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To mulch or to munch? Big modelling of big data

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ABSTRACT

African farmers are poorly resourced, highly diverse and aground by poverty traps making them rather impervious to change. As a consequence R4D efforts usually result in benefits but also trade-offs that constraint adoption and change. A typical case is the use of crop residues as mulches or as feedstock. Here we linked a database of household surveys with a dynamic whole farm simulation model, to quantify the diversity of trade-offs from the alternative use of crop residues. Simulating all the households in the survey (n = 613) over 99 years of synthetic climate data, showed that benefits and trade-offs from "mulching or munching" differ across agro-ecologies, and within agro-ecologies across typologies of households. Even though trade-offs between household production or income and environmental outcomes could be managed; the magnitude of the simulated benefits from the sustainable intensification of maize-livestock systems were small. Our modelling framework shows the benefits from the integration of socio-economic and biophysical approaches to support the design of development programs. Our results support the argument that a greater focus is required on the development and diversification of farmers' livelihoods within the framework of an improved understanding of the interconnectedness between biophysical, socio-economic and market factors.

1. Introduction

Across Sub Saharan Africa (SSA), crop residue biomass is a valuable and scarce household resource (Tittonell et al., 2015). Crop residues, containing Carbon (C) and Nitrogen (N) nutrients, are used either as livestock feed, a source of energy, building materials, source of cash, re-cycled back into the cropping system as mulches, or just burnt in the field. A key practice of conservation agriculture is the use of crop residues as mulches so that soil erosion is prevented and rainfall infiltration increased. However the appropriateness of the practice in SSA, widely adopted elsewhere, has been contentious (Derpsch et al., 2014; Giller et al., 2009), and calls for caution (Pittelkow et al., 2015) and pragmatism have been made (Giller et al., 2015; Mafongoya et al., 2016). Sources of concern relate to the availability of crop residues for mulching, the intertwined responses between crop responses across environments and time scales (Pittelkow et al., 2015), and the myriad of biophysical, market, and socio-economic conditions (Giller et al., 2009) that prevail across the region making it difficult to identify 'one-size fits-all' strategies.

Improving our understanding of the differences and similarities among households, in terms of constraints and opportunities for farmers to increase income and protect the soil capital, has helped better-target options among poorly resourced smallholder farmers (Giller et al., 2015; Tittonell et al., 2009a). Household surveys, visioning exercises (Tui et al., 2015), and ex-ante modelling exercises (Roxburgh and Rodriguez, 2016) have been all useful to narrow down the "basket" of options (Giller et al., 2015). Even though in general important assumptions and simplifications are needed for simulation modelling, household modelling has shown potential to quantify the more tractable benefits and trade-offs from alternative decisions, investments, farming systems designs, and intensification options in smallholder farming (Holzworth et al., 2014; Rodriguez and Sadras, 2011). Examples can be found in the evaluation of case study farms on soil nutrient and carbon dynamics (Tittonell et al., 2009b), to the quantification of interactions and synergisms between components within the farm system (van Wijk et al., 2009), such as alternative livestock diets (Rufino et al., 2009), irrigation strategies (Power et al., 2011), or farming systems designs (Rodriguez et al., 2014, 2011).

Despite the significant improvements in the understanding of poorly resourced smallholder households, a rather fundamental challenge remains: How to deal with the large variability in the population of farms and farmers? How to represent such diversity and quantify benefits and trade-offs from alternative pathways for development? The standard approach has been to develop a household typology, select a 'typical' or 'representative' farm from each of the farm typologies and

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perform analyses using the characteristics and management structure for this small set of contrasting farms (Herrero et al., 2014; Rodriguez et al., 2014; Rufino et al., 2011; Tittonell et al., 2009c). However, this approach ignores the large variability that is inherently present in the typologies (van Wijk, 2014). The problem was previously identified (van der Ploeg et al., 2009) who showed the large diversity of development pathways over time from an initial rather similar set of households. New analyses try to move away from the approach to first aggregate and then simulate, by applying modelling and intervention analyses across populations of farm households, and then explore and aggregate the results (Frelat et al., 2015). In statistical analyses it has been shown conclusively that 'first aggregation then simulation' can lead to different results from the 'first simulation then aggregation' approach in non-linear, complex systems. Here we explore this idea further by linking a large database of household survey data with a new whole farm model (APSFarm-LivSim). Interfacing the model with a database of a household survey allowed us to parameterize and simulate each of the 613 households in the survey, thereby retaining the base variations in farm characteristics and management throughout the assessment. Understanding the diversity of responses across the most vulnerable farmers' matters given the many examples of policy prescriptions and ill-informed institutionalization of technological packages across SSA (Valbuena et al., 2012). Here we propose that given the large disparity in responses i.e. benefits and trade-offs, identifying generalizable management strategies from the analysis of a few household case studies can be misleading if used to inform practice or policy at regional or national levels.

2. Material and methods

We used field and household level data from an extensive and homogeneous household survey (n = 613), to (i) describe the variability in household levels of endowment across Eastern and Western Kenya; and (ii) to parameterize a whole farm model (APSFarm-LivSim) that was used to quantify benefits and trade-offs in terms of changes in average ground cover, feedstock availability, heads of cattle sold, household maize production and income, and soil erosion from alternative uses of crop residues i.e. kept as mulches or fed to livestock, across all the farms in the survey. Distinctive from other studies is the dynamic coupling of whole farm models and databases of household data; and the fact that we dynamically modelled all the farms in a survey using ninety-nine years of climate records, and were able to clearly demonstrate the extent of the diversity of benefits and trade-offs across regions, and household typologies.

2.1. Baseline survey data

The survey was collected by the Sustainable Intensification of Maize-Legume Cropping Systems for Food Security in Eastern and Southern Africa (SIMLESA) program (http://aciar.gov.au/page/simlesa-program). The regions surveyed included Embu and Meru Counties in Eastern Kenya (n = 314), and Bungoma and Siaya Counties in Western Kenya (n = 299) (Fig. 1). The data was collected between January and April 2011. Survey design and data collection is described elsewhere (Frelat et al., 2015). Survey data included field and household level data. Household level data i.e. physical, financial and human capitals, was used both to describe the diversity of households by developing household structural typologies and to parameterize a dynamic whole farm model (APSFarm-LivSim, below). Briefly, factor analysis was used to extract linear combinations of the regressors that were independent (Venables and Ripley, 2000), to reduce the dimensions in the dataset. Variables showing a high correlation in the factor analysis were omitted from the cluster analysis to avoid extreme multi-co-linearity and singularity. However at a later stage, some of the variables excluded in the cluster analysis, were used to refine and help interpret the results, and to provide a more complete characterization of the household

