Agronomy for Sustainable Development (2022) 42:41
https://doi.org/10.1007/s13593-022-00768-6

REVIEW ARTICLE

Indifferent to difference? Understanding the unequal impacts of farming technologies among smallholders. A review

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Accepted: 1 March 2022

Abstract

With many of the world's poor engaged in agriculture, agricultural development programmes often aim to improve livelihoods through improved farming practices. Research on the impacts of agricultural technology interventions is dominated by comparisons of adopters and non-adopters. By contrast, in this literature study, we critically review how technology evaluation studies assess differentiated impacts in smallholder farming communities. We searched systematically for studies which present agricultural technology impacts disaggregated for poor and relatively better-off users (adopters). The major findings of our systematic review are as follows: (1) The number of studies that assessed impact differentiation was startlingly small: we were able to identify only 85, among which only 24 presented empirical findings. (2) These studies confirm an expected trend: absolute benefits are larger for the better-off, and large relative benefits among the poor are mostly due to meagre baseline performance. (3) Households are primarily considered as independent entities, rather than as connected with others directly or indirectly, via markets or common resource pools. (4) Explanations for impact differentiation are mainly sought in existing distributions of structural household characteristics. We collated the explanations provided in the selected studies across a nested hierarchy: the field, the farm or household, and households interacting at the farming system level. We also consider impact differentiation over time. With this, we provide a structured overview of potential drivers of differentiation, to guide future research for development towards explicitly recognizing the poor among the poor, acknowledging unequal impacts, aiming to avoid negative consequences, and mitigating them where they occur.

Keywords Research for development · Technology adoption · Evaluation · Distribution · Differentiation · Inequality · Inequity · Intervention

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Contents

Published online: 16 May 2022

1 Introduction

In 2015, the United Nations set an Agenda for Sustainable Development with ambitious goals: Zero Poverty and Zero Hunger. The 193 member states of the United Nations pledged to ensure that "no one will be left behind", and to "endeavour to reach the furthest behind first" (United Nations 2015). On the grounds that 60% of the world's poor work in agriculture (Olinto et al. 2013), many strategies to alleviate hunger and poverty revolve around improved farming. Agricultural research for development has generated abundant technological options to increase the quantity, quality, or efficiency of agricultural production, and these technologies have been widely disseminated among poor, rural populations. If we want to leave no one behind in progress out of poverty, we need to understand in what ways technologies reduce, perpetuate, or exacerbate existing social inequalities.

Technology uptake among resource-poor farmers always varies because people differ in terms of interest and capacity to implement a technology. There is a rich body of literature on the characteristics of those who do and do not adopt recommended technologies. Wealth and the use of improved technologies are often associated, but it is generally not possible to discern whether wealth is a result or rather an enabler of technology use (Mendola 2007; Alwang et al. 2019). Technology evaluation studies commonly compare livelihood indicators either among technology adopters and non-adopters, or for the same household before and after adopting a technology. Adopters are usually taken to be those who use the technology when the assessment takes place, or who have done so for at least a defined number of seasons. It is then concluded whether and by how much a technology could improve production and/or livelihoods—if adopted. Technology evaluation studies commonly present impacts in terms of averages (as was also noted for instance by Ainembabazi et al. 2018). Deviations from a mean may show that impacts vary, but do not reveal who benefits more and who benefits less. In other words, while variation in technology uptake is studied, diverse impacts at farm or household level receive scant attention (Ainembabazi et al. 2018; Glover et al. 2019).

This study critically reviews technology evaluation studies in terms of their assessment of differentiated impacts on livelihoods. Our specific research questions are the following:

(1) How are unequal impacts of technologies evaluated?
(2) How do the absolute and relative impacts of technologies on livelihoods compare among poor and better-off technology users?
(3) What factors are associated with the differentiated impacts of technology interventions in smallholder agriculture?

Through a systematic literature search, we identified agricultural technology evaluation studies that present impacts disaggregated for poor and better-off technology adopters or users. From the selected studies, we extracted how the absolute and relative impacts on the poor and better-off compared, and gathered the explanations provided for such differentiated impacts. We categorized and systematically discussed these explanations as part of a nested hierarchy—that is at the level of the field, the farm and household, and the farming system, and on a time scale—aiming to support better detection of unequal impacts in future technology evaluations.

Technology interventions are often exclusionary—as they are location specific, targeted at specific beneficiaries, or require resources in order to be taken up—and we are aware that the poorest were likely (unintentionally) excluded from interventions. Since our aim is to understand differentiated impacts of technology interventions, our review is limited to those included in a project intervention and those who actually use the technology (e.g. Fig. 1). Our approach therefore differs from (reviews of) impact assessments of technology interventions, such as those by Takahashi et al. (2020) and Muzari et al. (2012), that focus on the scale of impact achieved, and the factors influencing technology diffusion and adoption.

Below, we explain in more detail how we selected studies for our review (Section 2). In Section 3, we reveal the insights from the search process about the scope of empirical and modelling research on agricultural technologies (research question 1). We focus on the selected empirical studies in Section 4, and provide an overview of their findings on impacts among the poor and better-off rural households (research question 2). In Section 5, we discuss the explanations given for impact differentiation, at the level of the field, the farm and household, the farming system, as well as over time (research question 3). In Section 6, we provide suggestions for future research to investigate impact differentiation.

2 Systematic literature search

A systematic literature review was executed following the widely used PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework of Moher et al. (2010).

Fig. 1 Beneficiaries and researchers of an agricultural development project discuss the distribution of benefits of legume technologies in northern Ghana (photograph by Eva Thuijsman, 2019).

2.1 Search strategy

Our objective was to identify and understand differentiated impacts of agricultural technology interventions, so we searched for studies that met the following criteria:

(1) there was a distinct intervention event (or multiple);
(2) the intervention involved an agricultural technology;
(3) impact indicators relating to production (e.g. yield) or livelihoods were assessed (e.g. income and kcal available), empirically or using a model;
(4) impacts were presented for poorer and better-off technology users, per category or along a distribution (e.g. income levels, farm sizes, caste);
(5) the study was executed in a country considered to be a developing country, following the classification by the United Nations Development Programme (hdr.undp.org, 2020). Although technology impact assessments regularly appear in project reports (grey literature), our search was limited to peer-reviewed journal articles in English. Peer-review is taken as an added layer of confidence on the rigour and independence of the research and its methodologies.

