Technische Universität München
Professur für Waldinventur und nachhaltige Nutzung

Evaluating agroforestry from the farmers' perspective: Insights from robust multi-criteria optimisation in eastern Panama

Elizabeth Jane Gosling

Vollständiger Abdruck der von der TUM School of Life Sciences der Technischen Universität München zur Erlangung des akademischen Grades eines

Doktors der Naturwissenschaften

genehmigten Dissertation.

Vorsitzende:

Prof. Dr. Annette Menzel

Prüfer*innen der Dissertation:

1. Prof. Dr. Thomas Knoke
2. Prof. Dr. Carola Paul
3. Prof. Dr. Peter Annighöfer

Die Dissertation wurde am 29.03.2021 bei der Technischen Universität München eingereicht und durch die TUM School of Life Sciences am 23.07.2021 angenommen.

»Wie gut«, sagte der kleine Tiger, »wenn man einen Freund hat, der eine Regenhütte bauen kann. Dann braucht man sich vor nichts zu fürchten.«

Oh, wie schön ist Panama (Janosch)

Summary

Agroforestry (farming systems that mix trees with crops and/or livestock) is widely promoted as a promising strategy to address land-use problems in the tropics. However, adoption rates in many regions remain low. While agroforestry is known to have many ecological benefits, the advantages and disadvantages for smallholder farmers are not always clear. More research into the socio-economic aspects of agroforestry is urgently needed, to identify and promote the systems that best meet farmers' needs, and hence have the highest likelihood of adoption.

To help fill this research gap, this study presents a normative modelling approach for evaluating agroforestry from the farmers' perspective. This approach is novel for agroforestry research, because it simultaneously accounts for: a) farmers' multiple objectives, b) the effects of land-use diversification, and c) uncertainty, when assessing the socio-economic credentials of a given land-use system. Based on a case study in eastern Panama, the study showcases how the modelling approach can help identify socially-acceptable agroforestry systems, and provide insights into the conditions that may make agroforestry more (or less) attractive for different groups of farmers.

As a cumulative doctoral thesis, this study draws on four scientific papers. The first paper identifies efficient methods to capture farmer preferences, which the second and third papers integrate in a robust, multi-objective land allocation model. The second paper focuses on the underlying drivers of farmers' current land-use decisions, while the third investigates differences in the optimal land allocation for different types of farmers. The fourth paper integrates coefficients from an extended cost-benefit analysis in the optimisation model, and explores the socio-economic conditions that may promote greater adoption of agroforestry.

The study area, Tortí, is a farming region at the agriculture-forest frontier of eastern Panama. The study examines two novel agroforestry systems (silvopasture and alley cropping), as well as the most common land-uses in the region (conventional pasture and cropland, forest plantations and natural forest). Two datasets are used to evaluate each land-use against diverse, pre-selected socio-economic and ecological criteria (including long-term profitability, labour demand, investment costs and protection of soil resources). The first dataset is based on farmer knowledge and perceptions, which were captured during landholder interviews. The second dataset represents more detailed socio-economic coefficients, computed from a cost-benefit analysis that involved an extensive simulation study to measure the risks and returns of each land-use. By coupling these datasets with robust, multi-objective optimisation, the study explores the role of agroforestry in hypothetical land-use portfolios that reduce trade-offs between various farm-level objectives. Four research questions guide the analysis:

1. How do farmers perceive agroforestry relative to conventional land-uses?
2. According to these perceptions, would agroforestry help reduce trade-offs between farm level goals when accounting for uncertainty?
3. Which socio-economic and environmental conditions promote (or hinder) the selection of agroforestry within a diversified land-use portfolio?
4. Which data collection methodologies are most useful for evaluating agroforestry?

Results reveal a large difference in how farmers perceive the two agroforestry systems, with a clear preference for silvopasture. Farmers rated silvopasture highly for eight of the 10 socio-economic and ecological criteria, whereas alley cropping scored poorly against all criteria. Farmers' high opinion of silvopasture may reflect the cultural value of cattle in Panama and their importance for farmers' livelihoods. Strategies to increase on-farm tree cover in Tortí may therefore gain more traction with local farmers if they focus on tree-livestock (rather than tree-crop) systems.

Coupling the perception data with robust, multi-objective optimisation can provide insights into farmers' potential land-use decisions. Silvopasture dominated the optimal portfolio that minimised trade-offs between all 10 socio-economic and ecological criteria. Silvopasture may therefore be an attractive option for farmers seeking to reconcile a broad set of socio-economic and ecological goals. In contrast, the lack of alley cropping in the optimal portfolio suggests it is less able to achieve these goals. However, differences between the portfolios optimised for farmers with diverging land-use and income strategies point to potential differences in how these farmers may respond to each agroforestry system. Such information could help to target agroforestry extension programs to different groups of farmers in Tortí. For example, results suggest that farmers who derive most of their farm income from crops may be more willing to adopt silvopasture, while those who are more economically dependent on cattle may benefit from diversifying their farms with alley cropping.

Through a positive application of the (otherwise normative) optimisation model, the study explores the implicit goals driving farmers' current land-use decisions, to help identify key criteria that agroforestry must fulfill to meet farmers' needs. To this end, the study compares land-use portfolios optimised for various subsets of objectives with the current land-use composition of the study area; it is assumed that the portfolios most similar to the current land-use composition will reveal the objectives most important for farmers' decision-making. Interestingly, the objectives for which farmers judged silvopasture to contribute the most (long-term income and economic stability) appear to be the objectives that least influence farmers' land-use decisions. Instead, farmers appear to prioritise liquidity and household needs when deciding what to grow or produce on their farm. This reveals an important barrier to agroforestry adoption. If farmers in Tortí strive to maintain liquidity and meet household needs then, according to their perceptions, conventional pasture and cropland (and not agroforestry) would be the rational land-use choice. Widespread uptake of agroforestry in the study area may therefore rely on designing tree-based systems that provide more frequent cash flows and ongoing opportunities for food production.

While farmers' empirical ratings help us to understand the extent to which farmers perceive agroforestry to align with their objectives, they are ill-suited for detailed sensitivity analyses, because it is unknown how these ratings would change under different environmental, market or political conditions. Therefore, the study draws on more detailed socio-economic coefficients from an extended cost-benefit analysis to explore the factors that promote the selection of agroforestry in the optimal portfolio. Such analyses can shed light on the conditions which may make agroforestry a more desirable land-use option for local farmers and hence help overcome the identified barriers to adoption. Corroborating findings from the interview dataset, results suggest that agroforestry may be attractive for farmers who prioritise long-term income and are more tolerant of risk. This might include wealthier, commercially-oriented farmers with diversified income sources. However, given that most farmers in Tortí appear to prioritise food security and short-term cashflows over long-term profit, relying on long-term profitability as a selling point for agroforestry may result in low uptake in the study area.

Nonetheless, accounting for farmers' cultural preferences increased the share of silvopasture in the optimal portfolio, indicating that the tree-livestock system may appeal to a broader range of farmers in the study area (and not only those focused on profit). Moreover, poorer growing conditions for annual crops made silvopasture a more competitive land-use, suggesting it could be targeted towards farmers with less productive soils. However, farmers facing acute labour shortages may struggle to adopt silvopasture without additional assistance. The share of alley cropping and silvopasture in the optimal portfolio responded strongly to lower investment costs, supporting the efficacy of cost-sharing arrangements as a means to enhance the uptake of agroforestry in the region. Higher timber prices would also make agroforestry more attractive, but this may rely on fostering farmer capacity to improve knowledge of and access to timber markets.

As a practical guide for researchers who are considering using a similar methodology, this study compares the advantages and disadvantages of the two datasets (interview vs computed cost-benefit data) for evaluating the socio-economic potential of agroforestry. The interview data are

particularly helpful for identifying cultural barriers to agroforestry adoption and because the data capture farmers’ local knowledge and opinion, this methodology lends itself to participatory research approaches. In contrast, the ability to carry out in-depth sensitivity analyses and impose hard economic constraints in the optimisation model are key strengths of the computed dataset. Integrating these computed coefficients in the optimisation model thereby allows for more specific recommendations about the design of socially-acceptable agroforestry systems.

In general, the normative modelling approach of this study allows researchers to look beyond the current land-use patterns of a given region, to explore desirable land-use compositions that minimise trade-offs between different objectives. This can provide insights into the relative attractiveness of new agroforestry systems from the farmers’ perspective, when considering different household, market or environmental conditions: a task that may prove extremely difficult when relying on empiric methods alone. These insights can inform agroforestry research, policy and practice, for example by helping to identify the most promising agroforestry systems for on-farm trials. While this study demonstrates the modelling approach for a farming region in eastern Panama, it could be easily transferred to evaluate sustainable land-use systems in other tropical or temperate regions.

Zusammenfassung

Die Agroforstwirtschaft, welche Gehölze mit landwirtschaftlichen Pflanzen oder Tierhaltung kombiniert, wird als bedeutende Möglichkeit angesehen, Landnutzungsprobleme in den Tropen zu bekämpfen. Agroforstsysteme sind jedoch in vielen Regionen nach wie vor nur selten etabliert. Obwohl die Agroforstwirtschaft viele Vorteile für die Umwelt hat, sind die Vor- und Nachteile aus Sicht der Landwirte nicht immer klar. Mehr Forschung zu den sozioökonomischen Aspekten der Agroforstwirtschaft ist deshalb dringend notwendig, um Systeme zu identifizieren und zu fördern, welche die Bedürfnisse der Landwirte am besten erfüllen.

Im Rahmen dieser Doktorarbeit wird ein normatives multikriterielles Modell zur Bewertung von Agroforstwirtschaft aus der sozioökonomischen Sicht der Landwirte entwickelt. Der Ansatz ist neu in der Agroforstwirtschaft, da er gleichzeitig die Berücksichtigung a) vielfältiger Ziele b) möglicher Effekte der Landnutzungsdiversifizierung und c) der Planungsunsicherheit ermöglicht. Anhand einer Fallstudie im Osten Panamas wird in der Doktorarbeit gezeigt, wie der Modellierungsansatz dabei helfen kann, Agroforstsysteme mit hoher sozialer Akzeptanz zu identifizieren. Die Ergebnisse liefern Erkenntnisse über die Rahmenbedingungen unter denen Agroforstwirtschaft für verschiedene Typen von Landwirten eine attraktive Alternative darstellen könnte.

Diese kumulative Dissertation besteht aus vier publizierten Artikeln. Die erste Arbeit identifiziert effiziente Methoden zur Erfassung der Präferenzen der Landwirte. Diese fließen in der zweiten und dritten Arbeit in ein robustes, multikriterielles Landnutzungsmodell ein. Die zweite Arbeit verwendet das normative Modell im Rahmen eines deskriptiven Ansatzes und untersucht die zugrunde liegenden Motive für die aktuellen Landnutzungsentscheidungen der Landwirte. Die dritte Arbeit befasst sich schließlich mit den Unterschieden zwischen den optimierten Landnutzungsverteilungen für verschiedene Gruppen von Landwirten. Die vierte Arbeit integriert Koeffizienten aus einer erweiterten Kosten-Nutzen-Analyse in das Landnutzungsmodell: Es werden sozioökonomische Bedingungen untersucht, welche die Agroforstwirtschaft in den Tropen fördern können.

Das Untersuchungsgebiet ist die landwirtschaftlich geprägte Region Tortí im Osten Panamas. Für dieses Gebiet werden in der Doktorarbeit zwei neuartige Agroforstsysteme (ein silvopastorales System und ein silvoarables System namens „Alley-Cropping“) sowie die häufigsten Formen der Landnutzung in der Region (konventionelles Weide- und Ackerland, Forstplantagen und Naturwald) untersucht. Zwei Datensätze werden verwendet, um jede Landnutzung anhand verschiedener sozioökonomischer und ökologischer Kriterien (z.B. langfristiges Einkommen, Arbeitsaufwand, Investitionskosten und Schutz der Bodenressourcen) zu bewerten. Der erste Datensatz basiert auf dem

Wissen und den Präferenzen der Landwirte, die durch Befragungen erfasst wurden. Der zweite Datensatz stammt von einer Kosten-Nutzen-Analyse, welche auf einer umfangreichen Simulationsstudie zu den Erträgen und Risiken jeder Landnutzung basiert. Auf Grundlage dieser Datensätze wird in der Doktorarbeit mittels einer multikriteriellen Optimierung untersucht, ob Agroforstwirtschaft Teil eines Landnutzungsportfolios ist, welche verschiedene Zielsetzungen bestmöglich erfüllt. Vier Forschungsfragen leiten die Analyse:

1. Wie bewerten die Landwirte im Untersuchungsgebiet Agroforstwirtschaft im Vergleich zu den konventionellen Landnutzungen?
2. Kann Agroforstwirtschaft – basierend auf dieser (subjektiven) Bewertung – Zielkonflikte zwischen den vielfältigen Zielen der Landwirte und unter Berücksichtigung von Unsicherheiten reduzieren?
3. Welche sozioökonomischen und ökologischen Bedingungen fördern (oder behindern) die Integration von Agroforstwirtschaft in ein diversifiziertes Landnutzungsportfolio?
4. Welche Methoden der Datenerhebung sind für die Analyse der Agroforstwirtschaft am hilfreichsten?

Die Ergebnisse zeigen, dass die Landwirte die zwei Agroforstsysteme unterschiedlich bewerten, mit einer klaren Präferenz für das silvopastorale System. Sie gaben dem silvopastoralen System bei acht der 10 sozioökonomischen und ökologischen Kriterien gute Bewertungen. Im Gegensatz dazu schnitt Alley-Cropping bei allen Kriterien schlecht ab. Die positive Einschätzung der Landwirte zum silvopastoralen System spiegelt möglicherweise den kulturellen Wert der Viehhaltung in Panama und ihre Bedeutung für den Lebensunterhalt der Landwirte wider. Die Förderung von Agroforstwirtschaft könnte bei den Landwirten in Tortí daher mehr Anklang finden, wenn Baum-Vieh-Systeme (und nicht Baum-Ackerbau-Systeme) genutzt werden.

Die Kopplung der Interviewdaten mit robuster multikriterieller Optimierung kann Erkenntnisse über die potenziellen Landnutzungsentscheidungen der Landwirte liefern. Das silvopastorale System dominierte die optimierte Landnutzungsverteilung, welche die 10 sozioökonomischen und ökologischen Kriterien bestmöglich gleichzeitig erfüllt. Dieses Ergebnis weist darauf hin, dass das silvopastorale System hohes Potenzial hat die diversen Ziele der Landwirte zu befriedigen. Der Mangel an Alley-Cropping im optimalen Portfolio deutet dagegen darauf hin, dass dieses Agroforstsystem weniger geeignet ist, vielfältige Ziele auf Betriebsebene zu erfüllen. Dennoch gab es Unterschiede in der Zusammensetzung der Portfolios, welche für Landwirte mit abweichenden Landnutzungs- und Einkommensstrategien optimiert wurden. Dies deutet an, dass die einzelnen Agroforstsysteme für verschiedene Gruppen von Landwirten unterschiedlich relevant sein könnten. Diese Einblicke helfen, die Gestaltung von Agroforst-Beratungsprogramme in Tortí zu verbessern. Zum Beispiel könnten Landwirte, die ihr Einkommen hauptsächlich aus dem Ackerbau beziehen, eher bereit sein das silvopastorale System einzuführen. Landwirte die ihr Einkommen vor allem aus der Viehzucht beziehen, könnten dagegen von einer Diversifizierung ihrer Betriebe durch Alley-Cropping profitieren.

Durch eine deskriptive Anwendung des (ansonsten normativen) Optimierungsmodells werden in der Doktorarbeit die impliziten Ziele untersucht, welche die aktuellen Landnutzungsentscheidungen der Landwirte bedingen. Es sollen Schlüsselkriterien identifiziert werden, welche die Agroforstwirtschaft erfüllen muss, um den Bedürfnissen der Landwirte zu entsprechen. Zu diesem Zweck werden verschiedene Kombinationen von Zielen im Optimierungsmodell getestet. Es wurde angenommen, dass je ähnlicher die Zusammensetzung des optimierten Landnutzungsportfolios zur aktuellen Landnutzung des Untersuchungsgebiets ist, desto bedeutender sind die jeweiligen Ziele für die Entscheidungen der Landwirte. Die Ergebnisse zeigen, dass die Ziele (langfristiges Einkommen und wirtschaftliche Stabilität), bei denen das silvopastorale System am besten abschnitt, den geringsten Einfluss auf die aktuellen Landnutzungsentscheidungen haben. Stattdessen scheinen die Liquidität und die Deckung des Haushaltsbedarfs die wichtigsten Entscheidungskriterien für die Landwirte zu sein. Dies stellt ein wichtiges Hindernis für die Einführung von Agroforstwirtschaft dar: Wenn Landwirte in Tortí danach streben, ihre Liquidität zu erhalten und ihre Haushaltsbedürfnisse zu befriedigen, dann wäre ihrer Einschätzung nach konventionelles Weide- und Ackerland (und nicht Agroforstwirtschaft) die bessere Landnutzungswahl. Um diese Hindernisse zu überwinden, sind Agroforstsysteme auszuwählen und zu fördern, welche erstens frühe und häufige Einkommensströme sowie zweitens regelmäßige Ernten von landwirtschaftlichen Produkten ermöglichen.

Die Einschätzungen der Landwirte helfen uns zu verstehen, inwieweit die Landwirte die Agroforstwirtschaft als übereinstimmend mit ihren Zielen wahrnehmen. Die Daten sind jedoch für eine detaillierte Sensitivitätsanalysen unter veränderten Rahmenbedingungen schlecht geeignet, da nicht bekannt ist, wie sich die Einschätzungen der Landwirte unter verschiedenen Umwelt-, Markt- oder politischen Bedingungen verändern würden. Daher werden in der Doktorarbeit detailliertere sozioökonomische Koeffizienten aus einer erweiterten Kosten-Nutzen-Analyse verwendet, um Faktoren zu untersuchen, welche die Einbeziehung von Agroforstwirtschaft in optimierten Landnutzungsportfolios fördern. Solche Analysen können die Bedingungen identifizieren, die Agroforstwirtschaft zu einer wünschenswerteren Landnutzungsoption für lokale Landwirte machen. Im Einklang mit den Resultaten aus dem Interview-Datensatz deuten diese Ergebnisse darauf hin, dass Agroforstwirtschaft für risikotolerante Landwirte, die langfristiges Einkommen priorisieren, attraktiv sein könnte.

Doch da die meisten Landwirte in Tortí die kurzfristigen Ziele von Liquidität und Ernährungssicherheit zu priorisieren scheinen, sind die höheren langfristigen wirtschaftlichen Erträge möglicherweise kein überzeugendes Argument für die Etablierung von Agroforstwirtschaft im Untersuchungsgebiet.

Nichtsdestotrotz steigt der Anteil des silvopastoralen Systems im optimalen Portfolio, wenn die allgemeinen Präferenzen der Landwirte berücksichtigt werden. Das deutet darauf hin, dass das Baum-Vieh-System für mehr Landwirte im Untersuchungsgebiet attraktiv sein kann und nicht nur für diejenigen, die ein langfristiges Einkommen priorisieren. Unter schlechteren Wachstumsbedingungen der Ackerkulturen wird das silvopastorale System wettbewerbsfähiger. Es könnte daher besonders geeignet für landwirtschaftliche Betriebe mit weniger produktivem Boden sein. Ein Mangel an Arbeitskräften könnte jedoch die Einführung des silvopastoralen Systems erschweren. Sinkende Investitionskosten erhöhen den Anteil des Alley-Cropping und des silvopastoralen Systems im optimalen Portfolio. Dieses Ergebnis spricht für Subventionen als Mittel zur Förderung von Agroforstwirtschaft in der Region. Höhere Holzpreise würden die Agroforstwirtschaft ebenfalls attraktiver machen, aber dafür bräuchten die Landwirte einen besseren Zugang zu den Holzmärkten.

Die Doktorarbeit vergleicht die Vor- und Nachteile der beiden Methoden (Interview- vs. berechnete Kosten-Nutzen-Daten) zur Bewertung des sozioökonomischen Potenzials der Agroforstwirtschaft und bietet damit einen praktischen Leitfaden für Forscher, die eine ähnliche Methodik verwenden möchten. Die Interviewdaten sind besonders hilfreich, um kulturelle Hindernisse für die Einführung von Agroforstwirtschaft zu ermitteln. Da die Daten das lokale Wissen und die Meinung der Landwirte wiederspiegeln, eignet sich diese Methode für partizipative Forschungsansätze. Dagegen sind die Möglichkeiten, tiefgreifende Sensitivitätsanalysen durchzuführen und ökonomische Restriktionen im Optimierungsmodell einzubauen, die Stärken des berechneten Datensatzes. Durch die Integration der berechneten Koeffizienten im Optimierungsmodell können spezifischere Empfehlungen für die Gestaltung sozialverträglicher Agroforstsysteme abgeleitet werden.

Der normative Modellierungsansatz dieser Doktorarbeit ermöglicht es, über die aktuellen Landnutzungsmuster einer bestimmten Region hinaus zu schauen: Dadurch können erstrebenswerte Landnutzungszusammensetzungen identifiziert werden, welche helfen Zielkonflikte für Landwirten zu minimieren. Auch können Einblicke in die relative Attraktivität neuer Agroforstsysteme aus Sicht der Landwirte unter unterschiedlichen Haushalts-, Markt- oder Umweltbedingungen gewonnen werden. Mit diesen Erkenntnissen können vielversprechende Agroforstsysteme für weiterführende Feldversuche vorausgewählt werden. Diese Doktorarbeit demonstriert den Modellierungsansatz für eine Region im Osten Panamas. Die Methoden und Erkenntnisse sind jedoch auf nachhaltige Landnutzungssysteme in anderen tropischen oder gemäßigten Landschaften übertragbar.

List of acronyms and abbreviations

AF	Agroforestry
AHP	Analytic hierarchy process
FAO	Food and Agriculture Organization of the United Nations
MCDA	Multi-criteria decision analysis
MCS	Monte Carlo simulation
MPT	Modern portfolio theory
NPV	Net present value
RQ	Research question
SEM	Standard error of the mean
SD	Standard deviation
TUM	Technische Universität München (Technical University of Munich)

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Chapter 1: Introduction

1.1 Background

Meeting the food and energy demands of a growing population is a key challenge of the 21st century (Davis et al. 2016). The need to produce food, fibre and fuel often competes directly with environmental protection and provision of other ecosystem services, putting increasing strain on scarce land resources (Clough et al. 2016; Lambin and Meyfroidt 2011). Land degradation compounds the problem, driving further expansion of agricultural land and the subsequent loss of natural habitat (Fischer and Vasseur 2000). There is widespread consensus that agricultural innovations to transform existing farming systems are urgently needed if we are to meet global food and energy demand without further environmental destruction (Davis et al. 2016; Lambin and Meyfroidt 2011; Leakey 2020; Plieninger et al. 2020).

Agroforestry is receiving increasing attention as a potential strategy to address global land-use problems (Nair and Garrity 2012). For example, the FAO promotes agroforestry for sustainable development and landscape restoration (FAO 2013, 2017). Agroforestry represents a multi-functional form of agriculture that combines trees and crops or trees and livestock on the same piece of land. As a “land-sharing” approach, agroforestry systems have potential to bridge the competing land-use needs for production and environmental protection (Torralba et al. 2016). These systems are especially advocated in tropical regions as a means to reduce poverty, mitigate climate change and improve food security (Leakey 2020; Montagnini and Metzel 2018; Waldron et al. 2016).

The ecological benefits of agroforestry are clear. Compared to conventional, often single-species agriculture, agroforestry systems can enhance biodiversity and ecosystem services in farm landscapes, including nutrient cycling, water regulation, erosion control and carbon storage (Jose 2009; Lin 2010; Schroth et al. 2015; Torralba et al. 2016; Zomer et al. 2016). The socio-economic benefits of agroforestry systems for farmers, however, are more equivocal and often context dependent (Torralba et al. 2016). Agricultural production may benefit from enhanced water availability and resilience to drought (Lin 2010; Somarriba et al. 2012) or increased organic matter and nitrogen in soils (Dagang and Nair 2003). As an additional revenue source, tree products can also help diversify on-farm income to buffer financial risks (Cubbage et al. 2012; Thorlakson and Neufeldt 2012). However, agroforestry systems can also have major drawbacks compared to conventional agriculture, including high investment costs (Dagang and Nair 2003; Metzel and Montagnini 2014), lower crop yields (Bertomeu 2006; Clough et al. 2016; Palm et al. 2010; Reed et al. 2017), greater management complexity and delayed and less frequent returns from timber products (Cubbage et al. 2012; Do et al. 2020; Garen et al. 2009; Paul et al. 2017).

Because the decision to adopt agroforestry rests with the farmer, it is essential to understand the costs and benefits of different agroforestry systems from the farmers' perspective. As with any agricultural innovation, farmers will only integrate trees into their farming practices if they perceive agroforestry to align with their goals and available resources (Pannell et al. 2006). The uneven and relatively slow uptake of agroforestry in Central and Latin America (Dagang and Nair 2003; Frey et al. 2012a; Somarriba et al. 2012), however, suggests that not all farmers deem these systems to be a desirable land-use option (Do et al. 2020). More research on the socio-economic aspects of agroforestry is therefore needed to better understand the advantages and disadvantages for farmers. Such an understanding is critical to identify, design, test and effectively promote socially-acceptable tree-crop or tree-livestock systems.

This thesis evaluates the socio-economic potential of agroforestry systems from the perspective of smallholder farmers. Based on a normative modelling approach, I investigate whether agroforestry can help contribute to (and reduce trade-offs between) multiple goals at the farm level when accounting for uncertainty and farmers' attitudes towards risk. Using a case study of an agricultural frontier region in eastern Panama, I will demonstrate how the modelling approach, which simulates decision-making at the farm-level, can evaluate agroforestry systems as part of a diversified farm portfolio. My aim is to show how such an analysis can help to identify the conditions that promote or hinder agroforestry adoption, but also the types of farmers for whom agroforestry may be most attractive. These insights, which may be difficult to gain from empiric data alone, will help to identify the most socially-acceptable agroforestry systems that could then be further tested with on-farm trials. Modelling results can also inform the design of effective incentive programs to promote agroforestry adoption.

1.2 Contributing papers and thesis organisation

This cumulative doctoral thesis unites four scientific papers, the details and main contribution of which are summarised in Table 1. Papers 1 to 3 analyse an empiric dataset capturing farmers' judgement of different land-use systems, derived from landholder interviews in eastern Panama. Paper 1 is a methodological paper, providing practical insights into two methods for quantifying farmer knowledge. Papers 2 and 3 integrate the interview data in a multi-objective optimisation model, answering calls to incorporate farmer knowledge and preferences into land-use planning and the design of agroforestry systems (Díaz et al. 2018; Plieninger and Huntsinger 2018; Scholte et al.

2015). As a counterbalance to the interview data, Paper 4 integrates more detailed socio-economic coefficients in the optimisation model. This allows for an in-depth scenario analysis, to explore the conditions that promote the selection of agroforestry in a diversified land-use portfolio. Figure 1 illustrates the methods and scope of the four papers.

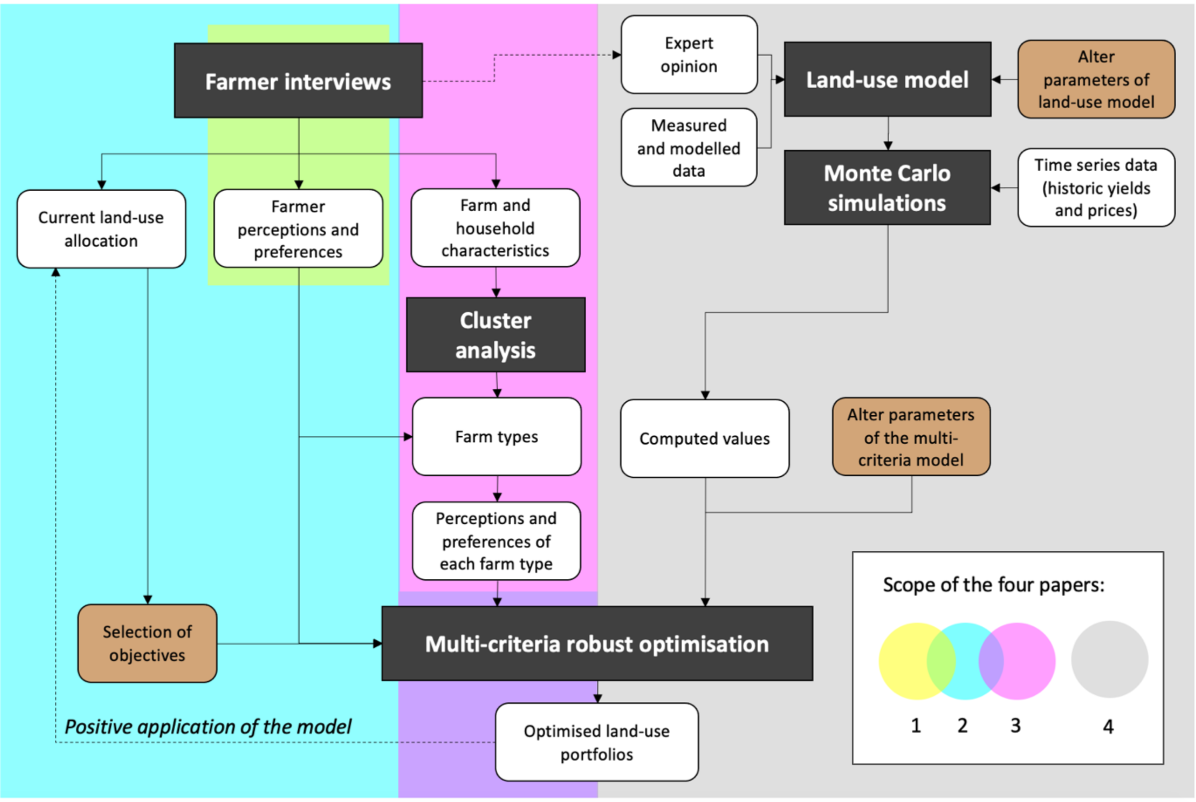

Figure 1: Overview of the methodology and scope of the four research papers and the links between them. The charcoal boxes represent the main methodological components of the papers, while the tan boxes represent post-hoc analyses carried out after the initial optimal land-use portfolios had been determined.

Table 1: Overview of the four papers contributing to the thesis. For author contributions EG = Elizabeth Gosling, ER = Esther Reith, CP = Carola Paul, TK = Thomas Knoke, AG = Andrés Gerique and ARC = Alyna Reyes Cáceres.

#	Paper	Status	Main contribution	Author contributions
1	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.	Submitted 24/05/2019 Revised 09/09/2019 Published online 23/10/2019	This methodological paper compares two techniques (the analytic hierarchy process and a simpler ranking and scoring method) for evaluating land-uses against socio-economic and ecological criteria, based on farmer opinion. Both methods produce numerical datasets that can integrate farmer knowledge into land-use modelling. By describing our experience with each method in eastern Panama, we offer recommendations for researchers looking to quantify farmer opinion.	Concept and design: EG; Data collection: EG & ER; Data analysis: EG & ER; Drafting of manuscript: EG; Editing and revising: EG and ER
2	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.	Submitted 21/06/2019 Revised 15/01/2019 Published online 02/03/2020	This paper integrates farmer perception data with goal programming to investigate if agroforestry appears in land-use portfolios that minimise trade-offs between farm-level objectives. We examine how the selection of objectives influences the optimal land-use composition. This includes a positive application of the (otherwise normative) optimisation model, in which we aim to replicate farmers' current land-use compositions as a means of uncovering the implicit preferences driving their land-use decisions.	Concept and design: CP, TK & EG; Data collection: EG & ER; Data analysis: EG; Drafting of manuscript: EG; Editing and revising: EG, ER, CP & TK
3	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.	Submitted 06/08/2019 Revised 21/02/2019 Published online 29/06/2020	This paper couples the robust optimisation model with a cluster analysis of the farmer interview data, to compare optimised land-use portfolios across groups of farmers with similar land-use and income characteristics. Here the focus lies on uncovering and exploring potential differences in farmers' willingness to adopt agroforestry, and discussing the suitability of the modelling approach for supporting participatory land-use planning.	Concept and design: EG, TK & CP; Data collection: EG & ER; Data analysis: EG; Drafting of manuscript: EG; Editing and revising: EG, ER, TK, CP & AG
4	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* (in press).	Submitted 01/09/2020 Revised 10/12/2020 and 22/01/2021 Published online 12/02/2021	This paper integrates more detailed socio-economic coefficients computed for seven land-use options in the robust optimisation model. The key contribution of this paper is a scenario analysis, in which we examine how the type and share of agroforestry in the optimal portfolio changes under different socio-economic, biophysical and political conditions. This allows us to explore the conditions that make agroforestry systems more (or less) attractive to farmers, and helps to identify criteria which agroforestry must meet to fulfil farmers' needs.	Concept and design: EG, CP; Data collection: EG, ER & ARC; Data analysis: EG; Drafting of manuscript: EG; Editing and revising: EG, TK, CP, ER & ARC

The following section (1.3) gives an overview of land-use change in Panama, highlighting the role of agroforestry in the government's strategy to combat deforestation and land degradation. Section 1.4 reviews the current state of agroforestry research, making the case for why we need land-use models capable of accounting for a) farmers' multiple objectives, b) the effects of land-use diversification and c) uncertainty, when evaluating the socio-economic potential of different agroforestry systems. This section ends with the overarching hypothesis and research questions which guide the subsequent analyses and results. Chapter 2 summarises the main methods of the thesis, including the robust multi-criteria optimisation modelling approach developed by Knoke and colleagues (2015; 2016) and the rapid rural appraisal methods used in the farmer interviews. The results and discussion are combined in Chapter 3. There I present the key findings for each research question and discuss the implications for agroforestry policy, practice and research. I also highlight the limitations of the optimisation approach and how these may be addressed in future studies (section 3.5). Finally, drawing on the study's key findings, Chapter 4 contains specific conclusions and recommendations for strategies to increase agroforestry adoption among smallholder farmers in eastern Panama. The four scientific papers contributing to the thesis are included in the appendix.

1.3 Land-use change in Panama: The need for sustainable solutions

Like many countries in Central and Latin America, the Republic of Panama (hereon shortened to Panama) is experiencing ongoing conversion of natural forest to agricultural lands (Fischer and Vasseur 2000; Garen et al. 2011; Paul et al. 2017). Deforestation rates peaked from the 1950s to 1980s, with forest cover declining from 70% of Panama's land area in 1947 to 49% in 1986 (ANAM 2011). This deforestation was largely driven by extensive cattle ranching, and supported by Panama's Agrarian Code of 1962 which promoted forest clearing as a precondition to secure land tenure (Fischer and Vasseur 2000). In the 1990s the Panamanian government introduced various measures to curb deforestation, most notably "Law 24" in 1992, which created generous financial incentives for afforestation (Fischer and Vasseur 2000). These laws were targeted at large companies, however, and provided limited incentives for small-scale farmers to plant trees (Fischer and Vasseur 2000; Garen et al. 2011; Sloan 2008). The subsequent increase in large-scale timber plantations (dominated by fast-growing exotic species, Garen et al. 2009) has led to afforestation alongside deforestation (Sloan 2008). For example, between 1992 and 2000, net forest cover in Panama increased by 0.36% a year, but mature forest cover fell by 1.3% (Wright and Samaniego 2008). In this time period, agricultural expansion was particularly intense in eastern Panama; forest cover decreased in the Darién and Panamá provinces by 1.7% and 1.5% each year, respectively, the second and third highest deforestation rates in the country (ANAM 2011). Recent data from the FAO show that in the last decade (2010-2020), Panama lost an average of 11,400 hectares of forest per year, representing an annual deforestation rate of 0.27% (FAO 2020).

Deforestation has led to biodiversity loss and environmental degradation in Panama, including erosion, sedimentation, reduced water supply and declining soil fertility (ANAM 2011; Fischer and Vasseur 2000). Moreover, the cultivation of soils ill-suited for agriculture coupled with poor land management have exacerbated productivity declines and degradation, to the point where 27% of Panama's land area is now degraded or semi-abandoned (ANAM 2011; Fischer and Vasseur 2000). This puts further pressure on forest ecosystems as farmers clear more land to offset declining yields (Fischer and Vasseur 2000; Paul et al. 2017). Agroforestry may offer a sustainable land-use alternative to help combat this cycle of deforestation and degradation, by increasing soil fertility and ecological functions on agricultural lands (Fischer and Vasseur 2000; 2002). Recognising this potential, the Panamanian Government promotes agroforestry as part of the "*Alianza por el Millón*" initiative to restore one million hectares of forest land (García et al. 2016; MiAmbiente 2019). This has included establishing a legal framework (enacted through Law 69 of October 30, 2017) for tax incentives and subsidies for agroforestry systems. Research into the socio-economic aspects of agroforestry can support the successful implementation of such policies, by helping to identify the tree-crop and tree-livestock systems best suited to meeting farmers' needs.

1.4 State of the art: Evaluating the socio-economic potential of agroforestry

Early agroforestry research predominately focused on biophysical characteristics (e.g. crop yields and soil biology) of different tree-crop and tree-livestock systems, with studies into socio-economic aspects first appearing in the 1990s (Montambault and Alavalapati 2005). The bulk of existing socio-economic studies have relied on econometric approaches to better understand agroforestry adoption (e.g. Fouladbash and Currie 2015; Pattanayak et al. 2003; Santos Martín et al. 2012; Simmons et al. 2002; Zabala et al. 2013). These studies often predict adoption as a yes/no decision based on household characteristics and farm endowments. Such analyses help to identify factors influencing adoption, but provide limited insights into the trade-offs of adopting agroforestry, especially in the context of diversified farm land-use systems. Moreover, because these methods rely on empiric data, it is difficult to investigate the socio-economic potential of new agroforestry systems not yet widespread in a region (Janssen and van Ittersum 2007; Paul et al. 2019).

Therefore, mechanistic models have become increasingly important for assessing the socio-economic credentials of new agroforestry systems (Burgess et al. 2019). Mechanistic models build on existing theory and knowledge to simulate system behaviour beyond the range of observed data, making them suitable for assessing agricultural innovations (Castro et al. 2018; Janssen and van Ittersum 2007; Jones et al. 2017a). Bio-economic models, for example, can combine knowledge of biophysical processes (e.g. to predict tree growth and crop yields) with economic coefficients (e.g. input costs and prices). Such bio-economic models have been used to compare the expected yields and profitability of agroforestry systems to those of monocultures (e.g. Do et al. 2020; Frey et al. 2010; Graves et al. 2007; Ramírez et al. 2001), but can also help evaluate agroforestry systems against a broader set of socio-economic and ecological objectives (e.g. García de Jalón et al. 2017; Palma et al. 2007; Rahman et al. 2017; Santos Martin and van Noordwijk 2011).

Studies based on bio-economic modelling often evaluate agroforestry and conventional land-use systems as separate (or discrete) land-use alternatives. Ramírez and colleagues (2001), for example, modelled the expected financial returns of different shade-cocoa agroforestry systems and the corresponding monocultures in western Panama. Palma and colleagues (2007) compared silvopastoral and conventional land-use systems in Europe, modelling their performance against various environmental and social indicators. Evaluating agroforestry as one of multiple, but mutually exclusive, land-use options can provide valuable insights into trade-offs between objectives and help decision-makers to select the most preferred land-use option for a given situation. However, evaluating agroforestry as a discrete land-use ignores diversification effects and may not reflect the reality of farmers' decision-making (Knoke et al. 2011). Farmers may be unlikely to allocate their entire farmland to a single land-use, given that land-use diversification is a key strategy to buffer risk (Baumgärtner and Quaas 2010; Di Falco and Perrings 2005) and meet multiple household needs (Knoke et al. 2017; Ochoa et al. 2019; Pannell et al. 2014).

Accounting for the benefits of land-use diversification requires a portfolio approach, capable of modelling land-use decisions at the farm level. Such models consider multiple land-use options simultaneously to identify the best land-use allocation (i.e. mix of land-uses) for achieving a given objective (Knoke et al. 2011; Knoke et al. 2020a). Existing studies that evaluate agroforestry in the context of a diversified land-use portfolio are mostly based on Markowitz's (1952) Modern Portfolio Theory (MPT) (e.g. Babu and Rajasekaran 1991; Bertomeu and Giménez 2006; Blandon 2005; Lilieholm and Reeves 1991; Ochoa et al. 2016; Paul et al. 2017). These studies account for uncertainty in yields and prices to determine efficient portfolios (land-use allocations) that maximise financial returns for a given level of risk (Matthies et al. 2019; Mercer et al. 2014). For example, Paul and colleagues (2017) coupled bio-economic modelling with MPT to compare the risk and return of different alley cropping systems to that of a diversified land-use portfolio, to identify economically competitive agroforestry layouts for eastern Panama. Like other MPT studies, Paul and colleagues

(2017) assumed that farmers follow a single objective of maximising profit and/or minimising risk. However, there is growing recognition that farmers are not motivated by profit or risk reduction alone, and instead often seek to reconcile multiple, potentially conflicting, goals (Janssen and van Ittersum 2007; Pannell et al. 2006; van Zonneveld et al. 2020). Hence, models that consider multiple objectives may more realistically represent farmers' decision-making (Castro et al. 2018; Janssen and van Ittersum 2007; Kaim et al. 2018).

One way to account for multiple objectives in land-use modelling is to monetise different indicators to compute the overall profitability of a given land-use or land-use allocation (Bateman et al. 2013; Kay et al. 2019; Kolo et al. 2020). However, not all of farmers' objectives may be adequately represented by monetary units (Fagerholm et al. 2016; Mercer et al. 2014). Moreover, combining multiple objectives into a single measure of profitability may lead to unbalanced solutions due to compensation effects. For example, a land-use that performs strongly for a single highly-priced indicator may dominate the portfolio despite its poor performance for other indicators (Kolo et al. 2020). As an alternative, multi-criteria decision analysis (MCDA) can integrate diverse economic, social and environmental indicators–which may be measured in different units–into land-use decisions (Palma et al. 2007; Uhde et al. 2015). For example, Palma et al. (2007) used outranking (a method based on pair-wise comparisons) to integrate social and ecological indicators in their assessment of silvopastoral systems, while Liu et al. (1998) used the analytic hierarchy process (AHP) and multi-utility approaches to evaluate farm-forestry systems against socio-economic objectives in China. These approaches, however, represent discrete MCDA methods that evaluate agroforestry as one of several, mutually exclusive land-use options: they do not account for diversification effects to model land-use decisions at the farm level.

In contrast, mathematical programming is a continuous form of MCDA which can solve land allocation problems to simulate whole farm decision-making. These programming methods can compare an infinite number of solutions to determine the optimal land-use portfolio for achieving a set of objectives (Janssen and van Ittersum 2007; Uhde et al. 2015). Goal programming is a well-known mathematical programming approach. Goal programming is often used to solve allocation problems in forestry (e.g. Aldea et al. 2014; Diaz-Balteiro and Romero 2008; Messerer et al. 2017) and agriculture (e.g. Ballarin et al. 2011; Biswas and Pal 2005; Knoke et al. 2015), but applications to evaluate agroforestry are rare. Mendoza and colleagues (1986, 1987), for example, present a multi-objective, portfolio optimisation approach based on goal programming for evaluating agroforestry systems, which García-de Ceca and Gebremedhin (1991) further develop and test using example data from Nigeria. More recently, Rollan and colleagues (2018) used goal programming to optimise the management of agroforestry systems in the Philippines based on multiple objectives, but they did not evaluate agroforestry in the context of a diversified farm portfolio. As an innovative example, Reith and colleagues (2020) use goal programming to assess the role of agroforestry within multi-functional landscapes that meet the broad socio-economic and ecological goals of Panamanian society.

There is therefore a lack of studies that take a portfolio approach to evaluate agroforestry against multiple objectives at the farm level. Another important research gap is the consideration of uncertainty in multi-criteria assessments of agroforestry (and multi-criteria optimisation approaches in natural resource management more generally, Castro et al. 2018; Paul et al. 2019). For example, the economic coefficients (prices, yields etc) in García-de Ceca and Gebremedhin's (1991) optimisation model are deterministic: the model assumes the coefficients can be precisely predicted. In reality, however, uncertain weather, prices and government policies ensure that the economic coefficients of most land-uses are far from certain (Rădulescu et al. 2014). This uncertainty plays an important role in agricultural decision-making, including the adoption of new farming systems (Lilieholm and Reeves 1991; Meijer et al. 2014; Rădulescu et al. 2014). Farmers are usually risk-averse (Baker et al. 2017; Clough et al. 2016; Pannell et al. 2014), and any farm model that ignores uncertainty may also neglect farmers' typical risk-reducing behaviour of diversifying land-use and income sources (Bowman and Zilberman 2013; Castro et al. 2018; Garrity 2004). Models that ignore uncertainty or farmers' attitudes toward risk may therefore fail to reflect farmers' true behaviour in terms of their land-use decisions and selection of agroforestry (Babu and Rajasekaran 1991; Castro et al. 2018).

Portfolio optimisation based on MPT is one way to recognise uncertainty and account for farmers' risk aversion when modelling land-use decisions (Knoke et al. 2011; Lilieholm and Reeves 1991). But because these models are restricted to a purely financial objective (usually maximising profit for a given level of risk), they may miss the broader range of motivations that can influence farmers' decision-making (Garen et al. 2009; Janssen and van Ittersum 2007; Mendoza et al. 1987; van Zonneveld et al. 2020). Farm level models that account for multiple objectives and risk/uncertainty are very rare (Castro et al. 2018).

A further research gap are studies that integrate farmers' local knowledge, empiric experience and cultural preferences in farm-level models. Understanding and accounting for such knowledge and preferences, however, is vital to identify socially-acceptable agroforestry systems with the highest likelihood of adoption (Garen et al. 2011; Plieninger and Huntsinger 2018). Previous research into farmers' knowledge and perceptions of agroforestry has mostly relied on qualitative methods (e.g.

Calle et al. 2009; Frey et al. 2012b; Garen et al. 2009; Hand and Tyndall 2018; Peterson St-Laurent et al. 2013). However, integrating farmer knowledge and perceptions into multi-criteria optimisation models requires quantitative data. Studies that use quantitative methods, such as AHP, to elicit farmer opinion of agroforestry systems are scarce and mostly limited to temperate regions (Laroche et al. 2018; Shrestha et al. 2004); Temesgen and Wu's (2018) Ethiopian study is a rare exception.

