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A scalable approach for efficient and comparable characterisation of smallholder farming systems
The Rural Household Multi-Indicator Survey RHoMIS

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School of Environment, Natural Resources and Geography,
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The Rural Household Multi-Indicator Survey
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If I have worked on this PhD for seven hours a day over three and a half years, then I've spent about 7,000 hours.

The RHoMIS dataset is now up to about 15,000 households interviewed. At approximately one hour per survey, that is 15,000 hours of time given by smallholder farmers. So the work is really more theirs than it is mine.

SUMMARY

There are approximately 500 million smallholder farmer households worldwide, at least half of which live in poverty and food insecurity. Scientific research underpins development efforts by providing options for improved varieties, breeds, or practices (termed “interventions”); and by providing analyses of how to increase the adoption and impact of those interventions. One of the most widely used method of data collection to evaluate or predict the impact of interventions is the household survey, but critical evaluations of the effectiveness of household survey data and methodologies are rare. Lack of standardised questions make efforts to aggregate findings across datasets challenging, given that different surveys often yield widely different data, both in terms of content and quality, which severely limits the comparability of those data (see Chapters 2 and 3).

Here I present an improved survey method to assess farm practices and food security for smallholder households in lower income countries, primarily tropical or sub-tropical. The tool is named the Rural Household Multi-Indicator Survey (RHoMIS). It makes use of recent advances in digital technologies, which enables quicker data collection and reporting than in previous generations of survey tools. The tool was designed to be rapid, lean, user-friendly, flexible and reliable (Chapter 3). The design ethic and advances in indicator formulation allowed data to be gathered on a wider range of topics over shorter time frames but still with adequate depth to permit effective analyses (Chapters 4, 5, and 6). During development RHoMIS was deployed by 13 organisations in 17 countries, with over 15,000 interviews conducted. The tool has the flexibility needed for application in many locations, sufficient standardisation to permit rapid analysis and data aggregation between sites, and enables more efficient characterisation of smallholder farming systems compared to previous efforts.

Findings of analyses presented in this thesis stress the need to understand the heterogeneity of smallholders, and to plan or evaluate interventions for specific subsets of households. Analyses presented in the research chapters show that the farm strategy of input intensification is better suited to larger farms, crop diversification is better suited to smaller farms, and that the effects are strongly influenced by the degree of commercialisation of livelihoods (Chapter 3), the use of collected resources can strongly benefit the poorest households (Chapter 4), and that off-farm incomes in combination with farm intensification hold the potential to raise the prosperity of about 90% of the households studied in Chapter 5 . Furthermore households show different levels of interest in trialling and adopting new practices which are not necessarily related to their assets or farm types, in Chapter 2 about one quarter of households were identified as likely to trial new practices. In particular the analyses highlights that those experiencing (or at risk of) extreme food insecurity benefited most from opportunities for off-farm income, whereas moderately poor households benefited more from agricultural intensification. These findings indicate that for agricultural intensification measures to raise households out of food insecurity and poverty they must be targeted to the appropriate group of smallholders, and to succeed must be in combination with opportunities to earn off farm income.

Acknowledgements

I have learned that no scientific work is done in isolation, even though it sometimes feels that way when spending long hours at a computer, or when trying and failing to explain what you do in your professional life to someone out of the loop.

I would therefore like to thank all of those who have made this work possible, but would fail as I am probably not even aware of the majority of the work which has led to my being able to write this thesis. Decades of diligent work by many many people have developed the theoretical foundations and the practical infrastructure on which this work has been based.

Zooming in to my immediate colleagues and those who have facilitated the work, I would like to thank Drs. Mark van Wijk and Tim Pagella for providing excellent, insightful, and generous supervision throughout. It has been a pleasure working together. I'd like to thank colleagues who have invested intellectually, and sometimes financially, in this work: Drs. Todd Rosenstock, Jacob van Etten, Nils Teufel. Collaborating with Simon Fraval has been invaluable. I'd also like to thank Professors Fergus Sinclair, Ingrid Öborn, and Xu Jianchu, for supporting me at key moments which led to the opportunity to conduct this research. To the many staff who organised and facilitated the field work, to the enumerators who conducted the interviews and the farmers who gave their time and submitted to our questioning, I extend my thanks, and hope to make good on their work.

The funding for this PhD has been from diverse sources, and the co-ordination of those sources has been no mean feat by the supervisory team. The primary sources of funds are listed here, in roughly chronological order: the BMZ/GIZ project Green Rubber (Project No. 13.1432.7-001.00), Humidtropics – a CGIAR Research Program, the CGIAR Research Program on Livestock, and its former incarnation the CGIAR Research Programs on Livestock and Fish, the CGIAR research program on Climate Change Agriculture and Food Security, the Surveillance of Climate-smart Agriculture for Nutrition project (SCANs), principally funded by UK AID through the Innovative Methods and Metrics for Agriculture and Nutrition Action (IMMANA) program, two of the USAID-funded Feed the Future programs the Sustainable Intensification Innovation Lab, and AfricaRISING, and finally the Bill and Melinda Gates funded LiveGAPS II project. The funding for much of the field work in which the RHoMIS tool was used to gather data is even more diverse and I will not report that here.

Finally I would like to extend personal thanks to my lovely wife and daughter for keeping my life in balance, to my parents for laying the necessary foundations that I could conduct a PhD, and to my office mates Tom, Jon and Evie who kept me entertained and well-caffeinated for much of the past few years.

Authorship information

All four of the research chapters of this thesis have been prepared for peer-reviewed publication. Chapters 2 and 3 are published in *Agricultural Systems.* Chapter 4 has undergone peer review and final editing for publication in an edited book to be published by Springer. Chapter 5 will be shortened and re-organised for submission to *Proceedings of the National Academy of Sciences*.

The author of this thesis is the lead author of each of the publications based on the research chapters. In addition to my supervisors, several co-authors are included on each manuscript, who have been instrumental in data collection, intellectual framing of the topic, or otherwise facilitating the research. The author list and references for the publications based on chapters are given below.

- Hammond, J., Fraval, S., van Etten, J., Suchini, J. G., Mercado, L., Pagella, T., Frelat, R., Lannerstad, M., Douxchamps, S., Teufel, N., Valbuena, D., van Wijk, M. T. (2017). The Rural Household Multi-Indicator Survey (RHoMIS) for rapid characterisation of households to inform climate smart agriculture interventions: Description and applications in East Africa and Central America. Agricultural Systems, 151, 225–233. https://doi.org/10.1016/j.agsy.2016.05.003
- Hammond, J., van Wijk, M. T., Smajgl, A., Ward, J., Pagella, T., Xu, J., Su, Y., Yi, Z., Harrison, R. D. (2017). Farm types and farmer motivations to adapt: Implications for design of sustainable agricultural interventions in the rubber plantations of South West China. Agricultural Systems, 154, 1–12. https://doi.org/10.1016/j.agsy.2017.02.009
- Hammond, J., van Wijk, M. T., Pagella, T., Carpena, P., Skirrow, T. and Dauncey, V. (2018) 'Shea butter: a pro-poor, pro-female route to increased income' in The Climate-Smart Agriculture Papers: Investigating the Business of a Productive, Resilient and Low Emission Future, Rosenstock, T., Nowak, A. Girvetz, E., eds. Springer International Publishing.
- Hammond, J., Pagella, T., Fraval, S., Wichern, J., Teufel, N., Kihoro, E., Herrero, M., Rosenstock, T.S., and van Wijk, M.T. (*in prep*) Rapid pace of change for rural smallholders in East Africa, where prosperity is driven by off farm income in tandem with agricultural intensification.

Furthermore, I will outline the work done in terms of designing and building the survey tool and associated infrastructure, the analyses, and the field work, in order to indicate the degree to which I have contributed to each.

I claim partial credit for the overall conceptual design of the RHoMIS tool, in collaboration with my supervisors Mark van Wijk and Tim Pagella. I also claim partial credit, shared with my supervisors, for the selection of topics to include in the core questionnaire. The indicators used to appraise those core topics have been referenced appropriately as few are original to this thesis; although some have been adapted to make them suitable for inclusion in RHoMIS.

I claim credit for the programming of the questionnaire into the ODK software framework (Hartung et al., 2010), and credit for the set up of the web infrastructure required to operate the tool. I did not write any of the software on which the tool or web infrastructure is based. I also claim credit for subsequent revisions of the questionnaire based on experiences and feedback from applications of the tool, and partial credit in varying degrees for authorship of additional modules for the questionnaire.

The data analysis can be broken into distinct stages. Data aggregation and exporting is done through the web server. Next R scripts are used to calculate the indicators. More R scripts are used for reporting of general findings is carried out, and then specific and more detailed analysis were carried out on a case by case basis. I claim credit for the data aggregation and exporting step, scripts for the reporting of general findings, and the detailed analyses which are presented in the research chapters and synthesis chapter of this thesis. The code for indicator calculations was written by Mark van Wijk. Data cleaning was carried out at multiple stages of the process, for which I claim partial credit.

The planning and implementation of data collection in field sites was carried out by a large number of actors, and I can only claim a small amount of the credit for these tasks. All field work were part of wider projects, and I did not have control over study design in any site, although I did contribute to discussions about sample frames in three studies, and frequently contributed to discussions on questionnaire design and analysis to answer the research needs of studies. I frequently provided training materials and guidance to trainers of enumerators, and twice led the training of enumerators. I was frequently in close contact with field teams and was available to make rapid adjustments to the questionnaire when the need arose.

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Abbreviations

CO_2 – carbon dioxide
CO_2eq – carbon dioxide equivalent
CSA – Climate Smart Agriculture
FA – Food Availability
GHG – Greenhouse Gas
ha – hectare
HH - Household
ICRAF – International Centre for Research on Agro-Forestry
ILRI – International Livestock Research Institute
kCal – kilo-Calories
kg – kilograms
km – kilometre
m – metres
mm – millimetres
NGO – Non-Governmental Organization
PPI – Probability of Poverty Index (formally Progress out of Poverty Indicator)
ns – not significant
NTFP – Non-Timber Forest Products
ODK – Open Data Kit
R4D – Research for Development
RHoMIS – Rural Household Multi-Indicator Survey
HFIAS – Household Food Insecurity of Access Scale
HDDS – Household Dietary Diversity Score
SDGs – Sustainable Development Goals
t – tons
TLU – Tropical Livestock Units
Tukey HSD – Tukey's test of Honest Significant Difference
TVA – Total Value of Activities
yr – year

CHAPTER 1: Introduction

This introductory chapter provides context for the work to follow. The work was conducted through two institutes whose mandate is applied science for rural development, or research for development as it is sometimes called (R4D). The goals of these institutes are located below in the context of global development priorities. Next, narratives on how to increase the impact of R4D are summarised, the role of the household surveys explained, and calls for the next generation of household survey tools reviewed. The aims of the thesis are then described. Finally a brief overview of the body of work upon which this thesis relies is outlined, and contribution of various individuals explained.

1. Development objectives and agricultural research for development

Rural poverty and food insecurity are still major challenges in the global efforts to achieve humane standards of living for all people. The Sustainable Development Goals (SDGs) were adopted by the United Nations General Assembly in 2015 (United Nations, 2015a) The first and second of the 17 goals are “No Poverty” and “Zero Hunger” by 2030. The role of agriculture and specifically smallholder farmers are mentioned by the UN in relation to those goals (United Nations, 2015b). In 2014 the African Union adopted the “Malabo Declaration for Accelerated Agricultural Growth and Transformation for Shared Prosperity and Improved Livelihoods” which contains commitments to end hunger in Africa by 2025 and to reduce poverty by half (African Union, 2014). Again, smallholder farmers are specifically mentioned in relation to those goals.

It is difficult to quantify the rural poor and the role of smallholder farming, as they tend to operate in data-sparse environments. In an analysis of sub-national census data across Sub-Saharan Africa, Asia and Latin America, 380 million smallholder families were identified (defined as households with less than 5ha of land) control 30% of the agricultural land and were estimated to produce 70% of the local foodstuffs (excluding imports) (Samberg et al., 2016). Another recent analysis of 55 countries found that smallholders (<2ha) produced about 30% of the foodstuffs on about 24% of the agricultural land (Ricciardi, Ramankutty, Jarvis, & Chookolingo, 2018). In a global analysis of national level census data, there were estimated to be more than 460 million small farms worldwide, operating on about 12% of the world's agricultural land (Lowder, Skoet and Raney, 2016). These numbers are broadly similar to estimates of 500 million small farms worldwide in other literature (Hazell et al., 2010; Wiggins, Kirsten and Llambí, 2010).

It is also difficult to quantify the poverty rates and food insecurity of smallholders at a global level, again due to challenges of data acquisition and aggregation. According to the Food and Agriculture Organisation (FAO) (FAO, 2018) interpretation of the World Bank’s Living Standards Measurement Survey data in 19 countries, typically 50% or more of smallholder farmers are living in poverty. Drawing on data from the FAO, Livingstone estimates that 75-80% of the poor of Sub-Saharan Africa live in rural areas (Livingston, Schonberger and Delaney, 2011). Macro-studies of smallholder nutrition generally find that there are major shortfalls, despite often diverse agricultural production (Herrero et al., 2017, Ricciardi, Ramankutty, Jarvis, & Chookolingo, 2018) In an older study of six African countries smallholder incomes were typically below the poverty line for all but the wealthiest quartile of farmers (Jayne et al., 2003).

Although hard data at the global level on smallholder farmers remains patchy, it is clear that there are many smallholders in the developing world, that they are important for food production, and that many of them are poor or very poor. Although an exclusive focus on smallholder agriculture is unlikely lead to the best overall outcomes for food security and national development (Collier and Dercon, 2014), the smallholder sector warrants sustained attention. Agriculture is the primary source of food and income for many of the poor worldwide. It is also a major way in which humans interact with the wider environment, both receiving benefits from ecosystems and impacting upon those ecosystems (Foley et al., 2011). The role of Agricultural Research for Development is to devote scientific expertise through agriculture towards the goals of poverty reduction, food security, and improving the environment.

There are many narratives describing how to go about assisting smallholder households: to produce food more efficiently (termed “intensification”) (Ejeta, 2010), to enhance and not degrade ecosystem services while producing more food (termed “sustainable intensification”) (Godfray et al., 2010; Tittonell and Giller, 2013), to adapt to changing weather patterns, mitigate greenhouse has emissions, and develop resilience (termed “climate smart agriculture”) (Neufeldt et al., 2013; Lipper et al., 2014), to boost the wider economy and the rural non-farm economy (Haggblade, Hazell and Reardon, 2010; Larson, Muraoka and Otsuka, 2016), to improve nutrition (Beal et al., 2017; Herrero et al., 2017), to promote gender equity (FAO, 2010; Farnworth et al., 2016), to build local institutions so that farmers can achieve group benefits such as more favourable market conditions (Barrett, 2008; Markelova et al., 2009), and to encourage the next generation to invest in agriculture rather than pursuing urban lifestyles (FAO, 2014). These narratives each have a whole literature associated with them, and present myriad intricacies when being applied.

This PhD is rooted in the concept of increasing the impact of R4D, regardless of the research narrative being pursued. Most of these narratives entail similar steps: understanding local situations, coming up with good ideas on how to improve things, testing those good ideas, figuring out how to get those good ideas widely adopted and practised in the general population, in order to achieve a big impact. This path to impact on general populations is difficult to achieve, and there is a body of research on how better to achieve impacts in R4D.

2. Research to increase impact

It is now recognised that it is not enough to come up with a good idea, test it, release it, and hope for impact. The context in which smallholders make their decisions has a large impact upon degree to which interventions are adopted, scaled up and achieve impact. Understanding this context and using the information to make better strategic decisions is one route to increase impact of R4D. Both the enabling factors for uptake on new practices, and the need for fine-scaled understanding of biophysical conditions such as soil quality and type, aspect, water availability and micro-climates has been recognised (Coe, Sinclair and Barrios, 2014) as such highly-localised variables tend to confound attempts to achieve “average” performance from crops or other land-based interventions

(Vanlauwe, Coe and Giller, 2016). Micro-level socio-economic conditions are also highly relevant, such as access to information, market infrastructure, extension services, farmer training, farmer networks, and security of land tenure (Franzel et al., 2004; Descheemaeker et al., 2016; Nelson, Coe and Haussmann, 2016). There have been efforts to integrate biophysical and socio-economic contextual factors and relate to the likelihood of adoption of technologies (Notenbaert et al., 2017). However, personal issues also drive adoption, including attitudes to risk, levels of trust in new information, the capacity to experiment, and differences in personality (Zubair and Garforth, 2006; Meijer et al., 2015), and there has been less work done understanding the role of those more personal issues in adoption.

Creating a facilitating environment for uptake of new practices and technologies is another major theme in efforts to increase impact, which must operate on many levels (Linn, 2012; Coe, Sinclair and Barrios, 2014; Wigboldus et al., 2016). Enabling factors such as policy environment, financial infrastructure, or farmer organisations are recognised as essential to enable uptake of new practices (Ampaire et al. 2013., Wigboldus et al. 2016). It has also been argued that R4D should follow an action-research style approach, whereby through the conducting of research, capacity is built in national agricultural research organisations and other stakeholders in the agricultural system (Schut et al., 2014). The capacity to innovate is important at multiple levels, for policy-makers, business people, and smallholder farmers themselves (Hall, 2005). Participatory field trials are one example of a solution which aims to build the innovation capacity of smallholder farmers, improve information sharing, and to select locally relevant options (Snapp et al., 2018).

3. The need for better survey tools

This thesis focuses on characterisation of smallholder households as an important step in scaling up the impact of R4D. The model is two-fold: that through better understanding of the needs of different groups of households, more useful and therefore more adoptable interventions can be promoted; and secondly that through the scaling up of characterisation across landscapes or to new landscapes where such data does not exist, general lessons can be drawn which aid increased adoption. Of course, care must be taken when scaling up lessons from characterisation and ground-truthing would be advisable to ensure that no perverse outcomes would be caused.

The household survey is probably the most widely used tool for gathering quantitative information on smallholder farm households. They are used for setting baselines and later assessing project impacts (ex-post); and they are used to establish better understanding of the context for R4D programs, sometimes with ex-ante assessments modelling potential impacts of new practices. Household surveys can be used as tools for characterisation of smallholder farmers.

Household surveys are so widely used because they appear simple to design, and because they deliver quantitative data which can be summarised, analysed for statistical significance and used as evidence of success (or failure). Both of these features can however lead to misuse of the survey. Poorly designed questionnaires yield poor quality information; and there are many ways in which questions can be poorly designed (Choi and Pak, 2005). Survey methods by necessity ask closed questions, to the exclusion of nuance and subtlety which is better captured through qualitative research methods. When this distinction is not respected poor quality data is obtained. Furthermore, the quantitative data can be over-interpreted without adequate consideration of the reliability and the validity of the data captured through the survey method (Heale and Twycross, 2015).

Survey duration is also important, although is rarely reported in survey datasets. Survey duration affects the quality and accuracy of responses (Kilic and Sohnesen, 2015). Beyond certain survey durations (estimated by the author at one to one and a half hours) data quality declines, and unless remuneration is offered (causing a different sort of bias), interviewees may come to resent the process, and thus the survey would undermine social capital built through other project activities. A viable balance must be struck between duration of the survey and quantity of data recorded: both considering the breadth of topics covered and the depth in which they are investigated. It is a tricky balance: for example, in a frank discussion article reflecting on the experience of conducting large scale impact evaluation surveys, site characterisation was explicitly excluded as an objective of the surveys (Förch et al., 2014).

Recent reviews of modelling issues related to smallholder food security found that higher level models do not take full advantage of household level data, and suggested that household data need not be highly detailed for use in such models if it were systematically gathered and could be aggregated effectively (van Wijk, 2014; van Wijk et al., 2014). However aggregation of data from multiple survey sources is a time consuming and challenging task, often yielding analyses which have sacrificed detail due to missing or incomparable information between datasets (Frelat et al., 2016; Waha et al., 2018). To aid in data aggregation, there have been calls for greater coordination between organisations gathering such data (Carletto, Jolliffe and Banerjee, 2015), and for greater coordination between the high level organisations who define the indicators to be used when reporting against development objectives (Rosenstock et al., 2017). There have also been calls to make use of well tested and standardised indicators which permit comparison between datasets (Kristjanson et al., 2017; Rosenstock et al., 2017). Furthermore, advances in digital technologies can make data collection, aggregation, and analysis a smoother and quicker process (Van Etten, Steinke and Van Wijk, 2017).

4. Aims and structure of the thesis

The overarching aims of the research were to develop characterisation tools and obtain insights into smallholder heterogeneity, to enable greater impact in agricultural research for development. To achieve these overarching aims specific objectives were addressed.

To develop characterisation tools:

- A1. Gain understanding of household characterisation tools and methods.
- A2. Design an improved tool for household characterisation.
- A3. Test and refine multiple iterations of the tool in different contexts.
- A4. Evaluate the tool for use in ex-post impact assessment.
- A5. Evaluate the tool for use in ex-ante or strategic assessments to inform future development work.

To obtain insights into smallholder heterogeneity:

- B1. Disaggregate observations of smallholders according to meaningful typologies, to better understand their heterogeneity (e.g. van der Ploeg et al., 2009).

B2. Explore the role of households' intrinsic motivations and innovation capacity in adoption of interventions (e.g. Meijer et al., 2014).

B3. Explore the role of off-farm incomes in the livelihoods of food insecure smallholders (e.g. Frelat et al. 2016).

B4. Explore the feasibility of agricultural intensification as a route out of food insecurity or poverty for smallholders (e.g. Harris and Orr, 2014).

B5. Explore the modulating effect of market access on which farm strategies led towards food security (e.g. Sibhatu and Qaim, 2018).

Each of the chapters of the thesis contributes towards these objectives, and therefore the overarching goal. The chapters are very briefly outlined in Table 1.1, and the contribution of each chapter to the thesis objectives made explicit.

These objectives can be summarised into a single guiding hypothesis: that it is possible to conduct meaningful and useful characterisation of smallholder households using rapid and replicable survey-based methods.

Table 1.1. Structure of the thesis, by chapter and objectives of the PhD.

Chapter	**Description**	**Methods**	**Objectives**
1. Introduction	Literature review and introduction to thesis	Review.	A1
2. Farm Types and Farmer Motivations to Adapt	Analysis of pre-existing survey data on farm type and farmer motivations.	Generation of novel indicators, data exploration through PCA, use of clustering algorithms, and significance tests (G-test, Anova, TukeyHSD)	A1, B1, B2
3. The Rural Household Multi-Indicator Survey (RHoMIS) for rapid characterisation of households	Summary of the design specifications for RHoMIS, the core indicators used, and results from two contrasting locations.	Review of indicators and smallholder survey methods. Indicator correlations analysed through Spearmans' rank and Wilcoxon rank-sum test. Household grouped by asset and strategy.	A1, A2, A3, A5, B1, B5
4. Shea butter: a pro-poor, pro-female route to increased income	Collaboration with an NGO to use RHoMIS in ex-post assessment of interventions around shea butter.	Households clustered according to thresholds, differences between control and treatment households assessed with Kruskal-Wallis test.	A3, A4, B1, B3
5. Rapid pace of change for rural smallholders in East Africa	Panel survey where RHoMIS was used during the second panel. Appraisal of drivers of household poverty dynamics.	Data preparation for comparison between datasets. Poverty classes based on thresholds and validated with other indicators. Changes in livelihood strategies assessed with Anova and TukeyHSD.	A1, A5, B1, B3, B4
6. Synthesis	Evaluation of work done and the degree to which objectives met.	Review.	A3, A4, A5

CHAPTER 2: Farm Types and Farmer Motivations to Adapt: Implications for Design of Sustainable Agricultural Interventions in the Rubber Plantations of South West China

Abstract

Tropical land use is one of the leading causes of global environmental change. Sustainable agricultural development aims to reduce the negative environmental impacts of tropical land use whilst enhancing the well-being of the smallholder farmers residing in those areas. Interventions with this goal are typically designed by scientists educated in the Western tradition, and often achieve lower than desired uptake by smallholder farmers. We build on work done in farm type classification and studies of factors that influence adaptation, trialling a suite of household survey questions to elucidate the motivational factors that influence a farmer's willingness to adapt to external change. Based on a sample of 1,015 households in the rubber growing region of Xishuangbanna, South-west China, we found that farm types based on structural characteristics (e.g. crops, livelihoods) could not be used to accurately predict farmers' motivations to adapt. Amongst all six farm types identified, the full range of motivational typologies were found. We found six motivational types, from most to least likely to adapt, named: Aspirational Innovators, Conscientious, Copy Cats, Incentive-centric, Well Settled, and Change Resistant. These groups roughly corresponded with those identified in literature regarding diffusion of innovations, but such classifications are rarely used in development literature. We predict that only one third of the population would be potentially willing to trial a new intervention, and recommend that those sectors of the population should be identified and preferentially targeted by development programs. Such an approach requires validation that these motivational typologies accurately predict real behaviour – perhaps through a panel survey approach. Dedicated data gathering is required, beyond what is usually carried out for ex-ante farm typologies, but with some refinements of the method presented here the process need not be onerous. An improved suite of questions to appraise farmers' motivations might include value orientations, life satisfaction, and responses to various scenarios, all phrased to be locally appropriate, with a scoring system that uses the full range of potential scores and a minimum of follow up and peripheral questions.

1. Introduction

Tropical land use for the past century has been dominated by conversion of forested lands to agricultural land, leading to loss of biodiversity (Barnes et al., 2014; Gibson et al., 2011), increased carbon emissions (Houghton et al., 2012; Le Quéré et al., 2014), changes in evapotranspiration patterns (Lawrence and Vandecar, 2015; Zhang et al., 2016), and the degradation of ecosystem services (Foley et al., 2005; Power, 2010). Proposed solutions tend to focus on the potential benefits that solutions could bring (e.g. Foley et al., 2011) or on evaluating the trade-offs in selecting one solution over another (Phalan et al., 2011). However, in most situations the decision to adapt one's behaviour is not taken by experts, but by smallholder farmers. In a recent review, enhanced adoption of sustainable agricultural interventions was linked to three features of projects: a fine-scale understanding of local needs, appropriate market and service mechanisms, and engaging adopters through the research process (Coe et al., 2014). These are particularly salient in situations of decentralised decision making, as occurs where many smallholder farmers are responsible for a mosaic landscape (Fox and Castella, 2013), which is the case across much of the tropics.

Rubber plantations in montane south east Asia have expanded leading to rapid replacement of diverse landscapes with monocultures, and giving rise to serious concerns about forest loss, ecosystem degradation, biodiversity loss and risky over-specialisation of livelihoods (Ahrends et al., 2015; Fox et al., 2014; Warren-Thomas et al., 2015; Ziegler et al., 2009). Scientific literature to date generally has focused on either potential management interventions (De Blécourt et al., 2014; Fu et al., 2010; Liu et al., 2015; Riedel et al., 2012; Thongyou, 2014; Viswanathan and Shivakoti, 2008), or potential policy interventions (Cotter et al., 2014; Smajgl et al., 2015b; Yi et al., 2014b). The efficacy of policy interventions is however determined by the interaction between policy mechanisms and the grass-roots responses (Smajgl et al., 2015a), therefore understanding the motivations of smallholder farmers to adapt their practices is essential in designing appropriate interventions.

Farm typologies are one method for understanding how different segments of a farming population might react to proposed interventions. Farm typologies are typically based on observable structural characteristics such as farm size, household size, crops grown, livestock raised, and incomes. These farm typologies are useful in determining which interventions are appropriate to specific types of farm and form the basis for many ex-ante intervention and prioritization analyses (Bongers et al., 2015; Herrero et al., 2014; Rufino et al., 2013; van Ittersum et al., 2008). The structural characteristics of a farm do not present the whole picture, however, and there is a temptation to use the structural characteristics to calculate the most efficient path to intensified production which disregards the system complexities that farmers deal with in their daily lives (van der Ploeg et al., 2009). Van der Ploeg et al (2009) found that consideration of the balance of livelihood activities and farmers' objectives can help to explain the plurality of farm styles, when considered in combination with the farm structural characteristics. Indeed, the diversity of farmers' characteristics can render interventions which try to address the 'average farmer' redundant (Marshall and Smajgl, 2013). Targeting interventions according to farmers’ motivations may be a more fruitful approach: for example, farmers with conservation oriented attitudes are correlated with a higher willingness to adapt practices in a way which enhances conservation goals, and that those farmers who are strongly economically oriented require financial incentives in order to adapt (Greiner et al., 2009). Meijer et al (2014) categorised factors influencing farmer motivations into 'extrinsic' and 'intrinsic' factors, where extrinsic are demographic, economic, geographical, and intrinsic are related to knowledge, perceptions, attitudes; and found that intrinsic factors in particular are often overlooked (Meijer et al., 2014). The goal of the present study was, therefore, to improve understanding of the relationship between the ‘structurally’ oriented farm types, and the different groups of factors which motivate farmers to adapt their behaviour. We posit that farmers' willingness to adapt is key to adopting new practices, and that understanding the farmers' motivations to adapt is therefore key to increasing adoption rates. From household survey data, we constructed one typology based on farm structural characteristics and livelihoods, and constructed a separate typology based on farmer motivations to adapt. We then assessed the linkages between the two groupings, and drew out the implications for design of agricultural interventions with a higher adoption potential.

2. Methods

Xishuangbanna is an autonomous prefecture of about 19,000 km^2 in Yunnan province, south west China. Together with Hainan island, it is the only area of sub-tropical forest inside China's borders. The average temperature in Xishuangbanna is 20-22.5°C, with an average high temperature of 25-27°C occurring in May-June. Average precipitation is 1200-1800mm per year and the wet season lasts from May to October during which 90% of the rain falls. The terrain is densely undulating, land elevation ranges from 400 to 2,400 metres above sea level, and there are four bio-climatic zones: warm temperate and moderately moist (high elevations); hot and moderately moist; extremely hot and moderately moist; and extremely hot and moist (low elevations) (Zomer et al., 2014). The primary crops are rubber, tea, and rice.

Xishuangbanna was originally heavily forested. In 1976 forests accounted for about 70% of land mass (Li et al., 2006). There has been a trend of deforestation since then. Accurate figures on deforestation are difficult to acquire from official governmental sources. However, two systematic studies of satellite imagery between 1976 and 2003 (Li et al., 2009, 2007) found that by 2003 forest cover in Xishuangbanna shrank from 69% to less than 50% of the landscape; that the important tropical seasonal rainforest shrank from 10.9% to 3.6%. There has been no systematic study of forest area since 2003; but we may infer that deforestation has increased, as the amount of land planted with rubber almost tripled between 2002 and 2010, from 153,000 ha to 424,000 ha (Xu et al., 2014).

Table 2.1. Sampling structure of the households surveyed within Xishuangbanna. Jurisdictional levels within the province of Xishuangbanna are county, township, village committee (a group of villages represented by a common government committee), and finally natural villages (normal villages – a group of houses located close to one another).

County	Townships	Village Committees	Natural Villages	Households
Jinghong	3	12	24	486
Mengla	4	13	26	529
Total	7	25	50	1015

Household survey data was gathered in a single campaign during 2010, in 50 villages, amongst two counties within the province of Xishuangbanna, South West China (Table 2.1). One thousand and fifteen households were interviewed. Villages were selected in discussion with government officials to cover the full altitude gradient of the rubber growing region, distributed across seven townships where rubber cultivation is prevalent. Three or four village committees were then randomly selected per township, and then two natural villages per village committee, making a total of 50 villages. Households were then selected at random from the government village register.

Altitude varied amongst the surveyed villages from 500m above sea level to 1600m. This altitude range has a strong effect on the viability of certain crops (rubber, coffee, tea); different ethnic groups tend to inhabit specific locations which can be defined by altitude; and altitude can also be seen as a rough proxy for development, where the communities at lower altitudes tend to have more developed educational, transport and market infrastructure.

The survey consisted of a ten-page printed questionnaire which took approximately one and a half hours to complete and which was originally written in English and then translated and implemented in Mandarin Chinese. The survey was written by Smajgl and Ward (co-authors to this manuscript), and has been described elsewhere (Hassenforder et al., 2015; Smajgl et al., 2016, 2015c, Smajgl and Ward, 2015, 2013). The main topics covered were household demographics, ownership of assets including land, livelihood activities and gross incomes (excluding consumption), personal value orientations, attitudes, perceptions of the likelihood of future events, and stated intentions to adapt under four hypothetical scenarios.

Household demographics included questions on family size, education, location, and ethnicity. Assets included farm size and land uses, as well as vehicles, machinery, and domestic appliances. The livelihoods section included crop and livestock yields and gross incomes, off-farm gross incomes, and non-cash gifts. Together, the data on household demographics, assets, and livelihoods are referred to from here on as ‘farm characteristics’.

The data on value orientations, attitudes, likelihood of future events and stated intentions to adapt are used to inform about farmers’ motivations to adapt their behaviour, and are referred to from here on as the ‘motivations’ data. The conceptual basis is that personal values influence value orientations, which influence attitudes and norms, which influence stated intentions, all of which influence actual behaviours. Through measurement of some of these variables it may therefore be possible to predict actual behaviour. A recent review explains this in more detail (Jones et al., 2016), and links between these variables have been well established (de Groot and Steg, 2007). Nevertheless, the degree to which a typology based on these variables can predict actual behaviour in a context of rural development has not been proven. Such a proof would require an initial survey to establish a baseline and a motivation typology, predictions to be made, and then a follow up survey to establish if the predictions were accurately matched actual behaviour. This work is only able to complete the initial steps of establishing a baseline and motivation typology, and making some predictions about farmer behaviour. A follow up survey would be required to establish the accuracy of the predictions. Acknowledging this limitation, we divide the population into sub-groups according to their differing motivational traits, where the assumption is that these sub-groups would behave differently. We then relate the motivational sub-groups to the more traditional typology based on observed ‘farm characteristics’.

Value orientations are based on the theory that there are underlying values which are common world wide, and which can be elucidated using a standardised set of questions (Schwartz, 1992; Schwartz and Bilsky, 1987). The standardised questions have been streamlined for easier use (Stern et al., 1999, 1998) and tested in subsequent work (de Groot et al., 2008; de Groot and Steg, 2007) which convincingly demonstrated the utility of the values in a European context. The value orientation theory has not previously been applied in a developing world context. The five value orientations are: altruistic, egoistic, biospheric, openness to change, and traditionalism. Altruistic, also referred to in the literature as self-transcendence, means having interests in the well being of others. Egoistic, also referred to as self-enhancement, means improving one’s own situation in life. Biospheric means having an interest in the well being of non-human life. Openness to change and traditionalism (also referred to as conservatism) represent opposite poles in terms of likelihood of trying out new ideas or practices. A more complete explanation of these terms and their empirical testing is provided in a recent review (Dietz, 2015). Three questions were used to appraise each of the five value orientations (Smajgl and Ward, 2015), and the mean was used to determine the score for each value orientation.

The interviewees' attitudes towards up to eight variables related to economy, environment and community were gathered using numerical scales between 0-10 to assess their perception of the 'importance of' each variable and their 'satisfaction with' each variable. Interviewees were asked to select up to eight variables from a longer list of 38 and then scored the selected variables. They were also asked to rate their overall life satisfaction on a scale of one to ten.

The subjects' predictions for near future changes regarding natural resource decline (e.g. water, soil), farming practices (e.g. mechanisation, market orientation) and wider socio-economic changes (e.g. urban employment, increased tourism) were gauged using a modified seven-point Likert scale for both perceived likelihood and perceived impact upon the household. Eight questions were asked for each futures theme (Ward and Poutsma, 2013), which were then used to determine a mean score for each theme.

Finally, four hypothetical scenarios were outlined with multiple choice answers offered to the respondent. The four scenarios were: a 50% drop in the value of their main crop, lucrative urban employment opportunities, unpredictable climate change (hotter and dryer), and a government subsidy program for native trees replacing rubber trees, matching present income. The four scenarios were chosen through a multi-level participatory process (Smajgl et al., 2015a; Smajgl and Ward, 2015), where the first three were selected as feasible future scenarios and the fourth as a potential government intervention (Smajgl et al., 2015b)

The options available to respondents were: to ignore the scenario and carry on as usual, modify their current behaviour in some way, completely replace their current behaviour, or leave and go to a new place. Follow up questions were then asked probing the reasons for their decision, and if they decided to modify their behaviour, what would they modify and to what degree, and if they chose to migrate where would they go, for how long, and what would they do. The full questionnaire has been archived on Dataverse.

Once gathered, the data was compiled into a Microsoft Excel spreadsheet. Four observations were dropped due to missing data points or inexplicably high outlier values. Data analysis was conducted using R (R Core Team, 2012) and R Studio software (RStudio Team, 2016), and using the following packages: vegan (Oksanen et al., 2016), multcomp (Hothorn et al., 2008), ggplot2 (Wickham, 2009a), and plyr (Wickham, 2009b).

The two datasets ('farm characteristics' and 'motivations') were analysed separately, although both datasets went through a similar analytical process. The objective was to generate a meaningful typology based on each dataset, and then explore to what degree a typology based on farm characteristics can predict farmers' motivations to adapt. Typologies were generated using a hierarchical cluster analysis (Kaufman and Rousseeuw, 2009) of the most informative variables in each dataset . The most informative variables were selected using principle component analysis (PCA) (Jolliffe, 2002). Once derived, all variables were mapped onto the clusters and the clusters were interpreted as typologies. Significance of difference between clusters ('farm types') for individual variables was tested using a post hoc Tukey test of honest significant difference (Jaccard et al., 1984). Up to this point the methodology followed the approach commonly outlined in manuals for multivariate statistical analyses (Coghlan, 2013; James et al., 2013). The independence of the 'farm characteristics' typology and the 'motivations' typology was tested using a Pearson's Chi squared test, and redundancy analysis (Legendre and Legendre, 2012; Ter Braak, 1986) was used to determine the degree to which certain farm characteristics variables could be used to predict farmers' motivations.

Prior to the PCA variables were excluded which strongly co-varied and measured similar traits, and remaining variables checked for normality of distribution. Where necessary and possible transformations were applied to bring distributions close to normal. Variables were dropped from further analysis if they were strongly correlated with another variable on all principle components, or if they showed little correlation with any principle component. Prior to cluster analysis variables were re-scaled to similar ranges. Cluster analysis was performed using a Gower dissimilarity matrix (Gower, 1971), which permits mixed data types including numeric, ordinal and categorical data. Some data that were not appropriate for principal component analysis (e.g. multiple choice scenario responses) could therefore be included in the cluster analysis, along with the variables identified as most important through the PCA. The Ward minimum variance clusters method (Ward, 1963) was used to perform the hierarchical cluster analysis on the dissimilarity matrix. The final number of clusters was selected according to the point at which the explanatory power of further cluster subdivisions plateaued (see Supplementary Material Figures S2.1 and S2.2; see Appendix 4).