Key terms, phrases, and synonyms were gathered from relevant papers after a scoping search in Google Scholar. With these, two standardized queries were developed for a systematic literature search in the bibliographic CAB Abstracts database. This database was chosen because it covers a wide range of journals in the fields of agronomy, rural development, and economics. Our initial search (Supplementary Materials 1) prompted 3507 journal articles in English, in September 2020. In response to reviewer comments, we executed another search in August 2021 (Table 1), which added another 1787 unique studies to screen for meeting our eligibility criteria.

2.2 Study selection and exclusion

The search results were first narrowed down on the basis of country: studies that did *not* take place in developing countries (989) were excluded. The remaining 4305 studies were examined in detail. Titles, abstracts, and (when necessary) full-length articles were screened to ensure the eligibility criteria were met. The vast majority of the queried papers was excluded, for reasons provided in Table 2 (reasons for exclusion per paper can be found in Supplementary Materials 2). Since we focus on differentiated impacts among technology adopters, studies that presented only average impacts (no household categories or distributions) were excluded, even if the technology was tested in a poor population and (potentially) beneficial for the poor. Similarly, studies that only focused on determinants of technology adoption were excluded. Only 85 studies met all of the selection criteria. These 85 studies took place in 36 countries.

Table 1 Query used for a systematic literature search in CAB Abstracts in August 2021. The rows show which terms and synonyms address relevant subjects. All rows together form the full query, which was used in a single search. adj4 = terms are next to each other, in any order, with up to three words in between. An asterisk is a replacement for any ending of the respective term. A dollar sign represents zero or one character. A question mark represents one character. The search was not restricted with regard to date of publication.

Subject	Query			
Agriculture			(agricultur* or agronom* or produc* or cultivat* or farming)	
Welfare distribution	and(	(	(quantile$ or percentile$ or class* or characteri?ation or characteri?ed or category or categories or categori?ation or typology or typologies or type$ or rich* or better-off or wealth* or poorest or caste$ or endow* or resource-endow* or stratum or strata or stratified or stratification or cluster*) adj4 (farm* or smallhold* or household*)	)
		or(	(impact or benefit$ or outcome$) adj4 (differentia* or distribution* or disaggregat* or heterogene* or inequalit* or equalit* or unequal or equal or inequit* or equit* or quantile$ or percentile$)	))
Livelihood indicators	and(	(	(food or nutrition) adj4 (secur* or sufficien* or availab*)	)
		or(	(poverty or risk$ or hunger) adj4 (alleviat* or reduc* or eradic* or mitigat*)	)
		or(	(labo?r or investment$ or cost$ or distribut*) adj4 (return* or response$)	)
		or(	gross adj4 (margin or returns)	)
		or	livelihood* or resilien* or income or yield or (gross margin) or profit* or welfare	)
Impact study	and(		impact* or contribut* or benefit* or technol* or intervention* or consequence* or evaluat* or RCT or "randomi?ed control trial" or "difference in difference$" or "difference-in-difference$" or "panel data" or "time series"	)
Database search			.mp [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes]	

2.3 Data extraction

From the 85 selected studies, we extracted information on study design, agricultural technology, sampling method, welfare classification strategy, relevant assumptions in simulation studies (such as fixed prices, freedom to re-allocate land, labour and capital), the assessed livelihood impact indicators, and the explanations provided for any differences in impacts among poorer and better-off beneficiaries. Not all of the selected studies referred to "impact" per se, but the technologies were proposed as means to improve the livelihoods of beneficiaries, and measured results (a change in yield or income for instance) were framed accordingly. In this paper, for convenience, we use the term "impact" to refer to changes in livelihood indicators that are at least partly attributed to a tested technology.

In the selected studies, we identified who were the poorer and the better-off among the intended beneficiaries, according to the categorisation used in that study (e.g. income level, farm size, resource endowment, caste, or combinations of these). We then recorded for the poor and the better-off what was the direction of technology impact: i.e. whether an impact indicator value increased, decreased, or remained the same when a technology was used, compared with the baseline or control used in the study. We also extracted whether absolute and relative impacts (a change in a livelihood indicator from a baseline value) were larger, smaller, or similar among the poor compared to the better-off. Absolute impacts could be derived

Table 2 Number of studies identified with the search, excluded (negative values) and remaining. A single reason was recorded even if there were multiple reasons for excluding the paper.

# studies	
Search outputs (English, peer-reviewed)	5294
Other topic (e.g. no agri. tech./no impact assessed/other topic such as medicine)	−2284
No agricultural technology intervention (e.g. subsidies, descriptions of farming systems)	−1032
Country (no developing country according to the UNDP classification)	−989
No household poverty categorisation/distribution (e.g. impact assessment was not disaggregated)	−488
No impact assessed (e.g. studies on reasons for [non-]adoption)	−300
Broad trends (e.g. discussions of the interregional effects of the Green Revolution, or gradual tech. diffusion)	−46
Publication type (slipped through CAB Abstracts filter for journal publications)	−26
No clear intervention (e.g. technology not specified)	−25
No access to the full publication	−11
Quality (insufficient to derive conclusions of impacts disaggregated for poorer and better-off technology user)	−8
Total included	85

from relative impacts and vice versa, but this was only done when a study provided sufficient information to derive this with certainty. The directions and comparative levels of impacts were derived from tables, figures, and text, and also recorded when no statistical tests for impact levels or differences were presented. We gathered this information for every technology and every impact indicator presented, for both a poor and a better-off category of beneficiaries. When more than two welfare categories of households were described, the poorest and the wealthiest were compared. Explanations provided for differences in impacts between poor and better-off technology users were recorded, taking care to distinguish statements supported with or without quantified evidence.

3 Assessments of differentiated impacts of agricultural technology

Our systematic search in the peer-reviewed literature revealed a paucity of empirical assessments of differentiated impacts among technology adopters: only 24 of the 85 identified studies were empirical evaluations of technologies' impacts on different categories of farming households. The other 61 studies used models to simulate possible differentiated impacts of alternative technologies.

Using models to assess technology impacts can be appealing: First, such ex ante assessments could inform the design and implementation of technology interventions. Second, with modelling, common methodological challenges involved in empirical impact studies can be handled more easily: through simulation, treatment effects can be isolated, confounding factors controlled, and hypothetical scenarios explored. In addition, modelling allows for explorations of intra- and inter-farm resource re-allocations and technology use, with an optimisation objective. The identified model-based studies usually built on empirical data from existing households (such as farm, household and herd sizes, incomes, current crop areas and yields) but tended to reduce some of the variation—for instance by assuming median crop area proportions for all households (e.g. Leonardo et al. 2018; Michalscheck et al. 2018).