In this section I have highlighted the lack of studies that evaluate agroforestry in a way that simultaneously accounts for: a) farmers' multiple and potentially conflicting objectives, b) the benefits of land-use diversification and c) uncertainty and risk aversion in land-use modelling. Also missing are studies that integrate farmer knowledge and preferences into the selection of optimal farm land-use portfolios. To address this research gap I use a robust, multi-criteria optimisation model to assess the socio-economic potential of different agroforestry systems, based on two datasets from eastern Panama (one quantifying farmers' knowledge and perceptions, the other drawing on an extended cost-benefit analysis). The overarching hypothesis guiding my research is:

> The inclusion of agroforestry in a diversified land-use portfolio will reduce trade-offs between farmers' multiple objectives when considering uncertainty.

To test this hypothesis I have divided my analysis and discussion into four parts, whereby I explore the following research questions:

1. How do farmers perceive agroforestry relative to conventional land-uses?
2. According to these perceptions, would agroforestry help reduce trade-offs between farm level goals when accounting for uncertainty?
3. Which socio-economic and environmental conditions promote (or hinder) the selection of agroforestry within a diversified land-use portfolio?
4. Which data collection methodologies are most useful for evaluating agroforestry?

Chapter 2: Materials and Methods

2.1 Robust multi-objective optimisation

The cornerstone method of this thesis is the robust multi-objective optimisation approach that Knoke and colleagues (2015; 2016) developed for land allocation problems in tropical areas, following the mathematical advances of Ben-Tal and colleagues (2009). The model, including its mathematical formulation, is described in detail in Paper 2 (and in the supplementary material of Papers 3 and 4). Here I summarise the key features of this modelling approach and highlight its advantages for evaluating the socio-economic potential of agroforestry. Figure 2 outlines the main components of the model, while Table 2 explains the most important variables to aid interpretation of the results.

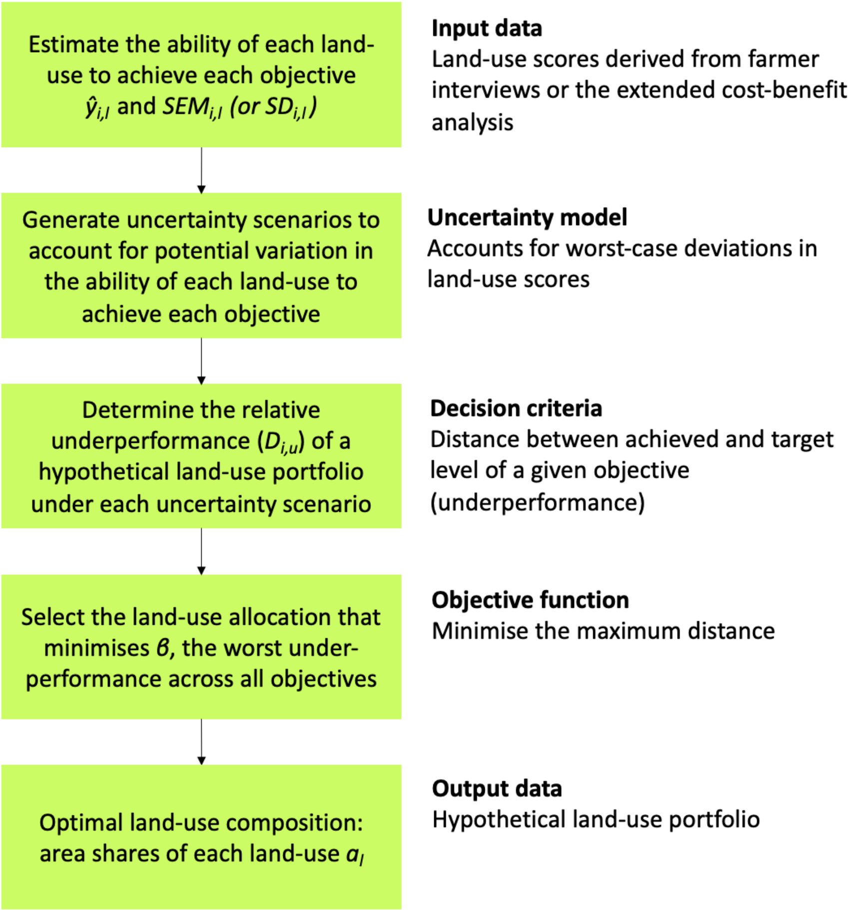

Figure 2: Overview of the optimisation procedure, adapted from Gosling et al. (2020b). All terms (e.g. $\hat{y}_{i,l}$, $D_{i,u}$ and β) and their indices are described in Table 2.

Table 2: Description of key variables in the robust, multi-criteria optimisation model (to aid interpretation of results).

Variable	**Description**
$\hat{y}_{i,l}$	The expected (mean) score for each land-use, l, for each indicator, i. Derived from the farmer interviews (Papers 2 and 3) or from the extended cost-benefit analysis (Paper 4). Represents our estimate of the ability of each land-use to achieve each indicator.
$SD_{i,l}$, $SEM_{i,l}$	The standard deviation and standard error of each land-use score ($\hat{y}_{i,l}$): used to quantify the uncertainty associated with our estimates of the ability of each land-use to achieve each indicator.
a_l	The area shares (expressed as decimal fractions) of a hypothetical farm allocated to each land-use option, l. These area shares define the optimal land-use portfolio and represent the decision variables in the multi-criteria optimisation model.
$D_{i,u}$	Distance between the target and achieved performance of a hypothetical land-use portfolio for a given indicator, i, and uncertainty scenario, u. The larger the distance, the worse the underperformance. $D_{i,u}$ is normalised between 0 and 100: a distance of 0 indicates a land-use portfolio has achieved the target (best possible) performance, a distance of 100 indicates a land-use portfolio has achieved the worst possible performance.
β	Worst underperformance (highest $D_{i,u}$) across all indicators and uncertainty scenarios; the objective function to be minimised in the optimisation model. β represents the poorest performance that a farmer would have to accept for any indicator in a worst-case scenario. It represents the largest shortfall between the target (best possible) and achieved level for any indicator, and thus quantifies trade-offs between objectives in the optimisation model.
$100 - \beta$	Guaranteed performance of a hypothetical land-use portfolio. It is the minimum performance attained for all indicators across all uncertainty scenarios, where 100% is the target level.
m	Factor used to compute unfavourable deviations of land-use performance (worst case estimates) within each uncertainty scenario: these deviations are computed by adding or subtracting a multiple, m, of the standard error, $SEM_{i,l}$ (or standard deviation, $SD_{i,l}$) from the expected (mean, $\hat{y}_{i,l}$) land-use score. The factor m dictates the size of these unfavourable deviations and hence the level of uncertainty considered in the optimisation model. The uncertainty level can simulate the decision-making of farmers with different attitudes towards risk. For example, $m = 0$ ignores uncertainty (the optimisation model considers mean values only), which could simulate the decision-making of a risk neutral farmer; $m = 1.5$ represents a moderate level of uncertainty, to simulate the decision-making of a moderately risk-averse farmer; and $m = 3$ represents a high level of uncertainty, simulating the decision-making of a highly risk-averse farmer.

The optimisation model is a variant of goal programming, a continuous MCDA technique. This allows us to simulate the decision-making of a hypothetical farmer who allocates his or her land to the considered land-uses in a way that best achieves a single or multiple objective(s). As a continuous MCDA method, the optimisation model can consider all possible combinations of these land-uses to find the best land-use mix (defined by the area shares allocated to each land-use) for achieving the given set of objectives. The model therefore accounts for the effects of land-use diversification to simulate decision-making at the farm level. The output of the optimisation model is a hypothetical land-use portfolio comprising various shares of the considered land-use options. In this thesis I use 'land-use portfolio' and 'land-use composition' as synonyms.

Recognising that farmers often consider a range of household goals (and not profit maximisation alone) when making land-use decisions (Kaim et al. 2018; Pannell et al. 2006; van Zonneveld et al. 2020), the optimisation approach accounts for multiple objectives when determining the optimal land-use composition. Multiple objectives are integrated in the model through a Min-Max (Chebychev) formulation (Romero 2001). For each objective we set a target level, and the model selects the land-use composition that minimises the worst shortfall between the achieved and target level (i.e. the maximum underperformance, β, see also description in Table 2) across all objectives. We use indicators to quantify the performance of a given land-use composition against each objective; performance is normalised between 0 and 100 to allow comparison between indicators with different units. Unless otherwise specified, all objectives (i.e. indicators) are weighted equally in the optimisation model. The Min-Max formulation results in compromise solutions, where high performance in one objective (e.g. long-term profit) cannot compensate for poor performance in another (e.g. meeting household food needs). In this way the model always focuses on improving the level of the worst performing objective (similar to a Rawlsian approach, Tamiz et al. 1998), rather than maximising the level of the best performing objective. This simulates "satisficing behaviour", a mix between satisfying and optimising behaviour, which may be a good fit for farmer decision-making (Knoke et al. 2020c; Le Gal et al. 2011).

As a normative research approach, the optimisation model allows us to look beyond farmers' current land-use decisions (what currently is – a positive approach), to determine the theoretically optimal land allocation for achieving a given set of objectives under different conditions. By exploring these optimal land-use portfolios I do not, however, intend to prescribe exact land-use compositions that farmers in the study area should adhere to. Instead, I seek to gain insights into farmer behaviour (including the potential adoption of agroforestry), as well as potential trade-offs between farm-level objectives. Such insights can help to better understand the circumstances under which agroforestry may be a useful complement to help meet farmers' needs.

The robust formulation of the optimisation model actively accounts for uncertainty in decision-making, an important influence on farmers' land-use decisions (Babu and Rajasekaran 1991; Castro et al. 2018). For this thesis I define uncertainty as the incomplete knowledge about how much a land-use will actually contribute to a given objective, both now and in the future (Gosling et al. 2020b). To account for this uncertainty the optimisation model considers potential fluctuations in the input values to find robust solutions, that is, solutions that perform well (or remain acceptable) across a wide-range of possible input values, including worst case scenarios (Härtl and Knoke 2019; Shavazipour and Stewart 2019).

Fluctuations in land-use performance are considered through so-called uncertainty scenarios. These uncertainty scenarios systematically combine best- and worst-case estimates for the performance of each land-use against each objective. For the best-case estimate we use the expected (mean) value for a land-use for a given objective. For the worst-case estimate we compute an unfavourable deviation from the expected value, by either adding or subtracting a multiple, m, of the standard error or standard deviation from the mean[1]. Collectively, the uncertainty scenarios represent all possible combinations of best (expected) and worst-case estimates across the considered land-use options, which provide the corner points (describe the surface) of the uncertainty spaces for each objective (Knoke et al. 2020a). The optimisation model considers all the corner points simultaneously, and hence the optimal land-use composition represents a feasible solution for all values included within the uncertainty space (Ben-Tal and Nemirovski 1999; Knoke et al. 2020a). Following Knoke and colleagues (2020a), the formulation of the optimisation model in this thesis (and associated papers) only considers unfavourable deviations from expected values, simulating the decision-making of a risk-averse farmer who is motivated to avoid losses.

The model does not assign probabilities to the potential deviations from the expected values: each uncertainty scenario is weighted equally. This form of non-stochastic, robust decision-making is often recommended when confronted with high levels of uncertainty, which is often the case when assessing agricultural innovations (Doole 2012; Walker et al. 2013). Our approach aligns with “Level 4” uncertainty described by Walker and colleagues (2013), in which we only know the range of values that may occur, but not the probability or likelihood with which they will occur. Robust optimisation has the further advantage of being “distribution free”; it does not make any assumptions about the underlying distribution of the data (Ben-Tal and Nemirovski 1999; Härtl and Knoke 2019). Moreover, because it is less data-demanding than stochastic alternatives, robust optimisation can help overcome problems of data scarcity (Messerer et al. 2017; Paul et al. 2019).

Few studies have taken a portfolio approach to assess agroforestry against multiple criteria, and those that exist have either not accounted for uncertainty in decision-making (e.g. Mendoza et al. 1986, 1987) or have been aimed at the landscape level (e.g. Reith et al. 2020). The scientific papers

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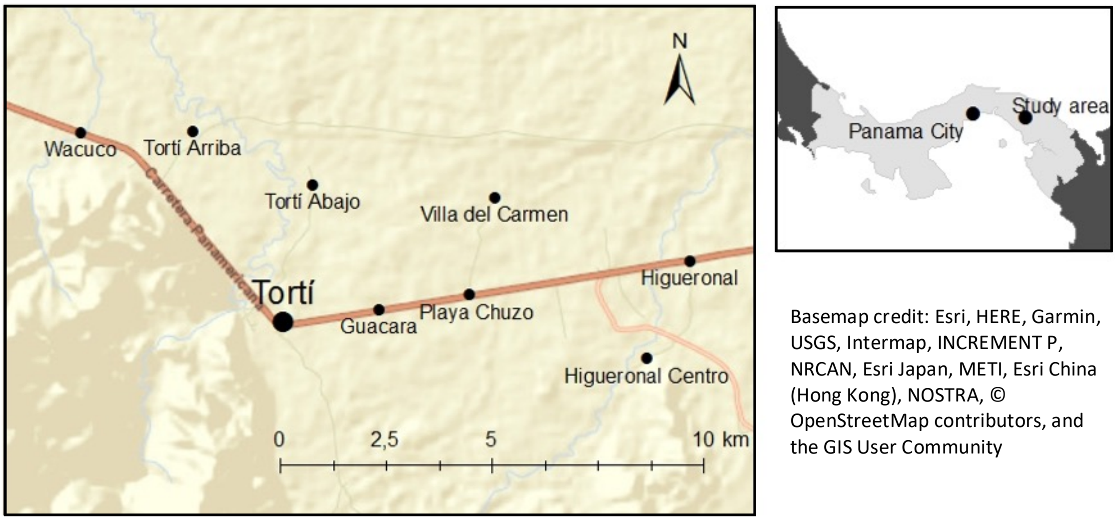
[1] For “more is better” indicators (indicators for which higher values are preferred, e.g. economic return) we compute an unfavourable deviation by subtracting a multiple of the standard error/deviation from the mean (e.g. $\hat{y}_{i,l} - m \times SEM_{i,l}$). For “less is better” indicators (such as labour demand) we compute the unfavourable deviation by adding a multiple of the standard error/deviation to the mean (e.g. $\hat{y}_{i,l} + m \times SEM_{i,l}$). See Table 2 for description of terms and their indices.

in this thesis represent the first application of robust multi-criteria optimisation to evaluate the socio-economic potential of agroforestry at the farm level. Moreover, Paper 2 demonstrates a positive application of the optimisation model, in which we explored the implicit drivers of farmers' land-use decisions by using the model to replicate their observed behaviour, showcasing the versatility of the modelling approach (Gosling et al. 2020a).

2.2 Study area

The study area for this thesis is a farming region at the agriculture-forest frontier[2] in eastern Panama, near the border of the Panamá and Darién provinces. The study area incorporates the township of Tortí (which has around 1,600 inhabitants (INEC 2010)) and its surrounding villages, which lie on the Pan-American Highway, around 125km east of Panama City (Figure 3). Tortí lies in the humid tropical zone, receiving 1,900 mm annual rainfall with a dry season from January to March (ETESA 2018). Tortí underwent intensive colonisation relatively recently: settlers from Panama's western provinces began arriving in the region in the 1970s, marking the start of widespread forest clearing (Paul 2014; Sloan 2008). Settlers brought their cattle ranching practices from the west (Paul 2014), and pasture now comprises 64% of the agricultural land-use of the wider Tortí region (INEC 2011). High clay content limits soil productivity (Paul 2014), and crops make up just 8% of farmland (INEC 2011). Large-scale teak (*Tectona grandis*) plantations are also common in the area, usually owned by international timber corporations (Sloan 2008).



Basemap credit: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCAN, Esri Japan, METI, Esri China (Hong Kong), NOSTRA, © OpenStreetMap contributors, and the GIS User Community

Figure 3: Tortí and its surrounding villages in eastern Panama are the focal point of this thesis. Map taken from Gosling et al. (2020a).

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[2] Frontier regions represent the outermost edge of human settlement, where agriculture is expanding into large tracts of ecologically intact natural forest (Bryant et al. 1997; Schiesari et al. 2013).

This thesis builds on previous studies in the Institute of Forest Management and (former) Chair of Silviculture at TUM, which have generated substantial knowledge of current farming practices in Tortí and experience in modelling potential agroforestry systems. This includes a field trial and economic analysis of *taunyga* agroforestry systems with exotic and native tree species (Paul 2014; Paul et al. 2015; Paul and Weber 2013), which informed Paul and colleagues' (2017) bio-economic modelling of different teak-maize alley cropping systems. Schuchmann (2011) interviewed farmers in Tortí to better understand their current management practices, including how they integrate trees into their pasture and farming systems, while Reyes Cáreces (2018) evaluated the economic potential of two silvopastoral systems based on MPT.

Outside of the TUM research group, Simmons and colleagues (2002) investigated factors affecting smallholder tree-planting in the wider Tortí region. Tscharkert and colleagues (2007) conducted surveys in the indigenous Ipetí-Emberá community (just west of Tortí), to better understand the household factors influencing indigenous farmers' land-use decisions, while Kirby and Potvin (2007) identified their preferred timber tree species. More recently, Peterson St-Laurent and colleagues (2013) carried out interviews and workshops to investigate the current land-use of colonist farmers in Tortí and their perceptions of forest management.

2.3 Datasets

This thesis draws on two datasets to evaluate the socio-economic potential of agroforestry in Tortí. The first dataset, which I derived from farmer interviews (n = 35), contains information about the land-use practices and household characteristics of farmers in the study area, as well as their knowledge and perceptions of different land-use systems (including two novel agroforestry systems). The second dataset comprises more detailed socio-economic coefficients which stem from an extended cost-benefit analysis of each land-use. For the cost-benefit analysis I developed a land-use model that integrates national data from Panama with measured and modelled data from Tortí, using Monte Carlo simulations (MCS) to account for potential variation in the yields, prices and inputs of each land-use.

Both datasets evaluate the socio-economic performance of two agroforestry systems–alley cropping and silvopasture–as well as the most common (conventional) land-use systems in the study area: pasture, cropland, forest plantation and natural forest. These land-uses are described in Table 3; the specifications for the land-use model (computed dataset) can be interpreted as an extension of the land-use descriptions used in the farmer interviews. While living fences and scattered trees in pastures are common silvopastoral systems in Tortí (Schuchmann 2011), the silvopastoral system investigated in this thesis represents a more intensive system with a much higher tree density. The design of the alley cropping systems was based on the bio-economic modelling of Paul and colleagues (2017), who found this tree density and layout to be an economically competitive land-use system in Tortí.

Table 3: Description of the six land-uses evaluated in the farmer interviews, and the specifications for how these land-uses were simulated in the land-use model (for the computed dataset). Adapted from Table 1 in Gosling et al. (2020b) and Table 1 in Gosling et al. (2021).

Land-use	Description (farmer interviews)	Specifications for land-use model (computed dataset)	Source
Cropland	Annual or (non-woody) perennial crops, grown as a monoculture or mix of crops on the same area or rotated over time.	I modelled two agricultural crops separately: maize (*Zea mays*) and rice (*Oryza sativa*). Traditional non-mechanised and non-irrigated system, with the use of fertiliser and pesticides	MIDA 2019a, 2019b; Schuchmann 2011
Pasture	Traditional pasture with 1.5-2 cows per hectare. Can include scattered trees.	Stocking rate of 2 cows per hectare on improved pasture. Mast system: young cows are bought, fattened on the pasture and sold the following year.	INEC 2011; Paul 2014; Reyes Cáceres 2018
Plantation	Teak plantation, trees planted with 3×3 m spacing, harvested after 20 years.	Initial tree density of 1100 stems per hectare. Undergoes two thinnings before final harvest.	Paul et al. 2017
Alley cropping	Lines of teak grown every 6 m, with rows of maize in between. Trees are grown for timber and harvested after 20 years; shading prevents crop growth after 5 years.	Initial tree density of 550 stems per hectare. Undergoes two thinnings before final harvest.	Paul et al. 2017
Silvopasture	Traditional pasture with a tree density of ≈200 trees per hectare and stocking rate of 1 cow per hectare. Trees are either planted or regenerate naturally (in which case they are guarded).	Improved pastures are planted with the native tree species Spanish cedar (*Cedrela odorata*). Initial stocking density of 200 trees and 1.9 cows per hectare. Trees are harvested for timber after 20 years.	Paul 2014; Reyes Cáceres 2018
Forest	Natural forest, can be used to collect firewood and fruits, but not for commercial timber production.	No active management – represents a “do nothing” option.	INEC 2011

2.4 Farmer interviews

The farmer interviews were conducted with the help of TUM students during a six-week research stay in Tortí from April-May 2018. We targeted farmers using a mixed sampling method: going door-to-door in Tortí and its neighbouring villages, approaching farmers at the local cattle market, and asking interviewees to suggest other farmers. The interview had two parts, which both borrowed methods from participatory and rapid rural appraisal (Kumar 2002; Riley and Fielding 2001). In the first part of the interview we used a semi-structured questionnaire and participatory resource mapping (whereby we asked farmers to draw a map of their farm, see Figure 4), to identify the current land-use shares and management practices of each farm and obtain data on household characteristics.

Figure 4: Farmer in Tortí drawing a map of their farm (right) during the interview.

In the second part of the interview we asked farmers to evaluate the six land-uses (outlined in Table 3) against the 10 socio-economic and ecological indicators outlined in Table 4. These indicators were pre-selected to reflect the socio-economic and ecological considerations that are likely to influence farmers' land-use decisions in Tortí, based on previous research in Panama and the tropics (e.g. Connelly and Shapiro 2006; Coomes et al. 2008; Garen et al. 2009; Metzel and Montagnini 2014; Tschakert et al. 2007). These indicators, which serve as farmers' objectives in the optimisation model, also reflect the potential benefits and drawbacks of agroforestry (Gosling et al. 2020a).

Farmers evaluated each land-use against each indicator using a ranking and scoring method (Gosling and Reith 2019). For each indicator we asked farmers to arrange six cards depicting each land-use in order from best to worst for achieving that indicator. Farmers then scored each land-use from 0 to 10, where the highest ranked land-use always received a score of 10 (Figure 5). From these scores we could then calculate the mean value, $\hat{y}_{i,l}$, for each land-use, l, for each indicator, i (and the associated standard error, $SEM_{i,l}$) across all farmers. For the "general preferences" indicator we simply asked farmers to order the land-use cards from the land-use they like best to the land-use the like least. The preference indicator measures the number of times a land-use was selected as the best or second-best option (Gosling et al. 2020a).

Table 4: The 10 indicators against which farmers evaluated the six land-uses. 'Protecting water supply' and 'protecting soil resources' are considered ecological indicators, the rest are socio-economic. Taken from Table 2 in Gosling et al. (2020b).

Name	**Description**	**Source**
Long-term income	Profit over 20 years	Connelly and Shapiro 2006; Coomes et al. 2008
Labour demand*	Man days (per hectare) needed to manage the land-use	Tschakert et al. 2007
Meeting household needs	The extent to which the land-use meets household needs for food and materials	Fischer and Vasseur 2002; Tschakert et al. 2007
Economic stability	The extent to which economic returns of the land-use can withstand the effects of extreme weather, pests and diseases and price fluctuations	Connelly and Shapiro 2006; Coomes et al. 2008
Liquidity	Regular cash income, including how easily the farmer can convert an investment to cash when needed	Coomes et al. 2008; Holmes et al. 2017b
Investment costs*	Up-front costs of establishing the land-use	Calle et al. 2009; Connelly and Shapiro 2006
Management* complexity	The need for special equipment, machinery, skills and knowledge	Calle et al. 2009; Connelly and Shapiro 2006
Protecting water supply	The extent to which the land-use can improve the availability and quality of freshwater	Garen et al. 2009; Metzel and Montagnini 2014
Protecting soil resources	The extent to which the land-use maintains long-term soil productivity	Calle et al. 2009; Garen et al. 2009
General preferences	Farmers' preferences for each land-use option (proxy for cultural values)	Knoke et al. 2014; Tsonkova et al. 2014

* Indicators where lower values are more desirable ("less is better") – for all other indicators "more is better"

Figure 5: Left: Farmer evaluating the land-uses during an interview. Right: the cards depicting each land-use.

We collected interview data from 35 farmers, who collectively managed 2681 hectares of land. Farm size ranged from five to 271 hectares, with a mean of 77 hectares. Eighty-one percent of the interviewees depended on their farm for all or most of their household income (Gosling et al.

2020a). The aggregated land-use of the farmer sample comprised 60% pasture, 26% cropland, 13% natural forest and one percent forest plantation (leftmost column Figure 6). The most common agroforestry systems practiced by the farmers were home gardens, living fences and scattered trees on pastures, with tree densities on some farms reaching 30 trees per hectare (Gosling et al. 2020a). The more intensive agroforestry systems investigated in this thesis, however, are not yet common in the study area and hence represent innovative land-use systems.

2.5 Identification of farm types

Based on the farm interview data, I used hierarchical cluster analysis to identify groups of farmers with similar land-use and income characteristics. The cluster analysis accounted for 12 variables relating to farm size and ownership, current land-use and management practices, income structure and labour availability (see Gosling et al. 2020b for details). To carry out the analysis I used standardised values (z-scores) for each variable, squared Euclidean distance as the similarity measure and Ward's method as the clustering algorithm. Following Hair and colleagues (2014), I used the agglomeration schedule to assess percentage changes in heterogeneity for each stage of the clustering procedure. This resulted in a three-cluster solution. I refer to each cluster as a farm type and named these farm types "Crop-based farms", "Diversified cattle farms" and "Non-diversified cattle farms". Table 5 summarises the characteristics of each farm type, while the aggregated land-use composition of each is shown in Figure 6.

Table 5: Summary of the three farm types identified via hierarchical cluster analysis, based on the household and farm data of interviewees. The number of farmers belonging to each group is given in brackets. Summarised from Table 4 in Gosling et al. (2020b).

Farm type	Description
Crop-based (17)	Farms comprise a large share of crops, from which farmers obtain at least half of their on-farm income. Farmland tends to be more diversified than the other farm types.
Diversified cattle (10)	Pasture dominates the land-use of these farms. Farmers obtain most (but not all) of their on-farm income from cattle.
Non-diversified cattle (8)	Farms dominated by pasture with no diversification of farm income: all farm revenues come from cattle. Farms are less intensified, with more household members working on the farm.

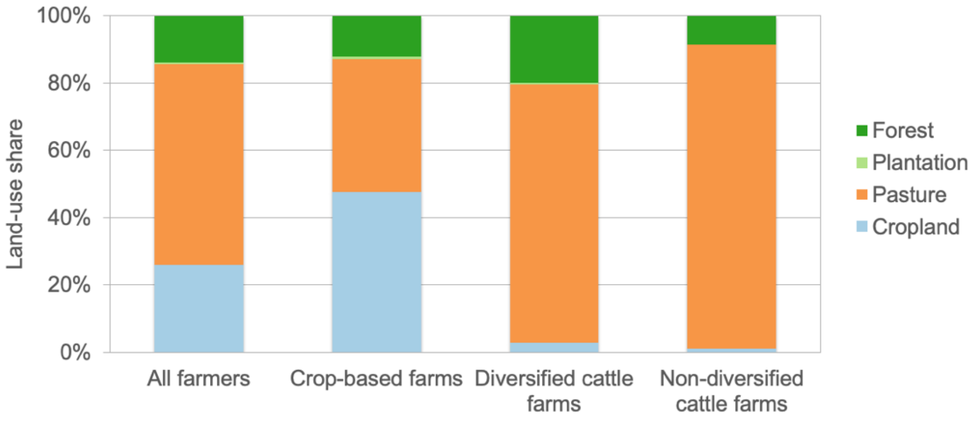

Figure 6: Aggregated land-use composition of the whole farmer sample and of farms within each farm type. Data from Gosling et al. (2020a; 2020b).

To reflect the perceptions and preferences of each farm type, f, I calculated the mean score, $\hat{y}_{i,l,f}$, and standard error, $SEM_{i,l,f}$, for each land-use and indicator from the responses of farmers belonging to that farm type (see Equations 1-4 in Gosling et al. 2020b). I used these group means and associated variation to determine the optimal land-use portfolio for each farm type (Figure 10).

2.6 Positive application of the optimisation model

The socio-economic and ecological indicators outlined in Table 4 are hypothesised objectives that I selected from the literature; this represents mechanistic goal selection (Sumpsi et al. 1997). Paper 2, however, explores an alternative method for selecting objectives based on farmers' revealed preferences (Gosling et al. 2020a). Here I tested different subsets or "bundles" of indicators in the optimisation model (see Table 6). I assumed that the subset that produces an optimised portfolio most similar to farmers' observed land-use decisions (i.e. the aggregated land-use composition of the interviewed farmers, see leftmost column of Figure 6), will reflect the underlying objectives driving farmers' current behaviour. This follows other studies that derive farmers' implicit preferences from empirical data of their behaviour (Amador et al. 1998; Gómez-Limón et al. 2002), and reflects a positive application of the otherwise normative optimisation model (Schreinemachers and Berger 2006).

Table 6: Overview of the six indicator bundles tested in the optimisation. Adapted from Table 4 in Gosling et al. (2020a).

Name	Indicators	Rationale
Socio-economic	Long-term income, Labour demand, Meeting household needs, Economic stability, Liquidity, Investment costs, Management complexity, General preferences	Socio-economic indicators and farmer preferences (as a proxy for cultural values)
Ecological	Protecting water supply, Protecting soil resources	Indicators reflecting environmental functions
Farmer priority	Meeting household need, Protecting water supply, Protecting soil resources	Top three priorities expressed by farmers during landholder interviews (see Gosling et al. 2020a)
Long-term	Long-term income, Economic stability	Reflect economic returns and risk from a long-term perspective (e.g. 20 years)
Short-term	Labour demand, Meeting household needs, Liquidity, Investment costs, Management complexity	Reflect shorter-term socio-economic goals
Immediate	Meeting household needs, Liquidity	Subset of short-term goals that reflect basic, immediate needs of food security and cash flow

I used the Bray-Curtis measure of dissimilarity to quantify the similarity between optimised and the current land-use portfolios. I computed the Bray-Curtis measure, $BC_{o,c}$, based on the land-use shares, a_l, of the optimal (index o) and the current (index c) land-use portfolios, where L is the total number of land-uses considered in the optimisation (Equation 1). Bray-Curtis values close to 0 indicate low dissimilarity and values close to 1 high dissimilarity.

$$BC_{o,c} = \frac{\sum_{l=1}^{L} |a_{l,o} - a_{l,c}|}{2} \qquad (1)$$

2.7 Extended cost-benefit analysis

As an alternative dataset to farmers' empiric rankings, I developed a discrete land-use model to compute more detailed socio-economic coefficients for the agroforestry and conventional land-use options via an extended cost-benefit analysis. This analysis focused on five socio-economic indicators, which are outlined in Table 7. The land-use model had two components. The first component was based on deterministic capital budgeting, whereby I estimated the expected costs, revenues and labour demand of each land-use system for each year of a 20-year period. These estimates were based on information from the Ministry for Agricultural Development of Panama (*Ministerio de Desarrollo Agropecuario de Panamá*, *MIDA*), measured and modelled data from the agroforestry trial in Tortí (Paul 2014; Paul et al. 2015; Paul et al. 2017) and local knowledge of key informants in the study area (see Gosling et al. 2021 for details).

The second component of the land-use model incorporated elements of uncertainty to account for: a) year-to-year fluctuations in yields and prices (to reflect variable environmental conditions and volatility of agricultural and timber markets), and b) potential variation in the investment costs and labour demand of each land-use (to reflect variability in inputs). This uncertainty component was based on MCS, which is a common method to account for stochastic variation in the economic performance of agroforestry and conventional land-use systems (e.g. Do et al. 2020; Frey and Cary 2020; Santos Martin and van Noordwijk 2011). For each run of the MCS, I used bootstrapping (sampling with replacement) from historic yield and price data series to adjust the expected prices and yields for each land-use for each year of the 20-year period (see Gosling et al. 2021 for details). Following Knoke and colleagues (2020a), I assumed a 10% coefficient of variation for the average labour demand and investment costs of each land-use. By repeating this process 10,000 times, I could generate frequency distributions for the values of each land-use for each of the five socio-economic indicators. From these frequency distributions I calculated the mean (expected) value, $\hat{y}_{i,l}$, for each land-use, l, for each indicator, i, and the associated standard deviation[3], $SD_{i,l}$.

Table 7: The five indicators assessed in the discrete land-use model (computed dataset). Asterisks denote indicators for which lower values are preferable. Summarised from Table 2 in Gosling et al. (2021).

Indicator	Unit	Description
Net present value (NPV)	\$/ha	Measure of long-term profitability. Sum of all discounted net cash flows (NCF) over a 20-year period, using a 5% discount rate: $NPV_l = \sum_t^T NCF_{l,t} \cdot (1.05)^{-t}$
Discounted payback period*	years	The first year (within the 20-year rotation) that has a positive discounted cumulative cash flow, based on a 5% discount rate. Reflects the time taken to earn back an initial investment, to account for cash flows and access to money.
Food production	Mcal/ha/yr	Mean annual energy production over a 20-year period. Accounts for the need to meet household food needs from farm produce.
Labour demand*	days/ha/yr	The mean number of labour days required to implement and manage a given land-use per year (averaged over a 20-year period). Accounts for potential farm-level constraints related to labour availability.
Investment costs*	\$/ha	Sum of all costs incurred in year 0 of the land-use model. Accounts for capital constraints.

Using the computed coefficients I derived the optimal portfolio for reducing trade-offs between the five socio-economic objectives (Gosling et al. 2021). I then carried out a detailed scenario analysis, in

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[3] Through the MCS I draw a sample of 10,000 means or sums, because for each simulate run I average or aggregate the value of each socio-economic indicator over the 20-year period of the land-use model. Therefore, for this analysis one can interpret the standard deviation as the standard error of the mean.

which I modified parameters and assumptions of the land-use and optimisation models to simulate different household, environmental, market and political conditions. Here I was interested to see how the type and share of agroforestry included in the optimal portfolio changed within the scenarios. Table 8 outlines the scenarios that I tested in this analysis. In the first set of scenarios I altered the parameters of the optimisation model, to mimic different characteristics of the decision-maker (e.g. to simulate the decision-making of farmers with different priorities, or facing hard economic constraints). In the second set of scenarios I altered the parameters of the land-use model to investigate how factors more external to the decision-maker (such as price changes or government subsidies) would change the socio-economic coefficients of the land-uses and hence the composition of the optimal portfolio. The overall aim of the scenario analysis was to explore the conditions that may make agroforestry more (or less) attractive to farmers.

Table 8: Overview of the scenarios tested in the sensitivity analysis, summarised from Table 5 in Gosling et al. (2021).

Type	Scenario	Description and rationale
Change parameters of the multi-criteria (optimisation) model	Prioritising individual objectives	Single indicators weighted as twice as important as the others in the optimisation model, to simulate the decision-making of a farmer who priorities one objective over the others.
	Farmer preferences	Farmers' general preferences (as measured in the farmer interviews) included as an additional indicator in the optimisation model as a proxy for cultural values.
	Investment and labour constraints	The total investment costs or labour demand of the optimal portfolio is restricted, to simulate hard economic constraints.
Change parameters of the land-use model	Lower crop yields	Decreases the expected yields of annual crops (timber and cattle yields remain unchanged), to simulate poorer site conditions.
	Agroforestry subsidy	Decreases the investment costs of alley cropping and silvopasture to simulate cost-sharing arrangements to promote agroforestry establishment.
	Higher timber prices	Increases the baseline price of teak and cedar to simulate favourable developments in wood markets.

Chapter 3: Results and Discussion

This chapter compiles the results of all four papers to answer the four research questions. To put my findings into context, I discuss the results for each research question (RQ) directly in the relevant subsection, highlighting important implications for agroforestry research and policy and acknowledging limitations where appropriate. The final section reflects on the overall modelling approach and gives an outlook for future research.

3.1 RQ 1: How do farmers perceive agroforestry relative to conventional land-uses?

3.1.1 Farmers' perceptions across the whole sample

To measure farmers' perceptions I use the mean land-use scores derived from the ranking and scoring exercise of the farmer interviews. These scores indicate how farmers, on average, evaluated the two agroforestry systems against the 10 socio-economic and ecological indicators; Figure 7 summarises the relative performance of each system (alley cropping and silvopasture) compared to the conventional land-uses.

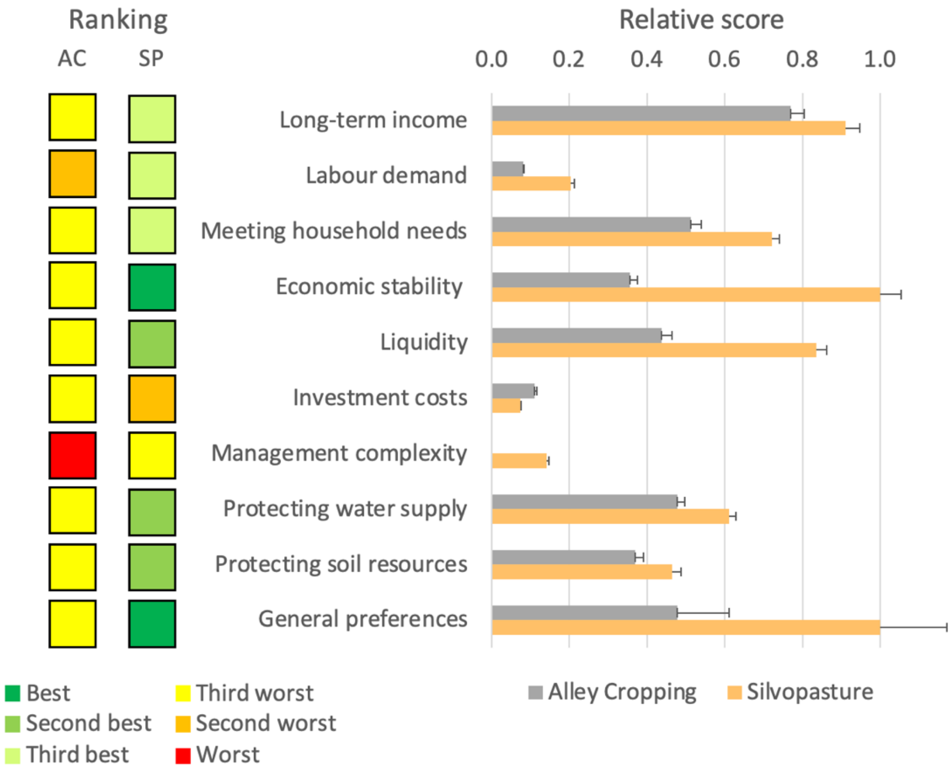

Figure 7: The rank and relative performance of the two agroforestry systems (AC = alley cropping, SP = silvopasture) as evaluated by the farmers. Results are based on the mean scores ($\hat{y}_{i,l}$) for each land-use, l, for each indicator, i, derived from the farmer interviews. Relative scores are normalised across all land-uses: 1 = the best land-use score for a given indicator, 0 = the worst land-use score for a given indicator. Error bars represent the $SEM_{i,l}$. Data taken from Table 3 in Gosling et al. (2020a).

We see from the rankings (left side of Figure 7) that farmers evaluated silvopasture more favourably than alley cropping – silvopasture was among the top three land-uses for eight of the 10 socio-economic and ecological indicators. In contrast, alley cropping was among the three worst performing land-uses for all 10 indicators. The only aspect in which alley cropping outperformed silvopasture was investment costs, which could reflect the high capital costs of purchasing cattle.

The difference in the relative performance of the two agroforestry systems (right side of Figure 7), was most pronounced for economic stability and general preferences – the two indicators for which farmers selected silvopasture as the best land-use option. Farmers also evaluated silvopasture to be almost two times better than alley cropping for maintaining liquidity. These findings are consistent with the "cattle culture" of Panama (Connelly and Shapiro 2006; Peterson St-Laurent et al. 2013). In pioneer areas of Central and South America cattle play an important role for smallholder livelihoods and owning cattle is a sign of prestige (Gosling et al. 2020b). A key benefit of cattle is their high liquidity value; they can be readily sold for cash if farmers face urgent or unexpected expenses. The ability to sell off cattle in times of need can function as a form of insurance, helping farmers to cope with emergencies and buffer against uncertainty (Coomes et al. 2008; Dagang and Nair 2003). Given that cattle prices and yields in Panama are generally very stable (Connelly and Shapiro 2006), the cattle component of the silvopasture system can offer an ongoing and stable source of income as the tree component develops. In contrast, yields and prices of annual crops, which are integrated in the alley cropping system, tend to be more volatile (Wright and Samaniego 2008).

Farmers' less favourable ratings of alley cropping (which in this study comprises teak and maize) may also reflect a general aversion to teak plantations. The financial incentives for afforestation afforded by Law 24 has led to the establishment of many large-scale, foreign-owned teak plantations in eastern Panama (Sloan 2008). This land-use change has driven up land prices in Tortí as investors buy land for plantations, to the point where it is no longer economically feasible for farmers to buy land for conventional cropping and grazing systems (A. Domínguez pers comm.). Peterson St-Laurent and colleagues (2013) also report that high land prices prevent farmers from buying or selling land. Farmers may therefore resent teak (and associated land-use systems) as a symbol of international interests prevailing over local livelihoods, and potentially perceive teak plantations as a threat to their rural way of life. Negative attitudes towards teak may also relate to the common perception that teak plantations hold low ecological value, causing many farmers in the area to describe them as "green deserts" (Grossman 2007; Reith et al. 2020). Hence, alley cropping systems that integrate native timber species (such as *C. odorata*, *Anacardium excelsum*, *Tabebuia rosea* or *Swietenia* *macrophylla*), may be viewed more favourably by local farmers (Kirby and Potvin 2007; Metzel and Montagnini 2014).

3.1.2 Farmers' perceptions across the three farm types

Looking now at the perceptions of farmers belonging to each farm type (Figure 8), we see that all groups evaluated silvopasture as superior to alley cropping for maintaining liquidity and economic stability, and expressed a higher general preference for the silvopastoral than the silvoarable system. Differences in farmer judgement were only moderate between the farm types. However, the comparison does reveal that the non-diversified cattle farmers had the most positive attitudes towards alley cropping, viewing it as a more profitable and environmentally-friendly land-use option (see higher scores for long-term income and the two ecological indicators). For these farmers, long-term profitability and protecting soil and water resources could be important motivations to adopt alley cropping. However, non-diversified cattle farmers also scored alley cropping more poorly than the other groups for labour demand and establishment costs, highlighting potential barriers to adoption.

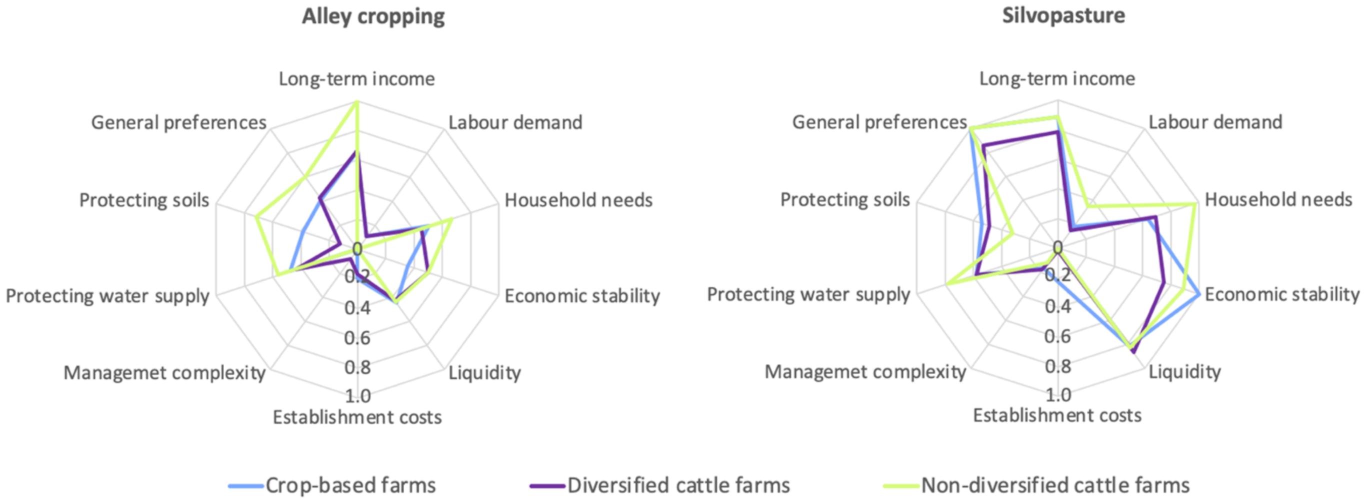

Figure 8: The relative performance of alley cropping (left) and silvopasture (right) as evaluated by each farm type. Results are based on the mean scores ($\hat{y}_{i,l,f}$) for each land-use, l, for each indicator, i, for each farm type, f, derived from the farmer interviews. Scores are normalised across all land-uses: 1 = the best land-use score for a given indicator, 0 = the worst land-use score for a given indicator. Data taken from Table S1 in Gosling et al. (2020b).

Compared to the other two farm types, diversified cattle farmers appear to have slightly less positive attitudes towards silvopasture. For example, the diversified cattle farmers expressed a marginally lower preference for silvopasture (for these farmers conventional pasture was the most preferred land-use option), and gave it a lower relative score for economic stability and long-term income. Of the three farm types, the crop-based farmers rated silvopasture the most highly for economic stability and also perceived it to be less expensive in terms of establishment costs. These farmers may therefore view the upfront costs of tree-planting as less of a barrier to agroforestry adoption. Although the comparisons between farm types are based on a small dataset and are descriptive in nature (Gosling et al. 2020b), my results represent a new contribution to agroforestry research; previous studies have not compared the views of farmers with different income and land-use characteristics (e.g. Frey et al. 2012b; Garen et al. 2009; Hand and Tyndall 2018).

We did not ask farmers about their absolute income levels during the interviews, but it may be possible to infer wealth levels from certain farm and household characteristics (Angelsen et al. 2014; Torres et al. 2018). For example, the non-diversified cattle farmers ran less intensive (i.e. less mechanised with less chemical inputs) farming operations with greater reliance on family labour, which could suggest that this group is the least well-off of the three farm types. Conversely, the crop-based farmers had the most diversified and intensified farms, and hence may be the most well-off. Viewed through this prism, it is plausible that the wealthier farmers with more diversified income sources (the crop-based farms) may judge investment costs to be less of a barrier to agroforestry adoption than farmers with fewer income sources (the non-diversified cattle farms). Wealthier farmers often have better access to credit (Baiyegunhi and Fraser 2014; Elias et al. 2015), and may be able to more easily overcome labour shortages by hiring day labourers (Pacheco 2009). In contrast, labour and investment constraints are likely to be more acute for poorer farmers (Pannell et al. 2014). For example, Tschakert and colleagues (2007) found that only richer households within the indigenous community west of Tortí could afford to adopt more environmentally-friendly land-use practices, while the poorest farmers were more constrained by household endowments, including lack of labour.