3. Results

3.1 Farm Characteristics: Site Overview

Households had a mean size of 4.3 members, median farm size of 2.9 ha, and median gross income of 7,500 US$ per year. All incomes are referred to in gross terms. Both the farm size and the total income were highly variable, with standard deviation approximately as large as the mean. The median amount of land per person was 0.75 ha and the median income per person was 5.1 dollars per day. Median agricultural incomes accounted for 5900 US$ per household per year (or 2900 US$ per hectare), and off-farm incomes 450 US$ per household per year. In terms of income the study population is wealthier than most farmers in developing countries, which is due to the prosperity brought by the rubber boom and also to the rapid and sustained growth in China’s economy.

The major crop for most households was rubber. Sixty-seven percent of households rated rubber as their most important and most reliable crop. Tea was rated as most important and most reliable by 24% of households and 4% of household rated maize as their most important and reliable crop. The most commonly practised agricultural activities were as follows; rubber (82%), rice (60%), maize (55%), livestock (54%), tea (37%), horticulture (15%), fruit trees (6%). Median annual incomes from those crops were as follows: rubber (5900 US$), rice (0 US$), maize (0 US$), livestock (250 US$), tea (1200 US$), horticulture (200 US$), fruit trees (450 US$). Rice and maize were widely grown crops but were generally used for household consumption and feeding of livestock – hence median income values of 0 US$ from those crops. Note that the median value of crops is calculated only from households who reported growing that crop. Other minor activities mentioned were fishing and aquaculture, forestry, forest products and mushroom cultivation. Households on average practised three agricultural activities.

Almost all households (97%) had some form of off-farm income, but usually from passive sources, such as state subsidies (which 72% of household received), income from rental of land (42% of households), pensions (18% of households), and governmental compensation for land lost to industrial developments (5%). Active employment is much less common. The main activities and the proportion of households who undertook active off-farm activities were as follows; family business (e.g. shop, restaurant) (9%), government employment (8%), agricultural labouring (5%), tourism (3%), construction (3%), services (2%), and remittances (1%). The passive activities are typically lower income. Median annual incomes from off-farm activities were as follows; subsidies and pensions (100 US$), land rental (950 US$), land compensation (650 US$), family business (2500 US$), government employment (200 US$), agricultural labour (650 US$), tourism (1500 US$), construction (1300 US$), services (450 US$), remittances (500 US$). Again the median values are calculated only from households who report receiving some income from that activity.

Six ethnic groups were reported. Listed in decreasing order of frequency, they were Dai, Akha, Yi, Bulan, Han, and 'other'. Household heads were typically reported to be male (96%) with an average age of 46 years. Fifty percent of household heads had received primary education and 19% reported basic secondary education. Twenty-five percent were illiterate. Youth education (youth defined as children of household head) was higher, with over fifty percent reporting basic secondary and approximately twenty percent reporting advanced secondary. Only 2% were illiterate. About half of the surveyed households were at lower elevations (500-700m), about one quarter at mid elevations (700-900m) and the remainder at high elevations (900-1600m).

3.2 Farm Characteristics Typology: Cluster Analysis

The following variables were used in cluster analysis: annual household income from rubber, fruit trees, tea, other agricultural sources combined, and off-farm incomes, number of agricultural and non-agricultural activities per household, farm size, age of household head, education level of household head and altitude above sea level. Selection of six clusters was identified as most appropriate, in order to keep the number of clusters manageable whilst showing the most meaningful diversity in farm characteristics (see figure S2.1 for justification). Whilst it could be argues that two clusters was mathematically optimal, the split between rubber-farmers and non-rubber farmers hid great variation within the rubber farmer sector, and so was not considered to be the most informative choice. Six clusters were therefore chosen, taking into account the diminishing explanatory power and the utility of the number of clusters in identifying meaningful differences between households. Verbal descriptions of the clusters are presented in Table 2.2 and numerical data (with significant differences marked) are presented in Table 2.3.

The six clusters (Tables 2.2 and 2.3) were named Young Rubber, Traditional Rubber, Rubber and Business, Mixed Cash Croppers, Tea Farmers, and Upland Mixed, and from here on will be referred to as ‘farm types’. In the first four farm types the main source of income was rubber, total income was relatively higher and farms were located at lower elevations. The latter two farm types were poorer, resided at higher elevations and derived the bulk of their income from sources other than rubber farming.

Household heads in the Young Rubber farm type were younger and better educated than others, and engaged in more off farm activities than Traditional Rubber farmers, although their off farm incomes were not significantly higher. Traditional Rubber farmers focused primarily on rubber for income, maintained medium level of diversity of subsistence crops, relied more upon remittances than other farm types, and were also the worst educated of all farm types. The Rubber and Business farm type showed the highest frequency of (and incomes from) off-farm activities of all farm types, in addition to their rubber farming activities. Although the Mixed Cash Croppers derived their main income from rubber, they also derived a substantial income from other agricultural activities, including livestock, horticulture, and most notably fruit trees and perennials, by far the most profitable of which was banana. The Tea Farmers reside at high elevations and relied on tea for the majority of their income, supplemented by some staple crops. Upland Mixed farmers were the poorest of all farm types, relying on a variety of staple crops, rubber and tea for income, as well as a moderate amount of off-farm work.

Livelihood activities per farm type are presented in Figure 2.1. Rubber was the major income source for the Young Rubber, Traditional Rubber, Rubber and Business, and Mixed Cash Crop farmers, generating a mean of around 9000 US$ per year per household (with standard deviation about the same as the mean, see Table 3 for means per farm type). Perennial fruits, such as banana, had the potential to generate large income of up to 10,000 US$ per year, although only the Mixed Cash Croppers generated such a high income so far, and even that was relatively few farmers (<10% of the cluster). Tea generated a substantial income for the Upland Mixed farm type, of 2000 – 3500 US$ per year per household. Although other farming activities were widely practised (rice, maize, livestock, horticulture) the products were mainly for self consumption and sales of those products generated between 5 and 20% of the household income. Most farm types derived a small proportion of their income from government subsidies and land rents (200 - 1000 US$ per year). Far fewer households in all farm types engaged in the more profitable off-farm activities incomes. The average incomes per activity were highest from private businesses (including restaurants, shops, and trading agricultural produce) for most clusters at 3000 - 6000 US$ per year. Farmers in the Upland Mixed and Rubber and Business farm types earned around 5000 US$ per year in industrial work, and the Young Rubber cluster derived significant income from farm labouring work, although frequency of participation was lower than for private businesses.

Table 2.2: Verbal descriptions and comparisons of the farm types based on structural characteristics and livelihoods. Differences mentioned are significant at 95%, tested with Tukey's HSD, and individual pairwise comparisons are shown in Table 2.3.

Name	n	Location	Annual Income	Main sources of Income	Cash Crops	Staple Crops	Off farm incomes	Demographics	Ethnicities
Young Rubber	96	Low elevation, smaller farms.	High	Rubber	Rubber, Livestock	Livestock, Rice, Maize	Family Business, Farm Labour	Best educated household heads and youth. Younger heads, smaller families.	Akha, Dai
Traditional Rubber	234	Low elevation, smaller farms.	High	Rubber	Rubber, fruit trees	Rice, Maize, Livestock	Family Business, Remittances	Worst education household heads and youths, medium family size.	Dai, Akha
Rubber and Business	204	Low elevation, smaller farms.	High	Rubber, Off Farm	Rubber, fruit trees	Livestock, Maize, Rice	Family Business, Industrial Work	Heads poorly educated, but youth better educated, largest family size.	Dai, Akha
Mixed Cash Croppers	188	Low elevation, smaller farms.	High	Rubber, Non-Rubber Agriculture	Fruit trees, Rubber	Maize, Rice, Livestock	Family Business, Service Sector	Medium education of head and youth, medium family size.	Dai, Akha, Bulan
Tea Farmers	191	High elevation, larger farms	Medium	Non-Rubber Agriculture, Off-Farm	Tea	Maize, Rice, Livestock	Family Business	Medium education of head and youth, low family size.	Yi, Akha, Han, Others
Upland Mixed	98	Mid elevation, larger farms	Low	Non-Rubber Agriculture, Off-Farm	Rubber, Tea	Maize, Rice, Livestock	Industrial Work, Family Business	Medium education of head and youth, medium family size.	Bulan, Akha, Yi

Table 2.3. Numerical descriptions of the farm types based on structural characteristics and livelihoods. Mean values are shown, with all incomes in US$ and gross values. Letters after the numbers indicate significant differences between clusters, at p<0.05, using the Tukey HSD test. Abbreviations: 'Agric.' means agricultural, 'excl.' means excluding, 'HH' means household. Educational level was converted from ordinal to numerical data, where 0 means illiterate, 1 literate, 2 primary, 3 secondary and 4 post-secondary.

n	Altitude (masl)	Farm Size (ha)	Annual Income (USD)	Income from Rubber	Agric. Income (excl. rubber)	Off-Farm Income	Agric. Activities (count)	Non-Agric. Activities (count)	Income per person per day	HH Members	Education HH Head	Education Highest in HH	Age of HH head
96	668^{a}	3.6^{a}	11630^{cd}	8925^{b}	1120^{ab}	1585^{a}	2.5^{a}	1.8^{c}	8.8^{d}	3.8^{a}	2.2^{e}	2.5^{c}	39^{a}
234	663^{a}	3.6^{a}	10334^{c}	8924^{b}	739^{a}	671^{a}	2.9^{b}	1.0^{a}	6.7^{cd}	4.4^{bc}	0.4^{a}	1.9^{a}	48^{cd}
204	666^{a}	3.3^{a}	13155^{d}	8651^{b}	937^{ab}	3567^{b}	2.5^{a}	2.8^{d}	8.1^{d}	4.7^{c}	0.7^{b}	2.3^{bc}	49^{d}
188	653^{a}	3.7^{a}	9829^{c}	6991^{b}	1698^{b}	1140^{a}	4.1^{d}	1.6^{bc}	6.3^{c}	4.4^{bc}	1.1^{c}	2.0^{ab}	45^{bc}
191	1379^{c}	6.5^{b}	5815^{b}	351^{a}	4449^{c}	1015^{a}	3.3^{c}	1.6^{bc}	4.1^{b}	4.0^{a}	1.4^{d}	2.3^{bc}	46^{bd}
98	1016^{b}	5.6^{b}	4100^{a}	1316^{a}	2034^{b}	749^{a}	4.1^{d}	1.4^{c}	2.7^{a}	4.2^{ab}	1.0^{c}	2.1^{ab}	44^{b}

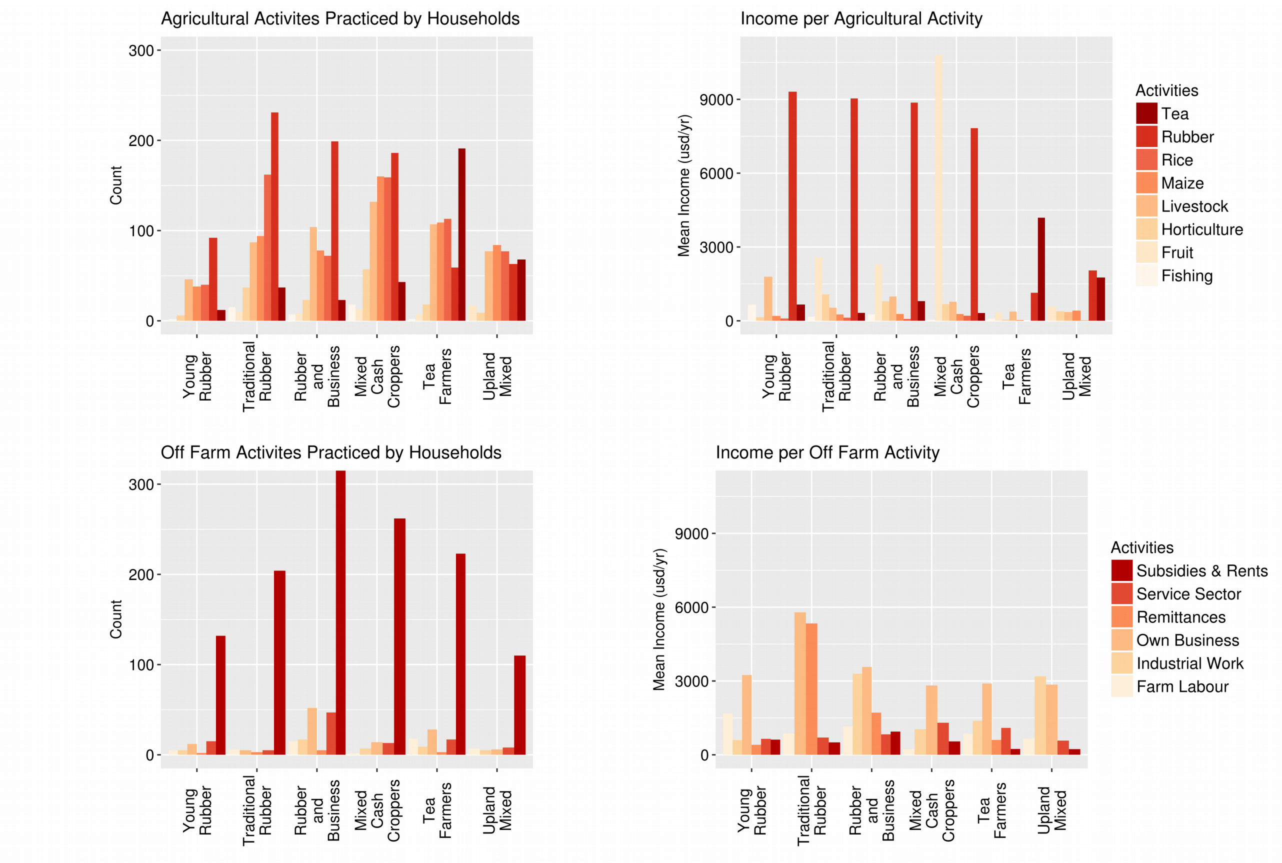

Figure 2.1. Livelihood activities by farm type. The frequency that agricultural activities and off-farm activities are reported for household and the mean income for each activity is shown. Note that the total height of the bars for mean income of each activity does not equal the mean income of a household in that cluster, as not every household takes part in every activity. The mean household incomes per farm type are shown in Table 3. The total number of activities reported may be larger than the number of households in a cluster because some of the categories are made up of a more than one activity. Note that the total number of activities relating to Subsidies and Rent reported by the Rubber and Business farm type was 434, but the axis scale was limited to enhance overall readability.

3.3 Farmer Motivations: Site Overview

Households rated their overall life satisfaction at a mean score of 7.6. Satisfaction with economic factors was rated at 7.3, family factors at 8.7, and natural environment 8.0. Importance of the economy was rated at 9.5, importance of family at 9.7, and importance of natural environment at 9.4. The distributions of all 'importance' and 'satisfaction' responses were highly skewed towards the upper end of the scale. There was a particularly low variance associated with measures of 'importance'.

Value orientations were calculated for five themes; egoistic, altruistic, biospheric, conservative, and innovation. Mean scores on a scale of 0 to 10 were as follows: egoistic 7.0, altruistic 7.8, biospheric 7.6, conservative 8.2, innovative 6.2. Conservative, altruistic, and biospheric value scores were skewed towards the upper end of the scale, while the egoistic and innovative values were approximately normally distributed.

Perceived likelihood of future events and estimated impact upon the household were calculated for three broad themes. Mean scores for likelihood, normalised to a scale of 0 to 10, were as follows; farming optimism 6.9, environmental pessimism 6.2, and sweeping socio-economic changes 3.9. Mean scores for impact were; farming optimism 6.1, environmental pessimism 6.7, and sweeping socio-economic changes 6.0. Distributions were approximately normal.

The four scenarios outlined to the farmers were: a) a 50% drop in value of main crop; b) lucrative urban employment opportunities; c) unpredictable climate change, and d) a government subsidy program for native trees to match present income. For a projected halving in the value of main crop, 41% of the population said they would ignore it and continue as normal, 57% said they would adjust their activities accordingly, 1% said they would totally replace their activities with something new, and 0.2% said they would leave and go somewhere else. Regarding the urban employment scenario, 73% said they would ignore the new opportunities, 23% said they would adjust their activities, 3% said they would completely change their activities, and 0.3% said they would leave and go somewhere else. Regarding the climate change scenario, 43% said they would ignore it, 50% said they would adjust their activities, 6% said they would completely replace their activities, and 1.4% said they would leave and go somewhere else. Regarding the native tree subsidies scenario, 30% said they would ignore it, 68% said they would adjust their activities, 0.5% said they would completely replace their activities, and 0% said they would leave.

When households were asked why they would not leave and go to a new place, the most frequent response for each scenario was “this is the village of our ancestors” (47-53% of responses chose this answer under each scenario). Other answers given were “we would not be affected”, “we're fine as we are”, “we like what we are doing”, and “we don't have the skills”. The other answers (“no money”, “need government support”, “too risky”, “no land in other place”) however were not consistently chosen between scenarios and were typically selected by around 10% of the population. When asked why households would not adjust their activities to respond to a scenario, the most common answers across all scenarios were “we like what we are doing” (20-40% selected this response). Other answers given were “we would not be affected”, “we're fine as we are”, “it would be too risky” and “we don't have the skills”.

3.4 Farmer Motivations Typology: Cluster Analysis

The following variables were retained and used in the cluster analysis: overall life satisfaction score, altruistic, egoistic, biospheric, and openness to change value scores, future environmental pessimism, future farming optimism, and frequency that the respondent reacted to the outlined scenarios. Six clusters were identified (see figure S2.2 for justification). Verbal descriptions of the farm types are presented in Table 2.4 and numerical data with significant differences between clusters are presented in Table 2.5.

Table 2.4: Verbal descriptions and comparisons of farmer motivations clusters. Differences mentioned are significant at 95%, tested with Tukey's HSD, and individual pairwise comparisons are shown in Table 2.5.

Name	n	Life Satisfaction	Value Orientations	Future Outlook	Stated Willingness to Adapt
Aspirational Innovators	272	Lowest in all categories	High open to change, high egoistic.	Environment is in strong decline, but farming or other opportunities will improve.	Highest
Conscientious	118	Highest in all categories	Low egoistic, high altruistic, high open to change.	Low environmental decline, expect to continue farming much as before.	High
Copy Cats	72	Upper Middle	Low open to change low egoistic.	Environment is in strong decline, but farming will get better.	High
Incentive-centric	221	Low in economic and overall satisfaction	High open to change, high egoistic.	Environment is in strong decline, but farming or other opportunities will improve.	Middle
Well Settled	111	Upper Middle	Lowest biospheric and altruistic, low open to change.	Environment is in decline, but expect to continue farming.	Middle
Change Resistant	217	Lower Middle	Low open to change.	Some environmental decline, but expect to continue farming much as before.	Low

Table 2.5. Numerical descriptions of the Farmer Motivation types. Mean values are shown, and all variables are scored between 0 and 10, except for 'Ignore Scenarios'. Ignore Scenarios is scored 0 to 4, where 0 means that the respondent chose to respond in some way to all four scenarios, and 4 means they chose to ignore (not respond) to all four scenarios. Letters after the numbers indicate significant differences between clusters, at p<0.05, using the Tukey HSD test.

Name	n	Life Satisfaction	Economic Satisfaction	Family Satisfaction	Environment satisfaction	Values: Egoistic	Values: Altruistic	Values: Biospheric	Values: Open to Change	Values: Traditionalism	Futures: Environmental Pessimism	Futures: Farm Optimism	Futures: Wider Changes	Ignore Scenarios
Aspirational Innovators	272	6.8^{a}	6.6^{a}	8.5^{a}	7.4^{a}	7.2^{c}	8.0^{b}	7.7^{b}	6.5^{c}	8.3^{b}	6.6^{d}	7.3^{b}	4.1^{b}	0.7^{a}
Conscientious	118	8.7^{d}	8.1^{d}	9.0^{c}	8.5^{b}	6.5^{a}	8.2^{c}	7.7^{b}	6.6^{c}	8.1^{ab}	5.0^{a}	6.2^{a}	3.7^{ab}	1.1^{b}
Copy Cats	72	7.9^{bc}	7.4^{bc}	8.9^{bc}	8.3^{b}	6.3^{a}	8.0^{bc}	7.8^{b}	4.8^{a}	8.1^{ab}	6.8^{d}	7.1^{b}	4.0^{ab}	1.5^{c}
Incentive-centric	221	7.3^{b}	7.2^{b}	8.6^{ab}	8.1^{b}	7.4^{c}	8.0^{b}	7.7^{b}	6.6^{c}	8.3^{b}	6.8^{d}	7.3^{b}	4.1^{b}	2.3^{d}
Well Settled	111	8.3^{cd}	7.8^{cd}	8.8^{ac}	8.4^{b}	6.6^{ab}	6.5^{a}	6.9^{a}	5.9^{b}	7.9^{a}	6.1^{c}	6.5^{a}	3.7^{ab}	2.3^{d}
Change Resistant	217	7.7^{b}	7.7^{cd}	8.8^{bc}	7.9^{b}	6.9^{b}	8.0^{b}	7.5^{b}	6.0^{b}	8.1^{a}	5.5^{b}	6.3^{a}	3.6^{a}	3.2^{e}

The six clusters were named Aspirational Innovators, Copy Cats, Conscientious, Incentive-centric, Well Settled and Change Resistant, and from here on will be referred to as ‘motivation types’. The Aspirational Innovators scored the highest on innovation related indices – openness to change and stated willingness to adapt to scenarios – and also expressed discontent with their economic, family and environmental circumstances, although they maintained a positive outlook for the future, and hence were interpreted as aspiring to improve their situation. The Conscientious cluster also scored highly on innovation indices, altruistic values, and showed the highest levels of concern regarding environmental and social issues, and very high satisfaction scores. The Copy Cat motivation type expressed high willingness to adapt their activities, but scored low on personal values relating to openness to change and egoistic behaviour, implying that they are not so strongly driven to experiment as some other motivation types. Therefore although they would be willing to adapt their activities, they might prefer to copy someone else rather than be the first to experiment. The Incentive-centric motivation type were primarily motivated by financial incomes and scored moderately on innovation indices. The Well Settled motivation type were generally satisfied with all aspects of their lives and did not feel much imperative to modify their activities. The Change Resistant cluster showed middling levels of satisfaction, no specific guiding values, and very little interest in altering their activities for any reason. The most numerous motivation types were Aspirational Innovators, Incentive-centric and Change Resistant, and the least numerous were the Copy Cats (see Tables 2.4 and 2.5).

Figure 2.2 shows the reasons given by respondents as to why they would choose not to respond to the scenarios which were outlined to them, broken down by motivation type. The Change Resistant motivation type presented the most reasons in total why they would choose not to respond to external stimuli, and they presented the most diverse reasons, followed by the Incentive-Centric type, and then the Well Settled type. Aspirational Innovators, Copy Cats and Conscientious motivation types showed similar profiles to one another in terms of total number of barriers reported and diversity of reasons. The most commonly cited barriers to adaptation did not differ between motivation types, and indeed were the most commonly reported for the whole study sample: “we like what we are doing” and that the change would “not affect us”. Lack of money and the perceived risk of making changes also feature highly for all motivation types. Lack of skills, knowledge, infrastructural support and land were cited as barriers to adaptation only by the most change adverse motivation types (Change Resistant and the Incentive-Centric).

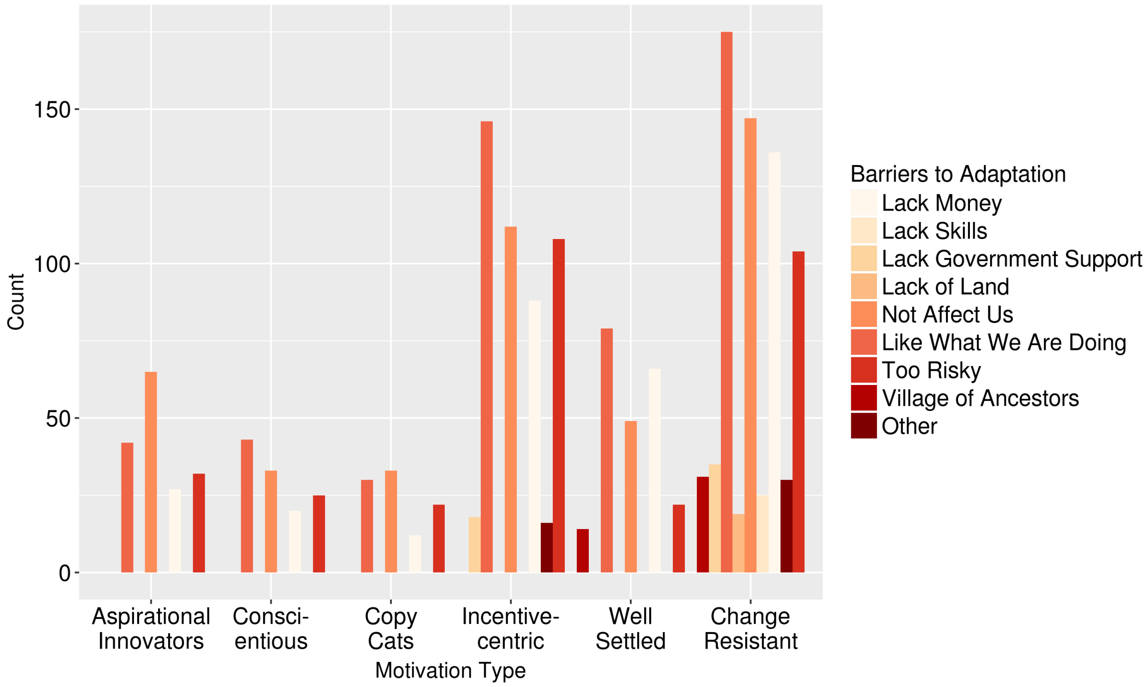

Figure 2.2. Reasons given by motivations clusters for why they would choose not respond to one or more of the four hypothetical scenarios outlined to them – i.e. why they would choose not to adapt their behaviour to an external stress. Some clusters chose not to respond to scenarios more frequently than others.

3.5 Linking the Farm Types and Motivation Types

The farm typology based on farming practices, livelihoods and household demographics showed almost no significant differences between the farm types in terms of motivations variables . Likewise the motivation typology groups showed few significant differences in terms of livelihoods, farm practices or demographics. The only exceptions were that Aspirational Innovators, Copy Cats and Conscientious clusters tended to have more off-farm income activities than the other motivations clusters. This implies that farmers' motivations to adapt cannot be inferred from standard farm typologies.

However, the frequency distribution of households in farm types and motivation types was significantly non-random (Pearson's Chi Squared, $p<0.01$), meaning that some motivation types are more common in some farm types. Figure 2.3 shows the proportions of different motivation types in each farm type. Each of the six farm types contains households in all six of the motivation types. Hence, there is no obvious, or invariant, link between farm characteristics and farmer motivations. Observations can be made by comparison of the observed frequencies of motivation types within each farm type, compared to the expected frequencies should motivations and farm types be independent, with the caveat that statistical significance cannot be attributed to individual observations. Figure 2.3 illustrates this point: the Traditional Rubber, Tea Farmer, and Upland Mixed farm types show a higher proportion of households in the Change Resistant motivation type than would be expected (given independent distributions), where as the Young Rubber, Rubber and Business, and Mixed Cash Croppers show a lower proportion of household in the Change Resistant motivation type than would be expected. The Traditional Rubber farm type showed about one third fewer of the Aspirational Innovator motivation type than would be expected, and also Traditional Rubber and Tea Farmer types showed a higher proportion of the Well Settled motivation type. The Rubber and Business farm type showed notably higher proportions of motivation types more likely to adapt – Aspirational Innovators and Conscientious – and lower proportions of the motivation types less likely to adapt. Overall, we found significant evidence that farm type was linked to motivational type, and trends could be observed that three of the farm types (Traditional Rubber, Tea Farmers and Upland Mixed) were generally less likely to adapt, and one farm type (Rubber and Business) was more likely to adapt.

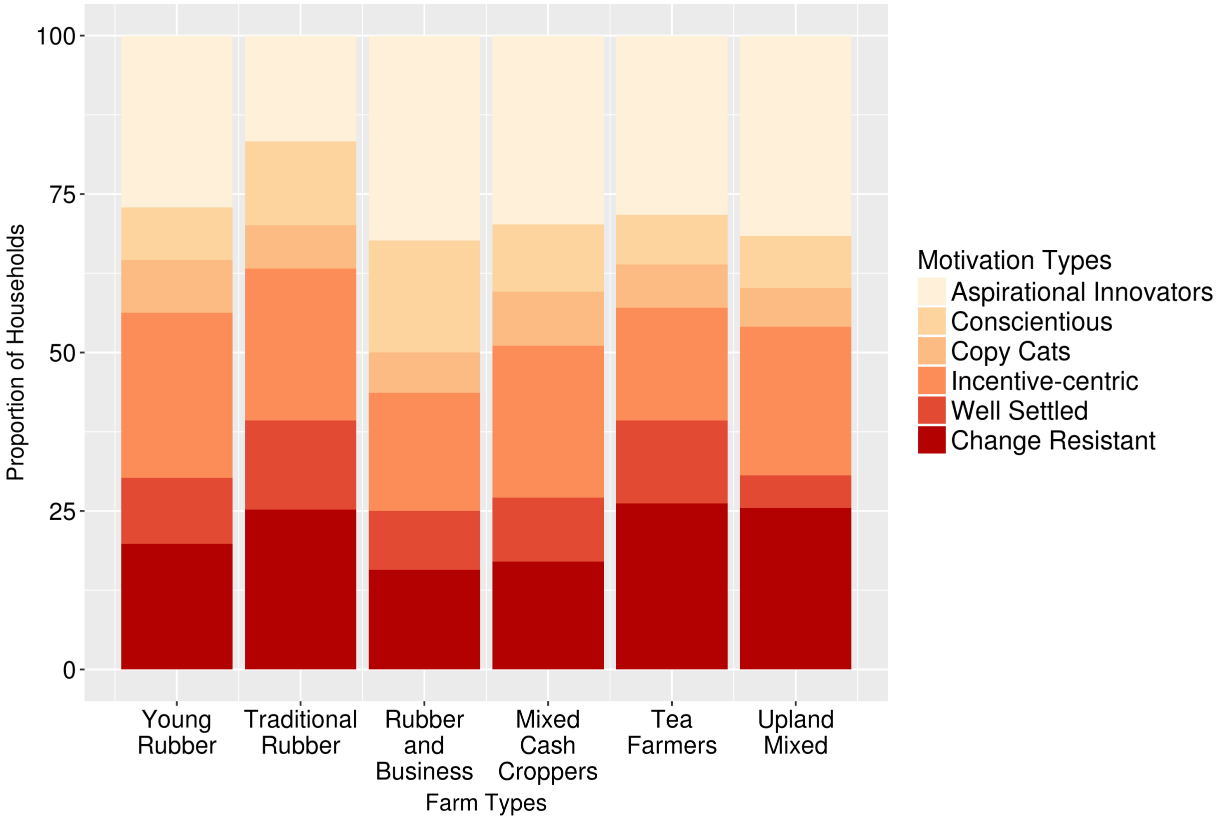

Figure 2.3: The proportions of motivation types found within each farm type. The distribution of motivation types amongst farm types is significantly non-random (Chi squared test, p<0.01), and it can be seen that some farm types contain visibly more of certain motivation types than others. Note that the motivation types are ordered from most likely to adapt ('Aspirational Innovators') to least likely to adapt ('Change Resistant').

Redundancy analysis confirmed that farm characteristics variables explained a significant but low proportion of the variance within the farmer motivations variables (5% of the variance, $p<0.001$). Livelihood strategy (income generating activities) explained 2.5% of the total variance in motivations variables, altitude explained 1.4 %, household demographic information explained 1.2%, the number of agricultural activities and off-farm activities explained 1% and farm size explained 0.2%.

4. Discussion

While we found a statistically significant link between farm types and farmers' motivations to adapt their behaviours, the predictive power was low. A farmer's motivations could not, in this case, be reliably inferred from his livelihood and farm characteristics without having gathered separate, specific information regarding motivations. Such data is not usually collected, and socio-demographic proxies are usually used instead (Pattanayak et al., 2003). In this study, the usual proxies (age, ethnicity, education) showed no significant predictive power of farmers' motivation type. Our results here show that predicting how likely a farmer is to adapt his behaviour based on the usual farm typology data of farm structural characteristics, livelihoods or demographics (van der Ploeg et al., 2009) is not a very reliable strategy, and that consideration of 'intrinsic motivations' (Meijer et al., 2014) should be done separately. However, we acknowledge that further work is required to test the degree to which these motivation types accurately predict actual behaviour. A panel survey approach would be very valuable in this regard, particularly where farmers' responses to an intervention or set of interventions could be monitored.

When considering the farmers' motivations types and the farm types in combination, the most striking observation was that the full range of motivations type was found in every farm type, albeit with some differences in relative proportions (see Figure 2.3). This has significance for the number of households who would be interested to adapt their behaviour, and potentially become adopters of a new practice, any program could realistically expect to engage: across the whole population only about 25-35% of households are motivated to and willing to try out new innovations (Aspirational Innovators and Conscientious motivation types), and potentially about 40% of households could be expected to take up innovations once proven successful by other users and assuming that appropriate support mechanisms were in place (Copy Cats, Incentive-centric and Well Settled motivation types), and the remaining 25% of households were very resistant to uptake of new innovations (Change Resistant) (Tables 2.4 and 2.5). In the 'diffusion of innovations' literature potential adopters are classified into five groups, ranked in decreasing order of eagerness to adopt new products or practices; innovators, early adopters, early majority, late majority and laggards (Rogers, 2010). These classifications could well apply in the present study, whereby the Aspirational Innovator type equates with the innovator group, Conscientious type the early adopters, Copy Cats early majority, Incentive-Centric and Well Settled types sitting somewhere between the early majority and the late majority, and finally the Change Resistant type as the laggards (although it should be stressed that the present study assessed willingness to adapt behaviour in a variety of ways, rather than willingness to adopt a specific practice). The relative proportions of the population who fall into these categories and their structural characteristics has long been studied in marketing literature (Uhl et al., 1970) but not so much in the development literature, so it is difficult to know if the proportions we have identified are replicated in other locations. There are also strategic implications as to which groups should be targeted by programs promoting new innovations – initial focus on the more innovative types is likely to bring about a higher adoption rate due to the higher willingness of those groups to adapt their behaviours, but the most innovative may not be the most in need of assistance.

The motivations data can also be used to inform the design of mechanisms that encourage farmers to adapt their behaviours. Typically such mechanisms are grouped into awareness raising/education, regulatory instruments, and economic incentives. Probably the most widely used mechanism is subsidy, although many others exist. We found that about half of the population appeared to be strongly motivated by economic factors – the Aspirational Innovators and Incentive-centric motivational types – but that only the Aspirational Innovators were generally willing to adapt and try out new practices (see Tables 2.4 and 2.5). The Incentive-centric cluster scored highly on innovation values, but showed a relatively low willingness to adapt their behaviour and cited more obstacles to behaviour change than most other clusters (see Figure 2.2), therefore subsidies alone are unlikely to motivate them to trial new practices. In line with other research in Xishuangbanna, we therefore suggest that subsidies are not the most appropriate mechanism to encourage a change in behaviour (Smajgl et al., 2015b; Wigboldus et al., 2016; Yi et al., 2014b), but should form part of a wider strategy of removing obstacles to adaptation. It is interesting to note that out of the four scenarios outlined to participants in this study, the one which elicited the most positive response from participants was the government subsidy program for native trees replacing rubber trees to match present income – but also that a small number of households also rejected this scenario with the reason that they did not believe it was feasible. With mean rubber incomes at around 9000 US$ per year for a rubber growing household at the time of the study (Table 2.3), it is indeed almost impossible that such a high subsidy scheme could be offered.

Awareness raising and educational mechanisms to encourage adoption appear to be the most necessary. The number one cited reason that households did not wish to adapt was that they did not see the relevance of external changes to themselves (Figure 2.2). In order to increase the perceived imperative to adapt, making interventions relevant to issues which the potential users consider important seems sensible. All groups reported strong identification with their sense of place (almost all respondents would not consider leaving) and reported high importance of family. Financial variables were considered very important for about half the households, and few groups reported much concern about environmental variables. Environmental benefit is a key driver for science and policy efforts to curb unsustainable land use (Ahrends et al. 2015), and although there is widespread agreement amongst respondents that ecosystem services related to water, soil and biodiversity are declining (Table 2.4), only about 11% of the surveyed population appeared motivated by such messages (the Conscientious motivation type). Messages which appeal to sense of place and long term benefit to family might therefore be more successful than messages relating to environmental impacts. These findings are in line with recent work based on integrative qualitative assessment in Xishuangbanna (Wigboldus et al., 2016).

More material barriers to adaptation such as lack of money, lack of skills or lack of land are cited considerably less frequently (Figure 2.2). Although this has also been reported elsewhere (Kiptot et al., 2007), it is often overlooked in the design of projects which aim to promote new agricultural practices. We found that general resistance to change was a greater impediment to adaptation than the more material or specific issues which government/development programs often seek to address. This trend is particularly marked for the clusters which are more likely to be early adapters – the Aspirational Innovators, Conscientious and the Copy Cats. These data suggest that in order to achieve higher adoption rates, interventions should be accompanied by educational and participatory components which respond to the needs identified as important to the farmers: an explanation of the problem the intervention addresses, a realistic exploration of the risk profile, and a sensitive, pragmatic consideration of how the intervention would interact with the farmers' existing work schedules. Such nuanced trappings require re-organization of traditional research modes into a more dynamic configuration (Schut et al., 2014), and need strong relationships with community members which preclude the falsely efficient 'one size fits all' development packages which can be deployed in multiple locations.

The overall picture from the survey data however is of a society which is fairly well satisfied, wealthier than most developing world farming communities, and quite mixed in terms of adaptation and trying new ideas. People are generally optimistic about their future, and believe that they will continue farming and their standard of living will continue to improve. This optimism may be founded upon the rapid upwards trajectory of development in Xishuangbanna and in China as a whole over the past few decades. We cannot say if the findings of the motivations typology and the weakness of the link between farm type and motivation type would be the same in poorer and more desperate locations. It would certainly be worth testing.

Whilst scientists are seriously concerned about the risks posed by declining levels of biodiversity, soil health and economic vulnerability due to rubber cropping (Ahrends et al., 2015; Warren-Thomas et al., 2015), concerns about economic well being predominate amongst the local population (Wigboldus et al., 2016) and rubber farming has been the route out of poverty for most households surveyed. This is not a society which would be easy to influence unless some sort of crisis were to destabilise the social equilibrium. Such an opportunity may be provided by the crash in rubber price from over 6 US$ per kg in 2011 to approximately 1.5 US$ per kg in 2013. The time may well be ripe for a combination of financial incentives and educational messaging which promotes alternative land use practices, with government and private sector efforts to develop associated infrastructure and markets for alternative crops. Motivations typologies might be useful in design and targeting of such a strategy.