The empirical studies of differentiated impacts of technologies could be categorized into three types of assessments (Table 3). A first type of study measured production in the fields of intended beneficiaries before and after technology uptake (at different degrees of researcher control), and combined this with household surveys to learn about household characteristics (Men et al. 2006; Zingore et al. 2008; Mtambanengwe and Mapfumo 2009; Ariza-Montobbio and Lele 2010; Kamanga et al. 2010; Zhang et al. 2015; Van Vugt et al. 2018; Franke et al. 2019; Jindo et al. 2020). In these studies, impacts were often assessed directly upon technology uptake, or within the first three seasons. A second type of empirical study built on classic adoption studies and prominently applied econometric tools to household survey data to assess ex post the contribution of the technology to the wealth of adopting households, by statistically identifying non-adopter counterfactuals and correcting for unobservables and selection biases (Ainembabazi et al. 2018; Euler et al. 2017; Krishna et al. 2017; Mendola 2007; Olagunju et al. 2020; Verkaart et al. 2017). In these studies, the time between technology intervention and impact assessment ranged between 1 and more than 20 years. A third type of empirical study captured impacts through the reports of study participants and addressed impacts explicitly, with no aim to quantify the isolated effects of a technology. Type 3 studies included qualitative methods (e.g. interviews with open-ended questions, participant observation; Fischer and Hajdu 2015; Tadesse et al. 2017) and (repeated) quantitative, structured surveys (Bhanja 1971; Swenson 1976; Bennett et al. 2004; Haneishi et al. 2013; Mazid et al. 2013; Kidoido and Korir 2015; Maggio and Asfaw 2020). Type 3 studies could cover different time periods between intervention and impact assessment.

Table 3 Summary of the features of studies on technology interventions, which presented impacts disaggregated for the poor and relatively better-off among the adopters—identified through a systematic search of peer-reviewed literature. [1]Field/herd: indicator measured in a field or herd (e.g. yield per ha, milk production per tropical livestock unit). [2]Field-to-household: indicator measured in a field, then translated to a household-level indicator (e.g. crop income derived from *yield * farm size * median price*). [3]Household: indicator measured at household level (e.g. total crop income asked in a survey, proportion of income from farming). [4]Household-to-population: indicator measured at household level, then translated to a population-level indicator/index (e.g. Gini index, percentage of food-secure households).

Percentage of 85 selected studies

Study type		Indicator type		Measurement level		Main basis for welfare categorisation	
Type 1 empirical	11%	Financial	84%	Field/herd[1]	21%	Farm/herd size	40%
Type 2 empirical	7%	Yield/production	25%	Field-to-household[2]	54%	Farm/herd size & capital	20%
Type 3 empirical	11%	Food security	19%	Household[3]	32%	Capital (income, assets)	18%
Model	72%	Labour	8%	Household-to-population[4]	13%	Mix: resources & other	9%
		Other	6%			Other: e.g. maize area, off-farm employment, cattle breed owned.	13%

Both model-based and empirical studies most commonly constructed wealth classes a priori, that is before technology impacts were modelled or measured, except for type 2 and type 3 empirical studies that may construct these categories ex post. Wealth categories or distributions were usually based on expert opinion or statistical means (using principal component analysis and clustering methods). "Structural" farm characteristics such as total farm area and herd size usually constituted the basis of the categorisation.

Financial indicators (e.g. value of produce, cost/benefit ratios) were most prominent in impact assessments, followed by food security (e.g. food self-sufficiency or number of months food secure), yield, labour burden, and production risk indicators. Rather than the types of indicators used, it was the level at which indicators were actually measured—and at what level estimated values are used—that distinguished differentiated impacts studies. For instance, model-based assessments and type 1 empirical studies predominantly used field-level measurements of technology effects as a starting point of analysis. Directly measured field-level indicators (e.g. crop yields) were then used to estimate higher-level indicators such as household income, by multiplying the measured yields by a farm area and a median price. The use of household-level indicators in studies may thus obscure the fact that such higher-level indicators are not actually measured, but researcher-constructed estimations.

Rather than aggregating field-level effects into (researcher-constructed) estimations of household level impacts, type 2 empirical studies measured such household-level indicators (e.g. reported total income) and then assessed how strongly technologies contributed to changes in these indicators among technology users (as compared to non-users). Type 3 empirical studies tended to combine field-level indicators (e.g. reported yields), household-level indicators (e.g. reported incomes), and population-level indicators (e.g. Gini index, poverty rates) to assess impacts. Such differences in measuring methods and starting level of analysis yielded different strengths and limitations for each type of study. For instance, whereas type 1 empirical studies that directly measure field-level indicators (production, yield) are very suitable for assessing differences in field-level management between the poor and the better-off, such studies may be less useful in accurately uncovering inequalities among households. Type 2 studies, on the other hand, are more likely to accurately distinguish inequalities among households and may be able to capture the contributions of technology to such inequalities. Yet, just as model-based studies, type 2 studies are less suitable for unpacking the (social) mechanisms that caused impact differentiation. Type 3 studies may be most likely to be able to capture such mechanisms, but were not always aimed at doing so in our selection.

In the next section, we focus on empirical assessments (types 1, 2, and 3) only as we summarize their findings on differentiated impacts among poor and better-off households. Insights from empirical and model studies are included both in Section 5, where we discuss factors associated with impact differentiation.

4 Empirical assessments of impact differentiation

We found a startlingly small number of empirical studies—just 24—that present the impacts of technology interventions as distributions or per welfare class. For most of the indicators measured, the better-off were able to benefit more, showing that agricultural technologies can increase social inequality among their users. We discuss the differentiated impacts found in empirical studies below, and a complete, tabulated overview of comparative impacts can be found in Supplementary Materials 3.