3.1.3 Empiric rankings as a means to predict land-use decisions

It is important to remember that the empiric rankings captured in this study reflect farmers' subjective perceptions of each land-use, and not necessarily objective fact. Such perceptions, however, will shape farmers' land-use decisions (Pannell et al. 2006). Nonetheless, it should be kept in mind that because the two agroforestry systems are not yet widespread in Tortí, farmers' evaluations of these systems may represent an informed guess. Moreover, farmers' rating of agroforestry may be subject to response bias. I discuss these points in more detail in section 3.4.3.

The empiric ratings analysed in this section provide insights into how farmers perceive the trade-offs associated with agroforestry and conventional land-use systems. However, the empiric ratings alone are not enough to understand farmers' potential land-use decisions (Gosling et al. 2020b). Rather than being forced to choose the single best land-use for their whole farm, farmers can select the most desirable mix of land-uses for achieving their objectives. What constitutes the most desirable mix will depend on how well the farmers expect each land-use to achieve each objective (i.e. the performance of each land-use relative to that of the other available land-use options), the uncertainty associated with this performance, and the farmers' individual attitude toward risk. Therefore, in the next section I couple the empiric rankings with robust farm-level optimisation, to find the most desirable land-use compositions for achieving different objectives under uncertainty.

3.2 RQ 2: According to farmers' perceptions, would agroforestry help reduce trade-offs between farm level goals when accounting for uncertainty?

3.2.1 Optimal portfolio for all farmers

By coupling the farmer perception data with robust optimisation, I determined the land-use composition that, based on farmers' opinion and preferences, would minimise trade-offs between the 10 socio-economic and ecological objectives for different levels of risk aversion (left plot, Figure 9 – see also Table 2 for an explanation of the uncertainty level, m). Silvopasture plays a key role in this land-use portfolio, comprising at least 45% of the land-use share across all uncertainty levels. This suggests that silvopasture is a promising land-use option to help reduce trade-offs between farm level goals, from the perspective of both a risk neutral and a strongly risk-averse decision-maker (represented by the optimal portfolios at $m = 0$ and $m = 3$, respectively). As shown in the previous section, however, farmers did not evaluate the two agroforestry systems equally. Alley cropping is absent from the optimised portfolio, suggesting it is less suited for reducing trade-offs between these multiple, farm-level objectives.

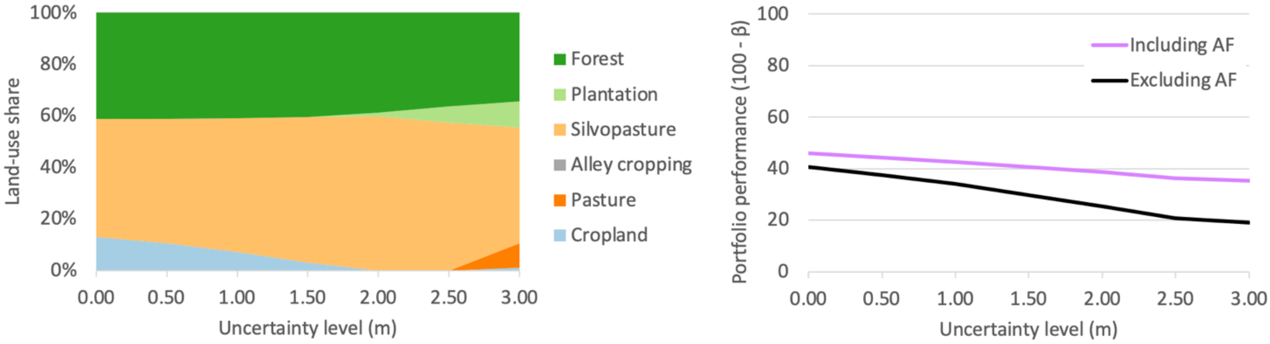

Figure 9: Left plot: Composition of the ideal farm (share of land area allocated to each land-use) under increasing levels of uncertainty, m, when considering all 10 indicators in the optimisation model. Right plot: Guaranteed performance (100 – β, where 100% is the target level) of the optimised farm portfolios when including and excluding agroforestry (AF). Figure adapted from Gosling et al. (2020a).

The right plot of Figure 9 shows the guaranteed performance ($100 - \beta$) of the optimal portfolio when including (purple line) and excluding (black line) agroforestry. We see that the optimal portfolio that includes agroforestry (in this case silvopasture) secures a higher minimum performance level than the portfolio that excludes agroforestry: on average the guaranteed performance is 11 percentage points higher from $m = 0$ to $m = 3$. Higher portfolio performance indicates reduced trade-offs between the individual objectives. In particular, including silvopasture in the optimal portfolio helps to improve performance for economic stability, investment costs and general preferences (Gosling et al. 2020a).

The dominance of silvopasture in the optimal portfolio is encouraging and suggests that farmers' perceptions of the tree-livestock system are not in themselves a barrier to agroforestry adoption. Instead, these perceptions may facilitate the uptake of silvopasture if farmers strive to minimise trade-offs between the 10 pre-defined objectives. In contrast, the absence of alley cropping in the optimal portfolio suggests that farmers' perceptions and cultural preferences may render alley cropping as less suitable for satisfying multiple farm-level objectives.

3.2.2 Optimal portfolio for each farm type

Agroforestry was prominent across all of the portfolios individually optimised for the three farm types (Figure 10). Silvopasture appears in each of these portfolios, but alley cropping is also selected in the portfolios optimised for diversified and non-diversified cattle farms. The total share of agroforestry was higher in the optimal portfolio for crop-based farms (42%), compared to 21% and 33% for the diversified and non-diversified cattle farms respectively. Differences in the type and share of agroforestry included in the optimal portfolios may provide insights into how willing farmers belonging to each farm type would be to adopt agroforestry. Understanding these differences can help to target extension programs to different groups of farmers (Köbrich et al. 2003). For example, my results suggest that farmers who derive most of their farm income from crops (the crop-based farms), may be more willing to substitute conventional pasture with larger shares of silvopasture. On the other hand, farmers who are more economically dependent on cattle (the two cattle-based farm types), may be more receptive to diversifying their land-use with alley cropping. It is plausible that the optimal land-use composition of farmers with diverging land-use and income strategies would differ, given the many empiric studies that link farm and household characteristics with farmers' land-use decisions, including degree of diversification (Ochoa et al. 2019; Torres et al. 2018) and adoption of agroforestry (Pattanayak et al. 2003; Zabala et al. 2013).

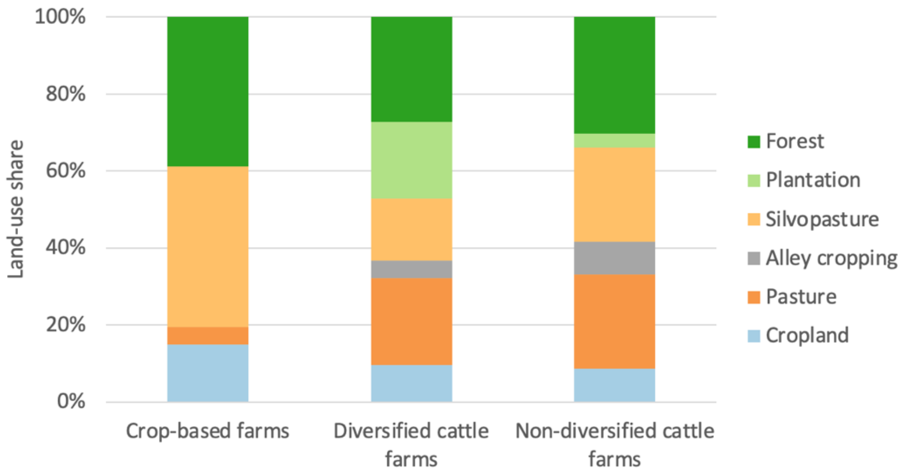

Figure 10: Optimised farm composition (share of land allocated to each land-use) for balancing the achievement of the 10 indicators under increasing uncertainty, based on the perceptions and preferences of farmers belonging to each farm type: a) crop-based farms, b) diversified cattle farms and c) non-diversified cattle farms. Optimisation carried out for a moderately-high level of uncertainty ($m = 2$). Adapted from Figure 4 in Gosling et al. (2020b).

3.2.3 Implicit drivers of farmers' land-use decisions

So far the analysis has weighted all indicators equally in the optimisation model. This simulates the decision-making of a farmer who strives to balance the achievement of all 10 socio-economic and ecological objectives. However, the composition of the optimal portfolios diverges strongly from the recorded land-use composition in the study area. For example, agroforestry and natural forest tend to be overrepresented in the optimal portfolio, while pasture is underrepresented (compare the first bar of Figure 6 or Figure 11 to the optimal portfolios in Figures 9 and 10). This divergence between the optimal and current land-use portfolios could suggest that farmers do not aim to balance the 10 socio-economic and ecological objectives when making land-use decisions (Gosling et al. 2020a). Instead, some objectives may be more important than others for farmers' decision-making. To explore this idea I tested different subsets (or bundles) of indicators in the optimisation, to see which indicator bundles produce optimal portfolios most similar to the current land-use composition in Tortí. This positive application of the model can provide insights into underlying objectives driving farmers' land-use decisions and whether or not agroforestry is compatible with these objectives.

Figure 11 shows the optimal land-use portfolio for the six indicator bundles outlined in Table 6, with the Bray-Curtis values indicating the similarity between each portfolio and the current land-use composition. We see that optimising for the socio-economic objectives only (i.e. excluding the two ecological indicators from the optimisation) produces a land-use portfolio identical to that when considering all 10 objectives (compare the second bar of Figure 11 to the optimal portfolio in Figure 9 for $m = 2$). This suggests that the two ecological indicators are redundant functions: they are already met through the three “less is better” indicators (labour demand, investment costs and management complexity), which contribute to a large share of forest in the optimal portfolio. When optimising for purely ecological goals, the optimal land-use portfolio would comprise 100% forest. The strong divergence between these two portfolios from the current land-use composition (Bray-Curtis value for each optimised portfolio = 0.86) indicates that both pure ecological objectives and the broader set of socio-economic objectives are a poor proxy for farmers’ actual goals.

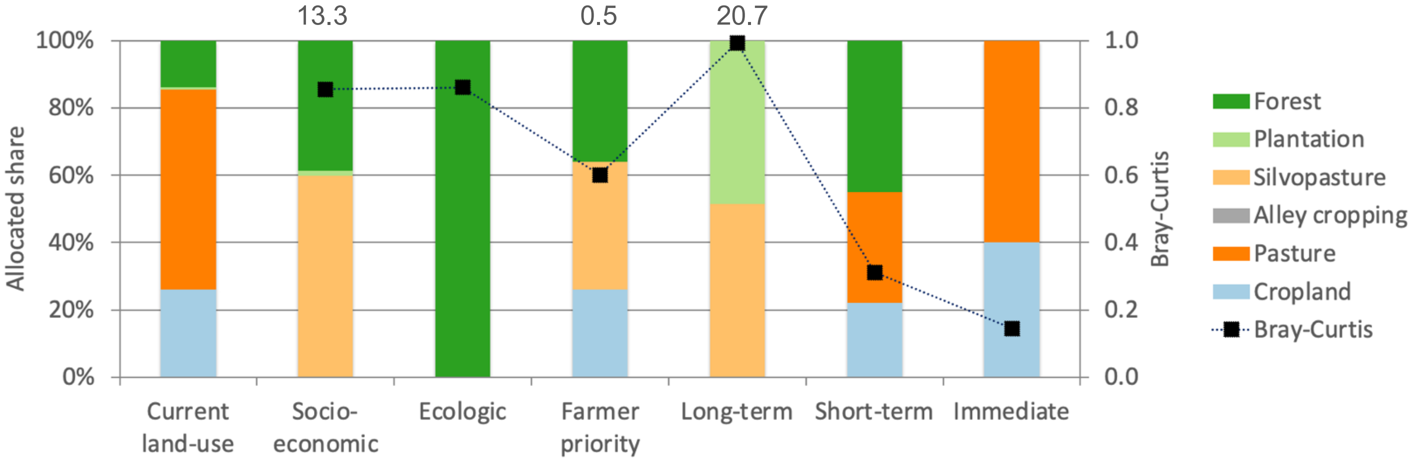

Figure 11: Ideal farm composition (share of land area allocated to each land-use option, left axis) when optimising for each indicator bundle for a moderately-high level of risk aversion ($m = 2$). The first column represents the current (aggregated) land-use in Tortí. Points represent the Bray-Curtis measure of dissimilarity ($BC_{o,c}$, right axis) between the ideal and current land-use composition for each indicator bundle: lower values indicate that a portfolio is more similar to the current land-use. Values above the socio-economic, farmer priority and long-term portfolios represent the drop in portfolio performance (change in $100 - \beta$) if agroforestry is excluded from the portfolio. Adapted from Figure 5 in Gosling et al (2020a).

When optimising for the “farmer priority” indicator bundle, cropland appears in the optimal portfolio (26% share), together with silvopasture (38%) and natural forest (36%). The moderately high Bray-Curtis value (0.60), however, suggests a mismatch between farmers’ stated priorities and the implicit priorities revealed by their actual land-use decisions. The “long-term” indicators also appear a poor fit for farmers’ current land-use decisions. This indicator bundle produces an optimal land-use portfolio split almost equally between silvopasture (52%) and forest plantation (48%). Of all the indicator bundles tested, the “long-term” portfolio is least similar to the current land-use (Bray-Curtis = 0.99).

In contrast, considering shorter-term socio-economic objectives in the optimisation produces an optimal portfolio more similar to the current land-use (Bray-Curtis = 0.31): this optimal portfolio comprises forest (45%), pasture (33%) and cropland (22%). Finally, when considering the two "immediate" indicators only, the optimal portfolio comprises 60% pasture and 40% cropland. With a Bray-Curtis value of 0.15, this portfolio is most similar to the current land-use. This suggests that together the indicators 'meeting household needs' and 'liquidity' can best explain farmers' current land-use decisions. This aligns with other studies that have found smallholder farmers often prioritise their families' immediate needs related to food security and cash flow when making land-use decisions (Affholder et al. 2010; Binh et al. 2008; Do et al. 2020; Frey et al. 2012b).

We see from Figure 11 that agroforestry (in this case silvopasture) was only included in the optimal portfolio for three of the six indicator bundles. Based on farmers' perceptions, silvopasture would help reduce trade-offs between the full set of socio-economic objectives, between farmers' stated priorities of meeting household needs and protecting soil and water resources, and between the longer-term goals of maximising income and reducing risk. For the considered uncertainty level ($m = 2$), silvopasture is most effective for reducing trade-offs between the two long-term indicators. Excluding silvopasture from this portfolio would result in a portfolio comprising entirely of teak plantation, reducing the guaranteed portfolio performance ($100 - \beta$) by 21 percentage points. In contrast, the exclusion of silvopasture only had a marginal effect on the performance level of farmers' stated priorities: for this indicator bundle a farm portfolio comprising 50% forest and 50% cropland would achieve a guaranteed performance only half a percentage point lower than the portfolio that includes silvopasture.

Results suggest that silvopasture may be most attractive for a) more profit-oriented farmers who seek to maximise long-term income while reducing economic risk, or b) farmers wishing to secure a broader set of objectives from their land-use portfolio (including ecological and longer-term economic goals). However, results also highlight a mismatch between the objectives which would potentially promote the selection of silvopasture and those that are driving farmers' current land-use decisions in the study area, revealing an implicit barrier to silvopasture adoption. My analysis identified immediate-term goals related to food security and cash flow as the underlying drivers of farmers' land-use decisions. If farmers do indeed prioritise meeting household needs and maintaining liquidity when deciding what to grow or produce on their farm, then according to their perceptions of each land-use system, conventional pasture and cropland (and not silvopasture or alley cropping) would represent the rational land-use choice (Gosling et al. 2020a). Meeting these basic, immediate-term needs may therefore limit a farmer's ability to invest in new land-use systems, including agroforestry, creating a potential trade-off with longer-term productivity gains and financial benefits (Do et al. 2020; Meijer et al. 2015; Pannell et al. 2014). My results therefore highlight two criteria that agroforestry systems must fulfil to be more attractive to farmers in the study area: they must provide early and frequent income flows (to help maintain liquidity) and ongoing opportunities to produce food (to help meet farmers' household subsistence needs). I discuss how this knowledge could help to identify and design agroforestry systems with the highest likelihood of adoption in section 4.2.

Results also have implications for selecting the appropriate objective function when evaluating the socio-economic potential of agroforestry systems. I found that the objectives for which farmers deemed silvopasture to be most beneficial (long-term income and economic stability), appeared to be the least important for explaining their current land-use decisions. Studies that follow a MPT framework to evaluate agroforestry based solely on economic return and risk (e.g. Bertomeu and Giménez 2006; Blandon 2005; Ochoa et al. 2016; Paul et al. 2017), may therefore miss important considerations for farmers' land-use decisions. While purely financial indicators like NPV may help understand the land-use choices of wealthier, more commercially-oriented farmers (especially if they have off-farm income to buffer intermittent income flows, Knoke et al. 2020c), I would warn against using NPV as the sole objective function for poorer, more subsistence-oriented farmers. Instead, the multi-criteria approach presented here can better capture additional household goals related to food production and cash flow. Alternatively, one could use a "safety first" model, whereby farmers first seek to secure household consumption needs before pursuing economic goals such as maximising income (e.g. Affholder et al. 2010; Umar 2013).

I have argued that the optimal portfolio considering all 10 socio-economic and ecological objectives (Figure 9), divergences strongly from the current land-use composition in the study area because farmers do not treat the 10 objectives equally in their decision-making. Another explanation for the divergence between the current and optimal land-use portfolios, however, could be a potential conflict between the land-use systems that farmers wish to have, and those that they are able to implement given their available resources and household constraints (Gosling et al. 2020b). If this is the case, the optimal land-use compositions that balance all 10 socio-economic and ecological objectives could be interpreted as "aspirational" farm portfolios. It is difficult to test the effect of hard economic constraints on the optimal portfolio when using farmers' empiric ratings, because these ratings do not quantify the labour demand or investment costs associated with each land-use in absolute terms. However, I do test the effect of such labour and investment constraints on the optimal portfolio when using more detailed socio-economic coefficients (see section 3.3.3).

3.3 RQ 3: Which socio-economic and environmental conditions promote (or hinder) the selection of agroforestry within a diversified land-use portfolio?

3.3.1 Optimal portfolio derived from the computed dataset

This section analyses the optimal portfolios derived from more detailed numerical coefficients obtained from the extended cost-benefit analysis. The analysis focuses on five socio-economic indicators (see Table 7), which serve as farm-level objectives relating to: long-term income (NPV), labour demand, investment costs, food production and payback periods (to account for cash flow issues). The performance of each land-use against each objective was quantified via a land-use model that integrates measured and modelled data from Panama and the study area (Gosling et al. 2021). The key advantage of using this computed dataset in the optimisation is the ability to carry out detailed sensitivity analyses, to better understand the factors that promote or hinder the selection of agroforestry in the optimal portfolio.

Figure 12 shows the optimal land-use portfolio for balancing the achievement of the five computed socio-economic objectives, for three levels of risk aversion, under baseline conditions. We see that agroforestry (in this case alley cropping) is only selected in low (≤ 3%) shares in the optimal portfolio. Annual crops instead dominate the portfolio, with large shares of conventional pasture also selected when risk aversion is considered. We also see a trend towards greater land-use diversification with increasing levels of uncertainty. The lower Bray Curtis values indicate that the two portfolios for risk-averse farmers (uncertainty levels $m = 1.5$ and $m = 3.0$) are more similar to the current land-use allocation in the study area (leftmost column in Figure 12) than the portfolio for a risk neutral farmer ($m = 0$). Given that it is reasonable to assume that smallholder farmers are risk-averse (Baker et al. 2017; Pannell et al. 2014), the similarity between the optimal and current land-use compositions speaks for the plausibility of model results.

The lack of agroforestry in the optimal portfolio suggests that, at least under the baseline conditions, conventional land-use systems represent a better alternative than agroforestry for reducing trade-offs between the five socio-economic objectives, when using indicators derived from a cost-benefit analysis. Scenario analyses are therefore needed to test which household, environmental, market or policy conditions could increase the share of agroforestry selected in the optimal portfolio (Table 8 outlines the tested scenarios). Such analyses can provide insights into the conditions under which agroforestry may become a more attractive land-use option for farmers.

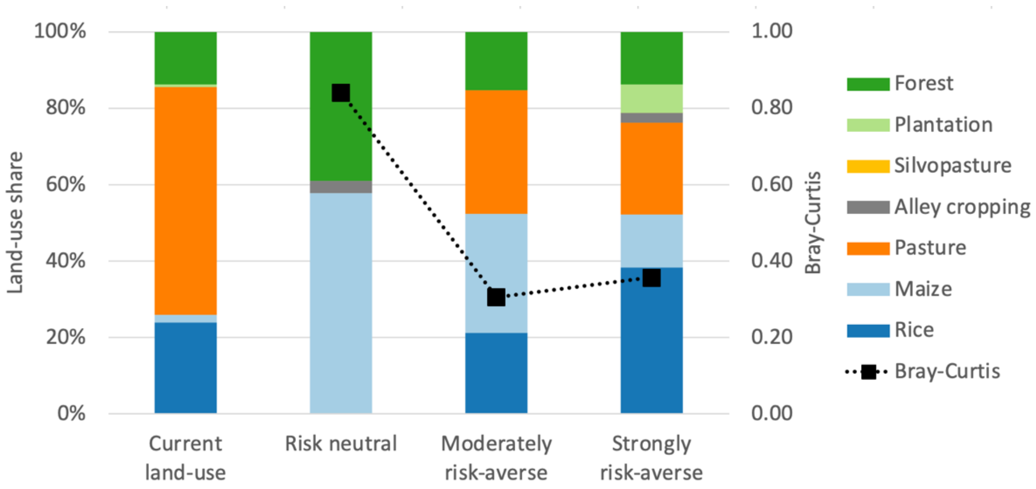

Figure 12: Composition of the optimised farm portfolio (share of land area allocated to each land-use, left axis) derived from the computed dataset for three levels of uncertainty: risk neutral ($m = 0$), moderately risk-averse ($m = 1.5$), and strongly risk-averse ($m = 3.0$) under baseline conditions. The first column represents the current (aggregated) land-use of farms in Tortí. Points represent the Bray-Curtis measure of dissimilarity ($BC_{o,c}$, right axis) between the current and optimised land-use compositions: lower values indicate that a portfolio is more similar to the current land-use. Adapted from Figure 2 in Gosling et al. (2021).

3.3.2 The effect of farmer and land-use characteristics on agroforestry selection

Figure 13 summarises the main findings from the scenarios that account for farmer priorities (rows a-e), or general land-use preferences (row f) in the optimisation, as well as from the scenarios that alter the socio-economic performance of certain land-uses by simulating agroforestry subsidies (row g), declining crop yields (row h), and higher timber prices (row i). The figure shows how much of each agroforestry system is selected in the optimal portfolio for each scenario for three levels of uncertainty. This provides an overview of how farmers' attitudes towards risk may influence the relative attractiveness of the agroforestry systems under each scenario.

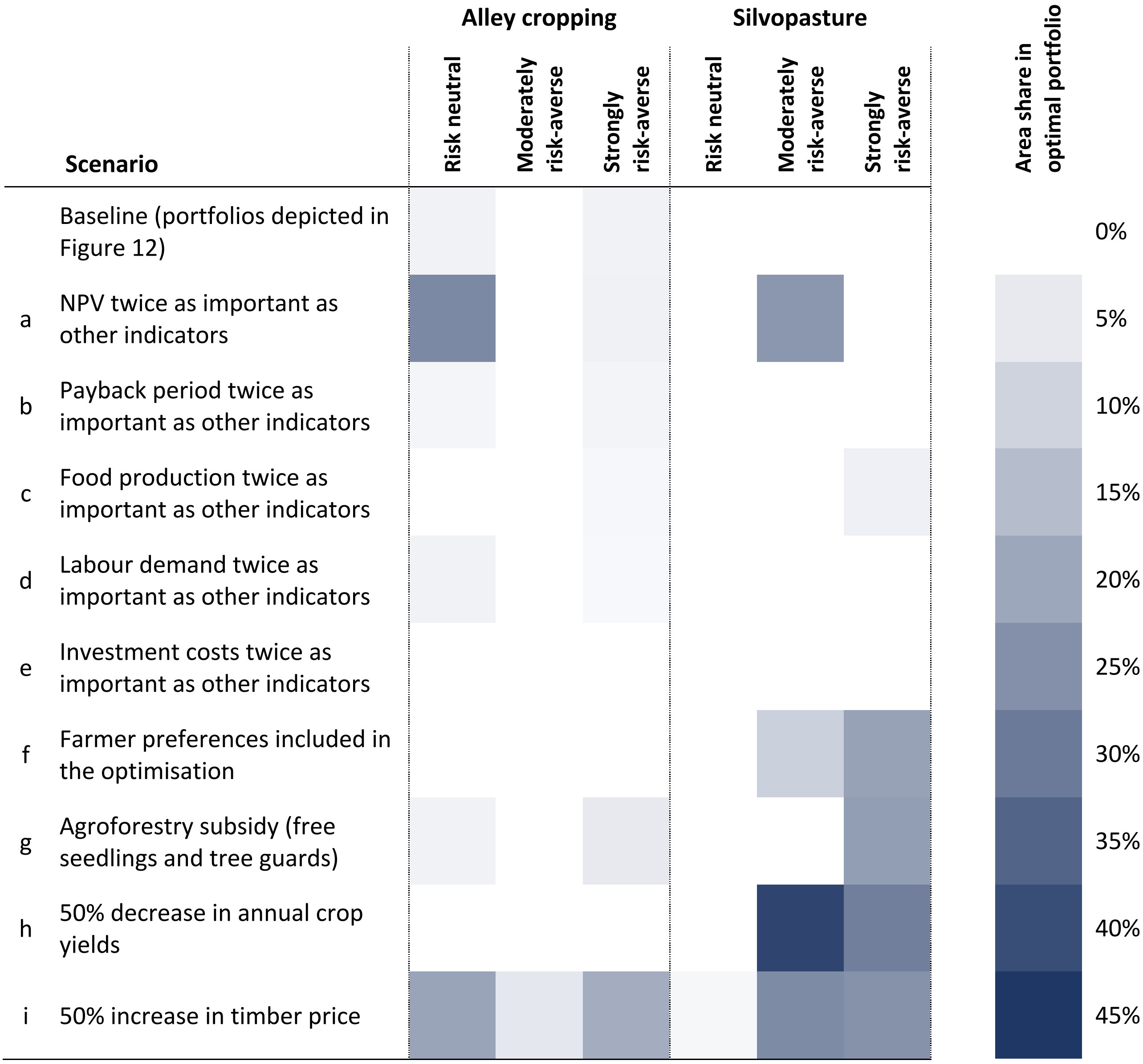

Figure 13: Summary of the results of the scenario analyses from Gosling et al. (2021). Colour bar denotes the share of each agroforestry system (alley cropping and silvopasture) included in the optimal portfolio under each scenario (rows) for three levels of risk aversion (columns).

3.3.2.1 Accounting for farmers' priorities and preferences

Looking first at the scenarios that simulate the decision-making of farmers with different priorities, we see that an emphasis on long-term income (whereby NPV is weighted as twice as important as the other socio-economic indicators – see row a in Figure 13), strongly increases the share of agroforestry selected in the optimal portfolios for risk neutral and moderately risk-averse farmers. For example, a risk neutral farmer who prioritises NPV would allocate 26% of his or her land to alley cropping while a moderately risk-averse farmer would opt for a 24% silvopasture share. A strongly risk-averse farmer, however, would choose annual crops over agroforestry (Gosling et al. 2021). This suggests that alley cropping and silvopasture may be attractive options for farmers who are more focused on longer-term profit but also more willing to accept risk. Increasing the relative importance of the other socio-economic indicators did not substantially change the amount of agroforestry selected in the optimal portfolio (rows b-e of Figure 13).

The results of this weighting exercise suggest that the alley cropping and silvopasture systems could find most acceptance among wealthier, more commercially-oriented farmers with diversified income sources. Such farmers may be less reliant on frequent cash flows from farm outputs and therefore be more focused on NPV, an economic indicator that disregards the distribution of incomes flows (Knoke et al. 2020c). Moreover, diversified income sources (including off-farm income) may help these wealthier farmers to buffer financial risks, making them more tolerant towards any uncertainty associated with agroforestry systems (Bowman and Zilberman 2013). However, as shown in the previous section, longer-term financial goals may not be the prime motivator of most farmers in the study area. Therefore, relying on NPV alone as a selling point for agroforestry may result in only minimal uptake among local farmers (Gosling et al. 2021).

Nonetheless, accounting for farmers' general preferences favours the selection of silvopasture in the optimal portfolio. For instance, when farmers' stated land-use preferences (as recorded during the farmer interviews) are included as an additional indicator in the optimisation model, the optimal portfolios for moderately- and strongly risk-averse farmers contain an 11% and 21% share of silvopasture respectively (row f in Figure 13). This suggests that silvopasture may have general appeal to a wider range of farmers, and not just those who prioritise long-term income. As already discussed, farmers' stated preferences may reflect the cultural importance of cattle as a sign of prestige and form of personal savings (Gosling et al. 2020b; Peterson St-Laurent et al. 2013). The farmer preferences scenario may represent a compromise between the two datasets (computed vs interview data), producing a land-use portfolio that integrates local cultural values with scientific knowledge of agroforestry systems (Fagerholm et al. 2016; Turnhout et al. 2012): I return to this point in section 3.4.2.

3.3.2.2 Simulating the effects of declining crop yields, subsidies and increasing timber prices

The lower crop yield scenario (row h, Figure 13), simulates the decision-making of a farmer with less productive land that cannot sustain the maize and rice yields modelled under the baseline scenario. For example, if the expected yields of rice and maize fell by 50% (in both the monoculture and alley cropping systems), a moderately risk-averse farmer would select a 42% share of silvopasture in his or her land-use portfolio, while a strongly risk-averse farmer would select a 29% share. This suggests that the tree-livestock system may become economically competitive on less productive land. Studies that explicitly examine the performance of agroforestry across different site conditions are rare, but Bannister and Nair (2003), Crestani and colleagues (2017), Messerer (2015) and Tsonkova and colleagues (2014) also suggest that agroforestry may be more advantageous on less fertile soils.

As a potential agroforestry subsidy, I found that providing tree seedlings and tree-guards free of charge led to a 5% share of alley cropping or a 22% share of silvopasture in the land-use portfolio optimised for a strongly risk-averse farmer (row g, Figure 13). This suggests that cost-sharing arrangements to reduce the financial burden of tree-planting could be an effective mechanism to increase agroforestry uptake in Tortí, at least among highly risk-averse farmers. Empiric studies have also found that government support (usually the provision of seedlings and materials) is an important driver of farmers' tree-planting behaviour in eastern Panama (Simmons et al. 2002). Such a subsidy would reduce total investment costs of alley cropping and silvopasture by 20% and 13% respectively. However, the investment costs of the two systems would need to be reduced by 50% and 40% before a moderately-risk averse farmer would select them in the optimal land-use portfolio (Gosling et al. 2021).

Finally, rising timber prices were a strong driver of agroforestry selection in the optimal portfolio (row i, Figure 13). For a risk neutral farmer, higher timber prices tended to favour alley cropping more than silvopasture; a 50% increase in the teak price would result in a 21% share of alley cropping in the optimal portfolio, while a 50% increase in the cedar price would only result in a 2% share of silvopasture. When assuming risk-aversion, however, higher timber prices tend to favour the selection of silvopasture more than alley cropping. For example, for a strongly risk-averse farmer a 50% increase in the respective timber prices results in a 25% share of silvopasture in the optimal portfolio compared to a 19% share of alley cropping.

Various market forces in Panama may have opposing effects on timber prices. On the one hand, an increasing supply of farm- and plantation grown timber may exert a downward pressure on prices (Bertomeu 2006; Paul 2014). On the other hand, new tax exemptions provided under Law 69 could increase the revenues smallholders receive from timber sales, effectively acting as a price increase. However, this assumes that farmers are earning enough to pay income tax, which may not be the case for many farm households (Díaz et al. 2012), and also that they are selling wood through official channels. Given the complex permit system in Panama for harvesting and selling timber from private land, many farmers opt to sell their timber on local markets, where they receive a lower price (Fischer and Vasseur 2002; Paul 2014; Somarriba et al. 2012). Streamlining this permit system and building farmers' capacity to access timber markets may therefore be important prerequisites to ensure that farmers receive a favourable price for farm-grown timber (Holmes et al. 2017a; Somarriba et al. 2012). Such capacity building could also include farmer training to improve silvicultural practices, to help farmers to produce higher quality timber and hence obtain higher prices (Bertomeu 2006; Gosling et al. 2021). I further discuss the importance of farmer capacity building in section 4.3.

3.3.2.3 The relative attractiveness of each agroforestry system for different levels of risk aversion

Looking across all scenarios in Figure 13, we can see two general trends. First, the share of agroforestry included in the optimal portfolio tends to increase with the level of risk aversion. When ignoring uncertainty (simulating the decision-making of a risk neutral farmer) the share of agroforestry selected in the optimal portfolio only exceeded 3% in two scenarios: prioritising NPV and higher teak prices resulted in a 27% and 21% share of alley cropping respectively. Second, portfolios optimised for the highest uncertainty level of $m = 3.0$ (simulating the decision-making of a strongly risk-averse farmer) tend to include more silvopasture than alley cropping. For this uncertainty level the mean share of silvopasture across the scenarios was 10%, compared to 4% for alley cropping.

The first trend highlights the importance of agroforestry as a diversification strategy to reduce risk (Baker et al. 2017; Waldron et al. 2016), while the second trend suggests that silvopasture may be the less risky of the two agroforestry systems. Silvopasture offers regular yearly income from cattle sales, the prices for which are generally stable in Panama (Connelly and Shapiro 2006), with the additional revenue from timber at the end of the rotation. In contrast, tree canopy shading is likely to prevent crop cultivation in the alley cropping system after three years, meaning that the bulk of revenue flows rely on timber harvest at the end of the rotation. This may make the alley cropping system inherently risky, because returns rely on favourable timber prices at the time of harvest. Paul and colleagues (2017) also report higher deviations in financial returns (as a measure of risk) for alley cropping compared to monoculture crops. Moreover, historical data show that teak prices are more variable than cedar prices, with coefficient of variations of 19% and 8%, respectively, between 2007-2020 (ONF 2020). Therefore, farmers' individual attitudes towards risk will influence the relative attractiveness of the two agroforestry systems; farmers who are more tolerant of risk may be drawn to the more profitable alley cropping system, while those wishing to avoid risk may opt for silvopasture (Gosling et al. 2021).

3.3.3 The effect of hard economic constraints on agroforestry selection

For the next scenarios I imposed fixed limits on the total investment costs and labour demand of the optimal portfolio, to test the potential effects of hard economic constraints on farmers' land-use decisions. For this analysis I focus on portfolios optimised for a strongly risk-averse farmer ($m = 3.0$), and also included farmers' stated land-use preferences as an additional indicator in the optimisation; at this uncertainty level the farmer preferences scenario increases the share of agroforestry in the initial (constraint-free) portfolio, and hence helps to more clearly show the effects of labour and budget constraints on the selection of agroforestry. As expected, the total share of agroforestry in the optimal portfolio declined with increasing labour and investment constraints (Figure 14). This is consistent with other studies in Central and Latin America, which report labour demand and investment costs as important barriers to agroforestry adoption (e.g. Calle et al. 2009; Cary and Frey 2020; Dagang and Nair 2003; Fischer and Vasseur 2000).

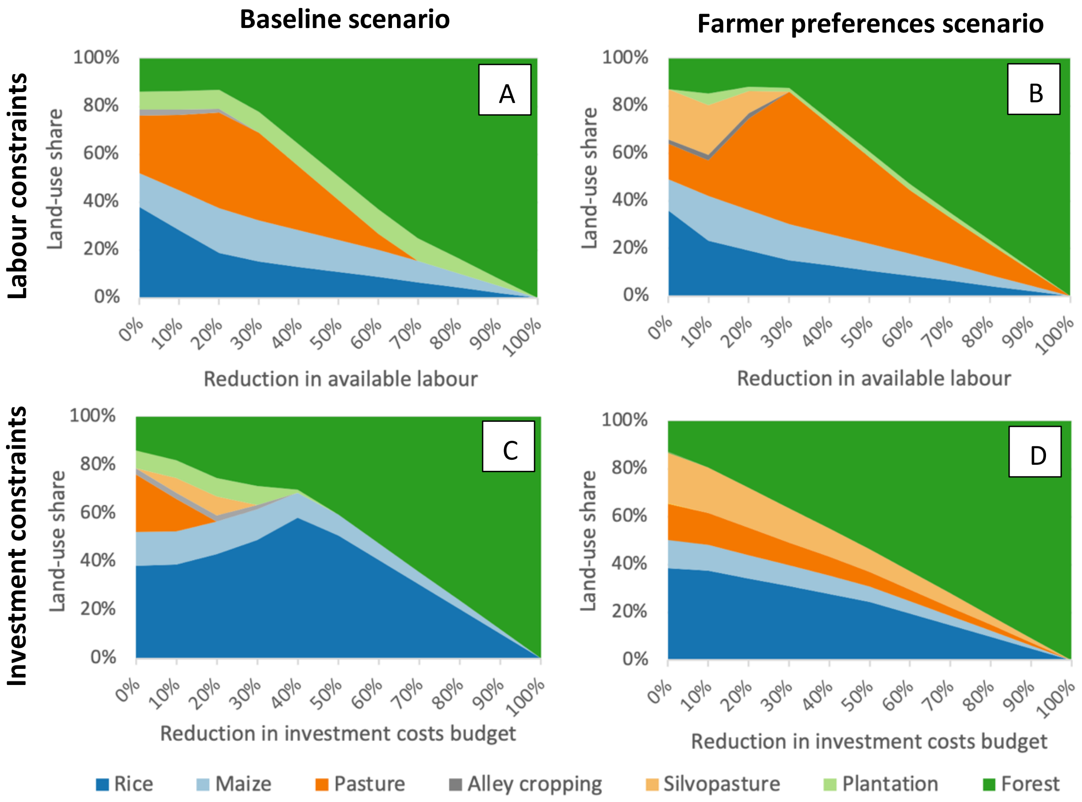

Figure 14: Composition of the ideal farm (share of land area allocated to each land-use option) for a strongly risk-averse farmer ($m = 3.0$), when imposing farm-level constraints in the *Baseline* (left plots) and the *Farmer preferences* scenarios (right plots), for which farmers' general preferences are included as an additional indicator in the optimisation model (see Table 8). In the upper plots the total amount of labour available to manage the land-use portfolio is progressively restricted. In the lower plots the total investment budget for establishing the land-use portfolio is restricted. Labour and investment budget are reduced proportionally, as a percentage of the total labour/investment costs needed to implement the optimal portfolio without any constraints. Adapted from Figure 4 in Gosling et al. (2021).

However, while previous studies tend to emphasise the importance of establishment costs, my results suggest that labour demand may pose the bigger barrier to agroforestry adoption, especially for silvopasture. For example, if labour availability is reduced by more than 30% (relative to the total labour needed for the optimal portfolio without constraints), agroforestry can no longer compete against a mixture of pasture, annual crops, teak plantation and forest (Figure 14a and 14b). In contrast, restricting establishment costs initially increases the share of silvopasture in the optimal portfolio to 6-8%, with agroforestry then disappearing from the portfolio once the investment budget decreases by 40% (Figure 14c). If farmers' general preferences are considered in the optimisation, however, silvopasture is consistently selected in the optimal portfolio (comprising a 21% share of non-forest land-uses), even under severe budget constraints (Figure 14d). The persistence of silvopasture in this optimal portfolio when restricting investment costs, but its disappearance when restricting labour availability, may reflect the greater trade-off in labour demand when choosing silvopasture over conventional pasture. The establishment costs for conventional pasture are only 27% lower than those of silvopasture, but it saves 39% of the labour demand of silvopasture (Gosling et al. 2021). As labour constraints increase, the model is therefore more likely to select pasture over silvopasture.

Many farmers in the study region already take out loans to purchase cattle (Peterson St-Laurent et al. 2013), and the state subsidies credit for cattle ranching (ANAM 2011). Therefore, the additional capital needed to plant trees may be attainable through such loans, offering a means for farmers to overcome investment constraints. The additional labour needed to manage the silvopastoral system, however, may be more problematic – especially for poorer farmers who are unable to hire additional labour. Promoting silvopasture among farmers facing acute labour shortages (which could potentially include the non-diversified cattle farmers from the previous analysis), may depend on identifying less labour-intensive systems. Tree species selection may be vital here. Rather than only planting cedar (a high-value timber species), farmers could integrate a mix of cedar and multi-purpose (e.g. fruit and fodder) trees in their pastures. This would help reduce the time farmers must spend controlling borer pests on cedar trees, and may also help improve economies of scope, whereby pruning could be combined with fodder production (Reyes Cáceres 2018). Where appropriate, small-scale mechanisation and greater use of herbicides (as a quicker alternative to manual removal of weeds) could also assist farmers to mitigate labour shortages (Bouwman et al. 2020).

3.4 RQ 4: Which data collection methodologies are most useful for evaluating agroforestry?

The two datasets analysed in this thesis both quantify the expected performance of different land-use systems against various socio-economic objectives, but these estimates (and the associated uncertainty) were derived in very different ways. The first dataset is based on farmers' empiric ratings captured during landholder interviews, while the second is derived from an extended cost-benefit analysis. In this section I review the advantages and disadvantages of each data collection methodology for evaluating the socio-economic potential of agroforestry (Table 9). I begin by comparing two survey methods that can be used to derive empiric rankings of land-use performance, based on farmer knowledge. I then outline the strengths and weaknesses of evaluating agroforestry based on empiric rankings vs an extended cost-benefit analysis, focusing on four aspects:

- the extent to which each dataset captures local knowledge and cultural values,
- validity of the data and potential sources of bias,
- transparency of the data and the ability to carry out sensitivity analyses, and
- the measurement effort associated with collating each dataset.

By presenting my own experience and learnings from eastern Panama, I hope to help other researchers to select the most appropriate data collection method for evaluating agroforestry against multiple criteria.

Table 9: Strengths and weaknesses of the two datasets for evaluating agroforestry (AF).

	Empiric rankings (Interview data)	**Extended cost-benefit analysis (Computed data)**
Strengths	• Captures local farmers' knowledge and preferences, including intangible values that may otherwise be difficult to measure • Can integrate a diverse range of opinions/perspectives • Dataset can be collated with relatively low measurement effort	• Greater transparency (all assumptions explicit) • Can change the assumptions of the land-use model to evaluate the performance of AF under different socio-economic and environmental conditions • Can impose hard constraints in the multi-criteria optimisation model
Weaknesses	• Farmers may be guessing • Farmer responses may be subject to social desirability bias • Rationale behind rankings unknown: it is unclear how rankings would change under different socio-economic or environmental conditions	• Data demanding • Dataset only as strong as available data and assumptions (if empiric data is lacking may rely on expert opinion, which itself could be subject to bias) • May overlook more intangible values
Recommended applications	• Assessing AF systems with which farmers are already familiar • Preliminary studies to pre-select the most promising (socially-acceptable) AF systems	• Assessing new AF systems • Extensive sensitivity analyses • More detailed planning (e.g. optimising AF layouts and management regimes)

3.4.1 Deriving empiric rankings from farmer knowledge

The ranking and scoring method used to evaluate agroforestry in the farmer interviews was adapted from rapid rural appraisal (Drinkwater 1993; Manoharan et al. 1993; Riley and Fielding 2001). Another possible method to quantify farmer opinion is AHP (Saaty 1987), a well-known MCDA method based on pairwise comparisons. Gosling and Reith (2019) tested both the ranking and scoring and AHP techniques in the study area as a way for farmers to evaluate agroforestry and conventional land-use systems against socio-economic and ecological criteria. We found that farmers were able to follow the AHP procedure, but it was a time-consuming process. In contrast, the ranking and scoring method was much faster: on average farmers took 19 minutes to evaluate land-uses against one criterion via AHP, compared to only three minutes for the ranking and scoring method (Figure 15). The length and complexity of the pairwise comparisons were a serious limitation of the AHP survey, reducing the amount and consistency of the data collected (Gosling and Reith 2019). Other researchers also warn of the time and concentration demands of the AHP when comparing a large number of alternatives (Pérez-Rodríguez and Rojo-Alboreca 2017; Qureshi and Harrison 2003). While AHP may be appropriate for smaller decision problems, for example in which farmers only need to compare three or four land-use alternatives, I would advise against using it for larger problems and instead recommend the ranking and scoring method (Gosling and Reith 2019).

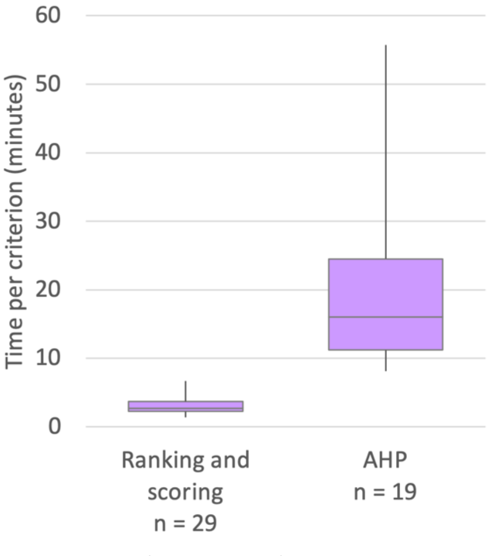

Figure 15: Box plots comparing the time (in minutes) it took farmers to evaluate land-uses against one criterion when using the ranking and scoring method and when using the analytic hierarchy process (AHP). Farmers evaluated seven land-uses per criterion for the AHP method and six land-uses for the ranking and scoring method. Derived from the dataset summarised in Table 3 in Gosling and Reith (2019).