If motivations data can be used to understand how many households might be expected to adapt, at what point in time (e.g. early adopters, late adopters), and to help design promotional mechanisms for interventions, farm structural characteristics data is useful to inform what those adaptations could be. Interventions proposed for making rubber more sustainable can be divided into four broad categories: improved farming practices and technology, improved knowledge and awareness, market and value chain measures, and policy measures. Market and value chain measures could be a promising avenue, as some households report running their own small businesses, and the entrepreneurial Rubber and Business farm type accounts for about 20% of the total population (Tables 2.2 and 2.3). Likewise, amongst the more impoverished upland farmers, private businesses are a major source of income and may indicate the entrepreneurial basis required for value chain developments. Farm practice interventions can be further subdivided into two types: modifying rubber management (e.g. less pesticides, planting density, alternative hybrids) and alternative crops (e.g. intercropping, land use zoning). Alternative crops obviously require a route to market in order to be a viable option, which is why the value chain measures are so important. Changes to rubber management may be easier therefore to achieve in the short term, but are affected by the concerns outlined regarding adoption rates and connecting to farmers' motivations. The Traditional Rubber farm type – the largest of all the farm types – would be the most difficult to influence regarding changes to farm management. The household heads tend to be older, less educated, they tend to have lower cropping diversity (Table 2.3), and the Tradition Rubber farm type contains more Change Resistant and Well Settled motivation types than any other farm type (Figure 2.3). Interventions regarding changes to farming practice may therefore be better targeted towards younger household heads (Young Rubber), or households which are already engaged in a greater diversity of cash crops (Mixed Cash Croppers) (see Tables 2.2 and 2.3). The Upland Mixed farming cluster are also worthy of further discussion: they were the poorest cluster, and had the lowest profit rubber plantations, which were established at elevations 700-900 metres, around the maximum elevation where rubber trees can be profitably grown (Yi et al., 2014a). These farmers may be especially hard hit by the rubber price crash, as their plantations are now unlikely to be viable. Subsidy schemes and participatory training methods to encourage alternative cropping linked with value chain developments and ecological management of high elevation water courses might be especially appropriate for the upland farmers.

The implications for improving adaptation rates through enhanced understanding of farmers' motivations have significance for tropical farming systems broadly, indeed in any site where the development interventions are proposed by actors who have a different world view and different priorities to the intended users. This appreciation of the users' needs and motivations has often been overlooked (Meijer et al., 2014; Pattanayak et al., 2003) and can help to achieve the appropriate service delivery mechanisms and co-learning methods identified as key to achieving up-scaling in agricultural development (Coe et al., 2014; Schut et al., 2014). The approach we trialled appears to yield useful information and we propose that it should be further developed and tested. Particularly useful were the questions on guiding values developed from the field of social psychology (de Groot et al., 2008). These questions were extensively tested in the European context (de Groot and Steg, 2007), and that they delivered useful findings in an Asian context is promising for the global applicability of this method. The value orientation questions could however be modified to better suit the local context, and the scoring system could be improved encouraging respondents to use the full range of the scale. The scenario questions were also very useful in determining stated willingness to adapt behaviour (contingent upon hypothetical events), and the perceived obstacles to adaptation, although most of the detail gathered in follow up questions was not useful in this analysis. In future it may be better to ask about more scenarios but with fewer follow up questions. The questions asked about attitudes, satisfaction and future perceptions were less useful in differentiating households in this study. With these further refinements it might be possible to develop a more streamlined suite of questions which would allow rapid exploration of farmer motivations, without resorting to inaccurate assumptions based on socio-demographics or livelihood proxies.

5. Conclusions

Six farm types were identified, four of which relied primarily on rubber crops and could be considered wealthy by regional standards. Six motivation types were also identified, ranging from farmers who were most likely to innovate, farmers motivated primarily by income or by community and environmental benefit, to farmers reluctant to innovate under any circumstance. The full range of motivations types were found in all six farm types, albeit with a small but significant variation in proportions between farm types. This has two implications: (i) when designing interventions for a group of farmers defined by their farming practice, the full diversity of motivational orientations should be considered, and only a sub-group of those farmers should be expected to engage actively with new interventions; and (ii) in order to understand farmer motivations additional data is required beyond the usual farm characteristics and livelihood information. We found that an assessment of value orientations (Smajgl and Ward, 2015; Stern et al., 1998), along with stated response to some hypothetical external influences and a simple rating of overall life satisfaction data types were the most useful in defining farmers' motivations to adapt their behaviour.

Rubber farmers in the study population are wealthy by developing world standards, and any proposed changes to their farming practice would need to compete economically with mean incomes of around 9000 US$ per year per household. However, due to the recent rubber price crash, households may now consider alternative activities with lower incomes. Maintaining adequate income is only one factor which motivates households, with about half the population strongly motivated by income, but messages which appeal to a sense of place and family well being have wider appeal. Without widespread awareness raising and education, arguments using environmental degradation as a motivating message for farmers to adapt their behaviour are unlikely to achieve much success. The obstacles to adaptation which were identified most frequently were conceptual rather than material: households felt that changing their behaviour would be unnecessary and irrelevant rather than feeling that they lacked the skills or capital in order to make changes. Amongst the study population, only about one third could be classed as keen to innovate and try out new practices, which, if found to be true elsewhere, explains in part the challenge of promoting new agricultural interventions more generally.

CHAPTER 3: The Rural Household Multi-Indicator Survey (RHoMIS) for rapid characterisation of households to inform Climate Smart Agriculture interventions: description and applications in East Africa and Central America

Abstract

Achieving climate smart agriculture depends on understanding the links between farming and livelihood practices, other possible adaptation options, and the effects on farm performance, which is conceptualised by farmers as wider than yields. Reliable indicators of farm performance are needed in order to model these links, and to therefore be able to design interventions which meet the differing needs of specific user groups.

However, the lack of standardization of performance indicators has led to a wide array of tools and ad-hoc indicators which limit our ability to compare across studies and to draw general conclusions on relationships and trade-offs whereby performance indicators are shaped by farm management and the wider social-environmental context .

RHoMIS is a household survey tool designed to rapidly characterise a series of standardised indicators across the spectrum of agricultural production and market integration, nutrition, food security, poverty and GHG emissions. The survey tool takes 40-60 minutes to administer per household using a digital implementation platform. This is linked to a set of automated analysis procedures that enable immediate cross-site bench-marking and intra-site characterisation. We trialled the survey in two contrasting agro-ecosystems, in Lushoto district of Tanzania (n=151) and in the Trifinio border region of Guatemala, El Salvador and Honduras (n=285). The tool rapidly characterised variability between farming systems at landscape scales in both locations identifying key differences across the population of farm households that would be critical for targeting climate smart agriculture (CSA) interventions.

Each farm system was characterised using data from the surveys. In both cases median farm size was around 0.8 ha, and median family size was 3.6 male adult equivalent persons (in terms of calorie demand). The Lushoto site, Tanzania, had higher livestock ownership (1.2 TLU per household) than Trifinio (0.2), and higher median crop diversity (2 in Lushoto, compared to 1 in Trifinio). Use of nitrogenous inorganic fertiliser was higher in Lushoto (10 kg/ha, compared to 5), as was the average proportion of farm produce sold (30% compared to 10%). In terms of household welfare, Trifinio showed higher potential access to total calories per household compared to Lushoto (9000kcal per day compared to 3000), but similar scores for the Household Food Insecurity of Access Scale and worse scores for Dietary Diversity. This may be indicative of the abundance of maize but very few other foodstuffs in the Trifinio region, causing the “hidden hunger” effect.

Next, in order to differentiate drivers of improvements in household welfare for different farm types in each site, households with large and small land and livestock holdings were analysed separately, and the outcomes of three strategies were analysed: increased use of inorganic fertiliser, increasing crop diversity, and increasing proportion of produce sold.Our results suggest that at both sites the climate smartness of different farm strategies is clearly determined by an interaction between the characteristics of the farm household and the farm strategy. In general strategies that enabled production intensification contributed more towards the goals of climate smart agriculture on smaller farms, whereas increased market orientation was more successful on larger farms. On small farms off-farm income needs to be in place before interventions can be promoted successfully, whereas on the larger farms a choice is made between investing labour in off-farm incomes, or investing that the labour into the farm, resulting in a negative correlation between off-farm labour and intensification, market orientation and crop diversity on the larger farms, which is in complete opposition to postive correlations found for the smaller farms. The balance of indicators selected gave an adequate snap shot picture of the two sites, and allowed us to appraise the 'CSA-ness' of different existing farm strategies, within the context of other major development objectives.

Key-words: farm household, smallholder farming, multiple indicators, monitoring

1. Introduction

At present approximately 75% of the world's poor live in rural areas (Livingston et al. 2011), and many of those are in areas where climate change is expected to have a significant detrimental impact on top of current and future agricultural demand and development challenges. Predicted changes in rainfall and temperature patterns will strongly affect agricultural production, with changed crop production and yields, causing increased vulnerability of many rural communities. As much as 22% of the cultivated area under the world’s most important crops is projected to experience negative impacts from climate change by 2050, with as much as 56% of the land area in sub-Saharan Africa being impacted (Campbell et al 2011). The overall aim of CSA is to ‘*support efforts from the local to global levels for sustainably using agricultural systems to achieve food and nutrition security for all people at all times, integrating necessary adaptation and capturing potential mitigation*’ (Lipper et al. 2014, see also Neufeldt et al. 2013). Climate smart agriculture therefore has three main pillars, to be considered at different spatial and temporal scales (FAO 2013): 1. achieve food security, 2. adapt and build resilience to climate change and 3. reduce greenhouse gas emissions to mitigate further climate change.

There is an urgent need to improve the characterisation of agricultural systems at household level to enable more efficient assessment of capacity for adoption of climate smart measures. Capacity to adopt is intrinsically linked with the potential success of those measures, which means assessing trade-offs amongst multiple outcome objectives for adopters. Local drivers and factors need to be identified that might constrain or provide opportunities within a specified agricultural system

(Carletto et al., 2015), while on the other hand generalizable standardised characteristics need to be identified that would allow robust comparisons between different systems (Frelat et al., 2016; Van Wijk, 2014). One way to improve the assessment of opportunities for climate smart agriculture (CSA) at smallholder farm household level can be through integration of standardized agricultural, poverty, nutrition and environmental indicators in the quantitative characterization of these households. This will allow us to assess how these performance indicators vary across a farm population, across different sets of farm practices present in the farm population and across different agro-ecological and socio-economic conditions as well as how they may change over time.

At present household level characterisation studies are hampered by a variety of problems. A recent analysis of farm household level survey data collected in different agricultural development oriented projects, showed large differences in content between different survey instruments, with lack of standardization of indicators and evidence that only a small amount of the information collected during lengthy surveys could actually be used for cross-site comparisons (Frelat et al., 2015). This lack of standardization in combination with often relatively poor data quality (Tiffen et al 2003), generally caused by unsuitable survey design (Randall & Coast 2015) or by biases due to perverse incentives (Sandefur & Glassman 2015), has led to a lack of quantitative insight beyond the locality of each study regarding the effect of interactions between proposed adaptation options and the wider socio-economic and biophysical environment on household level performance indicators. For example, we know little about how household food security has been affected by trends in agricultural production in different regions of the world (Carletto et al. 2013) or what the effects of adopting of CSA options are. The lack of integrated survey approaches hampers our knowledge of trade-offs and/or synergies between indicators at farm household level (e.g. Klapwijk et al., 2014), and of how these relationships and trade-offs are shaped by farm management and by social and bio-physical environments (Carletto et al., 2015; de Weerdt et al., 2015).

In this paper we describe a new standardised modular survey tool called RHoMIS (Rural Household Multi-Indicator Survey) that tries to overcome the current problems associated with household characterization surveys. The RHoMIS tool is constructed from a set of standardised performance indicators that run across the three pillars of CSA, and aims to allow us to quantitatively analyse the links between agricultural management strategies and farm household performance. RHoMIS is designed to provide rapid characterisations of both farm practices and farm performance in order to enable i) the assessment of the 'CSA-ness' of different farm practices and strategies, ii) how the achievement of 'CSA-ness' is associated with the achievement of other household development objectives, and iii) to identify which strategies are more effective for which groups of farmers. We applied the RHoMIS tool by carrying out two surveys in contrasting sites, one in Central America and one in East Africa, and evaluated the degree to which various farming strategies contribute towards the objectives of CSA, for different types of farmers.

2. Methods and Materials

2.1 Principles and general design of the RHoMIS tool

The RHoMIS (Rural Household Multiple Indicator Survey) tool consists of a farm household survey that can be conducted on a digital platform using smart phones or tablets using the Open Data Kit (ODK) suite of software installed on Android based mobile phones or tablets (Hartung et al. 2010). Data can be directly uploaded to a web-server, and an associated set of analysis tools programmed in R extract the data and calculate indicators. The framework has been set up in such a way that additional modules of questions and indicators can be incorporated and analysed depending on the local study needs. In the supplementary material the paper version of the survey is included, while the ODK source code is available on request from the corresponding author (see Appendix 3, or contact the author for other language translations). In the near future we will make the tools available through a website.

The survey tool was designed according to the following five principles:

i. the survey has to be *rapid* enough to avoid participants' fatigue or annoyance, and keeping costs low to allow for larger sample sizes on a limited budget;

ii. the survey has to be *utilitarian*, in that all questions asked in the survey are being used in pre-defined analyses, in order to minimise superfluous data collection;

iii. the survey has to be *user-friendly*, so that all participants in the process of collecting and analysing data can perform the tasks with minimum hassle and resistance, and therefore increase speed and data quality;

iv. the survey has to be *flexible*, so that it can be modified easily to suit the local context of the farming systems and farm households where it will be deployed;

v. the data gathered has to be *reliable*, in that questions should be easy for respondents to understand and the answers should be based on observable criteria or respondents' direct experience rather than abstract scales or abstract concepts.

2.2 Household Performance Indicators

The indicators that are captured by the RHoMIS framework were chosen to represent important factors across the agricultural production, nutrition and poverty relationships, while also capturing key indicators of interest related to climate smart agriculture (i.e. greenhouse gas emissions and gender equity). The survey tool was constructed in a modular way, with each module collecting the information needed to be able to calculate the performance indicator of interest. New indicators of interest to the user can therefore be added easily. The indicator set collected in the current version of the Rhomis framework consists of the following elements:

1) Food availability is a supply-based estimate of the potential amount of food that can be generated through on and off-farm activities by any one household, and is measured in kilo-calories (kCal) per person (male adult equivalent) per day (Frelat et al., 2016; Ritzema et al., submitted; Van Wijk et al., 2014). The indicator is calculated from on-farm consumption of food crops and livestock

products, and from the amount of food (local staple crop) that could be purchased using the cash incomes earned through selling farm produce and through off-farm activities. It ignores farm costs and household expenses, and therefore only gives an indication of whether certain activities lead to enough food being potentially available to feed the family, and the relative importance of these activities compared to each other. It does not quantify actual consumption.

2) The household dietary diversity score (HDDS) is calculated according to the number of different food groups consumed over a given reference period, and is a proxy indicator for diet diversity, the improvement of which is associated with a number of key health indicators such as birth weight, child anthropometric status, and improved haemoglobin concentrations. The HDDS score in RHoMIS follows the instructions of Swindale and Bilinsky (2006) in most aspects but departs from the standard advice in terms of reference time period. A 24 hour recall method is recommended, but we instead asked how often foodstuffs from each food group were eaten during a 4 week period in 'the good season' and 'the bad season'; where respondents could answer that they consume foods from each group either 'daily', 'weekly', 'monthly', or 'never/ less then monthly'. Whilst this approach might result in lower accuracy than a 24 hour recall, the required survey intensity is much less in order to capture seasonal variations. The 12 food groups used were standard, but locally appropriate examples were chosen in each location. The indicator results are on a scale of 0 to 12, where 12 is the most diverse diet in which all 12 food groups are eaten on at least a weekly basis. The data on consumption frequency within the recall period will allow us more complex interpretations in terms of micro-nutrient use, but will not be analysed in this study.

3) The Household Food Insecurity Access Scale (HFIAS) indicator estimates the prevalence of food insecurity and is based on the idea that the experience of food insecurity (access to food) causes predictable reactions and responses that can be captured and quantified through a survey and summarized in a scale. There are nine questions that represent a generally increasing level of severity of food insecurity, and nine "frequency-of-occurrence" questions that are asked as a follow-up to each occurrence question to determine how often the condition occurred (Coates et al. 2007). The approach has been applied successfully in numerous studies in developing countries (Coates et al. 2006). We asked respondents about food insecurity during the worst month ('bad season') of the previous year, and frequency options were again 'daily', 'weekly', 'monthly', or 'never/less than monthly'. The indicator is scored on a range of 0 to 27, where a higher number means a household experiences more food insecurity.

4) The Progress out of Poverty Index (PPI) is a widely used standard indicator of poverty (Desiere et al. 2015). The PPI is a rapid ten-question survey which estimates the likelihood that a household has an expenditure below a given poverty line, where the score ranges between 0 and 100, and a higher score means a household is less likely to be below the poverty line (Grameen Foundation 2015). The scorecard uses ten simple indicator questions based on observable household characteristics that are correlated with poverty levels using Living Standards Measurement Surveys or similar, detailed surveys. The PPI approach is now available for 55 countries, amongst which are Guatemala and Tanzania.

5) A gender equity indicator was included to quantify the role of women in decision-making and household resource management. The inclusion of gender in resilience and vulnerability assessments is a burgeoning topic (Smyth & Sweetman 2015; Morchain et al. 2015), and achieving gender equity is an aim of many policies in developing countries. The indicator is constructed based on three questions asked for each farm product or income source: who does most of the work, who usually decides when to eat it, and who sells it; where the possible answers are 'household males', 'household females' and/or 'children'. The information was aggregated to an overall score by weighing each activity along the importance it has in the food availability indicator, resulting in a final score between 0 and 1, where 1 implies that females decide completely what happens with the benefits generated by different on and off farm activities. This indicator therefore does not deal with ownership of resources, but with the agency to decide what to do with the benefits that result from these resources. We constructed a novel indicator in this case, because although alternatives do exist they were too detailed and complex for our purposes (Johnson & Diego-Rosell 2015). For example, the Women's Agricultural Empowerment Index requires 60-80 minutes of interview time per household (Alkire et al. 2013), which is longer than our target time for the full questionnaire.

6) Farm level estimates of Greenhouse Gas (GHG) emissions were calculated using the IPCC Tier 1 approach (IPCC 2006). Tier 1 was chosen because it is a recognised method and has low data demands. Although the Tier 2 approach yields a more detailed GHG assessment, the substantially higher data demands can lead to unreliable data when relying on farmer recall. Key determinants of the Tier 1 estimate of emissions for this indicator are number of cattle and other livestock, land use area and type, inputs of mineral fertilizer and the production and use of manure and crop residues. The indicator does not account for carbon sinks, land use change (even if implemented longitudinally), capital infrastructure, nor farm related electricity or fuel use. Farm greenhouse gas emissions are reported in kilograms CO2-equivalent per farm per year.

These were the six core indicators calculated with this version of the RHoMIS tool. They were selected as they are each rapid, independent, and are all (except for indicator 5) tested and validated elsewhere. The information used for the Food Availability indicator can also be disaggregated to provide a fairly comprehensive understanding of farm management. The information used to calculate these indicators was also used to calculate several other performance indicators: The questions used to calculate the Food Availability indicator were also used to quantify 7) Farm Productivity, measured in total kilo-calories produced per year per hectare; 8) Farm Produce Value, which is the calculated total value of everything produced on the farm, using local prices and reported in US dollars per year ; 9) Off farm income, also expressed in 2010 equivalent US dollars, as reported by the households. Finally, the GHG emission indicator and the agricultural production component of FA (including sales and consumption) , expressed in kcal per year, were used to calculate 10) GHG emission intensity, expressed in in kgCO2-eq/kCal.

2.3 Performance Indicators and CSA Outcomes

Performance indicators each link to one of the three pillars of climate smart agriculture: food security, adaptive capacity, and mitigation (FAO 2013). There is some disagreement in the literature about if the first pillar should be framed as "food security" or "agricultural productivity", with food security then an ultimate outcome which is also influenced buy adaptive capacity (FAO, 2013; Neufeldt *et al.*, 2013; Campbell *et al.*, 2014; Lipper *et al.*, 2014). Both arguments have merit, but in this ase we choose to frame food security as one pillar, in order to limit the levels in our conceptual model. In this way, the impacts of existing land use options, farm management practices and/or farm strategies on 'climate smartness' can be measured. By assessing household scores on each indicator, a measure of achievement towards CSA goals can be derived. The logic of this process is represented in Figure 3.1. Within this framework, food security is related to the indicators Food Availability, Farm Productivity, Household Food Insecurity of Access Score and Household Dietary Diversity Score. Adaptive capacity has been shown to be partially dependant on wealth (Delaney et al. 2014) and is therefore related to the PPI, Cash value of produce and also Gender Equity indicators. Mitigation is related to total GHG emissions per farm and GHG emission intensity.

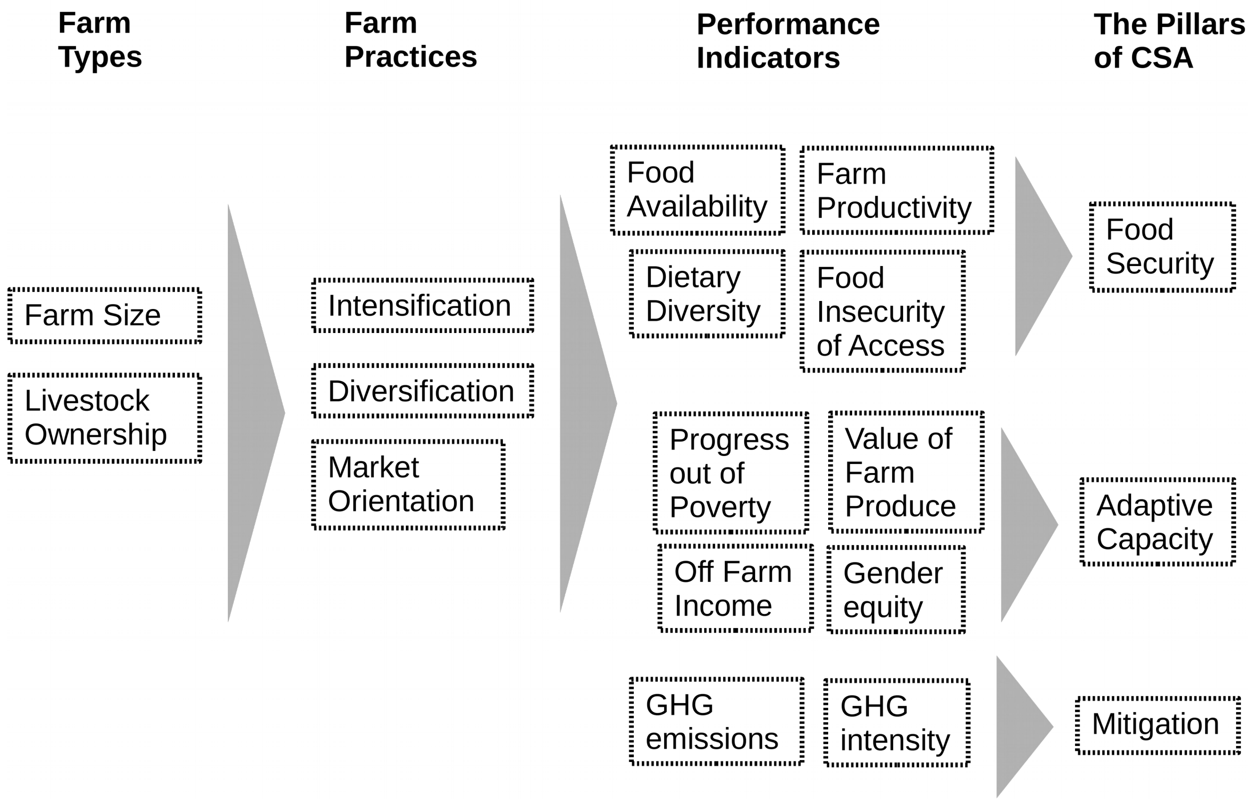

Figure 3.1. Schematic representation of the indicators gathered from the household surveys, and the analytical framework into which they are placed

2.4 Site Selection & Survey Implementation

Surveys were carried out in two contrasting sites: Trifinio border region of El Salvador, Guatemala and Honduras in Central America, and the Lushoto district in Tanzania, East Africa. Agriculture and livelihoods in both sites are vulnerable to climate change. The contrasting nature of the sites aims to demonstrate the wide applicability of the RHoMIS tool. The sites were selected because they are part of a concerted data gathering effort by various ongoing research programs and projects mentioned below. Lushoto is characterized by diverse micro eco-zones within a relatively small area with quite intensive farming systems present at higher elevations and agro-pastoral farming systems at lower elevation. The agricultural system in the Trifinio region in Central America is dominated by dry, steep land with sporadic rainfall and little to no irrigation infrastructure, where the major crops are maize and beans. Trifinio is part of the 'dry corridor' of Central America, and during the past few years rains have become more sporadic, leading to drought conditions since 2014. In both locations, specific climate-smart interventions had not been sufficiently widely trialled by households to allow for evaluation using household surveys.

In Lushoto, Tanzania, the survey was conducted on a re-sample of the farm households that were also surveyed in 2012 by the CCAFS research program (https://ccafs.cgiar.org/). In the 2012 survey 200 farm households were randomly selected within the 10 by 10km land block containing representative agroecologies in the study region (Rufino et al. 2013), The regions were chosen through a participatory process involving a wide range of partners and expert opinion (Kristjanson et al. 2012; Förch et al. 2014). Twenty villages within each block, and then 10 households on average within each village were randomly chosen (Kristjanson et al. 2012) for the household survey. In June 2015 150 households were randomly chosen from the 200 sampled in 2012, and they were interviewed in the first two weeks of July using the digital version of the RHoMIS survey tool. In Trifinio the survey was carried out in conjunction with the baseline survey for the USAID-funded Prueba3 project, implemented by Bioversity, CATIE and Zamorano in Trifinio to test Crowdsourcing Crop Improvement (van Etten 2011). Villages were selected by collaborating organizations as candidate villages for a bean variety introduction experiment, and a subset of 285 households was randomly selected for the RHoMIS survey from the full list of households taking part in the project.

Surveys were trialled with scientific experts in each study region; with scientific and technical staff resident in each study site; with the enumerators who would implement the surveys; and finally with rural households within the intended implementation area of the surveys. Specific changes were made on the phrasing and use of language, on local units of measurement used, on examples of locally available foodstuffs and other products (e.g. types of fertiliser), on the crops, livestock and livestock products commonly produced, routes to market, and common sources of off-farm income. The survey was conducted in Spanish in Trifinio, and in a mixture of English and Kiswahili in Lushoto.

2.5 Data analysis

Extraction of data and calculation of the indicators was done using scripts programmed in R (R Core team, 2012). To compare values of performance indicators between the sites, and to assess the overall patterns of and co-variances between the indicators in the two farm populations that were sampled correlations between the indicators and significance levels were quantified using Spearman's rank correlation. Comparisons to assess significant differences in indicator results between the two sites were performed with the Wilcoxon rank-sum test given non-normal distributions of the response variables.

A more detailed analyses to assess the climate smartness of different farming strategies was performed for both sites. We used farm size and livestock ownership as variables to define ‘small’ (i.e. farm land area smaller than 1 ha, and livestock ownership of less than 1 TLU) and relatively ‘large’ farms (i.e. farm land area larger than 1ha and livestock ownerships more than 1 TLU) and contrasted these farms in terms of their performance indicators, and in terms of the response of the performance indicators to different farm strategies.

We selected three common farming strategies to appraise in terms of impact upon climate smartness: Intensification, Diversification and Market Orientation. We selected those three because they have been discussed in literature as being of potential benefit to the goals of Climate Smart Agriculture (Campbell et al. 2014). Intensification was measured in terms of quantity of nitrogenous fertiliser per ha applied to the crops by the farm household, crop diversification was measured by the number of crop species grown by a household, and market orientation was calculated by using the ratio of agricultural production sold relative to the total agricultural production (both expressed in kcal terms). Again we used simple thresholds based on the median score for each farm strategy in each site, so that households could be divided into two groups – those who score higher than average on that practice and those who score lower than average, for example high crop diversity and low crop diversity.

3. Results

3.1 Implementation of the survey

Across both sites, the running time for the survey was 40-60 minutes per household (Table 3.1). Gathering data for the food availability indicator took the longest, between 15 to 35 minutes, as it attempts to comprehensively capture agricultural production, sales and off farm income. The dietary diversity indicator took the second longest to complete, at around 10 minutes per household, due to the complexity of explaining the different food types, and introducing the concepts of the ‘good season and ‘bad season’. All other indicators only took less than 5 minutes each (Table 3.1). The indicators were calculated successfully for most households, we were only unable to calculate less than 1% of all potential indicator data points due to lack of adequate responses.

The interviewers were asked to rate the ‘easiness’ of gathering the data at the end of each module, whilst undertaking the surveys. Ease related to both the ease of asking and phrasing questions, and the ease of extracting the right type of response from the informant. All modules were rated as ‘easy’ between 50-60% of the time, and rated as medium approximately 30% of the time, except for off-farm incomes, which was rated 'medium' more often than it was rated 'easy'. The Progress out of Poverty Indicator was rated as difficult only 5% of the time, and other modules rated as difficult 11-13% of the time (details shown in Table 1). This provides evidence that the survey is indeed user friendly.

Adaptation of the survey questions, language and training of interviewers took about two weeks in both Trifinio and Lushoto. In Lushoto, Tanzania, in two weeks of data collection with 3 interviewers the responses from 150 households were collected, at a total cost of around $5000, including the purchase of three tablets. The implementation in Trifinio was a little more complex, as the RHoMIS survey was only one of two surveys implemented as part of a larger project, so it is not possible to determine survey costs working only with RHoMIS. It does however illustrate that the tool is flexible enough to be used in conjunction with other research methods.

Table 3.1: Time taken to gather data for each indicator, and the ease of that data gathering, as rated by the interviewers during the Lushoto survey, n=151

Module	Mean time needed (minutes per household)	Proportion of times module perceived as easy (%)	Proportion of times module perceived as medium (%)	Proportion of times module perceived as difficult (%)
FA	15 –35	56	31	13
HFIAS	5	54	34	12
Dietary Diversity	10	54	34	12
PPI	5	61	34	5
Gender Equity	5	61	28	11
GHG Emissions	5	57	32	11

3.2 Indicator scores

The median indicator scores in both locations are shown in Table 3.2, along with the interquartile range. In both sites farm sizes were generally less than one hectare, and average family size was 4 people (3.6 adult male equivalent), although with quite high variability. Livestock ownership was significantly higher in Lushoto, as well as crop diversity and intensification. The reported values of these three variables were all low in Trifinio, indicative of a basic farming system where most households grow only one crop and keep a couple of chickens. Market orientation was significantly different in the two sites, with households in Trifinio purchasing on average about 10% of their food and households in Lushoto purchasing about 30%. Off-farm income was significantly higher in Trifinio than in Lushoto.

Food availability showed high variability between households in both locations, but median values were within the expected range (2000-4000 kcal per day per person) in Lushoto, but very high in Trifinio (median 9000 kcal per day per person). The higher values in Trifinio are likely due to the predominance of maize as the main and often only crop, thereby indicating the limitations of using this indicator which only uses energy as the common denominator. Productivity, measured in Mcal per hectare per year, was similar in both sites, although there was substantially higher variability in Lushoto. Dietary diversity scores in the good season were higher in both locations than in the bad season (as would be expected), and were significantly higher in Lushoto during both seasons. Household food insecurity of access scale (HFIAS) scores indicated moderate levels of food insecurity, with greater variability in Trifinio suggesting more households experiencing severe food insecurity, although overall there was no significant difference in the median HFIAS scores between sites. Progress out of Poverty Index scores were around the lower half of the scale in both locations, indicating that approximately 50% of households could be expected to be below the $1.25 poverty line. Cash value of production is higher in Trifinio than in Lushoto, a result of higher farm gate prices, especially for beans. The gender equity indicator showed median values of 0.5 in Lushoto and 0.6 in Trifinio, which suggests an approximately equal division of responsibility between men and women in the household over the use of farm produce, although there was higher variability in the Tanzanian site. Greenhouse gas emissions and emission intensity were significantly higher in the Tanzanian site, probably due to the significantly higher livestock ownership, and also higher fertiliser use. Both sites showed high variability in GHG emissions and emission intensities.

*Table 3.2: Results of Indicators and drivers, with units and the possible scoring ranges shown in parentheses. Significant differences between the sites were measured using the Wilcoxon rank-sum test and indicated by the following symbols: † p<0.1; * p<0.05; ** p<0.01, *** p<0.001, and IQR signifies inter-quartile range.*

Indicator	Trifinio (n=285)		Lushoto (n=150)	
(unit) (possible range)	Median	IQR	Median	IQR
Farm size (ha)	0.7	0.9	0.8	0.8
Livestock ownership (TLU) ***	0.2	0.3	1.2	2.2
Family Size (adult male equivalent)	3.6	2.5	3.6	2.0
Crop Diversity (number of crops grown) ***	1.0	1.0	3.0	2.0
Intensification (kg nitrogenous fertiliser per hectare) **	5.0	5.0	10.0	47.5
Market Orientation (0-1) ***	0.1	0.3	0.3	0.5
Food Availability (kcal per mae per day) ***	9922.7	20139.8	3174.3	5418.4
Farm Productivity (Mcal per hectare per year)	5104.0	5878.8	5007.8	8146.5
Household Food Insecurity Access Scale (HFIAS) (0-27)	8.0	9.0	9.0	6.0
Dietary Diversity (good season) (HDDS) (0-12) ***	7.0	4.0	9.0	3.0
Dietary Diversity (bad season) (HDDS) (0-12) ***	5.0	4.0	6.0	4.0
Progress out of Poverty Index (PPI) (0-100)	40.0	32.0	42.0	20.0
Off Farm Income (US$ per year) ***	489.1	1726.6	0.0	261.5
Value of Farm Produce (US$ per year)***	550.7	846.1	340.8	634.7
Gender Equity (0-1) †	0.6	0.3	0.5	0.5
GHG emissions (kgCO_2-eq per household per year) ***	498.9	966.0	2761.1	5560.1
GHG intensity (kgCO_2-eq per kcal) ***	0.1	0.2	0.5	1.6

3.3 Relationships between performance indicators

In both sites, there is a high degree of co-variance between the six main household performance indicators (Table 3.3), demonstrating that the challenges measured by these indicators are highly interlinked. Many of the typical expected relationships were found in both locations. Higher food availability was correlated with lower experience of food insecurity, lower poverty, and improved dietary diversity (the latter in the bad season only though). Dietary diversity in the good and bad seasons were highly correlated. Higher food insecurity scores (i.e. more food insecure households) were correlated with worse dietary diversity in both seasons, and worse poverty status. The correlation coefficients between progress out of poverty and the food security indicators are higher in Trifinio than in Lushoto, implying stronger relationships. This might imply that wealth and off farm income (see also Table 2) is a more important route to obtaining diverse and sufficient foodstuffs, whereas in Lushoto agricultural production is the more important route. However, it is risky to conclude this on a single survey like this, but it shows how such an integrated, multi-indicator survey tool can generate insights that open targeted avenues for further investigation. Higher gender equity showed negative correlations with food availability, dietary diversity, and progress out of poverty, although it also showed correlation with improved HFIAS score in Trifinio. Higher greenhouse gas emissions were correlated with improved food availability, dietary diversity, and food insecurity (more and stronger correlations in Trifinio). Significant correlation coefficients are mainly in the region 0.15 to 0.35, which implies that while the indicators are co-correlated, they are not the measuring the same phenomena.

*Table 3.3: Correlation table between the six main household performance indicators in Trifinio and Lushoto, using Spearman's Rho correlation test. The correlation co-efficient and significance values refer intra-site comparisons only, there are no correlations between the two sites presented in this table. Abbreviations: FA is Food Availability, HFIAS is the Household Food Insecurity Access Scale, HDDS is the Household Diet Diversity Score, PPI is Progress out of Poverty Index, GHGs is Greenhouse Gas emissions. Significance levels are denoted by: † p<0.1; * p<0.05; ** p<0.01, *** p<0.001.*

		Lushoto (n=150)						
	Variable name	FA	HFIAS	HDDS (good)	HDDS (bad)	PPI	Gender Equity	GHGs
Trifinio (n=285)	FA		-0.24**	0.11	0.21*	0.34***	-0.19*	0.27**
	HFIAS	-0.19**		-0.18*	-0.31***	-0.31***	-0.02	-0.12
	HDDS (good)	0.26***	-0.23***		0.51***	0.11	-0.08	0.20*
	HDDS (bad)	0.22***	-0.35***	0.55***		0.18*	-0.01	0.12
	PPI	0.23***	-0.51***	0.34***	0.35***		0.02	-0.04
	Gender Equity	-0.05	0.10†	-0.03	-0.15*	-0.15*		-0.21*
	GHGs	0.35***	-0.33***	0.28***	0.26***	0.39***	-0.17**	

3.4 Farming strategies and their 'Climate smartness'

In Lushoto (Figure 3.2; Table 3.4) intensification is associated with higher Food Availability, PPI and cash value of production, and to a smaller extent to higher GHG emissions (Figure 3.2a). Households who have intensified also have significantly higher market orientation and higher crop diversity (see Supplementary information, Appendix 4), so it is important to note that the three strategies are not independent. On large farms, intensification is also linked to significantly higher Productivity and Value of farm produce, while being related to significantly lower GHG intensity and gender equity. On small farms it is linked to improved HFIAS and dietary diversity scores and is associated with higher off farm income. Higher crop diversity shows very similar relationships with the performance indicators as intensification in Lushoto, except that the effects of higher crop diversity on the important food security indicators HDDS and HFIAS is still more pronounced (Figure 3.2b). So this indicates that intensification without increasing crop diversity does not necessarily lead to the same positive effects on diets and food security, compared to higher crop diversifity alone. Higher market orientation on large farms is negatively correlated with a strong in gender equity and off farm income, and positively correlated with productivity, but shows no significant relationships with the other performance indicators. In small farms in Lushoto higher market orientation is correlateded with higher values for PPI, but also with slightly negatively correlated with HFIAS and HDDS: the cash generated by selling produce is apparently not being spent on buying diverse food items.

