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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

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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 min 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 ($n = 150$) 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 CSA interventions.

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 labour into the farm, resulting in a negative association between off-farm labour and intensification, market orientation and crop diversity on the larger farms, which is in complete opposition to the associations 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.

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.

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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 assist the assessment of opportunities at smallholder farm household level for climate smart agriculture (CSA) can be through integration of standardised agricultural, poverty, nutrition and environmental indicators in the quantitative characterisation 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., 2016). This lack of standardization in combination with often relatively poor data quality (Tiffen, 2003), generally caused by unsuitable survey design (Randall and Coast, 2015) or by biases due to perverse incentives (Sandefur and 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 on 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 characterisation 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 tool 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. 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 tool 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 tool consists of the following elements:

1) *Food availability* is 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., 2016; Van Wijk et al., 2014a). 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 h 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 h 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 then 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 and 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 female decides 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 and Diego-Rosell, 2015). For example, the Women's Agricultural Empowerment Index requires 60–80 min 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 fertiliser 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 CO_2-equivalent per farm per year.

These were the six core indicators that can be quantified with this version of the RHoMIS tool. 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 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 kgCO_2-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). 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 Fig. 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.

2.4. Site selection and 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.

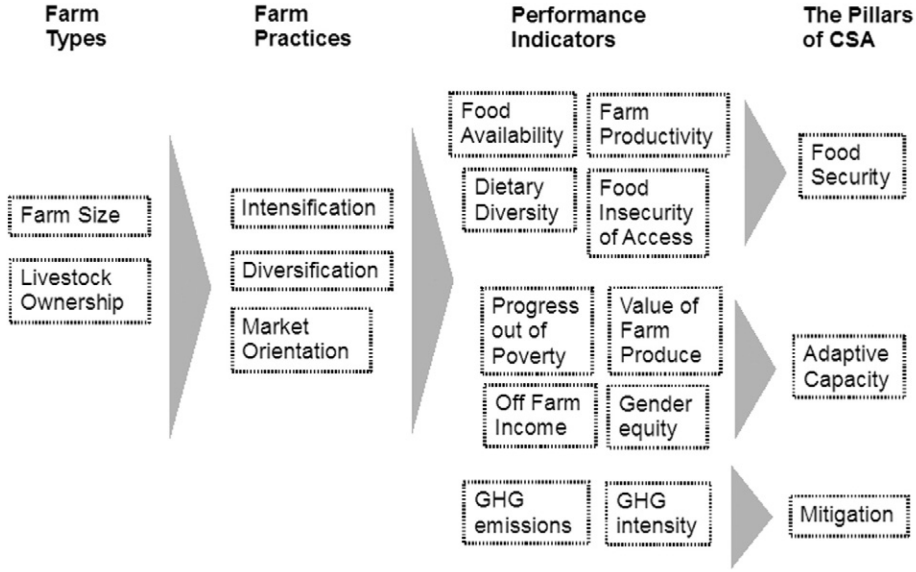

Fig. 1. Schematic representation of the indicators gathered from the household surveys, and the analytical framework into which they are placed.

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 part of the Eastern Arc Mountains of East Africa which is seen as a global hotspot for biodiversity with diverse micro eco-zones within a relatively small area; mixed crop-livestock, quite intensive farming systems in higher elevation and agro-pastoral farming systems in lower elevation. The Usambara Mountains are an important source of water for northeastern Tanzania and the Pangani River is utilized for urban water supply, irrigation and hydropower generation. Deforestation, poor land management and inadequate funds for watershed management pose a threat to the long-term supply of quality water from the Usambaras to downstream communities. The supply of water might be further affected by climate change with rainfall predicted to become more irregularly distributed. 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 Lushoto, Tanzania, the survey was conducted on a resample of the farm households that were also surveyed in 2012 with the CCAFS research program (https://ccafs.cgiar.org/). In the 2012 survey 200 farm households were randomly selected within the 10 by 10 km land block containing representative agroecologies in the study region that 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 Swahili in Lushoto.

2.5. Data analysis

Extraction of data and calculation of the indicators was done using scripts programmed in R. 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, 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 analysis 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 <1 tlu) and relatively ‘large’ farms (i.e. farm land area larger than 1 ha and livestock ownerships >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 chose to group the farms using land size and livestock numbers following the analyses of Frelat et al. (2016).