3.4.2 Capturing local knowledge and cultural values

Eliciting farmer opinion of different land-use systems not only captures landholders' experience-based knowledge (Turnhout et al. 2012), but also helps to capture more intangible cultural values that may otherwise be difficult to measure (Boeraeve et al. 2020; Tekken et al. 2017; Temesgen and Wu 2018). Thus, coupling the interview data with the optimisation model offers a means to integrate local knowledge and cultural preferences in land-use planning and the assessment of ecosystem services (Díaz et al. 2018; Scholte et al. 2015). This can help inform the design of socially-acceptable agroforestry systems (Díaz et al. 2018; Fagerholm et al. 2016; Scholte et al. 2015; van Zonneveld et al. 2020). Moreover, the approach can integrate the experience and preferences of a wide range of farmers in the decision model. This may help to address criticisms of the "top-down" approach of previous agroforestry projects in Panama; Fischer and Vasseur (2002) identified the failure of such approaches to incorporate traditional knowledge in the design of land-use systems as an important barrier to agroforestry adoption.

The computed dataset, on the other hand, is based on more diverse data sources and not farmer opinion alone. The land-use model that I used for the extended cost-benefit analysis draws on measured and modelled data from an agroforestry trial in the study area (e.g. Paul 2014; Paul et al. 2015; Paul et al. 2017), information from the Panamanian Government (e.g. MIDA 2019a) as well as the local knowledge of key informants (farmers and other agricultural/forestry experts) in the study area. Other studies, however, have used a similar capital-budgeting approach but relied more heavily on farmer input to estimate the costs, yields, output prices and risk associated with agroforestry systems (e.g. Do et al. 2020; Rahman et al. 2017). Therefore this methodology does not necessarily exclude farmer knowledge.

Nonetheless, relying on computed socio-economic indicators may overlook less-tangible motivations and cultural values that are important for farmers' decision-making (Duguma and Hager 2011; Plieninger and Huntsinger 2018). In my study, the socio-economic and cultural importance of cattle may be a good example of values that are difficult to measure with computed indicators. The payback period computed for each land-use, for instance, can help to account for cash-flow issues and access to money (Knoke et al. 2014; Mercer et al. 2014; Rahman et al. 2017). This economic indicator alone, however, may not fully capture the high liquidity/insurance value of cattle as a source of savings that can be readily sold for cash when needed, nor does it capture the social prestige associated with cattle ownership (Gosling et al. 2020b; Love and Spaner 2005; Peterson St-Laurent et al. 2013). Failing to account for these benefits may undermine the model's ability to gauge the social acceptability and cultural appropriateness of a given agroforestry system. This could speak for selectively combining the two datasets, for example by including farmers' general preferences as recorded in the farmer interviews as an additional indicator in the computed dataset (as per Knoke et al. 2016 and the "farmer preferences" scenario in Gosling et al. 2021).

3.4.3 Validity of the datasets and potential sources of bias

As with any modelling approach, the quality of the output data (in this case the credibility of the optimised land-use portfolios) will depend on the quality of the input data (Jones et al. 2017a). It is therefore important to understand the validity of each dataset, including potential sources of bias. For example, when interpreting the empiric rankings, it is important to remember that although farmers are undoubtedly experts in the prevailing agricultural practices of their region, they are not necessarily experts in agroforestry (Laroche et al. 2018). If farmers were unfamiliar with a particular agroforestry system, their responses may have been an informed guess. It may be particularly difficult for farmers to evaluate the long-term profitability of agroforestry, given the complexity and long planning horizons of these systems (Do et al. 2020). Therefore, the empiric rankings reflect farmers' *perceptions* of the agroforestry systems, which may or may not align with objective reality. Understanding these subjective beliefs and perceptions, however, is important, because they are likely to shape farmers' land-use decisions (Pannell et al. 2006).

A limitation of the empiric dataset is potential response bias. For example, farmers' responses, including their positive opinion of silvopasture, may have been partly shaped by social desirability bias, a phenomenon whereby interviewees tend to give answers that they think the interviewer will view favourably (Bryman 2012; Oppenheim 2004). Farmers may have evaluated silvopasture positively because they thought that would please us (myself and those helping with the interviews) as researchers (Meijer et al. 2015). To minimise social desirability effects we emphasised during the ranking and scoring exercise that there are no right or wrong answers, and that we wanted to learn from the farmer's own experience and knowledge. Moreover, the fact that farmers evaluated alley cropping very poorly against many of the socio-economic and ecological criteria, suggests that their responses were not only driven by a perceived social norm to evaluate "agroforestry as good".

Although potentially more objective than the empiric dataset, one cannot assume that the computed dataset is free from bias. Wishful thinking, for example, can influence assumptions in land-use models and the selection of input values (Do et al. 2020). In my case, I used consistent data sources (such as information from MIDA) to model each land-use, but relied on simplified assumptions to model tree-crop and tree-pasture interactions within the agroforestry systems (Gosling et al. 2021). Integrating more sophisticated bio-physical modelling to simulate tree, crop and pasture growth in each land-use system (e.g. by using WaNuLCAS, Santos Martin and van Noordwijk 2011), may provide a stronger data basis for the optimisation model. In any case, potential bias or uncertainty associated with my computed dataset (or indeed farmers' empiric rankings), reinforces the merits of using robust optimisation, which proactively accounts for this uncertainty directly in the analysis (Doole 2012, Knoke et al. 2016). The sensitivity (scenario) analysis provided a further means to account for uncertain input variables, whereby I tested how changing parameters of the land-use model influenced the optimisation results (Gosling et al. 2021).

3.4.4 Transparency and suitability for sensitivity analyses

The two datasets vary in their level of transparency, that is, the extent to which the assumptions behind each evaluation are clear. The empiric rankings do not capture the underlying rationale for farmers' ratings of the different land-use systems (Gosling and Reith 2019). Therefore it is not known how these ratings would change under different socio-economic or biophysical conditions. This limits the generalisability of results, but also limits the type of sensitivity analyses that can be carried out. For example, based on this dataset it is not possible to test how different market factors, climate scenarios or policy interventions would influence the relative attractiveness of agroforestry from the farmers' perspective. Furthermore, because the performance of each land-use against each indicator is quantified on a scale from 0 to 10, it is difficult to introduce meaningful constraints in the optimisation model, for example to limit the total labour resources (labour days/hectare) or investment budget ($/ha) available to implement the optimal portfolio. This may lead to a mismatch between the land-use composition which farmers deem desirable, and that which they can implement given their available resources and household constraints (Gosling et al. 2020b).

In contrast, a key strength of the computed data is its transparency: all the assumptions in the land-use model are explicit. Therefore, if a decision-maker is unsure about any assumption, he or she can test how changing that assumption would influence the model results through a sensitivity analysis (Castro et al. 2018; Rehman and Romero 1993). This is ideal for scenario testing, to see how different market or environmental conditions influence the relative attractiveness of agroforestry from the perspective of a risk-averse farmer (Gosling et al. 2021). Such sensitivity analyses are often an integral part of cost-benefit analyses of agroforestry systems (e.g. Bertomeu and Giménez 2006; Frey et al. 2010; Paul et al. 2017). Furthermore, because each indicator is quantified in absolute rather than relative units, it much easier to impose hard constraints in the optimisation model (see for example Figure 14 in section 3.3.3). Accounting for farm level constraints may lead to more realistic model results (Bright 2005; Schilizzi and Boulier 1997).

3.4.5 Measurement effort and recommended applications

Pragmatically speaking, the ranking and scoring exercise of the farmer interviews represents a relatively quick and easy method to compile data on the socio-economic potential of different agroforestry systems. Coming from the toolkit of rapid rural appraisal, it is a versatile and straightforward method that does not require extensive preparation (Chambers 2010). Constructing a land-use model to carry out an extended cost-benefit analysis is, by comparison, much more data demanding. It requires data on the expected input costs (including labour demand), yields and prices for each land-use system, as well as data on historic prices and yields (Gosling et al. 2021). Such data needed for agricultural models are often lacking, especially in less developed regions (Jones et al. 2017b). Therefore, the question is: for which applications would empiric rankings suffice (or indeed be preferable), and for which applications is a more data-intensive approach warranted?

The answer lies in part with the type of land-use systems investigated. For existing agroforestry (and other prevailing land-use) systems with which farmers are already familiar, empiric rankings may be an efficient way to capture farmers' knowledge of various attributes of each system. Differences between farmers' perceptions of each land-use system and those of scientists or researchers may create an opportunity to learn from one another (Quiroz Dahik et al. 2018). Such differences may also help identify knowledge gaps to be addressed through field trials or misconceptions to be addressed through communication programs.

However, as I have demonstrated in this thesis, the empiric rankings can also be useful to gauge farmers' perceptions of new agroforestry systems that are not yet widespread in a region. I see this as particularly helpful as a preliminary analysis to identify the most promising systems, that is, those that farmers perceive to be most compatible with their cultural preferences (Gosling et al. 2020b). In my study region I found a clear preference for silvopasture over alley cropping, suggesting that farmers will be more receptive to agroforestry systems that allow them to continue to keep cattle. Accounting for farmers' knowledge and views early on in the planning of agroforestry projects can help ensure that such projects focus on agroforestry systems with the highest chance of adoption (Fischer and Vasseur 2002; Riley and Fielding 2001). More detailed socio-economic modelling could then be carried out for the most promising agroforestry systems, to identify the designs and management regimes that best meet farmers' needs, which could then be further investigated through on-farm trials.

The empiric rankings also lend themselves to participatory research and land-use planning approaches. When paired with multi-objective optimisation, such rankings can be used to identify optimal landscape composition for different groups of farmers or stakeholders (Gosling et al. 2020b). Such portfolios could provide a helpful starting point for participatory land-use planning discussions, to support strategic thinking about sustainable land-use compositions (Le Gal et al. 2013), and to identify common ground between stakeholder groups (Temesgen and Wu 2018).

While empiric rankings are best suited for evaluating pre-defined agroforestry systems, the computed dataset offers greater flexibility to evaluate how alterations to the design of a given system would improve (or worsen) its performance for a given indicator or objective function. By constructing a land-use model, for example, the researcher can test how different planting densities, layouts and management regimes of a pre-selected agroforestry system would affect its ability to provide regular cash-flows or minimise labour demand. Such a dataset is therefore better suited for providing specific recommendations about how a specific agroforestry system should be designed to best meet farmers' needs under different environmental, socio-economic or political conditions (Gosling et al. 2021).

3.5 Reflections on the optimisation approach and outlook for future research

As outlined in section 1.4, a key strength of the optimisation approach used in this thesis is that it can simultaneously consider: a) multiple objectives, b) uncertainty and c) diversification effects when determining the optimal land allocation. These factors are likely to influence farmers' land-use decisions, including their decisions to adopt agroforestry (Janssen and van Ittersum 2007; Lilieholm and Reeves 1991; Pannell et al. 2014). However, previous agroforestry studies have failed to account for at least one of these aspects when evaluating the socio-economic potential of different tree-crop or tree-livestock systems (e.g. Do et al. 2020; García-de Ceca and Gebremedhin 1991; Paul et al. 2017). By bringing these three elements together, my study provides a novel contribution to agroforestry research. However, there are aspects that could be improved in future research.

First, the selection and validation of objectives in the optimisation model could be improved through greater farmer interaction. Using goal programming to model land-use decisions requires knowledge of farmers' objectives (Mendoza et al. 1987). Paper 2 highlights two methods to select objectives: a mechanistic approach that identifies farmers' goals based on scientific literature, and an indirect approach that identifies goals based on farmers' observed behaviour (Gosling et al. 2020a). But it is also possible to ask farmers directly (Sumpsi et al. 1997). From my experience in Panama, however, this is not an easy task: farmers often had trouble in the interviews to identify the goals most salient to their decision-making (Gosling et al. 2020a). Other authors also report that eliciting farmer objectives can be challenging (Kaim et al. 2018; Patrick and Blake 1980; Sumpsi et al. 1997), or have also revealed a mismatch between farmers' stated and revealed preferences (Paakala et al. 2020).

Nevertheless, by increasing the level of farmer interaction both before and after the optimisation procedure, future studies may be able to better account for the constraints and objectives influencing farmers' decisions. For instance, discussions prior to the optimisation may help to identify the farm-level constraints of an individual farmer (Groot et al. 2012). Once these constraints have been captured in the model, researchers could then discuss the model output with farmers. For example, researchers could show the farmer land-use portfolios optimised for various sets of objectives and ask them which of portfolios they would most prefer. This would avoid the problematic task of having to ask a farmer directly about his or her objectives, but still provide valuable information about the farmer's implicit priorities and preferences. Such discussions would also facilitate a feedback loop to help validate results and adjust model parameters where necessary (Groot et al. 2012; Stewart et al. 2004). Greater *a priori* and *a posteriori* interaction with farmers may help to identify the land-use patterns that best fulfil farmers' preferences (Kaim et al. 2018).

Second, future studies using robust optimisation to evaluate agroforestry could refine how uncertainty is represented within the robust optimisation framework. The key idea of robust optimisation is to find solutions that remain feasible for all possible realisations of uncertain parameters within a prescribed uncertainty set, *U*, where this uncertainty set has a specific geometric structure (Ben-Tal et al. 2009; Bertsimas and Brown 2009). Following Knoke and colleagues (2020a), I use box-shaped uncertainty sets in my study. However, box uncertainty sets are very conservative, because they implicitly consider (and give equal weighting to) all possible combinations of parameter values for the considered land-uses, even those combinations that may be very unlikely (Castro et al. 2018; Knoke et al. 2020b). Future studies could therefore test different uncertainty sets within the optimisation model. For example, Knoke and colleagues recently used less conservative ellipsoidal uncertainty spaces to model uncertainty when optimising tropical land-use (2020c) and temperate forest management (2020b).

Finally, the modelling approach could be expanded to better account for land-use diversification over space and time. The robust optimisation approach presented here is not spatially explicit. The model identifies what portions of a hypothetical farm should be allocated to each land-use option, but does not specify the exact location or arrangement of these land-use options (Bertomeu and Giménez 2006). This approach assumes homogeneous site conditions across a farm. Ignoring potential variations in land quality, however, may overlook an important consideration for agroforestry adoption, given that the results of my and other studies suggest that agroforestry may be most advantageous on poorer quality soils (Bannister and Nair 2003; Crestani et al. 2017; Gosling et al. 2021; Messerer 2015; Tsonkova et al. 2014). Paul and colleagues (2019) also identify spatially-explicit goal programming as a promising avenue for future ecological-economic models.

Accounting for the temporal dynamics of land-use decisions may further improve the robust optimisation approach, to better reflect the reality of farmers' decision-making. For example, Knoke and colleagues (2020a) recently published a dynamic variant of the robust optimisation model, in which they modelled farmers' land-use decisions in five-year intervals over a 55-year period. With this approach they could simulate land-use decisions of smallholder farmers in Ecuador that closely matched observed deforestation trends. A dynamic modelling approach would also allow farmers' goals to change over time and allow for more staggered tree-planting, which may be a more feasible way for smallholder farmers to adopt agroforestry (Bertomeu and Giménez 2006). A dynamic approach could also better account for the option value of agroforestry systems, for example the ability to postpone harvest if timber prices are unfavourable (Frey et al. 2013). Such temporal aspects of land-use decisions are overlooked in this thesis.

Chapter 4: Conclusions

In this final chapter I return to my overarching hypothesis, to reflect on the learnings from the research questions. In doing so I provide specific conclusions for agroforestry practice, policy and research.

4.1 Overarching hypothesis

This thesis was guided by the hypothesis that the inclusion of agroforestry in a diversified land-use portfolio will reduce trade-offs between farmers' multiple objectives when considering uncertainty. Based on farmers' perceptions, I identified silvopasture as a promising land-use option for reducing trade-offs between a broad set of pre-defined socio-economic and ecological objectives. Farmers also perceived silvopasture to be a desirable option for reducing trade-offs between longer-term economic goals of maximising profit while minimising risk. However, the positive application of the model revealed that the objectives to which silvopasture can contribute most, may be the objectives that are least important for farmers' decision-making. My analysis instead identified maintaining liquidity and meeting household needs as key drivers of farmers' current land-use decisions. According to farmers' perceptions, conventional pasture and cropland (and not silvopasture or alley cropping) are best suited to balancing these more immediate-term objectives, which could reveal an implicit barrier to agroforestry adoption.

The extended cost-benefit analysis (computed dataset) helped to reveal the conditions that may help to overcome these barriers, to make agroforestry an attractive land-use option for enhancing socio-economic performance at the farm level. Corroborating my findings from the first (farmer interview) dataset, I found that agroforestry may be most attractive for more commercially-oriented farmers who prioritise long-term profit. However, I also identified conditions under which agroforestry would be selected in portfolios that balance the achievement of a wider range of farm goals (including objectives related to food production and payback periods as a way of accounting for household needs and maintenance of cash-flows). Silvopasture tended to be more prominent in these optimal portfolios than alley cropping. Sensitivity analyses suggest silvopasture may be best placed to reduce trade-offs between the socio-economic goals on less productive land (which can only sustain lower-than-average yields for rice and maize). However, I also found that cost-sharing arrangements could make both agroforestry systems more attractive for farmers seeking to enhance farm-level socio-economic performance, as would favourable developments of timber markets. In terms of hard economic constraints, my results suggest that low labour availability may be particularly problematic for the wider adoption of silvopasture.

This thesis demonstrates how a normative modelling approach can deliver valuable insights into the socio-economic potential of agroforestry as a sustainable land-use strategy. Parallels with empiric studies speak for the plausibility of model results. This includes, for instance, previous studies that identified a conflict between farmers' immediate-term needs and their ability to invest in more sustainable farming practices (Affholder et al. 2010; Binh et al. 2008; Pannell et al. 2014), or the importance of financial assistance for on-farm tree planting in eastern Panama (Simmons et al. 2002). The extent to which the findings from this thesis can be generalised to other regions will depend in part on how similar the farming communities in those regions are to the farming community of Tortí, including the similarity in cultural values and prevailing farming practices. My results may well be relevant for other tropical regions where cattle ranching holds high cultural value and is integral to local people's livelihoods and where agriculture is predominately carried out through traditional methods, with only low levels of mechanisation and chemical inputs.

4.2 Conclusions for practice

From a practical perspective my results highlight key criteria that agroforestry systems must fulfil to be more attractive to farmers in the study area: they must provide early and frequent income flows (to help maintain liquidity) and ongoing opportunities to produce food (to help meet farmers' household subsistence needs). This knowledge can help to identify and design agroforestry systems with the highest likelihood of adoption.

For example, in this thesis I only tested agroforestry systems comprising a single tree species: teak for alley cropping and Spanish cedar for silvopasture. However, planting a mix of timber and multi-purpose trees within the agroforestry systems may be more appropriate for satisfying farmers' subsistence and cash-flow needs. Fruit trees, for instance, could provide food for household consumption, but also an additional income source from selling surplus harvest (Garen et al. 2011; Waldron et al. 2016). Alternatively, silvopastoral systems that integrate fodder trees may allow farmers to maintain higher stocking rates or increase cattle survivorship during the dry season (Esquivel-Mimenza et al. 2013; Love and Spaner 2005), thereby helping to secure food supply and liquidity throughout the year. The integration of fruit and fodder trees into the silvopastoral system may also benefit farmers facing labour shortages. First, it may allow farmers to combine pruning with fodder production, which could improve economies of scope. Second, reducing the density of cedar trees and 'hiding' them among other species may lower the risk of shoot borer attack (Paul and Weber 2013), and hence reduce the time a farmer must spend controlling such outbreaks.

Reducing the density of teak trees within the alley cropping system may also be a useful strategy to ensure farmers can continue to obtain food and revenue from annual crops. For example, the border planting layout tested by Paul and colleagues (2017), in which trees are only planted around the edge of a field, would reduce the canopy shading effects of teak, allowing food crops to be cultivated longer into the rotation. Reducing the density of high value timber trees within each agroforestry system (whether it be teak or cedar), would have the drawback of lowering revenues from timber sales. However, any loss in long-term profit may be acceptable for farmers, given that most farmers in the study area appear to prioritise short-term needs over long-term economic return.

4.3 Conclusions for policy

Of the two agroforestry systems investigated, I found silvopasture to have the highest potential to reconcile multiple farm-level goals at the study site. My results suggest that silvopasture not only aligns with farmers' cultural preferences (which can be important drivers or impediments to agroforestry adoption, Rahman et al. 2017; Tsonkova et al. 2014), but also appears compatible with risk-averse decision-making. Therefore, strategies to increase tree cover at the agricultural frontier in eastern Panama, will likely gain more traction with local farmers if they focus on silvopastoral (rather than silvoarable) systems. This also recognises the important role that cattle play for farmers' livelihoods in Tortí.

Currently, the Panamanian government provides subsidised credit to cattle farmers, a policy that has been criticised for accelerating pasture expansion and hence deforestation and land degradation (ANAM 2011). Given the importance of cattle for rural livelihoods, however, abolishing this credit program may harm many farmers. Instead, a compromise solution could be to adjust this credit program to favour the establishment of silvopastoral systems. For example, the subsidised interest rate could be subject to the requirement that farmers maintain a certain tree density on their pasture. This may be most effective in conjunction with other subsidies to provide farmers with tree seedlings and materials for tree guards free of charge. My results suggest that such cost-sharing arrangements could substantially increase the attractiveness of silvopasture for risk-averse farmers. Such policies could therefore facilitate a transition from extensive cattle ranching to silvopasture in eastern Panama, a transition that would continue to safeguard rural livelihoods.

Despite having lower general appeal than silvopasture, I found that alley cropping may still represent a desirable land-use option for certain groups of farmers. For example, results from the interview data suggest that alley cropping might be attractive as a diversification strategy for poorer farmers who depend heavily on cattle for their on-farm income. Moreover, results from the computed dataset revealed that the tree-crop system may also appeal to farmers who are more focused on long-term income and more tolerant of risk. These nuances speak against a blanket approach to promoting agroforestry, providing insights into how tree-crop systems could be effectively targeted towards farmers with particular land-use and income strategies.

An important finding of my study is that relying alone on long-term profit as a selling point for agroforestry may result in low uptake in the study area (because farmers in Tortí appear to base their land-use decisions on more immediate-term objectives). This highlights the importance of designing and promoting agroforestry systems that can meet a wider range of farmer objectives, including shorter-term needs relating to cash flow and food production (as outlined in section 4.2). Nonetheless, the additional income provided by timber sales remains a key economic advantage of the two agroforestry systems investigated in this thesis. This suggests two important preconditions for the adoption of these systems. First, the farmer must be at least partially motivated by economic return (as one of multiple household goals). Second, farmers must have the capacity to produce, but also market, high quality timber. While the first pre-condition is difficult to engender through policy, agricultural training and extension programs could help build farmer capacity to achieve the second. Such programs should ensure that farmers have access to high quality germplasm (Bertomeu 2006), and can acquire the skills and knowledge needed for proper silvicultural management. The latter is especially important given the lack of an agroforestry culture in Panama (Díaz et al. 2012); while cattle ranching traditions have been passed on for generations, there is no collective knowledge of farm-forestry (Fischer and Vasseur 2000; Paul 2014). Such capacity building programs should also focus on improving farmers' knowledge of and access to timber markets. This could be supported by a simplification of the tree harvesting permit system in Panama, to make it easier for farmers to sell their farm-grown timber through official channels.

4.4 Conclusions for research

The ranking and scoring exercise of the farmer interviews was a simple, but effective method for capturing farmers' knowledge and perceptions of conventional and tree-based land-use systems. Integrating these data into a robust, multi-objective modelling framework offers an opportunity to evaluate the socio-economic potential of agroforestry from the farmers' perspective. This robust modelling approach may be especially useful when dealing with small sample sizes (which may result in more uncertain datasets), because the model actively accounts for potential variation in farmer opinion when deriving optimal land-use portfolios. Coupling farmer interviews with robust optimisation may therefore be a pragmatic method to guide agroforestry research in cases where there are insufficient resources to carry out large-scale household surveys. This approach can pre-select the most socially-acceptable agroforestry systems, which could then be the subject of more detailed bio-economic modelling. In Tortí, for example, I would recommend further modelling of silvopasture systems, to determine the species compositions, planting layouts and management regimes that best meet farmers' needs. Ultimately, the modelling approach can help to identify the most promising agroforestry systems for on-farm trials – systems which have high potential of being adopted by farmers.

The positive application of the optimisation model revealed maintaining liquidity and meeting household needs as the key drivers of farmers' land-use decisions in Tortí. In contrast, long-term income appeared much less important for farmers' decision-making. Therefore, studies that only evaluate agroforestry in financial terms (e.g. based on NPV) may overlook important considerations for smallholders' management decisions, and hence fail to identify the most socially-acceptable systems. This finding underscores the need for MCDA methods when evaluating the socio-economic credentials of agroforestry from the perspective of smallholder farmers, to ensure that the analysis captures the full range of objectives that drive farmers' decision-making.

I see two broad avenues for advancing the use of multi-criteria, robust optimisation in future agroforestry research. First, the optimisation model could be integrated into more participatory research or land-use planning approaches, with greater interaction and co-learning between researchers and farmers. Second, the model could be expanded to better account for the spatial and temporal dynamics of farmers' land-use decisions. While I have tested the modelling approach for the agriculture-forest frontier in eastern Panama, it can easily be applied to investigate tree-based farming systems in other tropical or temperate regions.

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List of publications

The following peer-reviewed publications were completed during the time of the PhD (November 2017–March 2021):

- **Gosling E**, Bojarska K, Gula R, Kuehn R (2019) Recent arrivals or established tenants? History of wolf presence influences attitudes toward the carnivore. Wildlife Society Bulletin 43:639-650. https://doi.org/10.1002/wsb.1027
- **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 (in press). https://doi.org/10.1007/s00267-021-01439-0
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- 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

Manuscripts submitted for publication:

- Friedrich S, Hilmers T, Chreptun C, **Gosling E**, Jarisch I, Pretzsch H, Knoke T. The cost of risk management and multifunctionality in forestry – a simulation approach for a case study area in Southeast Germany. Submitted to European Journal of Forest Research

- Knoke T, **Gosling E**, Thom D, Chreptun C, Rammig A, Seidl R. Economic losses from natural disturbances in Norway spruce forests – a quantification using Monte-Carlo simulations. Submitted to Ecological Economics
- Knoke T, **Gosling E**, Reith E, Gerique A, Pohle P, Valle-Carrión L, Ochoa-Moreno WS, Castro LM, Calvas B, Paul C. What off-farm income can do to halt tropical deforestation – Learning from an innovative land-allocation model. Submitted to One Earth

Non peer-reviewed publications:

- **Gosling E**, Reith E, Paul C (2020) Agroforstwirtschaft – ein Gewinn für Landwirte und Umwelt? AFZ - Der Wald 17:26-28.
- Reith E, **Gosling E,** Knoke T, Uhde B, Paul C (2018) Ökosystemleistungen bewerten – Beispiele aus Chile und Panama. AFZ - Der Wald 14:13-15.

Acknowledgements

Firstly, I would like to thank my supervisors Thomas Knoke and Carola Paul for their excellent support and guidance, which provided the foundation for a successful and rewarding PhD experience. Thomas always had time for my “quick questions” and inspired me through the clear structure and elegant study design of his own research papers (not to mention his formidable Excel spreadsheets). Carola’s generosity in sharing her knowledge and providing moral support was limitless. Carola always listened patiently as I stressed over a seemingly grave problem, to respond with thoughtful advice for a clever (and often simple) solution.

I am also extremely grateful to my “Doktorschwester” Esther Reith, for being such a caring friend and supportive colleague throughout my PhD journey. I am so happy that we chose Team Panama! Many thanks too go to whole team at the Institute of Forest Management and my fellow PhD candidates past and present, who created such a fun and supportive working environment. I also thank Peter Annighöfer for being my third examiner and Annette Menzel for chairing my examination committee, as well as the German Research Foundation (DFG) who funded this project through the Grant PA 3162/1.

My time in Panama was a wonderful experience, and I am deeply grateful for the help and company of all those who were a part of it. Thank you to Fernando Lopez, Silke Berger and Monica Hary, who helped me find my feet in Panama and let me in to the very special world of *lo tuyo*. I couldn’t have asked for a better team of students to help me with the farmer interviews - Alyna Reyes Cáceres, Rodrigo Duarte and Peter Glatzle. Thank you so much for your commitment to the cause, and for all the laughs. I am also very thankful for Andrés Domínguez, who took our team under his wing and introduced us to the Tortí community. Thank you too to the rest of the staff at Hotel Avicar, who provided us with a home away from home. Importantly, I send a very special thanks to all the farmers who generously shared their time and knowledge to teach us about farming in Tortí. *De córazon muchas gracias por su gran ayuda y su amistad.*

Writing a PhD is not always easy, and I am grateful for my friends who were there to listen and offer happy distraction when needed. I am also proud to be part of the Münchener Tafel and thank all my Tafel friends who helped me balance out robust optimisation and uncertainty scenarios with laughter and chocolate pudding. My final thanks go to the most special people in my life: Dani, who helped me through all the challenges of the PhD and was there to celebrate all the wins; and my family in Rainbow Australia, who despite being on the other side of the world, never feel far away. Thank you for supporting me to do my best.

Appendices

Paper 1

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

SOCIETY & NATURAL RESOURCES
https://doi.org/10.1080/08941920.2019.1681569

RESEARCH NOTE

Capturing Farmers' Knowledge: Testing the Analytic Hierarchy Process and a Ranking and Scoring Method

Elizabeth Gosling and Esther Reith

Institute of Forest Management, TUM School of Life Sciences Weihenstephan, Technische Universität München, Freising, Germany

ABSTRACT

Integrating local and Indigenous knowledge into land-use planning and the assessment of ecosystems services requires reliable, quantitative data. We tested two approaches to obtain such data by quantifying farmer opinion of different land-covers in Eastern Panama using (1) the analytic hierarchy process (AHP) and (2) a simpler ranking and scoring technique. Both methods produce a set of numerical values reflecting the ability of land-covers to deliver ecological and socio-economic criteria. We present our experience with both methods and offer recommendations for researchers looking to quantify landholder opinion. The AHP survey was relatively long (on average it took 19 min to complete per criterion) and we faced problems with inconsistent responses. In contrast, the ranking and scoring method was much quicker (only 3 min per criterion) and therefore may be more suitable for gathering more data from a larger number of farmers.

ARTICLE HISTORY
Received 24 May 2019
Accepted 29 September 2019

KEYWORDS
Agroforestry; ecosystem service provision; farmer interviews; land-cover evaluation; matrix ranking and scoring; pairwise comparisons; rapid rural appraisal

Introduction

There are growing calls to integrate farmer knowledge and preferences into land-use planning and the assessment of ecosystem services (Díaz et al. 2018; Scholte, van Teeffelen, and Verburg 2015), for example, to inform the design of agroforestry and other sustainable land-use systems (e.g., Plieninger and Huntsinger 2018; Riley and Fielding 2001). Previous research into farmers' perceptions of agroforestry systems have mostly used qualitative methods (e.g., Frey et al. 2012; Garen et al. 2009; Hand and Tyndall 2018). Quantitative approaches, however, may be needed to generate statistically robust data to complement the depth and detail provided by qualitative surveys (Mayoux and Chambers 2005). In this research note, we present two methods to quantify landholder opinion of different land-covers. Both methods produce a set of numerical values or weights reflecting the ability of the land-covers to provide different ecosystem services. We share our experience of testing each method with smallholder farmers in a tropical forest frontier region.

Our first method is the analytic hierarchy process (AHP), a multi-criteria decision analysis technique developed by Saaty (1987). AHP reduces a decision problem to a

CONTACT Elizabeth Gosling ✉ elizabeth.gosling@tum.de 🖃 Institute of Forest Management, TUM School of Life Sciences Weihenstephan, Technische Universität München, Hans-Carl-von-Carlowitz-Platz 2, Freising 85354, Germany.

series of binary comparisons. Each alternative (in our case a land-cover) is systematically compared to all other alternatives, to produce a rating for pre-defined criteria (e.g., ecosystem services). Previous research has used AHP to evaluate farming systems against socio-economic indicators (e.g., Shrestha, Alavalapati, and Kalmbacher 2004; Toledo, Engler, and Ahumada 2011), but these studies usually rely on the opinion of scientists or agricultural consultants, rather than the landholders themselves. Studies using AHP to capture farmer knowledge and preferences are rare (e.g., Qureshi and Harrison 2003). As an alternative to AHP, our second method combines elements from the rapid rural appraisal, for example matrix ranking to evaluate crop types (e.g., Drinkwater 1993), with methods to elicit opinion of scientists and other specialists on ecosystem service provision (e.g., Burkhard, Kroll, and Müller 2010).

By describing our experience of using the two methods in Eastern Panama, we aim to aid other researchers in their selection of appropriate methods for capturing farmers' knowledge, to generate sound quantitative data for statistical analysis and land-use modeling.

Methods

Study Area and Survey Approach

Our study area centers on the township of Tortí, 125 km east of Panama City. Large-scale forest clearing began in this region in the 1970s, and cattle grazing now dominates the land-use (Sloan 2008). Education levels in the area are lower than the national average: 15% of local residents (10 years and older) have less than three years of formal schooling and 9% are illiterate (Instituto Nacional de Estadística y Censo 2010).

We carried out two separate surveys in the study area. Both surveys aimed to quantify farmer opinion of different land-covers (including two agroforestry systems), against various socio-economic and ecological criteria (see Table 1). One survey used AHP to quantify farmer opinion, and the other used the ranking and scoring technique. We selected farmers using a mix of random (going door-to-door) and nonrandom (approaching farmers at a local cattle auction) sampling methods. Surveys were conducted in Spanish and completed in April–May 2018.

Table 1. Land-covers and socio-economic and ecological criteria included in each survey.

	Land-cover	Criteria
Both surveys	• Conventional cropland • Conventional pastureland • Alley cropping (annual crops grown between lines of trees) • Silvopasture (pasture with ≈ 200 trees/ha) • Forest plantation (monoculture) • Natural (secondary) forest	• Long-term profitability • Liquidity (short-term cash flow) • Stability of economic returns • Food production • Protection of water resources • Protection of soil resources
AHP only	• Abandoned land (out of production for more than five years)	• Global climate regulation • Micro-climate regulation • Biodiversity • Scenic beauty
Ranking and scoring only	–	• Labor demand • Investment costs • Management complexity

The Analytic Hierarchy Process

In the first survey, we used AHP to elicit farmers' judgment of the ability of seven land-covers to achieve 10 ecological and socio-economic criteria (Table 1). Farmers answered a set of 21 comparisons for each criterion. For each comparison we showed farmers pictures of two land-covers and asked them which land-cover was better for providing a given criterion. We then asked them to indicate how much better the land-cover was for achieving the criterion on a nine-point scale, where 1 = the same, 3 = a little better, 5 = moderately better, 7 = much better, and 9 = extremely better (a sheet depicting the response scale was also visible to participants). After the participant had completed a set of 21 comparisons for one criterion, we either finished the interview or (if the participant was willing and able) proceeded with the next criterion. The criteria sequence varied between interviews.

Following Saaty (1987), we aggregated responses of the individual comparisons in a matrix to compute a participant's overall rating of each land-cover against a given criterion. We then calculated the mean rating (and associated standard error) across all farmers. An advantage of AHP is the ability to check for inconsistent responses through the consistency ratio (CR). This ratio reflects how consistent a participant is in their responses to the pairwise comparisons (e.g., if someone prefers A over B, and B over C, it follows that they should prefer A over C). We calculated the CR for each farmer, for each of the criteria they evaluated as follows:

$$\text{Consistency index (CI)} = \frac{\lambda_{\max} - n}{n - 1} \tag{1}$$

$$\text{Consistency ratio (CR)} = \frac{\text{CI}}{\text{RI}} \tag{2}$$

Where n is the number of alternatives being compared, and $\lambda_{\max}$ the principal eigenvalue, calculated from the product of the raw and normalized weights of each alternative derived from the pairwise comparisons (Saaty 1987). The consistency of a participant's responses, measured through the consistency index (CI), is compared to the random consistency index (RI), which reflects random judgment and is a value generated by Saaty (1987) based on the number of alternatives compared; for seven land-covers RI = 1.32.

Ranking and Scoring Technique

In a second (separate) survey, farmers rated the performance of six land-covers against nine socio-economic and ecological criteria (see Table 1) in a two-step process. For each of the criteria, we first asked farmers to arrange cards depicting each land-cover in order from best to worst for achieving that criterion (e.g., for generating long-term income). They then scored each land-cover on a scale of 0–10, where the highest-ranked land-cover was always given a score of 10. We calculated the mean score and associated standard error for each land-cover for each criterion across all farmers. The sequence in which farmers evaluated the criteria varied between interviews.

Table 2. Description of survey participants.

	AHP	Ranking and scoring
Sample size and gender	19 (one female)	35 (all male)
Age range (years)	22–80 (42% between 40 and 50)	32–81 (mean 51.9)
Ethnicity	All *mestizos* (of mixed Spanish and Indigenous decent)	All *mestizos*, except for one Emberá farmer
Years lived in Tortí (mean)	36	32
Education level (percent of participants)	not recorded	17% incomplete primary education 43% primary education 20% secondary education 6% tertiary education

Table 3. Number of criteria evaluated per participant and time (in minutes) needed to evaluate one criterion for each survey method.

		Number of criteria evaluated per participant				Time taken per criterion (min)			
Survey method	*N*	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD
AHP	19	1	3	1.6	0.7	8.1	55.7	19.3	12.1
Ranking and scoring	32	0	9	8.2	2.5	1.4	6.7	3.2	1.4

Farmers evaluated seven land-covers per criterion for the AHP method and six land-covers per criterion for ranking and scoring.

Comparison of Survey Methods

Sample Description, Completion Rate and Time Requirement

Table 2 describes the characteristics of the farmer sample of each survey. There was a partial overlap between the samples; six farmers took part in both surveys.

The first survey achieved a 100% completion rate; all farmers could follow the AHP logic and complete the pairwise comparisons for at least one criterion. However, it was a lengthy process. Participants took 19 min on average to evaluate the land-covers against one criterion during the AHP survey, compared to three minutes for the ranking and scoring (Table 3). The length of the pairwise comparisons limited the number of criteria that we could ask farmers to evaluate. Often we ended the interview after one criterion if a participant was starting to become restless or fatigued from the (relatively monotonous) comparisons. A third of farmers evaluated two criteria in one session and 14% evaluated three.

In contrast, when using the ranking and scoring method, we could collect data from the same farmer for more criteria (albeit for one less land-cover). Three participants in this survey were not able to score the performance of each land-cover against the nine criteria. These participants were the most elderly of the sample (≥72-years-old), with either no or only two years of formal schooling. These elderly participants could rank the land-covers against different criteria, but the task of allocating points seemed to cause them confusion and discomfort, and we did not pursue the method further. The remaining 32 farmers provided scores for each land-cover for all nine criteria in one session (91% completion rate).

Consistency of Farmers' Responses

Overall, we obtained 34 responses for the AHP survey; "response" refers to a completed set of pairwise comparisons for one criterion. Responses, however, were associated with high inconsistency. The lowest (best) consistency ratio of all responses was 12% and the

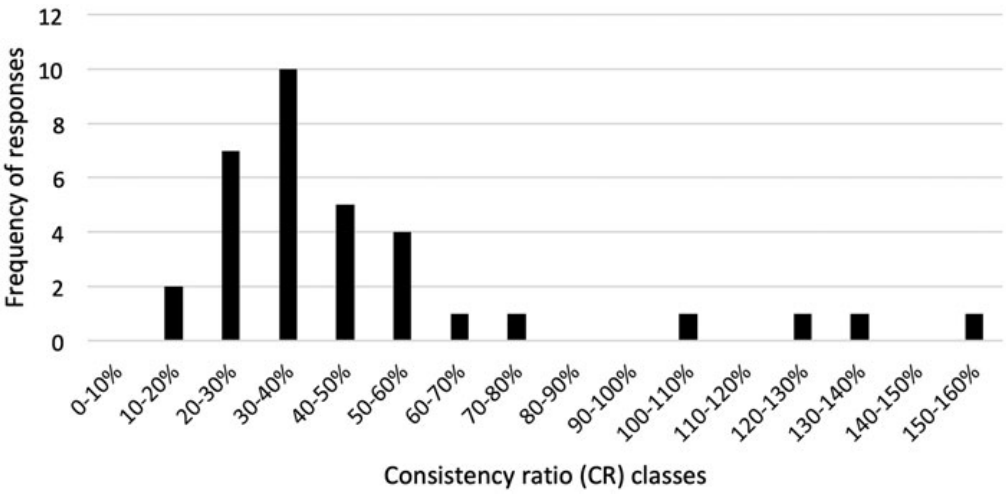

Figure 1. Histogram of responses in terms of their consistency ratio.

mean was 49%. The highest consistency ratio was 156% (Figure 1). According to Saaty (1987), consistency ratios should not appreciably exceed 10%, which in our sample could potentially disqualify all responses. Wedley (1993) accepts consistency ratios between 10 and 20% as moderately consistent, which would permit the use of two responses from our sample.

Complexity and fatigue are likely to have contributed to inconsistent responses. Although AHP reduces the decision problem to a series of pairwise comparisons, each pairwise comparison may still represent a complex decision in itself. For example, when comparing the profitability of alley cropping and conventional cropping, a farmer might need to consider investment costs, harvesting regimes and susceptibility to yield and price fluctuations in their decision. The AHP survey also included two similar land-covers: secondary forest and abandoned land (which in tropical areas can be thought of as regenerating secondary forest). This similarity may have further complicated the comparisons, as well as contributed to a sense of repetitiveness. Despite our efforts to simplify the procedure and present it as an analytical game, for many participants completing the 21 comparisons was a tiring task. It is understandable if farmers' concentration (and hence consistency) began to slip as they progressed through the comparisons.

We do not want to imply that farmers are incapable of providing consistent answers to complex questions. Instead, we think that for our decision problem, providing consistent responses that meet the relatively strict requirements of Saaty (1987) and Wedley (1993) is extremely difficult, regardless of profession or education level. For comparison, in a separate study a broader range of experts in Panama (including scientists and agency staff) evaluated the seven land-covers against the 10 criteria (also using AHP). While the mean consistency ratio (29%) was lower for the expert sample, 60% of responses still had a consistency ratio greater than 20%. This suggests that the length and complexity of the AHP survey were not only problematic for farmers with potentially low education levels but also posed a challenge to the experts who are likely to be more highly educated and more accustomed to such analytical tasks.

Unlike AHP, the ranking and scoring technique does not have a built-in consistency check and we are less able to assess the reliability of the data. Other authors, however, have promoted matrix ranking and scoring as means of obtaining high-quality data from local people, especially in regions with low literacy levels (e.g., Mayoux and Chambers 2005; Riley and Fielding 2001). We also argue that the simplicity of the method makes it less prone to problems of inconsistency compared to AHP; to rate seven land-covers, farmers would only have to make seven decisions (compared to 21 if using AHP), leaving fewer opportunities for inconsistencies to arise.

Consistency of responses, however, should not be confused with accuracy. Consistent judgment does not guarantee an accurate ranking (Wedley 1993). Therefore, for both methods triangulation is very important, that is, checking the plausibility of results against other sources, such as previous studies or qualitative surveys (Riley and Fielding 2001). Moreover, neither AHP nor ranking and scoring directly account for uncertainty inherent in the data. We, therefore, recommend incorporating measures of variation (such as the standard error) into calculations based on data from these evaluation methods. For example, the standard error could form the upper and lower limits of expected ecosystem service levels when using these estimates in land-use allocation models (see for example, Knoke et al. 2016; Uhde et al. 2017). Finally, both survey methods do not capture the underlying reasons for farmers' ratings of different land-covers. Combining these techniques with qualitative methods (e.g., semi-structured interviews) could provide a more in-depth understanding of the factors influencing participants' decisions.

Limitations and Recommendations

Table 4 summarizes the strengths and weaknesses of each survey method. Our study documents a new application of the AHP: to evaluate land-covers based on farmer

Table 4. Strengths and weaknesses of the analytic hierarchy process (AHP) and ranking and scoring as methods to quantify farmer opinion of land-covers against ecological and socio-economic criteria.

	Strengths	Weaknesses	Recommendations
AHP	• Participants respond to the pairwise comparisons in everyday language, without having to allocate points or think in numbers • Built-in quality control: can check reliability of responses through the consistency ratio	• Pairwise comparisons are time-consuming and relatively monotonous with high concentration demands: can only collect data for few criteria in one session • Complex decision problems may result in high inconsistences	• Limit survey design to six alternatives, collect data for three or fewer criteria per participant • Tolerate a higher level of inconsistency (if accuracy of data can be verified)
Ranking and scoring	• Relatively quick: can collect data for more criteria from the same farmer in one session	• Difficult to assess the reliability of data • Allocating scores may be challenging for some participants	• Pair with other interview methods to collect household data or qualitative insights
Both methods	• Objective methods to quantify landholder opinion • Can be presented as an analytical game, with a high visual element	• Do not capture underlying motives for participants' decisions • Do not account for uncertainty inherent in data	• Triangulation to compare results with other studies or knowledge sources • Use standard error to reflect variability in farmers' responses

Recommendations are based on our experiences implementing each survey method with farmers in Eastern Panama (April–May 2018).

knowledge in a tropical region with low literacy levels. When using visual aids and presenting comparisons one at a time, farmers could follow the AHP procedure. It is, therefore, a feasible technique to quantify landholder opinion to inform land-use planning decisions. However, the time needed for farmers to complete the AHP comparisons, coupled with the poor consistency of their responses, represent serious limitations. These shortcomings suggest that our survey design approached (or even exceeded) the limits of what smallholders could be reasonably expected to evaluate.

To reduce the burden of the evaluation task and improve the success of using AHP with farmers, we recommend including no more than six land-cover alternatives in the survey design; this would reduce the number of comparisons to 15 per criterion and shorten the survey time considerably. Ensuring that the land-covers (or other alternatives) selected are sufficiently distinct from one another should also help to make the pairwise comparisons less tedious. Likewise, dividing the criteria into distinct categories (e.g., economic, environmental and social objectives as per Qureshi and Harrison (2003)) and merging any similar criteria may help to avoid confusion and improve the clarity of the evaluation task.

Overall, we acknowledge that using AHP to elicit farmer opinion of many alternatives against multiple criteria is challenging. The length of the survey may tax the concentration of any farmer or individual, regardless of education level. Researchers using this method should, therefore, be prepared to obtain data for three or fewer criteria in one session. Tolerating a higher level of inconsistency (to avoid excessive data loss) may be justified if a plausibility check can verify the accuracy of the data.