In Trifinio (Figure 3.3; Table 3.5) intensification is related to higher values of PPI and HFIAS on both the small and large farms. On large farms it is also related to higher emissions, value of farm produce and productivity, while on small farms it is related to higher productivity and diet diversity. Gender equity on both farms tends to be lower with higher intensification on both farm types. Off farm income shows an opposite trend between the two farm types: higher intensification on large farms has a strongly negative correlation with off farm income, while on small farms there is a positive correlation, although it is not a very strong relation. Crop diversity effects on the performance indicators are less strong compared to intensification (Figure 3.3b), with farms with less crop diversity performing quite similar in terms of HFIAS, HDDS and PPI as farms with more different crops. The spider diagram ‘shape’ of higher crop diversity is very similar to the intensification one for large farms (Figure 3.3a). On small farms crop diversity, similar to the results in Lushoto, had a significantly positive relation with diet diversity, while it is also acorrelated with higher emissions and emission intensities. Higher market orientation (Figure 3.3c) follows quite similar patterns again as increased intensification, although the negative relationships with off farm income are more marked on both farm types. Similar to Lushoto, higher market orientation is correlated to significantly lower female decision making (gender equity indicator).

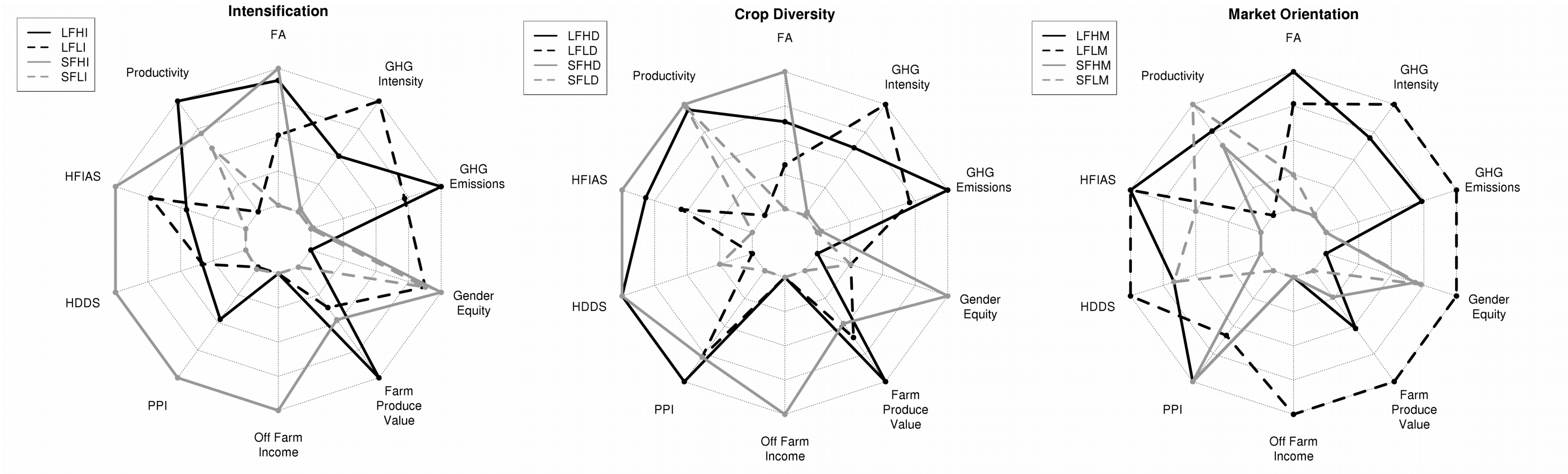

Figure 3.2. Farm performance scores for large and small farm types (LF and SF) , practising high and low farm intensification (HI and LI), crop diversification (HD and LD) and market orientation (HM and LM) for Lushoto, Tanzania. Abbreviations: FA is Food Availability, HFIAS is the Household Food Insecurity Access Scale, HDDS is the Household Diet Diversity Score, PPI is Progress out of Poverty Index.

*Table 3.4. The significance of differences in performance indicators for households who do and do not score highly on farm strategies, for Lushoto. All values refer to Figures 3.2. Abbreviations: FA is Food Availability, HFIAS is the Household Food Insecurity Access Scale, HDDS is the Household Diet Diversity Score, PPI is Progress out of Poverty Index, GHGs is Greenhouse Gas emissions. Significance levels are denoted by: ns not significant, † p<0.1; * p<0.05; ** p<0.01, *** p<0.001.*

	Farm Type	Practice	FA	Productivity	HFIAS	HDDS	PPI	Off Farm Income	Produce Value	Gender equity	GHG emission	GHG intensity
Lushoto, Tanzania	Large	Intensification	ns	†	ns	ns	*	†	ns	ns	†	ns
	Small	Intensification	†	†	**	**	***	**	*	ns	**	ns
	Large	Diversity	†	†	ns	*	ns	ns	ns	ns	†	ns
	Small	Diversity	ns	ns	ns	ns	ns	ns	ns	ns	ns	*
	Large	Market	ns	†	ns	ns	ns	ns	ns	*	ns	†
	Small	Market	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

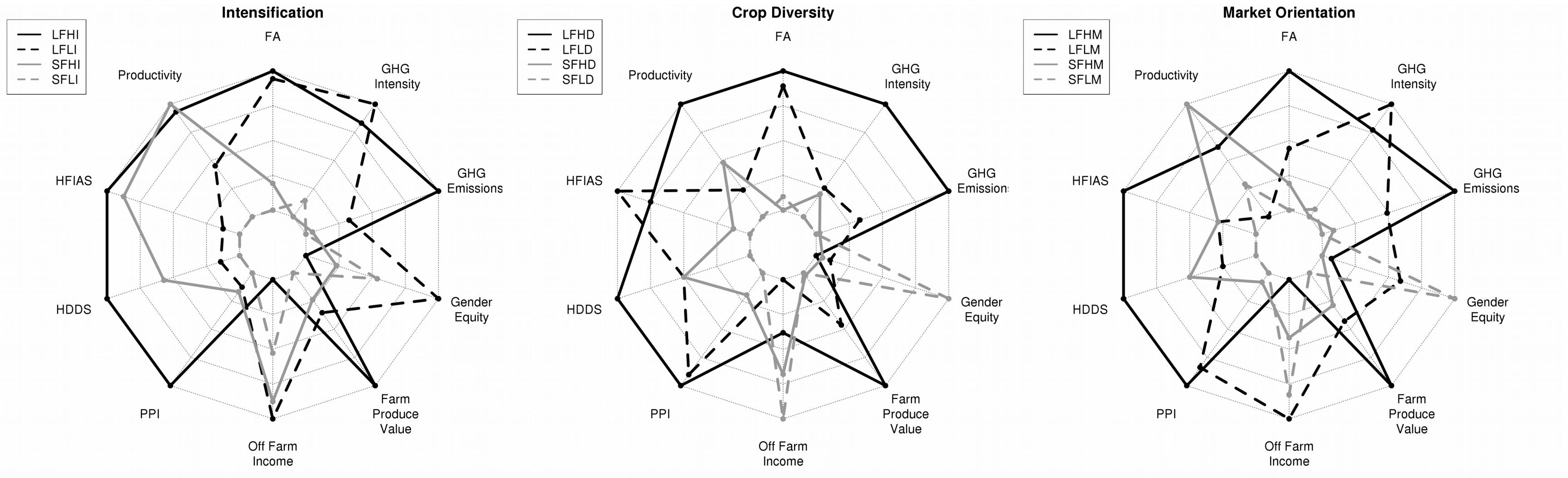

Figure 3.3. Farm performance scores for large and small farm types (LF and SF), practising high and low farm intensification (HI and LI), crop diversification (HD and LD) and market orientation (HM and LM) for Trifinio, Central America. Abbreviations: FA is Food Availability, HFIAS is the Household Food Insecurity Access Scale, HDDS is the Household Diet Diversity Score, PPI is Progress out of Poverty Index.

*Table 3.5. The significance of differences in performance indicators for households who do and do not score highly on farm strategies, for Trifinio. All values refer to Figures 3. Abbreviations: FA is Food Availability, HFIAS is the Household Food Insecurity Access Scale, HDDS is the Household Diet Diversity Score, PPI is Progress out of Poverty Index, GHGs is Greenhouse Gas emissions. Significance levels are denoted by: ns not significant, † p<0.1; * p<0.05; ** p<0.01, *** p<0.001.*

	Farm Type	Practice	FA	Productivity	HFIAS	HDDS	PPI	Off Farm Income	Farm Produce Value	Gender equity	GHG emission	GHG intensity
Trifinio	Large	Intensification	ns	ns	*	*	*	†	***	ns	*	ns
	Small	Intensification	ns	ns	†	ns	ns	ns	*	ns	ns	ns
	Large	Diversity	ns	*	†	ns	ns	ns	**	ns	***	ns
	Small	Diversity	ns	ns	ns	**	ns	ns	*	ns	**	*
	Large	Market	ns	†	†	**	ns	ns	**	ns	†	ns
	Small	Market	ns	**	ns	*	ns	ns	***	ns	***	ns

4. Discussion

In both study sites the RHoMIS tool met our stated goals of providing rapid, user friendly, and flexible output; both in terms of ease of implementation of the survey by enumerators and by providing efficient data management and analysis. Some of the indicators could be improved upon to give more nuanced interpretations, although there is always tension between speed of survey and detail of results (e.g. Mina et al., 2008; Coates, 2013; De Weerdt et al., 2015). When considering food security and nutrition there is a clear trade-off between the level of detail that can be achieved in quantifying intake of different foodstuffs of individual actors, versus the goal of obtaining a sufficiently accurate picture of the village or local eating habits. An example is the use of the household dietary diversity score (e.g. Kennedy et al., 2011). In nutrition oriented research the gold standard is (at the moment) the 24 hour recall collecting detailed information on what several individual members of a household consumed the previous 24 hours (Coates, 2013). However, this data is more time consuming to collect, plus provides only a current snapshot the nutritional situation. Several surveys per year are required to capture seasonal variation and repeat surveys to measure trends have to take place during the same season to avoid confounding effects. Our approach of asking about frequency of consumption (daily/weekly/monthly) in the 'good' and 'bad' seasons may be less accurate, but may obtain a general picture much more quickly, and appeared to function well at the level of detail required for the present study, and we could take the analysis one step further by calculating approximate vitamin input from the food groups). Potential improvements to the mitigation indicators could be inclusion of the IPCC Tier 2 methodology, which would allow for better evaluation of the GHG impact of livestock management and land use changes, and an evaluation of the sequestration potential of the farm system could be a useful addition (Lamb et al. 2016). Gender equity could be developed further, taking account of ownership of productive resources and household head status, allowing for more focused analysis on the relationships between food security and gender equity issues (Alkire et al, 2013, Mersha & Laerhoven, 2016). Given the modular design it is relatively straight-forward to expand the RHoMIS framework to take account of other topics, too, such as farmer motivations and attitudes to innovation and risk, or more advanced compound indicators to evaluate different types of sustainable and non-sustainable intensification.

Overall, the standardized indicator approach allows for comparison between the two sites, which, when applied to more locations, will be useful for gaining a better understanding of the interactions between household food security and trends in agricultural production in different regions of the world (Carletto et al. 2013). Interestingly, the Trifinio site scores high on food availability and productivity (energy based indicators), but scores low on food insecurity of access and household dietary diversity. This matches the observation of ‘hidden hunger’ in Guatemala whereby sufficient calorie intake is not matched by sufficient total nutrient or micro-nutrient intake (Hoddinott et al. 2008). Diets in the study area mainly consist of maize and beans with little else. This observation is also supported by the low crop diversity score. Because improved dietary diversity scores are generally correlated with higher crop diversity, intensification and market orientation, further yield increases in this system, for example in maize, will not necessarily lead to improved nutrition and food security (Harris and Orr, 2014; Frelat et al., 2016). In addition, maize yields in this system are highly unpredictable, considering the drought conditions which have persisted since 2014 until the time of writing. Our results suggest that interventions should focus on increasing the diversity of crops grown, incorporating drought tolerant, marketable crops, and on empowering women to gain better control over the cash generated by the crops in order to buy more diverse food items. In Lushoto, Tanzania, farms are more diverse in terms of the crops grown and there is more livestock, all leading to (relatively) better scores on diet diversity although the total energy available from food production is far less than in Guatemala. However, the scores of the various food-oriented indicators still represent poor nutrition and moderate experience of food insecurity.

If we use PPI, off farm income, total value of farm produce and gender equity as indicative of adaptive capacity, another key pillar of CSA (the only one not directly captured in one of the indicators available), then both sites have fairly similar scores: no significant difference in PPI scores, a small difference in gender equity and the farms in Trifinio generating more cash value for their produce and earning more off farm income. Income from the actual sale of produce shows significant correlation with improved status of all other indicators (see Supplementary Information, Appendix 4), and PPI shows correlation with improvements in most indicators (with the exception of greenhouse gas emissions in both cases). However, gender equity in general is negatively correlated with fertiliser intensification and market orientation, and households reporting a very high score on female decision making tend to be households where no male is present, either due to death or due to working away. These households have a shortage of labour and therefore tend to score lower on income, productivity and food security, restricting their ability to intensify and produce for the market (e.g. Njuli et al., 2011), thereby resulting in barriers to adoption that are different from those of male headed households (Mersha and Van Laerhoven, 2016).

Greenhouse gas emissions rise in tandem with most of the improvements to income and food security measured in this study. This presents a central challenge for climate smart interventions which aim to simultaneously mitigate emissions and improve food security. However, the results show how farm intensification can, on larger farms, lower the greenhouse gas intensity of production. Climate smart interventions need to balance the benefits that increased fertiliser use and animal husbandry bring to food security and adaptive capacity against the additional emissions generated. From this perspective, interventions improving the efficiency of the system (such as improving nitrogen use efficiency in manures and improving feed quality to reduce methane output and livestock weight gain) are preferable compared to interventions aiming only to increase the quantity of livestock or fertiliser used. However, when considering such trade-offs, it should be kept in mind that the absolute values of emissions from these systems are still relatively low compared to agricultural systems in the developed world (e.g. Henderson et al., 2016), especially in Trifinio where little livestock is present.

Closer examination of the farms with the most and least productive resources (land and livestock) in each site showed that the climate smartness of different farm strategies or interventions is strongly influenced by the characteristics of the farm household. For example, the intensification of production using chemical fertilisers on small farms in both sites appeared to be driven by off-farm income. The off farm income in these cases not only directly affects food security positively (e.g.

Otsuka and Yamano, 2006; Kristjanson et al., 2011), but is also likely to generate that bit of extra cash that supports investment in intensification of the system, with the knock-on improvements to food security. It seems that on small farms the boost of off-farm income needs to be in place before agricultural intensification (or other strategies) can be promoted successfully (see also Frelat et al., 2016). On large farms higher off farm income is associated with lower intensification, lower crop diversity and lower market orientation. This suggests that for the large farms a choice is made between investing labour in off farm incomes, or investing that the labour into the farm. This may be due to the higher labour required to manage a larger farm, or it may be that a larger farm can more easily produce the minimum requirement for subsistence, and thus the farmers feel less compelled to intensify production if they can also obtain an off-farm wage. It would be useful to find out if there are common thresholds of farm size or livestock ownership and at which household decision making changes.

5. Conclusions

The balance of indicators in the current iteration gave an adequate snapshot of the two sites, and appraised the 'CSA-ness' of farm strategies, and could be used in a post-hoc project evaluation of specific CSA interventions. The applications are not limited to CSA, however, as the RHoMIS framework aims to be a generic indicator framework, and after specific adaptations its potential list of application possibilities is large: integrated natural resource management, integrated nutrient management, conservation agriculture, organic agriculture, integrated pest management, agroforestry, integrated soil fertility management and many others (e.g. Lambrecht et al., 2016), while it can also be used for the construction of farm types to aid the targeting of interventions across farming systems (e.g. Sakane et al., 2013; Giller et al., 2011) or generate the right inputs to be used in modelling exercises for ex-ante impact assessments (e.g. Van Wijk et al., 2014b; Herrero et al., 2014). Providing a standardised baseline provides multiple benefits but indicator standardization is a line of research that has been largely ignored in the current literature (e.g. De Weerdt et al., 2015; Carletto et al., 2015).

Our results show that the climate smartness of different farm strategies or interventions not only depends on the strategy or intervention itself, but is also determined by an interaction between the characteristics of the farm household and the farm strategy (see also Coe, Sinclair, & Barrios, 2014). This finding stresses the importance of more granular farm household characterisation, where for some groups certain strategies or interventions are ‘smart’, and for other groups of households those strategies are less ‘smart’ (or even ‘stupid’). Avoiding strategies that are inappropriate from the outset may be one of the most important uses of the RHoMIS tool, and if sufficient RHoMIS data (or similar) could be gathered to allow scaling up of characterisation across larger geographical areas, implication could be drawn for scaling out of interventions.

CHAPTER 4: Shea butter: a pro-poor, pro-female route to increased income

Abstract

Raising agricultural productivity of the poorest households is often not a viable route out of poverty or hunger, as farm sizes are small and yield potential low. These challenges will be amplified by climate change. Off farm sources of income are often cited as a better alternative, but in remote communities off farm opportunities can be very limited. In northern Ghana, shea butter has been promoted as a climate smart option to increase household incomes. Here we present a quantitative study of 223 households, half of whom were exposed to improved value chain opportunities for sale of shea butter. The Rural Household Multi-Indicator Survey (RHoMIS) allowed rapid evaluation of the project impacts on multiple household welfare metrics: income, food security, and gender. The survey results showed that the poorest households self-selected to take part in shea butter production and sales activities, and that these activities and the income remained in the control of women. Incomes derived from shea by project beneficiaries were compared to a control population: the findings suggest that beneficiaries earned on average 30 US$ more per household per year. In such a cash-poor location, where median income per person per day is less than 0.10 US cents and 81% of the population are classed as severely food insecure, this increase in income caused a measurable impact. There were significantly less households below the 2,500 kcal per person 'calorie line' amongst project beneficiaries than amongst non-beneficiaries. Reasons for pro-poor self-selection, and how value chain development practices may have influenced the project are discussed below.

1. Introduction

People suffering extreme poverty are typically the most vulnerable to system shocks, including to the effects of climate change (FAO, 2016). Finding climate-smart interventions which effectively target the poorest, most vulnerable people is difficult because those people are typically the hardest to reach, being the least educated, least able to adopt new practices; with less resources to invest, less able to tolerate risk, and often underfed or undernourished (Ahmed *et al.*, 2007).

This chapter studies marginal smallholder farmers in the Sudanian zone, in Eastern Province, Northern Ghana, to explore whether shea butter production might offer a solution to help the most vulnerable. Whether the enhancements to the shea butter value chain could be considered as “climate smart agriculture” is discussed below. Furthermore, the chapter aims to illustrate how the rapid survey tool RHoMIS (Rural Household Multi-Indicator Survey (Hammond *et al.*, 2017)) was instrumental in collecting the evidence for the study.

Shea trees are highly abundant across the Sudanian region. Whilst the tree is culturally familiar and valued across the dry lands of West Africa (Carpena et al., 2016) it has yet to be domesticated (Hall et al, 1996). The fruits of the shea trees can be eaten, and the sun-dried kernels can be boiled down over a period of days producing a vegetable fat known as shea butter, used both in the food and cosmetics industry. Shea butter has been widely promoted as an agricultural intervention, as it is a freely accessible resource with a clear and reliable market value (Elias and Carney, 2007; Hatskevich, Jeníček and Antwi Darkwah, 2011; Pouliot and Elias, 2013). The trees also serve as a defence against encroaching desertification.

Shea products are generally viewed as a female commodity (Elias and Carney, 2007), and the processing of the nut is laborious and considered as a socially lowly form of work. respecitvely, these two factors make it an appropriate intervention for women (who tend to be more vulnerable than men) and for poorer households compared to wealthier households. The incomes from shea butter can be used to invest in nutritious foods or to buffer against other shocks, whilst the ecosystem benefits of preserving shea trees help in both the mitigation and adaptation to climate change.

The NGO TREE AID led a five year programme (2012 – 2017) aiming to: (i) increase income of communities involved in sourcing and processing shea nuts through increased product quality and quantity; (ii) increase women's empowerment through improved organizational capacity and commercial infrastructure including business groups, warehouses, and credit schemes; (iii) diversification of buyers' base to allow long-term and stable incomes for the producers involved in the shea nut sector; (iv) protection of ecosystems and promotion of climate resilience through the reduction of the environmental impact of shea nut sourcing and production. TREE AID supported producers to form second-tier "union" organisations to focus on regional marketing, services and value addition, and aimed to secure minimum price guarantees from national and international buyers of shea butter, in order to buffer against market fluctuations. Training was also given on improved methods for shea butter processing, and with hand tools and electric machinery (mill, roaster, crusher, churner) made available.

The programme was evaluated using the Rural Household Multi-Indicator Survey (RHoMIS), which is a carefully designed and well tested household survey tool designed to efficiently characterise farm systems in communities suffering from poverty and food insecurity (Hammond *et al.*, 2017). RHoMIS uses a standardised approach which can be quickly deployed in a variety of locations, but also allows flexibility to suit the local context. Such an approach was inspired by the multiplicity of indicators and incomparability of many survey instruments (Rosenstock *et al.*, 2017). In this case, the RHoMIS survey provided a quick and low-cost solution to evaluate the programme and build a case for the impact of this intervention.

1.1 But is it Climate Smart Agriculture?

The three pillars of climate smart agriculture are widely defined as increasing agricultural productivity and incomes, increasing adaptive capacity, and mitigation of greenhouse gas emissions (FAO, 2013; Neufeldt *et al.*, 2013; Campbell *et al.*, 2014; Lipper *et al.*, 2014). The pillars are sometimes defined more narrowly as increasing agricultural production, increasing adaptation to climate change, and reducing greenhouse gas emissions. The 'three pillar' framework can apply equally well to agriculture in many places and at different scales; it could be applied to industrialised monoculture crop systems, or to marginal substance smallholder agriculture systems. In the following chapter we apply the concept to marginal smallholder farmers in the Sudanian zone, in Eastern Province, Northern Ghana, and conceptualise the three pillars to suit the local context. Firstly, we consider food security over agricultural productivity. Secondly, we consider two routes to increasing adaptive capacity: (i) that through valorising the use of trees in the landscape, trees will continue to provide provisioning and buffering ecosystem services related to water, soil, and against desertification (Sinare, Gordon and Kautsky, 2016), and therefore help landscape scale adaptation to climate change; we also consider that (ii) through increased incomes and better developed business infrastructure households will be more able to adapt to negative events. Thirdly, we place decreased importance on the goal of mitigation of greenhouse gas emissions, due to the low emissions intensity of Ghana (most recent figures are 0.7 tCO_2eq per year per capita (National Carbon Accounting, 2015)), and in accordance with environmental justice arguments that the burdens of emission reduction should be allotted in accordance with the scale of historical emissions. The wider interpretations of the three pillars of climate smart agriculture is used here to explore the degree to which enhancing the shea value chain contributes towards the goals of climate smart agriculture.

2. Methods

The population surveyed was in the Upper East and Upper West regions of Northern Ghana, in the Lambussie Karni, Kassena Nankana East, and Kassena Nankana West districts. Interviews with 223 households were conducted in March 2017. Informants were selected randomly from 26 villages within the project area, where informants were either project beneficiaries (101 households) or were not beneficiaries – a 'control group' (122 households). The villages were selected according to already established relationships with partner organisations and the households taking part in the project were self-selecting – and so could be assumed to have an increased interest in shea compared to the entire population. The control group were households identified as future project beneficiaries so were considered by the local project partners to be living in very similar conditions to the beneficiary households. There was no baseline data available, so differences due to project activities were only observable through comparison of beneficiary and control households. This approach entails a degree of uncertainty which should temper interpretation of results.

The RHoMIS tool uses a modular, rapid (40 to 60 minute) digital survey to derive standardised indicators on agricultural practices, livelihoods, food security and dietary diversity, and gender roles (Hammond *et al.*, 2017). A survey module was developed to collect information on use of non-timber forest products (NTFPs) and woody environmental resources. The indicators used were food availability (Frelat *et al.*, 2016), which converts all household income and agricultural produce into a calorie per person score. Food availability was chosen in preference to cash incomes as it also takes account of self-produced and consumed items and thus provides a more comprehensive perspective on the livelihoods of very poor and food insecure (Ritzema *et al.*, 2017). Other rapid and well tested indicators were also gathered: experience of hunger was quantified using the Household Food Insecurity of Access Scale (HFIAS) (Coates, Swindale and Bilinsky, 2007); dietary diversity, which was assessed using the Household Dietary Diversity Score method

(Swindale and Bilinsky, 2006); and food groups from the Minimum Dietary Diversity for Women (FAO and FHI 360, 2016). The Progress out of Poverty Indicator was used to cross check the household incomes measured from direct questioning (IPA, 2015). The use of these standard indicators permits evaluation of the project impacts in a wider frame of reference than would otherwise be possible, and also permits comparison to other locations, or permit evaluation of changes over time should a further RHoMIS study be done at a later date.

Households were classified into three poverty classes, based on their food availability scores. Households with access to less than 2,500 kcal per male adult equivalent person per day were classed as 'below the calorie line'. Households above the calorie line but with a total value of activities (i.e. actual cash income plus the value of consumed agricultural produce) below US $1.90, were classed as 'below the poverty line'. Households with total value of activities above $1.90 were classed as 'above the poverty line'. Welfare indicators have been presented as medians per household group, and incomes have been presented as trimmed means, where 5% of the observations at either extreme of the scale were dropped to reduce the effect of outliers. The Kruskal-Wallis test for significance was used when comparing between beneficiary and non-beneficiary households within paired poverty classes, and unless otherwise stated all significance was attributed at the $p>0.95$ level.

3. Results

3.1 Household Livelihoods and Farm Characteristics

The majority of the population was very poor, and suffered from food insecurity. The median income per person per day was $0.09, or $144 per household per year. The progress out of poverty indicator predicted that 51% of households were below the $1.90 poverty line, although from reported household income we calculated that 99% of households were below that poverty line. Median household population was 8 persons, and median land owned was 2 ha per household, with 1.6 ha cultivated in the last year. Crops sales accounted for the majority of household income ($96 per year), followed by environmental resources, including woody resources and non-timber forest products ($33 per year). Livestock sales and off farm income were low, returning median values of zero, some household did derive income from these sources. Livestock were however widely kept, with 80% of the population keeping some form of livestock. The main crops grown were ground nut (85% of households), maize (82%), millet (58%), rice (53%), and sorghum (25%). The main livestock were goats (65%), chicken (48%), sheep (39%), and cattle (28%). The NTFPs reported were shea, baobab, and mango, with shea by far the most widely used product reported. Shea was gathered by 72% of the study population, baobab by 19% and mango by 8%. The environmental resources were fuelwood (65% of the population) and charcoal (5%).

Using the food availability indicator, we calculated that the median amount of kcal available per person (adult male equivalent) per day was 3,023; but that 42% of the population had less than 2,500 kcal available per day. Households reported on average three months during which it was difficult to source enough food, with the worst months being May to August. Using the HFIAS indicator, 81% of households were categorised as severely food insecure during the lean season, 9%

moderately food insecure, 3% mildly food insecure and 7% food secure. Dietary diversity was low during the lean season, with median score of 3 food groups eaten at least weekly. Outside the lean season the dietary diversity score was considerably better, with a median score of 7.

Very few households are considered above the poverty line, amongst beneficiaries or non-beneficiaries (see Figure 4.1). There were, however, more households in the poorest category (below the calorie line) amongst the non-beneficiary group than the beneficiaries (*p*<0.05). The plausible reason for this, looking at the sources of calories and income illustrated in Figure 4.1, is the major role played by NTFPs. The mean amount of income derived from NTFPs is greater amongst project beneficiaries. Amongst both beneficiaries and non-beneficiaries the importance (as a proportion of calorie provision) of NTFPs and woody resources is greater for poorer households.

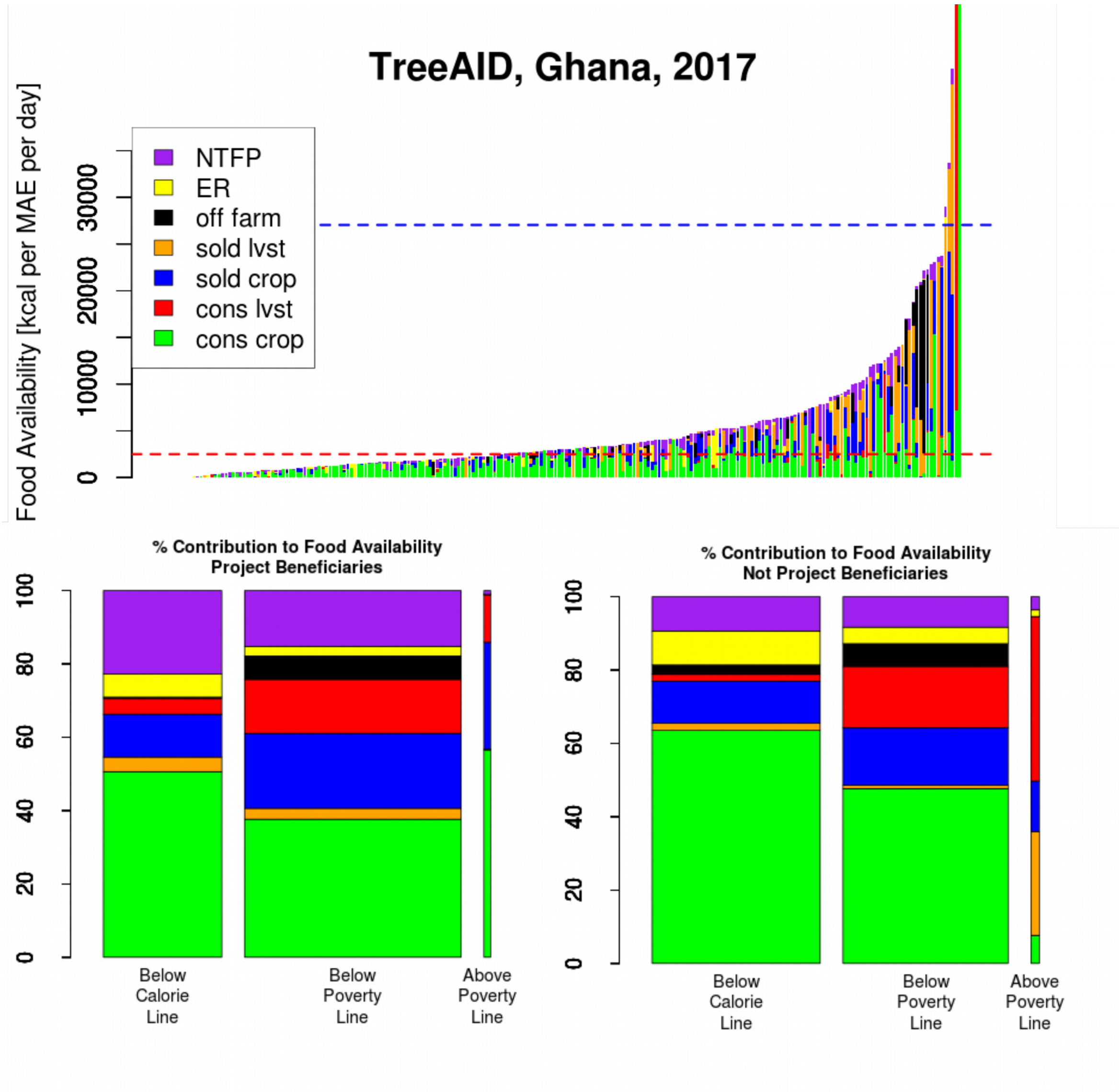

Figure 4.1. Household livelihoods displayed as potential food availability, kcal per male adult equivalent person per day. The upper panel shows the amount of calories potentially derived from different income (or food) sources, and each column represents an individual household. The horizontal dashed lines represent thresholds which have been used to divide the population. The red dashed line represents minimum calorie requirement per day (2,500 kcal per male adult

equivalent), and the blue line represents the amount of calories of staple foodstuffs that could be bought in local markets for $1.90 per person per day. The lower panel shows the mean proportion of income derived from each income source for households in three poverty classes: those below the 'calorie line', those below the poverty line, and those above the poverty line; where the width of the column represents the number of households in that category. The population is also divided into beneficiaries of the project, and non-beneficiaries. The livelihood sources are represented in the legend in the upper right corner, with the following abbreviations: 'NTFP' non-timber forest products, 'ER' environmental resources, 'lvst' livestock, 'cons' consumed.

3.2 The Impacts on Household Welfare Indicators

When looking at the whole population, significant effects on household welfare indicators were found (see Table 4.1). Beneficiary households had higher potential calorie availability, higher cash incomes, and better progress out of poverty scores. Furthermore, the lower number of households classified as severely food insecure (using the HFIAS indicator) scored a low but non-significant p value of 0.12, implying, in combination with the above mentioned significant effects, positive project outcomes on the beneficiary population.

The poorest households, below the calorie line, showed higher actual cash incomes from 0.01 US cents per person per day to 0.04 per person per day. Higher food availability score for beneficiary households below the poverty line was found to be significant only at the $p<0.1$ level.

Table 4.1. Household welfare indicators, by beneficiary and non-beneficiary (control) households, and by poverty class. Food availability is shown as kilocalories per male adult equivalent, the proportion of households suffering from severe food insecurity is determined using the household food insecurity of access scale (HFIAS), the dietary diversity score is determined using the household dietary diversity score method (HDDS) and the ten food categories from the MDD-W indicator, and the progress out of poverty indicator (PPI) is used to predict the likelihood of households to be in poverty using the $1.90 poverty line. All values shown are median averages, and statistical significance was established using the Kruskal-Wallis rank sum test, comparing between beneficiary and control households within the same poverty class. Differences significant at p<0.05 are marked with two asterisks **, and differences at p<0.1 with one asterisk *.

Project Beneficiary	Poverty Class	Food Availability (kcal/MAE)	Income $/pers/day	% hh Severley Food Insecure	Dietary Diversity Score (lean season)	Hungry Months	PPI predicted % under poverty line
Control	All	2558^{**}	0.05^{**}	84	3	3	51^{**}
Beneficiary	All	3885^{**}	0.14^{**}	76	3	3	35^{**}
Control	Below Calorie Line	1307	0.01^{**}	87	3	3	62
Beneficiary	Below Calorie Line	1277	0.04^{**}	83	2	3	51
Control	Below Pov Line	4756^{*}	0.17	83	3	3	35
Beneficiary	Below Pov Line	5548^{*}	0.24	73	4	3	35
Control	Above Pov Line	43795	1.92	67	4	1	10
Beneficiary	Above Pov Line	128014	1.15	50	3	2	17

3.3 Shea Derived Incomes

Table 4.2 shows a breakdown of incomes derived from shea and firewood, as well as proportions of the populations engaged in each activity. The project beneficiaries showed a statistically significant higher of income from sales of shea at the whole population level. The higher income was due to shea butter sales, and not from nuts or fruits. Furthermore the beneficiary population derived less income from sale of fuelwood compared to the control. The total number of households using shea was also higher in the beneficiary population (p<0.1), the total number selling shea butter was higher, and the total number selling fuelwood was lower.

When considering households of different poverty classes, those below the calorie line, showed the most marked changes: average income from shea butter was almost ten times higher amongst the beneficiary population, and more than twice the proportion of households took part in shea butter selling. A similar pattern was observed amongst the households below the poverty line, although effects were at the p<0.1 level, perhaps reflecting the greater variation in income sources amongst households in that poverty class. An unexpected observation was that the beneficiary households above the poverty line showed less income and engagement with shea than non-beneficiary households; although there were so few households in that class that the finding cannot be considered robust.

Table 4.2. The use of shea products and firewood by households, sub-divided into beneficiary and non-beneficiary (control) groups, and also separated by poverty class. Incomes presented are trimmed means, in US$ per household per year. Statistical significance was established using the Kruskal-Wallis rank sum test, comparing between beneficiary and control households within the same poverty class (using full not trimmed values). Differences significant at p<0.05 are marked with two asterisks **, and differences at p<0.1 with one asterisk *.

Project Beneficiary	Poverty Class	n	Shea Income $/yr	Shea % hh selling	Shea Butter Income $/yr	Shea Butter % hh selling	Shea Seed Income $/yr	Shea Seed % hh selling	Shea Fruit Income $/yr	Shea Fruit % hh selling	Fuelwood Income $/yr	Fuelwood % hh selling
Control	All	122	28**	60*	12**	29**	4	16	3	21	9**	37**
Beneficiary	All	101	57**	70*	40**	46**	3	19	3	18	3**	20**
Control	Below Calorie Line	60	15**	45*	4**	18**	0	7	3	22	9	38
Beneficiary	Below Calorie Line	35	49**	63*	42**	40**	2	17	2	14	6	29
Control	Below Pov Line	59	40	73	19*	36*	9	24	5	22	11**	34**
Beneficiary	Below Pov Line	64	67	75	45*	50*	4	20	3	19	3**	16**
Control	Above Pov Line	3	95*	100	73*	100**	22	67	0	0	33	67
Beneficiary	Above Pov Line	2	17*	50	0*	0**	0	0	17	50	0	0

4. Discussion

The impact evaluation of this project is based on the assumption that the beneficiary households and the control households can be meaningfully compared. Households within the villages were selected on the same basis, and villages were selected on the same basis, although five years later. However, comparison of difference can not be interpreted as conclusive evidence of impact, but rather as indications of impact. As the indications are that impact was achieved, it is worth exploring the factors which may have led to this impact.

What were the enabling factors in this project?

The reasons for the beneficiaries' higher incomes from shea are multiple. The survey data shows that the quantity of shea fruit gathered per household did not significantly differ between beneficiaries and non-beneficiaries (mean 130 kg/yr), but the amount converted into shea butter did. Beneficiaries households yielded on average 37 kg/yr of shea butter compared to 13 kg/yr for non-beneficiaries ($p<0.01$). The high difference in average shea butter production may be in part due to the higher number of beneficiaries who produced shea butter compared to non-beneficiaries, as well as more efficient production techniques, including access to tools and machines which reduced the drudgery of the process. The ability to store shea nuts or butter may also have contributed to reducing wastage. There was no significant evidence that beneficiaries sold more nuts or fruits compared to non-beneficiaries, and there was also no significant evidence that the project achieved higher sale prices for shea butter for beneficiaries (median price 1.5 $/kg). It therefore appears that the project created a greater “market pull” by facilitating easier and more efficient shea processing, and by establishing sales groups.

The different usage of fuelwood may be an important clue as to the production of shea butter. Non-beneficiaries collected the same amount of fuelwood than beneficiaries but sold more of it as fuelwood. It may be, therefore, that beneficiaries used the fuelwood they gathered, in combination with their shea transformation. This is strongly implied from the survey data, and if true would be a clear case of adding extra value to already gathered environmental resources. It also implies that total greenhouse gas emissions were not increased through increased shea production, as fuel wood was gathered in equal quantities by non-beneficiaries, but sold instead of used in shea production. Local informants believed that this fuel wood was not being sold to shea butter producers, but this was not established quantitatively and could undermine the conclusion.

