be best-suited under different conditions to foster a multifunctional landscape. Our approach, which is parsimonious in its data needs, may inform feasibility studies to derive insight into desirable forest landscape restoration concepts and landscape compositions. This helps to set priorities for further field-based research to investigate where exactly to put what kind of restoration, in terms of biophysical and economic considerations [11], and set priorities for funding specific options [86].

Supplementary Materials: The following are available online at www.mdpi.com/2071-1050/12/15/6074/s1, Method S1: Interviews to determine current landscape composition, Method S2: AHP survey, Figure S1: Example of AHP survey illustrating scale transformation, Table S1: Comparison of aggregated mean scores and standard deviations between all survey participants and participants with consistency ratio (CR) ≤ 20%, Table S2: Number of survey responses by ecosystem service indicator and survey group derived from AHP survey, Figure S2: Comparison of results from online and face-to-face surveys, Figure S3: Simplified example of uncertainty scenarios (u) for a robust multi-objective optimisation including three land-covers, Table S3: Coefficient of variation for land-cover types and ecosystem service indicators derived from AHP survey based on Table 3 (see main text), Table S4: Shannon index values of the remaining landscape portfolios when share of different land-covers (top row) are restricted between 0% and 90% of the landscape area (left column), Figure S4: Optimal landscape composition (share of land allocated to each land-cover type) to provide multiple ecosystem services, based on expert knowledge, Figure S5: Normalized indicator values achieved (piu) over different uncertainty scenarios per indicator for (a) optimized landscape portfolio including all seven land-cover types, (b) excluding both agroforestry systems at fu = 2 and (c) current landscape, Figure S6: Optimal land allocation and landscape performance for achieving each ecosystems service indicator individually.

Author Contributions: Conceptualization, C.P.; methodology, T. K.; formal analysis, E.R.; investigation, E.G. and E.R.; writing—original draft preparation, E.R.; writing—review and editing, E.R., E.G., T.K. and C.P; visualization, E.R.; supervision, T.K. and C.P.; project administration, C.P.; funding acquisition, C.P.. All authors have read and agreed to the published version of the manuscript.

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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

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*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 **1970s/80s** advancement in computer processing allow for computer-based modelling	**1982** inception of the journal "Agroforestry systems" **1987** Brundtland Commission report coined the term "sustainable development"	**1992** UN Conference on Environment and Development **1990s** agroforestry recognized for increasing landscape multifunctionality	**2000** UN's Millennium Development Goals (MDGs) **2004** first World Agroforestry Congress in Orlando, Florida	**2010s** rise of integrated landscape approaches (e.g., Forest Landscape Restoration) **2016** UN's Sustainable Development Goals (SDGs)	**2020** agroforestry increasingly included in national climate change adaptation strategies **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

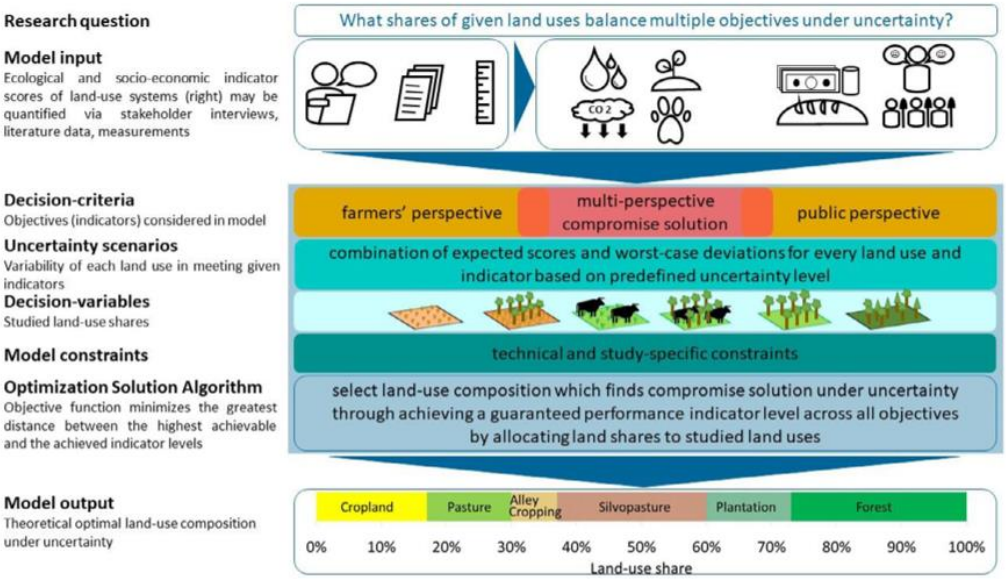


Fig. 1. Model concept of the robust multi-objective land-use allocation model. Model developed by Knoke et al. (2015, 2016) based on optimization solution algorithms presented by Ben-Tal et al. (2009).