For problems that require data on more than six alternatives for more than three criteria, we recommend the ranking and scoring method to rapidly collect more data from more farmers. Ranking and scoring may also be a time-efficient method for surveys that also aim to collect household data and qualitative insights (e.g., through participatory resource mapping or a semi-structured interview). Using the ranking and scoring method in these situations would help keep the overall survey length to a minimum.

The two methods we present here both provide quantitative data with a clear structure for statistical analysis. In our research project, we used the surveys to derive input data for multi-objective optimization of land-use allocation, following Knoke et al. (2016) and Uhde et al. (2017). Other applications could include bio-economic modeling of different land-use systems or mapping ecosystem services. We see great potential for both the AHP (when evaluating a small number of alternatives) and the ranking and scoring method as rapid assessment tools, to quantify farmer knowledge and perceptions and, ultimately, to inform sustainable land-use strategies.

Acknowledgments

We are grateful to Andrés Gerique for his input on the survey design, and for the assistance of Rodrigo Duarte, Peter Glatzle, and Alyna Reyes during the farmer interviews. We also thank all the farmers who shared their knowledge with us. Karen Grosskreutz, Carola Paul, Thomas Knoke, and Marie Louise Aastrup provided valuable comments on the manuscript. The approach to use AHP with multi-objective optimization was developed by Britta Uhde and Thomas Knoke.

Funding

This work was supported by the German Research Foundation (DFG) - Grant PA 3162/1.

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Paper 2

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

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Journal of Environmental Management 261 (2020) 110248

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: http://www.elsevier.com/locate/jenvman

Research article

A goal programming approach to evaluate agroforestry systems in Eastern Panama

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

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

ARTICLE INFO

Keywords:
Alley cropping
Farmer interviews
Land allocation
Robust optimisation
Silvopasture

ABSTRACT

Agroforestry is hypothesised to increase ecological and economic functions of farms. Yet it is unclear if and how much agroforestry should be embedded in diversified farming systems to satisfy farmers' needs while potentially enhancing environmental services. To address this research gap we use a mathematical programming model to investigate the role of different agroforestry systems in hypothetical farm portfolios that reduce trade-offs between farmers' goals. Our approach is innovative because it simultaneously considers multiple objectives and the effect of land-use diversification within a farm, is based on knowledge and perceptions of local farmers, and accounts for heterogeneity in farmer judgement. We test the model in a forest frontier region in Eastern Panama, using data from farmer interviews. Farmers evaluated conventional land uses and two agroforestry systems (silvopasture and alley cropping) against 10 pre-defined socio-economic and ecological objectives. First we determined the optimal farm land-use composition that reduces trade-offs between the 10 objectives. The model selects the mix of land uses that secures the best worst-case performance across all objectives, when considering uncertainty in the ability of each land use to achieve each objective (which we quantify by the variability in farmer opinion). Agroforestry dominates the optimised farm portfolio, which comprises 60% silvopasture, 39% forest and 1% plantation. This land-use portfolio, however, deviates strongly from the current land use of farmers, which is 59% pasture, 26% crops, 14% forest and 1% plantation. In a second step we explore the implicit objectives driving farmers' current land-use decisions. We find that immediate-term needs related to food security and liquidity best explain farmers' current land-use portfolio; optimising for these objectives produces a land-use portfolio comprising 60% pasture and 40% crops, which is similar to the current land use. This suggests that increasing agroforestry adoption in the study area will require systems that provide early and frequent returns and allow for ongoing crop production, to better satisfy farmers' cash flow and household consumption needs.

1. Introduction

Agroforestry is a promising approach to address global land-use problems (Nair and Garrity, 2012). By combining trees and crops or trees and livestock on the same piece of land, agroforestry has the potential to bridge competing land-use needs for production and environmental protection (Torralba et al., 2016). Agroforestry can enhance biodiversity and ecosystem services in farm landscapes (Jose, 2009; Schroth et al., 2015; Torralba et al., 2016). These systems can also benefit production by improving soil fertility, water availability and drought resilience (Dagang and Nair, 2003; Lin, 2010; Somarriba et al., 2012), while tree products can help diversify farm income to buffer against financial risks (Cubbage et al., 2012; Thorlakson and Neufeldt, 2012).

Nevertheless, agroforestry systems can have important drawbacks compared to conventional agriculture, such as high investment costs (Dagang and Nair, 2003; Metzel and Montagnini, 2014), lower crop yields (Clough et al., 2016; Reed et al., 2017), greater management complexity and delayed returns for timber products (Cubbage et al., 2012; Paul et al., 2017). Therefore, agroforestry systems may help farmers to achieve some of their household goals, but may hinder the achievement of others (Barrios et al., 2018; Fischer and Vasseur, 2002).

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[*] Corresponding author.
E-mail address: elizabeth.gosling@tum.de (E. Gosling).

https://doi.org/10.1016/j.jenvman.2020.110248
Received 21 June 2019; Received in revised form 14 January 2020; Accepted 5 February 2020

Our understanding of these trade-offs among ecological and socio-economic aspects of agroforestry is incomplete. Whether agroforestry can contribute to farmers' diverse goals remains a challenging question that lacks a universal answer.

Previous agroforestry research often uses econometric approaches to predict adoption based on household and farm characteristics (Pattanayak et al., 2003; Santos Martín et al., 2012; Simmons et al., 2002; Zabala et al., 2013). These positive research methods (describing what is or will be) help identify factors influencing adoption, but provide limited insights into the trade-offs of adopting agroforestry, especially within diversified farm land-use systems. In contrast, normative methods (describing what ought to be) to derive the optimal combination of land uses or management practices are a powerful tool to assess the suitability of different agroforestry systems for meeting farmers' objectives (Bertomeu and Giménez, 2006; Paul et al., 2017).

In this study, we use a normative optimisation model to assess if proposed agroforestry systems can help reduce trade-offs between farmers' objectives in Eastern Panama. Our model is based on a variant of goal programming, a continuous multi-criteria decision analysis (MCDA) technique. Goal programming has two main advantages for evaluating agroforestry. First, it allows us to consider multiple objectives when determining the optimal land-use allocation, to represent the diverse goals that can influence farmers' decision-making (Castro et al., 2018; Janssen and van Ittersum, 2007; Kaim et al., 2018). This advances on previous approaches that have used optimisation to evaluate agroforestry against a single objective only, usually profit maximisation or balancing risks and returns (Bertomeu and Giménez, 2006; Blandon, 2005; Ochoa et al., 2016; Paul et al., 2017). Second, goal programming can determine the best mix of land uses for achieving a set of objectives under uncertainty. It therefore allows us to account for the effects of land-use diversification to represent a whole farm perspective. This is important because diversification is a typical strategy among smallholders to reduce risk (Baumgärtner and Quaas, 2010; Di Falco and Perrings, 2005), and provide multiple products for subsistence needs (Ochoa et al., 2019; Pannell et al., 2014).

While goal programming has often been applied in forestry (Aldea et al., 2014; Diaz-Balteiro and Romero, 2008; Uhde et al., 2017) and agricultural contexts (Ballarin et al., 2011; Biswas and Pal, 2005; Knoke et al., 2015), applications to investigate agroforestry are scarce (García-de Ceca and Gebremedhin, 1991; Mendoza et al., 1987). Also missing are goal programming approaches that incorporate farmers' knowledge in the evaluation of land uses, which is vital to identify socially acceptable agroforestry systems (Garen et al., 2011; Plieninger and Huntsinger, 2018). Our study presents a variant of goal programming based on farmer knowledge and preferences, which we use to investigate the potential benefits and drawbacks of agroforestry systems from the farmers' perspective. Our research questions are:

> Will agroforestry appear in an optimised farm land-use composition that reduces trade-offs between multiple pre-defined farm objectives?
> Which of the pre-defined objectives best describe farmers' current land-use decisions, and is agroforestry compatible with these objectives?

2. Methods

2.1. Goal programming: a multi-criteria approach to simulate decisions of risk-averse farmers

Studies evaluating agroforestry against multiple criteria are quite rare. Those that exist usually rely on discrete MCDA methods to compare a finite set of land-use systems against various socio-economic and ecological criteria to generate a performance ranking of each land use. For example, Palma et al. (2007) used outranking (a method based on pairwise comparisons) to assess silvopastoral and conventional land-use systems in Europe against social and ecological indicators. Liu et al. (1998) combined the analytic hierarchy process (AHP) and multi-utility approaches to evaluate farm-forest systems against socio-economic objectives for landscape restoration in China. These discrete MCDA methods provide valuable insight into potential trade-offs between objectives. They can also identify the preferred land-use option for a given context, based on the performance of each land use against each objective and the decision-makers' weightings of those objectives. However, selecting the single most preferred land-use option may not reflect the reality of farmers' decision-making; farmers may be unlikely to allocate their farm land to a single land use, given the importance of diversification for reducing risk and meeting household needs (Baumgärtner and Quaas, 2010; Pannell et al., 2014).

To address this issue of land allocation we use a continuous MCDA method based on goal programming. This approach can consider an infinite number of land-use combinations and thus allows us to investigate the best mix of land uses to reduce trade-offs between a set of objectives. Moreover, because our approach accounts for uncertainty (i.e. potential fluctuations in the ability of a land use to achieve an objective), it captures the risk-reducing effects of land-use diversification (Knoke et al., 2016). These effects may strongly influence decisions of smallholder farmers, who are typically risk-averse (Baker et al., 2017; Bowman and Zilberman, 2013; Knoke et al., 2011; Pannell et al., 2014). Integrating uncertainty into MCDA represents a novel approach; it is often excluded from other multi-objective programming models (e.g. Chang et al., 1995; Estrella et al., 2014).

Applying goal programming to agricultural land-use decisions, however, requires knowledge of farmers' objectives. One approach is to select hypothesised objectives mechanistically, for example based on scientific literature or expert opinion (Sumpsi et al., 1997). Objectives can also be selected based on the stated goals of the decision-maker. This may be problematic, however, if farmers have difficulty to express their goals analytically (Kaim et al., 2018; Patrick and Blake, 1980). Alternatively, researchers can select objectives based on revealed preferences of the decision-maker, that is, objectives which are compatible with the decision-makers' actual behaviour, such as the farmer's current land-use (Sumpsi et al., 1997).

In this study we take a dual approach for selecting objectives (Fig. 1). First we optimise land-use allocation based on 10 socio-economic and ecological objectives identified from scientific literature. This analysis is intended to explore desirable land-use allocations for a compromise solution assuming a broad set of potential objectives. We then investigate the implicit goals that are revealed by farmers' current land-use decisions. This approach allows us to investigate whether agroforestry aligns with the key objectives driving farmers' decision-making. We define criteria that agroforestry must fulfil to better align with farmers' revealed goals, and therefore have a greater chance of adoption.

2.2. Measuring and reducing trade-offs with a min-max optimisation

Our optimisation model simulates the decisions of a risk-averse farmer, who allocates his or her land to different land uses in a way that minimises trade-offs in the achievement of pre-defined objectives. As input data we quantify the performance of six land-use options, l (described in section 2.6), against 10 socio-economic and ecological indicators, i (described in section 2.7), based on farmer interviews (see section 2.8). We solve the allocation problem using a robust optimisation technique developed by Knoke et al. (2015), which aims to secure minimum levels of single or multiple objectives when accounting for uncertainty. In our study uncertainty reflects variation in the ability of different land uses to achieve a given indicator. The robust optimisation technique has previously been used to analyse optimal land-use compositions in agricultural (Knoke et al., 2015, 2016) and forested landscapes (Messerer et al., 2017; Uhde et al., 2017). Our study is the first time the model has been applied at the farm level to evaluate agroforestry options.

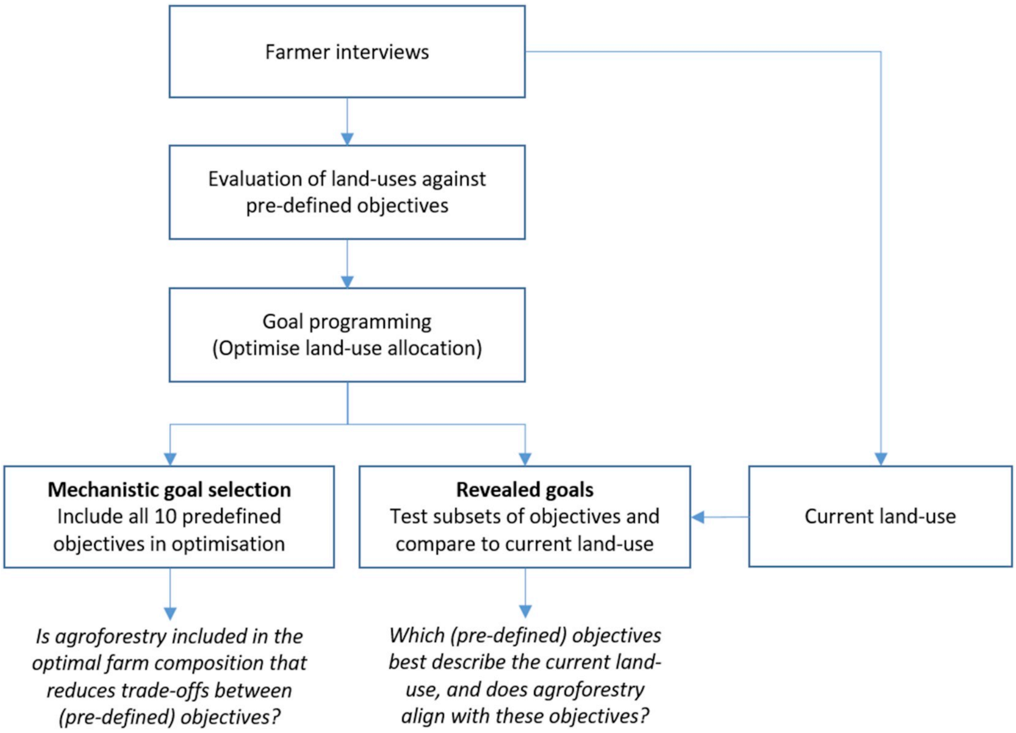


Fig. 1. Overview of research approach.

The optimisation model is formulated as a MIN-MAX (Chebyshev) problem, imitating a decision-maker who wants to improve the poorest performance across all objectives. For each indicator we set a target level, and the model chooses a solution (in our case a land-use composition) that minimises the maximum (worst) shortfall from the target level across all indicators (Romero, 2001). This objective function represents a non-compensatory approach – high performance in one indicator cannot compensate for low performance in another (Knoke et al., 2016). Instead, the model seeks a compromise solution that balances the achievement of different goals (Romero, 2001). This is a good match for our study, where we aim to minimise trade-offs between the achievement levels of different objectives. We define trade-offs as the shortfall between the best possible performance for an objective and the poorest performance achieved by a given land-use composition in a worst-case scenario.

Equations (1)–(4) formulate the optimisation problem. Our objective function is to minimise β (Eq. (1)), which denotes the worst underperformance of the land-use portfolio across all indicators, i, and uncertainty scenarios, u. We quantify underperformance with $\mathrm{D}_{\mathrm{i,u}}$, the distance between the target and achieved performance level of a given land-use portfolio for a given indicator. Uncertainty scenarios account for potential fluctuations in the ability of each land use to achieve each indicator, and are described in more detail below. Inequation 2 linearises the otherwise not smooth objective function (Tamiz et al., 1998) of minimising β; the inequation summarises individual constraints (representing 64 uncertainty scenarios for each indicator) as β on the left side and the distance to the target performance on the right side. To solve the allocation problem we define the land-use shares, a_l, as variables. This formulation of the problem can be solved by the Simplex algorithm, offering a global optimum (if it exists).

$$\text{Minimise } \beta \tag{1}$$

subject to:

$$\beta \geq D_{i,u}\ \forall_i \in \mathrm{I},\ \forall_u \in U_i \tag{2}$$

$$\sum_l a_l = 1 \tag{3}$$

$$a_l \geq 0 \tag{4}$$

We used Frontline Solvers Analytical Solver V2017-R2 (17.5.1.0) to carry out the optimisation, but it is also possible to use other optimisation software, for example the open source OpenSolver (2.9.0).

Input parameters for the model are the performance scores, $\widehat{y}_{i,l}$, of each land use for each indicator and the associated standard error, $SEM_{i,l}$, which we derive from the farmer interviews (Eq. (11)–(14), Table 4). These scores form our estimate of the ability of each land use to achieve each indicator. To account for the uncertainty inherent in the data (i.e. variability in farmers' opinion), the model considers potential deviations in the land-use scores. These deviations span from what we could expect in the best case (optimistic estimate, $y^{+}_{i,l}$), to what we could expect in the worst case (pessimistic estimate, $y^{-}_{i,l}$). For the optimistic estimate we use the mean score. For the pessimistic estimate we compute an unfavourable deviation, based on the $SEM_{i,l}$, the factor f_{U} and the direction of the indicator, i.e. whether higher or lower values are considered more desirable:

$$\text{Optimistic estimate } \mathrm{y}^{+}_{i,l} = \widehat{y}_{i,l}$$

$$\text{Pessimistic estimate } \mathrm{y}^{-}_{i,l} = \begin{cases} \widehat{y}_{i,l} - f_U \cdot SEM_{i,l} & \textit{if more is better} \\ \widehat{y}_{i,l} + f_U \cdot SEM_{i,l} & \textit{if less is better} \end{cases}$$

$$\text{for all indicators, } i = 1, 2, 3, \ldots, 10 \tag{5}$$

Because these deviations are based on the $SEM_{i,l}$, our measure of uncertainty reflects the variability in farmers' scoring and preferences. Moreover, by only focusing on unfavourable deviations of input values we assume that farmers are motivated to avoid losses. The factor f_U determines the size of these deviations and thus the uncertainty level assumed in the model, where $f_U = 0$ would exclude uncertainty, $f_U = 1.5$ represents a moderate level of uncertainty and $f_U = 3$ a high level of uncertainty (Knoke et al., 2016). We carried out each optimisation for seven discrete uncertainty levels equidistant between 0 and 3, to simulate the decisions of farmers with varying degrees of risk aversion. Uncertainty levels greater than $f_U = 3$ were excluded because they produce values far from the original land-use scores obtained during the interviews.

These optimistic and pessimistic estimates, which we refer to as uncertainty-adjusted values, $y_{i,l,u}$, form the basis of uncertainty scenarios, u. Each uncertainty scenario comprises a unique combination of optimistic and pessimistic estimates across the six land-use options. This results in an uncertainty set U_i comprising 2^L scenarios per indicator, where L is the number of land uses. The uncertainty scenarios can be seen in the optimisation sheet in the supplementary material, while Supplementary Fig. S1 gives a simplified example. In our study the optimisation considers up to 640 uncertainty scenarios (2^6 scenarios × 10 indicators).

The optimisation procedure applies the uncertainty-adjusted values to a hypothetical farm comprising various shares, a_l, of the six land uses. Specifically, it determines the farm-level performance, $Y_{i,u}$, of a hypothetical land-use composition for achieving each indicator in each uncertainty scenario. Farm-level performance is the sum of the uncertainty-adjusted values for each land use, weighted by the share of each land use in the hypothetical farm land-use portfolio:

$$Y_{i,u} = \sum_{l} y_{i,l,u} a_l \tag{6}$$

We then normalise the distance $D_{i,u}$ between the target level ($y^*_{i,u}$ or y_{i,u^*}) and the actually achieved level $Y_{i,u}$ between 0 and 100, where 100 represents the best possible performance for a given indicator and uncertainty scenario:

$$D_{i,u} = \begin{cases} \dfrac{y^*_{i,u} - Y_{i,u}}{\Delta_{i,u}} \cdot 100 \text{ } \textit{if more is better} \\[2ex] \dfrac{Y_{i,u} - y_{i,u^*}}{\Delta_{i,u}} \cdot 100 \text{ } \textit{if less is better} \end{cases} \tag{7}$$

$$\Delta_{i,u} = y^*_{i,u} - y_{i,u^*} \tag{8}$$

For "more is better" indicators, the best performance within an uncertainty scenario is given by the land use with the highest uncertainty-adjusted value, $y^*_{i,u} = \max_l \{y_{i,l,u}\}$. Conversely, for "less is better" indicators the best performance is given by the land use with the lowest uncertainty-adjusted value $y_{i,u^*} = \min_l \{y_{i,l,u}\}$. Finally, β represents the maximum $D_{i,u}$ across all indicators and uncertainty scenarios:

$$\beta = \max_{i,u} \{D_{i,u}\} \tag{9}$$

We use β to measure trade-offs between different indicators in the optimisation. Thus we measure trade-offs in terms of the worst underperformance (greatest distance between the achieved and target level) of any indicator across all uncertainty scenarios. This is the poorest performance that a farmer would have to accept for any indicator in a worst-case scenario. Conversely, $100 - \beta$ denotes the guaranteed performance of a hypothetical farm: the minimum performance attained for all indicators across all uncertainty scenarios, where 100% is the target level. We reduce trade-offs by finding the land-allocation that minimises the maximum underperformance, thereby increasing the guaranteed performance of a farm portfolio (Supplementary Fig. S2 illustrates this process).

2.3. Identifying farmers' implicit objectives

In the second part of the study we examine which objectives are most compatible with farmers' observed behaviour (i.e. their current land-use decisions recorded in the farmer interviews), given farmers' evaluation of the six land uses. To do this we include subsets of indicators (which we refer to as "indicator bundles") in the optimisation, and compare the optimised land-use composition for each indicator bundle with the current land-use composition. We list the indicator bundles in section 2.7. We assume that the indicator bundle that produces a land-use composition closest to the actual situation (i.e. the aggregated land-use composition of our sample), will best reflect the objectives driving farmers' actual decision-making. This follows the basic idea of previous studies that derived farmers' implicit preferences from empirical data of their behaviour (Amador et al., 1998; Gómez-Limón et al., 2002). It also reflects a positive use of the optimisation model, whereby we use the model to replicate farmers' actual land-use allocation (Schreinemachers and Berger, 2006).

We assessed the similarity between the ideal and current land-use compositions using the Bray-Curtis measure of dissimilarity, in line with Knoke et al. (2016). We computed the Bray-Curtis measure, $BC_{o,c}$, based on the land-use area shares, a_l, of the optimal (index o) and the current (index c) land-use portfolios. $BC_{o,c}$ values close to 0 indicate low dissimilarity and values close to 1 high dissimilarity.

$$BC_{o,c} = \frac{\sum_{l=1}^{6} \left| a_{l,o} - a_{l,c} \right|}{2} \tag{10}$$

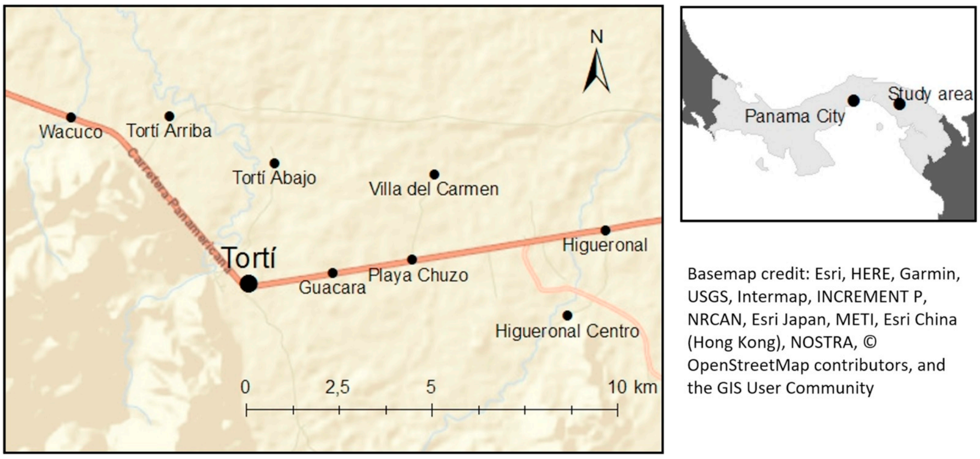
2.4. Study area

We demonstrate our modelling approach using farm data from a forest frontier region in Eastern Panama. Our study area centres around the township of Tortí and its neighbouring villages, about 125 km east of Panama City (Fig. 2). The natural vegetation is classified as humid tropical forest. Mean annual rainfall is 1910 mm, with a dry season from January to March when monthly rainfall is less than 22 mm (ETESA, 2019). The mean annual temperature is 26.4 °C and mean relative humidity 87.4%. The terrain is mostly flat and has an elevation of around 100 m above sea level; hills to the southeast reach 400 m in elevation (ANAM, 2010). Large-scale clearing began in Tortí in the 1970s, when settlers from western provinces started migrating to the area (Paul, 2014; Sloan, 2008). Settlers brought their cattle ranching practices from the west, and pasture now comprises 64% of farmland of the wider Tortí region (INEC, 2011; Paul, 2014). Soils are classified as vertisols; a high clay content limits agricultural productivity in the area (Paul, 2014), where crops make up 8% of the land use (INEC, 2011). Financial incentives for afforestation enacted in 1992 promoted large-scale plantations of teak (*Tectona grandis*) in the region, often owned by international timber corporations (Sloan, 2008). We identified the current land use of our farmer sample during the interviews.

2.5. Sampling and interview method

We obtained input data for the optimisation model via farmer interviews. We used a mixed sampling method to target farmers in the study area: 1) we randomly selected houses identified in an aerial photograph and asked the inhabitants if they manage agricultural land and would be willing to participate in the interview, 2) we approached farmers at a local cattle auction, and 3) we asked interviewees if they could recommend neighbours or acquaintances who may be willing to participate in the interview. Before starting the interview, we provided farmers with information about the purpose of the research and informed them that their participation was voluntary and all responses confidential.

The interview had two parts. We first collected household data and identified the current land use of each farm using a semi-structured interview and participatory resource mapping (Kumar, 2002), whereby farmers drew a map of their farm. In the second part we asked farmers their opinion about six pre-selected land uses. The interview took between 40 min and 3 h, and was usually carried out at the farmer's home or during a visit to their farm. All interviews were conducted in Spanish between April and May 2018. We obtained interview data for 35 farms, representing 2681 ha of managed land, with a mean farm size of



Basemap credit: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCAN, Esri Japan, METI, Esri China (Hong Kong), NOSTRA, © OpenStreetMap contributors, and the GIS User Community

Fig. 2. Tortí and the surrounding villages in Eastern Panama, where we interviewed farmers in April and May 2018.

77 ha (ranging from five to 271 ha). Eighty-one percent of the interviewed farmers depended on the farm for all or most of their household income.

2.6. Land-use options included in the optimisation model

Farmers evaluated six potential land uses in this study (Table 1). Pasture, cropland and teak plantation are the most common land uses in Tortí, whereas native forest represents a land-cover without active management (but for simplicity we refer to forest as a land use). Alley cropping and silvopasture are not widespread in the study area, and therefore these agroforestry systems represent alternative land-use options. While previous research found that living fences and scattered trees in pastures were common in Tortí (Schuchmann, 2011), our silvopastoral option represents a more intensive system with a much higher tree density. Alley cropping (growing annual crops between rows of trees) is not a common practice in Tortí, but a scientific trial carried out in the study area and coupled with bio-economic modelling found it to be an economically competitive land use (Paul et al., 2017).

The land uses included in this study represent land-use options available for inclusion in a stylised farm. Based on farmers' evaluation of each land-use option, the model determines an optimal land-use composition for reducing underperformance across socio-economic and ecological indicators. This optimal land-use composition is neither spatially explicit nor includes transition phases.

Table 1
Description of the six land-use options, *l*, which farmers evaluated during the interviews.

Land use	Description
Cropland	Various annual or (non-woody) perennial crops, either grown as a monoculture, a mix of crops on the same area, or rotated over time. Traditional planting method, with some herbicide and fertiliser use.
Pasture	Traditional pasture with a stocking rate of 1.5 to two cows per hectare, can include scattered trees.
Alley cropping	Trees and crops grown on the same parcel of land: lines of teak grown every 6 m, with maize (*Zea mays*) grown in between. Initial tree spacing is 3 × 6 m, representing 550 trees per hectare. Trees are grown for timber with a rotation length of 20 years; crops are no longer planted after year five due to shading.
Silvopasture	Trees and cattle on the same parcel of land: tree densities of around 200 trees per hectare on traditional pastures, with a stocking rate of one cow per hectare. Trees may be exotic or native, are either planted or regenerate naturally (in which case they are guarded). Trees may be harvested for timber after 20 years.
Plantation	Teak plantation, trees planted with 3 × 3 m spacing (initial tree density of 1110 trees per hectare), and are harvested after 20 years.
Forest	Natural forest of native species. May be used to collect firewood and fruits etc., but not for commercial timber production.

Of the farmers we interviewed, the aggregated land-use comprises 60% pasture, 26% crops, 13% forest and 1% plantation. We did not find any examples of alley cropping among the interviewed farms, nor did we find silvopastoral systems that met our definition of 200 trees per hectare. Nevertheless, other forms of agroforestry were present within our sample farms: living fences (recorded on 94% of farms) and scattered trees in pastures, with estimated tree densities on some farms approaching 30 trees per hectare.

2.7. Selection of objectives

Based on previous research in Panama and the tropics, we identified 10 criteria that could be relevant for farmers' land-use decisions in the study area (Table 2). These criteria function as performance measures that account for socio-economic (and also some ecological) motivations or constraints that may influence land-use selection among smallholders in Panama. The criteria also capture potential benefits and drawbacks of agroforestry systems. Discussions with farmers during the interviews confirmed the importance of these criteria for their decision-making. For this paper we refer to the criteria as indicators, and they serve as objectives in the optimisation. Direction refers to the most desirable state of an indicator (Romero, 2001).

Within the optimisation all objectives are weighted equally, to simulate the decision-making of a farmer seeking to balance the achievement of (and thereby reduce trade-offs between) all objectives. However, we also test the influence of weighing the indicators in a sensitivity analysis. We derived weights from the stated priorities of farmers (during the interviews we asked farmers which of the indicators were most important when deciding what to produce on their farm). To incorporate the weights in the optimisation we multiplied each $D_{i,u}$ by the weight, w_i, of the relevant indicator (see Supplementary Table S1, Eq. S1 and Fig. S7). In the second part of the study, we grouped the indicators into several bundles (Table 3), which we used to investigate the implicit objectives driving farmers' current land-use decisions. Although no weights were assigned to specific objectives in this analysis, a type of weighting was introduced through the in- and exclusion of specific indicators in the optimisation.

2.8. Deriving land-use performance scores

In MCDA selecting the alternatives to be evaluated and criteria against which they will be assessed is known as problem structuring. The next step is to estimate the performance of each alternative (in our case land use) against each criterion (indicator) (Saarikoski et al., 2016). We

Table 2

Description of the pre-defined 10 indicators, *i*, against which farmers evaluated the six land-use options. 'Protecting water supply' and 'protecting soil resources' are considered ecological indicators; all other indicators are classed as socio-economic. Direction refers to the most desirable state of an indicator.

i	Name	Description	Direction	Rationale
1	Long-term income	Profit made over 20 years	More is better	Profitability is an important characteristic influencing the adoption of land-use systems (Connelly and Shapiro, 2006; Coomes et al., 2008; Santos Martin and van Noordwijk, 2011)
2	Labour demand	Labour requirement (per hectare) needed to manage the land use	Less is better	Labour availability can be a key constraint for land-use decisions of smallholder farmers (Pichon, 1997; Santos Martin and van Noordwijk, 2011; Tschakert et al., 2007)
3	Meeting household needs	The degree to which the land use can meet household needs for food and materials	More is better	Smallholders may be constrained by the need to meet household food needs (Binh et al., 2008; Fischer and Vasseur, 2002; Tschakert et al., 2007)
4	Financial stability	The degree to which returns generated by the land use can withstand the effects of extreme weather events, pests and diseases and price fluctuations	More is better	The desire to minimise economic risk can strongly influence smallholders' land-use decisions (Connelly and Shapiro, 2006; Coomes et al., 2008; Santos Martin and van Noordwijk, 2011)
5	Liquidity	The degree to which the land use can provide regular cash income, including how easily the farmer can convert the investment to cash when needed	More is better	Cash flow can be an important concern or constraint for smallholder farmers (Coomes et al., 2008; Holmes et al., 2017)
6	Investment costs	The upfront costs of establishing the land use	Less is better	Given a lack of capital among smallholder farmers, high investment costs pose a potential barrier to agroforestry adoption (Calle et al., 2009; Connelly and Shapiro, 2006; Coomes et al., 2008)
7	Management complexity	The need for special equipment, machinery, skills and knowledge	Less is better	Increased management complexity and the need for specialised knowledge may represent a barrier to adoption (Calle et al., 2009; Connelly and Shapiro, 2006; Cubbage et al., 2012)
8	Protecting water supply	The degree to which the land use can improve the availability and quality of freshwater	More is better	Studies in Panama have found that farmers consider the need to protect water resources in their management decisions (Garen et al., 2009; Metzel and Montagnini, 2014)
9	Protecting soil resources	The degree to which the land use maintains soil health and fertility in the long-term	More is better	Avoiding productivity losses and fertility decline can influence smallholders' land-use decisions and be a strong incentive to adopt agroforestry (Calle et al., 2009; Garen et al., 2009)
10	General preferences	Farmers' preferences for each land-use option	More is better	Proxy for cultural benefits of each land use, to reflect less-tangible, intrinsic values not captured by the other criteria (Knoke et al., 2014; Scholte et al., 2015)

Table 3

Overview of the six indicator bundles tested in the optimisation.

Name	Indicators	Rationale
Socio-economic	Long-term income Labour demand Meeting household needs Financial stability Liquidity Investment costs Management complexity General preferences	Socio-economic indicators and farmer preferences (as a proxy for cultural benefits)
Ecological	Protecting water supply Protecting soil resources	Indicators reflecting environmental functions
Farmer priority	Meeting household needs Protecting water supply Protecting soil resources	Top three priorities expressed by sample during farmer interviews (see Table S1, supplementary material)
Long-term	Long-term income Financial stability	Reflect economic returns and risk from a long-term perspective (e.g. 20 years)
Short-term	Labour demand Meeting household needs Liquidity Investment costs Management complexity	Reflect shorter-term socio-economic goals
Immediate	Meeting household needs Liquidity	Subset of short-term goals that reflect basic, immediate needs of food security and cash flow (Affholder et al., 2010; Binh et al., 2008)

derive these estimates from the farmer interviews. Farmers rated the performance of each land use against the first nine indicators in a two-step process. This method combines elements from participatory research, for example to evaluate crop and land-use types (Drinkwater, 1993; Duguma and Hager, 2011), with matrix scoring methods to elicit expert opinion on ecosystem service provision (Burkhard et al., 2010). It also represents a discrete MCDA method to generate performance scores (which we then incorporate into goal programming, a continuous MCDA method). For each of the nine indicators, farmers arranged cards depicting each land use in order from best to worst for achieving that indicator. They then gave each land use a score between 0 and 10, where the highest ranked land use always received a score of 10. From the individual scores $y_{i,l,k}$, of each farmer, k, for each land use, l, against each indicator, i, we computed the mean score, $\hat{y}_{i,l}$:

$$\hat{y}_{i,l} = \frac{1}{K}\sum_{k=1}^{K} y_{i,l,k} \quad \text{for } i = 1,2,3,\ldots,9 \tag{11}$$

We then compute the standard error of the mean, $SEM_{i,l}$, where SD is the standard deviation:

$$SEM_{i,l} = \frac{SD_{i,l}}{\sqrt{K}} \quad \text{for } i = 1,2,3,\ldots,9 \tag{12}$$

To measure farmers' general preferences (indicator 10 in Table 2), we asked farmers to arrange the cards depicting each land use in order from the land use they like best to the land use they like least. Unlike the other indicators, our preference measure is not a mean score. Instead, following Knoke et al. (2014), our measure of preference $\hat{y}_{10,l}$ for a given land use, l, is the number of times that land use was ranked as the best or second best alternative:

$$\hat{y}_{10,l} = (\#best + \#second\ best)_l \tag{13}$$

The standard error of this estimate ($SEM_{10,l}$) was computed by:

$$p_l = \frac{\hat{y}_{10,l}}{\sum_l^L \hat{y}_{10,l}} = \frac{\hat{y}_{10,l}}{n}$$

$$SEM_{10,l} = n \cdot \sqrt{p_l \cdot (1 - p_l)/n} \tag{14}$$

where, n is the sum of all 'best' and 'second best' responses across all land uses, and p is the relative frequency of the responses 'best' and 'second best' for a given land-use option, l.

The land-use scores obtained from the farm interviews are shown in Table 4. On average, farmers rated plantation as the most profitable land use (mean score of 8.3 out of 10), and along with silvopasture the equal best for maintaining financial stability (mean scores of 7.8). They deemed cropland as the best land-use option for meeting household needs (mean score 9.6), and pasture the best for liquidity (mean score 9.9). Alley cropping was not rated as the best option for any indicator, but instead was considered the most complex land use to manage (mean score 8.6, where lower is better). Farmers rated forest as the best option for protecting soil and water resources, and for reducing labour demand, investment costs and management difficulty. Overall, participants expressed a strong general preference for silvopasture and pasture; they selected these land uses as the best or second best option 23 and 21 times respectively.

3. Results

3.1. Agroforestry and the achievement of multiple objectives at the farm level

The ideal farm composition for balancing the achievement of the 10 indicators is dominated by silvopasture and forest (Fig. 3). The predominance of silvopasture in the ideal farm reflects farmers' generally positive scoring of this land use; it was among the top three performers for eight of the indicators (Table 4). In contrast, alley cropping was absent from the ideal farm composition, reflecting its less favourable rating; it was among the three worst performing land uses across all indicators. Forest is included because of its superior performance for the two ecological indicators (protecting water resources and maintaining soil fertility), and the three "less is better" indicators (management complexity, labour demand and investment costs).

The composition of the ideal farm is relatively stable across increasing uncertainty levels. When ignoring uncertainty ($f_U = 0$), the ideal farm would comprise 46% silvopasture, 41% forest and 13% crops. This shows that even in the absence of uncertainty, land-use composition would be diversified to satisfy multiple objectives. The share of silvopasture increases with rising uncertainty, for example by 15 percentage points from $f_U = 0$ to $f_U = 2$. In contrast, the proportion of cropland declines until it is absent from the portfolio at $f_U = 2$, from which point the share of plantation increases. Pasture only appears in the portfolio at high levels of uncertainty, whereas alley cropping is completely absent for this range of f_U.

Excluding silvopasture and alley cropping from the optimisation helps us examine how the agroforestry systems can reduce underperformance of (and thereby trade-offs between) multiple objectives at the farm level. With both agroforestry options excluded, the ideal farm comprises pasture, plantation and forest (see Supplementary Fig. S3a). Fig. 4 compares the guaranteed performance of the optimised farm land-use portfolio that includes agroforestry (green line) to the optimised portfolio when agroforestry is excluded (red line), with the performance of the current land-use composition (blue line) given as a reference. Including agroforestry (in this case silvopasture) in the land-use portfolio achieves the highest minimum performance, i.e. provides the best portfolio (corresponding to the portfolio depicted in Fig. 3) for avoiding underperformance in any of the considered indicators across all uncertainty levels. This means that this composition does the best job of reducing trade-offs among objectives. Excluding agroforestry from the optimisation reduces the guaranteed performance across all indicators, meaning a farmer would need to accept a higher level of underperformance across the 10 indicators. This equates to an average reduction in guaranteed performance of 11 percentage points across $f_U = 0$ to $f_U = 3$ (compare green and red lines in Fig. 4).

This lower achievement level can be attributed to poorer performance of three indicators in worst case scenarios: economic stability,

Table 4
Mean scores ($\hat{y}_{i,l}$) and their standard errors (±SEM) obtained from the farmer interviews for each land use, l, and indicator, i (except general preferences) where 0 = low and 10 = high. Superscript denotes the direction of the indicator: (^{a}) = more is better, (^{b}) = less is better. Values for general preferences represent the number of times a land use was chosen as the best or second best option ($\hat{y}_{10,l}$). Values collectively comprise the input data for the optimisation model.

Indicator	N*	Cropland	Pasture	Alley cropping	Silvopasture	Plantation	Forest
Long-term income^a	32	6.3 ± 0.40	7.9 ± 0.40	7.1 ± 0.32	7.8 ± 0.31	8.3 ± 0.42	3.0 ± 0.47
Labour demand^b	32	8.3 ± 0.37	7.2 ± 0.36	7.8 ± 0.33	6.9 ± 0.30	6.5 ± 0.47	1.6 ± 0.38
Meeting household needs^a	32	9.6 ± 0.22	8.4 ± 0.23	6.8 ± 0.36	8.0 ± 0.22	4.3 ± 0.40	3.9 ± 0.51
Stability^a	32	5.7 ± 0.45	7.0 ± 0.53	6.4 ± 0.35	7.8 ± 0.42	7.8 ± 0.42	5.7 ± 0.67
Liquidity^a	32	7.5 ± 0.33	9.9 ± 0.07	5.9 ± 0.38	8.7 ± 0.28	5.2 ± 0.40	2.9 ± 0.47
Investment costs^b	32	7.3 ± 0.37	8.1 ± 0.37	7.4 ± 0.43	7.6 ± 0.36	7.3 ± 0.48	1.3 ± 0.33
Management complexity^b	32	8.1 ± 0.40	6.8 ± 0.36	8.6 ± 0.31	7.6 ± 0.32	7.0 ± 0.47	1.9 ± 0.38
Protecting water^a	32	4.0 ± 0.43	4.7 ± 0.41	6.8 ± 0.26	7.6 ± 0.21	7.2 ± 0.44	9.9 ± 0.09
Protecting soil^a	32	5.5 ± 0.46	5.0 ± 0.32	6.5 ± 0.40	6.9 ± 0.32	6.6 ± 0.46	9.1 ± 0.38
General preferences^a	35	15 ± 3.44	21 ± 3.85	11 ± 3.05	23 ± 3.94	0 ± 0.00	1 ± 0.99

*The three most elderly participants were not able to complete the scoring for the nine indicators, but they were able to provide their general preference.

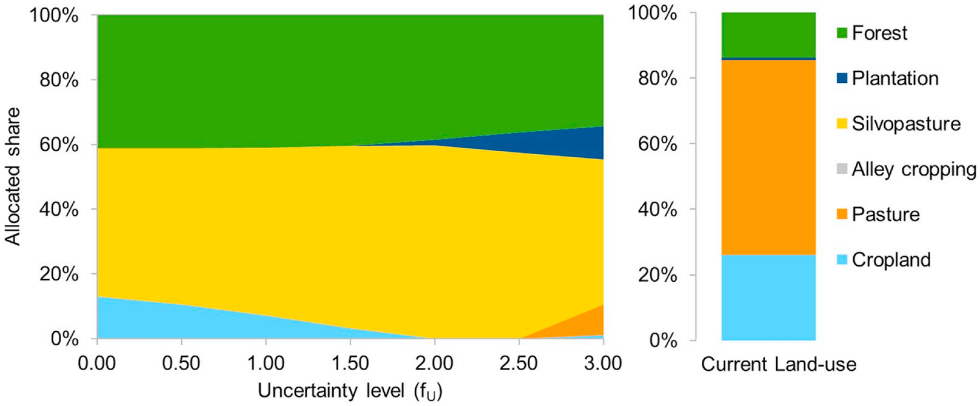


Fig. 3. Composition of the ideal farm (share of land area allocated to each land-use option) under increasing levels of uncertainty, f_U, when including the 10 indicators in the optimisation (left panel), compared to the aggregated current land-use composition of interviewed farmers (right panel).

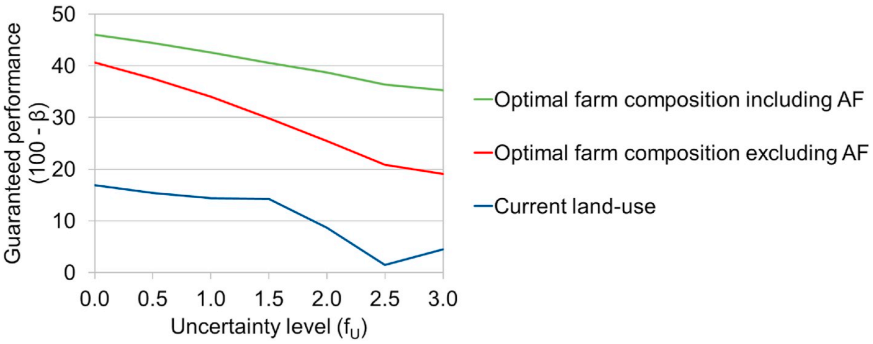


Fig. 4. Guaranteed performance (100 – β, where 100% is the target level) of the current land use compared to the optimised farm composition including and excluding agroforestry (AF), over increasing levels of uncertainty, f_U, when considering the 10 indicators in the optimisation.

investment costs and general preferences (see Supplementary Fig. S4). When agroforestry is excluded from the optimal portfolio composition, the share of pasture and plantation in the portfolio increases, while the share of forest declines. At a moderately high level of uncertainty ($f_U = 2$), the higher share of plantation drives underperformance of investment costs in pessimistic scenarios, whereas the higher share of pasture contributes to unstable economic returns. The lower performance for the general preference indicator reflects a general dislike of plantations as well as relatively low scores for pasture in pessimistic scenarios. From these shifts we learn that including silvopasture in the optimal land-use portfolio can help reduce trade-offs between a) economic stability, investment costs and farmers' general preferences, and b) the other socio-economic and ecological objectives.

Weighing the indicators based on farmers' stated priorities emphasises protecting water resources (see Supplementary Table S1). This further favours agroforestry in the optimal land-use portfolio, which comprises 73% silvopasture and 27% forest at $f_U = 2$ (Supplementary Fig. S7). Weighing all indicators equally or including weighing factors thus led to quite similar optimised land-use compositions, both dominated by silvopasture and forest. However, we found that many farmers had difficulty to identify which of the pre-defined objectives were most salient to their decision-making, and we often stopped the interview at this point. For example, of the 25 farmers who answered this question, four said that all the objectives were important, but could not specify if some were more important than others. Our weights may therefore not be a reliable measure of farmers' true priorities. We therefore abstained from using weighing factors in the main analysis, and instead include farmers' stated land-use preferences as one of the 10 indicators in the optimisation, and focus on identifying the implicit priorities revealed by farmers' observed behaviour.