The households below the calorie line showed a much higher adoption rate of shea and shea butter sales amongst the beneficiary group compared to the non-beneficiaries. This partly reflects the fact that shea butter is highly labour intensive and does not generate immediately a large amount of income. Consequently shea does not attract wealthier families who have more opportunities elsewhere. This may be both a blessing and a curse: it does not offer an easy path out of poverty, but due to the initial low cash investment and high labour cost, it may be a commodity which is well suited to modestly improving incomes and food security for the very poor and vulnerable.

The timing of the shea fruit season also makes it a useful crop to combat food insecurity, and may explain in part the popularity of the crop. Figure 4.2 shows the timings of reported lean season and NTFP harvesting, as reported by beneficiary and non-beneficiary households. It is clear that shea harvesting coincides well with the lean season, and that baobab and mango do not. Furthermore, it can be seen that the lean season starts a little later for project beneficiaries, possibly as an effect of the project interventions. The shea harvest seems to be particularly well timed to meet a local need.

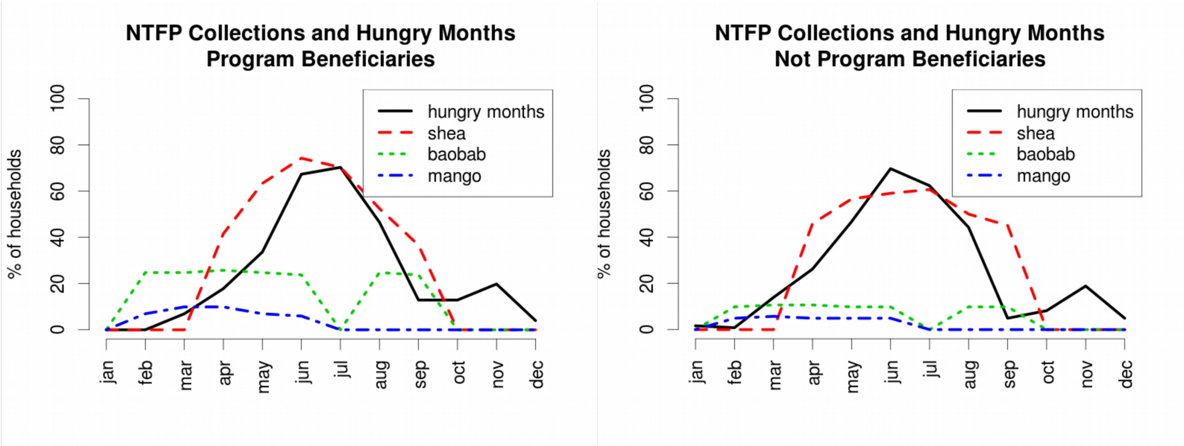

Figure 4.2. The timings of reported 'hungry months' during which food is in short supply, and of NTFP gathering. The collection of shea fruit seems to be well matched with the hungry season.

Shea collection is also a strongly gendered activity, practised mainly by females; 70% of households' surveyed reported females gathering shea, with only 21% reporting males involvement. Most importantly, the income is predominantly controlled by women, where 70% of households reported female control of shea incomes, and only 11% of households reported shea incomes as solely male controlled. The gender break down of work and income control did not differ significantly between the beneficiary and control populations. This gendered skew on shea activities may also have helped the project gain traction, in an environment where opportunities for women can be scarce, and where increasing female share of household income is often a challenge (Johnson *et al.*, 2016).

The project's implementing staff considered the construction of the warehouses for the union organizations to store shea products to be an important part in the project. The warehouses acted as a hub for the unions, a safe and pest free storage area, and a location to access machinery to process shea. The warehouses may have added to the female control of shea income, as they were not gendered spaces, and homesteads can have gender taboos associated with storage areas, making it difficult for women to extract full value from shea products. There were however some observations made as to what could have worked better at the warehouses: they were constructed late in the project, and had they been constructed earlier the unions may have been more successful in negotiating guaranteed minimum prices. A credit system whereby union members could receive some payment when depositing shea in the warehouses, to be set against the final payment they received when selling the shea butter would have benefited the programme, but unfortunately could not be established due to logistical complications.

5. Conclusion

This project demonstrated the usefulness of the RHoMIS tool in an ex-post project assessment. With minimal modifications it permitted evaluation of the project at low cost, and the data gathered can now be pooled with that from other sites and used to build a body of evidence on routes to achieving resilience of smallholder rural households. The use of a rapid and well-designed evaluation tool permitted a deeper understanding of the project impacts on household welfare than could otherwise have been achieved.

This study reveals the benefits of shea butter value chain work. The more successful interventions were training of households in shea butter extraction techniques and the formation of unions providing access to storage and machinery. The financial infrastructure proved more challenging to organize, with credit schemes and minimum price guarantees coming either too late or not at all. Despite these challenges, we have shown that the poorer sectors of society, and particularly females, benefited from the project in terms of income and food security.

A number of factors contributed to the success of this project and consideration of these may help improve other value-chain projects relating to climate-smart objectives.

i. Gender inclusive: Supporting shea chains makes it easy to reach women, as shea is already a gendered (female-biased) product and not linked to land ownership.

ii. Pro-poor: Due to the high labour requirements and low initial cash investments, shea butter is a commodity well-suited to improving incomes and food security for the very poor and vulnerable sections of society. It unattractive to wealthier households, which may create more opportunities for the poor.

iii. Culturally acceptable: Shea was already culturally well accepted, and abundant, with little risk entailed in entering the market.

iv. Timely: The timing of the potential shea fruit income suited a local need: income during the lean season.

v. Adoptable: The project interventions were simple and accessible to many households: hand tools, training, unions and access to storage space and machinery.

The project did reveal some challenges. The business training and value chain enhancement took longer to establish than was initially hoped, and price guarantees from buyers could not be secured. Earlier prioritisation of these activities may make them more successful in the future.

Evaluating the full environmental impact of the project was beyond the scope of the study, but there is no doubt that continued use of shea trees entails ecosystem benefits. One possible negative environmental consequence could be increased use of fuel wood for shea processing. We did not see evidence of this, but if it is found to be a problem, it could be managed by establishment of fuel lots. By preserving and encouraging the maintenance of trees in the landscape, shea production combats desertification and promotes preservation of soil and water resources. By providing both a source of food and opportunities for cash income, it contributes to healthier households and communities, making them more resilient in the face of environmental shocks. In this case, the facilitation of increased shea butter production and sales offered significant benefits to the most vulnerable smallholder farmers: decreasing in the number of people in extreme poverty.

The RHoMIS tool permitted evaluation of the project at low cost and also the data gathered can now be pooled with those from other sites and used to build a body of evidence on routes to achieving resilience of smallholder rural households. The project impact assessment could be taken further by calculating a return on investment figure, comparing investment by donors and the benefits to household incomes derived by project beneficiaries.

CHAPTER 5: Rapid pace of change for rural smallholders in East Africa, where prosperity is driven by off farm income in tandem with agricultural intensification

Abstract

Smallholder farmers are often portrayed as being trapped in poverty and static. We test this discourse by analysing a household panel survey in which 600 households were visited in 2012 and 2016 in four contrasting sites dominated by smallholder farming in East Africa. Small net population level changes in poverty and food insecurity hid great household variation: almost two thirds of households improved or declined in prosperity with the gap in prosperity and agricultural productivity increasing between households. Access to off farm income was the key driver of these changes and agricultural intensification was mainly seen in households that had more off farm income. Increases in gross crop value of around 1,000 to 3,000 US$ per hectare combined with off farm incomes of around 500 US$ per adult male adult equivalent household member was sufficient to lift households above the $1.90 poverty line. Roughly one half of this was needed for households to rise out of the worst poverty and food insecurity class. Differing interventions should be aimed at the more prosperous households and the less prosperous, with sustainable intensification of agricultural production serving the better off farms while the least prosperous households need access off farm opportunities to improve their situation.

Key words: smallholders, food security, poverty, East Africa, panel survey, RHoMIS

1. Introduction

1.1 Agriculture is changing rapidly in East Africa

Macro-level studies have found that the agriculture sector in East Africa is undergoing rapid change, precipitated by a booming population, competition for limited land, increasing market connectivity, and opportunities for off-farm incomes and employment (Headey and Jayne, 2014; Jayne, Chamberlin and Headey, 2014; Chamberlin, Jayne and Headey, 2015). Micro-level studies have also found agricultural and livelihood changes in a surprisingly short period of time (Fraval *et al.*, 2018). Classical farm system theory (Boserup, 1965) views agricultural intensification (i.e. the production of more foodstuffs from the same amount of land) as a logical response to increased population pressure and limited land resources; but such a clear relationship has not been found in contemporary studies (Headey and Jayne, 2014; Muyanga and Jayne, 2014; Ricker-gilbert, Jumbe and Chamberlin, 2014). Multiple responses of smallholder households are hypothesised, which include (i) agricultural intensification, (ii) shifting labour to rural non-farm activities, (iii) migration to other rural areas; (iv) migration to urban areas, and (v) reductions in human fertility rates (Jayne, Chamberlin and Headey, 2014); all of which ultimately impact poverty dynamics (Jayne, Yamano and Weber, 2003). This paper considers the first two of those hypotheses: agricultural intensification and off farm incomes, and their impacts upon poverty dynamics.

1.2 Agricultural intensification as a route out of poverty

Another perspective on agricultural intensification is as a narrative of progress: that it can help to feed a hungry planet whilst simultaneously enhancing ecosystem services if sustainability principles are followed (Foley *et al.*; Godfray *et al.*, 2012); or that it can feed African smallholders and help lift them out of poverty (Diao, Hazell and Thurlow, 2010; Ejeta, 2010; Larson, Muraoka and Otsuka, 2016). The fulfilment of the narratives surrounding sustainable intensification are of course much more difficult and complex than the agenda setting. The low hanging fruit of sustainable intensification for global benefit are not in Africa (West *et al.*, 2014). African farmers have typically not benefited from the potential yields offered by improved varieties (Tittonell and Giller, 2013), have generally not adopted fertilisers at high rates (Burke, Jayne and Black, 2017; Liverpool-tasie *et al.*, 2017), have not adopted irrigation widely (Headey and Jayne, 2014), and may be suffering from increasingly degraded soils (Vanlauwe *et al.*, 2011) - due in part to unsustainable intensification (Jayne, Chamberlin and Headey, 2014). Unfortunately - as the cited papers explain in detail - these “failures” are all for quite sensible reasons. Indeed there is much evidence that African smallholders cannot and should not be expected to achieve an Asian-style green revolution (Nin-pratt and Mcbride, 2014), and that if such a green revolution were to be forced it might have negative effects on the poorest and most vulnerable people (Dawson, Martin and Sikor, 2016). The methods of implementing agricultural intensification in Africa need to be - and are being - reconsidered (Tittonell, 2014a, 2014b), and the role of intensification in alleviating poverty and food insecurity need to be better understood.

Micro-level studies - studies centred around the smallholder household as the unit of analysis - provide an alternative vantage point from which to understand the ways in which agricultural intensification interacts with poverty dynamics. Micro-level studies provide an element of ground-truthing with which to double-check the validity of macro-level modelling exercises, and with which to evaluate the ground-level appetite for specific interventions, and the impacts of those interventions. Whilst micro-level studies are useful in establishing farmer behaviour, findings are rarely scaled up beyond the landscape level and there are few examples of higher level models making use of micro-level findings (van Wijk, 2014), although this would be a desirable approach (van Wijk *et al.*, 2014). Studies tend to either be located in a single site or landscape from which detailed farm characterisations can be developed and but findings are not necessarily widely scalable (Valbuena, Groot and Tittonell, 2015; Fraval *et al.*, 2018), or studies tend to pool data from from multiple sources, securing a wider base from which to extrapolate findings, but sacrificing detail as more nuanced information is rarely comparable between data sources (Harris and Orr, 2014; Frelat, Lopez-Ridaura, *et al.*, 2016; Waha *et al.*, 2018).

The loss of detail in analysis of pooled datasets does however in some cases lead to the creation of transparent and incisive indicators which facilitate comparison between multiple locations and deliver powerful insights. By examining the “income gap” between existing household incomes and poverty lines, it was found that in order for agricultural intensification to lift the majority of African smallholders out of poverty a ten- to one-hundred-fold increase in agricultural income per hectare would be required (Harris and Orr, 2014; Harris, 2018). The potential food availability indicator was created in order to compare agricultural production, agricultural sales, and off farm incomes, and is based on conversion of all foodstuffs consumed by the households into a calorie value, and conversion of all farm and off-farm incomes into the calorie value of local staple crops which could be bought with that income (Frelat, Lopez-Ridaura, *et al.*, 2016). The major components of livelihoods for households of different wealth strata could therefore be quickly and easily determined: and it was found that off farm income played a major role in livelihoods even where agricultural intensification was high (Frelat, Lopez-Ridaura, *et al.*, 2016; Ritzema *et al.*, 2017).

1.3 Farmer Strategies and Poverty Dynamics

Multi-time point studies, or studies of poverty dynamics, offer greater insights into the impact strategic choices made by households, although datasets supporting such work are uncommon. In a seven year study from Kenya (1997-2004), household poverty status was found to be fairly static, where more prosperous households had more land and better levels of education, the least prosperous households rely heavily upon low-return forms of off farm income, and households who managed to maintain non-poor status tended to invest more heavily in livestock (Burke *et al.*, 2007). The observation that low-return off-farm income can be a crutch and a poverty trap for very poor households has been established elsewhere, and conceptualised in opposition to the more profitable forms of off farm income (with higher entry prices) which are available to more prosperous households (Barrett, Reardon and Webb, 2001). Poverty traps have been defined as “any self-reinforcing mechanism which causes poverty to persist” (Azariadis and Stachurski, 2004), and it is acknowledged that while some households experience steady or gradual improvements in prosperity, interrupted by shocks and other set-backs, other households are locked into situations where the only (perceived) method of survival locks them into a situation in which there is no possibility for gradual improvement (Carter *et al.*, 2006). Mechanisms creating such poverty traps can be institutional, cultural, personal, or related to physical geography (Barrett *et al.*, 2013), but the overall effect is that a household cannot access adequate return on investment from the resources at their disposal in order to improve their situation. Removing the drivers of poverty traps may well entail different activities from aiding development of households who are not caught in poverty traps: a lesson which may explain why the poorest households are frequently observed to benefit the least from agricultural intensification measures (Orr, 2001; Kristjanson *et al.*, 2012; van Vugt, Franke and Giller, 2017).

A more narrative-oriented model of poverty dynamics is of “hanging-in, stepping-up, stepping-out” (Dorward, 2009), whereby households in the poverty trap or recovering from some shock just try to survive, households who have the opportunity spend resources in an attempt to generate more resources, and households who have gained sufficient capital (economic or otherwise) step out of poverty into more secure livelihoods. Dorward's model can be usefully applied to aid in the interpretation of empirical work, although the ease of moving between categories should not be over-stated. In a two time-point study in Western Kenya (2003-2013) household practices associated with stepping-up were identified as increasing off farm income and crop intensification, while households who were hanging-in sold assets (labour, land) in order to survive, and doing so deepened their position in the poverty trap (Valbuena, Groot and Tittonell, 2015). In a study between 2012 and 2015 in Tanzania Dorward's model was combined with more traditional farm typology work to find that about one third of households were considered as "stepping-up", and that they pursued either crop intensification or a combination of livestock intensification and off farm incomes (Fraval *et al.*, 2018). Those stepping-up households tended to accrue more land, which was considered a risky strategy by Fraval *et al.*, whereby some households would over-extend themselves and drop back into worse states of poverty, but some others would be able realise economies of scale and be able to step-out of poverty (Fraval *et al.*, 2018). The strategy of land acquisition as a means of stepping-put of poverty, or as an action by those who have already stepped-out, has been increasing in numerous locations and is termed rise of the medium scale farmer (Jayne *et al.*, 2014; Sitko and Jayne, 2014), although in East Africa trade in land is uncommon. There will almost certainly be a feedback effect upon the persistently poor and those attempting to step-up if land is increasingly controlled by medium-scale farmers - whether the feedback is negative or positive will depend upon policy decisions.

1.4 Requirements for monitoring smallholder households in a rapidly changing rural Africa

The issues reviewed above necessitate a new generation of tools to monitor smallholder farm management and livelihood decisions, and the impact of those decisions on food security and poverty dynamics, building on learnings from previous monitoring efforts (Förch *et al.*, 2014). The rapid pace of change (Jayne, Chamberlin and Headey, 2014; Fraval *et al.*, 2018) necessitates rapid tools which can be deployed quickly and cheaply; ideally at multiple time points, in order to better understand household dynamics (Burke and Jayne, 2014), and with sufficient comparability between individual studies to permit high level insights which can help achieve large scale impact. Recent developments in digital technologies allow efficiency increases in data processing which should be harnessed (van Etten, Steinke and van Wijk, 2017). Monitoring tools should systematically capture macro- and micro-drivers of change including land size, household population, livelihood reliance upon subsistence, sales and off-farm incomes (Headey and Jayne, 2014; Frelat, Lopez-Ridaura, *et al.*, 2016), as well as comparable and transparent indicators for outcomes towards development goals (e.g. poverty alleviation and food security, but there are others too) in an efficient manner (Kristjanson *et al.*, 2017; Rosenstock *et al.*, 2017). Data are also needed to understanding the determinants of household-level adoption of new practices or technologies: data are required on biophysical and institutional contexts (Coe, Sinclair and Barrios, 2014; Coe, Njoloma and Sinclair, 2016) as well as data on personal drivers of decision making such as (Meijer *et al.*, 2015; Hammond, Wijk, *et al.*, 2017). Large projects which apply harmonised monitoring tools in multiple locations yield powerful datasets (Kristjanson *et al.*, 2012), but an even better approach is to build monitoring tools which can be applied by multiple projects in even more locations; thus yielding larger harmonised datasets. The Rural Household Multi-Indicator Survey

(RHoMIS) tool, which was used to gather half of the data presented in this study, was designed based on these principles (Hammond, Fraval, *et al.*, 2017).

Here we present the results of a household panel survey exercise in which 600 households were visited in 2012 and re-visited approximately four years later, in four sites in East Africa. The sites have contrasting farming systems, but are all undergoing rapid development. Households were divided into prosperity groups in each panel, change between the groups was quantified, and assets and livelihood strategies of households on different trajectories compared. We do not delve into specific detail of each farming system, but the findings we do present are consistent across all sites and may therefore represent general principles of contemporary smallholder behaviour in land constrained and fast developing African locations. More data points, either in terms of longitudinal studies or more locations would serve to strengthen the findings.

2. Methods

Four sites were selected in East Africa: Lushoto in Tanzania, Rakai in Uganda, and Wote and Nyando in Kenya. All four were benchmark sites of the Climate Change, Agriculture and Food Security (CCAFS) program of the CGIAR and the Earth System Science Partnership (ESSP). Households in these sites were surveyed in 2012, using a questionnaire called “Impact-Lite” (Rufino *et al.*, 2013); and revisited in late 2015 (Lushoto), 2016 (Wote and Nyando) or early 2017 (Rakai) using the RHoMIS questionnaire.

The four sites were defined as rectangular blocks of land measuring approximately 10 km by 10 km. The research sites were chosen in a highly participatory manner with a wide range of partners from multiple sectors, selected to represent a range of key biophysical and agro-ecological conditions, agricultural production systems, and judged by expert opinion to represent a wide range of conditions faced by many rural farming households across each region. A more complete description is available (Kristjanson *et al.*, 2012), and detailed descriptions of the sites are available online at www.ccafs.cgiar.org/where-we-work/east-africa. Summary information abut each site is given below, after a description of the sampling approach.

Once the blocks were chosen and mapped, all villages within the block were enumerated and seven villages were randomly chosen within the block, and in turn 20 households within each village were randomly chosen. For the second set of interviews, a subset of the households was randomly identified from household lists, and non-available households were substituted with other households from the list of those originally interviewed. Due to resource constraints, approximately three quarters of the original households were interviewed.

2.1 Site Descriptions

Lushoto, Tanzania is characterized by mixed farming, with vegetable production for sales to Dar-es-Salaam playing an important role in recent years (Fraval *et al.*, 2018). The site ranges in elevation from 780 to 2010 meters above sea level. Rainfall is bi-modal, ranging from 690 to 1230 millimetres per annum, with heavier rains occurring from March to May, and from October to December. Population density was 120 people per km^2 in 2012. Many cultivated soils are degraded, with low levels of soil organic carbon indicating limited nutrient retention capacity (Winowiecki *et al.*, 2016), and observed deficiencies in phosphorous and nitrogen (Ndakidemi and Semoka, 2006). This site is an important catchment for the Pangani basin and hosts rich biodiversity sheltered by ancient forests. Of the 200 households surveyed in 2012, 147 randomly chosen households were resurveyed in 2015.

Rakai, southern Uganda, is a site with a steep rainfall gradient, with high rainfalls (>1400 mm) along Lake Victoria, rapidly declining to low into Western Rakai and Isingiro (<1000 mm). Population density was 154 people per km^2 in 2014. The production targeted is characterized as a mixed coffee–banana system with annuals and few local livestock included. Perennials (banana and coffee) form the basis of the cropping system, while the dominant annual crops are by maize, beans, cassava, groundnuts and sweet potatoes. The livestock is the system are mainly cattle, goats and poultry. Of the 200 households surveyed in 2012, 135 randomly chosen households were resurveyed in early 2017.

Wote, Eastern Kenya, is the driest site of the four sites included in this study with an average rainfall of 520 mm per year. Rainfall is bimodal, with the long rains in March–May and the short rains in October–December. Population density was 110 people per km^2 in 2009. Two main mixed systems are present, crop–livestock mixed with local sheep and crop–livestock mixed with dairy. Key crops in the region are sorghum and millet, cow pea and pigeon pea. A new development in the area is the production of mango, with trees scattered throughout the landscape. Of the 200 households surveyed in 2012, 160 randomly chosen households were resurveyed in 2016.

Nyando, Western Kenya, is characterized by a mixed crop-livestock system. Annual rainfall is highly variable, with values between 400 and 750 mm per year. Population density was 341 people per km^2 in 2009. Households that do sell produce usually sell vegetables and/or small livestock and animal produce. On-farm consumption is supplemented with off-farm produce as well, as the majority of households consume fruits and fish which are being harvested off-farm. Generally, maize, sorghum and beans have been cited as the three most important crops in this area, and fertilizer is not commonly used. Of the 200 households surveyed in 2012, 160 randomly chosen households were resurveyed in 2016.

2.2 Survey tools used

In the first panel round the Impact-Lite tool was used. The tool was designed to capture in detail agricultural practices, and has been described in detail elsewhere (Rufino *et al.*, 2013). For the latter round of household surveys a different survey tool was used: the Rural Household Multi-Indicator Survey (RHoMIS) (Hammond, Fraval, *et al.*, 2017). The RHoMIS survey was shorter in terms of interview duration (roughly one hour compared to two and a half hours). A thorough analysis of the comparability of data captured in the survey tools was carried out. The surveys were highly comparable for household composition and demographics, crop yields, products, and residues, livestock inventory and livestock products. Moderately comparable topics were land area and fertiliser use. Topics which were captured in both surveys but challenging to accurately compare were off farm income, dietary diversity and gender roles. Topics which were not captured in both surveys and therefore incomparable were asset-based measures of poverty, experience of food insecurity, innovation capacity, labour allocation, and spending. The main reason for difficulty to compare certain topics was a miss-match of granularity in data collection: Impact-Lite frequently collected information at sub-household and sub-annual levels, compared to RHoMIS where all data was collected at household or annual levels. For example, collection of information per plot and per season rather than per farm and per year, or per animal rather than per livestock breed. The challenge was particularly with plot sizes which did not add up to the total farm size, due to issues such as inter-cropping and seasonality inadequately taken into account. The data on farm size, and perhaps with a knock-on effect on yield calculations, should be interpreted cautiously. A similar issue plagued the off farm income calculations: the Impact-Lite data was highly disaggregated but lacked sufficient information in some cases to scale up to annual household values. In these cases averages of days worked per month or per season were taken from similar household performing similar work in order to achieve credible values. The precision of off farm income is therefore expected to be low in the Impact-Lite data. Other topics which were considered challenging to compare were excluded, but off farm income was kept due to the importance in farm-livelihood systems. Overall, with the information collected by both survey tools we could quantify land areas, livestock ownership, household demographics, crop production, livestock production, consumption and sales of farm produce, on and off farm income, and compare changes in these variables over time.

The RHoMIS questionnaire was also designed to capture various indicators of household welfare and food security: the Household Food Insecurity of Access Scale (Coates, Swindale and Bilinsky, 2007) which measures the frequency and severity of hunger, the Household Dietary Diversity Score which provides an indication of household nutrition status (using the household level methodology) (Swindale and Bilinsky, 2006) but more recent and more nutritionally relevant food group categories (FAO and FHI 360, 2016), and the Probability of Poverty Index (IPA, 2015), which is an asset-based scoring system to estimate the likelihood that a household is in poverty (previously known as the Progress out of Poverty Indicator). These indicators were used to validate the prosperity ranking of households based on their farm production and off-farm incomes.

2.3 Data processing and analysis

To compare between the two panel survey rounds, we calculated prosperity according to the total value of farm produce consumed (were it to be sold under local conditions), plus the total income from actual sales of farm produce, plus the total income from off farm sources. We term this “total value of activities” (TVA); and follow the method of the potential food availability indicator, which has been found to be a useful and reliable indicator in many locations in Sub-Saharan Africa (Frelat, Lopez-Ridaura, *et al.*, 2016; Ritzema *et al.*, 2017; Paul *et al.*, 2018). Whilst the potential food availability indicator is typically expressed in kCal per male adult equivalent person (Weisell and Dop, 2012), we choose to express the same information in terms of financial value, in order to make the results more accessible to a wider readership. The total value of activities indicator shows an oversupply compared to actual net income, the value of consumed crops is never realised, and it it does not intend to account for household expenses. All financial information is given in US$, adjusted to 2015 purchasing parity power, using World Bank conversion rates (Piburn, 2018).

We used the total value of activities indicator to assess changes in households' prosperity between the two panel survey rounds. Two thresholds were set: the lower threshold set at a total value of activities which would supply the basic calorific needs of all household members (3,000 kCal per male adult equivalent, higher than the 2,500 recommended level to account for the oversupply) and the upper threshold set at the $1.90 poverty line. This resulted in three levels of prosperity in each panel round: the lowest level of households unlikely to be able to supply their basic calorie needs, the middle level of households able to supply their basic calorie needs but still living below the international poverty line, and the highest level of households living above the international poverty line. The prosperity groups were validated against the welfare indicators gathered in the latter panel, which were based on independent data that were not used to calculate the TVA indicator used to define the prosperity groups.

Households were then analysed according to two different stratifications. Firstly the prosperity groups in the first and second panel were compared, in order to identify distinguishing characteristics of more or less prosperous households in each time point, and to investigate if these characteristics changed over the 4 year period. Secondly, the households were sorted into trajectory groups, according to the movement of the household between the two panel survey rounds (for example the Low to High trajectory was composed of households who rose from the low prosperity group in the first panel to the high prosperity group in the second panel). Characteristics of the trajectory groups were analysed to investigate what variables were associated with different trajectories, and the direction and magnitude of change of those variables. In both cases the household characteristics analysed were productive assets, measures of farm performance, and livelihood balance between farm consumption, farm sales and off farm incomes. The productive assets considered were: land area owned in hectares, livestock owned measured in tropical livestock units (TLU, e.g. 1 is equal to one cow, 0.2 is equal to one goat or sheep (Njuki *et al.*, 2011)), and number of household members (measured in individual people). The indicators of farm performance were total value of crop production, total value of livestock products, and total value of off farm incomes, per household per year. To assess intensification, three efficiency indicators were used: total value of crop produce per hectare of land owned, total value of livestock produce per TLU owned, and total value of off farm income per male adult equivalent household member. Livelihood balance was reported in both TVA per male adult equivalent per year and as a proportion of total TVA; for crop produce consumed, crop produce sold, livestock products consumed, livestock products sold, and off farm incomes. Finally, in an attempt to move beyond average values of trajectory groups, households were sorted according to their livelihood strategies: whether they derived the majority (>50%) of their TVA from farm sales, from off farm income, or from consumption of self-produced foodstuffs. If households did not derive the majority of their TVA from any one of those sources, they were categorised as “mixed” livelihood households. The counts of households pursuing each of those livelihood strategies were then reported, per trajectory group.

All data analysis was performed using the R language for statistical computing (R Core Team, 2012; RStudio Team, 2016),with packages for data manipulation (Wickham *et al.*, 2017; Wickham and Henry, 2018) and statistical analysis (Hothorn, Bretz and Westfall, 2008). Significant differences between subsets of households were analysed using Anova and Tukey's test of honest significant difference, where any *p* value greater than 0.95 was taken to be an indication of significance.

3. Results

3.1 Establishing confidence in the prosperity classes

The classes identified in the second panel survey showed significant and plausible correlations with five indicators of household welfare. The indicators used were built from entirely independent data to that which was used to calculate the prosperity classes. Households in more prosperous classes showed significantly lower likelihood of being in poverty, according to the probability of poverty index score (Fig 5.1A). The number of food shortage months reported by households was less for households in the high prosperity class compared to others (Fig 5.1B). The reported experience and severity of hunger (HFIAS) was less for more prosperous households (Fig 5.1C). The household dietary diversity score increased in both the post-harvest good season and the lean season, for households in higher prosperity classes (Figs 5.1D-E). This is evidence that the approach used to sort households into three prosperity classes was indeed meaningful and robust. Unfortunately, such independent welfare indicators were not gathered during the first panel survey so it was not possible to validate the prosperity classes for the first panel.

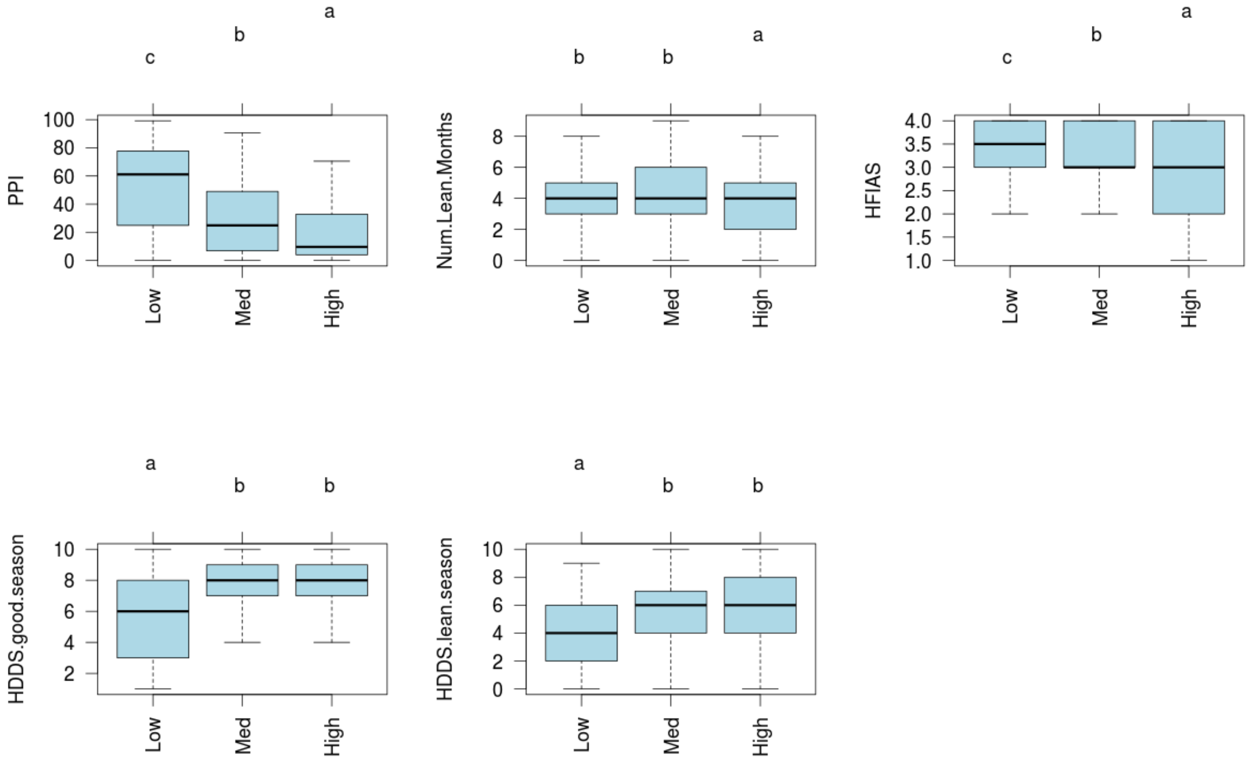

Figure 5.1. Household welfare indicators for the three prosperity groups identified through total value of agricultural and off farm activities, during second panel survey round. The differences between welfare prosperity classes for each welfare indicator are shown by the letters above each group.

3.2 The prosperity of households, and movement between the classes

The total number of households in each of the three classes showed no significant change between the first and second panel survey. However, almost two thirds of the households (61%) moved between poverty classes (see Figure 5.2A). When considering the changing poverty status of individual households, a highly significant effect was found (Chi sq test, $p<0.001$). The full range of movement between classes was detected: households moved from the poorest class to the wealthiest, from the wealthiest to the poorest, and everything in between. Within a four year period, this shows a very high degree of mobility in terms of household incomes and food security. Such mobility could also be called instability, or panarchy, and should be considered as a risk as well as an opportunity.

Similar patterns were seen in each of the four sites when analysed individually (Figures 5.2B-E). A high degree of mobility and movement between each class was detected. The individual sites differed in degree of effect rather than the overall patterns. The Kenyan sites showed more households above the poverty line in the first panel survey, but also showed more households falling below it. The Tanzanian site showed perhaps the most precarious situation, with more households trapped in the poorest category, but also opportunities for households to rise and fall. For a more focused analysis of this site see Fraval et al (Fraval *et al.*, 2018). The Ugandan site showed no households falling below the poverty line, which although surprising, may be explained by the very rapid pace of development and the economic opportunities in that site.

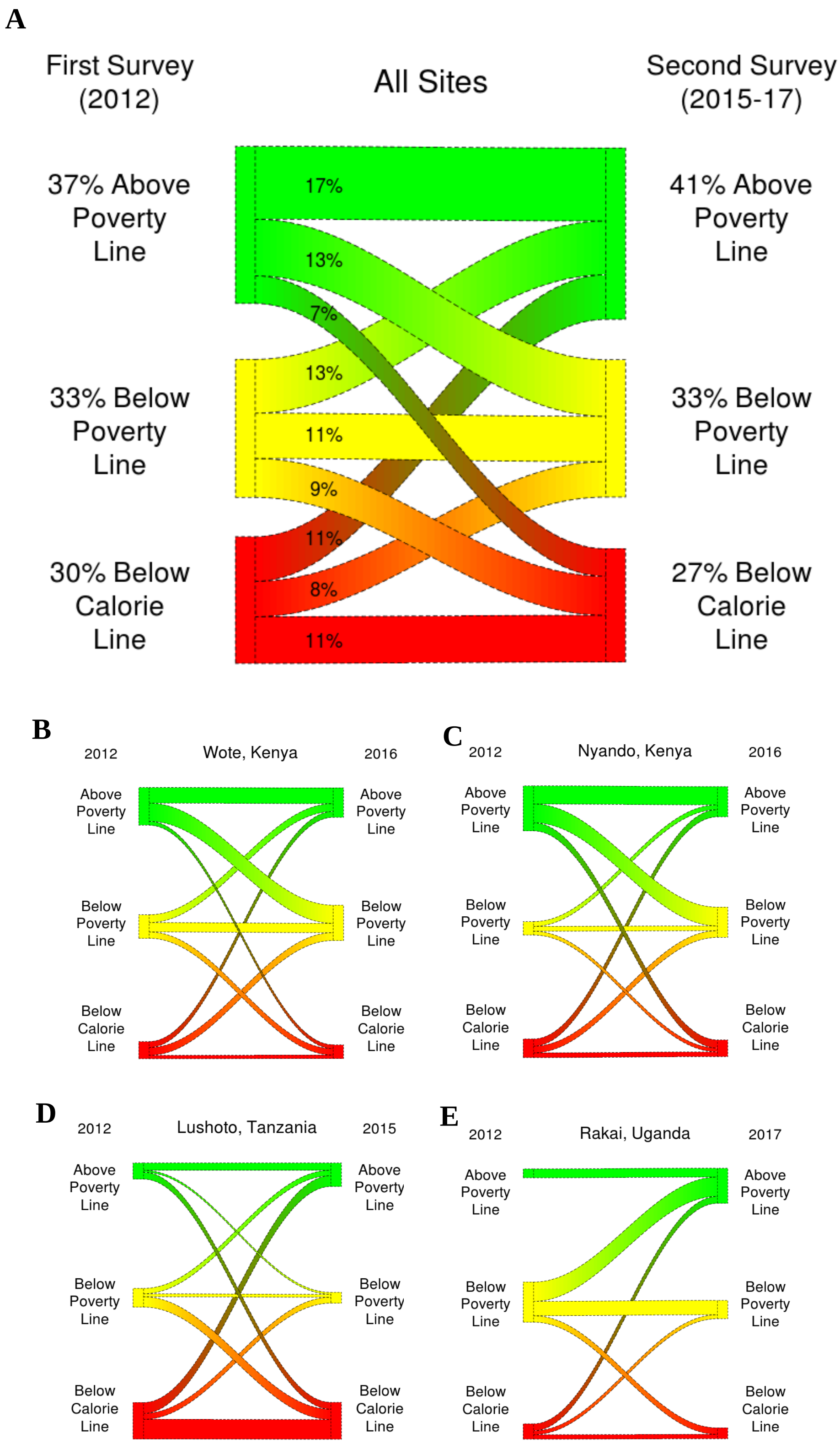

Figure 5.2. The proportions of households above and below the $1.90 poverty line, and above and below a calorie line set at 3,000 kCal per male adult equivalent person, for both panel survey rounds. The proportions of the study sample moving between groups are also shown. Figure 5.2A shows the entire study population, and Figures 5.2B-E show the results per study site.

3.3 Differences between the Prosperity Classes

3.3.1 Assets

In both panels, more prosperous household groups tend to have fewer household members, more land and more livestock (see Table 5.1). Farms were typically under 2 ha, median household size of 5 to 6 people, and herd size typically between 1 and 5 TLU.