While the direction of impacts (favourable, neutral, unfavourable) was usually the same for poor and better-off households—the magnitude of these impacts was not. The absolute impacts derived from a technology were almost always larger for the better-off. Relative impacts were frequently larger for poorer households. Their low baseline values are one explanation for this. One example is provided by Olagunju et al. (2020) in Nigerian study sites. Here, the adoption of drought-tolerant maize varieties raised per capita food expenditures by 80% at the bottom 15th wealth quantile, versus 27% at the 85th wealth quantile—corresponding to a rise in expenditure of 7,020 and 15,401 Nigerian Naira, respectively. Much larger relative impacts among the poorer were also found, for instance, by Mtambanengwe and Mapfumo (2009), who tested legume technologies in Zimbabwe. The soyabean yield response to fertilised maize in the previous season was > 500% among the poor, versus 30% among the better-off. Absolute soyabean yields were less than 2 t ha^{-1} for the better-off and less than 0.8 t ha^{-1} for the poor. Zhang et al. (2015) tested a technology that was purely based on saving resources, in a region in northwest China where over-application of nitrogen fertiliser was common. A reduction in the use of nitrogen fertiliser of 30% and even 50% led to greater relative savings among the poor, and greater absolute savings among the better-off, without yield penalties.

In a few cases, poorer households benefitted more than the better-off in absolute terms. Haneishi et al. (2013) for instance found that poorer farmers in Uganda allocated a larger proportion of their land and more labour inputs to a new rice variety than the better-off. Kamanga et al. (2010) found larger, favourable reductions in costs for poorer farmers upon the introduction of various legume technologies in Malawi—but also concluded that these technologies were not suitable for the poor after all, because poor participants did not want to sacrifice their maize area for another crop. Ainembabazi et al. (2018) analysed panel data of intervention sites in Burundi, Eastern DR Congo, and Rwanda, and found that poor households benefitted more from the adoption of improved varieties (legumes, maize, banana, or cassava) than the better-off, expressed in their welfare ratios (a household's spending ability relative to a poverty line of $1.25).

Several studies measured similar impacts among poor and better-off adopters. Jindo et al. (2020) described the impact of fertiliser use on maize, for Kenyan farmers of different welfare categories. Poorer and better-off farmers obtained similar yields, at similar costs, and did so on similar areas. Men et al. (2006) found that the pig diets tested in Vietnam did not differ significantly from the baseline diets in terms of pig weight gain, costs, and financial benefits, among the different household welfare categories. The broad panel study of Ainembabazi et al. (2018) showed that crop and natural resource management technologies (broadly defined) had similar effects on household spending ability relative to the poverty line, among the poorer and the better-off.

Ariza-Montobbio and Lele (2010) provide an example of unfavourable impacts for the poor and better-off both, upon the introduction of jatropha in an Indian intervention site. Jatropha had been promoted as a crop that could be pro-poor and tolerant to water scarcity, but adoption adversely affected food security as it replaced the area cropped with groundnut. In this region, groundnuts were an important source of income, food, fodder, and an accepted form of payment for labour. Because the poorer farmers devoted a larger proportion of their land to jatropha (75%, amounting to 0.6 ha) compared to the better-off farmers with larger farms (35%, amounting to 1.6 ha), the negative impacts on food security were larger for the poor.

Opposite impacts were observed by Kamanga et al. (2010) with intercropping and rotation in Malawi: some maize/legume technologies favourably reduced risk (chance of a low maize yield) for the better-off, while increasing that risk for the poor. The same study provided the only example we could identify of a technology that had a positive impact on poor and a negative impact on the better-off: an intercrop of maize and tephrosia (*Tephrosia vogelii*—a shrub legume used as green manure) without fertiliser favourably increased returns to labour costs for the poor, and reduced them for the better-off. However, yield returns to total investment were similar among both welfare categories and not advantageous compared with their respective baselines.

Maggio and Asfaw (2020) evaluated a number of technologies at once, measuring the impacts on the aggregate value of all crops per farm, among thousands of households in Malawi. For various land preparation technologies, impacts were not different among the poor and better-off. However, the adoption of legume intercropping and hybrid seed was associated with an increase in aggregate yields for poorer households and not for better-off households—and the effects were opposite for erosion control bunds and organic fertiliser use. Maggio and Asfaw (2020) explain only the latter trend, suggesting that poorer farmers were less likely to have access to the most appropriate tools to prepare soil erosion control bunds or to invest enough to cover the entire field with organic fertiliser.

In summary, most measured impacts were positive for the poor and the better-off adopters, but in absolute terms, the poor derived smaller benefits from technology interventions in agriculture than the better-off. In relative terms, benefits were frequently greater among the poor, as they started out from a very low baseline value.

5 Factors associated with impact differentiation of technology interventions

From the identified empirical and model studies, we extracted factors that were associated with differentiated impacts of technology interventions among poorer and better-off farming households. These studies were focused more on capturing impact differences than on explaining them: potential drivers of impact differentiation featured more often in discussion sections than in results sections of published papers, or were not discussed at all. Perhaps differentiated impacts were seen as largely self-explanatory: when impact differences are found among degrees of welfare, that must be *because* of the differences in welfare. Such apparent tautological explanations of differentiated impact are not necessarily wrong, but they do not contribute to understanding what it is about the poor and the better-off that makes a technology more or less beneficial for them, or what role a technology can play in changing social inequalities.

In the following sub-sections, we discuss the factors mentioned in the studies that also attempt to explain impact differentiation. We collated the measured, modelled, and suggested potential drivers of impact differentiation and categorized these by their level or (time)scale of operation: the field, the farm and household, the farming system, and over time (Fig. 2).

5.1 Field level

We focus here on impact differentiation due to differences among the poor and better-off in terms of technology implementation, field management, and soil fertility. These factors operate at field-level, even if they are expressions of household-level decisions and resource availability.

One of the reasons for variation in impacts is that farmers do not implement the technology in exactly the same way. In on-farm trials, farm management is not fully controlled. A technology may be specified (e.g. a recommended variety and a particular fertiliser rate) while other aspects of farm