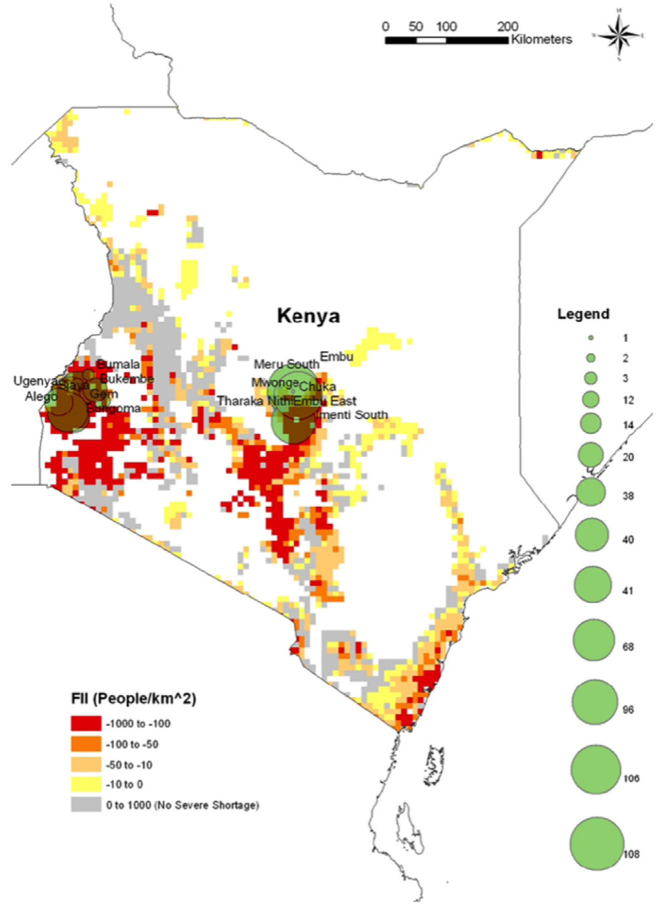

Fig. 1. Map of the distribution of the surveyed farms in Eastern and Western Kenya (n = 613), on a map showing a food insecurity index (FII, people km^{-2}) (Potgieter et al., 2013). The size of the circles indicates the number of households surveyed per village.

typologies. Categorical variables such as the gender of the household head, were only included in the cluster analysis. Factor analysis provides factor loadings for each variable, a measure of that variables contribution to each factor, or principal component. Variables having the largest loading values from the first most relevant principal components were examined, the first 5 (Eastern Kenya) or 9 (Western Kenya) components explained most of the variability of the total dataset. Each principal component was represented by one or two variables in the cluster analysis, and the selected variables were different between Eastern and Western Kenya. Household typologies were developed using hierarchical clustering (Ward's minimum variance linkage method) with the Euclidean distance of the normalized variables as a measure of similarity (Gong and Richman, 1995). All statistical analyses were done developing appropriate software using the R software (R Core Team, 2016).

2.2. The APSFarm-LivSim model

A combination of household and field level data collected in the survey was used to parameterize the model APSFarm-LivSim, for each farm in the database (Fig. 2). The whole farm model (APSFarm-LivSim) was derived from linking the APSFarm (Rodriguez et al., 2011 and Rodriguez et al., 2014) and LivSim (Rufino et al., 2009) models. Merging APSFarm and LivSim involved linking both mechanical and conceptual components of two distinct modelling frameworks. The simulation framework APSIM (Holzworth et al., 2014), the underlying engine of the APSFarm model, passes encoded messages between components that represent events in the system such as the transfer of resources between modules (e.g. water uptake by plants), the operation of farm level

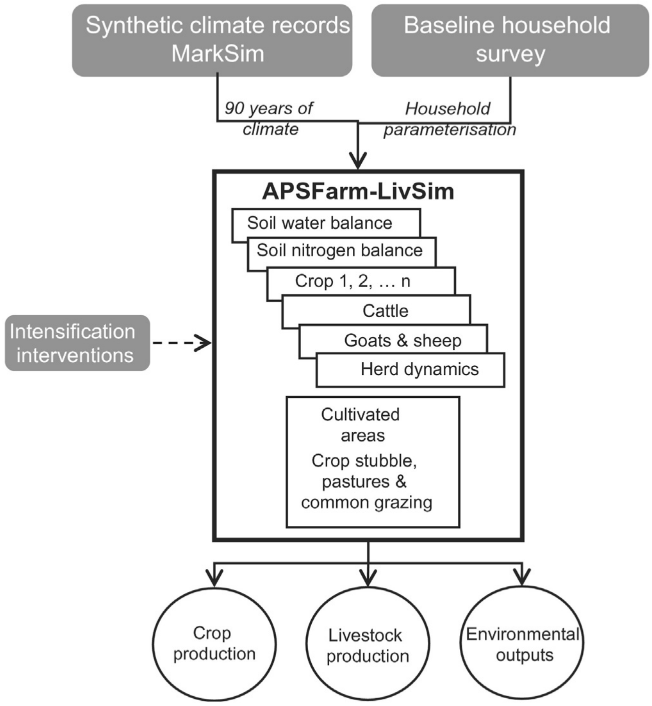

Fig. 2. Linking of the APSFarm-LivSim model with climate and household survey data.

management (e.g. planting a crop) and so on. LivSim, a standalone R script application, implements similar modularity via naming conventions applied to R data structures instead of messages, subroutine arguments instead of object encapsulation, and is coordinated by a "top level" loop running the simulation. Adding a scripting language component to an APSIM simulation is a common practice (Power et al., 2011; Rodriguez and Sadras, 2011 and Rodriguez et al., 2014), so grafting the livestock science modules from standalone LivSim into an APSIM component requires only that the state variables and events shared by both are correctly linked.

Scripted manager modules were written to buy and sell cattle, sheep and goats; another to maintain feed stores that the animals eat from, another to present a diet (dynamically calculated from available stores & pastures) to the animals. Each (monthly) time step, the LivSim component asks the system for this diet; models the herds biological processes including stochastic reproduction and mortality, updates internal state variables for the herd, sends back uncollected excreta to nominated grazing fields while collecting excreta for later applications at the sowing of crops.