3.2. Objectives driving farmers' decision-making

This section presents the ideal farm compositions for achieving different indicator bundles, as a means to explore the implicit preferences driving farmers' current land-use decisions. We present portfolios for a moderately high level of risk aversion ($f_U = 2$), but findings for other levels of uncertainty showed a similar pattern (Supplementary Fig. S5). Optimising for socio-economic goals only (i.e. excluding the two ecological indicators), generates an ideal farm composition identical to the one selected when optimising for 10 indicators (compare second bar in Fig. 5 with Fig. 3 for $f_U = 2$). This demonstrates complementarity between objectives: here the three "less is better" indicators (which promote forest in the land-use portfolio) help to satisfy the ecological goals. When optimising for the ecological goals only, forest dominates the ideal farm composition. Both these portfolios deviate strongly from the current land use (Bray-Curtis values = 0.86), suggesting that both the socio-economic and pure ecological objectives are a poor proxy for farmers' actual goals. When optimising for the "farmer priority" indicator bundle, the ideal farm composition contains a large share of silvopasture. A moderately high Bray-Curtis value (0.60) suggests a mismatch between farmers' stated priorities and the implicit priorities revealed by their actual land-use decisions. For comparison, the optimal portfolio that weighed all indicators (apart from general preferences) based on the farmers' stated priorities also did not align with the current land-use (Bray-Curtis = 0.86).

Looking at the gradient from long-to short-term goals, the ideal land-use portfolios become more similar to the current land use (shown by

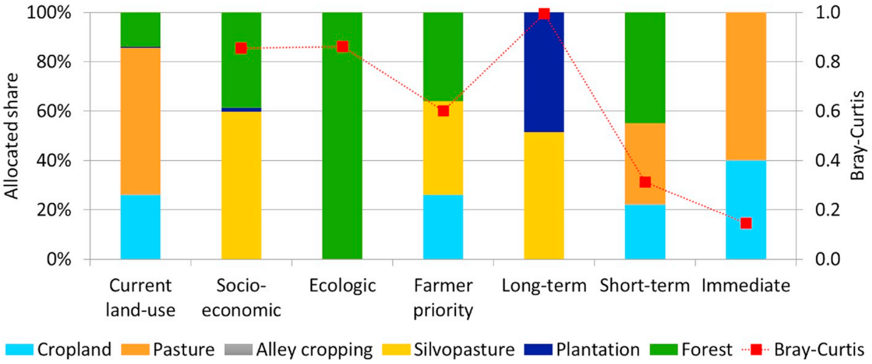


Fig. 5. Ideal farm composition (share of land area allocated to each land-use option, left axis) when optimising for each indicator bundle for a moderately high level of risk aversion ($f_U = 2$). The first column represents the current (aggregated) land use. Points represent the Bray-Curtis measure of dissimilarity ($BC_{o,c}$, right axis) between the ideal and current land-use composition for each indicator bundle.

declining Bray-Curtis values, Fig. 5). This suggests that when making land-use decisions, farmers may prioritise shorter- and immediate-term needs over longer-term goals of profit maximisation and risk reduction. In fact, the closest similarity was achieved when optimising for the two indicators in the "immediate" bundle (Bray-Curtis = 0.15). This suggests that together liquidity and meeting household needs do a better job of explaining farmers' decision-making than any other indicator bundle or single objective (see also Supplementary Fig. S6).

Comparing the guaranteed performance of the current and optimised farm composition when considering a) all 10 indicators, or b) the two "immediate" indicators, provides further insight into potential trade-offs between objectives and the rationale behind farmers' current land-use decisions. We see that the guaranteed performance level of the current land use is much closer to that of the ideal farm when optimising for the two "immediate" indicators (Fig. 6). This demonstrates that while the current land use may not be optimal for reducing underperformance across the 10 objectives, it represents a rational choice if farmers are trying to maintain liquidity and meet household consumption needs. Further, the guaranteed performance level is much lower when optimising for the 10 indicators. This shows that balancing the achievement of the 10 socio-economic and ecological indicators results in considerable trade-offs: farmers would have to accept much lower performance across the indicators, compared to if they focus on the two "immediate" objectives only. When optimising for all 10 objectives, the worst performing indicators are: investment costs, financial stability and meeting household needs, driven by the poor performance of silvopasture against these indicators in pessimistic scenarios.

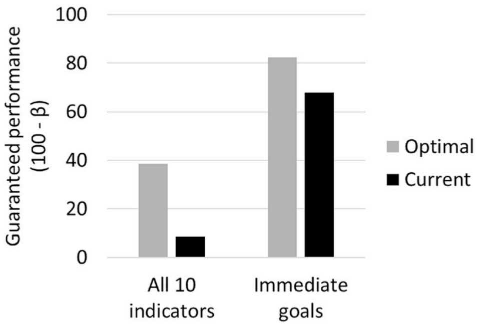


Fig. 6. Guaranteed performance (100 – β, where 100% is the target level) of an ideal farm composition (grey bars) and current land-use composition (black bars) when optimising for the 10 socio-economic and ecological indicators or the immediate indicator bundle (see Table 3). Results are given for a moderately high level of risk aversion ($f_U = 2$).

4. Discussion

4.1. *Agroforestry to enhance farmers' multiple goals*

Our optimisation approach allows the decision-maker to explore the optimal mix of land uses for achieving different sets of objectives while considering possible worst-case performance of each land use. This ability to account for both uncertainty and within-farm land-use diversification is a novel contribution not included in previous studies using multi-criteria methods to evaluate agroforestry (e.g. Liu et al., 1998; Mendoza et al., 1987; Palma et al., 2007). Moreover, by testing two methods for selecting objectives within the optimisation, we demonstrate a versatile approach for exploring the extent to which agroforestry should be embedded in diversified farm systems to satisfy different goals.

The mechanistic selection of objectives allowed us to examine agroforestry's potential to reduce trade-offs between a broad set of socio-economic and ecological goals taken from scientific literature. We found that when optimising for the 10 indicators, silvopasture dominated the ideal land-use portfolio: including silvopasture in the portfolio helped to secure a higher level of minimum performance across the objectives. In particular, as an alternative to conventional pasture and teak plantation, silvopasture helped to achieve a land-use composition with improved economic stability, lower investment costs and better compliance with farmers' preferences (as a proxy for cultural services). However, farmers did not evaluate the two agroforestry systems equally. The more favourable ratings for silvopasture compared to alley cropping in our study suggest that the farmers may be more receptive to agroforestry systems that allow them to continue to raise livestock and therefore align with the 'cattle culture' of Panamanian farmers (Connelly and Shapiro, 2006; Peterson St-Laurent et al., 2013).

The strong divergence between the optimal land-use portfolio and the current land use of our sample raises an important question: if farmers evaluate silvopasture so favourably, why is it not widely adopted in the study area? Forest is also overrepresented in the ideal land-use composition compared to its current share in the landscape, while pasture is underrepresented. One explanation for these discrepancies is that the farmers do not aim to balance the 10 socio-economic and ecological indicators when making land-use decisions. Therefore the positive application of the otherwise normative optimisation model (Schreinemachers and Berger, 2006) becomes important to explore which of the pre-defined objectives may be most important for farmers' actual land-use decisions.

Results suggest that maximising long-term income and reducing economic risk are a poor fit for explaining farmers' current land-use decisions. This speaks against a pure profit maximising/risk minimising objective when modelling land-use decisions (e.g. Bertomeu and

Giménez, 2006; Blandon, 2005; Ochoa et al., 2016; Paul et al., 2017). Instead, we observed that shorter-term objectives could better explain farmers' current land-use decisions. Meeting household needs and liquidity appear to be particularly important. The tendency for smallholder farmers to prioritise basic, immediate-term needs for food and cash has been recognised in other studies. For example, Affholder et al. (2010) and Umar (2013) used a "safety first" model, in which farmers first seek to secure household consumption needs before pursuing economic goals such as maximising income. Meeting these basic needs can constrain resource-poor farmers' ability to invest in new land-use systems, potentially creating a trade-off with long-term productivity benefits (Affholder et al., 2010; Binh et al., 2008; Pannell et al., 2014). High discount rates associated with subsistence farming can also contribute to preferences for cattle ranching (which can generate income quickly and frequently) over timber-based systems that represent a long-term investment with few opportunities for an early income (Frey et al., 2012; Garen et al., 2009; Sloan, 2008).

From a policy perspective, results highlight key requirements that agroforestry must fulfil to be more attractive to farmers in the study area. We contend that silvopasture (as defined in our study) may not align with these key requirements. If farmers prioritise liquidity and meeting household needs over long-term profit and economic stability, then pasture (with scattered trees) and not silvopasture (with 200 trees per hectare) would be the rational land-use choice for a risk-averse decision-maker. This demonstrates the need to select and promote agroforestry systems that provide early and frequent income flows, as well as ongoing opportunities to harvest food crops. In our example, this could mean silvopastoral systems with tree or woody species providing fodder (thus allowing higher stocking rates), or alley cropping systems with lower tree densities (to reduce the canopy shading effects on annual crops).

4.2. Incorporating farmer knowledge into land-use models

By coupling our optimisation approach with interview data, we present an objective method to account for farmers' empiric knowledge and subjective preferences in land-use planning decisions. This addresses growing calls to integrate local knowledge and preferences into land-use planning and the assessment of ecosystem services (Díaz et al., 2018; Scholte et al., 2015), including to inform the design of agroforestry systems (Plieninger and Huntsinger, 2018). An innovative aspect of our modelling approach is that it actively accounts for variability in farmers' opinion (as reflected by the SEM of the land-use scores), when selecting the optimal land-use composition. Therefore, our optimised land-use portfolio does not portray the ideal land use for a specific farmer, but instead represents a land-use composition that should be acceptable for a range of farmers in a given area. The optimised land-use portfolios may therefore provide a useful starting point for stakeholder group discussions as part of participatory land-use planning. In this study the optimisation treated all objectives equally, to allow a clear analysis of the trade-offs between them. However, indicator weights could be included in a second modelling stage, to reflect the preferences and priorities of different groups of farmers as part of a participatory approach (Paul et al., 2019; Saarikoski et al., 2016). Our sensitivity analysis shows that weighing indicators might lead to similar optimisation results, but we relied on a rudimentary measure of farmer priorities. Future studies could therefore refine the method for obtaining indicator weights, for example through in-depth group discussions or AHP pairwise comparisons.

The credibility of our optimal land-use portfolios rests on the validity of land-use scores generated through the farmer interviews, i.e. the extent to which the scores accurately capture farmers' perceptions of each land use. While scarce data makes it difficult to triangulate results, we find that the farmers' land-use ratings appear plausible and are generally consistent with the scientific literature. For example, farmers evaluated the two agroforestry systems as better than pasture and cropland for protecting soil and water resources, consistent with a large body of studies reporting ecological benefits of agroforestry (Dagang and Nair, 2003; Fischer and Vasseur, 2000; Jose, 2009). Farmers also rated silvopasture and alley cropping as more difficult to manage than conventional pasture and cropland respectively. Agroforestry studies often cite increased management complexity as a barrier to adoption (Calle et al., 2009; Cubbage et al., 2012), and the complicated tree-harvesting permit system in Panama may hinder the development of agroforestry systems (Fischer and Vasseur, 2002; Somarriba et al., 2012). Farmers' evaluation of alley cropping as more profitable and financially stable than conventional crops, but less able to meet household needs and maintain liquidity, is also consistent with bio-economic modelling of alley cropping and maize monocultures in the study area (Paul et al., 2017). Finally, farmers expressed a strong preference for the two cattle-based systems, which accords with the high social standing of cattle grazing in Panama (Connelly and Shapiro, 2006; Peterson St-Laurent et al., 2013).

We acknowledge that the small sample size and partial reliance on non-random sampling limits our ability to generalise results to other farmers. A dataset such as ours, however, can be compiled with reasonable effort, and thus may be a realistic basis for participatory policy-making. Moreover, when deriving the optimal land-use composition the model accounts for variability in farmer opinion, based on the SEM, which is itself dependent on the sample size (Eqs. (12) and (14)). This helps to buffer against the uncertainty associated with data obtained from a relatively small group of farmers.

4.3. Outlook for research

We have argued that silvopasture (with 200 trees/ha) is not included in the current land use of our farmer sample, despite its favourable ratings for many of the socio-economic and ecological indicators, because it does not align with the key objectives driving farmers' land-use decisions. We thus contend that meeting household needs and maintaining liquidity may hinder the adoption of agroforestry in our study area.

However, other factors not captured in our optimisation approach may also limit the adoption of silvopasture. For example, personal characteristics of the farmer including their social networks and self-efficacy, as well as their access to land, labour and capital assets, may influence the farmer's ability to implement new land-use systems (Hettig et al., 2016; McGinty et al., 2008). While it may be difficult to incorporate social-psychological variables into the modelling approach, household factors can be more easily integrated in the optimisation. A potential extension of the modelling approach would thus be to incorporate the resource endowments of individual (or groups) of farmers via "hard constraints". This could include specifying thresholds for labour demand or investment costs, which cannot be exceeded within a land-use portfolio. Another option would be to account for heterogeneous site conditions, which are likely to affect the socio-economic and ecological performance of different land-use systems. For example, European studies have found that the site quality affects the relative advantage of agroforestry compared to conventional agriculture for providing different ecosystem services (Palma et al., 2007; Tsonkova et al., 2014). Extending the modelling approach to account for site heterogeneity and resource constraints could generate relevant and site-specific results, and therefore add extra value to the model as a tool to support land-use planning discussions.

Understanding farmers' perceptions of agroforestry and conventional land-use systems is important, because perceptions, and not necessarily objective fact, shape farmers' land-use decisions (Frey et al., 2012; Pannell et al., 2014). Nevertheless, many of the indicators included in this study could also be calculated through measured and modelled data (e.g. based on expected yields and prices). Running the optimisation with computed input data could further assess the plausibility of model results, and identify possible biases or gaps in farmer knowledge. Using modelled data would also help to tease out the role of tree-crop-livestock interactions (such as risk of pests and diseases, competition and facilitatory effects and economies of scope) in determining the optimal land-use composition; these interaction effects are currently not made explicit in our modelling approach.

5. Conclusion

Our modelling approach allows us to investigate the potential of agroforestry to reduce trade-offs between various farm level goals. Based on farmers' evaluation of different land-use systems at our example study site, we found including silvopasture in a diversified farm portfolio may help to secure pre-defined socio-economic and ecological objectives. However, further analysis revealed that silvopasture may not align with the implicit goals that explain farmers' current land-use decisions, and we identified liquidity and meeting household needs as potential barriers to adoption. This comparison between a purely mechanistic and positive use of the optimisation approach may therefore help to derive recommendations for policy makers. For example in our study region, increasing agroforestry adoption may rely on identifying and promoting systems that provide early and constant income flows, as well as the ongoing opportunity to harvest food crops. A further strength of our modelling approach is its ability to account for variability in farmer opinion, which may make it a useful starting point for group discussions in participatory land-use planning. While we tested the approach in Eastern Panama, it would be easily transferrable to examine sustainable land-use systems in other tropical and temperate regions.

Declaration of competing interest

None.

CRediT authorship contribution statement

Elizabeth Gosling: Investigation, Formal analysis, Writing - original draft. **Esther Reith:** Investigation, Writing - review & editing. **Thomas Knoke:** Methodology, Supervision, Writing - review & editing. **Carola Paul:** Conceptualization, Funding acquisition, Writing - review & editing.

Acknowledgements

This work was supported by the German Research Foundation (DFG) – Grant PA 3162/1. We are very grateful to Andrés Gerique for his input on the survey design, and for the assistance of Rodrigo Duarte, Peter Glatzle and Alyna Reyes during the farmer interviews. We warmly thank all the farmers who shared their knowledge and experience with us, as well as Karen Grosskreutz and Allyson Cappello for their language editing of the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2020.110248.

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Paper 3

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

Agroforest Syst
https://doi.org/10.1007/s10457-020-00519-0

Exploring farmer perceptions of agroforestry via multi-objective optimisation: a test application in Eastern Panama

Elizabeth Gosling · **Esther Reith** · **Thomas Knoke** · **Andrés Gerique** · **Carola Paul**

Received: 6 August 2019 / Accepted: 18 June 2020

Abstract Understanding farmers' perceptions of and preferences towards agroforestry is essential to identify systems with the greatest likelihood of adoption to inform successful rural development projects. In this study we offer a novel approach for evaluating agroforestry systems from the farmer perspective. The approach couples rapid rural appraisal and normative optimisation techniques to determine favourable land-use compositions for meeting various socio-economic and ecological goals, based on farmers' empirical knowledge and preferences. We test our approach among smallholder farmers in Eastern Panama, obtaining data from household interviews and using hierarchical cluster analysis to identify farm groups with similar land-use and income characteristics. We found that moderate differences in farmers' perceptions between these groups altered the type and share of agroforestry included in the optimised land-use portfolios that balance the achievement of 10 pre-selected socio-economic and ecological objectives. Such differences provide valuable information about potential acceptability of agroforestry within each group. For example, we found that farmers who derive most of their farm income from crops may be more willing to adopt silvopasture, whereas farmers who are more economically dependent on cattle may benefit from diversifying their land-use with alley cropping. We discuss the potential of this modelling approach for participatory land-use planning, especially when dealing with small sample sizes and uncertainty in datasets.

Keywords Alley cropping · Hierarchical cluster analysis · Land allocation · Participatory rural appraisal · Robust optimisation · Silvopasture

Introduction

Agroforestry has clear potential to enhance ecosystem services within agricultural landscapes of tropical

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Electronic supplementary material The online version of this article (https://doi.org/10.1007/s10457-020-00519-0) contains supplementary material, which is available to authorized users.

E. Gosling (✉) · E. Reith · T. Knoke
Institute of Forest Management, TUM School of Life Sciences Weihenstephan, Technische Universität München, Hans-Carl-von-Carlowitz-Platz 2, 85354 Freising, Germany
e-mail: elizabeth.gosling@tum.de

A. Gerique
Department of Geography, Friedrich-Alexander University of Erlangen-Nürnberg, Wetterkreuz 15, 91058 Erlangen, Germany

C. Paul
Department of Forest Economics and Sustainable Land Use Planning, University of Göttingen, Büsgenweg 1, 37077 Göttingen, Germany

regions (Jose 2009). However, like any agricultural innovation, farmers will only integrate trees into their farming systems if they perceive agroforestry to align with their objectives and available resources (Pannell et al. 2006). Farmers' attitudes towards agroforestry will therefore play a key role for adoption (Frey et al. 2012; Meijer et al. 2014). Understanding how farmers perceive the advantages and drawbacks of different agroforestry systems will help to identify systems that best meet farmers' needs, and to target extension activities accordingly.

Previous research into farmers' knowledge and perceptions of agroforestry has typically relied on qualitative methods (e.g. Calle et al. 2009; Frey et al. 2012; Garen et al. 2009; Hand and Tyndall 2018). Quantitative studies are less common and have been mostly limited to temperate regions (Laroche et al. 2018; Shrestha et al. 2004). Quantitative data, however, are often needed for land-use modelling approaches. These models can help analyse trade-offs between various objectives achieved by different farming and agroforestry systems, providing a powerful decision support tool for researchers, policymakers and land managers (Kaim et al. 2018; Le Gal et al. 2011). Farm level models can also serve as a discussion aid to support co-learning between researchers and farmers (Le Gal et al. 2013; Voinov and Bousquet 2010).

Our study combines positive and normative approaches to investigate farmers' perceptions of agroforestry and conventional land-use systems (Fig. 1). We obtain quantitative data from farmer interviews using a rapid rural appraisal technique in which farmers evaluated the ability of six land-uses to achieve 10 pre-defined socio-economic and ecological objectives. In the first (empiric) analysis stage we aim to understand potential differences in how distinct groups of farmers perceive agroforestry. We use hierarchical cluster analysis to group farms with similar land-use and income strategies. It is known that farm and household characteristics can influence farmers' attitudes towards agricultural innovations (Meijer et al. 2014; Pannell et al. 2006). Therefore, we are interested to compare the perceptions of each farmer group to check for potential differences in how they rated agroforestry relative to the conventional land-use systems.

Empiric ratings, however, may not be enough to understand farmers' potential land-use decisions when striving to meet multiple household goals under uncertainty. These ratings can identify the best land-use for achieving a single objective, but identifying the best mix of land-uses to achieve multiple objectives is more difficult, especially if accounting for farmers' uncertainty about the ability of each land-use to achieve each objective. This uncertainty is important, given that in regions where agroforestry is not widespread, farmers may vary considerably in their knowledge and familiarity of the systems. Therefore, empiric ratings alone may be insufficient to assess agroforestry's potential to help meet the multiple needs and constraints of heterogeneous farmer groups.

In the second stage of the analysis we therefore move to a mechanistic, multi-objective modelling approach, to investigate if agroforestry, as part of a diversified land-use portfolio, might help to reduce trade-offs between farm-level goals. Based on the land-use perceptions of each group of farmers we derive theoretically optimal land-use compositions that balance the achievement of the pre-defined socio-economic and ecological objectives under uncertainty. This allows us to look beyond farmers' existing land-use decisions to investigate the likelihood of different farmer groups to adopt agroforestry.

Testing this approach in a forest frontier region of Eastern Panama, our research questions are:

- How do farmers with different land-use and income strategies perceive agroforestry relative to existing land-use systems?
- Will the type and share of agroforestry selected in an optimised land-use portfolio differ between farms with different land-use and income strategies?

By exploring these questions we aim to show how the coupled rapid rural appraisal and optimisation approach may help tailor policy recommendations to different groups of farmers, and to demonstrate its potential for informing group discussions in participatory planning processes.

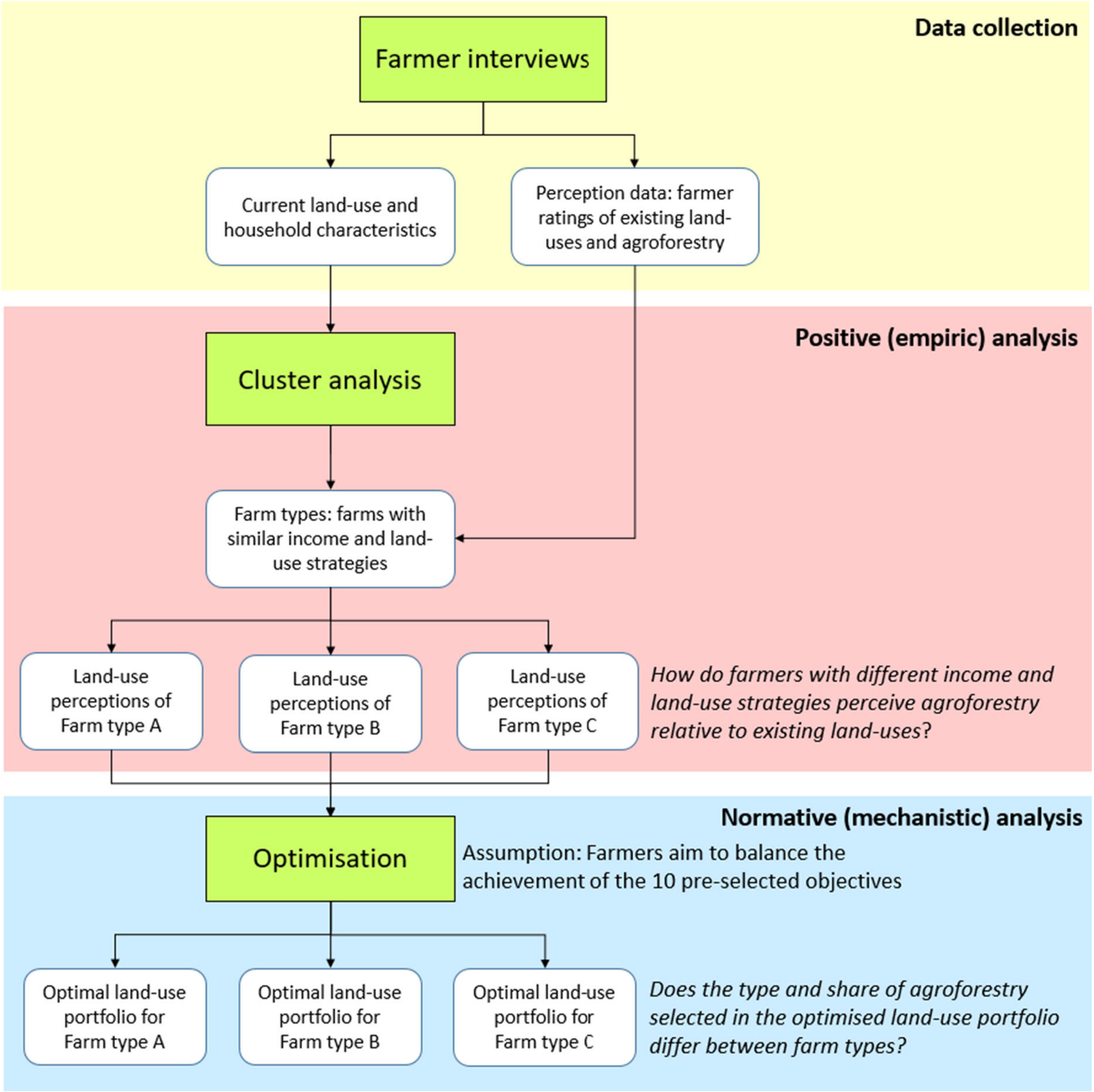


Fig. 1 Overview of research approach

Methods

Data collection

Study area and sampling method

We test our modelling approach with farmers in Tortí, a township with around 1600 inhabitants (INEC 2010) on the Pan-American Highway, around 125 km east of Panama City. The natural vegetation of the area is classed as humid tropical forest, with 1910 mm annual rainfall and a dry season from January to March (ETESA 2018). Large-scale forest clearing began five decades ago, when colonists from Panama’s western provinces began to settle in the region. Pasture for cattle grazing now comprises 64% of the land-use of the wider Tortí region, with 17% forest cover, 8% cropland and 8% fallow land (INEC 2011).

We targeted farmers using a mixed sampling method: going door-to-door in Tortí and its surrounding villages, approaching landholders at a local cattle auction, and asking interviewees to suggest other farmers. The interview had two parts. First we used a semi-structured questionnaire and participatory resource mapping (where farmers drew a map of their farm), to identify the current land-use composition of each farm and obtain household data. We used this data to identify groups of similar farmers via a cluster analysis. In the second part of the interview we quantified farmer opinion of different land-uses. We used this data to compare the perceptions of the different farm groups and to derive the optimised land-use portfolios for each group. The interviews took 40 min to 3 h to complete and were conducted in Spanish in April–May 2018.

Selected land-uses and indicators and their rapid appraisal

Our study quantifies farmers' perceptions of six land-uses (Table 1) against 10 socio-economic and ecological indicators (Table 2). Pasture, cropland, teak plantation and natural forest represent the most common land covers in the study area. In contrast, alley cropping and silvopasture (with a tree density of $\approx$ 200 trees per hectare) are not commonly practiced in Tortí: these two agroforestry systems represent innovative land-use systems for the region.

The 10 indicators against which farmers evaluated each land-use were identified from previous studies in Panama and Latin America (Table 2). They reflect different goals that farmers may consider when deciding what to produce on their farm, as well as potential benefits and drawbacks of agroforestry.

Borrowing techniques from rapid rural appraisal (Riley and Fielding 2001), we used ranking and scoring to quantify farmers' judgement of each land-use against each indicator. Before starting the evaluation task we described the land-uses with visual aids, discussing each system with the farmer to ensure a common understanding. Next we recorded farmers' general preferences by asking interviewees to rank the six land-uses from the one they like best to the one they like least (they did so by arranging six cards depicting each land-use in order of their preference). Farmers then evaluated the land-uses against the remaining indicators in two steps. First they ranked the land-uses (by arranging the cards) from best to worst for achieving a given indicator. They then scored the performance of each land-use for that indicator on a scale of 0–10. From these individual scores, $y_{i,l,k}$, of each farmer, k, for each land-use, l, and indicator, i, we computed the mean score, $\hat{y}_{i,l,f}$, for the farm types, f, identified in the cluster analysis (described next).

Empiric analysis to identify farm types and corresponding land-use perceptions

During the interviews we asked farmers to identify all land-uses on their farm and with the help of the farm map quantify the area (in hectares) of each. We also asked farmers about their management practices (e.g. whether they use fertiliser and pesticides) and household characteristics (e.g. size of the household, sources of on-farm income). Based on this interview data we

Table 1 Description of the six land-use options, l, that farmers evaluated

Land-use	Description	Source
Cropland	Annual or (non-woody) perennial crops, grown as a monoculture or mix of crops on the same area or rotated over time	Schuchmann (2011)
Pasture	Traditional pasture with 1.5–2 cows per hectare	INEC (2011)
Alley cropping	Lines of teak grown every six meters, with rows of maize in between. Trees are grown for timber; shading prevents crop growth after 5 years	Paul et al. (2017)
Silvopasture	Traditional pasture with a tree density of around 200 trees per hectare and stocking rate of one cow per hectare. Trees are either planted or regenerate naturally (in which case they are guarded)	Montagnini et al. (2013)
Plantation	Teak plantation, trees planted with 3 × 3 m spacing, harvested after 20 years	Paul et al. (2017)
Forest	Natural forest, can be used to collect firewood and fruits, but not for commercial timber production	INEC (2011)

Table 2 The 10 indicators, *i*, against which farmers evaluated the six land-uses

i	Name	Description	Source
1	Long-term income	Profit over 20 years	Connelly and Shapiro (2006) and Coomes et al. (2008)
2	Labour demand[a]	Man days (per hectare) needed to manage the land-use	Tschakert et al. (2007)
3	Meeting household needs	The extent to which the land-use meets household needs for food and materials	Fischer and Vasseur (2002) and Tschakert et al. (2007)
4	Economic stability	The extent to which economic returns of the land-use withstand the effects of extreme weather, pests and diseases and price fluctuations	Connelly and Shapiro (2006) and Coomes et al. (2008)
5	Liquidity	Regular cash income, including how easily the farmer can convert an investment to cash when needed	Coomes et al. (2008) and Holmes et al. (2017)
6	Investment costs[a]	Up-front costs of establishing the land-use	Calle et al. (2009) and Connelly and Shapiro (2006)
7	Management[a] complexity	The need for special equipment, machinery, skills and knowledge	Calle et al. (2009) and Connelly and Shapiro (2006)
8	Protecting water supply	The extent to which the land-use can improve the availability and quality of freshwater	Garen et al. (2009) and Metzel and Montagnini (2014)
9	Protecting soil resources	The extent to which the land-use maintains long-term soil productivity	Calle et al. (2009) and Garen et al. (2009)
10	General preferences	Farmers' preferences for each land-use option (proxy for cultural values)	Knoke et al. (2014) and Tsonkova et al. (2014)

'Protecting water supply' and 'protecting soil resources' are considered ecological indicators, the rest are socio-economic

[a] Indicators where lower values are more desirable ("less is better")—for all other indicators "more is better"

used hierarchical cluster analysis to identify groups of similar farms. We chose this analysis as an objective way to divide farmers into groups that may be relevant for political decision-makers. The cluster analysis included 12 variables related to farm size and ownership, current land-use and management practices, labour availability and income structure (Table 3). Sources of on-farm income included crops, cattle, timber and other processed products (e.g. honey from sugarcane). We used standardised values (z-scores) for each variable and squared Euclidean distance as the similarity measure. We chose Ward's method because of its tendency to generate homogeneous clusters that are relatively equal in size (Hair et al. 2014); this clustering algorithm is commonly used when identifying farm typologies (e.g. Köbrich et al. 2003; Nainggolan et al. 2013). Following Hair et al. (2014) we assessed the percentage changes in within-cluster heterogeneity via the agglomeration schedule, which suggested a three-cluster solution. This also allowed for a meaningful interpretation when comparing the characteristics of each cluster; we therefore decided to retain the three-cluster solution and refer to the clusters as farm types.

Based on the individual land-use scores, $y_{i,l,k}$, obtained in the farmer interviews, we computed the mean score, $\hat{y}_{i,l,f}$, for the first nine indicators for the three identified farm types, *f*, where *K* is the total number of farmers in each group:

$$\hat{y}_{i,l,f} = \frac{1}{K_f} \sum_{k=1}^{K_f} y_{i,l,k} \quad \text{for } i = 1, 2, 3, \ldots, 9; \quad \text{for } f = 1, 2, 3.. \tag{1}$$

We also computed the standard error of the mean, $SEM_{i,l,f}$, where *SD* is the standard deviation:

Table 3 Variables included in the cluster analysis

Name	Description
Farm area	Total area managed by the farmer (ha)
Percent owned	Share of the farm area owned by the farmer (%)
Percent pasture	Share of the farm area allocated to pasture (%)
Percent crops	Share of the farm area allocated to crops (%)
Percent plantation	Share of the farm area allocated to plantation (%)
Main income cattle	1 if > 50% of on-farm income comes from cattle, 0 otherwise
Main income crops	1 if ≥ 50% of on-farm income comes from crops, 0 otherwise
Intensification	Degree of land-use intensification: summed score of four bivariate variables (where 1 = yes, 0 = no): irrigated, mechanised, uses pesticides, uses fertiliser
Land-use diversification	Shannon diversity index of farm land-uses (Eq. S1 in supplementary material)
On-farm income diversification	Shannon diversity index of on-farm income sources (Eq. S2 in supplementary material)
Percent on-farm workers	Number of household members who work on the farm as a share of all household members (%)
Percent household income from farm	Share of total household income generated by the farm, derived from ordinal responses: none = 0%, a small amount = 25%, half = 50%, most = 75% and entire income = 100%

$$SEM_{i,l,f} = \frac{SD_{i,l,f}}{\sqrt{K_f}} \quad \text{for } i = 1, 2, 3, \ldots, 9; \quad \text{for } f = 1, 2, 3. \tag{2}$$

Following Knoke et al. (2014), we measured farmers' general preferences (the tenth indicator) as the number of times farmers from each farm type selected a given land-use as their first or second choice:

$$\hat{y}_{10,l,f} = (\#best + \#second\,best)_{l,f} \tag{3}$$

The standard error of this estimate ($SEM_{10,l,f}$) was computed within each farm type as follows (for clarity the subscript *f*, denoting farm type, has been omitted):

$$\begin{aligned} p_l &= \frac{\hat{y}_{10,l}}{\sum_l^L \hat{y}_{10,l}} = \frac{\hat{y}_{10,l}}{n} \\ SEM_{10,l} &= n \cdot \sqrt{p_l \cdot (1 - p_l)/n} \end{aligned} \tag{4}$$

where n is the total number of 'best' and 'second best' choices across all land-uses for each farm type, and p_l is the relative frequency of 'best' and 'second best' choices for a given land-use within that farm type.

Normative analysis to explore the potential of agroforestry to meet farmers' objectives

We couple the farm perception data of each farm type with a normative model to investigate the role of agroforestry in theoretical land-use portfolios that minimise trade-offs between farm-level goals. These optimised land-use portfolios represent a hypothetical farm comprising various shares of the six land-uses. We use the optimisation method developed by Knoke et al. (2015, 2016) for land allocation problems in tropical landscapes. The model is formulated as a Min–Max (Chebyshev) problem (Romero 2001) that considers multiple objectives. In our study the 10 indicators serve as objectives, which are weighted equally in the optimisation. For each indicator we set a target level and the model selects the mix of land-uses that minimises the largest (worst) shortfall between the target and achieved level across all indicators. This results in a compromise solution that balances the achievement of all indicators. High performance in one indicator does not compensate for poor performance in another; the model instead always seeks to improve the contribution of the worst performing indicator (Romero 2001).

A strength of the modelling approach is its ability to integrate uncertainty in land-use decisions. Here uncertainty describes our lack of knowledge about how much a land-use will actually contribute to a given objective now and in the future. The model captures this uncertainty through so-called "uncertainty scenarios", which describe potential fluctuations in the performance of each land-use against each indicator. The model searches for a land-use allocation that improves the minimum performance across all

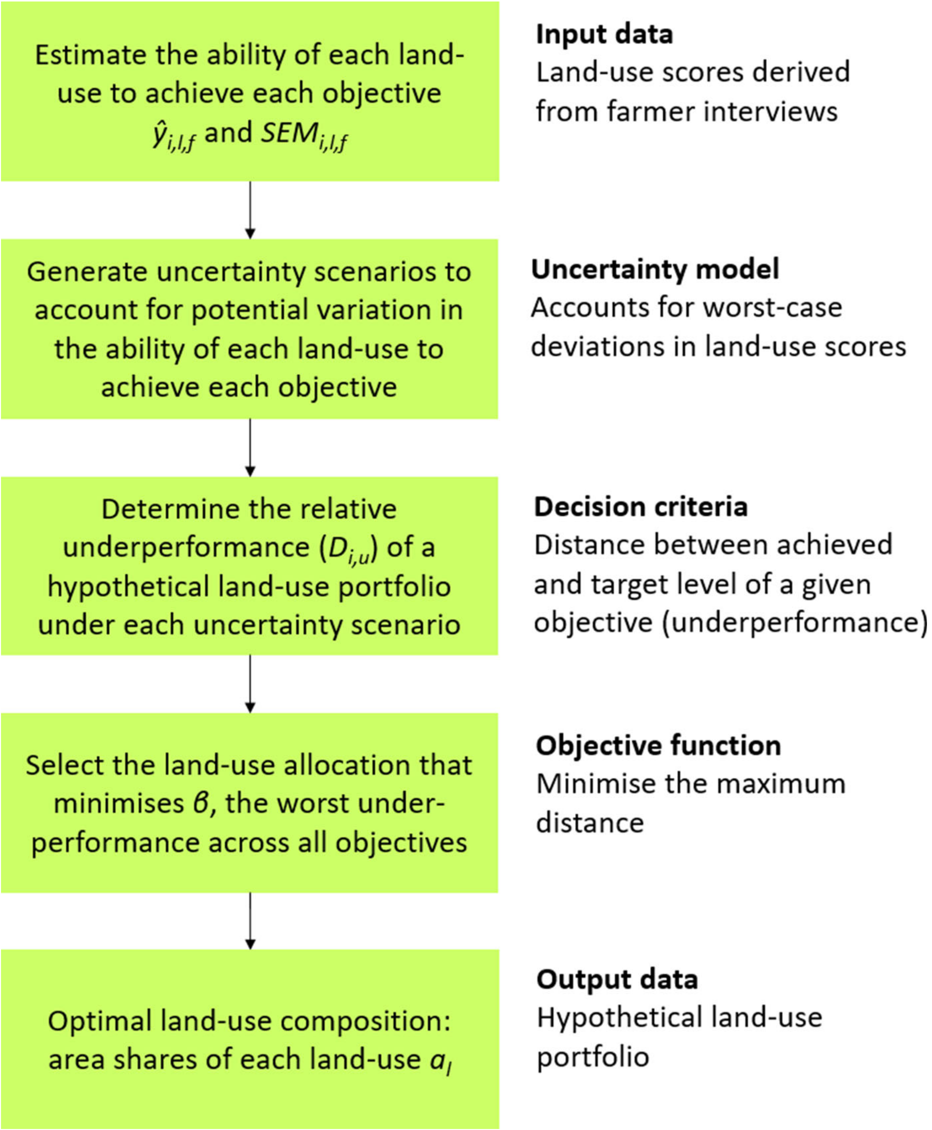
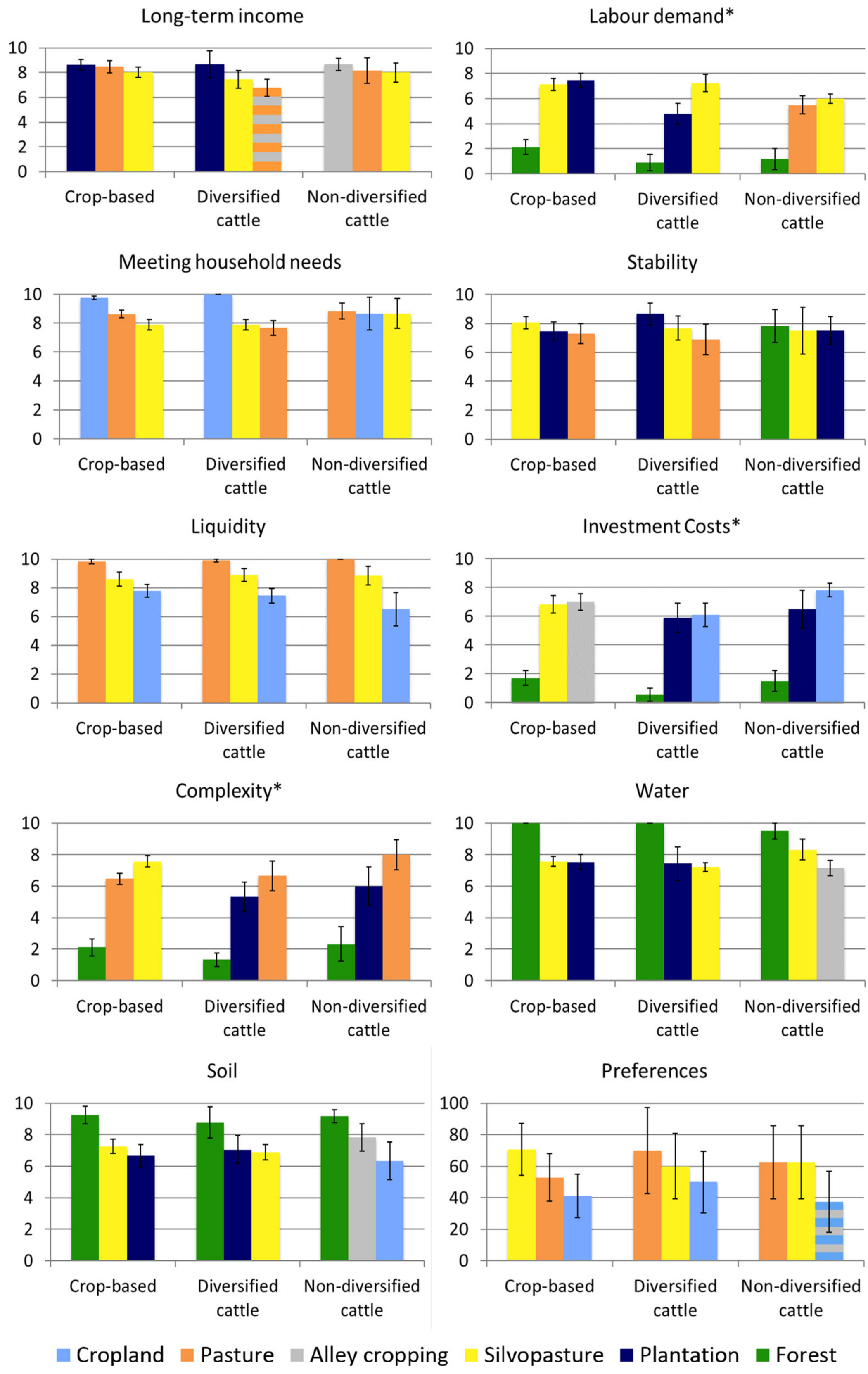


Fig. 2 Overview of the optimisation procedure

uncertainty scenarios and indicators, thereby guaranteeing a minimum performance level for each indicator even in worst-case situations. This is a form of robust decision-making, which is recommended when facing high levels of uncertainty (Walker et al. 2013). Essentially, our model simulates a risk averse decision-maker who seeks to minimise potential losses or poor performance of any indicator in worst cases (Knoke et al. 2015). Considering uncertainty promotes diversified land-use portfolios even when optimising for a single objective, because diversification provides insurance against poor performance of a single land-use for achieving that objective.

In our study we use the mean land-use scores, $\hat{y}_{i,l,f}$, derived from the interviews to estimate the ability of each land-use, l, to achieve each indicator, i, from the perspective of each farm type, f. To account for potential variation in these scores (and therefore in land-use performance) the model computes unwanted deviations within the uncertainty scenarios, by either


Long-term income
Labour demand*
Meeting household needs
Stability
Liquidity
Investment Costs*
Complexity*
Water
Soil
Preferences
0
2
4
6
8
10
20
40
60
80
100
Crop-based
Diversified cattle
Non-diversified cattle
Cropland
Pasture
Alley cropping
Silvopasture
Plantation
Forest

◀**Fig. 3** Mean scores ($\hat{y}_{i,l,f}$) of the three best performing land-uses, l, for each indicator, i, as rated by each farm type, f, where 0 = low and 10 = high. Asterisks denote indicators where a lower score is desirable. Values for general preferences ($\hat{y}_{10,l,f}$) are the percent of farmers who chose a given land-use as best or second best. Striped bars represent identical scores between two land-uses (both land-uses share third place). Error bars represent the $SEM_{i,l,f}$

adding or subtracting[1] multiples, f_U, of the $SEM_{i,l,f}$ to or from the mean scores (Eq. S3 in the supplementary methods). Therefore our measure of uncertainty is based on variability of farmer opinion within each farm type.

We ran the optimisation separately for each farm type using the land-use scores and SEM specific to each. The model calculates the distance, $D_{i,u}$, between the target (best possible) performance level and level achieved by a hypothetical farm portfolio for each indicator in each uncertainty scenario, u. These distances represent underperformance. The model then selects the land-use composition (mix of the six land-uses) that minimises the largest distance (worst underperformance, β) across all uncertainty scenarios. The optimised land-use portfolios therefore represent the land-use mix that minimises the worst underperformance of any indicator. We describe the optimisation procedure in detail in the supplementary material with an accompanying optimisation sheet (Excel file), while the main steps are summarised in Fig. 2. We also refer the reader to Knoke et al. (2020) for further details of the modelling approach.

For the main analysis we included all indicators and land-uses in the model and ran the optimisation for each farm type for f_U = 0, 0.5, 1, … 3. The factor f_U influences the size of the unwanted deviations of land-use scores within the uncertainty scenarios, and thus dictates the level of uncertainty included in the model: f_U = 0 ignores uncertainty and f_U = 3 represents a high level of uncertainty (Knoke et al. 2016). Hence, optimised land-use portfolios at lower f_U values are derived for less cautious decision-makers and the portfolios at higher f_U for more cautious decision-makers.

We also tested different model setups as sensitivity analyses. First we excluded the two agroforestry options from the optimisation to check the plausibility of the optimised land-use portfolios (Fig. 5). We also reran the optimisation using a relative SEM for all land-use scores (Eq. S3), to better understand the effect of uneven sample sizes. Lastly, we optimised each indicator individually to help understand potential drivers and barriers to agroforestry adoption (Fig. S1).

Results

Farm types identified through the cluster analysis

We interviewed 35 farmers who managed a total area of 2681 ha; farm size ranged from five to 271 ha (mean 77 ha). All farms had similar access to markets. Based on the cluster analysis we divided our sample into three farm types with different land-use and income characteristics: 'Crop-based farms', 'Diversified cattle farms' and 'Non-diversified cattle farms' (Table 4).