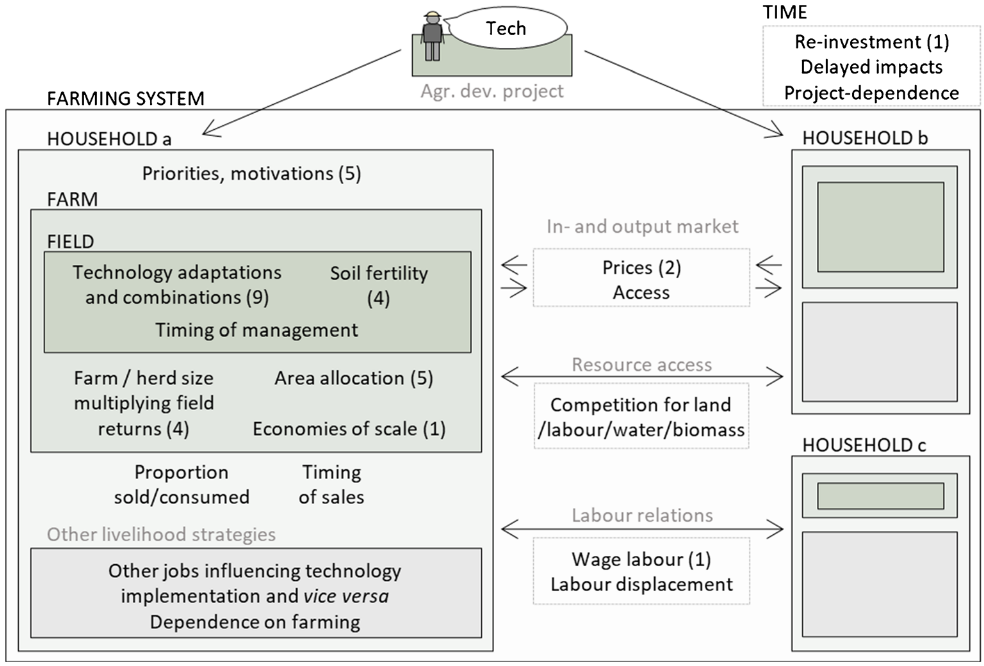

Fig. 2 Schematic representation of a farming system where a technology is introduced, with indication of factors driving differentiated technology impacts. Within the farming system are rural households whose livelihoods are derived from their own farm (consisting of fields) and other livelihood strategies. Households can interact with each other directly (employment and resource exchange) or indirectly (via markets). Per hierarchical level, the factors displayed are the ones associated with differentiated technology impacts among the households. Values show how many papers provided empirical evidence of that association. For example, nine empirical studies showed that different technology adaptations and combinations by the poor and better-off led to impact differentiation among them. Factors without a value were suggested by authors of the systematically identified empirical and model studies as possible explanations.

management (e.g. soil preparation, weeding, pesticide use) are managed according to a farmer's own preference, knowledge, and capacity. How this management differs is not usually specified, whereas it can be highly variable and affects the measured impact indicator (yield). Four of the empirical studies referred to a history of relatively favourable farm management on the land of the better-off compared with the poor (with more frequent use of larger quantities of mineral fertiliser and manure) which improved soil fertility and resulted in higher productivity (Franke et al. 2019; Kamanga et al. 2010; Mtambanengwe and Mapfumo 2009; Zingore et al. 2008). Haneishi et al. (2013) provide a contrasting example on the introduction of an improved rice variety in Uganda. They observed that poorer rural households applied much larger rates of inputs (seed, fertiliser, agrochemicals, labour) per unit area, and obtained higher rice yields than the better-off. The differences in field-level management were due to household-level motivations: the better-off (larger) farmers derived a much smaller proportion of their incomes from these technologies and pursued other livelihood strategies. Besides differences in (long-term) nutrient inputs, the households' labour allocations may differ as well. It tends to be urgent or relatively lucrative for the poor to generate incomes outside their own farms—on the land of the better-off, or off-farm. This can result in delayed or substandard management of their own field and can contribute to further soil fertility and productivity differences between the fields of the poor and the better-off (Kamanga et al. 2010; Chikowo et al. 2014). By contrast, Rusinamhodzi et al. (2015) and Jindo et al. (2020) found no correlation between wealth and past farm management and soil fertility.

Knowing that not all rural households have the same investment capacity and interests, some agricultural development programmes simultaneously offer multiple technology options (such as improved varieties and/or fertiliser; e.g. Mazid et al. 2013; Tadesse et al. 2019) so that participants can select what suits them. This means that participants ultimately apply varying (combinations of) technologies in their field. When multiple technology options are introduced, the poorer rural households may try out fewer components than the better-off, because of limited resources and risk aversion. Tadesse et al. (2019) for instance found that poorer farmers tried out new potato varieties and the practices of triple tilling and weeding, while the better-off tried out some additional components such as fertiliser application and planting in ridges—and generated larger returns. Van Vugt et al. (2018) observed that better-off households tended to try out multiple technology components at once, and benefitted from synergistic combinations (e.g. inoculant and phosphorus fertiliser on soyabean), while the poorer households did not.

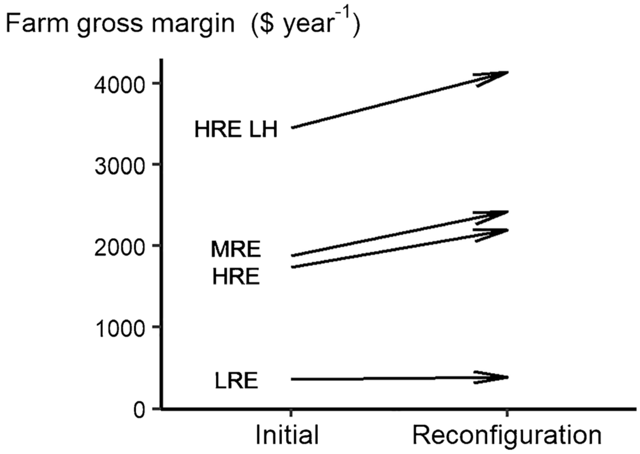

Fig. 3 Change in farm gross margin for different farm types as a result of targeted interventions in Koutiala, Mali, based on ex ante analysis. Farm types are based on resource endowment, HRE_LH: "High Resource Endowed Farms with large herds", HRE: "High Resource Endowed farms", MRE: "Medium Resource Endowed farms", LRE: "Low resource Endowed farms". Figure derived from data presented in Falconnier et al. (2017).

Rather than applying a single technology or a combination, rural households can also adapt a technology. They may decide to use smaller input rates than recommended or use lower-quality inputs (e.g. maize stalks rather than wooden sticks as staking material for beans; Franke et al. 2019). Many studies referred to limited investment capacity and high technology costs as actual or potential reasons for the poor to implement a technology in an adapted form, while the better-off are better able to adopt technologies as recommended (e.g. Ronner et al. 2018; Jindo et al. 2020)

In some cases, differences in field-level management among the poor and better-off were determined by the intervening programme. Falconnier et al. (2017), for instance, tailored technologies to what study participants wanted and could afford, in close collaboration with them. They then simulated impacts ex ante. The field-level options that were based on farmers' constraints and preferences could deliver only marginal returns for the poorer participants, while better-off households could obtain more favourable increases in gross margins (Fig. 3).