The integrated model is configured to simulate the impacts (economic, financial, environmental) of the alternative allocation of limited production resources (e.g. land, labour, time, irrigation water, machinery, and finance) across a number of alternative farm enterprises at the whole farm level. These alternative allocation strategies are each a simulation of each farm, spanning the ninety-nine years of stochastic climate records generated from MarkSim (Jones and Thornton, 2000) (Fig. 1). Several periodicities operate during this simulation in addition to the daily and monthly components above. Each year at the start of the dry season, the soil water content is reset to a starting value, and the animal herd is constrained to $\pm 50\%$ of its starting value: animals are sold if in excess, or purchased if in deficit. In long duration simulations with stochastic components, these constraints become important in low probability "edge" cases, such as the very low chances of (e.g.) a) an excessively wet finish leading to an unrealistically full profile at sowing, or b) a run of male calves growing into an entire herd of males with no calves being born. Manure application at sowing is carried out in the same proportions as recorded in the survey. Weed and crop residues are continuous, also incorporated at sowing. As this experiment is concerned with N rundown, soil fertility is unconstrained over the entire simulation, which can lead to depressed cereal yields over many years. Actual survey data used in the parameterization of each household included herd number and composition, the number and area of each field; the soil type characterized in terms of farmer self-assessed soil depth i.e. shallow, medium or deep, fertility i.e. high medium or low, and slope i.e. low, medium or high. The parameterisation of farmers' self-assessed soil fertility was based on the classification of soil fertility levels from APSIM's extensive data-base of African soils (APSoil, https://www.apsim.info/ApsoilWeb/ApsoilKML.aspx). Two years of crop sequences from each field were used to characterize the area sown to each crop i.e. maize, and or beans; fertilizer usage by each crop; manure application; weeding events per crop; form of tillage i.e. hoe, plough, direct seeding; residue management e.g. removed, fed to livestock, mulched, or burnt; and initial number of cattle, oxen, goats and sheep. Important assumptions were made (i) the area of common

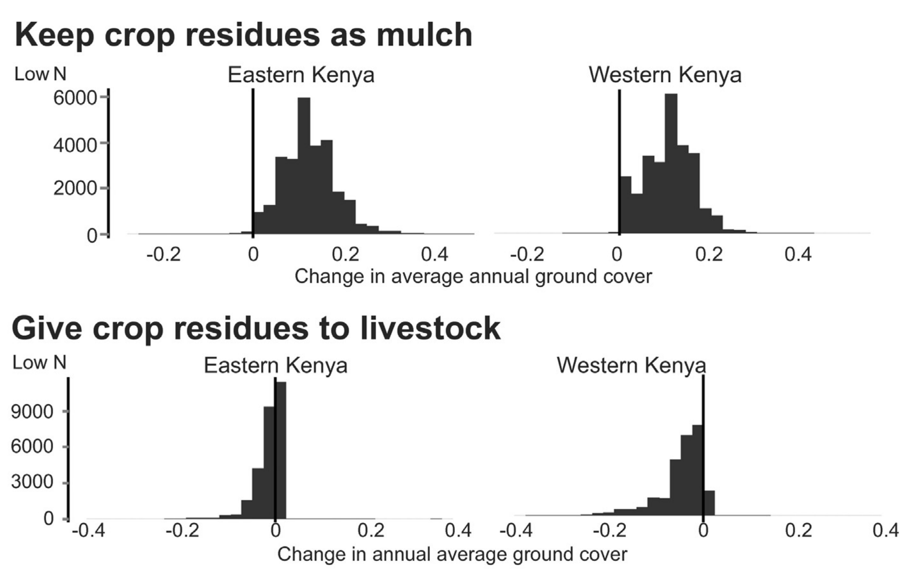

Fig. 3. Frequency graphs of the simulated change in annual average ground cover from present management i.e. as in the baseline survey, and when crop residues are kept as mulch on the maize crop (top graphs); and when crop residues are fed to the livestock (lower graphs), across all the surveyed households (n = 613) in Eastern and Western Kenya, simulated over 99 years of MarkSim climate records.

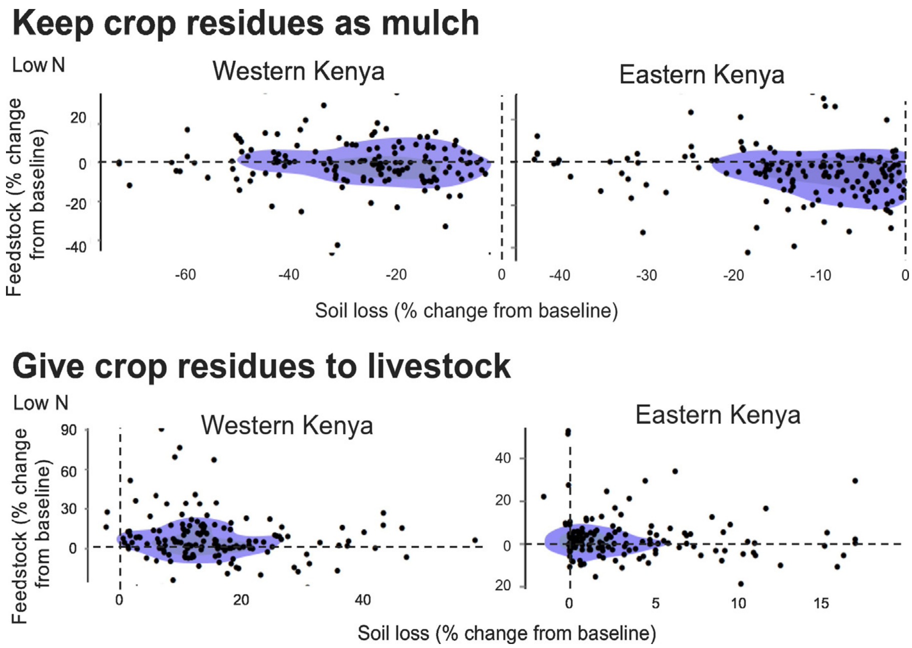

Fig. 4. Density plot i.e. the intensity of the shade indicates the density of households, of the simulated diversity of trade-offs between feedstock availability and soil loss, when crop residues are kept as a mulch (top graphs), and fed to the livestock (lower graphs), with respect to farmers' present management as in the baseline survey. Each point in each graph represents a household from the baseline survey, i.e. there are 314 points (households) in the Eastern Kenya plots, and 299 points in Western Kenya plots.

lands for grazing (1 cow ha^{-1}, 0.4 sheep or goat ha^{-1}) – as per agronomists from the Kenya Agricultural and Livestock Research Organization, (KALRO); and (ii) crop density, planting date and variety were assumed to be uniform across each region. To construct the model "input files" requires code to be written that translates database values into model inputs, a process that begins with a generic farm template containing all conceivable components in the household population, and for each household unit, switching on (or off) each component, parameterising the active remainders. This same code is also responsible for running the simulations in a distributed computing environment, and collating outputs for subsequent analysis.