There is some evidence of change in the drivers of prosperity between the first and second panel surveys. In the first panel, the productive assets of land and livestock were significantly higher amongst the most prosperous group compared to the others: in the latter panel, land and livestock were statistically similar amongst the high and medium prosperity groups. This implies that some other factors were also at play in determining whether a household would be in the medium or high prosperity groups. Either agricultural intensification (producing more value from the same amount of land or livestock) or off farm incomes are the two obvious options.

Table 5.1. Difference in household assets. The letters show results of pairwise comparison of anova between prosperity clusters within the same panel survey (i.e. no comparison has been made between the first and second panel surveys), using Tukey HSD method, $p<0.05$.

Prosperity	Panel	Household Members	Land Owned (ha)	Livestock (TLU)
Low	First	5[a]	0.8[a]	0.9[a]
Med	First	6[a]	1.2[a]	1.1[a]
High	First	5[b]	1.4[b]	3.6[b]
Low	Second	6[a]	1.1[a]	1.4[a]
Med	Second	6[a]	1.6[a,b]	5.1[b]
High	Second	5[b]	1.6[b]	5.0[b]

3.3.2 Livelihood Activities and Agricultural Production

When looking at the overall livelihoods of households in each prosperity group in the first and second panel surveys (Figure 5.3), it is clear that the most prosperous class relied proportionally more heavily on off farm income in the second panel compared to the first. The medium prosperity class relied more on off farm income and on sales of farm produce, and less upon self produced foodstuffs. The low prosperity class relied more heavily on sales of farm produce and consumption of self produced foodstuffs, and less on off farm incomes. Comparing between the two panel surveys, it is clear that off farm income contributes more heavily towards prosperity in the latter survey compared to the earlier. When considering absolute values of incomes or production, there are exponential increases between the prosperity classes.

The median values of crop produce, livestock products and off farm incomes per prosperity group in the first and second panel rounds are shown in Table 5.2. There is evidence that the high prosperity group are pulling away from the medium and low groups in terms of value of crops produced, off farm incomes, and to a lesser extent the value of livestock produced; due at least in part to increased intensity of production or earnings. In the first panel, the three prosperity groups frequently showed significant differences from low to medium to high, but in the second panel the significant differences are more frequently between the high prosperity group and the two others. This points towards an increasing degree of success for the most prosperous which is not being achieved by the others. In terms of absolute amounts of value of crops and livestock products, these are quite similar between the two panel surveys, but there is a large increase (almost double) in the amount of off farm income captured by the high prosperity households.

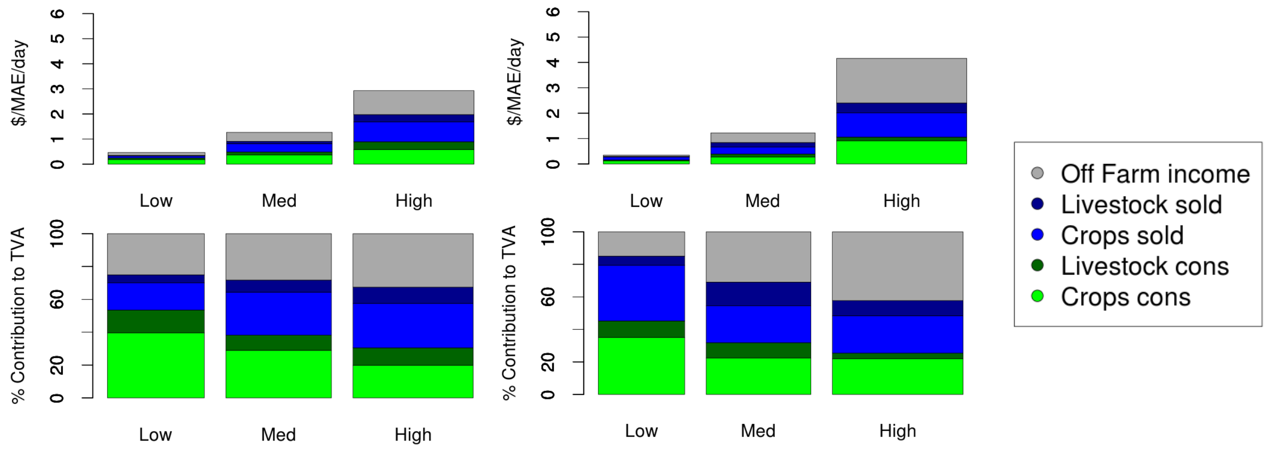

Figure 5.3. Value derived from livelihood activities, including sales of crops and livestock products, value of crops and livestock products consumed, and off farm incomes. The upper charts show the actual value in $/male adult equivalent/day, and the lower charts show the proportional importance of sources of value for each prosperity class.

Table 5.2. Household performance metrics: median total values of crops produced, total value of livestock products produced, and total value of off farm incomes. Efficiency measures are also provided as an indication of intensification - i.e. producing more with from the same amount of basic resource (land for crops, livestock for livestock products, and people for paid work). The letters show results of pairwise comparison of anova between prosperity clusters within the same panel survey (i.e. no comparison has been made between the first and second panel surveys), using Tukey HSD method, p<0.05.

Panel	Prosperity	Crop Value ($/yr)	Crop Intensity ($/ha/yr)	Lstk Value ($/yr)	Lstk Intensity ($/TLU/yr)	Off Farm Income ($/yr)	Off Farm Income Intensity ($/MAE/yr)
First	Low	325^{a}	430^{a}	45^{a}	70^{a}	75^{a}	19^{a}
First	Med	936^{b}	681^{b}	131^{b}	138^{a}	301^{b}	73^{a}
First	High	1545^{c}	931^{c}	697^{c}	202^{a}	1031^{c}	343^{b}
Second	Low	287^{a}	334^{a}	0^{a}	0^{a}	0^{a}	0^{a}
Second	Med	566^{a}	334^{a}	288^{b}	$62^{a,b}$	420^{a}	93^{a}
Second	High	1581^{b}	872^{b}	507^{c}	103^{b}	1953^{b}	522^{b}

When considering agricultural production as an issue of national strategic importance (supply of food and useful commodities) rather than as an activity for household subsistence, it is useful to consider who is producing these "goods" in high quantity. The high prosperity group produced vastly more, and the proportion produced by the more prosperous households increased between the two surveys. In the first panel, low prosperity households accounted for 30% of the study population, controlled 19% of the land and produced 10% of the foodstuffs reported. Medium prosperity households accounted for 33% of the population, controlled 31% of the land and produced 24% of the foodstuffs. High prosperity farmers accounted for 37% of the population, controlled 50% of the land and produced 66% of the foodstuffs. In the second panel low prosperity households accounted for 27% of the study population, controlled 14% of the land, and produced 6% of the foodstuffs reported. Medium prosperity households accounted for 33% of the population, controlled 29% of the land and produced 19% of the foodstuffs. High prosperity farmers accounted for 41% of the population, controlled 57% of the land and produced 76% of the foodstuffs. These figures point towards increasing intensification of agriculture by the most prosperous households, through production measures and through achieving higher sale prices per crop. The figures also imply that the low and medium prosperity households failed to intensify to the same degree as the high prosperity households.

3.4 Why did households move between prosperity classes?

It is informative to compare the 9 "trajectories" of households (e.g. Low to Low, Low to High etc.). Figure 5.4 shows the net changes between the first and second panel off farm income, value of crop produced, and value of livestock products for each trajectory group. Values are shown in absolute terms and in terms of intensity for each of those value streams: off farm income per adult male equivalent household member (i.e. how much off farm income is each person earning), crop value produced per unit of land, and livestock product value produced per unit of livestock (TLU).

Rising households (Low to Medium, Low to High, Medium to High) increased incomes from both off farm sources and crop sales/crop production. Rising households also showed small increases in value of livestock products. The rise in total values was driven by increasing intensity of production for crops, and increased intensity of earning for off farm sources. Households moving into the high prosperity class showed very large increases in both absolute value and intensity, where as households moving into the medium class showed more modest gains, and the relative importance of agricultural incomes was greater compared to off farm income gains.

Falling households showed the inverse: decreased value of crop production and off farm incomes, accompanied by a reduction in intensity. Households who fell from High to Low showed similar loss in overall crop and off-farm value compared to households who fell from High to Medium, but a greater dip in the intensity of crop value and off farm income. Livestock product value also dropped, more substantially for those going from High to Medium or High to Low, possibly demonstrating wholesale of livestock as a coping strategy.

Steady households - those who remained in the same prosperity class between the two surveys - showed less change in values of production and off farm incomes than rising or falling households. The households in the Medium to Medium trajectory showed a modest increase in crop productivity, where as the households in the High to High trajectory showed a substantial increase in off farm incomes, and modest decreases in crop production values, perhaps indicating increased focus on off farm incomes. Households in the Low to Low category were the poorest of the poor, and scored significantly lower on welfare indicators (see supplementary information Figure S5.1, Appendix 4) and on productive assets compared to other trajectory groups (median land size 0.8 ha compared to population median of 1.6 ha, median TLU of 0.8 compared to population median 4, see Tables S5.1 and S5.2).

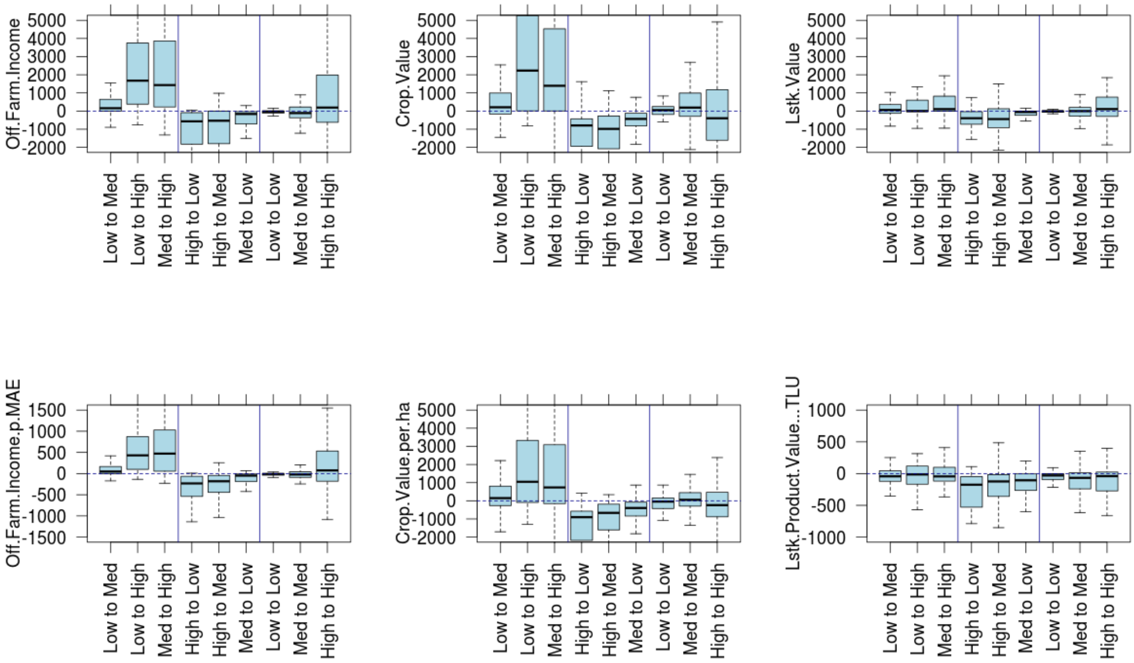

Figure 5.4. Net change in value of activities, and intensity of activities, between the first and second panel survey. All value reported are US$ purchasing parity power per household per year. The vertical lines indicate the position of "rising", "falling" or "steady" households. The horizontal dashed line indicates the location of '0', or no net change.

3.5 Do households choose to focus on agricultural intensification or off farm income, or do they choose both?

Average values for the trajectory groups may obscure different strategies being pursued by individual households. To investigate if all households within a trajectory group tended to pursue similar or different livelihood strategies, they were categorised according to the source of the majority of their total value of activities. The proportion of households in each trajectory group are plotted in Figure 5.5. Households who rose in prosperity more commonly derived the majority of their total value of activities from off farm sources, or on a mixture of off farm income and farm sales. Although some of the rising households did focus on farm sales, this was the minority, and it was more common amongst households who rose to the medium prosperity group rather than those who rose to the high prosperity group. Households who fell into the low prosperity group pursued each strategy in roughly equal measures, including subsistence agriculture. Households who fell into the low prosperity group reported frequent more focus on subsistence agriculture compared to households who had been in the low prosperity group in both panel rounds. Households on the Low to Low trajectory reported more frequent mixed livelihood strategy than any other trajectory group. Households on the Medium to Medium trajectory showed focus on mixed incomes or off farm incomes, demonstrating that primary reliance on farm sales was often not enough to maintain households on a level of medium prosperity (which is still below the $1.90 poverty line). Households on the High to High trajectory showed a frequent focus on off farm incomes, and also a minority of households focussed primarily on farm sales. Those households must have had highly productive farms in order to maintain their position as highly prosperous.

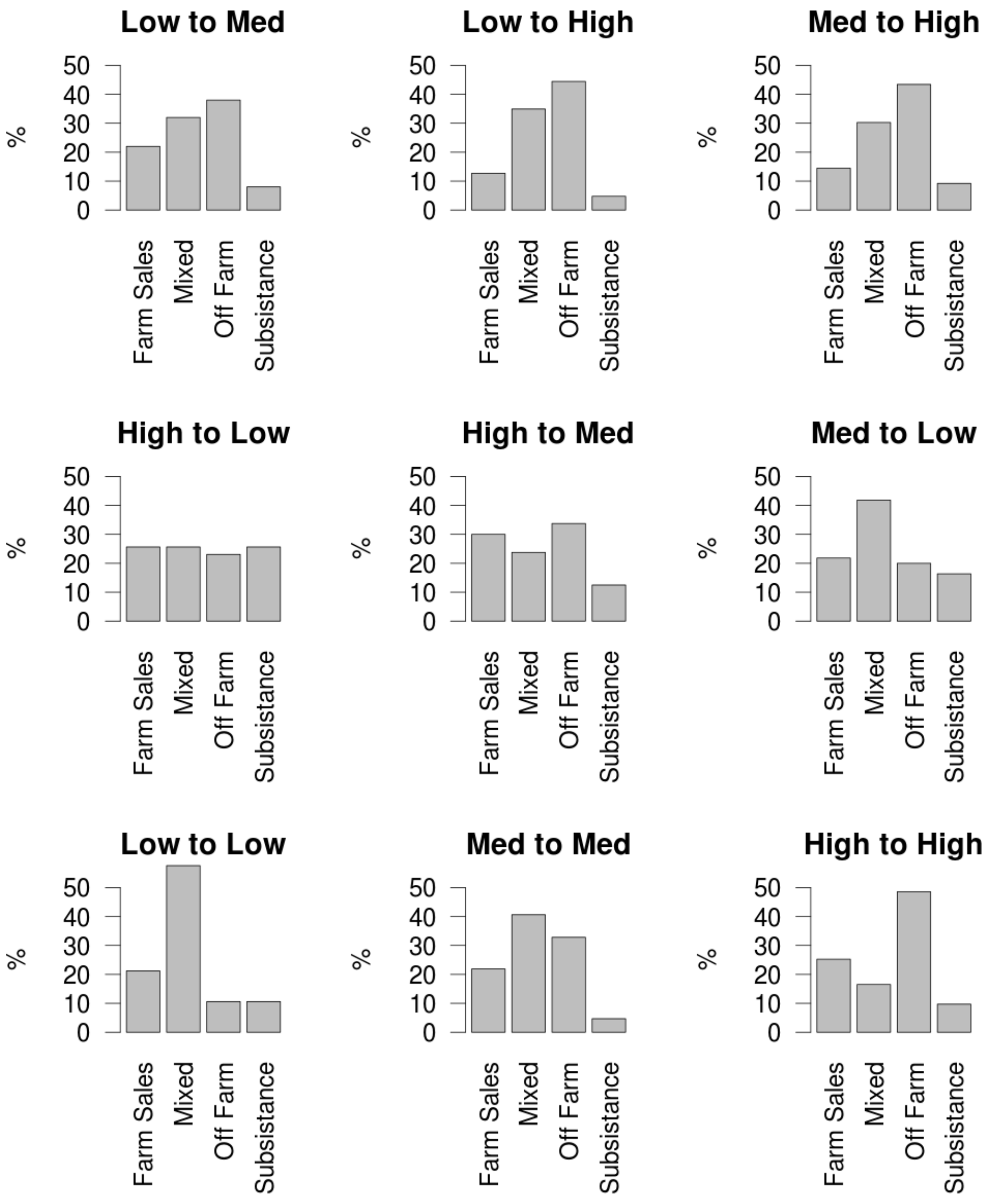

Figure 5.5. Households categorised according to the majority source of the total value of their activities, either from sales of farm products, off farm income, consumption of self produced foodstuffs, or where no single activity accounted for more than half, they were categorised as "mixed". The proportion of households following each livelihood strategy are shown per trajectory group.

4. Discussion

4.1 The pace of change and overall poverty rates

This work has shown that the pace of change is very high for smallholder households in relatively well populated rural East African locations, confirming findings from a recently published single-site analysis (Fraval *et al.*, 2018). Such rapid changes are contrary to older work finding that poverty changes could only be detected on an inter-generational basis (Walker and Ryan, 1990); although due to the short time-scale of this study (4 years) there is no evidence for the longevity of the changes observed. As well as increased pace of change we found an increased volume of households changing prosperity status. In similar (although not completely comparable) studies in Kenya, about 20% of households were found to be rising or falling in prosperity, and 16 to 19% of household persistently poor (Kristjanson *et al.*, 2004; Burke *et al.*, 2007). Here we found about 30% of households to be rising or falling, and 11% of households to be persistently poor. Despite the greater pace and volume of change, the net proportions of households living in poverty did not change, which is in keeping with other studies (Krishna, 2004; Kristjanson *et al.*, 2004; Burke *et al.*, 2007). With greater household mobility, the identification and exploitation of leverage points to reduce the number of households "falling back" would yield greater benefits than ever.

Indeed the category of households "falling back" should receive more attention. They are widely observed in the panel surveys cited, but identified only with a footnote in Dorward's "hanging in, stepping-up, stepping out" typology (Dorward, 2009). A fourth category of "falling back" could well be added to the conceptual framework. Smallholder development has recently been called a "moving target" (Valbuena *et al.*, 2015; Fraval *et al.*, 2018), but perhaps rather than aiming at the moving target, a better strategy would be to take advantage of the movement, making systematic interventions to increase the flow of upward mobility and stem the flow of downward mobility. The interventions to increase upward mobility and decrease downward mobility would most likely require different conceptualisation, actions, and policy measures (Krishna, 2004).

A weakness of the study is that only two time points considered, so it is unclear if changes in household prosperity are temporary or longer lasting. There were no major climatic shocks during the studied period, although minor climatic variation could have played a role in generating difference between the two years. Likewise, it has not been possible to disentangle extrinsic factors, such as economic growth, transport, or market developments from individual household strategies. However the cross-site analysis aspect of this study implies some degree of commonality in the findings reported.

4.2 Population pressure, land pressure, agricultural intensification, and off farm income

The population density of the sites reported here was approximately 150 people per km^2, except for the Kenyan Nyando site, which was 350 people per km^2, which are all comfortably below the threshold of 500 people per km^2 at which agricultural intensification had been found to plateau (Muyanga and Jayne, 2014). This study however is not well suited to exploration of the effects of population pressure; the data presented here is better used to understand the actions taken by smallholder households and the impacts of those actions, which can be compared against the meta-trends identified in other literature.

We did not find evidence of decreasing farm sizes, and in fact found evidence of increasing farm sizes in Wote, Kenya, weak evidence of increasing farm sizes in two of the sites (Lushoto, Tanzania, and Nyando, Kenya), and evidence for no net change in Rakai, Uganda. The changes in farm sizes were marginal however and we did not find evidence of the step-changes associated with the medium-scale farmer (Jayne *et al.*, 2016), although we did find evidence that more prosperous households were controlling more of the land in the landscape. In a more detailed analysis of the Lushoto site, increasing farm size was identified as a risky strategy, with some households failing to achieve sufficient returns on investment and falling back into worse levels of poverty (Fraval *et al.*, 2018). The observation was borne out in the wider dataset reported here, where households falling from High to Medium or High to Low prosperity showed significant increases in farm size; however this could be an artefact of the relatively short time period of the study, whereby households have invested heavily in a major asset, but expect to ultimately increase in prosperity as that asset becomes productive and profitable. Such observations would require longer term study and ideally more time points.

We did find evidence of increased intensification of crops between the two panels, amongst the more prosperous households. The median crop values for households rising out of poverty were around 1,400 US$ per hectare (see Tables S5.3 and S5.4). The observed median increases in crop value intensity for households rising out of poverty were around 1,000 US$ per hectare, with three quarters of the observations below 3,000 US$ per hectare. Households who fell in prosperity reported a similar average decrease in crop intensity or around 1,000 US$ per ha. These values are broadly similar to those calculated from secondary data (Harris, 2018). For households to rise from a level of poverty where they are likely to be experiencing regular and extreme food insecurity, but not above the $1.90 poverty line, an average increase in the value of crop produce of about 300 US$ per year was required. The values reported here however are gross income, not net, and do not exclude the role of off farm incomes in household prosperity: if off farm income were to be excluded the value obtained from crop intensification would need to be greater.

We found no evidence that crop or livestock intensification could be a prosperous livelihood strategy without off farm income. Off farm income was proportionally more important to overall household income as households became more prosperous, and the importance of off farm income increased between panel rounds. Households who raised their level of prosperity relied heavily upon household income, and households who fell in prosperity lost off farm income. The average total value of crop production remained slightly greater than the average value of off farm income, but there was evidence that households generally pursued both off farm incomes and agricultural intensification in tandem, possibly in a virtuous cycle (Pender, Place and Ehui, 2006). This is in keeping with trends identified from household level data in multiple other African sites (Frelat, Lopez-ridaura, *et al.*, 2016; Ritzema *et al.*, 2017), as well as from national level census data (Ricker-gilbert, Jumbe and Chamberlin, 2014). The findings here go beyond previous studies in quantifying the amounts of off farm income required, on average, for households to rise above the poverty line, in addition to increases in crop value: 2,000 US$ per household per year, or 500 US$

per male adult equivalent household member; and for households to rise from the lowest prosperity class to the middle prosperity class required on average 350 US$ per household per year.

4.3 Rising inequality and poverty traps

We found evidence of increasing inequality between the low, medium, and high prosperity groups, even within the four year time frame of this study. There was a greater divide in terms of total value of activities, assets owned, and in terms of intensification of agricultural activities, and off farm income per person. Similar patterns have been identified in other recent studies (Valbuena, Groot and Tittonell, 2015; van Vugt, Franke and Giller, 2017); and provides empirical evidence of the hypothesis put forward in 2001 that off farm incomes would boost the prosperity of the less-poor in rural Africa much more than they boosted the prosperity of the very-poor (Barrett, Reardon and Webb, 2001). This can explained by two factors supported by evidence from the present study: that the less-poor households have access to more lucrative forms of off farm income, and that the less-poor households are able to realise greater value from intensification of their farms (through owning better land, economies of scale, or other reasons). The difference in levels of off farm income for less prosperous households compared to more prosperous has been described as due to the "push" factor of desperation amongst the very poor, making them willing, or compelled, to take up very low return labour, and indeed is a poverty trap (Haggblade, Hazell and Reardon, 2010). We do not find evidence of the U-shaped relationship whereby low prosperity households rely heavily on off farm income, medium prosperity households do not rely on off farm income, and high prosperity households also rely heavily on off farm income (Haggblade, Hazell and Reardon, 2007). Instead we find a linear increase in reliance upon off farm income as households become more prosperous; this may be a positive development indicating the overall growth in the rural non-farm economy and that more middle value off farm activities are available, but requires further investigation.

Households who were in the low prosperity group in both panel surveys - the persistently poor - did report the lowest asset ownership of all groups in both panel rounds, and showed the highest proportion of households pursuing the mixed livelihood strategy. These facts support the concept that the poorest frequently worked for low income wage labour, and that their agricultural holdings were very small, and therefore would benefit relatively little from agricultural intensification. However there was evidence that households with a very low asset base (and in the low prosperity group) in the first panel survey could intensify their agricultural production and raise off farm incomes to a level which raised their overall prosperity and even lifted some above the poverty line (see Tables S5.1 and S5.2). It is not clear if those households were deep in the poverty trap, or whether they were suffering from a more temporary form of poverty, but the findings seem to support the concept that a stronger rural non-farm economy can work in harmony with agricultural intensification (Haggblade, Hazell and Reardon, 2010).

4.4 Raise households out of poverty, or generate more food in the landscape?

Much of this article has focussed on the drive to lift individual households out of food insecurity and poverty. But there are two wider issues which should also be considered: the total amount of food being produced, and the state of the provisioning ecosystem services, such as soil health and water cycling. The more prosperous households, those above the poverty line, accounted for less than half the population, but controlled more than half of the land and were responsible for more than three quarters of the agricultural production. These more prosperous households would be the sensible choice for policy measures or interventions aimed at sustainable intensification: measures which could further increase production and improve ecosystem services. Another sensible choice for measures to boost intensification and landscape sustainability would be the middle prosperity households who had recently declined from the high prosperity group. Furthermore there was evidence that households who had been in the high prosperity group in both surveys were not further intensifying agricultural production but focussing more on off farm incomes - such a decline would not be desirable from a landscape perspective as it could lead to underutilisation of good land and loss of human capital in the form of skilled farmers.

Policy measures or interventions aiming to help the least prosperous households should be different to those aiming to intensify the agricultural production of high and middle prosperity farmers. Measures for the least prosperous households should aim to break the negative cycle of low-income wage labour and low-return farming on a low asset base. Considering the importance of off farm incomes in raising prosperity, and the unequal benefits of intensification, measures to increase off farm income may be more effective than agricultural intensification to aid the poorest households in escaping the poverty trap.

5. Conclusions

The pace and volume of change is greater than previously identified. Such rapid changes require a new generation of monitoring tools which can gather indicators and data more quickly, cheaply, and with more systematic coverage of important issues than previous tools. The tool used in the second panel survey, RHoMIS, was a step in this direction. With greater household mobility, the identification and exploitation of leverage points to reduce the number of households “falling back” would yield greater benefits than ever.

Differing interventions should be aimed at the more prosperous households and the less prosperous. More prosperous households, and those falling from high prosperity, would be better served by support to sustainably intensify agricultural production. The least prosperous households may be better served by improved off farm opportunities. Increases in farm produce value and agricultural intensification generally went in tandem with increases of off farm income. The reverse was also true: losses in the value of agricultural produce generally went in tandem with losses in off farm income. Increases in gross crop value of around 1,000 to 3,000 US$ per hectare combined with off farm incomes of around 500 US$ per adult male adult equivalent household member was sufficient to lift households above the $1.90 poverty line. For households to rise out of the worst states of poverty and food insecurity class, total crop value per household of around 600 US$ and off farm income of around 500 US$ per household was required.

CHAPTER 6: Synthesis and Conclusions

1. Achievements of this work

The main achievement of the work is the RHoMIS tool. Since the time it was first designed and piloted in May 2015 until March 2018, it has been used by seven different research organisations, three NGOs, and three national donor organisations. It has so far been applied in 17 different countries and more than 15,000 households have been interviewed (see Figure 6.1, and Appendix 3). Demand for the tool is increasing, and the analytical possibilities of such a dataset have not yet been fully explored. We plan to provide open access to the RHoMIS dataset, which we hope will stimulate further interest in the tool, and perhaps more importantly provide opportunities for further insights to be obtained by a wide variety of actors.

The main product of this thesis is an actionable method. The intention is that due to increases in both efficiency and data quality, this tool will facilitate many more useful analyses and insights, the potential for which is demonstrated in the research chapters.

The research chapters of this PhD form a narrative of the development and application of the tool, but do not capture all of the work done during iterations developing and refining the tool, or the analysis work which was led by other parties using data gathered with the RHoMIS tool. This chapter reflects upon the research chapters, summarises the work not reported in the research chapters, and then goes on to evaluate the quality of the RHoMIS tool and derived data. Finally a discussion places the work in the wider context, and conclusions are drawn as to the identity, utility, and future of the work.

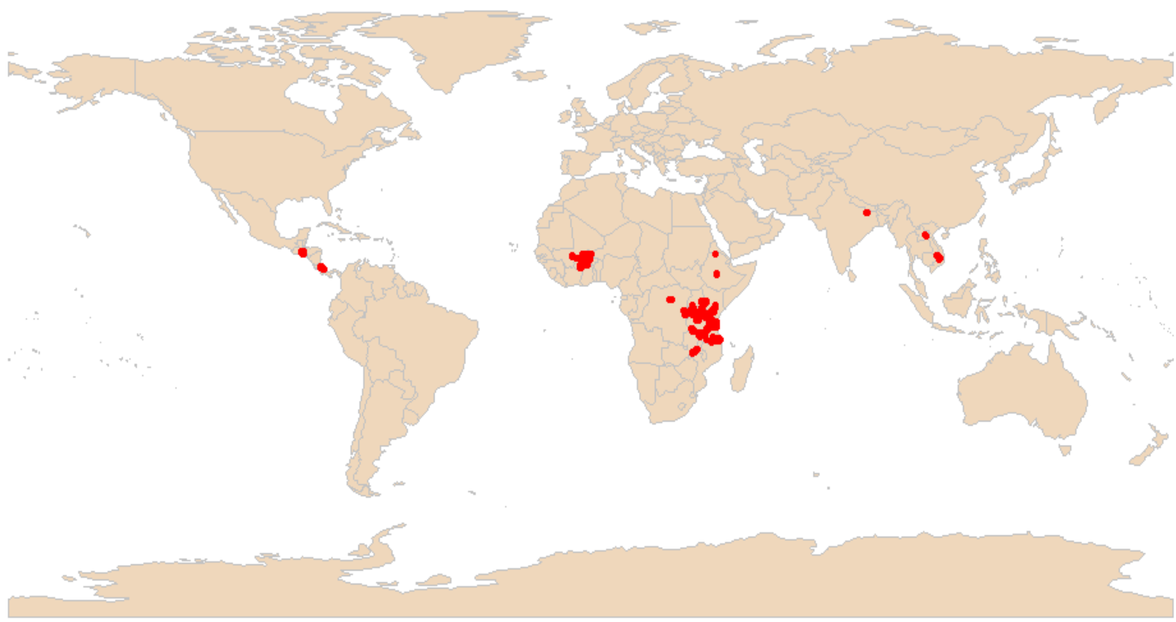

Figure 6.1. Map showing locations of RHoMIS survey applications, as of March 2018.

2. Reflection on the research chapters

Chapter 2 is an analysis based on a pre-existing household survey dataset, which led to two major outcomes. Firstly, the novel typology of "farmer motivations" in combination with the more common farm typology approach. Secondly, work on the paper inspired the approach developed in the RHoMIS tool. There was much to critique about the survey design: coverage of relevant issues in the questionnaire was patchy, the questions themselves were of variable quality and not linked to predefined or well tested indicators, all of which unavoidably led to an analysis process focused on dimension reduction and sifting for useful data. This experience, combined with similar experiences working on other household survey datasets (Su *et al.*, 2016), and, through reviewing attempts to merge multiple household survey data sets (Frelat *et al.*, 2016) led on to develop the approach outlined in Chapter 3.

Chapter 3 presents proof of concept of the RHoMIS tool, and explained the design principles behind the tool. The chapter also showed some empirical data gathered from two contrasting sites. The questionnaire functioned properly in the field, the digital infrastructure worked, and the analysis scripts indeed permitted rapid indicator calculation. In terms of analysis the differing roles of market orientation, crop intensification and crop diversification in achieving welfare gains are explored, and hint towards more powerful studies which would be possible with larger datasets. The selection of indicators used in RHoMIS were well correlated in the expected (logical) directions, meaning that even in contrasting locations they were functioning as intended.

Chapter 4 provides a case study in which the RHoMIS tool was applied to evaluate impact of a development project. The NGO who led the work (Tree Aid) were looking for a tool which could be used to quantitatively evaluate their projects, and were willing to try using RHoMIS. The "core" RHoMIS content was used, with an additional module collaboratively developed gathering information on Non Timber Forest Products (NTFPs), which were of specific interest to Tree Aid. The RHoMIS tool was applied by their field staff without incident, and was able to detect significant differences between "control" and "treatment" households, especially when disaggregated into wealth classes. The use of multiple indicators based on independent data provided confidence in findings. Tree Aid have now taken up RHoMIS as their main baseline and monitoring tool, and have now applied it in eight projects

Chapter 5 provides an example of using RHoMIS in a more complex research setting. The chapter compares panel survey data between four sites, two of which were in Kenya, one in Uganda, and one in Tanzania. The latter of the rounds of panel surveys used the RHoMIS tool, and the earlier round used a survey instrument called "Impact-Lite". A number of methodological issues were encountered through this work. Firstly, comparison of data from two different survey tools was not an easy process, due to different ways of formulating questions, and due to the use of different units of time (e.g. income per day or per month), or differing levels of functional units when gathering data (e.g. collecting yield information at plot level or at farm level). For example, Impact-Lite recorded off farm incomes as either daily, weekly, monthly or annual income, and recorded seasons worked, but did not record number of days or number of weeks worked per season. This made assumptions necessary to scale up the information to give annual or seasonal estimates. Secondly, comparison between time points allowed insights into dynamics as opposed to the usual snap-shot offered by one off surveys. This opened a rich vein for analysis and is the main theme of the chapter itself. Thirdly, the differences between sites had to be taken into account, and trends identified in the data had to be identified as either site specific or multi-site trends. Overall, the data from RHoMIS proved useful in a more complex analytical setting, and the tool would function well if it were applied multiple times in a single site in order to capture dynamics.

3. Summary of work conducted outwith the research chapters

Analytical work was done, by myself and others, with data obtained from RHoMIS applications which is not reported in the main chapters of this thesis. I used data to improve and evaluate the design and content of the questionnaire and other elements of the tool. I also contributed in a substantive way to five other research papers based on data from RHoMIS applications. Four of those papers are summarised in this section, and one unpacked in more detail in section 4.1.

3.1 Tool development

In the intervening time between work on the third chapter and work on the fourth and fifth chapters, there were a series of applications of the RHoMIS tool in South East Asia, East Africa, West Africa, and India; most of which are not reported in this thesis. These applications all served as learning cycles with which to improve the questionnaire design, the digital infrastructure set up, and the data processing scripts. Working with the various implementing partners gave new insights into the appropriate balance of flexibility required verses the degree of standardisation needed to produce comparable data and ensure that the data processing scripts could always run on the output survey data.

In addition to the core content of the questionnaire, a number of optional modules were developed and trialled in multiple applications. I developed, tested and refined novel modules, on tree use and non-timber forest products (as was used in Chapter 4), farmers' aspirations and motivations (developed from the work of Chapter 2), and exploration of perceived changes to farm and livelihoods over the past few years (verified against the panel survey data from Chapter 5). Various other modules were developed but only used in a single application, and thus have not been improved upon the first versions. In addition, other modules were trialled at the request of implementing partners, based on existing literature sources: perceptions of household vulnerability (Notenbaert et al., 2013), the Food Insecurity Experience Scale (Ballard, Kepple and Cafiero, 2013), the Coping Strategies Index and Reduced Coping Strategies Index (Maxwell and Caldwell, 2008), the Food Consumption Score (World Food Programme, 2008), and variations of the Dietary Diversity score, including the Minimum Dietary Diversity Score for Women (FAO and FHI 360, 2016). A list of modules developed and used is provided in Appendix 2.

3.2 “Livelihoods and food security in an urban linked, high potential region of Tanzania: Changes over a three year period”

The data from Lushoto, Tanzania reported in Chapter 2 was compared to panel survey data collected using the Impact-Lite tool, and a manuscript published which delineated a typology of households according to the change in their prosperity and their farming practices (Fraval et al., 2018). These are the same panel survey data which are used in Chapter 5 of this thesis, in combination with data from three other sites. Unlike Chapters 2 and 5 of this thesis, the manuscript drilled down into site level detail of farming practices and livelihoods, demonstrating the the tool could deliver such a site specific analysis.

A detailed characterisation of the farming practices within the site was performed using the RHoMIS data, including disaggregation of cash crops and staple crops, incomes from crops and livestock, market participation, intensification practices such as fertiliser additions, as well assessments of land areas used. Through comparison against the earlier panel data, households rising in prosperity were identified and compared to those who were subsisting. Comparison against the food security indicators independent of income (HFIAS, HDDS), showed that the groups identified through income comparisons were plausible. Farming strategies which were well linked to households who increased their prosperity could therefore be identified (in this case primarily vegetable production to serve the markets of Dar es Salaam).

3.3 “Pathways to food security in rural Burkina Faso: the importance of consumption of home-produced food versus purchased food”

Two sites were surveyed in the Sahel region of Northern Burkina Faso, and a model built for each site linking farming practices and livelihoods to food security outcomes (Fraval, Yameogo, et al., in review). Indicators for food security derived from the Household Food Insecurity of Access Scale (Coates, Swindale and Bilinsky, 2007) and Household Dietary Diversity Scale (Swindale and Bilinsky, 2006) were used as response variables and a models were built using farm practice and livelihoods data to predict the response variables. Significant differences were found between the two sites, where higher food security in one site was driven by increased crop sales, due to a combination of market access, increased increased use of inputs, and increased crop yields. In the other site higher food security was more driven by livestock ownership, especially large livestock. In both sites the purchase of foods was a major driver of increased dietary diversity during the lean season, although the source of the cash differed between the sites.

This paper demonstrated that RHoMIS data could be used in more involved modelling procedures; that the tool was sensitive enough to pick up differences between site specific differences even in locations which were not strongly contrasting in terms of climate or culture.

3.4 “Household Methodologies to Reduce Gender Inequality and Increase Climate Resilience: A case study from Malawi”

The RHoMIS tool was used as part of an impact assessment at the end of a project which aimed to increase the communication and work-sharing between the head couple of households in Southern Malawi (Stirling et al., in review). A participatory evaluation using the gender decision tree method evaluated levels of work sharing on a wide range of agricultural tasks, and the RHoMIS tool was used to evaluate farming practices and outcomes on food security and prosperity. The findings were that the project had increased the level of work sharing, and that in households were there was higher levels of work-sharing, there was evidence of improved prosperity and food security, and evidence of increased consumption of key nutritious food groups. Unfortunately the RHoMIS gendered decision making indicator was not used in this project, as the implementers did not see the value in duplicating gender role assessments.

The manuscript demonstrated that RHoMIS could work in combination with a participatory method, which provided the basis for subsetting the population into groups, and that the core indicators and farm practices and livelihoods information could then be used for impact assessment.