5.2 Farm and household level

Poverty is strongly associated with small landholdings, although the farms of the better-off are not always larger (e.g. Tittonell et al. 2009). Technologies may increase incomes of the near-landless, but only marginally because of the small scale of implementation (Mendola 2007). Some models explored options for the re-allocation of land, labour, and inputs within a farm, to test which configurations maximize benefits—and found wide impact disparities due to differences in scale (Leonardo et al. 2018; Michalscheck et al. 2018). In the studies of Franke et al. (2019) and Lodin et al. (2014), rural households of different welfare levels had access to similar land areas on average, but within each welfare level, female farmers had access to smaller plots. For that reason, their total production was less, despite the female farmers obtaining similar yields as the male farmers. Harris and Orr (2014) argue that many farms are simply too small to derive any significant benefit from the current technologies. They found that the median net income from improved technologies was \$558 per hectare per season in Africa and India—insufficient to exceed the poverty line for most small farmers. Using data on farm and household sizes from 11,789 households in fifteen sub-Saharan African countries, Harris (2019) calculated that even with technology returns of \$1000 per hectare per season, only 15% of rural households could potentially reach \$2 per person per day from their farm. Hence, a yield increase alone does not lift many people out of poverty when farms are small. This does not necessarily mean that small impacts are trivial, however, as a small increase in household nutrition security can be a meaningful one.

Those with access to more land can multiply benefits obtained from intensification and benefit from economies of scale, unless there are trade-offs associated with the technology—labour requirements for instance. Several researchers suggest that poor households with high family labour to land ratios are in a better position to benefit from labour-intensive technologies, than better-off households with large farms (Haneishi et al. 2013; Magombeyi et al. 2012; Niragira et al. 2015). Labour requirements are often considered in economic terms, estimating the costs of labour inputs to calculate returns—but drudgery and investments of time receive much less attention. Qualitative feedback from intended beneficiaries nevertheless prominently features concerns about labour availability, costs, and drudgery, especially among the poor (Haneishi et al. 2013; Michalscheck et al. 2018; Ronner et al. 2018).

Who benefits more or less from a technology also depends on the extent to which a household relies on farming for their livelihood. For instance, the adoption of improved chickpea varieties provided favourable income increases among poor farmers in Ethiopia, but contributed little to the wealth of the better-off who had larger and more diverse income streams (Verkaart et al. 2017). Similarly, Lopez-Ridaura et al. (2018) showed with simulations that conservation agriculture practices and a boost in milk production would have only marginal effects on the poorer farmers in their study population, simply because they derived the majority of their income from off-farm activities. In other cases, off-farm income sources enabled the better-off to invest more in farming and reap rewards (Cedamon et al. 2019; Paul et al. 2018). Yet another scenario is described by Krishna et al. (2017) and Euler et al. (2017) who studied the impacts of adopting oil palm in Indonesia, where it replaced rubber. Oil palm provided no higher profits than rubber, but it was a less labour-intensive crop. The saved labour provided an opportunity to pursue other income-generating activities and, in some cases, to expand the area under oil palm. Hence, those who benefitted most were those with the highest opportunity costs of labour and those who can access additional land for cultivation. Consequently, in these sites, oil palm adoption led to a much larger rise in total household consumption expenditure among the already better-off than among the poor.

Farming-based livelihood strategies differed as well, with the better-off households usually being more market-oriented, and the poorer households often (assumed to be) home consumption-oriented. Kamanga et al. (2010) and Homann-Kee Tui et al. (2015) found that poor farmers objected to some suggested rotations and intercropping plans, because these plans reduced the area under maize—which was their priority food crop. Ronner et al. (2018) describe a situation where the poor required cash rather than food: poor households were particularly enthusiastic about a climbing bean technology because it provided income twice a year (unlike maize and coffee) in the Ugandan highlands. These households relied on farming to provide income for school fees, whereas the better-off rural households relied on other sources. Poor and better-off households allocated land to the technology accordingly.

5.3 Farming system level

Rural households are usually examined as if they exist in isolation, with their own resource bases and enterprise patterns. Yet, they interact and exhibit varying degrees interdependency within a farming system (Giller 2013), for instance in the acquisition of resources, technology implementation, and marketing. Rural households may benefit differently from technologies as a result of (un)favourable collaboration, competition, or common resource pools—through direct and indirect relations with others. In this section, we first consider labour relations, then the limited natural resources for which different activities compete (land, water, biomass), and lastly interactions via markets.

New technologies are likely to change the labour requirements for production, and hence the labour hiring practices in rural areas. Mazid et al. (2013) presented the increased labour demand of a winter-sown chickpea variety as an employment opportunity for women, who usually carry out weeding operations in the Syrian study area. It is during cropping seasons that hunger most often occurs, so it is especially important that there are employment opportunities for the cash-constrained during that time. To carry out tedious tasks is a necessity rather than an opportunity though, and increased drudgery is hardly something to celebrate. It has been acknowledged that the bulk of heavy farm work can befall the poor as they engage in piecework to satisfy urgent food or cash needs, with the better-off hiring their labour for the most tedious jobs (Fischer and Hajdu 2015). Labour-intensive technologies may contribute to peaks in labour demand, which often involve a movement of poor labourers to the farms of the better-off who offer wages (La Rovere et al. 2008; Natcher et al. 2018). Selling labour can come at the cost of productive tasks on the labourers' own land. Simultaneously, poor labourers are at a disadvantage in making use of casual labour pools themselves (Singh and Jain 1981). Labour-reducing technologies can provide an opportunity to move away from backbreaking production, but can be problematic as well if they displace the labour of those whose livelihoods depend on hiring out their labour (e.g. Beuchelt and Badstue 2013). A study in Malawi for instance showed that better-off farmers using herbicides no longer required the weeding services of the poor, leaving them to go hungry (Bouwman et al. 2020). Hence, labour-saving and labour-requiring technologies can each have unintended negative impacts but also positive impacts, via labour relations and interdependencies among farming households.