The model was run for each of six treatments i.e. three residue management strategies and two levels of nitrogen supply. The residue treatments included present farmers' residue management (mulch/burn/sale/feed) from the baseline survey; universally keeping crop residues as mulch on maize crops; and universally feeding the crop residues to livestock. The two levels of fertilization included present farmers crop fertilization and manuring management as described in the baseline survey i.e. mostly low nitrogen availability; and increasing the supply of nitrogen to the maize crop by an additional 40 kg N ha^{-1} i.e. this is in addition to whatever N management the farmer was already using as per the baseline survey. Model outputs included measures of

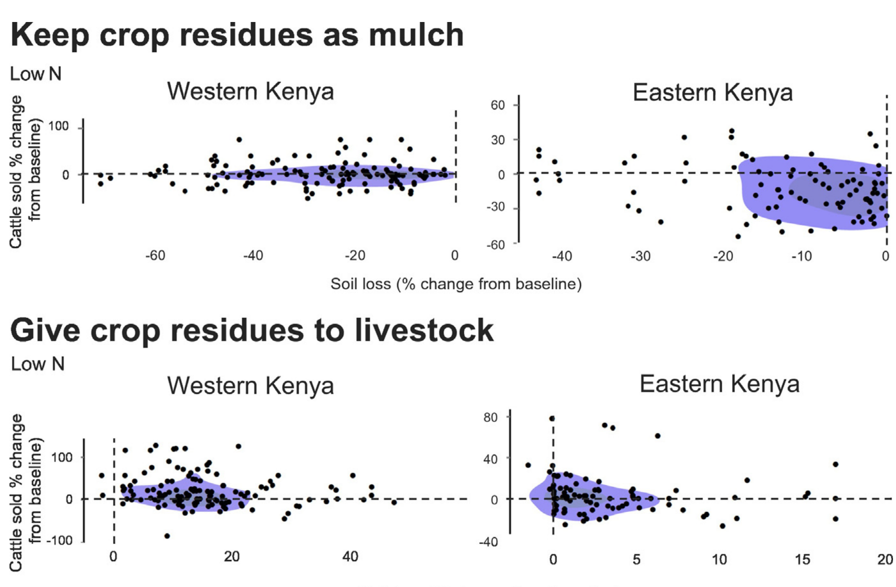

Fig. 5. Density plot i.e. the intensity of the shade indicates the density of households, of the simulated diversity of trade-offs between cattle sold and soil loss, when crop residues are kept as a mulch (top graphs), and fet to the livestock (lower graphs), with respect to farmers' present management as in the baseline survey. Each point in each graph represents a household from the baseline survey, i.e. there are 314 points (households) in the Eastern Kenya plots, and 299 points in Western Kenya plots.

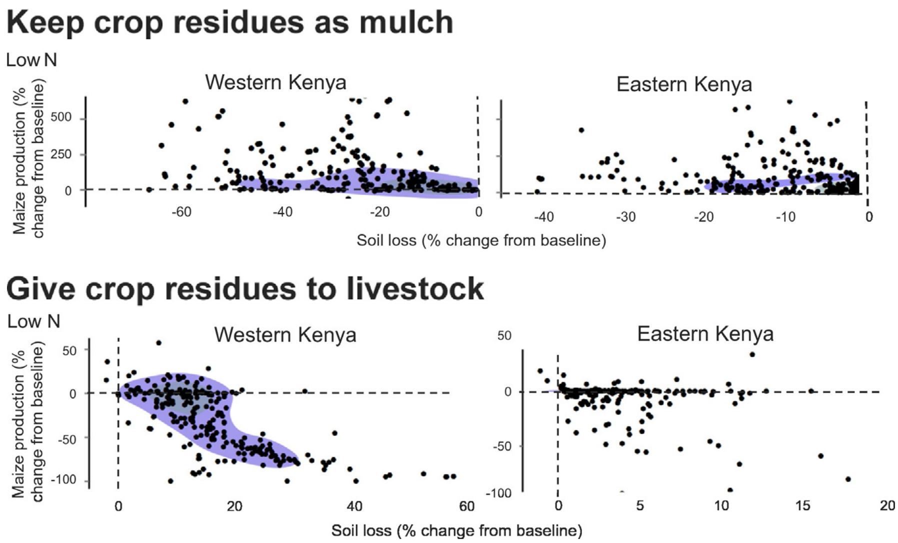

Fig. 6. Density plot i.e. the intensity of the shade indicates the density of households, of the simulated diversity of trade-offs between household maize production and soil loss, when crop residues are kept as a mulch (top graphs), and fet to the livestock (lower graphs), with respect to farmers' present management as in the baseline survey. Each point in each graph represents a household from the baseline survey, i.e. there are 314 points (households) in the Eastern Kenya plots, and 299 points in Western Kenya plots.

livestock i.e. cattle sold, household crop production and income, as well as indicators of environmental impact, i.e. ground cover (%), and soil erosion (t ha^{-1}). Changes from keeping residues as mulches or feeding residues to the livestock were represented as changes with respect to the present situation as in the baseline survey. Modelled results are presented for all the farms in each region, and for different household types as per an analysis of typologies.

3. Results

3.1. Simulated results

Compared to the baseline simulation, simulated ground cover was increased when crop residues were kept as mulch (Fig. 3, top graphs); and slightly reduced when fed to the livestock (Fig. 3, lower graphs). The small changes in ground cover simulated when all farms were forced – in the model - to use crop residues as feedstock indicate that most farmers already use crop residues to feed their livestock.

Density plots were used to represent the trade-offs between feedstock availability (Fig. 4), cattle sold (Fig. 5), maize production (Figs. 6, 8 and 9), household income (Figs. 10 and 11), and changes in soil loss for the different simulated crop residue management strategies. In these graphs individual dots represent individual households, while the darker areas represent the areas in the trade-offs having the largest concentration of households.

As expected mulching crop residues reduced soil loss; particularly in the higher rainfall environments of Western Kenya; and tended to reduce more the feed availability particularly in the dryer environments of Eastern Kenya. When crop residues were fed to the livestock APSFarm-LivSim simulated an increase in soil loss and mostly, increases in the availability of feedstock across all households (Fig. 4).

Keeping all crop residues as mulches, reduced the number of animals sold, particularly in the dryer environments of Eastern Kenya ca.

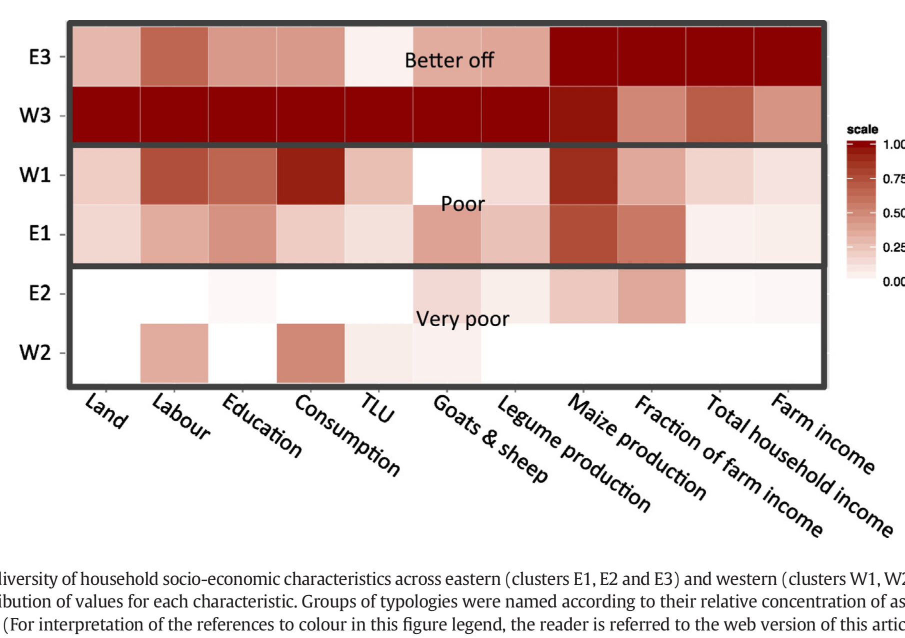

Fig. 7. Heat map showing the diversity of household socio-economic characteristics across eastern (clusters E1, E2 and E3) and western (clusters W1, W2 and W3) Kenya. The intensity of red indicates the relative distribution of values for each characteristic. Groups of typologies were named according to their relative concentration of assets and sources of livelihoods as better off, poor and very poor. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