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 min per household (Table 1). Gathering data for the food availability indicator took the longest, between 15 and 35 min, as it is based on the whole of agricultural production, sales and off farm income. The dietary diversity indicator took the second longest to complete, at around 10 min 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 <5 min each (Table 2). The indicators were calculated successfully for most households, we were only unable to calculate <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 and 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.

3.2. Indicator scores

The median indicator scores in both locations are shown in Table 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 Tanzania 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

Table 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: $^{\dagger}p < 0.1$; $^{*}p$; < 0.05; $^{**}p < 0.01$, $^{***}p < 0.001$.

Indicator (unit) (possible range)	Trifinio (n = 285)		Lushoto (n = 150)	
	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	20,139.8	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 (USD per year)***	489.1	1726.6	0.0	261.5
Value of Farm Produce (USD 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

Table 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	3–5	61	34	5
Gender Equity	5	61	28	11
GHG Emissions	5	57	32	11

significantly higher livestock ownership, and also higher fertiliser use. Both sites showed high variability in GHG emissions and emission intensities.

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), 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 decreased experience of food insecurity, decreased poverty, and improved dietary diversity (the latter in the bad season only though). Dietary diversity in the good and bad seasons was 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 food stuffs, where as in Tanzania 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. Increased 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. Increased 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.

3.4. Farming strategies and their 'Climate smartness'

In Lushoto (Fig. 2; Table 4) intensification is associated with higher Food Availability, PPI and cash value of production, and to a smaller extent to higher GHG emissions (Fig. 2a). Households who have intensified also have significantly higher market orientation and higher crop diversity (see Table S1), so it is important to note that the three strategies are not independent. On large farms, intensification is also linked to significant increases in Productivity and Value of farm produce, while being related to significant decreases in 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. Increased crop diversity shows very similar relationships with the performance indicators as intensification in Lushoto, except that the effects of increased crop diversity on the important food security indicators HDDs and HFIAs is still more pronounced (Fig. 2b). So this indicates that intensification without increasing crop diversity not necessarily leads to the same positive effects on diets and food security as with increased diversification. Increased market orientation on large farms is associated with a strong decrease in gender equity and off farm income and with higher productivity, but shows no significant relationships with the other performance indicators. In small farms in Lushoto increased market orientation is associated with higher values for PPI, but also with slightly lower values for HFIAS and HDDS: the cash generated by selling produce is apparently not being spent on buying diverse food items.

In Trifinio (Fig. 3; Table 4) 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 increased emissions, value of farm produce and productivity, while on small farms it is related to increased productivity and diet diversity. Gender equity on both farms tends to be lower with increased 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 association with off farm income, while on small farms there is a positive association, although it is not a very strong relation. Crop diversity effects on the performance indicators are less strong compared to intensification (Fig. 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 (Fig. 3a). On small farms crop diversity, similar to the results in Lushoto, had a significantly positive relation with diet diversity, while it is also associated with increased emissions and emission intensities. Increased market orientation (Fig. 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, increased market orientation is related to significantly lower female decision making (gender equity indicator).

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 h recall collecting detailed information on what several individual members of a household consumed the previous 24 h (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

Table 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 comaprsions 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: $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$, $^{***}p$ 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**	