Besides labour, other resources are shared, exchanged and competed for in farming systems. Profitable or labour-saving technology can intensify or expand production, which can come at a loss of commons. Ameur et al. (2017) for instance show how agricultural intensification in Morocco increased the demand for groundwater of wealthier, larger farmers, which drove further marginalization of small farmers who lacked capital to gain groundwater access and to deal with the risks of water shortages. Jatropha was introduced in Tamil Nadu as a crop that could respond to water scarcity, but instead led to overexploitation of the open-access water sources by the larger farmers, leading to tensions (Ariza-Montobbio and Lele 2010).

Access to resources beyond the farm can also be required for livestock technologies, for instance when use is made of common grazing land or crop residues on the farms of others. Technology packages such as conservation agriculture recommend that crop residues should be left on the soil surface—leading to a trade-off between residue retention and residues as livestock fodder (Rodriguez et al. 2017). Several simulation studies investigated what this trade-off means at farming system level, when residue retention is advised in mixed crop-livestock systems in Zimbabwe. Baudron et al. (2015) suggested that most equitable simulated outcomes were achieved when 40–60% of cereal residues were retained as mulch and when additional nitrogen inputs were applied, because this increased the proportion of poor farmers becoming better-off, while limiting the proportion of better-off farmers (with more cattle) becoming poor in the long term. Without additional nitrogen, residue retention was not favourable for the better-off and they might as well continue to feed their livestock with crop residues, as also found by Rufino et al. (2011), Pannell et al. (2014), Homann-Kee Tui et al. (2015), and

Rusinamhodzi et al. (2015). The poor with no or few cattle could obtain economic benefits from residue retention, but this required a large labour investment to prevent their residues being grazed by the cattle of the better-off. The poor would need to store the residues off the field in the period of free grazing during the dry season, and then return the residues to the field—or fence their land. From the better-off, no (or less) such investment was required as they could continue with their original practice and feed their livestock with crop residues. The studies conclude with warnings that by restricting access to residues, the poor might lose access to draught power exchange arrangements with cattle owners (Homann-Kee Tui et al. 2015), that the restricted access to residues could lead to reduced feed supply for cattle at the village scale (Rusinamhodzi et al. 2015), and that it may not be possible, cost-effective, or culturally appropriate to claim exclusive rights to crop residues (Pannell et al. 2014). When residue access is not restricted, residue mass and nutrients could concentrate on the farms with large herds (Rufino et al. 2011).

An additional form of competition occurs via markets. It is well-recognized that poor smallholders are constrained in terms of access to in- and out-put markets, due to their small scale of production and limited means of transport (e.g. Laborte et al. 2007). Farmers who sell their wares do not always receive the same prices. Urgent cash needs or limited storage capacity can compel the poor to sell produce when prices are low, while those with a resource buffer can wait for favourable prices and increase their returns to investment. Technologies are evaluated primarily in economic terms, yet the selected studies provided little insight in the variability of prices across household types. As farmers increase production through technology, this can change their competitive position. Michalscheck et al. (2018) collected feedback from farmers about modelled technology options, and some better-off farmers expressed concerns about how the technologies may strengthen the competitive position of poor farms that hitherto were no threat on the market—in spite of model results suggesting that the better-off would have larger absolute benefits. Simões et al. (2020) investigated in a model how increases in milk supply through improved livestock management on small and large farms would play out over time, considering market price changes, production expansion, and subsequent feedback loops through price fluctuations. Their scenarios indicated no impact distributions in which all farmers increased their income—larger farms were quicker to acquire a market share, and pushed smaller farmers out of farming by expanding onto their land and reducing output prices.

5.4 Temporal dimension

When some people benefit more from technology adoption than others, they may continue to do so every subsequent season, which drives social inequality. Another self-reinforcing feedback loop occurs when technology outputs are reinvested in the next season, whether in terms of cash or saved seed. An example of the latter is provided by Fischer and Hajdu (2015), who used open-ended interviews and participant observation to evaluate the long-term effects of the introduction of hybrid and genetically modified maize varieties by the Massive Food Production Programme in South Africa, 3 to 9 years after intervention. The programme had been focused on raising yields, but it was especially difficult for the poor to obtain those yield benefits when they were no longer supplied with inputs. The poorest had difficulty investing seasonally in new hybrid or genetically modified seed, and using saved seed led to reductions in maize yield and quality. Many among the poor resorted to saved seed nonetheless, but faced problems saving sufficient seed due to food scarcity and post-harvest losses due to grain weevil infestations. The better-off were better able to invest in pesticides and store their seed, or invest in new hybrid seed. Although no other studies among the ones selected provided measured evidence of the difficulties of re-investment—the majority of them warned that technology affordability challenged future technology use by the poor.

Some researchers therefore suggest technology packages that are sequentially rather than simultaneously implemented (e.g. Nezomba et al. 2014). In the same vein, the *ladder approach* for agricultural intensification in the Sahel allows some time to acquire the means for additional components (Aune and Bationo 2008). Farmers would start with labour-intensive technologies and then in a stepwise fashion move on to technologies that require increasing capital investment (e.g. fertiliser microdosing, and later higher fertiliser rates and seed densities), towards a more commercially oriented farming enterprise. While the better-off may be able to run up multiple rungs of the ladder at once, the poorer might catch up over time—even if the head start of the better-off is likely to remain in their favour.

The adoption of a new technology is associated with uncertainty. Farmers in general are considered to be risk-averse and out of necessity, poor farmers make short-term, operational decisions about farm management rather than long-term, strategic ones. This relates to the time scale at which benefits appear, and the risks associated with a new production technology. Technology adoption patterns have been shown to be inconsistent over consecutive seasons, as farmers experiment with technologies, adapt them or drop them (Ronner et al. 2018). While such behaviour need not necessarily be associated with wealth, a common, logical assumption is that poor households are more risk-averse than better-off households—considering the differences in their resource buffer (Molla et al. 2020). There is a lack of research, however, on whether and how these dynamic patterns of adoption may differ among the poor and the better-off, and how this may drive impact differentiation.

Several model studies used simulation to explore technology impacts in the future, in various *what if?*-scenarios. Traore et al. (2017) for instance explored the effect of a warmer future climate in Mali—although they assumed temporal dynamics to be the same for poor and better-off farmers (a reduction in maize and millet yields) over time. With improved technologies, all farmers could improve future yields somewhat, but only the better-off had large-enough farms to offset the reduced production induced by the future climate. Hence, climate change made situations more arduous, but the driver of differentiation was the difference in farm sizes. A different approach was taken for instance by Falconnier et al. (2018), who incorporated observed rates of population growth (equal) and rural-to-urban migration (larger for poorer households) in their model. These dynamics meant that over time, the benefits per capita of increased productivity became smaller on large farms (with faster-growing families) than on small farms.