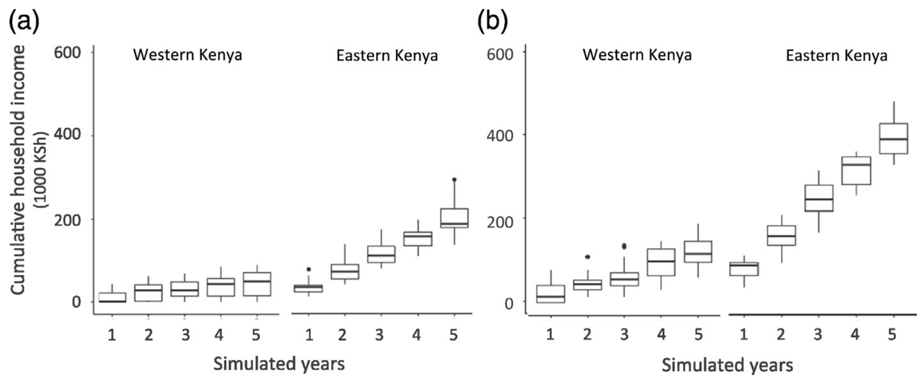

Fig. 8. Example of simulated cumulative income over five consecutive years, for two randomly selected households of Western, and Eastern Kenya; and (a) for the baseline scenario, and (b) a scenario where only half of the crop residues are fed to livestock and an additional 40 kg N ha^{-1} are used on the maize crops. Each box plot represents the variability observed from multiple five year runs over the total length of available climate records i.e. 99 years of synthetic MarkSim data.

20%. While feeding crop residues to the livestock increased the number of animals sold in the market; the trade-off with soil loss was particularly important in Western Kenya (Fig. 5).

Maize production increased when crop residues were kept as mulches and soil erosion was nearly halved (Western Kenya). Feeding the crop residues to the livestock reduced the household maize production in Western Kenya, while the effects on Eastern Kenya were small (Fig. 6). This was related to the observation (Tables 1 and 2) that in West Kenya farmers have more cattle; while in Eastern Kenya small ruminants predominate.

3.2. Household typologies

For both Western and Eastern Kenya three household typologies were identified based farmers' levels of endowment i.e. structural typologies (Tittonell et al., 2009a), and simply termed “Very Poor”, “Poor” and “Better Off” farmers. For Western Kenya the three groups of households were identified based on the diversity in farm-land area (ha), value of production assets (KSh), tropical livestock units, years of education and gender of the household head (Table 1). For Eastern Kenya the three contrasting structural farm typologies were identified based on

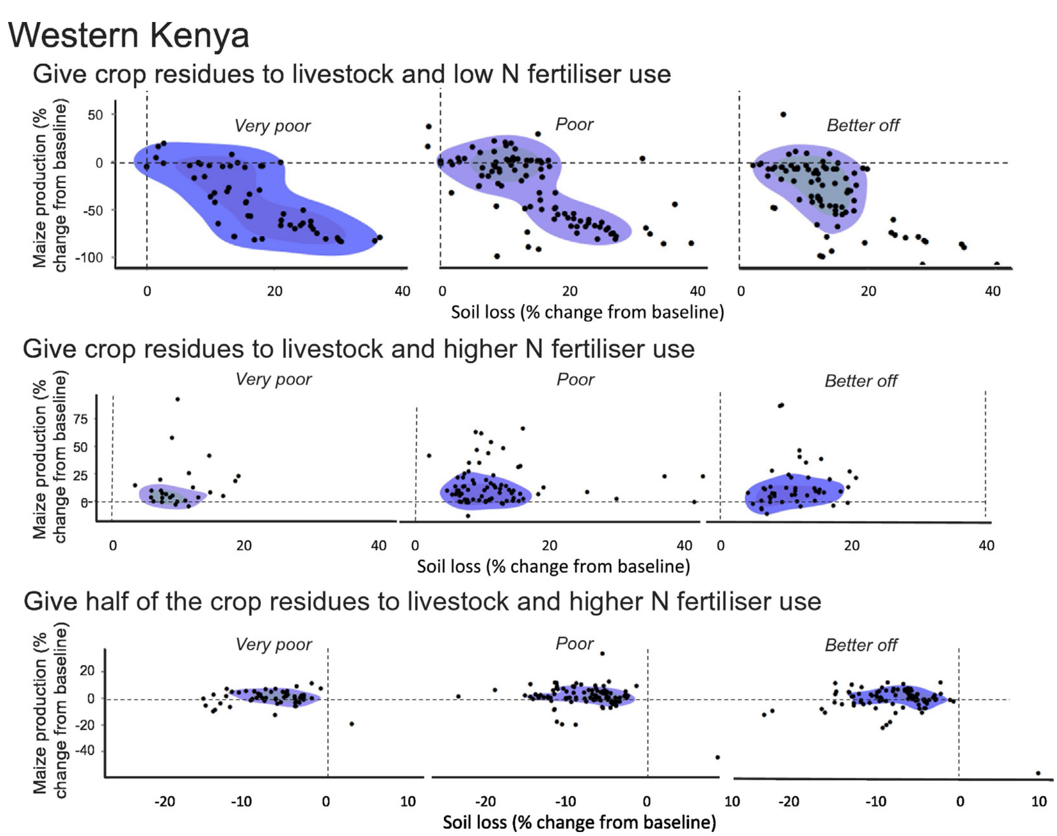

Fig. 9. Density plot i.e. the intensity of the shade indicates the density of households, of the simulated diversity of trade-offs between household maize production and soil loss in Western Kenya, when all crop residues are fed to livestock under low levels of nitrogen fertilizers use (top graphs); when all crop residues are fed to livestock though an additional 40 kg N are used on the maize (middle graphs); and when only half of the crop residues are fed to livestock and an additional 40 kg N are used on the maize (lower graphs). Changes are with respect to farmers' present management as in the baseline survey. Each point in each graph represents a household.