Crop-based farms is the largest cluster, comprising 17 farms. Crops provide at least half of farm income for all but one of these farms. Farms in this cluster comprise more crops (mean share 45%) and less pasture (mean share of 37%) than the other farm types; land-use is also more diversified (mean Shannon index of 0.8). The diversified cattle farms are typically dominated by pasture (mean share of 83%) and derive most, but not all, of their on-farm income from cattle. In contrast, non-diversified cattle farms obtain 100% of their on-farm income from cattle; on-farm income is therefore less diversified than for the other farm types. These farms comprise a high percentage of pasture (mean share 91%) and are less intensified than the other farm types. A higher proportion of household members (on average 87%) also work on the farm.

Alley cropping and silvopasture (as defined in Table 1) were not present on any of the interviewed farms. Therefore, the perceptions and opinions expressed by farmers towards these agroforestry systems represent the views of "non-adopters". A respective 76 and 45% of interviewees reported having indirect experience with silvopasture and alley

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[1] For "more is better" indicators the model computes an unwanted deviation by subtracting a multiple of the standard error from the mean score ($\hat{y}_{i,l,f} - f_U \times SEM_{i,l,f}$), while it adds a multiple to the mean score for "less is better" indicators ($\hat{y}_{i,l,f} + f_U \times SEM_{i,l,f}$).

Table 4 Comparison of the three farm types based on variables included in the cluster analysis (see Table 3)

	Crop-based	Diversified cattle	Non-diversified cattle
Number of farms	17	10	8
Farm area (ha)	81.7 ± 10.3	81.9 ± 19.5	59.1 ± 10.8
Percent owned	85.9 ± 8.0	90.4 ± 8.7	100 ± 0
Percent pasture	36.7^{b} ± 6.0	83.0^{a} ± 5.0	90.8^{a} ± 2.9
Percent crops	45.1^{b} ± 7.5	4.7^{a} ± 1.3	0.9^{a} ± 0.5
Percent plantation	0.2 ± 0.2	0.4 ± 0.2	0 ± 0
Main income cattle	0.1^{b} ± 0.3	1.0^{a} ± 0	1.0^{a} ± 0
Main income crops	0.7^{b} ± 0.1	0.0^{a} ± 0	0.0^{a} ± 0
Intensification	2.6^{a} ± 0.2	2.2^{a} ± 0.2	1.3^{b} ± 0.2
Land-use diversification	0.8^{b} ± 0.07	0.5^{a} ± 0.07	0.3^{a} ± 0.08
On-farm income diversification	0.5^{a} ± 0.05	0.6^{a} ± 0.02	0^{b} ± 0
Percent on-farm workers	45.7^{a} ± 6.8	37.1^{a} ± 5.3	86.5^{b} ± 7.0
Percent household income from farm	77.9 ± 6.7	82.5 ± 5.3	88.0 ± 4.7

Values represent the mean for each farm type ± SEM. Superscript denotes significant differences ($p < 0.05$) based on one-way ANOVA with Fischer's least significant difference (LSD) test used for post hoc comparisons

cropping systems similar to those included in our study, for example when visiting farms of relatives in other regions. A fifth (21%) of farmers, however, reported no experience with either system. Therefore their assessment was based on their general experience as farmers in Tortí and our descriptions of the agroforestry systems during the farmer interviews.

Farmers' perceptions of land-uses

Figure 3 displays the land-use scores ($\hat{y}_{i,l,f}$) of the three highest rated land-uses, l, for each indicator, i, for the three farm types, f. For many indicators the rankings were similar across farm types. All farm types rated pasture as the best option for maintaining liquidity, followed by silvopasture and cropland (Fig. 3). Each farm type also rated forests as the best choice for reducing labour demand, establishment costs and management complexity and for protecting soil and water resources. Finally, each group selected cropland, pasture and silvopasture as the best options for meeting household needs, and expressed strong general preferences for the two cattle-based land-uses (with crop-based farms expressing the highest preference for silvopasture).

For some indicators the rankings diverged between farm types. Each group rated a different land-use as the most stable against environmental and economic shocks: diversified cattle farms selected teak plantation, crop-based farms silvopasture and non-diversified cattle farms forest. Crop-based and diversified

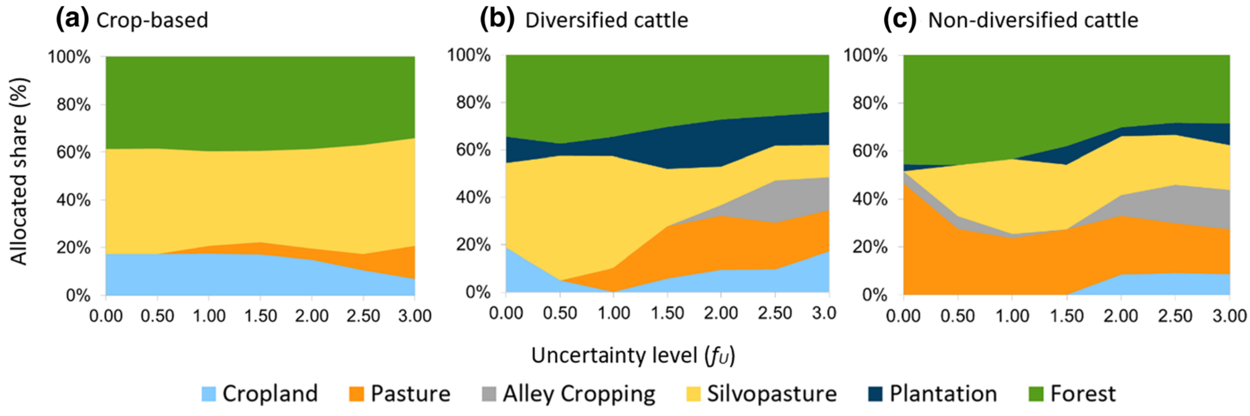

Fig. 4 Optimised farm composition (share of land allocated to each land-use) for balancing the achievement of the 10 indicators under increasing uncertainty, f_U, based on the perceptions and preferences of each farm type: **a** crop-based farms, **b** diversified cattle farms and **c** non-diversified cattle farms

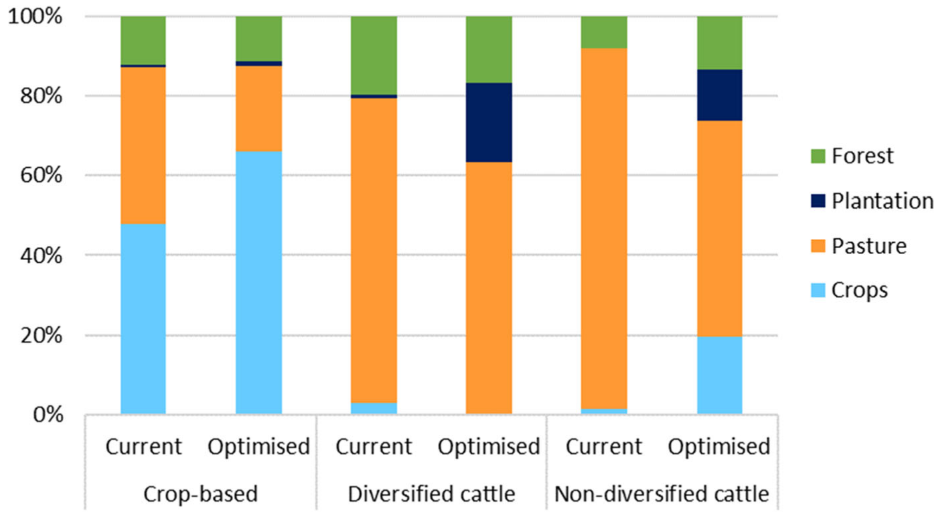

Fig. 5 Right columns: Optimised farm composition (share of land allocated to each land-use) for each farm-type for balancing the achievement of the 10 indicators under high uncertainty (f_U = 2.5) when excluding silvopasture and alley cropping from the optimisation. Left columns: Aggregated land-use composition of farms within each farm type (recorded in the farmer interviews)

cattle farmers rated teak plantation as the most profitable land-use, whereas non-diversified cattle farms selected alley cropping. Compared to the other farm types, the non-diversified cattle farmers perceived pasture and silvopasture to be less labour intensive, which could reflect that these farmers tended to run less intensified cattle operations with lower stocking rates. Interestingly, the crop-based farmers rated silvopasture and alley cropping more favourably for investment costs than the other farm types. This group also ranked silvopasture within the three least complex land-uses. This suggests that crop-based farmers may perceive establishment costs and management complexity to pose less of a barrier to agroforestry adoption.

Compared to silvopasture, farmers tended to express more negative opinions towards alley cropping; for five indicators each farm type ranked it in the three worst land-uses. The non-diversified cattle farmers were most positive towards alley cropping: scoring it higher for long-term income and the two ecological indicators and expressing a higher general preference. For these farmers long-term profitability and protecting soil and water resources could be important motivations to adopt the agroforestry system. However, the non-diversified cattle farmers also scored alley cropping more poorly for labour demand, management complexity and establishment costs (supplementary Table S1), highlighting potential barriers to adoption for this group of farmers.

Our comparison of land-use scores between the farm types is descriptive in nature. Significant differences between farm types at the 0.05 level were found for land-use scores within the indicators labour, investment costs and complexity, as well as for long-term income for $p < 0.06$ (based on one-way ANOVA with LSD post hoc comparisons—see Table S1). Our focus, however, is not on the absolute difference in land-use scores between each farm type. Instead, we want to understand differences in (a) how farmers' perceive the relative performance of agroforestry compared to the other land-use options, and (b) the variability of these perceptions (as a measure of uncertainty or risk). These relative differences are likely to be important drivers of modelled land-use decisions, but cannot be captured in a single statistical test. In the next section we show how our normative model, which accounts for the relative performance of all land-use options and their variability, allows us to analyse the possible consequences of different farmer perceptions for their simulated optimal land-use decisions.

Pairing empiric data with the normative model

Using the perceptions and preferences of each farm type, we determined the optimal land-use composition

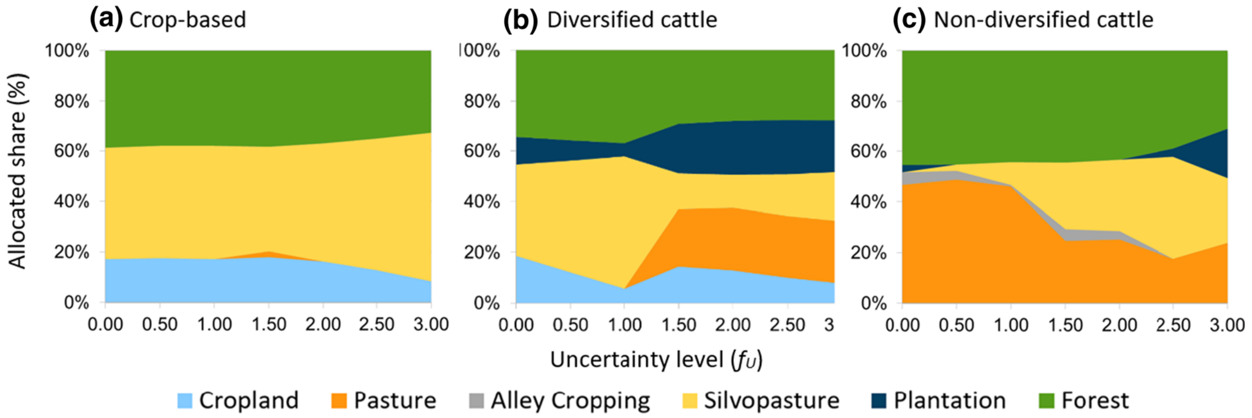

Fig. 6 Optimised farm composition (share of land allocated to each land-use) for balancing the achievement of the 10 indicators under increasing uncertainty, f_U, based on the mean land-use scores the three farm types ($\hat{y}_{i,l,f}$): **a** crop-based farms, **b** diversified cattle farms and **c** non-diversified cattle farms, using a relative standard error ($SEM_{i,l,f}^{relative}$)

to balance the achievement of the 10 socio-economic and ecological indicators. While agroforestry was always selected in the optimal land-use portfolio, we found that the type and share of agroforestry included in the portfolios differed considerably between farm types (Fig. 4). Looking first at an uncertainty level of $f_U = 2$ (representing the perspective of a more cautious decision-maker), we see that both silvopasture and alley cropping appear in the optimised portfolios of the two cattle-based farm types, but only silvopasture is present in the optimised portfolio of the crop-based farms. The overall share of agroforestry, however, was higher in the portfolio for the crop-based farms (42%) than in the portfolios for the two cattle-based farm types (21 and 33% respectively).

In all cases, the optimised portfolios are very different to the current land-use composition, where agroforestry is not present (Fig. 5, left bars). Excluding agroforestry from the optimisation produces land-use portfolios dominated by pasture for the cattle-based farm types, and by cropland at higher uncertainty levels for crop-based farms, with natural forest shares of 11–17% (Fig. 5, right bars). This is similar to the aggregated land-use of each farm type, although teak plantation is overrepresented in the optimised portfolios of the cattle-based farms.

Returning now to the portfolios including agroforestry, the ideal composition for the crop-based farms is quite stable across a wider range of uncertainty ($f_U = 0$ to $f_U = 3$). In contrast, the optimised portfolios of the two cattle-based farm types become more diversified with increasing uncertainty (Fig. 4). This reflects the relatively large $SEM_{i,l,f}$ for these farm types. When expressed as a proportion of the mean ($\hat{y}_{i,l,f}$), the average $SEM_{i,l,f}$ was 0.18 and 0.19 for the diversified and non-diversified cattle farms, compared to 0.12 for the crop-based farms. In our model, increasingly equal land-use shares at higher values of f_U is the result of a statistical averaging effect to buffer against uncertainty (Knoke et al. 2016). Higher f_U values enlarge the unfavourable deviations in land-use performance considered in the uncertainty scenarios (Eq. S3), and the model selects a more diversified land-use portfolio to protect against potential under-achievement of a given indicator. A high $SEM_{i,l,f}$ enhances this effect, and hence the trend towards greater diversification at higher uncertainty levels is more pronounced in the optimised portfolios of the two cattle-based farm types.

The differences in the type and share of agroforestry included in the optimal portfolios may therefore relate to (a) differences in farmers' perceptions of the land-uses, or (b) diversification effects driven by the smaller sample size and relatively large $SEM_{i,l,f}$ for the cattle-based farms. To check that our results were not predominantly driven by differences in the sample sizes, we reran the optimisation for each farm type, using the same land-use scores $\hat{y}_{i,l,f}$, but a relative standard error, $SEM_{i,l,f}^{relative}$, derived from the $SEM_{i,l}$ of all farms combined, which on average was 10% of the mean land-use scores (Eq. S12). This ensured that the size of the standard error as a proportion of the mean land-use score remained constant between farm types.

Using a relative standard error led to minimal changes in the optimal land-use portfolio for the crop-based farms (compare Fig. 4a and 6a). Using the $SEM_{i,l,f}^{relative}$ did, however, alter the ideal portfolios of the two cattle-based farm types; both became less diversified. For instance, alley cropping no longer appears in the optimal land-use portfolio of the diversified cattle farms under high uncertainty levels (compare Fig. 4b and 6b). Similarly, teak plantation and cropland are no longer included in the optimal portfolio of non-diversified cattle farms at moderately-high uncertainty levels, and the share of alley cropping reduces by five percentage points.

Nevertheless, after adjusting the standard error, differences remain in the type and share of agroforestry included in the optimal land-use portfolios of each farm type. The portfolio for crop-based farms still contains the largest share of agroforestry (e.g. 47% at $f_U = 2$) and the portfolio for diversified cattle farms the smallest (13% at $f_U = 2$). Alley cropping is only included in the optimal portfolio of the non-diversified cattle farms. This demonstrates that the selection of agroforestry systems is not only driven by diversification effects from small samples.

Portfolios optimised for individual objectives (Fig. S1) help to understand factors that may promote or hinder agroforestry adoption. We found that agroforestry was only selected in optimised portfolios for a small set of indicators (long-term income, household needs, economic stability and general preferences), which diverged strongly between farm types. For crop-based farms, agroforestry only appears in the optimised portfolios for economic stability and general preferences, where silvopasture comprises more than 70% of the land-use. The perceived superior performance of silvopasture for these two indicators contributes to its dominance in the multi-indicator portfolio for crop-based farms, i.e. in the portfolio that consider all 10 objectives simultaneously. For the cattle-based farm types, silvopasture appears in lower shares ($< 37\%$) in portfolios optimised for these two indicators, as well as in the portfolio optimised for long-term income for the diversified farms and in the portfolio optimised for meeting household needs for the non-diversified farms. Alley cropping is also selected for two indicators for the non-diversified cattle farms; it dominates (90% share) the portfolio optimised for long-term income and contributes 14% to the general preference portfolio. The favourable rating for long-term income (and to a lesser extent general preferences) is therefore likely to contribute to the selection of alley cropping in the multi-indicator portfolio of non-diversified cattle farmers.

Importantly, the inclusion of agroforestry (predominately silvopasture) within the general preference portfolio of each farm type suggests that the farmers' cultural preferences are compatible with (rather than posing a barrier to) agroforestry adoption. Similarly, the inclusion of silvopasture in the optimal portfolio for economic stability suggests that this indicator could be a potential driver of agroforestry adoption across all farm types.

Agroforestry was not selected in portfolios optimised for the remaining six indicators. These portfolios were very similar across the farm types, dominated by either pasture (for maintaining liquidity) or forest (for reducing labour demand, investment costs and management complexity, and protecting soil and water resources). The superior performance of forest for the latter indicators explains its consistently large share in the multi-indicator portfolios for each farm type. The absence of agroforestry in single-indicator portfolios suggest that these indicators may represent barriers to agroforestry adoption.

Discussion

Insights from the empiric and normative approaches

Within our sample we found only moderate differences in farmers' perceptions of the two agroforestry systems. Across all farm types, farmers tended to evaluate silvopasture more favourably than alley cropping against the 10 indicators. This aligns with the 'cattle culture' of pioneer areas in Central and South America, where owning cattle awards prestigious social status. Cattle also represent a way of accumulating wealth as a form of private insurance, which is especially important in regions with weak healthcare, loan and pension systems (Connelly and Shapiro 2006; Perz et al. 2006). Empiric rankings suggest differences in how the farm types perceived agroforestry in terms of investment costs, management complexity and long-term profitability, as well as in their general preferences towards the systems. Although based on a limited dataset, our findings represent a new contribution to agroforestry research, because previous studies on farmers' perceptions have not compared the views of farmers with different land-use and income characteristics (e.g. Frey et al. 2012; Garen et al. 2009; Hand and Tyndall 2018). The ranking of mutually exclusive land-use options alone, however, often does not reflect the farmer's reality. Decisions are usually taken at the farm level, including multiple land-use options that serve multiple needs of the farm/household. These complexities can hardly be incorporated into empiric rankings, but they may constitute important barriers to agroforestry adoption. Our approach therefore couples empiric data with farm-level optimisation, capable of considering uncertainty as well as multiple land-use options and farm-level objectives simultaneously.

Despite the moderate difference in the perception data of the empiric analysis, we found substantial differences in the type and share of agroforestry selected in the optimised land-use compositions of each farm type. This reveals that an overall positive ranking of agroforestry may alone be a misleading indicator of farmers' acceptance of agroforestry, if farm-level considerations are not sufficiently accounted for. Here, optimisation approaches may be a helpful methodological complement. Assuming that farmers strive to reduce underperformance of the 10 pre-selected indicators, the optimal portfolios suggest that crop-based farms would benefit from allocating a larger share of their land to silvopasture, while for cattle-based farms diversifying their farm with more land-uses (including alley cropping) may be advantageous. Differences in the optimal portfolios of farms with similar land-use and income patterns are plausible, given the many empiric studies that link farm and household characteristics with farmers' land-use decisions, including the degree of agricultural diversification (Ochoa et al. 2019; Torres et al. 2018), and adoption of agroforestry (Pattanayak et al. 2003; Zabala et al. 2013).

Differences in the optimised land-use portfolios provide us with important information, because it suggests that farmers belonging to each farm type may respond differently to agroforestry. Understanding these differences may help to design better policies to achieve agroforestry adoption by tailoring recommendations and extension programs to different groups of farmers (Köbrich et al. 2003). For our study region, agricultural extension staff could emphasise the long-term profitability of alley cropping systems (as evidenced by bio-economic modelling by Paul et al. (2017) based on local trials) when working with farmers with diversified farm income sources. We also found that farmers who derive most of their farm income from cattle may perceive management complexity and investment costs as a greater barrier to agroforestry adoption. Promoting agroforestry among these farmers may benefit, for example, from skill-sharing and training programs to enhance farmers' capacity to manage the systems, as well as financial incentives (e.g. subsidising the cost of tree seedlings and fencing material) to reduce up-front capital costs.

Critical appraisal of the modelling approach

The normative approach allows us to go beyond current land-use patterns to explore the potential of agroforestry to be part of diversified farm portfolios that meet multiple farm-level goals. Divergence between the optimised and existing land-use portfolios may signal a conflict between the land-use practices that farmers wish to have, and those that they can implement given their available resources and household needs. For example, the optimal portfolios derived from farmers' stated land-use preferences all contain agroforestry although it was absent on their own farms. To more realistically capture individual farm constraints within the optimised portfolios, it might be necessary to include calculated economic indicators in the optimisation. Such indicators could be derived from more intensive farm surveys, for example to determine expected costs and cash flows to better reflect hard economic constraints not reflected in farmer preferences. Other studies in Eastern Panama have also suggested a conflict between the forest-friendly farming practices that farmers deem desirable and those that are possible with their economic constraints (Tschakert et al. 2007). Our modelling approach revealed that individual goals such as reducing investment costs and management complexity as well as maintaining liquidity may impede agroforestry adoption. However, the approach also shows that diversified land-use portfolios can help buffer these constraints. For example, leaving land as forest can reduce overall investment costs and management complexity of a farm portfolio, while the inclusion of pasture helps maintain liquidity. This speaks for promoting agroforestry not as a stand alone land-use option, but as a potential complement to other land-use systems as part of a diversified farm portfolio.

The optimal farm compositions derived from our modelling approach assumes that the 10 socio-economic and ecological objectives are equally important for farmers' decision-making. While this is unlikely to be the case for an individual farmer, the assumption is appropriate for modelling the decision-making of a whole group of farmers, whose individual preferences and constraints are uncertain. This is a situation policy-makers often face. We account for potential variation in farmers' priorities by including a broader set of plausible objectives in the optimisation, which we weigh equally. The similarity between the existing and optimised land-use portfolios when excluding agroforestry vouches for the plausibility of model results, supporting our decision to weigh objectives equally.

Despite its normative nature, we found the model allows for a plausible representation of land-use trends, which Knoke et al. (2020) also demonstrated in a recent Ecuadorian case study. For instance, the expansion of forest cover in the optimised portfolios relative to the existing forest cover in our study area is consistent with forest transition theory, which has already been observed in Panama (Wright and Samaniego 2008). We also obtained more diversified land-use portfolios at higher levels of uncertainty, consistent with other applications of the model in Latin America (Knoke et al. 2016; Uhde et al. 2017). Finally, we obtained more diversified land compositions when considering multiple criteria in the optimisation compared to a single objective only, a trend which van der Plas et al. (2016) have shown empirically at the landscape scale.

We recognise that our results stem from a small dataset, where not all farmers had prior knowledge of the agroforestry systems in question. We tried to ensure a common understanding among all farmers by discussing each land-use before starting the evaluation task, but some farmer responses may still be "guesstimates". Other authors promote similar ranking and scoring methods for collecting high quality data from local people (Mayoux and Chambers 2005; Riley and Fielding 2001), but we also acknowledge the inherent uncertainty around the degree to which data accurately and consistently capture farmers' opinions (Gosling and Reith 2019). This, however, highlights a strength of our modelling approach which actively integrates uncertainty around farmer judgement and preferences in the optimisation. The measure of uncertainty used in the model ($SEM_{i,l,f}$) reflects variation in farmer opinion. We would expect this variation to increase when farmers are less sure of their responses, but also when sample sizes are small (Eqs. 2 and 4). The model accounts for this potential variation via the uncertainty scenarios, searching for solutions that are satisfactory for a wide range of land-use scores (Knoke et al. 2016). This results in a land-use composition that caters for a range of farmer opinions, and hence should be acceptable to all farmers comprising a farm type. Nevertheless, if sample sizes are too small (or reliability of the data too poor) the strong diversification effects resulting from high standard errors may mask potential differences between groups. We addressed this issue by using a relative standard error, but future research could investigate minimum sample sizes needed to achieve stable land-use portfolios.

Potential applications

Our data collection method represents a rapid appraisal tool (Riley and Fielding 2001), and when faced with small or uncertain datasets the model actively accounts for potential variation in farmer opinion. We therefore see it as a pragmatic approach to guide land-use planning and agroforestry policy decisions in regions where it may not be possible to carry out large-scale household surveys. In this context the optimisation approach is not designed to prescribe exact "ideal" farm compositions to be implemented by different groups of farmers, but instead to explore the conditions under which agroforestry might be a desirable complement to meet farmers' goals.

As an example application, practitioners could use our survey method to capture farmers' knowledge and perceptions of agroforestry during the development of incentive schemes and extension programs. We used cluster analysis to identify farms with similar land-use and income patterns, but farmers could also be grouped using much simpler methods (e.g. based on farm size, income level or the main farm enterprise). Understanding if and how perceptions deviate between different farmer groups could help policy-makers to prioritise further data collection and farmer collaboration. For instance, the inclusion of agroforestry systems in the optimal portfolio of a particular group of farmers suggests that the systems could be of interest to those farmers. More data could then be collected from such groups to better understand their constraints and the support needed to adopt agroforestry.

Our modelling approach could also be relevant for participatory land-use planning as a discussion tool to support strategic thinking about sustainable land-use compositions (Le Gal et al. 2013). Stakeholders could evaluate the pros and cons of different land-use compositions and generate a range of solutions by modifying the importance (weight) placed on each objective (Stewart et al. 2004). Ezquerro et al. (2019), for example, have shown how a similar modelling method can be used for stakeholder interaction in forest management. Our model is well suited to user interaction because it works off-line with open source software and short calculation times (for our problem less than 2 s per optimisation). This makes it possible to re-run the optimisation with altered parameters in situ, to facilitate a co-learning feedback loop between the researcher and farmer. In such a process the approach could be extended by including individual farm constraints that are not yet captured in the optimisation model.

Finally, the optimisation method can easily accommodate diverse data types, including measured, modelled and interview data (Knoke et al. 2016; Uhde et al. 2017). This creates an opportunity to bring together different sources of knowledge in land-use planning. For example, farmers' experienced-based knowledge (Turnhout et al. 2012), could be coupled with scientific data on ecological functions of different systems, such as their contribution to biodiversity and other ecosystem services. An optimisation incorporating these different perspectives could determine the ideal land-use composition at the landscape level. Such an approach could be used to investigate the role of agroforestry in multi-functional landscapes that enhance ecosystem services while accounting for farmers' needs and preferences.

Conclusions

By coupling empiric interview data of farmers in Eastern Panama with a mechanistic optimisation model, we demonstrate a new approach for investigating the potential of agroforestry to meet the multiple needs of different groups of farmers. We found that the type and share of agroforestry included in theoretically optimal land-use portfolios differed for farms with different land-use and income characteristics. Such differences can provide valuable information about the possible acceptability of different agroforestry systems among different groups of farmers. In our case study, for example, we found that farmers who derive most of their farm income from crops may be more willing to adopt silvopasture, whereas farmers who are more economically dependent on cattle may benefit from diversifying their land-use with alley cropping. We found that in our study region agroforestry (especially silvopasture) does not appear to conflict with farmers' general land-use preferences, but divergence between the optimal and current land-use portfolios suggest that hidden constraints not reflected in these preferences may hinder agroforestry adoption. Single-objective optimisations reveal that aspects such as reducing investment costs and management complexity and the need to maintain liquidity may be among these constraints. This speaks for the importance of promoting agroforestry as part of a diversified land-use portfolio to help buffer farm-level constraints. Such insights were revealed with comparably low measurement effort, and thus the coupled empiric-normative approach may be an important starting point for policy-makers and scientists to set priorities for follow-up research on policy design. We test the modelling approach in Eastern Panama, but think it could be easily transferred to other regions to better understand the socio-economic conditions under which agroforestry may be a desirable land-use alternative to meet farmers' needs.

Acknowledgements Open Access funding provided by Projekt DEAL. This work was supported by the German Research Foundation (DFG)—Grant PA 3162/1. We are very grateful to Rodrigo Duarte, Peter Glatzle and Alyna Reyes for their assistance with the farmer interviews, and warmly thank the farmers in Tortí who shared their knowledge and experience with us.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical standard The research complies with ethical standards for research involving human participants, including obtaining informed consent from all interviewees.

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Paper 4

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 (in press). https://doi.org/10.1007/s00267-021-01439-0

Environmental Management
https://doi.org/10.1007/s00267-021-01439-0

Which Socio-economic Conditions Drive the Selection of Agroforestry at the Forest Frontier?

Elizabeth Gosling[1] · **Thomas Knoke**[1] · **Esther Reith**[1] · **Alyna Reyes Cáceres**[1] · **Carola Paul**[2]

Received: 1 September 2020 / Accepted: 25 January 2021

Abstract

Models are essential to assess the socio-economic credentials of new agroforestry systems. In this study, we showcase robust optimisation as a tool to evaluate agroforestry's potential to meet farmers' multiple goals. Our modelling approach has three parts. First, we use a discrete land-use model to evaluate two agroforestry systems (alley cropping and silvopasture) and conventional land uses against five socio-economic objectives, focusing on the forest frontier in eastern Panama. Next, we couple the land-use model with robust optimisation, to determine the mix of land uses (farm portfolio) that minimises trade-offs between the five objectives. Here we consider uncertainty to simulate the land-use decisions of a risk-averse farmer. Finally, we assess how the type and amount of agroforestry included in the optimal land-use portfolio changes under different environmental, socio-economic and political scenarios, to explore the conditions that may make agroforestry more attractive for farmers. We identify silvopasture as a promising land use for meeting farmers' goals, especially for farms with less productive soils. The additional labour demand compared to conventional pasture, however, may prove an important barrier to adoption for farms facing acute labour shortages. The selection of agroforestry responded strongly to changes in investment costs and timber prices, suggesting that cost-sharing arrangements and tax incentives could be effective strategies to enhance adoption. We found alley cropping to be less compatible with farmers' risk aversion, but this agroforestry system may still be a desirable complement to the land-use portfolio, especially for farmers who are more profit-oriented and tolerant of risk.

Keywords Alley cropping · Goal programming · Panama · Robust optimisation · Scenario analysis · Silvopasture

Introduction

Agroforestry is a multifunctional form of agriculture that combines trees and crops and/or livestock on the same parcel of land. These systems are often advocated as a sustainable land-use strategy to reduce poverty, mitigate climate change and improve food security in tropical regions (Leakey 2020; Montagnini and Metzel 2018; Waldron et al. 2016). For example, in the Central American Republic of Panama, the government promotes agroforestry within its private–public initiative to restore 1 million hectares of forest land ("Alianza por el Millón"; Garcia et al. 2016; MiAmbiente 2019). This has included enacting a legal framework for tax exemptions and subsidies for agroforestry systems (Law No. 69 of October 30, 2017). However, the uneven and relatively slow uptake of agroforestry in Central and Latin America (Dagang and Nair 2003; Frey et al. 2012a; Somarriba et al. 2012) suggests that not all farmers deem these systems to be a desirable land-use option (Do et al. 2020). While the ecological advantages of agroforestry have been widely documented (e.g., Jose 2009), the socio-economic disadvantages that may constitute barriers to adoption have received less attention in the literature (Liu et al. 2019; Montambault and Alavalapati 2005). More research to better understand the socio-economic aspects of agroforestry is therefore needed, to help identify conditions that may make agroforestry more attractive for farmers.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00267-021-01439-0.

✉ Elizabeth Gosling
elizabeth.gosling@tum.de

[1] Institute of Forest Management, TUM School of Life Sciences Weihenstephan, Technische Universität München, Hans-Carl-von-Carlowitz-Platz 2, 85354 Freising, Germany

[2] Department of Forest Economics and Sustainable Land Use Planning, University of Göttingen, Büsgenweg 1, 37077 Göttingen, Germany

Given the cost and risks associated with field experiments, models are an important tool to assess the socio-economic potential of different agroforestry systems, to pre-select the most promising systems for on-farm trials (Bertomeu and Giménez 2006; Kaim et al. 2018; Le Gal et al. 2011). Within this context, goal programming has two advantages for evaluating agroforestry. First, as a multi-criteria decision analysis (MCDA) method, goal programming can consider multiple objectives and hence account for the diverse, and potentially conflicting, goals that drive farmers' decision-making (Janssen and van Ittersum 2007; Kaim et al. 2018; van Zonneveld et al. 2020). Second, as a continuous (rather than discrete) MCDA technique, goal programming can solve land allocation problems to simulate decision-making at the farm (rather than plot) level. For example, goal programming can be used to determine the optimal mix of land uses to achieve a set of objectives (Janssen and van Ittersum 2007; Uhde et al. 2015). This farm-level modelling accounts for land-use diversification, a common strategy among smallholders to meet different household needs (Knoke et al. 2017; Pannell et al. 2014) and reduce risk (Baumgärtner and Quaas 2010; Di Falco and Perrings 2005).

Goal programming can therefore complement previous modelling approaches that have evaluated agroforestry against socio-economic and ecological objectives at the plot level, but ignored the effects of land-use diversification on farmers' decision-making (e.g., Palma et al. 2007; Rahman et al. 2017; Santos Martin and van Noordwijk 2011). Conversely, by considering multiple objectives, goal programming can enrich previous economic analyses that account for diversified land-use portfolios (farm-level modelling), but only assess agroforestry against a single criterion of profit maximisation and/or risk reduction. This includes studies based on Markowitz's (1952) Modern Portfolio Theory (e.g., Bertomeu and Giménez 2006; Blandon 2005; Ochoa et al. 2016; Paul et al. 2017).

While goal programming has recently emerged as a tool to solve allocation problems in forestry (e.g., Aldea et al. 2014; Diaz-Balteiro and Romero 2008; Messerer et al. 2017) and agriculture (e.g., Ballarin et al. 2011; Biswas and Pal 2005; Knoke et al. 2015), applications to evaluate agroforestry are rare (García-de Ceca and Gebremedhin 1991; Mendoza et al. 1987). Recently, Gosling et al. (2020a, b) and Reith et al. (2020) used a variant of goal programming to investigate the role of agroforestry in optimised land-use portfolios that reduce trade-offs between different farm- and landscape-level objectives at the forest frontier in eastern Panama. These recent studies, however, relied solely on perception data from local farmers and relevant experts. Such data sets help us to understand the extent to which farmers perceive different agroforestry systems to be compatible with their objectives, but are less helpful for understanding the factors that could promote greater uptake of agroforestry. This is because it is unknown how farmer perceptions would change in response to market developments, policy interventions or changing environmental and household conditions. Perception data may also tend to reflect what farmers deem desirable, rather than what is actually feasible given their hard economic constraints (Gosling et al. 2020b). Moreover, farmers may find it difficult to appraise agroforestry systems with which they are not yet familiar given the complexity and long planning horizons of these systems (Do et al. 2020; Laroche et al. 2018).

To address these shortcomings, the current study couples goal programming with more detailed socio-economic coefficients to explore the conditions that may favour the adoption of agroforestry at the tropical forest frontier. Such socio-economic coefficients, which we derived from land-use models, may provide a more neutral basis to simulate decision-making, one which can more easily capture farmers' hard economic constraints as well as changing environmental or market conditions (such as poorer soils or rising timber prices). Our guiding research question is: Which environmental and socio-economic conditions drive the selection of agroforestry in a diversified farm portfolio that reduces trade-offs between multiple objectives under uncertainty? Exploring this question may reveal potential leverage points for increasing agroforestry adoption among different types of farmers, to inform the design of incentive schemes and help target extension programs.

Methods

We evaluate the potential of agroforestry to meet farmers' socio-economic goals in three steps (shown by the blue, mauve and yellow sections of Fig. 1). First we develop a discrete land-use model to quantify the performance of seven mutually exclusive land uses (including two agroforestry options) against five pre-defined, socio-economic indicators. Our land-use model integrates national data from Panama with measured and modelled data from the study area. It combines deterministic capital budgeting with Monte Carlo simulations to account for variability in inputs, outputs and prices. Using the land-use model, we generate predicted (mean) values, $\hat{y}_{i,l}$, and associated standard deviation $SD_{i,l}$, for each land use, l, for each indicator, i.

These values form the input data for the second stage of modelling: robust multi-criteria optimisation, a variant of goal programming. The five pre-defined indicators serve as farmers' objectives and represent our decision criteria in the multi-criteria (optimisation) model. The area shares of each land use within a hypothetical farm are the decision variables. The multi-criteria model selects the theoretically

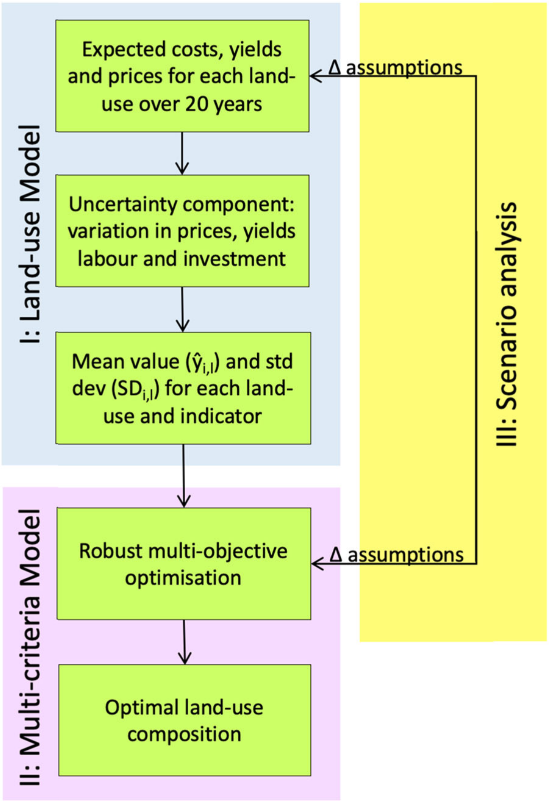

Fig. 1 The three components of the multi-criteria analysis

optimal mix of land uses (which we refer to as a land-use portfolio) for balancing the achievement of the five socio-economic objectives when accounting for uncertainty. Our optimisation approach follows Gosling et al. (2020a, b), but is expanded to include more detailed socio-economic coefficients for a wider range of land-use alternatives.

We further extend the modelling approach through a scenario analysis in the third part of the study (Fig. 1); here we modify parameters within the land-use and multi-criteria models to simulate different household, environmental, market and political conditions. We analyse how the type and amount of agroforestry selected in the optimal portfolio changes under these different scenarios, to better understand the factors and conditions that may make agroforestry more (or less) attractive for different farmers.

Study Area, Selected Land Uses and Indicators

We demonstrate our modelling approach for Tortí, a farming region in eastern Panama, near the border of the Panamá and Darién provinces. Tortí lies in the humid tropical zone, receiving 1900 mm rainfall per year, concentrated between April and December (ETESA 2018). Our study area covers around 9100 ha. The terrain is mostly flat at around 100 m above sea level; hills to the southeast rise to 400 m in elevation (ANAM 2011). Soils originate from sedimentary rock, including tertiary limestone, arenite and lutite, and are classified as vertisols, cambisols and nitisols (ANAM 2011; Gardi et al. 2015; Paul 2014).

The region is one of the last forest frontiers in Central America to undergo intense colonisation (Peterson St-Laurent et al. 2013). Colonists from Panama's western provinces began to settle the area in the 1970s, marking the start of widespread forest clearing (Paul 2014; Sloan 2008). Cattle grazing and agriculture now dominate the landscape; pasture and cropland comprise 60 and 26% of farmland in Tortí (Gosling et al. 2020a). Large-scale forest plantations of the exotic species teak (*Tectona grandis*) are also common in the study area, usually owned by foreign companies (Sloan 2008). The remaining natural forest cover comprises 14% of farmland (Gosling et al. 2020a).

Table 1 outlines the seven land uses investigated in this study. Following Odum's (1969) classic paper (Corman et al. 2019), we classify these land uses into productive, compromise and protective landcover types. We investigate four productive land uses: pasture for cattle grazing, rice (*Oryza sativa*) and maize (*Zea mays*), which are the most commonly grown annual crops in the study area (Duarte 2018), and teak plantation.

As compromise land uses, we investigate two agroforestry systems: alley cropping and silvopasture. These systems represent novel land uses, because they are not yet widespread in the study area. Currently, the most common forms of agroforestry practiced in Tortí are home gardens, living fences and scattered trees in pastures (Gosling et al. 2020a; Schuchmann 2011). Our silvopasture system represents a more intensive system with 200 trees per hectare. We selected the native tree Spanish cedar (*Cedrela odorata*) for the silvopastoral system based on its potential to produce high-value timber and local farmers' preference for this species (Reyes Cáceres 2018). The alley cropping system comprises rows of teak trees with maize cultivated in between. The species selection and layout are based on a local trial coupled with bio-economic modelling, which found this alley cropping system to be an economically competitive land use in the study area (Paul et al. 2015, 2017). Because canopy shading prevents maize production in the later part of the rotation, this tree–crop system can also be viewed as a taungya system (Fischer and Vasseur 2000; Paul et al. 2015).

Natural forest is a protective land use. It represents a landcover without active management, and therefore is not associated with any management costs or revenues. Forest can also be considered as long-term natural succession.

We aim to simulate the land-use decisions of a risk-averse farmer, who strives to reduce trade-offs between multiple farm-level objectives. We selected five hypothesised socio-economic objectives based on previous research in Panama

Table 1 Description of the seven land uses, *l*, selected in this study

Classification	Name	Description	Sources
Productive	Rice Maize	Traditional non-mechanised and non-irrigated system, with the use of fertiliser and pesticides: crops planted and harvested once per year.	MIDA (2019a, b)
	Pasture	Cows graze on improved pasture (*Brachiaria* spp) with a stocking rate of 2 animals per hectare. *Ceba* (Spanish for mast) system, whereby young cows are bought, fattened on pastures and sold the following year.	Paul (2014) and Reyes Cáceres (2018)
	Teak plantation	Monoculture of teak (*Tectona grandis*) planted at density of 1110 trees per hectare. Trees undergo two thinnings with a final harvest after 20 years.	Paul et al. (2017)
Compromise	Alley cropping	Maize is grown between rows of teak trees, until canopy shading prevents crop cultivation. Teak is planted at a density of 555 trees per hectare, it undergoes two thinnings with a final harvest after 20 years.	Paul et al. (2017)
	Silvopasture	Same production system as conventional pasture, but pastures are planted with the native tree species Spanish cedar (*Cedrela odorata*) at a density of 200 trees per hectare. Trees are harvested for timber after 20 years.	Paul (2014) and Reyes Cáceres (2018)
Protective	Forest	Natural secondary forest of native species. No active management, cannot be used for commercial timber production.	INEC (2011)

Classification categories refer to the framework of Odum (1969)

Table 2 The five indicators, *i*, used to quantify the contribution of each land use for achieving the five pre-defined socio-economic objectives

Indicator	Unit	Direction	Rationale	Calculation
Net present value (NPV)	\$/ha	More is better	Quantifies profitability for the objective of increasing long-term income. Profitability is an important characteristic influencing the adoption of land-use systems (Connelly and Shapiro 2006; Coomes et al. 2008).	Sum of all discounted net cash flows (NCF) over a 20-year period, using a 5% discount rate: $\mathrm{NPV}_l = \sum_t^T \mathrm{NCF}_{l,t} \times (1.05)^{-t}$
Payback period	Years	Less is better	We use payback period, i.e. the time taken to earn back the initial investment, to account for cash flow and access to money (Coomes et al. 2008; Holmes et al. 2017). This indicator relates to the objective of maintaining frequent cash flows.	As per Knoke et al. (2014), we compute a discounted payback period, defined as the 1st year (within the 20-year rotation) that has a positive discounted cumulative cash flow, based on a 5% discount rate.
Food production	Mcal/ha/yr	More is better	Smallholders' land-use decisions may be constrained by the need to meet household food needs (Binh et al. 2008; Fischer and Vasseur 2002; Tschakert et al. 2007).	Mean annual energy production over a 20-year period: we convert crop and meat yields to dietary energy (Mcal per hectare) using the USDA (2019) food composition database and technical conversion factors for agricultural commodities (FAO 2019)—see Table S10.
Labour demand	Days/ha/yr	Less is better	Labour availability can be a key constraint for land-use decisions of smallholder farmers (Pichón 1997; Tschakert et al. 2007; van Zonneveld et al. 2020).	The mean number of labour days required to implement and manage a given land use per year (averaged over a 20-year period).
Investment costs	\$/ha	Less is better	Given a lack of capital among smallholder farmers, high investment costs pose a potential barrier to agroforestry adoption (Calle et al. 2009; Connelly and Shapiro 2006; Coomes et al. 2008).	Sum of all costs incurred in year 0 of the land-use model.

Direction refers to the desired state of an indicator, i.e., whether higher or lower values are preferable

and the tropics: (1) increasing long-term income, (2) maintaining frequent cash flows, (3) increasing food production, (4) reducing labour demand and (5) reducing investment costs. These objectives reflect factors likely to influence farmers' land-use decisions, including their uptake of agroforestry (Connelly and Shapiro 2006; Fischer and Vasseur 2002; Holmes et al. 2017; Tschakert et al. 2007). We quantified the contribution of each land use for achieving each objective through the five indicators described in Table 2. Following Paul et al. (2017) and Pearce et al. (2003), we selected a 5% discount rate to calculate the net present value (NPV) and payback period of each land use.

Land-use Model

To quantify the performance of each land use (Table 1) against each indicator (Table 2), we collated a data set outlining the expected costs, yields, producer prices and labour requirement of each land use for each year of a 20-year period. We captured variability in these inputs and outputs through Monte Carlo simulations, basing yield and price fluctuations on historical data series. The assumptions and input data of the land-use model draw on our experience from a local field trial (Paul 2014) and subsequent financial analysis (Paul et al. 2015) and bio-economic modelling (Paul et al. 2017) of tree–crop and conventional land-use systems in the study area.