3.5 “Prioritizing household-specific options for agricultural development through the Positive Deviance approach”

Data gathered with the RHoMIS tool in South Eastern Tanzania was used to identify “positive deviant” farmers (Steinke et al., in review). Positive deviants were defined as those who performed better than average (compared to households with a similar asset base) in at least one domain, and not worse in any domains. Five domains were selected and measured using standard RHoMIS indicators (caloric food security, dietary diversity, cash income, greenhouse gas emissions, gender equity). The positive deviant farmers were then selected for follow up visits, and their practices evaluated using semi-structured interviews and farm tours. Finally, through referring to the RHoMIS data, the positive deviant practices were assessed as to the degree to which the impacts could be “scaled-up” and replicated by other members of the communities.

The development of this methodology demonstrated that RHoMIS could be used as a targeting mechanism for deeper, more participatory studies; and that the RHoMIS data could then be used to evaluate possibilities for scaling up interventions.

4. Evaluation of the quality of the RHoMIS survey and RHoMIS data

In addition to the evidence of rapid uptake of the RHoMIS tool, and the use of the data in a variety of publications, further evaluations of the quality of the tool are reported in this section. Quantitative evaluations are based on two approaches: from meta-data gathered within the tool itself on speed, reliability and ease of use, and secondly from evaluation of the quality of the data on crop yields and sale prices of farm produce, and comparison to similar data gathered through other survey tools. The qualitative evaluation is based on feedback gathered from users of the RHoMIS tool, and from literature sources which have referenced or discussed the RHoMIS tool.

4.1 “Making the most of imperfect data: a critical evaluation of standard information collected in cross-sectional farm household surveys”

In order to assess the quality of data from RHoMIS compared to other similar survey tools a piece of research was undertaken, led by Fraval but to which the author of this thesis contributed substantially (Fraval, Hammond, et al., in review). Data from RHoMIS surveys was compared to data from Impact-Lite surveys (Rufino et al., 2013) and the Living Standards Measurement Survey (LSMS) (World Bank, no date). One metric used was the proportion of observations which fell inside or outside of a “credible” range. The methods as described in the article under review (Fraval, Hammond, et al., in review) are reproduced below:

“Reported values and composite variables selected to assess credibility were market prices, crop productivity (a composite of estimated production and land area). Due to the limited availability of secondary data, market prices and productivity were assessed for only maize (*Zea mays* L.) and sorghum (*Sorghum bicolor* L. (Moench)), quantifying the yield per unit area (kg/ha) and the farm gate price per kilogram for each individual farm household. Farmer reported yields were compared with existing rain-fed yield statistics (historical yields from district/county level observations) and water constrained potential yield for specific climatic zones as reported in the Global Yield Gap Atlas (GYGA). Farm gate prices were compared against the median price for each location and survey tool as well as wholesale market prices in major cities. For these comparisons, we identify the proportion of households that are beyond upper or lower limits. Upper limits were set at the modelled potential for yields and the maximum market price; Lower limits were set at a conservative fraction of the median of available data. As the GYGA and the statistics on market prices are also confounded by their sampling and quantification approach, this analysis only provides information about the uncertainty surrounding yield estimates rather than an absolute benchmarking of data quality.

To assess the consequences of data credibility for more complex indicators we chose to examine indicators of food self-sufficiency and potential food availability (as detailed in Frelat et al., 2016). The food availability indicator quantifies the potential kilocalories available for each male adult equivalent per day consumed from farm production, and from cash obtained through sale of farm produce and off-farm income, where all income is converted to a calorific value based on the cost of a local staple crop. Results of these calculations can be used to perform a data quality assessment of information obtained on crop and livestock production, sales and consumption as well as off-farm income. Two problems with this composite indicator are commonly encountered. First, underestimating the calorie availability at the lower end of the scale, suggesting an extreme level of starvation, which may be a true representation of some households, but can also be an indication of missing information on income or food consumption. Second, a substantial over-estimation of consumption of crop and livestock products also for a large number of households, i.e. food self-sufficiency, indicating problems with yield, consumption and/or household size estimates.

The results from Frelat et al. (2016) can be used to demonstrate the extremes of apparent energy deficits and surpluses. Represented here in Figure 1 as the ratio of household energy needs, where the value 1 represents a case where 2,500 kilocalories are provided for each male adult equivalent (indicated with a horizontal dotted line). Also represented is the ratio of energy needs sourced directly from farm production (the grey area). Instances of apparent starvation are increasingly severe as the ratio decreases below 1; The second case of over-estimated consumption is apparent in households that have more energy sourced directly from the farm than is required (grey larger than 1).

In order to identify the credible range for this composite indicator, we quantified the proportion of households that purportedly consumed less than half of the daily male adult equivalent threshold of 2500 kilo-calories or a food self-sufficiency that is twice or more than this threshold."

Results of the "credible range" analysis are presented below in Tables 6.1, 6.2, and 6.3. The RHoMIS data compared favourably to data from the other surveys, which when considered in combination with the speed of data collection is a mark of success. The LSMS survey scored the highest proportion of observations within range on crop yields, followed by RHoMIS, followed by Impact-Lite. In terms of crop sale prices, RHoMIS scored the most observations within range, distantly followed by LSMS and Impact-Lite. When considering the compound indicator Food Availability, RHoMIS performed considerably better than the other surveys; scoring 10 to 20 % of households outside of credible range, where Impact-Lite scored 15 to 28% out of range, and LSMS scored 25 to 43% out of range. The most important variables when calculating Food Availability are farm production, product use (i.e. amount consumed, amount sold), sale prices, off-farm income and household size and composition. Low quality data in one or two of these variables could lead to inaccuracies in Food Availability calculations, even if other variables are of good quality. Consistency of data quality across multiple domains was another intentional feature of the RHoMIS questionnaire, and may well be one reason why the data credibility scored highest for the Food Availability indicator.

In summary, the manuscript from which these analyses are drawn supports the argument that the RHoMIS approach has generated data which is at best more reliable, and at worst not less reliable, than data gathered in more extensive, time consuming and expensive surveys.

Table 6.1. Household maize and sorghum yields relative to historical yields and potential water limited yields (% of households)

Application	Below range: 90% < GYGA statistics	Above range: > GYGA potential water limited yields	Total out of range
ImpactLite	39.1	0	39.1
RHoMIS	25	0.2	25.2
LSMS-ISA	9.1	2.4	11.5

Table 6.2. Price received for Maize by survey tool and crop relative to survey median prices (%)

Application	Below range: < 60% of median price	Above range: > maximum market price	Total out of range
ImpactLite	10.2	39	49.2
RHoMIS	2.3	11.4	13.7
LSMS-ISA	38.3	2.7	41

*Table 6.3. Food self-sufficiency and potential food availability: outside of credible range (% of households) *Based on 2010/11 survey round*

Application	Below range: Food Availability	Above range: Food Self-Sufficiency	Total out of range
LSMS-ISA Uganda*	10.6	14.7	25.3
LSMS-ISA Ethiopia*	39.6	3.3	42.9
LSMS-ISA Tanzania*	19.9	9.1	29.0
RHoMIS Nyando	6.8	3.7	10.5
RHoMIS Wote	8.1	6.2	14.3
RHoMIS Lushoto	17.5	2.3	19.8
ImpactLite Nyando	10.0	5.0	15.0
ImpactLite Wote	21.5	2.0	23.5
ImpactLite Lushoto	24.0	3.5	27.5

4.2 Metrics gathered from inside RHoMIS

Three metrics are presented here: duration of the interviews, and then the enumerator's perception of the reliability of the responses gathered, and the ease with which the enumerator established rapport with the interviewee. In the early stages of development of the questionnaire, enumerator feedback was also gathered per module, so that attention could be focused on modules which were not running as smoothly. Those are however not reported, as the total number of data points is few and the comparability of the questionnaires is lower compared to later iterations. The metrics reported here are drawn from a pool of just over 10,000 interviews. However complete data is only available for about two thirds of that number, due to differences in survey design (such as which questions were mandatory), and bugs within the time-stamp system of the JavaRosa language in which the survey software (ODK) is written.

Interview duration was between 30 and 90 minutes for 75% of the 5,367 interviews for which plausible data exists (see Figure 6.2). These interviews were conducted in nine different countries, by 11 different research projects, and included different extra modules and project-specific requirements. Considering the amount of data which is gathered, and how well it compares to other similar surveys in terms of reliability and coverage of the farm system, this is very fast.

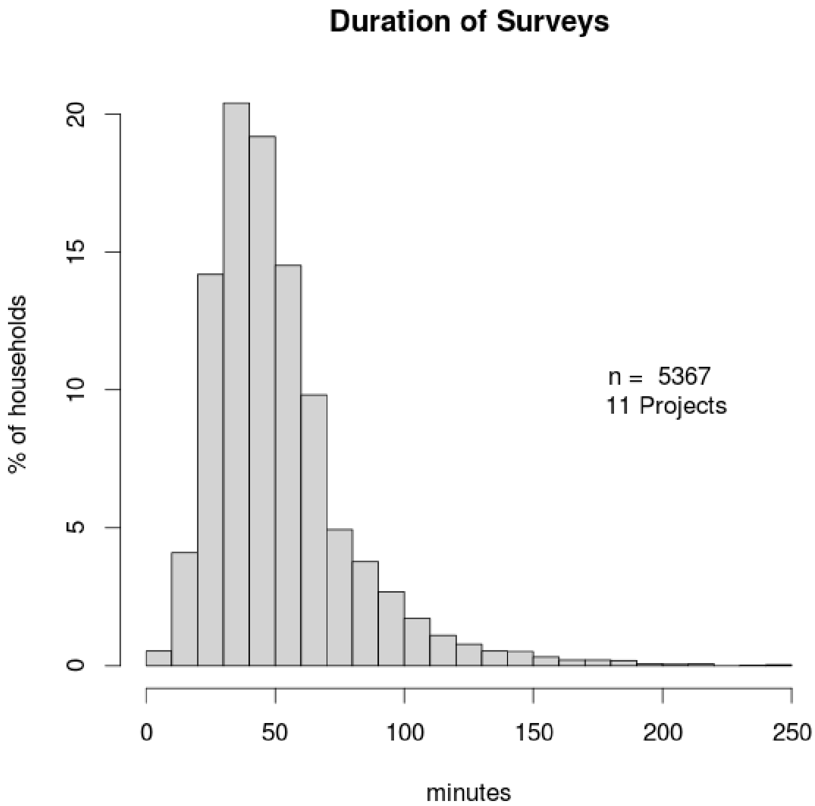

Figure 6.2. Histogram showing the duration of interviews using the RHoMIS survey. Interviews were from a variety of projects, locations, and contained different additional modules.

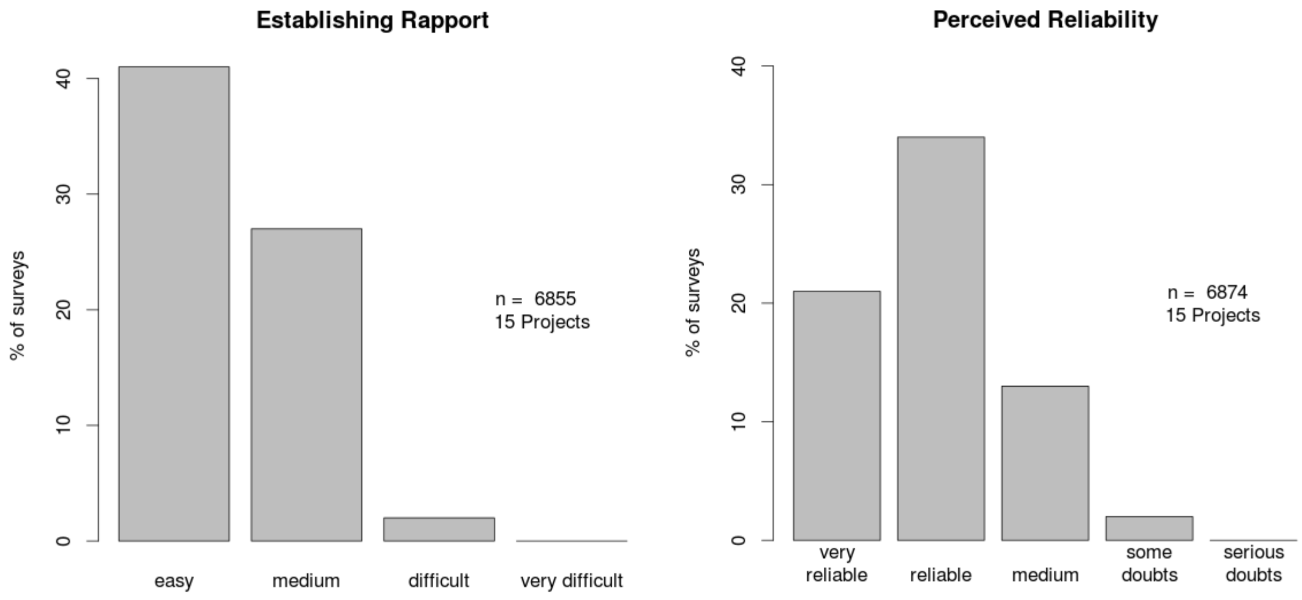

Figure 6.3. Bar charts showing feedback from enumerators, collected at the end of RHoMIS household interviews. Enumerators were asked to rate the ease of establishing rapport, and to provide subjective judgement on the reliability of the interviewee's responses.

Enumerators generally found establishing rapport "easy" or "medium", and perceived that the interviewees' responses were most commonly "reliable" or "very reliable" (Figure 6.3). Although many factors inevitably contribute to these metrics, the design of the survey must play a part. Two of the original goals of the survey design were to make the questionnaire user friendly for enumerators and to phrase questions in such a way that interviewees found them easy to answer; these goals were put in place to increase rapport, speed, and reliability.

Judging by the speed of the survey, the ease of establishing rapport using the tool, and the acceptable levels of reliability as perceived by the enumerator, RHoMIS has met the objectives of "user-friendly", and "rapid". The analyses conducted, both within and outwith this thesis demonstrate that the data is adequate for complex and nuanced studies, and that despite the shorter interview time compared to many tools with similar objectives, data quality has not been compromised.

5 Discussion

In the introduction to this thesis I set out a guiding hypothesis: that it is possible to conduct meaningful and useful characterisation of smallholder households using rapid and replicable survey-based methods. The subsequent work presented has, I believe, established this to be the case. The method has been repeated by 13 organisations in 17 countries. The analyses presented have led to insights worthy of publication in reputable academic journals, and have also garnered the interest of some development practitioners working in NGOs. The survey duration is under one hour, which is rapid considering the amount of information collected on the farm system. The approach warrants further development, and the data collected to date warrants deeper analysis. These themes are explored below.

5.1 References to RHoMIS in wider literature

The paper published based on Chapter 3 of this thesis (Hammond et al., 2017) has been cited in a number of research papers. The citations can be divided into three groups: those which comment on the possibilities opened up by the methodology of the tool, those which discuss the analytical potential of the indicators used, and those which refer to the findings of the analysis published (Hammond et al., 2017).

Three key features of the methodology are identified by van Etten et al.: the "lean data" approach, the possibilities for trade-off analysis due to the systematic coverage of issues with multiple indicators, and that the digital set-up of the tool permits rapid data processing, which in turn permits adaptive management of research or development projects applying the RHoMIS tool (van Etten, Steinke and van Wijk, 2017). The "lean data" narrative is also mentioned in Rosenstock et al. (2017), where they consider that the time efficient gathering of targeted metrics in RHoMIS offers the possibility of "generating uniquely multidisciplinary datasets for low cost" (Rosenstock et al., 2017). In a similar vein, Kristjanson et al. applaud the "focus on transforming our quantitative research approaches from extensive household-based surveys to more efficient survey tools that are designed to rapidly characterize a series of standardised indicators across the spectrum of agricultural production and market integration, nutrition, food security, poverty, and GHG emissions" (Kristjanson et al., 2017). The potential of multi-site analysis using data gathered with RHoMIS is discussed in two papers (Ritzema, Frelat, Hammond, et al., 2017; Thornton, Aggarwal and Parsons, 2017). Ritzema et al. state that most rural household modelling exercises are site specific, and that such a multi-site analysis could produce a more robust strategy for intervention formulation in many locations.

The combination of indicators covering farm practices, farm productivity, market orientation, incomes, food security, poverty indicators, greenhouse gas emissions and gender roles is considered to be useful for various reason by different authors. Establishment of the links between agricultural management strategies and farm household performance (Thornton, Aggarwal and Parsons, 2017), ability to assess the outcomes of agricultural intensification on productivity, welfare and emissions (Cramer et al., 2017; Torquebiau et al., 2018), and the possibility to identify intervention "win-wins" through trade off analysis (Snapp et al., 2018). The possibility of adding additional modules was also identified as a beneficial feature (van Etten et al., 2017).

Finally, some authors have referenced the analysis in Chapter 3. The finding of intensification benefiting small farms and market access benefiting larger farms is highlighted by Thornton et al. (Thornton, Aggarwal and Parsons, 2017). The correlations found between the Food Availability indicator and other independent indicators of food security is used as evidence for the reliability of the Food Availability indicator in five publications (Ritzema, Frelat, Douxchamps, et al., 2017; Ritzema, Frelat, Hammond, et al., 2017; Wichern et al., 2017; Lopez-Ridaura et al., 2018; Paul et al., 2018).

To date, the response in literature has been favourable to RHoMIS, although that may well change as the tool and the method become more visible with increasing publication of studies.

5.2 Critical feedback from users of RHoMIS and next steps

There are three major critiques of the RHoMIS tool: that it does not go into sufficient detail on certain topics, that it is based upon recall information and so is inherently of low reliability, and that the indicators have been slightly adapted from the recommended protocol.

Disciplinary specialists - for example economists, nutritionists, or agronomists - are sometimes unsatisfied that their area of interest has not been covered in sufficient depth by the RHoMIS questionnaire. For example crop researchers sometimes find that the livestock section is too detailed, or livestock researchers find that the crop section is too detailed. Economists have complained that it is impossible to calculate net income using the RHoMIS data, because household spending and labour time are not covered in the questionnaire. Similar critiques have been received about indicators of nutrition, gender roles, selection of crop varieties, livestock herd structure, diseases and pests, and so on. My response is that the purpose of RHoMIS is to give a rapid, comprehensive overview of the farm system, which can be used to identify hotspot issues and to develop an evidence base to target deeper research. Often the gathering of those more detailed data is not commensurate with a one-off household survey approach, and that data quality of both studies would be compromised.

The second critique faces any household survey method: that respondents' recall is subject to unconscious or unintentional errors. This can never be truly overcome, although it can be reduced and controlled, by application of good survey technique (Choi and Pak, 2005). Taking the example of measuring crop production, there are a huge variety of issues which can effect the accuracy of the estimate by the respondent. The gold standard approach is to take crop cuts, and asking farmers to recall production is a distant second (Murphy, Casley and Curry, 1991). An intermediary step between recall and direct physical measurement is the use of a diary to record events as they occur, which has been shown to be successful for crops harvests and consumption of foods, although resource intensive and requiring respondent literacy (Beegle et al., 2012). There are many possible sources of error when asking for farmers' recall, including that they cannot remember, that they never knew in the first place as they did not weigh their crop, multiple harvests throughout the year become confused, non-standard units were used (such as 'heaps'), moisture content was variable, and harvests may be reported in quite different ways (e.g. mature grain, immature grain, on the cob, off the cob) (Carletto, Jolliffe and Banerjee, 2015). Indeed the issues relating to farmer recall have not changed greatly in the 25 years between the above referenced works dealing with the topic (Fermont and Benson, 2011). There have been some studies done into the effects of altering recall periods for different crops (Beegle, Carletto and Himelein, 2012) and also on milk yield estimation (Zezza et al., 2016), which found that farmers' recall estimates were more reliable than had been expected, especially when the subject of the recall involved a significant transfer of cash (either coming in or going out). The approach taken in the RHoMIS questionnaire is to make the questions as easy for the respondents to answer as possible: which means asking only for topics of greater importance (e.g. for respondent-defined “important crops” rather than asking about all crops), constructing answers so that they easy to pick from (e.g. “about half, more than half, less than half”), and veering away from topics which cannot be meaningfully collapsed into simple terms (such as labour allocation). There is a balance to be stuck between demanding too much detail in the answers which then undermines the ability of the respondent to answer accurately.

The first and second critiques are perhaps unavoidable, and although RHoMIS is intended to be flexible, the principles of the tool should not be undermined. The choices made in tool design have led to a large dataset which is perhaps the most exciting outcome of this work. There is scope to test some of the major questions in rural development. Analysis in Chapter 5 showed some important findings in terms of the viability of agricultural intensification methods: if such findings could be scaled up across the full dataset they would be powerful and unique. Another topic for investigation is the interrelation between on-farm diversity, market access, dietary diversity, and food security (see for example Sibhatu and Qaim, 2018). Such analyses are only possible because of the design choices made in RHoMIS which led to rapid and widespread adoption, and which permit comparable analysis of the data. If novel insights can be gained, the findings can be verified using more detailed and more accurate research methods on a smaller sample.

A third critique is in the way that published indicators have been adapted into the RHoMIS tool. The household dietary diversity indicator is the prime example of this. The accepted “gold standard” approach in dietary diversity score based on recall is to ask for an open recall of every food item consumed in the last 24 hours, either by the individual under interview or by an individual who is knowledgeable and can answer on behalf of the entire household. This approach has been widely tested and validated (Swindale and Bilinsky, 2006; FAO and FHI 360, 2016). However there are a few drawbacks, which did not match with the ethos of the RHoMIS tool. Firstly, the approach requires open recall of any food stuff consumed, which means that the enumerator really needs to write down each foodstuff and then probe as to the ingredients of the foodstuff. This is not conducive to the digital interface (which presented mainly closed questions or lists of possible answers), and is not conducive to rapid analysis with pre-defined analysis scripts (as text entries are inevitably variable). Secondly, the while the 24 hour recall adds certainty that the respondent is recalling accurately, the short time frame does not allow insights de be derived at the household level, and even when scaling up the findings to community of landscape levels, the results are highly sensitive to the time of year in which the question is asked. Therefore in RHoMIS we adapted the dietary diversity indicator in two ways: using a list-based approach of foodstuffs rather than open recall (which is also suggested as a valid alternative in recent indicator guidelines (FAO and FHI 360, 2016)), and changing the recall period. The recall period is over two month of the past year, during the leanest month and the best month. This contrast allows understanding of the extremes and therefore the differences experienced on an annual basis. The unit of recall was also altered: respondents could answer that they consumed foodstuffs daily, most days, a few times per week, a few times per month, or never. This was generally easy for household to answer and seemed to produce meaningful data. However, a thorough evaluation of how these alterations compare to gold standard practices is required in order to establish confidence in the modified indicator.

Providing evidence that the novel or adapted indicators developed are reliable and relate in a predictable way to other well known indicators (and to the real situation, as much as that can ever be measured) has to be a priority issue in establishing the validity of the RHoMIS approach. Three indicators are currently slated for deeper analysis and ground-truthing. A study is planned comparing the RHoMIS household dietary diversity approach to the findings from a regular (monthly / bi-monthly) open 24 hour recall approach to measuring dietary diversity. Analysis comparing the responses to household dietary diversity score to the actual nutrient content of foodstuffs produced on farm has validated both indicators. Analysis work is ongoing evaluating the validity of the scores for gendered control of resources depending on the sex of the respondent (early results show that there is a skew depending on the sex, but that the overall patterns remain similar). The farmer motivations typology developed in Chapter 2 of this thesis has been refined and a module of questions developed and deployed in various RHoMIS surveys. Work is planned to compare the findings of the motivations module with actual adoption of technologies promoted in two different projects. Furthermore, an evaluation of the internal consistency of all RHoMIS data captured to date, using the approach outlined and section 4.1 of this chapter could be very useful in establishing the overall reliability of the data captured.

The RHoMIS tool could be adapted and taken up by actors from the research sector, NGO and development sector, or government and national statistics offices. Each group has slightly different needs. Scaling up the use of RHoMIS carries challenges relating to usability and standardisation, as many groups would want to modify the questionnaire, while the data should remain reasonably standardised to permit rapid analysis. However, use by especially government and national statistics organisations could deliver huge data. There is a demand for tracking progress towards international objectives such as the SDGs, the Paris Agreement, as well as tracking national development. With some collaborative design, RHoMIS could be used to track such progress in a far more efficient way than is usually conducted in lower income countries at present.

6. Conclusions

The overarching goal of the thesis was to develop characterisation tools and obtain insights to enable greater impact in agricultural research for development. It is not possible yet to categorically say that greater impact has been achieved through the work presented here, as there has been insufficient time for the tool and the insights to be applied. However, through this work I have developed a characterisation tool, which has been widely taken up, and through analysis of data gathered with this tool and from other sources, I have obtained insights which are relevant to contemporary debates in the field of agricultural development.

I have met the objectives outlined at the start of the thesis. Dealing first with the tool design: through the work in Chapters 1 and 2 I gained understanding of household survey data, techniques, and analytical methods. These aided in the design of the RHoMIS tool, as described in Chapter 3, which was trialled and refined through numerous iterations, as discussed in Chapter 6. Chapter 4 demonstrated that the tool was suitable for use in ex-post impact assessment, and Chapters 3 and 5 demonstrated that the data could be used for strategic and systematic appraisals of the complex, multivariate smallholder farm system: their assets bases, their livelihood strategies, the opportunities they might have for access to markets or off farm work, their welfare and food security. RHoMIS has been widely used and a large database of uniquely comparable data has been obtained. This database has not yet been properly interrogated and may well be the most valuable outcome of this thesis.

In terms of obtaining novel insights the objectives have also been met. The theme of the research has been gaining insights into smallholder heterogeneity, and how those insights can lead to improved impact of agricultural development. In every research chapter the importance of disaggregating the smallholder population into meaningful groups has been shown. Chapter 4 showed very clearly that the impact of shea processing interventions has a greater impact on the very poor, and a lesser impact on the less poor. Without disaggregating the population the average impact measured would have been much less, and of negligible importance, but by examining the impact on the very poor, it is clear that for those households the project had a large and important impact. Similarly, Chapter 5 showed that the poorest households could be lifted out of extreme food insecurity by increasing their household incomes by only a few hundred dollars per year, whereas for less poor households to cross the poverty line a few thousand were needed. Chapter 2 showed the importance of meaningful disaggregation: dividing the households by farm type was not meaningful in terms of understanding the likelihood of households to adopt a new practice. This implies that for greater uptake, interventions should be targeted towards not farm types but more innovative households. Chapter 3 showed that for large or small farms, there is a different role played by market access, intensification, and off farm incomes in securing dietary diversity and food security. The roles were also found to differ between sites, illustrating the need for caution and large datasets when attempting to establish general rules about behaviour of farm systems. Chapter 5 was the largest analysis conducted, based in 4 sites and two time points, and did attempt to find some rules applicable to all locations: most prominently that in multiple sites escape from food insecurity and even poverty was possible through agricultural means, but only when supported by off farm incomes.

I would like to conclude with three main points. First, that there is a need for more efficient, rapid, comparable household survey tools which allow characterisation of smallholder households. Second, that through characterisation of smallholders, it is possible to identify which groups are more likely to benefit from a certain intervention, and groups which are less likely to benefit. Use of this information in program design could lead to efficiency gains in terms of adoption rates and impact. Thirdly, the application of purely agricultural interventions is unlikely to benefit the poorest of the poor: they are less able to adopt or benefit from such practices. Measures to aid the poorest of the poor should focus on access to income which is not tied to land or agricultural assets. Households who are poor but not the poorest, or even those above the poverty line, are better placed to adopt, implement and benefit from measures aiming for sustainable intensification of agricultural production. The intentional targeting of such agricultural interventions to the poorest of the poor without adequate consideration of their constraints to adoption is not likely to lift them out of poverty, or to increase the amount of food produced in the landscape. Separate, but maybe interconnected, strategies are needed to alleviate extreme rural poverty and to sustainably intensify agricultural production.

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Appendix 1. The core RHoMIS questionnaire

The below is shared with potential users of the RHoMIS tool, to give them an idea of the content of the digital survey. The digital survey is superior in various ways, including containing flow logic whereby the answer to a previous question determines later questions, and thus is more efficient to navigate.

- RHOMIS -

Rural Household Multi-Indicator Survey

version 1.3 (April 2018)   http://rhomis.net

User instructions

RHoMIS is a questionnaire survey for interviewing smallholder farm households. It was developed for use on digital screens (phone/tablet). The digital package also includes infrastructure for data upload and storage, real time visualisation, rapid indicator calculation, and analysis functionality. The digital version is also available in multiple languages and with additional modules. The questionnaire in this document contains the core questions of RHoMIS, and is intended to be a guide to the digital version.

The questions are designed to be user-friendly and as quick as possible, while still gathering enough information to understand the farm system, livelihoods and food security. The interview should run more like a conversation, and take about 45 minutes. An excessive level of detail is not required. The meaning of the questions and answers should be clear and self-evident, although the language may need to be adapted for the local context.

Please read through the document before using it, to make sure all questions are understood:
- Answers should be clearly marked, either with a tick, a circle, or with text.
- Select one answer for each question, unless a question is marked with (M) for 'Multiple'.
- If a question is not relevant, please write N/A for 'Not Applicable'.
- If the respondent does not know the answer to a question, use the code “-999”.
- Always specify the units used. For example: local currency, units for land sizes, units for crop yields, units for sales of produce, income per day or per month, and so on.
- Examples of local food stuffs consumed as part of the Nutritional Diversity questions (page 17) should be provided separately to enumerators.
- The 'Progress out of Poverty' section (page 20) requires additional country-specific questions.

Metadata

Interviewer's name		
Date		
Time at beginning of survey	HH:	MM:
Country name		
Local currency		
Region name		
Sub-region name		
Village name		
Household (h/h) ID		
Is the household a beneficiary of the project?	yes	no
Consent to provide information for survey?	yes	no

Respondent Details

Respondent's name			
Is respondent male or female		male	female
Is respondent head of household?		yes	no
How are you related to the head? (ignore question of respondent is head of h/h)	Married to head		
	Child of head		
	Parent of head		
	Other family member		
	Not a family member		
Is the head person married or has a partner?	Has partner - married or non-married		
	Woman - single, widowed, divorced etc.		
	Man - single, widowed, divorced, etc		
Does the head person often live and work away from home for more than 3 months per year?	No		
	Man works away		
	Woman works away		
	Both work away		

How old is the head man of the h/h?		years
How old is the head/senior woman of the h/h?		years
What is the highest level of education the head person has completed?	No school	
	Primary	
	Secondary	
	Post-Secondary	
	Adult education, literacy school or parish school	

Household Population:

Now I will ask about the number of people who live in your household, and their age. This means anyone who usually lives, sleeps and eats in this house or compound. It includes anyone who is temporarily away for less than 3 months, or anyone who is staying for more than 3 months.

How many young children live in your household (h/h), aged 3 or under?	
How many children live in your h/h, aged between 4 and 10?	
How many boys and men live in your h/h, aged between 11 and 24?	
How many girls and women live in your h/h, aged between 11 and 24?	
How many men live in your h/h, aged between 25 and 50?	
How many girls and women live in your h/h, aged between 25 and 50?	
How many elder men, aged over 50, live in your h/h?	
How many elder women, aged over 50, live in your h/h?	

Farm Land Sizes

Does your h/h own land, rent land, use common land (for growing crops or grazing animals)? (M)	Own land	
	Rent in land for own use	
	Rent out land to others	
	Use common land	
	No, don't use any land	
How much land does your h/h own?		
What is the unit of land area that you use? (acre, hectare, etc)		
Who in the family owns your household's land? (M)	Male adult	
	Female adult	
	Male youth (15-30yrs)	
	Female youth (15-30yrs)	
	Male child (<15yrs)	
	Female child (<15yrs)	
About how much land does your household rent in for use?		
About how much land does your household rent out for other people to use?		
Who works on your land - household members or other people too? Consider crops, livestock, any farm activities. (M)	H/h members	
	Labour arrangements with family, friends or neighbours	
	Hired labour	
Is your land mostly flat (straight), sloping or steep slopes? (M)	Flat (or almost flat)	
	Sloping	
	Steep slopes	
Does your h/h have a kitchen garden or other place where you grow vegetables and fruits for home consumption?	yes	no
What is the total amount of land used by your household for growing crops?		

Crop Productivity

Which crops were grown by your h/h during the last 12 months?

Crop Name		Crop Name

Who decided which crops to plant? (M)	Male adult	
	Female adult	
	Male youth (15-30yrs)	
	Female youth (15-30yrs)	
	Male child (<15 yrs)	
	Female child (<15 yrs)	

What vegetables does your household grow? (excluding any already mentioned)

Vegetable Name		Vegetable Name

What fruit and fruit trees does your household grow? (excluding any already mentioned)

Fruit Name		Fruit Name

Did you harvest any of your crops early, before they were fully mature? (please list)		
Why did you harvest the crops early? (M)	Fear of theft	
	Hunger	
	Needed income	
	Erratic rainfall or poor weather	
	High market price for crop	
	Other (please specify)	

Out of all of the crops grown by your household in the last 12 months, please select the most important (quantity/bringing in food or money) and complete the following questions:

Insert crop name:	1	2	3	4	5	6
In which season did you plant this crop?						
Long						
Short						
Both						
Other (please specify)						
During the past 12 months, was the crop harvest good, normal, or bad?						
Good harvest						
Normal harvest						
Bad harvest						
About how much did you harvest? (specify units)						
Harvest quantity						
Units used						
Did you grow this crop intercropped with other plants?						
Grow alone						
Intercropped						
About how much of your land did you use for growing each crop during the last 12 months?						
All or nearly all (90-100%)						
More than half of it (60-90%)						
About half (40-60%)						
Less than half (10-40%)						
Small amount (1-10%)						
None (0%)						

Please use key below to answer the next questions:

1 = All or nearly all (90-100%)
2 = More than half of it (60-90%)
3 = About half of it (40-60%)
4 = Less than half of it (10-40%)
5 = A small amount (1-10%)
6 = None (0%)

Crop name	1	2	3	4	5	6
In the last 12 months, what proportion of each crop did you use for the following needs:						
Eat or Use at home						
Sell						
Feed to livestock						
Give away or exchange						
There was no harvest						
Saved for seeds						
How much money did you make from selling each crop during the last 12 months?						
Annual income (or specify price per unit)						

Who usually decides what to do with the income from selling this crop? (M)						
Male adult						
Female adult						
Male youth (15-30yrs)						
Female youth (15-30)						
Male child (<15 yrs)						
Female child (<15 yrs)						
Who usually decides when to eat this crop? (M)						
Male adult						
Female adult						
Male youth (15-30yrs)						
Female youth (15-30)						
Male child (<15 yrs)						
Female child (<15 yrs)						
What did you do with the crop residues during the last 12 months? (M)						
Leave it in the fields or return to soil						
Burn it in the fields						
Use it as a fuel						
Feed it to animals						
Make compost						
Use as construction materials						
Sell it						

Crop Products

Did you make any of your crops into products you can store or sell during the last 12 months? Please mark those that you sold and approximate income from the sales. Please specify units.		
Name of product e.g. drinks, flour, preserved or dried foods	Sold	Income

	Who decides when to eat or use these products? (M)	Who usually decides what do to with the income from selling these products? (M)
Male adult		
Female adult		
Male youth (15-30yrs)		
Female youth (15-30yrs)		
Male child (<15 yrs)		
Female child (<15 yrs)		

Land Management and Agricultural Inputs

Please answer the following questions with a list of crops, or if applicable, write 'None'

On which crops did you use fertilisers on during the last 12 months?	
How much fertiliser in total was used during the last 12 months? (specify units)	
What types of fertiliser does your h/h normally use?	
On which crops did you use manures or compost during the last 12 months?	
On which crops did you use pesticides during the last 12 months? Include herbicides, fungicides and similar chemicals.	
For which crops did you use improved seed varieties during the last 12 months?	

Crop Storage

How did you store your crops after the harvest during the last 12 months? (M)	In sacks	
	Sealed bags (hermetic)	
	Hard container (plastic, clay, metal)	
	Traditional granary	
	Other (please specify)	
Which crops did you store during the last 12 months?		
Did you add anything to help preserve the crops? (M)	Insecticide/chemicals?	
	Traditional (e.g. ash, leaves)	
	Other (please specify)	

Irrigation

If any, which crops did you irrigate during the last year? Including using bucket, pipe or stream				
What type of irrigation method did you use? (M)	Pouring water by hand (using container)			
	Basin dug around plant			
	Gravity-fed (river diversion)			
	Sprinkler			
	Drip			
	Electric or diesel pump			
	Other (please specify)			
What months did you irrigate? (M)	Jan	Feb	Mar	Apr
	May	Jun	Jul	Aug
	Sep	Oct	Nov	Dec

Integrated Farming

Does your h/h make use of any trees on your land? (M)	Yes	
	No	
	Only cut trees to clear land	
If relevant, how did your h/h till or plough your land during the last 12 months? (M)	By hand	
	Use animal power	
	Use a machine	

Did your h/h use legumes (peas/beans) to improve your soil fertility in the last 12 months? (M)	No, don't grow any.	
	No, just grow them as a crop for food or sale	
	Yes. Grow legumes mixed with other crops.	
	Yes. Grow legumes before/after other crops.	
Does your h/h grow trees and crops mixed together? Agroforestry e.g. coffee planted under shade or fruit trees in pasture fields	yes	no

Livestock

Does your h/h own any livestock, animals or beehives? If none, please skip to the next section.

Livestock Owned	Quantity

Does your h/h use any grazing land for your animals?	yes	no
Does your h/h own any of the grazing?	Own it	
	Do not own it	
	Own some it	

Please select up to six MOST IMPORTANT livestock that you own and answer the following questions. (important in terms of bringing food to home or making money)

Insert livestock name	1	2	3	4	5	6
If relevant, how many are used for draught power?						
Are they local breeds?						
Local						
Cross-bred or exotic						
Both						

Livestock name	1	2	3	4	5	6
Are they in a pen/stable at night?						
Always						
Sometimes						
Never						
Are they in a pen/stable during the day?						
Always						
Sometimes						
Never						
How many did you buy (or receive) in the last 12 months?						
How many live animals have you sold in the last 12 months?						
How much money did you make from the live sales in last 12m?						
How many have you slaughtered for meat in the past 12 months?						
How much money did you make from meat sales in the last 12m?						
Did any livestock die of natural cause during the last 12 months?						

Please use key below to answer the next questions, relating to the last 12 months:

1 = Male adult
2 = Female adult
3 = Male youth (15-30yrs)
4 = Female youth (15-30yrs)
5 = Male child (<15yrs)
6 = Female child (<15yrs)

Livestock	1	2	3	4	5	6
Who in the h/h owns the livestock? (M)						
Who usually decides what to do with the income from selling the live animals? (M)						
Who usually decides what to do with the income from selling the meat? (M)						
Who usually decides when to slaughter/eat meat? (M)						

Please use key below to answer the next questions, relating to the last 12 months:

1 = All or nearly all (90-100%)
4 = Less than half of it (10-40%)
2 = More than half of it (60-90%)
5 = A small amount (1-10%)

About how much of the meat did you eat?						
About how much did you sell?						
How much did you give away/exchange?						