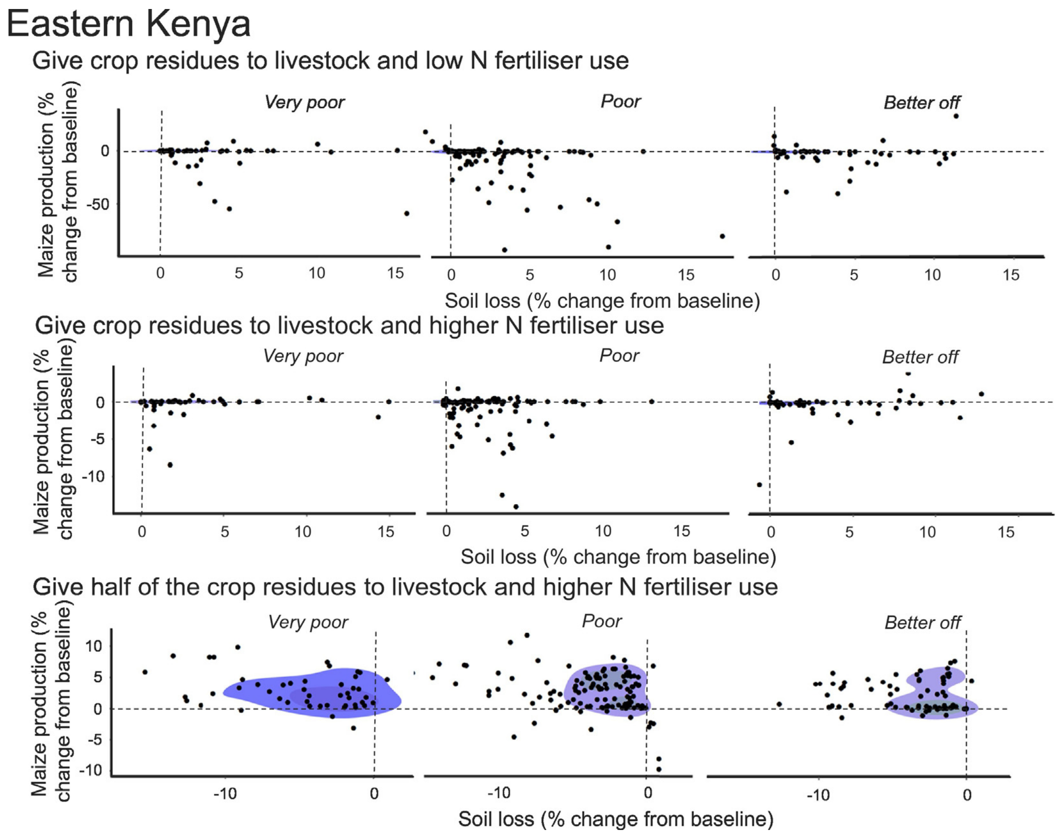

Fig. 10. Density plot i.e. the intensity of the shade indicates the density of households, of the simulated diversity of trade-offs between household maize production and soil loss in Eastern Kenya, when all crop residues are fed to livestock under low levels of nitrogen fertilizers use (top graphs); when all crop residues are fed to livestock though an additional 40 kg N are used on the maize (middle graphs); and when only half of the crop residues are fed to livestock and an additional 40 kg N are used on the maize (lower graphs). Changes are with respect to farmers' present management as in the baseline survey. Each point in each graph represents a household.

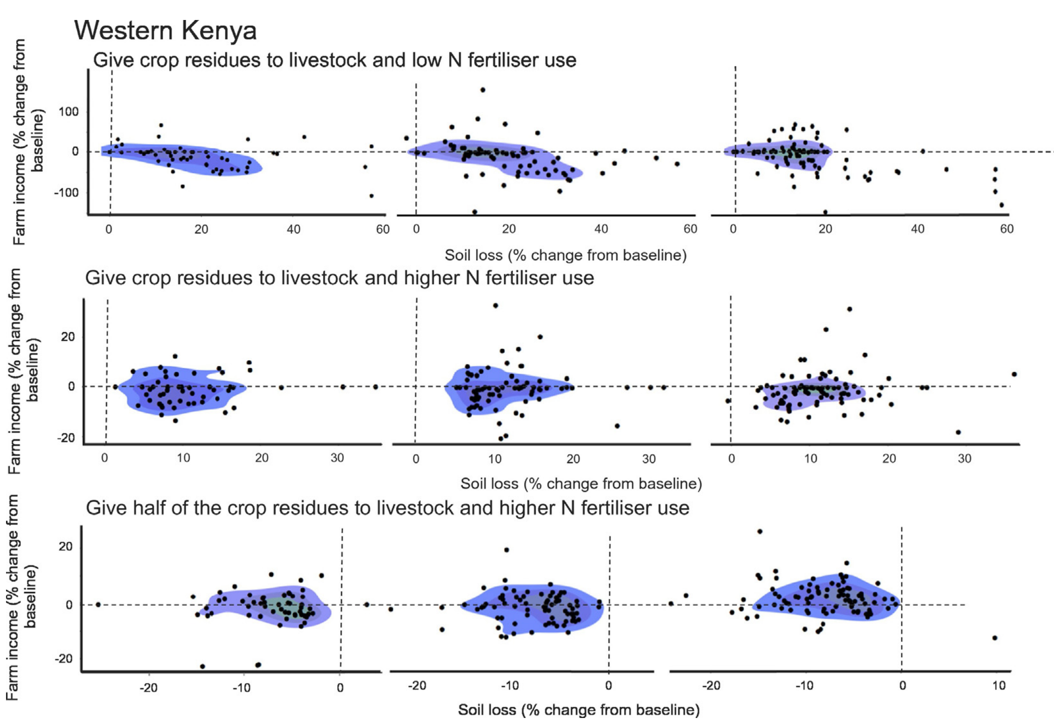

Fig. 11. Density plot i.e. the intensity of the shade indicates the density of households, of the simulated diversity of trade-offs between farm income and soil loss in Western Kenya, when all crop residues are fed to livestock under low levels of nitrogen fertilizers use (top graphs); when all crop residues are fed to livestock though an additional 40 kg N are used on the maize (middle graphs); and when only half of the crop residues are fed to livestock and an additional 40 kg N are used on the maize (lower graphs). Changes are with respect to farmers' present management as in the baseline survey. Each point in each graph represents a household.