Expected costs and revenues

The establishment costs for each land use (except native forest) include the costs of clearing secondary vegetation and weeds from fallow land. All labour costs are based on a daily wage of US\$17.33, the current salary for agricultural

Table 3 Thinning and pruning regimes for the three timber land-use systems (following Paul 2014 and Paul et al. 2017)

	Pure plantation	Alley cropping	Silvopasture
Species	*T. grandis*	*T. grandis* and *Z. mays*	*C. odorata*
Planting layout (tree spacing)	3 × 3 m	3 × 6 m	7 × 7 m
Initial tree density (stems/ha)	1110	555	200
Tree pruning (years after establishment)	1,2,4	1,2,3,5	4–7
Thinning	Year 4: 60% Year 10: 50%	Year 5: 50% Year 10: 50%	none
Final stem number (stems/ha)[a]	222	139	200

[a] Excluding tree mortality

workers in Panama (MIDA 2019a). Costs of purchasing land and taxes are excluded. All costs and revenues are presented on a per hectare basis and given in US$/ha, shortened to $/ha from here on.

The expected labour and input costs, yields and producer prices for agricultural crops were taken from technical notes from the Ministry of Agricultural Development of Panama (Ministerio de Desarrollo Agropecuario de Panamá, MIDA)—see Tables S1, S2 and S5 in the Supplementary material. These technical notes are compiled at the national level, but we selected the costs and yields for traditional (non-mechanised) planting techniques with some chemical inputs, which previous research identified as the common farming practice in Tortí (Gosling et al. 2020a; Paul et al. 2015; Schuchmann 2011). Costs for fencing and establishing pasture, as well as expected beef yields and prices, are based on national information from MIDA (2016) and adjusted to local conditions according to data from Paul et al. (2015) and experiences of key informants in the study area (see supplementary Tables S2 and S5).

Table 3 outlines the management regime for the three timber-based systems. Because Spanish cedar is susceptible to damage from the moth *Hypsipyla grandella*, which can reduce timber quality (Cordero and Boshier 2003), intensive pest management is carried out in the first 3 years to minimise damage. Following Paul (2014), cedar trees are then pruned annually in years 4–7. All management costs are detailed in Table S2. Timber prices for teak and cedar were obtained from the National Forest Office (ONF 2019) in Costa Rica—see Table S6.

Following Paul et al. (2015), we extrapolated the annual height and diameter growth (and thus net increment in standing timber volume) of teak and cedar in the pure plantation and agroforestry systems from initial growth data in the study area (Paul 2014). We assumed an annual tree mortality rate of 0.5% (Griess and Knoke 2011). To simulate shading in the alley cropping and silvopastoral systems, we extrapolated canopy development from the same initial growth data (for teak and cedar, respectively) using regression with diameter (dbh) as the predictor (Paul et al. 2015).

In the timber-based systems farmers clear all vegetation within a 1 m radius of each tree seedling, to reduce light and competition effects (Paul et al. 2015). This reduces the total area available for maize cultivation by 17% in the alley cropping system compared to the monoculture: we reduced the per hectare cultivation costs and expected yields of maize accordingly. Similarly, in the silvopasture system 5% less area is available for pasture, reducing the initial stocking rate to 1.9 cows per hectare.

We modelled the further reduction in maize yields due to canopy shading using the categories devised by Paul et al. (2015) that account for height and canopy development of teak trees (Table S4). Following this method, there was sufficient light for maize to be cultivated in the initial year of tree planting and the first 2 years thereafter (during which time we expect full yields). Canopy shading then prevents maize cultivation for the remainder of the rotation, except for in the years immediately following thinning (years 6 and 11 after tree establishment), when expected yields are reduced by a factor of 0.5. The alley cropping system accounts for economies of scope with reduced weeding costs for trees during maize cultivation. Furthermore, lower chemical inputs are required for maize in the alley cropping system compared to the monoculture, because maize is not cultivated every year (see Section 1.1 in the Supplementary material for details).

To account for the effect of shading on pasture productivity, we assume a 50% yield reduction of pasture underneath the tree canopy. This is likely to be a conservative assumption, because in the early years of the rotation when tree canopies are still sparse, low levels of shading may actually enhance pasture productivity (Andrade et al. 2008; Fassola et al. 2006) and potentially extend the growing season (Jose et al. 2017). We reduce the stocking rate, S_t, in the silvopasture system in year t of the rotation linearly:

$$S_t = S_0 \times \frac{A_{\mathrm{sun},t} + (0.5 \times A_{\mathrm{canopy},t})}{A_0} \quad (1)$$

where A_0 is the initial area of pasture, and $A_{\mathrm{sun},t}$ and $A_{\mathrm{canopy},t}$ the area of pasture in full sunlight and under the cedar canopy at year t of the rotation. By year 20, 36% of the initial pasture area is under the canopy of the cedar trees, reducing the stocking rate to 1.55 cows per hectare (see Fig. S2).

Variability in price, yields, labour demand and investment costs

The expected costs and revenues outlined above form the deterministic part of the land-use model. However, we also integrate an uncertainty component to capture inter-annual

Table 4 Mean (predicted) value $\hat{y}_{i,l}$ and standard deviation $\mathrm{SD}_{i,l}$ derived from the Monte Carlo simulations for each land use, *l*, for each indicator, *i*

	NPV ($/ha)	Payback period (years)	Food production (Mcal/ha/year)	Labour demand (days/ha/year)	Investment costs ($/ha)
Rice	8310 ± 1756	0 ± 0.4	6295 ± 143	32 ± 0.7	949 ± 95
Maize	8066 ± 2643	1 ± 1.6	9866 ± 417	22 ± 0.5	1073 ± 109
Pasture	3496 ± 522	5 ± 1.1	976 ± 3	8 ± 0.2	1433 ± 142
Teak plantation	5267 ± 2019	20 ± 0.0	0 ± 0	16 ± 0.6	2184 ± 218
Alley cropping	5690 ± 1792	8 ± 8.6	1551 ± 141	12 ± 0.4	1835 ± 185
Silvopasture	4914 ± 696	11 ± 2.8	814 ± 2	14 ± 0.4	1970 ± 196
Forest	0 ± 0	0 ± 0.0	0 ± 0	0 ± 0.0	0 ± 0

Data represent the socio-economic coefficients used in the baseline scenario of our optimisation

fluctuations in yields and prices (to reflect variable environmental conditions and the volatility of agricultural and timber markets), as well as potential variation in labour demand and investment costs (to reflect variability in inputs). For each year, *t*, considered in the land-use model, we adjust the expected yields and prices by bootstrapping from historical yield and price data for Panama (data from years 1997 to 2016: see Tables S8 and S9 as well as Eqs. (S2) and (S3) in the Supplementary material for further details). We also assume a 10% coefficient of variation for the investment costs and average labour demand of each land use. Using a Monte Carlo simulation with 10,000 repetitions, we then generate a frequency distribution of values of each indicator, *i*, for each land use, *l*. From these frequency distributions we can derive the mean scores $\hat{y}_{i,l}$ and standard deviations, $\mathrm{SD}_{i,l}$, which form the input data for our multi-criteria optimisation model (Table 4).

Multi-criteria Optimisation Model

The multi-criteria optimisation model selects the mix of land uses (defined by their area share in a hypothetical farm portfolio) that minimises trade-offs between the five socio-economic objectives. Our optimisation approach, which is a variant of goal programming, was first developed by Knoke et al. (2015, 2016) for land allocation problems in tropical regions. The model is formulated as a min-max problem (Romero 2001). For each indicator, we set the best possible performance as our target level, and the model selects a land-use composition that minimises the worst shortfall between the target level and achieved level across all indicators. This results in a balanced solution where high levels of one indicator do not compensate for low levels of another (Romero 2001). A min-max formulation simulates "satisficing"—a mix between satisfying and optimising—behaviour, which can be a good match for farmer decision-making (Knoke et al. 2020b; Le Gal et al. 2011).

Uncertainty is an important influence on farmers' decisions, especially as a driver of land-use diversification (Baumgärtner and Quaas 2010). Such uncertainty relates in part to our inability to know exactly how much a land use will contribute to a given objective, either now or in the future. We account for uncertainty through robust decision-making. When seeking the best solution, the optimisation model not only considers the predicted performance of each land use for achieving each objective ($\hat{y}_{i,l}$), but also potential fluctuations in this performance. The model then finds solutions that secure minimum levels of each objective, even in worst-case scenarios. However, we do not allocate probabilities to the predicted and worst-case scenarios. This form of non-stochastic, robust decision-making is often recommended when facing high levels of uncertainty (Walker et al. 2013).

The model computes potential fluctuations in land-use performance by adding or subtracting multiples, *m*, of the standard deviation, $\mathrm{SD}_{i,l}$ to or from the mean value of each land use, $\hat{y}_{i,l}$. For "less is better indicators", we add a multiple of the standard deviation to the mean, while for "more is better" indicators, we subtract a multiple (see Eq. (S6)). In this way, we always compute an unfavourable deviation from the mean. The factor *m* controls the size of these unfavourable deviations and hence the level of uncertainty considered in the model. We carry out the optimisation for three different uncertainty levels: $m = 0$, which ignores uncertainty (the model considers mean scores only), reflecting the decision-making of a risk neutral farmer; $m = 1.5$ representing a moderate level of uncertainty, which could reflect the perspective of a moderately risk-averse farmer; and $m = 3.0$ reflecting a high level of uncertainty and the decision-making of a strongly risk-averse farmer.

The mathematical formulation of the optimisation model is outlined in Section 6 of the Supplementary material, but we also refer the reader to Gosling et al. (2020a) and Knoke et al. (2020a) for further details of the optimisation approach.

To check the plausibility of baseline model results, we compare the optimised portfolio to the current land-use composition of the study area, using the Bray–Curtis measure of dissimilarity. We computed the Bray–Curtis measure, $\mathrm{BC}_{o,c}$, based on the land-use area shares, a_l, of the optimal (index *o*) and the current (index *c*) land-use portfolios (as recorded by Gosling et al. 2020a). $\mathrm{BC}_{o,c}$ values close to 0 indicate low dissimilarity and values close to 1 high dissimilarity:

$$\mathrm{BC}_{o,c} = \frac{\sum_{l=1}^{7} \left| a_{l,o} - a_{l,c} \right|}{2} \tag{2}$$

Scenario Analysis

The optimal portfolio represents the land-use composition that best reduces trade-offs between the five socio-economic objectives, accounting for different levels of risk aversion. The data outlined in Table 4 represent the socio-economic coefficients used in the baseline scenario of our optimisation. In the third part of the study, we rerun the optimisation for a series of scenarios (outlined in Table 5) that reflect different household, environmental, market and political conditions. For all scenarios we follow the principle of ceteris paribus, changing one variable or element at a time, to test how this change influences the type and amount of agroforestry included in the optimal portfolio.

In the first set of scenarios, we retain the socio-economic coefficients from Table 4, and instead change the structure of the multi-criteria optimisation model. These scenarios therefore mimic different characteristics of the decision-maker. For instance, in the baseline scenario the five socio-economic indicators are weighted equally, but in the "Prioritising individual objectives" scenario we explore the impact of putting more weight on single indicators, to reflect the optimal portfolio for farmers with different priorities (Section 7.1 in Supplementary material details the weighting procedure). In the scenarios "Investment constraints and Labour constraints", we impose fixed limits in the optimisation model to determine the optimal portfolio for farms with different labour or investment budgets. Moreover, we also tested these fixed limits when including farmers' land-use preferences, as measured by Gosling et al. (2020a), as an additional indicator in the multi-criteria optimisation model (see Section 7.2 in the Supplementary material for details). These preferences may serve as a proxy for farmers' cultural values (Knoke et al. 2014).

The second set of scenarios retain the baseline structure of the multi-criteria model (i.e., objectives weighted equally and no labour/investment constraints), and instead alter the assumptions and coefficients of the land-use model. These scenarios test environmental, market and political factors that are more external to the decision-maker. For example, in the "Lower crop yields" scenario we progressively decrease the expected yields of annual crops (rice and maize) within the monoculture and alley cropping systems, to simulate less productive soils and poorer growing conditions. In the scenario "Agroforestry subsidy", we decrease the investment costs associated with silvopasture and alley cropping; here we simulate government subsidies or cost-sharing arrangements that reduce the tree establishment costs for farmers wishing to adopt agroforestry. Finally, in the "Higher timber prices" scenario we simulate favourable development of wood markets, progressively increasing the expected (baseline) price of teak and cedar.

For the second set of scenarios, all changes to the land-use model were made proportionally: we increased or decreased a variable by 0–100% in 10% steps. For each 10% change, we reran the Monte Carlo simulations to generate a new mean and standard deviation for the relevant land uses and indicators, and then reran the multi-criteria model with these new input data. We present the results for a high level of uncertainty ($m = 3.0$), based on the assumption that smallholder farmers are likely to be strongly risk-averse (Baker et al. 2017; Pannell et al. 2014), but the results for a lower level of risk aversion ($m = 1.5$) are also given in the Supplementary material (Fig. S6). The overall aim of the scenario analysis was to explore the conditions under which agroforestry becomes a more (or less) attractive land-use option for a risk-averse farmer.

Results

Baseline Scenario

Figure 2 shows the optimal land-use composition for reducing trade-offs between the five socio-economic objectives under baseline conditions for the three levels of risk aversion. These optimal land-use compositions largely exclude agroforestry. Only alley cropping is selected in low (3%) shares: either to complement maize as a non-protective land-use when risk is disregarded, or as part of a diversification strategy at a high level of risk aversion.

According to the multi-criteria model, a risk neutral farmer (i.e., a farmer who disregards potential fluctuations in land-use performance) would allocate 58% of their land to maize, 3% to alley cropping and leave the rest as unmanaged forest (Fig. 2, second column from left). Maize dominates this farm portfolio because of its high predicted values for food production and NPV, while the large (39%) share of natural forest reduces the overall labour demand, investment costs and payback period of the portfolio. However, maize yields and prices vary quite strongly from year to year, making the maize monoculture a risky land use. Therefore at higher levels of risk aversion less maize is selected in the optimal portfolios, which become more diversified, also at the expense of protective land uses (natural forest). A moderately risk-averse farmer, for instance, would include a 33% share of pasture in their portfolio, reduce the maize share to 31% and supplement annual crop production with a 21% share of rice, leaving

Table 5 Overview of the scenarios tested in the sensitivity analysis

Type	Scenario name	Description	Changes in socio-economic coefficients	Justification
Assumptions of multi-criteria model	Prioritising individual objectives	The five indicators are no longer weighted equally in the optimisation. Instead we test the impact of making one indicator twice as important as the others. Weighting method described in Section 7 of Supplementary material.	None: all values as per Table 4.	Simulates the decision-making of a farmer who has a clear preference for one objective, but still considers the other household goals in their decision-making. Investigates how prioritising individual objectives may promote or hinder agroforestry adoption.
	Investment constraints	Introduce a constraint to restrict the total investment costs (per hectare) of the optimal portfolio.	None: all values as per Table 4.	In the baseline scenario, the multi-criteria model balances reducing labour demand and investment costs with the other socio-economic objectives. Optimal portfolios may exceed the labour availability and investment capacity of individual farms. For these scenarios, we set a limit for labour demand and investment costs, which the optimal portfolio cannot exceed. This is intended to simulate hard economic constraints.
	Labour constraints	Introduce a constraint to restrict the total labour demand (per hectare) of the optimal portfolio.	None: all values as per Table 4.	
Assumptions of land-use model	Lower crop yields	We proportionally decrease the expected yields of rice and maize. Timber and cattle yields remain unchanged.	Lowers NPV and food production and increases payback period of rice, maize and alley cropping. All other coefficients as per Table 4.	Simulates poorer site conditions, where lower yields from annual crops are expected. Sensitivity analysis in case yields in baseline scenario are too optimistic for the study area.
	Agroforestry subsidy	We proportionally decrease the investment costs of alley cropping and silvopasture.	Increases NPV and decreases payback period and investment costs of alley cropping and silvopasture. All other coefficients as per Table 4.	Simulates financial support from government programs to promote agroforestry establishment. For example, government agencies could provide free tree seedlings and/or fencing materials (for tree guards) to reduce the cost of establishing agroforestry.
	Higher timber prices	We proportionally increase the expected (baseline) timber price for teak and cedar.	Increases NPV and decreases payback period of alley cropping and teak plantation, increases NPV of silvopasture. All other coefficients as per Table 4.	Simulates favourable development of wood markets. Could also simulate tax exemptions on timber sales.

The scenarios can be divided into two groups: those that change the assumptions of the multi-criteria (optimisation) model, and those that change the assumptions of the land-use model

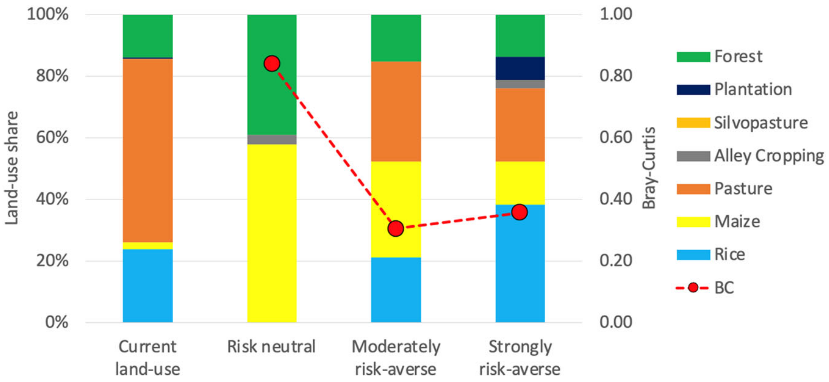

Fig. 2 Composition of the optimised farm portfolio (share of land area allocated to each land use, left axis) for three levels of uncertainty: risk neutral ($m = 0$), moderately risk-averse ($m = 1.5$), and strongly risk-averse ($m = 3.0$) under the baseline scenario. The first column represents the current (aggregated) land use of the study area (data from Gosling et al. 2020a). Points represent the Bray–Curtis measure of dissimilarity ($BC_{o,c}$, right axis) between the current and optimised land-use compositions: lower values indicate that a portfolio is more similar to the current land use

only 15% of the land as natural forest. A strongly risk-averse farmer would further diversify their land use with an 8% and 3% share of teak plantation and alley cropping, respectively. We therefore see that the optimal mix of land uses for achieving the five socio-economic objectives will depend on the decision-maker's attitude toward risk. The two portfolios derived for a moderately and strongly risk-averse decision-maker are more similar to the current land-use allocation in the study area (leftmost column of Fig. 2) than the portfolio derived for a risk neutral farmer, as shown by the lower Bray–Curtis values.

Accounting for Farmers' Priorities, Preferences and Constraints

In the "Prioritising individual objectives" scenario, we found that giving higher weight to NPV strongly affects the type and share of agroforestry selected in the optimal portfolio. Weighting NPV as twice as important as the other indicators results in an optimal portfolio containing a substantial share of alley cropping (23%) for a risk neutral farmer (Fig. 3). A moderately risk-averse farmer would instead opt for 24% silvopasture. A very cautious decision-maker who prioritises NPV, however, would replace conventional pasture with annual crops in the optimal portfolio, with only a minimal increase in agroforestry. Prioritising the other indictors only had a minor impact on the share of agroforestry in the optimal portfolio.

An alternative method to account for farmers' priorities would be to include their stated land-use preferences as an additional indicator in the multi-criteria model (see Section 7.2 of the Supplementary material). This approach favours the selection of agroforestry: the optimal portfolios that account for farmers' stated land-use preferences contain a 11% and 21% share of silvopasture for a moderate and high level of risk aversion, respectively (Supplementary Fig. S3).

Taking the perspective now of a strongly risk-averse farmer, we see that the share of agroforestry in the optimal portfolio declined with increasing "Labour constraints" and "Investment constraints" (Fig. 4). However, we also see that agroforestry disappears more rapidly from the optimal portfolio under labour constraints than under investment constraints. This trend is especially clear when including farmers' preferences as an additional indicator in the multi-criteria model, which increases the share of silvopasture in the constraint free portfolio.

For example, if labour is capped to less than 14 days per hectare per year, agroforestry could not compete with a mix of pasture, annual crops, teak plantation and forest (both under the baseline scenario and when considering farmer preferences: Fig. 4A, B). For a 50 ha farm, 2.3 workers would be needed to ensure 14 labour days are available per hectare per year[1]. As available labour continues to fall the share of productive land uses declines and forest cover increases (for both the baseline and farmer preference scenarios, Fig. 4A, B).

Decreasing the budget available for establishment costs initially leads to a small (6–8%) share of silvopasture in the optimal portfolio under the baseline scenario. But if a farmer cannot spend more than $1000 per hectare on land-use establishment, agroforestry is no longer included in the optimal portfolio (Fig. 4C). However, if farmers' general preferences are also considered in the multi-criteria model (Fig. 4D), silvopasture is consistently included in the optimal portfolio even under severe budget constraints: in this

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[1] This equates to 0.05 workers per hectare. By comparison, the average labour availability of farms interviewed by Gosling et al. (2020a) was 0.08 workers per hectare.

scenario silvopasture always comprises around 21% of the non-protective land area (i.e., the land area not allocated to natural forest).

The fact that silvopasture persists in the optimal portfolio when restricting investment costs (Fig. 4D), but is quickly replaced with conventional pasture when imposing labour constraints (Fig. 4B), in part reflects the greater trade-off in labour demand compared to investment costs when switching from conventional pasture to silvopasture. For instance, conventional pasture already entails high investment costs ($1433 per hectare, 54% of which is used to purchase cattle), which in our land-use model are only 27% lower than those of silvopasture ($1970 per hectare, Table 4). In contrast, the difference in labour demand between the two cattle-based systems is more pronounced: conventional pasture saves 39% of the labour demand of silvopasture (pasture requires an average of 8 labour days per hectare per year compared to 14 labour days for silvopasture, Table 4). Therefore, as labour constraints increase, the model is more likely to select pasture over silvopasture (see, e.g., the increasing share of pasture in Fig. 4B).

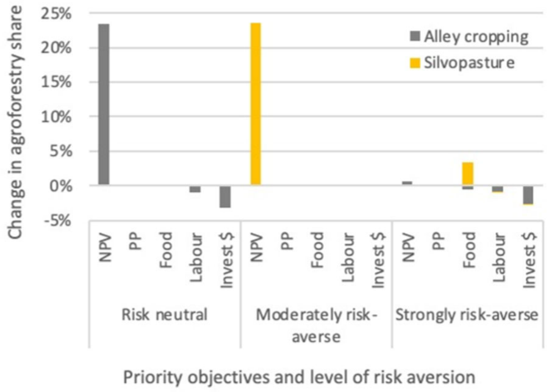

Fig. 3 Relative change in the share of agroforestry selected in the optimal portfolio when prioritising one of the five indicators (net present value (NPV), payback periods (PP), Food production, Labour demand, Investment costs), for three levels of risk aversion. Prioritisation (weighting) method outlined in Table 5 and Section 7.1 of the Supplementary material

Simulating Changes in Environmental, Market and Political Conditions

Figure 5 shows the relative change in the amount of agroforestry selected in the optimal portfolio when altering the assumptions and socio-economic coefficients of the land-use model. Across this group of scenarios, we see a stronger response of silvopasture than alley cropping; more

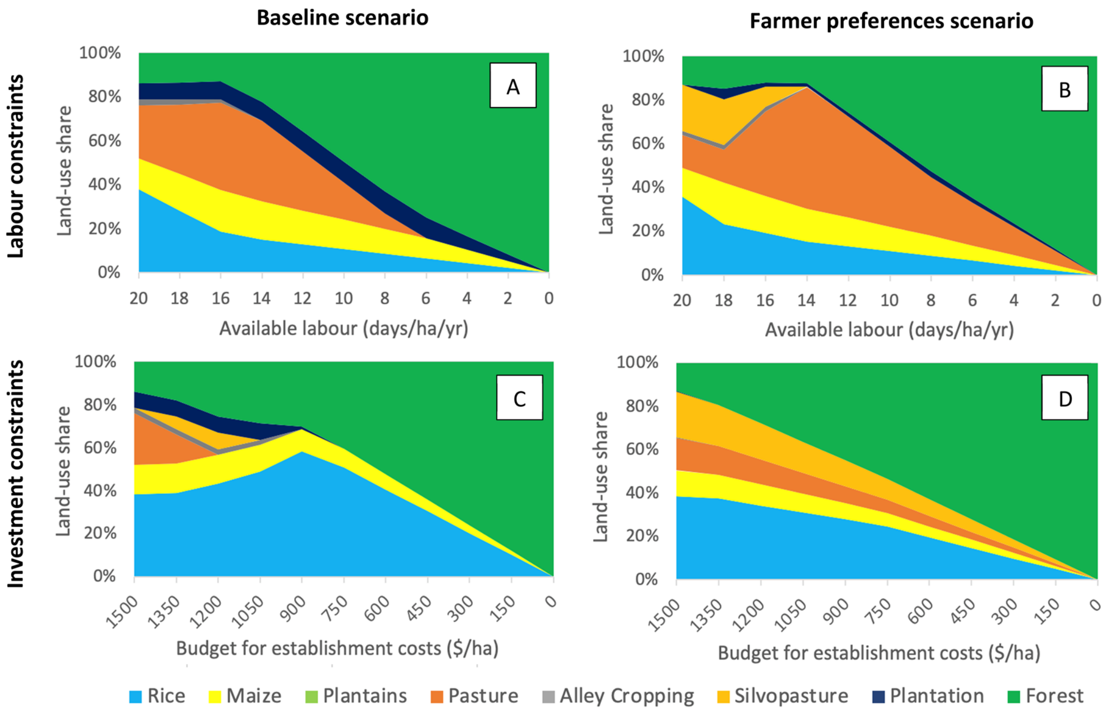

Fig. 4 Composition of the ideal farm (share of land area allocated to each land-use option) for a strongly risk-averse farmer ($m = 3.0$), when imposing farm-level constraints in the "baseline" (plots A and C) and the "farmer preferences" scenarios (plots B and D), for which farmers' general preferences are included as an additional indicator in the multi-criteria model (see Section 7.2 of the Supplementary material). In the plots A and B, the total amount of labour available to manage the land-use portfolio is progressively restricted. In plots C and D, the total investment budget for establishing the land-use portfolio is restricted

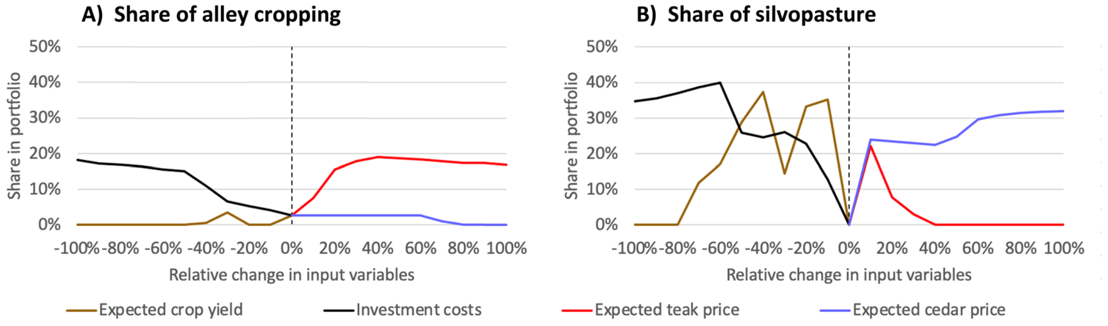

Fig. 5 Share of **A** alley cropping and **B** silvopasture selected in the optimal land-use portfolio when changing the assumptions and coefficients of the land-use model. Input variables of the land-use model are progressively increased or decreased under three scenarios: changes to expected crop yields relate to the "lower crop yields" scenario, changes in investment costs to "agroforestry subsidy" and changes in teak and cedar price to "higher timber prices". These scenarios are described in Table 5. Optimisation carried out from the perspective of a strongly risk-averse decision-maker ($m = 3.0$)

silvopasture appears in the optimal portfolio. For example, silvopasture reached a maximum share of 40% when investment costs fell by 60% (black line, Fig. 5B). In contrast, the maximum share for alley cropping in the optimal portfolio was only 19%, achieved with a 40% increase in teak price (red line, Fig. 5A). We found a similar pattern of results for a moderately risk-averse farmer (Supplementary Fig. S6).

Simulating "Lower crop yields" (e.g., to find the optimal land allocation for a farm with less fertile soils) tends to favour the selection of silvopasture in the optimal portfolio. For example, silvopasture reached a share of 37% when expected crop yields declined by 40% (brown line in Fig. 5 B). Conversely, the share of alley cropping selected in the optimal portfolio fell to zero as expected crop yields declined (brown line in Fig. 5A).

Reducing investment costs under the "Agroforestry subsidy" scenario increased the share of both agroforestry systems in the optimal portfolio, but silvopasture to a greater extent. On average the alley cropping share increased by 1.6 percentage points per 10% drop in investment costs. In contrast, the share of silvopasture increased by two and a half times this rate (3.9 percentage points per 10% drop in investment costs). Providing farmers with tree seedlings and tree guards free of charge would reduce the total establishment costs of alley cropping and silvopasture by 20% and 13%, respectively. This would result in a 5% share of alley cropping and 20% share of silvopasture in the optimal portfolio (Supplementary Fig. S5).

Similarly, "Higher timber prices" promoted both agroforestry systems in the optimal portfolio, but silvopasture in particular. On average the share of alley cropping rose by 1.4 percentage points per 10% increase in teak price, whereas the silvopasture share rose by 3.5 percentage points per 10% increase in cedar price. Interestingly, the share of silvopasture initially increases with rising teak prices as silvopasture replaces pasture in the optimal portfolio (Supplementary Fig. S4d).

Discussion

Agroforestry is not yet widespread in the study area, nor was it prominent in the optimised portfolio under baseline conditions. Here the similarity between the optimal portfolios for risk-averse farmers and the current land-use composition in Tortí (see Bray–Curtis values in Fig. 2) speaks for the plausibility of our model results. Given the Panamanian Government's policy to increase agroforestry practices in rural areas (MiAmbiente 2019), it is vital to understand the factors that could help facilitate a transition from conventional to more tree-based farming systems among smallholders. Our modelling approach is well suited to this task, because it allows us to look beyond the current land-use composition to investigate theoretically optimal land allocations under different environmental or socio-economic conditions. This scenario analysis allows us to explore the factors that may promote or hinder the selection of agroforestry within a diversified land-use portfolio: an analysis that may prove extremely difficult when relying on empiric methods alone.

Targeting Agroforestry: the Role of Farmer Priorities, Preferences and Attitudes toward Risk

Our model may help to understand the types of farmers for whom agroforestry may be most attractive, helping to target extension programs accordingly. For example, our "Prioritising individual objectives" scenario revealed large shares of agroforestry in the portfolios optimised for risk neutral and moderately risk-averse farmers who prioritise long-term income (quantified through NPV) over the other socio-economic objectives. This suggests that alley cropping and silvopasture may be attractive options for farmers who are more focused on longer-term profit but also more willing to accept risk. NPV could be an especially pertinent indicator for wealthy farmers, who may not depend as much on frequent and regular cash income from pastures or annual crops (Knoke et al. 2020b). The promotion of these agroforestry systems could therefore be targeted towards profit-oriented farmers managing larger farms, who have diversified income sources, including off-farm earnings, that help buffer financial risks (Bowman and Zilberman 2013).

Relying on NPV alone as a selling point for agroforestry, however, may limit the widespread adoption in regions where profit-oriented farmers are the exception rather than the rule. This may be the case in our study area. For instance, Gosling et al. (2020a) found that the shorter-term goals of maintaining liquidity and meeting subsistence needs (as opposed to long-term profit) could best explain farmers' current land-use decisions in Tortí. Other studies in the tropics have also found that smallholder farmers tend to prioritise immediate needs related to cash flow and food security over long-term goals of profit maximisation (Affholder et al. 2010; Umar 2013). It is therefore vital to explore the conditions under which agroforestry can help achieve a broader set of farm-level goals.

It is promising that accounting for farmers' stated land-use preferences as an additional indicator in the multi-criteria model (Fig. S3) enhanced the share of silvopasture in the optimised portfolio, because it suggests that this agroforestry system is compatible with farmers' cultural values. In contrast, the lack of alley cropping in this portfolio implies that the silvoarable system may be less socially acceptable for farmers (despite being more profitable and less labour intensive than silvopasture). Cultural values can be important barriers or drivers of agroforestry adoption (Rahman et al. 2017; Tsonkova et al. 2014). Therefore, we would recommend developing and promoting silvopastoral (rather than silvoarable) systems in the study area, to better align with the cultural preferences of local farmers, recognising the importance of cattle for farmers' livelihoods as a form of insurance and personal savings (Peterson St-Laurent et al. 2013). Nonetheless, demonstration farms that showcase alley cropping systems may help raise awareness and technical knowledge of this form of agroforestry among local farmers, which over time could foster greater acceptance of tree–crop systems within the farming community.

Farmers' individual attitudes towards risk, however, will also influence the relative attractiveness of the two agroforestry options. In general, the highest shares of agroforestry occurred in portfolios optimised for a highly risk-averse farmer. This highlights the advantage of agroforestry as a diversification strategy to reduce risk (Baker et al. 2017; Lin 2011; Waldron et al. 2016). Across the different scenarios we found that land-use portfolios optimised for risk-averse farmers generally contained more silvopasture than alley cropping. This suggests that silvopasture may be the better option for avoiding underperformance of the socio-economic objectives under uncertainty, because it holds relatively low risks. Silvopasture offers the security of annual income from cattle sales, for which yields and prices are typically stable (Connelly and Shapiro 2006), with the bonus of additional income from cedar at the end of the rotation. In contrast, alley cropping cannot guarantee an annual income because shading restricts maize cultivation from year 3 onwards. Instead, the bulk of revenue flows rely on timber prices at three points of time (the two thinnings and final harvest), which makes it inherently risky. Paul et al. (2017) also report elevated risk levels for alley cropping compared to monoculture crops. Therefore, alley cropping may be less compatible with risk-averse decision-making.

The Effect of Labour, Budget and Land Constraints

Despite farmers' preference for silvopasture (Gosling et al. 2020a), this agroforestry system is not common practice in the study area. This may reveal a conflict between the land-use systems that farmers wish to have, and those that they are able to implement given their hard economic constraints (Gosling et al. 2020b; Tschakert et al. 2007). Expanding on previous studies (Gosling et al. 2020a, b), we explore the role of such farm-level restrictions on the optimal land-use composition by imposing fixed limits for labour demand and investment budgets in the optimisation model.

As expected, we found that "Labour and Investment constraints" reduce the share of agroforestry selected in the optimal portfolio. This aligns with other studies that found investment costs and labour demand to be barriers to agroforestry adoption in Latin America (e.g., Calle et al. 2009; Dagang and Nair 2003; Frey et al. 2012b). We found that silvopasture persists in the optimal portfolio when restricting investment costs, but is quickly replaced with conventional pasture when imposing labour constraints, suggesting that labour demand may pose the bigger barrier to silvopasture adoption.

In our model, the relative increase in labour demand when selecting silvopasture over conventional pasture is greater than the relative increase in investment costs, meaning the agroforestry system is hit harder by labour constraints. In practice, labour constraints may also be harder to overcome than capital constraints for farmers in the study area. It is common for farmers in Tortí to take out a loan to buy cattle when establishing conventional pasture systems (Peterson St-Laurent et al. 2013); the additional capital needed to establish trees for silvopastoral systems may be attainable through such loans, offering a means to overcome investment constraints. Meeting the additional labour requirement for silvopasture, however, may be more problematic, especially in tight labour markets (Baker et al. 2017; Pichón 1997). Labour shortages could be exacerbated by a hollowing of the forest frontier, which Sloan (2008) has already observed in eastern Panama: this is a phenomenon where the population density of a deforested landscape declines as extensive farming practices increase. Peterson St-Laurent et al. (2013) also report strong out-migration in eastern Panama as young people move to cities. In the face of tight labour markets it may therefore be necessary to adapt silvopastoral systems to better meet the needs of farmers constrained by labour shortages. This could be done by improving economies of scope, for example, through the use of multi-purpose trees where pruning could be combined with fodder production (Reyes Cáceres 2018). Such economies of scope are already a key advantage of the alley cropping system, in which trees and crops are weeded simultaneously (Paul et al. 2017).

Farmers' land-use decisions will also be constrained by site conditions, which will influence the relative attractiveness of agroforestry. For example, simulating "Lower crop yields" increased the share of silvopasture selected in the optimal portfolio of a risk-averse decision-maker. This suggests that silvopasture may be a more attractive land-use option for farmers with less productive land (on which it is not possible to cultivate high yielding crops). These findings align with bio-economic studies that suggest agroforestry may be more advantageous on poorer growing sites (Crestani et al. 2017; Tsonkova et al. 2014). Moreover, the results underline the general importance of land condition (i.e., soil type and quality) for influencing the uptake of agroforestry and agricultural innovations (Pannell et al. 2014; Pattanayak et al. 2003).

Subsidies and Timber Prices to Promote Agroforestry Adoption

We found that the selection of agroforestry in the optimal portfolio was most responsive to a potential "Agroforestry subsidy" (lowering investment costs) and "Higher timber prices". This suggests that cost-sharing arrangements could be an effective strategy to boost agroforestry adoption in the study area. For example, providing farmers with free tree seedlings and tree guards resulted in a 5 and 20% share of alley cropping and silvopasture in the optimal portfolio. Given its higher labour demand compared to conventional pasture, greater adoption of silvopasture could generate employment opportunities in the region if farmers hire day workers to assist with tree planting and pruning (Frey et al. 2012a). Establishment grants for silvopasture could help farmers finance this additional labour. While the legal framework for such incentives exists, they are yet to be consistently implemented in the study area.

In our scenario testing, we found that moderate increases in timber prices could lead to substantial shares of agroforestry being selected in a land-use portfolio that balances trade-offs between the five socio-economic objectives. For example, a 30% increase in teak price would result in a 18% share of alley cropping in the optimal portfolio, while a 30% increase in the cedar price would lead to a 33% silvopasture share. We also found that a small (10%) increase in the teak price could favour the selection of silvopasture in the portfolio. As the rising teak price makes alley cropping and plantation more profitable, the underperformance of pasture in terms of NPV becomes too great and it is first replaced with silvopasture and then by alley cropping and teak plantation in the optimal portfolio as the teak price continues to increase (Supplementary Fig. S4d).

Timber prices strongly depend on market factors, and are thereby harder to engineer through government programs. However, the Panamanian Government's recently legislated tax exemptions for timber grown in agroforestry systems (Law 69, 2017) could increase revenues from timber sales. Such tax incentives could particularly benefit the selection of alley cropping, which would become more competitive against pure teak plantation. This assumes, however, that farmers are earning enough to pay income tax, which may not be the case for many farm households (Díaz et al. 2012). Alternatively, farmer training programs on tree management (e.g., pruning and pest control techniques) could improve silvicultural practices, helping farmers to produce higher quality timber and hence obtain higher prices. Training programs and certification schemes could also help farmers build their capacity to access markets and obtain price premiums (Holmes et al. 2017; Somarriba et al. 2012). Nonetheless, when considering current timber prices (baseline scenario), only very small shares of agroforestry were included in the optimal portfolio. This could signal that further development of timber markets is a prerequisite for widespread adoption of timber-based land-use systems among smallholder farmers in the study area.

Limitations of Modelling Approach and Research Outlook

Our study is a rare example of a multi-criteria evaluation of agroforestry that takes a portfolio approach to account for the effects of land-use diversification and uncertainty on farmers' land-use decisions. However, we acknowledge limitations of our study, which could be addressed in future research.

First, we rely on static modelling approaches in both the land-use and multi-criteria models. For instance, the land-use model ignores adverse environmental effects such as soil depletion over time (Janssen and van Ittersum 2007).

This may overestimate the productivity of conventional land uses, and hence downplay drivers of agroforestry adoption. Future studies could therefore integrate production decay functions (e.g., following Sanchez 1976) to better account for the effect of nutrient depletion and soil structural changes on crop yields. Similarly, the multi-criteria model identifies theoretically optimal land allocations, but not how these could be achieved over time. Using a more dynamic optimisation approach, such as the one Knoke et al. (2020a) recently developed to investigate smallholders' deforestation decisions in Ecuador, would allow us to simulate farmers' land-use decisions in smaller time steps. This would allow for staggered planting of trees, which might be a more feasible path for smallholders to adopt agroforestry (Bertomeu and Giménez 2006). A dynamic approach may also help to account for the option value of agroforestry systems and their conventional counterparts, an aspect which is overlooked in this study. In our land-use model, the timing of timber harvesting is fixed: this fails to capture the flexibility that a farmer has to postpone harvest if timber prices are unfavourable (Frey et al. 2013).

Second, our robust optimisation model is not spatially explicit. The model identifies what portions of a hypothetical farm could be allocated to each land-use option, but does not specify the exact location or arrangement of these land-use options (Bertomeu and Giménez 2006). This approach implicitly assumes homogeneous site conditions. Therefore, our multi-criteria model ignores the potential influence that farmers' existing land use as well as variation in soil quality, slope and distance from the farm homestead may have on their land-use decisions, including their adoption of agroforestry (Bannister and Nair 2003; Pannell et al. 2014; Pattanayak et al. 2003). Thus, caution is needed when generalising the model results to farms with highly heterogeneous soils and/or contrasting topography, both within and outside of the study area.

Third, we integrated tree–crop and tree–pasture interactions in our land-use model through plausible assumptions (Paul et al. 2015), rather than detailed biophysical modelling. Our projected tree growth and crop yields were comparable to those simulated for the study area using the tree–crop model WaNuLCAS (Paul et al. 2017), while the economic coefficients for pasture-based systems reflect the lower, but very stable economic returns of cattle grazing in Panama (Connelly and Shapiro 2006). Nevertheless, the modelling approach could be enhanced by integrating biophysical modelling to simulate tree, crop and pasture growth in monoculture and agroforestry systems (e.g., using WaNuLCAS, Santos Martin and van Noordwijk 2011). Such modelling could be particularly useful for evaluating different layouts of agroforestry systems, for example, to identify the most promising systems for field trials. Ultimately, such local field experiments are essential to obtain empiric data, which remains the best foundation for land-use planning (Reith et al. 2020).

In presenting our study, we recognise the usefulness, but also limits, of models as decision support tools. Our modelling approach explores theoretically optimal land allocations for achieving a particular outcome under a certain set of assumptions. We do not intend to prescribe exact farm compositions that farmers in the study area should adhere to. Instead, we seek to explore the conditions under which agroforestry might be a desirable complement to help farmers reduce trade-offs between socio-economic objectives. The decision of whether or not to adopt a given land-use system rests with the farmer, and will depend on his or her objectives and constraints (Janssen and van Ittersum 2007; Pannell et al. 2006). Our study therefore does not seek to develop a decision support tool for farmers, but is rather targeted at researchers and political decision-makers. For researchers our modelling approach may help to identify the agroforestry systems and conditions under which more detailed field trials are most warranted, because the systems show a high probability of being of interest to farmers. For policy-makers, such approaches can help to identify the circumstances under which promoting agroforestry appears to be promising without generating conflicts with farmers' goals.

However, as with any decision support tool, we acknowledge a potential gap between the results of our theoretical model and the reality of farmers' decision-making (McCown 2001). Such gaps between theory and practice may stem from potential biases and uncertainties in model input data. Although we actively account for such uncertainty by implementing a form of robust optimisation (Doole 2012; Knoke et al. 2015), field experiments remain crucial to deliver reliable empiric data. The gap between theory and practice may also stem from the assumptions and limitations of the multi-criteria model, which cannot capture all aspects influencing farmers' decisions. For example, in the scenario analysis we alter one aspect at a time to understand how this affects the share of agroforestry selected in the optimal portfolio. In reality, however, such aspects will be changing simultaneously, potentially leading to complex interactions that we do not account for. With these limitations in mind, care is needed when generalising our results to other areas: the more the region differs to the biophysical and socio-economic conditions of Tortí, the greater the gap is likely to be between our theoretical and the actually optimal land allocations. However, we again emphasise that we do not seek to give exact land-use recommendations for this study site, but rather demonstrate how such an approach may inform future research and policy design.

Finally, we see potential to further develop our approach through participatory and collaborative modelling. Indeed, greater farmer interaction is likely to help narrow the gap between scientific theory and real-world practice (Janssen and van Ittersum 2007; McCown 2001). For example, farmers could help to validate input data, based on their local knowledge and experience. Moreover, as simple, stylised land-use portfolios, we believe the output of the multi-criteria model could be readily interpreted and evaluated by smallholder farmers. Discussing model results with farmers in the study area could help to validate and improve the model, for example, by changing objectives or adding additional constraints to better match the local situation (Groot et al. 2012). Optimised portfolios might also provide a good starting point for stakeholder discussions as part of participatory land-use planning (Le Gal et al. 2013). For this type of landscape-scale planning the multi-criteria model could easily integrate ecological indicators (either based on expert opinion, e.g. Reith et al. 2020, or modelled and measured data, e.g. Knoke et al. 2020a), to derive the optimal land-use compositions for achieving a wider range of ecosystem services.

Conclusion

Insights gained through our modelling approach can help to identify socially acceptable agroforestry systems for on-farm trials, and to design effective and efficient incentive and extension programs. For our case study in eastern Panama, we found that silvopasture may be most suited for meeting the needs of a risk-averse farmer, given the frequent and stable returns from cattle and the compatibility of this system with local farmers' cultural values. Poorer growing conditions for annual crop are likely to enhance the attractiveness of silvopasture as a land-use option, as would government support to subsidise tree-planting costs. However, the uptake of silvopasture may be limited on farms where less labour is available. Despite being the more profitable agroforestry system, we found that alley cropping was less compatible with farmers' cultural values and risk aversion. This system may nonetheless be a suitable complement to a diversified farm portfolio for more risk-tolerant, profit-oriented farmers. While we present an example from a tropical forest frontier region, the multi-criteria optimisation method is transferable to investigate sustainable land-use systems in other agricultural or forested landscapes.

Data Availability

All data sources used are appropriately cited. Original model files are available from the authors upon request.

Acknowledgements This project was funded through the German Research Foundation (DFG, Grant number PA3162/1). We thank Fernando Lopez and Andrés Domínguez for their advice and assistance during our research stay in Panama, as well as Rodrigo Duarte and Peter Glatzle for their help with the farmer and expert interviews. Finally, we would like to thank the two anonymous reviewers for their insightful and constructive feedback on our paper.

Funding This project was funded through the German Research Foundation (DFG, Grant Number PA3162/1). Open Access funding enabled and organized by Projekt DEAL.

Compliance with Ethical Standards

Conflict of Interest The authors declare no competing interests.

Consent to Publish All authors agree with the content of this paper and have given explicit consent to submit it to *Environmental Management*.

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