In some cases, the effects of technology use are only seen after some time and they are amplified if used in combination with other technologies, which results in different rates of change for the poor and better-off. Simulations of zero tillage and mulching for instance showed that the technologies only became attractive in terms of income benefits for the poor after 20 years of incremental soil-fertility buildup, and 10 years earlier for better-off farmers who could afford performance-enhancing additional technologies such as herbicides and a seeder (Pannell et al. 2014). This offers another example of how a differentiating driver at field level (quantities and combinations of inputs applied) is reinforced over time.

6 Conclusions

Many agricultural technology interventions have led to positive impacts in poor populations across the world. Inevitably, not everybody benefits: some people are excluded from an intervention or passed by, some people do not have the capacity or interest to adopt a technology, and technologies cannot be beneficial everywhere. Research on agricultural technology interventions has largely focused on comparing adopters and non-adopters—ignoring impact distributions, and seldom investigating drivers of impact differentiation among those who try out a technology. Through a systematic search in peer-reviewed literature, we found only 85 studies that did, among which only 24 were empirical. We are aware that we may have missed relevant publications, such as impact assessments presented in non-peer-reviewed project reports. Yet, we are confident that the paucity of eligible papers is the result of an apparent gap in research rather than the result of our search strategy.

The studies confirmed an expected trend: in absolute terms, the poor derived smaller benefits from technology interventions in agriculture than the better-off. In relative terms, benefits were frequently greater among the poor—primarily as a result of starting out from a lower baseline value. We may celebrate when improvements are achieved in poverty-stricken populations, at the very least because it is better than no improvement. The populations that were included in the reviewed intervention studies were poor by global standards, also the better-off among them. Unequal benefits are not inherently problematic—but limited attention to impact differentiation and its drivers complicates our ability to assess whether unequal impacts are creating rather than addressing problems. We therefore investigated those studies that *do* distinguish impacts among the poor and the better-off, assuming that these would also explain impact distributions. It became clear however that potential drivers of differentiation were primarily mentioned in the discussion of potential impacts rather than with the results of observed impacts. In other words, they were suggested more often than assessed. It seemed that the household categories among whom impact disparities were observed, were also considered the explanation for those impact differences (why do the poor benefit less?—because they are poor).

Existing social inequalities inevitably give some people a head start—they are in a more favourable position to experiment than others. Identifying the poor and the better-off among the intended beneficiaries is a first step towards capturing unequal impacts. A next step is to study what is driving unequal impacts among them specifically—for instance issues of scale, management histories, motivations for resource allocations, competition for resources or prioritised income streams. Ignoring this may thwart a critical assessment of the goodness-of-fit between a technology and heterogeneous intended beneficiaries. It is within the responsibility of the technology design-process to safeguard a good fit between a technology and a target population (Sumberg 2005; Karlsson et al. 2018), and also to recognize it when other development approaches are more relevant to the needs of the poorer (Hellin and Fisher 2018).

The reviewed studies reported on a range of livelihood indicators relating to economic performance, production, risk, and food security. When small impacts were achieved among the poor, it was generally not clear if the change for the participating household was meaningful. Researchers have argued that among the poverty-trapped rural households with tiny landholdings, the role of agricultural technology may at best be sought in improving nutrition (e.g. Hellin and Fisher 2018; Alwang et al. 2019; Gassner et al. 2019), where a small improvement can have a strong impact. Recognizing that the poor can only achieve so much from their own (small) farms, it has been argued that the poor may indirectly benefit from technology use by the better-off, through price changes and employment opportunities (e.g. De Janvry and Sadoulet 2002). But the sword is double-edged—the better-off can also benefit at the expense of the poor due to increased competitiveness and labour displacement.

Changes in social inequalities and potential zero-sum consequences due to interventions may not be captured when a technology is treated as neutral (non-differentiating), and when analyses remain focused at the level of the field and the seemingly isolated household. Households are compared with each other, but interactions and interdependencies at farming system level are rarely considered. Methods of impact assessment in the agricultural sciences prove ill-equipped to identify what drives differentiated impacts, as they are not geared towards capturing the process of change that technologies set in motion. Even if it remains a challenge to identify causal drivers, much insight can be gained when multiple spatial levels and temporal scales are considered, moving from the field to the household, to interactions in a farming system, and over time.

Our review was focused on distributions of impacts among rural households, but it is important to note that impact differentiation can also occur within households, for instance when labour burdens disproportionally befall female household members (Mullins et al. 1996; Doss 2001). The studies identified within the limits of our search considered households mostly as homogeneous units, although a few of the selected studies pointed out that female farmers tended to be poorer than male farmers within each of the recognized welfare classes (Lodin et al. 2014; Van Vugt et al. 2018; Franke et al. 2019). Intra-household and gendered differentiation were beyond the scope of this study, but ostensibly require attention in further research on impact differentiation (Beuchelt 2016; Theis et al. 2018).

It is unlikely or impossible for a single (technology) intervention to realise equitable progress towards Zero Poverty and Zero Hunger among all kinds of farming households. It is therefore important to consider at least the following in the phases of technology development and evaluation: (1) recognize the poorer among the poor, (2) acknowledge unequal impacts, (3) explicitly aim to avoid negative consequences, and (4) include interventions to mitigate against these negative consequences where they occur. We offered a structured overview of factors associated with differentiated impacts at the level of the field, the farm and household, the farming system and over time, to guide future development-oriented research.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s13593-022-00768-6.

Acknowledgements We sincerely thank Bruno Gérard and Fred Kizito for their guidance throughout the study.

Authors' contributions Conceptualisation: EST, HJB, JAA, KD, KEG. Investigation: EST, HJB. Supervision: JAA, KD, KEG, FB, SLR, BV. Writing—original draft: EST. Writing—review and editing: HJB, JAA, KD, KEG, FB, SLR, BV. Funding acquisition: BV, KEG, FB.

Funding This study was funded by the CGIAR Research Program MAIZE (https://maize.org/) and the NWO-WOTRO Strategic Partnership NL-CGIAR.

Data availability Not applicable.

Declarations

Conflict of interests The authors declare no competing interests.

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Disclaimer Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the authors and do not necessarily reflect the view of CRP MAIZE or the institutions the authors are affiliated to.

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