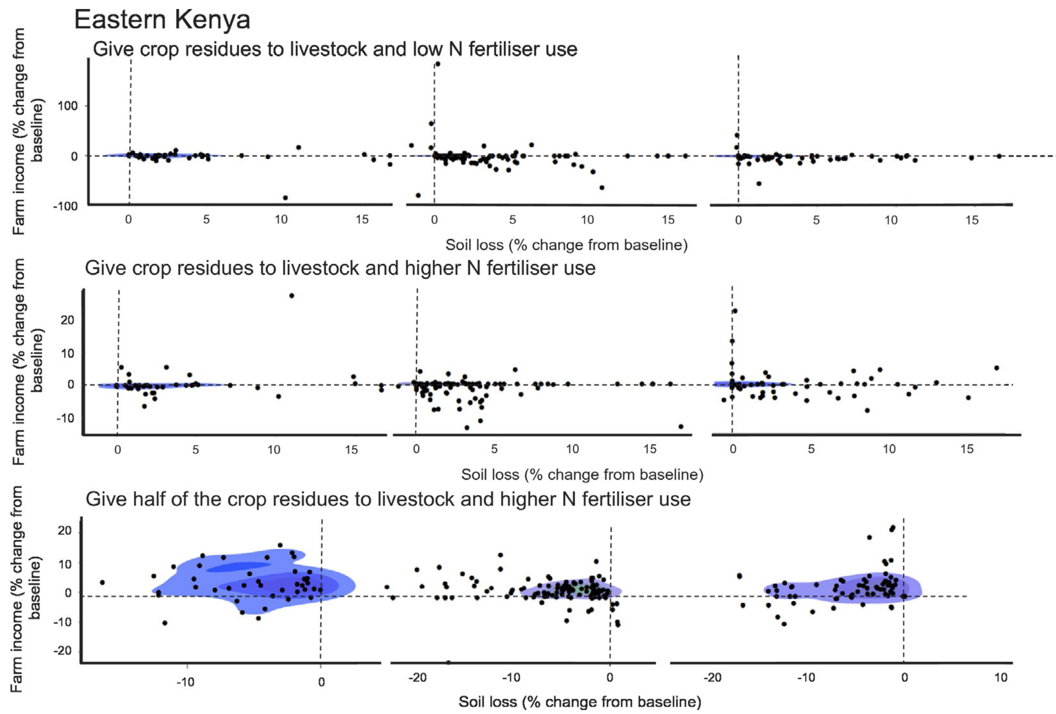

Fig. 12. Density plot i.e. the intensity of the shade indicates the density of households, of the simulated diversity of trade-offs between farm income and soil loss in Eastern Kenya, when all crop residues are fed to livestock under low levels of nitrogen fertilizers use (top graphs); when all crop residues are fed to livestock though an additional 40 kg N are used on the maize (middle graphs); and when only half of the crop residues are fed to livestock and an additional 40 kg N are used on the maize (lower graphs). Changes are with respect to farmers' present management as in the baseline survey. Each point in each graph represents a household.

total value of household assets, number of adult equivalents, number of sheep and goats, and the age and sex of the head of the household (Table 2). Most of the differences between household typologies in Tables 1 and 2 were statistically significant ($p < 0.05$), showing large differences between the classified groups.

In Western Kenya the poorest households (Typology W2 or "*Very poor*", 23.1% of the sampled population), had the smallest farm sizes, fewest head of cattle and production assets, the poorest levels of education, used the smallest amounts of fertilizers and manure and produced the least amounts of maize and legumes. They also had the lowest farm income; that mostly originated from off farm sources (75%) - as the income from the sale of animal products, maize or legume production was small (Table 1). In this group, a significant proportion the heads of the household (22.2%) was a female. The intermediate group (Typology W1 or "*Poor*", 39.8% of the sampled population) had intermediate levels of assets i.e. land and cattle; used fertilizers and manure and achieved higher levels of production, a proportion of which was sold in the market. They had a higher income, half of which originated from on-farm activities (Table 1). The wealthier "Better off" group of households (Typology W3 or "*Better off*", 37.1% of the sampled population) owned the largest farms and herds of cattle, had better levels of education, and the least dependence on sources of off-farm income. Most of household heads in this group were male.

In Eastern Kenya the poorest households (Typology E2 or "*Very poor*", 19.1% of the sampled population), had the smallest value of household assets, labour availability, and in a large proportion of the households the head was a female (27.1). Farm sizes were also the smallest, with few head of cattle and the household income was a 10th of the median income of the better off group. The intermediate and largest group (Typology E1 or "*Poor*", 55.4% of the sampled population) had intermediate size of land; used the largest amounts of fertilizers and manure and achieved higher levels of production, a proportion of which was sold in the market. More than half of the income in these households (61%) originated from on farm activities (Table 2). The wealthier "Better off" group of households (Typology E3 or "*Better off*", 25.5% of the sampled population) owned the largest farms, and most of their income (90%) was generated by on farm activities. No female heads of household was present in this group.

The diversity of household socio-economic characteristics across Western and Eastern Kenya is shown graphically in a heat map (Fig. 7) where the darkest colour represents the highest relative values for different household characteristics across all the typologies. Figure 3 shows that the *Better off* farms had higher levels of endowment (available resources) and performance (production and income) across most of the indicators, while the *Very poor* groups were consistently poor across all the socio-economic dimensions analysed here. The intermediate groups (*Poor*) showed more diversity in terms of resource availability and levels of performance.

3.3. Simulating households

Simulating individual farms showed a large diversity of responses for households having contrasting availability of resources, diversity of farm activities (cropping cereals, legumes, livestock etc.), contrasting managements, use of external inputs and manure, and consequently levels of performance and sensitivity to the simulated changes (Figs. 4–6). Cumulative income over five year simulation intervals of two randomly selected households provides an example of differences between regions, the baseline i.e. no change, and intensified simulated scenarios (Fig. 8), Disaggregating changes in maize production in Western and Eastern Kenya by household typology still, showed a large diversity of responses i.e. benefits and trade-offs from alternative scenarios across the different farm types (Figs. 9 and 10, and Tables S1 to S3). For Western Kenya feeding the crop residues to the livestock, at the presently low levels of fertilizers use, is likely to impact more severely the most vulnerable *Very poor* and *Poor* groups (about 63% of the sampled population) (top graphs in Fig. 9). If farmers would add an additional 40 kg N ha^{-1} to whatever rate of N use is indicated in the baseline survey data, the loss in maize production would be completely reversed, though still the soil loss would remain significant (middle graphs in

Fig. 9). However if only half of the available crop residues would be used to feed the livestock (and half kept as a soil mulch), soil loss would be reduced between 10 and 15%. Similar responses, though smaller differences between household types were found in Eastern Kenya (Fig. 10). In Eastern Kenya changes in erosion were much smaller given the dryer of the environment, though still partitioning the available crop residues between its use as mulch and feedstock and using small additional amounts of fertilizers had a small positive effect both in household maize production and erosion reduction.

In Western Kenya, feeding crop residues to livestock, at low levels of N supply, reduced the household income particularly among the poorer households (Fig. 11). Feeding crop residues to livestock at low levels of N use made more people poorer in Western Kenya, and more people richer in Eastern Kenya (Table A.1). Soil losses were halved with higher levels of N supply, though only the better off famers increased incomes and reduced soil losses when half of the crop residues were fed to the livestock and N supply was increased (lower graphs in Fig. 11, and Table A.1). In Eastern Kenya the benefits of using half of the available crop residues as mulch and half as feedstock produced larger benefits among the poorest farmers though only with additional levels of N fertilizers were used (Fig. 12 and Table A.1).