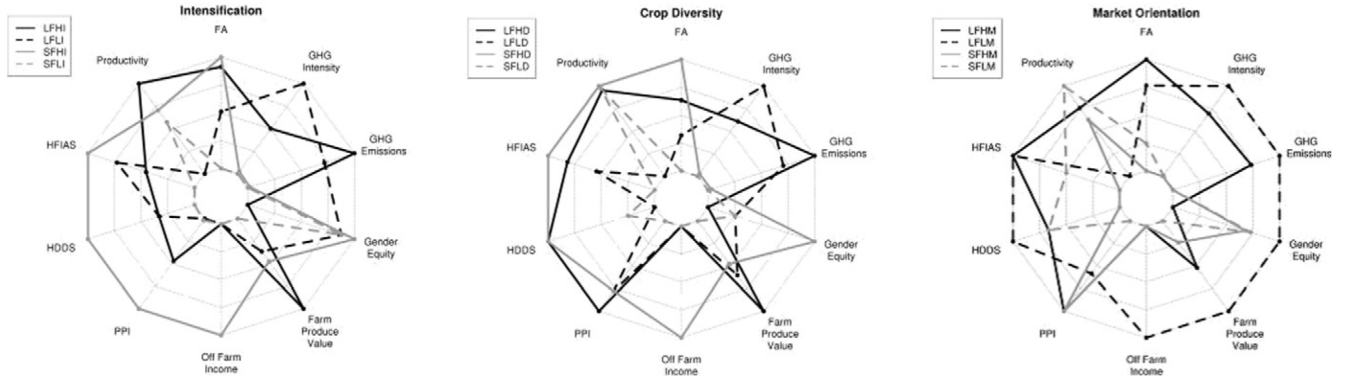

Fig. 2. Farm performance scores for large and small farm types (LF and SF), practising high and low farm intensification (HI and LI), crop diversification (HD and LD) and market orientation (HM and LM) for Lushoto, Tanzania. Abbreviations: FA is Food Availability, HFIAS is the Household Food Insecurity Access Scale, HDDS is the Household Diet Diversity Score, PPI is Progress out of Poverty Index.

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 and Van Laerhoven, 2016). Given the modular design it is relatively straightforward to expand the RHoMIS tool 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 standardised 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 increased 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 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

Table 4
The significance of differences in performance indicators for households who do and do not score highly on farm strategies, in Lushoto and in Trifinio. All values refer to Figs. 2 and 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, $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$, $^{***}p < 0.001$.

	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
	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

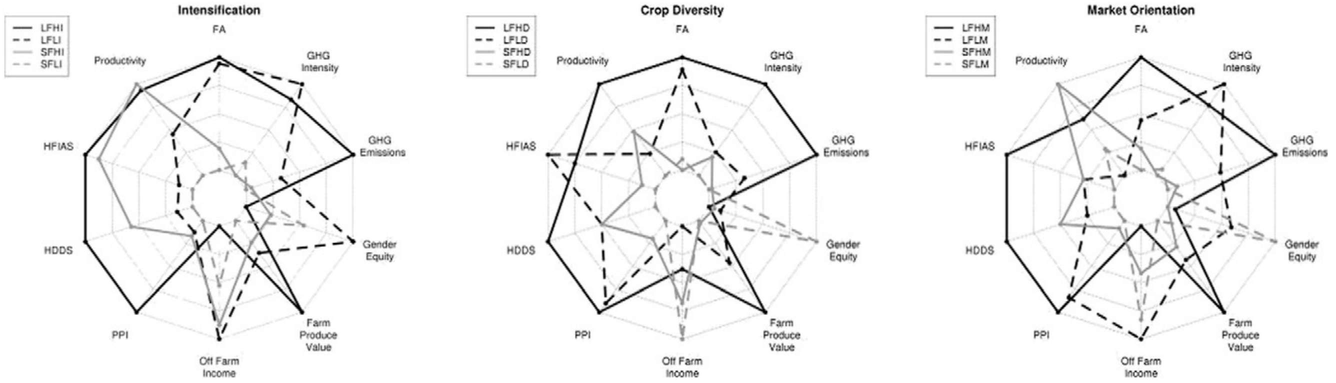

Fig. 3. Farm performance scores for large and small farm types (LF and SF), practising high and low farm intensification (HI and LI), crop diversification (HD and LD) and market orientation (HM and LM) for Trifinio, Central America. Abbreviations: FA is Food Availability, HFIAS is the Household Food Insecurity Access Scale, HDDS is the Household Diet Diversity Score, PPI is Progress out of Poverty Index.

correlation with improved status of all other indicators (see Table S1), 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 associated with increased 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. Njuki 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., 2010), 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 snap-shot 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 tool 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. Sakané 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 et al., 2014). This finding stresses the importance of more fine-grained farm household based analyses to assess for which groups certain strategies or interventions are ‘smart’, and for which households they 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, while identifying truly smart strategies will require not only ex ante analysis, but also experimentation and iterative evaluation.

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