Milk (please specify units)

Dairy animal name	1	2	3
About how much milk do the livestock produce during the good season?			
And in the bad season?			
How many animals do you milk per day?			

Please use key below to answer the next questions, relating to the last 12 months:

1 = All or nearly all (90-100%)
4 = Less than half of it (10-40%)
2 = More than half of it (60-90%)
5 = A small amount (1-10%)
3 = About half of it (40-60%)
6 = None (0%)

	1	2	3
About how much milk does the h/h consume?			
About how much milk does your h/h use for dairy products?			
About how much milk does your h/h sell?			
About how much milk does your h/h give away or exchange?			
How much money does your h/h make from selling milk? (please specify units)			

Please use key below to answer the next questions:

1 = Male adult
4 = Female youth (15-30yrs)
2 = Female adult
5 = Male child (<15yrs)
3 = Male youth (15-30yrs)
6 = Female child (<15yrs)

	1	2	3
Who usually decides what do to with the income from selling the milk? (M)			
Who usually decides when to eat milk? (M)			

Dairy Products

What dairy products does your h/h make? (M) e.g. butter, cheese			
Dairy product name	1	2	3
How much does your h/h usually produce? - specify units, e.g. litres per day			

Please use key below to answer the next questions, relating to the last 12 months:

1 = All or nearly all (90-100%)
2 = More than half of it (60-90%)
3 = About half of it (40-60%)
4 = Less than half of it (10-40%)
5 = A small amount (1-10%)
6 = None (0%)

About how much produce does your h/h keep for eating (or home use)?			
About how much produce does your h/h sell?			
About how much produce does your h/h give away or exchange?			
How much money does your household make from these sales?			

Please use key below to answer the next questions:

1 = Male adult
2 = Female adult
3 = Male youth (15-30yrs)
4 = Female youth (15-30yrs)
5 = Male child (<15yrs)
6 = Female child (<15yrs)

Who usually decides what do to with the sales income? (M)			
Who usually decides when to eat the dairy products? (M)			

Wool, skin, hides

Does your h/h collect wool, skin or hides from your animals?	yes	no
If sold, how much money did you make over the last 12 months?		

Medicines

Did you buy or use any medicines for your livestock in the last 12 months?	yes	no
What medicines does your household use? (M)	Vaccinations	
	De-worming	
	Antibiotics	
	Traditional medicines	
	Other (please specify)	
What animals does your household give the medicines to? (please specify)		

What does your household do with the manure from the animal's stables or pens? (M)	Put directly on soil	
	Store in a pile (for more than one month) before use	
	Store in an enclosed space (for more than one month) before use	
	Use as a fuel	
	Sell it	
	Dispose of it	
	Bio-Digester	

Eggs and Honey - please complete where relevant and specify units

	Eggs	Honey
What animals produce eggs for you?		
How many eggs are produced during the good season? (e.g. no. collected per day)		
And the bad season?		
How much honey did you collect in the last 12 months?		

Please use key below to answer the next questions, relating to the last 12 months:

1 = All or nearly all (90-100%)
2 = More than half of it (60-90%)
3 = About half of it (40-60%)
4 = Less than half of it (10-40%)
5 = A small amount (1-10%)
6 = None (0%)

	Eggs	Honey
About how much eggs/honey does your h/h keep for eating (or home use)?		
About how much eggs/honey does your h/h sell?		
About how much eggs/honey does your h/h give away or exchange?		
If applicable, how much money does your h/h make from selling the eggs/honey?		

Please use key below to answer the next questions:

1 = Male adult
2 = Female adult
3 = Male youth (15-30yrs)
4 = Female youth (15-30yrs)
5 = Male child (<15yrs)
6 = Female child (<15yrs)

	Eggs	Honey
Who usually decides what to do with the income from the sales of eggs/honey?		
Who usually decides when to eat the eggs/honey?		

Resources Gathered from the Environment

If any, what types of foods did you gather in the last 12 months? (M)	Forest Fruits	
	Mushrooms	
	Honey	
	Hunt animals	
	Catch Fish	
	Insects	
	Plants, leaves, roots	
	Nuts or seeds	

What times of year does your household collect wild foods? (M)	Jan	Feb	Mar	Apr
	May	Jun	Jul	Aug
	Sep	Oct	Nov	Dec
Does your household eat the wild foods or sell them? (M)	Eat/Use at home			
	Sell			
	Give away or exchange			
About how much money did you make from selling wild foods during the last 12 months?				

Please use key below to answer the next question:

1 = Male adult
2 = Female adult
3 = Male youth (15-30yrs)
4 = Female youth (15-30yrs)
5 = Male child (<15yrs)
6 = Female child (<15yrs)

Who usually decides what do to with the income from selling wild foods? (M)	

Please use key below to answer the next question:

1 = All or nearly all (90-100%)
2 = More than half of it (60-90%)
3 = About half of it (40-60%)
4 = Less than half of it (10-40%)
5 = A small amount (1-10%)
6 = None (0%)

Approximately how much of your household's food comes from wild foods?	

Food Security Status

Is there a time of year when there is less food compared to other times?	yes		no	
Which months were there food shortages in the last year? (M)	Jan	Feb	Mar	Apr
	May	Jun	Jul	Aug
	Sep	Oct	Nov	Dec

Which is the worst month of the year for food?	Jan	Feb	Mar	Apr
	May	Jun	Jul	Aug
	Sep	Oct	Nov	Dec

Which is the best month of the year for food?	Jan	Feb	Mar	Apr
	May	Jun	Jul	Aug
	Sep	Oct	Nov	Dec

Use key below to answer questions relating to your worst month (or if no worst, than the last month):

1 = Daily, or more than 3 times per week
3 = One to three times per month
2 = One to three times per week
4 = Never, or less than once per month

NOTE: Stop asking these questions as soon as the respondent answers any question with either 1, 2, or 3.	Worst Month
How often did somebody have to go a whole day and night without eating anything?	
How often did somebody have to go to sleep hungry at night because there was not enough food?	
How often was there no food to eat of any kind in your household?	
How often did somebody have to eat fewer meals than they wanted?	
How often did somebody have to eat smaller meals than they wanted?	
How often did somebody have to eat some foods that you really did not want to eat?	
How often did someone have to eat a limited variety of foods?	
How often was someone in the house not able to eat the kinds of food they wanted to eat?	
How often did you ever worry that there will not be enough food for your household?	

Nutritional Diversity

Please use the two keys below to answer the questions in the following table. See guidance document for examples of these foodtypes. If no worst or best month, provide answers for the most recent month.

1 = Daily, or more than 3 times p/week
2 = 1-3 times p/week
3 = 1-3 times p/month
4 = Never, or less than once per month

1 = Produced on farm
2 = Purchased
3 = Bought
4 = Gift, gathered or exchanged

How often did you eat these items in the corresponding month/s?	Monthy type:		Where does this food come from? (M)
	Worst	Best	
Think of: food made from grains, flour, or starchy white vegetables.			
Think of: beans, peas, lentils.			
Think of: nuts or seeds			
Think of: leafy green vegetables			
Think of: orange coloured vegetables or fruit			
Think of: other vegetables			
Think of: other fruit			
Think of: meat, poultry or fish			
Think of: eggs			
Think of: milk or dairy foods			

AID

Have you received aid from the government, NGOs, or other organisations in the last 12m?	yes	no
Have you received any gifts from family, friends, neighbours, in the past 12 months?	yes	no

What type of aid or gifts have been received during the last 12 months? (M)		
	Aid from government, NGOs, other organisations	Gifts from family, friends, neighbours
Food		
Agricultural Inputs (fertiliser, seeds, crops etc.)		
Animals		
Cash		
Other (please specify)		

Please use key below to answer the next question:

1 = All or nearly all (90-100%)
2 = More than half of it (60-90%)
3 = About half of it (40-60%)
4 = Less than half of it (10-40%)
5 = A small amount (1-10%)
6 = None (0%)

	Aid from government, NGOs, other organisations	Gifts from family, friends, neighbours
About how much of the food eaten by your household was from aid or gift sources?		

Does your household have any credit, debts or loans, or did you have any in the last 12m? (could be formal or informal)	yes	no
Did you ever find it difficult to pay the debts in the last 12 months?	yes	no

Off-Farm Income

Does your household have any sources of income apart from selling what you produce on the farm?	yes	no

Please use key below to answer the question in the right hand column below:

1 = Male adult
2 = Female adult
3 = Male youth (15-30yrs)
4 = Female youth (15-30yrs)
5 = Male child (<15yrs)
6 = Female child (<15yrs)

	Which months does your h/h earn money from this source? (Jan, Feb etc) (M)	Who decides how to spend the money from this source? (M)
Labour on other farms		
Labour, not on a farm		
Work in local business		
Have own business		
Remittances (send money)		
Work for government or public institution		
Rent out land to others		
Rent out equipment or animals to others		
Other (please specify)		

Consider all the money earned in the last 12 months from selling farm produce, and from the cash activities we just discussed. Did more money come sales of farm produce, or more from the off farm cash activities?	Almost All from farm	
	Most from farm	
	Half from off-farm	
	Most from off-farm	
	All or almost all from off-farm	

	Income source:	Off-farm	On-farm
What does your household spend your earnings on? Answer for both off-farm and on-farm incomes. (M)	Buying food		
	Buying possessions (clothes, household items, vehicles)		
	Improving the farm (livestock, fertilisers, crops, machines)		
	Spend on people (education, health care, travel)		

Progress out of Poverty Indicators

Questions to be compiled from the PoP database here: www.povertyindex.org

1	
2	
3	
4	
5	
6	
7	
8	
9	
10	

Closing

Thank you very much, we are now finished with the questions. Do you have any questions or comments?

Would you allow us to telephone you for a short conversation (5 or 10 minutes only), to follow up on this survey?	Phone number

Enumarator Metadata (to be answered by the enumerator only)

Household GPS Coordinates, if known		
How many people contributed to answering the survey?		
In your opinion, how easily did you establish rapport with the respondent?	Easily	
	OK	
	Difficult	
	Very difficult	
How reliable do you think these answers are? Consider the accuracy and willingness to answer.	Very reliable	
	Reliable	
	OK	
	Occasional doubts	
	Regular or serious doubts	
Do you have any notes or comments from the interview?		
I certify that I have checked the questionnaire two times to be sure that all the questions have been answered, and that the answers are legible.		
Signed:	Date:	

Survey complete!

- RHOMIS -

Appendix 2: List of modules compiled for the RHoMIS tool

Module	Time	Indicators	Core?
Farm Produce & Incomes	~20 mins	Crops, livestock, off farm incomes, total food availability (calories), market orientation, gross income.	Y
Farm Practices	~10 mins	Farm intensification, diversification, integration, productivity, GHG emissions (IPCC Tier1), inputs used.	Y
Household Demographics	5 mins	Basic demographics	Y
Food Security	<3 mins	Household Food Insecurity of Access Score (HFIAS)	Y
Nutrition	5-8 mins	Dietary diversity score (HDDS or MDDW), source of foods by nutritional category (bought/grown)	Y
Wildfoods	<5 mins	Wild foods gathered, degree of reliance on wild foods	Y
Progress Out of Poverty	<5 mins	Progress out of Poverty Indicator	Y
Gendered Control of Resources	5 mins	Household decision making, Ownership of productive resources	Y
WASH	5 mins	Water, sanitation and hygiene.	N
FIES	3-5 mins	Food Insecurity Experience Scale	N
FCS	3-10 mins	Food Consumption Score	N
rCSI	5-10 mins	Reduced Coping Strategy Index	N
Food Environments	5-10 mins	Questions regarding market accessibility	N
Debts and Aid	<5 mins	Quick indication of scale of reliance on these	N
Motivations	10 mins	Scoring of personal values according to Stern system (self oriented-community oriented; conservative-innovative); innovation capacity; aspirations for the future; commitment to agriculture	N
Recent Changes	5 mins	Farm and livelihoods changes made over past 5 years, and reasons for those changes	N
Tree Use	5-10 mins	Quantity and location of trees on farms, uses of trees on farms, support for more/less trees on farms.	N
Environmen	5-10 mins	More accurate quantification of wild foods and resources	N

tal Resources		gathered from landscape e.g. NTFPs, timber, charcoal. Compatible with Food Availability indicator.	
Cattle Feed	5-8 mins	Detailed information on cattle ownership and cattle feeding practices	N
Cattle Diseases	5-8 mins	Detailed information on cattle and other livestock diseases, mortality and measures taken to combat diseases.	N
Household Expenditure	5 mins	Approximate household expenditure for broad categories	N
Information sharing	3 mins	Sources of information and membership of groups	N
NTFPs	5-10 mins	Use of non timber forest products	N

Appendix 3: Timeline and locations of RHoMIS applications to date

Country (site/region)	Lead Institute implementing	Year	Nr of Households surveyed
Tanzania (Lushoto) **	ILRI	2015	150
Trifinio (Guatemala, El Salvador, Honduras) **	Bioversity	2015	300
Mali	ILRI	2015	200
Burkina Faso	ILRI	2015	200
Malawi (Lilongwe area) **	CIMMYT	2015	160
Kenya (Wote) *	ILRI	2016	160
Kenya (Nyando) *	ILRI	2016	160
India (Bihar) *	ILRI	2016	160
Cambodia (2 sites) **	CIAT	2016	600
Vietnam (Central Highlands; 2 sites) **	CIAT	2016	300
Laos (2 sites) **	CIAT	2016	300
Burkina Faso	ILRI	2016	400
Tanzania (national) *	ILRI	2017	1000
Tanzania (south - east)	Bioversity	2017	600
Ethiopia (Tigray)	Bioversity	2017	300
Kenya (Makueni)	Bioversity	2017	300
DRC (Central)	ICRAF	2017	400
Kenya (west & northern)	ICRAF	2017	400
Zambia (3 districts) **	ICRAF	2017	800
DRC (eastern) *	IITA-ILRI	2017	400
Ethiopia (central highlands) **	TreeAID-ILRI	2017	300
Ghana (northern) **	TreeAID-ILRI	2017	300
Mali (south east) *	TreeAID-ILRI	2017	300
Uganda (Rakai) *	Wageningen University	2017	130
Kenya (West) *	ILRI	2017	160
Costa Rica (national)	Bioversity	2017	200
Burundi *	ILRI	2018	400
Burkina Faso (national) **	TreeAID-ILRI	2018	1030
Tanzania	ICRAF	2018	800
Peru **	Cornell-McKnight	2018	180
Nicaragua	Bioversity	2018	300
Burkina Faso (national) *	TreeAID-ILRI	2018	1280
Ethiopia (central highlands) *	TreeAID-ILRI	2018	400
Ghana (northern) *	TreeAID-ILRI	2018	500
Ethiopia (4 sites) **	ILRI	2018	800
Palestine, West Bank *	FAO	2018	200
Cambodia *	RUA	2018	200
India (Bihar)	Bioversity	2018	750
Total			15520

*Asterisks denote the degree of involvement of the author of this thesis. ** denotes heavy involvement, for example in designing the content of the survey in relation to project goals, programming the questions into a RHoMIS, training of field staff, management of web servers and digital infrastructure, and analysis of output data. * denoted substantial involvement, for example in questionnaire design, digital infrastructure, and analysis of the output data. No asterisks denote light involvement by the author.*

Appendix 4: Supplementary Information

Supplementary Information for Chapter 2

Figure S2.1. Diagrams showing results of the Farm Characteristics Cluster Analysis. Number of clusters are usually selected according to the point at which there is an elbow in the line graph, which indicates that the increasing difference between the clusters no longer outweighs the complexity to interpret additional clusters. The panels on the left hand side are the same data but scaled differently, to show the position of the elbow in the curve from a more zoomed in and zoomed out perspective.

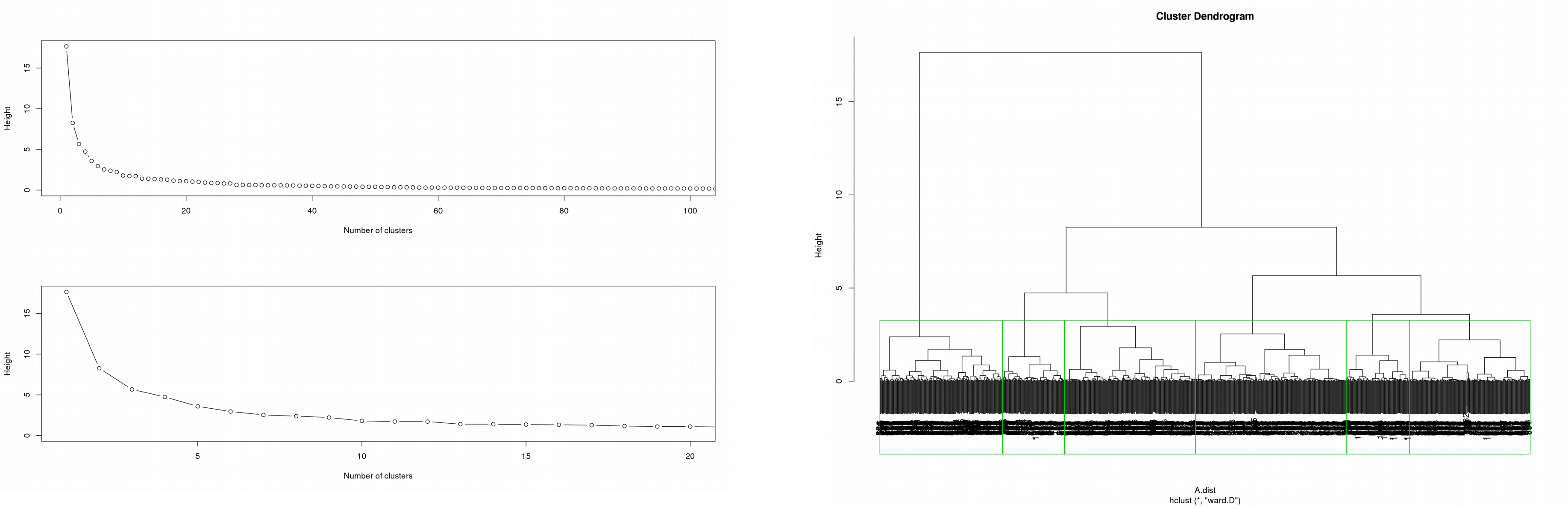
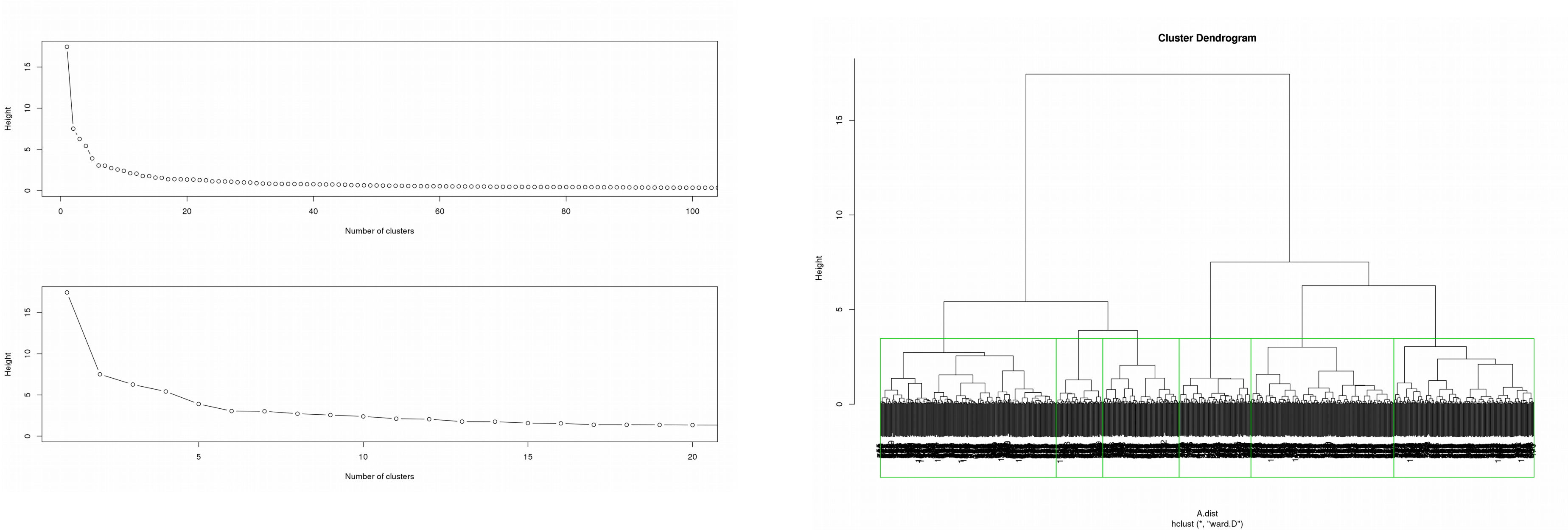


Figure S2.2: Diagrams showing Farmer Motivations Cluster Analysis. Number of clusters are usually selected according to the point at which there is an elbow in the line graph, which indicates that the increasing difference between the clusters no longer outweighs the complexity to interpret additional clusters. The panels on the left hand side are the same data but scaled differently, to show the position of the elbow in the curve from a more zoomed in and zoomed out perspective.



Supplementary Information for Chapter 3

Figure S3.1 Correlations between indicators, Lushoto, Tanzania.

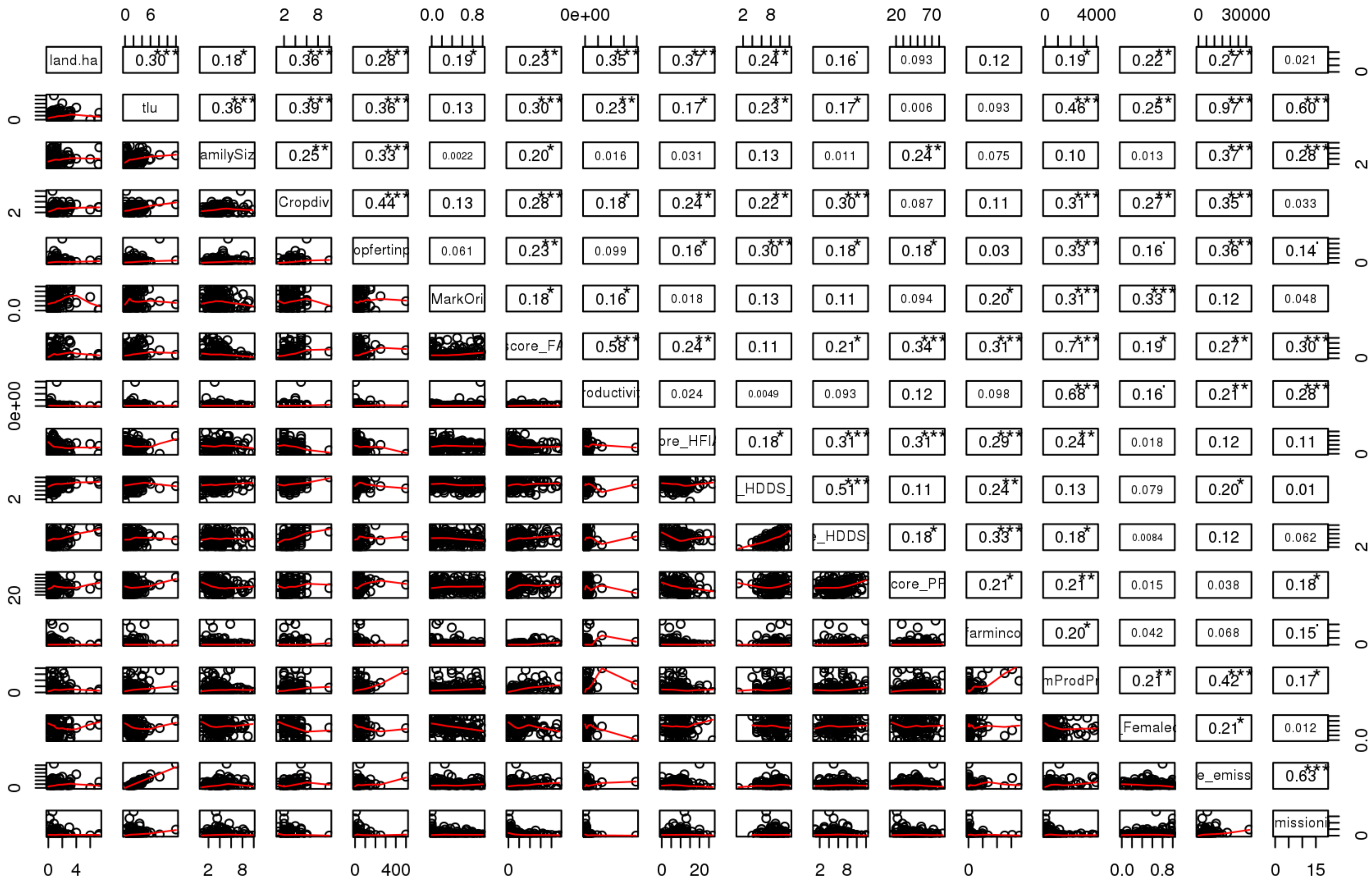


Figure S3.2 Correlations between indicators, Trifinio.

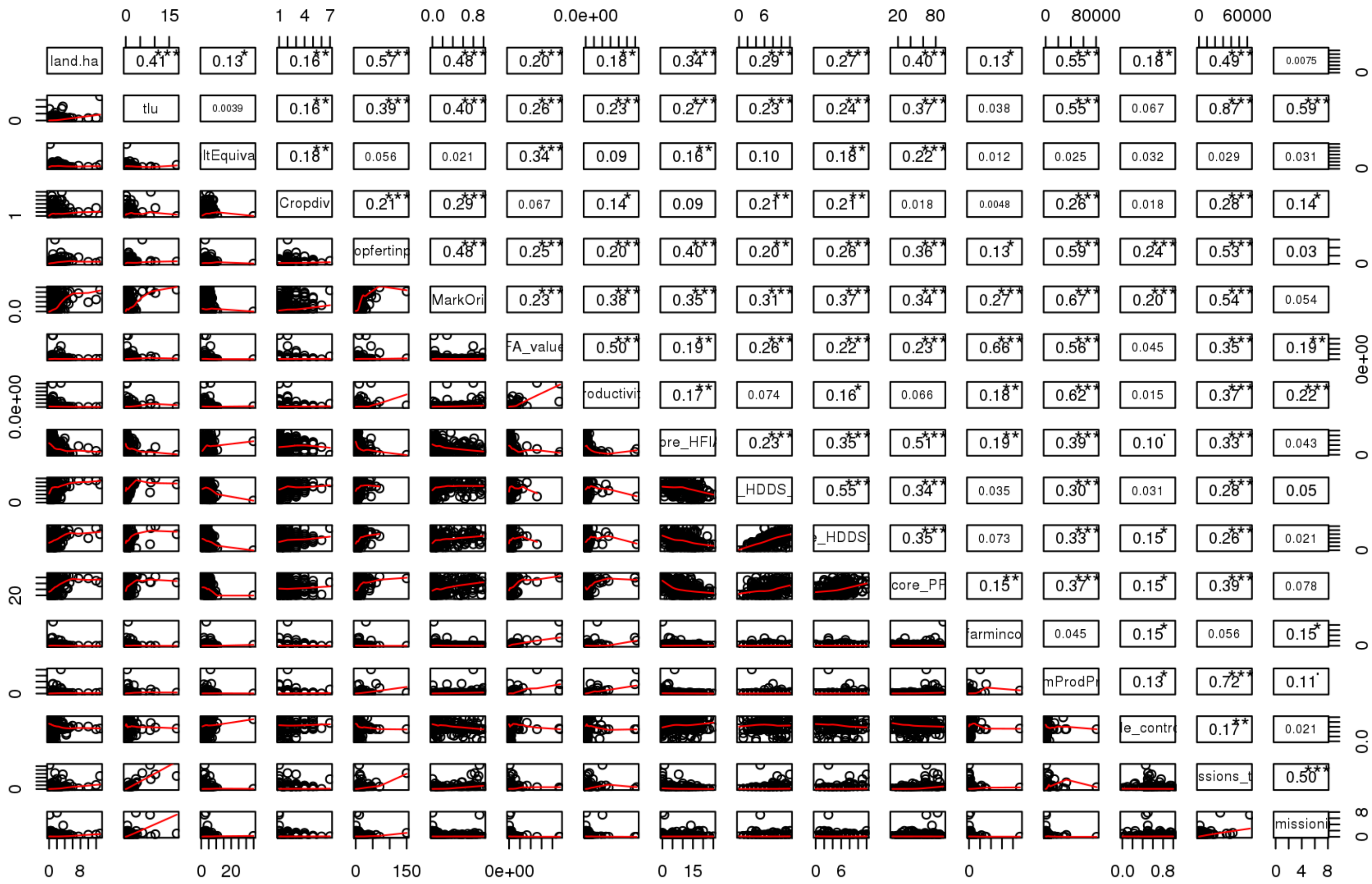


Table S3.1 Indicator results for subsets of households, Lushoto, Tanzania.

Farm Type	Practice	Households (n)	HFIAS	HDDS	FA	PPI	Gender equity	Emissions	Emission Intensity	Cash value of production	Off farm income	Fertilizer input	Market orientation	Nr of crop species
Large	Not Intensified	21	7	6	3772	38	0.5	4300	1.7	429	176	10	0.29	3.5
Large	Intensified	21	7.5	6.5	5075	50	0.44	6400	0.6	533	0	87	0.46	4
Small	Not Intensified	30	12	5	1885	38	0.9	52	0.04	104	0	0	0.01	2
Small	Intensified	7	5	9	5360	66	0.5	155	0.05	760	1339	50	0.24	3
Large	Low Market Orientation	14	7.5	6	3893	39	0.50	4500	2.2	582	88	25	0.01	3.5
Large	High market Orientation	28	7	6.5	4424	46	0.50	6200	0.8	444	0	35	0.6	4
Small	Low Market Orientation	21	11	6	2370	39	0.9	53	0.04	149	0	0	0.004	2

Small	High market Orientation	13	7	5.5	2152	47	0.5	212	0.05	340	0	3	0.5	2.5
Large	Low Crop diversification	17	9	5	3714	46	0.5	3270	1.4	378	0	0	0.20	2
Large	High Crop Diversity	25	7	7	5075	43	0.5	6000	0.9	533	0	30	0.41	4
Small	Low Crop diversification	31	11	5	2328	35	0.9	55	0.03	175	0	0	0.06	2
Small	High Crop Diversity	4	10	6	6653	52	0.6	86	0.1	184	670	10	0.11	3

Table S3.2 Indicator results for subsets of households, Trifinio.

Farm Type	Practice	Households (n)	HFIAS	HDDS	FA	PPI	Gender equity	Emissions	Emission Intensity	Cash value of production	Off farm income	Fertilizer input	Market orientation	Nr of crop species
Large	Not Intensified	19	11	4	16230.2	36	0.72	967.8	0.21	610	1050.4	3	0.08	1
Large	Intensified	73	4	7	16003.0	60	0.55	1827.6	0.13	1591	0	12	0.32	2
Small	Not Intensified	68	12	4	5772.1	30.5	0.67	200.3	0.1	249	573.6	3	0	1
Small	Intensified	18	6	5	7405	34	0.69	229.7	0	398	710.9	6	0	1
Large	Low Market Orientation	20	9	4	12921	51.5	0.6	1156.9	0.17	727	848.8	5	0.01	1

Large	High market Orientation	72	4.5	7	16198.2	55	0.55	1907.5	0.13	1558	85.5	11.8	0.38	2
Small	Low Market Orientation	66	12	3	5772.1	31	0.74	178.2	0.093	254	648.5	3	0	1
Small	High market Orientation	19	11	5	7202	34	0.55	341.3	0.09	497	428.1	3	0.18	2
Large	Low Crop diversification	45	3	5	15695.2	54	0.55	1132.3	0.125	889	74.74	6	0.12	1
Large	High Crop Diversity	47	6	7	17188.3	54	0.57	3007.3	0.21	1619	355.2	12	0.42	2
Small	Low Crop diversification	57	9	3	5789	31	0.72	180.1	0	249	581.1	3	0	1
Small	High Crop Diversity	29	11	5	5980	34	0.59	254.1	0.12	290	520.1	3	0.005	2

Supplementary Information for Chapter 5

Tables S5.1 and S5.2 showing Assets in first and second panel surveys for trajectory groups. Interesting to track how these change – for example as households rise in prosperity what do they invest in? Or when they fall what do they sell off? Also interesting to compare the asset base of a household before they changed – e.g. on paper Low to Low and Low to High households looked pretty similar in the first survey round, so they must have either made some canny strategic decisions, or been lucky enough to be in the right place at the right time.

Panel	Trajectory	Household Members	Land Owned (ha)	Livestock (TLU)
First	Low to Med	7	0.8	1.5
First	Low to High	6	0.9	1.0
First	Med to High	6	1.5	1.1
First	High to Low	4	1.1	2.8
First	High to Med	5	1.4	4.2
First	Med to Low	6	1.0	1.3
First	Low to Low	5	0.7	0.7
First	Med to Med	6	1.2	0.8
First	High to High	5	1.8	3.4

Table S5.1

Panel	Trajectory	Household Members	Land Owned (ha)	Livestock (TLU)
Second	Low to Med	6	1.2	2.8
Second	Low to High	6	1.2	3.0
Second	Med to High	6	1.6	3.5
Second	High to Low	6	1.6	3.6
Second	High to Med	6	2.1	8.7
Second	Med to Low	6	1.2	1.4
Second	Low to Low	6	0.8	0.8
Second	Med to Med	6	1.6	2.7
Second	High to High	5	2.4	7.9

Table S5.2

Tables S5.3 and S5.4 showing household performance in terms of crop value, crop intensity, livestock product value, livestock product intensity, off farm income, off farm income intensity for each of the trajectory groups, during the first and second panel surveys. Using these tables it is possible to compare the changes in median incomes and intensification for different household trajectories.

Panel	Trajectory	Crop Value ($/yr)	Crop Intensity ($/ha/yr)	Lstk Value ($/yr)	Lstk Intensity ($/TLU/yr)	Off Farm Income ($/yr)	Off Farm Income Intensity ($/MAE/yr)
First	Low to Med	387	456	95	90	120	24
First	Low to High	351	429	57	68	75	18
First	Med to High	1012	615	132	110	234	69
First	High to Low	1181	1246	475	206	640	289
First	High to Med	1545	904	943	203	1391	381
First	Med to Low	884	813	96	136	192	62
First	Low to Low	287	412	12	41	39	13
First	Med to Med	947	688	170	150	419	112
First	High to High	1752	924	579	195	1023	352

Table S5.3

Panel	Trajectory	Crop Value ($/yr)	Crop Intensity ($/ha/yr)	Lstk Value ($/yr)	Lstk Intensity ($/TLU/yr)	Off Farm Income ($/yr)	Off Farm Income Intensity ($/MAE/yr)
Second	Low to Med	661	417	2.8	172	494	116
Second	Low to High	2301	1438	3.0	167	1765	522
Second	Med to High	2882	1392	3.5	359	2023	554
Second	High to Low	258	202	3.6	25	44	9
Second	High to Med	422	201	8.7	477	405	105
Second	Med to Low	295	293	1.4	0	52	10
Second	Low to Low	282	352	0.8	0	0	0
Second	Med to Med	748	659	2.7	84	378	69
Second	High to High	913	495	7.9	930	1971	493

Table S5.4

Figure S5.1 Shows the Rhomis Welfare Indicators for trajectory groups. Generally the indicators are correlated in the expected and plausible directions. Vertical lines have been added to indicate (from left to right) the boundaries between rising trajectories, falling trajectories and steady trajectories.

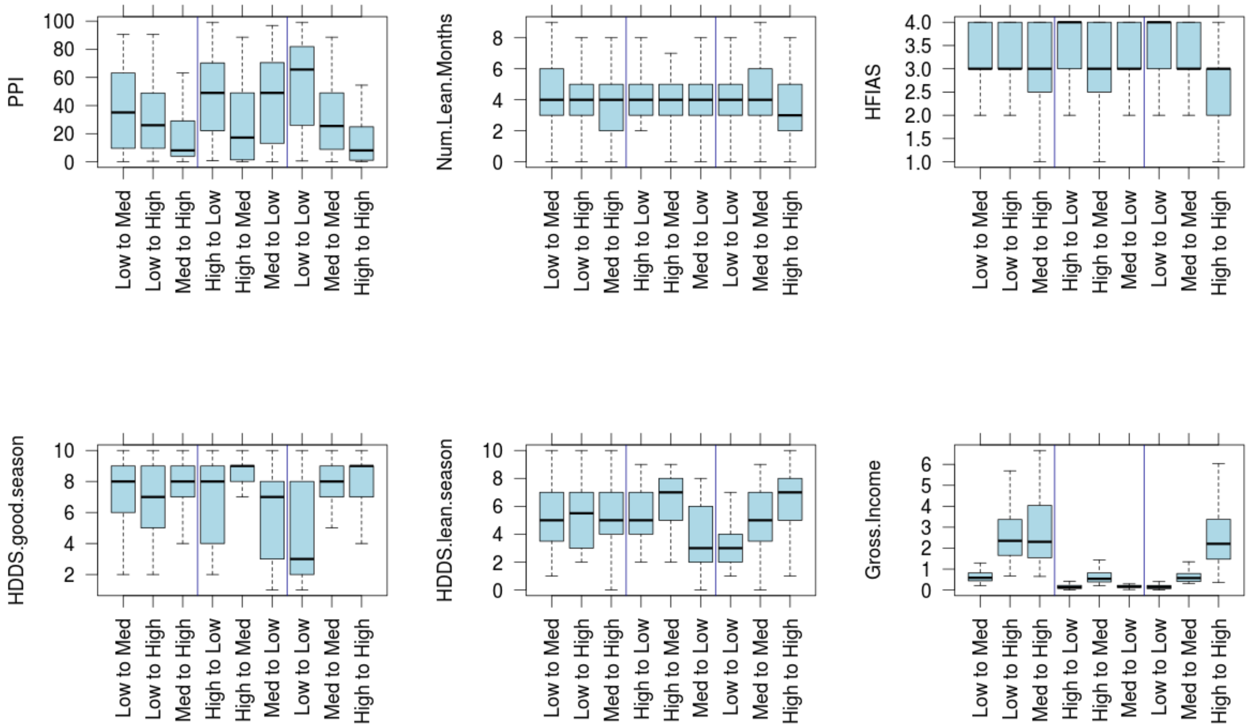


Figure S5.1