4. Discussion

The use of crop residues as mulches is a well-known and effective method to reduce soil loss and increase rainfall infiltration. However, in situations where livestock feedstock is limiting, poorly resourced farmers from SSA will allocate crop residues to the most profitable or socially preferable activity, i.e. usually to prevent herd losses. In order to manage the trade-off, options might include increasing the availability of biomass by fertilizing the maize crop, growing forages, and sharing the limited crop residues between protecting the soil and feeding the livestock. By simulating all the farms from a household survey ($n = 613$), we showed that, (i) the diversity of responses in benefits and trade-offs across regions, within regions, and within similar households from each region remained large; and (ii) that the magnitude of the benefits from increases in the use of fertilizers and changes in the allocation of crop residues between farm objectives are likely to be small. The observed diversity in households levels of endowment has been reported before (Tittonell et al., 2007), the same with the finding that increasing the productivity of the maize crop e.g. using nitrogen fertilizers, alleviates the biomass trade-offs was expected (Tittonell et al., 2015). Though, the small magnitude of the benefits i.e. increased farm income was small and worrying (Fig. 11 and 12). These results are similar to those by Frelat et al. (2015) which recommended focusing on improving market access and off-farm opportunities as a better strategy to increase food security in SSA. This means that increasing food availability in smallholder farming in Kenya is likely to remain a major challenge if the focus of donors and research for development is solely around increases in farm productivity. Our results question the value of investment programs and institutionalization of policies that propose simple technological solutions to complex and dynamic problems. Probably more drastic transformations in the farming system are required (Tui et al., 2015), interventions having a greater focus on improving the diversity of farmers' livelihoods (van Ginkel et al., 2013), that enhance both on-farm, and off-farm (Kristjanson et al., 2009) sources of income, and that improve market access and participation (Frelat et al., 2015; Dorward, 2006).

Here we have also shown how APSFarm-LivSim, a comprehensive and dynamic whole farm simulation model, can be used to quantify benefits and trade-offs of alternative management strategies by linking "big data" with "big modelling". To our knowledge, this is the first study that uses detailed dynamic household modelling across a population of hundreds of smallholder farmer households, to quantify benefits and trade-offs from alternative management strategies. Our results show that benefits and trade-offs from "mulching or munching" are likely to differ not only across agro-ecologies, but also within agro-ecologies, and within agro-ecologies between and within "homogeneous" groups of households or typologies (Tables A.1–A.3 in the Supplementary information). This is a challenge when in Africa simplicity and pragmatism are required to quickly scale out more productive and resilient practices across hundreds of thousands households. This could be achieved "distilling generalizable patterns" (Giller et al., 2011; Tittonell et al., 2015) to inform recommendations for practice change or policy development. However, here we showed that the magnitude of the diversity of household responses and trade-offs present wouldn't make this task any easy; particularly, if the traditional "representative farmer" approach is taken, as all of these studies have done up to now. Here we argue that traditional approaches are likely to lead to misleading results and an over-estimation of adoption potentials and/or benefits of interventions, and propose that more integrative systems analyses that provide situation-specific information on practices and marry biophysical, socio-economic and market constraints are required. For example, Table A.1 shows that even within the more homogeneous groups of households i.e. within typologies, only ca. 60% and 70% of the household showed positive changes in household income as a result of the improved management of crop residues and the use of N fertilisers, in Western and Eastern Kenya, respectively.

The question on whether "to mulch or to munch" crop residues has been dealt with, very recently and in great detail (Tittonell et al., 2015). Eleven articles included works from Southern Africa (Zimbabwe), Western Africa (Burkina Faso), Northern Africa (Morocco), Mesoamerica (Mexico), and Eastern Africa (Madagascar, Kenya and Ethiopia). Most studies included analyses based on the description or simulation of case studies identified during interviews or surveys usually over a very small number of households. In general, key learnings coincided with our observations and those in other recent publications (Frelat et al., 2015). For the particular case of Kenya, it is clear that at present farmers make extensive use of crop residues as a source of feedstock (Figs. 4 and 5), though this hardly means that farmers prioritize livestock feeding over improving the resource base (Castellanos-Navarrete et al., 2015; Tittonell et al., 2015), as most farmers might not be aware of the benefits of soil mulching for erosion control (Roxburgh and Rodriguez, 2016). Particularly in the case of the group of "very poor" farmers knowledge gaps on simple agronomic principles such as suitable plant populations, row spacing and sowing dates have been found to be the source of large yield gaps ca. 120% from 309 kg/ha to 682 kg/ha, among 17% of the population of farmers in Mozambique (Roxburgh and Rodriguez, 2016). Keeping crop residues as mulches significantly reduced soil loss, but also reduced farmers' availability to feedstock, particularly in the drier Eastern Kenyan sites. On the contrary feeding livestock the crop residues increased soil erosion, particularly in the wetter Western Kenyan sites. Large scattering of responses (households) was also present, reflecting the large diversity of simulated agro-ecological indicators, mostly farm size, livestock assets, soil fertility and climate variability, field and farm management, and crop diversity.

In Zimbabwe, multidisciplinary studies over 120 households (Tui et al., 2015) found that conservation agriculture practices are unlikely to be economically viable without the availability of fertilizer subsidies. Similarly, even when fertilizers would be available and used, reductions of poverty levels would be rather limited. These results are not too different from our findings, that the use of small amounts of fertilizers would still have very small effects on maize production (Fig. 9), and food availability (Frelat et al., 2015).

Advances in integrative analysis tools and their interaction with comprehensive household surveys data bases (Frelat et al., 2015), offers the potential to model individual households, household to household interactions, and their collective interactions with markets (An, 2012; Li et al., 2015; Valbuena et al., 2010). Dynamically modelling the interactions between households, between households and markets in the informal economies that dominate most Sub Saharan agricultural systems (Dorward and Chirwa, 2011; Dorward, 2006), is likely1 to help us step up from a sole focus of sustainable intensification of agriculture into the quantification of benefits and trade-offs from market innovations into the development of informal economies. It appears critical the need to encourage the formation of multidisciplinary teams in trans-disciplinary research approaches (Giller et al., 2015; Rodriguez and Sadras, 2011; van Ginkel et al., 2013).

Our results suggest that due to the large diversity in farmers' levels of resource endowment and sources of livelihoods better targeted technology recommendations and system changes will be required to suit the large diversity of constraints and opportunities across regions, villages and even within villages. The integration of socio-economic and biophysical approaches provides an opportunity to quantify benefits and trade-offs from alternative interventions and farming systems designs to support agriculture development programs.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.agsy.2017.01.010.

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