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

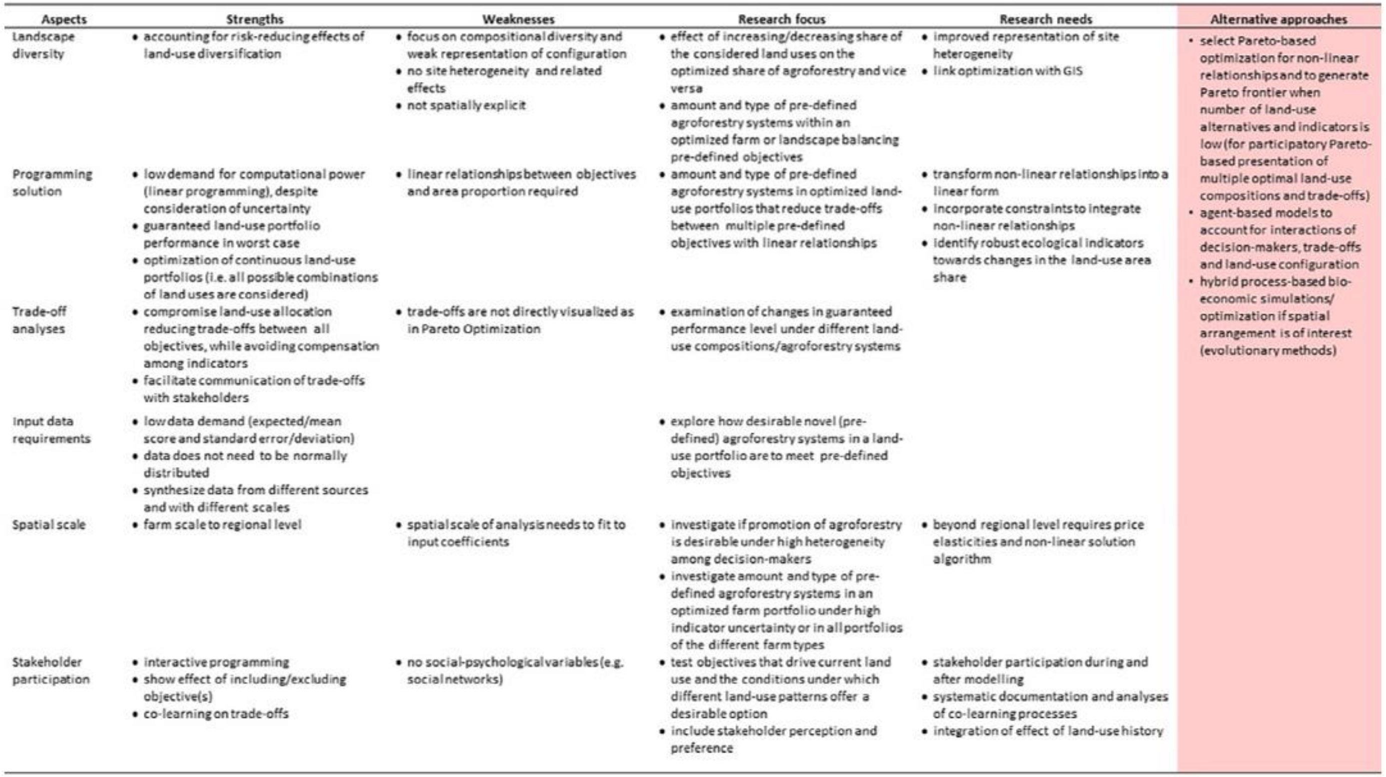
In this section we discuss six main model characteristics which may determine the suitability of our and other models to answer agroforestry research questions: (i) aspects of landscape diversity considered (composition vs. configuration), (ii) programming solution, (iii) trade-off analyses, (iv) required 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

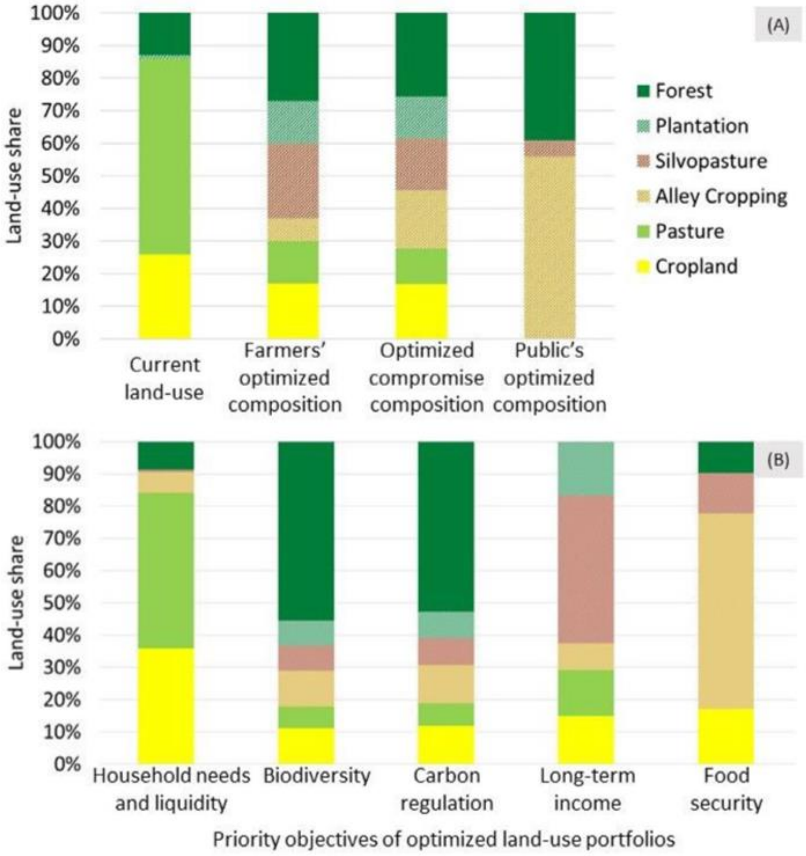


Fig. 2. Optimized land-use allocations derived for a moderate level of uncertainty. **(A)** Current land-use allocation of aggregated farms in the study region in eastern Panama and optimized land-use allocations from different perspectives (indicators weighed equally): farmers' perspective represented 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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